Simulation of Qanat Discharge in Balade Ferdows Using Machine Learning Algorithms Using Drought Indices

Mostafa Yaghoubzadeh[1], Mehdi Amirabadizadeh[2*], Amir Khayyat[3], Zahra Akhondi[4]

[1] Associate Professor, Department of Water Science and Engineering, Faculty of Agriculture, University of Birjand, and Head of the Drought and Climate Change Research Group, Birjand, Iran, Orchid ID: 0000-0002-1041-1941
[2] Associate Professor, Department of Water Science and Engineering, Faculty of Agriculture, University of Birjand, and Member of the Drought and Climate Change Research Group, Birjand, Iran, Orchid ID: 0000-0002-8626-4036
[3] Ph.D. Student, Irrigation and Drainage, Department of Water Science and Engineering, Faculty of Agriculture, University of Birjand, Iran, Orchid ID: 0009-0003-3450-8371
[4] M.Sc. in Hydraulic Structures, Department of Water Science and Engineering, Faculty of Agriculture, University of Zabol, Zabol, Iran, Orchid ID: 0009-0003-1368-7809

*Corresponding author: mamirabadizadeh@birjand.ac.ir

Abstract
In recent decades, the country has faced decreased rainfall, increased temperatures, and a severe decline in groundwater resources. Qanats, as one of the most important indigenous water supply systems in arid and semi-arid regions, have been severely affected by climate change and the recent droughts. In this regard, employing advanced machine learning models can play a key role in developing reliable forecasting systems to support climate change adaptation planning. The objective of this research is to simulate the monthly discharge of the Balade Qanat complex in Ferdows County using a set of machine learning models, including single algorithms such as XG Boost, SVR, Random Forest, and Gradient Boosting, as well as an advanced ensemble approach, Stacking. This simulation uses climatic, hydrological data, and drought indices over 10 years. The dominant approach in modelling is comparing the performance of individual models against the final ensemble model. The obtained results showed that under the region's variable climatic conditions, the Stacking ensemble approach exhibited a significantly stronger performance than single models like XG Boost. The Stacking model was selected as the optimal model, achieving the highest coefficient of determination (R^2) and the highest Kling-Gupta Efficiency (KGE = 0.93, R^2 = 0.92) with the lowest Root Mean Square Error (RMSE = 12.21). This superior performance emphasises the capability of Stacking models in reducing variance and correcting systematic biases of individual models when dealing with the complex and nonlinear behaviour of Qanat discharges. It is concluded that the Stacking model, due to its ability to extract complex nonlinear patterns and improve generalisation, is a superior management tool for decision-making in the sustainable exploitation of Qanat water resources in water-stressed climates.

Keywords: Qanat, Machine Learning, Ensemble Learning, Drought, Groundwater Resources

Introduction
Climate change, one of the most prominent environmental and geophysical challenges of the current century, has had extensive and profound impacts on the Earth system, particularly on the global water cycle and regional water resources. Long-term climatic trends indicate the continuation and intensification of these phenomena in the future (Almazroui et al., 2021). Consequently, these changes, through alterations in precipitation patterns, increased intensity and frequency of hydrological extreme events, and temperature fluctuations, lead to heightened water stress in arid and semi-arid regions (Ogunrinde et al., 2024; Samaniego, 2025; Scanlon et al., 2023; Stringer et al., 2021). Predictions from the Intergovernmental Panel on Climate Change (IPCC) also suggest that these regions will face a significant reduction in renewable water resources in the coming decades (Lane & Kay, 2021; Yang et al., 2021). Due to its unique

geographical location and predominantly arid climate, Iran is among the countries most vulnerable to climate change.

The effects of climate change on groundwater resources are also particularly significant in arid and semi-arid regions. Reduced aquifer recharge, changes in hydrological regimes, and increased evapotranspiration lead to a decline in groundwater levels and, consequently, a decrease in the discharge of traditional water sources such as springs and Qanats (Stringer et al., 2021). This trend not only threatens the drinking water security of local communities but also endangers the sustainability of agriculture and the livelihoods of millions worldwide. (Bartlett & Dedekorkut-Howes, 2023).

In the face of these complex challenges, the development of climate change adaptation strategies is considered essential and inevitable. These strategies include diversifying water sources, improving consumption efficiency, developing modern irrigation technologies, protecting aquifers, and optimising the use of traditional water resources like Qanats. Furthermore, employing advanced systems and accurate modelling of water resources plays a vital role in the sustainable planning and management of water resources under climate change conditions. (Ogunrinde et al., 2024). Among these, the preservation and restoration of traditional water systems like Qanats, as an important climate change-adaptive strategy, gains particular significance. Qanats, as an amazing and complex Iranian innovation for supplying agricultural water in arid and semi-arid regions, are not only technically efficient but also considered economically and environmentally sustainable. (Hosen et al., 2020). These valuable structures have played a significant role in the development of the agricultural sector. However, the indiscriminate extraction of groundwater through the digging of numerous wells and the lack of natural replenishment of aquifers have led to reduced discharge and the drying up of many Qanats.

Given the importance of groundwater resources, especially Qanats, comprehensive studies in this area can significantly aid in decision-making for optimal and sustainable extraction from these resources. (Mohtasham et al., 2017). One of the fundamental requirements for achieving sustainable planning in water resource management is the modelling and understanding of groundwater table behaviour, particularly during dry seasons. Today, controlling and managing groundwater aquifers has become a management tool for water productivity, and estimating the groundwater table level is considered one of the fundamental issues in agricultural planning, water resource management, and determining plant water requirements, especially in the application of water-saving strategies. (Rakhshandehroo et al., 2018).

Currently, South Khorasan Province has the highest number of Qanats, ranking first in the country with over 6,983 Qanat lines. Historically, the Baghestan rural district of Ferdows County has owed its economic and social life to the extensive network of Balade Qanats. However, climate change, the reduction in groundwater resources, and increased demand have made the necessity of predicting Qanat discharge more evident than ever for the optimal and sustainable management of these valuable resources. In this regard, the development of advanced modelling tools to predict the behaviour of Qanats under varying climatic conditions plays a key role in planning and implementing adaptation strategies. (Foruzanmehr & Khozeymehnezhad, 2023; Hosseini Fahraji & Sharifzadeh, 2016).

Traditional methods for predicting Qanat discharge are typically based on physical and hydrological models that require extensive and complex data, including geological, hydrological, and climatic parameters. Although these models possess relative accuracy, they have limitations in conditions where complete data is inaccessible or in the face of non-linear climatic changes.

Statistical techniques vary from simple methods such as linear regression to more complex methods such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forests (RF) (Fouladi Nasrabad et al., 2025; Nourani et al., 2019). In recent years, novel Machine Learning (ML) methods have attracted researchers' attention as powerful tools for simulating and predicting complex environmental processes. These algorithms are capable of automatically identifying non-linear relationships between input and output variables and providing acceptable results without the need for complex physical assumptions. (Reichstein et al., 2019). One of the most prominent machine learning algorithms is the XG Boost algorithm. XG Boost operates based on the Gradient Boosting method and contributes to error reduction and increased prediction accuracy by creating ensemble tree models. Due to its high capability in handling incomplete data, reducing overfitting, and fast processing, this algorithm has been successful in many hydrological studies and water flow predictions. Introduced by (Chen & Guestrin, 2016)This algorithm provides scalability for large datasets with features such as sparsity-aware algorithms for sparse data and a weighted quantile sketch for approximate tree learning. It supports parallel processing to speed up computations, regularisation techniques to reduce overfitting, and automatic handling of missing data, making it suitable for complex tasks such as regression, classification, and ranking.

In recent studies in the field of water resources engineering, Niazkar et al. reported that XG Boost performed better than traditional models in 74% of the 72 reviewed studies between 2018 and 2023. However, limitations exist, such as dependence on data quality and quantity, the inability to provide explicit mathematical equations due to its tree-based structure, and the need for hyperparameter tuning (Niazkar et al., 2024). They used XG Boost for short-term river discharge forecasting and showed that this model performed better than classical regressions and some neural networks. High accuracy, training speed, and the model's ability to handle noisy data were among its key findings. (Dey, 2025). Ali et al (2023) used XG Boost to downscale Terrestrial Water Storage Anomaly (TWSA) derived from GRACE from 1 degree to 0.25 degrees in the Indus Basin irrigation system, achieving better performance than Artificial Neural Networks based on metrics such as NSE = 0.99, R = 0.99, RMSE = 5.22 (Ali et al., 2023). Jiang et al. also confirm that XG Boost is an efficient tool for assessing hydrological drought features using GNSS data. (Jiang et al., 2022). In a study titled "Groundwater Level Dynamics in a Subtropical Fan Delta and Its Future Projection Using Machine Learning Tools," the results indicated that the XG Boost algorithm was the best model, followed by Random Forest regressions, Linear Regression, and Support Vector Regression. (Mahammad et al., 2023).

In one study, XG Boost was used to correct multivariate bias in Numerical Weather Prediction (NWP) forecasts across seven climatic regions in China, significantly improving short-term precipitation forecasts—especially in winter—and outperforming traditional methods like Empirical Cumulative Distribution Function (ECDF) matching (Dong et al., 2023). A review highlights the growing role of XG Boost in the spatial downscaling of satellite precipitation and its ability to capture non-linear relationships between meteorological variables—often further improved by post-processing techniques like residual correction for regional applications such as flood forecasting in temperate regions (Khosravi et al., 2025). In a separate investigation, researchers utilised the XG Boost algorithm to identify leaks in water distribution networks. By employing this machine learning algorithm, they were able to detect water leaks with high accuracy and improve the performance of distribution networks. The study's results demonstrated that XG Boost is an effective tool for monitoring and managing urban water networks, capable of reducing water loss and increasing the efficiency of distribution systems

(Wu et al., 2022). In another piece of research, an accurate model for predicting block-scale runoff flow was developed using XG Boost, revealing that different building configurations can have a significant impact on runoff management and the mitigation of urban flood risks (Zhou et al., 2022).

Other studies that have leveraged the XG Boost algorithm include those by (Alimkulov et al., 2025; Fouladi Nasrabad et al., 2025; khoshsimaie chenar et al., 2025; Liu, 2025; Piraei et al., 2023; Safira et al., 2024)

The application of XG Boost in modelling river flows, predicting groundwater levels, and analysing spring discharge has yielded promising results. However, limited studies have addressed the application of this algorithm in simulating Qanat discharge in Iran's arid regions; existing research has generally focused on the performance of other Artificial Intelligence and Machine Learning methods. For example, one study evaluated the performance of five machine learning models in predicting Qanat water flow in the Chogha Landi Aquifer in Iran. This study utilised 14 years of monthly data and employed five different models, including Artificial Neural Networks, Neuro-Fuzzy Inference Systems, Data Envelopment Analysis (DEA), Binary Genetic Programming, and Support Vector Machines. (Samani et al., 2024).

In the context of increasing frequency and intensity of climatic droughts, Qanats—as indigenous mechanisms for water scarcity adaptation—play a fundamental role in the ecological and livelihood sustainability of local communities. These systems, by utilising the natural gradient of aquifers and gravitational transfer of subsurface flow, enable sustainable water extraction without dependence on mechanical energy. The significance of Qanats during drought conditions extends beyond their technical aspects; they also serve as an effective socio-economic instrument to reduce the vulnerability of agricultural communities to climatic fluctuations. Consequently, analysing the hydrological behaviour of Qanats through modern data-driven models, such as machine learning, can play a key role in designing adaptation strategies and intelligent management of the country's groundwater resources.

Although numerous studies have applied traditional and AI models to predict Qanat discharge in various regions of Iran, Reinforcement Learning models like XG Boost have not been widely considered in this specific field. In particular, the Qanats of Balade, Ferdows, due to their arid climate conditions and high discharge variability, represent a suitable case study for evaluating the capability of XG Boost in predicting subsurface flows.

The objective of this study is to utilise machine learning algorithms to simulate the discharge of the Balade Qanat complex. By collecting 10 years of monthly data on discharge, precipitation, and other climatic and environmental variables, this research aims to develop an accurate and reliable model that can assist in the optimal management of water resources, agricultural planning, and the reduction of drought risks. The results are expected to not only provide a practical forecasting tool but also contribute to a better understanding of the hydrological behaviour of Qanats and the development of intelligent models for similar studies in other arid regions of Iran.

Subsequently, this article describes the methodology of modelling using Machine Learning algorithms, analyses the input data, and examines the accuracy of Qanat discharge simulation, comparing the resulting outcomes with Ensemble Machine Learning algorithms. The novelty of this research lies in its specific application and integration within the context of Qanat discharge simulation under drought conditions in an arid region of Iran. The findings of this study can serve as a starting point for the wider application of machine learning models in the sustainable management of water resources, Qanats, and improving water security in the country's dry regions.

Materials and Methods

Study Area

South Khorasan Province, with an area of approximately 151,193 square kilometres, is located in Eastern Iran, situated between the geographical parallels of 30°31′to 34°53′North latitude and 57°03′to 57°60′East longitude. This province is bordered by Razavi Khorasan to the north, Yazd and Kerman to the west, Sistan and Baluchestan to the south, and Afghanistan to the east. South Khorasan Province has an arid to semi-arid climate, with an average annual temperature ranging between 15to 20°Cand an annual precipitation between 100to 250 mm.

The study area is the Balade Qanats located in Ferdows County, South Khorasan Province. This region has an arid climate with an average annual rainfall of less than 150 mmand high evaporation rates. Groundwater resources in this area are primarily supplied through Qanats, and the recent decrease in the discharge of these Qanats has had a direct impact on the agriculture and livelihoods of the residents. The Balade Ferdows Qanats are considered among the most important and oldest Qanats in the region, located 22 kilometres northeast of Ferdows County. They are also listed on the UNESCO World Heritage list, and their discharge behaviour is highly dependent on climatic conditions and natural aquifer recharge.

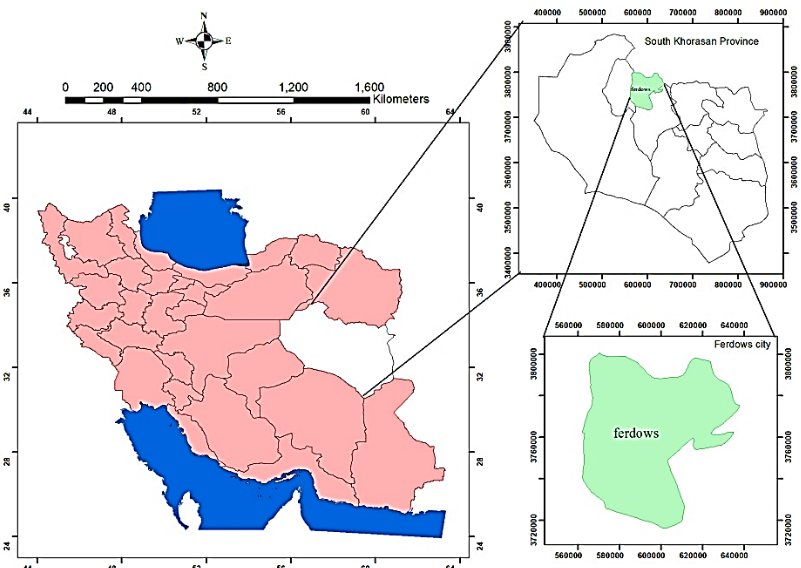

Fig 1. Study Area

The specifications of the meteorological observation station whose weather statistics were used in this research are presented in Table 1.

Table 1. Characteristics of the studied station

Station	Station type	Altitude above sea level (m)	Longitude (degrees)	Latitude (degrees)	Climate
Ferdows	Synoptic	1293	58.18	34.03	Dry

The historical Qanats of Ferdows city, due to their long history, the extent of their mother-well network, and their high sensitivity to water stress resulting from climate change and recent droughts, are considered a benchmark model for evaluating the resilience of traditional groundwater exploitation systems. The geographical location and the vital dependence of the region's economy on the water of these Qanats emphasise the necessity of accurate modelling of their discharge.

The key point regarding this system is the method of connection and flow rate measurement: 13 active Balade Ferdows Qanats connect to each other at the exit and end points of their paths, and their discharge becomes unified. Therefore, the discharge used in the modelling efforts is the total, aggregated discharge, which is measured after the final connection of the Qanats to each other, and in fact, the total outflow of the traditional system. This method provides a more comprehensive and accurate analysis of the entire network's discharge performance in response to environmental factors and considers the entire system as a single hydrological unit.

In this research, a multi-step approach was employed for model development and evaluation, the stages of which are illustrated in the flowchart below (Fig 2).

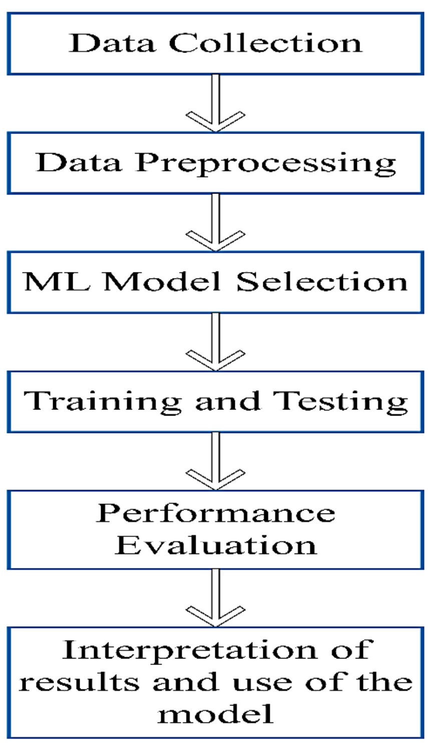

Fig 2. Research Methodology Flowchart

Data used

To compare the model data with observational data, monthly data for precipitation, minimum temperature, maximum temperature, and mean temperature from the Ferdows synoptic station for the 10-year statistical period (2015–2024) were obtained from the Provincial General Directorate of Meteorology. Concurrently, 10 years of monthly discharge data for 13 active branches of the Balade Ferdows Qanat complex were acquired from the Provincial Regional Water Authority. Data preprocessing includes missing and outlier analysis, normalisation, and lag data, which were applied in this research. Furthermore, drought indices—specifically the Standardised Precipitation Index (SPI) and the Standardised Precipitation Evapotranspiration Index (SPEI)—were calculated for the study period. The selection of these variables was intended to account for the simultaneous effects of precipitation, temperature, and drought on the Qanat discharge behaviour. The characteristics of these observational variables are presented in Table 2.

Table 2. Descriptive Statistics of the Studied Variables

Variable	Mean	Min	Max	Std. Dev
RAIN (mm)	12.05	0.00	81.01	18.09
TMAX (ºC)	31.14	13.30	43.60	7.86
TMIN (ºC)	5.98	-12.30	21.00	8.98
TMED (ºC)	34.13	8.85	53.05	12.15
DEBI(L/s)	174.36	91.00	303.00	48.84

Standardised Precipitation Index (SPI)

The Standardised Precipitation Index (SPI) is a climatic indicator used to determine precipitation deficits across various timescales. According to this method, a drought period occurs when the SPI is consistently negative, reaching a value of -1or less, and ends when the SPI value becomes positive. This index was introduced by McKee et al. (McKee et al., 1993). for the determination and monitoring of drought. The SPI is derived from the difference between precipitation and the mean for a specific timescale, normalised by the standard deviation, and precipitation is the sole factor influencing its calculation. The Standardised Precipitation Index is based on the probability of precipitation for each time interval and is highly significant for early warning and monitoring drought intensity. This index is designed to quantify precipitation deficits over multiple timescales. Based on the results of previous studies, this index fits the long-term recorded precipitation data to a probability distribution and then transforms it into a normal distribution, such that the mean of SPI for the specific location and time period is zero. (Mostafazadeh & Zabihi, 2016). In this research, after obtaining and preparing the observational data, the 12-month SPI was calculated for the Ferdows synoptic station for the period 2015–2024 using the R environment.

Standardised Precipitation-Evaporation Index (SPEI[1])

The role of temperature in drought has been emphasised in various studies due to the trend of global warming. Therefore, in this study, the Standardised Precipitation Evapotranspiration Index (SPEI) was utilised for monitoring and forecasting drought. This index is multivariate, combining data for both precipitation and temperature. In this index, considering the potential evapotranspiration, the balance is calculated using the difference between precipitation and potential evapotranspiration for the month. i., as shown in Equation 7:

[1] The Standardized Precipitation-Evapotranspiration Index

$$D_i = P_i - PET_i \qquad (1)$$

$$D_n^k = \sum_{n=0}^{k-1} P_{n-1} - PET_{n-i} \qquad (2)$$

Where $k$is the desired time scale (in months) and $n$is the month under consideration in the calculation. Subsequently, the SPEI value is extracted by fitting a Log-Logistic distribution to the values of $D$and transforming them into normal values.

XG Boost algorithm

In 2016, Chen and Guestrin introduced the XG Boost algorithm as an advanced method for solving classification and regression problems, which quickly gained the attention of researchers due to its high computational efficiency. (Chen & Guestrin, 2016) . The XG Boost algorithm is one of the most advanced machine learning methods based on Gradient Boosting. Due to its high accuracy, suitable computational speed, and ability to model complex non-linear relationships, it has been widely used in hydrology studies and water resource forecasting. (Chen & Guestrin, 2016; Nourani et al., 2021) This algorithm creates a powerful model by combining several weak decision trees, enabling it to extract hidden patterns in complex climatic and hydrological data. (Zounemat-Kermani et al., 2020).

Among the most important advantages of the XG Boost algorithm are automatic handling of missing data, the use of regularisation techniques to prevent overfitting, and high computational efficiency (Chen & Guestrin, 2016). This algorithm can model non-linear relationships between climatic variables such as precipitation, temperature, and drought indices with groundwater resources discharge, and has shown reliable performance under climate change conditions. (Mosavi et al., 2018).

The training process of the XG Boost algorithm is based on minimising a combined objective function that includes the loss function and the regularisation term. The objective function is defined as follows:

$$obj = \sum_{i=1}^{n} \Omega(f_k) + \sum_{k=1}^{K} (L y_{i,} \hat{y}_i) \qquad (3)$$

The expression represents the loss function, where $L(y_i, \hat{y}_i)$expresses the difference between the observed value and the predicted value of the target variable (Friedman, 2001) .The second term, the regularisation term, $\Omega(f_k)$, controls the model complexity and prevents overfitting (Hastie, 2009).

The regularisation term is expressed as follows:

$$_{j}^{2}\lambda \sum_{j=1}^{T} \omega \frac{1}{2} + \gamma T = \Omega(f) \qquad (4)$$

Where $T$is the number of decision tree leaves, $\omega$is the weight of each leaf, and $\gamma$and $\lambda These\ These\ These\ These\ These\ These\ These\ zone\ are$are the regularisation coefficients. This structure leads to a balance between prediction accuracy and model simplicity.

Gradient Boosting (GB[2])

The Gradient Boosting algorithm is a boosting method for decision trees in which weak models are trained sequentially, and each new model tries to reduce the error of the previous models. (Friedman, 2001). In essence, the final model is a weighted combination of these weak learners, which are gradually improved by utilising the gradient of the cost function. One of the key advantages of Gradient Boosting is its high accuracy, ability to model nonlinear relationships, and flexibility with respect to different loss functions. However, this method is sensitive to data noise and improper parameter tuning, and if deep trees or too many iterations are used without proper control, it may suffer from overfitting. (Natekin & Knoll, 2013).

$$F_M(x) = \sum_{m=1}^{M} \nu h_m(x) \tag{5}$$

where $h_m$are weak learners (usually decision trees), $\nu$is the learning rate, and $M$is the number of boosting stages. In many regression and classification problems, gradient boosting is used as a benchmark method for achieving high performance. In this study, the Gradient Boosting Regressor function was utilised.

Support Vector Machine (SVM)

The Support Vector Machine (SVM) algorithm, developed by Vapnik (Vapnik, 2000)It is a supervised machine learning model used for pattern recognition and data analysis. It has been widely employed in various fields such as agriculture, hydrology, meteorology, and environmental studies for both regression and prediction purposes. (Fan et al., 2018; Ghorbani et al., 2017; Shrestha & Shukla, 2015) .The SVM model estimates regression by utilising a set of kernel functions. These functions have the capability to implicitly transform low-dimensional input data into a higher-dimensional feature space. This very characteristic enables the modelling of non-linear relationships between variables. In this study, the SVR (Support Vector Regression) function was utilised. (Kramer, 2016).

Random Forest (RF)

The Random Forest algorithm is a tree-based ensemble method that constructs a collection of decision trees and produces the final output by either voting for classification problems or averaging for regression problems. (Breiman, 2001). In this model, each tree is trained using a random sample of the data, and at each node, only a subset of the features is considered for data splitting. This construction leads to increased generalisation capability and prevents overfitting. Advantages of RF include high stability, robustness against outliers, and the ability to calculate

---
[2] Gradient Boosting

feature importance. (Dhaliwal & Williams, 2024). In this study, the Random Forest Regressor function was utilised.

$$\widehat{y(x)} = \frac{1}{B}\sum_{b=1}^{B} h_b(x) \qquad (6)$$

In which $h_b(x)$ is the regression prediction of the b-th tree for input x.
It should be noted that the machine learning methods used in this research were implemented using the scikit-learn library.

Data Preprocessing

Before executing the machine learning models, the data underwent a preprocessing procedure, which comprised three main steps:

1. **Outlier and Missing Value Handling:** In the first step, the data were examined for the presence of missing and outlier values, and unrealistic or out-of-range values were corrected
2. **Normalisation:** In the second step, to reduce the effect of the scale difference of the variables and increase the efficiency of machine learning models, the data were normalised
3. **Data Splitting:** In the final step, after preparing the data, the dataset was divided into training and testing subsets. As the dataset is time series-based, chronological splitting was adopted instead of random shuffling. Specifically, 70% of the data was allocated for training the model, and the remaining 30% was reserved for evaluating the model's performance. This split facilitates the assessment of the model's generalisation capability and the examination of the simulation accuracy for Qanat discharge.

Selection of Input and Output Variables

To simulate the Qanat discharge, the following climatic variables were selected as model inputs: precipitation, maximum temperature, minimum temperature, mean temperature, Standardised Precipitation–Evapotranspiration Index (SPEI), and Standardised Precipitation Index (SPI).
Furthermore, to account for the temporal dependency of the hydrological time series, discharge values with a lag of one month prior to and three months prior to were calculated and added to the input features. Finally, the discharge variable was considered as the target variable.

Identification and Removal of Outliers

In the data preprocessing stage, the first step was to identify and correct outliers. Outliers are defined as values that significantly deviate from the general data pattern and can heavily influence the modelling results. The presence of these data points may cause a distortion in evaluation metrics and reduce the accuracy of the model's predictions. For this reason, examining outliers is considered a necessary step in improving data quality and increasing the reliability of the model. (Knoben et al., 2019).

Data Normalization

In order to increase the accuracy and stability of machine learning models and prevent the dominance of variables with larger numerical ranges over the learning process, the input data was normalised before modelling. The variables used in this research included parameters with different scales, such as Qanat discharge (litres per second), precipitation (millimetres), temperature (degrees Celsius), and dimensionless drought indices. This difference in scale can lead to a reduction in algorithm efficiency and an increase in prediction error.

With normalisation, data values are brought into a specific range, thereby reducing the influence of large-scale variables on the model. (Hosseini Fahraji & Sharifzadeh, 2016). In this study, the Min-Max normalisation method was employed to transform the data values into the [0, 1] interval. This technique is widely used in machine learning studies within the field of water resources due to its preservation of the relative data distribution and its good compatibility with tree-based algorithms. This method operates by calculating the ratio of the difference between each value and the data minimum to the overall data range (the difference between the maximum and minimum values) and is calculated using Equation 7.

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (7)$$

x is the original value of the variable.

x_{norm} is the normalised value of the variable.

x_{max} and x_{min} Are the maximum and minimum values of that variable in the dataset x, respectively.

Ultimately, the normalised data were utilised as input for the XG Boost model. The results demonstrated that data normalisation played an effective role in improving model convergence, reducing prediction oscillations, and increasing the simulation accuracy of the Qanat discharges for Balade Ferdows.

Data Splitting

A systematic approach to data partitioning was employed in this research to ensure both statistical correctness and realistic simulation of forecasting conditions. Following the completion of data preprocessing and normalisation, the dataset was divided into training and testing subsets. Specifically, 70% of the data was allocated for model training, and 30% was reserved for performance evaluation.

Given the time-series nature of hydrological data and the inherent temporal dependency between successive observations, the data split was conducted without random shuffling. This methodology preserves the chronological order of the data, which prevents information leakage from future observations into the past, thereby providing a more realistic assessment of the model’s performance. The training set was utilised for parameter tuning and learning the pattern of the relationship between the input variables and the Qanat discharge, whereas the testing set was employed to examine the model’s generalisation capability and evaluate the accuracy of its predictions.

Model Performance Evaluation Criteria

After the training phase, the discharge values for the Qanats of Baladeh in Ferdows County were simulated. To rigorously assess the model's performance, the following statistical indices were utilised:

The evaluation metrics employed included the Coefficient of Determination (R^2), the Root Mean Square Error (RMSE), and the Kling-Gupta Efficiency (KGE), which are calculated according to Equations (8), (9), and (10), respectively.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(Q_{obs} - Q_{mod})^2}{\sum_{i=1}^{N}(Q_{oi} - \bar{Q}_{oi})^2} \quad (8)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_{obs} - Q_{mod})^2} \quad (9)$$

x_{obs}, y_{mod} , n, are the values of the observational and modelled data, and the number of data points, respectively.

$$KGE = 1 - \sqrt{(r-1)^2 + (\beta-1)^2 + (\gamma-1)^2} \quad (10)$$

In equation (8):

$$\beta = \frac{\mu_P}{\mu_O} \quad (11)$$

$$\gamma = \frac{\sigma_P}{\sigma_O} \quad (12)$$

Where $P$and $O$are the values of the modelled and observed data, respectively, $r$is the trend similarity: the Pearson correlation coefficient between the observed and predicted values, $\beta$is the relative bias: the ratio of the mean prediction to the mean of observations, and $\gamma$is the relative variability: the ratio of the standard deviation of the prediction to the standard deviation of the observations.

Results and Discussion

To simulate the discharge of Balade Qanats in Ferdows County, data on Qanat discharge, precipitation, temperature, and the drought indices SPI and SPEI were prepared and calculated for the period spanning from 2015 to 2024. In this study, several machine learning models were employed, including RF, GB, SVR, XGB, and the Stacking method. The input data was first standardised using the Standard Scaler to equalise the feature scales and optimise the model training process. The base models (RF, GB, SVR, XGB) were trained independently on the standardised training data, and predictions for the test data were calculated. In the Stacking phase, the predictions from the base models were used as input for the meta-model to generate the final prediction. The performance of the models was evaluated using the metrics of the

Coefficient of Determination (*R-squared*), Kling-Gupta Efficiency (KGE), and Root Mean Squared Error (RMSE), which allowed for the combination of the strengths of different models to improve prediction accuracy.

The results obtained from evaluating the machine learning models for simulating the discharge of Balade Qanats in Ferdows County, South Khorasan Province, indicate that the accuracy and stability of the models representing the complex behaviour of Qanat yield vary. Based on the results in Table 3, the Stacking model achieved by achieving the highest Coefficient of Determination ($R^2 = 0.93$), demonstrates that it is capable of correctly explaining 93% of the observed variations in discharge. Furthermore, the much lower Root Mean Square Error (RMSE = 12.21 l/sCompared to other models, the Stacking model has less deviation in reproducing the actual Qanat discharge values. Additionally, the high KGE = 0.92value indicates a good fit of the model to the actual flow pattern and its ability to simultaneously preserve the correlation, mean, and variance of the discharge time series. These three criteria collectively confirm that Stacking is the best option for modelling Qanat discharge in the studied region.

The Gradient Boosting and Random Forest models have also presented acceptable performance. The R^2values for these two models are 0.89and 0.88, respectively, indicating that both have a relatively good ability to explain the discharge variations. Furthermore, the RMSEvalues of RMSE = 14.41 l/s for Gradient Boosting and RMSE = 15.5 l/s Random Forest shows that these models have lower accuracy compared to Stacking, but they are still capable of producing reliable predictions. The difference in the KGEmetric between these two models (0.85 and 0.81) also suggests that Gradient Boosting performed slightly better in simulating the Qanat discharge behaviour.

On the other hand, the XG Boost and SVR models demonstrated the weakest performance. Although the $R^2 = 0.87$value might appear close to the other models, the higher RMSEvalues (16.17 and 16.37 l/s, respectively) indicate that these models have greater error in estimating the actual discharge values.

Table 3. Performance evaluation results

Model	Evaluation criteria		
	R^2	RMSE(l/s)	KGE
Random Forest	0.88	15.5	0.81
Gradient Boosting	0.89	14.41	0.85
XG Boost	0.87	16.17	0.87
SVR	0.87	16.37	0.89
Stacking Model	0.93	12.21	0.92

Overall, the difference in performance among the models indicates that the complexity of the Qanat discharge behaviour is influenced by factors such as groundwater level fluctuations, climatic variations, and hydrogeological characteristics—requires models with the capability to combine multiple algorithms and more effectively extract non-linear patterns. Therefore, the Stacking model, which is an ensemble of several base models, has been able to provide the best fit and the most accurate simulation of the discharge of Balade Qanats in Ferdows County by aggregating their respective strengths. The obtained performance of the Stacking model (R^2 = 0.93) exceeds the predictive accuracy reported in many traditional regression-based hydrological models and several standalone machine learning approaches previously applied to groundwater systems in arid regions. Unlike physically based hydrological models, the proposed machine learning framework requires fewer hydrogeological parameters while still effectively capturing nonlinear relationships.

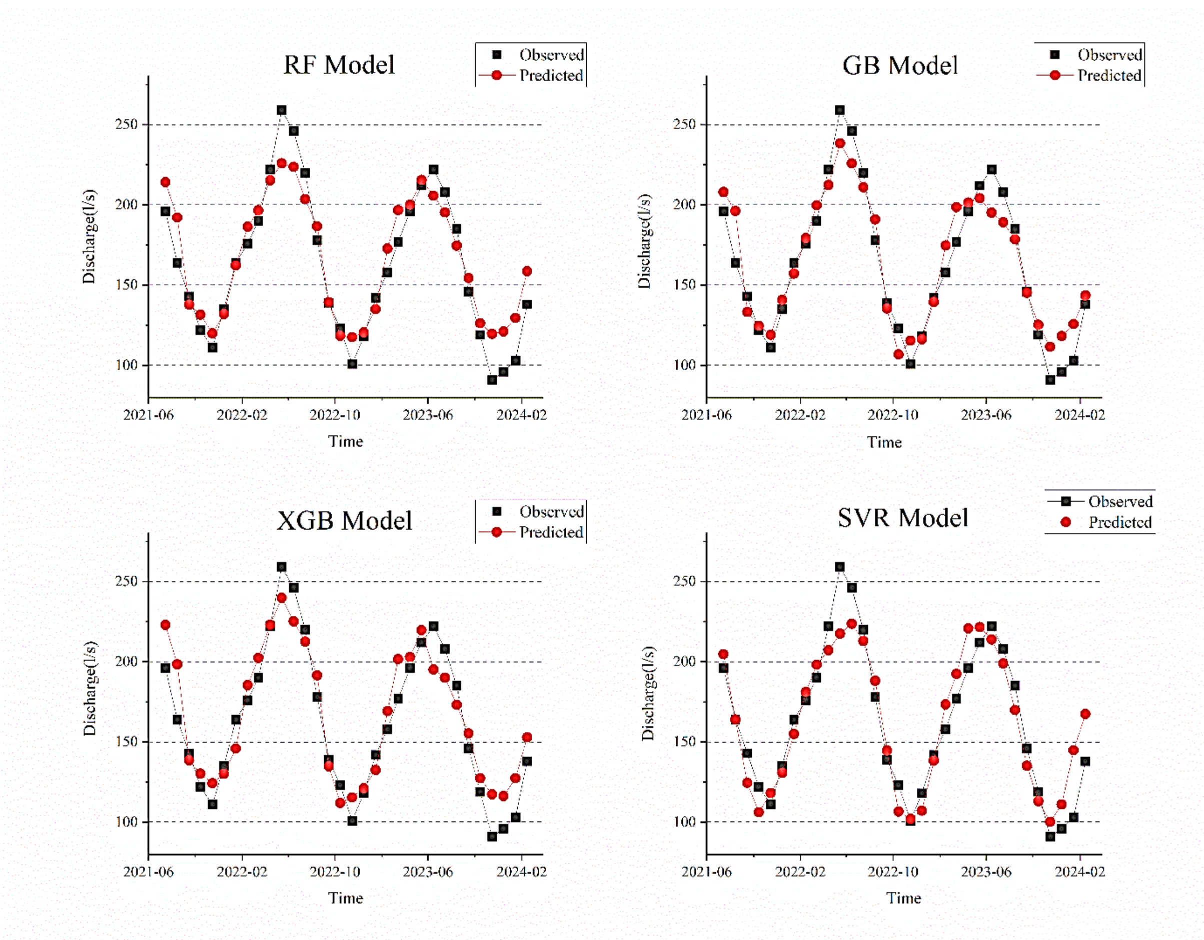

Fig 3. Time Series Plot of Observed and Simulated Values Using the Random Forest (RF)- Gradient Boosting (GB) - Extreme Gradient Boosting (XGB)- Support Vector Regression (SVR) Models during validation period

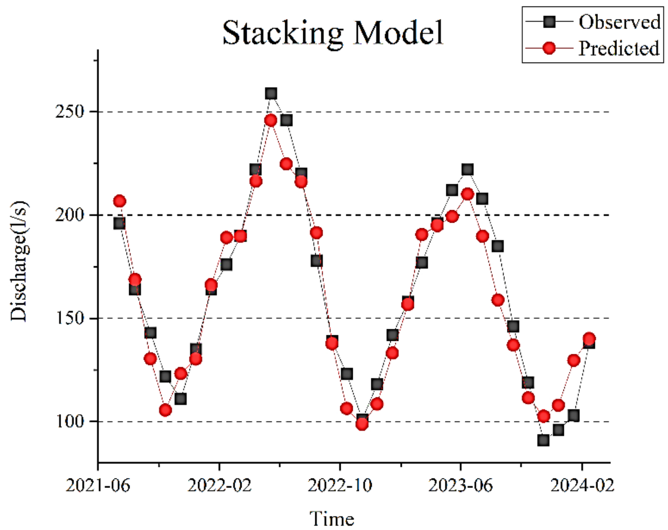

Fig 4. Time Series Plot of Observed and Simulated Values Using the Stacking Model during the validation period

Numerical evaluation of the results and the simulation graphs for the discharge of the Balade Qanats in Ferdows County shows that all employed machine learning models (RF, SVR, GB, XGB, Stacking Model) could reproduce the temporal pattern and seasonal fluctuations of the discharge in the period of 2021 to 2024. Specifically, the range of observed and simulated discharge variations is predominantly between 91 and 259 litres per second (l/s). The comparison of observed and predicted values indicates a suitable agreement between the models and the real data, such that the difference in most predictions compared to observed values is less than approximately 10 to 20 l/s. The largest errors are observed during peak discharge periods (above 230 l/s) and severe low-flow periods (below 120 l/s).

The trend of the numerical results demonstrates the high capability of machine learning models in simulating the hydrological behaviour of Qanats in the arid regions of Iran. Among the employed models, the Stacking model, which uses the predictions of the base models as its input, achieved higher accuracy, and its simulated data showed the best match with the actual data. Consequently, the Stacking model can be utilised as a management tool for prediction and decision-making in the sustainable operation of groundwater resources.

The comparison of the results of this research with previous studies indicates that the hybrid Stacking model has an acceptable performance in estimating Qanat discharge and is consistent with the findings of many similar studies in the field of water resources. For example, one study emphasised that the Stacking model, by combining the outputs of base models such as Random Forest and SVR, achieved the best performance in evaluating daily river flows. The authors concluded that Stacking minimizes prediction error by establishing a connection between the base learning models. (Dey & Mathur, 2023). In another investigation to predict water quality using advanced environmental and chemical data, researchers pointed to the superiority of Stacking, especially in complex, high-dimensional data. (Shams et al., 2024). They demonstrated that the Stacking model provided the lowest RMSE and the highest. $R^2$by combining the outputs of the base models, showing greater accuracy in geotechnical engineering and groundwater applications (Sun et al., 2025).

Conclusion

The Qanat, as one of the most complex and astonishing ancient Iranian engineering innovations, was crucial in Iran's arid and semi-arid regions. Among them, the Balade Qanat network in Ferdows County, South Khorasan Province, holds a unique position due to its historical age and the profound dependence of the region's economic and social livelihoods on it. South Khorasan, long known for having the highest number of Qanats in the country, is the region most in need of accurate modelling of its groundwater resources. The Balade Qanats of Ferdows are not merely an irrigation system but a symbol of historical adaptation to the harsh climatic environment of the region. By continuously supplying water for agriculture, these Qanats have guaranteed food security and the sustainability of local communities for centuries. However, like other Qanats across the country, this valuable network is severely affected by climate change, rising temperatures, and recent persistent droughts, leading to a noticeable decline in discharge in recent years. Therefore, accurate study and modelling of the discharge behaviour of these Qanats under variable climatic conditions is not only a scientific necessity but also a critical management issue for preserving this water heritage and ensuring the survival of regional agriculture in the coming decades.

The present research aims to simulate the discharge of the Balade Qanat complex in Ferdows County by employing the XG Boost machine learning algorithm. For this purpose, ten years of monthly data, including precipitation, minimum, maximum, and average temperature, drought indices (SPI and SPEI), and Qanat discharge from 2015 to 2024 were collected and, after preprocessing, fed into the models. Performance evaluation using statistical indices: Coefficient of Determination (R^2), Root Mean Square Error (RMSE), and Kling-Gupta Efficiency (KGE) against the RF, SVR, GB, and Stacking Model showed that the Stacking model, with an $R^2 = 0.93$, $KGE = 0.92$, and $RMSE = 12.21$ L/s, demonstrated a high capacity to reconstruct the temporal trend of Qanat discharge. The model's high accuracy in identifying discharge variation patterns suggests that hybrid machine learning models can be an effective substitute for traditional models in analysing the hydrological behaviour of Qanats in arid regions.

The findings of this study, while emphasising the efficiency of the Stacking ensemble model in accurately predicting the discharge of the Balade-Ferdows Qanats, highlight the strategic importance of Qanats under Iran's climate-stressed conditions. Due to their stable and low-cost structure, Qanats can be regarded as a natural approach to alleviating drought pressure on groundwater resources. The application of machine learning models in monitoring and forecasting Qanat behaviour provides a novel data-driven foundation for decision-making, which is essential for climate-adaptive planning, resilience enhancement, and sustainable aquifer management. The proposed framework is transferable to other Qanat systems and groundwater-dependent regions experiencing climatic stress, particularly in arid and semi-arid environments across Iran, Central Asia, and the Middle East. Because the methodology relies primarily on climatic and discharge data, it can be adapted to regions where detailed hydrogeological datasets are unavailable.

Reference

Ali, S., Khorrami, B., Jehanzaib, M., Tariq, A., Ajmal, M., Arshad, A., Shafeeque, M., Dilawar, A., Basit, I., & Zhang, L. (2023). Spatial downscaling of GRACE data based on an XGBoost model for improved understanding of hydrological droughts in the Indus Basin Irrigation System (IBIS). *Remote Sensing*, *15*(4), 873. https://doi.org/10.3390/rs15040873

Alimkulov, S., Makhmudova, L., Satenova, B., Tursunova, A., Birimbayeva, L., Talipova, E., Abdibekov, D., Smagulov, Z., & Alzhanov, O. (2025). Modelling Daily River Discharge Using Machine Learning Ensembles in the Context of Climate Change: Application to the Zhaiyk-Caspian Basin, Kazakhstan. *Earth Systems and Environment*, 1-28. https://doi.org/10.1007/s41748-025-00858-x

Almazroui, M., Islam, M. N., Saeed, F., Saeed, S., Ismail, M., Ehsan, M. A., Diallo, I., O'Brien, E., Ashfaq, M., & Martínez-Castro, D. (2021). Projected changes in temperature and precipitation over the United States, Central America, and the Caribbean in CMIP6 GCMs. *Earth Systems and Environment*, *5*(1), 1-24. https://doi.org/10.1007/s41748-021-00199-5.

Bartlett, J. A., & Dedekorkut-Howes, A. (2023). Adaptation strategies for climate change impacts on water quality: a systematic review of the literature. *Journal of Water and Climate Change*, *14*(3), 651-675. https://doi.org/DOI: 10.2166/wcc.2022.279.

Breiman, L. (2001). Random Forests. *Machine Learning*, *45*(1), 5-32. https://doi.org/10.1023/A:1010933404324

Chen, T., & Guestrin, C. (2016). *XGBoost: A Scalable Tree Boosting System* Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, California, USA. https://doi.org/10.1145/2939672.2939785

Dey, R., & Mathur, R. (2023). An ensemble learning method using stacking with a base learner for comparison. International Conference on Data Analytics and Insights, https://doi.org/10.1007/978-981-99-3878-0_14

Dey, S. (2025). Short-Term River Discharge Forecasting Using an XGBoost-Based Regression Model.

Dhaliwal, D. S., & Williams, M. M. (2024). Sweet corn yield prediction using machine learning models and field-level data. *Precision Agriculture*, *25*(1), 51-64. https://doi.org/10.1007/s11119-023-10057-1

Dong, J., Zeng, W., Wu, L., Huang, J., Gaiser, T., & Srivastava, A. K. (2023). Enhancing short-term forecasting of daily precipitation using numerical weather prediction bias correcting with XGBoost in different regions of China. *Engineering Applications of Artificial Intelligence*, *117*, 105579. https://doi.org/10.1016/j.engappai.2022.105579

Fan, J., Wu, L., Zhang, F., Cai, H., Wang, X., Lu, X., & Xiang, Y. (2018). Evaluating the effect of air pollution on global and diffuse solar radiation prediction using support vector machine modelling based on sunshine duration and air temperature. *Renewable and Sustainable Energy Reviews*, *94*, 732-747. https://doi.org/10.1016/j.rser.2018.06.029

Foruzanmehr, M., & Khozeymehnezhad, H. (2023). Investigation of spatial and temporal changes of qualitative parameters of the Qaen plain aquifer using interpolation methods. *Journal of Aquifer and Qanat*, *4*(1), 1-15. https://doi.org/10.22077/jaaq.2023.5130.1045

Fouladi Nasrabad, M., Pourreza Bilondi, M., Amirabadizadeh, M., & *Javaheri*, M. (2025). Performance of the XGBoost algorithm in downscaling temperature and relative humidity in a temperate climate: a case study in Kermanshah. *Water and Soil Management and Modelling*, *5*(Special Issue: Climate Change and Effects on Water and Soil), 215-232. https://doi.org/10.22098/mmws.2025.18179.1661

Friedman, J. H. (2001). Greedy function approximation: a gradient boosting machine. *Annals of statistics*, 1189-1232. https://doi.org/10.1214/aos/1013203451

Ghorbani, M. A., Shamshirband, S., Haghi, D. Z., Azani, A., Bonakdari, H., & Ebtehaj, I. (2017). Application of firefly algorithm-based support vector machines for prediction of field capacity and permanent wilting point. *Soil and Tillage Research*, *172*, 32-38. https://doi.org/10.1016/j.still.2017.04.009

Hastie, T. (2009). The elements of statistical learning: data mining, inference, and prediction. In: Springer.

Hosen, N., Nakamura, H., & Hamzah, A. (2020). Adaptation to climate change: Does traditional ecological knowledge hold the key? *Sustainability*, *12*(2), 676. https://doi.org/10.3390/su12020676.

Hosseini Fahraji, R. S., & Sharifzadeh, M. (2016). Qanat maintenance from key informants' viewpoint: A qualitative research in Taft County. *The Journal of Community Development (Rural-Urban)*, *8*(2), 295-312. https://doi.org/DOI: 10.22059/jrd.2016.63069

Jiang, X., Fan, C., Liu, K., Chen, T., Cao, Z., & Song, C. (2022). Centenary covariations of water salinity and storage of the largest lake of Northwest China reconstructed by machine learning. *Journal of Hydrology*, *612*, 128095. https://doi.org/10.1016/j.jhydrol.2022.128095.
Khoshsimaie Chenar, M., Noory, H., Liaghat, A., Soltani Salehabadi, F., & Motesharezadeh, B. (2025). Evaluation of the accuracy of different machine learning algorithms in predicting greenhouse cucumber crop evapotranspiration. *Water and Irrigation Management*, *15*(3), 563-583. https://doi.org/10.22059/jwim.2025.399994.1251
Khosravi, Y., Ouarda, T. B., & Homayouni, S. (2025). Developing an ensemble machine learning framework for enhanced climate projections using CMIP6 data in the Middle East. *npj Climate and Atmospheric Science*, *8*(1), 174. https://doi.org/doi:10.1038/s41612-025-01033-9
Knoben, W. J., Freer, J. E., & Woods, R. A. (2019). Inherent benchmark or not? Comparing Nash–Sutcliffe and Kling–Gupta efficiency scores. *Hydrology and Earth System Sciences*, *23*(10), 4323-4331. https://doi.org/10.5194/hess-23-4323-2019
Kramer, O. (2016). Scikit-learn. In *Machine learning for evolution strategies* (pp. 45-53). Springer. https://doi.org/10.1007/978-3-319-33383-0_5
Lane, R. A., & Kay, A. L. (2021). Climate change impact on the magnitude and timing of hydrological extremes across Great Britain. *Frontiers in Water*, *3*, 684982. https://doi.org/DOI: 10.3389/frwa.2021.684982.
Liu, X. (2025). Enhanced Prediction of Karst Spring Discharge Using a Hybrid LSTM-XGBoost Model Optimised with Grid Search. *Machine Learning With Applications*, 100740. https://doi.org/10.1016/j.mlwa.2025.100740
Mahammad, S., Islam, A., Shit, P. K., Islam, A. R. M. T., & Alam, E. (2023). Groundwater level dynamics in a subtropical fan delta region and its future prediction using machine learning tools: Sustainable groundwater restoration. *Journal of Hydrology: Regional Studies*, *47*, 101385. https://doi.org/10.1016/j.ejrh.2023.101385
McKee, T. B., Doesken, N. J., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. Proceedings of the 8th Conference on Applied Climatology,
Mohtasham, M., Dehghani, A. A., Akbarpour, A., & Meftah, M. (2017). Evaluation of Artificial Neural Networks and MODFLOW Numerical Model in Forecasting Groundwater Table (Case Study: Birjand Aquifer, Southern Khorasan). *Iranian Journal of Irrigation & Drainage*, *11*(1), 1-10. https://idj.iaid.ir/article_79421_a03adf46f077c337759e1acd7ad06fd5.pdf
Mosavi, A., Ozturk, P., & Chau, K.-w. (2018). Flood prediction using machine learning models: Literature review. *Water*, *10*(11), 1536. https://doi.org/10.3390/w10111536
Mostafazadeh, R., & Zabihi, M. (2016). Comparison of SPI and SPEI indices to meteorological drought assessment using R programming (Case study: Kurdistan Province). *Journal of the Earth and Space Physics*, *42*(3), 633-643. https://doi.org/10.22059/jesphys.2016.57881
Natekin, A., & Knoll, A. (2013). Gradient Boosting Machines: A Tutorial. *Frontiers in neurorobotics*, *7*, 21. https://doi.org/10.3389/fnbot.2013.00021
Niazkar, M., Menapace, A., Brentan, B., Piraei, R., Jimenez, D., Dhawan, P., & Righetti, M. (2024). Applications of XGBoost in water resources engineering: A systematic literature review (Dec 2018–May 2023). *Environmental Modelling & Software*, *174*, 105971. https://doi.org/10.1016/j.envsoft.2024.105971
Nourani, V., Behfar, N., Dabrowska, D., & Zhang, Y. (2021). The applications of soft computing methods for seepage modelling: A review. *Water*, *13*(23), 3384. https://doi.org/10.3390/w13233384
Nourani, V., Razzaghzadeh, Z., Baghanam, A. H., & Molajou, A. (2019). ANN-based statistical downscaling of climatic parameters using a decision tree predictor screening method. *Theoretical and Applied Climatology*, *137*(3), 1729-1746. https://doi.org/10.1007/s00704-018-2686-z
Ogunrinde, A. T., Adeyeri, O. E., Xian, X., Yu, H., Jing, Q., & Faloye, O. T. (2024). Long-term spatiotemporal trends in precipitation, temperature, and evapotranspiration across arid Asia and Africa. *Water*, *16*(22), 3161. https://doi.org/10.3390/w16223161.
Piraei, R., Afzali, S. H., & Niazkar, M. (2023). Assessment of XGBoost to estimate total sediment loads in rivers. *Water Resources Management*, *37*(13), 5289-5306. https://doi.org/10.1007/s11269-023-03606-w
Rakhshandehroo, G., Akbari, H., Afshari Igder, M., & Ostadzadeh, E. (2018). Long-term groundwater-level forecasting in shallow and deep wells using wavelet neural networks trained by an improved harmony search algorithm. *Journal of Hydrologic Engineering*, *23*(2), 04017058.
Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., & Prabhat, F. (2019). Deep learning and process understanding for data-driven Earth system science. *Nature*, *566*(7743), 195-204. https://doi.org/10.1038/s41586-019-0912-1

Safira, R. A. D., Anjasmara, I. M., & Awange, J. L. (2024). Predictive Modelling of Terrestrial Water Storage Anomalies in Kalimantan Basins: Bridging the GRACE and GRACE-FO Data Gap with Extreme Gradient Boosting. *GEOID*, *19*(3), 508-518. https://doi.org/10.12962/geoid.v19i3.2329

Samani, S., Vadiati, M., Kisi, O., Ghasemi, L., & Farajzadeh, R. (2024). Qanat discharge prediction using a comparative analysis of machine learning methods. *Earth Science Informatics*, *17*(5), 4597-4618. https://doi.org/10.1007/s11600-022-00964-8

Samaniego, L. (2025). Permanent shifts in the global water cycle. *Science*, *387*(6741), 1348-1350. https://doi.org/10.1126/science.adw5851.

Scanlon, B. R., Fakhreddine, S., Rateb, A., de Graaf, I., Famiglietti, J., Gleeson, T., Grafton, R. Q., Jobbagy, E., Kebede, S., & Kolusu, S. R. (2023). Global water resources and the role of groundwater in a resilient water future. *Nature Reviews Earth & Environment*, *4*(2), 87-101. https://doi.org/10.1038/s43017-022-00378-6.

Shams, M. Y., Elshewey, A. M., El-kenawy, E.-S. M., Ibrahim, A., Talaat, F. M., & Tarek, Z. (2024). Water quality prediction using machine learning models based on the grid search method. *Multimedia Tools and Applications*, *83*(12), 35307-35334. https://doi.org/10.1007/s11042-023-16737-4

Shrestha, N., & Shukla, S. (2015). Support vector machine-based modelling of evapotranspiration using hydro-climatic variables in a sub-tropical environment. *Agricultural and forest meteorology*, *200*, 172-184. https://doi.org/10.1016/j.agrformet.2014.09.025

Stringer, L. C., Mirzabaev, A., Benjaminsen, T. A., Harris, R. M., Jafari, M., Lissner, T. K., Stevens, N., & Tirado-von Der Pahlen, C. (2021). Climate change impacts on water security in global drylands. *One Earth*, *4*(6), 851-864. https://doi.org/10.1016/j.oneear.2021.05.010.

Sun, K., Gao, Y., He, W., Wang, L., & Sun, X. (2025). Prediction of soil-water retention curves in unsaturated soils based on stacked generalisation. *Journal of Rock Mechanics and Geotechnical Engineering*. https://doi.org/10.1016/j.jrmge.2025.12.016

Vapnik, V. N. (2000). *The Nature of Statistical Learning Theory*. Springer New York, NY. https://doi.org/10.1007/978-1-4757-3264-1

Wu, J., Ma, D., & Wang, W. (2022). Leakage identification in water distribution networks based on the XGBoost algorithm. *Journal of Water Resources Planning and Management*, *148*(3), 04021107. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001523

Yang, D., Yang, Y., & Xia, J. (2021). Hydrological cycle and water resources in a changing world: A review. *Geography and Sustainability*, *2*(2), 115-122. https://doi.org/10.1016/j.geosus.2021.05.003.

Zhou, S., Liu, Z., Wang, M., Gan, W., Zhao, Z., & Wu, Z. (2022). Impacts of building configurations on urban stormwater management at a block scale using XGBoost. *Sustainable Cities and Society*, *87*, 104235. https://doi.org/10.1016/j.scs.2022.104235

Zounemat-Kermani, M., Mahdavi-Meymand, A., Alizamir, M., Adarsh, S., & Yaseen, Z. M. (2020). On the complexities of sediment load modelling using integrative machine learning: Application of the great river of Loíza in Puerto Rico. *Journal of Hydrology*, *585*, 124759. https://doi.org/10.1016/j.jhydrol.2020.124759