

A study on the impact of GGDP on climate mitigation based on grey prediction

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Abstract. GGDP is a new measurement standard. It can deduct the cost of natural resource depletion and environmental degradation from GDP, and make us more aware of the resource depletion and environmental degradation caused by economic development. the modeling of GGDP value is in line with the development needs of the times and is important for coping with economic growth and sustainable development for the well-being and future of human beings. We deducted the cost of natural resource depletion and environmental degradation from GDP, developed a GGDP estimation model, and calculated GGDP for China in the last decade. global warming is an important factor contributing to climate deterioration, so we used CO₂ emissions to measure global climate change. Three indicators affecting CO₂ emissions were selected as independent variables, and GDP and GGDP were treated as independent mentionable. Two CO₂ emission prediction models based on multiple regression equations were developed separately, and the expected global impact on climate mitigation when GGDP is used as the main measure of a country's economic health was estimated by comparing different CO₂ emission calculations of the two models. To further analyze the impact of GGDP on climate change, we developed a dynamic climate projection model based on the quadratic regression equation of the EKC-like curve and verified the global applicability of the model. Our calculations show that GGDP can reduce more CO₂ emissions, slow down climate warming, and slow down glacier melting.

Keywords: GGDP; CO₂ emissions; Gray forecast model; Multiple regression.

1. Introduction

Gross domestic product (GDP) is the final result of the production activities of a country or region in a certain period, and it is an important indicator to measure the overall economic strength and economic development rate of a country or region. However, the traditional calculation of GDP indicators only considers the quantity of production and consumption but ignores the environmental and ecological costs, especially the impact of economic growth on environmental damage and sustainable development. Ecological environment and natural resources have a significant and long-term impact on economic health, and there is an urgent need to establish a new GDP indicator that includes environmental factors.

To fully reflect the impact of natural economic benefits on economic health. We calculate the value of GGDP by subtracting the cost of environmental pollution and the cost of resource consumption from GDP. As a world-renowned green trading country, China has a well-developed green economic system. Therefore, we quantified the value of China's GGDP from 2013-2022 by substituting the treatment cost of each major pollution component for the emission fee levied on each pollutant in China. Two prediction models of CO₂ emissions based on multiple regression equations were developed by choosing CO₂ emissions as the dependent variable and methane emissions, nitrous oxide emissions, and forest cover area as independent variables, respectively. The expected global impact on climate mitigation when GGDP is used as the primary measure of a country's economic health is estimated. To more accurately reflect the relationship between GGDP, GDP, and CO₂, we selected several representative countries inspired by the EKC curve and demonstrated that GGDP as a measure can have a beneficial impact on global climate.

2. GGDP estimation model

As the second largest economy in the world, China attaches importance to the development of a green economy, and in 2021, China's green trade volume reaches 1.16 trillion USD, accounting for about 14.6% of the global green trade market, becoming the world's largest green trade power. With a relatively complete green economic system and a high potential for green economy development, the data of China from 2012 to 2021 are selected to establish the GGDP calculation model. The GGDP estimation model established by this model is as follows.

$$GGDP = GDP - LNR - EPL \quad (1)$$

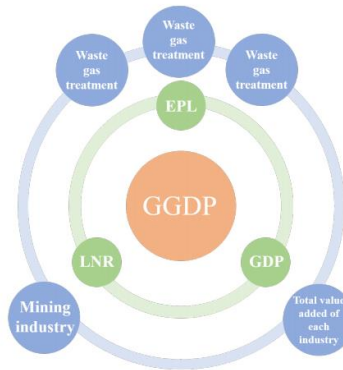


Fig. 1 Indicators for Calculating GGDP

2.1. Indicator selection and modeling

2.1.1 Gross Domestic Product

GDP is an important indicator of national economic accounting, and knowing GDP is equivalent to grasping the lifeblood of the economy and learning the full picture of the economy. We obtain China's GDP data from the China Bureau of Statistics from 2012 to 2021, as shown in Figure 2.

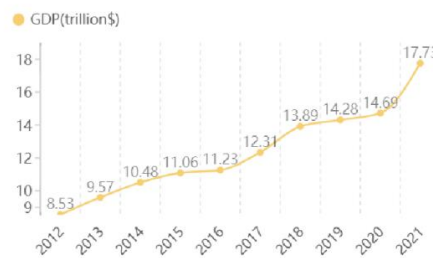


Fig. 2 2012-2021 China's GDP

2.1.2 Depletion of natural resources

Natural resource depletion represents the portion of GDP growth that results from the consumption of non-recyclable natural resources. Among the major natural resource depletion, mineral resources account for a significant part of it. Therefore, natural resource depletion can be calculated by subtracting the year-on-year value added by the mining sector from the GDP of the mining sector [2]. Based on past data, it can be concluded that the year-on-year value added to the mining sector is approximately 56.7% of GDP. The calculation is as follows:

$$LNR = \text{Gross industrial product of extractive industries} \times 43.3\% \quad (2)$$

2.1.3 Environmental pollution loss

Based on China's main environmental pollution components emission levy standards, we select the cost of treating pollutants such as mercury, cadmium, hexavalent chromium, lead, arsenic, volatile phenols, cyanide, petroleum-based emission substances and industrial solid waste as environmental pollution costs. The environmental pollution losses can be classified by categories such as exhaust

gas treatment, sewage treatment, and solid waste treatment costs. We obtain their correlations as follows.

$$EPL = W_t + G_t + S_t \quad (3)$$

Where W_t represents the sewage treatment cost in year t . G_t represents the waste gas treatment cost in year t . S_t represents the solid waste management costs in year t .

2.2. Calculation results

Based on the above algorithm, we calculate the GGDP of China from 2013 to 2022, as shown in Figure 3.

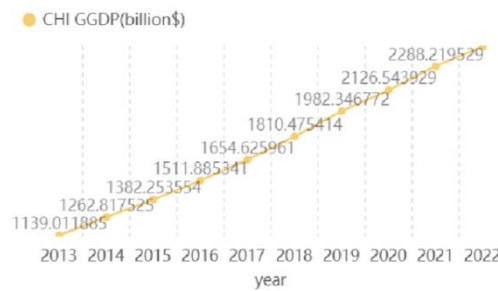


Fig. 3 2013-2022 China's GGDP

3. GGDP-Climate Change Prediction Model

3.1. Selection of important factors affecting GGDP

Large amounts of greenhouse gas emissions contribute to the increase in global average temperature and also to many climate extremes. In terms of percentage contribution to global warming, carbon dioxide has the largest share due to its high content. So we use carbon dioxide emissions as a measure to evaluate good or bad climate change [1]. Then we select seven factors that commonly affect climates such as primary energy generation, nitrous oxide, population, forest cover, methane emissions, and nitrous oxide emissions from 2013-2022 by using Stata for OLS Regression and Robust Standard Errors. The results are shown in Figure 4.

		Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]			
CO2 Emission (kt)							Number of obs	=	9
Primary energy generation (Hundreds of millions of kilowatt-hours)		-157.3815	28.299	-5.56	0.113	-516.9544 202.1914	F(5, 3)	=	5946.20
Nitric oxide (Hundreds of millions of kilowatt-hours)		1.885641	2.79395	0.67	0.622	-33.61486 37.38615	Prob > F	=	0.0000
Population (w)		-40.519	.6861157	-59.06	0.011	-49.23692 -31.80107	R-squared	=	0.9985
Forest cover (km2)		-14.99798	12.35543	-1.21	0.435	-171.9886 141.9926	Root MSE	=	2.0e+05
CH3 (Kilotons of carbon dioxide equivalent)		155.6189	9.438055	16.49	0.039	35.69701 275.5407			
N2O (Kilotons of carbon dioxide equivalent)		-3027.795	752.9876	-4.02	0.155	-12594.14 6538.549			
gdp		267136.1	55433.23	4.82	0.130	-437209.8 971482.1			
_cons		3.53e+07	2.86e+07	1.23	0.434	-3.26e+08 3.99e+08			

Fig. 4 Regression results

In linear regression, R-squared is the ratio of the sum of squares of the regression to the sum of squares of the total deviations. The larger the ratio, the larger the proportion of the total sum of squares can be explained by the sum of squares, the better the fit, and the more significant the regression effect. Numerically, the R-squared is between 0 and 1, and the closer it is to 1, the better the regression fit. The R-squared value of the above common variables is 0.99865, which has excellent good fit and good model fit.

When the confidence level is defined to be equal to 1 at the time of calculation, the larger the value of t ($p > |t|$), the less significant the regression effect is. Based on the above data, we eliminate the lower confidence level for nitric oxide, total population, and non-renewable energy generation.

3.2. Multiple regression results

We choose typical indicators of carbon dioxide emissions as the dependent variable, forest cover, methane emissions, nitrous oxide emissions, and GDP as independent variables for multiple regression analysis.

$$CO_2(G, t) = \alpha_1 GDP(G, t) + \alpha_2 Forest(G, t) + \alpha_3 CH_4(G, t) + \alpha_4 N_2O(G, t) \quad (4)$$

Where, $CO_2(G, t)$ represents the CO_2 premeasured amount including $GDP(G, t)$ in year t . $GDP(G, t)$ represents the solid waste management costs in year t . $Forest(G, t)$ represents the forest-covering area in year t . $CH_4(G, t)$ represents the methane emission in year t . $N_2O(G, t)$ represents the nitrous oxide emission in year t . $\alpha_1, \alpha_2, \alpha_3, \alpha_4$, are the parameters to be estimated.

We perform another multiple regression analysis by replacing GDP with GGDP without changing other quantities so that We can compare the different predicted values of carbon dioxide emissions to determine whether the replacement of GDP with GGDP has a mitigating effect on climate improvement.

$$CO_2(GG, t) = \beta_1 GGDP(GG, t) + \beta_2 Forest(GG, t) + \beta_3 CH_4(GG, t) + \beta_4 N_2O(GG, t) \quad (5)$$

Where, $CO_2(GG, t)$ represents the CO_2 premeasured amount including GDP in year t . $GGDP(GG, t)$ represents the solid waste management costs in year t . $Forest(GG, t)$ represents the forest-covering area in year t . $CH_4(GG, t)$ represents the methane emission in year t . $N_2O(GG, t)$ represents the nitrous oxide emission in year t . $\beta_1, \beta_2, \beta_3, \beta_4$ are the parameters to be estimated.

We use Stata to calculate the coefficients of the equation, and the results are shown in Figure 5 and Figure 6. So we can derive two regression equations.

$$CO_2(G, t) = 179535.3GDP(G, t) + 1.928Forest(G, t) - 7.316CH_4(G, t) + 157.889N_2O(G, t) + 5532552 \quad (6)$$

$$CO_2(GG, t) = 175863.7GGDP(GG, t) + 1.87Forest(GG, t) - 6.95CH_4(GG, t) + 123.76N_2O(GG, t) + 6976709 \quad (7)$$

	CO2 Emission (kt)	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
Forest cover (km2)		1.928052	.3923676	4.91	0.004	.919439 2.936665
gdp (w)		179535.3	22867.43	7.85	0.001	120752.7 238317.9
CH3 Emission (Kilotons of carbon dioxide equivalent)		-7.316423	2.150174	-3.40	0.019	-12.84362 -1.789225
N2O (Kilotons of carbon dioxide equivalent)		157.889	69.51735	2.27	0.072	-20.81101 336.589
_cons		5532552	2557187	2.16	0.083	-1040907 1.21e+07

Fig. 5 Regression results(GDP)

	CO2 Emission (kt)	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
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N2O (Kilotons of carbon dioxide equivalent)		157.889	69.51735	2.27	0.072	-20.81101 336.589
_cons		5532552	2557187	2.16	0.083	-1040907 1.21e+07

Fig. 6 Regression results(GGDP)

3.3. Forecast of indicators

We utilize the Grey Forecasting Model to estimate the precise trend with a limited number of data to collect the series data with the present plan for the following several years. We employ the GM (1, 1) model, the most popular Grey Forecasting Model, based on our presumption, to anticipate the value of 5 factors in our model, i.e. GDP, GGDP, forest coverage, methane emission, and nitrous oxide emission [4]. We use data from 2013 to 2022 for each factor (10 observations), which is adequate for the GM(1,1) model.

First, we let a set of observed data be

$$X^{(0)} = (X^{(0)}(1), X^{(0)}(2), \dots, X^{(0)}(n)) \quad (8)$$

Where $X^{(0)}(i)$ is the data that was observed about time i .

Then, we create the observed sequence $X^{(0)}(i)$ as the basis for the first-order accumulated generating operation (1 AGO) sequence $X^{(0)}(i)$.

$$X^{(1)} = (X^{(1)}(1), X^{(1)}(2), \dots, X^{(1)}(n)) \quad (9)$$

Where $X^{(1)}(k)$ is formed as the following formula.

$$X^{(1)}(k) = \sum_{i=1}^k X^{(0)}(i) = X^{(1)}(k-1) + X^{(0)}(k) \quad (10)$$

After that, we construct the series $X^{(1)}(k)$ first-order differential equation.

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = u \quad (11)$$

And then, we calculate the first-order AGO sequence.

$$\hat{X}^1(k+1) = (X^{(0)}(1) - \frac{u}{a})e^{-ak} + \frac{u}{a} \quad (12)$$

Let $\hat{a}$ be a sequence of parameters where $\hat{a} = [a; u]^T$, it can be solved as follow:

$$\hat{a} = (B^T B)^{-1} B^T Y_n$$

$$\text{where } B = \begin{bmatrix} -\frac{1}{2}(X^{(1)}(1) + X^{(1)}(2)) & 1 \\ -\frac{1}{2}(X^{(1)}(2) + X^{(1)}(3)) & 1 \\ \vdots & \vdots \\ -\frac{1}{2}(X^{(1)}(n-1) + X^{(1)}(n)) & 1 \end{bmatrix} \quad (13)$$

$$Y_n = [X^{(0)}(2), X^{(0)}(3), \dots, X^{(0)}(n)]^T$$

Using Matlab and the above formula, we predict the five index data as follows:

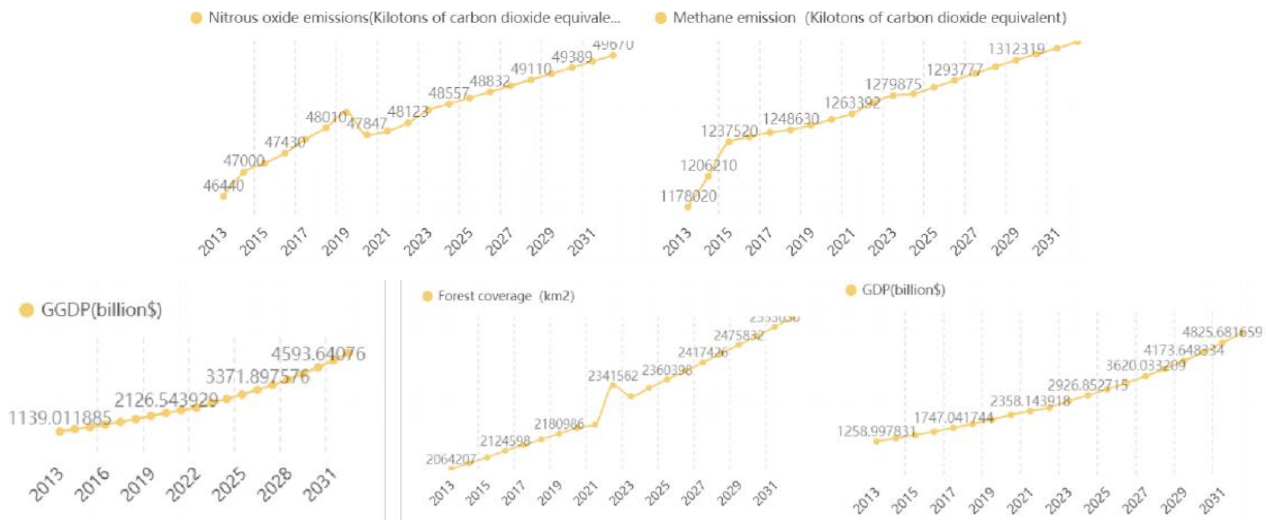


Fig. 7 Gray forecast results

3.4. Analysis of prediction results

We bring the predicted values of the above independent variables into each of the two regression equations to produce a data plot of the trend curve of carbon dioxide emissions when using GDP or GGDP, as shown in Figure 10. We then make another data plot of the trend curve for predicting future carbon dioxide emissions using only the raw carbon dioxide emission data on this figure.

After replacing GDP with GDD, the disadvantage of GGDP is that the initial carbon dioxide emission predicted based on GGDP is slightly larger than that predicted based on GDP. However, in the long run, the carbon dioxide emission predicted based on GGDP from 2025 to 2028 are the same as those predicted based on GDP. After 2028, the carbon dioxide emissions predicted based on GGDP are gradually smaller than those predicted based on GDP. Based on the above chart, it can be concluded that replacing the GDP index with the GGDP index can effectively reduce carbon dioxide emissions, reduce air pollution and restrain global warming.

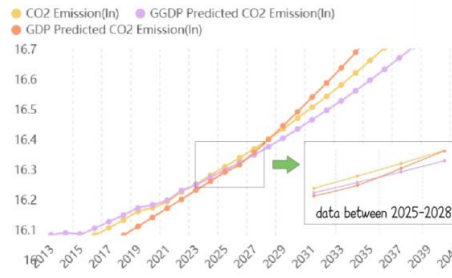


Fig. 8 Three Scenario Projections of Carbon Dioxide Emissions

4. Dynamic climate prediction model with EKC-like curves for GDP and GGDP

To make a deeper and more accurate quantitative analysis of the impact of the GGDP index on climate, inspired by EKC(Kuznets curve), a dynamic climate prediction model of GDP and GGDP was established to visualize the impact of GDP and GGDP on climate [3].

4.1. GDP Dynamic Prediction Models

Many domestic and foreign scholars conduct theoretical and empirical studies on EKC curves and come up with many regression models. Most scholars tend to use quadratic polynomial and cubic polynomial forms. Inspired by the EKC curve, we use the quadratic polynomial regression model in this model using carbon dioxide emissions and GGDP.

$$\ln y_{1t} = \beta_{10} + \beta_{11}(\ln x_{1t}) + \beta_{12}(\ln x_{1t})^2 + \varepsilon_{1t} \quad (14)$$

Where y_{1t} represents the carbon emission in year t , x_{1t} represents the GDP in year t , ε_{1t} is the random error term, β_{10} is the intercept, and β_{11} and β_{12} are the parameters to be estimated.

4.2. GGDP Dynamic Prediction Models

Similarly, we can make a quadratic regression model using CO_2 emissions and GGDP.

$$\ln y_{2t} = \beta_{20} + \beta_{21}(\ln x_{2t}) + \beta_{22}(\ln x_{2t})^2 + \varepsilon_{2t} \quad (15)$$

Where x_{2t} represents the GGDP in year t , ε_{2t} is the random error term, β_{20} is the intercept, and β_{21} and β_{22} are the parameters to be estimated.

4.3. Global Applicability

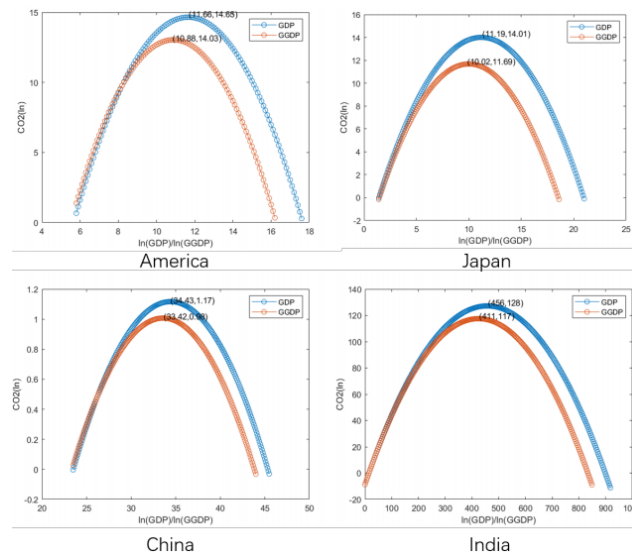


Fig. 9 Forecast Curve by Country

The data for the U.S. and Japan are substituted into the calculation of the GDP-based carbon dioxide prediction model. The results are shown in Figure 9. We can infer the corresponding years by comparing the GDP of the image vertices with the known GDP of the country. The peak years of carbon in the US and Japan are 2007 and 2013, respectively. The GGDP-based model calculates the year of carbon peak in 2003 and 2010, which are 4 years and 3 years ahead of the peak, respectively. Subsequently, the carbon dioxide emissions of the US and Japan start to decline gradually with the growth of GGDP in an inverted 'U' shape. In the current phase, China and India are also in the inverted U-shape, but at the left end of the inverted 'U' shape, with carbon emissions still increasing with GGDP growth. However, the replacement of GDP by GGDP in China and India can bring carbon dioxide emissions to the carbon peak earlier. After reaching the carbon peak, carbon emissions still decrease with the growth of GGDP. It shows that developed countries are gradually reducing their dependence on carbon dioxide emissions, but developing countries are still very dependent on carbon dioxide emissions and need to pay attention to reducing low carbon emissions.

5. Summary

In this paper, we develop a GGDP estimation model based on natural resource depletion and environmental degradation to compensate for the impact of GDP that ignores ecological and environmental economic benefits. We quantify natural resource depletion and environmental pollution depletion by choosing the price of each pollutant levied in China.

Also, to predict climate change. Annual CO₂ emissions, which have a significant impact on climate, are chosen as a measure of climate change. We also selected forest area, GDP, nitrous oxide emissions, GGDP and methane emissions as dependent variables based on confidence level and built a prediction model based on multiple linear regression. The calculation results show that the adoption of GGDP can help reduce CO₂ emissions and climate temperature rise.

We developed two EKC-like curve dynamic climate prediction models inspired by the EKC curve. The conclusions show that the dependence on carbon emissions in developed countries is gradually decreasing, while the dependence on carbon emissions in developing countries is still high and more attention needs to be paid to low-carbon environments.

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