A Review of Geological and Climatic Variables in Groundwater Availability Prediction in Africa: Machine Learning Approaches

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ABSTRACT

Groundwater is crucial for Africa's potable water supply, agriculture, and economic development. However, the continent faces challenges with groundwater scarcity due to factors like population growth, climate change, and over exploitation. Over the past ten years, machine learning has been increasingly and successfully used in groundwater level prediction across the world. This review paper explores the application of machine learning techniques in predicting groundwater levels in Africa. The methodology involved downloading relevant papers, identifying and categorizing the machine learning algorithms employed, and quantifying their use. Geological and climatic variables were also identified, analyzed and categorized to measure their usage frequency. The different algorithms and input variables extracted from each paper are graphically represented in this document highlighting the most employed ones. The findings suggest that the available literature on this topic in Africa is limited compared to the rest of the world. Tree-based algorithms are commonly used in machine learning in Africa, and the most employed input variables are related to geomorphology and temperature. The study highlights the potential of machine learning in improving water resource management and decision-making in the region.

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KEYWORDS: Groundwater level prediction, groundwater potential mapping, machine learning, Africa

1. Introduction

Groundwater, which is the water occupying all the voids within a geological stratum; or water occupying openings, cavities and spaces in rocks or earth materials is the main source of potable water for the majority of Africans (MacDonald et al., 2012). It has also been confirmed by the United Nations of Environment Programme (UNEP) that about 75% of Africans, mainly in Northern and Southern Africa, rely on groundwater as their primary supply of (Wang et al., 2014). It has been estimated that around 50% of the global population relies on groundwater for drinking water and various domestic and industrial purposes. The global population is increasing at a rate of 80 million people each year. This necessitates the identification of methods to augment the global water supply by an estimated 64 billion cubic meters annually (Chakkaravarthy et al., 2019). Due to the increase in population growth and urbanization, the dependence and demand for groundwater is anticipated to grow significantly within the next decade (Vörösmarty et al., 2000). This is expected to have a great impact on the water availability and accessibility in the future within a system of constant changing climatic variability in Africa.

The amount of water that infiltrates and percolates into the underground water source during rainfall is greatly influenced by the type of land cover and other properties of the soil. Urbanization, often associated with major construction activities in Africa leads to changes in land cover. This can affect how water interacts with the land surface, by increasing impervious surfaces which prevents water from infiltrating into the ground, causing variations in the rate of water infiltration leading to increase in runoff (Olarinoye et al., 2020). Vörösmarty et al., (2000) is of the view that changing land use practices with the potential of increasing soil impermeability has the potential of reducing groundwater recharge resulting in reduction in groundwater resources. According to Sharp et al., (2010) increasing urban areas may lead to a decrease in recharge in certain regions due to the increase in impervious surfaces created by developed infrastructures and soil compaction.

Furthermore, climate change and climate variability add another layer of complexity to this issue. Possible changes in precipitation patterns, leading to more intense rainfall events or prolonged droughts can impact groundwater recharge (Vörösmarty et al., 2000). Increased rainfall intensity can cause rapid runoff, preventing water from seeping into the ground. On the other hand, prolonged droughts can lower the water table and reduce the overall availability of groundwater. Water security in Africa can therefore be further compounded by climatic challenge and urbanization

Figure 1, shows the ranking of African countries based on their water security [data from Oluwasanya et al., (2022)]. Out of 54 countries only 13 (less than 25%) reached a modest level of water security in recent years, and around one-third are considered to have levels of water security below the threshold of 45. Water security is defined by the UNEP as ***"The capacity of a population to safeguard sustainable access to adequate quantities of acceptable quality water for sustaining livelihoods, human well-being, and socioeconomic development, for ensuring protection against waterborne pollution and water related disasters, and for preserving ecosystems in a climate of peace and political stability"*** (Bigas, 2013). This suggests that there is insufficient access to safe and reliable water sources, potentially leading to challenges in meeting basic water needs and increased vulnerability to water-related risks in Africa. In order to help achieve the Sustainable Development Goals (SDGs) especially SDG 6, that seeks to ensure availability and sustainable management of water and sanitation for all, there is the utmost need to monitor and quantify groundwater resources, facilitating groundwater level modeling and predictive capabilities crucial for informed decision-making. This can be achieved by the adoption dynamic and efficient methods in assessing the need and availability of groundwater resources especially in areas with high water scarcity and deteriorating quality (Oluwasanya et al., 2022).

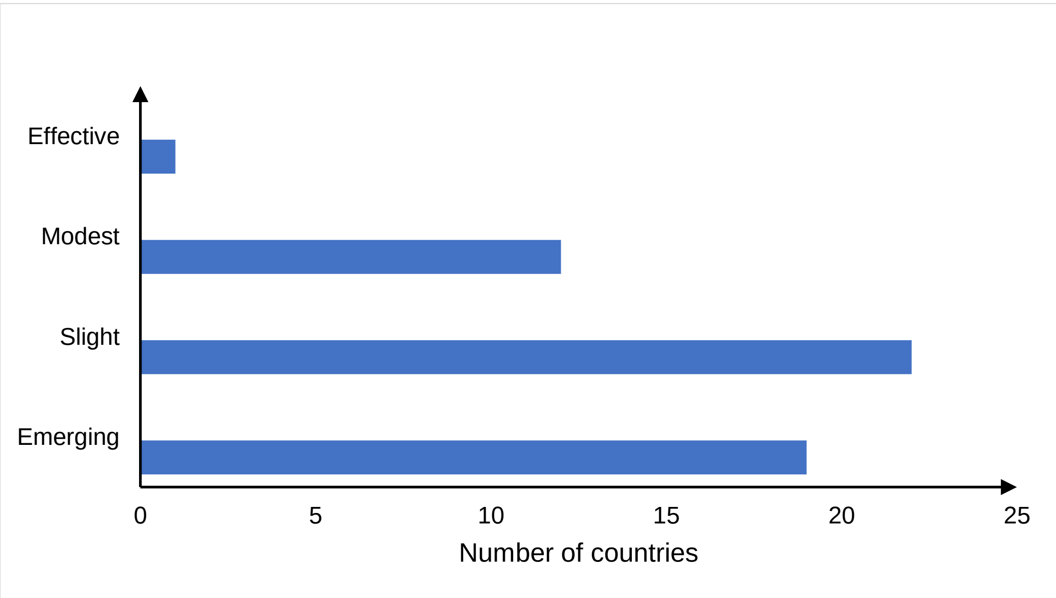

Fig 1 Water security score of African countries (data from Oluwasanya et al., 2022)

Over the past ten years, machine learning has been increasingly and successfully used in groundwater potential mapping across the world (Tao et al., 2022). Machine learning algorithms can analyze large datasets and identify complex patterns to accurately predict areas with high potential for groundwater. The method has shown efficiency in various studies because of its capability to incorporate various environmental variables and factors that affect groundwater availability, such as topography, soil characteristics, and rainfall patterns. For instance, Sarkar et al. (2022) employed a variety of input parameters, with some highlighting the importance of climatic variables (Gonzalez et al, 2021) and geological factors (Gómez-Escalonilla et al., 2022a).

The influence of geological and climatic variables on groundwater levels in Africa is a topic of significant interest and importance. Understanding the relationship between these variables can help inform groundwater management and policy on the African continent (Altchenko et al., 2019.; Cuthbert et al., 2019). The aim of this review paper is twofold: firstly, to conduct an extensive examination of the current literature concerning this subject, with a specific emphasis on research utilizing machine learning methods for data analysis. Secondly, to compile a comprehensive inventory of the diverse machine learning algorithms, as well as the climatic and geological variables employed by various researchers across Africa.

The rest of the paper is structured as follows, we discuss machine learning case studies for groundwater level prediction in the next section, then we locate the various African studies that have used machine learning algorithms for the same purpose, we continue with an explanation of the different algorithms employed by the different case studies before discussing the different input variables (geological and climatic variables) used in the algorithms in the following section.

2. Methodology

In this study, a thorough analysis of relevant African studies was conducted by downloading papers that focused on the topic. In order to gather the most relevant and recent data for this review, a comprehensive search was conducted using a combination of key terms including 'Groundwater level forecasting', 'Geological variables', 'Climatic variables', and 'Machine Learning Algorithms'. The search was refined to include only peer-reviewed articles written in English. A variety of scholarly databases were utilized for this search, such as Google Scholar, ScienceDirect. The geographical focus was narrowed down to Africa to align with the scope of this review.

The different algorithms employed were identified and attributed the most commonly used algorithms to their respective families (Table 1). Figure 2 shows the schematic diagram of the methodology used in this study. The frequency of utilization for each algorithm was quantified to determine the number of times they were employed in studies on the African continent. This analysis provides valuable insights into the prevalence and popularity of specific algorithms within the research landscape. Additionally, a comprehensive analysis was carried out to determine the prevailing geological and climatic variables used as input variables. By categorizing the different input variables into distinct groups, their frequency of usage was quantified. This quantitative assessment allowed for visual illustration of the distribution and prominence of these variables in African research.

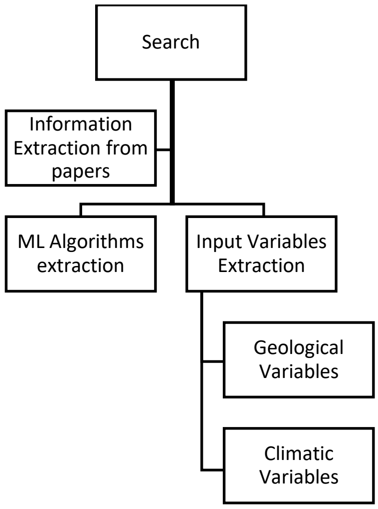

Fig 2. Schematic workflow for the study

3. Results and discussion

The majority of the studies conducted in Africa are concentrated in the northern and central regions of the continent. This geographical pattern is evident in the results of our study. Table 1 provides an overview of the various studies conducted, which will be discussed. It showcases the different algorithms employed during these studies and categorizes them based on their respective memberships.

Table 1 Different Algorithms utilized in machine learning-based groundwater studies in Africa

Algorithm Family	Utilized Algorithms	References
Neural Networks	Feedforward Neural Network with Multilayer Perceptron (FNN-MLP); Feedforward Neural Network with Extreme Learning Machine (FNN-ELM);	Siabi et. al., (2022) Derbela et. al, (2020) Gaffoor et. al., (2022)

	Long Short-Term Memory Neural Network (LSTM-NN); Artificial neural network (ANN); Neural Network Autoregression Model (NNAR); Artificial Neural Network with Perceptrons Multilayers (ANN-PMC); Discrete Wavelet Transform - Artificial Neural Network – Perceptrons Multilayers l Combination (DWT-ANN-PMC); Multiscale Feed Forward Neural Network Deep Belief Network (DBN)	Gibson (2020) Ibrahimi et. al., (2017) Kanyama et. al., (2020) Kalu et. al., (2022)
Tree-based family	Decision Tree (DT); AdaBoost; Gradient Boosting Decision Tree (GBDT); Extra-tree; Random Forest Regression (RFR); Extreme Gradient Boosting (XGB); Gradient Boosting Tree (GBT)	Gaffoor et al., (2022) Sahour et al., (2022) Kanyama et al., (2020) Gómez-Escalonilla, et. al., (2022a) Gómez-Escalonilla, et al., (2022b)
Regression Algorithms	Nonlinear AutoRegressive (NARX); Deep AutoRegressive Models; Logistic Regression (LR); Multi Linear Regression (MLR); Support Vector Regression (SVR) Support Vector Machines (SVM)	Aderemi et. al., (2023) Sahour et. al., (2022) Ibrahimi et. al., (2017) Kanyama et. al., (2020)

These findings suggest that the Neural-Network algorithms and the Tree-based algorithms have been widely employed by various searchers in Africa. Their efficiency, already proven worldwide (Tao et al., 2022), justifies their selection by African researchers. These studies have ultimately confirmed the reliability of these algorithms.

3.1 Locations of machine learning groundwater studies across Africa

A survey on African cases studies reveals that, there is a limited number of research/studies utilizing machine learning algorithms to predict groundwater levels. Specifically, there were two studies in West Africa (Ghana and Mali), one in Central Africa (Chad), three in North Africa (Morocco, Egypt, Tunisia) and five in South Africa. Figure 3 shows the location of the different studies in Africa.

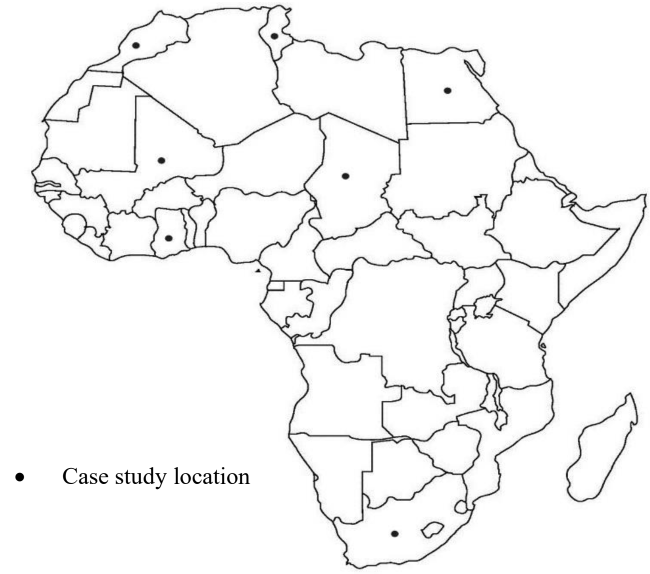

Fig 3 Locations of studies on machine learning in predicting groundwater levels across Africa.

The limited presence of research studies employing machine learning algorithms to predict groundwater levels in Africa is a noteworthy observation. This scarcity underscores the need for further exploration and innovation in this domain. If this research gap is addressed, we can unlock valuable insights into groundwater resources and enhance our capacity to manage and sustainably utilize this crucial water source. This presents an exciting opportunity to contribute to the advancement of groundwater mapping and make a meaningful impact in addressing water challenges across the continent.

3.2 Machine learning case studies of groundwater level prediction in Africa

Due to their potential for being less time-consuming and their capacity to produce relevant findings, machine learning models are interestingly becoming alternatives to process-based models (Kanyama et al., 2020). A large volume of literature is available on the applicability of machine learning algorithms to forecast groundwater level (GWL) in different regions of the world (Tao et al., 2022). This paper focuses on studies from Africa. region, where comprehensive details of the identified algorithms are presented (Table 1).

Siabi et al. (2022), for instance, used two artificial neural network (ANN) models, the Feedforward Neural Network with Multilayer Perceptron (FNN-MLP) and Extreme Learning Machine (FNN-ELM), to predict groundwater recharge in a data-scarce region of Ghana. The models were trained using the input variables of effective rainfall, potential evapo-transpiration (PET), and lagged groundwater recharge. The study found that the FNN-MLP model outperformed the FNN-ELM model in predicting groundwater recharge with R^2 ranging from 0.97 to 0.99.

To predict future groundwater levels based on hydrogeological variables such as rainfall, evapotranspiration, and initial water table level, artificial neural networks (ANNs) have been utilized by Derbela et al, (2020) in Nebhana aquifers (North-East Tunisia). The ANN architecture was composed of three layers: an input layer, which had a number of neurons equal to the number of input variables; a hidden layer, which contains three neurons; and an output layer with one neuron. The performance of the designed ANN was evaluated using various metrics such as relative error, root mean square error, determination coefficient, and Nash-Sutcliffe efficiency coefficient. The study finally showed that ANN algorithm has the potential to provide relatively good results with fewer input variables.

Gaffoor et al., (2022) employed two machine learning algorithms, gradient-boosted decision tree (GBDT) and long short-term memory neural network (LSTM-NN), to model groundwater level changes in the Shire Valley Alluvial Aquifer (Southern South-Africa). The algorithms were trained using hydro-climatic inputs and groundwater level changes from two boreholes (namely Ngabu and Nsanje). The authors set up experiments to train and test the algorithms to predict the change in the current month's groundwater level and the change in the following month's groundwater level. The algorithms were compared based on their R^2 scores, and the authors concluded that the LSTM outperforms the GBDT model, especially regarding slightly greater time series and extreme GWL changes.

In Aderemi et al., (2023)'s research at Karst belt in South Africa, they forecasted groundwater level using Regression Models such as SVM or LR, Deep Auto-Regressive models, and Nonlinear Autoregressive Neural Networks with External Input (NARX). These models were trained using four input variables, namely rainfall, temperature, groundwater usage, and precipitation. The findings showed that NARX and Support Vector Machine (SVM) have higher performance metrics and accuracy compared to the other models.

Kalu et al., (2022) developed a machine learning modelling framework based on the deep belief network (DBN) to predict changes in monthly groundwater levels at 1–5-month time scales for 27 groundwater wells over the southern Africa region. The predictor dataset used in the DBN network was constituted from hydrological parameters, groundwater level estimates, and global climate indices. The DBN network was trained on the predictor dataset to forecast changes in groundwater levels up to 5 months lead times at most locations in the study region. The results highlighted how deep learning can help make informed decisions to lessen the effects of climate extremes on people and their properties. The authors found it to be a key tool for evaluating hydrological processes that could lead to extreme weather.

Sahour et al., (2022) studied the relationship between Shallow Ground Water (SGW) occurrence (target) and their controlling factors (independent variables) using extreme gradient boosting (XGB), support vector machine (SVM), and logistic regression (LR) methods. The trained models were used to map Shallow Groundwater (SGW) locations across the entire Western desert of Egypt. The dependent variable was the spring locations, while the independent variables include remote sensing-based variables and geomorphological features indicative of current or paleo-discharge locations, such as elevation, slope, curvature, distance to sapping features, soil moisture, Normalized Differenced Vegetation Indices (NDVI), radar backscatter coefficient, and brightness temperature. The study also uses additional geological constraints to refine the outputs of the models, including the presence of shallow aquifers, Nubian water salinity, and thickness of post-Nubian successions. The research reveals that in both the training and testing stages XGB produced the highest accuracy among the other models used, followed by the SVM and LR.

Gibson, (2020) used the Neural Network Autoregression (NNAR) machine learning method to predict groundwater levels in the Steenkoppies compartment of the Gauteng and North West Dolomite Aquifer in South Africa. The input variables rainfall, temperature, groundwater usage, and spring discharge from the Maloney's Eye spring were used to train the model to learn the complex, interdependent relationships occurring in the groundwater system. The results indicate that the NNAR model was most accurate in predicting groundwater levels when the test data closely mirrored the training data. This is explained by the fact that ANNs, like NNAR, learn from the patterns in the training data. So, if the test data is too different, the model might struggle with predictions.

Ibrahimi et al., (2017) adopted a more comprehensive approach, utilizing three distinct models for groundwater level prediction of the surface water table in the Saïss Plain (North of Morocco). They incorporated input variables such as precipitation, temperature, and average groundwater levels into their analyses. The first model was the artificial neural network with perceptron multilayers (ANN-PMC). This model uses the input variables to train the neural network, which then predicted the groundwater level based on the input data. The second model was the discrete wavelet transform and artificial neural network with perceptron multilayers (DWT-ANN-PMC). This model used the discrete wavelet transform to extract features from the input data, which were then used to train the neural network. The trained neural network then predicted the groundwater level based on the input data. The third model was multiple linear regression (MLR). This model used the input variables to create a linear equation that predicted the groundwater level based on the input data. The performance of the three models were evaluated using statistical metrics such as mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R^2). The results indicate that the DWT-ANN-PMC model outperforms the other two models in predicting groundwater levels.

To also predict groundwater level in the Grootfontein Aquifer (South Africa) Kanyama et al., (2020) employed five different data-driven techniques, including support vector regression (SVR), gradient boosting trees, decision trees, random forest regression (RFR), and multilayer feed-forward neural network techniques. The chosen input variables were discharge, precipitation, and temperature. These variables were considered as model inputs for the four boreholes in the aquifer. The performance of the models was evaluated using two metrics: root mean squared error (RMSE) and coefficient of determination (R^2). These metrics were used to assess the accuracy and fit of the models. The gradient boosting (GB) algorithm performed the best among the five algorithms tested, achieving an R^2 score of up to 0.75 for one of the borehole sites. The multilayer feed-forward neural network (FFNN) algorithm also performed well, achieving the highest R^2 score of 0.77 for one of the sites. The results obtained suggested that the model performance is data-dependent and the variable responsible of that dependance was found to be the discharge rate.

Gómez-Escalonilla et al., (2022a) used a total of 20 machine learning classifiers, trained and tested them on a large borehole database to find meaningful correlation between the presence or absence of groundwater and the explanatory variables in the Koulikoro and Bamako regions (Mali). The performance of the classifiers was assessed using various machine learning metrics, including accuracy, F1 score, and area under the curve (AUC).

The same method has been applied in a region of eastern Chad (Gómez-Escalonilla et al., 2022b). In this case, the performance of the classifiers was evaluated using metrics such as AUC curve, test scores, and balanced score. The most relevant explanatory variables were identified based on the performance of the classifiers using these metrics. In the two cases, the best performing algorithms in identifying potential groundwater areas correlating with borehole data were found to be tree-based algorithms, including decision tree, random forest, AdaBoost classifier, gradient boosting, and extra trees (Gómez-Escalonilla et al., 2022a), random forest and extra-trees (Gómez-Escalonilla et al., 2022b).

The purpose of using multiple classifiers was to compare their performance and identify the most effective ones for mapping groundwater potential. The different machine learning classifiers have different strengths and weaknesses, and by testing a variety of classifiers, researchers can determine which ones perform the best for their specific dataset and research objectives. By using a diverse set of classifiers, the studies aimed to ensure robustness and accuracy in predicting groundwater potential. This approach helps to minimize the potential bias and limitations associated with relying on a single classifier, providing a more robust and comprehensive analysis.

3.3 Algorithms used in case studies

In this section, the various algorithms used in predicting groundwater availability based on the studies discussed in the previous session are presented. Figure 4 presents the most commonly utilized machine learning algorithms in predicting groundwater availability in Africa, as gathered from our comprehensive review. The Tree-based algorithm family (Table 1) emerges as the most frequently employed algorithm, accounting for 46% of the usage. Following that, the Neural-Network algorithm family is utilized at a rate of 29%, while Regression Algorithms come in at 25%.

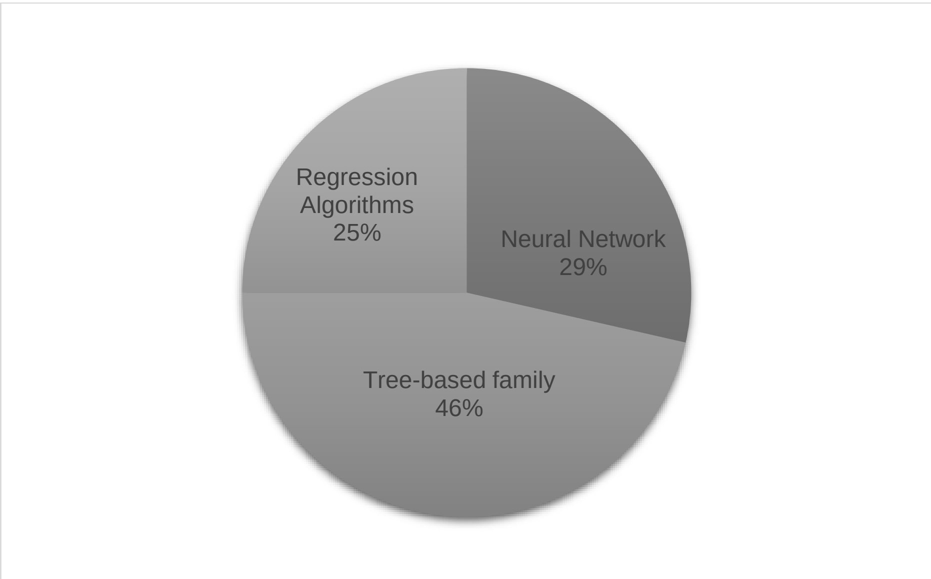

Fig 4 Most frequently used machine learning (ML) algorithms in Africa

This section goes into detail in describing each of these algorithms. The ANN model is, in general, a method for data processing that is largely inspired by the neural systems of humans and other animals. It is a non-linear statistical data analysis model between the input and output variables. This model has been used in various fields of science and technology such as pattern recognition, process control, and time series forecasting (Chen et al., 2022). The capacity of the ANN model to classify patterns in multi-variable datasets, manage complicated processes, and produce accurate predictions/results are among its most advantageous features. The choice of ANN type mostly depends on the nature of the problem and the availability of data. There are many different network types for the ANN model. Compared to other prediction techniques, ANN has the benefit of using less training data to provide better results (Rasool et al., 2022).

Gradient Boosting Decision Trees (GBDT), Extreme Gradient Boosting (XGBoost), Random Forest Regression (RFR) and Decision Trees are considered part of the tree decision family. Regression, classification, and ranking tasks respond well to these traditional machine learning methods (Gaffoor et al., 2022). GBDT is a machine learning algorithm that combines multiple decision trees to make predictions. It trains each tree in a sequential manner, where each subsequent tree corrects the errors made by the previous trees, resulting in a more accurate prediction. It uses a combination of gradient boosting and regularization techniques to improve model performance (Sahour et al., 2022). An extended Gradient Boost Machine is called XGBoost, which is an ensemble improving algorithm. The XGBoost model combines numerous weak learners (per tree) to produce a strong learner through additive learning. It enhances the workout, avoids over fitting, and reduces the loss function (Rasool et al., 2022). On the other hand, Random Forest Regression (RFR) is an ensemble learning algorithm that combines multiple decision trees to make predictions. It creates a "forest" of trees, where each tree independently predicts the target variable, and the final prediction is obtained by averaging or voting the predictions of all the trees (Gómez-Escalonilla, et al., 2022b). Decision Trees (DT), based on the provided input characteristics, predicts the target variable using a tree structure. The root node, or starting node, and the leaf node, or end node, make up the DT. The DT can calculate division values by exploiting impurities produced at each node (Kanyama et al., 2020). Deep Belief Networks (DBN) is a type of deep learning algorithm that consists of multiple layers of hidden units (Kalu et al., 2022). It is trained in a layer-by-layer manner using unsupervised learning and then fine-tuned with supervised learning. Another algorithm that has been utilized is the Support Vector Machines (SVM), which is used for both classification and regression tasks. SVM is a generalized linear classifier that is a supervised learning approach for classification and regression issues (Rasool et al., 2022). It finds an optimal hyperplane that maximally separates data points of different classes or predicts the value of a continuous variable based on support vectors. SVMs are effective in handling high-dimensional data and can handle non-linear relationships through the use of kernel functions. A variant of SVM is Support Vector Regression (SVR) also used for regression tasks. It predicts the value of a continuous variable by finding an optimal hyperplane that maximizes the margin while allowing a certain amount of error (Kanyama et al., 2020). Logistic Regression (LR) is a statistical regression algorithm commonly used for binary classification tasks. It models the relationship between the input variables and the probability of belonging to a certain class. Based on the values of a collection of explanatory factors, LR is a useful model for determining whether an outcome will occur or not (Sahour et al., 2022). Multiple Linear Regression MLR is a regression algorithm used to model the relationship between multiple input variables and a continuous target variable (Ibrahimi et al., 2017). It assumes a linear relationship between the inputs and the target and estimates the coefficients that minimize the sum of squared errors. These algorithms have been explored by authors in different regions of Africa using different set of variables. The input variables used in the studies depends mostly on data availability of the area and also on the understanding of the study area's geologic setting (Sahour et al., 2022).

3.4 Geological variables and their effects on groundwater occurrence and movement

The geology of an area plays a crucial role when it comes to hosting groundwater as well as surface water infiltrating into an aquifer system, through the features of porosity and permeability which are lithological features in studying assessment of groundwater potential in the Zambezi River Basin concluded that groundwater is normally found in the fissures, faults, and fractured zones within a geological formation. The presence and flow of groundwater are mainly determined by the porosity and permeability of the surface and subsurface rock types. The same type of rock can form different geomorphic structures, leading to variations in porosity and permeability. This, in turn, alters the potential of groundwater (Shahid et al., 2000). As also stated by Waikar et al. (2007) the presence of groundwater in a geological formation and the potential for its use is largely dependent on the formation's porosity. Areas with high elevation and sharp inclines lead to greater runoff, while regions with topographical low points enhance infiltration. Moreover, a region with a high density of drainage paths boosts surface runoff in comparison to an area with a less dense drainage network.

This highlight how understanding the geology of the investigated area is crucial in groundwater study purposes. A list of the geological variables used by some of the machine learning case studies in Africa are given in Table 2.

Table 2 Geological variables used by the different cases studies

Reference	Case study	Input variables	Output Parameters

Siabi et al., (2022)	Ghana	Recharge Runoff	Groundwater Recharge (GWR)
Gómez-Escalonilla et al., (2022)	Mali	Lithology Landforms Soil Expected thickness of the aquifer Water table depth Normalized Difference Vegetation Indices Normalized Difference Water Indices Slope Stream Power Index Drainage density Distance from channels Clay content Clay mineral alteration ratio	Groundwater Potential (GWP)
Gómez-Escalonilla et al., (2022)	Chad	Lithology Drainage density Fracture density Basement depth Fault density Elevation Slope Topographic Wetness Index Saturated thickness Hydraulic head	Groundwater Potential (GWP)
Kanyama et al., (2020)	South Africa	Discharge point of groundwater Monthly GWL	Groundwater Potential (GWP)
Sahour et al., (2022)	Egypt	Elevation Slope Curvature Distance to sapping features Soil moisture Normalized Difference Water Indices	Shallow Groundwater (SGW)
Gibson (2020)	South Africa	Spring recharge Groundwater level	Groundwater Potential (GWP)
Ibrahimi et al., (2017)	Morocco	Groundwater level	Groundwater Potential (GWP)

The topographic wetness index (TWI) indicate the effect of topography on an area (Prasad et al., 2020) and help to approximate moisture levels by identifying surface-saturation zones and the spatial distribution of soil moisture. Drainage density inversely affects water absorption, while distances to faults impact water penetration because faults give opportunities for water to penetrate into the subsurface. Slope influences the opportunity for surface water to infiltrate permeable soils. It is a physical indicator, which approximates the areas of surface-saturation spot and the spatial distribution of soil moisture. Waterways affect runoff, which, discourage water retention at locations along the drainage path and thus affect infiltration into the surface. Land use, affects the occurrence and availability of water to contribute to soil moisture and groundwater supply. As for altitude, it influences the direction and velocity of surface runoff and groundwater motion. In conclusion lower altitude, gentler slopes, can be associated with permeable materials presence, which will give greater infiltration system, which is conducive to greater likelihood of groundwater presence.

In some cases, authors found some vegetation related indices such as Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) to be necessary for their groundwater level prediction studies (Gómez-Escalonilla, et al., 2022a; Gómez-Escalonilla, et al., 2022b). High NDVI values from natural vegetation may potentially suggest the likelihood of groundwater availability (Sahour et al., 2022) as well as the NDWI which can detect water content and the presence of water bodies or moisture in the landscape. Land use and land cover integration is frequently employed in studies that map groundwater potential. This approach recognizes that land use changes, primarily driven by human activities, can significantly impact groundwater resources (Gómez-Escalonilla et al., 2022a). Geomorphology can be valuable in identifying characteristics that have the potential to facilitate groundwater infiltration and storage (Gómez-Escalonilla et al., 2022a). The depth of the water table is a valuable factor in mapping water tables as it helps identify the primary zones where aquifers are recharged and discharged (Gómez-Escalonilla et al., 2022a). Curvature describes the concavity or convexity of an area. Concave area, particularly those found at lower elevations, can indicate the distribution of depressions where groundwater is likely to be present (Sahour et al., 2022). In terms of groundwater, the distance to sapping features can be important for understanding their impact on groundwater flow and availability. The closer a sapping feature is to a location, the more likely it is to affect the groundwater dynamics in that area. Monitoring the distance to these features can help in assessing the potential for groundwater infiltration and storage in the surrounding region.

Figure 5, derived from our findings, shows the prevalence of geological variables in the studies examined. Geomorphology account for 38% of the usage followed by Hydrology making up 24% of usage in the studies. Topographic aspect had equal representation, each contributed 12%. Geological factors made up 26%. This suggests that geomorphology is the most studied geological variable, with hydrology following closely behind. Soil and topographic aspects have received equal attention, while geological factors are slightly more studied.

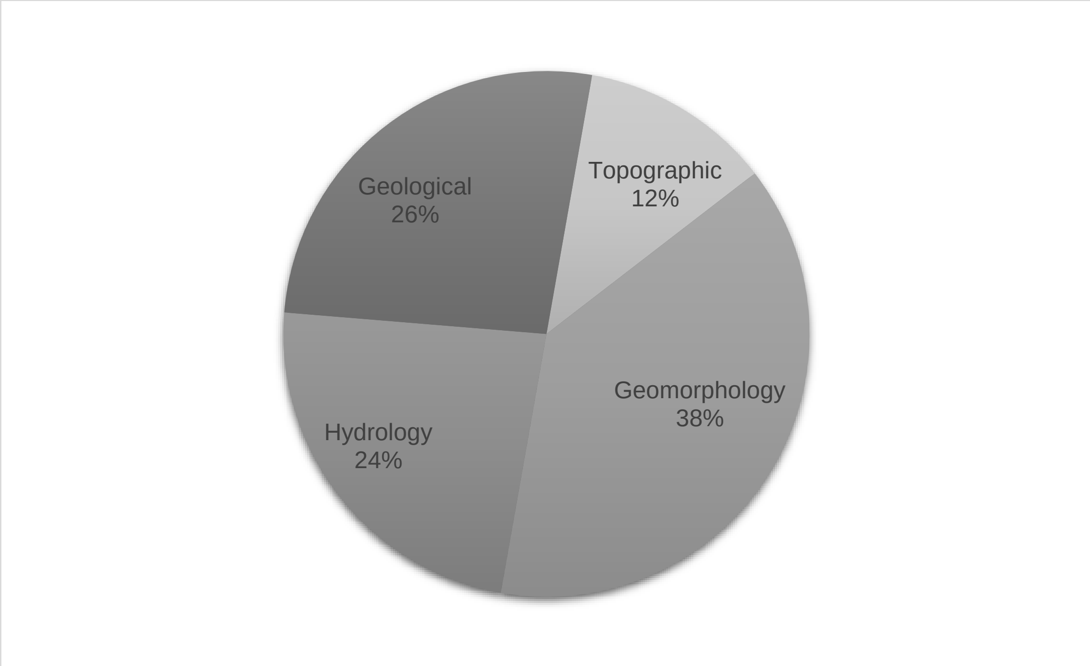

Fig 4 Frequently utilized geological input variables in ML studies across Africa.

3.5 Climatic variables affecting groundwater

Several studies such as Al-Gamal et al., (2009) ; Chen et al., (2004); Wu et al., (2020) examined the influence of climatic variables on groundwater levels in Africa and confirmed the serious impact of variation in precipitation, temperature, evapotranspiration on groundwater recharge. Table 3 shows the different climatic variables used in the different studies conducted in some African countries.

Table 3 Climatic variables used by the different case studies

References	Case study	Input variables	Output Parameters
Siabi et al., (2022)	Ghana	Potential Evapotranspiration Precipitation Temperature Rainfall	Groundwater Recharge (GWR)
Gómez-Escalonilla et al., (2022)	Mali	Rainfall	Groundwater Potential (GWP)
Gómez-Escalonilla et al., (2022)	Chad	Evapotranspiration Precipitation	Groundwater Potential (GWP)
Kanyama et al., (2020)	South Africa	Temperature Precipitation	Groundwater Potential (GWP)
Gaffoor et al., (2022)	South Africa	Evapotranspiration Rainfall Precipitation Temperature	Groundwater Level (GWL)
Aderemi et al., (2023)	South Africa	Rainfall	Groundwater Level (GWL)

		Temperature	
Kalu et al., (2022)	Southern Africa Region	Precipitation Temperature Global Climate Indices	Groundwater Level (GWL)
Sahour et al., (2022)	Egypt	Temperature	Shallow Groundwater (SGW)
Derbela et al., (2020)	Tunisia	Rainfall Evapotranspiration	Groundwater Level (GWL)
Gibson., (2020)	South Africa	Rainfall Temperature	Groundwater Level (GWL)
Ibrahimi et al., (2017)	Morocco	Precipitation Temperature	Groundwater Level (GWL)

Precipitation acts as the primary source of recharge for the aquifer according to Kanyama et al., (2020). Areas with high precipitation and low temperature had higher groundwater levels, while areas with low precipitation and high temperature had lower groundwater levels.

Changes in climate variables such as temperature, precipitation, evapotranspiration and rainfall can have a significant impact on the amount of water that seeps into the ground to replenish groundwater resources. For instance, increased temperatures and changes in precipitation patterns can lead to reduced groundwater recharge, while, increased evapotranspiration rates can further exacerbate this issue. Also, climate change can directly or indirectly impact groundwater resources (Wang et al., 2021). As such, understanding variation in climate, groundwater recharge is crucial for managing freshwater resources in a sustainable manner. The main source of groundwater recharge is rainfall. Recharge is influenced by the rate of precipitation as well as surface and subsurface elements that permit or prohibit infiltration (Gómez-Escalonilla et al., 2022a).

A large number of studies shows that groundwater level variation is indeed sensitive to variation in temperature (Chen et al., 2004; Hassan et al., 2022). A rise in temperature causes accelerated evaporation, lowering the recharge rate to the groundwater resource and leading to a drop in the groundwater table (Chen et al., 2004). In Africa, temperature can have a significant impact on groundwater due to the continent's diverse climate and geography. Variations in temperature can affect the rate of infiltration and groundwater recharge. Higher temperatures can increase evapotranspiration rates, which decreases the amount of water available for groundwater recharge. Based on this knowledge, we infer that with increased evapotranspiration and decreased precipitation, the impact of climate change will result in declining groundwater levels, which would cause some wells to become dry while others would become less productive due to the loss of available drawdown. Groundwater potential is largely influenced by groundwater recharge and recharge depends on five main factors which are climate (e.g. precipitation, temperature and potential evapotranspiration (PET)), soils (e.g.

texture, soil moisture), land cover (NDVI), geomorphology (e.g. landform surface slope and drainage density) and hydrology (e.g. streamflow and water table depth)(Gómez-Escalonilla et al., 2022a).

Our results enable us to visualize the ranks of different climatic variables based on their frequency of usage in studies analyzed (Figure 6). Temperature tops, with 36% of usage, followed by rainfall, appearing in 27% of the research h studies. Precipitation factors are also quite significant, making up 18%. Evapotranspiration is considered in 9% of the studies, while both Global Climate Indices and Potential Evapotranspiration seem to be less explored, each contributing to 5% of the studies. This implies that temperature and rainfall are the most commonly studied climate variables. Precipitation receives a fair amount of attention too. However, evapotranspiration, global climate indices, and potential evapotranspiration are studied less frequently, suggesting these areas might be ripe for further exploration in future research.

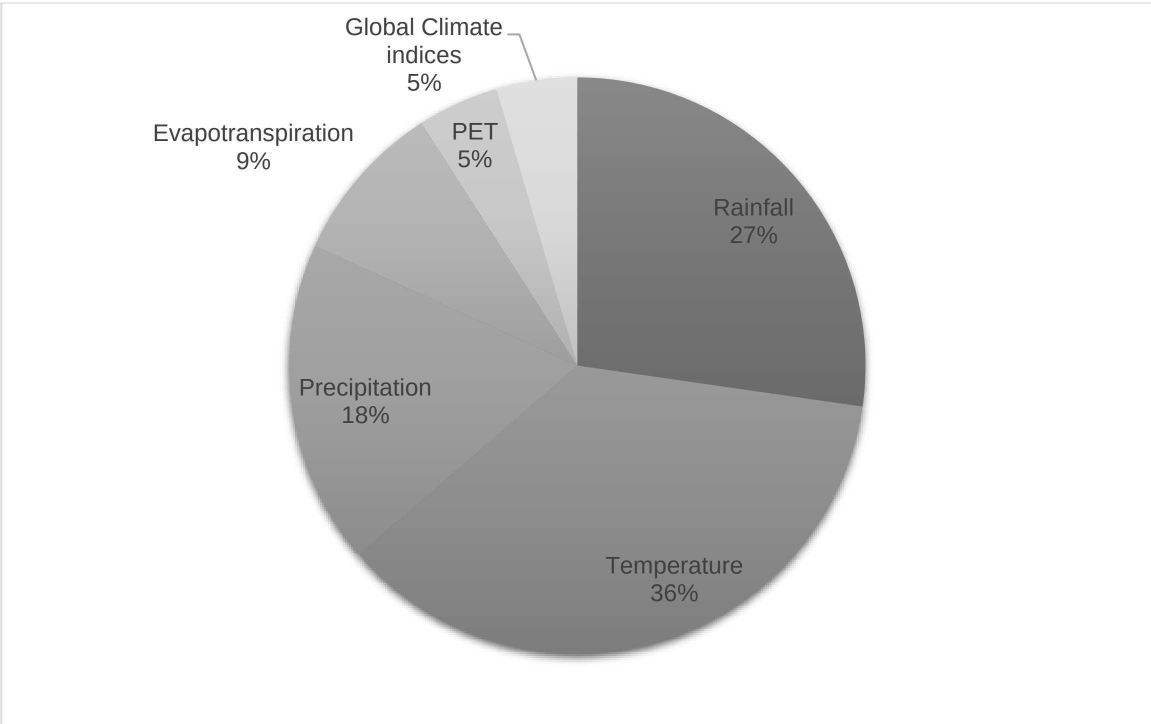

Fig 6 Frequently utilized climatic input variables in ML studies across Africa

4. Conclusion

This review aimed to conduct an extensive examination of the current literature concerning research utilizing machine learning methods for predicting groundwater availability and to compile a comprehensive inventory of the diverse machine learning algorithms, as well as the climatic and geological variables employed by the different researchers across Africa. The study, identified several essential elements in the existing ground water level (GWL) investigation models, including the algorithms used, input variables, and the target variables. One of the more significant findings from this study is that the available literature on GWL studies using machine learning methods in Africa is limited, but their widespread use and proven efficiency worldwide suggest that Africa could greatly benefit from relying on them in the field of groundwater. The second major finding was that, the most utilized algorithms for machine learning studies in groundwater investigation are the tree-based algorithms. In the studies we concentrated on, they predominantly demonstrated superior performance compared to other methods. Furthermore, we find that the most common input variables used for machine learning studies in groundwater investigations are the geomorphological parameters for geological inputs and temperature for climatic inputs. These findings have significant implications for the understanding of large-scale prediction of groundwater resources and how climate will affect groundwater resources going forward.

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