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Evaluation and Forecasting Models for GGDP

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Abstract. The evaluation and prediction of GGDP has important implications for global development. We derived positive and negative factors affecting climate change through indicator analysis. We then also developed a grey prediction model and a regression analysis model to predict global climate change. The analysis of the results shows that GGDP benefits from a reduction in carbon emissions of 1791.67665767 Mt C02/year. In addition, we used a quadratic non-linear regression model to analyze the environmental impact of the specific use of GGDP. The model proposed in this paper facilitates the evaluation and prediction of GGDP.

Keywords. GGDP, grey forecast, time series regression, non-linear regression model

1. Introduction

The development of countries often has certain negative effects such as increased income inequality, loss of leisure time and depletion of natural resources, especially the damage it can cause to the environment to a large extent [1]. To address the challenges posed by green growth and sustainable economic development, it is crucial that a new Green GDP (GGDP) indicator is created to quantify the costs of ecological and environmental degradation [2]. Although this indicator does not ideally reflect the true situation and improvement of countries, it can encourage individual countries and regions to focus on the level of green development and promote sustainable growth of a global green economy [3]. Therefore, it is crucial to properly assess GGDP and explore the mechanisms behind it.

2. Related Work

At present, relatively little research has been done on GGDP, focusing mainly on GGDP impact mechanisms. Liu et al [4] conclude that policy uncertainty mitigates GGDP across all quartiles using a panel quantile regression (PQR) analysis. Kousar et al [5] applied second generation unit root tests and cointegration techniques, CIPS unit root and

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Westerlund cointegration tests to establish stationarity of the series and cointegration between variables and found a negative and significant long-run association between GGDP and environmental degradation. Yi et al [6] proposed an integrated eco-efficiency framework based on energy value theory, GGDP and data envelopment analysis (DEA) to comprehensively assess regional sustainability. Other scholars have optimized traditional forecasting models to predict data under various scenarios. Deep learning techniques were found to be effective by Lim et al [7], who combined statistical models and deep learning models. By combining the ELES model and the GM (1,1) model, Luo et al. [8] examined and forecast the income elasticity of consumption demand in rural China. They discovered that while it was extremely high at the time, it would eventually trend lower. To predict the per capita income of rural residents, Meng et al. [9] built a fuzzy grey prediction model and tested the model's errors using fuzzy possibility. Lei et al.'s [10] proposal used small samples for precise long-term prediction to predict the income of rural residents in Shaanxi province using a grey model and an improved jellyfish search optimizer. There are also academics who forecast time series using different approaches. Maria [11] forecast tax revenue using digital tools, laying the groundwork for tax authorities to create policies. Neural network techniques were used by Timothy et al. [12] to predict hotel revenue, increasing the prediction's accuracy. In order to forecast China's fiscal revenue, Zhang et al. [13] took into account the impact factors of inflation and used time series methods.

The objective of this paper is to develop a model to assess the development of the country which needs to capture the impact of the climate environment. We need to model and analyze the effects of climate and discuss the advantages shown by models that take climate into account.

3. Model

3.1 Data

Based on the existing literature and the actual situation, we collected global data on environmental damage, resource depletion, weather conditions, etc. Due to the volume and complexity of the data content collected, we pre-processed the data before carrying out the data analysis. All missing values were removed by us. For outliers, we processed them using mean correction, using the average of the two observations before and after the outlier to correct the outlier.

3.2 GGDP Evaluation

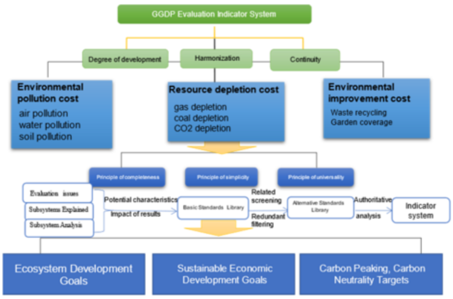

Figure 1. GGDP Construction Framework Diagram

Scholars have adopted the GGDP instead of GDP, which refers to a set of measures that adjust for social and environmental costs [14]. GGDP construction framework is shown in figure 1.

According to previous studies, GGDP can be divided into two types, for the first type of GGDP. First, GGDP = GDP-cost of resource depletion –cost of environmental pollution. But this type ignores the value of natural ecosystem services, so on this basis we have created a second type of GGDP. For the second type of GGDP: $SEP = ESP + GDP$. Here, SEP means Subtotal Ecological-economic Product, ESP is the abbreviation for Ecosystem Services Product, namely the value of ecosystem services. Although SEP is not GGDP, research has found it to be similar to GGDP.

One way of incorporating ecosystems into GDP accounting systems is green GDP accounting based on the value of ecosystem services. This approach allows for the introduction of external economies into market regulation. For ease of calculation, we have divided the green GDP accounting system into an economic, social, resource, and environmental systems. Specifically, the DDGP can be expressed by the following equation:

$$GGDP = k_1GDP + k_2GDP + k_3GDP + DES \tag{1}$$

$$k_1GDP + k_2GDP + k_3GDP = GDP \tag{2}$$

$$DES + ES1 + ES2 = ESP \tag{3}$$

Here, DES stands for direct ecosystem services. k_1, k_2 and k_3 represents the proportion of GDP generated by economy system, social system and resource system respectively. ESP stands for ecosystem services product. ES1 shows ecosystem welfare to other creature. ES2 shows ecosystem welfare to future generations. Therefore, the formula (1) can be abbreviated to formula (4).

$$GGDP = DGP + DES \tag{4}$$

Since the share of GDP and the share of the value of ecosystem services vary somewhat between countries and regions, k_1, k_2 and k_3 are not constants but have to be determined according to the characteristics of different situations. The SEEA system is a product of the consideration of SNA and the concept of a sustainable development economy. Based on the SEEA accounting system, the equation for GGDP can be expressed as:

$$GGDP = Traditional\ GDP - (Environmental\ pollution\ cost + Resource\ depletion\ cost) + Environmental\ improvement\ cost \tag{5}$$

The specific evaluation indicators and the calculation of the translation into economic benefits are as follows:

$$GGDP = GDP - (KtCO2 \times PCDM) - (Twaste \times 74kWh \times Pelect) - \left(\frac{GNI}{100} \times \%NRD\right) \tag{6}$$

where the first deduction presents the costs of CO2 pollution (as CO2 emissions times carbon market price), second the opportunity costs of one ton of waste that could be used in the production of electrical energy), and a third is the adjusted savings of natural resource depletion as a percentage of the gross national income per country.

3.3 Regression Analysis

In order to evaluate GGDP more specifically, we need to build a simple model to represent the impact on climate and carry out a global analysis. This can be done in terms of a time series regression analysis to analyze economic and climate change in the long term. The relationship between a set of predictor variables and a continuous response can be described using a fitted regression model and ordinary least squares. The independent variable is GGDP and the dependent variable is climate. We base our calculations on the historical statistics of the independent and dependent variables on which we model the regression equations, i.e. the regression prediction model

1) Model establishment

Through statistical analysis of the data collected, several key indicators affecting the GGDP have been selected. This section aims to develop a mathematical model of the relationship between global climate change and GGDP. Using the available annual data, with global climate y as the dependent variable and GGDP x as the independent variable, find a linear regression function or non-linear function $f(\beta, x1)$ that minimizes the sum of the squares of the errors between the sample data on global climate and the estimated global climate. The mathematical model of global climate change is:

$$\text{Objective function: } \begin{cases} y = f(\beta; x_1) + \varepsilon \\ E(\varepsilon) = 0 \end{cases} \tag{7}$$

$$\text{s.t. } \begin{cases} \min R(\beta) = \sqrt{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \\ \hat{y}_i = f(\beta, x_1)\ i = 1,2, \dots, n \\ m < n - 1 \\ n = n_y \text{ selected annual data} \\ f(\beta, x_1) \in C(x) \\ \beta \in R \end{cases} \tag{8}$$

2) Results

This subsection attempts to analyze the model solution for global climate using non-linear regression methods. Non-linear regression is used to examine the linear relationship between the independent and dependent variables. The p-value for the significance of the F-test is 0.001***, which presents a significance at the level and rejects the original hypothesis that the regression coefficient is 0. The model thus largely satisfies the need. From the analysis of the results, it can be concluded that GGDP and GDP have different impacts on the environment. After sensitivity analysis, GGDP is more suitable as an indicator for measuring climate. A quadratic non-linear model with global GGDP as the independent variable and global CO2 emissions intensity as the dependent variable is developed. Analysis of the F-test results shows a p-value of 0.000***, which is significant at this level. R2 indicates the degree of fit, and in our model, R2 is 0.832, indicating that the model has a good fit. The expression of the binary non-linear regression equation established is as follows:

$$y = -1.06118693e - 31x^2 + 1.07819204e - 17x + 2.92251097e - 4 \quad (9)$$

Results of the regression analysis are shown in figure 2 and table 1.

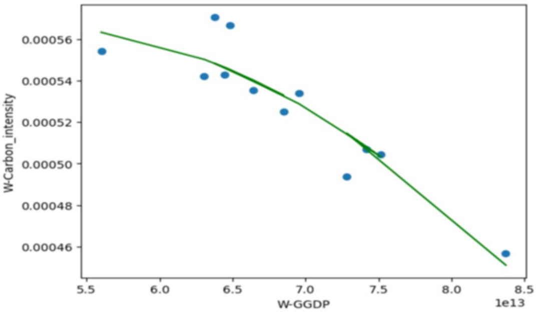

Figure 2. The result of the regression analysis

Table 1 World-Model fitting

Model	R^2	Adjusted-R^2	F	p
1	.832	.794	22.22	.000

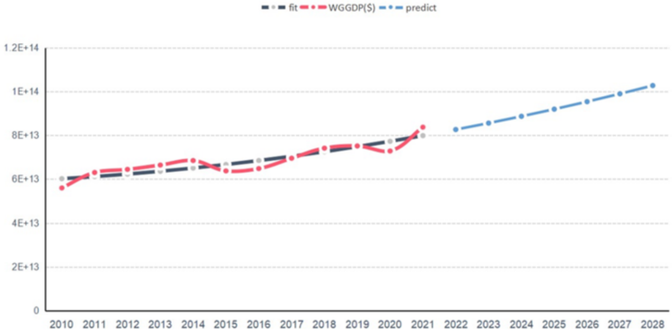

Figure 3. World GGDP projection chart for the next few years

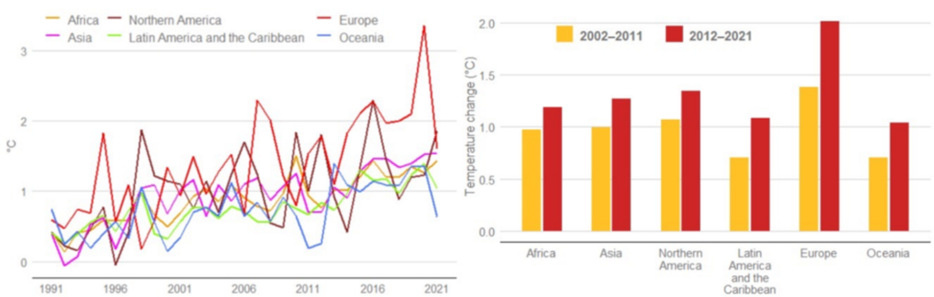

Figure 4. Global Temperature Change Comparison Chart

According to the results of the last decade, world GDP has been greater than GGDP and the slope of the two has been largely consistent. However, we have projected the trend of GDP and GGDP for the next few years and found that the use of GGDP would be beneficial in reducing carbon emissions and promoting a greener ecological environment. World GGDP projection chart for the next few years is shown in figure 3. Global Temperature Change Comparison Chart is shown in figure 4.

3.4 Prediction Model

1) Model establishment

Since GGDP will reduce pollution, it has environmental benefits while there are negative effects on the economy. Therefore, we still use the constructed correlation analysis or linear regression model to analyze the impact of GGDP. We developed a grey prediction model and a regression analysis model to predict the change in global climate after using GGDP.

Step1: From the given information a sequence of raw data of equal time interval is obtained:

$$X^0 = \{x_1^0, x_2^0, \dots, x_m^0\} \tag{10}$$

Step2: The original sequence of raw data: X^0 is cumulated once, and according to grey system theory, the cumulative data satisfies $x_k^1 = \sum_{i=1}^{k} x_i^0 (k = 1,2,\dots,m)$, from which the cumulative sum vector is calculated.

$$X^1 = \{x_1^1, x_2^2, \dots, x_m^1\} \tag{11}$$

Step3: For sequence X1, establish the differential equation in whitened form:

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

Parameters a and b are the parameters to be determined in the differential equation and are referred to as the development coefficient, whose magnitude reflects the growth rate of the series X0, and parameter b is the amount of grey action (endogenous variable). Parameters a and b can be solved by least squares.

Step4: Note that the parameter column $d = \begin{bmatrix} a \\ b \end{bmatrix}$, $B = \begin{bmatrix} -(x_1^1 + x_2^2)/2 & 1 \\ \cdot & \cdot \\ \cdot & \cdot \\ \cdot & \cdot \\ -(x_{m-1}^1 + x_m^1)/2 & 1 \end{bmatrix}$, $Y_n = (x_2^0, x_3^0, \dots, x_n^0)^T$. Then $d = (B^T B)^{-1} B^T Y_n$, $a = d(1)$ and $b = d(2)$. This leads to a differential equation model in whitened form:

$$x_{t+1}^1 = \left(x_1^0 - \frac{b}{a}\right) e^{-at} + \frac{b}{a} \tag{13}$$

Step5: After cumulative subtraction to obtain the forecast for year t+1:

$$x_{t+1}^{0} = x_{t+1}^{1} - x_{t}^{1} = (1 - e^{a})\left(x_{1}^{0} - \frac{b}{a}\right)e^{-at} \tag{14}$$

where x_t^0 reflects the original trend when $1 \leq t \leq m$ and is predicted when $t > m$.

2) Results

The grey forecasting model GM (1, 1) is based on historical period data to predict future period data and the average relative error of the model is 1.186%, implying a good model fit. Exploring the linear regression relationship between year and global GDP, the analysis of the results reveals that the F-test has a significant p-value of 0.000***, which is significant at the level and rejects the hypothesis that the regression coefficient is zero, therefore the model largely satisfies the demand.

The table below shows the development coefficients, the amount of grey action, and the posterior differential ratios. From the development coefficients and the grey role volumes, grey forecasting models can be constructed. The smaller the posterior difference ratio, the higher the accuracy of the grey forecast. From the table below, we can see that the posterior difference ratio is 0.107 and the model is highly accurate. Grey model construction is show in table 2.

Table 2 Grey model construction

Development factors a	Amount of grey effect b	Posteriori difference ratio c value
-0.009	34430825343.094	0.107

The table 3 shows the fitted results table for the grey prediction model. The smaller the relative error the better, in general, less than 20% means a good fit. As can be seen from the table, the average error of the model is 1.186%, which means that the model fits well.

Table 3 Model prediction results

Predicted order	Predicted value
1	38365813978.828
2	38702148055.023
3	39041430605.370
4	39383687477.680
5	39728944746.358
6	40077228714.396
7	40428565915.362

According to the python code results, a 0.1 increase in global GGDP is expected to reduce global carbon emissions intensity by 1791.67665767 Mt C02/year. According to the model results, it is worthwhile to use GGDP instead of GDP on a global scale as it helps to reduce carbon emission intensity and protect the environment. The above results show that the contradiction between environmental resources and economic development is gradually being eased under the promotion of energy-saving policies. Among them, carbon emission intensity is the main source of negative environmental impact.

A quadratic non-linear model with the independent variable being China's GGDP and the dependent variable being China's CO2 emission intensity was developed. Analysis of the F-test results shows that the pvalue is 0.000***, which is significant at this level. R2 indicates the degree of fit, and in our model, R2 is 0.917, indicating that the model has a good degree of fit. China-Model fitting results are shown in table 4. China's GGDP prediction results are shown in figure 5. The expression of the binary non-linear regression equation established is as follows:

$$y = 7.41265861e - 30x^2 - 2.38098704e - 16x + 2.60686400e - 03 \quad (15)$$

Table 4 China-Model fitting results

Model	R2	Adjusted-R2	F	p
2	.917	.898	49.558	.000

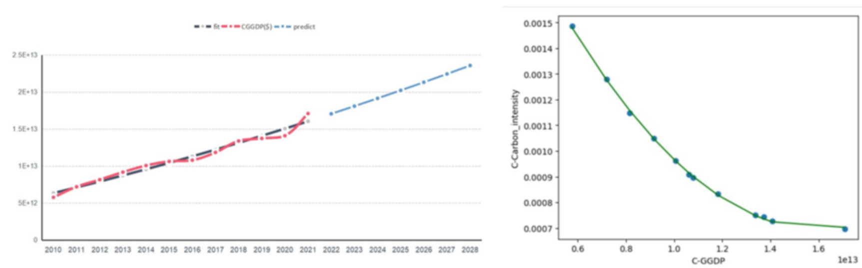

Figure 5. China's GGDP prediction results

4. Conclusions

In summary, a simple model for calculating GGDP was first developed through a review of the literature and available data. We then used the model to analyze the changes to the global climate. Finally, we have chosen a specific country for the analysis. The results of the data analysis show that the GGDP is worth replicating, as it can effectively reduce carbon emissions and facilitate green economic growth. Compared to traditional GDP, GGDP takes into account the environmental aspects of economic growth and has several advantages. (1) It facilitates the true measurement and evaluation of the actual level of economic growth. Since GGDP reflects the extent of natural resources consumed and environmental damage caused by human beings to promote economic growth, it can partially compensate for the shortcomings and deficiencies of traditional GDP. (2) Many countries and regions around the world are currently trying to compile GGDP, and China can learn from their experience. GGDP has strong operability and also facilitates international comparison.

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