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Machine Learning-Based Downscaling of GRACE-Derived Groundwater Storage for West Bengal, India.

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Abstract: Monitoring groundwater storage at actionable spatial scales remains a major challenge in regions experiencing chronic groundwater stress. This study presents a machine learning–based framework to downscale GRACE-derived Total Water Storage Anomalies (TWSA) from 111 km to 5 km over West Bengal, India, enabling improved characterization of spatial and seasonal groundwater variability. Three algorithms—XGBoost, Random Forest, and Support Vector Regression—were evaluated using multivariate hydroclimatic and vegetation predictors. Among them, XGBoost demonstrated superior performance ($R^2 = 0.91$, $NSE = 0.91$) and most effectively captured nonlinear groundwater dynamics.

The 5-km downscaled product reveals pronounced sub-regional heterogeneity and evolving groundwater depletion hotspots that are not detectable in native GRACE data. Seasonal analyses show weakening post-monsoon recovery and an expansion of groundwater stress from traditionally affected southwestern districts toward broader southern and western regions during 2003–2023. These results highlight a growing imbalance between recharge and extraction driven by hydroclimatic variability and anthropogenic pressure. By overcoming the spatial limitations of GRACE, this approach provides high-resolution insights critical for groundwater monitoring, management, and policy planning. The proposed framework is transferable to other data-scarce and hydrogeologically complex regions, supporting more informed groundwater sustainability assessments.

Keywords: GRACE mission, Groundwater storage, Downscaling, XGBoost, Machine learning.

I. INTRODUCTION

Groundwater is a critical freshwater resource worldwide, particularly in arid and semi-arid regions such as South Asia, where it supports domestic, agricultural, and industrial demands (Naghibi et al., 2016; Syed et al., 2008). However, rapid population growth, urbanization, and intensive irrigation have driven unsustainable extraction, resulting in declining water levels, deteriorating quality, and hydrogeological impacts such as land subsidence (Feng et al., 2013). Traditional in-situ well measurements provide accurate information but remain sparse and costly. The Grace Satellite missions revolutionized large-scale groundwater assessment by detecting terrestrial water storage anomalies (TWSA) from gravity variations (Tapley et al., 2004), revealing significant depletion in regions such as the Indo-Gangetic Basin, including West Bengal (Galodha et al., 2023). However, the coarse spatial resolution of GRACE Mascon products (~111 km) limits regional hydrological applications. Statistical and machine learning (ML) downscaling methods offer an efficient means to enhance spatial detail by relating GRACE signals to high-resolution predictors (Wilby et al., 1998; Ning et al., 2014), including precipitation, evapotranspiration, and vegetation indices. Recent studies demonstrate the potential of algorithms such as Random Forest, XGBoost, and Support Vector Regression to reconstruct fine-scale groundwater variability using datasets like GLDAS, ERA5, TerraClimate, and MODIS NDVI (Breiman, 2001; Chen & Guestrin, 2016; Abatzoglou et al., 2018; Majumdar et al., 2020; Valley et al., 2022; Pulla et al., 2023). Accordingly, this study applies ML-based statistical downscaling to refine GRACE Mascon groundwater storage estimates from 111 km to 5 km over West Bengal, enabling improved characterization of local hydroclimatic variability in a groundwater-stressed region.

II. STUDY AREA

West Bengal, the study region, is located in eastern India between 85°50′E–89°50′E and 21°38′N–27°10′N, covering about 88,752 km².It occupies the 13th position among the largest Indian states and shares boundaries with Jharkhand, Bihar, Odisha, Sikkim, and Assam, along with international boundaries touching Bangladesh, Bhutan, and Nepal. With Kolkata as the capital, the state hosts more than 100 million people and has a population density of around 1,028 persons per km² (Hasan et al., 2021). Figure 1 shows the study area extent.

Hydrologically, the state is influenced by two contrastive physiographic zones: the Himalayan foothills in the northern part and the Ganga deltaic plains in the south. The major rivers are the Ganga and its tributaries, the Teesta, Mahananda, Damodar, and Subarnarekha. The central and southern alluvial plains comprise highly productive groundwater provinces with aquifers in excess of 300 m in depth. The recharge potential is very different: the northern and central zones have high recharge, while western districts like Purulia, Bankura, and Birbhum have hard rock aquifers with low yield. Issues affecting the quality of groundwater include arsenic contamination in the Gangetic delta, fluoride in western districts, and coastal salinity intrusion (Chowdhury et al., 2000). There is strong spatial variability in the climatic environment of West Bengal, following a tropical monsoon system. The northern foothills are humid subtropical to temperate, while a tropical wet–dry climate characterizes the western plateau. The coastal areas, of which Kolkata is a part, possess a warm, humid tropical climate. The southwest monsoon brings in 70–75% of the annual rainfall, ranging from 1,500 mm in the west to over 3,000 mm in the northern districts. Temperatures range from about 12°C in winter to over 40°C in summer. The coastal belt is prone to cyclones and storm surges, with a rise in extreme events, influenced by climate change, affecting agriculture and thus groundwater recharge and water security. Understanding these hydrological, geological, and climatic variations is critically necessary for correct assessment and management of groundwater resources in a uniform manner throughout West Bengal.

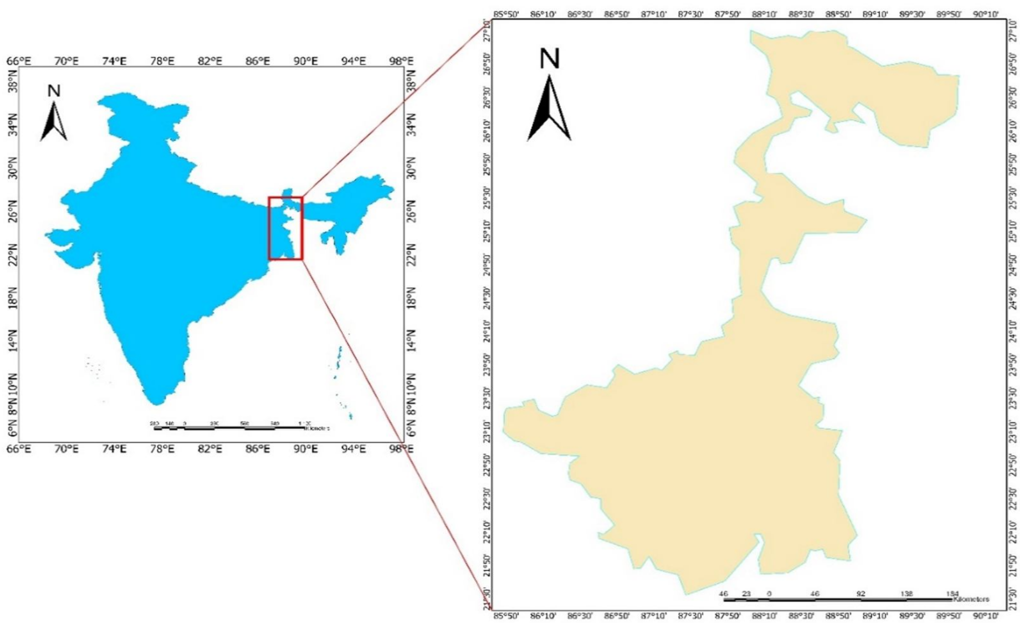

Figure 1 STUDY AREA OF WEST BENGAL

III. METHODOLOGY AND DATA SOURCES

Seven gridded datasets were used to develop the high-resolution groundwater storage downscaling framework (Table 1). Monthly Total Water Storage Anomalies (TWSA) from GRACE were used as the coarse-resolution target variable representing large-scale water mass variability. Groundwater Storage (GWS) was obtained from GLDAS-2.2, while hydro-meteorological predictors—total precipitation, total evaporation, and runoff—were extracted from ERA5-Land. Actual Evapotranspiration (AET) from TerraClimate and vegetation dynamics represented by the Normalized Difference Vegetation Index (NDVI) derived from MODIS were additionally incorporated. GRACE TWSA has a native spatial resolution of approximately 111 km, whereas all predictor datasets have finer spatial resolutions ranging from 0.5 to 27 km (Table 1), enabling spatial refinement during downscaling. All datasets were harmonized to a common monthly temporal resolution to ensure consistency during model training and inter-dataset comparison.

A. GRACE Data

GRACE monthly mass grid data (Release 6.1, Version 3) were used to extract TWSA. GRACE has been widely applied to assess groundwater storage variability and depletion at regional scales (Tapley et al., 2004; Majumdar et al., 2020; Galodha et al., 2023). In this study, only TWSA was used, without attempting to resolve groundwater flow direction or water quality components, consistent with known GRACE limitations.

B. GLDAS-2.2 Data

Groundwater Storage estimates were obtained from GLDAS-2.2, which provides physically consistent land surface water balance variables assimilated from multiple observations (Rodell et al., 2004). GLDAS-derived GWS has been extensively used as a subsurface predictor in groundwater and hydrological modelling studies (Zhang et al., 2021).

C. ERA5-Land Data

Monthly runoff, total precipitation, and total evaporation were obtained from ERA5-Land reanalysis products (Hersbach et al., 2020; Lavers et al., 2022). These variables were used as surface and atmospheric hydrological predictors influencing groundwater storage variability.

D. TerraClimate Data

Actual Evapotranspiration (AET) was extracted from the TerraClimate dataset, which provides high-resolution monthly climate and water balance variables (Abatzoglou et al., 2018). AET was used to represent land–atmosphere water exchange processes relevant to groundwater dynamics.

E. MODIS NDVI

Vegetation dynamics were represented using NDVI derived from MODIS. NDVI was used to capture vegetation and land-surface conditions influencing evapotranspiration and groundwater recharge processes.

Table 1 Datasets

Variables	Sources	Scale	Unit
TOTAL WATER STORAGE ANOMALIES	GRACE Monthly Mass Grids Release 6.3 Version 4 - Global Mascons	(111.66 KM)	Centimetre
RUNOFF	ERA5-Land Monthly Aggregated - ECMWF Climate Reanalysis	(11 KM)	Meter
TOTAL EVAPORATION	ERA5-Land Monthly Aggregated - ECMWF Climate Reanalysis	(11 KM)	Meter
TOTAL PRECIPITATION	ERA5-Land Monthly Aggregated - ECMWF Climate Reanalysis	(11 KM)	Meter
ACTUAL EVAPOTRANSPIRATION	Terr Climate: Monthly Climate and Climatic Water Balance for Global Terrestrial Surfaces, University of Idaho	(5 KM)	Millimetre
NDVI	MOD13A1.061 Terra Vegetation Indices 16-Day Global 500m	(500 METER)	
GROUND WATER STORAGE	GLDAS-2 . 2: Global Land Data Assimilation System	(27 KM)	Millimetre

IV. MACHINE LEARNING MODELS

Three machine-learning regression models—XGBoost, Random Forest (RF), and Support Vector Regression (SVR)—were employed to downscale GRACE-derived TWSA to finer spatial resolution using the same predictor set.

XGBoost was selected due to its demonstrated effectiveness in downscaling GRACE-based groundwater storage and handling correlated hydro-climatic predictors (Chen & Guestrin, 2016; Zhang et al., 2021). Random Forest was applied as a benchmark ensemble model due to its robustness and widespread application in hydrological and remote sensing studies (Breiman, 2001; L. Chen et al., 2019). Support Vector Regression was implemented to evaluate kernel-based nonlinear regression performance in groundwater modelling applications (Rafik et al., 2023).

Model hyperparameters were optimized using cross-validation, and model performance was evaluated using standard statistical metrics. The trained models were subsequently applied to generate high-resolution groundwater storage estimates across the study area.

V. DOWNSCALLING MODEL DESIGN

The three machine learning models used in this study—Random Forest (RF), Support Vector Regression (SVR), and XGBoost—were chosen for their proven performance and ease of implementation. The Whole Methodology with flow chart demonstrated in Figure 2.

GRACE, a joint NASA–DLR mission launched in 2002, measures Earth's gravity variations to track changes in terrestrial water storage (Sbref32, n.d.). Although GRACE provides valuable groundwater information, its native spatial resolution (~300 km) and even refined Mascon/Spherical Harmonic solutions (25–100 km) (Rafik et al., 2023) remain too coarse for local-scale groundwater assessment. In this study, GRACE data at 111 km resolution (January 2003–November 2023) were used.

To overcome the coarse resolution, GRACE was downscaled using machine learning by integrating higher-resolution hydrological variables—NDVI, precipitation, evaporation, runoff, groundwater storage, and evapotranspiration. The workflow involved training models at 111 km resolution and applying the learned relationships to 5 km datasets, with TWSA (Terrestrial Water Storage Anomaly) as the target variable. West Bengal was divided into 3,237 grids (5 km × 5 km) using ArcGIS Pro. For each grid, data from 2003 to 2023 were extracted using Google Earth Engine, organized by date and location, and combined into a structured feature dataset. The selected variables (precipitation, evaporation, runoff, evapotranspiration, NDVI, and groundwater storage) were used as predictors to downscale GRACE TWSA. Using this workflow, all three ML models were successfully applied to produce high-resolution groundwater anomaly estimates.

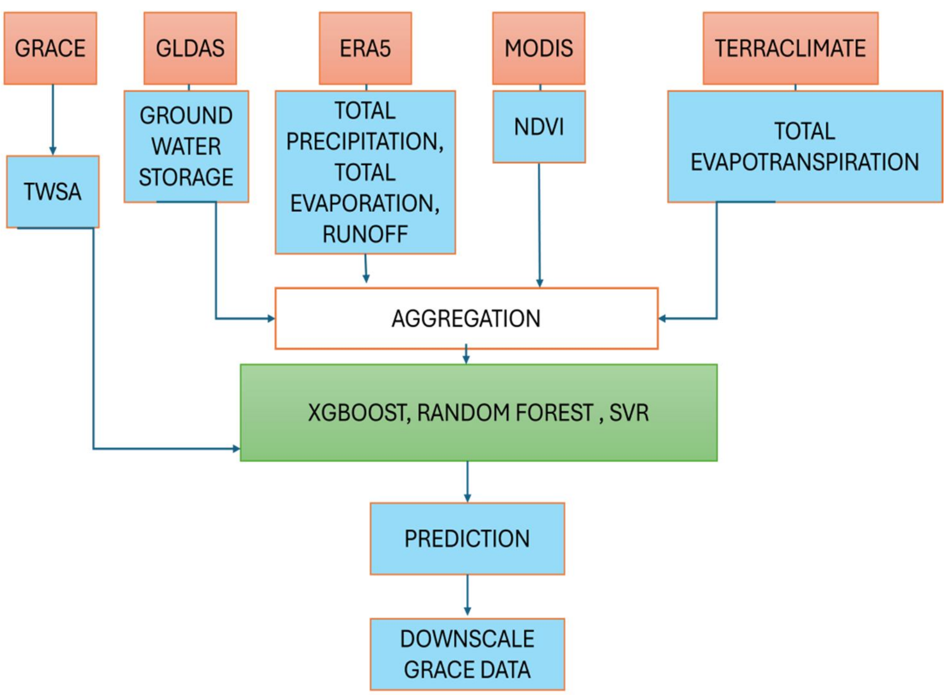

Figure 2 Methodology Flowchart

VI. DATA COMPARISION AND ERROR ANALYSIS

Model performance was evaluated using four statistical indices—coefficient of determination (R^2), percent bias (PBIAS), Nash–Sutcliffe efficiency (NSE), and root mean square error (RMSE)—computed from the testing dataset by comparing observed GRACE-derived values with model predictions. R^2 was used to quantify the agreement between observed and predicted values, with higher values indicating stronger correspondence. PBIAS was applied to assess systematic overestimation or underestimation in the model outputs, where values closer to zero represent lower bias. NSE was employed to evaluate predictive skill relative to observed variability, with higher values indicating improved model efficiency. RMSE was calculated to measure the magnitude of residual errors, with lower values reflecting better predictive accuracy. Together, these metrics provide a concise and complementary assessment of model performance for GRACE downscaling evaluation.

VII. RESULT

Three machine learning algorithms, XGBoost (XGB), Random Forest (RF), and Support Vector Regression (SVR), have been implemented to downscale GRACE data for West Bengal. Model performance evaluation based on R^2 , NSE, RMSE, and PBIAS (Table 2) shows that XGB always outperformed RF and SVR, giving the highest accuracy (R^2= 0.91, NSE=0.91) and the lowest error (RMSE=6.24cm,PBIAS = -3.91%). Scatter plots (Fig. 3) show, in addition, strong agreement between observed and predicted GRACE anomalies for XGB, while RF showed moderate dispersion and SVR exhibited systematic underestimation. These results identify XGB as the best model for spatially explicit groundwater reconstruction.

The time series corresponding to a downscaled resolution (2003-2023) retains the signature pre-monsoon depression and post-monsoon recharge phase in the groundwater resource in West Bengal (Fig. 4). After 2003-2017, there was further deposition that was partly compensated by monsoon recharge. Then in 2017-2020, there was some improvement in recharge, and after 2021, there is a subsequent period of deposition as well as lower efficiency in recharge. The downscaled dataset provides both current and detailed information not captured by GRACE.

One of the key novel findings from this research is the capacity to delineate groundwater depletion on a seasonal basis with sufficient resolution to identify spatial heterogeneity that cannot be resolved by GRACE alone. Comparisons of spatial differences between pre- and post-monsoon groundwater depletion conditions reveal characteristic transitions. 2003 Pre-monsoon There was severe depletion in the southwest districts (Purulia, Bankura, and some parts of West Midnapore), whereas the middle and northern part showed relatively stability (Figure 5A). 2003 post-monsoon Extensive recharge was noticed in the central & eastern districts, resulting in less depletion (Fig. 5B) Twenty years on, there have been radical changes in 2023 Pre-monsoon Depletion regions further stretched northwards and westwards, and strong anomalies continued to hover above southern and western West Bengal (Fig. 5C). 2023 Post-monsoon Recharge was not adequate in many districts, which suggests reduced monsoonal buffering capability compared to 2003 (Figure 5D). These results demonstrate the transition from localized depletion (2003) extensive, enduring depletion (2023), which occurs due to the effects of extraction pressure, urbanization, and hydro-climatic variations.

Table 2 Results of Modelling Accuracy Matrices Average of Three Machine Learning Method

MODELS	R^2	NSE	RMSE	PBIAS
XGBOOST	0.91	0.91	6.24 cm	-12.91%
RANDOM FOREST	0.88	0.88	7.21 cm	-5.18%
SUPPORT VECTOR REGRESSION	0.25	0.25	18.13 cm	20.49%

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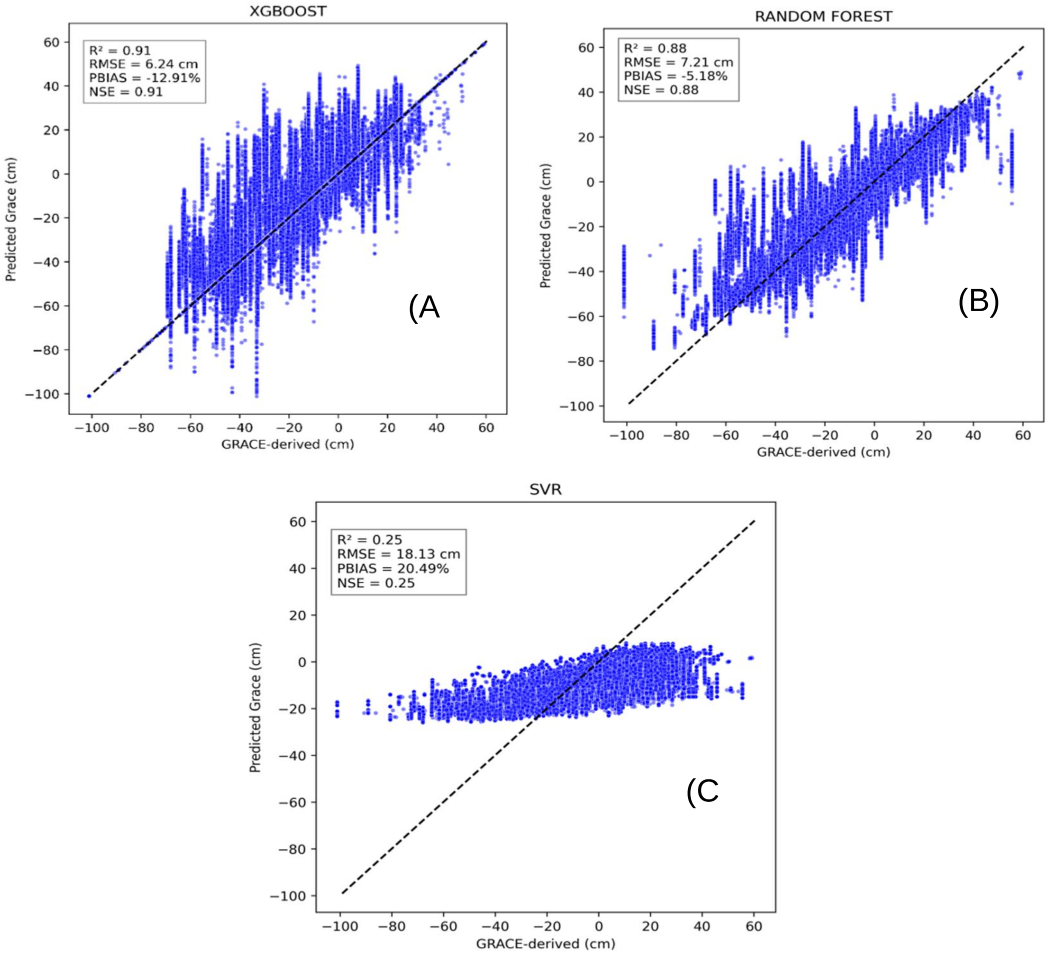

Figure 4 Accuracy estimation of machine learning method. (A) XGBOOST Model. (B) RANDOM FOREST Model. (C) SUPPORT VECTOR REGRESSION Model.

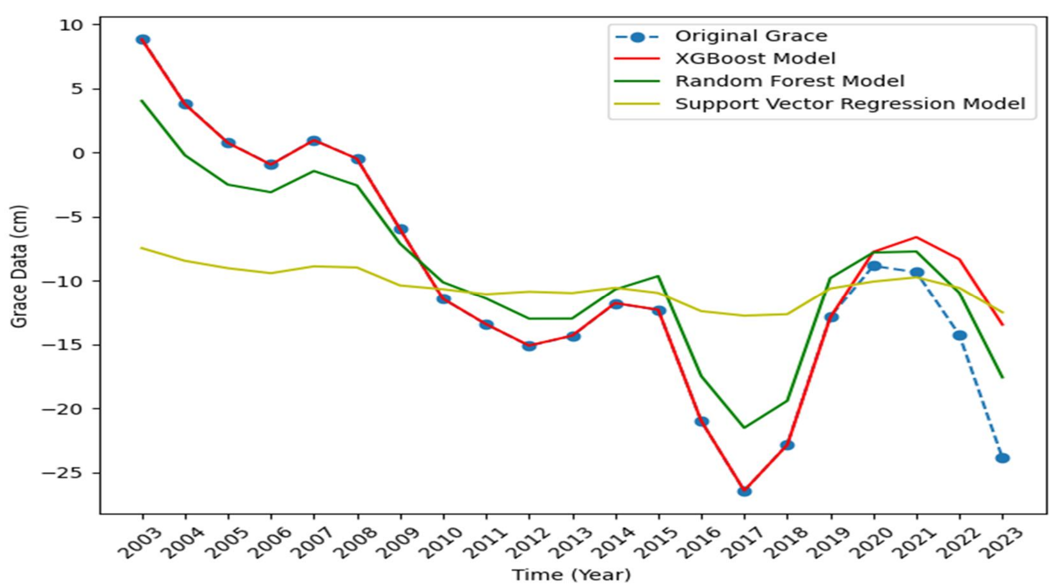

Figure 5 Regional timeseries for the original Grace Data and the Downscaled Machine Learning Models Over West Bengal.

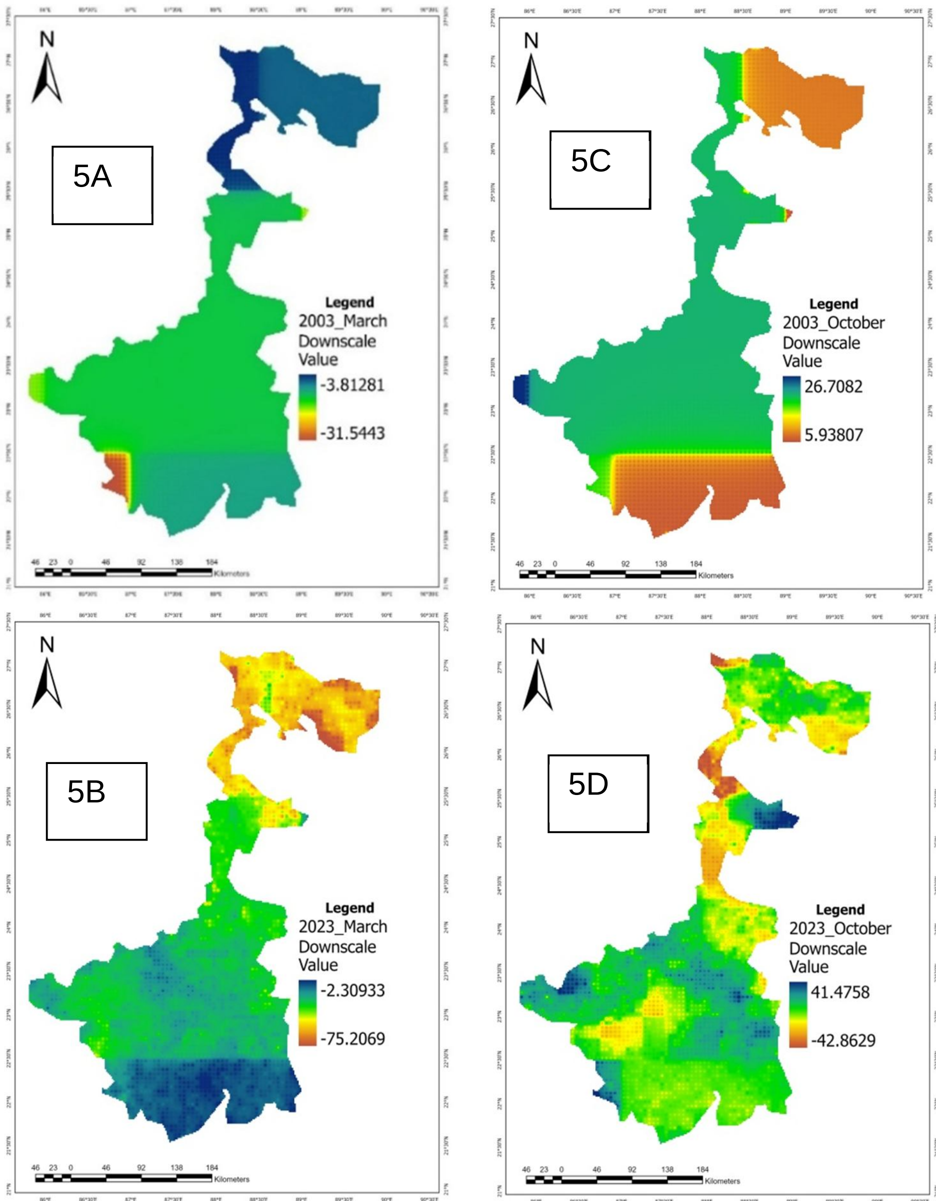

Figure 5 Pre Monsoon(March month) 5A 2003, 5B 2023 and Post Monsoon (October Month) 5C 2003, 5D 2023.

VIII. DISCUSSION

The current research proves the capability of machine learning in resolving the coarse spatial resolution issue of GRACE-discovered TWSA values by downscaling them from 111 km to 5 km in West Bengal. The downscaled results enable the accurate identification of groundwater extraction patterns, which cannot be achieved through GRACE-discovered TWSA values with less than annual frequency resolution. Among these three algorithms, XGBoost demonstrated the highest predictive skill and best captured GRACE-observed anomalies, which confirms the capability of capturing nonlinear hydroclimatic relationships between TWSA and its key drivers. Improved results emphasize the efficiency of tree-based ensemble learning in satellite-based regional groundwater reconstruction with scarce data. However, RF achieved a moderate accuracy, whereas SVR was unable to capture the spatial variability and showed systematic underestimation of depletion, confirming again that flexible nonlinear models offer increased capabilities for hydrological downscaling applications. The temporally reconstructed dataset shows that there is a developing trend in the dynamics of groundwater resources in the last two decades.

During 2003-2017, a periodic drawdown is partially refilled through recharge after monsoons; however, since 2021, there is a reduction in recharge through monsoons. This indicates that groundwater abstraction has crossed the recharge rate in some districts due to increasing irrigation demand because of developing agriculture and, in turn, due to urbanization and climatic changes. the downscaled result delineates the marked transition in the depletion hotspots. The initial depletion areas in the southwest (Purulia, Bankura, and West Midnapore) have extended northwards and towards the west by 2023, and the areas, which were previously under marked stability, are now under conditions of moderate decline. The result further delineates the drop in the recharging efficiency, especially in the post-monsoon interval. The capability to capture such detailed spatial and seasonal variability is a major breakthrough in groundwater assessment through GRACE. The 5-km downscaled dataset identifies specific stress points which would not be visible at the GRACE spatial resolution, aiding in planning, mobilization, and intervention in an area like West Bengal, where ground-level networks are not substantial. The overall outcome of the results effectively proves the applicability of machine learning techniques as an optimizing tool in the improvement of the accuracy of coarse-resolution satellite databases for better assessments of groundwater. Use of socio-hydro databases, well levels, and further satellite technologies could further improve the results for better estimation of groundwater resistance.

IX. CONCLUSION

A concept and results analysis is given regarding a data-driven framework that aims to improve the resolution of GRACE-derived groundwater storage anomalies in West Bengal at a resolution that is improved from 111 km to 5 km in a region that is under chronic groundwater stress. Based on GRACE TWSA and using multi-variate satellite hydrological predictors, a characterization that is not available through GRACE natural resolution is given. Among the algorithms used in this study, XGBoost had the best prediction performance and was effective in representing non-linear behavior in groundwater variability and is thus recommended. The 5km downscaled map depicts variability in groundwater stress on a seasonal basis from 2003 to 2023. Groundwater stress increased in magnitude and occupied larger geographic areas, transitioning from isolated hotspot areas in the southwest to southeastern and western parts. Inter-seasonal variations also reveal a decline in post-monsoon recharge in more recent years, reflecting a rising mismatch between recharge and withdrawals. These observed dynamics align with increased agricultural abstraction, precipitation variability, as well as rising urban-industrial water demands. High-resolution maps facilitate the demarcation of geographic areas that experience severe groundwater stress at a sub-district level, which also serve as inputs for decision-making. Methodologically speaking, this research Highlights inspires the capabilities of downscaling with an ML approach to extend available satellite data, contributing to better groundwater characterization in regions where data is scarce. It can easily apply to other basins on the planet, improving with data input on hydrological, levels, and future satellite mission data to better fill in data on groundwater management, especially in a climate where pressures increase every second with climate change.

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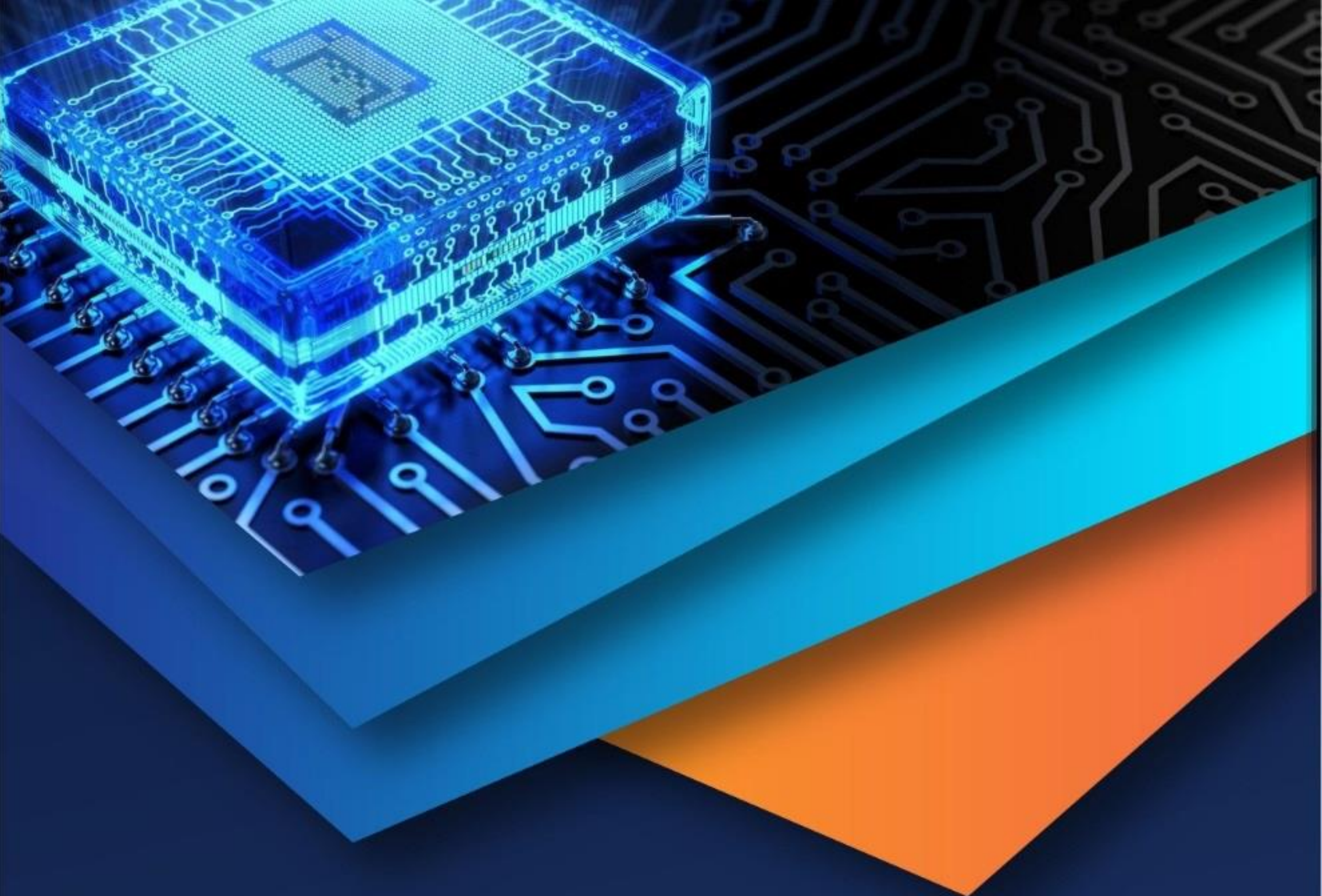

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