Response to reviewer's comments

Reviewer 2

We thank the reviewer for their comments. Our responses to all the comments are provided below.

Initial summary comment:

Strengths:

The manuscript by Suryawanshi et al. represents a strong effort to develop and validate a downscaling method for GRACE total water storage (TWS) anomalies over India. The authors propose a modified approach, called "Mascon-wise Mass Conserved" (MMC), building upon the methodology of Vishwakarma et al. (2021). The primary innovation lies in applying a mass conservation constraint at the native GRACE mascon scale (~3°x3°), rather than at the coarser catchment scale used in previous studies. A notable strength of the study is the large-scale validation framework, which integrates both statistical modeling and data assimilation within a hydrological context. The authors also compare MMC with previously published downscaling approaches, namely CMC (Vishwakarma et al., 2021) and DL (Gou and Soja, 2024). For this evaluation, they used the temporal "gain" metric introduced in a previous GRACE downscaling study in India (Pascal et al., 2022), which represents a positive step toward standardizing validation practices. The public release of the resulting dataset is also a valuable contribution to the community.

Weaknesses:

Despite these strengths, my principal concern relies on the hydrological validity of the downscaled product released. The manuscript lacks an appropriate discussion of the different hydrogeological contexts throughout India: huge irrigation, hydrogeological diversity, large dams and rivers, and small surface reservoirs simultaneously filling up with the monsoon and emptying with the dry season.

Response: We sincerely thank the reviewer for recognizing the strengths of our study, including the development of the Mascon-wise Mass Conserved (MMC) approach, the large-scale validation framework, comparison with previous methods (CMC and DL), use of the temporal *gain* metric, and the public release of the dataset. We greatly appreciate the positive assessment of these aspects.

We also thank the reviewer for highlighting the need to address the hydrological validity of the downscaled product across diverse contexts in India. In the revised manuscript, we will include a detailed discussion of different hydrogeological settings, including intensive irrigation areas, varied geological conditions, the influence of large dams and rivers, and small surface reservoirs that fill during the monsoon and drain during the dry season.

Comment 1: Missing downscaling methods and validation state of the art: The introduction does not adequately position the study relative to the state of the art, notably by failing to cite Pascal et al. (2022) as a framework for spatial and temporal validation of downscaling approaches in this specific Indian highly irrigated context. Missing downscaling studies in India should be discussed (Jyolsna et al., 2021 and Karunakalage et al., 2021). Similarly, the manuscript does not incorporate the full spatial and temporal validation approach proposed in Pascal et al., 2022. Should be justified or discussed somewhere.

Response 1: We appreciate the reviewer's comment. In the revised manuscript, we will strengthen the introduction by positioning our study relative to the current state of the art, including downscaling studies in India (e.g., Jyolsna et al., 2021; Karunakalage et al., 2021 and other).

I. We will do the following modification in introduction and will insert table of reference discussed in the introduction.

TWSA from GRACE is difficult to validate due to unavailability of in-situ TWSA 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). Another major challenging task to deal with is a coarse spatial resolution of GRACE data. Several hydrological, and agricultural studies demand regional/local scale inputs. To cater 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 depends on 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 model-based/statistical approach has gained popularity among researchers. Related studies are summarized in Table. The statistical approach has been primarily implemented in three ways: simple linear regression, multivariate linear regression, and machine learning algorithms. 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 (Karunakalage et al., 2021; Ning et al., 2014; Vishwakarma et al., 2021). To account for nonlinearity, researchers have also implemented machine learning algorithms such as random forest, artificial neural networks, and long short-term memory 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.

Table. 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	$1° \times 1°$	$0.1° \times 0.1°$	Greece
Yin et al. (2018)	Simple linear regression using ET	110 × 110 km	2 × 2 km	North China Plain
Multivariate linear regression				
Karunakalage et al. (2021)	Multivariate regression model with water budget closure constraint	$1° \times 1°$	$0.25° \times 0.25°$	Mehsana district, Gujarat, India
Ning et al. (2014)	Multivariate regression model with water budget closure constraint	$1° \times 1°$	$0.25° \times 0.25°$	Yunnan province, China
Vishwakarma et al. (2021)	Multivariate regression model with water budget closure constraint	$3° \times 3°$	$0.5° \times 0.5°$	Global
Machine learning algorithms				

Ali et al. (2021)	Artificial neural network and Random Forest	$1° \times 1°$	$0.25° \times 0.25°$	Indus basin irrigation system
Arshad et al. (2025)	Random forest, CART, Gradient tree boosting algorithms	55×55 km	1×1 km	Saudi Arabia
Chen et al. (2019)	Random Forest	$1° \times 1°$	$0.25° \times 0.25°$	Northeast of mainland China
Gorugantula and Kambhammettu (2022)	Long Short-Term Memory	$1° \times 1°$	$0.25° \times 0.25°$	Krishna River Basin, India
Gou and Soja (2024)	Convolutional eural network	$3° \times 3°$	$0.5° \times 0.5°$	Global
Jyolsna et al. (2021)	Multi variate regression, Random Forest	$1° \times 1°$	$0.25° \times 0.25°$	Four contrasting hydrogeological basins of India
Kalu et al. (2024)	Support Vector Machine (SVM) with water budget closure constraint	$1° \times 1°$	$0.25° \times 0.25°$	Northern Australia (the Cambrian Limestone Aquifer—CLA)
Miro and Famiglietti (2018)	Artificial neural network	2,00,000 km^2	16 km^2	California's Central Valley
Pascal et al. (2022)	Multi linear regression, Random Forest	$3° \times 3°$	$0.5° \times 0.5°$	A fractured crystalline aquifer in southern India

II. Section 3.3 will be modified to explain why only the temporal gain is implemented and not the spatial gain from Pascal et al. (2022).

3.3 Evaluation of downscaled products

First, validation of all three downscaled products is performed using Ref-GWSC measurements by computing the Correlation Coefficient (r) and Root-Mean-Square Error (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 low-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 validation 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, the reference values are uniform over each mascon.

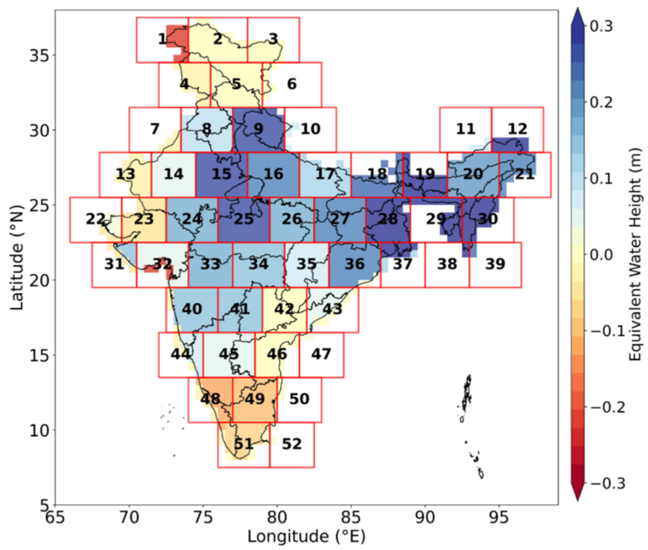

Figure x. GRACE mascons over India for September 2004. Red boxes represent mascon boundaries.

Comment 2: Missing Table 2 Specific Yield of aquifers: Methodologically, the transformation of groundwater levels into groundwater storage (GWS) relies on specific yield, yet Table 2, which should detail the assigned specific yield values for different aquifer types, is missing, limiting transparency and reproducibility. The choice of eight clusters for k-means clustering is arbitrary and unsubstantiated, raising concerns about the spatial reliability of the reference dataset (Ref-GWSC). The assigned specific yield values appear disconnected from geologically coherent units, and the exclusive use of temporal gain for validation neglects the assessment of spatial variability within mascons, which is a fundamental objective of downscaling.

Response 2: We thank the reviewer for these important comments. In the revised manuscript, we will address these points as follows:

1. We will include hydrogeological map (Figure and Table) (Bhanja et al., 2016) as shown below to clearly list the assigned specific yield values for different aquifer types, ensuring transparency and reproducibility of the groundwater storage calculation.

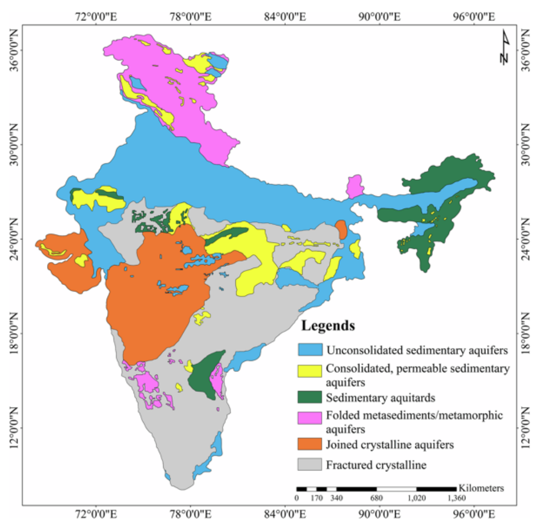

Figure. Hydrogeology map of India (Kuruva et al., 2025)

Table. Specific yield values for varying hydrogeologic setting shown Figure x (Source: Bhanja et al., 2016)

S.No	Hydrogeology	S_y range	Mean S_y
1	Unconsolidated sedimentary	0.06 to 0.20	0.130
2	Consolidated, permeable sedimentary	0 to 0.08	0.043
3	Sedimentary aquitards	0 to 0.03	0.018
4	Folded metasediments/metamorphics	0 to 0.03	0.018
5	Jointed crystalline	0.01 to 0.03	0.020
6	Fractured crystalline	0 to 0.04	0.023

2. We acknowledge that the choice of eight clusters for k-means clustering may appear arbitrary. We recognized that the use of k-means clustering on RGB values introduces unnecessary uncertainty and risks misclassifying hydrogeological units due to which we will replace this approach with a vectorization-based method using Quantum Geographic Information System (QGIS) as adopted by Kuruva et al. (2025). We will modify methodology as follows:

   3.1.1 Conversion of GWL changes to groundwater storage changes

   To compute GWSC (m EWH), quality controlled GWL change (GWLC) is multiplied with Specific Yield (SY). Where SY is a dimensionless factor that indicates the fraction of total ground water volume that would yield under gravity and is used to convert water level to water storage. Fundamentally it is a hydrogeological property of an aquifer.

   These SY values are extracted from hydrogeology map of India (Figure x and Table x. Source: Bhanja et al., (2016)) at quality-controlled well locations using vectorization method in Quantum Geographic Information System (QGIS) platform. The required raster layer of hydrogeology map is downloaded from https://doi.org/10.6084/m9.figshare.29293877.v3 (Kuruva et al., 2025). Then quality controlled GWLs are converted into point shape file and overlaid on this raster layer to extract SY values at each well location using “sample raster values” tool in QGIS. The obtained SY is multiplied with quality controlled GWLC to get reference groundwater storage changes referred as Ref-GWSC.

3. We didn’t extend the validation framework by incorporating the spatial gain metric as we are using GRACE JPL mascon as it is (i.e., without multiplying with scale factor) as our low-resolution reference in the present study. These scale factors are computed using a model and are multiplicative in nature, which means any uncertainty in GRACE product will be inflated by the scale factor if the model does not agree with the truth. Vishwakarma et al., 2017 has shown that scale factor method can do more damage than good. The mascons over India for September 2004 is shown below. The Figure demonstrates that there is no spatial variability within individual mascons. Therefore, the spatial gain metric is not incorporated in this study.

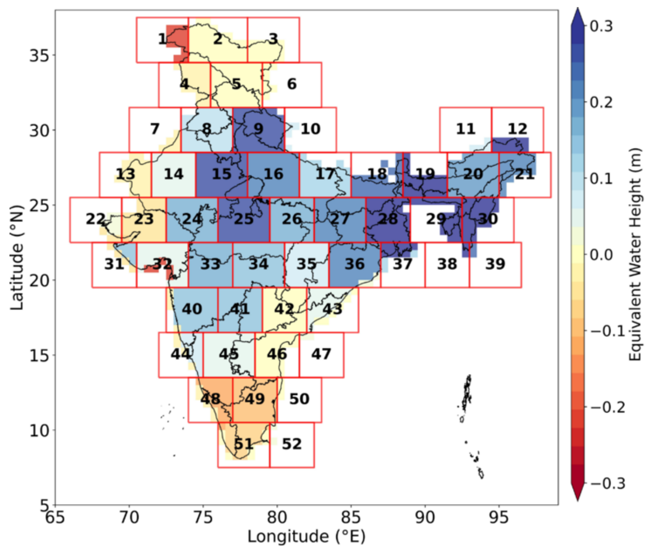

Figure. GRACE mascons over India for September 2004. Red boxes represent mascon boundaries.

Comment 3: Surface water fluctuation neglected: The validation relies on well-known Central Ground Water Board groundwater levels across 22 mascons, showing that native GRACE explains only 56% of in situ GWS variability. This implies that the remaining variability arises from surface and soil water storage, a well-documented phenomenon in both the Ganges-Brahmaputra basin (Salameh et al., 2017) and southern India, particularly Telangana. In Telangana, the cumulative capacity of large reservoirs on main rivers is estimated at 113 mm of equivalent water height, and small upstream reservoirs contribute an additional 30 mm, representing approximately 24% of the TWS signal over the period 2002–2021 (Pascal et al., 2021). This potential reservoir capacity of 143 mm represents about 24% of the annual GRACE TWS fluctuation in the area during 2002–2021 (600 mm). However, the authors interpretation that reservoirs are "rarely simultaneously full" is misleading: under the monsoonal regime, filling generally occurs simultaneously during the wet season and drawdown during the dry season as well. The decision to neglect this contribution can only be justified on practical grounds, namely the difficulty of obtaining reliable regional data on the filling dynamics of both large and small reservoirs, but not on theoretical arguments about negligible impact. Suryawanshi et al. consider surface water negligible based on tests over only two reservoirs, and they appear to generalize these results to the entire country, which is an overextension.

Response 3: We thank the reviewer for this insightful comment. In the revised manuscript, we will explicitly acknowledge the role of available surface water bodies as well as other components of water storages using WGHM (WaterGAP Hydrology Model) output. This TWS product comprises of various water storages such as canopy water storage, snow water equivalent, soil moisture, river streams, lakes, reservoir, wetlands and groundwater. To align with GRACE TWSA base line, we generated TWSA from WGHM by removing mean of baseline period (2004 to 2009). In addition, separate ground water storage product from WGHM is also downloaded and subtracted from WGHM TWS to isolate the water storages due to canopy, snow, soil moisture, river streams, lakes, reservoirs, and wetlands. This isolated water storage component is further used to sperate the groundwater storage component from TWSA products used in the study. Based on this validation methodology will be revised. For instance section 4.1 will be modified as follows and subsequently other sections will also be modified.

4.1 Validation statistics for GRACE GWSC at native resolution ($3^{\circ} \times 3^{\circ}$) across India

Figure 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, 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 clutered in the right side of the mascon, still showed a good correlation of 0.63. Whereas mascon 16 has a fairly well distributed network of wells, still 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 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.

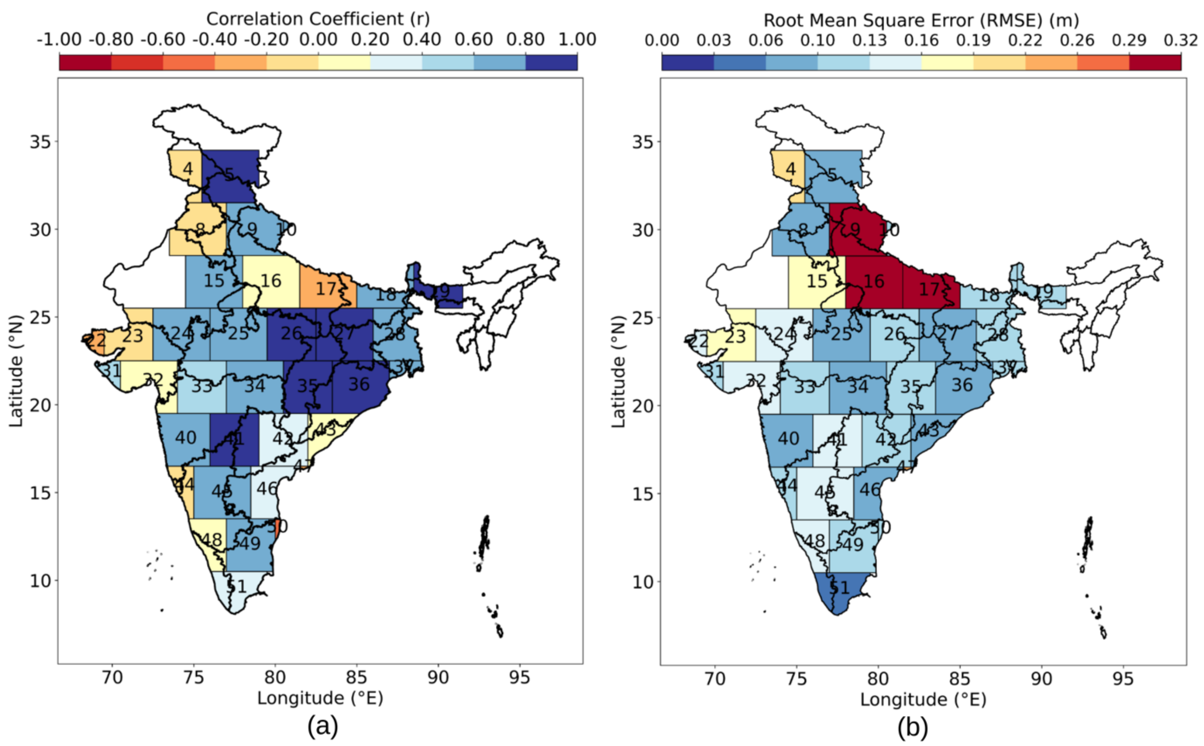

Figure. Mascon-wise maps of (a) the correlation coefficient (r) and (b) RMSE between GRACE GWSC and ref-GWSC over India.

Comment 4: Deconvolution problem for validation with the ref-GWSC: Consequently, the downscaling approach risks misattributing surface water fluctuations, due to reservoir filling and releases, to groundwater storage. By considering only surface soil moisture (~5 cm) and neglecting the majority of reservoirs, the study likely overestimates GWS, and the signal attributed to GWS becomes a hybrid of groundwater and surface water. Such misinterpretation can distort seasonal dynamics, for instance by incorrectly suggesting rapid aquifer recharge when TWS increases during monsoon reservoir filling. Overall, the study underestimates the importance of surface water in TWS deconvolution, and the resulting GWS product may therefore be systematically biased, which leads to an impossibility to validate this published downscaled TWS dataset.

Response 4: We thank the reviewer for this detailed and important comment. We acknowledge that by considering only surface soil moisture (~5 cm) and omitting most reservoirs, the downscaled product may partially conflate groundwater storage (GWS) with surface water fluctuations, potentially biasing seasonal dynamics. As mentioned in "Response 4" we will be using WGHM TWS products. In this product soil moisture storage is computed up to root zone depth ranging between 0.1 m to 4 m, which provides a more realistic representation of subsurface storage dynamics. Furthermore, the inclusion of surface water components such as rivers, lakes, wetlands, and reservoirs in WGHM will help reduce the risk of misattributing surface water variability to groundwater. This refinement should improve the physical consistency of the downscaled TWS–GWS separation and enhance the reliability of the validation against the ref-GWSC dataset.

Please note that additionally, in the revised manuscript, we will extend the Mascon-wise Mass Conservation (MMC) downscaled product up to December 2023, thereby improving the temporal coverage of the dataset.

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