International Journal of Innovation in Science and Mathematics
Volume 11, Issue 3, ISSN (Online): 2347–9051

Analysis of Climate Expectation Mitigation Based on Green GDP

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Date of publication (dd/mm/yyyy): 31/05/2023

***Abstract* – In the context of increasingly severe resource and environmental problems, the inadequacy of GDP as a core economic indicator that does not reflect resource and environmental factors is increasingly highlighted. In this regard, this paper analyzes the changes of other indicators such as climate globally under the influence of GGDP and the future evolution trend by collecting data on the impact of green GDP and other climate indicators in different countries worldwide and building a relevant machine learning model. Firstly, the green GDP is defined and the direct and indirect factors affecting the environment are selected as indicators, while the weight correction coefficients are introduced, and the green GDP model is revised using the entropy weight method combined with the variance coefficient method of combined weighting, resulting in the improved green GDP model. Subsequently, the factor system was constructed and the data were merged to establish a global climate mitigation expected impact model based on BP neural network, and the model generalization ability was better. On the basis of this, on behalf of the U.S. as an example, the green GDP data of the U.S. were substituted, and it was finally concluded that the change trend of the U.S. data was the same as that of the other four continents, and the model had good generalizability, and the accounting of green GDP could effectively mitigate the climate effect.**

***Keywords* – Green GDP, Portfolio Assignment Method, Climate Mitigation Expectations, BP Neural Network.**

I. Introduction

When the level of economic development was insufficient, the two functions of the environment for the economic system - providing resources and consuming waste - were considered unlimited. As the level of economic development increases and consumption upgrades, the demand for the two functions of the environment continues to grow rapidly, and their scarcity becomes increasingly prominent. At the same time, because the corresponding market mechanism is not sound, resources and environmental services are difficult to be optimally allocated through the market mechanism and have long been used as public resources without compensation, resulting in many problems such as excessive resource depletion and environmental pollution.

Against the background of scarce resources and increasingly severe environmental quality, GDP, as the core economic indicator, is not performing as well as it should, and the defects of neglecting resource input and environmental degradation are becoming more and more obvious. It cannot show the environmental situation corresponding to economic growth, cannot adapt to the requirements of sustainable development strategy, and cannot effectively measure and evaluate sustainable development. The reason is that in GDP accounting, resource and environmental factors are exogenous variables, and the potential assumption is that resource and environmental factors remain unchanged, but in reality, resources and environment have changed significantly, so the potential assumption is no longer valid, and it is necessary to make appropriate adjustments to GDP to

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obtain the real economic aggregate. Therefore, the inclusion of resource and environmental factors into the scope of GDP accounting has become a common expectation, and green GDP has emerged and become a hot topic in theory and practice for a while. However, green GDP accounting is a cutting-edge and innovative research project, and there is no successful experience in the international arena to learn from, so it takes a long time to explore and faces significant challenges to move from theory to practice.

Against the backdrop of global warming, the emergence of green GDP can promote a global movement for climate protection and make significant progress in mitigating the climate crisis. Therefore, green economic growth measurement methods still have a lot of research space and are of great practical importance.

II. Related Work

Back in 2012, Zhu used energy value theory to calculate the energy-monetary value of non-renewable environmental resources and non-renewable industrial auxiliary energy consumed by the agro-ecosystem in the Dongting Lake area of Hunan Province in 2009 by quantitatively analyzing the inputs and outputs of the agro-ecosystem, and then calculated the green GDP of the agro-ecosystem in the area [1]. Based on the data of Yulin city from 2006 to 2010, Zhang calculated the green GDP values and green GDP deduction indices of 12 districts and counties by estimating the depletion value of natural resources and pollution control costs. The green GDP value and green GDP deduction index of 12 counties were calculated by estimating the depletion value of natural resources and pollution control cost [2].

In 2013, Shen elaborated on the connotation of green GDP, combined with the characteristics of Baoding city's economic development and the existing statistical system, and constructed a green GDP accounting system for Baoding city, starting from two factors: natural resource depletion and environmental pollution loss [3]. Zhao analyzed the defects of the current GDP accounting and the problems faced by the implementation of the green GDP accounting system from the concepts of traditional GDP and green GDP. Zhao analyzes the shortcomings of the current GDP accounting system and the problems faced by the implementation of the green GDP accounting system, and points out the accounting methods of green GDP [4].

In 2016, Wang reviewed and summarized the concept of green GDP and the development and practice of its accounting methods in China and internationally. The analysis found that green GDP accounting monetizes the environmental impact of economic growth and deducts the cost of resource consumption and environmental degradation, and the obtained green GDP can reflect the actual growth of domestic economy more realistically, which can be used as a reference for management decisions [5]. Song constructed a system dynamics model to analyze the causal feedback model of the green accounting of the value of Chinese medicine resources, and studied the mechanism of the green development model of the Chinese medicine resources industry after the formation of the green accounting of the value of Chinese medicine resources [6].

In 2018, Wu developed an ecosystem GDP accounting system in Anhui Province under the framework of the Green GDP 2.0 accounting project to account for the total economic value of ecosystems and the products and services they provide to the region. The study showed that the accounting of ecosystem GDP can reflect the supporting role of ecosystem to economic and social development, and provide a basis for establishing an assessment mechanism for the effectiveness and efficiency of ecosystem protection [7]. Li established a green GDP accounting model based on the cost of pollution control in water environment. The analysis results showed

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that the green GDP index of Weichang County was 97.63%, and the intensity of industrial water pollution control was greater than that of livestock and poultry breeding wastewater and domestic wastewater pollution [8].

In 2021, Yin established the link between green GDP growth rate, green TFP growth rate, and integrated factor of production growth rate by drawing on the idea of Solow's total factor productivity measurement and conducting an empirical study on China's provincial data. The main driver of green GDP growth since the Tenth Five-Year Plan is the growth of integrated production factors [9]. In the same year, Jiang analyzed the status of GGDP accounting in the USA and Japan using literature collection, and comparative research methods. The results show that Japan focuses on environmental cost accounting and the US focuses on asset value accounting, both of which are based on the UN SEEA framework [11].

In 2022, Cai constructed China's green GDP accounting system based on the traditional national accounting system from the perspective of resources and environment, introducing relevant indicators such as the value of natural resource depletion and reduction, the value of environmental quality degradation, and the value of ecological benefit improvement, etc. Meanwhile, for the city of Chongqing, an example is given to account for the green GDP formed in 2018-2020, and the analysis shows that the city is developing [12].

III. Empirical Analysis

A. *Data Source*

The data in this paper come from the World Bank public database (https://data.worldbank.org.cn/), and we collected typical representative countries from five continents for analysis, which represent the overall global trend through five continents, including China (Asia), Germany (Europe), South Africa (Africa), Australia (Australia), and the United States (America). The information covers GDP, mineral resource depletion, energy depletion, net forest resource depletion, annual freshwater abstraction, nitrous oxide emissions, population density, electricity rate, and nitrogen dioxide emissions for these five countries. Some data presented are shown.

Table 1. Data source.

	1991	**1992**	**1993**	**2019**	**2020**
USA	6.16E+12	6.52E+12	6.86E+12	2.14E+13	2.11E+13
China	3.83E+11	4.27E+11	4.45E+11	1.43E+13	1.47E+13
Germany	1.87E+12	2.13E+12	2.07E+12	3.89E+12	3.89E+12
Australia	3.26E+11	3.26E+11	3.12E+11	1.39E+12	1.33E+12
South Africa	1.35E+11	1.47E+11	1.47E+11	3.89E+11	3.38E+11

The data exploration revealed some missing values in the extracted data, and these data's may have an adverse effect on the subsequent modeling results. Therefore, the data are pre-processed before the actual modeling. For some missing data, this paper adopts Lagrangian interpolation method for interpolation. Since the huge difference in the order of magnitude between the data will directly have a large impact on the results, in order to eliminate the influence of the order of magnitude between different indicators, this paper adopts the minmax standardization method to process the data. Subsequently, the changes of green GDP impact factors of each representative city are visualized and analyzed to grasp the overall trend of the data and facilitate the subsequent

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calculation, and the visualization results are shown in Figure 1.

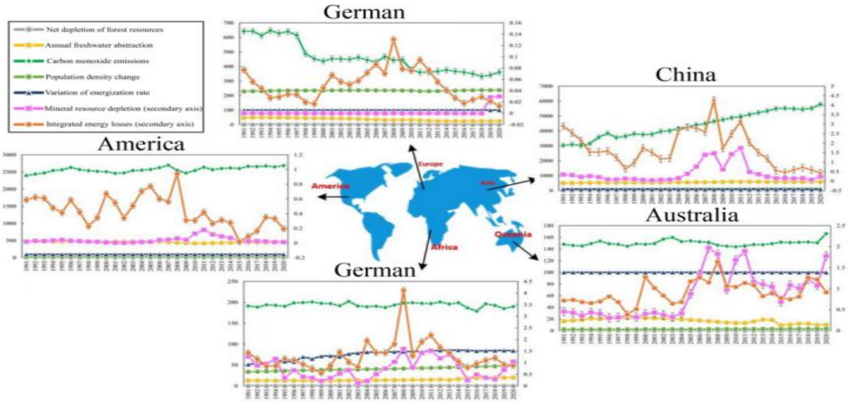

Fig. 1. The visualisation results.

B. *Construction of Green GDP Model Based on Meteorological Factors*

The current theoretical and empirical studies of green GDP differ in their formulation and lack a unified and standardized definition of green GDP. How to define green GDP is not just a conceptual debate, but a matter of whether it can conform to the accounting theory and further influence the accounting method and accounting scope. Based on the analysis, the definition of Green GDP in this paper is proposed: Green GDP is the total result of economic and environmental activities based on GDP by extending the scope of both inputs and outputs to the environment and resources, i.e., what is left of the current total GDP after deducting the cost of environmental resources and the cost of protection services to environmental resources. Therefore the formula for calculating green GDP, i.e. the existing model formula of GGDP, is confirmed as.

$$GGDP = GDP\text{-}M_1 - M_2$$

Where GDP is the gross domestic product, M1 is the cost of environmental resources, and M2 is the cost of environmental resource protection services.

We consider its impact on climate change and replace the cost of environmental resources and environmental resources protection services with the cost of consumption of direct climate impact factors (M1') and the cost of consumption of indirect climate impact factors (M2') according to different climate impact factors.

1. *Direct Climate Impact Factor Consumption Cost (M1')*

In the direct climate impact factor consumption costs, we consider the different regions of the five continents and consider that climate change directly affects the national mineral resource depletion (DMRC), the national combined energy depletion (DCEC), the net forest resource depletion (DFRC) and the annual freshwater extraction (DAFW) (billion cubic meters), as shown in the following equations.

$$M_1^{'} = DMRC + DCEC + DFRC + DAFW$$

2. *Indirect Climate Impact Factor Consumption Cost (M2')*

The indirect climate impact factor depletion costs are mainly from the loss of mining, energy, forest, and freshwater due to climate change fluctuations. It mainly includes the change in nitrous oxide emissions (InDNOE) due to the depletion of forest resources, the large change in population density (InDPD) due to the

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depletion of freshwater resources, and the change in energization rate (InDER) due to the depletion of energy and mineral resources, as follows.

$$M_2^{'} = InDNOE + InDPD + InDER$$

The finalized green GDP formula GGDP based on the impact of climate factorsc is as follows.

$$GGDP_c = GDP - M_1^{'} - M_2^{'}$$

Where, M1' is the consumption cost of direct climate impact factors and M2' is the consumption cost of indirect climate impact factors.

We then improved the model by assigning different weights a_1 and a_2 to the direct and indirect influencing factors, and the improved equation of the model is as follows.

$$GGDP_c = GDP - \alpha_1 \times M_1^{'} - \alpha_2 \times M_2^{'}$$

Then we used the entropy weighting method and the coefficient of variation method for the existing data collected to combine the weights and confirm the coefficient model, and the calculation process is as follows.

(1) First, the entropy weighting method is used to calculate the weighting of the direct climate impact indicators and the indirect climate impact indicators, according to the formula.

$$\omega_j = \frac{1-e_j}{n - \sum_{j=1}^{n} e_j}$$

where, e_j is the information entropy of j , $e_j = \frac{1-e_j}{ln(m)*sum(p_{ij}ln(p_{ij}))}$, m is the number of evaluation indicators, and p_{ij} is the proportion of indicators accounted for, calculated as follows.

$$p_{ij} = \frac{r_{ij}}{\sum_{j=1}^{n} r_{ij}}$$

Here, r_{ij} is each specific indicator, and finally we calculate the weight of each indicator W.

(2) Coefficient of Variation Method.

Depending on the impact of the different dimensions, we need to measure the degree of variation in each indicator using the coefficient of variation of each indicator with the following formula.

$$V_i = \frac{\theta_i}{\overline{z_i}}, \; i = 1, 2, \ldots, n$$

where V_i is the coefficient of variation of the indicator and O_i represents the standard deviation of the indicator, the weights of each indicator are,

$$W_i = \frac{V_i}{\sum_{i=1}^{n} V_i}, \; i = 1, 2, \ldots, n$$

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We assign weights $W1_i$ based on the weights obtained by the entropy weighting method and the weights $W2_i$ obtained by the coefficient of variation method by combining.

$$W_i = \frac{W_{1i} + W_{2i}}{2}$$

The direct and indirect indicator weights of climate impact factors for different representative countries are shown in Table 2.

Table 2. Indicator weights.

Countries	Methodology	DMRC	DCEC	DFRC	DAFW	InDNOE	lnDPD	InDER
China	CV	0.005	0.355	0.334	0.000	0.053	0.190	0.064
	EEM	0.180	0.076	0.073	0.029	0.233	0.186	0.233
United States	CV	0.007	0.323	0.444	0.000	0.061	0.046	0.118
	EEM	0.180	0.076	0.073	0.029	0.233	0.186	0.233
Germany	CV	0.006	0.134	0.269	0.000	0.318	0.258	0.014
	EEM	0.180	0.076	0.073	0.029	0.233	0.186	0.233
South Africa	CV	0.006	0.432	0.242	0.000	0.167	0.034	0.119
	EEM	0.180	0.076	0.073	0.029	0.233	0.186	0.233
Australia	CV	0.003	0.259	0.152	0.000	0.169	0.022	0.082
	EEM	0.180	0.076	0.073	0.029	0.233	0.186	0.233

The combined weight coefficients under different representative countries are finally solved in Figure 2.

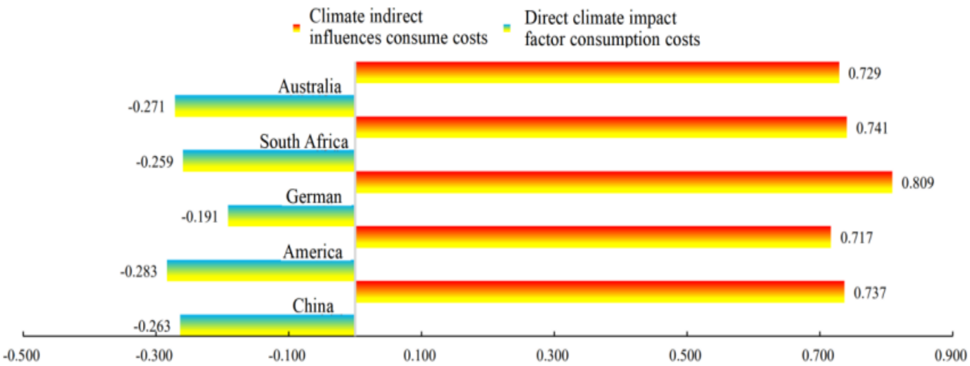

Fig. 2. Combined weighting factors under different representative countries.

The entropy weight method combined with the coefficient of variation method objectively calculates that the weight of the direct influence factor in the model is 0.254 and the weight of the indirect influence is 0.746, so we can conclude that the main factors affecting climate mitigation in different countries are some indicators that indirectly affect climate, but its analysis is relatively objective and more dependent on the change of data, so in the subsequent problem analysis, we will introduce human subjective factors, consider the actual situation, and analyze the changes of the model under different weights.

The final relationship between GDP and green GDP change for the five representative countries under this combined empowerment method is solved as shown in Figure 3.

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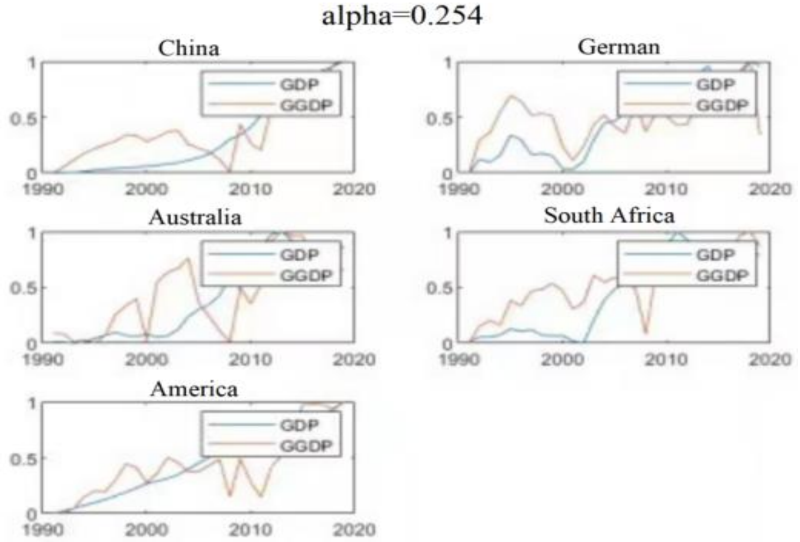

Fig. 3. The relationship between GDP and green GDP change in five representative countries.

C. *BP Neural Network-Based Model for Expected Climate Mitigation Impacts*

The BP (back propagation) neural network is a multilayer feedforward neural network trained according to the error back propagation algorithm, which is one of the most widely used neural network models, and was proposed by scientists led by Rumelhart and McClelland in 1986. In their influential book "perceptron", Minsky and Papert pointed out that a simple perceptron can only solve linear problems, and a network capable of solving nonlinear problems should have a perceptron layer, however, there is no reasonable theoretical basis for the learning law of hidden layer neurons.

Based on the different weight coefficients of direct and indirect influencing factors, we analyze the relationship between climate influencing factors and climate reduction, construct a nonlinear mapping relationship between them, and use a machine learning model to solve the model, and test the stability and accuracy of the model under different weight coefficients using the United States as an example. For climate change, we choose temperature (AT) and carbon dioxide (CO2) as evaluation indicators and construct a functional relationship with climate impact factors as follows.

$$(Y_1,\ Y_2) = f(X_1,\ X_2, ..., X_8)$$

Where X1 to X7 are the corresponding direct and indirect climate consumption costs, and X8 is the GDP data We used Pearson correlation analysis to test for the presence of multicollinearity between the variables and also to visualize the results. From the results, it is clear that there is no strong correlation between the variables, so all the variables can be used as inputs to build a machine learning model. On this basis, we take eight climate influencing factors as input variables and two climate change indicators as output variables to build a BP neural network model for training, and the data samples are all the data of four representative countries (China, Germany, South Africa, and Australia) from 1991 to 2020, and the four data sets are merged, and the size of the merged data set is 114 * 8. In the multiparameter in the BP neural network, the core content weights and threshold adjustment amount is used as a chain partial differential,In the model training process, the data set is shuffled, the proportion of the cut training set and validation set is 86% and 14%, and the planning and inverse planning are processed, and the final result of the model training is shown in the Figure 5.

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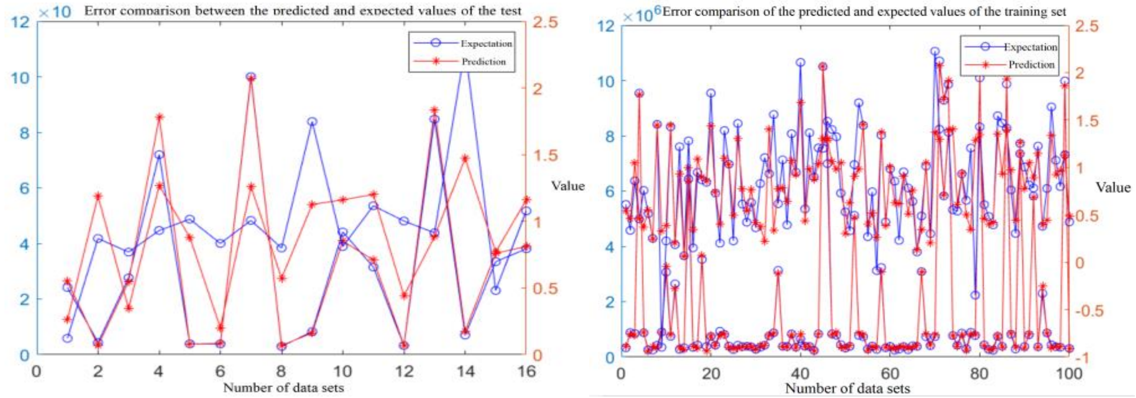

Fig. 5. BP neural network model training and fitting of predicted values to true values.

We then analyze the effect of green GDP data on the amount of temperature and carbon dioxide change under different countries. We use four continents to represent four countries with different characteristics, and take GDP with seven other influencing factors as input variables, and temperature and CO2 as output variables. The model is trained using BP neural network, based on which the GGDP under the four different countries is calculated separately, and the weights calculated using the combined assignment method in Problem 1 are substituted into the model for validation, and then the actual trends of temperature and carbon dioxide changes are analyzed with the trends of temperature and carbon dioxide changes after bringing the GDP into green GDP, as shown in Figure 6.

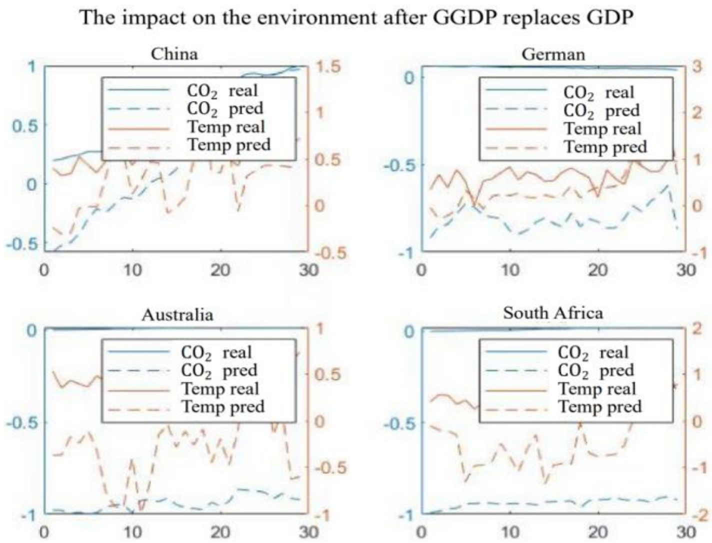

Fig. 6. Comparison of climate mitigation trends for four representative countries.

From the graph above, the overall trend after replacing GDP with green GDP is more moderate. The same conclusion can be drawn when the results of four different representative countries are combined. Therefore, it can be concluded that the replacement of green GDP contributes to climate mitigation on a global scale.

The four different countries represent the overall situation of these four different continents. Next, we will take the United States as an example to verify whether the weekly data has an impact on climate change reduction. We will calculate the green GDP data and the direct and indirect impact factors for the United States, and bring them into our previously trained model to verify whether the temperature and CO2 trends remain the same in the five different countries.

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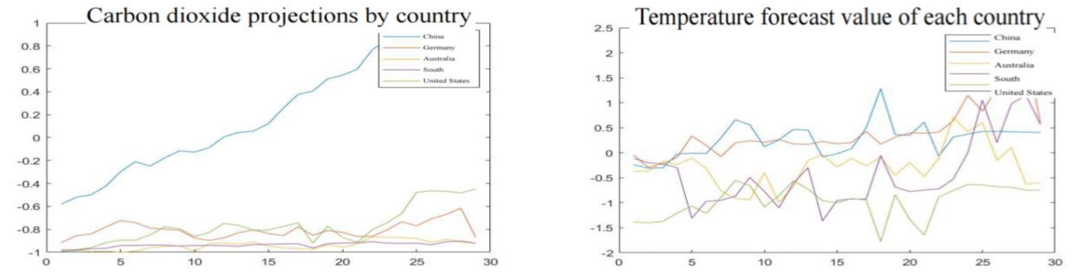

Fig. 7. Results of the validation of the US green GDP data compared to the other four countries.

Finally, the stability of the model is tested. Considering that the correction parameters of direct and indirect influences on the model are obtained by the objective assignment method and do not have certain realism, we further consider the human factors and re-correct the direct and indirect factors affecting climate by combining different geographical conditions, latitude and longitude, implementation policies and other subjective judgments. Four sets of cross-sectional comparison experiments are designed, with correction coefficients of 0.3, 0.4, 0.5 and 0.8 for direct climate influence factors and 0.7, 0.6, 0.5 and 0.2 for indirect climate influence factors, respectively, to observe whether the model remains stable under different weighting corrections. Again, green GDP data of the United States is used as an example for validation, and results obtained are shown in Figure 8.

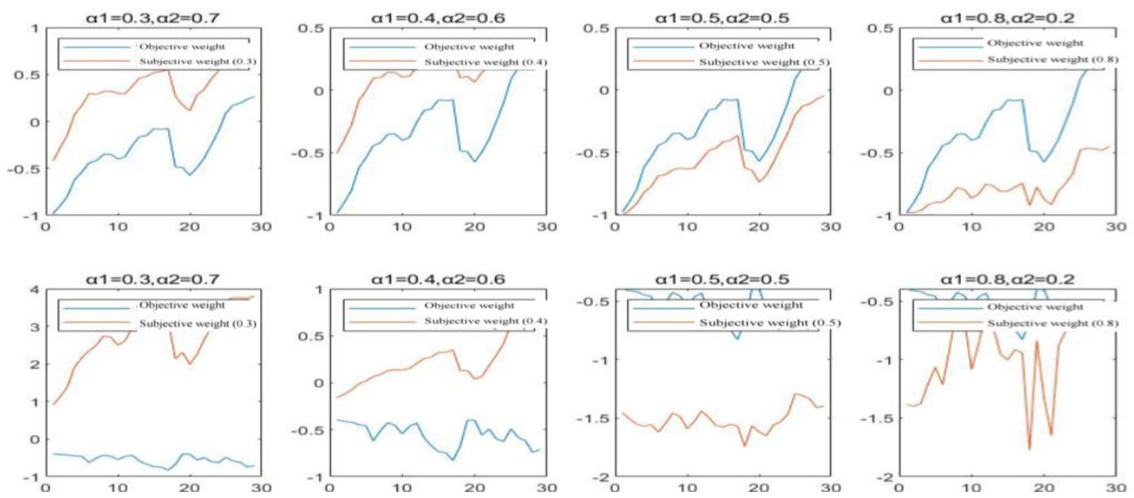

Fig. 8. Trends in temperature and CO2 versus the original control for different weighting correction factors.

As can be seen from Figure 8, the graphs maintain the same trend of change under different correction factors, in the change of CO2 emissions is to remain stable, fluctuate more when the temperature changes, but the overall tendency to rise.On this basis, we evaluate the model by calculating the generalization ability under each correction model based on the formulas of R2 (fitting coefficient), MSE (mean square error), RMSE (root mean square error), MAE (mean absolute error), and MAPE (mean absolute percentage error) this, and the results are shown in Table 3.

Table 3. Testing the generalization ability of the model with different weighting correction factors.

	$\alpha_1 = 0.254$	$\alpha_1 = 0.3$	$\alpha_1 = 0.4$	$\alpha_1 = 0.5$	$\alpha_1 = 8$
R^2	0.24547	0.70956	0.72782	0.74949	0.72216
RMSE	0.20354	0.21019	0.24715	0.21926	0.20747

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	$\alpha_1 = 0.254$	$\alpha_1 = 0.3$	$\alpha_1 = 0.4$	$\alpha_1 = 0.5$	$\alpha_1 = 8$
MAE	0.14208	0.16103	0.1886	0.17156	0.16297
MAPE	0.2155%	3.621%	13.7796%	1.1552%	0.98681%
ORD	5.4204	4.8404	3.9025	3.9615	4.758

IV. Conclusion

In this paper, we build a green GDP model to predict the mitigation effect of green GDP on climate, and we continuously improve the original green GDP model by assigning different weights and increasing the dimension of impact indicators for in-depth analysis. In the first part of the model, we consider the direct and indirect impact factors caused by climate, and analyze the data of five countries to represent the global data, and analyze more accurately through the combination of weighting method, except for the weight size of each indicator, to arrive at the improved green GDP model. In the second part, the expected impact of green GDP on climate mitigation is discussed in depth, a BP neural network model is constructed, the data of four countries are combined, and the conclusion that model has good generalizability is drawn from the data of the United States.

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