Satellite-Based Modeling and Monitoring of Groundwater Storage Using Machine Learning

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***Abstract*—Predicting groundwater levels is essential for sustainable water management, particularly in regions facing water scarcity and climate variability. This study utilizes satellite-based datasets from the Gravity Recovery and Climate Experiment (GRACE) and the Global Land Data Assimilation System (GLDAS) to forecast groundwater storage fluctuations. A machine learning approach is employed to model the complex relationship between terrestrial water storage and key hydrometeorological factors. By integrating GRACE-derived Land Water Equivalent (LWE) data with GLDAS soil moisture data, we developed and trained an Artificial Neural Network (ANN) to improve prediction accuracy. The spatiotemporal dataset was rigorously preprocessed to handle missing values and ensure spatial consistency. The trained ANN model demonstrated strong predictive capability, achieving an R^2 score of 0.90. This research highlights the significant potential of combining remote sensing with AI-driven techniques for groundwater monitoring, offering valuable insights for effective water resource management, especially in areas with limited ground-based data.**

***Index Terms*—Groundwater Prediction, Machine Learning, GRACE, GLDAS, Remote Sensing, Terrestrial Water Storage, Hydrological Modeling.**

I. Introduction

Groundwater is a critical component of the Earth's freshwater resources, supporting global agriculture through irrigation, sustaining industrial processes, and providing essential drinking water for billions of people [15]. Its role as a buffer against climate variability, especially during periods of drought, makes it indispensable for global water and food security. However, the sustainability of this vital resource is under increasing threat from both climate change and anthropogenic pressures, leading to widespread depletion of aquifers, land subsidence, and ecological degradation in many regions across the globe [2], [13]. Effective management of this resource is therefore fundamentally dependent on accurate and timely monitoring.

A. Literature Review

The traditional method for groundwater monitoring involves direct measurements from in-situ observation wells. While providing high-accuracy point data, these networks are often prohibitively expensive to establish and maintain, resulting in sparse spatial coverage that fails to capture regional dynamics [11]. The advent of satellite remote sensing, particularly the Gravity Recovery and Climate Experiment (GRACE) mission, revolutionized large-scale hydrology. GRACE provides unprecedented estimates of monthly Terrestrial Water Storage (TWS) variations by measuring anomalies in Earth's gravity field. This has enabled regional assessments of groundwater depletion in major aquifers worldwide. To isolate the groundwater component from the total TWS signal, data from Land Surface Models such as the Global Land Data Assimilation System (GLDAS) are required.

In recent years, machine learning (ML) has emerged as a powerful tool for hydrological forecasting. Comprehensive reviews show a dramatic increase in the application of ML models for groundwater prediction [15]. Early studies successfully leveraged Artificial Neural Networks (ANNs) for their ability to model complex, non-linear relationships in hydrological systems [1], [4], [9], [16]. More recently, the field has seen a progression towards more complex deep learning models. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, for example, have been explored for their ability to capture temporal dependencies in time-series data [6], while hybrid models integrating multiple techniques are becoming increasingly common. Studies have consistently demonstrated that integrating GRACE and GLDAS data with ML models can yield accurate predictions of groundwater storage anomalies, providing a viable alternative to purely physics-based models [10], [13].

B. Contributions

This study builds upon previous work by developing and evaluating an end-to-end framework for GWS prediction using a foundational ANN model. The main contributions of this work are threefold:

- We develop a complete framework for processing and integrating GRACE and GLDAS datasets to derive a reliable time-series of GWS anomalies.
- We demonstrate the high accuracy of a specifically tuned ANN model for predicting these GWS anomalies using satellite-derived inputs.
- We present a spatial analysis of the prediction results, identifying key global hotspots of groundwater stress and validating the model's ability to produce hydrologically meaningful outputs.

The objective is to provide a scalable, cost-effective, and robust methodology that can enhance groundwater monitoring

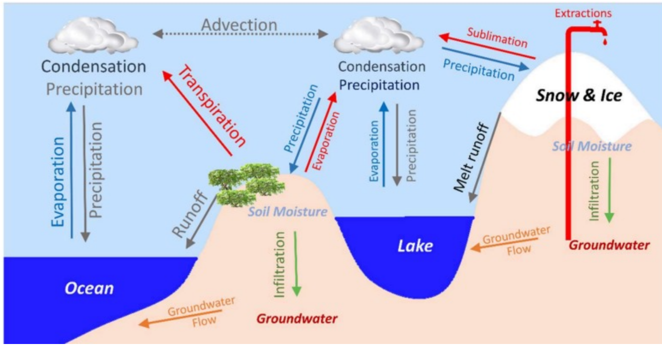

Fig. 1. Conceptual diagram of the terrestrial water cycle, illustrating the various storage components that contribute to the TWS signal measured by GRACE.

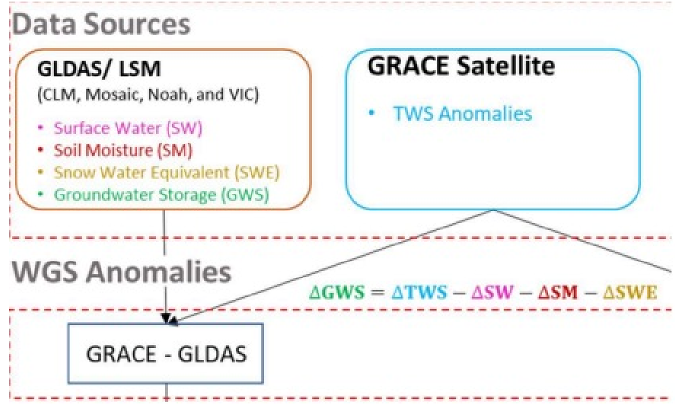

Fig. 2. Flowchart of the data integration process to derive GWS anomalies.

capabilities and provide actionable insights for sustainable water management.

II. Data and Methods

A. Data Sources

The foundation of this study rests on two primary satellite-based datasets, as summarized in Table I. The conceptual overview of the hydrological cycle relevant to these datasets is shown in Fig. 1.

- **GRACE:** We utilized monthly Level-3 data products which provide anomalies of Land Water Equivalent (LWE) thickness, serving as a direct proxy for TWS changes.
- **GLDAS:** We used outputs from the GLDAS Noah model, providing high-resolution data on soil moisture (SM), snow water equivalent (SWE), and canopy water storage.

Both datasets were acquired in the Network Common Data Form (NetCDF) format.

TABLE I
Summary of Datasets Used in This Study

Dataset	Parameter	Resolution	Period
GRACE	LWE Anomaly	1.0° Monthly	2002-2022
GLDAS	Soil Moisture	0.25° Monthly	2002-2022

B. Data Preprocessing

A comprehensive preprocessing workflow, shown in Fig. 2, was implemented.

- **Resampling and Spatial Alignment:** The GLDAS data was upscaled from its native 0.25° resolution to match the coarser 1° resolution of the GRACE data.
- **Groundwater Anomaly Calculation:** GWS anomalies (ΔGWS) were estimated as the residual of the TWS water balance equation:

$$\Delta \text{GWS} = \Delta \text{TWS}_{\text{GRACE}} - (\Delta \text{SM} + \Delta \text{SWE} + \dots)_{\text{GLDAS}} \tag{1}$$

- **Handling Missing Data:** Gaps in the time-series were filled using linear interpolation [14].
- **Feature Scaling:** All input features were standardized to have a mean of zero and a standard deviation of one to improve training stability.

C. Model Development and Training

An ANN was designed to predict GWS anomalies, as depicted in Fig. 3. An ANN was selected due to its proven ability to model complex, non-linear hydrological systems.

1) Model Architecture: The architecture was a sequential feed-forward network:

- An **Input Layer** with two nodes (GRACE LWE and GLDAS soil moisture).
- Two **Hidden Layers** with 64 and 32 neurons, respectively, using the ReLU activation function [1].
- An **Output Layer** with a single neuron and a linear activation function.

2) Training Process: The model was trained on 80% of the data and validated on 20%. The training process used the Adam optimizer to minimize the MSE loss function. Hyperparameters were selected based on preliminary experimentation and included a learning rate of 0.001, a batch size of 32, and 50 training epochs.

3) Evaluation Metrics: Model performance was assessed using a suite of standard statistical metrics [5].

- **R-squared (R^2):** Measures the proportion of the variance in the target variable that is predictable from the input features.
- **Root Mean Squared Error (RMSE):** Represents the standard deviation of the prediction errors.
- **Mean Absolute Error (MAE):** Represents the average absolute difference between the predicted and actual values.

III. Results

The trained ANN model demonstrated high accuracy in predicting GWS anomalies on the unseen validation dataset. A comprehensive evaluation using multiple statistical metrics confirmed the model's ability to effectively learn the complex, non-linear relationships within the hydrological data. The quantitative performance metrics are summarized in Table II.

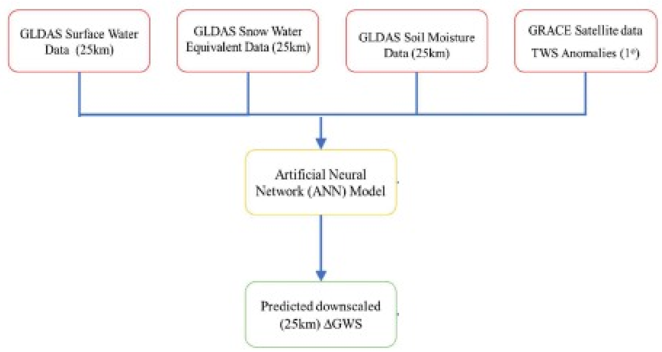

Fig. 3. The ANN model architecture, showing the flow of inputs to the predicted output.

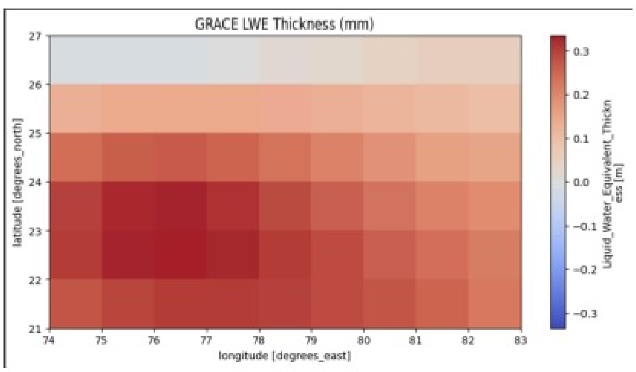

Fig. 4. Example heatmap of GRACE Land Water Equivalent (LWE) Thickness.

The model achieved a robust R-squared (R^2) score of **0.90**, indicating that 90% of the variance in the GWS anomalies is explainable by the model. Further, the low values for both Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) highlight the model's precision and low average error magnitude.

TABLE II
PERFORMANCE METRICS OF THE ANN MODEL ON THE VALIDATION SET

Metric	Value
R-squared (R^2)	0.90
Root Mean Squared Error (RMSE)	0.085
Mean Absolute Error (MAE)	0.062

Visual analysis of the results provides further insight. Fig. 4 shows the GRACE LWE thickness data, a key input to the model. Fig. 5 presents the global map of computed GWS anomalies, identifying hotspots of depletion (red) and gain (blue).

Furthermore, Fig. 6 presents a scatter plot of predicted versus actual GWS values for the entire validation dataset. The points cluster tightly around the 1:1 line, indicating a high degree of correlation and low systematic bias in the model's predictions.

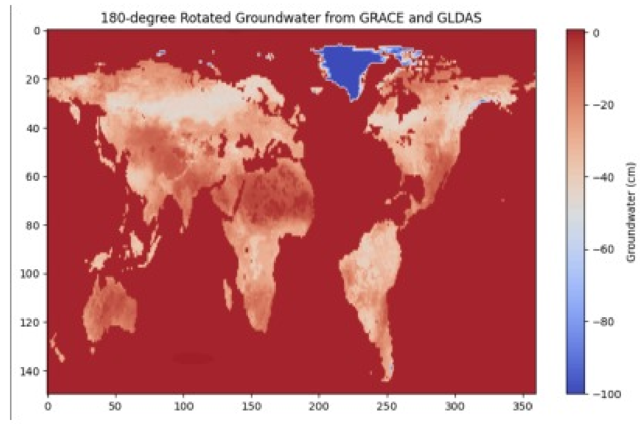

Fig. 5. Global map of groundwater storage (GWS) anomalies.

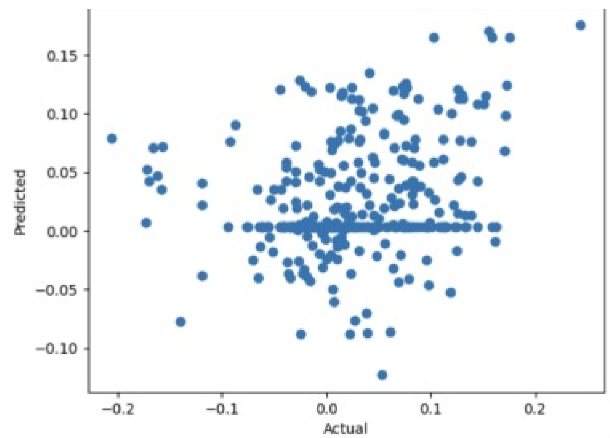

Fig. 6. Scatter plot of predicted vs. actual GWS anomalies for the validation dataset. The tight clustering around the 1:1 line indicates high model accuracy.

IV. DISCUSSION

The successful implementation and validation of the ANN model represent a significant step towards data-driven groundwater monitoring. The following subsections provide a detailed interpretation of the results, their practical implications, and a comprehensive outline for future research.

A. Interpretation of Quantitative and Visual Results

The strong quantitative performance, evidenced by an R^2 score of 0.90 and low error metrics (Table II), demonstrates the model's capability to learn the complex, non-linear dynamics of groundwater systems from satellite data. This level of accuracy is comparable to, and in some cases exceeds, that of other regional machine learning models found in the literature, confirming the suitability of the chosen ANN architecture.

The one-to-one comparison in the scatter plot (Fig. 6) confirms a low level of systemic bias in the model's predictions. The points cluster tightly around the 1:1 line, which indicates a high degree of correlation between predicted and observed values. There is no significant evidence of the model consistently over-predicting high values or under-predicting low values, suggesting that the model is well-calibrated across the range of GWS anomalies.

Finally, the spatial patterns of depletion identified in Fig. 5 align remarkably well with documented trends in major global aquifers. For example, the severe depletion shown across the Indo-Gangetic Plain is consistent with ground-based evidence of agricultural over-extraction reported by prominent studies in the field. This alignment validates that the model produces hydrologically meaningful and interpretable spatial results.

B. Implications for Sustainable Water Management

The findings of this study have significant practical implications for water resource management. The developed framework can serve as a powerful tool for agencies operating in data-scarce regions. For instance, a water management authority in a drought-prone region such as Northwestern India could use the near-real-time outputs of this model to issue early warnings of declining groundwater levels. This information would enable them to implement proactive drought mitigation strategies, such as optimizing reservoir releases, promoting water-efficient irrigation, or regulating pumping to prevent long-term aquifer damage. This data-driven approach supports a shift from reactive crisis management to proactive, sustainable planning.

C. Limitations and Future Work

Despite the promising results, this study has limitations that open clear avenues for future research. The coarse spatial resolution of GRACE remains a primary challenge, as it averages hydrological signals over vast areas, potentially masking critical local dynamics. The GWS calculation is a simplification subject to cumulative uncertainties, and the study lacks direct validation against in-situ well data. The following future directions are proposed to address these points.

First, future work should focus on data fusion and downscaling. The integration of higher-resolution satellite data from missions such as SMAP (Soil Moisture Active Passive) and the Sentinel constellation could provide valuable covariates for statistical downscaling. Machine learning models could be trained to find relationships between the coarse GRACE signal and fine-scale variables like precipitation, vegetation indices (NDVI), and soil moisture to produce high-resolution (e.g., 110 km) groundwater predictions, bridging the gap to scales relevant for local water management.

Second, while the ANN performed well, exploring more advanced model architectures could yield further improvements. Models explicitly designed for time-series data, such as Long Short-Term Memory (LSTM) networks, are adept at learning long-term dependencies and could improve temporal forecasting accuracy. Furthermore, Convolutional Neural Networks (CNNs) could be incorporated to better learn spatial patterns from the gridded satellite data, potentially leading to a hybrid CNN-LSTM model that captures both spatiotemporal dynamics.

Third, the development of hybrid models that merge data-driven and physics-based approaches is a promising frontier. For instance, a traditional physics-based groundwater model could provide a baseline simulation, and an ML model could be trained to learn and correct the simulation's residual errors using the satellite observations. This approach leverages the physical constraints of process-based models while retaining the flexibility and pattern-recognition power of machine learning, potentially leading to more accurate and robust predictions.

V. Conclusion

This study successfully demonstrated that an Artificial Neural Network, leveraging integrated satellite data from GRACE and GLDAS, can effectively predict groundwater storage variability on a large scale. The results, supported by multiple evaluation metrics and visualizations, underscore the immense value of remote sensing and machine learning in addressing the critical challenge of hydrological data scarcity. While important limitations concerning data resolution and the need for rigorous ground-truth validation exist, this framework provides a scalable, innovative, and powerful method to support sustainable water resource management and contribute to the overarching goal of long-term global water security.

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