A long-term statistical reconstruction of GRACE water storage to evaluate land surface models

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Water storage

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  - Limits evaluation potential for rare features (wet/dry extremes)
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  - Limits evaluation potential for rare features (wet/dry extremes)

- Can we reconstruct past conditions?
Outline

1. A statistical approach (methodology)

2. Comparison with physical models (e.g. LSMs, GHMs)

3. Open questions / discussion
Objective
A statistical reconstruction of TWS

- Based on atmospheric forcing from reanalysis
  - Precipitation & mean temperature (ERA-Interim)
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A statistical reconstruction of TWS

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- With uncertainty quantification
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- Focus on the anomalies (de-seasoned, de-trended signal)
Statistical modeling approach

- Anomalies

Full TWS signal (GRACE JPL Mascons)

Anomalies
Statistical modeling approach

- Anomalies

Full TWS signal (GRACE JPL Mascons)

Anomalies

This example is mascon #856

http://ccar.colorado.edu/grace/
Statistical modeling approach

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  - Exponential decay filter applied to precipitation (= linear store model)

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\[ TWS_{REC} = \beta_1 (P^{\tau}_{\text{inter+subseas}}) + \beta_2 T_{\text{inter}} + \epsilon \]

- Three free parameters \((\tau, \beta_1, \beta_2)\)
Results

Equivalent Water Height [mm]

Time


-600 -400 -200 0 200 400 600

GRACE
Reconstruction (r=0.89)
Results

- Short-term dynamics are coherent with physical models
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- Better representation of signal amplitude and inter-annual variability
Global model performance (comparing with GRACE)

Limitations

- Only climate-driven TWS is reconstructed
  - No representation of human influences (irrigation, dams, etc)
  - Climate-driven trends to be interpreted with caution

- Sensitive to the quality of the atmospheric forcing
Open question / discussion

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![Graph showing true precipitation and modeled precipitation over time.](image-url)
Open question / discussion

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  - Diagnose where the DA improvement comes from:
    - errors in modeled forcing VS errors in modeled response
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  - Would not replace Earth observations
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- Limitation
  - Would not replace Earth observations
  - Highly susceptible to errors in modeled forcing
    - In DA, leads to the confirmation of a model error!
Conclusions

- A data-driven statistical reconstruction of TWS
- For climate-driven TWS variability
- Potential for long-term ESM evaluation

Open-access TWS reconstruction dataset

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- For climate-driven TWS variability
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Thank you for your attention!

Open-access TWS reconstruction dataset

Back-up slides
Statistical modeling approach

- How to quantify the uncertainty?
How to quantify the uncertainty?

- Parameter uncertainty (through Markov Chain Monte Carlo)
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  - Residuals ($\approx$ unmodeled signals + noise)

Residuals: AR(1) Gaussian process, $\epsilon_t = \epsilon_{t-1} \cdot \rho + \mathcal{N}(0, \sigma)$
Statistical modeling approach

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  - Parameter uncertainty (through Markov Chain Monte Carlo)
  - Residuals ($\approx$ unmodeled signals + noise)
Statistical modeling approach

- How to quantify the uncertainty?
  - Parameter uncertainty (through Markov Chain Monte Carlo)
  - Residuals (≈ unmodeled signals + noise)
Cross-validation experiment

- Training on the period 2012-2015 (37 months)
- Testing on the period 2002-2010 (102 months)
- Minor degradation in model performance
- Model not prone to overfitting
Consistency check

- How does the reconstruction perform in the past?

- Compare the reconstruction with LSMs
  - 2002-2009 (left boxplots)
  - 1985-1992 (right boxplots)

- Reconstruction and LSMs compare similarly under present and past conditions
Trends in TWS (1)

- Trends should be considered very carefully
  - Potential drifts in land surface models
  - Reconstruction not explicitly calibrated/validated for trends

Non-seasonal global land water storage (excl. Greenland & Antarctica)

- Equivalent Water Height [mm]
- Time
- GRACE, GLDAS2-NOAH, WGHM, CLM, ERALand
Trends in TWS (2)
Over 2002-2009
Model performance (all)
Parameter identification

- Bayesian estimation of the parameter distribution
  - Using Marlo Chain Monte Carlo (algorithm of Haario et al. 2006)

- Three free parameters
  - $\tau$: steepness of the decay filter
  - $\beta_1$: scaling coefficient for precipitation
  - $\beta_2$: scaling coefficient for temperature
**Decay parameter**

- The $\tau$ parameter is a GRACE-driven estimate of residence time

Figure from: **Humphrey et al (2016)**. Assessing Global Water Storage Variability from GRACE: Trends, Seasonal Cycle, Subseasonal Anomalies and Extremes. *Surveys in Geophysics* 37(2)