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 Behnang et al. (2017, 2018); Swenson 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.

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)

Methods

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

\[ P_{j}^{m} = \sum_{n} \frac{\text{precip. errors prescribed as: } b - \log(1,0.5)}{\text{run model forward for one month, at the prescribed model time step}} \]

Step 2: At the end of the month update the precipitation errors using an ensemble Kalman Filter approach:

\[ b_{j}^{m} = b_{j}^{m-1} + K(Z - M(b^{m-1})) \]

- superscripts "*j*" and "m" indicate the posterior (after assimilation) and prior (before assimilation)
- \( Z \) is the GRACE TWS observations minus forecast observation predictions (i.e., innovations)
- \( K \) is the Kalman gain, obtained as: \( K = C_{w} (R + C_{w})^{-1} \)
- \( R \) is the measurement error covariance, and \( C_{w} \) the sample error covariance of the observation predictions.

Step 2: Refine the model to the beginning of the month and re-run the model with the updated (hopefully more realistic) precipitation inputs.

Observations for Validation

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

Results

- **Figure 5.** (a) Correlation coefficient between open loop (OL) and observed GRACE TWS. (b) Difference in skill (ΔR) between the data assimilation (DA) and open loop (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.

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:
  - 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 endemic basins?
  - Other explanations?

References: