Optimization and assessment of high-resolution regression mascons for multiple time intervals within the GRACE/GRACE-FO record

Bryant D. Loomis¹, Terence J. Sabaka¹, Kenny Rachlin¹, Dorothy K. Hall², Nicolo E. DiGirolamo², Michael J. Croteau¹

> ¹Geodesy and Geophysics Laboratory, NASA Goddard Space Flight Center ²Cryospheric Sciences Laboratory, NASA Goddard Space Flight Center



Background

• Multiple studies have demonstrated enhanced spatial resolution in mean field, trends, annual signal by stacking normal equations, e.g., series of GOCO (TU Graz) & EIGEN (GFZ/GRGS) models:



Kvas et al., (2020), Earth System Science Data, <u>https://doi.org/10.5194/essd-13-99-2021</u>

• Signal-to-noise improvements from global stacked high-resolution mascon trends:



Loomis et al., (2019b), Frontiers in Earth Science, https://doi.org/10.3389/feart.2019.00235



Loomis et al., (2021), JGR: Solid Earth, https://doi.org/10.1029/2021JB023024



Background



 Next logical step: Apply the same approach within the GRACE/GRACE-FO record to get both higher spatial resolution & temporal information



ARD Recent Science Application: Hall et al., 2024





NASA press release: https://www.nasa.gov/science-research/earth-science/nasa-satellites-find-snow-didnt-offset-southwest-us-groundwater-loss

Study summary:

Data sets

- Terrestrial water storage (GRACE/-FO)
- Snow mass (SWE, days snow cover, snow depth)
- Land surface temperature (MODIS)
- The 2002–2023 terrestrial water storage decline in the Great Basin (GB) is more pronounced in the western GB than in the eastern GB.
- Even in notable snow years like 2010–2011, 2016–2017, 2018–2019, and 2022–2023, mass losses observed by GRACE/-FO remain consistent, due to the downward trend of groundwater storage.

Hall, D. K., Loomis, B. D., DiGirolamo, N. E., & Forman, B. A. (2024). Snowfall replenishes groundwater loss in the Great Basin of the western United States, but cannot compensate for increasing aridification. *Geophysical Research Letters*, 51, e2023GL107913. <u>https://doi.org/10.1029/2023GL107913</u>

D. Recent Science Application: Hall et al., 2024





	Monthly trends		High-res trends	
	Rate (Gt/yr)	Total (Gt)	Rate (Gt/yr)	Total (Gt)
Oct 2002 – Sep 2011	-0.1	-0.6	-3.4	-30.5
Oct 2011 – Sep 2023	-4.4	-52.8	-3.2	-38.6
Sum of 1 st two rows		-53.4		-69.1
Oct 2002 – Sep 2023	-4.0	-85.7	-3.4	-74.1

• Use of high-res reveals consistent trends in the GB across 2002-2011 and 2011-2023, which is the *opposite conclusion* from the monthly mascons

- Use of high-res trends <u>reduces</u> the estimated GB trend magnitude to due the <u>mitigation of leakage</u> from the Central Valley
- Disconnected trend estimates can lead to large differences in estimates of total mass change

Challenges with Multi-span Regression

Challenge 1:

- a) How to select the regularization parameter, λ ? (challenge common to all regularized estimation)
- b) Should different temporal spans optimize λ separately, or use a common λ ?

 $\widehat{m}_i = \left(A^T W A + \lambda_i P\right)^{-1} A^T W d$

Overdamped solution: λ is too large



Underdamped solution: λ is too small





Challenge 2:

a) To recover total mass change over multiple spans, the regression model should enforce continuity (EIGEN RL04 does this to degree/order 90)

Challenges with Multi-span Regression

Challenge 1:

- a) How to select the regularization parameter, λ ? (challenge common to all regularized estimation)
- b) Should different temporal spans optimize λ separately, or use a common λ ?

Challenge 2:

a) To recover total mass change over multiple spans, the regression model should enforce continuity (EIGEN RL04 does this to degree/order 90) **Challenges 1b and 2a** are both addressed by modifying our regression model approach.

Original: Independent stacked regression solutions over multiple time intervals

New: Spline regression model over entire span

- Proof of concept 3 parameters consisting of 1 bias and 2 trends over the same two time intervals as the Great Basin study
- Future work Spline parameters can be expanded to include more than two time intervals and additional parameters, e.g., annual, semi-annual, x², x³, stochastic

First Results: Spline Regression Model



First Results: Spline Regression Model



Piecewise High-res Trends

Challenge 1a: How to select λ ?

Previous work for selecting λ :

- Monthly mascons use an approach that minimizes the spatial correlation between the estimate and change in the estimate due to increasing λ (Croteau et al., 2021)
- High-resolution trend estimation (Loomis et al., 2021) used the same approach as the monthly
- Hall et al. (2024) optimized Signal-to-Noise, for full span, and used the same λ for subintervals (where Signal ≡ Land RMS, Noise ≡ Sahara RMS)



Challenge 1a: How to select λ ?

Other potential approaches to select λ :

- L-curve criterion Previously explored and tends to provide overdamped solutions (Save et al., 2012)
- Mean Squared Error (MSE) = Sum of covariance and bias, where bias is a measure of smoothing/ leakage (Loomis et al., 2019a) – Difficult to interpret due to unknown truth vector, x



GODARD EARTH SCIENCES

Summary

Background:

- Stacking normal equations is very successful at enhancing spatial resolution and signal recovery
- Stacked regression mascons improve signal-to-noise via regularization
- We have successfully applied this method to specific science questions (e.g., Hall et al., 2024)

Today's presentation:

- We have demonstrated a new regularized regression spline estimator to further leverage this technique to maximize spatial resolution while also recovering valuable temporal information
- Selecting the regularization parameter, λ , remains a bit of an art form; current methods seem viable

Future work:

- Expand spline parameters and test for specific science questions Please reach out if interested!
- Improved uncertainty quantification (previous studies have used differences to GOCO-06S over common time span)