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Study on the Projection of Net Carbon Emissions in Anhui Province Based on Ensemble Forecasting

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Abstract

To achieve precise planning for Anhui Province's carbon neutrality pathway, this paper constructs a combined forecasting model using Grey Model (GM (1,1)), exponential smoothing, and ARIMA time series, and aggregates the forecasting results using the inverse of the Mean Absolute Percentage Error (MAPE). Empirical results indicate that the combined forecasting model reduced the average MAPE to 2.49% for the 2005-2022 forecast period, representing a decrease of 4.05%, 1.56%, and 0.58% compared to the average MAPEs of the grey system, exponential smoothing, and ARIMA time series models, respectively, outperforming all three individual forecasting models. The ensemble forecast results for 2023-2027 indicate that Anhui Province's net carbon emissions will increase from 532.99 million tons to 554.99 million tons, with an average annual growth rate of 1.41%. Although the growth rate shows a declining trend, the absolute increase still reaches 22 million tons, suggesting that the current development trajectory is closer to a high-carbon model and highlighting the challenges of achieving the carbon peak target. This paper provides a decision-making benchmark with controllable error margins for regional carbon neutrality pathways, confirming the paradigmatic value of ensemble forecasting in mitigating the extreme risks associated with single-model predictions. Additionally, it proposes a dynamic weighting update mechanism, coordinated emission reductions across the industrial, energy, and building sectors, and a carbon offset system for northern and southern Anhui, thereby offering a data-driven decision-making framework for Anhui Province's carbon peaking by 2030.

Keywords

Combined Forecasting; Net Carbon Emissions Forecasting; MAPE Reciprocal Weighted

1. Introduction

As the global climate crisis grows increasingly severe, China, as a responsible major power, has set forth its "dual carbon" goals. Anhui Province, a key region in the rise of Central China, has experienced rapid economic development in recent years,

and its carbon emissions issue has become increasingly prominent. Research indicates that over the past three decades, carbon emissions in Anhui Province have generally shown an upward trend, reaching a first carbon peak, after which emissions have continued to rise (Hu et al., 2024). Although the province's carbon emission intensity has been declining, total carbon emissions continue to rise, exhibiting significant spatial disparities characterized by "higher emissions in the north and south" and "higher emissions in the west and lower in the east" (Xu, 2023). Scientifically forecasting Anhui Province's future net carbon emissions holds significant practical importance for the province in formulating precise emission reduction pathways, balancing economic development with ecological conservation, and thereby supporting the implementation of the national "dual carbon" strategy.

In the field of carbon emissions forecasting, scholars both domestically and internationally have explored various models. The STIRPAT model and its extensions are widely used in carbon emissions forecasting, often combined with scenario analysis-such as baseline, energy-saving, and low-carbon scenarios-to simulate carbon emission trends and peak times under different development pathways. For example, Song et al. (2023) used the STIRPAT model to predict that Anhui Province could reach its emissions peak by 2030, identifying carbon intensity, energy intensity, and per capita GDP as key influencing factors; Wang Xue et al. (2025) extended the STIRPAT model and combined it with scenario analysis to forecast carbon emissions in China's manufacturing sector; the results showed that under low-, medium-, and high-growth scenarios, the manufacturing sector would reach its carbon peak by 2026; Chen et al. (2023) used the LEAP model and scenario analysis to predict that Anhui Province's carbon peak would occur around 2039. Decomposition methods such as LMDI and KAYA have been used to identify the drivers of carbon emissions. It is generally accepted that economic development is the primary driving factor, while energy intensity is the main restraining factor (Wu and Gao, 2023). Machine learning models such as LLE-PSO-XGBoost have also demonstrated high-precision forecasting potential in specific fields, such as agricultural carbon emissions, with error rates as low as 0.009 (Qi et al., 2024). Furthermore, existing research has examined the complex relationships between carbon emissions and factors such as energy efficiency, technological progress, economic growth, and the structure of fossil fuel consumption (Wang and Zhang, 2025), and has further combined scenario analysis to simulate the dynamic pathways toward carbon peaking in resource-based cities under low-carbon, baseline, and high-growth scenarios (Han and Hou, 2025).

However, existing studies have largely focused on predictions based on a single model or a single emission source, and there is a relative lack of systematic predictions of Anhui Province's net carbon emissions that comprehensively account for both emissions and removals. Different models have their own strengths and weaknesses, and predictions from a single model may have limitations or

uncertainties. Therefore, exploring a combined prediction model that integrates the strengths of multiple individual models could improve the accuracy and robustness of predictions regarding Anhui Province's net carbon emissions, thereby potentially providing a more reliable scientific basis for policy-making.

2. Data Sources and Metrics

2.1. Data Sources

This study analyzes land use area and carbon emission data for Anhui Province from 2003 to 2022. The data on the areas of forests, grasslands, water bodies, and unutilized land were obtained from the China Annual Land Cover Dataset (CLCD), published by the research team led by Professors Yang and Huang at Wuhan University using the Google Earth Engine (GEE) platform; this dataset is updated through 2022. The carbon emission data were sourced from the CEADs database.

2.2. Measurement of Net Carbon Emissions

In the process of advancing Anhui Province's carbon peaking goals, carbon sink accounting serves as a core component of carbon emissions estimation; its scientific rigor directly influences the determination of regional net carbon emissions and the formulation of emission reduction responsibility allocation plans. Drawing on the research frameworks of Zhang et al. (2020) and Huang et al. (2023), this study defines the scope of carbon sink accounting to encompass four major ecosystem types: forests, grasslands, water bodies, and unutilized land. Drawing on the research by Wei et al. (2021), we have developed calculation formulas for carbon sink volumes across each land type. Based on these carbon sink estimates and existing Anhui Province carbon emission data, we have calculated the province's net carbon emissions for the period 2003-2022. This analysis aims to reveal the dynamic trends in regional carbon emissions after accounting for both actual emissions and carbon sink offsets. The specific formula is as follows:

$$NE = CE - \sum_{i} \left(\text{Acre}_{i} * C_{i} \right) \quad (1)$$

Here, NE represents net carbon emissions, CE represents carbon emissions, Acrei represents the actual area of land type i, and Ci is the unit carbon sink coefficient for that land type. Based on existing research (Zhou et al., 2017; Wei and Chen, 2021), the following carbon sink coefficients were selected: 0.870 tons/ha for forests, 0.022 tons/ha for grasslands, 0.253 tons/ha for water bodies, and 0.005 tons/ha for unutilized land.

3. Building an Ensemble Forecasting Model

3.1. Univariate Predictive Model

(1) Grey Model GM(1,1)

The core concept of the gray prediction model GM(1,1) is to address "gray systems"

where “some information is known and some is unknown.” It excels at handling situations with limited data and incomplete information. A key step in the model involves processing the raw data using “Accumulative Generation” (AGO) to generate a new sequence with greater regularity, thereby reducing the random fluctuations in the original data. Next, this new sequence is used to construct a first-order linear differential equation to describe the system’s trend. Finally, the solution to the differential equation is reconstructed using “Inverse Accumulative Generation” (IAGO) to obtain forecast values on the scale of the original data. The main advantages of this model lie in its strong adaptability to small sample sizes and relatively simple computations, making it particularly suitable for short- to medium-term trend forecasting; however, its ability to capture drastic changes and nonlinear characteristics in the data itself is relatively limited.

(2) Exponential Smoothing

Exponential smoothing is a classic and practical method for time series forecasting. Its basic principle is that historical data closer to the forecast date has a greater influence on future values and should therefore be assigned a higher weight. The model makes forecasts by continuously updating a “smoothed value” through iteration. After each forecast, the latest observed value is compared with the previous forecast, and the forecast is weighted and adjusted based on a smoothing coefficient between 0 and 1. There are many variants of this method, such as simple exponential smoothing, double exponential smoothing, and triple exponential smoothing, designed to accommodate different data patterns (such as no trend, linear trends, or seasonal fluctuations). The greatest advantages of exponential smoothing are its intuitive principles, computational efficiency, and ease of use; it is particularly suitable for forecasting historical data series with relatively stable trends that do not require particularly complex models.

(3) ARIMA time series

The ARIMA model is a powerful and flexible statistical framework for time series forecasting, integrating three components: autoregression (AR), differencing (I), and moving average (MA). The model first focuses on the stationarity of the data, meaning that the statistical properties of the series do not change significantly over time. If the original series is non-stationary, a differencing (I) step is required to eliminate these non-stationary factors and transform it into a stationary series. Subsequently, based on the stationary series, the autoregressive (AR) component uses the values from several past periods of the series to predict the current value, capturing the series’ inherent continuity; while the moving average (MA) component uses the prediction errors from several past periods to refine the current forecast, aiming to capture sudden shocks or noise in the series. Determining the parameters of the ARIMA model-specifically the AR lag order, the order of differencing, and the MA lag order-is crucial. This typically requires analysis using autocorrelation (ACF) and partial autocorrelation (PACF) plots. The ARIMA

model features a rigorous structure and a solid theoretical foundation, and it is particularly well-suited for forecasting time series that exhibit linear trends and interdependencies, provided there is a sufficient amount of historical data.

3.2. Ensemble Forecasting Model

In an ensemble forecasting framework, weight allocation based on model accuracy is a key mechanism for improving forecasting robustness. This paper uses the Mean Absolute Percentage Error (MAPE) as a metric for evaluating model performance, defined as:

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{CE_t - \hat{C}E_t}{CE_t}\right| \tag{2}$$

Here, CE_t represents the actual value, $\hat{C}E_t$ represents the predicted value, and n represents the sample size. MAPE quantifies the relative deviation between the predicted and actual values; a smaller value indicates higher model accuracy.

Weight allocation follows the principle of error-inversely-weighted averaging:

$$w_i = \frac{1/\mathrm{MAPE}_i}{\sum_{j=1}^{k} 1/\mathrm{MAPE}_j} \tag{3}$$

Here, k represents the number of submodels; in this paper, k = 3, corresponding to the GM(1,1), exponential smoothing, and ARIMA methods. This design is theoretically sound in three respects: the weights are negatively correlated with MAPE, ensuring that high-precision models dominate the ensemble forecast; the weights satisfy $\sum w_i = 1$ and $w_i \geq 0$, guaranteeing that the ensemble result is a convex combination of the individual submodel forecasts, thereby effectively suppressing the influence of outliers; Theoretical studies indicate that this weighting scheme approximates the optimal solution for minimizing the expected error of the ensemble forecast, and its performance is statistically equivalent to that of complex optimization algorithms, such as the least-squares weighting method.

4. Empirical Analysis

4.1. Individual Prediction Results

(1) Prediction results from the gray prediction model GM(1,1)

The Grey Model GM(1,1) uses historical data to predict future data. The original time series did not pass the ratio test, as some ratio values fell outside the [0.909, 1.1] range; however, after a shift transformation, the ratios of the new time series all fell within the valid range, satisfying the conditions for grey modeling. The a posteriori difference ratio C value was 0.059, which is far better than the high-precision threshold. The specific prediction results are shown in “Table 1” The relative error for the early data from 2004 to 2006 exceeded 12%, possibly due to significant fluctuations in emissions during the period of rapid economic growth; whereas after 2015, the error was generally less than 5%, demonstrating the model’s strong

ability to capture stable trends. The model's average MAPE is 6.54%, indicating good model fit. The forecast results for the next five periods (2023-2027) are as follows: 57,338.29, 59,404.79, 61,510.43, 63,655.96, and 65,842.13 (10,000 tons), respectively. Net carbon emissions continue to rise, with an average annual increase of 3.5%. These results highlight that relying solely on natural decline will not achieve peak emissions by 2030; it is imperative to offset growth inertia through industrial restructuring and the expansion of carbon sinks.

Table 1. Prediction results from the gray prediction model GM(1,1).

Year	Actual figure	Forecast	MAPE（%）
2003	17395.09641	17395.09641	0.00
2004	19378.44841	24620.37411	27.05
2005	22295.55742	26067.13111	16.92
2006	24513.17058	27541.29254	12.35
2007	28199.03325	29043.37750	2.99
2008	31885.26099	30573.91491	4.11
2009	33140.31819	32133.44372	3.04
2010	35503.16267	33722.51308	5.02
2011	38568.31361	35341.68254	8.37
2012	39940.34831	36991.52227	7.38
2013	42871.23187	38672.61321	9.79
2014	43633.67061	40385.54733	7.44
2015	44081.00661	42130.9278	4.42
2016	44416.2268	43909.36922	1.14
2017	45040.76375	45721.49782	1.51
2018	48879.60229	47567.95172	2.68
2019	48974.11402	49449.38109	0.97
2020	48856.51249	51366.44844	5.14
2021	51459.96157	53319.82883	3.61
2022	51757.11826	55310.21010	6.86

(2) Forecast Results Using the Exponential Smoothing Method

This paper uses the average of the data from the previous two periods as the initial value and aims to minimize the RMSE to identify the optimal model parameters: an initial value of 18,386.772, an alpha value of 0.700, and quadratic smoothing. At this point, the RMSE is 1,566.658. The model was then constructed using these parameters to obtain the predicted values, as shown in "Table 2." The model's average MAPE is 4.05%. From 2020 to 2022, the error remained stable between 10 million and 20 million metric tons, representing approximately 3% to 4%, indicating that the model effectively captures emissions growth during the economic recovery period. The forecast results for the next five periods (2023-2027) are as follows: 52,830.32, 53,813.24, 54,796.16, 55,779.07, and 56,761.99 (million tons). The projections indicate that the growth rate of Anhui Province's net carbon emissions will decline to 1.8%, with net carbon emissions in 2027 being 90.8 million tons lower than the gray-scenario projection. These results support the feasibility of achieving carbon peaking during the 14th Five-Year Plan period; however, caution is warranted regarding the rebound risk indicated by the triple-smoothing model (potential secondary growth after 2024). It is recommended to consolidate emission reduction achievements by increasing the share of non-fossil energy consumption in Anhui Province to over 25%.

Table 2. Forecast Results Using the Exponential Smoothing Method

Year	Actual figure	Forecast	MAPE（%）

2003	17395.09641	18386.77241	5.70
2004	19378.44841	16998.42601	12.28
2005	22295.55742	19844.53613	10.99
2006	24513.17058	23956.25568	2.27
2007	28199.03325	26617.22671	5.61
2008	31885.26099	30985.93433	2.82
2009	33140.31819	35174.25533	6.14
2010	35503.16267	35696.67707	0.55
2011	38568.31361	37799.06146	1.99
2012	39940.34831	41154.49696	3.04
2013	42871.23187	42110.10489	1.78
2014	43633.67061	45236.16587	3.67
2015	44081.00661	45426.10792	3.05
2016	44416.2268	45191.17883	1.74
2017	45040.76375	45095.35909	0.12
2018	48879.60229	45628.31222	6.65
2019	48974.11402	50762.7532	3.65
2020	48856.51249	50434.42537	3.23
2021	51459.96157	49524.68116	3.76
2022	51757.11826	52760.23024	1.94

(3) ARIMA Time Series Forecast Results

The original time series is non-stationary but becomes significantly stationary after first-order differencing. The ACF plot shows a truncated pattern after the first order, while the PACF plot exhibits a trailing tail; therefore, an ARIMA(0,1,1) model is selected. The ADF test P-value is 0.006. This model achieves stationarity through first-order differencing, and its white noise residuals (Q6 P-value=0.972) and high goodness-of-fit (R^2 =0.975) confirm its statistical reliability. The specific forecast results are shown in "Table 3"; the model has an average MAPE of 3.07%, indicating excellent performance. The forecast results for the next five periods (2023-2027) are as follows: 51,760.09, 51,555.17, 51,142.34, 50,521.62, and 49,692.99 (million tons). The forecasts indicate that Anhui Province's net carbon emissions will decline at an average annual rate of 1.5% over the next five years, reaching 49,693 million tons by 2027. This aggressive downward trend is 12,149 to 16,149 million tons lower than the results of the other two models, highlighting the structural impact of the "dual carbon" policy. However, the 2025 forecast of 51,142 million tons remains higher than the peak emission target set by the national government for Anhui, necessitating further strengthening of non-fossil energy substitution. The significance of the MA (1) coefficient boundary (P=0.058) suggests a need to guard against risks associated with fluctuations in policy implementation.

Table 3. ARIMA Time Series Forecast Results

Year	Actual figure	Forecast	MAPE（%）
2003	17395.09641		
2004	19378.44841		
2005	22295.55742	24608.25392	10.37
2006	24513.17058	26588.30025	8.47
2007	28199.03325	28100.57465	0.35
2008	31885.26099	31597.5766	0.90
2009	33140.31819	35122.52183	5.98
2010	35503.16267	35893.25616	1.10
2011	38568.31361	38000.45667	1.47
2012	39940.34831	40919.63459	2.45
2013	42871.23187	41987.46969	2.06
2014	43633.67061	44789.58577	2.65
2015	44081.00661	45249.12162	2.65
2016	44416.2268	45399.8346	2.21
2017	45040.76375	45457.71232	0.93
2018	48879.60229	45846.85106	6.20
2019	48974.11402	49665.45506	1.41
2020	48856.51249	49511.77499	1.34

2021	51459.96157	49150.18236	4.49
2022	51757.11826	51666.33042	0.18

4.2. Combination Prediction Results

Based on the analysis of the individual forecast results described above, the average MAPE for the Grey System Model GM (1,1), the Exponential Smoothing method, and the ARIMA time series were 6.54%, 4.05%, and 3.07%, respectively. Using the principle of error-inversely-weighted averaging, the combination weights were determined to be 0.2106, 0.3402, and 0.4491, respectively, enabling a combined forecast of Anhui Province's net carbon emissions. This method scientifically reflects the relative contributions of the three model types to the accuracy of net carbon emission forecasts for Anhui Province. It not only aligns with the "dominant model" theory of ensemble forecasting but also is consistent with empirical results across multiple fields. The specific results of the ensemble forecast are shown in "Table 4.".

The ensemble forecast demonstrated a significant advantage in accuracy during the historical period (2005-2022). Its average MAPE was only 2.49%, representing reductions of 4.05%, 1.56%, and 0.58% compared to the average MAPEs of the grey system forecast, exponential smoothing, and ARIMA time series, respectively. This optimization stems from a multi-model error compensation mechanism: taking 2010 as an example, the grey system model underestimated the figure by 17.8 million tons (5.02%), the exponential smoothing method overestimated it by only 1.94 million tons (0.55%), and the ARIMA time series overestimated it by 3.9 million tons (1.10%); after weighted combination, the error was reduced to 1.34 million tons (0.38%); In 2015, the grey system model underestimated the figure by 19.5 million tons (4.24%), the exponential smoothing method overestimated it by 13.45 million tons (3.05%), and the ARIMA model overestimated it by 11.68 million tons (2.65%); the combined forecast reduced the error to 5.71 million tons (1.3%). The above demonstrates that this ensemble forecasting model effectively integrates the long-term trend inertia of the grey model, the capture of short-term fluctuations by exponential smoothing, and the policy decay effect of ARIMA, thereby avoiding the structural biases inherent in individual models.

Table 4. Combination Prediction Results

Year	Actual figure	Forecast	MAPE（%）
2003	17395.09641		
2004	19378.44841		
2005	22295.55742	23294.84775	4.48
2006	24513.17058	25893.56767	5.63
2007	28199.03325	27794.5007	1.43
2008	31885.26099	31173.85165	2.23
2009	33140.31819	34510.48344	4.13
2010	35503.16267	35369.11694	0.38
2011	38568.31361	37371.87752	3.10
2012	39940.34831	40172.09576	0.58
2013	42871.23187	41330.9297	3.59
2014	43633.67061	44013.8294	0.87
2015	44081.00661	44652.49714	1.30
2016	44416.2268	45014.8772	1.35
2017	45040.76375	45389.98733	0.78
2018	48879.60229	46135.0291	5.61
2019	48974.11402	49993.25262	2.08

2020	48856.51249	50216.33983	2.78
2021	51459.96157	50155.89219	2.53
2022	51757.11826	52806.04422	2.03

The results of the three individual and combined forecasts for Anhui Province's net carbon emissions from 2023 to 2027 are shown in "Table 5." The combined forecast indicates that Anhui Province's net carbon emissions will continue to rise steadily, but the growth rate will decrease year by year, at 2.98%, 1.27%, 1.10%, 0.93%, and 0.77%, respectively, with an average annual growth rate of 1.41%. This trend aligns with the "inverted U-shaped" inflection point predicted by Dai et al. (2022), indicating that emission reduction policies are gradually taking effect but have not yet entered a downward trajectory. These results reconcile the extreme discrepancies among the individual forecasts: the Grey System model, due to its overreliance on early high-growth data, predicts a figure of 658.42 million tons for 2027, representing a 27.21% increase from the actual net carbon emissions in 2022; the ARIMA time series, driven by policy sensitivity, made a radical prediction of 496.93 million tons by 2027, a 3.99% decrease from the 2022 actual value; and the exponential smoothing method predicted a moderate increase of 9.67% in net carbon emissions to 567.62 million tons by 2027 compared to the 2022 actual value. The ensemble forecast achieves a compromise between trends through weighted averaging, projecting net carbon emissions of 554.99 million metric tons in 2027-a 7.23% increase from the 2022 actual figure. This level has not yet reached its peak, and the peak is projected to occur later than in the ARIMA forecast, indicating that the current development trajectory is closer to a high-carbon pathway, posing challenges to the 2030 peak target.

Table 5. Forecast for 2023-2027

Year	Gray System	Exponential Smoothing	ARIMA	Combination Prediction
2023	57338.293	52830.317	51760.09	53299.20333
2024	59404.792	53813.236	51555.17	53976.86788
2025	61510.434	54796.155	51142.34	54569.39738
2026	63655.962	55779.074	50521.62	55076.95733
2027	65842.130	56761.994	49693.00	55499.70238

5. Conclusions and Policy Recommendations

The ensemble forecasting model weighted by the inverse of MAPE significantly improved forecasting accuracy. Empirical evidence shows that the average MAPE of the ensemble model for the period 2005-2022 was lower than that of any individual forecasting model, demonstrating that it effectively integrates the small-sample adaptability of the grey model, the short-term trend responsiveness of exponential smoothing, and the ability of ARIMA to capture linear patterns through bias compensation and variance suppression mechanisms. The composite forecast results for 2023–2027 indicate that Anhui Province's net carbon emissions will increase from 532.99 million metric tons to 554.99 million metric tons, with an average annual growth rate of 1.41%. Although the growth rate is declining, the absolute

increase still reaches 22 million metric tons, suggesting that the current development trajectory is closer to a high-carbon model, posing a severe challenge to the 2030 carbon peak target. Based on these findings, this paper proposes the following policy recommendations:

(1) Establish a provincial-level intelligent carbon emissions monitoring and early warning platform. Implement a dynamic weighting update mechanism to periodically optimize model parameters based on changes in the economy, energy, technology, and policy. Introduce AI-driven time-series analysis to correct residuals, thereby enhancing the system's responsiveness to economic fluctuations and policy adjustments. Set tiered early warning thresholds; once abnormal levels are exceeded, the system will automatically trigger measures such as production scheduling for high-energy-consuming industries, stricter energy assessments for projects, and quota adjustments. Through a closed-loop "monitoring-forecasting-early warning-response" system, provide support for macro-level decision-making.

(2) Promote coordinated emissions reductions across the three major sectors: industry, energy, and construction. In the industrial sector, accelerate the green replacement of high-carbon production capacity in industries such as steel and building materials; improve incentives for green manufacturing; and guide enterprises to replicate successful experiences in low-carbon transformation. In the energy sector, accelerate the large-scale development of wind and solar power; advance the flexibility retrofitting of coal-fired power plants; and increase the share of non-fossil energy. In the building sector, promote the integration of photovoltaics into new construction and increase electrification rates. Establish cross-departmental coordination mechanisms to form a three-pronged emissions reduction framework.

(3) Innovate regional collaborative governance and institutional safeguards. Establish a cross-city carbon compensation mechanism to quantify emissions responsibilities; build a provincial carbon emissions trading platform; and establish supporting funds for technology transfer and green development to guide capital and technology toward regions facing greater transition pressures. Through provincial legislation, clarify the 2030 carbon peak target and reinforce the responsibilities of all parties; incorporate the quality of urbanization and carbon budgets into performance evaluations; and establish a special fund for green and low-carbon transition to prioritize support for leading enterprises in coal consumption reduction, energy efficiency improvement, and green technology innovation. Through multi-dimensional institutional safeguards, inject sustained momentum into achieving the carbon peak on schedule.

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