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DEVELOPING AN URBAN TOURISM ATTRACTIVENESS INDEX: AN AHP–GIS FRAMEWORK FOR SPATIAL DECISION-MAKING

Abstract: Tourism plays a central role in shaping urban dynamics, particularly in cities with rich yet underutilized cultural and environmental assets. In many developing regions, including Algeria, its integration into urban planning remains limited due to fragmented governance and the absence of spatial decision-support tools. This study develops an Urban Tourism Attractiveness Index for Sétif, Algeria, using a hybrid approach that combines the Analytic Hierarchy Process (AHP) with Geographic Information Systems (GIS). A set of spatial indicators, covering tourism-related infrastructure, services, and natural and cultural resources, was identified through literature review and expert consultation. Weights were assigned using AHP, and spatial analysis in a GIS environment produced a tourism attractiveness map. Model performance was evaluated using the Area Under the ROC Curve (AUC), yielding a score of 0.84, indicating strong predictive accuracy. Results show that the highest attractiveness levels are concentrated in the historic core, while peripheral areas display moderate to low values. The findings highlight the value of integrating participatory multi-criteria analysis with geospatial tools to inform tourism planning. The study also proposes a mobile application concept to transform spatial data into accessible, user-friendly tools for both tourists and decision-makers. This framework is replicable and adaptable for

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cities in the Global South seeking to promote sustainable, evidence-based tourism development.

Keywords: tourism potential, decision support, sustainable urban planning, Urban tourism modelling, Multi-criteria decision analysis

Introduction

Tourism is widely recognised as a major spatial and socio-economic driver, capable of reshaping urban systems through its influence on infrastructure development, the valorisation of cultural heritage, and the management of local resources (Bertacchini, Liuzza, Meskell, & Saccone, 2016). Positioned at the intersection of temporary mobility and territorial embeddedness, tourism presents complex challenges for urban planners, including balancing heritage preservation with contemporary urban development, ensuring equitable access to attractions, and fostering community participation in tourism-related decision-making.

Recent scholarship highlights the urgent need for robust, data-driven, and spatially explicit planning tools capable of reconciling these objectives, particularly in contexts where tourism potential remains underexploited due to institutional fragmentation and technical limitations (Mariani & Baggio, 2022; Ramkissoon, 2022; Seyfi, Kim, Nazifi, Murdy, & Vo-Thanh, 2025; Skare, Gavurova, & Polishchuk, 2025). Spatial decision-support systems using GIS, especially those integrating methods like AHP, have emerged as effective frameworks for mapping tourism suitability, as illustrated by studies in Iran and India (Chouhan, Bhuyan, Anilkumar, & Aggarwal, 2023; M. Dadashpour Moghaddam, H. Ahmadzadeh, & R. J. S. I. R. Valizadeh, 2022).

These challenges are particularly pronounced in the Global South, where tourism planning often suffers from sectoral silos and insufficient consideration of spatial interdependencies among heritage assets, environmental systems, and socio-economic conditions (Rogerson & Rogerson, 2021). Specific issues include limited institutional coordination among tourism and planning agencies, inadequate spatial data infrastructure, poor integration of cultural heritage into urban development plans, and a lack of participatory mechanisms for including local stakeholders in tourism-related decisions. The role of GIS in fostering inclusive, environmentally responsible tourism strategies is increasingly recognized (Xing, 2024).

These dynamics are especially relevant in Algeria, which provides a pertinent case. Despite its extensive portfolio of natural and cultural resources, including UNESCO World Heritage Sites such as Djemila, diverse ecosystems, and a layered historical legacy, tourism remains marginal in national and urban planning agendas. The city of Sétif exemplifies this paradox: enriched with Roman ruins, high plateau landscapes, and traditional crafts, yet constrained by institutional fragmentation, outdated infrastructure, and limited regional connectivity. To date, no spatially explicit framework has systematically assessed tourism attractiveness in medium-sized Algerian cities such as Sétif, a gap this study seeks to address.

The objective of this study is to develop an Urban Tourism Attractiveness Index for Sétif by integrating the Analytic Hierarchy Process (AHP) with Geographic Information Systems (GIS) to systematically identify, classify, and map areas with the greatest potential to attract visitors. Eight thematic indicators, covering natural and cultural heritage, Tourism facilities, mobility and transport, social networks, ICT services, service quality, security, and environmental conditions, were selected through literature review and expert consultation. Weights were assigned using AHP with input from local experts; AHP is especially well-suited for complex, multi-criteria decision-making, as demonstrated in studies evaluating cultural heritage and touristic sites (Jewpanya, Nuangpirom, Nakkiew, Pitjamit, & Jaichomphu, 2025; Vukoičić et al., 2022). Spatial analysis then produced a comprehensive tourism attractiveness map for the city.

By advancing an integrated AHP-GIS framework, this study contributes both methodologically and contextually to the field of urban tourism planning. Methodologically, it offers a transparent, multi-criteria approach for weighting and spatializing diverse tourism-related indicators, supported by local expert knowledge. Contextually, it addresses a critical gap in the literature by applying this framework to a medium-sized city in the Global South, where tourism remains underrepresented in planning agendas. Beyond generating a spatially map of tourism attractiveness for the city of Sétif, the proposed Urban Tourism Attractiveness Index provides a decision-support tool that can help urban planners identify priority areas, allocate resources more effectively, and design targeted tourism strategies. In doing so, it not only facilitates the sustainable development of the tourism sector but also strengthens the integration of tourism into broader urban planning frameworks aimed at enhancing resilience, inclusivity, and local economic vitality.

The main achievement of this study lies in the development of a replicable Urban Tourism Attractiveness Index that merges expert-derived AHP weighting with GIS spatial analysis. This tool not only provides a strategic decision-making framework for Sétif but also offers a transferable methodology for other medium-sized cities facing similar planning challenges. Furthermore, the use of social media data for model validation introduces an innovative, scalable approach that can be adapted to different urban contexts with limited formal tourism data.

Methods and materials

Case Study

Sétif, Algeria (36.19°N, 5.41°E) (Figure 1), serves as the case study for this research. Located in the Wilaya of Sétif in north-eastern Algeria, the city spans 127 km² and has an estimated population of approximately 300,000 inhabitants (ONS, 2020). Situated in the High Plains region at the intersection of national east–west and north–south transport corridors, Sétif functions as both an administrative capital and a strategic economic and logistical hub within the country.

The Wilaya of Sétif recorded over 280,900 tourist arrivals in 2024, including 68,011 international visitors, reflecting the region's growing appeal as a tourism destination (Zoghbi, 2024). The accommodation network includes 95 classified hotels offering 6,969 beds, with an additional 602 beds added in 2024 through new hotel investments. While official data is reported only at the wilaya level, the city of Sétif, as the provincial capital and urban core, likely absorbs a substantial share of these arrivals due to its concentration of cultural sites, infrastructure, and services.

The city's tourism offer is anchored in a multi-layered historical legacy, encompassing Roman, Islamic, Ottoman, and colonial periods. Notable attractions include the Ain El Fouara Fountain, the National Museum, the Byzantine Fortress, and the 8 May 1945

Amusement Park, alongside modern developments such as the Park Mall shopping and leisure center. A 22.4 km tramway network with 22 stations enhances mobility across key cultural, commercial, and residential zones. Public green spaces and pedestrian areas contribute to the city's tourism experience and urban liveability.

Tourism in Sétif remains predominantly domestic, with most visitors arriving from neighbouring provinces such as Constantine and Béjaïa. International tourists, though fewer in number, typically originate from France, Canada, and Maghreb countries, in line with national tourism trends.

Fig. 1. Localisation of the city of Setif

Historically, tourism development in Sétif has been guided by national spatial planning strategies, including the Tourism Development Master Plan (Schéma Directeur d'Aménagement Touristique) (MATET, 2008), which promotes the valorisation of heritage, development of thermal tourism clusters (e.g., Hammam Guergour), and support for ecotourism in mountainous zones. At the municipal level, efforts have included infrastructure investments, site rehabilitation, and hotel sector growth. However, the city continues to face significant institutional challenges, including the absence of a dedicated urban tourism master plan, limited data systems, and weak coordination between local authorities and private stakeholders (BENGHADBANE & Al-Habees, 2023).

Beyond tourism, Sétif's economy is diversified and driven by manufacturing, trade, services, and a large informal sector. Industrial zones accommodate textile, electronics, and agri-food processing industries, attracting both domestic and foreign investment. While tourism remains a secondary economic activity, the city's cultural assets, growing infrastructure, and strategic location position it as an emerging urban tourism hub in north-eastern Algeria.

At an altitude of approximately 1,100 meters and situated 300 kilometers east of Algiers, the city serves as a critical transit corridor between the inland plateau and the Mediterranean ports of Jijel and Bejaïa, while facilitating interregional movement along national transport axes. This geographic positioning supports tourism development by improving accessibility from multiple directions, making Sétif a logical transit stop and a potential base for regional exploration.

Application of MCDM Method

Multi-Criteria Decision-Making (MCDM) methods are widely used to address complex decision problems where multiple, and often conflicting, criteria must be considered simultaneously (Malczewski, 1999; Triantaphyllou, 2000). These methods provide a systematic framework for integrating both qualitative and quantitative information, allowing decision-makers to structure problems, assign relative importance to different factors, and derive consistent prioritizations (Figueira, Greco, & Ehrgott, 2005).

In the context of spatial and potential mapping, MCDM is particularly valuable as it enables the assessment and ranking of diverse indicators that influence planning and policy decisions (Subramanian & Ramanathan, 2012). Among the various MCDM techniques, the Analytic Hierarchy Process (AHP) is one of the most widely applied approaches and is adopted in this study for weighting and prioritizing spatial criteria. Numerous studies have successfully applied AHP to urban tourism planning. For example, Vukoičić et al. (2022) used AHP to assess the tourism potential of cultural–historical areas in Serbia, identifying heritage accessibility and service quality as key factors. Jewpanya et al. (2025) applied both AHP and fuzzy AHP for destination selection in Thailand, highlighting the importance of individualized tourist preferences. These studies demonstrate AHP's flexibility and reliability for evaluating complex tourism systems and prioritizing spatial indicators.

Data preparation

To carry out this research, a structured set of indicators, sub-indicators, and variables was established based on a comprehensive literature review. This review included international studies that applied MCDM and AHP methods in tourism planning contexts (M. Dadashpour Moghaddam, H. Ahmadzadeh, & R. Valizadeh, 2022; Jewpanya et al., 2025), ensuring that the selected indicators aligned with best practices. These indicators and data sources were selected to analyse urban systems and guide planning decisions through a multidimensional lens. The selected framework reflects a mixed-methods approach, combining geospatial, statistical, and qualitative inputs to provide a holistic assessment of urban infrastructure, services, and quality of life, essential dimensions in tourism-oriented urban planning.

Table 1. Data collection Sources

Indicator	Sub-Indicator	Variable	Data Source(s)
Open Public Spaces	Green Spaces	Parks and Gardens	Field survey (2023), georeferenced with Google Earth Pro
	Forests	Forest Areas	*(OSM, 2024)*, Field survey (2023)
	Public Places	Squares, Plazas	Field survey (2023), Google Earth Pro
Heritage	Natural & Cultural Sites	Historical Monuments, Archaeology	Field survey (2023), Google Earth Pro
Tourism Facilities	Hospitality	Hotels, Youth Hostels, Agencies	Field survey (2023), Google Earth Pro
	Leisure	Theaters, Stadiums, Sports Complexes	Field survey (2023), Municipal data
	Cultural Facilities	Museums, Cultural Centers, Libraries	Field survey (2023), Ministry of Culture (2023)
	Commercial Facilities	Shopping Malls, Restaurants, Retail Stores, Banks	Field survey (2023), Google Earth Pro
	ICT Facilities	Mobile Operators: Coverage of Mobilis, Ooredoo, Djezzy	*(OSM, 2024),* Operators' public data, Field survey (2023)
Urban Accessibility	Road Network	Road Hierarchy, Connectivity	*(OSM, 2024)*
	Tramway	Stops, Lines	*(SETRAM, 2018), (OSM, 2024)*
	Parking	Parking Facilities	(OSM 2024), Field survey (2023)
	Taxi	Taxi Stations	*(DTT, 2023)*
	Bus	Stops, Lines	*(DTT, 2023),* (ETUS, 2023)
	Train	Stations, Lines	*(OSM, 2024)*
Service Quality	Hospitality & Food	Highly Rated Hotels, Restaurants	Google Maps Reviews (2023), Field verification (2023)
ICT Services	Network Performance	Signal Strength (2G, 3G, 4G)	Field survey (2023), measured via nPerf App
Security	Security Infrastructure	Police Stations	Field survey (2023), Google Earth Pro
	Crime Rate	Reported Incidents	*(DGSN, 2023)*
Noise Pollution	Environmental Condition	Noise Levels (dB)	Field survey (2023), measured via Sound Meter App

(Table 1) summarizes the main indicators, sub-indicators, variables, and corresponding data sources used in this study. The data were obtained from a combination of open-access geospatial platforms (e.g., OpenStreetMap), government agencies, official planning entities, and field-based data collection methods (including Google Earth Pro, mobile apps, and direct surveys).

Each variable was evaluated based on proximity, calculated using the Euclidean Distance to the nearest feature (in meter) (e.g., nearest theatre or stadium). For location-based amenities such as leisure and cultural facilities, spatial analysis was performed using georeferenced point data, with each facility represented as a mapped feature in the GIS environment. The influence of each variable was assessed by distance-based attractiveness rather than quantity or size.

Development of Base Maps (VECTOR)

This section involves the creation of foundational maps that serve as the basis for subsequent spatial analysis. The geospatial database underlying these maps is constructed using a combination of on-site field data collection and secondary data obtained from institutional sources, including the municipal administration, the tourism department, and other relevant public and private stakeholders.

Rasterization and Standardization

To facilitate spatial analysis and multi-criteria evaluation, all vector data (points, lines, polygons) were converted to a continuous raster format with a uniform cell size of 25 meters. This resolution was chosen to balance the spatial detail of urban features with computational efficiency for the study area of 127 km^2.

The transformation from vector to raster was performed using the Euclidean Distance algorithm, which calculates the straight-line distance from each raster cell to the nearest vector feature. This approach is based on the principle that the influence of a tourism attractiveness factor is proximity-based.

As illustrated in Table 2, the resulting distance rasters were then standardized to a common measurement scale (1 to 9) to allow for comparison and weighted overlay (see Figures 2–9). The standardization logic was applied as follows:

- **For positive factors (where proximity increases attractiveness):** e.g., Heritage sites, Green Spaces, Hotels. Shorter distances were assigned higher values (e.g., 9), and longer distances were assigned lower values (e.g., 1).
- **For negative factors (where proximity decreases attractiveness):** e.g., Noise Pollution sources, Industrial Zones. The distance raster was inverted so that larger distances from the source received higher attractiveness scores.

(Table 2) provides Urban Tourist Attractiveness indicators and each class based on proximity to the indicator used in the study.

Table 2. Urban Tourist Attractiveness indicators and Corresponding Thematic Maps (Figures 2–9)

Urban Tourist Attractiveness indicators

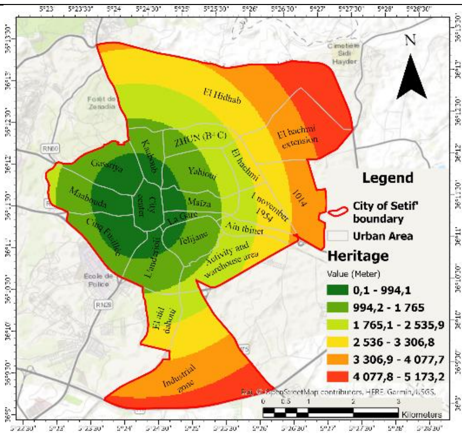

Figure 1. Heritage

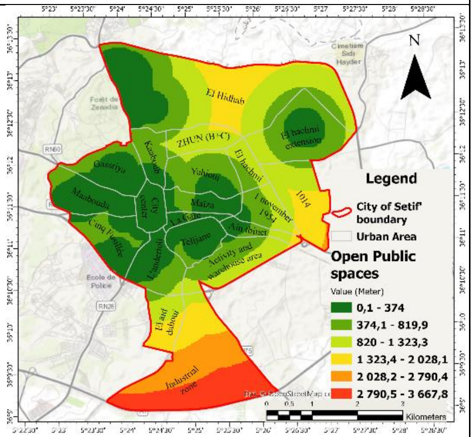

Figure 2. Open Public Spaces

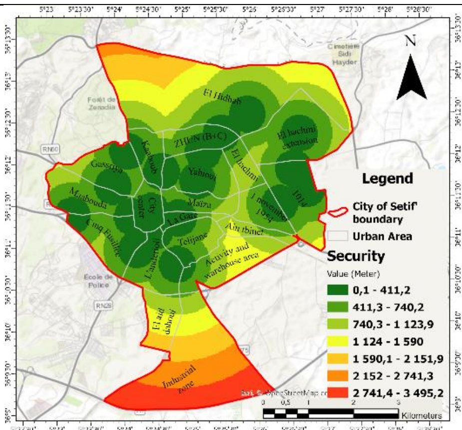

Figure 3. Security

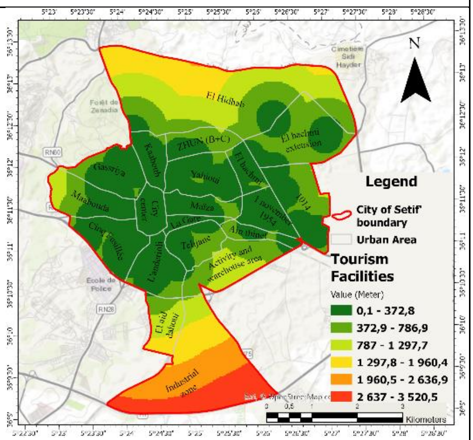

Figure 4. Tourism Facilities

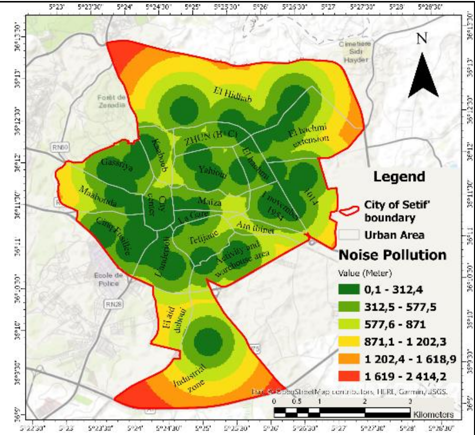

Figure 5. Noise Pollution

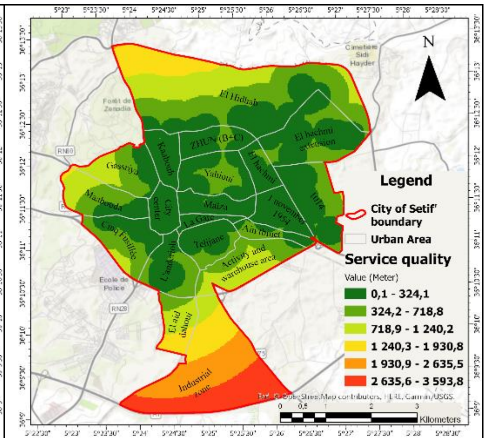

Figure 6. Service Quality

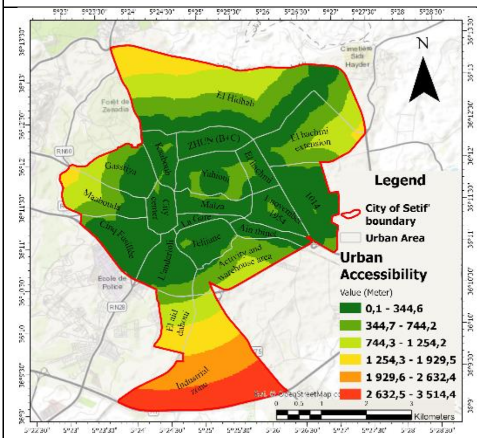

Figure 7. Urban Accessibility

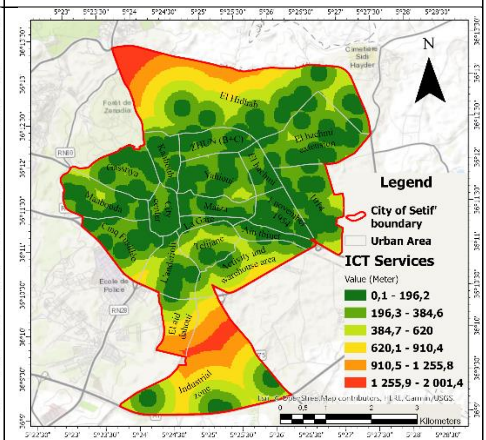

Figure 8. ICT Services

The Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) is a widely used multi-criteria decision-making (MCDM) method that allows for the prioritization of complex problems based on expert judgment. Developed by Thomas Lorie Saaty (2008), AHP establishes a priority scale through pairwise comparisons, reflecting the relative importance of various elements such as indicators, sub-indicators, or variables.

In this study, the AHP method was selected as the most suitable tool for assigning weights to the spatial indicators used in the tourism potential model. The process involved two main phases:

Phase 1: Construction of the Pairwise Comparison Matrix

According to Thomas Lorie Saaty (2008), each element is evaluated in relation to all others on a scale of 1 to 9, where:

1 = Equal importance, 2 = Weak or slight importance, 3 = Moderate importance, 4 = Moderate plus, 5 = Strong importance, 6 = Strong plus, 7 = Very strong or demonstrated importance, 8 = Very, very strong, 9 = Extremely important.

To ensure the judgments were informed by relevant academic and professional expertise, a panel of 20 experts was convened. All experts were researchers specializing in urban planning with a specific focus on tourism development. Each expert assessed the relative importance of indicators using the AHP scale. The resulting scores were used to build the pairwise comparison matrix.

Phase 2: Weight Calculation and Consistency Assessment

The AHP weight calculation was performed following the method described by Almansi et al. (2022), which involves the following steps:

Step 1: Column Sum Calculation (Equation 1)

The values in each column of the matrix were summed:

$$L_{ij} = \sum_{n=1}^{n} C_{ij} \tag{1}$$

L_{ij} represents the pairwise comparison matrix total column value.
C_{ij} represents the criteria applied for the analysis.

Step 2: Normalization of the Comparison Matrix (Equation 2)

Each element in the matrix was divided by its column total to normalize the values:

$$X_{ij} = \frac{C_{ij}}{\sum_{n=1}^{n} C_{ij}} \tag{2}$$

X_{ij} is the normalized pairwise comparison matrix.

Step 3: Calculation of Standard Weights (Equation 3)

The average of each row in the normalized matrix was computed to determine the weight for each criterion:

$$W_{ij} = \frac{\sum_{j=1}^{n} X_{ij}}{N} \tag{3}$$

W_{ij} is the standard weight.

These weights reflect the relative importance of each indicator in the decision-making process.

Phase 4: Consistency Ratio (CR) Assessment
To ensure the reliability of expert judgments, the Consistency Ratio (CR) was calculated using the following steps:
Step 1: Weighted Sum Vector
Each row of the original pairwise matrix was multiplied by the calculated weight vector to produce the weighted sum vector.
Step 2: Consistency Vector and λ Calculation (Equation 4)
Each element of the weighted sum vector was divided by the corresponding weight to obtain the consistency vector. The average of this vector is denoted as λ (lambda):

$$\lambda = \sum_{i=1}^{n} CV_{ij} \tag{4}$$

λ is the consistency vector.

Step 3: Consistency Index (CI) (Equation 5)

The Consistency Index (CI) quantifies the deviation from a perfectly consistent judgment:

$$CI = (\lambda - n)(n - 1) \tag{5}$$

the measure of inconsistency degree $(\lambda - n)$ evaluates the deviation from the expected level of consistency based on the number of parameters.

Step 4: Consistency Ratio (CR) (Equation 6)

Finally, the CR is calculated by comparing the CI with the Random Index (RI), which is based on a predefined table of random values:

$$\mathrm{CR} = \mathrm{CI}/\mathrm{RI} \tag{6}$$

RI is the random index. RI depends on the number of elements being compared (Table 3).

A CR value of less than 0.10 is considered acceptable and indicates that the judgments are reasonably consistent. If the CR exceeds this threshold, the matrix must be revised.

Table 3. Random inconsistency indices (RI)

n	RI
1	0.00
2	0.00
3	0.58
4	0.90
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45
10	1.48
11	1.49
12	1.51
13	1.56
14	1.57
15	1.59

Source: Thomas L Saaty, 1980.

The application of the AHP steps described above, ranging from matrix construction to consistency verification, resulted in the generation of (Table 4), which presents the pairwise comparison matrix of the spatial indicators used in the decision-support tool for evaluating tourism potential. Each value in the matrix reflects the relative importance of one indicator compared to another, as evaluated through expert consultation. These judgments were based on the AHP scale, and the matrix serves as the foundation for deriving the final weight vector used in the multi-criteria analysis.

Pairwise Comparison Matrix

The normalized pairwise comparison matrix (Table 5), highlights the relative importance of the selected urban planning criteria. The results presented in (Table 6), show that security (0,230), service quality (0,266), and heritage (0,186) emerge as the most influential factors, accounting for more than 60% of the total weight. These priorities indicate that stakeholders place greater emphasis on ensuring safe urban environments, maintaining high-quality services, and preserving cultural assets. In contrast, Tourism facilities (0,111) and urban accessibility (0,084) play a secondary role, while ICT (0,067), open public space (0,030), and noise pollution (0,026) are considered less critical in the decision-making process. The very low consistency index (CI = 0,048533) and consistency ratio (CR = 0,03442) as it is mentioned in (Table 7) confirm that the expert judgments used to derive these weights are highly consistent, reinforcing the robustness and reliability of the results.

Table 4. Pairwise comparison Matrix

	Security	Tourism Facilities	Open Public Space	Urban Accessibility	Heritage	Noise pollution	Service quality	ICT
Security	1	3	7	3	2	7	0,5	3
Tourism Facilities	0,33	1	5	2	0,33	5	0,33	2
Open Public Space	0,14	0,2	1	0,33	0,2	1	0,2	0,33
Urban Accessibility	0,3	0,5	3	1	0,33	4	0,33	2
Heritage	0,5	3	5	3	1	7	0,5	3
Noise pollution	0,14	0,2	1	0,25	0,14	1	0,14	0,33
Service quality	2	3	5	3	2	7	1	3
ICT	0,33	0,5	3	0,5	0,33	3	0,33	1

Table 5. Normalised Matrix

	Security	Tourism Facilities	Open Public Space	Urban Accessibility	Heritage	Noise pollution	Service quality	ICT
Security	0,2090	0,2632	0,2333	0,2293	0,3153	0,2000	0,1496	0,2045
Tourism Facilities	0,0697	0,0877	0,1667	0,1529	0,0526	0,1429	0,0997	0,1364
Open Public Space	0,0299	0,0175	0,0333	0,0255	0,0315	0,0286	0,0598	0,0227
Urban Accessibility	0,0697	0,0439	0,1000	0,0764	0,0526	0,1143	0,0997	0,1364
Heritage	0,1045	0,2632	0,1667	0,2293	0,1577	0,2000	0,1496	0,2045
Noise pollution	0,0299	0,0175	0,0333	0,0191	0,0225	0,0286	0,0427	0,0227
Service quality	0,4179	0,2632	0,1667	0,2293	0,3153	0,2000	0,2991	0,2045
ICT	0,0697	0,0439	0,1000	0,0382	0,0526	0,0857	0,0997	0,0682

Table 6. Weights (eigenvector)

Security	Tourism Facilities	Open Public Space	Urban Accessibility	Heritage	Noise pollution	Service quality	ICT
0,230	0,111	0,030	0,084	0,186	0,026	0,266	0,067

Table 7. AHP Consistency Metrics

λmax	CI	CR
8,339728	0,048533	0,03442

Results

The application of the MCDM method, using the previously defined indicators and incorporating the Euclidean distance (Table 2), generated the results presented in Figure 10. This figure illustrates the spatial distribution of the Urban Tourist Attractiveness Index within the city of Sétif, represented through a graduated color scale ranging from Very High to Very Low.

- Very High Attractiveness: covers 8.87 km² (29.33%) of the city, primarily concentrated in central neighborhoods such as the City Center, La Gare, Maïza, parts of Yahiaoui, Telijane, Cinq Fusillées, Maabouda, and Kaaboub.
- High Attractiveness: extends across 8.05 km² (26.52%), including Zhun B+C, El Hachmi, parts of the El Hachmi Extension, parts of Yahiaoui, 1st November 1954, and Ain Tbinet.
- Moderate Attractiveness: occupies 6.81 km² (22.44%), covering districts such as El Hidab, 1014, and El Aid Dahoui.
- Low Attractiveness: accounts for 2.98 km² (9.82%), located mainly in peripheral areas including parts of the industrial zones, El Hidab, El Aid Dahoui, and agricultural edges.
- Very Low Attractiveness: concentrated in the southern industrial zone and other peripheral districts, records the lowest levels of tourism potential (area and percentage to be specified).

Overall, the classification results show a strong concentration of Very High and High Attractiveness in the city center and surrounding districts, while the peripheral southern industrial zone registers the lowest values.

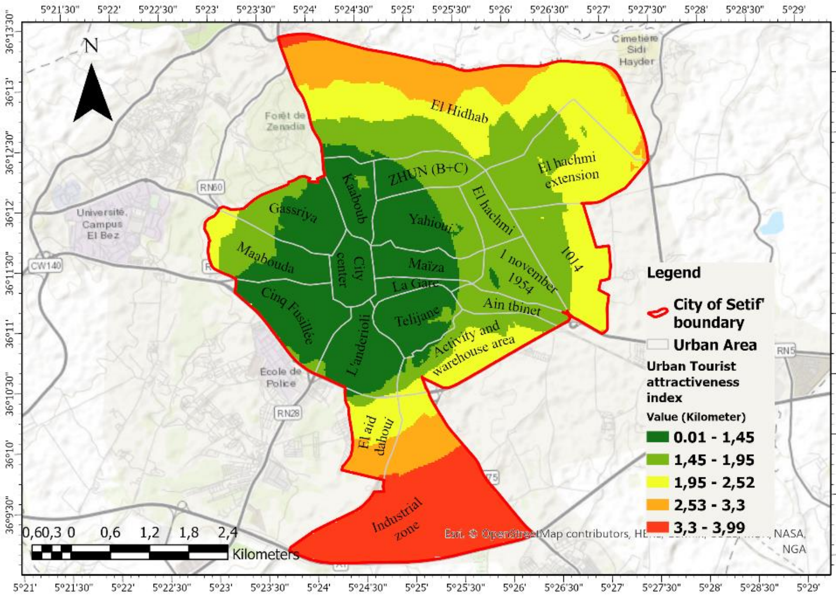

Fig. 9. Urban tourist attractiveness index

Model' Validation

Consistency Ratio

The Consistency Ratio (CR) was computed for each matrix to ensure reliability. All CR values were below the acceptable threshold of 0.10, indicating high consistency in expert judgments. Thomas Lorie Saaty (2008) was used to determine the Random Index (RI) based on the number of elements in each matrix.

Model Validation Using ROC Curve

To evaluate the predictive performance of the proposed tourism potential model, we conducted a Receiver Operating Characteristic (ROC) analysis, which is commonly used to assess the classification accuracy of spatial models.

To validate the Urban Tourism Attractiveness Index, social media metrics, specifically the number of pages and followers on platforms like Facebook, Instagram, and Twitter/X (Table 8), were employed as proxies for public engagement and perceived tourism appeal. Social media platforms serve as real-time mirrors of destination popularity, capturing user-generated content and interactions that reflect both resident and visitor interest (Cheng, 2025). This approach is particularly valuable in contexts, such as medium-sized cities in the Global South, where traditional tourism statistics are often sparse or outdated. In contrast, social media data are accessible, spatially explicit, and timely (Teles da Mota & Pickering, 2020; ZAjAdAcZ & MinkwitZ, 2020). Moreover, the literature confirms that social engagement metrics (e.g., likes, shares, comments, follower counts) significantly influence tourism perceptions and intentions, serving as credible indicators of attractiveness and travel behaviour (Susanto, Gaffar, Disman, Furqon, & Leisure, 2024). Therefore, leveraging social media statistics provides a dynamic, scalable, and replicable method to validate spatial models of tourism attractiveness.

Table 8. Attractive urban areas

Indicator	Sub-Indicator	Variable	Source
Social Networks	Facebook	Facebook Pages	Authors, 2023 (analysis via *Facebook, Instagram, Twitter* app statistics)
		Number of Followers	
	Instagram	Instagram Pages	
		Number of Followers	
	Twitter/X	Twitter Pages	
		Number of Followers	

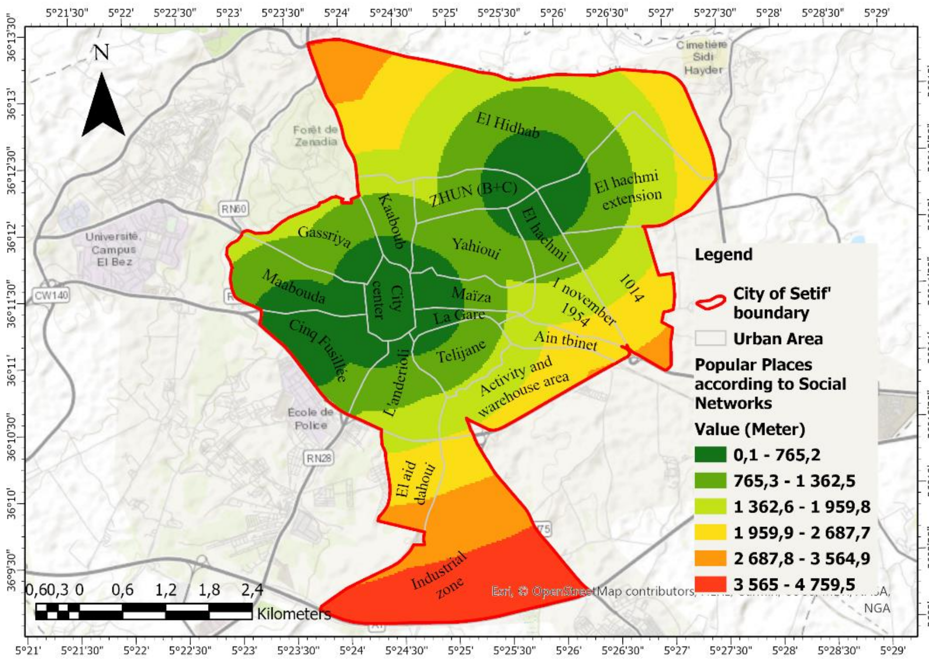

Fig. 10. Attractive Urban areas according to social Networks.

As illustrated in (Figure 12), the ROC curve plots the True Positive Rate (sensitivity) against the False Positive Rate (1 - specificity). The Area Under the Curve (AUC) was calculated to be 0.839, indicating high model accuracy. According to the scale proposed by Hosmer, Lemeshow, and Sturdivant (2000), an AUC between 0.8 and 0.9 reflects a "very good" discriminatory ability of the model.

This result confirms that the integration of AHP-derived weights and GIS-based spatial overlay produces a reliable classification of tourism potential across the urban territory. The model effectively distinguishes between areas of high and low tourism attractiveness, thus validating its utility as a decision-support tool for urban and tourism planners.

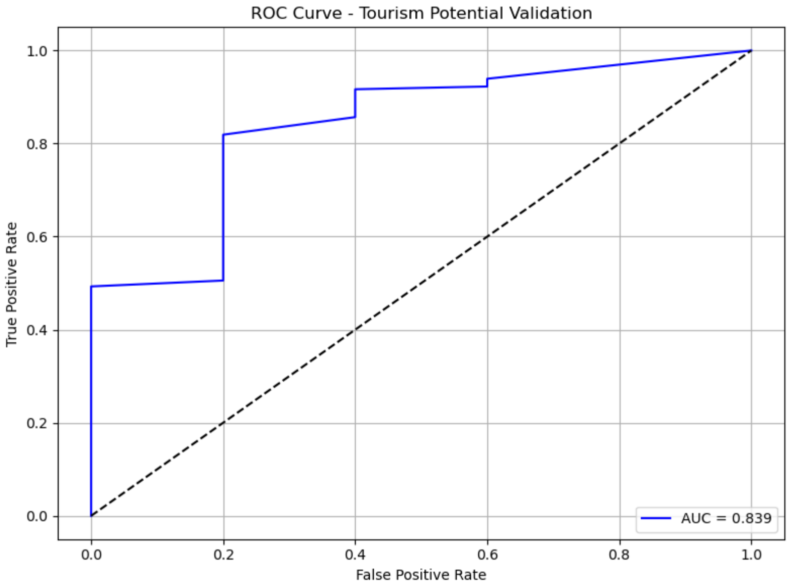

Fig. 11. ROC Curve – Urban Tourism attractiveness

Discussion

The tourism potential map derived from our AHP-GIS assessment (Figure 10) reveals a distinct spatial hierarchy across the city of Sétif, categorized into five classes from Very High to Very Low potential. This pattern is not merely descriptive; it offers a critical lens through which to examine the interplay of urban form, resource allocation, and tourism development strategies in a medium-sized city of the Global South.

The concentration of "Very High" and "High" potential in the historic core confirms the enduring power of urban centrality but also exposes the challenges of mono-centric tourism development. This pattern is characteristic of what can be termed a "tourist bubble" (Freitag, 1994), where cultural, commercial, and hospitality facilities agglomerate, creating a zone of high attractiveness that is somewhat insulated from the broader urban fabric. The presence of anchors like Park Mall, high-end hotels (Novotel, Ibis), and iconic landmarks (Ain El Fouara Fountain) creates a powerful economic gravity well. However, this dominance of the core can lead to a self-reinforcing cycle where investment continues to be funnelled into already saturated areas, potentially neglecting the development of a more resilient and distributed tourism economy (Müller & Jansson, 2006).

The gradual decline in attractiveness with distance from the center is a direct manifestation of the spatial mismatch between the peripheral location of neighbourhoods and the centralised distribution of tourism assets. This gradient reflects deeper urban inequities in infrastructure and service provision, common in cities experiencing rapid and often unplanned growth (Rogerson & Rogerson, 2021). Our model quantifies this gradient, showing that over 55% of the city's area falls into the Moderate to Very Low categories, highlighting a significant untapped potential and a substantial challenge for equitable tourism development.

The AHP weightings, derived from local expert judgment, are not merely technical outputs; they are a statement of strategic priorities. The fact that Security (0.230) and Service Quality (0.266) were weighted as the most critical factors, even above Heritage (0.186), is profoundly significant for policy. This suggests that for Sétif to realise its tourism potential, the foundational prerequisites of a safe and high-quality visitor experience are deemed more immediately influential than the raw presence of cultural assets themselves. This finding challenges a purely asset-led development model and argues for a strategy that prioritises:

1. Investment in the "Software" of Tourism: Before investing solely in new "hard" infrastructure (e.g., restoring more monuments), policymakers should focus on enhancing the quality of existing services, professionalizing the hospitality workforce, and ensuring visible and effective security presence, particularly in zones identified with High potential that are on the cusp of development.
2. Perception Management: The high weight for Security indicates that overcoming perceptions of risk is crucial. Marketing and branding campaigns should actively communicate Sétif as a safe and welcoming destination, supported by the tangible evidence of well-policed and managed public spaces.

The lower weights for Urban Accessibility (0.084) and ICT (0.067) are surprising yet instructive. They may reflect an expert consensus that current accessibility and digital infrastructure are perceived as adequate for the current level of tourism, rather than primary drivers of attractiveness. However, for future growth, especially to integrate peripheral attractions, improving multi-modal transport links and digital connectivity will become increasingly critical.

Our findings strongly align with theories of urban spatial structure, particularly the core-periphery model, demonstrating its applicability to the tourism landscape of a Global South city (Britton, 1991). The results validate that tourism attractiveness is not an innate property of a single site but a synergistic product of colocation and agglomeration economies. The value of a heritage site is significantly amplified by its proximity to high-quality hotels, restaurants, and secure, accessible public spaces.

From a practical planning perspective, the Urban Tourism Attractiveness Index provides a strategic decision-support tool that enables a move from blanket policies to targeted interventions:

- Consolidation Zones (Very High/High): Policy should focus on managing visitor flows, enhancing the pedestrian experience, and preserving the character and quality of services. Investments here should be about refinement and resilience, not just expansion.
- Intervention Zones (Moderate): These areas represent the greatest opportunity for strategic growth. Policy should focus on "stitching" these zones to the core through improved public transport links, incentivizing the development of complementary amenities, and upgrading public realms to activate their latent potential.
- Transformation Zones (Low/Very Low): In these largely peripheral areas, policy might focus on creating new, specialised attractions (e.g., ecotourism, agritourism) that do not rely on central proximity, while simultaneously addressing fundamental barriers like transportation access and environmental quality.

Notwithstanding its robust validation, this study has limitations that chart a course for future research. The reliance on Euclidean distance, while computationally efficient, overlooks network-based travel time and pedestrian accessibility barriers. Future models could integrate network analysis to provide a more realistic assessment of mobility. Furthermore, the index provides a static snapshot; incorporating dynamic data on seasonal visitor flows or event schedules would add a temporal dimension to the analysis. Finally, while expert judgment provides crucial insights, supplementing this model with surveys of tourist perceptions could help validate or contrast the expert-derived weights, particularly regarding factors like security and service quality.

In conclusion, this study demonstrates that spatially explicit assessments are indispensable for transitioning from abstract tourism development goals to concrete, location-specific actions. The framework presented here offers a replicable method for cities like Sétif to leverage their unique assets strategically, ensure tourism becomes a catalyst for broader urban improvement, and ultimately foster a more sustainable and equitable urban form.

Conclusion

This study developed an Urban Tourism Attractiveness Index for the city of Sétif, Algeria, through an integrated AHP-GIS framework that synthesizes multi-criteria decision-making with spatial analysis. Theoretically, this research contributes to urban tourism literature by empirically validating the core-periphery model and "tourist bubble" effect in a medium-sized Global South city, demonstrating how tourism assets and infrastructure concentrate in the historic core while peripheral areas remain underutilized. The expert-driven weighting process further revealed that security and service quality are perceived as more critical determinants of attractiveness than the mere presence of cultural heritage, highlighting the importance of experiential factors in tourism development.

From a practical perspective, this study provides a transparent, replicable decision-support tool for urban planners and policymakers. The spatially explicit output enables targeted interventions across different zones of attractiveness, from managing over-tourism in the core to activating potential in moderate zones and addressing structural barriers in peripheral areas. The proposed mobile application concept demonstrates how these spatial insights can be translated into accessible tools for both tourists and destination managers.

Several limitations should be acknowledged. The reliance on Euclidean distance measures rather than network-based accessibility represents a simplification of urban mobility patterns. Additionally, the model provides a static snapshot of attractiveness that does not account for temporal variations in visitor flows or seasonal dynamics. The dependence on expert judgment for weighting, while methodologically robust, could be complemented by incorporating tourist perceptions and preferences.

Future research should address these limitations by integrating network analysis to model actual travel times and pedestrian routes, incorporating temporal data to capture seasonal and event-based variations, and employing tourist surveys to validate and refine the expert-derived weights. Further application of this framework in other cities would enhance its transferability and comparative value.

In summary, this research demonstrates that spatially explicit, multi-criteria approaches are essential for transforming abstract tourism policies into concrete, location-specific strategies. The AHP-GIS framework developed here provides a foundation for more equitable and sustainable tourism planning that can help cities like Sétif leverage their unique assets while addressing spatial inequalities and fostering broader urban development.

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