The impact of income gap on the CO2 emission and grey trend prediction

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Research Article

Keywords: Income gap, CO2 emission, Non-equidistant grey model, Regional comparison

Posted Date: July 7th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1743779/v1

Abstract

The CO_2 emissions of urban and rural are different. The research on the life and production of urban and rural residents can help to adjust the carbon emission policy more accurately. The income gap between urban and rural residents is an important embodiment of the differences in the life and production of urban and rural. Taking the income gap between urban and rural residents as an input variable, the non-equidistant grey model with conformable fractional accumulation (CFNGM(1,1)) is used to predict the CO_2 emissions of six provinces in China. The CFNGM(1,1) model is a novel grey prediction model, which satisfies that the input sequence is non-equidistant sequence. The predicted results show that there is a large income gap in East China, and the CO_2 emissions are increasing. The income gap in Northwest China is relatively smaller, and the CO_2 emissions are gradually reduced. It is concluded that there is a positive correlation between the income gap and the CO_2 emission. Based on the cases analysis, it is verified that the life and production of urban and rural have different effects on CO_2 emission. Finally, based on the research results, the suggestions for sustainable development of environment and economy are put forward.

1 Introduction

1.1 Background

With the rapid development of economy, it is bound to be accompanied by energy consumption. Excessive energy consumption has caused damage to the atmospheric environment (Alvarez-Herranz et al. 2017). Over the past 20 years, China has accomplished two important tasks in the air pollution control. One is the peak sulfur dioxide emission from 2001 to 2010 (Zhong et al. 2021). The other is the comprehensive control of haze weather from 2011 to 2020, which is called “the battle of the blue sky” (Jiang et al. 2021). The above two tasks have been basically completed, but the pace of atmospheric governance cannot be slowed down. In 2021, the great blueprint of the carbon peak and the carbon neutrality are formally put forward at the National People's Congress of the People's Republic of China and the Chinese People's Political Consultative Conference (Fang et al. 2019). This also sets a new target for atmospheric governance of 2021 to 2030: “Carbon Peak”. Carbon emission is greenhouse gas emission, including CO_2, CH_4, N_2O and so on. Before the industrial era, carbon emissions mainly came from incineration and natural emissions. After the industrial era, carbon emissions increased exponentially. Carbon emission will cause the temperature rise of the surface and atmosphere (S.Shaikh et al. 2018). Then, the rise of temperature will cause a series of environmental hazards (Zheng et al. 2021). Under the global sustainable development strategy, carbon emission has become an important obstacle to the world's economic development (Fan and Lei 2016). Moreover, excessive carbon emissions have a lot to do with unbalanced economic development (Ali Bekhet et al. 2017). Research shows that more than 58% of carbon emissions come from 40% of high-income people (Liu et al. 2019). Due to the imbalance of the regional economic development in China, there is a significant income gap between urban and rural residents (Huang et al. 2020). The income gap between the east and the west is also getting more attention (Liu et al. 2021). In view of these imbalances caused by economic development, exploring the relationship between income gap and CO_2

emission is of great significance to alleviate the wealth gap and reduce the CO_2 emissions at the same time.

1.2 Related work

In the 21st century, the sustainable development of environment has become an international hot topic. Moreover, the discussion of environmental protection must include the influence of economic factors. In recent years, Chinese scholars have made many valuable achievements in the interdisciplinary of environment and economy. The first is air pollution. Wang et al. (2017) studied the emission source and proportion of SO_2, NO_x, shoot and dust in China. The results showed that Hebei and Shanxi were the main emission provinces of air pollutants. Coal energy and heavy industry were the main reasons of air pollution. The second is water pollution. Shi et al. (2021) studied the relationship between economic production development and sewage treatment capacity in 30 provinces of China. The results showed that the efficiency of sewage treatment needed to be improved. The third is soil pollution. Wu et al. (2021) studied the distribution and source of the industrial heavy metals in soil. The results showed that the content of heavy metals in industrial land was much higher than that in agricultural land.

Compared with above environmental pollution, carbon emission is even more frightening. Fortunately, human beings have not neglected the dangers of carbon emission. The coordinated development of carbon emission and economy has been an important study all over the world. Among them, the relationship between fossil energy consumption and carbon emission is the most concerned. The research on carbon emission of coal, oil and natural gas is helpful to put forward the policy of energy structure optimization (Wang and Yan 2022). In addition, the research on the relationship between the three major industries and carbon emission can accurately locate the source of carbon emission. It plays a guiding role in the adjustment of industrial structure (Zheng et al. 2020). The development of urbanization is also an important reason for carbon emission. Reasonable planning of urban energy supply is an important means to reduce carbon emissions (Lai et al. 2022). There are many studies on carbon emission and economic factors. However, these studies are aimed at the behavior of the government, enterprises and the market. Environmental protection is the responsibility for all mankind. So, it is also an important task for the government and researchers to raise people's awareness of carbon reduction. Based on the predicted results of grey prediction model, this paper explores the relationship between the income gap and the CO_2 emission in East China and Northwest China. The people's livelihood indicators are introduced into the study of carbon emission. This combination can not only improve the awareness of carbon reduction, but also strengthen people's awareness of supervision over the government and enterprises. There is no doubt that the participation of all people in carbon emission management will contribute to the rapid realization of the carbon peak.

To manage carbon emission reasonably, scientific data prediction is essential. Scientists have studied carbon dioxide since the 18th century. Since the beginning of the 21st century, the excessive emission of carbon dioxide has attracted the attention all over the world (Mostafaeipour et al. 2022). In order to explore the development trend of CO_2 emissions, a series of forecasting methods such as the Linear Regression Model (Zhao et al. 2018), the Neural Network Prediction Model (Lagesse et al. 2020), the Markov Chain

Prediction Model (Zhou et al. 2011) and the Grey Prediction Model (GM(1,1)) are proposed. Among them, the GM(1,1) has been widely used in energy consumption (Xu et al. 2015), (Wu et al. 2018) and air quality (Wu and Zhao 2018), (Chen and Yi 2015), (Comert et al. 2020). These researches have made outstanding contributions to the environmental science. With the continuous research, the GM(1,1) has been improved on many aspects, and it has been applied to a wide range of fields.

The improvements of the GM(1,1) are mainly reflected on the following two aspects. The first is the improvement of the accumulation mode. The original data is preprocessed by the accumulation operator to make it meet the data requirements of the GM(1,1). The accumulation operator is an important symbol that distinguishes the GM(1,1) from other models. The accumulation mode of the traditional GM(1,1) is 1-order accumulation. This accumulation mode leads to higher requirements and lower applicability for data. Wu et al. (2013) put forward the fractional order accumulation operator, which makes the accumulation order more flexible and improves the smoothness of the original sequence. Liu et al. (2021) proposed the reverse accumulation operator, which is suitable for decreasing sequences. The damping trend factor was introduced as a new parameter of grey generating operator to adjust the trend of the predicted results (Liu and Chen 2021). Tu and Chen (2021) proposed unequal accumulation, the loss of difference information can be effectively reduced. On the other hand, the second improvement is the expansion of the formula of the GM(1,1). Because the GM(1,1) has better compatibility, the improved model can be applied to many different researches. Xie and Liu (2009) proposed a discrete grey model which contributes significantly to the improvement of the GM(1,1). Taking the minimum absolute error as the objective function, Lee and Tong (2010) used the genetic algorithm to optimize the model parameters. Li et al. (2007) used the GM(1,1) Markov chain combination model to predict the number of Air China airlines. According to the modeling method of the GMC(1,1) model, a recursive discrete multivariate grey prediction model was proposed (Ma and Liu 2016). Wang et al. (2018) proposed the seasonal grey prediction model to buffer the influence of seasonal variation on the predicted results. In view of the influence of seasonal variation on prediction, Liu and Wu (2020) also introduced the grey generation operator into the Holt-winters seasonal data model.

The purpose of grey model innovation is to better solve practical problems. In the study of environmental pollution prediction, different grey models have been widely used. Wang and Lin (2019) used non-equilibrium grey verhulst model to study the relationship between CO_2 emission and economic growth. Li et al. (2020) studied the non-equilibrium grey Bernoulli model to analyze the relationship between economic growth and pollutants. At the same time, Zhou et al. (2020) also used the Bernoulli seasonal grey model to predict the air quality index of the Yangtze River Delta. The fractional hausdorff grey multivariable model is used to analyze the relationship between population density and air quality (Shi and Wu 2021). Xiong et al. (2020) applied the multivariable grey model to predict the measurable indexes of haze weather in Nanjing. Although the grey models mentioned above have their own advantages, there are also disadvantages. The input variable of some models cannot be non-equidistant sequence, and some models have limitations in the accumulation mode. The CFNGM(1,1) model solves these problems. In this paper, as a non-equidistant input variable, the income gap is used to predict CO_2 emissions. This method can not only predict data accurately, but also show the development relationship between the two variables. Meanwhile, in order to eliminate the influence of regional characteristic on the research conclusions, the predicted results in East

China and Northwest China are compared. Comparative study makes the research results more scientific for the actual situation of China.

This paper is divided into five parts. The second part introduces the research areas, data sources and the CFNGM(1,1) model. The third part verifies the validity and applicability of the model. In the fourth part, the predicted results are analyzed. The fifth part gives the conclusion of the study.

2 Research Preparation

2.1 Research area overview

This paper studies the impact of the income gap on the CO_2 emissions in six provinces (Jiangsu, Zhejiang, Fujian, Shaanxi, Gansu and Qinghai). The specific locations of these provinces are shown in Fig. 1. Jiangsu, Zhejiang and Fujian represent the economically developed eastern coastal areas. Shaanxi, Gansu and Qinghai represent the undeveloped northwest inland areas. Three provinces are selected in two regions respectively. The results are representative and credible. At the same time, through comparing the eastern coast with the northwest inland, the internal relationship between CO_2 emissions and the income gap can be summarized more comprehensively.

2.2 Data source

The income data of urban and rural residents come from the National Bureau of Statistics (https://www.data.stats.gov.cn/). After processing, the income gaps between urban and rural residents in six provinces are obtained. The detailed data are shown in Table 1 and Table 2. The CO_2 emissions of each province come from CEADs (https://www.ceads.net.cn/). Due to the late detection of CO_2 emissions in China, the data from 2013 to 2018 are used for the study.

Table 1
The income of urban and rural residents in six provinces (Ten Thousand Yuan)

Year	Jiangsu		Zhejiang		Fujian	
	Urban	Rural	Urban	Rural	Urban	Rural
2013	3.1585	1.3521	3.708	1.7494	2.8174	1.1405
2014	3.4346	1.4958	4.0393	1.9373	3.0722	1.265
2015	3.7173	1.6257	4.3714	2.1125	3.3275	1.3793
2016	4.0152	1.7606	4.7237	2.2866	3.6014	1.4999
2017	4.3622	1.9158	5.1261	2.4956	3.9001	1.6335
2018	4.72	2.0845	5.5574	2.7302	4.2121	1.7821
2019	5.1056	2.2675	6.0182	2.9876	4.562	1.9568
Year	Shaanxi		Gansu		Qinghai	
	Urban	Rural	Urban	Rural	Urban	Rural
2013	2.2346	0.7092	1.9873	0.5589	2.0352	0.6462
2014	2.4366	0.7932	2.1804	0.6277	2.2307	0.7283
2015	2.642	0.8689	2.3767	0.6936	2.4542	0.7933
2016	2.844	0.9396	2.5693	0.7457	2.6757	0.8664
2017	3.081	1.0265	2.7763	0.8076	2.9169	0.9462
2018	3.3319	1.1213	2.9957	0.8804	3.1515	1.0393
2019	3.6098	1.2326	3.2323	0.9629	3.383	1.1499

Table 2
The income gap between urban and rural residents (Ten Thousand Yuan)

Year	Jiangsu	Zhejiang	Fujian	Shaanxi	Gansu	Qinghai
2013	1.81	1.96	1.68	1.53	1.43	1.39
2014	1.94	2.1	1.81	1.64	1.55	1.5
2015	2.09	2.26	1.95	1.77	1.68	1.66
2016	2.25	2.44	2.1	1.9	1.82	1.81
2017	2.45	2.63	2.27	2.05	1.97	1.97
2018	2.64	2.83	2.43	2.21	2.12	2.11
2019	2.84	3.03	2.61	2.38	2.27	2.23

2.3 Model introduction

The procedures of the CFNGM(1,1) model are as follows (Xu et al. 2020).

There is an initial sequence $Y^{(0)}(x_i) = \left(y^{(0)}(x_1), y^{(0)}(x_2), \cdots, y^{(0)}(x_n)\right)$. If the gap of x_i is $\Delta x_i = x_i - x_{i-1} \neq c, i = 2, 3, \cdots, n,$ is a constant, then $Y^{(0)}(x_i)$ is called the non-equidistant sequence. $Y^{(r)}(x_i)$ is the -order accumulative sequence of $Y^{(0)}(x_i)$, is obtained by the Particle Swarm Optimization algorithm (PSO). Where

$$y^{(r)}(x_i) = \begin{cases} y^{(0)}(x_1) & i = 1. \\ y^{(0)}(x_1) + \sum_{j=2}^{i} \frac{y^{(0)}(x_j) \times \Delta x_j}{x_j^{1-r}} & i = 2, 3, \cdots, n. \end{cases} \qquad r \in (0, 1].$$

(1)

The contiguous even generating sequence of $Y^{(r)}(x_i)$ is

$$z^{(r)}(x_i) = \frac{1}{2}\left(y^{(r)}(x_i) + y^{(r)}(x_{i-1})\right).$$

(2)

The original form of the grey prediction model is a difference equation $y^{(0)}(x_i) + ay^{(0)}(x_i) = b.$ is the development coefficient and is the grey action. $y^{(0)}(x_i) + az^{(r)}(x_i) = b$ is called the even form of the CFNGM(1,1) model.

The whitening differential equation of the CFNGM(1,1) model is

$$\frac{dy^{(r)}}{dx} + ay^{(r)} = b.$$

(3)

The least square estimation of the $y^{(0)}(x_i) + az^{(r)}(x_i) = b$ satisfies

$$\begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y, \ where \ B = \begin{bmatrix} -z^{(r)}(x_2) & 1 \\ -z^{(r)}(x_2) & 1 \\ \vdots & \vdots \\ -z^{(r)}(x_2) & 1 \end{bmatrix}, \quad Y = \begin{bmatrix} \dfrac{y^{(r)}(x_2) - y^{(r)}(x_1)}{x_2 - x_1} \\ \dfrac{y^{(r)}(x_3) - y^{(r)}(x_2)}{x_3 - x_2} \\ \vdots \\ \dfrac{y^{(r)}(x_n) - y^{(r)}(x_{n-1})}{x_n - x_{n-1}} \end{bmatrix}.$$

(4)

Substituting $\hat{a}$, $\hat{b}$ into Eq. (3), the time response sequence of $\hat{Y}^{(r)}(x_i)$ can be obtained as

$$\hat{y}^{(r)}(x_i) = \begin{cases} y^{(0)}(x_1) & i = 1, \\ (y^{(0)}(x_1) - \dfrac{\hat{b}}{\hat{a}}) e^{-\hat{a}(x_i - x_1)} + \dfrac{\hat{b}}{\hat{a}} & i = 2, 3 \cdots n. \end{cases}$$

(5)

After reverse reducing on $\hat{Y}^{(r)}(x_i)$, the predicted sequence of $\hat{Y}^{(0)}(x_i)$ can be obtained as

$$\hat{y}^{(0)}(x_i) = \begin{cases} y^{(0)}(x_1) & i = 1. \\ \dfrac{x_i^{1-r}(\hat{y}^{(r)}(x_i) - \hat{y}^{(r)}(x_{i-1}))}{\Delta x_i} & i = 2, 3, \cdots, n. \end{cases}$$

(6)

We use the $\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n} \frac{\left| y^{(0)}(x_i) - \hat{y}^{(0)}(x_i) \right|}{y^{(0)}(x_i)}$ to measure the accuracy of the CFNGM(1,1) model. The smaller the MAPE value is, the better the model fitting accuracy is. Generally, MAPE less than 10% is considered as a valid prediction.

3 Verification Of The Model

3.1 Validity test of the CFNGM(1,1) model

The validity of the CFNGM(1,1) model is verified by the following two cases.

Case 1

According to the data in Reference (Xiong et al. 2015), the fitted results of the traditional non-equidistant model, the non-equidistant grey model (NGM(1,1,k)) and the CFNGM(1,1) model are compared. The main difference between the CFNGM(1,1) model and the other two models is the accumulation mode. The accumulation mode of the traditional non-equidistant model and the NGM(1,1,k) model is ordinary 1-order accumulation. However, the accumulation mode of the CFNGM(1,1) model is conformable fractional accumulation. This accumulation mode improves the fitting accuracy.

In this case, the optimal order of the CFNGM(1,1) model is 0.955. The final fitted results are shown in Table 3. The average fitting accuracies of the traditional non-equidistant model, the NGM(1,1,k) model and the CFNGM(1,1) model are 1.78%, 0.94% and 0.74% respectively. The average predictive errors are 7.19%, 1.18% and 0.94% respectively. Thus it can be seen that the accuracy of the CFNGM(1,1) model is higher than that of the NGM(1,1,k) model and the traditional non-equidistant model.

Table 3
Fitted results of three models in **case 1**

k_i	$x^{(0)}(k_i)$	**The traditional non-equidistant model**	**The NGM(1,1,k) (Zhang et al. 2019)**	**The CFNGM(1,1)**
1	9.28	9.28	9.28	9.28
25	10.71	10.95	10.86	10.71
53	11.31	11.25	11.21	11.25
83	11.64	11.59	11.58	11.67
116	12.00	11.98	11.98	12.06
147	12.23	12.38	12.37	12.42
177	13.05	12.78	12.75	12.74
237	13.16	13.39	13.28	13.25
MAPE	**-**	**1.78%**	**0.94%**	**0.74%**
269	13.61	14.05	13.82	13.69
355	13.94	14.94	14.48	14.34
MAPE	**-**	**7.19%**	**1.18%**	**0.94%**

Case 2: According to the model and data in Reference (Zeng 2018), the fitted and predicted values of the non-equidistant GOM(1,1), the non-equidistant $GOM^r(1,1)$ and the CFNGM(1,1) model are compared. This case is a classic application of reverse accumulation.

Through the calculation, we can get the results in Table 4. Among them, the average fitting accuracies of the non-equidistant GOM(1,1), the non-equidistant GOM^r(1,1) and the CFNGM(1,1) model are 0.67%, 0.65% and 0.30% respectively. The average predictive accuracies are 0.76%, 0.71% and 0.32% respectively. Thus it can be seen that whether fitting or predicting, the CFNGM(1,1) model is superior to the other two reverse cumulative grey prediction models. This shows that the accumulation mode of the CFNGM(1,1) model can predict the non-negative decreasing sequence more accurately.

Table 4
Fitted results of three models in **case 2**

k_i	$x^{(0)}(k_i)$	**The non-equidistant GOM(1,1)**	**The non-equidistant GOM^r(1,1)**	**The CFNGM(1,1)**
100	560	568.46	568.61	560
130	557.54	551.14	550.77	556.81
170	536.1	531.97	531.69	538.17
210	516.1	515.73	516.10	517.62
240	505.6	502.22	502.72	500.26
270	486.1	486.91	486.85	485.86
310	467.4	472.05	471.72	469.60
340	453.8	453.80	453.80	453.85
MAPE	**-**	**0.67%**	**0.65%**	**0.30%**
380	436.4	442.86	441.46	438.66
MAPE	**-**	**0.76%**	**0.71%**	**0.32%**

3.2 Applicability test of the CFNGM(1,1) model

The income gaps between urban and rural residents in Jiangsu, Zhejiang, Fujian, Shaanxi, Gansu and Qinghai provinces from 2013 to 2018 are treated as the input variables of the model. The CO_2 emissions from 2013 to 2017 are fitted, and the known CO_2 emission of 2018 is predicted. The calculated results and MAPE values are shown in Table 5.

As can be seen from the Table 5, the MAPE values of fitted CO_2 emissions in the six provinces are 1.61%, 0.53%, 2.73%, 0.52%, 0.57% and 2.04% respectively. The fitted errors are less than 10%. The MAPE values of predicted CO_2 emissions in 2018 are 2.03%, 0.78%, 5.27%, 1.97%, 2.32% and 2.92% respectively. The predicted errors are less than 10%. Therefore, it can be explained that the CFNGM(1,1) model is suitable for the study in this study.

Table 5
Fitted results of the CO_2 emission in six provinces

Year	**Jiangsu**			**Zhejiang**			**Fujian**		
	Income gap	**CO_2**	**Result**	**Income gap**	**CO_2**	**Result**	**Income gap**	**CO_2**	**Result**
2013	1.81	694.30	694.30	1.96	379.00	379.00	1.68	229.40	229.40
2014	1.94	704.50	719.63	2.1	375.30	373.61	1.81	243.40	237.47
2015	2.09	759.50	729.64	2.26	375.40	375.19	1.95	230.40	232.15
2016	2.25	724.00	734.45	2.44	372.00	376.97	2.1	213.00	226.56
2017	2.45	736.00	739.77	2.63	382.00	378.93	2.27	230.00	220.55
MAPE	**-**	**-**	**1.61%**	**-**	**-**	**0.53%**	**-**	**-**	**2.73%**
2018	2.64	764.00	732.49	2.83	388.80	381.00	2.43	261.50	214.52
MAPE	**-**	**-**	**2.03%**	**-**	**-**	**0.78%**	**-**	**-**	**5.27%**
Year	Shaanxi			Gansu			Ningxia		
	Income gap	CO_2	Result	Income gap	CO_2	Result	Income gap	CO_2	Result
2013	1.53	265.60	265.60	1.43	159.60	159.6	1.39	47.90	47.90
2014	1.64	277.20	277.68	1.55	162.73	162.8	1.5	48.50	48.91
2015	1.77	276.90	274.41	1.68	158.54	158.5	1.66	51.10	51.60
2016	1.9	265.00	267.71	1.82	154.14	154.1	1.81	56.00	53.24
2017	2.05	262.00	260.62	1.97	149.55	149.6	1.97	53.00	54.85
MAPE	**-**	**-**	**0.52%**	**-**	**-**	**0.57%**	**-**	**-**	**2.04%**
2018	2.21	276.20	250.72	2.12	163.0	144.94	2.11	51.90	55.70
MAPE	**-**	**-**	**1.97%**	**-**	**-**	**2.32%**	**-**	**-**	**2.92%**

4 Analyzing The Impact Of Income Gap On The Co Emission

In the field of environmental science, carbon emissions have been paid more and more attention in international exchanges. China's carbon emission in 2018 is 9507 million tons. It is the largest carbon emitter in the world (https://www.bp.com/). China is committed to achieving carbon peak by 2030. If we

want to achieve the goal of carbon peak, it is necessary to predict the future data and make an in-depth analysis of the sources and impacts of CO_2 emissions. Excessive carbon emissions have a lot to do with the imbalance of economic development. Through the analysis of the calculation process and predicted results, the relationship between the income gap and CO_2 emissions is explored. Finally, reasonable suggestions are put forward.

4.1 Calculation process and result

Through the sequences of income gap between urban and rural residents, the CO_2 emissions of six provinces from 2019 to 2023 are predicted. And the results are explained and analyzed. Taking Jiangsu as an example, the calculation process of the CFNGM(1,1) model is introduced as follows.

The income data of urban and rural residents from 2013 to 2018 are obtained from the National Bureau of Statistics, and the sequence of the income gap between urban and rural residents is obtained after data processing. Because of the obvious stable growth trend of the income gap, the average annual growth rate from 2013 to 2018 is used as the growth rate from 2019 to 2023. Then the predicted values of the income gap in these five years are obtained. The cumulative sequence of CO_2 emission is calculated with the order optimized by PSO. Then the development coefficient and grey action of the whitening equation are calculated by the least square method. The predicted values of income gap from 2019 to 2023 are substituted into the time response equation. Finally, the predicted values of CO_2 emissions from 2019 to 2023 can be obtained through reverse reducing.

Table 6 shows the predicted CO_2 emissions from 2019 to 2023 in Jiangsu, Zhejiang, Fujian, Shaanxi, Gansu and Qinghai. The predictive errors of these six provinces are 1.72% 0.57% 4.68% 1.79% 2.43% 2.20% respectively. The predictive errors are all less than 10%, indicating that the model is suitable for the prediction of the CO_2 emissions. The predicted results are as follows.

Table 6
Predicted results of the CO_2 emission in six provinces (Million tons)

Year	**Jiangsu**			**Zhejiang**			**Fujian**		
	Income gap	**CO_2**	**Result**	**Income gap**	**CO_2**	**Result**	**Income gap**	**CO_2**	**Result**
2013	1.81	694.30	694.30	1.96	379.00	379.00	1.68	229.40	229.40
2014	1.94	704.50	719.77	2.10	375.30	372.06	1.81	243.40	227.65
2015	2.09	759.50	727.56	2.26	375.40	375.02	1.95	230.40	231.29
2016	2.25	724.00	736.28	2.44	372.00	378.35	2.10	213.00	235.30
2017	2.45	736.00	746.54	2.63	382.00	382.07	2.27	230.00	239.72
2018	2.64	764.00	757.81	2.83	388.80	386.02	2.43	261.50	244.36
MAPE			**1.72%**			**0.57%**			**4.68%**
2019	2.84		769.26	3.03		390.12	2.61		249.24
2020	3.06		781.78	3.26		394.59	2.81		254.75
2021	3.30		795.72	3.51		399.56	3.02		260.95
2022	3.56		811.16	3.77		404.98	3.25		267.80
2023	3.84		828.17	4.06		410.89	3.50		275.38
Year	Shaanxi			Gansu			Qinghai		
	Income gap	CO_2	Result	Income gap	CO_2	Result	Income gap	CO_2	Result
2013	1.53	265.60	265.60	1.43	159.60	159.60	1.39	47.90	47.90
2014	1.64	277.20	274.49	1.55	163.50	159.13	1.50	48.50	49.45
2015	1.77	276.90	273.06	1.68	158.50	158.4	1.66	51.10	51.53
2016	1.90	265.00	271.56	1.82	152.00	157.63	1.81	56.00	52.51
2017	2.05	262.00	269.95	1.97	151.00	156.82	1.97	53.00	53.47
2018	2.21	276.20	268.21	2.12	163.00	156.00	2.11	51.90	53.65
MAPE	**-**	**-**	**1.79%**	**-**	**-**	**2.43%**	**-**	**-**	**2.20%**
2019	2.38		266.39	2.27		155.15	2.23		53.57
2020	2.56		264.43	2.45		154.21	2.41		54.27
2021	2.76		262.32	2.65		153.16	2.61		54.05

Year	Jiangsu			Zhejiang			Fujian		
	Income gap	CO_2	Result	Income gap	CO_2	Result	Income gap	CO_2	Result
2022	2.97		260.07	2.86		152.04	2.82		53.45
2023	3.20		257.67	3.09		150.83	3.05		52.48

4.2 Result analysis

4.2.1 East China

The income gaps between urban and rural residents in Jiangsu, Zhejiang and Fujian are increasing year by year. Zhejiang has the largest income gap, with 2.64 ten thousand yuan in 2018. Fujian has the smallest income gap, with 2.43 ten thousand yuan in 2018. The income gaps of the three provinces show a relatively stable growth state, as shown in **Fig. 2**. There are two main reasons, one is that the high-tech industries in the coastal areas of East China are developed. The other is that the development of rural economy is relatively slow compared with that of urban. The predicted income gaps between urban and rural residents in Jiangsu, Zhejiang and Fujian in 2023 are 3.84, 4.06 and 3.50 ten thousand yuan respectively. The gap in the predicted results of the three provinces is small and the growth rate is stable. It reflects the good integrity of economic development in East China.

Among the three provinces, Fujian has the smallest income gap, while Fujian has the lowest CO_2 emission, with 261.5 million tons in 2018. The income gap in Jiangsu is lower than that in Zhejiang. But the CO_2 emissions in Jiangsu are the highest, about twice of that in Zhejiang and four times of that in Fujian. The main reason is continuous growth of the industrial and construction industry in Jiangsu. From 2013 to 2018, Jiangsu ranked second among provinces in the country in terms of GDP, after Guangdong. The rapid development of industrial economy will inevitably lead to the decline of air quality. Judging from the development trend, the CO_2 emissions from three provinces reached a peak in 2015 and a nadir in 2016, as shown in **Fig. 3**. The implementation of the 13th Five-Year Plan in 2016 has put forward the task for the overall improvement of the ecological environment. “The Global Climate Change and Green Low-carbon Development Research Project” is adopted. The convening of the G20 summit in Hangzhou has increased the control of carbon emissions and improved the air quality in the southeast coastal areas. Although the predicted CO_2 emissions in the three provinces are also rising, the trend is very gentle.

4.2.2 Northwest China

Table 2 and **Fig. 4** show that the income gaps of Shaanxi, Gansu and Qinghai are lower than that of East China. The data of the three provinces are relatively close. Among them, Shaanxi has the highest income gap, with 2.21 ten thousand yuan in 2018. Qinghai has the lowest income gap, with 2.11 ten thousand yuan

in 2018. Similar to East China, the predicted results are also increasing. The main reason is that “the China Western Development Strategy” has increased the income of residents in urban areas. However, due to the inconvenient transportation in remote areas, rural development lags behind seriously. The growth trend of income gap in Northwest China is relatively slow. The predicted values of income gap in Shaanxi, Gansu and Qinghai in 2023 are 3.20, 3.09 and 3.05 ten thousand yuan respectively.

As shown in **Fig. 5**, the trends of CO_2 emissions in Shaanxi and Gansu are relatively consistent, with a significant rebound in 2018 after reaching a nadir in 2016 and 2017. The CO_2 emissions in Northwest China mainly come from industry and construction industry. The industrial added value of Shaanxi in 2018 is 963.48 billion yuan, an increase of 9.0% over 2017. The added value of the construction industry is 255.254 billion yuan, an increase of 15.1% over 2017 (Shaanxi Province Statistical Bulletin: http://www.tjcn.org/). The industrial added value of Gansu in 2018 increased by 4.3% over 2017. The added value of the construction industry increased by 2.7% over 2017 (Gansu Province Statistical Bulletin: http://www.tjcn.org/). Qinghai's CO_2 emissions have the opposite trend. It rises to a peak in 2016 and reaches a nadir in 2018. After the implementation of “The 13th Five-Year Plan” in 2016, Qinghai adjusted the management policy of carbon emissions in the agricultural production and advocated the environmental-friendly agriculture. Although the development trends of CO_2 emissions in the three northwestern provinces are different, the predicted results show that the CO_2 emissions will decline from 2019 to 2023. Environmental protection measures in Northwest China plays an important role. Establishing natural ecological reserves, adjusting the industrial structure and encouraging the development of environment-friendly enterprises are of reference significance for China to achieve carbon peak by 2030.

4.2.3 Regional comparison

In order to make the data change of CO_2 emissions more intuitive, the income gaps and CO_2 emissions area graphs of each province are shown in Fig. 6. Among them, the display range of the income gap is fixed between 1.2 and 4.2 ten thousand yuan. The display range of CO_2 emissions is appropriately reduced to make the changing trend more significant.

Figure 6 shows that the income gaps between urban and rural residents in Jiangsu, Zhejiang and Fujian are slowly increasing. However, Table 1 shows that the income of rural residents in three provinces exceeds the per capita income of rural residents in the country (The per capita income of Chinese rural residents is 1.46 ten thousand yuan in 2018. Data comes from the National Bureau of Statistics (https://www.data.stats.gov.cn/)). This shows that the widening income gap between urban and rural does not necessarily lead to social poverty. The non-synchronous development of urban and rural areas is the only way for China to achieve common prosperity. The figures and tables show that the income gap between urban and rural residents in the Northwest China is not much different from that in the East China. However, unlike the East China, the income of residents in the Northwest China is lower. In 2018, the incomes of rural residents in Shaanxi, Gansu and Ningxia provinces were only about 10 ten thousand yuan, about half of that in East China. The income gap in Northwest China reflects the unfair phenomenon.

Figure 7 can show the trend of the CO_2 emissions in six provinces more intuitively. East China not only far exceeds the Northwest China in terms of emissions. Moreover, the predicted CO_2 emissions in East China increase exponentially. This is a disadvantageous factor for China to achieve the carbon peak. The predicted results of CO_2 emissions in Northwest China show a downward trend. It has a lot to do with the strict policy on carbon emissions control in the Northwest China. Although the economic growth rate is far lower than that of East China, it has contributed to the sustainable development of the economy.

Through the above analysis, it can be found that China's economic and social development are in a period of contradiction. Taking East China as an example, if we want to achieve rapid economic development, we must pay the price of declining environmental quality. At the same time, taking the Northwest China as an example, if we want to alleviate the pollution of the atmospheric environment, the speed of economic development must slow down. It can be seen that weighing the pros and cons between economic development and environmental protection is an important task to achieve carbon peak in 2030.

4.3 Discussion

The predicted results show that there is a significant relationship between the income gap and the CO_2 emission. When the income gap is large, the CO_2 emission shows an upward trend. When the income gap is small, the CO_2 emission shows a downward trend. In order to explain this phenomenon, some concrete examples are listed as follows:

(1) The chemical industry is an important source of the CO_2 emissions. In order to support the complex and diverse e-commerce in East China, a large number of enterprises like metal, rubber, plastic, paint, textile have been established. These enterprises release a lot of CO_2 and air pollutants. The total greenhouse gas emissions in 2030 of the Yangtze River Delta will be 1.76 times of that in 2005 (Zheng et al. 2016). The chemical industry will be an important obstacle to the realization of the carbon peak.

(2) Automobile exhaust emission is getting worse and worse. At the end of 2018, the numbers of civil cars in Jiangsu, Zhejiang and Fujian were 1783.2, 1534 and 623.9 million respectively. The numbers of civil cars in Gansu and Qinghai were 358.5 and 110.32 million respectively (Statistical Bulletin: http://www.tjcn.org/). The number of cars in East China far exceeds that in the Northwest China. The traffic in East China is developed, and the car penetration rate is very high even in rural areas. Moreover, some rich people have poor awareness of energy conservation and emission reduction. There are many phenomena of large displacement cars and owning multiple cars.

(3) Due to natural, historical, political reasons, the economic level and resident income in the Northwest China are not high. Its income gap is relatively smaller than that of the East China, but the income inequality is more serious. Some people illegally set up chemical enterprises at the expense of environment resources. These chemical enterprises have high profits but serious pollution. Moreover, the rich mineral resources in Northwest China provide it with convenient raw materials. Due to the weak supervision of the relevant departments and the poor awareness of environmental protection of residents, the governance of the atmospheric environment has become slow.

(4) The real estate industry has always been the pillar industry of China's GDP. Since 2013, China's real estate industry has developed rapidly, especially the demolition and transformation of suburban areas. It has largely driven the economic development of the construction industry. The added values of construction industry in Jiangsu, Zhejiang, Fujian, Shaanxi, Gansu and Qinghai provinces from 2013 to 2018 are 913.45, 1356.3, 1259.1, 1016.2, 383.2 and 175.9 billion yuan respectively (Statistical Bulletin: http://www.tjcn.org/). However, according to the experience of developed countries, the development of urbanization in China still has a long way to go (Cheriyan and Choi 2020).

4.4 Suggestion

Based on the analysis of the relationship between the income gap and the CO_2 emissions, the following suggestions are put forward:

(1) The government of East China needs to strengthen the management of chemical enterprises with high pollution and improve the system of rewards and punishments. Enterprises that have achieved the pollution discharge targets set by the government shall be rewarded. Penalties should be increased for those enterprises that have not achieved the targets. If the punishment is less than the benefit of excessive discharge, the offending enterprise will further erode the environmental resources.

(2) Public transport facilities should be further improved. Especially long-distance public transport, including trains, high-speed trains, long-distance buses and so on. Traffic restrictions and other relevant regulations should be enforced strictly. A purchase tax will be imposed on the high-displacement cars and non-first cars. Restrictions will be imposed on the number of vehicles owned by individuals. At the same time, new energy vehicles should be encouraged.

(3) The strategy of China Western Development needs to be continued. The western region of China has rich natural resources and huge market potential. The local government should fully deploy the resources so that high-quality resources can become the driving force for economic development. The abuse of resources should be avoided. The discharge of chemical plants should be examined strictly. Enterprises that do not meet the standards will be severely punished or even blocked.

(4) The real estate industry should be controlled. In order to improve GDP in some areas, some unreasonable real estate projects have been developed. Not only these behaviors have potential harm to the national economy, but also excessive engineering development will produce a lot of carbon emissions. In recent years, the demolition and renovation have stopped in some places. After a period of management, the carbon emissions of the construction industry will certainly be reduced.

5 Conclusion

Based on the income gap between urban and rural residents from 2013 to 2023, this paper uses the CFNGM(1,1) model to fit and predict CO_2 emissions in six provinces. The results show that CO_2 emissions in East China are increasing from 2019 to 2023. It is mainly related to the developed industries in East

China. The CO_2 emissions in Northwest China decreased significantly. It is mainly related to the strict control of carbon emission and underdeveloped industries in the northwest region.

The wealth gap in East China is widening. But the income of rural residents is higher than the national average. Therefore, the widening wealth gap will not cause dissatisfaction among rural residents. The wealth gap in Northwest China is also widening. Different from East China, the income of rural residents in Northwest China is lower than the national average. The phenomenon of unfairness is more obvious.

To sum up, the CO_2 emissions in East China need to be controlled, and the wealth gap in Northwest China needs to be alleviated. These two problems show the contradiction between China's economic development and environmental protection: The CO_2 emission shows an upward trend when the income gap is large. Conversely, the CO_2 emission shows a downward trend when the income gap is small. Finding the balance between economic development and environmental protection, strictly implementing pollution control policies and adjusting rural industrial structure are the primary ways to achieve the carbon peak and improve citizens' well-being.

In the future, we consider improving the grey model. The predicted results can be changed by adjusting the parameters. Then the time of carbon peak is predicted. If the predictive effect is good, we consider applying it to the prediction of other air pollutants and sewage.

Declarations

Data availability

The income data of urban and rural residents come from the National Bureau of Statistics (https://www.data.stats.gov.cn/).

The CO_2 emissions of provinces come from CEADs (https://www.ceads.net.cn/).

The CO_2 emissions of countries come from bp (https://www.bp.com/).

The industrial indexes come from China Statistical Information (http://www.tjcn.org/).

Authors Contributions

Kai Cai: data curation, methodology, resources, validation, visualization, writing original draft. **Xiaoying Pan**: formal analysis, project administration, investigation. **Lifeng Wu**: conceptualization, funding acquisition, supervision.

Acknowledgments

The relevant researches are supported by the National Natural Science Foundation of China (71871084,U20A20316), Young talent support scheme of Hebei Province (360-0803-YBN-7U2C), the key

research project in humanity and social science of Hebei Education Department (ZD202211) and the Natural Science Foundation of Hebei Province (E2020402074).

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest

Ethics approval and consent to participate Not applicable, research does not report on or involve the use of any animal or human data or tissue.

Consent for publication Not applicable.

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Figures

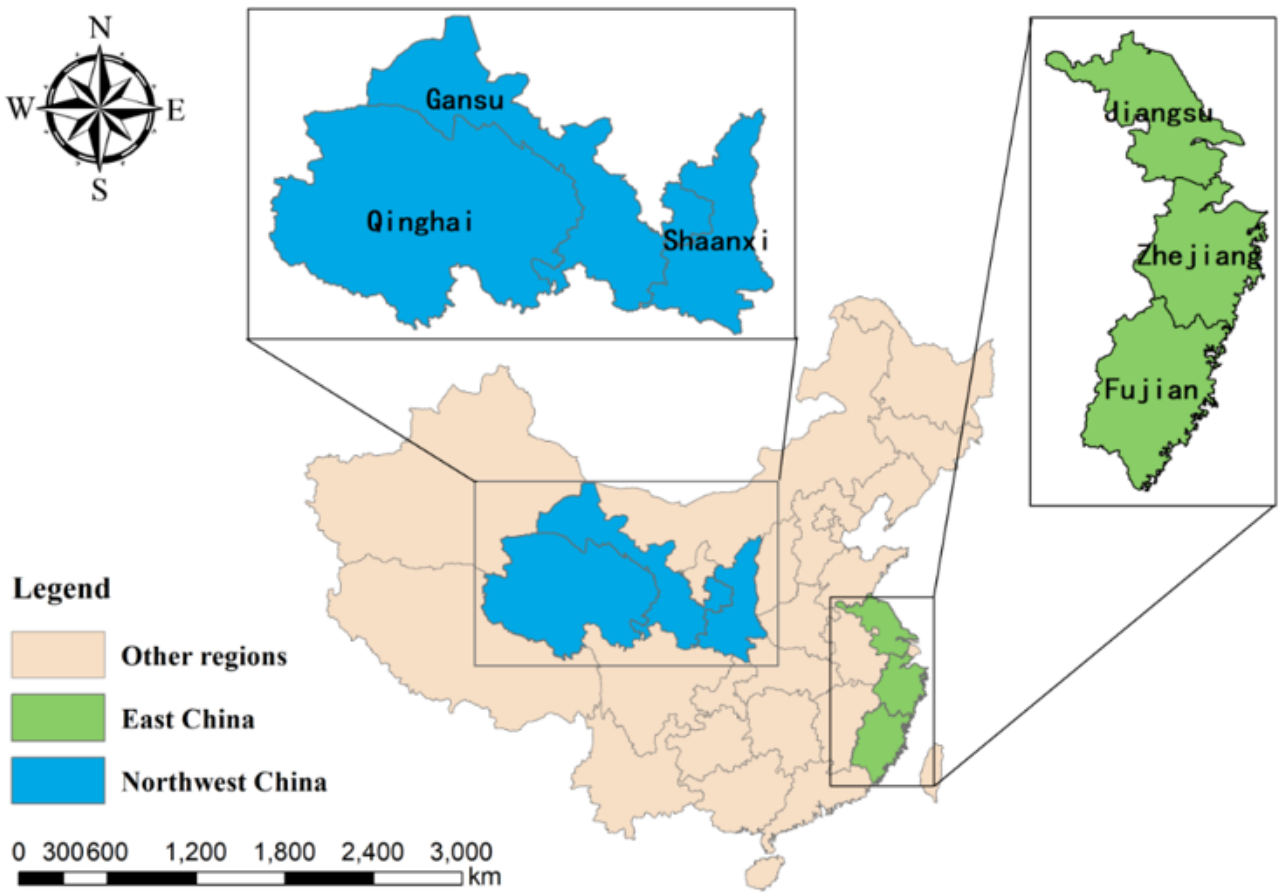

Figure 1

Distribution map of six provinces

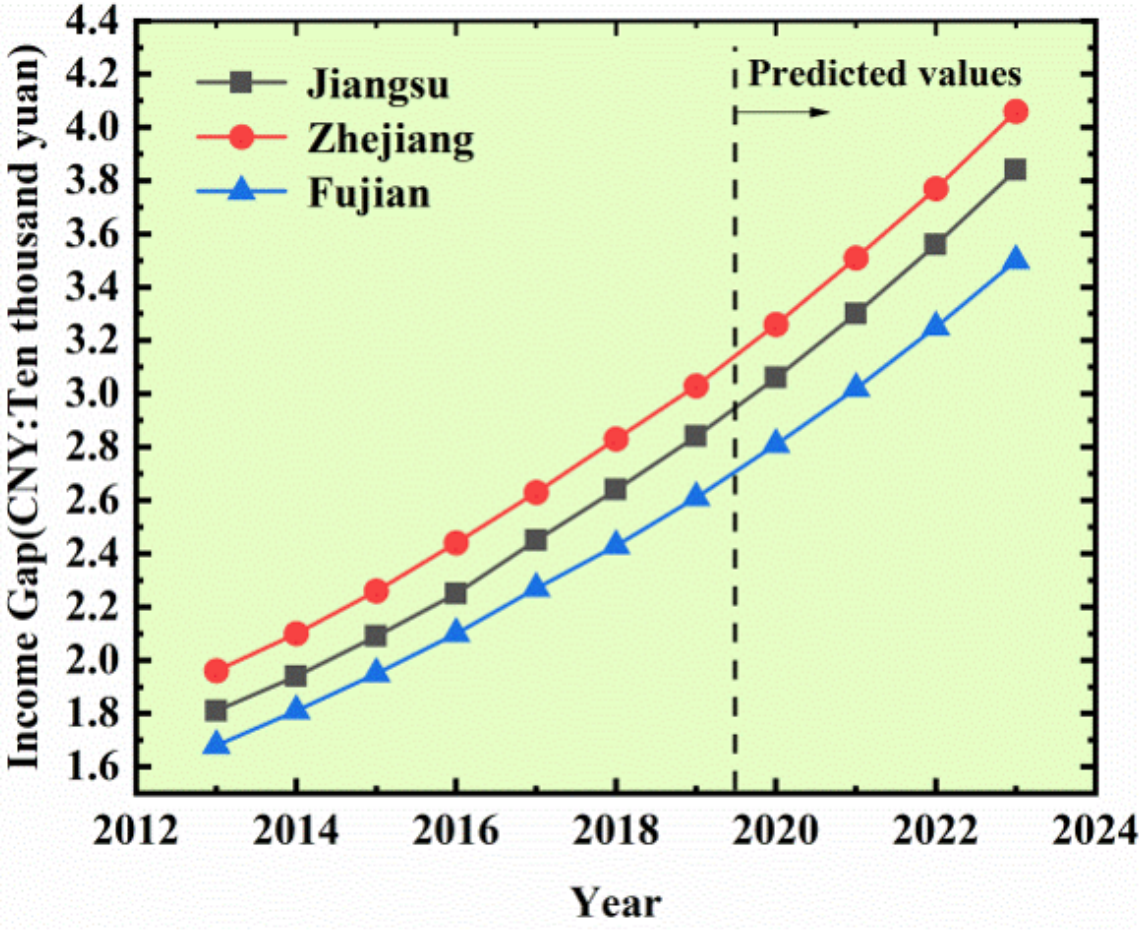

Figure 2

The income gap and predicted values in three provinces of East China

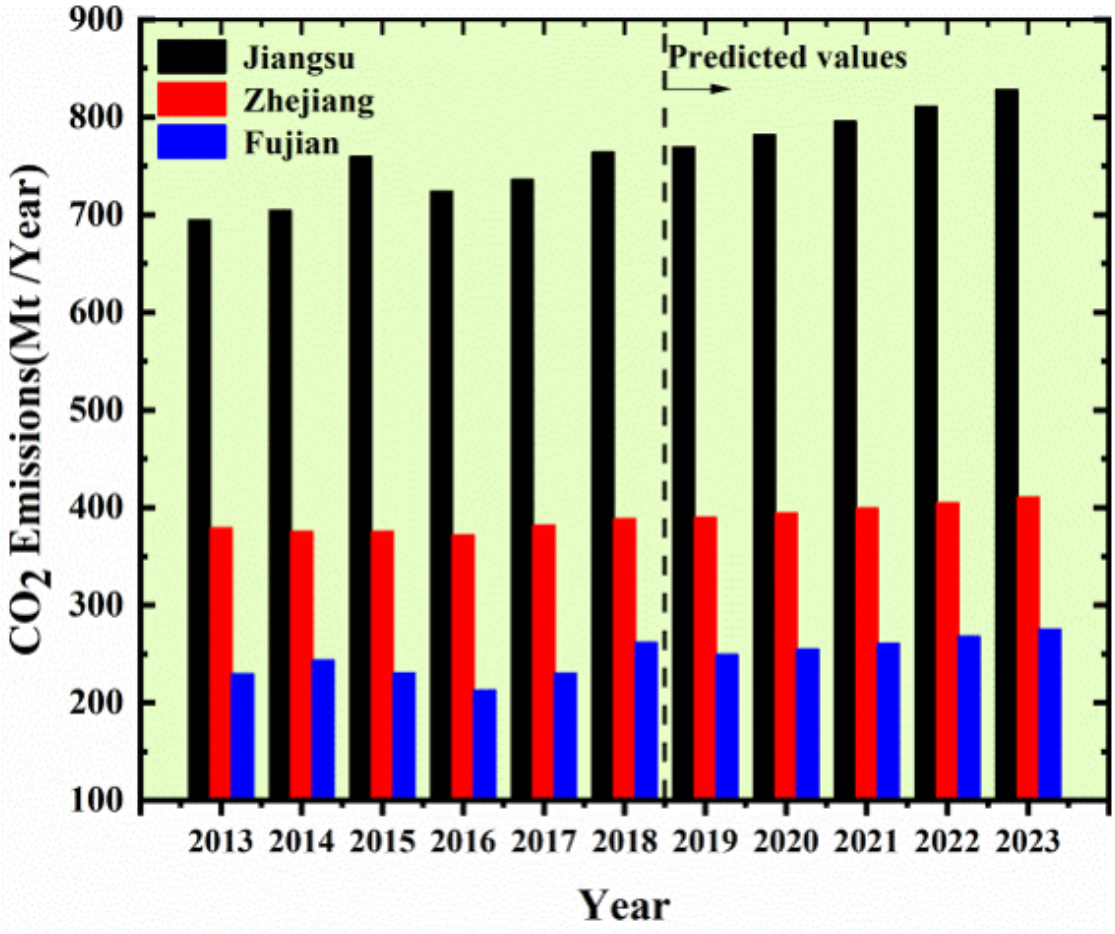

Figure 3

The CO_2 emission and predicted values in three provinces of East China

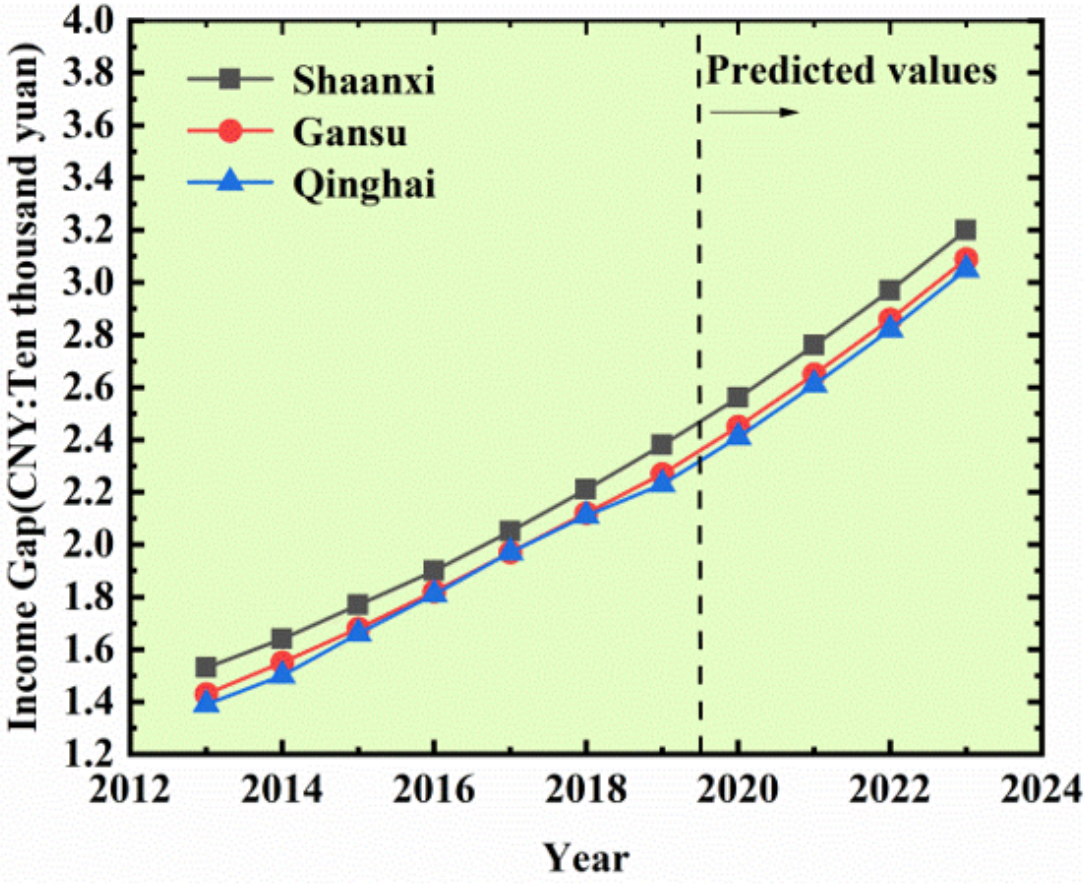

Figure 4

The income gap and predicted values in three provinces of Northwest China

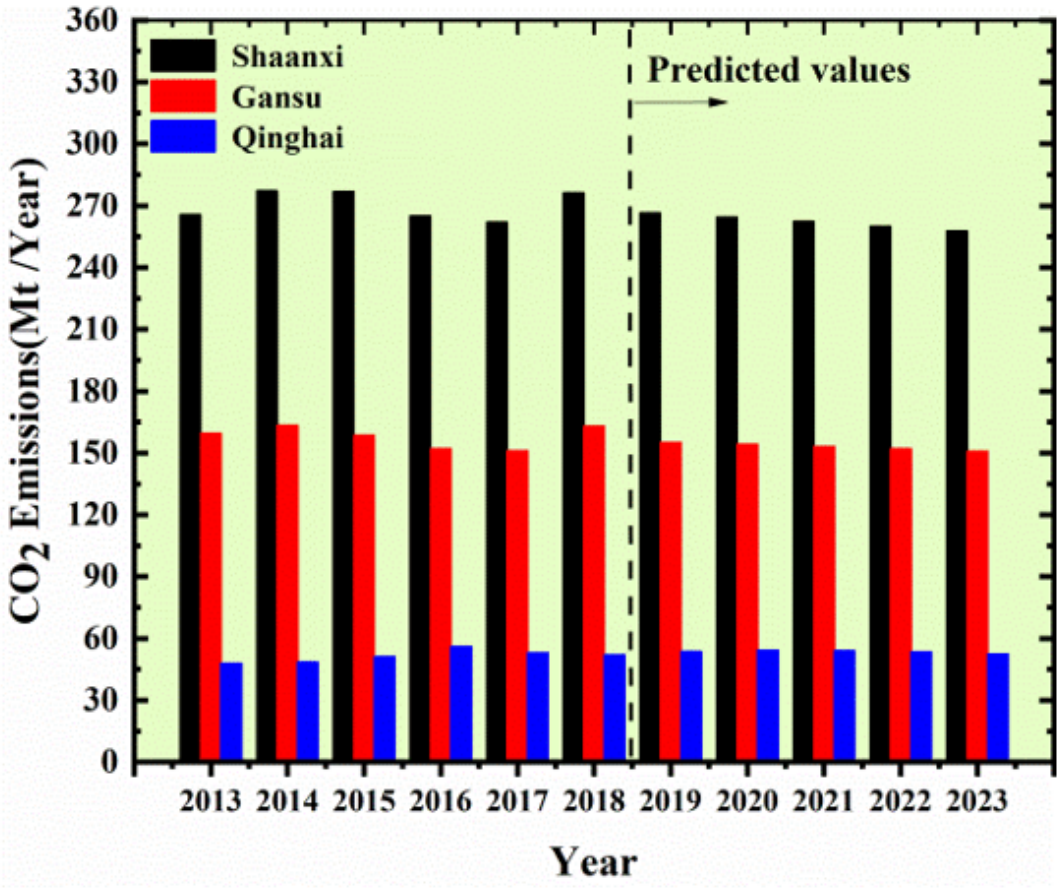

Figure 5

The CO_2 emission and predicted values in three provinces of Northwest China

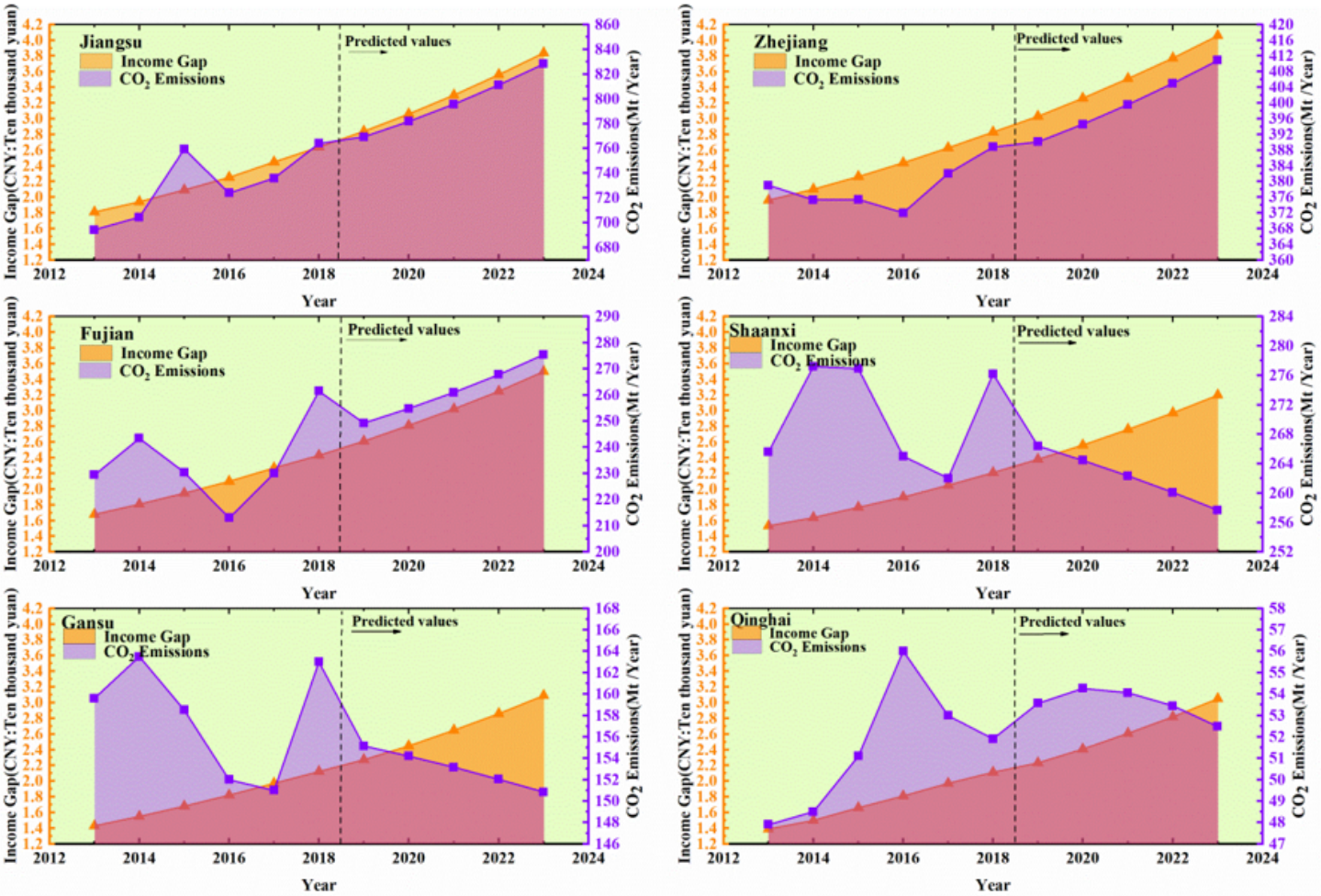

Figure 6

The income gaps and the CO_2 emissions area maps of six provinces

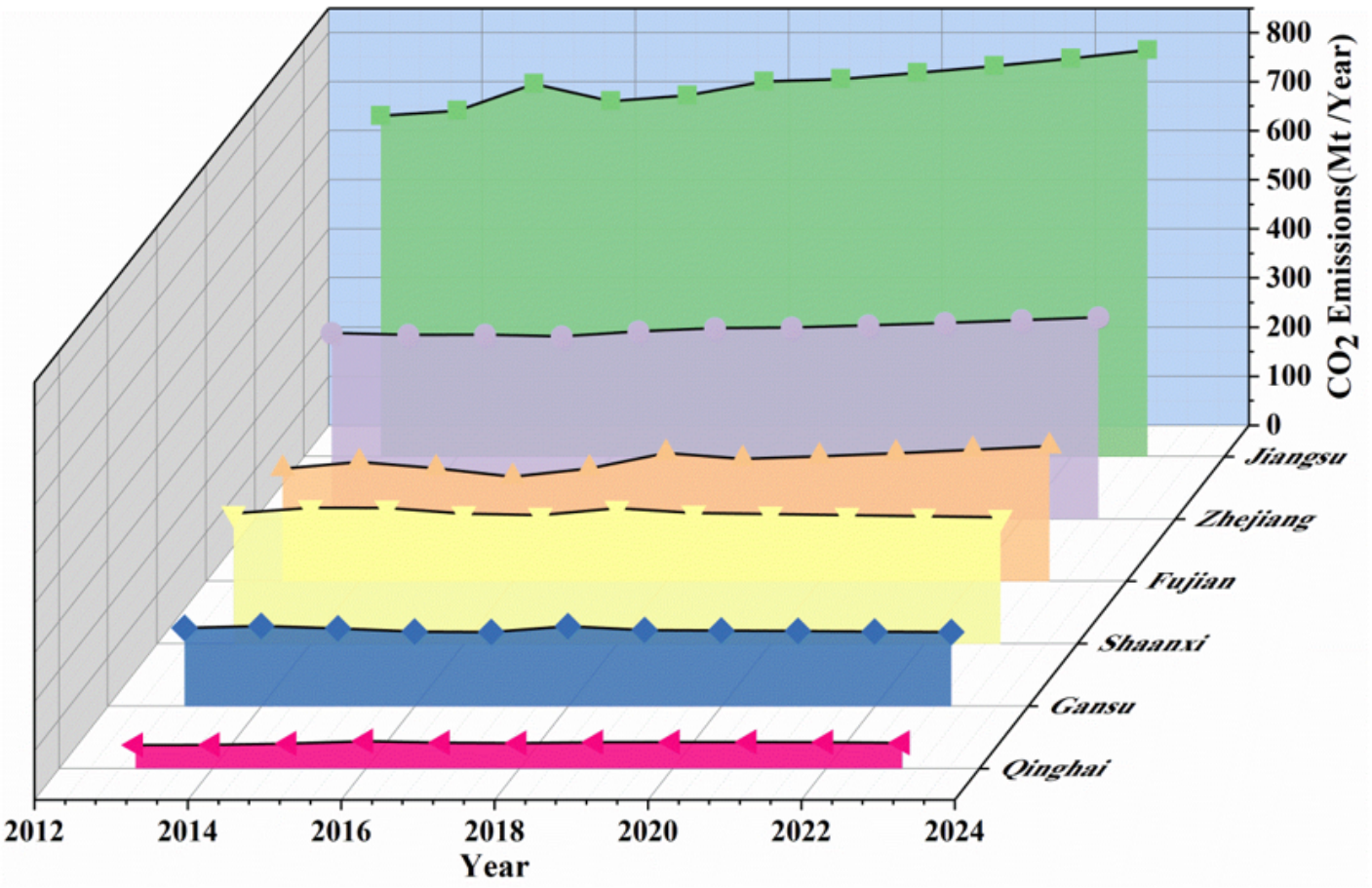

Figure 7

The CO_2 emission and predicted values in six provinces