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Analysis of PM$_{2.5}$ Synergistic Governance Path from a Socio-Economic Perspective: A Case Study of Guangdong Province

Kunkun Fan [1,2], Daichao Li [1,2,*], Cong Li [1,2], Xinlei Jin [1,2], Fei Ding [1,2] and Zhan Zeng [3]

1   The Academy of Digital China (Fujian), Fuzhou University, Fuzhou 350108, China;
     215527013@fzu.edu.cn (K.F.); 205520011@fzu.edu.cn (C.L.); 225527017@fzu.edu.cn (X.J.);
     225527006@fzu.edu.cn (F.D.)
2   Key Laboratory of Spatial Data Mining and Information Sharing of Ministry of Education, Fuzhou University,
     Fuzhou 350002, China
3   Hunan Cartographic Publishing House, Changsha 410007, China; hnmapsqzz@163.com
*   Correspondence: lidc@fzu.edu.cn

Abstract: Analyzing the influencing factors of PM$_{2.5}$ concentration, scenario simulations, and countermeasure research to address the problem of PM$_{2.5}$ pollution in Guangdong Province is of great significance for governments at all levels for formulating relevant policies. In this study, the ChinaHighPM$_{2.5}$ dataset and economic and social statistics for Guangdong Province from 2010 to 2019 were selected, and a PM$_{2.5}$ pollution management compliance path formulation method based on the multi-scenario simulation was proposed by combining the differences in city types and PM$_{2.5}$ concentration prediction. Based on the prediction model of PM$_{2.5}$ concentration constructed by the Ridge and SVM models and facing the PM$_{2.5}$ pollution control target in 2025, the urban PM$_{2.5}$ pollution control scenario considering the characteristics of urban development was constructed. According to the scenario simulation results of the PM$_{2.5}$ prediction model, the PM$_{2.5}$ pollution control path suitable for Guangdong Province during the 14th Five-Year Plan period was explored. The coupling coordination model was used to explore the spatial and temporal pattern evolution of PM$_{2.5}$ pollution collaborative governance in various prefecture-level cities under the standard path, and the policy recommendations for PM$_{2.5}$ pollution control during the 14th Five-Year Plan period are proposed. The results showed the following: ① in the case of small samples, the model can provide effective simulation predictions for the study of urban pollutant management compliance pathways. ② Under the scenario of PM$_{2.5}$ management meeting the standard, in 2025, the annual average mass concentration of PM$_{2.5}$ in all prefecture-level cities in Guangdong Province will be lower than 22 μg/m^3, and the annual average concentration of PM$_{2.5}$ in the whole province will drop from 25.91 μg/m^3 to 21.04 μg/m^3, which will fulfil the goal of reducing the annual average concentration of PM$_{2.5}$ in the whole province to below 22 μg/m^3, as set out in the 14th Five-Year Plan for the Ecological Environmental Protection of Guangdong Province. ③ Under the path of PM$_{2.5}$ control and attainment, the regional coordination relationship among prefecture-level cities in Guangdong Province is gradually optimized, the number of intermediate-level coordinated cities will increase, and the overall spatial distribution pattern will be low in the middle and high in the surrounding area. Based on the characteristics of the four city types, it is recommended that a staggered development strategy be implemented to achieve synergy between economic development and environmental quality. Urban type I should focus on restructuring freight transportation to reduce urban pollutant emissions. City type II should focus on urban transportation and greening. For city type III, the focus should be on optimizing the industrial structure, adjusting the freight structure, and increasing the greening rate of the city. For city type IV, industrial upgrading, energy efficiency, freight structure, and management of industrial pollutant emissions should be strengthened.

Keywords: PM$_{2.5}$; influencing factor; concentration prediction; SVM; scenario simulation

1. Introduction

$PM_{2.5}$ pollution has always been one of the major factors of atmospheric environmental problems in Guangdong Province [1–3]. The 2019 Bulletin on the State of the Environment in Guangdong Province showed that the annual average concentration of $PM_{2.5}$ in the province was 27 μg/m^3, which was still higher than the World Health Organization's $PM_{2.5}$ transition level 2 standard (25 μg/m^3). With the successive introduction of relevant policies during the 14th Five-Year Plan period, the new policies have put forward more stringent requirements for the treatment of $PM_{2.5}$ pollution in Guangdong Province. The 14th Five-Year Plan for Ecological Environment Protection of Guangdong Province proposes reducing the annual average concentration of $PM_{2.5}$ in the province to below 22 μg/m^3 by 2025. Therefore, finding a path to achieve $PM_{2.5}$ pollution control standards is of great significance for prefectural municipalities in Guangdong Province in formulating policies on environmental pollution control.

Currently, research on $PM_{2.5}$ pollution management pathways is mainly carried out in three aspects: analysis of $PM_{2.5}$ influencing factors [4–6], prediction model construction [7–9], and $PM_{2.5}$ pollution management [10–16]. In terms of $PM_{2.5}$ influencing factors, the existing research has only established indicator characteristics from the relationship between meteorological conditions [17–19] and $PM_{2.5}$ concentration to reveal the role of meteorological parameters in influencing the daily and seasonal changes in $PM_{2.5}$ concentration as well as its spatial distribution, ignoring the comprehensive impacts of economic development and policy adjustments on the management of $PM_{2.5}$ levels, such as industrial structure, energy consumption, and environmental protection policies. Therefore, this study integrated relevant statistical indicators on the basis of existing research and constructed an indicator system for $PM_{2.5}$ influencing factors from the perspective of socio-economic factors. In terms of $PM_{2.5}$ prediction models, traditional prediction models have certain limitations. Although the classical statistical model is easy to use, its prediction effect needs to be improved [20], the mechanism of the air quality model is complex, and the prediction performance is average [21]. With the maturity of machine learning methods, deep learning models based on neural networks are beginning to be used in the study of air pollution [22], and based on regression methods [23], neural networks [24], RF [25], LightGBM [26], and LSTM [27] have been widely used to study the nonlinear relationship between economic development and $PM_{2.5}$ concentration. Although machine learning-based models have superior predictive performance, they require a large number of samples to support them [28–30]. The coupling of multiple single models maximizes the integration of model strengths and improves prediction accuracy [31–34]. Therefore, this study explored hybrid models coupling classical statistical and machine learning approaches for more accurate $PM_{2.5}$ concentration predictions. In terms of $PM_{2.5}$ pollution management, the existing studies mainly focused on the construction of the same management scenarios for multiple cities within the study area, ignoring the differences in socio-economic characteristics between cities [35–38]. Therefore, this study constructed $PM_{2.5}$ management scenarios that take into account the socio-economic characteristics of the cities, and simulated the prediction and analysis of these scenarios. These predictions were combining with the coupled degree of coordination model to explore the evolution characteristics of the coupled coordination relationship of $PM_{2.5}$ pollution influencing factors in different scenarios, and we then analyzed the spatial and temporal patterns of $PM_{2.5}$ pollution management for the purpose of proposing paths of synergistic management of $PM_{2.5}$ pollution according to the local conditions, with a view to realizing the synergistic management of Guangdong Province and the sustainable development of the city.

This study used Guangdong Province as the study area; we combined air pollution control policies such as the Three-Year Action Plan for Winning the Battle for the Blue Sky with socio-economic indicators such as the influencing factors of $PM_{2.5}$ pollution, and analyzes the rationality of the indicators. Based on the historical data of $PM_{2.5}$ and influencing factors in each prefecture-level city, a hybrid model coupling Ridge and SVM was constructed to realize $PM_{2.5}$ concentration predictions. Based on the current development

status of each prefecture-level city, a scenario construction method that takes into account the characteristics of urban development was proposed, and the $PM_{2.5}$ management scenarios for each prefecture-level city in the 14th Five-Year Plan period were constructed using this method. Finally, based on the $PM_{2.5}$ prediction model, the $PM_{2.5}$ management scenario was simulated and predicted, and based on the results, the path of $PM_{2.5}$ pollution management in Guangdong Province during the 14th Five-Year Plan period was determined. The evolution of the spatial and temporal patterns of $PM_{2.5}$ pollution management processed and coupling coordination relationships were analyze by using the coupling coordination degree model to reveal the influence relationship among socio-economic development, air pollution management, and regional coordinated development. This research aimed to explore the interactions between economic and social development, environmental protection, and coordinated management through the prediction of $PM_{2.5}$ concentrations, simulation of management scenarios, and a comprehensive study of the coupling and coordination relationships, so as to provide scientifically sound policy recommendations for the $PM_{2.5}$ management targets of the 14th Five-Year Plan for Guangdong Province.

2. Materials and Methods

2.1. Study Area

Guangdong Province is located in the southeastern coastal region of mainland China, with 21 prefecture-level cities under its jurisdiction, mainly comprising the four regions of Eastern Guangdong, Western Guangdong, Northern Guangdong, and the Pearl River Delta (Figure 1), covering a total area of about 180,000 square kilometers and a population of more than 113 million. As one of the most populous and economically developed provinces in China, Guangdong Province brings together 8% of the country's population in less than 2% of the country's land area, with a well-developed socio-economy, and a Gross Regional Product (GRP) of approximately RMB 129,118,858,000,000 in 2022, which has ranked first in the country for the 31st consecutive year, and with manufacturing, trade, and services being the main drivers of the socio-economy in Guangdong Province. However, due to the problems brought about by its rapid economic development, the province's atmospheric environmental pollution problem has also become more and more serious. With the "Outline of the Fourteenth Five-Year Plan and Vision 2035 for the National Economic and Social Development of Guangdong Province", "Fourteenth Five-Year Plan for the Ecological Civilization Construction of Guangdong Province", and "Fourteenth Five-Year Plan for the Ecological Environmental Protection of Guangdong Province", etc., the management of $PM_{2.5}$ in Guangdong Province has entered into a new stage, and there are new objectives for the management of $PM_{2.5}$ in the new era and situation. In 2025, the average annual concentration of $PM_{2.5}$ in Guangdong Province will reach the target concentration of the 14th Five-Year Plan, and as the largest province in China in terms of economic output (GDP), with a complex and diverse industrial structure and a large population, Guangdong Province is facing the double pressure of economic development and environmental governance. In this context, exploring a path for $PM_{2.5}$ pollution management that minimizes the impact of urban socio-economic development has a profound significance for the governments of Guangdong Province at all levels in formulating and implementing the relevant management programs.

2.2. Variable Selection and Data Sources

Due to the late start of $PM_{2.5}$ concentration monitoring in the prefecture-level cities of Guangdong Province, which began in 2013, there are fewer samples of $PM_{2.5}$ annual average concentration data; however, the use of remote sensing imagery to estimate $PM_{2.5}$ concentrations can yield longer time series of $PM_{2.5}$ data. Wei et al. [39] generated the ChinaHighPM$_{2.5}$ dataset at a 1 km resolution from 2000 to 2020 based on ground-based measurements, satellite remote sensing products, and other data. Considering the great impact of the novel coronavirus epidemic in 2020 on the socio-economy of Guangdong Province and its significant difference from normal years [40], this research did not take it

as a valid research year to ensure that the accuracy and reliability of the data and that the results were not affected by bias. In this study, we selected the 2010–2019 annual average $PM_{2.5}$ concentration data from this dataset and extracted the $PM_{2.5}$ data for Guangdong Province using ArcGIS.
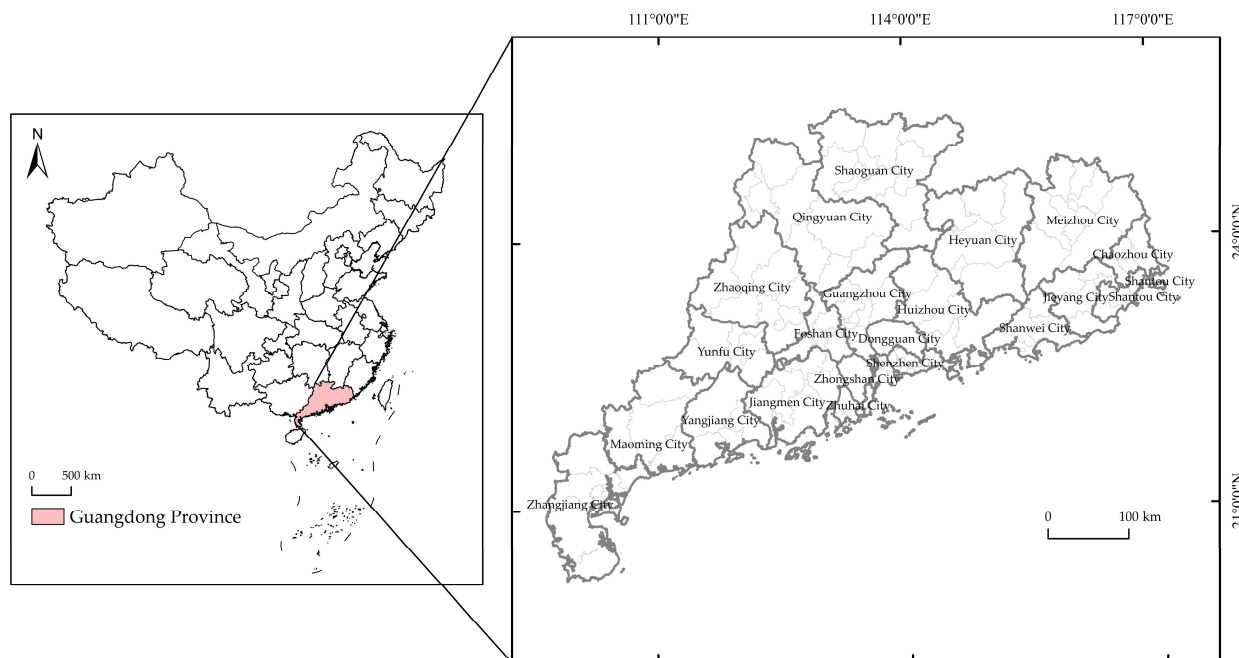
Figure 1. Location of the study area.

This research combined the Three-Year Action Plan for Winning the Battle for Blue Sky, the 14th Five-Year Plan, and related studies and to select the relevant indicators of influencing factors, which belong to six aspects: industrial structure, energy consumption, road traffic, cargo transportation, urban greening, and pollution emissions. In terms of industrial structure, the higher the proportion of secondary industries in GDP, the higher the $PM_{2.5}$ concentration, but with the increase in the proportion of tertiary industries, the tertiary industries catching up and overtaking the secondary industries can curb air pollution to a certain extent [41]. Therefore, the proportion of secondary industries in GDP (SGDP) and the proportion of tertiary industries in GDP (TGDP) were chosen to measure the city's industrial structure. In terms of energy consumption, reducing energy consumption per unit of GDP (ECPG) can help to improve economic efficiency and air quality [42], and this indicator was chosen to represent the intensity of urban energy consumption. In regard to road transportation, controlling the number of automobiles can help alleviate urban traffic congestion and tailpipe emissions, and therefore the growth rate of civilian vehicle ownership (GROC) was chosen to characterize urban road transportation. In terms of cargo transportation structure, since the total amount of road freight and waterway freight in Guangdong Province accounts for more than 95% of the total freight, the implementation of "public-to-water" measures was mainly taken into account, and the proportion of highway freight to total freight (HFTF) and the proportion of waterway freight to total freight (WFTF) were chosen to characterize the freight transportation structure. Regarding urban greening, this study selected urban green area per capita (GAPC) to measure the level of urban greening. Finally, urban industrial sulfur dioxide emissions (ISDE) was selected as an indicator to measure the level of urban pollution emissions.

In this study, SGDP, TGDP, GROC, and GAPC data were obtained from the Guangdong Provincial Statistical Yearbook; HFTF and WFTF data were obtained from the China Urban Statistical Yearbook; and ECPG and ISDE data were obtained from the Guangdong Provincial Government Information Disclosure System upon request. The period of the data spanned 2010–2019.

2.3. Research Methods

In this study, the RR-SVM hybrid model coupled with classical statistics and machine learning methods was used to predict PM$_{2.5}$ concentration. Based on this model, the research on PM$_{2.5}$ pollution control paths was realized by constructing and simulating governance scenarios. The main processes were as follows: first, we determined the reasonableness and validity of PM$_{2.5}$-influencing factors using grey correlation analysis. Second, we constructed the RR-SVM hybrid model based on the 2010–2019 PM$_{2.5}$ and variable data for each prefectural city in Guangdong Province, coupling Ridge regression and Support Vector Machine (SVM) methods, and used the Particle Swarm Optimization (PSO) algorithm to find the optimal parameters of the model. Then, based on the air pollution management policy and planning, the historical change pattern of variables, and the socioeconomic status of the study area, a basic library of PM$_{2.5}$ management scenarios was constructed. Then, the development status of each prefecture-level city was categorized according to its current development status; based on the categorization results, the PM$_{2.5}$ pollution management scenarios of each type of city were constructed in combination with the base scenario library. Finally, the scenario simulation prediction was carried out by using the hybrid model, and according to the results, the standard path of PM$_{2.5}$ pollution control in Guangdong Province during the 14th Five-Year Plan period was determined. Then, the coupling coordination degree model of the urban PM$_{2.5}$-influencing factors was constructed, and the spatial and temporal evolution laws of the coupling coordination relationship between urban PM$_{2.5}$-influencing factors in different prefecture-level cities are further explored based on six aspects: STIR, ECPG, WHFR, GROC, GAPC, and ISDE. The technical roadmap is shown in Figure 2.
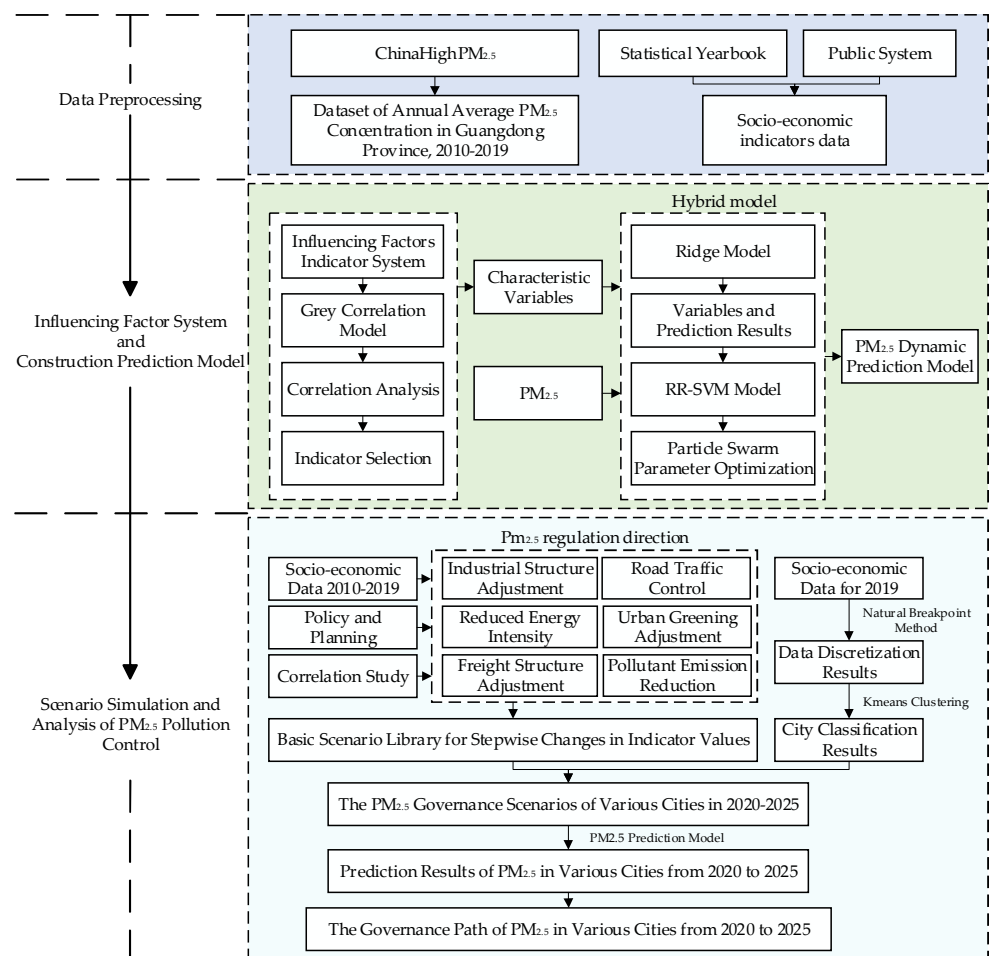

Figure 2. Technical roadmap.

2.3.1. Grey Correlation Model

According to the related study by He Xiang et al. [43], the steps for calculating the correlation between each influencing factor and the PM$_{2.5}$ concentration are as follows:

(1) First identify the sequence of features to be used as a reference and the sequence of factors to be compared:

The annual average PM$_{2.5}$ concentration values of each city for a total of 10 years from 2010 to 2019 were selected as the characteristic sequence $x_0(t)$, i.e., $x_0(t) = \{x_0(1), x_0(2), \cdots, x_0(10)\}$. The data for 8 influencing factors such as SGDP, TGDP, GROC, and GAPC of each city are selected as the factor series, i.e., $x_i(t) = \{x_i(1), x_i(2), \cdots, x_i(10)\}$, $i = 1, 2, \cdots, 8$.

(2) If the factors have different scales and the data are not directly comparable, they are standardized.

(3) Calculate the correlation coefficient:

$$\xi(x_0(t), x_i(t)) = \frac{\min_i \min_t |x_0(t) - x_i(t)| + \rho \max_i \max_t |x_0(t) - x_i(t)|}{|x_0(t) - x_i(t)| + \rho \max_i \max_t |x_0(t) - x_i(t)|} \tag{1}$$

In the formula, $x_0(t)$ is the characteristic sequence and $x_i(t)$ is the factor sequence; $\min_i \min_t |x_0(t) - x_i(t)|$ and $\max_i \max_t |x_0(t) - x_i(t)|$ are the minimum value and maximum value of extreme deviation, respectively; and ρ is the resolution, which generally takes a value of 0.5.

(4) Calculate the grey correlation R:

$$R_i = \frac{1}{10} \sum_{t=1}^{10} \xi(x_0(t), \, x_i(t)) \tag{2}$$

When $R \in (0, 0.3]$, the correlation is slight; when $R \in (0.3, 0.6]$, the correlation is medium; and when $R \in (0.6, 1.0)$, the correlation is strong [43].

2.3.2. PM$_{2.5}$ Prediction Model Approach

(1)   Ridge Regression

When socioeconomic factors are used for PM$_{2.5}$ concentration prediction, the high correlation between variables can lead to extreme instability and overfitting of traditional linear regression models. Meanwhile, the ridge regression model retains all the variables while resolving the multicollinearity among the variables [44]. The ridge regression model is formulated [45] as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \lambda \sum_{j=1}^{p} \beta_j^2 \tag{3}$$

where y is the PM$_{2.5}$ concentration; x_1, x_2, $\cdots$, x_p represent the eight influencing factors such as SGDP and TGDP; β_1, β_2, $\cdots$, β_p represent the regression coefficients; and λ is the regularization parameter.

(2)   SVM Model

The SVM model can solve the problems of non-linearity, small samples, and high dimensions, and effectively avoid over-fitting [46], and is thus often used in prediction or classification research. This study used this method to establish a nonlinear relationship between PM$_{2.5}$ and the influencing factors to achieve the prediction of PM$_{2.5}$ concentrations. The specific formula is as follows.

Let there be a total of n samples. Each sample x_i contains p influences such as SGDP ($x_{i,1}$, $x_{i,2}$, $\cdots$, $x_{i,p}$) and the target variable PM$_{2.5}$ concentration y. The SVM model equation [47] is

$$y = \sum_{i=1}^{n} \alpha_i K(x_i, x_j) + b - \lambda \sum_{i=1}^{n} \alpha_i^2 \tag{4}$$

where α_i is the Lagrange multiplier, $K(x_i, x_j)$ is the kernel function, b is a constant term, and λ is the regularization parameter.

In SVM modeling, the kernel function is used to map data from the original space to a higher dimensional space, thus enabling the model to deal with nonlinear relationships. The radial basis kernel (RBF kernel) is one of the most commonly used kernel functions, and is used in this study with the formula:

$$K(x_i, x_j) = e^{-\gamma \|x_i - x_j\|^2} \tag{5}$$

where γ is the parameter of the kernel function, which is used to control the distance between the samples in the high-dimensional space. To enable the model to achieve an ideal effect, the PSO algorithm was used to optimize the regularization parameter λ and the kernel function parameter γ.

(3)   R-SVM Model Construction Process

In this study, the ridge regression model was first constructed using the ridge module in the Sklearn package of the Python language based on the data for annual average PM$_{2.5}$ concentrations and socio-economic factors in each prefecture-level city from 2010 to 2019. Then, the variable data from 2010 to 2019 were used as input data and predicted using the ridge model to obtain the linear prediction result of PM$_{2.5}$ from 2010 to 2019, which was used as one of the input variables in the SVM model to explain the linear relationship between PM$_{2.5}$ and this variable.

In constructing the SVM model, the ridge model prediction results and the original independent variables were set as the characteristic variables of the model, and PM$_{2.5}$ was set as the model predictor variable. Although the SVM model is suitable for small sample datasets, there are only ten years of historical data for each city, which is still a small amount of data for modeling. For this reason, this study adopted the method used by Wang et al. [10], using the data of 21 cities as the training data of the model at the same time, and this method effectively improved the sample size and stability of the model and avoids overfitting.

In this study, the root mean square error (RMSE), mean absolute error (MAE), and goodness of fit (R^2) were used as model accuracy evaluation indexes.

2.3.3. Scenario Construction Method

Due to certain differences between the socio-economic characteristics of different prefecture-level cities, using the traditional method to construct the same scenario simulations for all prefecture-level cities will cause the loss of the socio-economic development characteristics of the city. To solve this problem, this study utilized the similarities and differences between the socio-economic characteristics of different prefecture-level cities to classify the cities, and based on the characteristics of each type of city, we constructed a PM$_{2.5}$ governance scenario intending to achieve the PM$_{2.5}$ governance standard in 2025. The flowchart of the method is shown in Figure 3.

The specific steps are as follows:

(1) According to the relevant policies and planning objectives of the study area, the historical pattern of change and the current development of PM$_{2.5}$-influencing factors, and relevant studies, we constructed a base scenario library with three levels of low, medium, and high numerical magnitude for each influencing factor indicator in terms of the direction of regulation for industrial structure, energy consumption, cargo transportation, road traffic, greening of cities, and pollutant emissions, and set three levels of regulation intensity for

each level (loose, intensive, and strict regulation) to match the degree of socio-economic development of different cities. The main role of this library was to provide a reference when constructing PM$_{2.5}$ governance scenarios for subsequent types of municipalities, and to select from the base scenario library the indicator regulation levels that match the socio-economic development of that type of municipality.

(2) The natural breakpoint method was used to grade the social and economic index data of each prefecture-level city in 2019 to establish the category characteristics of the social and economic variables of each prefecture-level city. We used the K-means algorithm to cluster the grading results and classified the cities according to the clustering results to obtain the city classification results.

(3) Based on the degree of development of socio-economic indicators in each type of city, we selected the matching indicator regulation intensity from the base scenario library and constructed the urban PM$_{2.5}$ pollution management scenarios for 2020–2025.
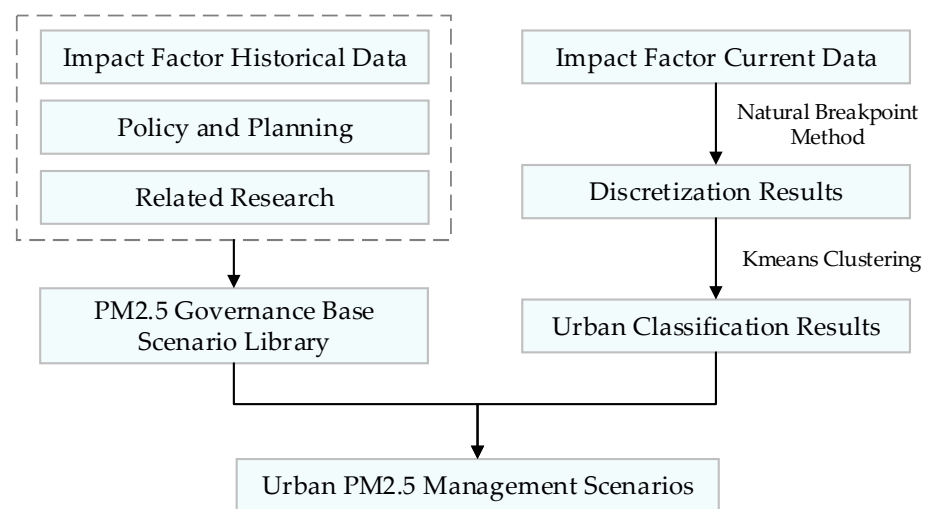
Figure 3. Flowchart of scenario construction methodology.

2.3.4. Coupling Coordination Degree Model

In this study, due to the differences in the unit magnitude of the data of each indicator, the efficacy of different indicators was found to have both positive and negative effects. To ensure the reasonableness of the evaluation results, it was necessary to standardize the indicators before each calculation to eliminate the differences in magnitude and direction between the original data, and the formulas [48] are as follows:

$$n_{ij} = \frac{o_{ij} - min(o_j)}{max(o_j) - min(o_j)}, \; n_{ij} \text{ is a positive indicator} \tag{6}$$

$$n_{ij} = \frac{max(o_j) - o_{ij}}{max(o_j) - min(o_j)}, \; n_{ij} \text{ is a negative indicator} \tag{7}$$

where n_{ij} is the standardized value of the indicator n_{ij}; o_{ij} is the original value; and $max(o_j)$ and $min(o_j)$ are the maximum and minimum values of indicator i, respectively. In this way, GAPC was found to be a positive indicator, while STIR, ECPG, WHFR, GROC, and ISDE were found to be negative indicators.

The coupling coordination degree model [49–51] further draws on the coordination degree model for the comprehensive evaluation and study of the whole system based on

the coupling degree. The functional relationship equation of the coupling coordination degree measurement model of multi-systems is as follows:

$$C = \left[\frac{\prod_{i=1}^{n} U_i}{\left(\frac{1}{n} \sum_{i=1}^{n} U_i\right)^n} \right]^{\frac{1}{n}} \tag{8}$$

where C is the value of the coupling degree, n is the number of subsystems, and U_i is the value of each subsystem.

The coupling coordination degree D is calculated as

$$T = \sum_{i=1}^{n} w_i U_i \tag{9}$$

$$D = \sqrt{CT} \tag{10}$$

where U_i is the normalized value of the ith subsystem and w_i is the weight of the ith subsystem. In most studies, it is assumed that the importance of each subsystem is the same, so w_i was set to be the same value and $\sum_{i=1}^{n} w_i = 1$. The classification criteria of the coordination level and coordination development degree are shown in Table 1 below.

Table 1. Standards for division of coordination level and coordination development degree.

| Coordination Degree	Coordination Level	Coordination Degree	Coordination Level
[0, 0.1)	Extreme imbalance	[0.5, 0.6)	Reluctant coordination
[0.1, 0.2)	Serious imbalance	[0.6, 0.7)	Primary coordination
[0.2, 0.3)	Moderate disorder	[0.7, 0.8)	Intermediate coordination
[0.2, 0.3)	Mild disorder	[0.8, 0.9)	Good coordination
[0.4, 0.5)	Endangered disorder	[0.9, 1)	Quality coordination

3. Results

3.1. PM$_{2.5}$ Concentration Prediction and Analysis of Influencing Factors

3.1.1. Correlation Analysis of PM$_{2.5}$-Influencing Factors

In this study, the correlation between PM$_{2.5}$ concentration values and indicators of influencing factors in all prefectural-level cities of Guangdong Province was calculated using grey correlation analysis based on the data for annual average PM$_{2.5}$ concentrations and indicators of the influencing factors from 2010 to 2019. In the existing studies, the correlation is considered mild when the grey correlation R $\in$ (0, 0.3], moderate when R $\in$ (0.3, 0.6], and strong when R $\in$ (0.6, 1.0] [43]. According to Figure 4, among the eight indicators, SGPD had the highest correlation with PM$_{2.5}$ concentration, with an average correlation of 0.85 for each prefecture-level city. The correlation between Dongguan City and Shanwei City reached 0.97 and 0.94, respectively, and the rest of the prefectures and cities were strongly correlated, except for Zhaoqing City; the average correlation between TGDP and PM$_{2.5}$ concentration of the prefectures and cities was 0.73, and the correlation was strong. Dongguan and Shanwei had the highest correlation between this indicator and PM$_{2.5}$ concentration, 0.97 and 0.91, respectively. The average correlation between ECPG and PM$_{2.5}$ concentration for each prefecture-level city in Guangdong Province was 0.84, and the correlation was strong, while Zhanjiang City had the lowest correlation of 0.62. The average correlation between WHFR and PM$_{2.5}$ concentration in each prefecture-level city was 0.77 and 0.74, and all cities had correlations greater than 0.6, which is a strong correlation. Except for the moderate correlation between GROC and PM$_{2.5}$ concentration in Shenzhen, the correlation of all other cities was strong. The correlations between GAPC and PM$_{2.5}$ concentration of Shantou City, Huizhou City, Zhongshan City, Zhuhai City, Jiangmen City, and Guangzhou City were lower than 0.6, which is a moderate correlation, and the

remaining 15 cities all had a strong correlation. The average correlation between ISDE and $PM_{2.5}$ concentration in Guangdong Province was 0.59, which is a moderate correlation.
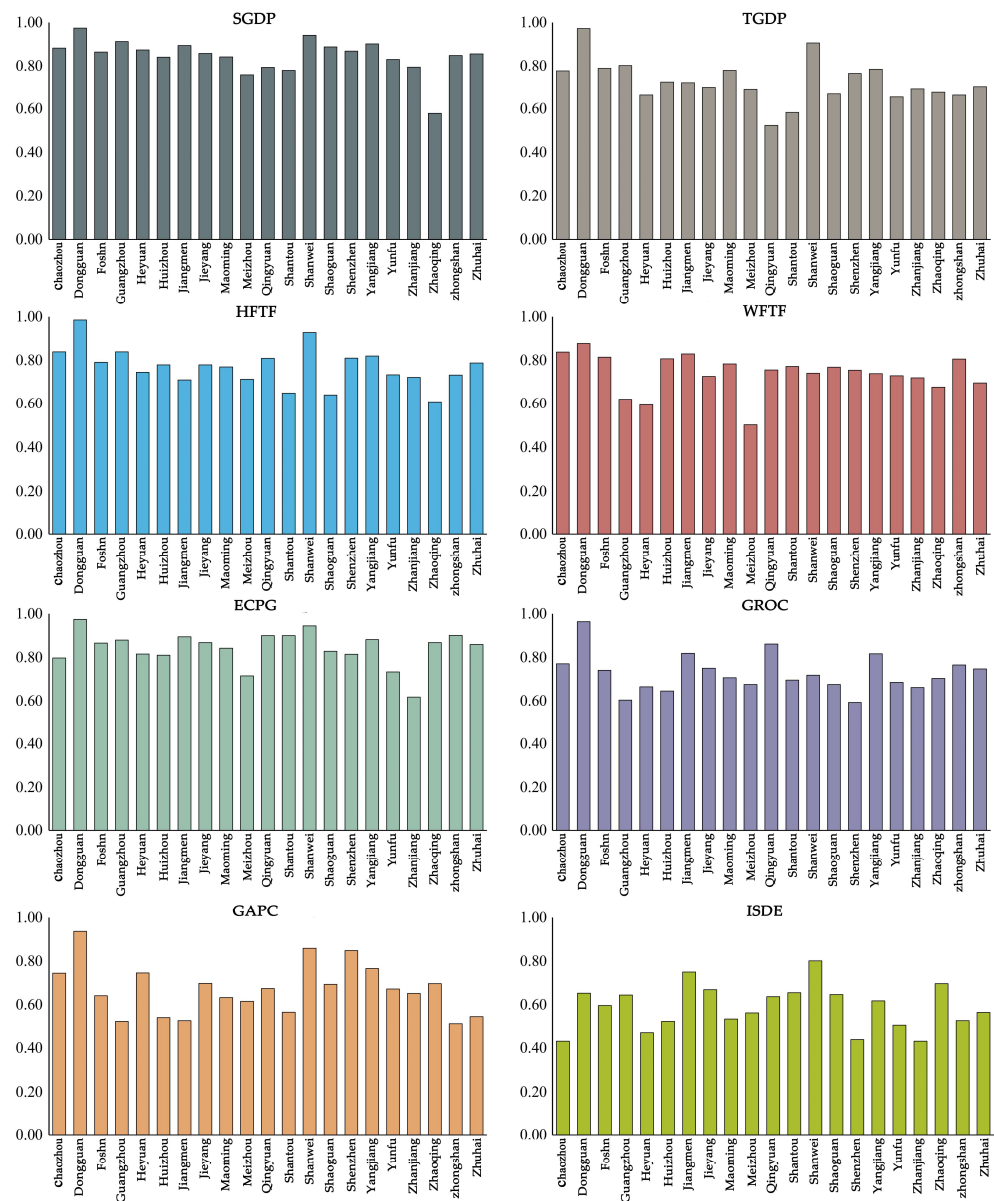
Figure 4. Correlation between $PM_{2.5}$ and influencing factors in various cities.

In terms of each indicator, the average correlation between ISDE and $PM_{2.5}$ in Guangdong Province was medium, and the average correlation between the rest of the indicators and $PM_{2.5}$ concentration was strong. This indicates that industrial structure, energy consumption, transportation, and urban greening in Guangdong Province have strong correlations with $PM_{2.5}$ concentrations, and have influenced $PM_{2.5}$ concentrations to a large extent in the past decade. Regionally, the grey correlations between $PM_{2.5}$ concentrations and socio-economic factors in each city were large, and their correlations were moderate or strong, indicating that the indicators played an important role in the changes in $PM_{2.5}$ concentrations, and the selection of indicators is reasonable.

3.1.2. PM$_{2.5}$ Concentration Prediction

Issues can arise due to the small sample size of the data for each prefecture-level city, while too many feature variables will lead to the overfitting phenomenon and reduce the generalization ability of the model. Linear transformation is one of the most common solutions for this issue, reducing the number of indicators and retaining the information of the original indicators when two indicators are highly correlated [52]. Therefore, in this model, the ratio of SGDP and TGDP (STIR) was used to represent SGDP and TGDP, and the ratio of HFTF and WFTF (WHFR) was used to represent HFTF and WFTF. Through this indicator compression, the original indicators can be preserved and the multicollinearity can be reduced. The results of the ridge regression model are shown in Table 1, and the results showed that the predicted values are in good agreement with the actual values, and the highest and lowest R^2 values in prefecture-level cities were 0.96 and 0.87, respectively, which better explains the PM$_{2.5}$ having a linear relationship with some of the influencing factors.

The ridge model prediction results with the original independent variables were set as the feature variables of the RR-SVM model, while PM$_{2.5}$ was set as the predictor variable, and the RR-SVM prediction model was obtained after training. The original independent variables and PM$_{2.5}$ were set as the feature variables and predictor variables of the single ridge and SVM models, and the single SVM prediction model obtained after training was used as the control group. The model results are shown in Table 2.

Table 2. Comparison of the accuracy of PM$_{2.5}$ prediction results for three models by city.

City	Ridge			SVM			RR-SVM		
	MAE/(μg·m^{-3})	RMSE/(μg·m^{-3})	R^2	MAE/(μg·m^{-3})	RMSE/(μg·m^{-3})	R^2	MAE/(μg·m^{-3})	RMSE/(μg·m^{-3})	R^2
Chaozhou	0.7586	0.9777	0.9493	1.2942	1.5536	0.8719	0.5200	0.6275	0.9791
Dongguan	1.0153	1.4954	0.9269	1.1974	1.4423	0.9320	0.4859	0.7184	0.9831
Foshan	1.5727	1.8879	0.9080	1.3962	1.8300	0.9136	0.4478	0.4959	0.9937
Guangzhou	1.3084	1.6678	0.9293	0.9040	1.1350	0.9673	0.6196	1.0397	0.9725
Heyuan	1.0393	1.3187	0.9384	2.2587	2.9273	0.6966	0.7832	1.0925	0.9577
Huizhou	0.9073	1.0530	0.9569	1.3760	2.0746	0.8326	0.3246	0.3654	0.9948
Jiangmen	1.0444	1.3588	0.9095	1.1114	1.3701	0.9080	0.3926	0.4750	0.9889
Jieyang	0.7701	0.8654	0.9564	1.2182	1.4342	0.8803	0.6250	0.7732	0.9652
Maoming	0.7926	0.9079	0.9589	2.4316	2.9650	0.6688	0.5461	0.8446	0.9731
Meizhou	1.6525	2.0368	0.8934	3.7907	4.4974	0.4804	1.2531	1.6352	0.9313
Qingyuan	0.8305	1.2200	0.9504	2.0922	2.3381	0.8180	0.5401	0.7001	0.9837
Shantou	0.8345	0.9589	0.9595	2.6883	3.1139	0.5730	0.6109	0.7544	0.9749
Shanwei	1.3367	1.7419	0.9258	2.2040	2.7585	0.8139	0.8290	1.2582	0.9613
Shaoguan	1.1424	1.2343	0.9446	1.4279	2.1250	0.8358	0.6569	0.9924	0.9642
Shenzhen	1.1022	1.4584	0.9064	1.4724	1.7932	0.8585	0.8423	1.0594	0.9506
Yangjiang	0.7186	0.8981	0.9402	1.3465	1.7569	0.7713	0.3907	0.4737	0.9834
Yunfu	1.4012	1.5357	0.9301	3.0842	3.9902	0.5279	0.9717	1.2663	0.9524
Zhanjiang	1.5875	1.9121	0.8671	2.4511	2.9479	0.6840	0.6862	0.9604	0.9665
Zhaoqing	1.3098	1.4348	0.9136	2.1075	2.6462	0.7062	0.5871	0.9006	0.9660
Zhongshan	1.0897	1.4074	0.9209	2.2536	2.4644	0.7576	0.7246	0.9455	0.9643
Zhuhai	0.9881	1.2581	0.9201	1.6543	2.1569	0.7653	0.5532	0.8312	0.9651

The results in Table 2 show that the RR-SVM model demonstrated better prediction performance than the single model. The RR-SVM model's R^2 ranged between 0.93 and 0.99, the MAE ranged between 0.32 and 1.25 μg/m^3, and the RMSE ranged between 0.365 and 1.635 μg/m^3. Compared with the single model, the RR-SVM model improved the R^2 by 0.041 on average, reduced the MAE by 0.446 μg/m^3 on average, and reduced the RMSE by 0.475 μg/m^3 on average; therefore, the RR-SVM model coupled with classical statistics and machine learning outperformed the single model. Therefore, the RR-SVM model coupling classical statistics and machine learning performs better than a single model. The RR-SVM prediction model can improve the prediction accuracy of PM$_{2.5}$ under small sample conditions and provide effective support for PM$_{2.5}$ prediction.

3.2. PM$_{2.5}$ Governance Scenario Construction and Simulation Analysis

To identify the PM$_{2.5}$ management path that minimizes the impact on urban socio-economic development, this study combined the expected targets of each indicator during the 14th Five-Year Plan period, the historical pattern of change, the current state of development, and related research, and is based on six modes of regulation, including industrial structure, energy consumption, freight transport structure, road traffic, urban greening, and pollution emissions. The base scenario library shown in Table 3 was constructed. This base scenario library provides a reference basis for the construction of subsequent urban PM$_{2.5}$ governance scenarios.

Table 3. Base scenario library.

Factor	Lower			Middle			High		
	Low Width	Low Strong	Low Severity	Middle Width	Middle Strong	Middle Severity	High Width	High Strong	High Severity
SGDP	Down 0.1%	Down 0.2%	Down 0.3%	Down 0.4%	Down 0.6%	Down 0.8%	Down 1.0%	Down 1.5%	Down 2.0%
TGDP	Up 0.1%	Up 0.2%	Up 0.3%	Up 0.4%	Up 0.6%	Up 0.8%	Up 1.0%	Up 1.5%	Up 2.0%
ECPG	Down [11%]	Down [12%]	Down [13%]	Down [14%]	Down [15%]	Down [16%]	Down [17%]	Down [18%]	Down [19%]
HFTF	Down 0.1%	Down 0.2%	Down 0.3%	Down 0.5%	Down 0.7%	Down 0.9%	Down 1.0%	Down 1.5%	Down 2.0%
WFTF	Up 0.1%	Up 0.2%	Up 0.3%	Up 0.5%	Up 0.7%	Up 0.9%	Up 1.0%	Up 1.5%	Up 2.0%
GROC	Down 2%	Down 3%	Down 4%	Down 5%	Down 6%	Down 7%	Down 8%	Down 10%	Down 12%
GAPC	Up [5%]	Up [10%]	Up [15%]	Up [20%]	Up [25%]	Up [30%]	Up [35%]	Up [40%]	Up [45%]
ISDE	Down [10%]	Down [15%]	Down [20%]	Down [25%]	Down [30%]	Down [35%]	Down [40%]	Down [45%]	Down [50%]

Note: Values with "[]" indicate the total amount of change for the period 2020–2025, while those without "[]" indicate the amount of change per year.

In the case that certain socio-economic indicator data are more dispersed, direct cluster analysis may be affected by extreme values. Therefore, in this study, based on the consideration of the distribution of the values of each indicator and the average level for the province or the country, the data for the socio-economic indicators of municipalities in 2019 were graded using the natural breakpoint method. Among them, STIR was categorized into five levels; ECPG, WHFR, GROC, and ISDE were categorized into four levels; and GAPC was categorized into three levels. The grading results are shown in Table 4.

Table 4. Classification results of indicators.

Rank	STIR	ECPG/(tce·10kCHY^{-1})	WFHR	GROC/%	GAPC/m^2	ISDE/10 kt
1	0.00–0.38	0.31–0.43	0.00–0.05	0.00–0.03	11.5–14.9	0.07–0.21
2	0.38–0.63	0.43–0.63	0.05–0.14	0.03–0.12	14.9–19.1	0.21–0.41
3	0.63–0.83	0.63–1.63	0.14–0.34	0.12–0.18	19.1–23.8	0.41–0.80
4	0.83–1.00	1.63–1.74	0.34–1.23	0.18–0.22		1.80–1.63
5	1.00–1.33					

Note: STIR is the ratio between the share of the secondary sector in GDP (SGPD) and the share of the tertiary sector in GDP (TGDP); ECPG is the energy consumption per unit of GDP; WHFR is the ratio between the share of waterborne freight traffic in total freight traffic (WHTF) and the share of highway freight traffic in total freight traffic (HFTF); GROC is the rate of growth of civilian car ownership; GAPC is the per capita area of green space in the city; and ISDE is the sulfur dioxide emissions of the urban industry.

The K-means algorithm was used to cluster the results of the grading of urban socio-economic indicators, and according to the clustering results, 21 cities were classified into different city categories based on similarities in socio-economic characteristics. Table 5 shows the clustering results of the graded data and city classifications of each socio-economic indicator.

Table 5. Clustering results of each indicator, classification data, and city classification results.

Category	City	STIR	ECPG	WHFR	GROC	GAPC	ISDE
Category 1	Guangzhou	1	1	4	2	1	2
	Meizhou	2	1	1	3	1	3
	Qingyuan	2	2	4	2	3	4
	Shaogua	2	2	3	3	2	3
	Shenzhen	2	1	3	1	3	1
	Yunfu	2	2	3	4	2	3
Category 2	Heyuan	2	2	1	3	3	1
	Jieyang	3	3	1	3	3	3
	Maoming	3	2	2	3	2	2
	Shanwei	3	2	1	4	3	1
	Yangjiang	3	3	1	3	2	3
Category 3	Chaozhou	5	1	3	2	3	2
	Dongguan	5	1	4	2	1	3
	Foshan	5	1	2	2	2	3
	Shantou	4	1	2	2	3	2
	Zhongshan	4	2	2	2	2	1
Category 4	Huizhou	5	4	4	2	2	4
	Jiangmen	4	2	3	2	1	3
	Zhangjiang	3	4	3	3	2	2
	Zhaoqing	4	3	3	2	1	4
	Zhuhai	3	3	3	2	1	1

Note: The numbers in the table are the classification levels of the corresponding indicators.

Combined with Tables 4 and 5, it can be observed that there were large differences in the socio-economic characteristics of various types of cities, and various types of cities had different development patterns and characteristics. The first category of cities was dominated by tertiary industry, with limited space for optimization of the industrial structure, lower energy consumption intensity but still with space for optimization, a higher carrying capacity of waterway freight transport, moderate automobile ownership, large differences in the green space area, and higher industrial sulfur dioxide emissions. In the second category of cities, secondary industry accounted for a lower proportion of GDP than tertiary industry, which can be appropriately transferred to the industrial structure, with a slightly higher intensity of energy consumption, a weaker carrying capacity of waterway freight transportation, fast growth in automobile ownership, the lowest per capita green space area, and higher industrial sulfur dioxide emissions. In the third category of cities, secondary industry accounted for a higher proportion of GDP, and these cities should promote the development of tertiary industry. In these cities, energy consumption intensity was the lowest, the waterway freight carrying capacity was moderate, the growth of automobile ownership was slightly lower, the per capita green space area was close to the average level of the province, and the industrial sulfur dioxide emissions were slightly higher. The fourth category of cities, demonstrating a similar proportion of GDP for the secondary and tertiary industries, should promote the development of tertiary industries. In these cities, the intensity of energy consumption was much higher than the average level of the province, there was a strong carrying capacity of waterway freight transportation, the growth of automobile ownership was relatively low, the per capita green space area was the highest, and the industrial sulfur dioxide emissions were higher.

Therefore, when developing urban $PM_{2.5}$ management scenarios, the differences between the socio-economic characteristics of various types of cities should be taken into account, and a targeted focus should be placed on the mode of regulation. To this end, this study categorized the indicators into high, medium, and low classes based on the results of their grading in Table 3, according to the space in which each indicator can be adjusted. For example, the STIR was generally low in the first category of cities, indicating that there is less room for industrial structure optimization in this category of cities, so the

STIR regulation needs were classified as low-grade, while the STIR was generally high in the third category of cities, so it was classified as high-grade. The specific results are shown in Table 6.

Table 6. Regulation of demand in each regulation mode.

Category	STIR	ECPG	WHFR	GROC	GAPC	ISDE
Category 1	Lower ↓	Lower ↓	High ↓	Middle ↓	Middle ↑	High ↓
Category 2	Middle ↓	Middle ↓	Lower ↓	High ↓	High ↑	Middle ↓
Category 3	High ↓	Lower ↓	Middle ↓	Lower ↓	Middle ↑	Middle ↓
Category 4	High ↓	High ↓	High ↓	Lower ↓	Lower ↑	High ↓

Note: "↑" and "↓" in the table represent the increase or decrease in the index, respectively.

According to the index control demand levels of each type of city in Table 6, the corresponding "low", "medium", or "high" control levels were selected from the base scenario library in Table 2, and three $PM_{2.5}$ pollution control scenarios were constructed for each type of city, namely loose, intensive, and strict, as shown in Table 7.

Table 7. $PM_{2.5}$ governance scenarios for each city category.

Factor	Category 1			Category 2			Category 3			Category 4		
	Loose Type	Intensive Type	Strict Type	Loose Type	Intensive Type	Strict Type	Loose Type	Intensive Type	Strict Type	Loose Type	Intensive Type	Strict Type
STIR	low width	low strength	low strictness	medium width	medium strength	medium strictness	high width	high strength	high strictness	high width	high strength	high strictness
ECPG	low width	low strength	low strictness	medium width	medium strength	medium strictness	low width	low strength	low strictness	high width	high strength	high strictness
WHFR	high width	high strength	high strictness	low width	low strength	low strictness	medium width	medium strength	medium strictness	high width	high strength	high strictness
GROC	medium width	medium strength	medium strictness	high width	high strength	high strictness	low width	low strength	low strictness	low width	low strength	low strictness
GAPC	medium width	medium strength	medium strictness	high width	high strength	high strictness	medium width	medium strength	medium strictness	low width	low strength	low strictness
ISDE	high width	high strength	high strictness	medium width	medium strength	medium strictness	medium width	medium strength	medium strictness	high width	high strength	high strictness

Note: The fields in this table correspond to those in Table 6. For example, "low width" in energy intensity corresponds to "low width" in energy intensity in Table 4, that is, [11%].

Based on the governance scenarios in Table 7, the socioeconomic data for 2020–2025 were calculated and used as input data for the $PM_{2.5}$ prediction model to predict the $PM_{2.5}$ concentration in each city. The results showed that among the first group of cities, Qingyuan City can reduce $PM_{2.5}$ concentration to below the target under the loose control scenario, while Meizhou City can achieve $PM_{2.5}$ concentration control by using only the Intensive scenario. In contrast, Guangzhou, Shaoguan, Shenzhen, and Yunfu would need to adopt the most stringent control intensity to keep the concentration below the target. Among the second group of cities, Heyuan and Shanwei were able to reduce $PM_{2.5}$ concentrations to below the target under the loose scenario, while Maoming and Yangjiang needed to adopt the intensive scenario to achieve the control target, and only Jieyang needed the strict scenario. Among the Category 3 cities, Chaozhou, Shantou, and Zhongshan can accomplish the control target by adopting the loose scenario, while Dongguan and Foshan need to adopt the strict scenario. In the fourth category of cities, Zhuhai City can adopt the loose scenario, while Huizhou City, Jiangmen City, Zhanjiang City, and Zhaoqing City need to adopt the intensive scenario to control the $PM_{2.5}$ concentration below the target. Therefore, all 21 prefecture-level cities in Guangdong Province can achieve the target of reducing $PM_{2.5}$ concentrations to below 22 μg/m^3 by 2025 with minimal impact on the socioeconomic development of the cities.

Therefore, under the premise of ensuring minimal impact on urban socio-economic development, and based on the $PM_{2.5}$ prediction results under different scenarios for each prefecture-level city, each prefecture-level city in Guangdong Province can adopt the $PM_{2.5}$ pollution management pathways shown in Table 8.

**Table 8.** PM$_{2.5}$ pollution control paths for each city.

City	SGDP	TGDP	ECPG	HFTF	WFTF	GROC	GAPC	ISDE
Chaozhou	down 1.0%	up 1.0%	down 2.48%	down 0.5%	up 0.5%	down 2.0%	up 3.08%	down 4.68%
Dongguan	down 2.0%	up 2.0%	down 2.86%	down 0.9%	up 0.9%	down 4.0%	up 4.47%	down 6.92%
Foshan	down 2.0%	up 2.0%	down 2.86%	down 0.9%	up 0.9%	down 4.0%	up 4.47%	down 6.92%
Guangzhou	down 0.3%	up 0.3%	down 2.29%	down 2.0%	up 2.0%	down 7.0%	up 4.47%	down 10.91%
Heyuan	down 0.4%	up 0.4%	down 2.48%	down 0.1%	up 0.1%	down 8.0%	up 5.13%	down 4.68%
Huizhou	down 1.5%	up 1.5%	down 3.25%	down 1.5%	up 1.5%	down 3.0%	up 1.60%	down 9.48%
Jiangmen	down 1.5%	up 1.5%	down 3.25%	down 1.5%	up 1.5%	down 3.0%	up 1.60%	down 9.48%
Jieyang	down 0.8%	up 0.8%	down 2.86%	down 0.3%	up 0.3%	down 12.0%	up 6.38%	down 6.92%
Maoming	down 0.6%	up 0.6%	down 2.67%	down 0.2%	up 0.2%	down 10.0%	up 5.77%	up 5.77%
Meizhou	down 0.2%	up 0.2%	down 2.11%	down 1.5%	up 1.5%	down 6.0%	up 3.78%	down 9.48%
Qingyuan	down 0.1%	up 0.1%	down 1.92%	down 1.0%	up 1.0%	down 5.0%	up 3.08%	down 8.16%
Shantou	down 1.0%	up 1.0%	down 2.48%	down 0.5%	up 0.5%	down 2.0%	up 3.08%	down 4.68%
Shanwei	down 0.4%	up 0.4%	down 2.48%	down 0.1%	up 0.1%	down 8.0%	up 5.13%	down 4.68%
Shaoguan	down 0.3%	up 0.3%	down 2.29%	down 2.0%	up 2.0%	down 7.0%	up 4.47%	down 10.91%
Shenzhen	down 0.3%	up 0.3%	down 2.29%	down 2.0%	up 2.0%	down 7.0%	up 4.47%	down 10.91%
Yangjiang	down 0.6%	up 0.6%	down 2.67%	down 0.2%	up 0.2%	down 10.0%	up 5.77%	up 5.77%
Yunfu	down 0.3%	up 0.3%	down 2.29%	down 2.0%	up 2.0%	down 7.0%	up 4.47%	down 10.91%
Zhanjiang	down 1.5%	up 1.5%	down 3.25%	down 1.5%	up 1.5%	down 3.0%	up 1.60%	down 9.48%
Zhaoqing	down 1.5%	up 1.5%	down 3.25%	down 1.5%	up 1.5%	down 3.0%	up 1.60%	down 9.48%
Zhongshan	down 1.0%	up 1.0%	down 2.48%	down 0.5%	up 0.5%	down 2.0%	up 3.08%	down 4.68%
Zhuhai	down 1.0%	up 1.0%	down 3.05%	down 1.0%	up 1.0%	down 2.0%	up 0.82%	down 8.16%

Note: The data in the table are year-to-year changes.

Figure 5 demonstrates the predicted 2020–2025 average annual PM$_{2.5}$ concentrations in Guangdong Province under the PM$_{2.5}$ pollution management pathways presented in Table 8. As can be seen from Figure 5, all cities in Guangdong Province will show a significant decrease in the annual average PM$_{2.5}$ concentration. Among them, Zhaoqing, Maoming, Jieyang, and Shantou will be the first to meet the 2025 PM$_{2.5}$ annual average concentration control requirement in 2023. By 2024, all cities will be able to achieve the PM$_{2.5}$ concentration control target, except for six cities, namely Yangjiang, Jiangmen, Yunfu, Foshan, Guangzhou, and Meizhou. By 2025, all 21 prefectural-level cities in Guangdong Province will be able to fulfil the PM$_{2.5}$ control targets during the 14th Five-Year Plan period, and the annual average concentration of PM$_{2.5}$ in Guangdong Province will drop from 25.91 μg/m^3 in 2019 to 21.04 μg/m^3, thus completing the task of controlling the concentration of PM$_{2.5}$ pollution.

3.3. Analysis of PM$_{2.5}$ Pollution Collaborative Governance Pattern

Figure 6 demonstrates the changes in the coupled coordination relationship of PM$_{2.5}$ pollution management for each prefecture-level city in Guangdong Province in 2020–2025 under the PM$_{2.5}$ pollution management compliance pathway. Combining Figures 4 and 5, it can be seen that under the scenario simulation of the attainment pathway, with the reduction of PM$_{2.5}$ concentration, the overall level of coupled coordination of factors influencing the management of PM$_{2.5}$ pollution in Guangdong Province in 2020–2025 shows an increasing trend. From 2000 to 2022, due to higher PM$_{2.5}$ concentrations, coupling coordination was dominated by moderate dissonance, mild dissonance, and near dissonance, with a lesser degree of reluctant coordination. After 2023, the environmental quality will be improved, the level of coordination will gradually rise, and some of the areas on the verge of dysfunction will be upgraded to barely coordinated and primary coordinated, which indicates that with the management of PM$_{2.5}$ pollution and the concentration of the standard, the regional coordination relationship will be gradually optimized, and the number of intermediate coordinated cities will increase, while the level of some barely coordinated cities will be upgraded to primarily coordinated.
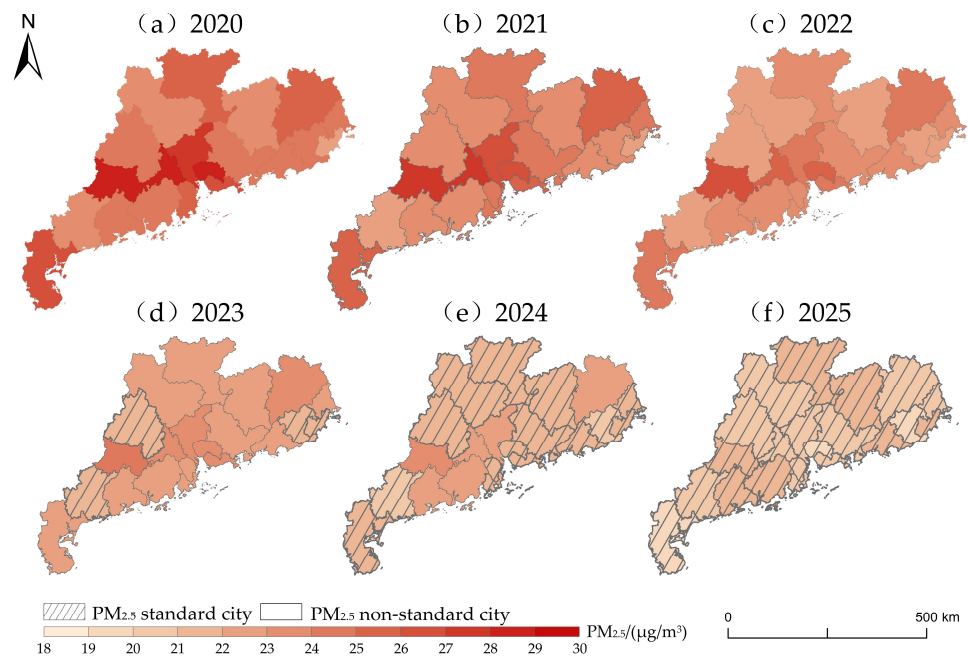
Figure 5. The predicted annual average concentration of PM$_{2.5}$ in Guangdong Province from 2020 to 2025.
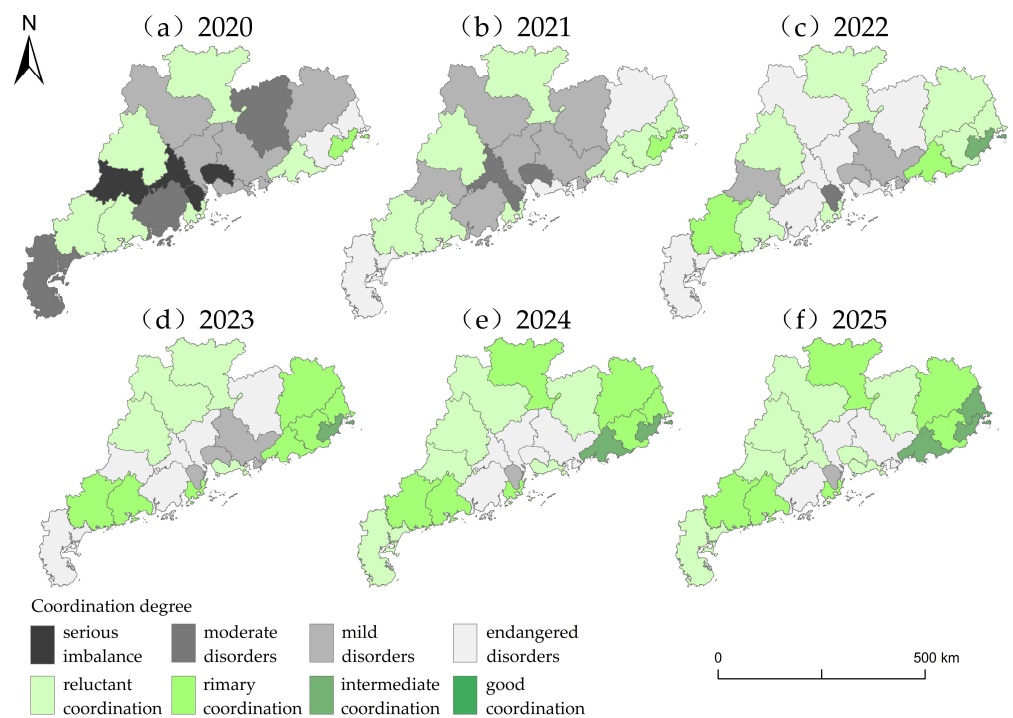
Figure 6. Coupling and coordination relationship of PM$_{2.5}$-pollution-influencing factors in Guangdong Province from 2020 to 2025.

From the evolution of the spatial patterns of PM$_{2.5}$ pollution management in Guangdong Province, the coupling and coordination of the relationship between the spatial differences are significant, demonstrating the distribution characteristics of being high in the center of the city and low in the surrounding areas. The eastern cities demonstrate a relatively good coupling and coordination degree, while cities in the central region generally display lower values, and in the same type of city, the same spatial accumulation characteristics are evident. The dissonant region is dominated by cities in central China,

mainly Jiangmen City, Foshan City, Guangzhou City, Dongguan City, Huizhou City, and other regions with high $PM_{2.5}$ concentrations. The rapid economic development of such cities is accompanied by an increase in industrialization, dense traffic, and construction activities, leading to a rapid accumulation of $PM_{2.5}$ and a decrease in air quality in the region, with a poorer degree of coordination. In barely coordinated regions, the regional distribution is more scattered, mainly relating to the lower $PM_{2.5}$ concentration of Zhaoqing City, Maoming City, Yangjiang City, and other cities. The level of socio-economic development in such cities is basically at the same level, socio-economic development tends to be stabilized, the differences between the various influencing factors are relatively small, and the city's economic development and environmental protection are relatively balanced, to ensure the stability of the city's air quality, and the level of its coupling and coordination is in the barely coordinated stage. High-level coordination areas are mainly distributed in the eastern part of the coastal economic belt, and from 2020 to 2022, they were mainly dominated by reluctant coordination and primary coordination, and there were fewer intermediate coordination areas. With the coordinated advancement of pollution reduction and economic development, Shantou Shanwei and other cities will start to progress from reluctant coordination to primary coordination and show a grouping trend by 2023 through measures such as strengthening environmental management and promoting industrial upgrading. By 2025, the overall spatial distribution pattern of $PM_{2.5}$ pollution control coupling and coordination relationships in Guangdong Province will be low in the center and high in the surrounding areas.

4. Conclusions

(1) In the case of small samples, the hybrid model coupling classical statistics and machine learning methods can achieve more accurate fitting, and the results are more stable and reliable compared with a single model, which can provide effective simulation prediction for the identification of urban pollutant management pathways to reach pollution targets.

(2) The results of the $PM_{2.5}$ scenario simulation for 2020–2025 show that the $PM_{2.5}$ synergistic management pathway proposed in this study can effectively reduce the average annual concentration of $PM_{2.5}$ in Guangdong Province and improve the coordination of urban economic and social development. Under the $PM_{2.5}$ synergistic management scenario, Guangdong Province will accomplish the expected goal of controlling the annual average $PM_{2.5}$ concentration in the "14th Five-Year Plan for Ecological Environmental Protection of Guangdong Province" by 2025, and realize the synergistic development of the economy and the environment.

(3) Considering the challenges of air pollution and the imbalances in economic development across the 21 prefecture-level cities in Guangdong Province, this study proposes $PM_{2.5}$ collaborative governance policy recommendations tailored to the social and economic characteristics of each city. These recommendations, focused on six key aspects including industrial structure, freight distribution, road traffic, energy consumption intensity, urban greenery, and urban pollutant discharge, offer valuable insights to enhance urban governance capacity, drive economic advancement, and facilitate pollution prevention and control during the 14th Five-Year Plan period.

5. Discussion

This study took Guangdong Province as the study area, and used the grey correlation, ridge, and SVM models to simulate and predict the $PM_{2.5}$ management scenarios in various cities. It analyzed the coupling and coordination relationship between $PM_{2.5}$-influencing factors, and identified the paths of $PM_{2.5}$ pollution control in various cities, which provides an important reference for the completion of $PM_{2.5}$ pollution control in Guangdong Province during the 14th Five-Year Plan period. For different prefecture-level cities, this paper proposes corresponding synergistic management measures.

(1) For Guangzhou City, Meizhou City, Shenzhen City, Shaoguan City, Yunfu City, and Qingyuan City, during the 14th Five-Year Plan period, priority should be given to adjusting the freight transport structure and reducing urban pollutant emissions to collaborate in combating $PM_{2.5}$ pollution. In terms of freight structure, Guangzhou, Shenzhen, Shaoguan, Yunfu, and Qingyuan are all located in the Pearl River water system area, so they can adjust the freight structure through joint planning and resource integration, developing waterways, improving shipping capacity, promoting multimodal transport, adopting waterway transport, etc., to achieve the efficient flow of goods and optimal transport routes, and to reduce the reliance on road transport, thus reducing the emission of related pollutants. Meizhou, on the other hand, can actively promote road transport and reduce the emission of related pollutants, while it can also actively develop public water intermodal transportation and coordinate the promotion of the construction of Meizhou Port. In terms of reducing pollutant emissions from urban industries, more stringent corporate pollution emission standards can be formulated, and measures such as increasing environmental protection inspections and upgrading equipment can be taken to reduce the direct emissions of pollutants. By optimizing the freight transport structure and reducing urban pollutant emissions, it not only helps to improve the efficiency of the flow of goods, but it also promotes the sustainable development of the economy in the region and reduces the impact of air pollution on people's health, thus realizing the synergistic development of $PM_{2.5}$ environmental management and economic and social development.

(2) For Heyuan City, Jieyang City, Maoming City, Shanwei City, and Yangjiang City, the main focus should be on urban road traffic and urban greening, supplemented by measures such as adjusting the industrial structure, lowering the intensity of energy consumption, and reducing pollutant emissions, to synergistically control $PM_{2.5}$ pollution and realize a virtuous cycle of economic development and environmental protection. To control urban road traffic pollution, new energy vehicles can be used to replace traditional fuel vehicles, and public transportation infrastructure can be improved to reduce vehicle emissions. In terms of urban greening, green belts can be constructed on both sides and in the center of the road to increase the adsorption rate of green plants and reduce the pollution caused by road traffic. At the same time, $PM_{2.5}$ pollution can also be treated by adjusting the industrial structure, reducing the intensity of energy consumption, and implementing and reducing pollutant emissions, among other measures. These initiatives will help to reduce the level of air pollution, improve the environmental quality of cities, and at the same time promote the sustainable development of cities.

(3) For Chaozhou City, Dongguan City, Foshan City, Shantou City, and Zhongshan City, the main direction of collaborative governance should be to optimize the industrial structure, adjust the structure of cargo transportation, and improve the urban greening rate, thus improving environmental quality, reducing pollutant emissions, and reducing the concentration of atmospheric pollutants to achieve a reduction in $PM_{2.5}$ concentrations and urban economic development through collaborative governance. In terms of optimizing the industrial structure, these five prefecture-level cities are dominated by secondary industries, and tertiary industries are developing slowly. It is necessary to encourage the upgrading and transformation of traditional industries, promote the development of high-end service industries through tax incentives, subsidies, and preferential policies, promote economic transformation and sustainable development, and improve the quality of urban development and people's quality of life. In terms of adjusting the structure of cargo transportation, Dongguan City, Foshan City, and Zhongshan City are located at the estuary of the Pearl River Delta, and so they can be integrated into the Pearl River transportation network to promote the transfer of road transportation to the waterway transportation. Chaozhou City and Shantou City can promote the transfer of bulk cargo from "road to water" through marine transportation. In terms of improving the urban greening rate, we can reduce the concentration of urban air pollutants by building urban green corridors or parks and building green space networks. By optimizing industrial institutions, adjusting the transportation structure, and increasing the greening rate of cities,

environmental quality can be effectively improved, pollutant emissions can be reduced, and the concentration of air pollutants can be lowered, thus realizing synergistic management of $PM_{2.5}$ and the development of the city's economy, and thereby injecting a new impetus into the city's sustainable development.

(4) For Zhanjiang City, Huizhou City, Jiangmen City, Zhaoqing City, and Zhuhai City, in addition to the small improvement effect of urban greening on air quality, from the perspective of $PM_{2.5}$ environmental governance and coordinated economic and social development, there is still much room for improvement in the industrial structure, energy consumption intensity, freight structure, and industrial pollutant emissions. In terms of industrial structure, Zhuhai City, Zhanjiang City, Huizhou City, Jiangmen City, and Zhaoqing City all have heavy industries as their leading industries. We should promote the development of high-tech industries, encourage the transformation and upgrading of traditional industries, improve production technology, develop clean energy, high-tech industries, green manufacturing, and other environmentally friendly industries, and improve the sustainability of economic development. In terms of energy consumption intensity, cities should implement energy conservation and emission reduction policies, improve energy management, identify energy consumption problems, and implement corrective measures to reduce energy consumption intensity. At the same time, governments should promote the replacement of traditional energy with clean energy, increase the reform of the energy supply structure, and promote the application of renewable energy. In terms of freight structure, Zhanjiang City and Zhuhai City are coastal cities, which can promote the transfer of freight transportation from road to sea and rail transportation by developing marine logistics and expanding port functions. Huizhou, Jiangmen, and Zhaoqing can adjust the freight structure by strengthening the construction of logistic centers and developing multimodal transport. In terms of pollutant emissions, cross-regional collaboration and cooperation should be strengthened, an effective information-sharing mechanism should be established, more stringent corporate emission standards should be formulated, environmental protection inspections should be strengthened, and enterprises should be encouraged to adopt cleaner production technologies and advanced equipment to reduce industrial pollutant emissions. Inter-regional consultations, joint actions, and the joint formulation of policy measures should be implemented to achieve the goal of collaborative governance. These measures will produce synergistic effects in the areas of industry, energy, transportation, and environmental protection, thus realizing the synergistic development of the economy and the environment.

However, this study still has some limitations. First, due to the difficulty in obtaining energy consumption data for each prefecture-level city, it failed to further consider the energy structure related to $PM_{2.5}$ concentration, such as the proportion of new energy sources like wind energy and electric energy and the use of new energy vehicles in transportation. In addition, this study only explored the coupled and coordinated relationship between $PM_{2.5}$-influencing factors under different scenarios of governance and failed to explore the coupled and coordinated relationship of $PM_{2.5}$ synergistic governance in terms of the three systems of economic, social, and ecological benefits. Future research can conduct an in-depth analysis on the evolution process and coupled coordination relationship of $PM_{2.5}$ synergistic governance by establishing a comprehensive $PM_{2.5}$ governance index system and combining it with a coupled coordination degree model. By comprehensively considering multiple aspects such as economic, social, and ecological benefits, we can gain a more comprehensive understanding of the effects and mutual influences of $PM_{2.5}$ governance, promote the effective synergistic utilization of resources in all aspects, and provide a scientific basis for decision-making on future $PM_{2.5}$ governance strategies.

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