Assessing the Climate Impact of Green GDP: A Model for Estimating Global Climate Mitigation Effects

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Abstract. This article develops a comprehensive model for estimating the global climate mitigation effects through the lens of Green GDP (GGDP). By integrating environmental costs—such as pollution treatment and natural resource consumption—into the traditional GDP framework, the study offers a more accurate representation of sustainable economic health. Key elements considered include air, soil, and water pollution treatment costs, as well as the consumption of natural resources. The model applies linear algebra to quantify the GGDP and analyzes the data for both China and the United States, demonstrating that while the U.S. experienced a 48.6% reduction in GGDP, China's GGDP became negative, reflecting severe environmental costs outweighing economic growth. Furthermore, the study builds a regression model to explore the relationship between environmental factors and global temperature, highlighting the significant impact of carbon dioxide emissions, water consumption, and solid waste on climate change. The findings underline the importance of GGDP as a measure of sustainable economic growth and its potential for guiding climate mitigation policies globally.

Keywords: Green GDP (GGDP), Climate Mitigation, Environmental Costs, Pollution Treatment Costs, Sustainable Economic Health.

1. Introduction

In recent years, space exploration has become increasingly popular. Elon Musk, the CEO of SpaceX, believes that humans need to become a "multi-planetary species" and eventually establish a presence on other planets for a variety of reasons. One of the most crucial factors, he believed, is that the earth is vulnerable and is continuously degrading because of the climate deteriorating and changing. While the prospect of colonizing other planets and discovering new forms of life is exciting, it is essential to remember the importance of protecting the environment on our own planet. The fragile systems that make space exploration possible serve as a reminder of just how delicate our planet is and how important it is to manage it carefully. Investing in environmental protection and taking steps to minimize our impact on the planet can help ensure a sustainable future for society and future generations.

Gross Domestic Product (GDP) is a commonly used measure of a country's economic performance. A high GDP is seen as an indicator of a strong and prosperous economy. However, when considering what real 'economic health' is, and a sustainable economy is a good economy. Xu Jiayin (2024) points out that traditional GDP overlooks critical environmental benefits, leading to an incomplete understanding of economic health [1]. Indeed, a rising corpus of research criticizes GDP for failing to account for environmental deterioration and natural resource depletion. Traditional GDP measurements, which concentrate on market-based transactions, neglect the externalities associated with environmental impact, resulting in a distorted image of economic well-being. This gap has prompted the development of more comprehensive metrics, such as Green GDP (GGDP), which aims to include environmental costs into economic calculations. Hence, whether Green GDP (GGDP) be a better and more rational way to measure the actual "economic health" with continuous development has been considered and discussed recently.

While GGDP provides a more complete method to measuring economic success by accounting for environmental costs, it is not without limits. Existing research has noted many problems, including a lack of defined methodology for estimating GGDP across nations. This variability makes it difficult to compare GGDP numbers globally. Furthermore, many GGDP models fail to take into account all essential environmental factors, including biodiversity loss and long-term natural resource depletion. This has reduced the use of GGDP as a tool for directing policy choices.

In light of these deficiencies, this study presents numerous significant additions. First, it provides a standardized methodology for measuring GGDP that accounts for cross-national differences, resulting in more accurate and comparable findings. Second, it broadens the definition of GGDP by include new environmental considerations including pollution treatment costs and total natural resource use. By improving the GGDP model, this study not only fills gaps in the current literature but also gives policymakers a more dependable tool for balancing economic development and environmental sustainability. Furthermore, via a rigorous examination of both established and emerging nations, the research provides insights into how economies at various stages of development might put GGDP into practice to achieve long-term growth.

2. GDP calculation method based on external environmental impact

According to the Accounting System of Green GDP from Feng, Ruiqi, Junyao (2020), this paper selects the most thoroughly and straightforward way to calculate Green GDP, which is to consider the impact of the external environment on top of the original basic GDP calculation formula, which only considers the total value of productivity within the country, while Green GDP mainly considers environmental issues and sustainable development policies besides the fundamental GDP. Green GDP offers a more rational way to measure the actual 'economic health' with continuous development, as it accounts for environmental degradation and the depletion of natural resources. Siyao Yi (2020) explains that Green GDP provides a more holistic assessment by incorporating the costs of resource depletion and pollution treatment [2]. Therefore, the indicators of green GDP in this paper will consider the factors that can be correlated with climate change. The variables selected in the model mainly include the cost of pollution control caused by natural resources and the value of natural resource consumption. Nawapanan et al. (2022) support the importance of categorizing pollution sources for accurate Green GDP calculation, noting three main pollution areas in their model: air pollution (e.g., CO_2 and SO_2 emissions), soil pollution (e.g., waste soil treatment), and water pollution (e.g., toxic wastewater impact) [3]. Therefore, Yang Qijie (2022) notes that integrating pollution sources, such as air and water pollution, is essential for accurately assessing the impact of economic activities on environmental health in Green GDP models [4]. The pollution factors can be divided into three areas. First, air pollution includes emissions of carbon dioxide and sulfur dioxide. Second, soil pollution costs include the treatment of waste soil generation and storage of waste soil. Finally, water pollution includes toxic wastewater that affects overall water quality. Also, the model needs to consider the value consumption of natural resources. Therefore, the model in this paper uses a direct input-output model. By calculating the original GDP data and then directly subtracting the multiple variables we considered using a linear relationship. This model considers the correlations between the variables. Through the equations of linear algebra, the model is formulated as.

$$\mathrm{GGDP} = \mathrm{GDP} - (\mathrm{E_a} + \mathrm{E_s} + \mathrm{E_w}) - \mathrm{R_c} \tag{1}$$

The final green GDP value presented in the formula will be measured consistently across countries in US dollars. Based on the model, this paper chooses two typical samples to explain and verify the model calculation, one of which is China, a developing country, and the other is the United States, a developed country. Through the calculation of the above variables, this paper will elaborate and explain the construction of the calculation model for GGDP. As Zhuo Wenjuan (2024) emphasizes, environmental regulation policies play a key role in reducing pollution and resource waste, which in turn can increase the proportion of Green GDP [5].

2.1. Air Pollution Treatment Costs

Air pollution is first calculated by separately calculating the cost of treatment consumed by the two reference samples carbon dioxide and sulfur dioxide. Similarly, GAO Xirong (2023) calculates the loss of natural assets by including factors such as energy consumption, water resources depletion, and soil degradation [6]. Thus, the cost of air pollution is calculated as follows:

$$E_a = (\alpha q_{co}) + (\beta_1 q_{so}) \tag{2}$$

The conservation factor and shadow price have important effects when converting the values of different items in the model. Similarly, Tong Chao (2024) explains that Green GDP accounting requires using shadow prices and conversion factors to accurately reflect the value of environmental treatment costs and resource depletion [7]. By definition, the conservation factor is an arithmetic multiplier used to convert a quantity expressed in one set of units into its equivalent expressed in another set of units. The formula is as follows:

$$\alpha = \frac{U_{new}}{U_{old}} \tag{3}$$

Where Unew represents the desired unit of the conversion and Uold represents the given unit of the quantity.

By definition, the conservation factor is an arithmetic multiplier used to convert a quantity expressed in one set of units into its equivalent expressed in another set of units. The formula is as follows:

$$\beta_1 = \lambda ME \tag{4}$$

In this formula, λ is the Lagrange multiplier that represents the marginal cost of reducing one more unit SO^2 emission. I denotes the marginal environmental damage cost of one more SO2 emission. Additionally, the formula of ME is given below:

$$ME = \omega Q^{\gamma} \tag{5}$$

Where ω is the parameter that illustrates the economic value of the environmental damage caused by one more unit of SO_2 emission; Qr reflects the quantity of SO_2 emission. Is the elasticity of the environmental damage function with respect to SO_2 emission?

Table 1. The Total Cost of Air Pollution in US & China (2017).

Country in 2017	α	q_{co}	β_1	q_{so}	E_a
US	1425$/ton	5131million Metric tons	0.266$/ton	2.404millions metric tons	7311.675billion USD
China	1425$/ton	10096 million metric tons	0.266$/ton	6.108million metric tons	14386billion USD

According to Table 1, it can be seen that the amount of carbon emission of US and China has been calculated and verified for double time. The total carbon emission's data is derived from macrotrends. Then, calculated from carbon emission per capita * population at that year for both countries, the result is the same. The conservation factor for carbon emission is calculated from the environmental impact evaluation method LIME2 (Kunanuntakij et al. 2017) [8]. The shadow price for sulfur emission is from Feng, Ruiqi, Junyao (2020) [9].

2.2. Solid Waste Treatment Costs

Solid waste is calculated by separately calculating the cost of treatment. Thus, the cost of soil contamination is calculated as follows:

$$E_s = (q_{sw} * C_{sw}) + (q_{ss} * C_{ss}) \tag{6}$$

Where C_{sw} represents the government cost of solid waste and C_{ss} represents the government cost of solid storage.

Table 2. The Total Cost of Solid Waste in US & China (2017).

Country in 2017	q_{sw}	c_{sw}	q_{ss}	c_{ss}	E_s
US	268 million tons	50.3$/ton	94.34 million tons	16.62$/ton	15.05billion USD
China	215.21 million tons	4.07$/ton	59.83 million tons	1.22$/ton	0.95billion USD

According to Table 2, all the quantity data are retrieved from Statista. The cost of both China and the US is calculated from the average gallon used per household / average price per household. The data is retrieved from Sarah (2023).

2.3. Wastewater Pollution Treatment Costs

Xiumei Cui (2022) discusses how wastewater pollution costs should be accounted for by considering both the volume of discharge and the financial investments in water resource recovery and quality maintenance. Including these elements in Green GDP calculations helps provide a more accurate reflection of environmental costs [10], the formula for calculating the cost is shown below:

$$E_w = q_{wp}C_{wp} \tag{7}$$

Where C_{wp} represents the government cost of water pollution.

Table 3. The Total Cost of Water waste in US & China (2017).

Country in 2017	q_{wp}	c_{wp}	E_w
US	22513 million tons	1.18$/ton	26.57billion USD
China	69970 million tons	0.40$/ton	27.99billion USD

According to Table 3, the amount of water waste is retrieved from Statista. The governance cost is from Feng, Ruiqi, Junyao (2020) and calculated by the percentage of each of the compositions inside the governance cost (e.g. industry is composed of 19% of the overall water waste, then uses 0.19 times the governance price of industry waste water)[9]. In this case, the governance cost is weighted proportionally.

2.4. Natural Resources Consumption Costs

Siyao,Yi (2020) highlights that the Green GDP model takes into account the extraction of natural resources and their consumption in day-to-day activities, emphasizing the need for sustainable practices in resource management [2].Therefore, the costing formula for the cost of natural resource consumption is as follows:

$$E_w = q_{wp}C_{wp} \tag{8}$$

In this paper, the shadow price β2 for fuel resource extraction is calculated as follows:

First, assuming away population change and the divergence between static and dynamic average utilitarianism (Arrow et al., 2012; Yamaguchi, 2018), let the social well-being at t period be:

$$V(K(t), S(t), t) = \int_t^\infty U\big(C(K(t), S(t), \tau)\big)e^{-\delta(\tau-t)}d\tau. \tag{9}$$

Where δ > 0 denotes the discount rate, and U(C) is the utility function of consumption C. K (t) denotes the production function of the sum of extracted fossil capital and fossil capital itself. And S (t) denotes the function of natural capital stock.

Thus, the shadow prices of capitals extracted can be derived by calculating the partial derivative of V (t) respect to K (t), which is:

$$\beta_2(t) = \frac{\partial V(t)}{\partial S(t)} \tag{10}$$

Table 4. The Total Cost of Natural Resource Consumption in US & China (2017).

Country in 2017	q_f	β_2	q_w	P_w	R_c
US	77.91quadrillion BTU	2.65$/million BTU	443937million tons	4.29$/ton	2110.634billion USD
China	4490million tons	4.95$/ton	567000million tons	0.74$/ton	441.805billion USD

According to Table 4, the data of fossil energy consumption and shadow price in the US retrieved from Statista. The unit is BTU (British thermal unit), which is different from tons. However, after multiplying the shadow price in dollars per million BTU, the result is still USD. China's statistics retrieved from China’s data yearbook.

2.5. Calculated GGDP Result

Table 5. The Calculated GGDP Result in US & China (2017).

Country in 2017	GDP	E_a	E_s	E_w	R_s	GGDP
US	19.48trillion USD	7311.675billion USD	15.05billion USD	26.57billion USD	2110.634billion USD	10.016trillion
China	12.31trillion USD	14386billion USD	0.95billion USD	27.99billion USD	441.805 billion USD	-2.55 trillion

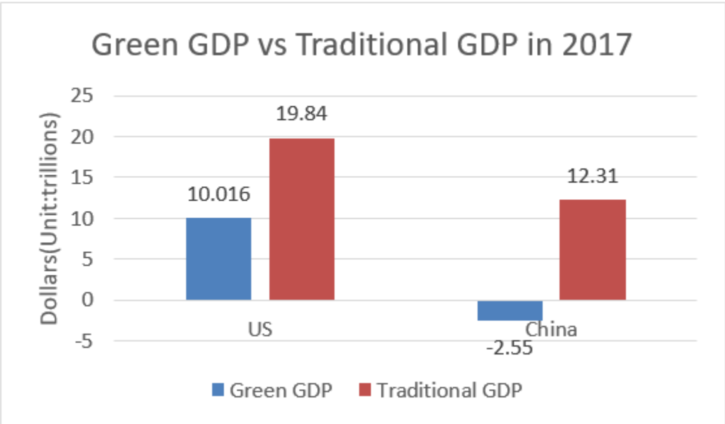

Fig 1. Green vs Traditional in US & China (2017).

According to Table 5 and Figure 1, it can be seen that,the result for both countries is using formulas to calculate the Green GDP in 2017 respectively. The calculated Green GDP for the US is 10.016 trillion, which decreased by 48.6%. The calculated Green GDP for China is -2.55 trillion, which decreased by 120.71%. From the result, one of the main reasons China became negative is the environmental costs associated with economic growth in China have outweighed the benefits.

3. Estimating global sulfur dioxide emissions using material balance method

There is a lack of comprehensive data on global SO_2 emissions. Therefore, this study aimed to estimate global SO_2 emissions from fuel burning using the material balance approach. The material balance approach is based on the conservation of mass principle, which states that the amount of sulfur in the fuel burned should be equal to the amount of SO_2 emitted. The equation to calculate SO2 emissions from fuel usage is:

$$\mathrm{SO2} = \mathrm{S} \cdot \mathrm{x} \cdot \mathrm{F} \cdot \mathrm{x} \cdot 2 \tag{11}$$

Where S is the sulfur content of the fuel burned, F is the quantity of fuel burned, and 2 is the conversion factor from sulfur to SO2.(Oregon DEQ , 2009) To estimate global SO2 emissions, we first specified the quantity of fuel burned into three categories: coal, natural gas, and oil consumption.

Obtained data on S and F from reputable sources, including the World Bank and Statista. Then applied the equation to calculate the estimation of SO_2 emissions.

Specifying the quantity of fuel burned into three categories, i.e., coal, natural gas, and oil consumption, is statistically good for several reasons:

(1)Better representation: Breaking down fuel consumption into three categories provides a better representation of the overall fuel usage. It helps to differentiate between the different types of fossil fuels and their respective contributions to overall emissions.

(2)Standardization: Coal, natural gas, and oil are three distinct and widely used fossil fuels, and they are standard measures of energy use. By breaking down energy consumption into these three categories, it is easier to compare data across different regions and time periods.

(3)Data accuracy: Using a few distinct categories instead of a single category provides better data accuracy. It is easier to track the usage of each fossil fuel separately, and it is less likely to get mixed up with other categories.

(4)Policy implications: Breaking down fuel consumption into three categories also has significant policy implications. Policies aimed at reducing greenhouse gas emissions can target specific fuels, and breaking down fuel consumption into three categories can help policymakers to understand the relative contributions of different fuels to overall emissions.

3.1. Solid Waste Discharge

Estimating global solid waste disposal requires a comprehensive understanding of the types and quantities of waste generated and disposed of in different regions and sectors. Dividing solid waste into categories such as e-waste, food waste, and plastic waste can provide a more accurate estimation of the total amount of waste generated globally.

Firstly, As Jiang Ya (2021) highlights, accounting systems that include specific waste types, such as plastics, are crucial for measuring their long-term impact on the environment and integrating these factors into Green GDP calculations [11].

Secondly, e-waste, which includes discarded electronics and electrical equipment, is also a significant contributor to the total solid waste generated. E-waste contains a range of hazardous materials, including lead, mercury, and cadmium, which can cause significant environmental and health risks.

Thirdly, food waste is a major contributor to the total solid waste generated and has significant environmental impacts. Food waste generates methane, a potent greenhouse gas that contributes to climate change.

3.2. Model Establishment

For problem two, multiple regression models are used to analyze the factors affecting global climate mitigation. Based on the calculation model of GGDP, this paper subdivides and extracts the variation variables of GGDP. Ea is divided into carbon dioxide emissions qco and sulfur dioxide emissions qso, and Es is divided into solid waste discharge qsw and solid waste storage qss. Ew wastewater pollution is also included. Rc is divided into fuel consumption qf and water resources qw. The principle formula of multiple regression model is as follows:

$$Y_i = B_0 + B_1 X_{1i} + B_2 X_{2i} + \cdots + B_n X_{ni} \tag{12}$$

Where n denotes the total number of samples, Bn denotes the regression coefficient, Xni denotes the ith value of the nth variable, and Yi is the ith prediction value.

The global average temperature is put into the model as the predicted value and the variable in the GGDP calculation model as the independent variable. The corresponding model is as follows:

$$Y_i = B_0 + B_1 q_{co(i)} + B_2 q_{so(i)} + B_3 q_{sw(i)} + B_4 q_{ss(i)} + B_5 q_{wp(i)} + B_6 q_{f(i)} + B_7 q_{w(i)} \tag{13}$$

Where Yi represents the average global temperature in ith year from a base year. Thus, it can be converted to form in matrix:

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \cdots \\ Y_n \end{bmatrix} = \begin{bmatrix} 1 & X_{21} & X_{21} & \cdots & X_{k1} \\ 1 & X_{22} & X_{22} & \cdots & X_{k2} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 1 & X_{2n} & X_{2n} & \cdots & X_{kn} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_0 \\ \vdots \\ \beta_0 \end{bmatrix} + \begin{bmatrix} w_0 \\ w_0 \\ \vdots \\ \vdots \\ w_0 \end{bmatrix} \tag{14}$$

By using the ordinary least square, the regression coefficient B' can be derived from the formula below:

$$\beta' = (X^T X)^{-1} X^T y = (\sum x_i x_i^T)^{-1} (\sum x_i y_i) \tag{15}$$

3.3. Model Results

In the first attempt, the model will consider all the above factors and assume the null hypothesis H0 that the total regression coefficient of 0. Through the regression method, P value of F test P=0.084>0.05 clearly does not reject the null hypothesis H_0. Therefore, the model does not show the significance of linear relationship. The main reason arises from the multicollinearity of factors. After observing the VIF value between q_{co} and q_f, the model will eliminate the independent variable q_f to achieve the more accurate regression model and reduce the collinearity intervention. According to stepwise regression, the model additionally eliminates the independent variables qsw and qwp.

Table 6 displays the linear regression analysis results, including the unstandardized coefficients, standard errors, and significance levels for each variable. As indicated, water resource depletion shows the most significant impact on global temperature (p < 0.05), with an adjusted R2R^2R2 of 0.64, suggesting a strong explanatory power for the model.

Table 6. Linear Regression Analysis Results after modification.

Linear regression analysis results n=11									
	unstandardized coefficient		standardized coefficient	t	P	VIF	R^2	Adjust R^2	F
	B	standard error	Beta						
constant	12.448	1.423	-	8.746	0.000***	-			
CO_2 emssion	-0.321	0.458	-0.218	-0.7	0.510	2.692			
$S0_2$ emission	0.417	0.959	0.1	0.435	0.679	1.472	0.784	0.64	F=5.44 P=0.034**
solid waste storage	-0.798	0.516	-0.381	-1.545	0.173	1.691			
water resource depletion	0.866	0.442	0.693	1.959	0.098*	3.475			
Dependent variable: global temp									

In the second attempt, the model calculated the remaining variables after removing the mutually collinear variables. By calculating the value of the F test, the statistical results show that P=0.034 which is less than 0.05. Thus, the test shows that the null hypothesis that the overall regression coefficient is 0 is rejected. This result shows that the explained variable global temperature and the independent variable qso, qss, and qw have a significant linear relationship on the horizontal level. R2=0.784 of the model reflects that the model fitting is highly correlated. The VIF values of all independent variables of the model are also kept within the safe range of less than 5. Combined with the standardized beta of each variable, water use, carbon dioxide emissions and solid waste emissions have the greatest impact on climate change. Therefore, according to the multiple linear regression coefficient B given by the data, the regression equation of global temperature and independent variables of multiple environmental factors is formulated as:

$$Y_i = 12.448 - 0.321 q_{co(i)} + 0.417 q_{so(i)} - 0.798 q_{ss(i)} + 0.866 q_{w(i)} \tag{16}$$

Where Y denotes to the global average temperature as shown in Figure 2.

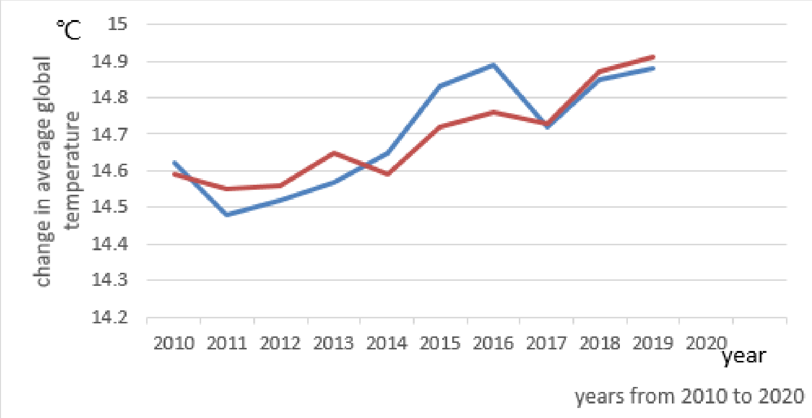

Fig 2. Line Chart of Average Temperature Change (2010-2020).

The blue line above represents the true value of global average temperature from 2010 to 2020, and the green line above represents the predicted value of global average temperature. Based on the prediction of Y in multiple regression models, the above trend chart shows the change value of global temperature from 2010 to 2020 based on the given independent variables of pollution and resource consumption. The fitting diagram illustrates the difference between the model prediction and the true value, which may be due to errors and random factors as shown in Fig 3.

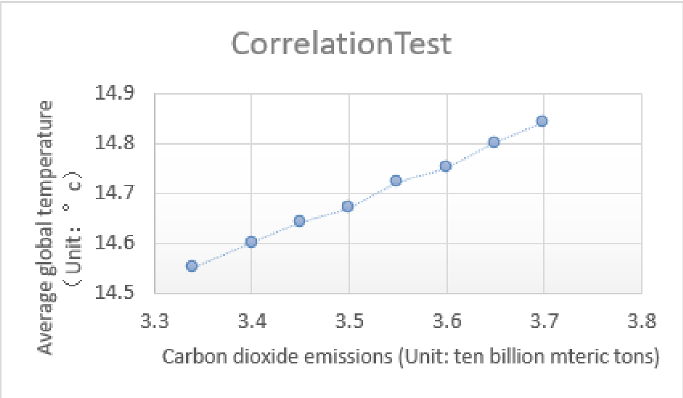

Fig 3. Correlation Test between CO2 and Average Global Temp.

Based on the regression model, the correlation between the core factor carbon dioxide emission and climate change has been further tested. The multiple regression model covers variables in many dimensions, carbon dioxide emissions will be affected by cross-dimensional interference of other factors in the multiple linear regression process. So, the significance and influence of this variable in the overall data will be covered. Through the scatter plot presented by the correlation test above, there is a positive correlation between changes in carbon dioxide and global temperature. This result also serves as a supplement to the regression model Y and an explanation for the variation of regression coefficient.

4. Conclusions

The article recommends for the use of Green GDP (GGDP) as a complete instrument for assessing the consequences of global climate change, taking pollution treatment and natural resource depletion into account in economic calculations. GGDP, which accounts for the costs of air, soil, and water pollution, provides a more exact depiction of long-term economic health than standard GDP indicators. The study's model demonstrates the striking discrepancy in environmental and economic results between the United States and China in 2017, with the former witnessing a 48.6% loss in GGDP and the latter becoming negative due to environmental costs outweighing economic gains. The regression study goes further into how crucial variables such as carbon dioxide emissions, water consumption, and solid waste affect global temperature fluctuations. The results highlight the vital need to link economic development with environmental sustainability, establishing GGDP as an important statistic for influencing climate policy. By quantifying the trade-offs between development and environmental deterioration, the model offers policymakers a tangible framework for pursuing successful climate mitigation initiatives while balancing economic goals.

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