

Article

Uncertainty-Aware Groundwater Potential Mapping in Arid Basement Terrain Using AHP and Dirichlet-Based Monte Carlo Simulation: Evidence from the Sudanese Nubian Shield

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Abstract

Groundwater sustains human activity in arid crystalline terrains where surface water is scarce and hydrogeological data are limited. However, most groundwater potential mapping approaches depend on deterministic weighting methods without quantifying model variability. This study describes an uncertainty-aware Remote Sensing and Geographic Information Systems (RS–GIS) framework to delineate groundwater potential zones in the Wadi Arab Watershed, Northeastern Sudan. Nine thematic factors—geology and lithology, rainfall, slope, drainage density, lineament density, soil, land use/land cover, topographic wetness index, and height above nearest drainage—were integrated using the Analytical Hierarchy Process (AHP), with acceptable consistency (Consistency Ratio (CR) < 0.1). To address subjectivity in weights, a Dirichlet-based Monte Carlo simulation (500 iterations) was implemented to perturb AHP weights whilst preserving compositional constraints. The resulting Groundwater Potential Index (GWPI) classified 32.69% of the watershed as high to very high potential, primarily associated with alluvial deposits and fractured crystalline rocks. Model validation using Receiver Operating Characteristic (ROC) analysis yielded an Area Under the Curve (AUC) of 0.704, indicating acceptable predictive performance. Uncertainty assessment showed low spatial variability (mean standard deviation (SD) = 0.215) and stable exceedance probabilities, verifying the robustness of predicted high-potential zones. The proposed probabilistic AHP framework augments decision reliability and provides a transferable, cost-effective tool for groundwater planning in data-limited arid basement environments.

Keywords: groundwater potential mapping; Analytical Hierarchy Process (AHP); Monte Carlo simulation; uncertainty analysis; GIS; remote sensing; crystalline basement aquifers; arid regions



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1. Introduction

Groundwater is a critical natural resource that sustains ecosystems and livelihoods, contributes to economic development, and buffers against drought and climate variability globally. It comprises one-third of Earth's total freshwater supply and is used for drinking water production, irrigation, and industrial processes [1,2]. Its comparative reliability relative to surface water have made it an important part of water security in arid and semi-arid

regions [3]. Nonetheless, groundwater resources and their quality are spatially heterogeneous due to the complicated interplay of geologic, geomorphic, hydrologic, climatic, and anthropogenic processes [4,5]. Despite these advantages, groundwater potential mapping remains challenging due to the spatial heterogeneity of controlling factors and the limited availability of field data in arid and semi-arid regions. In recent years, machine learning (ML) approaches such as Random Forest, Artificial Neural Networks, and XGBoost have been increasingly applied to groundwater potential mapping, offering strong predictive capabilities by integrating multi-source geospatial data. However, these data-driven approaches often require large, high-quality training datasets and may lack interpretability, particularly in data-scarce environments [6]. Robust implementation of machine learning models typically requires a sufficiently large number of training samples, often in the order of several hundred cases for stable training and validation [7]. In the present study area (WAW), the available dataset is limited to 61 wells with heterogeneous spatial distribution and varying data quality, which constrains the applicability of purely data-driven approaches. Under such conditions, machine learning models are prone to overfitting, spatial bias, and reduced generalization capability, particularly in arid basement environments where hydrogeological controls are highly heterogeneous and poorly sampled [8,9]. In addition, fuzzy logic and hybrid approaches have been applied to reduce subjectivity and improve classification performance; however, these methods often introduce additional model complexity and parameterization requirements, which may not be suitable for data-scarce environments [6,10]. Moreover, hybrid ML approaches further increase data and calibration requirements, thereby limiting their applicability in data-scarce environments; their performance strongly depends on the availability of representative training datasets, which are not available in the present study.

The Analytical Hierarchy Process (AHP) provides a transparent and structured framework that integrates expert knowledge, making it particularly suitable for hydrogeological applications where data availability is limited [11–13]. In contrast to data-driven approaches, AHP enables the integration of expert knowledge and physically meaningful hydrogeological relationships without requiring large training datasets, while maintaining full transparency and consistency in the weighting process. This makes it particularly suitable for the WAW context, where decision-making must rely on limited but physically interpretable information [14]. Nevertheless, most AHP-based groundwater studies adopt deterministic weighting schemes and rarely account for uncertainty in expert-derived weights. To address this limitation, probabilistic weight perturbation via Monte Carlo simulation provides an objective means of quantifying uncertainty and evaluating the spatial stability and predictive confidence of groundwater potential maps.

In crystalline basement aquifers, such as those of the Nubian Shield, groundwater is primarily hosted in weathered and fractured zones because the bedrock has inherently low primary porosity and permeability [15,16]. The spatial variability of these structural features, combined with limited and episodic recharge under arid conditions, makes groundwater evaluation and sustainable utilization particularly challenging [17]. In addition, due to population growth, agricultural development, and climate change, groundwater extraction has increased significantly, which has exceeded the natural recharge in some regions and caused local exhaustion and a lowering in the quality of water [18,19]. To overcome these limitations, geospatial technologies now offer affordable, geographically extensive options for groundwater appraisal. Conventional hydrogeological and geophysical studies are reliable but are costly, cover a limited spatial extent, and require time-consuming field work [20,21]. In this context, remote sensing (RS) and geographic information systems (GIS) have become powerful tools for groundwater prospecting as they facilitate a rapid and synoptic survey of extremely large and remote areas [22,23]. Multispectral and topographic

data of satellites like Landsat-8/9, Sentinel-2, and ASTER DEM are widely used to generate thematic layers such as lithology, slope, drainage density, lineament density, soil type, land use/land cover (LULC), rainfall, Height Above the Nearest Drainage (HAND), and topographic wetness index (TWI); all determining factors for groundwater potential [23].

The integration of all these factors requires robust decision-support systems for multi-criteria spatial data. Among these methods, AHP has been widely adopted as a multi-criteria decision-making tool due to its structured framework and ability to integrate heterogeneous hydrogeological factors through pairwise comparisons and consistency evaluation [11,24]. Compared with machine learning methods, AHP offers lower data dependency, explicit consistency checking, and greater interpretability, which are essential advantages in data-scarce arid environments [14]. Such integration enables the synthesis of the thematic layer, which represents different characteristics of the hydrogeological system and is used to delineate Groundwater Potential Zones (GWPZ) [25].

Additionally, recent studies have found the robustness and applicability of RS–GIS–AHP approaches in different hydrogeological settings, such as alluvial plains [9,22], volcanic terranes [23], and hard-rock environments [13]. Integrated approaches are helping delineate recharge areas and locate productive wells in both the arid basement aquifers of North Africa and most of the Middle East, including the Arabian–Nubian Shield (ANS) [26]. However, despite these advances, the Sudanese portion of the Nubian Shield remains under-investigated, with WAW obscured by a complex, spatially heterogeneous hydrogeological framework. Accordingly, this study aims to delineate groundwater potential zones in WAW using an integrated RS–GIS–AHP framework. The selected parameters, including geology, rainfall, slope, TWI, drainage density, lineament density, soil type, LULC, and HAND, represent the key factors controlling groundwater occurrence, flow, and recharge in the study area. By incorporating pairwise weighting, consistency checks, and layer overlay, this study aims to ensure that the resulting groundwater potential zonation is more accurate and interpretable in arid/semi-arid regions, providing a science-based foundation for sustainable groundwater development, well-site location, and water resource planning. Unlike conventional deterministic AHP approaches, this study introduces a probabilistic framework by integrating Dirichlet-based Monte Carlo simulation to explicitly quantify uncertainty in expert-derived weights. This approach enables the assessment of the stability and reliability of groundwater potential predictions under plausible variability in weighting schemes. By moving beyond fixed weights, the proposed framework provides an uncertainty-aware evaluation of groundwater potential, thereby improving the robustness and interpretability of results in arid crystalline basement aquifers.

2. Materials and Methods

2.1. Study Area

The WAW is located in the Red Sea Hills of northeastern Sudan and covers approximately 7744.20 km² (Figure 1). The watershed is hydrogeologically bounded by mountainous crystalline highlands in the east, which act as runoff source zones, and by low-relief alluvial plains in the west, where groundwater accumulation and recharge are concentrated. The watershed flows west toward the River Nile. Wadi Arab and its tributaries originate in the mountains, where steep slopes and fractured crystalline ridges converge to form temporary drainage networks. The upper watershed is over 1650 m high, while the lower plains are about 550 m above sea level. This strong elevation gradient controls surface runoff concentration and limits infiltration to low-lying areas, where recharge occurs primarily through episodic wadi flow, especially during short, heavy storms. The Köppen–Geiger classification describes the area as arid to hyper-arid [27]. Rainfall is usually less than 100 mm and mostly falls from July to October, while evapotranspiration is very high, ex-

ceeding 2000 mm per year. Temperatures remain high year-round, averaging about 30 °C, and relative humidity is consistently low, making the climate even harsher [28].

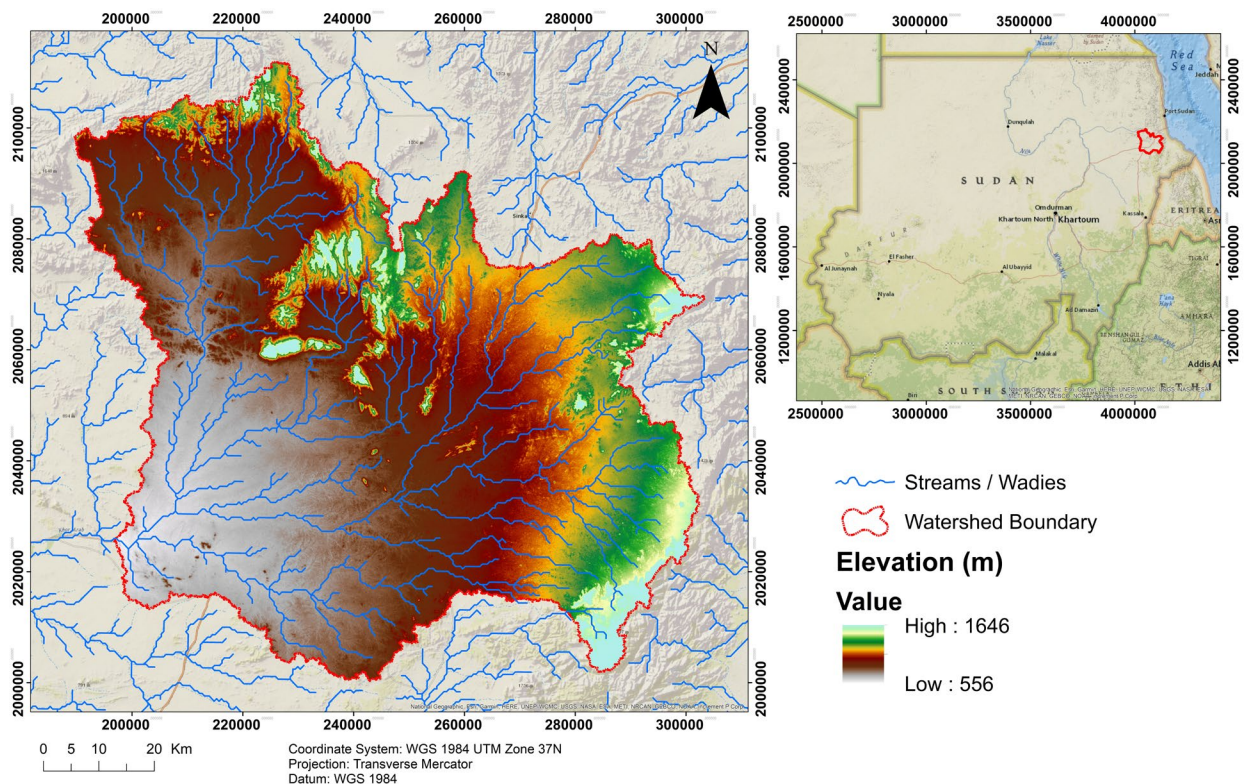


Figure 1. Location of WAW in northeastern Sudan, showing its geographic extent and major physiographical features: Base data were derived from the ASTER DEM (USGS, 30 m resolution), and administrative boundaries were obtained from ArcGIS Online datasets.

Geologically, the watershed lies within the Haya Terrane of the Arabian–Nubian Shield, dominated by Precambrian crystalline basement rocks and locally overlain by Quaternary alluvial deposits. The ANS is composed of low-grade juvenile arc terranes accreted during the Neoproterozoic [29–31]. Within this regional context, the Red Sea Hills are subdivided into five intra-oceanic terranes: Gerf, Gabgaba, Gebeit, Haya, and Tokar, as defined by [32]. The Haya Terrane is of late Neoproterozoic age (ca. 900–850 Ma) and is separated from the adjacent Gebeit island-arc terrane (ca. 830–720 Ma) by a northeast-trending shear zone delineated by the Oshib–Nakasib ophiolite complexes. Dominant lithologies in this terrane include greenschist-facies metavolcano-sedimentary rocks of the Nafirdeib Series, extensive batholithic granitoids, and minor ophiolitic remnants [32,33]. From a hydrogeological perspective, approximately 53% of the watershed is underlain by basement complex formations, while the remaining portion is covered by Quaternary alluvial sediments that fill wadis and depressions.

The main aquifer system in the WAW is located within Quaternary alluvial deposits, which sometimes extend into fractured and weathered basement areas. These unconsolidated sediments, composed of sand, gravel, and silty clay, form shallow and spatially discontinuous aquifers that are locally recharged by episodic wadi flow. In contrast, the underlying crystalline basement rocks exhibit very low primary porosity and permeability, limiting groundwater storage to weathered and fractured zones.

2.2. Data Sources and Collection

This study delineated groundwater potential zones in the Sudanese portion of the Nubian Shield using primary and secondary datasets. The datasets included field-based

discharge records derived from pumping tests, thematic maps, and satellite-based Earth Observation products, which were combined using GIS and AHP. In addition, a Monte Carlo-based uncertainty framework was implemented to evaluate the robustness of the thematic weight assignments and their influence on the final groundwater potential index (GWPI). Table 1 gives a comprehensive overview of all datasets and the thematic layers derived from them.

Table 1. Summary of datasets and derived thematic layers used in the study.

No.	Data	Source	Date	Thematic Map	Resolution
1	Geology and Lithology	Geological Research Authority, Sudan	Dec 2018	Geological map	30 m
2	Rainfall	PERSIANN-CDR (CHRS Data Portal, UCI)	Jan 2010–Jun 2025	Rainfall map	27 km
3	ASTER DEM	NASA, METI/ERSDAC	2019	Lineaments Density TWI map Drainage Density Slope map HAND map	30 m 30 m 30 m 30 m 30 m
4	Landsat 8 OLI	USGS	June 2020	Lineaments	30 m
5	Land use/Land cover	Esri	June 2021	LULC map	10 m
6	Soil	FAO	2019	Soil map	250 m
7	Well Discharge Data	Red Sea Water Corporation, Sudan	2015–2022	Model validation	

Remotely sensed products from open-access archives formed the primary datasets. Topographic parameters, including slope, drainage density, TWI, lineament density, and HAND, were derived from the ASTER 30 m DEM. Lineament extraction was supported by the Landsat 8 OLI image and ASTER DEM. Long-term rainfall data were obtained from the PERSIANN-CDR (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks—Climate Data Record) dataset, available through the CHRS Data Portal (University of California, Irvine, CA, USA). Daily precipitation records from January 2010 to June 2025 were aggregated to compute the long-term mean annual rainfall (mm/year) for the watershed.

Secondary data was obtained from national and international agencies. To understand the spatial distribution of rocks and structural features, which in turn control the groundwater occurrence, a geological map prepared by the Geological Research Authority of Sudan [34] was used as the primary source for lithological classification. Land use/land cover data were obtained from the Esri global land-cover dataset (10 m), and soil data were obtained from the FAO digital soil map [35]. For model validation, the dataset comprised groundwater discharge records from 2015 to 2022 for 61 boreholes, collected and prepared by the Red Sea Water Corporation. These well-discharge records were further used in Receiver Operating Characteristic (ROC) validation and probabilistic performance assessment of the Monte Carlo-derived GWPI outputs.

2.3. Data Processing

Groundwater potential analysis required systematic preprocessing and the generation of thematic layers within a unified geospatial framework. ArcGIS 10.8, ENVI 5.3, and PCI Geomatica 2016 were employed for image processing, feature extraction, and spatial modeling. Data organization was performed in Microsoft Excel, while statistical validation,

Monte Carlo simulations, sensitivity analysis, and Receiver Operating Characteristic (ROC) evaluation were performed in RStudio (Version 2025.05.1).

All spatial datasets were projected to UTM Zone 37N (WGS-84) to ensure coordinate consistency. Raster layers derived from the ASTER DEM and remotely sensed imagery were harmonized to a common 30 m reference grid to facilitate spatial overlay and weighted integration. Coarse-resolution datasets were handled carefully to avoid artificial spatial refinement. The FAO soil dataset was excluded from resampling and retained at its native 250 m resolution to preserve data integrity. Similarly, the rainfall dataset (native resolution ~27 km) was resampled to 30 m solely for spatial alignment during overlay analysis; no additional spatial detail was inferred from this resampling.

The geological map was scanned, georeferenced, and digitized into polygon features representing distinct lithological units. Attribute information was used to generate the geology and lithology thematic layers for the AHP framework.

Lineaments were extracted using a hybrid manual and semi-automated approach. Landsat 8 OLI imagery and ASTER DEM data were preprocessed through radiometric correction and histogram equalization. Principal Component Analysis (PCA) was applied to enhance geological discontinuities. Directional filtering in ENVI supported manual digitization in ArcGIS, with non-structural features removed through visual interpretation. Semi-automated extraction was conducted using LINE algorithm parameters (e.g., edge gradient threshold, curve length, and angular tolerance), which were iteratively calibrated to improve the extraction of geologically meaningful lineaments. Outputs from both approaches were integrated in a GIS environment to produce a consolidated lineament map. Redundant and overlapping segments were removed using the “Delete Identical” tool, followed by snapping and trimming within a defined tolerance. Where overlap occurred, manually interpreted lineaments were retained due to their greater continuity and reliability. The final cleaned network was rasterized to generate the lineament density layer.

The FAO soil dataset (250 m spatial resolution) was used directly without additional image enhancement, classification, or resampling. The dataset was reprojected and clipped to the watershed boundary. The original soil classes were preserved for AHP integration.

Land Use/Land Cover (LULC) data derived from Sentinel imagery (Esri, 10 m resolution) were mosaicked and clipped to the WAW boundary. The original classification scheme was retained for AHP integration.

Morphometric and hydrological parameters were derived from the ASTER 30 m DEM using Spatial Analyst and Hydrology tools in ArcGIS. Sink filling was applied before calculating flow direction and flow accumulation. Drainage networks were delineated using a flow accumulation threshold of 500 cells, corresponding to approximately 0.45 km² at a 30 m resolution. This threshold was selected through iterative testing and comparison with observed drainage patterns [36]. Derived terrain parameters included slope, drainage density, TWI, and HAND.

Continuous raster variables (slope, drainage density, rainfall, TWI, HAND, and lineament density) were classified into five classes using the natural breaks (Jenks) method to minimize intra-class variance and maximize inter-class discrimination prior to integration. The standardized thematic layers were prepared in a GIS environment to represent spatial variability of groundwater-controlling factors.

The standardized thematic layers were integrated using the Analytical Hierarchy Process to generate the deterministic Groundwater Potential Index [13,37]. To quantify uncertainty associated with expert-derived weights, a Monte Carlo framework (500 iterations) was implemented by perturbing AHP weights using a Dirichlet distribution while preserving their proportional structure. For each iteration, a GWPI map was generated and summarized to evaluate spatial variance and the probability of high-potential classes. In

addition, sensitivity analysis was conducted to assess the relative influence of each thematic factor on GWPI outputs.

Model validation was performed using discharge data from 61 wells. GWPI values at well locations were extracted and compared against observed discharge records. Both variables were dichotomized using a median split approach to compute sensitivity and specificity metrics. ROC analysis was used to evaluate predictive performance, and model accuracy was quantified using the Area Under the Curve (AUC), which provides a threshold-independent assessment of classification reliability.

During the preparation of this study, the authors used ChatGPT (OpenAI, San Francisco, CA, USA; ChatGPT Pro version, accessed in 2026) to assist in generating preliminary R scripts for statistical analysis and Monte Carlo simulations. The generated code was reviewed, tested, and substantially modified by the authors prior to implementation. The authors take full responsibility for the validity, accuracy, and originality of the analytical procedures and results presented in this study.

To provide a clear overview of the methodological framework, a stepwise workflow for data processing and analysis is presented in Figure 2.

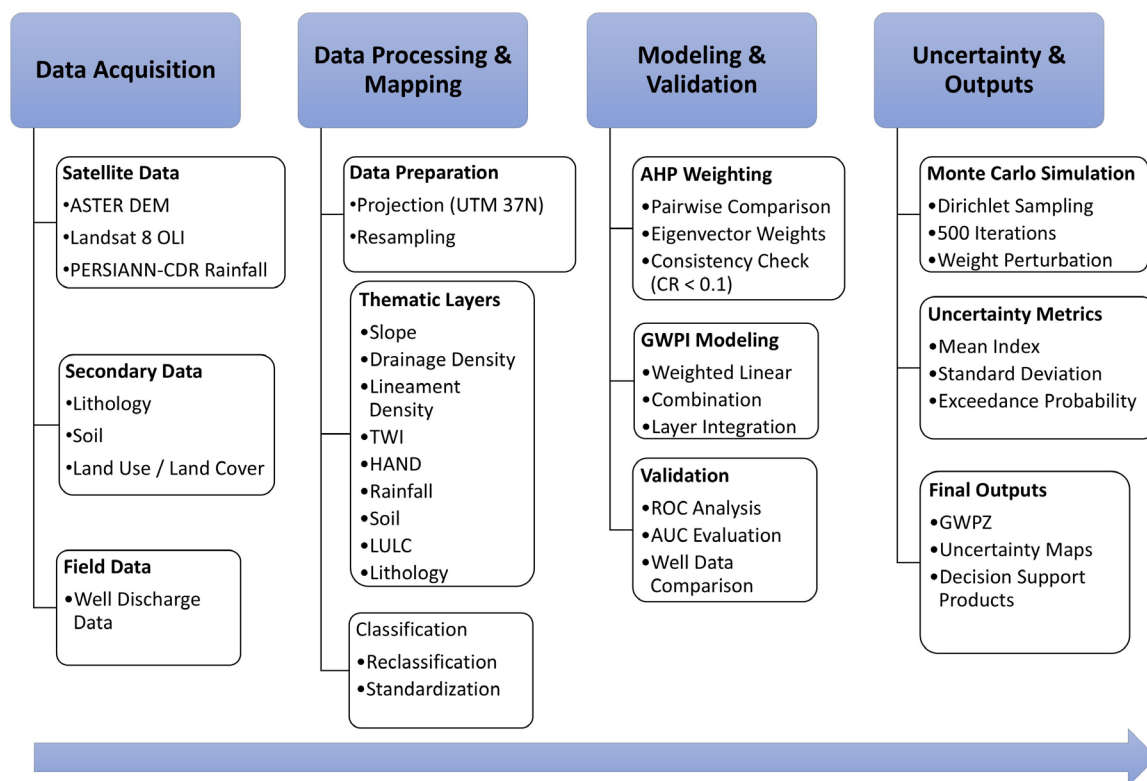


Figure 2. Workflow of the methodological framework showing data preprocessing, thematic layer generation, AHP weighting, Monte Carlo simulation, and validation.

2.4. Data Analysis Method for Thematic Layers

2.4.1. Geological and Lithological

The geological and lithological map (Figure 3), derived from the Geological Research Authority of Sudan [34]. It was used to characterize the spatial distribution of rock units controlling groundwater occurrence in the study area. The watershed is predominantly underlain by Precambrian crystalline basement rocks of the Arabian–Nubian Shield, including metamorphic, metavolcano-sedimentary, and intrusive igneous units, locally overlain by Quaternary alluvial and aeolian deposits [32,33].

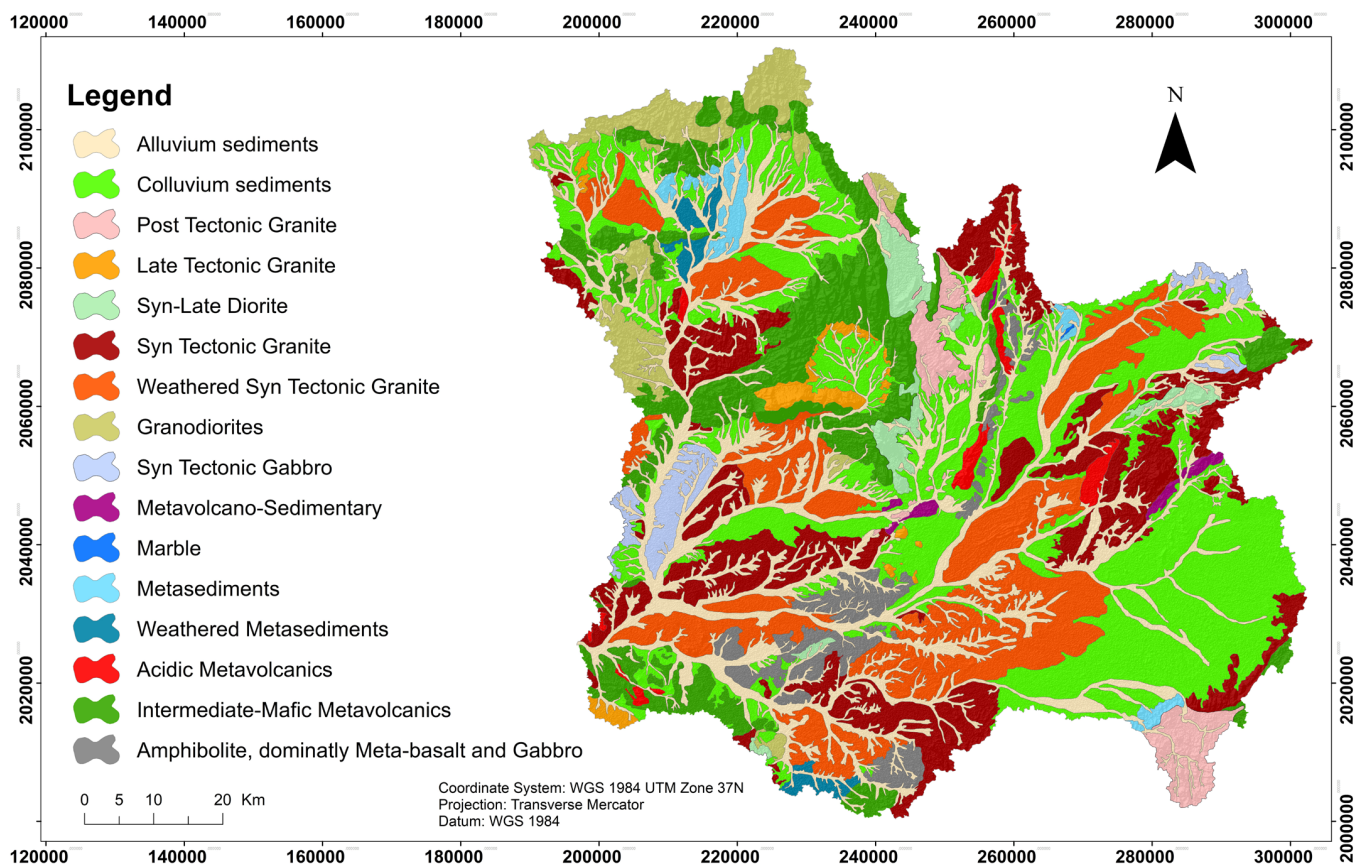


Figure 3. Geological and lithological map of WAW showing the different lithological units within the watershed boundary according to [34].

From a hydrogeological perspective, these lithological units were interpreted and classified based on their permeability, porosity, and degree of weathering. The Quaternary alluvial deposits, composed of gravels, sands, silts, and clays, were considered the most favorable units for groundwater occurrence due to their high primary porosity and permeability, particularly along wadi channels, where thickness may reach up to 45 m [34,38]. In contrast, the crystalline basement rocks exhibit negligible primary porosity, and groundwater occurrence is largely restricted to secondary structures such as fractures, joints, and weathered zones [15,16,39].

Metavolcano-sedimentary sequences and granitoid intrusions were interpreted to have moderate groundwater potential, where weathering and fracturing enhance secondary porosity [33,40]. Conversely, massive and less-deformed igneous and metamorphic units were assigned lower groundwater potential due to their limited storage capacity [39,40]. This lithological differentiation provides a critical basis for evaluating groundwater potential, as it reflects the spatial variability in aquifer properties across the watershed.

2.4.2. Rainfall

Precipitation is the primary climatic factor controlling surface runoff, overland flow, and groundwater recharge within the study area, despite the low annual totals (<100 mm), as it represents the only source of recharge. In WAW, rainfall occurs mainly between July and October and is associated with the seasonal monsoonal circulation affecting northeastern Sudan. Mean annual rainfall was derived from the PERSIANN-CDR dataset. Daily precipitation records for 2010–2025 were aggregated to compute the long-term mean annual rainfall (mm/year). The dataset has a native spatial resolution of 0.25° (~27 km) and

was clipped to the watershed boundary and resampled to 30 m for spatial compatibility with other thematic layers.

2.4.3. Lineaments Structure

Geological lineaments represent faults, fractures, and joints that are commonly expressed as linear features in satellite imagery. They play an important role in groundwater movement by increasing permeability and porosity in basement terrains [41,42]. Semi-automatic extraction was performed using the LINE algorithm in PCI Geomatica [41]. Results from both methods were combined to create a detailed lineament map. This map was then converted to raster format and viewed in ArcGIS 10.8. Lineament density was calculated in ArcGIS using a 1 km × 1 km moving window. Equation (1) was used to determine lineament density, as described in [42].

$$L_d = \frac{\sum_{i=1}^n L_i}{A} \quad (1)$$

where L_d is the lineament density (km/km²), $\sum L_i$ is the total length of all lineaments (km), and A is the total area of the watershed (km²). The resulting density values were reclassified into five categories: very low, low, moderate, high, and very high based on natural breaks to represent variations in structural intensity.

2.4.4. Soil Features

Soil characteristics strongly influence rainfall infiltration rates and the water-holding capacity of the vadose zone, thereby playing a crucial role in groundwater recharge and in delineating potential zones [43]. In the study area, soil types were identified according to the FAO–UNESCO Soil Map of the World [35]. Three major soil types were identified within the study area: Eutric Fluvisols (FLeu), medium- to fine-textured soils developed from riverine deposits; Eutric Regosols (RGeu), shallow, coarse- to fine-textured soils over unconsolidated materials; and Lithic Leptosols (Lpli) formed directly over hard rock within 25 cm of the surface. The spatial distribution of these soils provides insight into infiltration dynamics and recharge potential across WAW, supporting their inclusion as a key thematic layer in the groundwater potentiality analysis [35].

2.4.5. Land Use Land Cover

Land cover refers to the biophysical composition of the Earth's surface, encompassing vegetation, soil, water bodies, and artificial structures, whereas land use represents the functional utilization of this land by human activities [44]. Variations in land use and land cover (LULC) significantly influence groundwater potential, as they directly affect surface runoff, evapotranspiration, and infiltration processes [45]. In this study, LULC data were obtained from the ArcGIS Living Atlas Global Land Cover Explorer (2021) at a 10 m spatial resolution, derived from Sentinel imagery, providing a consistent and high-resolution representation of surface conditions supported by recent advances in multi-source geospatial data integration and land cover mapping [46]. The dataset was downloaded for the 2021 frame and subset to the WAW boundary using ArcGIS to represent the current land-use conditions of the study area. The map was clipped and prepared for integration into the groundwater potentiality model without further reclassification, serving as a direct thematic input for the AHP-based analysis. The LULC classes include built-up areas, vegetation, barren land, and water bodies, all of which influence recharge potential by modifying infiltration capacity and runoff behavior.

2.4.6. Drainage Density

The drainage system represents areas where fluvial processes dominate over hill-slope processes, enabling the development and maintenance of channel networks. Drainage density, first defined by [47], is calculated as the ratio of the total length of streams within a basin to the basin's total area. It varies depending on several factors, including rock type, surface permeability, infiltration capacity, soil texture, vegetation cover, relief, rainfall intensity and duration, antecedent moisture conditions, and human activities. High drainage density regions usually have low infiltration, large surface runoff, and generally erodible materials [48]. Ref. [49] also observed higher permeability in low-drainage-density regions than in higher drainage-density terrain. Ref. [50] had classified terrains with low drainage density as being relatively more porous and better for groundwater recharge. The ASTER DEM was used to derive the drainage network in ArcGIS 10.8 using hydrological tools. Drainage density was computed using the standard formulation proposed by [47] as the ratio of the total length of all streams within the basin to the total catchment area, as expressed in Equation (2):

$$D_d = \frac{L}{A} \quad (2)$$

where D_d is the drainage density (km/km²), L is the total length of all streams (km), and A is the total catchment area (km²).

2.4.7. Slope Steepness

Slope represents local and regional relief, which significantly impacts groundwater recharge into aquifers [51]. The slope gradient directly controls surface water infiltration and is commonly used to delineate GWPZ [52]. Because of increased runoff, a region with a steep slope gradient has a relatively low GWP. A low slope gradient, on the other hand, restricts water flow and thus increases infiltration rate [53]. The slope steepness map (in degrees) was generated from the ASTER DEM (30 m spatial resolution, 2019) using the Slope tool in a GIS environment.

2.4.8. Topographic Wetness Index

TWI is a widely used indicator for assessing the influence of terrain on hydrological processes, particularly in identifying potential groundwater infiltration and accumulation zones [54]. The *TWI* reflects the tendency of water to accumulate at any point in the landscape, based on both the upslope contributing area (α) and the local slope gradient (β). In this study, *TWI* was computed from the ASTER DEM using the Spatial Analyst and Map Algebra tools in ArcGIS 10.8, following the standard hydrological workflow for flow direction, flow accumulation, and slope derivation. The index was calculated using the standard Equation (3) according to [55]:

$$TWI = \ln\left(\frac{\alpha}{\tan\beta}\right) \quad (3)$$

where α represents the upslope contributing area per unit contour length (m²/m), and β is the local slope angle in radians.

2.4.9. Height Above Nearest Drainage

The HAND index represents the vertical distance of each terrain cell above the nearest downslope drainage channel and serves as an indicator of relative elevation, soil moisture, and groundwater recharge potential [56–58].

The HAND model is derived from a hydrologically conditioned DEM from ASTER and is widely used in groundwater and flood plain mapping studies to distinguish between

low-lying, potentially saturated valley zones and higher, well-drained uplands. In this study, HAND was generated using ArcGIS Spatial Analyst and Map Algebra tools. The processing workflow included sink filling, flow direction and accumulation calculation, stream network extraction, and vertical differencing between cell elevation and its corresponding downstream channel elevation. The HAND value for each raster cell was computed using the following equations [56]:

$$Stream(p) = \begin{cases} 1, & \text{if } FlowAcc(p) \geq \tau \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

$$z(p) = \begin{cases} z(p), & \text{if } Stream(p) = 1 \\ NoData, & \text{otherwise} \end{cases} \quad (5)$$

$$HAND(p) = z(p) - z(d(p)) \quad (6)$$

where $z(p)$ is the elevation at a specific cell in the DEM, $z(d(p))$ is the elevation of the closest downstream channel cell, $FlowAcc(p)$ is the flow accumulation value at each cell, and τ (tau) is the flow accumulation threshold used to define the drainage lines.

2.5. Analytical Hierarchy Process

The Analytical Hierarchy Process (AHP) is a widely used multi-criteria decision-making tool [59]. It is useful for comparing the relative importance of different factors using a simple, intuitive framework. AHP performs pair-wise comparisons and uses matrix algebra to produce attribute priority weights. The reciprocal rule is utilized in the comparison matrix: when one criterion is twice as important as another, the inverse of that value is used. The pairwise comparison matrices were normalized to derive the relative weights of thematic layers. The Saaty's scale of relative importance is given in Table 2.

Table 2. Measurement scale of AHP.

Definition	1	2	3	4	5	6	7	8	9
Intensity of importance	Equal importance	Weak or slight importance	Moderate importance	Moderate plus	Strong importance	Strong plus	Very strong importance	Very, very strong importance	Extreme importance

Weight Evaluation and Normalization

The AHP method was used to determine the relative importance of thematic factors controlling groundwater potential in WAW. The weighting procedure was based on a combination of evidence from peer-reviewed scientific literature and expert opinion, reflecting both hydrogeological knowledge and ANS characteristics.

Expert elicitation was conducted with a panel of four specialists in hydrogeology, groundwater modeling, GIS, and remote sensing in arid environments. The experts were selected based on their academic qualifications and experience in crystalline basement aquifers, particularly within the ANS context. Each expert independently completed the pairwise comparison matrix using Saaty's 1–9 scale. The individual judgment matrices were aggregated using the geometric mean method to obtain a single representative comparison matrix, following standard AHP group decision-making procedures. This approach minimizes individual bias and improves the robustness of the derived weights.

The nine thematic layers—rainfall, lineament density, drainage density, soil, LULC, TWI, lithology, slope, and HAND—were compared pairwise using Saaty's AHP scale. Comparative judgments were made on a scale from 1 to 9 according to [59], with each value between factors reflecting the relative importance of one factor compared to the others. This observation was corroborated by previous studies carried out under arid and

semi-arid conditions [13,60,61]. Pairwise comparison matrices were developed for both the main thematic layers and their respective subclasses to derive relative weights and scores. For clarity and conciseness, the pairwise comparison matrix is presented in Table 3, while the resulting normalized weights and subclass scores are presented in Table 4. These weights were computed using the eigenvector method, ensuring mathematical consistency and robustness. The “Score” represents the relative rating assigned to each subclass on a 1–9 scale based on its favorability for groundwater occurrence, following Saaty’s scale. The subclass weights (Class Weight %) were obtained by normalizing these scores within each thematic layer, ensuring that their sum equals 100%. In contrast, the criteria weights (Criteria Weight %) were derived independently from the normalized eigenvector of the AHP pairwise comparison matrix.

Saaty’s method was followed to calculate the Consistency Ratio (CR) to estimate the consistency of the experts’ judgments. The mathematical formula of the pairwise comparison matrix is given as Equations (7)–(11).

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \quad (7)$$

where:

$$a_{ij} = \frac{a_{ij}}{\sum a_{ij}} \text{ for } i, j = 1, 2, \dots, n \quad (8)$$

The eigenvector (W) and eigenvalue (λ) are then derived as:

$$W = \begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ W_n \end{bmatrix}, W_i = \frac{\sum a_{ij}}{n} \text{ for all } i = 1, 2, \dots, n \quad (9)$$

Finally, the Consistency Index (CI) and Consistency Ratio (CR) were calculated to verify the logical consistency of the pairwise comparisons using the following equations [59]:

$$CI = \frac{(\lambda_{\max} - n)}{(n - 1)} \quad (10)$$

$$CR = \frac{CI}{RI} \quad (11)$$

where RI is the Random Consistency Index, which depends on the matrix size. A $CR \leq 0.1$ indicates that the pairwise judgments are acceptably consistent, while higher values suggest that the comparisons must be re-evaluated. The pairwise comparison matrix developed for this study is presented in Table 3. The computed CR was 0.009, confirming the excellent consistency and reliability of the pairwise comparisons.

The final normalized weights derived from the consistent matrix were used to integrate all thematic layers into the AHP-based groundwater potential model, yielding a scientifically robust and regionally relevant delineation of GWPZs in WAW.

Table 3. Pairwise comparison matrix of the thematic layers.

Criteria	GL	TWI	RF	DD	LD	SL	SP	LULC	HAND
GL	1	2	3	2	1	4	9	8	5
TWI	1/2	1	1	1	1/2	1	5	3	2
RF	1/3	1	1	1/2	1/2	1	4	3	2
DD	1/2	1	2	1	1/2	2	6	4	3
LD	1	2	2	2	1	3	9	6	4
SL	1/4	1	1	1/2	1/3	1	3	2	1
SP	1/9	1/5	1/4	1/6	1/9	1/3	1	1/2	1/3
LULC	1/8	1/3	1/3	1/4	1/6	1/2	2	1	1/2
HAND	1/5	1/2	1/2	1/3	1/4	1	3	2	1

Note: GL = Geology; LD = Lineament Density; DD = Drainage Density; TWI = Topographic Wetness Index; RF = Rainfall; SL = Soil; HAND = Height Above Nearest Drainage; LULC = Land Use/Land Cover; SP = Slope.

Table 4. Final criteria weights (AHP-derived) and subclass weights (score-normalized) used in the groundwater potential model.

No.	Criteria	Criteria Weight%	Class	Reclasses	Score	Class Weight%
1	Geology	27.4	Alluvium sediments	G-1	9	41
			Colluvium sediments	G-2	7	24
			Weathered Metasediments	G-3	6	15
			Weathered Syn Tectonic Granite			
			Syn-Late Diorite	G-4	5	9
			Syn Tectonic Granite			
			Granodiorites			
			Late Tectonic Granite	G-5	4	6
			Syn Tectonic Gabbro			
			Post-Tectonic Granite			
			Metasediments	G-6	3	3
			Marble			
			Metavolcano-Sedimentary			
2	TWI	11.1	Acidic Metavolcanics	G-7	2	2
			Intermediate-Mafic			
			Metavolcanics			
			Amphibolite, dominantly	Very low	1	4
			Meta-basalt, and Gabbro			
			3.46–7			
3	Rainfall (mm/year)	9.2	7–9.5	Low	3	12
			9.5–13.6	Moderate	5	20
			13.6–18.9	High	7	28
			18.9–47.3	Very high	9	36
			73.9–86.7	Very low	1	4
			86.7–93.8	Low	3	12
			93.8–99.8	Moderate	5	20
			99.8–108.1	High	7	28
			108.1–119.2	Very high	9	36

Table 4. Cont.

No.	Criteria	Criteria Weight%	Class	Reclasses	Score	Class Weight%
4	Drainage density (km/km ²)	14.1	0.17–1.51	Very low	1	4
			1.51–2.2	Low	3	12
			2.2–2.77	Moderate	5	20
			2.77–3.39	High	7	28
			3.39–5.21	Very high	9	36
5	Lineament Density (km/km ²)	19.5	0.00–0.26	Very low	1	4
			0.26–0.67	Low	3	12
			0.67–1.11	Moderate	5	20
			1.11–1.65	High	7	28
6	Soil	7.7	1.65–3.63	Very high	9	36
			Fleu	Fleu	9	60
			Rgeu	Rgeu	5	33
			Lpli	Lpli	1	7
			0.00–3.40	Nearly flat	9	36
7	Slope	2.2	3.40–8.57	Gentle	7	28
			8.57–14.14	Moderate	5	20
			14.14–34.24	Steep	3	12
			34.24–63.07	Very steep	1	4
			Built-up Area	Built-up Area	1	4
8	LU/LC	3.4	Bare Land	Bare Land	3	12
			Scrub	Scrub	5	19
			Crops	Crops	7	27
			Vegetation	Vegetation	9	35
			Water Bodies	Water Bodies	1	4
9	HAND	5.4	338.2–777	Very high	1	4
			179.8–338.2	High	3	12
			85.3–179.8	Moderate	5	20
			27.4–85.3	Near channel	7	28
			0–27.4	Low terraces	9	36

The normalized eigenvector derived from the consistent matrix was used to assign the final percentage weights to each criterion and its reclassified classes (Table 4). These weights quantify the influence of each factor on groundwater occurrence and were subsequently used to compute the Groundwater Potential Index (GWPI).

2.6. Groundwater Potential Index

The Groundwater Potential Index (GWPI) is a dimensionless measure that quantifies an area's groundwater potential by combining the weighted effects of multiple factors. It considers hydrogeological, topographic, and climatic elements using the AHP-based multi-criteria evaluation framework. The GWPI was calculated with the Weighted Linear Combination method according to [37], as shown in Equation (12):

$$GWPI = \sum_{i=1}^m \sum_{j=1}^n (w_j \times x_i) \quad (12)$$

where W_j represents the normalized weight of the j th thematic parameter, x_i is the score or relative weight of the i th class within the parameter, m is the total number of parameters considered, and n is the number of classes within each parameter.

The computed GWPI is categorized into five classes: very poor, poor, moderate, high, and very high. These classes were classified using the Natural Breaks (Jenks) method based on the distribution of values. This classification highlights spatial variations in GWPZs across the WAW, reflecting differences in recharge capacity and subsurface storage potential.

2.7. Model Performance and Sensitivity Analysis

The validity of the model was tested by comparing calculated GWPI values with measured well discharge rates from 61 boreholes distributed across WAW. Discharge rates were derived from constant-pumping tests and reflect aquifer hydraulic characteristics. Dry boreholes were assigned a discharge of zero to preserve the observed spatial variability in groundwater occurrence. The predictive ability of the AHP-derived Groundwater Potential Index (GWPI) was assessed using ROC analysis because it provides a threshold-independent measure of model discrimination [62].

The median split approach was adopted to mitigate the effect of skewed discharge distributions and to ensure a balanced classification for ROC analysis. The observed well discharge values (Q) were classified into a binary variable Y using the median discharge (Q_{med}):

$$Y = \begin{cases} 1, & Q > Q_{\text{med}} \\ 0, & Q \leq Q_{\text{med}} \end{cases} \quad (13)$$

GWPI values extracted at well locations were converted into a binary predictor P using the median GWPI ($GWPI_{\text{med}}$):

$$P = \begin{cases} 1, & GWPI > GWPI_{\text{med}} \\ 0, & GWPI \leq GWPI_{\text{med}} \end{cases} \quad (14)$$

Using these binary classifications, a confusion matrix was constructed to compute performance metrics. Sensitivity (True Positive Rate), Specificity (True Negative Rate), and the False Positive Rate (FPR) were calculated as follows:

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (15)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (16)$$

$$\text{FPR} = 1 - \text{Specificity} \quad (17)$$

where TP (true positives) represents correctly identified high-yield wells, TN (true negatives) represents correctly identified low-yield wells, FP (false positives) represents low-yield wells incorrectly classified as high-yield, and FN (false negatives) represents high-yield wells incorrectly classified as low-yield.

The ROC curve was generated by plotting Sensitivity against FPR across varying classification thresholds. The Area Under the Curve (AUC) was used as a threshold-independent measure of model performance, ranging from 0.5 (no predictive skill) to 1.0 (perfect discrimination), as widely adopted in environmental modeling studies [62].

Sensitivity analysis was conducted to evaluate the influence of thematic layers on GWPI [63]. Map-removal sensitivity analysis was applied by removing one thematic layer at a time and recalculating the GWPZ map. Refs. [63,64] applied different techniques to define and assess map removal sensitivity analysis, and they used the following expression:

$$s_{ix} = \frac{P_i}{N} - \frac{Px_i}{n} \quad (18)$$

where S_{ix} is sensitivity associated with the removal of one map of parameter X , P_i is the computed potential value of the cell or the area, P_{xi} is the potential value of the cell or the area after excluding parameter X . N is the total number of used parameters for computing potential value of the cell or the area, n is the number of used parameters for computing potential value of the cell or the area after excluding one parameter.

2.8. Monte Carlo Uncertainty Propagation of AHP Weights

To quantify uncertainty in expert-derived AHP weights, a Monte Carlo simulation was implemented [65] by sampling alternative weight vectors from a Dirichlet distribution, which preserves the compositional constraint (weights are positive and sum to one) [66,67]. Let $w = (w_1, \dots, w_9)$ denote the baseline AHP weight vector. At each iteration $k = 1, \dots, 500$, an alternative weight vector was sampled as:

$$w^k \sim \text{Dirichlet}(\alpha w), \sum_{j=1}^9 w_j^k = 1 \quad (19)$$

where α is a concentration parameter controlling the magnitude of perturbation around the baseline weights. To evaluate the sensitivity of uncertainty propagation to this parameter, a range of concentration values ($\alpha = 25, 50, 75, 100, 125, 150, 175, 200$) was tested. The results indicate a systematic decrease in uncertainty as α increases, with the mean standard deviation of GWPI decreasing from approximately 0.45 at $\alpha = 25$ to 0.16 at $\alpha = 200$. Lower concentration values introduce excessive variability in the sampled weights, whereas higher values constrain the weights closer to the baseline AHP-derived proportions. Based on this analysis, $\alpha = 200$ was selected for the final simulations, as it provides a balance between stability and controlled uncertainty propagation.

For each sampled weight vector, the GWPI at pixel p recomputed using the weighted linear combination approach commonly applied in GIS-based multi-criteria decision analysis [37,59,68] as shown in Equation (20):

$$GWPI^{(k)}(p) = \sum_{j=1}^9 w_j^k S_{j(p)} \quad (20)$$

where $S_{j(p)}$ represents the standardized score of criterion j .

The ensemble of 500 realizations was then summarized by computing the mean GWPI and the exceedance probability of high-potential classes (Class ≥ 4), using standard Monte Carlo estimators [69], as expressed in Equations (21) and (22):

$$GWPI(p) = \left(\frac{1}{K} \right) \sum_{k=1}^K GWPI^{(k)}(p) \quad (21)$$

$$P(p) = \left(\frac{1}{K} \right) \sum_{k=1}^K \mathbb{I}(\text{Class}^{(k)}(p) \geq 4) \quad (22)$$

where $K = 500$ and $\mathbb{I}(\cdot)$ is an indicator function equal to 1 when the condition is satisfied and 0 otherwise.

These ensemble-based statistics provide spatially explicit measures of robustness and uncertainty, complementing the deterministic AHP-based GWPI.

3. Results

3.1. Geological and Lithological Units

The WAW contains a variety of rock types (Groups G1–G7) with varying levels of weathering, fracturing, and deformation. These factors affect how groundwater is stored and moves through the area (Figure 4a). The best formations for groundwater are the unconsolidated and highly weathered rocks. Group G1 (Alluvial sediments, 20.12%) and Group G2 (Colluvial sediments, 24.99%) are found in valley bottoms and foothills, where their high porosity and permeability make them favorable zones for groundwater accumulation and well productivity. Group G3 (Weathered metasediments and weathered syn-tectonic granites, 14.74%) includes moderately to highly weathered rocks that increase secondary porosity, which helps water infiltrate and supports shallow aquifers. In contrast, crystalline and metamorphic basement rocks have lower potential for groundwater storage

and rely mostly on fractures. Group G4 (Syn- to late-orogenic intrusive materials: diorite, granodiorite, and granite, 18.55%) stores water mainly along faults and shear zones. Group G5 (Late-tectonic granites, syn-tectonic gabbros, and post-tectonic granites, 5.31%) and Group G6 (Metasedimentary and metavolcano-sedimentary rocks, 2.52%) are dense and allow little water in, except where tectonic activity has created extra spaces. Group G7 (Amphibolite and intermediate to mafic metavolcanic rocks, 13.77%) comprises hard basement rocks, where groundwater is primarily found in fractures. Overall, Groups G1 to G3 are the main sources of groundwater, while Groups G5 to G7 have limited recharge unless structural features increase their permeability.

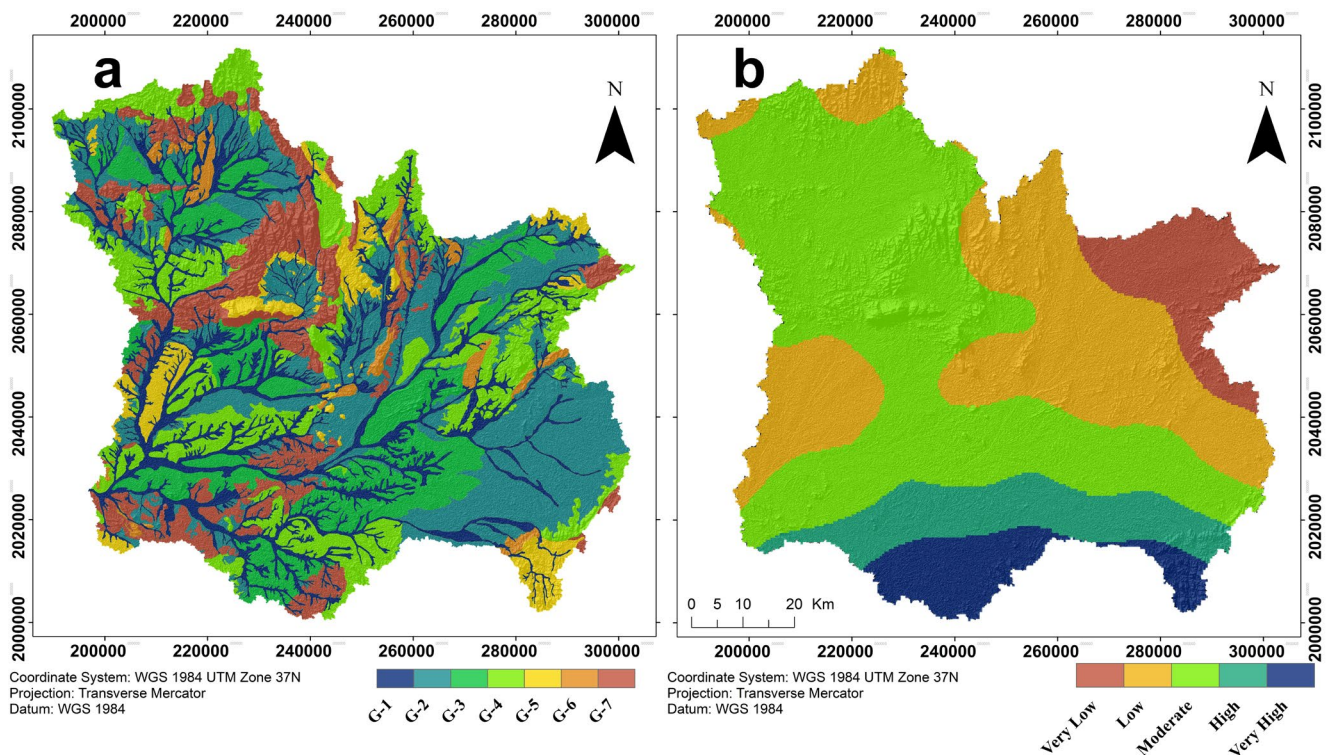


Figure 4. (a) Geological and lithological map of WAW, illustrating the spatial distribution of the lithologic groups based on the assigned weights. (b) Spatial distribution of rainfall classes across the WAW derived from PERSIANN-CDR (2010–2025) data.

3.2. Rainfall

Rainfall in the WAW region demonstrates pronounced spatial variability, primarily determined by elevation gradients and regional climatic factors (Figure 4b). Analysis of the PERSIANN-CDR dataset (2010–2025) indicates that mean annual rainfall ranges from approximately 73.9 mm to 119.2 mm, confirming the basin's arid-to-hyper-arid climate. Very low rainfall zones (73.9–86.7 mm/year) constitute 7.70% of the watershed, while low rainfall zones (86.7–93.8 mm/year) represent 29.75%. Moderate rainfall areas (93.8–99.8 mm/year) are predominant, covering 46.16% of the basin and establishing the principal climatic regime. High rainfall zones (99.8–108.1 mm/year) account for 9.96%, and very high rainfall areas (108.1–119.2 mm/year) comprise 6.42%, primarily located in southern sectors affected by topographic influences. The spatial distribution of rainfall suggests that, despite the dominance of moderate rainfall, areas with relatively high precipitation are spatially restricted, thereby limiting the potential for widespread recharge. As a result, rainfall was assigned a moderate weight in the Analytical Hierarchy Process (AHP) framework, acknowledging its climatic significance but recognizing its secondary influence relative to lithological and structural controls in this crystalline basement context.

3.3. Lineament Density

The lineament analysis across WAW revealed a complex structure with three main fracture directions: NNE–SSW (5°), W–E (273°), and NEE–SWW (75°), reflecting the tectonic variation of the Nubian Shield. In semi-automatic method, a higher total lineament length was produced, but manual extraction gave more reliable geological results, as shown in Figure 5b. The semi-automatic method recorded a maximum lineament length of 3759 km, while the manual method measured 1091 km (Figure 5c), which is about 22% of the semi-automatic total. This difference is mainly due to the LINE algorithm detecting more short, broken lineaments. Very low lineament density covers 32.54% of the watershed, low-density zones cover 27.96%, and moderate-density areas make up 20.82%. High-density zones account for 13.32%, and very high-density areas, marked by intense fracturing and faulting, cover 5.35% of the basin. These high-density zones occur in structurally controlled areas that enhance secondary porosity and permeability, both of which are important for groundwater recharge and flow. The final lineament density map (Figure 5d) shows how structural features influence the hydrogeology of WAW.

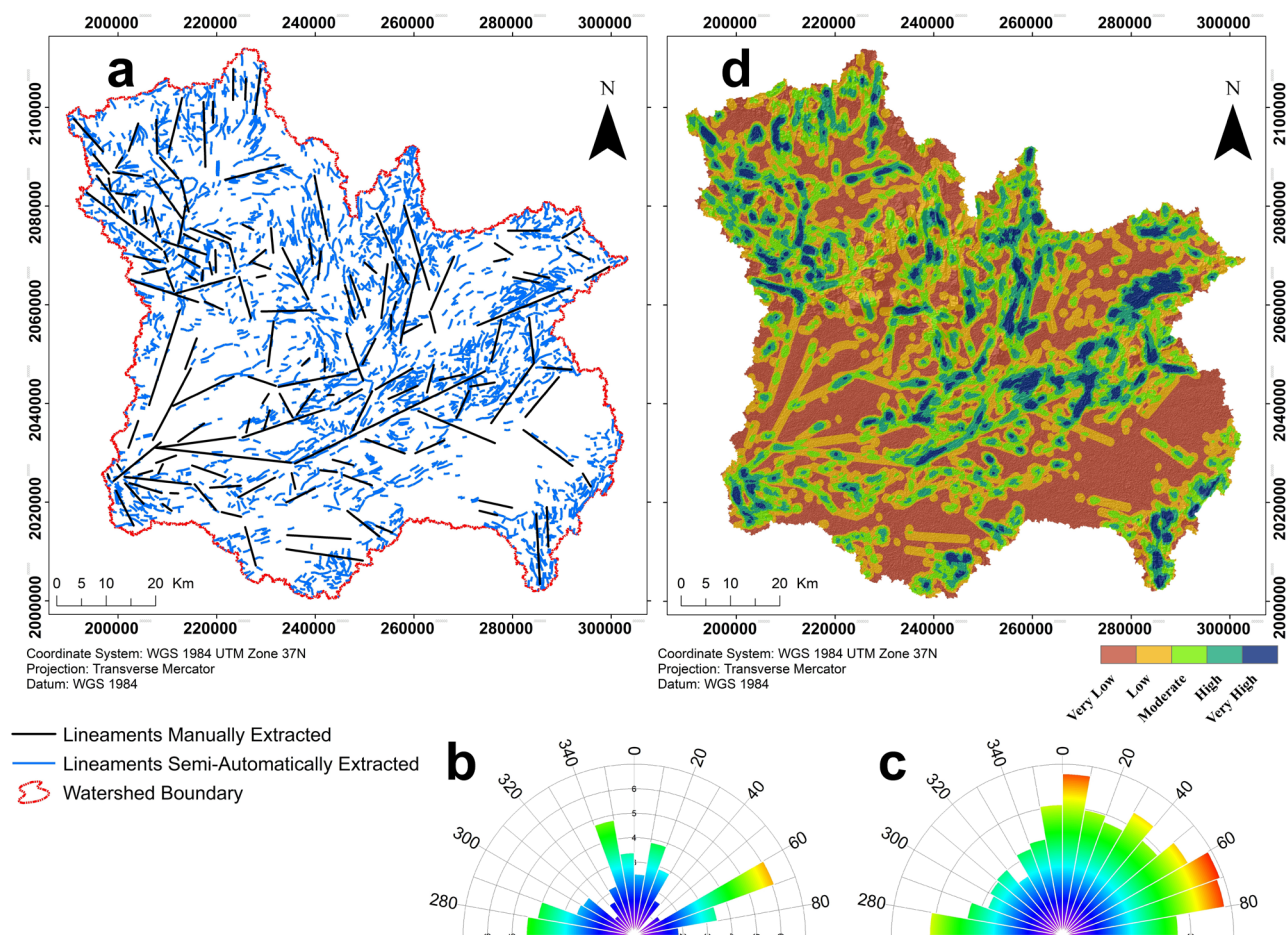


Figure 5. (a) Lineament map of WAW derived from ASTER DEM and Landsat imagery. (b) Rose diagram of manually extracted lineaments. (c) Rose diagram of semi-automatically extracted lineaments. (d) Lineament density map.

3.4. Soil Features

WAW has three main soil types, which are evenly distributed and strongly affect groundwater recharge (Figure 6a). Eutric Fluvisols (FLeu) represent about 38.61% of the area. These are wadi soils of medium to fine texture, formed from alluvium. They are loose; they readily absorb and retain water, allowing the ground to recharge. Approxi-

mately 7.45% of the basin area consists of Eutric Regosols (RGeu). The soils are generally shallow and composed of loose, fine-grained material. Lithic Leptosols (Lpli) represent approximately 53.93% of the study area. They are predominantly distributed across rocky uplands, where their shallow depth, coarse texture, and limited water retention capacity constrain infiltration and limit groundwater recharge potential, which in turn affects overall groundwater productivity.

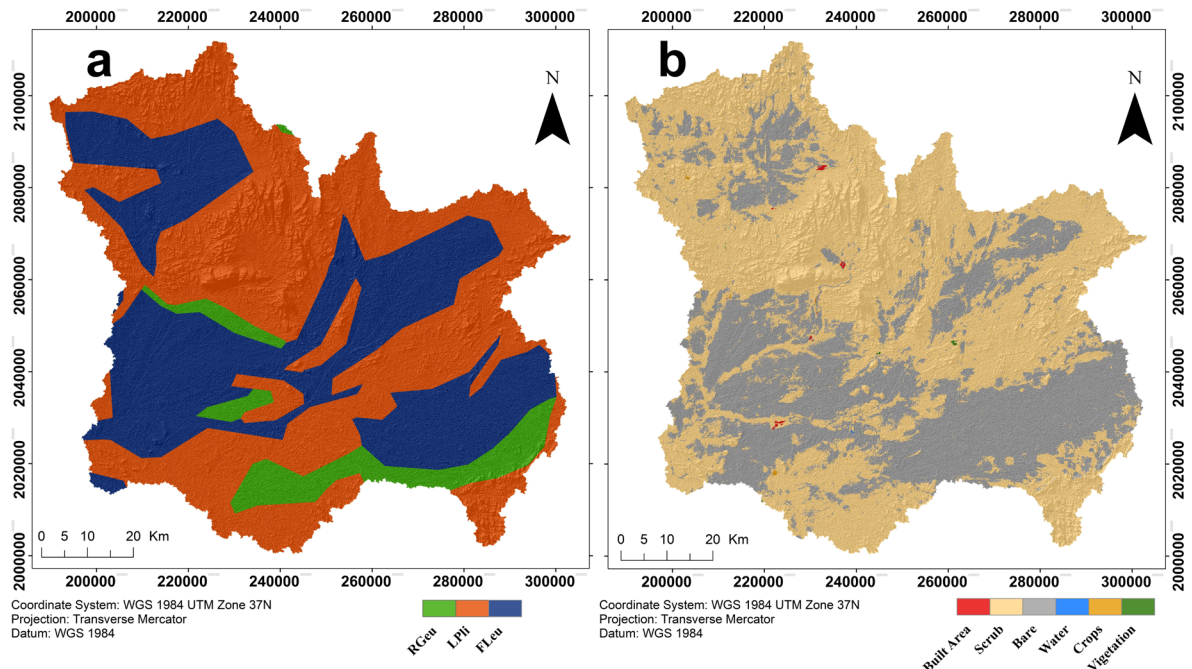


Figure 6. (a) Soil map of WAW derived from FAO-UNESCO data showing the distribution of three main soil units. (b) Distribution of Land use/land cover classes of WAW derived from Sentinel-2 imagery.

3.5. Land Use and Land Cover

The Land Use/Land Cover (LULC) distribution among WAW identified six main classes: scrub/shrub, bare land, water bodies, cropland, built-up areas, and vegetation (Figure 6b). Scrub and shrub lands make up about 62% of the area, while bare land covers around 38%. The other types of water bodies, cropland, built-up areas, and vegetation, each cover less than 0.1% of the watershed. The large areas of scrub and bare land reflect the region's arid to semiarid climate, where little vegetation and extensive exposed soil and rock result in limited water infiltration and increased surface runoff, thereby reducing groundwater potential.

Small patches of crop land and vegetation help surface water soak in locally because of better soil. Built-up areas, mostly near settlements, have hard surfaces that prevent water from infiltrating and increase runoff. Water bodies, such as wadis and temporary channels, help with short-term groundwater recharge during seasonal flows. The LULC pattern indicates that most of the WAW has low groundwater recharge potential because the land is largely bare and has little vegetation. The small areas with plants or crops act as local spots where more water can soak into the ground, a common feature in dry regions.

3.6. Drainage Density

The drainage network analysis of WAW shows an organized fluvial system shaped by structural features. Many drainage streams follow major faults, joints, and fractures, which guide surface flow and characterize channels. The watershed is an eighth-order basin, with all runoffs flowing to a single outlet. Most of the area has a dendritic drainage pattern,

which suggests uniform rock formations. Trellis and parallel patterns appear where local structure and rock types differ. Moderate drainage density covers the largest part of the watershed (30.25%), followed by high (27.34%) and low (20.65%) density zones. Very low- and very high-drainage-density areas account for 10.52% and 11.24%, respectively. High drainage density usually means impermeable rocks and fast runoff. However, in the WAW, these areas are linked to fractured and faulted zones that increase secondary porosity and facilitate groundwater recharge, even with little rainfall. For WAW, high-drainage density classes were given higher GWPI weights to reflect their role in subsurface water movement and recharge. The spatial pattern of drainage density is shown in Figure 7a.

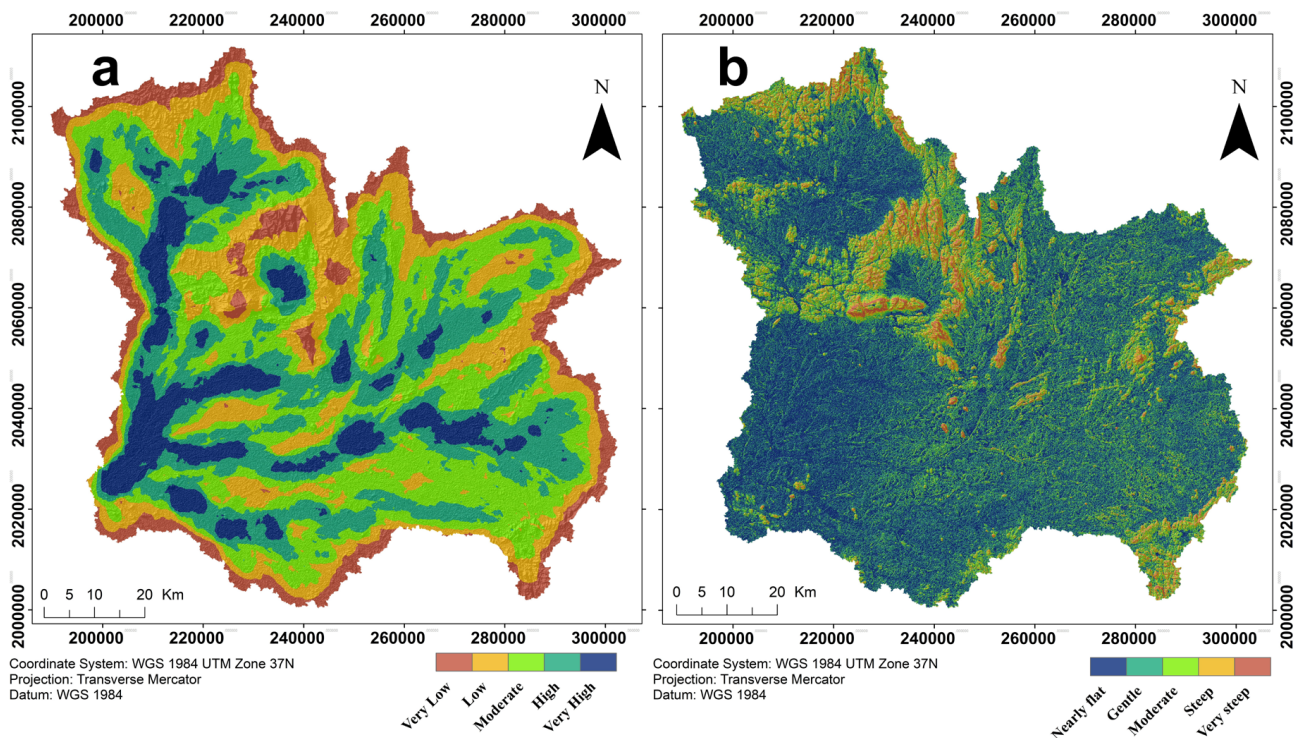


Figure 7. (a) Drainage density classes of WAW showing the spatial variability of stream network concentration. (b) Slope steepness map of WAW derived from the ASTER DEM (30 m), showing terrain classes.

3.7. Slope Steepness

The analysis of slope steepness in WAW reveals a wide range of gradient values. These differences affect how water runs off the surface and how much seeps into the ground. The data shows that 45.10% of the watershed is nearly flat, while 32.46% have gentle slopes. These areas are mostly low-relief plains and depositional surfaces, where water can readily infiltrate and recharge groundwater. Moderate slopes account for 13.29% of the basin and serve as a transition between lowlands and uplands. Here, groundwater recharge is more limited because runoff is higher. Steep and very steep slopes cover only 6.40% and 2.75% of the watershed, mostly in the northern and northeastern highlands. These regions have fast surface-water flow, low infiltration, and a higher risk of erosion, resulting in less groundwater recharge. Overall, the extensive areas of flat, gentle slopes suggest that most of the WAW have favorable conditions for groundwater recharge (Figure 7b).

3.8. Topographic Wetness Index

The Topographic Wetness Index analysis of WAW reveals clear differences in surface moisture and groundwater recharge across the area. About 80.8% of the watershed has

very low or low TWI values. These areas are mostly on higher ground or gentle slopes, where runoff is common and water does not soak in easily.

Moderate TWI values account for 10.67% of the watershed and mark areas where both runoff and infiltration occur. High and very high TWI zones occupy 6.82% and 1.72% of the land, respectively, in valley bottoms, depressions, and wadi. Here, water will pool and soak into the ground, helping recharge the groundwater. These findings indicate that the majority of the WAW indeed experiences dry to moderately wet conditions, consistent with its arid climate. However, specific low areas are significant for recharging, as illustrated in Figure 8a.

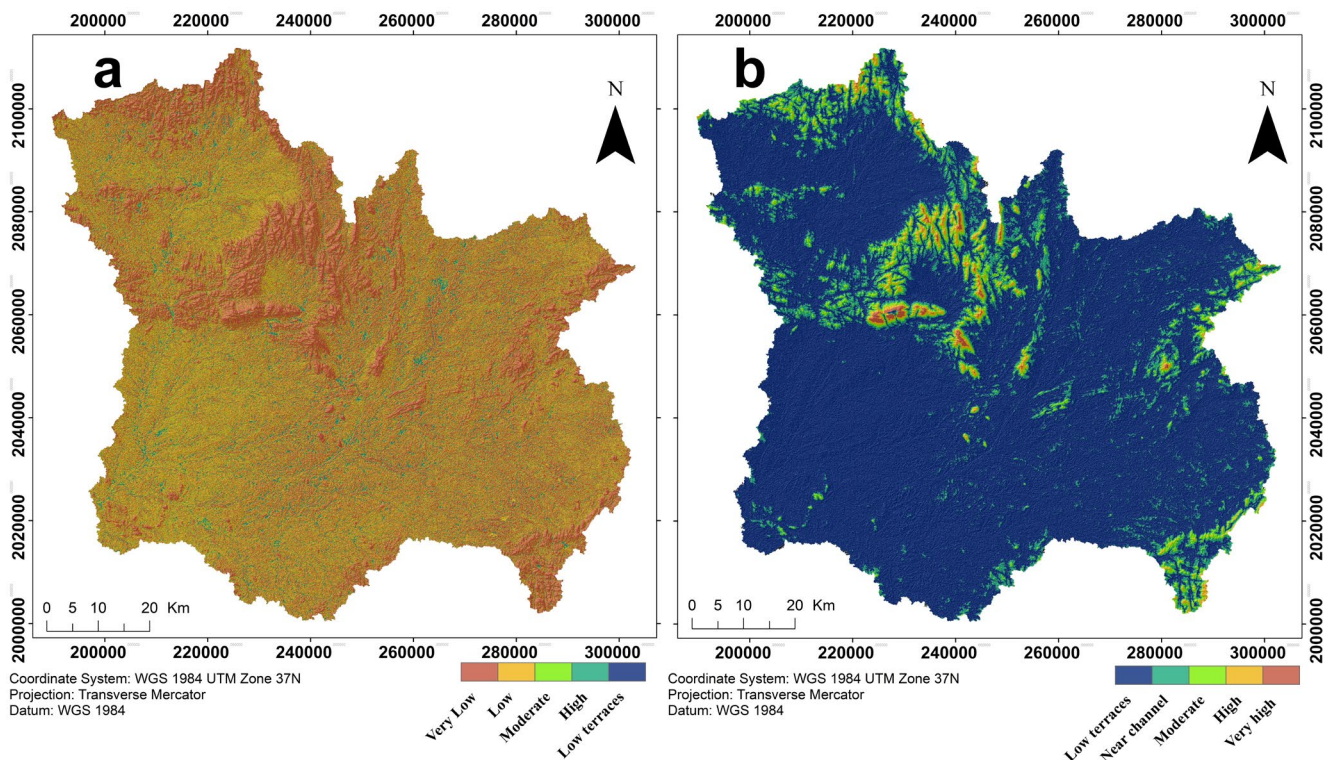


Figure 8. (a) TWI map along WAW highlighting moisture-accumulation patterns and surface-saturation potential. (b) HAND classes of WAW illustrate elevation differences relative to the drainage network.

3.9. Height Above Nearest Drainage

The HAND analysis of WAW demonstrates a strong topographic influence on potential groundwater recharge. The HAND values were stratified into five elevation ranges within the drainage network. The results reveal that low-terrace areas are the dominant landform in the watershed, accounting for approximately 83.71% of the total area. These are the gentle, nearly flat topographic features located near drainage lines, where surface water retention and infiltration are expected to be most favorable, implying the highest potential for groundwater recharge. The near-channel area zones, representing 10.81% of the watershed, also exhibit high recharge potential due to their proximity to stream channels, which facilitate percolation during runoff events. The intermediate HAND class accounts for 3.81% of the area and features transitional surfaces with a moderate runoff-infiltration pattern. On the other hand, high and very high HAND zones account for only 1.39% and 0.27%, respectively, and are found in high uplands and ridges, where poor drainage impedes both in-depth infiltration and groundwater recharge, and reduces storage capacity through rapid drainage. The HAND distribution shows that most of WAW lies at relatively

low elevations above the drainage channels, which is optimal for groundwater recharge, as shown in Figure 8b.

3.10. Groundwater Potential Index and Zonation

The GWPI values within the WAW study area were categorized as very poor, poor, moderate, high, and very high. The index value ranges from 2.7 to 7.3 across the watershed (Figure 9a). Spatial distribution analysis reveals that the moderate potential zone is widely distributed in the watershed, accounting for 38.26% of total area. This category comprises areas with relatively balanced hydrological conditions, where groundwater depletion is associated with moderate infiltration through fractured and weathered zones.

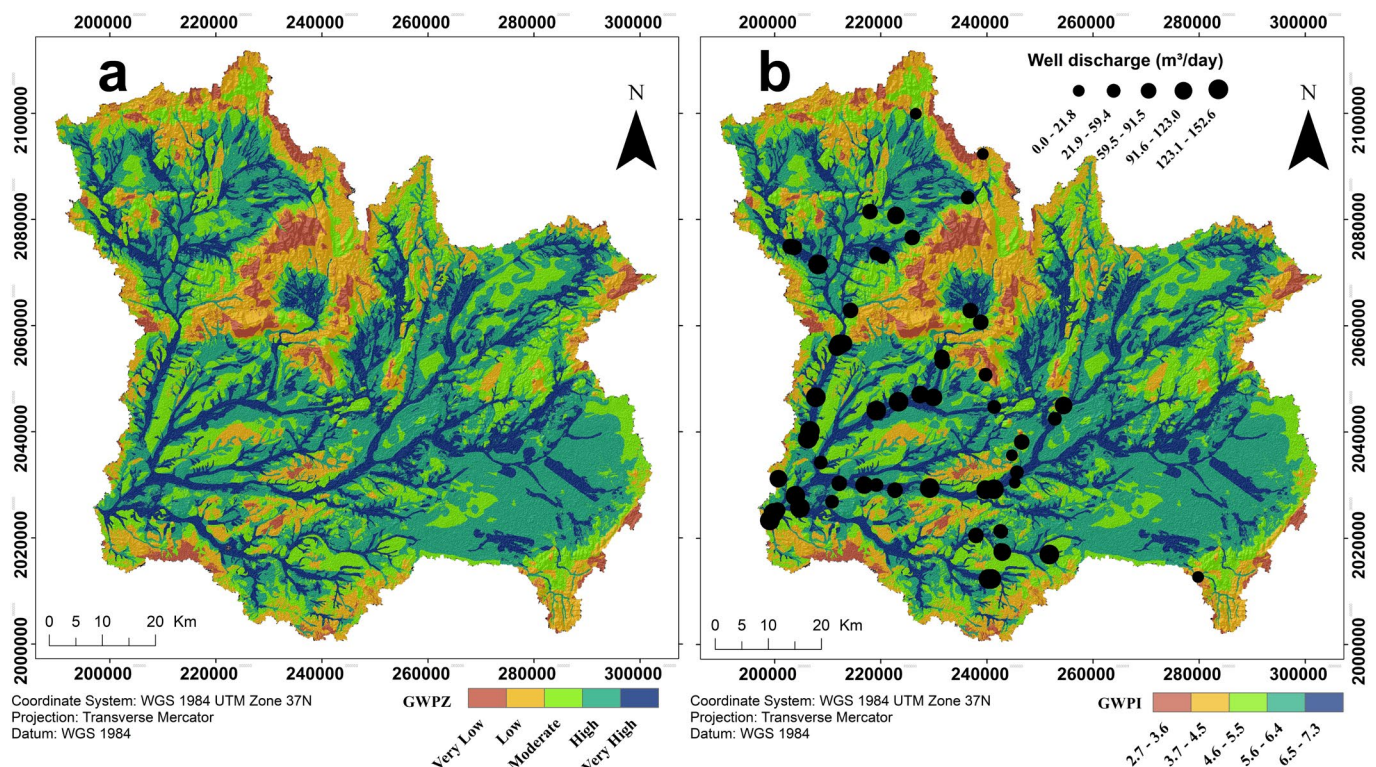


Figure 9. (a) GWPZ map of the WAW derived from the AHP-GIS model, classified into five potential classes. (b) Spatial distribution of well locations overlaid on the GWPZ map, illustrating the correspondence between observed well productivity and predicted GWPI classes.

The zone of high potential, covering 29.09% of the area, is characterized by good hydrogeological conditions due to the presence of permeable formations and structural control, resulting in a higher recharge rate. The low-potential zone, which covers 25.83%, is characterized by limited recharge capacity and compact ground-surface sediments. On the other hand, very-low-potential zones cover only 3.22% of the basin territory and are mostly associated with steep or less weathered areas where surface flow dominates over infiltration. In contrast, the very high-potential location zones (3.60%) are restricted to isolated sites with exceptional recharge capacity, characterized by high-permeability sediments and favorable geomorphological characteristics.

3.11. Model Performance and Sensitivity Analysis

The performance of the AHP-derived Groundwater Potential Index (GWPI) was evaluated by comparing GWPI values with well discharge data from 61 boreholes across WAW (Figure 9b). After classifying the well discharge and GWPI values into high- and low-yield groups using median thresholds, the ROC curve demonstrated the model's ability

to distinguish between productive and non-productive groundwater zones (Figure 10a). The ROC analysis produced an AUC of 0.704 (95% CI: 0.575–0.823), indicating acceptable model discrimination performance. In addition, Spearman's rank correlation revealed a moderate and statistically significant association between GWPI and well discharge ($\rho = 0.485$, $p = 7.57 \times 10^{-5}$), confirming that higher GWPI values correspond to higher well productivity.

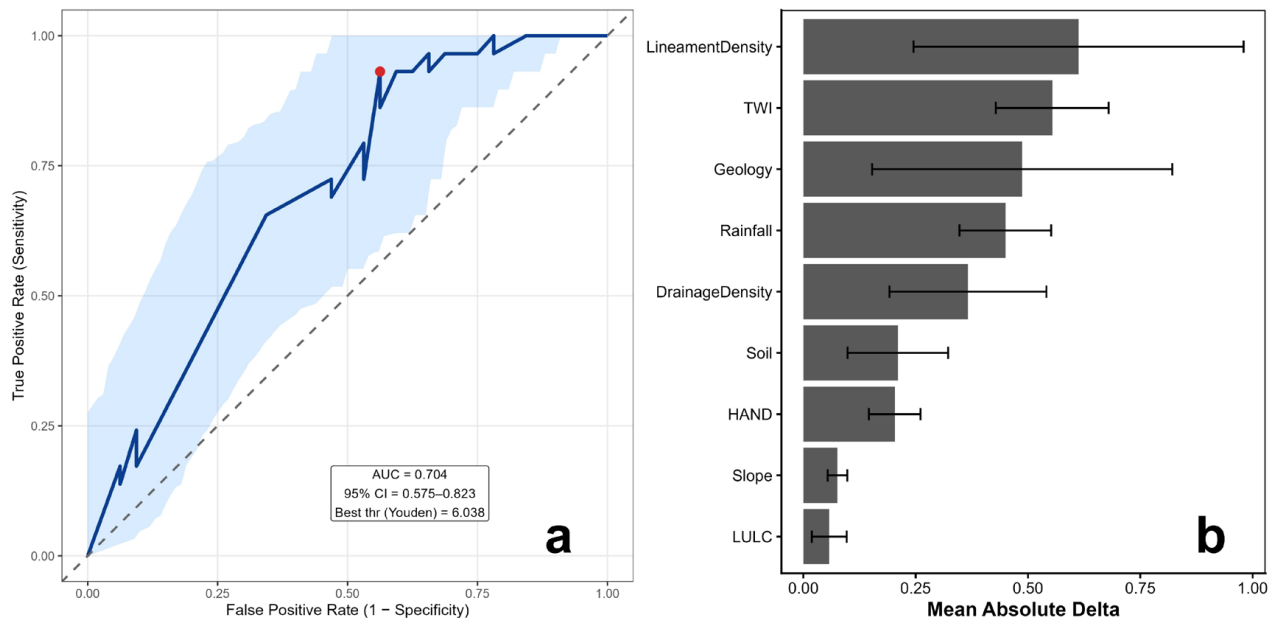


Figure 10. (a) ROC curve for the AHP-derived GWPI model, illustrating the relationship between Sensitivity and False Positive Rate and showing a moderate predictive performance (AUC = 0.704), where the solid blue line represents the ROC curve, the dashed diagonal line indicates random classification, and the red dot marks the optimal threshold based on the Youden index. (b) The map-removal sensitivity analysis (mean $|\Delta\text{GWPI}| \pm \text{SD}$) highlights the relative influence of the thematic layers on GWPI.

Significant variation in the impact of thematic layers on the final GWPI output was revealed by the map-removal sensitivity analysis (Figure 10b). Lineament density exhibited the highest sensitivity response, indicating that structural controls exert the strongest influence on groundwater potential in WAW. This was followed by TWI, geology, and rainfall, which also produced substantial changes in GWPI when excluded from the model. Drainage density showed moderate sensitivity, while soil and HAND demonstrated comparatively lower influence. In contrast, slope and LULC generated minimal changes in GWPI, suggesting a limited impact at the basin scale. Together, these results highlight that structural, lithological, and terrain-related factors are the dominant controls governing groundwater potential within the watershed.

3.12. Uncertainty Assessment

Monte Carlo simulation with 500 iterations, employing Dirichlet-distributed perturbation of AHP weights, demonstrated high stability in the groundwater potential model. The spatial standard deviation of GWPI values exhibited generally low variability across the watershed, with a mean of 0.215 (Figure 11a). Slightly elevated uncertainty was limited to transitional zones between moderate and high groundwater potential classes, while the core high- and low-potential regions remained consistently stable. These results indicate that the spatial configuration of groundwater potential is not highly sensitive to moderate variations in expert-derived weights.

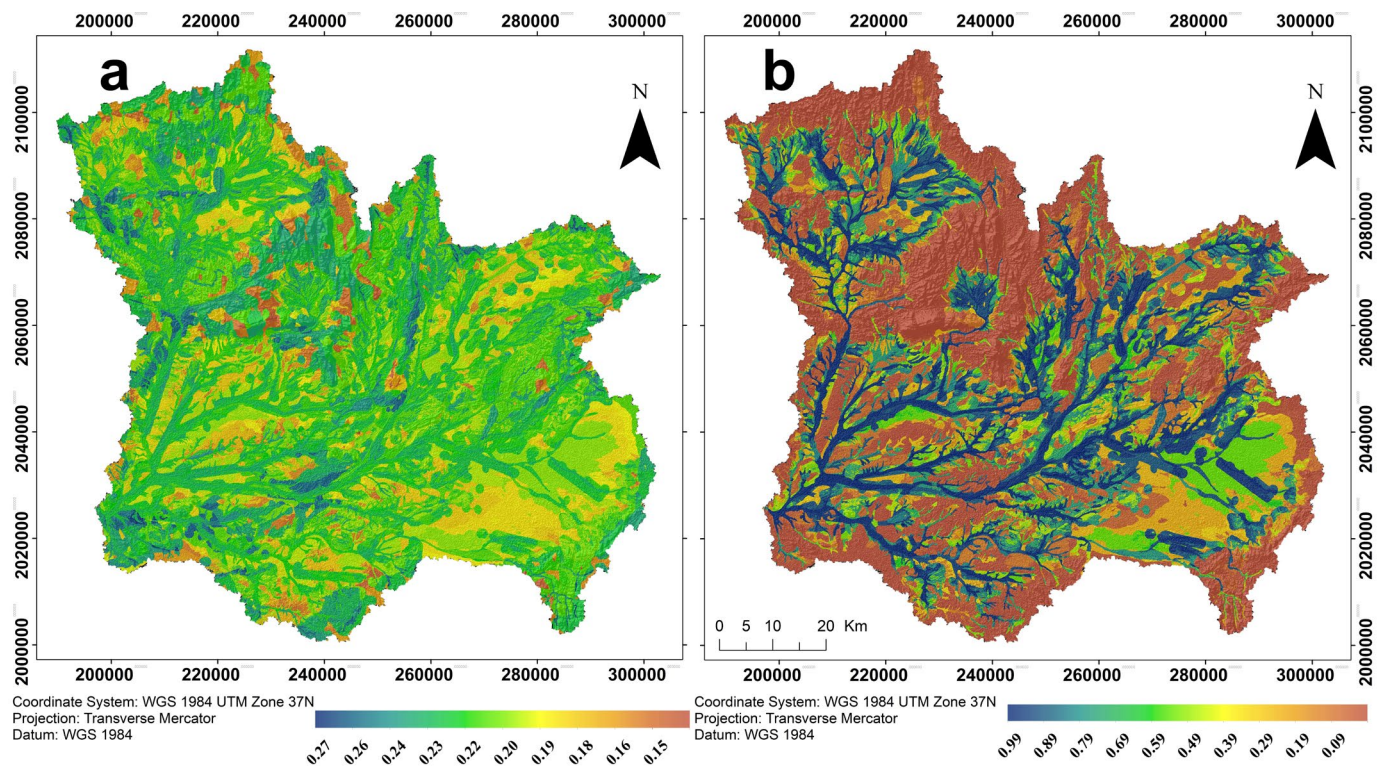


Figure 11. Monte Carlo uncertainty analysis (500 simulations) showing (a) spatial SD of GWPI (mean SD = 0.215) and (b) exceedance probability $P(\text{GWPI} \geq 4)$, confirming stable high-potential zones under weight uncertainty.

The exceedance probability analysis further supports the model's strength. The probability map $P(\text{GWPI} \geq 4)$ (Figure 11b) shows that high-potential zones retain spatial consistency across simulations, with an overall exceedance probability of 0.40 for high-class membership. The clustering of high-probability areas matches closely with structurally controlled alluvial valleys and fractured basement zones identified in the deterministic GWPI map. This confirms that the delineation of favorable groundwater zones is not an artifact of a single weight realization but remains stable under plausible perturbations of the weighting scheme.

Convergence analysis shows that the global mean GWPI, spatial standard deviation, and exceedance probability stabilize across iterations, suggesting that 500 simulations are sufficient to capture weight-induced uncertainty. Overall, the Monte Carlo analysis shows that the groundwater potential mapping framework is reasonably robust under tested uncertainty conditions, thereby increasing confidence in its application to groundwater exploration and planning in arid crystalline basement terranes.

4. Discussion

The delineation of groundwater potential zones (GWPZs) in the study area demonstrates that groundwater occurrence in arid crystalline basement environments is strongly influenced by geology, structural setting, topography, and climate when assessed using RS, GIS, and AHP. The results show that approximately 67.35% of the watershed falls within moderate-to-high groundwater potential classes, whereas about 29% is categorized as low-to-very-poor potential.

Lithology plays a major role in controlling groundwater distribution. Unconsolidated alluvial and colluvial deposits (corresponding to Groups G1 and G2), covering nearly 45% of the basin, represent the most favorable aquifer materials due to their high porosity and permeability. This finding is consistent with [13,40], who concluded that alluvial sediments

are key contributors to groundwater storage in arid regions. Weathered metasediments and granitic intrusive materials (Groups G3 and G4) also enhance groundwater occurrence by increasing secondary porosity through fracturing and weathering, as reported in studies of the Saudi Arabian basement terrain [40]. In contrast, dense crystalline units (Groups G5–G7) have restricted storage capacity and rely primarily on structural discontinuities, illustrating the importance of fracture-controlled permeability in basement aquifers.

Structural features strongly influence groundwater flow and recharge. The dominant NNE–SSW and W–E fracture orientations correspond to the regional tectonic framework of the Nubian Shield and facilitate groundwater movement along shear zones and fault corridors. This structural influence is consistent with observations from the Red Sea Hills [16] and Saudi Arabia [39], where major faults enhance groundwater circulation inside crystalline rocks.

Drainage density analysis shows that 57.6% of the watershed exhibits moderate to high drainage density, corresponding to areas of greater structural control and fracturing. Although high drainage density is typically associated with increased runoff and reduced infiltration, in structurally controlled arid basins, it commonly reflects fracture-guided channel development. Therefore, in WAW, high drainage-density zones coincide with enhanced secondary porosity and improved subsurface connectivity, consequently supporting recharge processes. Similar interpretations have been reported in the Arabian–Nubian Shield [70,71].

Topography and landforms also strongly influence groundwater potential. More than 77% of the watershed is characterized by nearly flat to gently sloping terrain, which facilitates water percolation and groundwater recharge [72]. In contrast, steeper slopes (~9%) promote rapid surface runoff, limit infiltration, and reduce recharge potential [73].

TWI analysis shows that very low and low wetness zones cover approximately 80.8% of WAW. These areas are generally elevated or moderately sloped, where runoff dominates over infiltration. In contrast, valley bottoms, wadis, and depressions (about 8.5%) are localized zones where water accumulates, promoting groundwater recharge. This finding is consistent with [74], who reported improved infiltration and ground moisture as TWI increased. The HAND analysis also confirms that most of the watershed (83.71%) lies in low- to moderately terraced areas along drainage channels, which are favorable for groundwater recharge [56]. Furthermore, ref. [58] similarly reported that lower HAND values are associated with higher groundwater potential. However, variations in lithology, fracture density, slope conditions, and local geomorphology produce distinct differences within and between wadi systems, demonstrating that the drainage network alone does not fully control groundwater occurrence and recharge.

Recharge patterns throughout the watershed are influenced by rainfall. More than 60% of the basin falls within dry or very dry rainfall classes. While topographic and structural conditions may locally enhance recharge efficiency, the overall limited precipitation constrains widespread groundwater replenishment. According to the LULC analysis, scrub/shrub (62.02%) and bare land (37.78%) dominate the watershed, indicating the semi-arid to arid climate with sparse vegetation cover. Such land-cover types enhance surface runoff and reduce infiltration [45,75]. Limited areas of cropland and denser vegetation may locally increase infiltration and recharge potential.

The AHP method successfully integrated multiple thematic layers by assigning weights informed by the literature and expert judgment. Rational consistency was ensured by a consistency ratio (CR) < 0.1. The resulting GWPZs align well with field observations and well discharge data. ROC analysis yielded an AUC of 0.704 (95% CI: 0.575–0.823), indicating good classification performance. The moderate yet statistically significant Spearman

correlation ($\rho = 0.485$, $p < 0.001$) confirms that higher GWPI values are associated with higher well discharge.

Monte Carlo uncertainty analysis further strengthens the reliability of the results. The low spatial variability (mean SD = 0.215) and stable exceedance probabilities of high-potential zones indicate that moderate perturbations in expert-derived AHP weights do not substantially alter the spatial configuration of groundwater potential classes. This confirms that the proposed RS–GIS–AHP framework is robust and reproducible under reasonable levels of uncertainty.

Compared with other GIS–AHP studies conducted in similar arid regions, including India [13], Iraq [76], and Iran [10], the thematic behavior of lithological and structural controls is consistent. However, in the present study, lineament density emerges as the most influential controlling factor, followed by terrain-related and lithological parameters, while slope, LULC, and HAND exert comparatively limited influence at the basin scale. This structural dominance reflects the fracture-controlled nature of groundwater storage and movement in crystalline basement terrains. Overall, the integration of AHP with GIS, remote sensing, and probabilistic uncertainty assessment provides a robust and transferable framework for groundwater potential mapping in arid crystalline regions such as the Nubian Shield.

Limitations and Recommendations

Despite the successful integration of RS, GIS, and AHP for groundwater potential mapping in WAW, three major limitations should be acknowledged. First, the AHP framework is inherently dependent on expert judgment and subjective weighting. Although the consistency ratio ($CR < 0.1$) confirms rational pairwise comparisons and Monte Carlo simulation demonstrated spatial robustness, the weighting structure remains knowledge-driven rather than data-driven. This may introduce structural bias in the representation of the relative importance of lithological, structural, and hydrological parameters. Future research should adopt hybrid weighting strategies, such as entropy-based methods or machine-learning-derived feature importance, to reduce subjectivity and enhance methodological objectivity.

Second, the model relies on moderate-resolution spatial datasets (30 m DEM and ~27 km rainfall), which may not adequately resolve small-scale fracture systems, micro-topographic depressions, and localized recharge pathways typical of crystalline basement terrains. Given that groundwater occurrence in the Nubian Shield is strongly controlled by fracture connectivity and weathering thickness, the use of higher-resolution DEM products, detailed structural mapping, and geophysical investigations would substantially improve the spatial representation of subsurface heterogeneity.

Third, the validation approach is constrained by temporal inconsistencies and a limited set of hydrogeological parameters. Well discharge data were collected under different pumping and hydrological conditions, and the model does not explicitly incorporate aquifer hydraulic properties such as transmissivity, hydraulic conductivity, storage coefficient, or dynamic groundwater-level fluctuations. Because basement aquifers exhibit strong spatial variability, static GWPI mapping cannot fully capture productivity variability. Future studies should integrate long-term groundwater monitoring, pumping-test interpretation, and physically based groundwater flow modeling to strengthen predictive reliability. Addressing these three limitations would enhance the robustness, physical realism, and applicability to management of groundwater potential mapping in WAW and other arid crystalline regions.

5. Conclusions

This study delineated groundwater potential zones within WAW, northeastern Sudan, using Remote Sensing, Geographic Information Systems, and the Analytical Hierarchy Process. The nine selected controlling factors (geology, rainfall, slope gradient, TWI, drainage density, lineament density, soil type, LULC, and HAND) provided a comprehensive multi-criteria framework designed for identifying the dominant controls on groundwater occurrence in this arid crystalline basement environment.

The GWPI map classified the watershed into five groundwater potential zones: very poor (3.22%), poor (25.83%), moderate (38.26%), high (29.09%), and very high (3.60%). Moderate- and high-potential zones, covering approximately two-thirds of the watershed, are mainly associated with weathered and fractured rocks, alluvial and colluvial deposits, structurally controlled wadis, and low-slope terrains near drainage channels. These conditions enhance infiltration and promote groundwater storage. In contrast, poor and very poor zones correspond to steep slopes, massive crystalline rocks, and dry upland areas where runoff dominates and recharge potential is limited.

Model validation by ROC analysis produced an AUC of 0.704 (95% CI: 0.575–0.823), indicating acceptable predictive performance. The statistically significant Spearman correlation ($\rho = 0.485$, $p < 0.001$) further confirms the positive relationship between GWPI values and well discharge. Sensitivity analysis demonstrated that lineament density is the most influential controlling factor, followed by terrain-related and lithological parameters, highlighting the dominant role of structural connectivity and fracture systems in regulating groundwater occurrence in WAW.

The results show that groundwater distribution in WAW is primarily governed by lithology, fracture connectivity, and geomorphological conditions, with precipitation acting as a secondary limiting factor in this hyper-arid setting. The combination of RS, GIS, AHP, uncertainty analysis, and statistical verification affords a robust and reproducible framework for groundwater potential assessment in arid crystalline terrains.

The generated GWPI map delivers a practical decision-support tool for well-site selection, groundwater exploration, and regional water-resource planning in the Arabian–Nubian Shield. The methodological model is transferable to other structurally controlled basement aquifers in data-limited arid regions.

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Abbreviations

The following abbreviations are used in this manuscript:

AHP	Analytical Hierarchy Process
ANS	Arabian–Nubian Shield
AUC	Area Under the Curve
CR	Consistency Ratio
DEM	Digital Elevation Model
GIS	Geographic Information System
GWPI	Groundwater Potential Index
GWPZ	Groundwater Potential Zones
HAND	Height Above Nearest Drainage
LD	Lineament Density
LULC	Land Use/Land Cover
MCS	Monte Carlo Simulation
ROC	Receiver Operating Characteristic
RS	Remote Sensing
SD	Standard Deviation
TWI	Topographic Wetness Index
WAW	Wadi Arab Watershed

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