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Delineating groundwater potential zones in Western Cameroon Highlands using GIS based Artificial Neural Networks model and remote sensing data

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ABSTRACT: For the sustainable use of groundwater, this study analyzes groundwater potential in Western Cameroon Highlands using artificial neural network model (ANN), GIS tools and remote sensing. Twelve factors believed to influence the groundwater occurrence were selected from literature and field investigations and used as input data. Satellite ALOS PALSAR, LANDSAT OLI, SRTM data processing techniques and GIS spatial analysis tools were used to prepare these maps. Pumping rates from 189 wells were considered as groundwater potential data and randomly divided into a training and a test sets. An ANN based on the relationship between groundwater productivity data and the above factors was implement on MATLAB. Each factor's weight and relative importance was determined by the backpropagation training method. Then the groundwater potential indices were calculated and the final map was created using GIS tools. The resulting groundwater potential map was validated using Area-Under -Curve analysis with data that had not been used for training. An average accuracy of 95% were obtained. As another validation, the groundwater potential map was validated by overlaying the actual pumping rates data with an overall accuracy of 83.2%. Five categories of groundwater potential zones have been demarcated. Major portions are areas with "good" (26.54%) as well as "Moderate" (28.73%) potentials while a few scattered areas have poor (17.66%) and very poor (9.02%). The "very good" potential areas (18.06%) are mainly concentrated at the eastern part of the study area. This groundwater potential information will be useful for effective groundwater management and exploration.

KEYWORDS: groundwater potential; remote sensing; GIS; artificial neural networks; Western Cameroon Highlands.

1 INTRODUCTION

Water is one of the most essential commodities for mankind. It the most significant natural resources which support both human needs and economic development. High increase in the agricultural, industrial and domestic activities in recent years has increased the demand for good quality water [1]. Surface water resources are inadequate to fulfill the water demand. It only accounts for 0.3 % of the fresh water that exists on earth in comparison to groundwater which represents 30 % [2]. Nowadays, usages of groundwater has increased because of factors such as high obtainability, excellent quality, and low development cost [3]. Productivity through groundwater is quite high as compared to surface water. It has become crucial not only for targeting groundwater potential zones, but also monitoring and conservation are necessary. In Cameroon, mostly used targeting methods are based on hydrogeological studies, geophysical inference operation, and field surveys [4] [5] [6]. These methods require considerable finances and time, have poor success rate and do not always consider diverse factors affecting the presence of groundwater.

However, Integration of remote sensing, geographic information system (GIS) and statistics models together with hydrogeological and geophysical information, has proved to be extremely useful for groundwater studies [7] [8] [9] [10]. Remote sensing with its advantages of spatial, spectral and temporal availability of data covering large and inaccessible areas within short time, has become a very handy tool in assessing, monitoring and conserving groundwater resources [11]. Investigation of remotely sensed data for drainage map, geological, and geomorphological characteristics of terrain facilitates effective evaluation of ground water potential zones. Integrating information on these parameters is achieved through GIS which is an effective tool for storage, management and retrieval of spatial and non-spatial data [12] [13] [14]. According to [3], these methods lack prediction ability as they have no built-in function for interpretation of multi-dimensional data and identifying spatial correlations between a dependent and independent variables. Methods such as Frequency Ratio [15], weights of evidence [16] [17], decision tree [14] and Artificial Neural Network (ANN) [18] [19] [3] are probabilistic models capable to predict spatial relations between groundwater potentials zones and its controlling parameters.

The present study attempts to delineate suitable areas for groundwater exploration in West Cameroon using integrated approach of remote sensing, GIS techniques, field survey and ANN. Processing of LANDSAT OLI, ALOS PALSAR and SRTM data have been applied in order to generate and analyze thematic layers controlling groundwater potential in Western Cameroon such as altitude, geology, lineament density, lineament distance, slope, soil, drainage density, groundwater depth and landuse. These layers have been combine with other hydrogeological factors like permeability, alteration thickness, infiltration and pumping rate in a GIS. Finally, the ANN approach used to study the sensibility of these factors is presented and used to map good potential groundwater areas of the region.

2 MATERIALS AND METHODS

2.1 THE STUDY AREA

The study area considered is South Mifi River reservoir Watershed (SMRW) located in Western Cameroon Highlands (**Fig 1**). It lies between the latitudes 05°15 N to 05°42 N and longitudes 10°5 E to 10°30 E covering an area of 973.36 km^2. The major source for recharge of water in SMRW is rainfall with an annual average of around 1850 mm. This watershed enjoys a umid tropical climate with a maximum temperature of 24°C and a minimum temperature of 18°C. South Mifi River, the major river system, is marked by numerous falls, cascades and straight drains imitating fractures. Altitude varies between 720 and 2740 m above mean sea level. Vegetation is a shrubby savannah tessellated with small forest galleries and crops. Basaltic red soil is the predominant soil type and main occupation in SMRW is agriculture. The bedrock geology of SMRW consists of Precambrian crystalline and granitic rocks surrounded by hills and volcanic rocks (Basalt, trachyte, phonolite, rhyolites, tuffs, ignimbrites). Groundwater in SMRW mostly occurs in fractured and highly weathered zones. This area generally surfers water supply problems due to rapid population growth, climate change and increased demand for groundwater reserves.

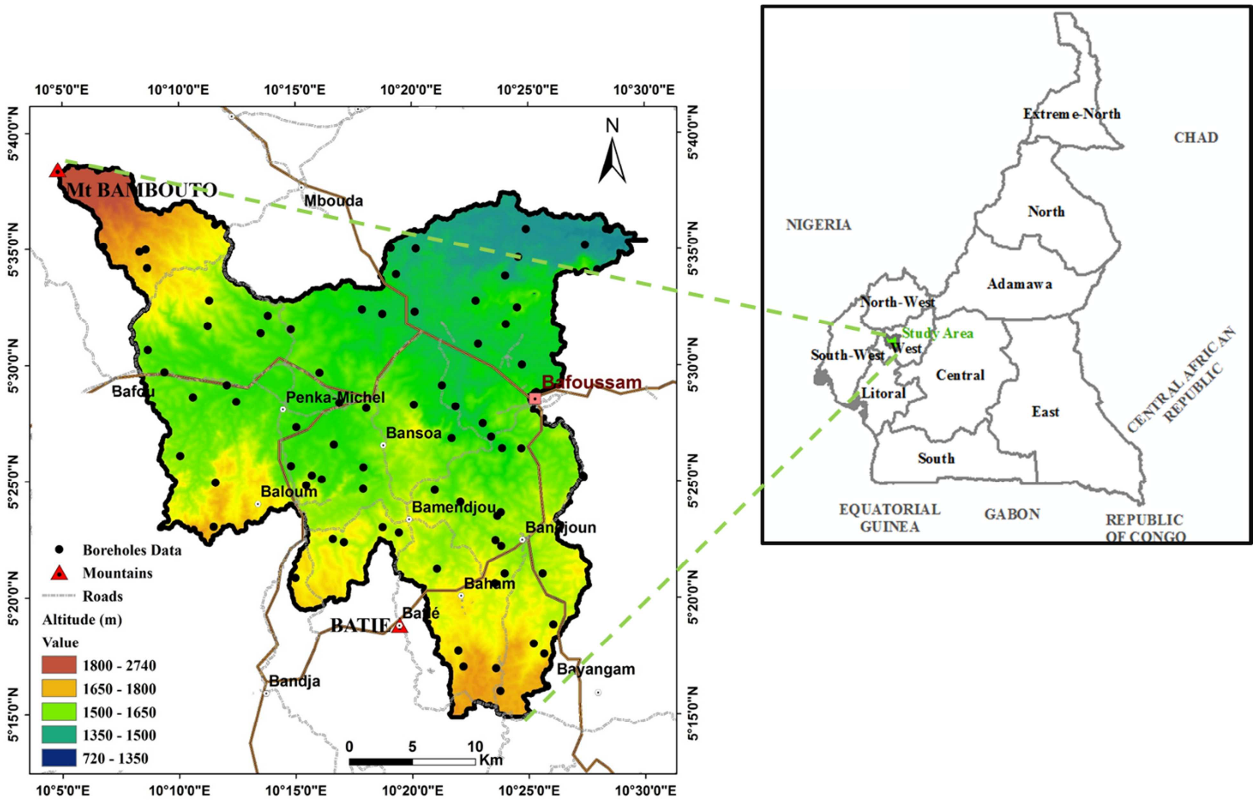


Fig. 1. Study area in Western Cameroon highlands, showing land-surface elevation from a digital elevation model and borehole data collected

2.2 METHODOLOGY

The adopted methodology is summarized in 4 parts: collecting of geospatial data, preparation of thematic maps, modelling of groundwater potential zones with ANN models, and validation.

2.2.1 COLLECTING GEOSPATIAL DATA

In order to map groundwater potential zones in SMRW, different thematic maps of 12 variables (altitude, geology, lineament density, lineament distance, slope, soil, drainage density, groundwater depth, landuse, permeability, weathering thickness, recharge and pumping rate) controlling groundwater in Western Cameroon Highlands were prepared from remote sensing data, topographic maps and bore well data.

Satellites images such as USGS LANDSAT 8 OLI (path-186 and 187 / row – 056), ALOS PALSAR (provided by European Space Agency) and SRTM Digital Elevation Model have been used. Also, survey of Douala toposheet (Douala East and West), geologic and soil maps at 1:200 000 scales, fields and borehole data including pumping rates, permeability, recharge, groundwater depth and weathering thickness were collected. Finally, GIS and image processing supports (ArcGis, ERDAS IMAGINE and MATLAB) were used for spatial analysis, mapping and ANN modelling.

2.2.2 PREPARATION OF THEMATIC MAPS

Twelve different dependent and independent factors (**figure 3**) have been considered in this study to map the potential areas for groundwater storage (altitude, geology, lineament density, lineament distance, slope, soil, drainage density, groundwater depth, landuse, permeability, weathering thickness, recharge and pumping rate which is the dependent variable). Altitude plays significant role in infiltration and is also an important factor influencing groundwater because it governs the occurrence and movement of groundwater. In the low altitude area, the surface runoff is slow, allowing more time for rainwater to percolate, whereas, high altitude area facilitates high runoff allowing less residence time for rainwater and hence comparatively less infiltration. High infiltration amounts imply the possibility of high groundwater potential while low infiltration indicates low groundwater potential. Land cover influences the ground water infiltration and alters the rate of percolation of precipitation on the hill slope. Lithology controls the quantity and quality of groundwater occurrence and represents the distribution of different rock units. Drainage density indirectly indicates the groundwater potential of an area due to its relation to surface run-off and permeability. The less permeable rocks are, the less the infiltration and lineaments, which conversely tends to be concentrated in surface run-off. Groundwater potential is found to be poor in very high drainage density area. On the contrary low drainage density, low groundwater depth, high lineament density, high permeability, highly weathered areas permit more infiltration and recharge to the groundwater and therefore have more potential for groundwater occurrence.

Altitude map with 30 × 30 m was made using elevation values taken from newly published SRTM Digital Elevation Model (DEM) data after elimination (sink and fill commands) of internal drainage area in the elevation grid. Slope map was derived from DEM and classified in five classes based on practical applications and land suitability. Available maps were assembled in the digital form and properly registered to make sure spatial component overlaps correctly. Digitizing of maps (topographic, geologic and soil maps) and importing of groundwater well data, followed by transformation and conversion from vector to raster, gridding, buffer analysis, box calculation, interpolation (IDW method) and other GIS processes produced derived layers such as drainage, drainage density, soil type, groundwater depth, permeability, and weathering thickness. As Slope, theses layers were classified based on practical applications and land suitability. Analysis and interpretation of satellite data were made in order to produce thematic maps, such as lithology, structural and landcover maps. Initially, all the images were rectified using the registered Douala Toposheet. This was followed by processing the digital images using the various preprocessing (reduction of speckles on ALOS PALSAR images, radiometric and atmospheric correction of LANDSAT 8 OLI images) and processing techniques (enhancement, directional filtering, and supervised classification). Subsequently, selective field checking was carried out. Lineaments and fracture were extracted from processed ALOS PALSAR images provided by European Space Agency. The maximum likelihood decision rule, the most common supervised classification method used with remotely sensed imagery data was used to perform the supervised classification of LANDSAT 8 OLI image. The study area was classified into 5 land cover classes namely, forest, bush land, agriculture, water and urban areas. Lithology map was prepared using ALOS PALSAR and LANDSAT OLI Digital images and simultaneously ground check verification based on rock reflectance properties and spectral arrangement of different tones and textures. Four types of lithological units which are basalts, granites, trachyte, and gneiss were observed and classified according to their groundwater yield capacity. Spatial distribution of infiltration was generated using to python version of the WETSPASS model and reclassified into five classes. Drainage density and Lineaments density were generated using kernel density analysis tool in ARCGIS. The resulting maps were then grouped in to five classes based on their importance to groundwater. Finally, to investigate the impact of distance to lineaments, six type of buffer zone range from 150 to 600 meter were created from extracted lineaments. All these thematic maps were converted into raster format with the same spatial resolution of 30 m and was integrated as input for an ANN model.

2.2.3 MODELLING GROUNDWATER POTENTIAL ZONES WITH ANN MODELS

An Artificial Neural Network (ANN) is a simulation inspired by human nervous system and able to acquire, represent, and compute a mapping from one multivariate space of information to another, given a set of data representing that mapping' [19]. ANN can learn associative patterns and approximate the functional relationship between a set of input (independent variable) and output (dependent variable). The purpose of an ANN is to build a model of the data-generating process, so that the network can generalize and predict outputs from inputs that it has not previously seen.

The multilayer perceptron (MLP) trained by the back-propagation algorithm is one of the most widely implemented neural network topologies. This training uses a set of examples of associated input and output values. This learning algorithm is a multi-layered neural network which consists of an input layer, hidden layers, and an output layer. The hidden and output layer neurons process their inputs by multiplying each input by a corresponding weight, summing the product, and then processing the sum using a nonlinear transfer function to produce a result [3]. Weights errors of neurons between the actual output values and the target output values are then adjusted at the end of the training stage in order to provide a model that should be able to predict a target value from a given input value.

The network used in this study consisted of three layers (**Fig. 2**). The first layer is the input layer, where the nodes were thematic maps of 12 variables controlling groundwater in western Cameroon highlands. The second layer is the internal or "hidden" layer. The third layer is the output layer that presents the output data. This data consists of groundwater potential areas (training sites). Each node in the hidden layer is interconnected to nodes in both the preceding and following layers by weighted connections [17]. Using the back-propagation training algorithm, weights of each factor can be determined. [20],

[19], and [3] described a method for determining the weights using back-propagation ANN. For this study, ANN were simulated in the neural network module of MATLAB.

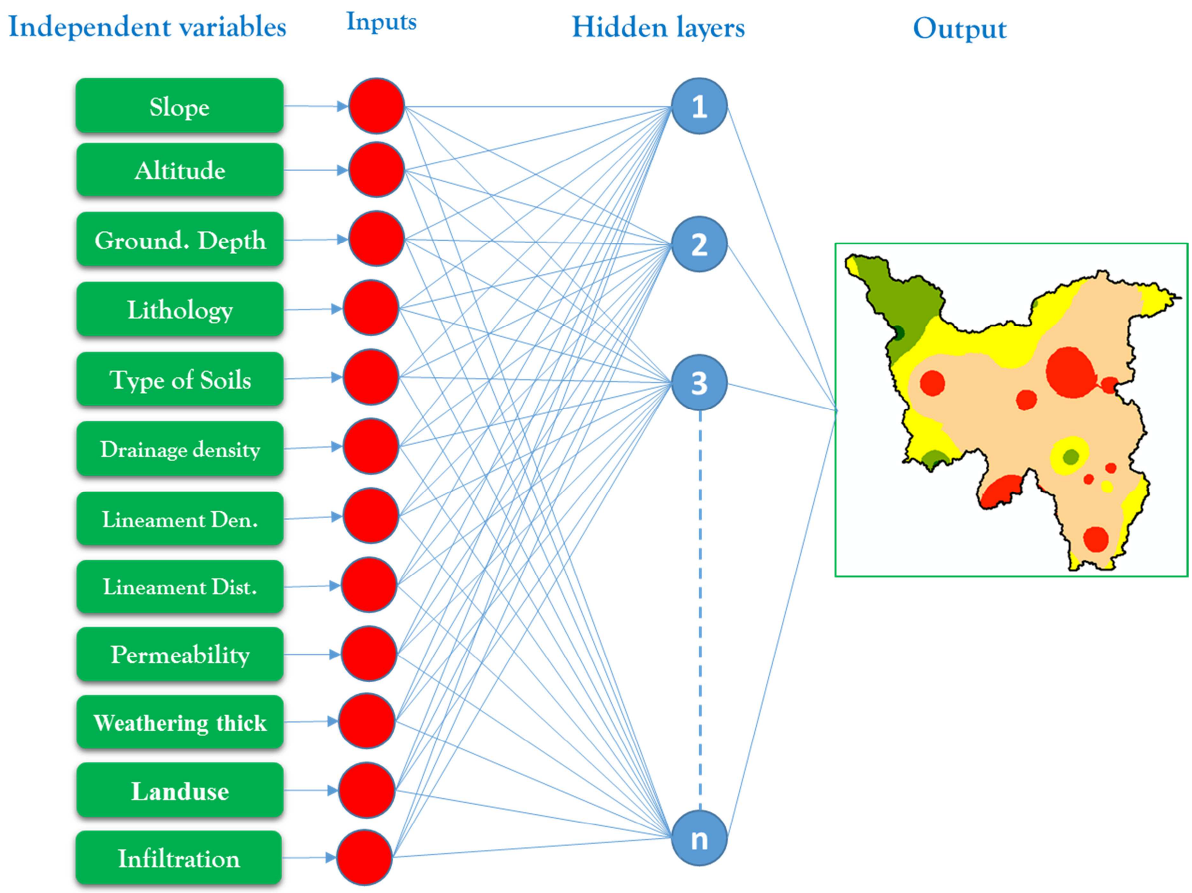


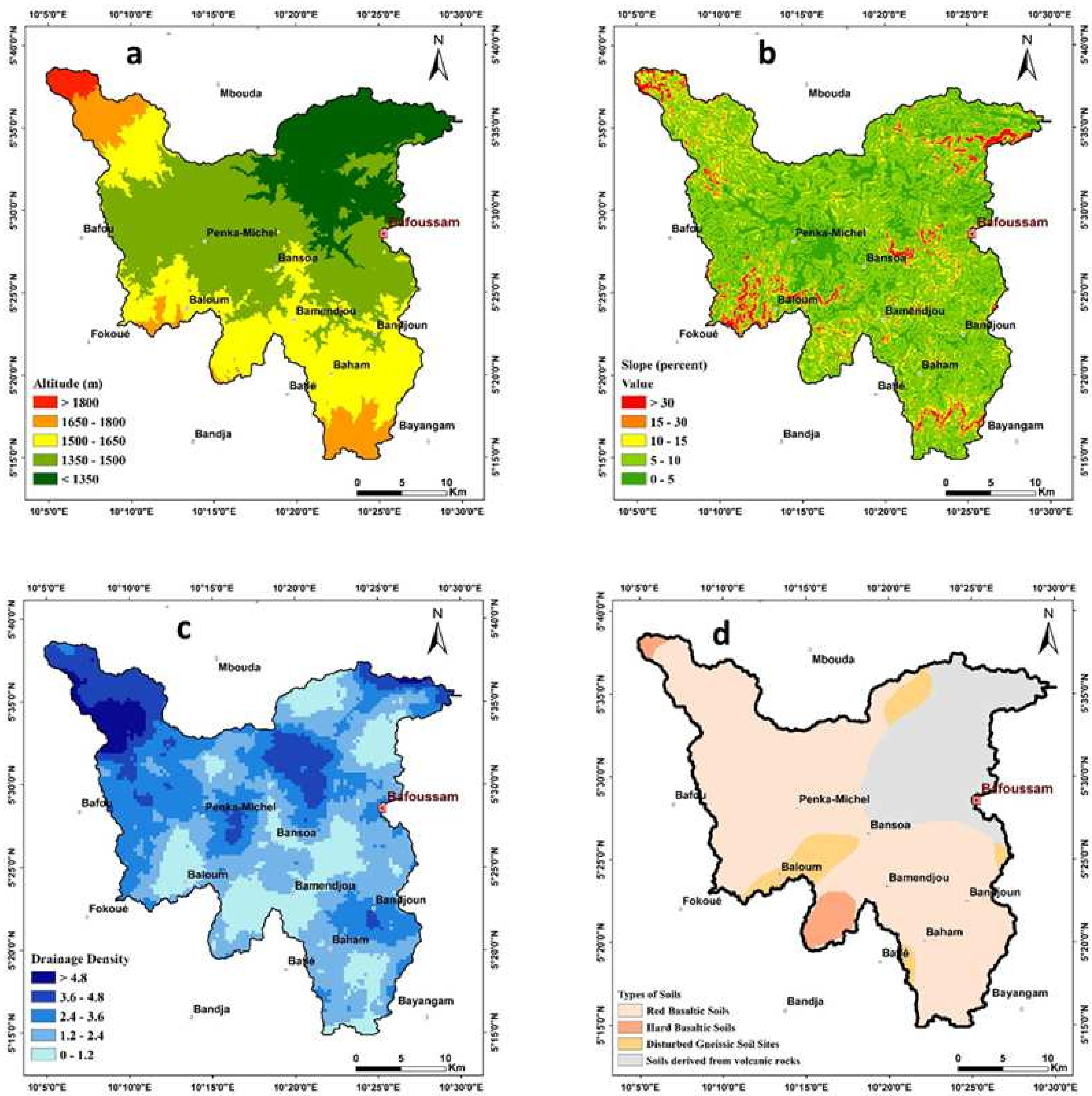
Fig. 2. Artificial Neural Network Architecture

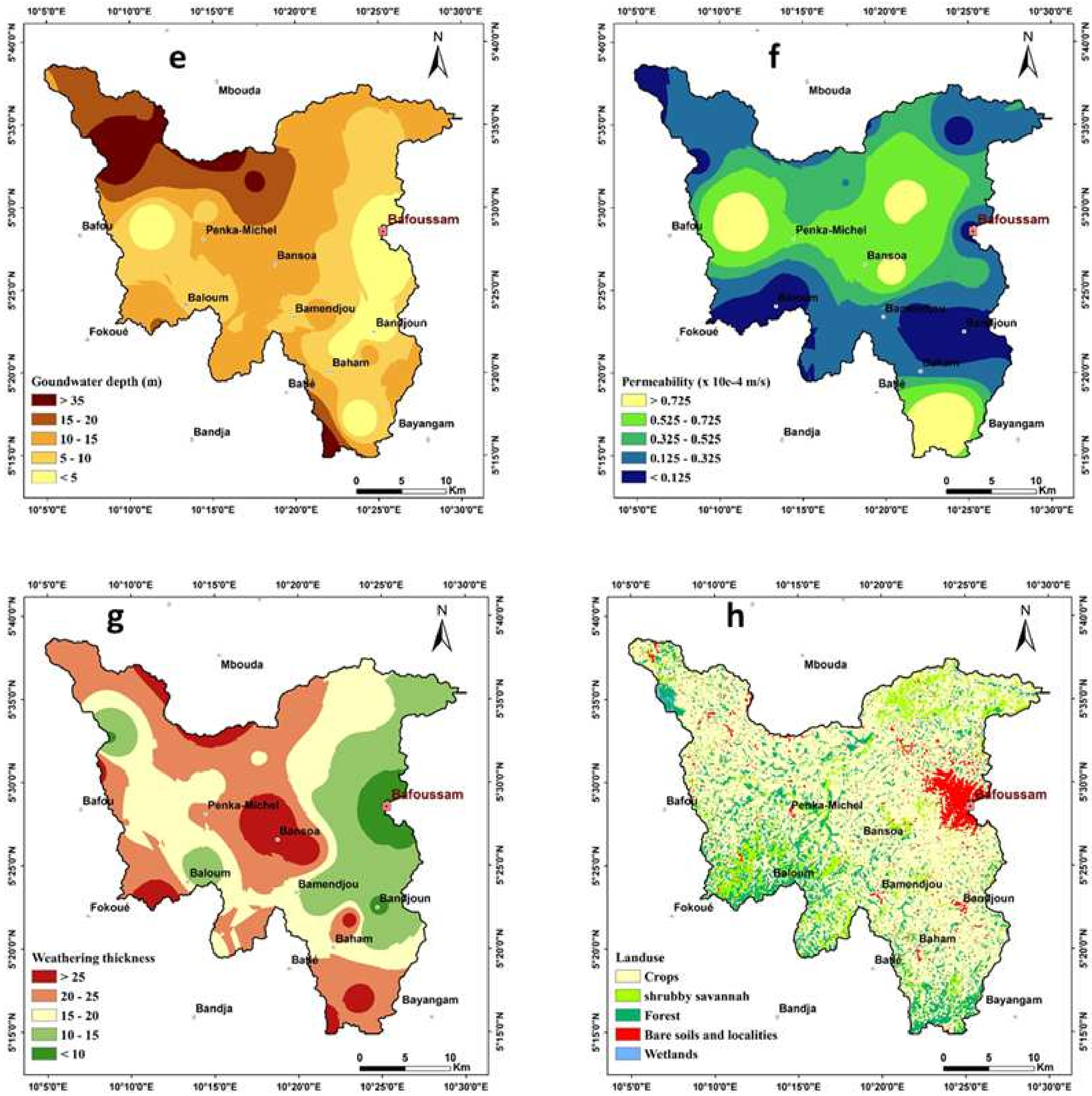
Before running the ANN program, the groundwater suitable and non-suitable areas were selected as training sites. Pumping rate (PR), considered as dependent variable, was interpolated on the study area, and reclassified in two classes based on scientific [21] [22] [23] and objective criteria proposed by the Inter-African Committee for Hydraulic Studies. Areas with PR data greater than 5 m^3/hour were classified as groundwater suitable area training dataset, and areas with PR data less than 5 m^3/hour were classified into non suitable areas dataset. Then, on the obtained binary map, 25 000 pixels were randomly selected within area with PR data greater than 5 m^3/hour. 75 % of these pixels was randomly selected for training and the remaining 25 % were used for validation.

The back-propagation algorithm was then applied to calculate the weights between the input and hidden layers and between the hidden and output layers. 12-12-1, 12-24-1, 12-36-1, 12-48 -1, 12-60 -1 architectures were selected for the network, with input data normalized between 0 and 1. The learning rate was set to 0.01, and the initial weights were randomly selected to values between 0.1 and 0.3. The back-propagation algorithm was used to minimize the error between the predicted output values and the calculated output values. The algorithm propagated the error backwards, and iteratively adjusted the weights. The number of epochs was set to 1000, and the root mean square error (RMSE) value used for the stopping criterion was set to 0.05. The final weights between layers acquired during training of the neural network and the contribution or importance of each of the 12 factors was used to predict groundwater potentials. Finally, the weights were applied to the entire study area, and groundwater potential map was created. The values were classified by equal areas and natural breaks (jenks) classification methods and grouped into five classes (very low, low, moderate, high and very high) for visual interpretation.

2.2.4 VALIDATION

The outputs of the neural network model after their spatialization, are presented in the form of maps. In this case, both physical, statistical and Receiver Operating Characteristic (ROC) model validations of these outputs have been done. The groundwater potential analysis results were verified using non interpolated pumping rates of 189 well locations. These locations were overlaid on the predicted map. This method is mostly used for validation of groundwater potential maps in African bedrocks aquifers [21] [22]. Finally, a ROC curve was created and area under curve (AUC) were calculated. The ROC curve explains how well the model and attributes predict groundwater potentials. In the ROC curve, the sensitivity of the model (the percentage of boreholes pixels correctly predicted by the model) is plotted against 1 - specificity (the percentage of predicted boreholes pixel over the total). ROC analysis is also considered as a powerful method for the validation of groundwater potential models [19] [3]. The AUC describes the quality of a forecast system through the system's ability to correctly predict the occurrence or non-occurrence of groundwater [24]. The ideal model yields an AUC value close to 1 (perfect fit), whereas a value close to 0.5 indicates an inaccurate model (random fit).




e
Goundwater depth (m)
> 35
15 - 20
10 - 15
5 - 10
< 5
f
Permeability (x 10e-4 m/s)
> 0.725
0.525 - 0.725
0.325 - 0.525
0.125 - 0.325
< 0.125
g
Weathering thickness
> 25
20 - 25
15 - 20
10 - 15
< 10
h
Landuse
Crops
shrubby savannah
Forest
Bare soils and localities
Wetlands
Mbouda
Bafou
Penka-Michel
Bafoussam
Bansoa
Baloum
Bamendjou
Fokoué
Bandjoun
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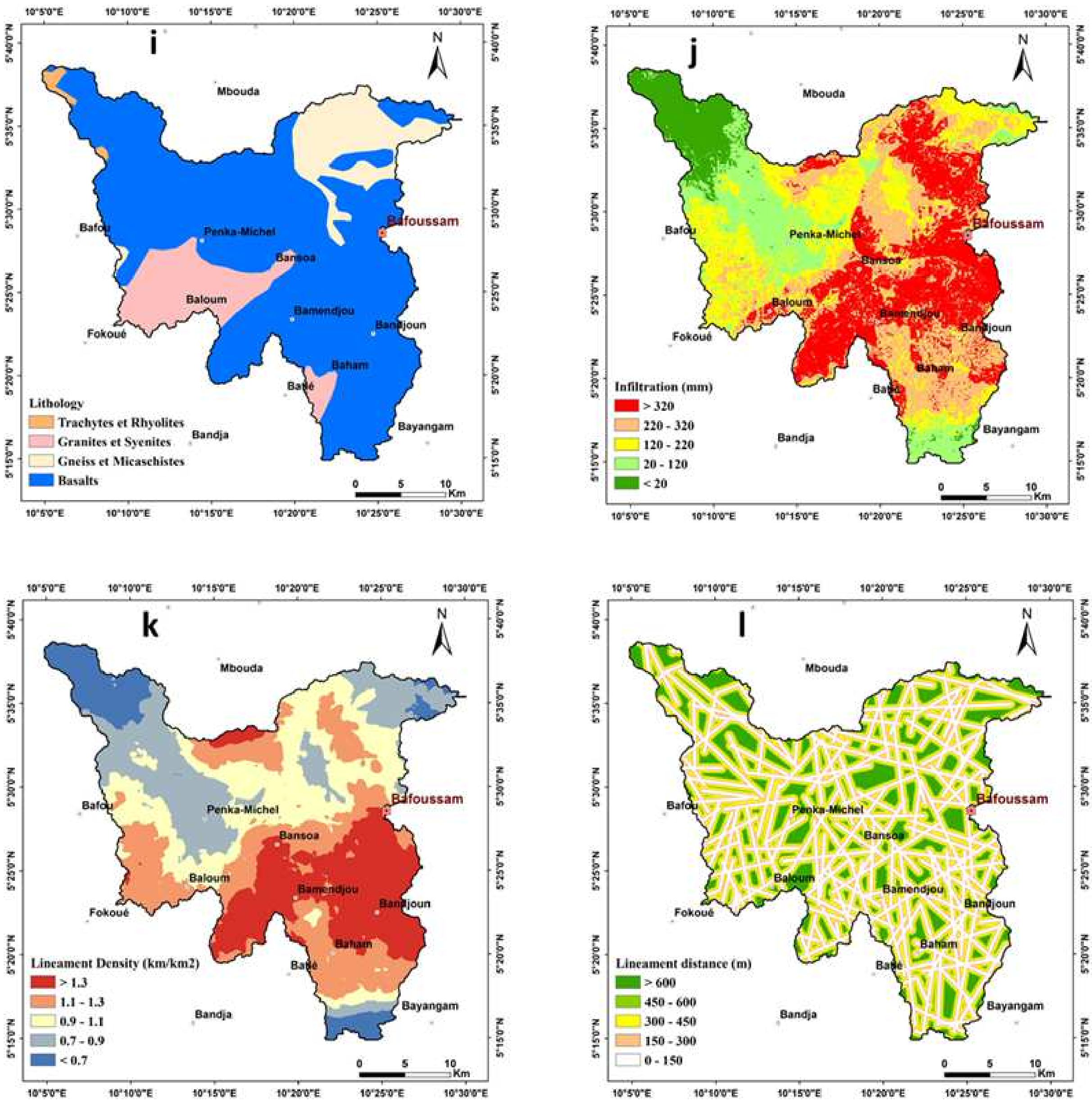

Fig. 3. Factors influencing groundwater potential in Western Cameroon Highlands; a altitude; b slope; c drainage density; d type of soils; e groundwater depth; f permeability; g weathering thickness; h landuse; i lithology; j infiltration; k lineament density; l lineament distance

3 Results

3.1 Groundwater potential mapping

The importance and weights of each of the 12 variables used to predict the groundwater potentials are shown in **Table 1**. The weights are calculated from 5 different neural networks architectures. For quick interpretation, the average values of weights of each factor were calculated. Results show that in the western Cameroon Highland, permeability, lineament density, Weathering thickness, groundwater depth, altitude, and lithology are the most important factors influencing groundwater potential and productivity conditions. The weights for these factors were 0.189, 0.101, 0.0862, 0.1438, 0.0874 and 0.1175 respectively. On the other hand, the other factors (distance to lineaments, drainage, slope, infiltration, type of soils, and landcover) had a minor effect on groundwater potential. To obtain the final groundwater potential map, weights were applied to the entire study area.

Table 1. Weights of factors considered in the Groundwater potential mapping

Variable	Weights	Relative Importance
Landuse	0,0283	15,0%
Distance to lineament	0,0273	14,5%
Permeability	0,1888	100,0%
Weathering thickness	0,0862	45,7%
lithology	0,1175	62,3%
groundwater depht	0,1438	76,2%
Altitude	0,0874	46,3%
Infiltration	0,0381	20,2%
Drainage	0,0779	41,3%
Slope	0,0353	18,7%
Type of soils	0,0686	36,4%
Lineament density	0,1008	53,4%

The obtained groundwater potential map (**Fig. 4**) was then classified into five classes (very low, low, moderate, high and very high) based on natural break classification scheme. The area covered by high and very high classes are distributed over an area of 44.6 %.

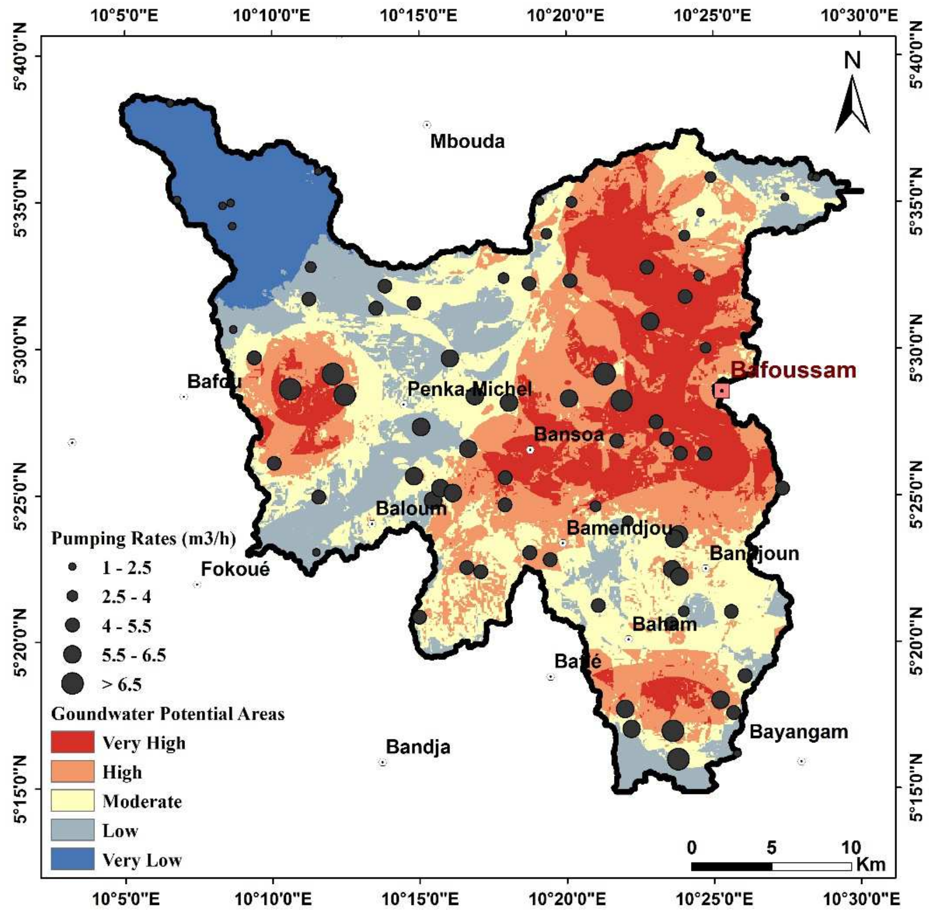

Fig. 4. Groundwater Potential Map of the study area

3.2 Validation

Firstly, 189 pumping rates GPS data locations have been collected, classified into five classes according to criteria proposed by the Inter-African Committee for Hydraulic Studies (CIEH), and used to verify the model output. The result shows in much cases (**Fig. 5**), agreement between high pumping rates and high groundwater potential areas with an overall accuracy of 83.2%. Secondly, the ROC curve have been used for examining the quality of deterministic and probabilistic detection of groundwater potential zones. **Fig. 5** shows the ROC curve of the 5 ANN models performed.

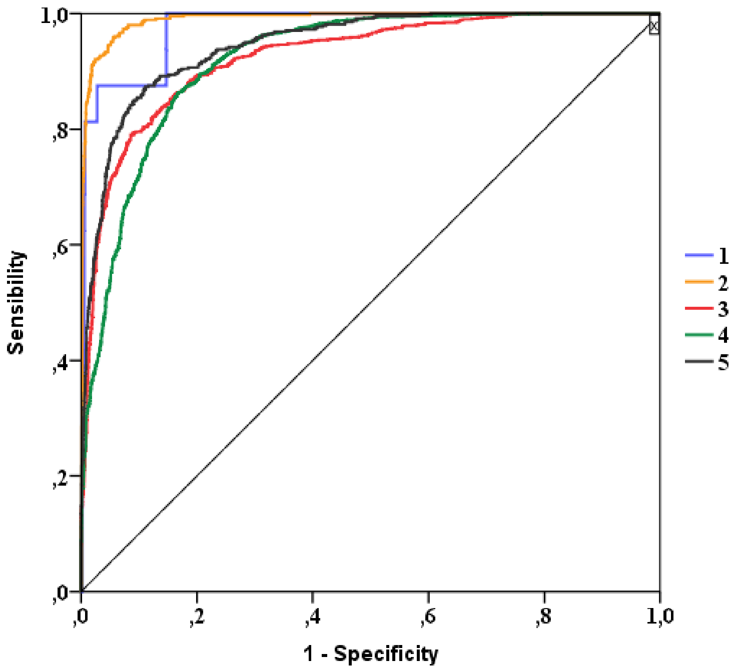

Fig. 5. ROC curve evaluations of the groundwater potential map of the 5 tested ANN architecture

The AUC values of each model are presented in **Table 2**. High obtained values of AUC (between 0.9 and 1) indicate the good ability of ANN models to demarcate groundwater potential zones.

Table 2. AUC and the precision accuracies of the 5 different ANN models

NETWORKS	AUC	Accuracy
1	0,977	97,70%
2	0,95	95,00%
3	0,925	92,50%
4	0,921	92,10%
5	0,946	94,60%

4 Discussion

In this study, twelve factors (altitude, geology, lineament density, lineament distance, slope, soil, drainage density, groundwater depth, landuse, permeability, weathering thickness, and recharge) were investigated to map groundwater potentials in western Cameroon Highlands. Each factor is important for a proper determination of a groundwater potential map. ANN model calculated the relative importance and weights of these factors with an average accuracy of 95%. Hydrogeological factors such as permeability (0.189), groundwater depth (0.438), lithology (0.1175) and lineament density (0.1008) showed the highest weight values and relative importance (100%, 76, 2%, 62, 3% and 53, 4% respectively) in the study area. The results obtained agree with previous studies [4] [5] [6] mostly based on relations between the above factors and groundwater. [6] studied through field surveys, the influence of lithology, and lineament density on groundwater potential. [4] proved that low groundwater depth are mostly found in high groundwater potential areas. According to [21], [25] [26] and [23], permeability may have significant influences on groundwater formation. In Western Cameroon Highlands, controlling variables such as altitude, weathering level of rocks, and drainage density also play a significant role in mapping groundwater potential with relative importance of 46.3%, 45.7% and 41.3%. Other factors like landuse, slope, infiltration and distance to lineaments have low influence although they are mostly used in previous studied carried in Africa [7] [5] [27] [6] [8] [9] [10].

A simple arithmetical model has been adopted to integrate the weighted thematic maps and the final groundwater potential map was categorized into five zones. Validation show an overall accuracy of 83.2%. Very high and high groundwater potential areas were distributed in areas with metamorphic (gneiss) and volcanic (basalts, tuffs, ignimbrites…) rocks and soils of low drainage, low altitude, high lineament density, high permeability, very high infiltration and very low groundwater depth.

GIS, remote sensing and ANN models have proved to be powerful and cost effective method for determining groundwater potential in Western Cameroon Highlands. Some weaknesses of this methodology can be pointed out. In ANN models, it is difficult to follow the internal process of the procedure. ANN entails a long execution time with a heavy computing load. Also, there is a need to convert data to another format like ASCII for usages in an ANN program. Finally, dealing with continuous and discrete data in an ANN program is an intriguing task. Nevertheless, in some cases, maps can be predicted maps from ANN with higher accuracy like others predictors such as frequency ratio model [28] [15], weights of evidence [16] [17], and decision tree [14].

5 CONCLUSION

This study demonstrates the capabilities of remote sensing, GIS and ANN models for demarcation of different groundwater potential areas in Western Cameroon Highlands. The occurrence of groundwater in the study area is controlled by altitude, geology, lineament density, lineament distance, slope, soil, drainage density, groundwater depth, landuse, permeability, weathering thickness, and infiltration as revealed from literature, GIS analyses and field investigations. Remote sensed ALOS PALSAR, LANDSAT OLI, SRTM – DEM data, digital image processing techniques and GIS tools helped in generating thematic maps. Additionally, using an artificial neural network, the relative importance and weight of these factors were calculated. These weights indicate that the hydrogeological factors such as permeability, lineament density, weathering thickness, groundwater depth, altitude, and lithology were more important factors than distance to lineaments, drainage, slope, infiltration, type of soils, and landuse, in terms of their effect on the groundwater-potential map in this study. The resultant groundwater-potential map can be applied to the establishment of development and management plans for use of groundwater resources, such as for regional groundwater development planning, decisions about promising areas for groundwater development, and control over water supply system. This maps also can help planners choose locations suitable for implementing further detailed explorations. Moreover, the use of the same analysis in other regions of Cameroon with similar topographic and geological conditions is necessary and could result in time and cost savings in predicting groundwater potentials areas.

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