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RESEARCH ARTICLE

Groundwater potential assessment based on GIS-based Best–Worst Method (BWM) and Step-Wise Weight Assessment Ratio Analysis (SWARA) Method

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Abstract
In this study, the most suitable areas in terms of groundwater potential within the borders of the adjacent area of Sivas Municipality (Sivas/Turkey) were determined with the help of Geographic Information System (GIS)-based Best–Worst Method (BWM) and Step-Wise Weight Assessment Ratio Analysis (SWARA) methods. Slope, drainage density, Topographic Position Index (TPI), lineament density, lithology, soil types, land use, geomorphology, and rainfall criteria were selected to determine groundwater potential areas. These criteria were weighted with the help of BWM, SWARA, and BWM-SWARA methods and the Groundwater Potential Index (GPI) was calculated according to the weighted linear combination method. According to the calculated GPI values, the groundwater potential of the study area was represented as "excellent," "very good," "good," "moderately good," "low," and "very low." According to all three methods, areas in the "excellent" class constituted 10.99%, 8.40%, and 11.16% of the study area, respectively, while areas in the "very low" class covered 8.33%, 7.98%, and 9.04% of the study area, respectively. The linear correlation coefficient (R^2) values of the BWM, SWARA, and BWM-SWARA methods were calculated as 0.80, 0.82, and 0.75, respectively, while the area under the curve (AUC) values were determined as 0.83, 0.79, and 0.81, respectively. These results showed that the accuracy of the model was "very good" overall. As a result, groundwater potential mapping created for the study area will contribute to better development of groundwater resources and water management planning.

Keywords Groundwater potential mapping · BWM · SWARA · GIS

Introduction

Water is one of the most basic resources for humanity. Groundwater resources provide 34% of the world's freshwater resources (Ghosh et al. 2016; Murmu et al. 2019). Groundwater resources are the most important natural resource that supports both human needs and economic development (Kumar et al. 2016). Groundwater plays an important role in ensuring the continuity of the geoenvironment and in the balance of the ecosystem (Huang et al. 2022). Groundwater resources are used worldwide for various purposes such as drinking water supply, agricultural, and industrial activities. Around 2.5 billion people worldwide depend solely on groundwater resources to meet their daily water needs (UNESCO 2015). Groundwater resources are considered a safer water source compared to surface water, as they are treated and protected by the vadose zone of the earth (Subba Rao et al. 2018; Naghibi et al. 2017). Surface water resources are insufficient during the dry seasons and therefore groundwater resources become the main water source for drinking water supply, agricultural, and industrial activities (Mukherjee and Singh 2020; Assaf and Saadeh 2008).

Groundwater, which is very important in ensuring economic continuity, has a very important place in the dry months in terms of water supply, especially in southeast monsoon countries. Groundwater resources play an important role in the survival of wildlife and plants at high temperatures. Groundwater contributes significantly to increasing water levels in rivers. Groundwater recharge, also known

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as deep drainage, is also an important part of the groundwater hydrological process, as the water moves downwards from the surface through two types of circulation, natural and artificial (Ghosh et al. 2022). The biggest advantages of groundwater are its high potential for formation area, better natural protection area, low operating and development costs, and application flexibility for water demand (Erdoğan et al. 2019; Anteneh et al. 2022).

Groundwater is under stress due to population growth, urbanization, agricultural, and industrial activities throughout the world, and it is very difficult to meet these needs with existing groundwater resources (Saha 2017). Due to the increasing demand for groundwater as a result of rapid urbanization, overpopulation, and increasing industrialization, scarcity may be faced in some parts of the world (Choudhary et al. 1996; Neelakantan and Yuvaraj 2012). In order to prevent groundwater scarcity worldwide, researches on groundwater potential have become very important. Most groundwater potential exploration techniques (geophysical methods, ground-based exploration, and exploratory drilling) are uneconomical, time consuming, and require large datasets (Nampak et al. 2014). Contrary to these methods, GIS-Remote Sensing (RS) integration can provide the appropriate platform for groundwater potential mapping, evaluating large volumes of data together and understanding the hydrological system (Tolche 2021). GIS-RS integration is widely used in the determination of groundwater supply and discharge areas as well as groundwater potential regions (Andualem and Demokrate 2019; Russo et al. 2015; Tolche 2021).

The formation and movement of groundwater in a region depend on factors such as lithology, geological structure, soil, linear features, slope, drainage pattern, geomorphology, land use/land cover, and the relationships between these factors (Jha et al. 2010; Chowdhury et al. 2010). By analyzing these factors with the help of the spatial analysis tool of the GIS, groundwater potential maps based on the weighted overlay approach can be produced (Saraf and Choudhary 1998; Sikdar et al. 2004). Most groundwater potential mapping models use an expert knowledge-based approach where the quality of groundwater data is poor or the use of data-based methods is insufficient (Díaz-Alcaide and Martínez-Santos 2019). Therefore, these models use a GIS-based multi-criteria decision analysis (MCDA) approach, taking into account weighted criteria (rainfall, lithology, landform, lineaments, soils, land use, slope, flow accumulation, etc.) evaluated by experts to highlight more favorable areas for groundwater potential (Steele et al. 2009). The GIS-MCDA approach introduces a method that combines the definition of relevant criteria (spatial data layers), standardization of criteria values, criteria prioritization, and preferential criteria to obtain a final score (Fildes et al. 2022). The result of this method is a suitability map that shows the potential of a particular location (Greene et al. 2011). The GIS-RS-based MCDA can combine all spatial data to create a composite groundwater potential map (Anteneh et al. 2022).

Used in combination with RS and GIS, MCDA has opened up a new field of scientific research in hydrogeological studies. RS is a very useful tool in obtaining appropriate information about the different variables that control groundwater formation (Aluko and Igwe 2017). In the determination of areas with groundwater potential, methods based on hydrogeological, geophysical, and drilling techniques and GIS-RS-based MCDA methods provide great convenience before the detailed investigation of the sources (Fenta et al. 2014). The biggest advantage of MCDA models is the assignment of weight values according to the criteria. Since the criterion weights have an important effect on the decision-making process, the principle of objectivity should be taken into account in the determination of the criterion weights (Pamučar et al. 2018). GIS-based MCDA methods have very good functionality for mapping groundwater potential regions (Rahmati et al. 2015). Many methods are mentioned in the literature for groundwater potential mapping using the GIS-RS-based MCDA method (Table 1).

The city of Sivas met all of its drinking and utility water needs from 27 deep wells in Tavra Valley until April-2007. With the commissioning of the 4 Eylül Dam in 2007, Sivas city started to provide about half of its drinking water needs from the 4 Eylül Dam and the other half from the wells. Today, well waters in the Tavra Valley water basin constitute the drinking and utility water source of approximately 49% of the city with a flow rate of 400–550 lt/s. The wells drilled in the basin generally cut the 10-m-thick clayey-sandy alluvium and then pass into the units consisting of conglomerate, sandstone, and heavily fractured limestones in the form of reservoirs. The levels where the clayey sections in the alluvium are concentrated partially cover the basin and reduce the permeability. On the other hand, the sections where clayey-sandy sections are dense cause the water infiltrating underground to be partially cleaned (Yildiz and Karakus 2015). Groundwater demand in Sivas city is constantly increasing due to anthropogenic activities and population. As in the whole world, hydrometeorological changes due to climate change also negatively affect surface and underground water resources in Sivas. Therefore, it is very important to understand the spatial distribution and potential regions of groundwater within the borders of the adjacent area of Sivas Municipality.

The aim of this study is to determine the groundwater potential areas within the boundaries of the study area in Sivas with the help of GIS-based MCDA (BWM and SWARA) methods. The objectives of the study are listed as follows: (1) evaluation and mapping of criteria that are effective in groundwater potential mapping; (2) determination of criterion weights based on BWM, SWARA, and BWM-SWARA methods; (3) determination of suitable

Table 1 Studies on groundwater potential mapping

Used technique	Used criteria	Study area	References
GIS-RS with AHP (Analytic Hierarchy Process)	Geology, geomorphology, drainage density, lineament density, land use, slope, soil texture, ırrigation	Maharashtra, India	Sahu et al. 2022
GIS-RS with WLC (Weighted Liner Composition)	Land use, soil, slope, rainfall, elevation, lithology, lineament density drainage density	The Azraq Basin, Jordan	Al-Shabeeb et al. 2018
GIS with fuzzy AHP	Geology, geomorphology, slope, soil, land use, and drainage density	Titel Municipality, Serbia	Radulovic et al. 2022
GIS-RS with AHP	Geomorphology, geology, lineament density, land use, soil, drainage density, rainfall, slope, curvature, and topographic wetness index	Coimbatore district, India	Kom et al. 2022
GIS-RS with AHP and TOPSIS (Technique for Order of Preference by Similarity to İdeal Solution)	Land use, soil, slope, geology, geomorphology, drainage density, lithology, elevation, and rainfall	Madhya Pradesh, India	Patidar et al. 2022
GIS-RS with AHP and TOPSIS	Slope, land-use, drainage density, spring density, lithology, lineament density, and rainfall	Tarom Region, Iran	Shabani et al. 2022
GIS with AHP and Fuzzy TOPSIS	Lithology, rainfall, vegetation cover, lineament density and distance, elevation, slope, land surface temperature, land use and drainage density	Silakhor Plain, Iran	Saeidi et al. 2021
GIS-RS with Full Consistency Method (FUCOM), BWM, and AHP	Elevation, surface slope, aspect, relative slope position, plan curvature, topographic wetness index, terrain ruggedness index, drainage density, land use, lithology	Sarakhs plain, Turkmenistan	Akbari et al. 2021
GIS with BWM, (SWARA), Support Vector Machine Learning Method (SVR), Harris Hawk optimization (HHO), and Bat Algorithms (BA)	Altitude, slope, plan curvature, land use, soil, lithology, distance to river, drainage density, TWI (Topographic Wetness Index), SPI (Stream Power Index), rainfall, NDVI (Normalized Difference Vegetation Index)	Sarab Plain, Iran	Paryani et al. 2022
GIS-RS with AHP	Geology, rainfall, soil, geomorphology, land use, slope, lineament density, drainage density, drainage proximity	Basement Complex terrain, Nigeria	Fashae et al. 2014
GIS with AHP	Geomorphology, geology, drainage density, slope, rainfall, soil texture, groundwater depth, soil depth, lineament and land user	Bemetara district, India	Jhariya et al. 2016
GIS with AHP	Geology, slope, lineament density, drainage density, rainfall, land use, soil type, soil depth, TWI, plane curvature, profile curvature	Gazipur district, Bangladesh	Rahman et al. 2022
GIS with WLC	Slope, TWI, geomorphology, drainage density, lithology, lineament density, rainfall, soil type, soil thickness land-use	Coruh River Basin, Turkey	Yıldırım 2021
GIS with AHP	Land use, soil, geomorphology, geology, aquifer, drainage density, rainfall, slope, lineament density, terrain class	Harran Basin, Turkey	Aslan and Çelik 2021
GIS with AHP and WLC	Aquifer lithology, slopes, land use, soil types, drainage density, geological lineament density, flow accumulation, and TWI	Manyara fractured aquifer, Tanzania	Makonyo and Msabi 2021
GIS with AHP and TOPSIS	Slope, geomorphology, water table, thickness of alluvium, hydraulic transmissivity, land use, water quality, drainage density, and infiltration coefficient	Sarkhoon Plain, Iran	Kamangar et al. 2019

areas in terms of groundwater potential based on BWM, SWARA, and BWM-SWARA methods; (4) analysis of the accuracy of groundwater potential maps with the help of linear regression analysis and receptor operating characteristic (ROC) methods. As seen in Table 1, most of the studies on groundwater potential mapping consist of applications of similar methods (predominantly AHP method) in different regions. This study aims to evaluate the land and watershed characteristics with GIS-based MCDA methods based on expert opinions and compare these methods; it is a study that will assist planners, policy makers, and local governments in reducing groundwater vulnerability in this area through appropriate use and management practices. This study is important in terms of applying BWM and SWARA methods, which are not used much in determining groundwater potential regions, on a regional scale (study area); developing a sustainable water resources system; presenting a method for groundwater management; and contributing to the literature.

Material and methods

Study area

The province of Sivas is located in Central Anatolia's upper Kızılırmak Region. The province, which after Konya has the second-largest size in Turkey with a total area of 28,488 km^2, is situated between 36° and 39° east longitude and 38° and 41° north latitude (Fig. 1). Sivas province has a plateau-like form overall, with valleys between individual mountains or mountain ranges, sunken plains, and hills. The coldest region of Central Anatolia is the province of Sivas. Winters are bitterly cold while summers are hot and arid. The summer season is brief. Between the summer and winter seasons, as well as between day and night, there are noticeable temperature differences. The temperature may go to 40 °C in the summer and to − 33 °C in the winter. Sivas's annual average temperature is 9.03 °C, and it receives 440.28 mm of precipitation on average per year. When the study area's population statistics for the reference years are analyzed, it is found that the province's population in 1990 was 767,481, but that number fell by 15.75% to 646,608 in 2018. Urban population ratio climbed from 49.77 to 72.78% over the relevant years, while the province's rural population ratio fell from 50.23 to 27.22% (TSI 2021).

The Kızılırmak River and its tributaries are located within the study area's boundaries, and the river's annual average flow rate is 39.42 m^3/s (Karakuş 2020). In general, the study area shows a structure rising north-northeast and south-southeast of the city center. The study area is between 1245 and 1769 m above sea level. The study area, which has a 512 km^2, is the border of the Sivas Municipality adjacent area (Fig. 1).

Data

In this study, 9 criteria were used for groundwater potential mapping. These criteria have been chosen by considering the criteria given in Table 1, which are the most widely used in the literature (Sahu et al. 2022; Al-Shabeeb et al. 2018; Radulovic et al. 2022; Kom et al. 2022; Shabani et al. 2022; Akbari et al. 2021; Paryani et al. 2022; Jhariya et al. 2016) for groundwater potential mapping (Table 2). Slope, drainage density, and TPI criteria were generated using a 27-m resolution Digital Elevation Model (DEM) (Al-Djazouli et al. 2021; Salar et al. 2018; Rahaman et al. 2022). In order to obtain the lineament density criterion, firstly, the lineament data were obtained with the help of Landsat 8-OLI satellite image (Moodley et al. 2022). Lithology (GDMIE (2005), soil types (GDRS 2001), land use (GSDP 2015), and geomorphology criteria were obtained from the relevant institutions in vector data format (.shp). Annual average precipitation data between 1990 and 2020 were obtained from the relevant institution in Excel (.xlsx) format. By mapping these precipitation data with the help of IDW (Inverse Distance Weighted) method, precipitation criteria for a 30-year time period were obtained. Well locations and groundwater level data of these wells, which are reference data for the accuracy analysis of the groundwater potential maps obtained within the scope of the study, were obtained from Sivas Municipality (Turkey) in Excel (.xlsx) format (Table 2). With the help of the ground water level data of the well locations, the underground water level map of the study area was created with the help of the IDW method. The projection information of all criteria was set to UTM 37N and the datum information is set to ED50. All criteria are stored in raster data format with a cell size of 10 m × 10 m. Excell 2017 software was used to determine the relative weight values of all criteria and to evaluate the accuracy. The linearity structure of the study area was obtained with the help of Catalyst Professional software (PCI 2022). ArcGIS 10.8 software was used for spatial distribution mapping of all criteria and classified criteria, groundwater level mapping, and groundwater potential mapping based on BWM, SWARA, and BWM-SWARA methods.

Methods

The main stages of the method used to perform groundwater potential mapping in this study are as follows: (i) database design and criteria selection, (ii) conversion of all data to raster data format and preparation of layers in GIS environment, (iii) criteria standardization, (iv) multi-criteria determination of criterion weights based on decision methods (BWM, SWARA, and BWM-SWARA), (v) obtaining underground potential maps according to criterion weights, (vi) accuracy analysis. Database design and criteria selection,

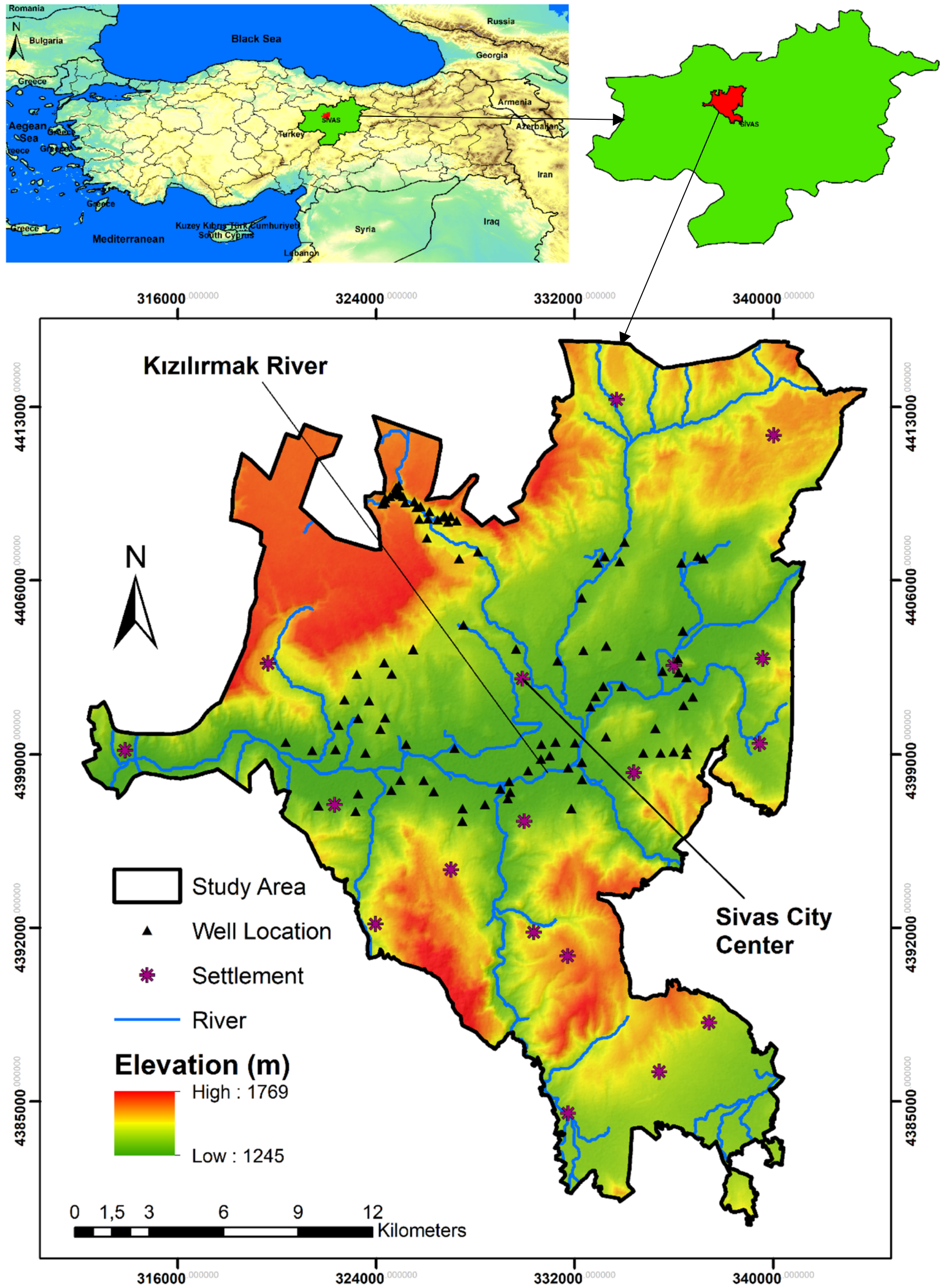

Fig. 1 Location map of the study area

which is the first step of the method, is very important for determining the most suitable places in terms of groundwater potential in the study area. The database design and criteria selection were made by considering the literature sources given in Table 1. During the data collection stage, remote sensing data (slope, drainage density, TPI, lineament density), digital maps (lithology, soil types, land use, geomorphology), and other data (Rainfall) were obtained from relevant sources (Table 2). Standardization process was carried out for all criteria converted to raster data format. After the criteria weights were determined based on BWM, SWARA, and BWM-SWARA methods, groundwater potential maps were obtained according to the criteria weights determined according to all three methods. In the last stage of the study, the accuracy analysis of the obtained groundwater potential maps was performed (Fig. 2).

Table 2 The criteria used in the groundwater potential assessment and the features of the criteria

Data name	Criteria name	Data source	Data format
DEM	Slope	US Geological Survey/digital elevation model (DEM), resolution: 27 m	Raster layer (grid)
	Drainage/drainage density	US Geological Survey/digital elevation model (DEM), resolution: 27 m	Raster layer (grid)
	TPI	US Geological Survey/digital elevation model (DEM), resolution: 27 m	Raster layer (grid)
Landsat-OLI	Lineament/lineament density	US Geological Survey (Landsat-8 OLI Satellite Image, resolution: 30 m-24/08/2020)	Raster layer (Geotiff)
Geology map	Lithology	General Directorate of Mineral Research and Explorations, Ankara (Turkey), scale: 1/25.000	Vector-polygon layer (.shp)
Soil map	Soil types	Ministry of Food, Agriculture and Livestock, Ankara (Turkey), scale: 1/25.000	Vector-polygon layer (.shp)
Land use map	Existing land use	Ministry of Environment and Urban Planning General Directorate of Spatial Planning, Ankara (Turkey), scale: 1/25.000	Vector-polygon layer (.shp)
Geomorphology map	Geomorphological units	Sivas Cumhuriyet University, Faculty of Education, Department of Geography	Vector-polygon layer (.shp)
Rainfall	Rainfall	Meteorology Directorate, Sivas (Turkey)	Excel (.xls)
Well Location	-	Sivas Municipality, Sivas (Turkey)	Vector-point layer (.shp)

Groundwater potential mapping

Groundwater potential maps can be an important source of information about productive water wells for domestic and other purposes for groundwater development (Niway et al. 2022). Groundwater potential mapping is a widely used method in areas where aquifer recharge is poorly characterized and data is scarce. Groundwater potential maps can be obtained based on currently available information and estimates via RS/GIS (Díaz-Alcaide and Martínez-Santos 2019). Groundwater yield (extraction volume and groundwater velocity) at various measurement points is very important for groundwater potential mapping. While geological, topographic, and anthropogenic factors affect the yield of groundwater, the yield of groundwater is also directly related to groundwater potential (Abdulkareem et al., 2018). Various techniques can be applied to groundwater potential mapping, including direct drilling for hydrological tests and geophysical models. Such methods are suitable for determining the hydrological properties of groundwater but are time consuming and costly in money (Lee et al. 2020). Soil, lithology, geomorphology, land use, slope, drainage density, lineament density, curvature, TWI, roughness, and Topographic Position Index (TPI) criteria are known as 12 important criteria in the groundwater potential mapping process (Yifru et al. 2020; Kumar et al. 2016). These criteria, which can be obtained from various surface datasets, are generally included in the study in regional scale studies for the evaluation of groundwater resources. RS and GIS techniques are widely used in the processing and management of these data sources and hydrological parameters for groundwater potential mapping (Mogaji et al. 2015; Machiwal et al. 2011; Madan et al. 2010). Groundwater potential map can be obtained by integrating all thematic layers with the help of weighted total thrust analysis tool in GIS environment (Kom et al. 2022). Groundwater potential map can be obtained by integrating all thematic layers with the help of weighted total thrust analysis tool in GIS environment (Kom et al. 2022). With the help of GIS-based MCDA methods, groundwater potential maps can be produced by taking into account hydrogeological and hydrological parameters, and these methods can reveal a qualitative estimation of groundwater resources (Celik and Aslan 2020).

Best–Worst Method (BWM)

The BWM method is a method that shows easy and precise values and is widely used to improve the consistency ratio by allowing less pairwise comparison (Rezaei 2015; Rezaei et al. 2015). BWM method provides more reliable results when compared to methods such as AHP, ANP, and Simple Multi-Attribute Rating Technique (SMART) (Rezaei 2015). This method can be used to make decisions on different MCDA problems such as sustainability assessment, supplier selection, risk assessment, airport assessment, location and equipment selection, urban transportation network assessment, water management, logistics performance assessment, and efficiency (Yucesan and Gul 2019; Haseli et al. 2021). Reference comparisons in BWM determine the advantages of the best criteria over all other criteria and reveal the

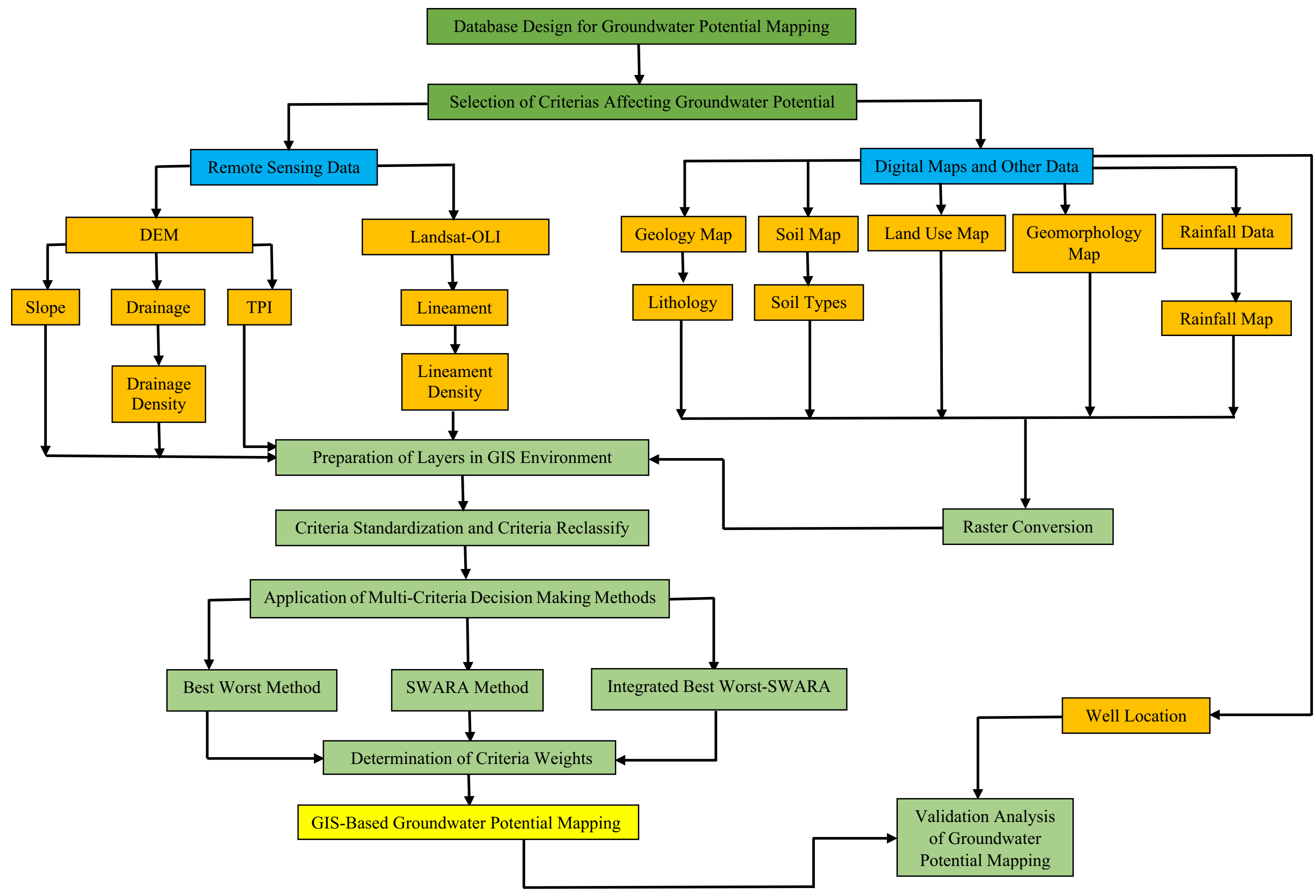

Fig. 2 Flowchart of the method used in the study

superiority of other criteria over the worst criterion. This method is much easier, more precise, and eliminates unnecessary comparisons (Akbari et al. 2021).

This method used in criterion weighting is based on a systematic comparison between two criteria. With the number of criteria (n), pairwise comparisons ($2n - 3$) are made. Developed by Jafar Rezaei in 2015, this method has been used in many decision-making problems that require criterion weighting. The BWM method consists of the following stages (Rezaei 2015; Demir and Bircan 2020):

Stage 1: Criteria determination

Stage 2: Determination of the best (most desirable, most important) and worst (least desirable, least important) criteria

At this stage, the criteria definition is based on the opinion of the decision-maker, the values of the criteria are not taken into account in this stage and no comparisons are made.

Stage 3: Prioritizing the best criterion

$$A_{(\mathrm{best})} = (a_{(\mathrm{best}(1))}, a_{(\mathrm{best}(2))}, \dots, a_{(\mathrm{best}(n))})_{ss}$$

At this stage, the priority of the best criterion is determined according to all other criteria by using the numbers 1–9.

Stage 4: Prioritizing the worst criterion

$$A_{(\mathrm{worst})} = (a_{(\mathrm{worst}(1))}, a_{(\mathrm{worst}(2))}, \dots, a_{(\mathrm{worst}(n))})$$

At this stage, the priority of the worst criterion is determined according to all other criteria by using a pairwise comparison scale between 1 and 9. Explanations on the pairwise comparison scale in the BWM method are given in Table 3.

Stage 5: Determination of optimal weights

$$\min \xi_L \quad |w_{(\mathrm{best})} - a_{(\mathrm{best}(j))}.w_j| \text{ for } \leq \xi_L \text{ and } \forall_j \tag{1}$$

$$|w_j - a_{jw}.w_{(\mathrm{best}(j))}| \text{for} \leq \xi_L \text{and} \forall_j \tag{2}$$

$$\sum_{j=1}^{n} w_j = 1$$
$$w_j \geq 0 \tag{3}$$

where $w_{(\text{best})}$ is the relative weight of the best criterion, $w_{(\text{worst})}$ is the relative weight of the worst criterion, $a_{(\text{best}(j))}$ is the preference over the criterion for the most suitable (best) criterion, and $a_{(\text{worst}(j))}$ is the preference for criterion j over worst (least important) criterion

Stage 6: Calculating the consistency ratio

This stage is to check the consistency of the comparisons and to understand whether the results are reliable. The smaller the consistency ratio, the more consistent the comparisons are. The values of the Consistency Index (CI) used in the BWM method are given in Table 4.

Consistency Ratio (CR) can be calculated using ξ_L and CI as follows:

$$\text{Consistency ratio (CR)} = \xi_L/\text{Consistency Index (CI)} \tag{4}$$

where the ξ_L value is the consistency rate of the analyses performed. The CI is the maximum possible value of ξ_L. The closer the consistency ratio is to zero, the more consistent the resulting vector will be, and vice versa. In general, if the consistency ratio is ≤ 0.1, this value indicates that the resulting vector is acceptable.

Step-Wise Weight Assessment Ratio Analysis (SWARA)

The SWARA method was first introduced by Keršuliene et al. (2010). The SWARA method, which is one of the MCDA methods, is one of the most capable methods used in various environmental issues (Akhanova et al. 2020; Panahi et al. 2017a, b). The most important aspect in this method is that experts consider their priorities according to their past experience and current conditions (Hashemkhani Zolfani et al. 2018). In the SWARA method, the subjective opinions of the decision makers are reflected and the preferences of the decision makers directly affect the analysis process (Hashemkhani Zolfani and Saparauskas 2013). In SWARA method, the weight of each criterion is optimized in line with expert opinions and the criteria priorities are determined. Considering the knowledge and experience of each expert, the most important and least important criteria are determined and the highest and lowest grades of these criteria are scored. The general rankings of the experts are obtained according to the highest and lowest averages of the criteria (Keršulienė and Turskis 2011). This method, which allows decision-makers to prioritize their decisions, determines the most important criterion and does not require further evaluation or ranking of the criteria (Hashemkhani Zolfani and Saparauskas 2013). The SWARA method, which determines the relative weights of the criteria, consists of the following stages (Stanujkic et al. 2015; Torkashvand et al. 2021):

Table 3 Pairwise comparison scale by BWM method (Rezaei 2015)

Important level	Explanation
1	Equally important
2	Equally moderately important
3	Moderately more important
4	Moderately much more important
5	Strongly important
6	Very important as strong
7	Important as very strong
8	More important as very strong
9	Quite very important

Stage 1: Ranking the criteria from the most important to the least important

Stage 2. Evaluation of the relative importance of the j criterion for the (j – 1) criterion for each specific criterion

Here, starting from the second criterion, relative importance levels are determined for each criterion. For this, criterion j is compared with the previous criterion ($j-1$). S_j (comparative significance of mean value, $0 \leq S_j \leq 1$) is taken into account in this comparison process (Keršuliene et al. 2010).

Step 3: Determination of the coefficient (K_j)

K_j can be determined by the following equation:

$$K_j = \begin{cases} 1 & J = 1 \\ S_j + 1 & J > 1 \end{cases} \tag{5}$$

Stage 4: Determination of the recalculated weight (Q_j)

Q_j can be determined by the following equation:

$$Q_j = \begin{cases} 1 & J = 1 \\ \frac{Q_{j-1}}{K_j} & J > 1 \end{cases} \tag{6}$$

Stage 5: Calculating the relative weights (W_j) of the criteria

W_j can be determined by the following equation:

$$W_j = \frac{Q_j}{\sum_{j=1}^{m} Q_j} \tag{7}$$

where W_j is the relative weight of criterion j, and m is the number of criteria.

The most important issue in the SWARA process is the evaluation of each criterion according to the previous criterion weight. In this method, the comparative significance of the mean value (S_j) reveals the degree of importance of

Table 4 CI values used in BWM method (Rezaei 2015)

$a_{(\text{best–worst})}$	1	2	3	4	5	6	7	8	9
CI	0.00	0.44	1.00	1.63	2.3	3.00	3.73	4.47	5.23

criterion j over criterion $j+1$. The following formula can be used to evaluate S_j and measure the average ranking of the criteria defined by a group of experts (Keršulienė and Turskis 2011).

$$S_j = \frac{\sum_i^n A_i}{n} \tag{8}$$

where n is the number of experts, A_i is the recommended ranking of each criterion by experts, and j is the number of criteria.

Criteria standardization and reclassification

The reclassification technique can be used to identify the potential groundwater zone or any selection considerations. This process simplifies raster datasets by replacing single values with new significant values (Halder and Bandyopadhyay 2022). In this process known as criterion standardization or reclassification, the relative weights of the criteria are adjusted and this process is carried out by giving numerical values with a certain range such as 0–1, 0–5, 0–10, or 0–100 to the sub-units of the criteria. The main purpose of this process is to score the sub-criteria of each criterion and to standardize the ranking made according to this scoring (Karakuş et al. 2020). In this process, each sub-criteria can be of different types, such as a classified map (e.g., land use) or a value map (e.g., slope). The basis of the standardization process is the conversion of values and classes of all maps to a common scale to reduce dimensionality in decision analysis (Sharifi and Retsios 2004). As a result of this process, highly standardized values are assigned to highly suitable cells in a map for different purposes, and less suitable cells are scored lower (Rahman et al. 2012).

In this study, primarily slope, drainage density, TPI, lineament density, lithology, soil types, land use, geomorphology, and rainfall criteria are divided into sub-criteria in terms of effectiveness levels in groundwater potential mapping. Then, numerical values ranging from 0 to 5 were given to the sub-units of each criterion, and the values of 5, 4, 3, 2, 1, and 0 used in terms of groundwater potential were respectively "excellent," "very good," "good," "moderately good," "low," and "very low" (Dar et al. 2021; Sahu et al. 2022; Melese and Belay 2022). The thematic maps of the criteria (Fig. 3) have been reclassified according to the effect levels of the criteria given in Table 5 on groundwater potential mapping (Fig. 4).

Groundwater Potential Index (GPI) and weighted overlay

Aquifer properties and spatial dimensions of aquifer properties are the two most important factors affecting groundwater potential. In order to map groundwater potential regions, the importance levels of individual factors affecting groundwater formation can be indexed (Arulbalaji et al. 2019). The integration of all factors affecting groundwater formation and movement is known as the GPI (Ahmad et al. 2020). GPI is a unitless parameter used to index the probability of occurrence of groundwater potential zones in a given basin. This index can characterize groundwater potential regions as good, medium, and poor on quantitative-based groundwater classifications (Tamiru and Wagari 2021).

In this study, the rank score values (ability values) assigned to the sub-units of each criterion and required for the reclassification process were multiplied by the weight value of each criterion obtained with the help of BWM, SWARA, and BWM-SWARA methods. By using the linear combination method, these multiplication results of all criteria were collected and GPI values were obtained (Malczewski 1999; Sar et al. 2015). The mathematical expression of this process is given below (Sar et al. 2015).

$$\text{GPI} = \sum_{i=1}^{n} w_i x cv_i \tag{9}$$

where w_i is the criterion weight, and cv_i is the ability value.

Within the scope of the GPI formula given in Eq. 9, the classified maps of the criteria and the weight values of the criteria obtained from the BWM, SWARA, and BWM-SWARA methods were evaluated with the help of the Raster Calculator in the Spatial Analysis tool of ArcGIS 10.8 software and thus groundwater potential maps of the study area were obtained. High GPI values represent the most suitable areas in terms of groundwater potential (Kumar et al. 2016; Yeh et al. 2016).

Accuracy analysis

Lineer regression analysis Linear regression analysis is the most widely used method in determining the relationships between variables. In this method, the value of the Y variable is plotted on the graph and the X value is reached. This method provides metrics that show how there is a linear relationship between two variables. The correlation coefficient (R^2) used in this method can have positive or negative values and shows whether an increase or decrease in the

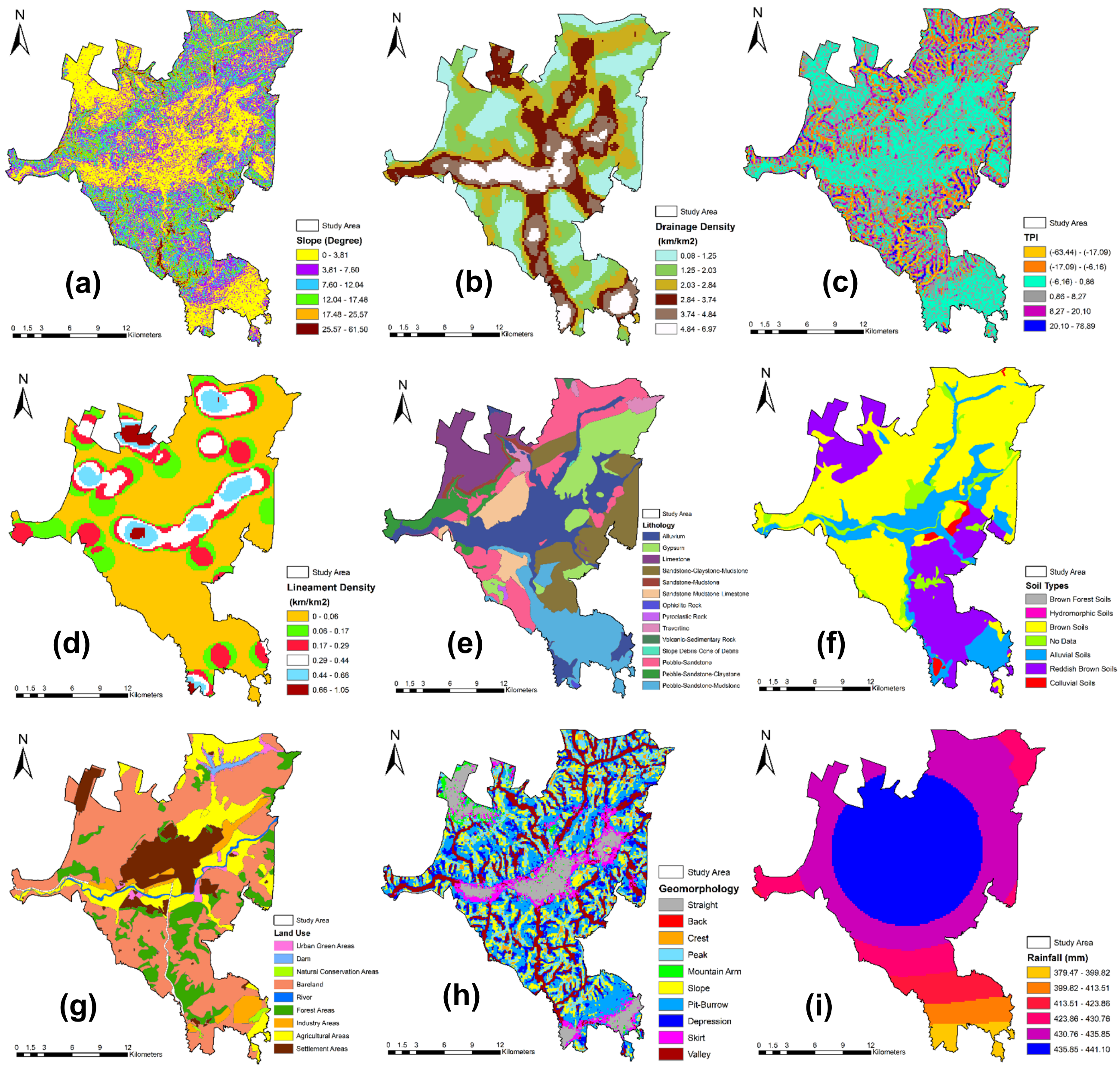

Fig. 3 Criteria maps of the study area for groundwater potential

independent variable will cause an increase or decrease in the other variable (Farhadi et al. 2020).

Receiver operating characteristic (ROC) method The accuracy of groundwater potential mapping can be ensured by overlaying the groundwater potential map with the existing groundwater well data. To determine this accuracy, ROC curve and the area under the ROC curve (AUC) are used (Pourghasemi et al. 2012; Naghibi et al. 2016). The ROC curve is a graphical representation of the balance between false negative (*X*-axis) and false positive (*Y*-axis) rates for each possible cut-off value (Pourghasemi et al. 2013). The basis of ROC analysis is to predict whether predefined events occur correctly depending on the AUC and to reveal the accuracy of a prediction system (Bui et al. 2012; Jaafari et al. 2014). The ROC curve is defined as the graph drawn between the sensitivity of a diagnostic test on the vertical axis versus the specificity on the horizontal axis. While the ratio determines the sensitivity of the correctly made estimation subject (determining the groundwater potential regions in this study), the proportion of pixels that are not suitable for the correctly defined estimation subject determines the specificity (Karakuş and Yıldız

Table 5 Intervals of standardization of the evaluation criteria and potentiality for groundwater storage

Criteria	Sub-criteria (class)	Sub-criteria scores	Area coverage (km^2)	Area coverage (%)	Suitability level for groundwater storage
Slope (°)	0–3.81	5	184.99	36.14	Excellent
	3.81–7.60	4	129.7	25.34	Very good
	7.60–12.04	3	94.61	18.48	Good
	12.04–17.48	2	63.46	12.40	Medium good
	17.48–25.57	1	31.27	6.11	Poor
	25.57–61.50	0	7.83	1.53	Very poor
Drainage density (km/km^2)	0.08–1.25	5	108.97	21.29	Excellent
	1.25–2.03	4	121.4	23.72	Very good
	2.03–2.84	3	96.3	18.81	Good
	2.84–3.74	2	88.31	17.25	Medium good
	3.74–4.84	1	55.48	10.84	Poor
	4.84–6.97	0	41.4	8.09	Very poor
TPI	(− 63.44)–(− 17.09)	5	20.95	4.09	Excellent
	(− 17.09)–(− 6.16)	4	75.91	14.83	Very good
	(− 6.16)–0.86	3	207.27	40.49	Good
	0.86–8.27	2	132.91	25.97	Medium good
	8.27–20.10	1	59.18	11.56	Poor
	20.10–78.89	0	15.64	3.06	Very poor
Lineament density (km/km^2)	0.66–1.05	5	7.69	1.50	Excellent
	0.44–0.66	4	27.35	5.34	Very good
	0.29–0.44	3	48.49	9.47	Good
	0.17–0.29	2	63.4	12.39	Medium good
	0.06–0.17	1	81.6	15.94	Poor
	0–0.06	0	283.33	55.35	Very poor
Lithology	Alluvium	5	104.569	20.43	Excellent
	Slope debris-cone of debris	5	0.45	0.09	Excellent
	Travertine	4	10.71	2.09	Very good
	Pebble-sandstone	4	85.601	16.72	Very good
	Limestone	4	46.48	9.08	Very good
	Gypsum	4	58.7	11.47	Very good
	Pebble-sandstone-claystone	3	23.55	4.60	Good
	Sandstone-mudstone-limestone	3	28.6	5.59	Good
	Pebble-sandstone-mudstone	3	67.92	13.27	Good
	Sandstone-mudstone	2	7.56	1.48	Medium good
	Sandstone-claystone-mudstone	2	75.22	14.70	Medium good
	Pyroclastic rock	1	1.03	0.20	Poor
	Volcanic-sedimentary rock	1	0.87	0.17	Poor
	Ophiolite rock	0	0.6	0.12	Very poor
Soil types	Alluvial soils (A)	5	88.29	17.25	Excellent
	Reddish brown soils (F)	5	122.55	23.94	Excellent
	Hydromorphic soils (H)	4	1.55	0.30	Very good
	Brown forest soils (M)	3	0.0028	0.00	Good
	Brown soils (B)	2	266.48	52.06	Medium good
	Colluvial soils (K)	1	29.1572	5.70	Poor

Table 5 (continued)

Criteria	Sub-criteria (class)	Sub-criteria scores	Area coverage (km^2)	Area coverage (%)	Suitability level for groundwater storage
Land use	River	5	5.45	1.06	Excellent
	Dam	5	3.6	0.70	Excellent
	Forest	4	63.79	12.46	Very good
	Agriculture	3	85.57	16.72	Good
	Natural conservation areas	2	1.7	0.33	Medium good
	Urban green areas	1	8.5	1.66	Poor
	Bareland	1	257.36	50.28	Poor
	Settlement	0	64.62	12.62	Very poor
	Industry	0	21.27	4.16	Very poor
Geomorphology	Straight	5	45.22	8.83	Excellent
	Depression	5	8.32	1.63	Excellent
	Valley	4	69.26	13.53	Very good
	Pit-burrow	4	59.13	11.55	Very good
	Skirt	3	30.9	6.04	Good
	Crest	2	7.58	1.48	Medium good
	Mountain arm	2	76.66	14.98	Medium good
	Slope	2	139.71	27.29	Medium good
	Back	1	63.48	12.40	Poor
	Peak	0	11.6	2.27	Very poor
Rainfall (mm)	416.73–441.10	5	442.34	86.42	Excellent
	379.47–416.73	4	69.52	13.58	Very good

2022). The sensitivity and specificity can be calculated as follows (Rahmati et al. 2019):

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{10}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{FP} + \text{TN}} \tag{11}$$

where FN (false negative) and FP (false positive) are the numbers of pixels erroneously predicted, whereas TN (true negative) and TP (true positive) are the numbers of pixels that are correctly predicted.

In this method, which is used to evaluate the accuracy of the model, the area under the ROC curve value varies between 0.5 and 1.0 values (Nandi and Shakoor 2009). If the AUC value is equal to 0.5, it is not possible to observe groundwater formation (Dar et al. 2021). According to Razandi et al (2015), AUC values corresponding to prediction accuracy in accuracy analysis were classified as bad (0.5–0.6), moderate (0.6–0.7), good (0.7–0.8), very good (0.8–0.9), and excellent (0.9).

Result and discussion

Criteria and reclassification of suitability criteria

In this section, information about the thematic maps of the criteria that have been taken into account in groundwater potential mapping and that reveal the general characteristics of the study area is given (Fig. 3). These criteria were classified by taking into account the efficiency levels and suitability value ranges in groundwater potential mapping (Table 5), and classified raster maps of these criteria were created (Fig. 4). All criteria were evaluated in terms of groundwater potential mapping with 6 classes ("excellent," "very good," "good," "medium good," "poor," "very poor").

Slope

Slope is a criterion that directly affects the infiltration of precipitation into the ground and can be considered as one of the indicators of groundwater potential accessibility. The slope can also be used as a reference data source in

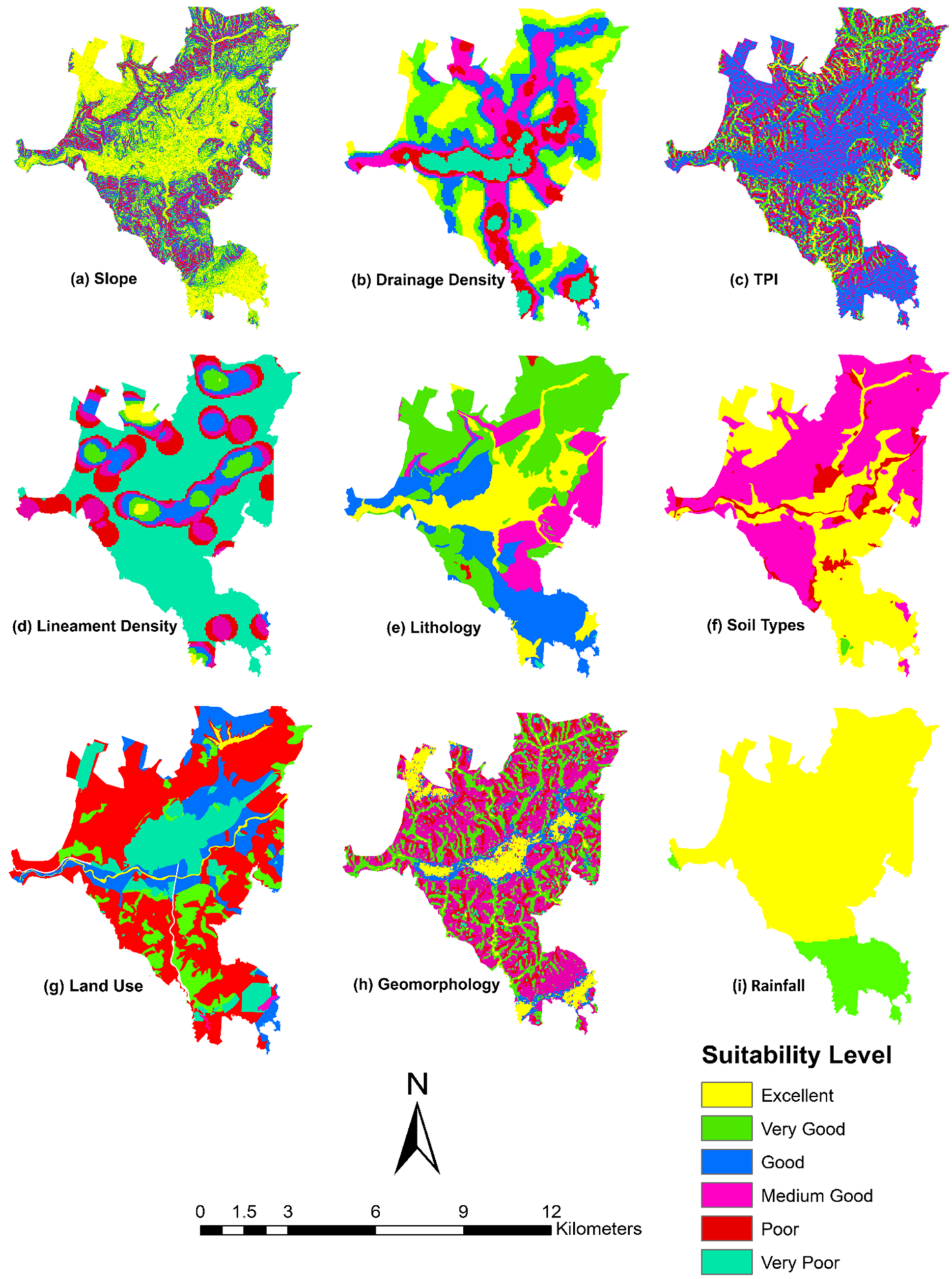

Fig. 4 Classified maps of standardized criterias for groundwater potential

determining the groundwater flow direction (Tolche 2021). In places with low slopes, infiltration to the ground occurs more because the surface flow will be less. As the slope rate increases, the surface flow increases and the infiltration to the ground decreases (Çelik 2019). In areas with flat, light, moderate, steep, and very steep slopes, the groundwater probability is very high, high, medium, low, and very low, respectively (Elewa and Qaddah 2011). Therefore, lower weight scores are given to steep and very steep slope classes when groundwater potential is determined (Mukherjee and Singh 2020).

The slope of the study area varies between 0 and 61.50° (Fig. 3a). Slope classes in the study area in terms of groundwater potential are excellent (0–3.81°), very good (3.81–7.60°), good (7.60–12.04°), medium good (12.04–17.48°), poor (17.48–25.57°), and very poor (25.57–61.50°). Areas with a slope of 0–3.81° (with 5 points) cover the majority of the study area (36.14%), and these areas are the most suitable areas in terms of groundwater potential. These areas were generally distributed in the center, northwest, and south of the study area. Sloping areas (with 0 points) in the "very poor" (25.57–61.50°) class in terms of groundwater potential have the least areal distribution (1.53%) (Fig. 4a, Table 5).

Drainage density

Drainage density can be determined by dividing the total length of all rivers in a drainage basin by the total area of the drainage basin. Structural analysis of the drainage network helps to evaluate the characteristics of a groundwater recharge zone (Yeh et al. 2016). Drainage density is an inverse function of permeability and is therefore an important parameter in the evaluation of the groundwater zone. High drainage density values are suitable for runoff, but these values mean low groundwater potential. For this reason, the highest weighting points are assigned to the lowest drainage density values, while the lowest weighting points are assigned to the highest drainage density values (Shekhar and Pandey 2015). Drainage density can be calculated with the help of the following equation (Eq. 12) (Radulović et al. 2022).

$$\mathrm{DD} = \sum L_{\mathrm{ws}}/A_{\mathrm{ws}} \tag{12}$$

where DD is the drainage density, L_{ws} is the total length of drains in the drainage basin, and A_{ws} is the area of the drainage basin.

The drainage density of the study area is between 0.08 and 6.97 km/km^2. Approximately 50% (0.08–2.03 km/km^2) of the total area has a low and very low drainage density, while approximately 20% (3.74–6.97 km/km^2) has a high and very high drainage density (Fig. 3b). An area of high drainage density increases runoff compared to an area of low drainage density. The highest value of the drainage density leads to less infiltration, indicating the highest flow state (Saranya and Saravanan, 2020). Hence, areas with the highest drainage density (4.84–6.97 km/km^2) were assigned 0 points as "(very poor)," while areas with the lowest drainage density (0.08–1.25 km/km^2) were assigned "(excellent)" with 5 points in terms of groundwater potential (Fig. 4b, Table 2).

TPI

TPI is a widely used algorithm for measuring topographic slope locations and automating landform classifications (De Reu et al. 2013). The TPI determines which areas are valleys, ridges, or flats and standardizes the cell size by using the height for each cell and subtracting the average height of the cell's neighbors (Khali et al. 2020). Many physical processes such as hill top, valley floor, exposed ridges, plain, and upper and lower slope movements in the landscape are associated with TPI (Arulbalaji et al. 2019). While the TPI values are high in the areas near the summit of the hills, the TPI values are low in the foothills of the hills. TPI value is close to zero in regions with moderate slope (Arya et al. 2020; Nair et al. 2017; Arulbalaji et al. 2019). A lower TPI value is assigned a higher weighting score for groundwater potential (Hema et al. 2017; Mukherjee and Singh 2020; Sarkar et al. 2022). TPI can be calculated using the following equation (Eq. 13) (Salar et al. 2018; Rahaman et al. 2022):

$$\mathrm{TPI} = \frac{M_0 - \sum_{n-1} M_n}{n} \tag{13}$$

where M_0 denotes the elevation of the model point, M_n denotes the elevation of grid, and n denotes the total number of surrounding points.

TPI values in the study area ranged from − 63.44 to 78.89 (Fig. 3c). For groundwater potential, the lowest TPI value (− 63.44)–(− 17.09) was assigned the highest score (5—"excellent") (Mukherjee and Singh 2020). Groundwater recharge is insufficient because high TPI value will cause more surface runoff and less swelling (Rahaman et al. 2022). TPI values in the study area are categorized as "excellent" [(− 63.44)–(− 17.09)], "very good" [(− 17.09)–(− 6.16)], "good" [(− 6.16)–(0.86°)], "medium good" (0.86–8.27°), "poor" (8.27–20.10), and "very poor" (20.10–78.89) (Fig. 4c, Table 5).

Lineament density

Lineament is known as a linear feature that is an indication of the basic geological structure in a geographical landscape. Lineament density is defined as the total length of all recorded lineaments divided by the area in question (Melese and Belay 2022). Lineament density is a criterion that ultimately determines the permeability. Linearity (faults, fractures, and discontinuity surfaces) provides groundwater flow paths (Abdallah 1995). Groundwater potential is higher in these regions due to higher water circulation in areas with high lineament density (Lentswe and Molwalefhe 2020). Lineament density can be calculated as the total lineament length in a unit area using the following equation (Eq. 14) (Chaudhry et al. 2021).

$$Ld = \frac{\sum_1^n Li}{A} \tag{14}$$

where Li indicates the length of lineament and A is the unit area.

The linearity density of the study area is shown in Fig. 3d. Lineament density is very high (0.66–1.05) in a part of the center and northwest of the study area. These areas, which were assigned with 5 points (excellent) in terms of groundwater potential, represented 1.50% of the study area. Areas with low lineament density in the range of 0–0.06 (with 0 points) showed a homogeneous distribution throughout the study area with a value of 55.35% (Table 5). Since infiltration is a direct function of lineament density, areas with high lineacity density are given high weight scores, and areas with low lineament density are given low weight scores (Githinji et al. 2022, Fig. 4d).

Lithology

Lithology plays an important role in the formation and distribution of groundwater by controlling the infiltration rate and flow (Kumar et al. 2016; Tolche 2021). Swelling and flow rate mostly depend on the porosity of certain rock types (Yeh et al. 2016; Abijith et al. 2020). Porosity, the size of the pore space, and the ease with which the pore spaces are interconnected affect the availability of groundwater by controlling the permeability of the geological environment (Anteneh et al. 2022). Permeable formations promote the infiltration of water through underground flows. Conversely, impermeable rocks such as crystalline rocks support runoff (Benjmel et al. 2020).

There are 14 lithological units in the study area. Alluvium is the unit with the highest distribution (20.43%) in the study area, while pyroclastic rock, volcanic-sedimentary rock, and ophiolite rock are the units with the least distribution (0.68%) (Fig. 3e, Table 5). The pebble-sandstone and limestone units "very good" (4 points) are a good aquifer (Yılmaz and Atmaca 2004), and these units constitute 25.80% of the study area. Alluvium is concentrated in the central region of the study area, and pebble-sandstone and limestone units are mostly concentrated in the north and southwest of the study area (Fig. 3e). Alluvium and limestone deposits are lithological units with high groundwater potential because of their better permeability and productivity (Şener et al. 2010; Kebede 2013). Ophiolite rocks are impermeable (Kebede 2013) and are lithological units with low groundwater potential. Sedimentary formations such as slope debris and debris cones are formed by the materials that were transported by the streams from the surrounding hills and slopes. These irregular sedimentary agglomerations, which are very young, not yet consolidated, thick, and loose, cause local permeability increases according to the units they come upon, and thus they form the groundwater reserve hydrogeologically (Taşdelen et al. 2016). Within the framework of this information, alluvium and slope debris-debris cones lithological units were represented by the "excellent (5 points)" class in terms of groundwater potential. The lithological units of the ophiolite rock type in the study area were categorized as "very poor (0 points)" (Fig. 4e, Table 5).

Soil types

Soil has an important place in the spatial variation in the quantity and quality of groundwater in a region (Anteneh et al. 2022). By analyzing the soil properties of an area, groundwater holding capacity, penetration rate, precipitation infiltration, and groundwater recharge can be estimated (Rana et al. 2022). Soil texture and hydraulic properties are very important to evaluate the infiltration rate. The rainfall-runoff relationship directly affects the soil type, soil permeability, soil moisture content, thickness, and infiltration rate (Rahman et al. 2022). Generally, soil permeability, water holding capacity, and soil type affect swelling rates. Since the porosity and permeability of sandy soils are relatively higher than clay soils, the groundwater storage capacity of these soils is high (Kom et al. 2022).

Brown soils are the soil type with the highest distribution (52.06%) in the study area (Fig. 3f), and these soils were classified as "medium good (2 points)" in terms of groundwater potential. Alluvial and reddish brown soils were represented by the "excellent (5 points)" class (Fig. 4f) in terms of groundwater potential due to their high permeability and lower water holding capacity, and these soils showed a distribution of 41.19% in the study area. These soil types are mostly located in the central, south, and northeast of the study area (Fig. 3f). Due to their low permeability and higher water holding capacity, colluvial soils (5.70%) are unsuitable soil types in terms of groundwater potential and this soil type is categorized as "poor (1 point)" (Fig. 4g, Table 5).

Land use

Land use is an important factor controlling soil moisture, penetration, and runoff rate, which directly regulates groundwater recharge (Yeh et al. 2016). Land use is the controlling factor for groundwater storage and determination of groundwater availability during complex geological processes (Senapati and Das 2022). Vegetation is directly related to the runoff, and areas covered with vegetation affect the recharge capacity. The higher the density of the vegetation increases the swelling rate and decreases the flow from the surface. Areas with water bodies have the highest recharge capacity for groundwater potential. In urban areas, recharge capacity is low due to the construction of asphalt surfaces that significantly facilitate flow (Kumari et al. 2022). Roots of plants in vegetation and forest covered lands have high water holding capacity. On the other hand, infiltration into the ground is reduced as the surface flow is very high in residential areas and bare lands. Therefore, while the areas covered by vegetation show high groundwater potential, the groundwater potential is lower in built up areas and bare lands (Ghosh et al. 2020a, b).

The land use type with the highest distribution in the study area is bare land, which covers 50.28% of the study area (Fig. 3g). The land use forms in the river and dam pond class, which are in the "excellent (5 points)" class in terms of groundwater potential, constitute 1.76% of the study area. Forest areas in the "Very good (4 points)" class constituted 12.46% of the study area. The residential and industrial areas in the "very low (0 points)" class have a distribution of 16.78% in the study area, and these areas are mostly located in the central region of the study area (Figs. 3g and 4g, Table 5).

Geomorphology

Geomorphology is a key characteristic factor that defines the shape and topography of a region, plays an important role in groundwater availability and distribution, and is used to identify potential groundwater areas (Dar et al. 2021). Geomorphology has a positive effect on the infiltration of water on the earth. Geomorphology is recognized as an important component for groundwater recharge, as the evolution of landforms explains the porous and permeable regions (Pathmanandakumar et al. 2021).

There are 10 geomorphological units in the study area. The geomorphological units with the highest distribution in the study area are "slope (27.29%)," "mountain arm (14.98%)," and "valley (13.53%)." The geomorphological units with the lowest distribution in the study area are "depression (1.63%)" and "crest (1.48%)." Straight areas (8.83%) including a part of Sivas city center are located in the middle and north-west parts of the study area (Fig. 3h, Table 5). In general, most of the geomorphological units showed a homogeneous distribution in the study area. As a general view, "peak" and "mountain arm" units, which show an increase in altitude, increase when moving away from the city center, while the alluvial plains in the Kızılırmak bed, where the city of Sivas was founded, are surrounded by high mountainous areas. In this way, alluvial plains lie in the center, mountainous areas in the outermost areas, and plateau areas between the two areas. In the study area, apart from the valleys of Kızılırmak and its tributaries, there are many valleys extending from the mountainous areas to the base of the plain. High terrain (peak) and steep slopes provide higher flow, while topographic depressions and straight areas increase infiltration (Kabeto et al. 2022). According to this explanation, in terms of groundwater potential, straight and depression areas in the study area are represented by the "excellent (5 points)" class, while the peak areas are represented by "very poor (0 points)" class (Fig. 4h, Table 5).

Rainfall

Rainfall is one of the important factors in determining groundwater potential regions, and groundwater is a dynamic natural resource supported by precipitation. By directly controlling the infiltration of surface water, rainfall increases groundwater recharge and improves groundwater resource potential (Maity and Mandal 2019; Tolche, 2021). There is a strong positive relationship between rainfall and groundwater (Das 2019).

Regions with heavy rainfall in the study area are known as the most suitable areas in terms of groundwater potential. According to the precipitation map created according to the Inverse Distance Weighted Interpolation Method (IDW) for the study area using the 30-year average total precipitation data between 1990 and 2020, the annual average rainfall values vary between 379.47 and 441.10 mm (Fig. 3i). In terms of groundwater potential, areas with precipitation values in the "excellent (5 points)" and "very good (4 points)" categories showed a distribution of 86.42% and 13.58%, respectively. The areas with the least precipitation are located in the south of the study area (Figs. 3i and 4i, Table 5).

Determination of criterion weights according to BWM and SWARA

BWM method and SWARA method, which is a very new method in the literature, were preferred to determine the relative weights of 9 criteria determined in accordance with the literature (Table 1) for groundwater potential mapping. Codings corresponding to these criteria were made (Table 6). In order to apply both methods, 12 hydrogeologists who are experienced in groundwater studies were included in the study as decision-maker (DM). Six hydrogeologists evaluated the BWM method, and the other 6 hydrogeologists as the DM for the SWARA method.

Six DM determined the best and worst criteria from 9 criteria (Table 6) that are effective in groundwater potential mapping for the BWM method. As a result of determining the best and worst criteria according to these DMs, they were first graded from 1 to 9 from the best to the others. Grades of importance were determined with the evaluation matrix (1: equally important, 3: moderately more important, 5: strongly important, 7: ımportant as very strong, 9: quite very important). These DMs then rated the criteria from 1 to 9, from the others to the worst, and determined their degree of importance with the evaluation matrix. Table 7 shows the criteria evaluations of 6 DMs. According to Table 7, the preference of the best criteria to the other criteria and the preference of other criteria to the worst criteria according to all DMs were taken into account, a linear programming model was established, and analysis was made by considering the equations in the "Best–Worst Method (BWM)" section. According to this analysis, the consistency ratios and main criterion weights of all DMs were calculated, and finally the average consistency ratio for all DMs and the average criterion weights for all criteria were determined (Table 10).

In the SWARA method, all DMs have listed the 9 criteria (Table 6) taken into account for groundwater potential mapping, with the most important being the first (Table 8). First of all, each DM determined the importance levels of all criteria according to the graded evaluation scale (0.05: little important, 0.1: moderately important, 0.15: important, 0.20: very important, 0.25: very very important, 0.30: absolutely important), starting from the most important criterion in Table 8 (Table 9). According to the results of this evaluation, the criterion weights of each DM were calculated with the help of the equations in the SWARA section, and the average criterion weights and criterion rankings of each criterion were determined by using these criterion weights (Table 10).

For the BWM method, CR of all criteria was calculated as 0.0995, according to the linear programming model made by considering the evaluations of all DMs given in Table 7. This value satisfies $CR \le 0.1$ condition and shows that the obtained vector is acceptable and the decision-makers' comparisons are consistent. According to the analyses made according to the BWM and SWARA methods, rainfall, lithology, and slope criteria were determined as the criteria with the highest weight in groundwater potential mapping, while geomorphology, lineament density, and TPI criteria were determined as the criteria with the lowest weight value (Table 10). Lithology, rainfall, and slope criteria have been considered as the most important criteria in many studies (Das et al. 2019; Benjmel et al. 2020; Abdalla et al. 2020; Das 2019; Mallick et al. 2019; Mandal et al. 2021) conducted with different methods (AHP, Fuzzy AHP, TOPSIS etc.) related to groundwater potential mapping, and the most important criteria rankings obtained according to both methods in this study supported the literature information.

Groundwater potential map

The GPI method based on the weighted linear combination method was used to obtain the groundwater potential mapping of the study area. GPI represents a dimensionless number used to estimate potential groundwater regions (Malczewski 1999; Shekhar and Pandey 2015). With the help of BWM and SWARA methods, the weight values obtained for the criteria (Table 10) were evaluated together and the relative weight values of the BWM-SWARA integration were obtained. According to this integration, slope, lithology, and rainfall criteria were found to be the criteria with the highest weight value in groundwater potential mapping (Table 11).

The GPI values given in Eq. 9 based on the weighted linear combination method were calculated by using the sub-criteria scores of the criteria (Table 5) and the weight values of the criteria obtained by the BWM, SWARA, and BWM-SWARA methods (Table 11).

$$\begin{aligned} GPI_{BWM} = & [(0.140 \times \text{slope}) + (0.107 \times \text{drainage density}) + (0.043 \times \text{TPI}) \\ & + (0.137 \times \text{lineament density}) + (0.170 \times \text{lithology}) \\ & + (0.088 \times \text{soil types}) + (0.073 \times \text{LULC}) \\ & + (0.052 \times \text{geomorphology}) + (0.190 \times \text{rainfall})] \end{aligned}$$

$$\begin{aligned} GPI_{SWARA} = & [(0.119 \times \text{slope}) + (0.113 \times \text{drainage density}) + (0.097 \times \text{TPI}) \\ & + (0.094 \times \text{lineament density}) + (0.136 \times \text{lithology}) \\ & + (0.110 \times \text{soil types}) + (0.095 \times \text{land use}) \\ & + (0.092 \times \text{geomorphology}) + (0.120 \times \text{rainfall})] \end{aligned}$$

$$\begin{aligned} GPI_{INTEGRATED} = & [(0.143 \times \text{slope}) + (0.104 \times \text{drainage density}) \\ & + (0.035 \times \text{TPI}) + (0.130 \times \text{lineament density}) \\ & + (0.199 \times \text{lithology}) + (0.091 \times \text{soil types}) \\ & + (0.060 \times \text{land use}) + (0.041 \times \text{geomorphology}) \\ & + (0.196 \times \text{rainfall})] \end{aligned}$$

Classified raster maps (Fig. 4), which were created according to the effect levels of the criteria on groundwater potential mapping, and criterion weights (Table 11) obtained by the integration of BWM, SWARA, and BWM-SWARA were used for all three methods, considering the GPI formulas given above. Then, groundwater potential maps of all three methods (Figs. 5, 6 and 7) were obtained with the help of ArcGIS 10.8 software. These maps were created based on weighted index overlay analysis by summing the weight value of each thematic layer. In these maps, regions with high weighted value showed high groundwater potential (Ibrahim-Bathis and Ahmed 2016).

The GPI values calculated for the study area varied in the range of 1.0–4.5 for BMW, SWARA, and BWM-SWARA methods. The suitability categories revealed by

Table 6 Codings corresponding to the criteria for groundwater potential mapping

C1	C2	C3	C4	C5	C6	C7	C8	C9
Slope	Drainage density	TPI	Lineament density	Lithology	Soil types	Land use	Geomorphology	Rainfall

C, criteria.

Table 7 Evaluations of the decision-maker (DM) expert group for BWM method

Assessment of DM1									
Most important criterion: **C9**	Least important criterion: **C7**								
Pairwise comparisons of the most important criterion against other criteria									
	C9 (1st place)	C5 (2nd place)	C6 (3rd place)	C1 (4th place)	C2 (5th place)	C8 (6th place)	C3 (7th place)	C4 (8th place)	C7 (9th place)
Preference rate of the most important criterion (C9) over other criteria	1	3	5	3	1	5	1	5	9
Pairwise comparisons of other criteria by least important criterion									
Preference rate of other criteria according to the least important criterion (C7)	9	9	7	5	3	3	1	3	1
Assessment of DM2									
Most important criterion: **C2**	Least important criterion: **C8**								
Pairwise comparisons of the most important criterion against other criteria									
	C2 (1st place)	C1 (2nd place)	C5 (3rd place)	C9 (4th place)	C3 (5th place)	C4 (6th place)	C7 (7th place)	C6 (8th place)	C8 (9th place)
Preference rate of the most important criterion (C2) over other criteria	1	1	3	3	5	5	7	7	7
Pairwise comparisons of other criteria by least important criterion									
Preference rate of other criteria according to the least important criterion (C8)	7	7	7	5	5	5	3	3	1
Assessment of DM3									
Most important criterion: **C7**	Least important criterion: **C9**								
Pairwise comparisons of the most important criterion against other criteria									
	C7 (1st place)	C6 (2nd place)	C2 (3rd place)	C3 (4th place)	C1 (5th place)	C4 (6th place)	C5 (7th place)	C8 (8th place)	C9 (9th place)
Preference rate of the most important criterion (C7) over other criteria	1	3	5	5	3	1	5	7	9
Pairwise comparisons of other criteria by least important criterion									
Preference rate of other criteria according to the least important criterion (C9)	9	7	7	5	3	3	3	3	1
Assessment of DM4									
Most important criterion: C5	Least important criterion: **C7**								
Pairwise comparisons of the most important criterion against other criteria									
	C5 (1st place)	C9 (2nd place)	C6 (3rd place)	C8 (4th place)	C1 (5th place)	C3 (6th place)	C2 (7th place)	C4 (8th place)	C7 (9th place)
Preference rate of the most important criterion (C5) over other criteria	1	3	5	5	7	7	5	7	9
Pairwise comparisons of other criteria by least important criterion									
Preference rate of other criteria according to the least important criterion (C7)	9	7	3	5	3	1	3	3	1
Assessment of DM5									
Most important criterion: C5	Least important criterion: C3								
Pairwise comparisons of the most important criterion against other criteria									
	C5 (1st place)	C1 (2nd place)	C6 (3rd place)	C9 (4th place)	C2 (5th place)	C7 (6th place)	C4 (7th place)	C8 (8th place)	C3 (9th place)

Table 7 (continued)

Preference rate of the most important criterion (C5) over other criteria	1	1	3	3	5	5	7	7	9
Pairwise comparisons of other criteria by least important criterion									
Preference rate of other criteria according to the least important criterion (C3)	9	9	7	7	5	5	3	1	1
Assessment of DM6									
Most important criterion: C5	Least important criterion: C9								
Pairwise comparisons of the most important criterion against other criteria									
	C5 (1st place)	C6 (2nd place)	C1 (3rd place)	C4 (4th place)	C2 (5th place)	C7 (6th place)	C3 (7th place)	C8 (8th place)	C9 (9th place)
Preference rate of the most important criterion (C5) over other criteria	1	3	3	5	5	5	7	7	7
Pairwise comparisons of other criteria by least important criterion									
Preference rate of other criteria according to the least important criterion (C9)	7	7	5	5	5	3	3	3	1

DM: decision-maker.

the groundwater potential maps obtained for all three methods were categorized as “excellent,” “very good,” “good,” “medium good,” “poor,” and “very poor.” In all three methods, “good” and “medium good” suitability categories made up the majority of the study area. According to the BWM, SWARA, and BWM-SWARA methods, the regions in the “excellent” class constituted 10.99%, 8.40%, and 11.16% of the study area, respectively. These regions were concentrated mainly in the center and northwest of the study area in all three methods. Tavra region, which is located in the northwest of the study area and where drinking water wells are very dense, was in the “excellent” category in terms of groundwater potential. Regions in the “very poor” class were mostly concentrated in the south and west of the study area.

As can be seen in Figs. 5, 6 and 7, areas with “excellent” and “very good” groundwater potential are concentrated in regions with alluvial and limestone units (Fig. 3e). These formations have a high groundwater retention potential as they allow maximum infiltration with the presence of high primary and secondary porosity (Ibrahim-Bathis and Ahmed 2016). The carbonates, the product of the lacustrine environment, located on the coarse-grained clastic rock types, which are the product of the Upper Miocene-Pliocene aged fluvial environment, are aquifers rich in groundwater. Alluviums are generally represented by unconsolidated or loosely anchored gravel, sand, and mud deposits that have undergone the transport phase. Alluviums are generally represented by unconsolidated or loosely fixed and transported gravel, sand, and mud deposits that have undergone the transport phase. Alluviums located along the Kızılırmak valley and on the valleys or slopes reaching Kızılırmak form the levels over which the surface waters flow. The sections of these formations that serve as beds for the waters filtering from the gypsum aquifers around them are aquifers containing groundwater (Yılmaz and Atmaca 2004). Also, in regions with high linearity density (Fig. 3d), the groundwater potential is in the “excellent” and “very good” class. Areas with “poor” and “very poor” groundwater potential are distributed in regions with high drainage density (Fig. 3b). In the study area, flat areas, low slope areas, alluvial soils, water structures, and forest areas in terms of land use played an important role in the formation of regions with high groundwater potential.

Masoud et al (2022) obtained groundwater potential maps with the help of GIS-based AHP and FR (Frequency Ratio) techniques. Researchers stated that the underground water potential is high in these regions due to the high hydraulic conductivity of the underground rocks in the study area, the presence of the lake area, and the permeable surface lithology in these areas. Emphasizing that the areas outside these regions have low permeability, high altitude, and steep slopes, the researchers revealed that the groundwater potential in these areas is low. According to Ghosh et al (2022) and Bera et al (2020), geomorphology, slope, land cover,

Table 8 Criteria sorting at DM level for SWARA

Criteria	DM7	DM8	DM9	DM10	DM11	DM12
C1	4	2	5	5	2	3
C2	5	1	3	7	5	5
C3	7	5	4	6	9	7
C4	8	6	6	8	7	4
C5	2	3	7	1	1	1
C6	3	8	2	3	3	2
C7	9	7	1	9	6	6
C8	6	9	8	4	8	8
C9	1	4	9	2	4	9

and soil type criteria are listed as the most important criteria that can affect the groundwater potential in an area. Due to urbanization and industrial growth exacerbating water scarcity, areas with cones of depression correspond to shallow aquifers (Noyola-Medrano et al. 2009; López-Álvarez et al. 2014, 2013). On the other hand, impermeable surfaces that increase with urbanization tend to reduce infiltration and groundwater formation (Martín Del Campo et al. 2014). Paryani et al (2022) determined the most suitable regions in terms of groundwater potential based on BWM and SWARA models. According to the results of the researchers, the lowest slope degree (0–12.9°) showed the greatest potential. It has been observed that the groundwater potential decreases with the distance from the river. It has been observed that drainage density is directly related to the probability of groundwater formation (Paryani et al. 2022). In this study, according to all three methods, the most suitable regions in terms of groundwater potential are high rainfall, lithologically permeable units, presence of permeable soils, low slope, high drainage density, geomorphologically flat and depression areas, presence of surface water source, and linearity density are listed as the main reasons for the high groundwater potential.

In many studies on groundwater potential mapping based on GIS-MCDA (Ghosh et al. 2022; Fashae et al. 2014; Andualem and Demokrate 2019; Al-Djazouli et al. 2021), slope, lineament density, precipitation, and geology criteria were determined as the criteria with the highest weight values. The results of the criterion weights in this study showed similar features to the results obtained from previous studies.

The AHP method has been widely used in the majority of recent studies in the creation of groundwater potential mapping based on GIS-based MCDA methods (Roy et al. 2022; Akbari et al. 2021; Zhang et al. 2021; Amponsah et al. 2022; Sarkar et al. 2021). There are very few studies (Paryani et al. 2022; Akbari et al. 2021) based on BWM and SWARA methods on groundwater potential mapping. Gigović et al. (2019) used the BWM method to generate a landslide susceptibility map in Serbia. The researcher's results proved that the BWM model validated its power to produce accurate results and the BWM model outperformed SWARA. The SWARA model has also been used in various spatial modeling studies and it has been stated that good results have been obtained from these studies. Wang et al (2019) used the SWARA method to prepare the flood susceptibility map. The results obtained by the researcher revealed that the SWARA method can be a very suitable method to show the degree of correlation between parameters and floods.

The final weights from BWM are highly reliable as they provide consistent comparisons. In most MCDM methods (e.g., AHP), the consistency rate is a measure to check whether comparisons are reliable, while in BWM, the consistency rate is used to see the level of reliability as the output of BWM is always consistent. In the comparison matrix, it is used in fractional numbers as well as integers. Only integers are used in BWM, which makes it much easier to use (Rezaei 2015; Demir and Bircan 2020). SWARA is a simple, less binary comparison, not using a 1–9 scale-like AHP or BWM, and benefiting from the knowledge and experience of experts when evaluating the criteria. The strong point of the method is that it does not have a complex structure, it prepares the ground for experts to easily work together (Demir 2021).

The weighting process made with the help of the AHP method to create the potential aquifer map may not fully reflect the sensitivity of the terrain (Benjmel et al. 2020). In general, the number of criteria to be compared in the AHP method, the number of paired comparisons required, and the uncertainty of the criteria considered will increase (Ildoromi et al. 2019; Sepehri et al. 2020). In future studies, it is recommended to use BWM and SWARA methods to increase the overall consistency in pairwise comparisons between criteria and to reduce potential problems (Moharrami et al. 2020; Wang et al. 2019).

Accuracy assessment

Accuracy assessment was performed for groundwater potential mapping based on the linear regression method and the ROC curve method. In order to create the groundwater level map, which was considered as the source data in the accuracy assessment for the linear regression method,

Table 9 SWARA significance levels by DM

Order of criteria according to ımportance level	DM7		DM8		DM9		DM10		DM11		DM12	
1	C9	-	C2	-	C7	-	C5	-	C5	-	C5	-
2	C5	0.30	C1	0.10	C6	0.15	C9	0.10	C1	0.05	C6	0.10
3	C6	0.20	C5	0.05	C2	0.05	C6	0.20	C6	0.05	C1	0.05
4	C1	0.15	C9	0.05	C3	0.05	C8	0.05	C9	0.05	C4	0.05
5	C2	0.10	C3	0.20	C1	0.05	C1	0.10	C2	0.10	C2	0.10
6	C8	0.05	C4	0.05	C4	0.05	C3	0.05	C7	0.15	C7	0.05
7	C3	0.10	C7	0.05	C5	0.05	C2	0.05	C4	0.15	C3	0.10
8	C4	0.10	C6	0.05	C8	0.05	C4	0.10	C8	0.05	C8	0.10
9	C7	0.15	C8	0.05	C9	0.05	C7	0.10	C3	0.05	C9	0.10

the groundwater level data of 99 wells drilled by the Sivas Municipality in the study area were mapped with the help of the IDW method (Fig. 8). According to Fig. 8, groundwater level values in the study area vary between 2.00 and 33.90 m. Areas with high groundwater levels are concentrated in the center and northwest of the study area, while areas with low groundwater levels are located in the west and east of the study area. The groundwater level map (Fig. 8) and groundwater potential maps (Figs. 5, 6 and 7) were superimposed for accuracy assessment (Murmu et al. 2019; Serele et al. 2020). Based on this superimposing, a scatter plot was drawn between the groundwater level data in the study area and the corresponding GPI (Fig. 9a, b, c). The linear regression coefficients (R^2) for the BWM, SWARA, and BWM-SWARA methods were 0.80, 0.82, and 0.75, respectively, which confirms the reliability of the methodology. As a result of superimposing the groundwater level map with the groundwater potential maps, it was seen that most of the areas with low groundwater level correspond to poor groundwater potential regions. In other words, in areas with high GPI values throughout the study area, groundwater level values were high. These results showed that there is a strong correlation between the groundwater potential maps created for all three methods and the available groundwater level data.

The suitability categories revealed by the groundwater potential maps created for all three methods and the groundwater level data of the wells drilled by Sivas Municipality

Table 10 Final criteria weights according to BWM and SWARA methods

Criteria	BWM							
	DM1	DM2	DM3	DM4	DM5	DM6	Average weight	Criteria ranking
C1	0.111	0.260	0.107	0.065	0.268	0.138	0.14	3
C2	0.181	0.260	0.064	0.091	0.065	0.083	0.107	5
C3	0.029	0.067	0.064	0.036	0.024	0.059	0.043	9
C4	0.066	0.067	0.200	0.065	0.046	0.083	0.137	4
C5	0.111	0.112	0.064	0.356	0.268	0.323	0.17	2
C6	0.066	0.048	0.107	0.091	0.108	0.138	0.088	6
C7	0.037	0.048	0.321	0.051	0.065	0.083	0.073	7
C8	0.066	0.027	0.046	0.091	0.046	0.059	0.052	8
C9	0.332	0.112	0.026	0.152	0.108	0.033	**0.19**	**1**
CR	0.151	0.074	0.121	0.102	0.057	0.092	**Average CR: 0.0995**	
Criteria	SWARA							
	DM7	DM8	DM9	DM10	DM11	DM12	Average weight	Criteria ranking
C1	0.108	0.135	0.109	0.104	0.138	0.127	0.119	3
C2	0.099	0.149	0.12	0.094	0.114	0.11	0.113	4
C3	0.085	0.102	0.114	0.099	0.078	0.095	0.097	6
C4	0.077	0.097	0.104	0.086	0.086	0.121	0.094	8
C5	0.15	0.129	0.099	0.159	0.145	0.146	**0.136**	**1**
C6	0.125	0.088	0.126	0.12	0.132	0.133	0.110	5
C7	0.067	0.093	0.145	0.078	0.099	0.104	0.095	7
C8	0.094	0.084	0.094	0.115	0.082	0.086	0.092	9
C9	0.195	0.123	0.09	0.144	0.125	0.078	0.12	2

Table 11 The benchmark weight values obtained by BWM, SWARA, and BWM-SWARA integrated analysis

Criteria	Weight value		
	BWM	SWARA	Integrated
Slope	0.140	0.119	0.143
Drainage density	0.107	0.113	0.104
TPI	0.043	0.097	0.035
Lineament density	0.137	0.094	0.130
Lithology	0.170	0.136	0.199
Soil types	0.088	0.110	0.091
Land use	0.073	0.095	0.060
Geomorphology	0.052	0.092	0.041
Rainfall	0.190	0.120	0.196

in the study area were evaluated with the help of the ROC curve (Nandi and Shakoor 2009; Pal et al. 2020) and the accuracy of the groundwater potential maps were analyzed. For the ROC curve, a data set containing the pixel numbers corresponding to the existing classes in the groundwater potential maps and the groundwater level data of the existing wells was prepared. Data from 99 wells available in the study area were used to calculate the AUC in the ROC method (Figs. 5, 6 and 7). The AUC values of the ROC curve for the BWM, SWARA, and BWM-SWARA methods were calculated as 0.83, 0.79, and 0.81, respectively (Fig. 9d, e and f). According to these results, the performances of the BWM and BWM-SWARA models were categorized as "very good (0.8–0.9)" and the performance of the SWARA model as "good (0.7–0.8)." Other studies have reported similar results applying multi-criteria decision methods for groundwater potential zoning (Chatterjee and Dutta 2022; Andualem and Demokrate 2019; Das 2019). Bourjila et al (2021) used the water level (mbgl) data of 44 wells for the accurate analysis of the groundwater potential obtained for the study area. This same validation process was also used by Patra et al (2018) and the accuracy performance of the model for groundwater potential mapping was found to be 75%. In another study (Ghosh et al. 2020a, b), they used data from 89 water wells to validate the areas determined for groundwater potential in West Bengal, India, and found the accuracy performance to be 79.77%. According to the AUC values obtained from our study, the estimation accuracy of all three GIS-based models can be considered satisfactory. These models can be used as a simple tool for establishing potential groundwater regions (Uc Castillo et al. 2022; Das and Mukhopadhyay 2020). The studies mentioned above support the validation methodology used in our study.

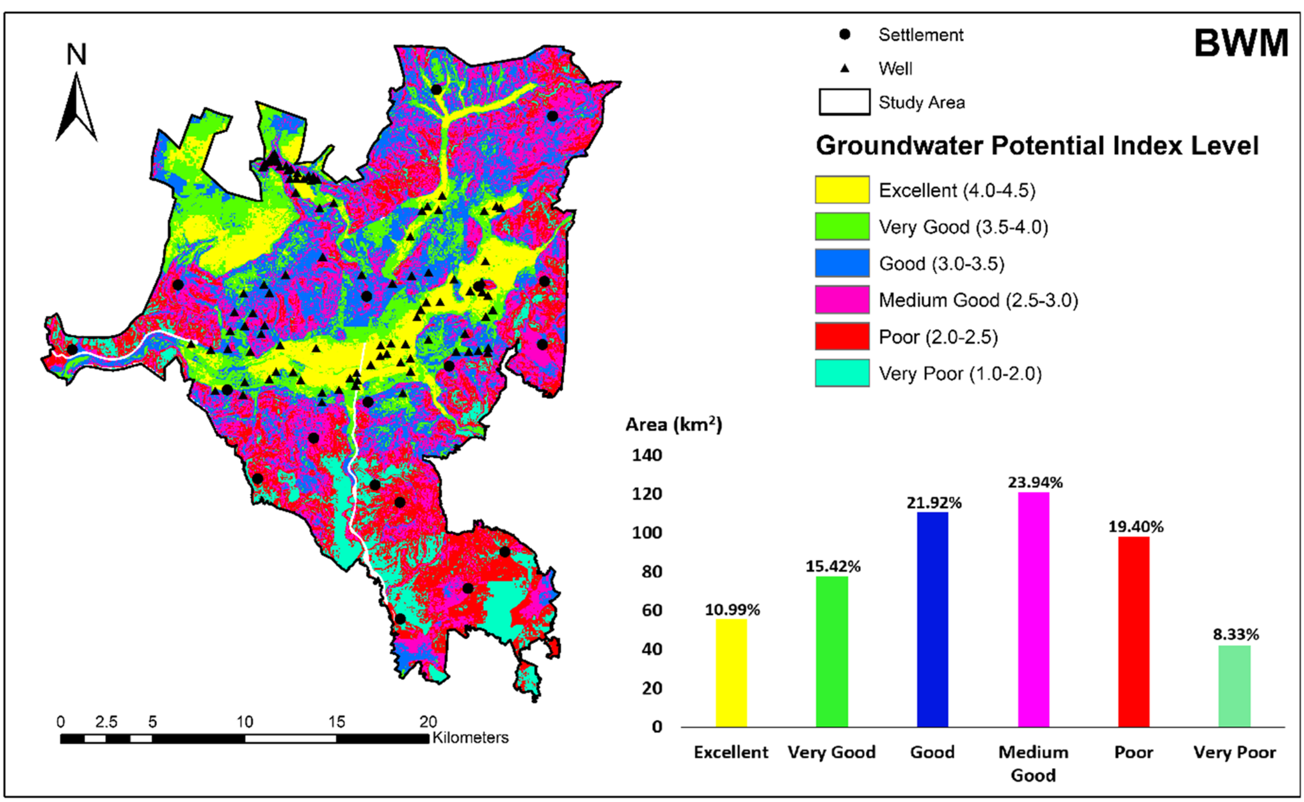

Fig. 5 Groundwater potential map of the study area according to the BWM method

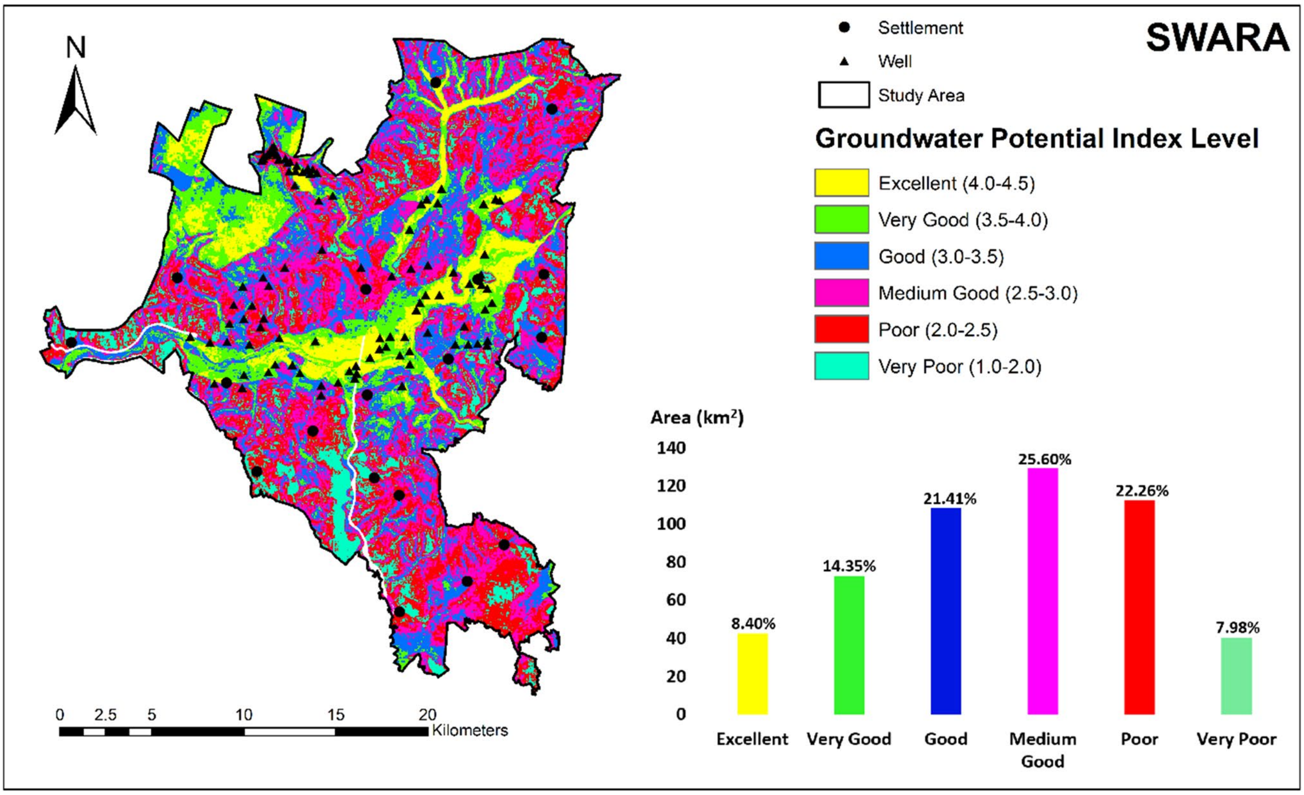

Fig. 6 Groundwater potential map of the study area according to the SWARA method

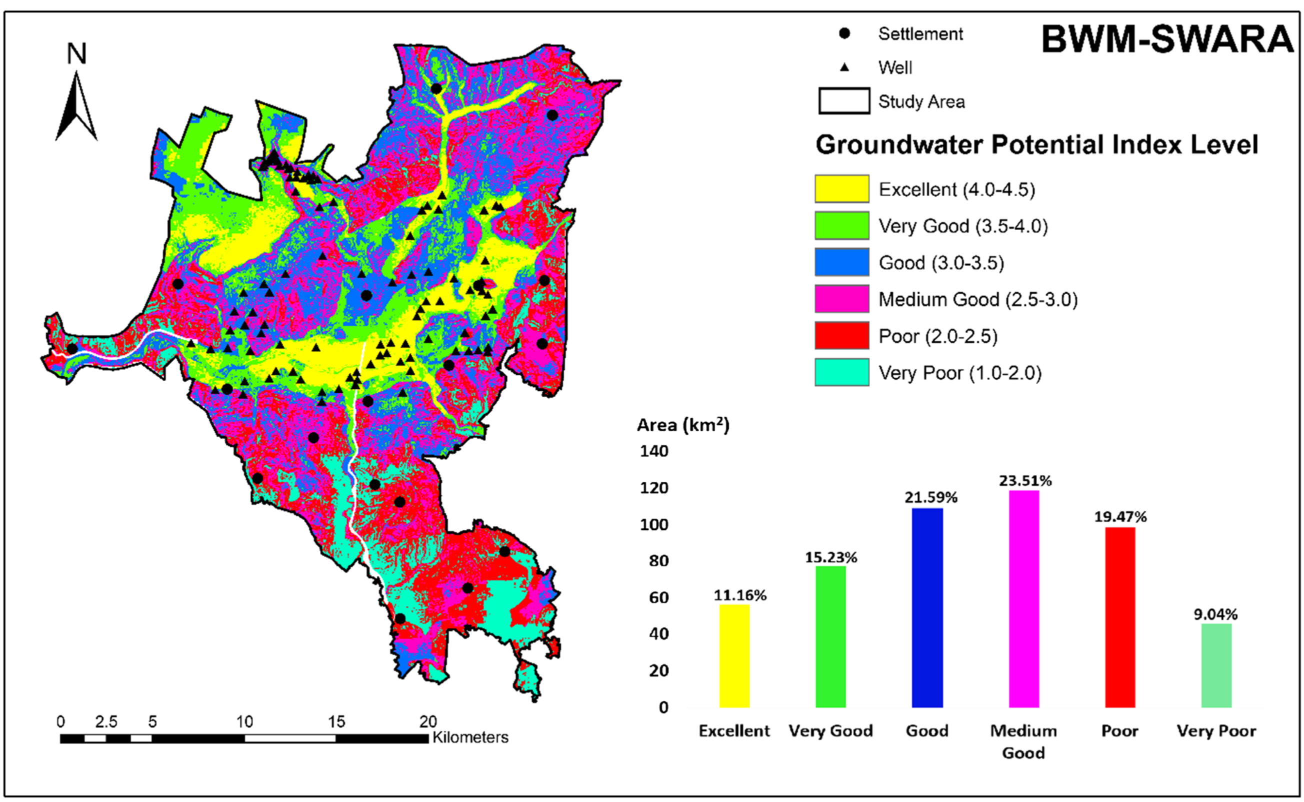

Fig. 7 Groundwater potential map of the study area according to the BWM-SWARA method

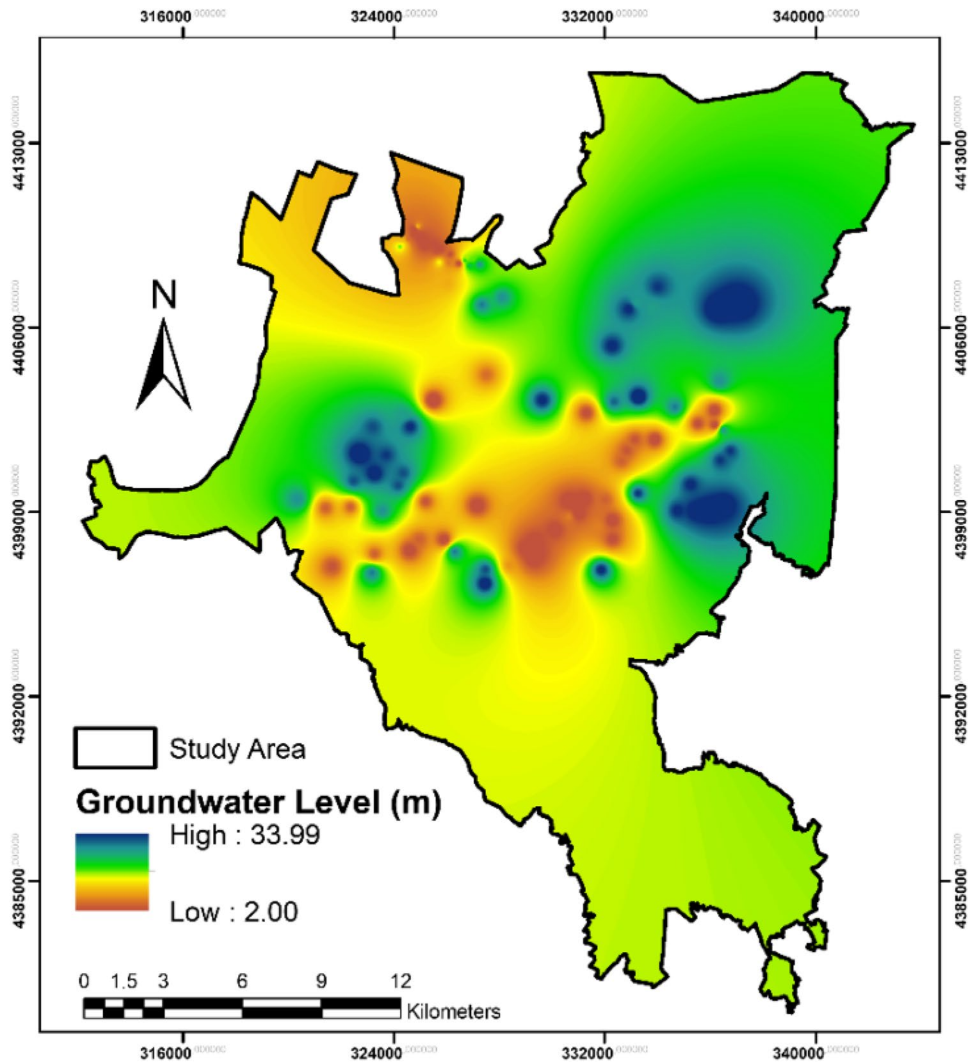

Fig. 8 Groundwater level map of study area

According to the BWM, SWARA, and BWM-SWARA methods, the number of wells that superimpose with the areas in the "excellent" class in terms of groundwater potential is 34, 19, and 32, respectively. The vast majority of wells currently drilled in the study area fall into the "very good" category. None of the wells in the study area coincides with the regions in the "very low" category in terms of groundwater potential (Table 12). In a study by Anteneh et al (2022), it has been revealed that 31 of 37 water wells overlap with groundwater potential regions. Regarding this overlap, the accuracy value indicating the reliability of the method was determined as 83.8%. As in our study, other researchers have also used validation of groundwater potential regions using water well data (Fenta et al. 2014; Kumar et al. 2020; Murmu et al. 2019; Panahi et al. 2017a, b).

Conclusion

This study presents a multi-criteria index approach including GIS-based BWM, SWARA, and BWM-SWARA methods to generate groundwater potential maps within the Sivas Municipality adjacent area boundaries. In line with the purpose and method of the study, 9 criteria (slope, drainage density, TPI, lineament density, lithology, soil types, land use, geomorphology, rainfall) were used. According to all three methods, slope, lithology, and rainfall criteria have the highest weight value, while geomorphology and TPI criteria have the lowest weight value. The regions with the best groundwater potential are generally concentrated in the center and northwest of the study area. This concentration can be attributed to the alluvium and limestone units found in this region, high linearity density, low drainage density, flat land structure, low slope, alluvial soil types, and presence

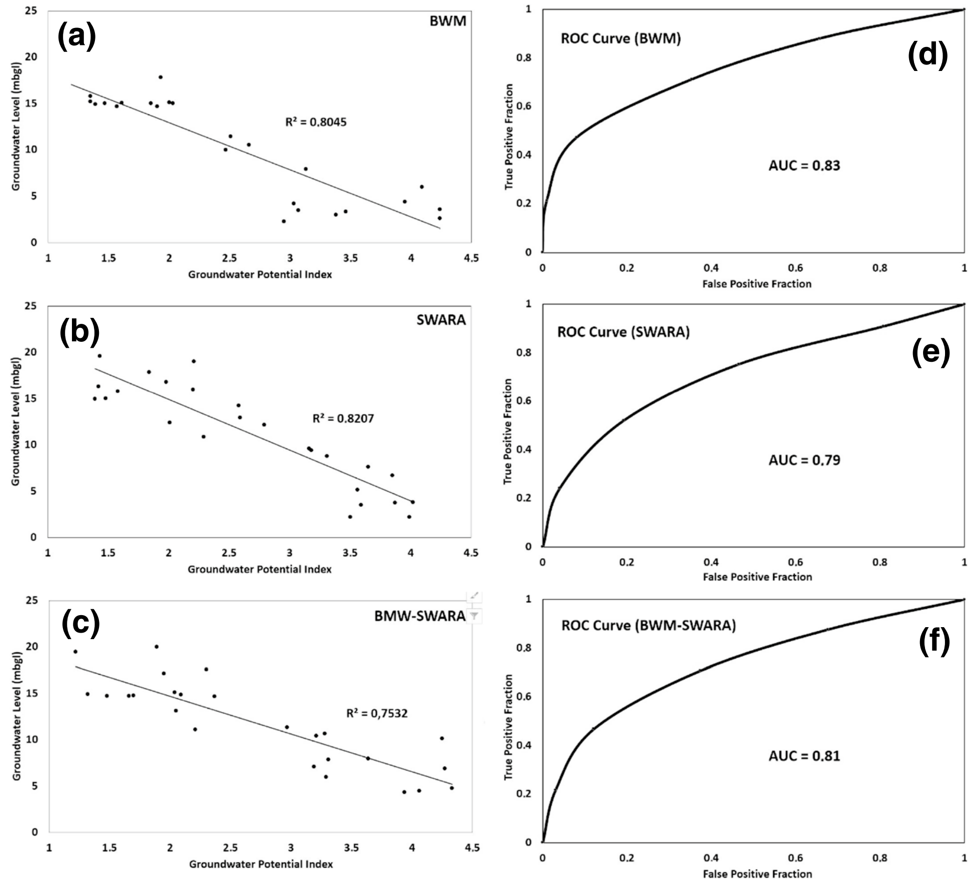

Fig. 9 Scatter plot and ROC curve for the obtained groundwater potential maps (*mbgl—meter below ground level*)

of water structures. According to BWM-SWARA integration, approximately 27% of the study area has "excellent" and "very good" groundwater potential, while approximately 30% has "poor" and "very poor" groundwater potential.

Groundwater potential maps obtained according to all three methods were verified by superimposing with the groundwater level map created for the study area. The validation made as a result of this superimposing showed a high and satisfactory correlation (R^2). AUC values, another indicator of the accuracy of groundwater potential mapping, showed that the performances of the BWM and BWM-SWARA models are "very good (0.8–0.9)" and the performance of the SWARA model is "good (0.7–0.8)."

Table 12 Comparison of and number of wells of different groundwater potential recharge zones through BWM, SWARA, and BWM-SWARA methods in the study area

Class	Number of wells		
	BWM	SWARA	BWM-SWARA
Excellent	34	19	32
Very good	30	34	30
Good	27	27	25
Medium good	7	15	9
Poor	1	4	3
Very poor	-	-	-

Since BWM and SWARA methods determine the most important criteria, these methods can reveal much more precise results in environmental studies and do not allow unnecessary comparisons. The efficiency, capability, and usability of the BWM method, which is a new MCDA method, and the SWARA method in groundwater potential mapping have been demonstrated in this study. The results of this study reveal that integrating GIS-based BWM and SWARA methods offers a valuable tool for improved estimation, monitoring, and planning of water resources in arid and extremely arid regions. The results obtained can be used as a preliminary reference data in the investigation of groundwater resources and in finding effective drilling sites. This study has proven that with the integrated use of RS and GIS, efficient results can be achieved for the identification of groundwater potential areas in terms of minimizing cost, time, and effort. These results can be helpful to authorities dealing with water resource management and land use planning. As a result, groundwater development activities should be preferred in areas with high groundwater potential.

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Author contribution Author developed to conception, idea, and design of the study. Material preparation, data collection and analysis, mapping, and discussion of all results were performed by author. In addition, the frst draft of the manuscript was written and prepared by author.

Data availability Data are available upon request on the corresponding author.

Code availability Not applicable.

Declarations

Ethical approval Not applicable.

Consent to participate Not applicable.

Consent to publish Not applicable.

Conflict of interest The authors declare no competing interests.

References

Abdalla F, Moubark K, Abdelkareem M (2020) Groundwater potential mapping using GIS, linear weighted combination techniques and geochemical processes identification, west of the Qena area. Upper Egypt J Taibah Univ Sci 14(1):1350–1362
Abdallah H, Memmi L, Damotte R, Rat P, Magniez-Jannin F (1995) Le Crétacé de la chaıne nord des Chotts (Tunisie du centre-sud): biostratigraphie et comparaison avec les régions voisines. Cretac Res 16(5):487–538
Abdulkareem JH, Pradhan B, Sulaiman WNA, Jamil NR (2018) Quantification of runoff as influenced by morphometric characteristics in a rural complex catchment. Earth Syst Environ 2:145–162
Abijith D, Saravanan S, Singh L, Jennifer JJ, Saranya T, Parthasarathy KSS (2020) GIS-based multi-criteria analysis for identifcation of potential groundwater recharge zones—a case study from Ponnaniyaru watershed, Tamil Nadu, India. HydroResearch 3:1–14
Ahmad I, Dar MA, Teka AH, Teshome M, Andualem TG, Teshome A, Shafi T (2020) GIS and fuzzy logic techniques-based demarcation of groundwater potential zones: a case study from Jemma River basin. Ethiopia J Afr Earth Sci 169:10386
Akbari M, Meshram SG, Krishna RS, Pradhan B, Shadeed S, Khedher KM, Darabi F (2021) Identification of the groundwater potential recharge zones using MCDM models: full consistency method (FUCOM), best worst method (BWM) and analytic hierarchy process (AHP). Water Resour Manag 35(14):4727–4745
Akhanova G, Nadeem A, Kim JR, Azhar SA (2020) Multi-criteria decision-making framework for building sustainability assessment in Kazakhstan. Sustain Cities Soc 52:101842
Al-Djazouli MO, Elmorabiti K, Rahimi A, Amellah O, Fadil OAM (2021) Delineating of groundwater potential zones based on remote sensing, GIS and analytical hierarchical process: a case of Waddai, eastern Chad. GeoJournal 86(4):1881–1894
Al-Shabeeb AAR, Al-Adamat R, Al-Amoush H, AlAyyash S (2018) Delineating groundwater potential zones within the Azraq Basin of Central Jordan using multi-criteria GIS analysis. Groundw Sustain Dev 7:82–90
Aluko OE, Igwe O (2017) An integrated geomatics approach to groundwater potential delineation in the Akoko-Edo Area, Nigeria. Environ Earth Sci 76:1–14
Amponsah TY, Danuor SK, Wemegah DD, Forson ED (2022) Groundwater potential characterisation over the Voltaian basin using geophysical, geological, hydrological and topographical datasets. J African Earth Sci 192:104558
Andualem TG, Demeke GG (2019) Groundwater potential assessment using GIS and remote sensing: a case study of Guna tana landscape, Upper Blue Nile Basin. Ethiopia J Hydrol Reg Stud 24:100610
Anteneh ZL, Alemu MM, Bawoke GT, Kehali AT, Fenta MC, Desta MT (2022) Appraising groundwater potential zones using geospatial and multi-criteria decision analysis (MCDA) techniques in Andasa-Tul watershed, Upper Blue Nile basin. Ethiopia Environ Earth Sci 81(1):1–20
Arulbalaji P, Padmalal D, Sreelash K (2019) GIS and AHP techniques based delineation of groundwater potential zones: a case study from southern Western Ghats. India Sci Rep 9(1):1–17
Arya S, Subramani T, Karunanidhi D (2020) Delineation of groundwater potential zones and recommendation of artificial recharge structures for augmentation of groundwater resources in Vattamalaikarai Basin. South India Environ Earth Sci 79(5):1–13
Aslan V, Çelik R (2021) Integrated gis-based multi-criteria analysis for groundwater potential mapping in the euphrates's sub-basin, Harran Basin. Turkey Sustain 13(13):7375
Assaf H, Saadeh M (2008) Geostatistical assessment of groundwater nitrate contamination with reflection on DRASTIC vulnerability assessment: the case of the upper Litani Basin. Lebanon Water Resour Manag 23(4):775–796
Benjmel K, Amraoui F, Boutaleb S, Ouchchen M, Tahiri A, Touab A (2020) Mapping of groundwater potential zones in crystalline terrain using remote sensing, GIS techniques, and multicriteria data analysis (Case of the Ighrem Region, Western Anti-Atlas, Morocco). Water 12(2):471
Bera A, Mukhopadhyay BP, Barua S (2020) Delineation of groundwater potential zones in Karha river basin, Maharashtra, India, using AHP and geospatial techniques. Arab J Geosci 13(15):1–21
Bourjila A, Dimane F, Ouarghi HE, Nouayti N, Taher M, Hammoudani YE, ... Bensiali A (2021) Groundwater potential zones mapping by applying GIS, remote sensing and multi-criteria decision analysis in the Ghiss basin, northern Morocco. Groundw Sustain Dev 15:100693
Bui DT, Pradhan B, Lofman O, Revhaug I, Dick OB (2012) Landslide susceptibility mapping at Hoa Binh province (Vietnam) using an adaptive neuro-fuzzy inference system and GIS. Comput Geosci 45:199–211
Celik R, Aslan V (2020) Evaluation of hydrological and hydrogeological characteristics affecting the groundwater potential of Harran Basin. Arab J Geosci 13(4):1–13
Chatterjee S, Dutta S (2022) Assessment of groundwater potential zone for sustainable water resource management in south-western part of Birbhum District. West Bengal Appl Water Sci 12(3):1–16
Chaudhry MA, Kumar AK, Alam K (2021) Mapping of groundwater potential zones using the fuzzy analytic hierarchy process and geospatial technique. Geocarto Int 36:2323–2344
Choudhary BS, Kumar M, Roy AK, Ruhal DSPR (1996) Application of remote sensing and Geographic Information Systems in ground water investigations in Sohna block, Gurgaon district, Haryana (India). Int Arc-Hive Photog Rem Sens XXXI B6:21
Chowdhury A, Jha MK, Chowdary VM (2010) Delineation of groundwater recharge zones and identification of artificial recharge sites in West Medinipur District, West Bengal using RS, GIS, and MCDM techniques. Environ Earth Sci 59(6):1209–1222
Çelik R (2019) Evaluation of groundwater potential by GIS-based multicriteria decision making as a spatial prediction tool: case

study in the Tigris River Batman-Hasankeyf Sub-Basin. Turkey Water 11(12):2630

Das B, Pal SC, Malik S, Chakrabortty R (2019) Modeling groundwater potential zones of Puruliya district, West Bengal, India using remote sensing and GIS techniques. Geol Ecol Landsc 3(3):223–237

Das N, Mukhopadhyay S (2020) Application of multi-criteria decision making technique for the assessment of groundwater potential zones: a study on Birbhum district, West Bengal. India Environ Dev Sustain 22(2):931–955

Dar T, Rai N, Bhat A (2021) Delineation of potential groundwater recharge zones using analytical hierarchy process (AHP). Geol Ecol Landsc 5(4):292–307

Das S (2019) Comparison among influencing factor, frequency ratio, and analytical hierarchy process techniques for groundwater potential zonation in Vaitarna basin, Maharashtra, India. Groundw Sustain Dev 8:617–629

De Reu J et al (2013) Application of the topographic position index to heterogeneous landscapes. Geomorphology 186:39–49

Demir G (2021) Performance analysis in private equity deposit banks: SWARA-RAFSI integrated model application. Atatürk University J Eco Adm Sci 35(4):1359–1382

Demir G, Bircan H (2020) Comparison of BWM and FUCOM methods of criteria weighting and an application. Cumhur Un J Econ and Adm Sci 21(2):170–185

Díaz-Alcaide S, Martínez-Santos P (2019) Advances in groundwater potential mapping. Hydrogeol J 27(7):2307–2324

Elewa HH, Qaddah AA (2011) Groundwater potentiality mapping in the Sinai Peninsula, Egypt, using remote sensing and GIS-watershed-based modeling. Hydrogeol J 19:613–628

Erdoğan IG, Fosso-Kankeu E, Ntwampe SKO et al (2019) Groundwater as an alternative source to irregular surface water in the O'Kiep area, Namaqualand. South Africa Phys Chem Earth 114:102801

Farhadi H, Fataei E, Kharrat Sadeghi M (2020) The relationship between nitrate distribution in groundwater and agricultural land use (case study: Ardabil Plain, Iran). Anthropog Pollut 4(1):50–56

Fashae OA, Tijani MN, Talabi AO, Adedeji OI (2014) Delineation of groundwater potential zones in the crystalline basement terrain of SW-Nigeria: an integrated GIS and remote sensing approach. Appl Water Sci 4(1):19–38

Fenta AA, Kife A, Gebreyohannes T, Hailu G (2014) Spatial analysis of groundwater potential using remote sensing and GIS-based multi-criteria evaluation in Raya Valley, northern Ethiopia. Hydrogeol J 23:195–206

Fildes SG, Bruce D, Clark IF, Raimondo T, Keane R, Batelaan O (2022) Integrating spatially explicit sensitivity and uncertainty analysis in a multi-criteria decision analysis-based groundwater potential zone model. J Hydrol 610:127837

GDMIE (2005) 1/25.000 scale digital geological map of the study area, General Directorate of Mineral and Investigational Exploration, Ankara

GDRS (2001) 1/25.000 scale digital soil map of the study area, T.C. Ministry of Food, Agriculture and Livestock, General Directorate of Rural Services (GDRS), Ankara

Ghosh A, Adhikary PP, Bera B, Bhunia GS, Shit PK (2022) Assessment of groundwater potential zone using MCDA and AHP techniques: case study from a tropical river basin of India. Appl Water Sci 12(3):1–22

Ghosh D, Mandal M, Banerjee M, Karmakar M (2020) Impact of hydro-geological environment on availability of groundwater using analytical hierarchy process (AHP) and geospatial techniques: a study from the upper Kangsabati river basin. Groundw Sustain Dev 11:100419

Ghosh D, Mandal M, Karmakar M, Banerjee M, Mandal D (2020) Application of geospatial technology for delineating groundwater potential zones in the Gandheswari watershed. West Bengal Sustain Water Resour Manag 6(1):1–14

Ghosh PK, Bandyopadhyay S, Jana NC (2016) Mapping of groundwater potential zones in hard rock terrain using geoinformatics: a case of Kumari watershed in western part of West Bengal. Model Earth Syst Environ 2(1):1

Gigović L, Drobnjak S, Pamučar D (2019) The application of the hybrid GIS spatial multicriteria decision analysis best–worst methodology for landslide susceptibility mapping. ISPRS Int J Geo Inf 8(2):79

Githinji TW, Dindi EW, Kuria ZN, Olago DO (2022) Application of analytical hierarchy process and integrated fuzzy-analytical hierarchy process for mapping potential groundwater recharge zone using GIS in the arid areas of Ewaso Ng'iro–Lagh Dera Basin, Kenya. HydroResearch 5:22–34

Greene R, Devillers R, Luther JE, Eddy BG (2011) GIS-based multiple-criteria decision analysis. Geogr. Compass 5(6):412–432

GSDP (2015) 1/100.000 scale environmental plan map, Ministry of Environment and Urbanization, General Directorate of Spatial Planning (GDSP), Ankara

Halder B, Bandyopadhyay J (2022) Potential sites selection of groundwater zones using AHP and GIS-based multi-criteria approach of Kolkata Municipal Corporation. Int J Energy Water Res 1–18

Haseli G, Sheikh R, Wang J, Tomaskova H, Tirkolaee EB (2021) A novel approach for group decision making based on the Best–Worst method (G-BWM): application to supply chain management. Mathematics 9(16):1881

Hashemkhani Zolfani S, Saparauskas J (2013) New application of SWARA method in prioritizing sustainability assessment indicators of energy system. Eng Econ 24(5):408–414

Hashemkhani Zolfani S, Yazdani M, Zavadskas EK (2018) An extended stepwise weight assessment ratio analysis (SWARA) method for improving criteria prioritization process. Soft Comput 22:7399–7405

Huang P, Ma C, Zhou A (2022) Assessment of groundwater sustainable development considering geo-environment stability and ecological environment: a case study in the Pearl River Delta. China Environ Sci Pollut Res 29(12):18010–18035

Ibrahim-Bathis K, Ahmed SA (2016) Geospatial technology for delineating groundwater potential zones in Doddahalla watershed of Chitradurga district. India Egypt J Remote Sens Space Sci 19(2):223–234

Ildoromi AR, Sepehri M, Malekinezhad H, Kiani-Harchegani M, Ghahramani A, Hosseini SZ, Artimani MM (2019) Application of multi-criteria decision making and GIS for check dam layout in the Ilanlu Basin, Northwest of Hamadan Province. Iran Phys Chem Earth Parts a/b/c 114:102803

Jaafari A, Najafi A, Pourghasemi HR, Rezaeian J, Sattarian A (2014) GIS-based frequency ratio and index of entropy models for landslide susceptibility assessment in the Caspian forest, northern Iran. Int J Environ Sci Technol 11:909–926

Jha MK, Chowdary VM, Chowdhury A (2010) Groundwater assessment in Salboni Block, West Bengal (India) using remote sensing, geographical information system, and multi-criteria decision analysis techniques. Hydrogeol J 18(7):1713–1728

Jhariya DC, Kumar T, Gobinath M, Diwan P, Kishore N (2016) Assessment of groundwater potential zone using remote sensing, GIS and multi criteria decision analysis techniques. J Geol Soc India 88(4):481–492

Kabeto J, Adeba D, Regasa MS, Leta MK (2022) Groundwater potential assessment Using GIS and remote sensing techniques: Case study of West Arsi Zone Ethiopia. Water 14(12):1838

Kamangar M, Katorani S, Tekyekhah J, Sohrabnejad C, Haderi FG (2019) A novel hybrid MCDM model to select a suitable location for implement groundwater recharge. Plant Arch 19(2):87–98

Karakuş CB (2020) Evaluation of water quality of Kızılırmak River (Sivas/Turkey) using geo-statistical and multivariable statistical approaches. Environ Dev Sustain 22(5):4735–4769

Karakuş CB, Yıldız S (2022) GIS-multi criteria decision analysis-based land suitability assessment for dam site selection. Int J Environ Sci Technol 1–20

Kebede S (2013) Groundwater in Ethiopia. Features, numbers and opportunities. Heidelberg, Germany: Springer Hydrogeology

Keršulienė V, Turskis Z (2011) Integrated fuzzy multiple criteria decision making model for architect selection. Technol Econ Dev Econ 17(4):645–666

Keršuliene V, Zavadskas EK, Turskis Z (2010) Selection of rational dispute resolution method by applying new Step-Wise Weight Assessment Ratio Analysis (SWARA). J Bus Econ Manag 11(2):243–258

Khali H, Mishra AP, Singh R (2020) Delineation of groundwater potential zone: remote sensing and GIS approach in doon valley, Dehradun. Uttarakhand Indian J Ecol 47(4):910–916

Kom KP, Gurugnanam B, Sunitha V (2022) Delineation of groundwater potential zones using GIS and AHP techniques in Coimbatore district, South India. Int J Energy Water Res 1–25

Kumar P, Herath S, Avtar R, Takeuchi K (2016) Mapping of groundwater potential zones in Killinochi area, Sri Lanka, using GIS and remote sensing techniques. Sustain Water Resour Manag 2(4):419–430

Kumar V, Mondal NC, Ahmed S (2020) Identifcation of groundwater potential zones using RS, GIS and AHP techniques: a case study in a part of Deccan Volcanic Province (DVP), Maharashtra, India. J Indian Soc Remote Sens 48:497–511

Kumari S, Poddar A, Kumar N, Shankar V (2022) Delineation of groundwater recharge potential zones using the modeling based on remote sensing, GIS and MIF techniques: a study of Hamirpur District, Himachal Pradesh. India Model Earth Syst Environ 8(2):1759–1770

Lee S, Hyun Y, Lee S, Lee MJ (2020) Groundwater potential mapping using remote sensing and GIS-based machine learning techniques. Remote Sens 12(7):1200

Lentswe GB, Molwalefhe L (2020) Delineation of potential groundwater recharge zones using analytic hierarchy process-guided GIS in the semi-arid Motloutse watershed, eastern Botswana. J Hydrol Reg Stud 28:100674

López-Álvarez B, Ramos-Leal JA, Carbajal N, Hernández-García G, Morán-Ramírez J, Santacruz-DeLeón G (2014) Modeling of groundwater flow and water use for San Luis Potosí Valley Aquifer System. J Geogr Geol 6:147–161

López-Álvarez B, Ramos-Leal JA, Moran-Ramírez J, Cardona-Benavides A, Hernández-Garcia G (2013) Origen de la calidad del agua del acuífero colgado y su relación con los cambios de uso de suelo en el Valle de San Luis Potosí. Boletín De La Soc Geológica Mex 65:9–26

Machiwal D, Jha MK, Mal BC (2011) Assessment of groundwater potential in a semi-arid region of India using remote sensing, GIS and MCDM techniques. Water Resour Manag 25:1359–1386

Madan KJ, Chowdary VM, Chowdhury A (2010) Groundwater assessment in Salboni Block, West Bengal (India) using remote sensing, geographical information system and multi-criteria decision analysis techniques. Hydrogeol J 18:1713–1728

Maity DK, Mandal S (2019) Identification of groundwater potential zones of the Kumari river basin, India: an RS & GIS based semi-quantitative approach. Environ Dev Sustain 21:1013–1034

Makonyo M, Msabi MM (2021) Identification of groundwater potential recharge zones using GIS-based multi-criteria decision analysis: a case study of semi-arid midlands Manyara fractured aquifer, North-Eastern Tanzania. Remote Sens Appl Soc Environ 23:100544

Malczewski J (1999) GIS and multicriteria decision analysis. Wiley, New York

Mallick J, Khan RA, Ahmed M, Alqadhi SD, Alsubih M, Falqi I, Hasan MA (2019) Modeling groundwater potential zone in a semi-arid region of Aseer using fuzzy-AHP and geoinformation techniques. Water 11(12):2656

Mandal P, Saha J, Bhattacharya S, Paul S (2021) Delineation of groundwater potential zones using the integration of geospatial and MIF techniques: a case study on Rarh region of West Bengal. India Environ Challenges 5:100396

Martín Del Campo MA, Esteller MV, Expósito JL, Hirata R (2014) Impacts of urbanization on groundwater hydrodynamics and hydrochemistry of the Toluca Valley aquifer (Mexico). Environ Monit Assess 186:2979–2999

Masoud AM, Pham QB, Alezabawy AK, El-Magd SAA (2022) Efficiency of geospatial technology and multi-criteria decision analysis for groundwater potential mapping in a Semi-Arid region. Water 14(6):882

Melese T, Belay T (2022) Groundwater potential zone mapping using analytical hierarchy process and GIS in Muga Watershed, Abay Basin. Ethiopia Glob Challenges 6(1):2100068

Mogaji KA, Lim HS, Abdullah K (2015) Regional prediction of groundwater potential mapping in a multifaceted geology terrain using GIS-based Dempster-Shafer model. Arab J Geosci 8(5):3235–3258

Moharrami M, Naboureh A, Gudiyangada Nachappa T, Ghorbanzadeh O, Guan X, Blaschke T (2020) National-scale landslide susceptibility mapping in Austria using fuzzy best-worst multi-criteria decision-making. ISPRS Int J Geo-Inf 9(6):393

Moodley T, Seyam M, Abunama T, Bux F (2022) Delineation of groundwater potential zones in KwaZulu-Natal, South Africa using remote sensing, GIS and AHP. J African Earth Sci 104571

Mukherjee I, Singh UK (2020) Delineation of groundwater potential zones in a drought-prone semi-arid region of east India using GIS and analytical hierarchical process techniques. CATENA 194:104681

Murmu P, Kumar M, Lal D, Sonker I, Singh SK (2019) Delineation of groundwater potential zones using geospatial techniques and analytical hierarchy process in Dumka district, Jharkhand. India Groundw Sustain Dev 9:100239

Naghibi SA, Moghaddam DD, Kalantar B, Pradhan B, Kisi O (2017) A comparative assessment of GIS-based data mining models and a novel ensemble model in groundwater well potential mapping. J Hydrol 548:471–483

Naghibi SA, Pourghasemi HR, Dixon B (2016) GIS-based groundwater potential mapping using boosted regression tree, classification and regression tree, and random forest machine learning models in Iran. Environ Monit Assess 188:1–27

Nair HC, Padmalal D, Joseph A, Vinod PG (2017) Delineation of groundwater potential zones in river basins using geospatial tools – an example from Southern Western Ghats, Kerala. India J Geovis Spat Anal 1(1):1–16

Nampak H, Pradhan B, Manap MA (2014) Application of GIS based data driven evidential belief function model to predict groundwater potential zonation. J Hydrol 513:283–300

Nandi A, Shakoor A (2009) A GIS-based landslide susceptibility evaluation using bivariate and multivariate statistical analyses. Eng Geol 110(1–2):11–20

Neelakantan R, Yuvaraj S (2012) Evaluation of groundwater using geospatial data-a case study from Salem Saluk Tamil Nadu. India Int J Rem Sens Geosci 1(2):7

Niway WF, Molla DD, Lohani TK (2022) Holistic approach of GIS based multi-criteria decision analysis (MCDA) and WetSpass

models to evaluate groundwater potential in Gelana water-shed of Ethiopia. J Groundw Sci Eng 10(138):152
Noyola-Medrano MC, Ramos-Leal JA, Domínguez-Mariani E, Pineda-Martínez LF, López-Loera H, Carbajal N (2009) Factores que dan origen al minado de acuíferos en ambientes áridos: Caso Valle de San Luis Potosí. Rev Mex Cienc Geol 26:395–410
Pal S, Kundu S, Mahato S (2020) Groundwater potential zones for sustainable management plans in a river basin of India and Bangladesh. J Clean Prod 257:120311
Pamučar D, Stević Ž, Sremac S (2018) A new model for determining weight coefficients of criteria in MCDM models: Full Consistency Method (FUCOM). Symmetry 10(9):393
Panahi MR, Mousavi SM, Rahimzadegan M (2017) Delineation of groundwater potential zones using remote sensing, GIS, and AHP technique in Tehran-Karaj plain. Iran Environ Earth Sci 76:1–15
Panahi S, Khakzad A, Afzal P (2017) Application of Stepwise Weight Assessment Ratio Analysis (SWARA) for copper prospectivity mapping in the Anarak region, central Iran. Arab J Geosci 10(22):484
Paryani S, Neshat A, Pourghasemi HR, Ntona MM, Kazakis N (2022) A novel hybrid of support vector regression and metaheuristic algorithms for groundwater spring potential mapping. Sci Total Environ 807:151055
Pathmanandakumar V, Thasarathan N, Ranagalage M (2021) An approach to delineate potential groundwater zones in Kilinochchi District, Sri Lanka, using GIS techniques. ISPRS Int J Geoinf 10(11):730
Patidar N, Mohseni U, Pathan AI, Agnihotri PG (2022) Groundwater potential zone mapping using an integrated approach of GIS-based AHP-TOPSIS in Ujjain District, Madhya Pradesh, India. Water Conserv Sci Eng 1–16
Patra S, Mishra P, Mahapatra SC (2018) Delineation of groundwater potential zone for sustainable development: a case study from Ganga Alluvial Plain covering Hooghly district of India using remote sensing, geographic information system and analytic hierarchy process. J Clean Prod 172:2485–2502
PCI (2021) PCI Catalyst training guide. Canada: Geomatica. Retrieved from https://www.catalyst.earth (Access date: May 2022)
Pourghasemi HR, Moradi HR, Fatemi Aghda SM (2013) Landslide susceptibility mapping by binary logistic regression, analytical hierarchy process, and statistical index models and assessment of their performances. Nat Hazards 69:749–779
Pourghasemi HR, Pradhan B, Gokceoglu C (2012) Application of fuzzy logic and analytical hierarchy process (AHP) to landslide susceptibility mapping at Haraz watershed. Iran Nat Hazards 63(2):965–996
Radulović M, Brdar S, Mesaroš M, Lukić T, Savić S, Basarin B, ... Pavić D (2022) Assessment of groundwater potential zones using GIS and fuzzy AHP techniques-a case study of the Titel Municipality (Northern Serbia). ISPRS Int J Geoinf 11(4):257
Rahaman MH, Sajjad H, Masroor M, Bhuyan N, Rehman S (2022) Delineating groundwater potential zones using geospatial techniques and fuzzy analytical hierarchy process (FAHP) ensemble in the data-scarce region: evidence from the lower Thoubal river watershed of Manipur. India Arab J Geosci 15(8):1–20
Rahman MA, Rusteberg B, Gogu RC, Ferreira JL, Sauter M (2012) A new spatial multi-criteria decision support tool for site selection for implementation of managed aquifer recharge. J Environ Manage 99:61–75
Rahman M, AlThobiani F, Shahid S, Virdis SGP, Kamruzzaman M, Rahaman H, ... Ghandourah EI (2022) GIS and remote sensing-based multi-criteria analysis for delineation of groundwater potential zones: a case study for industrial zones in Bangladesh. Sustain 14(11):6667
Rahmati O, Nazari Samani A, Mahdavi M, Pourghasemi HR, Zeinivand H (2015) Groundwater potential mapping at Kurdistan region of Iran using analytic hierarchy process and GIS. Arab J Geosci 8(9):7059–7071
Rahmati O, Kalantari Z, Samadi M, Uuemaa E, Moghaddam DD, Nalivan OA, ... Tien Bui D (2019) GIS-based site selection for check dams in watersheds: considering geomorphometric and topo-hydrological factors. Sustain 11(20):5639
Rana MSP, Hossain MA, Nasher NR (2022) Identification of groundwater potential zone using geospatial techniques of agriculture dominated area in Dinajpur district. Bangladesh Environ Challenge 7:100475
Razandi Y, Pourghasemi HR, Neisani NS, Rahmati O (2015) Application of analytical hierarchy process, frequency ratio, and certainty factor models for groundwater potential mapping using GIS. Earth Sci Inform 8:867–883
Rezaei J (2015) Best-worst multi-criteria decision-making method. Omega 53:49–57
Rezaei J, Wang J, Tavasszy L (2015) Linking supplier development to supplier segmentation using Best Worst Method. Expert Syst Appl 42:9152–9164
Roy S, Bose A, Mandal G (2022) Modeling and mapping geospatial distribution of groundwater potential zones in Darjeeling Himalayan region of India using analytical hierarchy process and GIS technique. Model Earth Syst Environ 8(2):1563–1584
Russo TA, Fisher AT, Lockwood BS (2015) Assessment of managed aquifer recharge site suitability using a GIS and modeling. Groundwater 53(3):389–400
Saeidi M, Komasi M, Hasanpor S (2021) Potential mapping groundwater resources by using an integrated approach AHP and fuzzy TOPSIS (Case Study: Silakhor Plain). Hydrogeomorphology 8(26):59–41
Saha S (2017) Groundwater potential mapping using analytical hierarchical process a study on Md Bazar Block of Birbhum District West Bengal. Spat Inf Res 25(4):615–626
Sahu U, Wagh V, Mukate S, Kadam A, Patil S (2022) Applications of geospatial analysis and analytical hierarchy process to identify the groundwater recharge potential zones and suitable recharge structures in the Ajani-Jhiri watershed of north Maharashtra. India Groundw Sustain Dev 17:100733
Salar SG, Othman AA, Hasan SE (2018) Identification of suitable sites for groundwater recharge in Awaspi watershed using GIS and remote sensing techniques. Environ Earth Sci 77(19):1–15
Sar N, Khan A, Chatterjee S, Das A (2015) Hydrologic delineation of ground water potential zones using geospatial technique for Keleghai river basin. India Model Earth Syst Environ 1(3):1–15
Saraf A, Choudhary P (1998) Integrated remote sensing and GIS for ground water exploration and identification of artificial recharge site. Int J Remote Sens 19:1825–1841
Saranya T, Saravanan S (2020) Groundwater potential zone mapping using analytical hierarchy process (AHP) and GIS for Kancheepuram District, Tamilnadu. India Model Earth Syst Environ 6(2):1105–1122
Sarkar B, Das P, Islam N, Basak A, Debnath M, Roy R (2021) Land suitability analysis for paddy crop using GIS-based fuzzy-AHP (F-AHP) method in Koch Bihar district, West Bengal. Geocarto Int 1–27
Sarkar SK, Esraz-Ul-Zannat M, Das PC, Ekram KMM (2022) Delineating the groundwater potential zones in Bangladesh. Water Supply 22(4):4500–4516
Senapati U, Das TK (2022) GIS-based comparative assessment of groundwater potential zone using MIF and AHP techniques in Cooch Behar district. West Bengal Appl Water Sci 12(3):1–18
Sepehri M, Malekinezhad H, Jahanbakhshi F, Ildoromi AR, Chezgi J, Ghorbanzadeh O, Naghipour E (2020) Integration of interval

rough AHP and fuzzy logic for assessment of food prone areas at the regional scale. Acta Geophys 68:477–493

Serele C, P´erez-Hoyos A, Kayitakire F (2020) Mapping of groundwater potential zones in the drought-prone areas of south Madagascar using geospatial techniques. Geosci Front 11(4):1403–1413

Shabani M, Masoumi Z, Rezaei A (2022) Assessment of groundwater potential using multi-criteria decision analysis and geoelectrical surveying. Geo Spat Inf Sci 1–19

Sharifi MA, Retsios V (2004) Site selection for waste disposal through spatial multiple criteria decision analysis. J Telecommun Inf Technol 3:1–11

Shekhar S, Pandey AC (2015) Delineation of groundwater potential zone in hard rock terrain of India using remote sensing, geographical ınformation system (GIS) and analytic hierarchy process (AHP) techniques. Geocarto Int 30(4):402–421

Sikdar P, Chakraborty S, Enakshi A et al (2004) Land use/land cover changes and groundwater potential zoning in and around Raniganj coal mining area, Bardhaman District, West Bengal – a GIS and remote sensing approach. J Spatial Hydrol 4(2):1–24

Steele K, Carmel Y, Cross J, Wilcox C (2009) Uses and misuses of multicriteria decision analysis (MCDA) in environmental decision making. Risk Anal 29(1):26–33

Subba Rao N, Sunitha B, Rambabu R, Rao PVN, Rao PS, Spandana BD, Sravanthi M, Marghade D (2018) Quality and degree of pollution of groundwater, using PIG from a rural part of Telangana State. India Appl Water Sci 8(8):1–13

Şener Ş, Şener E, Nas B, Karagüzel R (2010) Combining AHP with GIS for landfill site selection: a case study in the Lake Beyşehir catchment area (Konya, Turkey). Waste Manag 30(11):2037–2046

Tamiru H, Wagari M (2021) Evaluation of data-driven model and GIS technique performance for identification of Groundwater Potential Zones: a case of Fincha Catchment, Abay Basin. Ethiopia J Hydrol Reg Stud 37:100902

Taşdelen S, Güngör M, Aydın A (2016) Shallow groundwater hydrogeological investigation of Çukurköy (Denizli). Pamukkale Uni J Eng Sci 22(3):206–212

Tolche AD (2021) Groundwater potential mapping using geospatial techniques: a case study of Dhungeta-Ramis sub-basin. Ethiopia Geol Ecol Landsc 5(1):65–80

Torkashvand M, Neshat A, Javadi S, Yousefi H (2021) DRASTIC framework improvement using Stepwise Weight Assessment Ratio Analysis (SWARA) and combination of genetic algorithm and entropy. Environ Sci Pollut Res 28(34):46704–46724

TSI (2021) Population data of Sivas province for the years 1990–2018. Access address:(www.tuik.gov.tr)

Uc Castillo JL, Martínez Cruz DA, Ramos Leal JA, Tuxpan Vargas J, Rodríguez Tapia SA, Marín Celestino AE (2022) Delineation of groundwater potential zones (GWPZs) in a semi-arid basin through remote sensing, GIS, and AHP approaches. Water 14(13):2138

UNESCO (2015) The United Nations world water development report 2015: water for a sustainable world. UNESCO Publishing, Paris

Wang Y, Hong H, Chen W, Li S, Panahi M, Khosravi K, Shirzadi A, Shahabi H, Panahi S, Costache R (2019) Flood susceptibility mapping in Dingnan County (China) using adaptive neurofuzzy inference system with biogeography based optimization and imperialistic competitive algorithm. J Environ Manag 247:712–729

Yeh HF, Cheng YS, Lin HI, Lee CH (2016) Mapping groundwater recharge potential zone using a GIS approach in Hualian River. Taiwan Sustain Environ Res 26(1):33–43

Yıldırım Ü (2021) Identification of groundwater potential zones using GIS and multi-criteria decision-making techniques: a case study upper Coruh River basin (NE Turkey). ISPRS Int J Geoinf 10(6):396

Yılmaz A, Atmaca E (2004) Environmental geology of Sivas city solid waste landfill. I. National Environment Congress, 13–15 October 2004, Sivas (Turkey)

Yifru BA, Mitiku DB, Tolera MB, Chang SW, Chung IM (2020) Groundwater potential mapping using SWAT and GIS-based multi-criteria decision analysis. KSCE J Civ Eng 24(8):2546–2559

Yildiz S, Karakus CB (2015) Obtaining of the maps of groundwater level by using GIS: the example of Sivas city. Int J Sci Technol Res 1(2):11–22

Yucesan M, Gul M (2019) Failure prioritization and control using the neutrosophic Best Worst Method. Granul Comput 6(2):435–449

Zhang S, Liu X, Wang X, Gao Y, Yang Q (2021) Evaluation of coffee ecological adaptability using fuzzy, AHP, and GIS in Yunnan Province. China Arab J Geosci 14(14):1–18

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