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Integrated Fuzzy AHP-TOPSIS Model for Assessing Managed Aquifer Recharge Potential in a Hot Dry Region: A Case Study of Djibouti at a Country Scale

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Abstract: Given the prevailing arid climate and rapid population growth, groundwater resources face unprecedented challenges globally, including depletion, seawater intrusion, and contamination. Managed aquifer recharge (MAR) technologies have emerged as valuable solutions to address these pressing issues. However, identifying suitable regions for MAR activities is a complex task, particularly at the country level. Therefore, in this study, we propose a robust approach that combines the fuzzy analytical hierarchy process (AHP) and the technique for order of preference by similarity to ideal solution (TOPSIS) to delineate suitable sites for MAR structures. The proposed model was applied to Djibouti, a hot, dry, and water-stressed country. We identified a set of nine decision criteria and conducted a pairwise comparison survey to determine their relative importance. Additionally, the TOPSIS method was employed to integrate the decision layers and prioritize the study area. The results highlight the significance of rainfall, the slope, and the NDVI as the most influential decision parameters, while the drainage density has the least impact. A suitability analysis reveals that 16.38%, 17.96%, and 30.41% of the country have a very high, high, and moderate potential for MAR activities, respectively. Furthermore, a sensitivity analysis demonstrates the stability of the proposed model, affirming the usefulness of the generated suitability map.

Keywords: managed aquifer recharge; suitability mapping; fuzzy AHP; TOPSIS; sensitivity analysis; groundwater

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1. Introduction

The escalating demand for groundwater due to population growth, coupled with a drying climate that limits recharge, is exacerbating the water situation and intensifying the deterioration of subsurface resources [1]. In the Horn of Africa (Djibouti, Somalia, Ethiopia, and Eritrea), water scarcity and climate variability have already manifested in many challenges threatening millions of humans and living species. For instance, Djibouti's population heavily relies on groundwater resources, as permanent surface water sources, such as rivers and lakes, are nonexistent. However, the heavy abstraction of underground resources for several decades, coupled with highly variable rainfall in the region, has caused significant water table declines and seawater intrusion, forcing more rural dwellers and herders to seek refuge in urban areas after losing their livelihood sources [2]. The situation in Somalia is much worse, as recurrent droughts in the region caused by four consecutive failed rainy seasons have resulted in unsustainable means of groundwater extraction, including the creation of more wells and boreholes, further aggravating environmental degradation [3]. Consequently, about 6.1 million Somalis have been impacted by the consequences of these droughts, leading to massive internal population displacement [3].

The need to implement sustainable practices to mitigate the challenges faced by aquifer systems has become increasingly pressing. In this regard, managed aquifer recharge (MAR) has emerged as a promising technology that can address the risks confronting subsurface water resources while simultaneously promoting groundwater recharge [4]. MAR is also an efficient sustainable urban water management technique [5]. The technology involves the intentional injection of reclaimed water into an aquifer for subsequent retrieval or the achievement of environmental objectives [6]. Various built recharge structures are used to facilitate the accelerated replenishment of natural underground reservoirs [7]. An example of a widely embraced MAR technology in arid and semi-arid regions is rainwater harvesting (RWH). RWH involves the collection and storage of storm runoff to augment the water supply for domestic and agricultural purposes while also replenishing local aquifers [8]. Infiltration basins serve as another effective method of MAR, relying on the infiltration process whereby water is spread over wide areas using basins, dams, and channels to recharge an aquifer [9,10]. In cases where confined layers are present, deep injection wells are commonly used to convey water to the aquifer system [11]. On the other hand, vadose zone wells (i.e., drywells) offer advantages over other MAR techniques in recharging shallow urban aquifers due to their minimal land requirement and cost-effectiveness [12–14]. In general, Bouwer [15] asserted that the utilization of MAR systems offers numerous advantages compared to traditional water storage methods such as large dams. The artificial recharge of underground water via MAR technology not only minimizes water loss due to evaporation but also enables a smaller spatial footprint requirement and enhanced long-term storage capacity with lower costs [16].

In the context of MAR technologies, identifying suitable locations for recharge structures during the design stage of MAR projects is a challenging task, given the multiple factors involved. Consequently, the research community has developed several approaches to tackle this issue. For example, Anbazhagan and Ramasamy [17] utilized geophysical methods (particularly resistivity surveys) to identify appropriate sites for artificial recharge. Similarly, Christy and Lakshmanan [18] employed electrical resistivity and ground-penetrating radar methods to delineate feasible locations for MAR structures in Chennai, India, aiming to address saltwater intrusion. Brown et al. [19], on the other hand, proposed a statistical analysis-based methodology to determine suitable sites for Aquifer Storage and Recovery (ASR) projects. In a different vein, Zaidi et al. [20], Tiwari et al. [21], and Ahirwar et al. [22] utilized an integrated geographic information system (GIS) and remote sensing methods to pinpoint promising regions for MAR activities. Nevertheless, the application of coupled GIS and multi-criteria decision analysis (GIS-MCDA) techniques can be regarded as one of the most embraced approaches for delineating sites favorable for MAR applications [23–28]. Hence, the ability of a GIS to store and process spatial data [1] and the robustness of MCDA methods in resolving multi-tiered decision-making problems [29] make their integration a promising alternative for identifying regions promising for MAR implementation.

Sallwey et al. [30] noted that the most commonly adopted GIS-MCDA approaches in the relevant literature for determining the importance levels of decision parameters and combining thematic layers are the analytic hierarchy process (AHP) and the weighted linear combination (WLC), respectively. To exemplify this, Kazakis [25] applied AHP-WLC to identify potential MAR sites as a means to mitigate and prevent saltwater intrusion in a coastal aquifer. Similarly, Zhang et al. [31] employed the AHP to assess the significance levels of criteria and employed the WLC to combine thematic layers, leading to the production of a final MAR suitability map for the water-stressed West Coast region of South Africa. The authors claimed that the combination of the AHP with WLC offers an effective approach to address spatial decision-making problems. In line with this, Shadmehri Toosi et al. [32] applied the AHP to derive the weights of the utilized decision parameters (namely, slope, rainfall, soil type, soil depth, land use, and drainage density) to delineate suitable sites for RWH structures. However, it should be noted that some scholars have highlighted the limitations of the standard AHP, particularly in incorporating the inherent fuzziness of human judgment [33]. Consequently, hybridizing fuzzy set theory and the AHP technique has been widely acknowledged by various researchers in recent attempts [4,10,34]. In addition, various MCDA-based prioritization techniques, such as the evaluation based on distance from average solution (EDAS), simple additive weighting (SAW), and the technique for order of preference by similarity to ideal solution (TOPSIS), have been utilized in the pertinent literature [35–38].

From a spatial aspect, the assessment of MAR potential has been extensively conducted at the watershed or district scale. However, it is imperative to emphasize the significance of examining MAR potential at a countrywide level, particularly in regions where MAR is a relatively new concept. In this regard, Mahmoud et al. [39] developed an RWH site suitability map for Egypt at a national scale to promote the sustainability of subsurface resources and address water scarcity across the country. Likewise, Mahmoud and Tang [40] generated an RWH potential map for the entire United Kingdom considering divergent decision attributes, including rainfall, slope, curve number, land cover/use, and soil texture. Bonilla Valverde et al. [24] mapped the potential of MAR technology (notably surface-spreading techniques) in Costa Rica at the country scale based on four decision factors, namely, the hydrogeological aptitude, slope, soil texture, and drainage network density. Kadhem and Zubari [41] prioritized the Kingdom of Bahrein in terms of MAR suitability as a means to address the groundwater table decline and saltwater intrusion in the country. Notably, Mati et al. [42] conducted the largest-scale assessment of MAR potential, evaluating RWH technology for ten African countries, namely, Botswana, Ethiopia, Kenya, Malawi, Mozambique, Rwanda, Tanzania, Uganda, Zambia, and Zimbabwe.

This study entailed the assessment of MAR potential in a hot and arid region through the utilization of a novel hybrid fuzzy AHP and TOPSIS approach. The proposed framework was applied to the water-stressed country of Djibouti, where ensuring the long-term sustainability of groundwater resources is of paramount importance for the local population's survival. The research objectives can be summarized as follows: (i) conduct a comprehensive assessment of MAR potential in Djibouti for the first time, (ii) identify a comprehensive set of surface, environmental, and subsurface decision factors based on an extensive review of the literature to determine regions suitable for MAR activities, (iii) initiate a pairwise comparison questionnaire involving experts from various backgrounds and ensure the consistency of the preferences of the participants, (iv) employ the fuzzy AHP algorithm to determine the importance levels of the decision criteria while utilizing the TOPSIS method to prioritize the study area based on different degrees of suitability, (v) perform a two-stage sensitivity analysis to assess the stability and reliability of the proposed model, which represents an initial attempt in the existing literature, and (vi) utilize the web-based INOWAS tool to select feasible MAR techniques for the study region and assess their suitability in terms of their implementation in Djibouti.

2. Materials and Methods

The present research aimed to establish a robust decision framework encompassing the adoption of different MCDA techniques. Hence, a thorough literature survey was conducted first, leading to the extraction of decision criteria that influence the determination of (non-) suitable MAR regions. To quantitatively evaluate the corresponding decision criteria, this study introduced the fuzzy AHP algorithm with the triangular fuzzy membership function. It is important to note that, along with dealing with interpersonal uncertainty by adopting fuzzy set theory, the reliability of the subjective judgments of the experts and the stability of the entire criteria weighting process were ensured by consistency ratio checks and a sensitivity analysis, respectively. Given the necessity to mimic real-world conditions in this analysis to extrapolate the results that can potentially be applied in regions of interest, this research further integrated the criteria weights with the current values of the decision criteria in the TOPSIS analysis in order to designate the MAR-suitable regions in Djibouti. The research steps considered in this study are depicted in Figure 1.

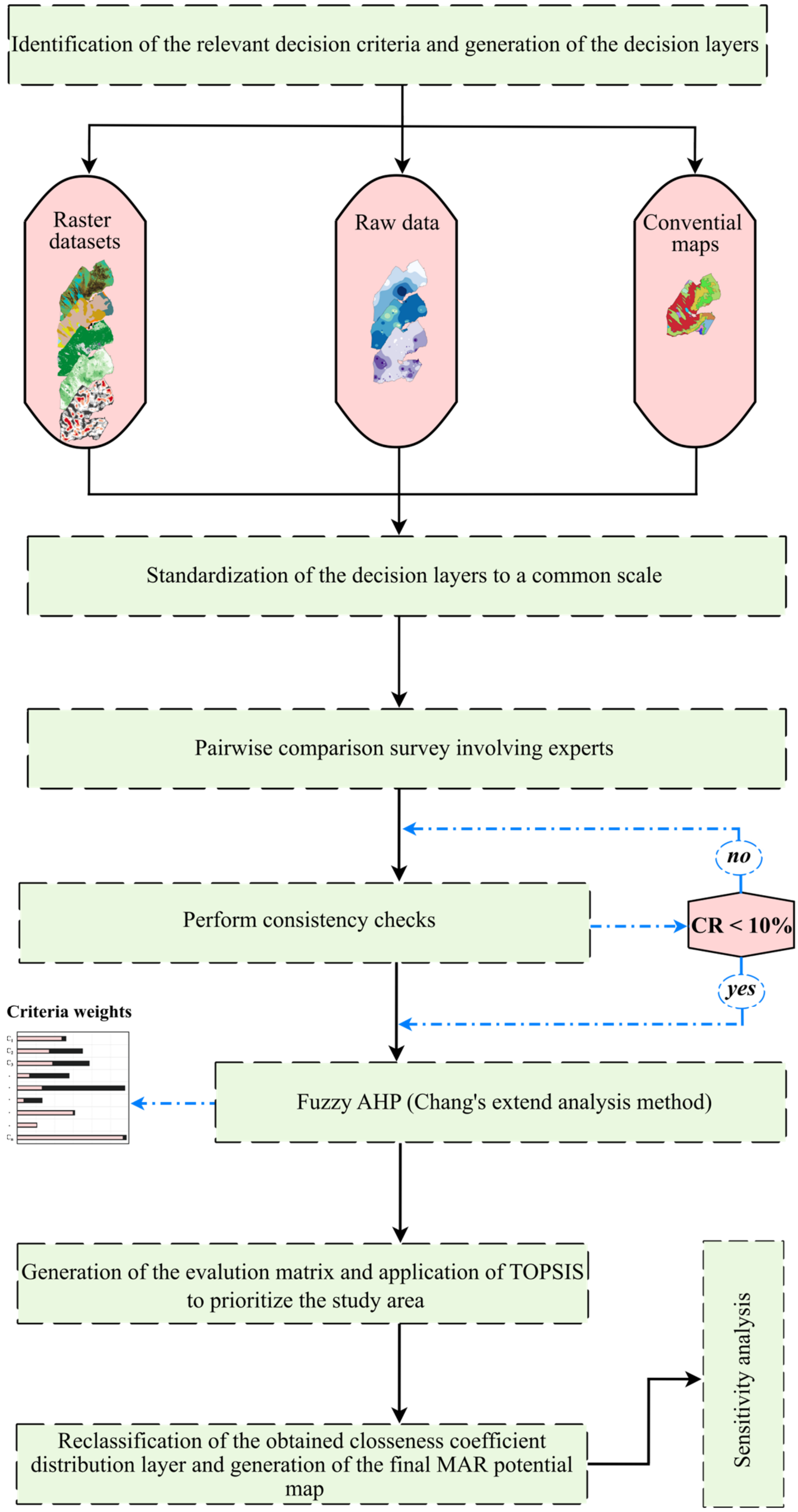

Figure 1. Flow of the research steps.

2.1. Study Area

Djibouti, situated in the Horn of Africa, is the smallest country in the region, with a land area of approximately 23,200 km^2 (Figure 2). The country has a current estimated population of one million and shares terrestrial borders with Eritrea, Ethiopia, and Somalia, as well as maritime borders with Yemen. The climate of Djibouti is characterized by hot and arid conditions, with an annual mean rainfall of 150 mm and temperatures ranging from 20 °C to 30 °C in winter (October to April) and 30 °C to 45 °C in summer (May to September) [43]. In Djibouti, the principal groundwater reserves consist of fractured volcanic aquifers, primarily represented by three geological formations: the Dalha basalts, the Stratoid basalts, and the Mabla rhyolites [44,45]. These geological formations serve as the main sources of groundwater supply, characterized by a fractured nature and high permeability, allowing for substantial quantities of groundwater to be extracted. Furthermore, sedimentary aquifers with a transmissivity between 5.6 × 10^{-6} and 1.3 × 10^{-3} m^2/s [44] are present along some watersheds and the eastern coastal part of the study region.

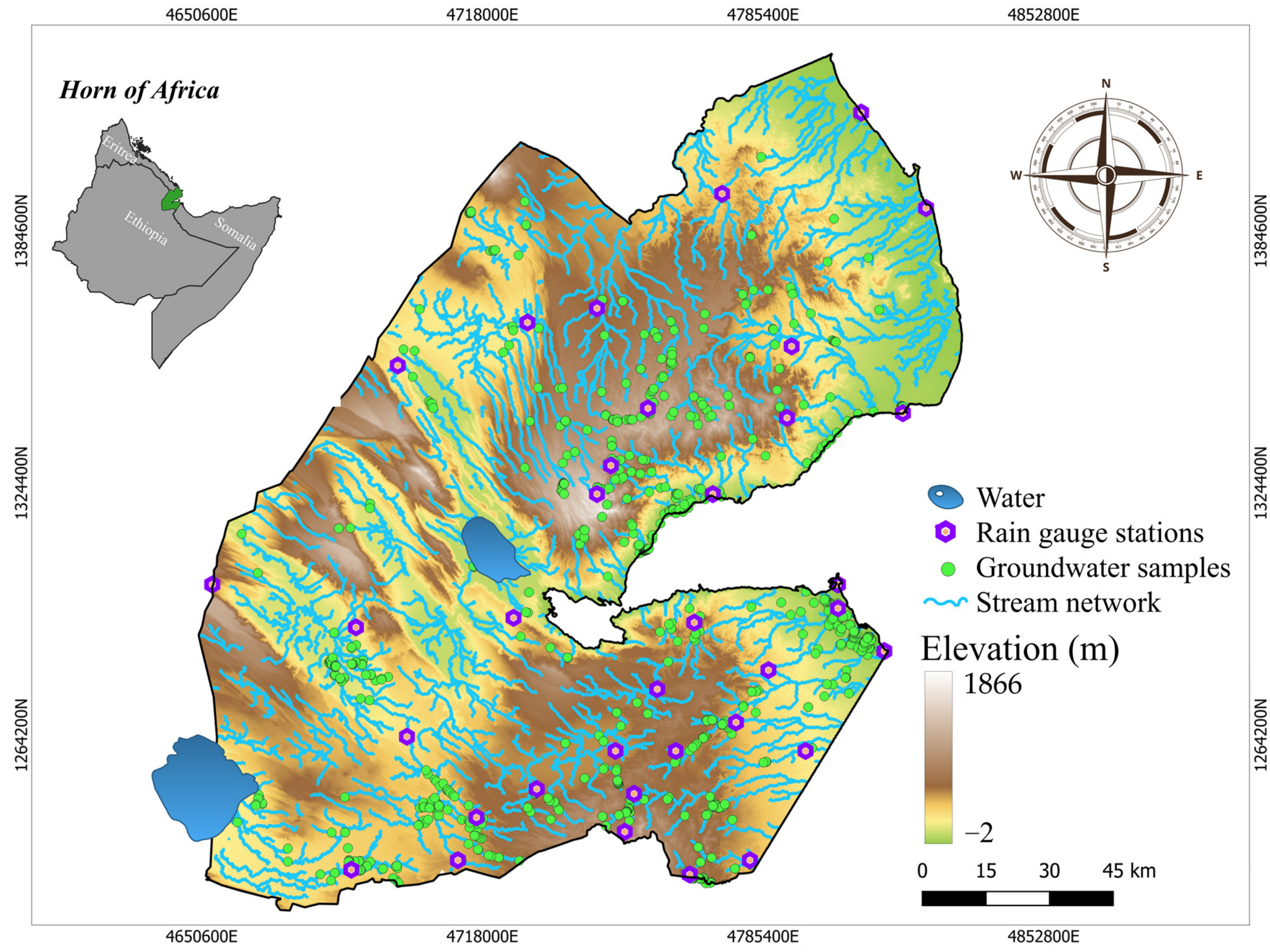

Figure 2. Study area.

The ability to meet the water demand of the country heavily relies on groundwater due to the absence of permanent surface water resources. This overdependence has led to the widespread use of abstraction wells without proper planning or sustainable management practices [46]. Consequently, this excessive groundwater extraction, coupled with reduced recharge rates due to climate variability, poses substantial challenges to subsurface resources (i.e., depletion, contamination, and saltwater intrusion). In light of these challenging circumstances, investigating the feasibility of MAR in Djibouti assumes great importance, as it presents a viable solution to mitigate water shortage and achieve long-term sustainability.

2.2. Data Source and Layer Processing

After performing an extensive review of the existing literature and consulting with experts in the field, a comprehensive analysis resulted in the identification of nine pertinent parameters for delineating regions suitable for MAR activities. These selected criteria were subsequently categorized into three primary clusters, each encompassing three criteria, in order to establish an improved hierarchical framework (Table 1). The surface cluster consisted of the slope, soil texture, and curve number, while rainfall, the normalized difference vegetation index (NDVI), and drainage density were incorporated into the decision framework under the umbrella of the environmental cluster. Lastly, the subsurface cluster comprised depth to groundwater, geology, and groundwater quality (specifically the electrical conductivity in this investigation). Additionally, a concise description of the influence of each criterion in the MAR potential mapping decision framework can also be found in Table 1.

The generation of a spatial thematic layer for each factor involved in the decision framework represents an important step in MAR mapping. In line with this, a raster layer was generated for each criterion based on various data sources. For instance, slope and drainage density maps (depicted in Figures 3a and 3f, respectively) were derived from the ALOS World 3D (AW3D) digital elevation model with a 5 m resolution [47]. The available slope analysis tools in QGIS were used to generate the slope layer of the study region in percent, while the drainage density raster layer was obtained by applying the line density interpolation algorithm. Soil texture was obtained from the Harmonized World Soil Database version 2.0 (HWSD v2.0) [48], and the resulting map is given in Figure 3b. The curve number map (Figure 3c) of the study region was clipped from the global curve number (GCN250) dataset provided by Jaafar and Ahmad [49]. The GCN250 dataset has a resolution of 250 m and can be downloaded in raster format. To establish the rainfall distribution throughout the country, the average annual rainfall at various stations was acquired from Dabar et al. [50], and the precipitation raster layer (Figure 3d) was generated using the inverse distance weighting (IDW) interpolation method. Regarding the calculation of the NDVI illustrated in Figure 3e, Sentinel 2 imagery was employed, and the following formula was applied:

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}} \quad (1)$$

where NIR and RED represent the near-infrared and red bands, respectively. The acquisition of Sentinel imagery from Google Earth Engine and the necessary computations to obtain the NDVI were performed using the Geemap Python package [51]. The geological representation of the country was digitized from a technical report [46], while the layers depicting depth to groundwater and electrical conductivity were generated using IDW interpolation based on raw data obtained from the Ministry of Agriculture, Water, Fisheries and Livestock, in charge of Fishery Resources (MAEPE-RH) of Djibouti. Hence, Figure 3g–i illustrate the depth to groundwater, geology, and electrical conductivity maps, respectively. It is important to highlight that all geoprocessing tasks in this research were conducted using QGIS 3.28 [52].

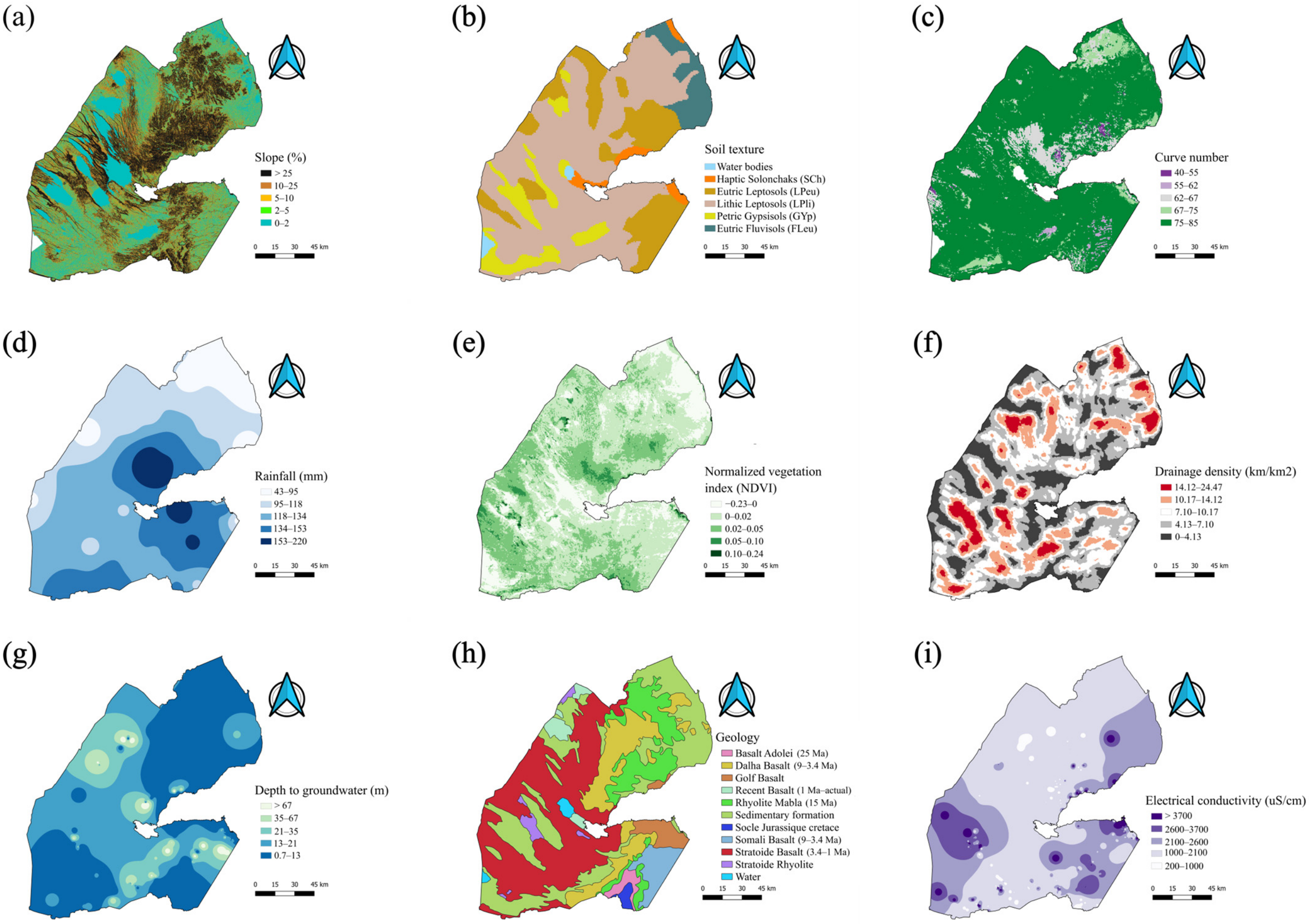

Figure 3. Thematic maps of the relevant decision criteria for MAR potential mapping: (**a**) slope, (**b**) soil texture, (**c**) curve number, (**d**) rainfall, (**e**) normalized difference vegetation index, (**f**) drainage density, (**g**) depth to groundwater, (**h**) geology, and (**i**) electrical conductivity.

During this stage, the need for standardizing the decision layers becomes imperative due to their diverse nature in this study. The existing literature encompasses various standardization techniques, including fuzzy membership functions, stepwise functions, AHP, and the utilization of rates/scores for feature classes [23,24,31,32,53–55]. Consequently, this study employed the rating technique to reduce the complexity of the proposed framework, whereby a score of 5 was assigned to cells exhibiting high suitability for MAR potential, while a rating of 1 was attributed to the least suitable cells (Table 1).

Table 1. List of selected decision criteria, accompanied by their corresponding descriptions, along with the ratings assigned to the criteria classes.

Clusters	Criteria	ID	Classes	Rating	Source Reference
Surface	Slope [a] (%)	S	0–2	5	AW3D [47]
			2–5	4	
			5–10	3	
			10–25	2	
			>25	1	
	Soil texture [b]	ST	Eutric Fluvisols (FLeu)	5	HWSD v2.0 [48]
			Petric Gypsisols (GYp)	4	
			Eutric Leptosols (LPeu)	2	
			Lithic Leptosols (LPli)	2	
			Haptic Solonchaks (SCh)	1	

Table 1. *Cont.*

Clusters	Criteria	ID	Classes	Rating	Source Reference
	Curve number [c]	CN	75–85	5	Jaafar and Ahmad [49]
			67–75	4	
			62–67	3	
			55–62	2	
			40–55	1	
Environment	Rainfall [d] (mm)	R_l	153–220	5	Dabar et al. [50]
			134–153	4	
			118–134	3	
			95–118	2	
			43–95	1	
	Normalized difference [e] vegetation index	NDVI	0.10–0.24	5	Sentinel 2 [56]
			0.05–0.10	4	
			0.02–0.05	3	
			0–0.02	1	
	Drainage density [f] (km/km^2)	DD	0–4.13	5	AW3D [47]
			4.13–7.10	4	
			7.10–10.17	3	
			10.17–14.12	2	
			14.12–24.47	1	
Subsurface	Depth to groundwater [g] (m)	DG	0.7–13	1	MAEPE-RH
			13–21	5	
			21–35	3	
			35–67	2	
			>67	1	
	Geology [h]	G	Sedimentary formations	5	MAEPE-RH [46]
			Recent basalt (1 Ma-actual)	3	
			Stratoid basalt (3.4–1 Ma)	2	
			Golf basalt (3.4–1 Ma)	2	
			Somali basalt (9–3.4 Ma)	2	
			Dalha basalt (9–3.4 Ma)	2	
			Adolei basalt (25Ma)	2	
			Stratoid rhyolite	1	
			Mabla rhyolite	1	
			Cretaceous–Jurassic base	1	
	Groundwater quality [i] (µS/cm)	EC	200–1000	5	MAEPE-RH
			1000–2100	4	
			2100–2600	3	
			2600–3700	2	
			>3700	1	

Notes: [a] Slope serves as a highly utilized decision criterion in the context of MAR mapping due to its significant influence on the convergence and divergence of runoff water, ultimately affecting the infiltration capacity [24]. [b] Rajasekhar et al. [57] noted that the soil type plays a critical role in regulating both infiltration rates and the potential generation of runoff. Specifically, soils with a high clay content tend to display diminished infiltration rates and increased runoff, whereas soils with a high sand content tend to exhibit enhanced infiltration rates and reduced runoff. [c] As a dimensionless index that characterizes the soil's ability to absorb water, the curve number can be used to indirectly estimate the volume of runoff that can be harvested in a particular area for MAR usage [58]. [d] Rainfall plays a pivotal role in MAR mapping since rainwater represents the main source of water for MAR projects worldwide [59]. [e] According to Ansems et al. [60], high-NDVI regions could be indicative of the temporal availability of water and thereby have the potential to reclaim large volumes of water. [f] Drainage density is inversely proportional to permeability such that areas with a high drainage density indicate the presence of low-permeability rock, whereas a low drainage density suggests the presence of more permeable rock [61]. [g] The depth to groundwater influences the feasibility of the MAR project as well as the recharge rates [20]. [h] The rock type prevalent in a given region plays a vital role in governing the movement and distribution of groundwater [62]. [i] Injecting reclaimed water into a poor-groundwater-quality region could jeopardize the MAR benefit; therefore, it is important to include groundwater quality parameters in the decision framework [58].

2.3. MCDA Rationale

MCDA is a technique used in complex decision-making processes. MCDA methods are generally employed to evaluate alternative options by considering multiple criteria or objectives, and rather than providing an ideal solution, they enable the extraction of a compromise solution [63]. With the MCDA rationale, the first step involves identifying criteria to consider in the decision-making process, which represent the metrics used to evaluate the alternatives. Subsequently, weighting is applied to assign importance degrees to the identified criteria, reflecting their relative significance. Following that, each alternative is subjected to a performance evaluation based on the predefined criteria involving the objective evaluation of the alternatives' performance. Finally, by utilizing the corresponding outcomes, an aggregation method is employed to determine the overall performance of the alternatives, aiding in ranking the alternatives and identifying the optimal solution(s). MCDA is applied in various domains, including business [64], public policy [65], environmental management [66], and healthcare [67] projects. Different techniques and tools are available within the MCDA framework, including the AHP, analytic network process (ANP), TOPSIS, and preference ranking organization method for enrichment evaluations (PROMETHEE). However, the choice of technique depends on the specific characteristics of the decision problem, the available data, and the preferences of the decision-makers. Overall, MCDA provides a structured and systematic approach to decision making, enabling stakeholders to consider multiple criteria and objectives in a comprehensive manner. It supports more informed and rational decision making, especially in complex situations where there are trade-offs and conflicting preferences among different criteria.

2.3.1. Description of the Fuzzy AHP Algorithm

The AHP, introduced by Saaty [68], is frequently employed to construct a hierarchical framework that captures intricate problem structures, aligning with the subjective assessments of experts. This methodological framework enables a detailed and granular analysis of complex problems, allowing for the incorporation of the subjective judgments of experts while maintaining scientific rigor. The AHP employs a systematic approach to hierarchically structure a problem, beginning with a primary goal and progressively delving into criteria, sub-criteria, and subsequent levels, ultimately encompassing a comprehensive set of alternatives [69]. This hierarchical representation offers experts a comprehensive understanding of the intricate relationships inherent in the context, enabling a holistic view of the problem. Furthermore, it aids in evaluating the comparability of elements at the same level, allowing for meaningful comparisons and assessments [33]. Subsequently, elements are subjected to pairwise comparisons on a nine-level scale to derive their relative weights, facilitating [70,71] the quantification of their respective importance in the decision-making process. Although the primary objective of the AHP is to incorporate expert knowledge, the classical AHP method falls short in addressing the non-numeric uncertainties inherent in human thinking processes. Consequently, the implementation of the fuzzy AHP to provide more robust solutions has gained much more interest in the recent decade. The fuzzy AHP method integrates the principles of fuzzy sets (initially introduced by Zadeh [72]) to address the intricate and ambiguous nature of the environment and experts' preferences. The fuzzy AHP tackles the challenges posed by vagueness and imprecision in decision making by enabling fuzzy linguistic assessments and the representation of interpersonal uncertainties through fuzzy numbers. By capturing and quantifying the inherent ambiguity, the fuzzy AHP offers a more reliable and comprehensive approach to handling complex problems and supports more informed decision-making processes. When decision-makers evaluate criteria and alternatives, they can utilize natural language expressions alongside precise numerical values. Therefore, the fuzzy AHP method closely resembles human thinking and perceptions. As a result, it has been consistently employed by numerous researchers across various fields [70,71,73].

In the initial step of utilizing the fuzzy AHP, the decision hierarchy structure is established by incorporating all the criteria, including primary criteria, sub-criteria, goals, and alternatives. To determine the order, each pair of items is compared using a nine-point significance scale. The steps of the fuzzy AHP approach are commonly arranged in the following manner:

1. After the hierarchical structure is revealed, decision-makers construct binary comparison matrices in accordance with their perspectives. These matrices encompass the relative evaluations and favored choices among components at each level of the hierarchy. The reciprocals of linguistic variables regarding the importance degrees of the criteria are incorporated into the preferences of the experts who attended the surveys. Thus, l_{ij}, m_{ij}, and u_{ij}, indicating the lower, mean, and upper widths of the pairwise judgments of the experts for criterion i compared to criterion j, respectively, are determined (Table 2).

Table 2. Linguistic scales and triangular fuzzy reciprocals of AHP and fuzzy AHP.

Linguistic Variables	**AHP**		**Fuzzy AHP**	
	Importance	**Value for Reciprocals**	**Triangular Fuzzy Numbers** $\left(l_{ij}, m_{ij}, u_{ij}\right)$	**Triangular Fuzzy Reciprocals** $\left(1/u_{ij}, 1/m_{ij}, 1/l_{ij}\right)$
Equally important	1	(1/1)	(1,1,1)	(1,1,1)
Intermediate value	2	(1/2)	(1,2,3)	(1/3,1/2,1)
Moderately important	3	(1/3)	(2,3,4)	(1/4,1/3,1/2)
Intermediate value	4	(1/4)	(3,4,5)	(1/5,1/4,1/3)
Important	5	(1/5)	(4,5,6)	(1/6,1/5,1/4)
Intermediate value	6	(1/6)	(5,6,7)	(1/7,1/6,1/5)
Very important	7	(1/7)	(6,7,8)	(1/8,1/7,1/6)
Intermediate value	8	(1/8)	(7,8,9)	(1/9,1/8,1/7)
Extremely important	9	(1/9)	(9,9,9)	(1/9,1/9,1/9)

2. In the fuzzy AHP approach, an additional step is implemented to verify the consistency of experts' pairwise comparisons. This is achieved by calculating the consistency ratio (CR), where CR values exceeding 0.1 indicate inconsistent judgments made by respondents, while CR values below the threshold indicate a more consistent set of expert preferences. The following expression can be utilized to determine the CR values, thus assessing the level of consistency in the decision-making process.

$$CR = \frac{\frac{\lambda_{max} - n}{n-1}}{RI} \tag{2}$$

where λ_{max} and n denote the maximum eigenvalue of the matrix and the number of criteria in the matrix, respectively. In addition, RI is the random index, which was introduced by Saaty [74] and is based on the size of the matrix (Table 3).

Table 3. Random index.

n	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Random Index	0	0	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49

3. In this step, the fuzzy equivalents of each linguistic variable are calculated. Equation (3) outlines the method for determining the lower (l_{ijk}), mean (m_{ijk}), and upper (u_{ijk}) widths of the fuzzy equivalents using the triangular membership function.

$$l_{ij} = \left(\prod_{k=1}^{K} l_{ijk}\right)^{1/K}; \; m_{ij} = \left(\prod_{k=1}^{K} m_{ijk}\right)^{1/K}; \; u_{ij} = \left(\prod_{k=1}^{K} u_{ijk}\right)^{1/K} \tag{3}$$

in which K is the total number of respondents.

4. To address the inherent vagueness and uncertainty in experts' judgments (Table 4), Chang's [75] extent analysis was employed. In this approach, crisp mathematical notations were utilized to obtain fuzzy quantities. The object set, represented by $X = \{x_1,\ x_2, x_3, \ldots, x_n\}$, and the goal set, denoted by $U = \{u_1,\ u_2, u_3, \ldots, u_n\}$, were considered in the extent analysis. For each goal, denoted by u_i, extent analysis values represented by m are obtained for each object.

$$l_{ij} = \left(\prod_{k=1}^{K} l_{ijk}\right)^{1/K};\ m_{ij} = \left(\prod_{k=1}^{K} m_{ijk}\right)^{1/K};\ u_{ij} = \left(\prod_{k=1}^{K} u_{ijk}\right)^{1/K} \tag{4}$$

Table 4. Profiles of the experts who performed pairwise comparisons.

ID	Sector	Job Description	Background	Experience (Years)
Expert 1	Academia	Professor	Civil and Environmental Engineering	16
Expert 2	Academia	Associate Professor	Environmental Engineering	11
Expert 3	Municipality	Head of Department	Civil Engineering (PhD)	20
Expert 4	Municipality	Planning Engineer	Architecture (MSc)	6
Expert 5	Water administration	Unit Manager	Civil Engineering	8
Expert 6	Water administration	Technical Office Engineer	Geological Engineering (MSc)	5
Expert 7	Private sector	General Manager	Environmental Engineering (MSc)	15
Expert 8	Private sector	Modeling and Design Engineer	Geological Engineering	6

To calculate M_{gi}^{j}, the fuzzy extent analysis M value addition operation is performed on the matrix. This operation involves adding each triangular fuzzy number (TFN) in each row of the matrix using the addition operation, as described in Equation (5).

$$\sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j\right) \tag{5}$$

with $i = 1,\ 2,\ \ldots, n$. The score $\left[\sum_{j=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right]^{-1}$ is obtained by calculating the sum of the entire triangular fuzzy number set $M_{gi}^{j}(j = 1,\ 2,\ \ldots, m)$.

$$\left[\sum_{j=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right] = \left[\sum_{j=1}^{n}\sum_{j=1}^{m} l_j, \sum_{j=1}^{n}\sum_{j=1}^{m} m_j, \sum_{j=1}^{n}\sum_{j=1}^{m} u_j\right] \tag{6}$$

The inverse of the initial equation can be computed using the formula presented in Equation (7).

$$\left[\sum_{j=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_1}, \frac{1}{\sum_{i=1}^{n} m_1}, \frac{1}{\sum_{i=1}^{n} l_1}\right) \tag{7}$$

A comparative calculation is performed to assess the level of possibility between fuzzy numbers. This comparison is utilized to determine the weight value assigned to each criterion. When comparing two triangular fuzzy numbers $M_1 = (l_1,\ m_1,\ u_1)$ and $M_2 = (l_2,\ m_2,\ u_2)$, where the probability level $S_2 \geq S_1$, a definition can be established.

$$(M_2 \geq M_1) = \begin{cases} 1, & if\ m_1 \geq m_2 \\ 0, & if\ l_1 \geq l_2 \\ \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, & for\ others \end{cases} \tag{8}$$

To compare M_1 and M_2, it is necessary to calculate the values V ($M_1 \geq M_2$) and V ($M_2 \geq M_1$). Once the fuzzy synthetic values have been compared, the minimum value is determined using Equation (9).

$$D'(A_i) = minV(S_i \geq S_k) \tag{9}$$

For each k value ranging from 1 to n, where $k \neq i$, the weight vector is calculated to facilitate the interpretation of the defined criteria.

$$W' = \left[d'(A_1), d'(A_2), \ldots, d'(A_n)\,\right]^T \tag{10}$$

where $A_i (i = 1, 2, \ldots n)$ is n elements, and $d'(A_i)$ is the score describing each decision attribute of the compared options.

Subsequently, the weights are normalized using Equation (11) to transform the values in the weight vector into analog weights. This normalization process ensures that the weights consist of non-fuzzy numbers.

$$d(A_i) = \frac{d'(A_i)}{\sum_{i=1}^{n} d'(A_i)} \qquad for\ i = 1, 2, \ldots, n \tag{11}$$

5. The last step is considered crucial in determining the degrees of importance for the considered criteria [76]. Therefore, a sensitivity analysis was conducted to examine the variations in criteria importance based on different degrees of fuzziness. The initial degree of fuzziness in the adopted FAHP method was set to 1, determined by the distances between l, m, and u values (Table 2). Additionally, five additional fuzziness degrees (1.2, 1.4, 1.6, 1.8, and 2.0) were explored in the current study. Consequently, if the order of importance remains relatively unchanged, it can be concluded that the decision analysis framework yields reliable results and is not significantly influenced by changes in fuzziness degrees [77].

2.3.2. Description of the TOPSIS Algorithm

The TOPSIS method is a well-established decision-making technique that has been widely used in various fields. According to Hwang and Yoon [78], TOPSIS is based on the concept of ranking alternatives by their relative proximity to the ideal solution. On the one hand, the positive ideal solution represents the alternative that maximizes benefit criteria and minimizes cost criteria. On the other hand, the negative ideal solution minimizes benefit criteria and maximizes cost criteria. The selection of the most suitable alternative is performed based on its proximity to the positive ideal solution and distance from the negative ideal solution. The TOPSIS method provides a systematic approach to decision making, considering multiple criteria simultaneously. Overall, the TOPSIS method has proven to be effective in evaluating and ranking alternatives, and its application has been documented in numerous scientific studies [79–81].

The TOPSIS essentially contains six steps:

1. Defining the Decision Matrix: A decision matrix is formulated, encompassing all available alternatives along with their corresponding performance values on various criteria. The decision matrix is typically represented as an $m \times n$ matrix, where m is the number of alternatives and n is the number of criteria. The decision matrix according to the TOPSIS method is shown in Equation (12).

$$A_{ij} = \begin{bmatrix} a_{11} & a_{12} & \ldots & a_{1n} \\ a_{21} & a_{22} & \ldots & a_{2n} \\ . & . & . & . \\ . & . & . & . \\ a_{m1} & a_{m2} & \ldots & a_{mn} \end{bmatrix} \tag{12}$$

In this study, the generation of the decision matrix involved several steps. Initially, a rectangular grid layer with a spatial resolution of 500 m × 500 m was created and subsequently clipped with the study area vector layer to confine the analysis within the defined study boundaries. Then, the zonal statistics tool was employed to calculate the mean value for each pixel, considering the nine decision layers as input raster layers. Consequently, the outcome of this process yielded a decision matrix consisting of 90,177 rows and 9 columns.

2. Normalizing the Decision Matrix: The decision matrix is normalized to eliminate any scale differences among the criteria. This step ensures that all criteria are given equal weightage in the decision-making process. Various normalization methods can be used, such as min–max normalization or vector normalization. The normalization of the decision matrix can be calculated through the formula depicted in Equation (13).

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{k=1}^{m} a_{kj}^2}} \qquad (i = 1,\ 2,\ \ldots, m; j = 1,\ 2,\ \ldots,\ n) \tag{13}$$

3. Assigning Weights to the Criteria: The relative importance or weights of the criteria are determined. The weights reflect the significance of each criterion in the decision-making process. The determination of weights can be subjective, based on expert judgment, or derived using mathematical techniques, such as the analytic hierarchy process (AHP) or Entropy Weight Method. At this stage, the weighted decision matrix is obtained by multiplying the data in the normalized decision matrix, obtained in the second step of the TOPSIS method, by the weight values determined through the previously conducted weighting method. The sum of the data obtained from the weighting method must be equal to 1.
4. Determining the Positive and Negative Ideal Solutions: The positive ideal solution and the negative ideal solution are identified based on the maximum and minimum values, respectively, for each criterion. The positive ideal solution represents the alternative that achieves the maximum benefit and the minimum cost, while the negative ideal solution represents the alternative that minimizes the benefit and maximizes the cost. The TOPSIS method assumes that each criterion exhibits a monotonically increasing or decreasing trend. To determine the ideal solution set, the maximum value of the column in the weighted decision matrix is selected. If the criterion is cost-oriented or in a minimization direction, the smallest criterion is chosen. The relevant formula for the ideal solution set is shown in Equation (14).

$$A^{+} = \left\{ \left(max\, v_{ij} \middle| j\ \in J \right), \left(min\, v_{ij} \middle| j\ \in J' \right) \right\} \tag{14}$$

In the negative ideal solution set, the smallest values of the data in the columns containing criterion values in the weighted decision matrix are examined. The formula for the negative ideal solution set is shown in Equation (15).

$$A^{-} = \left\{ \left(min\, v_{ij} \middle| j\ \in J \right), \left(max\, v_{ij} \middle| j\ \in J' \right) \right\} \tag{15}$$

5. Calculating Euclidean Distances: The Euclidean distance between each alternative and the positive and negative ideal solutions is calculated. The Euclidean distance represents the overall proximity or distance of each alternative to the ideal solutions in the multi-dimensional criteria space. As a result of this process, the deviation values for the alternatives are defined as the ideal separation (S_1^{+}) and negative ideal separation (S_1^{-}) measures. The formulas for ideal separation and negative ideal separation are shown in Equations (16) and (17).

$$S_1^{+} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^{+} \right)^2} \tag{16}$$

$$S_1^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \quad (17)$$

6. Calculating the Proximity to Ideal Solutions: The relative proximity of each alternative to the positive and negative ideal solutions is determined. This can be achieved by calculating the relative closeness coefficient, which is the ratio of the distance from the negative ideal solution to the sum of the distances from the positive and negative ideal solutions. The calculation of the relative closeness to the ideal solution is shown in Equation (18).

$$CC_i = \frac{S_1^-}{S_1^- + S_1^+} \quad (18)$$

The obtained CC_i value takes a value in the range of $0 \leq CC_i \leq 1$. $CC_i = 1$ indicates the absolute proximity of the alternative to the ideal solution, while $CC_i = 0$ indicates the absolute proximity of the alternative to the negative ideal solution. The ranking of alternatives is determined by sorting the obtained CC_i values in descending order, indicating their level of importance.

3. Results

3.1. Criteria Weighting

This research has explored the role of different criteria in assessing the MAR mapping based on three dimensions, i.e., surface, environment, and subsurface. The fuzzy AHP technique was employed not only to reveal the contribution of each dimension but also to demonstrate the impact of nine different criteria on the MAR suitability assessments. Hence, the present study utilized the outcomes of the judgments of the expert group (Table 4) to compute the weights of both the main clusters and the corresponding criteria. To ensure the reliability of the obtained results, consistency ratios were initially investigated. It is especially worth mentioning that obtaining CR values smaller than 10% indicates that the decision framework is consistent, and further computations, including criteria weighting, can be pursued. Figure 4 reveals that all the experts were quite consistent in pairwise comparisons. In qualitative assessments, the experts may be confused about their results due to the complex nature of the pairwise comparison matrix, leading to inconsistent evaluations. However, this research refined the list of criteria (3×3) and the main clusters (1×3), and the experts yielded consistent results in the first round of the surveys.

Table 5 highlights that, among the three main clusters, the environment dimension (with a weight of 48.85%) was determined as the most significant, followed by the surface (30.36%) and subsurface (20.79%) dimensions, respectively. Table 5 also includes the local and global weights of the criteria considered. Accordingly, in the surface cluster, the slope was the most determinant criterion, as it gained the highest weight with 43.92%, while the curve number and soil texture followed the slope with 31.27% and 24.81%. In addition, the rainfall criterion (62.80%) outperformed the NDVI (24.33%) and drainage density (12.86%) with respect to the criteria weights calculated through the fuzzy AHP. The local criteria weights regarding the subsurface dimension depict a more homogeneous distribution among the three considered criteria, i.e., groundwater quality (37.27%), geology (33.41%), and depth to groundwater (29.32%), indicating that each criterion has no distinctive impact on the determination of suitable MAR sites.

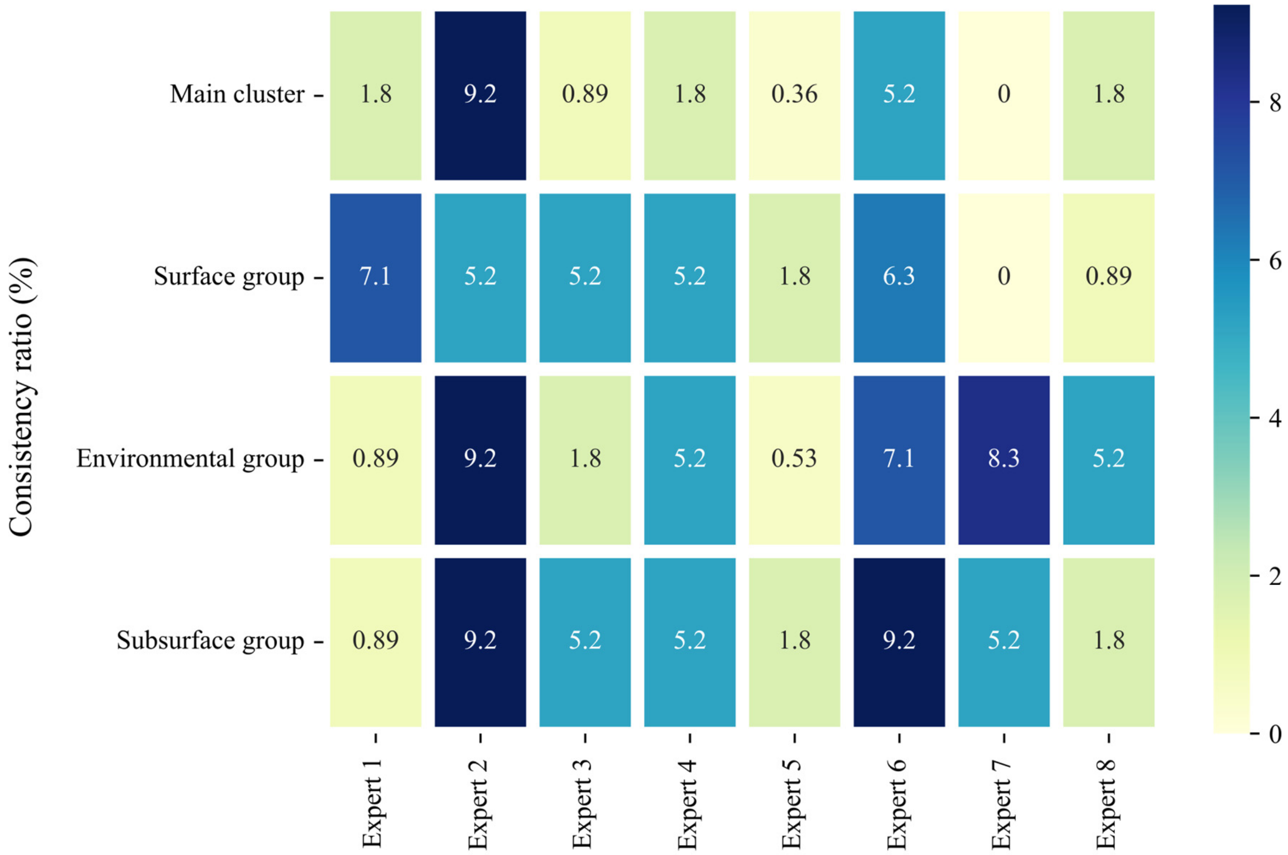

Figure 4. Consistency ratios of the experts who completed the pairwise comparison questionnaire.

Table 5. Decision criteria weights and their respective ranking.

Cluster	Weight	Criteria	Weight		Rank	
			Local	Global	Local	Global
Surface	30.36%	Slope	43.92%	13.33%	1	2
		Soil texture	24.81%	7.53%	3	6
		Curve number	31.27%	9.50%	2	4
Environment	48.85%	Rainfall	62.80%	30.68%	1	1
		Normalized difference vegetation index	24.33%	11.89%	2	3
		Drainage density	12.86%	6.28%	3	8
Subsurface	20.79%	Depth to groundwater	29.32%	6.10%	3	9
		Geology	33.41%	6.95%	2	7
		Groundwater quality (EC)	37.27%	7.75%	1	5

Furthermore, global weights, which directly indicate the contribution of each criterion to the final suitability assessment of the study region, are also presented in Table 5. According to the results obtained, rainfall, having a global weight of 30.68%, outperformed its counterparts. In addition, rainfall was followed by the slope (with a global weight of 13.33%) and NDVI (with a global weight of 11.89%). On the other hand, among the nine decision criteria, the fuzzy AHP assessments underestimated the role of depth to groundwater, drainage density, and geology, as the lowest weights were assigned to these factors.

3.2. Sensitivity Analysis

In this study, a sensitivity analysis with respect to different fuzziness degrees was implemented to ensure the stability of the obtained results as well as underscore the transparency of the criteria weighting attempts. Hence, in addition to dealing with interpersonal uncertainty by utilizing the fuzzy AHP rationale [82], the robustness of the criteria assessments is ensured via the sensitivity analysis conducted through different fuzziness degrees (i.e., 1.2, 1.4, 1.6, 1.8, and 2.0). This method was embraced due to its previous implementations [83]. Fuzziness degrees capture the level of ambiguity or uncertainty associated with linguistic judgments or criteria weights in the AHP. A sensitivity analysis helps understand the impact of variations in fuzziness degrees on the final results, enabling better management and the interpretation of uncertainty (Figure 5). The most significant aspect of assessing the sensitivity plot is focusing on variations in the criteria importance order. The figure reveals that, with regard to the alterations in fuzziness degrees, the fuzzy AHP results yielded consistent outcomes, as there are no considerable variations in criteria rankings. Therefore, one can conclude that the factors having a significant impact on model outcomes account for the similar importance considering various fuzziness degrees. The level of confidence/agreement in the decision process is ensured with the sensitivity analysis, and it is highlighted that the quality of the experts' preferences is aligned with the consistent decision context (Figure 5).

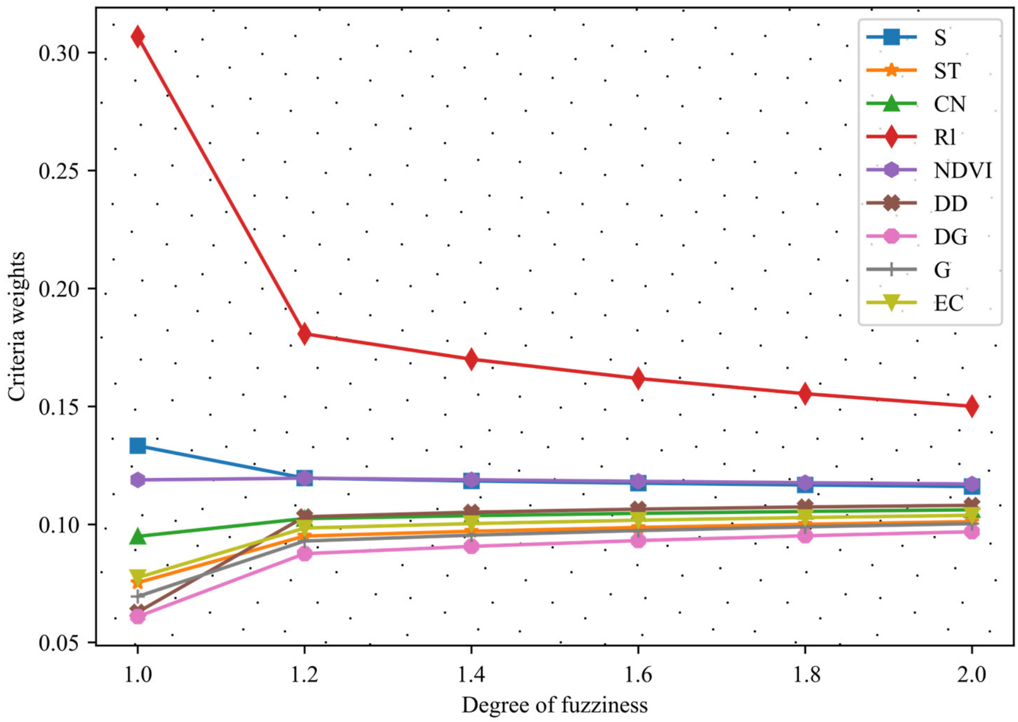

Figure 5. Sensitivity analysis with respect to different fuzziness degrees.

In this study, an additional sensitivity analysis approach was conducted. To accomplish this aim, the weight of each criterion was shifted to another criterion, and the obtained results were compared with the baseline scenario (i.e., originally obtained criteria weights) with respect to the root mean square error (RMSE) computations (Table 6). The results showed that the vast majority of the scenarios yielded considerably lower RMSE values, except when R_l (i.e., rainfall) was exchanged with its counterparts. The corresponding results can be explained by the fact that rainfall was originally overestimated by the experts, illustrating its high influence on the final MAR suitability decision.

Table 6. Sensitivity analysis results based on shifting criteria weights.

Scenario ID	Shift	RMSE	Scenario ID	Shift	RMSE	Scenario ID	Shift	RMSE
Scenario 1	S–ST	0.0209	Scenario 13	ST–DG	0.0062	Scenario 25	R_1–G	0.1932
Scenario 2	S–CN	0.0259	Scenario 14	ST–G	0.0014	Scenario 26	R_1–EC	0.1519
Scenario 3	S–R_1	0.1416	Scenario 15	ST–EC	0.0008	Scenario 27	NDVI–DD	0.0242
Scenario 4	S–NDVI	0.0075	Scenario 16	CN–R_1	0.2059	Scenario 28	NDVI–DG	0.0327
Scenario 5	S–DD	0.0366	Scenario 17	CN–NDVI	0.0190	Scenario 29	NDVI–G	0.0213
Scenario 6	S–DG	0.0384	Scenario 18	CN–DD	0.0130	Scenario 30	NDVI–EC	0.0182
Scenario 7	S–G	0.0239	Scenario 19	CN–DG	0.0095	Scenario 31	DD–DG	0.0005
Scenario 8	S–EC	0.0246	Scenario 20	CN–G	0.0154	Scenario 32	DD–G	0.0028
Scenario 9	ST–CN	0.0126	Scenario 21	CN–EC	0.0067	Scenario 33	DD–EC	0.0037
Scenario 10	ST–R_1	0.1687	Scenario 22	R_1–NDVI	0.1234	Scenario 34	DG–G	0.0036
Scenario 11	ST–NDVI	0.0141	Scenario 23	R_1–DD	0.1633	Scenario 35	DG–EC	0.0046
Scenario 12	ST–DD	0.0049	Scenario 24	R_1–DG	0.1938	Scenario 36	G–EC	0.0030

3.3. MAR Potential Mapping

The current research analyzed the suitability of MAR potential in Djibouti using the TOPSIS approach. To accomplish this aim, the criteria weights obtained through the fuzzy AHP analysis were integrated with the actual values of the corresponding criteria in the field and then subjected to the TOPSIS algorithm, aiding in exploring the prioritization of suitable regions. Figure 6 encompasses two different sub-figures, in which (a) the first represents the map generated based on the closeness coefficients, whereas (b) the latter provides the reclassification of the suitability assessments based on the closeness coefficients using the Jenks natural break method. In addition, the higher the closeness coefficient, the higher the suitability of MAR implementation. Hence, one can conclude that the northern and western parts of the country (with orange and red colors) are less suitable compared to other regions (Figure 6a). Conversely, the middle- and south-eastern parts of the country, mainly covering the vicinity of the Gulf of Tadjourah, are more suitable for MAR applications. In addition to the western part of the country, south Djibouti demonstrated very high suitability for MAR implementation (Figure 6b). The corresponding results can further be explained by the decision criteria; for example, highly suitable parts are significantly correlated to high rainfall values (Figure 3d), which was found to be the most determinant decision criterion.

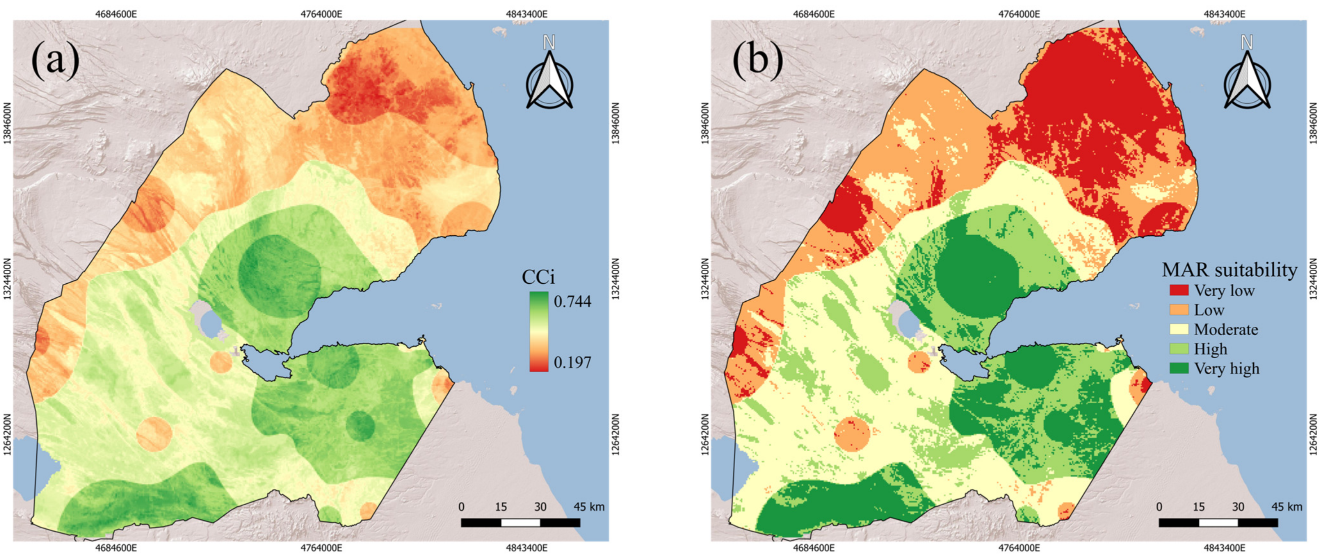

Figure 6. MAR suitability potential of Djibouti based on the integrated FAHP-TOPSIS approach: (**a**) the closeness coefficient (CCi) distribution and (**b**) the reclassified version of it.

Furthermore, Figure 7 illustrates the distribution of the different suitability clusters based on the corresponding regions' surface areas. According to the figure, one can conclude that nearly one-third of the country is moderately suitable for MAR implementation. Likewise, one-third of the country is suitable (high and very high suitability) for the corresponding sustainable solutions, whereas the remaining parts are not (low and very low suitability). The obtained results, on the one hand, showed that approximately 16.38% of the country demonstrates very high suitability for MAR implementation, and these regions are mainly located in the middle and southern parts. On the other hand, nearly 15.76% of the entire country is mainly located in the north-eastern part, which implies very low suitability for MAR solutions.

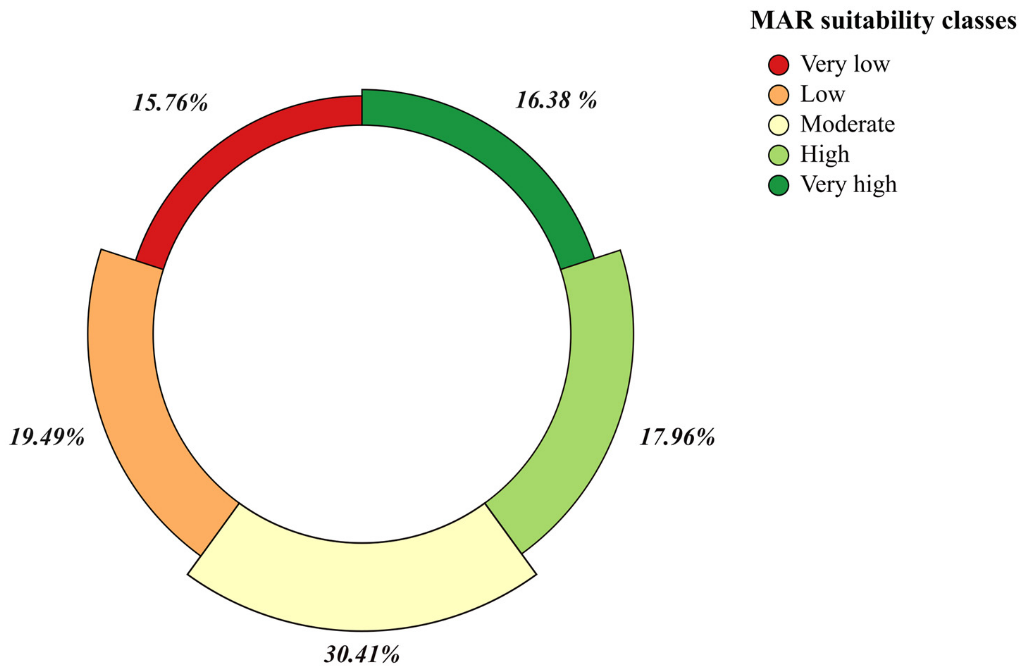

Figure 7. Percentage distributions of the different suitability classes in terms of surface area.

4. Discussion

4.1. Assessment of the Decision Criteria

The current research found that rainfall was the most influential decision criterion in assessing the MAR suitability of a region. Here, the corresponding result is consistent with nature, as it is well established that not only the amount of rainfall but also the frequency of rainfall events is significantly influential in terms of the recharge potential of the area of interest [84,85]. Accordingly, regions characterized by higher rainfall rates can be regarded as more favorable for the implementation of MAR techniques, in contrast to regions experiencing limited amounts of rainfall. Additionally, alongside the rainfall amount, the intensity of rainfall events holds paramount importance, as it directly affects the efficiency of recharge. For example, intense rainfall events can result in runoff, reducing the effectiveness of recharge efforts, whereas gentle and steady rainfall facilitates better infiltration and a higher recharge efficiency [86]. Given all these facts, taking the amount and characteristics of rainfall into account is essential when determining suitable regions, allowing for the better planning, implementation, optimization, and long-term sustainability of MAR initiatives. Table 5 also illustrates that the slope is the second most determinant factor in assessing the MAR suitability potential, with a global weight of 13.33%. Here, the existing literature further recognizes the critical role played by the slope factor such that not only hydro-morphological variabilities (such as infiltration rates, surface water flow, sedimentation, etc.) [87,88] but also the feasibility of the MAR techniques (engineering considerations, compatibility with land use, etc.) [89] are ascertained based on the topographical conditions. For instance, Fathi et al. [90] highlighted that steep slopes generally result in faster runoff, which limits the amount of water available for recharge, and gentle slopes, on the other hand, promote the penetration of water, allowing for higher recharge rates and the improved effectiveness of MAR techniques. Compatibility with real-world conditions is also critical, particularly considering that steep slopes can require additional efforts (stabilization, erosion control structures, etc.) [91] to ensure the stability and longevity of recharge facilities. Likewise, the slope impact may differentiate the MAR type that is planned to be installed. For instance, steeper slopes may be less suitable for certain recharge methods, such as infiltration basins [87,92], due to limited space and the potential for erosion. Gentle slopes provide more opportunities for siting and integrating recharge facilities within the existing landscape, considering factors such as land availability, land use restrictions, and environmental compatibility.

According to the criteria evaluations, the NDVI was found to be the third most influential factor, with a global weight of 11.89%. As it reflects the vegetation condition of the study region, the NDVI provides valuable insights into the suitability of MAR selection mechanisms. Since the NDVI measures the amount of live green vegetation in an area [93], it plays a vital role in enhancing infiltration and reducing runoff, making areas with higher NDVI values more conducive to recharge efforts. In addition, monitoring NDVI variabilities helps estimate water loss due to evapotranspiration, aiding in quantifying the water demand in regions. Consequently, one can assess the potential availability of water for recharge purposes. Focusing on NDVI values further aids in taking the infiltration capacity of soils [94], ecological considerations [95], and land use patterns [96] into account and thereby gaining a better overview regarding the suitability of MAR attempts. The fuzzy AHP analysis conducted based on pairwise comparisons underestimated the role of geology (global weight of 6.95%), drainage density (global weight of 6.28%), and depth to groundwater (global weight of 6.10%), as they ranked at seventh, eighth, and ninth, respectively. It is especially worth noting that these factors influence the selection of suitable sites for potential MAR implementations; however, their impact was found to be limited compared to other criteria incorporated into the decision framework.

4.2. Assessment of the Adopted Decision Framework and Its Limitations

This research introduces a holistic hybrid MCDA framework aimed at identifying favorable regions for MAR activities in the arid country of Djibouti as a response to the groundwater challenges faced by the nation. To determine the relative importance of individual decision parameters, the fuzzy AHP method was employed. Additionally, the TOPSIS technique was utilized to prioritize the study region and generate a countrywide MAR potential map. Although previous studies have separately applied the fuzzy AHP and TOPSIS methods [10,38], the integration of these approaches has been largely overlooked in the existing literature, with Mouhoumed et al. [4] being the only previous authors to attempt to adopt a similar combination. However, their framework was limited to a city-scale assessment covering an area of 218.53 km^2 and, more importantly, was focused on a predefined MAR technology, namely, drywells. In contrast, this research focused on an assessment at the country scale, and rather than concentrating on a specific approach, all MAR techniques are targeted.

Refining the list of decision parameters poses a challenge in multi-tiered decision problems, and this challenge is also evident in the context of MAR potential mapping. As highlighted by Sallwey et al. [30], the choice of criteria for site delineation is influenced by the problem definition. The average number of selected decision factors in the relevant literature tends to be around eight [30]. However, the corresponding number of decision parameters tends to be lower in country-level cases, likely due to data availability and accessibility limitations in such large areas. Mahmoud et al. [39], Mahmoud and Tang [40], and Mati et al. [42], for instance, used a set of five criteria to map MAR at a country scale, while Bonilla Valverde et al. [24] selected four decision variables. However, it is worth noting that in a recent study conducted by Kadhem and Zubari [41] to identify optimal locations for MAR in Bahrain, eight decision criteria were utilized. The present research incorporated the largest criteria set (nine factors) into a country-level MAR potential assessment.

The validation of the proposed models further represents an additional burden in MAR site suitability studies [53]. Apart from the meticulous selection of the number and nature of parameters involved in the decision framework, assigning appropriate weights to individual parameters can also introduce ambiguity since they highly rely on the subjective judgments of the pairwise survey participants. The scarcity of reported successful MAR projects in many countries, particularly in regions where MAR is a relatively novel topic, renders commonly used validation techniques less applicable. Nevertheless, some scholars argue that a combined consistency check and sensitivity analysis are enough to validate proposed models [25,97]. In line with this, several sensitivity analysis approaches have been proposed so far, ranging from the adoption of different weighting schemes [53], the addition or removal of relationships in the case of the multi-influence factor (MIF) method [24], or changes in the linguistic quantifier when applying the ordered weighted averaging (OWA) technique [97,98]. While the fuzzy AHP algorithm incorporates the inherent ambiguity of human decision making, we also tested the robustness of our model by adjusting the degree of fuzziness within the fuzzy AHP framework. This application of sensitivity analysis by modifying the degree of fuzziness represents a rare endeavor in the literature, further enhancing the novelty of the proposed framework.

This research further compared the current attempt with previously applied studies, as depicted in Table 7. The table illustrates that most of the efforts regarding MAR implementation were devoted to a watershed-scale analysis, while problem statements, i.e., major objectives, were diverse among the research community. In addition, a diligent review of the pertinent literature also demonstrated that the vast majority of studies have utilized traditional MCDA techniques for both criteria weighting and alternative prioritization, such as the AHP and WLC, respectively. As mentioned before, the MCDA rationale is implemented based on the preferences of experts having divergent backgrounds regarding the topic of interest. Despite this fact, only two of the past studies, i.e., Sandoval and Tiburan [27] and Shadmehri Toosi et al. [32], provided details of the experts who attended pairwise comparison surveys. From a different aspect, although Kharazi et al. [36] and Itani et al. [99] used the preferences of local experts for their criteria weight assessment, the researchers presented limited information regarding their fields of expertise. Given the importance of providing transparency and clarity to MCDA attempts, this study further provided the job description, role, and experience in the relevant field of the experts who were incorporated into the decision-making framework. Still, such a clear demonstration of experts' backgrounds has not been acknowledged in the pertinent literature. Along with the experts' profiles, the number of experts contributing to the analysis is of critical importance in managing decision processes. Including a limited number of experts may restrict the generation of creative ideas, whereas a high number of experts may endanger the diversification of the criteria weights, especially in fuzzy AHP analysis. Hence, the present research benefited from the preferences of a total of eight experts, who all provided reliable outcomes based on consistency checks. Finally, one can also consider performing a sensitivity analysis in order to ensure the stability of the criteria weighting attempts. In this regard, only three of the past studies, i.e., Kazakis [25], Fuentes and Vervoort [53], and Itani et al. [99], conducted sensitivity analyses to ensure the stability of MCDA outcomes. At this point, it is especially worth noting that this study is also differentiated from its counterparts as it covers two different types of sensitivity analyses. First, this research sought to explore the impact of fuzziness degrees on the criteria weights, and secondly, it applied 36 additional MCDA analyses (i.e., $9 \times 8/2$) based on shifting the weight of one criterion to another. Such a comprehensive evaluation of reliability control regarding criteria weighting and alternative prioritization can be considered a first attempt in the pertinent literature. It is also significant to mention that changing the fuzziness degrees has little impact on criteria weighting, and a similar conclusion can be drawn for the subsequent sensitivity checks, as the computed RMSE values are considerably low.

Table 7. Comprehensive evaluation of the present study compared with past attempts.

Reference	Country	Scale	Problem	I	II	III	IV	V	VI
Kazakis [25]	Greece	Watershed	Saltwater intrusion	10	AHP	WLC	✗	✗	✓
Fuentes and Vervoort [53]	Australia	Watershed	Water table decline	9	AHP	WLC	✗	✗	✓
Sandoval and Tiburan [27]	Philippines	Watershed	Groundwater depletion	10	AHP	WOA	✓	7	✗
Kharazi et al. [36]	Iran	Watershed	Water scarcity	16	N/A	AHP, TOPSIS, and EDAS	✗	7	✗
Itani et al. [99]	Lebanon	Watershed	Saltwater intrusion	9	AHP	WLC	✗	4	✓
Hussaini et al. [55]	Afghanistan	City	Water table decline	7	AHP and ANP	FL and WOA	✗	✗	✗
Papadopoulos et al. [10]	Greece	Watershed	Excess water storage	9	Fuzzy AHP	FIS	✗	✗	✗
Zhang et al. [31]	South Africa	Watershed	Water scarcity	12	AHP	WLC	✗	✗	✗
Arshad et al. [61]	India	Watershed	Chemical contamination	7	AHP	WOA	✗	✗	✗
Shadmehri Toosi et al. [32]	Iran	Watershed	Water scarcity	6	AHP	WLC	✓	✗	✗
Ezzeldin et al. [100]	Egypt	Watershed	Water scarcity	11	AHP	WLC	✗	✗	✗
This Study	Djibouti	Country	Water scarcity and saltwater intrusion	9	Fuzzy AHP	TOPSIS	✓	8	✓

Notes: **I:** Number of decision criteria; **II:** criteria weighting technique; **III:** alternative prioritization techniques; **IV:** experts' details; **V:** number of experts; **VI:** sensitivity analysis; WOA: weighted overlay analysis; FL: fuzzy logic; FIS: fuzzy inference system.

Despite the valuable insights offered by this research in assessing MAR potential at a countrywide level, as well as the type of MAR technologies feasible in Djibouti, there are still some limitations that need to be covered in follow-up attempts. The model could be challenged at a watershed scale, resulting in much lower resolution MAR site suitability maps. The number of decision factors could also be increased in future research by incorporating different dimensions that encompass divergent criteria (such as socio-economic parameters) in MAR potential mapping. Other MCDA methods could be introduced for similar objectives regarding both the criteria weight assessment process (e.g., ANP) and the alternative prioritization phase (e.g., VIKOR and PROMETHEE, as well as their fuzzy variants). In addition, despite the TOPSIS method possessing a more advanced mathematical foundation for prioritizing alternatives, in contrast to the commonly employed GIS overlay techniques found in the relevant literature, it is imperative to substantiate its superior accuracy compared to the latter techniques in effectively delineating locations suitable for MAR implementation. This can be achieved by comparing TOPSIS with WLC, WOA, and other MCDA-based prioritization techniques that address some of the limitations of TOPSIS, serving as a guideline for future research. Furthermore, along with comparing the performance of the proposed decision-making process with the traditional approaches (such as BWM or AHP), evaluating it based on more recent techniques, e.g., RANCOM [101], would not only strengthen the provided scheme but also ensure valuable insights in follow-up studies. In addition, future research can also incorporate probabilistic approaches (e.g., Monte Carlo simulations) into both criteria weighting and alternative prioritization in order to deal with intrapersonal uncertainties that exist in such decision frameworks. Finally, the current study performed two types of sensitivity analyses and employed similarity checks based on RMSE computations. However, different metrics (such as the WS rank similarity coefficient and weighted Spearman correlation coefficient) [101] can also be adopted for the extraction of ranking similarities and the performance evaluation of the sensitivity checks.

4.3. Feasible MAR Technologies in Djibouti and Practical Utilization of the Proposed Framework

MAR potential maps serve as effective tools for evaluating the artificial recharge feasibility of large areas. However, one limitation of such broad-scale MAR assessments is their inability to provide insights into the feasibility of specific MAR technologies within a focused region. For instance, in the case of Djibouti, where permanent rivers are absent, bank filtration technology is deemed unfeasible. Fortunately, several tools have been developed to enhance the practicality of MAR and address the complexities associated with its implementation. Among these tools, the web-based INOWAS platform stands out, providing a diverse array of functionalities aimed at facilitating MAR initiatives (such as groundwater flow/transport numerical and analytical simulation models, MAR databases, data-driven tools, etc.). Specifically, tool no. 6 within the platform enables the selection of appropriate MAR techniques based on specific characteristics and conditions of the area of interest, including factors such as the availability of water sources and other pertinent considerations. Notably, the development of this tool by the INOWAS research group is based on extensive investigations encompassing several hundred MAR studies conducted worldwide [102]. Therefore, the data-driven tool was used to assess the type of MAR techniques feasible in Djibouti, and the result is depicted in Figure 8. The findings revealed that Aquifer Storage and Recovery (ASR) and Aquifer Storage Transfer and Recovery (ASTR) technologies could be adopted to store reclaimed water in the aquifer for future recovery or to address environmental concerns such as saltwater intrusion. These techniques could potentially utilize the treated water from the wastewater treatment plant in Douda, having a daily capacity to treat 2000 m^3 of water [103], and from the Ambouli dam, storing a considerable amount of water that can be diverted for MAR activities alongside its flood mitigation purpose. Additionally, surface-spreading techniques (such as infiltration ponds, ditches, and furrows, as well as barriers, bunds, etc.) requiring rainwater as target sources were found to be feasible for recharging local aquifers. Furthermore, drywells and flooding MAR techniques show promise in recharging shallow aquifers in the country, aiming to achieve groundwater sustainability and address recurring droughts.

As mentioned earlier, this research contains a comprehensive MCDA analysis containing the implementation of fuzzy AHP and TOPSIS algorithms to identify the suitability of MAR techniques in Djibouti. To provide valuable insights to both policymakers and decision-makers, the practical utilization of such a framework is needed. Figure 9 provides an example of how the corresponding decision-making framework is used in conjunction with real-world implementation scenarios. As depicted in the figure, these analyses start by gathering relevant data and are followed by pairwise comparison surveys to explore the importance of differences in the criteria considering potential application regions. It is therefore important to identify key stakeholders carefully, since the contribution of the criteria taken into account may vary based on the focus region. Once the judgments of the experts are collected, criteria weights are computed. Subsequently, the actual data, which can be obtained from either model outcomes, in situ measurements, or remote sensing products, were incorporated into criteria weights to determine the site suitability map for MAR implementation. The resultant maps illustrate the regions suitable for the application of MAR technologies (from very high to very low suitability). The final step of the analysis covers the determination of the type of MAR technique, which is beyond the scope of the current research. Once the decision is made and the selected MAR technique is implemented, the outcomes based on various aspects are evaluated to review the impact of the corresponding solutions. Finally, based on the performance evaluation of the employed MAR technique(s), the entire framework is repeated to ensure the continuous improvement of the decision-making scheme.

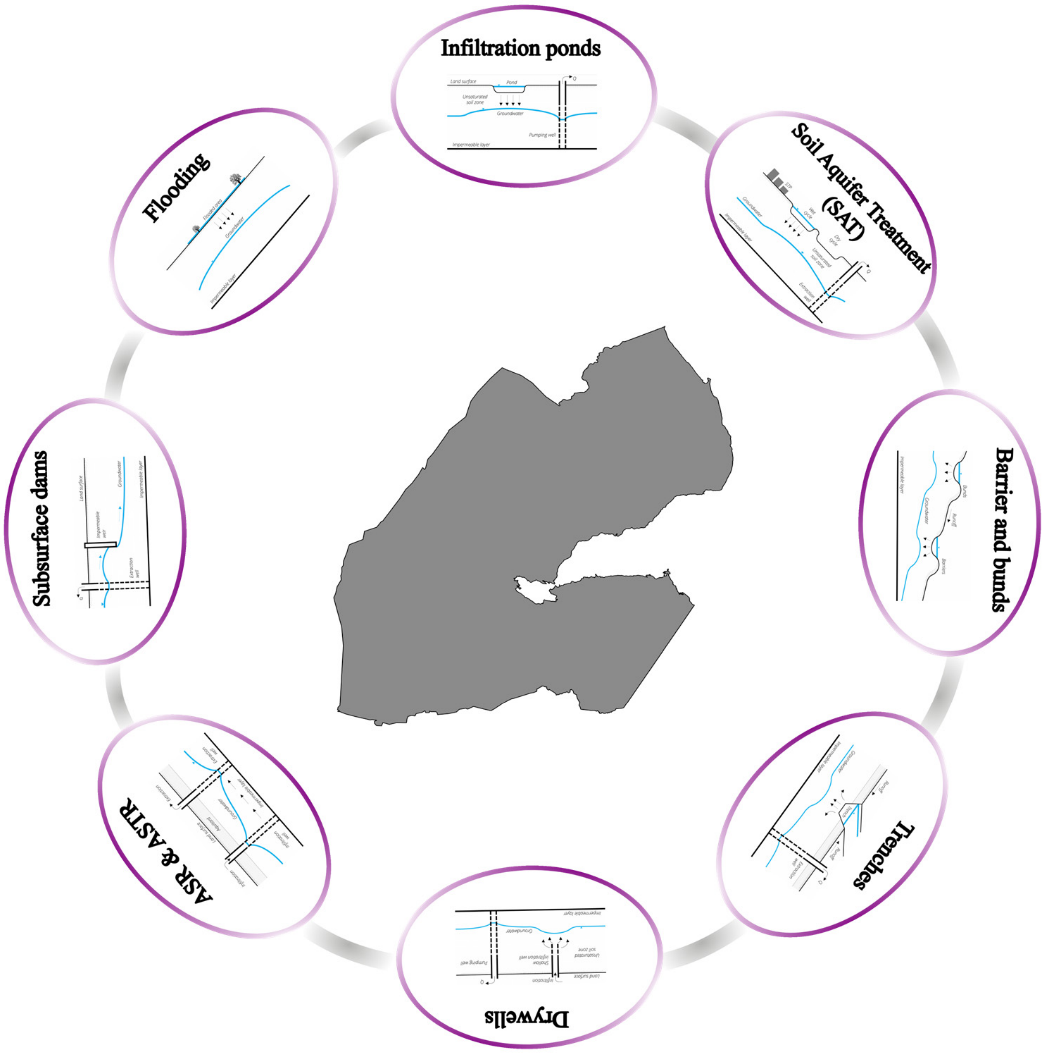

Figure 8. Graphical representation of the feasible MAR techniques in Djibouti.

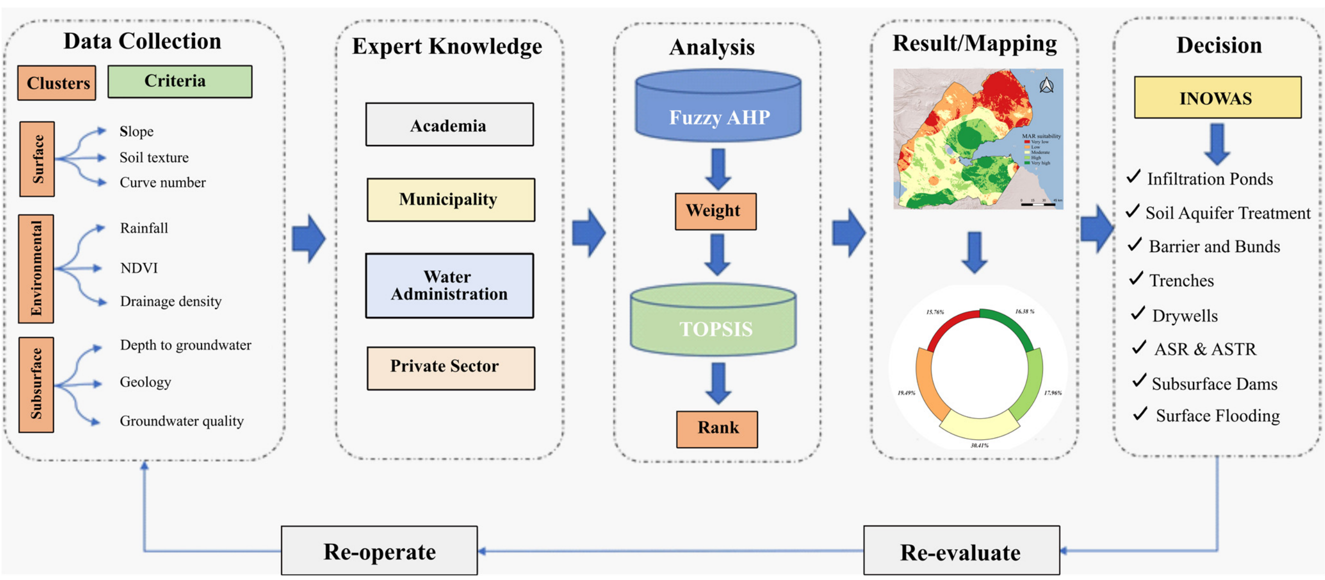

Figure 9. Practical utilization of the constructed decision-making scheme.

5. Conclusions

The existing literature recognizes the promising role played by the integration of GIS and MCDA techniques for conducting MAR potential investigations. Thus, establishing a robust GIS-MCDA scheme enables the assessment of large areas while mitigating the computational burden and financial constraints. Consequently, in this study, a coupled model combining the fuzzy AHP and TOPSIS was proposed to evaluate the MAR potential at a country level, considering Djibouti as the specific case study. A comprehensive set of criteria pertaining to the surface, environmental, and subsurface dimensions were identified, and their relative importance was determined using the fuzzy AHP algorithm. Subsequently, the TOPSIS technique was employed to prioritize the study area based on the weighted decision layers. A sensitivity analysis was also employed to ensure the robustness and stability of the decision framework.

The results of the analysis highlighted the significance of rainfall, the slope, and the NDVI as the most influential decision criteria in identifying regions suitable for MAR implementation. Conversely, the fuzzy AHP determined that depth to groundwater and the drainage density were comparatively less influential in the decision-making process. In terms of the prioritization of the study area, it was observed that approximately 10.63%, 23.20%, and 31.06% of the country, corresponding to approximately 2466 km^2, 5382 km^2, and 7206 km^2, respectively, exhibited very high, high, and moderate suitability for hosting MAR activities. Furthermore, the sensitivity analyses conducted to evaluate the stability of the framework indicated its robustness, as there were no significant changes in the ranks of the criteria with respect to the various degree-of-fuzziness values, and considerably less variation was observed in RMSE values computed based on closeness coefficients.

Overall, the comprehensive approach proposed in this study empowers policymakers and stakeholders to identify and prioritize areas with promising MAR potential, facilitating informed decision making and the efficient allocation of resources for sustainable water management practices.

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