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Forecasting Carbon Dioxide Emission Regional Difference in China by Damping Fractional Grey Model

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Abstract: The emission of carbon dioxide is the main reason for many global warming problems. Although China has made tremendous efforts to reduce carbon emission, the space–time dynamics of the carbon emission trend is still imbalanced. To forecast CDED in China, the Dagum Gini coefficient was applied to measure regional CDED. Then, a grey correlation model was used to select potential influence factors and a wrapping method for selecting the optimal subset. DGMC is proposed to forecast CDED. The research results showed that the DGMC generalization performance is significantly superior to other models. The *MAPE* of DGMC in six cases are 1.18%, 1.11%, 0.66%, 1.13%, 1.27% and 0.51%, respectively. The *RMSPEPR* of DGMC in six cases are 1.08%, 1.21%, 0.97%, 1.36%, 1.41% and 0.57%, respectively. The *RMSPEPO* of DGMC in six cases are 1.29%, 0.69%, 0.02%, 0.58%, 0.78% and 0.32%, respectively. In future trends, the eastern carbon dioxide emission intraregional differences will decrease. Additionally, the intraregional differences in western and middle-region carbon dioxide emissions will expand. Interregional carbon emission difference will display a narrowing trend. Compared with the traditional grey model and ANN model, integrating the influence factor information significantly improved forecasting accuracy. The proposed model will present better balanced historical information and accurately forecast future trends. Finally, policy recommendations are proposed based on the research results.

Keywords: carbon dioxide emission; regional difference; DGMC(1,n); Dagum Gini coefficient; grey relation analyze

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1. Introduction

The carbon cycle is closely related to social clean and sustainable development [1]; however, the acceleration of industrialization has led to human activity over-emitting carbon dioxide into the atmosphere. Carbon dioxide excess emissions have led to severe climate change problems. People were surprised to discover the world has become warmer [2]. Global warming will result in the melting of polar region glaciers and rising sea levels, seriously threatening coastal area residents' safety. Global warming will increase global extreme weather frequency and reduce agricultural production [3]. Governments have attached great importance to the global warming problem and hope to reduce carbon dioxide emission and realize green economic development [4]. Therefore, carbon dioxide peaking and neutrality-controlling goals have become the focus of global attention within this last decade [5]. The sustainable development goal has indicated that the world would take emergency actions to combat the global climate change problem. The Paris agreement established a global climate change control target. All countries should shoulder the burden of carbon reduction responsibility. In the past two decades, Chinese carbon dioxide emission has grown steeply. The carbon dioxide emission trends in China are shown in Figure 1. As the largest developing country, Chinese economic development pressure difficulty to achieving carbon decoupling in the short term. The achievement of carbon emission peaking and neutrality goals have attracted significant attention in China.

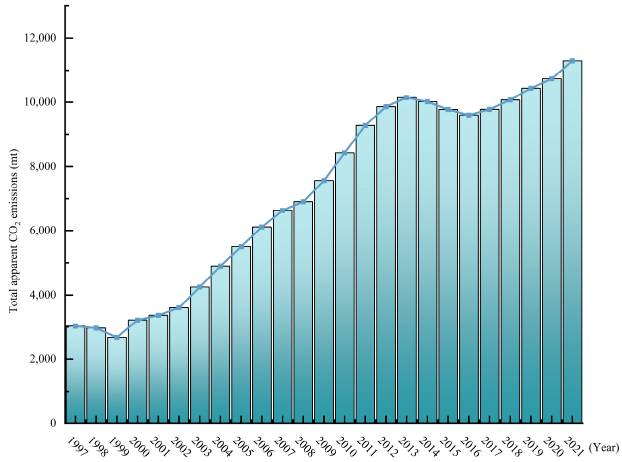

Figure 1. Carbon dioxide emissions in China from 1997 to 2021.

The Chinese government has pledged to make independent national contributions. In order to actively fulfil international commitments, the Chinese government established a specialized climate change deliberative coordination institution in 2007 and set up eight carbon-trading market pilots. However, as the largest developing country, the energy consumption and industrial structure characteristics involved in carbon emission reduction have faced enormous pressure. The carbon dioxide emission reduction pressure is higher than the national average level in 41.38% provinces and 49.65% cities [6]. Present studies indicate that energy structure and efficiency are essential factors in influencing carbon dioxide emission levels. Chinese fossil energy inefficiency consumption is the main reason for excessive carbon dioxide emission [7,8]. Li and Jiang have shown carbon dioxide emission reduction linked to energy efficiency improvement and clean renewable energy application in Russia [9]. Therefore, energy consumption structure and efficiency improvement are important measures for controlling excess carbon dioxide emission. It is necessary to improve Chinese energy structure and leave behind inefficient and high-emission energy consumption pattern.

However, the Chinese economic structure and ecological-carrying capacity have distinctly heterogeneous characteristics [10]. China should pay attention to environmental equity issues, balance socioeconomic development and ecological protection tasks and form environmental policies to achieve carbon dioxide emission reduction and economic development as a win–win result [11]. However, the current carbon reduction policy may enhance the carbon emission inequality problem. The Chinese carbon-trading emission pilot policy has led to carbon emission source shifts and aggravated regional carbon emission differences [12,13]. The policy reduced carbon dioxide emission intensity in pilot areas but exacerbated emission in the surrounding regions [14]. Therefore, the carbon dioxide emission equitability difference issue has become a new research area. Chen [15] believes that carbon emission right allocation should pay attention to regional equity issues. The regional development stage is an important influence factor in regard to carbon emission right allocation. Regional carbon emission difference reduction is vital to achieving environmental equity. Carbon dioxide emission has significantly difference in China from 2005 to 2015. The secondary industry scale and economic structure are the main reasons for CDED [16]. The Chinese logistics industry carbon emission difference study showed that intraregional differences are the primary CDED resource. The energy consumption difference is a significant reason behind carbon emission spatial difference [17]. The Chinese primary CDED sources range from population size, economic development, to energy intensity [18]. In addition, energy efficiency is also an important source of CDED. Energy consumption volume is the main motivation for carbon dioxide emission spatial heterogeneity [19]. Energy consumption demand and intensity are the main reasons for enhancing the regional energy consumption volume [20]. The Chinese province's energy efficiency has significant differences. Energy efficiency spatial characteristics have shown a gradual decline trend from the eastern to western in China [21]. Economy, technology, energy and urbanization directly affect energy efficiency [22]. Therefore, economic, technological, and energy structure factors have increased CDED. Regional energy efficiency common advances will shrink CDED. Carbon emission reduction requires concern for energy efficiency and CDED synergy functions. Carbon dioxide reduction should focus on regional energy consumption structure and efficiency difference characteristics to reduce CDED by moderating critical influencing factors in China.

Carbon dioxide emission has significantly spatial correlation characteristic [23]. Therefore, forecasting the CDED trend requires a suitable model. The grey forecasting model fully excavates system information from incomplete information. It is structured to describe future trends based on system hierarchy characteristics. The carbon dioxide emission problem is complex. The current theory is difficult to investigate due to its dynamic evolution rhythm. The grey forecasting model can effectively target current environmental problems and widely excavate hidden information. Therefore, the grey forecasting model has become an important research method for forecasting environmental development trends. Guo et al. [24] used a compound accumulative grey model to achieve air quality forecasting in 18 Henan Province cities. The results show that new grey model has good forecasting accuracy. The grey model can effectively identify the primary pollutants in Henan. Li et al. [25] established a grey Bass extended model to study new energy vehicle demand in France, Norway and the EU. Grey model achieved highly forecasting accuracy compared to available models. Qiao et al. [26] applied the grey model to forecast the water consumption of 31 Chinese provinces. Ma et al. [27] designed an energy consumption time lag fractional order accumulative grey model to forecast Chongqing's natural gas and coal consumption. Zeng and Li [28] forecasted the gas production shale volume scientifically. It has also been demonstrated that the optimized grey model can also be applied to forecasting coalbed methane production [29]. Ding studied the grey forecasting model to forecast nuclear energy consumption volume [30] and new energy vehicle sales volumes [31]. The forecasting results show that the grey model not only has good forecasting accuracy in regard to traditional environmental problems but also has a satisfactory forecasting ability in regard to the renewable energy industry field. Fractional order is an expansion of integer order derivative and integral. Fractional order is characterized by memorability and forgetfulness. It is more flexible in regard to describing complex dynamic systems. Chen et al. [32] improved the adaptive genetic algorithm based on a fractional order derivative theory for multi-parameter model identification of lithium battery charge state estimations. Yang et al. [33] proposed electrochemical impedance spectroscopy and relaxation time distribution methods to solve the unreasonable physical results and numerical instability of fractional order in lithium-ion batteries. Mok et al. [34] proposed a smoothing function algorithm to identify the variables of linear and nonlinear subsystems in the continuous time fractional order Hammerstein model. By integrating existing research, the fractional order can capture the historical information and long-term trend more accurately. Fractional order has enhanced characterization ability of system states. It has become the new trend in the grey time series model.

This study focuses on the CDED problem in China, aiming to identify sources of CDED and forecast future trend. Firstly, influencing factors were selected based on literature studies. Filtering and wrapping methods were used to select features. A grey correlation index was used to eliminate unimportant influence factors. FGM is used to forecast feature set trend, and a new damping grey multivariable convolution model is proposed to forecast carbon dioxide regional differences. The new grey model validity is tested by comparing it with the existing model. DGMC empirically analyzes regional CDED in China and provides policy recommendation.

This study structure is as follows: The study region and CDED influence factors are discussed in Section 2. Empirical method set is given in Section 3. The CDED empirical analysis is in Section 4. In the final part, the research conclusion and policy recommendation are introduced. Meanwhile, the study limitations and future research directions are identified.

2. Study Region and CDED Influence Factor

2.1. Region Subpopulation Design

The Chinese economic regional emergence results from economic development and the geographic location's long-term evolution process. The ecological environment has regional heterogeneity and cross-regional linkage characteristics. Regional carbon emission differences are the result of multiple influence factors and interaction functions [35]. Industrial structure, economy, energy intensity are the main causes of CDED [36,37]. Therefore, according to Chinese regional characteristics, the carbon dioxide emission subpopulation was divided into the eastern, middle and western regions. To ensure comparability, the study sample did not include province-level municipalities and special administrative regions. The subpopulation also excluded the Xizang autonomous, Hong Kong, Macau and Taiwan regions because of data deficiency. The carbon dioxide emission subpopulation is divided as shown in Figure 2.

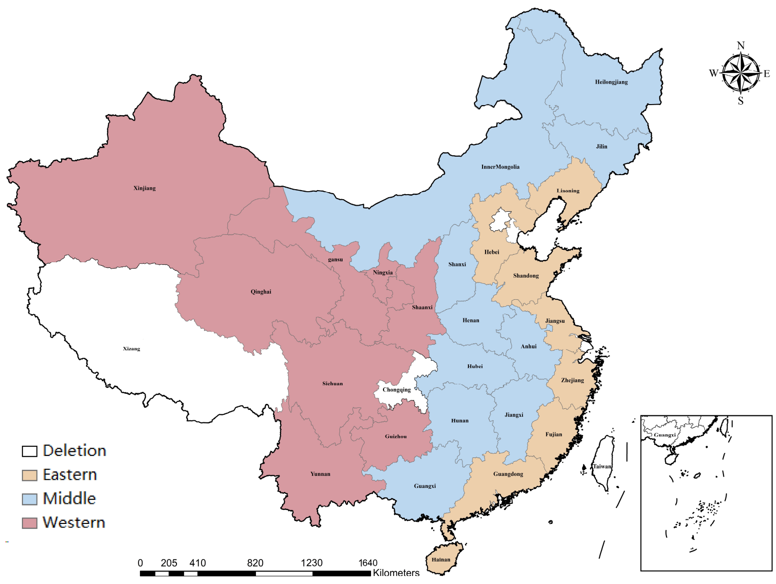

Figure 2. Carbon dioxide emission subpopulation.

The eastern region includes eight provinces, including Hebei, Liaoning, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan. The eastern region is the coastal region of China. The eastern region's topography is gentle. It has a superior geographical location, a complete industrial system, robust production technology, and an obviously labour concentration effect. It is economically developed but lacks water, forests, and other resources. The natural resource demand of the eastern region exceeds its supply, so eastern ecological environmental protection is under tremendous pressure.

The middle region includes eleven provinces, including Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, Guizhou and Guangxi. The middle region is rich in energy, metal and non-metal mineral resources. Its industrial structure is mainly based on heavy industry. The total output values of its energy and heavy chemical industries are significantly higher than the national average level. Therefore, the middle region has faced serious pressure to reduce carbon dioxide emission.

The western region includes eight provinces, including Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang. Its wide area has rich natural resources. It is an important ecological function area in China and contributes significantly to the maintenance of national environmental security. Its economic development and technical management level is significantly different from the other two regions.

2.2. Regional Difference Influence Factor Measurement

Economy. Economic scale is one of the most important reasons for CDED. The economic scale increase is based on production activity and energy consumption. Economic expansion will increase carbon emission. The economic model is another reason for CDED. If the region is integrated into the global supply chain for energy-intensive industry, it will increase carbon emission. Foreign investment in infrastructure and the energy economy will also increase carbon emission. The economic market is also an important influence on CDED. The demand side of the energy market will influence enterprise production behavior. Economic market differential demand will create differentiated development pathways between regions. Therefore, GDP, GDP per capita, total imports/exports and the total retail sales of consumer goods are used to reflect regional differences in economic development.

Government. Government directly influences the regional carbon emission trend through environmental regulation in administrative form and green subsidy in market form. The government invests in green project and promotes green technology by financial subsidy. Meanwhile, the government increases the transparency of carbon emission monitoring by increasing environmental monitoring investment. However, under the background of fiscal decentralization, the local government may also relax environmental regulation to increase fiscal revenue and increase regional carbon emission. Therefore, fiscal revenue and fiscal expenditure are selected to reflect government impacts on CDED.

Science and education. Science and education are important factors influencing CDED. Science and technological innovation is an important driving force for the transformation and upgrading of the regional economy model. Traditional production technology has a high emission feature. Green technological progress has reduced unit output in regard to carbon emission. Technological progress has a significant spillover effect. Government investment in science and technology can promote technical public product supply and upgrade the region economy model. Modern technology has increased the demand for high-skilled labour. Government expenditure on education provides human capital for green technology application. Therefore, patent granted, education expense and science and technology expenditure were selected to reflect regional differences in science and education.

Digital economy. Th digital economy promotes economic transformation, optimizes industrial structure, improves energy efficiency and reduces reliance on traditional carbon-emitting industry. The digital economy promotes information and intelligent management, thereby reducing carbon emission. The information transmission network accelerates information and communication technology application, promotes telecommuting, smart city construction and green transformation. It will reduce regional dependence on energy-intensive industry and lower carbon emission. Therefore, mobile telephone exchange capacity, long-distance fibre-optic cable line length and fibre-optic cable line length were chosen to reflect regional digital economy development differences.

Energy consumption. Energy consumption plays a crucial role in shaping CDED. Energy structure and consumption pattern directly affect carbon emission levels. Energy consumption not only depends on total consumption but also relies on regional production and living features. Electricity energy, as the basic energy for production and life, better reflects regional energy demand. Therefore, it has been chosen to reflect regional difference in energy consumption.

Infrastructure. Transport and logistic infrastructure scales and efficiency play an important role in CDED formation. Cargo turnover reflects the regional dynamism in logistics and transport. Interregional logistic infrastructure difference not only affect transport efficiency but also directly determine the contribution of carbon emission. Therefore, cargo turnover was chosen to reflect interregional infrastructure differences.

3. Empirical Method

The traditional grey model structure lacks adaptive characteristics. It cannot effectively capture the nonlinear and long-term memory characteristics of complex systems, and it is sensitive to noise. Fractional order adjusts the flexibility of the grey model to reflect complex nonlinear spatial-temporal dynamics by introducing non-integer orders. The fractional-order adaptive adjusting model memory functions in pursuit of minimizing accuracy loss, sensitively capturing time series dependency features. Therefore, this study attempted to optimize the traditional grey model with a fractional order structure. Meanwhile, the influence factor of information was added to increase the model accuracy.

3.1. Dagum Difference Measurement

The Dagum difference measure is a methodology used to measure regional inequality [38]. This approach highlights the crosscutting effect between groups. It can capture inequality sources more delicately. The method decomposes total inequality into three components: intracluster differences, intercluster differences and super-efficiency differences. To provide a comprehensive picture of CDED, this research chose the Dagum difference measure to examine CDED in China. It was calculated as follows:

$$G_w = \sum_{j=1}^{k} G_{jj} P_j S_j \tag{1}$$

$$G_{jj} = \sum_{i=1}^{n_j} \sum_{m=1}^{n_j} \left| C_{ji} - C_{jm} \right| / 2{n_j}^2 \overline{C}_j \tag{2}$$

$$G_{nb} = \sum_{j=2}^{k} \sum_{h=1}^{j-1} G_{jh} (P_j S_h + P_h S_j) D_{jh} \tag{3}$$

$$G_{jh} = \sum_{i=1}^{n_j} \sum_{r=1}^{n_h} \left| C_{ji} - C_{hr} \right| / n_j n_h (\overline{C}_j + \overline{C}_h) \tag{4}$$

$$P_j = \frac{n_j}{n}; S_j = \frac{n_j \overline{C}_j}{n \overline{C}} \tag{5}$$

G_w reflects the intraregional difference. G_{nb} reflects the interregional difference. C_{ji} reflects the jth subgroup carbon emission in the ith province. C_{hr} reflects the hth subgroup carbon emission the in r province.

3.2. Feature Selection

The carbon dioxide emission sources are widespread. According to current studies, regional economic and social heterogeneity are the reason for the carbon dioxide emission regional difference. However, the carbon emission difference reasons do not reach a consistent conclusion. Therefore, to forecast CDED, evaluating an optimal forecast feature index is necessary. Grey relation analyze is a method of measuring influence factors. Its correlation coefficient can reflect the geometry similarity degree between carbon dioxide emission in regional difference sequences with potential influence factor sequences. Grey correlation comparative sequence sorts the significance of the systematic influence factor. Therefore, in the research referencing Wang et al. [39], a grey relation analysis is used to explain the effect of influence factors on carbon dioxide emission in regard to regional difference to an important degree. Specifically, the grey relation analyze process as is follows:

The CDED sequence is defined as ${C_0}^{(0)}$ = $\{{C_0}^{(0)}$ (1), ${C_0}^{(0)}$ (2), ${C_0}^{(0)}$ (3), . . ., ${C_0}^{(0)}$ $(n)\}$, and m potential influence factor set are CDED potential influence factors.

$$\begin{cases} {C_1}^{(0)} = \left\{ {c_1}^{(0)}(1), c1^{(0)}(2), {c_1}^{(0)}(3), \ldots, {c_1}^{(0)}(n) \right\} \\ {C_2}^{(0)} = \left\{ {c_2}^{(0)}(1), {c_2}^{(0)}(2), {c_2}^{(0)}(3), \ldots, c2^{(0)}(n) \right\} \\ {C_3}^{(0)} = \left\{ c3^{(0)}(1), {c_3}^{(0)}(2), {c_3}^{(0)}(3), \ldots, {c_3}^{(0)}(n) \right\} \\ \ldots \\ {C_m}^{(0)} = \left\{ {c_m}^{(0)}(1), {c_m}^{(0)}(2), {c_m}^{(0)}(3), \ldots, {c_m}^{(0)}(n) \right\} \end{cases} \tag{6}$$

The grey relational coefficient λ is the ${C_i}^{(0)}$ potential influence factor and the carbon dioxide emission regional difference ${C_0}^{(0)}$ in time j is:

$$\lambda(c0^{(0)}(j), {c_i}^{(0)}(j)) = \frac{\min_i \min_j \left| c0^{(0)}(j) - {c_i}^{(0)}(j) \right| + 0.5 \max_i \max_j \left| c0^{(0)}(j) - {c_i}^{(0)}(j) \right|}{\left| c0^{(0)}(j) - {c_i}^{(0)}(j) \right| + 0.5 \max_i \max_j \left| c0^{(0)}(j) - {c_i}^{(0)}(j) \right|} \quad (7)$$

The grey relational degree of the i influence factor is:

$$Grey\_relational = \frac{1}{n} \sum_{j=1}^{n} \lambda(c0^{(0)}(j), {c_i}^{(0)}(j)), j = 1 \ldots m \quad (8)$$

Filtering and wrapping are two important methods for feature selection. However, the filtering method ignores mutual influences between features. The wrapping method search space is oversized, which limits the efficiency of feature selection. Therefore, this research combined filtering and wrapping methods to select an optimal forecasting feature subset. Grey correlation method filters out features with grey correlation coefficient below 0.7. A multivariate time series was used with the forecasting grey model to select the optimal feature subset.

3.3. FGM(1,1) Forecasting Model

Wu first used FGM(1,1) to realize the information first principle [40]. FGM(1,1) changed the traditional grey model and the adaptive adjusting weight accumulation information. FGM(1,1) can give greater weight to new information. Therefore, FGM(1,1) was used to forecast influence factors. The forecast process is as follows.

Firstly, assume a non-negative sequence $C^{(0)}(i) = \left\{ c^{(0)}(1), c^{(0)}(2), \ldots, c^{(0)}(n) \right\}$. The ς-order accumulation generating operator is defined as follows:

$$C^{(\varsigma)}(k) = \sum_{i=1}^{K} C_{k-i+\varsigma-1}^{k-i} c^{(0)}(i), k = 1, 2, \ldots, n \quad (9)$$

Set $C_{\varsigma-1}^{0} = 1, C_{k}^{k+1} = 0, C_{k-i+\varsigma-1}^{k-i} = \frac{(k-i+\varsigma-1)(k-i+\varsigma-2)\ldots(\varsigma+1)\varsigma}{(k-i)!}$.

When $\varsigma = 1, C_{k-i+\varsigma-1}^{k-i} = C_{k-i}^{k-i} = 1$ ς-FGM is defined as $c^{(1)}(k) = \sum_{i=1}^{k} c^{(0)}(i)$, it is degenerated into traditional GM(1,1).

Secondly, the FGM(1,1) whitenization equation is established as follows:

$$\frac{dci^{(\varsigma)}}{dk} + aci^{(\varsigma)} = b \quad (10)$$

a, b are estimated parameters. To accurately estimate parameters, a continuous differential equation is transformed into a discrete difference equation. The forecasting problem is transformed into a linear mathematical problem. Therefore, the least squares method is used to minimize the fitting error for the unknown parameters. The parameters solution with least-squares.

$$\begin{bmatrix} \hat{a} \\ \hat{b} \end{bmatrix} = (B^T B)^{-1} B^T Y \quad (11)$$

where

$$B = \begin{bmatrix} -\frac{c^{(\varsigma)}(1)+c^{(\varsigma)}(2)}{2} & 1 \\ -\frac{c^{(\varsigma)}(2)+c^{(\varsigma)}(3)}{2} & 1 \\ \cdots & \cdots \\ -\frac{c^{(\varsigma)}(n-1)+c^{(\varsigma)}(n)}{2} & 1 \end{bmatrix} Y = \begin{bmatrix} c^{(\varsigma)}(2) - c^{(\varsigma)}(1) \\ c^{(\varsigma)}(3) - c^{(\varsigma)}(2) \\ \cdots \\ c^{(\varsigma)}(n) - c^{(\varsigma)}(n-1) \end{bmatrix} \quad (12)$$

Thirdly, the approximate function is:

$$ci^{(\varsigma)}(k+1) = (ci^{(0)}(1) - \frac{b}{a})e^{-ak} + \frac{b}{a} \tag{13}$$

In the end, the inverse accumulated generating operator in:

$$\alpha^{(\varsigma)}c^{(0)} = \left\{\alpha^{(1)}c^{(1-\varsigma)}(1), \alpha^{(1)}c^{(1-\varsigma)}(2), \ldots, \alpha^{(1)}c^{(1-\varsigma)}(n)\right\} \tag{14}$$

The fitting value is $\hat{c}^{(0)}(\varsigma) = \hat{c}^{(1)}(\varsigma) - \hat{c}^{(1)}(\varsigma - 1)$.

3.4. Establish a Grey Multivariable Convolution Model with a Damping Accumulation Operator

Tien first used a grey multivariable convolution feature index set to improve the traditional GM(1,n) model [41]. However, the grey multivariable convolution model is difficult to smooth in terms of the fitting data and flexibly adjusting the future trends. To solve this problem, Liu introduced the damping accumulation operator and proved the damping operator information priority characteristics by the matrix perturbation bound theory [42]. Therefore, we introduce the damping accumulated operator into the traditional grey multivariable convolution model to better reflect information priority. The damping accumulation operator can adapt to future trends. The new model is called DGMC(1,n). The new grey model can more fully reflect system characteristics and obtain more accurate forecast results. The DGMC(1,n) is as follows.

Firstly, the ψ-order (according to particle swarm optimization identify optimum accumulation order) accumulation sequence is:

$$c^{(\Psi)}(k) = \sum_{i=1}^{k} \frac{c^{(0)}(i)}{\Psi^{i-1}},\ 0 < \Psi \leq 1 \tag{15}$$

Secondly, the grey convolution sequence is:

$$\frac{dc_0^{(\Psi)}(k)}{dk} + bc_0^{(\Psi)}(k) = b_1c_1^{(\Psi)}(k) + b_2c_2^{(\Psi)}(k) + \ldots + b_nc_n^{(\Psi)}(k) + \mu, k = 1, 2 \ldots n \tag{16}$$

The estimated parameters are b, b_1, b_2, …, b_n and μ. By the least squares test, the solution estimated parameters are:

$$\begin{aligned}
&[b, b_1, \ldots, b_n, \mu] = \left(N^T N\right)^{-1} N^T Y, \\
&Y = \begin{bmatrix} c_0{}^{(\Psi-1)}(2) \\ c_0{}^{(\Psi-1)}(3) \\ \ldots \\ c_0{}^{(\Psi-1)}(n) \end{bmatrix} \\
&N = \begin{bmatrix} -\frac{c1^{(\Psi)}(1)+c1^{(\Psi)}(2)}{2} & \frac{c2^{(\Psi)}(1)+c2^{(\Psi)}(2)}{2} & \ldots & \frac{cn^{(\Psi)}(1)+cn^{(\Psi)}(2)}{2} & 1 \\ -\frac{c1^{(\Psi)}(2)+c1^{(\Psi)}(3)}{2} & \frac{c2^{(\Psi)}(2)+c2^{(\Psi)}(3)}{2} & \ldots & \frac{cn^{(\Psi)}(1)+cn^{(\Psi)}(2)}{2} & 1 \\ \ldots & & & & \\ -\frac{c1^{(\Psi)}(n-1)+c1^{(\Psi)}(n)}{2} & \frac{c2^{(\Psi)}(n-1)+c2^{(\Psi)}(n)}{2} & \ldots & \frac{cn^{(\Psi)}(1)+cn^{(\Psi)}(2)}{2} & 1 \end{bmatrix}
\end{aligned} \tag{17}$$

Thirdly, the time response function of DGMC(1,n) is:

$$\begin{aligned}
&\widehat{c}\,1^{(1)}(k) = c_0{}^{(0)}(1)e^{-b(k-1)} + \sum_{\varphi=2}^{u}\left\{e^{-b(k-\varphi+1/2)}\frac{f(\varphi)+f(\varphi-1)}{2}\right\} \\
&f(\varphi) = b_1c_1^{(\Psi)}(\varphi) + b_2c_2^{(\Psi)}(\varphi) + \ldots + b_nc_n^{(\Psi)}(\varphi) + \mu
\end{aligned} \tag{18}$$

In the end, the fitting sequence is:

$$\begin{cases} \hat{c}1^{(0)}(1) = c1^{(0)}(1) \\ \hat{c}1^{(0)}(i) = \Psi^{i-1}\left(\hat{c}1^{(\Psi)}(i) - \hat{c}1^{(\Psi)}(i-1)\right) \end{cases} \tag{19}$$

After designing the DGMC model, it is necessary to test the new model's forecast accuracy. Model accuracy tests can reflect the fitting and prediction errors comprehensively. The accuracy test equation is:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{c}1^{(0)}(i) - c1^{(0)}(i)}{c1^{(0)}(i)}\right| \tag{20}$$

$$RMSPEPR = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\frac{\left(\hat{c}1^{(0)}(i) - c1^{(0)}(i)\right)^2}{c1^{(0)}(i)^2}} \tag{21}$$

$$RMSPEPO = \sqrt{\frac{1}{nf}\sum_{i=n+1}^{n+nf}\frac{\left(\hat{c}1^{(0)}(i) - c1^{(0)}(i)\right)^2}{c1^{(0)}(i)^2}} \tag{22}$$

${c_1}^{(0)}(i)$ represents original data and $\hat{c}_1^{(0)}(i)$ represents fitted data, nf is the prediction value. The *MAPE* is used to measure the average relative error between the fitted value and the original value. The *RMSPEPR* is used to measure the average relative error in the fitted data. This indicator is mainly used to reflect the model-fitting ability. The *RMSPEPO* is used to measure the average relative error in the test data. This indicator is mainly used to reflect the generalization ability of the model in order to better demonstrate the empirical process. The data analysis and forecasting process in this research is shown in Figure 3.

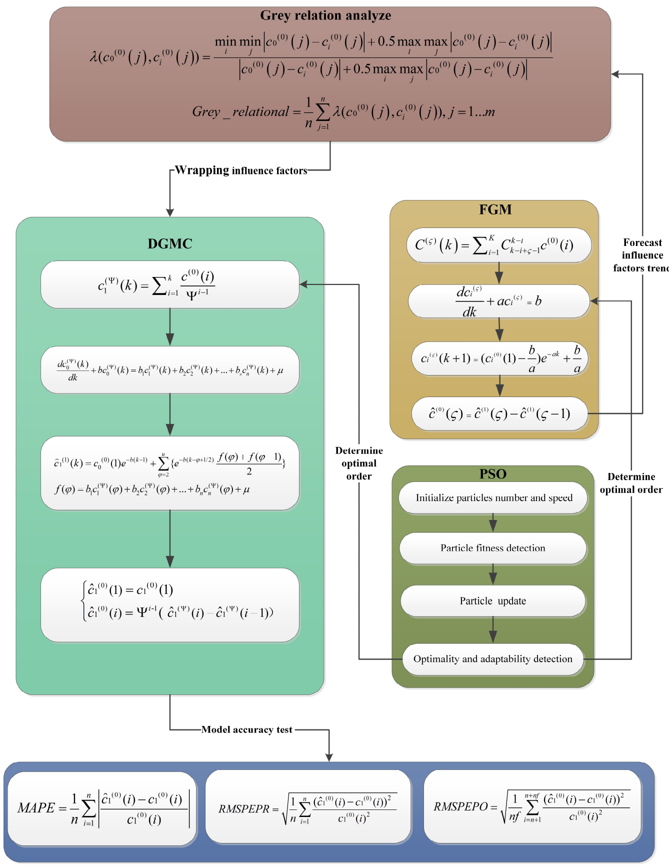

Figure 3. The data analysis and forecasting process.

4. Empirical Results

4.1. Intraregional Differences Forecast

4.1.1. Eastern Region

Eastern region carbon dioxide emission intraregional differences are shown in Figure 4. The accuracy test results are shown in Table 1. We found that carbon dioxide emission intraregional difference in the eastern region showed a fluctuating downward trend from 2012 to 2021. Overall, carbon dioxide emission intraregional difference in eastern region shows a fluctuating upward trend between 2012 and 2020, followed by a significant decline after 2020. The ANN model deviates significantly from the actual data. The AGMC also produces large deviations due to discarding excessive historical information. The DGMC performed significantly better compared to the other models.

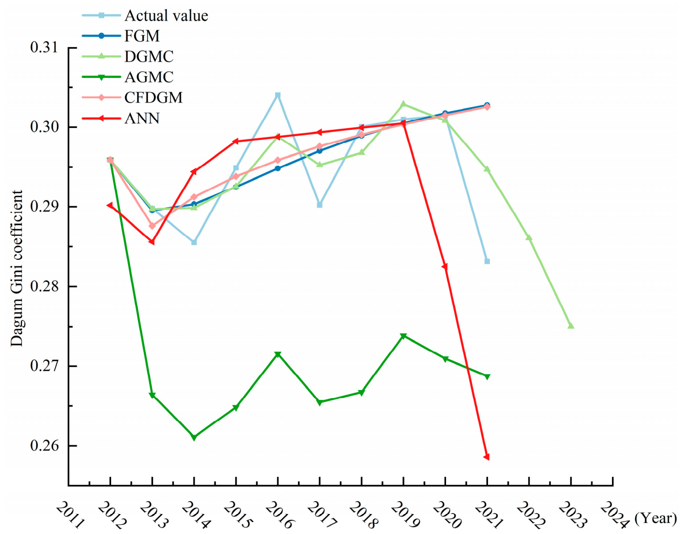

Figure 4. Carbon dioxide emission intraregional difference in eastern region.

Table 1. The accuracy test result in the eastern region.

	FGM	DGMC	AGMC	CFDGM	ANN
MAPE (%)	1.55	1.18	8.14	1.57	2.77
RMSPEPR (%)	1.43	1.08	9.05	1.43	2.78
RMSPEPO (%)	2.19	1.29	1.61	2.17	2.74

According to DGMC, the comparative series change forecast showed results. In the next two years, the eastern region's carbon dioxide emission intraregional difference will show an downward trend. The feature selection identified import/export, patent granted and long-distance fibre cable as the main influencing factors. The eastern region is an economic activity intensive region in China. The eastern region government attaches importance to innovative and synergistic development, builds open platforms, and integrates advantageous resources within the region. The eastern region is guaranteed by basic industries, with high-tech industries acting as the leading industries and related industries supporting development, with tremendous industrial development potential and high energy efficiency. Energy efficiency improvements decreased carbon emission and reduced resource consumption. The technology-led development model accelerates economic and carbon emission decoupling and achieves low-carbon economic balanced development in the eastern region. The eastern region's upstream and downstream enterprises are well defined and te industrial collaboration effect is significant. With information technology spreading, cross-regional collaboration and the sharing economy have been promoted, low-carbon technology applications have been promoted through platform-based resource scheduling, and reduced resource wastage has occurred in high-carbon emitting regions.

Therefore, in the future forecast interval, the open economy of informatization and regional integration will decrease the CDED in the eastern region.

4.1.2. Middle Region

The middle region's carbon dioxide emission intraregional difference is shown in Figure 5. The accuracy test results are shown in Table 2. We found that the middle region's carbon dioxide emission intraregional difference showed an upward trend from 2012 to 2021. The middle region's carbon dioxide emission intraregional difference remained relatively stable between 2013 and 2017 and showed a continued upward trend in 2018. It decreased in 2021 but still showed an overall upward trend. The model comparison results showed that DGMC model has superior fitting and a generalization ability. The ANN model deviated significantly from the actual value. The other models performed similarly.

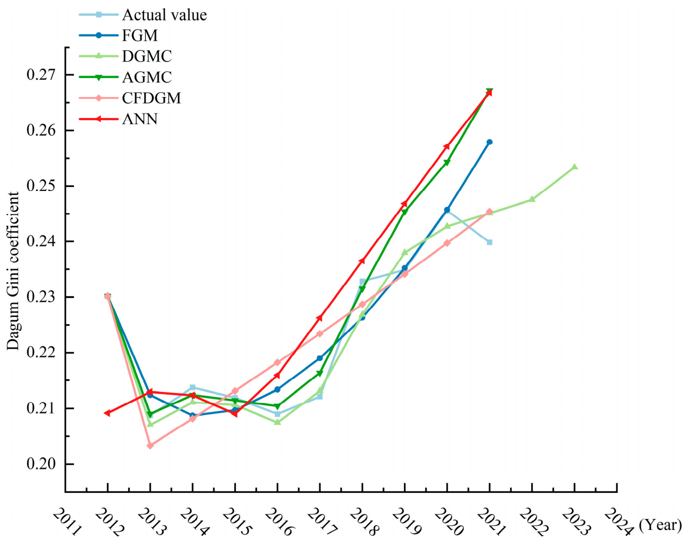

Figure 5. Carbon dioxide emission intraregional difference in the middle region.

Table 2. The accuracy test results in the middle region.

	FGM	DGMC	AGMC	CFDGM	ANN
MAPE (%)	2.10	1.11	2.37	2.23	4.57
RMSPEPR (%)	1.90	1.21	2.05	2.80	4.65
RMSPEPO (%)	2.39	0.69	3.61	0.74	3.56

According to DGMC, the comparative series change forecast showed results. The middle regional carbon dioxide emission intraregional difference will continuously show a slight increase trend in the next two years. Fiscal revenues, total exports, education expense and the total retail sales of consumer goods are the main factors in this trend. Fiscal revenue difference creates infrastructure development and industrial development difference and expands CDED. Government spending will go towards education-promoted technological progress and industrial upgrading in some regions, forming low-carbon pilot zones and expanding CDED. The total retail sales of consumer goods will reflect the increase in consumer demand differences. Consumption demand difference is transmitted to production and expanding CDED. The total export difference increased will reflect the different degrees of economic openness between regions. Export-dependent regions generally experience higher energy consumption and discharge from production, resulting in increased CDED increased. Therefore, within forecast intervals, CDED will show upward trend in the middle region.

4.1.3. Western Region

The carbon dioxide emission intraregional difference in the western region is shown in Figure 6. The accuracy test results are shown in Table 3. We found western region carbon dioxide emission intraregional difference showed inverted the U-curve trend from 2012 to 2021. It increased in 2012–2016, decreased in 2017–2018 and fluctuated in 2019–2021. The forecasting models showed that the ANN model deviated significantly from the actual value. FGM and CFDGM deviated significantly from the future trend. AGMC and DGMC fitted and forecasted well. DGMC had a better overall performance than AGMC.

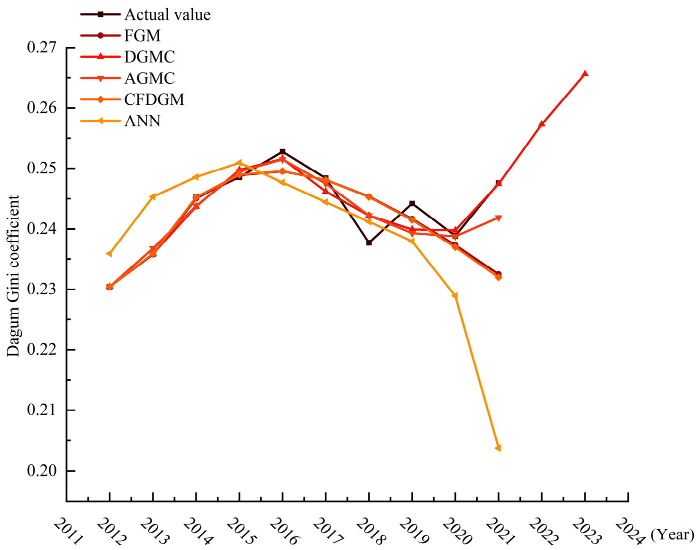

Figure 6. Carbon dioxide emission intraregional difference in the western region.

Table 3. The accuracy test result in the western region.

	FGM	DGMC	AGMC	CFDGM	ANN
MAPE (%)	1.26	0.66	0.85	1.30	3.82
RMSPEPR (%)	1.23	0.97	0.98	1.23	2.52
RMSPEPO (%)	1.93	0.02	0.73	1.99	5.60

According to DGMC, the comparative series change forecast showed results. Carbon dioxide emission intraregional difference reduction in the western region is driven by DGP, the total retail sales of consumer goods and fiscal revenue. Unfortunately, in future next two years, western region's carbon dioxide emission intraregional difference will display a slight increasing trend. The total retail sales of consumer goods difference in the declining trend means that social consumption will develop trend balanced in the western region in the future. High carbon emission commodity consumption will rise in the western region. However, differences in economic and fiscal revenues will expand in the CDED in the western region. Developed regions are usually accompanied by higher levels of industrialization, urbanization, and energy consumption. Economic expansion often is accompanied with higher carbon emissions Western regions are resource-rich. The resource curse has led some high-income local governments to rely on resource taxation. Economically backward regions lack smaller industrial scales despite lower carbon emissions in total but are unable to effectively reduce emissions through technological innovation. Financial resources are difficult to sustain in regard to energy transition investment. Therefore, western regions face the double dilemma of energy inefficiency and insufficient low-carbon technology in the future. CDED will show an upward trend.

4.2. Interregional Differences Forecast

4.2.1. Eastern–Middle Regions

The Eastern–Middle interregional CDED curve is shown in Figure 7. The accuracy test results are shown in Table 4. The overall interregional difference in the eastern-middle region showed a fluctuating upward trend. The forecasting model comparison showed that the ANN model has a large deviation from the actual value in general. FGM and CFDGM have better fitting performance, but the generalization performance is inferior. AGMC and DGMC obtains excellent performance through multivariate feature. DGMC accurately forecast future trends by capturing features of the CDED relationship through an adaptive accumulation process.

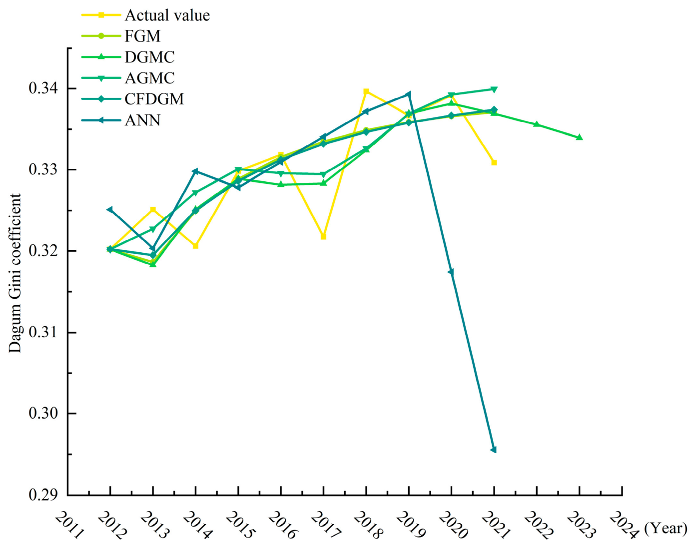

Figure 7. Carbon dioxide emission interregional difference between the eastern and middle region.

Table 4. The accuracy test result in the eastern–middle region.

	FGM	DGMC	AGMC	CFDGM	ANN
MAPE (%)	1.16	1.13	1.09	1.16	2.92
RMSPEPR (%)	1.56	1.36	1.31	1.51	2.79
RMSPEPO (%)	0.59	0.58	0.87	0.62	3.38

The feature selection results showed that difference between the eastern–middle regions mainly result in total import/export differences. As the economic centre of China, the eastern regions have a well-developed industrial base and high-technology equipment for production and processing. With the industrial shift to the middle region, the rapid development of an open economy in the middle will reduce the CDED. Eastern companies' transfer provides advanced management and production technology and improves energy utilization efficiency. External financial investment provides funds for cleaner production technology transformations in the middle region. The middle region integrated into an open economy extends the industrial chain and increases product's added value. The differences with the traditional economically developed regions will be gradually reduced. As interregional linkages strengthen, interregional CDEDs will consequently decrease.

4.2.2. Western–Eastern Region

The eastern–middle interregional CDED curve is shown in Figure 8. The accuracy test results are shown in Table 5. The overall interregional differences in the eastern–middle regions showed a fluctuating upward trend. The forecasting model comparison showed that the ANN model has a large deviation from the actual value in general. FGM and CFDGM have better fitting performance, but the generalization performance is inferior.

AGMC and DGMC obtain excellent performance through multivariate features. DGMC accurately forecast future trends by capturing features of CDED relationship through an adaptive accumulation process.

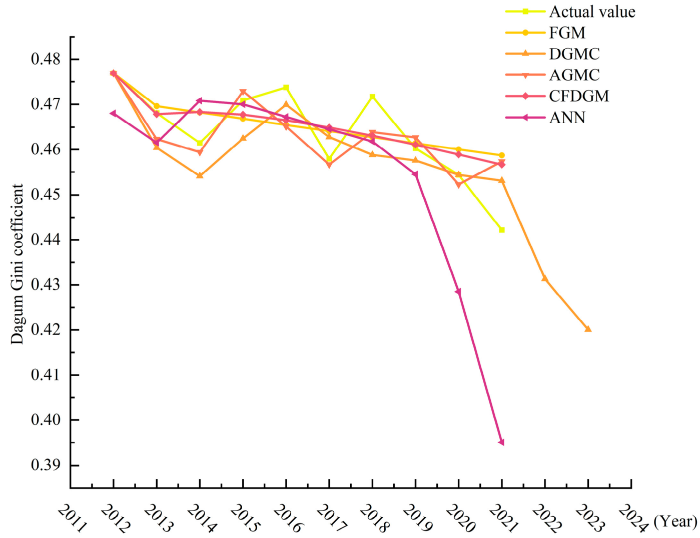

Figure 8. Carbon dioxide emission interregional difference between the western and eastern region.

Table 5. The accuracy test result in the western-eastern region.

	FGM	DGMC	AGMC	CFDGM	ANN
MAPE (%)	1.28	1.27	1.03	1.15	2.80
RMSPEPR (%)	1.20	1.41	0.97	1.14	2.40
RMSPEPO (%)	1.18	0.78	1.08	1.03	3.37

The feature selection results showed that differences between the western and eastern regions mainly result from the total import/export, GDP, GDP per capita, and patent granted. The total import/export and GDP are important indicators of the current state of regional economic development. Economic differences narrowed, meaning the level of economic development in various regions has balanced. Economic development model in Western-Eastern region has been transformed from traditional high-energy-consuming industry to technology-intensive, service and other low-carbon industry. Interregional synergistic development effect has been significantly enhanced. Technology diffusion not only reduced interregional technological difference, but also increased the accessibility of low-carbon technology. GDP per capita difference narrowed signalled homogenizing living standard and consumption capacity in Western-Eastern region. It will probably lead to similarities in consumption patterns, further reducing interregional CDED.

4.2.3. Western–Middle Region

The western–middle region interregional CDED curve is shown in Figure 9. The accuracy test results are shown in Table 6. The western–middle region interregional CDED is on a steady downward trend. The ANN model significantly differed from the actual value. FGM and CFDGM showed a smooth trend. The generalization of the model is low. DGMC and AGMC provided a better generalization performance by incorporating multivariate features. DGMC has a better generalization through preserving historical data feature.

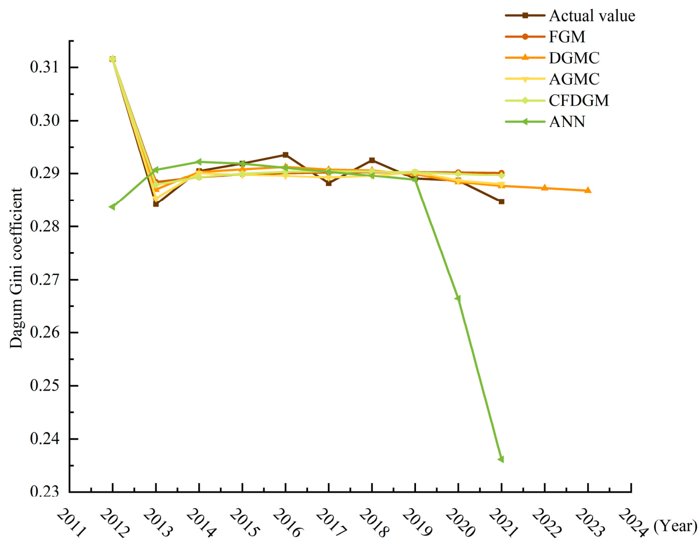

Figure 9. Carbon dioxide emission interregional difference between western and middle region.

Table 6. The accuracy test result in the western–middle region.

	FGM	DGMC	AGMC	CFDGM	ANN
MAPE (%)	0.81	0.51	0.56	0.75	3.92
RMSPEPR (%)	0.79	0.57	0.65	0.73	4.03
RMSPEPO (%)	0.59	0.32	0.36	0.54	5.40

According to feature selection results showed that difference between the western and middle region mainly resulted from cargo turnover, the total retail sales of consumer goods and the patent granted. The total retail sales of consumer good demonstrates the further expansion of consumption capacity and consumer market in the middle region. With the development of online trading platform and green logistics technology, retail industry carbon emissions reduced. Despite the high level of logistics activity in the middle region, the logistics industry carbon emissions have not increased significantly or benefitted from technology optimization. Production technology advance has increased energy consumption and carbon emission in the western region. Therefore, industrial upgrading and green technology application reduced the trend of carbon emission expansion in the middle region. Productivity improvement has increased carbon emissions in the western region. The western–middle regions' CDED will show a decreasing trend in the next two years.

5. Conclusions and Policy Recommendation

5.1. Conclusions

The research takes the carbon dioxide emission regional difference problem as the main line of research. Carbon dioxide regional difference forecast target is realized based on a multidimensional Dagum Gini coefficient difference correlation relationship. After empirical research, the specific research findings and policy suggestions are as follows.

(1) The Dagum Gini coefficient can correctly reflect the regional CDED. The Dagum Gini coefficient can reflect CDED in China. Filtering and wrapping methods are useful for multivariate grey time series forecasting. The grey correlation method can effectively eliminate unnecessary influencing factors. It significantly saves the time overhead of wrapping feature selection. Compared with other grey forecasting models, the new multivariate convolution DGMC model can achieve better forecasting results. The damping operator introduced into the current multivariate grey convolution model forecast field can better forecast CDED in China.

(2) The research analyzed CDED intraregional differences in the Chinese eastern, middle, and western regions. The results show that the eastern region's CDED intraregional differences will narrow. However, the western and middle region CDED intraregional differences will increase in the next two years.
(3) The research analyzes and forecasts interregional CDED in the eastern, middle, and western regions. In the two years, the eastern–middle, western–eastern and western–middle carbon dioxide emission interregional differences will decrease. CDED interregional differences will show significantly improvement.

5.2. Policy Recommendations

The emitter burden carbon emission cost is a vital way to achieve carbon peaking and neutrality goals. The carbon emission cost internalization will also impact social welfare. Regional historical CDED will directly affect carbon credit allocation. Therefore, carbon credit allocation is a crucial factor affecting emission reduction targets and maximizing social welfare achievements. It is necessary to pay attention to regional CDED sources and future trends and design emission reduction policies to achieve emission reduction targets. Therefore, the following recommendations are proposed after the research.

(1) Chinese CDED has both an interregional and intraregional presence. Therefore, the current stage of carbon dioxide emission reduction tasks in China should pay attention to regional differences and customize differentiated carbon reduction policies. Regional carbon emission credits should allocate energy consumption, residents' lives, and industrial structure as decision factors, guaranteeing regional economic and social development momentum.
(2) Interregional geographic, demographic, economic, and energy elements differ significantly. Middle and western regional governments should sufficiently consider regional industrial structures, energy intensity and residents life differences while designing carbon emission reduction tasks. The intraregional city should explore resource endowment to develop industries and form industrial mutual assistance and synergistic development models. The eastern advanced demonstration area should spread its mature energy consumption and environmental protection technology to promote cleaner production in other regions and achieve carbon capture and storage at carbon emission sources.
(3) Central government should pay attention to managing carbon emission regional equity issues in the future. Intraregional governments should pay attention to management carbon dioxide emission sources, strengthen industrial collaboration within urban clusters, improve factor resources spatial allocation efficiency, and promote city cluster industry-coordinated development. The middle and western regions should prevent the influx of high-energy-consuming and high-emission enterprises in undertaking industrial transfer processes to achieve economic growth and carbon emission decoupling.

5.3. Research Limitations

In addition, the study also has some shortcomings. Firstly, the study only researched the Chinese CDED problem and lacks a more comprehensive range of institutional, cultural background CDED empirical research. Secondly, the research only considers mainly CDED source influence factors from the present literature, and future research will screen a more extensive range of index to forecasting results accurately.

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Data Availability Statement: All data sets used for this paper are available at the CSMAR database and the carbon emission account datasets.

Conflicts of Interest: The author declares no conflicts of interest.

Abbreviations

CDED	carbon dioxide emission differences
GM	Grey model
FGM	Fractional-order grey model
DGMC	Damping grey multivariable convolution model
AGMC	Adjacent grey multivariable convolution model
ANN	Artificial neural network
CFDGM	Conformable fractional discrete grey model
MAPE	Mean absolute percentage error
RMSPEPR	Root Mean Square Percentage Error of Predicted Results
RMSPEPO	Root Mean Square Percentage Error of Predicted Outputs

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