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Analysis of the Factors Influencing the Spatial Distribution of PM2.5 Concentrations (SDG 11.6.2) at the Provincial Scale in China

Jun Li [1,2], Yu Chen [2,3,*] and Fang Chen [2,3]

[1] College of Geomatics and Geoinformation, Guilin University of Technology, Guilin 541006, China; lijunglut@163.com
[2] International Research Center of Big Data for Sustainable Development Goals, Beijing 100094, China; chenfang@radi.ac.cn
[3] Key Laboratory of Digital Earth Science, Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing 100094, China
* Correspondence: chenyu@radi.ac.cn

Abstract: This study investigated the spatiotemporal characteristics and influencing factors of PM2.5 concentrations at the provincial scale in China. The findings indicate significant spatial autocorrelation, with notable high–high agglomerations in East and North China and mixed patterns in the northwest. The spatial Durbin model (SDM) with fixed effects, validated through comprehensive tests, was utilized to analyze data on 31 provincial scale regions from 2000 to 2020, addressing spatial autocorrelation and ensuring model reliability. The research delved into the effects of 21 variables on PM2.5 concentrations, identifying synergistic and trade-off effects among environmental and socioeconomic indicators. Environmental measures like vegetation protection and sulfur dioxide emission reduction correlate with lower PM2.5 levels, whereas economic growth and transport volume often align with increased pollution. The analysis reveals regional variances in these effects, suggesting the need for region-specific policies. The study underscores the intricate relationship between environmental policies, economic development, and air quality, advocating for an integrated approach to air quality improvement. It highlights the necessity of balancing industrial growth with environmental sustainability and suggests targeted, region-specific strategies to combat PM2.5 pollution effectively. This study offers crucial insights for policymakers, emphasizing that enhancing air quality requires comprehensive strategies that encompass environmental, economic, and technological dimensions to foster sustainable development.

Keywords: particulate matter 2.5 (PM2.5); SDG11.6.2; Sustainable Development Goals (SDGs); inverse distance matrix; spatial Durbin model

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Citation: Li, J.; Chen, Y.; Chen, F. Analysis of the Factors Influencing the Spatial Distribution of PM2.5 Concentrations (SDG 11.6.2) at the Provincial Scale in China. *Sustainability* **2024**, *16*, 3394. https://doi.org/10.3390/su16083394

Academic Editor: Ljubomir Jankovic

Received: 3 March 2024
Revised: 13 April 2024
Accepted: 15 April 2024
Published: 18 April 2024

1. Introduction

Particulate matter 2.5 (PM2.5) constitutes a form of inhalable particulate matter pervasive in the atmospheric milieu, exerting a pronounced impact on human health through its association with respiratory, cardiovascular, and even dementia diseases [1–3]. Beyond its health ramifications, PM2.5 adversely affects vegetation growth and soil and water quality, thereby disrupting ecological balance, biodiversity, and contributing to climate change [4], impacting the economic and social development [5]. Consequently, the United Nations has officially designated PM2.5 as a key indicator within the framework of Sustainable Development Goals, specifically identified as SDG 11.6.2 [6].

Over the years, research has primarily focused on the meteorological factors responsible for the formation of PM2.5 [7,8] and its health impacts [3]. However, in recent years, there has been an increasing attention on the influence of socioeconomic factors [9]. Amid ongoing urbanization and industrialization, a combination of socioeconomic factors including industry, transportation, energy consumption, agriculture, combustion, and vegetation collectively influences localized PM2.5 levels [10,11]. Studies show that PM2.5 concentrations, characterized by its spatial attributes, exhibit a distinct degree of spatial heterogeneity [12]. For example, some research findings underscore the exacerbating impact of urbanization on air pollution, with economic urbanization exhibiting a particularly heightened influence on PM2.5 compared to land-based and population-based urbanization [13]. The correlation between China's PM2.5 levels and economic development aligns with the environmental Kuznets curve (EKC) hypothesis, depicting an inverted U-shaped relationship with per capita GDP [14,15]. Furthermore, scholarly investigations reveal that green technological innovation, foreign investment, and expanded green vegetation areas are crucial in reducing PM2.5 concentration in both local and adjacent areas [16,17]. In China, a provincial-scale study indicates that economic activity is still the main factor to promote the increase of PM2.5 emissions, but its effect decreases [18]. Moreover, PM2.5 is influenced not only by various local factors but also by meteorological conditions such as air diffusion, leading to inter-regional air quality impacts and demonstrating a pronounced spatial correlation [19].

Many models have been used to analysis these factors of PM2.5 concentrations, such as the correlation analysis method [12], machine learning method [20], geographical detector [21–23], spatial econometric model (SEM) [24], geographically weighted regression model [25–27], spatial regression model [28], land-use regression model [29], and other models [30]. This study focuses on the spatiotemporal differentiation characteristics of PM2.5 at provincial scale in China and investigates the spatial spillover effect intensity of potential socioeconomic factors affecting PM2.5 concentrations across different provincial units. Among the above models, SEMs are highlighted as key in addressing issues of spatial heterogeneity, spillover effects, and their influencing factors. Scholars have employed the spatial error model (SEM) to study the heterogeneous impact of the secondary industry on PM2.5 [31], and the spatial Durbin model(SDM) to calculate the effect of urbanization on PM2.5 concentrations [32]. Furthermore, SEMs have been utilized to discover that the deployment and usage of natural gas pipelines can effectively mitigate PM2.5 concentrations [33]. Current research primarily employs traditional spatial weight matrices such as contiguity, economic, inverse distance, and nested matrices [34], focusing on the overall calculation of the spatial spillover effect of independent variables on dependent variables, yet lacking a quantitative analysis within regions. Therefore, to quantitatively calculate the spatial spillover effects of PM2.5 and its potential influencing factors among multiple factors and across several provinces in China, this study iteratively reduces the traditional inverse distance matrix, retaining the spatial distance weights between a single region and other regions [35]. Based on the new inverse distance matrix, the study calculates the spatial spillover effect values of multiple indicators between provinces on PM2.5 and conducts an analysis. This refined approach enables a detailed analysis of the spatial spillover effects of PM2.5 and its influencing factors at the provincial scale in China, providing robust support for the governance of air pollution and the promotion of sustainable development practices.

This manuscript is structured as follows. Section 2 details the data and methodology, covering data collection, preprocessing, and the steps to construct the spatial inverse distance matrix, as well as the implementation of Moran's I test and the SDM. Section 3 delves into the empirical findings regarding the spatial spillover effects of PM2.5, and analyses conducted from the perspectives of indicators and provinces. It identifies the directions of the spillover effects of various provinces and influencing factors on PM2.5. We also tried to analyze the reasons for the occurrence of trade-off effects by focusing on the most significant influencing factors and provinces with apparent spillover effects. In Section 4, we summarize the experimental results and discuss their limitations. Additionally, some policy recommendations are proposed.

2. Data and Methods

2.1. Data Selection and Preprocessing

This study utilized statistical panel data from 2000 to 2020, covering 31 provincial-scale administrative regions in China (excluding Hong Kong, Macao, and Taiwan). The data originate from several authoritative sources, including the *National Statistical Yearbook*, *China Environmental Statistical Yearbook*, *China Energy Statistical Yearbook*, and information from the Ministry of Civil Affairs of the People's Republic of China. In this study, the concentration of PM2.5 (SDG 11.6.2) was selected as the dependent variable. To identify the factors influencing PM2.5 levels, we meticulously selected a suite of explanatory variables based on their potential impact. This selection process was informed by a thorough review of relevant literature and the invaluable insights of experts in the field. Our methodical approach ensured the inclusion of the most pertinent factors affecting PM2.5 concentrations, establishing a robust foundation for further analysis. Due to the accessibility of the data, the variables we have selected, while not fully aligned with the specific nuances of the official United Nations SDG indicators, can to a certain extent represent the corresponding SDG indicators or targets. Consequently, we annotated each variable with the SDG indicators it supports. We ultimately selected 21 explanatory variables, with Table 1 presenting a detailed list of these indicators. In this table, a positive designation in the Direction column signifies advancement towards a more sustainable world, while a negative designation implies a trajectory that is antithetical to the attainment of sustainable development goals. For example, an increased "industrial water reuse rate" denotes a positive shift towards sustainability, thus the direction for this indicator is deemed positive. In contrast, a higher concentration of PM2.5 is detrimental to progressing towards a sustainable world; hence, the direction for this indicator is considered negative.

Table 1. Meaning of variables.

Variables	Indicator/Target	Indicator/Target Short Name	Indicator Construction Method	Direction
Explained variable	SDG11.6.2	Concentration of PM2.5	Concentration of PM2.5	Negative
Explanatory variables	SDG6.3	Water quality	Industrial water reuse rate	Positive
	SDG6.4.1	Water-use efficiency	(total GDP/total water consumption + industrial GDP/industrial water consumption)/2	Positive
	SDG6.4.2	Water stress	Total water consumption/total water resources	Negative
	SDG6.6	Water-related ecosystems	Nature reserve area	Positive
	SDG6.a	Wastewater treatment, recycling and reuse	Investment in wastewater treatment project	Positive
	SDG7.1.2	Reliance on clean energy	Gas penetration rate	Positive
	SDG7.3.1	Energy intensity	Electricity consumption per 10,000 yuan of GDP	Negative
	SDG8.1.1	Real GDP per capita growth rate	Per capita GDP growth rate	Positive
	SDG9.1.2	Passenger and freight volume	Average freight volume and passenger volume	Positive
	SDG9.2.1	Manufacturing value added	Secondary industry value added/GDP	Positive
	SDG9.4	Sustainable and clean industries	Carbon dioxide emissions	Negative
	SDG9.b.1	Medium and high-tech industry value added	Tertiary industry value added/GDP	Positive
	SDG11.2.1	Convenient access to public transport	Number of buses per 10,000 people	Positive
	SDG11.3.1	Land consumption	Urban built-up area growth rate/population growth rate	Negative
	SDG11.6.1	Municipal solid waste	Per capita solid waste generation	Negative
	SDG11.7.1	Open space for public use	Per capita park green space area	Positive
	SDG12.2.1	Material footprint	Per capita sulfur dioxide emissions	Negative
	SDG12.5.1	National recycling rate	Comprehensive utilization rate of industrial solid waste	Positive
	SDG15.1.1	Forest area	Forest coverage rate	Positive
	SDG15.2	Sustainable forests management	Artificial afforestation area	Positive
	SDG15.4	Conservation of mountain ecosystems	Proportion of protected areas to jurisdiction area	Positive

For the incomplete portions of the data, which do not exceed 5% for any given year, linear interpolation was employed to fill in the gaps [36]. Furthermore, to mitigate the effects of different dimensions of statistical data and outliers on the results, the original data were subjected to min-max normalization after trimming the extreme values at the 2.5% level [37]. Additionally, the direction of the negative indicator was adjusted to facilitate the analysis of the experimental result, as detailed in Formulas (1) and (2). Table 2 presents the descriptive analysis results of the normalized data, including the number of observations, mean, and standard deviation. Among the 22 variables, SDG 15.4 (protecting mountain ecology) exhibits the largest standard deviation of 29.52, while SDG 11.3.1 (land consumption) has the lowest standard deviation of 15.87. Generally, the normalized variable data show minimal fluctuation.

Table 2. Descriptive analysis of variables and VIF of explanatory variables.

Variable	Sample Size	Mean	Std	VIF
SDG11.6.2	651	49.05	22.8	/
SDG6.3	651	71.31	29.5	2.25
SDG6.4.1	651	20.33	22.79	2.34
SDG6.4.2	651	88.2	20.13	2.49
SDG6.6	651	11.24	20.95	3.13
SDG6.a	651	26.34	23.98	2.04
SDG7.1.2	651	72.71	27.86	3.19
SDG7.3.1	651	75.28	22.6	2.67
SDG8.1.1	651	45.94	23.93	1.49
SDG9.1.2	651	38.79	25.16	2.45
SDG9.2.1	651	64.4	24.55	5.19
SDG9.4	651	66.99	26.95	3.42
SDG9.b.1	651	29.62	21.7	5.76
SDG11.2.1	651	34.69	20.37	2.6
SDG11.3.1	651	36.59	15.87	1.08
SDG11.6.1	651	81.57	21.68	2.59
SDG11.7.1	651	25.51	22.32	2.94
SDG12.2.1	651	71.38	22.62	3.2
SDG12.5.1	651	61.02	24.39	1.31
SDG15.1.1	651	13.53	18.53	2.15
SDG15.2	651	27.93	25.56	1.64
SDG15.4	651	44.08	29.52	2.54

The forward normalization formula used was:

$$X' = \frac{(X - X_{min})}{(X_{max} - X_{min})} \times 100 \quad (1)$$

The inverse normalization formula used was:

$$X' = \frac{(X_{max} - X)}{(X_{max} - X_{min})} \times 100 \quad (2)$$

In (1) and (2), X is original data of any given variable, X_{max} and X_{min} represent the 2.5% maximum and 2.5% minimum value of the variable. X' is the normalized result of X.

To assess whether there is a multicollinearity problem between variable data, which would interfere with the experimental results, this study calculated the variance inflation factor (*VIF*) for each variable.

$$VIF = \frac{1}{(1 - R^2)} \quad (3)$$

In Formula (3), R^2 represents the correlation coefficient between this variable and other independent variables [38]. *VIF* can quantify how much the variance of an independent variable is inflated due to its correlation with other independent variables [38]. A *VIF* value of 10 or greater typically indicates significant multicollinearity among variables [38,39]. Table 2 presents the *VIF* of each variable studied in the last column, with the maximum value recorded at 5.76. This suggests that there is no significant multicollinearity among the variables selected for this experiment.

2.2. Method

2.2.1. Spatial Moran Index

The multi-year local Moran index can be used to assess the presence of spatial autocorrelation and to detect changes in its autocorrelation state over time [40,41]. For the *i*-th region, the local Moran index I_i is defined as follows:

$$I_i = \frac{x_i - \overline{x}}{S^2} \sum_{j=1}^{n} w_{ij} \left(x_j - \overline{x} \right), \text{ and } i \neq j \tag{4}$$

$$S^2 = \frac{1}{n} \sum_{i=1}^{n} \left(x_i - \overline{x} \right)^2 \tag{5}$$

In Formulas (4) and (5), n represents the total number of spatial regions of the research variable, x_i represents the variable value of the *i*-th region, x_j represents the variable value of the *j*-th region, $\overline{x}$ represents the average value of all variable values, w_{ij} is the spatial weight matrix, and S^2 represents the sample variance.

When $I_i > 0$, it indicates the presence of positive spatial correlation, typically manifested as either a high–high agglomeration (areas with high values surrounded by areas with high values) or a low–low agglomeration (areas with low values surrounded by areas with low values); conversely, when $I_i < 0$, it indicates negative spatial correlation, which is manifested as either a low–high agglomeration (areas with low values are surrounded by areas with high values) or a high–low agglomeration (areas with high values are surrounded by areas with low values).

2.2.2. Spatial Econometric Models (SEMs)

This study used SEMs to study spatial spillover effects. The currently popular SEMs include the spatial Durbin model (SDM), spatial lag model (SLM), and spatial error model (SEM), et al. The SDM studies the variable relationship between adjacent observation areas by processing spatially weighted spatial panel data. The formula of the SDM model is as follows [42,43]:

$$\mathrm{y} = \lambda \mathrm{Wy} + \mathrm{X}\beta + \mathrm{WX}\delta + \varepsilon \tag{6}$$

In (6), y is the explained variable, X represents the explanatory variable, W is the spatial weight matrix, and λ is the spatial regression coefficient for the dependent variable, quantifying the influence of neighboring values of (y). β represents the regression coefficient of the independent variable within the region, reflecting how changes in (X) influence (y) locally. δ is the spatial regression coefficient of the independent variable, capturing the impact of neighboring values of (X) on (y). ε represents the error term; λWy represents the influence of dependent variables from adjacent areas. Xβ represents the influence of independent variables in this area, WXδ represents the influence of independent variables from adjacent areas. When $\lambda \neq 0, \beta \neq 0, \delta = 0$, the model is identified as SLM; when $\lambda = 0, \beta \neq 0, \ \delta \neq 0$, it is classified as SEM [43].

The spatial weight matrix plays an important role in spatial econometric models, particularly in studying spatial spillover effects. Typical spatial weight matrices include proximity matrix, inverse distance matrix, economic matrix, and nested (economic, distance) matrix. Due to the significant distance-related characteristics of PM2.5 spatial overflow, this study adopted an inverse distance weight matrix. Additionally, to capture the differentiated spatial distribution characteristics of PM2.5 across various provincial scale regions, 31 inverse distance weight matrices were constructed for the 31 provincial administrative units in the study. Each matrix was uniquely modified to focus solely on the spatial relationships between a given area (i) and other areas, ensuring that weights between non-focal areas were zero [35]. This modification was crucial for accurately calculating the spatial overflow relationships between area (i) and other areas, as detailed in Formula (7).

$$W_{ij} = \begin{Bmatrix} 0 & \cdots & w_{1i} & \cdots & 0 \\ \cdots & & \cdots & & \cdots \\ w_{i1} & \cdots & 0 & \cdots & w_{in} \\ \cdots & & \cdots & & \cdots \\ 0 & \cdots & w_{ni} & \cdots & 0 \end{Bmatrix} \tag{7}$$

2.3. Model Validity Test

2.3.1. Lagrange Multiplier Test

The Lagrange multiplier test (LM test) is used to determine the presence of spatial autocorrelation in the data, which informs the applicability of spatial econometric models. The test operates under the null hypothesis that there is no serial correlation in the data residual, versus the alternative hypothesis of p-order autocorrelation [44]. When the significance level value of the statistic is less than 0.05, the null hypothesis should be rejected. indicating autocorrelation and the suitability of SEMs. Conversely, acceptance of the null hypothesis suggests an absence of autocorrelation, and SEMs are not recommended. Formula (8) calculates the LM test statistic, where T represents the time period, $\overline{R}_u^2$ is the goodness of fit for the model with explanatory variables, and $\overline{R}_{ur}^2$ includes both explanatory variables and individual random effects. The LM test was used in this study to preliminarily determine the suitability of the data for spatial econometric modeling.

$$LM = T \times \left(\overline{R}_u^2 - \overline{R}_{ur}^2\right) \tag{8}$$

2.3.2. Hausman Test

The Hausman test is employed to evaluate and compare the estimation results of two distinct models, characterized by either fixed or random parameters. The foundational null hypothesis posits that both the random effects model and the fixed effects model yield consistent estimates concerning the systematic error term, indicating an absence of systematic difference in their parameter estimates [45]. When the significance level attains a value of $p < 0.05$ or $p < 0$ [46], the null hypothesis is consequently rejected, prompting the adoption of fixed effects in the model. Otherwise, the null hypothesis is accepted and random effects are used. The Hausman statistic, calculated as Formula (9), where $\hat{\beta}_{\mathrm{RE}}$ and $\hat{\beta}_{\mathrm{FE}}$ represent the estimated outcomes of the random effects model and the fixed effects model, respectively, guides the decision on whether to adopt fixed or random effects in the model. This methodology was integral to this study's approach to model selection between fixed and random effects.

$$\mathrm{H} = \left(\hat{\beta}_{\mathrm{RE}} - \hat{\beta}_{\mathrm{FE}}\right)' \left[\mathrm{Var}\left(\hat{\beta}_{\mathrm{RE}} - \hat{\beta}_{\mathrm{FE}}\right)\right] - 1\left(\hat{\beta}_{\mathrm{RE}} - \hat{\beta}_{\mathrm{FE}}\right) \tag{9}$$

2.3.3. Likelihood Ratio Test

The likelihood ratio test (LR test) is a statistical test method commonly used to compare the adequacy of two models under different constraints. The null hypothesis asserts estimated likelihood function values from the unconstrained and constrained models are substantially equivalent [47]. When the significance value of $p < 0.05$ is achieved, preference is given to the constrained model; otherwise the unconstrained model is favored. In this study, the LR test was applied to assess the efficacy of model selection involving individual, time, and dual fixed effects, as well as to determine whether SDM would reduce to SLM and SEM.

3. Results and Analysis

3.1. PM2.5 Spatial Aggregation Characteristics

Figure 1 presents the local Moran indicators of spatial association index (LISA) for PM2.5 concentrations in the years 2005, 2010, 2015, and 2020, demonstrating significant spatial autocorrelation. Notably, regions of high–high agglomeration are predominantly observed in East and North China, whereas both low–low and high–low agglomerations are prevalent in the northwest. These observations highlight the persistent nature of PM2.5 spatial agglomeration throughout the specified period, emphasizing the stable spatial relationships of PM2.5 concentrations across different regions.

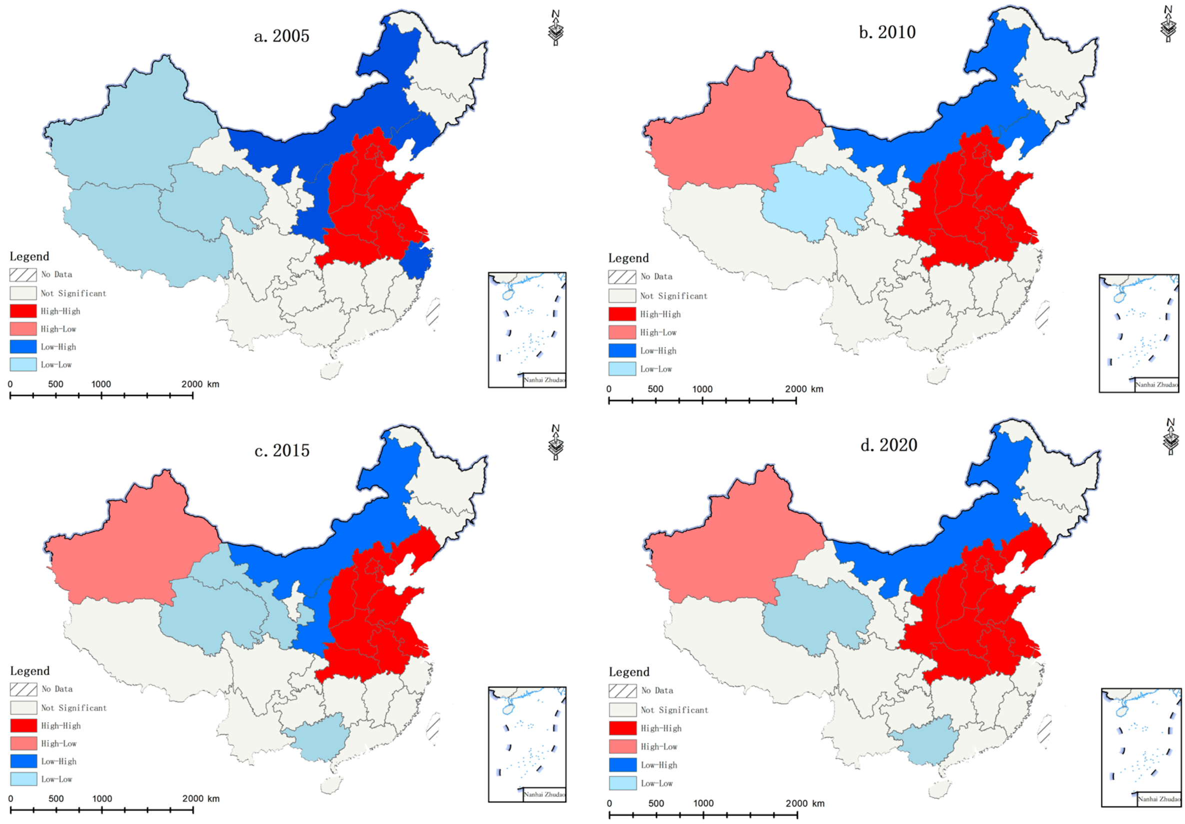

Figure 1. Local Moran LISA, (**a**) 2005 (**b**) 2010 (**c**) 2015 (**d**) 2020.

3.2. Determination of Spatial Econometric Model

Table 3 presents the detailed model validity test results obtained using 31 spatial inverse distance matrices. The significance levels (P values) are provided in parentheses. Notably, the LM test or robust LM test rejected the null hypothesis at the 5% significance level, indicating that there was spatial autocorrelation between variables [48], so the spatial econometric model could be used for preliminary judgment. The results of the Hausman test all rejected the null hypothesis at the 5% significance level, proving that the model had better results when using fixed effects, so the spatial econometric model used fixed effects. The LR test also rejected the null hypothesis at the 5% significance level, confirming that SDM would not degenerate into SLM and SEM, so SDM was selected in this study.

The panel data constructed for this study had a temporal dimension of 20 years and a cross-sectional dimension covering 31 provincial scale regions, which was a short panel [49]. Therefore, it was challenging to ascertain the presence of autocorrelation within the random disturbance terms associated with reaction time effects. Consequently, these terms were assumed to be independent and identically distributed, and the SDM was employed using individual effects to achieve better results [50]. To confirm the validity of this assumption, the LR test was utilized to compare the model fit of individual fixed effects against dual fixed effects (individual and time). The results indicated that the model employing individual fixed effects demonstrated superior performance compared to the dual fixed effects (Table 4). Accordingly, this study adopted SDM with individual fixed effects.

Table 3. Model validity test results.

Province \ Test	LM Spatial Error	Robust LM Spatial Error	LM Spatial Lag	Robust LM Spatial Lag	Hausman	LR Test SDM SLM	LR Test SDM SEM
Anhui	35.59 (0)	2.97 (0.085)	53.78 (0)	21.16 (0)	−20.33 (<0)	108.95 (0)	119.55 (0)
Beijing	130.1 (0)	5.19 (0.023)	129.1 (0)	4.153 (0.042)	−38.99 (<0)	179.32 (0)	185.72 (0)
Fujian	30.84 (0)	28.55 (0)	16.61 (0)	14.31 (0)	−40.26 (<0)	205.12 (0)	178.81 (0)
Gansu	8.67 (0.003)	0.002 (0.964)	11.49 (0.001)	2.82 (0.093)	47.79 (0.0012)	259.18 (0)	275.79 (0)
Guangdong	17.58 (0)	13.39 (0)	41.21 (0)	37.01 (0)	−23.14 (<0)	169.32 (0)	152.95 (0)
Guangxi	26.7 (0)	5.556 (0.018)	44.99 (0)	23.85 (0)	−21.91 (<0)	172.3 (0)	156.6 (0)
Guizhou	30.56 (0)	0.434 (0.51)	32.59 (0)	2.466 (0.116)	−21.89 (<0)	141.77 (0)	143.17 (0)
Hainan	2.095 (0.148)	33.24 (0)	13.48 (0)	44.63 (0)	47.02 (0.0015)	244.74 (0)	271.82 (0)
Hebei	61.67 (0)	4.896 (0.027)	94.07 (0)	37.3 (0)	−12.15 (<0)	75.54 (0)	73.04 (0)
Henan	77.66 (0)	33.66 (0)	51.33 (0)	7.327 (0.007)	−31.44 (<0)	152.49 (0)	153.59 (0)
Heilong jiang	0.858 (0.354)	20.93 (0)	0.512 (0)	20.58 (0)	−10.06 (<0)	348 (0)	347.89 (0)
Hubei	49.29 (0)	0.002 (0.967)	58.2 (0)	8.912 (0.003)	−17.71 (<0)	134.09 (0)	127.02 (0)
Hunan	25.78 (0)	7.512 (0.006)	49.39 (0)	31.12 (0)	−23.9 (<0)	147.37 (0)	137.21 (0)
Jilin	1.135 (0.287)	46.77 (0)	25.01 (0)	70.65 (0)	−26.48 (<0)	211.54 (0)	306.08 (0)
Jiangsu	38.12 (0)	10.23 (0.001)	66.81 (0)	38.91 (0)	−18.8 (<0)	134.71 (0)	158.67 (0)
Jiangxi	13.9 (0)	56.81 (0)	45.23 (0)	88.14 (0)	−95.63 (<0)	139.38 (0)	125.57 (0)
Liaoning	6.818 (0.009)	22.33 (0)	30.57 (0)	46.08 (0)	−13.16 (<0)	212.74 (0)	262.84 (0)
Nei Mongol	3.34 (0.068)	32.43 (0)	2.261 (0)	31.35 (0)	−127 (<0)	327.52 (0)	400.1 (0)
Ningxia	3.412 (0.065)	9.97 (0.002)	10.93 (0.001)	17.48 (0)	139.2 (0)	348.65 (0)	354.94 (0)
Qinghai	0.253 (0.615)	5.656 (0.017)	1.233 (0.267)	6.635 (0.01)	−115.8 (<0)	399.63 (0)	297.6 (0)
Shandong	48.25 (0)	0.385 (0.535)	63.57 (0)	15.71 (0)	−14.32 (<0)	181.13 (0)	185.45 (0)
Shanxi	7.794 (0.005)	13.34 (0)	26.94 (0)	32.49 (0)	−25.56 (<0)	266.21 (0)	241.61 (0)
Shaanxi	3.262 (0.071)	6.538 (0.011)	13.11 (0)	16.38 (0)	−19.79 (<0)	260.29 (0)	298.36 (0)
Shanghai	61.19 (0)	2.269 (0.132)	59.81 (0)	0.889 (0.346)	−3.69 (<0)	281.47 (0)	274.72 (0)
Sichuan	3.166 (0.075)	5.585 (0.018)	11.24 (0.001)	13.66 (0)	−23.54 (<0)	220.31 (0)	236.99 (0)
Tianjing	22.55 (0)	5.728 (0.017)	47.96 (0)	31.14 (0)	−6.8 (<0)	119.37 (0)	129.15 (0)
Xizang	0.046 (0.029)	0.258 (0.611)	0.002 (0.063)	0.214 (0.644)	−229.9 (<0)	461.58 (0)	403.97 (0)
Xinjiang	2.289 (0.13)	23.06 (0)	0.891 (0)	21.66 (0)	41.68 (0.00680)	357.28 (0)	337.12 (0)
Yunnan	27.66 (0)	31.57 (0)	9.418 (0)	13.33 (0)	2.93 (1)	275.63 (0)	286.55 (0)
Zhejiang	47.91 (0)	0.194 (0.66)	49.53 (0)	1.812 (0.178)	−45.64 (<0)	130.13 (0)	125.76 (0)
Chongqing	28.18 (0)	9.984 (0.002)	53.19 (0)	34.99 (0)	−21.85 (<0)	172.61 (0)	147.2 (0)

Note: The p value is in parentheses.

Table 4. Model goodness of fit for individual and dual fixed effects.

Province	Ind	Both
Anhui	0.6679	0.0068
Beijing	0.7036	\
Fujian	0.6849	0.0537
Gansu	0.6958	0.0276
Guangdong	0.6868	0.1608
Guangxi	0.6925	0.0071
Guizhou	0.6942	0.0508
Hainan	0.6209	0.1727
Hebei	0.6905	0.3943
Henan	0.6695	0.0162
Heilong jiang	0.6772	0.1642
Hubei	0.6819	0.3182
Hunan	0.6963	0.1046
Jilin	0.5696	0.021
Jiangsu	0.6918	0.0856
Jiangxi	0.685	0.0357
Liaoning	0.6835	0.3069
Nei Mongol	0.6836	0.0225
Ningxia	0.6991	0.1531
Qinghai	0.6991	0.0012
Shandong	0.6972	0.4073
Shanxi	0.6857	0.2835
Shaanxi	0.6974	0.1732
Shanghai	0.694	\
Sichuan	0.6966	0.03
Tianjing	0.6845	0.3102
Xizang	0.7141	\
Xinjiang	0.6944	0.2579
Yunnan	0.6987	0.0002
Zhejiang	0.6866	0.15
Chongqing	0.6944	0.0034

Note: \ indicates that the model has no goodness of fit.

3.3. Analysis of the Factors Influencing the Spatial Distribution of PM2.5

The direct, indirect, and total effects of 21 independent variable indicators on the dependent variable SDG11.6.2 (concentration of PM2.5) across provincial scale administrative regions in China are shown in Supplementary Figures S1–S21. In the subsequent section, the analysis of the results from the perspectives of both indicators involved and provincial scale regions will be detailed.

3.3.1. Analysis of the Results from the Perspectives of Relevant Indicators Involved

The majority of the results were consistent with the conclusions of previous studies or traditional understanding. For example, the indicators SDG11.7.1 (open space for public use, Figure S16a), SDG15.1.1 (forest area, Figure S19a) and SDG6.6 (water-related ecosystems, Figure S4a) exhibited a synergistic relationship on the direct effect with SDG11.6.2 (concentration of PM2.5) in almost all the regions, suggesting that enhancing the vegetation protection and afforestation can reduce the PM2.5 concentrations for the local areas. The indicators SDG8.1.1 (real GDP per capita growth rate, Figure S8a) and SDG9.1.2 (passenger and freight volume, Figure S9a) exhibited a trade-off relationship on the direct effect with SDG11.6.2 (concentration of PM2.5) in some regions, suggesting that the economic growth and social development of these areas might have negatively impacted on the air quality of these local regions (such as Nei Mongol, Jilin, Hubei, Anhui Sichuan, and Guangxi Province). For SDG6.4.1 (water-use efficiency), some of the regions except Jilin Province exhibited a synergistic relationship on the indirect and total effect (Figure S2b,c) with SDG11.6.2 (concentration of PM2.5), suggesting that improving water use efficiency of local and surrounding areas had contributed to the improvement of air quality for these areas. Similarly, for SDG12.2.1 (material footprint), Beijing and its surrounding areas displayed a synergistic relationship on the indirect and total effect (Figure S17b,c) with SDG11.6.2 (concentration of PM2.5), suggesting that reducing sulfur dioxide emissions of local and surrounding areas had also contributed to the improvement of air quality for these areas.

Additionally, some indicators exhibited varying spatial interrelationships with SDG 11.6.2 (concentration of PM2.5) across different geographical regions. For example, SDG9.1.2 (passenger and freight volume) demonstrated a synergistic effect in both the indirect and overall impact with SDG11.6.2 (concentration of PM2.5) within some southern regions of China, yet manifested a trade-off relationship in some northern regions, including Nei Mongol, Xinjiang, and Tianjin (Figure S9b,c). This divergence may be attributed to the accelerated adoption of new energy vehicles within the passenger and freight sectors in the southern provinces compared to the northern provinces. Such discrepancies could potentially result in a spillover effect, adversely impacting the air quality of the northern regions and their surrounding areas. Therefore, intensifying the promotion of new energy vehicles is essential to realize their potential impact on reducing PM2.5 levels [51]. SDG12.5.1 (national recycling rate) displayed a synergistic effect in both the indirect and overall impact with SDG11.6.2 (concentration of PM2.5) in Sichuan and Nei Mongol, yet manifested a trade-off relationship in Beijing, Tianjin, Hebei, Jiangsu, Henan, and Chongqing (Figure S18b,c). The data used in this study to measure SDG12.5.1 were the comprehensive utilization rates of industrial solid waste, which primarily impacts soil, water, and air quality. This trade-off relationship observed in several economically advanced regions such as Beijing, Tianjin, Jiangsu, Chongqing suggests that the off-site recycling and processing of industrial solid waste can still impact the environmental quality of these areas, owing to spatial spiller over. Enhanced recycling and processing technologies for industrial solid waste are crucial to mitigate further negative impacts. Inappropriate waste disposal methods, such as direct incineration, exacerbate air pollution [52,53]. Table 5 presents the average coefficients of direct, indirect, and total effects of 21 indicators on SDG 11.6.2 (concentration of PM2.5) in all provincial scale regions. From the analysis of average indirect and total effect coefficients, some indicators exhibited significant synergistic effects (an average effect value greater than 1.00), including SDG 15.4 (conservation of mountain ecosystems), SDG 9.4 (sustainable & clean industries), and SDG 6.3 (water quality), and some indicators displayed slightly synergistic effects (an average effect value greater than 0 and less than 1.00), including SDG 6.4.1 (water-use efficiency), SDG6.a (wastewater treatment, recycling, and reuse), SDG7.1.2 (reliance on clean energy), SDG9.1.2 (passenger and freight volume), SDG11.6.1 (municipal solid waste), SDG11.7.1 (open space for public use), SDG12.2.1 (material footprint) and SDG15.1.1 (forest area). Most of these indicators are directly related to the environment, indicating that improvement of natural environment-related indicators can promote the quality of the air environment in the local and surrounding regions. Conversely, indicators showing a trade-off on average indirect and total effect coefficients including SDG6.4.2 (water stress), SDG6.6 (water-related ecosystems), SDG 7.3.1 (energy intensity), SDG 9.2.1 (manufacturing value added), SDG9.b.1 (medium and high-tech industry value added), SDG11.2.1 (convenient access to public transport), SDG 11.3.1 (land consumption), SDG 12.5.1 (national recycling rate), and SDG15.2 (sustainable forests management) are mostly social and economic related indicators. This suggests that the enhancement of socioeconomic-related indicators may, to a certain extent, be achieved at the detriment of air quality in the region and its surrounding areas, an issue that warrants close attention in future development initiatives. Regarding the average direct effect, 11 of the 21 indicators exhibited an insignificant impact on SDG 11.6.2 (concentration of PM2.5) in all provincial-scale regions. The reason for this phenomenon can be attributed to the complexity of the factors influencing PM2.5 concentrations. Despite the potential impact of the 21 indicators selected for this study on PM2.5 concentrations, the variability across different regions—owing to disparities in socioeconomic development and natural resource allocations—necessitates a more granular analysis. This is further compounded by the intricate interplay of regional policy effects, underscoring the need for a broader array of sample sizes. The observational data's limitations, encompassing a 21-year span from 2000 to 2020 for each region, hinder the ability to conclusively ascertain the influence of each indicator. In contrast, when considering the indirect and total effects, the number of observed indicators escalated to 651, due to the inclusion of elements from neighboring areas, thereby unearthing certain significant correlations.

Table 5. Average coefficients of direct, indirect, and total effects of 21 indicators on SDG 11.6.2 (concentration of PM2.5) in all provincial-scale regions.

Indicator	Average of Direct Effect	Average of Indirect Effect	Average of Total Effect
SDG6.3	−0.0731	1.0892	1.0800
SDG6.4.1	\	0.9863	0.8947
SDG6.4.2	\	−0.6270	−0.6630
SDG6.6	0.3213	−5.3188	−4.2059
SDG6.a	\	0.1396	0.1403
SDG7.1.2	\	0.1607	0.0918
SDG7.3.1	0.0858	−0.2974	−0.1009
SDG8.1.1	−0.0338	0.0463	−0.0306
SDG9.1.2	−0.0419	0.1926	0.1813
SDG9.2.1	0.1119	−0.9859	−0.8227
SDG9.4	\	1.3328	1.4353
SDG9.b.1	0.1338	−0.2971	−0.1134
SDG11.2.1	\	−0.5387	−0.5223
SDG11.3.1	\	0.1655	0.1705
SDG11.6.1	\	0.6828	0.8798
SDG11.7.1	0.0922	−0.0290	0.2980
SDG12.2.1	\	0.4358	0.7830
SDG12.5.1	\	−0.5060	−0.5488
SDG15.1.1	0.2703	0.0870	0.6032
SDG15.2	\	−0.1080	−0.0715
SDG15.4	−0.2630	3.5340	3.3798

Note: \ means the result is not significant.

3.3.2. Analysis of the Results from the Provincial-Scale Regions

Table 6 presents the maximal, minimal, and average coefficients of the 21 indicators for their direct, indirect, and total effects on SDG 11.6.2 (concentration of PM2.5) across all provincial-level regions of China. Figure 2 also presents these average values in map form. The results reveal that all 31 observed provincial-scale regions demonstrated a synergistic effect on the average direct effect, which suggests that holistic enhancement of various indicators has had a positive impact on the improvement of PM2.5 in all the local region. This indicates that the policies and measures implemented by the Chinese government have generally played a positive role in reducing PM2.5 levels. Particularly noteworthy is the government's promulgation in 2011 of the "*Weight Method for the Determination of PM10 and PM2.5 in Ambient Air*", marking a significant step forward in environmental regulation. Subsequently, a series of policy documents has been issued to provide guidance to local governments on air quality management. These include the "*Technical Specification for the Installation and Acceptance of Continuous Automatic Ambient Air Particulate Matter (PM10 and PM2.5) Monitoring Systems*" in 2013, the "*Technical Guidance for the Development of Primary Source Emission Inventories of Atmospheric Respirable Particulates (Trial)*" in 2014, and the "*Technical Requirements and Test Methods for Continuous Monitoring Systems for Flue Gas (SO_2, NOX, Particulate Matter) Emissions from Stationary Sources*" in 2018. These initiatives demonstrate a comprehensive approach to controlling air pollution and underscore the proactive stance of the Chinese government in enhancing air quality. This aligns with the overarching conclusions drawn from previous research [54,55].

Table 6. The maximal, minimal, and average coefficients of the 21 indicators for their direct, indirect, and total effects on SDG 11.6.2 (concentration of PM2.5) across all provincial-level regions of China.

Province	Maximum			Minimum			Average		
	Indicator	Value	Effect Type	Indicator	Value	Effect Type	Direct Effect	Indirect Effect	Total Effect
Anhui	SDG15.1.1	0.29	Direct	SDG6.3	−0.0669	Direct	0.0707	/	/
Beijing	SDG12.2.1	1.328	Total	SDG7.3.1	−2.647	Indirect	0.0910	−0.2538	−0.1874
Fujian	SDG6.4.1	1.312	Total	SDG9.2.1	−1.03	Indirect	0.1304	0.5430	0.5670
Gansu	SDG6.4.1	0.71	Indirect	SDG9.2.1	−1.209	Indirect	0.0767	−0.0989	−0.0974
Guangdong	SDG15.1.1	0.264	Direct	SDG11.6.1	−1.623	Indirect	0.0727	−1.0108	−1.0018
Guangxi	SDG11.6.1	1.715	Total	SDG6.4.2	−3.292	Indirect	0.0937	−0.4343	−0.4075
Guizhou	SDG9.4	2.235	Indirect	SDG9.2.1	−0.769	Indirect	0.1061	0.3004	0.3190
Hainan	SDG9.4	2.365	Total	SDG15.1.1	−1.66	Indirect	0.0806	0.7784	0.9211
Hebei	SDG15.4	8.056	Indirect	SDG6.6	−10.63	Indirect	0.0714	−0.6027	−0.6017
Henan	SDG15.4	12.4	Indirect	SDG6.6	−15.29	Indirect	0.0912	−0.2632	−0.2365
Heilongjiang	SDG6.4.1	1.182	Indirect	SDG7.3.1	−1.866	Indirect	0.1111	−0.4598	−0.5265
Hubei	SDG11.6.1	2.146	Total	SDG6.3	−1.936	Total	0.0611	−0.0138	−0.0194
Hunan	SDG9.4	2.633	Total	SDG15.1.1	−1.115	Indirect	0.0784	0.2058	2.6330
Jilin	SDG6.6	8.23	Total	SDG6.4.2	−2.43	Total	0.1114	0.8340	0.9050
Jiangsu	SDG15.4	3.477	Indirect	SDG12.5.1	−0.573	Indirect	0.0757	0.5461	0.1183
Jiangxi	SDG6.6	0.351	Direct	SDG15.4	−3.551	Total	0.1140	−1.6323	−3.5510
Liaoning	SDG6.3	2.166	Indirect	SDG11.2.1	−0.85	Indirect	0.0836	0.6100	0.6020
Nei mongol	SDG15.1.1	2.932	Total	SDG9.b.1	−0.788	Total	0.0573	0.4350	0.5924
Ningxia	SDG7.3.1	0.654	Total	SDG15.2	−0.249	Direct	0.0646	0.2322	0.3098
Qinghai	SDG6.6	1.248	Total	SDG15.1.1	−2.026	Indirect	0.0799	−0.6404	−0.5391
Shandong	SDG6.3	5.409	Indirect	SDG6.6	−11.28	Indirect	0.1233	−0.6105	−0.5888
Shanxi	SDG9.4	1.903	Total	SDG9.2.1	−0.774	Indirect	0.1509	0.4583	0.7027
Shaanxi	SDG7.3.1	0.939	Total	SDG15.1.1	−1.198	Indirect	0.1302	−0.0475	0.1953
Shanghai	SDG6.3	7.424	Indirect	SDG11.2.1	−0.174	Indirect	0.1457	1.5297	1.7957
Sichuan	SDG7.3.1	1.5	Total	SDG9.2.1	−1.227	Indirect	0.0838	0.1375	0.1884
Tianjing	SDG6.3	1.568	Indirect	SDG6.4.1	−0.304	Total	0.0714	0.3426	0.3526
Xizang	SDG15.4	4.412	Indirect	SDG6.6	−3.52	Indirect	0.0942	0.1934	0.2478
Xinjiang	SDG9.4	1.142	Indirect	SDG9.b.1	−0.471	Indirect	0.0651	0.0413	0.3476
Yunnan	SDG9.4	1.42	Indirect	SDG11.2.1	−0.942	Indirect	0.1043	0.5568	0.4674
Zhejiang	SDG6.4.1	0.873	Indirect	SDG11.7.1	−0.476	Indirect	0.1115	0.3098	0.5063
Chongqing	SDG6.4.1	0.913	Indirect	SDG12.5.1	−0.664	Indirect	0.0995	−0.0980	0.1285

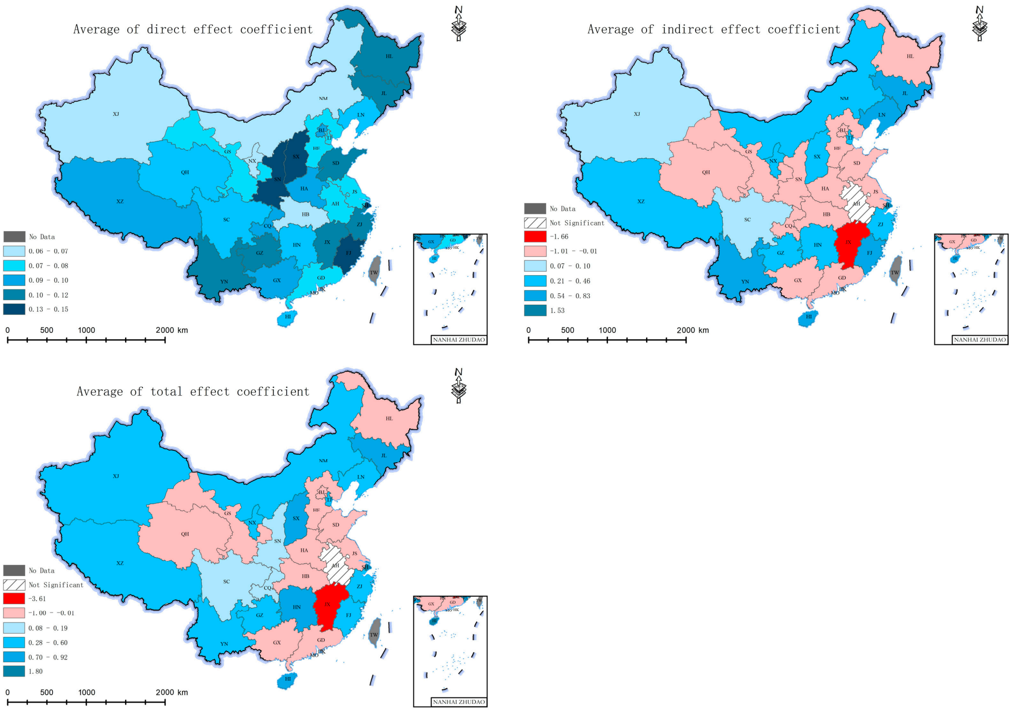

Figure 2. Average coefficients of the 21 indicators for direct, indirect, and total effects on SDG 11.6.2 (concentration of PM2.5) across all provincial-level regions of China. (AH: Anhui; BJ: Beijing; FJ: Fujian; GS: Gansu; GD: Guangdong; GX: Guangxi; GZ: Guizhou; HI: Hainan; HE: Hebei; HA: Henan; HL: Heilongjiang; HB: Hubei; HN: Hunan; JL: Jilin; JS: Jiangsu; JX: Jiangxi; LN: Liaoning; NM: Nei Mongol; NX: Ningxia; QH: Qinghai; SD: Shandong; SX: Shanxi; SN: Shaanxi; SH: Shanghai; SC: Sichuan; TJ: Tianjing; XZ: Xizang; XJ: Xinjiang; YN: Yunnan; ZJ: Zhejiang; CQ: Chongqing; MO: Macao; HK: Hong Kong; TW: Taiwan).

For the indirect and total effects, regions with a larger average of synergy effects included Shanghai, Hainan, Jilin, Hunan, etc. Among these regions, Shanghai has a developed economy and exhibited the largest synergy on the average total effect. The *China Statistical Yearbook* data showed that tertiary industry's added value accounted for 73.1% in 2020. Shanghai has significantly enhanced its environmental protection and urban development, following a seven-round, 3-year environmental protection action plan through 2020. The area of green space in Shanghai has expanded from 6561 hectares in 1995 to 171,200 hectares in 2021. Meanwhile, environmental investment soared from RMB 4.65 billion in 1995 to RMB 92.35 billion in 2017. Additionally, there were reductions in smoke emissions and sulfur dioxide exhaust, decreasing from 207.8 thousand tons and 534.1 thousand tons, respectively [56]. Successful industrial transformation has promoted the improvement of air quality. On the other hand, the regions with larger trade-off effects on the average of total effect included Jiangxi, Guangdong, Hebei, Shandong, etc. Most of these are regions with a large proportion of industry and manufacturing. Therefore, while promoting industrial transformation, it is necessary to improve technology and strengthen pollutants, harmless treatment, and secondary utilization [24].

Through the analysis of maximum and minimum indicators related to PM2.5 across 31 province-scale regions in China, it was observed that indicators manifesting maximum values on three or more occasions included SDG6.3 (water quality), SDG6.4.1 (water-use efficiency), SDG6.6 (water-related ecosystems), SDG7.3.1 (energy intensity), SDG9.4 (sustainable and clean industries), SDG15.1.1 (forest area), and SDG15.4 (conservation of mountain ecosystems). Conversely, indicators presenting minimum values more than three times were SDG6.6 (water-related ecosystems), SDG9.2.1 (manufacturing value added), SDG11.2.1 (convenient access to public transport), and SDG15.1.1 (forest area). This highlights the imperative of prioritizing these indicators in the trajectory towards sustainable development.

4. Conclusions and Discussion

This study investigated the spatial autocorrelation and agglomeration characteristics of SDG11.6.2 (concentration of PM2.5) across China from 2000 to 2020, employing spatial econometric models to analyze the influence of various socioeconomic and environmental indicators on PM2.5 distribution. The study's findings highlight significant spatial autocorrelation in PM2.5 concentrations, with pronounced high–high agglomerations in East and North China, indicating that local governments in this region particularly need to strengthen cooperation to control and prevent air pollution. Using 31 spatial inverse distance matrices for model validation, the study adopted the SDM with individual fixed effects, justified by various model validity tests (LM, robust LM, Hausman, and LR tests) that confirmed the presence of spatial autocorrelation between variables and the superiority of fixed effects in capturing these relationships. The chosen SDM model, applied to panel data encompassing 20 years and 31 provincial regions, effectively addressed the challenges of autocorrelation in the disturbance terms, thereby ensuring model reliability.

In contrast to previous studies, this research systematically analyzed the direct, indirect, and total effects of various influencing factors on PM2.5 at the provincial scale in China. The results reveal the individual influencing factors for each provincial unit, providing auxiliary support for differentiated policymaking in each province. Overall, in all regions with significant results, environmental indicators such as vegetation protection, afforestation, water-use efficiency, and sulfur dioxide emission reduction exhibited synergistic direct effects in lowering PM2.5 levels. Conversely, indicators linked to economic growth and social development, including SDG8.1.1 (real GDP per capita growth rate) and SDG9.1.2 (passenger and freight volume,) showed trade-off direct effects, particularly in regions like Nei Mongol and Jilin, where they correlated with poorer air quality. These regions are primarily characterized by underdeveloped economies, indicating that economic growth in some of China's less developed provinces still comes at the expense of the environment to a certain extent, without having reached the inflection point of the environmental Kuznets curve.

The study further explored the spatial variance of these effects across provincial-scale regions, revealing a complex phenomenon where some indicators demonstrated synergistic effects in certain regions while exhibiting trade-offs in others. For instance, the adoption of new energy vehicles in southern provinces showed a positive indirect and total effect on air quality improvement, in contrast to northern regions. Similarly, the study identified a trade-off in the comprehensive utilization rate of industrial solid waste in economically advanced areas, suggesting a need for improved recycling and waste processing technologies. Analysis of average coefficients for direct, indirect, and total effects of the indicators underscores the nuanced influence of environmental and socioeconomic factors on SDG11.6.2 (concentration of PM2.5). Some indicators, such as SDG 15.4 (conservation of mountain ecosystems), SDG 9.4 (sustainable and clean industries), and SDG 6.3 (water quality) consistently showed significant positive impacts, advocating for their prioritization in sustainable development efforts. In contrast, certain socioeconomic indicators revealed negative effects, highlighting the critical need for industrial transformation, technological advancement, and effective pollution control measures, especially in industrial-heavy regions. The provincial scale analysis further accentuated the diverse impacts of these indicators across China, with regions like Shanghai showing significant synergies in improving air quality due to successful economic and industrial transformation. On the other hand, provinces with a heavy industrial base face challenges in air quality management, necessitating a balanced approach to industrial growth and environmental sustainability.

However, it is necessary to recognize the potential limitations that may exist in this study. In an effort to quantitatively ascertain the spatial spillover effects of PM2.5, along with its potential influencing factors across a multiplicity of variables and throughout provincial-scale regions in China, this study adopted an iterative approach to refine the conventional inverse distance matrix. This method preserved spatial distance weights between a singular region and its counterparts, thereby generating discrepancies in the outcomes of the direct effect when compared to the indirect and total effects across certain regions and indicators. While such variances might mirror real-world scenarios, they could also stem from biases induced by an inadequate sample size for observation, which was underscored by the pervasive presence of non-significant outcomes in the direct effects observed. Therefore, confirming the reliability of the conclusions derived from this study necessitates further observed data and methodological enhancements for adequate support and verification in the future.

5. Policy Recommendations

The study's comprehensive analysis illustrates the intricate interplay between environmental policies, socioeconomic development, and air quality. It underscores the importance of a holistic approach to air quality improvement that integrates environmental conservation, economic transformation, and technological innovation. Tailored policies that consider the unique characteristics and needs of each region are imperative for effectively mitigating PM2.5 pollution across China. This nuanced understanding of the factors influencing PM2.5 distribution provides valuable insights for policymakers, suggesting that enhancing air quality necessitates not only environmental measures but also socioeconomic adjustments to foster sustainable development. Based on the study's findings, here are some policy recommendations to reduce PM2.5 concentrations in China.

1. Enhance inter-regional collaboration: Develop mechanisms for stronger cooperation among local governments, especially in East and North China, to address the high–high agglomerations of PM2.5. This could involve sharing technologies, strategies, and information on successful pollution control measures.
2. Promote environmental conservation measures: Prioritize environmental indicators that have shown synergistic effects in lowering PM2.5 levels, such as vegetation protection, afforestation, water-use efficiency, and sulfur dioxide emission reduction. Implement national and local programs to expand green spaces and urban forests, enhance water conservation practices, and accelerate the shift to cleaner energy sources.
3. Adjust economic and industrial policies: For regions with underdeveloped economies showing a trade-off between economic growth and air quality, policies should encourage industries to adopt cleaner and more sustainable practices. This includes investing in new energy vehicles in the northern provinces, improving the comprehensive utilization rate of industrial solid waste with better recycling and waste processing technologies, and supporting the transition towards sustainable and clean industries.
4. Tailor policies to regional needs and characteristics: Recognize the diverse impact of socioeconomic and environmental indicators across provinces. Implement policies that are customized to the specific needs and challenges of each region, considering their economic, environmental, and social contexts. This may involve differential strategies for regions with heavy industrial bases versus those undergoing economic and industrial transformation.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su16083394/s1, Figures S1–S21: Direct effect, indirect effect, and total effect for different explanatory variables on the dependent variable SDG11.6.2 (PM2.5 concentration).

Author Contributions: Conceptualization, Y.C.; methodology, J.L. and Y.C.; formal analysis, Y.C.; data curation, J.L. and Y.C.; writing—original draft preparation, J.L.; writing—review and editing, Y.C. and F.C.; supervision, F.C. All authors have read and agreed to the published version of the manuscript.

Funding: This study was supported by the National Key R&D Program of China (Grant No. 2022YFC3800703), the International Research Centre of Big Data for Sustainable Development Goals (CBAS) [grant numbers CBASYX0906] and the key project of sustainable development international cooperation program by NSFC (Grant No. 42361144883).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

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