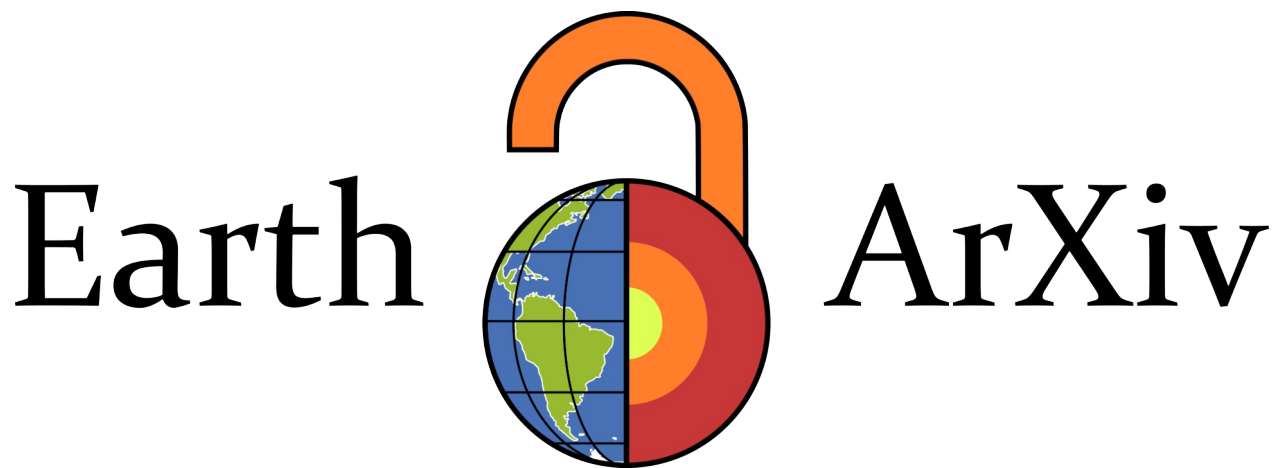




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Research Article

Groundwater Potential Mapping in Northwestern Nigeria: A Comparison of the Analytic Hierarchy Process and Galileo-Enhanced CAT-XGB

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Abstract

Global water scarcity intensifies the need for high-resolution groundwater assessment tools, yet traditional approaches struggle to reconcile qualitative expert weights with the extensive spatial coverage offered by remote sensing data. This study presents a comparative framework evaluating expert-driven Multi-Criteria Decision Analysis (a ten-layer Analytic Hierarchy Process (AHP)) against data-driven ensemble machine learning for groundwater potential mapping in the geologically complex terrain of Northwestern Nigeria. Standard thematic layers were integrated with embeddings from a pretrained remote sensing foundation model to train ensemble classifiers, with groundwater potential validated against Vertical Electrical Sounding (VES) data. The foundation-model-enhanced CAT-XGB ensemble achieved notable predictive performance, consistently outperforming standalone tree-based classifiers and traditional AHP. Spatial difference mapping revealed that the enhanced ensemble captured critical, localized hydrogeological anomalies smoothed over by expert-driven weighting. Bridging heuristic decision-making with foundation-model-enhanced machine learning significantly improves spatial precision and reliability, potentially providing a field-validated tool for optimizing borehole siting and sustainable aquifer management in data-scarce, geologically complex regions.

Impact Statement

As water scarcity grows in arid and data-scarce regions, finding reliable groundwater in geologically complex terrain remains a major challenge. Traditional groundwater mapping may overlook smaller, localized water sources. This study combines satellite foundation models with ensemble machine learning to map groundwater potential, with results validated by available field measurements. By identifying hydrogeological patterns that conventional mapping approaches may miss, the method offers a potential tool for hydrogeologists, water authorities, and planners. More accurate groundwater maps could help guide borehole placement, reduce unsuccessful drilling, and support long-term water security in vulnerable communities.

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1. Introduction

Groundwater is the most extracted natural resource in the world: it represents around 20% of the demand for global freshwater and over 40% of irrigated agriculture across the world (Biswas et al., 2020). The global aquifer systems are under unprecedented stress due to the combined pressures of rapid population growth, expanding agricultural demands and accelerating climate variability. United Nations projections indicate that over 5.7 billion people will live in areas with at least one month of severe water scarcity each year by 2050, placing groundwater at the heart of global food and water security (UNESCO 2022). In data-scarce parts of Sub-Saharan Africa, South Asia and parts of Latin America, groundwater is often the only reliable source of fresh water. Thus, accurate mapping of its spatial extent is not just an academic exercise but a development imperative. (Touré et al 2024).

Traditional methods of groundwater exploration include geophysical surveys, electrical resistivity tomography, and exploratory drilling, which produce data points of high accuracy. However, these methods are costly and logistically complex and are unable to provide spatially continuous assessments over large or inaccessible terrains (Morgan et al 2023). In geologically complex terrains, a single borehole can cost more than tens of thousands of dollars. Failure rates can be as high as 30–40% when siting is based only on field reconnaissance (Adama et al 2024). This economic and logistic burden has motivated a strong shift toward remote sensing (RS) and Geographic Information Systems (GIS)-based techniques for the delineation of Groundwater Potential Zone (GWPZ).

The GWPZ mapping evolution has passed through three paradigms. The first paradigm, knowledge-based, employs Multi-Criteria Decision Analysis (MCDA) frameworks, especially the Analytic Hierarchy Process (AHP), to integrate thematic layers by means of structured pairwise comparisons (Hilal et al 2024; Saaty 1980). AHP is robust and interpretable, but limited by the subjectivity of the weighting and the incapability to model non-linear interactions between hydrogeological parameters. The second paradigm was born with the machine learning revolution, which brought data-driven algorithms, like Random Forest, Support Vector Machines and gradient boosting variants, capable of detecting complex, non-linear patterns in multi-modal satellite datasets (Tseng et al 2025). However, standalone machine learning algorithms often suffer from instability in data-poor environments where borehole inventories are sparse or non-existent. In this study, the third and emerging paradigm is proposed, which combines heuristic knowledge and ensemble machine learning in a hybrid intelligence framework. The complementary strengths of the two approaches are leveraged. (Ajay Kumar et al 2020; Sarkar et al 2021).

Existing GWPZ literature has advanced significantly, but a longstanding gap remains in the rigorous, field-validated comparison of expert-driven and data-driven approaches. Although both AHP and machine learning methods have been independently validated in many regional applications, direct comparative studies that benchmark both paradigms against independent field data (rather than against each other, or against the absence of ground truth) remain relatively rare, especially in data-scarce, geologically complex basement-complex terrains such as Northwestern Nigeria (Touré et al 2024). In addition, a new generation of pretrained self-supervised remote sensing foundation models have recently demonstrated strong performance across a wide range of Earth observation tasks (Tseng et al 2025). Their application to groundwater potential mapping, and their comparative value relative to both AHP and conventional hand-engineered-feature ensemble classifiers remains largely unexplored.

This study seeks to fill these gaps by: (i) building a ten-layer AHP model for groundwater potential mapping, weighted using structured pairwise comparison and validated for internal consistency; (ii) training and evaluating ensemble machine learning classifiers, including Random Forest (RF), XGBoost (XGB), CatBoost, and their combined ensembles named CatBoost-XGBoost (CAT-XGB) and CatBoost-RF (CAT-RF), using both hand-engineered thematic layers and embeddings extracted from the Galileo pretrained remote sensing foundation model (developed by NASA Harvest, McGill University, and the Allen Institute for AI (Ai2)); and (iii) independently assessing both the AHP classification and the machine learning algorithms against groundwater potential class labels derived from Vertical Electrical Sounding (VES) field data, providing a direct, field-grounded comparison of expert-driven and data-driven approaches. The multi-modal data architecture consists of static geomorphological parameters obtained from Copernicus DEM, dynamic spectral indices from Sentinel-2, lithological and pedological data from United States Geological Survey (USGS), and rainfall data from IMERG NASA. The resulting framework provides a statistically rigorous and field-validated basis for selecting appropriate groundwater potential mapping methodologies in data-scarce and geologically complex environments.

2. Literature Review

2.1. The Analytic Hierarchy Process in Groundwater Potential Mapping

The Analytic Hierarchy Process (AHP) proposed by (Saaty 1980), and developed in subsequent works, has been a cornerstone methodology in GWPZ delineation owing to its systematic and transparent way to deal with multi-criteria decision-making. The AHP framework decomposes complex spatial problems into hierarchical structures and allows the quantitative integration of expert hydrogeological knowledge by means of structured pairwise comparison matrices. Its key advantage lies in the Consistency Ratio

(CR) metric, which formally limits the inconsistency of judgments to be below the threshold of 0.10, thus ensuring the logical consistency of weight assignments (Saaty 2008).

Recent applications of AHP in groundwater potential mapping have demonstrated its applicability in different geological and climatic settings from data-limited areas to groundwater stress areas (Falowo and Ojo 2023; Ifediegwu 2022; Saidu et al 2024; Tripathi et al 2025). In the Subarnarekha Basin of India, (Jain et al 2025) showed that using Fuzzy-AHP considerably improved the accuracy of delineating high-potential zones in hard-rock aquifer systems, with AUC validation scores of 0.88. Similarly, (Twaha et al 2024) applied GIS-AHP for the Great Ruaha River catchment, Tanzania and confirmed lithology and lineament density as the dominant parameters controlling groundwater in crystalline basement terrains. In Southern China, studies combining AHP with fuzzy membership functions were able to classify the groundwater potential with spatial consistencies of more than 85% when validated against spring discharge points in mountainous areas. Moses and Sathiyamoorthy (2025) demonstrated the efficiency of AHP-GIS integration in coastal aquifer environments, with NDWI and drainage density as the major discriminators in seawater intrusion zones.

However, the fundamental limitation of AHP is its inherent subjectivity. Weight assignments derived from expert judgment may differ significantly between practitioners leading to systematic bias, especially in geologically complex terrains where hydrogeological relationships are non-linear and spatially heterogeneous (Morgan et al 2023). The use of AHP based weighted overlay analysis, which uses linear additive models on fundamentally non-linear interactive hydrogeological systems, can lead to smooth potential gradients that may obscure localized anomalies that are of practical significance for bore-hole siting. These limitations have led to the systematic adoption of machine learning approaches as complementary or successor methodologies.

2.2. Machine Learning Approaches for Groundwater Potential Mapping

The delineation of GWPZ has witnessed a rapid expansion in the use of machine learning (ML) applications in the last decade, facilitated by advances in computational capability, the democratization of cloud-based geospatial platforms, and the growing availability of high-resolution satellite data archives. Recent groundwater potential studies have shown good predictive capability of machine learning and ensemble methods in various hydrogeological environments (Halder et al 2024; Hosseini et al 2025).

Among individual ML classifiers, Random Forest (RF) has been the most frequently used classifier for GWPZ mapping because of its resistance to overfitting, native capacity to deal with high-dimensional feature space, and interpretable variable importance. In drought-prone Eastern India, studies revealed RF accuracies of 0.943 for delineating GWPZ in the Bankura district, with lineament density and TWI ranked as the most influential predictors (Halder et al 2024). Support Vector Machines (SVM) have also consistently performed but their computational demands and sensitivity to kernel function selection limit their application in large-area studies (Slanič et al 2021). Deep Neural Networks (DNN) represent the most computationally intensive approach but require a lot of training datasets that are rarely available in data-scarce groundwater mapping contexts (Nguyen et al 2024).

The Extreme Gradient Boosting (XGBoost) algorithm has emerged as one of the best performing individual models for spatial groundwater prediction. XGBoost uses L1 and L2 regularization, second-order gradient statistics for accurate tree splits and in-built missing value handling, making it highly robust in heterogeneous, sparse geospatial datasets (Chen and Guestrin 2016). The applications in Luoning County, China, showed XGBoost with an accuracy of 89.9%, with TPI, distance to rivers, and TWI as the dominant predictors (Xiong et al 2023). In Vietnamese Gia Lai Province, XGBoost

outperformed CatBoost and DNN on all evaluation metrics including RMSE, MAE and AUC (Nguyen et al 2024). A meta-analysis of XGBoost applications in GWPZ studies have found consistent accuracies above 80% across diverse geological settings, ranging from 81.8% in Busan metropolitan contexts to 98.3% in Balochistan alluvial systems (Rasool et al 2022).

More recently, CatBoost (Categorical Gradient Boosting) has also gained substantial traction in the GWPZ mapping, particularly for datasets with categorical variables, such as lithology classes, LULC categories, and soil texture types. Compared to XGBoost, which requires explicit one-hot encoding or target encoding of categorical predictors, CatBoost natively handles categorical data with ordered boosting and statistical encoding techniques, lowering the risk of target leakage and overfitting (Prokhorenkova et al 2018). Hosseini et al (2025) reported that a Bayesian-optimized CatBoost model had an AUC of 0.8778 in Fars Province, Iran, which was higher than a similarly tuned Random Forest model (AUC = 0.8396). The study additionally employed Boruta-XGBoost feature selection and SHapley Additive exPlanations (SHAP) - based interpretability. This helped identify geology, lineament density and TWI as the vital factors and it also matches with what other studies have found.

2.3. Ensemble Learning Architectures in Spatial Hydrology

The frontier of GWPZ modeling is the ensemble learning architectures that integrate multiple base learners to obtain better predictive stability, lower bias and variance, and more effective generalization across various geological contexts (Sarkar et al 2021). Ensemble methods can be classified into bagging methods (e.g. Random Forest), boosting methods (e.g. AdaBoost, XGBoost, CatBoost, and LightGBM), and stacking methods that use a meta-learner to combine the predictions of heterogeneous base models.

The use of stacking ensemble models that incorporate boosting techniques has shown great promise for the use of spatial hydrology. Recent research has shown the effectiveness of using ensemble and explainable machine learning models for the prediction of groundwater potential by incorporating the ability to utilize several hydrogeologic and environmental predictors (Hosseini et al 2025; Kasahun et al 2026). A recently developed stacking ensemble involving RF, XGBoost, LightGBM, and CatBoost for downscaling the groundwater storage anomalies from GRACE in Sri Lanka produced more accurate results compared to individual component models because of its ability to detect both spatial and temporal variation (Karunarathna et al 2026). Similarly, Halder et al (2024) demonstrated that voting ensembles consisting of the combination of XGBoost and AdaBoost algorithms always performed better than any single algorithm when applied to the problem of droughts in India, scoring F1-scores of 0.958. Such results are consistent with the theoretical perspective proposed by (Sarkar et al 2021), who found that ensembles reduce variance in prediction by 15-25%.

The specific combination of CatBoost and XGBoost in the framework of the Galileo-enhanced CAT-XGB approach explored in this paper utilizes a complementary duality whereby XGBoost's proficiency in the numerical feature optimization and regularization is supplemented by the intrinsic ability of CatBoost to cope with categorical variables thus contributing to a more thorough representation of the heterogeneous space of mixed features typical for multi-modal groundwater datasets (lithological classes together with continuous topographic and spectral bands). The studies of (Xiong et al 2023) and (Nguyen et al 2024) independently validated the idea of the complementary nature of errors made by both algorithms when they were applied to GWPZ datasets, with XGBoost performing better on numerical gradient features (SPI, TWI) while CatBoost showing its superiority in classification of categorical inputs (LULC, soil type, lithology).

2.4. *Foundation Models and Self-Supervised Embeddings*

A relatively newer approach in geospatial machine learning involves the training of pre-trained self-supervised foundation models for remote sensing, where feature representations (embeddings) are learned in a generalizable manner from large amounts of unlabeled and multimodal earth observation data, as opposed to manually engineered thematic layers such as NDVI and TWI. While the individual classifiers and ensembles described above take manual indices of the spectra and geomorphology as their input, the pre-trained models do not require any additional feature engineering before being used in downstream applications through methods like nearest-neighbor classification, linear probing, or finetuning.

One of the most recent and versatile models within this framework is Galileo (Tseng et al 2025), which uses the global and local self-supervised learning objective for joint representation of optical, radar, elevation, weather, and other remote sensing modalities at multiple levels of resolution and time scale and achieves state-of-the-art results on eleven remote sensing benchmarking datasets including both classification and segmentation tasks. However, despite the fact that the model itself and other foundation models (such as AlphaEarth Foundations) have recently found their application in landslide susceptibility mapping, fuel moisture content calculation, and groundwater depth estimation in data-limited catchments, their use for groundwater potential zones classification, especially in the comparison with AHP and conventional ensemble models, is still unexplored, to the best of our knowledge. Therefore, we fill this gap by testing if Galileo-based embeddings enhance the groundwater potential classification accuracy when used as an input to CAT-XGB ensemble in contrast to hand-engineered thematic layers.

2.5. *Multi-Modal Data Frameworks for Groundwater Analysis*

The effectiveness and generalizability of the newer GWPZ models are inherently dependent on the size and detail of the multimodal data inputs. Four major types of data have been identified to provide the necessary characterizations of the hydrogeological system (Kanito et al 2025). Topographical data, especially parameters derived from DEMs, are crucial for geomorphological GWPZ modeling. The Copernicus DEM with a global 30-m resolution allows calculating the Topographic Wetness Index (TWI), which is an indicator of how prone a cell is to accumulating water, as well as the slope gradient and the drainage network structure. The TWI has been established to be one of the most important predictive variables in machine learning models applied to GWPZ prediction and ranked first in 67% of all analyzed cases (Kanito et al 2025).

Vegetation and thermal spectral indices derived from Sentinel-2 and Sentinel-3 remote sensing data act as proxy indicators for the occurrence of shallow groundwater. Normalized Difference Vegetation Index (NDVI) is an indicator of soil moisture content and plant health status, where anomalous high NDVI in desert areas would be a sign of the existence of a shallow water table feeding phreatophytes (Moses and Sathiyamoorthy 2025). Normalized Difference Water Index (NDWI) focuses on detecting open water and soil moisture content. LULC classification considers landscape dynamics controlled by recharge mechanisms.

The integration of meteorological information, especially the spatial distribution of rainfall patterns, has become one of the key factors behind the evaluation of the dynamic GWPZ. The data provided by the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) and Integrated Multi-satellite Retrievals for the Global Precipitation Measurement mission (IMERG) are examples of precipitation estimates based on satellite observation at a resolution of about 10 km per day, allowing the characterization of recharge drivers at the scale of aquifer management (Touré et al 2024). IMERG data used in this research is the newest generation of multi-satellite precipitation data.

The lithological and pedological data from the USGS database gives the geological background description that is needed for understanding the distribution of the permeability and aquifer geometry. The lineament density, which results from structural geology interpretation, shows the channels for the deep groundwater flow through faults, fracture and dykes, which is of utmost importance when dealing with crystalline basement and volcanic terrain areas. It is precisely this integration of all four sets of data in one multi-modal system that is the most advanced technique in the modern science of GWPZ characterization.

2.6. AHP versus Machine Learning

While a considerable amount of literature independently has been accumulated on AHP-based and ML-based methods of groundwater potential zoning discussed above, research comparing both paradigms in terms of their performance on a common independent ground-truth data set is rather scarce. While most of the ML-based GWPZ research validate models' performance by splitting boreholes or springs data set into train-test parts, AHP-based research is mostly conducted on a qualitative basis or through checking of results against non-standardized field data (Ajay Kumar et al 2020). Comparing both approaches under the same conditions in relation to a common independent dataset would help water resource managers decide on using either expert-driven or data-driven methods of groundwater zoning.

Vertical Electrical Sounding (VES), a resistivity geophysical technique that has gained wide use for aquifer characterization and borehole site selection in basement-complex environments (Adama et al 2024) is an alternative, practical source of labels from field-based groundwater classes in areas where borehole yield databases are rare or absent. Despite being employed for point scale hydrogeological analysis for decades, systematic application of VES to independent testing of AHP and ensemble machine learning models and allowing for direct comparison of the two approaches through their field-based outputs is not well explored in existing literature. This work seeks to fill this research gap by comparing AHP and various ensemble machine learning models with both engineered features and foundation models on the same VES-based ground truth in the data-scarce basement complex environment.

3. Methodology

3.1. Study Area

The study region lies within northwestern Nigeria, and includes eight states: Sokoto, Kebbi, Zamfara, Katsina, Kaduna, Kano, Niger, and the Federal Capital Territory (Abuja). This is an area of complex geological structure which involves heterogenous lithologic assemblage (see Figure 1 below), diverse topographic relief, and variable rainfall patterns. In such conditions, the region is a good place to conduct research on the basis of ensemble intelligence because of the presence of pronounced spatial variability in hydrogeological features, challenging the linear and weighting-based mapping techniques.

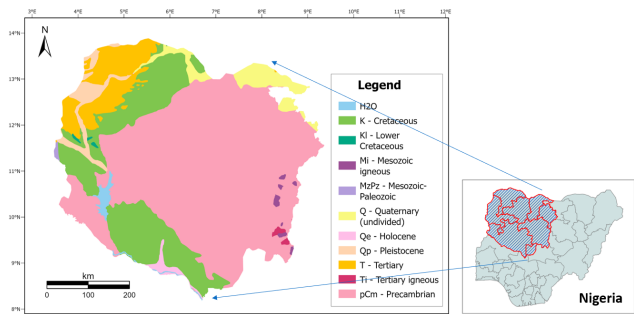


Figure 1. Area of Study Map and Geological Map of the Area of Northwestern Nigeria.

3.2. Overview of the Dual-Pathway Framework

Figure 2 shows the entire workflow for groundwater potential mapping employed in the current study. It involves the development of thematic layers based on remote sensing, DEM-derived parameters and traditional geospatial datasets. The thematic layers serve as common factors associated with groundwater for both parallel paths in the process of groundwater potential mapping. In the first path, the Analytic Hierarchy Process (AHP) is used for the purpose of classifying and weighing the thematic factors before integration into a GIS environment to produce the groundwater potential map by AHP method. In addition to the first path, the second path is concerned with machine-learning methods. It involves individual machine learning methods such as Random Forest (RF), XGBoost (XGB), and CatBoost (CAT), as well as the ensembles of CAT-RF and CAT-XGB. Once the model is chosen, trained, and predicted, the machine-learning method results in producing the groundwater potential map. Finally, the outputs obtained from the two paths can be evaluated by using the same validation dataset, thereby making comparison possible between them.

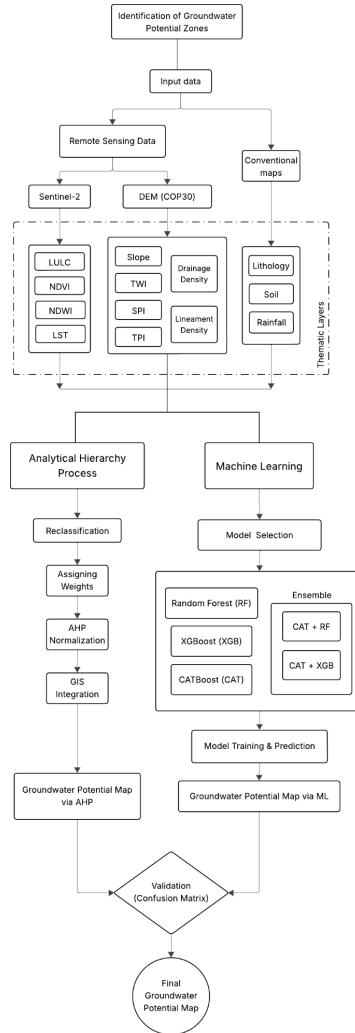


Figure 2. Schematic workflow of the dual-pathway ensemble intelligence framework.

3.3. Multi-Modal Data Acquisition and Thematic Layer Preparation

The multi-modal data set used for this study is classified into three complementary classes that together encompass the static geomorphology, dynamic environment surface characteristics, and meteorological driving forces of the groundwater system.

Static geomorphological layers were derived from the Copernicus Digital Elevation Model (DEM) with 30-m spatial resolution (year of data acquisition: 2020) which constitutes the most sophisticated, global coverage topographical dataset currently available to support hydrological operations. From the DEM data set, the following five important indices have been selected: (i) Slope, which defines the steepness of the terrain and influences runoff generation; (ii) Topographic Wetness Index (TWI), calculated as;

$$TWI = \ln \left(\frac{\alpha}{\tan \beta} \right) \quad (3.1)$$

where α is the specific upslope contributing area and β is the local slope gradient, serving as a primary proxy for soil moisture distribution and subsurface saturation potential; and (iii) Drainage Density, calculated using the stream network derived from the DEM, is the measure of surface drainage channel density per unit area that represents the measure of subsurface permeability, infiltration, and recharge capacity, with low values of drainage density being associated with high infiltration and groundwater recharge.

Lineament Density was generated using lineament extraction techniques based on hill-shade raster images and validated with available structural geology data, where it described the density of fractures and fault systems that act as primary conduits for deep circulation of ground water in crystalline bedrock terrain. Soil type and lithology data were extracted from the USGS databases to provide the geological substratum necessary for permeability and aquifer type analysis.

Dynamic Environmental Layers were generated using Sentinel-2 MultiSpectral Instrument (MSI) imagery because of its high resolution and revisit frequency of 5 days. Seasonal composite images were generated to avoid the issue of clouds in the imagery. Three spectral indices were calculated:

(i) **Normalized Difference Vegetation Index (NDVI)**

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (3.2)$$

where NIR represents the near-infrared wavelength and Red represents the red-light wavelength. NDVI serves as a proxy for vegetation health, soil moisture, and a potential shallow groundwater influence on surface vegetation;

(ii) **Normalized Difference Water Index (NDWI)**

$$NDWI = \frac{Green - NIR}{Green + NIR} \quad (3.3)$$

where Green represents the green-light wavelength and NIR represents the near-infrared wavelength. NDWI directly targets surface water bodies and soil moisture signatures;

(iii) **Land Use/Land Cover (LULC)**, generated through supervised classification of Sentinel-2 imagery into primary cover categories relevant to groundwater recharge dynamics.

Meteorological data in terms of spatially distributed rainfall were collected from the IMERG NASA dataset with daily precipitation at a spatial resolution of 0.1°. IMERG Late Run products have been used due to their best trade-off between timeliness and calibration accuracy. Rainfall accumulation per year and per season was calculated to describe the recharge potential of the aquifer and its temporal variability. The variable ‘rainfall’ has been used as a recharge agent in the AHP weighting method and as an input variable for the Galileo-Enhanced CAT-XGB machine learning ensemble model.

Data from all sources have been resampled to the same 30 m resolution and projected to the same coordinate reference system. Missing data resulting from satellite data gaps and cloud presence have been

accounted for by temporal compositing and spatial interpolation based on inverse distance weighting. Standardization was done before the training of machine learning models.

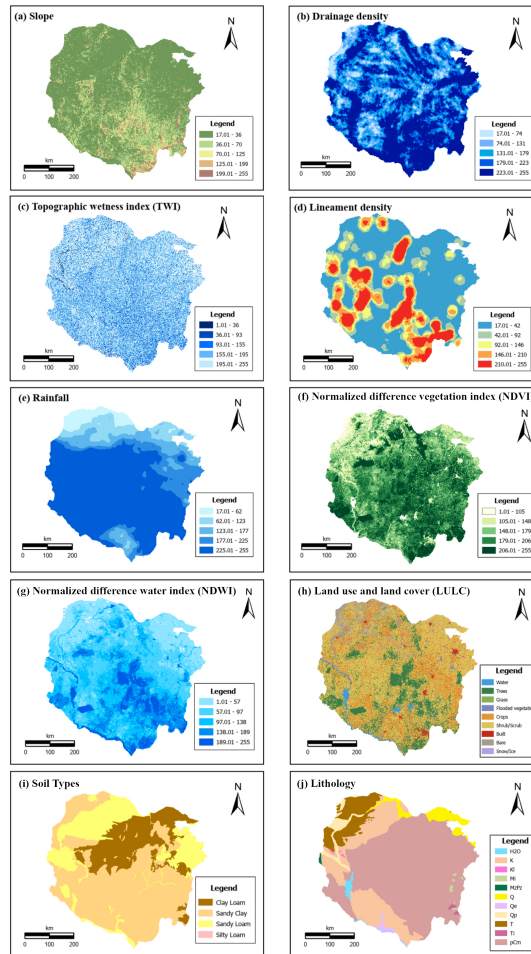


Figure 3. Input thematic layers used for AHP and machine-learning groundwater potential mapping.

3.4. Analytic Hierarchy Process (AHP) for an Expert-driven Groundwater Potential Mapping

Application of the AHP technique was carried out in a sequential four-step process after Saaty (Saaty 1980, 2008). In the first step, the groundwater potential issue was structurally arranged in the form of hierarchy with ten criteria layers - Lithology, Lineament Density, Rainfall, Drainage, Slope, TWI, Soil, LULC, NDVI, and NDWI, while five groundwater potential classes (Very High, High, Moderate, Low, and Very Low) were considered as decision alternatives. In the second step, pair-wise comparison matrices were formed for all criteria in which pair-wise comparison scores were given using Saaty's 1-9 basic scale after considering hydrogeological literature and expert opinion. Weights generated by the principle eigenvector of the decision matrix revealed that Lithology (29.4%) and Lineament Density (21.5%) are the dominant criteria which together comprise more than half of the total weight of the

model which is in accordance with the nature of the fracture dominated hydrogeology of the crystalline basement terrain of the study area. Consistency Ratio (CR = 3.2%) ensured consistency of pair wise judgment.

Table 1. *AHP-derived weights and relative ranking of the ten groundwater-conditioning layers..*

Input Layer	Weight (%)	Rank	Standard Deviation (%)
Lithology	29.4	1	10.9
Lineament Density	21.5	2	6.8
Rainfall	15.4	3	4.5
Drainage Density	10.9	4	3.2
Slope	7.6	5	2.3
TWI	5.4	6	1.7
Soil Type	3.8	7	1.2
LULC	2.7	8	0.9
NDVI	1.9	9	0.7
NDWI	1.5	10	0.7

The thematic layers after combining were then classified into five possible classes using the Jenks' natural breaks classification system. The classes were then integrated using weighted linear combinations to develop the baseline AHP groundwater potential map.

3.5. *Galileo-Enhanced CAT-XGB Ensemble Machine Learning Architecture*

Labels of the five groundwater potential classes for machine learning model training were produced from unsupervised Gaussian Mixture Model (GMM) clustering on the multi-modal predictor space. The predictor set included the ten groundwater-conditioning thematic maps listed in Section 3.3, taking into consideration the Galileo-derived representations in the foundation model enriched version. Clusters found with the help of the GMM method consisted of five hidden categories that represent different combinations of hydrogeological and environmental settings in the region under study. Due to the fact that there is no ordering within GMM clusters related to hydrogeology, further interpretation of the clusters was performed based on their predictors' combination and groundwater-favorable conditions such as high topographic wetness, high lineament density, favorable lithological setting, and low slope. The obtained clusters were classified into the following five groundwater potential classes: Very Low (1), Low (2), Moderate (3), High (4), and Very High (5). Pseudo-labels received from the GMM rather than the AHP classification became the five-class target labels for supervised machine learning.

In order to improve the spatial characteristics of the classical thematic predictors, embeddings of the pretrained Galileo remote sensing foundation model were used within the ML pipeline. Galileo offers learned representations of Earth observation data at different spatial scales and different remote-sensing modalities (Tseng et al 2025). The generated Galileo feature representation was evaluated using Random Forest, XGBoost, CatBoost, CAT-RF, and CAT-XGB classifiers within the same five-class groundwater potential framework. CAT-XGB is an architecture combining the CatBoost and XGBoost, which are both gradient-boosting algorithms with distinct learning approaches. While XGBoost applies regularized gradient boosting with second-order optimization, CatBoost utilizes ordered boosting to lower the prediction bias and to effectively learn complex interactions among features (Prokhorenkova et al 2018), thus capturing complex nonlinear dependencies (Chen and Guestrin 2016).

In the process of developing the model, the GMM-labeled dataset was split into 70% training and 30% testing data sets through stratified random sampling so as to maintain the same distribution ratios of all five classes of groundwater potentials. Optimization of hyperparameters for each model in the ensemble was carried out by a grid search method with cross-validation through parameters such as learning rate, maximum depth of trees, number of estimators, strength of regularization, and subsampling rate. In developing the final CAT-XGB ensemble, a soft voting mechanism was used to combine class probability outputs of two independently trained CatBoost and XGBoost models based on their validation accuracy levels. This developed ensemble produced a five-class continuous groundwater potential map, which was further tested using classification metrics and compared with other Galileo models. Field validation of the model against 86 VES data points was carried out independently as explained in Section 3.6.

3.6. Independent VES-Based Field Validation

The AHP classification and CAT-XGB prediction methods were independently verified against 86 field Vertical Electrical Sounding (VES) measurements obtained in the Northwestern Nigeria study area. As part of the validation process, these 86 VES field points were not used in the generation of either classification method (i.e., neither in the determination of weights for the AHP-based classification nor in pseudo-labeling of samples for the CAT-XGB model training using Gaussian Mixture Models (GMM)). For each model, the locations of the VES points were overlayed onto the respective 5-class prediction maps, and the predicted groundwater potential class was obtained at each VES point. This resulted in 86 paired observations (class according to VES vs. model prediction) for each classification technique. These results were compiled in the form of a confusion matrix for each classification method, allowing for calculation of the following parameters: Overall Accuracy, Precision, Recall, F1-score, and Cohen's Kappa for all classes. Using the same validation procedure and metric set for both classification techniques allows for a direct and field-tested comparison of the results.

The paired VES and class predictions were used to generate confusion matrix and compute values of Overall Accuracy, Precision, Recall, F1-score, and Cohen's Kappa (κ) (Landis and Koch 1977) [Refer Table 2]. Cohen's Kappa takes into account the possibility of agreement by chance and its formula is expressed by the equation:

$$\kappa = \frac{p_o - p_e}{1 - p_e} \quad (3.4)$$

where p_o represents the observed proportion of agreement between the predicted and VES-derived groundwater potential classes, and p_e represents the expected proportion of agreement by chance.

The validation of the VES and the performance measurements were carried out for both AHP and machine learning models so as to have a consistent comparison of the two different methodologies used to create maps for groundwater potential on the basis of field results. In the case of the machine learning approach, however, the prediction performance of the model on the test data set was separated from the VES validation results.

4. Results

4.1. AHP-Based Groundwater Potential Map

The resulting AHP groundwater potential map (Figure 6, left panel) exhibited spatially coherent zones of varying groundwater favourability, with Very High potential zones clustered in areas that combined low-slope alluvial plains, high lineament density and high TWI, consistent with expected

hydrogeological patterns for the study geology. The High and Very High classes form discrete patches: the largest lies in the south-central part of the study area, with smaller ones along the western margin, in the southeast, and in a narrow north–south band in the north-central part. Low potential covers most of the eastern half, and the Very Low class is confined mainly to a large area in the north.

The pattern is shaped mainly by lineament density and rainfall, the second- and third-ranked layers (21.5% and 15.4% of the total weight). High-potential patches coincide with the lineament-density hotspots, and the northern Very Low area in the north sits where rainfall scores are lowest and lineaments are sparse. The circular halos visible across the Low and Moderate areas appear to be inherited from the lineament-density layer. Overall, the AHP surface is smooth and patchy, serving as a traditional baseline for groundwater potential analysis.

4.2. Galileo-Enhanced CAT-XGB Groundwater Potential Map

The resulting Galileo-enhanced CAT-XGB groundwater potential map (Figure 6, right panel) shows a similar broad trend as the AHP map, however, it exhibits a highly detailed, data-driven spatial pattern that contrasts sharply with the smooth appearance of AHP baseline. Instead of isolated patches, the High and Very High potential classes form a pronounced, spatially continuous corridor extending through the south-central portion of the region, accompanied by prominent High-potential belts along the western and southwestern margins. The Moderate potential class occupies a broad central-to-eastern transition zone, while the Very Low and Low classes dominate the northern and northeastern extents.

Unlike the AHP surface, which inherits distinct circular halos from the buffered lineament-density layer, the CAT-XGB map displays sharp class boundaries and localized spatial variation, reflecting the non-linear decision boundaries learned by the gradient-boosted trees. By integrating multi-scale foundation-model embeddings with surface hydrogeological predictors, the model captures fine-grained spatial transitions, yielding a potential surface that highlights interconnected high-yield zones while suppressing artifact-driven smoothing.

4.3. Galileo-Enhanced CAT-XGB Ensemble Performance and Model Comparison

The Galileo-Enhanced CAT-XGB ensemble model demonstrated exceptional predictive performance across all evaluation metrics, substantially and consistently outperforming each of the three individual benchmark models tested under identical training conditions. A detailed comparison of comprehensive performance of all tested models is presented in Table 2.

Table 2. Performance Comparison of Machine Learning Models for Groundwater Potential Classification.

Model	Accuracy	F1-Score	AUC	Cohen’s Kappa	Rank	Remark
Galileo-Enhanced CAT-XGB (Ensemble)	0.9501	0.9483	0.9976	0.9324	1	Highest accuracy and F1-score
XGB	0.9492	0.9476	0.9975	0.9313	2	Strong performance, closely following CAT-XGB
CAT	0.9451	0.9423	0.9971	0.9256	3	Consistent classification performance
CAT-RF (Ensemble)	0.9429	0.9400	0.9968	0.9227	4	Competitive ensemble performance
RF	0.9208	0.9179	0.9938	0.8931	5	Lower performance relative to the other evaluated models

The Galileo-Enhanced CAT-XGB ensemble achieved an overall accuracy of 0.9501, an F1-score of 0.9483, AUC of 0.9976 and Cohen’s Kappa value as 0.9324, placing this study among the highest-performing GWPZ ensemble frameworks in recent literature. For comparison, a recent optimized CatBoost implementation in Iran achieved an AUC of 0.8778 (Hosseini et al 2025), an SSA-XGBoost framework for groundwater potential mapping in China achieved an AUC of 0.8812 (Zhao et al 2026), and stacked ensemble approaches in Sri Lanka reported their highest AUC through the ensemble combination rather than any individual model (Karunaratna et al 2026). The Galileo-Enhanced CAT-XGB ensemble’s AUC of 0.9976 demonstrates strong discriminative performance within the internal evaluation framework. This high AUC indicates that the ensemble can effectively distinguish among the groundwater potential classes obtained from the GMM-based pseudo-labeling framework. However, since these pseudo-labels were used as a proxy for training targets and not independent field observations, the model’s generalizability was further evaluated on the independent VES dataset.

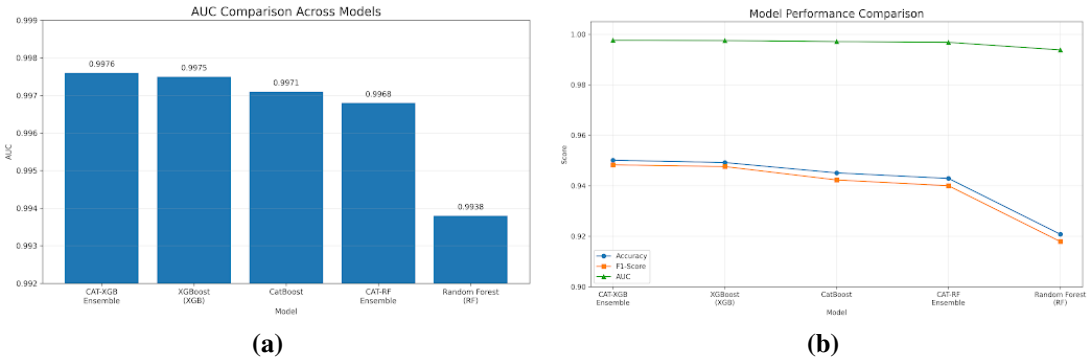


Figure 4. Comparison of machine-learning model performance: (a) AUC values across the evaluated models and (b) comparison of Accuracy, F1-score, and AUC across models..

The Galileo-Enhanced CAT-XGB ensemble model achieved the best overall performance of the evaluated models with an accuracy of 0.9501, F1-score of 0.9483, and AUC of 0.9976. Its performance was closely followed by XGBoost (ACC: 0.9492, AUC: 0.9975), CatBoost (ACC: 0.9451, AUC: 0.9971),

the CatBoost-RF ensemble (ACC: 0.9429, AUC: 0.9968), and Random Forest (ACC: 0.9208, AUC: 0.9938). The good performance of the CAT-XGB ensemble shows that by combining complementary model characteristics marginal improvements in classification can be expected. This observation is consistent with the broader motivation for ensemble learning where complementary patterns of prediction can be informative for model robustness (Sarkar et al 2021). The macro F1-score (0.9483) and accuracy (0.9501) of the CAT-XGB model indicates relatively consistent performance across the five groundwater potential classes.

4.4. Confusion Matrix Analysis

The confusion matrix analysis was used to evaluate the performance of the Galileo-Enhanced CAT-XGB model against the independent VES-derived groundwater potential classes. The final five-class groundwater potential map generated by the CAT-XGB model was spatially overlaid with the VES field locations. The predicted groundwater potential class was extracted at each corresponding VES coordinate, and these predictions were then compared with the VES-derived reference classes, enabling model performance to be assessed independent of the data used during model development.

The normalized confusion matrix showed strong diagonal concentration across the five groundwater potential classes, implying a strong agreement between the CAT-XGB predictions and the VES-derived reference classifications (Figure 5). The Moderate class showed the highest agreement at 96.6% while the Low class exhibited a slightly higher confusion with neighboring groundwater potential categories. Most classification disagreements occurred between adjacent classes, suggesting that the model generally preserved the ordinal groundwater potential pattern even where exact class assignments differed.

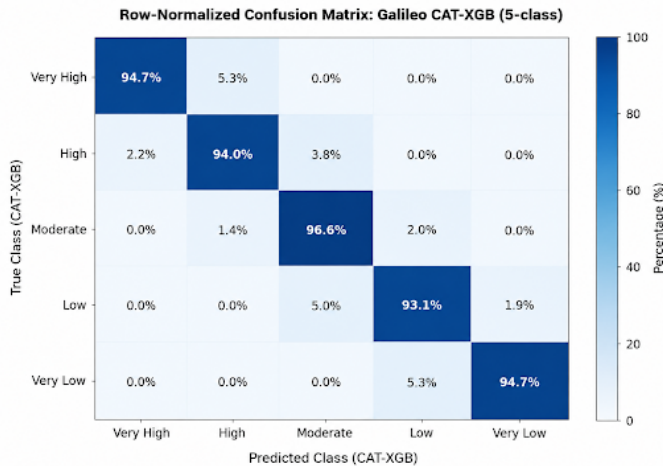


Figure 5. Row-normalized confusion matrix comparing the five-class Galileo-Enhanced CAT-XGB groundwater potential predictions with the VES-derived reference classes..

Overall, the confusion matrix shows strong correspondence between the spatial predictions produced by the Galileo-Enhanced CAT-XGB model and the independent VES-based reference data. Because the VES observations were used only for post-hoc validation and not as model inputs or training labels, this comparison provides an independent field-based assessment of the model’s ability to represent groundwater potential conditions at the available VES locations.

4.5. Comparison of AHP and Galileo-enhanced CAT-XGB validated by VES observations

Comparing the two 5-class groundwater potential maps derived using the traditional AHP method and the Galileo-enhanced CAT-XGB method, we can tell the two maps agree on the broad layout, placing the highest potential in the western and south-central parts of the study area and the lowest in the north (Figure 6). However, they differ in texture: the AHP map appears more patchy, with circular halos around its high-potential cores, whereas the CAT-XGB map forms smoother, more contiguous zones with less noise and fewer isolated cells.

The most noticeable refinements occur along lithological boundaries, structurally controlled lineament corridors, drainage networks, and areas exhibiting strong topographic variation. As Galileo preserves the ranked contribution of each conditioning factor during feature fusion, high-priority variables such as rainfall, lithology, lineament density, and topographic wetness exerts a greater influence while still allowing the ensemble to learn higher-order interactions with the remaining variables. Consequently, the Galileo-enhanced CAT-XGB model reduces false-positive high-potential zones produced by isolated favorable factors and produces more spatially coherent groundwater potential classes that better reflect the combined hydrogeological processes governing groundwater occurrence. These refinements demonstrate the advantage of combining expert hydrogeological knowledge with data-driven ensemble learning, resulting in a prediction surface that is both physically meaningful and statistically robust.

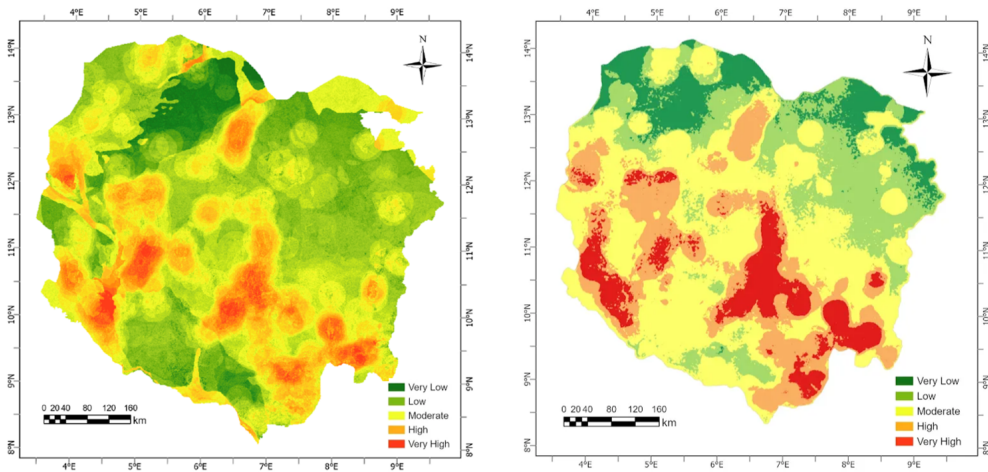


Figure 6. AHP Map and Galileo-Enhanced CAT-XGB Ensemble Map for Northwestern Nigeria Groundwater Prediction Mapping.

Then we extracted the predicted class at each of the 86 VES sites and compared it with the VES class. Noticeably, the VES sites sample only a small part of the study area, so all statistics below describe agreement at those locations and should not be read as pixel-wise map accuracy. As shown in the confusion matrices (Figure 7), CAT-XGB reproduced the VES class exactly at 27 of the 86 sites (31.4%), against 15 sites (17.4%) for AHP. The matrices also imply that AHP tends to concentrate predictions toward High and Very High classes even when VES indicates lower classes, while CAT-XGB achieved more diagonal matches and corresponds with VES better than AHP in exact classification.

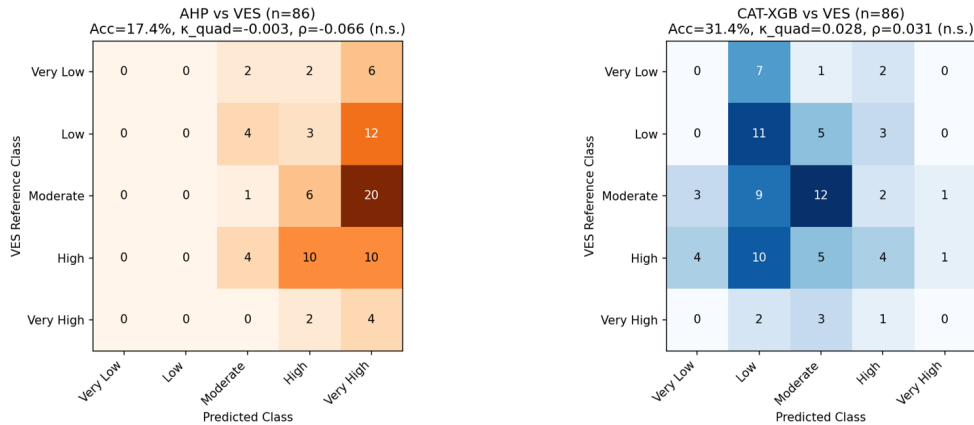


Figure 7. Comparison of confusion matrices of AHP vs VES and CAT-XGB vs VES.

The class-distance distribution (Figure 8) between predicted and VES classes provides more information than comparing at exact agreement alone, as it shows how far each prediction misses. The result shows that CAT-XGB errors were concentrated mostly at short distances: 66.3% of its predictions (57 sites) lay within one class of the VES class, against 47.7% (41 sites) for AHP. The pattern reversed at long distances. Errors of two classes or more affected 33.7% of CAT-XGB sites (29) and 52.3% of AHP sites (45), and only AHP produced errors of four classes (6). Overlaying the VES sites on the two maps (Figure 9) further shows where these errors fall spatially.

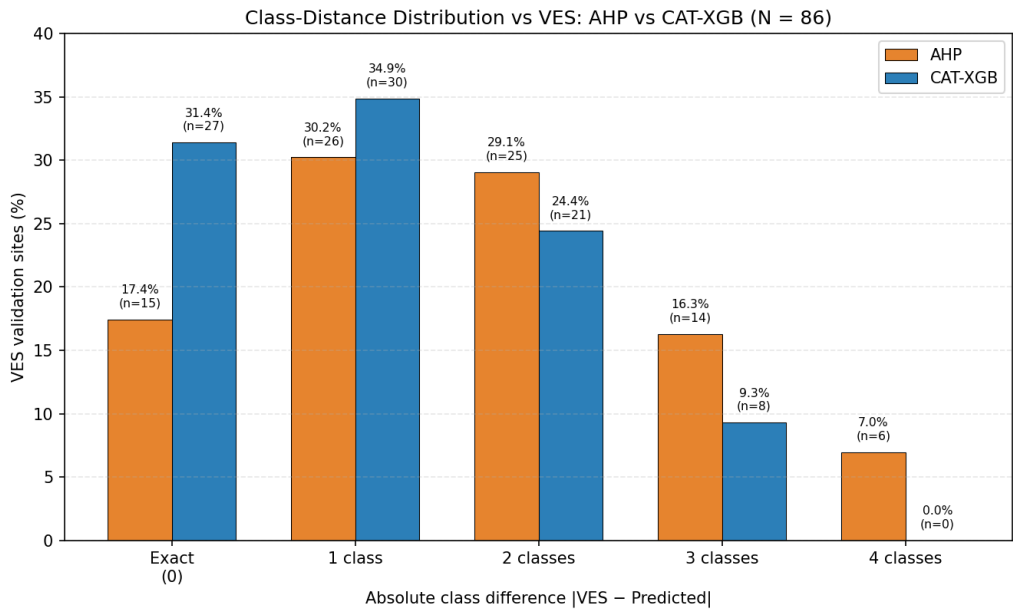


Figure 8. Comparison of Class Distance Distribution compared to VES validation sites.

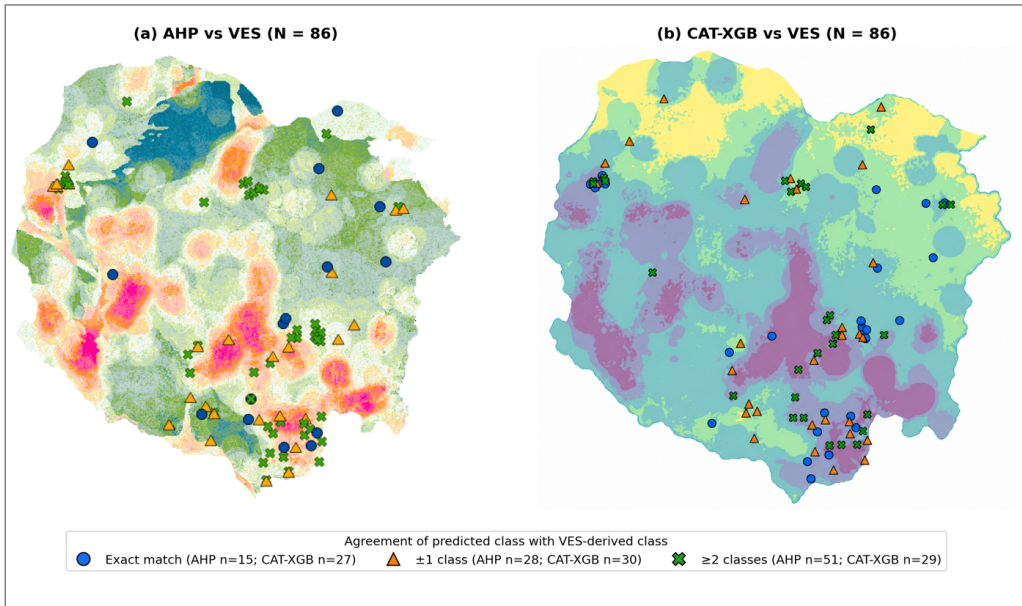


Figure 9. Visualization of agreement of predicted class with VES-derived class between AHP and CAT-XGB.

The two methods were then further compared at each site in pairs by the absolute difference between the predicted and VES class (Figure 10). CAT-XGB was closer to the VES class at 49 of the 86 sites, AHP at 26, and the two were equally close at 11. Mean absolute error fell from 1.65 classes for AHP to 1.12 for CAT-XGB, and a paired Wilcoxon signed-rank test found the difference to be significant ($p = 0.005$). For exact matches alone the advantage was of borderline significance (McNemar's exact test, $p = 0.073$), so the gain lies mainly in the size of the errors rather than in the number of exact hits. AHP remained closer at 26 sites (30%), meaning the improvement is one of central tendency instead of uniform superiority. Taken together, the paired comparison indicates that CAT-XGB predictions lie systematically closer to the VES-derived classes than AHP predictions do, mainly because CAT-XGB avoids the large errors that AHP makes.

Across all of these comparisons, the Galileo-enhanced CAT-XGB pipeline agreed more closely with the VES observations than AHP. It reproduced more VES classes exactly (31.4% versus 17.4%), kept more predictions within one class (66.3% versus 47.7%), produced fewer large errors, and was significantly closer to the VES class at the site level ($p = 0.005$). Despite neither map being significantly correlated with the VES classes (Spearman $\rho = 0.031$, $p = 0.776$ for CAT-XGB; $\rho = -0.066$, $p = 0.548$ for AHP), as 86 VES sites cover only a small fraction of the study area, the evidence supports a relative conclusion: the data-driven pipeline approximates the VES-derived groundwater potential more closely than the expert-weighted overlay.

Does CAT-XGB improve agreement with VES relative to AHP? (paired comparison, n=86)

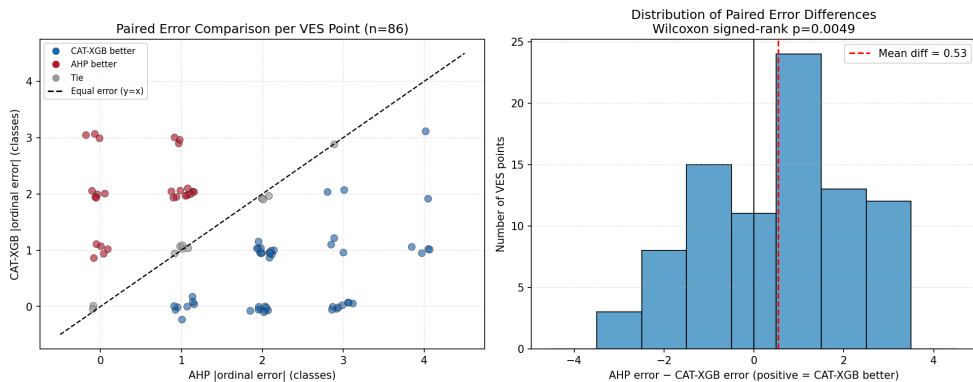


Figure 10. Site-by-site comparison of AHP and CAT-XGB errors at 86 VES sites. (a) Absolute class error of CAT-XGB plotted against that of AHP at each site (points jittered for visibility). (b) Distribution of the difference in absolute class error (AHP minus CAT-XGB) over the same sites..

5. Discussion

5.1. Independent expert and data-driven pathways

The core design of this study is to keep expert-driven AHP mapping and supervised ensemble classification strictly parallel, and compared only after both outputs were generated. We derived AHP weights from pairwise comparisons across ten thematic layers (CR = 3.2%) and deliberately avoided using them as training labels. Instead, we trained the supervised models on five-class targets produced by GMM clustering of the multi-modal predictor space. These clusters were then ranked to the ordinal groundwater-potential scale based on the hydrogeological characteristics of their cluster centroids. To ensure an unbiased evaluation, we held back all VES observations (n = 86) from weighting, clustering, and training, using them solely for post-hoc spatial validation of both final maps.

This separation avoids two common weaknesses in groundwater-potential studies. First, it avoids the circular logic where an AHP map is both the training target and the benchmark. Second, it allows the ensemble to learn non-linear structure in the predictor space rather than to reproduce a linear weighted overlay. The agreement between CAT-XGB and AHP is therefore consistent with a shared hydrogeological signal rather than label leakage. Where the two maps disagree, the ensemble may refine the expert map, although we did not test where such disagreement occurs.

GMM labels function as a proxy: they capture recurring patterns in surface and near-surface predictors instead of direct borehole yields. The independent VES validation is what links both maps to field-interpreted aquifer conditions. In data-scarce basement terrains, combining expert overlay, unsupervised labelling, ensemble prediction, and a withheld geophysical sample offers a practical substitute for a dense yield inventory, so long as the distinction between internal test metrics and field-agreement is kept explicit.

5.2. Why Does CAT-XGB Outperform AHP?

The post-hoc field validation suggests that the Galileo-enhanced CAT-XGB framework matches the VES-derived classes more closely than the conventional AHP method. The experiment tests an integrated pipeline that combines GMM-derived pseudo-labeling, self-supervised spatial embeddings,

and gradient-boosted decision trees, so the contribution of each component cannot be isolated. The following factors may contribute to the difference.

First, the two methods integrate the evidence layers under different assumptions. AHP combines the conditioning factors linearly, with a set of pre-fixed weights from expert judgment, and treats them as independent and additive. In crystalline basement aquifers, groundwater storage and yield may depend on conditional interactions that a weighted sum cannot express. Decision tree ensembles can capture conditional splits and higher-order interactions, and their underlying architecture may therefore better reflect the non-linear behavior of subsurface hydrology.

Second, the spatial patterns are consistent with this difference. The AHP map contains smooth gradients and roughly circular zones around lineament hotspots. Because lineament density is calculated with a moving window, a linear aggregation passes this smoothing directly into the final score. The CAT-XGB map shows sharper transitions between classes and more contiguous prospective zones, as a result of using a decision structure that examines multi-variable threshold combinations as opposed to applying the same linear scaling to individual layers.

Third, the input representations differ. AHP and the plain-ML approach use per-pixel indices such as NDVI, TWI, and slope, each describing one location through one variable. In contrast, embeddings obtained from the self-supervised Galileo foundation model contain multi-modal and multi-scale contextual information across spatial neighborhoods. In the absence of dense borehole monitoring networks for supervised training in data-scarce hydrogeological settings, such embeddings provide useful spatial context that single-pixel indices lack, allowing for local hydrogeological anomalies extraction amidst global trends.

5.3. Limitations and Practical Implications

The VES validation (Section 4.4) provides an important field-based perspective on the two mapping approaches. CAT-XGB produced smaller class errors than AHP, although exact agreement with the VES-derived classes remained modest for both methods. The advantage of CAT-XGB was therefore more apparent in reducing the magnitude of disagreement than in achieving exact class matches. Given the regional scale of the study and the limited number of independent field observations, these results should be interpreted as evidence of relative predictive performance rather than as a measure of spatially exhaustive field accuracy.

Several factors help explain the remaining differences between mapped and VES-derived classes. First, the 86 VES sampling sites are sparsely and unevenly distributed across the expansive study area, offering localized points of reference that may not fully capture the pronounced hydrogeological heterogeneity of the entire region. Second, VES and RS-based classification characterize groundwater potential from different perspectives: VES classes are derived from subsurface geoelectrical properties, whereas CAT-XGB predictions are based on surface and environmental predictors summarized through GMM-derived pseudo-labels. Some disagreement between adjacent classes is therefore expected because the two approaches do not represent exactly the same physical attributes. In this context, exact class agreement is a stringent criterion, and the lower class error observed for CAT-XGB provides a more informative indication of relative performance than exact matches alone. Finally, the Galileo embeddings were used as fixed representations without task-specific fine-tuning. Although the Galileo-enhanced CAT-XGB model achieved the strongest overall internal performance, controlled ablation experiments would be needed to separate the contribution of the foundation-model representations from that of the ensemble models themselves.

Despite these limitations, this study offers a compelling groundwater prediction framework for data-scarce, hydrogeologically complex terrains like Sub-Saharan Africa, where extensive borehole yield inventories and regional geophysical campaigns remain cost-prohibitive. By coupling self-supervised remote sensing representations, gradient-boosted decision trees, and a sparse set of post-hoc geophysical field surveys, this workflow provides a scalable, low-cost methodology for prioritizing regional groundwater exploration targets prior to localized drilling. Future efforts will incorporate expanded field VES surveys to enable sub-regional stratified evaluations and benchmark frozen versus fine-tuned foundation model embeddings.

6. Conclusion

This study compared an expert-driven ten-layer AHP with ensemble machine-learning models enhanced by Galileo embeddings for groundwater potential mapping across Northwestern Nigeria. We built the two mapping pathways independently and then evaluated both outputs against the same set of 86 VES observations withheld from weighting, clustering, and training.

Among the Galileo-enhanced classifiers, the CAT–XGB soft-voting ensemble achieved the strongest internal test-set performance (overall accuracy 0.9501, macro F1-score 0.9483, AUC 0.9976, Cohen’s $\kappa = 0.9324$). Gains over standalone XGBoost (accuracy 0.9492) and CatBoost (accuracy 0.9451) were incremental, which is consistent with complementary error patterns between the two boosters instead of a transformation of the feature space. CAT-XGB matched the VES class exactly at 31.4% of sites against 17.4% for AHP, kept 66.3% of predictions within one class against 47.7%, and was significantly closer to the VES class on average (paired Wilcoxon $p = 0.005$).

The contribution of this work therefore lies in the field-based comparison: the Galileo-enhanced pipeline produced smaller errors and fewer large misses than the AHP overlay when both were evaluated against independent VES observations. Because it works from the same expert-selected thematic layers and can represent nonlinear interactions among them, a data-driven pipeline may complement expert-driven groundwater mapping. The present design does not show which component (labeling, embeddings or classifier) accounts for the improvement.

The framework is transferable to other data-scarce crystalline terrains where borehole-yield inventories are incomplete but multi-modal satellite layers and a modest VES campaign can be assembled. As a limitation, GMM pseudo-labels impose an unsupervised structure which may not align with aquifer yield; we used Galileo embeddings as frozen representations instead of task-finetuned features. Future work should add seasonal time-series predictors, SHAP or related attribution for class-wise hydrogeological interpretation and, where possible, validation against measured borehole yields rather than resistivity-derived classes.

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Competing Interests. None

Data Availability Statement. The Python source code and computational workflows supporting this study are publicly available through the GitHub repository *groundwater-potential-nigeria* and have been permanently archived on Zenodo (version v1.0.0): <https://doi.org/10.5281/zenodo.23199771>. The repository includes workflows for geospatial data preprocessing, groundwater potential modeling, machine-learning analysis, and model evaluation.

Ethical Standards. The research meets all ethical guidelines, including adherence to the legal requirements of the study country.

Author Contributions. Conceptualization: D.J., J.O.O.; Methodology: D.J., J.O.O.; Software: S.S.U., M.L.; Data curation: J.O.O., M.L.; Formal analysis: J.O.O., S.S.U.; Investigation: D.J., J.O.O.; Validation: M.L., S.S.U.; Visualization: S.S.U., M.L.; Project administration: D.J.; Supervision: D.J., J.O.O.; Writing – original draft: J.O.O., S.S.U., M.L.; Writing – review & editing: D.J., J.O.O., S.S.U., M.L. All authors reviewed and approved the final manuscript.

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