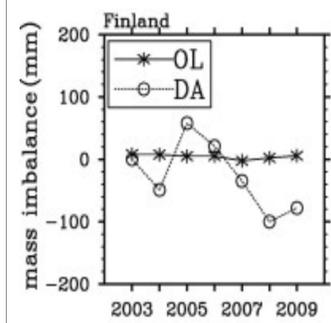


Data Assimilation of Terrestrial Water Storage to Adjust Precipitation Fluxes

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Motivation & Background

Quantification of precipitation errors has been a longstanding challenge (Adler et al., 2012). Previous work by Behrangi et al., (2017, 2018); Swensen et al., (2010); Humphrey et al., (2016) indicates that GRACE is a viable alternative to constrain precipitation estimates. Existing GRACE data assimilation schemes typically update **prognostic hydrological states** (i.e., groundwater, soil moisture, and snow water equivalent variables). We propose an alternate approach in which precipitation fluxes are adjusted.

Potential limitations of the methods:

- The assumption that all errors in TWS originate from errors in precipitation.

Potential benefits of the alternate approach:

- The water balance is maintained, as opposed to having to add increments to the prognostic states
- The model automatically determines how to distribute the updates among the prognostic states

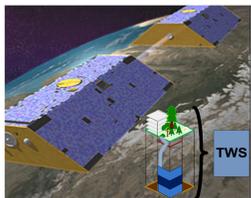
Fig. 1. Annual mass imbalance for open loop (OL) (i.e., no assimilation) and for the data assimilation (DA) of GRACE-DA for a watershed in Finland. (figure from Li et al., 2012). The DA case does not maintain the water balance ($\Delta TWS = P - ET - Q$)

GRACE Observations

- Gravity observations to provide Terrestrial Water Storage (TWS) anomalies
- Launched Mar 2002
- Sensitive to mass changes of the prognostic hydrological states (e.g., groundwater, soil moisture, snow, etc.)
- Coarse temporal resolution (**monthly**); Coarse spatial resolutions (~300 km)

Fig 2. GRACE satellites.

*TWS = groundwater (GW) + soil moisture (SM) + surface water storage + snow (SWE) + canopy storage



Methods

- **Step 1:** for each month (m) and each model grid, generate an ensemble (j is an ensemble realization) of precipitation fluxes (P):

$$P_j^- = b_{j,m}^- \cdot P_{nom} \quad \text{where } b_{j,m}^- \text{ are the precip. errors prescribed as: } b \sim \text{Log}(1, 0.5)$$

- **Step 2:** run the model forward for one month, at the prescribed model time step
- **Step 3:** at the end of the month update the precipitation errors using an ensemble Kalman Filter approach:

$$b_{j,m}^+ = b_{j,m}^- + K[Z_j - M(b^j)] \quad ; \text{ where:}$$

- superscripts "+" and "-" indicate the posterior (after assimilation) and prior (before assimilation)
- $Z_j - M(b^j)$ are the GRACE TWS observations minus forecast observation predictions (i.e., innovations)
- K is the Kalman gain, obtained as: $K = C_{bM}[R + C_{MM}]^{-1}$
- R is the measurement error covariance, and C_{MM} the sample error covariance of the observation predictions.

- **Step 4:** rewind the model to the beginning of the month and re-run the model with the updated (hopefully more realistic) precipitation inputs

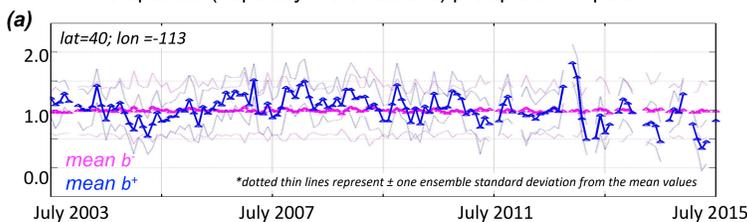
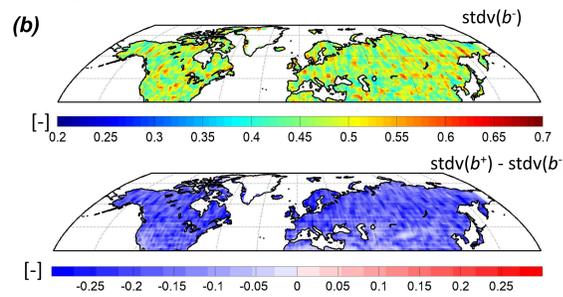


Fig. 3. (a) Example time series of the precipitation errors for a grid in Utah. (b) top: typical monthly ensemble standard deviation (i.e., ensemble spread) of the openloop (i.e., no assimilation), bottom: reduction in ensemble standard deviation ($DA_{stdv} - OL_{stdv}$) between the data assimilation (DA) and openloop for the precipitation errors (b).



Experiment Setups

- Catchment Land Surface Model (CLSM), GEOS-5 to solve: $\frac{dTWS(t)}{dt} = [P(t) - ET(t) - Q(t)]dt$
- Period of investigation: July 2003 to July 2016
- Domain: North Hemisphere above 30 deg. North at spatial res. 36 km EASEv2 grid;
- Nominal precipitation (P_{nom}) from MERRA-2 AGCM (non corrected, Reichle et al. 2017)
- Experiment #1: Open loop (OL), or free model run
- Experiment #2: Data assimilation (DA) where GRACE TWS are assimilated to update precip. errors

TWS components:
 [1]: catchment deficit
 [2]: root zone excess
 [3]: surface soil excess
 [4-6]: snow
 [7]: canopy storage

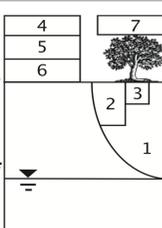


Fig 4. Schematic of Catchment Model [Koster et al., 2000].

Observations for Validation

- Global Precipitation Climatology Project (GPCP, Adler et al., 2003). Monthly global precipitation data on a 2.5deg resolution.

Results

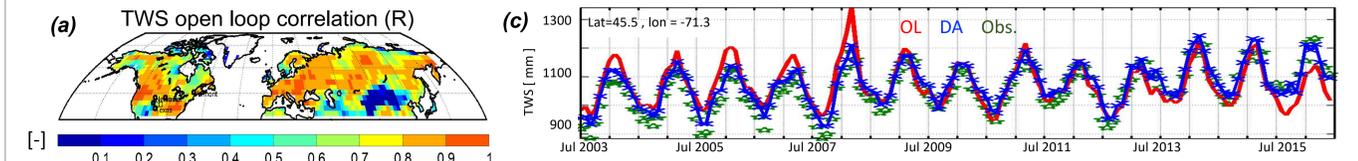


Figure 5. (a) Correlation skill between open loop (OL) and observed GRACE TWS. (b) difference in skill (ΔR) between the data assimilation (DA) and openloop (i.e., no assimilation) TWS. (c) Example OL, DA and observed TWS for a location in Vermont. This is a consistency check, it indicates that the assimilation of TWS brings modeled TWS closer to the observed TWS

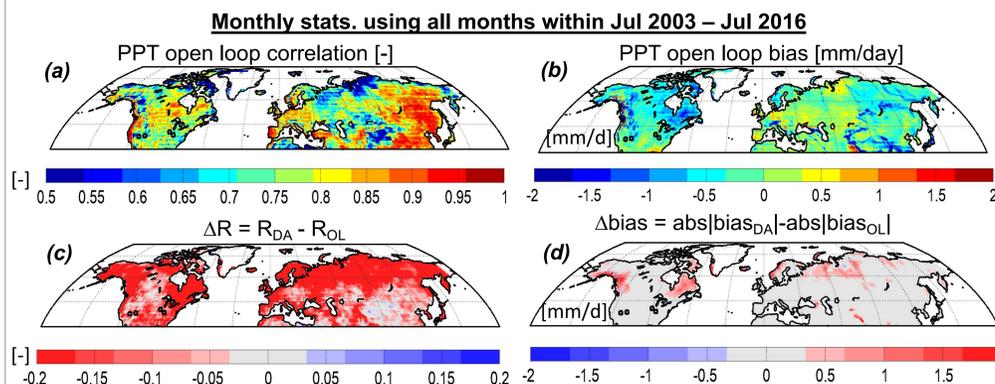


Figure 6. (a) Correlation R and (b) bias skill between open loop (OL) and observed GPCP precipitation (bias is calculated as $obs. - OL$). (c) ΔR and (d) $\Delta bias$ difference in skill (between the data assimilation (DA) and openloop (i.e., no assimilation) TWS. This is an independent validation and it suggests that the assimilation of TWS leads to degraded precipitation estimates.

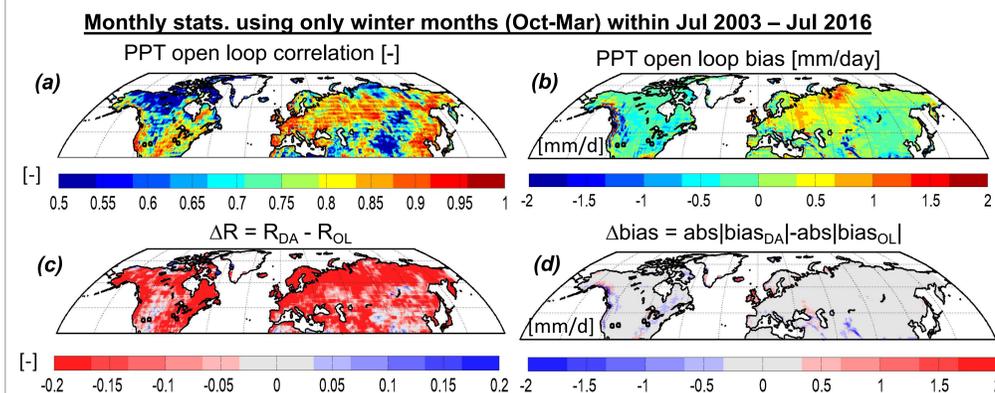


Figure 7. Same as Figure 6 but using only winter months (Oct-Mar) within the July 2003 - July 2016 period. This suggests that the assimilation of TWS leads to degraded precipitation R skills but to some very marginal improvements on winter season bias.

Conclusion and Open Questions

- By adjusting precipitation fluxes we can retrieve the assimilated GRACE TWS (Figure 5)
- But, the DA estimated precipitation fluxes are degraded (Figure 6, 7)
- Potential explanations and areas of further analysis:
 - Precipitation is not the only source of uncertainty for TWS. Are we neglecting other sources of errors (e.g., runoff, ET partitioning)?
 - Are we neglecting temporal/spatial scale mismatches between the assimilated observations and precipitation? E.g., should we just focus on winter times? Or endorheic basins?
 - Other explanations?

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