Groundwater potentiality mapping using ensemble machine learning algorithms for sustainable groundwater; case of Ouled Bousbaa area (Morocco)

Hanane Toudamrini*, Ahmed Algouti, Abdellah Algouti and Akram Elghouat
Cadi Ayyad University, Faculty of Sciences, Department of Geology, Geosciences, Geotourism, Natural Hazards and Remote Sensing Laboratory, Marrakech, MOROCCO
*toudamrinihanane2@gmail.com

Abstract
Groundwater recharge is crucial for managing freshwater resources and has become a global issue due to climatic changes, particularly in arid and semi-arid areas. This study uses machine-learning algorithms (MLA) to facilitate groundwater potentiality mapping (GWPM) via spatial modeling. For high precision, Extreme Gradient Boosting (XGB) and Random Forest (RF) have been tested for GWPM. For this reason, a database of springs and well inventories have been prepared and randomly divided into 75% for training and 25% for model validation. GWPM is also statistically linked to various relevant factors conditioning groundwater recharge including LS factor, elevation, MRVBF, curvature, NDVI, NDWI, TWI, drainage density, distance to the river, rainfall, permeability and fault density.

Validating GWP models uses the receiver operating characteristic curve (ROC-AUC). The results show that RF (AUC=0,995) and XGB (AUC=0,990) are included in excellent class based on the ROC curve method. Furthermore, GWPMs are efficient techniques for sustainable groundwater resource management.

Keywords: Groundwater potentiality, Ouled Bousbaa, Machine-learning Algorithms, Random Forest, Extreme Gradient Boosting.

Introduction
One of the primary objectives of development projects globally is to ensure access to safe drinking water [59]. In many developing nations, groundwater is the preferred source for supplying potable water due to its superior quality. As such, a comprehensive understanding of groundwater storage and reserves is essential to inform and optimize hydrogeological exploration efforts[12]. Groundwater is a highly valuable resource with a potential global need because of its importance and intensive daily consumption[34,45,51,55]. It accounts for a large portion (about 96%) of all available freshwater resources and may be most essential in arid regions where there is little surface water[28,45].

The detailed investigation of water scarcity through different studies, warns that in the coming years, water scarcity could affect 27 countries including Morocco[2,5,31]. To preserve groundwater reserves in the face of depletion, natural and artificial recharge of aquifers is gaining importance[6,29,41,46,48,60,62]. Groundwater potential modeling has not gained much importance, unlike its prospective modeling[23]. Exploration of groundwater potential areas promotes the continuity of water resources and significantly facilitates the preparation of a strategic plan to improve the quality and management of groundwater resources[50]. Innovative machine learning algorithms have been applied in predictive modeling to develop highly accurate models[26,36].

In addition to classical modeling methods, Random Forest and XGB are powerful predictive modeling algorithms that can adapt to different variables and handle missing values and relationships between predictors[15,57]. The ROC curve is used to compare and validate the predictive accuracy of generated models. Machine learning is gaining widespread popularity because of its ability to predict variables such as groundwater potential, solely from historical data sets. The goal is to equip communities and decision-makers with a database and a collection of maps to manage drinking water resources effectively.

Study Area
The Ouled Bousbaa basin is a vast Eocene-Cretaceous synclinal area covered by Plio-Quaternary extending over an area of about 4640 Km² (Fig. 1). Several aquifer systems characterize this basin, limited to the south by the mountains of the Western High Atlas, to the north by the Jarfa Mountain, to the east by a tributary of the Oued Chichaoua and to the west by the synclinal basin of Essaouira. The Jurassic and the Cretaceous dominate respectively the north and the south of the area, while the Eocene, the Mio-Pliocene and the Quaternary are found in the central region. There are also quaternary formations in the bed of the main river, Tensift. The climate of the study area is arid in the plain and semi-arid in the mountain parts. Ouled Bousbaa has been divided into several communes that are expanding or being settled and have a large population in terms of water use.

Material and Methods
Material and Data: Groundwater mapping using machine-learning algorithms requires a dataset and several techniques for successful modeling (Fig. 2). In this study, a diagram of 1874 water points was randomly separated into two parts. 75% is used for model training and the remaining 25% is for model validation[25].

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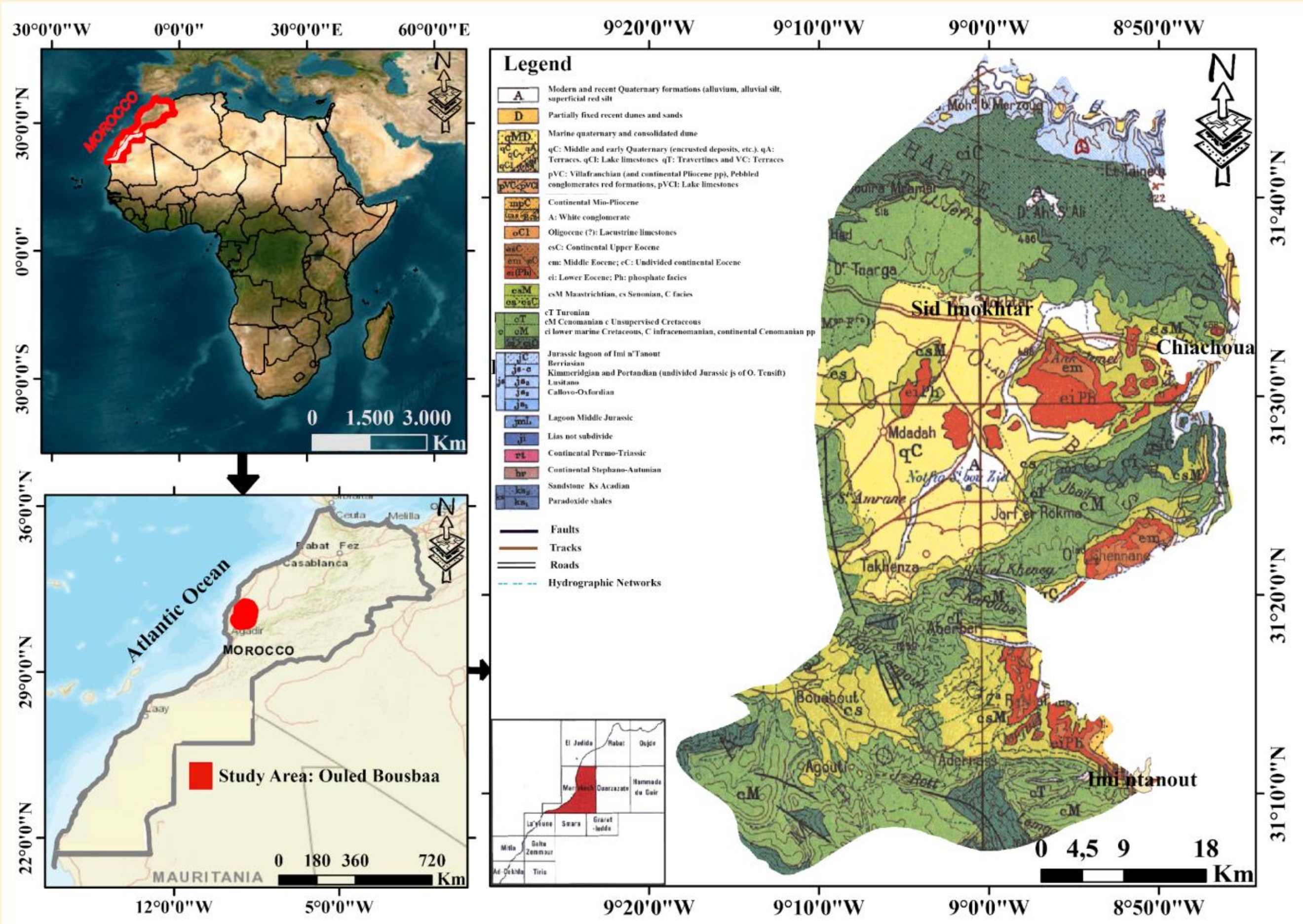

Fig. 1: Geographical location of the study area Ouled Bousbaa

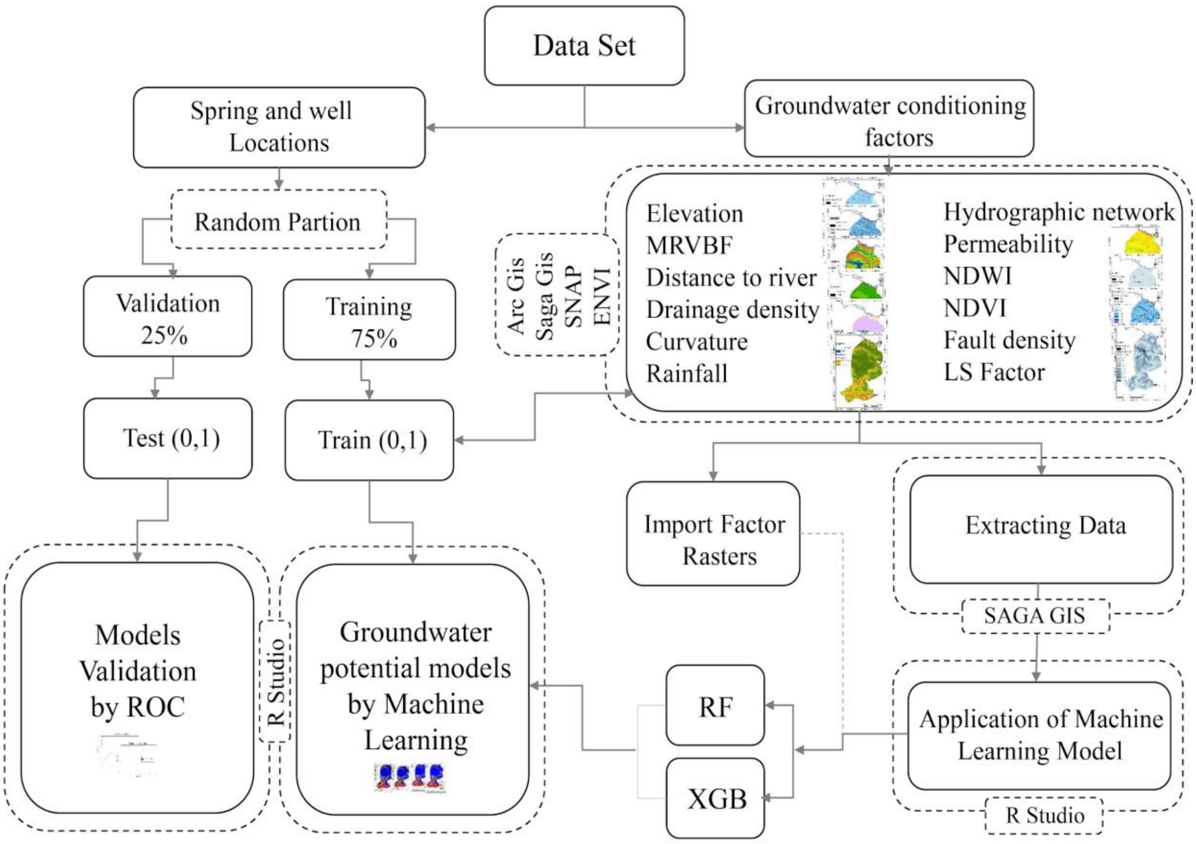

Fig. 2: Flowchart of the methodology adopted in the present study

A global digital elevation model (spatial resolution: 12.5 meters) was used to extract climatic and hydrologic topographic parameters and SRTM (30-meter resolution) and Landsat8 Operational Land Imager (OLI) collection-2 level-2 images were acquired via download from the United States Geological Survey (USGS). Hydroclimatic data consisting of annual rainfall from 1960 to 2016 and streamflow from 1994 to 2016 was measured in the stations owned by and near the study area. The utilization of remote sensing and GIS technology enabled the pinpointing of boreholes with minimal uncertainty, but additional techniques were recommended, especially for water exploration[37].

Several GIS software packages were used to process this dataset. ENVI and q-gis software ere used for lineament extraction and digitization while Arc-gis and Saga-gis are used to make the different maps of groundwater storage parameters to generate models representing groundwater potential by adopting the programming language R (Foundation for Statistical Computing).

Groundwater Inventory: Within the framework of this study, an inventory graph of 1874 points was collected generally based on reference to historical records of various resources and a detailed site inspection. A random separation of the entire groundwater and non-groundwater (spring) database was grouped into 75% (1474 points) and 25% (404 points) as training and testing datasets (Fig. 3). The distribution of this dataset covers almost the entire area of Ouled Bousbaa, which favors the feasibility of modeling with a low failure rate. The groundwater and non-groundwater training datasets are used for model training, while the testing datasets are devoted to the validation of GPM model[25].

Methodology of the study: Hydrological modeling of groundwater potential requires the creation of a hydrogeological database representative the study area (morphology, geology, climatology etc.). The methodology adopted in this study includes multiple phases which are presented schematically in fig. 2. The approach begins with the preparation of the water point inventory (boreholes, springs etc.). Then the identification and classification of factors related to the storage of groundwater were made and their thematic maps were created based on sources of available data (Hydrogeological, Climatic etc). These factors are used to develop the groundwater potentiality model to show the availability of water and how it can be used. Then the production of these models by applying approaches was based on machine learning algorithms. Finally, the validation of the results was done using the ROC method by calculating the air under the curve.

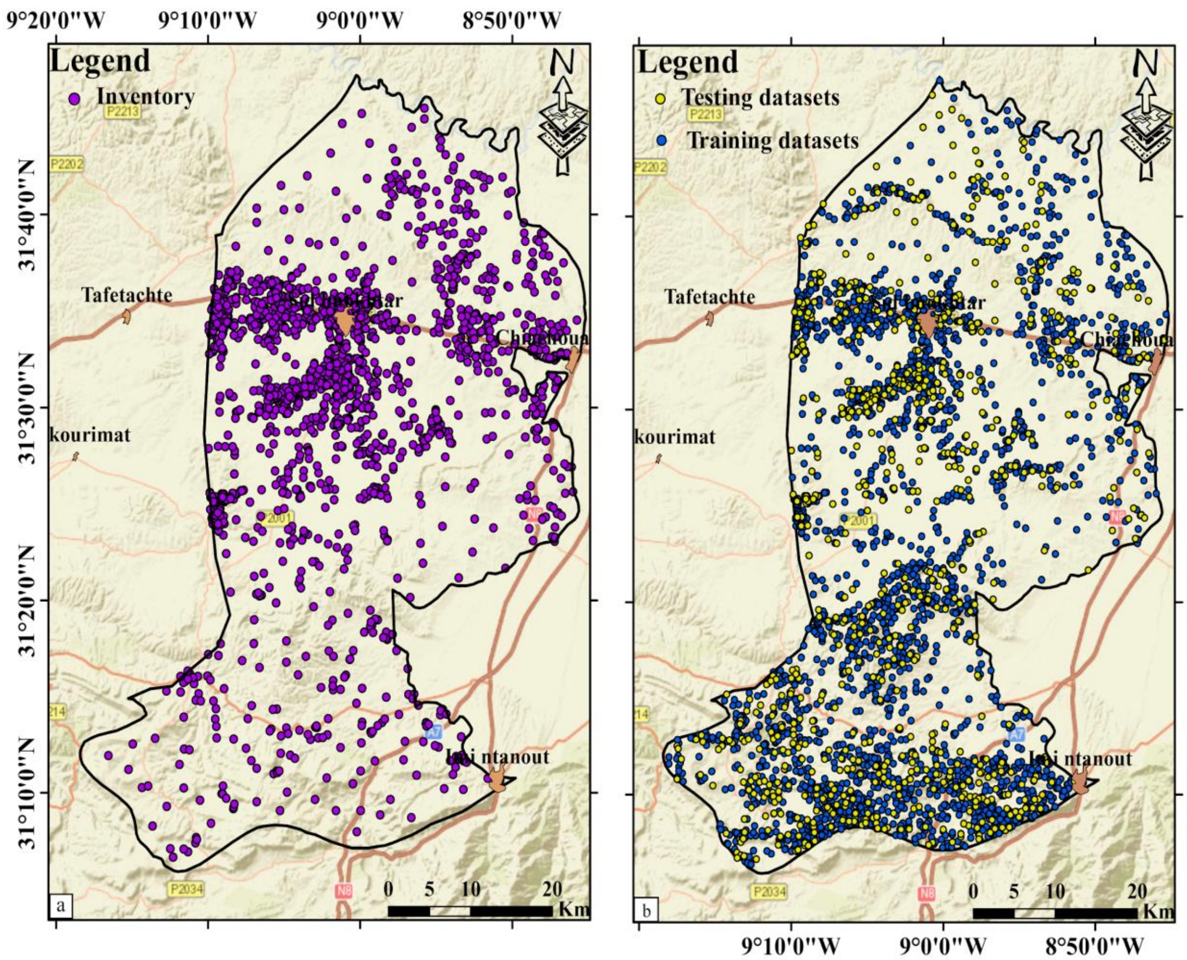

Fig. 3: Location of datasets inventory analysed in this study (training and testing dataset)

Preparation of Thematic Maps of conditioning Factors: Thematic maps of causative factors were created by utilizing Saga-gis, Envi, SNAP, arc-gis and q-gis software to extract and collect a comprehensive database to produce final models of groundwater potentiality. For this objective, groundwater conditioning factors must be well chosen, because of their direct influence on the predictive analysis of machine learning algorithms[39]. Several variables were targeted including topographic, geologic, hydrologic, climatic and land cover factors (Fig. 4). Their thematic maps are created using a shapefile to delineate the study area and to apply a classification using the "unsupervised classification" extension in a GIS environment[3, 49]. This method aims to organize an image into several spectral classes united and combined to give them a thematic meaning[8].

Methodology of Groundwater Potentiality Mapping

Random Forest: The researchers Breiman[7] and Golkarian et al[19] introduced the RF algorithm as a classification and regression system based on binary decision trees. It allows for the analysis of many parameters through a statistical approach[18,42,63], the creation of multiple trees from a random bootstrap and using the RF algorithm parameters[7, 30].

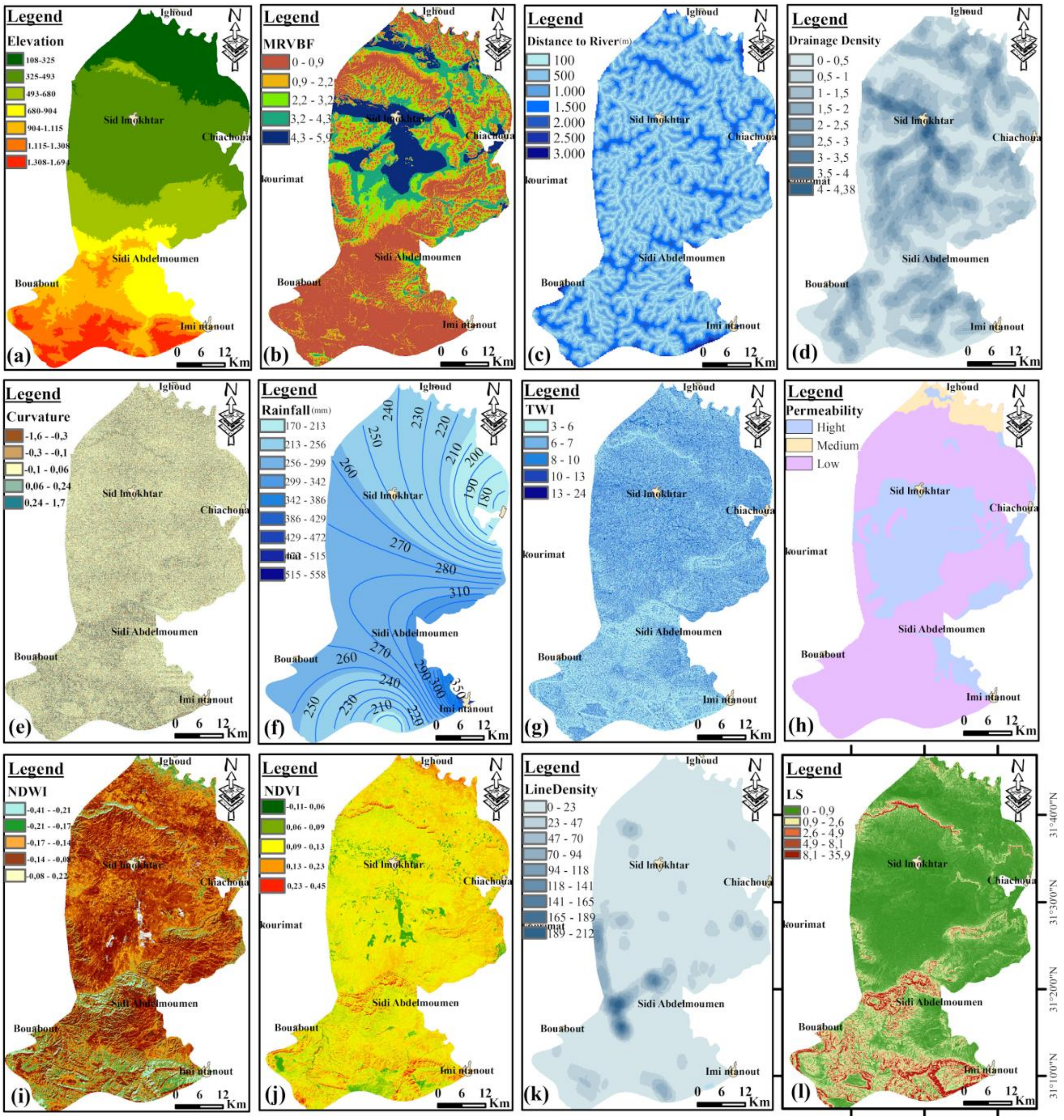

Fig. 4: Maps of the analysis of conditioning factors for groundwater recharge: (a) Elevation, (b) MRVBF, (c) Distance to river, (d) Drainage density, (e) Curvature, (f) Rainfall, (g) TWI, (h) Permeability, (i) NDWI, (j) NDVI, (k) Fault density and (l) LS Factor

It is also used to analyze nonlinear and hierarchical interactions between response and explanatory variables, using a huge database with good predictions for new cases[36,44]. The RF algorithm requires tuning the number of trees and variables and the maximum number of nodes as follows[24,58]:

$$h\ (x,ik),\ k=1,\ 2,\ .\ .\ .\ n \tag{1}$$

whee ik are factors that control groundwater storage and 1, 2, 3, 4, 5, 6, 7, ... n are input vectors *x*. The general errors in modeling by the RF algorithm are determined as follows[27]:

$$GE = Px,y\ (\ mg\ (x,y) < 0\ ) \tag{2}$$

where *x* and *y* are factors controlling groundwater storage and mg is the margin function.

Extreme Gradient Boosting: The XGB algorithm was developed by Chen and Guestrin[10]. It is a recent application of gradient boosting machines. XGB is used for classification problems and also regression. It is often used by researchers because of its high running speed[10] and also adjusts the modeling variables without affecting the objective model based on boosting from machine learning[14]. The execution of this algorithm starts by producing an initial learner from the database of all groundwater conditioning parameters. The process continues until the last indices to make the final model[14]. XGB also uses trials to reduce the required computation time[14, 33] furthermore when using a full database. It can become stronger compared to other algorithms. In the case of our study, to apply XGB, the caret package is used in the software of statistical calculations R.

ROC Curve Validation and AUC Analysis: The accuracy of the modeling predictions was confirmed by using a validation database to evaluate the results of the applied algorithms[1,16,21,22,43,54,56]. The ROC curve has been widely used by researchers to evaluate the efficiency and performance of machine learning models, as well as to assess the analytical capability and strength of machine learning algorithms. This evaluation is typically performed by analyzing the area under the ROC curve (AUC), which indicates the accuracy and high performance of the model. When we talk about a high AUC value (AUC greater than 0.7), it automatically reflects the effectiveness of the model[35,47,52,53].

In this investigation, the ROC curve was used to evaluate the predictive accuracy of the RF and XGB models. It is created with specificity (true positive rate) and sensitivity (false positive rate) on both the X-axis and Y-axis respectively, to evaluate the accuracy of the model's results of groundwater recharge[11,20,25]. Specific accuracy indices were created for each element of the ROC curve to assess the accuracy of the groundwater potential model[47]. This ROC curve-based validation approach identifies five ranks of area-under-the-curve (AUC) zonation values to gain a better understanding of the performance level. According to Yesilnacar[61], the ROC_AUC category magnitudes are as follows: Excellent (0.90 - 1.00), Good (0.80 - 0.90), Fair (0.70 - 0.80), Poor (0.60 - 0.70), Fail (0.50 - 0.60).

Results

Application of RF and XGB Algorithms: The exploration of the high groundwater potential areas in this study was carried out using several techniques to collect a complete set of data. Then, the created database is imported to the statistical software R to apply the machine learning algorithms Random Forest and XGB. After an essential phase of preprocessing which facilitates and guarantees a good predictive analysis with the least error rate, a reliable groundwater potential model was used.

Validation of Groundwater Potential Models: According to several researchers[52,53], the higher is the area under the curve, the more accurate is the predictive analysis (significant level 0.5) and is therefore, a successful groundwater recharge model. The ROC curve is used to determine the accuracy of the models by calculating the AUC and the significant level of the ROC curve to validate the accuracy of the models. The AUC site calculated using the ROC curve confirmed the acceptability of both models with good performance, as they show a value above 80% indicating the accuracy of the model prediction. The groundwater potential modeling results are statistically significant in this study. The models RF and XGB performed better in the test, their AUCs are 0.995 _ 0.990 (Fig. 5).

Groundwater Potential Maps: The groundwater potentiality maps of the two models for the Ouled Bousbaa region were classified into five categories with the method of classification of natural breaks according to their potential in zones: Very low, Low, Moderate, High, Very high.

The present model, which was generated utilizing the Random Forest algorithm, demonstrates that areas with a significant and elevated groundwater potential comprise the majority of the area (ranging from 60% to 65%) and are generally situated in the central part of the basin, at the level of the basin and further downstream, north of Ouled Bousbaa. Although the areas with low and very low groundwater potential cover a relatively small portion of the region (30%), they are situated in the upstream areas, characterized by steep slopes and high runoff, which limits infiltration (Fig. 6a).

The groundwater potential models created using the advanced XGB algorithm demonstrate that areas of very high to high potential cover a large portion of the study area, with a significant concentration in the northern part of Ouled Bousbaa. In contrast, regions with very low to low groundwater potential are primarily situated in the southern part, characterized by mountainous terrain and pronounced relief (Fig. 6b).

Table 1
Parameters of the used machine learning algorithms for GWPM

Model	Description of the parameters of the algorithms
RF	Number of Tree-500, Node size-13, Seed-10, Importance-True
XGBoost	Number of integration-200, max depth-6, minim number-2, Learning rate-0.3, Subsample-1

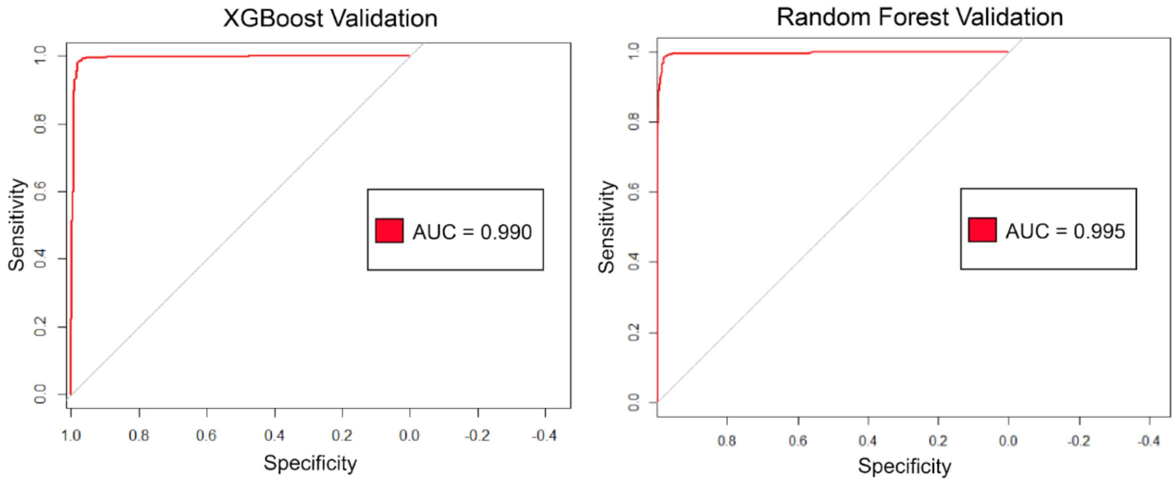

Fig. 5: Validation of Groundwater Potentiality Maps using ROC

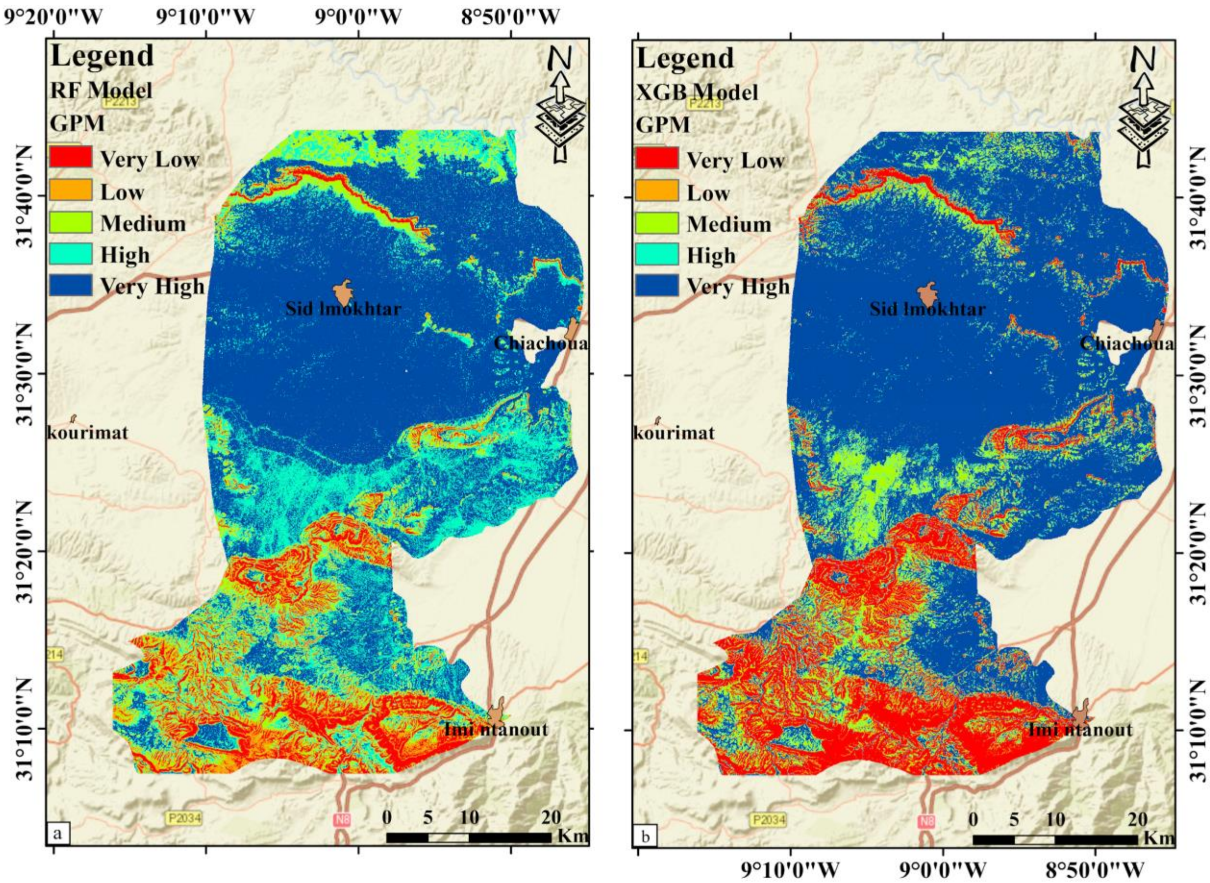

Fig. 6: The Groundwater Potentiality Maps produced by the RF (a) and XGBoosting (b) model

Confirmation of the Usability of Groundwater Potential Models: The validation of the groundwater potential models was conducted by comparing the coordinates of water points and springs, which were categorized into three distinct intervals based on their flow rates. A comprehensive analysis reveals that the flow rates of both springs and wells correlate strongly with the groundwater potential classes identified in the generated models. Specifically, springs exhibiting high flow rates are predominantly situated in high-potential zones, while those with lower flow rates are generally found in low-potential areas, with only a few exceptions (Fig. 7). Therefore, according to the analysis of the projected boreholes on the final models,

- 80% of the wells and springs with high flow rates are located in areas of high to very high potential
- 20% to 25% of the wells with low flow rates are located in areas of low to medium potential

As a result, the models developed are satisfactory according to the test of confirming exploitability by springs and wells flow rates.

Discussion

The global scarcity of groundwater reserves is generally related to resource accessibility and management, implying a global need to accurately identify potential areas using algorithmic prediction. This is to cope with the water stress that is expected to affect most of the world's inhabitants in the coming years[13]. In this study, the problem to solve is the accurate identification of potential groundwater areas using dual machine learning algorithms including RF and XGB. The effective factors were determined by examining each other, namely drainage density, LS Factor, lineament density, elevation, curvature, rainfall and MRVBF. The areas of high groundwater potentiality are located in the downstream of our region and in depressions with fractures and permeable soil, to promote groundwater recharge. The opposite is true for drainage density, distance to the river and water index by normalized difference.

Therefore, the topographic and climatic factors are most critical for groundwater storage in the Ouled Bousbaa area (Fig. 8). It is also worth mentioning that our study draws the intention on other factors (Vegetation index, slope, altitude, topographic moisture index) that have a significant impact on water storage[32]. The OCR-AUC validation model shows that both AMLs have good predictive accuracy with the ability to analyze a large database using maximum assembly of decision and classification trees[9, 17]. Therefore, this new study on mapping groundwater potential areas using machine-learning algorithms (RF and XGB) reveals a good predictive result, which implies the use of MLAs to have better modeling of groundwater potentiality.

Conclusion

Due to the increasing scarcity of water in recent decades, driven by inadequate management practices and the critical role of water in supporting economic development and population well-being, it is imperative to adopt innovative approaches, such as machine learning, to mitigate these impacts and to enhance water resource management.

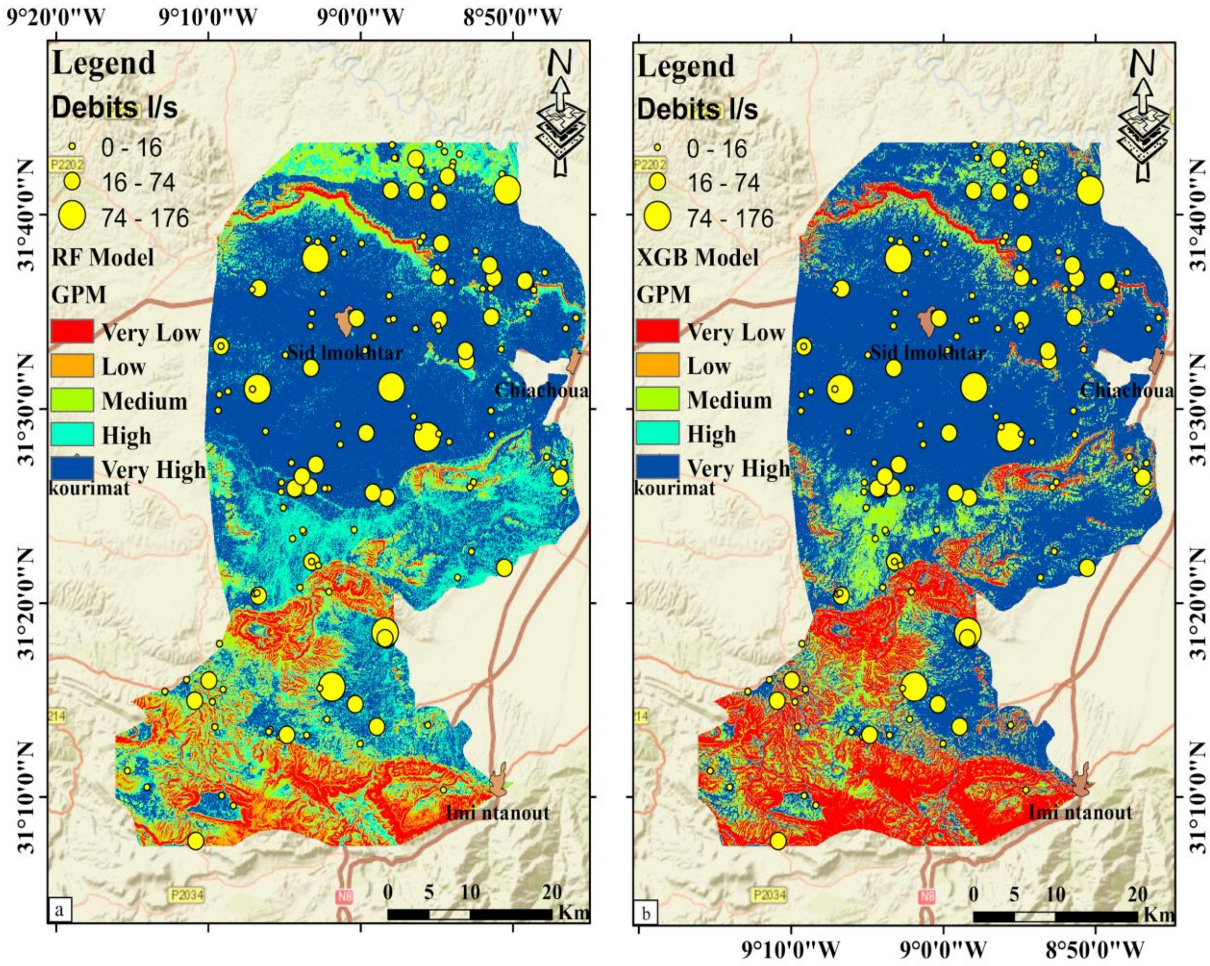

Fig. 7: Boreholes location and productivity in the GW Potentiality maps (a) according to RF and (b) XGBoosting

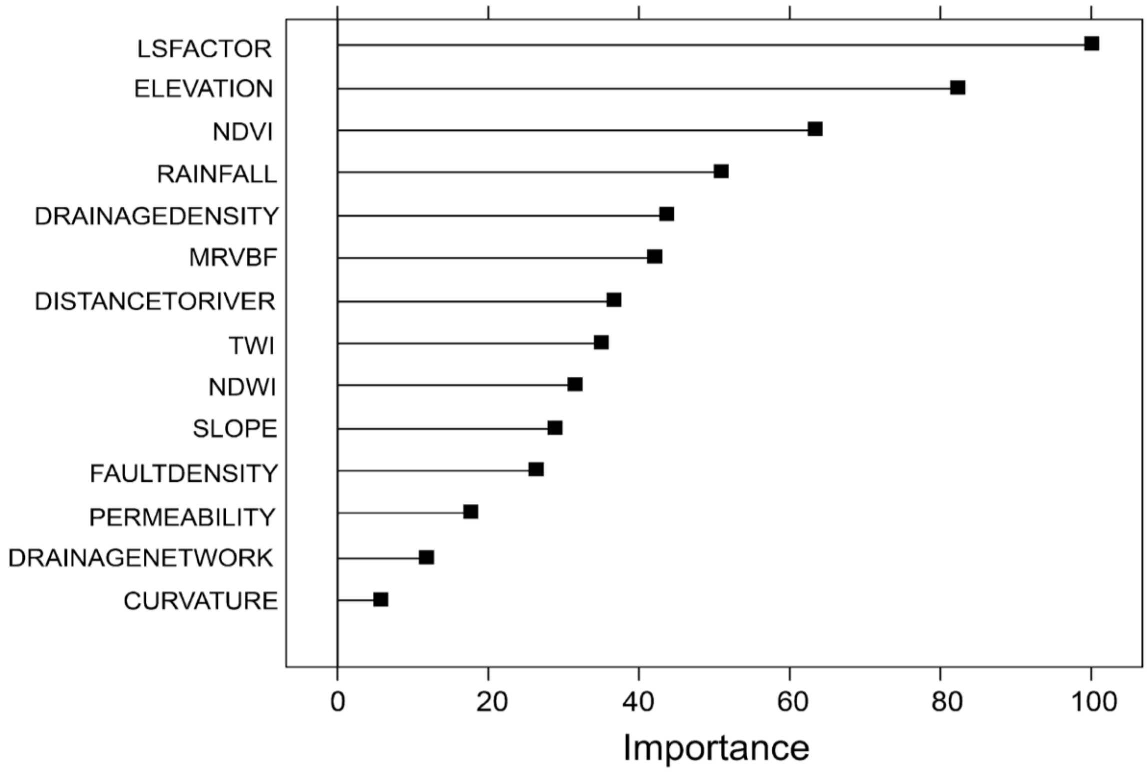

Fig. 8: Analysis of Variable Importance

This study aims to strengthen the understanding of groundwater systems to support effective management strategies that address population needs. Through detailed exploration, it seeks to identify optimal locations for implementing productive water drilling projects. The Random Forest (RF) and Extreme Gradient Boosting (XGB) algorithms were applied utilizing data associated with 13 parameters influencing groundwater storage, alongside additional factors derived from geospatial datasets and water point inventory. These factors are incorporated into a machine-learning framework to implement innovative approaches leveraging advanced machine-learning algorithms. The results were validated using the Receiver Operating Characteristic (ROC) method by calculating the area under the curve (AUC).

Additionally, the usability of the generated models was assessed using a database of well and spring flow rates. The final maps indicate that the study area exhibits significant groundwater potential, with 70% to 80% of the region classified as having high potential. These models serve as a crucial decision-support tool, enabling the identification of optimal areas for the implementation of future drilling projects.

The results demonstrate that the models developed using the applied algorithms exhibit excellent performance. Specifically, the Random Forest (RF) algorithm achieved an AUC value of 0.995, while the Extreme Gradient Boosting (XGB) algorithm attained an AUC value of 0.99, highlighting their high predictive accuracy. Lithology, elevation and the LS factor have emerged as the most influential parameters in the groundwater potential modeling.

The approaches employed in this study are cost-effective, demonstrating both reliability and accuracy in mapping groundwater resources. Furthermore, these methodologies can be adapted and applied to other regions to enhance the assessment of groundwater potential and to identify high-potential areas. These models also serve as valuable tools for guiding the selection of suitable locations for drilling activities.

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