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GGDP-Driven Carbon Peaking Trajectories: Multiscenario Forecasting with STIRPAT-Convolutional LSTM

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Abstract: *Accurately identifying the core drivers of carbon emissions and scientifically forecasting the pathway to carbon peaking are pivotal theoretical foundations for advancing the "Dual Carbon" strategic goals. This study focuses on Guangdong Province and innovatively incorporates green GDP (GGDP) as a core driver into the carbon peaking prediction model, addressing the limitations of environmental cost accounting in traditional forecasting methods. Based on the United Nations System of Environmental-Economic Accounting (SEEA) framework, we calculate Guangdong's GGDP from 2013 to 2023, analyze carbon emission trends using the emission coefficient method, identify key drivers—including population, GGDP contribution rate, industrial structure, and energy structure—through the STIRPAT model, and perform time-series forecasting using a CNN-LSTM hybrid model. Findings indicate that multi-scenario simulations project Guangdong's carbon emissions to peak in 2028 (baseline), 2027 (low-carbon), and 2026 (optimized-growth). Crucially, GGDP, by internalizing environmental costs, provides a scientifically superior basis for carbon peaking targets compared to conventional GDP.*

Keywords: *Green GDP (GGDP); Carbon Emission Prediction; STIRPAT Model; CNN-LSTM Model*

1. Introduction

With rapid economic development, the issue of CO_2 emissions has become increasingly severe, prompting nations worldwide to establish carbon neutrality targets. China has explicitly set its "Dual Carbon" goals: achieving carbon peaking by 2030 and carbon neutrality by 2060. As a major energy-consuming province, Guangdong's carbon emissions have drawn significant attention. In February 2023, Guangdong released its *Carbon Peaking Implementation Plan*, targeting carbon by 2030, maintaining leading national standards in energy consumption and carbon emissions per unit GDP, and raising the share of non-fossil energy to approximately 35%.

While conventional GDP effectively measures economic growth, it overlooks critical factors such resource depletion and environmental degradation. Rapid economic expansion has intensified resource consumption and pollution, particularly due to the strong linkage between economic growth and energy use, thereby driving carbon emissions. Consequently, this study prioritizes green GDP (GGDP),following Yang (2022) who highlighted its role in guiding sustainable development and green transformation pathways [1]. As a comprehensive metric, GGDP integrates economic performance with natural resource costs and environmental protection expenditures, offering a clear perspective on the relationship between regional development and environmental sustainability.

In carbon emission research, scholars such as Zhong et al. (2024) have explored diverse spatial predominantly analyzing influencing factors and emission predictions through theories linking growth and energy consumption [2]. Methods often employ econometric models or GDP-centric evaluation systems. However, the limitations of conventional GDP in carbon emission forecasting—specifically its failure to reflect environmental externalities—have become apparent. This gap motivated the emergence of GGDP. Following the UN's *System of Environmental-Economic Accounting (SEEA)* handbook (1993) [3], a multi-phase accounting framework evolved globally. China launched the *Green National Accounting Study* project in 2004[4]; though initially delayed, it resumed 2015 (Phase 2.0), spurring scholarly exploration. Recent studies investigate correlations between and carbon emissions, with some proposing GGDP-based prediction models. For instance, Wang et al.[5] applied EDA methods to examine synergies between environmental mechanisms and urban development across 211 Chinese cities. Others like Wang et al. (2023) implemented "greening" conversions of economic outputs by deducting environmental resource costs in GGDP calculations[6].

This study transcends traditional GDP-centric frameworks to explore GGDP's potential for carbon emission and peaking predictions. Adopting the GGDP accounting system as an innovative carbon measurement approach enables more accurate emission quantification and trend analysis, thereby advancing Guangdong's "Dual Carbon" objectives. Based on the UN SEEA framework and emission coefficient method, we calculate Guangdong's carbon emissions, utilize the STIRPAT model to identify key drivers, and integrate CNN-LSTM hybrid modeling for dynamic time-series simulation and carbon peaking pathway projection. This work aims to provide theoretical and practical guidance for achieving carbon peaking and neutrality.

2. Introduction to research methods and model construction

2.1 Green GDP Accounting Method under the SEEA System

This study requires GGDP accounting to predict Guangdong Province's carbon peak and examine the relationship between its GGDP and carbon emissions. Conventional GDP accounting overlooks environmental costs, while subsequent adjustments face controversies in quantifying environmental costs and defining accounting boundaries. Adopting the United Nations' System of Environmental-Economic Accounting (SEEA) framework[7],this research calculates Guangdong's GGDP, leveraging its authority and comprehensiveness to establish a scientific accounting framework. The GGDP accounting system comprises three modules: natural resource depletion cost, environmental pollution damage cost, and resource/environmental improvement value. Indicator selection adheres to these principles,as shown in Table 1.

Table 1: Green GDP Indicator System

Tier 1 Indicator	Tier 2 Indicator	Indicator Description
Natural Resource Depletion Costs	Energy Resource Depletion Costs	Assesses the environmental loss caused by energy extraction and usage by selecting coal, petroleum, and natural gas, and quantifying the restoration cost per unit of energy.
	Cultivated Land Depletion Cost	The annual net reduction in cultivated land area is determined by the difference between the current year's cultivated land area and that of the previous year.
	Water Resource Depletion Cost	Measures the depletion cost of water resources using the actual compensation fees incurred for water resources.
	Mineral Depletion Costs	Evaluates the environmental cost of mineral resource development by calculating the total output value loss resulting from mineral resource extraction.
Environmental Pollution Loss Costs	Wastewater Treatment Cost	Assesses the economic burden of wastewater treatment by calculating the product of wastewater discharge volume and treatment cost.
	Waste Gas Treatment Cost	Assesses the economic burden of waste gas treatment by calculating the product of waste gas emission volume and treatment cost.
	Solid Waste Treatment Cost	Assesses the economic burden of solid waste treatment by calculating the product of solid waste generation volume and treatment cost.
Resource and Environment Improvement Benefit Value	Forest Resource Improvement Benefit	Evaluates the economic benefit derived from forest resource improvement by calculating the product of afforestation area and forest value.

Based on the above analysis, the GGDP calculation in Guangdong Province consists of the cost of natural resource consumption reduction, the cost of environmental pollution loss, and the value of

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resource and environmental improvement benefits. The GGDP calculation formula is as follows:

GGDP = GDP- Cost of natural resource depletion - Cost of environmental pollution loss + Benefits of resource and environmental improvement(1)

Based on the above formula and referring to the literature of Du et al.[8], the above indicators were calculated by the following method, as shown in Table 2.

Table 2: Accounting Methods for Tier 2 Indicators

Tier 2 Indicator	Accounting Method
Energy Resource Depletion Costs	Energy Resource Depletion Cost = Annual Energy Depletion Volume × Unit Resource Restoration Cost.
Cultivated Land Depletion Cost	Cultivated Land Depletion Cost = Annual Cultivated Land Depletion Volume × Unit Resource Restoration Cost.
Water Resource Depletion Cost	Water Resource Depletion Cost = Annual Water Resource Depletion Volume × Unit Compensation Fee.
Mineral Depletion Costs	Mineral Depletion Cost = Total Mineral Industry Output Value × Resource Depletion Coefficient.
Wastewater Treatment Cost	Wastewater Treatment Cost = Wastewater Discharge Volume × Unit Treatment Cost.
Waste Gas Treatment Cost	Waste Gas Treatment Cost = Waste Gas Emission Volume × Unit Treatment Cost.
Solid Waste Treatment Cost	Solid Waste Treatment Cost = Solid Waste Generation Volume × Unit Treatment Cost.
Forest Resource Improvement Benefit	Resource and Environment Improvement Benefit Value = Annual Afforestation Area × Unit Forest Value Price.

2.2 Carbon emission calculation based on the emission factor approach

This study systematically estimates the total carbon emissions of Guangdong Province using the emission factor approach. Based on disaggregated energy consumption data and corresponding emission factor parameters, an accounting framework for carbon emissions is established, enabling precise quantitative analysis of regional carbon emissions. This method demonstrates high applicability, strong practical utility, and operational straightforwardness. The calculation formula is as follows:

$$\mathrm{C} = \sum_{i=1}^{9} \mathrm{E_i} \times \mathrm{NCV_i} \times \mathrm{CEF_i} \tag{2}$$

Where, C represents the total carbon emissions; E_i denotes the consumption of the i energy type; NCV_i is the average net calorific value (lower heating value) of the i energy type; CEF_i signifies the carbon emission factor of the i fossil energy type. i indicates the energy category, encompassing: coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, liquefied petroleum gas (LPG), and natural gas. The corresponding carbon emission coefficients for each energy type are provided in Table 3.

Table 3: Energy Characteristics and CO_2 Emission Factors

Energy	Avg. Low Calorific Value/kj · $\mathrm{kg^{-1}}$	Standard Coal Equivalent/kgce · $\mathrm{kg^{-1}}$	Carbon Content per Unit Heat/ $(\mathrm{t-c/TJ})$	Carbon Oxidation Rate/%	CO_2 Emission Factor/$(\mathrm{kg-CO^2/kg})$
Raw Coal	20908	0.7143	26.37	0.94	1.9003
Coke	28435	0.9714	29.42	0.93	2.8604
Crude Oil	41816	1.4286	20.08	0.98	3.0202
Gasoline	43070	1.4714	18.9	0.98	2.9251
Kerosene	43070	1.4714	19.6	0.98	3.0179
Diesel	42652	1.4571	20.2	0.98	3.0959
Fuel Oil	41816	1.4286	21.1	0.98	3.1705
LPG	50176	1.7143	17.2	0.98	3.0119
Natural Gas	38931	1.3300	15.32	0.99	2.1622

2.3 Model construction

This study utilizes an integrated STIRPAT and CNN-LSTM model to develop a carbon emission forecasting model for Guangdong Province[9], thereby predicting the carbon peak for the region. First, data on influencing factors are collected, and the STIRPAT model is employed to identify the primary drivers of carbon emissions. These factors include total population, the contribution share of GGDP to GDP, the proportion of non-fossil energy consumption, the value-added ratio of the secondary industry, and foreign trade dependence. Subsequently, a CNN-LSTM forecasting model is constructed incorporating the aforementioned influencing factors to predict Guangdong Province's carbon emissions. This enables the prediction of both the timing and magnitude of Guangdong's carbon peak.

2.3.1 Construction of the STIRPAT Model

Within carbon peak accounting, researchers have developed various methodologies, including the Kaya identity, Long-range Energy Alternatives Planning System (LEAP), and mass balance approaches. The STIRPAT model—an analytical tool derived from the IPAT framework—enhances environmental impact assessment by incorporating stochasticity and error terms. Drawing on prior research[10,11,12] and Guangdong's specific context, this study selects five key variables: total population, GGDP contribution to GDP, non-fossil energy consumption share, secondary industry value-added ratio, and foreign trade dependence. These encompass socioeconomic development, economic status, and direct and indirect carbon emission drivers. We thus construct a regional STIRPAT forecasting model for carbon emissions.

$$\mathrm{lnC = a + blnP + clnR + dlnJ + flnI + glnF + \varepsilon} \tag{3}$$

Where, a is the constant term; C denotes total carbon emissions; P represents total population; R indicates the contribution share of GGDP to GDP; J signifies industrial structure, measured by the value-added ratio of the secondary industry; I reflects energy structure, calculated as the proportion of non-fossil energy consumption; F represents foreign trade dependence, defined as the ratio of total annual import-export value to GDP; b, c, d, f, g is the logarithmic constant term.

2.3.2 Construction of CNN-LSTM-based Carbon Emission Prediction Model

This study employs TensorFlow to construct a hybrid CNN-LSTM neural network model. The CNN component first extracts features from high-dimensional data, while the LSTM module subsequently processes temporal sequences. Within this architecture, the CNN network handles feature extraction, and the LSTM model performs carbon emission forecasting.

Convolutional Neural Networks (CNN) represent a deep learning architecture whose core structure comprises an input layer, multi-level feature extraction layers (a modular combination of convolutional and pooling layers), and an output layer. The feature extraction layers capture spatial features through convolutional operations and achieve dimensionality reduction while preserving critical information via pooling operations. This study utilizes two-dimensional convolution operations for processing high-dimensional data:

$$\mathrm{Y(i,j) = f\left(\sum_{m=1}^{M}\sum_{n=1}^{N} X\,(i+m-1, j+n-1)\cdot K(m,n) + b\right)} \tag{4}$$

And apply the maximum pooling method in the pooling layer to reduce the data dimension:

$$\mathrm{Y(i,j) = \max_{m=1}^{M}\max_{n=1}^{N} X(i+m-1, j+n-1)} \tag{5}$$

Where, $Y(i,j)$ denotes the value of the output feature map at position (i,j); $X(i+m-1, j+n-1)$ represents the value of the input data at position $(i+m-1, j+n-1)$; $K(m,n)$ indicates the weight value of the convolution kernel at position (m,n); M and N are the height and width of the convolution kernel, respectively; f stands for the activation function; b is the bias term.

LSTM, an enhanced Recurrent Neural Network (RNN) introduced by Hochreiter & Schmidhuber (1997), mitigates short-term memory limitations in traditional RNNs through memory cells and a gating mechanism (forget/input/output gates). This architecture dynamically regulates temporal information flow, significantly enhancing long-range dependency capture. The key variables comprise the input x_t, forget gate f_t, input gate i_t, cell state c_t, output gate o_t and hidden state $\mathrm{h_t}$. The forget gate selects retention from $\mathrm{h_t} - 1$ and x_t:

$$\mathrm{f_t = \sigma(W_f \cdot x_t + W_f \cdot h_{t-1} + b_f)} \tag{6}$$

Input gate outputs: update signal i_t, state candidate $\tilde{c}_t$:

$$\mathrm{i_t = \sigma(W_i \cdot x_t + W_i \cdot h_{t-1} + b_i)} \tag{7}$$

$$\mathrm{\tilde{c}_t = tanh(W_c \cdot x_t + W_c \cdot h_{t-1} + b_c)} \tag{8}$$

Cell state update and output gating:

$$\mathrm{c_t = f_t \otimes c_{t-1} + i_t \otimes \tilde{c}_t} \tag{9}$$

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$$o_t = \sigma(W_o \cdot x_t + W_o \cdot h_{t-1} + b_o) \quad (10)$$

The output of the $LSTM$ model is:

$$h_t = o_t \otimes \tanh(c_t) \quad (11)$$

3. Analysis of Empirical Findings

3.1 GGDP

Guangdong's GGDP dynamics are presented in Table 4

Table: 4 Green GDP 2013-2023

Year	2013	2014	2015	2016	2017	2018
GGDP	57692.1	61949.8	68337.9	78338.6	87157.6	94845.8
Year	2019	2020	2021	2022	2023	
GGDP	105786.8	109553.6	123023.3	127078.5	133868.7	

3.2 Carbon Emission Calculation Results

Using the emission coefficient method, Guangdong's carbon emissions were calculated (Figure 1). Data from 2013-2023 indicate an overall upward trajectory from 493.09 Mt to 676.10 Mt, with significant interannual fluctuations.

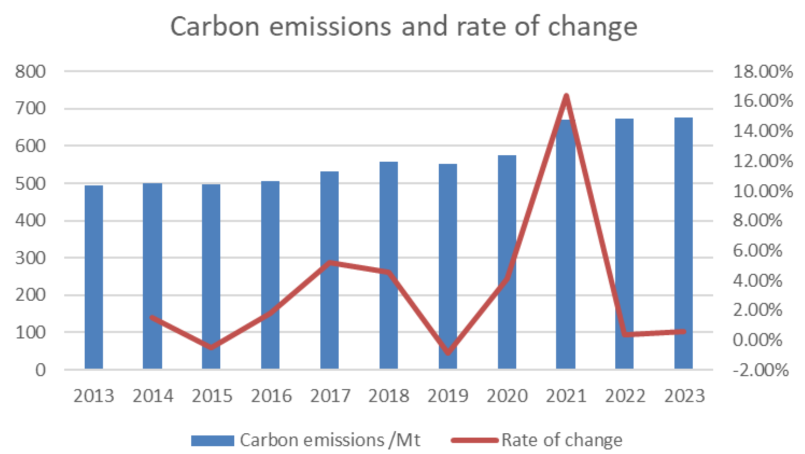

Figure 1: Carbon emissions and rate of change

3.3 Analysis of Carbon Emission Drivers Using the STIRPAT Model

The multivariate regression achieved $R^2 = 0.881$, explaining 88.1% of carbon emission variance. Significant linear relationships were confirmed (F=7.375, p<0.05) among the five predictors. However, VIF values >100 in Table 5 indicate severe multicollinearity.

Table 5: VIF values for each variable

Variable	VIF
Total population	262.208
GGDP contribution to GDP	15.033
Industrial structure	56.023
Energy structure	59.325
Foreign trade degree	663.417

Consequently, ridge regression was employed, introducing an L2-norm regularization term to the least squares framework, thereby mitigating multicollinearity interference among variables.

Table 6: Ridge Regression Diagnostic Metrics

K	R^2	F	P
0.149	0.936	5.642	0.023**

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Table 6 demonstrates improved fit with L2 regularization. At $k = 0.149, R^2 = 0.936$ indicates 93.6% emission variance explained by five predictors.The model shows statistical significance ($F = 5.642, p = 0.023 < 0.05$), yielding the ridge regression equation:

$$\ln C = 0.91\ln P + 0.165\ln A - 0.316\ln I - 0.226\ln E - 0.079\ln F - 3.372 \tag{12}$$

3.4 Multi-Scenario Carbon Emission Projections Using CNN-LSTM

3.4.1 Parameter Determination and Scenario Analysis

This study constructs a predictive model using the STIRPAT framework with five indicators: total population, GGDP-to-GDP ratio, non-fossil energy share, secondary industry value-added ratio, and trade openness. Three scenarios were established, drawing on recent research (2021–2025) on carbon peaking strategies for eastern China and multi-scenario national carbon emission pathways[13,14]: Baseline: Maintains historical change rates per Guangdong's 12th Five-Year Plan, ensuring socioeconomic stability; Low-Carbon: Imposes stringent carbon constraints, moderating indicator fluctuations while balancing development and ecological benefits; Optimized-Growth: Prioritizes economic expansion through accelerated change rates,minimizing administrative intervention to achieve short-term economic objectives.

3.4.2 Prediction Model Calibration and Accuracy Evaluation

The Mean Absolute Percentage Error ($MAPE$), a standardized forecast accuracy metric, quantifies deviations between predicted and actual values. Selected for $CNN-LSTM$ evaluation, its normalization of individual errors eliminates scale dependence. Lower MAPE indicates higher precision, computed as:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \tag{13}$$

Where,y_i $is\ the\ true\ value$,$\hat{y}_i$ $is\ the\ predicted\ value.$

For LSTM model training, 2013–2023 data were partitioned 80%-20% into training and validation sets. The resulting MAPE of 2.765% demonstrates high predictive accuracy in capturing carbon emission trends.

3.4.3 Multi-scenario carbon emission Forecast for Guangdong Province from 2024 to 2035

The carbon emission model, parametrized with five key drivers under baseline, low-carbon, and optimized-growth scenarios, projects China's emissions for 2024–2033. Outcomes are shown in Figure 2.

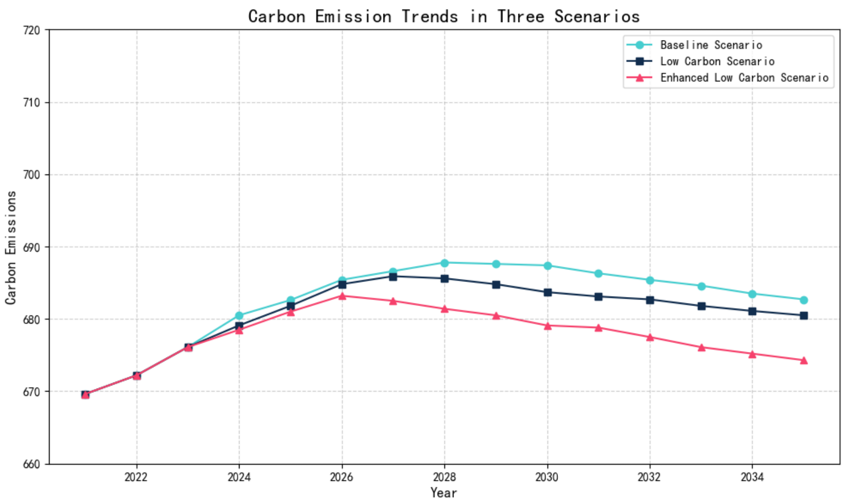

Figure 2: Carbon emission Trends in Three Scenarios

Under three scenarios, emissions peak in 2028 at 687.8 Mt (baseline), 2027 at 685.9 Mt (low-carbon), and 2026 at 683.2 Mt (optimized-growth). Evidently, enhanced mitigation efforts progressively advance peak timing and reduce emission magnitudes, validating policy adjustments' critical role in low-carbon transitions.

3.4.4 Forecast Comparison: Traditional and GGDP-Augmented Specifications

Figure 3reveals significant divergences among actual emissions, conventional model projections, and GGDP-augmented model predictions during 2013–2023. The conventional model exhibits substantial post-2020 deviations, whereas the GGDP-augmented trajectory demonstrates superior alignment with empirical data, statistically outperforming the benchmark model.

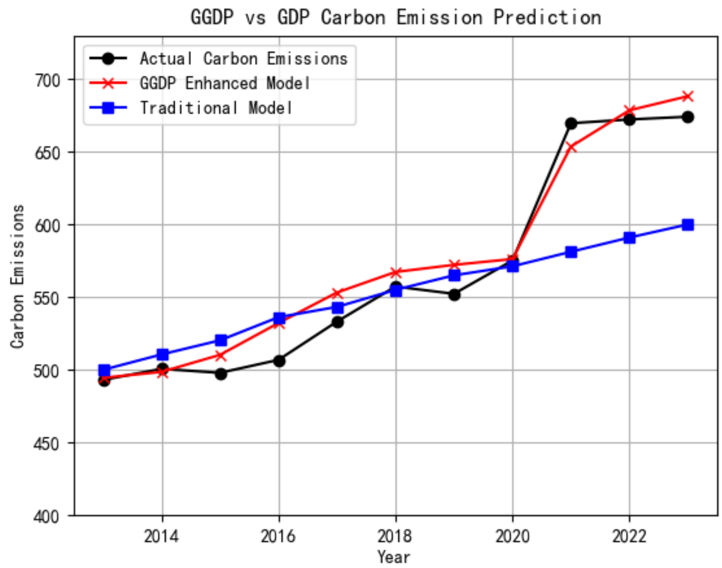

Figure 3: GGDP and GDP Carbon Emission Prediction

4. Conclusion

This study pioneers the integration of Green GDP (GGDP) into carbon peak forecasting for Guangdong Province. Utilizing the SEEA framework and emission coefficient method, we quantified GGDP and carbon emissions from 2013–2023. Key drivers—population, GGDP contribution ratio, industrial structure, and energy mix—were identified through the STIRPAT model, with multi-scenario projections conducted via a CNN-LSTM hybrid model. Results demonstrate that GGDP-driven green transition policies significantly accelerate carbon peaking: occurring in 2028 (baseline), 2027 (low-carbon), and 2026 (optimized-growth) scenarios. Our findings delineate distinct development pathways' impacts on peak timing and magnitude, highlighting green policy's critical role in low-carbon development while providing theoretical foundations for regional/national decarbonization.

Notwithstanding these contributions, limitations persist. Data constraints, particularly granular GGDP accounting metrics, may have compromised precision. Moreover, Guangdong-focused analysis necessitates further validation for broader regional applicability.

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Author contributions Zhong, Du, and You all contributed equally to all aspects of this work.Guorui Zhao coordinated all the work of the entire paper. All authors reviewed the manuscript.

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