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# Assessment of Artificial Intelligence and Remote Sensing-Based groundwater storage management workflow

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**Abstract**
Groundwater is a vital freshwater reserve that is increasingly threatened by climate change and mounting anthropogenic pressure on global water resources. While arti- ficial intelligence (AI) has shown promise in groundwater monitoring in conjunction with remote sensing (RS), its integration with traditional technology remains bound to outdated hydrological assumptions, limiting the adaptability of the integrated approach across diverse regions and conditions. Here, we develop a hydrology- independent workflow using an explainable AI framework based on satellite obser- vations to monitor and forecast groundwater storage dynamics. Tested in a case study on a dataset of Morocco, our approach measured groundwater storage variations with high accuracy, without relying on conventional drivers such as precipitation. Model performance revealed robust spatiotemporal scalability and interpretabil- ity, promising broader applications across data-scarce environments. These findings demonstrate that moving away from classical hydrological dependencies and inte- grating AI-based frameworks can enhance the flexibility of groundwater modeling, offering a pathway toward more adaptive and scalable groundwater management, especially under climate uncertainty.
**Keywords***:* *Groundwater management, Artificial intelligence, Remote Sensing, Hydrology, Data Science processes, machine learning, Workflow, Explainability, XAI*

## Introduction

Estimating and managing groundwater (GW) storage is crucial for maintaining water security, particularly as global popula- tion growth intensifies pressure on natural freshwater resources (Ibrahimb et al., 2024; Rahimi and Ebrahimi, 2023). Groundwater serves critical roles in agri- culture, drinking water supply, and industry, parti-cularly in arid and semi-arid regions, where surface water is limited or unreliable (Abdelkareem et al., 2023). However, persistent groundwater depletion, driven by over extraction and climate variability, has become widespread, particularly where recharge rates fail to keep pace with with- drawals (Sahour et al., 2022). Recent large-scale observations using Gravity Recovery and Climate Experiment (GRACE) satellite data have also documented significant spatiotemporal variability in groundwater storage, highlighting its sensitivity to climatic drivers and hydrological context (Magaji Ibrahim et al., 2024). Groundwater storage dynamics are influenced by several factors, including climate change, aquifer structure, geology, topography, land use and land cover (LULC), pumping practices, recharge-discharge ratios, and GW–surface water interactions (Ibrahim et al., 2024). Conventional approaches, although effective in localized studies, struggle to integrate these com-plex and interrelated drivers at broader spatial and temporal scales. Moreover, these methods are labor-intensive, time-consuming, and ill-suited for near-real-time monitoring, particularly in data-scarce or remote regions. GIS-based spatial zoning has been shown as an effective tool for groundwater quality management, demonstrating the need for multi-dataset integration. Recent advancements in remote sensing (RS) and artificial intelligence (AI) offer promising al-

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ternatives to traditional hydrological methods. RS technologies such as satellite imagery and ground-based sensors enable large-scale, continuous observation of groundwater storage and land dynamics (Drogkoula et al., 2023; Ibrahim et al., 2024) When integrated with AI, especially machine learn- ing (ML) and deep learning (DL), these data streams can be analyzed with higher accuracy, efficiency, and generalizability, making groundwater modeling more adaptive and scalable (Singh and Sharma, 2023). Recent studies further demon- strate that the integration of remote sensing, GIS, and advanced statistical or AI-driven techniques significantly enhances the evaluation of groundwater quality, supports informed environmental monitoring, and strengthens decision-making for sustainable water resources management (Hamal et al., 2025; Majumdar et al., 2024; Zhou et al., 2024). Numerous studies have demonstrated the potential of RS in supporting groundwater management (Abdelkareem et al., 2023; Alshehri et al., 2020; Gokmen et al., 2013; Le Page et al., 2012; Safari et al., 2023). RS methods often rely on the fusion of data from multiple sources, en-hanced through multivariate statistical analysis and the integration of ground-based observations, which improves data accuracy (Congalton, 1991). Commonly used RS modal- ities include multispectral and hyperspectral data, LiDAR, InSAR, GPR, and more recently, GRACE and GRACE-FO missions (Ibrahim et al., 2024). Alongside RS, AI has been widely adopted across scientific domains (Nkoulou et al., 2022). In Morocco, for example, ML models have proven more effective than classical methods in crop yield prediction (Ed-Daoudi et al., 2023) and AI applications to GW mapping have gained traction (Phong et al., 2021; Chen et al., 2022; Nguyen et al., 2024; Singh et al., 2024). ML models demonstrate strengths in accuracy, generalization, and predictive capability, surpassing conventional techniques in several contexts (Yassen, 2023). Remote sensing (RS) technologies have played a transformative role in groundwater monitoring by enabling large-scale, continuous observations of groundwater storage, recharge, and depletion. For instance, GRACE satellite data revealed alarming groundwater losses in Turkey, with declines of 92.88 $km^3$ in total water storage and 73.62 $km^3$ in groundwater storage over an 18-year period (Khorrami and Gündüz, 2023). (Similarly, high-resolution RS methods based on spectrum-sharing techniques have proven effective in data fusion and classification (Duan and Duan, 2021). However, RS methods used in groundwater applications must be tailored to specific geophysical contexts, as overlooking key parameters can reduce their reliability. Synthetic Aperture Radar (SAR) is often employed for detecting surface deformation, while Ground Penetrating Radar (GPR) is more effective for subsurface imaging in areas with limited access to other methods (Ibrahim et al., 2024). In arid regions such as northwestern Morocco, RA5-Land data have been shown to be particularly well-suited for identifying groundwater anomalies. When integrated with artificial intelligence (AI) techniques, including machine learning (ML) and deep learning (DL), RS data offer enhanced capabilities for modeling groundwater dynamics. For example, Alshehri et al. (2023) achieved a 92% accuracy rate in predicting shallow groundwater distribution using an artificial neural network with temporal RS-derived inputs. Fur- thermore, studies such as Lee et al. (2020) demonstrated that AI algorithms maintain strong predictive performance even in data-scarce regions, reinforcing the potential of combining RS with AI for more adaptive and data-resilient groundwater assessment. In Morocco, the imbalance between GW extraction and recharge has led to depletion depths ranging from 20 to 65 cm over the past 30 years (Jari et al., 2023). Urbanization has been responsible for 98% of this abstraction (Deng and Chen, 2017). To address this crisis, Morocco launched its National Water Strategy and National Water Plan in 2009 (Hssaisoune et al., 2020). These initiatives could greatly benefit from the integration of AI and RS for improved monitoring and decision-making. For instance, ML models such as RF-Adaboost have shown promising results in mapping groundwater potential in arid regions like Tan-Tan, achieving an AUROC of 94.02% and overall accuracy of 94% (Jari et al., 2023). Yet, few studies have explored groundwater storage (GWS) estimation using ML in conjunction with multi-sensor RS data. Existing research often relies on conventional hydrological indicators, such as precipitation, rather than fully leveraging AI–RS frameworks to independently capture the underlying mecha- nisms of groundwater storage dynamics. Recent research has begun integrating multi-sensor RS data (e.g., GRACE, GLDAS, MODIS) with AI models for regional GWS estimation (Sahour et al., 2022), but challenges persist around interpretability and model robustness, particularly for black-box neural networks. Explainable AI (XAI) has thus emerged as a critical pathway to improving transparency, stakeholder trust, and adoption. This study investigates the efficacy of combining AI and RS approaches for estimating groundwater storage and proposes a robust, explainable workflow leveraging multi-sensor satel- lite data and AI

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models. The goal is to contribute to scalable and sustainable groundwater management strategies, particularly in vulnerable arid regions. To validate the proposed approach, we conducted a case study using satellite-based data from Morocco. The model successfully estimated groundwater storage variations with high accuracy, without depending on conventional hydrological inputs such as precipitation. Its performance demonstrated strong spatiotemporal generalizability and interpretability, making it well-suited for deployment in data-limited settings. These results highlight the potential of AI-driven methods to move beyond traditional hydrologi- cal assumptions and offer a flexible, scalable framework for groundwater monitoring, especially in the face of increasing climatic variability and data scarcity. To summarize, the unique contributions of the current work are as follows:

- Setting an end-to-end workflow for predicting spatiotemporal groundwater.
- Experimentation of an AI-based groundwater predict-tion pipeline: The current study contributes to the field of groundwater-driven pipeline assessment by identi-fying the most crucial stages for predictive models.
- Application of XAI: the work contributes to the develo- ping field of XAI by using Python's SHAP module to unravel the complex connections among groundwater- affecting factors.

## Study area and data sources

### Study area

Morocco is a sizable nation in northwest Africa, stretching from the northernmost point of the continent to the Sahel coun- tries in its center. Its terrain and climate are diverse, with a total size of around 446, 300 km$^2$, 34°160-40°300*N* is the latitude, while 113°140 -119°300 E is the longitude. The nation has a tropical climate overall, with highs up to 35°C (95°F ) and lows of 5°C (41°F) in the Sahara. Inland regions have a hotter, drier continental climate, whereas the coast has a warm, Mediterranean climate that is mode-rated on the eastern coast by southwest trade winds. Throughout the year, the south of the country experiences extremely hot and dry weather. The potential yearly evaporation ranges from 1,400 to 900 mm. The mean perennial precipitation ranges from 500 to 600 mm, while the mean annual temperature ranges between 8 and 15°C. About 22% of the nation's GDP, or gross domestic product, comes from agriculture, which is important to the economy of the nation. Water resources have therefore played an important role in the social and economic development of the region. Groundwater contributes up to 20% of freshwater supply, the remaining 80% coming from surface water (Ahmed et al., 2021). Due to the restricted and unequal distribution of precipitation caused by several years of drought, groundwater extraction represented about half 74% of the water supply in 2000. Additionally, there is a trend toward a constant increase in the yearly groundwater withdrawal from the shallow aquifer. Long-term excessive groundwater pump- ing has resulted in many grave issues, including salinization, land subsidence, wetlands shrinkage, and a steadily falling groundwater level (Kendy et al.., 2003).

### Multi-Satellite data sources

Once the challenge has been identified, one may search for suitable data sets to forecast or estimate groundwater storage (GWS), which is measured by GRACE and GRACE-FO. The most common datasets include meteorological variables like temperature, precipitation, soil moisture in different depths, evaporation, and land cover, such as NDVI, etc. One lists every feature in Table 1 , and their maps in Figure 1 .

### GRACE and GRACE-Follow-On Satellite-based terrestrial water storage anomaly (TWSA)

GRACE and GRACE-FO are very impactful satellite missions in the water monitoring domain, put in place with the col- laboration of the US and German space agencies (NASA and DLR). GRACE is a 13-year twin satellite project launched in March 2002 to record data related to Earth's gravity field changes. This project has revolutionized the investigation of Earth's water reservoirs in many environments (land, ocean, and ice), as well as earthquakes and crustal deformations. After being decommissioned, the twin satellites were succeeded by GRACE-FO (The Gravity Recovery and Climate Experiment Follow-On), which consisted of twin satellites for the continuation of the mission. GRACO-FO continues to track Earth's water movement to monitor the changes over time. The GRACE and GRACE-FO datasets used in this study are obtained from Tellus Monthly Mass Grids. Monthly gravi- tational anomalies are provided by GRACE Tellus Monthly Mass Grids for a time-mean baseline spanning 2004 to 2010. The data available in this dataset is expressed in "Equiva- lent Water Thickness" units, which quantify mass deviations in terms of water's vertical extent expressed in centimeters. Three

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**Table 1** *Remote sensing datasets were used in this study*

| Feature | Product | Dataset provider | Resolution (m) | Period | Description |
|---|---|---|---|---|---|
| Precipitation | CHIRPS | UCSB/CHG | 0.05 | 1981-2023 | Climate Hazards Group InfraRed Precipitation With Station Data |
| Temperature | GLDAS-2.1 | NASA GES DISC | 0.25 x 0.25 | 2000-2024 | Global Land Data Assimilation System |
| Soil Moisture | GLDAS-2.1 | NASA GES DISC | 0.25 x 0.25 | 2000-2024 | Global Land Data Assimilation System |
| NDVI | MODIS Terra Daily NDVI | Google | 463.313 | 2000-2023 | Normalized Difference Vefetation |
| UDWI | MODIS Terra Daily NDVI | Google | 463.313 | 2000-2023 | Index Normalized Difference Water |
| GRACE | GRACE | NASA Jet Propulsion Laboratory | 0.25 x 0.25 | 2002-2017 | Index GRACE Monthly Mass Grids- |
| GRACE-FO | GRACE-FO | NASA Jet Propulsion Laboratory | 0.25 x 0.25 | 2018-2023 | Land GRACE Monthly Mass Grids-Land |

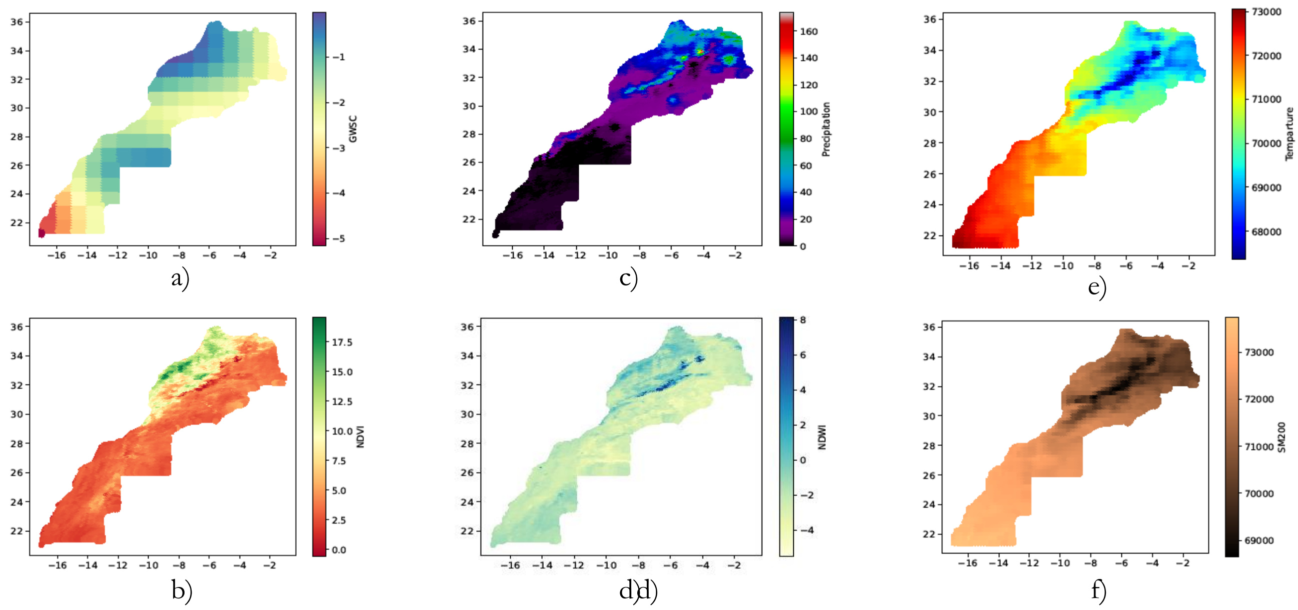


**Figure 1.** *Color map of groundwater storage (GWS) and used features (Precipitation, Temperature, Soil moisture, NDVI, and NDWI) datasets in Morocco in the beginning of 2017. (a) Precipitation at the resolution of 2 km; (b) Temperature at the resolution of approximately 110 km; (c) the gridded GRACE-derived GWS data at the resolution of approximately 110 km; (d)NDVI at the resolution of 2 km*

centers, GFZ (GeoForschungsZentrum Potsdam), JPL (NASA Jet Propulsion Laboratory), and CSR (U. Texas/Center for Space Research), produce the GRA-CE Tellus (GRCTellus) Monthly Mass Grids dataset. Each center contributes to the GRACE Ground Sy-stem and produces the spherical harmonic fields, or Le-vel-2 data, that are utilized in this collection. The out-put consists of the dealiasing fields and the gravity field's spherical harmonic coefficients, which were computed. The outcomes could change slightly because the coefficients are independently produced by each center. Trends in groundwater storage (from GRACE and GRACE-FO) in three different places (Morocco) are graphically reported in Figure 2 . Negative trends indicate an average decline in ground-water storage, while positive trends indicate an average increase in ground- water storage over the period from 02/2002 to 05/2023. rends in groundwater storage (from GRACE and GRACE- FO) in three different places (Morocco), negative trends indi- cate an average decline in groundwater storage while positive trends indicate an average increase in groundwater storage over the period from 02/2002 to 05/2023.

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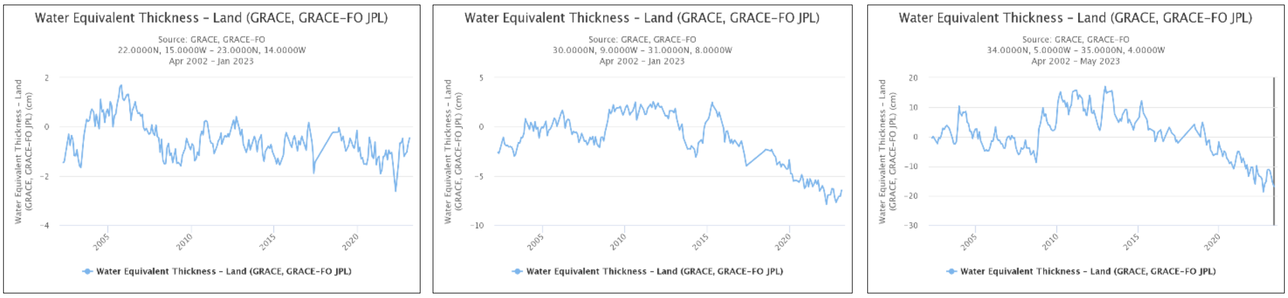


**Figure 2.** *Monthly changes of groundwater storage from different evapotranspiration products for three Moroccan regions (north, middle and south). GWSC time series for specific regions (a) region A, (b) region B, and (c) region C for facilitating a comparison of TWSA from GRACE and GRACE-FO.*

**CHIRPS precipitation**

The precipitation data utilized in this study were derived from CHIRPS (Climate Hazards Group InfraRed Precipitation with Station Data), which is a quasi-global rainfall dataset span- ning over 30 years since 1981. CHIRPS uses 0.05° resolution (approximately 5566 meters) satellite images combined with in-situ station data to generate gridded rainfall time series for trend analysis and seasonal drought monitoring.

**Landsat satellite-land cover index (NDVI, NDWI)**

The Normalized Difference Vegetation Index (NDVI) is cal- culated using the Near-IR and Red bands of each scene as $(NIR-Red)/(NIR+Red)$ and ranges from $-1.0$ to 1.0. This index is calculated using the MODIS/006/MOD09GA surface reflectance composites. The daily data from MODIS Terra has a spatial resolution of 463.313 meters. Like NDVI, the MODIS (006, MOD09GA) surface reflectance composites are used to construct the Normalized Difference Water Index (NDWI). NDWI is sensitive to changes in the liquid water content of vegetation canopies. It is derived from the Near-IR band plus a second IR band, around $1.24\mu m$ when accessible, or the near- est available IR band otherwise. Its value ranges between $-1.0$ and 1.0. The MODIS Terra Daily NDWI is available from 2000 to 2023 at a spatial resolution of 463.313 meters. Additional details can be found in (Gao, 1996).

**<u>Workflow design and methodology</u>**

As previously mentioned, in order to build a general pipeline of groundwater management based on AI and remote sensing, we will try to subject some examples of AI and remote sensing- based groundwater management models from the literature to the data science process to see if they consider the data science philosophy of building such models or not. The CRISP-DM (Cross Industry Standard Process for Data Mining) is a process model that serves as the foundation for a data science process. There are various data science pipelines described in the literature; the most well-known, with typical steps, is shown in Figure 3. A data science process or pipeline (DSP) is a collection of procedures that transform unprocessed data into useful responses to business queries. Data science pipelines automate the transfer of data from the source to the target, giving you the knowledge you need to make business.

**Problem statement and hypotheses**

The first phase in the DSP is business understanding, which refers to the definition of the business problem and the identification of the analysis's purpose. Reviewing the majority of remote sensing (RS) and artificial intelligence (AI) ground- water management systems reveals that the majority of them revolve around the prediction or forecasting of groundwater, either storage, recharge, etc., utilizing multi-satellite datasets and AI approaches. The problem can then be generalized through AI and RS-based groundwater management. Even if researchers don't explicitly articulate their hypotheses in their studies, it is impossible to figure out how to find the right datasets for a given topic without doing so. Accordingly, for that reason, and as we previously indicated, the majority of research studies start with the hydrology findings as the correct hypothesis. For instance, there is a regression between groundwater storage and various characteristics like precipitation, temperature, soil moisture, NDVI, etc. We will test some hypotheses in feature engineering to provide an example of AI and RS-based methodologies that may start from hydrological results or hypotheses, not to check the correctness of those studies, but at the same time, one shouldn't ignore some key data science process phases

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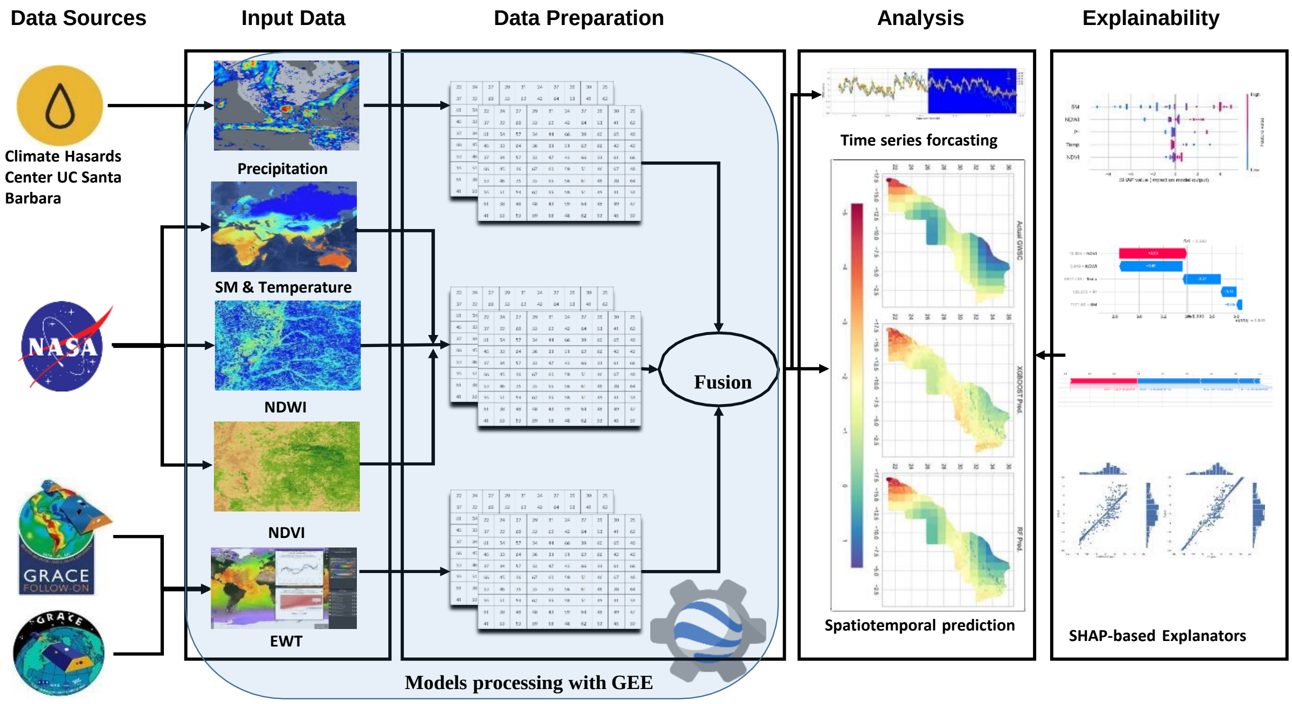


**Figure 3.** *Groundwater storage management workflow using artificial intelligence and remote sensing adapted to thedata science process.*

like hypothesis testing and feature engineering. As an illustration, the stated hypothesis in numerous GWS studies (Su et al., 2020, Wang et al., 2024; Jiang et al., 2025) is that GWS is heavily dependent on precipitation (Pr), and they concluded by verifying this hypothesis. For our region of interest (ROI), the same remote sensing datasets with identical fea- tures were used. In order to get an understanding of our dataset and subsequently develop the intuition needed to formulate our hypothesis. The process of testing hypotheses begins with the formulation of the null hypothesis, which holds that ground- water storage (GWS) is only highly dependent on precipitation (Pr)

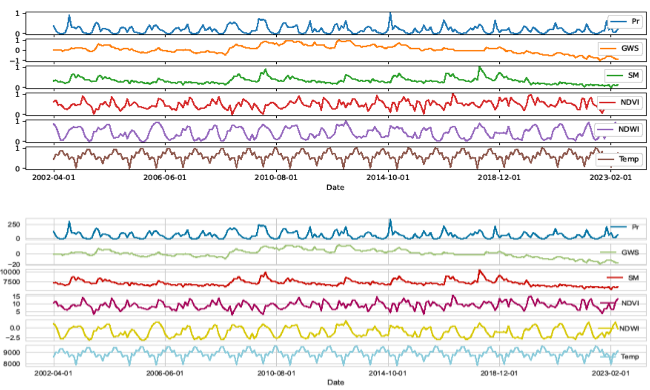


**Figure 4.** *Place 1: GWS time series (subfigure 1 normalized values, subfigure 2 actual values) as the dependent variable, as well as independent variables such as Pr, SM, Temp, and NDVI*

and that the alternative is not. The following is a test of that hypothesis utilizing statistical functions and figures as hypothesis testing methods. The analysis begins by examining the relationship between precipitation and groundwater storage, focusing on the null hypothesis that precipitation is the only factor influencing groundwater storage. Table 2 shows that the extremely low p-values of 1.866949 exp−46 for the temporal dataset and 0.0 for the spatial dataset, at a 5% significance level, provide strong evidence to reject this null hypothesis. This rejection suggests that other factors, such as soil moisture, temperature, land use, and geological characteristics, play significant roles in influencing groundwater storage. This finding highlights the limitations of relying solely on precipitation data for modeling groundwater systems and underscores the need for a multi-variable approach to achieve more accurate predictions. Figures 5a) and b) show that the regression analysis reveals no significant relationship between precipitation and groundwater storage for both temporal and spatial datasets. This lack of a direct relationship further supports the rejection of the null hypothesis and indicates that precipitation alone cannot explain variations in ground water storage. Potential reasons for this include time lag effects, where groundwater systems respond slowly to precipitation due to delayed infiltration processes, and spatial heterogeneity, where factors like soil type,

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topography, and vegetation cover disrupt the direct relationship. Additionally, the relationship between precipitation and groundwater storage may be non-linear, requiring more advanced modeling techniques to capture the underlying dynamics. Examining the normality of the variables provides further insights. As shown in Figures 5 c) and d), precipitation exhibits a non-normal distribution, which is common in hydro-logical datasets due to the episodic and highly variable nature of rainfall events. This non-normality may violate the assump- tions of parametric statistical tests, suggesting the need for data transformations or non-parametric methods to address skewness or outliers. In contrast, groundwater storage shows a normal distribu-tion for both temporal and spatial datasets (Figures 5 e) and f), making it suitable for parametric anal- yses. This difference in distribution between precipitation and groundwater storage further emphasizes the complexity of their relationship and the need for careful conside-ration when analyzing their interactions. Beyond pre-cipitation, several other factors likely influence ground-water storage. Soil moisture acts as an intermediary, affecting how much precipitation infiltrates into the ground- water system. Temperature influences evapo-transpiration rates, which determine the amount of water available for recharge. Land use and vegetation cover can alter infiltration rates and surface runoff, while geological characteristics, such as aquifer porosity and permeability, determine how efficiently water is stored and transmitted. Incorporating these variables into a multivariate model would provide a more comprehensive understanding of groundwater storage dynamics and improve the accuracy of predictions. The analysis also highlights the importance of considering both spatial and temporal dimensions. Temporal data-sets capture changes over time but may miss spatial variability, such as localized rainfall events that do not significantly impact regional groundwater storage. Spatial datasets, on the other hand, reveal regional differences but may not account for temporal trends, such as areas with similar precipitation pat- terns but different groundwater storage levels due to varying soil types or land use. Addressing these limitations requires time-lagged correlation analyses for temporal data and spa- tial clustering or geostatistical analyses for spatial data. These approaches would help uncover hidden patterns and relation- ships that are not apparent in simple analyses. To further deepen the analysis, several next steps can be taken. Multivariate modeling incur-porating additional predictors like soil moisture, tempe-rature, and land use would provide a more accurate representation of groundwater storage dynamics. Time

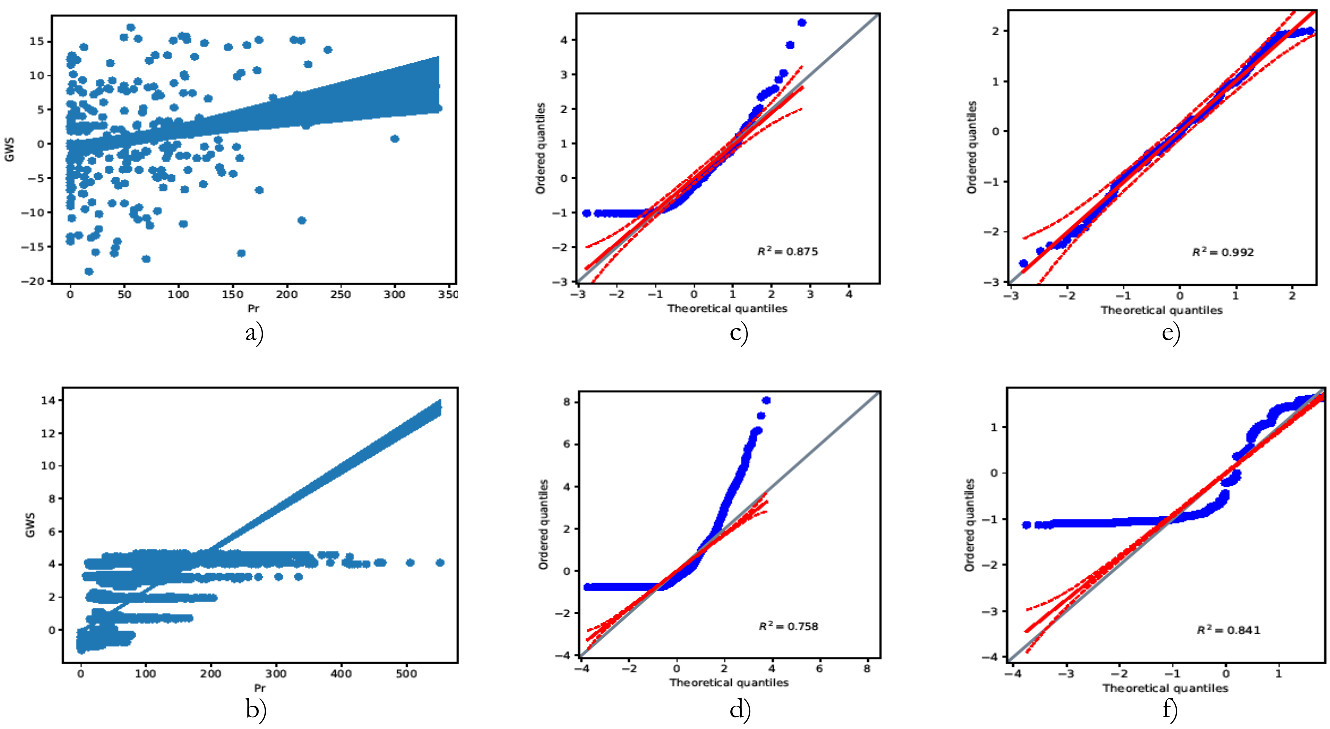


**Figure 5.** *Regression relationship between precipitation (Pr) and groundwater storage (GWS) variables* a) *temporal dataset,* b) *spatial dataset). Normality of precipitation (Pr) variable for both datasets:* c) *temporal,* d) *spatial. Normality of GroundwaterStorage (GWS) variable for both datasets:* e) *temporal,* f) *spatial.*

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**Table 2** *T-test of null hypothesis for both datasets distribution temporal and spatial*

| | T | dof | alternative | p-val | CI95% | cohen-d | BF10 | power |
|---|---|---|---|---|---|---|---|---|
| Temporal distribution | 15.89825 | 506 | two-sided | 1.866949e-46 | [54.16, 69.43] | 1.410742 | 8.132*e* + 42 | 1.0 |
| Sptatial distribution | 68.206265 | 7792 | two-sided | 0.0 | [45.63, 48.33] | 1.065337 | inf | 1.0 |

series analysis could investigate time-lagged series analysis could investigate time-lagged relation-ships to account for delayed recharge processes, while geospatial analysis using GIS tools could identify hot-spots of groundwater recharge or depletion. Exploring nonlinear regression techniques or machine learning models, such as random forests or neural networks, could help capture com- plex relationships between variables. Additionally, scenario analysis could simulate the impacts of climate change, such as altered precipitation patterns and increased temperatures, on groundwater storage, providing valuable insights for future water resource management. Furthermore, Figure 4 demonstrates that there is no corre lation between GWS and precipitation (Pr) but rather between GWS and soil moisture (SM). This notion is supported by datasets from other locations and does not account for the impact of precipitation, which has been extensively demon- strated in the literature Su et al. (2020) and Wang et al. (2024). This hypothesis is supported by Figure 6 , which depicts the importance of the features. XGBoost and Random Forest (RF) are two ensemble learning techniques that are used to determine the importance of features. Similar study in Morocco recently reported the low importance of rainfall in mapping groundwater using ML learning algorithms such as Random Forest (RF), Adaboost, K-Nearest Neighbors (KNN), and Gaussian Process (Jari et al., 2023).

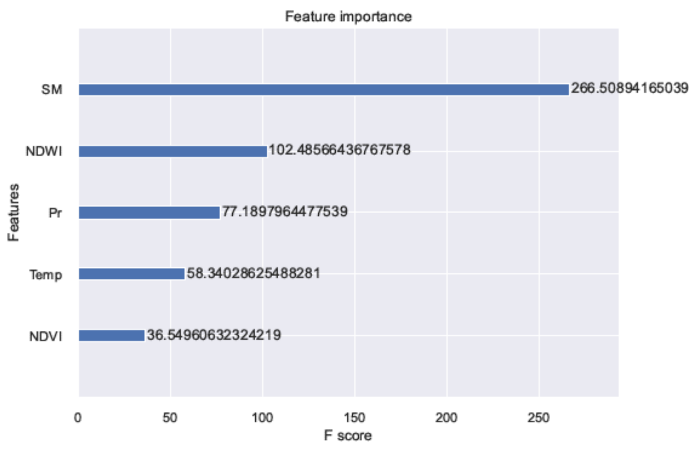


**Figure 6.** *Features importance using XGBoost as Embed- ded Method*

## Feature engineering and data preparation

Given that the combined final dataset comes with a variety of issues, including dataset availability, the fusion of various dates leading to missing values, a constrained study period, etc. Resampling, imputation, normalization, and numerous other data preparation manipulations are necessary for the merg- ing of datasets with spatiotemporal resolution. Missing values: When a dataset is combined from several sources and contains a large number of missing values, one option for treatment is to use a method like (1) simple imputation by mean, median, etc., (2) imputation by regression, (3) imputation by KNN, etc. Since it is a regression problem, normalization may be done on all variables using methods like max-min, z-score, etc. Given that there are three possible scenarios for features—positive, negative, and neutral—feature engineering is a crucial stage in data wrangling. One of the three approaches—filter, wrapper, or embed-ded—can be used to choose features; embedded methods com- bine the advantages of filter and wrapper methods. Algorithms with built-in feature selection techniques, including decision- tree-based algorithms, are used to implement it. Figures 7 and 8 , which show Mean absolute error dependent on the thresh- old and number of most crucial features, respectively, exhibit the outcomes of feature selection using the Random Forest and XGBoost approaches.

Soil moisture (SM) is the most important feature, followed by NDVI, temperature (Temp), and finally precipitation (Pr) as shown in Figure 6, with gains of 14.80, 3.08, 2.93, and 1.92 respectively. As stated previously, most hypotheses in the literature (Su et al., 2020; Wang et al., 2024). point to precipitation as the most essential feature, which is not the case in our study and contradicts our data analysis. This is not to say that research ends with incorrect conclusions, but that these studies cannot be duplicated in different areas and regions. This could be because other factors, such as depletion, have an impact on GWS in our location but are not in other regions. As a result, a broad strategy that considers all options is required.

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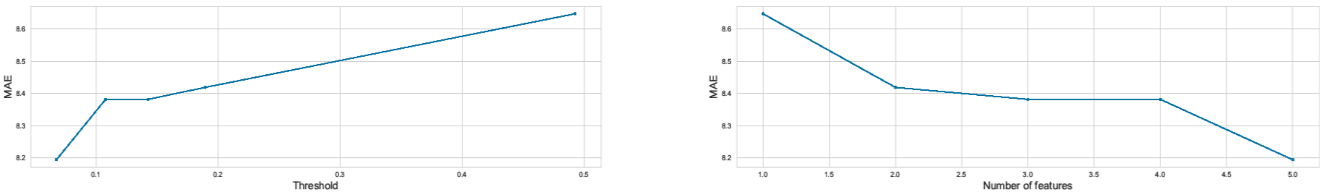


**Figure 7.** *XGBoost-based Mean Absolute error depending on the threshold and Number of most important selected features.*

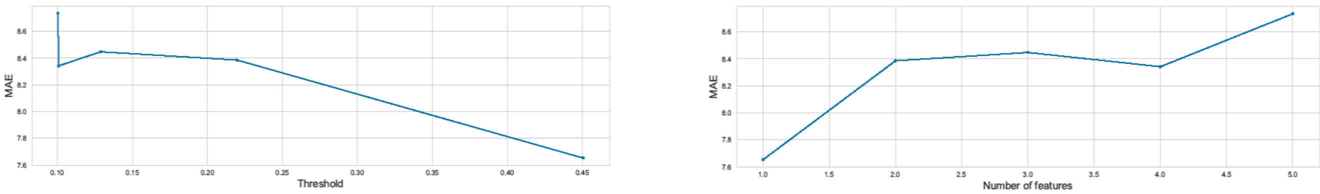


**Figure 8.** *Random Forest-based Mean absolute error depending on the threshold and number of most important selectedfeatures.*

**Hyperparameters tuning(HPO)**

Table 4 shows the optimization range of values, optimal values for both techniques XGBoost and Random Forest.

## Results and Discussions

### Temporal groundwater storage change prediction

Monthly GWSC data for Morocco was utilized to visually assess the performance of the proposed machine learning mod- els based on test period results. The real data were compared to the values generated using the two proposed deep learning models. The results on the accuracy of GWS prediction by the two machine learning algorithms over actual values are presented through two graphical models. Firstly, in one plot model, the accuracies of the XGBoost method and the Random Forest method in the study region are presented in Figures 9 and 10, respectively. Secondly, these accuracies can be observed in separate plot models in Figures 11 and 12 for the prediction accuracy of the XGBoost and Random Forest methods, respectively. We then visualized the performance of the two machine learning models in terms of their GWSC prediction accuracies, using actual measurement data to validate the models' Figure 15. In the Tan-Tan region (Morocco), the Random forest method has already shown the highest success in predicting groundwater potential (GWP) on a 75/25% cross validation (Jari et al. (2023)). XGBoost is an improved gradient-boosting decision tree model, that shows effectiveness in handling noise, imbalanced samples, and uneven distri-

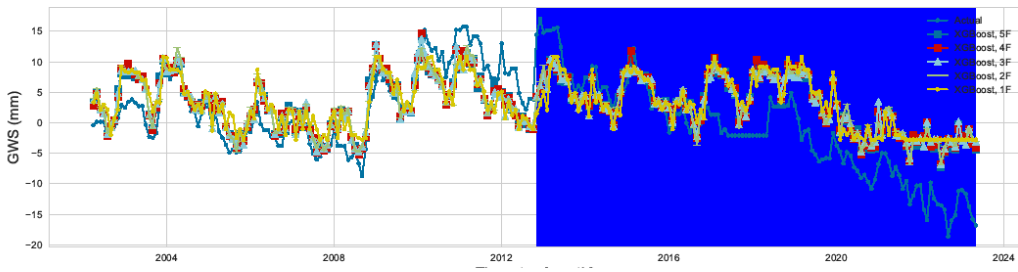


**Figure 9**
*Comparison of mean actual and XGBoost predicted groundwater storage (GWS) over the region of interest for different selected features, all curves in one plot.*


***Figure 10***
*Comparison of mean actual and Random Forest predict-ted groundwater storage (GWS) over the region of interestfor different selected features, all curves in one plot.*

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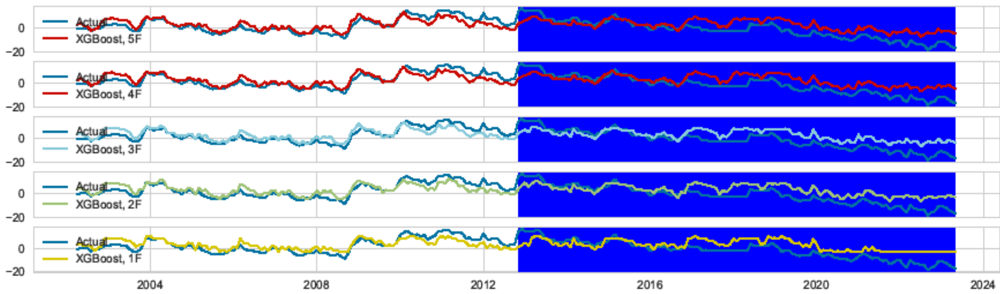


**Figure 11**
*Comparison of mean actual and XGBoost predicted groundwater storage (GWS) over the region of interest for different selected features, each curve in a separate subplot.*

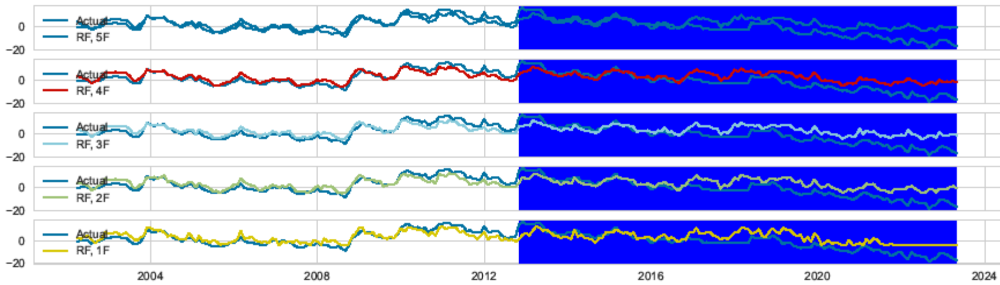


**Figure 12**
*Comparison of mean actual and Random Forest predicted groundwater storage (GWS) over the region of interestfor different selected features, each curve in a separate subplot.*

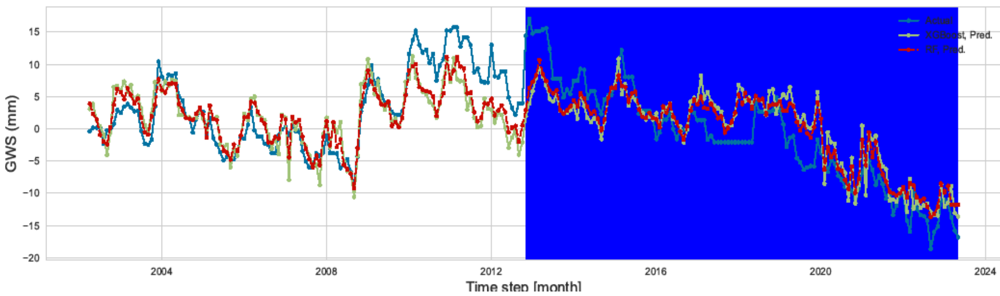


**Figure 13**
*GWSC comparisons predictted by Random Forest (red dotted line in (a), and XGBoost (green line in (b)) modelswith actual values (blue line).*

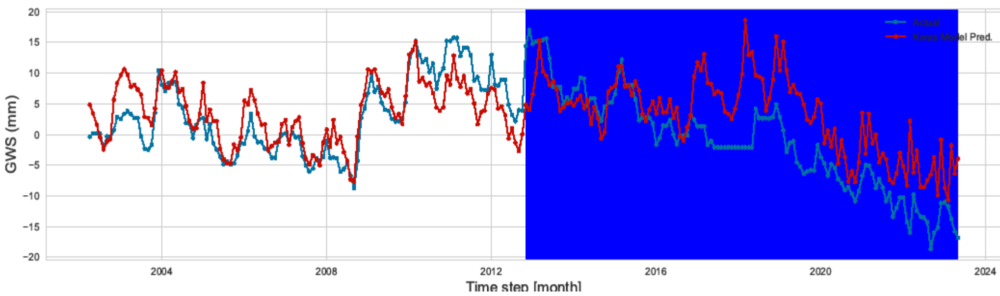


**Figure 14**
GWSC comparisons predicted by Keras model (red line) prediction with actual values (blue line).

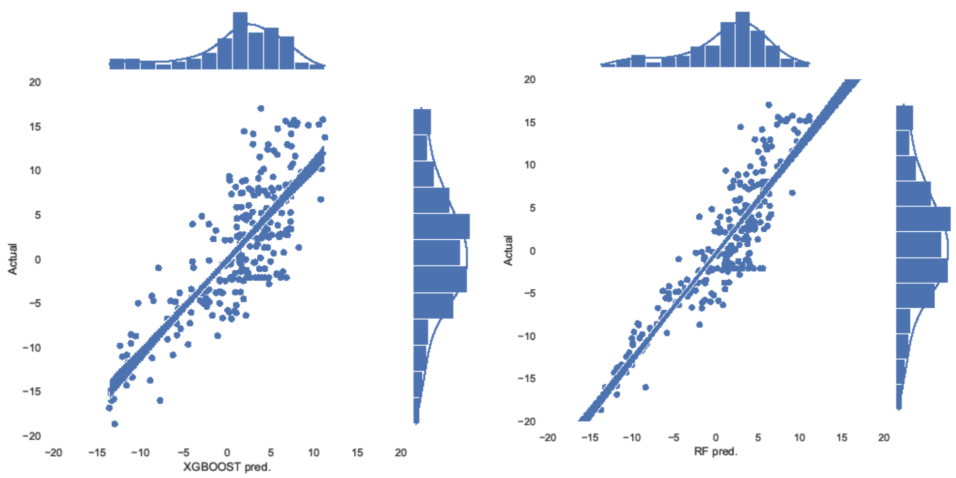


**Figure 15**
*Residuals of XGBOOST and Random Forest*

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**Table 3**
*Test error metrics obtained using different AI-based algorithms with tuned hyperparameters, groups of selectedfeatures.*

| Model | HPO, number of features | MSE value (mm/month) |
|---|---|---|
| RF | No HPO, all features | 4.30 |
| | HPO, all featuresHPO, 4 features | 4.39 |
| | HPO, 3 features | 4.37 |
| | HPO, 2 features | 4.54 |
| | HPO, 1 features | 4.47 |
| | | 4.46 |
| XGBoost | No HPO, all features | 4.70 |
| | HPO, all featuresHPO, 4 features | 4.66 |
| | HPO, 3 features | 4.44 |
| | HPO, 2 features | 4.55 |
| | HPO, 1 features | 4.54 |
| | | 4.45 |
| RF, Normalzed Values | No HPO, all features | 4.30 |
| | HPO, all featuresHPO, 4 features | 4.39 |
| | HPO, 3 features | 4.37 |
| | HPO, 2 features | 4.54 |
| | HPO, 1 features | 4.47 |
| | | 4.46 |
| XGBoost, Normalized values | No HPO, all features | 4.70 |
| | HPO, all featuresHPO, 4 features | 4.66 |
| | HPO, 3 features | 4.44 |
| | HPO, 2 features | 4.55 |
| | HPO, 1 features | 4.54 |
| | | 4.45 |

**Table 4**
*Hyperparameters of the deep learning models and the optimization range of values.*

| Model | Hyperparameter | Optimization range of values | Optimal value |
|---|---|---|---|
| Random Forest | Number of estimators | {100, 500, 900, 1100, 1500} | 900 |
| | learning rate min | {0.05, 0.1, 0.15, 0.20} | 0.05 |
| | child weightmin | {1, 5, 10} | 10 |
| | samples leafmax | {1, 3, 4} | 1 |
| | features max depth | ['auto', 'sqrt'] | sqrt |
| | | {10, 20, ⋯, 120} | 50 |
| XGBoost | Number of estimators | {100, 500, 900, 1100, 1500} | 1500 |
| | learning rate min | {0.05, 0.1, 0.15, 0.20} | 0.05 |
| | samples split | {2, 6, 10} | 10 |
| | gamma subsample | {0.5, 1, 1.5, 2, 5} | 5 |
| | colsample bytree | {0.6, 0.8, 1.0} | 1.0 |
| | max depth | {0.6, 0.8, 1.0} | 0.8 |
| | | {2, 3, 5, 10, 15} | 2 |

**Table 5.** *Temporal test error metrics obtained using different AI-based algorithms with tuned hyperparameters, groups ofselected features.*

| Model | MAE | MSE | RMSE | R2 | RMSLE | MAPE | TT (Sec) |
|---|---|---|---|---|---|---|---|
| Random Forest Regressor(RF) | 4.0875 | 25.2834 | 4.9674 | 0.0983 | 0.8351 | 3.6847 | 0.2210 |
| AdaBoost Regressor(ADA) | 4.1388 | 25.2425 | 4.9856 | 0.1012 | 0.8604 | 3.7378 | 2.4830 |
| CatBoost Regressor(CATBOOST) | 4.4932 | 31.0758 | 5.5176 | -0.1145 | 0.8581 | 3.9763 | 2.0280 |
| Extreme Gradient Boosting(XGBOOST) | 4.4273 | 31.4678 | 5.5270 | -0.1467 | 0.9024 | 3.5475 | 0.0720 |
| Decision Tree Regressor(DT) | 5.0624 | 41.8946 | 6.3890 | -0.5478 | 0.9531 | 4.6479 | 0.1130 |
| Keras Model | 2.8436 | 12.75868 | 3.5719 | -2.7024 | Nan | 10.3525 | 0.169 |

**Table 6.** *Spatial Test error metrics obtained using different AI-based algorithms with tuned hyperparameters, groups ofselected features*

| Model | MAE | MSE | RMSE | R2 | RMSLE | MAPE | TT (Sec) |
|---|---|---|---|---|---|---|---|
| catboost CatBoost Regressor | 0.5746 | 0.7029 | 0.7148 | -14.1879 | 0.2525 | 1.3093 | 1.1920 |
| xgboost Extreme Gradient Boosting | 0.5992 | 0.7770 | 0.7472 | -14.9847 | 0.2646 | 1.3110 | 0.0700 |
| rf Random Forest Regressor | 0.5981 | 0.7682 | 0.7493 | -14.1619 | 0.2673 | 1.4093 | 0.5740 |
| ada AdaBoost Regressor | 0.7947 | 1.0345 | 0.8956 | -25.2449 | 0.3252 | 1.7441 | 1.0690 |
| dt Decision Tree Regressor | 0.6855 | 1.1096 | 0.9033 | -20.9942 | 0.3327 | 1.5289 | 0.0180 |
| Keras Model | 1.9799 | 4.8415 | 2.2003 | -5.1017 | Nan | 1.3938 | 1.3 |

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bution (Bai et al., 2024). As a result, we can see from Figure 16 that the machine learning models Random Forest and XGBoost showed good perfor- mance over time in predicting groundwater storage change, except years after 2012, while the graph in Figure 17 appears to show low accuracy for the Keras model predicting GWS. For demonstration purposes in the region of interest, the groundwater storage change (GWSC) was mapped using both models in comparison with the actual GWSC, as shown in Figures 16 and 17. Sahour et al. (2022) has shown the effectiveness of machine learning methods in locating Egypt's desert areas where shallow groundwater appears. This study identified the extreme gradient boosting (XGB) method as the best-performing method capable of predicting the occurrence of shallow groundwater in the desert with an efficiency of 0.93. The authors concluded that the methods are affordable and could be replicated in other desert areas of the African and Arabian Sahara.

**Spatiotemporal groundwater storage change prediction**

We evaluated all the regressor models available in the literature for spatial prediction, just as we did for temporal prediction. We discovered that CatBoost Regressor, Extreme Gradient Boosting, Random Forest Regressor, AdaBoost Regressor, and Decision Tree Regressor are the most relevant in terms of several performance measures such as MSE, RMSE, and so on. The table below (Table 6) provides details for comparing all models.

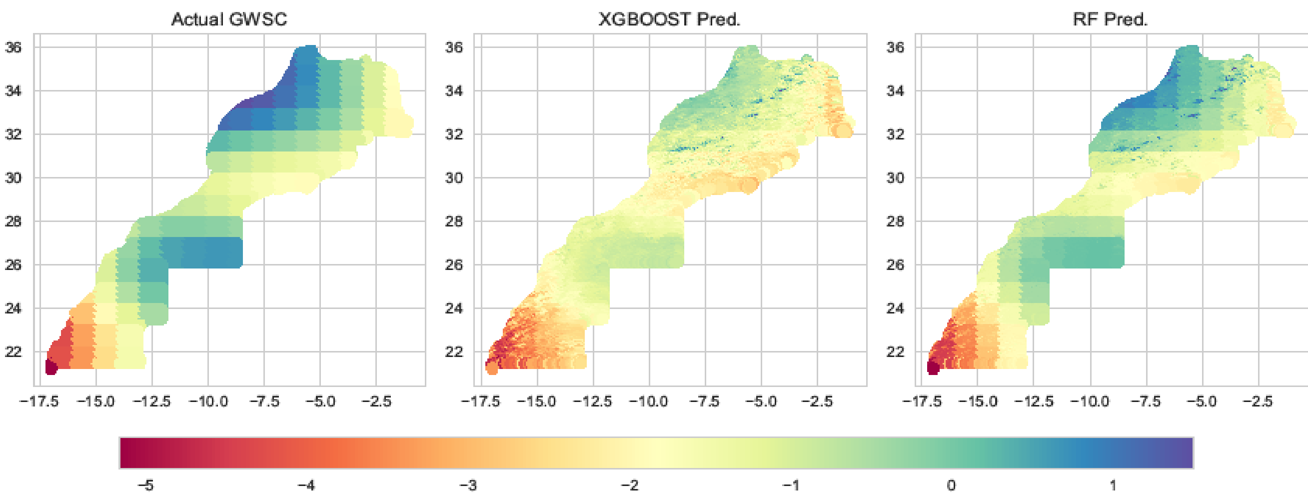


**Figure 16.** *Comparison of GWSC maps predicted by Random Forest and XGBoost models with the actual measurement map.*

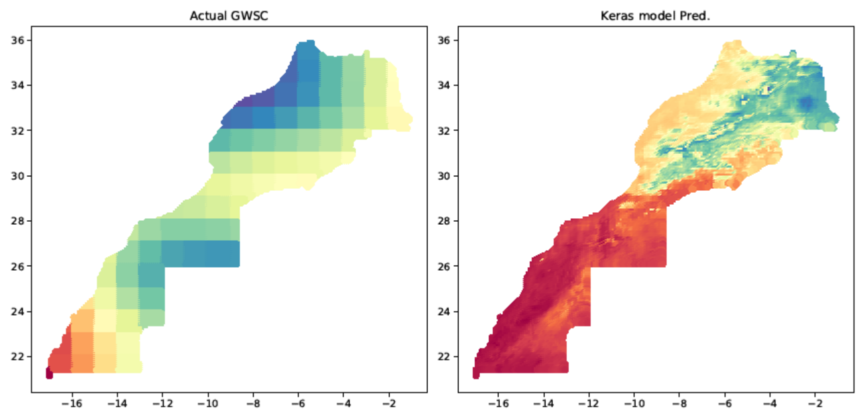


**Figure 17**
*GWSC Keras model prediction map with actual measurements map.*

**Explainability and interpretation of model outputs**

This delves into the critical role of understanding and inter- preting decisions or predictions made by machine learning algorithms, particularly in the context of groundwater storage (GWS) analysis. Explainability is achieved through various methods, such as SHAP (Shapley Additive Explanations) and ICE (Individual Conditional Expectation), which are used to demystify

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the "black box" nature of neural network models. These methods provide insights into the relationships between predictors and groundwater recharge rate estimates, with SHAP focusing on the importance of individual predic- tors by comparing model performance with and without each feature. The SHAP Waterfall plot (Fig. 18) illustrates the contribution of each feature to the groundwater storage prediction. The base value of GWS is 3.393, while the average value is 3.849. The plot reveals that INDVI (Normalized Difference Vegetation Index) is the only feature with a positive contri bution to GWS, with a weight value of +0.56. In contrast, INDWI (Normalized Difference Water Index), temperature (Temp), precipitation (Pr), and soil moisture (SM) negatively impact GWS, with weight values of −0.52, −0.31, −0.13, and −0.05, respectively. This aligns with studies by Wang et al. (2024) which highlight a strong positive corre- lation between NDVI and soil moisture storage, particularly in groundwater dominated areas. ..The recovery of vegetation in drylands, facilitated by GWS through capillary action, further explains this relationship, as GWS replenishes soil moisture deficits caused by insufficient precipitation. The Force plot (Fig. 19 ) provides a more granular view of how individual features influence GWS predictions. INDVI drives GWS to a high value of 10.824, while INDWI, tem- perature, precipitation, and soil moisture push GWS to lower values of 0.919, 8617.418, 123.573, and 7171.62, respectively. This underscores the importance of groundwater as a primary water source for vegetation, particularly in arid regions. The interactions between these factors are crucial for ecohydrolog- ical processes, as highlighted by Bai et al. (2024). The lack of correlation between precipitation and GWS can be fur- ther explored by examining whether cumulative precipitation in previous years exceeds the annual average. This historical perspective may explain increases in GWS even when current precipitation levels are low, as suggested by Deng and Chen (2017).

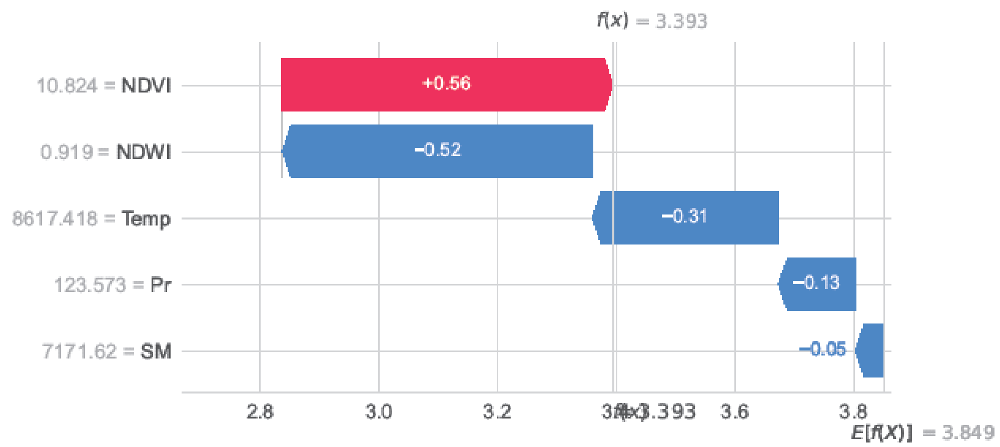


**Figure 18**
*Waterfall plot*

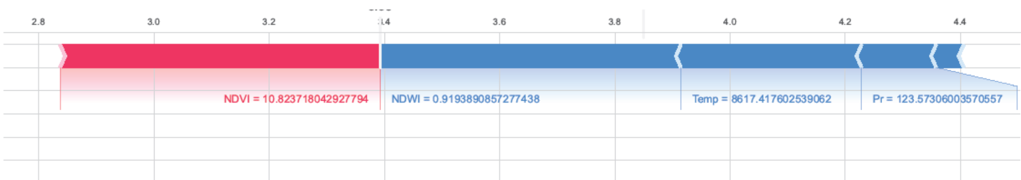


**Figure 19**
*Force plot chart*

The Beeswarm plot (Fig. 20) offers a comprehensive visualization of the distribution of SHAP values for each fea- ture. GWS values range from −6 to +6, with the majority falling between −2 and +2. Soil moisture (SM) exhibits a wide distribution along the x-axis, reflecting its significant influence on GWS due to variations in soil type and density. Precipitation contributes negatively to GWS at low levels but positively at high levels (above 4), which is intuitive since low precipitationleads to depletion, while high precipitation enhances storage. Temperature also plays a role, with lower values (close to 0) reducing evaporation and positively impacting GWS. INDVI values range from −2 to +2, with a predominantly positive influence on GWS, as indicated by the prevalence of red points in the distribution. The findings from the Beeswarm plot are corroborated by the SHAP Bar plot (Fig. 21), which ranks features based on their absolute SHAP values across the dataset. Soil moisture (SM) emerges as the most important feature with a value of +2.73, followed by

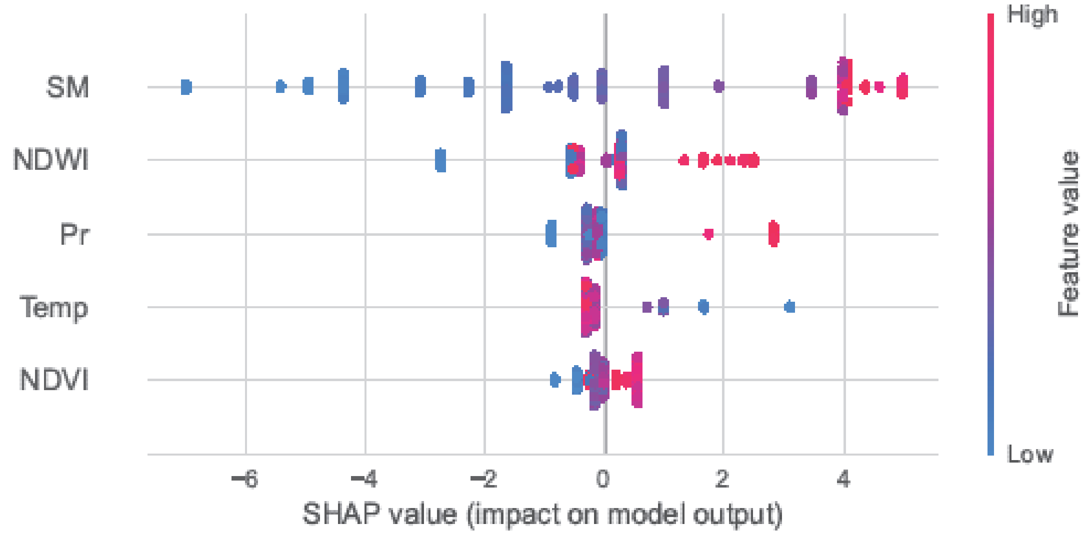


**Figure 20**
Beeswarm plot

NDWI (+0.71), precipitation (+0.48), tem- perature (+0.43), and NDVI (+0.26). This ranking highlights the relative contributions of each feature to GWS predic- tions, providing valuable insights for decision-makers tasked with managing groundwater resources. The SHAP method has proven effective in numerous studies for understanding the influence of environ- mental factors on GWS monitoring, as demonstrated by Alshehri and Rahman (2023). In summary, the analysis of explainability using SHAP and ICE methods provides a detailed understanding of the factors influencing groundwater storage. The SHAP Waterfall plot, Force plot, Beeswarm plot, and Bar plot collectively reveal the contributions of INDVI, INDWI, temperature, precipitation, and soil moisture to GWS predictions. These visualizations highlight the complex interplay between environmental factors and groundwater dynamics, offering actionable insights for sustainable water resource management. By leveraging these explainability techniques, decision-makers can better under- stand the drivers of groundwater storage and implement tar- geted interventions to address challenges such as water scarcity and ecosystem health. By default, a SHAP bar plot will take the mean absolute value of each feature over all the instances (rows) of the dataset. The SHAP method is used in evaluating the contribution of features such as climate, topography, and edaphic on fractional vegetation cover for its correlation with groundwater (Bai et al. (2024)). In the present study, the SHAP plot showed that all features (05) used are important in predicting GWS but identify SM and NDWI as the two most important. This infor- mation should therefore help decision-makers for the GWS management in the study area because the SHAP method has contributed in many studies to understand the influences of environmental factors on GWS monitoring (Alshehri and Rahman, 2023). The result drawn from the Beeswarm plot is supported by the Barplot (Fig. 21), which ranks the variables accord- ing to their absolute SHAP value across the whole data set. This places SM at the top with a value of +2.73, followed by NDWI, Pr, Temp, and NDVI, which have values of +0.71, +0.48, +0.43, and +0.26, respectively. SHAP values assign each feature an importance score based on its contribution to the difference between the actual predic- tion and the average prediction. These values can be visualized in various ways, such as summary plots or force plots, to under- stand the impact of each feature on individual predictions. By default, a SHAP bar plot will take the mean absolute value of each feature on all instances (rows) of the dataset.

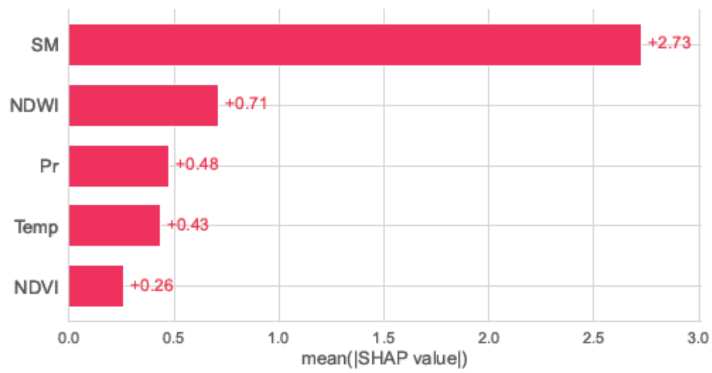


**Figure 21.** *SHAP values (Mean)*

The analysis leads to several key conclusions:

• Multiple Factors Influence Groundwater Storage: Groundwater storage is not solely dependent on precip- itation but is influenced by a combination of factors, including vegetation (INDVI), soil moisture,

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temperature, and surface water interactions (INDWI). This underscores the need for a holistic approach to groundwater modeling and management.

• Nonlinear and Cumulative Effects Matter: The relation- ship between precipitation and GWS is nonlinear, with cumulative precipitation over time playing a more sig- nificant role than short-term rainfall events. This high- lights the importance of considering historical climate data in groundwater assessments.

• Vegetation Plays a Critical Role: INDVI's positive con- tribution to GWS demonstrates the importance of vege- tation in facilitating groundwater recharge, particularly in water-scarce regions. Efforts to restore and conserve vegetation could enhance groundwater sustainability.

• Soil Moisture is a Key Mediator: Despite its negative SHAP value in some contexts, soil moisture is the most important feature for predicting GWS. Improving soil moisture retention through sustainable practices could significantly enhance groundwater recharge.

• Explainability Tools are Essential for Decision-Making: SHAP and ICE methods provide valuable insights into the drivers of groundwater storage, enabling decision- makers to prioritize interventions and allocate resources effectively. These tools bridge the gap between com- plex machine learning models and actionable policy recommendations.

•Adaptive management is needed. Given the dynamic interplay between environmental factors and ground-water systems, adaptive management strategies that account for spatial and temporal variability are essen-tial. This includes monitoring key indicators like soil moisture, vegetation health, and temperature to inform real-time decision-making.

The above-mentioned conclusions result in some sugges tions for further research such as:

• Incorporate Additional Variables: Future studies should explore the inclusion of additional factors, such as land use, geological characteristics, and human activi- ties (e.g., irrigation, groundwater extraction), to further refine GWS predictions.

• Explore Time-Lagged Relationships: Investigating time-lagged effects of precipitation and other variables on GWS could provide deeper insights into recharge processes and improve predictive accuracy.

• Leverage High-Resolution Data: Using high-resolution spatial and temporal data could enhance the precision of SHAP and ICE analyses, enabling more targeted interventions.

• Integrate Machine Learning Models: Combining SHAP and ICE with advanced machine learning techniques, such as deep learning or ensemble models, could improve the robustness of groundwater predictions.

• Promote Stakeholder Engagement: Engaging stakehold- ers in the interpretation of explainability results can ensure that management strategies are practical, context- specific, and aligned with local needs.

## Conclusions

In the face of climate change, population growth, and agricul- tural intensification, groundwater resources are under severe stress globally, particularly in arid and semi-arid regions like Morocco. This study leverages remote sensing and AI tools, including XGBoost, Random Forest, and ANN, applied to GRACE and GRACE-FO satellite data, to analyze ground- water storage (GWS) dynamics. Using SHAP (Shapley Addi-tive Explanations), the research identifies key environmental drivers of GWS, revealing that INDVI (Normalized Difference Vegetation Index) is the sole feature with a positive contri- bution (+0.56), while soil moisture (SM) ranks as the most influential factor (+2.73), followed by NDWI (+0.71), precipi- tation (+0.48), temperature (+0.43), and NDVI (+0.26). These findings underscore the critical role of vegetation and soil moisture in groundwater recharge and high-light the non linear relationships between environ-mental factors and GWS. The study demonstrates the power of AI and explainability methods in providing actionable insights for sustainable groundwater mana-gement. By prioritizing soil moisture retention, vegeta-tion restoration, and long-term climate data integra-tion, decision-makers can develop targeted strategies to mitigate water scarcity. This research offers a robust frame- work for understanding groundwater dynamics, emphasizing the need for holistic, data-driven approa-ches to ensure water security in vulnerable regions worldwide.

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**Competing interests**

The authors declare no competing interests.

**Ethical approval**

This article does not contain any studies with human partici-pants performed by any of the authors.

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