Hindawi
Journal of Mathematics
Volume 2021, Article ID 4959457, 14 pages
https://doi.org/10.1155/2021/4959457

Research Article

Using the Quarterly Compound Fractional Grey Model to Predict the Air Quality in 22 Cities of China

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Received 12 April 2021; Accepted 26 August 2021; Published 23 September 2021

Academic Editor: Musavarah Sarwar

The rapid development of industrialization leads to more and more serious air pollution, which affects human health and sustainable development of society. Predicting air quality is an important link in preventing air pollution and improving the atmospheric environment. In this paper, 22 cities of China with poor air quality in recent years are selected as the research objects. A quarterly compound accumulation grey model is used to predict the concentrations of $PM_{2.5}$, PM_{10}, SO_2, and NO_2 in the 22 cities. Two parameters are introduced into the model to optimize the accumulation method of the grey model. Also, seasonal factors are introduced to better simulate air quality. The forecasting results show that air quality in these cities, although varies widely on a quarterly basis, tends to decline overall. The concentrations of $PM_{2.5}$ and PM_{10} in most cities will still exceed the standard in the next few years, especially in the first and fourth quarters of each year. The prediction results can provide reference for relevant departments.

1. Introduction

The pollution of the ecological environment is becoming more and more serious with the development of cities. The destruction of the environment seriously affects people's life and health. At present, improving air quality is a pressing problem. Generally, people evaluate the air quality of a region via the concentrations of $PM_{2.5}$, PM_{10}, SO_2, and NO_2. When the concentrations of the pollutants are too high, it can cause harm to the human body and ecological environment [1]. At least 1 million deaths a year are linked to $PM_{2.5}$, especially in areas where the $PM_{2.5}$ concentration exceeds the limit. People with low immunity, such as the elderly and newborns, make up a larger proportion [2]. PM_{10} increases the infectivity of virus by damaging cells, which leads to severe damage to human lungs [3]. SO_2 can react in the air to form acid substances and then form acid rain to destroy the ecological environment and harm human health. Excessive exposure to SO_2 in pregnant women increases the risk of developing diabetes during pregnancy [4]. Long-term exposure to high levels of NO_2 can cause chronic lung disease. NO_2 enters the bloodstream and forms nitric and nitrous acids, which can cause nervous system disorders. NO_2 can lead to the exacerbation of respiratory diseases such as asthma [5].

In order to improve air quality, we need to predict the concentrations of these pollutants and then make an effective treatment plan according to the predicted results. The 22 cities with poor air quality in the past few years were mainly in Henan, Hebei, Shanxi, Shandong, and Shaanxi provinces, according to an analysis of the annual air quality report published on the official website of China's Ministry of Ecology and Environment (http://www.mee.gov.cn). Therefore, this paper selects these 22 cities as research objects. The 22 cities are shown in Table 1.

This paper is divided into 5 Sections. The research overview of domestic and foreign scholars on air quality in recent years is given in Section 2. The introduction of the model used in this paper and the verification of its accuracy are in Section 3. The air quality forecast for 22 cities is in Section 4. The conclusion and prospect of the thesis are in Section 5.

2. Literature Review

Many countries around the world face the problem of improving air quality, and an important part of improving air quality is to predict and analyze the air quality. At present, many scholars at home and abroad have performed a lot of research on air quality prediction, so as to provide reference value for local government and put forward the improvement measures. For example, a hybrid model combining deep learning and multitask learning is used to predict $PM_{2.5}$ concentrations at three monitoring stations in Lanzhou [6]. Mao et al. used deep learning methods to predict areas of China with high air pollution [7]. To improve the accuracy of the prediction model, Liu and Chen proposed a hybrid model that combines analysis and three-stage feature selection and enhanced extremum learning mechanisms [8]. An optimized convnet and RNN are used to predict urban $PM_{2.5}$ concentrations [9]. To address the shortage of data at monitoring stations, a transfer learning-based stacked bidirectional Long Short-Term Memory network is proposed. This method combines the deep learning technique and the transfer learning strategy to improve the prediction accuracy of the model [10]. As the $PM_{2.5}$ data collected are nonlinear and complex, it is difficult to make long-term predictions. A convolutional neural network based on frequency characteristics is used to group the data, and a predictor based on the empirical mode to decompose $PM_{2.5}$ data is proposed [11]. An air quality prediction system based on the neural fuzzy network is proposed. The system uses historical data to derive a set of fuzzy rules and added fuzzy elements to the prediction system [12]. Zhou applied the Gaussian Process Mixture model to air quality prediction [13]. Sun and Xu proposed a deep random subspace learning framework based on long-term memory and combined the random subspace learning with the deep learning algorithm to build an air quality prediction model [14]. A multitask learning neural network model based on deep confidence network prediction training is used to predict pollutant concentrations in the atmosphere [15]. A foreign scholar proposes a recursive neural network based on Long Short-Term Memory to predict urban air quality [16]. In order to reduce the concentrations of pollutants in the air around the airport, a model based on the mixed supervised learning method is proposed and used to predict the air quality of the airport [17]. Xu and Wu proposed an integrated fractional accumulation grey dual exponential smoothing model and an adjacent accumulation grey dual exponential smoothing model to predict $PM_{2.5}$ concentration and PM_{10} concentration [18]. In order to predict the concentrations of air pollutants, Dun and Wu combined the grey multivariable regression model, fractional accumulation model, and support vector regression model to predict the concentrations of air pollutants in Shijiazhuang and Chongqing [19]. Wu and Zhao used a fractional grey model to predict the concentration of $PM_{2.5}$ and pollution days in the Beijing-Tianjin-Hebei region [20]. To predict the composite AQI, Wu and Xu used the grey Verhulst model to predict and analyze the AQI in Beijing, Tianjin, and Shijiazhuang, respectively [21]. A novel FGRM (1, 1) model is proposed by Gao et al., and the performance of the model is optimized. Then, the model is used to forecast CO_2 emissions in China, the United States, and Japan [22]. Shi and Wu analyzed the socio-economic factors affecting air quality in Xingtai by using the grey correlation analysis method. Then, the air quality index of Xingtai is predicted by the grey multivariate convolution model [23].

The above research mainly focuses on the prediction of air quality in individual regions or individual indicators; however, the prediction of multiregions and multi-indicators is less. Because improving air quality is a long-term project, we need to have a comprehensive understanding of the overall air condition. This paper makes quarterly air quality forecasts for 22 cities of China with poor air quality in recent years. These indicators include $PM_{2.5}$, PM_{10}, SO_2, and NO_2. The concentrations of pollutants in the air vary greatly from season to season. Therefore, quarterly forecasting can better analyze the reasons for the increase of urban pollutant concentration in different quarters and provide the reference value for relevant departments.

In this era of big data, a large amount of data can be used for accurate information orientation and analysis. But not all information has a lot of data. Grey system theory provides us with a reliable research method when we come across cases that have very small amounts of data. Grey system theory has been widely concerned since it is put forward. In recent years, a large number of scholars have emerged to innovate and study this theory. For example, Zhao and Wu proposed a neighboring cumulative discrete grey model and used it to predict the consumption of nonrenewable energy in the ASIA-PACIFIC Economic Cooperation [24]. Liu and Wu proposed a new adjacent nonuniform grey model, which focuses on the study of the weight relationship between the latest data and historical data. The model is used to predict the consumption of renewable energy in Europe [25] Xiao et al. improved the GM (1, 1) model and obtained the coupling coordination degree by estimating the coordinate parameters with an intelligent algorithm. Subsequently, the coordination degree of technology and economy in China was evaluated using the modified model [26]. A new unbiased nonlinear Bernoulli model is proposed and applied to estimate the consumption of hydropower in China [27]. Sun proposed a grey spatiotemporal incidence model and used it to analyze the influencing factors of air quality in southern Jiangsu Province [28]. A discrete grey model is used to predict the consumption of natural gas [29]. A compound grey model is used to predict air quality in Henan Province [30]. Ma et al. proposed a new fractional discrete multiple grey model, which introduces the grey wolf algorithm to obtain the optimal fractional order [31]. Xiao et al. developed a novel NGBM (1, 1) model and used it to predict the biomass energy consumption in four countries [32]. An adaptive grey model has been used to predict China's greenhouse gas emissions [33]. An unequal-order adjacent grey model is developed to predict urban air quality [34]. However, these models and methods are difficult to fit and forecast the data with quarterly changes. To solve this problem, this paper presents a quarterly compound

Table 1: Research cities.

Anyang	Baoding	Yuncheng	Linyi
Jiaozuo	Handan	Jinzhong	Liaocheng
Hebi	Xingtai	Zibo	Xianyang
Xinxiang	Tangshan	Zaozhuang	Xian
Zhengzhou	Jincheng	Jinan	Weinan
Luoyang	Yangquan		

accumulation grey model (QCGM (1, 1)). This model integrates the fractional order accumulation grey model [35] and the weighted accumulation discrete grey model [36] and, on this basis, adds quarterly weight. The fractional order accumulation model has been favored by many scholars since it is put forward. For example, Jiang proposed a nonlinear grey multivariable model with fractional order accumulation and used it to analyze the relationship between foreign direct investment and China's CO_2 emissions [37]. A new fractional grey cumulative model has been developed to predict China's nuclear energy consumption [38]. Meng used the fractional order discrete grey model to predict SO_2 emissions in China [39]. The QCGM (1, 1) model proposed in this paper combines the fractional order accumulation grey model and weighted discrete grey model to adjust the accumulation sequence jointly by two parameters. Because the difference of pollutant concentration in different quarters is too great, quarterly weight is added to the model, which greatly improves the fitting and prediction accuracy of the model.

3. Models and Methods

First of all, this section describes the modeling process for the QCGM (1, 1) model. Secondly, in order to verify the accuracy of the QCGM (1, 1) model, three kinds of grey models are used to predict the NO_2 concentration in Tangshan. Finally, the model is evaluated and its initial value is verified to be valid.

3.1. The Modeling Process. We will collect the data with quarterly fluctuation and conduct the following processing.

Step 1: the original nonnegative data sequence is

$$M^{(0)} = \left\{m^{(0)}(1), m^{(0)}(2), \ldots, m^{(0)}(n)\right\}, \tag{1}$$

where $m^{(0)}(k) \geq 0$, $k = 1, 2, \ldots, n$.

Quarterly coefficient: $h(i) = \overline{m}_N^{(0)}(i)/\overline{m}_{NQ}^{(0)}(i)$ $i = 1, 2, 3, 4$, $\overline{m}_N^{(0)}(i)$ is the average for the i^{th} quarter, and $\overline{m}_{NQ}^{(0)}(i)$ is the average for all quarters. Thus, the quarterly coefficient can be obtained:

$$H = \{h(1), h(2), h(3), h(4), h(1), h(2), \ldots, h(3), h(4)\}. \tag{2}$$

Step 2: the sequence is obtained by converting the original sequence through the quarterly coefficient:

$$M_s^{(0)} = \left\{m_s^{(0)}(1), m_s^{(0)}(2), \ldots, m_s^{(0)}(n)\right\}, \tag{3}$$

where $M_s^{(0)} = M^{(0)}/H$.

The r-order accumulation sequence of $M_s^{(0)}$ is

$$M_s^{(r)} = \left\{m_s^{(r)}(1), m_s^{(r)}(2), \ldots, m_s^{(r)}(n)\right\}, \tag{4}$$

where $m_s^{(r)}(k) = \sum_{i=1}^{k} C_{k-i+r-1}^{k-i} m_s^{(0)}(i)$, $k = 1, 2, \ldots, n$:

$$\begin{aligned} C_{k-i+r-1}^{k-i} &= \frac{(k-i+r-1)(k-i+r-2)\ldots(r+2)(r+1)r}{(k-i)!}, \\ C_{r-1}^{0} &= 1, \\ C_{k}^{k+1} &= 0, \\ m_s^{(r)}(1) &= m_s^{(0)}(1). \end{aligned} \tag{5}$$

The weighted accumulation sequence of $M_s^{(r)}$ is

$$M_s^{(r,\lambda)} = \left\{m_s^{(r,\lambda)}(1), m_s^{(r,\lambda)}(2), \ldots, m_s^{(r,\lambda)}(n)\right\}, \tag{6}$$

where $m_s^{(r,\lambda)}(k) = \sum_{i=1}^{k} \lambda^{k-i} m_s^{(r)}(i)$, $k = 1, 2, \ldots, n$.

So, the conformable fractional weighted accumulation sequence is

$$M_s^{(r,\lambda)} = \left\{m_s^{(r,\lambda)}(1), m_s^{(r,\lambda)}(2), \ldots, m_s^{(r,\lambda)}(n)\right\}. \tag{7}$$

Step 3: first-order differential equation with one variable is

$$\frac{\mathrm{d}m_s^{(r,\lambda)}}{\mathrm{d}t} + a m_s^{(r,\lambda)} = b. \tag{8}$$

Solve the above equation, and the time response function of the QCGM (1, 1) model is obtained:

$$\widehat{m}_s^{(r,\lambda)}(k) = \left(m_s^{(0)}(1) - \frac{b}{a}\right)e^{-a(k-1)} + \frac{b}{a}, \quad k = 1, 2, \ldots, n. \tag{9}$$

Step 4: the least square method is used to find a and b:

$$\begin{bmatrix} a \\ b \end{bmatrix} = \left(B^T B\right)^{-1} B^T Y, \tag{10}$$

where

$$B = \begin{bmatrix} -\dfrac{\left(m_s^{(r,\lambda)}(1) + m_s^{(r,\lambda)}(2)\right)}{2} & 1 \\ -\dfrac{\left(m_s^{(r,\lambda)}(2) + m_s^{(r,\lambda)}(3)\right)}{2} & 1 \\ \vdots & \vdots \\ -\dfrac{\left(m_s^{(r,\lambda)}(n-1) + m_s^{(r,\lambda)}(n)\right)}{2} & 1 \end{bmatrix}, \tag{11}$$

$$Y = \begin{bmatrix} m_s^{(r,\lambda)}(2) - m_s^{(r,\lambda)}(1) \\ m_s^{(r,\lambda)}(3) - m_s^{(r,\lambda)}(2) \\ \vdots \\ m_s^{(r,\lambda)}(n) - m_s^{(r,\lambda)}(n-1) \end{bmatrix}.$$

Step 5 : the weighted inverse cumulative generation sequence is

$$\widehat{M}_s^{(r)} = \left\{\widehat{m}_s^{(r)}(1), \widehat{m}_s^{(r)}(2), \ldots, \widehat{m}_s^{(r)}(n)\ldots\right\}, \tag{12}$$

where

$$\widehat{m}_s^{(r)}(k) = \widehat{m}_s^{(r,\lambda)}(k) - \lambda \widehat{m}_s^{(r,\lambda)}(k-1). \tag{13}$$

The predicted values $\widehat{M}_s^{(0)}$ can be obtained:

$$\widehat{M}_s^{(0)} = \left\{\widehat{m}_s^{(0)}(1), \widehat{m}_s^{(0)}(2), \ldots, \widehat{m}_s^{(0)}(n)\ldots\right\}, \tag{14}$$

where

$$\begin{aligned} &\widehat{m}_s^{(0)}(1) = m^{(0)}(1), \\ &\widehat{m}^{(0)}(k) = \widehat{m}^{(r)(1-r)}(k) - \widehat{m}^{(r)(1-r)}(k-1), \quad k = 2, 3, \ldots, n. \end{aligned} \tag{15}$$

Step 6 : the forecasting sequence is

$$\widehat{M}^{(0)} = \left\{\widehat{m}^{(0)}(1), \widehat{m}^{(0)}(2), \ldots, \widehat{m}^{(0)}(n)\ldots\right\}, \tag{16}$$

where

$$\widehat{M}^{(0)} = \widehat{M}_s^{(0)} \times H. \tag{17}$$

Step 7 : in this paper, the average absolute percentage error (MAPE) is used to evaluate the accuracy of the model:

$$\text{MAPE} = \frac{1}{n} \sum_{k=1}^{n} \frac{\left|\widehat{m}^{(0)}(k) - m^{(0)}(k)\right|}{m^{(0)}(k)} \times 100\%. \tag{18}$$

3.2. Model Evaluation. In order to analyze whether the fitting effect of the QCGM (1, 1) model meets the accuracy requirements, this paper adopts the GM (1, 1) model and the FGM (1, 1) model, respectively, for comparison. The prediction result of NO_2 concentration and MAPE values in Tangshan by the three models is shown in Table 2. Figure 1 shows the concentration curves of the three models simulating the results and real values of NO2 in Tangshan.

Table 3 shows the accuracy test grade table to facilitate us to analyze whether the fitting accuracy of the model meets the accuracy requirements.

According to the analysis of Table 2 and Figure 1, the QCGM (1, 1) model has the smallest fitting result. By comparing the accuracy test grades in Table 3, it can be seen that the fitting results of the QCGM (1, 1) model meet the level 2 standards. The GM (1, 1) model and the FGM (1, 1) model meet the level 4 standards. Therefore, the QCGM (1, 1) model has a good fitting ability.

Next, this article examines whether the initial values of the model are valid. Because in the case of a small amount of data, it is very necessary to fully exploit and use each data information. In this paper, the GM (1, 1) model is used for comparison, and the two models are, respectively, used to predict and analyze the concentration of NO_2 in Tangshan. At the same time, this paper changes the first number of the original sequence to 75 and then carries on the fitting again. Of course, this value is chosen arbitrarily. Finally, the results are collated in Table 4.

According to the Table 4, the initial value of the GM (1, 1) model is invalid because its change does not affect the fitting result of the whole sequence. After the initial value of the QCGM (1, 1) model is changed, the fitting results of the whole sequence are changed. Therefore, the initial value of the QCGM (1, 1) model is valid.

4. Forecast Results and Analysis of Air Pollutants

The 22 cities studied in this paper are located in Henan, Hebei, Shanxi, Shandong, and Shaanxi Provinces. In this section, the air quality of cities in these provinces will be predicted in this order. The raw data on pollutants' concentrations in these cities come from the China air quality online monitoring and analysis platform (http://www.aqistudy.cn).

4.1. Air Quality Forecast for Six Cities in Henan Province. Henan Province, located in the central plains, is a populous province in China. Industrialization, urbanization, and agricultural modernization of the province are formidable tasks. In addition, the industrial structure is heavy, and the energy structure is unreasonable. In the past few years, relevant departments have responded positively to national policies. Departments at all levels have strictly enforced law enforcement and supervision in order to improve air quality. Although the overall environmental quality has improved, it is still facing a very severe environmental quality situation. This part makes a forecast for six cities in Henan Province, and the six cities are Anyang, Jiaozuo, Hebi, Xinxiang, Zhengzhou, and Luoyang. Figure 2 shows the original results of pollutant concentrations for the six cities as well as the predicted results.

Table 2: The fitting results of NO_2 concentration by three models in Tangshan (unit: $\mu g/m^3$).

Quarter	Actual value	GM (1, 1)	FGM (1, 1)	QCGM (1, 1)
2015-1	68	68	68	68
2015-2	54	60	55	54
2015-3	50	59	56	49
2015-4	68	59	57	69
2016-1	61	58	58	66
2016-2	52	58	59	54
2016-3	47	57	59	48
2016-4	73	57	59	67
2017-1	68	56	58	64
2017-2	56	56	58	52
2017-3	50	55	57	46
2017-4	61	55	57	64
2018-1	56	54	56	60
2018-2	49	54	55	49
2018-3	41	53	54	43
2018-4	60	53	53	60
2019-1	56	52	52	57
2019-2	44	52	51	46
2019-3	42	51	50	41
2019-4	59	51	49	56
MAPE (%)		13.47	12.89	4.09

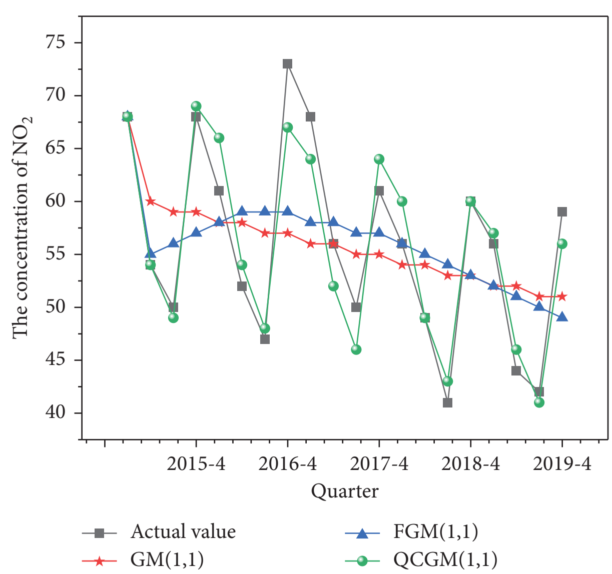

Figure 1: The fitting results of NO_2 concentration by three models in Tangshan.

In order to better analyze the future air quality index level of each city, Table 5 shows the concentration limits for different levels of $PM_{2.5}$, PM_{10}, SO_2, and NO_2.

As can be seen from Figure 2, the concentrations of the four pollutants in these six cities all show a trend of decline in the next few years. By comparing Table 5, it can be seen that the concentration of SO_2 in these six cities meets the level 1 standard. The concentration of NO_2 in Anyang, Jiaozuo, and Hebi does not fluctuate much, and almost all of them meet the level 1 standards. In Xinxiang, Zhengzhou, and Luoyang, the concentration of NO_2 can reach the level 1 standards in the second and third quarters of each year. The concentration of PM_{10} in these six cities fluctuates a lot in different quarters, among which Xinxiang and Zhengzhou have an obvious downward trend, and the concentration of PM_{10} gradually reaches the level 2 standards after 2022. PM_{10} in the other four cities only meets the level 2 standards in the second and third quarter of each year. Although the concentration of $PM_{2.5}$ in all six cities shows a downward trend, it still fails to meet the level 2 standards in most quarters.

As the air quality problem in Anyang is the most serious in Henan Province, we analyze and discuss the air quality in Anyang. Located at the junction of Henan, Hebei, and Shanxi provinces, Anyang is a transport channel for air pollution in the Beijing-Tianjin-Hebei region. At the same

Table 3: Table of accuracy levels for MAPE values.

Precision grade	Level 1	Level 2	Level 3	Level 4
MAPE	0-1%	1%–5%	5%–10%	10%–20%

Table 4: The fitting results of the two models (unit: $\mu g/m^3$).

Quarter	Actual value	GM (1, 1)	QCGM (1, 1)	New sequence	GM (1, 1)	QCGM (1, 1)
2015-1	68	68	68	75	75	75
2015-2	54	60	54	54	60	49
2015-3	50	59	49	50	59	42
2015-4	68	59	69	68	59	65
2016-1	61	58	66	61	58	67
2016-2	52	58	54	52	58	56
2016-3	47	57	48	47	57	51
2016-4	73	57	67	73	57	72
2017-1	68	56	64	68	56	69
2017-2	56	56	52	56	56	55
2017-3	50	55	46	50	55	48
2017-4	61	55	64	61	55	66
2018-1	56	54	60	56	54	62
2018-2	49	54	49	49	54	48
2018-3	41	53	43	41	53	42
2018-4	60	53	60	60	53	56
2019-1	56	52	57	56	52	52
2019-2	44	52	46	44	52	40
2019-3	42	51	41	42	51	34
2019-4	59	51	56	59	51	46

time, the industrial structure of Anyang is heavy, and the industries with high energy consumption account for a high proportion, especially the iron and steel, metallurgy, and coal chemical industry. These reasons lead to the poor air quality in Anyang. As can be seen from Figure 2, the air quality of Anyang has been improved to some extent under the regulation and rectification of government departments in recent years. But without fundamental changes to Anyang's industrial structure, the city's air quality will remain a serious problem. In the future, Anyang will accelerate the transformation of the industrial structure and continue to promote the adjustment of the industrial and energy structure. Only in this way can the city's air quality be fundamentally improved.

4.2. Air Quality Forecast for Four Cities in Hebei Province. Hebei Province, located in the North China Plain, is one of the birthplaces of the Chinese nation. But in recent years, with the rapid development of the city, the ecological environment and air quality in Hebei province have become very poor. On the one hand, the industrial structure of Hebei Province is seriously unreasonable, and steel, electricity, petrochemical and other industries are relatively dense. On the other hand, the province's energy consumption remains high. As a result, the concentrations of pollutants in the air in Hebei Province exceeded the standard seriously. This part forecasts air quality in four cities in Hebei Province, and the four cities are Baoding, Handan, Xingtai, and Tangshan. Figure 3 shows the raw data of pollutant concentrations for the four cities and the predicted results.

As can be seen from Figure 3, the concentrations of the four pollutants in cities tend to decline. The concentration of SO_2 in the four cities reaches the level 1 standards. The concentration of NO_2 in Baoding and Handan meets the level 1 standards. Although the concentration of NO_2 in Tangshan and Xingtai do not reach the level 1 standards, it could also reach the level 1 standards in the near future according to the decreasing trend. The decreasing trend of PM_{10} concentration in the four cities is obvious. After 2022, the concentration of PM_{10} in Baoding, Handan, and Xingtai gradually meets the level 2 standards. Although the concentration of $PM_{2.5}$ in the four cities shows a downward trend, it only meets the level 2 standards in the second and third quarters of each year.

Located at the border of Hebei, Henan, Shandong, and Shanxi provinces, Handan is a heavy industrial city dominated by steel, and its air quality is very poor. The unreasonable industrial structure leads to a large amount of energy consumption and serious environmental pollution, which is a typical feature of heavy industrial cities. Heating northern cities in winter consumes a lot of coal, which also increases the burden on the environment. The key to improve Handan's air quality is to accelerate the green transformation of key industries and promote the green development of all industries. Use clean energy to replace coal and strictly control the consumption of coal. At the same time,

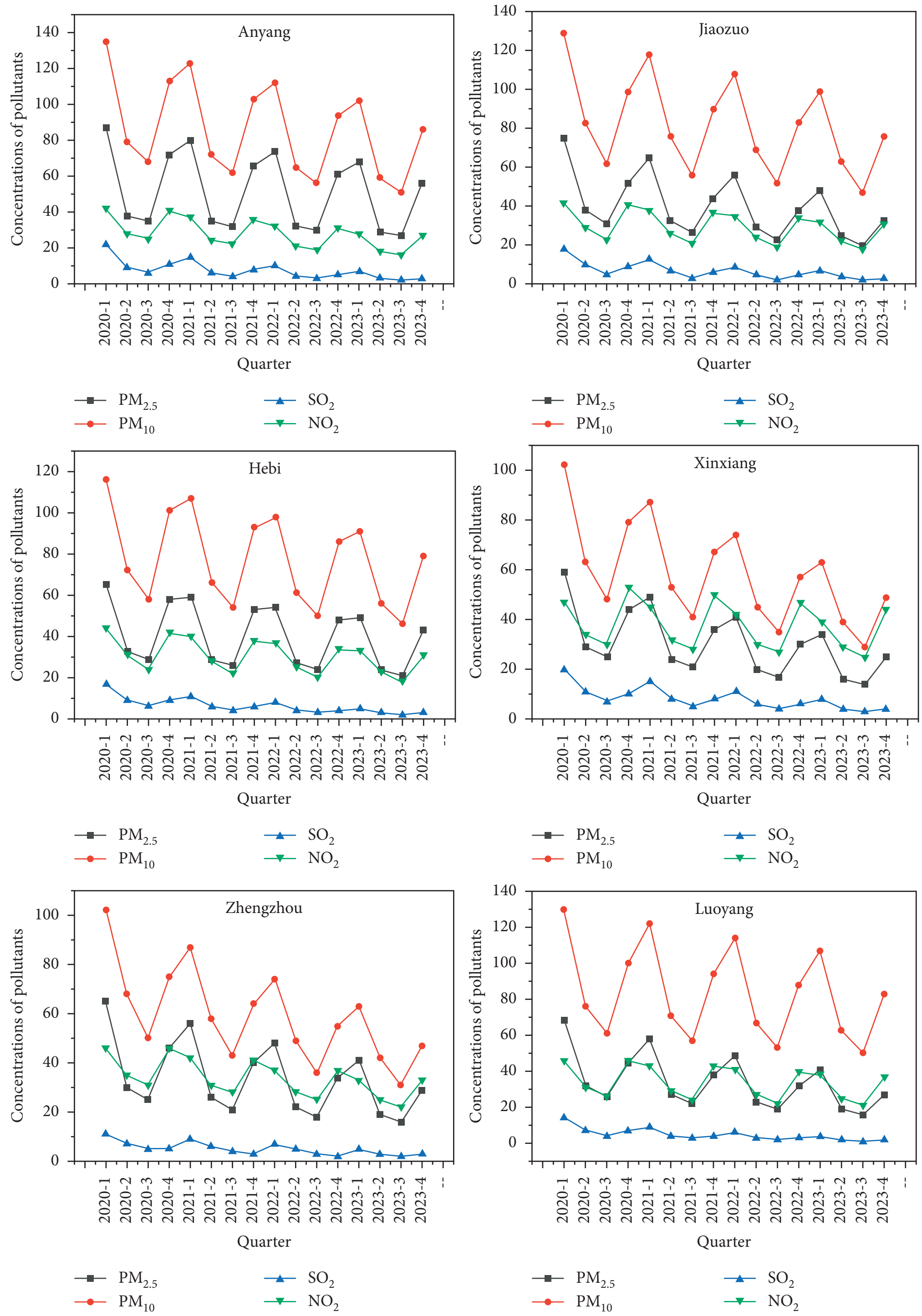

Figure 2: The predicted concentrations of four pollutants in six cities in Henan Province.

Table 5: Quality levels and corresponding concentration limits of $PM_{2.5}$, PM_{10}, SO_2, and NO_2.

Pollutants	Level 1 (unit: $\mu g/m^3$)	Level 2 (unit: $\mu g/m^3$)
$PM_{2.5}$	15	35
PM_{10}	40	70
SO_2	20	60
NO_2	40	40

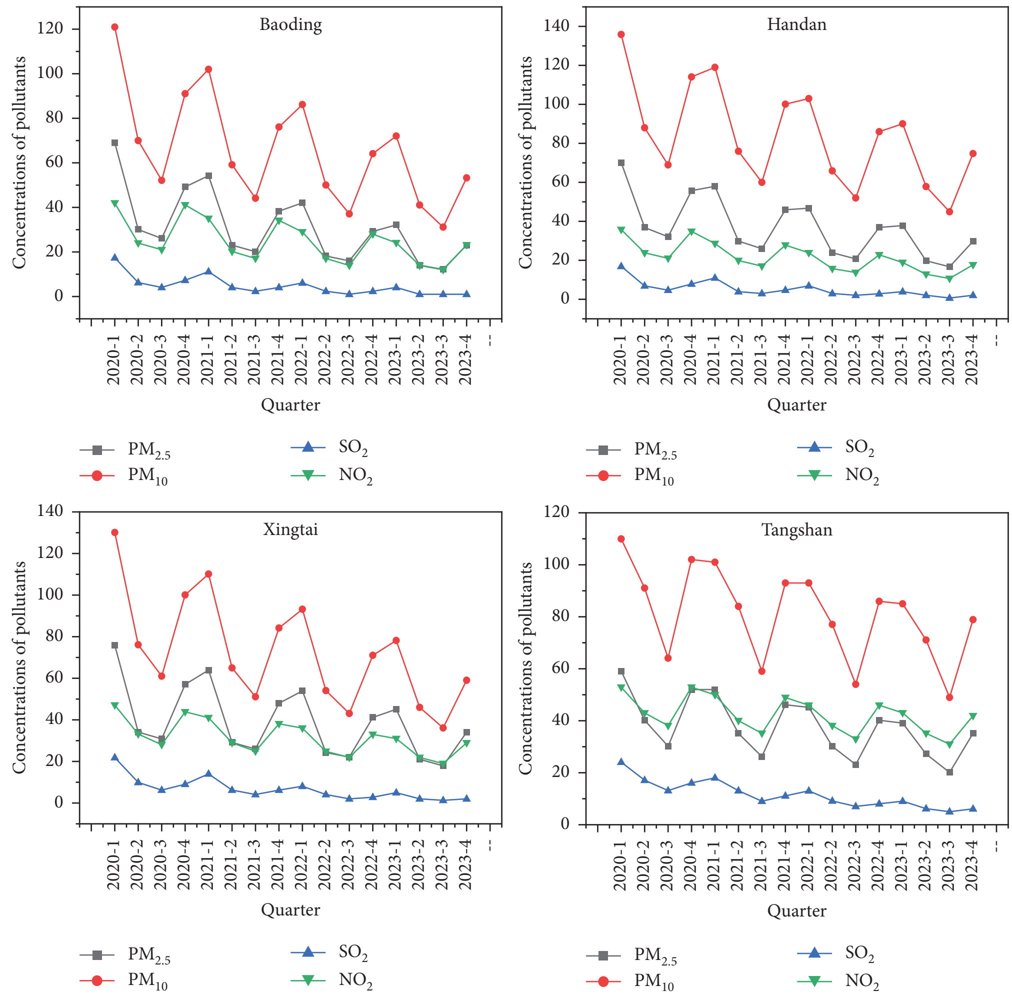

Figure 3: The predicted concentrations of four pollutants in four cities in Hebei Province.

government departments should carry out comprehensive treatment of the heavily polluted areas in Handan to fundamentally improve the environmental pollution problem.

4.3. Air Quality Forecast for Four Cities in Shanxi Province. Shanxi Province, located west of Taihang Mountain, is known as the cradle of Chinese civilization. But, at present, Shanxi Province is facing a serious problem of air pollution. The province's two main industries are coal and steel. In particular, coal resources are so abundant that many heavy industries are building in Shanxi. The coal these companies consume during production releases a lot of pollutants. This has led to worsening air quality in Shanxi Province. This section forecasts the air quality of four cities in Shanxi Province, and the four cities are Jincheng, Yangquan, Xingtai, and Tangshan. Figure 4 shows the raw pollutant concentration data of the four cities and the predicted results.

As can be seen from Figure 4, the concentrations of all pollutants more or less tend to decrease. The decreasing trend of PM_{10} concentration in Jincheng and Yuncheng is not obvious, and neither of them reached the level 2 standards. The PM_{10} concentration in Yangquan and Jinzhong shows a significant downward trend and reaches the level 2 standards after 2021. According to the decreasing trend, in the near future, the PM_{10} concentration in Yangquan and Jinzhong will reach the level 1 standards. The concentrations of SO_2 and NO_2 in the four cities will reach the level 1 standards after decreasing. The $PM_{2.5}$ concentration in Yangquan and Jinzhong falls rapidly and gradually reaches the level 2 standards after 2022. The concentration of $PM_{2.5}$ in Jincheng and Yuncheng do not fluctuate much and neither reaches the level 2 standards.

Jincheng has always enjoyed the reputation of being the home of coal and iron and is a typical coal-fired city in China. The city favors a high energy consumption industrial structure, with its pillar industries being coal, electricity, steel, etc. Although energy consumption drives rapid economic growth, excessive consumption of resources can inhibit Jincheng's sustainable development and bring serious pollution problems. The environmental problems caused by the massive consumption of coal for winter heating are yet to be solved. In the future, reasonable planning should be carried out for air quality in Jincheng, promoting efficient production methods, optimizing the industrial structure, and accelerating the promotion of new energy sources.

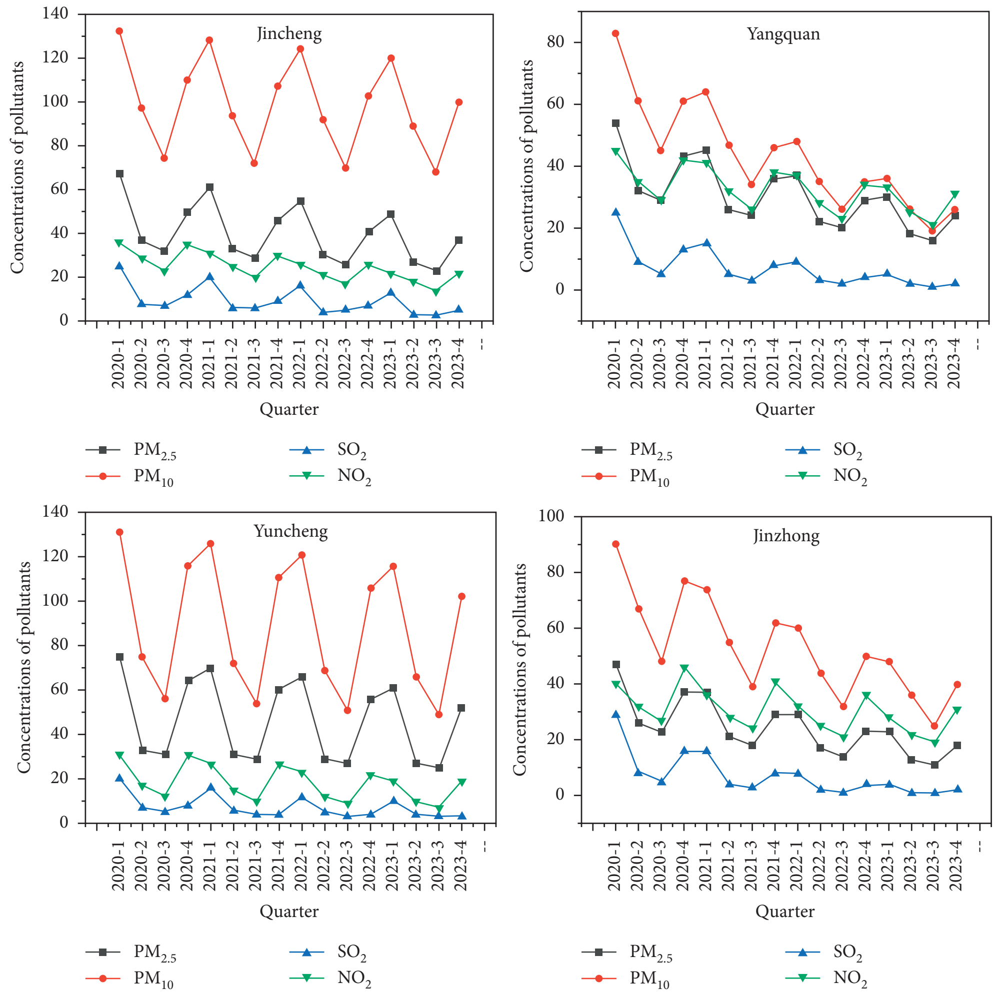

FIGURE 4: The predicted concentration of four pollutants in four cities in Shanxi Province.

4.4. Air Quality Forecast for Five Cities in Shandong Province. Shandong Province is a large agricultural province in China, located in the east coast of China, the lower reaches of the Yellow River area. The province has a very developed industry, with heavy industry including mining, electricity, steel, and petrochemical developing rapidly. This has resulted in severe air pollution in most parts of Shandong Province. Especially in winter, the haze phenomenon is endless. In this part, the air quality of five cities in Shandong Province is predicted. The five cities are Zibo, Zaozhuang, Jinan, Linyi, and Liaocheng. Figure 5 shows the original data and forecast data of pollutant concentration in Zibo, Zaozhuang, Jinan, and Linyi. Figure 6 shows the original data and forecast data of pollutant concentration in Liaocheng.

It can be seen from Figures 5 and 6 that the concentrations of $PM_{2.5}$, PM_{10}, SO_2, and NO_2 in these five cities all tend to decrease. Among them, the decrease trend of PM_{10} concentration is obvious, but it is difficult to reach the level 2 standards. After 2023, the concentration of PM_{10} in Zibo and Jinan will gradually reach the level 2 standards. $PM_{2.5}$ concentration in the five cities, although showing a downward trend, still did not reach the level 2 standards. The concentration of NO_2 in Zibo, Zaozhuang and Linyi meets the level 1 standards. Most of the NO2 concentration in Jinan and Liaocheng meet the level 1 standards. The concentration of SO_2 in the five cities all meets the level 1 standards.

The topography of Zaozhuang is high in the north and low in the south and high in the east and low in the west, and it is surrounded by mountains on three sides. These natural topographical reasons are not conducive to the diffusion of pollutants in the city. In addition to topographical factors, the main factor leading to poor air quality is the excessive emission of pollutants. At present, Zaozhuang has a large share of thermal power, cement, and other heavy chemical industries. In addition, the city's energy consumption structure is dominated by coal. This makes Zaozhuang's air quality always in a serious pollution state. In the future, Zaozhuang government should establish a more perfect governance system and speed up the green reform of energy. For the problems of industrial waste emission, dust from roads, and excessive coal consumption, the governance should be increased.

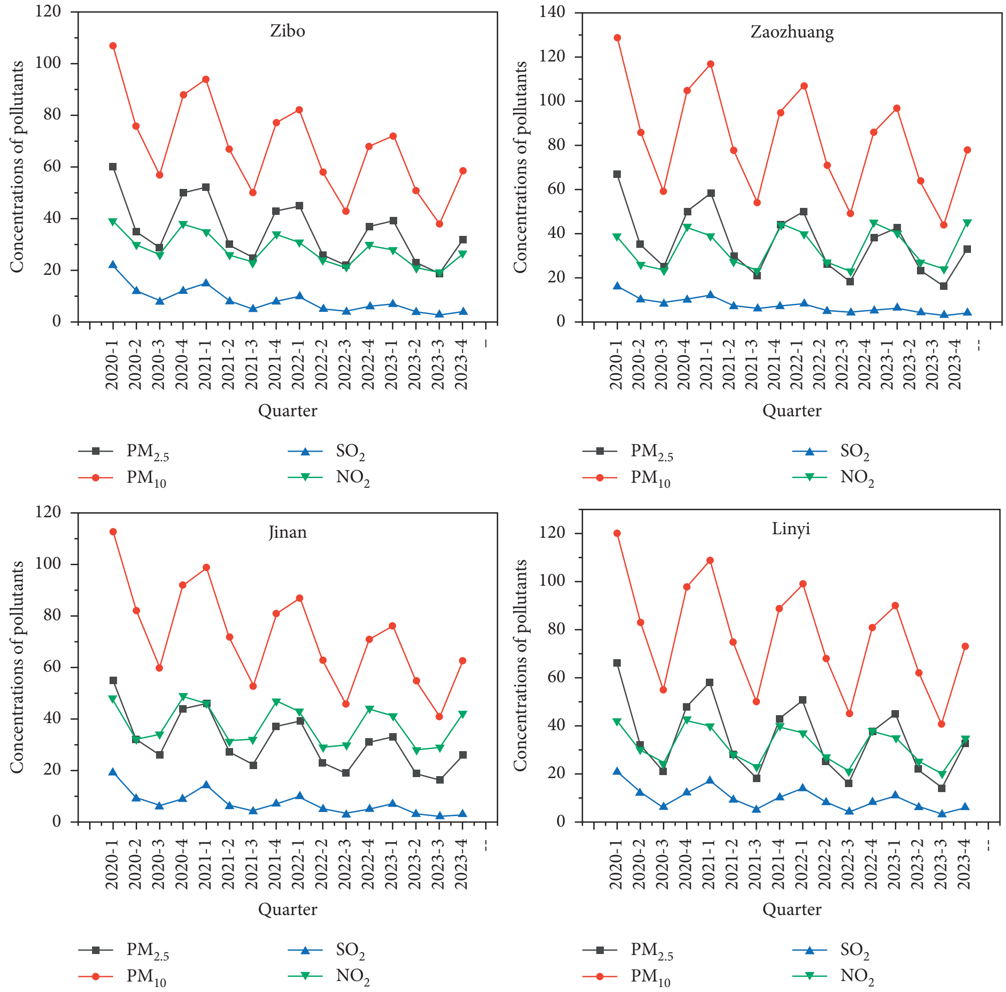

FIGURE 5: The predicted concentrations of four pollutants in four cities in Shandong Province.

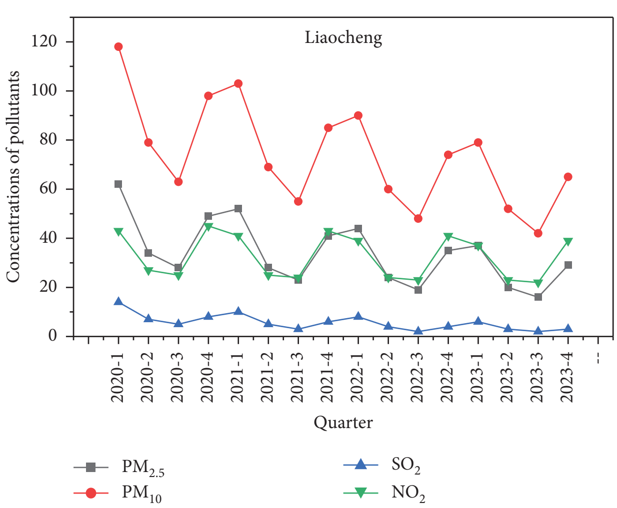

FIGURE 6: The predicted concentrations of four pollutants in Liaocheng.

4.5. Air Quality Forecast for Three Cities in Shaanxi Province. Shaanxi Province, located in the northwest of China, is one of the important cradles of the Chinese nation Huaxia culture. In recent years, Shaanxi Province has been the phenomenon of excessive air pollutants concentration. The objective factor is the topography of Shaanxi Province. The province is generally high in the north and south and low in the central part of the province, which makes it difficult for pollutants to disperse. The subjective factor is the influence of human activities. For example, pollution from motor vehicles, coal burning, and so on. In this part, three cities in Shaanxi Province are selected for prediction, and the three cities are Xianyang, Xi'an, and Weinan. Figure 7 shows the raw data of pollutant concentrations for the three cities and the predicted results.

As can be seen from Figure 7, the concentrations of pollutants in these three cities have a trend of decline. Among them, the decline trend of PM_{10} concentration is particularly obvious. After 2021, PM_{10} concentration in the three cities gradually reaches the level 2 standards. Weinan shows the fastest trend of $PM_{2.5}$ concentration decline and reaches the level 2 standards after 2021. The concentration of $PM_{2.5}$ in Xianyang and Xian meets the level 2 standards in the second and third quarters of each year. The concentration of NO_2 in Xian is slightly higher than the level 1 standards. The concentration of NO_2 in

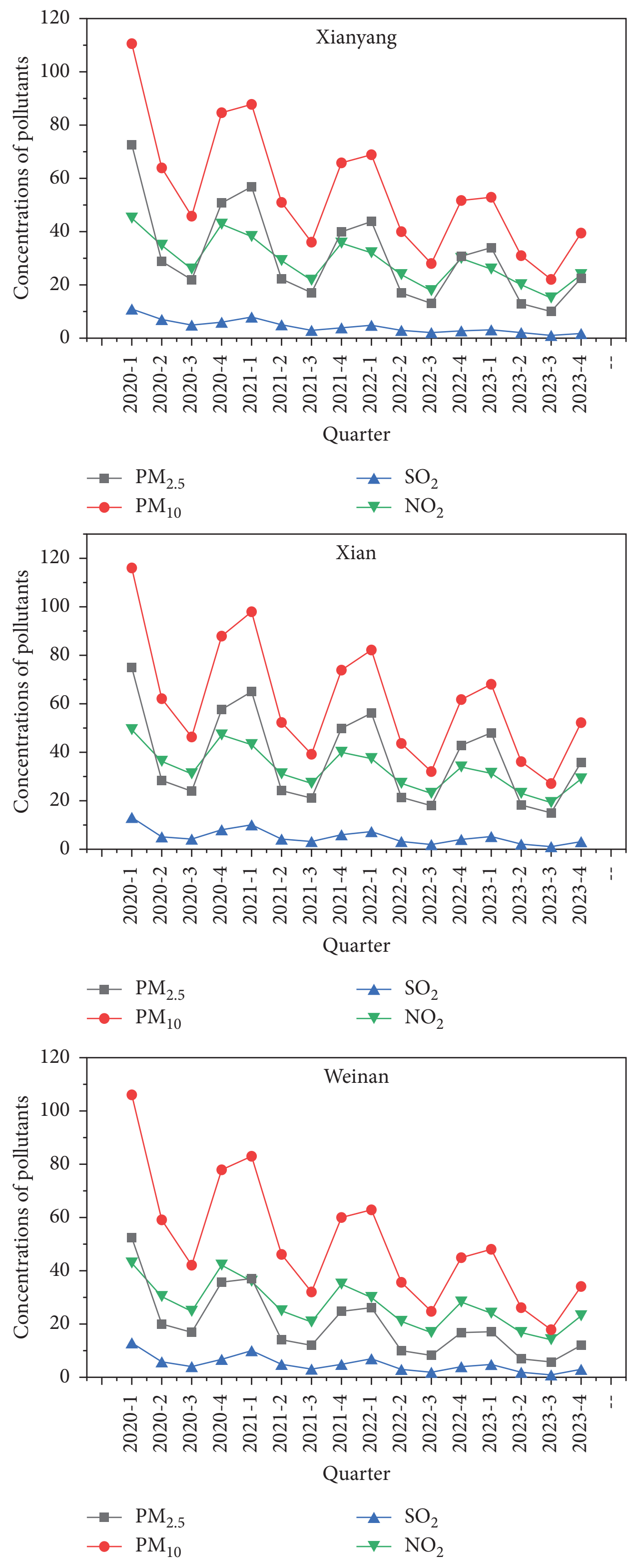

Figure 7: The predicted concentrations of four pollutants in three cities in Shaanxi Province.

Xianyang and Weinan meets the level 1 standards. The concentration of SO_2 in the three cities meets the level 1 standards.

Xi'an is located in the Guanzhong Plain, north of the Qinling Mountains. Due to the obstruction of the mountain range, it is difficult for pollutants to spread. As the capital of Shaanxi Province, Xi'an combines economy, politics, culture, and technology. The rapid development of the city has led to a large consumption of energy. Xi'an has fewer real industries, compared to the more rapidly growing construction industry. This has led to a significant increase in construction pollutants as well as road dust. At the same time, the city is overly densely populated and has a high level of vehicle ownership. All of these reasons contribute to Xi'an's poor air quality. In response to these conditions, the Xi'an government should continue to strengthen dust management, implement new initiatives to restrict motor vehicle traffic, and increase the market share of environmentally friendly energy sources, among others.

4.6. Summary of Air Quality in 22 Cities. It can be seen from the above conclusion that the air quality of these 22 cities has a trend of improvement to some extent. Pollutants' concentrations vary widely on a quarterly basis. The concentrations of $PM_{2.5}$, PM_{10}, SO_2, and NO_2 in the second and third quarters of each year are relatively low. But in the first and fourth quarters of each year, pollutants' concentrations are higher. Because after entering the winter, a variety of uncontrollable factors lead to a greater probability of heavy pollution weather. Therefore, we should focus on how to improve the air quality in the first and fourth quarters.

Through the efforts of the past few years, the pollutants' concentrations in these 22 cities show a trend of decline. However, this can only represent past efforts. Environmental governance is a long-term project, and these cities must not let down their guard in the future. In the past, the country focused on economic development and ignored the importance of environmental protection. Therefore, when the economy develops rapidly, air quality and ecological environment are seriously damaged. Now, we should protect the environment we live in while developing the economy.

Protecting the ecological environment and improving air quality are important tasks. Government departments must really find the problem and the root of the problem to solve the problem. The environmental protection department must be timely, accurate, and open in air quality forecast so that people can better understand the air conditions. Regulators should also step up inspections and be more serious and responsible about companies that have been ordered by the state to rectify. For those key areas of the investigation work should not be underestimated, so as to better urge enterprises to improve the level of emission technology. Government departments may also hold activities to reward reports and encourage the public to actively expose illegal acts. People's daily consumption of coal is also one of the main sources of pollution. Especially in the north, people use too much coal in winter. Therefore, government departments should actively promote the implementation of clean energy instead of coal burning work.

In a word, environmental protection in our country cannot be relaxed. If we slack off in environmental governance, our previous efforts will be in vain.

5. Conclusions

In this paper, the QCGM(1, 1) model is used to study 22 cities with poor air quality in China. The model optimizes the accumulation of the grey model by introducing two parameter variables to regulate the accumulation sequence. In order to solve the problem that different pollutant concentrations show large variability in different seasons, a seasonal factor is introduced into the model. Compared with the traditional GM(1, 1) model, the initial value of the model is effective and the fitting accuracy is greatly improved. The predicted results show that the concentrations of the four pollutants in these cities are likely to decline in the next few years. Although the concentrations of SO_2 and NO_2 have met the level 1 standards, the concentrations of $PM_{2.5}$ and PM_{10} in most cities are far higher than the level 2 standards. Therefore, we should focus on how to reduce the concentrations of $PM_{2.5}$ and PM_{10} in the first and fourth quarters.

In the future, we still need to continue to strengthen our air management efforts. For those areas with poor air quality, we should do more to improve it. Of course, the model proposed in this paper can also be applied to the case prediction of water resources, energy consumption, and other data with significant quarterly fluctuations. The predicted results can provide reference for relevant departments and make a better contribution to the society.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

The study was supported by the National Natural Science Foundation of China (71871084) and the Excellent Young Scientist Foundation of Hebei Education Department (SLRC2019001).

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