An empirical spatial downscaling of GRACE by statistical assimilation of multiple hydrological variables

Jinwei Zhang, Nico Sneeuw

Institute of Geodesy, University of Stuttgart

Introduction

The global coverage of GRACE allows to monitor the water mass change. However, the coarse spatial resolution of GRACE products limits GRACE large-scale applications. The increasing demand of small-scale hydrological studies drives us to improve the spatial resolution of GRACE. Apart from expecting a highly improved resolution from the next generation of GRACE, one possibility is to downscale the GRACE product by assimilation with data in finer resolution. Therefore, in this study, we propose a statistical empirical model for spatial downscaling of GRACE by assimilating GRACE data with terrestrial water storage change from WGHM and multiple hydrological variables from highly-resolved models. In contrast with conventional assimilation approaches, our algorithm is implemented without any dynamic model assumptions.

Methodology

A moving average partial least-squares regression (MA-PLR) model is applied for assimilation of GRACE and WGHM.

- Expand observation matrix ***L*** by a moving-average ensemble

$$L_i = \begin{bmatrix} L(t_1) & L(t_1-1) & \cdots & L(t_1-k+1) \\ L(t_2) & L(t_2-1) & \cdots & L(t_2-k+1) \\ \vdots & \vdots & \ddots & \vdots \\ L(t_n) & L(t_n-1) & \cdots & L(t_n-k+1) \end{bmatrix},$$

$$L = \begin{bmatrix} L_1 & L_1 & \cdots & L_i \end{bmatrix}$$

- Calculate cross-covariance matrix C_{LS} between observations ***L*** and predictands ***S***
- Apply singular value decomposition on covariance matrix***:***

$$C_{LS} = L_0^T S_0 = U_C \Sigma_C V_C^T$$

- Recast the regression model into

$$U_L = L_0 U_C,$$

$$S_0 = L_0 H = U_L U_C^T H = U_L K$$

- Train the prediction matrix ***K*** on the joint modes from ***L***

$$\hat{K} = (U_L^T U_L)^{-1} U_L^T S_0$$

- Transform the prediction matrix from mode level to signal level

$$\hat{H} = U_C \hat{K}$$

- Predict ***S*** by ***H:*** $\hat{S} = L \cdot \hat{H}$

Table 1: *Observation and predictand matrices in training and predicting.*

	Observations *L*	Predictands *S*
Training	• TWS residual aggregates from GRACE • Ensembles of *P, ET, R* residuals from models	Differential TWS by subtracting the GRACE full signal from WGHM $\Delta TWS_{\mathrm{WGHM}} = TWS_{\mathrm{WGHM}} - TWS_{\mathrm{GRACE}}$
Predicting	• TWS residual aggregates from GRACE • Ensembles of *P, ET, R* residuals from models	Assimilated Δ*TWS*

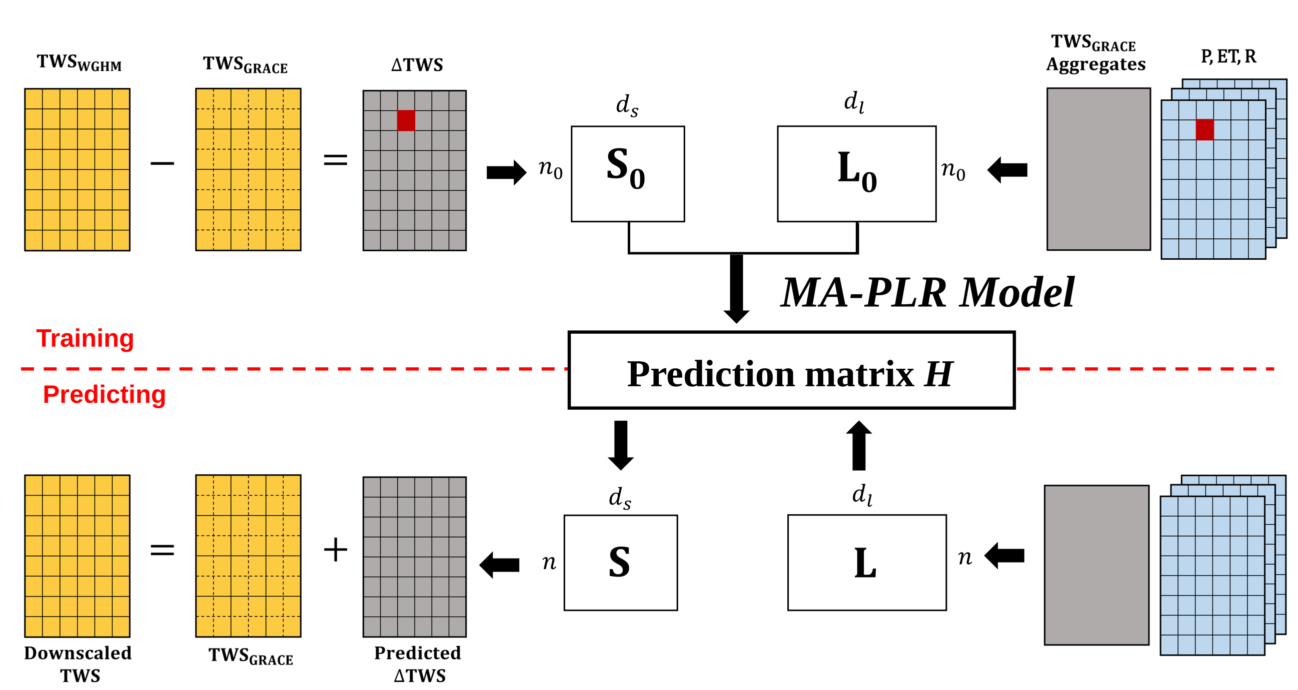

Figure 1: *Illustration of the scenario for GRACE product downscaling. Moving average partial least-squares regression (MA-PLR) model is employed for training and predicting.*

Assimilation Results

Table 2: *Datasets which are used in the assimilation. All the datasets are* $1° \times 1°$ *averages, and therefore the TWS are assimilated into a* $1° \times 1°$ *grid.*

Variables	Datasets and resolution
TWS	GRACE , WGHM (0.5° × 0.5°)
P	GPCP (2.5° × 2.5°), GPCC (0.5° × 0.5°), TRMM (0.5° × 0.5°), PERSIANN (0.5° × 0.5°), ECMWF (0.5° × 0.5°)
ET	ECMWF (0.5° × 0.5°), GLEAM (0.5° × 0.5°)
R	GLDAS-NOAH (0.25° × 0.25°), GLDAS-CLM (1° × 1°), GLDAS-MOS (1° × 1°)

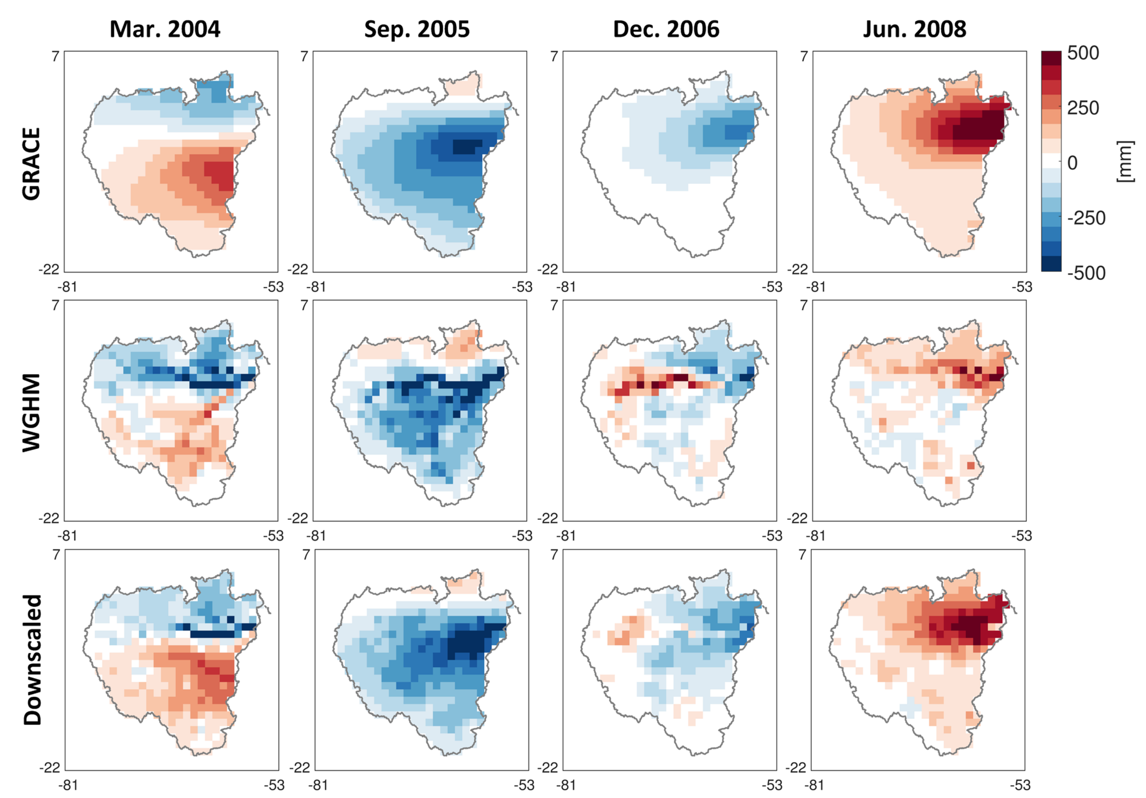

Figure 2: *The TWS in Amazon basin is downscaled to a* $1° \times 1°$ *grid by statistical assimilation of multiple hydrological models, comparing with TWS grids from GRACE and WGHM, at four different epochs (i.e., March 2004, September 2005, December 2006, June 2008).*

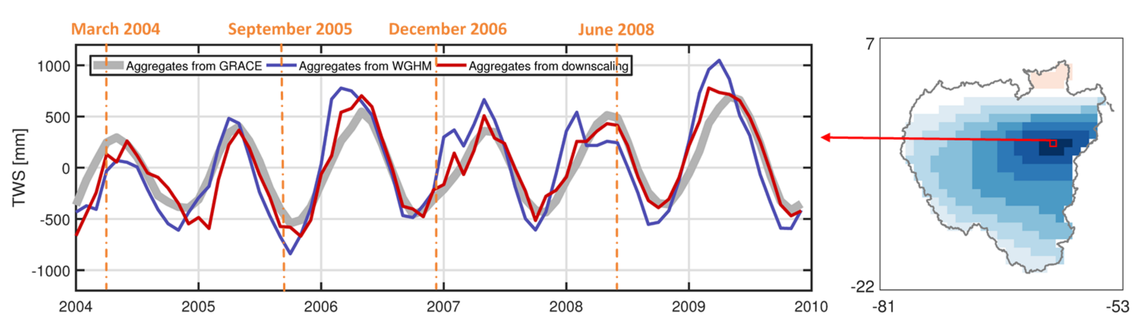

Figure 3: *Monthly assimilated TWS of one arbitrary grid point in Amazon, comparing with TWS from GRACE and WGHM. The four epochs represented in Figure 2 are marked by orange dashed lines.*

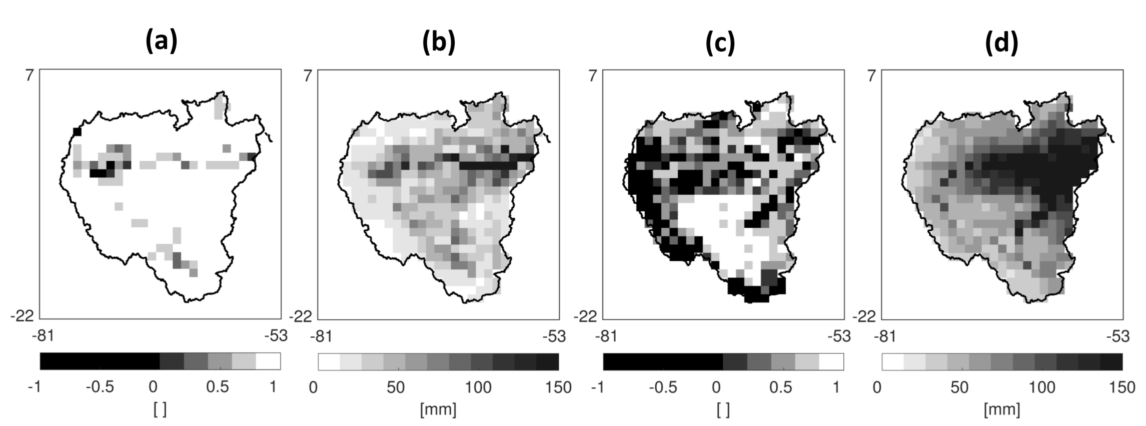

Figure 4: *(a) The NSE and (b) the RMSE of downscaled TWS in the Amazon basin with respect to GRACE. (c) The NSE and (d) the RMSE of downscaled TWS with respect to WGHM. From black to white color indicates better performances.*

Results Analysis

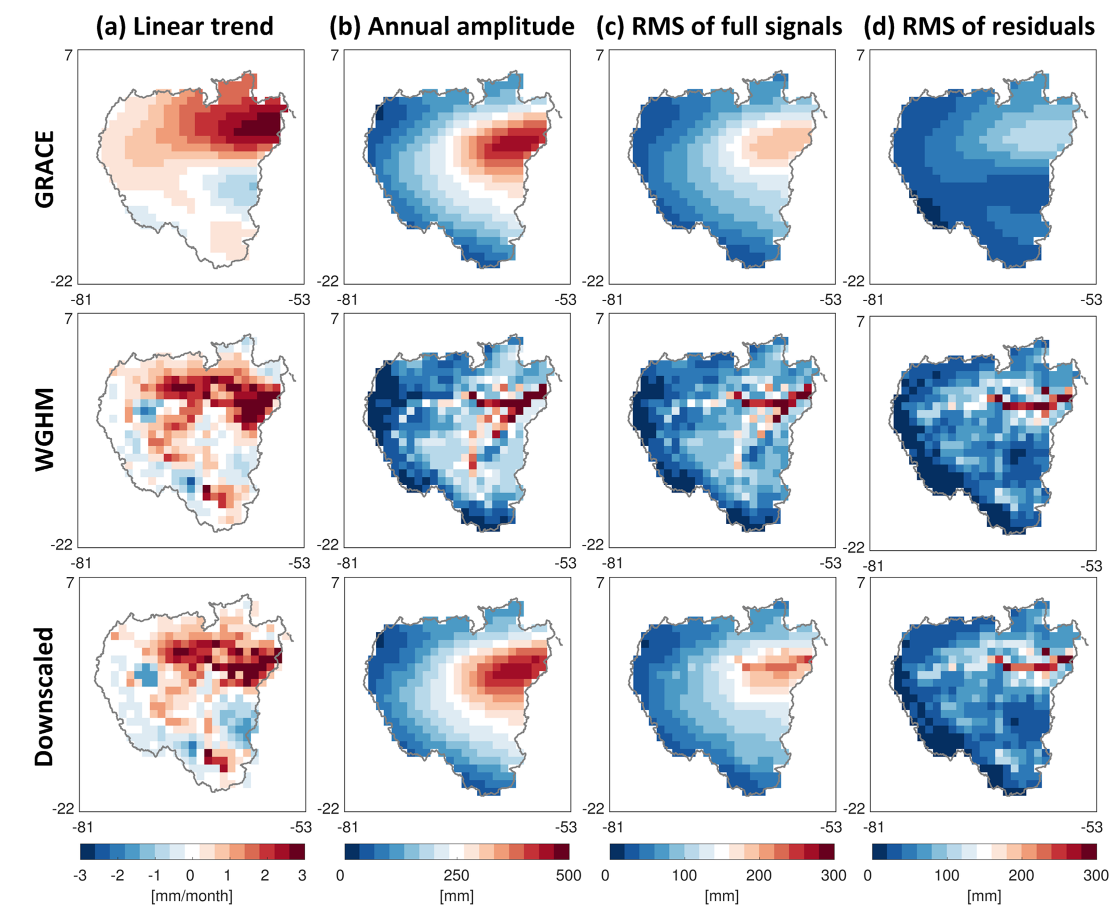

Figure 5: *(a) The linear trends, (b) the annual amplitudes, (c) the RMS of full signals, and (d) the RMS of the residuals of TWS grids in Amazon basin from GRACE, WGHM and downscaling. The linear trend and annual amplitude are quantified by a least-squares linear and harmonic regression.*

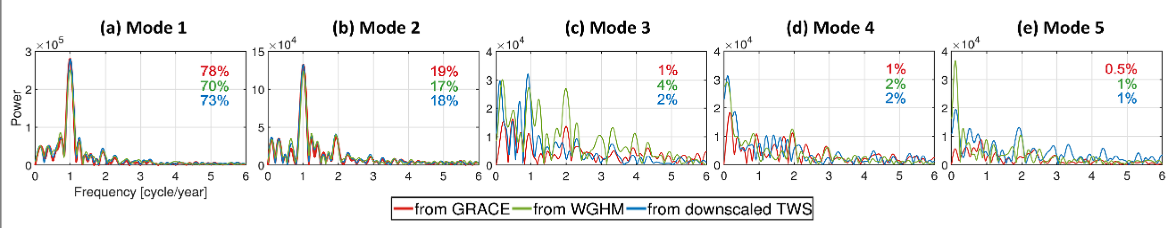

Figure 6: *The power spectra of the temporal PCs from the first 5 modes of the TWS in the Amazon basin, which are obtained from GRACE, WGHM and assimilation, respectively. Mode 1 and 2 of all three fields contain annual components. Mode 3, 4, 5 explain the differences among GRACE, WGHM and downscaling results in Figure 5.*

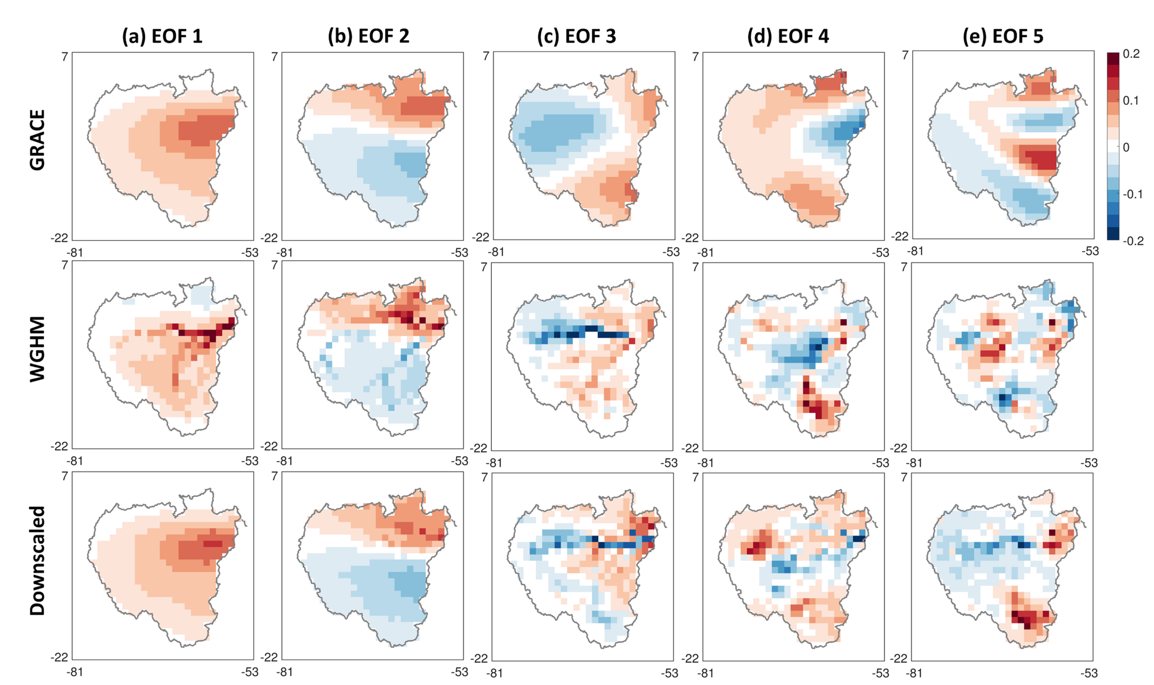

Figure 7: *The spatial EOFs of the first 5 modes, corresponding to the temporal PCs of TWS in the Amazon basin, produced from GRACE, WGHM and assimilation results. The assimilation inherits the mode 1 and 2 in GRACE, retaining the annual variation, while makes use of mode 3, 4, 5 in WGHM, improving the spatial resolution of GRACE.*

Validation

- The misclosure ε of terrestrial water balance in a catchment is calculated by $\varepsilon = P - ET - R - \dfrac{dM}{dt}$
- The water storage flux is calculated by the first derivative of water storage change $\dfrac{dM}{dt} = \dfrac{TWS(t+\Delta t) - TWS(t-\Delta t)}{2\Delta t}$

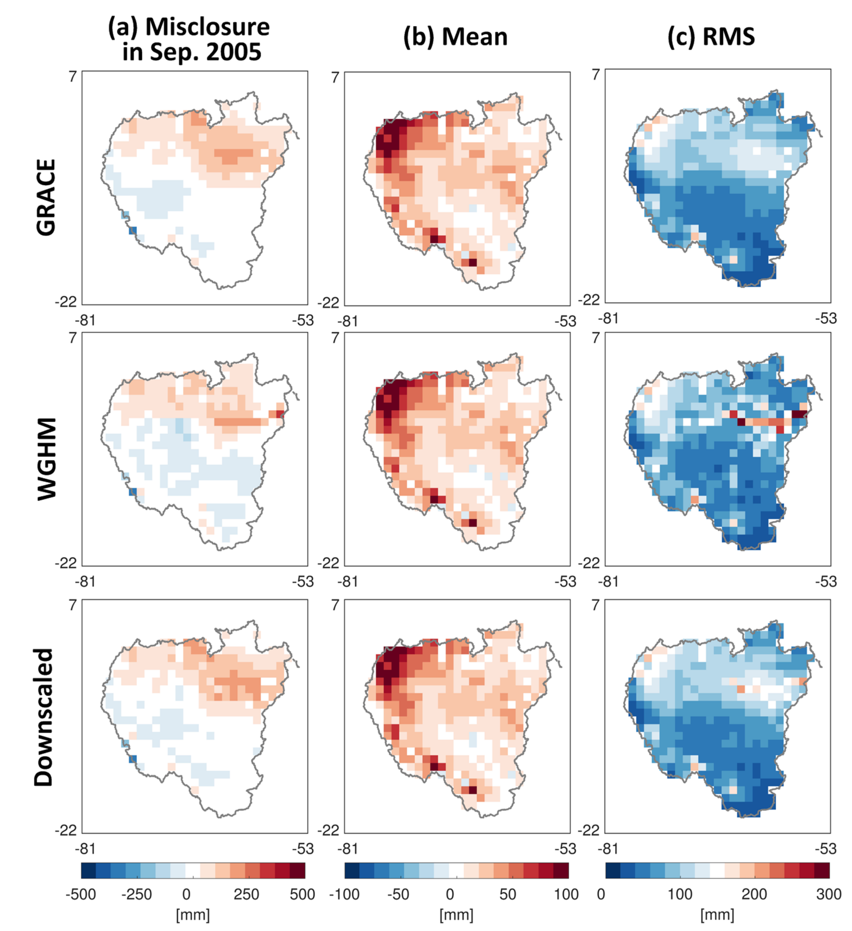

Figure 8: *(a) The misclosure of the water balance in Amazon basin at epoch September 2005, and its (b) mean and (c) RMS from GRACE, WGHM and assimilation results. The consistency between downscaled grids and GRACE suggests that this assimilation maintains the same level of accuracy as GRACE, although it does not evidently improve the accuracy of TWS observed by GRACE .*

The ensemble means of all the models listed in Table 2 for each variable P, ET, R are used to calculate the imbalance of water budget in the Amazon basin.

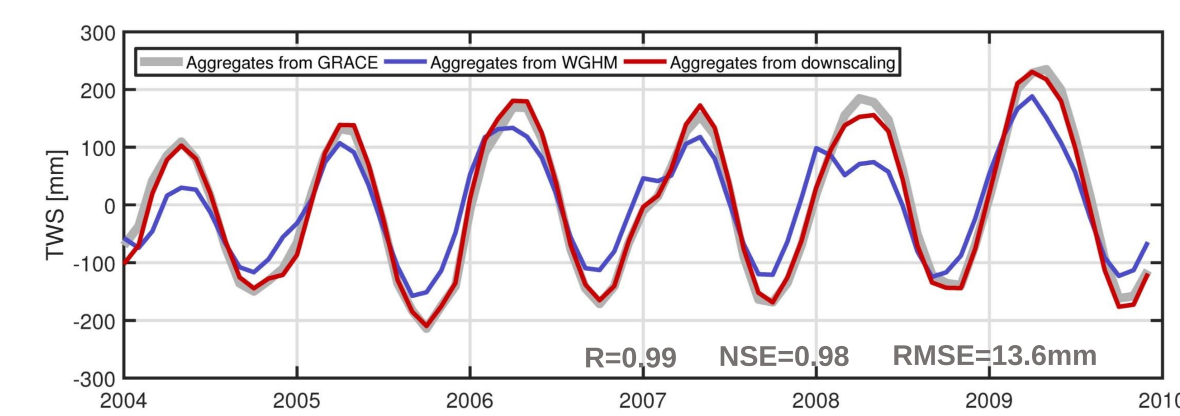

Figure 9: *Monthly aggregates of TWS over the Amazon basin from assimilation, comparing with TWS aggregates from GRACE and WGHM. The consistency of aggregated TWS with GRACE satisfies the condition of mass conservation. The correlation (R), NSE and RMSE of assimilated TWS with respect to GRACE are shown in the figure.*

Conclusion, Discussion and Outlook

- A higher spatial resolution of TWS is achieved with empirical information from WGHM.
- The assimilated TWS retains the dominant signals from GRACE.
- MA-PLR model demonstrates its capability and potential in data assimilation and statistical downscaling.
- Further validation with in-situ ground measurements still needs to be done in the future.
- It is still uncertain that our downscaling framework is also applicable for boreal catchments, which contain both solid and liquid mass variation.

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zhang@gis.uni-stuttgart.de
sneeuw@gis.uni-stuttgart.de
https://www.gis.uni-stuttgart.de/