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Spatiotemporal Evolution of Coupling Coordination Between Technological Innovation and the Ecological Environment in the Yangtze River Economic Belt and Its Associated Factors: An XGBoost-SHAP Analysis

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Abstract

Against the backdrop of tightening ecological constraints and the accelerating transition toward high-quality development, the coordinated development of technological innovation and the ecological environment has become an important topic in regional sustainability research. Using 111 cities in the Yangtze River Economic Belt from 2013 to 2023 as the study sample, this study applied principal component analysis and a coupling coordination model to measure the coupling coordination degree between technological innovation and the ecological environment. It further employed the XGBoost-SHAP model to investigate the factors associated with their coordinated development. The results showed that: (1) During the study period, both the comprehensive development level of technological innovation and that of the ecological environment level increased, although a pronounced spatial mismatch existed between them. The former exhibited an east-to-west declining gradient, whereas the latter followed a spatial pattern of the middle reaches > upper reaches > lower reaches. (2) The overall coupling coordination level transitioned from the low coordination stage to the primary coordination stage. Significant regional disparities were observed, with the coupling coordination degree decreasing progressively from east to west. (3) The XGBoost-SHAP results indicated that the urbanization level and fiscal autonomy were important factors associated with the coordinated development of technological innovation and the ecological environment. Furthermore, the marginal contributions of the individual factors exhibited complex nonlinear patterns. These findings enhance the understanding of the coordinated development of technological innovation and the ecological environment and provide empirical evidence for differentiated governance and policy design across the Yangtze River Economic Belt.

Keywords: technological innovation; ecological environment; coupling coordination; spatiotemporal variation; XGBoost-SHAP; nonlinear relationship

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1. Introduction

Currently, with the continued advancement of the technological revolution and industrial transformation, technological innovation has become an important driving force for green transformation and high-quality development. Meanwhile, challenges such as climate change, resource constraints, and ecological degradation are intensifying, making sustainable development a common concern for humanity. Against this background, technological innovation and the ecological environment do not develop independently. Technological innovation can improve ecological performance through technological progress, the optimized allocation of resources, and green governance [1], whereas the ecological environment influences the direction and efficiency of innovation activities through environmental carrying capacity, resource conditions, and policy constraints [2]. In regional development practice, however, technological innovation capacity and ecological environment level often exhibit a spatial mismatch. Developed regions tend to concentrate innovation resources while facing considerable ecological pressure, whereas less-developed regions may possess a relatively sound ecological foundation but lack sufficient support for innovation [3]. Therefore, systematically examining the coupling coordination relationship between technological innovation and the ecological environment is important for simultaneously advancing high-quality development and ecological conservation.

Early studies on technological innovation and the ecological environment primarily focused on the unidirectional effects between the two systems. On the one hand, researchers examined the effects of technological innovation on the ecological environment, arguing that technological progress could improve environmental performance by enhancing resource-use efficiency, promoting cleaner production, and facilitating the low-carbon transition [4–7]. On the other hand, from the perspectives of ecological constraints and environmental regulation, researchers investigated the feedback effects of resource and environmental pressures on green innovation activities [8–10]. With the growing prominence of sustainable development in the late twentieth century, scholarly attention gradually shifted toward bidirectional feedback and systemic coupling between the two systems. Most studies have been conducted at the national, urban-agglomeration, or provincial levels [11–14]. These studies have generally used data on patents, science and technology expenditure, and pollutant emissions to characterize regional technological innovation and ecological environment levels [15,16] and have developed analytical frameworks involving green innovation efficiency [17], the digital economy [18], and ecological efficiency [19]. Methods such as the coupling coordination model, panel method-of-moments quantile regression, the bootstrap autoregressive distributed lag model, the panel vector autoregression model, and the geographically and temporally weighted regression model have also been applied to analyze the spatiotemporal evolution of interactions between technological innovation and the ecological environment [20–23]. These studies have identified factors such as advances in communication technology and the efficient allocation of resources as being associated with the coordinated development of the two systems. Although this body of research has established a solid foundation for understanding their relationship, further investigation is needed. In terms of research scale, the existing literature has mainly characterized overall patterns at the national, provincial, or broad urban-agglomeration level. Fine-grained analyses at the prefecture-level city scale remain limited for river basins such as the Yangtze River Economic Belt, which exhibits pronounced internal development gradients. Methodologically, conventional studies have largely relied on static assessments of coordination status or linear attribution analyses, which may be insufficient to identify the nonlinear associations and stage-specific turning points of key factors across different development stages [24,25].

Accordingly, this study extends the existing literature in two respects. First, it focuses on the Yangtze River Economic Belt, which spans eastern, central, and western China. Its upper, middle, and lower reaches differ substantially in resource endowments, industrial foundations, innovation capacity, and ecological conditions. These development gradients provide a representative setting for identifying spatial mismatches and coupling coordination patterns between technological innovation and the ecological environment. Moreover, the Yangtze River Economic Belt performs important national functions in innovation-driven development and ecological security. Its level of coordinated development therefore has important practical implications for basin governance and regional sustainable development. Second, methodologically, this study incorporates the XGBoost-SHAP framework into the coupling coordination analysis to identify the importance of the relevant factors and their nonlinear associations with the coupling coordination level. Compared with descriptive mapping and conventional regression methods, this framework can better capture potential nonlinear relationships within complex systems and interpretably quantify the marginal contributions of individual factors to model predictions. This study therefore addresses three questions: How did the technological innovation and ecological environment levels in the Yangtze River Economic Belt change from 2013 to 2023? What spatiotemporal patterns characterized the coupling coordination level between the two systems? Which factors were closely associated with variations in the coupling coordination level, and what nonlinear patterns did these associations exhibit? By identifying the factors associated with the coordinated development of technological innovation and the ecological environment, this study seeks to provide empirical evidence for region-specific governance and differentiated policy formulation.

2. Materials and Methods

2.1. Study Area and Data Sources

The Yangtze River Economic Belt covers 11 provinces and municipalities, namely Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, Hunan, Chongqing, Sichuan, Yunnan, and Guizhou (Figure 1). Anchored by the Yangtze River's "major navigational artery" and a multi-tiered urban agglomeration system, this region plays a crucial role in both the construction of China's national innovation system and the maintenance of its ecological security framework [26]. Owing to differences in geographical location and resource endowments, the lower reaches are characterized by a high concentration of innovation resources but face considerable ecological pressure, the middle reaches undertake the dual tasks of industrial relocation and ecological restoration, and the upper reaches possess a relatively sound ecological foundation but a comparatively weak innovation base. The selection of 111 cities as the study sample facilitates the identification of spatial differentiation within the basin.

The study period extended from 2013 to 2023. Data on ecological, socioeconomic, and technological indicators were primarily obtained from the China City Statistical Yearbook, the China Statistical Yearbook on Science and Technology, and local statistical bulletins. All monetary indicators were measured using the original RMB values reported in official statistical yearbooks and statistical bulletins, and no currency conversion was involved. In addition, some autonomous prefectures, forest districts, and special administrative units were excluded from the analysis because key indicators, such as technology contract transaction value, environmental investment, and pollutant emissions, had substantial missing values or were not reported in sufficient detail. This exclusion was intended to avoid potential bias in the estimation results. For a small number of missing observations in individual cities, such as Anshun, Bijie, and Liupanshui, linear interpolation was applied to ensure the completeness of the panel dataset.

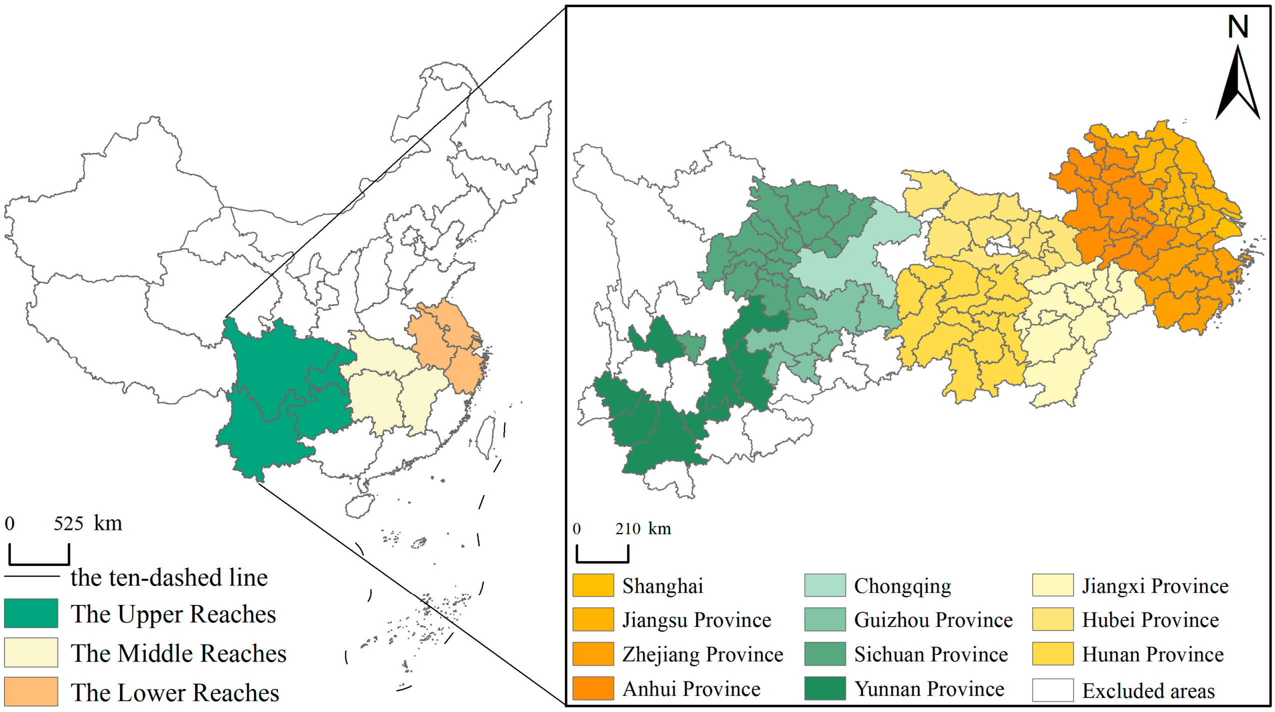

Figure 1. Study area.

2.2. Variable Selection

2.2.1. Evaluation Indicator System for Technological Innovation and Ecological Environment

Based on the principles of scientific validity, systematic comprehensiveness, and data accessibility, and with reference to previous studies [27–30], this study constructed comprehensive evaluation indicator systems for technological innovation and the ecological environment, respectively (Table 1).

Table 1. Evaluation indicators for technological innovation and ecological environment.

Primary Indicator	Secondary Indicator	Indicator Description	Unit	Indicator Direction	Weight
Technological innovation	Innovation inputs	The number of R&D personnel	persons	+	0.090
		Internal expenditure on R&D	10^4 CNY	+	0.089
		The proportion of R&D expenditure to regional GDP	%	+	0.065
		The proportion of science and technology expenditure in the general public budget	%	+	0.075
	Innovation environment	The number of students enrolled in regular higher education institutions	10^4 persons	+	0.046
		The number of organizations engaged in R&D activities	unit	+	0.081
	Innovation outputs	The number of patents granted	item	+	0.082
		The value of technology contract transactions	10^8 CNY	+	0.079

Table 1. *Cont.*

Primary Indicator	Secondary Indicator	Indicator Description	Unit	Indicator Direction	Weight
Ecological environment	Environmental pressure	Industrial sulfur dioxide emissions	10^4 tonnes	−	0.011
		Energy consumption per unit of regional GDP	tce/10^4 CNY	−	0.035
		Urban population density	persons/km^2	−	0.064
		Industrial wastewater discharge	10^4 tonnes	−	0.054
	Environmental governance	The proportion of environmental protection investment to regional GDP	%	+	0.025
		The sewage treatment rate	%	+	0.063
	Environmental conditions	Green coverage rate in built-up areas	%	+	0.071
		Public green space per capita	m^2/person	+	0.069

Note: "+" indicates that an increase in the indicator has a positive impact, and "−" indicates that an increase in the indicator has a negative impact.

To capture the concentration of technological innovation resources and the overall level of technological innovation development across regions, the technological innovation system was evaluated along three dimensions: innovation inputs, innovation environment, and innovation outputs. Specifically, innovation inputs were measured using the number of R&D personnel, internal expenditure on R&D, the proportion of R&D expenditure to regional GDP, and the proportion of science and technology expenditure in the general public budget, thereby reflecting the human capital, financial resources, and policy support underpinning innovation activities. The innovation environment was characterized by the number of students enrolled in regular higher education institutions and the number of organizations engaged in R&D activities, which reflect the regional reserve of innovation resources and the organizational foundation for innovation. Innovation outputs were measured using the number of patents granted and the value of technology contract transactions to capture the generation of innovation outcomes and their commercialization capacity.

The ecological environment system was characterized along three dimensions: environmental pressure, environmental governance, and environmental conditions. The environmental pressure dimension included industrial sulfur dioxide emissions, energy consumption per unit of regional GDP, urban population density, and industrial wastewater discharge, which collectively reflected the environmental pressure generated by socioeconomic activities. The environmental governance dimension was measured by the proportion of environmental protection investment to regional GDP and the sewage treatment rate, capturing local governments' investment in ecological protection as well as their governance capacity. The environmental conditions dimension included the green coverage rate in built-up areas and public green space per capita, which characterized the quality of urban ecological spaces and their capacity to support green development.

2.2.2. Selection of Explanatory Variables for Coupling Coordination

The coupling coordination between technological innovation and the ecological environment is jointly associated with multiple factors. To identify the key factors related to regional coordinated development, six explanatory variables were selected for analysis [31] (Table 2). Specifically, the share of industrial electricity consumption (IEC) and fiscal autonomy (FIS) represent the regional level of industrialization and energy consumption structure, and the fiscal capacity of local governments, respectively. GDP per capita (PGDP) and industrial structure upgrading (IS) reflect the stage of economic development and the extent of structural transformation, respectively. The urbanization level (UL) and degree of openness (OPEN) characterize socio-spatial development and the capacity to access external resources, respectively. The units listed in the table refer to the original measurement units of the variables. However, before entering the XGBoost model, all continuous predictors were normalized. Therefore, the threshold values reported in the SHAP dependence plots below represent normalized dimensionless values.

Table 2. Description of explanatory variables associated with coupling coordination.

Variable Name	Variable Description	Unit
Fiscal autonomy (FIS)	Local general public budget revenue/ local general public budget expenditure	%
Industrial electricity consumption (IEC)	Industrial electricity consumption/ total electricity consumption	%
Per capita gross regional product (PGDP)	Regional GDP/permanent population	10^4 CNY/person
Industrial structure upgrading (IS)	Value added of tertiary industry/ value added of secondary industry	Dimensionless ratio
Urbanization level (UL)	Urban permanent population/ total population	%
Degree of openness (OPEN)	Total imports and exports/regional GDP	%

2.3. Methods

2.3.1. Principal Component Analysis

To avoid potential bias arising from subjective weighting and eliminate differences in measurement units among the indicators, principal component analysis (PCA) was performed using SPSS 26.0 to comprehensively measure the comprehensive development levels of technological innovation and the ecological environment level [32]. First, to ensure dimensional consistency among the indicators while preserving comparability over time, all panel observations were processed jointly; that is, the full sample comprising all regions and all years was subjected to a unified dimensionless transformation.

For positive indicators:

$$X'_{ijt} = \frac{x_{ijt} - min(x_j)}{max(x_j) - min(x_j)} \tag{1}$$

For negative indicators:

$$X'_{ijt} = \frac{max(x_j) - x_{ijt}}{max(x_j) - min(x_j)} \tag{2}$$

where X_{ijt} denotes the original value of indicator j for region i in year t; max(X_j) and min(X_j) denote, respectively, the maximum and minimum values of indicator j across the entire panel dataset; and X'_{ijt} represents the processed indicator value.

Second, the Kaiser-Meyer-Olkin (KMO) test was used to assess the shared variance among variables and the sampling adequacy of the data, while Bartlett's test of sphericity was employed to determine whether the correlation matrix differed significantly from an identity matrix. A relatively high KMO value together with a significant result from Bartlett's test indicated that the variables exhibited a correlation structure suitable for principal component extraction. Before extracting the principal components, the KMO test and Bartlett's test of sphericity were conducted separately for the technological innovation and ecological environment indicators. The results showed that the KMO value for the

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ecological environment subsystem was 0.610, while Bartlett's test of sphericity yielded an approximate chi-square value of 1481.466 with 28 degrees of freedom and was significant at the 1% level. For the technological innovation subsystem, the KMO value was 0.796, and the approximate chi-square value was 7230.839 with 28 degrees of freedom, which was also significant at the 1% level. For the integrated system, the KMO value was 0.815, and the approximate chi-square value was 11,336.569 with 120 degrees of freedom, which was significant at the 1% level. These results indicate that the indicators were sufficiently correlated and therefore suitable for principal component analysis.

Principal components were subsequently extracted from the correlation matrix. The cumulative variance explained by the retained principal components was 61.679% for the ecological environment subsystem, 71.293% for the technological innovation subsystem, and 75.300% for the integrated system. The component loadings of each indicator on the retained principal components were then calculated. Finally, each principal component was weighted according to the proportion of its variance contribution rate in the cumulative variance contribution rate of all retained principal components. On this basis, the comprehensive development level of technological innovation (U_1) and the ecological environment level (U_2) were obtained. Since the PCA composite scores were obtained as linear combinations of dimensionless variables, the unprocessed composite scores may contain negative values, whereas the coupling coordination degree model requires the comprehensive evaluation values of the subsystems to be non-negative. Therefore, to eliminate dimensional differences and satisfy the range requirements of the coupling coordination degree model for subsystem evaluation values, the composite evaluation scores were further transformed through dimensionless interval scaling, as follows:

$$I_{it} = 0.001 + 0.999 \times \frac{S_{it} - S_{min}}{S_{max} - S_{min}} \tag{3}$$

where S_{it} denotes the original PCA composite score of city i in year t; S_{min} and S_{max} denote the minimum and maximum PCA composite scores, respectively, for the corresponding subsystem across all city-year observations from 2013 to 2023; and I_{it} denotes the dimensionless composite index after transformation.

2.3.2. Coupling Coordination Degree Model

To accurately characterize the joint development and relative compatibility of the technological innovation and ecological environment subsystems, this study employed the coupling coordination model [33].

First, the coupling coefficient C between the two systems was calculated as follows:

$$C = \frac{2\sqrt{U_1 U_2}}{U_1 + U_2} \tag{4}$$

where (U_1) represents the comprehensive development level of technological innovation and (U_2) represents the ecological environment level.

Secondly, the comprehensive coordination index T was constructed to reflect the overall development level of the two subsystems:

$$T = \alpha U_1 + \beta U_2 \tag{5}$$

where α and β denote the weights assigned to the two subsystems. Following the relevant literature [33], both weights were set to 0.5.

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Finally, the coupling coordination degree D was calculated as follows:

$$D = \sqrt{C \times T} \tag{6}$$

where $C \in [0, 1]$ and $D \in [0, 1]$. Given that the assigned weights may affect the estimated coupling coordination degree, a sensitivity analysis was conducted using different weight combinations for the ecological environment and technological innovation subsystems. The results showed that the mean coupling coordination degree generally increased as greater weight was assigned to the ecological environment. Nevertheless, the temporal trends and regional spatial patterns remained consistent across the different weighting scenarios. Throughout the study period, the coupling coordination degree of the Yangtze River Economic Belt increased under all weighting scenarios. Regarding regional differences, the lower reaches consistently exhibited higher coupling coordination levels than the middle and upper reaches under all five weight settings. Moreover, the Spearman correlation coefficients between each alternative weighting scenario and the baseline scenario were all greater than 0.970, indicating a high degree of consistency in the city rankings. Therefore, the baseline setting of $\alpha = \beta = 0.5$ did not affect the main conclusions regarding the spatiotemporal variation and regional differentiation of the coupling coordination level, demonstrating the robustness of the results. Following the existing literature [34], the coupling coordination degree D was further classified into six major categories, as shown in Table 3.

Table 3. Types of coupling coordination.

Imbalanced Development Range		**Coordinated Development Range**	
D	Coordination level	D	Coordination level
(0, 0.2]	Severe Imbalance	(0.4, 0.5]	Primary Coordination
(0.2, 0.3]	Moderate Imbalance	(0.5, 0.7]	Good Coordination
(0.3, 0.4]	Low Coordination	(0.7, 1.0]	High-quality Coordination

2.3.3. XGBoost-SHAP Interpretable Machine Learning Model

To further identify the explanatory variables closely associated with the coupling coordination level and their nonlinear association patterns, this study developed an interpretable machine-learning framework integrating XGBoost and SHAP. XGBoost is an ensemble learning algorithm built on gradient-boosted trees, capable of fitting residuals through multiple iterations and exhibiting strong advantages in handling multicollinearity and complex nonlinear relationships. To enhance interpretability, SHAP was employed as the core interpretive approach, which not only quantifies the average marginal contribution of each explanatory variable to the model predictions but also interprets the predictions of complex models and ranks the variables by importance. Detailed methodologies are available in the relevant literature [35].

2.4. Research Framework

This study employed principal component analysis and the coupling coordination degree model and introduced interpretable machine learning to investigate the coordinated development of regional technological innovation and the ecological environment (Figure 2). The research procedure comprised the following steps. First, an evaluation indicator system was established for technological innovation and the ecological environment. Principal component analysis and the coupling coordination model were then applied to examine the spatiotemporal variations in technological innovation, the ecological environment, and their coupling coordination levels across the upper, middle, and lower reaches of the Yangtze

River Economic Belt from 2013 to 2023. Second, the XGBoost algorithm was used to evaluate model predictive performance, and variable substitution, winsorization, and sample-period adjustment were employed to test the stability of the identified results. Model accuracy was assessed using the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). Finally, the SHAP interpretive framework was introduced to analyze the feature importance and nonlinear associations of the associated factors, thereby identifying important explanatory variables closely related to the coupling coordination level between technological innovation and the ecological environment.

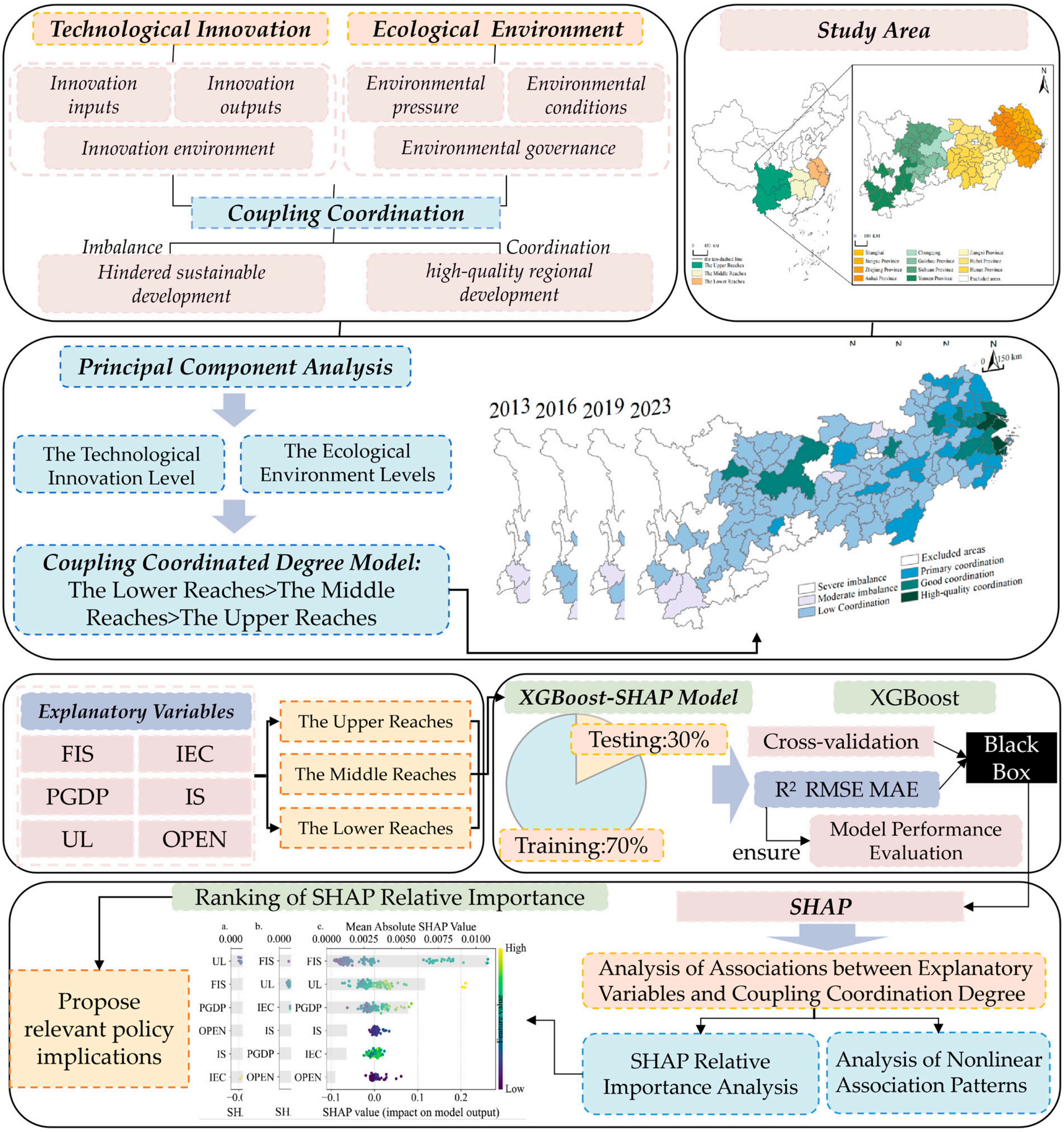

Figure 2. Research framework.

3. Results

3.1. Spatiotemporal Evolution of the Comprehensive Development Level of Technological Innovation

As shown in Table 4 and Figure 3, the comprehensive development level of technological innovation in the Yangtze River Economic Belt increased steadily overall during the study period. However, pronounced regional disparities persisted, with a clear spatial pattern characterized by higher levels in the east and lower levels in the west.

Table 4. Mean comprehensive development level of technological innovation.

Region	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Upper Reaches	0.067	0.068	0.070	0.072	0.074	0.078	0.081	0.085	0.090	0.093	0.097
Middle Reaches	0.071	0.073	0.075	0.077	0.080	0.086	0.090	0.095	0.102	0.111	0.121
Lower Reaches	0.112	0.115	0.119	0.124	0.128	0.137	0.144	0.157	0.173	0.185	0.207

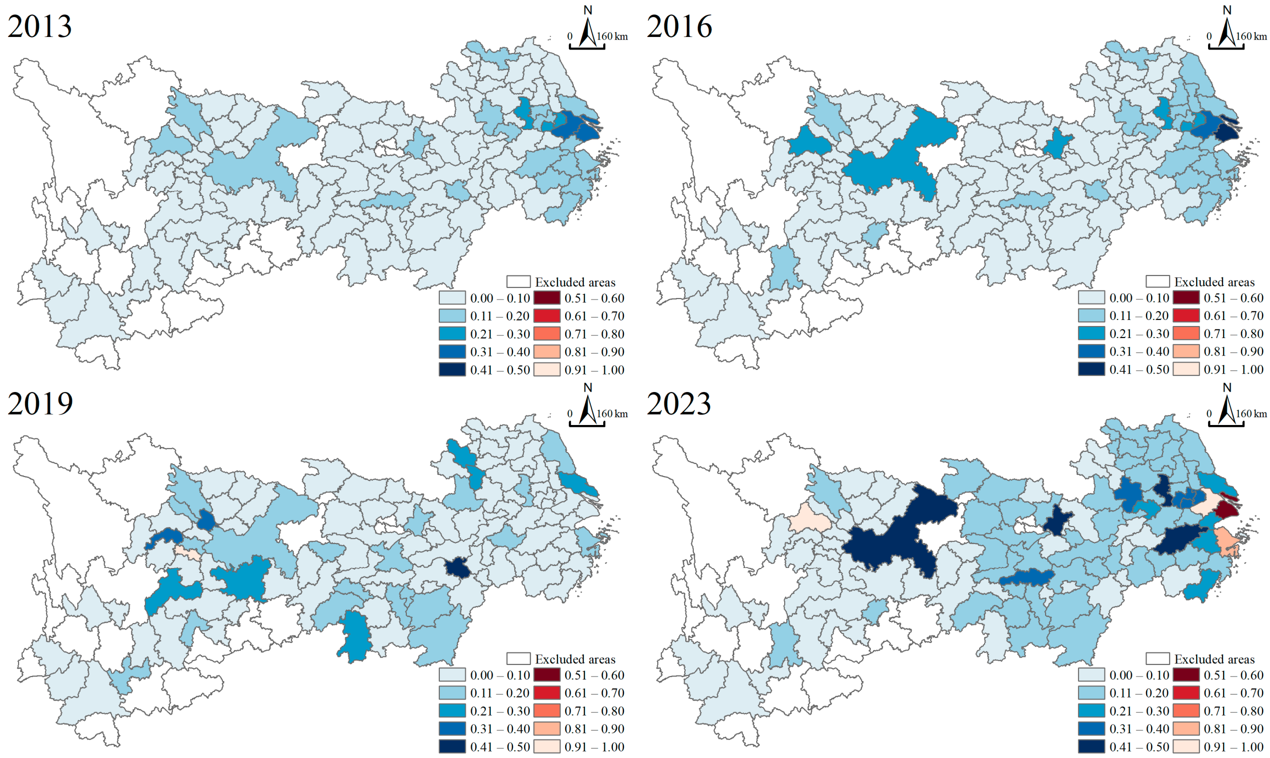

Figure 3. Spatial variation in the comprehensive development level of technological innovation.

From a temporal perspective, the comprehensive development level of technological innovation increased steadily across all three regions. The lower reaches recorded the fastest growth, rising from 0.112 to 0.207, an increase of approximately 84.821%. The middle reaches followed, increasing from 0.071 to 0.121, or approximately 70.423%. Growth was comparatively slower in the upper reaches, where the overall development level increased from 0.067 to 0.097, representing an increase of only 44.776%. Meanwhile, the interregional gap widened from 0.045 in 2013 to 0.110 in 2023, indicating an increasingly pronounced concentration of innovation resources in the lower reaches and a further widening of regional disparities. Spatially, technological innovation in the Yangtze River Economic Belt exhibited an east-to-west declining gradient, with high-value areas gradually expanding from isolated points into contiguous clusters. In 2013, low-value areas predominated across the study area, while high-value cities were sparsely distributed. Between 2016 and 2019, regional technological innovation levels increased, accompanied by a gradual expansion of high-value areas. By 2023, contiguous high-value clusters had emerged in the lower reaches, while distinct high-value areas were also observed around the provincial capitals of Wuhan, Changsha, and Nanchang in the middle reaches. The Chengdu–Chongqing region in the upper reaches showed a comparatively modest improvement.

These patterns may be attributed to differences in regional economic foundations and the distribution of innovation resources. The lower reaches have a high concentration of universities, research institutions, and high-tech enterprises [36], which facilitates the intensive allocation of innovation factors. In contrast, the upper reaches, constrained by geographic conditions and their stage of development, face a relative scarcity of innovation resources. Moreover, the tendency for innovation factors to flow toward higher-tier regions has, to some extent, reinforced spatial differentiation.

3.2. Spatiotemporal Evolution Characteristics of the Ecological Environment Level

As shown in Table 5 and Figure 4, the ecological environment level of the Yangtze River Economic Belt exhibited an overall fluctuating upward trend during the study period. Its spatial distribution differed markedly from that of technological innovation, displaying a clear spatial mismatch. Overall, the pattern was characterized by higher levels in the middle reaches, followed by the upper reaches, and relatively lower levels in the lower reaches.

Table 5. Mean values of the ecological environment level.

Region	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Upper Reaches	0.575	0.584	0.603	0.624	0.632	0.648	0.662	0.666	0.667	0.672	0.684
Middle Reaches	0.600	0.606	0.614	0.627	0.639	0.628	0.652	0.666	0.670	0.679	0.691
Lower Reaches	0.598	0.604	0.615	0.625	0.636	0.641	0.649	0.651	0.654	0.658	0.664

From a temporal perspective, the average ecological environment levels across the three major regions increased steadily. In the upper reaches, the ecological environment level increased from 0.575 to 0.684, an increase of approximately 18.957%; in the middle reaches, it increased from 0.600 to 0.691, around 15.167%; and in the lower reaches, it rose from 0.598 to 0.664, an increase of about 11.037%. Notably, the levels across the three regions were relatively close in 2013, but by 2023, the middle reaches had surpassed the upper reaches to become the highest, while the lower reaches lagged behind. The ecological environment level exhibited an interregional pattern of "middle reaches > upper reaches > lower reaches", reflecting a degree of structural adjustment in regional ecological development. From a spatial perspective, ecological conditions in the Yangtze River Economic Belt generally followed a pattern of higher values in the central region and relatively lower values in the east and west. In 2013, most areas fell within the range of 0.41–0.60, with high-value zones scattered sporadically. Between 2016 and 2019, ecological environment levels improved in the middle and upper reaches, predominantly falling within the range of 0.61–0.70. By 2023, contiguous high-value zones had emerged along the border between Hubei and Hunan in the middle reaches, in the mountainous areas of Hunan and Jiangxi, and in the southern parts of Sichuan and Chongqing in the upper reaches, while riverine areas in the lower reaches also showed notable improvement. Overall, spatial disparities in ecological environment levels gradually narrowed over time.

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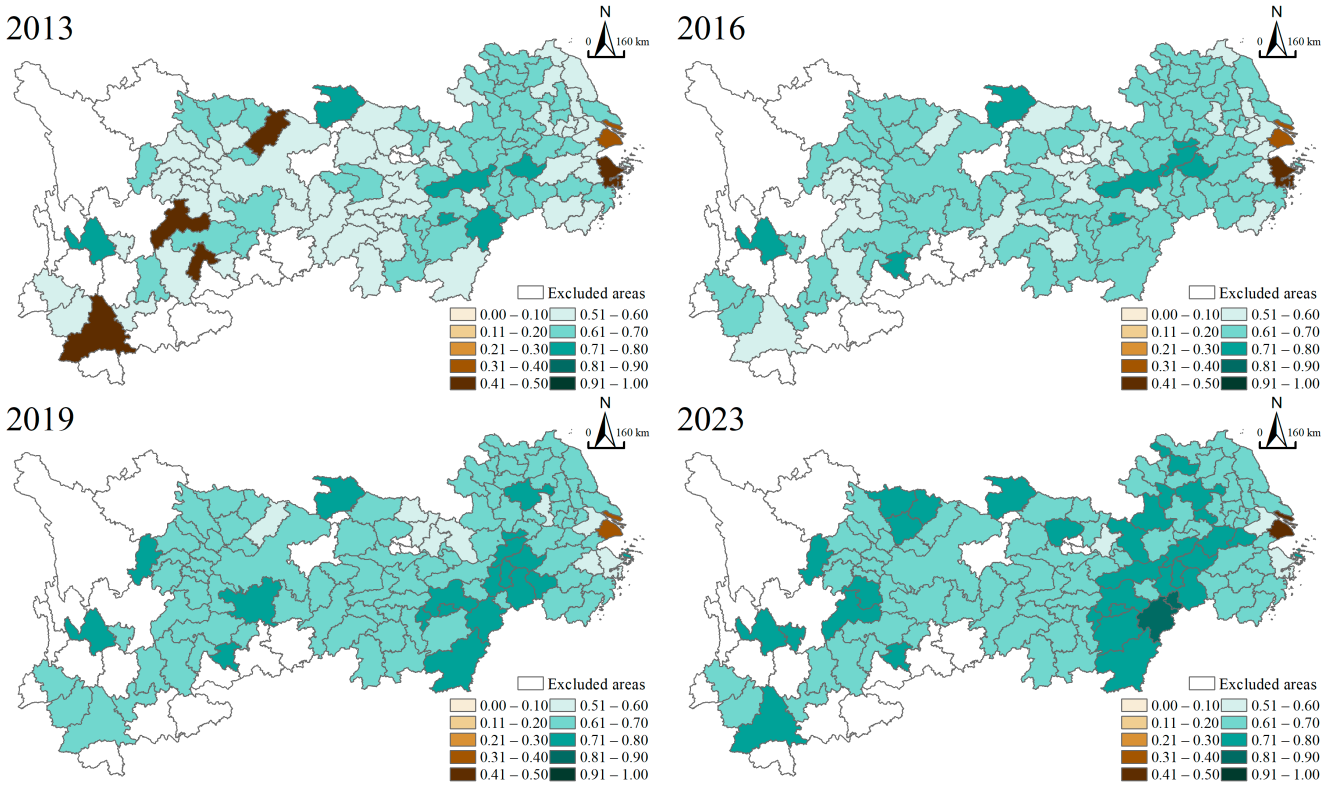

Figure 4. Spatial variation of ecological environment level.

These patterns are partly related to regional natural conditions and the intensity of human activities. The middle and upper reaches benefit from superior natural foundations, giving them a higher ecological carrying capacity than the lower reaches. Although the lower reaches have experienced steady improvements in the ecological environment level through environmental governance, their ecological environment level remains relatively low due to high population density and land development pressures [37]. Moreover, national strategies have continuously strengthened ecological protection efforts. Following the implementation of the Yangtze River Economic Belt strategy in 2014 and the establishment of the "prioritizing protection over development" policy in 2016, pollution control, ecological restoration, and river basin management have been coordinated across the regions along the river [38], resulting in a significant enhancement of overall ecological environment quality.

3.3. Spatiotemporal Differentiation of Coupling Coordination Level

Based on model estimations (Table 6 and Figure 5), the coupling coordination degree between technological innovation and the ecological environment in the Yangtze River Economic Belt exhibited an overall fluctuating upward trend over the study period. Spatially, it followed a clear gradient pattern, decreasing progressively from east to west. This indicates that under the strategic orientation of prioritizing ecological conservation and promoting green development, the region's development level has steadily improved, although internal disparities and structural imbalances remain pronounced.

From a temporal perspective, the coupling coordination degree across the three major regions increased steadily, although the growth rates varied considerably. The lower reaches experienced the largest increase, rising from 0.414 to 0.461 (an 11.353% increase) and consistently maintaining a leading position. The middle reaches ranked second, with the coupling coordination degree increasing from 0.338 in 2013 to 0.398 in 2018, declining to 0.346 in 2019, and subsequently recovering steadily. In the upper reaches, it rose slowly from 0.334 to 0.347, representing the smallest increase of 3.892%. These patterns may be primarily attributed to regional heterogeneity in the overall development levels and structural characteristics of technological innovation and the ecological environment. Owing to its strong innovation foundation and sustained ecological governance, the lower reaches achieved a positive development pattern in which innovation facilitated ecological improvement [39]. In the middle reaches, the concentrated implementation of water-source protection, pollution-source control, and ecological restoration across the Yangtze River Economic Belt produced periodic improvements in environmental governance in several cities. The subsequent industrial transformation and continued industrial expansion may have increased energy consumption and environmental pressure, resulting in a temporary fluctuation [40]. Although the upper reaches possess a sound ecological foundation, their relatively weak technological innovation base limits the effective technical support available for ecological governance, thereby constraining improvements in the coupling coordination degree.

Table 6. Mean values of coupling coordination level.

Region	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Upper Reaches	0.334	0.335	0.338	0.337	0.334	0.337	0.342	0.341	0.342	0.344	0.347
Middle Reaches	0.338	0.338	0.346	0.340	0.339	0.398	0.346	0.352	0.356	0.365	0.376
Lower Reaches	0.414	0.415	0.420	0.416	0.416	0.420	0.428	0.430	0.441	0.449	0.461

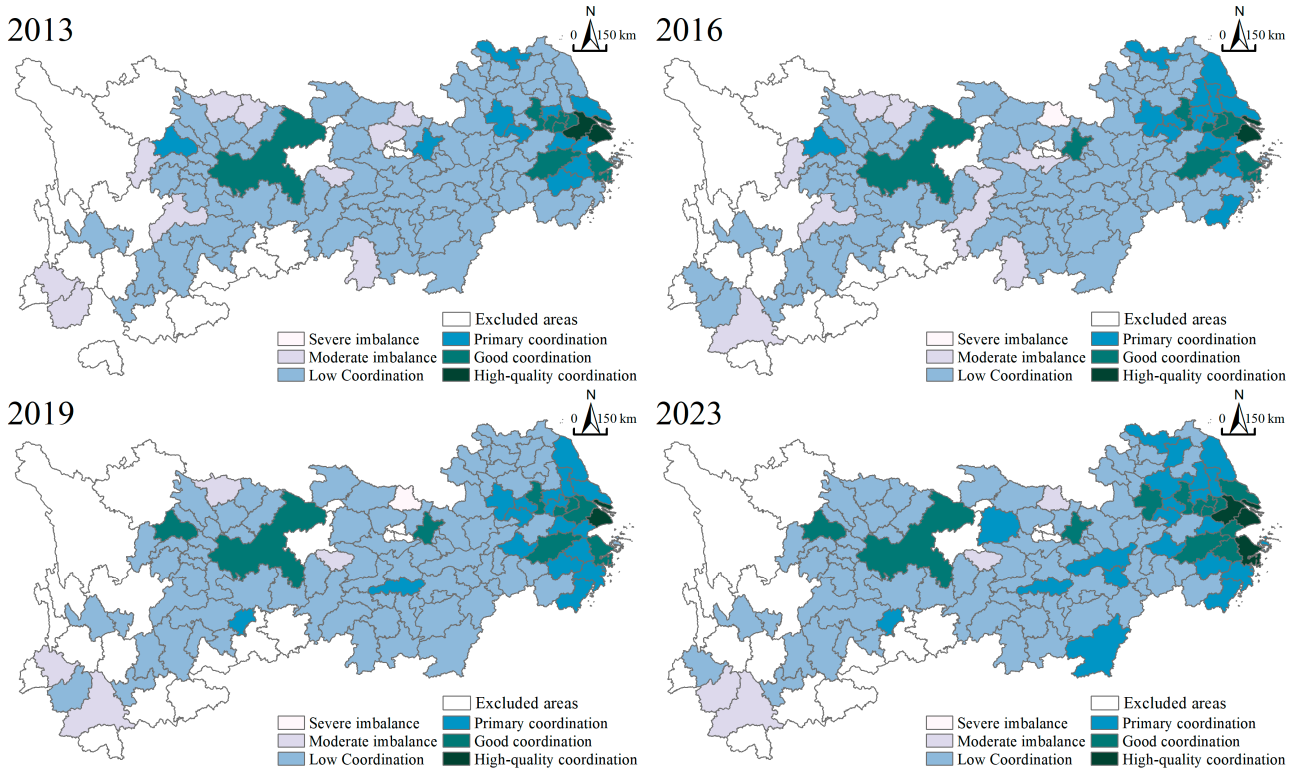

Figure 5. Spatiotemporal distribution of coupling coordination level.

In terms of spatial patterns, the coupling coordination degree exhibited a clear "higher in the east, lower in the west" distribution. In 2013, the study area was predominantly at the barely coordinated stage. Cities with higher coordination levels were concentrated in the core area of the Yangtze River Delta in the lower reaches and around provincial capitals in the middle reaches, while 21.212% of the cities in the upper reaches remained in a state of imbalance. By 2023, 63.415% of the cities in the lower reaches had entered the primary coordination stage, and primary coordination had become increasingly evident among provincial capital urban clusters along the Yangtze River in the middle reaches. However, most cities in the upper reaches (approximately 84.848%) remained at the barely coordinated stage. This spatial pattern may be associated with two interrelated factors. First, the lower reaches are characterized by a concentration of innovation resources and relatively strong environmental governance capacity, corresponding to a high level of synergy between technological innovation and ecological development. Second, the agglomeration of innovation resources in the lower reaches may constrain knowledge spillovers and resource diffusion to the middle and upper reaches. Combined with underdeveloped mechanisms for cross-regional ecological compensation and collaborative governance, these conditions are associated with widening spatial disparities and the pronounced concentration of cities with high coupling coordination levels in the eastern part of the Yangtze River Economic Belt.

3.4. SHAP-Based Global Importance Analysis of Explanatory Variables Associated with the Coupling Coordination Degree

3.4.1. Machine Learning Model Training

The coupling coordination degree was used as the prediction target, and six associated factors were included as input features to construct separate XGBoost regression models for the upper, middle, and lower reaches. To eliminate differences in measurement scales and improve training stability, all continuous variables were normalized. The samples were randomly divided into training and test sets at a ratio of 70:30. To ensure the reproducibility of the results, fixed random seeds were used during the training–test split, cross-validation, and model training. Hyperparameter tuning was performed only within the training set. GridSearchCV combined with five-fold cross-validation was used to evaluate the predictive performance of different parameter combinations. Specifically, the candidate numbers of decision trees were 100, 120, 140, 160, 180, and 200; the candidate maximum tree depths were 3, 4, 5, and 6; and the candidate learning rates were 0.01, 0.03, 0.05, and 0.10. Based on these candidate values, the optimal combination of hyperparameters was selected for each regional model. Finally, the regional models used 160 decision trees, a random seed of 296, a maximum tree depth of 4, a learning rate of 0.05, reg_alpha = 0, reg_lambda = 1, subsample = 0.8, and colsample_bytree = 0.8, and the objective function was set to squared-error regression. The results showed that the coefficients of determination for the upper, middle, and lower reaches were 0.859, 0.858, and 0.909, respectively, and all RMSE values were below 0.05 (Table 7).

Table 7. Results of the robustness checks for the XGBoost model.

Region	Evaluation Metric	Base Model	Variable Substitution	Winsorization	Exclusion of Later-Period Observations
Upper Reaches	R^2	0.859	0.810	0.738	0.751
	RMSE	0.031	0.025	0.030	0.027
	MAE	0.026	0.017	0.019	0.018
Middle Reaches	R^2	0.858	0.781	0.716	0.700
	RMSE	0.029	0.021	0.023	0.023
	MAE	0.023	0.015	0.018	0.017
Lower Reaches	R^2	0.909	0.915	0.859	0.879
	RMSE	0.042	0.030	0.038	0.034
	MAE	0.031	0.021	0.025	0.021

To reduce the risk of temporal information leakage that may arise from random splitting and further evaluate the cross-time predictive ability of the models, this study adopted a time-based validation approach. The normalization parameters were estimated exclusively from the training data and then applied to the corresponding test or validation data to avoid information leakage. Considering the size of the initial training sample, the years 2016–2023 were used as rolling validation years. For each validation year, all observations before that year were used as the training set, and observations from the validation year were used as the validation set. For example, the 2016 validation used data from 2013–2015 for training, the 2017 validation used data from 2013–2016 for training, and so forth, until data from 2013–2022 were used to predict the 2023 observations. To avoid temporal information leakage, observations from the validation year were not used for model training, learning of encoding rules, or parameter specification. The time-based validation experiments used a pre-specified XGBoost parameter combination, and no hyperparameter tuning was conducted based on the validation-year samples. The results showed that the R^2 values for the upper, middle, and lower reaches were 0.893, 0.811, and 0.886, respectively, while both RMSE and MAE were below 0.04, indicating that the models had good out-of-time predictive ability within the study area.

In addition, considering the potential spatial dependence among neighboring cities, a global Moran's I test was further conducted based on out-of-sample prediction residuals. A six-nearest-neighbor spatial weight matrix and 999 permutation tests were used. The results showed that the residual Moran's I values for the upper, middle, and lower reaches were 0.139, 0.117, and 0.170, respectively, with corresponding p-values of 0.081, 0.109, and 0.062. None of these values reached the 5% significance level. This indicated that under the spatial weight specification used in this study, the out-of-sample prediction residuals did not exhibit significant global spatial autocorrelation.

3.4.2. Robustness Tests

To assess the robustness of the feature importance estimates derived from the interpretable machine-learning models, three tests were conducted (Table 7). First, a variable substitution test was performed by replacing IEC with the cultural environment variable and retraining the models to determine whether indicator selection affected model interpretation. Second, the continuous variables were winsorized at the 1st and 99th percentiles to reduce the influence of extreme values on model training and the SHAP-based feature importance rankings. Third, the models were retrained after excluding observations from the later years of the study period to examine whether changes in the macroeconomic environment or observations from exceptional periods affected the results. The repeated validation results showed that the model evaluation metrics remained generally consistent under most specifications, although the degree of stability varied across regions. The results for the lower reaches were relatively stable: the relative importance of FIS and UL consistently ranked among the top three, and the top-three feature rankings were largely consistent between the winsorization test and the exclusion of later-period observations. In the upper reaches, UL and FIS maintained relatively high importance under most specifications, but the correlation of feature rankings declined after later-period observations were excluded. The middle reaches were more sensitive to variable substitution; under some specifications, the model R^2 declined, and the ranking of explanatory variables fluctuated to some extent. Overall, the core explanatory variables in the upper, middle, and lower reaches exhibited a certain degree of stability, although the results for the upper and middle reaches were relatively sensitive to some variable specifications and sample-period adjustments.

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3.4.3. Importance of Explanatory Variables

Feature-importance plots were generated to reveal the relative importance of each variable for the coupling coordination level (Figure 6). The SHAP relative importance was calculated based on the mean absolute SHAP values of the explanatory variables, expressed as the proportion of the mean absolute SHAP value of a given explanatory variable in the sum of the mean absolute SHAP values of all explanatory variables. The results showed that, overall, FIS and UL exhibited relatively high and stable importance across the upper, middle, and lower reaches. However, the importance of the explanatory variables varied across regions. Specifically, in the upper reaches, the urbanization level had the highest relative importance, accounting for 36.363%, followed by fiscal autonomy and GDP per capita, each accounting for 22.727%. The degree of openness, industrial structure upgrading, and the share of industrial electricity consumption showed relatively limited importance. In the middle reaches, fiscal autonomy, the urbanization level, and the share of industrial electricity consumption each accounted for 25.000%, while the other factors showed relatively limited importance. In the lower reaches, fiscal autonomy was the most important feature, with a relative importance of 42.308%, followed by the urbanization level at 26.923% and then by PGDP, IS, IEC, and OPEN.

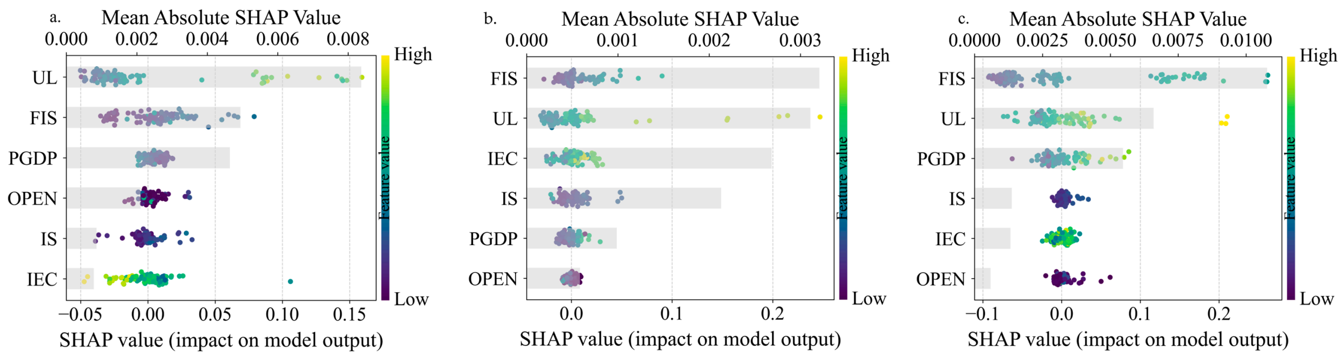

Figure 6. Feature importance ranking of explanatory variables associated with the coupling coordination degree: (**a**) upper reaches of the Yangtze River Economic Belt; (**b**) middle reaches of the Yangtze River Economic Belt; (**c**) lower reaches of the Yangtze River Economic Belt.

3.5. Nonlinear Characteristics of Explanatory Variables

To more clearly illustrate the complex nonlinear associations between the explanatory variables and the response variable, locally weighted scatterplot smoothing (LOWESS) was used to visualize the relationships between the associated factors and the coupling coordination degree between technological innovation and the ecological environment in the Yangtze River Economic Belt. Each dot represents a city-year observation, and its color indicates the normalized value of the corresponding feature, ranging from low (dark purple) to high (yellow).

The results presented in Figure 7 showed the nonlinear associations between the explanatory variables and the coupling coordination degree in the upper reaches. When IS, FIS, and UL exceeded 0.167, 0.119, and 0.528, respectively, their SHAP values shifted to positive values. This finding was consistent with previous studies, suggesting that industrial structure upgrading, a higher urbanization level, and greater fiscal autonomy were associated with more favorable coupling coordination between technological innovation and the ecological environment [41]. Meanwhile, when IEC and PGDP exceeded 0.694 and 0.391, respectively, their SHAP values shifted to negative values. This pattern suggested that, in the upper reaches, some cities still relied on resource-intensive industries or traditional manufacturing for economic development, which may have reduced ecological performance [42]. Similarly, excessively high industrial electricity consumption may have been accompanied by greater energy consumption and environmental pressure, corresponding to a relatively lower coupling coordination level [43]. The effect of OPEN on the coordination degree showed a pattern of first decreasing and then increasing, indicating that the marginal explanatory direction of openness for the coupling coordination level varied across different value ranges.

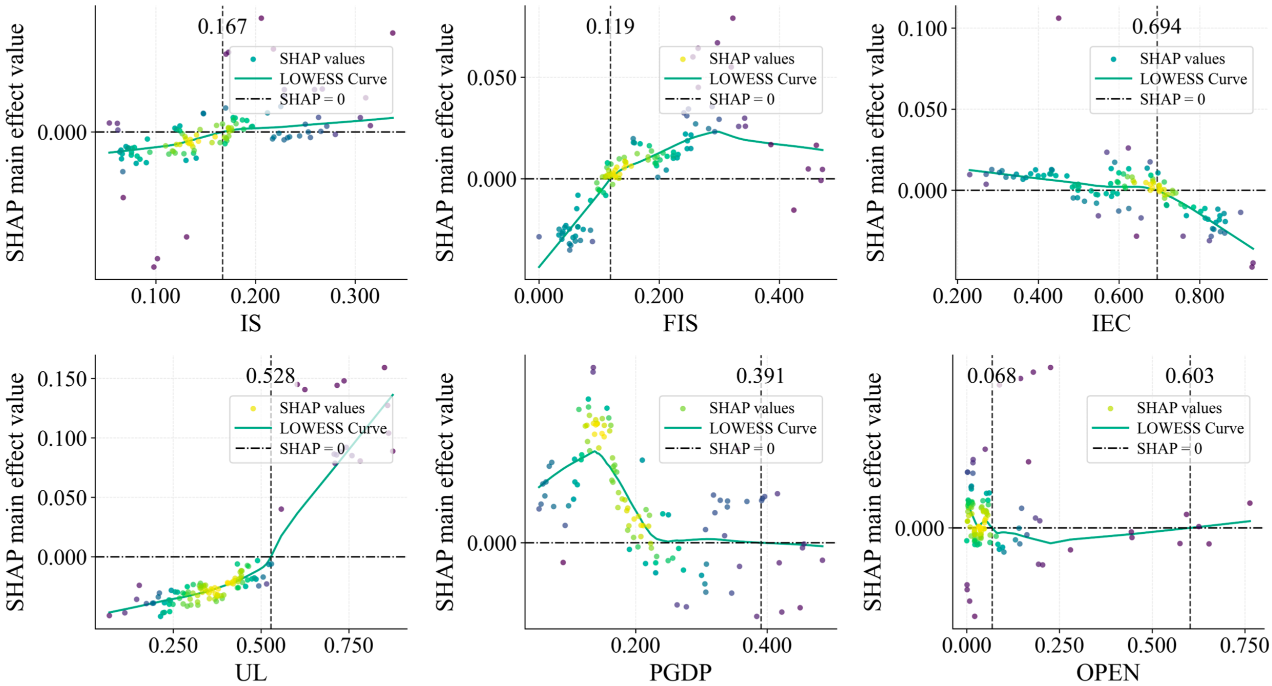

Figure 7. Nonlinear associations between explanatory variables and the coupling coordination degree in the upper reaches.

As shown in Figure 8, when FIS, IEC, UL, and PGDP in the middle reaches exceeded 0.233, 0.551, 0.573, and 0.280, respectively, these factors were positively associated with the coupling coordination degree. This indicated that in the middle reaches, stronger local public fiscal capacity, improved urban infrastructure, and more favorable economic conditions corresponded to a higher level of coordination between technological innovation and the ecological environment [44]. IS exhibited an inverted U-shaped pattern. Given the relatively high level of industrialization in the middle reaches, a larger share of traditional industries may have increased environmental pressure, thereby showing a negative association with the coupling coordination level [45]. By contrast, OPEN was negatively associated with the predicted coupling coordination degree. When OPEN exceeded 0.052, its SHAP value shifted from positive to negative, possibly because the beneficial technological and environmental effects of opening-up activities in the middle reaches have not yet been fully realized [46].

As shown in Figure 9, IS, FIS, UL, and PGDP all exhibited clear positive associations with the coupling coordination degree in the lower reaches. This pattern may have been related to the stronger local fiscal capacity, higher urbanization level, and more solid economic foundation of the lower reaches, which were generally accompanied by greater investment in technological innovation, better environmental infrastructure, and stronger capacity for green technology application. When IEC exceeded 0.640, its SHAP value shifted from negative to positive; however, the SHAP value began to decline at approximately 0.700. This pattern suggested that within a certain range, industrial activity was associated with economic growth and innovation output, whereas an excessively high share of industrial electricity consumption may also correspond to greater energy consumption and environmental pressure. For OPEN, SHAP values were positive within the range of 0.03–0.20, whereas they were close to zero within the range of 0.20–0.75. This indicated that the degree of openness had relatively limited marginal explanatory strength for the coupling coordination level in the lower reaches [47].

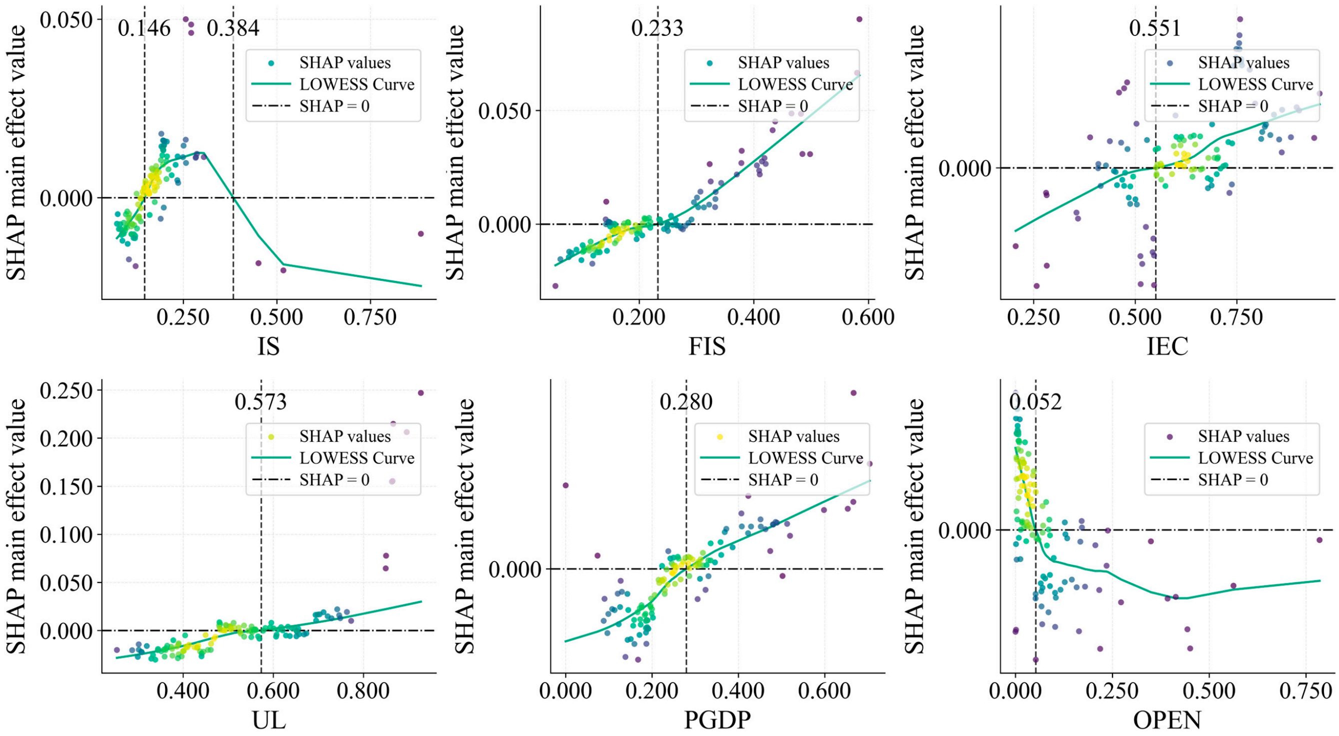

Figure 8. Nonlinear associations between explanatory variables and the coupling coordination degree in the middle reaches.

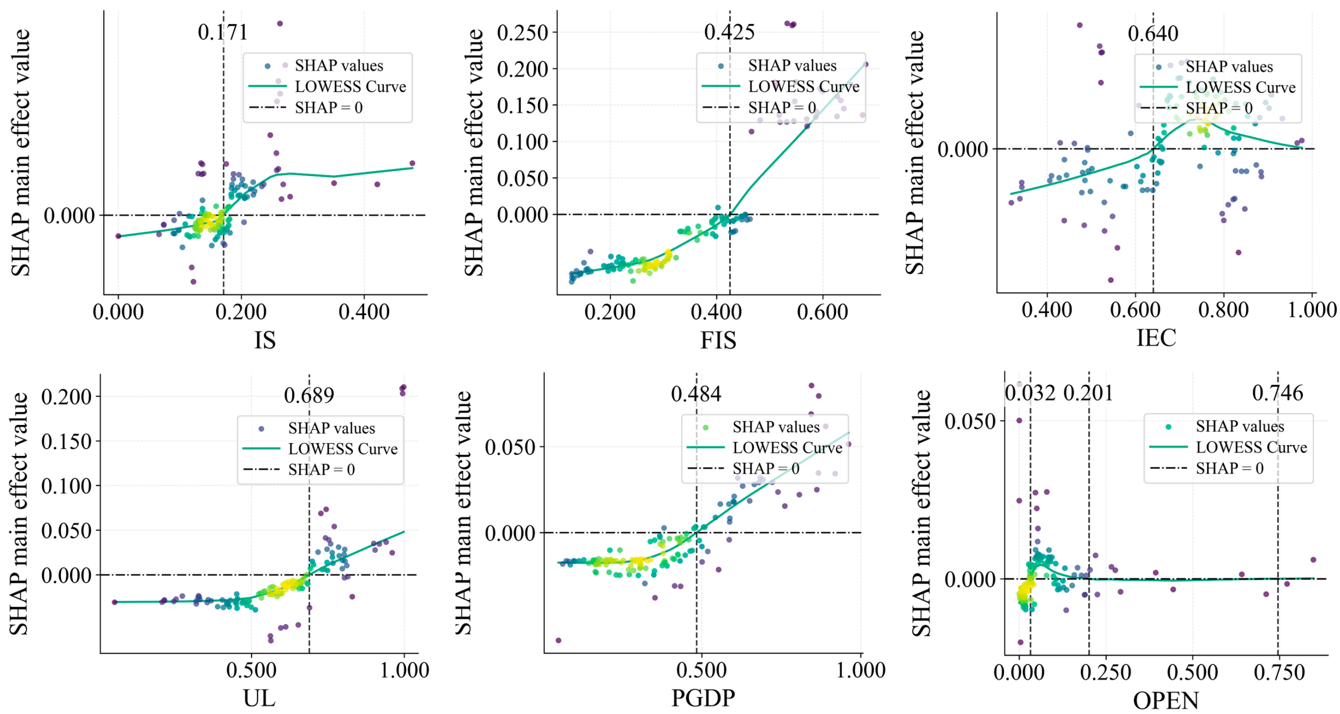

Figure 9. Nonlinear associations between explanatory variables and the coupling coordination degree in the lower reaches.

4. Discussion and Limitations

4.1. Discussion

Investigating the coupling coordination between technological innovation and the ecological environment helps overcome the limitations of evaluating the two systems separately. It enables an integrated examination of the degree of alignment between innovation-driven development and ecological protection, facilitates the identification of potential spatial mismatches between the concentration of innovation resources and ecological foundations, and provides a reference for differentiated policies concerning innovation support, industrial transformation, and ecological governance. Taking the Yangtze River Economic Belt as the study area, this study divided the area into the upper, middle, and lower reaches to examine regional differences in the coupling coordination between technological innovation and the ecological environment, with the aim of providing useful insights for future sustainable development.

First, the overall temporal trend and spatial pattern identified in this study are consistent with the findings of Zheng et al. [48]. During the study period, the concentration of technological innovation resources, the comprehensive development level of technological innovation, and the ecological environment level of the Yangtze River Economic Belt all improved. These changes were accompanied by continued improvements in regional innovation investment, environmental governance, and green development. However, technological innovation and the ecological environment did not exhibit synchronous spatial evolution. This finding indicates that a higher level of technological innovation does not necessarily correspond to better ecological conditions. The relationship between innovation activities and the ecological environment may also be associated with industrial structure, patterns of energy use, conditions for technology application, and environmental governance capacity.

Second, the coupling coordination level exhibited a pronounced regional gradient, suggesting that the observed association patterns differed across regions. The upper reaches have relatively favorable ecological foundations but comparatively weak economic and innovation capacities, and stable technological linkages between ecological conservation and industrial development have yet to be fully established. This pattern suggests that ecological advantages alone may be insufficient to sustain improvements in coupling coordination. The middle reaches are undergoing both continued industrialization and industrial restructuring. Environmental pressures associated with traditional industrial activities coexist with the potential green benefits of industrial upgrading, corresponding to a more stage-dependent and fluctuating pattern of coordinated development. The lower reaches possess relatively strong fiscal capacity, abundant innovation resources, and a more developed system for translating research outcomes into practical applications, providing more favorable conditions for applying technological innovation to environmental governance. Nevertheless, the high concentration of population and industrial activities is also associated with continued pressure on land, energy resources, and ecological space. These regional differences indicate that there is no single pathway applicable to all regions. Instead, coordinated development requires consideration of the relationships among innovation investment, industrial transformation, urbanization, and environmental carrying capacity in accordance with each region's development stage.

Finally, the XGBoost-SHAP model was used to analyze the relative importance of each explanatory variable for the coupling coordination level. The results showed that fiscal autonomy and the urbanization level were important factors associated with the coupling coordination level, while the roles of the share of industrial electricity consumption, industrial structure upgrading, GDP per capita, and the degree of openness also exhibited clear regional differences and nonlinear variations.

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In summary, differentiated policy priorities should be established according to regional development conditions. The upper reaches should improve technological innovation capacity and public services while preserving their ecological foundations. The middle reaches should place greater emphasis on the alignment among industrial restructuring, energy use, and ecological governance. The lower reaches should focus on the efficiency with which innovation outcomes are applied to green development and the ecological pressures associated with intensive development. At the basin level, mechanisms for interregional innovation cooperation, ecological compensation, and coordinated pollution control should be further improved.

4.2. Limitations

First, owing to the limitations of city-level macro panel data, this study gives limited consideration to climate, water temperature, land use, ecosystem services, and related factors. It therefore cannot fully capture the vulnerability and diversity of ecosystems across the Yangtze River Economic Belt. In addition, the technological innovation index does not adequately account for innovation capacity or innovation efficiency. Second, cities in different geographical locations vary substantially in their natural endowments, policy advantages, and socioeconomic conditions, while the present analysis does not fully capture complex within-city dynamics. Following the relevant literature [49], future research could incorporate multisource data, including remote-sensing, meteorological, and hydrological data, as well as indicators such as R&D expenditure per capita, R&D intensity, and patents per 10,000 persons. It will also broaden the indicator dimensions of technological innovation and the ecological environment and employ city fixed-effects models, spatial econometric methods, and causal machine-learning approaches to identify within-city changes and assess potential causal relationships, thereby improving the rigor and explanatory power of the findings.

5. Conclusions

This study examined 111 prefecture-level and higher-level cities in the Yangtze River Economic Belt from 2013 to 2023. An indicator system was constructed for technological innovation and the ecological environment. Principal component analysis and the coupling coordination model were used to measure the comprehensive development level of technological innovation, the ecological environment level, and the coupling coordination degree between the two systems. An interpretable machine-learning model integrating XGBoost and SHAP was subsequently employed to identify the key factors associated with the coupling coordination level. The main conclusions are as follows.

(1) During the study period, both the comprehensive development level of technological innovation and the ecological environment level increased, although a pronounced spatial mismatch existed between them. Technological innovation exhibited a stable east-to-west declining pattern, with regional disparities widening over time. By contrast, owing to intensive development pressure in the lower reaches and the ecological conservation advantages of the middle and upper reaches, the ecological environment level was generally highest in the middle reaches, followed by the upper reaches and then the lower reaches. This finding indicates that the spatial concentration of technological innovation resources does not fully correspond to the distribution of ecological conditions.

(2) The coupling coordination level improved from a relatively low baseline and exhibited a pronounced spatial gradient. Overall, the Yangtze River Economic Belt underwent a gradual transition from the barely coordinated stage to the primary coordination stage. By 2023, 63% of the cities in the lower reaches had entered the primary coordination category. The middle reaches remained in a transitional stage characterized by fluctuating improve-

ment, whereas most cities in the upper reaches remained at the barely coordinated level, with only limited improvement.

(3) The XGBoost-SHAP results indicated that urbanization level and fiscal autonomy exhibited relatively high importance across the upper, middle, and lower reaches. However, the importance rankings and marginal contribution patterns of the individual factors exhibited regional heterogeneity and nonlinear variation.

Overall, promoting the coordinated development of technological innovation and the ecological environment in the Yangtze River Economic Belt requires full consideration of differences in regional conditions, the implementation of differentiated development strategies, and greater emphasis on interregional coordination and cooperation.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

IEC: industrial electricity consumption; FIS: fiscal autonomy; PGDP: per-capita gross regional product; IS: industrial structure upgrading; UL: urbanization level; OPEN: degree of openness; KMO: Kaiser–Meyer–Olkin; PCA: Principal Component Analysis.

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