Evaluation of Green GDP Implementation's Impact on Climate Change Mitigation Based on the AHP-CRITIC-CEI Model Under the Dual Carbon Goals

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Abstract. This study, based on the dual carbon goals, constructed an AHP-CRITIC-CEI integrated model to evaluate the impact of Green GDP implementation on climate change mitigation. By using AHP and CRITIC methods, multiple indicators were weighted and applied to the dataset of 44 countries. The grey prediction model was used for longitudinal analysis of the pre- and post-Green GDP reform conditions, and the results showed that the implementation of Green GDP significantly improved the relevant indices. Subsequently, an entropy-based K-means clustering method was used for horizontal comparison of the climate friendliness indices among countries, validating the positive impact of Green GDP on climate change mitigation and the adaptability of the model, providing scientific evidence for achieving the dual carbon goals.

Keywords: Green GDP; Entropy Method; RSR-VIKOR-PNA Integrated Model; K-means.

1. Introduction

Green Gross Domestic Product (GGDP) improves the representation of the output process by incorporating environmental physical variables and energy consumption indicators. The GGDP evaluation model includes physical variables such as resource consumption rate, pollutant diffusion rate, and energy efficiency, which allows for a more comprehensive reflection of material conservation, energy conversion, and system load during the production process. Compared to traditional GDP, GGDP focuses more on optimizing resource use and the physical constraints of environmental costs, thus providing important insights for improving system efficiency and long-term stability. This study will establish an evaluation model for GGDP by selecting key physical variables and analyze the model's impact on system stability and resource efficiency across different countries or regions, thereby providing technical support for optimizing production systems.

2. Method

2.1. Selection of the GGDP Accounting Model

The green GDP (GGDP) accounting system in this study is based on SEEA (2012), incorporating natural resources and environmental factors into the accounting framework to establish GGDP indicators. SEEA is the first environmental-economic accounting standard that combines national economic accounting with sustainable development principles. It retains the core structure of GDP accounting while adding statistical indicators for natural resources and the environment. Through accounting for environmental degradation and resource depletion, SEEA allows for the assessment of GGDP and its relationship with resource and environmental factors[4].

Based on the SEEA accounting system, the GGDP accounting equation can be expressed as:

$$GreenGDP = GDP - C_e - C_r \tag{1}$$

Where C_e represents the cost of environmental degradation, and C_r represents the cost of resource depletion.

1. Environmental Degradation Cost: Refers to the value of environmental pollution losses and the cost of environmental protection, covering air, water, and soil pollution. To provide a more

comprehensive assessment of environmental costs, this study selects carbon and SO_2 emissions as representatives of air pollution, wastewater discharge for water pollution, and solid waste emissions and storage for solid pollution, to estimate environmental pollution costs.

2. Resource Depletion Cost: Refers to the value of resources consumed during economic activities. This study calculates resource depletion costs based on fossil energy and water resource consumption.

Although environmental improvement costs (such as waste utilization and ecological benefits of urban green spaces) have a minor impact on GGDP calculations, this study adopts the accounting system shown in Fig. 1. The GGDP calculation method involves first estimating the physical quantities of environmental pollution and resource depletion based on industrial data, then converting them into monetary values. Finally, environmental degradation and resource depletion costs are subtracted from traditional GDP to derive GGDP.

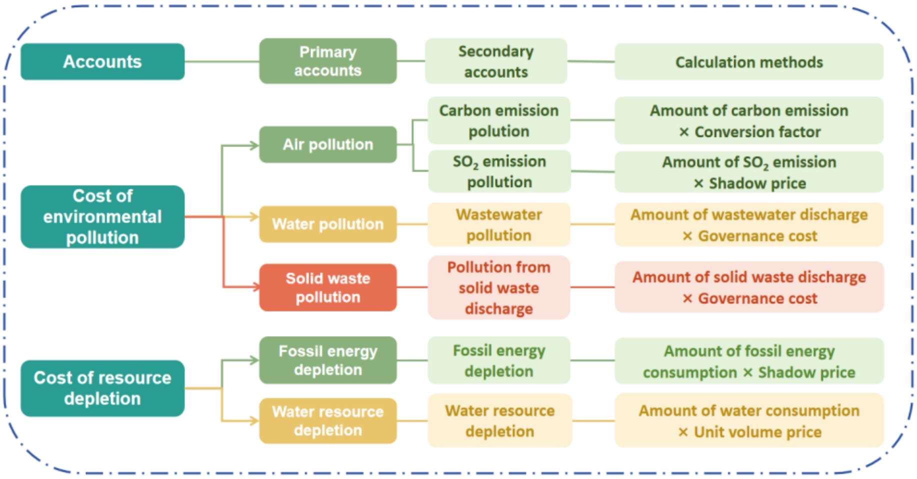

Fig. 1 GGDP Accounting System

2.2. Indicator Selection

1. Land Use Change: The distribution of carbon sources and sinks is mainly influenced by land use changes[1], which in turn have long-term effects on atmospheric greenhouse gas concentrations. We define land use changes as changes in the area of cultivation, abandonment, deforestation, afforestation, and crop rotation, and use these to estimate the annual carbon flux resulting from land use changes.

2. Agricultural Activities: The treatment of crop residues and the management of livestock manure are major sources of greenhouse gas emissions (CO_2, CH_4, N_2O), affecting climate change. By estimating the area of crop residue treatment and the scale of livestock farming, combined with emission factors, we calculate the annual flux of greenhouse gases.

3. Fossil Fuels: The variation in fossil fuel consumption between countries makes it difficult to assess their contributions to mitigating climate change. We will use the Energy Consumption Structure Index (ECSI) [3] to measure a country's dependence on fossil fuels.

4. Aerosols: The impact of aerosols on climate is complex[5], with negative effects mainly assessed through OC (organic aerosols) and SO_4^{2-} (inorganic aerosols), to evaluate their impact on the climate system.

In summary, the framework for measuring these impacts is illustrated in Fig. 2.

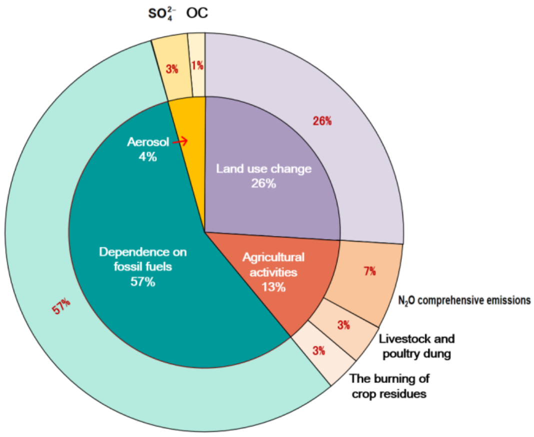

Fig. 2 Framework of Impact Indicator System

2.3. Calculation of Secondary Indicator Weights Based on the CRITIC Method

The CRITIC method [8] objectively determines indicator weights by measuring differences and conflicts between indicators, serving as an improvement over the entropy method. It accounts for both inter-indicator variation and correlation.

The calculation process is as follows: first, benefit and cost-type indicators with differing trends are normalized using vector normalization to achieve dimensionless values.

$$x_{ij}^{*} = \begin{cases} x_{ij} \Big/ \sqrt{\sum_{i=1}^{n} x_{ij}^{2}} \\ \sqrt{\sum_{i=1}^{n} x_{ij}^{2}} \Big/ x_{ij} - 1 \end{cases} \tag{2}$$

Where x_{ij} represents the initial value of each indicator; x_{ij}^{*} represents the normalized value of the indicator. Next, the weight of secondary indicators is calculated.

Calculate the information and conflict of the indicators using the following formula:

$$S_i = \sqrt{\frac{1}{n}\sum_{j=0}^{n}(X_{ij} - \overline{X}_{ij})^2} \tag{3}$$

$$\rho_{ij} = \mathrm{cov}(x_i^{'}, x_j^{'}) \big/ (s_i, s_j) \tag{4}$$

Where S_i represents the standard deviation of the normalized indicator i; $\overline{x_{ij}}$ is the average value of x_{ij}; ρ_{ij} is the correlation coefficient between indicator i and j.

The formula for calculating the amount of information E_j contained in indicator j is:

$$E_j = \zeta_j \sum_{i=1}^{n}(1 - \rho_{ij}) \tag{5}$$

The larger the value of E_j, the greater the weight of the indicator.

Based on the calculated amount of information, the weight σ_j of each indicator j is calculated as follows:

$$\sigma_j = E_j / \sum_{j=1}^{n} E_j \tag{6}$$

Finally, the weights of the secondary indicators are determined. For agricultural activities, the weights for burning crop residues, livestock manure, and NO_2 comprehensive emissions are 18%, 19%, and 63%, respectively. For aerosols, the weights for OC and sulfate are 33% and 67%, respectively.

2.4. Calculation of Primary Indicator Weights Based on AHP

The Analytic Hierarchy Process (AHP)[9] assigns weights through subjective judgment by decision-makers, dividing elements into hierarchical levels and establishing a judgment matrix. This study uses the common 1–9 scale to construct the judgment matrix and evaluate the importance of indicators. The process is as follows:

Calculate the primary indicator weights. The weight coefficients are obtained through the normalization process as follows:

$$W_i = \sqrt[n]{\prod_{j=1}^{n} C_{ij}} \Big/ \sum_{j=1}^{n} \sqrt[n]{\prod_{j=1}^{n} C_{ij}} \tag{7}$$

Where W_i is the eigenvector of the matrix and C_{ij} represents the matrix elements.

Perform a consistency check to ensure the reasonableness of the weight assignments and avoid conflicts. The consistency coefficient is calculated and compared to 0.1. If CI<0.1, the matrix passes the consistency check.

$$CR = CI / RI < 0.1 \tag{8}$$

$$CI = (\lambda_{\max} - n)/(n-1) \tag{9}$$

Where CI is the consistency index, λmax is the maximum eigenvalue, n is the order of the matrix, and RI is the random consistency index.

After these calculations, the primary indicator weights are determined as follows: land use change 26%, agricultural activities 13%, fossil fuel dependence 57%, and aerosols 4%.

2.5. AHP-CRITIC-CEI Model

Based on the existing Climate-Economy Index (CEI) model[1], this study integrates the Analytic Hierarchy Process (AHP) with the CRITIC method[10], normalizes the weighted Climate Friendliness Index (CFI), and incorporates it into the predictive model to develop the AHP-CRITIC-CEI multidimensional climate-economic prediction model. The specific formula is as follows:

$$\begin{cases} \mathrm{Climate_{ij}} = \mathrm{index_{climate\ ij}(normalzation)} \\ \Delta\mathrm{Climate_{ij}} = \sum_{p=1}^{j-1} \theta_1 \times \Delta\mathrm{Climate_{ip}} + \sum_{p=1}^{j-1} \alpha_i \times \Delta\mathrm{GDP_{ip}} + e_i\,, \theta_1 = \frac{\mathrm{Climate_{ip}}}{\mathrm{GDP_{ip}}} \\ \Delta\mathrm{Climate_{ij}} = \sum_{p=1}^{j-1} \theta_2 \times \Delta\mathrm{Climate_{ip}} + \sum_{p=1}^{j-1} \beta_i \times \Delta\mathrm{GGDP_{ip}} + e_i\,, \theta_2 = \frac{\mathrm{Climate_{ip}}}{\mathrm{GGDP_{ip}}} \end{cases} \tag{10}$$

Where $\mathrm{Climate_{ij}}$ reflects the climate situation of country i in year t, and $\Delta\mathrm{Climate_{ij}}$ reflects the climate change; $\mathrm{index_{climate\ ij}(normalzation)}$ is the normalized Climate Friendliness Index for country i in year t; θ_1 and θ_2 represent the coefficients reflecting the relationship between current and past climates; α_i and β_i represent the relationship between GDP, Green GDP (GGDP), and climate change; $\mathrm{GDP_{ip}}$ and $\mathrm{GGDP_{ip}}$ represent the normalized GDP and GGDP for country i in year t, respectively; $\Delta\mathrm{GDP_{ip}}$ and $\Delta\mathrm{GGDP_{ip}}$ represent changes in GDP and GGDP; and e_i represents the error term.

3. Experimental Analysis

3.1. GGDP Model Results Analysis

We input data from 44 countries between 1991 and 2010 into the model and used the least squares method to minimize the sum of squared deviations between observed and estimated values, calculating the relationship coefficients α_i and β_i for GDP, Green GDP, and climate change for each country. The results show that 39 out of 44 countries have a relationship coefficient $\alpha_i>0$, indicating that after adopting the Green GDP system, climate change has slowed in most countries, with a potential reduction in extreme weather events, suggesting that replacing GDP with Green GDP can promote climate mitigation and economic diversification. Conversely, 27 countries show a GDP relationship coefficient $\beta_i<0$, suggesting that focusing solely on GDP growth may lead to increased carbon emissions and resource overuse, exacerbating climate change and hindering sustainable development.

3.2. Feasibility Verification Results Analysis

3.2.1 Longitudinal Comparison

Among the 44 selected countries, we define those that implemented Green GDP reforms as "green countries" and the rest as "non-green countries." To evaluate the impact of Green GDP reforms on climate, we conducted a longitudinal comparison of climate changes before and after the reforms. Based on the literature, we identified that Switzerland, Ireland, France, and five other countries have implemented Green GDP reforms, and we determined their reform timelines. Using four primary indicators and seven secondary indicators from before the reforms, we applied grey theory[7] to predict the five-year post-reform outcomes. The forecast results for these countries without reforms were compared with the actual Climate Friendliness Index values. The comparison, as shown in Fig. 3, indicates that all countries' Climate Friendliness Index values post-GGDP reforms are higher than the hypothetical non-reform values. For instance, Switzerland's index after the reform is 0.9714, while the predicted value without reform is only 0.9280. This demonstrates that adopting GGDP instead of GDP encourages governments and businesses to focus more on sustainable development and environmental protection, positively impacting climate mitigation.

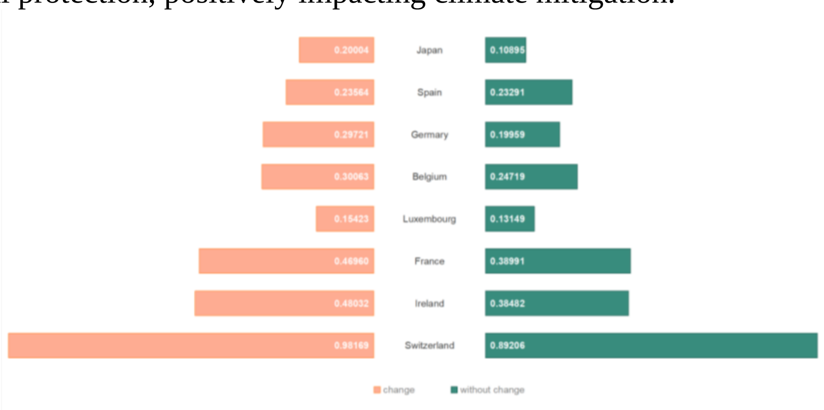

Fig. 3 Longitudinal Comparison Results

3.2.2 Horizontal Comparison

In 3.2.1, we conducted a longitudinal comparison of countries implementing GGDP reforms. Now, we compare the Climate Friendliness Index across countries using a clustering method based on entropy-enhanced K-means[6]. The results, shown in Fig. 4, group the 44 countries into three categories: environment-friendly, moderate, and environment-unfriendly. Countries that have implemented Green GDP reforms, such as Switzerland, Ireland, and Luxembourg, are classified as either environment-friendly or moderate, with none in the environment-unfriendly category. Conversely, most countries without Green GDP reforms fall into the environment-unfriendly group. This demonstrates that incorporating Green GDP, which accounts for resource consumption, environmental pollution, and ecological degradation, encourages governments to adopt policies promoting renewable energy and environmental protection, thereby reducing greenhouse gas emissions and mitigating climate change.

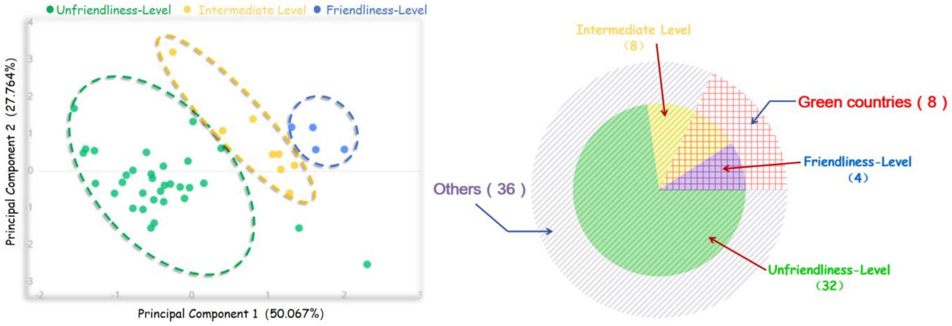

Fig. 4 Visualization of E-K-means Clustering Result

4. Summary

Through the comprehensive analysis of multiple environmental physical parameters, this study developed an AHP-CRITIC-based Green GDP accounting model and validated its effectiveness in climate mitigation. Data analysis and E-K-means clustering results show that Green GDP reforms significantly promote environment-friendly countries, confirming the model's physical feasibility and technical value. The case study of Chile, combined with ARIMA forecasts, indicates that the proposed policies have long-term environmental optimization potential. Sensitivity analysis revealed the dynamic behavior of key parameters, providing insights for future model improvements. Overall, this study offers robust scientific evidence for driving green economic transformation through physical modeling.

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