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Tourism Ecological Security Assessment and Its Driving Mechanisms in Anhui Province: An Integrated DPSIR–SBM-DEA Framework

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Abstract: Tourism ecological security is crucial for regional sustainable development and risk management. This study constructed an evaluation framework based on the DPSIR model and Remote Sensing Ecological Index (RSEI) to assess 16 prefecture-level cities in Anhui Province from 2008 to 2019. SBM-DEA, Sen–Mann–Kendall trend analysis, spatial autocorrelation, and Geo-Detector models were employed to investigate spatiotemporal evolution and driving mechanisms.

Results show: (1) Tourism ecological security exhibited a fluctuating upward trend with narrowing regional disparities and continuous environmental improvement. High-security areas expanded, concentrating in southern and central-eastern Anhui, whereas northern areas remained relatively low. (2) Significant spatial clustering formed a “high-south, low-north” pattern. Hotspots were concentrated in Huangshan, Chizhou, Xuancheng, and Hefei, while cold spots were mainly in Bengbu and northern Anhui. (3) Spatial differentiation was primarily driven by tourist arrivals, population density, NDVI, star-rated hotels, tourism revenue share, tertiary industry share, fiscal expenditure, and domestic waste treatment rates, all of which exhibited significant regional heterogeneity in their effects.

Keywords: Tourism Ecological Security; DPSIR Model; SBM-DEA Model; Geo-Detector; Sen’s Slope Estimator and Mann–Kendall Trend Analysis; Spatial Autocorrelation

1. Introduction

Global ecological and environmental issues are increasingly prominent, posing severe threats to the sustainable development of human society[1]. The topic of ensuring ecological security has gradually attracted widespread attention in the academic community[2]. Currently, tourism is developing rapidly worldwide, bringing substantial economic and social benefits, and has long been considered a “smoke-free industry”[3]. However, tourism, essentially an ecological consumption activity, is gradually exhibiting negative effects[4]. Large-scale spatial migration of tourists and overdevelopment of tourist areas impact local ecosystems, leading to a series of adverse consequences such as environmental pollution and traffic congestion[5]. The

concept of “harmonious coexistence between humans and nature” has drawn global attention[6]. Tourism ecological security is a crucial component of sustainable tourism development, emphasizing that tourism development can only be achieved when natural resources and the ecological environment are maintained in a balanced state[7]. Key factors for tourism development, including a healthy ecological environment and abundant natural resources, serve as primary indicators for the long-term sustainable development of regional tourism[8].

China, as the world's largest developing country, has experienced a rapid expansion of its tourism industry. Although COVID-19 has severely affected China's tourism sector in recent years, tourism continues to play a vital role in both economic and social development[9]. Specifically, the rapid growth of tourism has contributed significantly to political, economic, and social progress; however, it has also generated a range of adverse impacts, including ecosystem degradation in tourist destinations, environmental pollution, and traffic congestion[10]. In response to these tourism-related challenges, the Chinese government has been committed to promoting the vision that “lucid waters and lush mountains are invaluable assets.” Benefiting from the promotion of the “Beautiful Anhui, Welcoming the World” brand and the implementation of comprehensive ecotourism development initiatives, Anhui Province has attracted a large number of visitors, resulting in substantial growth of its tourism industry. Driven by the rapid expansion of the tourism economy, increasing attention has been directed toward evaluating resource and environmental carrying capacity[11]. Meanwhile, the scientific assessment and effective maintenance of tourism ecological security have become increasingly important for achieving high-quality tourism development in Anhui Province.

Tourism ecological security has become an important research topic within the broader field of sustainable tourism development. Existing studies have explored various aspects of tourism ecological security, including assessment and measurement[12], dynamic simulation[13], obstacle factor diagnosis[14], early-warning analysis[15], trend prediction[16], spatiotemporal evolution[17], and classification and zoning[18]. Methodologically, researchers have employed a range of approaches, such as the ecological footprint method[19], grey relational analysis[20], TOPSIS, the standard deviation ellipse model[21], and Markov chain models[20]. These studies have been conducted across diverse geographical contexts, including coastal areas[22], islands[23], wetlands[24], scenic destinations[25], cities[26], and provincial regions[27]. Consequently, tourism ecological security has evolved into a multidisciplinary research field integrating tourism geography, environmental science[11], and ecology[28]. Despite these advances, several limitations remain[29]. First, there is still no widely accepted and comprehensive framework for measuring tourism ecological security. As a complex socio-ecological system, tourism ecological security involves intricate interactions among economic development, tourism activities, environmental pressures, ecological conditions, and governance responses. Existing studies often focus on specific dimensions, such as environmental management[30] or resource assessment[31], while overlooking the systemic relationships among multiple subsystems[32]. In this regard,

the Driving Force–Pressure–State–Impact–Response (DPSIR) framework provides a comprehensive analytical perspective by integrating five interrelated subsystems[33]. Owing to its clear causal logic and feedback structure, DPSIR has been widely applied in ecosystem service assessment[34], water resource management[31], and environmental sustainability studies[35]. More importantly, the framework facilitates the identification of key issues and policy intervention points through the interactions among Driving Forces (D), Pressures (P), States (S), Impacts (I), and Responses (R)[36]. Second, although previous studies have identified numerous factors influencing tourism ecological security, limited attention has been paid to the underlying driving mechanisms through which these factors operate[37]. Furthermore, methodological innovation remains relatively insufficient. To address this issue, [2]suggested extending ecological efficiency approaches to studies of ecological security and sustainable development. Following this perspective, Data Envelopment Analysis (DEA) has been introduced into tourism ecological security assessment and has demonstrated considerable effectiveness in empirical studies such as those conducted in the Yangtze River Delta[38]. Another notable gap concerns the spatial scale of analysis. Existing studies have primarily focused on tourist destinations, scenic areas, and major tourism cities, whereas research at the prefecture-level city scale remains relatively scarce. As important spatial units linking regional economic development, tourism resource allocation, and ecological governance, prefecture-level cities play a pivotal role in balancing tourism growth and environmental protection. Investigating tourism ecological security at this scale can therefore provide valuable insights into regional sustainable development and spatial governance. Against this background, this study focuses on the 16 prefecture-level cities of Anhui Province. By integrating the DPSIR framework with the DEA model, a comprehensive tourism ecological security evaluation system is established to measure the level of tourism ecological security. ArcGIS 10.8 and GeoDa 0.95i are employed to examine spatiotemporal dynamics and spatial clustering characteristics, while the Geographic Detector model is used to identify key driving factors and reveal their interaction mechanisms. The study aims to enrich the theoretical understanding of tourism ecological security at the prefecture-level city scale and provide scientific evidence for promoting coordinated development between tourism growth and ecological conservation in Anhui Province.

2. Study Area and Data Sources

2.1. Study Area

Anhui Province is located in eastern China (29°41′N–34°38′N, 114°54′E–119°37′E), covering approximately 140,100 km² and comprising 16 prefecture-level cities (Fig. 1). Situated between the Yangtze and Huaihe River basins, it features diverse topography, including mountains and hills in the south, the Jianghuai hilly region in the center, and plains in the north. It is an important cultural region where Huizhou, Huaihe, and Wanjiang cultures converge. By 2025, it had over 650 A-grade tourist attractions, and in 2019 it received over 800 million tourist visits and generated about 800 billion RMB in tourism revenue. Rapid tourism development has increased

environmental pressures, making it a representative case for tourism ecological security analysis.

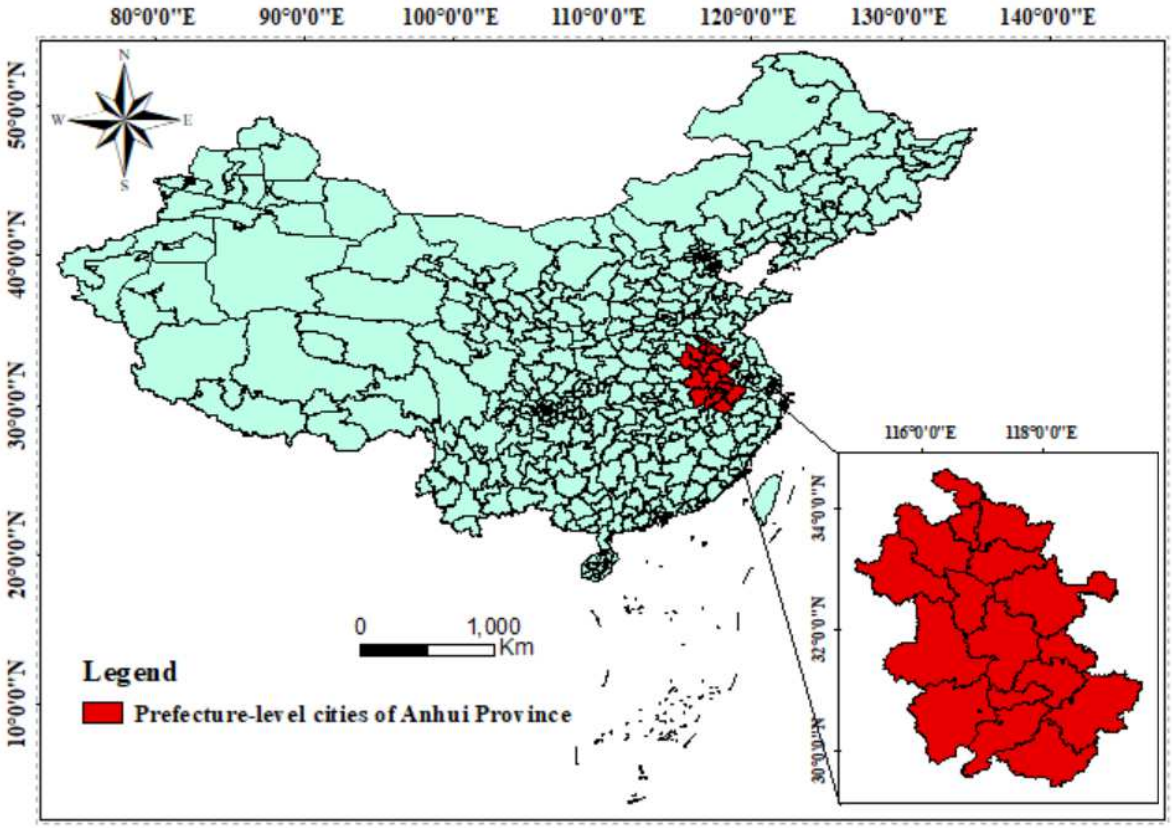


Figure 1. Study area.

2.2. Data sources

This study uses 16 prefecture-level cities of Anhui Province as sampling units, with the study period limited to 2008–2019 due to COVID-19 impacts during 2020–2022. Socio-economic and tourism data were obtained from national, provincial, and municipal statistical yearbooks, supplemented by official communiqués and reports, with missing values filled via linear interpolation. Remote sensing data for RSEI calculation were derived from Landsat TM/OLI/TIRS imagery provided by USGS. High-quality images with low cloud cover were selected and preprocessed using Google Earth Engine (GEE).

3. Methods

3.1. Research methods

3.1.1. DPSIR–DEA model

The DPSIR model evolved from the PSR and DSR frameworks and was first established and applied by the European Environment Agency (UNPE)[39]. This model can capture the relationship between tourism activities and the ecological environment from a systems perspective and reveal the continuous feedback mechanisms among its subsystems[40]. It has been widely applied in various fields, including sustainable tourism development assessment in heritage sites[41], wetland ecological security evaluation[42], and low-carbon urban ecological security assessment[43].

Data Envelopment Analysis (DEA), proposed by Charnes, Cooper, and Rhodes in 1978, is a method for measuring relative efficiency. Based on the classical CCR and BCC models, Tone introduced the SBM model, which addresses issues related to non-zero input or output slacks and undesirable outputs[44]. To better differentiate the efficiency of relatively effective decision-making units, Tone further proposed the Super-SBM model[45]. The SBM-DEA model effectively resolves the problem of undesirable outputs and can measure environmental efficiency[38]. In this study, the SBM-DEA model is employed to quantify the relative efficiency of regional tourism ecosystems, which is then used to evaluate regional tourism ecological security. The calculation formula is as follows:

$$\rho^{*}=min\rho=min\frac{1-\left(\frac{1}{N}\sum_{n=1}^{N}\frac{S_n^{\mathrm{x}}}{x_n^{\mathrm{k}\prime}}\right)}{1+\left[\frac{1}{M+1}\left(\sum_{m=1}^{M}\frac{S_{\mathrm{m}}^{\mathrm{y}}}{y_{\mathrm{m}}^{\mathrm{k}\prime}}\right)+\sum_{i=1}^{\mathrm{I}}\frac{S_{\mathrm{j}}^{\mathrm{b}}}{\mathrm{b}_i^{\mathrm{k}\prime}}\right]}$$

$$s.\mathrm{v.}\begin{cases}\sum_{k=1}^{K}z_k^{y}y_m^{k}-s_m^{y}=y_m^{k'},m=1,\cdots,M;\\ \sum_{k=1}^{K}z_k^{y}\,\mathrm{b}_{\mathrm{i}}^{k}+s_i^{b}=b_n^{k'},i=1,\cdots,I;\\ \sum_{k=1}^{K}z_k^{x}\,\mathrm{x}_n^{k}+s_{\mathrm{m}}^{x}=x_n^{\mathrm{k}'},n=1,\cdots,N\\ z_i^{k}\geq 0,s_m^{y}\geq 0,s_i^{b}\geq 0,s_n^{x}\geq 0,k=1,\cdots,K\end{cases}\qquad(1)$$

In the equation, ρ^{*}represents tourism ecological security. N, M, and I denote the number of inputs, desirable outputs, and undesirable outputs, respectively. (s_m^{y}, s_i^{b},s_n^{x}), (y_m^{k},$\mathrm{b}_i^{\mathrm{k}}$,$x_n^{\mathrm{k}}$), and ($z_k^{\mathrm{y}}$,$z_k^{x}$) represent the slack variables of inputs and outputs, the input–output values of decision-making unit K at time v, and the corresponding weights of each input and output, respectively. A larger value of ρ indicates a higher level of tourism ecological security. In the DEA framework, Driving Forces, Tourism

Pressure, and Social Response are inputs; State and Impact are desirable outputs, while Ecological Damage Pressure is an undesirable output.

3.1.2. Calculation of RSEI

Within the State (S) subsystem of DPSIR, the Remote Sensing Ecological Index (RSEI) evaluates ecological environmental quality through principal component analysis of dryness, heat, humidity, and greenness[46]. RSEI integrates NDSI, LST, Wet, and NDVI to represent dryness, heat, humidity, and greenness, offering a comprehensive measure of ecological environmental quality[47].

In this study, remote sensing data were processed using the Google Earth Engine (GEE) platform. High-quality remote sensing images covering the study area were selected through the GEE platform and subjected to radiometric correction, cloud removal, and masking procedures. Subsequently, annual NDVI, LST, Wet, and NDSI layers were calculated for the study period. According to the statistical principles of Principal Component Analysis (PCA), the first principal component (PC1) generally contains the largest proportion of information from the original variables and therefore best reflects the overall ecological condition. Consequently, the PC1 score was selected to construct the original Remote Sensing Ecological Index ($RSEI_0$) in this study. The calculation formula is expressed as follows[48]:

$$RSEI_0 = 1 - PC1\left[f\left(NDVI, WET, NDSI, LST\right)\right] \quad (2)$$

where $RSEI_0$ is the original Remote Sensing Ecological Index; PC1 denotes the first principal component derived from PCA; and f represents the normalized value of each indicator. Among the four ecological indicators, NDVI, Wet, NDSI, and LST correspond to greenness, wetness, dryness, and heat, respectively.

The RSEI was calculated by applying a normalization procedure to $RSEI_0$. The max and min values of $RSEI_0$ are denoted as $RSEI_0max$ and $RSEI_0min$, respectively. The calculation formula is expressed as follows[48]:

$$RSEI = \left(RSEI_0 - RSEI_{0\,\min}\right)/\left(RSEI_{0\,\max} - RSEI_{0\,\min}\right) \quad (3)$$

where RSEI denotes the Remote Sensing Ecological Index, with values ranging from 0 to 1. A value closer to 1 indicates better ecological environmental quality, whereas a value closer to 0 indicates poorer ecological environmental quality.

3.1.3. Sen's slope estimation and mann-kendall test

The Sen–Mann–Kendall method is widely used for long-term time series analysis. The Theil–Sen estimator quantifies trend magnitude and direction, while the Mann–Kendall (MK) test evaluates statistical significance. As non-parametric

methods, they are robust to outliers and distribution-free, making them suitable for trend detection in ordered data. The corresponding trend classification criteria are shown in Table 1, and the calculation formula is given as follows[49].

$$\mathrm{Sen} = \mathrm{median}\left(\frac{\mathrm{DRSEI_j} - \mathrm{DRSEI_i}}{\mathrm{j} - \mathrm{i}}\right) \quad (4)$$

$$Z = \begin{cases} S - \frac{1}{\sqrt{\mathrm{var}(s)}} & S>0 \\ 0 & S=0 \\ S + \frac{1}{\sqrt{\mathrm{var}(s)}} & S<0 \end{cases} \quad (5)$$

$$S = \sum_{i=1}^{n-1}\sum_{j=i+1}^{n} sgn\left(a_j - a_i\right) \quad (6)$$

$$\mathrm{sgn}\left(a_j - a_i\right) = \begin{cases} +1 & \left(a_j - a_i > 0\right) \\ 0 & \left(a_j - a_i = 0\right) \\ -1 & \left(a_j - a_i < 0\right) \end{cases} \quad (7)$$

In the above equations, Sen represents the magnitude and direction of changes in RSEI. When Sen > 0, RSEI shows an increasing trend; when Sen < 0, it indicates a decreasing trend; and when Sen = 0, RSEI remains stable over time. Z denotes the standardized test statistic used to assess the significance of the trend, and sgn() represents the sign function. a_j and a_i correspond to the observed values at time points j and i, respectively.

Table 1. Trend according to the Sen+MK method

Sen	MK salience	Trend type determination	Ecological meaning explained
Sen≥0.0005	Z＞1.96	Significant increase （SI）	persistent and statistically significant increasing trend
	Z≤1.96	not significantly increased （NSI）	The indicator shows an overall increasing trend, although the change is not statistically significant
-0.0005<Sen<0.0005	-	basically stable (BS)	The indicator exhibits minor fluctuations with no

			evident trend.
Sen≤-0.0005	Z≤1.96	not significantly decreased(NSD)	The indicator shows a decreasing trend, but the change is not statistically significant.
	Z＞1.96	Significant decrease（SD）	The indicator exhibits significant degradation

3.1.4. Spatial autocorrelation analysis

3.1.4.1. Global spatial autocorrelation analysis

Spatial autocorrelation was employed to analyze the spatial characteristics of the study area. Moran’s I was used to quantify the spatial autocorrelation, and its calculation formula is presented as follows[50]:

$$I=\frac{N}{S_0}\times\frac{\sum_{i=i}^{N}\sum_{j=1}^{N}w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}(x_i-\bar{x})^2} \quad (8)$$

where I denotes Moran’s index, ranging from -1 to 1; N is the number of observations; x_i and x_j represent the observed values in regions i and j, respectively; $\bar{x}$ is the mean of the observed values across all regions; S_0 is the sum of all elements in the spatial weight matrix; and w_{ij} represents the spatial weight between regions i and j.

3.1.4.2. Local spatial autocorrelation analysis

Local spatial autocorrelation was used to measure spatial heterogeneity and to identify the spatial distribution patterns of high-value clusters and low-value clusters. The Getis-Ord Gi* statistic was employed to assess local spatial heterogeneity and to detect the spatial distribution of cold spots and hot spots, using the following mathematical expression[50]:

$$G_i^*(d)=\sum_{j=1}^{n}w_{ij}x_j/\sum_{j=1}^{n}x_j \quad (9)$$

In the equation, nnn denotes the number of spatial units; x_i and x_j represent the

attribute values of spatial units i and j, respectively; and w_{ij} refers to the spatial weight matrix. If G_i^* is positive and statistically significant, it indicates that the value at location i and its surrounding areas are relatively high, representing a high-value clustering area (hot spot). Conversely, if G_i^* is negative and statistically significant, it suggests that the values around location i are lower than the average level, indicating a low-value clustering area (cold spot).

3.1.5. Geo-detector

The Geographical Detector is primarily used to detect and utilize spatial heterogeneity[51]. It mainly includes four types of detectors: factor and stratified heterogeneity detection, interaction detection, risk area detection, and ecological detection. In this study, the factor and stratified heterogeneity detection model was applied to investigate the spatial heterogeneity of tourism ecological security in Anhui Province and to assess the extent to which each indicator explains the spatial variation of tourism ecological security[52]. The Geo-Detector method used here effectively identifies the key driving factors of regional tourism ecological security. The calculation formula is as follows[53]:

$$q=1-\frac{1}{n\sigma_U^2}\sum_{i=1}^{m} n_{D,i}\,\sigma_{U_{D,i}}^2 \qquad (10)$$

In the equation, q represents the explanatory power of the detection factor D ; n denotes the total sample size of the study area; $n_{D,i}$ is the number of samples in sub-region i; m represents the number of sub-regions; σ_U^2 is the variance of tourism ecological security values; and $\sigma_{U_{D,i}}^2$ is the variance within sub-region i. The value of q ranges from 0 to 1, where a larger q value indicates a stronger influence of factor D on tourism ecological security.

3.2. Selection of indicators

Tourism ecological security evaluation indicators include inputs and outputs, and their selection determines assessment validity. Based on existing studies, this study considers tourism industry development, economy, population, environment, and resources across the tourism ecological system[54].

(1) Driving forces (D)[55]: This subsystem is measured by GDP per capita, total population at the end of the year, tourist arrivals, and urbanization rate. These indicators are key inputs of the tourism ecological system, where tourist arrivals reflect tourism development, while the others represent socio-economic conditions.

(2) Pressure (P)[56]: Socio-ecological pressure and natural ecosystem carrying

capacity are key components of tourism ecological security pressure. Socio-ecological pressure is represented by tourist density, population density, and household water consumption, while the tourism spatial index reflects natural ecosystem carrying capacity based on tourist numbers per land area.

(3) State (S)[57]: Five indicators are selected as output variables, including the number of star-rated hotels, the number of A-level scenic spots, NDVI, WET, and RSEI. The state indicators are mainly derived from the perspectives of ecological environment and tourism development. Specifically, NDVI, WET, and RSEI reflect the ecological environmental quality of tourist destinations. The numbers of star-rated hotels and A-level scenic spots are utilized to gauge the service capacity of tourism reception facilities and the tourist reception capacity of the destination, respectively.

(4) Impact (I)[58]: Three output variables are selected, including per capita tourism expenditure, the proportion of total tourism revenue in GDP, and the proportion of the tertiary industry in GDP. These indicators reflect tourism industry development and socio-economic development, where they represent tourism consumption contribution, economic contribution, and macro-level tourism development.

(5) Response (R)[59]: Three indicators are selected as input variables, including the proportion of fiscal expenditure in GDP, the sewage treatment rate, and the harmless treatment rate of domestic waste. The proportion of fiscal expenditure in GDP reflects the economic support for environmental protection investment. In addition, the sewage treatment rate and the harmless treatment rate of domestic waste are key contributing factors to the sustainable development of the ecological environment.

In accordance with the requirements of the DPSIR and DEA models and data availability, this study selects five primary indicators—Driving forces, Pressure, State, Impact, and Response—and 19 secondary indicators. Among them, Driving forces, Pressure, and Response are treated as input variables, while State and Impact are regarded as desirable output variables. Finally, all indicators are standardized, and their weights are determined using the entropy method[58]. The evaluation index system is presented in Table 2.

Table 2. Evaluation index system of tourism ecological security in Anhui Province.

Dimension		Index	Index meaning	Weight
Driver		D1 GDP per capita(yuan)	It reflects the impact of the economic development of tourist.	0.0487
		D2 Population at the end of the year(ten thousand people)	growth on ecological environment.	0.0501
		D3 Number of visitors (ten thousand people)	destination on ecological environment of tourist destination.	0.0804
		D4 Urbanization rate(%)	It reflects the impact of tourist urban development and population.	0.0268
Pressure	Social population pressure	P1 Visitor density	It reflects the disturbance of tourists to the residents'life,the ratio of the number of tourists to the population at the end of the year is used to represent.	0.0967
		P2 Population density (person /km²)	It reflects the degree of land area occupied by residents in tourist destinations, the ratio of permanent resident population to land area is used to represent.	0.0406
		P3 Residential household water consumption(10,000m³)	It represents the water resource stress of the tourism destination.	0.1358
	ecosystem carrying capacity	P4 Tourism space index (person/km²)	It reflects the tourist carrying capacity of the tourist destination,the ratio of the number of tourists to thelocal land area is used to represent.	0.0685
State		S1 Number of star hotels (amount)	It represents the service capacity of tourism reception facilities.	0.0597
		S2 Number of A-level scenic spots(amount)	It reflects the tourist reception capacity of the tourist destination.	0.0727
		S3 NDVI	It reflects the vegetation condition of the tourist destination.	0.0105
		S4 LST	It reflects the thermal environment of the tourist destination.	0.0303
		S5 RSEI	It reflects the ecological environment quality condition of thetourist destination.	0.0103
Impact		I1 Tourism expenditure per capita(yuan)	It reflects the contribution of resident tourism consumption to tourism revenue.	0.0438
		I2 Proportion of total tourism revenue in GDP(%)	It reflects the economic contribution of tourism industry in tourist destination.	0.1141
		I3 Proportion of the tertiary industry in GDP(%)	It reflects the macroscopic situation of tourism development in tourist destination.	0.0254
Response		R1 Proportion of fiscal expenditure in GDP(%)	It reflects the investment strength of the tourist destination government to improve the ecological environment.	0.0781
		R2 Domestic sewage treatment rate(%)	It reflects the level of environmental pollution control in tourist destination.	0.0050
		R3 Harmless treatment rate of municipal solid waste(%)	It reflects the efficiency of the government's treatment of municipal solid waste in tourist destinations.	0.0025

4. Results

4.1. Spatiotemporal characteristics of tourism ecological security

4.1.1. Temporal evolution characteristics

Based on Equation (1), the DEA (SBM-DEA) model was used to assess tourism ecological security in Anhui Province from 2008 to 2019. As shown in Table 3, tourism ecological security followed a pattern of "fluctuating adjustment–phased improvement–high-level stability". The annual mean values ranged from 1.0150 to 1.1401, indicating a generally favorable state. All evaluation values exceeded 1, suggesting that the tourism ecological system consistently remained above the safety threshold throughout the study period.

From the perspective of temporal evolution, the process can be divided into three typical stages:

(1) Fluctuation adjustment stage (2008–2010): During this stage, the tourism ecological security index exhibited relatively large fluctuations, decreasing from 1.1401 in 2008 to 1.0150 in 2009, and then rapidly rebounding to 1.1369 in 2010, showing a typical "V-shaped" pattern.

(2) Staged fluctuation phase (2011–2014): The tourism ecological security index fluctuated slightly within the range of 1.0951–1.0678, reaching a temporary low value of 1.0678 in 2013.

(3) Optimization and improvement stage (2015–2019): After 2014, the index rebounded to 1.1242 and remained stably above 1.10 during 2016–2019, with a noticeably reduced fluctuation range, indicating that the system gradually entered a high-level stable state.

From the perspective of driving mechanisms, 2014 was a critical turning point. With China's ecological civilization construction strategy, Anhui Province promoted green development, ecotourism development, and the all-for-one tourism strategy. Due to policy lag effects, improvements emerged after 2015, leading tourism ecological security from short-term fluctuation to long-term stable optimization.

Table 3. Tourism ecological security evaluation values of Anhui Province.

City	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Hefei	1.1896	1.2222	1.2284	1.3169	1.3028	1.3113	1.3184	1.2875	1.2994	1.2208	1.2065	1.2495
Wuhu	1.0609	1.0679	1.1127	1.0986	1.0648	1.0557	1.0479	1.0485	1.0576	1.0563	1.0749	1.0606
Bengbu	1.0474	1.0208	1.0244	0.5414	0.5833	0.5209	0.7157	0.7412	1.0059	1.0025	1.0053	0.687
Huainan	1.004	0.0076	1.0225	0.7942	1.026	0.7389	1.079	1.1331	1.0897	1.0837	1.1018	1.1666
Maanshan	1.0055	1.0105	1.0118	1.0118	1.0041	0.6892	1.0189	1.005	1.0242	1.0814	1.0626	1.1151
Huaibei	1.082	0.0095	1.1168	1.1025	1.0892	1.2218	1.2216	1.2125	1.2152	1.117	1.1377	1.1341

Tongling	1.2001	1.086	1.3171	1.2689	1.2645	1.2361	1.2769	1.1171	1.0752	1.0751	1.0831	1.0756
Anqing	1.0565	1.0942	1.1223	1.0698	1.111	1.1021	1.1167	1.1131	1.1205	1.1245	1.1368	1.1562
Huangshan	1.4197	1.3499	1.338	1.3247	1.3051	1.2819	1.1892	1.1771	1.1488	1.1468	1.1406	1.1699
Chuzhou	1.0381	1.0015	1.0492	1.0356	1.0472	1.0777	1.1125	1.0877	1.0724	1.0811	1.0903	1.1149
Fuyang	1.115	1.0576	1.0248	1.0251	1.0493	1.0748	1.1352	1.0843	1.0703	1.0747	1.0583	1.0618
Suzhou	1.0475	1.0541	1.0676	1.0514	1.0313	1.0349	1.0889	1.0438	1.0235	1.0372	1.048	1.0263
Luan	1.0731	1.0997	1.2402	1.3166	1.2735	1.2259	1.1975	1.1544	1.1089	1.1131	1.1207	1.0986
Bozhou	1.2106	1.1541	1.2178	1.1902	1.1698	1.162	1.1905	1.1822	1.1311	1.1828	1.1768	1.146
Chizhou	1.5048	1.7926	1.077	1.1212	1.0677	1.0547	1.0154	1.0339	1.0663	1.1037	1.0871	1.0773
Xuancheng	1.1865	1.2124	1.2205	1.2534	1.2855	1.2981	1.2638	1.2255	1.2447	1.2679	1.2383	1.2744
Mean	1.1401	1.0150	1.1369	1.0951	1.1046	1.0678	1.1242	1.1029	1.1096	1.1105	1.1105	1.1008

4.1.2. Temporal dynamics and current status of RSEI

This study utilized the capabilities of the Google Earth Engine (GEE) platform to derive the RSEI of Anhui Province from 2008 to 2019 using Equations (2) and (3). High-quality RSEI remote sensing images within the study area were selected through the GEE platform for data processing. Finally, the Sen + MK method was applied to analyze the temporal dynamics and current status of RSEI. Figure 2 presents the RSEI remote sensing images of Anhui Province from 2008 to 2019.

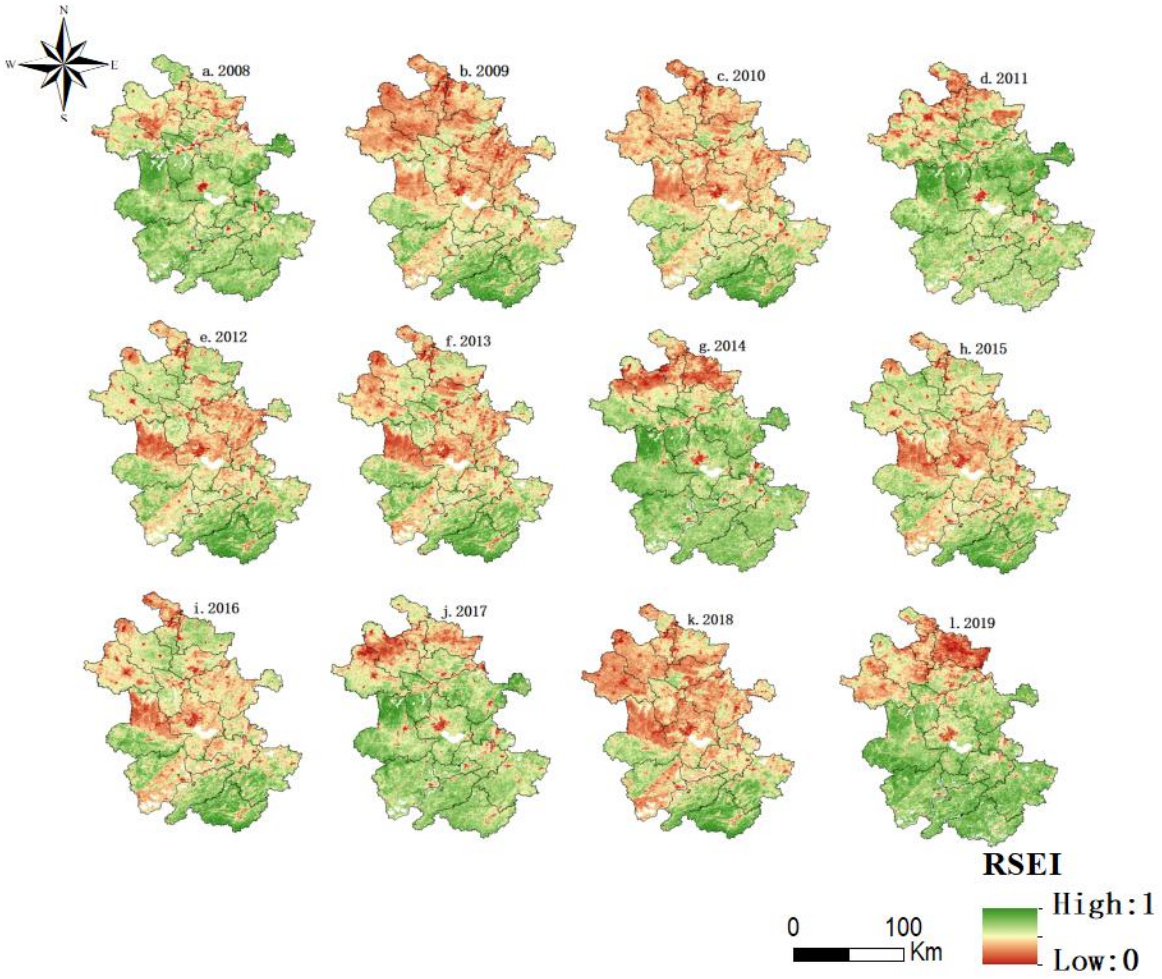


Figure 2. RSEI remote sensing images of Anhui Province from 2008 to 2019.

The Sen + MK analysis (Figure 3) shows that RSEI in Anhui Province generally exhibited "predominant significant improvement with localized non-significant degradation" during 2008–2019. Sen slope values ranged from −0.05 to 0.05, indicating limited ecological change and an overall improving trend. Spatially, positive changes were widely distributed, especially in southern mountainous areas and central Anhui, while negative changes were scattered in high-development regions, showing clear spatial heterogeneity. According to MK classification, SI and NSD were dominant, while NSI and SD were minor. Overall, Anhui Province experienced stable ecological improvement, reflecting effective ecological protection.

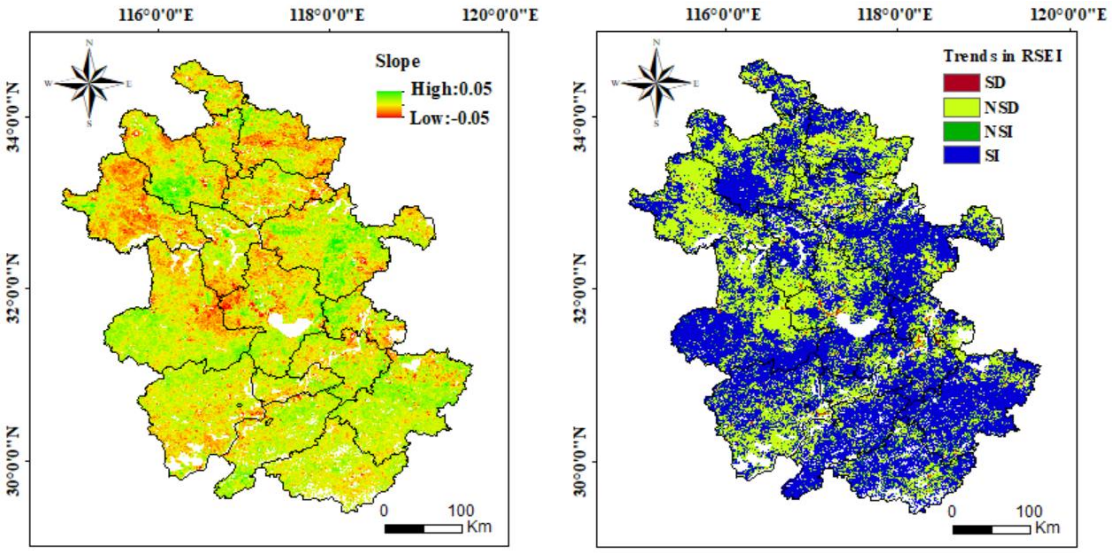


Figure 3. Analysis of the evolution trend of ecological environmental quality in Anhui Province from 2008 to 2019.

4.1.3. Spatial pattern and development characteristics

4.1.3.1. Global spatial distribution

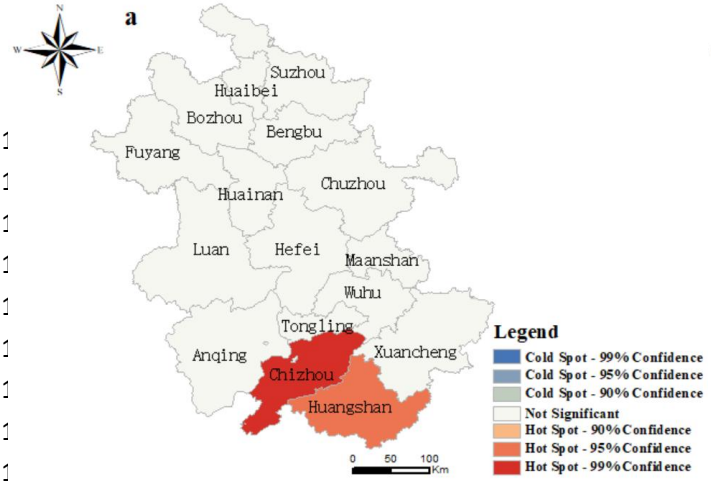
The Moran's I values of tourism ecological security in Anhui Province from 2008 to 2019 indicate a transition from significant spatial clustering to a random distribution (Table 4). Only in 2008 did Moran's I (0.482) pass the significance test ($P < 0.05$), indicating significant clustering. In subsequent years, Moran's I fluctuated between positive and negative values but remained insignificant ($P > 0.05$), showing a random spatial pattern. Overall, Moran's I declined and became mostly negative after 2010, suggesting weakened spatial autocorrelation and low interregional dependence without significant spatial spillover effects.

Table 4. Moran's I values of tourism ecological security in Anhui Province.

Year	Moran's I	Z(I)	P(I)	Spatial pattern
2008	0.482	2.612	0.008	Clustered distribution
2009	0.033	0.492	0.622	Random distribution
2010	-0.171	-0.446	0.655	Random distribution
2011	0.046	0.545	0.585	Random distribution
2012	0.053	0.621	0.534	Random distribution
2013	-0.087	-0.093	0.925	Random distribution
2014	-0.127	-0.306	0.759	Random distribution
2015	-0.127	-0.316	0.751	Random distribution
2016	-0.257	-0.862	0.388	Random distribution
2017	-0.154	-0.402	0.687	Random distribution
2018	-0.186	-0.536	0.591	Random distribution
2019	-0.088	-0.128	0.897	Random distribution

4.1.3.2. Local spatial pattern

To further examine local spatial patterns, the Getis–Ord Gi* statistic was calculated using ArcGIS 10.8, and the hot–cold spot evolution map was generated (Figure 4). The results show that hot spots and cold spots were relatively limited, whereas sub-hot spots, sub-cold spots, and ordinary areas occupied larger proportions and exhibited notable temporal variation. Hot spots were initially concentrated in southern Anhui, particularly Huangshan and Chizhou (around 2008), and gradually shifted toward Hefei and Xuancheng during 2016–2018. Sub-hot spots mainly occurred in Tongling and Huangshan in the early stage and later expanded toward Hefei. In contrast, cold spots and sub-cold spots were primarily distributed in central and northern Anhui. Bengbu remained a persistent cold spot during most years, although its intensity fluctuated over time. Meanwhile, cities such as Fuyang, Bozhou, and Anqing remained largely stable as ordinary areas. Overall, the spatial pattern evolved from an early-stage southern hot-spot aggregation to a later configuration characterized by central-northern cold-spot dominance. Hot spots became concentrated in southern and central-eastern Anhui, whereas cold spots persisted in central and northern areas, forming a distinct "south (central-east) hot–north (central-north) cold" spatial pattern.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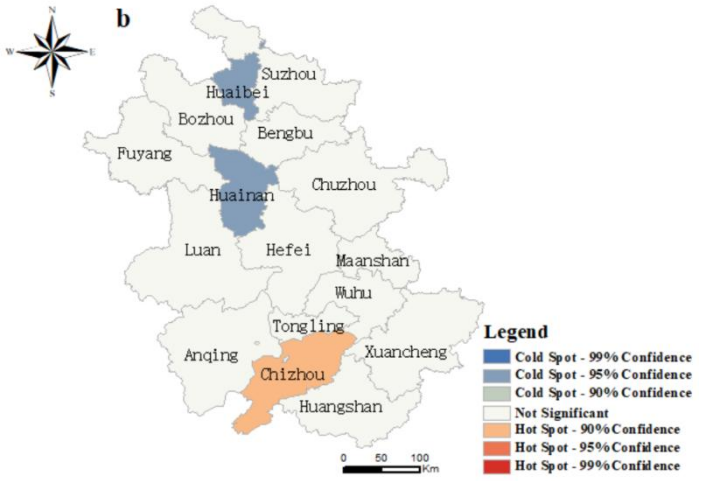
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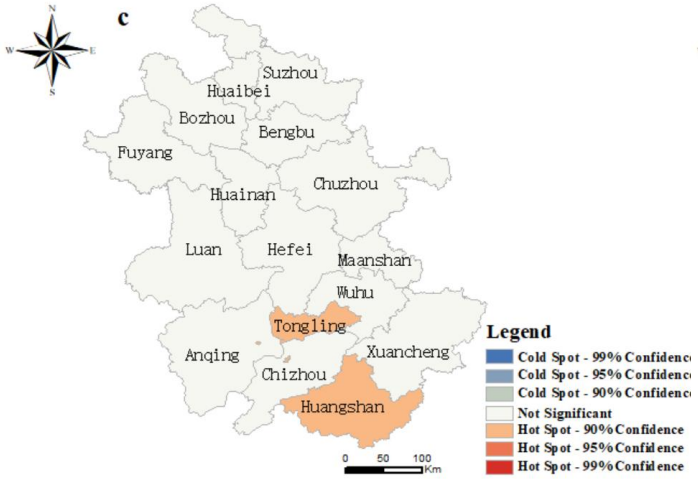
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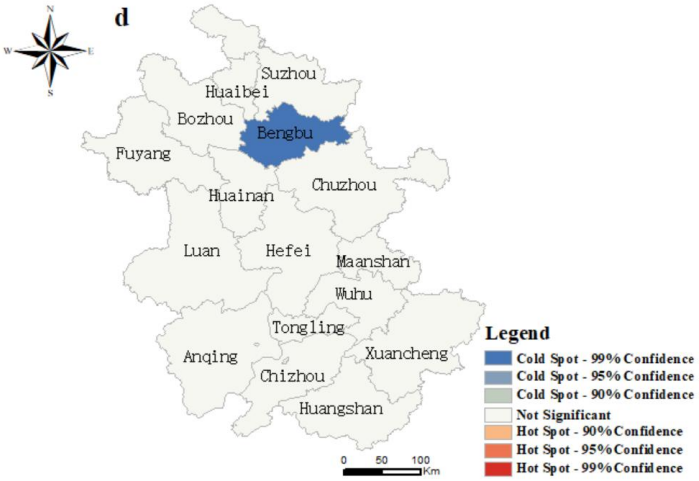
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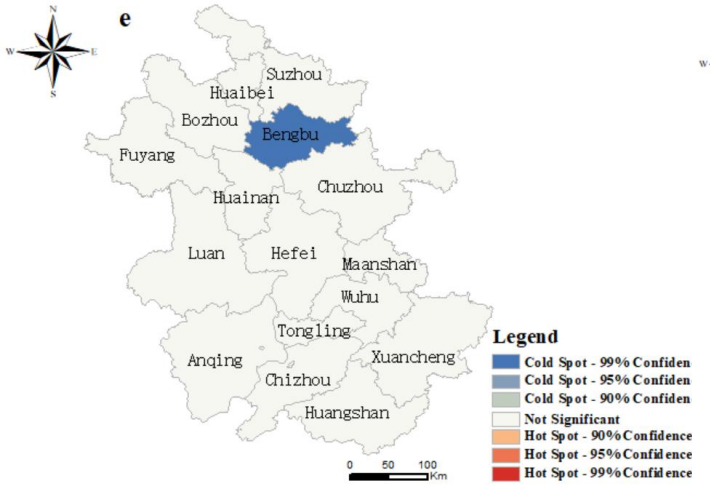
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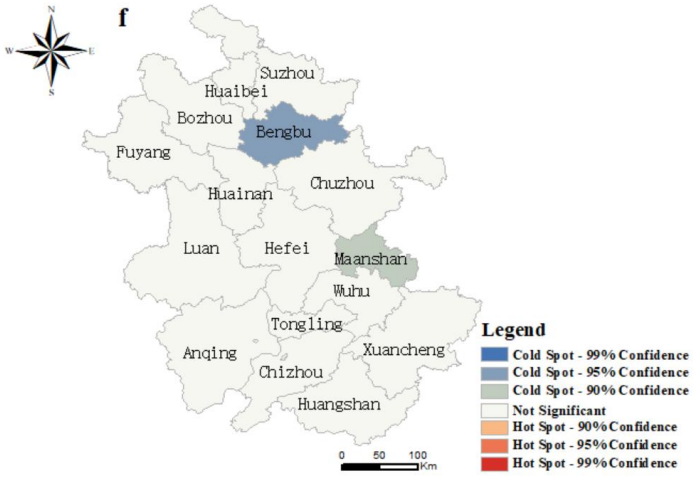
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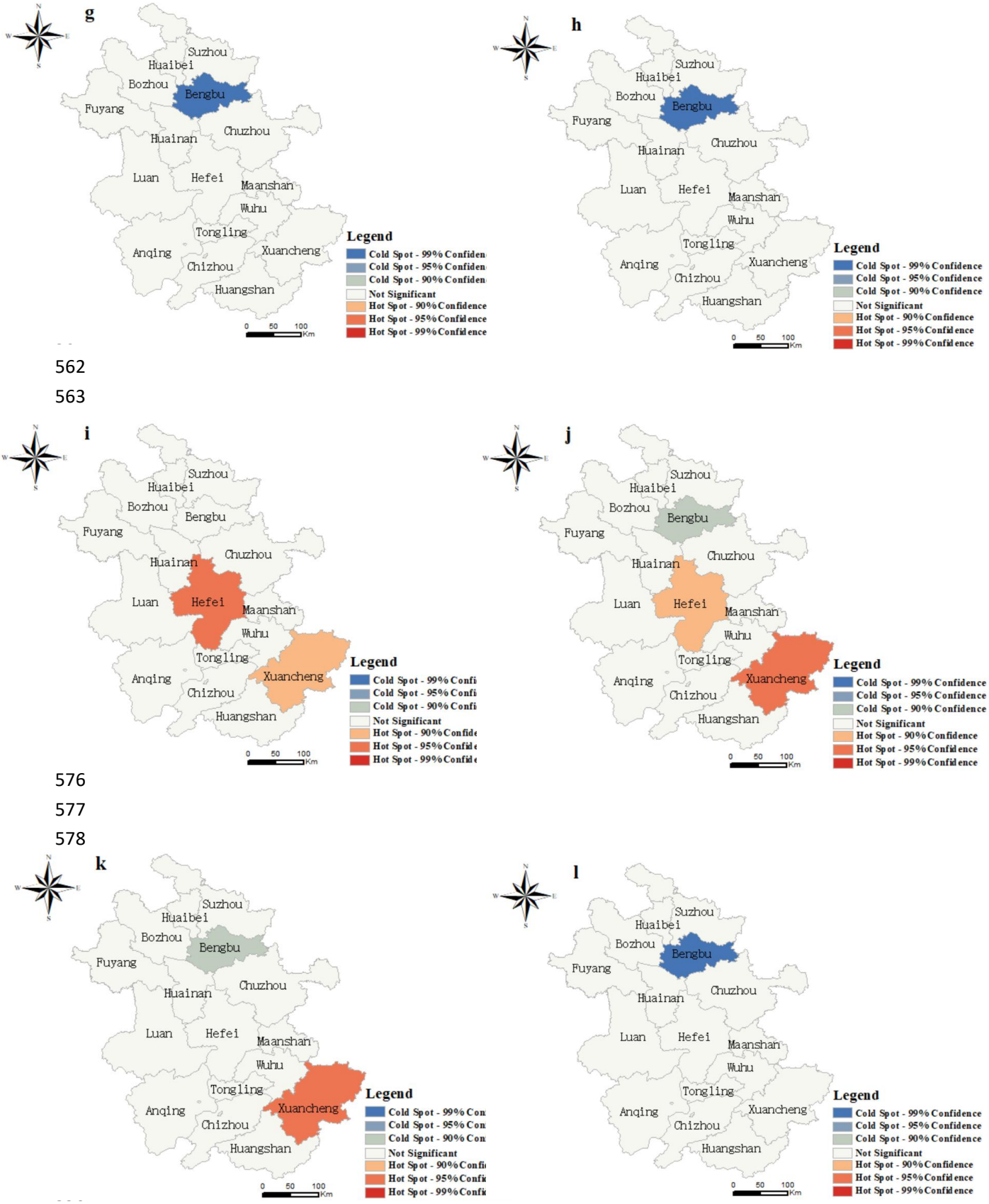

Figure 4. (a–l) Hot and cold spots of tourism ecological security in Anhui Province, 2008–2019.

4.2. Driving mechanisms of tourism ecological security

To identify the driving mechanisms of tourism ecological security in Anhui Province, 19 evaluation indicators were analyzed using the Geo-Detector method.

Tourism ecological security data for 2008, 2012, 2015, and 2019 were classified using the Jenks natural breaks method in ArcGIS 10.8 and transformed into categorical variables. The processed data were then input into the Geo-Detector model to quantify the influence of each factor on tourism ecological security (Table 5).

Table 5. Results of influencing factors of tourism ecological security in Anhui Province.

Detection factor	Detection index	q in 2008	q in 2012	q in 2015	q in 2019	Mean	Rank
Driver(D)	D1 GDP per capita(yuan)	0.687	0.301	0.213	0.353	0. 388	15
	D2 Population at the end of the year(ten thousand people)	0.403	0.491	0.351	0.41	0. 413	14
	D3 Number of visitors (ten thousand people)	0.517	0.521	0.493	0.247	0. 444	12
	D4 Urbanization rate(%)	0.488	0.486	0.197	0.205	0. 344	18
Pressure(P)	P1 Visitor density	0.649	0.376	0.175	0.211	0. 352	17
	P2 Population density (person /km²)	0.808	0.487	0.533	0.531	0. 589	2
	P3 Residential household water consumption(10,000m³)	0.473	0.528	0.496	0.551	0. 512	6
	P4 Tourism space index (person/km²)	0.419	0.391	0.485	0.543	0. 459	10
State(S)	S1 Number of star hotels (amount)	0.848	0.441	0.326	0.556	0. 542	5
	S2 Number of A-level scenic spots(amount)	0.091	0.825	0.211	0.683	0. 452	11
	S3 NDVI	0.605	0.679	0.714	0.546	0. 636	1
	S4 LST	0.645	0.331	0.443	0.514	0. 484	7
	S5 RSEI	0.473	0.285	0.388	0.367	0. 378	16
Impact(I)	I1 Tourism expenditure per capita(yuan)	0.815	0.408	0.331	0.306	0. 465	9
	I2 Proportion of total tourism revenue in GDP(%)	0.826	0.463	0.587	0.358	0. 558	3
	I3 Proportion of the tertiary industry in GDP(%)	0.467	0.493	0.631	0.342	0. 483	8
Response(R)	R1 Proportion of fiscal expenditure in GDP(%)	0.729	0.479	0.613	0.351	0. 543	4
	R2 Domestic sewage treatment rate(%)	0.301	0.275	0.255	0.442	0. 318	19

	R3 Harmless treatment rate of municipal solid waste(%)	0.661	0.091	0.932	0.001	0. 421	13

(1) Within the driving force subsystem, total population at the end of the year and tourist arrivals exhibit relatively high q-values, with their mean values ranking second and first among the four driving indicators, respectively. This indicates that both total population at the end of the year and tourist arrivals play a strong driving role in the economic development of Anhui Province's prefecture-level cities, thereby exerting a significant influence on tourism ecological security.

(2) In the pressure subsystem,population density has the highest mean q-value among the four indicators, highlighting its dominant role. Due to dense population distribution and rapid tourism development, cities such as Hefei, Wuhu, Anqing, and Huangshan face intensified resource and environmental pressures. Household water consumption, tourism spatial index, and tourist density also contribute to system pressure.

(3) In the state subsystem,NDVI has the highest mean q-value (0.636) among the five indicators, indicating its critical role in tourism ecological security. Benefiting from favorable climatic conditions, Anhui supports strong vegetation growth. The number of star-rated hotels and A-level scenic spots also significantly influences the subsystem, reflecting tourism development while potentially increasing ecological pressure through excessive resource exploitation.

(4) In the impact subsystem, Among the three impact indicators, the proportion of total tourism revenue in GDP and the proportion of the tertiary industry in GDP show the highest mean q-values, indicating their critical driving effects on tourism ecological security. These variables reflect tourism's contribution to local economic development and the overall level of tourism development.

(5) In the response subsystem, the proportion of fiscal expenditure in GDP and the harmless treatment rate of domestic waste show relatively high q-values, ranking among the top two indicators. These results indicate their pivotal roles in tourism ecological security in Anhui Province's prefecture-level cities and their capacity to directly improve the ecological environment.

According to ecosystem theory, the influencing factors of tourism ecological security affect its cyclical operational state. To maintain the stable functioning of the tourism ecological security system, it is necessary to effectively control its key driving factors[60]. Therefore, this study ranks the mean q-values of each indicator from 2008 to 2019 (Table 5) and selects the two indicators with the highest mean q-values within each subsystem. The selected indicators are total population at the end of the year, tourist arrivals, population density, household water consumption, number of star-rated hotels, NDVI, proportion of total tourism revenue in GDP, proportion of the tertiary industry in GDP, proportion of fiscal expenditure in GDP, and harmless treatment rate of domestic waste. Based on these results, a driving mechanism

diagram of tourism ecological security in Anhui Province is constructed (Figure 5).

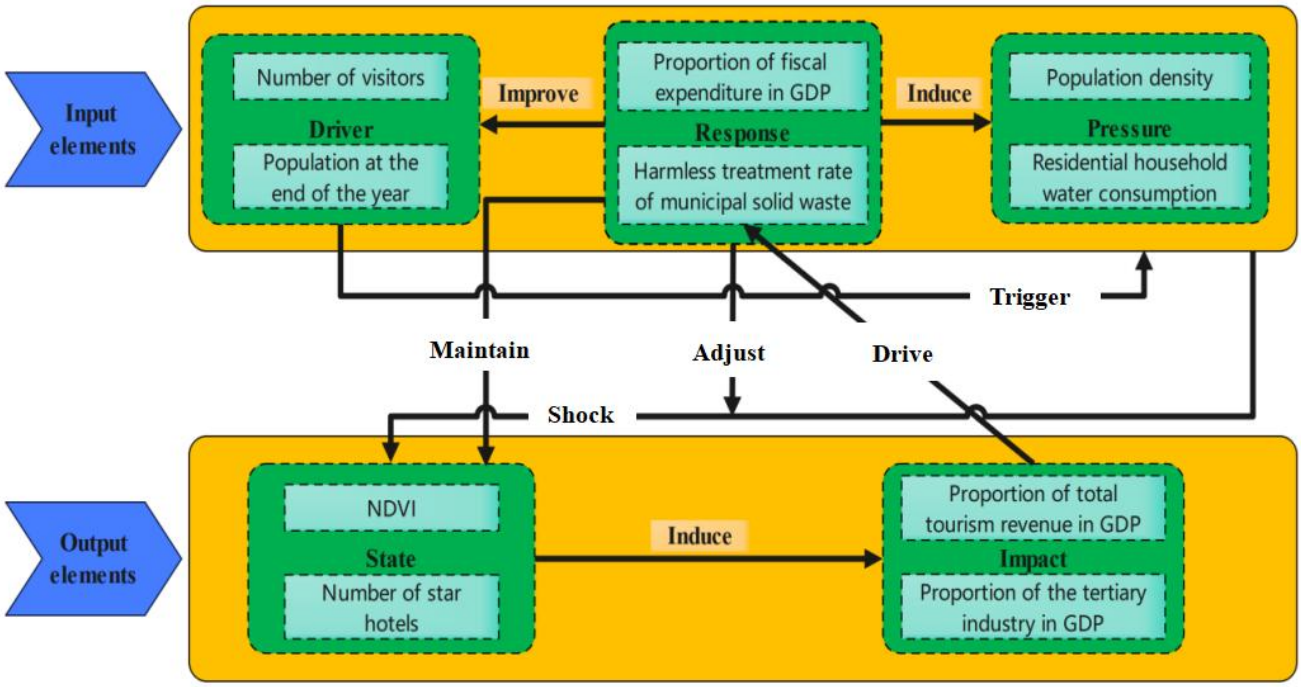

Figure 5. Driving mechanism of tourism ecological security in Anhui Province.

This study divides the tourism ecological system into input (Driving forces, Pressure, Response) and output (State and Impact) components, forming a dynamic coupling and feedback loop essential for tourism ecological security. In Anhui Province, Driving forces such as population growth and increasing tourist arrivals indicate expanding socio-economic development and tourism demand, which stimulate economic growth but also impose ecological pressure. In the Pressure subsystem, rising population density and household water consumption, combined with tourism activities, intensify resource consumption and ecological space occupation. This pressure is transmitted to the State subsystem, where increasing star-rated hotels reflect improved tourism capacity but may also cause ecological disturbance, while NDVI indicates vegetation and ecosystem health that may decline under excessive development. The State changes are reflected in the Impact subsystem, where tourism and tertiary industry contributions to GDP highlight economic benefits but also risks of overdependence and resource overexploitation. The Response subsystem, measured by fiscal expenditure and waste treatment rate, reflects governance capacity to mitigate pressure and improve environmental conditions. Overall, Anhui exhibits a DPSIR-type dynamic system, and coordinated optimization of all subsystems is essential for improving tourism ecological security and sustainable development.

5. Discussion

Positioned as a key region for ecological civilization construction and the Yangtze River Delta green development strategy, Anhui Province faces increasing ecological pressure from tourism. This study analyzes the spatiotemporal evolution and driving factors of tourism ecological security to explore the coupling between tourism development and the ecological environment.

5.1. Theoretical contributions

This study draws on the DPSIR framework and the SBM-DEA model to construct a theoretical framework and indicator system for evaluating tourism ecological security in Anhui Province. It provides a novel interpretation of tourism ecological security by incorporating multiple relevant indicators and elucidating the relationship between tourism ecological security and environmental ecosystems[34]. At the same time, the model evaluates tourism ecological security from the perspective of efficiency, emphasizing "quality" rather than "quantity" in the assessment[61]. The evaluation of tourism ecological security is considered central to research on tourism sustainability. Previous studies have primarily employed methods such as the ecological footprint[19], grey relational analysis[20], TOPSIS (Order Preference Technique for Similarity to an Ideal Solution), the standard deviation ellipse model[21], and the Markov chain model[20]. These approaches mainly adopt a quantitative perspective, often neglecting the dynamic input–output processes within tourism ecosystems. By contrast, this study approaches tourism ecological security from a new efficiency-based perspective and, combined with the actual conditions of Anhui's prefecture-level cities, not only deepens the research on tourism ecological security but also significantly advances the theoretical development of tourism ecosystems[38].

Building on the five subsystems of the DPSIR framework, this study selects corresponding influencing factors to construct a comprehensive indicator system for evaluating tourism ecological security in Anhui Province. In particular, the Remote Sensing Ecological Index (RSEI) is incorporated into the State (S) subsystem of the DPSIR framework[47], providing a more comprehensive reflection of ecological environmental quality in the study area. Previous studies on tourism ecological security often employed indicators such as per capita park green space[62] or urban green coverage[63]; however, these indicators cannot fully capture the ecological conditions of the study area. Furthermore, some studies argue that single indicators cannot accurately characterize the status of tourism ecological security[3]. Therefore, in this study, the RSEI is introduced into the State subsystem to represent the overall ecological environmental quality of Anhui Province.

5.2. Practical implications

This This study analyzes tourism ecological security in Anhui Province at the prefecture-level city scale by integrating Sen + MK trend analysis, spatial autocorrelation, and Geo-Detector methods. Sen + MK results show an overall pattern of "predominant significant improvement with localized degradation" in RSEI from 2008–2019. Moran's I and Getis–Ord Gi* indicate a shift from spatial clustering to a more random distribution, with hot spots in southern and central-eastern Anhui and persistent cold spots in the north. This reveals strong spatial heterogeneity and a clear hot–cold evolution process. Compared with traditional methods, this study better captures long-term trends, spatial dynamics, and nonlinear driving mechanisms. Geo-Detector further identifies key influencing factors, overcoming limitations of linear models. Based on the DPSIR framework, the study reveals subsystem interactions and feedback mechanisms, providing a scientific basis for differentiated ecological governance, resource allocation, and sustainable tourism development in Anhui Province.

5.3. Policy Implications

Based on the analysis results of the spatiotemporal evolution characteristics and driving mechanisms of tourism ecological security in Anhui Province, and in conjunction with the intrinsic logical relationships among the five subsystems of the DPSIR framework—Driving force, Pressure, State, Impact, and Response—this study proposes the following policy implications from the perspective of coordinated governance between high-quality regional tourism development and ecological environmental protection.

First, the positive guiding role of the driving force subsystem should be fully leveraged to promote the green and high-quality development of the tourism economy. The driving force subsystem indicates that total year-end population and tourist arrivals are key factors influencing tourism ecological security in Anhui Province. Population growth and tourism agglomeration stimulate consumption, infrastructure development, and the service sector, but also increase resource and environmental pressure. Therefore, Anhui should shift from extensive growth to a green, low-carbon, and high value-added tourism model. Relying on resources such as Huangshan, Jiuhua Mountain, and Huizhou culture, the province should develop ecotourism, cultural tourism, and health tourism, while optimizing the spatial layout of population and tourism flows. In addition, stronger green fiscal investment, eco-friendly technologies, and industrial restructuring are needed to balance tourism development and ecological protection.

Second, effective measures should be taken to alleviate the constraining effects of the pressure subsystem on the tourism ecological environment. The pressure subsystem shows that population density and household water consumption are key factors affecting tourism ecological security in Anhui Province. Population agglomeration and tourist flows increase resource consumption and reduce environmental carrying capacity, especially in Hefei, Huangshan, and Wuhu.

Therefore, the government should strengthen tourism carrying capacity assessment and establish a dynamic monitoring and early-warning system. During peak seasons, intelligent tourism platforms and traffic management should be used to regulate tourist flows and prevent overload. Promoting water-saving cities and green scenic areas can improve water-use efficiency, while enhancing public awareness of resource conservation and low-carbon travel helps reduce ecological pressure.

Third, continuous efforts should be made to optimize the state of the tourism ecological environment and enhance regional ecosystem stability. The state subsystem shows that the number of star-rated hotels and NDVI are key factors influencing tourism ecological security in Anhui Province. Star-rated hotels reflect tourism reception capacity, while NDVI represents vegetation coverage and ecological quality. However, rapid hotel expansion may intensify land development and threaten ecosystem stability. Therefore, green development should guide tourism infrastructure construction by strictly controlling high energy-consuming and polluting projects and promoting green hotels, scenic areas, and low-carbon facilities. Ecological protection and vegetation restoration should be strengthened, especially in southern Anhui mountainous areas and the Yangtze River coastal region, along with improving the ecological red-line system and strengthening dynamic monitoring to prevent ecological degradation.

Fourth, the positive impact effects of tourism industry development should be strengthened to promote the coordinated development of the regional economy and ecological environment. The impact subsystem shows that the proportion of total tourism revenue to GDP and the proportion of the tertiary industry in GDP are key factors affecting tourism ecological security in Anhui Province. Tourism and the tertiary industry significantly promote economic growth, employment, income increase, and industrial structure optimization. Therefore, Anhui should strengthen the integration of tourism with modern service industries and develop green sectors such as digital tourism, cultural and creative tourism, sports tourism, and rural tourism. Industrial restructuring should reduce dependence on resource-intensive industries and enhance the tertiary sector. Regional coordination should be improved through the Southern Anhui International Cultural Tourism Demonstration Zone and Yangtze River Delta integration, promoting resource sharing, joint ecological governance, and industrial linkage.

Finally, the ecological governance capacity of the response subsystem should be enhanced in order to establish a long-term guarantee mechanism for tourism ecological security. The response subsystem shows that the proportion of fiscal expenditure to GDP and the harmless treatment rate of domestic waste are key factors influencing tourism ecological security in Anhui Province, highlighting the role of fiscal investment and environmental governance capacity. Continuous investment in ecological protection and tourism infrastructure is needed to improve governance and public services. Priority should be given to waste classification, sewage treatment, and pollution control in key tourism areas. Green and low-carbon technologies, along with

remote sensing, big data, and AI-based monitoring, should support dynamic early-warning systems. Strengthening talent development and innovation can promote collaborative governance among government, enterprises, tourists, and the public for sustainable tourism development.

5.4. Limitations and future research directions

The tourism ecological security (TES) system is a complex dynamic system formed by tourism, ecological environment, and socio-economic interactions. Based on panel data from Anhui Province (2008–2019), this study analyzes the spatiotemporal evolution and driving mechanisms of TES. However, several limitations remain. First, data availability is constrained by incomplete indicators, inconsistent statistical standards, and missing values, limiting the study period to 2008–2019. Second, the indicator system still lacks emerging big data variables, and future research could integrate AI, cloud computing, and remote sensing for real-time monitoring and early warning. Third, cultural and social perception factors, including Huizhou culture and tourism behavior, are insufficiently considered due to reliance on macro-statistical data. Finally, this study focuses on evolution and mechanisms, while future work should incorporate machine learning and system dynamics for prediction and dynamic risk warning of TES.

6. Conclusion

This study is based on tourism ecological security theory and takes 16 prefecture-level cities in Anhui Province as the research objects. By integrating the DPSIR model with the DEA model, and combining the RSEI remote sensing ecological index, Sen + MK trend analysis, spatial autocorrelation, and Geo-Detector methods, this study systematically investigates the spatiotemporal pattern evolution characteristics and driving mechanisms of tourism ecological security in Anhui Province from 2008 to 2019. The main conclusions are as follows:

(1) In terms of temporal evolution, from 2008 to 2019, Anhui Province showed overall improving ecological environmental quality with regional disparities. Sen + MK results indicate dominance of SI and NSI, while some areas still face degradation risk. Tourism ecological security evolved from fluctuating improvement to stable enhancement with clear spatial heterogeneity.

(2) In terms of spatial pattern, tourism ecological security in Anhui Province shows strong spatial autocorrelation and heterogeneity, forming a “south (central-east) hot–central-north cold” pattern. Hotspots shifted from southern Anhui (e.g., Huangshan, Chizhou) to central-eastern cities (Hefei, Xuancheng), while coldspots remained in Bengbu and northern Anhui.

(3) Local spatial autocorrelation shows clear clustering of tourism ecological security in Anhui Province. Hot spots are in high ecological quality, resource-rich, and economically developed areas, while cold spots are concentrated in central and northern cities with higher environmental pressure. Over time, hot spots expanded

toward economically and ecologically coordinated regions, while cold spots remained stable, indicating spatial spillover effects and regional interaction dynamics.

(4) Geo-Detector results show that tourism ecological security in Anhui Province is mainly influenced by population, tourism activity, resource use, ecological condition, economic structure, and governance factors. Tourist arrivals, population density, and NDVI are the primary determinants with the highest q-values. Tourism growth increases resource pressure, while vegetation condition and fiscal environmental support significantly enhance ecological security.

(5) From the perspective of driving mechanisms, the tourism ecological security system in Anhui Province follows a DPSIR dynamic feedback mechanism. Tourism growth and population agglomeration promote economic development but increase ecological pressure, while ecological improvement, fiscal investment, and governance enhance tourism ecological security. Overall, its evolution results from the interaction of natural conditions, tourism development, and socio-economic activities, requiring a balance between tourism development and ecological protection to achieve green and high-quality development.

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optimization of typical copper deposits in the western section of the Awulale Metallogenic Belt, western Tianshan" (YZD2025Z01).

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Availability Statement: The data that support the findings of this study are available from publicly accessible sources. The socioeconomic and tourism-related data were obtained from the Anhui Provincial Statistical Yearbooks and the statistical yearbooks of each prefecture-level city, which can be accessed at (http://tjj.ah.gov.cn/). The Remote Sensing Ecological Index (RSEI) was derived from Landsat series satellite imagery processed via the Google Earth Engine (GEE) platform (https://earthengine.google.com/). The original Landsat imagery is freely available through the United States Geological Survey (USGS) Earth Explorer platform (https://earthexplorer.usgs.gov/) or directly within the GEE data catalog. Processed data used in the analysis are available from the corresponding author upon reasonable request.

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