Researches in Earth Sciences

Journal homepage: https://esrj.sbu.ac.ir

Research Article

Integrated ecological suitability assessment for sustainable ecotourism development: A case study of khodabandeh county, Iran

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Received: 05 Jul 2026 Accepted: 30 Aug 2026

Abstract

Sustainable ecotourism development requires an integrated evaluation of ecological capacity, environmental constraints, and spatial accessibility. This study assesses the ecological suitability of Khodabandeh County, northwestern Iran, for sustainable ecotourism development by integrating fuzzy logic, the Analytic Network Process (ANP), Random Forest (RF), and Geographic Information Systems (GIS). Six key ecological and infrastructural criteria—water availability, climate, landform, land use, conservation status, and accessibility—were identified through expert consultation and authoritative sources. Criterion weights were determined using a Delphi-based ANP framework implemented in Super Decisions software. To address uncertainty and gradual transitions in environmental variables, all criteria were standardized using fuzzy membership functions and integrated through weighted linear combination to generate a fuzzy ecological suitability map. In parallel, a five-class Random Forest model was trained using 411 spatial reference points labeled by a panel of 20 experts. Established natural, cultural, and historical tourist attractions were assigned to the highest suitability class, whereas the remaining points were classified through joint evaluation of the relevant thematic layers. Because the labels relied on variables also used in the ANP–fuzzy analysis, the RF model was treated as a complementary spatial-consistency assessment rather than as an independent validation framework. On the test subset, the RF model achieved an overall accuracy of 0.8226 and a macro-averaged F1-score of 0.7935, with all misclassifications occurring between adjacent suitability classes. The final ANP–fuzzy–GIS suitability map classified 8% of Khodabandeh County as completely suitable, 26% as suitable, 31% as relatively suitable, 22% as unsuitable, and 13% as completely unsuitable, with the first three classes collectively accounting for 65% of the study area.. The overlay comparison between the ANP–fuzzy–GIS and RF maps yielded an exact spatial agreement of 39.83% and a Cohen’s kappa coefficient of 0.247, whereas 90.57% of pixels were classified within one adjacent suitability class. This contrast indicates that most disagreements involved shifts between neighboring ordinal categories rather than opposing suitability levels, supporting broad spatial consistency but not pixel-level equivalence. These findings can support differentiated spatial planning aimed at balancing ecotourism development with ecological protection in Khodabandeh County. Subject to local recalibration of the criteria, suitability thresholds, expert weights, and spatial datasets, the framework may also be applicable to other ecologically sensitive regions.

Keywords: ANP–Fuzzy–Random Forest framework; Ecotourism suitability; GIS-based land suitability analysis; Khodabandeh County; Sustainable tourism planning

Citation: Kalantari, M. et al, 2026. Integrated ecological suitability assessment for sustainable ecotourism development …, *Res. Earth. Sci:* 17(3), (103-127) DOI: 10.48308/esrj.2026.107468

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Introduction

Ecotourism seeks to generate social and economic benefits from nature-based tourism while maintaining the ecological integrity of destination areas and supporting local communities (Pforr, 2001). However, tourism development in ecologically sensitive landscapes can intensify habitat degradation, landscape fragmentation, and pressure on natural resources when the location and intensity of tourism activities are not aligned with environmental capacity (Huo and Peng, 2023; Xu et al, 2021). The central planning problem is therefore not simply to identify areas with tourism attractions, but to determine where tourism development is ecologically acceptable, spatially accessible, and compatible with conservation requirements (Suvdantsetseg Balt et al, 2012; Suvdantsetseg, 2011; Kiper, 2013). Ecological suitability assessment addresses this problem by integrating the environmental opportunities and constraints that influence tourism development. Such assessments require the simultaneous consideration of topography, climate, land use, water availability, conservation status, and accessibility (Hall, 2010; Brian, 2012). These factors are spatially heterogeneous, may interact with one another, and frequently lack sharply defined suitability thresholds. Consequently, methods based on isolated criteria or rigid classifications may not adequately represent the complexity and uncertainty of ecotourism planning (Borzoei et al, 2014; Ghasemi et al, 2023; Nakhle et al, 2024; Tóthová and Heglasová, 2022). Geographic Information Systems provide the spatial platform needed to integrate these heterogeneous datasets, while multi-criteria decision-making methods support the systematic evaluation of their relative importance. The Analytic Network Process is particularly appropriate where criteria are interdependent, and fuzzy membership functions allow gradual ecological transitions to be represented instead of imposing abrupt class boundaries. Machine-learning methods provide a complementary perspective by identifying nonlinear relationships and interactions directly from spatial reference data (Prato, 2007; Liu, 2003; Kabir et al, 2014; Thommandru et al, 2023). Random Forest was selected for the data-driven component because it can accommodate nonlinear relationships, correlated predictors, mixed environmental variables, and relatively limited sample sizes without requiring distributional assumptions. It also provides directly interpretable measures of predictor importance and is generally less dependent on extensive parameter tuning than boosting algorithms such as XGBoost and LightGBM. Although SVM can perform effectively in high-dimensional classification, its results depend strongly on kernel and parameter selection and provide less direct interpretation of predictor contributions. In the present study, RF was therefore used as a complementary spatial-comparison method rather than as a fully independent validation model. Previous research has demonstrated the usefulness of ANP and fuzzy methods for integrating expert knowledge and environmental uncertainty, while other studies have used RF to model nonlinear suitability relationships (Aminu et al, 2014; Aminu et al, 2013; MirarabRazi et al, 2020; Esmaeil Zaei, 2013; Sharpley, 2015). The methodological gap is therefore not the complete absence of hybrid approaches. Rather, limited attention has been given to the transparent spatial comparison of expert-weighted and machine-learning suitability outputs when both approaches rely on related thematic variables. Existing ANP–fuzzy frameworks frequently conclude with a single aggregated suitability map, whereas standalone RF studies commonly emphasize classification accuracy without examining exact and ordinal spatial agreement with an expert-driven model. This limits understanding of where the two approaches converge, where they differ, and whether their disagreements represent major contradictions or shifts between neighboring suitability classes. Khodabandeh County provides an appropriate setting for examining this issue because it combines pronounced elevation and climatic variation, environmentally sensitive areas, dispersed natural and cultural attractions, and uneven tourism accessibility. Attractions such as Katale Khor Cave, the Sojas River, and the Qeydar Nabi Tomb indicate substantial tourism potential, while infrastructure limitations and ecological restrictions complicate the spatial allocation of tourism development (Management and Planning Organization of Zanjan, 2023). The coexistence of tourism opportunities and environmental constraints makes the county suitable for testing an integrated and uncertainty-aware spatial assessment framework. Accordingly, this study aims to assess the ecological suitability of Khodabandeh County for sustainable ecotourism using a Delphi–ANP–fuzzy–GIS framework and an RF-based comparative analysis. The scientific contribution of the study lies in linking expert-based network weighting and fuzzy spatial standardization with a five-class machine-learning model, while explicitly distinguishing complementary spatial-consistency assessment from independent validation. The study also evaluates both exact pixel-level agreement and agreement within adjacent ordinal classes, allowing disagreements between the two outputs to be interpreted according to their severity. This provides a more transparent basis for identifying suitable development zones, environmentally constrained areas, and methodological uncertainty in regional ecotourism planning.

Literature review

Ecotourism suitability studies have primarily followed two methodological trajectories: expert-driven multi-criteria decision-making and data-driven spatial modeling. Among MCDM techniques, the Analytic Hierarchy Process has been widely used because of its simple structure, transparent pairwise comparisons, and ease of implementation. Shaghaghipour and Larijani (2017), for example, applied AHP to prioritize ecotourism zones using environmental and infrastructural criteria. However, AHP assumes that the evaluated criteria are independent, an assumption that may be unrealistic in ecological systems where climate, topography, land use, accessibility, and conservation constraints interact with one another (Shaghaghipour and Larijani, 2017). The Analytic Network Process addresses this limitation by allowing interdependence and feedback among criteria. García-Melón et al. (2012) used ANP to support sustainable tourism planning in protected areas (García-Melón et al, 2012), while Fung and Wong (2007) demonstrated its usefulness for integrating stakeholder perspectives and multi-level influences (Fung and Wong, 2007). Compared with AHP, ANP provides a more realistic representation of complex socio-ecological relationships. Its application, however, requires a larger number of expert judgments and remains sensitive to the consistency of the pairwise-comparison matrices and the structure assigned to the decision network. Hybrid ANP approaches have incorporated Delphi procedures and fuzzy logic to improve expert consensus and represent uncertainty (Arsić et al, 2017) Delphi-based consultation can reduce dispersion among expert judgments, while fuzzy membership functions avoid the abrupt boundaries imposed by crisp classification and better represent gradual environmental transitions(Cinelli et al, 2020). These approaches are particularly useful in data-scarce regions because they provide a transparent link between expert knowledge and spatial decision rules. Nevertheless, their outputs remain dependent on the selected criteria, expert-derived weights, membership functions, suitability thresholds, and aggregation procedures. The studies reviewed here generally emphasize the production of a final expert-weighted suitability map, with less attention given to systematic comparison with a separately constructed data-driven output. Machine-learning methods offer a complementary approach by learning relationships directly from labeled spatial observations. Random Forest has been increasingly used in ecological and tourism suitability studies because it can model nonlinear relationships, accommodate correlated and heterogeneous predictors, and estimate the relative importance of input variables. (TAN et al, 2024), applied RF to tourism suitability assessment in mountainous environments, while (Li et al, 2025) used it to identify ecotourism potential by combining environmental and accessibility variables. In environmental applications in Iran, RF has also shown competitive classification performance relative to methods such as SVM and artificial neural networks (Tahmasebi et al, 2021). Compared with ANP–fuzzy models, RF requires labeled reference samples but does not require an explicitly predefined additive weighting structure. It can therefore reveal nonlinear interactions that may not be captured by weighted linear combination. However, RF performance depends on the representativeness and independence of the reference labels. In spatial applications, random train–test partitioning may also be affected by spatial autocorrelation, and high sample-level accuracy does not necessarily constitute independent validation of the resulting suitability map. RF should therefore be interpreted as a complementary data-driven model unless its labels are derived from independent field observations. The comparison indicates that expert-driven and machine-learning approaches address different dimensions of suitability assessment. ANP–fuzzy models make expert priorities, ecological thresholds, and uncertainty explicit, whereas RF evaluates patterns represented in labeled spatial samples and provides empirical variable-importance estimates. Within the literature reviewed here, limited attention has been given to distinguishing exact spatial disagreement from minor disagreement between adjacent ordinal suitability classes. Consequently, two maps may exhibit low exact pixel-level agreement even when most differences represent only a one-class shift rather than a fundamental contradiction between suitable and unsuitable areas. The present study addresses this methodological limitation by integrating a Delphi–ANP–fuzzy–GIS model with a five-class RF analysis and by explicitly treating RF as a complementary spatial-consistency tool rather than fully independent validation. The value added by the proposed framework lies in comparing the two outputs through exact agreement, Cohen's kappa, agreement within one adjacent class, quadratic weighted kappa, and class-specific spatial agreement. This analytical structure allows the severity of disagreement to be evaluated and clarifies whether differences between the two maps reflect major spatial contradictions or shifts between neighboring suitability categories. The approach therefore extends conventional ANP–fuzzy suitability mapping by adding a transparent, ordinal, and class-specific comparison with a data-driven spatial model.

Materials and Methods

Study Area

Khodabandeh County is located in the southwestern part of Zanjan Province in northwestern Iran, extending between latitudes 35°34′–36°25′ N and longitudes 47°52′–48°56′ E. The county exhibits considerable topographic diversity, with elevations ranging from 1,418 m to 2,776 m above sea level and a mean altitude of approximately 1,809 m. This pronounced altitudinal variation is associated with heterogeneous climatic, landform, and land-cover conditions. The main vegetation and land-cover types represented in the study area include dense, semi-dense, and sparse rangelands, native vegetation, forested areas of varying density, rainfed agricultural land, irrigated agricultural areas, and orchards. This environmental heterogeneity creates substantial spatial variation in ecological suitability for nature-based tourism. The region is characterized by a rich assemblage of natural and cultural resources that provide a strong foundation for ecotourism development. Notable attractions include Katale Khor Cave—one of the largest and oldest limestone caves in Iran—the Sojas River, which plays a key role in supporting regional biodiversity and agricultural activities, and the Qeydar Nabi Tomb, a site of significant historical and religious value. Despite its considerable natural and cultural tourism potential, Khodabandeh County has faced persistent constraints related to tourism infrastructure and accessibility. In particular, previous reports on Katale Khor Cave have identified inadequate access conditions and the need for further development of tourism infrastructure, including visitor facilities and supporting services, as important limitations on the tourism function of the area (IRNA, 2017; Cultural Heritage, Tourism and Handicrafts Department of Zanjan Province, 2020). These conditions reinforce the need for a systematic spatial suitability assessment to identify areas where ecotourism development can be promoted without intensifying environmental constraints. Khodabandeh County was selected as the study area because it combines substantial environmental heterogeneity with a spatially dispersed set of natural and cultural tourism resources. The pronounced elevation gradient, contrasting climatic and land-cover conditions, protected and environmentally sensitive areas, and uneven accessibility create marked spatial differences in ecotourism suitability across the county.At the same time, the coexistence of established tourist attractions and areas with limited tourism infrastructure provides an appropriate setting for evaluating whether an integrated expert-based and data-driven framework can distinguish between development opportunities and ecological constraints. These characteristics make Khodabandeh County a suitable case for testing the proposed spatial suitability framework. The geographical location of the study area within Zanjan Province is illustrated in Figure 1.

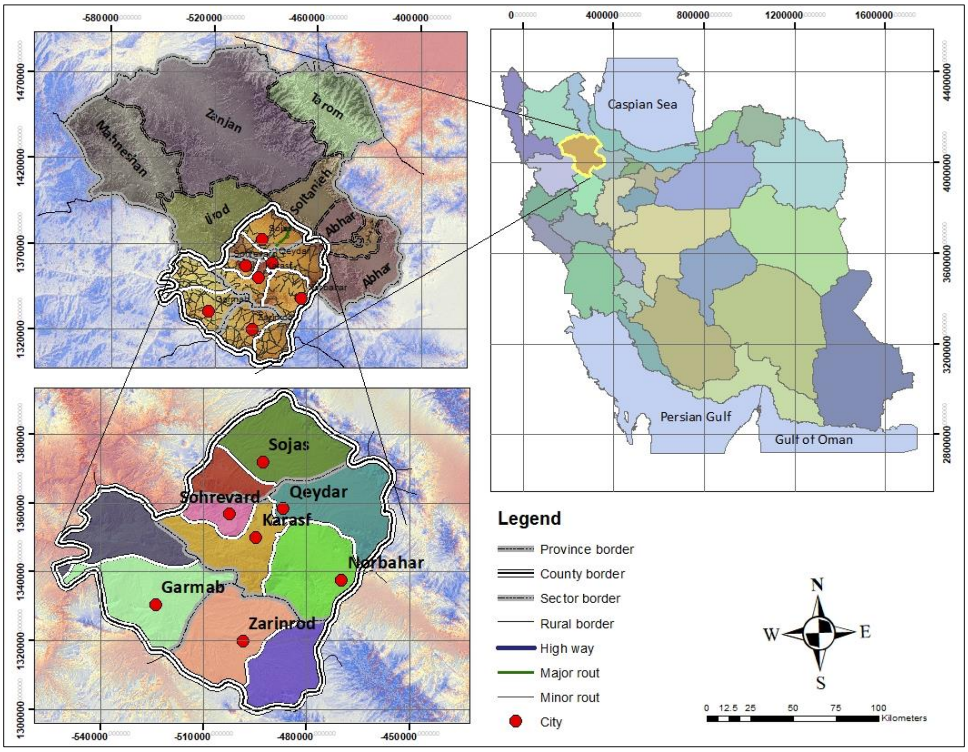


Fig. 1: Geographic location of Khodabandeh County in Zanjan Province, northwestern Iran. Coordinate Reference System: WGS 1984 / UTM Zone 39N, based on the Transverse Mercator projection with a central meridian of 51°E, false easting of 500,000 m, and a scale factor of 0.9996. Linear units are meters. Source: Authors' GIS processing, 2025.

Research Design

This study adopted an applied, descriptive–analytical research design to evaluate the ecological suitability of Khodabandeh County for sustainable ecotourism development. The analytical framework combined expert-based assessment, spatial multi-criteria analysis, fuzzy standardization, and machine-learning-based comparison. The Delphi technique was first used to refine the criteria and subcriteria, followed by the Analytic Network Process (ANP) to derive their relative priorities. Fuzzy membership functions were then applied to standardize the environmental layers, which were integrated through GIS-based weighted linear combination to generate the primary ecotourism suitability map (Saaty, 1999; Gómez-Navarro et al, 2009; Cinelli et al, 2020). In parallel, a five-class Random Forest model was developed using 411 spatial reference points labeled by a panel of 20 experts. Established natural, cultural, and historical tourist-attraction locations were assigned to the highest suitability class, whereas the remaining reference points were classified through expert evaluation of the combined thematic conditions represented by the environmental, topographic, climatic, accessibility, conservation, and tourism-related layers. The RF labels were not directly extracted from the final ANP–fuzzy suitability map. However, because both approaches relied on related thematic information, the RF model was used as a complementary data-driven tool for spatial-consistency assessment rather than as a fully independent validation framework. Details of the labeling procedure, train–test partitioning, and RF configuration are provided in the Random Forest modeling subsection.

Ecological Criteria and Subcriteria

The ecological criteria were selected through a sequential screening procedure combining literature review and expert assessment. First, a preliminary pool of environmental and tourism-related variables was compiled from previous ecotourism suitability studies, particularly those employing GIS-based multi-criteria approaches (Withanage et al, 2024; Waswa Wanyonyi et al, 2016; Jovanovic et al, 2022; Aşilioğlu, 2021). The candidate variables were then reviewed by the expert panel with respect to their ecological relevance to ecotourism, applicability to the environmental conditions of Khodabandeh County, availability and spatial consistency of the required datasets, and potential redundancy with other variables. Following two Delphi rounds, overlapping or locally less informative variables were excluded or consolidated, resulting in six major criteria: water availability, landform characteristics, land use and vegetation, conservation status, climate conditions, and proximity to tourist attractions. These criteria collectively represent the principal environmental constraints and opportunities affecting ecological integrity, visitor accessibility and comfort, and the spatial feasibility of ecotourism development.

Water Availability: Distance to rivers, and other surface water bodies.

Landform Characteristics: Including slope, elevation, and aspect, which influence accessibility, landscape aesthetics, and ecological sensitivity.

Land Use and Vegetation: Existing land cover types, vegetation density, and habitat conditions.

Conservation Zones: Protected areas, environmentally sensitive habitats, and biodiversity-rich zones.

Climate Conditions: Temperature and sunshine duration were retained as the principal climatic subcriteria because they provide direct and readily interpretable indicators of outdoor thermal conditions, seasonal recreational suitability, and visitor comfort. The climatic component was intentionally restricted to a parsimonious set of variables to minimize redundancy among closely related environmental indicators and to maintain a transparent and interpretable suitability framework. The selected variables were therefore intended to represent the dominant climatic influence on ecotourism suitability at the regional scale rather than to provide an exhaustive characterization of all climatic processes.

Proximity to Tourist Attractions: Accessibility to natural, cultural, and historical sites.

These criteria were decomposed into a network-based structure of interrelated subcriteria to support multi-level analysis within the ANP framework. The selection and structuring of criteria are consistent with previous studies emphasizing the ecological and functional dimensions of sustainable ecotourism planning (Withanage et al, 2024; Waswa Wanyonyi et al, 2016; JOVANOVIC et al, 2022; Aşilioğlu, 2021). The selected criteria were organized into a network-based structure of interrelated subcriteria to support the ANP analysis. The hierarchical and network structure of the criteria and subcriteria is presented in Figure 2.

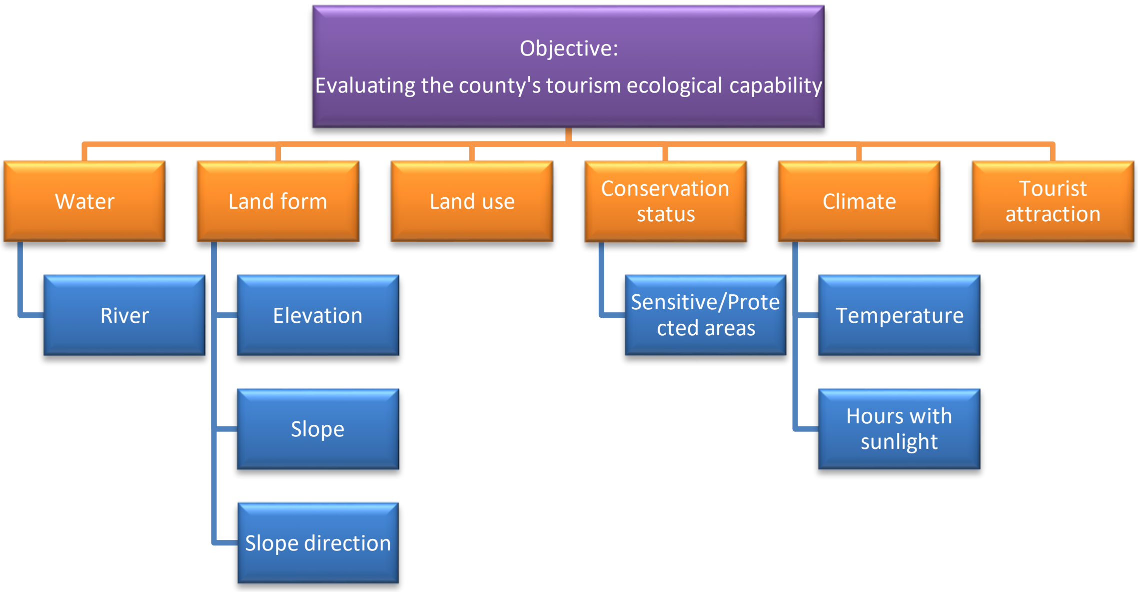


Fig. 2: The ecological criteria and subcriteria used to assess the land capability for ecotourism development in Khodabandeh County.

The final ecological subcriteria, their suitability ranges, standardized ordinal codes, and the corresponding literature sources used to define the suitability thresholds are summarized in Table 1. The standardized codes were consistently ordered from 1 (completely suitable) to 5 (completely unsuitable) to provide a common suitability direction across the heterogeneous environmental variables.

Table 1: Standardized classification of ecological subcriteria used for evaluating ecotourism capability in Khodabandeh County.

Slope	Standard code	Sunlight	Standard code	Slope direction	Standard code
0-5	4	10-15	1	Flat, northwest	1
5-10	2	8-10	2	Northeast, west	2
10-20	1	6-8	3	North, southeast, southwest	3
20-35	3	3-6	4	south	4
+35	5	-3, +15	5		
Land use	Standard code	Elevation	Standard code	Tourism attraction	Standard code
Semi-dense forest, water bodies, riverbed	1	-1200	2	0-1000	1
Dense forest, thin forest, land with native vegetation	2	1200-1500	1	1000-5000	2
Rocky outcrop, dense, semi-dense, and thin pastures	3	1500-1750	3	5000-10000	3
Rainfed agriculture and gardens, city and village	4	1750-2500	4	10000-20000	4
Aquaculture and water gardens, barren land, mixture of garden and tree	5	+2500	5	+20000	5
River	Standard code	Conserved areas	Standard code	Temperature	
0-1000	1	0-500	5	16-20	1
1000-5000	2	500-1000	4	20-23	2
5000-10000	3	1000-5000	3	23-26	3
10000-20000	4	5000-10000	2	26-30	4
20000-50000	5	+10000	1	-16 +30	5

Source: Makhdoum (2004); Mokhtari (2006); Servati (2009); Rahnamaei (2010); Makhdoum (2004); Expert assessment and literature review (2025).

These standardized suitability ranges provided the basis for subsequent fuzzy transformation and spatial integration.

Methodological Workflow

The methodological workflow consisted of six main steps: 1) collection and preprocessing of spatial datasets, 2) expert consultation using the Delphi method, 3) weighting of ecological criteria and subcriteria through the Analytic Network Process, 4) fuzzy standardization of environmental variables, 5) GIS-based spatial integration using weighted linear combination, and 6) Random Forest modeling for comparative spatial assessment. The overall workflow of the proposed framework is illustrated in Figure 3.

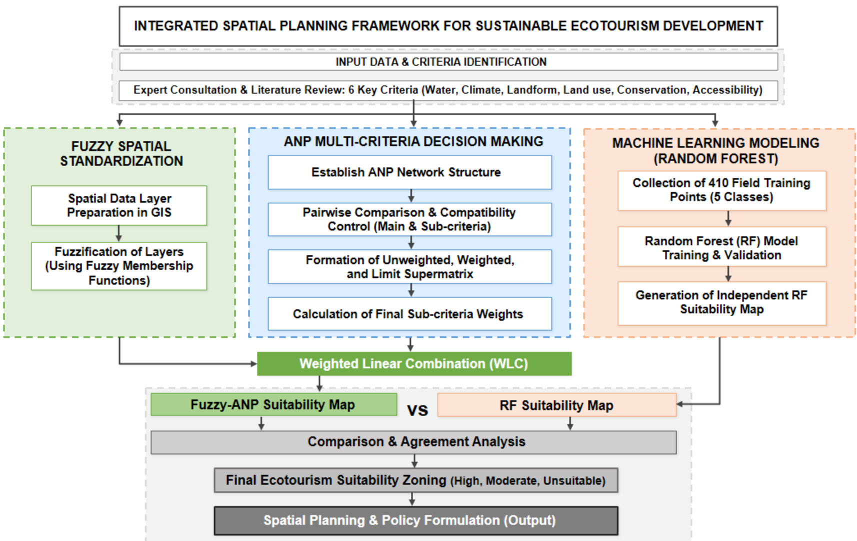


Fig. 3: Workflow diagram for evaluating ecological capability of ecotourism in Khodabandeh County.

Data Collection and Preprocessing

A range of spatial datasets was compiled to evaluate the ecological suitability of Khodabandeh County for ecotourism development. The datasets included:

- Digital Elevation **Model** (DEM): Used to derive slope, elevation, and aspect layers, obtained from the United States Geological Survey (USGS Topoview 2024) with a spatial resolution of 30 m.
- Land Use/Land Cover (LULC): Land-use and land-cover data were obtained from the Iranian Department of Environment for 2023 and were used to represent the spatial distribution of agricultural land, rangelands, forested areas, orchards, built-up areas, and other relevant land-cover classes.
- Hydrological Data: The river network used to represent surface-water accessibility was obtained from Zanjan Regional Water Company at a resolution of 5 meters. River-distance layers were subsequently generated in GIS and used as the water-availability subcriterion.
- Climatic Data: Long-term average temperature and sunlight hours obtained from the WorldClim database (WorldClim 2025).
- Protected Areas and Conservation Zones: Sourced from the Department of Environment of Iran to identify environmentally sensitive and restricted areas.
- Tourist Attraction Locations: Collected through field surveys and local administrative records to represent existing natural, cultural, and historical tourism sites.

All spatial datasets were projected to the UTM Zone 39N coordinate reference system and harmonized to ensure spatial consistency. Vector layers were rasterized where required, and all raster datasets were resampled and aligned to a common spatial resolution of 30 m. The resulting layers were then standardized and prepared for subsequent fuzzy transformation and GIS-based multi-criteria integration. All thematic layers and suitability maps were processed and produced in 2025.

Expert Consultation Using the Delphi Technique

The Delphi technique was employed to establish expert consensus on the selection, relevance, and organization of the ecological criteria and subcriteria used in the suitability assessment. A panel of 20 experts was purposively selected from academic and professional backgrounds relevant to environmental planning, ecotourism development, GIS, and spatial analysis. The panel included university faculty members and experts from relevant governmental and professional organizations whose fields of activity were directly related to environmental assessment, tourism planning, land-use planning, and spatial analysis. The composition of the expert panel is summarized in Table 2.

Table 2: Composition of the expert panel participating in the Delphi procedure.

Expert group	Position	Main field of expertise	Number
University academics	Associate professors	Environmental planning and assessment	4
University academics	Associate professors	Urban planning	3
University academics	Associate professors	Tourism and ecotourism planning	4
University academics	Associate professors	GIS and spatial analysis	3
Organizational experts	Senior experts	Environmental and land-use planning	3
Organizational experts	Senior experts	Tourism planning and development	3
Total	—	—	20

The consultation was conducted in two iterative Delphi rounds. During the first round, the experts evaluated the relevance and appropriateness of the proposed ecological criteria and subcriteria. Their assessments were compiled and reviewed to identify areas of disagreement and to refine the structure of the criteria. The revised criterion set was subsequently returned to the panel in the second round for reassessment.

This iterative procedure was intended to reduce dispersion among expert judgments and establish a stable set of criteria for subsequent ANP analysis. Consensus was evaluated using the coefficient of variation (CV), with values below 10% considered indicative of an acceptable level of agreement among experts (Goktas and Yumusak, 2024). The Delphi process was conducted in two rounds. Following the second round, all retained ecological criteria achieved a coefficient of variation (CV) below 10%, indicating an acceptable level of consensus among the experts. The finalized criteria and subcriteria were subsequently used for weighting and prioritization within the Analytic Network Process (ANP).

Analytic Network Process (ANP)

The Analytic Network Process (ANP) was used to determine the relative priorities of the ecological criteria and subcriteria while accounting for interdependencies and feedback relationships among the decision elements (Saaty 2004). Following the Delphi procedure, expert judgments were translated into pairwise comparison matrices using Saaty's fundamental 1–9 scale (Saaty, 1999). The numerical judgments represented the relative importance of one element over another, with reciprocal values assigned to inverse comparisons. The scale used for the pairwise comparisons is presented in Table 3. The pairwise comparison matrices were processed using Super Decisions software. For each matrix, the consistency of expert judgments was evaluated using the Consistency Ratio (CR), with values below 0.10 considered acceptable (Saaty, 1999). Only judgments satisfying this consistency criterion were retained for the final ANP calculations. The resulting local priorities were incorporated into the unweighted, weighted, and limit supermatrices to account for dependencies among the criteria and subcriteria. The final priorities extracted from the limit supermatrix were subsequently normalized so that the sum of the global weights of all terminal subcriteria equaled 1.00. These normalized global weights were used directly in the fuzzy weighted linear combination within the GIS environment. The final weights and corresponding consistency information are reported in the Results section. The consistency of each pairwise comparison matrix was evaluated using the Consistency Ratio (CR), with CR < 0.10 considered acceptable. The resulting CR values are reported in the Results section.

Table 3. Saaty's scale used for pairwise comparison in the ANP model.

Importance Level	Definition	Description
1	Equal importance	Both elements contribute equally
3	Moderate importance	Slight preference based on experience
5	Strong importance	Strong preference based on evidence
7	Very strong importance	Demonstrated dominance in practice
9	Extreme importance	Absolute preference
2, 4, 6, 8	Intermediate values	Between the above scales

(Saaty, 2006; Saaty, 1996)

Fuzzy Standardization of Ecological Parameters

Environmental parameters relevant to ecotourism suitability often exhibit uncertainty, gradual transitions, and spatial heterogeneity rather than well-defined thresholds. To account for these characteristics, fuzzy logic was employed to standardize all ecological subcriteria into a continuous suitability scale ranging from 0 (completely unsuitable) to 1 (Completely suitable) (Zadeh, 1965).

Membership Functions

Fuzzy membership functions were assigned according to the ecological response pattern of each subcriterion and the suitability thresholds summarized in Table 1. Fuzzy standardization was used to transform heterogeneous environmental variables into a common continuous suitability scale ranging from 0 to 1, where values approaching 1 represent higher ecological suitability and values approaching 0 represent lower suitability. The threshold ranges used to characterize the ecological response of each variable were derived from the environmental-planning references reported in Table 1 and were adapted, where necessary, to the conditions of Khodabandeh County through expert assessment. The direction of fuzzy standardization was defined according to the expected relationship between each environmental variable and ecotourism suitability. For river proximity and tourist-attraction proximity, smaller distance values represented more favorable conditions; therefore, these continuous distance rasters were standardized using a Small fuzzy membership function. Based on the suitability thresholds defined in Table 1, a midpoint of 7,500 m and a spread of 5 were specified for both distance-based variables. For elevation, slope, aspect, land use/land cover, and conservation-related conditions, the ecological suitability ranges presented in Table 1 were first converted to ordinal suitability codes ranging from 1 (completely suitable) to 5 (completely unsuitable). These coded rasters were subsequently transformed using a Small fuzzy membership function with a midpoint of 3 and a spread of 5, so that lower suitability codes received higher fuzzy membership values. Sunshine duration was standardized using a Gaussian membership function because the highest suitability occurred within an intermediate optimum range rather than following a strictly increasing or decreasing relationship. Based on the optimum range of 10–15 h defined in Table 2, the Gaussian midpoint was set at 12.5 h, with a spread of 0.1 and no fuzzy hedge. For the temperature criterion, the retained ArcGIS geoprocessing history confirmed the use of a Gaussian fuzzy membership function. In this transformation, the midpoint represents the input value associated with maximum membership, whereas the spread controls the rate at which membership declines as values depart from the midpoint. For the annual temperature raster, the recorded parameters were a midpoint of 9.6208 and a spread of 0.1, with no fuzzy hedge applied. The fuzzy standardization approach, response direction, and parameter settings used for all terminal subcriteria are summarized in Table 4.

Table 4: Fuzzy standardization approach and membership specifications used for the ecological subcriteria.

Subcriterion	Input / preprocessing basis	Fuzzy membership function	Parameters / implementation
Slope	Suitability codes 1–5 derived from Table 2	Small	Midpoint = 3; Spread = 5
Aspect / slope direction	Suitability codes 1–5 derived from Table 2	Small	Midpoint = 3; Spread = 5
Land use / land cover	Suitability codes 1–5 derived from Table 2	Small	Midpoint = 3; Spread = 5
Elevation	Suitability codes 1–5 derived from Table 2	Small	Midpoint = 3; Spread = 5
Conserved areas	Suitability codes 1–5 derived from Table 2	Small	Midpoint = 3; Spread = 5
River proximity	Continuous distance raster	Small	Midpoint = 7,500 m; Spread = 5
Tourist-attraction proximity	Continuous distance raster	Small	Midpoint = 7,500 m; Spread = 5
Temperature	Continuous annual-temperature raster	Gaussian	Midpoint = 9.6208; Spread = 0.1; Hedge = None
Sunshine duration	Continuous sunshine-duration raster	Gaussian	Midpoint = 12.5 h; Spread = 0.1; Hedge = None

Note: Suitability codes were ordered from 1 (completely suitable) to 5 (completely unsuitable). For the coded subcriteria, the Small membership transformation preserved this suitability direction by assigning progressively lower fuzzy membership values to higher ordinal codes. A midpoint of 3 and a spread of 5 were used for the coded subcriteria. For river and tourist-attraction proximity, a midpoint of 7,500 m and a spread of 5 were specified based on the intermediate 5,000–10,000 m suitability interval defined in Table 2. For sunshine duration, the Gaussian midpoint was set at 12.5 h, corresponding to the center of the optimum 10–15 h range, with a spread of 0.1 and no fuzzy hedge. For temperature, the Gaussian parameters recorded in the retained ArcGIS processing history were a midpoint of 9.6208 and a spread of 0.1, with no fuzzy hedge.

Fuzzy standardization was implemented according to the data structure of each subcriterion. Continuous distance-based variables, including river and tourist-attraction proximity, were transformed directly from their raster values. In contrast, variables represented by ecological suitability ranges or categorical conditions were first reclassified into ordinal suitability codes ranging from 1 (completely suitable) to 5 (completely unsuitable) and were subsequently transformed into continuous fuzzy memberships. Temperature was standardized directly using the Gaussian function documented in the ArcGIS processing history. The resulting fuzzy layers, expressed on a continuous 0–1 scale, were then combined with the normalized ANP-derived weights in the weighted linear combination model.

Random Forest (RF) Modeling

To complement the expert-based ANP–fuzzy suitability assessment and enhance model robustness, a Random Forest (RF) machine-learning approach was implemented. RF is well suited for spatial suitability modeling due to its ability to handle nonlinear relationships, manage multicollinearity among predictors, and reduce overfitting through ensemble learning (Breiman, 2001). In this study, RF was used to generate a complementary suitability map for comparative spatial-consistency analysis rather than as a replacement for the MCDM-based framework.

Input Variables

The RF model incorporated the same set of environmental and infrastructural variables used in the ANP–fuzzy analysis, including:
- Slope, elevation, and aspect
- Land use/land cover
- Distance to rivers and tourist attractions
- Temperature and sunshine duration
- Conservation and protection status

Model Training and Comparative Assessment

A total of 411 spatial reference points were prepared for Random Forest modeling and assigned to five ordinal ecotourism suitability classes by a panel of 20 experts. Locations corresponding to established natural, cultural, and historical tourist attractions were assigned to the highest suitability class because they represented confirmed tourism destinations within the study area. The remaining reference points were labeled through the joint examination of all relevant thematic layers, including topography, climate, land use, river proximity, conservation status, accessibility, and proximity to tourist attractions. Points located in areas where most environmental and accessibility conditions were favorable were assigned to the higher suitability classes, whereas points characterized by multiple unfavorable conditions, ecological restrictions, or limited accessibility were assigned to the lower classes. Intermediate classes were allocated to locations showing mixed suitability conditions across the thematic layers. The labels were determined through expert evaluation of the combined spatial evidence and were not directly extracted from the final ANP–fuzzy suitability map. Nevertheless, because the labeling process relied on thematic variables also used in the ANP–fuzzy analysis, the resulting reference dataset was not considered completely independent. Therefore, the RF model was interpreted as a complementary spatial-consistency assessment rather than as independent ground-truth validation of the ANP–fuzzy–GIS output.The dataset was then randomly divided into training and testing subsets, with 70% of the samples used for model training and 30% used for model testing. The RF model was configured with 290 decision trees, and the Gini impurity index was used as the splitting criterion. Predictor importance was quantified using the Gini-based feature importance measure, also referred to as Mean Decrease in Impurity (MDI). This measure represents the normalized total reduction in Gini impurity contributed by each predictor across all decision trees in the forest. To quantify the correspondence between ANP-derived global weights and RF predictor-importance rankings, Spearman's rank correlation coefficient and Kendall's tau-b were calculated across the nine common predictor variables. The RF model was applied to generate a complementary data-driven suitability map and to compare its spatial pattern with the ANP–fuzzy–GIS suitability output. Model performance was assessed using test-set classification metrics, while predictor contribution was evaluated using Gini-based feature importance (MDI)... However, because the sample labels were derived from suitability classes and the spatial data may exhibit autocorrelation, the RF accuracy should be interpreted as an internal sample-level performance indicator rather than as independent ground-truth validation. Therefore, the RF output was used primarily for comparative spatial assessment and consistency analysis, not as a standalone validation of ecological suitability.

GIS-Based Spatial Integration

The fuzzy-standardized ecological layers were integrated using a weighted linear combination (WLC) approach within ArcGIS 10.8 and ArcGIS Pro 3.5 environments. In this process, the ANP-derived criterion weights were multiplied by their corresponding fuzzy membership layers and aggregated to generate the primary ecotourism suitability map. The WLC approach enabled the systematic combination of multiple weighted criteria while preserving their relative importance and spatial variability. The Random Forest (RF) model output was subsequently compared with the ANP–fuzzy–GIS suitability map using both visual interpretation and pixel-based overlay agreement analysis. This comparison was intended to evaluate spatial consistency between the expert-based and data-driven outputs, while avoiding interpretation of the RF result as a complete independent validation framework.

Overlay-Based Spatial Agreement Analysis

Prior to the overlay analysis, the ANP–fuzzy–GIS and RF suitability maps were harmonized with respect to coordinate reference system, spatial resolution, processing extent, snap raster, and NoData mask to ensure pixel-to-pixel comparability. Both maps were represented using the same five ordinal suitability classes: 1 = completely suitable, 2 = suitable, 3 = relatively suitable, 4 = unsuitable, and 5 = completely unsuitable. The RF raster, originally coded from 0 to 4, was recoded to the corresponding 1–5 ordinal scale used for the ANP–fuzzy–GIS map. A pixel-based cross-tabulation matrix was then generated to quantify spatial agreement between the two suitability maps. Exact overall agreement was calculated as the proportion of pixels located on the main diagonal of the cross-tabulation matrix. Cohen's kappa coefficient was additionally calculated to measure exact agreement after accounting for agreement expected by chance. Because the five suitability classes have an inherent ordinal structure, exact agreement alone may overstate the importance of small disagreements between adjacent classes. Therefore, two ordinal agreement measures were also calculated. First, agreement within one suitability class was defined as the proportion of pixels for which the absolute difference between the ANP‑fuzzy‑GIS and RF class codes was ≤ 1. Second, quadratic weighted kappa was calculated to assign progressively greater penalties to disagreements spanning larger ordinal distances while assigning smaller penalties to adjacent-class disagreements. Class-specific spatial agreement was additionally quantified using the intersection-over-union (IoU) criterion. For each suitability class, IoU was calculated as the area classified identically by both models divided by the union of the area assigned to that class by either model. The overlay analysis was used as a measure of comparative spatial consistency between the two modeling approaches and was not interpreted as independent ground-truth validation.

Suitability Classification and Assessment

The continuous final suitability index generated by the ANP–fuzzy–GIS model was classified into five ordered suitability categories: 1) completely suitable, 2) suitable, 3) relatively suitable, 4) unsuitable, and 5) completely unsuitable. The same ordinal class terminology and coding scheme were subsequently used for comparison with the Random Forest suitability output. The final continuous suitability index was divided into the five classes using the Natural Breaks (Jenks) classification method in ArcGIS, which identifies class boundaries by minimizing within-class variance and maximizing differences between classes. The suitability outputs were further examined through a qualitative expert-based plausibility assessment involving the same 20-member expert panel that participated in the Delphi and ANP stages. The assessment focused on three predefined aspects: i) whether high- and low-suitability zones were ecologically consistent with the environmental conditions represented by the input layers; ii) whether the modeled spatial pattern corresponded reasonably with the distribution of known natural, cultural, and historical tourist attractions; and iii) whether any spatially implausible or contradictory suitability patterns were evident in the final map. Expert feedback was documented using a structured assessment sheet organized according to these three evaluation dimensions. Comments were compiled and reviewed descriptively to identify recurring observations, areas of agreement, and any spatial patterns considered inconsistent with expert knowledge. The feedback was used solely as an interpretive quality-control and plausibility-assessment step and did not alter the numerical ANP weights, RF predictions, or final suitability classes. Because no systematic GPS-based field-validation dataset was available, this expert assessment was not treated as independent ground-truth validation. Accordingly, the expert review and comparison with known tourist locations were interpreted as qualitative plausibility checks rather than independent validation. Future studies should incorporate independently collected field observations to provide stronger external validation of the final suitability classes.

Results and Discussion

Results

Criteria Weighting Using the Delphi–ANP Approach

Following the Delphi-based expert evaluation and pairwise comparisons within the Analytic Network Process (ANP), priorities were derived for the ecological criteria and terminal subcriteria. The pairwise comparison matrices for the main criteria and climatic subcriteria are presented in Tables 5 and 6, respectively.

Table 5: Pairwise comparison matrix of the main ecological criteria.

	Water	Landform	Land use	Tourism attractions	Conserved areas	Climate
Water	1	5	1	0.2	0.25	0.5
Landform		1	0.2	0.2	0.2	0.2
Land use			1	0.2	0.25	1
Tourism attractions				1	1	5
Conserved areas					1	4
Climate						1

Source: Authors' calculations based on expert judgments, 2025.

At the subcriterion level, the climate criterion comprised temperature and sunshine duration. The pairwise comparison matrix for the climatic subcriteria is presented in Table 6. Temperature received a higher relative priority than sunshine duration, indicating its greater contribution to the climatic component of the ANP model.

Table 6: Pairwise comparison matrix of climatic subcriteria.

	Sunshine duration	**Temperature**
Sunshine duration	1	0.75
Temperature	1.33	1

Source: Authors' calculations based on expert judgments, 2025.

The pairwise comparison matrices were processed in Super Decisions to construct the unweighted, weighted, and limit supermatrices. The consistency of the pairwise judgments was assessed using the Consistency Ratio (CR), with CR < 0.10 considered acceptable. The available consistency results are summarized in Table 7.

Table 7: Consistency assessment of the ANP pairwise comparison matrices.

Pairwise comparison matrix	**CR**	**Consistency status**
Main criteria	0.07291	Acceptable
Climate subcriteria	0.0000	Acceptable
Landform subcriteria	0.0014	Acceptable

Source: Authors' calculations based on expert pairwise judgments and Super Decisions output, 2025.

The consistency results confirmed that the available pairwise comparison judgments satisfied the predefined acceptance criterion. Final priorities were extracted from the limit supermatrix and normalized across the nine terminal subcriteria using $w_i^N = w_i / \sum_{j=1}^{9} w_i$, where w_i^N is the normalized global weight of subcriterion i. By construction, the normalized weights sum to 1.00. Owing to six-decimal rounding, the values reported in Table 8 sum to 0.999999, which is numerically equivalent to 1.000000. These normalized global weights were subsequently used directly in the fuzzy weighted linear combination. The final normalized global weights are presented in Table 8. Tourism attractions received the highest global weight (0.229441), followed by temperature (0.215646), sunshine duration (0.161313), river proximity (0.150468), elevation (0.092966), slope (0.068691), conserved areas (0.038716), slope direction/aspect (0.034282), and land use/land cover (0.008476). The sum of the terminal-subcriterion weights was approximately 1.00, confirming their normalization prior to spatial integration.

Table 8: Final global ANP-derived weights of terminal subcriteria used in the fuzzy weighted linear combination.

Criteria	**Sub- Criteria**	**Weights**
Water	River	0.150468
Climate	Temperature	0.215646
	Sunshine duration	0.161313
Landform	Elevation	0.092966
	Slope direction	0.034282
	Slope	0.068691
	Tourism attractions	0.229441
	Conserved areas	0.038716
	Land use	0.008476
	Total	1

Source: Authors' calculations based on expert judgments and Super Decisions output, 2025.

Conserved areas and land use/land cover received comparatively lower global weights than the other terminal subcriteria. These lower weights indicate that, within the expert-derived ANP structure, they contributed less strongly to differentiation of the final suitability index than tourism accessibility, climatic conditions, water proximity, and topographic factors.

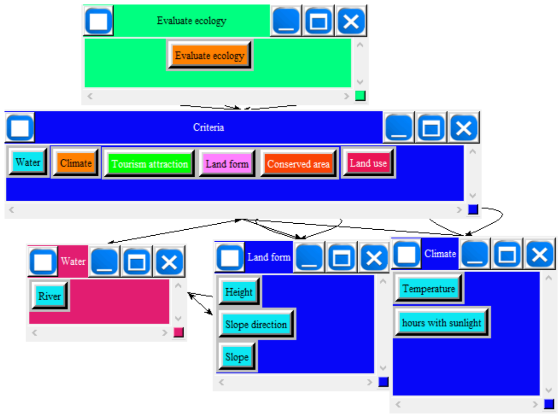


Fig. 4: Displays the ANP network structure used in the evaluation model.

Spatial Zoning of Subcriteria

Each ecological subcriterion was spatially mapped and classified within the GIS environment to illustrate variations in suitability across Khodabandeh County (Figs. 5–13). The resulting maps reveal distinct spatial patterns that reflect the heterogeneous environmental conditions influencing ecotourism development in the region.The spatial distribution of hours of sunlight indicates generally favorable conditions across large portions of the county, suggesting a broad potential for outdoor recreational activities. In contrast, temperature suitability exhibits more constrained patterns, with extensive areas classified as unsuitable or completely unsuitable. This pattern highlights the limiting role of thermal conditions, particularly in high-altitude zones and climatically harsh areas, in shaping seasonal and spatial ecotourism potential. Similarly, environmentally sensitive and protected areas are predominantly classified as unsuitable, reflecting regulatory restrictions and ecological vulnerability rather than physical limitations. Topographic subcriteria display differentiated spatial responses. Elevation and land use are mainly classified within the relatively suitable to unsuitable categories, indicating moderate constraints associated with terrain ruggedness and existing land-cover patterns. These conditions suggest that ecotourism development in such areas may require careful planning and low-impact strategies. In contrast, slope and aspect demonstrate more favorable suitability patterns, with extensive areas classified as suitable or relatively suitable. Gentle slopes and favorable slope orientations enhance accessibility, landscape visibility, and visitor safety, thereby supporting ecotourism activities such as hiking, nature observation, and cultural site visitation. Overall, the spatial zoning of individual subcriteria reveals that ecotourism suitability in Khodabandeh County is shaped by a complex interaction of climatic limitations, topographic conditions, and environmental protection constraints. These spatial patterns provide critical insight into the localized strengths and limitations of the landscape, which are subsequently synthesized through fuzzy standardization and weighted spatial integration in the final suitability assessment.

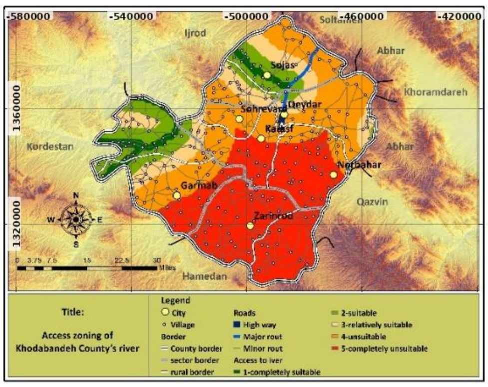


Fig. 5: Access zoning of Khodabandeh County's river (Source: Hydrological dataset; authors' GIS processing, 2025)

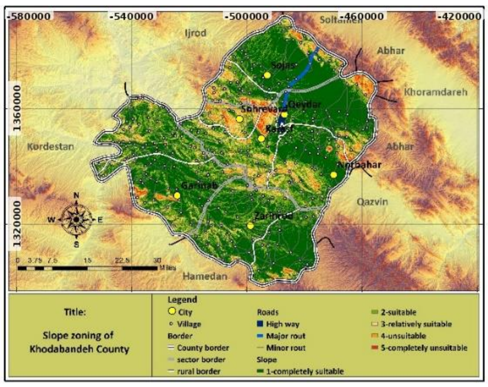


Fig. 6: Slope zoning of Khodabandeh County (Source: Authors' GIS processing based on USGS DEM, 2025)

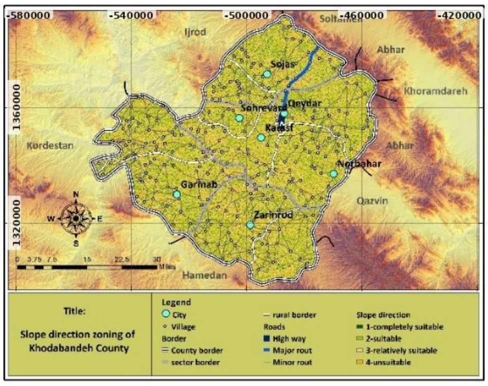


Fig. 7: Slope direction zoning of Khodabandeh County (Source: Authors' GIS processing based on USGS DEM, 2025)

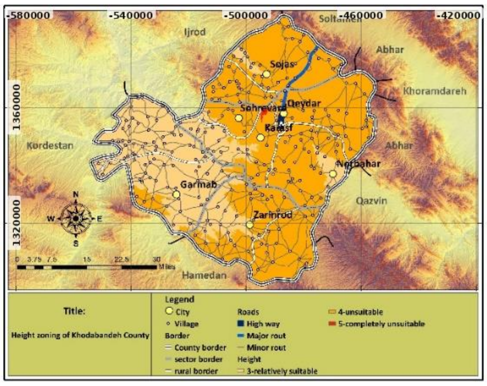


Fig. 8: Elevation zoning of Khodabandeh County (Source: Authors' GIS processing based on USGS DEM (2024), 2025)

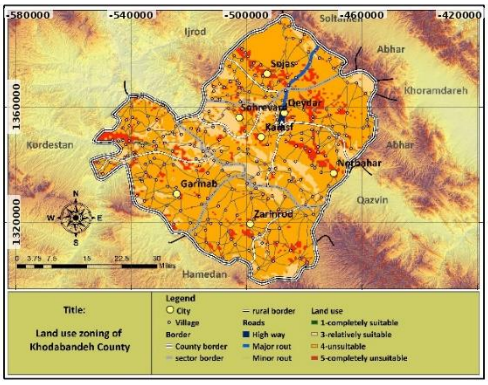


Fig. 9: Land use zoning of Khodabandeh County (Source: Iranian Department of Environment; authors' GIS processing, 2025.)

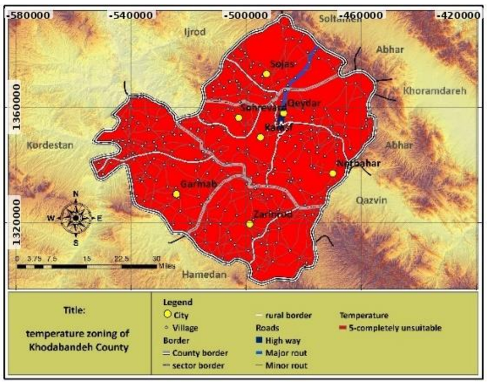


Fig. 10: Temperature zoning of Khodabandeh County (Source: WorldClim; authors' GIS processing, 2025)

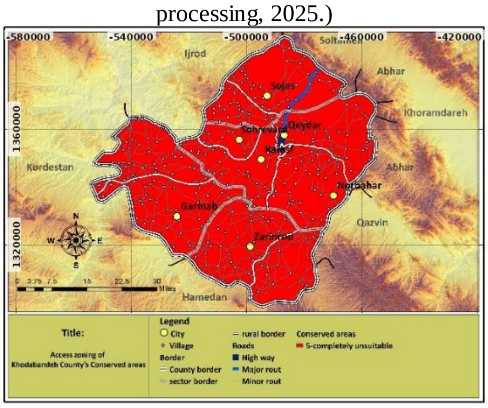


Fig. 11: Conserved area zoning of Khodabandeh County (Source: Iranian Department of Environment; authors' GIS processing, 2025)

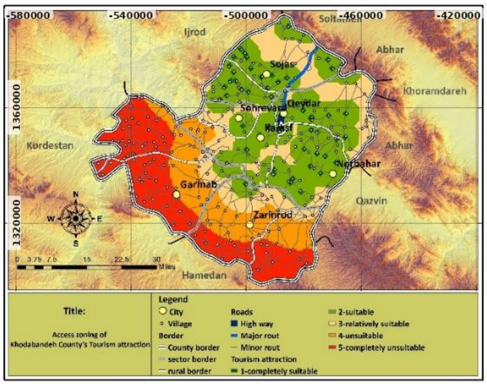
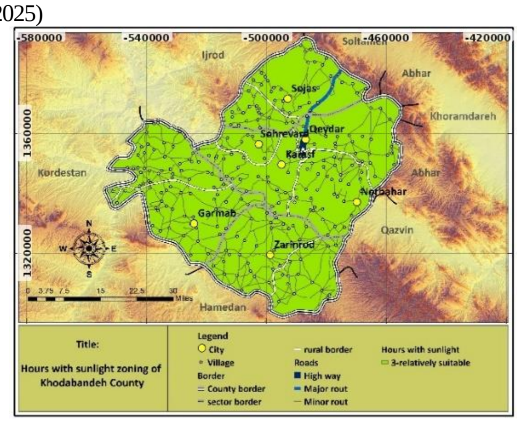


Fig. 12: Tourism attractions zoning of Khodabandeh County



Figu. 13: Sunshine duration zoning of Khodabandeh County (Source: WorldClim; authors' GIS processing, 2025)

Final Ecotourism Suitability Mapping

The final ecotourism suitability map of Khodabandeh County was generated by integrating the fuzzy-standardized ecological layers with their normalized ANP-derived global weights through weighted linear combination. The resulting spatial distribution of the five suitability classes is presented in Figure 14. The relatively suitable class occupied the largest proportion of the study area (31%), followed by the suitable class (26%). Unsuitable and completely unsuitable areas accounted for 22% and 13% of the county, respectively, whereas completely suitable areas represented 8% of the total area and were concentrated mainly in the northern parts of Khodabandeh County. Taken together, the completely suitable, suitable, and relatively suitable classes accounted for approximately 65% of the study area, whereas the unsuitable and completely unsuitable classes represented the remaining 35%. This result indicates ecological suitability rather than immediate development feasibility. Areas identified as completely suitable or suitable should therefore be regarded as priority zones for further site-level assessment rather than as areas automatically suitable for tourism development. The practical development potential of these zones also depends on additional considerations that are not fully represented by the ecological suitability index, including regulatory restrictions, conservation requirements, existing access and tourism infrastructure, service availability, land-use compatibility, and site-specific ecological carrying capacity. Accordingly, even zones with high modeled ecological suitability may require development restrictions where legal, conservation, or infrastructural constraints are present. From a planning perspective, the suitability map should therefore be interpreted as a spatial screening tool for identifying areas with comparatively favorable ecological conditions. Completely suitable and suitable zones may be prioritized for subsequent field assessment and infrastructure feasibility analysis, relatively suitable zones require more cautious site-specific evaluation, and unsuitable or completely unsuitable areas should generally receive stronger conservation-oriented management and development restrictions.

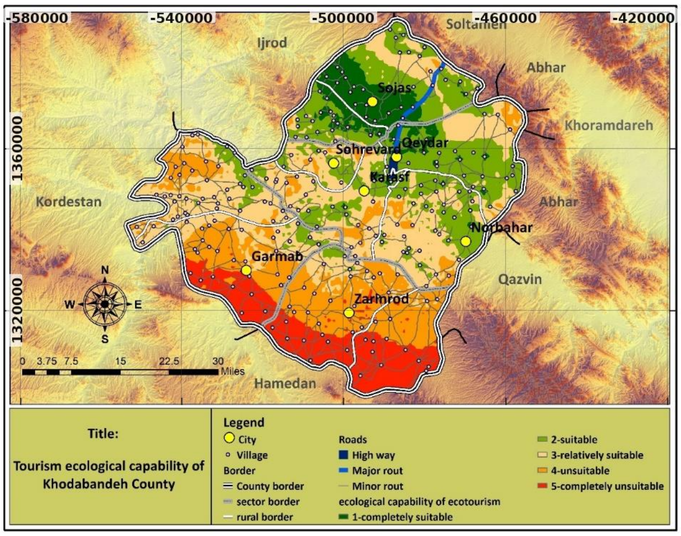


Fig. 14: Final ecotourism ecological suitability map of Khodabandeh County. (Source: Authors' GIS analysis and processing, 2025)

Random Forest Model Performance and Variable Importance

The Random Forest model was used as a complementary data-driven approach to examine the spatial consistency of the ANP–fuzzy–GIS suitability results. The model was trained using nine environmental and tourism-related predictor variables and configured with 290 decision trees. On the test set, the Random Forest model achieved an overall accuracy of 0.8226, a balanced accuracy of 0.7916, and a Cohen's kappa coefficient of 0.7726. The macro-averaged precision, recall, and F1-score were 0.8060, 0.7916, and 0.7935, respectively, whereas the corresponding weighted values were 0.8381, 0.8226, and 0.8259. Class-specific performance metrics are presented in Table 9.

Table 9: Class-specific performance of the Random Forest model on the test set.

Suitability class	Precision	Recall	F1-score	Support
Completely suitable	0.9756	1.0000	0.9877	40
Suitable	0.8889	0.8421	0.8649	19
Relatively suitable	0.7222	0.6190	0.6667	21
Unsuitable	0.5385	0.7368	0.6222	19
Completely unsuitable	0.9048	0.7600	0.8261	25
Macro average	0.8060	0.7916	0.7935	124
Weighted average	0.8381	0.8226	0.8259	124

Source: Authors' calculations from the RF test set.

The confusion matrix presented in Table 10 shows that 102 of the 124 test observations were classified correctly. All 22 misclassified observations were assigned to an adjacent suitability class, and no error extended across two or more ordinal classes. Consequently, agreement within one suitability class reached 100%, while the quadratic weighted kappa coefficient was 0.9617. The completely suitable class showed the highest classification performance, whereas discrimination between the relatively suitable and unsuitable classes was comparatively weaker.

Table 10: Confusion matrix of the Random Forest model on the test set.

Actual / Predicted	CS	S	RS	US	CUS
CS	40	0	0	0	0
S	1	16	2	0	0
RS	0	2	13	6	0
US	0	0	3	14	2
CUS	0	0	0	6	19

Note: CS = completely suitable; S = suitable; RS = relatively suitable; US = unsuitable; CUS = completely unsuitable.
Source: Authors' calculations from the RF test set.

The RF-derived suitability map showed a spatial pattern broadly consistent with the ANP–fuzzy–GIS output. Completely suitable and suitable zones were mainly concentrated in the northern and northeastern parts of Khodabandeh County, whereas unsuitable and completely unsuitable zones were mostly located in the southern and southwestern areas. This spatial pattern suggests that the RF model provides complementary evidence for the broad spatial consistency of the expert-based ANP–fuzzy–GIS output, particularly at the regional pattern level. Predictor importance was evaluated using Gini-based feature importance, also referred to as Mean Decrease in Impurity (MDI). The importance score represents the normalized cumulative contribution of each predictor to reductions in Gini impurity across the trees of the Random Forest ensemble. The normalized importance values sum to 1.00, with higher values indicating a greater relative contribution to class discrimination.

Table 11: Gini-based relative importance of predictor variables in the Random Forest classes.

No.	Predictor Variable	Importance Score
1	Sun	0.0711
2	Temperature	0.1101
3	Slope	0.0828
4	Aspect	0.0725
5	Land Use	0.0799
6	Elevation	0.0820
7	Tourism Attraction	0.2546
8	Conserved Areas	0.0711
9	River	0.1759

Source: Authors' calculations from the RF model.

Tourism-attraction proximity showed the highest relative importance (0.2546), followed by river proximity (0.1759) and temperature (0.1101). Slope (0.0828), elevation (0.0820), and land use/land cover (0.0799) showed intermediate contributions, whereas aspect (0.0725), sunshine duration (0.0711), and conserved areas (0.0711) had comparatively lower importance scores. These values represent relative contributions within the fitted RF model and should not be interpreted as causal effects.

Spatial Agreement Between ANP–Fuzzy–GIS and RF Maps

In addition to the sample-based RF performance assessment, a pixel-based overlay analysis was conducted to evaluate wall-to-wall spatial agreement between the ANP–fuzzy–GIS and RF suitability maps. This analysis represents comparative spatial consistency rather than independent ground-truth validation. The pixel-based overlay analysis showed an exact overall agreement of 39.83% (3,216 of 8,074 valid pixels) between the ANP–fuzzy–GIS and RF maps, with a Cohen's kappa coefficient of 0.247. When the ordinal structure of the five suitability classes was considered, however, 90.57% of pixels (7,313 of 8,074) were located either in the same class or within one adjacent class, and the quadratic weighted kappa reached 0.715. Among pixels that were not classified identically by the two approaches, approximately 84.3% differed by only one ordinal class. The large difference between exact and adjacent-class agreement reflects both the continuous nature of ecological suitability and the different decision structures of the two models. The ANP–fuzzy–GIS model generates suitability through weighted aggregation of continuous fuzzy surfaces, whereas the RF model assigns classes through nonlinear decision-tree partitions learned from expert-labeled reference samples. Pixels located near class boundaries can therefore shift from, for example, suitable to relatively suitable or from relatively suitable to unsuitable even when the underlying ecological conditions are similar. Such boundary effects reduce exact pixel agreement while preserving the broader ordinal spatial pattern. The cross-tabulation also indicates a systematic difference in the distribution of suitability classes between the two maps. The RF output assigned a larger proportion of the mapped area to the unsuitable and completely unsuitable classes than the ANP–fuzzy–GIS map, whereas the latter allocated a larger proportion to the suitable and relatively suitable classes. Therefore, the relatively low exact agreement and Cohen's kappa indicate that the two maps should not be regarded as interchangeable at the individual-pixel level. Conversely, the high adjacent-class agreement and quadratic weighted kappa indicate that their broader ordinal spatial patterns remain substantially consistent. For planning purposes, this means that areas located near class boundaries should be interpreted cautiously and should not be prioritized solely on the basis of a single exact class assignment.

Table 12: Pixel-based cross-tabulation matrix between ANP–fuzzy–GIS and RF suitability classes.

ANP \ RF	CS	S	RS	US	CUS	Row total
CS	372	317	20	1	9	719
S	379	478	869	420	24	2170
RS	167	145	590	1456	110	2468
US	6	4	42	795	858	1705
CUS	0	0	0	31	981	1012
Column total	924	944	1521	2703	1982	8074

Note: CS = completely suitable; S = suitable; RS = relatively suitable; US = unsuitable; CUS = completely unsuitable
Source: Authors' calculations from the pixel-based overlay analysis, 2025.

Class-specific spatial agreement was quantified using the intersection-over-union (IoU) criterion. For each suitability class, IoU was calculated as the number of pixels assigned to the same class by both models divided by the union of pixels assigned to that class by either model:

$IoU_i = N_{ii} / (N_{i+} + N_{+i} - N_{ii})$,

where N_{ii} denotes the number of pixels assigned to class i by both models, N_{i+} is the corresponding ANP–fuzzy–GIS row total, and N_{+i} is the corresponding RF column total. The class-specific IoU values were 29.27% for completely suitable, 18.13% for suitable, 17.36% for relatively suitable, 22.00% for unsuitable, and 48.73% for completely unsuitable. The highest class-specific spatial agreement therefore occurred for the completely unsuitable class, whereas the relatively suitable class showed the weakest spatial overlap.

Table 13: Overlay-based spatial agreement indicators between ANP–fuzzy–GIS and RF suitability maps.

Indicator	Value
Exact overall spatial agreement	39.83%
Cohen's kappa agreement	0.247
Agreement within ±1 suitability class	90.57%
Quadratic weighted kappa	0.715
Agreement in completely suitable class	29.27%
Agreement in suitable class	18.13%
Agreement in relatively suitable class	17.36%
Agreement in unsuitable class	22.00%
Agreement in completely unsuitable class	48.73%

Source: Authors' calculations from the pixel-based overlay analysis, 2025.

The RF-based spatial classification map (Figure 14) reveals a clear north–south gradient in ecological suitability across Khodabandeh County. Northern and northeastern areas are predominantly classified as completely suitable and suitable, whereas southern and southwestern regions are characterized mainly by unsuitable and completely unsuitable classes. Central areas largely fall within the relatively suitable to suitable categories, forming a transitional spatial pattern between the northern and southern portions of the county. Overall, the RF and ANP–fuzzy–GIS outputs exhibited greater agreement in the ordinal arrangement of suitability than in exact pixel-level class assignment. Accordingly, the RF model is interpreted as a complementary spatial-consistency assessment rather than as independent validation of the ANP–fuzzy–GIS map.

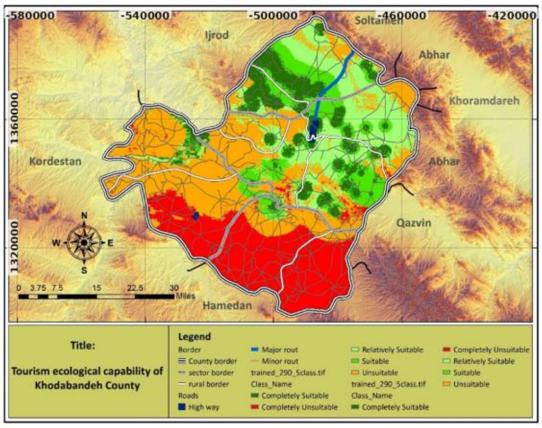


Fig. 15: Spatial distribution of ecotourism suitability classes derived from the Random Forest (RF) model in Khodabandeh County (Source: Authors' Random Forest modeling and GIS processing, 2025.)

Discussion

The findings of this study provide a comprehensive understanding of the ecological suitability patterns for sustainable ecotourism development in Khodabandeh County. The spatial results indicate that suitability is not uniformly distributed across the region but is shaped by a complex interaction of environmental, climatic, and accessibility-related factors. Areas identified as completely suitable and suitable are predominantly concentrated in the northern and central parts of the county, while southern and southwestern zones exhibit substantial ecological constraints. The weighting results derived from the Delphi–ANP approach highlight the dominant influence of proximity to tourist attractions and climatic conditions, which together account for more than 40% of the total weight. This finding is consistent with previous ecotourism studies (García-Melón et al. 2012; Fung and Wong 2007; Huang et al. 2022; Prato 2007; Borzoei et al. 2014) emphasizing visitor accessibility, comfort, and experiential quality as critical determinants of tourism suitability. In contrast, land use and conservation zones received relatively lower weights, reflecting their restrictive or regulatory role rather than their direct contribution to tourism attractiveness. These results demonstrate the importance of distinguishing between enabling and limiting factors in ecotourism planning. The spatial suitability patterns further reveal that favorable topographic conditions, particularly gentle slopes and suitable aspect orientations, play a key role in enhancing ecotourism potential. Such conditions improve accessibility, safety, and visual landscape quality, which are essential for nature-based tourism activities. Conversely, high-altitude areas and environmentally sensitive zones were largely classified as unsuitable, underscoring the need to balance tourism development with ecological protection and regulatory constraints. The ANP–fuzzy–GIS and RF-derived suitability maps showed broadly similar spatial patterns, particularly in identifying higher-suitability zones in the northern and northeastern parts of Khodabandeh County and lower-suitability zones in the southern and southwestern parts. However, the pixel-based overlay analysis provided a more nuanced interpretation of this relationship. Exact overall agreement was 39.83%, and Cohen's kappa was 0.247, indicating fair exact agreement beyond chance. Nevertheless, 90.57% of pixels were classified within one adjacent suitability class, and the quadratic weighted kappa reached 0.715. These results suggest that most disagreements between the two models occurred between neighboring suitability categories rather than between completely contrasting classes. Therefore, the RF output should be interpreted as complementary quantitative support for the broad spatial consistency of the ANP–fuzzy–GIS pattern, not as complete standalone validation. The apparent difference between the high RF test-set accuracy and the lower pixel-level agreement should be interpreted in light of the different evaluation units used by the two assessments. The RF accuracy reflects classification performance on sampled testing points, whereas the overlay indicators evaluate wall-to-wall spatial agreement between two independently generated suitability rasters. Therefore, the lower exact agreement and kappa value do not necessarily invalidate the RF model; rather, they show that the two approaches differ in the precise allocation of suitability classes at the pixel level. The high agreement within one adjacent class and the substantial quadratic weighted kappa indicate that most disagreements are ordinally moderate and occur between neighboring suitability categories. The correspondence between the ANP-derived global weights and the RF variable-importance rankings was further examined quantitatively using rank-based correlation analysis across the nine predictor variables. Spearman's rank correlation indicated a moderate positive association between the two rankings ($\rho = 0.569$, $p = 0.110$), while Kendall's tau-b yielded a similar pattern ($\tau = 0.423$, $p = 0.116$). Although both coefficients indicate a positive tendency toward agreement, neither association reached statistical significance at the 0.05 level, likely reflecting the small number of predictors and differences in the underlying logic of the two approaches. The strongest consistency was observed for tourist-attraction proximity, which ranked first in both approaches, while temperature, river proximity, and elevation also showed relatively similar positions. In contrast, sunshine duration and land use exhibited larger rank differences. These findings therefore suggest partial, rather than complete, correspondence between expert-derived ANP priorities and RF-based predictor importance. The RF findings are broadly consistent with previous spatial ecotourism studies emphasizing the combined role of accessibility and environmental conditions in determining tourism suitability. GIS-based multi-criteria studies such as Fung and Wong (2007) and García-Melón et al. (2012) similarly demonstrate the importance of integrating environmental constraints with tourism-related accessibility and stakeholder-based priorities. More recent RF-based studies, including Tan et al. (2024) and Li et al. (2025), further show the usefulness of nonlinear machine-learning models for identifying tourism-potential zones from environmental and accessibility predictors. In the present study, tourist-attraction proximity, river proximity, and temperature dominated the RF importance ranking, while the Delphi–ANP model also assigned substantial global weights to tourism attractions, temperature, and river proximity. This partial correspondence suggests that both expert-driven and data-driven components identify accessibility, water availability, and climatic conditions as important dimensions of suitability, although their relative rankings are not fully consistent. Nevertheless, the two approaches differed in the relative contribution assigned to several secondary variables, particularly sunshine duration and topographic factors. This difference is partly attributable to the structure of the RF reference sample and illustrates why the RF results should be interpreted as complementary rather than as a direct replication of the ANP-derived priorities. From a spatial planning perspective, the results emphasize the necessity of a differentiated development strategy. Northern and central zones with high ecological suitability offer opportunities for controlled ecotourism expansion, whereas southern areas require conservation-oriented management and low-impact tourism practices. These insights provide a clear analytical foundation for translating ecological assessments into practical planning and policy interventions, as outlined in the following section. A limitation of this study is that the suitability outputs were not validated using a systematic independent field survey dataset. Although the modeled spatial patterns were compared with known tourist attractions, expert judgment, and the RF-based suitability map, these procedures should be interpreted as comparative and plausibility-based assessments rather than full ground-truth validation. Future studies should incorporate GPS-based field observations, visitor-use data, local stakeholder interviews, and site-level ecological indicators to provide stronger empirical validation of ecotourism suitability classes.

Conclusion

This study developed an integrated spatial decision-support framework for ecotourism suitability assessment by combining Delphi-based expert elicitation, the Analytic Network Process (ANP), fuzzy standardization, GIS-based spatial integration, and Random Forest (RF) modeling. The methodological contribution of the study lies not merely in combining these techniques, but in linking an expert-driven multi-criteria suitability model with a complementary data-driven classification approach and evaluating their correspondence at both the sample and spatial levels. This design allows expert-derived priorities, continuous fuzzy suitability surfaces, machine-learning classification, and ordinal map agreement to be examined within a single analytical workflow. The resulting ANP–fuzzy–GIS map showed that approximately 65% of Khodabandeh County falls within the completely suitable, suitable, or relatively suitable classes, whereas the remaining 35% is classified as unsuitable or completely unsuitable. Higher-suitability areas were concentrated mainly in the northern and parts of the central county, while lower-suitability classes were more prevalent toward the southern and southwestern areas. These results identify areas with comparatively favorable ecological conditions for ecotourism; however, they should not be interpreted as direct evidence of development feasibility, because regulatory restrictions, infrastructure availability, site-level ecological carrying capacity, and other implementation constraints require separate assessment. A further contribution of the study is the explicit comparison between the expert-driven and data-driven components rather than treating RF as an independent validation tool. The RF model achieved satisfactory test-set classification performance, while the map-level comparison revealed 39.83% exact spatial agreement, 90.57% agreement within one adjacent suitability class, and a quadratic weighted kappa of 0.715. The contrast between exact and ordinal agreement demonstrates that the two approaches reproduce the broader suitability ordering more consistently than exact pixel-level class boundaries. This distinction is important for spatial decision-making because it prevents high ordinal agreement from being interpreted as complete spatial equivalence between the two models. From a planning perspective, the framework provides a structured basis for prioritizing areas for subsequent field investigation and site-specific feasibility assessment. Completely suitable and suitable zones may be considered priority areas for further evaluation, whereas relatively suitable areas require closer examination of local constraints. Unsuitable and completely unsuitable zones warrant more restrictive and conservation-oriented management. In this sense, the resulting maps should be used as spatial screening and decision-support tools rather than as stand-alone development prescriptions. The principal methodological novelty of the study is therefore the integration of expert-based network weighting, fuzzy spatial standardization, machine-learning classification, and ordinal spatial agreement analysis within a unified ecotourism suitability framework. By distinguishing between model performance, spatial correspondence, and independent validation, the proposed workflow provides a more transparent basis for interpreting agreement between knowledge-driven and data-driven suitability models. Although further validation using independent field observations, visitor-use data, and site-level ecological information is required, the framework offers a transferable analytical structure that can be adapted to other ecologically sensitive regions where spatial planning must combine expert knowledge with limited empirical data.

Limitations and Future Research Directions

Despite the integrative and multi-method nature of the proposed framework, several limitations of the present study should be acknowledged, highlighting opportunities for future research in ecological capability assessment for sustainable tourism. First, the dynamic behavior of ecosystems poses inherent challenges to ecological suitability modeling. Climatic variability, seasonal environmental fluctuations, and ongoing land-use changes may alter ecological conditions over time and consequently affect the stability of suitability classifications. Because the present study provides a static spatial assessment, future research should incorporate temporal environmental information, long-term monitoring, and scenario-based modeling to evaluate the persistence and stability of suitability patterns under changing ecological and climatic conditions. Second, data quality, spatial resolution, and temporal currency constitute important limitations, and their potential influence is not uniform across all input layers. In the present analysis, the most consequential datasets are those associated with tourist-attraction proximity, river proximity, and climatic conditions because these variables received comparatively high importance in both the expert-driven and data-driven components of the framework. In the ANP model, tourist-attraction proximity (0.2294), temperature (0.2156), sunshine duration (0.1613), and river proximity (0.1505) received the largest global weights. Similarly, the RF analysis assigned its highest relative importance to tourist-attraction proximity (0.2546), river proximity (0.1759), and temperature (0.1101). Consequently, positional inaccuracies in attraction and river layers, coarse climatic surfaces, or temporal mismatches among these datasets may exert a comparatively greater influence on the final suitability pattern than equivalent uncertainty in lower-weighted predictors. Future studies should therefore prioritize higher-resolution and temporally updated climatic data, verified hydrographic and tourism-attraction databases, and more detailed land-use, biodiversity, and infrastructure information.

Third, the present framework primarily emphasizes ecological and environmental criteria, whereas sustainable ecotourism development is also influenced by socio-economic, cultural, institutional, and demand-side conditions. Future research should extend the framework by incorporating variables such as local community readiness, tourism demand, accessibility to services, infrastructure capacity, land ownership and regulatory constraints, and site-level ecological carrying capacity. Methodologically, RF should be benchmarked against alternative nonlinear learning algorithms, including XGBoost, LightGBM, and support vector machines, using identical training and testing datasets and consistent evaluation metrics. Ensemble approaches may also be investigated to determine whether combining multiple classifiers improves the stability and generalizability of suitability predictions. Model interpretation could further be strengthened through explainable machine-learning techniques, such as SHAP-based analysis, to examine both global and location-specific predictor effects. Future studies should also adopt multi-temporal spatial analysis rather than relying on a single static representation of environmental conditions. Time-series satellite imagery and multi-year climatic records could be used to quantify land-use/land-cover change, vegetation dynamics, hydrological variability, and climatic trends. Suitability maps generated for multiple time periods or under alternative climate and land-use scenarios would make it possible to identify areas characterized by persistent suitability, emerging development opportunities, or increasing ecological vulnerability. Such analyses would provide a more dynamic basis for adaptive ecotourism planning under environmental and climatic change. Fourth, the RF component should not be interpreted as fully independent validation of the ANP–fuzzy–GIS model. The RF reference classes were derived from expert-labeled spatial samples, and the two modeling approaches were informed by related environmental and tourism-related variables. Moreover, the study did not include a systematic independent field-validation dataset. These characteristics limit the strength of claims regarding external predictive validity and mean that the RF analysis is more appropriately interpreted as a complementary data-driven assessment of spatial consistency. Future research should therefore incorporate independently collected GPS-based field observations, visitor-use records, site-level ecological measurements, and spatially explicit validation samples. Where sufficient observations are available, spatially blocked or geographically separated cross-validation should also be considered to reduce the influence of spatial dependence on model-performance assessment. Addressing these limitations would enhance the reliability, transferability, and practical relevance of ecological suitability assessments and support more adaptive, evidence-based strategies for sustainable tourism planning in Khodabandeh County and other ecologically sensitive regions.

Acknowledgment

The authors declare that they received no financial support from any organization or institution for the conduct of this research.

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