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LEVERAGING MACHINE LEARNING ALGORITHMS TO IDENTIFY POTENTIAL GEOSITES FOR GEOTOURISM PROMOTION IN ZIZ UPPER WATERSHED IN SOUTHEASTERN MOROCCO

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Abstract: The present study aims to tackle the complex task of identifying optimal areas for defining geomorphosites in large regions, considering various influencing factors. The study focuses on Ziz Upper Watershed (ZUW), southeast Morocco, and evaluates the effectiveness of the commonly used machine learning classifier (MLC) in mapping potential geomorphosite areas. The identification and mapping of such areas are crucial for attracting and enhancing geotourism in the region. Initially, a comprehensive inventory of 120 geomorphosites was conducted, and precise measurements of three topographical parameters were taken at each site. Subsequently, the machine learning algorithm, namely Bagging was employed to develop predictive model. The performance, achieving an area under the curve (AUC) of 0.935. This models successfully identified highly favorable areas, encompassing approximately 12% of the study area. These favorable areas were predominantly situated in the western region of the study area, characterized by mountainous terrain with relatively shorter slope lengths and high altitudes. The findings of this research provide valuable guidance to decision-makers, offering a roadmap for improving the chances of discovering geomorphosites.

Keywords: geosites, geotourism, geomorphosite, geopark, machine learning, SE Morocco

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INTRODUCTION

Geosites, comprising a wide range of natural features like rock formations, cliffs, canyons, caves, fossil sites, volcanic landscapes, glaciers, and various geological formations, serve as the fundamental elements for establishing geoparks and promoting the growth of geotourism (Zgłobicki et al., 2024). These sites offer valuable insights into the planet's evolution and serve as significant resources for geotourism, geoheritage, and geoconservation. Their assessment enhances geo-education and geotourism, which are crucial for increasing awareness of geological heritage (Spyrou et al., 2024). This includes areas with geological relevance, such as volcanic sites (Ramos et al., 2024), or archaeological sites (Kudla et al., 2024) that contribute to our understanding of the Earth's geological processes and the interactions between humans and the environment. The preservation and sustainable management of these sites are essential for promoting geotourism, conserving geoheritage, and fostering geoconservation efforts (Carrión-Mero et al., 2024).

In recent years, the significance of geoheritage studies has attracted a growing number of researchers, leading to increased efforts to promote geotourism and geoconservation. These studies have sparked interest and exploration in various countries worldwide. The analysis of scientific contributions indicates a growing body of work in this field, encompassing various countries, including Romania (Herman et al., 2024), Kazakhstan (Yakupova et al., 2024), South Africa (Rogerson and Rogerson, 2024), Malaysia (Abd Halim et al., 2024), and Indonesia (Mulyadi et al., 2024). This global engagement reflects the recognition of the value of geoheritage and the importance of integrating it into geotourism and geoconservation initiatives (Herrera-Franco et al., 2022). In Morocco, there has been a growing focus on the concept of geoheritage at the national level, resulting in a noteworthy emphasis on geoconservation (Errami et al., 2015a, b; Enniouar et al., 2015; Errami et al., 2024; Elkaichi et al., 2024; El Hamidy et al., 2024). This commitment to preserve and promote geoheritage is further reinforced by geomorphosite inventory initiatives undertaken by various Moroccan universities (Baadi et al., 2023; Louz et al., 2023; Bussard, 2023). These initiatives employ inventory and evaluation methodologies that aim to identify, assess, and enhance the country's rich geoheritage (Louz et al., 2023). The integration of these studies

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and initiatives not only contributes to the scientific understanding of Morocco's geological heritage but also supports the development of sustainable geotourism and effective strategies for geoconservation in the country.

The literature commonly acknowledges the matter of objectivity in geosites inventorying and assessment methods, but it falls short in providing a comprehensive exploration of its inherent nature (Cameron, 2024). The inventory process serves as the most classical effective method for identifying and highlighting the representative sites within the regional geological context. This method effectively identified and highlighted nine Devonian geosites of significance in Morocco (Akhlidej et al., 2024). However, it's important to recognize that inventory is just the initial step in gaining a comprehensive understanding of the potential heritage within a specific area. It provides managers with a valuable database to implement measures for geoconservation. Current methods, including inventories and multi-criteria analyses (such as AHP and PROMETHEE), are subject to distinct limitations. One significant limitation is the inherent subjectivity of evaluations, wherein assessments based on individual expertise can differ (Bilgiç et al., 2024), resulting in varied interpretations of geological significance. Additionally, these methods may not be optimally suited for large-scale analyses, thereby complicating the identification of geosites across extensive areas (Ferrando et al., 2024).

As geosciences enter the era of big data, machine learning for the geosciences presents many challenges and opportunities (Karpatne et al., 2018; Zhao et al., 2024). However, for the purpose of improving geomorphosites assessment, a recent study conducted in the High Atlas region has made significant strides. The study specifically focused on evaluating the suitability of geotouristic stations utilizing a GIS-based multi-criteria decision analysis. As a case study, the research examined the M'Goun UNESCO Geopark, offering valuable insights into the geotourism potential of the region (Elkaichi et al., 2023).

To address the identified research gaps, this study aims to establish a comprehensive decision-making framework designed to enhance the prediction of potential geomorphosites within the mountainous regions of the eastern High Atlas in Morocco. This framework innovatively builds upon traditional GIS-based methodologies by integrating statistical analyses and machine learning algorithms, specifically targeting the identification of candidate geomorphological sites to promote geotourism. The novelty of this research lies in its methodological integration of three topographical factors with the frequency ratio (FR), a Bagging machine learning classifier, and the area under the curve of the receiver operating characteristics (AUC-ROC) metrics. This multifaceted approach seeks to improve the prediction of geomorphosites that could support geotourism initiatives in the Ziz Upper Watershed (ZUW).

GEOGRAPHICAL AND GEOLOGICAL SETTING OF THE STUDY AREA

The ZUW is located in the southeastern region of Morocco, specifically between 32°05′48″ and 32°64′19″ N latitude, and between 04°11′72″ and 5°46′20″ W longitude (Figure 1), experiences a semi-arid climate with cold winters and dry summers (Manaouch et al., 2021). Annual precipitation ranges from 119 to 377 mm, while average annual temperatures vary between 10.2 and 19.2 °C (Manaouch et al., 2022). The elevation within the catchment spans from 1023 to 3687 meters above sea level, and the slopes typically have angles between 0 and 66° (Manaouch et al., 2023).

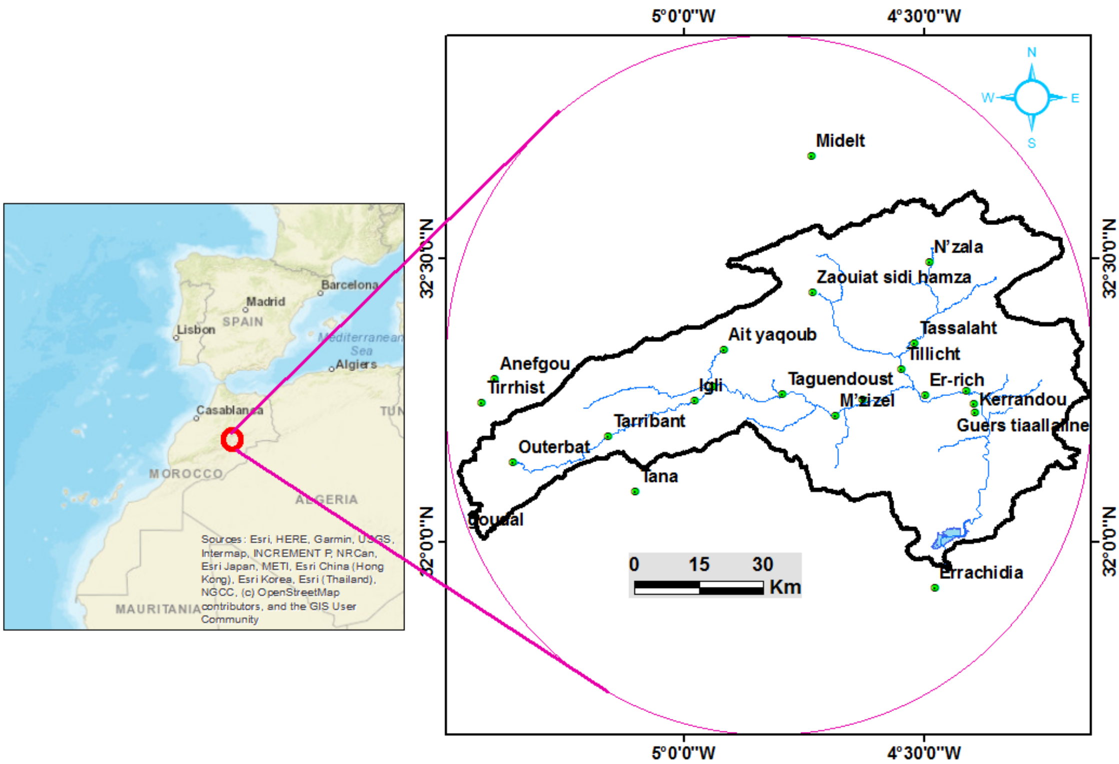

Figure 1. Location of the Ziz Upper Watershed in southeast Morocco

While Holm oak (Quercus ilex) forests are not widespread across the landscapes of the ZUW, there are a few restricted areas where these forests still exist. These remaining Holm oak forests hold significant value and have been designated as protected reserves to ensure their preservation. The ZUW is a region teeming with heritage, characterized by a wide array of sedimentological, paleontological, karstic, and geomorphological features. The geodiversity of the area is derived from a wide range of geological formations (Figure 2), spanning from the Triassic period to the more recent Quaternary era (Navas et al., 2009). However, to accurately inventory these geomorphosites, alternative techniques beyond traditional methods are required. To fill this void, the aim of this study is to address the abundant heritage of ZUW by conducting a thorough inventory using machine learning algorithms. The evaluation findings will form the basis for suggesting measures to conserve and protect the geological treasures of the region.

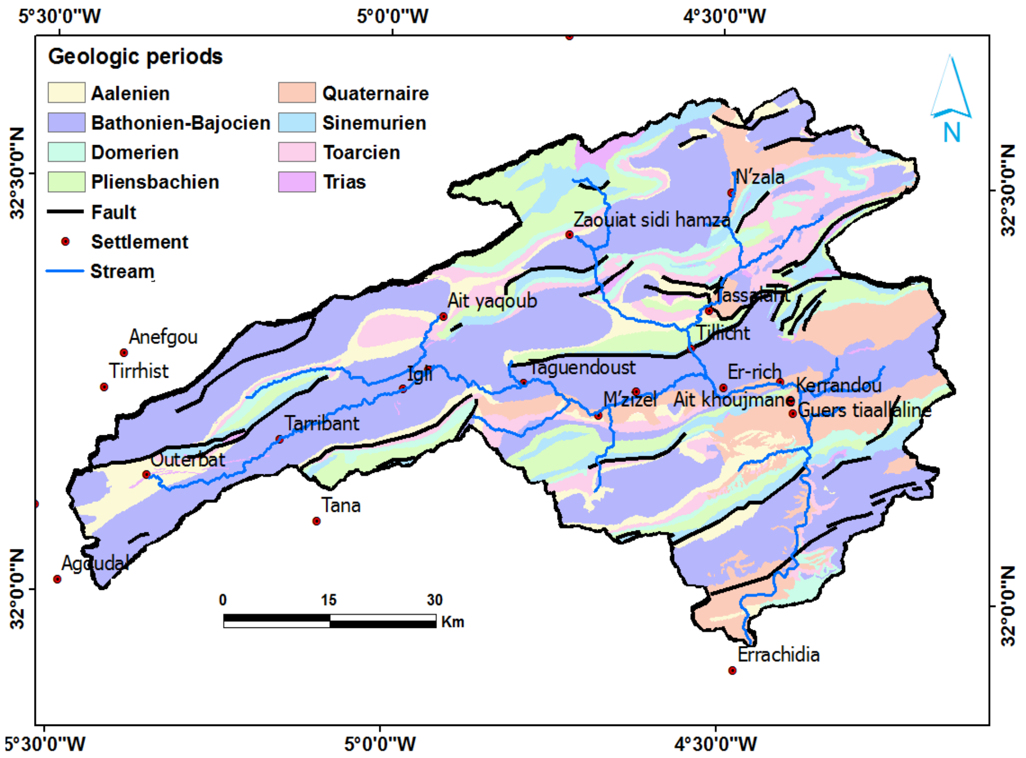

Figure 1. Geology and structural setting of the study area (Source: Nouayti et al., 2015)

The ZUW harbors a multitude of geomorphosites that serve as captivating showcases of the region's distinctive geological and geomorphological characteristics. These geomorphosites not only offer valuable insights into the geological history of the area but also provide opportunities for scientific exploration, educational endeavors, and tourism. Among the noteworthy geomorphosites within the ZUW, the Gorges of Ziz stand out prominently. These remarkable limestone gorges have been intricately carved by the Ziz River over countless millennia, resulting in a breathtaking landscape characterized by towering cliffs and meandering canyons. The allure of these geomorphosites lies in their geological importance and picturesque beauty, drawing the attention of geologists and nature enthusiasts alike.

MATERIALS AND METHODS

This section outlines the materials and methods used for the geosite inventory. Data were gathered from geological surveys and field observations to ensure a thorough assessment of the study area's geological features. The methodologies for compiling and analyzing this data are detailed below.

Data used and geomorphosites inventory

To precisely identify the regions where a particular phenomenon will occur, it is crucial to conduct a comprehensive analysis of the intricate relationship between the manifestation of the phenomenon and the underlying factors that have contributed to its occurrence (Al-Abadi, 2018). In order to achieve accurate identification and selection of geomorphological sites, extensive field visits were conducted within the ZUW. Through these visits, a total of one hundred twenty geomorphosites (Table 1) were identified and included in the modeling process, while an equivalent number of non-geomorphosites were also considered. This meticulous approach ensures the precision and reliability of the site selection process. Given the interconnection between geomorphological sites and topographic features, this study integrated three conditioning factors for geomorphosites (GCF), which included slope, length of slope and elevation. These factors serve as independent variables that influence the suitability of areas for the presence of geomorphological sites. These variables were measured for the 240 sites selected in the inventory (Figure 3).

To adhere to standard spatial modeling practices, the dataset was divided into two classes: training data comprising 70% and validation data comprising 30%. Data processing was carried out using ArcGIS 10.5 and SPSS[1] Statistics 26 software, both of which possess robust geoprocessing capabilities for converting geospatial data into a tabular format. This

[1] Statistical Package for the Social Sciences

conversion entails a series of steps, including importing geospatial data, defining attributes, executing geoprocessing tools, configuring parameters, and performing geoprocessing operations.

Table 1. Coordinate system of the 120 inventoried geosites

Site N°	X[2]	Y*	Site N°	X*	Y*	Site N°	X*	Y*	Site N°	X*	Y*
1	-4.36806	32.17361	31	-4.54833	32.32222	61	-4.36222	32.13417	91	-4.36806	32.09083
2	-4.36861	32.17389	32	-4.54806	32.32278	62	-4.36194	32.13472	92	-4.36917	32.09083
3	-4.36333	32.17389	33	-4.52139	32.22167	63	-4.36194	32.13472	93	-4.36972	32.09111
4	-4.36556	32.17278	34	-4.52639	32.22083	64	-4.36278	32.13417	94	-4.37028	32.09083
5	-4.37222	32.17167	35	-4.53028	32.21972	65	-4.36167	32.13556	95	-4.37111	32.09056
6	-4.37306	32.17083	36	-4.50028	32.22639	66	-4.36139	32.13556	96	-4.37111	32.09028
7	-4.36722	32.15389	37	-4.49861	32.22833	67	-4.36111	32.13556	97	-4.37222	32.09028
8	-4.37000	32.15361	38	-4.49389	32.22611	68	-4.36472	32.13278	98	-4.37306	32.09028
9	-4.36861	32.15361	39	-4.49333	32.23028	69	-4.36306	32.13389	99	-4.37306	32.09056
10	-4.37944	32.11000	40	-4.49417	32.22917	70	-4.36222	32.13500	100	-4.37222	32.09056
11	-4.38861	32.10583	41	-4.49806	32.22833	71	-4.36222	32.13500	101	-4.37611	32.10306
12	-4.39167	32.10361	42	-4.49194	32.22972	72	-4.36194	32.13556	102	-4.37667	32.10278
13	-4.39278	32.10139	43	-4.48556	32.23139	73	-4.35944	32.12528	103	-4.37750	32.10222
14	-4.38528	32.10778	44	-4.48528	32.23194	74	-4.35944	32.12500	104	-4.37778	32.10250
15	-4.37972	32.10972	45	-4.48111	32.23222	75	-4.35972	32.12500	105	-4.37889	32.10222
16	-4.37667	32.11361	46	-4.47833	32.23361	76	-4.35944	32.12472	106	-4.38028	32.10167
17	-4.37167	32.14444	47	-4.47528	32.23556	77	-4.35944	32.12444	107	-4.38111	32.10139
18	-4.37222	32.14361	48	-4.47472	32.23472	78	-4.35972	32.12417	108	-4.38139	32.10139
19	-4.37361	32.14389	49	-4.47472	32.23500	79	-4.35972	32.12361	109	-4.38167	32.10111
20	-4.37500	32.14389	50	-4.47444	32.23528	80	-4.36000	32.12361	110	-4.38389	32.10056
21	-4.35778	32.14056	51	-4.47389	32.23556	81	-4.36028	32.12306	111	-4.38333	32.10028
22	-4.35722	32.14083	52	-4.47306	32.23611	82	-4.36028	32.12278	112	-4.38417	32.09972
23	-4.35750	32.13500	53	-4.47278	32.23639	83	-4.36444	32.09222	113	-4.38722	32.09778
24	-4.35306	32.13389	54	-4.36028	32.15944	84	-4.36333	32.09222	114	-4.38806	32.09667
25	-4.35222	32.13389	55	-4.36750	32.17194	85	-4.36528	32.09139	115	-4.38833	32.09611
26	-4.35083	32.13389	56	-4.38139	32.14722	86	-4.36611	32.09139	116	-4.38889	32.09500
27	-4.36167	32.13861	57	-4.36222	32.13444	87	-4.36667	32.09139	117	-4.38972	32.09333
28	-4.36111	32.13833	58	-4.36306	32.13333	88	-4.36667	32.09111	118	-4.38972	32.09278
29	-4.36444	32.14639	59	-4.36278	32.13361	89	-4.36722	32.09111	119	-4.39000	32.09222
30	-4.36361	32.14444	60	-4.36278	32.13389	90	-4.36806	32.09111	120	-4.39056	32.09083

Additionally, to ensure the accuracy and performance of the model, the area under the curve (AUC) of the receiver operating characteristics (ROC) was utilized for validation. The AUC/ROC method is widely employed in geospatial modeling studies, as emphasized by Manaouch et al. (2021), to assess and validate the reliability of the models.

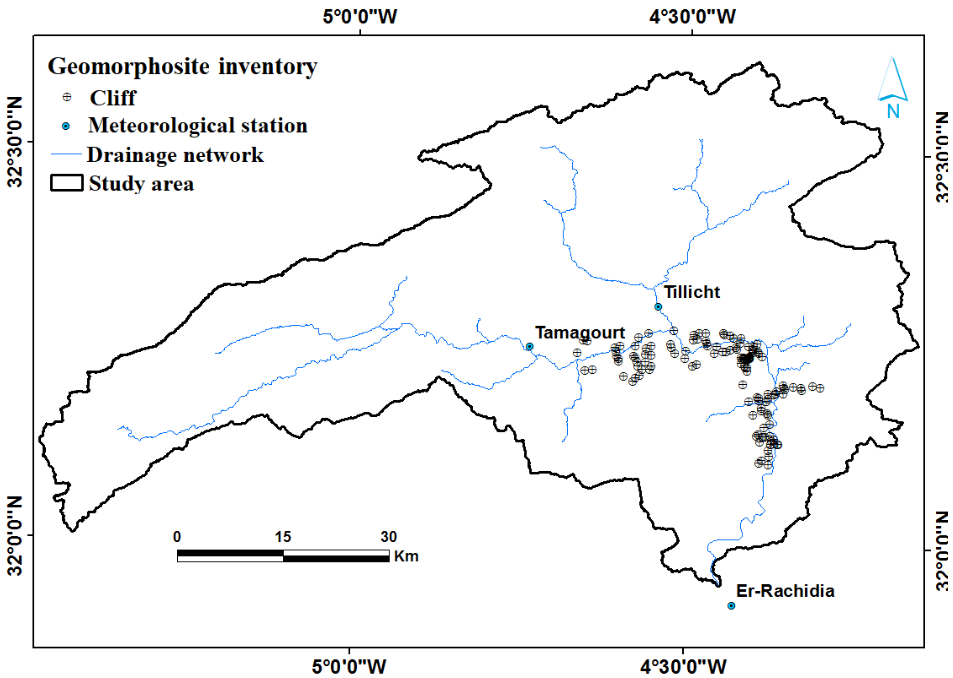

Figure 3. Geomorphosite inventory map (data collected from field surveys, 2024)

[2] Lambert Conformal Conic projection

Variety of gemorphological sites

Geotourism is centered around the exploration and appreciation of geomorphosites, which encompass captivating natural features such as canyons and cliffs. These remarkable geological formations serve as major attractions, drawing visitors and tourists from far and wide. Within the ZUW, canyons and cliffs hold a pivotal position in the realm of geotourism, offering abundant opportunities for exploration, learning, and the unveiling of geological marvels within the region. Scattered along the Ziz valley, these sites entice tourists and visitors, inviting them to pause and capture breathtaking photographs during their journeys. The following figure (Figure 4) illustrates examples of geomorphosites found along the Ziz valley, including tabular structures, inclined formations, canyons and cliffs.

Figure 4. Examples of geomorphosites identified within the study areas include inclined formations (a) in Hammat Moulay Ali Cherif, canyon (b) at Zaabal Tunnel, tabular formations (c) in Hammat Moulay Ali Cherif, and col (d) in Tamrakecht (Source: Jbdodane, 2024

METHODOLOGY

Figure 5 depicts a flowchart that shows the step-by-step process of mapping the suitability of geomorphosites utilizing an advanced machine learning algorithm. The subsequent sections delve into a more comprehensive explanation of this methodology.

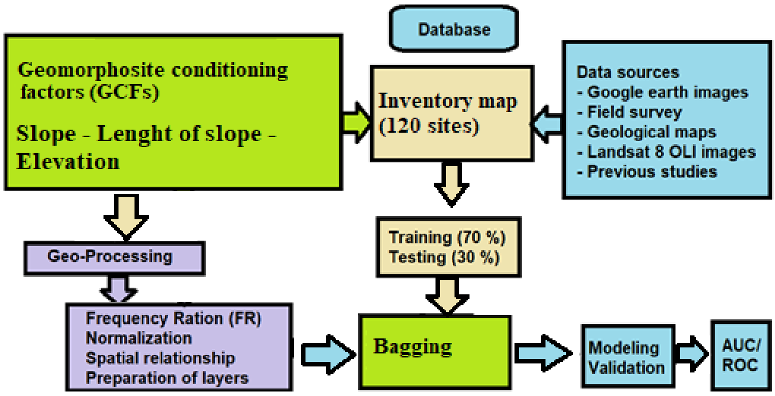

Figure 5. Flow chart of the modelling strategy used

Geomorphosites conditioning factors (GCFs)

Geomorphosites are influenced by key topographic data such as slope, slope length, and elevation. These factors shape the characteristics and distribution of these remarkable landforms. Figures 6, 7 and 8 display the maps depicting each factor (slope, slope length, and elevation) within the studied area.

Slope

A slope in the context of geomorphosites refers to the angle or gradient of a landform's surface. Geomorphosites are specific locations on Earth that have significant geological, geomorphological, or paleontological value. They can include features such as cliffs, mountains, canyons, and other landforms. The formula for calculating slope in ArcGIS is derived from the change in elevation between adjacent cells in a Digital Elevation Model (DEM) raster dataset, which was obtained from the Shuttle Radar Topography Mission (SRTM) provided by the U.S. Geological Survey (USGS) through the EarthExplorer portal (https://earthexplorer.usgs.gov/). The slope is calculated as the ratio of the vertical change in elevation (rise) to the horizontal distance (run) between the cells. The formula for calculating slope in ArcGIS is generally expressed as:

$$\text{Slope} = \text{Rise} / \text{Run} \quad (1)$$

Where Rise is the change in elevation between two neighboring cells in the DEM dataset and the Run present the horizontal distance between the two neighboring cells.

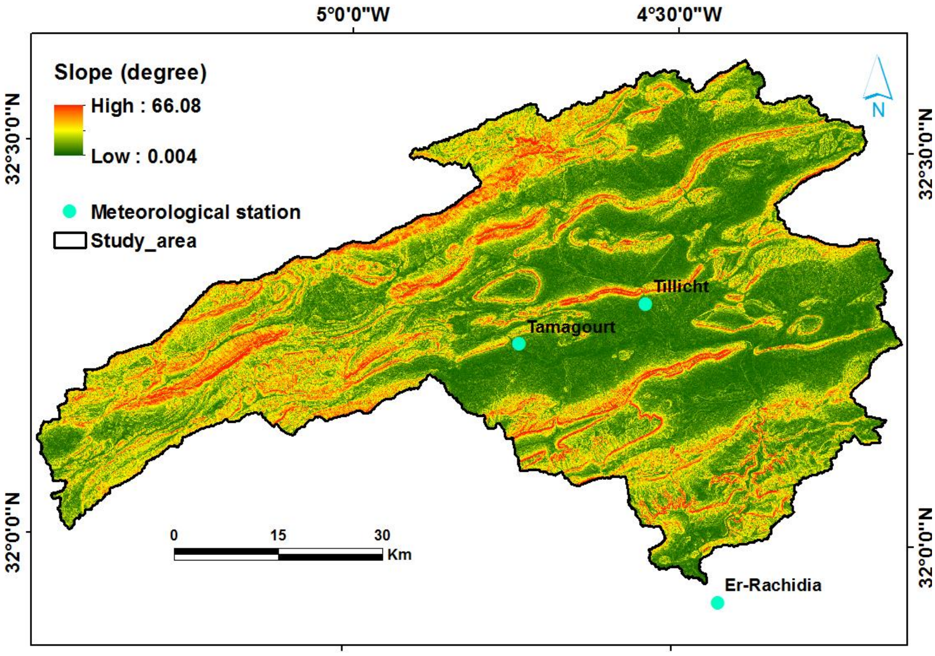

Figure 6. The slope map of the studied area

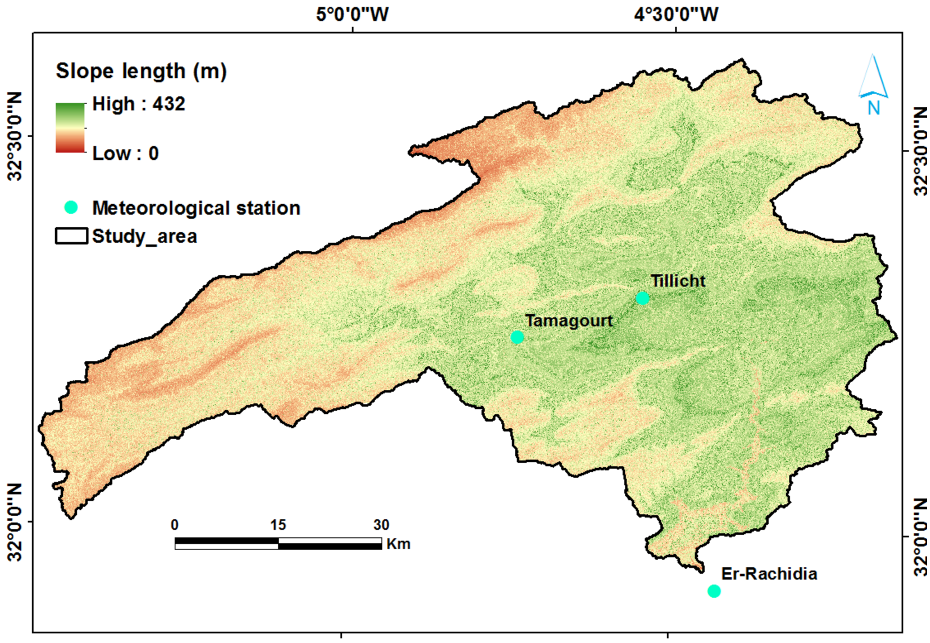

Figure 7. The slope length map of the studied area

Length of slope (LS)

The measurement of slope length is a significant factor when describing and defining landforms within geomorphosites. Geomorphosites can consist of different types of slopes, including hillsides, cliffs, and valleys. Quantifying the length of slope aids in assessing the size and magnitude of these landforms. In this study, the LS factor map, displayed in Figure 7, was derived from the Digital Elevation Model (DEM) using ArcGIS 10.5 software. The LS factor values range from 0 to

432 meters. This extraction was performed based on the formula developed by Bizuwerk et al. (2003), which follows the methodology established by Wischmeier and Smith (1978):

$$LS = \left(\frac{L}{22.13}\right)^{m}(65.41 sin^{2}(S) + 4.56 \sin(S) + 0.065) \quad (2)$$

Where: LS is the Slope length (m); L= flow accumulation × DEM spatial resolution and S is the slope gradient (in %).

m: Constant which is equal to: 0.5 for slopes greater than 5%; 0.4 for slopes of 3.5 to 5%; 0.3 for slopes of 1 to 3.5% and 0.2 for slopes of less than 1%.

These values of slope gradient and the corresponding constant are used to determine the slope length in the equation.

Elevation

In relation to geomorphosites, elevation is an important characteristic used to describe and differentiate various landforms. Geomorphosites can have different elevations, ranging from low-lying areas such as valleys or plains to high-elevation features like mountains or plateaus. Elevation influences the climate, vegetation, and geological processes occurring within a geomorphosite. Measuring elevation is typically done using surveying techniques, satellite-based systems (e.g., GPS), or remote sensing methods such as Light Detection and Ranging (LiDAR) or radar. These technologies provide accurate elevation data that can be used to create digital elevation models (DEMs) or topographic maps. Elevation, within the context of geomorphosites, refers to the vertical distance or height of a point or location above a reference datum. It is a fundamental parameter used to describe the vertical position of landforms and is essential for understanding the characteristics, processes, and geological significance of geomorphosites.

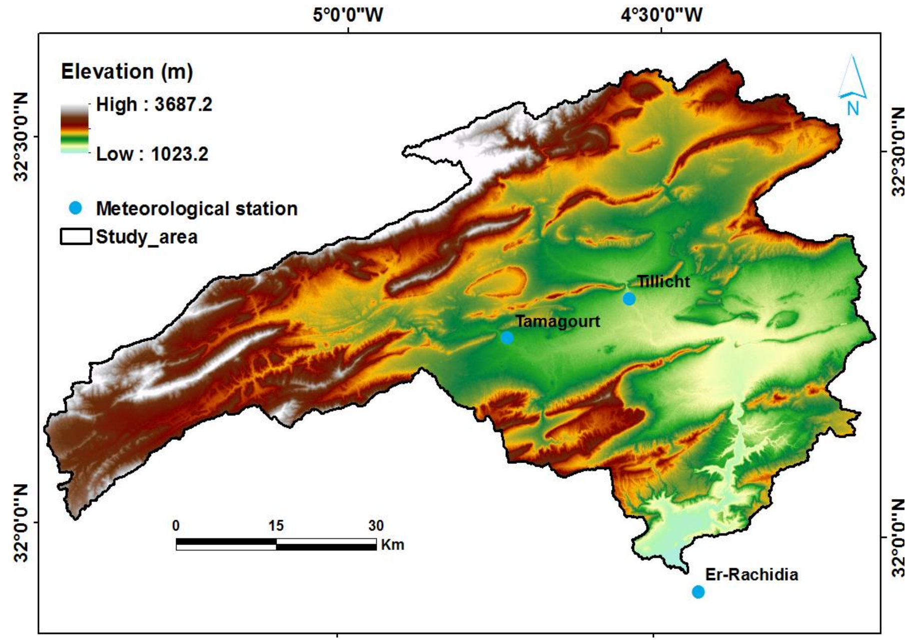

Figure 8. The altitude map of the studied area

Bagging and Frequency ratio (FR)

The Bagging method, derived from "Bootstrap Aggregating," involves two primary steps as outlined by Breiman (2001). The initial step involves bootstrapping the samples extracted from the raw data, resulting in multiple training datasets. Subsequently, multiple models are constructed using these training datasets. The ultimate predictions are derived by aggregating the results of these models to obtain a final outcome. The Bagging model is extensively employed in geospatial modeling, such as in the assessment of landslide susceptibility conducted by Zhang et al. (2024), and in the evaluation of agricultural land suitability conducted by Agrawal et al. (2024).

Frequency ratio (FR): The geomorphosites conditioning factors database aims to select and analyze the relationship between various parameters associated with geomorphosites. These parameters undergo normalization using methods like the frequency ratio, as described by Manaouch et al. (2024). The frequency ratio compares the percentage of geomorphosites' presence to the percentage of area occupied by different classes of each conditioning factor. An increased frequency ratio, as noted by Samanta et al. (2018), indicates a higher likelihood of phenomenon occurrence.

$$FRi = (Ni/N)/(Si/S) \quad (3)$$

Where FRi denotes the frequency ratio of the i^{th} class of a conditioning factor. Ni signifies the count of geomorphosites within the i^{th} class, while Si represents the area size of that class. N corresponds to the total number of geomorphosites present in the study area, and S indicates the total area encompassed by the study. The results section presents the calculated frequency ratio values for the three conditioning factors, each comprising multiple classes. To facilitate analysis, these values are normalized using the normalize filter method, which transforms them into a range of 0.1 to 0.9. A normalized value closer to 1 indicates a stronger association between geomorphosites and the corresponding factor, whereas a value closer to 0 indicates a weaker association. The spatial relationship between the conditioning factors and geomorphosites is assessed through the frequency ratio calculation, the outcomes of which are displayed the results section for all factors.

Performance and model's validation

Ensuring the validation of results is crucial in any modeling process. In this study, the evaluation of the generated map indicating potential geomorphosites areas was performed using the area under the curve (AUC) of the receiver operating characteristics (ROC). The AUC/ROC analysis involved 120 geomorphosites along with the classified map depicting potential geomorphosites within the study area. The geomorphosites suitability map was categorized into four groups based on actual and predicted labels: true positive (TP), true negative (TN), false positive (FP), and false negative (FN) events, as outlined in Table 2.

Table 2. Data labeling (predicted and actual)

Actual label	Predicted label	
	Positive	Negative
Positive	TP	TN
Negative	FP	FN

The values of TP are True Positive, FP are False Positive, TN are True Negative and FN are False Negative. TPR (True Positive Rate) and FPR (False Positive Rate) were computed using the provided equations. Following that, the ROC curve was generated by plotting the FPR values on the X-axis and the TPR values on the Y-axis:

$$TPR = TP/(TP + FN) \quad (4)$$

$$FPR=FP/(FP+TN) \quad (5)$$

RESULTS

Geomorphosites and conditioning factors

The assessment results of the spatial relationship between GCF (Geomorphosites Conditioning Factors) and geomorphosites points using frequency ratio (FR) are presented in Table 3.

Table 3. Spatial relationship between slope and geomorphosites points using frequency ratio (FR)

GCF	Class	No. of pixels in class	% of class	No. of sites	% of sites	Frequency Ratio	
						FRi	FRn
Slope (°)	1	1809027	0.37	2	0.016	0.045	0.1
	2	1250863	0.25	9	0.075	0.3	0.12
	3	881995	0.18	16	0.13	0.74	0.15
	4	672053	0.14	24	0.2	1.43	0.21
	5	304042	0.06	69	0.575	9.58	0.9
Elevation (m)	1	393526	0.08	1	0.0083	0.1	0.1
	2	850896	0.17	4	0.033	0.2	0.1
	3	837542	0.17	14	0.116	0.69	0.13
	4	885384	0.18	0	0	0	0.1
	5	655483	0.13	3	0.025	0.2	0.1
	6	552065	0.11	0	0	0	0.1
	7	409303	0.08	73	0.608	7.6	0.55
	8	240897	0.05	25	0.208	4.17	0.34
	9	92885	0.02	0	0	0	0.1
Length of slope (m)	1	21828	0	0	0	0	0.1
	2	76772	0.02	0	0	0	0.1
	3	1015571	0.21	4	0.033	0.16	0.11
	4	1949329	0.4	24	0.2	0.5	0.24
	5	1855923	0.38	92	0.7666	2.02	0.81

Geomorphosites suitability map

Figure 9 depicts the geomorphosites suitability map generated by the Bagging classifier.

The map highlights that the northern and western regions exhibit higher suitability for potential geomorphosites compared to other areas. In order to better understand the reasons behind the observed variations and to comprehend the factors contributing to the suitability or unsuitability of specific areas, we sought the expertise of local experts who possess extensive knowledge of the region. Additionally, we validated our findings by cross-referencing them with images obtained from Google Earth. Figure 11 shows the respective area percentages of these suitability classes for the generated map.

Model's performance

The Bagging classifier's effectiveness was evaluated using the AUC/ROC method. In the training phase, the classifier achieved an average accuracy rate of 97.29%. During the validation phase, notable variation in classifier performance was observed, as shown in Figure 10. The AUC value obtained was 0.935, indicating that the Bagging classifier was effective in modeling geomorphosites suitability mapping in ZUW.

DISCUSSION

Analysis of Precision: The performance of machine learning models (MLMs) can vary depending on the specific algorithm employed. In the case of Bagging, its performance was assessed using the 10-fold cross-validation method during the training phase, resulting in a high level of performance with an AUC value of 0.972. However, during the validation phase, the performance of Bagging decreased to 93.5%, as shown in Figure 10. It is generally observed that algorithms with higher AUC values tend to exhibit more accurate and efficient prediction capabilities, as noted by Su et al. (2021). Based on the current AUC value of Bagging, it can be inferred that Bagging performs comparatively lower than the results reported by Manaouch et al. (2023) in predicting potential reforestation areas. However, it is important to note that Bagging still exhibits a favorable level of accuracy and efficiency, as evidenced by its AUC value of 0.935.

Distribution of suitable geomorphosites areas

The data attribute obtained from ZUW underwent preprocessing using the stored version of the Bagging classifier. During this preprocessing step, geomorphosite suitability indices were calculated for each pixel within the study area. To classify these suitability indices, the "Natural breaks" algorithm was utilized, resulting in the creation of four classes: low, moderate, high, and very high. This process led to the creation of a geomorphosite suitability map, depicted in Figure 9. The results indicate that approximately 12% of the entire study area consists of areas classified as highly suitable for potential geomorphosites, as shown in Figure 10. According to the Bagging model, the southern parts exhibit low suitability for potential geomorphosites, while the mountainous regions to the west and north demonstrate high suitability. Additionally, the Bagging model reveals that areas classified as very highly suitable for geomorphosites are scattered along the Ziz wadi, located to the south of ZUW.

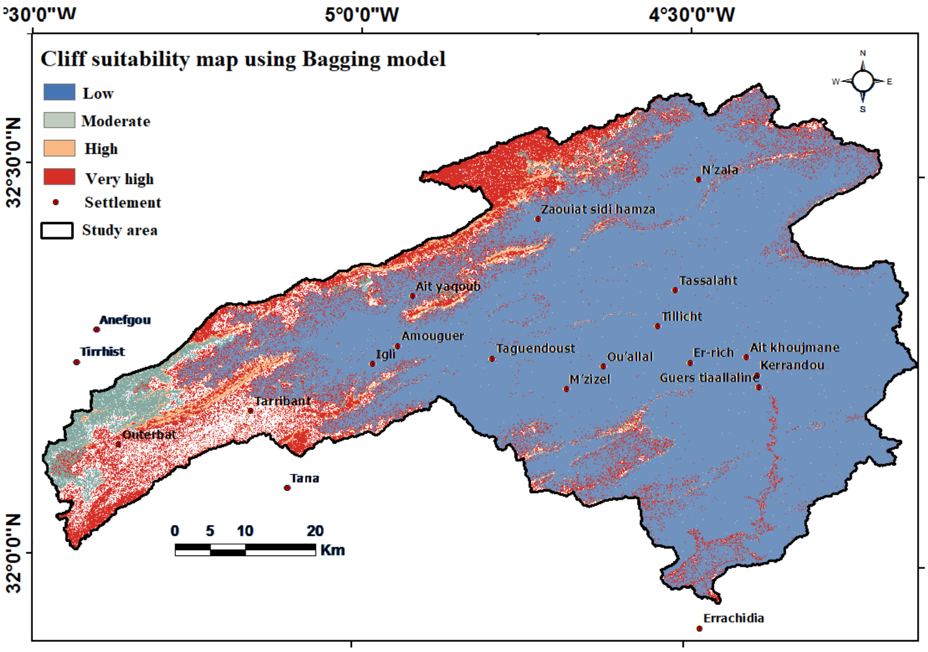

Figure 9. Generated geomorphosite suitability map using Bagging

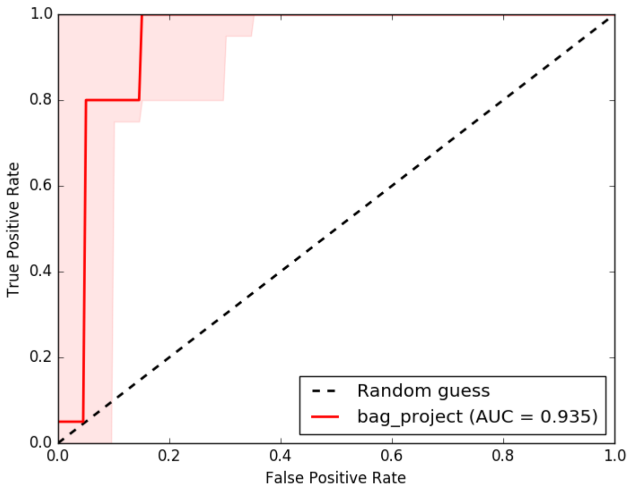

Figure 10. Prediction rate curve for geomorphosite suitability map produced by Bagging

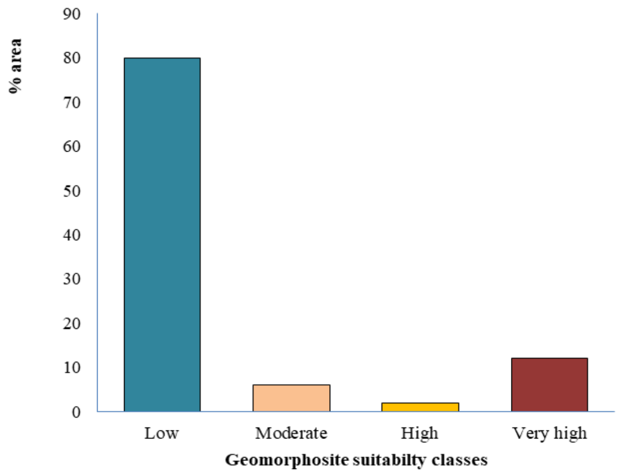

Figure 11. Percentage of geomorphosites suitability classes' areas for Bagging model

CONCLUSION

The integration of topographical data and Bagging offers significant potential for enhancing geotourism through the identification of suitable geomorphosites. By testing Bagging classifier that utilize topographical features such as slope, length of slope, and elevation, and validating the resulting map using the AUC/ROC metric, valuable insights can be obtained to identify potential geotourism sites in the ZUW in Southeast Morocco.

By incorporating slope, length of slope, and elevation as input variables, Bagging can accurately predict and map areas with high geotourism potential within a future geopark in the Ziz region. Based on the findings, the potential areas for geomorphosites, accounting for approximately 12%, are dispersed primarily in the northern and western regions, as well as around the Ziz wadi, particularly in the downstream part of the study area.

In the current study, the AUC/ROC evaluation metric, which provides a reliable measure of the algorithms' ability to differentiate between suitable and unsuitable geotourism geomorphosites, achieved an impressive score of approximately 93.5%. This indicates that Bagging performed exceptionally well in accurately identifying and distinguishing potential geotourism sites. This validation approach ensures the reliability and accuracy of the generated map, enabling decision-makers and stakeholders in the tourism industry to confidently identify and prioritize areas for geotourism development. Through the strategic utilization of integrated topographical data and machine learning algorithms, stakeholders in the geotourism sector can make well-informed decisions pertaining to site selection and investment. This approach plays a crucial role in fostering the sustainable development of geotourism destinations within the ZUW, specifically in the context of establishing a future geopark. By leveraging the power of advanced data analysis and predictive modeling, stakeholders can accurately identify and prioritize areas with the highest geotourism potential, ensuring optimal allocation of resources and maximizing the positive impact on both the environment and local communities. This approach promotes the preservation of natural and cultural heritage, fosters economic growth, and enhances the overall visitor experience, ultimately advancing geotourism in the region.

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