https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

On the efficacy of downscaled GRACE total water storage products

Maya Raghunath Suryawanshi[1], Kuruva Satish Kumar[1], Amin Shakya[2], Shard Chander[3], Bhaskar R. Nikam[4], Nagesh Kumar Dasika[5], Bramha Dutt Vishwakarma[1,6]

[1]Interdisciplinary Centre for Water Research, Indian Institute of Science, Bengaluru, 560012, India
[2]Faculty of Geo-Information Science and Earth Observation, University of Twente, Enschede, 7500 AE, The Netherlands
[3]Land Hydrology Division, Space Applications Centre, Indian Space Research Organisation, Ahmedabad, 380015, India
[4]Indian Institute of Remote Sensing, Indian Space Research Organisation, Dehradun, 248001, India
[5]Department of Civil Engineering, Indian Institute of Science, Bengaluru, 560012, India
[6]Centre for Earth Sciences, Indian Institute of Science, Bengaluru, 560012, India

Correspondence to: Maya Raghunath Suryawanshi (maya2509.surya@gmail.com)

Abstract. The Gravity Recovery and Climate Experiment (GRACE) satellite mission provides estimates of total water storage anomalies (TWSA) referred as "mascons" stands for mass concentration blocks. This TWSA represents integrated changes due to all forms of water including soil moisture, groundwater, surface water, canopy, and snow. However, the coarse spatial resolution of GRACE mascons (~3°) limits its utility for regional-scale hydrological analysis. Although several downscaling methods have been proposed to improve resolution, none have been comprehensively validated against in-situ observations. In this study, we are validating both mascon and downscaled GRACE TWSA products against well-based in-situ groundwater observations across India. Furthermore, we develop an improved downscaling method by modifying the approach of Vishwakarma et al. (2021), i.e., incorporating mass conservation constraints at the GRACE mascon scale instead of catchment scale to better capture spatial variability at a finer 0.5° grid scale. We assessed the efficacy of our downscaled product and two existing downscaled GRACE products (Gou and Soja, 2024; Vishwakarma et al., 2021) using performance metrics such as gain in correlation (r) and gain in root mean square error (RMSE) relative to GRACE mascon product. The entire India is spanned in 52 mascons. Out of these 52 mascons groundwater observations are available only at 22 mascons. Our modified approach shows improved performance across 17 mascons in India, with median gain in r ranging from 1.62% to 52.49% and median gain in RMSE improvements from 4.75% to 44.68%. Whereas, the Vishwakarma et al. (2021) and Gao and Soja (2024) methods perform well in 6 and 16 mascons, respectively. These results demonstrate that our enhanced downscaling approach provides more accurate and spatially resolved estimates of groundwater storage changes, offering a valuable tool for regional water resource assessments in India. Further, the downscaled GRACE product developed in this study (Mascon wise Mass Conservation product) is publicly accessible at https://doi.org/10.6084/m9.figshare.29196617.

https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

1 Introduction

Freshwater is a critical resource for sustainable development, therefore, understanding changes in its availability is one of the top priorities for researchers, governments and water resource managers. The fundamental process which regulates freshwater availability is the water cycle and by studying its components, we enhance our understanding of water availability. Total Water Storage (TWS) is an important part of the water budget, which is written as a sum of soil moisture, groundwater, surface water, snow water, and canopy water storage (Girotto and Rodell 2019). Since TWS provides an estimate of water available to sustain lean phases, understanding the spatiotemporal variations in TWS and their drivers is essential to manage future water crises. Since collecting global subsurface in-situ data is nearly impossible and traditional remote-sensing satellites only provide surface information, TWS was not observable until the launch of the Gravity Recovery and Climate Experiment (GRACE) satellite mission in 2002. GRACE measures precise changes in the distance between two identical satellites flying in the same orbit, one after the other. These range measurements are then used to estimate the gravitation potential variations from one month to the other. Since gravity field perturbations at monthly scale are driven by hydrology, potential anomalies are converted to TWS Anomalies (TWSA) (Tapley et al. 2004; Wahr et al. 2004). The signal is a superposition of signals from all TWS compartments mentioned earlier and has advanced hydrology significantly in the last two decades. From this integrated signal, non-groundwater components are removed using hydrological models to derive GroundWater Storage Anomalies (GWSA).

Although GRACE provides valuable insights, it presents two significant challenges. The first one is, GWSA from GRACE is difficult to validate due to unavailability of in-situ GWSA data (Scanlon et al., 2016) but not impossible if one compartment of TWSA is changing rapidly while others stay stable, especially over India where groundwater decline is alarming (Sarkar et al., 2020). And the second challenging task to deal with is a coarse spatial resolution ($3° \times 3°$) of GRACE data. Several hydrological, and agricultural studies demand regional/local scale inputs. To cater to this demand several attempts to downscale GRACE TWSA have been conducted. Broadly those downscaling methods are categorised in two types: model-based/dynamic and data-based/statistical method. The model-based/dynamic approach is physically based, strongly influenced by boundary conditions and computationally expensive (Schumacher et al., 2018; Sun et al., 2023). Whereas in the data-based/statistical approach an empirical relationship is developed between coarse scale variables and fine scale variables. Owing to its computational efficiency and ease of implementation, the data-based/statistical approach has gained popularity among researchers. The statistical approach has been primarily implemented in three ways: simple linear regression, multivariate linear regression, and machine learning algorithms (related studies are summarized in Table 1). In simple linear regression, a single variable is regressed against GRACE TWSA. For instance, Gemitzi et al. (2021) and Yin et al. (2018) used only precipitation and evapotranspiration, respectively, to downscale GRACE data, as these were identified as the dominant drivers in their respective regions. To address cases where a single variable is insufficient to explain TWSA variability, multivariate linear regression with a water budget constraint has been applied (Ning et al., 2014; Karunakalage et al., 2021; Vishwakarma et al., 2021). To account for nonlinearity, researchers have also implemented machine learning algorithms such as Random

https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

Forest (RF), Artificial Neural Networks (ANN), and Long Short-Term Memory (LSTM) etc. (Ali et al., 2021; Arshad et al., 2025; Chen et al., 2019; Gorugantula and Kambhammettu, 2022; Gou and Soja, 2024; Jyolsna et al., 2021; Kalu et al., 2024; Miro and Famiglietti, 2018; Pascal et al., 2022). Despite ongoing efforts to enhance the spatial resolution of GRACE data, continued advancements in data processing techniques and the availability of improved data products offer substantial scope for further improvement.

In traditional data-based/statistical downscaling approach 1. GRACE data serve as the truth 2. Dependent high-resolution variables are averaged to coarse resolution of GRACE 3. Model is trained at low resolution to obtain coefficients (link between the variables) 4. Then fine scale data is scaled using the coefficients to compute downscaled product. Indeed, this approach rests on the hypothesis that the physical and hydrological processes linking fine and coarse scale variables are identical at all resolution (i.e., same coefficient for all finer grids lying within a coarse grid of GRACE data). However, it suffers from two major drawbacks, first, uncertainties in GRACE data and in other variables which inflates with improvement in resolution. Second drawback lies in its hypothesis i.e., processes linking fine and coarse scale variables are identical at all resolutions. This is not true as different process become dominant at different spatial resolution. For example, groundwater change has a larger spatial wavelength compared to soil moisture, hence if a model related soil moisture observations and simulated groundwater to TWS, it will assume the relation to be same at fine and coarse scales. Thus, to overcome these two drawbacks a novel data driven approach with a twist of data assimilation approach is implemented by a very few researchers (Gou and Soja 2024; Vishwakarma et al. 2021). In this novel approach, the model is trained at fine resolution and both GRACE and hydrologic model TWSA are considered as references. Specifically, long term-trend and spatial variability are preserved in GRACE data and hydrologic model, respectively. Although this approach has shown their downscaled estimates to be superior in terms of catchment scale mass conservation and effectively redistributing mass changes closer to the water bodies such as rivers and reservoirs, they lack comprehensive validation. Further, Gou and Soja (2024) study does not regress on residuals of predictor variables suggesting downscaling relies on default trend and seasonality of GRACE data. Although Vishwakarma et al. (2021) worked on residuals they removed the trend and seasonality at catchment scale instead of GRACE mascon scale ($3° \times 3°$). Hence the trends and seasonality in Vishwakarma et al. 2021, lacks the spatial granularity.

In the present study, we used Jet Propulsion Laboratory (JPL) GRACE mascon (mass concentration block) solution to address the limitations of previous studies through three specific objectives. First, we validate GRACE-derived GWSA at the mascon resolution ($3° \times 3°$) using in situ well observations. Second, we downscale GRACE TWSA to a finer resolution ($0.5° \times 0.5°$) by improving upon the approach of Vishwakarma et al. (2021). Specifically, our downscaling is performed using Partial Least Squares Regression (PLSR), incorporating mass conservation at GRACE mascon resolution, in contrast to the catchment-scale approach used by Vishwakarma et al. (2021). This newly developed downscaled product is referred to as the Mascon-wise Mass Conserved (MMC) product, whereas Vishwakarma et al. (2021) product is referred as the Catchment-wise Mass Conserved (CMC) product. Finally, we validate and evaluate the efficacy of the MMC product against existing downscaled products (CMC, Gou and Soja (2024) developed Deep Learning (DL) product) using a temporal gain metric (Pascal et al., 2022) along with classical evaluation metrics such as correlation coefficient (r) and Root Mean Square Error (RMSE). To the

https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

best of our knowledge, this study presents the first comprehensive validation of GRACE-derived GWSA at mascon resolution
100 across India, introduces a novel MMC downscaling approach using PLSR, and systematically evaluates the efficacy of multiple downscaled products using both classical and temporal gain metrics.

Table 1. Summary of the statistical downscaling studies applied to GRACE data.

Reference	Statistical downscaling method	Original resolution	Downscaled resolution	Study region
Simple linear regression				
Gemitzi et al. (2021)	Simple linear regression using GPM-IMERG precipitation	1° × 1°	0.1° × 0.1°	Greece
Yin et al. (2018)	Simple linear regression using evapotranspiration	110 × 110 km	2 × 2 km	North China Plain
Multivariate linear regression				
Karunakalage et al. (2021)	Multivariate regression model with water budget closure constraint	1° × 1°	0.25° × 0.25°	Mehsana district, Gujarat, India
Ning et al. (2014)	Multivariate regression model with water budget closure constraint	1° × 1°	0.25° × 0.25°	Yunnan province, China
Vishwakarma et al. (2021)	Multivariate regression model with water budget closure constraint	3° × 3°	0.5° × 0.5°	Global
Machine learning algorithms				
Ali et al. (2021)	Machine Learning Models: Artificial Neural network and Random Forest	1° × 1°	0.25° × 0.25°	Indus basin irrigation system
Arshad et al. (2025)	Multimodel ensemble machine learning algorithm: Random Forest, CART, Gradient Tree Boosting algorithms	55 × 55 km	1× 1 km	Saudi Arabia
Chen et al. (2019)	Machine Learning Model: Random Forest	1° × 1°	0.25° × 0.25°	Northeast of mainland China
Gorugantula and Kambhammettu (2022)	Deep learning model: Long Short-Term Memory	1° × 1°	0.25° × 0.25°	Krishna River Basin, India
Gou and Soja (2024)	Deep learning model: Convolutional Neural Network	3° × 3°	0.5° × 0.5°	Global
Jyolsna et al. (2021)	Machine Learning Models: Multi-Linear regression and Random Forest	1° × 1°	0.25° × 0.25°	Four contrasting hydrogeological basins of India
Kalu et al. (2024)	Regression using Machine Learning Model: Support Vector Machine with water budget closure constraint	1° × 1°	0.25° × 0.25°	Northern Australia (the Cambrian Limestone Aquifer—CLA)

https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

Miro and Famiglietti (2018)	Machine Learning Model: Artificial Neural Network	2,00,000 km^2	16 km^2	California's Central Valley
Pascal et al. (2022)	Machine Learning Models: Multi-Linear regression and Random Forest	3° × 3°	0.5° × 0.5°	A fractured crystalline aquifer in southern India

2 Study region and data

2.1 Study region

India is the seventh-largest country in the world, covering a total area of 297 million hectares, and it ranks first in terms of population. It receives an average annual precipitation of 118 cm mostly concentrated in a few months, which is insufficient to meet the demands of the country's large agriculture-based population through multiple cropping seasons. As a result, groundwater resources have been over-exploited. According to a report by the Central Ground Water Board (CGWB), India withdrew 239.16 billion cubic meters of groundwater in 2022. Notably, northwest India plays a significant role in this depletion, with groundwater levels declining at an alarming rate of 1.5 cm per year, primarily due to intensive irrigation practices (Mishra et al., 2024). Therefore, there is an urgent need to study groundwater storages at local/ regional scale in India for sustainable water resource management.

2.2 Data

2.2.1 GRACE: Total water storage anomalies

In this study we downscale GRACE TWSA from mascon resolution of approximately 3° to 0.5°. One way is to process level 2 spherical harmonic solutions from GRACE data centres, which requires several post processing steps to reach gridded mass change products. Alternatively, mascon solutions can be used, as they reduce leakage errors, better separate land and ocean signals compared to spherical harmonic solutions (Scanlon et al., 2016). Thus, to downscale GRACE TWSA, we choose JPL (RL06M) level 3 monthly mascon product for the period 2004-2023 (http://grace.jpl.nasa.gov). Although the mascon product is provided at 0.5° × 0.5° its resolution is 3° × 3°. This is illustrated in Figure 1a, where the data appear as a 3° × 3° patches i.e., mascons. Although the product is provided on a 0.5° × 0.5° grid, these finer cells inherit a constant value within each mascon, resulting in no internal spatial variability. Consequently, despite the finer grid spacing, the spatial pattern reflects the coarser 3° × 3° resolution of the mascon structure. Also note that mascon represents TWSA w.r.t. baseline period of 2004 to 2009 (January-December) in terms of metre of equivalent water height (EWH).

https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

2.2.2 Central groundwater board: Groundwater levels

The Central Ground Water Board (CGWB), India, provides seasonal measurements (January, March/April/May, August, November) of in situ groundwater levels (GWLs), in terms of meters below ground level (m bgl) across India (https://indiawris.gov.in/wris/#/) for the period 2004 to 2015. To obtain quality controlled GWL measurements, only those wells are selected where positive GWL measurements are available for at least three values (out of four) in a year without repeating any measurement throughout the study period (2004-2015) (Figure 1b). The obtained quality controlled GWLs are used to validate the GRACE Ground Water Storage Changes (GWSC).

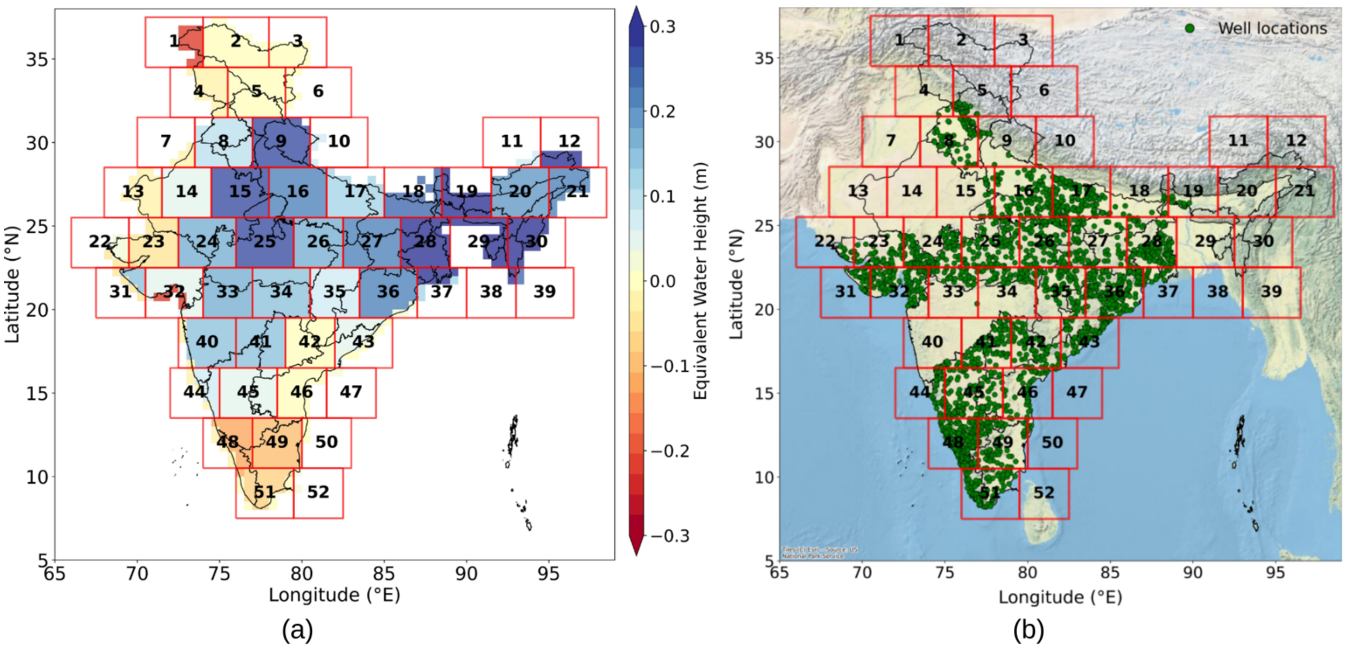

Figure 1. (a) TWSA for September 2004 over India, expressed in meters of EWH, obtained from JPL mascon data. The red boxes indicate the mascon boundaries, and the numbers denote the respective mascon numbers. (b) Green dots represent the filtered groundwater wells across India, Basemap: Esri world physical map; ArcGIS Online.

2.2.3 WaterGAP Global Hydrology Model: Total water storage anomalies

We downloaded monthly TWS and GWS outputs of WaterGAP Global Hydrology Model (WGHM) at spatial resolution of 0.5° × 0.5 (https://gude.uni-frankfurt.de/entities/researchdata/7d500a84-9a36-4cd2-9f76-a4081f9ee94e/details) (Muller Schmied et al., 2024). The TWS product comprises of various water storages such as canopy water storage (CS), snow water equivalent (SnS), soil moisture (SMS), river streams, lakes, reservoir, wetlands (four compartments combinedly referred as SWS) and groundwater (GWS). From this TWS, GWS component is removed to isolate the water storages due to CS, SnS, SMS, and SWS. This isolated water storage compartments are further used to sperate the groundwater storage compartment

https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

from GRACE and other downscaled TWSA products used in the study. WGHM TWS/GWS is converted to TWSA/GWSA by removing mean of baseline period (2004 to 2009) to align with GRACE TWSA.

2.2.5 Global Land Data Assimilation System: Precipitation, Evapotranspiration and Runoff

We used monthly Precipitation (P), Evapotranspiration (ET) and Runoff (R) (surface runoff, baseflow-groundwater runoff and snow melt) from NASA Global Land Data Assimilation System Version 2 (GLDASV2.1) available at spatial resolution of 0.25° × 0.25° .(https://disc.gsfc.nasa.gov/datasets/GLDAS_NOAH025_M_2.1/summary?keywords=GLDAS). These high resolution (0.25° × 0.25°) products of P, ET, and R, are resampled to 0.5° by averaging. As P (variable name is Rain_f_tavg) and ET (Evap_tavg) is measured in kg/m²/s, they are converted into m EWH using Eq. 1. Since, each monthly average quantity has units of per 3 hours, to convert P and ET of a given month (For e.g., April) into m EWH using below equation.

$$P \; or \; ET \; (m) = \left[P \; or \; ET \left(\frac{kg}{m^2 s}\right) \times 10800 \left(\frac{s}{3hr}\right) \times 8 \left(\frac{3hr}{day}\right) \times 30 \; (days) \right] \times 0.001 (mm \; to \; m) \tag{1}$$

R is sum of Qs_acc, Qsb_acc and Qsm_acc. Where Qs_acc, Qsb_acc and Qsm_acc represents storm surface runoff, baseflow-groundwater runoff and snow melt. As unit of R is in kg/m²/3hr, to convert it to m EWH Eq.2 is used.

$$R \; (m) = \left[R \left(\frac{kg}{m^2 3hr}\right) \times 8 \left(\frac{3hr}{day}\right) \times 30 \; (days) \right] \times 0.001 (mm \; to \; m) \tag{2}$$

All datasets used in the present study are summarized in Table 2.

Table 2. Data used in the present study.

Type of observation	Variables	Spatial Resolution	Source	Duration
Satellite	Total water storage anomalies (TWSA) (m EWH)	(3° × 3°)	GRACE JPL mascon	2004 - 2023
In-situ	Groundwater level (m bgl)	Point data	Central Ground Water Board (CGWB)	2004 - 2015
Hydrologic Model	Total water storage, snow water equivalent, water storges dues to canopy, river, soil moisture, lake, wetland, and reservoir, (kg/m²)	0.5° × 0.5°	WaterGAP Global Hydrology Model (WGHM)	2004 - 2023
	Precipitation (kg/m²/s), Evapotranspiration (kg/m²/s), and Runoff (kg/m²)	0.25° × 0.25°	Global Land Data Assimilation System (GLDAS)	2004 - 2023
Existing GRACE downscaled product	Total Water Storage Anomalies (TWSA) (m EWH)	0.5° × 0.5°	Vishwakarma et al., 2021	2004 - 2015
			Gou and Soja, 2024	2004 - 2019
			Downscaled product generated in the present study	2004 - 2023

https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

3 Methodology

3.1 Validation of GRACE GWSC with Ref GWSC

In the present study, GRACE derived GWSC (for both mascon and downscaled product) obtained after removing water storages due to CS, SnS, SMS, and SWS from WGHM model, are validated against in-situ GWSC measurements (Ref GWSC) using methodology shown in Figure 2.

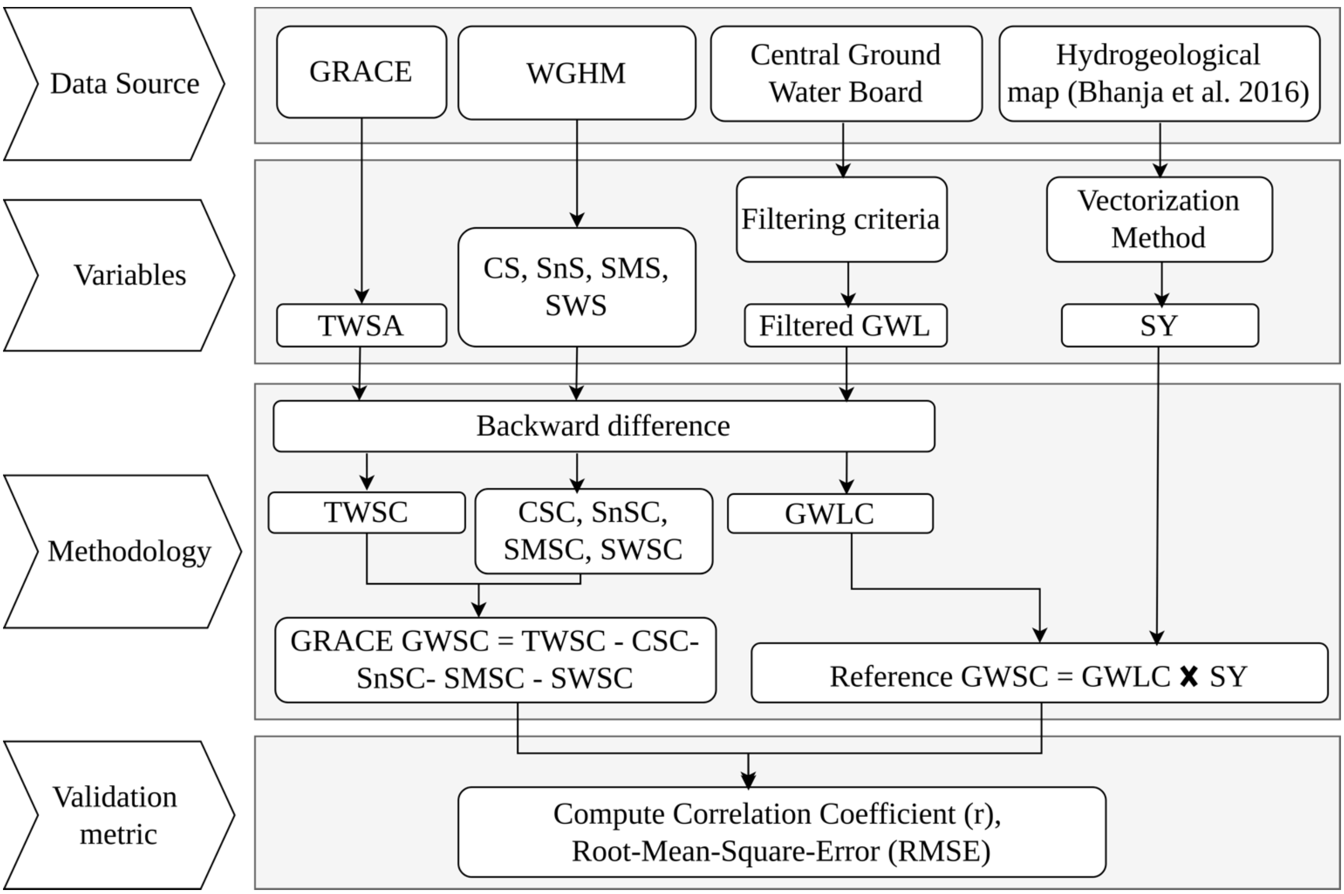

Figure 2. Methodology for validating GRACE GWSC.

GRACE TWSA, originally provided in cm of EWH, are first converted into meters (m) of EWH for consistency. Contemporaneous datasets, including quality-controlled GWL observations and storage compartments such as CS, SnS, SMS, and SWS, are then compiled for analysis. The GRACE TWSA is referenced to a Long-term Mean over the period 2004-2009 ($LM_{2004-2009}$) and is available at a monthly temporal resolution, whereas in situ GWLs from CGWB are available only at a seasonal (quarterly) scale, with a maximum of four observations per year. This temporal mismatch limits direct comparison

https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

between GRACE TWSA and in situ GWL. To address this, a difference-based validation approach is adopted instead of interpolating seasonal groundwater data to monthly resolution, which may introduce additional uncertainties.

In this difference-based validation approach, only those months data is retained for which GWL observations are available. Let i and j denote two observation months within a given year such that $j > i$, where both correspond to months with available GWL measurements (e.g., January/May/August/November). The change in GRACE TWSA ($TWSC_{ji}$) between these two-time steps is expressed as follows

$$TWSA_i = TWS_i - LM_{2004-2009} \tag{3}$$

$$TWSC_{ji} = \Delta TWSA_{ji} = TWSA_j - TWSA_i = TWS_j - TWS_i \tag{4}$$

where the long-term mean cancels out, ensuring that the anomaly difference is equivalent to the actual storage change. Using Eq. 5 $GRACE\ GWSC$ of jth month w.r.t. ith month ($GRACE\ GWSC_{ji}$) is computed after removal of Canopy Storage Changes (CSC_{ij}), Snow Storage Changes ($SnSC_{ij}$), Soil Moisture Storage Changes ($SMSC_{ij}$), and Surface Water Storage Changes ($SWSC_{ij}$) which includes storages changes due to river streams, lakes, reservoirs, and wetlands. The resulting $GRACE\ GWSC_{ij}$ are validated against Ref GWSC.

$$GRACE\ GWSC_{ij} = TWSC_{ij} - CSC_{ij} - SnSC_{ij} - SMSC_{ij} - SWSC_{ij} \tag{5}$$

The corresponding $Ref\ GWSC_{ji}$ from in situ GWL observations is estimated as:

$$Ref\ GWSC_{ji} = (GWL_j - GWL_i) \times SY \tag{6}$$

where GWL_j and GWL_i represent the representative GWLs of a given mascon at time steps j and i, respectively. These are derived from quality-controlled GWLs observations. Within each mascon, multiple wells are available after quality control filtering. Each well is assigned a specific yield (SY) value, which is a dimensionless hydrogeological parameter representing the fraction of groundwater that can be released under gravity. It is used to convert groundwater level changes into equivalent storage changes. The SY values are extracted at individual well locations from the hydrogeological map of India (Bhanja et al., 2016). The raster layer of the hydrogeological map is obtained from Kuruva et al. (2025) and processed using the Quantum Geographic Information System (QGIS) platform. Quality-controlled GWL observations are converted into point shapefiles and overlaid on the raster layer. SY values corresponding to each well location are then extracted using the "Sample Raster Values" tool in QGIS.

At the mascon scale, the representative SY is computed by averaging the SY values of all wells within the mascon. Similarly, a representative GWL for the mascon is obtained (e.g., using the median of well observations) for each observation month. These representative values are then used to compute the $Ref\ GWSC_{ji}$ using Eq. 6. Further, for the downscaled product, however, the median GWL is computed at a finer spatial resolution of 0.5° grid to ensure consistency with the downscaled dataset.

Overall, this generalized difference-based framework provides a robust and consistent basis for validation, particularly in regions such as India where GWLs are sparse and temporally discrete (seasonal interval). By avoiding interpolation and

https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

minimizing uncertainties associated with long-term mean referencing, the approach ensures a more reliable assessment of GRACE-derived GWSC.

3.2 Statistical downscaling to generate Mascon wise Mass Conservation (MMC) downscaled product

We used PLSR method to downscale GRACE mascons 3° × 3° to 0.5° × 0.5°. Flow chart of the methodology is as shown in Figure 3. Our method is a modified version of the method elaborated in Vishwakarma et al. (2021) which uses regression model as shown in Eq.7.

$$S = LH \tag{7}$$

Where S represent predictand matrix with n (total number of months) × g (total number of 0.5° × 0.5° grids in a mascon) dimensions. WGHM TWSA performs the role of a predictand matrix (S). L is a predictor matrix i.e., observations matrix. Its dimensions are $n \times d$. Where d represent columns of P, ET, R, and GRACE TWSA. Eq. 7 is solved to obtain H (prediction matrix, $d \times g$). The modification we implemented here is that mass is conserved at mascon scale instead of catchment scale i.e., for whole set of operations Vishwakarma et al. (2021) unit was a catchment; in this study it is changed to a mascon.

Establishing the predictor matrix (L) is the first and very important step here. L consists of residuals of four variables (P, ET, R, and GRACE TWSA). In fact, there exist a temporal lead or lag amongst the water budget components (P, ET and R). Hence, K (=1 to 12) shifted time series of these datasets are generated and cyclostationary mean is removed to obtain residuals. To generate residuals of GRACE TWSA trend and annual cycle is removed from it.

Consider a mascon where total 36 (0.5° × 0.5°) grids are present. Our study period (January 2004 –December 2023) contains total 240 months. Thus, data matrix dimensions for a given mascon are 240 (rows) × 36 (columns). To generate 12 months shifted time series of P, ET and R, data from January 2003 is required. When $K = 1$, rows run from Jan 2003 to Dec 2022. For $K = 2$, row starts with Feb 2003 and ends at Jan 2023 and it goes on. In the end for k=12, rows run from Dec 2003 to Nov 2023. To remove cyclostationary mean, month wise average is computed for the period between 2004 and 2023 resulting into 12 values which are removed from individual datasets. Thus, for a single variable after combining all 12 shifted timeseries, matrix dimensions become 240 × 432. Next, GRACE TWSA are detrended and annual cycle is removed to obtain residuals (240 × 36). Combining P, ET, R and GRACE TWSA generates our final observation matrix (L) with dimensions (240 × (1332=432+432+432+36)). Thereafter, residuals of WGHM TWSA are obtained after removal of GRACE annual mean. This represents S (240 × 36) in Eq. 6.

Eq. 6 represents ideal case but in reality, measurements contain inherent noise. Thus, multivariate model becomes:

$$S = LH + E \tag{8}$$

Where E in Eq. 8 represents the noise. Once Eq. 7 is set up, PLSR obtains Principal Components (PCs) via Singular Value Decomposition (SVD). i.e., H will be computed. Please note dimensions of H is $d \times g$, which suggests grid wise coefficient will be determined unlike traditional regression method.

To solve Eq. 8, covariance matrix (C) is computed using Eq. (9) which is decomposed via SVD (Eq. 10).

https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

$$C = L^T S \tag{9}$$

$$C = U_C \Sigma_C V_C^T \tag{10}$$

Where U_C $(d \times r)$ and V_C $(r \times d)$ are canonical modes (joint normalised eigen vectors for L and S), Σ_C $(r \times r)$ is a diagonal matrix which will contain covariance between L and S. r represents canonical modes from SVD. To obtain PCs of L (U_L) which are significantly correlated with S , L is projected on U_C using Eq. 11

$$U_L = LU_C \tag{11}$$

Rearranging Eq. 11, Eq. 12 can be obtained as follows

$$L = U_L U_C^T \tag{12}$$

Eq. 12 substituted to Eq.8 gives,

$$S = U_L U_C^T H + E \tag{13}$$

This can be written as

$$S = U_L K + E \tag{14}$$

Where K $(r \times g)$ is transformed regression matrix obtained by projecting H on U_C. Now, we want to conserve the mass over a mascon unlike a catchment (Vishwakarma et al., 2021) even after downscaling, a mass budget constraint is applied here. i.e.,

$S = \Delta M =$ Average TWSA over a mascon

$$\Delta M = U_L K + E \tag{15}$$

Finally bringing the constraint in the observation space and solving for K using least squares method,

$$K = (X^T X)^{-1} X^T Y \tag{16}$$

$$X = \begin{pmatrix} U_L \\ U_L \end{pmatrix} \text{ and } Y = \begin{pmatrix} S \\ \Delta M \end{pmatrix} \tag{17}$$

In a simplified manner Eq. 17 suggests that solutions should converge to S and further only those solutions should be retained which will conserve the mass over a mascon. The K obtained after solving is substituted in Eq.18 to obtain H.

$$H = U_c K \tag{18}$$

This computed H when put back to Eq. 7 with already prepared L matrix a downscaled GRACE residuals are obtained. To which trend and annual cycle are added back to obtain final downscaled GRACE TWSA referred as MMC downscaled product.

https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

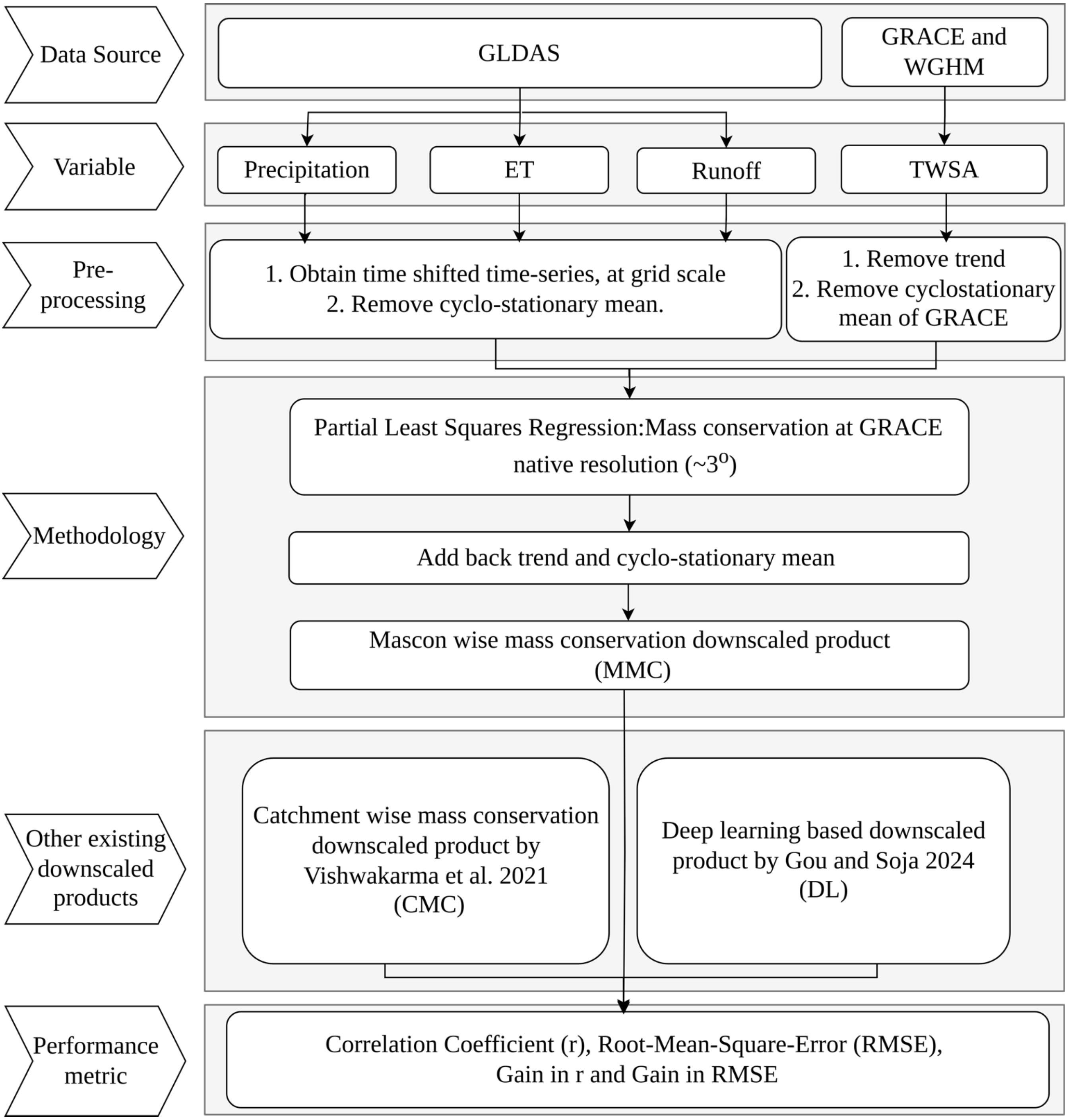

Figure 3. Flow chart of methodology for downscaling GRACE TWSA and its evaluation in comparison to other existing downscaling products.

https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

3.3 Evaluation of downscaled products

First, validation of all three downscaled products (MMC, CMC, DL) is performed using Ref GWSC measurements by computing the r and RMSE. In addition to these classical evaluation metrics, the temporal metric gain proposed by Pascal et al. (2022) is implemented to compare the performance of the downscaled products. As noted by Pascal et al. (2022) most studies do not assess the performance of downscaled GRACE products relative to the original GRACE data. By using the temporal gain metric, we can quantitatively evaluate the accuracy of the downscaled products.

In the present study, GRACE JPL mascon data are used as the coarse resolution reference without applying the scale factor. These scale factors, being multiplicative and model-based, can amplify any uncertainties in the GRACE product if the model does not align with reality. Vishwakarma et al. (2017) and Pascal et al. (2022) have shown that applying the scale factor can degrade rather than improve the results. Consequently, we have not extended the evaluation framework to compute spatial gain, since our low-resolution reference does not incorporate the scale factor and thus does not contain spatial variability. As illustrated in Figure 1a, the reference values are uniform over each mascon.

Formulas to compute temporal gain metric (G) for r and RMSE are shown below,

$$G = \frac{|M_{opt}-M_{LR}|-|M_{opt}-M_{HR}|}{|M_{opt}-M_{LR}|+|M_{opt}-M_{HR}|} \quad (19)$$

With M_{LR} denotes the value of metric for Low Resolution (LR) GRACE TWSA, M_{HR} denotes the values of metric for downscaled/High Resolution (HR) product, and M_{opt} the optimal value of this metric i.e., 1 for r and 0 for RMSE. Thus, gain in r (G_r) and RMSE (G_{RMSE}) are as follows:

$$G_r = \frac{|1-r_{LR}|-|1-r_{HR}|}{|1-r_{LR}|+|1-r_{HR}|} \quad (20)$$

$$G_{RMSE} = \frac{RMSE_{LR}-RMSE_{HR}}{RMSE_{LR}+RMSE_{HR}} \quad (21)$$

Whereas to quantify the effectiveness of approach in capturing the variability of WGHM model, r w.r.t. WGHM is computed. Mascons that show a positive gain in r and RMSE with respect to GRACE, as well as a positive r with respect to WGHM, are considered to be reliable downscaling estimates. After comparing the products from three approaches (MMC, CMC and DL), the approach which retained the maximum number of mascons after meeting these conditions is considered as the best approach.

4 Results and discussions

4.1 Validation statistics for GRACE GWSC at mascon resolution (3° × 3°) across India

Figure 4 indicates mascon-wise maps of r and RMSE between GRACE GWSC and Ref GWSC across India. The validation is performed only for 36 mascons out of 52 owing to missing well observations. Out of 36, 28 mascons showed positive r ranging from 0.06 to 0.91. Mascons 5 and 27 showed a maximum r value of 0.91, indicating that GRACE is capable of explaining 83% of GWSC variability in these mascons. Mascons 19, 26, 35, 36 and 41 showed r values varying between 0.83 to 0.86 explaining the variability of GWSC between 69% to 74%. For mascons 9, 10, 15, 18, 24, 25, 28, 34, 37, 40, 45, 49 r is ranging between

0.63 and 0.79, explaining 40% to 60% of GWSC variability. These results indicates that GRACE GWSC is capable of explaining variability in GWSC over 40% for majority of the mascons. In contrast, mascons 16, 32, 43, and 48 showed low r values (0.15, 0.06, 0.17 and 0.10, respectively), indicating that GRACE is not even capturing a 3% of GWSC variability. Mascons 4, 8, 17, 22, 23, 44 and 50 exhibited negative correlations. RMSE values observed to be ranging between 0.06 m to 0.32 m. The best (minimum) RMSE is observed for mascon 6 whereas worst (maximum) is shown by mascon 16. Overall RMSE remained low for majority of the mascons (< 0.16 m) whereas mascon 9, 16, 17 showed higher RMSE varying between 0.29 m and 0.32 m.

Interestingly, we also found that the validation performance is independent of number and distribution of wells in the mascon. For instance, mascon 17, with 112 wells, yielded (exhibited) a negative correlation of -0.32, whereas mascon 5, with only 33 wells showed maximum correlation of 0.91. Similarly, mascon 15, where all wells are clustered in the right side of the mascon, still showed a good correlation of 0.63. Whereas mascon 16 wells are with fairly well distributed wells, showed a poor correlation of 0.15. Thus, the failure of GRACE in capturing groundwater signal in some mascons can be attributed to multiple factors such as, errors in measurements of GWL, high irrigational activities occurring at local scales, inadequacy of WGHM model in computing exact storages of canopy, snow, soil moisture, river streams, lakes, reservoirs, and wetlands. Conversely, in some mascons (5 and 27) GRACE performs exceptionally well, achieving r = 0.91 and RMSE = 0.09 m. The strong agreement also underscores the superiority of the difference-based validation method, as it preserves the integrity of observed data and yields more reliable results than approaches that rely on temporal interpolation of CGWB measurements.

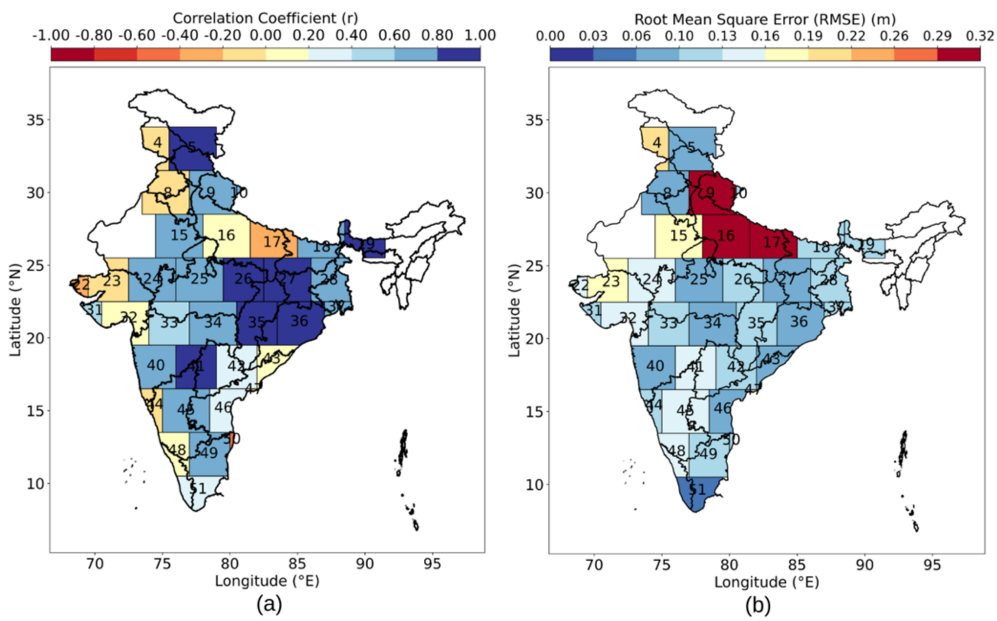

Figure 4. Mascon-wise maps of (a) r and (b) RMSE between GRACE GWSC and Ref-GWSC over India.

https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

4.2 Validation and evaluation of GRACE GWSA downscaled products

Figure 6 shows MMC approach derived downscaled TWSA (0.5°) over India for the month of September 2004. Spatial variability introduced in the data due to downscaling is evident and consistent when compared with Figure 1a showing JPL mascon data at mascon resolution for the same month. Further, to study improvements of MMC approach over CMC explicitly, a case study of mascon 24 is discussed in Section 4.2.1. Next, across India performances of both products (MMC, CMC) are discussed in Section 4.2.2. Section 4.2.3 discusses the validation and efficacy of DL product and in the end performance of all the three products is discussed.

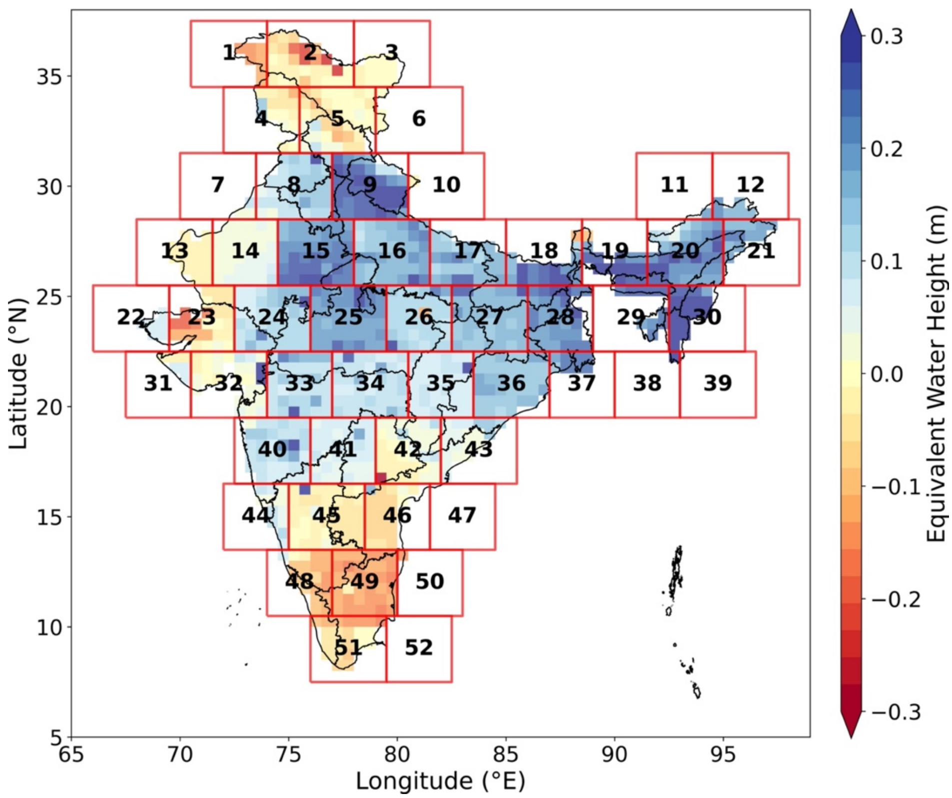

Figure 5. Downscaled (0.5° × 0.5°) TWSA of September 2004 obtained from JPL mascon 3° × 3° using MMC approach over India.

4.2.1 Comparison between MMC and CMC downscaled products: Mascon 24

Grid wise comparison map of r and gain in r for mascon 24 obtained for both the methods (MMC and CMC) is shown in Figure 6. Figure 6a shows that for majority of the grids, CMC method showed negative r which is not correct as we are comparing same quantity here. Thus, expecting positive r. Whereas MMC method showed evident improvement in r (Fig. 6b) by showing positive r for grids except 1. Similarly Figure 6c showed very high negative gain in r for majority of the grids

https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

indicating poorer performance of CMC w.r.t to original GRACE product. Whereas CMC approach showed less negative gain in r and some grids it changed to positive (Fig. 6d). The case study over mascon 24 indicates that MMC method outperforms CMC method. This improvement in MMC over CMC confirms that conserving mass over mascon resulted into better distribution of mass in each grid than in conserving mass over catchment.

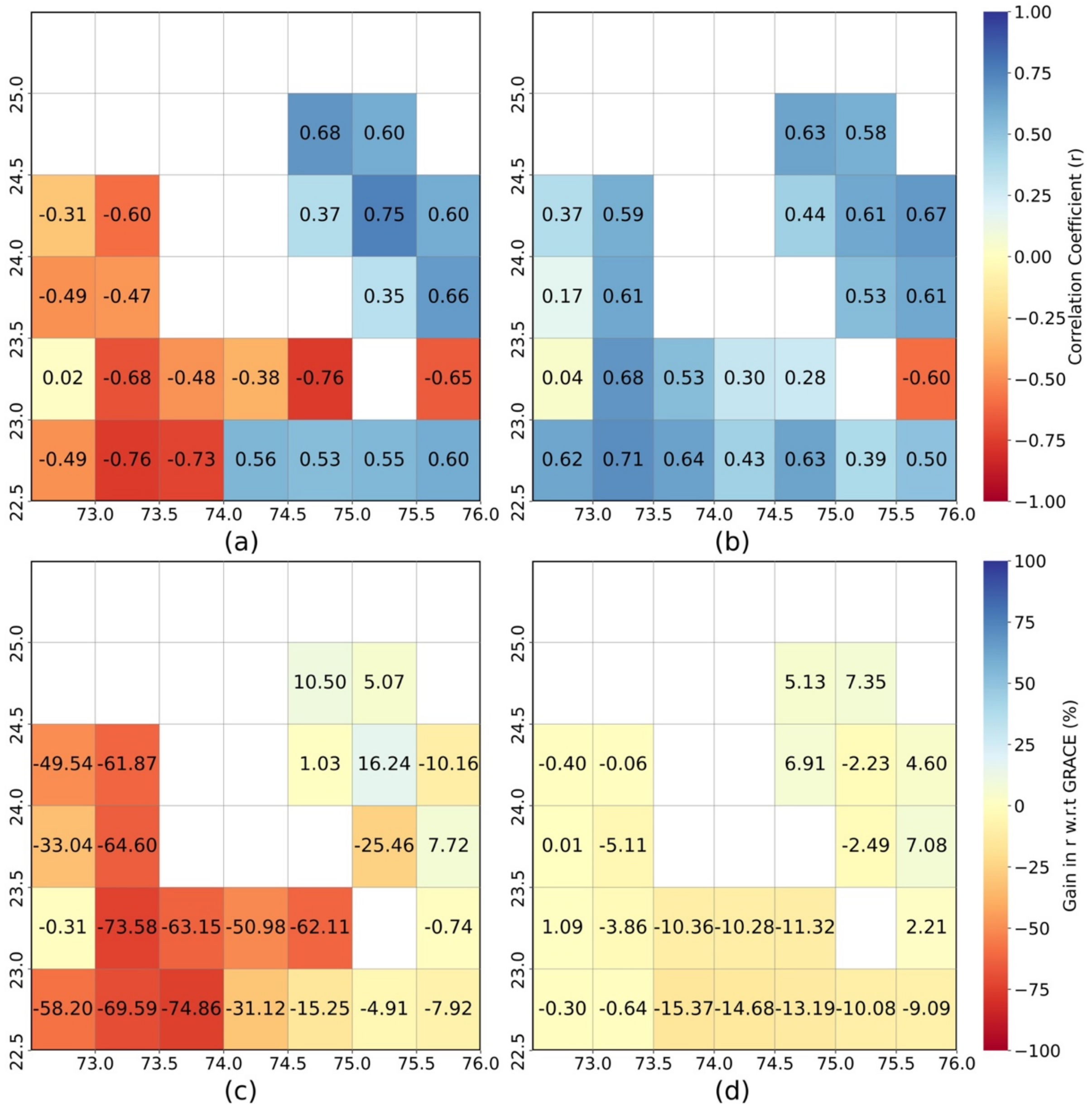

Figure 6. For GRACE mascon 24: grid wise r of downscaled GWSC obtained using a) CMC method and b) MMC method; grid wise gain in r (%) for c) CMC method and d) MMC method when GRACE GWSC is compared with Ref-GWSC.

https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

There are a few more mascon's (28,32,36,46,48,49 and 51) similar to mascon 24 where CMC method shows strong negative r values whereas MMC approach showed marked improvement in r. The observed improvement can be attributed to MMC method. However, CMC approach does perform equally well for remaining mascons. The performance of different approaches can be attributed to water holding capacity of region and consequently the aquifer type. There are studies which indicate that downscaling method performance is season dependent due to their dynamic and aquifer type (Pascal et al. 2022). However, for aquifers which are less sensitive to seasons, both approaches may work well.

4.2.2 Statistical comparison between MMC and CMC downscaled products across India

Figure 7 shows statistical comparison between both MMC and CMC downscaled GWSC over India when validated w.r.t. Ref GWSC. The plot shows median values of r and RMSE obtained over mascons. As mentioned earlier out of 52, well data is available only on 36 mascons. Then only those mascons median is plotted where comparison for at least 10 subgrid points is performed which leads to further reduction in mascon mumber. In case of MMC approach out of 22, 21 mascons, showed positive r whereas CMC resulted into 13 mascons with positive r (Fig. 7a). Specifically, MMC method showed positive r over mascons 24, 28, 32, 36, 46, 48, 49, and 51 where CMC method showed negative r. For the same mascons even GRACE original data showed positive r. Figure 7a also shows that in majority of the mascons not only MMC method showed positive r but improved r in comparison to original GRACE (mascons 16, 17, 24, 25, 26, 28, 32, 33, 34, 35, 36, 48, and 51). This evidence again supports that MMC outperforms CMC. Figure 7b shows that although RMSE values are almost nearby for all three products, CMC as well as MMC product showed lesser values in comparison to original GRACE for majority of the mascons. In case of some mascon (28, 36) MMC showed marked improvement by showing RMSE values 0.17 m and 0.10 m, respectively where CMC showed very high (poor performance) RMSE values 0.28m and 0.21m. In terms of RMSE also it can be concluded that MMC outperforms CMC.

https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

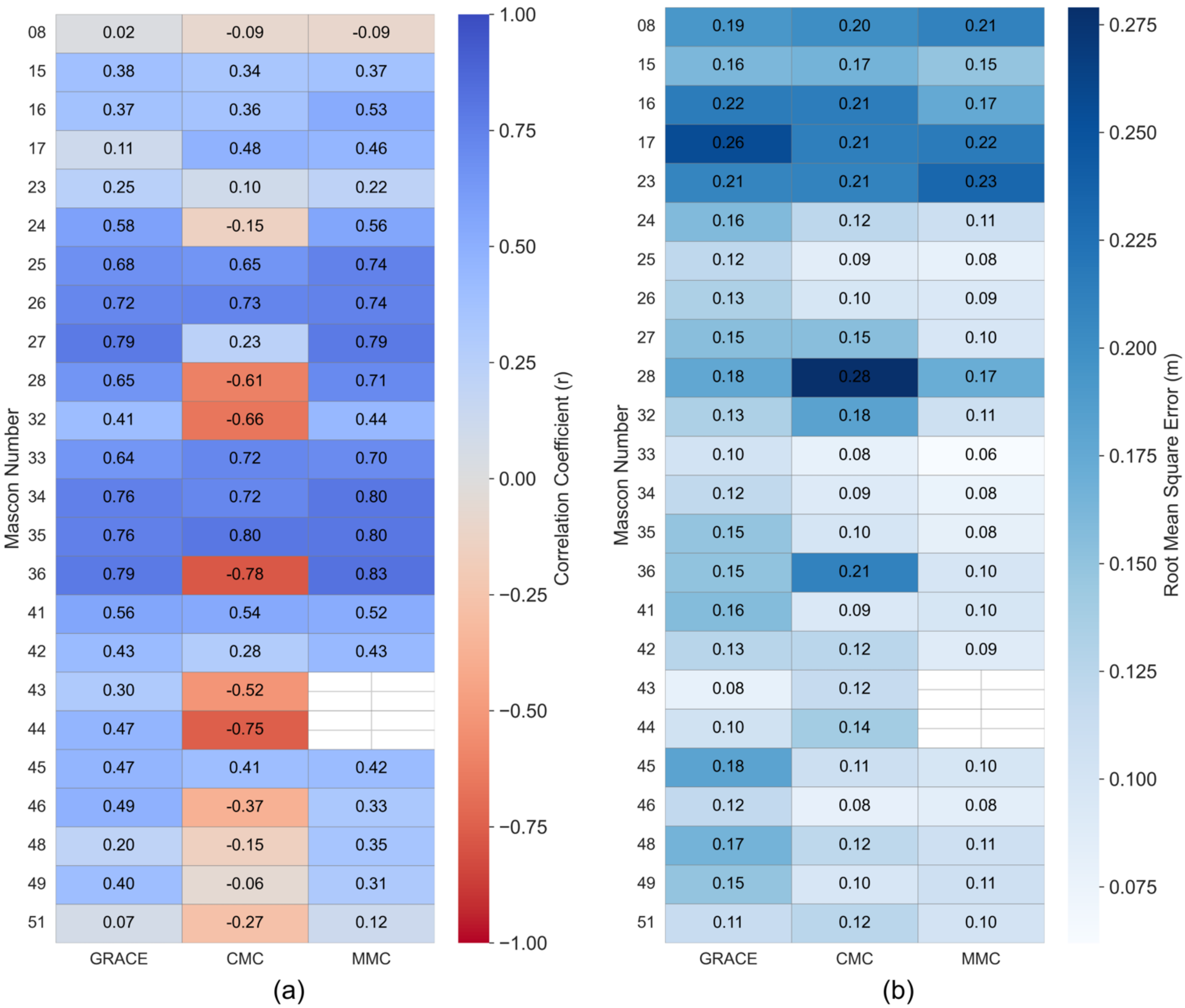

Figure 7. Heat map for (a) r (b) RMSE of GRACE, CMC and MMC products over India.

Figure 8a demonstrates median gain in r w.r.t. GRACE computed for MMC and CMC products. The MMC product showed positive gain in r for a greater number of mascons in comparison to CMC approach. Indeed, CMC product showed positive gain in r for only 3 mascons (17, 35 and 42) with maximum reaching to 21.84% for mascon17 whereas for MMC product mascons with positive gain are 13 in number (15, 16, 17, 25, 26, 32, 33, 34, 35, 36, 42, 48 and 51) with maximum reaching to 23.32% for mascon 17. This indicates that for 13 mascons MMC product showed improvement over GRACE whereas CMC showed improvement for only 3 mascons.

https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

Figure 8b displayed median gain in RMSE w.r.t. GRACE computed for MMC and CMC products. It indicates positive gain for all the mascons except mascon 8 and 23. Whereas CMC product showed negative gain in RMSE for most of the mascons (8, 23, 27, 28, 32, 36, 43, 44 and 51). Maximum gain in RMSE reported for CMC and MMC are 26.23% (mascon 41) and 27.98% (mascon 45). These inferences confirms that MMC performs better over CMC as well as GRACE products.

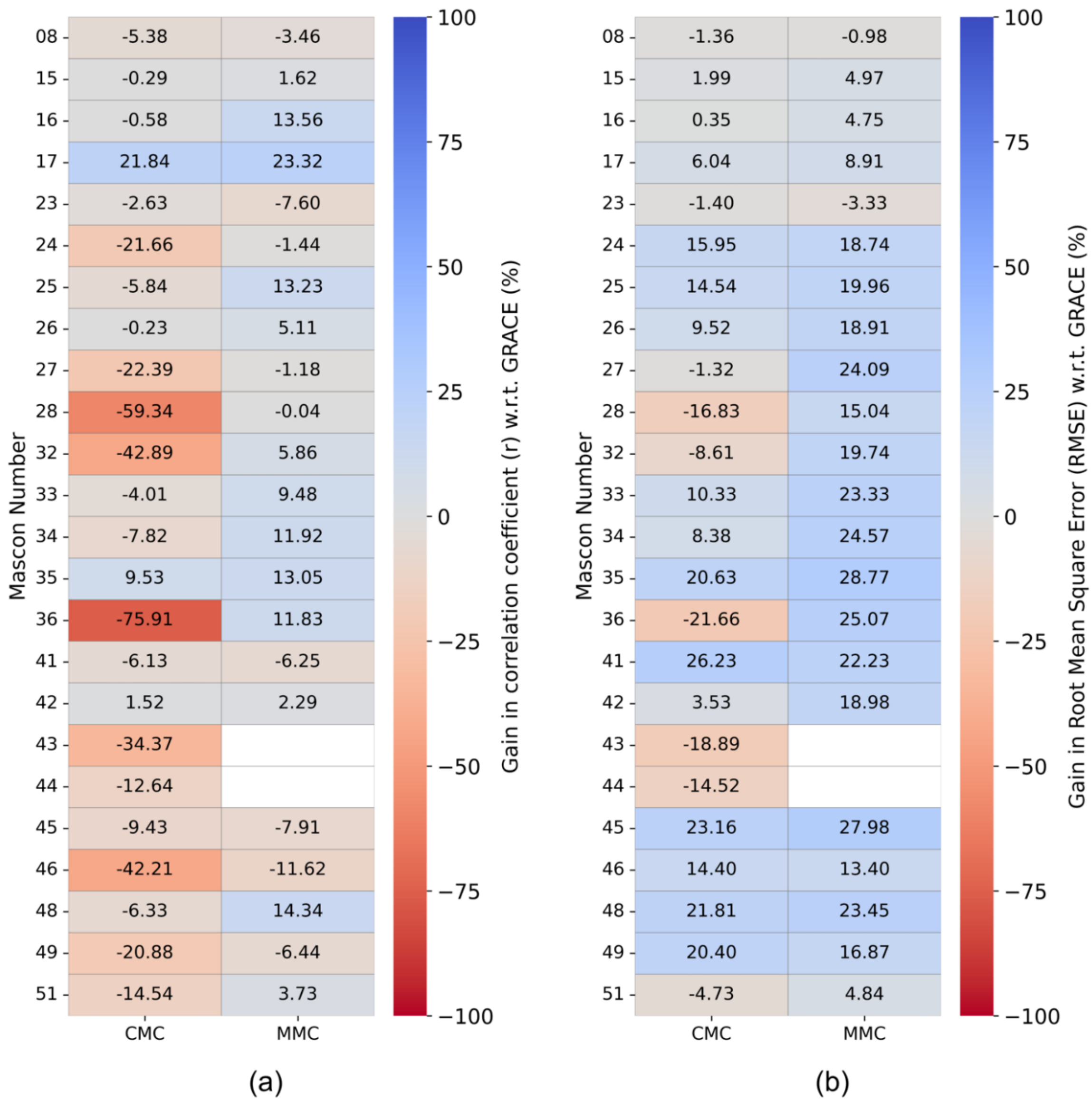

Figure 8. Heat map for gain in (a) r (b) RMSE CMC and MMC product w.r.t. GRACE over India.

https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

Figure 9 shows r when MMC and CMC products are compared with WGHM. CMC product showed negative value of r for mascons 28, 29, 30, 32, 36, 43, 44, 46,48, 49, and 51. But MMC approach showed positive gains for all mascons except a couple of mascons (mascon 23 and 51). Positive r describes the effectiveness of downscaled model in capturing the variability of WGHM. High positive r indicates better performance of the model. This result also suggests that MMC method is performing better in terms of mimicking the model variability in comparison to CMC method.

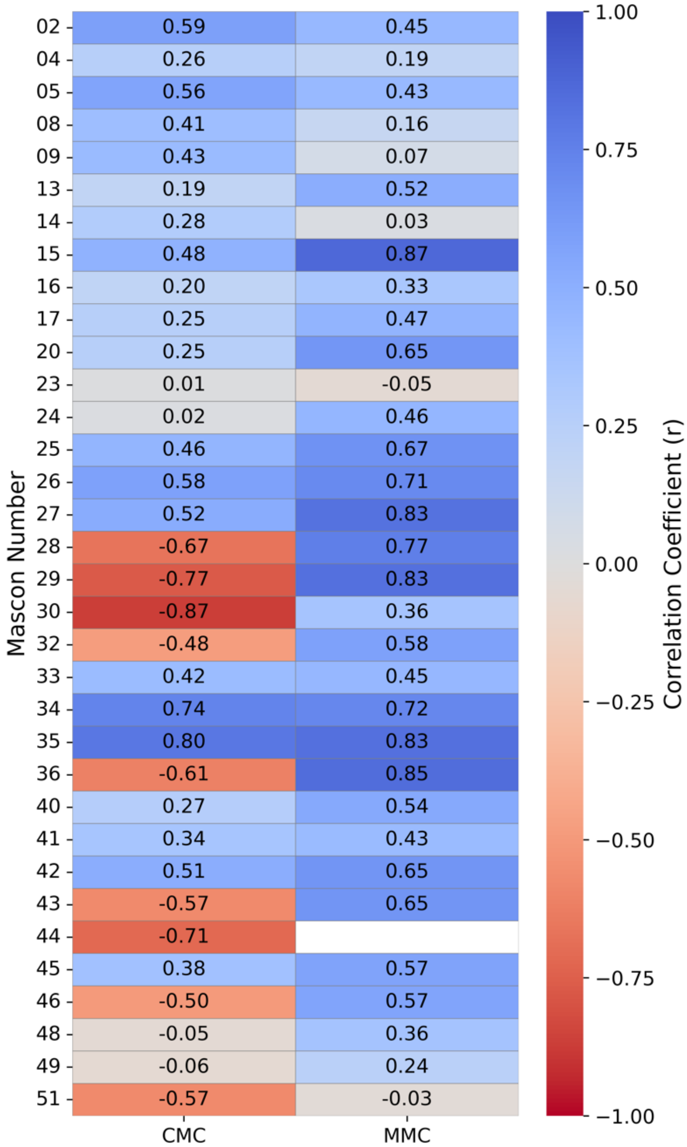

Figure 9. Heat map for r of CMC and MMC w.r.t WGHM over India.

https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

4.2.3 Validation and efficacy of DL downscaled products across India

Figure 10. displays r, RMSE, gain in r, gain in RMSE w.r.t. GRACE and r w.r.t. WGHM for DL method. It is observed that positive r values obtained for all 21 mascons with lower variability similar to that of MMC approach. Also, positive gains in r w.r.t. GRACE are observed for 10 mascons with maximum gain reaching to 9.68% for mascon 48. Gain in r w.r.t. WGHM is also observed to be positive for all mascons. Indicating DL also performs better in comparison to CMC approach.

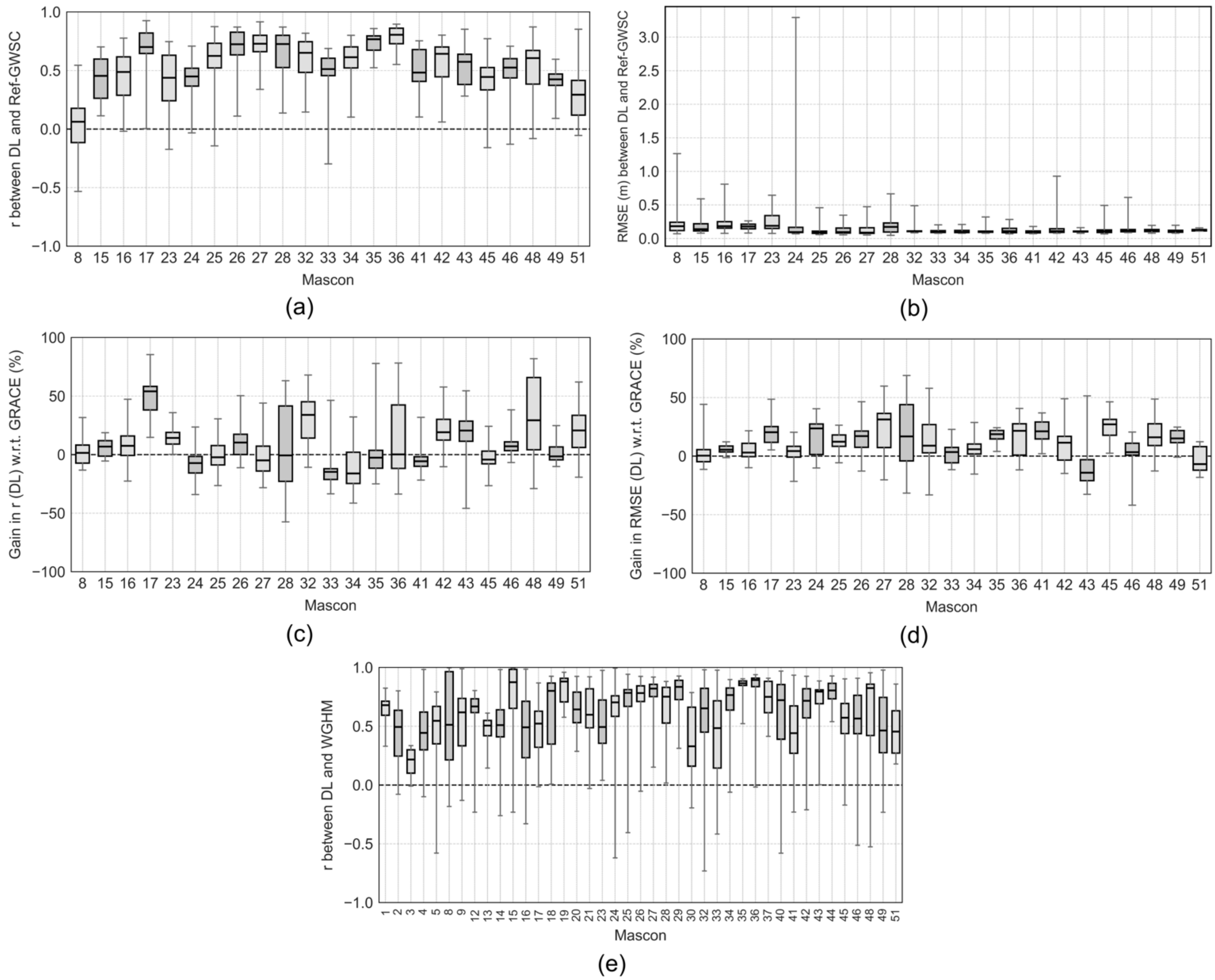

Figure 10. Box plots of (a) r (b) RMSE (c) Gain in r w.r.t GRACE (d) Gain in RMSE w.r.t GRACE (e) r w.r.t. WGHM for DL product over India.

Overall, it is observed that MMC approach is producing reliable downscaled product over majority of the mascons in comparison to CMC and DL. Implementing reliable downscaled product criteria, MMC approach retained 17 mascons whereas CMC and DL approach showed 6 and 16 masons, respectively suggesting MMC is outperforming CMC and DL. However, it

https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

is also observed that MMC is not able to produce downscaled product for some mascons despite that MMC found to be a superior downscaled product that produces more reliable estimates at fine resolution over a greater number of mascons. Finally, r and RMSE for all products i.e., GRACE original, CMC, MMC and DL is presented as shown in Figure 11. It is evident from the Figure 11a that DL outperforms in comparison to other products if basis is r, followed by MMC. This indicates DL efficiently captures the spatial variability as that of WGHM. But in terms of RMSE, MMC outperforms the rest product owing to mascon wise mass conservation. However, CMC is performing the worst amongst all.

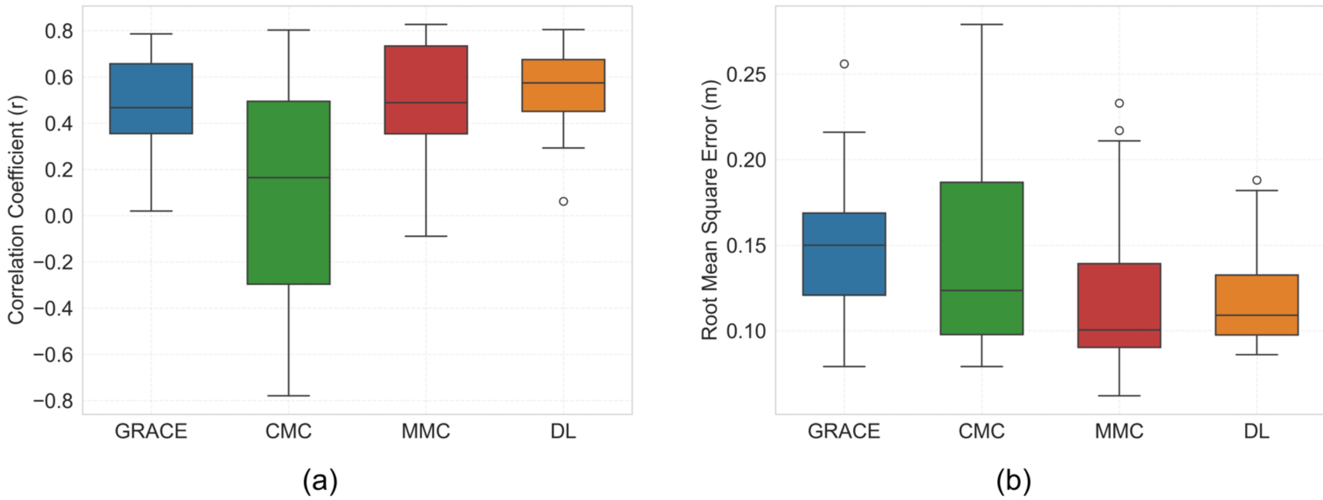

Figure 11. Box plots of (a) r for GRACE original, CMC, MMC and DL product over India when compared with in situ observations.

4.3 Limitations

This study presents a framework for the validation and downscaling of GRACE-derived GWSA; however, several limitations should be acknowledged. First, the validation approach assumes a temporally invariant SY to convert GWLC observations into GWSA. This assumption is a major simplification, as SY is known to vary spatially and temporally in response to lithological heterogeneity, recharge dynamics, and sustained anthropogenic groundwater abstraction (Lv et al., 2021). The use of a constant SY may therefore introduce systematic biases in the estimated GWSA. Second, the validation is constrained by the temporal resolution of in situ GWL observations. GWL data from the CGWB are available at a seasonal scale, whereas GRACE provides monthly estimates. This temporal mismatch limits the ability to rigorously assess the performance of GRACE in capturing intra-seasonal variability and short-term groundwater dynamics. Third, the separation of groundwater storage from total water storage relies on the WGHM to remove non-groundwater components. Thus, uncertainties in simulating soil moisture and surface water storage propagate directly into the derived GWSA, affecting both validation and interpretation. Finally, the downscaling approach based on the MMC integrates hydro-meteorological variables (P, ET, and R) from GLDAS. These inputs are themselves subject to uncertainties arising from model structure. Consequently, errors in the predictor variables may propagate into the downscaled GWSA estimates. Despite these limitations, the proposed framework provides a useful basis for regional-scale groundwater assessment. Future work focuses on incorporating spatially and temporally variable aquifer properties, improving the temporal resolution of in situ datasets, and integrating more robust hydrological model outputs constrained through assimilation of satellite-based observations to reduce overall uncertainty.

5 Conclusions

In this study, we carried out validation and downscaling of GRACE observations over India. For proper validation of GWSC specifically contributions from other storage components such as CS, SnS, SMS, and SWS removed from GRACE TWSA. We conclude that GRACE mascon when compared with in-situ well data yielded varied performance across. At some mascons GRACE successfully captures the observed variations with moderate r (> 0.86) and RMSE (< 0.16 m) values. However, there were a few mascons where GRACE didn't perform well possibly due to errors in GWL data and inadequate accounting of water storages other than groundwater. By implementing modified downscaling approach, a new downscaled product (MMC) is developed and compared with existing downscaled products (CMC, DL). Over several mascons MMC approach showed a drastic improvement by converting negative correlation seen in CMC into positive ones over CMC approach. The DL approach also performs better than CMC but in terms of RMSE, MMC outperformed both CMC and DL when validated with in-situ.

The resulting high-resolution GWSA dataset hold immense potential for a wide range of scientific and practical applications in water resource research and management. By providing spatially varied information on groundwater storages, they can significantly improve drought characterization and severity mapping, especially in regions with sparse in-situ data. These downscaled products can serve as critical inputs to hydrologic and groundwater models, enabling more accurate representation of subsurface storage dynamics at regional and basin scales. These all together can help in evaluating effectiveness of groundwater recharge/extraction policies. The fine resolution information can further support in basin-planning, watershed restorations and river rejuvenation initiatives by helping to identify zones of water stress and potential recharge areas. Consequently, the developed downscaled storage product can play a crucial role in guiding sustainable groundwater management, enhancing climate resilience and informed evidence-based decision making for India's ongoing water resource and rejuvenation program.

Data and Code Availability

The downscaled TWSA product (MMC) generated in this study is publicly available at: https://doi.org/10.6084/m9.figshare.29196617. The raw data used in this study are publicly available. The JPL GRACE mason product is available at https://grace.jpl.nasa.gov/. The WGHM TWSA simulations are available at https://doi.org/10.1594/PANGAEA.948461. The CDS soil moisture product is available at https://cds.climate.copernicus.eu.

https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

The CGWB data is available at https://indiawris.gov.in/wris/#/. GLDAS datasets are available at https://disc.gsfc.nasa.gov/datasets/GLDAS_NOAH025_M_2.1/summary?keywords=GLDAS.

Author contributions

BDV conceived and supervised the study. MRS processed the data and performed the experiments and drafted the manuscript. KSK contributed in developing example dataset. AS developed validation algorithm at initial steps. All authors contributed to the analysis of the results and commented on the manuscript.

Competing interests

The contact author has declared that none of the authors has any competing interests.

Acknowledgements

We thank ISRO STC program for their generous financial support, the STC cell at IISc and SAC team for continuous support. We are extremely thankful to India-WRIS CGWB for giving access to data.

References

Ali, S., Liu, D., Fu, Q., Cheema, M.J.M., Pham, Q.B., Rahaman, M.M., Dang, T.D. and Anh, D.T.: Improving the resolution of GRACE data for spatio-temporal groundwater storage assessment. Remote Sensing, 13(17), p.3513, https://doi.org/10.3390/rs13173513, 2021.

Arshad, A., Shafeeque, M., Tran, T.N.D., Mirchi, A., Xiang, Z., He, C., AghaKouchak, A., Besnier, J. and Rahman, M.M.: Multi-model ensemble machine learning-based downscaling and projection of GRACE data reveals groundwater decline in Saudi Arabia throughout the 21st century. Journal of Hydrology: Regional Studies, 60, p.102552, https://doi.org/10.1016/j.ejrh.2025.102552, 2025.

Bhanja, S.N., Mukherjee, A., Saha, D., Velicogna, I. and Famiglietti, J.S.: Validation of GRACE based groundwater storage anomaly using in-situ groundwater level measurements in India. Journal of Hydrology, 543, pp.729-738, http://dx.doi.org/10.1016/j.jhydrol.2016.10.042, 2016.

Chen, L., He, Q., Liu, K., Li, J. and Jing, C.: Downscaling of GRACE-derived groundwater storage based on the random forest model. Remote Sensing, 11(24), p.2979, https://doi.org/10.3390/rs11242979, 2019.

Gemitzi, A., Koutsias, N. and Lakshmi, V.: A spatial downscaling methodology for GRACE total water storage anomalies using GPM IMERG precipitation estimates. Remote Sensing, 13(24), p.5149, https://doi.org/10.3390/rs13245149, 2021.

https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

Girotto, M. and Rodell, M.: Terrestrial water storage. In Extreme hydroclimatic events and multivariate hazards in a changing environment (pp. 41-64). Elsevier, https://doi.org/10.1016/B978-0-12-814899-0.00002-X, 2019.

Gorugantula, S.S. and Kambhammettu, B.P.: Sequential downscaling of GRACE products to map groundwater level changes in Krishna River basin. Hydrological Sciences Journal, 67(12), pp.1846-1859, https://doi.org/10.1080/02626667.2022.2106142, 2022.

Gou, J. and Soja, B.: Global high-resolution total water storage anomalies from self-supervised data assimilation using deep learning algorithms. Nature Water, 2(2), pp.139-150, https://doi.org/10.1038/s44221-024-00194-w, 2024

Jyolsna, P.J., Kambhammettu, B.V.N.P. and Gorugantula, S.: Application of random forest and multi-linear regression methods in downscaling GRACE derived groundwater storage changes. Hydrological Sciences Journal, 66(5), pp.874-887, https://doi.org/10.1080/02626667.2021.1896719, 2021.

Kalu, I., Ndehedehe, C.E., Ferreira, V.G., Janardhanan, S., Currell, M. and Kennard, M.J.: Statistical downscaling of GRACE terrestrial water storage changes based on the Australian Water Outlook model. Scientific reports, 14(1), p.10113, https://doi.org/10.1038/s41598-024-60366-2, 2024.

Karunakalage, A., Sarkar, T., Kannaujiya, S., Chauhan, P., Pranjal, P., Taloor, A.K. and Kumar, S.: The appraisal of groundwater storage dwindling effect, by applying high resolution downscaling GRACE data in and around Mehsana district, Gujarat, India. Groundwater for Sustainable Development, 13, p.100559, https://doi.org/10.1016/j.gsd.2021.100559, 2021.

Kuruva, S.K., Suryawanshi, M.R., Shakya, A., Va, C., Shaw, B., Sukumaran, V., Kour, R., Kochar, A., Chander, S., Nikam, B.R. and Dasika, N.K.: Quality controlled, reliable groundwater level data with corresponding specific yield over India. Scientific Data, 12(1), p.1609, https://doi.org/10.1038/s41597-025-05899-5, 2025.

Lv, M., Xu, Z., Yang, Z., Lu, H., and Lv, M.: A Comprehensive Review of Specific Yield in Land Surface and Groundwater Studies. J Adv Model Earth Syst. 13, e2020MS002270, https://doi.org/10.1029/2020MS002270, 2021.

Miro, M.E. and Famiglietti, J.S.: Downscaling GRACE remote sensing datasets to high-resolution groundwater storage change maps of California's Central Valley. Remote Sensing, 10(1), p.143, https://doi.org/10.3390/rs10010143, 2018.

Mishra, V., Dangar, S., Tiwari, V.M., Lall, U. and Wada, Y.: Summer monsoon drying accelerates India's groundwater depletion under climate change. Earth's Future, 12(8), p.e2024EF004516, https://doi.org/10.1029/2024EF004516, 2024.

Müller Schmied, H., Cáceres, D., Eisner, S., Flörke, M., Herbert, C., Niemann, C., Peiris, T. A., Popat, E., Portmann, F. T., Reinecke, R., Schumacher, M., Shadkam, S., Telteu, C.-E., Trautmann, T. and Döll, P.: The global water resources and use model WaterGAP v2.2d: Model description and evaluation. Geosci. Model Dev., 14, 1037–1079, https://doi.org/10.5194/gmd-14-1037-2021, 2021.

Ning, S., Ishidaira, H. and Wang, J.: Statistical downscaling of GRACE-derived terrestrial water storage using satellite and GLDAS products. 70(4), pp.I_133-I_138, 2014. https://doi.org/10.2208/jscejhe.70.I_133.

Pascal, C., Ferrant, S., Selles, A., Maréchal, J.C., Paswan, A. and Merlin, O.: Evaluating downscaling methods of GRACE (Gravity Recovery and Climate Experiment) data: a case study over a fractured crystalline aquifer in southern India. Hydrology and Earth System Sciences, 26(15), pp.4169-4186, https://doi.org/10.5194/hess-26-4169-2022, 2022.

https://doi.org/10.5194/egusphere-2026-5587
Preprint. Discussion started: 29 September 2026

Sarkar, T., Kannaujiya, S., Taloor, A.K., Ray, P.K.C. and Chauhan, P.: Integrated study of GRACE data derived interannual groundwater storage variability over water stressed Indian regions. Groundwater for sustainable development, 10, p.100376, https://doi.org/10.1016/j.gsd.2020.100376, 2020.

Scanlon, B.R., Zhang, Z., Save, H., Wiese, D.N., Landerer, F.W., Long, D., Longuevergne, L. and Chen, J.: Global evaluation of new GRACE mascon products for hydrologic applications. Water Resources Research, 52(12), pp.9412-9429, https://doi.org/10.1002/2016WR019494, 2016.

Schumacher, M., Forootan, E., van Dijk, A.I., Schmied, H.M., Crosbie, R.S., Kusche, J. and Döll, P.: Improving drought simulations within the Murray-Darling Basin by combined calibration/assimilation of GRACE data into the WaterGAP Global Hydrology Model. Remote Sensing of Environment, 204, pp.212-228, https://doi.org/10.1016/j.rse.2017.10.029, 2018.

Sun, J., Hu, L., Chen, F., Sun, K., Yu, L. and Liu, X.: Downscaling simulation of groundwater storage in the Beijing, Tianjin, and Hebei regions of China based on GRACE data. Remote Sensing, 15(6), p.1490, https://doi.org/10.3390/rs15061490, 2023.

Tapley, B.D., Bettadpur, S., Ries, J.C., Thompson, P.F. and Watkins, M.M.: GRACE measurements of mass variability in the Earth system. science, 305(5683), pp.503-505, https://doi.org/10.1126/science.1099192, 2004.

Vishwakarma, B.D., Zhang, J. and Sneeuw, N.: Downscaling GRACE total water storage change using partial least squares regression. Scientific data, 8(1), p.95, https://doi.org/10.1038/s41597-021-00862-6, 2021.

Wahr, J., Swenson, S., Zlotnicki, V. and Velicogna, I.: Time-variable gravity from GRACE: First results. Geophysical Research Letters, 31(11), https://doi.org/10.1029/2004GL019779, 2004.

Yin, W., Hu, L., Zhang, M., Wang, J. and Han, S.C.: Statistical downscaling of GRACE-derived groundwater storage using ET data in the North China plain. Journal of Geophysical Research: Atmospheres, 123(11), pp.5973-5987, https://doi.org/10.1029/2017JD027468, 2018.