Research Article

Analyzing the Relationship between the PM_{2.5} Concentration and the Gini Coefficient Using the Grey Model

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To explore the relationship between the PM_{2.5} concentration and the gap between the rich and the poor, the PM_{2.5} concentration in 26 provincial regions of China is predicted by using the Gini coefficient as the independent variable. The nonequidistant fractional grey prediction model (CFNGM (1, 1)) is used for data fitting and predicting. The validity of the model is verified by comparing with the traditional nonequidistant grey model. The predicting results show that the PM_{2.5} concentration in many provinces of China presents a roughly downward trend. In the past nine years, the Gini coefficients have declined in more than 70% of the 26 provinces. However, the development of the Gini coefficient in Northwest China fluctuates greatly and even has an upward trend in recent years. According to the predictive results, reasonable suggestions can be put forward for the effective control of PM_{2.5} emission in China.

1. Introduction

Air pollutants have become an urgent environmental pollution problem in China, which mainly include particulate matter, sulfur oxides, nitrogen oxides, carbon oxides, and hydrocarbons [1]. The particulate matter is a prominent problem and has seriously affected people's normal life and health [2]. Since 2012, China began to conduct scientific observation of PM_{2.5}. With the support of data, many scholars have conducted a large number of studies on PM_{2.5}, especially on the causes of PM_{2.5}. According to the studies of scholars, the anthropogenic causes of PM_{2.5} mainly include industrial combustion emissions, automobile exhaust emissions, coal-fired rural heating [3], and agricultural incineration [4]. Among them, industrial combustion emissions are the most serious [5]. Therefore, scientific research on air pollutants and environmental protection policies are particularly important.

The "Blue Sky Protection Plan" of the Chinese government has effectively reduced the concentrations of PM_{2.5} and PM₁₀ in cities. The plan provides a new idea for developing countries to implement air pollution control

policies [6]. With the deepening of research, scholars begin to explore the relationship between air pollution and economic factors. The concentration levels of air pollutants in different cities are significantly different [7]. Meanwhile, in one city, the driving direction and driving intensity of various economic factors on air quality improvement are significantly different [8]. Among the factors, the tertiary industry has a more positive impact on air quality than the construction industry. Both motor vehicles and the residential population have a negative impact on air quality [9]. However, air pollution will not only affect plant growth and animal health but also change the market balance of agricultural input and output in the food supply chain [10].

However, at present, most scholars are looking into the direct causes of PM_{2.5}. The PM_{2.5} concentration has a great relationship with the speed of economic development obviously. On the contrary, the imbalanced economic development also has a huge impact on the PM_{2.5} concentration. The Gini coefficient is an index reflecting the degree of inequality of regional economic development [11] and is an important analysis index for judging the gap between the rich and the poor in a region. In order to further reveal the

relationship between environmental science and economic factors, we use the improved grey prediction model to predict the $PM_{2.5}$ concentration by using the Gini coefficient as the independent variable. Meanwhile, it verifies the effectiveness of the improved grey prediction model in this research field.

In the study of $PM_{2.5}$, the traditional prediction model cannot predict the air quality data more accurately because the data related to the atmospheric composition are too few to constitute large sample data. The grey prediction model based on small sample data can solve this problem perfectly. Since Professor Deng proposed the grey model (GM (1, 1)) in 1982, many scholars have made a lot of innovations based on the original model and applied them to various fields. The innovation of the grey model can be divided into two directions. The first is to reduce the predictive error. Wu applied the fractional order idea to the grey prediction model and verified the rationality of the optimal order [12]. Mao proposed a novel fractional grey model based on the principle of new information priority, and it can overcome the GM (1, 1) model class ratio test restrictions and has higher modeling precision [13]. Zeng proposed a multivariate grey prediction model based on the dynamic background value coefficient, which improved the accuracy of the multivariate grey prediction model [14]. Liu and Wu introduced grey generating operator into the Holt–Winters model for the seasonal data [15]. Liu proposed a modified grey prediction model with a damping trend factor, which could flexibly adjust the prediction trend of the grey model [16]. The other direction is to expand the application scope of the grey model. Wang proposed a seasonal grey prediction model to buffer the error of seasonal changes on the prediction results [17]. After that, Xiao proposed an improved grey prediction model for seasonal rolling, which showed the inherent grey index law after sequence processing [18]. Cui proposed a new grey prediction model, which is suitable for the prediction of data series with the nonhomogeneous exponential law [19]. Xie proposed a feedback multifactor discrete grey prediction model based on Solow's residual method and a new prediction method for the interval grey number sequence, which solved the problems of collinear independent factor aggregation and interval grey number sequence prediction [20, 21]. Tu and Chen used the unequal fractional-order discrete multivariable grey model to predict the public concern about air pollution in three cities of China [22]. Yu combines ElasticNet and multiobjective optimization. This method effectively solves the essential defect of the ill-posed problem of the NGBMC (1, n) model [23]. Meanwhile, Wang proposed a novel Hausdorff fractional NGMC (p , n) grey prediction model based on the NGMC (1, n) model. The applicable scope of the NGMC (1, n) model is enlarged [24]. The application of the grey prediction model, especially the prediction of energy consumption and environmental quality, has developed into a mature field of scientific research.

Many scholars have realized valuable applications by using the grey prediction model. Xiong applied the multivariable grey prediction model based on the interval number sequence to the simulation and prediction of measurable

indicators of haze weather in Nanjing [25]. Li proposed a new fractional-order bidirectional weakening buffer operator to verify the effectiveness of the new model and forecast the daily average AQI index of six cities in Hebei [26]. These scholars make the grey system theory more perfect by optimizing the background values, expanding equations, and correcting residual errors and other innovations. These innovations provide better research methods for some new fields. However, when the input variable is the nonequigap sequence, the above grey model will be no longer applicable. The nonequigap fractional grey model solves this problem. Moreover, the introduction of the fractional order idea improves the prediction accuracy and makes the research results more valuable. The grey model used in this paper is introduced in the next part.

This research focuses on the relationship between the $PM_{2.5}$ concentration and the Gini coefficient and draws valuable conclusions. To a certain extent, the $PM_{2.5}$ concentration will also increase as the Gini coefficient increases. Both are unbalanced social phenomena caused by human social activities. When the environmental protection regulations are formulated, the causes of the gap between the rich and the poor can be referred to. Similarly, measures to alleviate the gap between the rich and the poor can be enlightened by the process of atmospheric governance. Multielement and comprehensive research is of great significance. As the result, the scientific $PM_{2.5}$ governance measures can be formulated simultaneously with plans to alleviate the gap between the rich and the poor. The environmental science and the economic indicators are linked in this paper, providing new research ideas for environmental science.

This paper is divided into five parts. Section 2 is the literature review of this research problem. Section 2 introduces the concrete content of the model. Section 3 verifies the validity of the model. In Section 4, the prediction results are divided into seven regions to analyze. Section 5 gives the conclusion of the study.

2. Introduction to the Model

2.1. Research Area Overview. The relationship between the $PM_{2.5}$ concentration and the Gini coefficient in 26 provinces, municipalities, and autonomous regions in China is studied. According to their geographical locations, the 26 provinces are divided into seven regions: Northeast China, North China, Northwest China, Central China, South China, East China, and Southwest China, as shown in Figure 1. In particular, air quality control in the Beijing-Tianjin-Hebei region has become the primary task of environmental protection [27]. By studying the relationship between the $PM_{2.5}$ concentration and the local Gini coefficient, a new research direction is proposed by combining air quality with economics.

2.2. Data Analysis. The Gini coefficient data are derived from calculations. The $PM_{2.5}$ concentration data is from the Ministry of Ecology and Environment of the People's

FIGURE 1: Distribution map of regions in China.

Republic of China (<https://www.mee.gov.cn/>). Due to China's late monitoring of the $PM_{2.5}$ concentration, the data of recent years are used as the research sample. In addition, because the traditional statistical prediction model is not suitable for this kind of small sample prediction, the non-equigap GM (1, 1) model with the conformable fractional accumulation (CFNGM (1, 1)) is used for prediction.

2.3. Model Introduction. The steps of the CFNGM (1, 1) are as follows [28].

There is an original sequence $X^{(0)}(t_k) = (x^{(0)}(t_1), x^{(0)}(t_2), \dots, x^{(0)}(t_n))$. If the gap is $\Delta t_k = t_k - t_{k-1} \neq c, k = 2, 3, \dots, n$, then c is a constant, and $X^{(0)}(t_k)$ is called a nonequigap sequence. $X^{(r)}(t_k)$ is the r order cumulative sequence of $X^{(0)}(t_k)$, where

$$X^{(r)}(t_k) = \begin{cases} x^{(0)}(t_1) & k = 1 \\ x^{(0)}(t_1) + \sum_{j=2}^k \frac{x^{(0)}(t_j) \times \Delta t_j}{t_j^{1-r}} & k = 2, 3, \dots, n \end{cases}, \quad r \in (0, 1]. \quad (1)$$

The contiguous mean generation sequence of the non-equigap sequence $X^{(r)}(t_k)$ is $Z^{(r)} = (z^{(r)}(2), z^{(r)}(3), \dots, z^{(r)}(n))$, where

$$z^{(r)}(t_k) = \frac{1}{2} (x^{(r)}(t_k) + x^{(r)}(t_{k-1})), \quad (2)$$

$$x^{(0)}(t_k) + az^{(r)}(t_k) = b,$$

which is called the mean value form of the CFNGM (1, 1). Its whitening differential equation is

$$\frac{dx^{(r)}}{dt} + ax^{(r)} = b, \quad (3)$$

where a is the development coefficient and b is the grey action. The least square estimation of CFNGM (1, 1) model satisfies

$$\begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y, \quad (4)$$

where

$$B = \begin{bmatrix} -z^{(r)}(t_2) & 1 \\ -z^{(r)}(t_2) & 1 \\ \vdots & \vdots \\ -z^{(r)}(t_2) & 1 \end{bmatrix},$$

$$Y = \begin{bmatrix} \frac{x^{(r)}(t_2) - x^{(r)}(t_1)}{t_2 - t_1} \\ \frac{x^{(r)}(t_3) - x^{(r)}(t_2)}{t_3 - t_2} \\ \vdots \\ \frac{x^{(r)}(t_n) - x^{(r)}(t_{n-1})}{t_n - t_{n-1}} \end{bmatrix}. \quad (5)$$

The initial condition of the differential equation in equation (3) is $x^{(r)}(t_1) = x^{(0)}(t_1)$.

The time response equation can be obtained as

$$\hat{x}^{(r)}(t_k) = \left(x^{(0)}(t_1) - \frac{\hat{b}}{\hat{a}} \right) e^{-\hat{a}(t_k - t_1)} + \frac{\hat{b}}{\hat{a}}. \quad (6)$$

Proof of equation (6): from whitening differential equation (3), we can have

$$x^{(r)}(t_k) = C e^{-at_k} + \frac{b}{a}. \quad (7)$$

When $k = 1$, $x^{(r)}(t_1) = x^{(0)}(t_1)$ is substituted into the above equation. We can get

$$C = \left(x^{(0)}(t_1) - \frac{b}{a} \right) e^{at_1}. \quad (8)$$

So,

$$x^{(r)}(t_k) = \left(x^{(0)}(t_1) - \frac{b}{a} \right) e^{-a(t_k - t_1)} + \frac{b}{a}. \quad (9)$$

Proof completed.

So, the reduction sequence of $\hat{x}^{(r)}(k)$ can be obtained as

$$\hat{x}^{(0)}(t_k) = \begin{cases} \hat{x}^{(1)}(t_1), & k = 1, \\ \frac{t_k^{1-r} (\hat{x}^{(r)}(t_k) - \hat{x}^{(r)}(t_{k-1}))}{\Delta t_k}, & k = 2, 3, \dots, n. \end{cases} \quad (10)$$

We use the MAPE to measure the stability of the model, as shown in the following equation:

$$\text{MAPE} = \frac{1}{n} \sum_{k=1}^n \frac{|x^{(0)}(k) - \hat{x}^{(0)}(k)|}{x^{(0)}(k)}. \quad (11)$$

3. Validation of the Model

3.1. Verify the Validity of CFNGM(1, 1) Model by Comparison. The validity of the CFNGM(1, 1) model is verified by the following case.

According to the model and data in [29], the fitting result of CFNGM(1, 1) and the traditional nonequidistant model are compared. Among them, the order of the nonequidistant model used in [29] is 1 (the traditional first-order accumulation generation sequence). The optimal order of the CFNGM(1, 1) model of the reference case data is 0.955, with the parameters $a = -0.00058$ and $b = 9.20$. The final fitting results are shown in Table 1. It can be seen from Table 1 that the fitting error of the CFNGM(1, 1) model is 0.74% and the traditional nonequidistant model is 1.78%. The average predictive error of the CFNGM(1, 1) model for the two sets of data is 0.94%, and the average predictive error of the traditional nonequidistant model is 7.19%. According to the results, the fitting and prediction accuracy of the CFNGM(1, 1) model is higher than that of the traditional nonequidistant model. Therefore, it can be considered that the CFNGM(1, 1) model is better than the traditional nonequidistant model.

3.2. Applicability Test of the Model in China's Coastal and Inland Areas. Jiangsu and Shaanxi are selected to verify the applicability of the model. The verification results are shown in Table 2. In the verification process, the data from 2006 to 2015 are selected for fitting, and the data in 2016 is used for predicting. The MAPE is calculated by comparing the predicted results of 2016 with the actual values. The MAPE in Table 2 is less than 10%, which shows that the model is suitable for the $\text{PM}_{2.5}$ concentration prediction in various provinces of China.

4. Analyze the Relationship between the $\text{PM}_{2.5}$ Concentration and the Gini Coefficient

Human factors of $\text{PM}_{2.5}$ production can be divided into stationary sources and mobile sources. The stationary sources mainly include various fuel combustion sources, such as smoke and dust discharged in various industrial combustion processes. The mobile source is mainly the exhaust gas discharged into the atmosphere by all kinds of vehicles in the process of running. From this, we can infer the potential relationship between the $\text{PM}_{2.5}$ concentration and the Gini coefficient: the provinces with high $\text{PM}_{2.5}$ concentration are generally the areas with more developed industries. The rapid development of industry has taken up rural resources, which intensifies China's urban-rural dual economic structure. The results directly widen the urban-rural gap and lead to the rise of the Gini coefficient. Therefore, the imbalance and incoordination between economic development and environmental development are an important issue to be solved urgently. Studying the relationship between $\text{PM}_{2.5}$ concentration and the Gini coefficient is of great significance to the governance of $\text{PM}_{2.5}$ and the elimination of the gap between the rich and the poor.

TABLE 1: Compare the predicted results of different models in the case.

k_i	$x^{(0)}(k_i)$	Ref. [29]	CFNGM (1, 1)
1	9.28	9.28	9.28
25	10.71	10.95	10.71
53	11.31	11.25	11.25
83	11.64	11.59	11.67
116	12.00	11.98	12.06
147	12.23	12.38	12.42
177	13.05	12.78	12.74
237	13.16	13.39	13.25
MAPE	—	1.78%	0.74%
269	13.61	14.05	13.69
355	13.94	14.94	14.34
MAPE	—	7.19%	0.94%

TABLE 2: The result of the CFNGM (1, 1) model in two provinces.

Year	Jiangsu			Shaanxi		
	Gini coefficient	PM _{2.5}	CFNGM (1, 1)	Gini coefficient	PM _{2.5}	CFNGM (1, 1)
2006	0.369	53.7	53.7	0.461	56.1	56.1
2007	0.371	61.1	62.1	0.459	56.1	58.1
2008	0.372	57.5	62.3	0.462	47.8	58.1
2009	0.377	66.2	62.7	0.456	57.8	58.0
2010	0.378	61.7	63.2	0.456	64.4	58.0
2011	0.354	66.6	61.6	0.405	67.5	57.6
2012	0.350	56.3	59.6	0.404	61.2	57.2
2013	0.363	59.2	60.2	0.399	61.4	57.2
2014	0.345	62.5	59.9	0.387	54.3	57.0
2015	0.351	58.6	59.1	0.404	47.0	57.1
MAPE	—	—	4.67%	—	—	9.07%
2016	0.338	50.2	58.6	0.403	51.1	57.2
MAPE	—	—	3.78%	—	—	8.98%

4.1. Calculation Results and Analysis. The prediction results will be divided into seven parts for analysis. There are regional differences in economic development and PM_{2.5} concentration distribution among provinces in China. According to the unique characteristics of different regions, the prediction results of each region are analyzed pertinently. The results of the analysis have more profound significance for air pollution control and the study of the gap between rich and poor in various provinces.

4.1.1. East China. We study the relationship between the PM_{2.5} concentration and the Gini coefficient in six provinces in East China (Shanghai, Jiangsu, Zhejiang, Fujian, Anhui, and Jiangxi). Firstly, according to the PM_{2.5} concentration and the Gini coefficient, the parameters a and b in the CFNGM (1, 1) model are calculated. The fitting sequence of

the PM_{2.5} concentration is obtained. Secondly, the Gini coefficients of each province from 2006 to 2016 are calculated by the first author. Since the Gini coefficient has no obvious trend of increase or decrease, the average annual growth rate from 2007 to 2016 is used to predict the Gini coefficient of 2017 to 2019. Finally, the parameters a and b are substituted into equation (6) to obtain the time response equation, and then, the predicted values of the Gini coefficient from 2017 to 2019 are input into the time response equation to obtain $x^{(r)}$. The PM_{2.5} concentration from 2017 to 2019 can be calculated by equation (10). We are taking Jiangsu Province as an example to illustrate this process in detail.

The Gini coefficient is taken as the independent variable and the PM_{2.5} concentration as the dependent variable. There is a sequence of Gini coefficients:

$$t_k = (0.369, 0.371, 0.372, 0.377, 0.378, 0.354, 0.350, 0.363, 0.345, 0.351, 0.338). \quad (12)$$

And, the initial sequence of PM_{2.5} concentrations is

$$X^{(0)}(t_k) = (53.7, 61.1, 57.5, 66.2, 61.7, 66.6, 56.3, 59.2, 62.5, 58.6, 50.2). \quad (13)$$

Step 1: calculate $\Delta t_k (k = 2, 3, \dots, n)$:

$$\Delta t_k = (0.002, 0.001, 0.005, 0.001, -0.024, -0.005, 0.014, -0.019, 0.006, -0.012). \quad (14)$$

Step 2: the particle swarm optimization algorithm is used to solve the optimal fractional order $r = 0.896$,

according to which the cumulative sequence can be obtained:

$$x^{(0.896)} = (53.7, 53.8, 53.9, 54.3, 54.3, 52.6, 52.3, 53.2, 51.9, 52.2, 51.6). \quad (15)$$

Step 3: the continuous mean generation sequence of nonequigap sequence $X^{(0.896)}(t_k)$ can be obtained as

$$Z^{(0.896)} = (53.8, 53.9, 54.1, 54.3, 53.4, 52.4, 52.7, 52.5, 52.1, 51.9). \quad (16)$$

Step 4: the matrixes B and Y are expressed as

$$B = \begin{bmatrix} -53.8 & 1 \\ -53.9 & 1 \\ -54.1 & 1 \\ -54.3 & 1 \\ -53.4 & 1 \\ -52.4 & 1 \\ -52.7 & 1 \\ -52.5 & 1 \\ -52.1 & 1 \\ -51.9 & 1 \end{bmatrix}, \quad (17)$$

$$Y = \begin{bmatrix} 67.8 \\ 63.7 \\ 73.3 \\ 68.3 \\ 74.2 \\ 62.8 \\ 65.8 \\ 69.8 \\ 65.4 \\ 56.2 \end{bmatrix}.$$

According to the least squares method, the values of parameters $\hat{a}$ and $\hat{b}$ are obtained:

$$\begin{aligned} \hat{a} &= -3.494, \\ \hat{b} &= -118.830. \end{aligned} \quad (18)$$

Step 5: the parameters $\hat{a} = -3.494$ and $\hat{b} = -118.830$ are substituted into equation (6):

$$\hat{x}^{(0.896)} = (53.7, 53.8, 53.9, 54.3, 54.3, 52.7, 52.4, 53.3, 52.1, 52.4, 51.7). \quad (19)$$

Step 6: the reduction sequence of fitted values is

$$\hat{x}^{(0)} = (53.7, 62.3, 62.6, 63.3, 64.1, 61.1, 58.0, 59.2, 58.4, 57.2, 56.3). \quad (20)$$

Step 7: the average growth rate of the Gini coefficient from 2006 to 2016 is -0.0083 . Based on this growth rate, the Gini coefficient for 2017–2019 is predicted to be

$$\begin{aligned} t_{12} &= 0.336, \\ t_{13} &= 0.333, \\ t_{14} &= 0.330. \end{aligned} \quad (21)$$

Step 8: the 2017–2019 Gini coefficient values are substituted into equation (6), and the time response

sequence is

$$\begin{aligned}\hat{x}^{(0.896)}(t_{12}) &= 51.5, \\ \hat{x}^{(0.896)}(t_{13}) &= 51.3, \\ \hat{x}^{(0.896)}(t_{14}) &= 51.2.\end{aligned}\quad (22)$$

Step 9: the reduction sequence of the predicted values of the PM_{2.5} concentration from 2017 to 2019 is

$$\begin{aligned}\hat{x}^{(0)}(t_{12}) &= 54.8, \\ \hat{x}^{(0)}(t_{13}) &= 54.2, \\ \hat{x}^{(0)}(t_{14}) &= 53.7.\end{aligned}\quad (23)$$

Table 3 shows the predicted values of the PM_{2.5} concentration in Jiangsu, Shanghai, Zhejiang, Fujian, Anhui, and Jiangxi from 2017 to 2019. The fitting errors of these six provinces, respectively, are 4.67%, 6.22%, 3.75%, 6.89%, 4.29%, and 6.30%.

From the prediction results of six provinces in East China, the predictive error is concentrated between 3% and 7%. It satisfies the constraint that the effective predictive error is less than 10%. This model is suitable for the prediction of the PM_{2.5} concentration of six provinces in East China. Except for Shanghai, the Gini coefficients of the five provinces generally show a downward trend, as shown in Figure 2. After reaching a peak in 2007, the PM_{2.5} concentration began to decline slowly, as shown in Figure 3. The main reason is that China began to implement the 11th Five-Year Plan in 2006 to accelerate the adjustment of industrial structure and strengthen pollution control. According to the data, there is generally a positive correlation between the Gini coefficient and the PM_{2.5} concentrations. The chart shows that the model's prediction of the PM_{2.5} concentration is declining slowly since the 11th Five-Year Plan. This is in line with China's sustainable development policy.

4.1.2. North China. The PM_{2.5} concentration prediction in North China, including Beijing, Hebei, Shanxi, and Inner Mongolia Autonomous Region, is shown in Table 4. The average Gini coefficient growth rate of the four provinces in North China from 2006 to 2016 is used to calculate the Gini coefficient from 2017 to 2019. The predicted value of the Gini coefficient is substituted into the model to get the predicted value of the PM_{2.5} concentration from 2017 to 2019.

As can be seen from Table 4 and Figures 4 and 5, the Gini coefficient of the four provinces in North China has a slow upward trend since 2006. However, in 2009, the government issued a series of people's livelihood policies. These policies include increasing the income of the low-income groups and further optimizing the structure of fiscal expenditure to ensure and improve people's livelihood. The central government's expenditure on agriculture, rural areas, and farmers reached 716.14 billion yuan (http://www.stats.gov.cn/ztfj/zgxxbjjps/201003/t20100308_53538.html). For these reasons, the Gini coefficient showed an obvious downward trend in the next four years and suddenly

increased since 2014. However, it slowly declined again after reaching a peak in 2015. This may be because the appreciation of RMB in 2015 widened the gap between domestic and foreign grain prices. Grain prices inversion resulted in a significant increase in grain imports and a sharp decline in domestic grain prices. Grain imports were 125million tons in 2015, more than 20% of the total grain output in China (<https://data.stats.gov.cn/easyquery.htm?cn=C01&zxb=A060701&sj=2015>).

The large-scale import of grain directly leads to a decrease in farmers' income. The main reason for the high Gini coefficient of China's provinces is that the income gap between the urban and rural residents is large [30]. The decline of grain price indirectly leads to the rise of the Gini coefficient. The PM_{2.5} concentration in Inner Mongolia has fluctuated up and down since 2006, but the overall data is stable. This is mainly due to the fact that the livestock industry is the main economic industry in the Inner Mongolia Autonomous Region and the secondary industry is relatively underdeveloped. The PM_{2.5} concentrations in Beijing, Hebei, and Shanxi are roughly synchronized. After falling in 2006, it began to rise in 2008 and then fell again after reaching two peaks in 2010 and 2013. The chart shows that despite the increasing efforts in air pollution control, the basic industrial pollution and the inherent dust weather in North China will not be completely cured in a short time. Combined with the continuous increase of car ownership, the PM_{2.5} concentration is difficult to maintain in a stable state. It also calls on the government and relevant departments to control air pollution at no time and to be ready to fight back against environmental pollution.

4.1.3. Northeast China. The PM_{2.5} concentrations in Heilongjiang and Liaoning show a fluctuating trend of rising. However, after reaching the peak in 2014, it began to decline significantly. The Gini coefficient of Liaoning shows a slow downward trend. The Gini coefficient of Heilongjiang decreases sharply from 2006 to the lowest point of 0.267 in 2013. It increases again and reaches a stable state in 2016. The PM_{2.5} concentration in Heilongjiang is only higher than that in Tibet and Hainan. This phenomenon shows that the lack of people in remote areas plays a decisive role in atmosphere protection.

4.1.4. Northwest China. The Gini coefficients of the five provinces in Northwest China are very similar in value and fluctuation, as shown in Figure 6. Although the Gini coefficients of the five provinces show an obvious downward trend from 2009 and reach a minimum value in 2012–2013, they then continue to rise and reach a peak again in 2015. Compared with other regions, the Gini coefficient of Northwest China is higher, which is similar to the remote regions such as Guizhou and Guangxi. It reflects that the characteristics of slower economic development and a larger number of low-income people lead to the increase of the Gini coefficient. Among these five provinces, Shaanxi and Xinjiang have the highest PM_{2.5} concentrations, as shown in Figure 7, with the average concentrations of 56.8 ug/m³ and

TABLE 3: Fitting results of the $PM_{2.5}$ concentrations in East China.

Year	Jiangsu			Shanghai			Zhejiang		
	Gini coefficient	$PM_{2.5}$	Result	Gini coefficient	$PM_{2.5}$	Result	Gini coefficient	$PM_{2.5}$	Result
2006	0.369	53.7	53.7	0.311	50.8	50.8	0.361	46.5	46.5
2007	0.371	61.1	62.3	0.303	59.1	54.4	0.362	48.9	49.0
2008	0.372	57.5	62.6	0.303	51.6	53.8	0.362	47.8	49.0
2009	0.377	66.2	63.3	0.295	59.0	53.1	0.361	48.5	48.9
2010	0.378	61.7	64.1	0.281	48.4	51.3	0.354	46.7	48.3
2011	0.354	66.6	61.1	0.277	52.5	49.9	0.333	47.3	46.2
2012	0.350	56.3	58.0	0.278	50.0	49.7	0.322	47.3	44.0
2013	0.363	59.2	59.2	0.282	47.4	50.1	0.329	44.5	43.7
2014	0.350	62.5	58.4	0.276	49.6	49.8	0.322	46.8	43.7
2015	0.351	58.6	57.2	0.276	51.9	49.4	0.307	41.9	42.1
2016	0.338	50.2	56.3	0.327	43.3	53.6	0.311	35.7	41.4
MAPE	4.67%			6.21%			3.70%		
2017	0.336		54.8	0.329		58.1	0.306		41.3
2018	0.333		54.2	0.332		58.5	0.302		40.7
2019	0.330		53.7	0.334		59.0	0.298		40.2

Year	Anhui			Fujian			Jiangxi		
	Gini coefficient	$PM_{2.5}$	Result	Gini coefficient	$PM_{2.5}$	Result	Gini coefficient	$PM_{2.5}$	Result
2006	0.415	58.9	58.9	0.380	30.7	30.7	0.367	47.1	47.1
2007	0.410	68.7	67.0	0.382	33.6	30.3	0.379	50.1	49.3
2008	0.411	61.2	66.9	0.388	28.4	30.7	0.376	44.7	49.0
2009	0.404	68.2	66.7	0.385	31.4	30.9	0.377	47.1	49.2
2010	0.380	71.3	65.7	0.408	29.7	32.1	0.360	49.6	46.9
2011	0.368	69.9	64.6	0.395	32.6	32.7	0.336	49	43.6
2012	0.353	61.8	63.7	0.377	31.6	30.8	0.341	48.4	44.2
2013	0.362	67.2	63.5	0.380	29.9	30.0	0.332	44.4	43.1
2014	0.349	68	63.4	0.332	28.6	27.6	0.337	44.4	43.7
2015	0.375	58.9	63.8	0.352	25.6	26.1	0.330	37.6	42.7
2016	0.368	52.9	64.4	0.348	24.3	26.9	0.319	37.3	41.2
MAPE	6.81%			4.29%			6.30%		
2017	0.364		64.1	0.346		26.6	0.314		40.6
2018	0.360		63.8	0.343		26.3	0.310		40.0
2019	0.356		63.6	0.341		26.1	0.306		39.5

FIGURE 2: The Gini coefficients and prediction values of East China.

55 $\mu\text{g}/\text{m}^3$. In Table 5, the predictive errors of the five provinces remain between 5% and 10%, so this model is suitable for the prediction of the $PM_{2.5}$ concentration in Northwest China. During the 13th Five-Year Plan period, Shaanxi gradually paid attention to the management of

FIGURE 3: The $PM_{2.5}$ concentrations and prediction values of East China.

carbon emissions in the agricultural production process and actively integrated the environmental protection concepts with the green development of agriculture. Ningxia actively responded to the government's energy structure adjustment

TABLE 4: Fitting results of the $PM_{2.5}$ concentrations in North and Northeast China.

Year	Beijing			Hebei			Shanxi		
	Gini coefficient	$PM_{2.5}$	Result	Gini coefficient	$PM_{2.5}$	Result	Gini coefficient	$PM_{2.5}$	Result
2006	0.279	77.1	77.1	0.358	83.6	83.6	0.414	56.7	56.7
2007	0.281	69.8	72.3	0.350	71.0	76.5	0.416	50.1	54.8
2008	0.296	70.3	72.6	0.376	75.0	76.1	0.415	45.6	54.7
2009	0.292	71.3	69.5	0.380	71.6	75.4	0.426	50.9	53.7
2010	0.252	66	67.9	0.373	72.7	75.5	0.411	59.1	54.1
2011	0.263	73.7	76.6	0.369	85.9	75.8	0.403	82.5	56.3
2012	0.256	63.8	73.6	0.356	71.5	76.1	0.390	64.6	58.5
2013	0.251	84.6	74.6	0.349	91.2	76.6	0.388	64.5	60.1
2014	0.274	79.5	77.7	0.330	82.4	77.2	0.374	56.4	61.9
2015	0.295	78.5	73.9	0.349	74.8	77.2	0.437	50.7	56.8
2016	0.286	69.5	69.4	0.343	67.3	76.9	0.397	50.4	54.4
MAPE	4.67%			6.20%			3.75%		
2017	0.287		71.2	0.342		77.0	0.396		58.5
2018	0.288		71.0	0.341		77.1	0.395		58.7
2019	0.290		70.9	0.339		77.1	0.394		58.9

Year	Inner Mongolia			Liaoning			Heilongjiang		
	Gini coefficient	$PM_{2.5}$	Result	Gini coefficient	$PM_{2.5}$	Result	Gini coefficient	$PM_{2.5}$	Result
2006	0.399	26.9	26.9	0.357	46.8	46.8	0.386	21.5	21.5
2007	0.388	21.8	24.2	0.358	37.1	44.5	0.380	19.2	23.9
2008	0.397	22.1	24.7	0.367	46.9	46.0	0.374	23.5	24.4
2009	0.413	25.3	25.0	0.363	44.0	45.6	0.372	20.8	24.9
2010	0.398	26.7	24.3	0.343	39.9	42.4	0.336	25.8	25.3
2011	0.378	26.5	23.9	0.342	46.1	41.6	0.300	32.1	28.1
2012	0.361	24	23.7	0.325	38.3	39.1	0.275	26.0	31.1
2013	0.372	24.3	24.3	0.346	41.5	41.8	0.267	29.8	33.4
2014	0.376	26.1	24.3	0.360	49.2	44.5	0.295	40.1	34.7
2015	0.389	24.8	24.6	0.352	49.0	43.7	0.366	35.9	32.0
2016	0.373	21.8	23.9	0.330	37.8	40.0	0.327	25.3	25.8
MAPE	4.67%			6.40%			10.91%		
2017	0.371		24.1	0.327		39.1	0.323		29.0
2018	0.368		24.0	0.325		38.7	0.320		29.3
2019	0.366		24.2	0.323		38.3	0.316		29.6

FIGURE 4: The Gini coefficients and prediction values of North China.

FIGURE 5: The $PM_{2.5}$ concentrations and prediction values of North China.

policy. It transformed heating boilers by using clean coal, natural gas, and other clean energy sources for heating. Carrying out the coal quality supervision and the total consumption control largely alleviated the air pollution problem in Ningxia. Among the five provinces, Qinghai has

the minimum average $PM_{2.5}$ concentration of $35.1 \mu g/m^3$. The $PM_{2.5}$ concentrations in the five northwest provinces are average compared to other regions, but the Gini coefficients are generally higher. At present, Northwest China is in the contradiction between the higher pollution of the traditional

FIGURE 6: The Gini coefficients and prediction values of Northwest China.

FIGURE 7: The $PM_{2.5}$ concentrations and prediction values of Northwest China.

industry and the immaturity of the economic industry transformation. Therefore, Northwest China should focus on developing the “low-carbon industry” to reduce energy consumption and pollution based on ensuring revenue. Since the concept of the “low-carbon economy” was put forward, the environmental protection policies such as the “low-carbon city” and the “low-carbon agriculture” have been derived.

4.1.5. Southwest China. The $PM_{2.5}$ concentration prediction results in Southwest China are shown in Table 6. Southwest China includes Sichuan, Chongqing, Guizhou, and Xizang, among which Guizhou is a special province. The average $PM_{2.5}$ concentration in Guizhou from 2006 to 2016 is $38.2 \mu g/m^3$. It is only two-thirds of that in the neighboring province Sichuan. However, the average Gini coefficient of Guizhou is 0.452, the highest among 26 provinces. This phenomenon reflects the backwardness of Guizhou’s economy and the extreme imbalance between urban and

rural development. Guizhou is the only province in China without a plain, with the lowest GDP per capita. Speeding up the construction of public transportation and the development of tourism is the primary task for Guizhou to get rid of poverty. The annual $PM_{2.5}$ concentration in Tibet Autonomous Region is only $7.1 \mu g/m^3$, less than one-tenth of that in Henan. The “Last Pure Land” of mankind should be safeguarded by continuing to strengthen environmental and cultural protection.

4.1.6. Central China. The $PM_{2.5}$ concentration prediction of two provinces in central China is shown in Table 6. The predictive errors are 7.15% and 8.03%. Therefore, it shows that the model is suitable for the prediction of $PM_{2.5}$ concentration in this region. The $PM_{2.5}$ concentration in Central China, represented by Henan and Hubei, is higher than that in other provinces. In particular, the average $PM_{2.5}$ concentration in Henan from 2006 to 2016 reached $79 \mu g/m^3$, which is the highest among the 26 provinces. It is much higher than $64 \mu g/m^3$ in the neighboring province Hubei and even higher than Beijing and Hebei, which are seriously polluted all the year round. However, the Gini coefficients of Henan and Hubei are close and stable at around 0.360. This is mainly related to the large population base of Henan and the economy of industry and construction industry. Therefore, speeding up the economic transformation of the tertiary industry in Henan province is an important way to relieve the population pressure and prevent air pollution.

4.1.7. South China. This section includes the $PM_{2.5}$ concentration prediction of Guangdong, Guangxi, and Hainan provinces in South China. The results are shown in Table 7. Guangxi has the highest average Gini coefficient and the $PM_{2.5}$ concentration among the three provinces. The central region of Guangxi has relatively developed industry and large air pollution emissions. The air pollutants produced by industry tend to gather due to the poor diffusion conditions. However, because of the neutralization of the lower $PM_{2.5}$ value in the south, the $PM_{2.5}$ concentration in Guangxi is not very high. Therefore, air pollution is serious in the more populated central region. Guangdong is an experimental base for the reform and opening up. But the rapid economic growth has also taken its toll on the environment. In recent years, the Pearl River Delta region has stopped building new high-polluting enterprises and gradually implemented stricter emission standards. Since 2011, the $PM_{2.5}$ concentration has declined significantly. Hainan’s economic source is mainly tourism. Because it is surrounded by the sea and the atmospheric pollutant diffusion conditions are superior, the $PM_{2.5}$ concentration has always been in a low state. The average Gini coefficient in Hainan is less than 0.4 and shows a slowly decreasing trend. Continuing the development of the tourism economy and developing the economy based on environmental protection are conducive to narrowing the gap between the rich and the poor.

TABLE 5: Fitting results of the $PM_{2.5}$ concentrations in Northwest China.

Year	Shaanxi			Gansu			Qinghai		
	Gini coefficient	$PM_{2.5}$	Result	Gini coefficient	$PM_{2.5}$	Result	Gini coefficient	$PM_{2.5}$	Result
2006	0.461	56.10	56.10	0.482	45.90	45.90	0.473	32.40	32.40
2007	0.459	56.10	58.09	0.490	41.50	43.44	0.474	33.60	35.56
2008	0.462	47.80	58.12	0.477	41.00	43.49	0.486	34.50	35.58
2009	0.456	57.80	58.06	0.478	47.00	43.63	0.481	35.20	35.60
2010	0.456	64.40	57.96	0.435	48.40	44.14	0.452	40.20	35.54
2011	0.405	67.50	57.17	0.396	53.80	45.15	0.402	42.00	35.41
2012	0.404	61.20	56.37	0.364	47.70	46.02	0.359	35.70	35.26
2013	0.399	61.40	56.27	0.355	49.20	46.53	0.332	38.80	35.14
2014	0.387	54.30	56.01	0.386	43.00	46.25	0.358	35.90	35.14
2015	0.404	47.00	56.07	0.469	38.70	44.84	0.444	29.20	35.33
2016	0.403	51.10	56.32	0.430	39.80	44.31	0.396	28.50	35.39
MAPE	9.07%			7.87%			8.66%		
2017	0.398		56.23	0.427		44.82	0.391		35.30
2018	0.393		56.08	0.424		44.89	0.386		35.28
2019	0.388		55.93	0.421		44.97	0.381		35.27

Year	Ningxia			Xinjiang		
	Gini coefficient	$PM_{2.5}$	Result	Gini coefficient	$PM_{2.5}$	Result
2006	0.444	60.00	60.00	0.436	54.70	54.70
2007	0.448	44.30	44.79	0.428	58.40	52.99
2008	0.453	38.20	44.80	0.433	52.50	53.29
2009	0.442	46.80	44.80	0.427	48.50	53.09
2010	0.433	53.40	44.78	0.386	61.00	53.13
2011	0.377	51.40	44.73	0.342	51.30	54.32
2012	0.348	45.60	44.67	0.310	55.60	55.60
2013	0.368	47.80	44.66	0.313	60.90	56.96
2014	0.358	40.10	44.67	0.345	59.10	57.40
2015	0.466	39.40	44.74	0.399	49.20	56.57
2016	0.394	40.30	44.77	0.385	53.80	54.25
MAPE	8.77%			5.84%		
2017	0.392		44.71	0.382		54.76
2018	0.390		44.71	0.378		54.88
2019	0.388		44.71	0.375		54.99

4.2. Discussion. In this section, the CFNGM (1, 1) model is used to predict the $PM_{2.5}$ concentrations in 26 provinces of China from 2017 to 2019 with the Gini coefficient as the input variable. Then the prediction results of each region are analyzed. The prediction results show that there is not a simple positive correlation between the Gini coefficient and the $PM_{2.5}$ concentration, as shown in Figures 8–11. To explain this economic phenomenon, the analysis is made from the two aspects: the rich and the poor.

4.2.1. The Impact of the Behavior of the Rich. The vehicle emissions are a major source of $PM_{2.5}$. China has issued a series of traffic management regulations to control air pollution, including restrictions on travel. But it is no longer rare for the rich to own two or more private cars. Taking Beijing as an example, according to the statistical bulletin released by Beijing in 2018, Beijing's permanent resident population was 21.542 million at the end of 2018, and the number of motor vehicles in the city was 6.084 million with an average of one car for every 3.5 people (<http://www.tjcn.org/tjgb/01bj/35844.html>). Especially among wealthy families, the large-displacement cars are common. In 2013, CCTV News reported that the large-displacement cars could

not be sold abroad. But because of their ostentation, they had a market in China (<http://jingji.cntv.cn/2013/11/11/ART11384126140946599.shtml>). These phenomena show that the majority of families own more than one car, and the rich have a weak awareness of energy conservation and emission reduction. This behavior undoubtedly violates the government's advocacy of restricted travel and slows down the country's efforts to combat $PM_{2.5}$.

It can be found that the average $PM_{2.5}$ concentration of Guangdong, Guangxi, and Hainan in South China is lower than that in the economically developed areas, but the Gini coefficient is higher. The $PM_{2.5}$ concentrations in Beijing and Shanghai are high but the Gini coefficient is very low. This is an abnormal phenomenon found in the study of the relationship between the $PM_{2.5}$ concentration and the Gini coefficient. One reason for the former is that some wealthy retirees buy houses for retirement in southern China with a good environment [31]. This phenomenon of southward migration is particularly common among the older people in big cities. According to a survey report by the Hainan Provincial People's Political Consultative Conference, from October 2017 to April 2018, 932,900 people aged 60 or above spent the winter in Hainan. The migration of rich people directly increases the gap between the rich and the poor.

TABLE 6: Fitting results of the $PM_{2.5}$ concentrations in southwest and central China.

Year	Chongqing			Sichuan			Guizhou		
	Gini coefficient	$PM_{2.5}$	Result	Gini coefficient	$PM_{2.5}$	Result	Gini coefficient	$PM_{2.5}$	Result
2006	0.447	72.3	72.3	0.403	70.1	70.1	0.488	37.3	37.3
2007	0.427	61.8	70.0	0.403	59.4	64.0	0.489	39.7	38.6
2008	0.419	67.4	66.6	0.395	59.0	63.4	0.478	36.1	38.5
2009	0.416	63.5	65.4	0.405	60.8	63.5	0.482	38.0	38.5
2010	0.429	72.2	66.6	0.394	76.1	63.3	0.464	39.4	38.4
2011	0.390	71.6	63.7	0.387	69.8	61.9	0.433	45.7	38.2
2012	0.377	68.6	58.2	0.351	66.4	58.7	0.419	48.6	38.1
2013	0.372	59.6	56.4	0.351	64.8	56.1	0.409	35.3	38.0
2014	0.331	53.1	52.1	0.359	54.3	56.6	0.427	36.0	38.0
2015	0.411	46.2	55.9	0.388	45.0	59.4	0.454	32.6	38.2
2016	0.349	45.2	57.6	0.373	44.3	60.4	0.453	30.9	38.3
MAPE	9.74%			13.20%			9.58%		
2017	0.342		51.0	0.370		59.1	0.449		38.3
2018	0.336		49.9	0.368		58.7	0.446		38.2
2019	0.329		48.7	0.366		58.3	0.443		38.2

Year	Tibet			Henan			Hubei		
	Gini coefficient	$PM_{2.5}$	Result	Gini coefficient	$PM_{2.5}$	Result	Gini coefficient	$PM_{2.5}$	Result
2006	0.394	6.7	6.7	0.394	82.8	82.8	0.389	60.5	60.5
2007	0.358	7.3	7.1	0.392	81.4	78.9	0.386	65.6	68.7
2008	0.349	8.2	7.1	0.397	72.0	78.9	0.386	63.3	68.5
2009	0.360	6.8	7.1	0.407	75.1	79.0	0.388	68.7	68.6
2010	0.413	6.5	7.1	0.392	84.0	79.0	0.370	74.2	67.8
2011	0.363	6.3	7.1	0.362	90.6	78.7	0.347	76.4	65.6
2012	0.307	8.0	7.1	0.338	77.1	78.5	0.333	61.4	63.8
2013	0.303	6.1	7.2	0.336	89.5	78.4	0.327	69.3	62.8
2014	0.323	7.7	7.2	0.328	77.2	78.3	0.323	64.5	62.3
2015	0.410	6.7	7.1	0.357	73.7	78.4	0.342	57.8	63.0
2016	0.406	7.6	7.1	0.363	65.7	78.6	0.345	50.5	64.1
MAPE	8.23%			7.15%			8.03%		
2017	0.410		7.1	0.360		78.6	0.341		64.1
2018	0.414		7.1	0.357		78.6	0.337		63.7
2019	0.419		7.1	0.355		78.6	0.333		63.3

TABLE 7: Fitting results of the $PM_{2.5}$ concentrations in South China.

Year	Guangdong			Guangxi			Hainan		
	Gini coefficient	$PM_{2.5}$	Result	Gini coefficient	$PM_{2.5}$	Result	Gini coefficient	$PM_{2.5}$	Result
2006	0.410	41.9	41.9	0.435	45.8	45.8	0.375	21.1	21.1
2007	0.408	43.1	38.4	0.451	45.1	44.3	0.383	24.7	19.3
2008	0.407	43.0	38.1	0.449	45.3	45.2	0.378	23.9	19.1
2009	0.405	41.9	37.8	0.454	39.1	45.4	0.380	17.9	19.1
2010	0.438	38.3	41.1	0.430	42.5	44.2	0.383	16.0	19.3
2011	0.426	43.3	43.3	0.433	49.0	42.9	0.424	24.5	21.8
2012	0.409	36.9	40.2	0.399	47.0	41.1	0.367	15.8	18.8
2013	0.437	36.0	41.4	0.403	40.5	39.4	0.372	20.7	18.6
2014	0.368	35.6	37.3	0.393	40.3	39.1	0.356	16.6	17.7
2015	0.375	30.7	31.5	0.382	35.4	38.0	0.367	15.9	18.2
2016	0.372	28.6	31.9	0.405	32.2	38.6	0.365	15.9	18.2
MAPE	7.48%			7.25%			13.20%		
2017	0.369		31.4	0.403		39.8	0.364		18.1
2018	0.366		30.9	0.400		39.5	0.364		18.1
2019	0.363		30.4	0.398		39.2	0.363		18.1

However, due to the underdevelopment of the industry and the low vehicle ownership, the $PM_{2.5}$ concentration in South China is not very high. The main reason for the latter is the

influx of middle-income people into big cities. It alleviates the gap between the rich and the poor. On the surface, this phenomenon has narrowed the gap between the rich and the

FIGURE 8: The Gini coefficient and the PM_{2.5} concentration of Jiangsu.

FIGURE 10: The Gini coefficient and the PM_{2.5} concentration of Gansu.

FIGURE 9: The Gini coefficient and the PM_{2.5} concentration of Hebei.

poor. In fact, it leads to the loss of the middle-income people in other regions and increases the Gini coefficient.

4.2.2. The Impact of the Behavior of the Poor. Most rural areas in China can only use cheap coal for heating due to the dispersed living, economic backwardness, and imperfect rural construction, which increases the emission of PM_{2.5}. As we know, the coal-fired heating is an important cause of air pollution. It not only emits a large amount of particulate matter and carbon oxides but also produces the harmful gases of sulfide and nitrogen compounds, which seriously affect human health. Without solving the widespread problem of the coal-fired heating in rural areas, air pollution will be difficult to be completely solved.

In some remote and poor areas, residents have a low average education level and lack the skills to earn a living.

In order to improve their living conditions and live a prosperous life, the residents open up chemical plants such as oil refining and metallurgy at the cost of environmental pollution. Such small chemical plants have high profits, but the pollution to the environment is huge. Illegal construction of factories and excessive pollution in many regions of China have been blamed on the weak regulators. This unfair means of profit-making not only exacerbates the gap between the rich and the poor but also greatly pollutes the atmosphere. It runs counter to the government's strategy of sustainable development.

The reasons analyzed in this section represent the general explanation for the phenomenon that the large gap between the rich and the poor leads to the rise of PM_{2.5} concentration. It conforms to the prediction rule of this paper and once again verifies the applicability of the CFNGM (1, 1) model in this research field.

4.3. Suggestion. In view of the above analysis and the discussion in Section 4, the following suggestions are put forward:

- (1) Limit the number of vehicles owned by individuals, improve the public transportation laws and regulations, and truly achieve fair travel with restrictions on vehicles and people. This suggestion is not just for environmental protection. Considering the social cost of the various air pollutants, equity is more important than climate uncertainty [32]. Relevant restrictive policies should be implemented for the large-displacement vehicles. For example, taxes on the large-displacement cars should be raised to encourage the production and use of small cars. New policies on energy conservation and environmental protection should be introduced to limit the use of high-emission vehicles.

FIGURE 11: The Gini coefficient and the PM_{2.5} concentration of Chongqing.

- (2) Local governments should adhere to the implementation of talent introduction plans to retain their talents. The middle-income group should always take up a relatively large proportion. More funds should be allocated to remote areas to attract talents and maintain a reasonable proportion of people at all levels of income.
- (3) Improve the rural natural gas collective heating project and the government subsidy policies so that the rural people can also use the clean and cheap heating energy for heating.
- (4) Stricter rules on building factories are more effective than tougher environmental penalties. Like some scholars have suggested on the high carbon emission of the Bitcoin mining, moving away from the current punitive carbon tax policy to a site regulation policy of the Bitcoin mining is more effective in limiting the carbon emission of Bitcoin blockchain operation [33].

5. Conclusion

Based on the data from 2006 to 2016, the CFNGM (1, 1) model is used to predict the PM_{2.5} concentrations in 26 regions in China. The results show that the PM_{2.5} concentration fluctuates in North China and Northwest China. The main reason is that the inherent dust weather and the traditional polluting industries in these two regions, which contradict the government's increasingly strict environmental protection policies. Eventually, the PM_{2.5} concentration fluctuates greatly, but there is no downward trend. The PM_{2.5} concentrations in East, Southwest, Central, and South China show a slow trend of decline, especially after 2014. It reflects the effective implementation of environmental protection policies in the 12th Five-Year Plan.

The economically developed regions have lower Gini coefficient. Northwest China represented by Gansu and Qinghai and the mountainous provinces such as Guangxi

and Guizhou has the highest Gini coefficient. This reflects the rapid development of large cities in the remote mountainous provinces, while the development of rural areas is hindered due to the inconvenience of transportation. As a result, the urban-rural dual economic structure is becoming more and more serious, which eventually leads to the widening gap between the rich and the poor. The Gini coefficients of Beijing and Shanghai are the lowest among the 26 regions. These cities have a large number of middle-income classes. This shows that accelerating urban-rural integration and developing high-tech industries are effective ways to eliminate the gap between the rich and the poor.

The predictive error of the PM_{2.5} concentration prediction based on the CFNGM (1, 1) model is concentrated at about 5%. However, considering that the PM_{2.5} concentration and the Gini coefficient belong to two different research fields, the results have shown a correlation between the two research variables. Further research in these different fields is of great significance.

In view of the increasingly serious air pollution, the following suggestions are put forward: firstly, the government will tighten pollution control, encourage the development of environment-friendly factories, and increase investment in clean energy heating projects in rural areas. Secondly, the research of high technology for environmental purification should be vigorously developed. This will reduce existing pollution while controlling pollutant emissions. Thirdly, stricter vehicle emission control measures should be implemented. The government will encourage the popularity of new energy vehicles and formulate restrictions on high-emission vehicles. Lastly but most importantly, residents' awareness of environmental protection needs to be improved consciously. Do not use disposable plastic products, and do not burn domestic waste and crop straws. It will truly achieve environmental protection with the participation of everyone.

In the future, we will use the updated data to predict the PM_{2.5} concentration, while considering the impact of other economic factors on the PM_{2.5} concentration to make the prediction results more accurate. The initial value of the CFNGM (1, 1) model needs to be optimized. The weighted average of each component of the accumulated sequence is planned to be used as the initial value of optimization. The specific weight calculation method is still under study. It can be seen from the prediction results that the CFNGM (1, 1) model has a smaller predictive error in the prediction of the PM_{2.5} concentration in East China. Therefore, we consider applying this model to the prediction of other air pollutants in East China.

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.

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