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Forecast data of provincial carbon emissions in China from 2025 to 2035: based on ARIMA-BP model

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ABSTRACT

China is an important contributor to global carbon emissions. Accurately estimating carbon emissions is crucial for reducing carbon emissions in accordance with the United Nations Sustainable Development Goals and China's carbon neutrality strategy. This study selected energy consumption data from Chinese provinces from 2000 to 2021, calculated carbon emissions using the carbon emission factor method, and then predicted carbon emissions data for 2022-2035 using the ARIMA-BP model. This dataset can be used to describe the spatiotemporal evolution trend of carbon emissions in China. This study can provide policy basis and wisdom for China's carbon reduction efforts.

1. Introduction

Global climate change is an urgent and important issue that requires joint efforts from the international community to mitigate its impact. As one of the world's largest economies and greenhouse gas emitters, China plays a crucial role in the global fight against climate change. The United Nations Sustainable Development Goals (SDGs), especially the Climate Action Goals, emphasize that countries must take urgent action to address climate change and its impacts. To this end, China has committed to achieving carbon neutrality by 2060, marking a significant commitment to reducing its carbon footprint and transitioning to a low-carbon economy. [1]

Accurately estimating and predicting carbon emissions is crucial for policy-making, evaluating the effectiveness of carbon reduction measures, and tracking progress towards carbon neutrality. However, previous estimates of China's carbon emissions have mainly relied on short-term data, which limits the ability to comprehensively capture the evolution trend of carbon emissions and long-term emission reduction effects.

To bridge this gap, there is an urgent need for comprehensive and long-term carbon emission data that can reveal trends in China's carbon emissions, regional differences, and the impact of policy interventions. Such data will enable policy makers, researchers, and stakeholders to develop more precise and effective carbon reduction strategies, promote international cooperation, and drive innovation in low-carbon technologies [2][3][4].

In this context, this article uses carbon emission data from 2000 to 2024 as input and predicts China's carbon emission data from 2025 to 2035 through the ARIMA-BP model, generating a comprehensive dataset of China's carbon emissions. Using internationally recognized carbon emission factor methods, we strive to provide reliable and standardized estimates of China's carbon emissions during this period. This dataset not only fills the gap in existing carbon emission data, but will also become a valuable resource for future research, policy evaluation, and public awareness activities.

Given China's commitment to carbon neutrality and the growing global attention to climate action, this study is timely and relevant. By promoting a scientific understanding of China's carbon emissions, this study aims to provide information and support for mitigating climate change and promoting sustainable development

2. Methods

Our goal is to calculate the carbon emissions from the energy consumption data of China provinces from 2000 to 2024, and then use ARIMA-BP model to predict the carbon emissions data from 2025 to 2035.

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(1) Calculate the average carbon emissions of each province from 2000 to 2024.

In this paper, the carbon emission of energy consumption in three major industries (primary industry, secondary industry and tertiary industry) is calculated by using the guidelines issued by official website, the Intergovernmental Panel on Climate Change of the United Nations, and the carbon emission factor method recommended by provincial units in China. The specific formula is as follows:

$$EC = \sum_{i=1}^{3} \sum_{j=1}^{6} E_{ij} r_j \times \frac{44}{12} \quad (1)$$

The explanations of the variables in Formula (1) are shown in Table 5.

Table 1: Explanation of carbon emission measurement variables

Variable Name	Variable interpretation and assignment	Unit
EC	Energy carbon dioxide emissions	Ten thousand tons tCO2
i	Energy consumption category	\
Eij	The j-th energy consumption in the I-industry	Kilogram standard coal
rj	Carbon emission coefficient of the j-th energy source	tC/1012J
44/12	Conversion coefficient of carbon and carbon dioxide	\

(2) Forecast the carbon emissions of each province from 2025 to 2035.

Considering that the total carbon emission is a typical time series data, this paper uses ARIMA-BP neural network combination model to forecast.

1.ARIMA model

In this study, ARIMA model is constructed by three steps: stationarity test of time series, determination of order P of ARIMA model and parameter estimation and diagnostic test, and the prediction results and error sequence are obtained (see Formula 2 for details). Firstly, the ADF method is used to test the stationarity of time series, and the DCI series is obtained by taking the first-order difference of each series. After the ADF test, the adjoint probability T statistic is -2.97~-2.99, and the unit root hypothesis is rejected at the statistical level of 1%. After the first-order difference, the carbon emission intensity series is stable. Then, the autocorrelation (AC) coefficient and partial autocorrelation (PAC) coefficient are adopted, and according to the order determination principles such as AIC, as can be seen from Figures 3 and 4, the (1,1,0) model is adopted according to the comprehensive analysis of AC and PAC images and data and the inspection table. Finally, the significance of model parameters is tested and predicted.

$$y_t = \mu + \sum_{i=1}^{p} \gamma_i y_{t-1} + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \quad (2)$$

2. ARIMA-BP neural network combination model

Establish a two-layer hidden layer (Formula 4) BP neural network with one neuron (Formula 3) and three neurons. Input the error data into the neural network in time sequence, with the input node set to 4 and the output node set to 1. By rolling the window, the error of the previous period will continue to be transmitted into the neural network, and as part of the input, the model will be continuously revised and predicted. Finally, the combination model is used to predict the change of carbon emission intensity. The specific formula is as follows:

$$g(x) = \frac{1}{1+e^{-x}} \quad (3)$$

$$H_k = f\left(\sum_{i=1}^{m} xi \cdot w_{ik} - a_k\right) \quad (4)$$

(3) Display of data prediction effect

From Table 6 and Figure 5, it can be seen that the MSE fluctuation range of carbon emission intensity of the three major industries is 0 to 0.633, and the regression coefficient is high and close to 1, which shows that the simulation prediction effect is good and the prediction data is reliable. As can be seen from Figure 12, from 2000 to 2035, China's industrial energy consumption intensity was "secondary industry > tertiary industry > primary industry", in which the energy intensity of primary industry decreased from 0.0039 to 0.0001, that of secondary industry decreased from 0.0525 to 0.0041, that of tertiary industry decreased from 0.0024 to 0.0003, and that of secondary industry decreased. It shows that the reduction of China's energy consumption intensity is mainly concentrated in the secondary industry. Although there is still a certain gap between China's energy intensity and that of European and American countries, with the adjustment of China's industrial structure, diversification of energy structure and continuous improvement of industrialization level, there is still room for a certain decline in energy intensity.

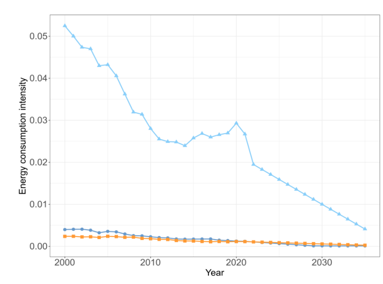

Figure 1: Forecast chart of energy consumption intensity from 2000 to 2035

Table 1: Prediction results of carbon emission intensity of three major industries

Industry	*Collect*	*MSE*	*RMSE*	*MAE*	*MAPE*	R^2
primary industry	*Training set*	*0.002*	*0.039*	*0.028*	*6.221*	*0.998*
	Test set	*0*	*0.004*	*0.004*	*0.969*	*0.912*
secondary industry	*Training set*	*0.097*	*0.312*	*0.265*	*13.485*	*0.932*
	Test set	*0.633*	*0.795*	*0.783*	*39.613*	*0.916*
service sector	*Training set*	*0.002*	*0.047*	*0.04*	*12.999*	*0.999*
	Test set	*0.001*	*0.036*	*0.036*	*11.437*	*0.998*

Data Description

Firstly, economic output is divided into three different sectors: primary industry, secondary industry, and tertiary industry (see Figure 1 for details). The primary industry is mainly composed of agricultural and forestry consumption sectors, including activities related to cultivation, forestry, and related services. The secondary industry covers both the industrial consumption sector and the energy consumption sector, including manufacturing, mining, and energy production and distribution. Finally, the tertiary industry includes the construction consumption sector and the

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transportation consumption sector, covering services, trade, and other non-material production activities. [3]

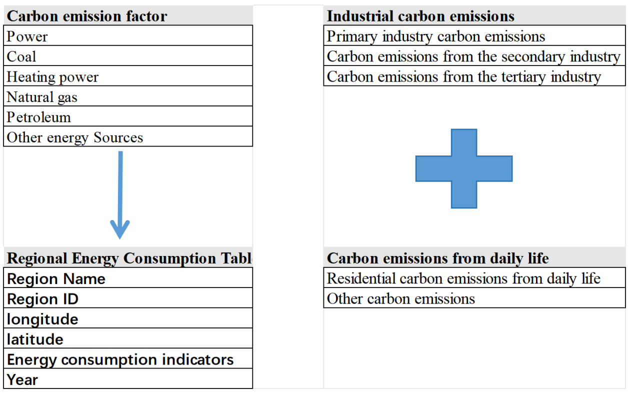

Figure 2: Data classification

To gain insights into the energy efficiency of each industry, we calculate the energy consumption per unit of GDP for each sector. This metric provides a clear understanding of how much energy is required to produce a dollar's worth of goods or services in each industry. By multiplying the energy consumption per unit GDP by the respective industry's output value, we can obtain the total energy consumption for each sector.

In this paper, we employ the average carbon emission factor over the past ten years as the benchmark for calculating carbon emissions. This factor is derived from comprehensive data on various energy sources and their respective carbon footprints. By multiplying the total energy consumption of each industry by this carbon emission factor, we can estimate the carbon emissions associated with that industry's energy use. Furthermore, to convert these emissions into a common unit for aggregation, we apply a conversion coefficient. By summing up the carbon emissions from all three industries, we obtain the total carbon emissions for the economy.

The variables involved in this paper are primarily focused on the energy consumption of the three major industries, as well as the output value of each industry. Additionally, we consider population and economic variables that may influence carbon emissions. The descriptive statistics of these main variables are presented in Table 2, which provides an overview of their distribution, range, and other relevant statistical measures. This comprehensive approach allows us to gain a deeper understanding of the factors driving carbon emissions and to explore potential strategies for reducing them [3][5][6][7][15][16][17][18].

Table 2 Descriptive statistics of main variables

Variable name	Sample size	Maximum	Minimum value	Average value	Standard deviation
Power	3284	5600.89	0.39	253.72	568.89
Coal	3142	11526.60	0	631.16	1416.13
Heating power	1738	142256	0	5607.78	11401.62
Natural gas	2017	165.13	0	10.47	18.05
Petroleum	3277	2653	0.17	247.06	343.55
Other energy Sources	778	1556.51	0	79.72	131.59
Output value of primary industry	661	6029	40.1	1421.4	1255.14
Output value of Secondary Industry	661	52678.7	80.9	7132.35	8185.50
Output value of Tertiary industry	661	69179	127.6	8084.38	9974.76
Regional GDP	661	124720	263.7	16638.12	18777.37

Note: As there are many energy sources, the six categories of energy sources are described and counted by combined data.

Table 2 Carbon emissions from the three major industries

Year	Primary industry carbon emissions	Carbon emissions from the secondary industry	Carbon emissions from the tertiary industry	Total carbon emissions	Residential carbon emissions from daily life
2025	78.70333333	10850.90224	494.5285714	15189.26745	3765.133307
2026	80.07666667	11193.64739	511.3957143	15744.5507	3959.430926
2027	81.45	11536.39255	528.2628571	16337.86488	4191.75948
2028	82.82333333	11879.1377	545.13	16990.50027	4483.40924
2029	84.19666667	12221.88285	561.9971429	17681.27644	4813.199781
2030	85.57	12564.62801	578.8642857	18408.62852	5179.566229
2031	86.94333333	12907.37316	595.7314286	19138.09127	5548.043346
2032	88.31666667	13250.11831	612.5985714	19840.57162	5889.538066
2033	89.69	13592.86347	629.4657143	20469.319	6157.299823
2034	91.06333333	13935.60862	646.3328571	20984.03186	6311.027049
2035	92.43666667	14278.35377	663.2	21350.77213	6316.781692

Table 3 Carbon emission prediction results (partially displayed)

Year	Shanghai	Yunnan	Neimenggu	Beijing	Jinlin
2025	163.2628381	129.8292857	1212.658562	156.0412563	353.8101793
2026	166.7915476	134.0728571	1312.772693	158.7876606	363.3339693
2027	170.3202571	138.3164286	1416.639802	161.5053578	372.8500109
2028	173.8489667	142.56	1524.375188	164.2327529	382.363618
2029	177.3776762	146.8035714	1635.936239	166.9568718	391.8764603
2030	180.9063857	151.0471429	1751.338703	169.6820974	401.3890623
2031	184.4350952	155.2907143	1870.57676	172.4069492	410.9015887
2032	187.9638048	159.5342857	1993.652561	175.1319273	420.4140915
2033	191.4925143	163.7778571	2120.565311	177.8568627	429.9265867
2034	195.0212238	168.0214286	2251.315303	180.5818126	439.4390797
2035	198.5499333	172.265	2385.90243	183.3067576	448.9515719

Collect energy consumption data from different provinces, such as electricity, coal, heating, natural gas, oil, and other energy sources. Then, these data need to be classified according to the primary industry, secondary industry, and tertiary industry. Next, the energy consumption of each industry needs to be multiplied by the corresponding year's carbon emission factor, and then the carbon dioxide emissions can be obtained through conversion coefficients. Finally, add the carbon emissions of all industries to the carbon emissions of household consumption to obtain the total emissions [8][9][10][11][12].

Visualize the spatiotemporal evolution trend of carbon emissions using ArcGIS software and obtain the results shown in Figure 3:

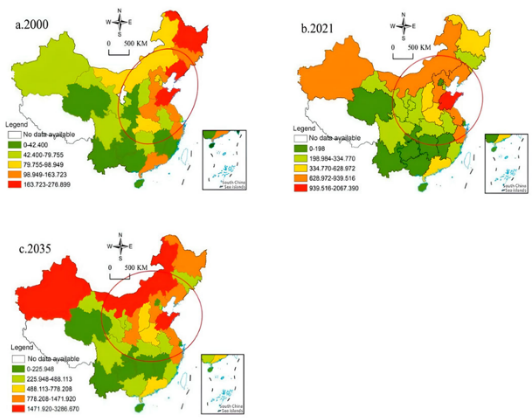

Fig 3 Spatial and Temporal Evolution of Carbon Emissions from 2000 to 2035

As illustrated in Figure 2, from the year 2000 to 2035, there has been a significant surge in carbon emissions across different industrial sectors. Specifically, the primary industry witnessed an increase in carbon emissions from 44 million tons to 92 million tons, marking a substantial growth of 208%. The secondary industry, on the other hand, experienced an even more pronounced increase, with carbon emissions jumping from 2.070 billion tons to 14.278 billion tons, representing a whopping 690% surge. Meanwhile, the tertiary industry also saw its carbon emissions rise from 73 million tons to 663 million tons, which translates to a 91% increase. Notably, the secondary industry currently has the highest carbon emissions among the three sectors.[3][12]

The economic landscape of China has entered a new era, characterized by a shift towards high-quality development. This transformation is accompanied by a significant restructuring and upgrading of the industrial sector. As a result, the proportion of the secondary industry is expected to decline steadily. In response to this trend, China is actively promoting the upgrading of its manufacturing sector, aiming to transform it into a high-end manufacturing hub. This ambition encompasses the research, development, and application of cutting-edge manufacturing technologies, such as artificial intelligence, big data analytics, and robotics.
Moreover, with the relentless advancement of science and technology, agricultural modernization has emerged as a prominent trend for the future. This modernization will not only bolster the efficiency of agricultural production but also enhance the quality and competitive edge of agricultural products in the global market[13].

Against the backdrop of a new wave of industrial transformation and upgrading, new urbanization initiatives, and an uptick in residents' consumption quality, the tertiary service industry in China is poised to encounter fresh opportunities for growth. This sector is increasingly becoming the linchpin of economic development, further underscoring its leading role in shaping the country's economic future. As China continues to navigate through these transformative changes, it remains committed to striking a balance between economic growth and environmental sustainability, ensuring a greener and more prosperous future for its citizens.

3. Limitation

Despite the efforts made in this study to provide a comprehensive and accurate estimation of China's carbon emissions from 2000 to 2021, several limitations should be acknowledged.
Firstly, the study relies on the internationally recognized carbon emission factor method to calculate carbon emissions. While this method is widely adopted, it may introduce some uncertainties due to variations in emission factors across different energy sources and regions. Additionally, the study assumes that the emission factors remain constant over the study period, which may not fully reflect the actual changes in emission factors due to technological advancements or policy interventions.
Secondly, the dataset used in this study is based on energy consumption data collected from various sources. The accuracy and completeness of these data may vary across different regions and time periods, which could affect the accuracy of the carbon emission estimates. Moreover, due to data availability issues, the study does not include carbon emissions from electricity and heat in the consumer sector, which may lead to an underestimation of total carbon emissions.
Thirdly, the study focuses on the estimation and prediction of carbon emissions at the national level, without delving into the details at the provincial or city level. While this provides a broad overview of China's carbon emissions trends, it may not capture the regional variations and nuances in carbon emission patterns.
Furthermore, the study assumes that the relationship between energy consumption and carbon emissions remains constant over time. However, in reality, this relationship may be affected by various factors such as changes in energy efficiency, technological advancements, and policy interventions. These factors could potentially alter the trends in carbon emissions and limit the predictive power of the study.
Finally, while the study highlights the importance of accurate estimation and prediction of carbon emissions for policy formulation and evaluation, it does not provide specific policy recommendations based on the findings. Future studies could explore the potential impacts of different policies on carbon emissions and offer more concrete policy guidance to support China's carbon neutrality goals.

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