Explainable Ensemble for Groundwater Vulnerability Mapping Under Climate Uncertainty

A progress report submitted for the partial fulfillment of BS-MS dual degree dissertation in Earth & Environmental Sciences

Progress Report

By

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Certificate

This is to certify that the project report titled ***Explainable Ensemble for Groundwater Vulnerability Mapping Under Climate Uncertainty*** submitted by **Iman Mahato (Reg No. - 21096)** to the Indian Institute of Science Education and Research Berhampur, for the partial fulfillment of BS-MS dual degree programme. It is a bona fide record of the original work carried out by him, and the contents of this project report, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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Declaration

The work titled ***Explainable Ensemble for Groundwater Vulnerability Mapping Under Climate Uncertainty*** presented in this dissertation has been carried out by me under the guidance of **Dr. Pragnaditya Malakar** at the Indian Institute of Science Education and Research, Berhampur.

This work has not been submitted in part or in full for a degree, a diploma, or a fellowship to any other university or institute. Whenever contributions from others are involved, every effort is made to indicate this clearly, with due acknowledgement of collaborative research and discussions. This thesis is a bona fide record of original work done by me, and all sources listed within have been detailed in the bibliography.

Iman Mahato

Date: November 10, 2025 Registration No. - 21096

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Abstract

India is the world's largest user of groundwater, and changes in groundwater storage play a critical role in shaping the country's hydrological dynamics. Drought conditions diminish recharge, leading to declines in groundwater levels and withdrawal potential, which in turn contribute to agricultural losses and, often, irreversible impacts such as land subsidence. The GRACE and GRACE-FO satellite missions provide gravity-based measurements that enable monitoring of terrestrial water storage changes, though at relatively coarse spatial resolution. This study introduces a novel hybrid machine learning framework to downscale GRACE-derived groundwater storage anomalies (GWSA) to a finer resolution, and subsequently employs this enhanced dataset to conduct the first high-resolution, nationwide assessment of long-term groundwater storage trends in India. Our methodology employs a two-stage, hybrid model. First, a robust, ensemble-mean GWSA target variable was created for the 2003-2025 period by averaging the outputs of three GLDAS Land Surface Models (Noah, CLSM, and VIC). This ensemble GWSA, along with coarse-averaged climate data and GRACE TWS, is fed into a Convolutional Long Short-Term Memory (ConvLSTM) network to learn complex spatio-temporal dynamics. Second, a Random Forest model integrates these learned features with high-resolution static (topography, soil) and dynamic (precipitation, NDVI) variables to perform the final regression-based downscaling. Following development, the framework's validity will be confirmed by comparing the finer resolution GWSA time-series against in-situ well observations. Once validated, this new high-resolution dataset will be used to generate the primary scientific output of a high-resolution map of statistically significant long-term groundwater storage trends, revealing depletion hotspots with spatial detail. Furthermore, SHAP will be employed to deconstruct the model, quantifying the site-specific drivers. As its final objective, the validated framework will be applied as a prognostic tool to assess the impacts of future climate change. By driving the hybrid model with CMIP6 climate projections (SSP2-4.5 and SSP5-8.5), this study will generate high-resolution maps of groundwater storage vulnerability for the 21st century. These projections will identify future depletion and recharge hotspots, providing a critical, data-driven tool for long-term strategic planning and climate adaptation in India's most at-risk regions.

Contents

List of Tables

List of Figures

Chapter 1

Introduction :

1.1 Background :

Groundwater is one of Earth's most essential freshwater resources, supporting agriculture, drinking water supply, and ecosystem services. It acts as a natural buffer during droughts and seasonal dry spells, especially in semi-arid and monsoon-dependent regions. Unlike surface water, groundwater is stored in the pore spaces of rock formations known as aquifers. These aquifers vary in depth, permeability, and storage capacity, depending on the underlying geology, such as unconsolidated alluvial deposits or fractured crystalline bedrock.

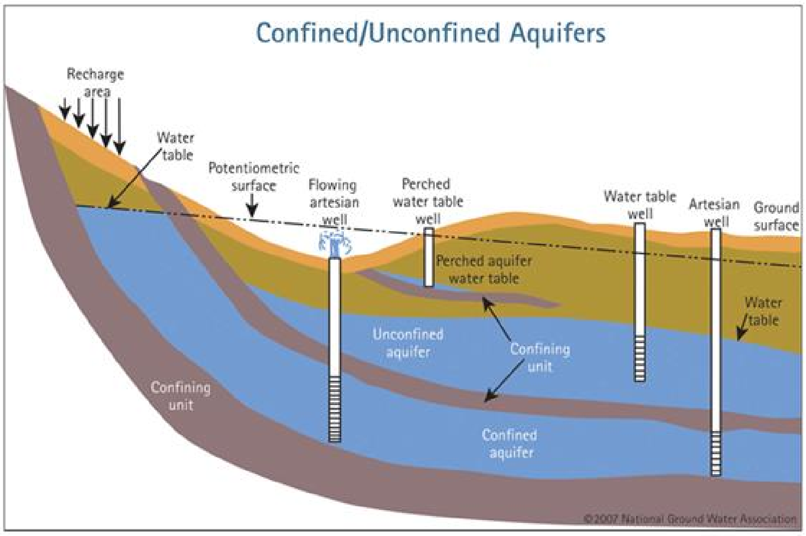


Figure 1.1: Illustration of confined and unconfined aquifers within geological formations.

With rapid population growth, agricultural intensification, and expanding urbanization, pressure on aquifer systems has increased globally. In India, for instance, nearly 60% of irrigation relies on groundwater, leading to significant extraction in many regions. This stress is further intensified by climate change, which alters precipitation patterns, increases evaporation, and drives more frequent and severe hydroclimatic extremes.

Traditional methods of assessing groundwater availability, such as well measurements and in-situ hydrogeological surveys, are often spatially limited, labor-intensive, and difficult to scale over large regions. While highly accurate at their specific locations, these wells are too few and far between (i.e., too sparse) to provide a complete, nationwide picture of groundwater dynamics. This spatial and temporal data gap makes it incredibly difficult to create effective, targeted water management policies.

1.2 Motivation :

The Gravity Recovery and Climate Experiment (GRACE) satellite mission (2002-present) provided a revolutionary breakthrough. For the first time, GRACE allowed scientists to measure the total change in Terrestrial Water Storage (TWS) – the sum of all water on and in the land (groundwater, soil moisture, surface water, snow, and ice) – on a monthly basis across the globe. By using a water balance equation and subtracting the other components (primarily soil moisture and surface water, often sourced from physical models like the Global Land Data Assimilation System, or GLDAS), we can isolate the signal for Groundwater Storage Anomalies (GWSA). This GRACE-derived GWSA data is the only tool available that provides a consistent, large-scale view of groundwater trends across all of India.

However, this solution introduced two new, significant challenges that motivate this project:

1. **The Scale Gap:** GRACE's primary limitation is its coarse spatial resolution of approximately 110 km (1 degree). While excellent for understanding regional or national trends, this "blurry" picture is useless for local water management, which happens at the district, village, or watershed level. Policymakers need to know which specific areas are in crisis, not just that a large 110 km by 110 km block is under stress.

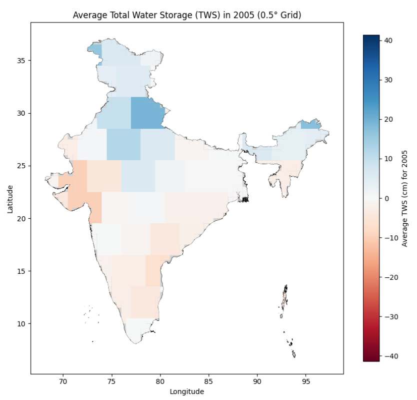
2. **The Transparency Gap:** To bridge this "scale gap," many researchers have begun using machine learning (ML) models to "downscale" the coarse GRACE data. These models are powerful, but most of them (e.g., Random Forests, deep learning) operate as "black boxes." They can produce a high-resolution map, but they cannot explain why a certain area is predicted to be depleting. Is the depletion caused by a lack of rainfall, a shift in crop patterns, or an increase in irrigation? Without a reason, policymakers are hesitant to trust or act on the model's outputs.

1.3 Problem Statement :

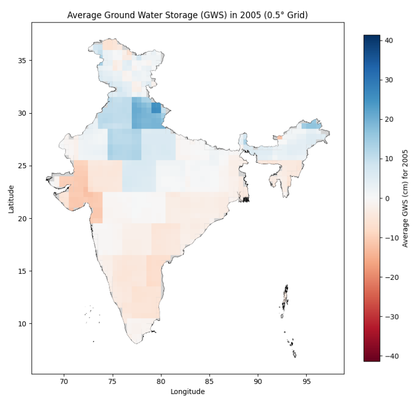
Estimating groundwater storage is difficult because it lies below the surface and is rarely measured consistently across space and time. While satellite missions like GRACE help monitor water storage at large scales, their coarse resolution limits their usefulness for local planning and management.
This project addresses the clear scientific and policy need for groundwater data that is not only spatially precise but also scientifically trustworthy.

Therefore, the central problem is to design, build, and test a new framework that can:

- Downscale coarse, 110 km monthly GRACE-derived GWSA data to a fine, 10 km policy-relevant resolution across India.
- Be fully "explainable". It should not be a "black box," and it should identify the specific drivers (e.g., rainfall, irrigation, soil type) behind the predicted groundwater trends at any 10 km location.



(a) Terrestrial Water Storage(TWS) in 2005 from GRACE data.



(b) Ground Water Storage Anomaly (GWSA)(derived) in 2005.

Figure 1.2: Map of the Indian Sub-Continent showing Water Storage Anomaly.

1.4 Proposed Solution and Objectives:

To solve this problem, this thesis proposes a novel, Explainable, Hybrid Machine Learning Framework. This framework is designed to capture the complex, non-linear relationships between large-scale climate patterns and local-scale groundwater behavior.

The core of the methodology is a two-stage hybrid model:

1. **A Convolutional Long Short-Term Memory (ConvLSTM)** 1.3a network will be used to process the coarse-scale, time-series data (GRACE, GLDAS). This model is excellent at learning complex spatio-temporal patterns (i.e., how conditions in one area and at one time affect another area at a later time).

2. **A Random Forest (RF)** 1.3b model will then integrate the features learned by the ConvLSTM with a suite of high-resolution, static data (like topography, soil type, land use, and river density) to perform the final regression-based downscaling to 10 km.

The specific objectives of this project are:

1. To collect and pre-process all required datasets for the 2002-2025 study period, including GRACE TWS, GLDAS land surface variables, and high-resolution static geospatial data.

2. To build and train the proposed ConvLSTM-RF hybrid model to generate a new, 10 km resolution monthly GWSA dataset for all of India.

3. To validate the 10 km GWSA output by comparing it against independent, in-situ groundwater well data.

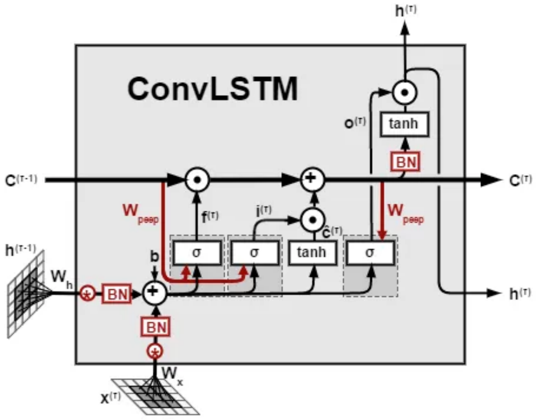
4. To apply the non-parametric Mann-Kendall (MK) test and Theil-Sen's slope estimator to the newly generated 10 km dataset to create the first-ever 10 km resolution map of significant long-term groundwater trends across India.

5. To employ Explainable AI (XAI) techniques, specifically SHapley Additive exPlanations (SHAP), to analyze the trained model and quantify the specific drivers of groundwater depletion in India's most critical regions.

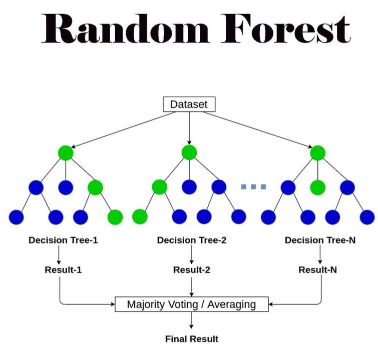
6. To leverage the validated framework as a prognostic tool by forcing it with future climate projection data (e.g., from CMIP6) to forecast 10 km resolution GWSA trends through 2050 and 2100 under various climate scenarios.

1.5 Scope and Societal Relevance :

The scope of this thesis is to create a validated, high-resolution (10 km) monthly groundwater dataset for the entirety of India from 2002 to the present, and to develop a framework capable of forecasting future trends.



(a) A ConvLSTM cell. Source: Medium.



(b) Random Forest. Source: Medium.

Figure 1.3: ConvLSTM and Random Forest models.

This project contributes directly to the global goal of developing scalable, data-driven tools for environmental monitoring, particularly in regions where in-situ observations are sparse or unavailable. By bridging satellite observations, physical models, and explainable AI, this framework aims to fundamentally improve our understanding of how India's complex groundwater systems respond to both natural climate variability and human activities.

The societal and scientific applications of this work are direct and substantial. The outputs are designed to be a foundational decision-support tool, enabling government bodies, policymakers, and researchers to:

- **Provide Early Warnings for Geohazards:** Use the high-resolution 10 km data to provide early warnings for critical issues like land subsidence caused by excessive groundwater extraction, especially in vulnerable alluvial and unconsolidated sedimentary aquifers.
- **Identify and Manage Depletion Hotspots:** identifies emerging groundwater depletion hotspots at a high-impact, 10 km resolution. This precision allows water managers to move beyond simple crisis monitoring and implement forward-looking, proactive management strategies, particularly in vulnerable semi-arid and monsoon-dependent regions.
- **Design Targeted, Defensible Policy:** Use the XAI/SHAP outputs to understand why an area is depleting (e.g., rainfall or irrigation), allowing for targeted interventions (e.g., recharge structures or crop diversification policies).
- **Create High-Resolution Vulnerability Maps:** Integrate the 10 km GWSA trends with existing geological and soil data to map regional groundwater vulnerability, guiding sustainable irrigation practices and identifying high-potential zones for recharge.

- **Build Trust in Data-Driven Management:** Overcome the "black box" problem by providing transparent, explainable results that policymakers can trust, act upon, and defend.
- **Assess Future Hydroclimatic Stress:** Use the forecasting component as a critical tool for long-term infrastructure planning and climate change adaptation, securing India's future water and food security.

Chapter 2

Literature Review :

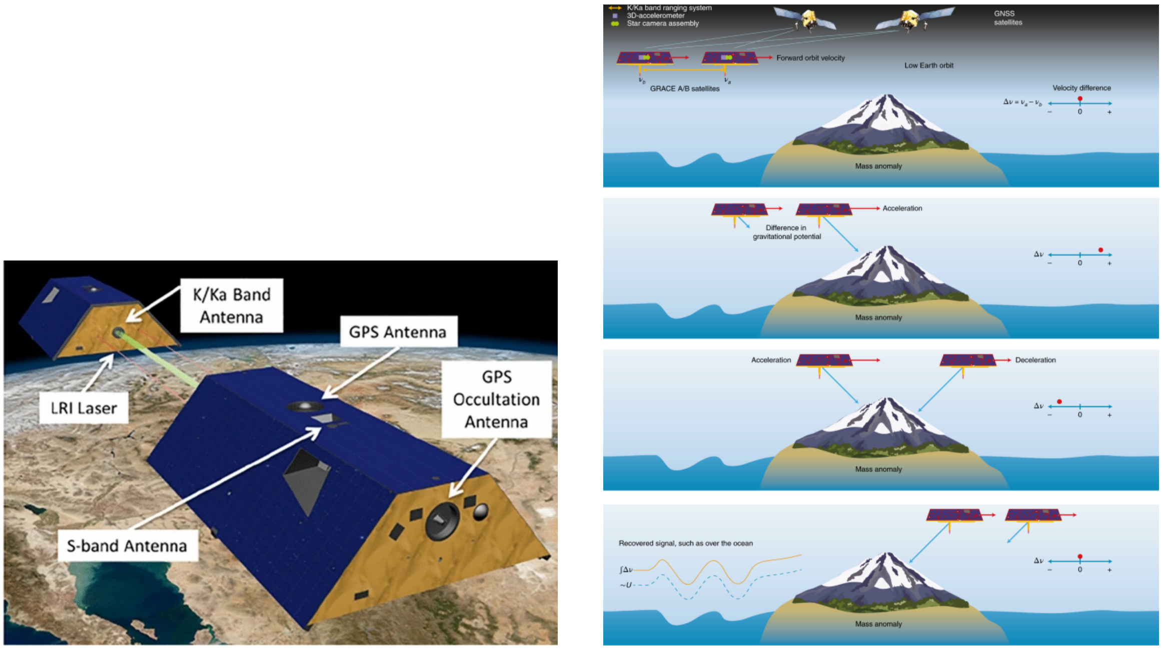
2.1 Introduction: The GRACE Revolution:

The launch of the Gravity Recovery and Climate Experiment (GRACE) mission in 2002, and its successor GRACE-Follow On (GRACE-FO), fundamentally transformed large-scale hydrology. For the first time, GRACE provided a direct, global measurement of Terrestrial Water Storage (TWS), offering a "top-down" regional view of water resource dynamics (Rodell et al., 2009). By isolating the groundwater component (GWSA) from TWS, typically by subtracting soil moisture (SMS) and evapotranspiration (EVT) components from land surface models like GLDAS, researchers gained an invaluable tool for assessing large-scale aquifer depletion, particularly in data-sparse regions like India (Tiwari et al., 2009).

However, the primary limitation of GRACE has always been its coarse spatial resolution (approx. 110 km). While suitable for continental-scale analysis, this resolution is insufficient for the local-scale water management required by policymakers. This "scale gap" created an immediate and well-defined scientific challenge: a need to downscale the coarse GRACE data to a policy-relevant resolution.

2.2 Machine Learning Applications for GRACE Downscaling:

The initial solution to the "scale gap" has been the widespread application of machine learning (ML). This approach trains an ML model (e.g., Random Forest, Support Vector Machine) to learn the statistical relationship between the coarse GRACE GWSA signal and a suite of high-resolution, static and dynamic variables (e.g., precipitation, temperature, land use, topography, soil type).



(a) GRACE Twin Satellite. Source: *Xia et al., 2020*.

(b) GRACE Working principle. Source: *Martino Travagnin, 2020*.

Figure 2.1: GRACE Satellite and its Working principle.

Numerous studies have successfully demonstrated this approach. For example, Yin et al. (2022) and Agarwal et al. (2023) effectively used machine learning downscaling schemes to improve the resolution of GRACE-based water storage estimates. Similarly, Hadavi et al. (2024) and Satizábal-Alarcón et al. (2024) applied ML models to downscale GRACE data for robust groundwater characterization in Iran and the Amazon River Basin, respectively. These studies established that ML, particularly models like Random Forest, are highly effective at this non-linear regression task, providing a robust baseline methodology(Wang, Li et al., 2024).

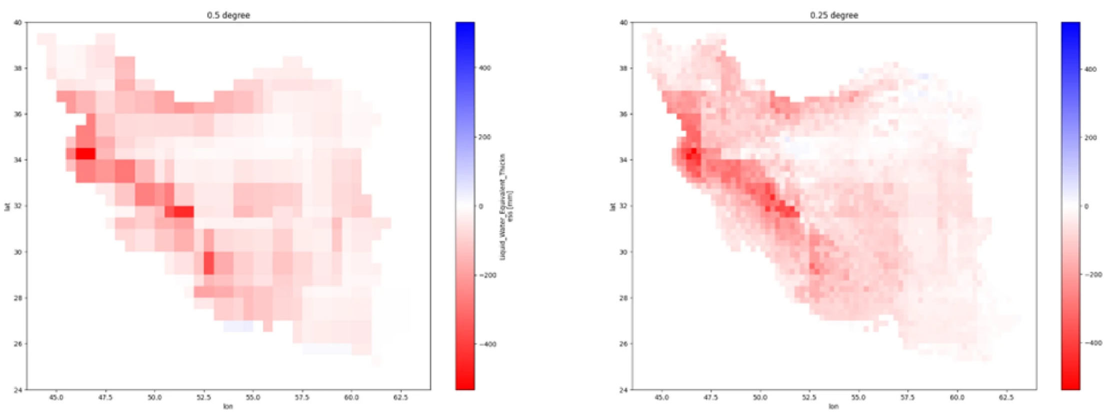


Figure 2.2: GRACE TWSA resolution after downscaling (sample date: August 2010)(Kashani et al., 2025).[**?**]

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2.3 Limitations of Static Models and Advancements in Spatio-Temporal Deep Learning:

While standard ML models (like Random Forest) are powerful, they often treat data points as independent. They struggle to learn the complex, time-dependent (temporal) and neighborhood-dependent (spatial) relationships inherent in hydrological systems. A pixel's groundwater storage is not just a function of its own rainfall and soil type; it is also a function of last month's rainfall (temporal dependency) and the neighboring pixel's climate (spatial dependency).

This limitation has led researchers to explore deep learning models that are explicitly designed to handle "spatio-temporal" data. Models like the Long Short-Term Memory (LSTM) network and its variants are adept at learning from time-series data. Even more advanced are Convolutional LSTM (ConvLSTM) networks, which combine the time-series power of an LSTM with the spatial-processing power of a Convolutional Neural Network (CNN). This allows the model to learn from data as a "video" (a time-series of maps), capturing how large-scale patterns move and evolve through both space and time (Shi et al., 2015). This is a critical advancement for modeling dynamic hydrological processes.

2.4 Model Interpretability and the Role of Explainable AI (XAI) :

Whether using standard ML or advanced deep learning, the majority of downscaling studies produce a "black box" model. The model may be accurate, but it is not interpretable. It cannot answer the simple, critical question from a policymaker: Why is the groundwater declining in this 10 km pixel? Is it due to a lack of rainfall, or is it due to a specific land use practice?

This "transparency gap" is a major barrier to the real-world adoption of ML models in environmental policy. A new and cutting-edge field, Explainable AI (XAI), has emerged to solve this. Techniques like SHapley Additive exPlanations (SHAP) (Lundberg & Lee, 2017) provide a mathematically sound method to "open the black box." SHAP can take a complex model's prediction for a single pixel and precisely quantify how much each input feature (e.g., precipitation, topography, land use) contributed to that specific prediction. This moves the research from just mapping to understanding and explaining the drivers of hydrological change.

2.5 Research Gap and Thesis Contribution :

This literature review reveals a clear evolution and three distinct gaps in the current research. While standard ML models (Section 2.2) are common, they are temporally simple. Deep learning models (Section 2.3) are more powerful but are often used in isolation. Finally, very few studies from either category (Section 2.4) have addressed the critical ”black box” problem.

This thesis will be the first, to our knowledge, to synthesize all three of these advanced components into a single, optimized framework.

The research contribution is a novel hybrid ConvLSTM-RF + XAI framework. This model is not just a standard ML model or a standalone deep learning model. It is a specialized, two-stage system:

1. A ConvLSTM will be used as a ”spatio-temporal feature extractor” to learn the complex, dynamic patterns from the coarse GRACE and GLDAS time-series.
2. A Random Forest will be used as the final, high-resolution downscaling regressor, integrating the learned dynamic features from the ConvLSTM with high-resolution static data (topography, soil, etc.).
3. SHAP will be applied to the entire validated framework to provide the first-ever 1 km-scale, explainable map of groundwater drivers across India.

This hybrid approach strategically uses the best model for each part of the problem, directly addressing the scale, spatio-temporal, and transparency gaps identified in the literature.

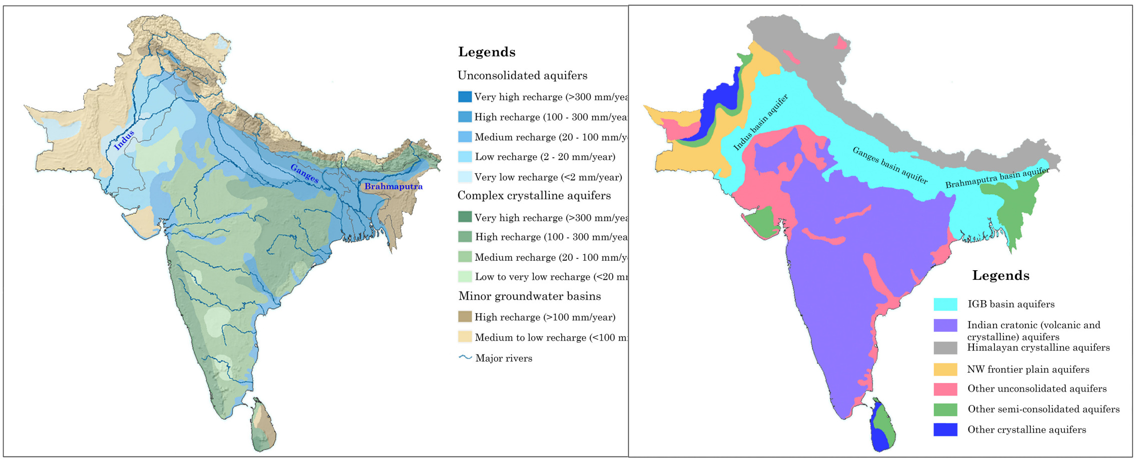
Table 2.1: Comparison of Selected Studies on Groundwater Estimation

Study	**Model Used**	**Input Data**	**Limitations**
Wenjie Yin et al. (2022)	RF downscaling; PCR-GLOBWB v2.0 model	GRACE TWSA, GLDAS, MODIS, Insitu well data	Limited spatial features; interpretability not addressed
Diego Satizábal-Alarcón et al. (2024)	ML (RF, AdaBoost)	GRACE-FO, GLDAS, CHIRPs, GLEAM, DEM, RIMAS and SIAGAS	Weak in capturing temporal trends; focused on Amazon basin
Vibhor Agarwal et al. (2023)	ConvLSTM	GRACE, climate variables	Limited explainability; No extrapolation, Limited Time Span: GRACE Data Ends in 2016
Ali Kashani and H.R. Safavi (2025)	ML(XGBoost) + SARIMA	In-situ wells, GRACE and Complex setup	No explainable AI tools; Sparse well network; lacks spatial downscaling
Ehsan Foroumandi et al.(2023)	ConvLSTM + RF + FFNN	MODIS, TRMM, FLDAS, SRTM, GRACE	No surface water data used; No uncertainty quantification; No analysis after 2016; No agricultural or human activity input data
Hai Tao et al. (2023)	RF, SVM, ANN	GRACE, ERA5	Lack of Ground Truth Data for Validation, Poor in desert regions, Dependence on ERA5 Reanalysis Data Alone, No physics used etc.
This Study	ConvLSTM + RF	GRACE, ERA5, MODIS, Static Layers (SRTM, soil, etc.)	In progress; full feature integration ongoing

Chapter 3

Methodology :

3.1 Study Area :



(a) Map of the Indian Sub-Continent showing major rivers and recharge rates.

(b) Map of the Indian Sub-Continent showing all major aquifers.

Figure 3.1: Major river systems and aquifer distribution across India. (Mukherjee et al., 2015)

The geographical scope of this study encompasses the entire Indian subcontinent, a region defined by its immense population, vast agricultural sector, and critical dependence on groundwater. India is one of the world's largest users of groundwater, which supplies over 80% of domestic water needs and over 60% of irrigation for its food-secure agriculture.

The region is characterized by extreme hydro-climatic diversity, dominated by the South Asian monsoon, which provides the majority of the annual precipitation in a short, intense season. This variability, combined with intense extraction, has placed immense stress on its primary aquifer systems.(Karunakalage, A.A. et al. (2021)) The study will cover all major river basins and hydrogeological zones across the country.

This comprehensive scope ensures the model is developed for diverse hydrological conditions, including the severely stressed alluvial aquifers of the Indo-Gangetic Basin as well as the hard-rock aquifers of Peninsular India. The goal is to develop a nationally scalable groundwater management framework.

3.2 Data Acquisition and Pre-processing :

This research is built on a diverse suite of satellite remote sensing data, land surface model outputs, static geospatial datasets, and in-situ observations. All datasets will be acquired for the study period of January 2002 to August 2025. All pre-processing steps, including spatial resampling (to a 10 km grid) and temporal aggregation (to a monthly step), are conducted in Python and Google Earth Engine.

3.2.1 GRACE/GRACE-FO Terrestrial Water Storage (TWS) Data:

- **Source:** JPL Mascon (Mass Concentration) solution (JPL RL06.3_v04).
- **Variables:** Terrestrial Water Storage Anomaly (TWS), expressed as an equivalent water height (cm). Mascons are preferred over traditional spherical harmonics as they have a higher signal-to-noise ratio and do not require empirical destriping or Gaussian filtering.
- **Resolution:** 0.5-degree grid (effective resolution ∼110 km).
- **Temporal:** Monthly. The brief data gap between the two missions (July 2017 – May 2018) is treated as missing data (NaN values) in the time series.

3.2.2 GLDAS Land Surface Model Data

To isolate the groundwater component from TWS, outputs from the Global Land Data Assimilation System (GLDAS) are required. To reduce the uncertainty associated with any single Land Surface Model (LSM), this study will use an ensemble of three different GLDAS models: Noah, CLSM, and VIC.

- **Source:** NASA Goddard Earth Sciences Data and Information Services Center (GES DISC).
- **Models and Native Resolutions:**

1. **Noah (GLDAS-2.1):** 0.25-degree resolution.
2. **CLSM (GLDAS-2.1):** 1-degree resolution.
3. **VIC (GLDAS-2.1):** 1-degree resolution.

- **Component Variables:**

  1. **Noah (GLDAS-2.1, 0.25-degree):**
     - SoilMoi0_10cm_inst (Soil moisture 0-10 cm)
     - SoilMoi10_40cm_inst (Soil moisture 10-40 cm)
     - SoilMoi40_100cm_inst (Soil moisture 40-100 cm)
     - SoilMoi100_200cm_inst (Soil moisture 100-200 cm)
     - SWE_inst (Snow water equivalent)
     - Qs_acc_cm (Surface runoff)

     Total Soil Moisture is calculated by summing its four layers: SoilMoi0_10cm_inst, SoilMoi10_40cm_inst, SoilMoi40_100cm_inst, and SoilMoi100_200m_inst. Snow Water Equivalent (SWE_Noah) is SWE_inst.

  2. **CLSM (GLDAS-2.1, 1-degree):**
     - SoilMoist_S_inst (Surface soil moisture)
     - SoilMoist_RZ_inst (Root zone soil moisture)
     - SWE_inst (Snow water equivalent)
     - Qs_acc_cm (Surface runoff)
     - TWS_inst (Model-total terrestrial water storage)

     Total Soil Moisture (SMS_CLSM) is calculated by summing SoilMoist_S_inst (surface) and SoilMoist_RZ_inst (root zone). Snow Water Equivalent (SWE_CLSM) is SWE_inst.

  3. **VIC (GLDAS-2.1, 1-degree):**
     - SoilMoi0_30cm_inst (Soil moisture layer 1)
     - SoilMoi_depth2_inst (Soil moisture layer 2)
     - SoilMoi_depth3_inst (Soil moisture layer 3)
     - SWE_inst (Snow water equivalent)
     - Qs_acc_cm (Surface runoff)

     Total Soil Moisture (SMS_VIC) is calculated by summing its three layers: SoilMoi0_30cm_inst, SoilMoi_depth2_inst, and SoilMoi_depth3_inst. Snow Water Equivalent (SWE_VIC) is SWE_inst.

- **Temporal:** Monthly.

3.2.3 Derivation of the Target Variable (GWSA):

The target variable for the machine learning model is the ensemble-mean, coarse-resolution Groundwater Storage Anomaly (GWSA). This is derived by calculating GWSA individually for each of the three GLDAS models first, and then averaging the results. This process requires a hierarchical resampling strategy to bring all component data to the 0.5-degree GRACE Mascon grid.

1. **Data Resampling to 0.5° Grid:**
   - **TWS:** The TWS_GRACE data is already at the 0.5-degree resolution.
   - **Noah (0.25° → 0.5°):** This is an aggregation. For each 0.5-degree GRACE pixel, the SMS_Noah and SWE_Noah values are calculated by taking the mean of the four 0.25-degree Noah pixels that fall within it.
   - **CLSM & VIC (1° → 0.5°):** This is a disaggregation/replication. For each 1-degree CLSM and VIC pixel, the SMS and SWE values are assigned to the four 0.5-degree GRACE pixels that fall within its boundaries.
2. **Individual GWSA Calculation (at 0.5°):** After resampling, all components exist on the 0.5-degree grid. GWSA is then calculated for each model (omitting Canopy Water Storage as a negligible component):
   - GWSA_Noah = TWS_GRACE - (SMS_Noah + SWE_Noah + Qs_acc_cm)
   - GWSA_CLSM = TWS_GRACE - (SMS_CLSM + SWE_CLSM + Qs_acc_cm)
   - GWSA_VIC = TWS_GRACE - (SMS_VIC + SWE_VIC + Qs_acc_cm)
3. **Final Ensemble GWSA Calculation:** The final, robust target variable is the ensemble mean of the three individual GWSA calculations:

$$GWSA_{\text{Ensemble}} = \frac{GWSA_{\text{Noah}} + GWSA_{\text{CLSM}} + GWSA_{\text{VIC}}}{3} \tag{3.1}$$

   This GWSA_Ensemble dataset, at 0.5-degree monthly resolution, serves as the definitive target variable (the ”y” value) for training the downscaling framework.

3.2.4 High-Resolution Static Variables :

These variables represent the static, unchanging characteristics of the land surface that govern where and how groundwater is stored. All will be resampled to the target 10 km resolution.

Table 3.1: Summary of Climate and Remote Sensing Variables Used in the Study

Variable	**Dataset**	**Source**	**Native Resolution**	**Temporal Resolution**
Precipitation	CHIRPS/IMERG	UCSB/NASA	0.05°/0.1°	Monthly
Temperature	ERA5-Land	ECMWF	0.1° (∼11 km)	Monthly
Vegetation Index (NDVI)	MODIS (MOD13A3)	NASA LP DAAC	1 km	Monthly
Irrigation(McDermid et al., 2023)	Aquastat databases, FAOSTAT	UN FAO	1 km	5yearly

Table 3.2: Summary of Datasets and Variables Used to Calculate GWSA in This Study

Data Category	**Dataset & Variables**	**Source**	**Spatial Res.**	**Temporal Res.**	**Temporal Span**
TWS (Target)	**GRACE/GRACE-FO Mascons (RL06.3_v04)** Variable: Terrestrial Water Storage Anomaly: lwe_thickness*scale_factor	JPL PO.DAAC	0.5°	Monthly	2002–Present
LSM Components	**GLDAS 2.1 Noah** Variables (SMS): SoilMoi0_10cm_inst, SoilMoi10_40cm_inst, SoilMoi40_100cm_inst, SoilMoi100_200cm_inst Variable (SWE): SWE_inst Variable (Surface Water): Qs_acc	NASA GES DISC	0.25°	Monthly	2000–Present
LSM Components	**GLDAS 2.1 CLSM** Variables (SMS): SoilMoist_S_inst, SoilMoist_RZ_inst Variable (SWE): SWE_inst Variable (Surface Water): Qs_acc	NASA GES DISC	1.0°	Monthly	2000–Present
LSM Components	**GLDAS 2.1 VIC** Variables (SMS): SoilMoi0_30cm_inst, SoilMoi_depth2_inst, SoilMoi_depth3_inst Variable (SWE): SWE_inst Variable (Surface Water): Qs_acc	NASA GES DISC	1.0°	Monthly	2000–Present

Table 3.3: Summary of Static Variables Used for GWSA Downscaling Framework

Variable Category	Predictor Variable	Source	Native Resolution
Topography	Digital Elevation Model (DEM)	SRTM 1 Arc-Second	∼30 m
Topography	Slope	Derived from SRTM	∼90 m
Topography	Aspect	Derived from SRTM	∼90 m
Soil	Sand Content (%)	SoilGrids	250 m
Soil	Silt Content (%)	SoilGrids	250 m
Soil	Clay Content (%)	SoilGrids	250 m
Soil	Bulk Density (kg/m^3)	SoilGrids	250 m
Land Use	Land Use/Land Cover Class	ESA WorldCover	10 m
Hydrography	Rivers	Derived from SRTM	∼90 m
Hydrography	Distance to Nearest Water Body	Derived from SRTM	∼90 m

- **Topography:** Digital Elevation Model (DEM), Slope, and Aspect, derived from the SRTM (Shuttle Radar Topography Mission) 1 arc-second (∼30m) dataset.

- **Soil Characteristics:** Volumetric soil properties including sand, silt, and clay content (%), and bulk density (kg/m^3) for multiple soil depths. *Source:* SoilGrids (10 km).

- **Land Use/Land Cover (LULC):** Categorical data (cropland, forest, urban, etc.). *Source:* ESA WorldCover 10m dataset, aggregated to 10 km to show the dominant LULC class for each pixel.

- **Hydrography:** Features such as river density and distance to the nearest surface water body, derived from the SRTM DEM.

3.2.5 High-Resolution Dynamic Variables :

These variables represent the time-varying climatic and surface drivers that govern the recharge and discharge of groundwater.

- **Precipitation:** Monthly rainfall data. Source: IMD high-resolution (0.25-degree) gridded rainfall dataset or the CHIRPS (0.05-degree) dataset.

- **Temperature:** Monthly mean air temperature. *Source:* IMD gridded temperature data or ERA5-Land (0.1-degree).

- **Evapotranspiration:** Monthly Potential/Actual Evapotranspiration (PET/ET). *Source:* MODIS MOD16A2 (500m) product.

- **Vegetation:** Monthly vegetation health/density. *Source:* MODIS MOD13A2 Normalized Difference Vegetation Index (NDVI) (10 km), aggregated to monthly.

3.3 Spatio-Temporal Trend Analysis :

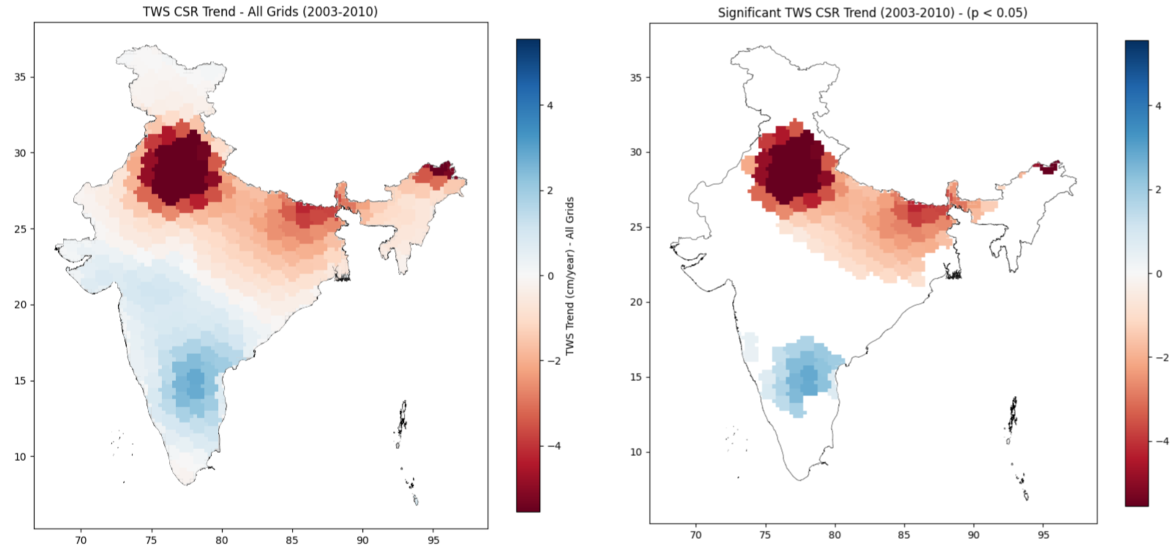
To extract actionable insights, these datasets are analyzed using non-parametric statistical tests to identify long-term trends and patterns.

3.3.1 Mann-Kendall (MK) Test

The Mann-Kendall (MK) test, a non-parametric method, is applied independently to each pixel's time series. This test is widely used in hydrology because it is robust to missing data (like the GRACE data gap) and does not require the data to be normally distributed. It will be used to determine whether a pixel has a statistically significant positive (recharging) or negative (depleting) trend. The output will be a map of p-values, allowing for the identification of statistically significant trend hotspots.

3.3.2 Theil-Sen's Slope Estimator

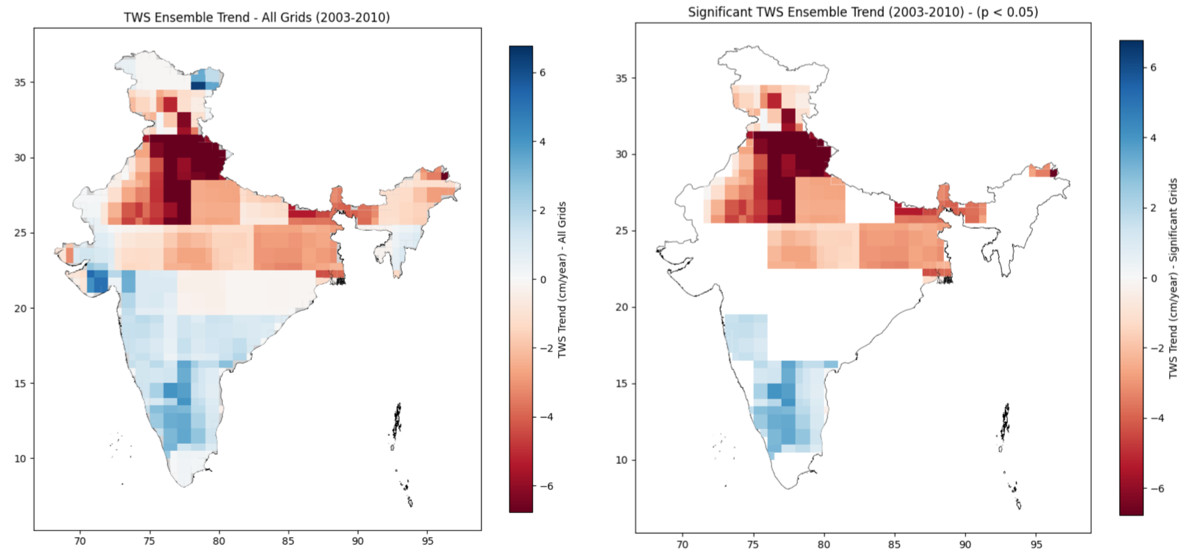
For all pixels identified as "significant" by the MK test, Theil-Sen's Slope estimator has been applied. This non-parametric method calculates the median of the slopes between all pairs of points in the time series. It is highly robust to outliers (e.g., an extreme flood or drought month). The output will be a map showing the magnitude of the long-term groundwater trend (e.g., in cm/year) for all significant regions. This map illustrates groundwater depletion and recharge across India.



(a) Spatial Distribution of Terrestrial Water Storage (TWS) Trends Across India.

(b) Statistically Significant Terrestrial Water Storage (TWS) Trend Hotspots in India.

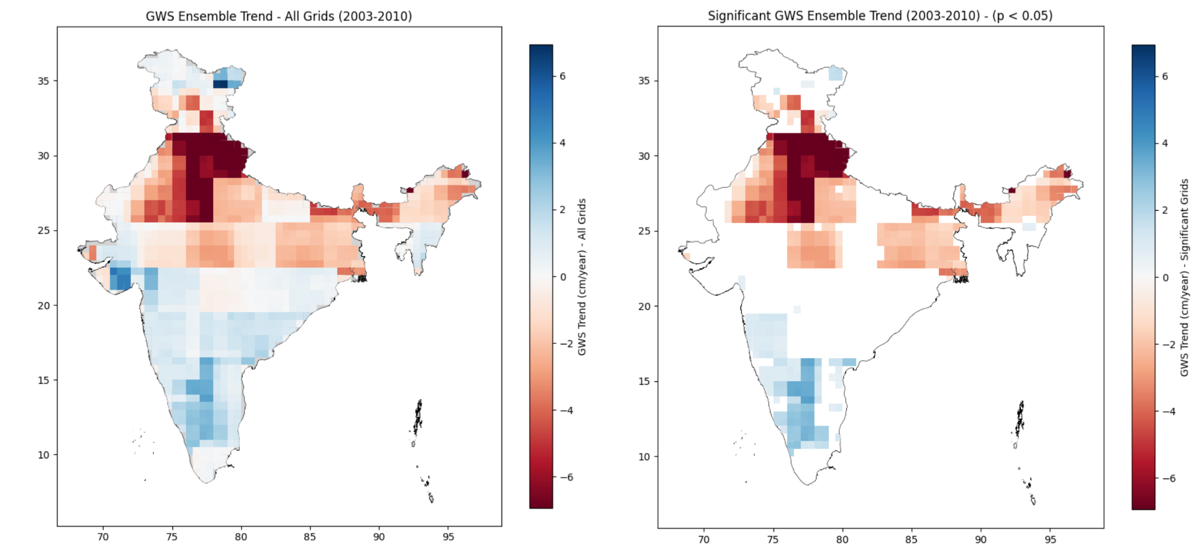
Figure 3.2: Mann-Kendall (MK) Test and Theil-Sen's Slope over India from 2002 to 2010 on GRACE CSR data.



(a) Spatial Distribution of Terrestrial Water Storage (TWS) Trends Across India.

(b) Statistically Significant Terrestrial Water Storage (TWS) Trend Hotspots in India.

Figure 3.3: Mann-Kendall (MK) Test and Theil-Sen's Slope over India from 2002 to 2010 on GRACE JPL data.



(a) Spatial Distribution of Ground Water Storage (GWS) Trends Across India.

(b) Statistically Significant Ground Water Storage (GWS) Trend Hotspots in India.

Figure 3.4: Mann-Kendall (MK) Test and Theil-Sen's Slope over India from 2002 to 2010 on GRACE JPL data.

3.4 Overall Methodological Framework :

The core of this thesis is a novel hybrid machine learning framework designed to perform a statistical downscaling. The framework's objective is to learn the complex, non-linear relationship between the coarse-scale (0.5-degree) spatio-temporal water balance (GWSA_Ensemble, dynamic climate data) and the fine-scale (10 km) static and dynamic properties of the land surface (topography, soil, vegetation).

The methodology is structured as a two-stage process, as illustrated in the conceptual flowchart :

1. **Spatio-Temporal Feature Extraction.** A Convolutional Long Short-Term Memory (ConvLSTM) network is used as a sophisticated "encoder." Its purpose is to analyze the coarse-resolution time-series data (the coarse GWSA_Ensemble and coarse-averaged dynamic variables like precipitation). It processes this data as a "video," learning the complex patterns of hydrological lag, accumulation, and spatial relationships. The output is a set of "learned features" that represent this high-level spatio-temporal context.

2. **High-Resolution Downscaling Regression.** A Random Forest (RF) model performs the final downscaling. For each 10 km pixel, this model integrates two sets of information: a) The static and dynamic high-resolution predictors

for that specific pixel (e.g., its exact elevation, soil type, and NDVI). b) The ”learned spatio-temporal context” provided by the ConvLSTM (from Stage 1) for the coarse parent grid cell that the pixel belongs to.

This hybrid approach is designed to leverage the unique strengths of each model: the ConvLSTM excels at understanding complex, large-scale spatio-temporal dynamics, while the Random Forest excels at high-dimensional regression using a mix of static and dynamic features.

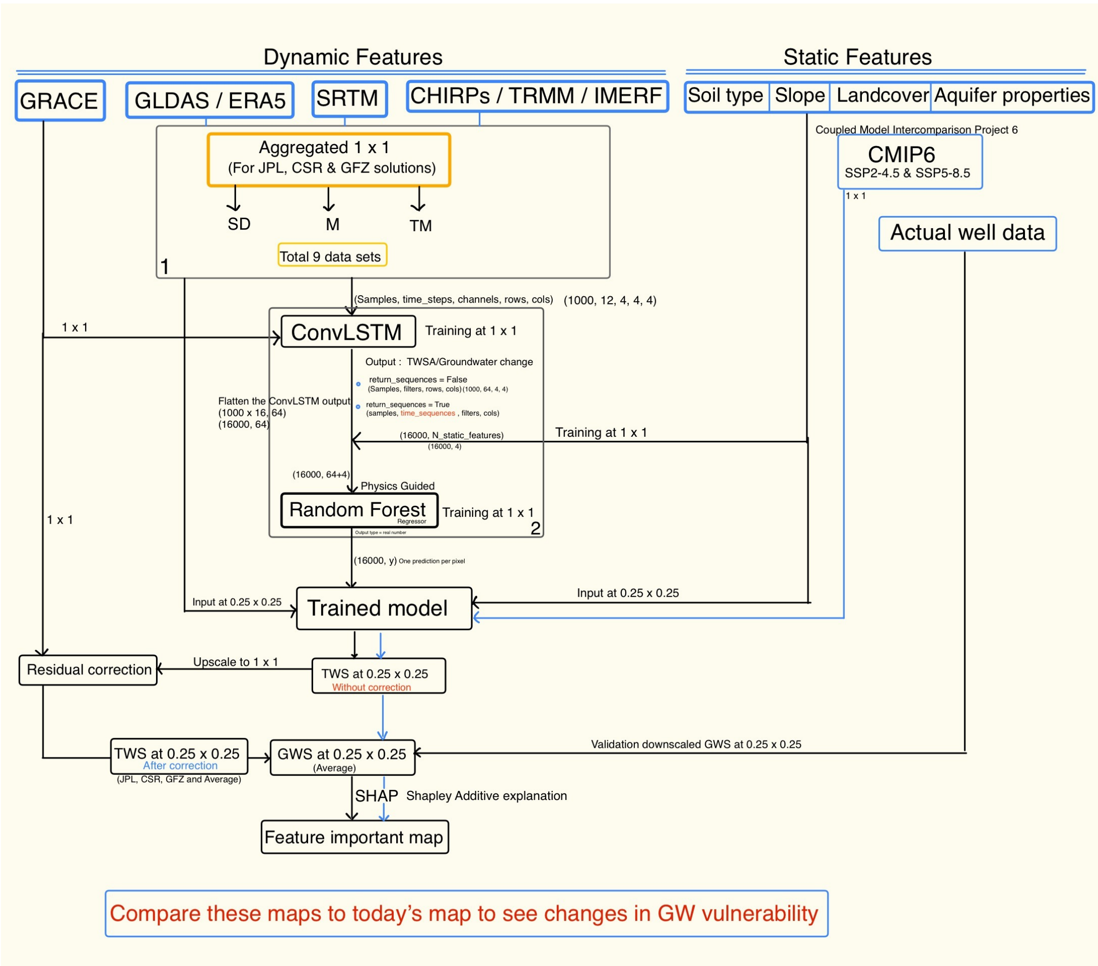


Figure 3.5: Hybrid ConvLSTM and Random Forest model architecture for groundwater storage estimation.

3.5 The Hybrid Downscaling Model: Architecture and Training (Proposed) :

3.5.1 Stage 1: Spatio-Temporal Feature Extraction (ConvLSTM)

The ConvLSTM network, first proposed by Shi et al. (2015), is an extension of the standard LSTM that replaces internal matrix multiplications with convolution operations. This allows it to learn spatial patterns (like a CNN) and temporal patterns (like an LSTM) simultaneously.

1. Role: To act as a spatio-temporal feature encoder.
2. Input Data: The inputs will be sequences of coarse-resolution (0.5-degree) maps. The input tensor will have a shape of (batch_size, sequence_length, height, width, features).
   - sequence_length: A critical hyperparameter representing the "look-back" period (e.g., 12, 24, or 36 months) used to make a prediction.
   - height, width: The dimensions of the coarse 0.5-degree grid over India.
   - features: The coarse resolution dynamic variables, including the target GWSA_Ensemble and key drivers(e.g., coarse-averaged precipitation, temperature, and NDVI)
3. **Output:** The ConvLSTM will process this input "video" and its final hidden state will be a set of learned feature maps that encapsulate the complex hydrological context for that time step.

3.5.2 Stage 2: High-Resolution Regression (Random Forest)

The Random Forest is an ensemble learning method that operates by constructing a multitude of decision trees at training time. It is highly effective for high-dimensional regression, is robust to outliers, and can handle a mix of categorical and continuous data.

- Role: To act as the final downscaling regressor, predicting the 10 km GWSA value for a single point in time (t).
- Training Data Construction: A training dataset will be constructed where each row corresponds to a single 10 km pixel at a single month. The features (X) for that pixel will be:

1. Static 10km Features (Physics): DEM, Slope, Aspect, Soil Clay %, Soil Silt %, Land Use Class, River Density, etc.
2. Dynamic 10km Features (Drivers): Precipitation at time t, NDVI at time t, Temperature at time t.
3. Learned Context Features (Dynamics): The output features from the ConvLSTM (Stage 1) for the corresponding parent 0.5-degree grid cell at time t.

- Target Variable (y): The coarse GWSA_Ensemble value (at 0.5-degree) for that pixel's parent grid cell at time t.

During training, the model learns to use the 10 km features to ”distribute” the coarse 0.5-degree GWSA value among its constituent 10 km pixels. When fully trained, it can be run in ”prediction mode” on the 10km data alone to generate the final high-resolution map.

3.5.3 Data Handling and Training/Validation/Test Strategy :

To ensure a robust evaluation, the dataset will not be split randomly. A temporal (time-based) split is mandatory to test the model's ability to predict for time periods it has never seen.

- **Training Set (e.g., 2002–2018):** Will be used to train the ConvLSTM and Random Forest models.
- **Validation Set (e.g., 2019–2021):** Will be used to tune model hyperparameters (e.g., number of trees in the RF, sequence length for the ConvLSTM).
- **Test Set (e.g., 2022–2025):** The final model performance will be reported only on this unseen data to prevent any data leakage or overfitting.

3.6 Model Performance Evaluation (Proposed) :

Once the hybrid model is fully trained on the Training Set (e.g., 2002-2018) and tuned on the Validation Set (e.g., 2019-2021), its final performance will be rigorously evaluated on the completely unseen Test Set (e.g., 2022-2025). This evaluation will be conducted by comparing the model's 10 km downscaled GWSA predictions against the independent in-situ well data from the CGWB (as defined in Section 3.2.6).

3.6.1 Validation Against In-Situ Well Data :

The primary validation will assess the model's ability to replicate the "ground truth" water level fluctuations observed in actual monitoring wells.

The process will be as follows:

1. The trained hybrid model will be used to generate the final 10 km monthly GWSA time series for the entire test period (2022-2025).

2. For each validation well in the CGWB network, the 10 km pixel from the model's output map that corresponds to the well's latitude and longitude will be identified.

3. The predicted 10 km GWSA time series for that pixel will be extracted.

4. This predicted time series will be plotted and statistically compared against the observed (in-situ) anomaly time series from the well.

This step is designed to confirm that the model's 10 km outputs are not just statistical artifacts but are physically realistic representations of local groundwater changes.

3.6.2 Statistical Performance Metrics :

To quantify the model's accuracy, a standard suite of statistical metrics will be employed to compare the predicted and observed time series at each well location.

- **Coefficient of Determination ($\mathbf{R^2}$):** This will be used to measure the proportion of the variance in the in-situ well data that is successfully captured by the model. It provides a measure of overall goodness-of-fit.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3.2}$$

- **Root Mean Square Error (RMSE):** This will be used to quantify the average magnitude of the model's error in the original units (equivalent cm of water). It provides a clear, interpretable measure of prediction error.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3.3}$$

- **Kling-Gupta Efficiency (KGE):** This is a robust hydrological metric that provides a more comprehensive evaluation than R^2. The KGE (ranging from $-\infty$ to 1) decomposes the error into three distinct components, which is critical for understanding why a model is performing well or poorly (Akl et al. 2026):

  1. Correlation (r): The timing of the predicted peaks and troughs.
  2. Bias Ratio (β): The model's tendency to overestimate or underestimate the total volume.
  3. Variability Ratio (γ): The model's ability to match the range of fluctuation in the observed data.

$$KGE = 1 - \sqrt{(r-1)^2 + (\beta-1)^2 + (\gamma-1)^2} \tag{3.4}$$

where

$$\beta = \frac{\mu_s}{\mu_o}, \qquad \gamma = \frac{\sigma_s/\mu_s}{\sigma_o/\mu_o} \tag{3.5}$$

A model will be considered successful if it achieves high R^2 and KGE (approaching 1) and low RMSE across the majority of the validation wells in the test dataset.

3.7 Advanced Framework Applications (Proposed) :

Beyond generating the 10 km historical dataset, the fully validated framework will be leveraged for two advanced applications that form the core scientific contribution of this thesis: model interpretation and future forecasting.

3.7.1 Model Interpretation (SHAP) :

To address the "black box" problem, the trained hybrid model will be analyzed using Explainable AI (XAI). The chosen method will be SHapley Additive exPlanations (SHAP) (Lundberg & Lee, 2017), a game theory-based approach that is model-agnostic and provides mathematically sound, consistent feature attributions.

The SHAP analysis will be used to answer the critical question: "Why is the model predicting depletion or recharge in a specific 10 km pixel?"

This will be implemented in two ways:

1. **Global Feature Importance:** A summary plot will be generated to show the overall ranking of every input variable (e.g., Precipitation, DEM, Soil Type,

NDVI) based on its average SHAP value across all predictions. This will reveal the most dominant drivers of GWSA on a national scale.

2. **Local Feature Attribution:** This is the most powerful application. SHAP values will be calculated for individual 10 km pixels in critical hotspots (e.g., in the Indo-Gangetic Basin). This will allow for the generation of maps that show not just the trend (from Section 3.6), but the primary driver of that trend. For example, it will be possible to distinguish if a depletion hotspot is caused primarily by low rainfall (a climatic driver) or by high irrigation potential (a land use/static driver).

This step is designed to make the model's outputs transparent, trustworthy, and directly actionable for policymakers.

Chapter 4

Future Projections and Vulnerability Assessment (2026-2100) :

This chapter outlines the methodology for the final and most advanced objective of the thesis: leveraging the validated hybrid model (from Chapter 4) as a prognostic tool to forecast future groundwater vulnerability. This analysis will provide critical, policy-relevant insights into how India's groundwater resources may respond to different climate change scenarios(Mishra et al., 2020)(Aadhar et al., 2020).

4.1 Future Climate Scenario Inputs (CMIP6) (Proposed) :

The primary inputs for the forecasting phase will be future climate projection data.

- **Source:** The data will be sourced from the Coupled Model Intercomparison Project Phase 6 (CMIP6), which provides the scientific basis for the IPCC Assessment Reports.
- **Scenarios:** To capture a range of plausible futures, two distinct Shared Socioeconomic Pathways (SSPs) will be analyzed:
    1. **SSP2-4.5:** This "middle-of-the-road" or "intermediate" scenario assumes moderate climate change mitigation policies are put in place.
    2. **SSP5-8.5:** This "fossil-fueled development" or "high-emissions" scenario assumes a continued reliance on fossil fuels with minimal climate action, leading to a "worst-case" warming outcome.
- **Variables:** The key dynamic variables required by the model (Precipitation, Temperature) will be extracted from the CMIP6 outputs.

- **Pre-processing:** The coarse-resolution CMIP6 data is not directly usable. It will require a two-step pre-processing pipeline:

    1. **Statistical Downscaling:** The data will be statistically downscaled from its native (e.g., 100-200 km) resolution to the model's required 10 km resolution.
    2. **Bias Correction:** The downscaled data will be bias-corrected against the historical 10 km observational datasets (used in Chapter 3) to remove systematic model biases (e.g., a climate model being consistently "too wet" or "too cold" for India).

4.2 Projected GWSA Forecasts (Proposed) :

Once the future 10 km climate inputs are prepared, they will be fed into the already trained and validated hybrid ConvLSTM-RF framework. The static 10 km features (Topography, Soil, Land Use) will be held constant, assuming no major changes in land cover or geology.

The model will then be run to generate two new, independent 10 km monthly GWSA datasets for the entire Indian subcontinent:

1. One dataset for the SSP2-4.5 scenario (2026-2100).
2. One dataset for the SSP5-8.5 scenario (2026-2100).

Expected Outcome: The primary output of this step will be a series of maps presenting the projected 10 km GWSA. These maps (e.g., for the years 2050 and 2100) will visually illustrate the divergent futures for India's groundwater under the two different climate scenarios.

4.3 Future Vulnerability Mapping (Trend Analysis) (Proposed)

The final step of the analysis will be to quantify the long-term future trends. The spatio-temporal trend analysis methods from Section 3.6 will be applied to the two newly generated future datasets.

1. **Mann-Kendall (MK) Test:** The MK test will be applied to each 10 km pixel's future time series (2026-2100) to identify where significant trends (depletion or recharge) are projected to occur.

2. **Theil-Sen's Slope Estimator:** The Sen's slope will be calculated for all significant pixels to determine the rate of future depletion/recharge (in cm/year).

Expected Outcome (The Final Product): This analysis will produce the capstone scientific product of the thesis: a set of high-resolution (10 km) Groundwater Vulnerability Maps for India. These maps will show the projected rate of groundwater change for the rest of the 21st century under both moderate and severe climate change scenarios, highlighting the regions most at-risk.

Chapter 5

Conclusion and Future Scope :

5.1 Summary :

This project addresses the critical need for high-resolution, explainable groundwater monitoring in India. The research is designed to overcome the "scale gap" of coarse GRACE/ GRACE-FO satellite data and the "transparency gap" of conventional "black box" machine learning models.

To achieve this, a novel, hybrid machine learning framework is proposed. The framework consists of a Convolutional LSTM (ConvLSTM) to act as a spatio-temporal feature extractor and a Random Forest (RF) to perform the final 10 km downscaling regression. The target variable is a robust ensemble-mean GWSA derived from GRACE and three different GLDAS land surface models (Noah, CLSM, and VIC). The primary outputs of this framework are projected to be:

1. A validated, 10 km monthly GWSA dataset for India from 2002-2025.
2. The first-ever 10 km resolution maps of historical groundwater trends (2002-2025), derived from Mann-Kendall and Theil-Sen's slope analysis.
3. A corresponding map of depletion/recharge drivers based on SHAP (Explainable AI), which quantifies why these trends are occurring at a local scale.
4. A set of future groundwater vulnerability maps for 2050 and 2100 under both moderate (SSP2-4.5) and severe (SSP5-8.5) climate change scenarios.

5.2 Summary of Contributions :

The primary scientific contribution of this work will be the development and application of a single, end-to-end framework that synthetically addresses three major challenges in satellite hydrology:

- Scale: It is planned to successfully downscale 110 km satellite data to a 10 km policy-relevant resolution.
- Spatio-Temporal Dynamics: It moves beyond static ML models by using a ConvLSTM to effectively learn complex time-lags and spatial relationships.
- Transparency: It will provide a fully explainable model (via SHAP) where the drivers of every 10 km prediction can be identified, building trust and enabling targeted policy.

This project will provide a validated, data-driven tool that can bridge the gap between large-scale remote sensing and local, actionable water resource management.

5.3 Future Scope and Research Directions :

While this project will deliver a comprehensive framework, it also opens several avenues for future research. Based on the limitations, the following ”next steps” are recommended:

- **Inclusion of Dynamic Land Use:** The single greatest limitation of this study will be the use of a static LULC map. A future study should integrate dynamic, time-series LULC data (e.g., annual crop maps) to capture the impact of changing agricultural patterns on groundwater.
- **Integration of Pumping Data:** This model infers human water use (pumping) indirectly through its drivers (e.g., LULC, precipitation). A more advanced model could directly incorporate proxy data for pumping, such as irrigation statistics or dam operation records, to improve accuracy.
- **Development of an Operational Web-Based Tool:** The framework developed in this project is a static scientific product. A significant future engineering challenge would be to convert this model into a cloud-based, operational ”Groundwater Early Warning System” or data dashboard that could provide running monthly updates to policymakers and water managers.
- **Advanced Model Architectures:** Future work could explore more advanced deep learning architectures, such as graph neural networks (GNNs) to model river basin connections, or transformer-based models to capture even longer-range spatio-temporal dependencies.

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