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Article

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Spatiotemporal Patterns, Spatial Spillovers, and Nonlinear Drivers of Sports Tourism Ecological Development in China

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Abstract: Integrating the development foundations, market performance, and ecological conditions of sports tourism into a unified evaluation framework is essential for assessing the sustainability of regional sports tourism development. Based on panel data for 31 provincial-level regions in China from 2013 to 2023, together with georeferenced data on sports tourism projects, this study employs the entropy-weighted TOPSIS method to construct a composite index of sports tourism ecological development and conducts empirical analyses using a two-way fixed-effects spatial Durbin model and the XGBoost-SHAP framework. The results show that sports tourism ecological development followed a fluctuating upward trend during the study period, with urbanization exerting a significant positive effect on local development. A clear regional gradient of "eastern–central–northeastern–western China" is observed, with intra-regional disparities constituting the primary source of overall inequality and relatively less-developed regions, particularly western and northeastern China, exhibiting greater potential for improvement. Economic development, road density, and railway density generate positive spatial spillover effects on neighboring regions, whereas green technological innovation and annual mean NDVI exhibit negative spillovers. Further analysis indicates that sports tourism ecological development is also associated with cross-provincial transportation-network coordination, consumption expansion driven by urbanization, and interactions between green technological innovation and underlying ecological conditions. Moreover, the contribution of green technological innovation exhibits a relatively stable nonlinear transition interval.

Keywords: sports tourism ecological development; sustainable tourism; spatial Durbin model; spatial spillover effects; XGBoost–SHAP; nonlinear relationships

1. Introduction

The United Nations 2030 Agenda for Sustainable Development emphasizes the need to balance economic growth, resource use, environmental protection, and ecological well-being (United, 2015). ourism contributes to regional development through consumption, employment, and inter-industry linkages(Lee & Chang, 2008). but its expansion may also intensify pressures on energy, water, land, and ecological space (Buckley, 2012; Lenzen et al., 2018). Regional differences in resource endowments, infrastructure, industrial foundations, and environmental governance further generate substantial spatial heterogeneity in tourism development (Yang & Fik, 2014). while transportation networks can strengthen cross-regional tourism linkages and spillovers (Gong et al., 2023) . Consequently, tourism assessment has increasingly shifted from a narrow focus on visitor volumes and economic returns toward broader frameworks incorporating development conditions, market performance, and ecological sustainability.

Sports tourism is particularly relevant to this transition because many activities depend directly on natural and ecological resources. Mountain recreation, ice and snow tourism, water-based sports, and camping rely on landscapes, climate, and water resources while also requiring market demand, infrastructure, and supporting services. Sports tourism therefore represents not only an integration of sport and tourism activities but also a development process shaped by economic, social, and environmental conditions (Hinch et al., 2016). Assessing it solely through tourism revenue, visitor numbers, or project scale may therefore overlook the ecological constraints that shape long-term development. In this study, sports tourism ecological development refers to the coordinated state of sports tourism development and ecological conditions under regional environmental constraints (Fang et al., 2025).

Despite growing research on sports tourism and sustainable tourism, several gaps remain. First, relatively few studies have integrated development foundations, market performance, resource supply, and ecological conditions within a unified framework for assessing sports tourism developmentt (Mascarenhas et al., 2021). Second, regional statistical analyses and georeferenced tourism project studies have generally been conducted separately, leaving limited evidence on how overall regional development relates to the spatial organization of specific sports tourism projects (Wang et al., 2020). Third, although spatial dependence and spillovers have been widely documented in tourism research, the interprovincial effects of economic, transportation, industrial, technological, and ecological factors on sports tourism ecological development remain insufficiently understood (Jiao et al., 2025). Finally, conventional econometric approaches mainly capture average effects and may overlook nonlinear and condition-dependent relationships. Although XGBoost-SHAP has recently been applied in sustainable tourism research to identify nonlinearities and interactions (Jia et al., 2025). ts application to sports tourism ecological development remains limited.

Accordingly, this study examines 31 provincial-level regions in China from 2013 to 2023 and develops an integrated framework combining composite evaluation, project-level spatial analysis, spatial econometrics, and interpretable machine learning. The analysis focuses on four interrelated dimensions: spatiotemporal evolution, the spatial organization of sports tourism projects, interprovincial spillover effects, and nonlinear relationships. Entropy-weighted TOPSIS and the Theil index are used to assess development levels and regional disparities, GIS-based methods characterize project-level spatial patterns, the spatial Durbin model distinguishes local from cross-provincial effects, and XGBoost-SHAP identifies nonlinear responses and interactions. Together, these approaches establish the analytical framework shown in Fig. 1.

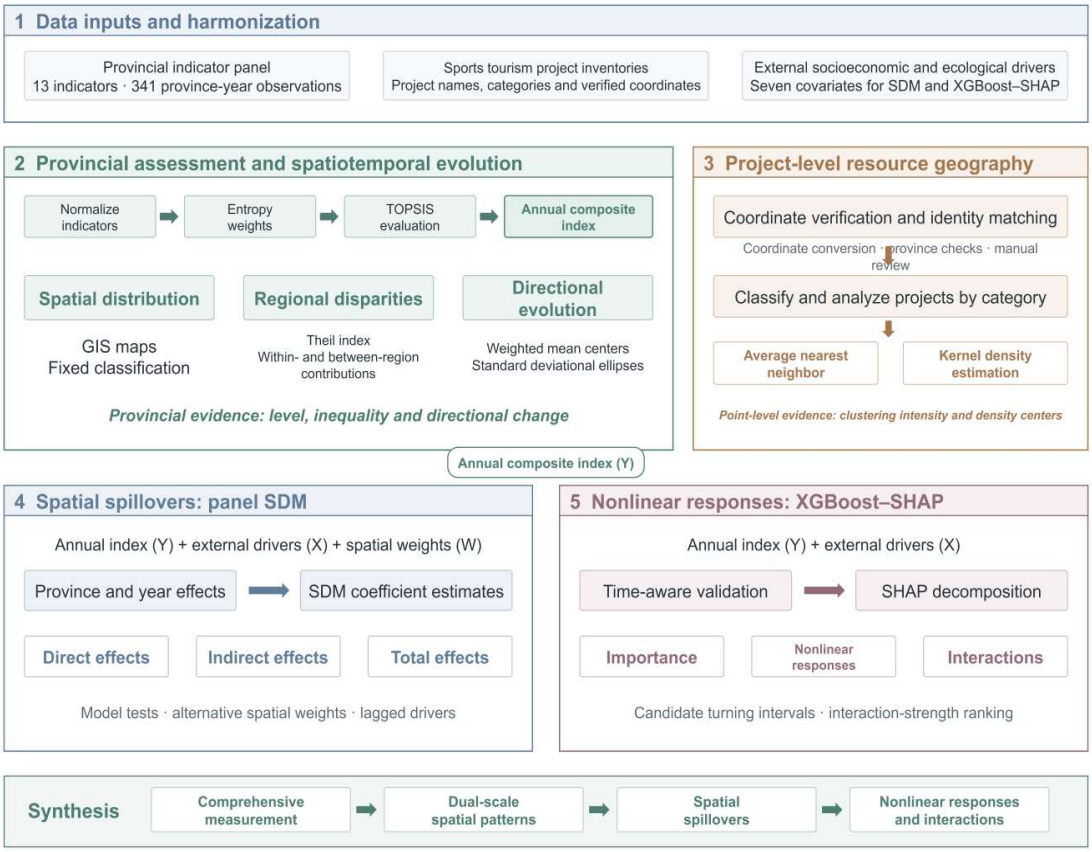


Figure 1. Analytical framework of the study

2. Literature Review

2.1 Conceptualization and Measurement Logic of Sports Tourism Ecological Development

Sports tourism ecological development refers to the coordinated interaction among sports tourism resources, industrial foundations, and environmental conditions under ecological constraints, with the aim of balancing economic benefits, resource use, and environmental protection (Fang et al., 2025). Unlike conventional tourism assessment, which often emphasizes visitor numbers and economic returns, ecological development gives greater attention to resource-use efficiency, environmental carrying capacity, and long-term sustainability (Nguyen et al., 2024). Sustainable tourism research further suggests that tourism development is shaped jointly by economic, environmental, social, infrastructural, and governance conditions and should therefore be evaluated through an integrated framework (Punzo et al., 2022). Related studies further indicate that the level of tourism development depends not only on market size and economic output, but also on the joint effects of resource endowments, infrastructure, public services, and environmental governance capacity (Zhao & Li, 2025).

This integrated perspective is particularly relevant to sports tourism because many activities depend directly on natural spaces, including mountains, forests, water bodies, and snow- and ice-covered areas. Their development requires not only resource endowments, market demand, and supporting services, but also suitable ecological conditions and environmental governance capacity (Cheng et al., 2025). ports tourism ecological development therefore reflects the coordination between industrial development capacity and ecological constraints rather than industrial expansion alone. Consistent with recent sustainable-tourism measurement research (Antolini et al., 2024). this study evaluates that coordination through two interdependent dimensions—sports tourism development and the ecological environment—which together capture regional development

capacity, market performance, resource conditions, and environmental sustainability.

2.2 Spatial Characteristics of Sports Tourism Ecological Development

Tourism development is inherently spatial because resource endowments, market demand, infrastructure, and tourist mobility are unevenly distributed across regions. As a result, tourism activities commonly exhibit spatial agglomeration, regional differentiation, and interregional dependence (Yang & Wong, 2012).

Existing studies generally follow two spatial analytical approaches. One uses provincial- or city-level statistical data to examine regional disparities, spatial dependence, and heterogeneity (Zhou et al., 2021). Twhile the other relies on geocoded tourism resources or project data to analyse location, concentration, and spatial organization (Zikirya & Zhou, 2023). These approaches capture complementary dimensions of tourism space, but they have often been applied separately, leaving limited evidence linking regional development conditions with project-level spatial patterns.

Spatial interactions in tourism may involve both diffusion and competition. Transportation connectivity, market sharing, and industrial cooperation can generate positive spillovers, whereas locally embedded resource advantages may redirect tourists, capital, and projects toward particular destinations. Distinguishing local effects from cross-regional spillovers is therefore essential for understanding the spatial mechanisms of sports tourism ecological development.

2.3 Nonlinear Responses and Interaction Effects

Sports tourism ecological development is jointly shaped by economic, transportation, industrial, social, and ecological conditions. Spatial econometric models can capture spatial dependence and decompose effects into direct and indirect components, but standard linear specifications mainly reflect average relationships and may overlook changes across different variable ranges or combinations of conditions (LeSage & Pace, 2009).

Interpretable machine-learning methods provide a useful complement. XGBoost can capture complex nonlinear relationships, while SHAP can identify feature contributions, nonlinear response patterns, and interactions among predictors (Chen & Guestrin, 2016). Recent tourism research has similarly applied XGBoost-SHAP to examine nonlinear and interactive relationships among socioeconomic and environmental drivers (Wang et al., 2025).

Accordingly, combining spatial econometrics with XGBoost-SHAP allows this study to examine both average spatial effects and condition-dependent predictive relationships. The SHAP results are interpreted as predictive associations rather than causal effects.

2.4 Literature Review Summary

Existing studies have advanced research on tourism sustainability and spatial development, but important gaps remain in sports tourism ecological development, particularly in integrating regional assessment with project-level spatial patterns, distinguishing local from interprovincial spillovers, and examining nonlinear relationships. To address these gaps, this study combines composite evaluation, georeferenced project analysis, spatial econometrics, and XGBoost-SHAP within a unified framework, thereby linking cross-scale spatial patterns, spillover effects, and condition-dependent relationships.

3. Data and Methods

3.1 Data Sources and Spatial Data Processing

This study uses panel data for 31 provincial-level regions in China from 2013 to 2023, comprising 341 province-year observations. Data for the composite evaluation are mainly drawn from the China Statistical Yearbook, China Sports Yearbook, China Culture and Tourism Statistical Yearbook, China Environmental Statistical Yearbook, and provincial statistical yearbooks. Sports tourism project data are obtained from official lists released by the General Administration of Sport of China and geocoded according to project names and administrative locations. Economic development, urbanization, road density, railway density, and industrial structure are compiled from provincial statistical sources; green technological innovation is measured using the CNRDS Green Patent Database, and annual mean NDVI is derived from Google Earth Engine.

Project-level spatial analyses use the CGCS2000 China Albers Equal Area Conic projection. Duplicate coordinates are removed for average nearest neighbor analysis to avoid bias in nearest-neighbor distances, whereas original project records are retained for analyses of project scale and spatial density. The spatial econometric analysis uses a Queen contiguity matrix as the baseline specification and a four-nearest-neighbor (4-NN) KNN matrix for robustness checks.

3.2 Research Methods

3.2.1 Construction of the Evaluation Indicator System

The evaluation system adopts a three-level structure of "dimension–supporting component–indicator" and comprises two primary dimensions: the ecological environment and sports tourism development (Table 1). This framework reflects the interaction between the ecological carrying capacity of destinations and the development capacity of the sports tourism industry.

The ecological environment dimension includes environmental pressure, ecological foundations, and environmental governance. These components capture pollution stress, ecological endowments, and regional environmental management capacity. The sports tourism development dimension comprises sports development support, outdoor resource supply, and tourism industry development, reflecting the availability of industrial inputs, natural and recreational resources, and tourism market performance. The specific indicators, directions, entropy weights, and rankings are reported in Table 1.

Table 1. Comprehensive Evaluation Indicator System for Sports Tourism Ecological Development

Primary dimension	Secondary dimension	Tertiary indicator	Direction	Weight	Rank
Ecological Environment	Environmental Pressure	Carbon emission intensity	−	0.0188	10
		Annual mean PM2.5 concentration	−	0.0181	11
	Ecological Foundations	Per capita urban park green space	+	0.0304	9
		Green coverage of built-up areas	+	0.0305	8
		Forest coverage	+	0.0966	5
	Environmental Governance	Harmless treatment rate of municipal solid waste	+	0.0085	12
		Wastewater treatment rate	+	0.0035	13
		Environmental infrastructure investment intensity	+	0.0918	7

Primary dimension	Secondary dimension	Tertiary indicator	Direction	Weight	Rank
Sports Tourism Development	Sports Development Support	Sports investment	+	0.1475	2
		Sports industry employment	+	0.0948	6
	Outdoor Resource Supply	Outdoor recreation resource density	+	0.2148	1
	Tourism Industry Development	Tourism revenue intensity	+	0.1266	3
		Number of tourist visits	+	0.1181	4

3.2.2 Entropy-Weighted TOPSIS Method

To reduce subjectivity in indicator weighting and ensure comparability across years, all 341 province-year observations are first normalized using the min–max method. The entropy weighting method is then applied to determine the weights of individual indicators, and the TOPSIS method is subsequently used to calculate the composite index. Positive and negative indicators are normalized as follows:

$$z_{qj} = \begin{cases} \frac{x_{qj} - \min(x_j)}{\max(x_j) - \min(x_j)}, \\ \frac{\max(x_j) - x_{qj}}{\max(x_j) - \min(x_j)}, \end{cases} \quad (1)$$

where x_{qj} denotes the value of the jth indicator for the qth province-year observation, and z_{qj} denotes the corresponding normalized value. Normalized values equal to zero are replaced with 0.0001 to avoid undefined logarithmic operations in the subsequent entropy calculation.

Next, the proportion, entropy value, and weight of each indicator are calculated as follows:

$$p_{qj} = \frac{z_{qj}}{\sum_{q=1}^{M} z_{qj}}, \qquad e_j = -\frac{1}{\ln M} \sum_{q=1}^{M} p_{qj} \ln p_{qj} \quad (2)$$

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{J} (1 - e_j)} \quad (3)$$

where n=341 and M=13; e_j denotes the entropy value of indicator j, and w_j represents its corresponding weight. The same set of indicator weights is applied to all years to ensure intertemporal comparability. The weights of the primary and secondary dimensions are obtained by summing the weights of their corresponding tertiary indicators.

The weighted normalized decision matrix is then constructed, and the positive and negative ideal solutions are determined as follows:

$$(v_{qj} = w_j z_{qj}, \qquad v_j^+ = \max_q(v_{qj}), \qquad v_j^- = \min_q(v_{qj})) \quad (4)$$

where v_{qj} represents the weighted normalized value, w_j represents the indicator weight, and v_j^+ and v_j^- denote the positive and negative ideal solutions of indicator j, respectively.

The Euclidean distances between each observation and the positive and negative ideal solutions were calculated as follows:

$$D_q^+ = \sqrt{\sum_{j=1}^{J}(v_{qj} - v_j^+)^2}, \qquad D_q^- = \sqrt{\sum_{j=1}^{J}(v_{qj} - v_j^-)^2} \quad (5)$$

The composite index is expressed as follows:

$$C_q = \frac{D_q^-}{D_q^+ + D_q^-} \quad (6)$$

A larger C_q value indicates that the province's overall performance in sports tourism ecological development is closer to the positive ideal solution. The annual average indices for China as a whole and the four regions were calculated using the arithmetic mean of the composite indices of the corresponding provinces.

3.2.3 Theil Index

To measure regional disparities in sports tourism ecological development across Chinese provinces, this study employs the Theil index and further decomposes the overall disparity into between-region and within-region components. The Theil index is calculated as follows:

$$T = \frac{1}{N}\sum_{i=1}^{N}\frac{y_i}{\bar{y}}\ln\left(\frac{y_i}{\bar{y}}\right) \quad (7)$$

where $T =$ represents the Theil index, N denotes the number of provinces, y_i represents the sports tourism ecological development composite index of province i, and $\bar{y}$ denotes the average composite index across all provinces. A larger value of T indicates greater regional disparities.

The overall Theil index is further decomposed into interregional and intraregional disparities:

$$T = T_B + T_W \quad (8)$$

where T_B and T_W represent interregional and intraregional disparities, respectively. Their contributions to the overall disparity are measured by their respective proportions of the total Theil index.

3.2.4 Spatial Center of Gravity and Standard Deviational Ellipse

To identify the migration trajectory of the spatial center and the directional characteristics of sports tourism project distributions, this study employs the spatial center of gravity and standard deviational ellipse methods. The spatial center of gravity is calculated as follows:

$$\bar{X} = \frac{\sum_{i=1}^{n} w_i X_i}{\sum_{i=1}^{n} w_i}, \qquad \bar{Y} = \frac{\sum_{i=1}^{n} w_i Y_i}{\sum_{i=1}^{n} w_i} \quad (9)$$

where X_i and Y_i denote the longitude and latitude coordinates of the i-th sports tourism project, respectively, and w_i represents the project weight. Since all projects are treated equally in this study, w_i=1.

3.2.5 Average Nearest Neighbor Analysis

To examine the spatial distribution characteristics of sports tourism projects, this study employs the Average Nearest Neighbor (ANN) index to test the degree of spatial clustering among project locations. The calculation formula is as follows:

$$ANN = \frac{\bar{D}_O}{\bar{D}_E} \quad (10)$$

where $\bar{D}_O$ represents the observed average nearest neighbor distance, and $\bar{D}_E$ denotes the expected average nearest neighbor distance under a completely random spatial distribution. When ANN<1, the projects exhibit a clustered distribution; when ANN=1, the projects follow a random distribution; and when ANN>1), the projects show a dispersed distribution. The spatial pattern is further evaluated based on the Z-score and significance level to determine whether the observed distribution significantly deviates from a random spatial pattern.

3.2.6 Kernel Density Estimation

To identify the spatial agglomeration areas and density distribution characteristics of sports tourism projects, this study applies Kernel Density Estimation (KDE) to conduct spatial smoothing analysis of project locations. The calculation formula is as follows:

$$f(x) = \frac{1}{nh^2}\sum_{i=1}^{n} K\left(\frac{d_i}{h}\right) \quad (11)$$

where $f(x)$ represents the kernel density value at location x, n denotes the number of project locations, h represents the bandwidth, d_i denotes the distance between location x and the i-th project location, and $K(\cdot)$ represents the kernel function. A higher kernel density value indicates a

greater degree of spatial agglomeration of sports tourism projects in the corresponding area.

3.2.7 Spatial Econometric Model

To examine the spatial dependence of sports tourism ecological development and the spatial spillover effects of its influencing factors, this study employs the Spatial Durbin Model (SDM) for empirical analysis. The model is specified as follows:

$$(Y_{it} = \rho \sum_{j=1}^{N} w_{ij} Y_{jt} + X_{it}\beta + \sum_{j=1}^{N} w_{ij} X_{jt}\theta + \mu_i + \lambda_t + \varepsilon_{it}) \quad (12)$$

where Y_{it} represents the composite index of sports tourism ecological development for province i in year t; W denotes the spatial weight matrix; ρ represents the spatial autoregressive coefficient; X_{it} denotes the vector of explanatory variables; β represents the coefficient of local effects; θ denotes the coefficient of spatially lagged explanatory variables; μ_i and λ_t represent province fixed effects and time fixed effects, respectively; and ε_{it} represents the random disturbance term.

3.2.8 XGBoost–SHAP Analysis

To identify the nonlinear relationships and interaction patterns among the influencing factors of sports tourism ecological development, this study employs the Extreme Gradient Boosting (XGBoost) model and combines it with the SHapley Additive exPlanations (SHAP) method to interpret the model outputs. XGBoost constructs decision trees iteratively and continuously reduces prediction errors by updating residuals, enabling effective identification of complex nonlinear relationships and interactions among variables. The objective function is expressed as follows:

$$Obj^{(t)} = \sum_{i=1}^{n} l\,(y_i, \hat{y}_i^{(t)}) + \sum_{k=1}^{t} \Omega\,(f_k) \quad (13)$$

where $\mathscr{L}$ denotes the loss function, and $\Omega(f_k)$ represents the complexity penalty term of the model.

3.3 Variable Selection

The selected variables capture the major socioeconomic, infrastructural, technological, industrial, and ecological conditions associated with sports tourism ecological development. ECO represents regional economic foundations and market support capacity, while URB reflects population concentration and urban service conditions. ROAD and RAIL capture regional accessibility and interregional connectivity, respectively. IS represents industrial upgrading and servitization, GTI reflects green innovation capacity, and NDVI characterizes underlying ecological conditions. The SDM and XGBoost-SHAP analyses employ the same set of explanatory variables, allowing the average spatial effects estimated by the econometric model to be compared with the nonlinear predictive contributions identified by the machine-learning framework. The definitions and measurements of all variables are presented in Table 2.

Table 2. Factors influencing

Variable type	Dimension	Abbreviation	Indicator	Description
Dependent variable	Sports Tourism Ecological Development	STED	Composite index of sports tourism ecological development	Overall status of sports tourism development and the ecological environment
Core explanatory variable	Economic Development Level	ECO	Economic development indicator	Regional economic foundation and market support capacity
Control variable	Urbanization Level	URB	Urbanization rate	Population agglomeration and urban public service conditions
	Road	ROAD	Road density	Regional road accessibility

Variable type	Dimension	Abbreviation	Indicator	Description
	Transportation			
	Railway Transportation	RAIL	Railway density	Interregional railway connectivity
	Industrial Structure	IS	Industrial structure upgrading	Degree of industrial upgrading and servitization
	Green Technological Innovation	GTI	Green patent indicator	Regional green innovation capacity
	Ecological Environmental Quality	NDVI	Annual mean NDVI	Vegetation coverage and ecological conditions

4. Results

4.1 Temporal Evolution and Regional Disparities

Based on the entropy-weighting results, the sports tourism ecological development index for China was calculated for the period 2013–2023. As shown in Fig. 2, the overall level of sports tourism ecological development exhibited a fluctuating upward trend during the study period, with relatively distinct stage-specific characteristics. The national average composite index increased steadily from 0.2387 in 2013 to 0.3206 in 2019, before declining to 0.2756 in 2020. It subsequently entered a period of fluctuating recovery, reaching 0.3140 in 2023. Compared with 2013, the national average composite index increased by 31.56% in 2023, although it remained 2.06% below the interim peak recorded in 2019. Overall, sports tourism ecological development improved over the study period, although the magnitude of change varied considerably across different stages.

From a stage-based perspective, the period from 2013 to 2019 can be characterized as a phase of sustained improvement. During this period, sports investment, outdoor recreation resource density, tourism revenue, and the number of tourist visits generally increased, broadly corresponding with the continuous rise in the composite index. This pattern suggests that the simultaneous expansion of sports tourism resource supply, development investment, and market scale provided important support for improvements in the overall level of sports tourism ecological development. The period from 2019 to 2020 was characterized by a marked decline, during which the national average tourism revenue and number of tourist visits decreased by 47.27% and 40.49%, respectively. Tourism demand and population mobility were substantially affected during this period. Given that tourism revenue intensity and the number of tourist visits are relatively highly weighted market indicators in the comprehensive evaluation system, the contraction of the tourism market may have been an important contributor to the pronounced decline in the composite index. From 2021 to 2023, sports tourism ecological development entered a phase of recovery and adjustment. As tourism demand and market activity gradually recovered, tourism-related indicators improved, contributing to an overall rebound in the composite index. However, because the market recovery continued to exhibit year-to-year fluctuations and sports tourism development was simultaneously shaped by multiple dimensions, including resource supply, development investment, and ecological and environmental conditions, the composite index had not yet established a sustained and stable upward trajectory.

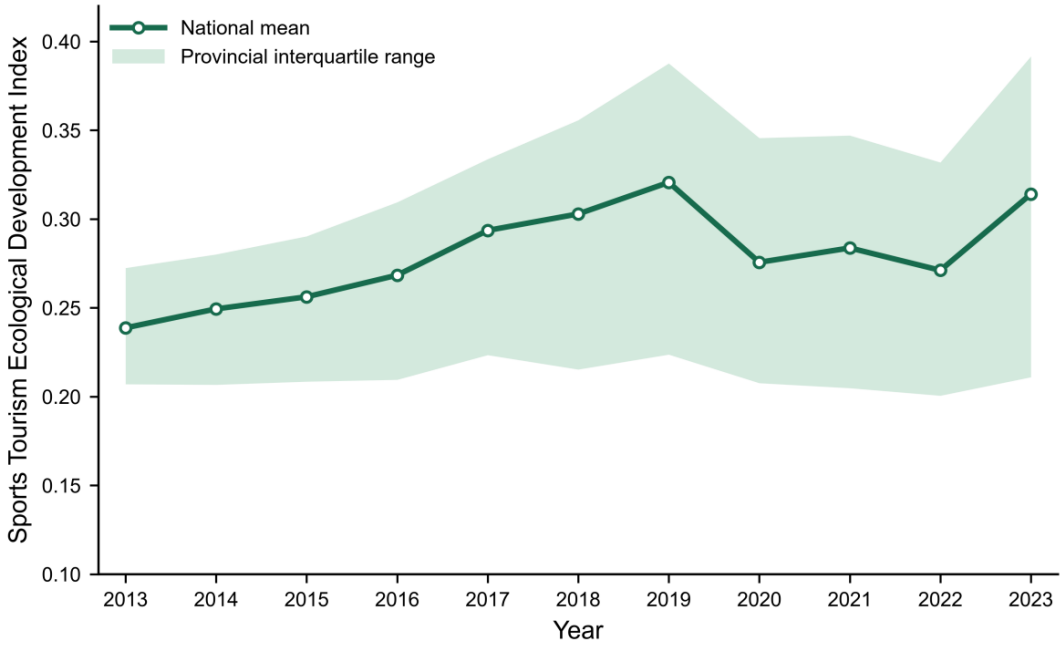


Fig. 2. Sports Tourism Ecological Development Index and Interprovincial Disparities in China

Based on the provincial-level results, the sports tourism ecological development indices for eastern, central, western, and northeastern China were calculated through regional aggregation. As shown in Fig. 3, the level of sports tourism ecological development generally increased across all four regions, despite some fluctuations during individual periods. At the same time, pronounced spatial disparities persisted among regions. Eastern China consistently recorded the highest index values, whereas western China remained at a relatively low level, forming a clear regional gradient of "eastern > central > northeastern > western China." The index for eastern China remained above the national average throughout the study period, while those for western and northeastern China were generally below the national average. These results indicate the presence of a distinct spatial stratification in sports tourism ecological development over the observation period.

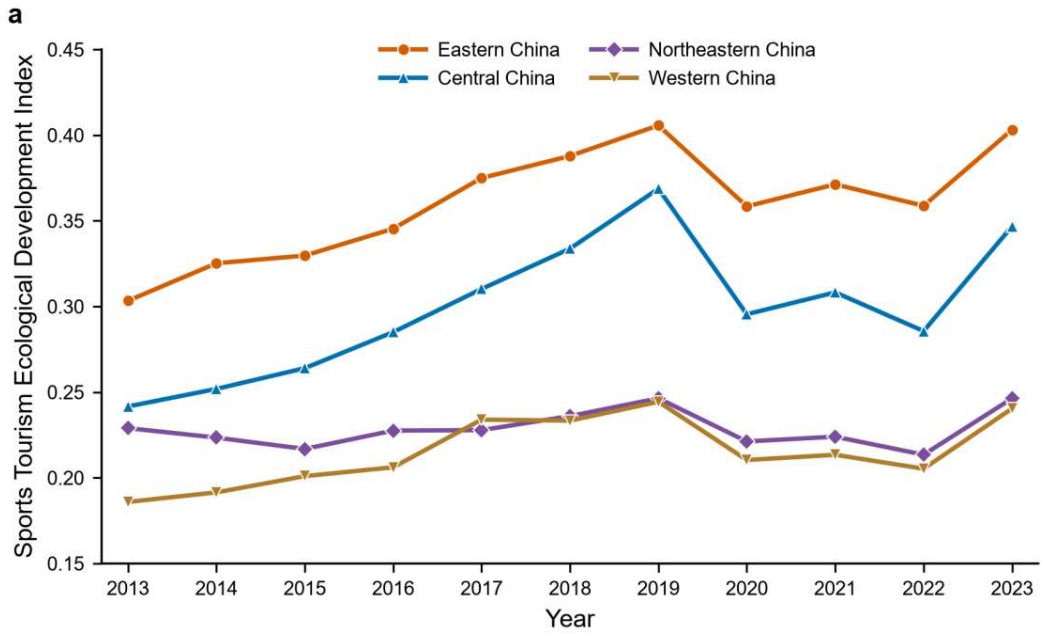


Fig. 3. Trends in Sports Tourism Ecological Development across Four Regions

The Theil index decomposition method was further employed to examine overall disparities,

intra-regional disparities, and interregional disparities in sports tourism ecological development. As shown in Table 3, the overall disparity in sports tourism ecological development across China exhibited a persistent upward trend over the study period. Intra-regional disparities showed pronounced heterogeneity and constituted the primary source of overall inequality, with their contribution increasing over time. This pattern indicates a growing divergence among provinces within the four major regions in terms of sports tourism resource endowments, ecological foundations, and industrial development. By contrast, although interregional disparities fluctuated slightly, their relative contribution continued to decline, suggesting that differences in average development levels among the four regions were not the dominant source of overall inequality.

From the perspective of contribution shares, intra-regional disparities accounted for the dominant proportion of overall inequality, whereas interregional disparities were relatively limited. This suggests that the imbalance in sports tourism ecological development across China is driven less by differences among the four major regions than by divergence in development levels among provinces within the same region. In other words, substantial internal inequality persists in sports tourism ecological development within individual regions. Overall, the national pattern is characterized by increasing within-region differentiation alongside a relative moderation of between-region disparities.

Table 3. Theil Index Decomposition of Sports Tourism Ecological Development

Year	Overall Theil Index	Interregional Disparity	Intra-regional Disparity	Interregional Contribution (%)	Intra-regional Contribution (%)
2013	0.0492	0.0212	0.0280	43.13	56.87
2015	0.0545	0.0232	0.0313	42.57	57.43
2018	0.0695	0.0263	0.0433	37.78	62.22
2020	0.0736	0.0276	0.0460	37.54	62.46
2023	0.0806	0.0269	0.0536	33.42	66.58
Mean	0.0674	0.0260	0.0413	39.13	60.87

The interprovincial heat map (Fig. 4) further shows that the sports tourism ecological development index generally increased across Chinese provinces from 2013 to 2023, although substantial interprovincial disparities persisted over time, revealing pronounced spatial differentiation. The temporal heat-map results indicate that eastern coastal provinces such as Shanghai, Jiangsu, Zhejiang, Guangdong, and Shandong consistently remained in the high-value group, with composite index values significantly higher than those of most other provinces throughout the study period. By contrast, western provinces such as Tibet, Qinghai, Ningxia, and Gansu, together with some provinces in northeastern China, remained in the low-value group for an extended period, with relatively limited growth. From a temporal perspective, the index increased steadily in most provinces over time, although some provinces experienced a temporary decline in 2020 followed by a subsequent rebound, reflecting the short-term disturbance of external shocks on the sports tourism ecological system.

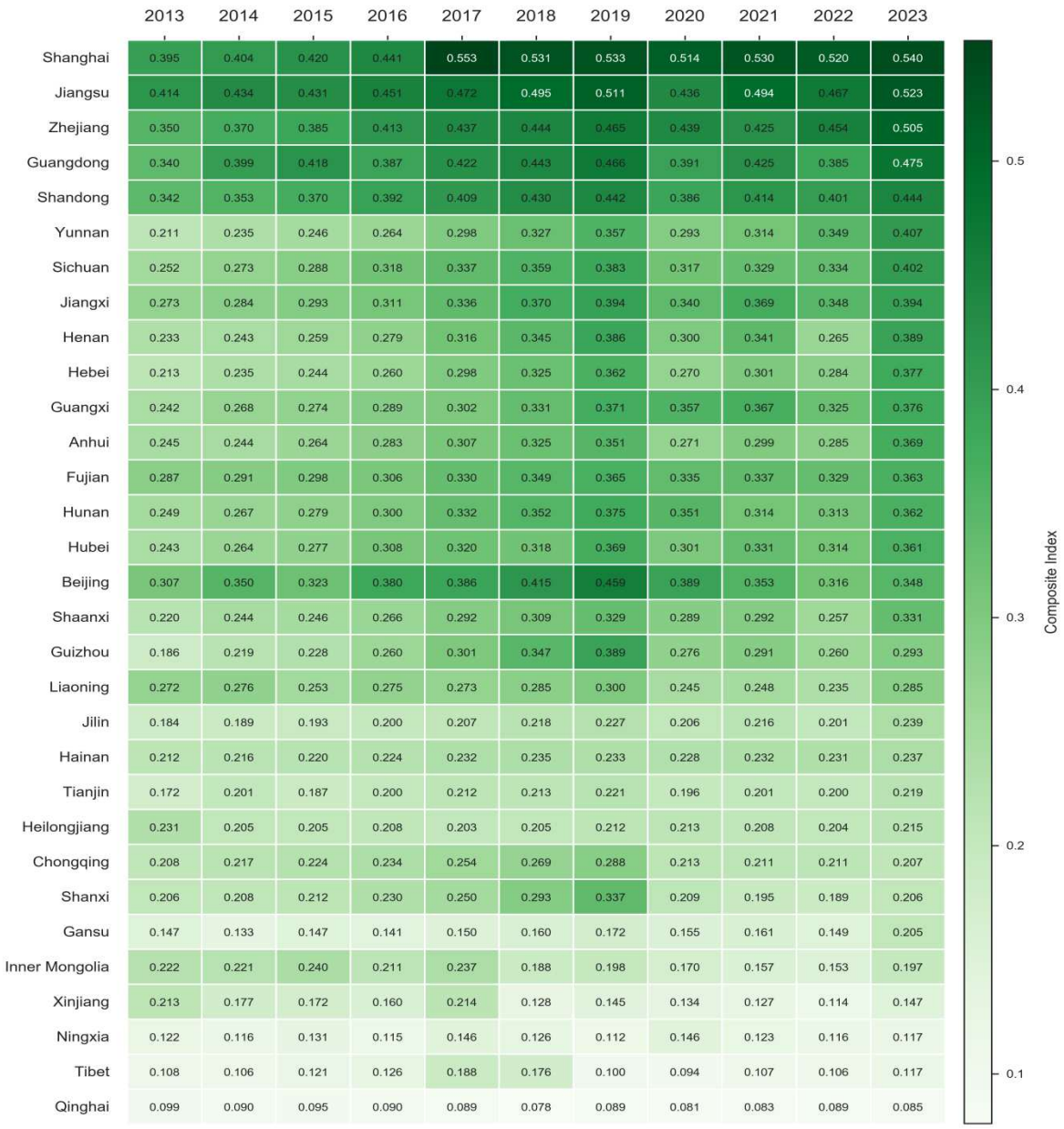


Fig. 4. Sports Tourism Ecological Development Index across Provinces

The three-period spatial distribution maps (Fig. 5) further provide an intuitive illustration of the evolution of the spatial pattern. In 2013, high-value areas were concentrated in the eastern coastal provinces and displayed a pattern of localized clustering. By 2018, the high-value range had gradually expanded from the eastern region toward central and southwestern China, and the number of provinces at intermediate development levels had increased markedly. By 2023, the spatial clustering pattern had become more pronounced: the contiguous high-value pattern along the eastern coast remained firmly established, while provinces in central and southwestern China showed substantial upgrading in their development levels. In contrast, northwestern China and the Qinghai–Tibet Plateau region remained at relatively low levels over the long term. Overall, the level of sports tourism ecological development in China exhibits a clear spatial pattern characterized by "high in the east and low in the west," with coastal areas outperforming inland regions. High-value

areas gradually expanded from isolated eastern clusters toward a more contiguous pattern spanning eastern and central China, while interprovincial gradient differentiation persisted over time, accompanied by notable differences in the pace of improvement among provinces within regions.

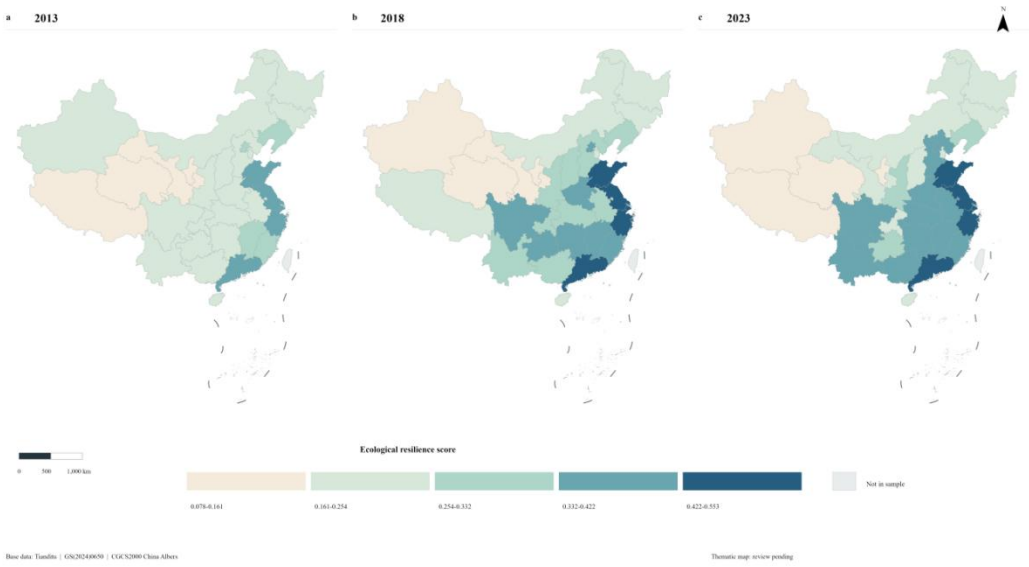


Fig. 5. Interprovincial Spatial Evolution of Sports Tourism Ecological Development

4.2 Spatial Distribution of Sports Tourism Projects

4.2.1 Center-of-Gravity Migration and Directionality

From 2013 to 2023, the center of gravity of sports tourism projects remained within central China and its adjacent areas (Fig. 6), ranging from 111.1238°E to 114.1456°E in longitude and from 32.3316°N to 35.4518°N in latitude. The center shifted from 113.7028°E, 32.3316°N in 2013 to 111.1238°E, 32.9959°N in 2023, corresponding to a net migration distance of 249.57 km and an overall northwestward shift. Over the entire study period, the cumulative migration distance reached 1,183.50 km, approximately 4.74 times the net displacement. This substantial difference indicates that the spatial center underwent repeated stage-specific adjustments rather than a stable, unidirectional shift.

The standard deviational ellipses for different project types reveal clear differences in spatial orientation. The center of ice and snow tourism is located farther north, whereas that of water-based sports is shifted toward the southeast. Ice and snow tourism has the largest major-axis standard distance (1,441.60 km), while water-based sports exhibit the smallest minor-axis standard distance (713.21 km). The major-to-minor axis ratios for water-based sports, sports and leisure towns, ice and snow tourism, and aviation sports are 1.491, 1.414, 1.405, and 1.357, respectively, indicating relatively stronger directional characteristics. By contrast, scenic areas and destinations, integrated bases and industrial projects, camping and self-driving tourism, and outdoor sports display spatial configurations closer to balanced diffusion.

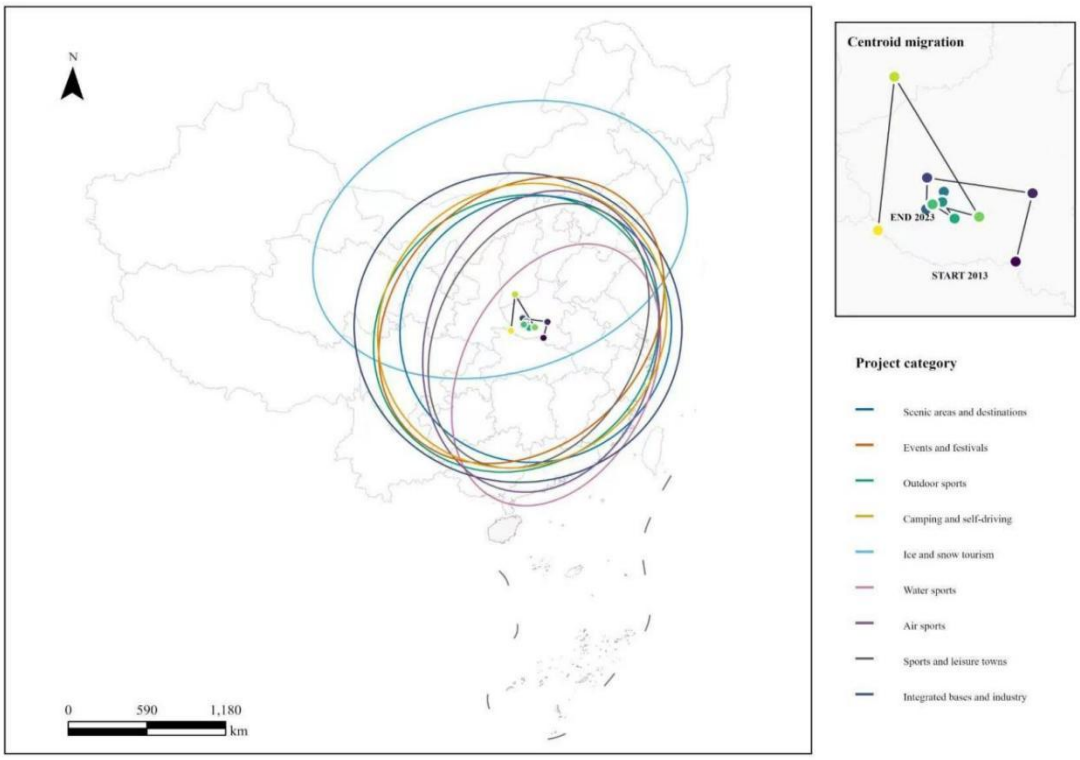


Fig. 6. Spatial Migration and Directionality of Sports Tourism Projects

4.2.2 Spatial Clustering and Kernel Density Distribution

After removing duplicate coordinates, the observed mean nearest-neighbor distance of sports tourism projects nationwide was 26.849 km, significantly lower than the expected distance of 39.335 km under complete spatial randomness. The nearest-neighbor ratio was 0.683, with ($Z=-23.798$) and ($p<0.001$), indicating significant spatial clustering of sports tourism projects. The nearest-neighbor ratios for all nine project categories were below 1 and statistically significant at the 1% level, although the degree of clustering varied across categories. Water-based sports (0.608), ice and snow tourism (0.616), aviation sports (0.654), and scenic areas and destinations (0.674) exhibited the strongest clustering, whereas integrated bases and industrial projects (0.821) and sports and leisure towns (0.862) displayed relatively weaker clustering (Fig.7).

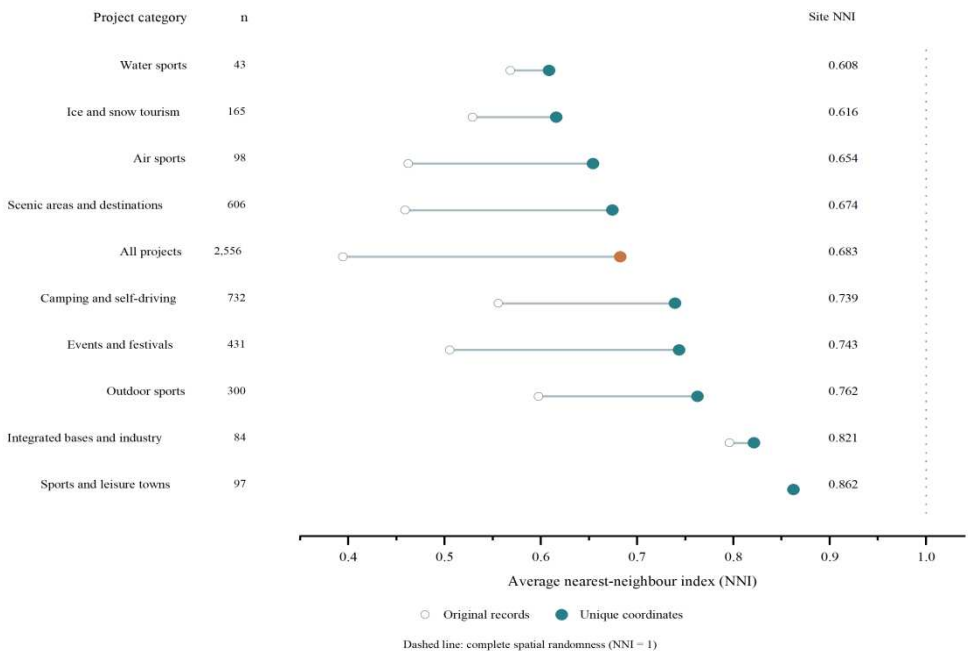


Fig. 7. Nearest-Neighbor Index of Sports Tourism Projects by Type

As shown in Fig. 8, the kernel density results reveal a multicentric spatial pattern characterized by high concentrations in eastern China with localized extensions toward central and western regions. The highest-density area is located in northern Zhejiang and extends toward southern Jiangsu, Shanghai, and southeastern Anhui. Secondary high-density clusters are observed in Beijing and northern Hebei, central Shandong, the Hubei–Anhui–Jiangxi border area, and central Sichuan. The category-specific results further indicate that different types of sports tourism projects do not follow a uniform spatial organization pattern. Ice and snow tourism is more strongly dependent on climatic conditions and specialized facilities, whereas water-based sports are more closely associated with coastal and inland water resources. By contrast, scenic areas and destinations, sporting events and festivals, and outdoor sports are more likely to spatially overlap with established tourism destinations.

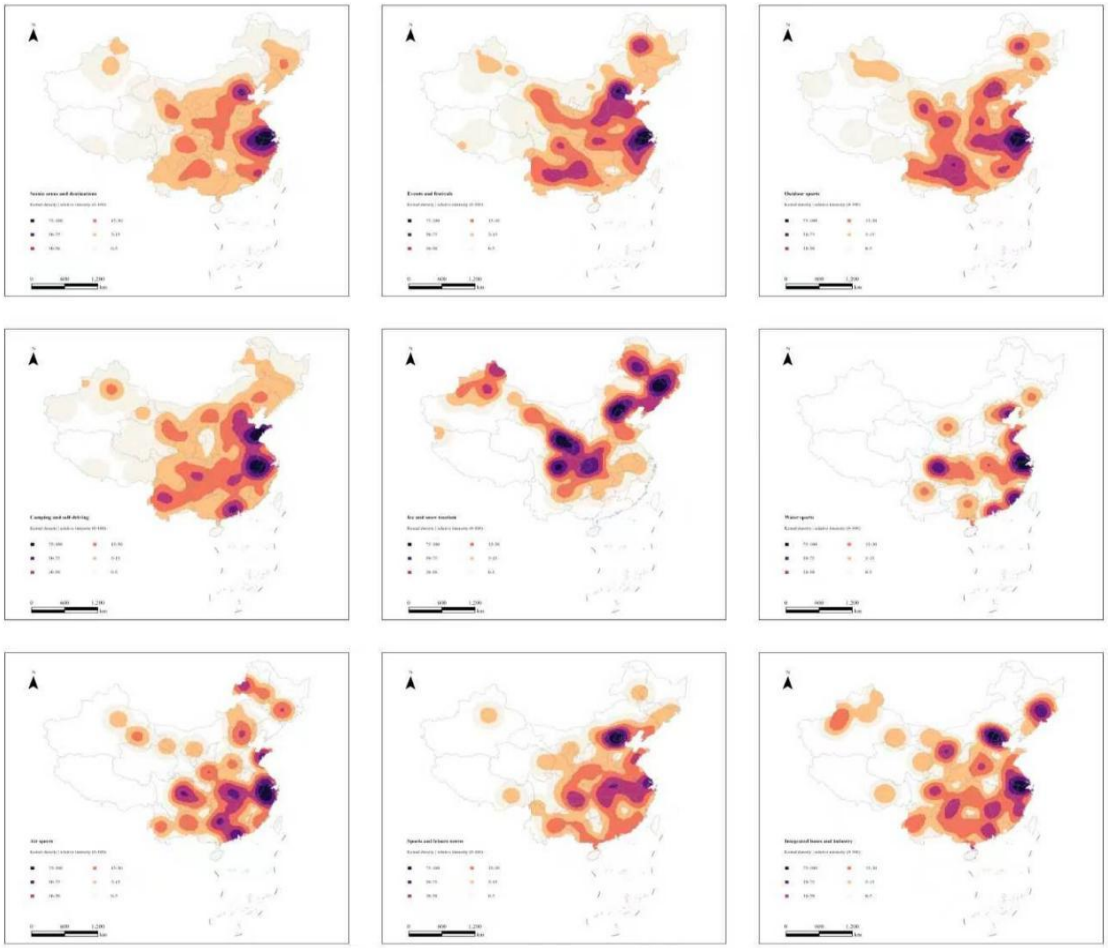


Fig. 8. Kernel Density Distribution of Sports Tourism Projects by Type

4.3 Spatial Effects Analysis

4.3.1 Model Selection and Diagnostic Tests

The model selection and diagnostic tests are summarized in Table 4. The LM-lag and Robust LM-lag tests are significant at the 1% level, while the LM-error test is also significant at the 1% level, indicating significant spatial dependence among provinces. The Mundlak test rejects the exogeneity assumption of the random-effects specification, supporting the use of fixed effects. The LR tests confirm the inclusion of both province and year fixed effects. Furthermore, the Wald and LR tests reject the simplification of the SDM into either a spatial autoregressive model (SAR) or a spatial error model (SEM). Therefore, a two-way fixed-effects spatial Durbin model is employed for subsequent analysis.

Table 4. Spatial panel model tests

Test	Test item	Statistic	P-value
LM-error	Lagrange multiplier	22.587	0.0000***
LM-error	Robust LM	2.761	0.0993*
LM-lag	Lagrange multiplier	69.114	0.0000***
LM-lag	Robust LM	49.243	0.0000***
LR	Both-Ind	69.571	0.0000***

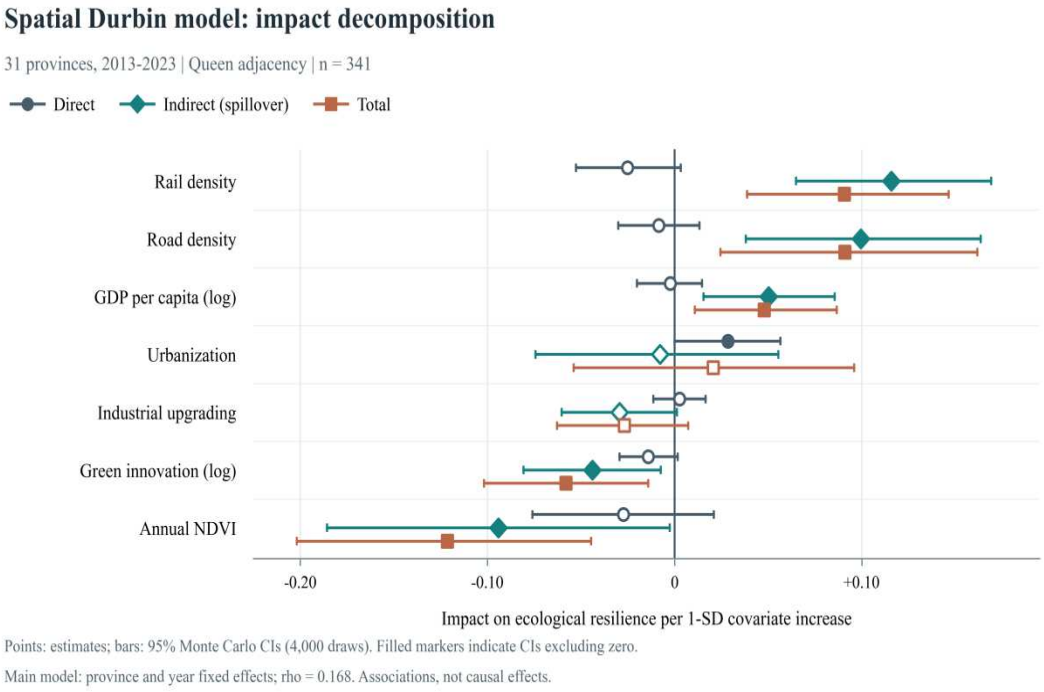
Test	Test item	Statistic	P-value
LR	Both-Time	442.057	0.0000***
Wald	SDM → SAR	74.037	0.0000***
Wald	SDM → SEM	75.365	0.0000***
LR	SDM → SAR	73.444	0.0000***
LR	SDM → SEM	79.135	0.0000***
Mundlak	random-effects exogeneity	78.515	0.0000***

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.3.2 Direct and Indirect Effects

The effect decomposition results under the Queen contiguity matrix show clear differences between direct and indirect effects (Fig. 8). For direct effects, economic development, road density, railway density, and green technological innovation exhibit negative coefficients. Among them, railway density and green technological innovation are significantly negative at the 10% level, with coefficients of −0.0251 and −0.0141, respectively, whereas the effects of economic development, road density, and annual mean NDVI are not statistically significant. By contrast, urbanization and industrial structure show positive direct effects, with urbanization reaching significance at the 5% level (0.0285).

For indirect effects, all variables except urbanization are statistically significant at the 10% level. Economic development, road density, and railway density generate significant positive spatial spillovers, with coefficients of 0.0502, 0.0995, and 0.1158, respectively. In contrast, industrial structure, green technological innovation, and annual mean NDVI exhibit negative indirect effects, indicating adverse spillovers on neighboring provinces. Overall, the results reveal substantial asymmetry between local and cross-provincial effects, suggesting that the influence of individual factors differs across spatial scales.



4.3.3 Robustness Tests

Table 5 reports the robustness results using a four-nearest-neighbor (4-NN) KNN matrix

instead of the Queen contiguity matrix. The indirect effect of economic development is 0.0515, which is nearly identical to the baseline estimate of 0.0502, indicating that the main spatial spillover result is robust to alternative spatial weight specifications. The direct effects of urbanization and green technological innovation retain their original signs, while the indirect effects of road and railway density remain positive and comparable in magnitude to the baseline estimates. The indirect effects of NDVI and industrial structure also remain negative, although their significance levels vary slightly. Overall, the main conclusions are robust to changes in the spatial weight matrix.

Table 5. Robustness Test

Variable	Direct Effect		Indirect Effect	
	Queen	4-NN KNN	Queen	4-NN KNN
Economic Development	−0.0023	0.0114	0.0502***	0.0515***
	(0.0089)	(0.0086)	(0.0178)	(0.0212)
Urbanization	0.0285**	0.0253*	−0.0078	−0.0170
	(0.0144)	(0.0133)	(0.0330)	(0.0384)
Road Density	−0.0084	0.0075	0.0995***	0.1673***
	(0.0112)	(0.0116)	(0.0324)	(0.0342)
Railway Density	−0.0251*	−0.0119	0.1158***	0.1588***
	(0.0144)	(0.0124)	(0.0268)	(0.0347)
Industrial Structure	0.0026	0.0011	−0.0294*	−0.0241
	(0.0071)	(0.0072)	(0.0158)	(0.0188)
Green Technological Innovation	−0.0141*	−0.0079	−0.0439**	−0.0283
	(0.0079)	(0.0078)	(0.0188)	(0.0223)
Annual Mean NDVI	−0.0273	−0.0490**	−0.0941**	−0.0755**
	(0.0249)	(0.0230)	(0.0467)	(0.0386)

4.4 XGBoost–SHAP: Nonlinear Predictive Relationships and Interaction Effects

4.4.1 Out-of-Sample Predictive Performance and Benchmark Comparison

Rolling time validation shows that XGBoost outperformed the Ridge benchmark ($R^2 = 0.823$ vs. 0.618), supporting the presence of nonlinear predictive relationships between the explanatory variables and sports tourism ecological development (Table 6). However, its performance did not exceed the previous-year or historical provincial-mean benchmarks, indicating strong temporal persistence in the provincial index. Province-grouped five-fold cross-validation yielded substantially lower performance ($R^2 = 0.472$), suggesting limited generalizability to provinces not represented in the training data. These results indicate that the primary value of XGBoost lies in identifying nonlinear predictive patterns rather than substantially improving year-ahead forecasting accuracy.

Table 6. XGBoost Predictive Performance

Validation / Model	R^2	RMSE	MAE
Rolling Time Validation: XGBoost	0.823	0.0479	0.0384
Rolling Time Validation: Ridge	0.618	0.0704	0.0596
Previous-Year	0.880	0.0382	0.0287

Validation / Model	R^2	RMSE	MAE
Provincial Index			
Province-Grouped Five-Fold CV: XGBoost	0.472	0.0759	0.0582
Historical Provincial Mean	0.832	0.0466	0.0364
XGBoost vs. Ridge	—	31.91% lower	35.61% lower

4.4.2 Variable Importance and Direction of Effects

The mean absolute SHAP values indicate that green technological innovation (GTI) is the dominant predictor, followed by annual mean NDVI and road density. Together, these three variables account for 75.52% of the total predictive contribution (Fig. 9).

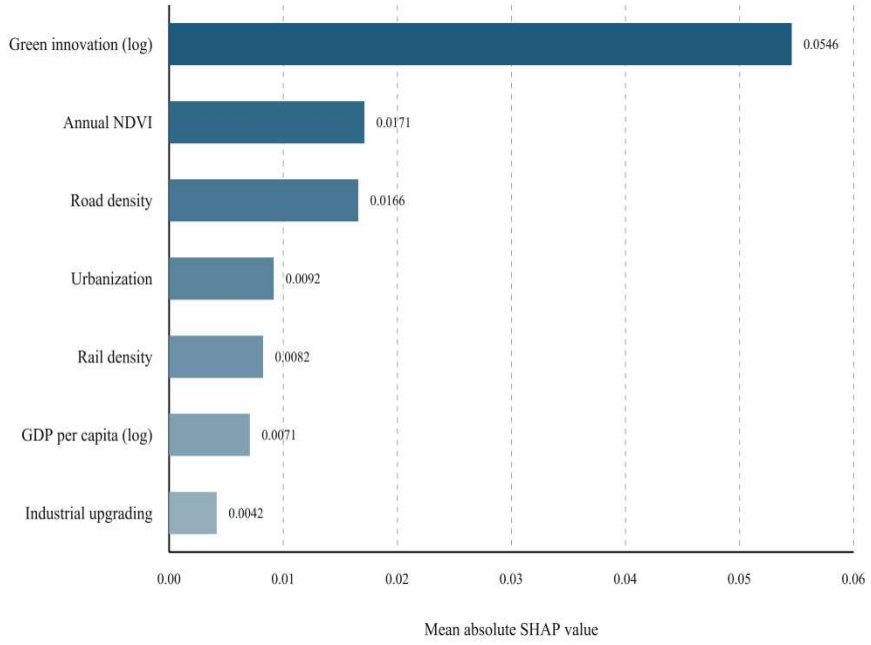


Fig. 9. SHAP Feature Importance

The direction of the SHAP effects also varies across variables. The contribution of GTI generally shifts from negative to positive as its value increases, while higher NDVI, road density, and economic development are more often associated with positive contributions. By contrast, the contributions of urbanization, railway density, and industrial structure upgrading tend to weaken or become negative at higher values.

4.4.3 Nonlinear Responses and Candidate Turning Intervals

SHAP dependence analysis indicates clear nonlinear predictive relationships among the explanatory variables (Fig. 10). Green technological innovation shows the most stable transition, with a candidate turning point of 6.571 (95% CI: 6.437–6.715) based on 300 bootstrap replications. Below this interval, its SHAP contribution is generally negative, whereas above it the contribution gradually becomes positive.

Other variables also exhibit nonlinear patterns, but their turning positions are less stable or are crossed by relatively few provinces during the study period. These positions should therefore be interpreted as within-sample transition intervals rather than universal development thresholds, causal turning points, or policy cutoffs.

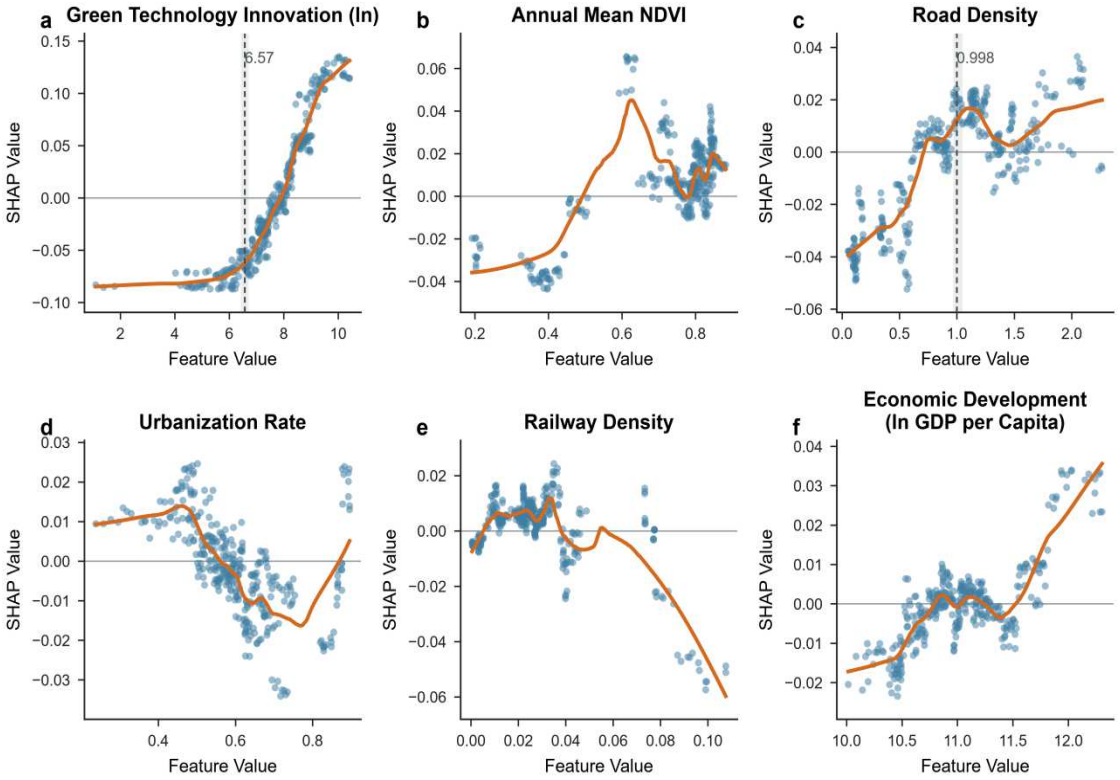


Fig. 10. SHAP Dependence and Candidate Turning Points

4.4.4 Variable Interaction Effects

SHAP interaction analysis reveals substantial heterogeneity across variable combinations (Fig. 11). GTI × NDVI exhibits the strongest interaction, with a mean absolute interaction strength of 0.0142 (95% CI: 0.0123–0.0163), and ranks first in all 2,000 province-clustered bootstrap replications. ROAD × NDVI and URB × GTI are the next strongest interactions. The signed effect of GTI × NDVI varies across observations, indicating that the contribution of green technological innovation depends on underlying ecological conditions. Overall, the interaction results suggest that the effects of individual drivers are condition-dependent rather than uniform across provinces.

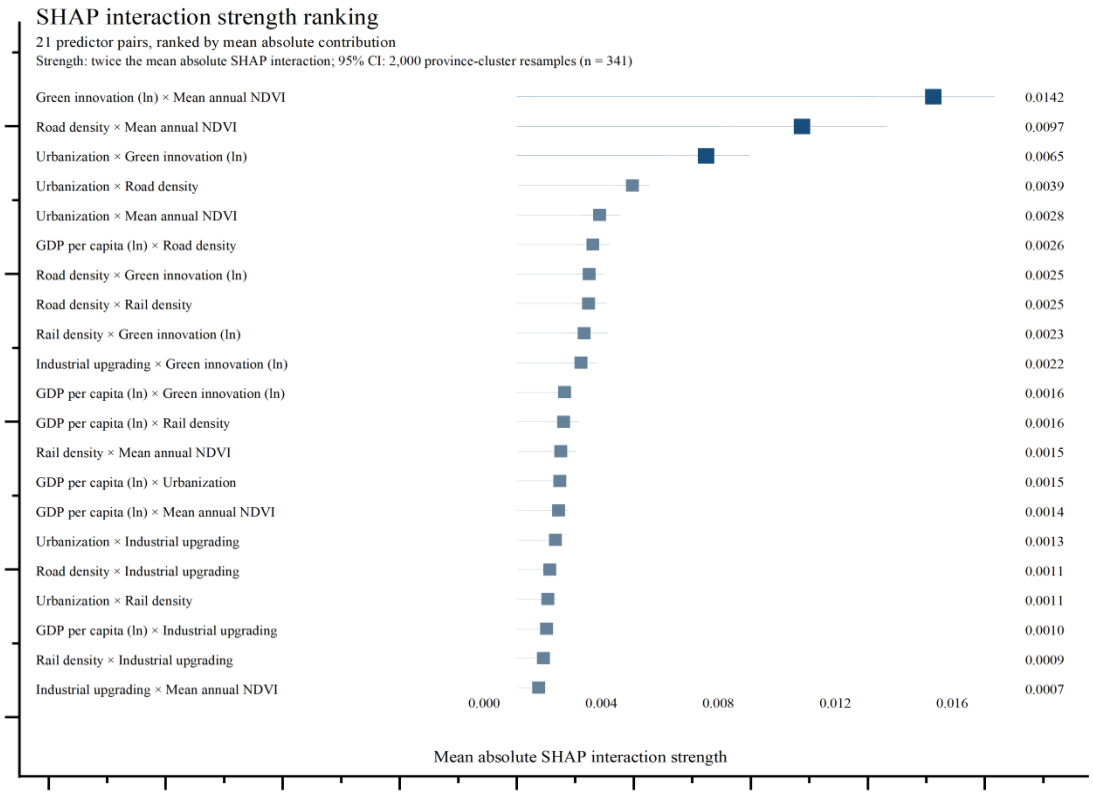


Fig. 11. SHAP Interaction Effects

5. Discussion

This study reveals substantial temporal, spatial, and nonlinear heterogeneity in sports tourism ecological development across Chinese provinces. Three findings are particularly noteworthy: regional inequality is driven primarily by within-region disparities, interprovincial spillovers differ markedly across economic, transportation, technological, and ecological factors, and several determinants exhibit nonlinear and condition-dependent relationships. These findings are discussed below in relation to existing research and the mechanisms underlying regional differentiation, spatial interactions, and nonlinear responses.

5.1 Temporal Evolution and Regional Differentiation

The level of sports tourism ecological development in China followed a fluctuating upward trajectory, with sustained growth before 2020 and an uneven recovery thereafter. Large-scale mobility evidence shows that public health emergencies can substantially disrupt cross-regional tourist flows, with considerable variation in recovery speed across cities (Yu et al., 2023). Consistent with this evidence, the present study further finds that sports tourism ecological development remains sensitive to changes in tourism demand and population mobility. Its temporal evolution therefore reflects the coexistence of long-term improvement and short-term market fluctuations. Stable tourism demand may consequently be necessary for converting resource inputs and ecological conditions into sustained development outcomes.

At the regional level, sports tourism ecological development exhibited a persistent spatial gradient. Previous research has documented substantial regional heterogeneity in tourism efficiency, its determinants, and its spatiotemporal evolution (Chen et al., 2022). In line with this evidence, the present study further finds that eastern China maintained a relatively high development level, while central China showed faster growth. However, this localized catch-up did not produce nationwide convergence because the east–west gap and overall interprovincial dispersion continued to widen. These findings reveal the coexistence of localized catch-up and overall divergence. They also indicate that resource endowments require complementary market

foundations, infrastructure, public services, and institutional capacity to generate sustained development advantages.

5.2 Spatial Clustering and Type-Specific Differentiation of Sports Tourism Projects

Sports tourism projects in China displayed significant spatial clustering and a multicentric distribution pattern, with high-density areas concentrated primarily in eastern China. Previous research suggests that destinations with larger markets are more likely to attract tourists and tourism facilities and form relatively stable core–periphery structures (Gao et al., 2022) Building on this research, the present study further finds that project agglomeration depends on both resource endowments and destination-level development conditions. Strong market foundations, transportation accessibility, and tourism services may strengthen spatial linkages among projects and facilitate the formation of high-density clusters.

The spatial organization of sports tourism projects also differed considerably across project types. Water-based sports, ice-and-snow tourism, and aviation sports exhibited relatively strong spatial concentration. Water-based sports, sports and leisure towns, ice-and-snow tourism, and aviation sports also displayed stronger directional extension. By contrast, scenic areas and destinations, sporting events and festivals, and outdoor sports overlapped within several high-density areas. These findings indicate that sports tourism projects do not follow a uniform spatial organization pattern. Resource-dependent projects tend to concentrate around specialized environmental conditions and facilities. More comprehensive projects are more likely to rely on established destinations and share tourist markets, transportation networks, and service facilities.

5.3 Local Direct Effects on Sports Tourism Ecological Development

Urbanization exerts a significantly positive local effect on sports tourism ecological development. This finding is consistent with previous research showing that urbanization can support tourism development through improved transportation, technological capacity, and public service provision (Tan et al., 2025) .This association may reflect the combined effects of concentrated demand, stronger public services, improved tourism reception capacity, and more efficient transportation organization.

By contrast, the weakly negative direct effects of railway density and green technological innovation suggest that greater infrastructure and innovation inputs do not automatically translate into local development gains. Railway networks may provide limited local benefits unless effectively connected with tourism destinations and project nodes, while green technological achievements may not yet have been fully converted into practical applications in sports tourism (Zhou et al., 2021). These findings highlight the importance of effectively integrating transportation and innovation resources into destination operations.

5.4 Interprovincial Spatial Spillover Effects of Sports Tourism Ecological Development

The indirect-effect results show that economic development, road density, and railway density generate significant positive effects on sports tourism ecological development in neighboring provinces. Existing evidence indicates that transportation infrastructure can promote tourism growth in surrounding regions by facilitating cross-regional tourist mobility and strengthening destination connectivity (Tian et al., 2022). Consistent with this evidence, the present study further finds that economic and transportation advantages extend beyond provincial boundaries. Economic development can expand regional tourism markets, while road and railway networks reduce interprovincial travel costs and strengthen route connectivity. These conditions allow local market and accessibility advantages to diffuse through broader regional tourism networks.

By contrast, green technological innovation and annual mean NDVI exhibit significantly negative indirect effects, while industrial structure upgrading shows a weakly negative spatial association. Emili and Galli (Emili & Galli, 2023) found that neighbouring tourism destinations may generate both positive and negative spatial spillovers, depending on the types of inputs and destinations involved. In light of the present findings, ecological and innovation-related factors may follow spatial transmission processes that differ from those associated with economic development and transportation infrastructure. Ecological resources are strongly place-bound, meaning that

superior environmental conditions in one province may strengthen its relative attractiveness and divert tourists, investment, and projects from neighbouring provinces. Similarly, differences in the capacity to absorb and apply green technologies may cause innovation-intensive provinces to attract mobile resources rather than automatically transmitting benefits to surrounding areas. These negative indirect effects should therefore be interpreted as conditional spatial competition rather than as evidence that ecological improvement or green technological innovation is inherently detrimental.

5.5 Nonlinear Responses and Interaction Effects

XGBoost outperformed the linear benchmark model in predictive performance, supporting the presence of pronounced nonlinear predictive relationships between sports tourism ecological development and its associated factors. (Hou et al., 2026)similarly found that the effects of tourism facilities and ecological conditions vary across different levels of development and exhibit clear nonlinear responses and threshold characteristics. This suggests that the average effects identified by linear models may not fully capture changes in the direction and magnitude of predictive contributions across different ranges of explanatory variables.

Among the examined factors, green technological innovation exhibits the most pronounced nonlinear pattern, with its predictive contribution gradually shifting from negative to positive beyond a certain level, whereas the SDM captures an overall negative spatial association on average. The present study therefore further indicates that the same factor may generate different predictive contributions at different development levels, revealing a clear stage-dependent pattern in sports tourism ecological development. The interaction analysis further shows that these nonlinear responses are conditioned by combinations of ecological conditions, transportation infrastructure, urbanization, and economic development. In other words, the predictive contribution of a single factor is not constant, but varies according to both its stage of development and the broader conditions in which it operates. Sports tourism ecological development thus exhibits nonlinear response patterns characterized by the coexistence of stage dependence and condition dependence.

5.6 Research Limitations and Future Directions

Several limitations should be acknowledged. First, the analysis is conducted at the provincial level and relies mainly on officially recognized sports tourism projects, which may not fully capture the spatial heterogeneity of ordinary projects at the city and county levels. Future research could therefore employ finer spatial units and incorporate additional data sources, such as POIs, tourist flows, and project-operation information. Second, the 2013–2023 study period spans phases of market expansion, external shocks, and recovery, meaning that short-term disturbances may overlap with longer-term structural trends. Extending the time series would help assess the stability of the observed temporal and regional patterns. Third, the methods used in this study identify spatial patterns, spatial associations, and nonlinear predictive relationships rather than causal effects. Although the SDM and XGBoost-SHAP provide complementary evidence on spillovers and condition-dependent relationships, they cannot directly reveal the underlying transmission mechanisms. Future studies could combine finer-scale spatial data, tourist-flow networks, policy shocks, and spatial causal inference or dynamic spatial models to further examine these mechanisms.

5.7 Research Contributions

This study contributes to the literature in three main ways. First, it integrates a province-level composite index with georeferenced sports tourism project data, linking regional development conditions with project-level spatial organization within a unified framework. Second, it extends the analysis from within-province differences to interprovincial spatial linkages by distinguishing local direct effects from cross-provincial spillovers, thereby revealing heterogeneous spatial transmission patterns across economic, transportation, technological, and ecological factors. Third, by combining the spatial Durbin model with XGBoost-SHAP, the study complements average spatial associations with evidence on nonlinear and condition-dependent relationships. This integrated approach advances the analysis of sports tourism ecological development beyond single-scale and average-effect perspectives toward a framework that simultaneously considers spatial dependence, cross-regional interactions, and nonlinear heterogeneity.

6. Management Implications

6.1 Regionally Differentiated and Tiered Development Strategies

Regions should adopt differentiated strategies according to their existing development foundations. High-performing eastern provinces should shift from expanding the number of projects toward improving the quality of existing projects, with greater emphasis on facility utilization, service quality, and ecological carrying pressure. Rapidly improving regions in central and southwestern China should strengthen the integration of sporting events, outdoor routes, and established scenic destinations to extend the sports tourism consumption chain. Western and northeastern regions should prioritize transportation connections, emergency rescue capacity, and public services, rather than directly replicating the development models of high-density regions. Additional financial support should be linked to project operating performance and ecological improvement outcomes to enhance the efficiency with which resource inputs are converted into development benefits.

6.2 Optimizing the Spatial Layout and Type Configuration of Sports Tourism Projects

In areas with a high concentration of sports tourism projects, proposed new projects should be evaluated in terms of overlap with existing projects of the same type, market coverage, and ecological carrying capacity before approval, so as to reduce low-level duplication and encourage differentiated operation and joint promotion among neighboring projects. In areas where projects are relatively sparse, priority should be given to cultivating core nodes with favorable resource conditions and high transportation accessibility, followed by the development of high-quality routes linking surrounding projects. Project planning should also reflect differences across tourism types. Ice and snow tourism should be developed primarily around northern snow and ice resources, water-based sports should be concentrated along coastal areas and major water bodies, and outdoor sports and camping projects should be developed in an orderly manner according to mountain resources and ecological carrying capacity. Sports and culture–tourism authorities could further establish an integrated geospatial database of project locations and incorporate project density, overlap among project types, and ecological conditions into project approval and spatial planning.

6.3 Strengthening Interprovincial Transport Connectivity and Product Coordination

The positive spatial spillovers associated with economic development and road and railway networks suggest that neighboring provinces can jointly develop sports tourism routes around major transport corridors and cross-provincial sporting events, while establishing coordinated mechanisms for tourist-flow information sharing, integrated ticketing, event scheduling, and emergency response. The focus of transportation development should shift from simply increasing network density toward improving effective accessibility by strengthening connections among transport hubs, scenic destinations, sporting events, and outdoor recreation nodes. To address competition for cross-provincial tourist markets, neighboring regions should enhance complementarity through differentiated products and joint marketing, thereby reducing repetitive development of similar projects across adjacent areas.

6.4 Promoting Green Technology Application and Stage-Specific Regulation

Green technology policies should shift from emphasizing patent counts toward evaluating practical application performance. Priority should be given to promoting the use of energy-efficient facilities, low-carbon transportation, ecological monitoring, waste and wastewater treatment, and outdoor safety technologies in sports tourism projects. Evaluation systems could incorporate indicators such as the adoption rate of green technologies, energy consumption per tourist, pollutant emission reductions, and ecological restoration outcomes. The nonlinear turning intervals identified by XGBoost-SHAP can be used to help assess the development stages of different regions, but they should not be directly adopted as uniform administrative thresholds. Local governments should instead conduct comprehensive assessments based on project utilization, ecological carrying capacity, and fiscal costs, and use these results to determine investment priorities and the appropriate pace of policy adjustment.

7. Conclusion

Based on panel data for 31 Chinese provinces from 2013 to 2023 and georeferenced data on sports tourism projects, this study constructs a comprehensive evaluation system for sports tourism ecological development. The entropy-weighted TOPSIS method and the Theil index are employed to assess its spatiotemporal patterns, while a two-way fixed-effects spatial Durbin model and the XGBoost-SHAP framework are used to examine spatial spillover effects and nonlinear driving mechanisms.

The main findings are as follows. First, the overall level of sports tourism ecological development exhibited a fluctuating upward trend, while sports tourism projects showed significant spatial clustering and a multicentric distribution pattern. Second, sports tourism ecological development displayed significant spatial spillover effects. Economic development and transportation infrastructure, particularly road and railway networks, generated positive cross-provincial spillovers on neighboring provinces, whereas green technological innovation and ecological endowments exhibited negative spillover effects. At the local level, urbanization emerged as the primary positive driver. Third, sports tourism ecological development followed a clear regional gradient of "eastern–central–northeastern–western China," with intra-regional disparities constituting the dominant source of overall inequality. Its development was further associated with mechanisms involving cross-provincial transportation-network coordination, consumption expansion driven by urbanization, and the combined interactions between green technological innovation and ecological conditions.

Overall, sports tourism ecological development is not driven by a single linear factor, but is characterized by the coexistence of spatial dependence, stage dependence, and condition dependence. Accordingly, future development should emphasize cross-provincial network coordination, differentiated regional governance, and the effective transformation and application of green technologies.

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During the preparation of this manuscript, the authors used ChatGPT (OpenAI) for language editing and improving the clarity and readability of the manuscript. The authors reviewed and edited the output and take full responsibility for the content of this publication.

Author Contributions

Z.M. conceived and designed the study, collected and organized the data, conducted the entropy-weighted TOPSIS, Theil index, spatial analysis, spatial econometric, and XGBoost-SHAP analyses, prepared the figures and tables, and drafted the manuscript. T.W. contributed to data organization, interpretation of the findings, supervision of the study, and critical revision of the manuscript. Both authors have read and approved the final version of the manuscript.

Data Availability

The data supporting the findings of this study are provided in the accompanying Supplementary Data files. Supplementary Data 1 contains the province-year indicator dataset used to construct the

sports tourism ecological development index through the entropy-weighted TOPSIS method, comprising 341 observations for 31 provincial-level regions in China from 2013 to 2023 and 13 evaluation indicators. Supplementary Data 2 contains the province-year dataset used for the spatial Durbin model and XGBoost-SHAP analyses. Supplementary Data 3 contains the geocoded sports tourism project data used for the spatial analyses, including project year, location, type, and geographic coordinates. The underlying statistical and project data were compiled from the sources described in the manuscript. No human-participant or personally identifiable data are included.

Additional Information

Competing Interests

The authors declare no competing interests.

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Ethical Approval

This study did not involve human participants, human biological materials, or identifiable personal data. Therefore, ethical approval was not required.

Informed Consent

Not applicable.

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