


Article

Study on Spatial Effects of Influencing Factors and Zoning Strategies for PM_{2.5} and CO₂ Synergistic Reduction

Zimu Jia ¹, Shida Sun ² , Deming Zhao ³, Yu Bo ^{3,*} and Zifa Wang ¹

¹ State Key Laboratory of Atmospheric Boundary Layer Physics and Atmospheric Chemistry, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing 100029, China; jiazimu@mail.iap.ac.cn (Z.J.); zifawang@mail.iap.ac.cn (Z.W.)

² Ministry of Education Key Laboratory for Earth System Modeling, Department of Earth System Science, Tsinghua University, Beijing 100084, China; sunshida.2021@tsinghua.org.cn

³ Key Laboratory of Regional Climate and Environment for Temperate East Asia, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing 100029, China; zhaodm@tea.ac.cn

* Correspondence: boyu@mail.iap.ac.cn

Abstract: China has identified the synergistic reduction of pollution and carbon emissions as a critical component of its environmental protection and climate mitigation efforts. An assessment of this synergy can provide clarity on the strategic management of both air pollution and carbon emissions. Due to the extensive regional differences in China, the spatial effects of influencing factors on this synergy exhibit variation across different provinces. In this study, the reduction indexes of PM_{2.5} and CO₂ were calculated based on their reduction bases, reduction efforts, and reduction stabilities across provinces. Then, the synergistic reduction effect was assessed using an exponential function with the PM_{2.5} reduction index as the base and the CO₂ reduction index as the exponent. Next, the MGWR model was applied in order to analyze the influencing factors of the synergistic reduction effect, considering natural settings, socioeconomic conditions, and external emission impacts. Finally, the k-means clustering method was utilized to classify provinces into different categories based on the degree of impact of each influencing factor. The results indicated that air circulation, vegetation, tertiary industry ratio, and emission reduction efficiency are major impact indicators that have a positive effect. The topography and emissions from neighboring provinces have a statistically significant negative impact. The spatial influences of different factors exhibit a distribution trend characterized by a high-high cluster and a low-low cluster. A total of 31 provinces are divided into three categories, and suggestions on the corresponding category are proposed, to provide a scientific reference to the synergistic reduction of PM_{2.5} and CO₂.

Keywords: synergistic reduction; evaluation index; influencing factors; spatial effects; zoning strategies



Citation: Jia, Z.; Sun, S.; Zhao, D.; Bo, Y.; Wang, Z. Study on Spatial Effects of Influencing Factors and Zoning Strategies for PM_{2.5} and CO₂ Synergistic Reduction. *Toxics* **2024**, *12*, 498. <https://doi.org/10.3390/toxics12070498>

Academic Editor: Matthias Karl

Received: 10 June 2024

Revised: 5 July 2024

Accepted: 7 July 2024

Published: 9 July 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

China is facing the dual pressures of reducing air pollution and carbon emissions [1,2]. In response to this challenge, a series of policies have been implemented by the Chinese government. The Air Pollution Prevention and Control Action Plan was issued in 2013, followed by the Three-Year Action Plan for Winning the Blue Sky Defense Battle in 2018, aiming to improve nationwide air quality [3]. Meanwhile, China has acknowledged its commitment to reducing CO₂ emissions to combat global warming, as stipulated in the Paris Agreement. For example, China has formally committed to “double carbon” targets, striving to achieve a carbon peak by 2030 and carbon neutrality by 2060 [4]. For a long time, air pollution and carbon emissions were treated as two separate issues with different strategies [5]. Actually, air pollutants and CO₂ are derived from similar sources and are released simultaneously, implying that effective management of both air pollution and carbon emissions can result in a synergistic reduction [6]. In 2022, the Chinese government

announced the Implementation Plan for Synergic Efficiency in Reducing Pollution and Carbon, explicitly promoting a strategy for the synergistic reduction of air pollutants and CO₂ emissions. Given China's extensive regional differences in terms of meteorological conditions, topography, population density, economic growth, energy structure, energy efficiency, technological innovation, etc., the directions and mechanisms of the impacts of different factors on the synergistic reduction may vary between provinces. Combining various drivers with positive and negative effects can reveal the spatial disparity of synergistic reduction effects at the provincial level in China, thereby avoiding a one-size-fits-all policy.

Since air pollution and greenhouse gas emissions have the same origin and spatial consistency, they should be assessed together rather than separately [7,8]. Existing studies have confirmed that there is a synergistic reduction between air pollutants and greenhouse gases, and often focus on the magnitude of the decrease in emissions [9–11]. It is feasible to quantify the degree of synergistic reduction by constructing and calculating an indicator or index. Ref. [12] captured the damage value weights of air pollutants and CO₂ and combined all the emissions as an air pollutant equivalence (AP_{eq}) to reflect the co-control effect. The co-reduction coordinate system and cross-elasticity are also commonly used for evaluating synergies [13–15]. Ref. [13] analyzed the co-benefits of reducing air pollutants and CO₂ emissions from electric private cars, taxis, and buses by using the co-control coordinate system and pollutant reduction cross-elasticity. Ref. [15] applied different cross-elasticities to quantitatively assess the co-benefits of lowering CO₂ and atmospheric pollutants of various measures in the Air Pollution Prevention and Control Action Plan in the Jing-Jin-Ji region of China. These two methods can show the positive and negative effects of synergies based on the reductions in air pollutants and CO₂. Other scholars analyzed the effect with models such as life cycle assessment (LCA) [16], greenhouse gas and air pollution interactions and synergies (GAINS) [17,18], and the long-range energy alternatives planning system (LEAP) [19,20]. Much of the literature focuses on the synergies between air pollutants and CO₂ in terms of the quantities of reductions. Actually, according to China's 2030 carbon peaking plan, carbon emissions are expected to continue rising in the coming years [21], leading to the carbon reduction that is encouraged but not compulsory. Therefore, negative synergies may be a prevalent phenomenon, meaning a decrease in air pollutants with a concomitant increase in carbon emissions. Additionally, extensive research observes the synergistic effect from a single perspective by examining the actual emission reductions, but ignores the contribution of emissions at the initial time point and how the reduction stability changes over time. The actual emission reductions reflect the direct effectiveness of a region, but if the initial emissions are disregarded, it tends to exaggerate the reduction efforts of the region and weaken the need for emission reductions. Furthermore, a consistent decrease in emission reduction levels or pollution concentrations within a certain area can also suggest that reduction policies and measures have played a stabilizing role without being ineffective.

The emissions of air pollutants and CO₂ are closely related to fossil fuel consumption. The increase in energy demand during rapid economic development is a driver of air pollution and CO₂ emissions [22,23]. Burning coal produces about 70% of the CO₂ released into the air in China [24], and more than 80% of PM_{2.5} pollution comes from the coal used in the electricity and metal industries [25]. Therefore, coal combustion is considered an important factor in air pollution and CO₂ emissions. Previous studies have also revealed that the expansion of PM_{2.5} and CO₂ emissions is attributed to economic growth [26–28]. Particularly, the secondary industry in China includes energy-intensive and high-polluting sectors, indicating that the augmentation of the proportion of secondary industry contributes to air pollution and CO₂ emissions [26,27]. Ref. [29] found that several factors—such as urbanization, industry, economy, energy, and so on—influenced the synergistic degree of air pollution control and CO₂ reduction, thereby causing regional disparities. Additionally, the synergistic reduction of air pollutants and CO₂ can be achieved through technological innovation [30]. For example, digital technologies have been used to monitor and analyze energy consumption in real time by many companies, enabling more efficient minimization

of air pollution and carbon emissions [31,32]. Several researchers believe that the implementation of relevant policies for emission reduction is an important reason for the change in synergistic benefits, such as the Air Pollution Prevention and Control Action Plan [3], environmental protection tax [33], carbon pricing policy [34], low-carbon city pilot [35], etc. Generally, the existing studies focus on exploring the impacts of socioeconomic influencing factors on the synergistic reduction of air pollutants and CO₂, but few investigate how natural factors such as meteorological and topographical conditions influence this synergy. In addition, research on influencing factors has only been carried out in a certain region, which fails to deal with the impact of emissions from adjacent areas.

In this study, an evaluation index was developed to comprehensively reflect the effectiveness of synergistic PM_{2.5} and CO₂ reductions in each region. Compared with previous studies, the index integrates and quantifies PM_{2.5} emissions, PM_{2.5} annual average concentration, and CO₂ emission intensity in terms of the reduction basis, reduction efforts, and reduction stability. In addition, this study thoroughly examines the impacts of the natural environment, socioeconomic conditions, and external emission factors on the spatial variations in the effectiveness of synergistic emission reductions across different areas. The findings can serve as a guide for the future implementation of tailored emission reduction policies.

The rest of the paper is organized as follows. Section 2 describes the methodology in detail, which mainly consists of the multiscale geographically weighted regression (MGWR) model and the k-means clustering method. In addition, data sources are represented in this section. Section 3 presents the outcomes of the spatial distribution patterns, including constructed indexes, coefficients of affecting factors, and zoning information. Discussions based on the results and conclusions are provided in Sections 4 and 5, respectively.

2. Materials and Methods

2.1. Data Collection

The study covered 31 provinces in China, except for Hong Kong, Macau, and Taiwan, due to insufficient data. PM_{2.5} and CO₂ emission data were taken from the Multi-Resolution Emission Inventory for China (<http://meicmodel.org.cn> (accessed on 5 July 2024)), established by Tsinghua University. The annual average concentration of PM_{2.5} was derived from reports on the state of the ecology and environment in 31 provinces, published by the provincial Department of Ecology and Environment. Boundary layer height and wind speed were collected from the ERA5 database (<https://cds.climate.copernicus.eu> (accessed on 5 July 2024)). The information on the Digital Elevation Model (DEM) and Normalized Difference Vegetation Index (NDVI) was obtained from the Resource and Environment Science and Data Center (<https://www.resdc.cn> (accessed on 5 July 2024)). Data on economic development, energy consumption, and forest cover were obtained from the China Statistical Yearbook and the China Energy Statistical Yearbook, released by the National Bureau of Statistics of China. All the data contain values spanning from 2016 to 2020.

2.2. Evaluation Index for PM_{2.5} and CO₂ Reductions

This study evaluates the relative effects of PM_{2.5} and CO₂ reductions on different emitting entities during a given period from three perspectives: the targeted reduction, the actual reduction, and the fluctuation. PM_{2.5} reduction includes the decrease in emissions and annual concentration, and CO₂ reduction refers to the decrease in emission intensity. The target reduction is the difference between the emission result of an emitting entity and the corresponding standard in the starting year, which mainly assesses the basis for reductions in the emitting entity. Corresponding standards can be explicitly issued by the state—for example, ambient air quality standards, or those that are difficult to specify at this stage but are considered theoretically necessary to achieve, e.g., zero emissions. The actual reduction refers to the difference in emission results between the starting year and the target year, and is used to evaluate reduction efforts. The fluctuation value means the disparity between the sum of the absolute value of the actual reduction over a specified

period, such as one year or one month, and the absolute value of the actual reduction over the entire period. The stability of reductions by emitting entities is primarily measured by the fluctuation value.

Since PM_{2.5} and CO₂ reductions involve variables with different scales and units, they need to be converted to the same range for comparison and analysis. This will eliminate the discrepancy between scale and unit. The Sigmoid function will be able to map a number to the interval (0,1). Compared to the Min-Max Scaling normalization method, the Sigmoid function is not affected by extreme values and is more resistant to interference. However, the Sigmoid function belongs to the one with a saturated S-curve at both ends, and when the values on both sides of the definition domain exceed a certain range, the Sigmoid function curve tends to flatten. Therefore, the Sigmoid function input values need to be scaled by the same proportion. In this study, the Sigmoid function was used to calculate the targeted reduction index, the actual reduction index, and the fluctuation rate, based on which the reduction index was obtained. The equations are as follows:

$$I_{TR} = \frac{1}{1 + e^{(x_1 - x_s)/m}} \quad (1)$$

$$I_{AR} = \frac{1}{1 + e^{(x_n - x_1)/m}} \quad (2)$$

$$FR = \frac{1}{1 + e^{(|x_n - x_1| - \sum_{i=2}^n |x_n - x_{n-1}|)/m}} \quad (3)$$

$$I_R = I_{TR} + I_{AR} - FR \quad (4)$$

where I_{TR} is the targeted reduction index; I_{AR} is the actual reduction index; FR is the fluctuation rate; I_R is the reduction index; x_s is the corresponding standard value, $x_s = 35 \mu\text{g}/\text{m}^3$ (for PM_{2.5} annual average concentration) or $x_s = 0$ (for PM_{2.5} emissions and CO₂ emission intensity); x_1 is the actual value in the starting year; x_n is the actual value in the target year; m is the scaling factor, $m = 10$ (for PM_{2.5} emissions and annual average concentration) or $m = 1$ (for CO₂ emission intensity). In the study, the starting year is 2016 and the target year is 2020.

During this study, the evaluation index for PM_{2.5} and CO₂ reductions was calculated in the form of an exponential function. For the exponential function $y = a^x$, when $0 < a < 1$ and $x \geq 0$, the exponential function has the following properties: (1) y takes on the range of (0,1]; (2) the function monotonically decreases; and (3) if x is the same, y increases as a increases. In this study, the PM_{2.5} reduction index and CO₂ reduction index have values in the range of [0,1] basically, which can be used as the base and exponent of the exponential function to convert the final evaluation result to the (0,1] interval. The reduction index is a positive indicator—the greater the number, the better. However, the decreasing monotonicity of the function implies that the smaller the value at the exponential position, the better. Therefore, it is necessary to transform the PM_{2.5} reduction index or CO₂ reduction index located at the exponential position. According to the property (3), the base and the function value keep the same increase and decrease. For the reduction index at the base position, it can be intuitively reflected as a positive indicator without the need for formal transformation. Compared with CO₂ emissions, PM_{2.5} emissions have a more direct and intense impact on public health and socioeconomic development. China has been carrying out nationwide PM_{2.5} pollution control since 2013, and it was not until 2020, when the “dual carbon” target was proposed, that CO₂ emission reduction was elevated to the same importance as PM_{2.5} pollution control. Therefore, the PM_{2.5} reduction index was applied as the base and the CO₂ reduction index as the exponent. Since PM_{2.5} reduction includes emissions and annual concentration, the PM_{2.5} reduction index was calculated by using the exponential function,

with the $PM_{2.5}$ concentration reduction index as the base and the $PM_{2.5}$ emission reduction index as the exponent. The equations are as follows:

$$I_{R_PM_{2.5}} = I_{RC}^{(1-I_{RE})} \quad (5)$$

$$EIPC = I_{R_PM_{2.5}}^{(1-I_{R_CO_2})} \quad (6)$$

where $I_{R_PM_{2.5}}$ is the $PM_{2.5}$ reduction index; $I_{R_CO_2}$ is the CO_2 reduction index; I_{RC} is the $PM_{2.5}$ concentration reduction index; I_{RE} is the $PM_{2.5}$ emission reduction index; $EIPC$ is the evaluation index for $PM_{2.5}$ and CO_2 reductions.

2.3. Multiscale Geographically Weighted Regression

Ordinary least squares (OLS) is a global regression model that overlooks differences in variables due to spatial locations. Geographically weighted regression (GWR) extends OLS by assuming that the relationships between the response variable and explanatory variables change over space. Hence, GWR estimates a separate model with local parameters for each geographical location [36]. The bandwidth of an explanatory variable indicates its spatial scale of influence. GWR considers a fixed bandwidth for all parameters. Actually, a fixed bandwidth is not valid when phenomena involve multiple spatial processes with diverse explanatory variables [37]. MGWR allows relationships between the response variable and explanatory variables to change at different spatial scales [38,39]. This multi-bandwidth approach produces a more accurate result for the regression, representing spatial phenomena in the real world. The equation is as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^m \beta_{bwk}(u_i, v_i)x_{ik} + \varepsilon_i \quad (7)$$

where u_i and v_i are the coordinates of each explanatory variable at position i ; $\beta_0(u_i, v_i)$ is the intercept value at position i ; bwk is the bandwidth of the k th explanatory variable at position i ; $\beta_{bwk}(u_i, v_i)$ is the regression coefficient of the k th explanatory variable at position i ; m is the number of explanatory variables; ε_i is the error value.

In this study, EIPC was utilized as the response variable for MGWR. According to the previous studies [27–30] and the data availability, explanatory variables comprised air circulation level (ACL), topographical relief level (TRL), NDVI, forest coverage rate (FCR), stock volume of forest (SVF), gross domestic product (GDP), proportion of the tertiary industry (PTI), emission reduction efficiency (ERE), $PM_{2.5}$ emissions from neighboring provinces (ENP), and net electricity demand from other provinces (NED). The variables mentioned in the MGWR model were computed as the average values across the years 2016 to 2020. ACL is constructed by multiplying boundary layer height by average wind speed, which determines the dispersion of pollutants. For two places with identical emissions levels, the one with a higher ACL experiences lower $PM_{2.5}$ pollution [40]. TRL is the average of the difference between the DEM of each city boundary in a province and the average DEM of the plains within that city. A greater TRL indicates that the province may possess more cities of the basin type, which can result in the accumulation of pollutants. Vegetation plays an important role in absorbing carbon dioxide and reducing the concentration of particles. Its growth stage and health level also affect its ability to eliminate CO_2 and particles [41]. NDVI is often used to assess the spatial distribution and growth status of vegetation. However, NDVI is processed using nonlinear stretching in the calculation process, resulting in a low sensitivity to highly vegetated areas. Combining other data can provide more comprehensive vegetation information. Forests, as one of the most important components of ecosystems, are vital for carbon sequestration and particle removal compared to other vegetation systems, such as grasslands. FCR is the ratio of forest area to total land area within the administrative region, and SVF refers to the total stock volume of tree trunk timber in a given forest area. These two indicators reflect, to some extent, forest resources in terms of quantity and quality. China is currently in the industrialization stage and

relies on substantial energy inputs, resulting in a certain positive correlation between economic development and air pollution and carbon emissions. Increased PTI contributes to improved energy efficiency and reduced energy use, lowering pollutants and carbon emissions from industrial production [30]. One region is susceptible to PM_{2.5} emissions from neighboring provinces due to atmospheric transport. NED is the difference between annual electricity consumption and annual electricity generation. A positive value indicates that electricity needs to be imported from other provinces, resulting in the transfer of air pollution and carbon emissions from electricity-consuming to electricity-producing areas. ERE suggests the efficiencies of technologies and management levels in the process of PM_{2.5} and CO₂ emission reductions while keeping all inputs constant. In this paper, ERE was calculated by adopting the data envelopment analysis (DEA) approach. DEA does not require prior assumptions of functional relationships between inputs and outputs, and can avoid man-made subjectivity for parameter weighting [42]. This model has been extensively utilized to assess energy efficiency and CO₂ emission efficiency [43]. In the developed DEA model, PM_{2.5} and CO₂ emission reductions were taken as outputs, while coal consumption for thermal power, coal consumption for industry, coal consumption for residents, and completed investment in projects for treating waste gases were viewed as inputs.

2.4. K-Means Clustering

The k-means clustering method involves an unsupervised recognizable pattern in which the objects prepared to be classified in a data set are efficiently computed and categorized into proper groups. The classification of objects is based on several types of indicator, which are appropriate for describing the characteristics of objects. In this study, the regression coefficients for different explanatory variables of each province were generated by the constructed MGWR model. These regression coefficients are the classification criteria of the k-means clustering. Provinces are categorized into corresponding categories to identify the similarities and distinctions observed among diverse groups.

As the k-means clustering method requires the user to prespecify the number of clusters, it is indispensable for measuring the clustering quality. The silhouette coefficient combines both cohesion and separation, and is rather independent of the number of clusters. The optimal clustering number can be obtained by calculating the average silhouette coefficient of all the provinces. For one cluster with k categories, the average silhouette coefficient refers to the average of the silhouette coefficients of provinces belonging to the cluster [44].

3. Results

3.1. Spatial Characteristics of Reduction Indexes

The reduction index values have the potential to range from 0 to 1. A province's effectiveness in reduction increases as the value approaches 1. The values were categorized using the natural breakpoint classification method in the ArcGIS 10.6 software (Environmental Systems Research Institute, Redlands, CA, USA). For the PM_{2.5} reduction index, Xinjiang has the lowest value and is categorized separately (Figure 1). Four provinces have a value greater than 0.81 and are deemed to have relatively better effectiveness in controlling PM_{2.5}, namely Xizang (0.9999), Hainan (0.9820), Fujian (0.8724), and Qinghai (0.8453) (Table 1 and Figure 1). The values are generally higher in the provinces of the southwestern and southern regions compared to those in the provinces of the northern and central areas. For the CO₂ reduction index, the results for Ningxia and Inner Mongolia are below zero because of the significant fluctuations in their annual falls of CO₂ emission intensity (Table 1). Seven provinces have a rating above 0.34 and are considered more successful in managing CO₂ emission intensity, namely Beijing (0.4327), Shanghai (0.3848), Guangdong (0.3674), Chongqing (0.3533), Zhejiang (0.3532), Sichuan (0.3531), and Hunan (0.3485) (Table 1 and Figure 2). The southern provinces outperform the northern provinces in reducing CO₂ emission intensity. For the evaluation index of PM_{2.5} and CO₂ reductions, Xinjiang is the

region with the lowest value (0.0006) and is classified as its own category. Tibet, Hainan, and Fujian obtained scores exceeding 0.9 and are recognized as top performers (Table 1 and Figure 3). Furthermore, approximately half of the provinces achieved moderate outcomes in terms of synergistic reductions in PM_{2.5} and CO₂, with scores between 0.57 and 0.74.

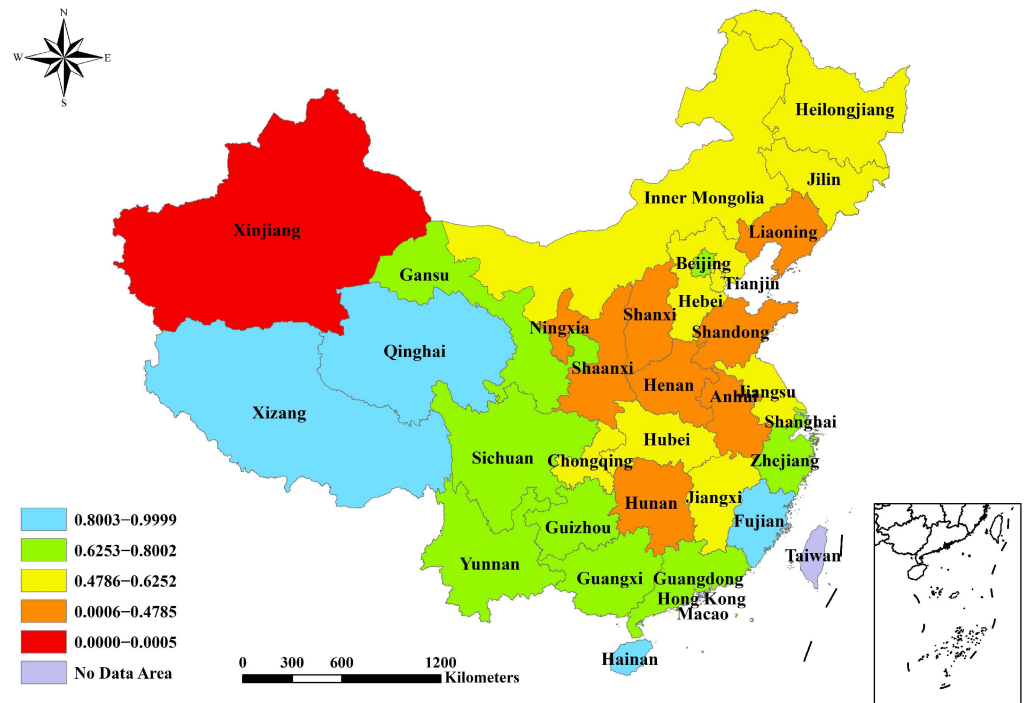


Figure 1. Spatial characteristics of PM_{2.5} reduction index 2016–2020.



Figure 2. Spatial characteristics of CO₂ reduction index 2016–2020.

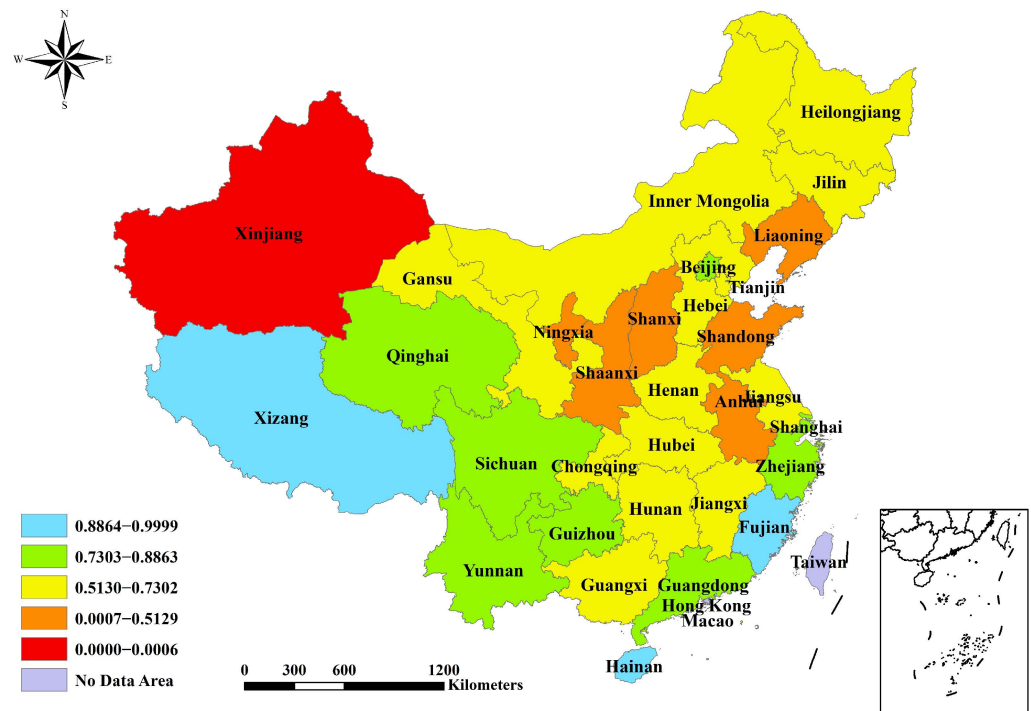


Figure 3. Spatial characteristics of evaluation index for PM_{2.5} and CO₂ reductions from 2016–2020.

Table 1. Evaluation results of reduction indexes of 31 provinces from 2016 to 2020.

| Province | $I_{R_PM_{2.5}}$ | $I_{R_CO_2}$ | $EIPC$ |
|----------------|-------------------|---------------|--------|
| Beijing | 0.6605 | 0.4327 | 0.7904 |
| Tianjin | 0.5300 | 0.3364 | 0.6562 |
| Hebei | 0.6113 | 0.1506 | 0.6584 |
| Shanxi | 0.3606 | 0.0936 | 0.3967 |
| Inner Mongolia | 0.6098 | −0.0811 | 0.5858 |
| Liaoning | 0.3454 | 0.1966 | 0.4256 |
| Jilin | 0.5822 | 0.2624 | 0.6710 |
| Heilongjiang | 0.5740 | 0.2189 | 0.6482 |
| Shanghai | 0.6794 | 0.3848 | 0.7883 |
| Jiangsu | 0.5363 | 0.3307 | 0.6590 |
| Zhejiang | 0.7799 | 0.3532 | 0.8515 |
| Anhui | 0.3954 | 0.2522 | 0.4997 |
| Fujian | 0.8724 | 0.3249 | 0.9120 |
| Jiangxi | 0.6252 | 0.2989 | 0.7194 |
| Shandong | 0.3494 | 0.2634 | 0.4610 |
| Henan | 0.4785 | 0.3177 | 0.6047 |
| Hubei | 0.5522 | 0.3300 | 0.6717 |
| Hunan | 0.4253 | 0.3485 | 0.5729 |
| Guangdong | 0.8002 | 0.3674 | 0.8685 |
| Guangxi | 0.6613 | 0.2397 | 0.7302 |
| Hainan | 0.9820 | 0.3174 | 0.9877 |
| Chongqing | 0.5416 | 0.3533 | 0.6726 |
| Sichuan | 0.6730 | 0.3531 | 0.7740 |
| Guizhou | 0.7849 | 0.2572 | 0.8353 |
| Yunnan | 0.7389 | 0.2510 | 0.7972 |
| Xizang | 0.9999 | 0.3347 | 0.9999 |
| Shaanxi | 0.4152 | 0.2403 | 0.5129 |
| Gansu | 0.6817 | 0.1421 | 0.7198 |
| Qinghai | 0.8453 | 0.2822 | 0.8863 |
| Ningxia | 0.3973 | −0.3884 | 0.2776 |
| Xinjiang | 0.0005 | 0.0293 | 0.0006 |

3.2. Spatial Characteristics of Coefficients in MGWR

Table 2 compares the fitting results of the OLS, GWR, and MGWR models. The outputs suggest that the MGWR model outperforms OLS and GWR, with lower AICc and higher R² and Adj-R². The AICc, R², and Adj-R² values offer more precise assessments of the model fit. The lower AICc value and higher R² and Adj-R² values indicate a superior fit.

Table 2. Model diagnostics for OLS, GWR, and MGWR.

| Diagnostic Information | OLS | GWR | MGWR |
|------------------------|--------|--------|--------|
| AICc | 82.605 | 82.390 | 76.671 |
| R ² | 0.778 | 0.807 | 0.928 |
| Adj. R ² | 0.667 | 0.684 | 0.857 |

The coefficients' statistical results are presented in Tables 3 and 4. Each explanatory variable's coefficient was classified into five levels based on the natural breakpoint approach (Figure 4). In the MGWR model, the coefficient of ACL is positive and statistically significant at the 1% level. The coefficient varies between 0.5682 and 0.5692, showing a decline from the northeast to the southwest of the country. For the TRL, the coefficient is negative and statistically significant at the 1% level, with values ranging from −0.4233 to −0.4248. Significant relationships mainly occur in the southwestern and southern provinces of China. The coefficients for NDVI and FCR are both positively and significantly correlated at the 1% level. The western regions are more responsive to NDVI changes. The significant impacts of the latter are mainly located in the northeastern and northern regions. The regional differentiation of the SVF coefficient is comparable to that of the ACL, demonstrating a positive and statistically significant relationship at the $p < 0.1$ level, with values ranging from −0.1803 to −0.2160. The PTI has a positive coefficient that spans 0.1706 to 0.1715, which is statistically significant at the $p < 0.1$ level. There is a decreasing tendency observed from the west to the east. For the ERE, the positive coefficient is statistically significant at the 1% level, and there are considerable variations among the provinces, varying from 0.2507 to 1.2097. The western and northern provinces have a greater coefficient than the other provinces. The ENP coefficient is negatively significant at the $p < 0.1$ level, indicating a more obvious negative impact in southern areas. There is no statistically significant difference in the coefficients for GDP and NED.

Table 3. Descriptive statistics of coefficients in the MGWR model.

| Variable | Maximum | Minimum | Mean | Standard Deviation |
|----------|---------|---------|---------|--------------------|
| ACL | 0.5692 | 0.5682 | 0.5686 | 0.0002 |
| TRL | −0.4233 | −0.4248 | −0.4241 | 0.0003 |
| NDVI | 1.1436 | 1.1422 | 1.1429 | 0.0003 |
| FCR | 0.8499 | 0.8475 | 0.8490 | 0.0005 |
| SVF | 0.2160 | 0.1803 | 0.1972 | 0.0083 |
| GDP | −0.1266 | −0.1290 | −0.1279 | 0.0006 |
| PTI | 0.1715 | 0.1706 | 0.1709 | 0.0001 |
| ERE | 1.2097 | 0.2507 | 0.5887 | 0.2110 |
| ENP | −0.0158 | −0.6201 | −0.1100 | 0.1231 |
| NED | 0.1603 | 0.1592 | 0.1598 | 0.0002 |

Table 4. Coefficients of explanatory variables for OLS, GWR, and MGWR.

| Variable | OLS | | GWR | | MGWR | |
|----------|---------|------------|----------------|-------------------|----------------|-------------------|
| | β | p -Value | β (Mean) | p -Value (Mean) | β (Mean) | p -Value (Mean) |
| ACL | 0.398 | 0.070 *** | 0.405 | 0.062 *** | 0.569 | 0.001 * |
| TRL | −0.371 | 0.044 ** | −0.370 | 0.043 ** | −0.424 | 0.001 * |
| NDVI | 0.961 | 0.008 * | 0.967 | 0.009 * | 1.143 | 0.000 * |

Table 4. Cont.

| Variable | OLS | | GWR | | MGWR | |
|----------|---------|-----------------|----------------|------------------------|----------------|------------------------|
| | β | <i>p</i> -Value | β (Mean) | <i>p</i> -Value (Mean) | β (Mean) | <i>p</i> -Value (Mean) |
| FCR | 0.880 | 0.003 * | 0.873 | 0.004 * | 0.849 | 0.000 * |
| SVF | 0.277 | 0.054 *** | 0.273 | 0.056 *** | 0.197 | 0.073 *** |
| GDP | −0.137 | 0.434 | −0.133 | 0.430 | −0.128 | 0.281 |
| PTI | 0.196 | 0.147 | 0.191 | 0.148 | 0.171 | 0.062 *** |
| ERE | 0.786 | 0.000 * | 0.762 | 0.000 * | 0.589 | 0.005 * |
| ENP | −0.041 | 0.095 *** | −0.032 | 0.080 *** | −0.061 | 0.058 *** |
| NED | 0.180 | 0.356 | 0.177 | 0.348 | 0.160 | 0.255 |

* indicates a statistically significant *p*-value ($p < 0.01$); ** indicates a statistically significant *p*-value ($p < 0.05$); *** indicates a statistically significant *p*-value ($p < 0.1$).

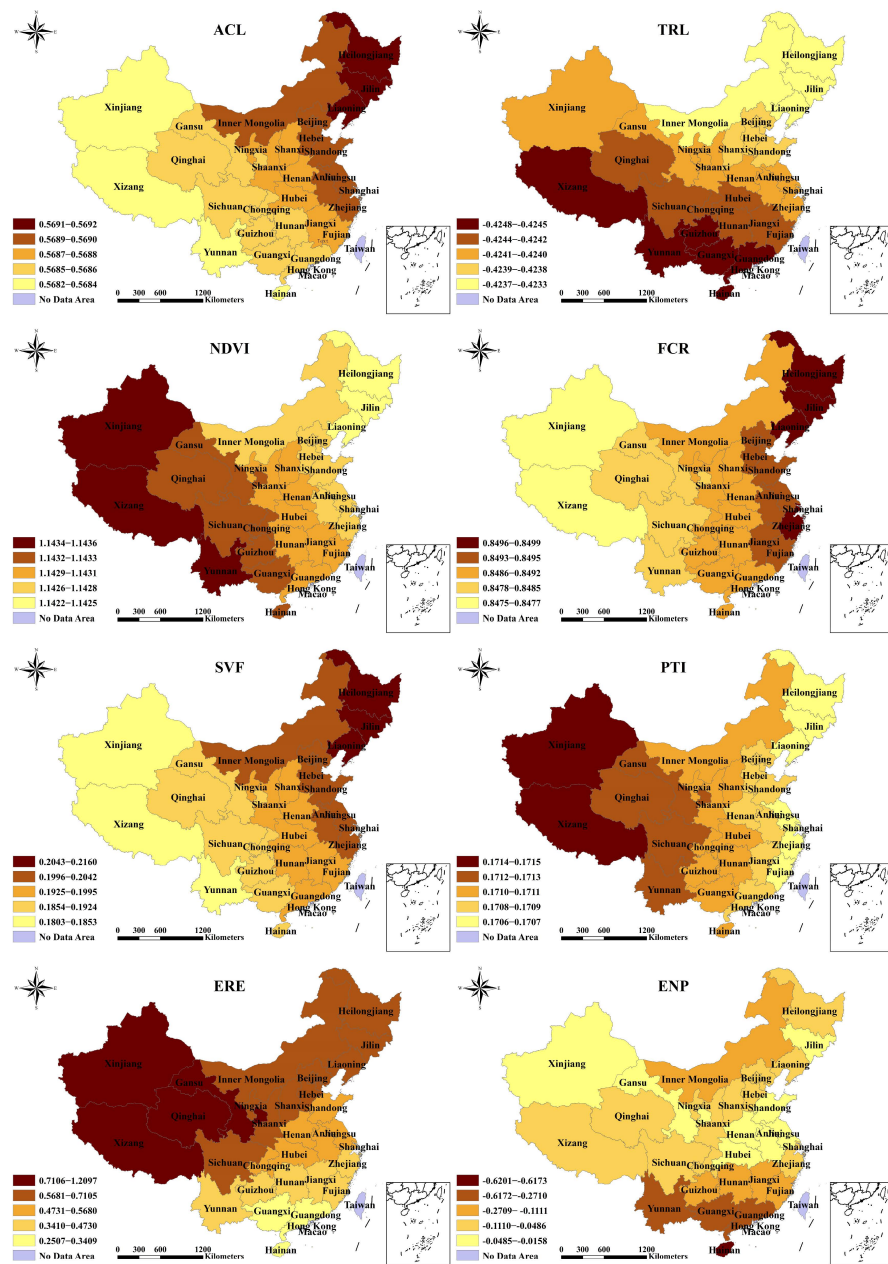


Figure 4. Spatial characteristics of statistically significant coefficients in MGWR 2016–2020.

3.3. Clustering and Zoning of Provinces

The MGWR model generated numerous local coefficients, which can be divided into different categories according to their correlations. The k-means clustering analysis was conducted using the statistically significant coefficients from 31 provinces in China. Given the number of provinces, the zoning number should be less than 10 [44]. The clustering analysis was carried out on 2 to 10 clusters using Python, and the average silhouette coefficient versus the clustering number was plotted, as shown in Figure 5. A higher value represents better clustering quality. The average silhouette coefficient reached its peak at 0.402 when $k = 3$. Therefore, the optimal clustering observed at $k = 3$ was used for the zoning, i.e., categorizing 31 provinces into 3 sub-areas (Figure 6).

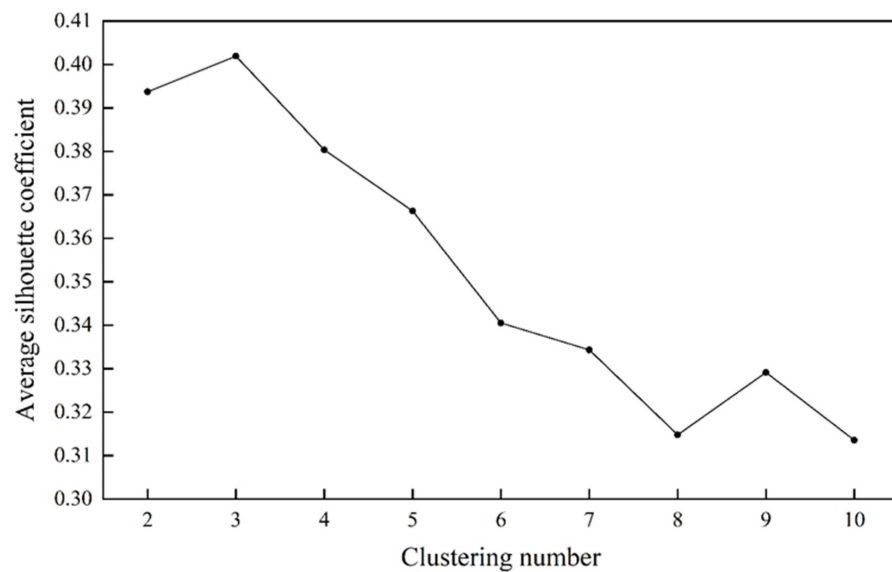


Figure 5. Average silhouette coefficient versus clustering number.



Figure 6. Zoning result of provinces.

4. Discussion

4.1. Analysis of Influencing Factors and Their Spatial Effects

The northeastern part of China has been an important base for heavy industry, while the Beijing–Tianjin–Hebei and Yangtze River Delta urban agglomerations are characterized by developed economies and large populations. Moreover, central heating in northern areas requires a large amount of coal burning. Therefore, these regions are important sources of PM_{2.5} and CO₂ emissions and are more sensitive to air circulation. Enhanced air circulation facilitates the dispersion of atmospheric pollutants, leading to a notable reduction in pollution levels. The southwestern region is dominated by plateaus and basins, featuring mountainous terrain and significant differences in elevation. The topography of basins causes air pollution to accumulate, making it challenging to disperse and remove.

Western China experiences arid conditions—characterized by plateaus and deserts, including the Gobi Desert—which significantly restrict vegetation development. Air pollution and carbon reduction are more sensitive to spatial changes in vegetation form, cover degree, health state, and other properties. Hence, a one-unit rise in NDVI results in a more pronounced increase in the reduction index as compared to the eastern region. In some eastern provinces like Shandong and Jiangsu, where FCR and SVF have low national rankings, the advantages of forest resources for carbon reduction and particle removal are not obvious. Therefore, there is a greater potential to enhance the quantity and quality of forest resources to decrease pollution and carbon emissions.

The tertiary industry has developed rapidly in the eastern provinces. The tertiary sector's share in the western region is typically lower than in the eastern region, although there is a higher likelihood of the ratio rising. Thus, the evaluation index for PM_{2.5} and CO₂ reductions is more responsive to increases in PTI in western areas. Climate mitigation and pollution control policies result in geographical variations in technology efficiency and management levels due to the optimization of energy structures and environmental protection investments. In northern and western regions, there is a noticeable beneficial effect, highlighting the necessity to improve the effectiveness of technology and management.

The joint prevention and control of regional air pollution has been a key focus for improving regional air quality since China issued the Action Plan for Air Pollution Prevention and Control in 2013. The Beijing–Tianjin–Hebei, Yangtze River Delta, and Fenhe–Weihe River Plain regions have experienced the most serious air pollution problems. Adjacent cities in these areas are more inclined to collaborate on environmental management strategies and establish targets with consistent levels of strictness. Therefore, the effects of PM_{2.5} emissions from neighboring provinces are less remarkable.

4.2. Zoning Features and Policy Implications

Category one is a region characterized by its sensitivity to environmental factors, mostly found in the northern and eastern provinces. Air circulation and forest growth play a significant role in reducing PM_{2.5} and CO₂ levels in this area. On the one hand, establishing ventilation corridors is crucial. A multi-level ventilation corridor system is constructed in the city based on the prevailing wind direction and existing natural cold sources such as green areas, parks, forests, rivers, and lakes. Building new high-rise structures along these ventilation corridors is strictly prohibited. On the other hand, forest conservation efforts need to be improved. Activity involving greenery and afforestation initiatives should be increased, focusing on reforesting shallow and barren slopes and expanding forested areas in the plains. The use of equipment and infrastructure to improve technical capacity for managing and monitoring forest resources should be expanded. The surveillance, prevention, and management of wildlife disease reservoirs to promote the health of forest ecosystems should also be enhanced.

Category two denotes the integrated sensitivity type, primarily affecting provinces in northwestern China. Variables such as vegetation cover, the proportion of tertiary industry, and emission reduction efficiency have an important effect on air pollution and carbon reductions in these provinces. Firstly, afforestation, returning farmland to

forests, returning pasture to grassland, and other greening efforts will be consistently implemented. Secondly, this category focuses on developing tourism, culture, exhibition, and other industries based on available resources and comparative advantages. It also aims to strengthen logistics, commerce, finance, and information services to enhance the tertiary industry's development and competitiveness. Thirdly, the region should accelerate the transition of energy systems and enhance the development of clean energy. Furthermore, enterprises should be incentivized to enhance reduction efficiency through strategies including process improvement, energy substitution, energy saving, and a more thorough approach to treatment.

Category three is classified as a passive influence and is mainly located in the southern and southwestern provinces. This group shows better a performance in $PM_{2.5}$ and CO_2 reduction, and the influence of topographical relief and $PM_{2.5}$ emissions from neighboring provinces is relatively greater. However, these provinces find it challenging to alter or adapt to these pressures by changing themselves. Therefore, regional joint prevention and control is necessary to establish a unified planning, monitoring, supervision, and evaluation mechanism among provinces. This involves categorizing areas into key control zones and general control zones based on geographic features, socioeconomic development levels, atmospheric pollution degrees, city distributions, and atmospheric pollutant transport patterns. Targeted pollution prevention and control strategies can then be developed accordingly.

4.3. Research Limitations and Future Prospects

The data used in this study were collected at the provincial level and represent each province's average. In provinces with vast land areas like Inner Mongolia, specific variables like ENP might either enhance or diminish their impacts on other provinces, thereby causing a bias in the regression outcomes. The influencing factors selected are not comprehensive enough. For instance, the ERE indicator should also consider the emission reduction efficiencies of transportation and industrial end-of-pipe measures. In addition, economic policies such as environmental taxes and carbon emissions trading were not included as influencing factors due to data availability.

A city is characterized by high-density human socioeconomic activities, and is the primary source of air pollutants and CO_2 emissions. Consequently, a city is the most critical entity in effectively managing local air pollutants and CO_2 emissions, as well as the solution to the issues associated with air pollution and climate change. In further studies, detailed data will be gathered for research on an urban scale. Reduction measures will be refined, such as upgrading industrial boilers, promoting clean fuels in the residential sector, phasing out yellow-label and old vehicles, revising economic policies, etc. This may offer valuable insights into the regional variations in the driving effects of synergistic reduction, as well as insights into appropriate strategies for the co-control of local air pollutants and CO_2 .

5. Conclusions

In this study, the reduction indexes of $PM_{2.5}$ and CO_2 were calculated by carefully considering their reduction bases, reduction efforts, and reduction stabilities. Then, the synergistic reduction effect was evaluated by an exponential function with the $PM_{2.5}$ reduction index as the base and the CO_2 reduction index as the exponent. The results indicate that, except for the southeastern and southwestern provinces, the remaining provinces are ineffective in synergizing $PM_{2.5}$ and CO_2 reductions. Next, the elements concerning the synergistic reduction effect were analyzed based on natural settings (air circulation, topography, and vegetation), socioeconomic conditions (economic level and emission reduction efficiency), and external emission impacts. The MGWR model was utilized to examine the directions and magnitudes of the impacts of various influencing factors. The results demonstrate that air circulation, vegetation, tertiary industry ratio, and emission reduction efficiency are major impact indicators that have a positive effect. The topography and the emissions from neighboring provinces have a statistically significant negative impact. The varying degrees of influence from different factors exhibit a spatial distribution trend

characterized by high-high aggregation and low-low aggregation. Finally, the k-means clustering method was applied in order to identify the similarities and differences between the coefficients of influencing factors across the 31 provinces. A silhouette coefficient was created to assess the quality of clustering and identify a suitable number of clusters. The results prove that the highest average silhouette coefficient occurs when $k = 3$, indicating that the most ideal clustering number is 3. Thus, the 31 provincial administrative regions were divided into three categories. Following this, suggestions on the corresponding categories have been proposed, to provide a scientific reference to the synergistic reduction of $PM_{2.5}$ and CO_2 . The relevant findings can clarify the direction of the synergistic management of air pollution and carbon emissions across different regions, in light of their natural environmental characteristics and socioeconomic development conditions. On this basis, more scientific and reasonable policies and measures for synergistic reduction can be formulated to achieve optimal allocation and efficient utilization of resources in all aspects.

Author Contributions: Conceptualization, Z.J.; formal analysis, Z.J. and S.S.; funding acquisition, D.Z.; methodology, Z.J., S.S. and Y.B.; resources, D.Z.; writing—original draft, Z.J. and Y.B.; writing—review and editing, Z.J., Y.B. and Z.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the National Key R&D Program of China (grant no. 2023YFC3709500 and 2023YFC3804902), and the National Key Scientific and Technological Infrastructure project “Earth System Science Numerical Simulator Facility” (EarthLab).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

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

References

1. Xu, F.; Xie, Y.; Zhou, D. Air pollution’s impact on the settlement intention of domestic migrants: Evidence from China. *Environ. Impact Assess. Rev.* **2022**, *95*, 106761. [[CrossRef](#)]
2. Wang, K.-L.; Xu, R.-Y.; Jiang, W.; Liu, Y. Impact of National Industrial Relocation Demonstration Zones (NIRDZs) policy on urban carbon emissions in China. *Environ. Impact Assess. Rev.* **2023**, *102*, 107165. [[CrossRef](#)]
3. Shi, Q.; Zheng, B.; Zheng, Y.; Tong, D.; Liu, Y.; Ma, H.; Hong, C.; Geng, G.; Guan, D.; He, K.; et al. Co-benefits of CO_2 emission reduction from China’s clean air actions between 2013–2020. *Nat. Commun.* **2022**, *13*, 5061. [[CrossRef](#)] [[PubMed](#)]
4. Wang, Y.; Niu, Y.; Li, M.; Yu, Q.; Chen, W. Spatial structure and carbon emission of urban agglomerations: Spatiotemporal characteristics and driving forces. *Sustain. Cities Soc.* **2022**, *78*, 103600. [[CrossRef](#)]
5. Xian, B.; Xu, Y.; Chen, W.; Wang, Y.; Qiu, L. Co-benefits of policies to reduce air pollution and carbon emissions in China. *Environ. Impact Assess. Rev.* **2024**, *104*, 107301. [[CrossRef](#)]
6. Zhang, Q.; Yin, Z.; Lu, X.; Gong, J.; Lei, Y.; Cai, B.; Cai, C.; Chai, Q.; Chen, H.; Dai, H.; et al. Synergetic roadmap of carbon neutrality and clean air for China. *Environ. Sci. Ecotechnol.* **2023**, *16*, 100280. [[CrossRef](#)] [[PubMed](#)]
7. Yang, X.; Yang, X.; Zhu, J.; Jiang, P.; Lin, H.; Cai, Z.; Huang, H.; Long, J. Synergic emissions reduction effect of China’s “Air Pollution Prevention and Control Action Plan”: Benefits and efficiency. *Sci. Total Environ.* **2022**, *847*, 157564. [[CrossRef](#)] [[PubMed](#)]
8. Chen, S.; Tan, Z.; Wang, J.; Zhang, L.; He, X.; Mu, S. Spatial and temporal evolution of synergizing the reduction of pollution and carbon emissions and examination on comprehensive pilot effects—evidence from the national eco-industrial demonstration parks in China. *Environ. Impact Assess. Rev.* **2023**, *101*, 107147. [[CrossRef](#)]
9. Portugal-Pereira, J.; Koberle, A.; Lucena, A.F.P.; Rochedo, P.R.R.; Império, M.; Carsalade, A.M.; Schaeffer, R.; Rafaj, P. Interactions between global climate change strategies and local air pollution: Lessons learnt from the expansion of the power sector in Brazil. *Clim. Chang.* **2018**, *148*, 293–309. [[CrossRef](#)]
10. Jiao, J.; Huang, Y.; Liao, C. Co-benefits of reducing CO_2 and air pollutant emissions in the urban transport sector: A case of Guangzhou. *Energy Sustain. Dev.* **2020**, *59*, 131–143. [[CrossRef](#)]
11. Wei, X.; Tong, Q.; Magill, I.; Vithayasrichareon, P.; Betz, R. Evaluation of potential co-benefits of air pollution control and climate mitigation policies for China’s electricity sector. *Energ. Econ.* **2020**, *92*, 104917. [[CrossRef](#)]
12. Mao, X.; Zeng, A.; Hu, T.; Zhou, J.; Xing, Y.; Liu, S. Co-control of local air pollutants and CO_2 in the Chinese iron and steel industry. *Environ. Sci. Technol.* **2013**, *47*, 12002–12010. [[CrossRef](#)] [[PubMed](#)]

13. Adila, A.; Jiang, P. Synergy and co-benefits of reducing CO₂ and air pollutant emissions by promoting electric vehicles—A case of Shanghai. *Energy Sustain. Dev.* **2020**, *55*, 181–189.
14. Chen, Y.; Zhao, Z.; Yi, W.; Hong, J.; Zhang, B. Has China achieved synergistic reduction of carbon emissions and air pollution? Evidence from 283 Chinese cities. *Environ. Impact Assess. Rev.* **2023**, *103*, 107277. [[CrossRef](#)]
15. Lu, Z.; Huang, L.; Liu, J.; Zhou, Y.; Chen, M.; Hu, J. Carbon dioxide mitigation co-benefit analysis of energy-related measures in the Air Pollution Prevention and Control Action Plan in the Jing-Jin-Ji region of China. *Resour. Conserv. Recycl. X* **2019**, *1*, 100006. [[CrossRef](#)]
16. Xue, B.; Ma, Z.; Geng, Y.; Heck, P.; Ren, W.; Tobias, M.; Maas, A.; Jiang, P.; Puppim de Oliveira, J.A.; Fujita, T. A life cycle co-benefits assessment of wind power in China. *Renew. Sustain. Energy Rev.* **2015**, *41*, 338–346. [[CrossRef](#)]
17. Dong, H.; Dai, H.; Dong, L.; Fujita, T.; Geng, Y.; Klimont, Z.; Inoue, T.; Bunya, S.; Fujii, M.; Masui, T. Pursuing air pollutant co-benefits of CO₂ mitigation in China: A provincial leveled analysis. *Appl. Energy* **2015**, *144*, 165–174. [[CrossRef](#)]
18. Liu, F.; Klimont, Z.; Zhang, Q.; Cofala, J.; Zhao, L.; Huo, H.; Nguyen, B.; Schöpp, W.; Sander, R.; Zheng, B.; et al. Integrating mitigation of air pollutants and greenhouse gases in Chinese cities: Development of GAINS-City model for Beijing. *J. Clean. Prod.* **2013**, *58*, 25–33. [[CrossRef](#)]
19. Hernández, K.D.; Fajardo, O.A. Estimation of industrial emissions in a Latin American megacity under power matrix scenarios projected to the year 2050 implementing the LEAP model. *J. Clean. Prod.* **2021**, *303*, 126921. [[CrossRef](#)]
20. Kuylenstierna, J.C.I.; Heaps, C.G.; Ahmed, T.; Vallack, H.W.; Hicks, W.K.; Ashmore, M.R.; Malley, C.S.; Wang, G.; Lefèvre, E.N.; Anenberg, S.C.; et al. Development of the Low Emissions Analysis Platform—Integrated Benefits Calculator (LEAP-IBC) tool to assess air quality and climate co-benefits: Application for Bangladesh. *Environ. Int.* **2020**, *145*, 106155. [[CrossRef](#)] [[PubMed](#)]
21. Zhao, X.; Ma, X.; Chen, B.; Shang, Y.; Song, M. Challenges toward carbon neutrality in China: Strategies and countermeasures. *Resour. Conserv. Recycl.* **2022**, *176*, 105959. [[CrossRef](#)]
22. She, Q.; Cao, S.; Zhang, S.; Zhang, J.; Zhu, H.; Bao, J.; Meng, X.; Liu, M.; Liu, Y. The impacts of comprehensive urbanization on PM_{2.5} concentrations in the Yangtze River Delta, China. *Ecol. Indic.* **2021**, *132*, 108337. [[CrossRef](#)]
23. Kılıç, Ş.; Krajačić, G.; Duić, N.; Rosen, M.A.; Al-Nimr, M.d.A. Advances in integration of energy, water and environment systems towards climate neutrality for sustainable development. *Energy Convers. Manag.* **2020**, *225*, 113410. [[CrossRef](#)]
24. Jia, Z.; Lin, B. How to achieve the first step of the carbon-neutrality 2060 target in China: The coal substitution perspective. *Energy* **2021**, *233*, 121179. [[CrossRef](#)]
25. Fu, Z.; Li, R. The contributions of socioeconomic indicators to global PM_{2.5} based on the hybrid method of spatial econometric model and geographical and temporal weighted regression. *Sci. Total Environ.* **2020**, *703*, 135481. [[CrossRef](#)] [[PubMed](#)]
26. Liu, Z.; Wang, F.; Tang, Z.; Tang, J. Predictions and driving factors of production-based CO₂ emissions in Beijing, China. *Sustain. Cities Soc.* **2020**, *53*, 101909. [[CrossRef](#)]
27. Zhu, L.; Hao, Y.; Lu, Z.-N.; Wu, H.; Ran, Q. Do economic activities cause air pollution? Evidence from China's major cities. *Sustain. Cities Soc.* **2019**, *49*, 101593. [[CrossRef](#)]
28. Jiang, F.; Chen, B.; Li, P.; Jiang, J.; Zhang, Q.; Wang, J.; Deng, J. Spatio-temporal evolution and influencing factors of synergizing the reduction of pollution and carbon emissions—Utilizing multi-source remote sensing data and GTWR model. *Environ. Res.* **2023**, *229*, 115775. [[CrossRef](#)] [[PubMed](#)]
29. Yi, H.; Zhao, L.; Qian, Y.; Zhou, L.; Yang, P. How to achieve synergy between carbon dioxide mitigation and air pollution control? Evidence from China. *Sustain. Cities Soc.* **2022**, *78*, 103609. [[CrossRef](#)]
30. Hu, J. Synergistic effect of pollution reduction and carbon emission mitigation in the digital economy. *J. Environ. Manag.* **2023**, *337*, 117755. [[CrossRef](#)] [[PubMed](#)]
31. Makov, T.; Meshulam, T.; Cansoy, M.; Shepon, A.; Schor, J.B. Digital food sharing and food insecurity in the COVID-19 era. *Resour. Conserv. Recycl.* **2023**, *189*, 106735. [[CrossRef](#)] [[PubMed](#)]
32. Holzmann, P.; Gregori, P. The promise of digital technologies for sustainable entrepreneurship: A systematic literature review and research agenda. *Int. J. Inf. Manag.* **2023**, *68*, 102593. [[CrossRef](#)]
33. Gao, X.; Liu, N.; Hua, Y. Environmental Protection Tax Law on the synergy of pollution reduction and carbon reduction in China: Evidence from a panel data of 107 cities. *Sustain. Prod. Consum.* **2022**, *33*, 425–437. [[CrossRef](#)]
34. Li, M.; Zhang, D.; Li, C.-T.; Mulvaney, K.M.; Selin, N.E.; Karplus, V.J. Air quality co-benefits of carbon pricing in China. *Nat. Clim. Chang.* **2018**, *8*, 398–403. [[CrossRef](#)]
35. Li, Z.; Bai, T.; Tang, C. How does the low-carbon city pilot policy affect the synergistic governance efficiency of carbon and smog? Quasi-experimental evidence from China. *J. Clean. Prod.* **2022**, *373*, 133809. [[CrossRef](#)]
36. Fotheringham, A.S.; Charlton, M.E.; Brunson, C. Geographically weighted regression: A natural evolution of the expansion method for spatial data analysis. *Environ. Plann. A Econ. Space* **1998**, *30*, 1905–1927. [[CrossRef](#)]
37. Mansour, S.; Al Kindi, A.; Al-Said, A.; Al-Said, A.; Atkinson, P. Sociodemographic determinants of COVID-19 incidence rates in Oman: Geospatial modelling using multiscale geographically weighted regression (MGWR). *Sustain. Cities Soc.* **2021**, *65*, 102627. [[CrossRef](#)] [[PubMed](#)]
38. Fotheringham, A.S.; Yang, W.; Kang, W. Multiscale Geographically Weighted Regression (MGWR). *Ann. Am. Assoc. Geogr.* **2017**, *107*, 1247–1265. [[CrossRef](#)]
39. Zhao, J.; Guo, F.; Zhang, H.; Dong, J. Mechanisms of non-stationary influence of urban form on the diurnal thermal environment based on machine learning and MGWR analysis. *Sustain. Cities Soc.* **2024**, *101*, 105194. [[CrossRef](#)]

40. Hering, L.; Poncet, S. Environmental policy and exports: Evidence from Chinese cities. *J. Environ. Econ. Manag.* **2014**, *68*, 296–318. [[CrossRef](#)]
41. Zhai, H.; Yao, J.; Wang, G.; Tang, X. Study of the effect of vegetation on reducing atmospheric pollution particles. *Remote Sens.* **2022**, *14*, 1255. [[CrossRef](#)]
42. Zhang, J.; Zeng, W.; Shi, H. Regional environmental efficiency in China: Analysis based on a regional slack-based measure with environmental undesirable outputs. *Ecol. Indic.* **2016**, *71*, 218–228. [[CrossRef](#)]
43. Zhang, J.; Zeng, W.; Wang, J.; Yang, F.; Jiang, H. Regional low-carbon economy efficiency in China: Analysis based on the Super-SBM model with CO₂ emissions. *J. Clean. Prod.* **2017**, *163*, 202–211. [[CrossRef](#)]
44. Jia, Z.; Cai, Y.; Chen, Y.; Zeng, W. Regionalization of water environmental carrying capacity for supporting the sustainable water resources management and development in China. *Resour. Conserv. Recycl.* **2018**, *134*, 282–293. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.