

Interpretable Machine Learning for Evaluating Industry–Ecology Coupling in the Beijing–Tianjin–Hebei Region

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Abstract

The transformation of industrial structures and growing environmental pressures have created challenges for coordinated regional development. As a major urban agglomeration in China, the Beijing–Tianjin–Hebei region faces disparities in economic development and ecological conditions, making the identification of coordination patterns and underlying drivers important. This study investigates the spatiotemporal evolution and driving mechanisms of the coupling coordination degree between industrial structure and ecological environment across cities in the BTH region during 2010–2023. A city-level CCD model is combined with XGBoost–SHAP analysis to quantify key influencing factors' effects and heterogeneity. The results demonstrate considerable spatial differentiation and nonlinear temporal dynamics. Beijing and Tianjin maintain relatively high coordination levels, while most cities in Hebei remain in lower coordination stages. Despite overall improvement after 2015, coordination fluctuates substantially, characterized by alternating declines and recoveries. The SHAP analysis further reveals heterogeneous effects of industrial and ecological factors, with temporal dynamic features exerting the strongest influence, indicating path dependence. Based on the resulting feature profiles, cities are categorized into four coordination types with distinct development trajectories. These findings highlight the differentiated nature of industrial–ecological coordination and underscore the need for place-specific strategies to promote sustainable and balanced regional development.

Keywords: Coupling Coordination Degree, XGBoost, SHAP, Driving Mechanisms, Spatial Heterogeneity, Spatiotemporal Analysis, Sustainable Development.



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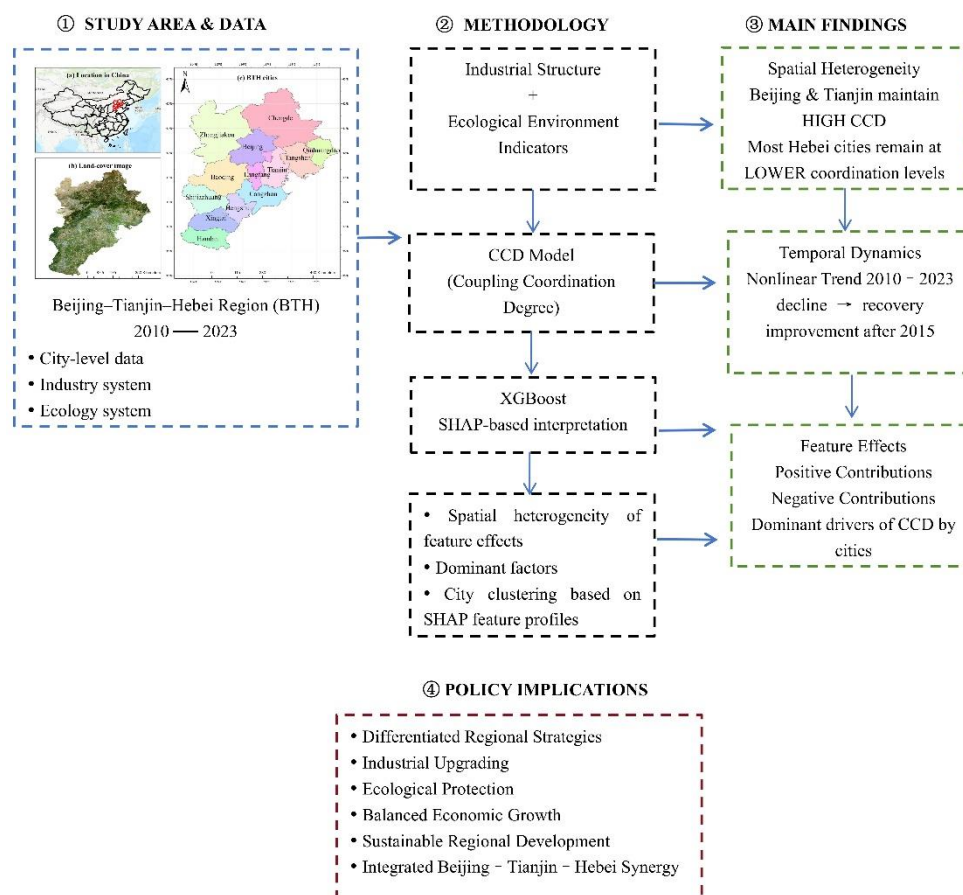
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Graphical abstract



1. Introduction

Balancing economic development with ecological protection has become a critical challenge for achieving sustainable development worldwide (Zhang & Wen, 2008). This challenge is particularly pronounced in countries and regions undergoing rapid industrialization and urbanization, where ecological burdens are intensifying and conflicts between industrial development and environmental protection are becoming increasingly prominent (Liang *et al.*, 2019). As the largest developing country in the world, China faces especially complex ecological and environmental issues due to its rapid urbanization and industrial expansion. The Beijing–Tianjin–Hebei (BTH) region, as one of China's political and economic hubs, has experienced swift industrialization and urbanization, while simultaneously confronting severe environmental challenges, including air pollution, water contamination, and land degradation.

The BTH region represents a typical case of tension between economic growth and environmental constraints. As one of China's most significant economic zones, the region possesses a robust industrial base but also exhibits marked spatial disparities (Chu *et al.*, 2018; Tian *et al.*, 2022). Core cities such as Beijing and Tianjin have

undergone substantial industrial upgrading and environmental improvements, whereas many cities in Hebei Province remain reliant on resource-intensive and highly polluting industries (Chang & Zhang, 2020). This imbalance has resulted in persistent environmental pressures and uneven levels of regional coordination. In response, a range of policy measures, including regional integration strategies and increasingly stringent environmental regulations, have been implemented to promote more coordinated and sustainable regional development. Nevertheless, despite these policy efforts, how regional coordinated development dynamically evolves and the mechanisms underlying this process remain insufficiently understood.

Industrial restructuring is widely recognized as a key driver of economic growth (Dong *et al.*, 2025); however, it often accompanies increased resource consumption, environmental pollution, and ecological degradation (Audretsch *et al.*, 2002; Destek, 2021). With the growing emphasis on green economy and sustainable development, scholars increasingly argue that industrial development and ecological protection are not necessarily mutually exclusive (Tariq *et al.*, 2024). Through industrial upgrading, technological innovation, and the promotion of green industries, it is possible to achieve a win-win outcome for

both the economy and the environment. Accordingly, whether industrial development and ecological protection can be harmonized has become a critical research question. The concept of coupling coordination degree (CCD) provides an effective framework for quantifying the interactions between these two subsystems and has been widely applied in regional sustainability research.

The coordination between ecological environment and industrial development is not a simple linear relationship but rather a complex system influenced by multiple factors and dimensions (Chen & Zhao, 2019; Niu *et al.*, 2023). Quantifying and optimizing this coordination have become a focal point in both academic and policy research. Traditional methods for assessing coordination primarily include multiple regression, panel data regression, spatial regression, as well as composite index approaches such as entropy method and principal component analysis (Cartone & Postiglione, 2021; Wu *et al.*, 2022). These methods can assess linear relationships, spatial spillover effects, and lagged impacts of industrial and ecological indicators on CCD. Entropy method and principal component analysis are commonly used for weighting composite indicators and dimensionality reduction (Wu *et al.*, 2022). However, these methods share common limitations: they assume linear or globally uniform variable relationships, have difficulty capturing nonlinear and complex interactions, are limited in handling high-dimensional, multicollinear data, and often fail to fully incorporate temporal dynamics and path dependencies (Zhang *et al.*, 2024). In contrast, the CCD method directly quantifies the coupling and coordination between industrial and ecological systems, providing an intuitive assessment of their interactions. When combined with time-series analysis (Yang & Yuan, 2026), it can further capture the temporal evolution of coordination, thereby enabling a more comprehensive assessment of economic–environmental harmonization.

Against this backdrop, increasing attention has been devoted to artificial intelligence (AI) and data-driven approaches for characterizing complex environmental and socioeconomic systems and supporting evidence-based decision-making (Pimenov *et al.*, 2025). Recent studies have demonstrated the potential of AI-enabled methods to integrate prediction, optimization, and governance under complex and dynamic conditions (Li *et al.*, 2023; Shao & Zhang, 2026; Su *et al.*, 2025). These developments provide a methodological basis for applying machine learning to investigate the nonlinear and interactive determinants of CCD. In particular, Extreme Gradient Boosting (XGBoost) is capable of accommodating nonlinearities, high-dimensional predictors, and complex interactions, while Shapley Additive Explanations (SHAP) facilitates model interpretation by quantifying the magnitude and direction of individual feature contributions (Chen *et al.*, 2024). The integration of XGBoost and SHAP therefore provides a flexible and interpretable method for identifying the key drivers of CCD and their heterogeneous effects under complex and dynamic conditions. By combining predictive capability with interpretable insights into industrial–

ecological coordination, this method enhances the understanding of CCD dynamics and strengthens the empirical basis for linking prediction and optimization with differentiated regional governance. It thus extends conventional industry–ecology coupling analysis and supports sustainable development strategies in the BTH region.

The XGBoost model, an extreme gradient boosting algorithm, is selected due to its strong predictive performance and ability to capture nonlinear relationships and interactions among variables (Guo & Chang, 2022). XGBoost combines multiple weak learners (decision trees) and iteratively optimizes model performance to achieve highly efficient and accurate predictions (Demir & Sahin, 2023). Its capacity to handle large-scale, high-dimensional datasets has led to extensive applications in environmental science, finance, healthcare, and other fields. However, a key limitation of XGBoost is its “black-box” nature: although the model delivers high-accuracy predictions, its internal decision-making process and feature contributions are not readily interpretable (Guleria, 2026). In the analysis of industrial–ecological coordination, interpreting the determinants underlying model predictions is crucial for elucidating the mechanisms of coordinated development and informing evidence-based policy formulation. As an explainable machine learning approach, SHAP provides a rigorous method for interpreting model outputs by quantifying the magnitude and direction of individual factors’ contributions to industrial–ecological coordination.

To enhance interpretability, this study applies Shapley Additive Explanations (SHAP) to decompose the XGBoost predictions into additive contributions of individual features. Based on cooperative game theory, SHAP values quantify the marginal contribution of each feature to the predicted CCD, enabling both global and local interpretability (Chen *et al.*, 2025). The study uses SHAP in two ways. First, by analyzing SHAP values, it identifies the positive and negative impacts of industrial structure and ecological indicators on urban coordinated development (CCD), clarifying how each factor contributes to CCD. Second, by calculating the average SHAP vector for each city and performing cluster analysis based on the similarity of driving patterns, cities are classified according to their dominant development mechanisms (Li *et al.*, 2025). This approach not only highlights the primary factors influencing urban coordination but also uncovers variations in development mechanisms across cities.

This study integrates coupling coordination degree measurement, XGBoost, and SHAP analysis to investigate the spatiotemporal evolution and driving mechanisms of coordinated industrial and ecological development in the BTH region from 2010 to 2023. The CCD method is employed to quantify the coupling and coordination between industrial and ecological subsystems, while time-series analysis is used to characterize temporal trends in coordination evolution. Building on this assessment, XGBoost captures nonlinear and interactive relationships among potential drivers, and SHAP quantifies the

magnitude and direction of their contributions, thereby revealing heterogeneous driving mechanisms across cities. This integrated research and analytical procedure provides a more comprehensive understanding of industrial–ecological coordination and its determinants by combining coordination measurement with interpretable machine learning. It advances methodological approaches in urban coordinated development research and offers a data-driven basis for formulating differentiated and adaptive regional policies. Moreover, it provides a transferable approach for assessing industrial–ecological coordination and offers valuable insights for promoting coordinated, green, and sustainable urban development beyond the BTH region.

2. Methodology

2.1. Study area

The Beijing–Tianjin–Hebei (BTH) region, also known as the Jing–Jin–Ji urban agglomeration (total 218000 km²), is located in northern China and consists of two municipalities (Shen & Yao, 2022), Beijing and Tianjin, and 11 prefecture-level cities in Hebei Province, including Shijiazhuang, Tangshan, Qinhuangdao, Handan, Xingtai, Baoding, Zhangjiakou, Chengde, Cangzhou, Langfang, and Hengshui (**Figure 1**). As one of the most important urban agglomerations in China, the BTH region plays a crucial role in the country's economic development, industrial restructuring, and regional integration (Liu *et al.*, 2023). It is also a core area for implementing major national strategies, including coordinated regional development and ecological environmental governance.

The BTH region covers a wide range of natural and socioeconomic conditions, with marked differences in topography, resource endowment, urbanisation level, and industrial structure (Lu & Zhang, 2022). Beijing and Tianjin are highly urbanised and economically advanced, whereas many cities in Hebei Province have long relied on heavy industry and resource-intensive production. This uneven development pattern has resulted in significant spatial differences in economic performance, land use, environmental pressure, and ecological quality across the region (Liu *et al.*, 2021). At the same time, the concentration of population, industry, and transport infrastructure has intensified conflicts between development and environmental protection.

In recent decades, the BTH region has faced prominent ecological and environmental challenges, including high energy consumption, industrial emissions, air pollution, and land-use pressure (Wang *et al.*, 2018). These issues are particularly important under the context of China's "dual carbon" goals (peaking carbon emissions by 2030 and achieving carbon neutrality by 2060) and the transition towards high-quality development (Zhu & Gong, 2025). Therefore, the BTH region provides a representative case for examining the interaction between industrial development and the ecological environment. Its strong internal heterogeneity and strategic policy significance make it an ideal study area for analysing the

spatiotemporal dynamics and coordination relationship between industrial structure and ecological environment.

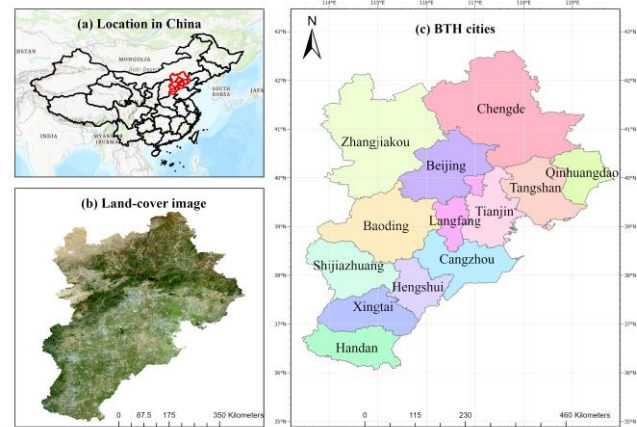


Figure 1. Location of the Beijing–Tianjin–Hebei region in China, satellite imagery of the study area, and the administrative boundaries of its 13 prefecture-level cities

2.2. Indicator system

The indicator system for the industrial structure–ecological environment (IS–EE) system was constructed based on the principles of scientific relevance, representativeness, and data availability. Data for the period 2010–2023 were collected from multiple authoritative sources, mainly including the China Urban Statistical Yearbook and the China Urban Construction Statistical Yearbook. Data on government expenditure on environmental protection was further supplemented from the statistical yearbooks of the respective cities. In addition, several indicators were derived from the original statistical data, such as per-person public green space and population density. For variables with incomplete statistical records, supplementary authoritative sources were adopted. In particular, PM_{2.5} annual concentrations for 2018–2023 were obtained from the China Urban Statistical Yearbook. Because comparable PM_{2.5} records for 2010–2017 were unavailable from this source, the earlier observations were supplemented using estimates from the Atmospheric Composition Analysis Group at Washington University in St. Louis. This dataset integrates satellite observations, aerosol optical depth retrievals, and the GEOS–Chem chemical transport model to estimate ground-level PM_{2.5} concentrations. These data together ensured the completeness and reliability of the indicator system (**Table 1**).

Industrial structure reflects not only the proportional composition of primary, secondary, and tertiary industries, but also the efficiency of resource allocation among sectors and the direction of structural transformation (Krüger, 2008). Therefore, the industrial structure subsystem was represented by industrial structure rationalization (ISR) and industrial structure upgrading (ISU), which capture complementary aspects of structural transformation (Hu *et al.*, 2023). ISR describes the correspondence between sectoral output and employment distributions and was operationalized using the Theil index following (Chunhui *et al.*, 2011):

$$Theil_{i,t} = \sum_{m=1}^3 y_{i,m,t} \ln \left(\frac{y_{i,m,t}}{l_{i,m,t}} \right), (m=1,2,3) \quad (1)$$

Where $Theil_{i,t}$ represents the ISR value of city i in year t ; $y_{i,m,t}$ denotes the share of industry m 's value added in the city's gross domestic product; $l_{i,m,t}$ shows the employment share or number of employees in industry m in city i in year t ; and $m=1,2,3$ refer to the primary, secondary, and tertiary industries, respectively. Thus, Equation (1) compares each sector's share of total value added with its corresponding

share of total employment. The Theil index measures the disparity between the output and employment shares of the primary, secondary, and tertiary sectors, ranges from 0–1. A value closer to zero indicates a closer alignment between sectoral output and employment distributions and, therefore, a more rational industrial structure. Conversely, a higher value indicates greater structural mismatch. Accordingly, although the underlying concept of ISR is positive, its Theil-based operational measure was treated as a negative indicator during normalization.

Table 1. Indicator system and data sources for industrial structure and ecological environment

Subsystem	First-grade index	Basic-grade index	Property*	Data source
Industrial Structure (IS)	Industrial Structure Rationalization	TL	–	China Urban Statistical Yearbook
	Industrial Structure Upgrading	TS	+	
Ecological Environment (EE)	Pressure	Annual Quantity of Wastewater Discharged in Built District (10,000 m ³)	–	China Urban Construction Statistical Yearbook
		Volume of Industrial Particulate Emission (ton)	–	China Urban Statistical Yearbook
		Volume of Industrial Sulphur Dioxide Emission (ton)	–	China Urban Statistical Yearbook
		Volume of Nitrogen Dioxide Emission (ton)	–	China Urban Statistical Yearbook
		Population Density (person/km ²)	–	Calculated from urban population and urban area data in China Urban Construction Statistical Yearbook
		Annual Mean Concentration of PM2.5 (µg/m ³)	–	China Urban Statistical Yearbook (2018–2023); Atmospheric Composition Analysis Group, Washington University in St. Louis (2010–2017)
	State	Area of Industrial Land (km ²)	–	China Urban Construction Statistical Yearbook
		Per-person Public Green Space (m ²)	+	Calculated from green area and urban population data in China Urban Construction Statistical Yearbook
		Rate of Green Areas in Developed Areas (%)	+	China Urban Construction Statistical Yearbook
	Response	Ratio of Centralized Waste Water Treatment to Sewage Work (%)	+	China Urban Construction Statistical Yearbook
		Rate of Domestic Garbage Harmless Treatment (%)	+	China Urban Construction Statistical Yearbook
		Government Expenditure for Environment Protection (billion yuan)	+	Statistical yearbooks of each city

Note: “+” indicates a positive indicator, while “–” indicates a negative indicator.

Source: Developed by the authors based on the industrial structure measures proposed by Chunhui et al. (2011), the Pressure–State–Response framework (Hughey et al., 2004; OECD, 1991).

Industrial Structure Upgrading (ISU) reflects the process through which the industrial system shifts from lower-level to higher-level sectors, especially from secondary-industry dominance toward a greater contribution from the tertiary sector (Yu & Zheng, 2024). Following Chunhui (2011), ISU was measured using the ratio of tertiary-industry value added to secondary-industry value added:

$$TS_{i,t} = Y_{i,3,t} / Y_{i,2,t} \quad (2)$$

where $TS_{i,t}$ denotes the ISU value of city i in year t , $Y_{i,3,t}$ and $Y_{i,2,t}$ represent the value added of the tertiary and secondary industries in city i and year t . A higher $TS_{i,t}$ value indicates a more advanced industrial structure. Unlike ISR, ISU is a positive indicator, as higher values represent stronger structural upgrading. The tertiary-to-secondary value-added ratio was selected because it directly captures the principal direction of structural upgrading from manufacturing-oriented development towards a more

service-oriented economy. Compared with a broader composite advancement index, this measure reduces potential overlap with the Theil-based ISR indicator and avoids introducing additional indicators for which consistent city-level time-series data are unavailable.

The ecological environment subsystem was organized using the Pressure–State–Response framework (Hughey *et al.*, 2004; OECD, 1991). Pressure indicators, such as pollutant emissions, population density, and industrial land area, were selected to capture the environmental burdens associated with industrial production, population concentration, and urban expansion in the Beijing–Tianjin–Hebei region. State indicators concerning urban green-space availability and coverage were used to represent existing ecological conditions, while response indicators related to pollution treatment and environmental expenditure reflected the capacity and efforts of local governments to address environmental pressures. Pressure indicators were treated as negative, whereas state and response indicators were treated as positive.

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Overall, the IS–EE indicator system comprises two industrial structure indicators (ISR and ISU) and 12 ecological environment indicators categorized within the PSR framework. Together, these indicators capture industrial transformation, environmental pressure, ecological conditions, and governance responses, providing a systematic basis for evaluating industrial structure–ecological environment coupling coordination across the BTH region. Detailed indicator definitions, units, directions, and data sources are provided in **Table 1**.

2.3. Coupling coordination degree (CCD) model

To evaluate the coordinated development between the industrial structure (IS) system and the ecological environment (EE) system, the Entropy Weight Method (EWM) and the Coupling Coordination Degree (CCD) model were employed (Li *et al.*, 2022; Wu *et al.*, 2022). First, the EWM was used to determine the objective weights of each indicator according to the variation and information carried by the original data. Based on these weights, the comprehensive development indices of the IS system and the EE system were calculated separately.

The comprehensive evaluation indices of the industrial structure system and ecological environment system are expressed as follows:

$$U_1 = \sum_{j=1}^m w_j x_{ij} \quad (3)$$

$$U_2 = \sum_{j=1}^n w_j x_{ij} \quad (4)$$

where U_1 and U_2 are the comprehensive indices of the IS and EE systems, respectively, w_j represents the weight of indicator j ; and x_{ij} is the standardized value of indicator j for city i . A higher value of U_1 or U_2 indicates a better development level of the subsystem.

The coupling degree C was then calculated to reflect the interaction between the two subsystems:

$$C = 2 \left[\frac{U_1 \times U_2}{(U_1 + U_2)^2} \right]^{\frac{1}{2}} \quad (5)$$

Although C shows the strength of interaction, it does not fully capture whether the two systems develop in a coordinated way. Therefore, the composite index T and coupling coordination degree D were further calculated as follows:

$$T = \alpha U_1 + \beta U_2 \quad (6)$$

$$D = \sqrt{C \times T} \quad (7)$$

where T represents the overall development level of the two subsystems, and α and β are contribution coefficients. Since industrial structure and ecological environment are considered equally important in this study, $\alpha = \beta = 0.5$. The value of D ranges from 0 to 1, with a higher value indicating a better coordination level between the IS and EE systems.

2.4. Machine learning model (XGBoost) and SHAP-based interpretation

The coupling coordination degree (CCD) calculated for each city-year observation was used as the dependent variable in the machine-learning analysis. The explanatory variables comprised the current-year normalized industrial structure and ecological environment indicators, their one-year lagged values, and their two-year rolling means. This specification was designed to capture both current conditions and short-term temporal dependence in industrial-ecological coordination. Although the CCD assessment covered 2010–2023, the effective modelling period was 2011–2023 because constructing the one-year lagged predictors required observations from the preceding year.

Extreme Gradient Boosting (XGBoost) was employed because it can accommodate nonlinear relationships, interaction effects, and complex data structures without imposing a predetermined functional form (Shi *et al.*, 2026). It also combines multiple decision trees through sequential gradient boosting and incorporates regularization and structural constraints to control model complexity (Wang *et al.*, 2021; Wang *et al.*, 2025). In the

final model, the maximum tree depth was set to 2, the row subsampling rate to 0.70, and the feature subsampling rate to 0.85. L2 regularization was retained at ($\text{reg_lambda}=1$), while (reg_alpha) and (gamma) were set to 0. These settings were intended to limit tree complexity and reduce the risk of overfitting while preserving the model's capacity to represent nonlinear relationships (Rizk *et al.*, 2024; Sibindi *et al.*, 2023).

Model performance was assessed using the training set, an independent test set, and GroupKFold cross-validation (Kadim & Al-Behadili, 2026), with cities used as the grouping variable. Grouping observations by city prevented records from the same city from being included simultaneously in the training and validation subsets within each fold, thereby providing a more stringent assessment of spatial generalizability. Because the near-perfect training fit indicated a potential risk of overfitting (Chapi *et al.*, 2026), two additional robustness procedures were conducted. First, temporal holdout validation was performed by training the model using observations from 2011–2020 and evaluating its performance for 2021–2023. Second, parameter sensitivity was examined by refitting the model under alternative values of maximum tree depth, learning rate, number of estimators, subsampling rate, feature subsampling rate, and L2 regularization. Model performance was evaluated using the coefficient of determination R^2 and mean absolute error (MAE). The corresponding results are reported in Section 3.2.

Model interpretation was conducted using SHapley Additive exPlanations (SHAP), an approach based on cooperative game theory that decomposes each model prediction into the contributions of individual predictors (Lundberg & Lee, 2017; Shi *et al.*, 2026). A positive SHAP value indicates that a predictor contributes towards a higher predicted CCD, whereas a negative value indicates a contribution towards a lower predicted CCD. Global SHAP importance was used to identify the most influential predictors, while signed city-level SHAP values were used to examine spatial variation in the direction and magnitude of their contributions. These values represent model-based predictive contributions rather than independent causal effects.

In this study, SHAP was used in two ways. First, SHAP values were examined to identify the positive and negative effects of individual industrial structure and ecological environment indicators on CCD, thereby clarifying how each factor contributes to coordinated development. Second, the mean SHAP vector of each city was calculated and used for clustering analysis to classify cities according to similarities in their driving patterns. This approach not only reveals the main factors influencing CCD but also helps uncover differences in the underlying development mechanisms across cities.

3. Results and Discussion

3.1. Spatiotemporal evolution of CCD

Figure 2 shows the city-level temporal trends of CCD in the Beijing–Tianjin–Hebei region from 2010 to 2023. Overall, the CCD values show clear spatial heterogeneity among the

13 cities, indicating that the coordination between industrial structure and ecological environment developed unevenly across the region. This spatial disparity is consistent with the broader literature on regional coordinated development, which emphasizes that economic upgrading and environmental improvement may proceed at different speeds across regions (Cai *et al.*, 2024). Most cities remained within the basic to primary coordination range, while Beijing and Tianjin generally maintained relatively higher CCD levels than many surrounding cities. This suggests that the core cities had stronger coordination capacity, possibly due to their more advanced industrial structure, higher economic development level, and stronger environmental governance capacity.

From a temporal perspective, the CCD trends did not show a simple linear increase. Instead, several cities experienced fluctuations during the study period. Beijing maintained a relatively high and stable level of coordination, although slight variations can still be observed across different years. Tianjin also showed a relatively high CCD level, but its trend displayed more fluctuation, reflecting changes in the balance between industrial development and ecological pressures. In contrast, cities such as Baoding, Handan, Hengshui, Xingtai, and Cangzhou generally showed lower CCD values, suggesting that their industrial transformation and ecological improvement remained less coordinated during the study period. These temporal fluctuations indicate that coordination is a dynamic process rather than a simple linear trajectory, and may be influenced by economic cycles, policy shifts, and changing environmental pressures (Görg *et al.*, 2017).



Figure 2. City-level temporal trends of CCD in the BTH area, 2010–2023.

A noticeable feature is that some cities experienced a decline or stagnation in CCD during certain years, indicating that industrial development did not always translate into improved coordination with the ecological environment. For example, Tangshan, Handan, Cangzhou, and Xingtai showed relatively lower or fluctuating CCD values, suggesting that cities with a strong industrial base may have faced greater environmental pressure from emissions, energy consumption, and land use expansion. These pressures could have weakened the coordination between industrial upgrading and ecological improvement. This finding suggests that industrial expansion alone does

not necessarily improve coordination; when economic growth is accompanied by high energy consumption, pollution emissions, and land-use pressure, the environmental subsystem may become a stronger constraint on CCD (Ahmad *et al.*, 2021). In contrast, some cities showed moderate recovery or improvement in later years. For instance, Zhangjiakou and Chengde displayed relatively stable or improving coordination trends, while Beijing and Tianjin maintained comparatively high CCD levels over most of the study period. This suggests that environmental regulation, industrial upgrading, and regional coordinated development policies may have gradually contributed to better subsystem coordination in some parts of the region.

The spatial changes in CCD across the BTH region during three sub-periods, namely 2010–2015, 2015–2020, and 2020–2023, as well as the overall change from 2010 to 2023 are shown in **Figure 3**. The results show that CCD changes were uneven across cities and varied between periods. During 2010–2015, CCD changes showed a mixed spatial pattern. Several cities experienced a decline, particularly in the northern and some central parts of the BTH region, while a few cities recorded slight improvements. Tianjin and Hengshui showed relatively stronger positive changes during this stage, suggesting an improvement in the coordination between industrial development and ecological conditions. In contrast, cities such as Zhangjiakou, Chengde, and Baoding showed negative changes, indicating that their coordination level weakened during the early stage. Before the introduction of the Beijing–Tianjin–Hebei coordinated development strategy in 2014, the region was undergoing rapid industrialization and urbanization, with a strong reliance on heavy industry and growing pressures from energy consumption and pollutant emissions (Fang *et al.*, 2019; Zhao *et al.*, 2024). Meanwhile, weak regional industrial specialization and fragmented environmental governance, compounded by administrative fragmentation and industrial convergence, exacerbated tensions between industrial expansion and environmental sustainability, thereby contributing to the declining coordination between industrial development and the ecological environment across most BTH cities.

During 2015–2020, the spatial pattern shifted, with more cities showing positive CCD changes. Zhangjiakou, Baoding, and Xingtai displayed relatively strong increases, while Chengde, Beijing, Langfang, and Shijiazhuang also showed moderate improvement. However, Qinhuangdao, Tangshan, Tianjin, and Cangzhou showed negative or limited changes, suggesting that improvement was uneven across the region. This stage indicates a partial recovery or strengthening of coordination in several Hebei cities, but the eastern coastal and core-adjacent areas still showed signs of stagnation or decline. The partial recovery observed after 2015 may be associated with regional integration strategies and strengthened environmental regulations, which potentially promoted ecological improvement and industrial restructuring.

From 2020 to 2023, the pattern changed again. The strongest positive changes were observed in Tangshan and Cangzhou, while Zhangjiakou, Qinhuangdao, and Handan also showed improvement. However, Chengde, Beijing, Shijiazhuang, and Xingtai experienced negative changes during this period. This suggests that recent changes in CCD were more spatially fragmented, with some industrial cities improving while several previously stable or higher-level cities showed slight declines. The emergence of renewed spatial fragmentation after 2020 suggests that improvements in the coordination between industrial development and the ecological environment remain uneven across the region and may be particularly sensitive to external shocks, such as the COVID-19 pandemic, as well as variations in policy implementation.

For the whole period from 2010 to 2023, Hengshui showed the most notable improvement, followed by cities such as Xingtai, Langfang, Tianjin, and Zhangjiakou. In contrast, Chengde, Qinhuangdao, Beijing, and Cangzhou showed negative overall changes. These staged results indicate that CCD evolution was not linear, and some cities experienced decline and recovery across different periods.

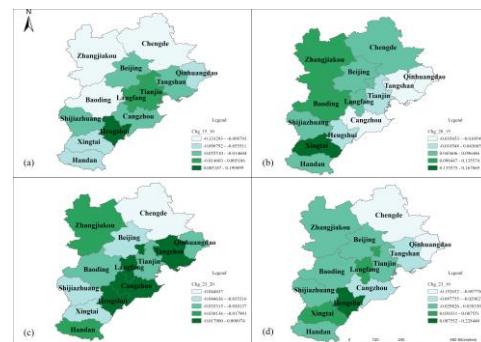


Figure 3. Spatial changes in CCD in the BTH region: (a) 2010–2015, (b) 2015–2020, (c) 2020–2023, and (d) 2010–2023.

3.2. XGBoost model performance and robustness

Table 2 summarizes the performance and robustness of the XGBoost model. Although the near-perfect training fit indicates a potential risk of overfitting, the model retained satisfactory performance under the original chronological test. In this primary evaluation, the model was trained using observations from 2011–2019 and tested using observations from 2020–2023. Its reliability was subsequently examined through city-grouped validation, an alternative temporal-holdout design, a history-only specification, and parameter-sensitivity analysis.

The original test and the additional temporal holdout represent two related but distinct chronological evaluations rather than two completely independent datasets. In the temporal-holdout assessment, the training period was extended through 2020, while the final three years, 2021–2023, were retained for evaluation. The strong performance under both temporal divisions indicates that the findings were not dependent on a single cutoff between the training and testing periods. In particular, the temporal-holdout result suggests that incorporating the additional 2020 observations did not weaken the model's ability to generalize to the subsequent three years.

Five-fold GroupKFold validation provided a more demanding assessment of spatial generalizability by excluding entire cities from model fitting within each fold. Its lower performance relative to the two chronological evaluations indicates that transferring the model to cities not represented in the training sample was more challenging than transferring it across time within the same regional set of cities. Nevertheless, all five folds produced positive R^2 values, suggesting that the model captured relationships that were not restricted entirely to individual city trajectories. The history-only model also retained substantial explanatory performance after contemporaneous indicators were excluded, indicating that lagged and short-term historical conditions contained meaningful information about subsequent CCD variation.

The results were also stable under reasonable changes in model specification. Across the one-at-a-time parameter perturbations, temporal-holdout R^2 values remained between 0.9507 and 0.9766, while MAE values ranged from 0.0126 to 0.0203. The principal SHAP rankings were similarly consistent, with a mean Spearman correlation of

0.8679 and a mean top-10 Jaccard overlap of 0.9464 relative to the original model. Although the complete SHAP rankings showed moderate stability across the city-grouped folds, industrial structure rationalization, industrial structure upgrading, annual mean PM2.5, per capita green space, and lagged industrial structure upgrading were consistently identified among the ten most influential predictors.

Overall, the complementary validation procedures reduce the concern that the results depend solely on the near-perfect training fit, a single temporal cutoff, or one particular parameter configuration. The model demonstrated stronger temporal than spatial transferability, while the principal SHAP interpretations remained broadly consistent across reasonable parameter changes. However, because CCD was constructed from the indicators included as predictors, the XGBoost results are interpreted primarily as a nonlinear decomposition of the factors associated with coordination rather than as independent causal evidence.

Table 2. XGBoost model performance and robustness assessment

Validation method	R^2	MAE
Training set	1.0000	0.0004
Independent test set	0.9207	0.0215
Five-fold GroupKFold	0.6007 ± 0.0838	0.0450 ± 0.0358
Temporal holdout	0.9724	0.0136
History-only temporal holdout	0.8267	0.0347

Note: GroupKFold results are reported as mean $\pm$ standard deviation. The history-only specification excludes contemporaneous indicators and retains lagged indicators, trailing historical means, and the year index.

3.3. Spatial heterogeneity of feature effects

The signed SHAP results provide further insight into why CCD differed across cities by showing whether each feature contributed positively or negatively to model predictions (**Figure 4**). Positive values indicate that the corresponding feature raised the predicted CCD, whereas negative values indicate that it reduced the predicted CCD.

A clear city-level contrast can be observed in the positive SHAP effects. Beijing shows the most pronounced positive contributions, especially from U1_roll2_mean, U1_ind, U2_env, and U2_roll2_mean. This indicates that both industrial structure and ecological environment conditions played a supportive role in Beijing's CCD prediction. The positive contributions from both industrial and ecological variables in Beijing suggest a relatively mature coordination mechanism in which economic development and environmental protection can reinforce each other. Similar but weaker positive effects are also found in Tianjin, Langfang, Zhangjiakou, and Shijiazhuang, suggesting that these cities benefited from certain industrial or ecological factors, but with lower intensity. By comparison, several Hebei cities show only small positive effects, implying that the driving role of these indicators was more limited.

The negative SHAP effects reveal another side of the spatial heterogeneity. Xingtai and Hengshui show relatively strong negative values for U1_roll2_mean and U1_ind, suggesting

that the industrial structure-related features did not consistently support CCD improvement in these cities. The negative industrial effects observed in Xingtai and Hengshui may indicate that their existing industrial structures are relatively inefficient or more pollution-intensive, thereby limiting their contribution to industrial–ecological coordination. Baoding and Chengde also show negative effects from industrial-related variables, although with smaller magnitudes. For ecological-related variables, negative effects are more evident in Tianjin, Tangshan, Shijiazhuang, Handan, and Xingtai, especially for U2_env. This suggests that environmental pressures or weaker ecological performance may have constrained CCD in these cities. Similarly, the negative ecological effects observed in several cities suggest that environmental conditions remain a key constraint even where industrial restructuring is taking place (Zhang *et al.*, 2019).

These results indicate that the influence mechanism of CCD was not uniform across the Beijing–Tianjin–Hebei region. In Beijing, the model identified stronger positive effects from both industrial and ecological dimensions, while in several Hebei cities, some industrial or ecological variables were associated with negative contributions. This spatial heterogeneity is consistent with the place-based development perspective, which emphasizes that the same policy or factor may generate different outcomes under different local institutional and economic conditions

(Rodríguez-Pose & Wilkie, 2017). This city-specific pattern supports the need for differentiated coordination strategies rather than a single regional policy approach. For cities where industrial variables show negative effects, further industrial restructuring and efficiency improvement may be more important. For cities where ecological variables exert negative effects, pollution control, ecological investment, and environmental governance should remain central priorities.

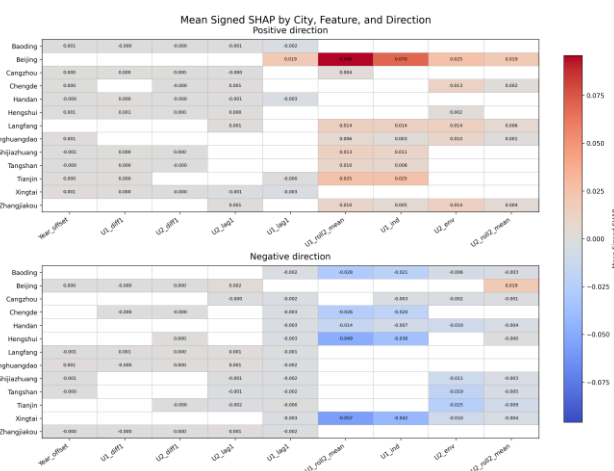


Figure 4. Spatial heterogeneity of signed SHAP effects across cities

3.4. Dominant factors

After identifying the direction of feature effects, the dominant SHAP drivers were further examined to compare the main factor types influencing CCD across cities. The results show that the most influential driver type varied spatially, indicating that different cities were shaped by different mechanisms rather than by one common factor.

Temporal dynamics, including rolling and lagged effects, formed the dominant driver type in most cities. Beijing showed the highest mean SHAP importance, suggesting that its CCD prediction was strongly influenced by accumulated and delayed effects of previous industrial and ecological conditions. Xingtai, Hengshui, Tianjin, Baoding, Chengde, and Handan were also mainly affected by temporal dynamic features. This indicates that CCD in these cities was not only related to current-year conditions but also depended on short-term historical changes in industrial structure and ecological environment. The strong influence of lagged and rolling features suggests that CCD has a path-dependent component, whereby past industrial and environmental conditions continue to shape current coordination outcomes. This also implies that short-term interventions may not immediately generate measurable improvements because their effects can accumulate over time (Naz *et al.*, 2026). Therefore, consistent and long-term policy commitment is essential, particularly in cities where historical industrial patterns have created persistent environmental pressures (Michailidis *et al.*, 2025).

In contrast, eco-environmental factors were the dominant drivers in Tangshan, Zhangjiakou, Cangzhou, Shijiazhuang, and Qinhuangdao. This suggests that ecological conditions and environmental pressures played a more important role in shaping CCD in these cities. For these areas,

improvements in pollution control, ecological restoration, and environmental governance may be particularly important for enhancing coordination. Langfang was the only city where industrial structure was identified as the dominant driver, implying that changes in industrial structure had a stronger influence on its CCD than ecological or temporal factors. Therefore, for Langfang, restructuring and upgrading the industrial structure is a key measure for promoting greater coordination between industrial development and the ecological environment.

The ranking of mean SHAP importance also shows clear differences in driver strength. Beijing had the strongest overall dominant-driver importance, followed by Xingtai and Hengshui, while cities such as Qinhuangdao, Shijiazhuang, and Cangzhou showed relatively lower values. This suggests that the model identified more pronounced driving effects in some cities, whereas CCD formation in others was influenced by weaker or more dispersed factors. These results further support the spatial heterogeneity identified in the previous section and highlight the need for city-specific coordination strategies in the BTH region. Furthermore, the findings indicate that effective policy interventions require not only identifying the factors that are most critical, but also understanding whether their effects are immediate or cumulative, and whether they operate through supportive or constraining mechanisms (Ding *et al.*, 2025).

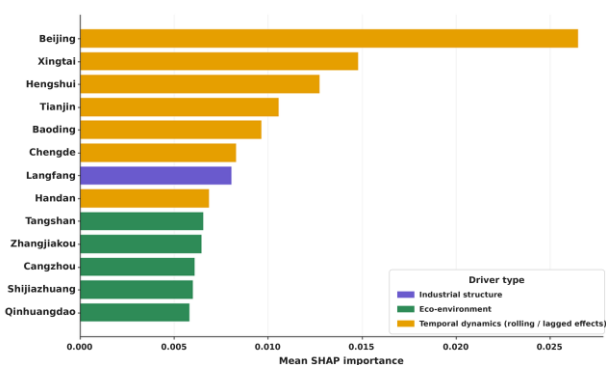


Figure 5. Dominant drivers of CCD by cities (SHAP-based)

3.5. City clustering based on SHAP feature profiles

To further identify city-specific coordination mechanisms, the 13 cities were classified according to their SHAP feature profiles. The clustering was based on the dominant signed effects of industrial structure and ecological environment variables, especially U1_ind and U2_env. Four types of cities were identified, reflecting different pathways through which industrial structure and ecological environment factors influenced CCD.

Table 3 summarizes the cluster classification, key feature profiles, and interpretation of each city type. Cluster 1 is an industrial-driven but environment-constrained type. Cities in this group are characterized by positive U1_ind effects and negative U2_env effects, indicating that coordination improvement was mainly supported by industrial structure change, while the environmental subsystem remained a constraint. Cluster 2 is the environment-improvement-led type, where U2_env shows a positive effect and U1_ind is close to zero. This suggests that CCD improvement was

mainly driven by environmental improvement rather than industrial restructuring. Cluster 3 is the dual-system synergy type, with both U1_ind and U2_env showing positive effects, indicating that industrial restructuring and environmental improvement jointly promoted coordination. Cluster 4 is the industrial structure

Table 3. City clustering classification

Cluster	Type name	Key feature profile	Interpretation
1	Industrial-driven but environment-constrained type	U1_ind (+), U2_env (-)	Coordination improvement is mainly supported by industrial structure change, while the environmental subsystem remains a constraint.
2	Environment-improvement-led type	U2_env (+), U1_ind (~0)	Coordination improvement is mainly driven by environmental improvement rather than industrial restructuring.
3	Dual-system synergy type	U1_ind (+), U2_env (+)	Both industrial restructuring and environmental improvement jointly promote coordination.
4	Industrial structure constrained type	U1_ind (-), U2_env (~0)	Industrial structure-related factors hinder coordination improvement, with limited positive support from the environmental subsystem.

Figure 6 shows the spatial distribution of the four city clusters. The industrial-driven but environment-constrained type is mainly distributed in southern and eastern cities, including Handan, Shijiazhuang, Tianjin, and Tangshan. These cities have relatively strong industrial foundations, but their environmental pressures may weaken the positive effects of industrial development on CCD. The environment-improvement-led type is the most widely distributed cluster, including Zhangjiakou, Chengde, Qinhuangdao, Langfang, and Cangzhou. This pattern suggests that ecological improvement played a more important role in shaping CCD in these cities. The dual-system synergy type is represented by Beijing, where both industrial structure and ecological environment features contributed positively to coordination. The industrial structure constrained type includes Baoding, Hengshui, and Xingtai, indicating that industrial structure-related factors may have limited CCD improvement in these cities.

The clustering results further confirm that the formation of CCD in the BTH region was spatially differentiated. Different cities were not only at different coordination levels but were also shaped by different driving mechanisms. These findings underscore the need to move beyond one-size-fits-all approaches in regional development policy. Instead, policy interventions should be tailored to the specific constraints and drivers shaping industrial–ecological coordination within different city clusters (Yang & Zhou, 2025), thereby enabling more context-sensitive and effective policy responses. Cities in the industrial-driven but environment-constrained group should focus on reducing environmental pressure during industrial upgrading, while environment-improvement-led cities should continue strengthening ecological governance and translate environmental gains into broader coordination improvements. For Beijing, maintaining the synergy between industrial transformation and ecological quality is important, whereas cities in the industrial structure constrained group require deeper industrial restructuring to improve coordination. This differentiated

constrained type, where U1_ind shows a negative effect and U2_env is close to zero, suggesting that industrial structure-related factors hindered coordination improvement, with limited positive support from the environmental subsystem.

policy implication is particularly important because the results show that industrial upgrading and ecological improvement do not automatically generate the same coordination benefits across cities. Instead, effective governance should be matched to the specific development pathway and constraint structure identified by the SHAP-based analysis. Moreover, strengthening inter-city collaboration and promoting the diffusion of successful practices, such as the synergistic development observed between Beijing and Tianjin, could help narrow regional disparities and improve the overall coordination between industrial development and the ecological environment.

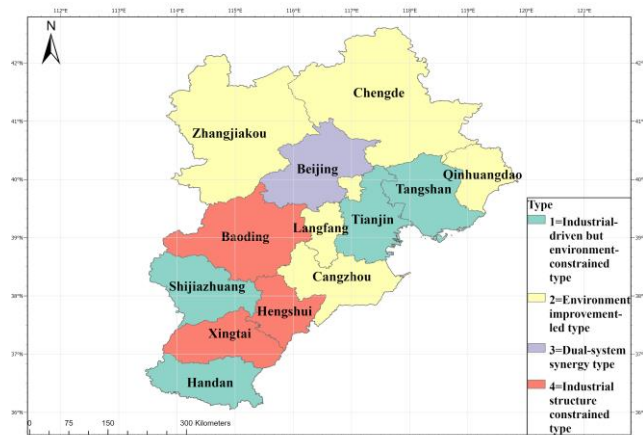


Figure 6. Spatial distribution of SHAP-based city clusters according to industrial structure and ecological environment feature effects

4. Conclusions

This study analyzed the spatiotemporal evolution and driving mechanisms of the coupling coordination degree (CCD) between industrial structure and ecological environment in the Beijing–Tianjin–Hebei (BTH) region from 2010 to 2023. Furthermore, the integration of temporal analysis, XGBoost modeling, and SHAP-based interpretability analysis enabled a more comprehensive

understanding of the temporal patterns of CCD and the potential mechanisms underlying these patterns.

The results indicate that core cities, such as Beijing and Tianjin, exhibit higher CCD levels, driven by advanced industrial bases and robust environmental governance. These cases demonstrate that fostering a positive interaction between economic growth and ecological protection is essential for achieving high-level coordination. In contrast, other cities, particularly in Hebei Province, face pronounced tensions between industrial transformation pressures and ecological improvement, reflecting risks of industrial–ecological imbalance.

Applying SHapley Additive exPlanations (SHAP) analysis, this study identifies the key drivers of CCD variation across cities. The findings underscore the need for context-specific policies: cities with strong industrial foundations but strained ecological environments require targeted ecological governance and industrial restructuring to reduce environmental burdens and enhance sustainable development potential. At the regional policy level, the study emphasizes the importance of coordinated strategies that ensure rational resource allocation and consistent environmental standards. Such policies facilitate positive interactions among cities, improve ecological conditions, and lay a foundation for long-term economic growth.

Cluster analysis revealed four coordination pathways. Industry-driven but environmentally constrained cities struggle to balance growth with ecological limits, while environmentally driven cities rely on ecological investment to enhance coordination despite weak industrial support. Beijing, as the sole dual-system case, exemplifies a balanced model, though its replicability is limited without strong institutional backing. Cities constrained by industrial structure face structural challenges, where outdated industries impede coordinated development despite minimal environmental pressures.

The policy implications can be summarized in three aspects. First, strategies should be context-specific: industrial cities require greener transitions, environmentally driven cities should strengthen the integration of ecological benefits with economic development, and structurally constrained cities necessitate deeper and more comprehensive industrial reforms. Second, recognizing the significance of temporal dynamics, policies should be designed to ensure stability and long-term continuity. Third, regional cooperation should be reinforced to narrow inter-city disparities and facilitate coordinated development across the region.

In conclusion, this research offers a novel perspective on coordinated development in the BTH region and provides empirical guidance for policy formulation. Future efforts should focus on balancing economic growth and ecological protection, expanding regional development models, and integrating successful practices from other regions to advance comprehensive regional integration. By optimizing policy frameworks and collaborative mechanisms, the BTH region holds substantial potential to achieve higher levels of coordination across economic, social, and

environmental dimensions, providing valuable insights for sustainable development in other contexts.

Abbreviations

Table 4. Abbreviations and corresponding full names used in this study

Abbreviation	Full name
CCD	Coupling Coordination Degree
BTH	Beijing–Tianjin–Hebei
AI	Artificial Intelligence
XGBoost	Extreme Gradient Boosting
SHAP	Shapley Additive Explanations
IS–EE	Industrial Structure–Ecological Environment
AOD	Aerosol Optical Depth
ISR	Industrial Structure Rationalization
ISU	Industrial Structure Upgrading
PSR	Pressure–State–Response
IS	Industrial Structure
EE	Ecological Environment
EWM	Entropy Weight Method
MAE	Mean Absolute Error

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Competing Interests

No potential conflict of interest was reported by the author(s).

Data availability statement

The publication incorporates all the research data acquired throughout this study. Upon request, the unprocessed data might be provided.

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