

## Identification of groundwater potential zones in the Jel Basin: A geospatial-based multi-criteria evaluation

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### ABSTRACT

Groundwater is the main water resource of the semi-arid Jel Basin (Guercif Province, Morocco), where surface supplies are shrinking and irrigated agriculture relies increasingly on pumping. This study delineates groundwater potential zones (GWPZ) by combining remote sensing, GIS and two multi-criteria weighting schemes: the analytic hierarchy process (AHP) and the multiple influencing factors (MIF) method. Eight thematic layers were integrated: geology, geomorphology, slope, lineament density, drainage density, soil, land use/land cover and rainfall. The AHP pairwise matrix proved consistent ( $\lambda_{\max} = 8.234$ ;  $CR = 0.024$ ), with geology and rainfall carrying the highest weights (26.02% each). A weighted overlay produced one potential map per method; in the AHP map, the high-potential class is concentrated in the southern and southeastern parts of the basin. Both maps were tested against 20 boreholes classified from pumping-test discharge (13 productive,  $Q \geq 2.5$  L/s; 7 unproductive,  $Q < 1.0$  L/s) using ROC analysis, and both models reached an AUC of 93.4%. Piezometric records from seven ABHM stations (2002–2020) were then examined with the Mann–Kendall test and Sen's slope at monthly and annual scales. Significant monthly trends appeared only in March and April, and the annual series showed a significant trend ( $p = 0.043$ ; Sen's slope =  $-0.044$  m/year). The results provide a spatial baseline, tested against field boreholes, to guide borehole siting and aquifer management in the Jel Basin.

**Keywords:** groundwater potential zones; Jel Basin (Morocco); remote sensing; analytic hierarchy process; multiple influencing factors; ROC/AUC validation; Mann–Kendall and Sen's slope

### INTRODUCTION

The world's oceans and seas serve as the primary reservoirs of water, a substance capable of transitioning between liquid, solid, and gaseous states (Nouayti et al., 2015a). Because seawater is highly saline, it is unsuitable for direct consumption, so drinking water supplies depend heavily on

surface and groundwater (Elbarghmi et al., 2026). Aquifers provide nearly 26% of the planet's total renewable freshwater resources (Baki et al., 2017). This concentration in the oceans restricts the freshwater share to only 2.8% (Saadi et al., 2021a). Within this small fraction, surface water represents 2.2%, while groundwater accounts for the remaining 0.6% (Nouayti et al., 2022a). In the

province of Jel, groundwater is the fundamental resource for human survival and economic activities, providing nearly 80% of the rural drinking water supply and meeting half of the urban demand. Furthermore, these resources satisfy over 50% of the national agricultural sector's requirements (Azzirgue et al., 2023a).

The pressure on the Jel Basin's aquifers is escalating due to the combined effects of population growth and economic development, even as available reserves decline (Elbarghmi et al., 2024).

The basin is critically dependent on its groundwater, which satisfies 95% of domestic needs and 70% of agricultural demand (Ahalli et al., 2025). In the northern part of the Jel basin, water scarcity has become a primary constraint on agricultural productivity and development (Suzuki et al., 2025). In recent decades, extracting water via steep-sided ravines has been the preferred strategy for maintaining distribution in the Jel plain (Chen et al., 2022). However, the region is currently experiencing acute water stress, primarily driven by intensified groundwater withdrawal (El Boujnouni et al., 2022).

In response to such challenges, scientific research on identifying and evaluating Groundwater Potential Zones (GWPZ) has seen significant progress (Laghzal & Nouayti, 2018a). Traditionally, groundwater exploration relied on localized and expensive geophysical methods (Oussama, 2024a). However, recent advancements have shifted toward the integration of remote sensing (RS) and geographic information systems (GIS) (Hairchi et al., 2024). Modern methodologies now emphasize multi-criteria decision-making (MCDM) approaches, which allow for the simultaneous analysis of various thematic layers such as lithology, slope, land use, and drainage density (Najy et al., 2023). This evolution in research enables a more accurate, cost-effective, and large-scale assessment of aquifer potential, providing essential data for sustainable water management (Taoufiq et al., 2023).

This study aims to map aquifer potential areas within the Jel basin using this modern methodological approach, based on satellite imagery and the application of AHP (Analytic Hierarchy Process) and MIF (Multi-Influence Factor) models integrated into a GIS (Chen et al., 2022). Despite the presence of surface water in the Jel plain district (Nouayti et al., 2015b), the population remains heavily reliant on aquifers for daily household tasks and irrigation (Singh & Devi, 2022).

the Jel aquifer has been declining rapidly due to climate change, which disrupts the natural infiltration and renewal of groundwater (Amaya et al., 2021a). Rainfall in the region is scarce and irregular, occurring only during a short season and leaving a water deficit for most of the year (Hafiane et al., 2020). Consequently, farmers in this agricultural region prioritize pumping large quantities of groundwater for their crops over using surface water (Brahimi et al., 2015). This excessive use, where withdrawals exceed natural replenishment, leads to a drop in the piezometric level and threatens the sustainability of the resource (Laghrib et al., 2024a). Unregulated management may result not only in the depletion of the aquifer but also in the degradation of its physical and chemical properties (Agli et al., 2024). Therefore, rational governance is imperative to ensure the preservation and monitoring of this strategic resource (Lazarides et al., 2025). While many studies rely on single-model GIS assessments, this research introduces a more robust approach by comparing AHP and MIF multi-criteria approaches and validating them against field piezometric data, providing a dynamic perspective often missing in conventional groundwater potentiality studies (Toulotte et al., 2022a). Achieving this requires a rigorous quantification of stocks by delineating high-potential aquifer zones (Rane et al., 2024). To date, research evaluating aquifer potential in this specific area remains limited (Sadeq et al., 2021).

## STUDY AREA

### Geographical location of the study area

The Jel basin is bounded by the Middle Atlas to the southwest (55,000 km<sup>2</sup> in area). The Debdou chain to the southeast, and the Beni-Bou-Yahi - Beni-Snassène chain to the north (Frappart & Ramillien, 2018a). It is situated between the west-east corridors of Taza and Taourirt and between the south-north corridors of Average and Basse-Moulouya (Meng et al., 2019). This region constitutes, in many respects, a transition zone. It is cut in two by the Moulouya wadi, which receives water on the left bank. The wadis Mel-loulou and Msoun (Jilali et al., 2018). originating respectively from the Middle Atlas and the Rif. It can be divided into four plains: in the center and to the west. The plain of Jel, with an area of 650 km<sup>2</sup> (A. Nouayti et al., 2019) and an average

altitude of 350 m, lies to the east. The Tafrata plain (500 km<sup>2</sup> in area and 500 m in average altitude) (Agli et al., 2024); to the north, the Sangal plain (200 km<sup>2</sup>; 300 m); to the south. The plain of Mahrouf (150 km<sup>2</sup>; 700 m) (Ehsan et al., 2024). The climate zone affects air conditioning and the Atlantic gateway (which modifies the flow and promotes a stable atmospheric environment) (Hairchi et al., 2024). Geomorphologically. The Jel basin consists of a Pliocene-Villafranchian surface covered in the center by a more recent filling (El Hamdi et al., 2023). The study area is shown in Figure 1.

## Geology

The Jel Basin, located at the crossroads of the Middle Atlas, the Rif, and the eastern Meseta, has a complex geological structure marked by faults inherited from the Variscan period (NE-SW, E-W, NW-SE) and reactivated by Atlas-Alpine tectonics (Pande et al., 2021a). Its evolution is characterized by a major Neogene subsidence phase linked to the establishment of the Rif nappes, followed by a Pliocene-Quaternary compressive regime that reactivated inversion structures and led to the formation of salt domes (Suzuki et al., 2025). In paleogeographic terms, intense tectonic activity led to an early narrowing of the Rif marine corridor during the Messinian, triggering the Messinian salinity crisis before the transition to continental sedimentation (Rabearisoa et al., 2024). This dynamic context also favored, in the

north, the Saka volcanism in the Pliocene-Quaternary (Q. Li et al., 2017), which manifests itself in a magmatic sequence beginning with altered basalts, followed by orthoclase-rich trachytic flows, and ending with healthy basalts with columnar flow (Al-Raggad et al., 2021a), the whole being closely structured by regional faults and thrust movements (Taoufiq et al., 2025).

## Hydrogeology

The unconfined aquifer consists of Quaternary alluvial deposits (silt, sand, conglomerates) (Mukhtar et al., 2025), resting on impermeable Miocene marls. Its hydraulic conductivity ranges from  $1 \times 10^{-6}$  to  $1 \times 10^{-4}$  m/s (Peltier et al., 2018). The depth of the water table ranges from 40 to 60 meters (Save et al., 2016). This groundwater resource supports the irrigation of approximately 17,358 hectares (Bourjila et al., 2020). Annual withdrawals are estimated at 52.3 million cubic meters for agriculture and 2.1 million cubic meters for drinking water supply (A. Nouayti et al., 2019).

## MATERIALS AND METHODS

### Data sets

In the Jel basin, underground flow vectors are driven by a synergy between structural discontinuities (lithology, fracturing, drainage) and morpho-pedological parameters, thereby

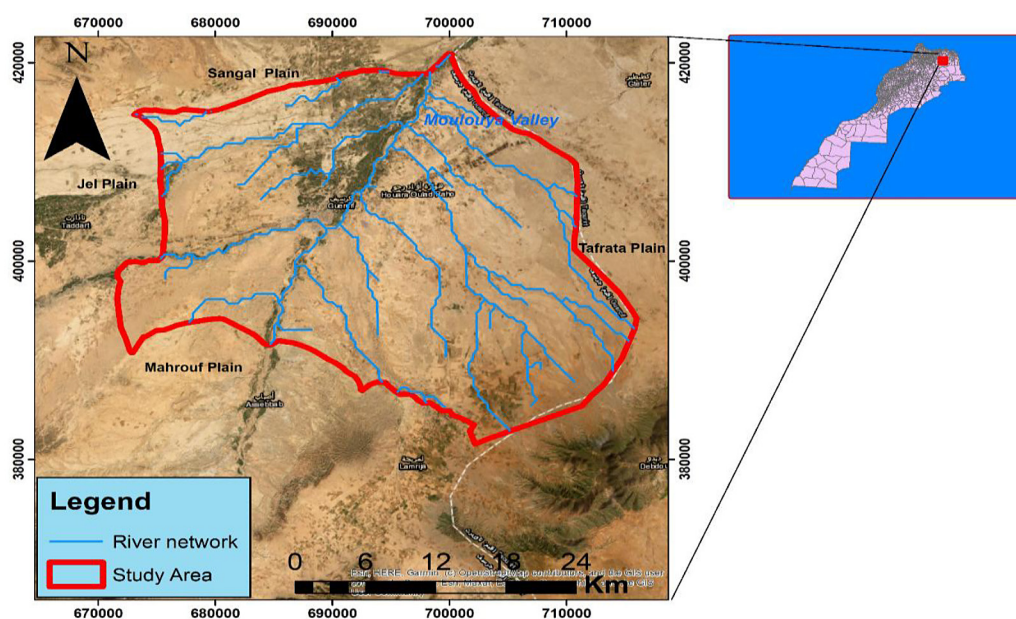


Figure 1. Geographical location of the study area

defining the hydrogeological behavior of the environment (Baki et al., 2017). The hydrodynamics of this area result from dual controls: structural and morpho-pedological for flow circulation, and climatic and anthropogenic (land-use) for recharge processes (Zaki et al., 2019). To identify areas of high aquifer productivity, the analysis must integrate structural discontinuities and pedological features, while weighing the effects of vegetation cover and rainfall on infiltration rates (Laghzal & Nouayti, 2018a). eight geo-environmental criteria were used, including geology, geomorphology, slope, drainage and lineament densities, land use (LULC), precipitation, soil (Ennaji et al., 2024).

The weighting of these parameters is based on a hybrid decision-making approach, combining two multi-criteria decision-making (MCDM) models to ensure a more robust ranking and minimize uncertainties related to weight allocation (Taoufiq et al., 2024). The weighting coefficients were determined by combining two multi-criteria analysis protocols: the analytic hierarchy process (AHP), based on pairwise comparison, and the multiple influence factors (MIF) method. This methodological combination aims to minimize the subjectivity inherent in expert opinion and increase the stability of the weights assigned to each variable (F. Wang et al., 2020). The thematic variables, compiled from multiple data sources (Table 1), were homogenized using a rasterization procedure (Ziani et al., 2021). A sampling step of 12.5 m was applied to the entire dataset to ensure the geometric consistency required for weighted overlay analysis (Alifujiang

et al., 2023). All geospatial layers were projected to Merchich / Nord Maroc. Topographical sinks in the ALOS PALSAR DEM (12.5 m) were removed using the ‘Fill’ tool in ArcGIS 10.8 (Mikkonen, 2021). The drainage network was automatically generated using the D8 algorithm with a flow accumulation threshold of 1000 cells. Structural lineaments were extracted from Band 5 of Landsat 8/9 OLI using directional Sobel filtering (0°, 45°, 90°, 135°) and checked against the 1:50,000 geological map to eliminate roads and canals. Lineament and drainage densities were calculated using the ‘Line Density’ tool with a search radius of 2.5 km (Madani et al., 2024). Continuous factors (slope, precipitation, densities) were classified using the Natural Breaks (Jenks) method (Kalu et al., 2024). While 20 boreholes with pumping-test discharge data were compiled for spatial ROC validation, long-term continuous monthly piezometric time series (2002–2020) were available for only seven (7) official monitoring stations (PZ-01 to PZ-07) maintained by the Moulouya River Basin Agency (ABHM). The remaining 13 boreholes lacked multi-decadal historical tracking and presented significant data gaps (>45% missing values), making them unsuitable for time-series trend analysis. For the 7 selected reference piezometers, minor missing monthly values (<5% of total records) were completed using linear interpolation and spatial kriging to ensure time-series continuity for the Mann–Kendall and Sen’s slope tests. The original and imputed monthly piezometric data for these 7 stations are provided in Supplementary Table S1 and Table S8.

**Table 1.** Primary data sources, native resolution, and characteristics of the geo-environmental factors used in this study

| Series No. | Variable            | Data type      | Data sources & specific datasets                          | Native resolution       | Acquisition / reference date |
|------------|---------------------|----------------|-----------------------------------------------------------|-------------------------|------------------------------|
| 1          | Geomorphology       | Polygon        | Geomorphological Atlas, Oriental Morocco sheet            | Vector (1:50,000)       | 2018                         |
| 2          | Geology (Lithology) | Polygon        | Geological Map, Guercif Sheet (MEM)                       | Vector (1:50,000)       | 2015                         |
| 3          | Lineament density   | Line / Raster  | Landsat 9 OLI (Collection 2, Level-2, Path 199, Row 36)   | 30 m                    | July 2022 (cloud cover < 2%) |
| 4          | Slope               | Raster         | ALOS PALSAR RTC DEM (ASF DAAC)                            | 12.5 m                  | 2020                         |
| 5          | LULC                | Raster         | Sentinel-2 MSI (Level-2A), supervised classification      | 10 m                    | Summer 2022                  |
| 6          | Soil                | Polygon        | Harmonized World Soil Database (HWSD v2.0, FAO)           | ~1 km (30 arc-sec)      | 2023                         |
| 7          | Drainage density    | Raster         | Derived from ALOS PALSAR DEM                              | 12.5 m                  | 2020                         |
| 8          | Precipitation       | Point / Raster | Moulouya River Basin Agency (ABHM) (Interpolated via IDW) | Meteorological stations | 2002–2022 average            |

## Methodologies

The assessment of groundwater potential is based on a four-part methodological protocol, carried out in a GIS environment (Sepúlveda-Oviedo et al., 2023). This approach enabled transforming heterogeneous variables into consistent spatial indicators through four successive processing steps (Moro et al., 2018).

The preliminary stage involved compiling and integrating a multi-source dataset in a GIS environment, which formed the analytical basis for the hydrogeological assessment (N. Li et al., 2025).

The subsequent phase was dedicated to determining the weighting coefficients for each thematic layer (Sohail, 2026). To increase the robustness of the decision-making process, we opted for a hybrid approach combining the analytic hierarchy process (AHP) and the multiple influencing factors (MIF) method (Sun et al., 2020).

During the third phase, these weightings were aggregated using a weighted overlay protocol in a GIS environment, resulting in the final spatialization of the hydrogeological potential (Mikkonen, 2021). Finally, the model's reliability and accuracy were rigorously tested by analyzing the receiver operating characteristic (ROC) curve, as shown in Figure 2 (Kabenla et al., 2024).

At the same time, the temporal dynamics of the aquifers were put into perspective by zoning

potentiality to corroborate the consistency between the observed piezometric fluctuations and the modeled aquifer potential (Agrawal, 2021). Multi-decadal monthly piezometric monitoring (2002–2020) was recorded for 7 reference stations (PZ-01 to PZ-07; >95% completeness) managed by the ABHM, with minor missing data (<5%) gap-filled via linear interpolation. An independent dataset of 20 field-verified boreholes (13 productive, 7 unproductive) was utilized for static single-point spatial validation. (Chen et al., 2022). The non-parametric Mann-Kendall test was applied to detect monotonic trends, while Sen's slope estimator was used to determine the rate of change. The analysis was conducted at two complementary time scales (Elbarghmi, Ghalit, Abourrich, El khalki, et al., 2024): first, on a monthly basis to capture seasonal variations, and second, on an annual basis to evaluate the long-term interannual trend (Ennaji et al., 2022). Figure 2 shows the methodology used.

## Analytic hierarchy process

The analytic hierarchy process provides a rigorous formalization framework for solving multidimensional decision-making problems, allowing complex issues to be broken down into a coherent hierarchical structure (N. Nouayti et

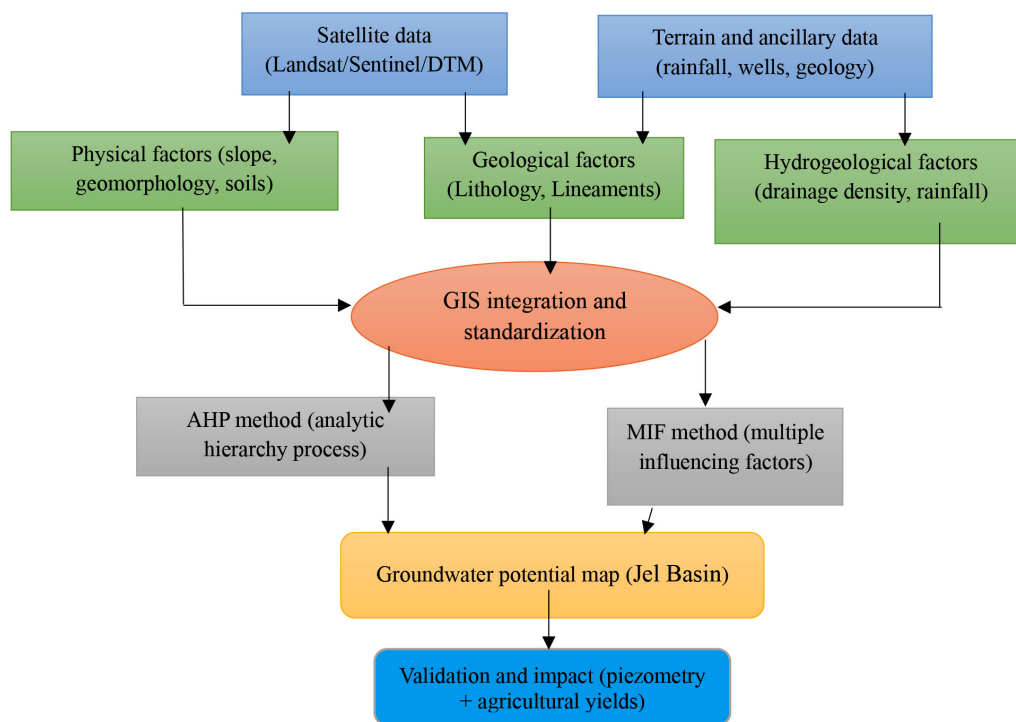


**Figure 2.** The methodological flowchart for this study

al., 2022b). In this investigation, this method was used to quantify the relative weights of each geo-environmental descriptor and rank their contributions to the occurrence of groundwater resources (Akoteyon, 2013). The operational application of the AHP was conducted using a four-part approach, ensuring a structured breakdown of the decision-making process (Table 2):

- Structuring the decision hierarchy: The model is organized according to a multi-level progression, placing the estimation of water potential as the highest point of convergence for all analysis variables (Awadh et al., 2016). Under the top-level objective, the lower-level groups group key geo-environmental descriptors (lithology, slope, fracturing, etc.), thereby forming the basis for the multi-criteria analysis (F. A. Saadi et al., 2024).
- Construction of the pairwise comparison matrix: Interactions between criteria are formalized within a square matrix of dimension ( $n \times n$ ). Each parameter is systematically compared with the others according to Saaty's fundamental scale, graded from 1 (equivalent influence) to 9 (absolute dominance) (Laghzal & Nouayti, 2018b).
- Calculation of priority vectors: This phase is based on the standardization of the judgment matrix; each value is reported to the cumulative total of its respective column (Talbi et al., 2022). This process generates a normalized matrix from which the specific weight of each variable is extracted (Frappart & Ramillien, 2018b). The principal eigenvector ( $W$ ) is obtained by averaging the normalized matrix's horizontal components, thereby determining the final weighting coefficients for each geo-environmental descriptor (Smith Sr et al., 2020).

- Consistency check: To verify the rationality of pairwise comparisons and rule out any inconsistency bias in subjective judgments, the robustness of the matrix is checked by calculating the Consistency Ratio (CR) (Fikri et al., 2024). This quality control is based on the following mathematical formalism:

For the  $8 \times 8$  pairwise comparison matrix (Table 2), the principal eigenvalue was computed as  $\lambda_{\max} = 8.234$ , yielding a consistency index of  $CI = 0.033$  (Mekkaoui et al., 2026). Using the standard Random index for  $n = 8$  ( $RI = 1.410$ ), the final consistency ratio was determined as  $CR = 0.024$  (2.4%) (Toulotte et al., 2022b). Because this value is well below the critical threshold of 0.10 (10%), the pairwise comparison matrix demonstrates acceptable mathematical consistency and the expert judgments are considered robust. The full step-by-step intermediate calculations and normalization matrices are provided in Supplementary Table S3 (Al-Raggad et al., 2021b).

The pairwise matrix was normalized using Equation (1) (N. Nouayti et al., 2022c):

$$r_{ij} = a_{ij} / \sum a_{kj} \quad (1)$$

where:  $r_{ij}$  – normalized value of the element in row  $i$  and column  $j$ ,  $a_{ij}$  – initial judgment value comparing criterion  $i$  to criterion  $j$  (from 1 to 9),  $\sum a_{kj}$  – sum of all values in column  $j$ .

The weight ( $Wi$ ) of each factor was calculated by averaging each row (N. Nouayti et al., 2015c):

$$Wi = (1/n) \cdot \sum r_{ij} \quad (2)$$

where:  $Wi$  – priority weight of criterion  $i$  (expressed as a percentage  $\sum Wi = 100\%$ ),  $n$  – total number of conditioning criteria

**Table 2.** Pairwise comparison AHP matrix

| Criteria          | C1  | C2  | C3  | C4  | C5  | C6  | C7  | C8 | Weight (%) |
|-------------------|-----|-----|-----|-----|-----|-----|-----|----|------------|
| C1. Geology       | 1   | 1   | 2   | 3   | 4   | 5   | 6   | 7  | 26.02%     |
| C2. Precipitation | 1   | 1   | 2   | 3   | 4   | 5   | 6   | 7  | 26.02%     |
| C3. Slope         | 1/2 | 1/2 | 1   | 2   | 3   | 4   | 5   | 6  | 17.15%     |
| C4. Lineament     | 1/3 | 1/3 | 1/2 | 1   | 2   | 3   | 4   | 5  | 11.57%     |
| C5. Drainage      | 1/4 | 1/4 | 1/3 | 1/2 | 1   | 2   | 3   | 4  | 7.81%      |
| C6. LULC          | 1/5 | 1/5 | 1/4 | 1/3 | 1/2 | 1   | 2   | 3  | 5.28%      |
| C7. Soil          | 1/6 | 1/6 | 1/5 | 1/4 | 1/3 | 1/2 | 1   | 2  | 3.60%      |
| C8. Geomorphology | 1/7 | 1/7 | 1/6 | 1/5 | 1/4 | 1/3 | 1/2 | 1  | 2.55%      |
| Total             |     |     |     |     |     |     |     |    | 100.00%    |

evaluated ( $n = 8$ ),  $r_{ij}$  – normalized value in row  $i$  and column  $j$ .

The consistency index was calculated using Equation (3) (Assouani et al., 2024):

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

where:  $CI$  – consistency index,  $\lambda_{\max}$  – principal eigenvalue of the pairwise matrix (for our matrix,  $\lambda_{\max} = 8.234$ ),  $n$  – size of the matrix/number of criteria ( $n = 8$ ).

The consistency ratio was determined using Equation (4) (Elbarghmi, Ghalit, Abourrich, El Khalki, et al., 2024):

$$CR = CI / RI \quad (4)$$

where:  $CR$  – consistency ratio ( $CR = 0.024$  or  $2.4\%$ ),  $CI$  – consistency index ( $CI = 0.033$ ),  $RI$  – random inconsistency index ( $RI = 1.41$  for an  $8 \times 8$  matrix).

## Multi-influential factors method

In contrast to the strictly top-down hierarchy of the AHP, the Multiple Influencing Factors (MIF) technique investigates systemic interdependencies and causal feedback mechanisms operating among hydrogeological variables (O. Saadi et al., 2021a). This empirical framework evaluates how each geo-environmental parameter shapes and is shaped by other system components. The methodology was applied across the eight (8) selected conditioning factors through a structured three-stage protocol (Ennaji et al., 2022):

### 1) Delineation and scoring of interrelationships:

Direct and indirect interactions between pairs of factors were identified based on physical hydrologic behavior. A dual-weighting numerical scale was applied:

- A score of 1.0 was attributed to major influences, where a factor exerts a direct, primary control over another (e.g., bedrock lithology fundamentally governing lineament patterns and infiltration capacity) (Boutsougame et al., 2022).
- A score of 0.5 was assigned to minor influences, representing secondary or indirect effects (e.g., vegetative land cover exerting subordinate control on infiltration pathways and surface runoff) (Andalu et al., 2026).

### 1. Aggregation of cumulative influence scores:

For each specific descriptor, the individual values of major (1.0) and minor (0.5) interactions

were summed to establish its overall cumulative impact score ( $S_i$ ) (Siderska et al., 2023a).

2. Normalization and weight allocation: The final relative weight ( $W_i$ ) of each variable was computed by normalizing its cumulative score against the grand total of interaction scores generated across all eight descriptors ( $\sum S = 20.0$ ). This standardization is expressed as follows (Ahmed et al., 2025):

The assignment of major (1.0) and minor (0.5) influence scores is grounded in the physical and hydrogeological mechanics governing groundwater dynamics within the basin (Andalu et al., 2026). Geology exerts a major control (1.0) on lineament development, geomorphological features, and soil type, as lithological properties directly dictate rock deformation, fracture density, topographic relief, and weathering profiles (Oussama, 2024b). Conversely, geology has a minor influence (0.5) on drainage density, as drainage pathways are primarily controlled by surface slope and local precipitation patterns, with lithology playing only a secondary modifying role (Pande et al., 2021b). Similarly, precipitation exerts a major influence (1.0) on surface drainage density and soil moisture replenishment, but a minor influence (0.5) on slope stability and LULC dynamics. Geomorphology directly shapes slope gradients, surface runoff accumulation, and pedogenesis (1.0 each), while indirectly driving LULC patterns (0.5) (Agyemang et al., 2025a). Lineaments serve as primary structural conduits that govern local drainage network development and lithological exposure (1.0 each), while playing a minor role in overall geomorphological evolution (0.5) (Andrade & Barbosa, 2015). Finally, LULC and soil parameters exhibit subordinate, secondary interactions (0.5) on infiltration rates and surface drainage pathways, acting predominantly as local regulating factors rather than primary drivers of the basin-scale hydrogeological regime (Kabenla et al., 2024).

To ensure complete methodological transparency and full reproducibility of expert assessments, the raw pairwise interaction matrix detailing major (1.0), minor (0.5), and zero (0.0) influence scores assigned between all eight geo-environmental factors is provided in Supplementary Table S4.

For each factor, the cumulative score ( $S_i$ ) was calculated using Equation (5) (Taibou et al., 2025):

$$S_i = \sum (Major \cdot 1.0) + \sum (Minor \cdot 0.5) \quad (5)$$

**Table 3.** Effect of influencing factor, relative rates, and score for each potential factor at the Jel Basin level

| Factors          | Major influences<br>(score 1.0 each)      | Minor influences<br>(score 0.5 each) | Total score | Weight (%) |
|------------------|-------------------------------------------|--------------------------------------|-------------|------------|
| Geology          | Lineament, geomorphology,<br>soil (1+1+1) | Drainage density (0.5)               | 3.5         | 17.50%     |
| Geomorphology    | Slope, drainage density,<br>soil (1+1+1)  | LULC (0.5)                           | 3.5         | 17.50%     |
| Precipitation    | Drainage density, soil (1+1)              | Slope, LULC (0.5+0.5)                | 3           | 15.00%     |
| Slope            | Drainage density, soil (1+1)              | LULC (0.5)                           | 2.5         | 12.50%     |
| Lineament        | Drainage density,<br>geology (1+1)        | Geomorphology (0.5)                  | 2.5         | 12.50%     |
| Drainage density | Soil (1.0)                                | Slope, geomorphology<br>(0.5+0.5)    | 2           | 10.00%     |
| Soil             | LULC (1.0)                                | Drainage density, slope<br>(0.5+0.5) | 2           | 10.00%     |
| LULC             | None (0)                                  | Soil, drainage density<br>(0.5+0.5)  | 1           | 5.00%      |
| Total            |                                           |                                      | 20          | 100.00%    |

where:  $S_i$  – total cumulative score of factor  $i$ , *Major* – number of major direct influences exerted by factor  $i$  (assigned a score of 1.0 each), *Minor* – number of minor indirect influences exerted by factor  $i$  (assigned a score of 0.5 each).

The final normalized weight was computed using Equation (6) :

$$W_i = (S_i / \Sigma S) \cdot 100 \quad (6)$$

where:  $W_i$  – final normalized weight of factor  $i$  (%),  $S_i$  – cumulative score of factor  $i$ ,  $\Sigma S$  – sum of cumulative scores across all 8 criteria ( $\Sigma S = 20.0$ ).

### GIS integration and weighted overlay analysis

The concluding phase of the predictive workflow involves merging the thematic spatial indicators into a consolidated Groundwater Potential Index (GWPI) (Dey et al., 2025b). Executed within the ArcGIS 10.8 environment, this spatial integration was achieved through the Weighted Overlay Analysis (WOA) tool, wherein the spatial contribution of each predictor is governed by the importance coefficients derived independently from the AHP and MIF models (Agyemang et al., 2025b). The procedure followed two sequential steps, detailed in Table 4:

- Layer discretization and attribute standardization: Because the eight geo-environmental indicators are characterized by disparate dimensional units and measurement scales (e.g.,

angular slopes, lineament densities, millimeter precipitation, and categorical lithologies), they were transformed into dimensionless, commensurable numerical classes. Each parameter was classified into homogeneous sub-units and assigned a suitability score ( $R_i$ ) ranging from 1 to 9 based on its physical influence on groundwater recharge (Y. Wang et al., 2023). Classes that actively foster percolation such as gentle topographic slopes that reduce runoff velocity, intensely fractured zones, and permeable Quaternary sands received the highest scores (e.g., 8 or 9). Conversely, unfavorable features that accelerate surface drainage or restrict permeability (e.g., steep gradients and massive crystalline basements) were assigned low scores (e.g., 1 or 3) (Ahmadi et al., 2024).

- Spatial weighted overlay and derivation of the GWPI: The standardized thematic layers were spatially integrated using a pixel-by-pixel multi-attribute overlay algorithm (Neyshabouri et al., 2026). In this computation, each cell value represents the sum of the subclass ratings ( $R_i$ ) weighted by their respective percentage coefficients ( $W_i$ ), generating a continuous raster surface of hydrogeological prospectivity across the basin. To guarantee complete transparency and an unambiguous numerical reconstruction of the predictive rasters, the explicit final contribution of each subclass ( $W_i \cdot R_i$ ) is detailed alongside the weights and ratings in Table 4, according to Equation (7):

$$GWPI = (W_1 \cdot R_1) + (W_2 \cdot R_2) + \dots + (W_n \cdot R_n) = \sum (W_i \cdot R_i) \quad (7)$$

**Table 4.** Thematic layers with subclasses, their ranks and weightage in the Jel basin

| Factor        | Sub-class                          | AHP weight | AHP rank | AHP score | MIF weight | MIF rank | MIF score |
|---------------|------------------------------------|------------|----------|-----------|------------|----------|-----------|
| Geology       | Sand / Alluvium                    | 26.02%     | 9        | 2.342     | 17.50%     | 9        | 1.575     |
| Geology       | Limestone                          | 26.02%     | 8        | 2.082     | 17.50%     | 8        | 1.4       |
| Geology       | Clay                               | 26.02%     | 3        | 0.781     | 17.50%     | 3        | 0.525     |
| Geology       | Granite                            | 26.02%     | 1        | 0.260     | 17.50%     | 1        | 0.175     |
| Precipitation | 180 – 200 mm                       | 26.02%     | 9        | 2.342     | 15.00%     | 9        | 1.35      |
| Precipitation | 160 – 180 mm                       | 26.02%     | 7        | 1.821     | 15.00%     | 7        | 1.05      |
| Precipitation | 140 – 160 mm                       | 26.02%     | 5        | 1.301     | 15.00%     | 5        | 0.75      |
| Precipitation | 120 – 140 mm                       | 26.02%     | 3        | 0.781     | 15.00%     | 3        | 0.45      |
| Precipitation | 100 – 120 mm                       | 26.02%     | 1        | 0.260     | 15.00%     | 1        | 0.15      |
| Slope         | 0 – 5°                             | 17.15%     | 9        | 1.544     | 12.50%     | 9        | 1.125     |
| Slope         | 5 – 15°                            | 17.15%     | 7        | 1.201     | 12.50%     | 7        | 0.875     |
| Slope         | 15 – 30°                           | 17.15%     | 5        | 0.858     | 12.50%     | 5        | 0.625     |
| Slope         | 30 – 45°                           | 17.15%     | 3        | 0.515     | 12.50%     | 3        | 0.375     |
| Slope         | > 45°                              | 17.15%     | 1        | 0.172     | 12.50%     | 1        | 0.125     |
| Lineament     | 0.48 – 0.60 km/<br>km <sup>2</sup> | 11.57%     | 9        | 1.041     | 12.50%     | 9        | 1.125     |
| Lineament     | 0.36 – 0.48 km/<br>km <sup>2</sup> | 11.57%     | 7        | 0.810     | 12.50%     | 7        | 0.875     |
| Lineament     | 0.24 – 0.36 km/<br>km <sup>2</sup> | 11.57%     | 5        | 0.579     | 12.50%     | 5        | 0.625     |
| Lineament     | 0.12 – 0.24 km/<br>km <sup>2</sup> | 11.57%     | 3        | 0.347     | 12.50%     | 3        | 0.375     |
| Lineament     | 0.00 – 0.12 km/<br>km <sup>2</sup> | 11.57%     | 1        | 0.116     | 12.50%     | 1        | 0.125     |
| Drainage      | 0.00 – 0.50 km/<br>km <sup>2</sup> | 7.81%      | 9        | 0.703     | 10.00%     | 9        | 0.9       |
| Drainage      | 0.50 – 1.00 km/<br>km <sup>2</sup> | 7.81%      | 7        | 0.547     | 10.00%     | 7        | 0.7       |
| Drainage      | 1.00 – 1.50 km/<br>km <sup>2</sup> | 7.81%      | 5        | 0.391     | 10.00%     | 5        | 0.5       |
| Drainage      | 1.50 – 2.00 km/<br>km <sup>2</sup> | 7.81%      | 3        | 0.234     | 10.00%     | 3        | 0.3       |
| Drainage      | > 2.00 km/km <sup>2</sup>          | 7.81%      | 1        | 0.078     | 10.00%     | 1        | 0.1       |
| LULC          | Water bodies /<br>Rivers           | 5.28%      | 9        | 0.475     | 5.00%      | 9        | 0.45      |
| LULC          | Agricultural<br>crops              | 5.28%      | 7        | 0.370     | 5.00%      | 7        | 0.35      |
| LULC          | Trees /<br>Vegetation              | 5.28%      | 6        | 0.317     | 5.00%      | 6        | 0.3       |
| LULC          | Rangeland /<br>bare ground         | 5.28%      | 4        | 0.211     | 5.00%      | 4        | 0.2       |
| LULC          | Built-up area                      | 5.28%      | 1        | 0.053     | 5.00%      | 1        | 0.05      |
| Soil          | Regosols                           | 3.60%      | 8        | 0.288     | 10.00%     | 8        | 0.8       |
| Soil          | Technosols                         | 3.60%      | 3        | 0.108     | 10.00%     | 3        | 0.3       |
| Geomorphology | Sandy plains                       | 2.55%      | 9        | 0.230     | 17.50%     | 9        | 1.575     |
| Geomorphology | Limestone<br>outcrops              | 2.55%      | 7        | 0.179     | 17.50%     | 7        | 1.225     |
| Geomorphology | Dissected clay<br>slopes           | 2.55%      | 3        | 0.077     | 17.50%     | 3        | 0.525     |
| Geomorphology | Granitic massif                    | 2.55%      | 1        | 0.026     | 17.50%     | 1        | 0.175     |
| Total         | —                                  | 100.00%    | —        | Max: 8.97 | 100.00%    | —        | Max: 8.90 |

**Note:** Score represents the final numerical contribution calculated as weight · rank ( $W_i \cdot R_i$ ).

where:  $GWPI$  – is the groundwater potential index,  $W_i$  – is the normalized weight of factor  $i$  (derived from AHP or MIF),  $R_i$  – is the rank of the subclass of factor  $i$ .

The explicit mathematical formulation for the AHP-based  $GWPI$  model is defined as:

$$GWPI_{AHP} = (0.2602 \cdot R_{Geol}) + (0.2602 \cdot R_{Rain}) + (0.1715 \cdot R_{Slope}) + (0.1157 \cdot R_{Lin}) + (0.0781 \cdot R_{Drain}) + (0.0528 \cdot R_{LULC}) + (0.0360 \cdot R_{Soil}) + (0.0255 \cdot R_{Geomorph})$$

The explicit mathematical formulation for the MIF-based  $GWPI$  model is defined as:

$$GWPI_{MIF} = (0.1750 \cdot R_{Geol}) + (0.1750 \cdot R_{Geomorph}) + (0.1500 \cdot R_{Rain}) + (0.1250 \cdot R_{Slope}) + (0.1250 \cdot R_{Lin}) + (0.1000 \cdot R_{Drain}) + (0.1000 \cdot R_{Soil}) + (0.0500 \cdot R_{LULC})$$

### Validation of this study using ROC analysis

The model-building and validation datasets were strictly separated. The AHP and MIF models were constructed using eight spatial conditioning factors (Chen et al., 2022): geology, geomorphology, slope, lineament density, drainage density, soil, land use/land cover, and rainfall (J. Li et al., 2026). The AHP weights were derived from the pairwise comparison matrix, while the MIF scores were assigned according to the relative influence of the conditioning factors (Pande et al., 2021b). The 20 boreholes listed in Supplementary Table S5 were used exclusively for independent post-hoc validation (Agyemang et al., 2025a). They were not used to select the conditioning factors, assign or modify the AHP/MIF weights, define the reclassification thresholds, or tune the models. The AHP and MIF maps and parameters were finalized before the borehole scores were extracted for ROC/AUC analysis (Ahmadi et al., 2024). The predictive reliability of the generated groundwater prospectivity maps was quantitatively validated using receiver operating characteristic (ROC) analysis (Al-Kilabi, 2018). Ground-truth verification was performed using a curated spatial dataset of 20 field-audited boreholes obtained from the official monitoring records of the Moulouya River Basin Agency (ABHM), distributed across the physiographic sub-basins of the Jel plain (Al-Paruany et al., 2017). To implement the binary performance test, the 20 control boreholes were divided into two distinct operational classes

according to in-situ hydrogeological characteristics (Ouakhir et al., 2025):

- Positive group (P = 13): High-to-moderate productivity water points defined by an extraction discharge  $Q \geq 2.5$  L/s and accessible water table levels ( $< 40$  m) (Elbarghmi, Ghalit, Abourrich, El khalki, et al., 2024).
- Negative group (N = 7): Low-yielding, marginal, or unproductive wells exhibiting a discharge  $Q < 1.0$  L/s or dry borehole columns (Hafiane, Tahri, Nouayti, El Jarmouni, Arifi, et al., 2020).

To prevent data contamination and ensure an authentic assessment of model predictability, an independent validation protocol was maintained:

- Spatial predictors (lithology, geomorphology, slope, lineaments, drainage, soils, precipitation, and land cover) were utilized exclusively for multi-criteria model construction (AHP and MIF) (Laghrib et al., 2024b).
- The 20 control boreholes were preserved strictly as an external, post-hoc benchmark for statistical validation and were not involved in weight assignments or thematic standardization (Ahmed et al., 2025).
- The 7 continuous piezometric stations evaluated for multi-year dynamic trends (2002–2020) represent a subset of monitored points with long-term monthly records, distinct from the static single-point pumping discharge measurements of the 20 validation boreholes, thereby avoiding data redundancy or circular reasoning (Agyemang et al., 2025a).

The receiver operating characteristic (ROC) curve evaluates classification performance across continuous decision thresholds ( $t$ ) by plotting the true positive rate against the false positive rate (Kabenla et al., 2024):

$$ROC(t) = (FPR(t), TPR(t)) \quad (8)$$

where:  $ROC(t)$  – spatial coordinate pair on the ROC curve at decision threshold  $t$ ,  $t$  – numerical cut-off threshold applied to the groundwater potential index ( $GWPI$ ),  $TPR(t)$  – true positive rate (sensitivity) plotted along the vertical y-axis,  $FPR(t)$  – false positive rate ( $1 - \text{specificity}$ ) plotted along the horizontal x-axis.

The sensitivity ( $TPR$ ) and false positive rate ( $FPR$ ) coordinates are calculated from the 20 reference wells (Equation 9 and 10):

$$TPR(t) = TP(t) / P = TP(t) / 13 \quad (9)$$

$$FPR(t) = FP(t) / N = FP(t) / 7 \quad (10)$$

where:  $TPR(t)$  – proportion of actual productive boreholes correctly classified as favorable,  $FPR(t)$  – proportion of non-productive boreholes incorrectly identified as favorable,  $TP(t)$  – count of true positive boreholes with  $GWPI \geq t$ ,  $FP(t)$  – count of false positive boreholes with  $GWPI \geq t$ ,  $P$  – total number of positive productive control wells ( $P = 13$ ),  $N$  – total number of negative low-yield control wells ( $N = 7$ ).

The global predictive accuracy of the AHP and MIF models is quantified through the area under the curve (AUC) using trapezoidal numerical integration (Pande et al., 2021b):

$$AUC = \sum [(TPR_k + TPR_{k-1}) / 2] \cdot (FPR_k - FPR_{k-1}) \quad (11)$$

where:  $AUC$  – area under the ROC curve (yielding 93.4% for AHP and MIF),  $TPR_k$  and  $TPR_{k-1}$  – true positive rates computed at successive decision thresholds  $k$  and  $k-1$ ,  $FPR_k$  and  $FPR_{k-1}$  – false positive rates computed at successive decision thresholds  $k$  and  $k-1$ ,  $\Sigma$  – cumulative summation of all individual trapezoidal areas from  $FPR = 0$  to  $FPR = 1$ .

The individual borehole attributes, geographic coordinates, measured discharge rates, and extracted GWPI scores are cataloged in Supplementary Table S5 and Supplementary Data S1.xlsx. Detailed step-by-step contingency tables and ROC threshold coordinates are presented in Supplementary Tables S6a and S6b.

### Mann-Kendall test and sen slope at the Jel basin level

The non-parametric Mann-Kendall test was used to evaluate monotonic groundwater trends over the 2002–2020 period (Chen et al., 2022). The test statistic ( $S$ ) was calculated using Equation (12):

$$S = \sum_{k=1}^{N-1} \sum_{j=k+1}^N \text{sgn}(x_j - x_k) \quad (12)$$

where:  $S$  – Mann-Kendall test statistic,  $N$  – number of observation years in the time series ( $N = 19$ ),  $x_j$  – groundwater level recorded in year  $j$ ,  $x_k$  – groundwater level recorded in year  $k$  (with  $j > k$ ),  $\text{sgn}(x_j - x_k)$  – sign

function comparing two temporal measurements (Ehsan et al., 2024).

The sign function  $\text{sgn}(x_j - x_k)$  was defined using Equation (13) (Ennaji et al., 2022):

$$\begin{aligned} \text{sgn}(x_j - x_k) &= +1 \text{ if } (x_j - x_k) > 0 \\ \text{sgn}(x_j - x_k) &= 0 \text{ if } (x_j - x_k) = 0 \\ \text{sgn}(x_j - x_k) &= -1 \text{ if } (x_j - x_k) < 0 \end{aligned} \quad (13)$$

where:  $+1$  – indicates an increase in groundwater table over time,  $0$  – indicates no change (equal consecutive observations),  $-1$  – indicates a decrease in groundwater table over time.

The variance of  $S$ , accounting for tied values (equal depths), was calculated using Equation (14) (O. Saadi et al., 2021a):

$$Var(S) = [N \cdot (N - 1) \cdot (2N + 5) - \sum tp \cdot (tp - 1) \cdot (2tp + 5)] / 18 \quad (14)$$

where:  $Var(S)$  – variance of the Mann-Kendall statistic  $S$ ,  $N$  – length of the monitoring timeframe ( $N = 19$ ),  $tp$  – number of tied data points in group  $p$ .

The standardized test statistic ( $Z$ ) was computed using Equation (N. Nouayti et al., 2016) (15):

$$\begin{aligned} Z &= (S - 1) / \sqrt{Var(S)} \text{ if } S > 0 \\ Z &= 0 \text{ if } S = 0 \\ Z &= (S + 1) / \sqrt{Var(S)} \text{ if } S < 0 \end{aligned} \quad (15)$$

where:  $Z$  – standardized Mann-Kendall test statistic,  $S$  – Mann-Kendall test statistic,  $Var(S)$  – variance of  $S$ .

Note: At  $\alpha = 0.05$ , a value of  $|Z| > 1.96$  confirms a statistically significant trend (positive  $Z$  = rising water table; negative  $Z$  = declining water table).

The rate of annual change was estimated using Sen's slope estimator across all distinct pairs ( $M = 171$  pairwise combinations) using Equation (16) (Chen et al., 2022):

$$Qm = (x_j - x_k) / (j - k) \text{ for } 1 \leq k < j \leq N \quad (16)$$

where:  $Qm$  – individual slope between groundwater measurements at years  $j$  and  $k$ ,  $x_j$  and  $x_k$  – groundwater depths measured at years  $j$  and  $k$ ,  $j$  and  $k$  – observation year indices.

The true median annual drift ( $\beta$ ) was calculated using Equation (17) (O. Saadi et al., 2021b):

$$\beta = \text{Median}(Q_m) \quad (17)$$

where:  $\beta$  – Sen's slope estimator expressed in meters per year (m/year),  $Q_m$  – set of all 171 individual slopes calculated across the 19-year period, Median – middle value of all ranked slopes (positive  $\beta$  = rising water table; negative  $\beta$  = water table drawdown).

## RESULTS AND DISCUSSIONS

### Criteria influencing groundwater in the Jel Basin

#### Geomorphology

Figure 3 shows the geomorphology map of the Jel basin, which is a transition zone between mountainous terrain and plains (Xanke & Liesch, 2022). This map is divided into four classes below (Huguet, 2023):

- Granitic massif: Granite is a hard, crystalline plutonic rock which, from a geomorphological point of view, corresponds to high-altitude areas (Save et al., 2016).
- Limestone outcrops: This is a permeable rock, which is absorbed by the soil. Geomorphologically, it corresponds to medium-altitude areas (A. Nouayti et al., 2019).
- Dissected clay slopes: This is an impermeable rock, which means that erosion is the dominant

phenomenon (O. Saadi et al., 2021a). From a geomorphological point of view, it corresponds to medium-altitude areas.

- Sandy plains: This is a class corresponding to high permeability, with a very high recharge rate (Ennaji et al., 2022). From a geomorphological perspective, it is a low-altitude area.

From a hydrological point of view, the hydrographic network (blue line) is denser, indicating significant runoff, with a strong erosive response during precipitation (Rhazi et al., 2017). The integration of the 'Distance to surface water' criterion significantly refined the model's predictive accuracy (Meng et al., 2019). In the Jel Basin, riparian zones often coincide with Quaternary alluvial deposits (sands and gravels) characterized by high hydraulic conductivity ( $10^{-4}$  m/s) (Azzirgue et al., 2023b), the strong spatial correlation between high-potential zones and the hydrographic network is attributed to the presence of an alluvial aquifer (bank storage) recharged through direct infiltration from the Moulouya and Melloulou wadis, particularly during seasonal flood events (Darkaoui et al., 2022).

#### Geology

Figure 4 shows the geological (lithological) map of the Jel basin, which plays a key role in groundwater storage and is composed of five main units (Hafiane, Tahri, Nouayti, El Jarmouni, Rochdi, et al., 2020):

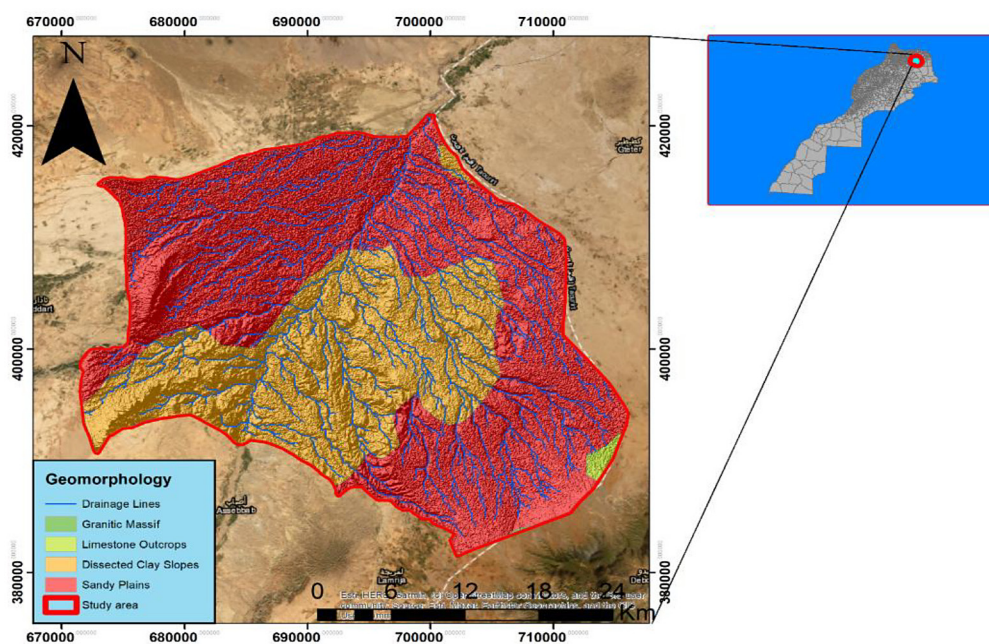


Figure 3. The geomorphology map of the Jel Basin

- Granite: A crystalline and compact igneous rock that is impermeable from a hydrogeological point of view. It delimits the extent of the Jel aquifer (Siderska et al., 2023b).
- Limestone: A permeable rock that contains a lot of water (Elaaraj et al., 2025). Its permeability is too high, and limestone plays a very important role in the transfer of surface water to deep aquifers. From a geological perspective, it is a carbonate sedimentary rock. Therefore, the Jel aquifer contains natural drains (Hasanuzzaman et al., 2022).
- Clay: This is an impermeable rock with a very low infiltration rate (Dey et al., 2025a). It protects the aquifer from pollution. Geologically, it is a very fine-grained rock (Amaya et al., 2021b).
- Sand: This is a permeable rock, and rainwater easily penetrates the soil. In our study, this is the most important class (Neyshabouri et al., 2026).

### Soil

Figure 5 shows the soil map at ground level, which contains two main classes:

- Regosols: These are soils formed on loose outcrops such as clay and sand (Sastanti & Fibriani, 2019). From a geological perspective, Regosols are deposited on active sedimentary formations, indicating that our area is an active sedimentary basin.
- Technosols: These are anthropogenic materials. From a hydrogeological perspective, they

prevent rainwater from infiltrating vertically. This indicates a reduction in direct recharge (Ahmadi et al., 2024).

### Slope

Figure 6 shows the slope map, which divides the area into three zones:

- Low slope area ( $0-5^\circ$  and  $5-15^\circ$ ). From a hydrogeological perspective, this is an area with high recharge potential (Collon et al., 2015). Gentle slopes ( $0-5^\circ$  and  $5-15^\circ$ ) reduce runoff velocity, increasing contact time and promoting vertical rainwater infiltration into the aquifer (Ennaji et al., 2022).
- Medium slope area ( $15-30^\circ$  and  $30-45^\circ$ ). In the Jel basin, water flows rapidly downstream under gravity, with the average slope varying with runoff and erosion. The water then flows towards the plains. Due to the flow rate, the aquifer does not allow for effective direct recharge (Laghrib et al., 2024b).
- Steep slope area ( $>45^\circ$ ). At the Jel aquifer level, runoff is almost torrential, with virtually no infiltration (Elbarghmi, Ghalit, Abourrich, El khalki, et al., 2024). It depends on wadi formation during rainy periods (Ennaji et al., 2024).

### Rainfall

Figure 7 shows the precipitation map for the Jel basin. It shows rainfall variation from 100 to 200 mm/year. This map is divided into five

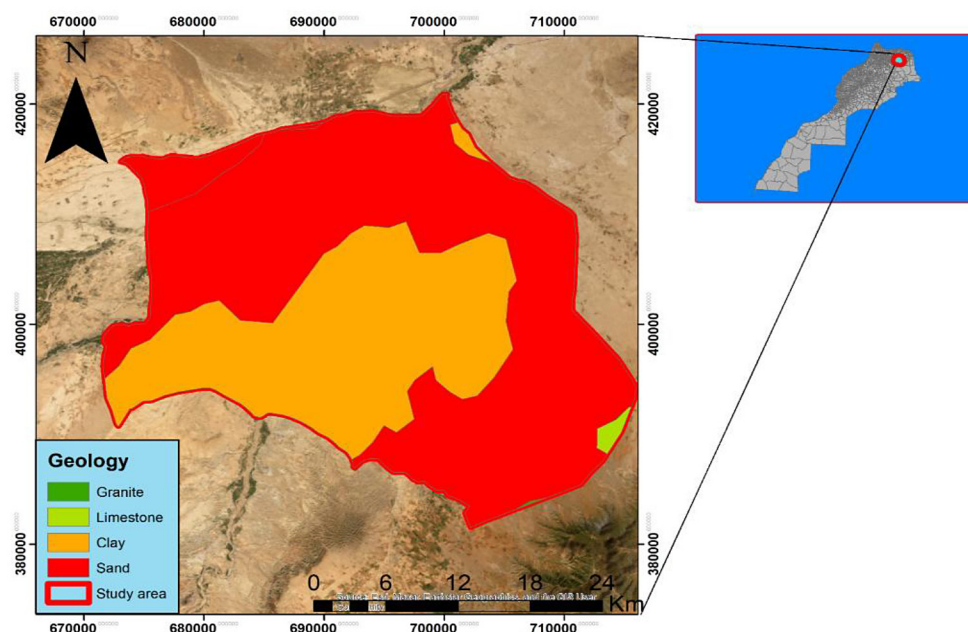


Figure 4. Lithological map of the Jel Basin

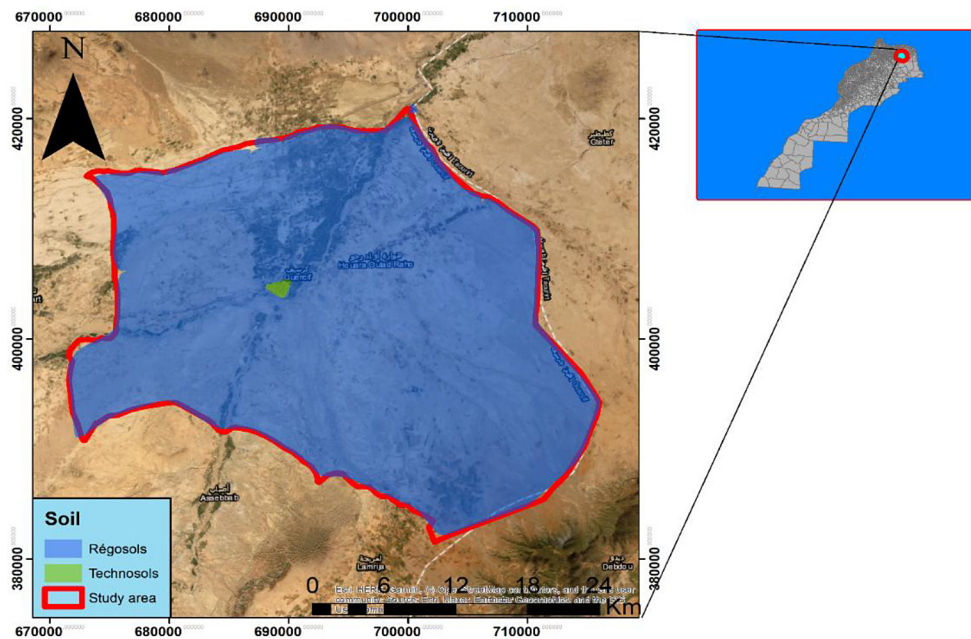


Figure 5. The soil map at the Jel basin level

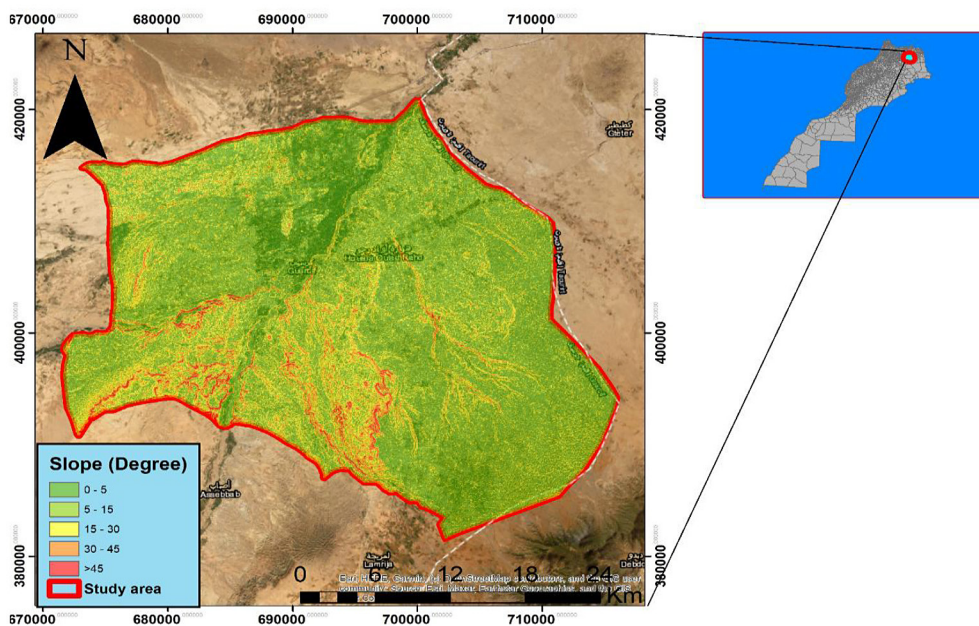


Figure 6. The slope map at the Jel basin

classes, showing an upward gradient from south to north:

- Lower class of 100 to 120 mm: This class is located in the south-central part of the Jel basin, which means that this area is arid, where the recharge of the Jel aquifer is almost zero due to a water deficit (Chen et al., 2022).
- Middle class from 120 to 160 mm: Covers the central part of the Jel basin, showing that annual inflows are moderate and constant (Hamid et al., 2024).

- Upper class of 160 to 200 mm: located on the northern and northwestern edges. From a hydrogeological point of view, recharge to the Jel aquifer is higher, indicating an increase in the piezometric level (Andalu et al., 2026).

#### LULC

Figure 8 shows the LULC (Land Use Land Cover) map for the Jel aquifer, which directly affects water consumption and recharge quality. This map is divided into four classes:

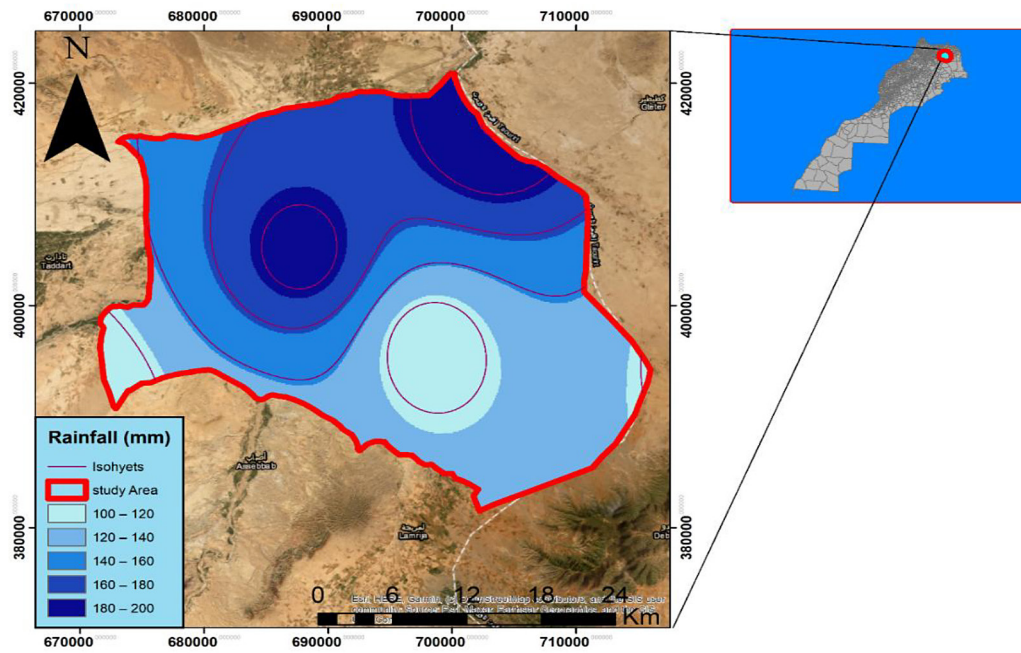


Figure 7. The rainfall map of the Jel basin

- Crops: This is the most important class for the hydrogeological study of the Jel aquifer, with agricultural areas distributed along the central axis of the study area (Sastanti & Fibriani, 2019). In a semi-arid context (100 to 200 mm of precipitation), irrigation of these crops becomes essential. This highlights the importance of pumping groundwater from the Jel aquifer (Taibou et al., 2025).
- Built Area: Located in the urban center of the city of Guercif, this is an area that depends on an increase in human resources (Andrade & Barbosa, 2015). From a hydrogeological point of view, the recharge of this aquifer is limited. This is because there is a risk of pollution (vulnerability of the water table).
- Rangeland/Bare Ground: These are the most important classes in terms of surface area, reflecting the semi-desert nature of our region (STEP, for example) (Zhao et al., 2026). From a hydrogeological point of view, these are natural recharge areas, which means there is

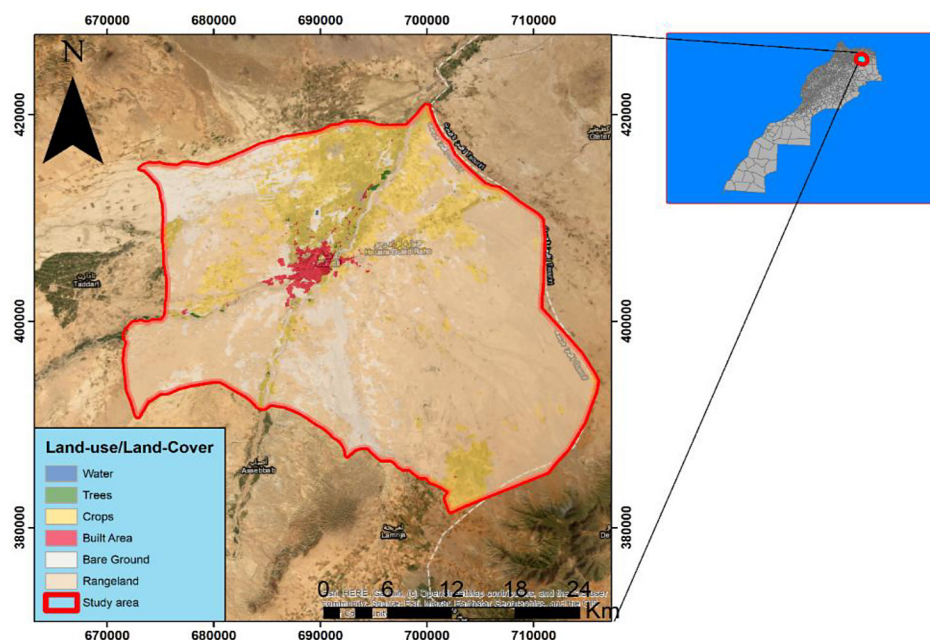


Figure 8. LULC of the Jel aquifer

no vegetation, allowing rainwater to reach the ground directly. On bare ground, the steep slope increases erosion (GOMES & Bias, 2018).

- **Trees/Water:** These classes are located at the Moulouya and Melloulou wadis. From a biological perspective, vegetation dominates. Regarding the region's hydrogeology, we observe an exchange between the water table and the river (Jel water table fed by rivers), indicating that the Jel aquifer supports the wadi's flow during droughts (Atoui & Agoubi, 2026).

#### Lineament density

The lineament density map of the Jel basin (Figure 9) contributes to the recharge of the eastern aquifers. This map was created from band 5 of Landsat OLI 9 using ArcGIS 10.8. From this result, we observe that in the red zone ( $0.48\text{--}0.60\text{ km/km}^2$ ), there is a significant concentration of lineaments in the southeastern part of the Jel aquifer (Ahmed et al., 2025). In the yellow zone ( $0.00\text{--}0.12\text{ km/km}^2$ ), the density is low in the northern part of the Jel aquifer. From a hydrogeological perspective, the increase in lineament density in the red color facilitates the infiltration of surface water into the deep groundwater table (A. Nouayti et al., 2019). This area is favorable for drilling wells due to fractures in rocks such as limestone, which indicates that permeability is high in the region (Najy et al., 2023).

#### Drainage density

Figure 10 shows the drainage density map for the Jel basin, which illustrates how rainwater flows and then infiltrates into the water table (N. Nouayti et al., 2017). This map varies from  $0.00\text{ km/km}^2$  to over  $2\text{ km/km}^2$ . In the red zone ( $>2\text{ km/km}^2$ ), we observe a high drainage density, indicating that water flows easily and infiltrates. However, in the yellow zone ( $0.00\text{ km/km}^2$ ), drainage density is low, contributing to infiltration into the eastern groundwater table (Taoufiq, Kacimi, Saadi, Nouayti, et al., 2023).

From a hydrological perspective, the dense hydrographic network indicates excessive runoff during precipitation events in the Jel basin (Chen et al., 2022).

#### Groundwater potential map for the Jel basin

Groundwater potential within the Jel aquifer was independently derived through two distinct multi-criteria frameworks, namely AHP (Figure 11b) and MIF (Figure 11b). Both outputs were subsequently reclassified into three discrete potentiality tiers (Y. Wang et al., 2023). For the AHP-based delineation, the resulting zonation reveals the following spatial arrangement:

- **High-potential sector:** concentrated mainly across the southern and southeastern portion of the study area, where the combined influence

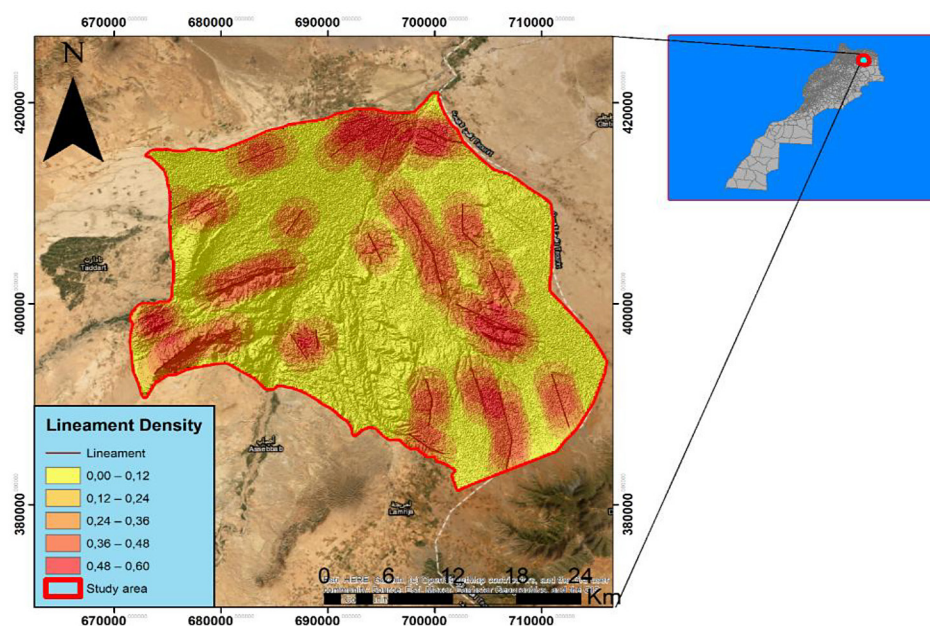


Figure 9. The density map of lineaments at the Jel aquifer

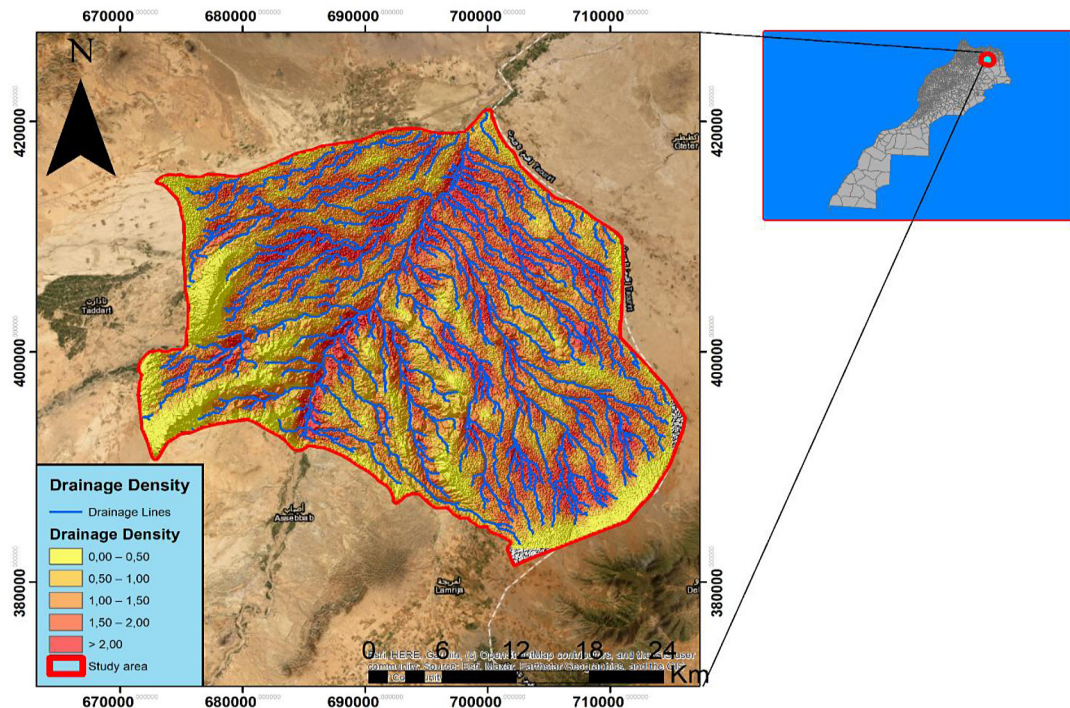


Figure 10. The drainage density map at the Jel water table level

of lithology and structural discontinuities enhances water infiltration into the subsurface (Ahmadi et al., 2024).

- Moderate-potential sector: extending over the central and northern stretch of the basin, corresponding to a transitional zone where hydrogeological conditions are only partially favorable (Agyemang et al., 2025a).
- Low-potential sector: appearing as isolated patches scattered throughout the northern edge of the basin, reflecting locally reduced fracturing and limited recharge capacity (Atoui & Agoubi, 2026).

The MIF-derived output, by contrast, produces a markedly different spatial signature:

- High-potential sector: restricted to a few discontinuous pockets located near the central portion of the basin (Elbarghmi, Ghalit, Abourrich, El khalki, et al., 2024).
- Moderate-potential sector: dominant across the central-to-southern stretch of the study area (Ennaji et al., 2022).
- Low-potential sector: prevailing over the northern and northwestern margins, where lithological units appear less conducive to groundwater storage (Hafiane, Tahri, Nouayti, El Jarmouni, Arifi, et al., 2020).

The strong agreement between the AHP and MIF results, reflected by their comparable AUC

values of 93.4%, further demonstrates the robustness and reliability of the delineated groundwater potential zones. This high level of agreement stems from the uniform quality of the input datasets and the consistent professional judgment applied during the weighting process (Baki et al., 2017). Since these two independent decision-making frameworks produce nearly matching spatial patterns, it suggests that the selected geo-environmental indicators for the Jel Basin are highly representative and that the final output remains stable, regardless of the specific mathematical algorithm employed (Meng et al., 2019).

### Validation of this study using the ROC method

To quantitatively ascertain the spatial predictability and practical reliability of the delineated groundwater potential zones, a receiver operating characteristic (ROC) analysis was conducted (Figure 12). Ground-truth performance was assessed against an independent, field-audited inventory of 20 representative boreholes obtained from the official archives of the Moulouya River Basin Agency (ABHM) (A. Nouayti et al., 2019). These validation points were segregated into two hydrogeologically defined operational categories: 13 productive boreholes characterized by sustained discharge rates ( $Q \geq 2.5$  L/s) and shallow

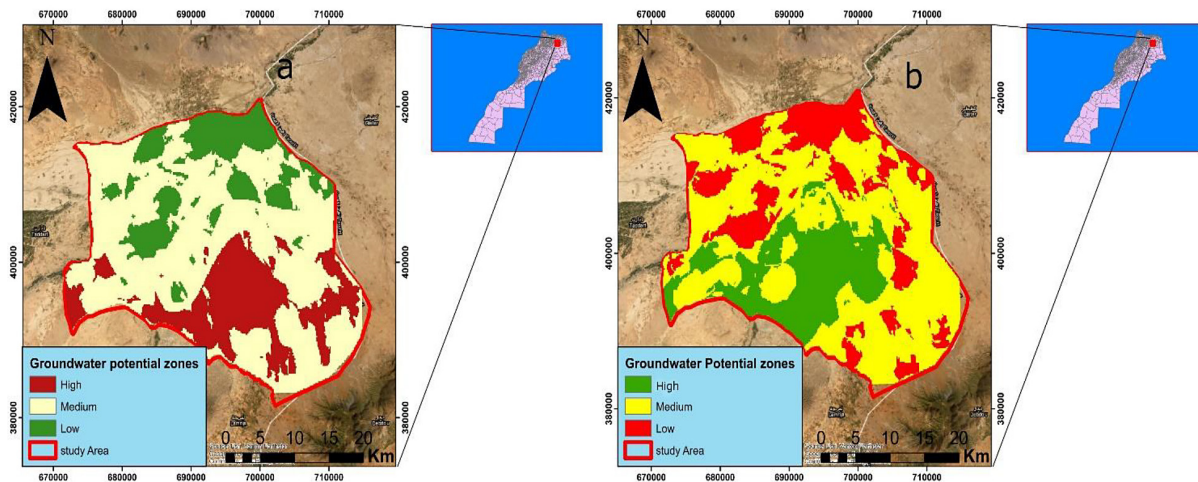


**Figure 11.** Groundwater potential (GWPZ) in the Jel basin: (a) AHP model, (b) MIF model

water tables ( $< 40$  m), and 7 unproductive or marginal wells exhibiting minimal yields ( $Q < 1.0$  L/s) or dry columns. To avoid circular reasoning, this validation dataset was preserved strictly as an external testing benchmark and was not involved in parameter weighting or GIS thematic layer reclassification (Ziani et al., 2021). As illustrated by the empirical step-wise ROC curves, both multi-criteria frameworks demonstrated robust predictive capability, significantly outperforming

the baseline random chance threshold ( $AUC = 50.0\%$ ). Both multi-criteria frameworks demonstrated identical high predictive capability ( $AUC = 93.4\%$ ), confirming that both the hierarchical pairwise structuring of AHP and the systemic interaction scoring of MIF are robust and well-suited for groundwater potential delineation in this basin, which captures subtle relative influences among structural lineaments, slope gradients, and Quaternary alluvium permeability more

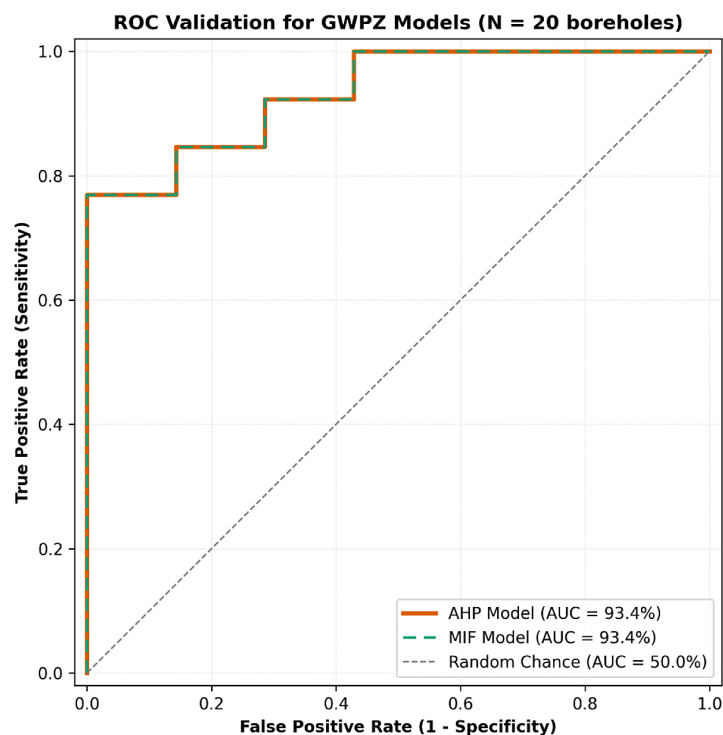


**Figure 12.** Receiver operating characteristic (ROC) validation curves for the AHP ( $AUC = 93.4\%$ ) and MIF ( $AUC = 93.4\%$ ) groundwater potential models, independently validated against 20 field-monitored boreholes in the Jel Basin ( $P = 13$  productive points,  $N = 7$  non-productive points) referenced with a spatial distribution map of piezometric levels and aquifer depths (Figure 13) (N. Nouayti et al., 2017)

effectively. Conversely, the MIF technique confirmed its validity as a dependable semi-quantitative screening alternative, reaching strong concordance with observed field productivity (A. Nouayti et al., 2019). The complete ground-truth borehole inventory (N=20)—incorporating geographical coordinates, pumping yields, binary operational classes (P=13, N=7), and predicted GWPI values is cataloged in Supplementary Table S5. Detailed threshold evaluation matrices and step-by-step trapezoidal AUC derivations are provided in Supplementary Tables S6a (AHP) and S6b (MIF). Furthermore, the entire computational workflow and visualization routines are fully reproducible using the standalone R script provided in Supplementary File (Script\_R\_ROC\_Analysis.R) (Chen et al., 2022).

The geographic coordinates, observed water levels, and borehole extraction yields used for this ground validation are documented in Supplementary Table S5, with ROC cut-off coordinates given in Supplementary Table S6a and S6b. This empirical validation provides a practical ‘ground-truth’ by comparing theoretical GWPZ classes with the basin’s actual hydraulic performance (Derviş, 2019). The findings indicate that areas designated as high-potential sectors consistently overlap with regions where the water table is most accessible and extraction yields are highest (Merigó & Yang, 2017). This strong correlation between multicriteria decision-making (MCDM) outputs and field observations confirms that the AHP and MIF frameworks accurately reflect the physical hydrogeological dynamics of the Jel aquifer (Hassan & Duarte, 2024).

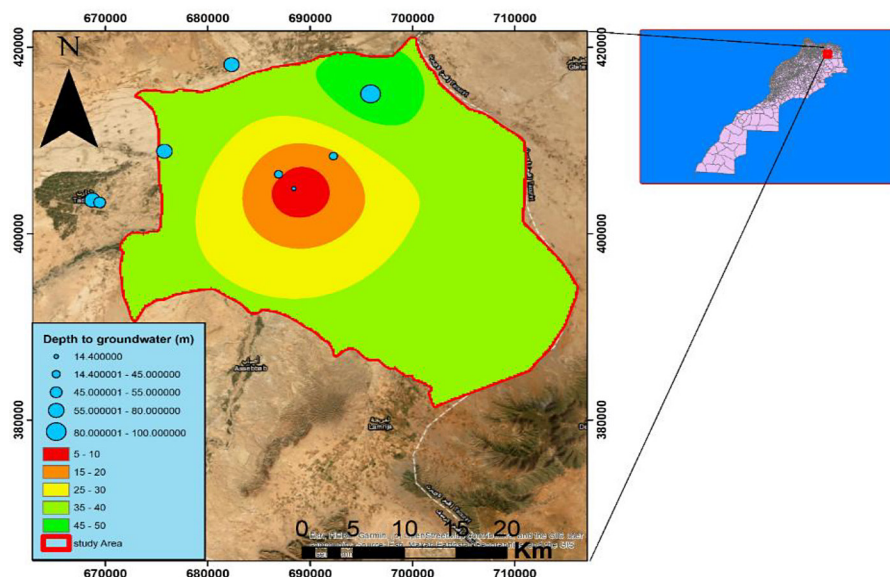


**Figure 13.** Spatial distribution map of the piezometric monitoring network in the Jel Basin, showing the 7 official ABHM reference stations (PZ-01 to PZ-07) used for multi-decadal trend analysis (2002–2020)

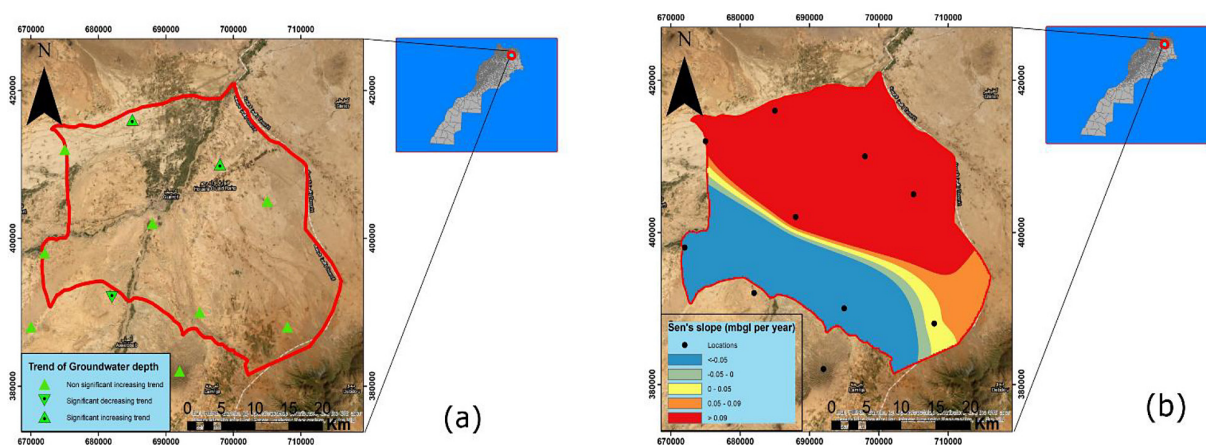


**Figure 14.** (a) Spatial distribution of Mann–Kendall trend outcomes and (b) Sen’s slope interpolation (mbgl/year) across the 7 official reference piezometric stations (PZ-01 to PZ-07) in the Jel Basin (2002–2020)

**Table 5.** Mann-Kendall test, and slope of sen at the Jel water table

| Month     | p-value | Z      | H0 (no trend) | Sen slope | Trend direction                 |
|-----------|---------|--------|---------------|-----------|---------------------------------|
| January   | 0.283   | 1.073  | Yes           | 0.193     | No trend                        |
| February  | 0.233   | 1.192  | Yes           | 0.143     | No trend                        |
| March     | 0.007   | 2.702  | No            | 0.948     | Significant increase            |
| April     | 0.002   | 3.139  | No            | 0.832     | Significant increase (recharge) |
| May       | 0.45    | -0.755 | Yes           | -0.063    | No trend                        |
| June      | 0.088   | -1.709 | Yes           | 0         | No trend                        |
| July      | 0.905   | -0.119 | Yes           | 0         | No trend                        |
| August    | 0.068   | -1.828 | Yes           | 0         | No trend                        |
| September | 0.34    | 0.954  | Yes           | 0.063     | No trend                        |
| October   | 0.361   | -0.914 | Yes           | -0.382    | No trend                        |
| November  | 0.32    | 0.993  | Yes           | 0.2       | No trend                        |
| December  | 0.218   | -1.232 | Yes           | -0.483    | No trend                        |
| Annual    | 0.043   | -2.027 | No            | -0.044    | Significant decline             |

### Mann-Kendall tests and the slope to determine the trend in groundwater levels

The Mann-Kendall (Figure 14a) and Sen's slope (Figure 14b) tests were performed on monthly records across the 2002–2020 period to identify seasonal variations, as well as on annual averages to determine the long-term direction of the water table (Table 5) (Kendall, 1975). The complete raw and gap-filled monthly and annual piezometric time series (2002–2020) for all seven reference stations are explicitly compiled in Supplementary Table S8. All intermediate statistical derivations, including the Mann-Kendall S statistic, test variance  $\text{Var}(S)$ , standardized Z score, p-value, and the 171 pairwise slope evaluations, are comprehensively documented in Supplementary Table S7 and Supplementary Data S1. The results show that there is no significant trend for most months (January, February, and May to December), as their p-values are greater than 0.05. In contrast, both March ( $p = 0.007$ ,  $Z = 2.702$ ) and April ( $p = 0.002$ ,  $Z = 3.139$ , Sen's slope = 0.832 m/year) exhibit statistically significant upward trends, reflecting seasonal aquifer recharge during the spring period (Kendall, 1975; Agyemang et al., 2025a; O. Saadi et al., 2021a).

### CONCLUSIONS

This study combined remote sensing, GIS and two multi-criteria decision frameworks, the analytic hierarchy process and the multiple

influencing factors method, to delineate groundwater potential zones in the Jel Basin from eight thematic layers. The AHP pairwise matrix proved consistent ( $CR = 0.024$ ), with geology and rainfall carrying the highest weights (26.02% each). High-potential zones, favored by fracturing and lithological permeability, cover 117 km<sup>2</sup> (18%) and lie mainly in the southern and southeastern sectors. The moderate class dominates with 357 km<sup>2</sup> (55%), while low-potential areas (176 km<sup>2</sup>, 27%) occupy the northern and northwestern margins. Validation against 20 boreholes (13 productive and 7 unproductive) gave an AUC of 93.4% for both models. Despite their different weighting algorithms, AHP and MIF therefore produce complementary spatial patterns that are consistent with observed borehole yields. AHP is preferable when a formal consistency check is required, whereas MIF offers a simple option for exploratory screening. Mann-Kendall and Sen's slope analyses of the 2002–2020 records from the seven ABHM stations revealed significant monthly trends only in March and April, consistent with spring recharge, and a slight but statistically significant annual decline ( $p = 0.043$ ; Sen's slope = -0.044 m/year). Validation relies on 20 boreholes and 7 monitoring stations, so the zoning should be refined as denser, logger-equipped monitoring becomes available. Even so, this work establishes the first integrated hydrogeological benchmark for the Jel Basin, linking multi-criteria spatial potential with two decades of piezometric behavior to support site-specific borehole siting and long-term aquifer management.

## Data and code availability statement

Data and Code Availability Statement: The raw satellite data used in this study (ALOS PAL-SAR DEM, Landsat 8/9 OLI, and Sentinel-2) are publicly available from the USGS EarthExplorer (<https://earthexplorer.usgs.gov/>) and Copernicus Open Access Hub, with complete scene metadata detailed in Supplementary Table S2. All primary spatial datasets, standardized factor rasters, and final potential rasters (AHP and MIF models) generated in this study are provided in machine-readable GeoTIFF format (.tif), standardized to the Merchich / Nord Maroc coordinate system (EPSG:26191) at a 12.5 m spatial resolution. For time-series trend analysis, long-term continuous monthly monitoring records (2002–2020) were available only for the 7 official ABHM piezometric stations (PZ-01 to PZ-07; >93% completeness), with minor missing values (<7%) imputed via linear interpolation or kriging, as detailed in Supplementary Table S1 and Table S8. The remaining 13 boreholes were utilized exclusively as an independent, static single-point validation dataset (N=20, Supplementary Table S5). All spatial layers, time-series data, AHP/MIF matrices, and R validation scripts (Script\_R\_ROC\_Analysis.R) are made available as Supplementary Material attached to this article.

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