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Research on Spatial Heterogeneity, Impact Mechanism, and Carbon Peak Prediction of Carbon Emissions in the Yangtze River Delta Urban Agglomeration

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Abstract: Urban agglomerations with a high economic activity and population density are key areas for carbon emissions and pioneers in achieving carbon peaking and the Sustainable Development Goals (SDGs). This study combines machine learning with an extended STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model to uncover the mechanisms driving carbon peaking disparities within these regions. It forecasts carbon emissions under different scenarios and develops indices to assess peaking pressure, reduction potential, and driving forces. The findings show significant carbon emission disparities among cities in the Yangtze River Delta, with a fluctuating downward trend over time. Technological advancement, population size, affluence, and urbanization positively impact emissions, while the effects of industrial structure and foreign investment are weakening. Industrially optimized cities lead in peaking, while others—such as late-peaking and economically radiating cities—achieve peaking only under the ER scenario. Cities facing population loss and demonstration cities fail to peak by 2030 in any scenario. The study recommends differentiated carbon peaking pathways for cities, emphasizing tailored targets, pathway models, and improved supervision. This research offers theoretical and practical insights for global urban agglomerations aiming to achieve early carbon peaking.

Keywords: cluster analysis; carbon peaking pathways; scenario analysis; grey theory; heterogeneity analysis

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1. Introduction

One of the 17 Sustainable Development Goals (SDGs) of the 2030 United Nations Agenda for Sustainable Development is to build inclusive, safe, resilient, and sustainable cities and human settlements. Cities are the main carriers of human socioeconomic activities [1]. Although they only occupy 3% of the Earth's landmass, they account for 75% of the world's energy consumption and 80% of the world's CO_2 emissions [2]. Urban carbon emissions and the accompanying climate issues have gradually come to the attention of the world in recent years [3]. In recent decades, emerging economies such as China have experienced accelerated urbanization and industrialization. In this process, 85% carbon emissions in China may be attributed to urban emissions [4], and the tension between economic development and emission reduction is palpable. The "dual carbon" goal put forward by China in 2020 is China's emission reduction commitment to actively participate in global governance, as well as a necessary basic for promoting a high economy with a low-carbon transformation [5]. Urban agglomerations with an extremely high density of population and economy will inevitably become the "hardest hit areas" regarding carbon emissions [6]. The Yangtze River Delta (YRD) region, which is geographically composed of 41 cities, accounting for about one-fifth of emissions in China, is a region with a relatively concentrated energy demand and greater pressure to reduce emissions, while its GDP growth is at the forefront from a national perspective. However, within the region, there are great differences among cities in natural conditions, resource endowment, the industrialization process, and economic development stage [7]. For example, the economic development of the Jiangsu and Zhejiang Provinces and Shanghai is apparently faster than that of Anhui Province. Therefore, to achieve the overall carbon peak goal in the YRD region, it is essential to consider the heterogeneity of urban development phases within the region and distinguish the differences between cities of different types in their time of carbon peaking, to explore differentiated emission reduction policies.

Most of the existing studies have explored the drivers of urban carbon emissions and carbon peaking pathways, but few studies have comprehensively considered the multiple heterogeneity characteristics within urban agglomerations and how these characteristics affect the differences in the timing of carbon peaking between cities. To this end, this paper adopts a research method that combines a machine learning approach with the STIRPAT model extended with multidimensional influencing factors, aiming to deeply analyze the mechanism of urban heterogeneity's influence on carbon emissions and explore the path patterns of regional carbon peaks. This study not only enriches the theoretical framework of urban carbon peaking but also provides differentiated policy recommendations for urban agglomerations to achieve carbon peaking, which have important theoretical and practical significance.

This study intends to contribute to the development of sustainable cities and human settlements (SDG11). The following are the major contributions of this paper: (1) Innovatively using machine learning to classify cities in thr Yangtze River Delta urban agglomeration and consider the impact of urban heterogeneity on emission reduction policies. (2) Categorical regression was used to identify the internal reasons for the differences in the carbon peaking of different cities, so as to provide a basis for formulating differentiated urban emission reduction policies coordinating the contradiction of development and emission reduction. (3) Based on the clustering results, the GM (1, n) forecasting model was used to comprehensively reflect the differentiated characteristics of different types of cities from the perspective of carbon peaking time and carbon emission levels at the peaking time. This improved on the shortcomings of previous studies that only focused on peaking time.

The remaining sections of this paper are organized as follows. Section 2 presents a summary of the relevant literature. Section 3 introduces the model, estimation techniques, and data. Section 4 provides the new empirical findings. Section 5 concludes the paper.

2. Literature Review

Existing research regarding China's carbon emissions can be briefly summarized into two aspects: one is about an analysis of the driving factors of carbon emission growth, and the other is about the prediction of carbon peaking time, together with an exploration of the emission reduction pathway. Identifying the drivers and trends of carbon emission growth is a necessary prerequisite for judging the peaking time and exploring the path of emission reduction [8]. In earlier studies, decomposition based on IPAT (Impact of Population, Affluence, and Technology) identity expansion, such as exponential decomposition (IDA) and structural decomposition (SDA), could be used to separate the various factors driving carbon emission growth from the total effect, determine the system of influencing factors, and quantify their actual contribution to carbon emissions [9]. The LMDI (Logarithmic Average Dieter Index) model is widely used in decomposing driving factors because of its advantages in completely decomposing residuals and solving the zero value problem on the basis of a Kaya extension [10]. For example, He et al. and Yu et al. [11], respectively, used the LMDI to quantify the contribution of driving factors affecting the carbon emissions of China's electricity industry (CEEI) and civil aviation industry. However, LMDI is essentially a decomposition method of carbon emission changes based on the Kaya identity, which can usually consider limited common factors like population, energy intensity, and so on [12], which means that all potential influencing factors cannot be fully considered. Overcoming the linear decomposition defect of decomposition, the STIRPAT model, which converts IPAT from a multiplier form to measurement form, has unique advantages in investigating the driving factors influencing carbon emissions and further expands the investigation scope of the carbon emission influencing factor system [13]. For example, Liang et al. [14] combined the STIRPAT and geographically weighted regression (GWR) models to explore the extent to which socioeconomic factors influence energy-related CO_2 emissions globally and locally. Huang et al. [15] focused on the key areas and paths of carbon emission reduction in Beijing under six policy scenarios from 2015 to 2060 based on the STIRPAT and the LEAP-Beijing model. Zhou et al. [16] quantified the impact of regional development patterns and determinants on CO_2 emission intensity in China through STIRPAT. Therefore, STRIPAT is selected to screen the key factors influencing carbon emission changes in the YRD region.

The existing studies have shown that urban carbon emissions are mainly affected by social economy, government policies, resource endowment, and other potential dimensions. Population expansion, increasing urbanization [17], and economic and financial growth have also been proven to have a strong positive correlation with CO_2 emissions. In addition, urban agglomeration has been taken by many scholars as an more valuable research object to reveal the mechanism of the spatial agglomeration effect of population, economy, and technology on the reduction of carbon emissions. For example, Yan and Huang found that measures such as service industry agglomeration, industrial structure optimization, and technology innovation were three important and effective channels to reduce carbon intensity [18]. Wang et al. [19] came to the opposite conclusion, arguing that there was an obvious bidirectional inhibitory relation between regional carbon emission intensity and economic agglomeration. Fang et al. [20] found that the agglomeration of producer services brings an improvement in regional carbon emission efficiency, while the agglomeration of the manufacturing industry brings an opposite effect. However, the inverted U-shaped Kuznets curve (EKC) fitted with the growth of carbon emissions shows that there may be diametrically opposite relationships between different economic levels and carbon emissions. This means that there is a strong need to comprehensively consider the phased characteristics of cities' different development levels, formulate carbon peaking targets according to the development conditions of different cities, and explore differentiated emission reduction paths. Considering the impact mechanism of integrated coordinated development or the agglomeration effect on the realization of regional carbon peaking goals, most of the existing city-level research studies on carbon peaking take the overall urban agglomerations as their research objects. However, few studies pay attention to the multiple heterogeneous characteristics of cities within urban agglomerations. Whether the city as an individual can reach the peak on time and how the carbon emissions change after reaching the peak will definitely affect the achievement of the overall regional peaking goals [21]. Therefore, it is necessary to classify cities in order to distinguish the differences between cities, focusing on carbon peaking time, and formulate targeted emission reduction measures, while striving to realize carbon peaking in the region as a whole.

The existing research methods for city classification can be summarized into two types: classification based on a single factor and classification based on combination factors. Classification based on a single factor is mainly according to the development stage of the city or the characteristics of its industrial structure. Ramaswami et al. [22] divided 285 cities in China into three types, namely industrial cities, commercial cities, and mixed economy ones according to their pillar industries. However, such studies lack comprehensiveness because they only focus on a single influencing factor. Classification based on combination factors is more comprehensive when considering more influencing factors. This type of research mainly uses clustering analysis and machine learning algorithms such as classification tree, in which cities are classified comprehensively by considering their various characteristics. For example, Hu et al. [23] used the K-means clustering method and evolutionary tree model to divide the evolution trend of energy structures in 144 countries and regions into four different types. Cheng et al. [24] utilized a hierarchical clustering analysis and Gini-coefficient decomposition to examine the multisectoral determinants of China's urban greenhouse gas inequality.

In terms of the forecasting method for carbon emissions, some scholars have built econometric models, obtaining the elastic coefficient between influencing factors and carbon emissions through regression analysis to achieve the purpose of making predictions [25]. Fang et al. [13] predicted the carbon peaking time of China's 30 provinces based on the regression analysis results of influencing factors. However, limited by the linear assumptions of the econometric model itself, a regression model cannot properly deal with the nonlinear factors involved in the prediction. In order to better deal with nonlinear factors, some scholars have introduced methods such as machine learning in the field of artificial intelligence into the prediction of carbon emissions; for example, Ren and Long used a fast learning network model to explore whether Guangdong Province can achieve China's "dual carbon" goal [26]. Xu et al. [27] utilized a dynamic nonlinear artificial neural network method to predict the peaking level of carbon emissions. Although this method can obtain a high prediction accuracy, due to the lack of the large amount of data required for model training, it is difficult to give full play to its powerful nonlinear computing ability in the face of small sample data, and this may even lead to local optimization or over-fitting [28]. Compared with the above two methods, the grey prediction model was introduced with the aim of modeling small data systems, and it can not only deal with nonlinear problems but also shows a good forecasting ability under the circumstances of small samples and poor information, thus being frequently employed in studies that predict carbon emissions. Ma et al. [29] selected five influencing factors and predicted China's carbon emissions under different scenarios through an optimized grey model. Ding et al. [30] adopted a discrete grey forecasting model to estimate China's energy-associated CO_2 emissions. However, there are various connections among subjects in the grey system, which are open to be interference by external factors, which weakens the accuracy of the original model [19]. To better involve related factors on system changes during the modeling process and make better use of the information contained in related sequences, a grey multivariable prediction model (GM (1,n) was proposed. GM (1,n) contains a system behavior variable and $n - 1$ influence factor variables [31], for which it has the ability to analyze the influence of multiple factors and variables on system behavior and improve the accuracy of its predictions [32]. The existing prediction studies focus too much on improving the prediction accuracy of the model but neglect the compatibility between the model and carbon emission data. As carbon emission data are apparently a small sample data set, the application of a neural network prediction method can improve the accuracy of the prediction, but it will reduce the scientific nature of prediction due to the lack of training samples. Therefore, the GM (1, n) model, suitable both for processing small sample data sets and for accuracy, is selected in this paper. This model can maintain a good prediction performance under small sample data sets and is suitable for predicting carbon emissions. It also provides more scientific support for the analysis of the heterogeneity in peaking time of different cities in this paper.

Although the existing studies have explored the drivers of China's carbon emissions, carbon peaking time forecasts, and emission reduction pathways from multiple perspectives, this study makes new contributions in the following aspects. First, this study deeply analyzes the heterogeneity between cities, and by combining the machine learning method with the STIRPAT model extended with multidimensional influencing factors, it analyzes in detail the influencing mechanism of carbon emissions in different cities, which provides scientific support for the development of differentiated emission reduction strategies. Second, this study sets up various policy scenarios for the Yangtze River Delta city cluster, simulates the time and peak value of carbon peaks under different interventions, and provides more operational suggestions for policy makers. Third, this study has constructed the city cluster carbon peak pressure index, carbon emission reduction potential index, and carbon emission reduction peak power index models, which can more accurately reflect the different pressures and potentials of each city in the process of carbon peaking and provide a basis for the development of personalized emission reduction pathways. Finally, this study chooses a grey prediction model that is suitable for dealing with small sample data, which improves the scientific nature and accuracy of the prediction. Through these innovations, this study not only fills gaps in the existing research but also provides systematic and scientific methodological support for realizing the goal of regional carbon peaking.

3. Methodology and Data

3.1. Construction of City Classification Model

Clustering is a technical data mining algorithm that is prevalent in regional classification [11]. Clustering analysis is a process in which the optimal division is obtained in an unsupervised state on the basis of the similarity or variance of the sample's characteristics, and finally, the samples within the group will show the greatest similarity and the samples between groups will show a high degree of heterogeneity. In this paper, the K-means clustering algorithm was selected to classify the cities in the YRD region. The algorithm initializes the C centroid randomly from all data points. The remaining data points are then assigned to their nearest center of mass to form the C cluster. In turn, the centroid is updated as the average of the data points in the cluster. The allocation of data points and centroid update are iterated repeatedly until the centroid remains unchanged [33].

Firstly, to eliminate the influence of different index dimensions, all clustering indicators are standardized in this paper to form a sample set $\mathrm{X} = \{\mathrm{x}_1, \mathrm{x}_2, \cdots \mathrm{x}_n\}$, in which each sample is a D-dimensional real vector. Secondly, K sample points are assigned at random as the initial grouping center. Then, the distance between every sample and the class centroid is computed, and each sample is assigned to the center class with the shortest distance to generate the initial clustering result. Finally, the mean value of all types of samples is determined as the newly formed class center, and the preceding stages are carried out until n samples are divided into k sets ($k \leq n$), and the sum of squares within the group is minimized to find the clustering S_i satisfying Formula (1).

$$\underset{S}{\operatorname{argmin}} \sum_{i=1}^{k} \sum_{x \in S_i} \| x - \mu_i \|^2 \quad (1)$$

3.2. Construction of Spatial Correlation Model

The STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model rejects the unit elasticity hypothesis of the IPAT (Impact of Population, Affluence, and Technology) identity in order to improve the randomness of the prediction model, which allows us to examine the effects of urbanization, industrial structure, energy structure, and other driving factors putting stress on the environment. The basic expression is

$$I = aP^b A^c T^d e \quad (2)$$

P, A, and T, respectively, represent the population, affluence, and technology factors that affect environmental stress factor I. a stands for the model coefficient; b, c, and d represent the influencing factor index; e is the error term.

In this paper, the logarithmic form of the STIRPAT model was applied and extended accordingly. We analyze the mechanism of the influencing factors based on theoretical studies, and the results are shown in Figure 1.

To better analyze the influencing factors of urban carbon emissions and identify the key emission reduction paths, the FDI, urbanization level, and industrial structure were further included in Equation (2) based on previous studies and the actual development of urban agglomeration and Equation (2) converted to logarithmic form. The specific model is shown as follows:

$$\ln I = \ln a + a_1 \ln P + a_2 \ln A + a_3 \ln T + a_4 \ln F + a_5 \ln U + a_6 \ln R + \ln e \quad (3)$$

where I represents carbon emissions, P represents the total population, A represents affluence (measured by per capita GDP, unit: yuan), T represents the level of technology (measured by carbon emission intensity, unit: tons/10,000 yuan), F represents the use of foreign capital (measured by foreign direct investment, unit: ten thousand dollars), U represents the level of urbanization (measured by urbanization rate), and R represents the industrial structure (measured by the proportion of secondary industry). At the same time, we put forward the following hypotheses based on the mathematical models and theoretical research: population, affluence, and urbanization rate have a positive impact on carbon emissions; technology level and foreign direct investment have a negative impact; and industrial structure has a comprehensive impact.

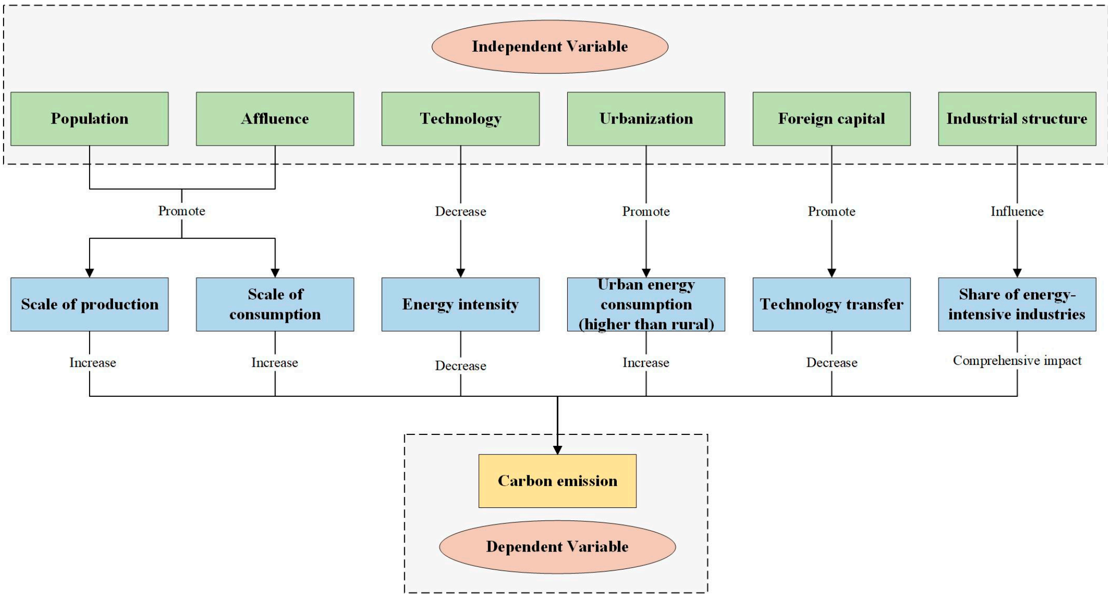

Figure 1. Mechanisms of influencing factors.

3.3. Scenario Analysis

The aim is to explore the influence of different paths and policy tools on the time process of carbon peaking and the emission trend after peaking in cities of the Yangtze River Delta. This paper is based on China's basic national conditions, policy mechanisms with Chinese characteristics, and the existing research results [13]. Two dynamic scenarios of setting and emission reduction are summarized into three time periods, namely 2021–2025, 2026–2030, and after 2030, as shown in Table 1.

Table 1. Scenario setup.

Scenario	Period	P	UR	GDP/P	IS	FDI	CEI
DP	2021–2025	0.50%	0.60%	1.50%	−0.82%	1.50%	−0.66%
	2026–2030	0.30%	0.40%	1.30%	−0.70%	1.04%	−0.76%
	Post–2030	−0.04%	0.20%	1.14%	−0.56%	1.00%	−0.80%
ER	2021–2025	0.45%	0.50%	1.00%	−0.92%	1.04%	−0.92%
	2026–2030	0.25%	0.30%	0.92%	−0.80%	0.62%	−1.02%
	Post–2030	−0.54%	0.10%	0.78%	−0.70%	0.58%	−1.04%

Notes: P, UR, GDP/P, IS, FDI, and CEI will be introduced in detail in Section 3.6. DP and ER are development and emission reduction, respectively.

(1) Development scenario: This scenario continues the "14th Five-Year Plan" and the policies before it, without considering the adoption of new technologies and further emission reduction policies. The improvement in urbanization rate, the change in industrial

structure, and the utilization of foreign capital are mainly dependent on the social and economic development drive.

(2) Emission reduction scenario: This scenario takes into account the commitments made in the *Sino-US Joint Statement on Climate Change* and the *Paris Agreement*, and further sets the change rate of each driving factor based on the *Comprehensive Work Plan for Energy Conservation and Emission Reduction during the 14th Five-Year Plan.*

3.4. Construction of GM (1, n) Predicting Model

The GM (1, n) predicting model is currently widely used in multiple fields; the sequence of variables ($X1^{(0)}$) and the sequence of related factors ($X2^{(0)}, \ldots, XN^{(0)}$) are

$$\begin{aligned} X_1{}^{(0)} &= (X_1{}^{(0)}(1), X_1{}^{(0)}(2), \cdots, X_1{}^{(0)}(n)) \\ X_2{}^{(0)} &= (X_2{}^{(0)}(1), X_2{}^{(0)}(2), \cdots, X_2{}^{(0)}(n)) \\ &\vdots \\ X_N{}^{(0)} &= (X_N{}^{(0)}(1), X_N{}^{(0)}(2), \cdots, X_N{}^{(0)}(n)) \end{aligned} \tag{4}$$

where N represents the number of variables and n represents the number of elements in the sequence.

Assuming the sequence $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n))$ and $x^{(0)}(k) \geq 0, k = 1, 2, \ldots, n$, then $X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n))$ is the one-time summation of the sequence $X^{(0)}$ to generate the sequence (1-AGO), where

$$X_i{}^{(1)}(k) = \textstyle\sum_{h=1}^{k} x_i{}^{(0)}(h), (i = 1, 2, \cdots N; k = 1, 2, \cdots n) \tag{5}$$

The immediate mean sequence of $X_i{}^{(1)}$ is represented by $Z_1{}^{(1)}$:

$$Z_1{}^{(1)}(k) = \frac{1}{2}\left[X_1{}^{(1)}(k) + X_1{}^{(1)}(k-1)\right], (k = 2, 3, \cdots n) \tag{6}$$

The GM (1, n) model is further obtained as follows:

$$x_1{}^{(0)}(k) + aZ_1{}^{(1)}(k) = \textstyle\sum_{i=2}^{N} b_i x_1{}^{(1)}(k) \tag{7}$$

where a represents the development coefficient, b_i represents the driving coefficient, and $b_i x_i{}^{(1)}(k)$ represents the driving term. Then let B and Y be

$$B = \begin{bmatrix} -Z^{(1)}(2) & x_2{}^{(1)}(2) & \cdots & x_N{}^{(1)}(2) \\ -Z^{(1)}(3) & x_2{}^{(1)}(3) & \cdots & x_N{}^{(1)}(3) \\ \vdots & \vdots & \vdots & \vdots \\ -Z^{(1)}(n) & x_2{}^{(1)}(n) & \cdots & x_N{}^{(1)}(n) \end{bmatrix}, Y = \begin{bmatrix} x_1{}^{(0)}(2) \\ x_1{}^{(0)}(3) \\ \vdots \\ x_1{}^{(0)}(n) \end{bmatrix} \tag{8}$$

Let $\beta = (a, b_1, b_2, \ldots, b_N)^T$; $\beta = (\beta^T\beta)^{-1}B^TY$ can be obtained from the least square parameter estimation, then the approximate time corresponding formula of GM (1, n) can be expressed as

$$\hat{x}_1{}^{(1)}(k+1) = \left[x_1{}^{(0)}(1) - \frac{1}{a}\textstyle\sum_{i=2}^{N} b_i x_i{}^{(1)}(k+1)\right]e^{-ak} + \frac{1}{a}\textstyle\sum_{i=2}^{N} b_i x_i{}^{(1)}(k+1) \tag{9}$$

Its decremental reduction represents the final forecasting result:

$$\hat{x}_1{}^{(0)}(k+1) = \hat{x}_1{}^{(1)}(k+1) - \hat{x}_1{}^{(1)}(k) \tag{10}$$

The data set of carbon emissions is a typical small sample data, and there is a nonlinear correlation between variables. The predicting model constructed in this paper can handle the nonlinear relationship between variables and also shows a good prediction ability under the condition of small sample data and poor information, thus being suitable for the prediction of carbon emissions.

3.5. Construction of Dynamic Index of Carbon Emission Pressure Potential

(1) Carbon peaking pressure index (CPPI): For each urban agglomeration, the carbon peak time is the first pressure to achieve the goal of carbon peaking. Carbon emissions and growth rate are the other two pressures for urban agglomerations to achieve carbon peaking. Therefore, this paper constructs the carbon peak pressure index of urban agglomerations from the three perspectives of time, scale and speed. The carbon peak pressure index of the constructed urban agglomeration is as follows:

$$I_{\mathrm{Pr}} = \gamma I_{Tav} + \delta I_c + \theta I_{cg} \tag{11}$$

Among them, I_{Pr} is the carbon peak pressure index of urban agglomeration; I_{Tav} is the target pressure index of urban agglomeration, which reflects the average year of achieving carbon peaking under different situations; the pressure index of I_C's contribution to the carbon emissions of urban agglomerations reflects the relative size of their average carbon emissions, which represents the pressure brought by the responsibility of helping the whole country to achieve peaking; I_{Cg} is the original pressure index of the urban agglomeration, which reflects the relative size of the average growth rate of carbon emissions in different situations of each urban agglomeration and represents the pressure faced by achieving carbon peaking under their respective carbon emission growth rates. γ, δ, and θ are the weights of each pressure index. Considering the different units of each pressure index, deviation treatment is carried out for each index value.

(2) Carbon emission reduction potential index (CERPI): Based on efficiency and fairness, this paper constructs an index to evaluate the potential of reducing carbon emissions of urban agglomerations. Regarding efficiency, the higher the carbon emission intensity, the lower the carbon emission efficiency, indicating the greater the potential is of carbon emissions through technological and structural upgrading. From the perspective of fairness, the higher the per capita carbon emissions are, the greater is the potential of carbon emissions through the means of economic regulation and control. The carbon emission reduction potential index of the urban agglomeration constructed by the processing of potential index values is as follows:

$$I_{\mathrm{Po}} = \rho I_{ef} + \sigma I_{fa} \tag{12}$$

Among them, I_{Po} is the CERPI of urban agglomeration; I_{ef} is the efficiency potential index of urban agglomerations. I_{fa} is the fair potential index of urban agglomerations. ρ and σ are the weights of the efficiency and equity potential indexes, respectively.

Peak power index of carbon emission reduction (PPI): Urban agglomerations need to comprehensively consider their carbon peaking pressure and carbon emission reduction potential to formulate comprehensive and scientific emission reduction plans and carbon peaking targets. According to the above-mentioned carbon peaking pressure index and carbon emission reduction potential index, this paper constructs the PPI reduction in urban agglomeration as follows:

$$I_{fo} = \varphi I_{\mathrm{Pr}} + \omega I_{Po} \tag{13}$$

Among them, I_{fo} is the power index of carbon emission reduction peaking in urban agglomeration, and φ and ω are the weights of the CPPI and CERPI of urban agglomerations, respectively.

3.6. Indicator Selection and Data Sources

The index system of carbon emission and peaking driving factors should be scientific, systematic, and operable. In the construction of the index system, all potential factors affecting carbon emission and peaking should be included. Comprehensively considering the existing research results [27,29,34] and the development characteristics of the YRD region, six indicators, namely P, UR, GDP/P, IS, FDI, and CEI, were selected for the clustering analysis and carbon peaking prediction of these 41 prefecture-level cities. The specific descriptions for these indicators are as follows:

Population. More people lead to more energy demand, as well as more carbon emissions from energy consumption. The size of the city population is represented by the total population of the city at the end of the year.

Urbanization rate. During the process of urbanization, urban expansion will drive the construction of infrastructure like housing and will also influence urban carbon emissions by changing the level of carbon sources and sinks in cities. In this paper, the urbanization rate is selected to characterize the urbanization level of different cities.

GDP per capital. Economic development involves the input and use of energy resources. According to the EKC, as the level of economic development changes, the level of carbon emissions will initially increase and then decrease. In this paper, GDP per capita is used to express the level of urban economic development.

Industrial structure. The burning of fossil energy in the secondary industry (especially in energy-intensive industries) is an important source of urban carbon emissions, for which the proportion of the output value of the secondary industry in the total output value is selected to represent the urban industrial structure.

Foreign direct investment. The inflow of foreign capital increases the capital stock of a country and inevitably causes environmental pollution while driving economic growth. FDI is chosen as the measure of foreign capital in this paper.

Carbon emission intensity. A nation has attained a sustainable development pattern with its carbon emissions per unit of gross domestic product decreasing at the same time as its economy is growing. Carbon emission intensity (carbon dioxide emission per unit of GDP) is used in this paper to quantify the connection between the national economy and carbon emissions.

The relevant carbon emission data in this paper are derived from the CEADs database, and the socioeconomic data are mainly from the China Urban Statistical Yearbook and the statistics bureau of prefecture-level cities, in which the GDP/P index data are uniformly converted to constant prices in the 2000 base period to exclude the potential impact of inflation. Figure 2 shows the research framework of this study.

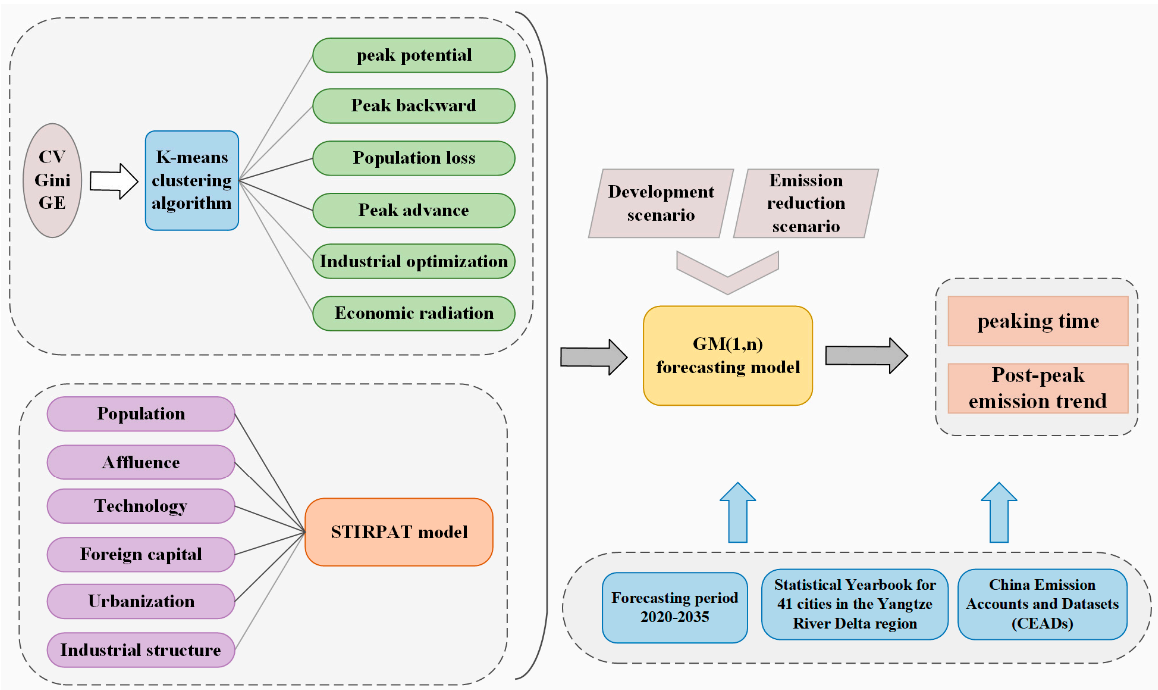

Figure 2. Research framework of study.

4. Empirical Results and Analysis

4.1. Regional Carbon Emission Disparities

4.1.1. Quantitative Assessment of Carbon Emission Disparities

Drawing on nearly two decades of carbon emission data from the urban agglomeration, this study applies the Gini coefficient (Gini), coefficient of variation (CV), and Theil index (GE) to quantitatively assess disparities in carbon emissions. Using 2000 as the base year, a 3D wall chart (Figure 2) was constructed from the relative values of these indicators, providing a clear visualization of the temporal dynamics in emission disparities.

Figure 3 illustrates that carbon emission disparities have fluctuated but generally decreased over the past 20 years, following a "decline–rise–decline" trajectory. From 2000 to 2014, the disparities steadily narrowed, with the CV, Gini, and GE reaching their lowest points in 2014. The consistent trends observed across these three metrics, with synchronous peaks and troughs, underscore their reliability in capturing carbon emission disparities. Additionally, the absolute values reveal a significant regional variation, driven by variations in economic growth, industry composition, and energy use patterns. High-emission regions face increased environmental and reduction pressures, while low-emission regions encounter limitations in economic growth and energy supply, complicating climate action and meeting emissions goals. Accordingly, classifying the 41 cities is essential to examine the mechanisms and pathways for achieving carbon peaking.

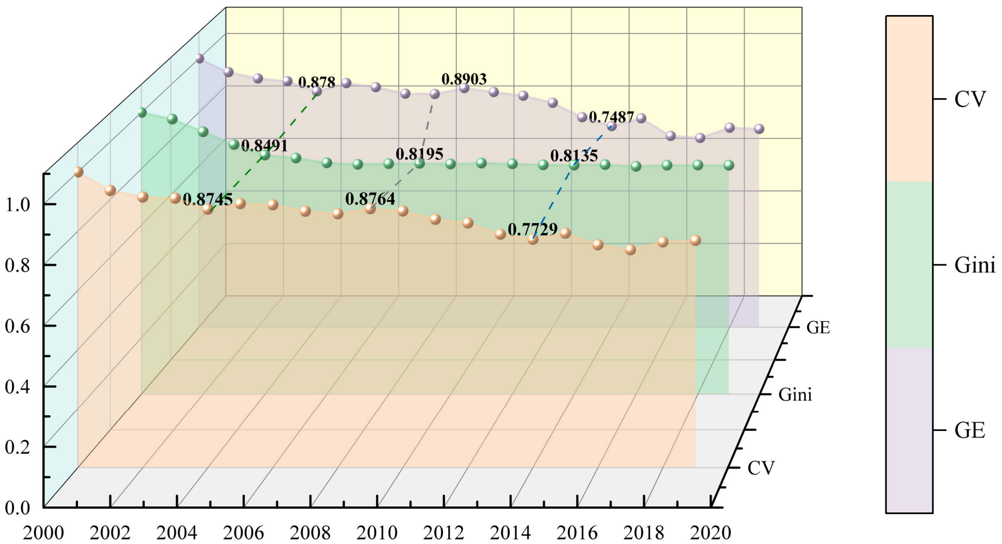

Figure 3. Evolution of carbon emission disparities.

4.1.2. City Classification

The six key indicators—P, UR, GDP/P, IS, FDI, and CEI—were standardized, and the K-means clustering algorithm was used to group the 41 prefecture-level cities in the Yangtze River Delta into six categories. The results and classifications are shown in Table 2 and Figures 4 and 5.

Class 1 cities, distinguished by a mid-to-high GDP per capita, robust industrial structures, and the efficient use of foreign capital, feature moderate population sizes and a low carbon intensity, positioning them as prime candidates for low-carbon economic growth.

Class 2 cities, with a lower GDP per capita, foreign investment, and urbanization levels, possess relatively strong industrial bases, providing potential for timely carbon peaking.

Class 3 cities, marked by population decline, exhibit moderate economic development, smaller populations, and average levels of foreign investment and urbanization. Although their carbon intensity is low, they suffer from significant population outflow to more developed regions, undermining their economic performance.

Table 2. City classification.

Classification	Characteristic	Specific Cities
Class 1 (six cities)	Peak potential	Nantong, Yangzhou, Taizhou (JS), Hangzhou, Ningbo, Zhoushan.
Class 2 (five cities)	Peak backward	Huainan, Fuyang, Suzhou (AH), Luan, Bozhou.
Class 3 (eight cities)	Population loss	Bengbu, Huaibei, Anqing, Huangshan, Chizhou, Xuancheng, Jinhua, Lishui.
Class 4 (six cities)	Peak advance	Shanghai, Nanjing, Wuxi, Changzhou Suzhou (JS), Zhenjiang.
Class 5 (eight cities)	Industrial optimization	Tongling, Chuzhou, Xuzhou, Lianyungang, Suqian, Wenzhou, Quzhou, Taizhou (ZJ).
Class 6 (eight cities)	Economic radiation	Hefei, Wuhu, Maanshan, Huaian, Yancheng, Jiaxing, Huzhou, Shaoxing.

Notes: JS, AH, and ZJ are Jiangsu Province, Anhui Province, and Zhejiang Province, respectively.

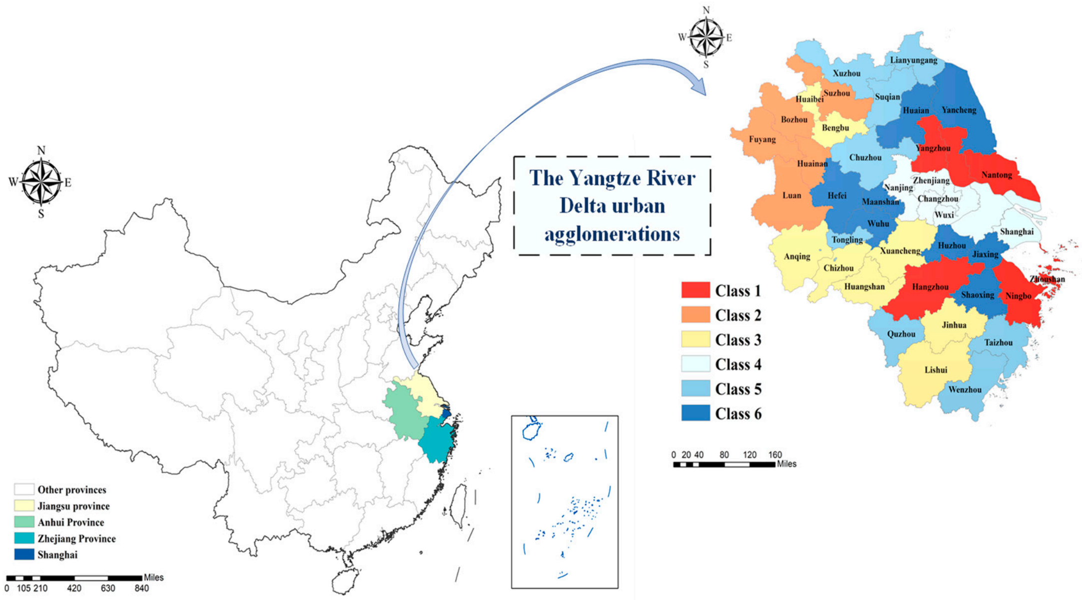

Figure 4. Clustering results of cities.

Class 4 cities, serving as demonstration models for carbon peaking, feature large populations, high foreign investment, elevated carbon emissions, and advanced urbanization with a concentrated spatial distribution. Heavily influenced by Shanghai, these economically advanced cities have already transitioned to low-carbon industrial structures and are well-positioned to achieve carbon peaking on schedule.

Class 5 cities, centered on industrial optimization, encompass both heavy (e.g., Xuzhou) and light industrial centers (e.g., Wenzhou), characterized by a dominant secondary sector and a high carbon intensity, with economies largely dependent on traditional industries.

Class 6 cities, functioning as economic radiation hubs, are less developed than Class 1 but benefit significantly from their proximity to more advanced urban centers.

4.2. Mechanisms Influencing Carbon Emissions

This study uses an extended STIRPAT model, incorporating multiple influencing factors, applied to 20 years of panel data from 41 prefecture-level cities. Combined with the clustering results, the model facilitates a categorized regression analysis, examining how variables such as P, UR, GDP/P, IS, FDI, and CEI impact carbon emissions across different city types. The findings are detailed in Table 3 and Figure 6. This result verifies the hypothesis presented in the previous section.

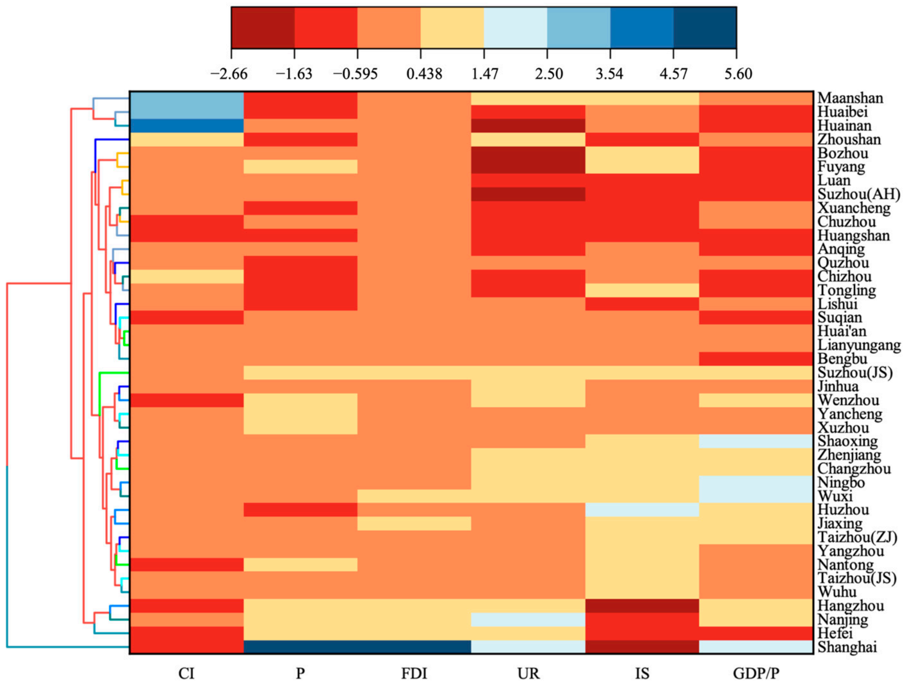

Figure 5. Clustering results of influencing factors.

Table 3. Analysis of carbon emission influencing factors.

Variation		Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
Coef.	CEI	0.907 *** (0.000)	0.934 *** (0.000)	0.916 *** (0.000)	0.915 *** (0.000)	0.885 *** (0.000)	0.879 *** (0.000)
	P	0.816 *** (0.000)	0.928 *** (0.000)	0.887 *** (0.000)	0.89 *** (0.000)	0.865 *** (0.000)	0.815 *** (0.000)
	GDP/P	0.377 *** (0.000)	0.939 *** (0.000)	0.738 *** (0.000)	0.718 *** (0.000)	0.486 *** (0.000)	0.517 *** (0.000)
	IS	−0.08 (0.427)	0.39 *** (0.004)	0.174 ** (0.014)	0.131 (0.138)	0.063 (0.500)	−0.068 (0.519)
	FDI	0.153 *** (0.000)	0.001 (0.971)	0.07 *** (0.001)	0.132 *** (0.000)	0.107 *** (0.000)	0.133 *** (0.000)
	UR	1.339 *** (0.000)	0.427 ** (0.017)	0.555 *** (0.002)	0.343 (0.055)	1.146 *** (0.000)	0.875 *** (0.000)
St. Err	CEI	0.026	0.050	0.035	0.028	0.027	0.038
	P	0.027	0.041	0.035	0.029	0.031	0.040
	GDP/P	0.060	0.091	0.095	0.068	0.062	0.078
	IS	0.100	0.131	0.070	0.087	0.093	0.106
	FDI	0.021	0.022	0.020	0.020	0.019	0.019
	UR	0.128	0.175	0.176	0.177	0.133	0.163
t-value	CEI	35.030	18.530	26.480	32.940	33.270	23.410
	P	30.310	22.880	25.370	30.490	27.610	20.170
	GDP/P	6.320	10.340	7.770	10.490	7.900	6.590
	IS	−0.800	2.970	2.480	1.490	0.680	−0.650
	FDI	7.350	0.040	3.520	6.720	5.690	7.030
	UR	10.430	2.440	3.150	1.940	8.600	5.360
R-squared		0.978	0.965	0.966	0.978	0.966	0.952
Akaike crit.		−77.136	−65.430	−99.471	−56.958	−71.452	−29.437
Bayesian crit.		−57.624	−47.193	−77.945	−37.445	−49.926	−7.911

Note: *** and ** denote significant at 1% and 5% confidence levels, respectively.

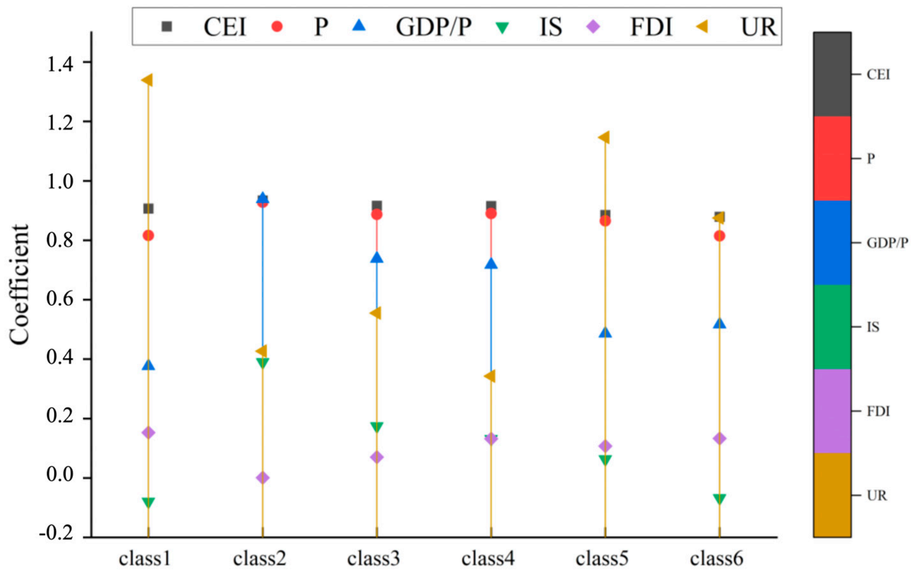

Figure 6. Comparative analysis of influencing factors.

CEI, P, GDP/P, and UR exert significant positive effects on carbon emissions across all six city types, while IS impacts emissions only in Class 2 and Class 3 cities. Population growth (P) is the primary driver of rising emissions, whereas technological advancement, indicated by a lower CEI, facilitates substantial emission reductions. Economic affluence (GDP/P) and urbanization (UR) further contribute to emissions, with GDP/P having a particularly pronounced effect in Class 2 cities, underscoring the central role of economic growth in driving emissions in less developed areas. These cities face the critical challenge of balancing development with emission reduction.

Across all the models, technological progress, reflected by reductions in CEI, significantly aids carbon reduction, which is consistent with the findings of Jian et al. [35] A 1% decrease in CEI leads to a 0.906% reduction in emissions in the Yangtze River Delta, with the CEI's elasticity nearing 1, indicating the efficacy of clean production technologies. This finding not only emphasizes the importance of technological progress for emission reductions but also implies that technological progress may have reached a certain level of maturity in a given region, where its emission reduction effects are more immediate and significant. However, it also implies that in the case of diminishing marginal benefits of technological progress, new paths of technological innovation need to be explored to achieve deeper emission reduction goals.

The regression coefficients for population (P) are positive across all models, confirming that population growth significantly drives carbon emissions, which is consistent with the findings of Si et al. [36] In Class 1 cities, a 1% population increase results in a 0.816% rise in emissions, assuming other factors remain constant. The elasticity of population with respect to emissions is below 1, indicating diminishing marginal emissions growth as populations expand, likely due to efficiency gains from economies of scale and improved infrastructure use. Moreover, the consistently significant effects of both CEI and population (P) across all city types underscore their central role in driving emissions, regardless of development levels.

Urbanization is closely linked to industrialization and service sector expansion. On the one hand, concentrated economic activity driven by urbanization leads to higher emissions, particularly in Class 1 and Class 5 cities, where the elasticity of urbanization (UR) with respect to emissions exceeds 1, indicating resource-intensive development models and underutilized technological innovation. On the other hand, urban agglomeration can enhance energy efficiency, reducing marginal emissions, as seen in Class 4 cities, where advanced urbanization correlates with lower marginal carbon emissions. The two-sided nature of urbanization is reflected here. While urbanization has the potential to promote both the efficient use of resources and energy efficiency, excessive urbanization may also lead to the overconsumption of resources and increased environmental pollution. Therefore, how to achieve green and sustainable development while promoting urbanization is a key concern for future urban planning and management.

The impact of IS and FDI on carbon emissions is relatively minor. IS only affects the peak-reaching backward type and the population loss type, while the effect on the carbon emissions of other types of cities is not significant. This may be due to the weaker economic base of these two types of cities or the reduction in the labor force due to population exodus, which makes the adjustment of the industrial structure a key way to reduce carbon emissions. In contrast, other types of cities may see a relatively small impact of industrial structure on their carbon emissions due to factors such as stronger economic strength, a full utilization of foreign investment, or having completed their low-carbon transformation. At the same time, the advantages of the industrial structure of late-peaking cities provide potential conditions for them to reach the peak on time, so that these cities tend to harmonize and balance an urban economy and carbon emission reduction under the constraints of the regional peak carbon target, whereas cities facing population loss have weak economic development due to their irrational industrial structure, and the space for employment and industrial development is limited, which is in line with the actual situation.

FDI shows little impact in Class 2 cities, such as Huainan, Fuyang, and Bozhou, where insufficient foreign investment has failed to drive substantial industrial restructuring or reduce emissions. For example, Bozhou's economy remains reliant on traditional industries like herbal medicine and liquor production, while Fuyang's slow urbanization and delayed infrastructure development limit the effectiveness of foreign investment in transforming energy systems or promoting low-carbon transportation. This underscores the need for cities to attract more foreign investment, while adopting modern energy-efficient and emission-reduction technologies alongside effective energy management systems.

To assess the model's empirical robustness, diagnostic tests with AIC and BIC were performed. The results confirm that the model successfully avoids the "curse of dimensionality" typical in complex modeling, ensuring both accuracy and reliability, thus providing a valuable tool for carbon peaking research.

4.3. Pathways to Carbon Peaking

4.3.1. Carbon Peaking Forecast

This study projects carbon emissions for each city through 2035 under two scenarios: DP and ER (Figure 7). In the DP scenario, rapid economic and social development drives significant emission increases, while slow technological progress hampers emission reductions, delaying carbon peaking. In this scenario, the city's development model still relies on traditional high carbon-emitting industries and lacks sufficient technological innovation and green transformation, thus slowing down the process of carbon peaking. In contrast, the ER scenario, characterized by slower economic growth and accelerated technological advancements, results in faster emission reductions, with the peaking timeline depending on the interplay of these factors. This scenario sees cities focusing more on green development and technological innovation and taking more aggressive measures to reduce emissions, thus accelerating the pace of carbon peaking.

Class 5 cities are expected to achieve carbon peaking by 2030 in both scenarios. Their slower economic growth and successful industrial restructuring position them to effectively balance high-emission industries with emission reduction efforts. Notably, Class 5 cities peaked as early as 2017, with an average peak emission level of 342 Mt, placing them in the mid-range among cities in the Yangtze River Delta.

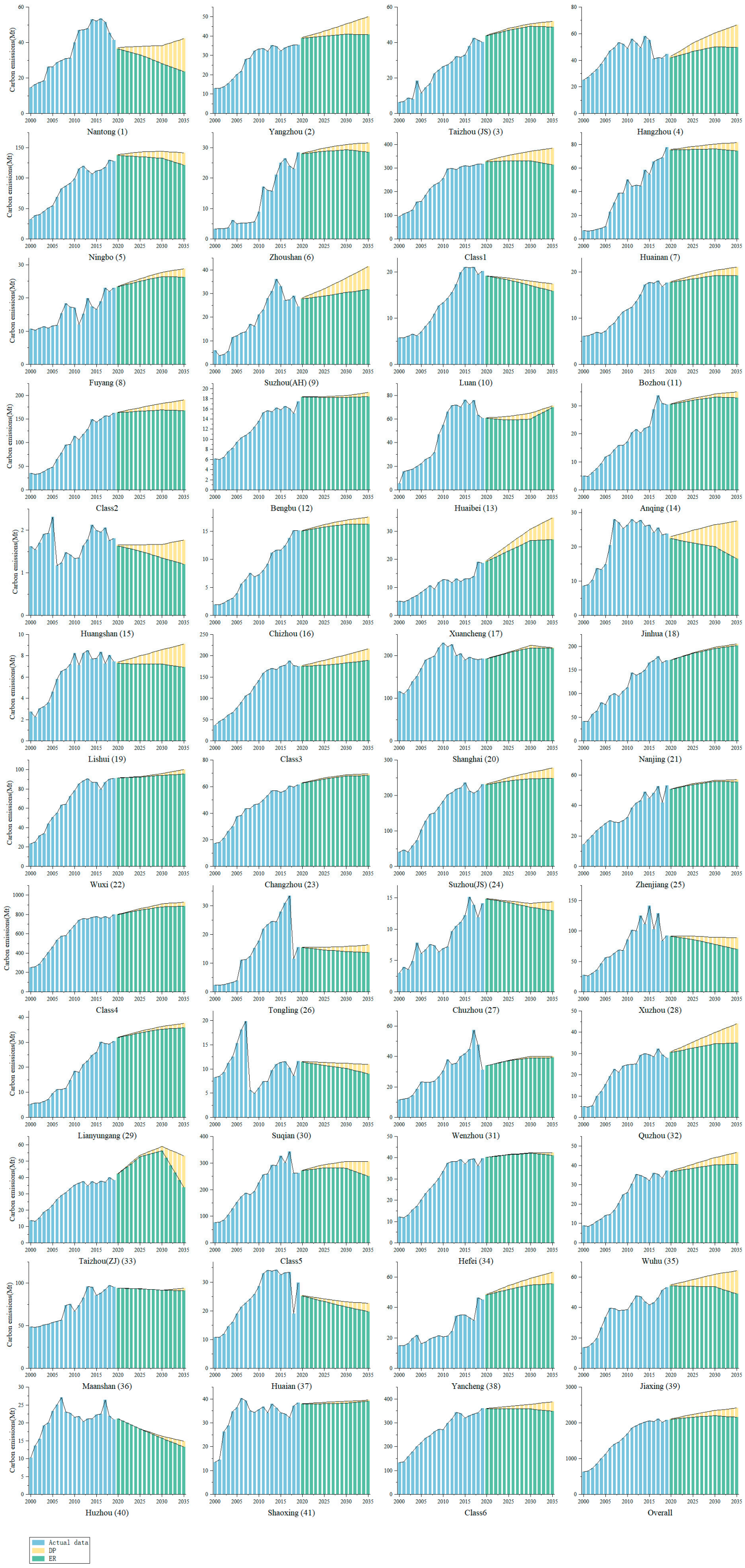

Figure 7. Carbon peaking forecast for Yangtze River Delta.

Class 1, 2, and 6 cities are projected to achieve carbon peaking only under the ER scenario, with peak emissions of 357 Mt, 180 Mt, and 374 Mt, respectively, between 2016 and 2030. Class 1 cities, with advanced economies and low-carbon industrial frameworks, are poised to meet peaking targets on schedule, driven by the dual pressures of high-quality development and carbon reduction goals. However, slower economic growth and limited foreign investment have delayed carbon peaking in Class 2 and 6 cities.

Class 3 cities, still undergoing rapid economic expansion and absorbing carbon-intensive industries from more developed regions, face challenges in achieving early carbon peaking. Meanwhile, Class 4 cities, having transitioned to high-quality growth, should prioritize strategic technologies such as carbon sequestration agriculture and carbon capture, utilization, and storage (CCUS) to become leaders in low-carbon innovation and meet peaking targets on time.

4.3.2. Further Research

This study also develops a carbon peaking pressure index to evaluate the pressures faced by different city types. These pressures arise from two sources: target pressure (external mandates from higher authorities) and internal pressures (stemming from the city's own emissions and emission growth rates). As shown in the table, Class 4 cities experience the highest pressure, with an index of 1. Class 1, 2, and 3 cities face moderate pressure, with indices between 0.45 and 0.65, while the remaining cities experience a relatively low pressure.

The previously constructed carbon reduction potential index model balances both equity and efficiency. As shown in Table 4 below, Class 4 and Class 6 cities exhibit a higher carbon reduction potential, with indices exceeding 0.55. Class 1 and Class 3 cities have a moderate potential, ranging between 0.25 and 0.45, while the remaining cities show a relatively low potential.

Table 4. Carbon peaking pressure and potential index results.

Variation		Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
Carbon Peaking Pressure	Target Pressure	0.7222	0.8611	1	1	0	0.5556
	Responsibility Pressure	0.2436	0	0.0315	1	0.2238	0.2666
	Inherent Pressure	0.7756	0.3437	0.4969	1	0.0378	0.0479
Carbon Reduction Potential	Efficiency Potential	0	0.3623	0.6670	0.1320	0.2069	1.0000
	Equity Potential	0.5093	0	0.2291	1	0.2132	0.5801
Carbon Reduction and Peaking Motivation	Carbon Peaking Pressure Index	0.5893	0.4993	0.6088	1	0.0747	0.3673
	Carbon Reduction Potential Index	0.2546	0.1812	0.4480	0.5660	0.2100	0.7901
	Carbon Reduction and Peaking Motivation Index	0.4220	0.3402	0.5284	0.7830	0.1424	0.5787
Rank		4	5	3	1	6	2

When determining carbon peaking pathways for urban agglomerations, it is essential to consider both their carbon peaking pressure and reduction potential. To this end, this study further develops a Carbon Reduction and Peaking Motivation Index under performance evaluation metrics. Class 3, 4, and 6 cities show a strong motivation for carbon reduction and peaking. Among them, Class 3 and 4 cities face a high carbon peaking pressure but possess significant reduction potential, acting as key drivers of carbon reduction. These cities should prioritize low-carbon industrial transformation, foster green collaborations, and adopt advanced technologies to expedite peaking. Although Class 6 cities face a lower peaking pressure, they also have substantial reduction potential and should focus on clean energy use, optimizing energy structures, and creating a diversified energy system centered on renewable sources, with energy storage for load balancing.

Class 1 and 2 cities exhibit moderate carbon reduction motivation, with motivation index values ranging from 0.3 to 0.45. These cities face a moderate peaking pressure but have limited reduction potential. Therefore, they should emphasize cultivating strategic emerging industries and promoting the digital and green transformation of manufacturing to enhance their low-carbon industrial development. In contrast, Class 5 cities have the weakest carbon reduction motivation, with an index of 0.1424, and all three indices are at low levels. As previously noted, Class 5 cities are experiencing slower economic and social development, making them likely to achieve carbon peaking earliest, even without additional measures.

5. Conclusions and Policy Recommendations

5.1. Key Findings

Urban agglomerations are at the forefront of China's carbon peaking efforts. However, differences in the foundational conditions across cities lead to varying emission reduction pressures, peaking timelines, and policy approaches. This study quantitatively assesses carbon emission disparities among 41 cities in the Yangtze River Delta, classifies them through machine learning, and applies an extended STIRPAT model to analyze emission drivers across city types. Using the GM (1, n) model, the study forecasts peaking timelines and peak emission levels and proposes tailored carbon peaking pathways based on assessments of peaking pressure, reduction potential, and driving forces that scientifically guide differentiated emission reduction strategies, which is of great scientific and practical significance. Our key conclusions include the following:

1. The coefficient of variation, Gini coefficient, and Theil index reveal significant disparities in carbon emission levels among the 41 cities in the Yangtze River Delta, with a general trend of fluctuating decreases over time. Utilizing machine learning to analyze key indicators—population size, affluence, technological advancement, urbanization, and industrial structure—cities are classified into six categories: potential peaking, late peaking, population loss, peaking demonstration, industrial optimization, and economic radiation cities.

2. The extended STIRPAT model effectively enhances the study's explanatory power and research credibility, striking a good balance between complexity and fit. CEI, P, GDP/P, and UR all strongly contribute to carbon emissions across the six city types, while IS and FDI have relatively weak impacts. The influence of IS is limited to Class 2 and Class 3 cities. Technological level and population size have the most consistent effects on carbon emissions, regardless of city development levels. Economic development remains the key driver of emissions in less developed cities, while the effect of urbanization on emissions diminishes as urbanization deepens.

3. Industrial optimization cities were the first to achieve carbon peaking in 2017 and are projected to sustain this through 2035 under both the DP and ER scenarios. Potential peaking, late peaking, and economic radiation cities will meet peaking targets on time only under the ER scenario, with stable post-peak emissions. In contrast, population loss and peaking demonstration cities are unlikely to peak before 2030 in either scenario. The study calculates carbon peaking pressure, reduction potential, and peaking motivation indices for each city type. Population loss and peaking demonstration cities exhibit a strong motivation, facing high pressure and a significant reduction potential. Economic radiation cities experience lower pressure but retain substantial reduction potential. Potential and late-peaking cities show a moderate motivation, with moderate pressure and limited reduction potential. Industrial optimization cities, having peaked early, display a lower motivation across all indices, which remain at low levels.

5.2. Policy Recommendations

To expedite carbon peaking in the Yangtze River Delta, the following targeted policy recommendations are proposed, based on regional emission characteristics:

1. Set differentiated carbon peaking targets. Cities should set carbon peaking goals aligned with their socioeconomic stages and current conditions, incorporating future development scenarios and the GM (1, n) model's predictions for peaking timelines and emission levels. Cities with favorable conditions, such as potential peaking, late peaking, and economic radiation cities, should aim for early peaking through energy transitions and industrial optimization, targeting 2025–2029, with emissions capped at 357 Mt, 180 Mt, and

374 Mt, respectively, allowing more flexibility for later-peaking regions. Cities experiencing population loss, undergoing rapid economic growth, should shift from labor-intensive to knowledge- or technology-intensive industries. Although early peaking is more challenging, they should aim for 2030 with emissions capped at 203 Mt. Peaking demonstration cities should capitalize on their advanced transformation experience to serve as models for others, accelerating research into and the application of low-carbon technologies, with a target of peaking by 2030 and emissions capped at 900 Mt.

2. Advance differentiated carbon peaking pathways. Cities should adopt tailored strategies based on their specific carbon peaking pressures, reduction potentials, and motivation indices. Population loss and peaking demonstration cities, as key drivers of emission reduction, should deploy advanced technologies to foster green and low-carbon transitions in high-emission sectors. Economic radiation cities should focus on developing integrated wind/solar storage systems and promoting carbon sink development and CCUS application. Potential and late-peaking cities should prioritize green technology innovation, leveraging the spillover effects to assist other regions in achieving earlier peaks. Industrial optimization cities should maintain a steady reduction trajectory, while supporting continued population and industrial growth.

3. Enhance carbon peaking monitoring and evaluation systems. Establish comprehensive carbon emission standards for urban agglomerations, refine evaluation and carbon labeling systems, and align internal plans with national benchmarks, elevating standards as needed. Key sectors should formulate carbon peaking action plans, implement classified carbon intensity management, and improve synergies between pollution control and carbon reduction. Cities should set clear timelines and peak emission targets, develop roadmaps, establish dynamic monitoring systems, and introduce third-party verification. They should implement a carbon emission reporting system with annual inventories, integrate peaking targets into performance accountability frameworks, and establish a tiered warning and reward system with penalties. Finally, they should strengthen international cooperation and align with global standards.

5.3. Research Limitations and Prospects

This study also has the following shortcomings: (1) Although this study adopts a variety of data sources and advanced analytical methods, the data for some indicators in some cities may be incomplete or inaccurate due to the limitations of data acquisition. Especially under the small sample data set, the reliability and representativeness of the data still need to be further verified. (2) When constructing the carbon peak pressure index, carbon emission reduction potential index, and carbon emission reduction peak power index models, some of the assumptions may be too idealized in order to simplify the calculation and improve the operability of the models. There are still the following areas that can be improved in this study: (1) Future studies can improve the completeness and accuracy of the data through more data collection and finer data processing methods. (2) The existing model can be further optimized by introducing more dynamic factors and nonlinear relationships to make it closer to the actual situation.

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