Towards near real-time daily GRACE gravity field solutions

Andreas Kvas, Torsten Mayer-Gürr

Geodetic Week 2015, Stuttgart

Outline

- Near real-time gravity fields
- Kalman filter approach
- State-space model estimation
- Evaluation of state-space model

Near real-time GRACE gravity fields

- As part of the EGSIEM project, a tech demonstrator for near real-time gravity service will be established

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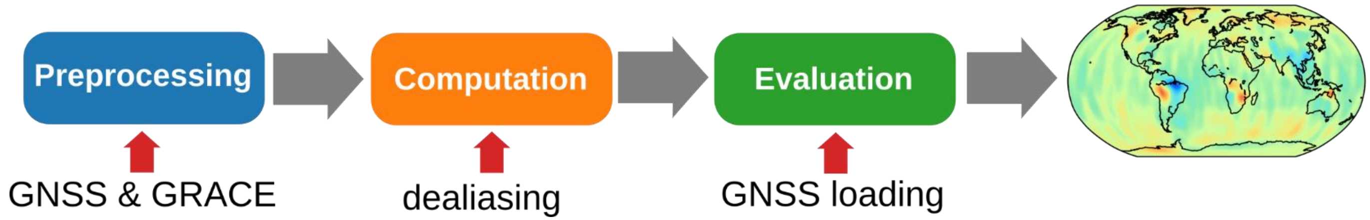
EGSIEM
European Gravity Service for Improved Emergency Management

- Scope: daily L2 and L3 GRACE products with a time delay of five days



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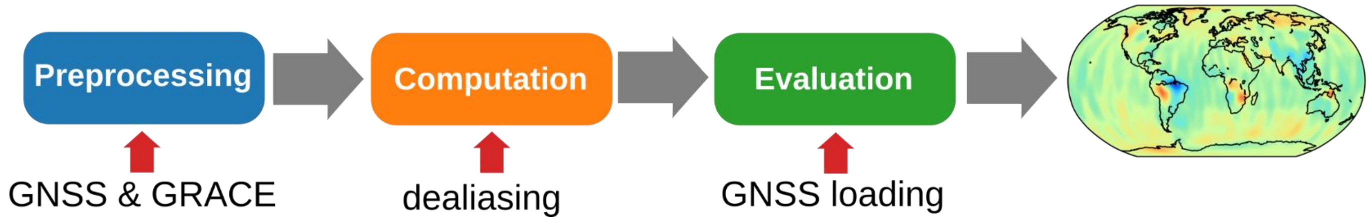

- Current work: Adapting and improving algorithms and methods from post-processing for near real-time capability

Kalman filter approach (1)

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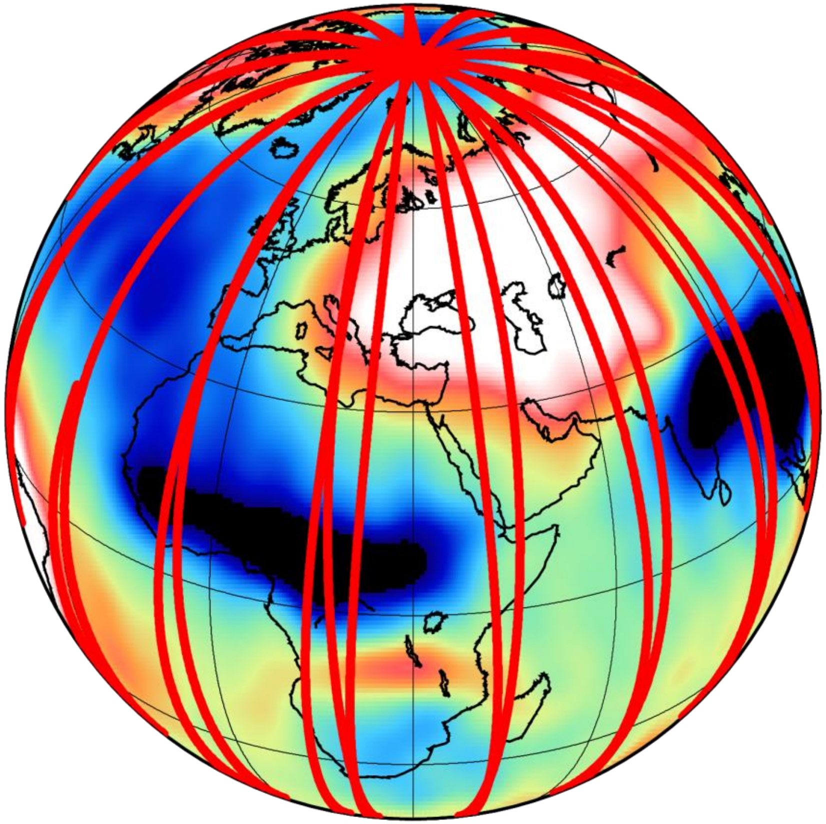

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Kalman filter approach (1)

- Daily GRACE gravity field solutions require prior information due to limited data coverage

- Assumptions:
  - The gravity field does not change arbitrarily, but is (somehow) predictable:

$$\mathbf{x}_t = \mathbf{B}\mathbf{x}_{t-1} + \mathbf{w} \qquad \mathbf{w} \sim \mathcal{N}(0, \mathbf{Q})$$

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prediction error covariance matrix

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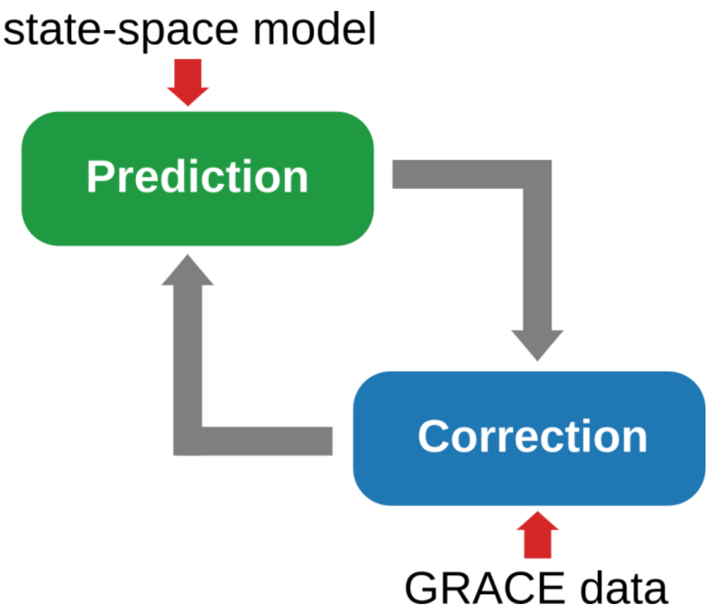
Kalman filter approach (2)

- We can combine the state-space model with GRACE observations in a Kalman filter (see Kurtenbach et al. 2012)



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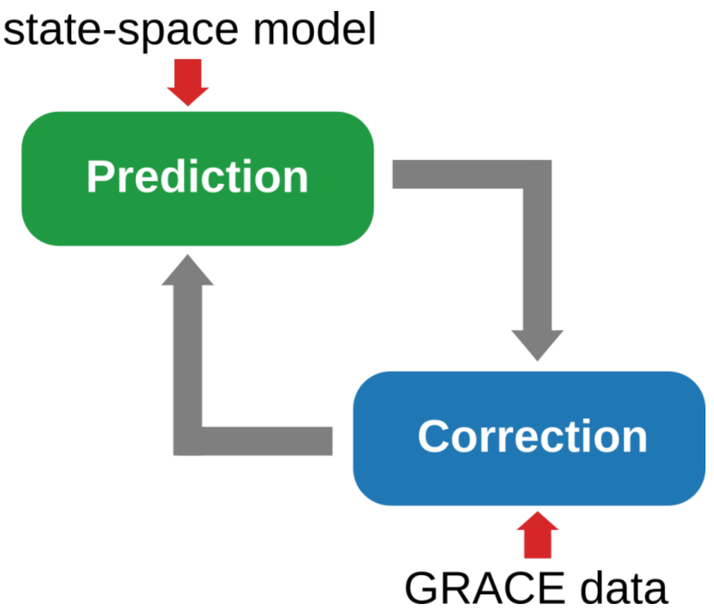

- But: true state-space model of Earth is not accessible
  - → we need an estimate

State-space model estimation (1)

- However: if the covariance structure of consecutive epochs is known, we can use least squares prediction:

$$\mathbf{B} = \Sigma_\Delta \Sigma^{-1} \qquad \mathbf{Q} = \Sigma - \Sigma_\Delta \Sigma^{-1} \Sigma_\Delta^T$$

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- Still, actual correlations are not known:
  - covariance matrices are approximated with empirical estimates from geophysical models

State-space model estimation (2)

- Which geophysical models are used? (What constitutes “the process”?)
  - Errors in dealiasing product (atmosphere and ocean)
  - Unmodeled geophysical signals (continental hydrology and cryosphere)

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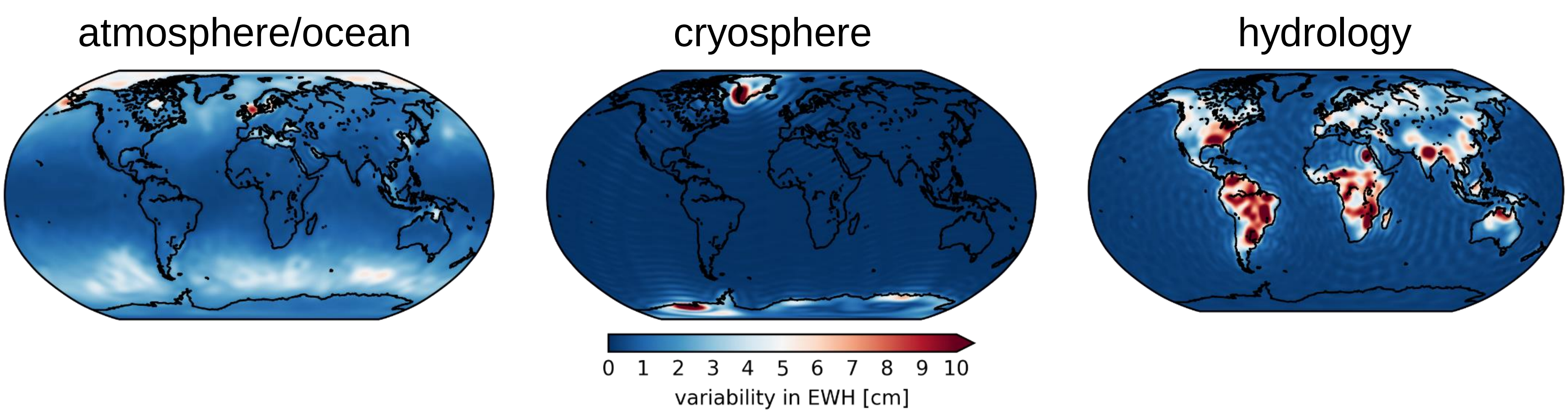
- We use the difference between the ESA ESM and AOD1B as an approximation



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State-space model estimation (2)

- Problem: only short time series are available
  - For degree and order 40, we need to estimate 2.8 million coefficients from 4380 epochs → redundancy of about 2.6
  - Akaike information criterion: we need more than 850 years of data!

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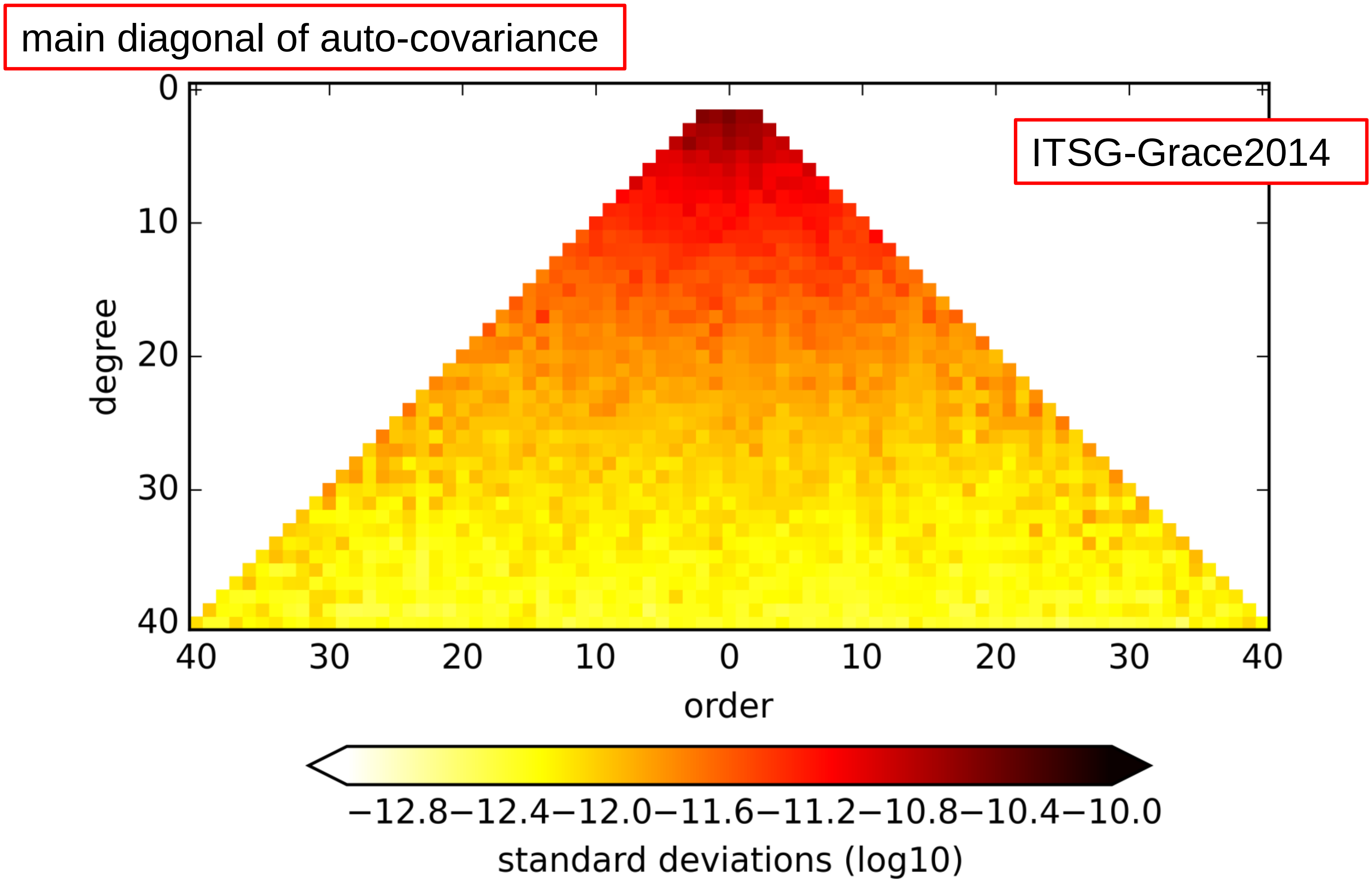
- We use the following constraints:
  - Hydrology: River basins are uncorrelated
  - Atmosphere/Ocean: Northern/southern hemisphere and tropics are uncorrelated
  - Cryosphere: Greenland/Antarctica are uncorrelated

State-space model estimation - Results



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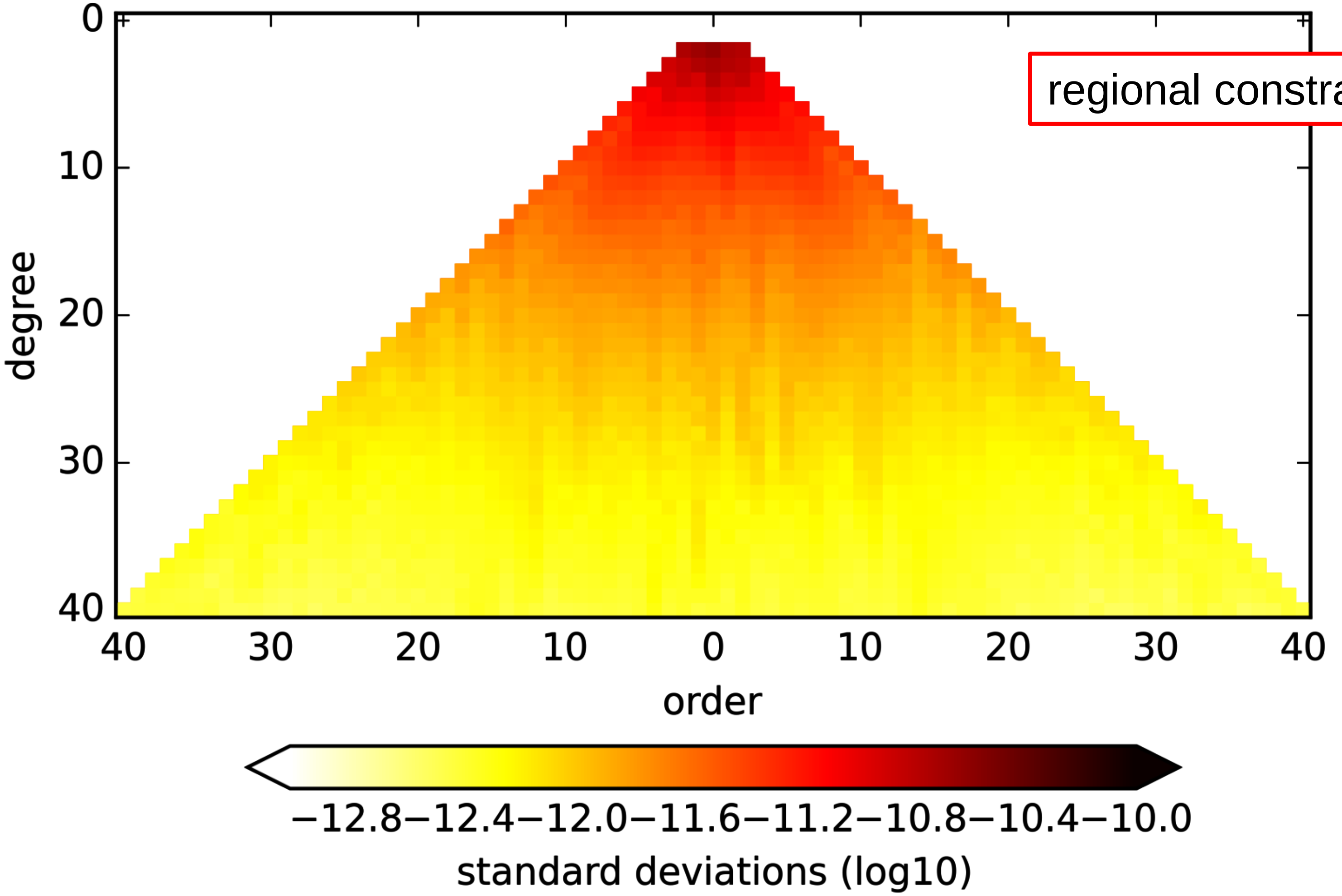
State-space model estimation - Results

main diagonal of auto-covariance



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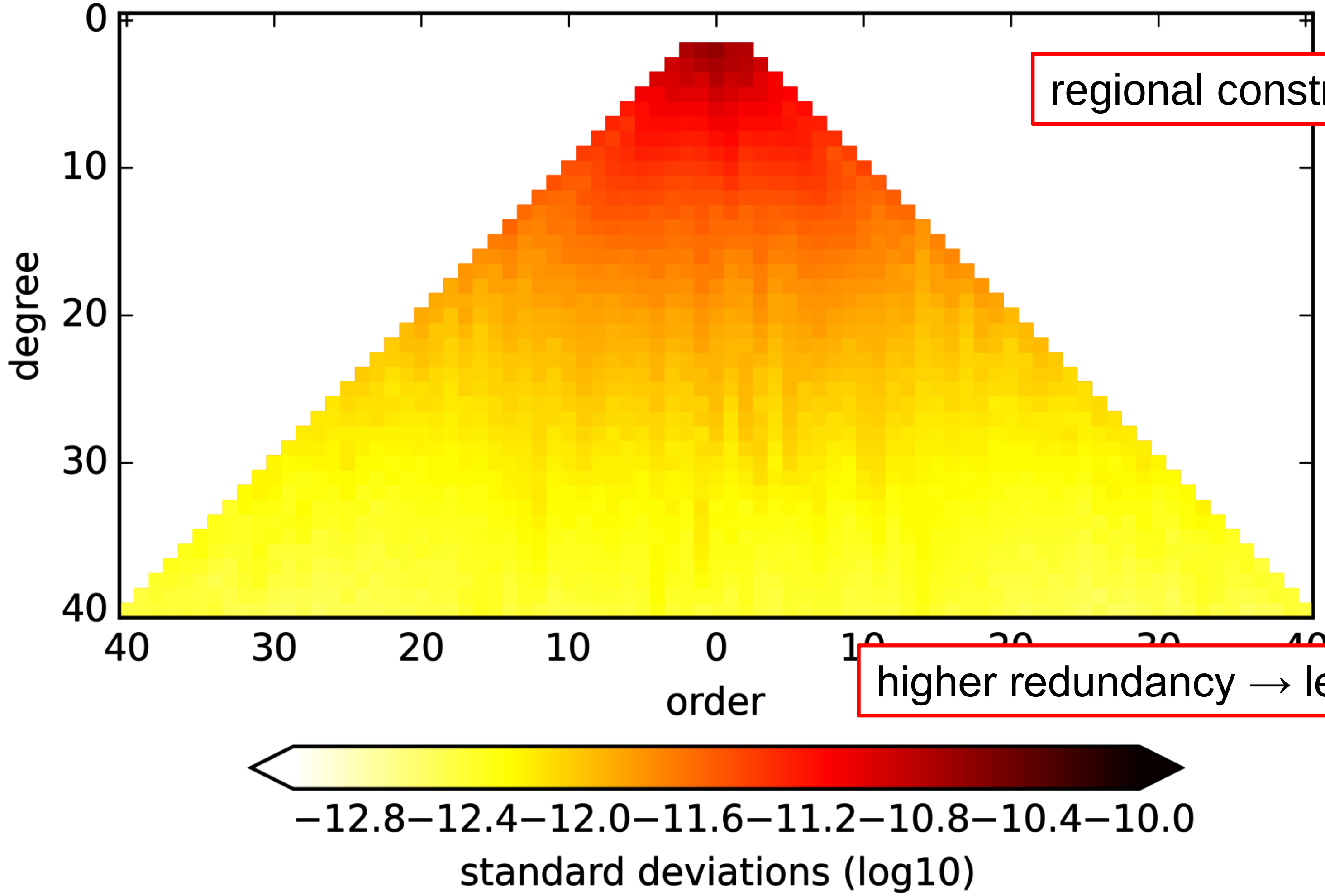

regional constraint

higher redundancy → less noise

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Evaluation of state-space model

- Question 1:
  - How well does the predicted state fit the GRACE observations?
  - Comparison of a-priori range rate residuals in time and space domain

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- Question 1:
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- Question 2:
  - Are there Kalman filter artifacts in the computed gravity field solutions?
  - Non-geophysical signals in area mean time series (for example river basins)

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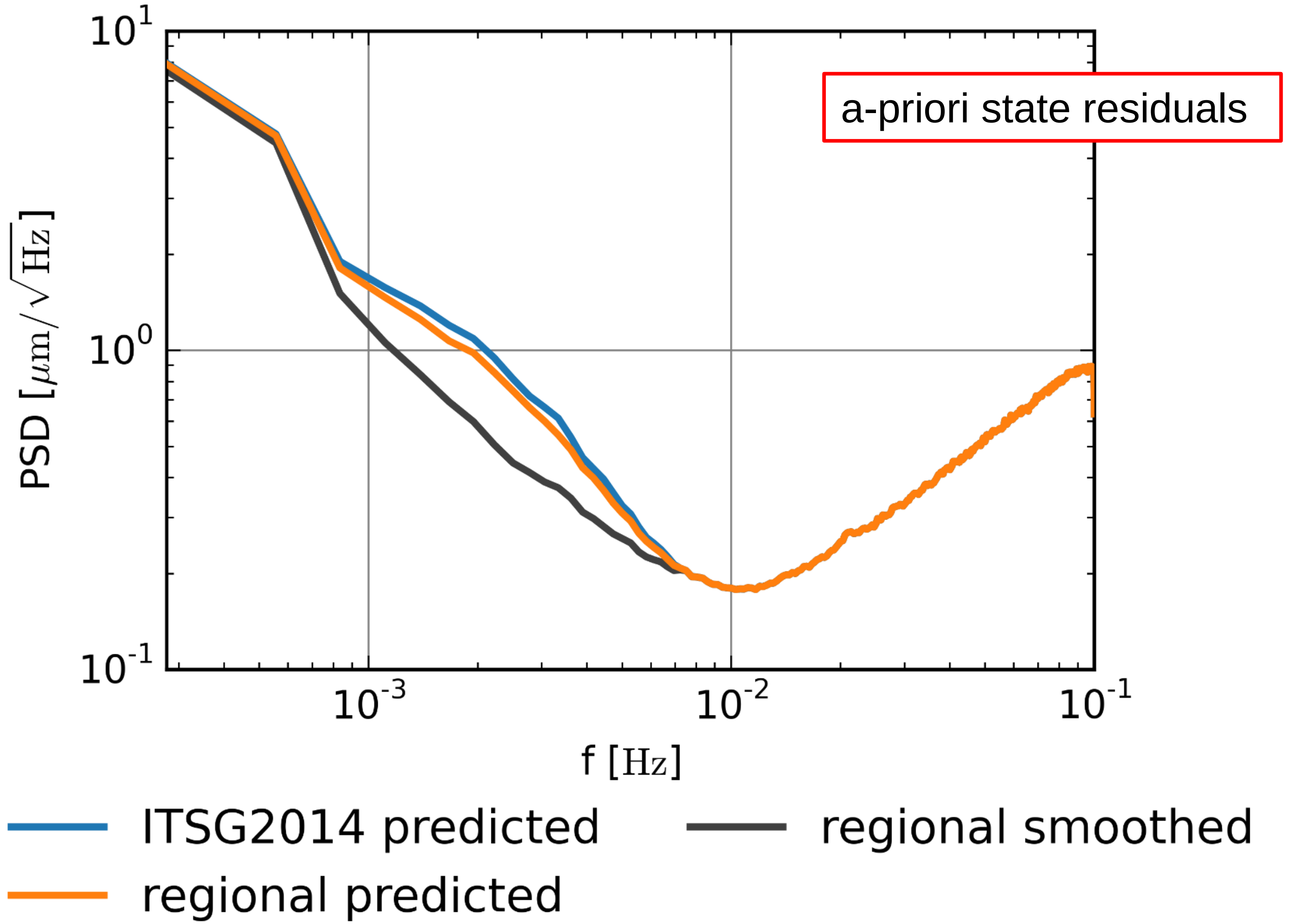

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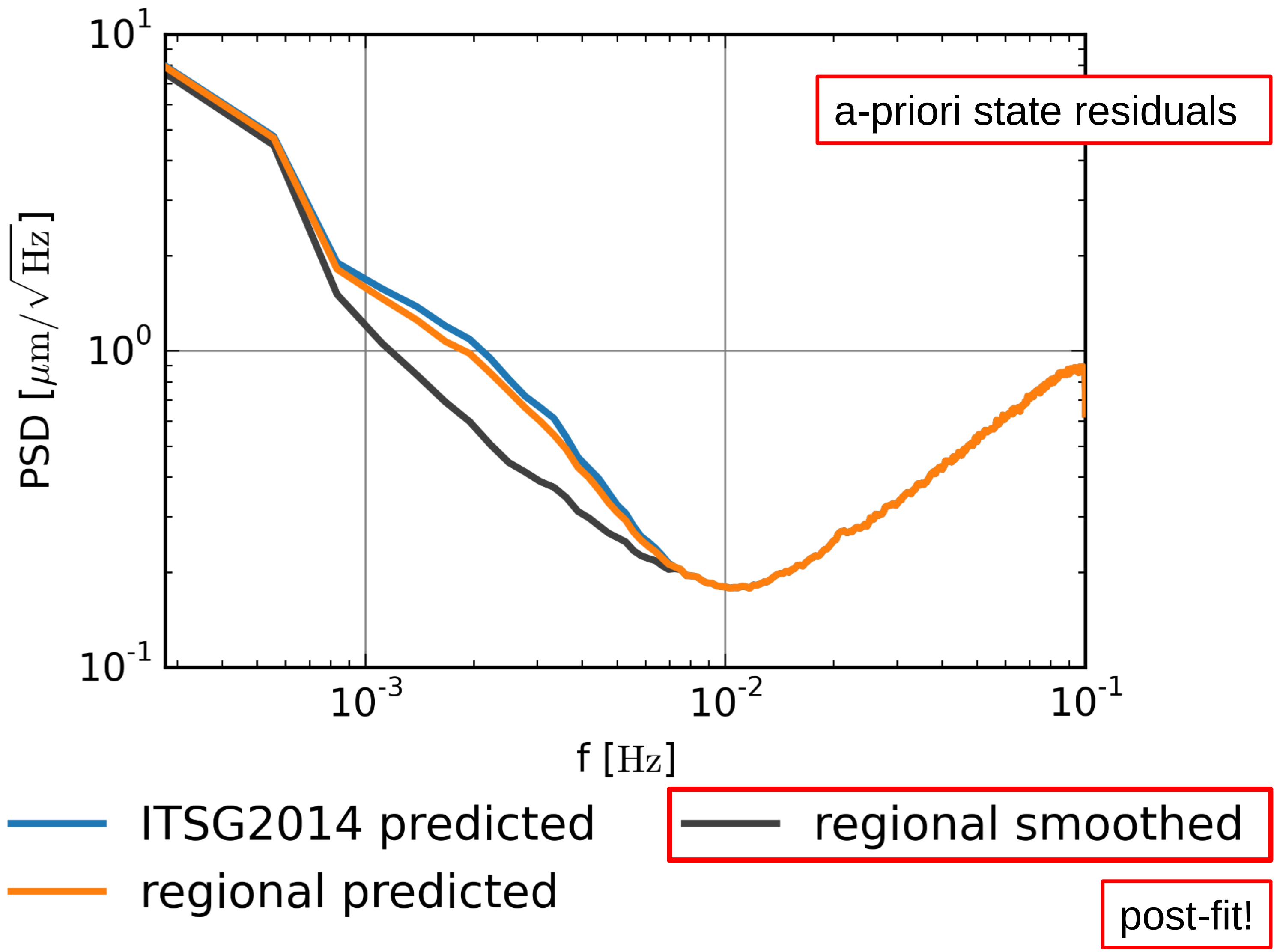

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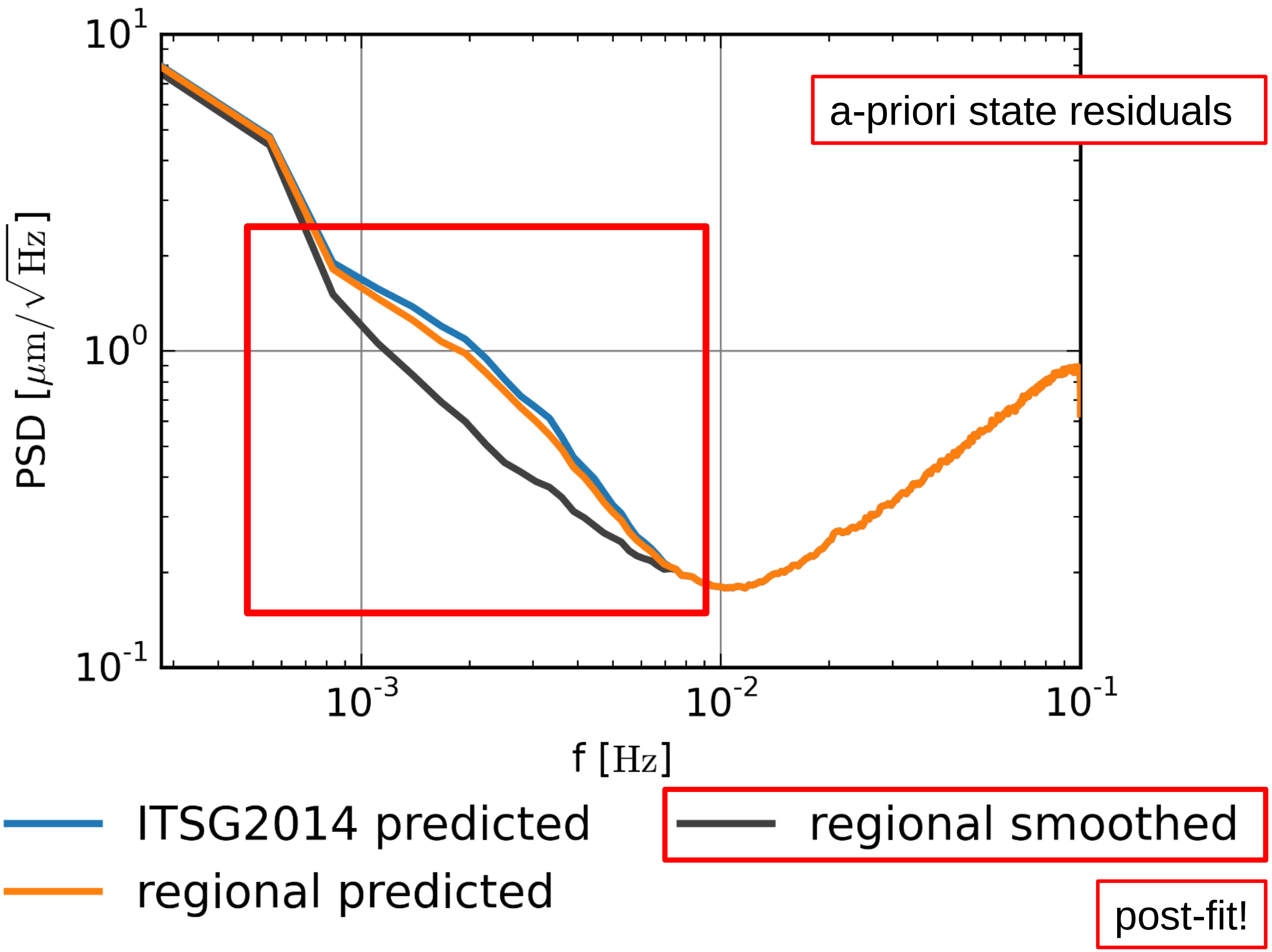

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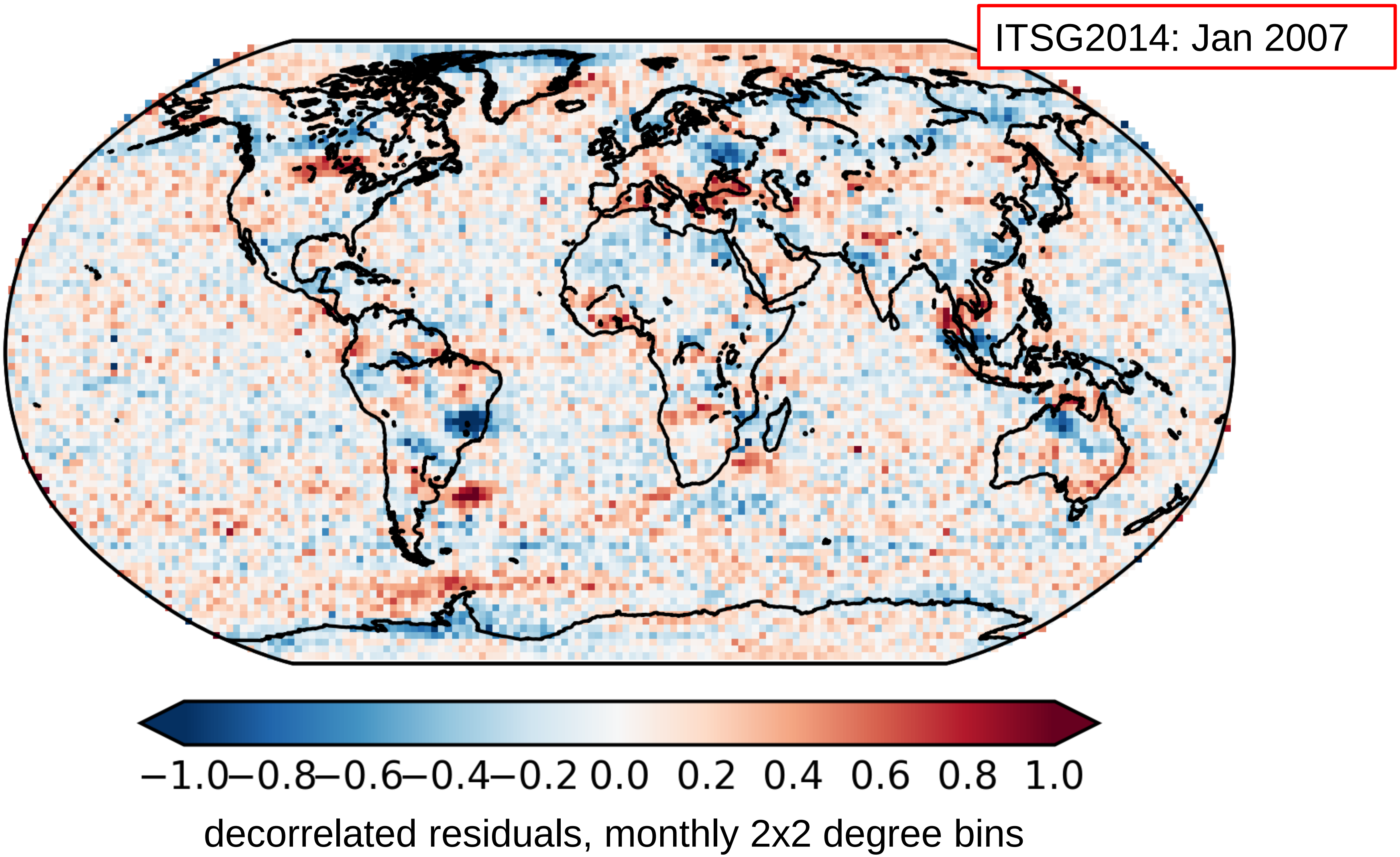

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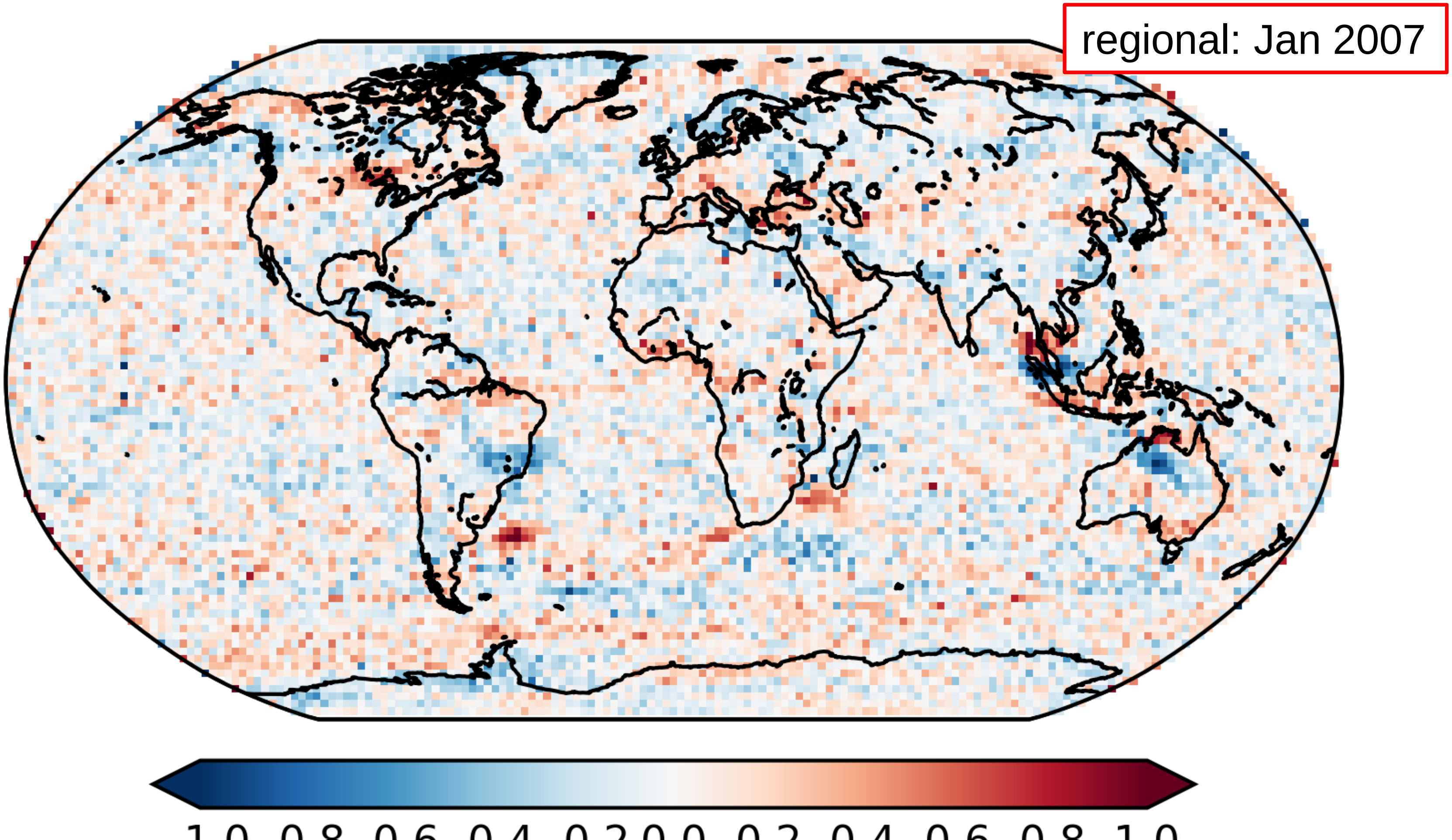

decorrelated residuals, monthly 2x2 degree bins

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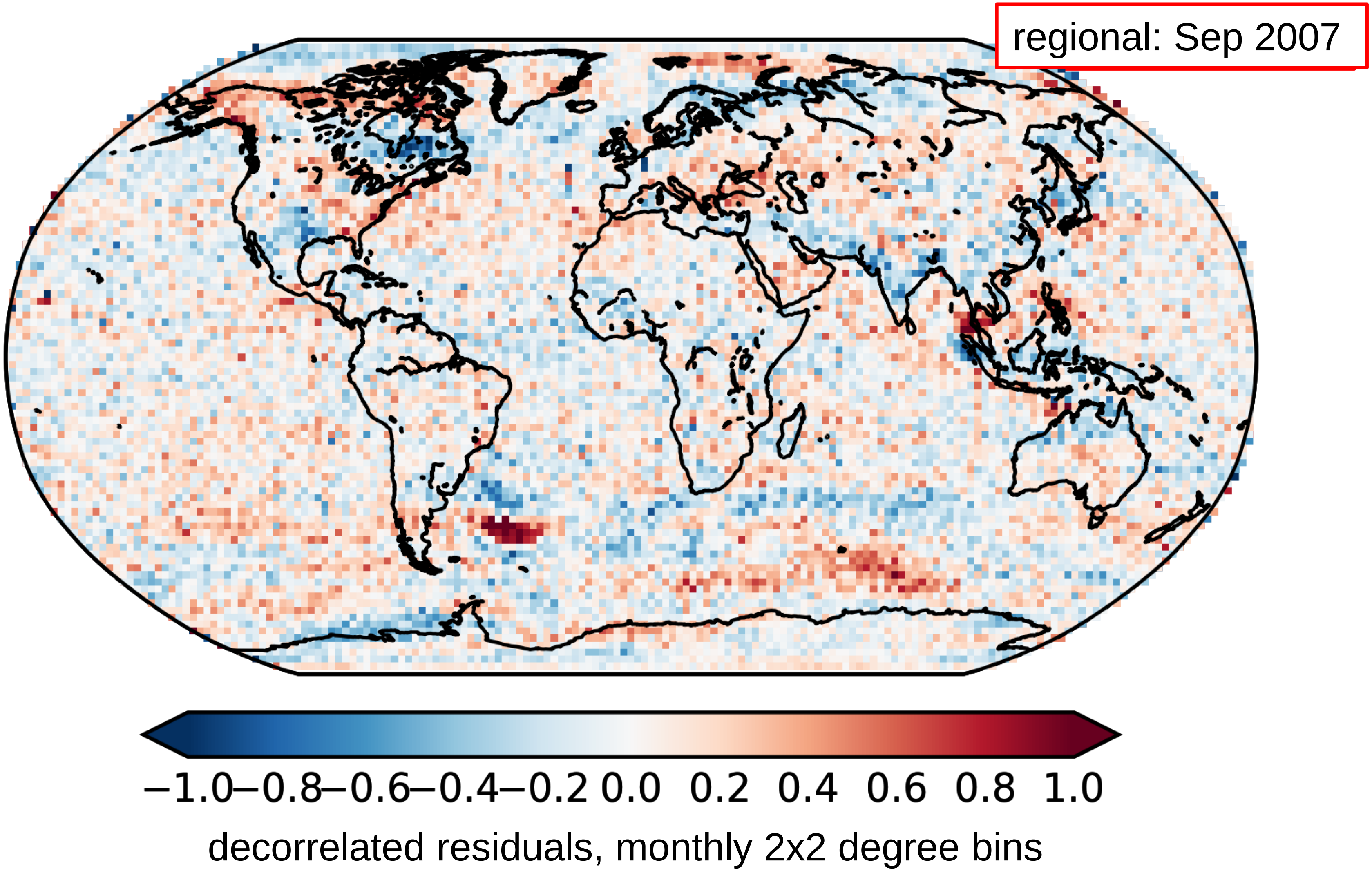

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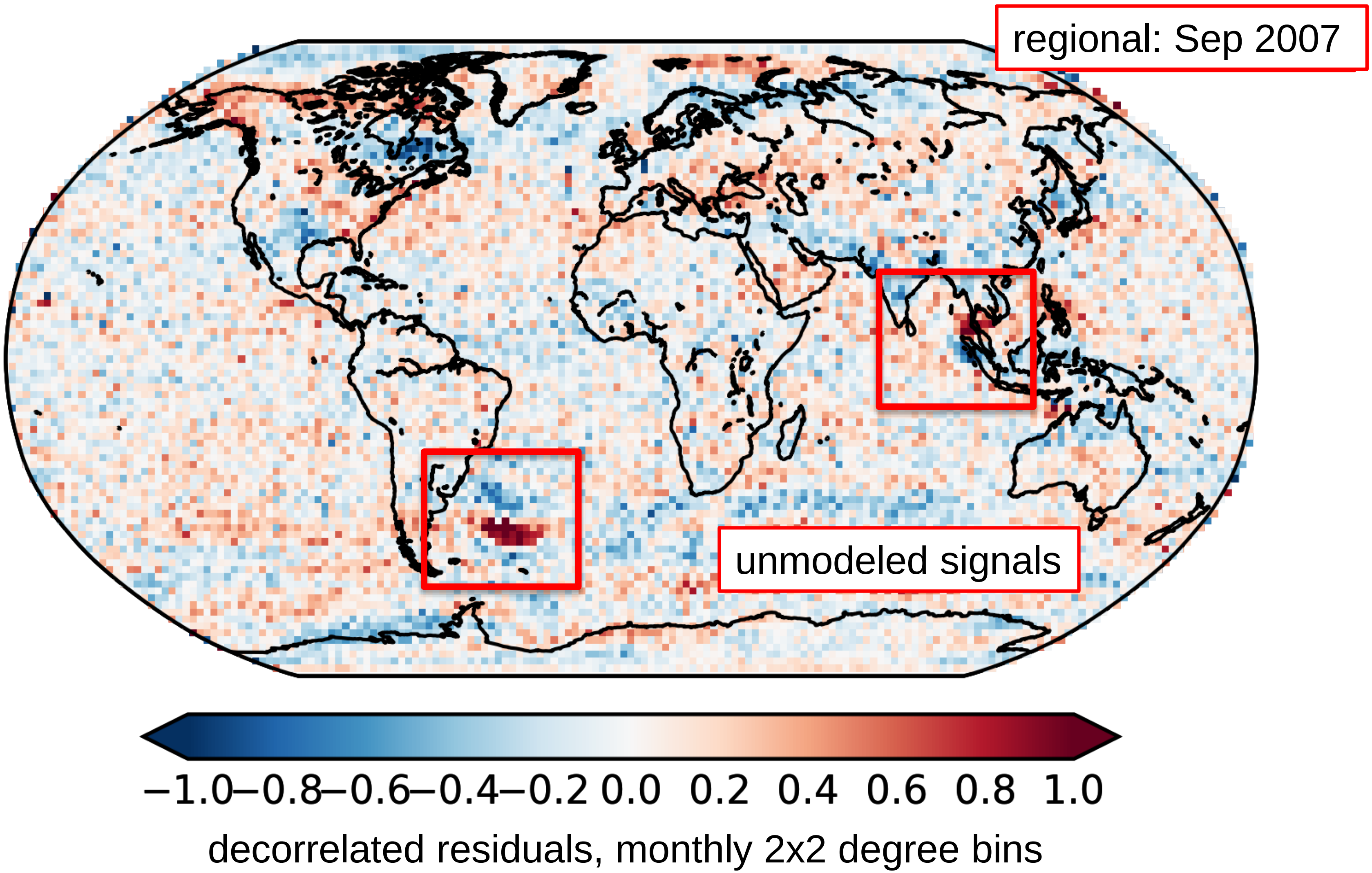

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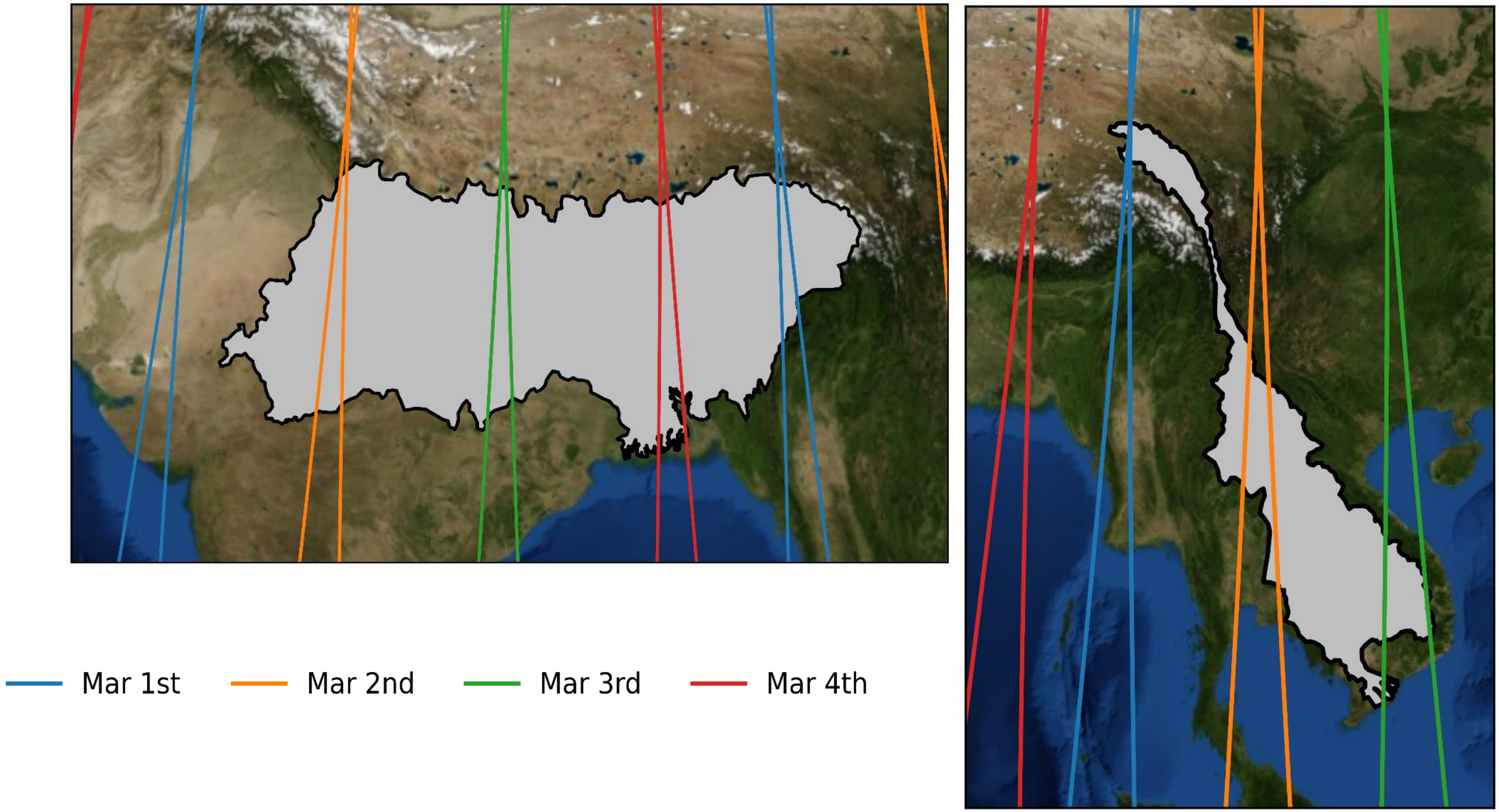

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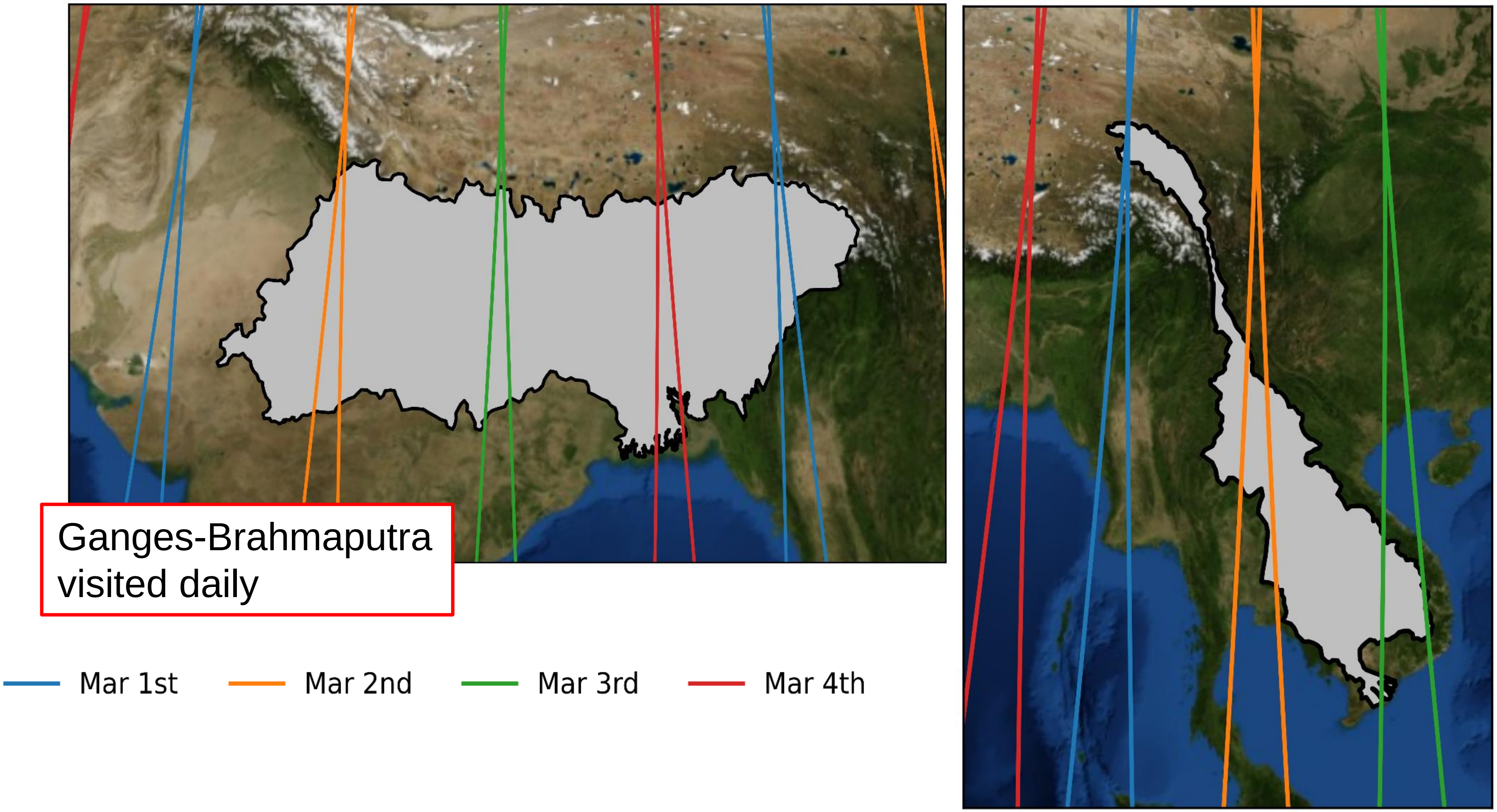

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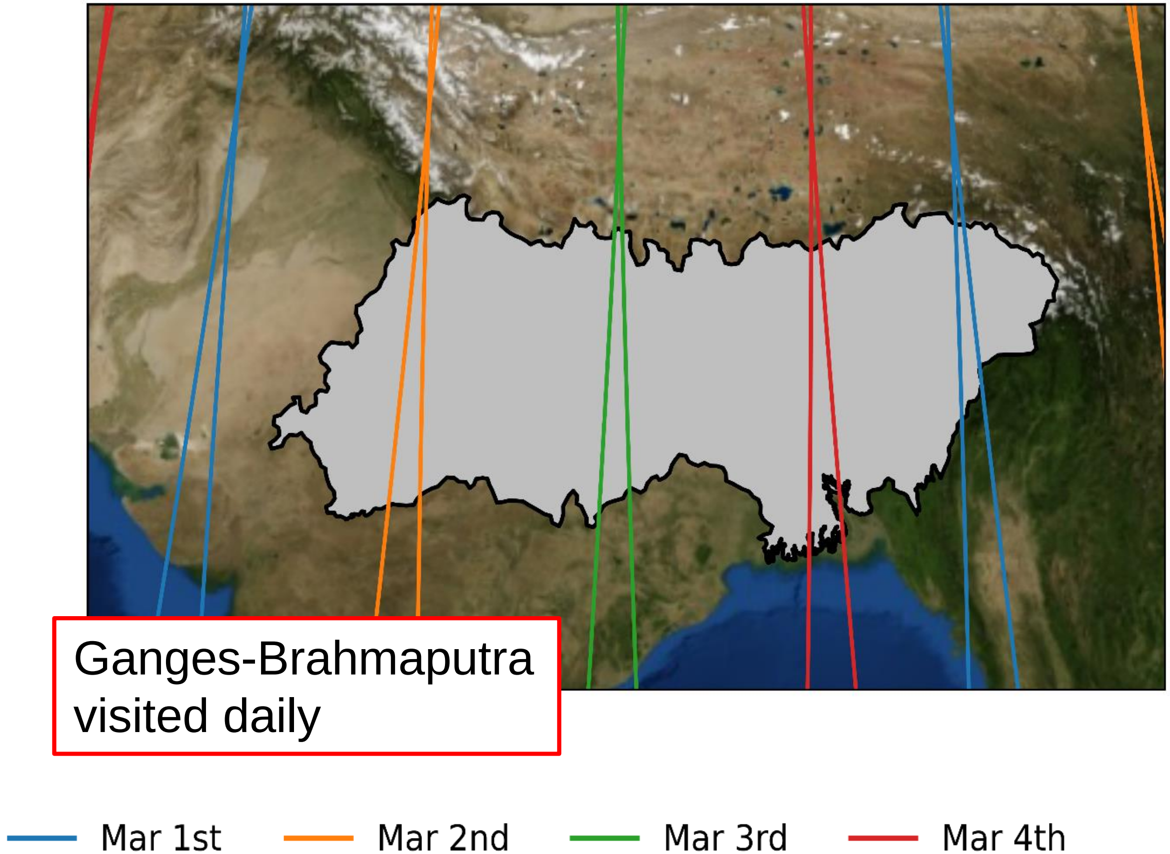
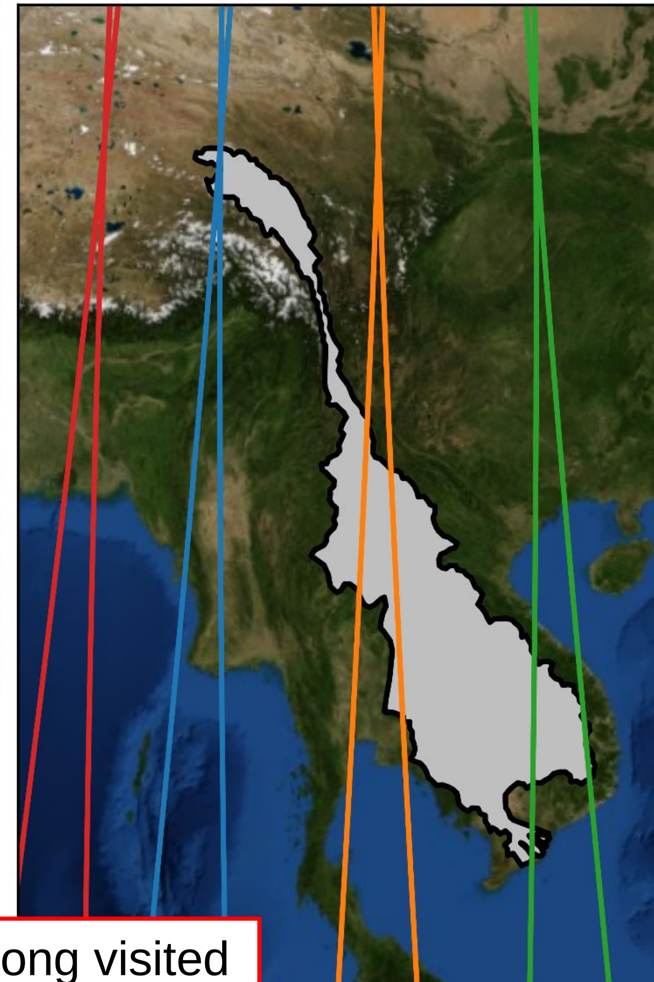


Ganges-Brahmaputra visited daily



Mekong visited approximately every four days

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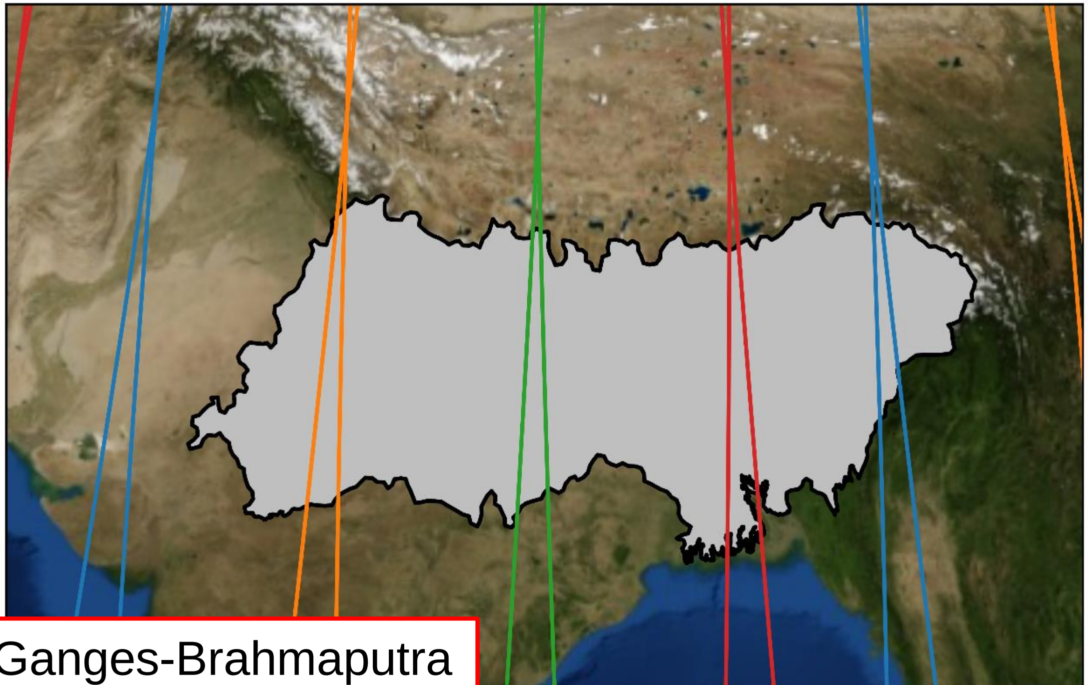

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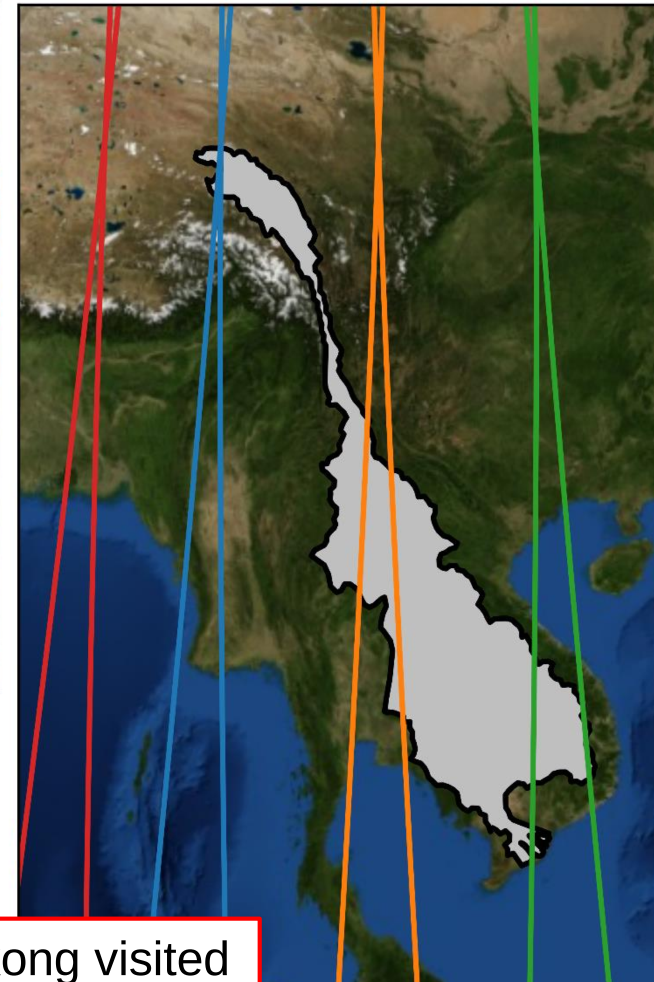

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Improved prediction translates to area mean time series

Conclusion and Outlook

- Regional constraint improves state-space model estimate

- Improvements in prediction also translate to gravity field solutions

- There are still unanswered questions:
  - Are all assumptions valid?
  - How to deal with unmodeled signals?

Thank You!

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Horizon 2020

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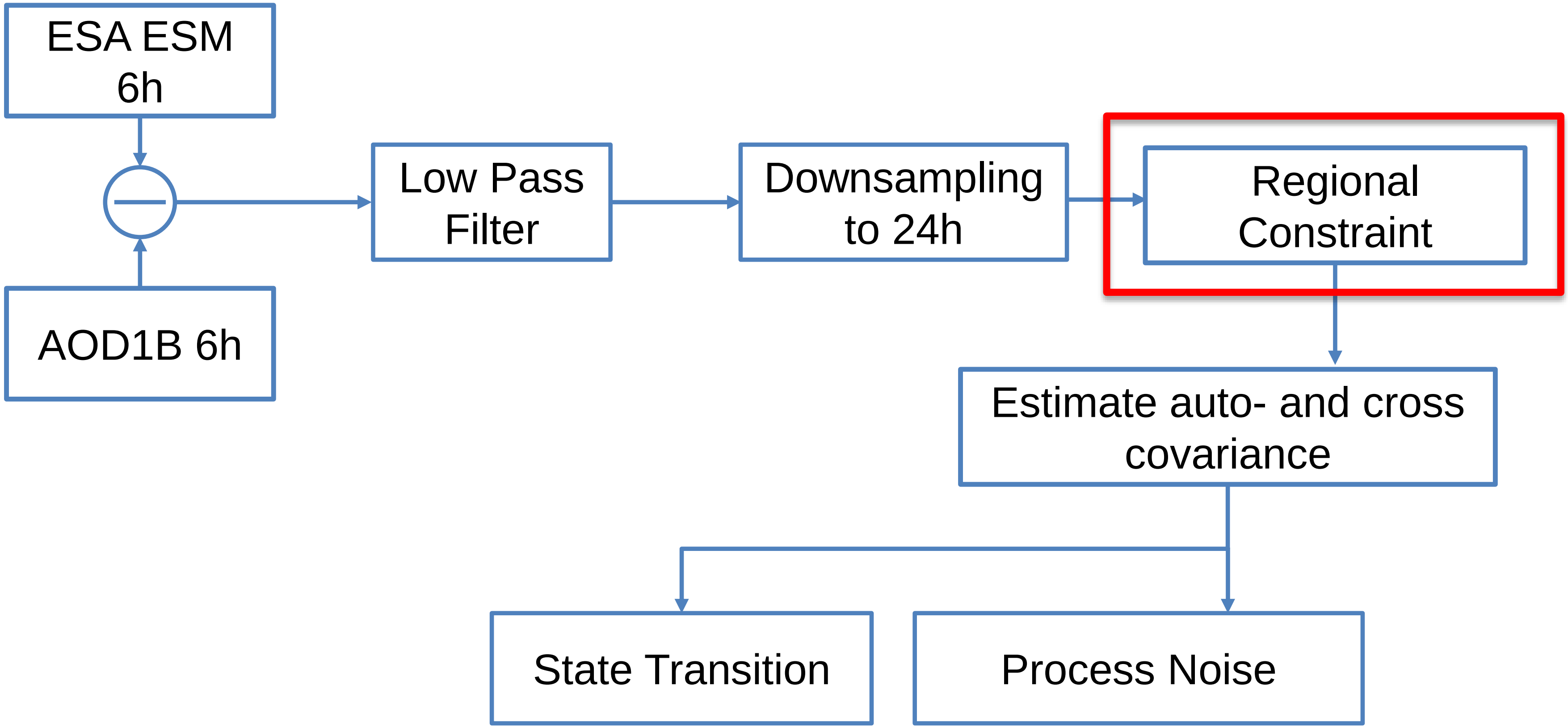
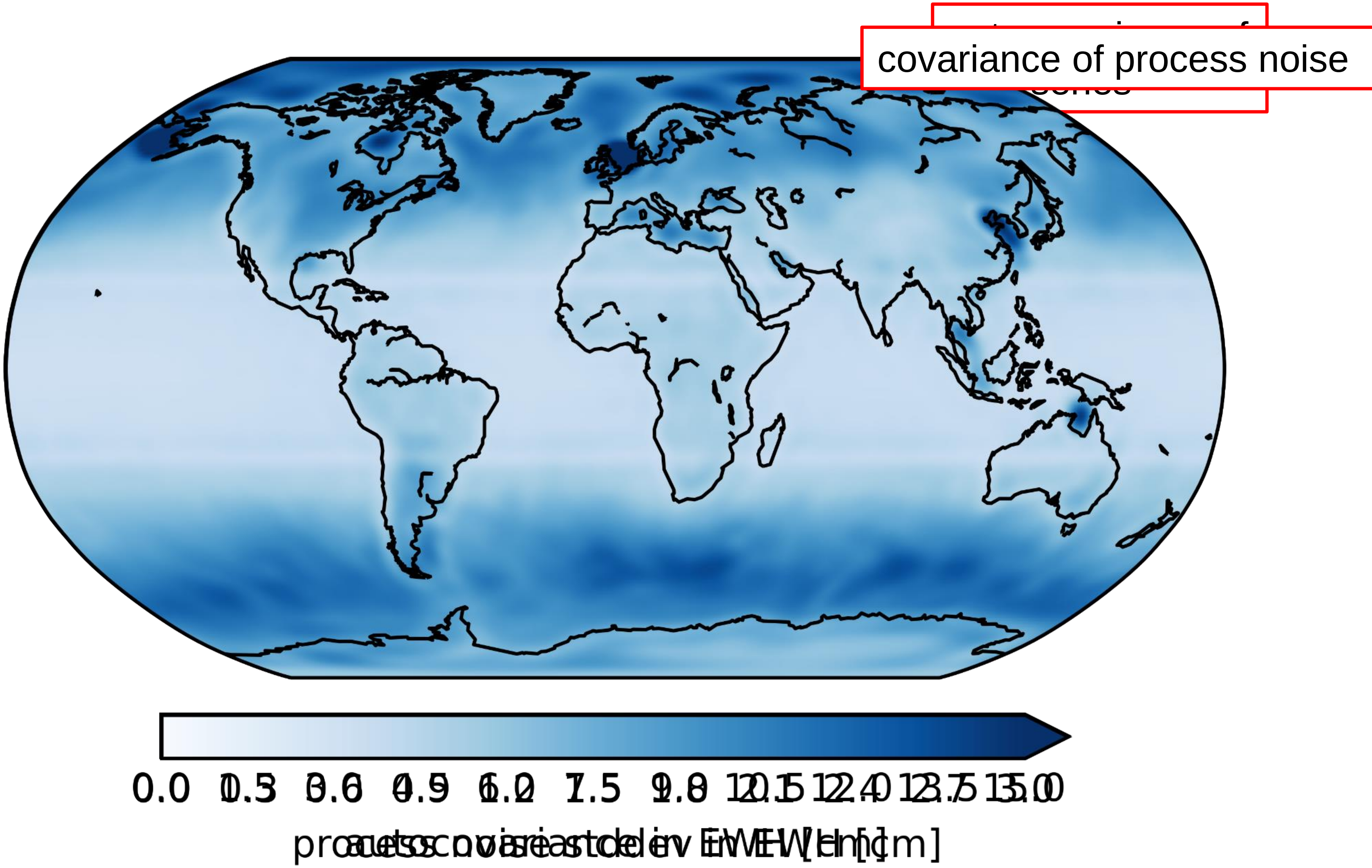
State-space model estimation



Regional constraint (2)



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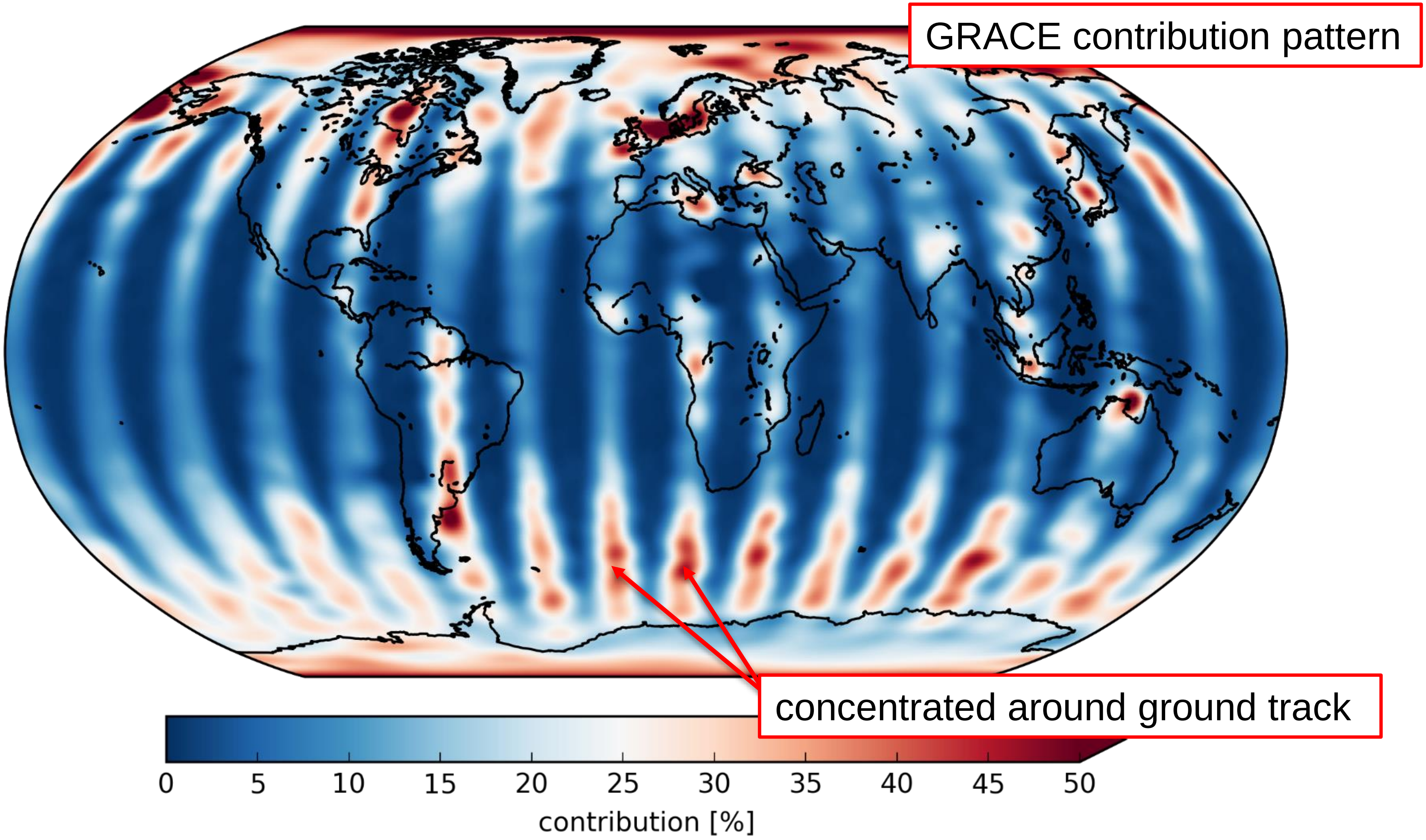

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