EVALUATION AND FORECASTING OF CARBON EMISSIONS FROM BUILDINGS: A CASE OF JIANGSU PROVINCE IN CHINA

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Abstract. Excessive carbon emissions are driving global warming and greenhouse effects, demanding urgent global intervention. The construction industry, a significant contributor to both energy consumption and carbon emissions, plays a pivotal role in addressing emissions within this sector. This study aims to comprehensively analyze the factors influencing carbon emissions throughout the entire life-cycle of buildings in Jiangsu Province, China. Furthermore, it seeks to evaluate and forecast carbon emissions in the province's construction sector for the upcoming decade. To accomplish this, the paper employs a multivariate linear regression model, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method, and the Autoregressive Integrated Moving Average model (ARIMA) model to assess and forecast residential building carbon emissions in the 13 prefectural-level cities in Jiangsu Province, China. The research findings indicate that various factors have substantial impacts on the overall carbon emissions throughout a life-cycle of a building. Notably, total carbon emissions exhibit a positive correlation with energy consumption and a negative correlation with energy sources. The results of this study offer valuable insights for optimizing carbon emissions associated with building construction and present opportunities for reducing emissions from buildings. Furthermore, this research holds significant implications for shaping low-carbon policies in other cities, emphasizing the need for immediate global efforts to control carbon emissions.
Keywords: *building carbon emissions, Multivariate Linear Regression Model, TOPSIS and ARIMA method, evaluate, sustainability*

Introduction

As per the Sixth Assessment Report released by The Intergovernmental Panel on Climate Change (IPCC) in 2023, human activities have unequivocally induced global warming. This has led to a global surface temperature increase of 1.1°C for the period 2011-2020 compared to the 1850-1900 baseline, with a likely range of 0.95°C to 1.20°C (IPCC, 2022). Recognizing the urgency of the climate crisis, President Xi Jinping announced on September 22, 2020, during the 75th session of the United Nations General Assembly, China's commitment to peak its carbon dioxide emissions before 2030 and achieve carbon neutrality by 2060. The construction industry, one of the world's three major carbon-emitting sectors (alongside heavy industry and transportation), stands as the largest contributor to carbon emissions. In 2020, China's buildings, over their entire life cycle, generated a staggering 5.08 billion tons of CO_2, accounting for 50.9% of the nation's total carbon emissions. This context underscores the pivotal role of low-carbon construction in China's ambitious agenda to enhance energy efficiency, reduce emissions, and combat climate change.

The construction sector is a substantial contributor to global greenhouse gas (GHG) emissions, accounting for around one-third of the world's total emissions, along with a significant 40% of global energy consumption (United Nations Environment Programme,

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2009). Carbon emissions associated with the entire life-cycle of residential buildings are influenced by a multitude of factors, including regional disparities, design standards, climate conditions, architectural styles and energy use. Precise forecasting of these emissions is crucial for crafting effective emission reduction policies and optimizing low-carbon building design, underscoring the enduring importance of research in low-carbon construction. Jiangsu Province in China, a significant hub for both energy consumption and carbon emissions, plays a vital role in the construction industry. The carbon emissions from the whole building process in Jiangsu province, China from 2006 to 2022 are illustrated in *Figure 1*. The comprehensive construction process encompasses various stages, such as the production and transportation of building materials, actual construction activities, sourcing energy, building demolition, waste management, renovations, and updates, as well as energy consumption. The detailed process is shown in *Figure 2*. Given its status, this paper centers its attention on the carbon emissions originating from the construction sector across the thirteen cities in Jiangsu Province, China. The primary objectives include data collection and analysis, model development, and the identification of pivotal indicators with quantifiable correlations to factors like building design standards, regional variations, climate impacts, building material production and transportation, energy consumption during construction and demolition, architectural preferences, energy consumption during usage, building types, and more. These indicators will be harnessed to conduct a comprehensive assessment of carbon emissions throughout the entire life-cycle of residential buildings. Subsequently, this research will provide valuable insights into future development trends in the region, thereby contributing to the achievement of dual carbon goals.

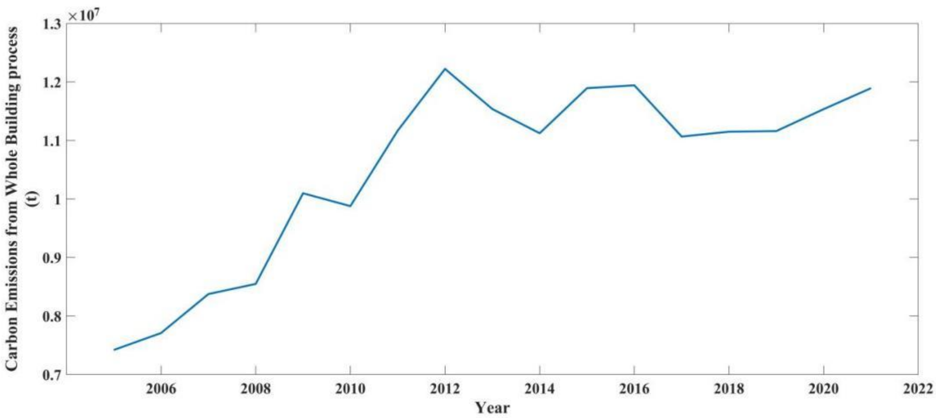

Figure 1. *Carbon Emissions from the Whole Building Process in Jiangsu Province, China from 2006 to 2022*

The energy demand encompasses heating, cooling, and other building requirements, with corresponding carbon emissions data collected for Jiangsu Province in China from 2000 to 2021 (refer to *Table 1*). The analysis indicates a gradual increase in carbon emissions from heating and cooling systems. However, their contribution to the overall carbon emissions of buildings remains minimal due to their relatively small proportion in the broader context, as depicted in *Figure 3*.

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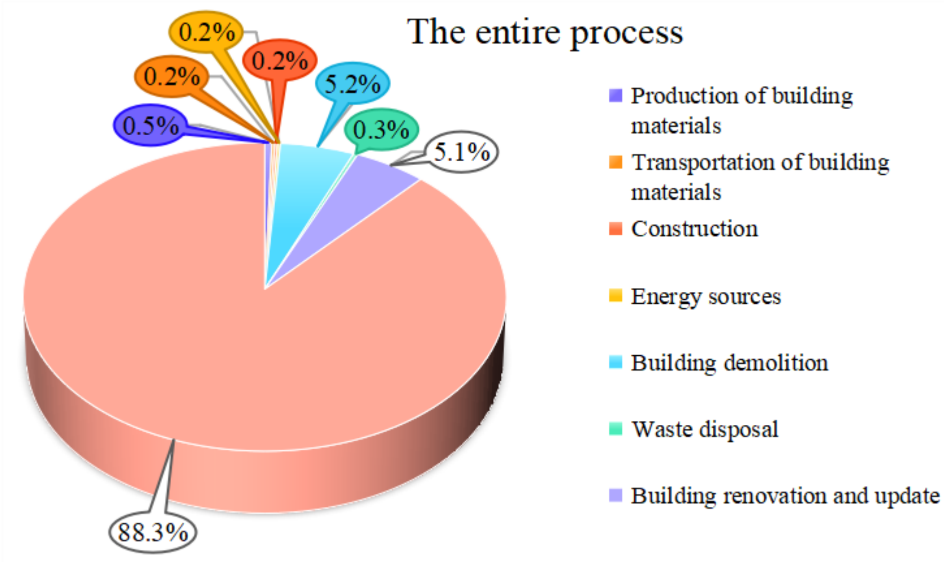

Figure 2. *The entire process of building construction*

Table 1. *The carbon emissions from building heating and cooling in Jiangsu Province, China from 2000 to 2021*

Year	**Carbon Emissions from Building Heating and Cooling (10^3t)**
2000	2,214.410,041
2001	2,321.177,177
2002	2,496.583,420
2003	2,288.447,287
2004	2,409.385,650
2005	3,070.369,440
2006	2,972.336,026
2007	2,852.262,968
2008	3,328.164,423
2009	3,366.125,361
2010	3,039.596,389
2011	4,171.915,525
2012	3,291.358,063
2013	3,550.809,804
2014	3,804.404,299
2015	4,109.214,550
2016	3,559.031,125
2017	4,152.435,387
2018	4,052.366,961
2019	3,978.936,781
2020	4,040.245,116
2021	4,596.366,136

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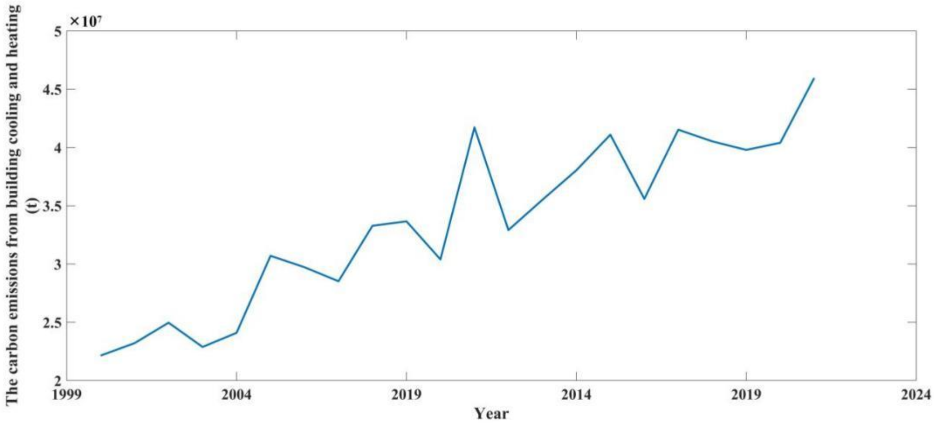

Figure 3. *The trend of carbon emissions from building heating and cooling in Jiangsu Province, China from 2000 to 2021*

Literature Review

Global warming has taken center stage in academia and on the international platform, driving countries worldwide to actively seek pathways for carbon emissions reduction. In China, low-carbon construction stands as an indispensable pillar of the nation's comprehensive efforts to bolster energy efficiency, slash emissions, and combat climate change. Carbon emissions throughout the entire life-cycle of residential buildings are intricately linked to a web of factors, including regional variances, design standards, climate considerations, architectural styles, and energy consumption during usage. Precise carbon emission assessment and forecasting play a pivotal role in shaping emission reduction policies and providing crucial benchmarks for the optimization of low-carbon building designs.

In terms of factors affecting building emissions, Li et al. (2023b) used The Kaya Identity and the Logarithmic Mean Divisia Index (the Kaya-LMDI decomposition) method to study the impact parameters on public buildings. Du et al. (2022) employed the emission factor method and the Logarithmic Mean Divisia Index-Long-range Energy Alternatives Planning Model (LMDI-LEAP) to investigate the carbon emission trends and influencing factors in typical villages in southern China. Yang et al. (2023) utilized the Stochastic Impacts by Regression on Population, Affluence, and Technology model (STIRPAT) to analyze the driving factors behind carbon emissions evolution. Xu et al. (2022) conducted an evaluation of various factors related to implicit carbon emissions using the structural decomposition analysis method. As tools for analyzing factors influencing building emissions, based on these methods, scholars have explored the impact of factors such as per capita GDP, population, building area, building types, and urbanization on building carbon emissions.

From existing research, scholars have predominantly focused on carbon emissions accounting for buildings (Wang, 2007; Cai et al., 2017; Huo et al., 2018), factors influencing carbon emissions and their trends (Ma and Song, 2022), life cycle carbon assessment of buildings (Li et al., 2022), and the study of future development paths for low-carbon construction (Xi and Cao, 2022), among others. The development of reliable evaluation and forecasting models can provide valuable foundations for the formulation of sound policies at national, regional, and industrial levels to support carbon reduction efforts. In recent years, some scholars have also begun to use simulation and prediction

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methods for carbon emissions. Most of these studies are primarily based on traditional econometric and statistical principles. For instance, Liu et al. (2022) calculated threshold effects in selected variable relationships using the Smooth Transition Regression (STR) model. Tang et al. (2021) used time series analysis and spatial analysis to forecast that CO_2 emissions in the Heilongjiang tourism industry are still on the rise. Wang et al. (2023) used the Kaya constant equation to predict the spatiotemporal evolution of carbon emissions in the Chinese construction industry from 2022 to 2050. As methods continue to evolve, more and more scholars are turning to non-numeric simulation research using artificial intelligence software. Bamisile et al. (2023) developed three neural network models to predict future carbon emission trends in the African continent. Based on the LMDI model and artificial neural network model, it was discovered that carbon sinks and carbon capture and storage (CCS) and BECCS (bioenergy and CCS) are the preferred options for achieving carbon neutrality in China (Ru et al., 2022). Zhang et al. (2022) used scenario analysis with scenarios set as low-carbon, baseline, and high-carbon modes to predict carbon emissions in Jiangsu Province. Zhou and Li (2023a) developed an Input-Output Bayesian Neural Network (IO-BNN) method, and the results indicated that under different environmental protection policies, carbon emissions in Guangdong would peak between 2025 and 2035 and then continue to decline from 2036 to 2050. Furthermore, some scholars have used System Dynamics-coupled Building Life Cycle Carbon Emission (SD-BLCA) combined with scenario analysis and the Monte Carlo method for prediction. The results showed that by increasing the proportion of renewable energy generation and retrofitting existing buildings, carbon emission growth can be offset, and carbon peak emissions can be achieved by 2025 (Li et al., 2023b).

The multivariate linear regression equation model can accurately describe the correlation between carbon emissions and their influencing factors. It has a simple model structure that is easy to understand. By using the optimal combination of multiple indicators to predict or estimate the dependent variable, it is more effective and realistic compared to evaluating with single indicators. In this paper, multivariate linear regression will be employed to describe the relationship between carbon emissions and various factors, including carbon emissions from building material production, carbon emissions from building material transportation, and carbon emissions during construction processes. This approach will be used to assess and predict carbon emissions from buildings in Jiangsu Province.

The calculation models for carbon emissions can produce differing results due to the multitude of factors influencing them, particularly in energy conversion (Pu et al., 2022). While many scholars primarily focus on the influence of population and urban development on building carbon emissions, they often neglect other essential factors. These factors include carbon emissions during the production of building materials, emissions generated during waste disposal, and energy consumption, all of which can significantly contribute to increased building carbon emissions. Consequently, scholars have observed substantial disparities in carbon emission predictions across different regions, highlighting the complexity of the issue.

In summary, the current research by scholars mostly focuses on national-level predictions of building carbon emissions, with limited attention given to regional or sector-specific studies. There is a lack of evaluation and forecasting of building carbon emissions at the provincial or municipal levels. This study aims to assess and predict carbon emissions from buildings in the thirteen prefectural-level cities of Jiangsu

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Province. It seeks to make a valuable contribution to achieving the carbon peak and carbon neutrality goals in Jiangsu Province.

Research Methods and Models

In this paper, we adopt a structured approach to study building carbon emissions. Initially, a multivariate linear regression model is employed to explore the relationships between various factors and building carbon emissions. Following this, we identify the primary influencing factors based on the research results. These key factors are subsequently used in an evaluation of carbon emissions from buildings across the thirteen cities in Jiangsu Province, China, applying the TOPSIS model. Furthermore, we integrate these influencing factors with carbon emissions data from Jiangsu Province in China spanning from 2006 to 2022. This combined data-set is then subjected to the ARIMA model to forecast carbon emissions for the forthcoming decade. This methodological framework allows for a comprehensive assessment of carbon emissions and provides valuable insights into future trends in Jiangsu Province's construction sector.

Multivariate Linear Regression Model

Regression analysis serves as a pivotal statistical tool for comprehending the interplay between a dependent variable and independent variables. Its core purpose lies in the identification and estimation of parameters that encapsulate the optimal-fitting function for a specific data-set (Al-Said, 2017). Given the manifold factors impacting carbon emissions across a building's entire life-cycle, our selection aligns with the utilization of a multivariate linear regression model. The goal here is to discern the key influencing factors of carbon emissions throughout a building's life-cycle. In this paper, we employ the multivariate linear regression model to establish the linkage between a building's total carbon emissions throughout its life-cycle and the factors influencing it, as demonstrated below:

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_m x_m + \epsilon \tag{Eq.1}$$

Eq(1) is an observable random variable influenced by $\beta_0, \beta_1, \beta_m$ and ϵ, where $\beta_0, \beta_1, \beta_m$ represents an unknown parameter, ϵ is referred to as the regression coefficient, and represents random error.

Pearson Correlation Coefficient

The Pearson correlation coefficient stands as the most frequently utilized linear correlation coefficient. In this study, we utilize it to analyze the correlation between energy consumption and carbon emissions.

Consider a scenario where there are m objects and n indicators, constituting a data matrix $X = \left(x_{xij}\right)_{m\times n}$. In this investigation, we focus on the correlation between the a-th column x_a and the b-th column x_b within the research matrix. Denote the correlation coefficient for columns a and b as $rho(a, b)$.

$$rho(a, b) = \frac{\sum_{i=1}^{m}(x_{a,i} - \overline{x_a})(x_{b,i} - \overline{x_b})}{\sum_{i=1}^{m}(x_{a,i} - \overline{x_a})^2 \sum_{j=1}^{m}(x_{b,j} - \overline{x_b})^2} \tag{Eq.2}$$

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In *Eq(2)*, the correlation coefficient, denoted as r, varies between -1 and +1, where m represents the length of each column. A value of -1 signifies a complete negative correlation, indicating a perfect inverse relationship. Conversely, a value of +1 represents a complete positive correlation, indicating a perfect direct relationship. A value of 0 implies no correlation between the columns.

In this study, we focus on the energy required in the construction process and utilize the Pearson correlation coefficient to analyze the relationship between energy consumption and carbon emissions. *Table 2* details the annual consumption of building materials and the associated carbon emissions from their production in Jiangsu Province, China.

Table 2. *Consumption of construction materials and carbon emissions from building materials production in Jiangsu Province, China over the years (Zhang et al., 2022)*

Year	Steel (t)	Cement (t)	Glass (Weight Box)	Aluminum (t)	Carbon Emissions (10^3t)
2006	19,365,741	82,523,173	5,807,113	722,611	10,412.65
2007	24,896,823	91,657,074	6,090,033	829,837	12,292.25
2008	30,475,791	118,258,785	10,392,076	780,865	14,892.72
2009	35,532,626	152,498,685	16,587,859	1,079,470	18,644.98
2010	40,618,866	157,705,493	17,325,388	1,301,559	20,465.46
2011	47,989,650	182,777,750	14,408,094	1,738,724	24,388.89
2012	141,117,794	754,308,672	18,685,165	7,466,010	89,863.45
2013	130,393,503	316,346,453	20,494,290	17,162,732	83,597.11
2014	79,550,112	245,611,224	177,321,086	4,397,407	41,305.15
2015	86,746,631	271,234,936	22,840,682	4,136,138	42,787.49
2016	90,703,898	245,411,043	26,027,869	5,243,690	44,554.21
2017	90,562,639	241,763,822	20,947,231	4,293,637	42,154.00
2018	93,709,279	239,359,027	25,063,438	4,493,855	43,079.64
2019	100,465,171	257,666,274	26,811,036	4,107,839	44,638.29

As depicted in *Figure 4*, the computational analysis reveals correlation coefficients between carbon emissions and steel, cement, glass, and aluminum of 0.97, 0.87, 0.13, and 0.86, respectively. A significant positive correlation is evident, with the highest observed between steel and carbon emissions.

Hence, to mitigate the energy consumption of buildings, it is valuable to explore the substitution of renewable energy for materials like steel and cement, which are associated with substantial carbon emissions. This entails advocating for the widespread adoption of green building materials, promoting the use of renewable energy, and initiating architectural photovoltaic initiatives. These combined efforts can lead to a significant reduction in carbon emissions from buildings.

The TOPSIS Method

The TOPSIS method stands out as a widely adopted and comprehensive evaluation technique for ranking alternative solutions. It operates by scrutinizing ideal-positive and ideal-negative solutions for each decision criterion, and it is often referred to as TOPSIS (Krishnan et al., 2023). Its core principle revolves around ranking based on the measurement of the distance between evaluated objects and the best and worst solutions (Zhang and Zhu, 2017; Shi et al., 2023). An optimal solution, in this context, is one that

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closely approaches the best solution while distancing itself from the worst solution; otherwise, it does not meet the criteria for optimality. The optimal solution attains the best values across all evaluation criteria, while the worst solution exhibits the poorest values for each evaluation criterion. The fundamental steps are depicted in *Figure 5*. Given the diverse factors impacting carbon emissions at various stages of a building's lifecycle, we employ this method in our study to identify the key factors influencing carbon emissions throughout a building's lifecycle. We assign distinct weights to each indicator and execute an integrated assessment of residential carbon emissions.

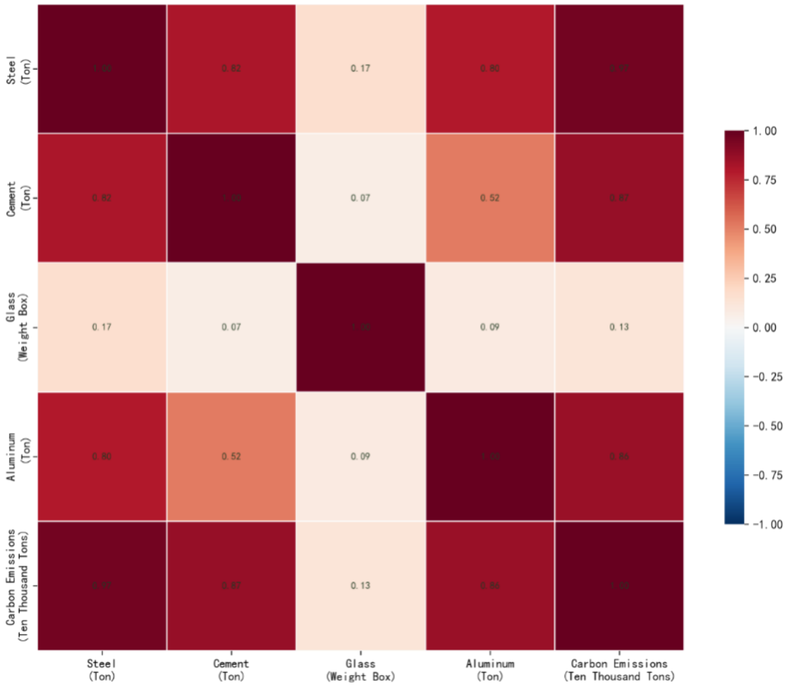

Figure 4. *The correlation between energy consumption and carbon emissions*

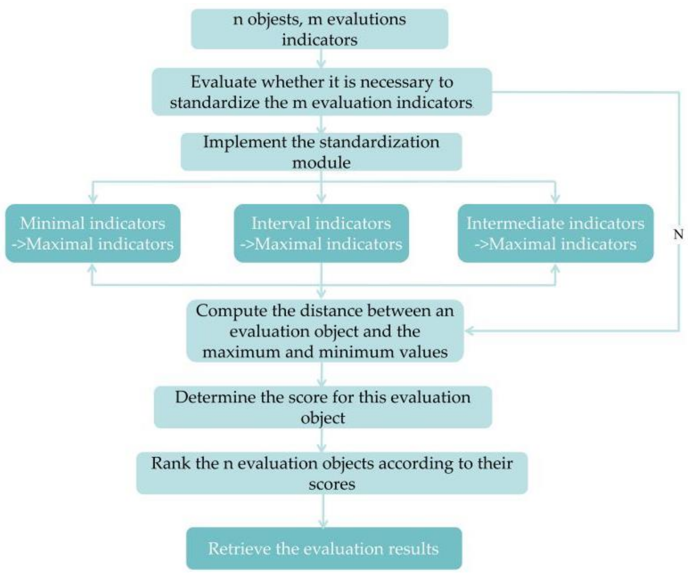

Figure 5. *Flowchart of the TOPSIS Method Model*

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To account for the diverse units associated with the selected indicators, it is imperative to standardize these indicators, thus eliminating the impact of unit discrepancies.

$$x = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \quad \text{(Eq.3)}$$

In *Eq(3)*, the standardized matrix of the matrix is denoted as Z, with each element in Z represented as:

$$\overline{x_{ij}} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \quad \text{(Eq.4)}$$

In *Eq(4)*, there is only one indicator, the formula for calculating the score is constructed as follows:

$$\frac{x-min}{max-min} \quad \text{(Eq.5)}$$

In *Eq(5)*, when dealing with multiple indicators, it can be analogous to a single indicator. Assuming there are n evaluation objects and a standardized matrix of m indicators:

$$Z = \begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1m} \\ z_{21} & z_{22} & \cdots & z_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ z_{n1} & z_{n2} & \cdots & z_{nm} \end{bmatrix} \quad \text{(Eq.6)}$$

Defining the maximum and minimum values in In *Eq(7)* and *Eq(8)*:

$$\begin{cases} Z^{+} = (Z_1^{+},\ Z_2^{+},\ \cdots,\ Z_m^{+}) \\ Z^{-} = (Z_1^{-},\ Z_2^{-},\ \cdots,\ Z_m^{-}) \end{cases} \quad \text{(Eq.7)}$$

$$Z^{-} = (Z_1^{-},\ Z_2^{-},\ \cdots,\ Z_m^{-}) \quad \text{(Eq.8)}$$

The distance between the ith evaluation object and the maximum and minimum values in *Eq(9)*:

$$\begin{cases} D_i^{+} = \sqrt{\sum_{i=1}^{m}\left(z_j^{+} - z_{ij}\right)^2} \\ D_i^{-} = \sqrt{\sum_{i=1}^{m}\left(z_j^{+} - z_{ij}\right)^2} \end{cases} \quad \text{(Eq.9)}$$

Using the *Eq(9)*, you can compute the unnormalized score for the nth evaluation subject as follows:

$$S_i = \frac{P_I^{-}}{P_I^{+} + P_I^{-}} \quad \text{(Eq.10)}$$

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In *Eq(11)*, to mitigate the impact of varying units associated with the selected indicators, standardization is essential.

$$\overline{s_i} = \frac{s_i}{s_1 + s_2 + \cdots + s_n} \quad \text{(Eq.11)}$$

The ARIMA Method

The Autoregressive Integrated Moving Average model (ARIMA) is a widely recognized and commonly used statistical technique for time series forecasting (Wu et al., 2018). It falls under the category of models that can effectively capture various typical temporal patterns within time series data and excel in modeling linear relationships between time series data points. However, ARIMA encounters challenges when dealing with nonlinear components (Ni et al., 2023). The lag terms within the forecasting equation that pertain to a stationary sequence are termed 'autoregressive' terms, while the lags associated with forecast errors are referred to as 'moving average' terms. To transform a non-stationary time series into a stationary one, differencing is employed, and ARIMA essentially combines these stationary time series components.

The general equation for an AR(p) process is:

$$x_t = \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \cdots + \varphi_p x_{t-p} + \varepsilon_t \quad \text{(Eq.12)}$$

In *Eq(12)*, ε_t denotes white noise, and $\varphi_1, \varphi_2, \cdots, \varphi_p$ represents the autoregressive parameter. If we utilize the lag operator, denoted as L to represent this, the equation above can be expressed as a polynomial of the lag operator with a pth-order.

$$\emptyset(L)x_t = \left(1 - \varphi_1 L_1 - \varphi_2 L_2 - \cdots - \varphi_p L_p\right)x_t = \varepsilon_t \quad \text{(Eq.13)}$$

In *Eq(13)*, $\emptyset(L) = 1 - \varphi_1 L_1 - \varphi_2 L_2 - \cdots - \varphi_p L_p$ is referred to as the characteristic polynomial or autoregressive operator.

If the time series x_t satisfies the equation:

$$x_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \quad \text{(Eq.14)}$$

In *Eq(14)*, x_t is characterized as a qth Moving Average process, indicated as $MA(q)$, where ε_t signifies white noise, and $\theta_1, \theta_2, \cdots, \theta_q$ denotes the parameters of the moving average model.

Autoregressive Moving Average processes display stochastic characteristics and consist of two distinct components: autoregressive and moving average. If we employ p to denote the upper limit of the order for the first component and q to represent the upper limit of the order for the second component, the Autoregressive Moving Average process can be represented as ARIMA.

The integrated expression is as follows:

$$x_t = \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \cdots + \varphi_p x_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \quad \text{(Eq.15)}$$

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In *Eq(15)*, $\varphi_1, \varphi_2, \cdots, \varphi_p$ represents the parameters of the autoregressive model, ε_t is white noise, and $\theta_1, \theta_2, \cdots, \theta_q$ represents the parameters of the moving average model.

When a time series is determined to be non-stationary through testing, it must undergo differencing to be transformed into a stationary time series. Upon differencing, if the time series is confirmed to be stationary, one can then establish the corresponding stationary stochastic model. A non-stationary time series that has undergone differencing dtimes to attain stationarity is known as a differenced autoregressive integrated moving average time series, commonly denoted as ARIMA.

The two prevalent methods for identifying time series models are the autocorrelation function (ACF) and the partial autocorrelation function (PACF).

Based on the provided information, the flowchart for constructing the ARIMA model is as shown in *Figure 6*.

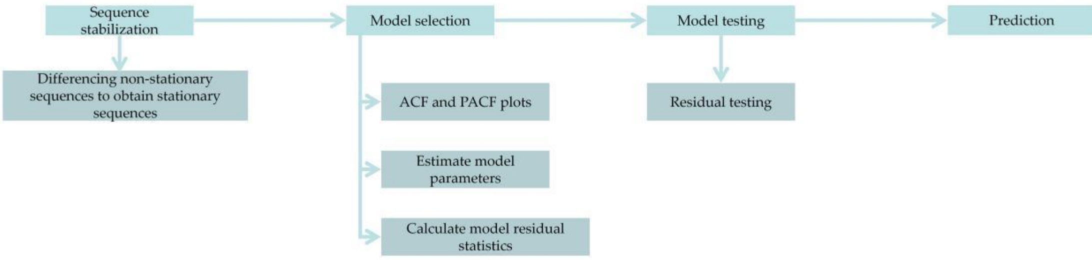

Figure 6. *Specific Principles and Process Diagram of the ARIMA Model*

Data Analysis

The original data utilized in this article have been obtained from multiple sources, including the Carbon Emission Accounts and Datasets (CEADs database), China Statistical Yearbook, Jiangsu Statistical Yearbook, China Construction Statistical Yearbook, and China Energy Statistical Yearbook spanning from 2006 to 2022.

Table 3 displays the carbon emissions data for Jiangsu Province spanning from 2006 to 2022, while *Table 4* provides information on the pertinent factors influencing carbon emissions for the prefecture-level cities in Jiangsu Province in the year 2022.

Green building entails construction practices that, over the entire lifespan of a structure, optimize resource efficiency by conserving energy, land, water, and materials (http://www.gbwindows.org/upFiles/infoImg/202209/202209181328157432.pdf). It aims to safeguard the environment, minimize pollution, and provide occupants with a healthy, adaptable, and efficiently utilized space. This approach embodies a symbiotic relationship with nature. In Jiangsu Province, the proportion of newly constructed green buildings in urban areas increased from 53% in the early stages of the 13th Five-Year Plan to 98.0% by the end of the plan period. Throughout the 13th Five-Year Plan period, Jiangsu Province augmented its inventory with 860 million square meters of energy-efficient buildings, culminating in a cumulative total of 2.3 billion square meters. This constitutes 63.3% of the overall existing urban building stock, solidifying its status as the largest scale of energy-efficient buildings nationwide.

Multivariate Linear Regression Analysis

Within this article, the construction materials production stage serves as an illustrative example, wherein a multivariate linear regression model has been employed to identify

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the primary influencing factors. This method is consistently applied to other stages as well. The outcomes of the multivariate linear regression analysis, conducted using SPSS 26, are presented in *Table 5*.

Table 3. *Carbon Emissions Data for Jiangsu Province from 2006 to 2022*

Year	**Building Carbon Emissions (10^3t)**	**The construction area of the building (10^3m^3)**
2006	7,420.419,74	63,140.49
2007	7,710.150,07	79,901.63
2008	8,375.983,18	90,144.64
2009	8,549.023,88	99,659.92
2010	10,098.111,77	119,035.52
2011	9,878.986,54	145,451.48
2012	11,168.620,72	166,779.12
2013	12,223.454,99	196,739.85
2014	11,537.352,50	213,038.78
2015	11,124.620,64	215,591.97
2016	11,894.464,29	221,493.57
2017	11,942.992,49	232,034.24
2018	11,067.165,88	249,419.75
2019	11,150.422,79	255,156.66
2020	11,160.960,08	267,407.73
2021	11,535.859,19	273,427.96
2022	11,894.464,29	275,135.00

The model's R-squared value of 1,000 signifies that carbon emissions resulting from factors like energy consumption, building renovations and updates, as well as emissions occurring at various stages of the building life-cycle (including carbon emissions during the production of building materials, their transportation, energy consumption in waste disposal, carbon emissions during building demolition, carbon emissions during construction, and energy sources) collectively account for 100.0% of the variation in total carbon emissions over the building's life-cycle. When the model's F-statistic was tested, it successfully passed the F-test $(F = 5035.874，p = 0.000 < 0.05)$, indicating that at least one of the factors, such as carbon emissions from energy consumption and building renovations and updates, exerts a significant impact on total carbon emissions. Furthermore, upon evaluating the model for multicollinearity, it was determined that all Variance Inflation Factor (VIF) values were below 5, demonstrating the absence of collinearity issues. The Durbin-Watson (D-W) statistic, hovering around 2, suggests the absence of autocorrelation within the model, meaning that the sample data points are not correlated with each other, affirming that the model is well-fitted.

The regression coefficients for carbon emissions from energy consumption, carbon emissions from building renovations and updates, carbon emissions during the production of building materials, carbon emissions during the transportation of building materials, energy consumption in waste disposal, carbon emissions during building demolition, carbon emissions during construction, and energy sources are as follows: $1{,}120\ (t = 111.984, p = 0.000 < 0.01)$, $3{,}248.990\ (t = 0.896, p = 0.421 > 0.05)$, $2{,}557.141\ (t = 0.886, p = 0.426 > 0.05)$, $-1{,}683.827\ (t = -0.547, p = 0.614 > 0.05)$, $-3{,}985.045\ (t = -0.936, p = 0.402 > 0.05)$, $7{,}754.516\ (t = 2.404, p = 074 > 0.05)$, $-4{,}555.926\ (t = -1.589, p = 0.187 > 0.05)$, $-93{,}287.094\ (t = -0.898, p = 0.044 < 0.05)$.

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Table 4. *Carbon Emissions Data for Factors Related to Buildings in Prefecture-Level Cities in Jiangsu Province in 2022*

Region	Carbon Emissions during the Production of Building Materials	Carbon Emissions during the Transportation of Building Materials	Carbon Emissions during Construction	Energy Sources	Carbon Emissions during Building Demolition	Energy Consumption in Waste Disposal	Carbon Emissions from Building Renovations and Updates	Carbon Emissions from Energy Consumption	Total Carbon Emissions over the Building's Lifecycle
Nanjing	308,581.00	19,602.00	318,066.00	2.79	6,082.60	6,150.60	2,950.70	5,479,504.21	6,140,937.11
Wuxi	176,932.00	22,899.00	182,289.00	2.66	2,731.20	6,205.60	1,466.80	3,096,717.484	3,489,241.084
Xuzhou	258,876.00	16,533.00	265,942.00	2.70	4,912.80	4,391.20	2,204.40	3,651,468.08	4,204,327.48
Changzhou	128,989.00	12,622.00	131,321.00	2.75	3,162.40	4,289.40	1,748.30	2,559,346.936	2,841,479.036
Suzhou	272,833.00	12,908.00	278,067.00	2.71	2,716.90	5,007.50	2,222.50	4,791,607.704	5,365,362.604
Lianyungang	75,013.00	29,339.00	77,076.00	2.70	3,990.60	3,855.70	1,681.60	1,380,691.392	1,571,647.292
Huai'an	99,795.00	30,160.00	102,694.00	2.77	3,956.70	3,667.30	1,759.60	1,585,924.956	1,827,957.556
Yancheng	121,864.00	24,738.00	125,432.00	2.76	5,034.90	4,852.20	2,511.10	1,982,495.289	2,266,927.489
Yangzhou	92,051.00	12,906.00	94,845.00	2.74	3,810.30	4,389.60	1,769.70	1,601,080.64	1,810,852.24
Zhenjiang	83,215.00	10,116.00	85,961.00	2.72	2,938.40	4,221.20	1,843.70	1,491,583.156	1,679,878.456
Taizhou	81,462.00	17,902.00	84,157.00	2.76	3,558.30	3,690.20	1,641.60	1,577,443.616	1,769,854.716
Suqian	45,452.00	7,729.00	46,944.00	2.74	3,334.60	3,326.60	1,529.70	859,307.839	967,623.739
Nantong	147,508.00	25,785.00	150,406.00	2.77	4,532.50	4,122.50	2,041.40	2,419,210.236	2,753,605.636

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Table 5. *Analysis of Factors Affecting Carbon Emissions over the Building's Life-cycle*

	Non-standardized coefficients		**Standardized Coefficients**	***t***	***p***	**VIF**
	B	**Standard Error**	**Beta**			
Constant	2,552,862.792	884,408.072	-	2.887	0.045*	-
Carbon Emissions from Energy Consumption (t)	1.120	0.010	0.999	111.984	0.000**	3.207
Carbon emissions from construction, renovations, and updates (t)	3,248.990	3,625.302	0.008	0.896	0.421	3.258
Carbon emissions during the production of building materials (t)	2,557.141	2,887.136	0.006	0.886	0.426	2.067
Carbon emissions during the transportation of building materials (t)	-1,683.827	3,080.333	-0.004	-0.547	0.614	2.352
Energy consumption in waste disposal (t)	-3,985.045	4,258.147	-0.010	-0.936	0.402	4.495
Carbon emissions during building demolition (t)	7,754.516	3,226.306	0.019	2.404	0.074	2.581
Carbon emissions during construction (t)	-4,555.926	2,867.498	-0.011	-1.589	0.187	2.039
Energy sources (t CO_2/t energy)	-932,387.094	321,730.653	-0.022	-2.898	0.044*	2.243
R^2	1.000					
Adjusted R^2	1.000					
F	$F(8,4) = 5{,}035.874, P=0.000$					
D-W value	1.943					

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Considering the conclusions derived from the analysis, the primary factors influencing carbon emissions over the building's life-cycle are determined to be energy consumption, energy efficiency, energy consumption in waste disposal, and the building's operational lifespan.

Throughout the entire lifecycle of residential buildings (construction, operation, demolition), numerous factors influence carbon emissions, including building design standards, climate, production and transportation of building materials, regional variations, energy consumption during construction and demolition, interior design styles, energy consumption during use, and building types. The application of a multiple linear regression model aims to identify indicators that are highly correlated and easily quantifiable among these factors. Based on these indicators, we conduct a comprehensive evaluation of carbon emissions throughout the entire lifecycle of residential buildings. Through calculations, conclusions are drawn regarding the dominance of operational energy consumption and energy sources in total energy consumption. While this conclusion may not be novel, in future research, this method can be utilized to explore relationships between other factors and building carbon emissions, reduce errors in the calculation process, make the study more comprehensive, and advance further research on building carbon emissions.

TOPSIS Analysis

In this article, we focus on the production stage of building materials in 13 cities within Jiangsu Province as a case study. We aim to identify the key factors influencing carbon emissions throughout the lifecycle of residential buildings. To achieve this, we employ the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method, which enables a comprehensive assessment of carbon emissions from residential buildings in the 13 prefecture-level cities of Jiangsu Province for the year 2021. The resulting rankings are presented in *Table 6*.

Table 6. *Rankings of Carbon Emissions from Residential Buildings in Jiangsu*

Ranking	Prefecture-Level Cities	Resident Population (10^3)	The construction area of the building (10^3m^3)
1	Chang Zhou	534.96	13,030.24
2	Su Zhou	1,284.78	16,435.66
3	Xu Zhou	902.85	10,364.27
4	Nan Jing	942.34	26,469.92
5	Wu Xi	747.95	4,590.11
6	Su Qian	499.90	6,495.22
7	Tai Zhou	452.18	33,945.67
8	Yan Cheng	671.30	11,815.31
9	Yang Zhou	457.70	32,531.73
10	Lian Yungang	460.20	3,917.38
11	Nan Tong	773.30	99,443.02
12	Zhen Jiang	321.72	2,197.21
13	Huai An	456.22	12,192.22

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Validation and Prediction of Building Carbon Emissions ARIMA Model

Validation of the ARIMA Model

Initially, the data undergoes a stationarity transformation. In this context, we employ the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests to evaluate the data's stationarity. Upon conducting these tests, we obtain ADF=1 and KPSS=0, confirming the stationarity of the data.

Next, we proceed with the selection of the specific ARIMA model, employing the method of lag values to determine the values for p and q. The results of this analysis are presented in the following *Table 7*.

Table 7. *Providing the basis for determining the values of p and q*

	Value	Standard Error	T Statistic	p Value
Constant	180.2	570.9	0.31565	0.75227
AR{1}	0.32535	2.519	0.1507	0.88021
AR{2}	0.0045494	0.2842	0.016008	0.98723
MA{1}	-0.39119	2.1607	-0.18105	0.85633
Variance	4.2299e+05	1.8309e+05	2.3103	0.020874

Based on the information in the table, we can ascertain that the values for p and q are $p = 2$ and $q = 1$. Therefore, we opt for the ARIMA model as the final model for this study. *Figure 7* illustrates the data distribution, autocorrelation, partial autocorrelation, and normality testing results for this model.

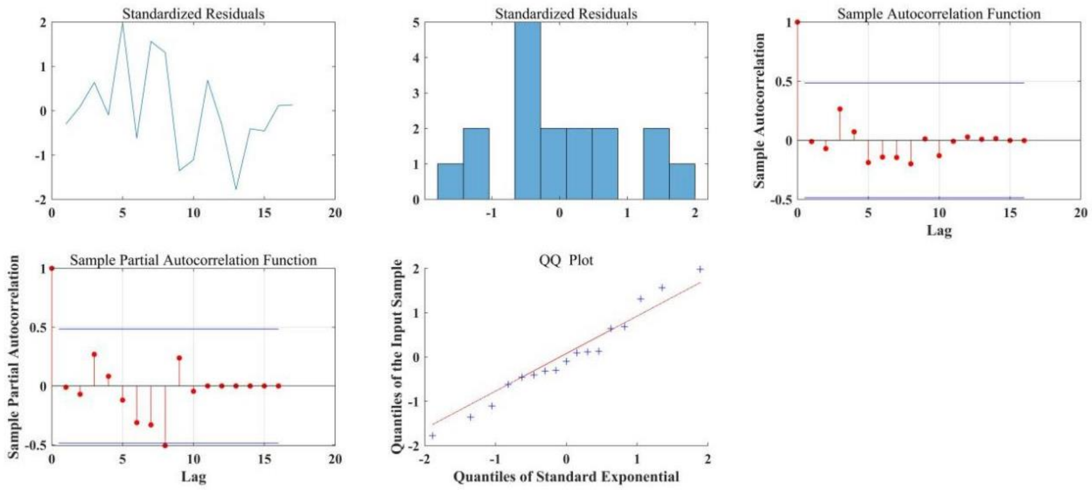

Figure 7. *Data Distribution, Autocorrelation, Partial Autocorrelation, and Normality Testing Results*

Considering the test results and the Durbin-Watson (D-W) value of 2.014, it is safe to conclude that the ARIMA model developed for this problem demonstrates strong performance and is well-suited for accurately addressing the issue at hand. This model holds the potential to offer more precise predictions for carbon emissions from buildings in Jiangsu Province.

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The Prediction Results

Through meticulous data selection and processing, the judicious choice of appropriate TOPSIS and ARIMA models, and rigorous model validation conducted using Matlab, we have successfully forecasted carbon emissions from buildings in Jiangsu Province for the next ten years.

Based on the data analysis and processing outlined above, we have generated a forecast for carbon emissions from buildings in Jiangsu Province over the next ten years. As illustrated in *Figure 8*, carbon emissions in Jiangsu Province displayed an overall increasing trend from 2006 to 2022. Utilizing the ARIMA model for forecasting with a 95% confidence interval, it is evident that carbon emissions from buildings in Jiangsu Province are projected to continue rising from 2023 to 2033. However, the rate of increase is gradually slowing down. This implies that there is a need for further efforts to reinforce carbon emissions control within the building sector in Jiangsu Province.

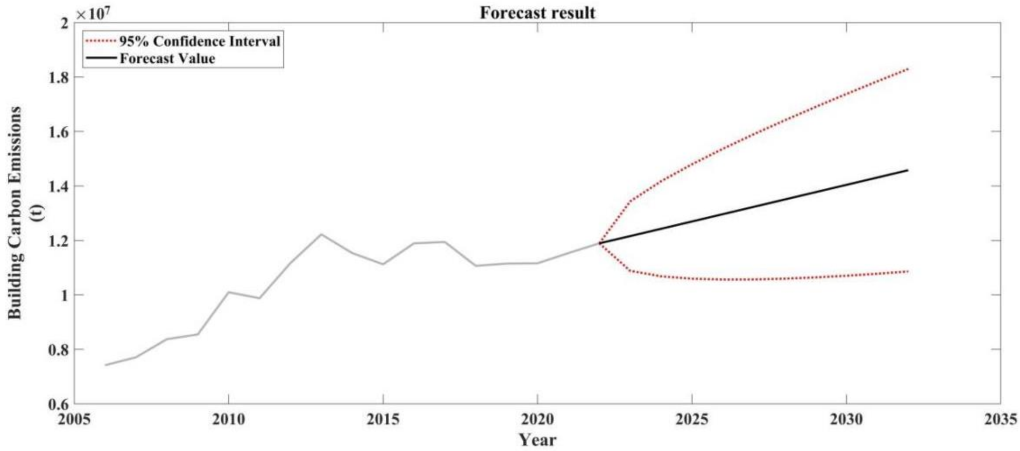

Figure 8. *Visualization of the Predicted Carbon Emissions over the Entire Building Life-cycle in Jiangsu Province*

In a groundbreaking move in 2023, Jiangsu became the first in the country to establish the 'Urban and Rural Construction Carbon Peak and Carbon Neutrality Pioneer Zone.' This pioneering initiative sets explicit indicators, including 'near-zero carbon emissions in parks, communities, or campuses' and 'super-low energy consumption/near-zero energy consumption building area.' The primary objective is to concentrate efforts in specific areas, exploring technological pathways and implementing policy measures for the large-scale development of super-low energy consumption and near-zero energy consumption buildings. This initiative comprehensively promotes the reduction of carbon emissions in the regional construction sector, fostering the integrated development of green, low-carbon, super-low energy consumption, smart, and healthy buildings. It actively advances the large-scale development of super-low energy consumption and near-zero energy consumption buildings. Scholars have demonstrated that incorporating renewable energy and energy-saving technologies can significantly reduce the carbon emissions of buildings. Carbon reinforced concrete (CRC) materials have proven to be excellent candidate materials for concrete-based nZEBs since they are characterized by a significantly lower CO_2 consumption during component production and much a longer lifecycle (Kraft et al., 2022). As an integral component of China's '13th Five-Year Plan,'

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there is a dedicated focus on advancing research in high-performance structures and materials. This initiative involves the development of high-performance steel structural systems, including innovative shear walls, novel frame types, plate-column combinations, and interleaved truss combinations. The tangible outcomes of these research endeavors find practical application in significant projects such as expo pavilions, the Shenzhen-Zhongshan Corridor, the Nairobi-Malaba Railway, and the China-Malaysia Friendship Bridge, contributing substantially to the reduction of carbon emissions in buildings. Through various investigations, it has been unequivocally established that the application of renewable energy and energy-saving technologies is indispensable for mitigating carbon emissions in construction projects.

Conclusions

In this study, we employed a multivariate linear regression model to analyze the factors influencing carbon emissions over the entire life-cycle of buildings. Additionally, we utilized the TOPSIS model and the ARIMA model to evaluate and forecast building carbon emissions in Jiangsu Province from 2022 to 2023. The main research findings are summarized as follows:

(1) Carbon emissions from buildings in Jiangsu Province displayed fluctuating growth between 2006 and 2022. Beyond 2012, the growth rate decelerated, ultimately stabilizing. This observation implies that the building sector in Jiangsu Province has demonstrated characteristics akin to an initial carbon peak condition.

(2) Carbon emissions resulting from energy consumption exhibit a notably positive correlation with the total carbon emissions across a building’s life-cycle, whereas the energy source exhibits a considerable negative correlation with total carbon emissions. We considered various factors, encompassing energy consumption, construction and transportation methods, material carbon emissions, material production, building demolition, and waste disposal factors. Among these, carbon emissions from energy consumption significantly contribute to the overall carbon emissions over a building’s life-cycle, underscoring the pivotal role of energy consumption in influencing total carbon emissions. Consequently, in the pursuit of carbon reduction, the building industry in Jiangsu Province should prioritize the reduction of carbon emissions arising from energy consumption, the gradual shift away from conventional energy sources, and increased investments in alternative energy sources.

(3) The forecasted results suggest that from 2023 to 2033, carbon emissions are anticipated to continue increasing, although the rate of increase is gradually slowing down and approaching stability. It is evident that during this period, endeavors to reduce carbon emissions still require intensification.

(4) This article meticulously chose several indicators with a strong correlation to building carbon emissions and constructed a carbon emissions prediction model for Jiangsu Province. The model offers a precise and user-friendly approach to assess the 13 prefecture-level cities in Jiangsu Province. While it may not encompass the comprehensive evaluation capabilities of traditional methods, it effectively mirrors regional building carbon emissions and is in alignment with the contemporary context.

(5) The research scope could be broadened. This article predominantly centers on the evaluation and forecasting of building carbon emissions in Jiangsu Province, with limited exploration at provincial, national, or international scales. Additionally, there are substantial variances in the progress of low-carbon development in China’s central and

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western regions, encompassing disparities in the timing and occurrence of carbon peaks and emissions spikes. It is imperative to monitor and account for these variations in the future. Investigating diverse trends in building carbon emissions across different regions will facilitate the development of more effective energy-saving and emission-reduction policies by both national and regional governments.

(6) In practical scenarios, the factors impacting building carbon emissions are multifaceted. This article scrutinized and evaluated only a limited number of indicators. To further enhance the model's efficacy, it is advisable to encompass as many relevant indicators as possible, thereby rendering the entire assessment system more comprehensive and credible.

Based on the aforementioned research, our findings indicate that the primary source of carbon emissions from buildings is indirect emissions stemming from building materials (Jiang et al., 2017). Luo et al. (2016) found that steel, concrete, and other materials are the main sources affecting carbon emissions from buildings, consistent with the conclusions drawn in this paper. The present paper delves into the analysis of carbon emissions from buildings in Jiangsu Province, presenting an opportunity for a more comprehensive examination of building carbon emissions and providing valuable guidance for future studies in this field.

We conducted a comprehensive review of literature relevant to the topic and assessed the outcomes of the proposed research. In future studies, certain limitations need improvement. Firstly, our study evaluated carbon emissions from buildings in 13 prefecture-level cities in Jiangsu Province based on selected key factors. To minimize errors, future research should more thoroughly consider various influencing factors. Secondly, our study lacked a detailed classification of buildings. Therefore, in future research, a more nuanced categorization of building types is recommended to investigate the specific carbon emission characteristics of each type. Lastly, concerning future carbon emission forecasts for the 13 cities in Jiangsu Province, our study only considered primary influencing factors. In subsequent research, it is crucial to further consider other energy-related carbon emission factors to enhance the accuracy of predictions.

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