Study on the Effectiveness of Green GDP Accounting System in Mitigating Climate Change- Based on ARIMA-LSTM Model

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Abstract. At present, the most widely used composite index to measure economic growth in the world is GDP and its growth rate, but this composite index does not sufficiently emphasize the importance of climate environment. In order to emphasize the greenness of development, it is necessary to establish a green GDP accounting system and test whether the green gdp system can mitigate climate change. In this paper, we first select seven direct climate impact indicators, including energy consumption and indirect climate impact indicators, and assign weights to the direct climate impact indicators by entropy weighting method to establish a green GDP accounting system. Then the climate prediction model based on ARMIMA-LSTM is established with CO2 emission and temperature change as evaluation indicators, and the model is trained to obtain the climate change under the GGDP system. This paper is important for measuring green GDP.

Keywords: ARIMA-LSTM; GGDP; Entropy method.

1. Introduction

Gross Domestic Product (GDP) is the final product of production activities of all the resident units in a country (or region) in a certain period. However, with the continuous development of the economy, more and more people point out that traditional GDP accounting does not take resource consumption and pol-lution into account.

GGDP (Green GDP) is GDP after deducting the cost of economic losses caused by envi-ronmental pollution, degradation of natural resources, poor education, population loss, mis-management, and other factors. "Green" refers to the inclusion of environmental and sustaina-bility perspectives and factors. This index essentially represents the net positive effect of na-tional economic growth. If nations change the ways they evaluate the health of economies, using GGDP instead of GDP, national governments may change their behaviors, stimulating policies and projects that are better for environmental health. This paper will establish a green GDP accounting system and test whether the green gdp system can mitigate climate change.

The measurement of green Total Factor Productivity (TFP) and its implications for sustainable development have been explored in various studies. Wang et al. (2018) utilized multiple variables and a slacks-based measure to derive green TFP, but their approach may overlook certain nuances and limitations[1]. The role of higher education in building a green economy has been emphasized by Gao et al. (2019), yet their empirical study may have limitations in capturing the complex relationship between higher education and economic development[2]. Spatial distribution analysis of green GDP in China was conducted by Yu et al. (2019), but the study's reliance on aggregated data may overlook regional variations and unique characteristics[3-4]. Hoff et al. (2020) analyzed Denmark's implementation of Green National Accounting, but their theoretical approach may not fully capture the political and administrative complexities involved[5-6]. The implications of trade openness on sustainable development in India were examined by Sheikh et al. (2020). However, the study's empirical examination may not account for all relevant factors influencing the trade-environment nexus[7-8]. Zheng et al. (2020) investigated the impact of promotion incentives on air pollution in China, but their reliance on panel data and specific time periods may limit the generalizability of their findings. Kalantaripor et al[9]. (2021) studied the spatial effects of energy consumption and green production in Shanghai Cooperation Organization member states, yet their focus on a specific region may limit the broader applicability of their results[10].

While these studies contribute to the literature, they have certain disadvantages such as overlooking nuances, limited generalizability, reliance on aggregated data, and potential gaps in capturing complex relationships. Our research addresses these limitations to further advance our understanding of green GDP and its implications for sustainable development.

To establish a green GDP accounting system, after searching for basic methods of calculation of GGDP, we choose one of the calculation methods - GGDP under SEEA framework. We selected climate data of 5 representative countries, combined this calculation method with climate fac-tors, and obtained GGDP Based on Climate Factors using Entropy Weights method. To test whether the green gdp system can mitigate climate change, we combined the collected indicators with GDP, took carbon dioxide emission and temperature change as evaluation indicators, built an ARMIMA-LSTM-based climate prediction model, and conducted training on the model. On this basis, GGDP of different countries is calculated respectively, and the weight calculated is brought into the model for verification, and then the actual change trend of temperature and carbon dioxide and the trend of temperature and carbon dioxide after GDP is replaced by GGDP are analyzed. Finally, the United States is taken as an example to test the stability of the model under different weight coefficients.

2. GGDP Based on Climate Factors

In terms of the specific accounting methods of GGDP, we select Resource And Environmental Value Loss Method, and revise the traditional GDP by constructing the account of "Resource Consumption Value" and "Environmental Pollution Value". The calculation method of GGDP is as follows:

$$GGDP = GDP - V_{RC} - V_{EP} \tag{1}$$

In Equation (1), V_{RC} represents "Resource Consumption Value", V_{EP} represents "Environmental Pollution Value".

On the basis of Equation (1), we consider the impacts of climate mitigation. Based on different climate factors, V_{RC} and V_{EP} are replaced by "Direct Climate Impact Cost" and "Indirect Climate Impact Cost" respectively. The calculation method of $GGDP_C$ is as follows:

$$GGDP_C = GDP - CIC_D - CIC_{IN} \tag{2}$$

In Equation (2), $GGDP_C$ represents GGDP considering climate factors, CIC_D represents "Direct Climate Impact Cost", CIC_{IN} represents "Indirect Climate Impact Cost". The specific details are as follows Figure 1:

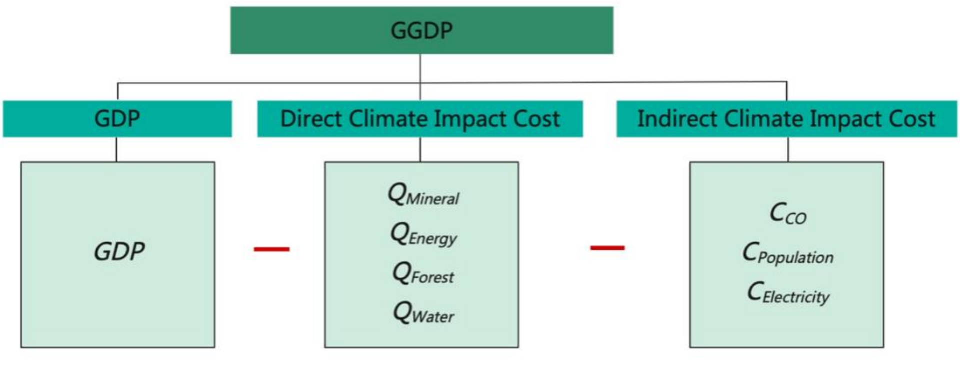

Figure 1: Calculation of GGDP

(1) "Direct Climate Impact Cost" contains factors that have a direct effect on climate. Based on comprehensive consideration, we selected four factors: National Consumption of Mineral Resources

($Q_{Mineral}$), National Energy Consumption (Q_{Energy}), Reduction of Forest Resources (Q_{Forest}), and Annual Freshwater Use (Q_{Water}). The calculation method of CIC_D is as follows:

$$CIC_D = Q_{Mineral} + Q_{Energy} + Q_{Forest} + Q_{Water} \tag{3}$$

(2) "Indirect Climate Impact Cost" contains factors that have an indirect effect on climate. Based on comprehensive consideration, we selected three factors: Changes in Nitric Oxide Emissions (C_{NO}), Changes in Population Density ($C_{Population}$), and Changes in Electrical Rate ($C_{Electricity}$). The calculation method of CIC_{IN} is as follows:

$$CIC_{IN} = C_{NO} + C_{Population} + C_{Electricity} \tag{4}$$

2.1. GGDP Based On Entropy Weights Model

Considering that "Direct Climate Impact Cost"(CIC_D) and "Indirect Climate Impact Cost"(CIC_{IN}) have different impacts on GGDP, we assign coefficients α_1 and α_2 to CIC_D and CIC_{IN} $respectively$. The improvement formula of $GGDP_C$ is as follows:

$$GGDP_C = GDP - \alpha_1 \times CIC_D - \alpha_2 \times CIC_{IN} \tag{5}$$

2.1.1 Data Processing and Visualization

Using the World Bank's publicly available database, we have selected five representative countries - America, Britain, China, Australia, and Congo - from five continents to reflect global trends. After considering the integrity and continuity of data, we merged data of seven climate indicators ($Q_{Mineral}$, Q_{Energy}, Q_{Forest}, Q_{Water}, C_{NO}, $C_{Population}$, $C_{Electricity}$) for the five countries from 1991 to 2020.

2.1.2. The Establishment of Entropy Weights Model

The Entropy Weights Method (EWM) is a widely-used information-weighting technique in decision-making, particularly in comprehensive evaluation studies that utilize various evaluation indexes. This method calculates the weights of different indexes based on their degree of dispersion. The index with a smaller entropy value indicates a higher degree of dispersion and consequently, a greater impact on the overall evaluation. Therefore, it should be assigned a greater weight.

In this topic, entropy weights of elements of "Direct Climate Impact Cost"(CIC_D) and "Indirect Climate Impact Cost"(CIC_{IN}) are determined to evaluate the extent to which they affect the Green GDP. This allows for a more accurate impact on measurable climate mitigation if Green GDP takes the place of GDP as the primary measure of economic health. The specific details are as follows:

(1) Determine if there are negative numbers in the input matrix and if there are, re-normalize to a non-negative interval. For 30 objects (30 years) to be evaluated and 7 evaluation indexes (7 climate factors), a forward matrix is constructed:

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1j} \\ \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} \end{bmatrix} \tag{6}$$

i is an integer in the range of [1,30], and j is an integer in the range of [0,7].

(2) Convert the forward matrix to the normalized matrix Z:

$$Z = \begin{bmatrix} z_{11} & \cdots & z_{1j} \\ \vdots & \ddots & \vdots \\ z_{i1} & \cdots & z_{ij} \end{bmatrix} \tag{7}$$

The elements in Z are denoted as:

$$z_{ij} = \frac{x_{ij} - min\{x_{1j,}x_{2j,}x_{3j,\ldots}x_{ij}\}}{max\{x_{1j,}x_{2j,}x_{3j,\ldots}x_{ij}\} - min\{x_{1j,}x_{2j,}x_{3j,\ldots}x_{ij}\}} \tag{8}$$

(3) Calculate the probability matrix M, and the specific calculation formula of element N in M is as follows:

$$p_{ij} = \frac{z_{ij}}{\sum z_{ij}} \tag{9}$$

Calculate the information entropy：

$$q_j = -\frac{1}{ln\, n}\sum_{i=1}^{n} p_{ij}\, ln(p_{ij})\ (j = 1,2,3,4,5,6,7) \tag{10}$$

Information utility value is defined as:

$$d_j = 1 - q_j \tag{11}$$

(4) The entropy weight of each climate factor can be calculated. The specific calculation formula is as follows:

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j}(j = 1,2,3,4,5,6,7) \tag{12}$$

The weights of each climate factor in five different countries are shown below Table 1:

Table 1: Weight Table of Climate Factors in Five Different Countries

	$Q_{Mineral}$	$\boldsymbol{Q_{Energy}}$	Q_{Forest}	$\boldsymbol{Q_{Water}}$	$\boldsymbol{C_{NO}}$	$\boldsymbol{C_{Population}}$	$\boldsymbol{C_{Electricity}}$
China	0.056	0.054	0.091	0.170	0.135	0.163	0.331
America	0.040	0.064	0.040	0.228	0.128	0.156	0.344
Britain	0.037	0.046	0.157	0.251	0.066	0.118	0.323
Congo	0.120	0.148	0.089	0.028	0.286	0.132	0.197
Australia	0.218	0.038	0.053	0.154	0.027	0.082	0.428

2.1.3. Results

We have selected five representative countries to calculate the weight of climate factors, so we weighted and averaged the weight of different climate factors in five countries to get the corresponding weight for Global.

Table 2: Weight Table of Climate Factors for Global

	$\boldsymbol{CIC_D}$				$\boldsymbol{CIC_{IN}}$		
	$Q_{Mineral}$	$\boldsymbol{Q_{Energy}}$	Q_{Forest}	$\boldsymbol{Q_{Water}}$	$\boldsymbol{C_{NO}}$	$\boldsymbol{C_{Population}}$	$\boldsymbol{C_{Electricity}}$
Global	0.094	0.070	0.086	0.166	0.129	0.130	0.325
Sum	0.417				0.583		

As can be seen from Table 2, the weight of CIC_D is 0.417 and the weight of CIC_{IN} is 0.583. The weight of CIC_{IN} is larger. Therefore, we believe that "Indirect Climate Impact Cost" (CIC_{IN}) has a greater impact on GGDP. Although the coefficient and weight are not directly equal, we roughly assign the weight to the coefficient α_i in this section. The calculation is shown below:

$$GGDP_C = GDP - 0.417 \times CIC_D - 0.583 \times CIC_{IN} \tag{13}$$

3. Climate Mitigation Prediction Based on ARIMA-LSTM Model

3.1. The Foundation of model

A novel combined nonlinear ARIMA-LSTM model is constructed by combining the advantages of neural networks and traditional time series forecasting models.
The original data are first decomposed into linear and nonlinear components and processed separately, for a given time series can be composed of linear$L_t$and nonlinear components N_t:

$$Z_t = L_t + N_t \tag{14}$$

The linear part $L_t$is fitted by ARIMA model and the nonlinear part $N_t$is fitted by LSTM model. The original data were fitted by the ARIMA model to obtain the predicted values $\hat{L}_t$ and residuals et:

$$e_t = Z_t - \hat{L}_t \tag{15}$$

In the ARIMA model, if the linear model is well defined, the statistical tests should not find linear correlations on the residual series. Therefore, it can be considered that the fitting of the error series is the treatment of the nonlinear relationships in the original data. The residual series are fitted by the LSTM model to obtain the predicted values $\widehat{N_t}$:

$$\widehat{N}_t = f(e_{t-1}, e_{t-2}, \dots, e_{t-n}) + \varepsilon_t \tag{16}$$

A nonlinear combined ARIMA-LSTM model was constructed with the help of a neural network tool. After combining Eqs. (9) and (10) and obtaining the prediction results for the linear and nonlinear parts, the LSTM model is used again, and the predicted values obtained from the above steps are used as inputs to find the complex connections between them by means of a deep neural network, and finally the prediction results are output:

$$\hat{Z}_t = f\left(\hat{L}_t, \widehat{N}_t\right) \tag{17}$$

In order to analyze the relationship between GGDP based on climate factors and climate mitigation, carbon dioxide and temperature are introduced as evaluation indicators to construct a functional relationship between them and GGDP:

$$(Y_1, Y_2) = f(X_1, X_2, \dots, X_8) \tag{18}$$

where $X_1 \sim X_7$ represent climatic factors, X_8 represents GDP
Afterwards, a heat map is drawn using MATLAB:

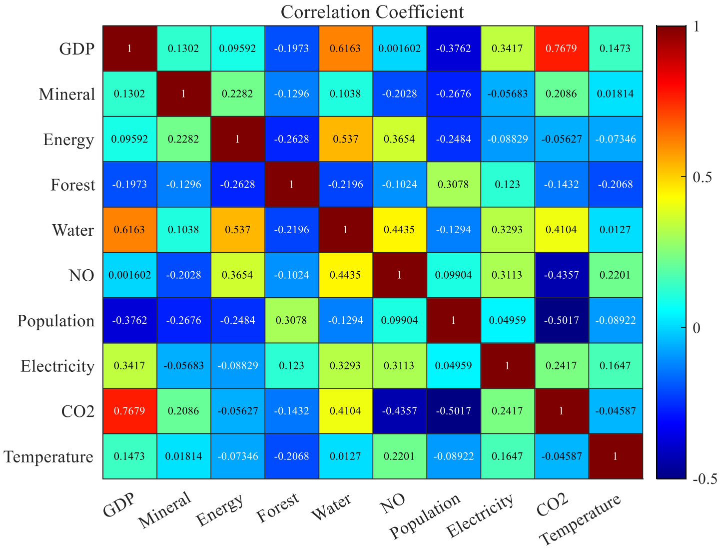

Figure 2: Heat Map of Climatic Factors and Evaluation Indicators

As shown by the Figure 2, the correlation between the variables is weak. $X_1 \sim X_8$ are input variables, Y_1 *and* Y_2 are output variables, ARIMA-LSTM models are constructed for prediction. Among them, the data used are those related to China, UK, Australia and Congo.

3.2. The Result of Model

The predicted samples were put into the ARIMA-LSTM model. Although the prediction results show a local estimation phenomenon, the overall prediction results are basically consistent with the measured values. The mean square error is 0.031229, indicating that the ARIMA-LSTM model can better predict the impact on climate mitigation.

3.3. Model Evaluation Indicators

In order to evaluate the prediction results from different perspectives, the mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE), respectively, are given by the following equations:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|f_t - d_t| \tag{19}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(f_t-d_t)^2}{n}} \tag{20}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{f_t-d_t}{d_t}\right| \times 100\% \tag{21}$$

The results are shown below Table 3.

Table 3: Evaluation Indicators

MAE	*RMSE*	*MAPE*
1.81	*2.15*	*2.02*

3.4. Comparison of Climate Mitigation Due to GDP Replacement of GGDP

The GDP and climate factors of four countries, China, Britain, Congo and Australia, are selected, and the GGDPs of different countries are calculated by combining the weights in problem 1 and brought into the BP neural network model for training to obtain the predicted temperature and CO2. the GGDP replaces the GDP leading to the climate mitigation change trend as shown in Figure 3:

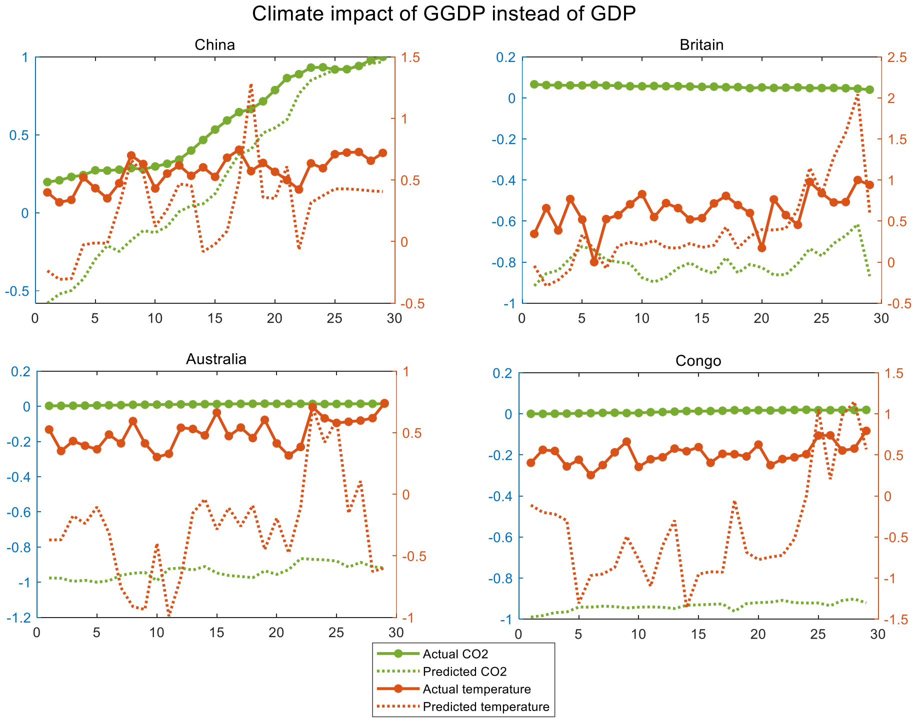

Figure 3: Comparison of Climate Mitigation Trends

The Figure 3 shows that both CO2 and temperature decrease after GGDP replaces GDP, and the overall trend is more moderate, so GGDP replacing GDP contributes to climate mitigation on a global scale.

3.5. Model Stability Test

The parameters obtained from Climate Mitigation Model are based on historical data by the entropy weighting method, while future climate changes are also influenced by various factors such as policies and geographical locations and so on. Thus, the coefficients of direct climate influences and indirect climate influences are adjusted to observe whether the model remains stable under different weights. In the validation process, the correction coefficients for direct climate impact factors are 0.3, 0.4, 0.5, and 0.8, while the correction coefficients for indirect climate impact factors are 0.7, 0.6, 0.5, and 0.2. The following figure 4 shows the results of four comparative experiments, using data on the green GDP of the United States for verification:

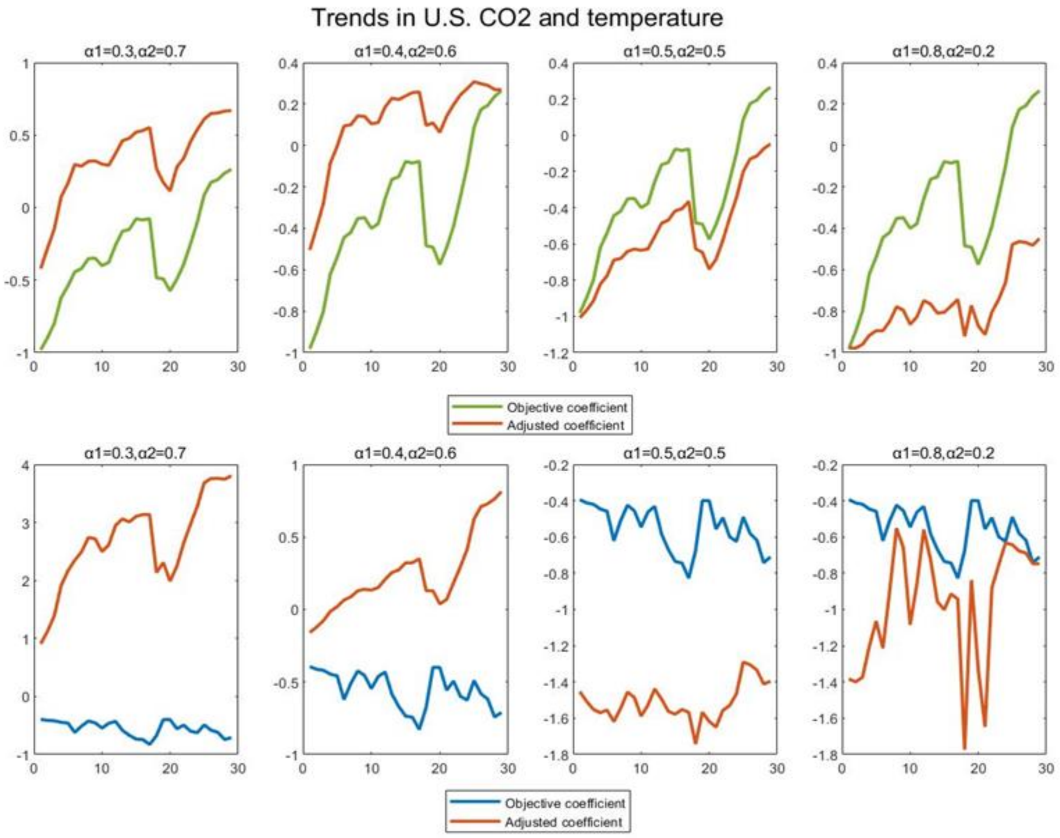

Figure 4: Temperature and CO_2 Trends In U.S.

From the Figure 4, it can be seen that the model has stable changes in CO2 emissions under different coefficients generally. And the temperature fluctuates, but the overall upward trend, so the model stability is relatively good.

4. Conclusions

In order to maximize returns, investors will often buy and sell volatile assets, and each transaction usually requires a certain commission. The time, frequency and quantity of the purchase and sale will have a key impact on the investor's return rate. This paper establishes a prediction and decision-making model based on data from all past trading days for us, and provides investment advice for investors in order to maximize returns. Then, a climate mitigation prediction model is developed using the ARIMA-LSTM methodology, with temperature and carbon dioxide serving as the assessment indicators. Through model training, a mean square error of 0.031229 is achieved, indicating excellent generalization ability. To further validate the stability of the model, various weight coefficients are imple-mented and the resulting trends are analyzed, ultimately confirming consistency.

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