GGDP that Change the Climate

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Abstract. In this paper, we use the Entropy Weight Method (EWM) to calculate the weights and TOPSIS Algorithm to calculate the score. Then, we made a preliminary comparison between the results of the two systems. Then, in order to obtain precise relation, we use Grey Correlation Analysis to reflect the correlation between variables. By comparing the grey correlation coefficient between different years and different countries, it is concluded that the correlation between GGDP and climate is higher than GDP. Due to the nature of cross-sectional data, we introduce time series data for the exploration of long-term trend. Through establishing the Grey System Prediction GM (1,1) model based on the grey system theory, we forecast GDP and GGDP of different countries from 2020 to 2024 which is based on the data from 2010-2019. We use multiple linear regression to predict carbon emissions, and present the results with the change trend of carbon emissions.

Keywords: GGDP, Entropy weight method, TOPSIS, Grey Correlation Analysis.

1. Introduction

Today, the sea level is rising, the ozone layer is destroyed, acid rain corrodes farmland, and human diseases are increasing, which is mainly caused by air pollution, toxic waste and so on. Meanwhile, the world's economic system is booming and efficient in creating and distributing wealth, but it does not perform well in terms of resource utilization and sustainability. It can be seen that economic development is at the cost of ecological destruction [1]. Therefore, the creation and optimization of a good economic evaluation system that takes climate into account deserves our attention.

2. Using EWM-TOPSIS algorithm to build Climate model

We used cross-sectional data for 15 countries in 2019 to evaluate their climate conditions.

2.1. Calculate wights

Different indicators measuring climate have different impacts on climate. We use of entropy weight method (EWM) to calculate because of its objectivity. The EWM in information theory reflects the degree of information disorganization. It can measure the amount of information. The more information an indicator carries, the greater its impact on decision making [2]. When the values of evaluation objects of a certain index differ more, the entropy value is smaller, indicating that the index provides more information and the weight of that index should be larger. We can utilize the entropy theory of information to evaluate the orderliness and utility of each index [3]. The judgment matrix composed of the evaluation index values determines the weights.

First, based on the standardized indicators, we calculate p_{ij}, which is the proportion of the value of the *j*th indicator for the *i*th country. The n is the number of countries we select.

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} (0 \geq p_{ij} \leq 1) \tag{1}$$

Next, calculate e_j representing the entropy value of the *j*th indicator and its g_j representing coefficient of variation.

2.2. TOPSIS method

TOPSIS method is a multi-objective decision-making method [4]. The principle of TOPSIS method is to measure the positive ideal solution and negative ideal solution in the priority scheme, calculate the distance from each evaluation object to positive ideal solution and negative ideal solution respectively [5]. Then it obtains the relative proximity between each evaluation object and the optimal scheme, thus it can rank the evaluation objects.

We combine the relevant operational concepts and methods of entropy weight method and TOPSIS method to build the Climate Model. In order to further improve the objectivity and universality of the climate model, we use entropy weight w_i to construct a weighted normalized evaluation matrix Y, which is calculated as follows:

$$Y = \begin{bmatrix} y_{11} & y_{12} & y_{13} \\ y_{21} & y_{22} & y_{23} \\ \vdots & \vdots & \vdots \\ y_{n1} & y_{n2} & y_{n3} \end{bmatrix} = \begin{bmatrix} x_{11}w_1 & x_{12}w_2 & x_{13}w_3 \\ x_{21}w_1 & x_{22}w_2 & x_{23}w_3 \\ \vdots & \vdots & \vdots \\ x_{n1}w_1 & x_{n2}w_2 & x_{n3}w_3 \end{bmatrix} \tag{2}$$

Let *Y+* be the maximum value of the *j*th index in the evaluation data in the *i*th country, which is called positive ideal solution; *Y_* is the minimum value of the *j*th index in the evaluation data in the *i*th country, called the negative ideal solution, calculated as follows:

$$Y^{+} = \{maxy_{ijj} |\, j = 1,2,3\} = \{y_1^{+}, y_2^{+}, y_3^{+}\} \ \ (1 \le j \le 3) \tag{3}$$

$$Y^{-} = \{miny_{ijj} |\, j = 1,2,3\} = \{y_1^{-}, y_2^{-}, y_3^{-}\} \ \ (1 \le j \le 3) \tag{4}$$

We use the Euclidean distance formula [6]. Let D_i^+ be the distance between the *j*th index and Y_j^+, and D_i^- be the distance between the *j*th index and Y_j^-, calculated as follows. Where, Y_{ij} is the normalized value of the *j*th index in the *i*th country after weighting, and $Y_j^+$and $Y_j^-$are the most preferred and least preferred options of the *j*th index in the *i*th country.

$$D_i^{+} = \sqrt{\sum_{j=1}^{m} (y_j^{+} - y_{ij})^2} \tag{5}$$

$$D_i^{-} = \sqrt{\sum_{j=1}^{m} (y_j^{-} - y_{ij})^2} \tag{6}$$

Let T_i be the comprehensive evaluation index of the ith country, and its value range is between [0,1], calculated as follows:

$$T_i = \frac{D_i^{-}}{D_i^{+} + D_i^{-}} \tag{7}$$

Obviously, the larger the T_i, the better the evaluation effect of the sample.

3. The GGDP-Climate-Long term Model

3.1. Grey Relation Analysis: Based on historical data

In order to further explore the relationship between climate and GGDP and GDP, we introduce the time series data of 15 countries from 2010 to 2019 for grey correlation analysis.

Due to the magnitude difference between GGDP and GDP, we normalize it and adopt the initial value processing, where *i* is the number of indicators affecting climate, and *k* is the number of different moments.

$$x_i'(k) = \frac{x_i(t)}{x_i'(1)}, k = 1,2,\ldots,n \tag{8}$$

We have constructed the correlation formula of GGDP, GDP and climate:

$$\gamma(x_o, x_1) = \frac{1}{n}\sum_{k=1}^{n} \gamma(x_o(k), x_i(k)) \tag{9}$$

Where $\gamma(x_0,x_1)$ is the correlation coefficient of factor$x_i(k)$ to $x_0(k)$ at time k. And

$$\gamma(x_o(k), x_i(k)) = \frac{\min_i \min_k |x_0(k)-x_0(k)| + \zeta \max_i \max_k |x_0(k)-x_0(k)|}{|x_0(k)-x_0(k)| + \zeta \max_i \max_k |x_0(k)-x_0(k)|} \tag{10}$$

Among them, ξ is the resolution coefficient, and ξ E (0,1).

3.2. Forecast: Based on future verification

The grey prediction model is a model to reveal the continuous development and change process of things in the system, which is generally described by differential equation [7]. We choose the most typical GM (1,1) model [8].

With original time series data:$X^{(0)} = (X^{(0)}(1), X^{(0)}(2), \ldots, X^{(0)}(n))$, and $X^{(0)}(i)>0$, i=1,2,...,n. The steps to establish GM (1,1) model using the timeries data are as follows:

Step 1: Do 1−*AGO* generation. The sequence X (0) is generated by first-order accumulation, and the accumulated data sequence X (1) is obtained:

$$X^{(1)} = (X^{(1)}(1), X^{(1)}(2), \ldots, X^{(1)}(n)) \tag{11}$$

Where $X^{(1)}(1) = (X^{(0)}(1)$, $X^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)$, $k = 2,3,\ldots,n$.

Step 2: Build the GM (1,1) model from the first-order cumulative sequence, and obtain the corresponding first-order linear differential equation of GDP and time, where *a* is the development coefficient and *b* is the grey action.

$$\frac{dX^{(1)}(t)}{dt} + aX^{(1)}(t) = b \tag{12}$$

The corresponding grey differential equation is:

$$X^{(0)}(k) + aZ^{(1)}(k) = b, \quad k = 2,3,\ldots,n \tag{13}$$

According to the above differential equation, original data and processed data, the least squares regression test is performed to calculate the values of parameters *a* and *b*, and the calculation results are as follows:

$$\hat{a} = (a,b)^T = (B^T B)^{-1} \cdot B^T \cdot Y_n \tag{14}$$

Step 3: Model accuracy test. Use the above model to calculate the simulation value:

$$\widehat{X^{(1)}} = (\widehat{X^{(1)}}(1), \widehat{X^{(1)}}(2), \ldots, \widehat{X^{(1)}}(k)) \tag{15}$$

Do 1-AGO restore:

$$X^{(0)}(k) = X^{(1)}(k) - X^{(1)}(k-1) \tag{16}$$

Similarly, we forecast the GGDP, GM (1,1) model is:

$$\frac{dy^{(1)}}{dt} - 0.0808y^{(1)} = 3005463204656.00 \tag{17}$$

4. Results

4.1. Evaluation score of each country's climate

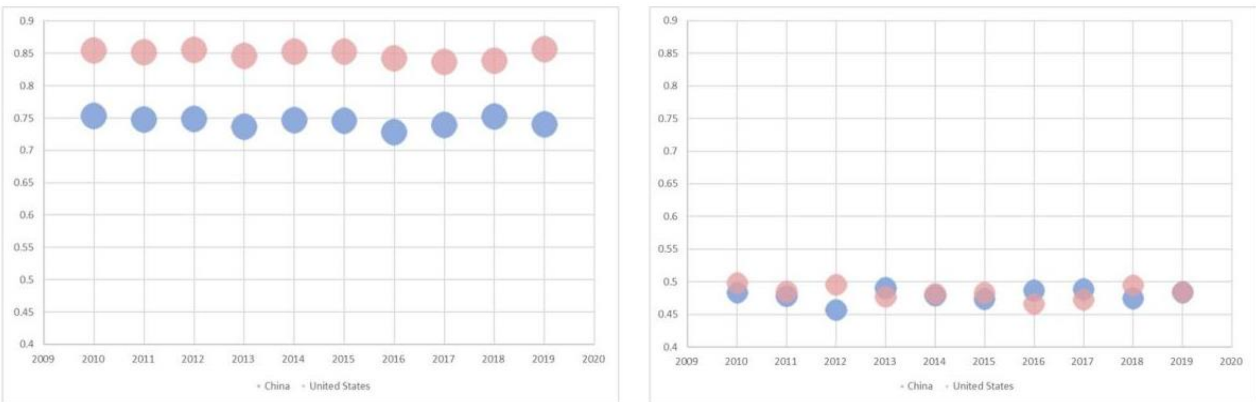
Based on the above discussion, we have obtained the final evaluation score of each country's climate. Ranking the overall scores of the selected countries in descending order. The result show in Table 1:

Table 1. Relevant values of weight of different countries with two methods

Rank	Country	Score
1	Brazil	0.91
2	United Kingdom	0.87
3	Denmark	0.84
4	Singapore	0.76
5	Egypt	0.74
6	India	0.68
7	Peru	0.63
8	Poland	0.55
9	Japan	0.48
10	China	0.43
11	Russia	0.37
12	South Africa	0.36
13	Canada	0.21
14	United States	0.18
15	Australia	0.12

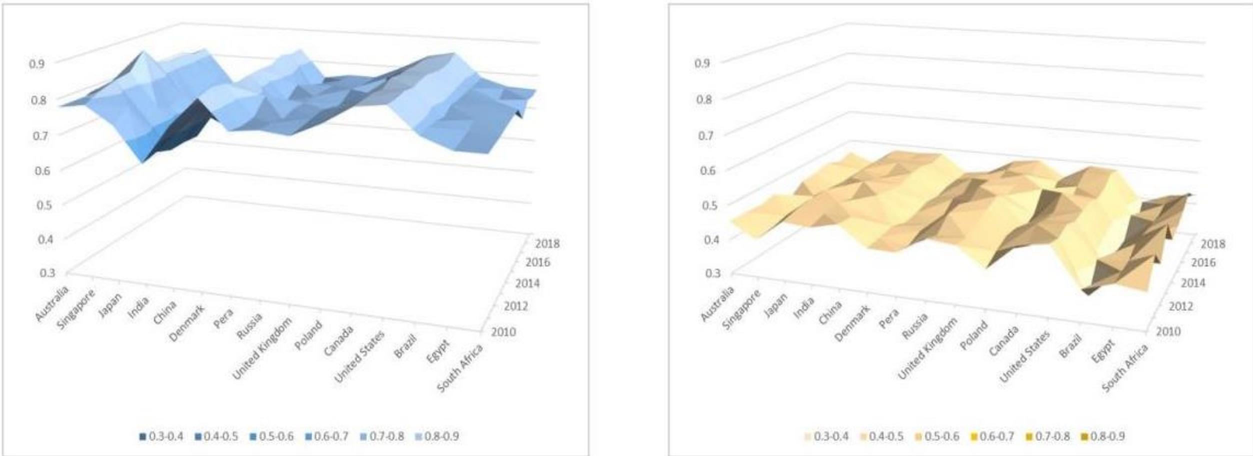
4.2. The results of the GGDP-Climate-Long term Model

Due to space limitation, we only show the results of the United States and China in figure1 and figure 2:



GGDP GDP

Figure 1. Grey correlation coefficient of GDP and GGDP



GGDP GDP

Figure 2. Grey correlation coefficient of GDP and GGDP in three-dimensional

The mean value of the grey correlation coefficient of each factor from 2010 to 2019 is obtained show in figure 3:

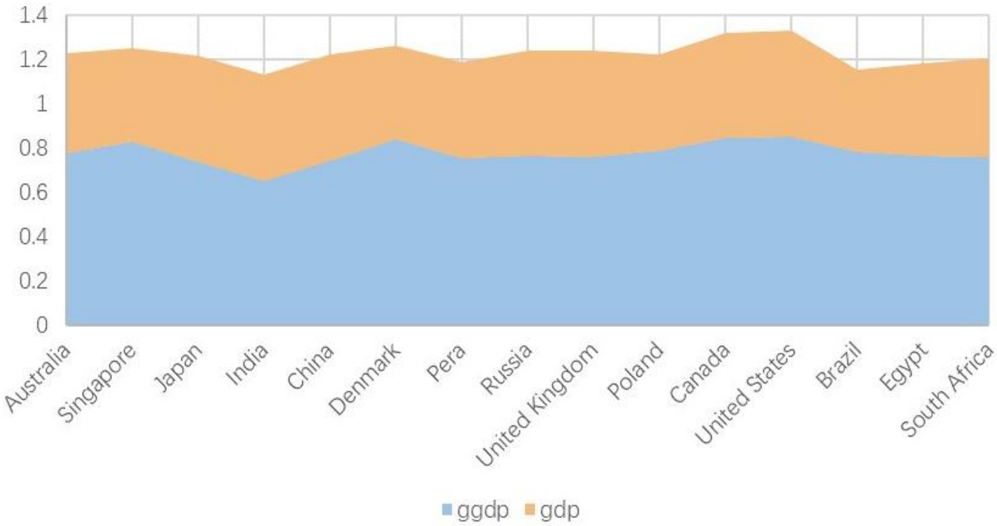


Figure 3. Mean value of grey correlation coefficient of DGP and GGDP

Based on the above results, the grey correlation coefficient between GGDP and climate is greater than 0.5, indicating that the correlation between GGDP and climate is very high and the impact on climate is strong; the grey correlation coefficient between GDP and climate is less than 0.5, indicating that the correlation between GDP and climate is low and the impact on climate is small.

4.3. Results of predictive value

Small error probability $P = 1 > 0.95$. Since the development coefficient $A = -0.0743 > -0.3$, the GM (1,1) model can be used for medium and long-term prediction. Posterior error ratio $C = 0.13086 < 0.35$, small error frequency $= 1 > 0.95$, so the accuracy of the model is level 1, and the model has excellent prediction effect.

Small error probability $P = 1 > 0.95$. Since the development coefficient $A = -0.0808 > -0.3$, the GM (1,1) model can be used for medium- and long-term prediction. Posterior error ratio $C = 0.13739 < 0.35$, small error frequency $= 1 > 0.95$, so the accuracy of the model is level 1, and the model has excellent prediction effect.

The predicted values of GDDP and GDP show in figure 4:

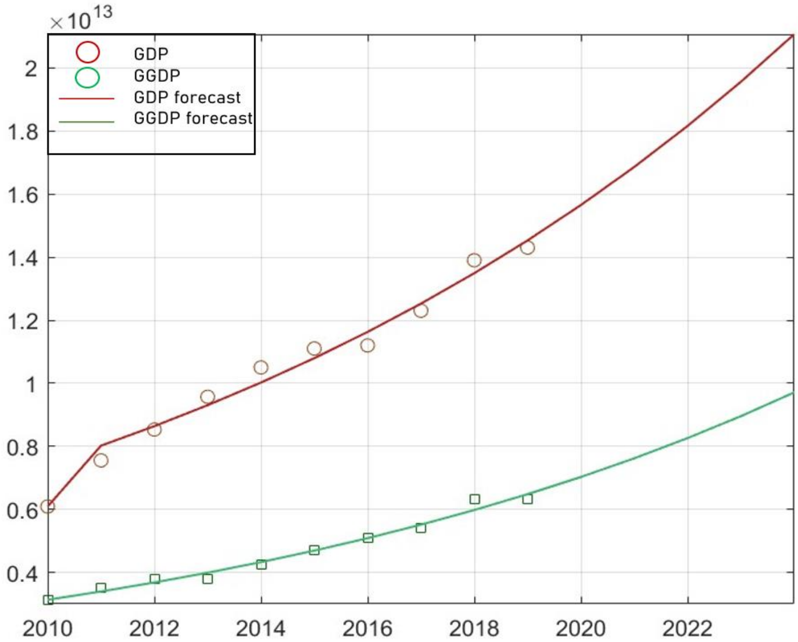


Figure 4. The predictive value of GDP and GGDP from 2020 to 2024

We select the data of GGDP and GDP of China from 2010-2024 and PCE for regression analysis to obtain the regression equations. We forecast PCE, and the results show in figure 5.:

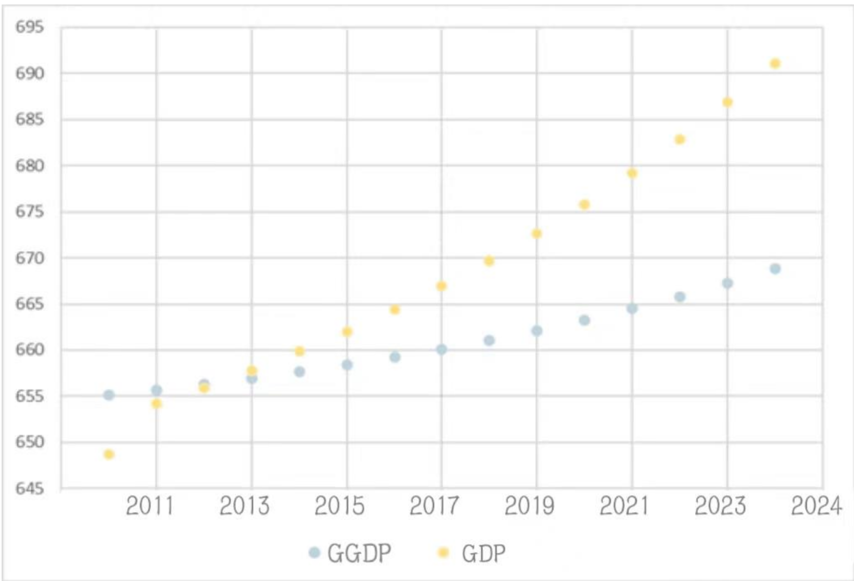


Figure 5. The PCE trend

5. Conclusion

There is a growing awareness of the imperative to decouple growth from environmental destruction. A sustainable development model that balances socio-economics and natural [9] ecology is applicable to tackle environmental challenges, and where development will no longer cost the Earth. Therefore, green GDP has attracted considerable attention from governments and the international community. Green GDP can effectively compensate for the shortcomings of traditional GDP evaluation that ignores energy efficiency and environmental pollution losses, and plays an important role in promoting the transformation and upgrading of industrial structure and transforming the economic and social development mode [10].

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