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Empirical Analysis of Risk Assessment of Ecotourism Scenic Spots Based on Remote Sensing and AHP-EW

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Abstract: This study builds a complete evaluation system that combines remote sensing with the analytic hierarchy process-entropy weighting approach for composite weighting in an attempt to properly assess the sustainability concerns of ecotourism scenic sites. Taking a typical ecotourism scenic spot as the research subject, the study utilizes remote sensing imagery and digital elevation model data to extract 10 evaluation indicators across three dimensions: natural geography, ecosystem condition, and human intervention. The comprehensive weights of indicators are also determined using the Analytic Hierarchy Process-Entropy Weight (AHP-EW) method. Moreover, a comprehensive risk assessment is achieved through the weighted superposition method, which spatially aggregates the risk values of different indicator layers based on their specific weights to generate a total risk distribution map. The results indicated that the highest composite weights were assigned to land use classification, vegetation coverage, and soil erosion sensitivity, with values of 0.1795, 0.1615, and 0.1365, respectively. From the perspective of risk sources, the human intervention criterion layer exhibited the highest risk level. Its combined area of high-risk and medium-to-high-risk zones accounted for 45.04%, significantly exceeding that of natural geographic elements and ecosystem conditions. From the perspective of the overall risk pattern, the study area exhibited a low-to-moderate risk level, with nearly 75% of the region classified as medium risk or below. High-risk zones accounted for only 8.09%. This suggests that human intervention is the dominant factor driving the spatial differentiation of ecological risks within the scenic area, while the area's superior natural ecological foundation plays a crucial buffering role. Meanwhile, by leveraging the complementary advantages of objective data and expertise, the composite weighting method employed in this study enhances the reliability of risk assessment results. This approach provides decision support for the sustainable management and targeted conservation of ecotourism scenic spots.

Keywords: Ecotourism, risk assessment, Analytic Hierarchy Process (AHP), entropy weighting method, remote sensing, sustainable development.

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1. Introduction

Currently, global attention to sustainable development is growing, and people's ecological awareness is also increasing. Ecotourism, as a new tourism model, has consequently emerged. Ecotourism scenic spots serve not only as vital engines for regional economic growth but also as critical areas for maintaining biodiversity and ecological balance (Rahmafitria and Kaswanto 2024; Shang et al., 2024; Batool et al., 2025). In recent years, however, the rapid expansion of tourism activities and excessive human intervention have posed significant threats to the sustainable development of ecotourism scenic spots. Effective risk assessment has thus become an urgent challenge requiring resolution (Correa Machado et al., 2023). In the field of ecotourism risk assessment, scholars both domestically and internationally have conducted extensive research, developing various evaluation models and indicator systems. Weight determination is a core component of these assessment methods, with existing approaches broadly categorized into two types: Subjective Weighting (SW) methods and Objective Weighting (OW) methods (Chen et al., 2023; Huskanović et al., 2023; Van Dua et al., 2024). Represented by the Analytic Hierarchy Process (AHP), SW methods effectively incorporate experts' domain knowledge, experience, and decision preferences while handling qualitative indicators with theoretical rigor. In contrast, OW methods, such as the Entropy Weighting (EW) method, allocate weights solely based on the intrinsic variability of indicator data, thereby eliminating human interference. However, existing research often struggles to effectively combine the spatial accuracy of Remote Sensing (RS) monitoring with a mixed weighting mechanism that balances expert consensus and data objectivity. Most evaluations rely too heavily on either qualitative expert ratings or quantitative statistical data, failing to capture the complex spatial heterogeneity of scenic spots. Based on previous work, the research primarily closes this gap using the coupled RS-AHP-EW framework.

To address these concerns accurately, this research spatially evaluates ecological risks in complex tourism environments, aiming to achieve two primary objectives. First, a multidimensional risk assessment framework should be established that integrates natural and human factors. Second, a hybrid weighted model should be developed to reduce bias. To overcome the limitations of single weighting methods and effectively integrate subjective prior knowledge with objective data characteristics, this study developed an integrated risk assessment system for the sustainable development of ecotourism scenic spots. This system combines RS monitoring with an AHP-EW combination approach. A typical ecotourism scenic spot is taken as the empirical case study. First, utilizing Remote Sensing Imagery (RSI) and Digital Elevation Model (DEM) data, a series of spatial evaluation indicators, including vegetation coverage, land use types, and topographic factors, are extracted through standardized data preprocessing. A comprehensive Risk Assessment Index System (RAIS) encompassing three dimensions, namely natural geography, ecosystem condition, and human intervention, is also established. Finally, the comprehensive weights of each indicator are determined using the AHP-EW combination model. Through weighted superposition analysis, a quantitative assessment of ecotourism risks in the study area is achieved, aiming to accurately identify risk sources in ecotourism scenic spots.

2. Research Design

2.1. RSI and Vegetation Terrain Data Processing

In the risk assessment of sustainable ecotourism scenic spots, the spatial consistency and accuracy of data form the foundation for subsequent ecological risk evaluations. Taking a specific ecotourism scenic spot as the subject of study, this research employs Quantum Geographic Information System (QGIS) software to perform standardized preprocessing on core data sources, including topographic and RSI data. Raw RS data is vulnerable to interference from atmospheric conditions, sensor performance, and lighting conditions during the preprocessing of RSI data. Direct application for extracting ecological risk indicators, such as vegetation coverage and land use types, may introduce data bias (Jiang et al., 2023; Sun and Zheng, 2023; Zhang et al., 2023). Therefore, the study performs three-step preprocessing on the scenic area's RSI within QGIS: radiometric calibration, atmospheric correction, and image cropping. This restores the true spectral information of ground features. Following the preprocessing of the RSI, vegetation coverage is calculated. The Normalized Difference Vegetation Index (NDVI) effectively distinguishes between vegetated and non-vegetated land cover and is sensitive to vegetation growth conditions (Li et al., 2023; Niraj et al., 2023; Singh et al., 2024). Therefore, the study utilizes preprocessed RS data as the source, calculates NDVI and derives vegetation coverage within QGIS software. The specific operational steps are illustrated in Fig. 1.

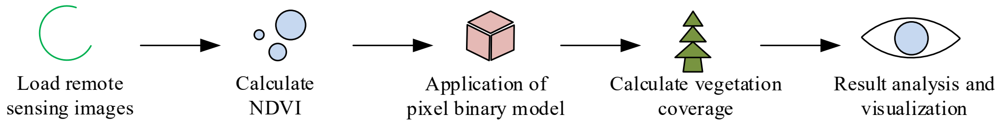

Fig. 1. Operation steps for NDVI calculation and vegetation coverage inversion

As shown in Fig. 1, the RSI is first loaded by using the "add raster layer" function to load the preprocessed RS image data. Next, it goes to the "Processing Toolbox". The "Band Calculator" tool is searched for and selected. In the dialog box that appears, the NDVI calculation formula is entered, as shown in Eq. (1) (Farooque et al., 2023).

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{1}$$

In Eq. (1), NIR means the near-infrared band, and RED means the red light band. In addition to vegetation coverage, terrain conditions are also a significant factor influencing the risk of ecotourism scenic spots. The study primarily utilizes DEM as the data source, performing terrain data standardization and factor extraction within QGIS to calculate slope, aspect, terrain roughness, and terrain wetness.

2.2. Establishment of a Risk Assessment System for Ecotourism Scenic Spots

After completing the preprocessing of RS image data and establishing vegetation coverage and topographic factors, the study further constructs an ecotourism scenic spot risk evaluation system. The accuracy and guidance value of the evaluation results are directly influenced by the rationality of the indicator system (Zhang et al., 2024). Following relevant principles and screening procedures, the study ultimately selected 10 core indicators. The constructed RAIS for ecotourism scenic spots is illustrated in Fig. 2.

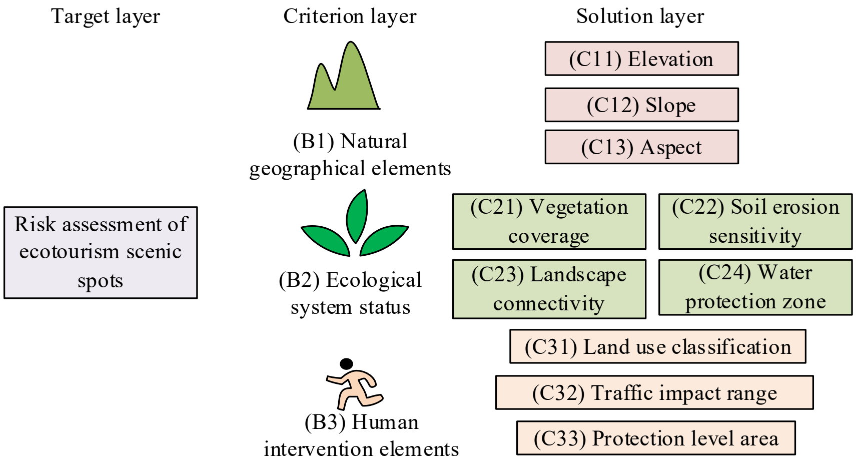

Fig. 2. RAIS for ecotourism scenic spots

Fig. 2 shows the RAIS for ecotourism scenic spots, which includes natural geographic elements, ecosystem condition, and human intervention elements. The natural geographic elements layer contains three evaluation indicators: aspect, slope, and elevation. Ecosystem condition encompasses four evaluation indicators: aquatic buffer zones, soil erosion sensitivity, vegetation coverage, and landscape connectivity. Human intervention elements comprise three indicators: traffic impact range, land use classification, and protection area level. To achieve spatial quantification of risks, this study employs geographic information system spatial analysis techniques to reclassify each evaluation factor and assign corresponding risk values. The study, drawing on numerous practical cases of ecotourism scenic spots, proposes two hypotheses. H1: Among the various factors constituting the risks to the sustainable development of ecotourism scenic spots, human intervention elements are the dominant risk source. H2: Under intense human intervention, the natural ecological baseline conditions of scenic areas can serve as a buffer against environmental degradation.

2.3. Establishing Evaluation Indicator Weights based on the AHP-EW Method

In the risk assessment system of sustainable ecotourism scenic spots, although AHP effectively captures experts' macro understanding of ecotourism risks, it has a high degree of subjectivity. The EW method objectively reflects the variability of RS data indicators but may overlook some important indicators with small data fluctuations (Chen et al., 2023; Yu et al., 2023). Therefore, this study adopts a comprehensive weighting strategy combining AHP and Electronic Warfare (EW) to organically combine qualitative analysis of experts with quantitative analysis of RS data, achieving complementary advantages. In AHP, first, a hierarchical model for risk assessment is constructed, which decomposes the evaluation objectives into the objective layer, criterion layer, and Scheme Layer (SL). Subsequently, experts from fields such as ecotourism and environmental science are invited to compare pairwise indicators at the same level using a 1-9 scale method, and a Judgment Matrix (JM) is constructed. These experts are selected based on the following criteria: holding a senior professional title or higher, having at least 10 years of experience in ecological tourism planning or environmental management research or practice, and being familiar with the specific geographical conditions of the research area. By calculating the Ranking Weights (RW) of each indicator and conducting Consistency Tests (CT), when the Consistency Ratio (CR) is less than 0.1, the matrix is valid and Subjective Weights (SW) are obtained. In OW, the Entropy Weight (EW) method is used to calculate the OW. This method assigns weights based on the Information Entropy (IE) of the data, with indicators with lower IE being given higher weights. Finally, the AHP-EW linear combination model is adopted to integrate the SW of AHP and the OW of EW. By determining the optimal coefficients, the final comprehensive weight is set as the average of SW and OW, in order to obtain a more scientific evaluation result.

3. Results and Analysis

3.1. Weighting of Evaluation Indicators

Based on the constructed evaluation indicator system and the combined weighting model of AHP and EW, this study calculates and assigns weights to risk evaluation indicators for sustainable ecotourism scenic spots. The SWs of each indicator are calculated using the AHP approach. Fifteen experts in ecology, geographic information science, and tourism management are invited to score the indicators, yielding the criterion-level JM shown in Fig. 3. The WV computed from the matrix is (0.200, 0.400, 0.400), with a maximum eigenvalue of 3.000 and CR=0.000, indicating perfect consistency.

The judgment matrices for each SL are shown in Fig. 4. In Fig. 4(a), the WV is calculated as (0.167, 0.500, 0.333) for the SL matrix under the natural geographic element's criterion layer. The maximum eigenvalue is 3.004, and CR=0.003<0.1. The CT indicates that the assigned weights are appropriate. Fig. 4(b) shows the JM for the sub-SL under human intervention elements. After calculation, the WV of this matrix is (0.500, 0.333, 0.167), with a maximum eigenvalue of 3.000 and CR=0.000. This indicates that the matrix exhibits perfect consistency. The CT confirms that the assigned weights are appropriate. Fig. 4(c) presents the JM for the sub-SL under the ecosystem condition. Calculations yield the WV (0.383, 0.283, 0.191, 0.143) for this matrix. The maximum eigenvalue is 4.015, with CR=0.006<0.1.

	B1	B2	B3
B1	1.00	1/2	1/2
B2	2.00	1.00	1.00
B3	2.00	1.00	1.00

Fig. 3. Criterion layer judgment matrix

	C11	C12	C13
C11	1.00	1/3	1/2
C12	3.00	1.00	3/2
C13	2.00	2/3	1.00

(a) Natural geographic elements

	C31	C32	C33
C31	1.00	3/2	3.00
C32	2/3	1.00	2.00
C33	1/3	1/2	1.00

(b) Ecological system status

	C21	C22	C23	C24
C21	1.00	3/2	2.00	3.00
C22	2/3	1.00	3/2	2.00
C23	1/2	2/3	1.00	3/2
C24	1/3	1/2	2/3	1.00

(c) Human intervention elements

Fig. 4. Judgment matrix for each indicator layer

In the AHP software system, the importance of each risk factor varies. Among them, in Table 1, the C31 land use classification combination has the highest weight, at 0.176, ranking first. Experts generally believe that direct human transformation and development activities on land are the primary drivers of ecological risks. The weights of C21 vegetation coverage and C22 soil erosion sensitivity are 0.158 and 0.131, respectively, ranking second and third. Meanwhile, the combined weights of the C32 traffic impact range and the C12 slope are 0.115 and 0.103, respectively. In contrast, factors such as C11 elevation, C24 water conservation area, and C33 conservation area classification have relatively lower weights.

Table 1. Combination weight and ranking of indicator layer by AHP

Criterion Layer	Criterion weight	Solution layer	SL weight	Combination weight	Rank
B1	0.214	C11	0.192	0.041	10
		C12	0.481	0.103	5
		C13	0.327	0.07	7
B2	0.435	C21	0.363	0.158	2
		C22	0.301	0.131	3
		C23	0.205	0.089	6
		C24	0.131	0.057	9
B3	0.351	C31	0.501	0.176	1
		C32	0.328	0.115	4
		C33	0.171	0.06	8

Then, the EW method is used to objectively allocate weights to the evaluation index system, as shown in Table 2. The C31 land use classification showed the highest OW of 0.183. This indicates that the distribution of land types within the study area is highly uneven, characterized by strong spatial heterogeneity. Next are C21 vegetation coverage and C22 soil erosion sensitivity, with weights of 0.165 and 0.142, respectively. This indicates that these two indicators show significant spatial changes within the scenic area, making them key objective factors for identifying ecosystem conditions. In contrast, the C33 protection level area and the C32 traffic impact area have the lowest weight.

The study further combines the SWs calculated by AHP with the OWs obtained from the EW method through linear combination, assigning equal contribution to both. The final comprehensive weights and rankings are presented in Table 3. The composite weights for C31 land use classification, C21 vegetation coverage, and C22 soil erosion sensitivity consistently ranked in the top three at 0.1795, 0.1615, and 0.1365, respectively. Based on expert experience and the spatial heterogeneity of the data, it is evident that the intensity of human-induced landform alterations and the intrinsic health status of ecosystems are the most critical factors determining risk. Meanwhile, the C32 traffic impact range ranked fourth in SW and fifth in the final comprehensive ranking. This suggests that spatial variability in road data within the study area is not pronounced. However, experts caution that its potential ecological risks should not be overlooked. Conversely, indicators such as C33 protection level area and C11 elevation are relatively low in weighting within the comprehensive evaluation.

Table 2. OWs and ranking of evaluation indicators by the entropy method

Indicator layer	IE	OW	Rank
C11	0.931	0.076	7
C12	0.895	0.115	4
C13	0.952	0.063	8
C21	0.841	0.165	2
C22	0.868	0.142	3
C23	0.925	0.081	6
C24	0.938	0.071	9
C31	0.822	0.183	1
C32	0.96	0.058	10
C33	0.975	0.046	5

Table 3. Comprehensive weight and ranking

Indicator layer	SW	OW	Comprehensive weight	Final rank
C11	0.041	0.076	0.0585	9
C12	0.103	0.115	0.109	4
C13	0.07	0.063	0.0665	7
C21	0.158	0.165	0.1615	2
C22	0.131	0.142	0.1365	3
C23	0.089	0.081	0.085	6
C24	0.057	0.071	0.064	8
C31	0.176	0.183	0.1795	1
C32	0.115	0.058	0.0865	5
C33	0.06	0.046	0.053	10

3.2. Risk Assessment of Ecotourism Scenic Spots

Based on the constructed evaluation index system and comprehensive weighting results, the study continues to conduct a spatial evaluation of individual risk factors within the research area, as shown in Table 4. The natural geographical conditions of the research area usually exhibit low-risk characteristics. Among them, the slope coefficient has the lowest risk, with areas exceeding 53% classified as low-risk gentle terrain (0-8 °), indicating a lower potential risk of geological hazards. The altitude factor is mainly divided into low-risk and medium-low-risk categories, accounting for more than 75% of the region. Indicating that most areas within the scenic area have moderate elevations, and there are few environments with extreme height differences.

Then, the study extracts various data under standard ecosystem conditions and classifies the risk. The results are shown in Table 5. From the perspective of ecosystem status, over 64% of the region is composed of high-quality forest areas with vegetation coverage exceeding 0.8. Meanwhile, soil erosion sensitivity and landscape connectivity also exhibit low risk levels, with over 50% of areas classified as low- or medium-low-risk. Although water conservation areas show high risk in areas adjacent to riverbanks, over 45% of the total area is within low-risk areas beyond a 100-meter buffer distance. This indicates that the core ecosystem within the scenic area is relatively stable.

The study continues to extract data on land use classification, traffic impact range, and protection level area from the human intervention elements criteria layer, followed by risk classification. Results are shown in Table 6. All three indicators under the human intervention criteria layer exhibit high risk levels. Land use is predominantly low-risk forested land, accounting for 62.2% of the area. However, traffic impact and protection level factors introduce significant risks. Over 36% of the area falls within the high-risk zone, located within 100 meters of roads, while 55% is situated in the least regulated peripheral control zone. This indicates that the intensity of human activities and planning controls are key negative factors determining ecological risk levels within the scenic area.

Table 4. Risk classification results of natural geographic element criteria layer

Ecological risk level	Low-risk area	Low-to-medium risk area	Medium-risk area	Medium-to-high-risk areas	High-risk area
Elevation (m)	<200	200-300	300-400	400-500	>500
Area (km^2)	23.25	18.35	8.10	3.51	1.79
Percentage (%)	42.27	33.37	14.73	6.38	3.25
Slope (°)	0-8	8-15	15-25	25-45	>45
Area (km^2)	29.54	13.50	9.25	2.56	0.15
Percentage (%)	53.71	24.55	16.81	4.65	0.28
Aspect	Flat land, due south	Southeast and Southwest	Due east, due west	Northeast and Northwest	Due north
Area (km^2)	9.85	16.21	14.79	10.30	3.85
Percentage (%)	17.91	29.47	26.89	18.73	6.99

Table 5. Risk classification results of ecosystem status criteria layer

Ecological risk level	Low-risk area	Low-to-medium risk area	Medium-risk area	Medium-to-high-risk areas	High-risk area
Vegetation coverage	0.8-1.0	0.6-0.8	0.4-0.6	0.2-0.4	0.0-0.2
Area (km^2)	35.53	9.2	3.93	3.1	3.24
Percentage (%)	64.6	16.73	7.15	5.63	5.89
Soil erosion sensitivity	Micro degree	Mild	Moderate	Intensity	Extreme intensity
Area (km^2)	21.38	17.22	9.81	4.88	1.71
Percentage (%)	38.87	31.31	17.84	8.87	3.11
Landscape connectivity	High	Medium-High	Medium	Medium-Low	Low
Area (km^2)	17.55	12.65	10.7	8.35	5.75
Percentage (%)	31.91	23	19.45	15.18	10.46
Water protection zone (m)	>100	75-100	50-75	25-50	0-25
Area (km^2)	25.1	8.55	8.05	5.95	7.35
Percentage (%)	45.64	15.55	14.63	10.82	13.36

Table 6. Risk classification results of human intervention elements criteria layer

Ecological risk level	Low-risk area	Low-to-medium-risk area	Medium-risk area	Medium-to-high-risk areas	High-risk area
Land use classification	Woodland	Water body	Grassland	Unutilized land and cultivated land	Construction land
Area (km^2)	34.21	5.96	3.33	6.65	4.85
Percentage (%)	62.2	10.84	6.05	12.09	8.82
Traffic impact range (m)	>400	300-400	200-300	100-200	0-100
Area (km^2)	7.55	6.1	8.15	13.05	20.15
Percentage (%)	13.73	11.09	14.82	23.72	36.64
Protection level area	Core area	First level protected area	Second level protected area	Third level protected area	Peripheral control area
Area (km^2)	3.95	10.15	8.5	2.15	30.25
Percentage (%)	7.18	18.45	15.45	3.92	55

Building upon the single factor risk assessment, this study employs a weighted superposition method to conduct comprehensive risk evaluations across three criterion layers: natural geography, ecosystems, and human intervention. The weight of each indicator within a criterion layer is determined by the ratio of its final composite weight to the total weight of that criterion layer. The summary table of comprehensive risk evaluation results for each criterion layer is presented in Table 7. The risk patterns for natural geographic elements and ecosystem condition are similar, both dominated by low-risk and low-to-medium-risk zones. Together, they account for 73.71% and 71.97% of the total. Conversely, high-risk and medium-high-risk zones for human intervention elements collectively accounted for 45.04%, while low-risk zones constituted only 9.35%, indicating that human intervention is the primary risk pressure source in the scenic area. This result validates research hypothesis H1: human intervention is the dominant factor driving the spatial differentiation of ecological risks in scenic areas.

Table 7. Summary of comprehensive risk assessment results for each criterion layer

Ecological risk level	B1		B2		B3	
	Area (km^2)	Percentage (%)	Area (km^2)	Percentage (%)	Area (km^2)	Percentage (%)
Low-risk area	24.51	44.56	25.43	46.24	5.14	9.35
Low-to-medium-risk area	16.03	29.15	14.15	25.73	10.21	18.56
Medium-risk area	9.75	17.73	9.06	16.47	14.88	27.05
Medium-to-high-risk areas	3.61	6.56	3.98	7.23	10.62	19.31
High-risk area	1.1	2	2.38	4.33	14.15	25.73

The study finally employs a weighted superposition method to integrate the risk assessment results from the three criterion layers, yielding the comprehensive risk evaluation results for ecotourism scenic spots in the study area, as shown in Table 8. The study area exhibits a moderate to low risk level overall. Among these, the moderate-to-low risk zone covers the largest area, accounting for 32.05%. Nearly 75% of the region falls under moderate or lower risk levels. Spatially, medium-high and high-risk zones account for approximately 25% of the area, representing overlapping zones with the highest risk of human interference and relatively fragile ecosystems. This result confirms research in H2: the scenic area’s excellent natural and ecological baseline conditions play a crucial buffering role against the risks of high-intensity human activity. It ensures overall risks remain controlled at relatively low levels.

Table 8. Comprehensive risk assessment results of ecotourism scenic spots

Ecological risk level	Area (km^2)	Percentage (%)
Low-risk area	9.25	16.82
Low-to-medium-risk area	17.63	32.05
Medium-risk area	14.1	25.64
Medium-to-high-risk areas	9.57	17.4
High-risk area	4.45	8.09

4. Discussion

To scientifically assess the sustainability risks of ecotourism scenic spots, this study developed an integrated evaluation system combining RS monitoring with an AHP-EW combination. An empirical study was conducted on a specific scenic area. Results revealed that human intervention elements were the dominant factor driving spatial differentiation of ecotourism risks in the study area, while the superior natural ecological foundation provided effective resilience. Based on the evaluation results, the highest overall risk was identified at the human intervention guideline level. High-risk areas accounted for 25.73% of the total area, significantly exceeding the 2.00% attributed to natural geographic elements and 4.33% attributed to ecosystem condition. This finding was consistent with the conclusions of numerous scholarly studies. Yuanyuan and Yao (2024) similarly noted in their research on the Wulingyuan Scenic Area that human activities such as road networks and tourism facilities were the most direct sources of ecological risk pressure. Wei et al.’s (2024) assessment of the Huangshan Ecotourism Area also revealed a significant positive correlation between human intervention intensity and ecological risk values. High-risk zones were concentrated in areas with dense tourism facilities, accounting for 23.1% of the total area, aligning closely with the study’s findings.

The overall pattern of the research evaluation results was dominated by medium-to-low risk, with nearly 75% of the area classified as medium risk or below. This indicated that high-quality ecosystems may act as a buffer against intense human impacts, reflecting the picturesque area’s existing positive ecological status. Meanwhile, high-quality vegetation covered more than 64% of the research area, while the combined percentage of low-risk and medium-to-low-risk zones in the ecosystem condition criterion layer surpassed 71%. This was consistent with ecological theories on ecosystem services, which suggests that large areas of high-quality ecological sources could effectively absorb and mitigate the negative impacts from small-scale, high-intensity human activity sinks (Rodrigues-Filho et al., 2023).

Additionally, the integrated weighting model, which combines AHP and EW, employed in this study, provided an effective approach for quantifying the importance of various risk factors. While SW methods, like AHP alone, could reflect expert experience, they were susceptible to cognitive biases. Conversely, OW methods such as EW alone could reflect the data itself but tended to overlook certain indicators that were theoretically important yet exhibited weak spatial variability in the data (Barman et al., 2024). Based on the evaluation results, the study provides specific management insights. Due to human intervention being identified as the primary risk source, managers should implement differentiated zoning control strategies to mitigate this risk. Strict capacity and traffic restrictions must be implemented in high-risk areas, particularly those concentrated near road networks and construction sites, to alleviate ecological pressure. Conversely, strict monitoring should be prioritized in low-risk areas with high vegetation coverage to prevent new tourism facilities from encroaching upon them and to maintain their buffering function.

5. Conclusion and Recommendations

To assess the sustainability risks of ecotourism scenic spots, this study integrated RS monitoring with the AHP-EW combination model to construct a comprehensive evaluation system and conduct empirical analysis. The results suggest that the combined weighting model, which effectively balances the strengths and weaknesses of both approaches by combining expert subjective judgment with objective data variability, is a suitable method for indicator weighting. Land use classification had the highest composite weight, with a value of 0.1795. Vegetation coverage and soil erosion sensitivity had composite weights of 0.1615 and 0.1365, respectively. Together with land use classification, these three factors were the most significant determinants of comprehensive risk in scenic areas. This indicated that the intensity of human-induced surface alterations and the inherent health status of ecosystems were the core components of risk formation. In the spatial risk pattern assessment, human intervention at the guideline level exhibited the highest risk classification, with high-risk and medium-high-risk areas collectively accounting for 45.04% of the total area. In contrast, risks associated with natural geographic elements and ecosystem conditions were significantly lower. Low-risk and medium-low-risk zones for these two factors covered 73.71% and 71.97% of the total area, respectively. This indicated that human activities were the dominant factor driving the spatial differentiation of ecotourism risks within the study area. Based on the final comprehensive risk assessment, the study area overall exhibited a low-to-moderate risk level, with nearly 75% of the region classified as medium risk or below. High-risk zones accounted for only 8.09%. The natural ecological baseline of the scenic area played a crucial buffering role in this outcome. In summary, the combination of RS monitoring and the AHP-EW model effectively quantifies the relative importance of various risk factors, providing reliable support for decision-making in sustainable development ecotourism areas. However, the risk assessment in the study is based on a single temporal RS dataset, which limits the ability to capture dynamic risk changes driven by seasonal climate change. Meanwhile, the universality of specific risk thresholds may be affected by the unique geographical features of the case study area. To enhance the model's adaptability, future research should incorporate multi-temporal data and conduct broader cross-regional comparisons.

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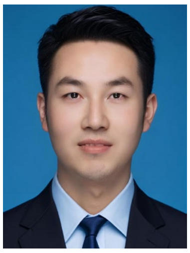

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