

Article

From Spatial Evolution to Low-Carbon Transition: Regional Heterogeneity and Stage Diagnosis of Carbon Emissions Across 19 Urban Agglomerations in China

Ye Duan ^{1,*} , Minghan Yang ¹, Zhaowei Hou ², Hongye Wang ³ , Albert Fekete ⁴  and Dongge Ning ⁴

¹ School of Geography, Liaoning Normal University, Dalian 116029, China; 15942988323@163.com

² Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China; hzw92302@163.com

³ School of Energy and Power Engineering, Dalian University of Technology, Dalian 116024, China; wanghongye@dlut.edu.cn

⁴ Institute of Landscape Architecture, Urban Planning and Garden Art, Hungarian University of Agriculture and Life Sciences, 1000 Gödöllő, Hungary; feket.albert@uni-mate.hu (A.F.); ningdongge@phd.uni-mate.hu (D.N.)

* Correspondence: dydl@lnnu.edu.cn

Abstract

Understanding the spatiotemporal dynamics of carbon emissions and developing differentiated governance strategies for urban agglomerations are essential for achieving regional low-carbon transformation. This study aims to identify the spatiotemporal patterns, driving mechanisms, and development-stage differences of carbon emissions across China's urban agglomerations and to establish a type-specific governance framework. Based on multi-source geospatial and socioeconomic data from 19 urban agglomerations for the period 2006–2023, this study integrates spatial autocorrelation analysis, standard deviation ellipse analysis, hotspot analysis, random forest regression with SHAP interpretation, K-medoid clustering, and the Environmental Kuznets Curve (EKC) model to systematically examine emission evolution, influencing factors, and governance pathways. The results indicate the following: (1) carbon emissions in China's urban agglomerations increased continuously during the study period and exhibited significant spatial heterogeneity, characterized by a "high east–low west" pattern, expanding eastern emission hotspots, and a gradual south–west shift in the emission centroid; (2) industrial structure and economic development level were identified as the dominant factors associated with carbon-emission differences, while energy efficiency, urbanization, and population density showed heterogeneous relationships across regions; (3) five carbon-emission development types were identified, including high-carbon high-development, transition-pressure, resource-dependent, stable-development, and low-carbon potential agglomerations, each exhibiting distinct development characteristics and governance requirements; and (4) EKC analysis revealed differentiated development stages among these types, suggesting that carbon governance should be tailored according to regional development conditions, dominant drivers, and emission-transition stages. This study provides an integrated geospatial modeling framework for understanding carbon-emission heterogeneity and offers scientific support for differentiated low-carbon planning and collaborative governance of urban agglomerations.

Keywords: urban agglomeration carbon emissions; spatiotemporal patterns; geospatial modeling; random forest; Environmental Kuznets Curve (EKC); differentiated governance



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1. Introduction

Climate change has become one of the most critical challenges for global sustainable development, and reducing carbon dioxide emissions is central to climate change mitigation and a low-carbon transition [1,2]. As the world's largest developing country and one of the major carbon emitters, China has announced the strategic goals of reaching carbon peak before 2030 and achieving carbon neutrality before 2060 [3]. These goals require not only national-level emission control but also spatially targeted governance because economic activities, energy consumption, industrial production, and population mobility are unevenly distributed across regions [4]. During the 14th Five-Year Plan period, China's low-carbon transition has entered a stage in which emission reduction is closely linked with energy-structure optimization, industrial upgrading, technological innovation, and regional coordinated development [5]. Identifying where carbon emissions concentrate, what factors drive their changes, and how governance strategies should differ across regions has become a key scientific and policy issue.

Urban agglomerations provide an important spatial scale for addressing this issue. In China's new-type urbanization and regional development strategy, urban agglomerations are major carriers of population concentration, industrial division, infrastructure networks, and intercity flows of capital, labor, energy, technology, and information [6,7]. These characteristics make them both engines of economic growth and important areas of energy consumption and carbon emissions [8]. Compared with individual cities, carbon emissions in urban agglomerations are shaped by more complex spatial processes, including cross-city industrial linkages, transportation connections, land-use expansion, infrastructure sharing, and factor mobility [9]. Central and peripheral cities are connected through production networks, commuting systems, public services, and ecological constraints, which may generate spatial spillovers and cross-boundary effects in both emissions and emission-reduction outcomes [10]. Consequently, carbon governance at the urban-agglomeration scale cannot rely only on aggregate emission control; it also requires a differentiated understanding of spatial heterogeneity, development stages, and dominant driving factors.

Existing studies have provided valuable evidence on the spatiotemporal patterns of carbon emissions. With the increasing availability of gridded emission datasets, nighttime-light data, land-use data, and socioeconomic statistics, geospatial modeling methods have been widely used to describe the spatial distribution and temporal evolution of carbon emissions [11]. Spatial autocorrelation analysis and hotspot analysis have been used to identify emission clustering and local high-emission areas, while standard deviation ellipse analysis has been applied to reveal the directional migration and spatial concentration of emission centers [12,13]. In China, empirical studies have examined carbon-emission patterns in typical urban agglomerations such as Beijing–Tianjin–Hebei [14], the Yangtze River Delta [15,16], the Pearl River Delta [17], and the Middle Yangtze River urban agglomeration [18]. These studies have improved the understanding of regional emission differences and spatial associations. However, many of them focus on a single urban agglomeration, several typical regions, or a specific period. A systematic comparison of multiple urban agglomerations at the national scale remains insufficient, especially from a long-term perspective that combines temporal evolution, spatial pattern identification, and development-stage diagnosis.

Beyond spatial patterns, the driving mechanisms of carbon emissions have also received increasing attention. Prior research has examined the effects of economic development, industrial structure, energy consumption, energy efficiency, urbanization, population density, technological innovation, and environmental regulation on carbon emissions [19,20]. Traditional econometric and spatial statistical models are useful for testing linear relationships and spatial dependence, but carbon-emission processes are

often nonlinear and involve interactions among socioeconomic, energy-related, and spatial variables [21]. In recent years, machine learning methods have been introduced into carbon-emission research to capture nonlinear relationships and improve predictive and explanatory performance [22]. Random forest models are particularly suitable for identifying complex variable interactions and ranking the relative importance of multiple factors [23]. Meanwhile, SHAP interpretation provides a way to explain how each factor contributes to model outputs and whether its influence is positive or negative under different regional conditions [24]. Nevertheless, existing machine learning studies often emphasize model accuracy or variable importance, while the connection between interpretable driver identification, urban-agglomeration classification, development-stage judgment, and differentiated governance remains underdeveloped.

From the perspective of low-carbon governance, the Environmental Kuznets Curve (EKC) provides a useful framework for understanding the relationship between economic development and environmental pressure [25]. The EKC hypothesis suggests that environmental pressure may first increase and then decrease with economic growth, although the existence and shape of this relationship vary across regions, indicators, and development stages [26]. For urban agglomerations, the EKC relationship may be affected by industrial upgrading, energy transition, technological innovation, and intercity industrial transfer [27,28]. Identifying whether different types of urban agglomerations are in the rising stage, near the turning point, or entering a declining stage can help clarify their transition pressures and policy priorities. However, existing EKC studies are often conducted at national, provincial, or city scales [29,30], whereas relatively few studies integrate EKC-stage diagnosis with spatial clustering and machine learning-based driver interpretation for multiple urban agglomerations.

Overall, existing studies have made substantial progress in describing carbon-emission patterns, identifying influencing factors, and discussing regional collaborative governance. However, the relationship among spatial pattern evolution, nonlinear driving mechanisms, development-stage differences, and governance responses has not yet been fully integrated within a unified analytical framework. In particular, it remains insufficiently understood how carbon emissions have evolved across China's major urban agglomerations over a long period, whether dominant emission drivers differ among regions with different development conditions, and how these differences can be translated into more targeted governance strategies. This limitation restricts the explanatory power of existing studies, because the analysis often remains at the level of describing emission distributions or ranking influencing factors, without sufficiently clarifying the pathway from spatial heterogeneity to differentiated governance.

To address this gap, this study constructs an integrated geospatial modeling framework for China's 19 urban agglomerations for the period 2006 to 2023. The analysis first identifies the temporal evolution, spatial clustering, hotspot distribution, and directional shift in carbon emissions using spatial autocorrelation analysis, hotspot analysis, and standard deviation ellipse analysis. It then employs random forest regression and SHAP interpretation to reveal the nonlinear effects and relative contributions of socioeconomic, energy-related, and spatial factors. Furthermore, K-medoid clustering and the Environmental Kuznets Curve model are combined to classify urban agglomerations according to their emission characteristics and development stages. On this basis, the study links spatial patterns, driving mechanisms, and differences in EKC stage to propose type-specific governance pathways for China's urban agglomerations.

The significance of this study is three-fold. Theoretically, this study shifts the analysis of urban-agglomeration carbon emissions from pattern description to mechanism explanation and governance interpretation. By linking spatiotemporal evolution, driving-

factor heterogeneity, emission-type classification, and EKC-stage diagnosis, it provides a more systematic understanding of why carbon-emission trajectories differ among urban agglomerations and how such differences are related to their development conditions. Methodologically, this study integrates geospatial analysis, interpretable machine learning, clustering, and EKC modeling into a coherent analytical framework. This integrated framework improves the ability to identify nonlinear drivers, explain regional heterogeneity, and connect quantitative modeling results with policy-oriented classification. Practically, the findings provide evidence for differentiated low-carbon governance in China's urban agglomerations. Instead of applying uniform emission-reduction measures, the proposed framework helps identify which urban agglomerations require industrial restructuring, energy-efficiency improvement, technological innovation, ecological protection, or cross-regional collaborative governance. This study thus offers scientific support for type-specific low-carbon planning, regional collaborative emission reduction, and the implementation of China's carbon peak and carbon neutrality goals.

Figure 1 illustrates the research framework of this study.

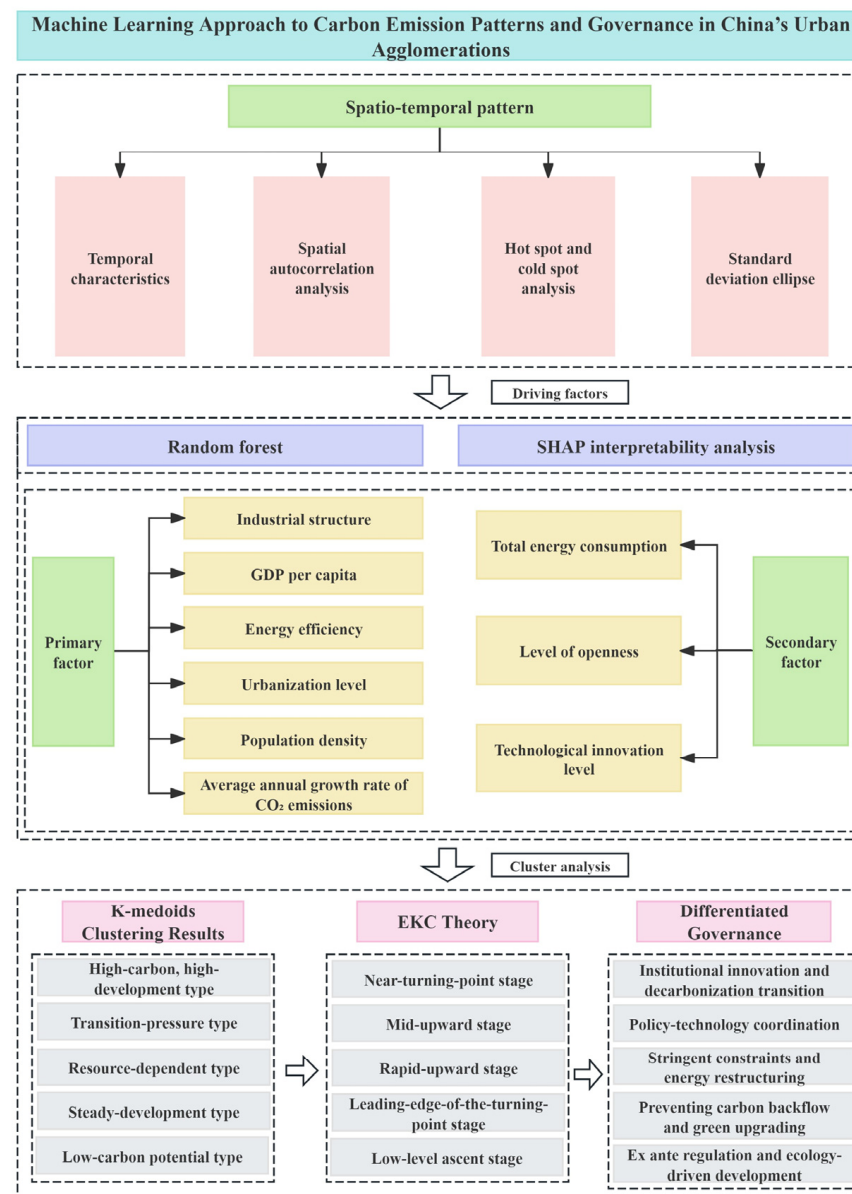


Figure 1. Research framework.

2. Materials and Methods

2.1. Study Area

This study focuses on the 19 urban agglomerations identified in China's "14th Five-Year Plan", which represent the major population and economic concentration areas in the country. These urban agglomerations include the Yangtze River Delta, Pearl River Delta, Beijing–Tianjin–Hebei, Middle Yangtze River, Chengdu–Chongqing, Central and Southern Liaoning, Shandong Peninsula, Guangdong–Fujian–Zhejiang Coastal, Harbin–Changchun, Central Plains, Guanzhong Plain, Beibu Gulf, Northern Slope of Tianshan Mountains, Central Shanxi, Hohhot–Baotou–Ordos–Yulin, Central Yunnan, Central Guizhou, Lanzhou–Xining, and Ningxia Yellow River urban agglomerations. These regions were selected because they encompass diverse geographical conditions, resource endowments, industrial structures, and development stages, providing a comprehensive representation of China's urbanization patterns.

These urban agglomerations are distributed across the major geographical regions of China, including the eastern coastal, central, western, and northeastern regions (Figure 2). The Yangtze River Delta, Pearl River Delta, and Beijing–Tianjin–Hebei urban agglomerations are located in the eastern coastal economic belt and represent China's most developed metropolitan regions, characterized by high population density, advanced industrial systems, and intensive economic activities. The Shandong Peninsula and Central Plains urban agglomerations serve as important economic centers in northern and central China, with strong manufacturing capabilities and industrial foundations.

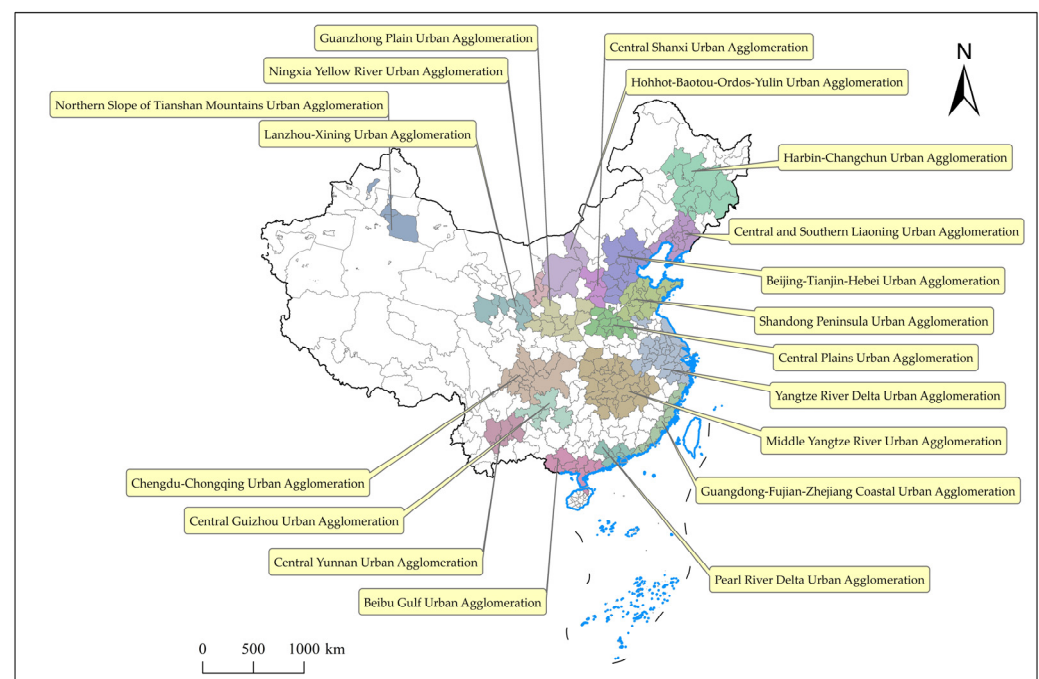


Figure 2. Spatial distribution of urban agglomerations.

The spatial heterogeneity among these urban agglomerations in terms of economic development, industrial composition, and energy consumption patterns leads to distinct carbon-emission characteristics and transition trajectories. Therefore, these regions provide an appropriate research framework for investigating the spatial differentiation and temporal evolution of CO₂ emissions across different urban development contexts.

2.2. Methods

2.2.1. Spatiotemporal Evolution of CO₂ Emission Patterns

- (1) This study used the gridded CO₂ emission dataset from the Emissions Database for Global Atmospheric Research (EDGAR) covering the period from 2006 to 2023 as the primary emission source [31]. The annual CO₂ emission data were retained to construct a longitudinal panel dataset for analyzing the spatiotemporal evolution of carbon emissions [32]. Specifically, CO₂ emissions of each urban agglomeration were calculated separately for each year between 2006 and 2023, resulting in a balanced dataset consisting of 19 urban agglomerations and 18 years (342 observations).

EDGAR provides spatially explicit CO₂ emission estimates based on sectoral activity data and emission factors under the IPCC greenhouse gas inventory framework. The EDGAR raster layers were first projected into a consistent coordinate system and spatially aligned with the boundaries of the 19 urban agglomerations. The raster data were then clipped to each urban agglomeration boundary, and CO₂ emissions within each boundary were aggregated using pixel-area weights. For pixels partially overlapping an urban-agglomeration boundary, only the overlapping area was included in the aggregation. The total CO₂ emissions of each urban agglomeration in each year were calculated as follows:

$$CE_{it} = \sum_{p=1}^n (I_p \times A_p) \quad (1)$$

where CE_{it} represents the total CO₂ emissions of urban agglomeration i in year t , I_p denotes the CO₂ emission value or emission intensity of raster pixel p in year t , A_p represents the area weight or overlapping area of pixel p within the corresponding urban-agglomeration boundary, and n is the total number of raster pixels covered by the urban-agglomeration boundary.

- (2) Spatial Autocorrelation Analysis: Spatial autocorrelation analysis was conducted to identify the spatial dependence and clustering characteristics of CO₂ emissions among urban agglomerations [33]. A spatial weight matrix was constructed based on the first-order Queen contiguity criterion, where two urban agglomerations were considered spatially connected if they shared a common boundary or vertex. The corresponding spatial weight was assigned as 1 for neighboring urban agglomerations and 0 otherwise [34]. The diagonal elements were set to zero to exclude self-interaction. To eliminate the influence of different numbers of neighboring regions, the spatial weight matrix was row-standardized before calculation.

Based on this spatial weight matrix, the Global Moran's I index was calculated to evaluate the overall spatial autocorrelation of CO₂ emissions among the 19 urban agglomerations [35]. The calculation formula is as follows:

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n W_{ij} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (2)$$

In the formula, n is the number of urban agglomerations; W_{ij} represents the spatial weight between urban agglomerations i and j ; and x_i , x_j are the CO₂ emissions of urban agglomerations i and j , respectively. $\bar{x}$ denotes the mean CO₂ emission of all urban agglomerations. The value range of Moran's I is $[-1, 1]$: a Moran's I greater than 0 indicates positive spatial autocorrelation, a value less than 0 indicates negative spatial autocorrelation, and a value equal to 0 suggests that the data are randomly distributed in space with no spatial autocorrelation.

- (3) **Hot Spot and Cold Spot Analysis:** Hot spot and cold spot analysis was performed to identify the local spatial clustering characteristics of CO₂ emissions among urban agglomerations [36]. The Getis–Ord G_i^* statistic was applied to detect statistically significant clusters of high and low emission values. The spatial weight matrix used in the G_i^* analysis was consistent with that used in the Global Moran’s I analysis, which was constructed based on the first-order Queen contiguity criterion and row-standardized before calculation.

The Getis–Ord G_i^* statistic for urban agglomeration i was calculated as follows:

$$G_i^* = \frac{\sum_{j=1}^n W_{ij}x_j}{\sum_{j=1}^n x_j} \quad (3)$$

$$Z(G_i^*) = \frac{\sum_{j=1}^n W_{ij}(x_j - \bar{x})}{S \sqrt{\frac{\left[n \sum_{j=1}^n W_{ij}^2 - \left(\sum_{j=1}^n W_{ij} \right)^2 \right]}{n-1}}} \quad (4)$$

$$S = \sqrt{\frac{\sum_{j=1}^n x_j^2}{n-1} - (\bar{x})^2} \quad (5)$$

In the equation, S represents the sample standard deviation. G_i^* is the local autocorrelation index for city i ; W_{ij} is the spatial weight matrix; x_i and x_j are the CO₂ emissions of cities i and j ; n is the total number of cities in the study area. The G_i^* statistic was standardized as a z -score, and its statistical significance was evaluated using p -values. A significantly positive G_i^* z -score indicates that the urban agglomeration and its neighboring units form a high-emission cluster, namely a hot spot. Conversely, a significantly negative G_i^* z -score indicates a low-emission cluster, namely a cold spot. The results were visualized using ArcGIS 10.8 (Esri, Redlands, CA, USA).

- (4) **Standard Deviation Ellipse:** The standard deviation ellipse is used to quantify the spatial distribution characteristics of CO₂ emissions, analyzing the concentration and directional expansion of emissions [37]. By utilizing key parameters such as the centroid coordinates, azimuth angle, standard deviation along the major axis, and standard deviation along the minor axis, the standard deviation ellipse effectively illustrates the spatial distribution patterns of CO₂ emissions.

The mean center is

$$\bar{X}_W = \frac{\sum_{i=1}^n \omega_i x_i}{\sum_{i=1}^n \omega_i} \quad (6)$$

$$\bar{Y}_W = \frac{\sum_{i=1}^n \omega_i y_i}{\sum_{i=1}^n \omega_i} \quad (7)$$

The azimuth is

$$\tan \theta = \frac{\left(\sum_{i=1}^n \omega_i^2 \tilde{x}_i^2 - \sum_{i=1}^n \omega_i^2 \tilde{y}_i^2 \right) + \sqrt{\left(\sum_{i=1}^n \omega_i^2 \tilde{x}_i^2 - \sum_{i=1}^n \omega_i^2 \tilde{y}_i^2 \right)^2 + 4 \sum_{i=1}^n \omega_i^2 \tilde{x}_i \tilde{y}_i}}{2 \sum_{i=1}^n \omega_i^2 \tilde{x}_i \tilde{y}_i} \quad (8)$$

The standard deviation along the X-axis and Y-axis is

$$\sigma_x = \sqrt{\frac{\sum_{i=1}^n (\omega_i \tilde{x}_i \cos \theta - \omega_i \tilde{y}_i \sin \theta)^2}{\sum_{i=1}^n \omega_i^2}} \quad (9)$$

$$\sigma_y = \sqrt{\frac{\sum_{i=1}^n (\omega_i \tilde{x}_i \sin \theta - \omega_i \tilde{y}_i \cos \theta)^2}{\sum_{i=1}^n \omega_i^2}} \quad (10)$$

In the formula: $\bar{X}_W$ and $\bar{Y}_W$ represent the weighted mean center of the study objects; x_i and y_i are the geometric coordinates; ω_i is the weight; σ_x and σ_y are the standard deviations along the x -axis and y -axis, respectively; $\tilde{x}_i$ and $\tilde{y}_i$ are the coordinate deviations of each study object's location from the mean center; θ is the azimuth of the ellipse, indicating the angle between true north and the major axis of the ellipse.

2.2.2. GeoAI-Based Driver Identification: Random Forest and SHAP Interpretation

Within the GeoAI-assisted workflow, random forest was used primarily as an interpretable driver-identification model [38]. As an ensemble learning method, random forest constructs multiple decision trees through bootstrap sampling and integrates their outputs, enabling the identification of nonlinear relationships and interactions among socioeconomic, energy-related, and spatial variables [39]. This makes it suitable for detecting the dominant factors associated with CO₂ emissions across urban agglomerations [40].

To improve the reproducibility and robustness of the model, key hyperparameters, including the number of trees, tree depth, and feature selection strategy at each split, were specified before model training [41]. These parameters were determined by considering the characteristics of the dataset and the need to balance model complexity and generalization ability under a relatively limited sample size. Other model settings followed the default configuration of the random forest implementation.

The ensemble output of the random forest model can be expressed as follows:

$$\hat{f}(x) = \frac{1}{B} \sum_{b=1}^B T_b(x) \quad (11)$$

In the equation, B represents the number of decision trees, and $T_b(x)$ denotes the output of the b -th tree.

To enhance the interpretability and policy relevance of the model results, this study adopts the SHAP (Shapley additive explanations) method, which is based on cooperative game theory, to decompose the marginal contribution of each feature to both individual and overall model outputs [42]. SHAP values quantify variable importance, identify whether each factor is associated with higher or lower model-estimated carbon emissions, and reveal heterogeneous mechanisms across observations.

In addition, to examine whether the contribution ranking of the same factor differs across urban agglomerations, the absolute SHAP values were normalized within each agglomeration. The resulting agglomeration-specific relative importance values were used as a supplementary interpretation of the overall feature-importance ranking.

To evaluate the reliability and robustness of the random forest model, model performance was assessed using three validation components: training-set performance, five-fold cross-validation, and spatial blocked validation. The coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE) were used as evaluation metrics [43]. During five-fold cross-validation, standardization and random forest regression were combined within a modeling pipeline so that the scaler was fitted only to the training subset within each fold, thereby reducing potential information leakage.

Considering that the RF-SHAP analysis was based on a 2023 cross-sectional dataset with a limited number of urban agglomerations, a spatial blocked validation strategy was further adopted [44]. Specifically, a leave-one-urban-agglomeration-out procedure was used, in which one urban agglomeration was excluded from model training and then used as an independent validation block in each iteration. This procedure was designed to test whether the model could maintain reasonable explanatory stability when applied to unseen urban agglomerations. The validation framework not only evaluated the in-sample fitting ability of the model but also examined its out-of-sample stability and spatial generalization under the small-sample setting.

2.2.3. K-Means Clustering Algorithm and K-Medoid Clustering Algorithm

Cluster analysis is an important unsupervised learning method that is suitable for identifying the intrinsic structure within data and can effectively divide the research subjects into several categories with similar characteristics. This method has significant advantages in studies such as spatial differentiation and type identification, and is particularly suitable for research units like urban agglomerations, which exhibit significant heterogeneity in aspects such as economic and social development, as well as resource and environmental conditions.

Common clustering algorithms include K-means, K-medoids, hierarchical clustering, DBSCAN, and others. Among these, the K-means algorithm is widely used due to its high computational efficiency and simplicity of implementation. The K-medoids algorithm, on the other hand, uses actual sample points as cluster centers, making it more robust to noise and outliers [45]. To scientifically identify the carbon-emission types of China's urban agglomerations and explore the adaptability and classification performance of different algorithms on heterogeneous data, this study systematically compares the K-means and K-medoids algorithms. Although the K-means algorithm is more efficient, it determines cluster centers through mean iteration, which makes it susceptible to the influence of extreme values. This can lead to distortion in classification when the data distribution is uneven or when outliers are present. In contrast, the K-medoids algorithm selects actual observations as center points, which better reflects the true distribution of the data and reduces the impact of outliers.

To objectively assess the clustering performance of the two algorithms in the data environment of this study and determine the more suitable classification method, this study compares and validates K-means and K-medoids from the perspective of clustering effectiveness. Internal evaluation metrics, including the silhouette coefficient (SC), Davies–Bouldin index (DBI), Gap statistic (Gap), and Calinski–Harabasz index (CHI) [46], are used to comprehensively compare the performance of the two algorithms regarding intra-cluster consistency and inter-cluster separation. This provides a methodological basis for accurately classifying types of carbon emissions from urban agglomerations in subsequent analyses.

2.2.4. Environmental Kuznets Curve Model

To identify the relationship between economic development and CO₂ emissions among different types of urban agglomerations, this study adopted an Environmental Kuznets Curve (EKC) framework [47]. Considering the classification results obtained from clustering analysis, the EKC relationship was examined separately for each urban agglomeration category.

A quadratic function was used to characterize the nonlinear relationship between economic development and carbon emissions:

$$CO_2 = a(PGDP)^2 + b(PGDP) + c \quad (12)$$

where CO₂ represents the total CO₂ emissions of urban agglomerations, and PGDP denotes per capita GDP. The coefficients a, b, and c represent the quadratic, linear, and constant terms, respectively.

The quadratic-fitting approach was applied to identify the potential EKC characteristics of different urban agglomeration types. When the coefficient of the quadratic term (a) is negative, the relationship exhibits an inverted U-shaped pattern, indicating that CO₂ emissions initially increase with economic growth and subsequently decline after reaching a turning point. The turning point of per capita GDP was calculated as

$$PGDP^* = -\frac{b}{2a} \quad (13)$$

where PGDP* represents the economic development level corresponding to the maximum CO₂ emission point.

Based on the fitted curves and turning points, different urban agglomeration categories were further identified according to their emission development stages [48], including rising, approaching the turning point, and entering a declining stage. This analysis provides additional evidence for understanding differentiated carbon transition pathways among urban agglomerations.

2.3. Multi-Source Geospatial Database Construction and Processing

To support geospatial AI-assisted modeling and cross-agglomeration comparison, this study constructed a multi-source geospatial database at the urban-agglomeration scale. The data used in this study primarily include the following sources: First, CO₂ emission data were obtained from the Emissions Database for Global Atmospheric Research (EDGAR) (https://edgar.jrc.ec.europa.eu/dataset_ghg2024 (accessed on 25 January 2026)). The EDGAR gridded emission layers for 2006–2023 were processed using R software (R Foundation for Statistical Computing, Vienna, Austria) and aligned with the boundaries of the 19 urban agglomerations. Second, energy consumption data were obtained from the “China City Statistical Yearbook,” provincial and municipal statistical yearbooks, and statistical bulletins of prefecture-level cities, covering data from 2006 to 2023. Specifically, this includes annual electricity consumption, total supply of coal gas and natural gas, liquefied petroleum gas supply, and the standardized coal gas coefficients for natural gas and liquefied petroleum gas [49]. Additionally, the calculation method for energy consumption involves triple distribution based on total electricity, coal gas, and natural gas supply, and liquefied petroleum gas supply. The related energy consumption data is obtained through standardized analysis and combined with GDP to calculate energy consumption intensity [50]. Third, socioeconomic data, including population density, per capita GDP, urbanization rate, and industrial structure, are sourced from the “China City Statistical Yearbook” (<https://www.stats.gov.cn/sj/ndsj/> (accessed on 25 January 2026))

(2007–2024), municipal statistical yearbooks, and social development bulletins. Missing data are supplemented using linear interpolation.

3. Results

3.1. Spatio-Temporal Pattern Analysis of CO₂ Emissions in China's Urban Agglomerations

To comprehensively elucidate the evolutionary dynamics of carbon emissions in China's urban agglomerations, this study conducts an in-depth analysis from both temporal and spatial perspectives.

3.1.1. Temporal Characteristics of CO₂ Emissions in China's Urban Agglomerations

Between 2006 and 2023, the total CO₂ emissions of 19 urban agglomerations in China showed a continuous increasing trend, rising from 5.36 billion tons to 9.39 billion tons, with an average annual growth rate of 3.2%. This growth reflects the combined impact of multiple factors, including industrialization, urbanization, and the rising demand for energy.

In the time series, the CO₂ emission changes in some urban agglomerations show notable volatility (Table 1). For example, while the Yangtze River Delta urban agglomeration's emission share was 19.17% in 2006, it gradually decreased in the following years, reaching 18.25% in 2023. This change indicates that the Yangtze River Delta has gradually undertaken industrial upgrading and a transition to clean energy, leading to a slowdown in carbon emission growth. In contrast, the emission share of the Pearl River Delta urban agglomeration remained relatively stable but showed a slight declining trend between 2014 and 2018, dropping from 4.11% in 2006 to 3.52% in 2023. This decline may be attributed to the optimization of the industrial structure and the gradual application of green technologies in the region.

Table 1. Proportion of CO₂ emissions by urban agglomerations in China.

Urban Agglomeration	2006	2010	2014	2018	2023
Yangtze River Delta Urban Agglomeration	19.1706	19.2073	19.1160	18.9198	18.2505
Pearl River Delta Urban Agglomeration	4.1137	3.5633	3.4016	3.3293	3.5209
Beijing–Tianjin–Hebei Urban Agglomeration	11.9804	12.5117	12.5818	12.0248	11.1117
Shandong Peninsula Urban Agglomeration	13.7283	12.8740	12.8343	13.2152	12.5314
Central Plains Urban Agglomeration	6.0396	5.9912	5.8045	5.6242	5.4396
Harbin–Changchun Urban Agglomeration	3.1652	3.0140	2.8573	2.8536	2.7962
Central Guizhou Urban Agglomeration	1.6933	1.3371	1.3631	1.5279	1.5223
Lanzhou–Xining Urban Agglomeration	1.4600	1.4125	1.3040	1.3651	1.3343
Central and Southern Liaoning Urban Agglomeration	4.5667	4.8784	4.8532	4.7238	4.6457
Guanzhong Plain Urban Agglomeration	4.0110	4.4197	4.2773	4.1564	4.0877
Northern Slope of Tianshan Mountains Urban Agglomeration	0.9231	0.9883	1.0793	1.0858	1.0595
Central Shanxi Urban Agglomeration	3.2847	3.3186	3.3868	3.1622	3.4875
Hohhot–Baotou–Ordos–Yulin Urban Agglomeration	3.6878	4.0347	4.1432	4.6408	5.9889
Ningxia Yellow River Urban Agglomeration	1.2836	1.4798	1.4914	1.7869	2.0847
Middle Yangtze River Urban Agglomeration	10.1782	10.1644	10.1202	10.0868	10.2521
Chengdu–Chongqing Urban Agglomeration	4.6321	4.3422	4.3865	4.3105	4.2444
Guangdong–Fujian–Zhejiang Coastal Urban Agglomeration	2.8135	3.1110	3.2038	3.3737	3.5498
Beibu Gulf Urban Agglomeration	1.7121	1.8837	2.2400	2.3487	2.7636
Central Yunnan Urban Agglomeration	1.5561	1.4681	1.5556	1.4646	1.3291

Additionally, the emission share of the Beijing–Tianjin–Hebei urban agglomeration remained relatively stable during this period, slightly decreasing from 11.98% in 2006 to 11.11% in 2023, indicating that the region has slowed the growth of carbon emissions while maintaining economic growth. The emission share of the Shandong Peninsula urban agglomeration also showed a relatively steady change, decreasing slightly from 13.73% in

2006 to 12.53% in 2023, suggesting a reduced dependence on carbon emissions in its overall economic development.

In the central and western regions, the emission share of the Hohhot–Baotou–Ordos–Yulin urban agglomeration and the Northern Slope of Tianshan Mountains urban agglomeration has been increasing year by year, particularly for the Hohhot–Baotou–Ordos–Yulin urban agglomeration, which rose rapidly from 3.69% in 2006 to 5.99% in 2023. This change indicates that carbon emission growth in resource-based urban agglomerations is relatively fast, reflecting their high dependence on traditional energy sources, with this dependence further intensifying in recent years.

In contrast, regions with relatively slower economic development, such as the Central Guizhou urban agglomeration, Lanzhou–Xining urban agglomeration, and Beibu Gulf urban agglomeration, have lower and more stable total carbon emissions. For example, the emission share of the Central Guizhou urban agglomeration decreased from 1.69% in 2006 to 1.52% in 2023, indicating that carbon emissions in this region are growing at a slow pace.

In summary, although different urban agglomerations exhibit varying trends in CO₂ emissions, overall, the emission share in the more developed eastern regions has been decreasing year by year, while the emission share in the central and western regions is growing rapidly. This indicates significant regional disparities in carbon reduction efforts among China's urban agglomerations. These differences are primarily influenced by industrial structure adjustments, changes in energy consumption patterns, and policy guidance. The temporal characteristics of carbon emissions in each region reflect the differences in development stages and emission-reduction pathways.

3.1.2. Spatial Evolution Characteristics of CO₂ Emissions in China's Urban Agglomerations

From 2006 to 2023, CO₂ emissions in China's urban agglomerations exhibited significant spatial agglomeration characteristics: the global Moran's I index for each year passed the 1% significance test, showing positive spatial autocorrelation. This indicates that carbon emissions in urban agglomerations exhibit stable spatial dependence and agglomeration, with high-emission and low-emission urban agglomerations demonstrating distinct spatial clustering patterns.

Building on the significant global spatial correlation, the local cold- and hot-spot patterns further reveal the temporal changes in the agglomeration structure (Figure 3). Overall, during the study period, the emission pattern exhibited a “high in the east, low in the west” gradient differentiation. In 2006, hot spots (high-high agglomeration) were mainly distributed in clusters along the eastern coastal areas and their adjacent regions, forming a continuous high-value agglomeration belt. Cold spots (low-low agglomeration) were relatively scattered, primarily appearing in the western and southwestern regions. In 2010 and 2014, the core areas of the hot spots remained generally stable, with minor changes in the shape of the hot spot belt. However, certain “secondary hot spot” transitional patches began to appear in the central region, indicating that high-emission agglomerations were beginning to penetrate inland. After 2018, while the coastal hot spots continued to strengthen, the hot spot/secondary hot spot patches in the northern inland and central regions became more distinct, with the spatial pattern gradually evolving from a single coastal core to a “stable coastal-growing inland” structure. By 2023, the hot spot areas had expanded further inland while maintaining the eastern core, while the cold spot areas remained relatively limited, mainly concentrated in parts of the northwest and southwest regions.

To characterize the directional distribution and dispersion of emissions, the results of the standard deviation ellipse (Figure 4) show that from 2006 to 2023, the standard deviation ellipse of CO₂ emissions in China's urban agglomerations has always been centered in the central and eastern regions, with a significant extension in the “northeast-southwest”

direction. The azimuth angle gradually adjusted from 19.21° in 2006 to 17.13° in 2023, indicating that the dominant direction remained generally stable while slightly converging towards a more north–south orientation. Simultaneously, both the major and minor axes, as well as the area of the ellipse, have steadily increased, reflecting an expansion of the emission spatial distribution range and enhanced spatial heterogeneity.

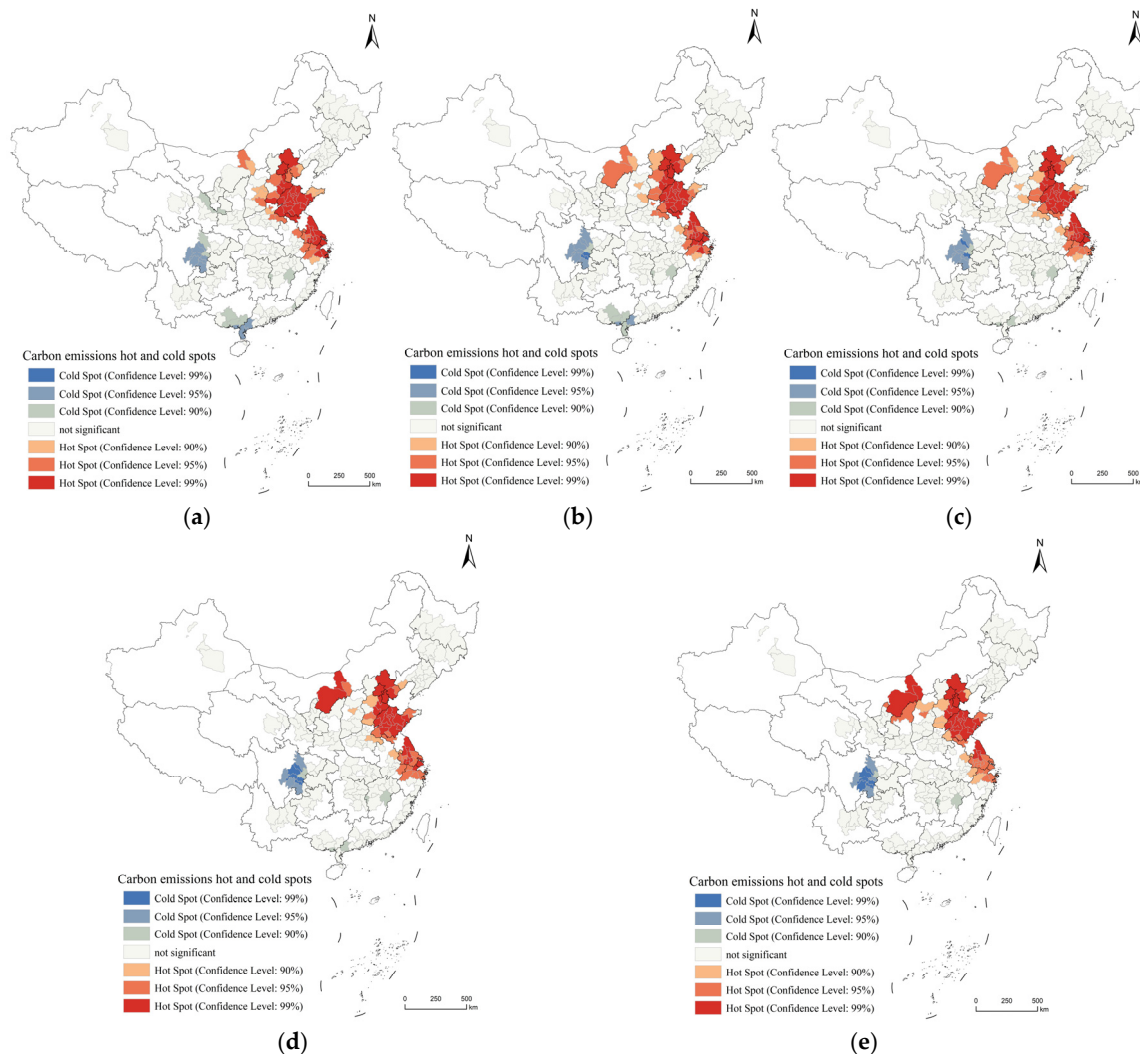


Figure 3. Spatial distribution of CO₂-emission hot and cold spots in Chinese urban agglomerations: (a) 2006; (b) 2010; (c) 2014; (d) 2018; (e) 2023.

From the perspective of centroid migration, the emission centroid has consistently been located in the middle and lower reaches of the Huai River (near northern Anhui). In 2006, the centroid coordinates were (116.348° E, 33.001° N), and by 2023, it had moved to (116.225° E, 32.900° N), shifting approximately 16.06 km southwest. Between 2006 and 2010, there was a small northeastward fluctuation of about 4.33 km, but after 2010, the centroid consistently moved southwest, with the largest shift occurring between 2018 and 2023 (approximately 13.19 km). This trajectory indicates that the high-emission urban agglomerations along the eastern coast still form the main support of the national emission pattern, while in recent years, emissions in the central and inland regions have contributed more to the overall growth, driving a spatial response that adjusts the national emission centroid towards the inland (southwest).

The above trends indicate that spatial coordination in governance is crucial. Carbon governance in different regions should be coordinated to avoid spatial imbalances, espe-

cially in cross-regional collaboration, ensuring that policies can adapt to dynamic spatial changes in each region.

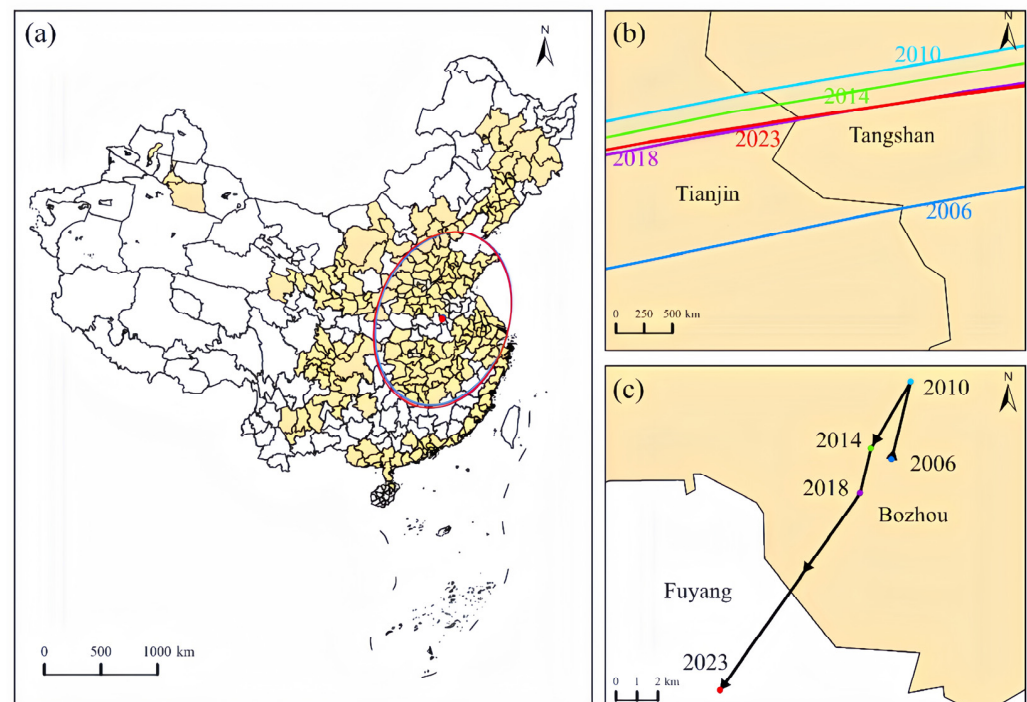


Figure 4. Standard deviational ellipses and gravity-center trajectories of CO₂ emissions in Chinese urban agglomerations: (a) standard deviational ellipses for 2006, 2010, 2014, 2018, and 2023; (b) enlarged view of changes in ellipse orientation; (c) enlarged view of gravity-center trajectories.

3.2. Cluster Analysis of CO₂ Emissions in China's Urban Agglomerations

To build an urban agglomeration classification system that can scientifically characterize the driving mechanisms of carbon emissions, it is necessary to systematically identify the key factors influencing CO₂ emissions in urban agglomerations. Drawing on theoretical frameworks related to carbon emissions and existing research, this study considers multiple dimensions—including economic structure, development level, energy use, social processes, and technological conditions—and preliminarily selects potential driving factors such as total energy consumption; industrial structure (represented by the share of the tertiary sector); GDP per capita; the level of openness; energy efficiency (defined as economic output created per unit of energy consumption, commonly measured as the inverse of energy intensity, e.g., the reciprocal of energy consumption per 10,000 RMB of GDP, or by energy-intensity indicators); population density; urbanization level; and technological innovation capacity, thereby constructing a candidate indicator set. To reduce potential subjectivity in indicator screening and improve the scientific rigor and objectivity of variable selection [51], a random forest regression model was employed to identify the relative explanatory contribution of these factors. Because the sample includes only 19 urban agglomerations, the model is interpreted as an exploratory tool for screening relatively important drivers and nonlinear associations, and the added LOOCV and bootstrap SHAP procedures are used only as sensitivity diagnostics for the driver-identification results. Detailed diagnostics are reported in Section 3.2.1.

3.2.1. Results of Driver Identification Based on Random Forest

Based on the feature-importance estimates derived from the random forest model (Figure 5a), the explanatory contributions of the selected factors to CO₂ emissions varied markedly across urban agglomerations. Industrial structure exhibited the highest impor-

tance, showing the largest relative contribution to the model-estimated differences in CO₂ emissions among urban agglomerations. GDP per capita ranked second, indicating that differences in economic development level were also closely associated with variations in model-estimated emissions. Energy efficiency, urbanization level, and population density also showed relatively high importance and contributed to explaining emission differences among urban agglomerations. By contrast, total energy consumption, openness level, and technological innovation displayed relatively lower importance, although they remained part of the explanatory structure of the random forest model.

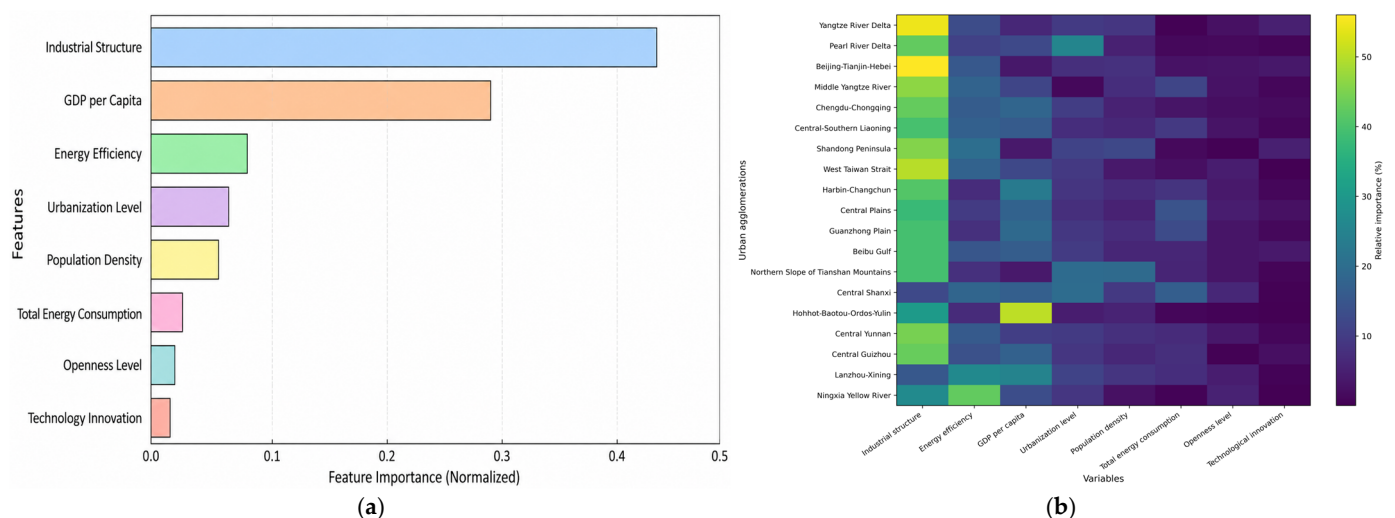


Figure 5. Feature-importance results based on the random forest model and SHAP local importance: (a) overall feature-importance ranking based on the random forest model; (b) agglomeration-specific heatmap of relative feature importance based on normalized absolute SHAP values.

Considering the differences among urban agglomerations in industrial characteristics, resource endowments, city size, and development stage, the agglomeration-specific relative contribution of each factor was further examined using normalized absolute SHAP values (Figure 5b). The results show that the high overall importance of industrial structure was also observed in most individual urban agglomerations. Industrial structure showed a high relative contribution in the Yangtze River Delta, Beijing–Tianjin–Hebei, Shandong Peninsula, Guangdong–Fujian–Zhejiang Coastal, Middle Yangtze River, Chengdu–Chongqing, Central Yunnan, and Central Guizhou urban agglomerations.

The heatmap also reveals differences in the relative importance of the other factors among urban agglomerations. GDP per capita showed a particularly high relative contribution in the Hohhot–Baotou–Ordos–Yulin urban agglomeration. Energy efficiency ranked relatively high in the Ningxia Yellow River and Lanzhou–Xining urban agglomerations. In the Pearl River Delta, the Northern Slope of the Tianshan Mountains, and Central Shanxi urban agglomerations, urbanization level and/or population density were relatively more important. Overall, the heatmap indicates that the major factors identified by the model were broadly shared among urban agglomerations, whereas their relative contributions differed across regions.

To evaluate whether the RF-SHAP interpretation was supported by sufficient model reliability, the predictive performance of the random forest model was assessed using the training set, five-fold cross-validation, and spatial blocked validation. The evaluation metrics included the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). RMSE and MAE were reported in million tonnes of CO₂ emissions.

As shown in Table 2, the random forest model achieved an R^2 of 0.849 on the training set, with an RMSE of 10.803 million tonnes and an MAE of 7.287 million tonnes. These

results show that the selected socioeconomic, energy-related, and spatial variables captured a substantial proportion of the cross-sectional variation in CO₂ emissions among the 19 urban agglomerations. However, the five-fold cross-validation results showed lower out-of-sample performance, with an average R^2 of -1.333 , an RMSE of 25.570 million tonnes, and an MAE of 20.544 million tonnes. The spatial blocked validation, implemented using a leave-one-urban-agglomeration-out strategy, produced an R^2 of -0.078 , an RMSE of 28.850 million tonnes, and an MAE of 20.139 million tonnes.

Table 2. Model accuracy and validation performance of the random forest model.

Validation Strategy	R^2	RMSE	MAE
Training set	0.849	10.803	7.287
Five-fold cross-validation	-1.333	25.570	20.544
Spatial blocked validation	-0.078	28.850	20.139

The validation errors were higher than the corresponding training-set errors, indicating greater model uncertainty when the model was applied to unseen urban agglomerations. The negative validation R^2 values also show that, under the small-sample cross-sectional setting, the model should not be interpreted as a purely high-precision predictive model. Accordingly, the random forest model was used primarily as an interpretable driver-identification tool, and the subsequent SHAP analysis focused on the relative importance, contribution direction, and heterogeneous response patterns of the selected factors rather than on point-prediction accuracy alone.

After identifying the relative importance of the factors in Figure 5, SHAP values were further used to examine the direction, magnitude, and heterogeneous response patterns of the major factors (Figure 6). Industrial structure and GDP per capita exhibited the widest SHAP-value ranges and the largest contributions to the model outputs. When the share of the tertiary sector was low, and GDP per capita was high, the corresponding SHAP values were predominantly positive, indicating an association with higher model-estimated CO₂ emissions. In contrast, a higher tertiary-sector share was generally associated with lower or negative SHAP values and, consequently, with lower model-estimated emissions.

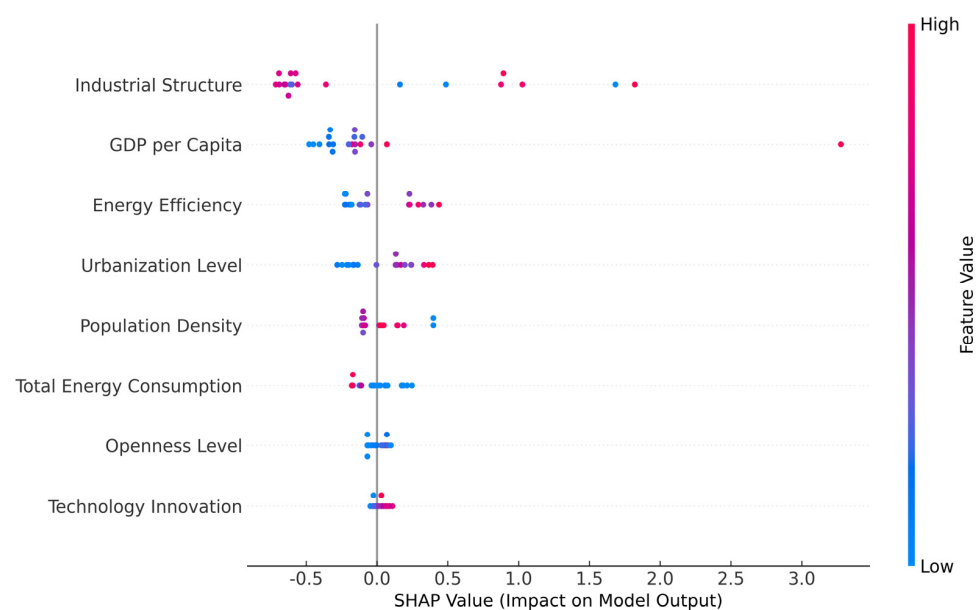


Figure 6. SHAP interpretability analysis.

From the technological and social perspectives, observations with high energy efficiency mainly corresponded to negative SHAP values and lower model-estimated emission levels. The SHAP values of total energy consumption were largely distributed in the positive range. Although total energy consumption was not identified as the most important factor, higher energy consumption was generally associated with higher model-estimated emissions in energy-intensive urban agglomerations. Urbanization level also showed predominantly positive SHAP values, with higher urbanization levels generally corresponding to higher model-estimated emissions. By comparison, the SHAP-value distribution of population density was more dispersed, showing that its association with model-estimated emissions varied among observations and exhibited a nonlinear pattern.

In addition to the model-accuracy assessment and spatial blocked validation, a bootstrap SHAP diagnostic was conducted to examine the stability of the rankings of the major factors under repeated resampling. Industrial structure entered the top three variables in 93% of bootstrap samples, with a median mean absolute SHAP value of 6.402 million tonnes. Energy efficiency entered the top three variables in 58% of bootstrap samples, with a median mean absolute SHAP value of 2.521 million tonnes. GDP per capita entered the top three variables in 49% of bootstrap samples, with a median mean absolute SHAP value of 2.712 million tonnes. These diagnostic results show that industrial structure had the most stable high-ranking position, while energy efficiency and GDP per capita also showed relatively high explanatory contributions to CO₂-emission differences among urban agglomerations.

The spatialized SHAP maps further show agglomeration-level heterogeneity in the major factors associated with CO₂ emissions in 2023 (Figure 7). As shown in Figure 7a, the SHAP values of industrial structure exhibited a fragmented spatial pattern. Strong positive SHAP values were observed in the Beijing–Tianjin–Hebei, Hohhot–Baotou–Ordos–Yulin, Yangtze River Delta, and Shandong Peninsula urban agglomerations, whereas negative values were observed in several northeastern, southwestern, and coastal urban agglomerations. This distribution shows that the direction and magnitude of the contribution of industrial structure differed across urban agglomerations. Figure 7b shows that the SHAP contribution of GDP per capita was more spatially concentrated. The highest positive contribution was observed in the Hohhot–Baotou–Ordos–Yulin urban agglomeration, where GDP per capita showed the strongest positive association with model-estimated CO₂ emissions among the urban agglomerations. As illustrated in Figure 7c, energy efficiency displayed a mixed spatial pattern. Negative SHAP values were observed in the Yangtze River Delta, Chengdu–Chongqing, Beibu Gulf, and Middle Yangtze River urban agglomerations, whereas positive values were observed in the Ningxia Yellow River, Beijing–Tianjin–Hebei, and Shandong Peninsula urban agglomerations. Taken together, Figure 7a–c show that the spatial distributions and contribution directions of industrial structure, GDP per capita, and energy efficiency differed among the 19 urban agglomerations.

3.2.2. Indicator Selection

Based on the feature-importance ranking obtained from the random forest model and the SHAP-based interpretation presented in Section 3.2.1, five core static indicators were selected: industrial structure, GDP per capita, energy efficiency, urbanization level, and population density. These indicators represent differences among urban agglomerations in economic structure, development level, energy-use efficiency, urbanization, and spatial population distribution. In addition, the average annual growth rate of CO₂ emissions was included as a dynamic indicator to characterize differences in emission trajectories among urban agglomerations.

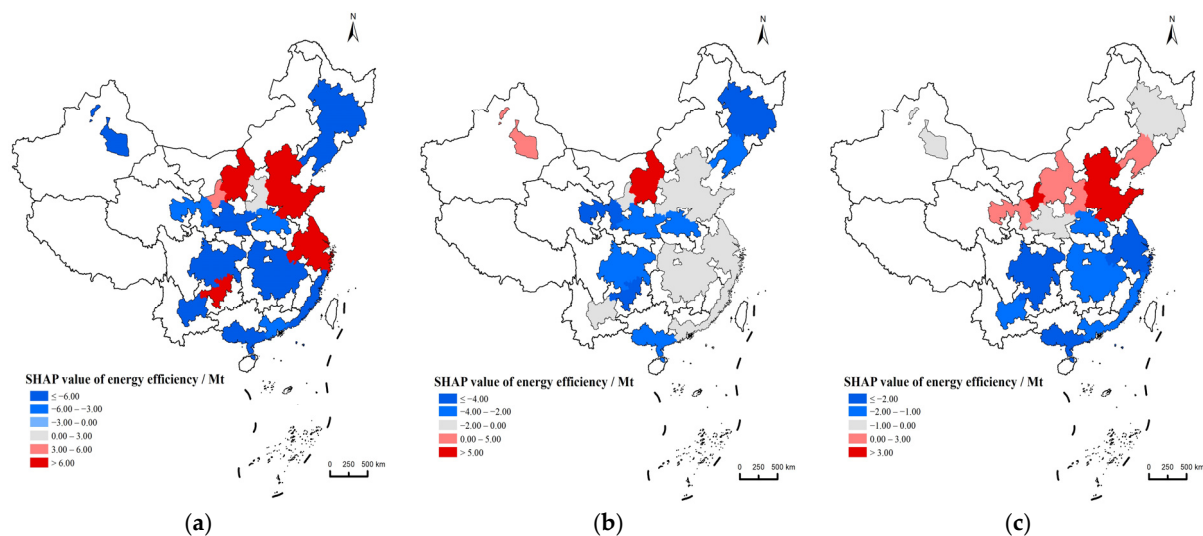


Figure 7. Spatialized SHAP values of key carbon-emission drivers across China’s urban agglomerations in 2023: (a) SHAP values of industrial structure; (b) SHAP values of GDP per capita; (c) SHAP values of energy efficiency.

As shown in Table 3, the selected indicators exhibited different distributional characteristics across the urban agglomerations. Industrial structure had a mean of 0.1427 and a standard deviation of 0.0907, showing that the share of the tertiary sector was relatively concentrated across most urban agglomerations. GDP per capita averaged 83.436 thousand CNY, with a minimum of 48.831 thousand CNY and a maximum of 167.382 thousand CNY, demonstrating a relatively wide range across urban agglomerations. Energy efficiency had a mean of 0.4692 and a standard deviation of 0.0412, indicating relatively limited variation across urban agglomerations. The urbanization level had a mean of 0.6581 and a standard deviation of 0.0873, showing a moderate degree of variation. The natural-log-transformed population density had a mean of 5.6838 and a standard deviation of 0.8514, reflecting a relatively dispersed distribution. The average annual growth rate of CO₂ emissions had a mean of 0.0395 and ranged from 0.0203 to 0.0736, showing differences in emission-growth trajectories among urban agglomerations.

Table 3. Descriptive statistics of the selected indicators for cluster analysis.

Indicator	Mean	Standard Deviation	Median	Minimum	Maximum
Industrial structure (%)	0.1427	0.0907	0.1176	0.0597	0.4740
GDP per capita (10,000 CNY)	8.3436	3.2303	7.3589	4.8831	16.7382
Energy efficiency (%)	0.4692	0.0412	0.4752	0.3867	0.5348
Urbanization level (%)	0.6581	0.0873	0.6566	0.5355	0.8314
Population density [ln(persons/km ²)]	5.6838	0.8514	5.6951	3.6899	6.8212
Average annual growth rate of CO ₂ emissions (%)	0.0395	0.0147	0.0343	0.0203	0.0736

Population density was natural-log transformed before clustering to reduce right skewness; therefore, the values in this row are ln(persons/km²), not raw persons/km².

Overall, the selected indicators differed in both scale and degree of dispersion. GDP per capita and the average annual growth rate of CO₂ emissions exhibited relatively wide ranges, whereas energy efficiency and industrial structure were more concentrated. Because K-means updates cluster centroids through mean-based iterations, the wide ranges of some indicators may increase its sensitivity to extreme observations and affect the representation of heterogeneity among urban agglomerations. On this basis, K-medoids was considered more appropriate than K-means for the subsequent classification analysis.

3.2.3. Cluster Analysis

To compare the clustering performance of K-means and K-medoids, the two algorithms were evaluated using the same indicator system. Four internal validity metrics were employed, namely the silhouette coefficient (SC), Davies–Bouldin index (DBI), Gap statistic, and Calinski–Harabasz index (CHI). As reported in Table 4, K-medoids produced an SC of 0.63, a DBI of 0.65, a Gap statistic of 0.06, and a CHI of 0.55, whereas the corresponding values for K-means were 0.60, 0.70, 0.05, and 0.45, respectively. Compared with K-means, K-medoids thus yielded higher SC, Gap-statistic, and CHI values and a lower DBI value. Based on the combined results of the four metrics, K-medoids was selected for the subsequent classification, and the optimal number of clusters was set to five.

Table 4. Comparison of clustering performance metrics between K-means and K-medoids.

Method	Silhouette Coefficient (SC)	Davies-Bouldin Index (DBI)	Gap Statistic	Calinski-Harabasz Index (CHI)
K-means	0.60	0.70	0.05	0.54
K-medoids	0.63	0.65	0.06	0.55

The K-medoids results divided the 19 urban agglomerations into five clusters (Table 5). Cluster 1 contains the Yangtze River Delta, the Pearl River Delta, the Beijing–Tianjin–Hebei, Central and Southern Liaoning, and the Shandong Peninsula urban agglomerations. Cluster 2 consists of the Chengdu–Chongqing, Harbin–Changchun, and Lanzhou–Xining urban agglomerations. Cluster 3 comprises the Northern Slope of the Tianshan Mountains, as well as the Hohhot–Baotou–Ordos–Yulin and Ningxia Yellow River urban agglomerations. Cluster 4 includes the Middle Yangtze River, Guangdong–Fujian–Zhejiang Coastal, Central Plains, Guanzhong Plain, Beibu Gulf, Central Shanxi, and Central Yunnan urban agglomerations. Cluster 5 contains only the Central Guizhou urban agglomeration.

Table 5. Cluster analysis results.

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Yangtze River Delta Urban Agglomeration; Pearl River Delta Urban Agglomeration; Beijing–Tianjin–Hebei Urban Agglomeration; Central and Southern Liaoning Urban Agglomeration; Shandong Peninsula Urban Agglomeration	Chengdu–Chongqing Urban Agglomeration; Harbin–Changchun Urban Agglomeration; Lanzhou–Xining Urban Agglomeration	Northern Slope of Tianshan Mountains Urban Agglomeration; Hohhot–Baotou–Ordos–Yulin Urban Agglomeration; Ningxia Yellow River Urban Agglomeration	Middle Yangtze River Urban Agglomeration; Guangdong–Fujian–Zhejiang Coastal Urban Agglomeration; Central Plains Urban Agglomeration; Guanzhong Plain Urban Agglomeration; Beibu Gulf Urban Agglomeration; Central Shanxi Urban Agglomeration; Central Yunnan Urban Agglomeration	Central Guizhou Urban Agglomeration

Figure 8 presents the distributions of the six clustering indicators across the five clusters. For industrial structure (Figure 8a), Cluster 5 has the highest single observed value. Clusters 1 and 2 show similar and relatively concentrated distributions, while Cluster 4 has a wider range and a slightly lower central value. Cluster 3 records the lowest central value among the five clusters. For GDP per capita (Figure 8b), Cluster 3 has both the highest central value and the widest range, followed by Cluster 1. Cluster 4 occupies an intermediate position, whereas Clusters 2 and 5 have comparatively low values.

For the energy-efficiency indicator (Figure 8c), Cluster 3 displays the highest central value and the largest within-cluster variation. Clusters 1 and 2 have intermediate and partially overlapping distributions; Cluster 4 has a lower and relatively concentrated distribution; and Cluster 5 has the lowest single observed value. Regarding urbanization level (Figure 8d), Cluster 3 has the highest median, followed by Cluster 1. Clusters 2 and 4

are distributed at lower levels, although Cluster 4 exhibits a wider range. Cluster 5 records the lowest value.

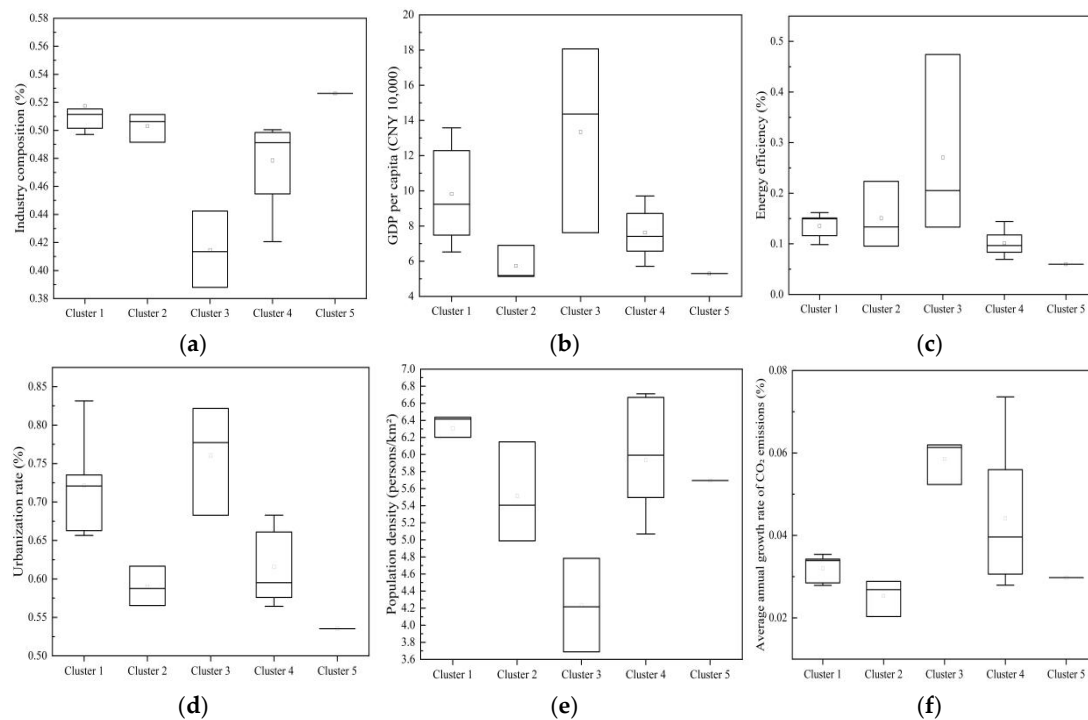


Figure 8. Indicator characteristics of urban-agglomeration types: (a) industrial structure; (b) GDP per capita; (c) energy efficiency; (d) urbanization level; (e) population density; (f) CO₂-emission growth rate.

Population density also differs markedly among the clusters (Figure 8e). Cluster 1 has a high and relatively concentrated population density distribution. Cluster 4 shows the widest range, with its upper values approaching or exceeding those of Cluster 1. Cluster 2 occupies an intermediate position, Cluster 3 has the lowest central value, and Cluster 5 records a single value between those of Clusters 2 and 4. For the average annual growth rate of CO₂ emissions (Figure 8f), Cluster 3 has the highest central value. Cluster 4 has the largest within-cluster variation and includes the highest individual growth rate. Cluster 1 has a relatively narrow distribution at a moderate-to-low level, Cluster 2 has the lowest overall distribution, and Cluster 5 records a single value close to that of Cluster 1. Because Cluster 5 contains only one urban agglomeration, its values in Figure 8 represent a single observation rather than a within-cluster distribution.

Figure 9 shows the fitted relationships between GDP per capita and CO₂ emissions for the five clusters. The fitted curves for Clusters 1, 2, and 4 are concave downward and contain predicted turning points.

For Cluster 1, the estimated turning point occurs at a GDP per capita of 111.4 thousand CNY, corresponding to CO₂ emissions of approximately 60.18 million tons. The maximum observed GDP per capita in this cluster is approximately 104.0 thousand CNY, which remains below the estimated turning point. Cluster 2 has a predicted turning point at a GDP per capita of 94.7 thousand CNY and CO₂ emissions of approximately 25.13 million tons. Its maximum observed GDP per capita is approximately 60.1 thousand CNY, leaving a larger distance from the fitted turning point than that observed for Clusters 1 and 4. For Cluster 4, the predicted turning point occurs at a GDP per capita of 80.8 thousand CNY and CO₂ emissions of approximately 33.35 million tons. Its maximum observed GDP per capita, approximately 77.5 thousand CNY, is the closest to the corresponding turning point among the three clusters with inverted U-shaped curves.

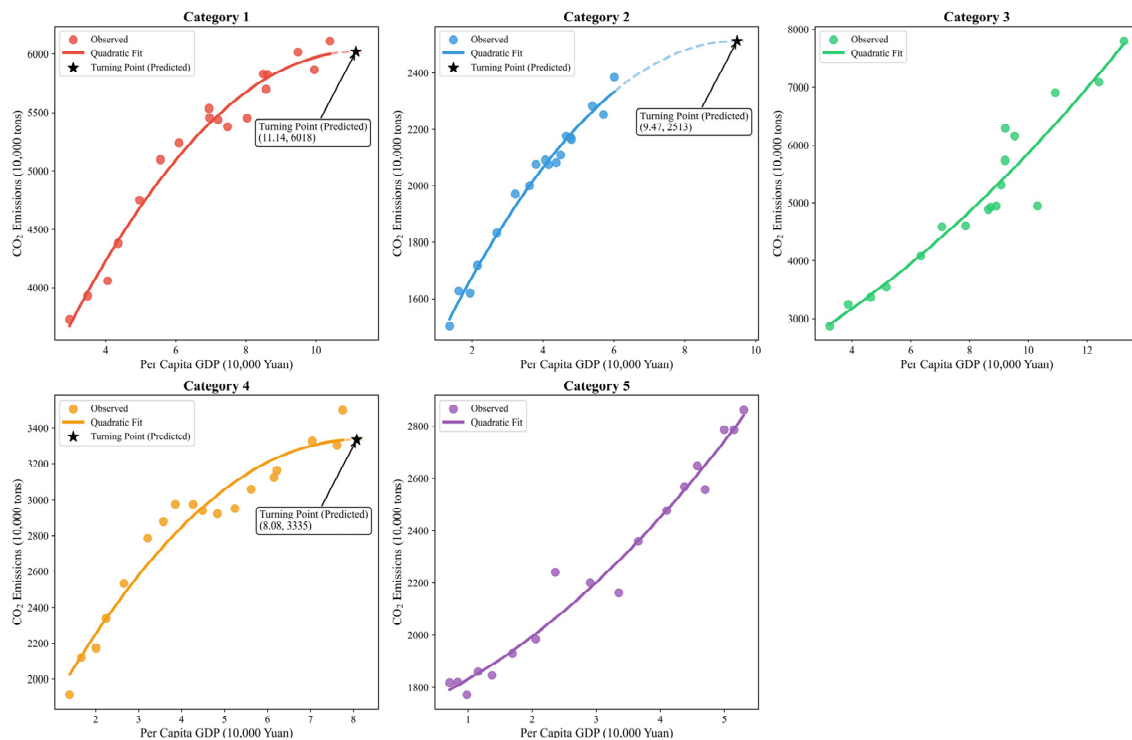


Figure 9. EKC for different categories of urban agglomerations in China.

In contrast, the fitted curves for Clusters 3 and 5 increase throughout the observed GDP per capita range, and no turning point is identified within the fitted range. Cluster 3 covers the highest GDP per capita and CO₂ emission values among the five fitted groups and shows a continuously increasing relationship. Cluster 5 remains within a lower range of GDP per capita and CO₂ emissions, but its fitted curve also increases over the observed period.

Based on the combined indicator distributions and EKC fitting results, the five clusters were labeled as follows. Cluster 1 is classified as the “high-carbon high-development” type, characterized by relatively high GDP per capita, urbanization, and population density, together with a comparatively low-to-moderate CO₂-emission growth rate and an estimated position close to the EKC turning point. Cluster 2 is classified as the “transition-pressure” type; it has relatively low GDP per capita and urbanization levels, the lowest overall emission-growth distribution, and an estimated turning point located beyond its current observed development range. Cluster 3 is classified as the “resource-dependent” type, with high GDP per capita, high CO₂-emission growth, low population density, and a continuously rising fitted relationship between economic development and emissions. Cluster 4 is classified as the “steady-development” type, showing generally intermediate indicator levels, comparatively large within-cluster variation in population density and emission growth, and the shortest distance between the observed GDP per capita range and the estimated turning point. Cluster 5 is classified as the “low-carbon potential” type and is represented solely by the Central Guizhou urban agglomeration; it has relatively low GDP per capita, urbanization, and CO₂-emission levels, while its fitted relationship remains upward sloping within the observed range.

Overall, the five types correspond respectively to a near-turning-point stage, a mid-upward stage, a rapid-upward stage, the leading edge of the turning point, and a low-level upward stage. These results demonstrate clear differences among the clusters in their multidimensional indicator profiles and their fitted positions relative to the EKC turning point.

3.3. Comprehensive Analysis of Carbon Emission Characteristics and Transition Pathways

By integrating the results of spatial evolution, driving-factor identification, urban-agglomeration classification, and EKC analysis, several consistent patterns can be identified. The spatial analysis indicates that carbon emissions in China's urban agglomerations have gradually expanded from the eastern coastal regions toward inland areas, while the driver analysis further suggests that such spatial differentiation is closely associated with differences in industrial structure, economic development level, and energy efficiency. Meanwhile, the classification results demonstrate that urban agglomerations with similar emission levels may follow different transition pathways due to variations in development conditions and dominant drivers. The EKC analysis further confirms that these differences correspond to distinct stages of carbon transition, ranging from rapid emission growth to approaching or passing the turning point.

The comparison across different urban agglomeration types further reveals that emission magnitude alone cannot determine transition performance. High-carbon high-development agglomerations generally have stronger economic foundations and technological capabilities, providing greater potential for deep decarbonization, whereas resource-dependent agglomerations face stronger constraints due to fossil-energy dependence and industrial lock-in. In contrast, low-carbon potential agglomerations currently maintain relatively low emission levels but require early intervention to avoid future carbon-intensive development. These findings highlight that effective carbon governance should simultaneously consider current emission characteristics, underlying driving mechanisms, and future transition trajectories.

4. Discussion

4.1. Spatial and Temporal Patterns of Carbon Emissions, Driving Mechanisms, and Classification Comparison of China's Urban Agglomerations

This study systematically analyzes the spatiotemporal patterns, driving mechanisms, and typological characteristics of carbon emissions across China's urban agglomerations and, drawing on the EKC framework, reveals stage-specific features among different agglomeration types. The results show that, from 2006 to 2023, total carbon emissions from China's urban agglomerations increased continuously. The spatial pattern exhibits a pronounced "higher in the east, lower in the west" gradient and a stable tendency toward spatial clustering. This macro-level pattern is broadly consistent with prior work: Liu et al. [52], using nighttime light data, reported that the eastern region consistently accounts for the largest share of emissions; Xu [53] emphasized the absolute dominance of emissions in the more developed eastern urban agglomerations; and Hao et al. [54] found that high-emission areas remain concentrated in North China, Central China, the eastern coastal zone, and provincial-capital agglomerations in western China, with clustering strengthening after 2005. Standard deviation ellipse and center-of-gravity migration analyses in this study indicate a slight southwestward shift in the national center of gravity of urban-agglomeration carbon emissions, which differs somewhat from the southeastward shift reported by Liu et al. [52]. Nevertheless, both findings underscore the dynamic complexity of China's carbon-emission spatial structure and persistent regional development disparities. The southwestward shift is primarily driven by faster emission growth in resource-oriented urban agglomerations in central and western China, such as Hohhot–Baotou–Ordos–Yulin and the northern slope of the Tianshan Mountains. These results help address the limited attention in the literature to dynamic changes in central and western regions and are consistent with observations by Nie and Mo [55].

In the analysis of driving mechanisms, a random forest model combined with SHAP-based interpretability indicates that industrial structure and the level of economic develop-

ment (GDP per capita) are the primary determinants of inter-agglomeration differences in carbon emissions, with pronounced heterogeneity in the effects of individual factors. This finding is highly consistent with Wei et al. [56]. The SHAP results show that industrial structure and GDP per capita exert the strongest influences and display wide distributions across observations; energy efficiency exhibits a generally stable mitigating effect; urbanization level tends to promote emissions; and the effect of population density is nonlinear and jointly moderated by industrial structure and energy efficiency. These patterns provide cross-method validation of the conclusions of Liu et al. [57], who, using an ST-IDA framework, likewise highlighted industrial-structure upgrading and improvements in energy efficiency as key levers for carbon mitigation in urban agglomerations. By contrast, the importance of trade openness for carbon emissions in southern urban agglomerations appears comparatively limited [58], suggesting that the drivers are context-dependent. This also implies that the shift from traditional econometric approaches to machine learning-based methods enables a more granular and dynamic identification of the underlying mechanisms.

From the perspective of differentiated governance, this study applies K-medoid clustering to classify 19 urban agglomerations into five groups: high-carbon, high-development; transformation-pressure; resource-dependent; stable-development; and low-carbon-potential. Compared with the classification of 286 prefecture-level cities by Guo et al. [59], the two approaches share a conceptual orientation yet differ in scale and criteria. Guo et al. [59] used cities as the unit of analysis and combined K-means with a Monte Carlo approach to derive five city types, whereas this study focuses on urban agglomerations as collaborative units, adopts K-medoids to accommodate highly heterogeneous data, and constructs the typology using multidimensional indicators, including industrial structure, GDP per capita, energy efficiency, urbanization rate, and carbon-emission growth. The resulting categories show clear correspondences. For example, the resource-dependent type is highly consistent with the urban-agglomeration profiles in terms of industrial structure and emission characteristics, and the low-carbon-potential type is comparable in terms of development stage and the emissions baseline. Notably, many “low-carbon demonstration cities” identified by Guo et al. [59] are core cities within the high-carbon high-development urban agglomerations in this study. Although these core cities have achieved decoupling between carbon emissions and economic growth, their surrounding agglomerations still contain a large number of industrial cities with high emissions baselines and have not yet reached peak emissions. This highlights the tension inherent in the “core-periphery” structure within urban agglomerations and underscores the complex relationship, in cross-scale research, between aggregate characteristics and internal heterogeneity.

Building on EKC theory, we further examined the stage-specific characteristics of the relationship between carbon emissions and economic development across the five types of urban agglomerations. Cluster 1, the “high-carbon, high-development” type, is overall close to the EKC turning point, indicating that advanced regions, through industrial upgrading and a transition toward cleaner energy, have approached—or locally surpassed—the turning point; this is consistent with Zhao et al. [60], who suggested that higher economic growth rates may bring forward the carbon turning point. Clusters 2 (“transition-pressure”) and 3 (“resource-dependent”) largely remain in the upward phase; in particular, resource-dependent urban agglomerations (e.g., Hohhot–Baotou–Ordos–Yulin) exhibit a “resource curse” pattern with rapid increases, supporting the conclusion of Wang et al. [61] that emissions growth is faster and transition pressure is greater in central and western regions. Cluster 4, the “steady-development” type, lies at the leading edge of the turning point and is well positioned to be among the first nationwide to achieve a carbon-emissions peak. Cluster 5, the “low-carbon potential” type, remains on the left side of the EKC

in a low-level ascent phase and should guard against the risk of “carbonization before affluence.” This stage-based classification not only deepens our understanding of the evolutionary patterns of carbon emissions across urban agglomerations but also provides a theoretical basis for implementing targeted governance that is region-specific, type-specific, and stage-specific.

4.2. Policy Recommendations for Differentiated Carbon Emission Governance in China's Urban Agglomerations

The results show pronounced heterogeneity among China's urban agglomerations in terms of emission scale, growth trajectory, industrial structure, energy efficiency, spatial organization, and EKC stage. Consequently, a governance framework based on uniform targets and homogeneous policy instruments may not adequately address the different constraints faced by individual agglomeration types. Differentiated governance should instead follow a coordinated “type–stage–mechanism” logic: the type identifies the main structural characteristics, the EKC stage indicates the current transition position, and the dominant drivers determine the policy instruments that are most relevant.

At the national and interregional levels, differentiated governance should be coordinated along four dimensions: industrial-structure optimization, energy-efficiency improvement, spatial coordination, and institutional innovation. Industrial structure and economic development were the dominant factors associated with emission differences, while energy efficiency represented an important adjustable factor. In addition, the spatial expansion of hotspots and the movement of the emission centroid demonstrate that carbon governance must account for cross-regional industrial transfer and intercity production linkages. Type-specific measures should be combined with mechanisms that coordinate carbon constraints, technology diffusion, and industrial policies across urban agglomerations.

For high-carbon high-development urban agglomerations, the main task is to accelerate the transition toward and beyond the carbon-emission turning point. These regions have strong economic, technological, and institutional capacities, but they are also constrained by large emissions baselines, high-carbon legacy assets, and carbon-intensive supply chains. Governance should therefore combine industrial upgrading with the decarbonization of the energy system. An integrated cross-regional carbon-market mechanism can improve the consistency of carbon-price signals and resource allocation [62], while a dual-constraint system combining carbon budgets with project-access requirements can limit new high-carbon investment. Meanwhile, the deployment of green hydrogen, carbon capture, utilization and storage, energy storage, and renewable-energy systems can facilitate the replacement of fossil-energy consumption in heavy industry and support the transition from relative efficiency improvements to absolute emission reductions.

For transition-pressure urban agglomerations, policies should address the simultaneous pressures of industrial restructuring, employment stability, financing constraints, and energy-efficiency improvement. Because these agglomerations remain in the upward stage of the EKC, abrupt restrictions that ignore development and employment needs may increase transition costs without changing the underlying industrial structure. A combined mechanism of transition finance, employment protection, and low-carbon technology diffusion is therefore required. Low-carbon transition funds, green credit, and supply-chain finance can provide financial support for the retirement or renovation of carbon-intensive capacity. Simultaneously, vocational retraining and employment-support measures can reduce the social costs of industrial adjustment. Distributed renewable energy, end-use electrification, and the diffusion of energy-saving technologies should be promoted to reduce the additional emissions associated with continuing economic growth [63].

For resource-dependent urban agglomerations, the priority is to weaken the coupling between resource-based economic growth and carbon emissions. Because no turning point

was identified within the observed range, incremental energy-saving measures alone are unlikely to change the existing trajectory. Stronger constraint-based governance is needed, including carbon-intensity accountability, differentiated energy and resource taxation, and factor-price reforms that incorporate environmental and carbon costs [64]. These constraints should be accompanied by industrial diversification and energy-value-chain upgrading. Rather than remaining dependent on the extraction and direct export of fossil-energy resources, these regions should promote the integration of renewable electricity, green hydrogen, energy storage, and lower-carbon chemical production. Circular utilization of mineral and industrial resources can further reduce the dependence of economic growth on primary resource extraction.

For steady-development urban agglomerations, the principal objective is to prevent carbon-intensive industrial transfer from delaying an otherwise approaching emissions peak. Carbon-performance assessments should therefore be incorporated into investment promotion, industrial-transfer agreements, project approval, and land-use allocation [65]. A green-entry mechanism can prevent the relocation of outdated and energy-intensive production capacity from more developed coastal regions. Simultaneously, cross-regional networks for green-technology diffusion should be strengthened so that energy-saving equipment, carbon-management systems, and clean-production technologies can be adopted more rapidly [66]. The coordinated development of intelligent transportation, near-zero-energy buildings, compact urban form, and clean-energy infrastructure can align urban expansion with the objective of reaching a stable emissions peak.

For low-carbon-potential urban agglomerations, governance should focus on *ex ante* prevention rather than *ex post* remediation. Because these regions have not yet formed a large stock of carbon-intensive industry and infrastructure, early institutional design can influence their long-term development trajectory. Ecological red lines, carbon-emission entry thresholds, and environmental-performance requirements should be incorporated into industrial and infrastructure planning to prevent the indiscriminate introduction of energy-intensive industries. A coordinated mechanism combining ecological compensation, carbon-sink trading, and fiscal incentives can convert ecological advantages into financial resources for local development [67]. Green agriculture, ecological tourism, environmentally oriented manufacturing, and the digital economy can provide alternative sources of growth without reproducing the high-carbon industrialization pathway of more developed regions.

In addition to type-specific policies, cross-agglomeration coordination is required to avoid the spatial displacement of emissions. Industrial transfer should be accompanied by the transfer of environmental standards, carbon-accounting requirements, and clean-production technologies. Mutual recognition of carbon standards and coordinated project-access rules can reduce the possibility that differences in local regulation create “carbon leakage” between neighboring agglomerations. A unified monitoring and accounting system would also support comparison of policy implementation and improve the consistency of emission-reduction actions across administrative boundaries.

Overall, differentiated governance should integrate structural, stage-based, and collaborative considerations. At the structural level, industrial restructuring should be coordinated with energy-efficiency improvement and energy-system transformation. At the stage level, the strength of emission constraints and the selection of technological pathways should be adjusted according to each type’s position relative to the EKC turning point. At the collaborative level, interregional mechanisms for carbon accounting, industrial transfer, technology diffusion, and policy coordination should be strengthened. This approach can translate the observed heterogeneity in emission patterns, dominant drivers, and development stages into governance measures that are more consistent with the actual conditions of different urban agglomerations.

5. Conclusions

Responding to the need for spatially targeted and type-specific carbon governance raised in the Introduction, this study aimed to identify the spatiotemporal patterns, driving mechanisms, development-stage differences, and governance pathways of CO₂ emissions across China's urban agglomerations. Based on multi-source geospatial and socioeconomic data for 19 urban agglomerations from 2006 to 2023, this study integrated spatial autocorrelation analysis, hotspot analysis, standard deviation ellipse analysis, random forest regression with SHAP interpretation, K-medoid clustering, and the Environmental Kuznets Curve model. This framework links emission-pattern identification, nonlinear driver interpretation, type classification, and stage-based governance diagnosis within a unified analytical process.

The results show that CO₂ emissions in China's urban agglomerations increased continuously from 2006 to 2023, with total emissions rising from 5.36 billion tons to 9.39 billion tons. Spatially, emissions displayed a persistent “high east–low west” pattern, significant positive spatial clustering, and expanding hotspots in the eastern coastal and central inland regions. The standard deviation ellipse and gravity-center analysis further revealed an overall northeast–southwest distribution pattern and a slight southwestward shift in the emission center, indicating that the national urban-agglomeration emission pattern is increasingly shaped by both coastal high-emission cores and growing inland emission increments.

The RF-SHAP results indicate that industrial structure, GDP per capita, and energy efficiency are the main factors shaping inter-agglomeration differences in CO₂ emissions, while urbanization level, population density, openness, and technological innovation show more heterogeneous or context-dependent effects. The clustering and EKC analyses further classified the 19 urban agglomerations into five emission-development types: high-carbon high-development, transition-pressure, resource-dependent, stable-development, and low-carbon potential. These types correspond to different EKC stages and transition pressures, suggesting that carbon governance should not follow a uniform pathway. Instead, governance strategies should be tailored according to each type's dominant drivers, development stage, and emission-transition trajectory.

Several limitations should also be acknowledged. Although this study constructed a multi-source geospatial database for 19 urban agglomerations, future research could further improve spatial precision by incorporating higher-resolution datasets and extending the analysis to city-level panel data or longer time series. In addition, the RF-SHAP diagnostics and validation procedures were used mainly to support driver identification and robustness assessment, rather than to establish causal relationships or conduct scenario simulations. Future studies could combine spatial econometric models, network analysis, and causal-inference approaches to better examine interregional spillovers, policy effects, and dynamic feedback mechanisms in differentiated carbon governance.

Overall, this study shows that China's urban agglomerations differ not only in emission levels and spatial patterns but also in driving mechanisms, development stages, and governance priorities. By linking spatial evolution, interpretable driver identification, emission-development classification, and EKC-stage diagnosis, this study provides a more coherent explanation of why carbon-emission trajectories differ among urban agglomerations and how such differences can be translated into differentiated governance pathways. This integrated “pattern–driver–type–stage–policy” framework helps bridge quantitative geospatial modeling and policy-oriented urban carbon governance and can support the implementation of China's carbon peaking and carbon neutrality goals by aligning governance measures with regional development conditions and transition pathways.

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