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Assessment and delineation of groundwater potential zones using integrated geospatial techniques and analytic hierarchy process

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Abstract

Hydrogeologists and other allied professionals involved in the exploration and management of water resources have benefited greatly from the integration of geospatial techniques and remote sensing (RS) applications for identifying prospective or possible groundwater availability zones. This method is progressively becoming a viable alternative to the traditional geophysical survey for groundwater (GW) exploration, which is costly, time-consuming, and labour-intensive. This research explored the applicability of integrating RS, geospatial technologies and multi-criteria decision analysis (MCDA) for mapping and classifying GW potential zones in Bosso Local Government Area of Niger State in Northern-Nigeria. Five thematic maps were produced which represent the factors that influence and control the occurrence and transportation of GW. These factors are geology, lineament density, slope, land use and land cover, and drainage density. Normalized weights were assigned to these factors using analytic hierarchy process (AHP) based on their relative influence on occurrence and transportation of GW. Weighted overlay was implemented in a GIS environment to model the MCDA resulting to a GW potential map (GWPM). The produced GWPM was classified into four classes: 'Very low', 'Low', 'Moderate', and 'High' representing 3, 1, 85 and 11% of the total study area, respectively. The obtained result was validated using datasets obtained via hydrogeophysical techniques (vertical electrical sounding), and the result shows 68% positive correlation with the integrated remote sensing approach. The generated GWPM is recommended as an essential tool for water resource developers, and government agencies in charge of sourcing and distributing potable water resource in the study area.

Keywords Groundwater potential zone mapping \cdot Analytical hierarchy process (AHP) \cdot Geospatial technologies \cdot Weighted overlay \cdot Vertical electrical sounding \cdot Hydrogeophysical survey

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Introduction

Globally, the need for groundwater (GW) increases as population in a region increases. Recently, excessive quantity or volume of groundwater has been dug to meet water demand of this increasing population (Mahamat et al. 2020). It is considered as a valuable natural resource for agriculture in different communities, and it is relatively healthy for human consumption compared to other hydrological structures (especially surface water) since its exposure to pollution is less (Oke and Fourier 2017; Naghibi et al. 2016). Unfortunately, over \$250 billion is spent globally on an annual basis due to short supply of sanitation and healthy drinking water, hence, the need to explore the potential availability of groundwater in a cost-effective manner.

Conventionally, different disciplines have attempted the delineation of GW potential zones. In geophysics, diverse



Fig. 1 Study area

surface geophysical techniques have been used in exploring groundwater including gravity, seismic refractive, radioactivity, magnetic, electromagnetic and electrical resistivity methods (Theophilus et al. 2018). These methods often require very deep penetration of geological materials for the purpose of examining these materials which are indicators of potential groundwater. Among these techniques, the electromagnetic and electrical resistivity methods have been reported to be the most utilized globally because they are capable of burrowing deeper into harsh rock terrains and have proven to be very effective when compared to other geophysical techniques (Oladejo et al. 2015; Mohameden and Ehab 2017). However, these techniques are still limited as they require rigorous field works, sensitive and expensive equipment, cumbersome analysis of geology and tectonic situations on a large scale, a detailed understanding of aquifer types, and in some cases, they require wide and deep puncturing of ground surfaces, leaving the area of interest vulnerable to environmental hazards and a deteriorated public health (Shadrach and Osazee 2020). Added to the weaknesses of conventional approach of GW exploration is the necessity of integrating two or more of these techniques before optimal results can be achieved (Okpoli and Ozomoge 2020). Remarkably, in developing countries like most African Countries, mapping of GW takes a limitless amount of time, and additional efforts traceable to lack of required human and financial resources. Also, the success rate of conventional approaches is a pointer to its inefficiency. Diaz-Alcaide et al. (2017) identified some regions in Mali where GW exploration (through borehole drilling) success rate falls below 40%. Muchingami et al. (2019) likewise reported a 25% success rate in crystalline areas of Zimbabwe. Therefore, there is need to explore a more sophisticated, timely and efficient method of delineating GW potential zones so as to meet the rising portable water need of a rising global population.

Improved access, integration, processing, manipulation and interpretation of GW-related data have enhanced the creation of sophisticated, less-expensive, efficient and self-sufficient technique of exploring GW. Advancement in computer vision and tools employed in environmental earth studies have facilitated the deployment of geospatial technologies for identifying different natural resources (Dano et al. 2019) including GW potential areas. Mitchell (1997) categorized the available and computer-based techniques of assessing GW potential zones into two: machine learning (ML) approaches and combination of space technologies (Remote Sensing), and these techniques have been widely applied in the field of discourse, especially for mapping GW potential zones. ML simply defines the ability of computer algorithms to learn patterns in a large dataset. This technological method makes informed inferences from statistical analysis of very large datasets (Rowe 2019). In recent years, interest to employ ML to GW modelling is on the increase (Chen et al. 2020; Hussein et al. 2020; Farzin et al. 2021). However, the data required for training 'machines' which in turn predicts the possibility of a location to yield GW are sourced from geospatial technology. Though, this approach of mapping GW potential zones can be automated and has been widely employed, its need for a large set of data for accurate training of the machine is its major limitation. This characteristic of ML is common to all fields where it is employed. From a systematic review of the literature conducted by Arman et al. (2022), about 10–12 years of data (with monthly temporal resolution) are needed for developing an accurate and acceptable ML model for zoning GW potentials. This weakness of ML is limiting its wide deployment in mapping GW potential zones.

Conversely, remote sensing (RS) has become a useful technique of providing overviews of water cycle components on a large scale. Current developments of RS technologies (its sensor and processing techniques) have made significant advances in spatial and temporal resolution. Observations and models from RS techniques are useful and efficient resources for monitoring and managing GW resources. Thematic maps of factors influencing the retention and movement of GW (such as slope, rainfall, land use/land cover,

drainage density, and lineament) are derivable from remotely sensed data and are best analysed using geographical information system (GIS).

For over two decades, numerous scientific studies have combined or integrated RS and GIS technologies, exploiting these factors controlling GW existence, for understanding and defining GW potential zones in a region (Chowdhury et al. 2009; Zoheir and Emam 2014; Al-Djazouli et al. 2019; Jadhav et al. 2022). Findings from these scientific studies show that the results obtained were satisfactory. Gyeltshen et al. (2020) investigated the possibility of improving the output of geospatial technology by integrating the techniques with geophysical approach. While the geophysical survey conducted only served the purpose of categorizing aquifers in the study area, the emphasis was mainly on the geospatial techniques.



Fig. 2 Flowchart of methods

Table 1Data used and theirmetadata

S/No	Data	Metadata
1	Sentinel 2A	Acquired date: 2021-11-24, Tile ID: T095329
2	SRTM DEM	30 m spatial resolution
3	Geological structure shapefile	Sub-set of National geological map of Nigeria Vector dataset
4	Hydrogeological structure shapefile	Sub-set of National hydrological map of Nigeria Vector dataset

Also, several researchers have successfully embraced geospatial technologies over the last two decades for the delineation of potential GW regions (Solomon and Quiel 2009, Chowdhury et al. 2009; Elbeih 2015; Agarwal and Garg 2016). However, a proper ranking and hierarchical combination of GW indicators will enhance and increase the reliability of geospatial approach of mapping and zoning GW potential areas. According to Machiwal et al. (2011), multi-criteria decision-making will furnish an operative system for managing water by adding rigour, transparency and framework decisions. Therefore, to optimize the resultoriented and cohesive system that RS and GIS provide for managing and combining different variables that influence GW availability and movement, there is need for an integration of these tools using multi-criteria decision analysis (MCDA) (Abrams et al. 2018; Altafi et al. 2020). Remarkably, previous studies have combined two or all of RS, GIS and MCDA for mapping and delineating GW potential zones in different regions, and outputs from these researches reveal that they remain as robust as possible, with much more benefits (including simplicity, transparency, and reliability) than the automatic (machine) learning approaches (Abrams et al. 2018; Ejepu et al. 2022).

Analytic hierarchy process (AHP) is the most used MCDA technique. Since its development by Saaty (1987), it continuously finds usefulness in different scientific studies. It has recently found application in geology, most notably in GW-related investigations, where it has performed excellently, particularly in determining GW potential zones (Mogaji and San 2017; Kumar and Krishna 2018). In implementing AHP for modelling any decision-based problem, hierarchical or a network structure is used to represent such problem and a pairwise comparison to establish relations within the structure. Saaty and Vargas (1987) established that dominance matrices result from a discrete case and a kernel of Fredholm operators when dealing with continuous cases. In the cases, ratio scales are derived in a form of principal eigenvectors or functions. AHP has the tendency of being inconsistent with its measurement and dependence within and between the groups of elements of its structure, hence, the need to always check for its consistency. Consistency in AHP is an approach of monitoring the reliability of the eigenvector or functions developed for assigning weight (degree of importance) to factors identified for concerned multi-criteria evaluation (MCE). Consistency is a ratio of consistency index (C.I) to random index (R.I) as presented in Eq. (1).

ConsistencyRatio(C.R) =
$$\frac{C.I}{R.I}$$
 (1)

Consistency index can be computed using Eq. (2)

$$C.I = \frac{\delta_{\max} - n}{n - 1}$$
(2)

where δ_{max} is an eigenvalue, *n* is the number of determining factor that influences the potentiality of GW in a location. On the other hand, R.I is obtainable from AHP random consistency index table. It is imperative that when implementing AHP in MCDA, Saaty's scale of pairwise comparison should be adopted for assigning weight/scores to determining factors.

GW is the key source of drinking water in communities of Bosso Local Government (Muhammad et al. 2020). Most dwellers of this local government lack sustainable access to these natural resources and are faced with water scarcity.

Tab	le 2	Software	used
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S/No	Software	Purposes
1	ERDAS Imagine 14.0	Used for supervised image classification, to produce land use and land cover map of the study area
2	ArcGIS 10.4	Used for production of the maps representing factors indicating the presence or absence of GW, weighted overlay of concerned factors, production of GW potential map of the study area, and the cartographical design of all maps
3	Microsoft office suite (excel spreadsheet)	Used for calculation of criteria weight needed for AHP

2, 4, 6 and 8 are intermediate values

5 I I I I I I I I I I I I I I I I I I I					
Intensity of importance	Definition	Definition explanation			
1	Equal importance	Two events add equally to the objectives			
3	Moderate importance	Experience and judgement moderately favours one event over the other			
5	Strong importance	One activity strongly favours the decision-making process than the other			
7	Very strong importance	One activity very strongly favours the decision-making process than the other			
9	Extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation			

Table 3 Saaty's pairwise comparison scale

To worsen this, there is a rapid growth in the population of the local government (due to existence of many economic facilities and headquarters of government institutions in the local government), and this has aggravated the shortage of portable water supply. In order to solve this lingering menace, there is need to explore cost-effective and reliable methods of delineating GW potential zones and resources in the area. In this study, the integrated approach of GIS and RS coupled with AHP was used to map and classify GW potential zones of Bosso Local Government, using hydrological, hydrogeological and topographical properties of the area. Criteria that influence GW retention and discharge, including land use land cover, slope, drainage density, lineament density, and geology, were considered. Contrary to studies like Ejepu et al. (2022), rainfall was not considered as an influencing factor since a constant rainfall distribution is constantly experienced across the study area. AHP was used to determine the relative weight of each criterion, and they were implemented using weighted overlay tool in ArcGIS environment to produce GW potential zones map of the study area. This map is a necessity for water resource managers in the province for making precise water management plans for GW exploration.

Study area

Bosso Local Government Area (LGA) is one of the LGAs in Niger State, North-central Nigeria. It has a total land-mass of about 1592 km² and a population of about 146,359

at the 2006 Nigeria Population Census. It lies between Latitude N9°39'12.02" and N9°39'12.03", and Longitude 6°30'58.00"E and 6°30'58.01"E. It is bounded to the North and East by Shiroro LGA, to the South by Paikoro and Katcha LGAs, and to the West by Gbako and Wushishi LGAs.

The study area (Fig. 1) experiences an approximate annual rainfall which falls within the range of 1100–1600 mm, and a maximum temperature not exceeding 94 °C which is often experienced between the months of March and August, while December and January are the months with the lowest temperature. The hydrological and soil properties of the study area make the area suitable for the cultivation of most staple crops, and the area is appropriate for animal grazing, freshwater fishing, etc. Most localities in the study area are overwhelmed with limited and insufficient access to potable water (Idris-Nda et al. 2013), while drilled bore holes and dug wells are the major sources of water.

Geology of the study area

Just like many of the States in the North-Central region of Nigeria, the geology of the study area is characterized by its existence within the Basement Complex Terrain of Nigeria. It is an integral part of the West African Craton underlying above 50% of Nigeria's land mass (Obaje 2009). More technically, the geological setting of the study area is made up of the Precambrian basement complex rocks; a heterogeneous accumulation, including gneisses, schists, migmatites, phyllites, quartzites and granites (Adelana et al. 2008), and a

Factors	Geology	Lineament Density	Drainage Density	Slope	LULC
Geology	1	3	7	9	9
Lineament Density	0.3	1	3	5	5
Drainage Density	0.2	0.3	1	2	2
Slope	0.11	0.2	0.2	1	2
LULC	0.11	0.2	0.5	0.5	1
$\sum_{i=1}^{5}$ factors	1.72	4.74	11.70	17.50	19.0

Table 4Pairwise comparisonmatrix of influencing factors

part submerged in the Nupe Basin. The lithologic units seen in the entire Niger State are majorly Nupe sandstones of the Bida Basin, migmatite–gneiss complex, the metasediments and the older Granites. Rocks with older granite content consist of coarse porphyritic biotite and hornblende granite having bright contacts with pegmatite and gneiss where they are exposed. The metasediments have amphibolite, schist, quartzite, and phyllite which are regarded as upper Proterozoic in age. The migmatite–gneiss complex contains the most unstable rocks in the basement complex. These groups of rocks are called basement complex sensu stricto which contains migmatites, orthogneisses, calc–silicate rocks, biotite hornblende schist and paragneisses (Dada 2006).

The earlier mentioned lithologic units of the study area's geology have two major fracture orientations, one NE-SW and NW-SE (Opara et al. 2014). These fractures are parallel to the Schists Belts of the country and Cretaceous Bida Basin which controls the directions of flow and drainage of surface water sources in the area. According to Ige et al. (2021), the existence or presence of these fractures in crystalline rocks has been recognized to be good indicators of GW sources, allowing the possibility of exploring tube, drilled and handdug wells for the provision of potable water and for economic activities such as industrial and agricultural purposes. However, there is an inverse variation between the width of these fractures, as depths through the rocks increase with associated weathered and unconsolidated regolith materials having pore gaps that serve as inlet for rainfall infiltration. Rains during the raining season (which serves as the major source of groundwater recharge in the study area) infiltrate deeply weathered regolith, which, in turn, stores and transforms into reservoir and source of potable water during the dry season (Mazurek et al. 2020).

Hydrogeological composition of the study area

For precise exploration of GW resources in an area, understanding of the hydrogeological structure of the area is very important. Basement complex rocks become aquiferous (yielding water) only after fracturing and weathering of the rock units because they lack the inherent basic permeability and porosity. There is a wide variation in the occurrence, distribution, recharge and discharge system, movement and quality of GW in these aquifers. Many times, even boreholes sited at a very close distance, having same lithological structure, exhibit these variations (Ejepu et al. 2022). Lithological, climatological, hydrogeological, hydrogeochemical and geomorphological factors are causes of these variations (Dash et al. 2019).

According to Eduvie et al., (2003), weathered regolith in the study area ranges between < 2 m and 45 m depth. At the minimum depth of 2 m, it is technically impracticable to obtain GW. Therefore, there is possibility of digging
 Table 5
 Normalized relative weight of influencing factors

Factors	Geology	Line- ament density	Drainage density	Slope	LULC
Geology	0.58	0.64	0.60	0.51	0.47
Lineament density	0.17	0.21	0.26	0.29	0.26
Drainage density	0.12	0.06	0.09	0.11	0.11
Slope	0.06	0.04	0.02	0.06	0.11
LULC	0.06	0.04	0.04	0.03	0.05
$\sum_{i=1}^{5}$ factors	1.00	1.00	1.00	1.00	1.00

wells to a depth close to 45 m before a productive aquifer is found. However, many of the dug wells within the study area have been observed to either dry up or produce extremely low yields in the dry season. For drilled holes, the water yields vary in their productivity with lower aquifer horizon usually producing relatively more high-volume yields. This productivity has been traced to the interconnection of rock fracture systems which serve as channel of transmission on a regional scale. Hence, borehole drilling campaigns in the basement complex are targeted towards fractured bedrock (Raji and Abdulkadir 2020). Therefore, it is expected that locations with high lineament density will yield GW resources than places with low lineament density. Generally, regions of basement complex like the study area have low or moderate GW productivity. As expressed by Adelana et al., (2008), older and younger granites found beneath Niger State are poor aquifers. There is existence of broken mantle of weathered rocks or fracture and joint structures in the un-weathered basement which serves as an alternative reservoir. These decomposed mantles sometimes are too thin to accommodate large water quantities and are commonly filled with clay, making the fluid extremely porous.

Materials and methods

The step-by-step procedure that described the methods used in this study is presented as a flowchart in Fig. 2.

Data used

The data used in this study and their metadata are itemized in Table 1. These data are required for producing and extracting geological, hydrogeological and topographical information about the study area which are factors determining the potentiality of a location for producing potable water.

The methods used for the acquisition of the datasets used for this study are described in the following subsections. These datasets include the Sentinel 2A satellite image, the SRTM DEM, and the geological and hydrological structure shapefile of the study area generated from the national hydrological map of Nigeria.

Sentinel 2A

This dataset was downloaded from the portal of the United States Geological Surveys (USGS) (www.earthexplorer. usgs.gov). Sentinel-2A (S2A) is a unique environmental monitoring satellite mission designed for earth observation. S2A has 13 spectral bands ranging from the visible and the near-infrared to the shortwave infrared, at different spatial resolutions ranging from 10 to 60 m. This dataset as contained in Table 1 was captured by Sentinel satellite on 24th of November 2021 and covers tile 'T095329'. The RGB composite band (with suffix TCI) served as the input data

during image classification which was used for the production of LULC map of the study area.

SRTM DEM

Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) was downloaded using the URL: www.dwtkns. com/srtm30m/. It is a web-based platform with features that simplify the process of downloading 30-m resolution DEM data from the SRTM. These types of data are in tiles, and the tile covering the study area was selected and downloaded from the web-page. The DEM data formed the major dataset used for detecting and mapping GW potential zones in the study area. It was used to extract elements that are indicators of GW availability in the location. These include slope, lineaments, and drainage. The data was processed in ArcGIS for the extraction of these elements or indicators.

Geological and hydrogeological structure shapefile

For the purpose of mapping the geological and hydrogeological formation of the study area, a national-gridded



Fig. 3 Lithological units in the study area

geological and hydrogeological shapefile of the study area was downloaded from https://www2.bgs.ac.uk/africagrou ndwateratlas/downloads/Nigeria.zip. It is also a web-based platform that allows users to access and download data related to GW-related parameters, especially geological and hydrogeological information.

Software used

For the processing and analysis of the acquired data, the software packages itemized in Table 2 were used.

Image classification

Image classification is the grouping of different spectral reflectance on a satellite image into predefined land use and or land cover. Maximum likelihood classifier was used for the supervised classification of the Sentinel-2A images used for this study in ERDAS Imagine 14.0. In doing this, a signature file (training set) that defines each land use and land cover class to the classifying machine was created in the classification interface. The output of the implemented supervised image classification is a land use and land cover (LULC) map of the study area. Based on the number of spectral classes on the satellite imagery and different land covers that are indicators (or can be explored) for GW, the LULC classes in the study area were grouped into six (6): built-up areas, water bodies, flooded vegetation, vegetation (vegetation covers with insufficient water nutrient), bare soil, and rocks/hard soils.

DEM data processing

Slope map

Slope reveals the topographic configuration of an area. It explains what relationship exists between local and regional relief conditions of the area. Effect of gravity on motion of water bodies is governed by slope, and hence, it indicates the general direction of GW flow and its effect on GW recharge and discharge. Slope can be represented as a measure of angle (degrees) or in percentage of gradient. In this study, the slope map was produced from the SRTM DEM data and was prepared in degrees from ArcMap.



Fig. 4 Composite hillshade map



Fig. 5 Lineaments density map

Lineament and lineament density map

Lineament reveals a general surface occurrence of underground fractures, with intrinsic features of permeability and porosity of the beneath materials, occurring as a result of tectonic activities. On the other hand, lineament density is a ratio of length of a particular lineament to the surface area of its environment. This relationship is mathematically shown in Eq. (3). For the purpose of extracting lineaments from the DEM data, hillshade relief maps were produced with varied sun azimuth and elevation angles. From the generated or produced hillshade relief maps, linear features (raster cells) depicting lineaments were digitized for each of the produced hillshade relief maps. These digitized polyline features (composited using a polyline shapefile) afterwards served as the input data for 'line density' implementation for mapping the lineament density of the study area. 25° and 45° are the sun elevation angles used, and each was combined with azimuth values 75°, 90°, 150°, 225°, 270° and 315°, making it twelve (12) produced hillshade (relief) maps. The essence of varied sun azimuth and elevation angles is to visually detect as many

lineaments as possible, which at a single combination may not be detectable.

$$LD = \sum_{i=1}^{n} \left(\frac{L_i}{A}\right)$$
(3)

where LD is lineament density, L_i is lineament length, *i* is number of lineament, and *A* is surface area.

Drainage density (DD)

Drainage in an area is a determinant for GW exploration in a locality. The drainage feature of an area relies on the characteristics of its subsurface and slope. The natural water bodies in an area have a lot to do with its drainage pattern. DD, however, is the ratio of the overall length of all streams and rivers in a basin to the total area of such basin. By this, the stream and river features in the study area were mapped. Linear shapefile representing streams and rivers within the study area was utilized for mapping the drainage density. This linear feature class served as the input for line density



Fig. 6 Slope map

tool in Arcmap (just as in the case of lineament density). Equation (4) shows how the drainage densities within the study area were computed.

$$DD = \sum_{i=1}^{n} \left(\frac{D_i}{A}\right) \tag{4}$$

where DD is drainage density, D_i is drainage length, i is number of drainages, and A is surface area.

AHP

Analytic hierarchy process (AHP) is an effective approach of assigning weights to different determining or influencing factors in an MCDA. Having arrived at the influencing factors for GW exploration in this study, their comparison, ranking or weighing was done using Saaty's pairwise comparison scale. The scale has values ranging from 1 to 9 with different levels of importance for relative ranking of influencing factors in an MCDA. Table 3 contains the relative comparison scale and their interpretation as propounded by Saaty (1987).

Since each of the influencing factors considered in this study was mapped, the raster outputs have varied classes, hence, the need for assigning weight to classes of each of the factors. In order to ensure an appropriate pairwise comparison between factors and ranking of their respective classes, other sources/literature were consulted (Abebe 2021; Ajay et al. 2020; Mahamat et al. 2020; Rajesh et al. 2021; Ejepu et al. 2022).

From the scale used for assigning different importance to the identified influencing factors, a pairwise comparison matrix was generated which was afterwards used for computing normalized relative weight, normalized principal eigen weight (also known as priority vector), and consistency ratio (C.R). Equation and processes for computing C.R have been stated earlier in Eq. (1).

From these computed weights and associated map of each influencing factors, the map depicting GW potential zones was derived from the formulation in Eq. (5).



Fig. 7 Drainage density map

GWpotentialzones =
$$\sum_{i=1}^{m} \sum_{j=1}^{n} M_i x D_j$$
 (5)

where M_i is the normalized weight of the *ith* criteria layer, D_j is the normalized weight of the *jth* criteria map (or layer), m and n are the total number of criteria considered in this study, and the total number of classes in each criteria layer, respectively. The 'weighted overlay' tool of spatial analyst in Arcmap was used to create the GW potential zones map of the study area.

Reclassification and ranking

Reclassification was carried out to enable the input of scale values, no data values, and restricted values. It is a necessary process prior to weighted overlay to ensure classes of each influencing factors are recognized and used during the overlay. Reclassification was done in this study to define the level of importance of each classes in each of the influencing factors. However, definition of these influencing factors was done using Saaty's scale. Aside the purpose of assigning ranks to classes of each influencing factors, the weighted overlay tool constrains the various raster input (denoting the influencing factors) to be integers, while floating-point rasters have to be reclassified before they are fit for use.

Weight assignment

Implementation of pairwise comparison

Table 4 shows the pairwise comparison matrix generated from ranking of each of the influencing factors. Interpretation of this table (matrix) becomes very easy when Table 3 is well comprehended (Saaty's pairwise comparison scale).

Table 4 shows the relative level of importance within the different GW-influencing factors in the study area. The conducted pairwise comparison in this study yielded results that are similar to results of the studies carried out by Mahamat et al., (2020), Osinowo and Arowoogun (2020), Abebe (2021), Verma and Patel (2021) and Ejepu et al., (2022).

Having developed the pairwise comparison matrix, the priority vector was thereafter computed using the steps highlighted as follows:



Fig. 8 LULC map of Bosso LGA

Table 6	LULC	class	analysis
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LULC classes	Raster count	Percentage coverage (%)	
Built-up areas	1,877,114	11.82	
Rocks/Hard soils	7,489,315	47.18	
Flooded vegetation	547,169	3.45	
Water bodies	282,771	1.78	
Bare soil	3,091,644	19.48	
Vegetation	2,586,493	16.29	
Sum	1,587,456	100	

Step 1: The individual element of each column was divided by the sum of the columns. This is to obtain the normalized relative weight where the sum of each column is 1.

Step 2: Computation of the normalized principal eigenvector (W) which is obtainable by averaging across the rows –

	Geology			
W =	LineamentDensity			
	DrainageDensity			
	Slope			
	LULC			
		, ,		
	0.58 + 0.64 + 0.60 + 0.51 + 0.47			2.81
	0.17 + 0.21 + 0.26	1	1.19	
=	$\frac{1}{5}$ 0.12 + 0.06 + 0.09	0 + 0.11 + 0.11	$=\frac{1}{2}$	0.49
	$\begin{bmatrix} 0.06 + 0.04 + 0.02 \end{bmatrix}$	2 + 0.06 + 0.11	Э	0.29
	0.06 + 0.04 + 0.04	1+0.03+0.05		0.23
	•			

	Geology		0.56	
	LineamentDensity		0.24	
W =	DrainageDensity	=	0.10	
	Slope		0.06	
	LULC		0.04	

Table 7 Weights of factors andranking of their classes

Factors	Weights (%)	Classes	Ranking	GW potentiality
Geology	56	Basement complex	5	Relatively high
		Nupe Basin	2	Relatively low
Lineament density	24	0-0.073	1	Very low
,		0.073-0.187	2	Low
		0.187-0.307	3	Medium
		0.307-0.457	4	High
		0.457-0.850	5	Very high
Drainage density	10	0-0.072	5	Very high
с .		0.072-0.197	4	High
		0.197-0.329	3	Medium
		0.329-0.497	2	Low
		0.497-0.839	1	Very low
Slope	6	0-1.95	5	Very high
		1.95-3.76	4	High
		3.76-6.55	3	Medium
		6.55-12.12	2	Low
		12.12-35.53	1	Very low
LULC	4	Built-up areas	1	Extremely low
		Rocks/Hard soils	2	Very low
		Flooded vegetation	5	High
		Water bodies	6	Very high
		Bare soil	3	Low
		Vegetation	4	Medium

Each element of the priority vector (weight matrix), W, shows the relative weight of its corresponding influencing factor. For example, of all considered factors, lineament density has 24% influence on the recharge and movement of GW in the study area. To ensure the reliability of W, it is important to check its consistency using Eqs. (1) and (2). The following steps were followed for the computation of C.I of W.

Step 1: Principal Eigen value (δ_{max})

 δ_{max} is the multiplicative addition of sum of each row with their respective weight elements.

$$\begin{split} \delta_{max} = & 1.72(0.56) + 4.70(0.24) + 11.70(0.10) \\ & + 17.5(0.06) + 19.00(0.05) = 5.10 \end{split}$$

Step 2: Computation of CI from Eq. (2)

$$CI = \frac{(5.10 - 5)}{(5 - 1)}$$

$$=\frac{1}{(4)}$$

= 0.025

Step 3: Computation of CR using Eq. (1)

 $CR = \frac{CI}{RI}$

The RI for five factors was obtained from RI table as 1.23. Hence,

$$CR = \frac{0.025}{1.23} = 0.020$$

The CR value obtained (2.0%) in the five-factored MCDA implies that the inconsistency of the pairwise comparison is acceptable because Saaty suggested that if CR is less than or equal to 12%, then the inconsistency is acceptable and the judgement (pairwise comparison) can be trusted, and hence, the matrix needs no adjustment (Table 5).

Class ranking of each influencing factors

Weighted overlay involves the ranking of classes contained in each of the influencing factors. Based on the relationship of each of the factors with the recharge and movement of GW in a location, their included classes were ranked. Lineament densities, as earlier noted, have a direct relationship with the presence of GW in an area. Hence, classes of the lineament density factor were rated in an increasing pattern as



Fig. 9 Numeric GWPM

the densities also increase. Simply put, high lineament densities were given relatively higher GW potential rank than the other elements or factors. Contrarily, drainage densities have an inverse relationship with the recharge and movement of GW in an area. The classes of drainage density factor were ranked based on this fact. Therefore, raster classes of the drainage density map with higher values were relatively assigned less values and vice versa.

Also, slope factor classes were ranked in an inverse order, similar to drainage density, since areas with low slope value ranges permit infiltration of surface water than areas with high slope value ranges. Furthermore, for LULC factor, the type of land cover present influences the approach of ranking classes because LULC has a direct link with the infiltration and percolation of rain beneath the surface. Therefore, the presence and distribution of GW have a lot to do with the type of LULC in the area (Pande et al. 2017). Built-up areas in an area block the paths of GW movement, since excavation of the subsurface is always done prior to the construction of these urbanization elements. Hence, this LULC class was ranked to have an opposing influence on the presence of GW in the study area. On the contrary, water bodies enhance the process of infiltration; hence, this land class was assigned higher value. Other LULC classes in the study area include 'flooded vegetation', 'vegetation', 'bare soil', and 'rocks/hard soil'. Flooded vegetation, because of the presence of water which with time infiltrates the ground, was ranked higher than 'vegetation' class, while 'Bare soil' was ranked higher than 'built ups' class.

Result validation

Hydrogeophysical survey: vertical electrical sounding (VES)

In geophysics, hydrogeophysical technique is the most popular and verified reliable approach of exploring groundwater. This approach examines the change in subsurface formation resistivity with depth, with the goal of finding surface impacts caused by the movement of electric current within the earth (Bahri et al. 2017, Epuh et al.



Fig. 10 Reclassified GWPM

government area

Table 8 GWP zoning of S/No GWP class Localities Bosso localities in Bosso local 1 Very low Maraya, Yankpako, Ganabigi, Ewonko Ganabigi 2 Nangau, Babegi Low 3 Moderate Bako, Kangwo, Sheta, Kuyi, Tundun Fulani, Maikunkele, Naguin, Kuyi, Shaukika, Bosso, Nini, Tundun Wada, Zokwogi, Tungawigi, Beji, Cachala 4 High Petta Feta, Jangaru, Maitumbi, Mapi, Epigi, Lashanbi

2019). The state of aquifers is deducible from difference in potential differences obtained from two potential electrodes, which is an integral part of VES systems.

The depth to basement (DB) (output from processed VES data) of sampled stations across the study area, which were sourced from Ejepu et al., (2021), was utilized for validating the geospatial output of this study. The data acquired from this secondary source, however, covered only the eastern region of Bosso Local Government. By sampling technique, these sourced data are enough for validation, nevertheless, possible DB values of selected locations in other regions of the study area were obtained by prediction (interpolation and extrapolation).

According to Ejepu et al. (2021), Geotron resistivity meter was used for the resistivity field measurements, while Schlumberger electrode configuration was used for the VES.

Table 9Sampled point'slocation and their respectivedepth to basement values

S/N	X (m)	Y (m)	Depth to basement	S/N	X (m)	Y (m)	Depth to basement
1	204,453.899	1,073,676.079	44	20	208,025.781	1,046,688.525	14
2	202,548.895	1,072,802.952	43	21	208,343.282	1,041,926.015	26
3	197,627.635	1,071,929.825	37	22	214,931.420	1,064,627.311	27
4	201,040.767	1,068,516.694	29.44	23	216,201.422	1,070,501.073	34
5	206,438.278	1,059,309.175	31.5	24	214,058.293	1,073,517.329	31.9
6	208,660.782	1,056,292.919	18	25	217,074.549	1,061,134.804	43.9
7	204,612.649	1,045,894.773	27	26	220,011.430	1,063,039.808	42
8	214,058.293	1,050,974.783	28.3	27	231,758.953	1,057,245.421	40
9	198,659.512	1,062,642.932	15	28	232,459.890	1,066,194.750	31
10	227,155.194	1,074,946.081	47	29	233,252.730	1,065,820.160	46
11	228,425.197	1,071,294.824	36	30	232,206.920	1,064,597.820	40.06
12	236,203.962	1,064,865.436	43.3	31	235,172.085	1,072,247.326	27
13	236,600.838	1,059,864.801	45	32	195,008.255	1,053,197.288	22
14	240,410.846	1,059,150.425	39	33	192,785.751	1,050,419.157	11
15	234,775.210	1,056,292.919	26	34	200,802.642	1,046,688.525	8
16	221,202.057	1,053,276.663	22	35	191,235.412	1,067,399.521	29
17	217,074.549	1,057,007.296	34	36	224,021.955	1,080,282.383	12
18	216,915.799	1,053,911.664	16	37	194,030.107	1,077,146.872	20
19	220,567.056	1,046,688.525	40.5	38	192,735.005	1,060,174.212	43.4



Fig. 11 Depth to basement map



Fig. 12 Map showing an overlay of GWPM and DB contour values distribution

Table 10 Correlations

		Hydrogeophysic	Geospatial
Hydrogeophysi- cal	Pearson correlation	1	.681**
	Sig. (2-tailed)		.005
	Ν	15	15
Geospatial	Pearson correlation	.681**	1
	Sig. (2-tailed)	.005	
	Ν	15	15

The double asterisk (**) shows that the correlation is significant at 0.01 level

Results and discussion

Geology

The lithological units in the study area, clipped from the National geological map, are majorly two: the basement complex and Nupe basin. As presented in Fig. 3, the basement complex covers 97% of the entire study area with just 3% of the area covered by the Nupe Basin. The Nupe

Basin is seen along the south-western region of the study area (dominated by localities like Yankpako, Maraya, and Ganabigi). Though the two geological classes mapped in this study generally have moderate rate of GW yield, the basement complex which contains cretaceous sediments and associated rocks has higher productivity (for GW) because of their ability to permeate surface water and, at times, produce extensive aquifers than the Nupe basin (Adelana et al. 2008; Ige et al. 2021).

Hillshade map

Figure 4 shows the produced map from composited hillshades (of varied sun elevation and azimuth values). The relief seen across the study area ranges from 0° to 231° with larger percentage of the relief distribution ranging between 0° and 30°. Hillshade maps were used for extracting lineaments found across the study area which are lines indicating fractures that are mostly seen between regions of higher relief values.

Lineament density map

The lineament density (LD) values of the study area range between 0 and 0.850 km/km². The varying density values were grouped (as shown in Fig. 5) into five: 0-0.073, 0.073-0.187, 0.187-0.307, 0.307-0.457 and 0.457-0.850. Regions of highest lineament densities (0.457-0.850) are scattered across the study area and cover about 8% of the entire area. Generally, regions with very low lineament density largely cover the entire study area. Bosso, a core locality in the local government, is remarkably seen to fall in relatively low lineament density range. This is a confirmation of the water scarcity that characterized this particular axis of the study area. Dug wells and other GW sources always dry up or experience a reduced water yield during the dry season, since the infiltration and percolation of rainfall in the area are very low. The western region of Chanchaga Local Government (the carved-out province within the study area) is seen to have a remarkably high LD range and, hence, can be predicted to be less burdened by water scarcity compared to Bosso town.

Slope map

Figure 6 shows that the slope of the study area ranges between 0° and 35.53° . The slope was, however, categorized into five classes: 0–1.95, 1.95–3.76, 3.76–6.55, 6.55–12.12, 12.12–35.53, all in degrees. Since locations with decrease or small slope values have a small surface flow, regions in the study area with a perfect slope value (in degrees) occupy about 64% of the whole area.

Drainage density map

Figure 7 shows the drainage density distribution of the study area. Many drainage lines in the study area are observed to follow the same direction as that of the lineaments. Hence, it is rational to conclude that the built ups (with high relief) in the study area control its drainage system. The drainage density values (in km/sq.km) range between 0 and 0.839 and have been classified into five: 0-0.072, 0.072-0.197, 0.197-0.329, 0.329-0.497 and 0.497-0.839. Though the drainage densities of the study area have a close look with that of the lineament densities, expectedly, their graphical representation (comparing Fig. 6 with Fig. 4) is inversely related which confirms that increased lineament density value and decreased drainage density values are good combination for the presence of GW in a location.

LULC map

As presented in Fig. 8, the LULCs of the study area were categorized into six (6) classes: built-up areas, rocks/hard soils, flooded vegetation, water bodies, bare soil, and vegetation. The built-up areas, earlier explained to block the movement of GW in the subsurface, are seen to dominantly exist in the eastern region of the study area, with Bosso locality having the thickest distribution of this land use class. Also, water bodies in the area are quite hard to notice because they are sparsely distributed which confirms the lack of adequate water resources frequently experienced in the study area. It is predicted that the GW potentials across the study area may be very poor due to this condition and other factors earlier mapped. Table 6 shows the percentage coverage of each of the LULC classes.

Weights, ranks of influencing factors and their associated classes

Table 7 shows the factor weights, classes of each factors and their respective ranking.

Groundwater potential map (GWPM)

As shown in Fig. 9, the GW potential map of the study area (which is the output of the implemented weighted overlay) has values ranging from 2.0 to 5.0. Five thematic maps representing each of the influencing factors served as the input of the overlay, with their respective sub-classes accordingly ranked during the reclassification in ArcGIS. The weighted overlay tool of ArcGIS converted each of the thematic layers to matrices form, performing arithmetic addition of the matrix components to generate the GWPM. Based on the weight of the influencing factors, values of the study area's GWPM have a direct relationship with GW potentiality across the study area. This implies that regions with low GWP value (such as 2-3) have very low potentials of yielding GW in the study area and vice versa. It is observed from Fig. 8 that no location in the study area has GWPM value of 1.0 or less than 2.0, implying that no region is absolutely poor for yield of GW.

The GWPM was, however, reclassified for a textual interpretation (as shown in Fig. 10). Four GW potential zones have been identified and delineated: 'Very low', 'Low', 'Moderate' and 'High'. About 85% of the entire study area was geospatially mapped to have moderate potential for generating GW. This large percentage can be traced to the geological structure of the study area, with basement complex constituting 97% of the area's geological setting. Added to this is the fact that geology as an

influencing factor has 56% influence on the weighted overlay, consequentially dominating the output of the MCDA. 'High' potential zones are seen scattered around the study area but with a spatial coverage of less than 11% of the entire area. Beside the effect of the geological structure beneath the 'High' GWP, these regions have high lineament densities and low drainage densities, and hence, areas with favourable geological structure, high lineament densities and low drainage densities are ideal locations for exploring GW resources. 'Low' GWP regions are also scattered around southern region of the study area, covering less than 2% of the entire area. Due to the presence of an unfavourable geological structure, the south-western region of the study area was found to have 'very low' potential for producing GW. These locations with 'very low' potential also have very low lineament densities but high drainage densities, contrary to locations with 'high' potentials.

For ease of use and decision-making by agencies responsible for sourcing and distribution of water resources, the GWPM was used to classify localities in the study area based on their potentials for producing GW as presented in Table 8 and Fig. 10.

Depth to basement contour map

Table 9 shows the positions of sampled points and their respective depth to basement (as extracted from Ejepu et al. 2021 and predicted values). Figure 11 is the contour map showing existing pattern of depth to basement across Bosso Local Government Area.

Depth to basement (DB) contour map of the study area shows that the study area has passed through some weathering which varies geographically. The thicker the weathering profile of the basement, the more water it accumulates, therefore, places with higher weathered thickness will have higher weathered aquifer potential. Ejepu et al. (2021) affirmed that DB is a very important in geophysics to evaluate potentiality of a location for groundwater exploration; the thicker the DB, the more groundwater the area accumulates and the higher the viability of such location to yield groundwater.

As observed in Fig. 11, averagely, the Eastern part of the study area (enclosing Chanchaga local government) is seen to have the highest possibility of yielding groundwater, having DB values ranging from 32 to 50. Noteworthy, DB values in this geographical location were obtained directly from the secondary source and not part of the predicted values. Also, the map shows that the south-eastern region of the study area (and adjoining part of Paiko local governments) has similar potential for groundwater as the eastern region. Also, the south-western region of the study was mapped to have lighter depth to basement pattern (DB values ranging between 4.5 and 13.7) and, hence, have very poor potential for groundwater. Generally, based on geophysical outputs, possibility of the study area to yield groundwater increases towards the east and decreases towards the western region except for few locations in the north-western regions (like Debbi) which geological structure proves otherwise.

Comparative analysis between geospatial and hydrogeophysical outputs

Figure 12 shows an overlay of depth to basement contour values on GWPM of the study area. It was also observed that locations mapped to have high GW potentials also have the highest range of DB values. Also, 'very low' potential areas were mapped to have the least DB value ranges. Therefore, this shows a direct and positive relationship between the two approaches—proving geospatial techniques (employed in this study) of exploring GW to be reliable and sufficient. To further examine the existence (or lack thereof) of any significant difference (correlation or decorrelation) between the the geospatial and hydrogeophysical approaches, statistical two-tailed Pearson correlation was conducted on the results.

Pearson correlation

The numeric GWPM and DB values of randomly selected fifteen (15) locations within the study area were tested for the level of correlation between geospatial technique and validating output of the hydrogeophysical technique. Table 10 shows the statistical analysis from the correlation test. It shows that there is a positive and strong Pearson correlation (0.681) equating to 68% similarities in the two outputs. This correlation coefficient value, however, may increase if the entire population (DB and numeric GWP values) are considered.

Conclusion

This study has successfully applied geospatial technologies (GIS and Remote Sensing) and AHP for mapping and zoning GW potential areas in Bosso Local Government area of Minna in Niger State, Nigeria. Satellite data and vector shapefiles are the major dataset utilized in this study, with most image processing and analysis carried out in ArcGIS environment. Application of AHP preceded the GIS-based MCDA so as to ensure a technically sound, and accurate assignment of weight to GW influencing factors with a CR of assigned weights of less than 10%. A weighted overlay operation was performed to merge the influencing factors, hence, producing a GWPM. The GWPM was classified textually into four classes: Very low', 'Low' 'Moderate' and 'High', with each of these classes covering 3, 1, 85 and 11%, respectively, of the study area. This study observed that the geological structure of an area has the largest influence on the recharge and movement of GW. A favourable geological structure, high lineament density, and low drainage density are good indicators of the presence of GW resource in an area. The GWPM shows that the north eastern part of the study area is characterized by high GW potentials, while the south-western region is found to be unfavourable for GW exploration because of the very low GW potential of the area. In order to validate output of the geospatial approach, hydrogeophysical technique was explored. DB from VES survey carried out shows a similar display of GW potentiality across the study area when compared with the geospatial approach. Though this study was carried out on sub-regional level, the methodological approach utilized in this study can be successfully adopted at regional and national level with very high potentials of obtaining reliable mapping and zoning of GW potential. The findings of this study will be an essential tool for water infrastructure developers, government agencies in charge of sourcing and distributing potable water resource in the study area, private sectors interested in exploring GW resources, and even scientific researchers who will want to investigate the methods of GW exploration. More specifically, the south-western region of the study area where the influencing factors were found to be unfavourable for exploring GW should be given more attention, to ensure adequate provision of potable water for the dwellers. Further studies will seek to investigate the effect of spatio-temporal changes on the potentiality of the study area for producing GW resource, with an intention of incorporating other related factors such as soil type and geomorphology that have not been considered in this current study.

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Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethical approval The authors declare that this study was conducted in compliance with all known ethical standards. Also, they have no known

competing interests or conflict of interests to declare that are relevant to the content of this article.

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