

Algorithmic Approaches For Optimising Ecotourism Routes And Forest Resource Management In Rural Areas

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Ecotourism is a significant component of the global tourism industry, particularly in rural areas abundant in biodiversity and natural habitats... AHP prioritized criteria such as scenic value, safety, and environmental impact, while GWO identified the most sustainable routes. The River Path achieved the highest Composite Route Utility Score of 834.2, with 86% of respondents preferring low-impact, uncrowded routes (less than 10% crowding, under 15% degradation). Community involvement positively influenced over 70% of participants, with 86% agreeing it improves route sustainability. This framework helps policymakers design routes that maximize visitor satisfaction while promoting ecological conservation and sustainable tourism.

Keywords: Ecotourism, Route Optimization, Analytical Hierarchy Process, Grey Wolf Optimizer, Sustainable Resource Management.

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1. Introduction

Preserving nature and ensuring the well-being of local populations present significant challenges [1], [2]. which are simultaneously beneficial to nature. Route optimization models must balance two objectives [3]. Ecotourism routes the quick rise in the number of tourists, often directed towards areas with rich ecological resources, could result in reduced biodiversity in these areas [4]. Besides, if the tourism spending [5]. The infrastructure that is poorly built, uncontrollable, and improperly planned is one of the issues [6]. Perception-integrated AHPGWO framework balances sustainability, visitor experience, and route efficiency. To address these problems, it proposes a multi-criteria optimization model that combines AHP and GWO. AHP model eco-friendly tourism routes.

- This study leverages survey data to gain insights into the preferences, perceptions. Sample Size: A total of 350 participants, including 250 tourists and 100 local community members, was recruited

- The study investigates five key questions: how tourist preferences affect the effectiveness of ecotourism route optimization (RQ1); the impact of tourists' environmental awareness on their acceptance of routes with ecological protection constraints (RQ2); how perceived crowding influences tourist satisfaction with optimized routes (RQ3); the role of local community perceptions in supporting sustainable forest resource management (RQ4); and how stakeholder trust in datadriven planning affects acceptance of recommended ecotourism routes (RQ5).
- H1: Tourist preferences regarding route safety, distance, and scenic value significantly influence the effectiveness of ecotourism route optimization.
- H2: Tourists with higher environmental awareness show greater acceptance of ecotourism routes with ecological protection constraints.
- H3: Higher levels of perceived crowding are associ-

ated with lower tourist satisfaction with optimized ecotourism routes.

- H4: Positive perceptions of local community involvement significantly enhance support for sustainable forest resource management in ecotourism planning.
- H5: Higher levels of trust in data-driven ecotourism planning are associated with greater acceptance of recommended ecotourism routes.

The paper has five sections: Section 2 reviews literature and gaps, Section 3 details methodology, Section 4 shows results, Section 5 concludes.

2. Materials and methods

These studies collectively highlight the role of evolutionary algorithms route optimization. Several studies have examined to spatial suitability assessments and decision-support systems. Kolkos et al. [7] proposed Machine learning and data-driven methods have become increasingly popular among researchers. K. Sun et al., [8] developed a Rural Ecotourism Suitability Random Forest model, Yuan et al. [9], Wang [10] used deep learning for experience enhancement tourist

3. Research gap

A significant methodological gap exists in translating human-centered views into algorithmic systems for sustainable forest-based ecotourism. Current optimization models often exclude stakeholder input, limiting adaptability to varying tourist preferences with the GWO to provide a unified framework for ecotourism route optimization [11]. Environmental protection is treated as a rigid constraint, neglecting a balance with tourist satisfaction and accessibility. Therefore, a comprehensive framework integrating perception-based data, multi-criteria decision-making, and metaheuristic optimization is needed. Existing studies separate MCDA and optimization; this integrates AHP and GWO for unified ecotourism route optimization. AHP is a well-established multi-criteria decision-making method.

4. Methodology for ecotourism route optimization and forest resource management

It based on a combination of Multi-Criteria Decision Analysis (MCDA) and metaheuristic optimization to identify optimal ecotourism routes that balance ecological protection with visitor experience. EIA indicators assess ecological impacts; normalized inputs support AHP weighting and GWO fitness evaluation. Ecological protection uses

AHP-weighted soft constraints and strict hard limits to eliminate invalid routes are shown in Fig. 1. Survey: Collect tourist preferences, awareness, crowding, community involvement, and trust.

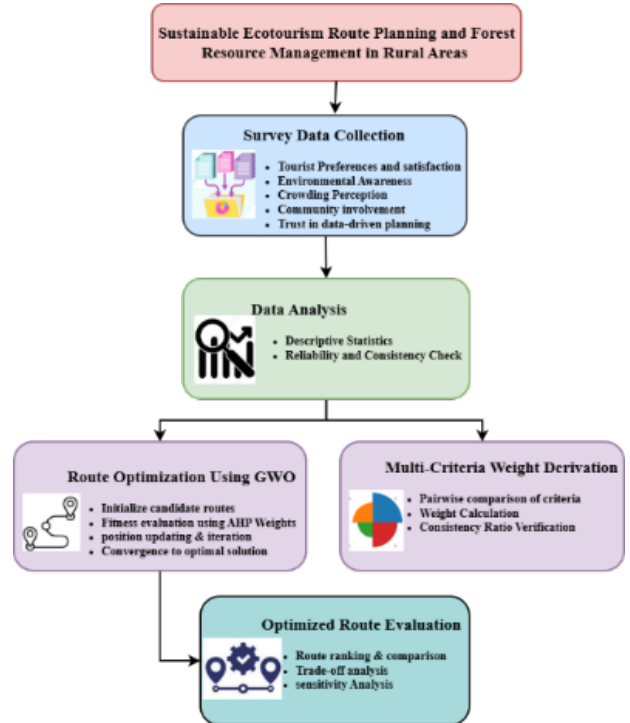


Fig. 1. Workflow of Ecotourism Route Optimization Framework

- Analysis: Apply descriptive statistics and reliability checks.
- AHP: Derive criteria weights and check consistency.
- GWO: Optimize routes using AHP-weighted fitness.
- Evaluation: Rank routes and perform trade-off and sensitivity analysis.

4.1. The Study Purpose, Hypotheses and Conceptual Model

The evaluation takes place through the framework, which incorporates data-driven planning.

4.2. Hypotheses Development & Conceptual Model

H1: Tourists are more likely to have satisfying experiences if the routes are set, distance, and beauty of nature.

H2: Environmentally aware tourists' routes with protection constraints.

H3: Higher levels of perceived crowding are associated with lower tourist satisfaction with optimize ecotourism

routes.

H4: Tourists who perceive positive community involvement are more likely to support conservation efforts.

H5: Greater trust in data-driven planning increases acceptance of ecotourism routes. The conceptual framework, based on the stated hypotheses, is that the independent variables, and trust in data-driven planning.

5. Methods

5.1. Research Approach

This study employs a quantitative approach to examine variables. It prioritizes tourist preferences, his/her recognition of the environmental safeguards.

Table 1 summarizes dataset characteristics, participants, demographics, variables, data types, and survey method. The survey assessed preferences, perceptions, environmental awareness, and trust in data-driven planning. Data collection focused on tourists and local community members. (<https://forms.gle/cBt8BfLo8gM7wKZw5>) Experiments ran on an i7 system with 16GB RAM, Windows 11. Data analyzed using Python with NumPy, Pandas, and Matplotlib. AHP-GWO implemented via scripts; survey data from Google Forms CSV.

6. Data collection and recruitment

6.1. Data Collection Method

Structured survey questionnaires distributed to participants through in-person and online channels. Survey collected ecotourism responses using a five-point Likert scale. Expert review ensured validity of questionnaire items. Reliability confirmed through Cronbach's alpha for internal consistency.

6.2. Survey Components

The survey used in this study comprises six main components to capture comprehensive insights from tourists and local communities:

1. Demographics
2. Tourist Preferences
3. Environmental Awareness
4. Perceived Crowding & Satisfaction
5. Local Community & Forest Resource Management
6. Trust in Data-Driven Planning

6.3. Study Variables

This study examines tourist satisfaction, ecological compliance, and control variables included.

Fig. 2 shows how community participation, tourist factors.

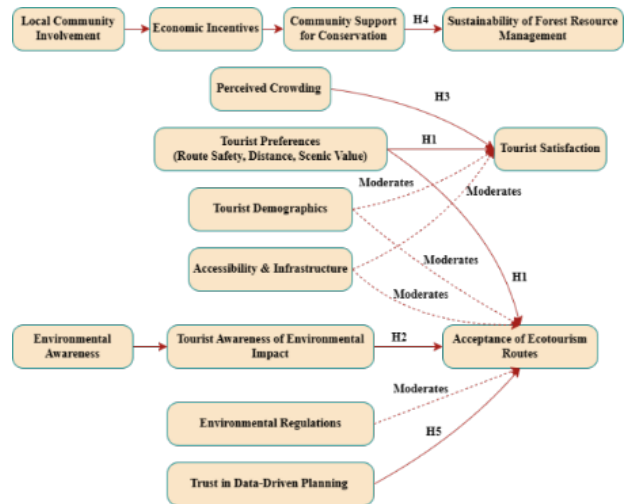


Fig. 2. Conceptual Framework for Ecotourism Route Optimization Study

6.4. Descriptive Data Analysis

Descriptive analysis summarizes and interprets the survey data and interpretation of the data.

6.5. Analytical Hierarchy Process (AHP)

AHP is a well-established multi-criteria decision-making method. AHP decomposes complex problems into a hierarchical structure with the overall goal at the top. The second step involves the pairwise comparison AHP then uses these comparisons to compute the weights of each criterion and sub-criterion, thereby attributing their influence on the final decision.

Fig. 3 shows AHP hierarchy: optimization multi-tier layer integrates ecological, experiential, and governance metrics. Ecological includes biodiversity, erosion, carbon, and resource conservation.

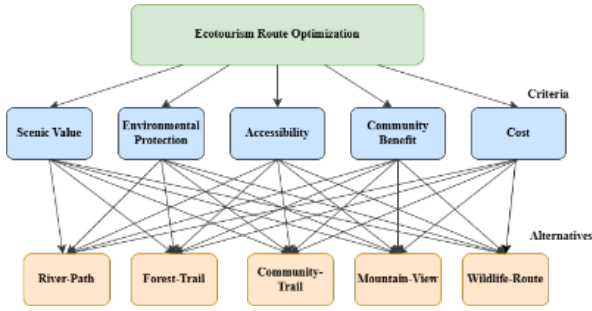
Experiential and governance capture perceptions, community benefits, and resource management.

6.6. Define Problem and Decision Goal

AHP uses the Saaty 1-9 scale for pairwise comparisons, derives weights using the principal eigenvector, evaluates consistency through λ max, CI, and RI, and ensures reliability with a CR below 0.1. Sensitivity analysis perturbed pairwise inputs; stable weights and unchanged rankings confirmed robustness of the AHP weighting process.

Table 1. Dataset Characteristics

Characteristic	Details
Total Participants	350
Tourists	250
Local Community Members	100
Age Range	18–65 years
Gender Distribution	Male/Female: ~ 50% each
Education Level	High school, undergraduate, postgraduate
Variables Collected	Demographics, tourist preferences, environmental awareness, perceived crowding, community involvement, trust in data-driven planning
Data Type	Categorical, numerical
Survey Method	Structured questionnaire (online and in-person)

**Fig. 3.** AHP Diagram for Ecotourism Route Optimization

6.7. Construct Pairwise Comparison Matrix

The decision-makers assign a numerical value to each comparison from a scale of 1 to 9, as shown in Eq. (1)

$$w_{ij} = \frac{a_{ij}}{\sum_{i=1}^n a_{ij}} \quad (1)$$

where W_{ij} is the normalized value, and the sum is over rows i for a fixed column j .

6.8. Calculate Weights from Pairwise Matrix

Logical consistency of the pairwise comparison matrix is verified through a reliability and consistency check by calculating the Consistency Ratio (CR). The consistency ratio compares the Consistency Index (CI) of the pairwise comparison matrix with the Random Index (RI), as shown in Eq. (2).

$$CR = \frac{CI}{RI} \quad (2)$$

Where CI represents the consistency index and RI denotes the random index corresponding to the matrix size.

6.9. Consistency Check

The Consistency Index (CI) is calculated using the maximum eigenvalue of the pairwise comparison matrix, as shown in Eq. (3).

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (3)$$

The value of λ_{\max} is obtained by multiplying the pairwise comparison matrix. The average of these values gives the final value of λ_{\max} . A pairwise comparison matrix is considered consistent when the value of CR is less than 0.1 ($CR < 0.1$). If the value exceeds this threshold, the pairwise comparisons should be revised to improve consistency.

The Table 2 represents the average consistency index obtained from randomly generated pairwise comparison matrices and varies depending on the matrix size.

6.10. Synthesize Results and Rank Alternatives

The outcomes lead to a clear ranking that facilitates decision-making, as shown in Eq. (4),

$$w_i = \frac{1}{n} \sum_{j=1}^n a_{ij} \quad (4)$$

Where, w_i is the weight of criterion i , and a_{ij} is the value from the pairwise comparison matrix.

6.11. GWO For Route Optimization and Resource Management

GWO simulates how wolf packs hunt by having alpha, beta, and delta wolves guide the pack toward prey. GWO used 30 agents, 100 iterations, adaptive parameter decreasing, convergence criterion, and solution dimensions based on ecotourism sites.

Table 3 compares the performance of GWO and Genetic GA in handling the multimodal search landscape, complexity, exploration-exploitation balance, and convergence efficiency in the ecotourism route optimization problem.

6.12. Initialization of Grey Wolves (Population Initialization)

GWO initializes set according to problem limits, as shown in Eq. (5).

Table 2. Random Index (RI) Values

Matrix Size (n)	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Table 3. Comparison of GWO and GA for Ecotourism Route Optimization

Aspect	GWO	GA
Search Landscape	Efficient at navigating multimodal landscapes and complex search spaces [web:59].	May struggle with premature convergence to local optima in difficult search spaces [web:63].
Combinatorial Complexity	Handles complexity well due to its hierarchical structure and cooperative search behavior [web:59].	Complexity increases with population size, selection, crossover, and mutation operators [web:63].
Exploration–Exploitation	Provides a strong balance between exploration and exploitation in many applications [web:59].	Exploration can become insufficient, which may lead to local optima in complex problems [web:63].
Convergence	Can converge relatively quickly, although standard GWO may stagnate or slow in later stages [web:59].	Often converges more slowly on complex multimodal landscapes [web:63].

$$X_i = (x_{i1}, x_{i2}, \dots, x_{id}) \tag{5}$$

Where, X_i is the position of wolf i , and x_{id} is the position of the wolf in the d -th dimension. Each GWO agent encodes a route as ordered site indices, ensuring feasible, connected paths through adjacency constraints, as shown in Eq. (6).

Maximize $F(\mathbf{r}) = w_1 \cdot \text{Scenic}(\mathbf{r}) + w_2 \cdot \text{Safety}(\mathbf{r}) + w_3 \cdot \text{Access}(\mathbf{r}) - w_4 \cdot \text{Envlmpact}$

$$(\mathbf{r}) - w_5 \cdot \text{Cost}(\mathbf{r}) \tag{6}$$

where $\text{Scenic}(\mathbf{r})$, $\text{Safety}(\mathbf{r})$, and $\text{Access}(\mathbf{r})$ represent the positive attributes of the route, while $\text{Envlmpact}(\mathbf{r})$ and $\text{Cost}(\mathbf{r})$ denote the environmental impact and travel cost, respectively. The weights w_1, w_2, w_3, w_4 , and w_5 are derived using the AHP method.

6.13. Fitness Evaluation

Route fitness uses a compound function integrating scenic, environmental, crowd, and community factors. The fitness value F is defined as shown in Eq. (7)

$$F = w_1S - w_2E - w_3C + w_4B \tag{7}$$

S, E, C , and B denote scenic, environmental, crowding, and community factors, weighted by AHP-derived $w_1 - w_4$ for balanced route optimization. The weights derived from the AHP analysis are incorporated into the fitness function of the Grey Wolf Optimizer to guide the optimization process. Each evaluation criterion is multiplied

by its corresponding AHP weight during fitness computation, ensuring that criteria with higher importance have a greater influence on the objective value.

These weighted scores are used to evaluate candidate routes at each iteration, and the resulting fitness values guide the position update of search agents. This approach ensures consistency between decision-making priorities and the optimization process. Composite utility uses AHP-weighted scalarization; GWO optimizes balanced trade-offs between experience and conservation. Seasonal tourist data are used to recalibrate the crowding coefficient within the optimization framework. Normalized visitor density values collected across different seasons are incorporated into the fitness evaluation process. Based on these values, the Grey Wolf Optimizer dynamically adjusts route selection according to changes in visitor distribution. This mechanism enables adaptive route planning under seasonal tourism fluctuations.

The normalized weights derived from the AHP analysis were integrated into the Grey Wolf Optimizer during the fitness evaluation stage. These weights were applied to scale factors such as scenic value, environmental impact, crowding, and community benefit when calculating the fitness score of each candidate route.

This weighted evaluation guided the iterative position updates of wolves, allowing the algorithm to identify routes that balance environmental sustainability and visitor perception. Stakeholder surveys provided community participation indicators which researchers converted into a standardized numerical format through min-max normal-

ization. This process scaled every socio-economic variable that benefited the community to a standard range of $[0, 1]$, which matched other optimization criteria.

The fitness evaluation used normalized values to calculate the community benefit parameter B , which provided a consistent method for measuring socio-economic effects during route optimization. The community participation indicators were standardized using the min-max normalization method as shown in Eq. (8):

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (8)$$

where X represents the original value of the indicator, while X_{min} and X_{max} denote the minimum and maximum values in the dataset. This transformation scales the socio-economic variables between 0 and 1, ensuring consistent integration into the optimization model.

6.14. Exploration Phase & Exploration phase

In the Grey Wolf Optimization (GWO) algorithm, the position of a search agent is updated based on the distance between the current wolf. The distance vector is calculated as shown in Eq. (9):

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_p(t) - \vec{X}(t) \right| \quad (9)$$

The position of the wolf in the next iteration is then updated as shown in Eq. (10):

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \quad (10)$$

where $\vec{X}_p(t)$ represents the position vector of the prey (best solution), and $\vec{X}(t)$ denotes the current position vector of the grey wolf. The coefficient vectors \vec{A} and \vec{C} as shown in Eq. (11):

$$\begin{aligned} \vec{A} &= 2\vec{a} \cdot \vec{r}_1 - \vec{a} \\ \vec{C} &= 2\vec{r}_2 \end{aligned} \quad (11)$$

where \vec{r}_1 and \vec{r}_2 are random vectors in the range $[0, 1]$, and \vec{a} decreases linearly from 2 to 0 during the optimization process to balance exploration and exploitation. The balance between exploration and exploitation in the Grey Wolf Optimizer is controlled by an adaptive coefficient a , which decreases linearly during the optimization process as shown in Eq. (12).

$$a = 2 - \frac{2t}{T} \quad (12)$$

where t represents the current iteration and T denotes the maximum number of iterations, while its gradual reduction enhances local exploitation around the best candidate

solutions, thereby improving convergence behavior within the routing optimization domain as shown in Eq. (13).

$$X_i = X_{alpha} - A \cdot D_{alpha} \quad (13)$$

Here, X_t represents the current wolf's position at iteration t , X_a is the alpha wolf's position and $D_a = X_a - X_t$ is the between the current wolf and the alpha wolf as shown in Eq. (14).

$$\text{Convergence if } |f(X_{best}(t+1)) - f(X_{best}(t))| < \epsilon \quad (14)$$

where $f(X)$ represents the fitness value of the best solution at iteration t . This section presents the core findings.

7. Results and discussion

The highest-ranked routes, such as River Path, have minimal environmental impact and low crowding. These findings indicate an increasing trend. The following figures and tables present the outcomes and facilitate interpretation of optimal routes Demographic analysis includes age, gender, education, and occupation of respondents as shown in Fig. 4.

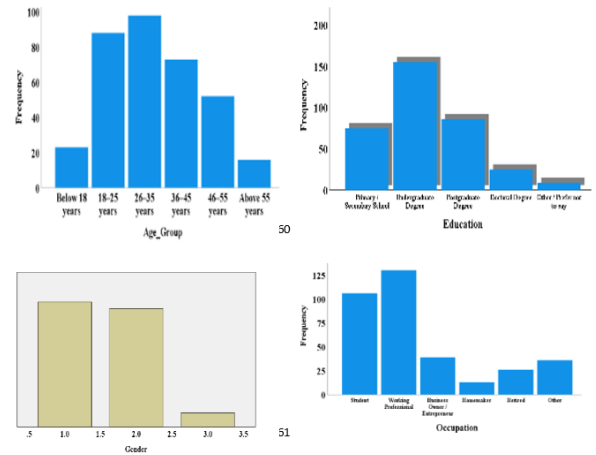


Fig. 4. Demographic Analysis of Survey Respondents

The frequency with which respondents use eco-tourism routes is shown in Table 4. A total of 313.4% of the respondents fall into the 'Never' category. Usage varies: Very Frequently (24.6%) highest, followed by Occasionally (22.3%), Rarely (20%), Frequently (19.7%), and Never 5 (13.4%), totaling 100%.

7.1. Ecotourism Route Optimization and Evaluation

Table 5 ranks routes: River-Path first, followed by Forest-Trail and Community-Trail; Mountain-View and Wildlife-

Table 4. Frequency Distribution of Ecotourism Route Usage

Frequency	Frequency (Count)	Percent (%)	Valid Percent (%)	Cumulative Percent (%)
Never	47	13.4	13.4	13.4
Rarely (once in a few years)	70	20.0	20.0	33.4
Occasionally (once or twice a year)	78	22.3	22.3	55.7
Frequently (multiple times a year)	69	19.7	19.7	75.4
Very Frequently (monthly or more)	86	24.6	24.6	100.0

Table 5. Optimized Route Selection Ranking

Rank	Route Name	Composite Route Utility Score	Length (km)	Duration (hours)	Difficulty	Safety Score	Scenic Score	Environmental Impact	Crowding Level	Community Access
1	RiverPath (Route A)	834.2	4.8	2.0	Easy	77.3	74.2	Very Low	Low	Medium
2	ForestTrail (Route B)	752.8	5.2	2.5	Moderate	86.9	83.5	Low	Medium	High
3	Community-Trail (Route C)	742.2	3.9	1.5	Easy	86.9	65.0	Low	Low	Very High
4	Mountain-View (Route D)	656.6	6.1	3.5	Challenging	67.6	92.8	Medium	High	Low
5	WildlifeRoute (Route E)	601.5	5.7	3.0	Moderate	77.3	83.5	High	Medium	Medium

Route rank lower due to difficulty and impact. The Composite Route Utility Score (CRUS) ranks optimized routes using a weighted sum of multiple evaluation criteria. Each criterion’s weight comes from AHP analysis, and route scores are normalized.

Table 6 weighted scores use normalized weighted aggregation, not direct summation of raw scores. Forest-Trail ranks third with good performance in safety, scenic value, and natural attractions. Community-Trail is characterized by safety and comfort. Each criterion (e.g., safety, distance, accessibility) is first normalized to ensure scale consistency. The final Weighted Score is computed as a weighted sum of normalized criterion scores, where each weight is derived from AHP, linking individual criterion values to the aggregated score.

Fig. 5 route A is the optimal one Regression analysis shows environmental awareness increases route acceptance. Higher perceived crowding slightly reduces acceptance. The statistical significance was confirmed with p-values ($p < 0.05$) and the model showed moderate explanatory power (R^2). H3 shows the strongest positive correlation (0.635), H3 has the highest correlation at 0.635 (** $p < 0.01$), H2 at 0.322 (* $p < 0.05$), H1 at 0.095, H5 (-0.003) and H4 (-0.003) with no significant association. H1 (Safety Distance) shows a very low positive correlation (0.095). A correlation threshold of 0.3 is used as a reference to indicate a moderate level of association between variables.

Table 7 shows crowding negatively and awareness posi-

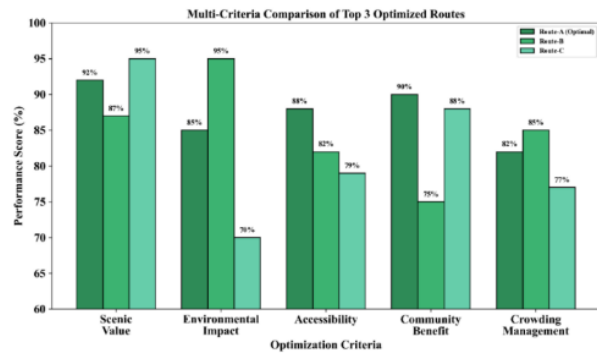


Fig. 5. Multi-Criteria Comparison of Top 3 Optimized Routes

tively affect route acceptance. Model explains 52% variance with significant predictors ($p < 0.05$).

7.2. Route Performance Summary and Tourist Preference Evaluation

GWO compared with PSO, GA, and ACO using utility score, convergence time, and environmental impact metrics.

Table 8 shows GWO outperforming PSO, GA, and ACO in utility, convergence, and environmental impact. GWO improves utility by 2.96% over PSO, 4.86% over GA, and 4.18% over ACO, demonstrating superior optimization performance compared to baseline algorithms.

Hypothesis Testing, Environmental Impact and Sensitivity Analysis

Table 6. Route Comparison Matrix Based on Multiple Criteria

Route	Weighted Score	Safety	Distance	Scenic	Natural	Comfort	Env.-Impact	Crowding	Community	Length	Difficulty
Community Trail	67.3	90	61	70	70	90	80	100	100	3.9 km	Easy
RiverPath	65.9	80	52	80	80	90	100	100	65	4.8 km	Easy
ForestTrail	64.3	90	48	90	90	80	80	70	85	5.2 km	Moderate
Wildlife Route	54.6	80	43	90	90	60	40	70	65	5.7 km	Moderate
MountainView	52.5	70	39	100	100	70	60	40	40	6.1 km	Challenging

Table 7. Regression Analysis for Route Acceptance

Variable	Regression Coefficient (β)	pvalue	Interpretation
Perceived Crowding	-0.34	0.021	Negative effect on route acceptance
Environmental Awareness	0.41	0.008	Positive effect on route acceptance
Model R ²	0.52	-	Moderate explanatory power

Table 8. Comparative Performance of GWO and Baseline Optimization Methods

Method	Key Limitation(s)	Composite Route Utility Score	Convergence Time (s)	Environmental Impact (Lower is better)
PSO	Prone to local optima	810.2	48	Medium
GA	Sensitive to parameter tuning	795.5	60	Medium-High
ACO	Slower convergence	800.7	55	Medium
GWO	Balances exploration and exploitation efficiently	834.2	40	Very Low

Table 9. Statistical Significance of Hypothesis Testing Results

Hypothesis	Coefficient (β)	p-value	95% Confidence Interval	Significance
H1	0.095	0.182	[-0.04, 0.23]	Not Significant
H2	0.322	0.008	[0.09, 0.55]	Significant
H3	-0.635	0.001	[-0.78, -0.41]	Highly Significant
H4	-0.003	0.964	[-0.15, 0.14]	Not Significant
H5	-0.003	0.971	[-0.16, 0.15]	Not Significant

Table 9 Hypothesis testing shows crowding and awareness significant ($p < 0.01$), others insignificant ($p > 0.05$) at $\alpha = 0.05$. Route-A always performs better than the Current Route.

In Table 10 Optimized routes outperform baseline with lower impact, less crowding, higher satisfaction, and better efficiency.

Fig. 6 shows sensitivity analysis of scenic value weights on route fitness scores. Route B shows the most stable performance. At the optimal Scenic Value weight of 0.35, Route A achieves its maximum fitness score.

Fig. 7 shows AHP-ranked ecotourism route optimization. The criterion of Scenic Value comes first, receiving 32% of the weight.

8. Practical implications

The findings have practical implications for ecotourism route planning and management and management of ecotourism routes. The stakeholders can develop eco-tourism

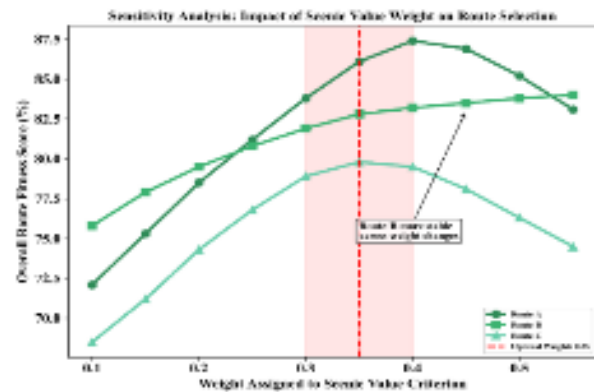


Fig. 6. Sensitivity Analysis. Impact of Scenic Value Weight on Route Selection

that [12]. The obtained insights, and further advance ecotourism as a sustainable development strategy as a phenomenon that simultaneously achieves environmental con-

Table 10. Comparison of Optimized Routes with Existing (Baseline) Route

Route Type	Avg. Satisfaction Score	Environmental Impact	Crowding Level	Route Efficiency
Current Route	62.4	High	High	Moderate
River-Path	80.9	Very Low	Low	High
Forest-Trail	79.1	Low	Medium	High
Community Trail	82.6	Low	Low	High

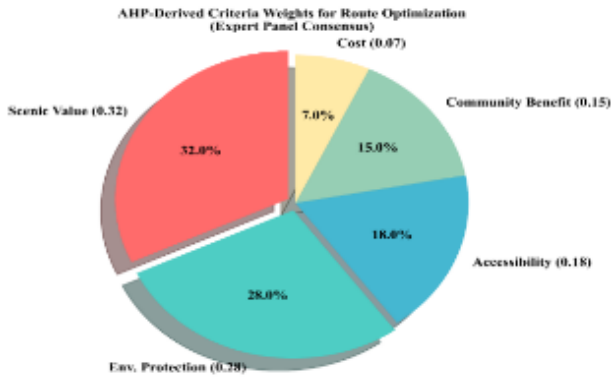


Fig. 7. AHP-Derived Criteria Weights for Route Optimization (Expert Panel Consensus)

ervation and economic development.

9. Environmental impact and sustainability

In Environmental Impact and Sustainability, this finding aligns with recent studies emphasizing that ecotourism routes must be environmentally sustainable to prevent habitat degradation [13].

10. Tourist preferences and route suitability

This finding is consistent with previous research [14]. By aligning route features with tourist demand. These insights are crucial for developing ecotourism routes.

11. Conclusion

This study assessed ecotourism route optimization and resource management based on key factors including scenic value, environmental impact, community access, and safety. River Path ranked first with a Composite Route Utility Score of 834.2. Mountain View and Wildlife Route received lower scores of 656.6 and 601.5, respectively. Forest Trail excelled in safety and scenic value. Furthermore, the study showed that perceived crowding (correlation = 0.635) and environmental awareness (correlation = 0.322) significantly influence route preferences. EIA results demonstrated that optimized routing strategies reduce impacts on bio- diversity, soil erosion, and water resources compared

to current routes. Framework links perception-based evaluation, MCDA, and optimization for sustainable route planning, addressing sensitivity and geographic limits, with future work exploring real-time environmental monitoring solutions. Future research should investigate adaptive management strategies that incorporate realtime environmental monitoring to respond to changing conditions along ecotourism routes by incorporating additional variability into optimization processes. Additionally, incorporating regional variation in visitor preferences can inform context-specific route management strategies

12. Acknowledgements

Not applicable

13. Declarations

14. Funding

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15. Conflict of interest

The authors declare that they have no conflicts of interest regarding this work.

16. Data availability

The survey and route optimization datasets generated and analyzed during this study are available from the corresponding author upon reasonable request.

17. Code availability

Not applicable.

18. Author contributions

Li Yan: Conceptualization, Methodology, Formal analysis, Writing—original draft preparation, Supervision.

Wenqing Wu: Data curation, Investigation, Visualization, Writing-review & editing.

Ke Wang: Software, Validation, Resources, Project administration.

References

- [1] M. Heshmati, M. Gheitury, and S. Shadfar, (2022) "Factors affecting possibility of ecotourism development and sustaining natural resources using SWOT approach in west Iran" **International Journal of Geoheritage and Parks** 10(2): 173–183. DOI: [10.1016/j.ijgeop.2022.03.004](https://doi.org/10.1016/j.ijgeop.2022.03.004).
- [2] M. Godovykh, A. Fyall, and A. Pizam, (2025) "Exploring the Impacts of Tourism on the Well-Being of Local Communities" **Sustainability** 17(13): 5849. DOI: [10.3390/su17135849](https://doi.org/10.3390/su17135849).
- [3] K. Kotis et al., (2022) "Towards Optimal Planning for Green, Smart, and Semantically Enriched Cultural Tours" **Smart Cities** 6(1): 123–136. DOI: [10.3390/smartcities6010007](https://doi.org/10.3390/smartcities6010007).
- [4] S. Seifollahi-Aghmiuni, Z. Kalantari, G. Egidi, L. Gaburova, and L. Salvati, (2022) "Urbanisation-driven land degradation and socioeconomic challenges in peri-urban areas: Insights from Southern Europe" **Ambio** 51(6): 1446–1458. DOI: [10.1007/s13280-022-01701-7](https://doi.org/10.1007/s13280-022-01701-7).
- [5] F. Nocca, M. Bosone, P. De Toro, and L. Fusco Girard, (2023) "Towards the Human Circular Tourism: Recommendations, Actions, and Multidimensional Indicators for the Tourist Category" **Sustainability** 15(3): 1845. DOI: [10.3390/su15031845](https://doi.org/10.3390/su15031845).
- [6] O. Mazele and C. Amoah, (2022) "The causes of poor infrastructure management and maintenance in South African municipalities" **Property Management** 40(2): 192–206. DOI: [10.1108/PM-06-2021-0042](https://doi.org/10.1108/PM-06-2021-0042).
- [7] G. Kolkos, (2025) "Geospatial Decision Support for Forest Trail Constructions Allocation Using GIS-Network Analysis and Hybrid MADM Methods (AHP–PROMETHEE II)" **Geographies** 5(4): 72. DOI: [10.3390/geographies5040072](https://doi.org/10.3390/geographies5040072).
- [8] K. Sun, Z. Xing, X. Cao, and W. Li, (2021) "The Regime of Rural Ecotourism Stakeholders in Poverty-Stricken Areas of China: Implications for Rural Revitalization" **International Journal of Environmental Research and Public Health** 18(18): 9690. DOI: [10.3390/ijerph18189690](https://doi.org/10.3390/ijerph18189690).
- [9] J. Yuan, H. Gao, Y. Shen, and G. Ma, (2024) "Spatial Differentiation of Ecotourist Perceptions Based on the Random Forest Model: The Case of the Gansu Section of the Yellow River Basin" **Land** 13(4): 560. DOI: [10.3390/land13040560](https://doi.org/10.3390/land13040560).
- [10] X. Wang, (2024) "The analysis of rural tourism image optimization under the internet of things and deep learning" **Scientific Reports** 14(1): 29898. DOI: [10.1038/s41598-024-81868-z](https://doi.org/10.1038/s41598-024-81868-z).
- [11] S. Ferdowsi, (2025) "Site selection of ecotourism eco-camps for sustainable development of rural areas" **Journal of Ecotourism** 24(2): 95–113. DOI: [10.1080/14724049.2024.2366928](https://doi.org/10.1080/14724049.2024.2366928).
- [12] R. Pitakaso, T. Srichok, S. Khonjun, S. Gonwirat, N. Nanthasamroeng, and C. Boonmee, (2024) "Multi-objective sustainability tourist trip design: An innovative approach for balancing tourists' preferences with key sustainability considerations" **Journal of Cleaner Production** 449: 141486. DOI: [10.1016/j.jclepro.2024.141486](https://doi.org/10.1016/j.jclepro.2024.141486).
- [13] R. Samal and M. Dash, (2023) "Ecotourism, biodiversity conservation and livelihoods: Understanding the convergence and divergence" **International Journal of Geoheritage and Parks** 11(1): 1–20. DOI: [10.1016/j.ijgeop.2022.11.001](https://doi.org/10.1016/j.ijgeop.2022.11.001).
- [14] J. Li, J. A. Coca-Stefaniak, T. H. H. Nguyen, and A. M. Morrison, (2024) "Sustainable tourist behavior: A systematic literature review and research agenda" **Sustainable Development** 32(4): 3356–3374. DOI: [10.1002/sd.2859](https://doi.org/10.1002/sd.2859).