Intelligent Geoengineering 3 (2026) 57–69

Contents lists available at ScienceDirect

Intelligent Geoengineering

journal homepage: www.keaipublishing.com/en/journals/ige/

Full length article

A bio-inspired artificial intelligence framework leveraging remote sensing for groundwater storage modeling in climate-stressed regions

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ARTICLE INFO

Keywords:
Artificial intelligence
Swan Optimization Algorithm
Groundwater storage
Arid and semi-arid region
Climate change

ABSTRACT

This study presents an AI-driven framework for predicting groundwater storage (GWS) in the arid to semi-arid regions of Agdz and Zagora in southern Morocco, where sustainable water resource management is increasingly critical. Four machine-learning models Random Forest (RF), CatBoost, AdaBoost, and Multi-Layer Perceptron (MLP) were trained using a comprehensive dataset integrating Gravity Recovery and Climate Experiment (GRACE) mission-derived Terrestrial Water Storage (TWS), remote sensing indicators such as The Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST), and key climatic variables. To improve predictive accuracy, model hyperparameters were optimized using the Swan Optimization Algorithm (SOA), a bio-inspired metaheuristic technique. Among the tested models, RF achieved the highest performance, with root mean square error (*RMSE*) values of 4.70 mm and 4.29 mm and *NSE* scores of 0.998 and 0.999 for Agdz and Zagora, respectively. TWS consistently emerged as the most influential predictor across all models. These results highlight the potential of integrating artificial intelligence, satellite remote sensing, and bio-inspired optimization for periodically updated monitoring and prediction of groundwater storage in data-scarce regions. The proposed framework provides a valuable decision-support tool for smart irrigation planning and climate-resilient water management in agriculture-dependent areas.

1. Introduction

Machine learning (ML) and remote sensing have revolutionized groundwater storage prediction by integrating GRACE/GRACE-FO satellite data with in-situ observations, providing innovative tools for water resource management in semi-arid environments (Dharpure et al., 2025; Foroumandi et al., 2023; Ibrahim et al., 2024). In Morocco's Draa Basin including Agdz and Zagora GWS is crucial for sustaining agriculture, particularly date palm cultivation, in a climate where annual rainfall rarely exceeds 140 mm (Schulz et al., 2008). Recent advances highlight the effectiveness of ensemble machine learning models, such as Random Forest and CatBoost, which have demonstrated strong predictive performance and robustness in modeling complex nonlinear environmental processes (Huang et al., 2019; Pham et al., 2021), as well as deep learning models such as LSTM (Deng et al., 2025), in capturing nonlinear hydrological dynamics more effectively than traditional methods.

However, climate change continues to amplify groundwater-related challenges, increasing drought frequency, reducing recharge rates, and elevating evapotranspiration (Karmaoui et al., 2023; Karmaoui and Moumane, 2016; Moumane et al., 2021). Combined with intensified agricultural use and groundwater overexploitation, these dynamics threaten aquifer sustainability across Morocco (Elmotawakkil et al., 2025b; Heidecke, 2010; Moumane et al., 2025, 2026). Moreover, the coarse resolution of GRACE data limits its practical application for local-scale groundwater management (Shilengwe et al., 2024), necessitating more precise, machine learning-based solutions tailored to regional contexts.

Peer review under responsibility of Chinese Society for Rock Mechanics and Engineering

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https://doi.org/10.1016/j.ige.2026.04.001
Received 2 November 2025; Received in revised form 11 March 2026; Accepted 8 April 2026
Available online 23 April 2026

This study evaluates four ML models RF, AdaBoost, CatBoost, and Multi-Layer Perceptron to predict GWS from 2003 to 2024 in Agdz and Zagora. The models are optimized using the Swan Optimization Algorithm, a nature-inspired method that enhances hyperparameter tuning efficiency (Mumtahina et al., 2024). Key predictors, such as Terrestrial Water Storage obtained from GRACE satellite observations, offer valuable insights into large-scale variations in groundwater and overall water balance. Such datasets have significantly improved the monitoring and analysis of hydrological processes and climate-related water dynamics (Elmotawakkil et al., 2025b; Khorrami and Gündüz, 2025; Wang et al., 2023), are assessed to support smart agriculture through accurate irrigation scheduling, and enable evidence-based monitoring to limit groundwater depletion (Abbas et al., 2025). This integrated approach builds on recent advances and addresses the limitations of coarse satellite data, offering a scalable and adaptable framework for regional GWS prediction aligned with broader sustainability efforts (Jaramillo et al., 2024; Mohasseb et al., 2024).

Despite the increasing use of satellite observations such as GRACE mission for monitoring terrestrial water storage, several limitations remain in the existing literature. First, most studies focus on large-scale hydrological assessments, while limited research has explored groundwater storage prediction at regional scales in arid and semi-arid basins, particularly in North Africa. Second, although machine learning models have been widely applied in hydrological prediction, comparative analyses involving multiple algorithms optimized using bio-inspired metaheuristic techniques remain relatively limited. Third, the potential of integrating GRACE-derived Terrestrial Water Storage with remote sensing indicators and climatic variables for groundwater storage prediction in the Draa Basin has not been thoroughly investigated. Therefore, this study aims to address these gaps by developing a machine learning framework that compares four models Random Forest, CatBoost, AdaBoost, and Multi-Layer Perceptron optimized using the Swan Optimization Algorithm for predicting groundwater storage in the Agdz and Zagora regions.

From a policy perspective, this work provides a robust foundation for informed water governance. Reliable GWS predictions can inform smart irrigation policies, optimize resource allocation, and prevent unsustainable aquifer drawdown. By highlighting critical environmental variables like TWS, this study supports targeted investments in monitoring technologies, including IoT sensors, that enable real-time agricultural decision-making (Assimakopoulos et al., 2025). This aligns with Morocco's national water resilience strategy, contributing to the intersection of artificial intelligence, environmental sustainability, and policy planning.

2. Related work

In recent years, the integration of remote sensing data with machine learning techniques has gained significant attention for groundwater storage prediction and monitoring, particularly in regions facing data scarcity or climatic challenges; various frameworks and models have been developed to enhance the accuracy and reliability of groundwater predictions by incorporating multi-source datasets, including satellite-derived indices and environmental variables.

Recent studies have highlighted the increasing role of artificial intelligence and machine learning techniques in groundwater prediction and management. Hybrid AI approaches have been widely explored to improve prediction accuracy and support sustainable groundwater resource management (Zaresefat and Derakhshani, 2023). Comparative studies have also shown that machine learning models, including neural networks and ensemble algorithms, can outperform traditional statistical approaches in groundwater level prediction tasks (Poursaeid et al., 2022). Beyond hydrological applications, machine learning methods have demonstrated strong capability in modeling complex geotechnical and environmental processes, particularly where nonlinear relationships exist between multiple variables (Shilengwe et al., 2024). Furthermore, recent reviews emphasize the growing integration of AI-based computational approaches in geotechnical and environmental engineering, highlighting their potential for improving predictive modeling and decision-making in earth system sciences (Liu et al., 2024).

Several studies have employed ensemble machine learning, deep learning, and statistical models, leveraging data from GRACE, Landsat, MODIS, and in-situ measurements (Huang et al., 2019; Pham et al., 2021) have reported the successful application of ensemble learning techniques, particularly Random Forest and CatBoost, in environmental modeling, demonstrating their robustness and high predictive performance when dealing with complex nonlinear datasets.

Deng et al. (2025) introduced a refined downscaling framework in the Tarim River mainstream using geographically weighted regression and an LSTM model to forecast GWSA under future climate scenarios. Elmotawakkil et al. (2024) focused on predicting groundwater levels in Morocco's Rabat-Salé-Kenitra region using a variety of machine learning models, with Gradient Boosting Regression yielding the best performance. Li et al. (2024) analyzed groundwater storage fluctuations in Shandong Province, demonstrating the superiority of SVM for short-term GWS forecasting. Shilengwe et al. (2024) applied a threefold downscaling framework using Random Forest for generating high-resolution GWSA datasets, while Wang et al. (2023) used a back-propagation neural network (BPNN) to downscale GRACE-derived GWSA data in China.

These studies illustrate the effectiveness of combining advanced machine learning techniques and remote sensing data to improve groundwater predictions, offering valuable insights for sustainable water management in different environments.

Bio-inspired algorithms have been widely used for hyperparameter optimization in groundwater modeling. For example, Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Whale Optimization Algorithm (WOA) have demonstrated strong performance in training ensemble and deep learning models (Abualigah, 2025). However, these algorithms may suffer from premature convergence or insufficient exploration when dealing with highly nonlinear optimization problems. In contrast, the Swan Optimization Algorithm (SOA), introduced by Dhiman and Kumar (2019), employs dynamic movement and adaptive search strategies that improve the balance between exploration and exploitation during the optimization process. This mechanism reduces the risk of convergence to local minima and enhances the generalization capability of optimized machine learning models.

3. Materials and methods

This study adopts a systematic methodology to design and assess machine learning models for predicting groundwater levels in Morocco's semi-arid agricultural regions. The framework consists of three main phases. First, the study area is examined to understand the geographic and climatic factors that contribute to groundwater variability. Second, data acquisition and preprocessing are performed, incorporating historical climate data and groundwater level observations. In the final phase, various machine learning models are developed, and their hyperparameters are optimized using a Swan-inspired algorithm. Model performance is then evaluated using key metrics such as *MSE*, *RMSE*, *MAE*, and *NSE* to ensure both accuracy and robustness.

By integrating remote sensing data, historical records, and advanced machine learning techniques, this research provides a data-driven solution aimed at enhancing irrigation practices and supporting sustainable water resource management in Moroccan agriculture Fig. 3.

This research focuses on two locations in Morocco Agdz and Zagora both located in the Draa Basin Fig. 1. This region plays a vital role in supporting agriculture and depends heavily on groundwater as a primary water source (Kaczmarek et al., 2025). Situated in southern Morocco, the Draa Basin is characterized by a semi-arid to arid climate, where rainfall is not only scarce but also highly unpredictable

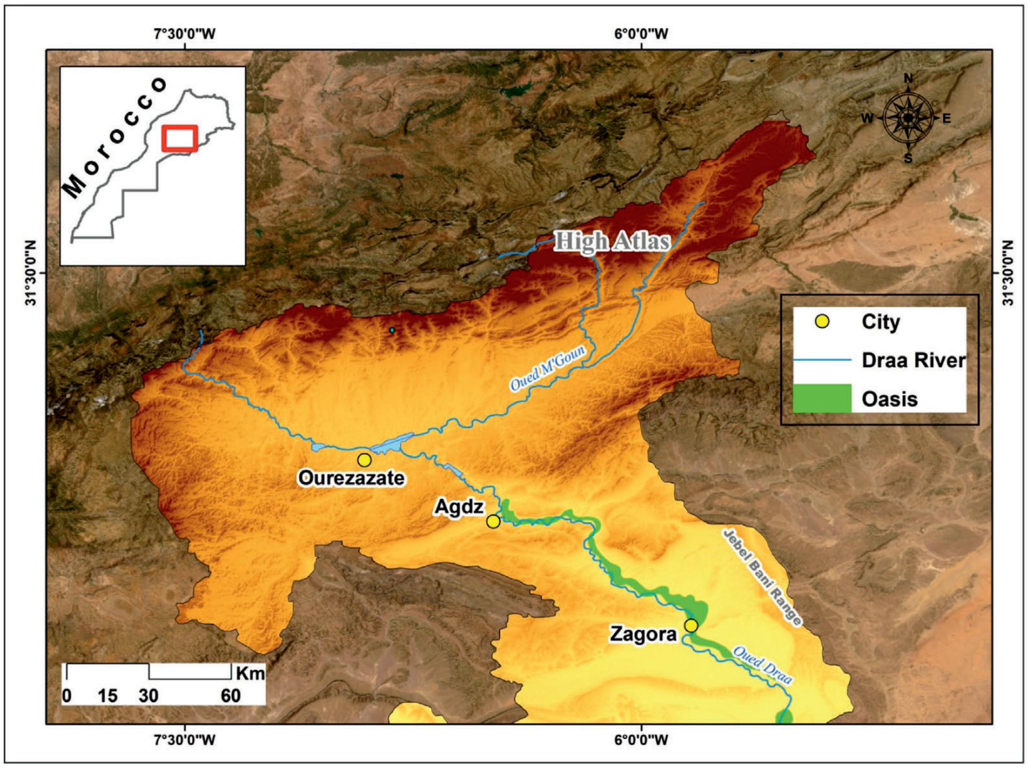

Fig. 1. Geographical distribution of study areas in the Zagora Province, Morocco.

(Elmotawakkil et al., 2025a). These challenging conditions make soil moisture monitoring essential for ensuring sustainable water use and enabling more efficient irrigation practices (Elmotawakkil et al., 2025c; Karmaoui and Moumane, 2016; Moumane et al., 2025).

The climate in these regions is characterized by hot, dry summers and mild winters, with annual rainfall rarely going beyond 140 mm (Schulz et al., 2008). Such extreme weather conditions often lead to recurring droughts and unstable soil moisture levels, posing serious challenges for farmers. One of the region's main crops, the date palm, depends heavily on water management practices to grow successfully (Fico, 2024; Heidecke, 2010).

The study area is underlain by alluvial and semi-confined sedimentary aquifers that are the main sources of groundwater for domestic and agricultural use. Depth to groundwater ranges from 10 to 150 m, with recharge primarily from sporadic rainfall and upstream wadis, while major discharge occurs through irrigation pumping and natural outflows to lowlands. Several monitoring wells exist across the Zagora plain, indicating a gradual decline in water levels in heavily pumped zones, reflecting the sensitivity of these aquifers to extraction and climate variability (Ait Lemkademe et al., 2023; Boudellah et al., 2023).

The soil types across the study areas vary from sandy and loamy to clay-rich soils which significantly influences how well the soil holds water and how much moisture is available for plants (Klose, 2009; Moumane et al., 2024).

Given these environmental pressures, the ability to accurately groundwater storage predict becomes critical for promoting smart agriculture. It supports informed irrigation planning and helps make the most of limited water resources (Ahmed et al., 2023). Choosing these diverse locations allows the study to capture a broad range of groundwater and climate conditions, offering insights that can strengthen agricultural sustainability and resilience in the face of climate change.

3.1. Dataset description

This study is based on a rich and diverse dataset combining soil moisture records, climatic data, and remote sensing indicators.

The dataset brings together ground-based measurements of soil moisture with key meteorological variables such as precipitation, temperature, humidity, and evapotranspiration. It also includes remote sensing-derived features like the NDVI, LST, and other vegetation indices, extracted through Google Earth Engine Table 1.

To further improve model accuracy, soil characteristics such as texture and organic matter content were also integrated. Given the region's climatic instability and frequent drought conditions, this comprehensive dataset offers a solid foundation for developing machine

Table 1
Summary of environmental and remote sensing variables utilized for groundwater prediction in semi-arid Moroccan regions.

Variable	Units	Min	Max	Source
Average Surface Temperature	K	179.818	324.265	(Wan et al., 2021)
Evapotranspiration	mm	—	—	The Food and Agriculture Organization (FAO, 2020)
Groundwater Storage (GWS)	mm	77.0153	3599.01	(Rodell et al., 2004)
Land Surface Temperature (LST)	K	7500	65,535	(Adler et al., 2017)
Precipitation	mm/day	0	—	(Adler et al. 2017)
Root Zone Soil Moisture	kg/m^2	32.3665*	478.397	(Rodell et al. 2004)
Soil Texture	—	—	—	(Hengl, 2018)
Terrestrial Water Storage (TWS)	mm	109.394	5084.16	(Rodell et al. 2004)

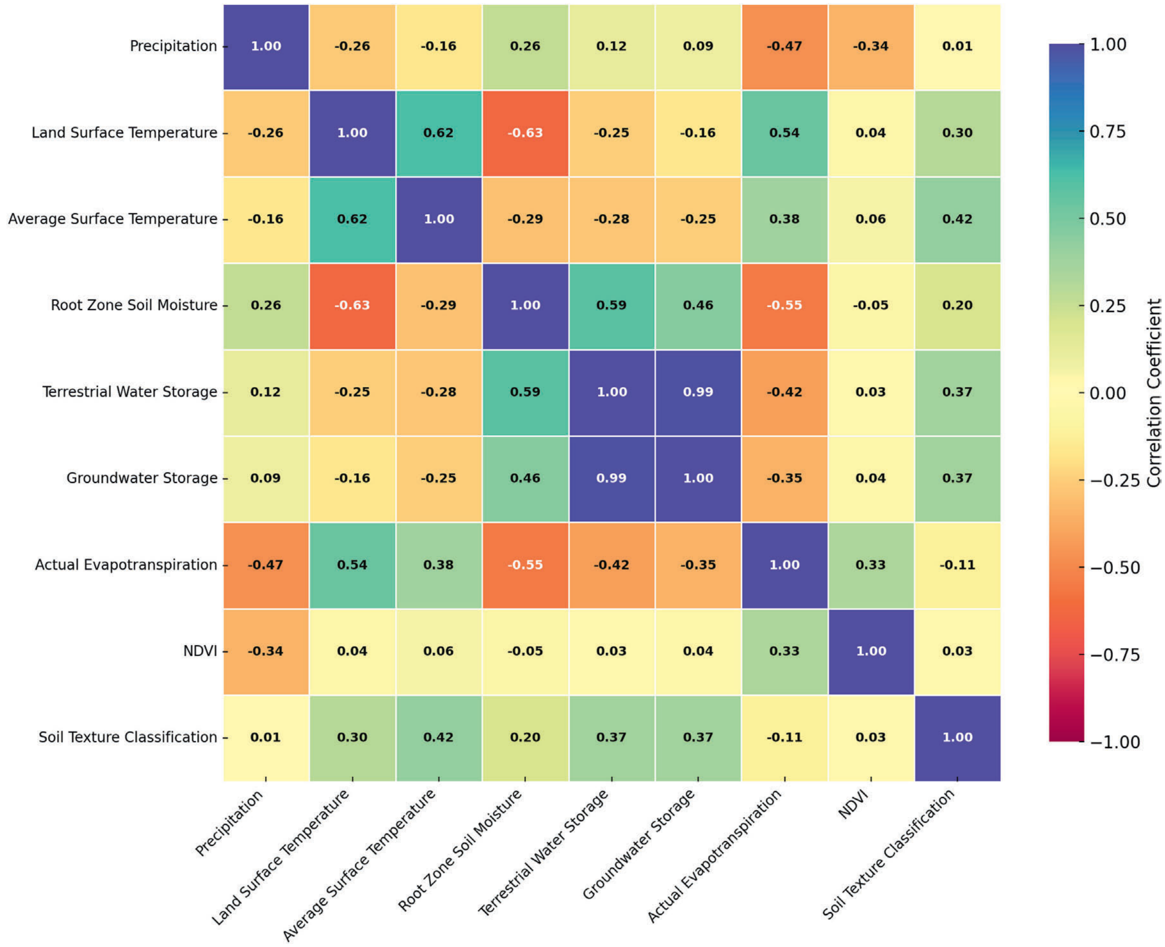

Fig. 2. Correlation matrix of groundwater and environmental factors.

learning-based soil moisture prediction models. These models can provide actionable insights to support precision irrigation and promote sustainable agriculture in water-limited environments Fig. 2.

3.2. Data preprocessing

To ensure that the dataset was clean, consistent, and suitable for machine learning analysis, several preprocessing steps were performed. Missing values were addressed using appropriate strategies depending on the data type. Temporal gaps in time-series data were filled using linear interpolation, while numerical features were imputed using a k-Nearest Neighbors (KNN) interpolation approach to preserve underlying data patterns. Sensor-related outliers were detected using a z-score–based filtering procedure and removed to minimize their potential impact on model performance. The interpolation process relied on a predefined number of neighbors, and additional details regarding parameter settings and the complete preprocessing workflow are available in the implementation scripts, which can be provided to interested researchers upon reasonable request.

To better capture temporal trends and improve model accuracy, additional features were engineered, including lagged soil moisture variables, moving averages of climatic parameters, and scaled vegetation indices. These features help represent temporal dependencies and underlying patterns in the dataset. All continuous variables were normalized using Min–Max scaling to ensure consistency among features and facilitate stable model training. The dataset was then divided into training (80%) and testing (20%) sets while preserving the temporal distribution to maintain the chronological structure of the data and avoid potential bias during evaluation.

To further ensure robust model assessment and enhance generalization capability, a 5-fold cross-validation strategy was applied during model training. In this approach, the training dataset was partitioned into five subsets; in each iteration, four subsets were used for training while the remaining subset served as the validation set. This process was repeated five times so that each subset was used once for validation. The final performance metrics were obtained by averaging the results across all folds, providing a more reliable estimate of the model's predictive performance and reducing the risk of overfitting.

3.3. Machine learning models

To ensure accurate and reliable groundwater predictions, four machine learning models were utilized: Multi-Layer Perceptron, Random Forest, CatBoost, and AdaBoost. These models were selected due to their proven effectiveness in time-series forecasting, hydrological analysis, and agricultural prediction tasks.

The chosen models represent a balanced mix of learning approaches: MLP, a deep learning model, is well-suited for capturing temporal dependencies in the data, while RF, AdaBoost, and CatBoost are tree-based models known for their strong performance and interpretability. Detailed explanations of each model's mathematical basis and implementation are provided in the following sections.

3.4. AdaBoost algorithm

Adaptive Boosting (AdaBoost) is a widely used ensemble learning technique introduced by Freund and Schapire (1997). It builds a strong classifier by sequentially combining several weak learners, typically decision stumps, and assigning them weights based on their performance. In each iteration, AdaBoost increases the focus on misclassified instances by updating their weights, allowing subsequent learners to better address these harder cases.

The final strong classifier $H(x)$ is a weighted majority vote of the weak learners $h_t(x)$, given by:

$$H(x) = \text{sign}\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right)$$

where α_t is the weight assigned to the t^{th} weak learner based on its accuracy, and T is the total number of boosting rounds.

AdaBoost has shown great success in classification tasks, especially in applications involving hydrological prediction and environmental modeling.

3.5. CatBoost

CatBoost is an advanced gradient boosting algorithm specifically designed to handle categorical features and high-dimensional datasets effectively (Luo et al., 2021). It enhances model accuracy by employing techniques such as ordered boosting, which helps mitigate prediction bias, and efficient encoding strategies for categorical variables during training.

The general objective of gradient boosting in CatBoost is to minimize a regularized loss function, expressed as:

$$L(\theta) = \sum_{i=1}^{n} l(y_i, f(x_i, \theta)) + \lambda||\theta||^2$$

here, $L(\theta)$ represents the overall loss, $f(x_i, \theta)$ is the model's prediction for input x_i, l is the loss function measuring the prediction error, and $\lambda||\theta||^2$ is a regularization term to prevent overfitting.

3.6. Multi-layer perceptron (MLP)

The Multi-Layer Perceptron is a class of feedforward artificial neural networks that consists of an input layer, one or more hidden layers, and an output layer. It is widely used in regression and classification tasks, particularly where complex nonlinear relationships exist, such as in groundwater modeling and environmental data forecasting (Gardner and Dorling, 1998).

Each neuron in the hidden layers computes a weighted sum of its inputs, adds a bias, and applies a nonlinear activation function. This process is mathematically expressed as:

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right)$$

where x_i are the input features, w_i are the associated weights, b is the bias, and f is the activation function (e.g., ReLU or sigmoid). MLPs are trained using backpropagation to minimize prediction error by adjusting weights iteratively.

Due to their ability to capture temporal and spatial patterns, MLPs are highly applicable to hydrological and agricultural modeling problems.

3.7. Random forest (RF)

RF is an ensemble learning method that combines multiple decision trees to enhance prediction accuracy and robustness (Breiman, 2001). It applies bootstrap aggregation (bagging), where each tree is trained on a random subset of data. The final prediction is obtained by averaging (regression) or majority voting (classification):

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} h_t(x)$$

where $h_t(x)$ represents an individual tree's prediction, and T is the total number of trees.

3.8. Evaluation metrics

To evaluate the performance of the machine learning models, four widely recognized metrics were used: Mean Squared Error (*MSE*), *RMSE*, Nash-Sutcliffe Efficiency (*NSE*), and Mean Absolute Error (*MAE*). Each of these metrics offers a different perspective on model accuracy, helping ensure a well-rounded assessment of predictive quality.

MSE measures the average of the squared differences between the predicted and actual values. This metric gives more weight to larger errors, making it sensitive to outliers:

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

where y_i and $\hat{y}_i$ are the observed and predicted values, respectively, and n is the number of observations (Willmott, 1981).

RMSE, the square root of *MSE*, provides error estimates in the same unit as the target variable, making it more interpretable in practical terms:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

Lower *RMSE* values indicate more accurate predictions (Chai and Draxler, 2014).

NSE compares the performance of the model to that of a simple mean predictor. It is commonly used in hydrology and ranges from 1 (perfect prediction) to negative values (poor performance):

$$NSE = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$$

where $\bar{y}$ is the mean of observed values (Nash and Sutcliffe, 1970).

MAE captures the average absolute difference between the actual and predicted values. It is less sensitive to outliers than *MSE* and offers a straightforward interpretation of average error:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i |$$

This metric is especially useful for understanding the model's general accuracy in real-world applications like hydrological forecasting (Willmott and Matsuura, 2005).

The typical interpretation ranges for each of these metrics are summarized in Table 2.

3.9. Swan optimization algorithm for hyperparameter tuning

To enhance model performance, the Swan Optimization Algorithm was employed for hyperparameter tuning. SOA is a recent nature-inspired metaheuristic that mimics the flocking behavior of swans, focusing on exploration and exploitation of the solution space to find optimal parameter configurations. Its dynamic movement strategy allows the algorithm to avoid local minima and converge efficiently towards global optima.

Table 2
Typical interpretation of evaluation metrics.

Metric	Interpretation
MSE	Lower is better (ideal: close to 0)
RMSE	$<$ 5: Excellent; 5–10: Good; $>$ 10: Poor
NSE	0.75–1.00: Excellent; 0.50–0.75: Acceptable; $<$ 0.50: Poor
MAE	$<$ 3: Excellent; 3–7: Good; $>$ 7: Poor

In this study, SOA was used to optimize key hyperparameters such as learning rate, number of estimators, and maximum depth in models like Random Forest, AdaBoost, CatBoost, and MLP. The fitness of each candidate solution was evaluated using a predefined performance metric through cross-validation. The optimization process iteratively updated the population of solutions based on the swans' adaptive movement rules.

Integrating SOA into the modeling workflow aimed to improve generalization and ensure that each model was optimized for robust performance in groundwater prediction tasks (Fig. 3).

4. Result

The performance of four machine learning models Random Forest, AdaBoost, CatBoost, and Multilayer Perceptron was evaluated for predicting groundwater storage at two locations, Agdz and Zagora. The evaluation was based on multiple metrics, across both training and testing datasets. Additionally, predictive accuracy, feature importance, and statistical significance of performance differences were analyzed to provide a holistic assessment of the models.

The models were initially evaluated using *RMSE* and *MAE* metrics, as illustrated in Fig. 4, which presents a comparison across training and testing sets for both study locations. At Agdz, the Random Forest model recorded the lowest *RMSE* during training (1.25), followed by CatBoost (2.78), MLP (3.84), and AdaBoost (9.42). In the testing phase, RF continued to outperform the others with an *RMSE* of 4.70, closely trailed by MLP (4.62), CatBoost (5.36), and AdaBoost (10.91). The *MAE* results showed a consistent pattern, with RF achieving the lowest values in both training (0.85) and testing (3.43), whereas AdaBoost registered the highest errors (8.12 and 8.75, respectively).

At Zagora, the RF model once again demonstrated superior performance, achieving the lowest *RMSE* values in both the training (1.20) and testing (4.29) phases. In contrast, AdaBoost recorded the highest *RMSE* values, with 16.96 for training and 23.42 for testing. A similar trend was observed for *MAE*, where RF produced the smallest errors (0.78 for training and 2.91 for testing), while AdaBoost showed the largest (14.18 and 20.10, respectively). A detailed summary of additional metrics such as *MSE* and *NSE* is presented in Table 3.

Following the numerical analysis presented in Table 3 a temporal evaluation was performed to examine the ability of each model to replicate the temporal patterns of groundwater storage over the period from 2003 to 2024. As shown in Figs. 4 and 5, all models were generally successful in capturing the seasonal and interannual fluctuations of GWS, with their predicted values closely reflecting the observed rises and declines. Notably, the Random Forest and CatBoost models demonstrated the strongest alignment with the observed data, particularly

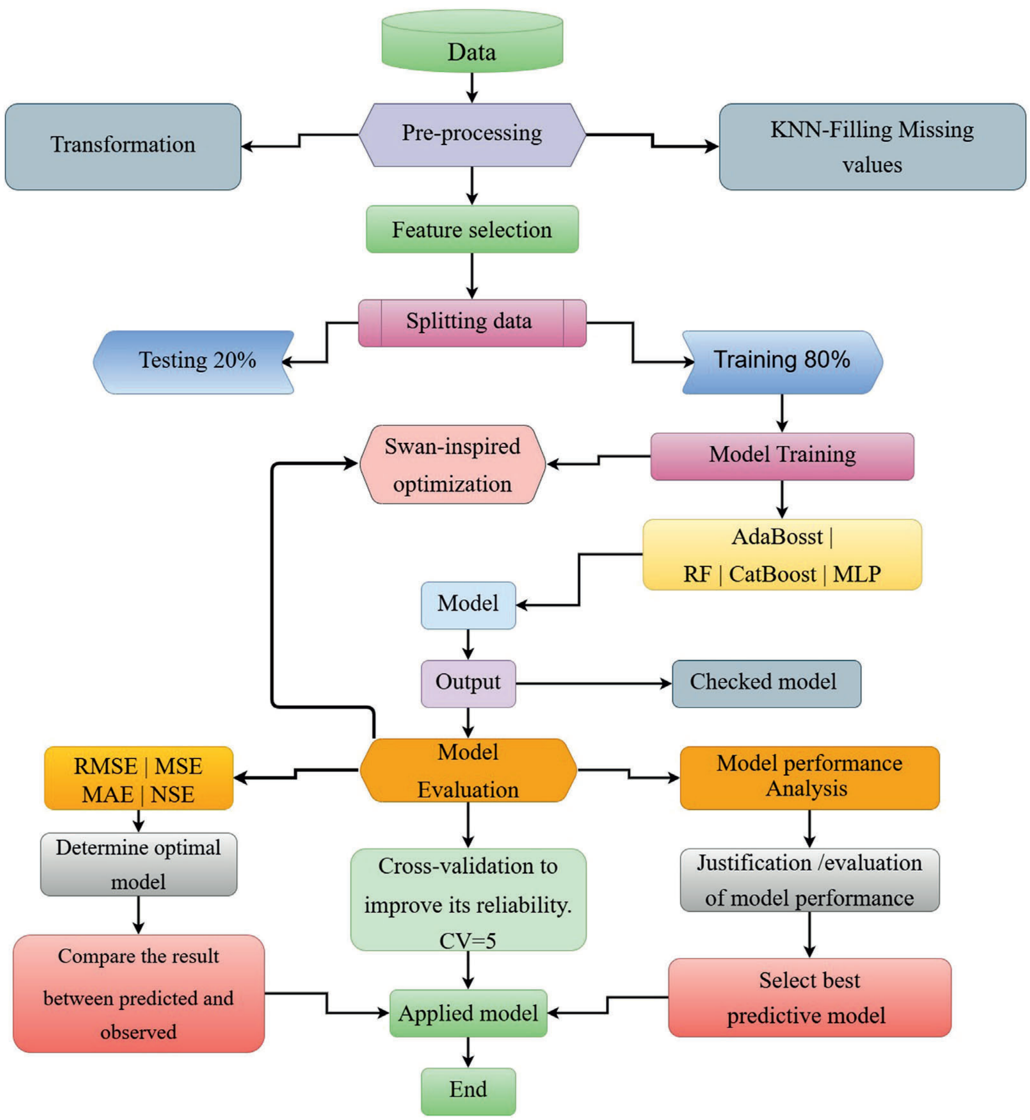

Fig. 3. Machine learning workflow for groundwater storage prediction.

Table 3
Performance metrics (training and testing) for each model at Agdz and Zagora.

Location	Model	Training				Testing			
		RMSE	***MAE***	***MSE***	***NSE***	***RMSE***	***MAE***	***MSE***	***NSE***
	RF	1.246	0.845	1.552	0.99989	4.697	3.432	22.064	0.99843
Agdz	AdaBoost CatBoost	9.416	8.122	88.653	0.99390	10.914	8.749	119.119	0.99154
		2.783	2.139	7.745	0.99947	5.359	3.913	28.719	0.99796
	MLP	3.843	2.896	14.769	0.99898	4.625	3.524	21.387	0.99848
	RF	1.203	0.784	1.447	0.99993	4.292	2.913	18.423	0.99907
Zagora	AdaBoost CatBoost	16.961	14.178	287.690	0.98602	23.418	20.098	548.415	0.97241
		2.888	2.304	8.340	0.99959	6.951	5.013	48.322	0.99757
	MLP	6.985	6.534	48.791	0.99763	6.674	6.227	44.543	0.99776

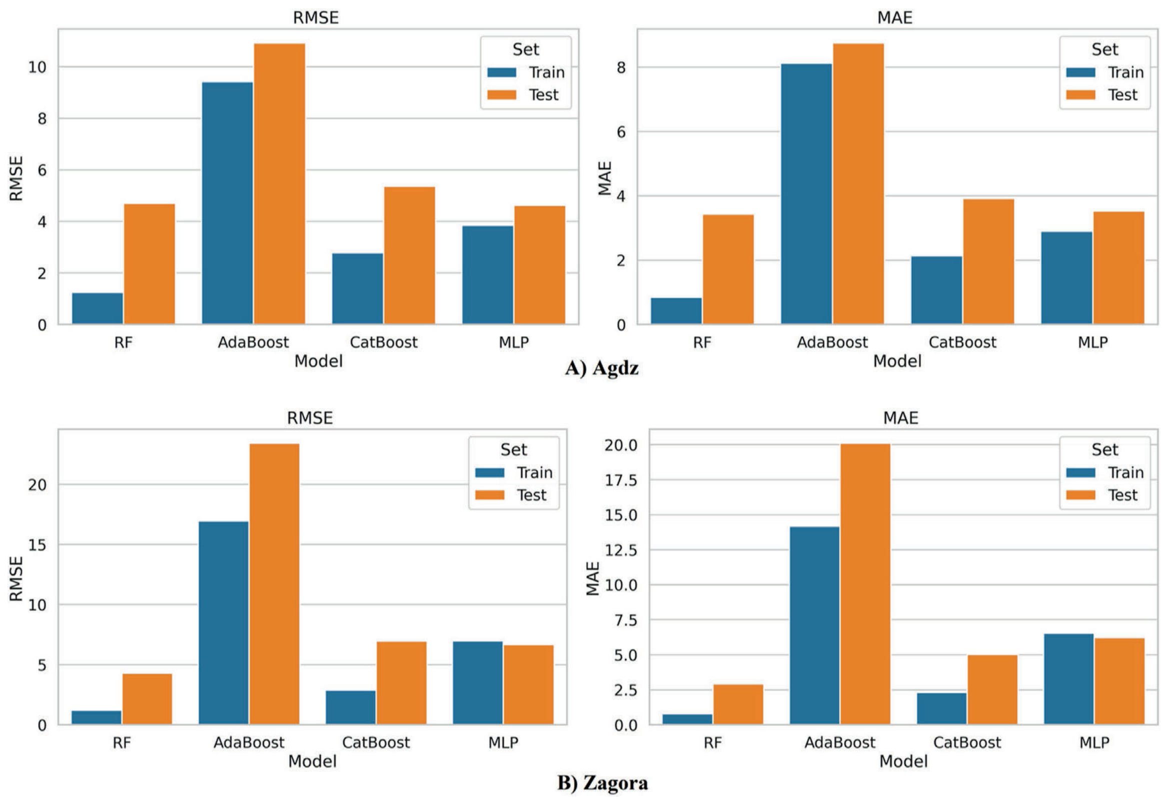

Fig. 4. Comparison of *RMSE* and *MAE* values for four machine learning models (RF, AdaBoost, CatBoost, MLP) across training and testing sets at two locations: (A) Agdz and (B) Zagora.

during periods of elevated groundwater storage, such as those occurring around 2010 and 2020. In contrast, AdaBoost tended to systematically overestimate GWS during these intervals, while MLP showed moderate accuracy, albeit with some discrepancies across different time frames.

To further assess the predictive performance of the models, The Fig. 6 were utilized to analyze the correlation coefficient, standard deviation, and centered RMSE for both training and testing datasets at the Agdz and Zagora sites, as presented in Fig. 6. At Agdz, all models demonstrated exceptionally strong correlations with the observed groundwater storage values ($r > 0.99$). Among them, the Random Forest and Multilayer Perceptron models exhibited the lowest standard deviations and centered *RMSE* values, indicating a high degree of agreement with the measured data. At Zagora, a similarly high level of correlation was observed across all models. However, AdaBoost displayed a noticeably higher standard deviation particularly on the testing set underscoring its tendency to overestimate groundwater storage during the evaluation period.

Fig. 7 comparing predicted and observed groundwater storage values, providing a clear visual assessment of model performance. At the Agdz site, predictions from both Random Forest (RF) and CatBoost closely followed the 1:1 reference line in both the training and testing sets, indicating strong agreement with actual measurements. In contrast, AdaBoost's predictions were more scattered, especially during testing, reflecting its lower accuracy and higher prediction errors. A similar trend was observed at the Zagora site, where RF and CatBoost continued to align well with observed values. AdaBoost, however, displayed noticeable deviations particularly when GWS values were higher highlighting its tendency to overestimate in such conditions.

Feature importance analysis was conducted to determine the most influential variables contributing to the prediction of groundwater storage, with the results presented in Fig. 8. Across all models and both locations, Terrestrial Water Storage consistently emerged as the most dominant predictor. In the CatBoost model at Agdz, TWS exhibited the highest importance score (99.53), followed by Root Zone Soil Moisture (5.80) and Land Surface Temperature (Day) (4.18). A similar pattern was observed at Zagora, where TWS retained its leading position with an even higher importance score (134.57), followed by Root Zone Soil Moisture (11.66) and NDVI (0.92). In the Random Forest model, TWS

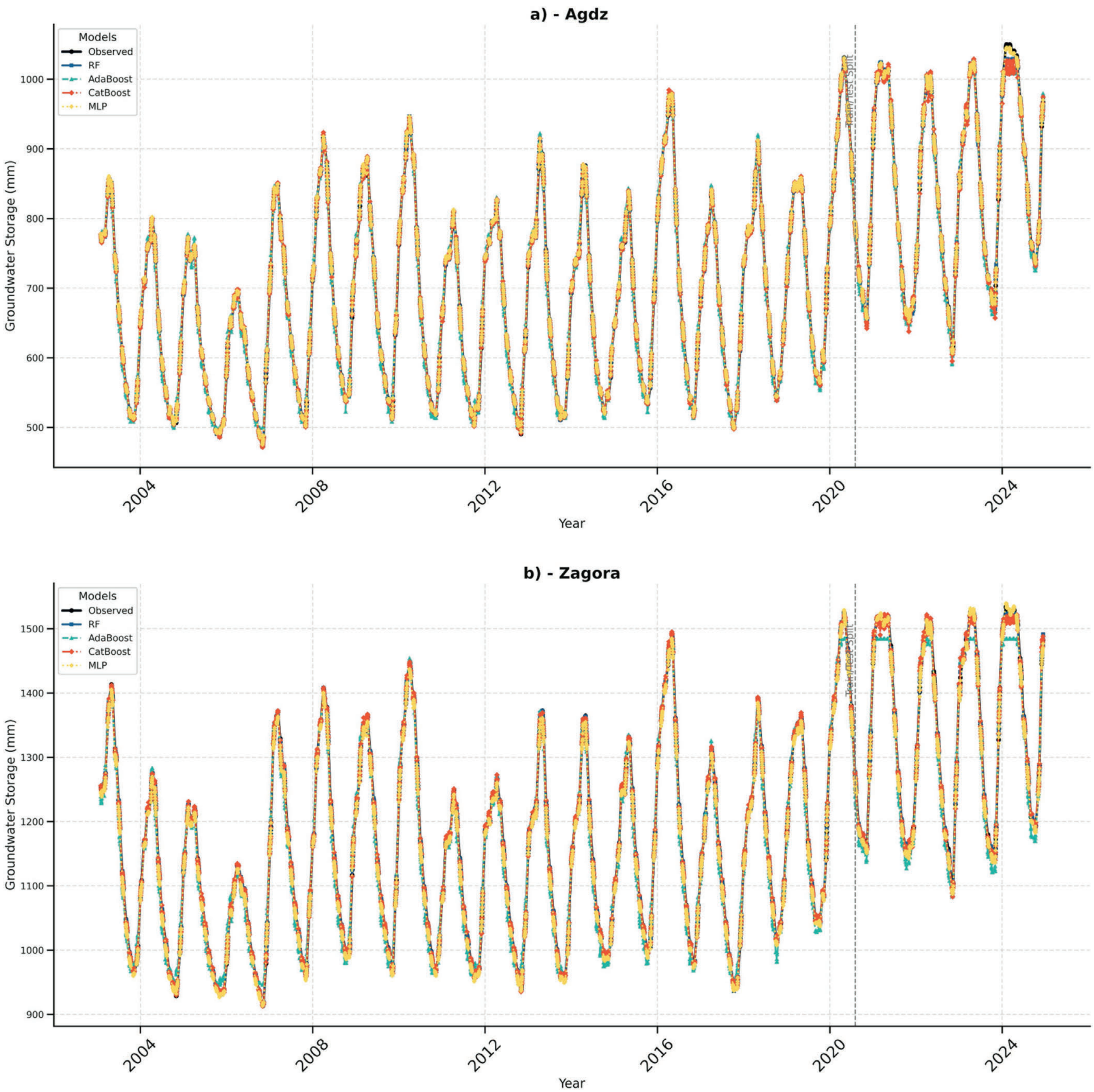

Fig. 5. Observed vs. predicted groundwater storage (2003–2024) at Agdz and Zagora.

was again the most significant feature, although its importance scores were comparatively lower (2.11 at Agdz and 2.26 at Zagora). Likewise, both AdaBoost and Multilayer Perceptron identified TWS as the most influential predictor, with importance values ranging from 1.96 to 2.81 across both locations. Conversely, variables such as elevation consistently demonstrated negligible importance in all models.

To assess the statistical significance of differences in model performance, paired T-tests and Wilcoxon signed-rank tests were applied to *RMSE* values across all pairwise model combinations. As shown in Table 4, all comparisons at both the Agdz and Zagora sites returned p-values of 1.0, indicating no significant differences at the 0.05 level. Although Random Forest consistently achieved the lowest error metrics, these results suggest that the observed performance variations are not statistically meaningful and may be due to sample variability or limitations in sensitivity. This highlights the importance of supporting numerical evaluations with statistical testing to ensure robust and unbiased model comparisons. Full test results are provided in Appendix.

Overall, the Random Forest model stood out as the most reliable option for predicting groundwater storage at both Agdz and Zagora. It consistently achieved the lowest error rates and the highest *NSE* values, showing strong alignment with observed data. CatBoost and MLP also performed well particularly on the testing datasets while AdaBoost lagged behind, often overestimating GWS values. Across all models and locations, Terrestrial Water Storage emerged as the most important feature, reinforcing its key role in groundwater prediction.

However, despite the numerical advantage of RF, statistical tests revealed no significant differences between the models. This suggests

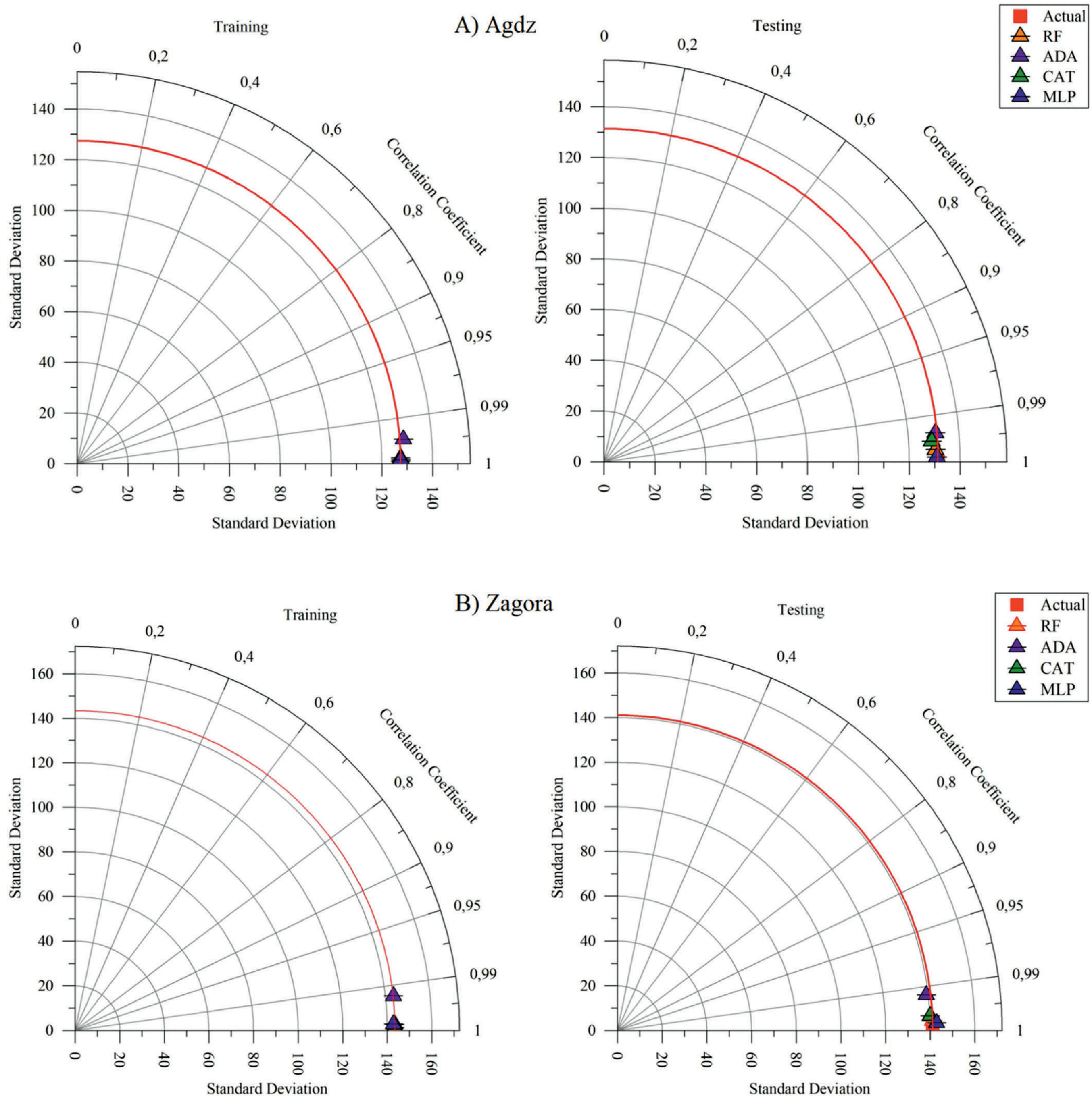

Fig. 6. Taylor diagrams comparing model performance (RF, AdaBoost, CatBoost, MLP) against observed groundwater storage values for training and testing sets at (A) Agdz and (B) Zagora.

that the performance variations might simply be due to natural variability in the data rather than a true difference in model capability. As a result, choosing the best model may come down to practical factors such as ease of use, training time, or suitability for specific applications rather than just minor differences in accuracy.

Although this study is based on satellite-derived data, the results align with known hydrological patterns in the Draa Basin. The high importance of TWS confirms its relevance in capturing groundwater recharge potential during rainfall events and depletion trends in drought periods. These dynamics are critical in regions like Agdz and Zagora, where groundwater serves as the main source of freshwater. Model outputs thus reflect real-world hydrological responses to climate and agricultural pressures.

5. Discussion

This study evaluated the performance of four machine learning models Random Forest, AdaBoost, CatBoost, and Multi-Layer Perceptron for predicting groundwater storage in the semi-arid regions of Agdz and Zagora. Among the evaluated models, Random Forest showed the most consistent predictive behavior; however, statistical tests such as the Wilcoxon and paired *t*-tests indicated that the differences among models were not statistically significant. This suggests that the predictive performance was strongly influenced by the characteristics of the input data rather than by intrinsic model superiority. Feature importance analysis revealed that terrestrial water storage derived from the GRACE mission played a dominant role compared to

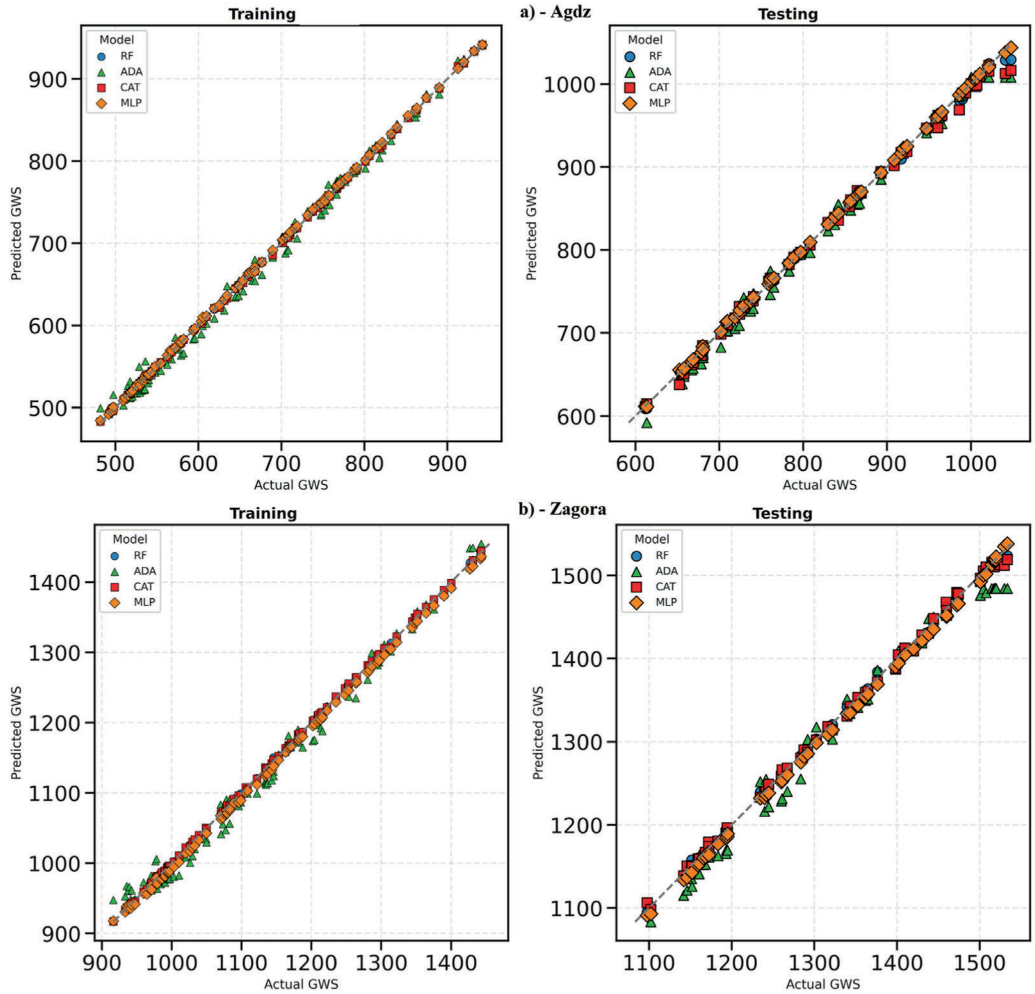

Fig. 7. Scatter plots of predicted vs. observed groundwater storage for training and testing datasets across four models (RF, AdaBoost, CatBoost, and MLP) at (a) Agdz and (b) Zagora.

vegetation and thermal indicators such as NDVI and land surface temperature. This dominance can be explained by the hydrogeological characteristics of the Draa Basin, where groundwater dynamics are closely linked to large-scale water storage variations rather than short-term surface vegetation responses. In contrast, NDVI and LST mainly reflect surface environmental conditions and vegetation stress, which may only indirectly relate to subsurface water storage dynamics in arid environments. Nevertheless, the use of GRACE-derived variables also introduces uncertainty due to their relatively coarse spatial resolution, which may limit the representation of local groundwater variations. Despite this limitation, the integration of GRACE observations with remote sensing indicators and climatic variables provides valuable insights into regional groundwater dynamics and offers a promising framework for groundwater monitoring in data-scarce environments.

RF's strength lies in its ability to handle non-linear relationships and reduce overfitting through ensemble techniques (Breiman, 2001). Terrestrial Water Storage was consistently identified as the most influential predictor, confirming its critical role in hydrological modeling (Liu et al., 2024; Wang et al., 2023). CatBoost and MLP also performed well, particularly in capturing temporal dynamics, while AdaBoost was less effective, potentially due to sensitivity to noise or limited weak learners (Freund and Schapire, 1997).

Using the Swan Optimization Algorithm for hyperparameter tuning proved valuable in improving generalization. Compared to traditional tuning approaches (Elmotawakkil et al., 2024; Shilengwe et al., 2024) SOA offered a flexible and efficient method for achieving optimal model settings.

Although this study is based on satellite-derived data, the results align with known hydrological patterns in the Draa Basin. The high importance of TWS confirms its relevance in capturing groundwater recharge potential during rainfall events and depletion trends in drought periods. These dynamics are critical in regions like Agdz and Zagora, where groundwater serves as the main source of freshwater. Model outputs thus reflect real-world hydrological responses to climate and agricultural pressures. Moreover, GRACE data provide regional-scale insights but are associated with inherent uncertainties, typically ranging from $\pm$ 1.5 to $\pm$ 2.5 cm monthly. These uncertainties may impact ML predictions. This study mitigates such effects by employing ensemble modeling and robust optimization through SOA, improving the generalizability of forecasts. The proposed models support adaptive irrigation strategies and informed aquifer management. Accurate forecasts can guide local authorities in controlling irrigation weir openings, conserving water for drinking during low-storage periods, and aligning usage with Morocco's national water resilience policies.

These findings have practical implications. RF's strong performance and feature interpretability support its application in precision irrigation and smart agriculture (Ahmed et al., 2023). The models' ability to track seasonal and annual GWS variability also strengthens their potential in long-term groundwater monitoring.

Looking forward, integrating real-time monitoring systems with high-frequency remote sensing data, IoT sensors, and adaptive AI models could offer timely insights for water management. Policymakers could benefit from this by deploying smart irrigation strategies and making informed decisions to ensure sustainable groundwater use in semi-arid regions.

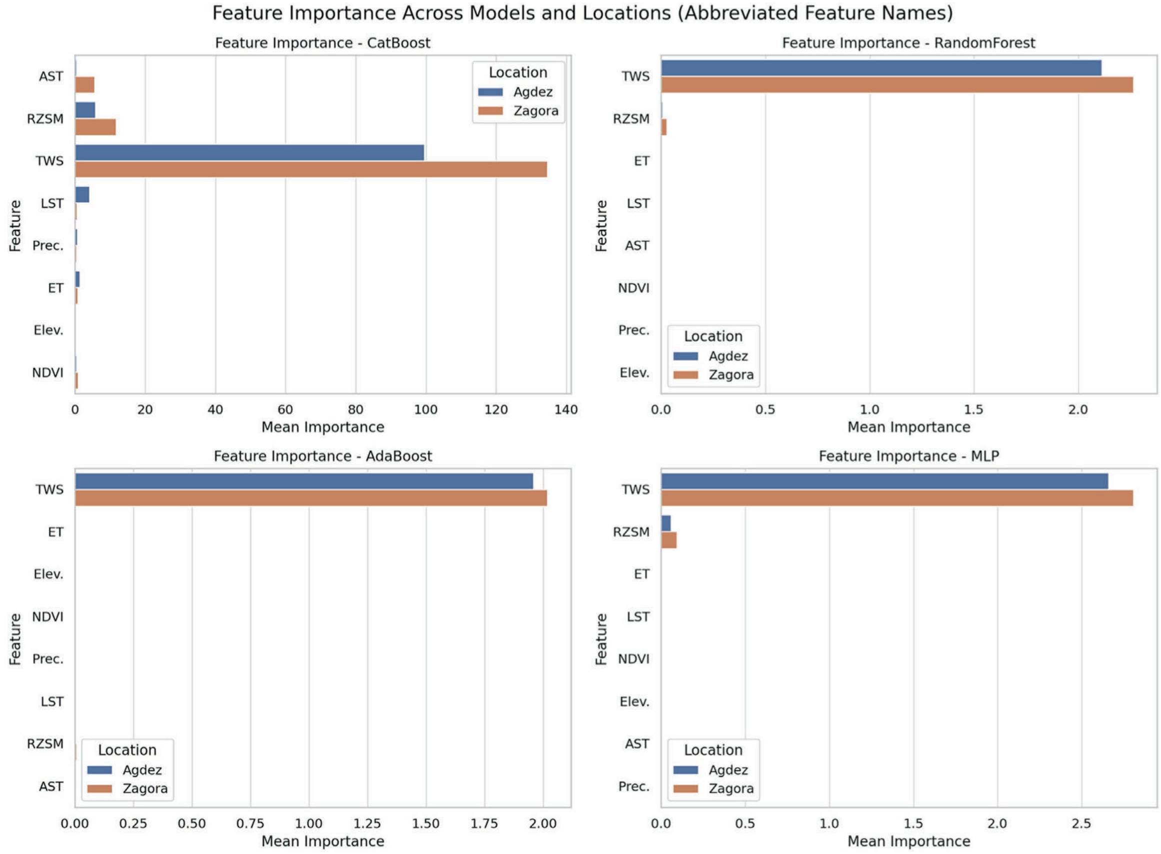

Fig. 8. Feature importance for groundwater storage prediction across four models (CatBoost, Random Forest, AdaBoost, and MLP) at Agdz and Zagora using abbreviated feature names.

Table 4
List of abbreviations.

Abbreviation	Full Term
ML	Machine Learning
RF	Random Forest
MLP	Multi-Layer Perceptron
GWS	Groundwater Storage
TWS	Terrestrial Water Storage
LST	Land Surface Temperature
NDVI	Normalized Difference Vegetation Index
SOA	Swan Optimization Algorithm
GRACE	Gravity Recovery and Climate Experiment
NSE	Nash-Sutcliffe Efficiency
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error

Despite the promising results, this study has some limitations. In particular, the analysis relies on terrestrial water storage derived from the GRACE mission, whose relatively coarse spatial resolution may introduce uncertainty when interpreting groundwater variations at local scales. In addition, the availability of high-resolution hydrogeological and groundwater abstraction data in the Draa Basin remains limited, which may affect the representation of localized groundwater dynamics.

Additionally, future studies could explore the integration of socio-economic indicators, such as water demand, land use change, and population dynamics, to capture human influences on groundwater trends. This interdisciplinary approach could better align AI-powered groundwater monitoring systems with regional policy goals and agricultural development strategies.

In summary, RF demonstrated high potential for predicting GWS in water-scarce regions. While model differences were not statistically significant, the results support the integration of ensemble models and nature-inspired optimization for robust, interpretable, and scalable groundwater forecasting systems. These advances offer a valuable contribution toward data-driven agriculture and climate-resilient water policies.

6. Conclusion

This study explored the potential of machine learning models to predict groundwater storage in the semi-arid regions of Agdz and Zagora in southern Morocco, where water resources are essential for agriculture. Among the four evaluated models RF achieved the best predictive performance, with the lowest *RMSE* values (4.70 mm for Agdz and 4.29 mm for Zagora) and the highest *NSE* scores (0.998 and 0.999). The MLP model also showed strong predictive capability with comparable accuracy. These results demonstrate the effectiveness of machine learning models in capturing complex relationships in groundwater storage dynamics.

Feature importance analysis indicated that terrestrial water storage derived from the GRACE mission was the most influential predictor, reflecting its strong connection with groundwater variability in the Draa Basin. However, the relatively coarse spatial resolution of GRACE data may introduce uncertainty for local-scale applications.

Overall, the integration of satellite observations, climatic variables, and machine learning provides a promising framework for groundwater monitoring in data-scarce regions. Future research should incorporate higher-resolution datasets and additional hydrogeological variables to further improve prediction reliability and support sustainable water management.

CRediT authorship contribution statement

ELMOTAWAKKIL Abdessamad: Writing – original draft, Methodology, Conceptualization. **Ali Ait Youssef:** Software, Resources, Data curation. **Saad Jaldi:** Visualization, Validation, Formal analysis. **Mohammed Bouhassane:** Project administration, Data curation, Conceptualization. **Adnane Al Karkouri:** Writing – original draft, Validation. **Adil Moumane:** Writing – review & editing, Validation, Supervision.

Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Data Availability

The data that support the findings of this study are available on request from the corresponding author.

Declaration of Competing Interest

The authors declare that they have no competing interests.

Appendix

Wilcoxon signed-rank test results for RMSE comparisons between model pairs at Agdz and Zagora. No statistically significant differences were observed at the 0.05 level.

Location	Model Pair	p-value	Significant ($p < 0.05$)
Agdz	RF vs. AdaBoost	1.000	No
	RF vs. CatBoost	1.000	No
	RF vs. MLP	1.000	No
	AdaBoost vs. CatBoost	1.000	No
	AdaBoost vs. MLP	1.000	No
	CatBoost vs. MLP	1.000	No
Zagora	RF vs. AdaBoost	1.000	No
	RF vs. CatBoost	1.000	No
	RF vs. MLP	1.000	No
	AdaBoost vs. CatBoost	1.000	No
	AdaBoost vs. MLP	1.000	No
	CatBoost vs. MLP	1.000	No

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