Earth's changing mass distribution: Making the most of GRACE

Frederik J Simons

F. A. Dahlen, Jessica C. Hawthorne, Dong V. Wang
Princeton University

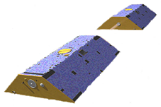
Mark A. Wieczorek
IPG Paris

Lei Wang
Ohio State University

Shin-Chan Han
NASA Goddard

Chris T. Harig, Kevin W. Lewis, Alain Plattner
Princeton University

Outline

- The GRACE mission, in a nutshell 

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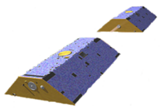
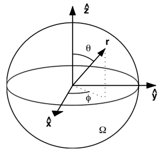
- The GRACE mission, in a nutshell 

- *Theory:* Analysis of **noisy** and **incomplete** data on a **sphere** 

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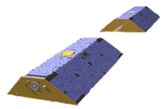
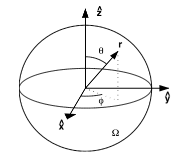
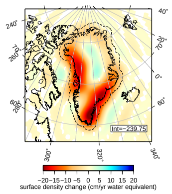
- The GRACE mission, in a nutshell 

- *Theory:* Analysis of **noisy** and **incomplete** data on a **sphere** 

- *Application 1:* Quantifying mass loss from glaciated regions 

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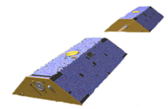
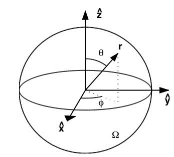
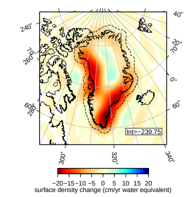
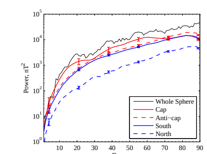
- The GRACE mission, in a nutshell 

- *Theory:* Analysis of **noisy** and **incomplete** data on a **sphere** 

- *Application 1:* Quantifying mass loss from glaciated regions 

- *Application 2:* The spectral signature of the Martian magnetic field 

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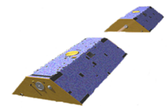

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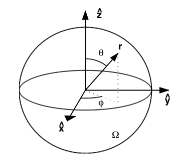

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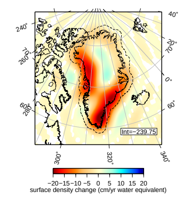

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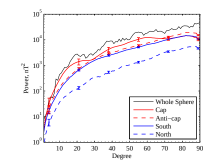
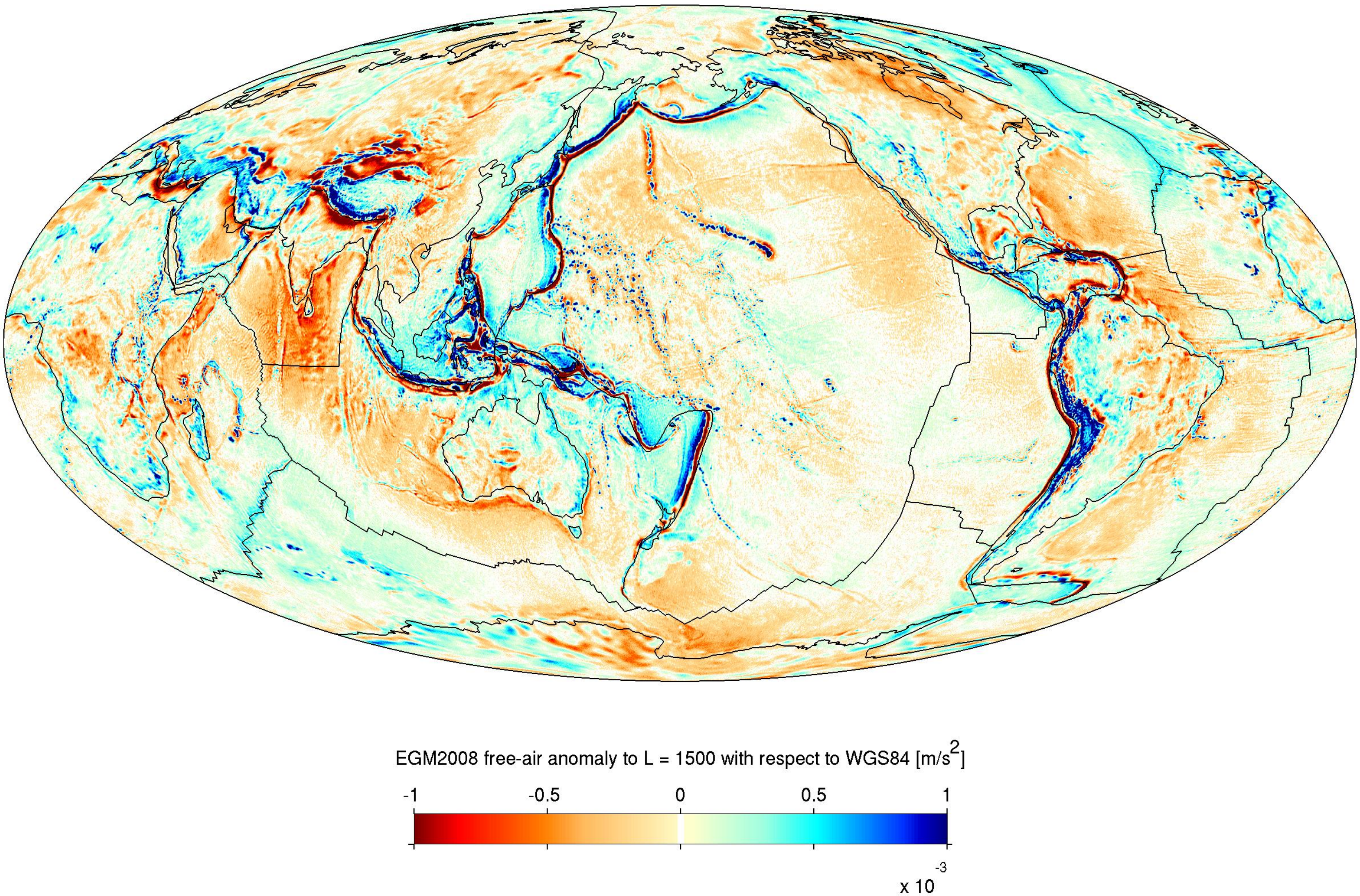
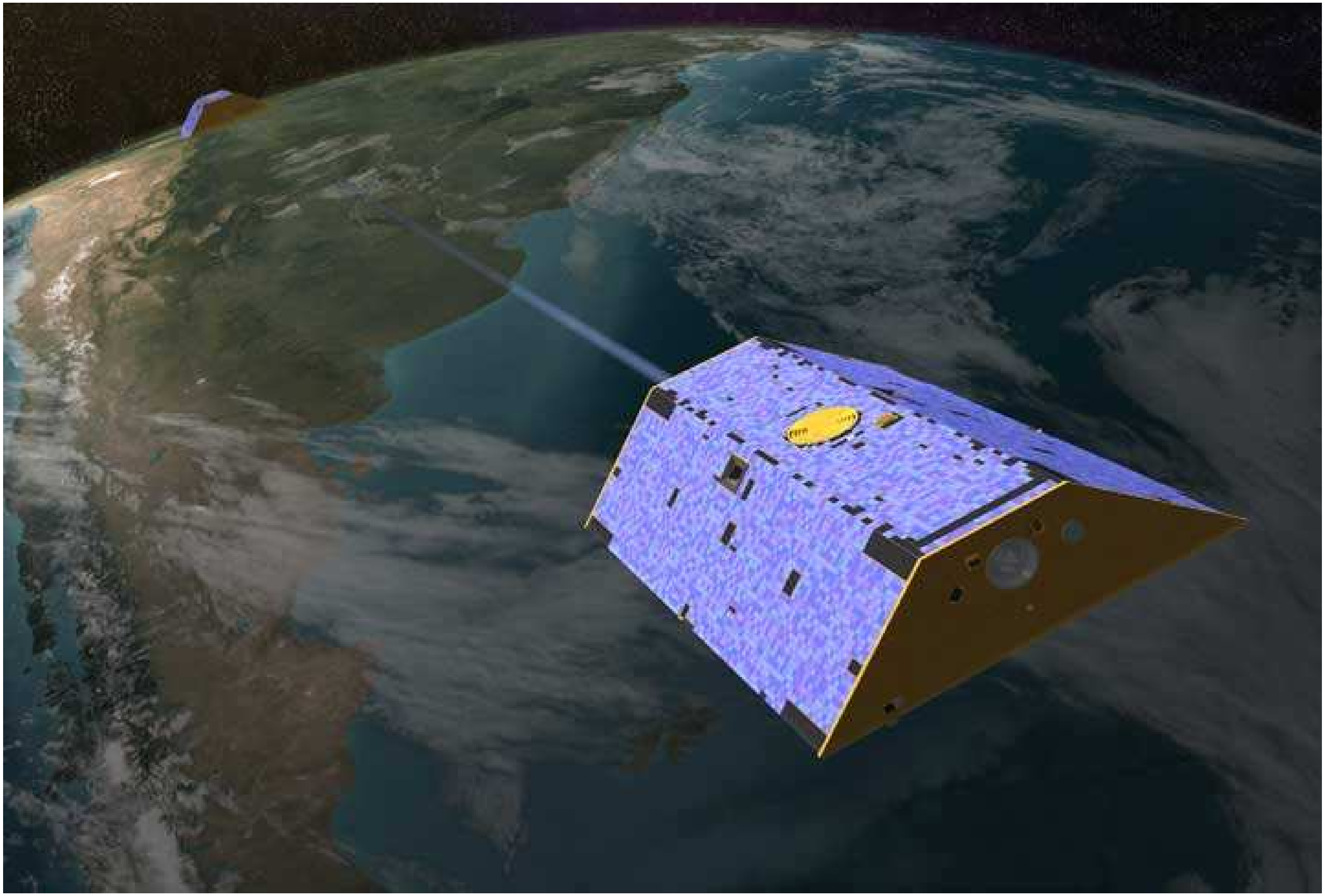


- *What have we learned? Conclusions & Outlook*

Earth's gravity field is highly variable...



...and it changes over time



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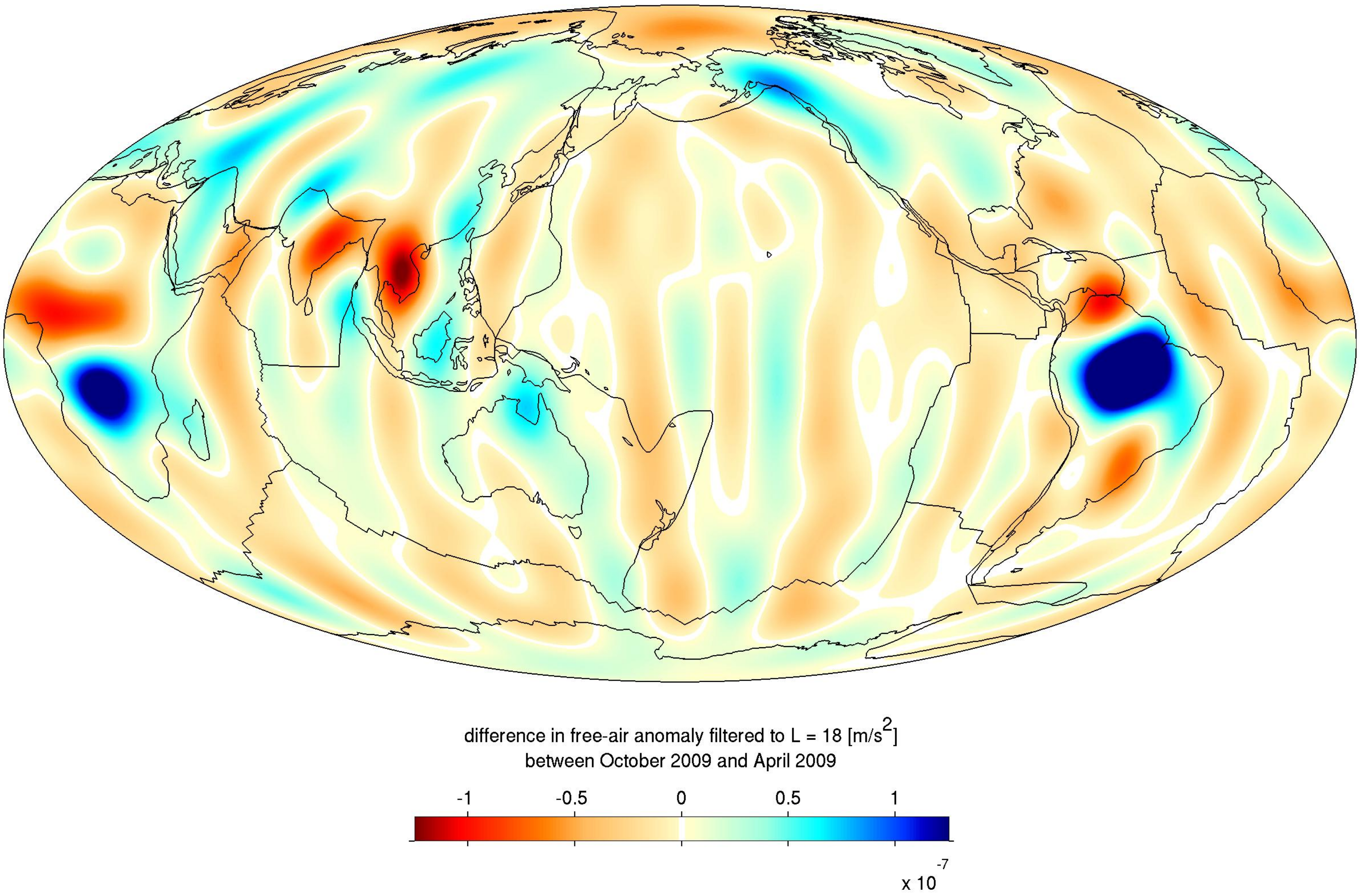
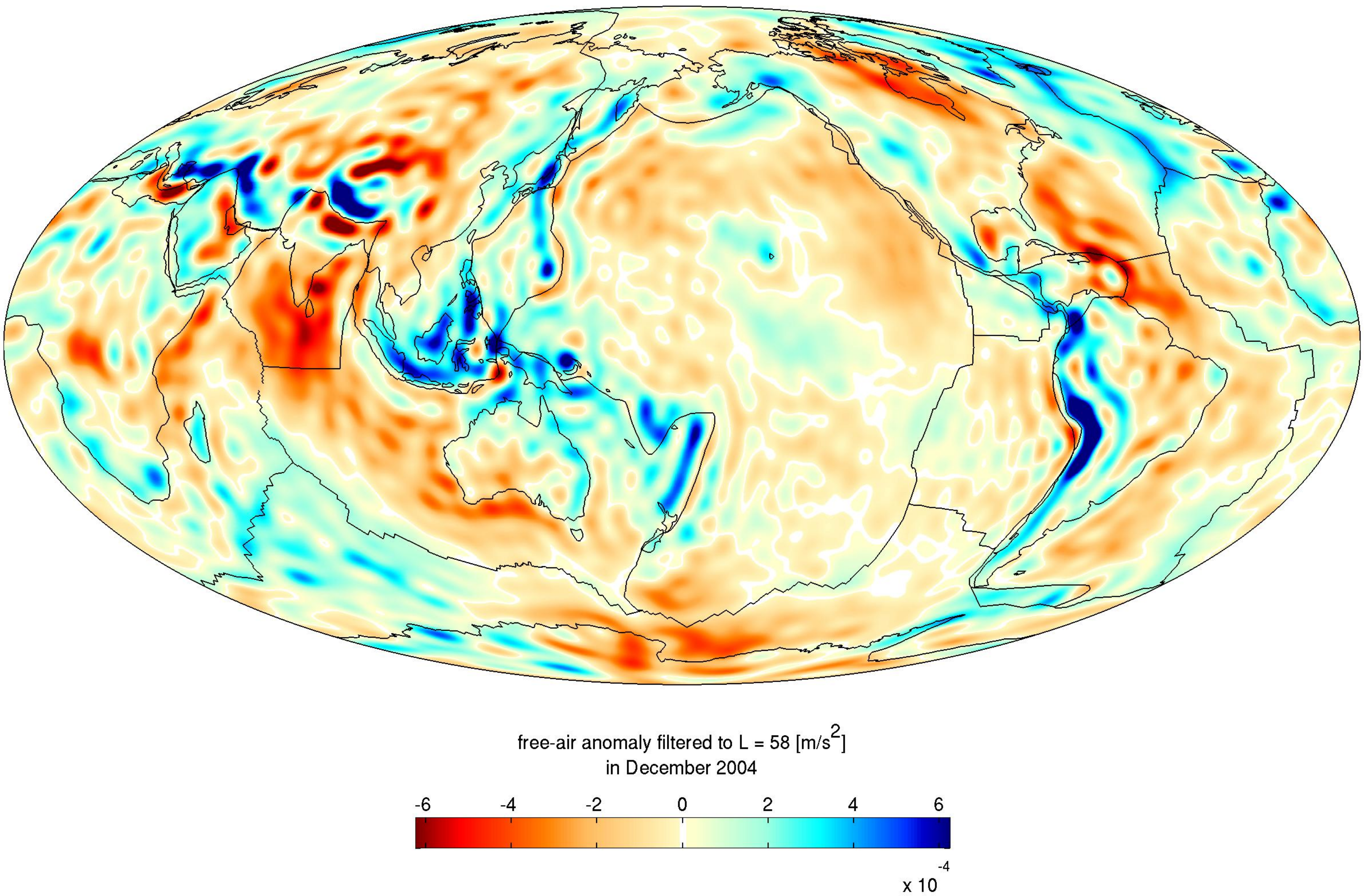
- **The question is, of course:**
  with what *spatial*, *temporal*, and *spectral* resolution?

The hydrological signal is big and large



What lurks in the high-frequency “noise”? – 1



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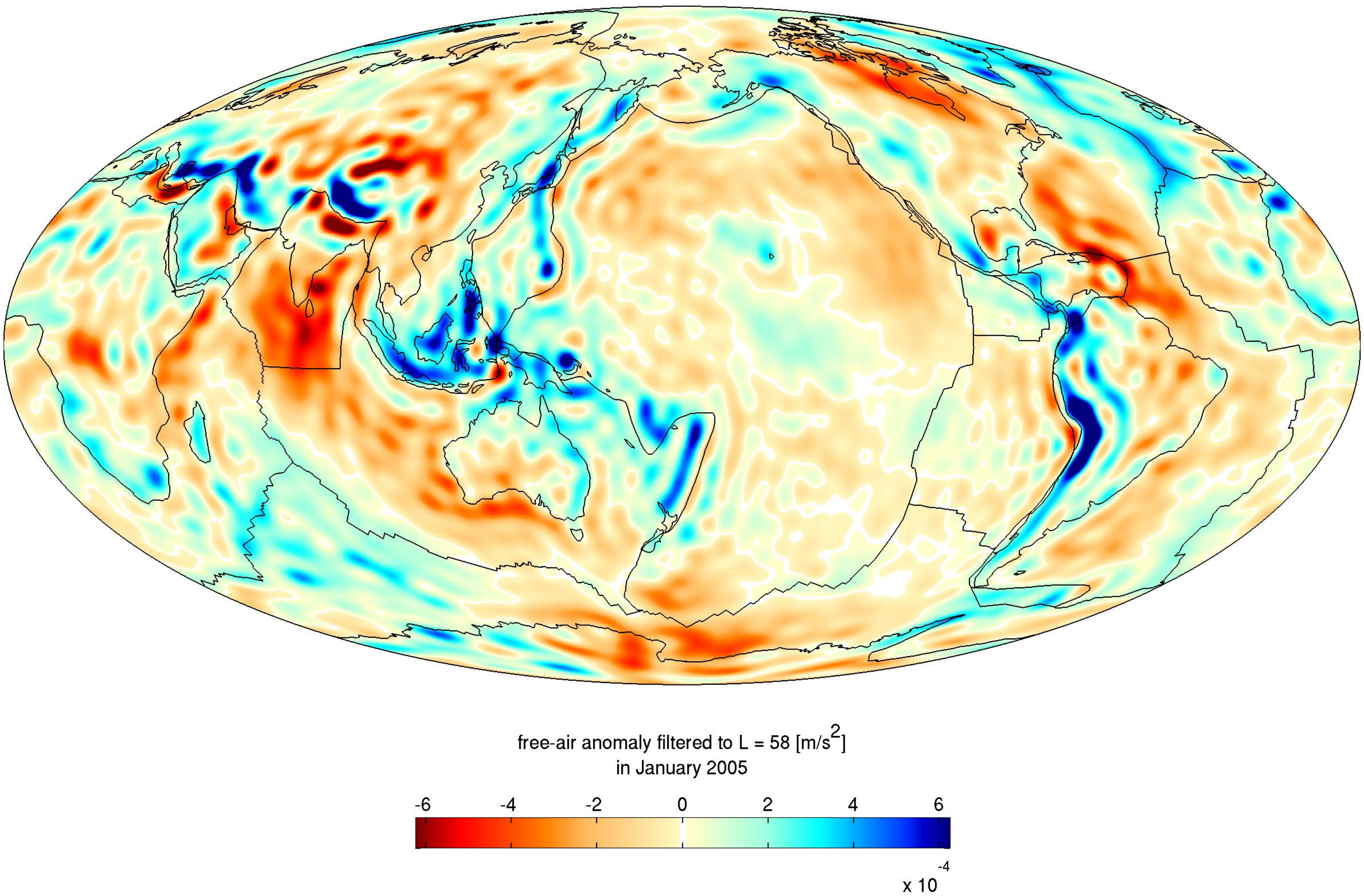
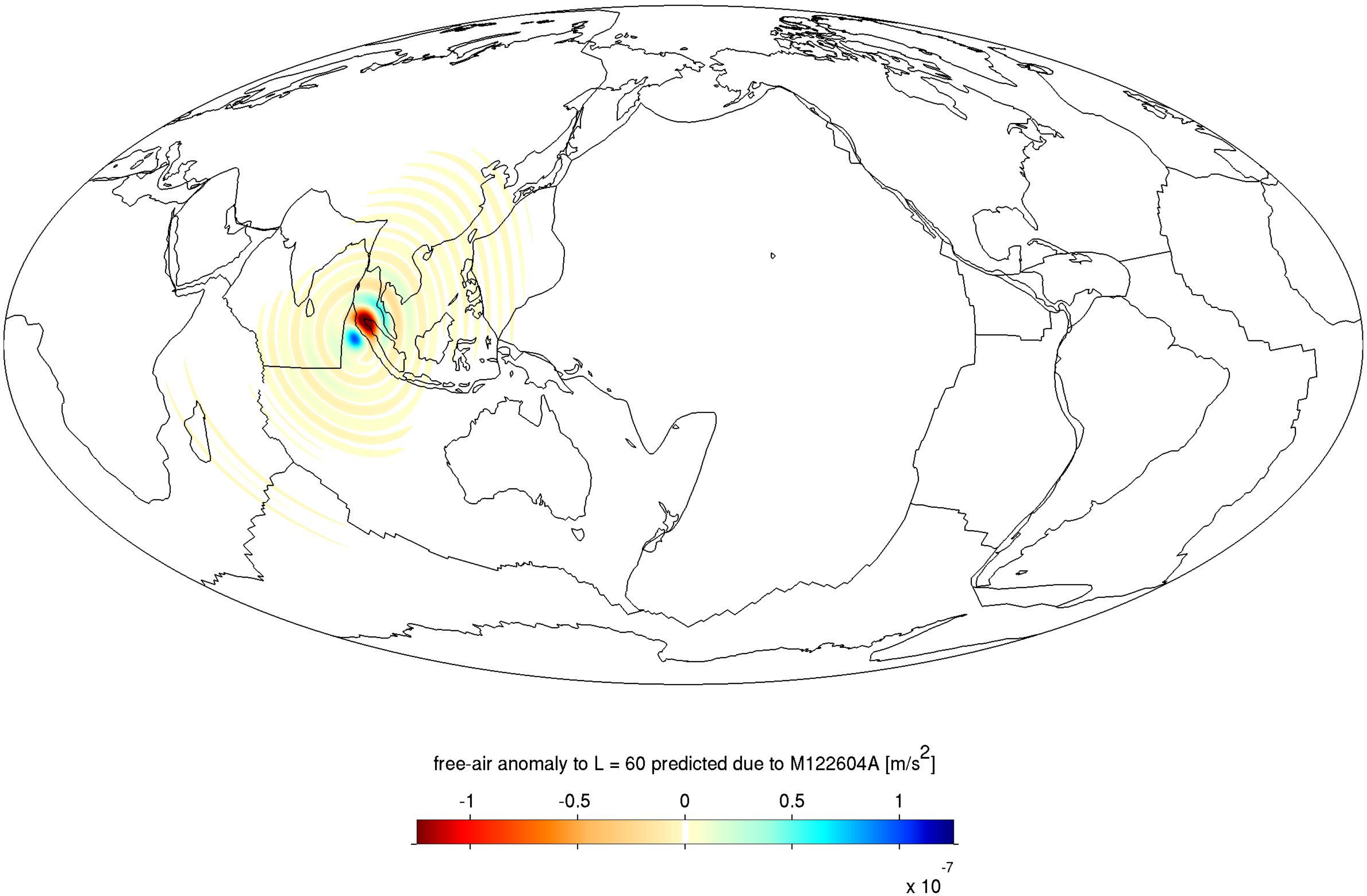
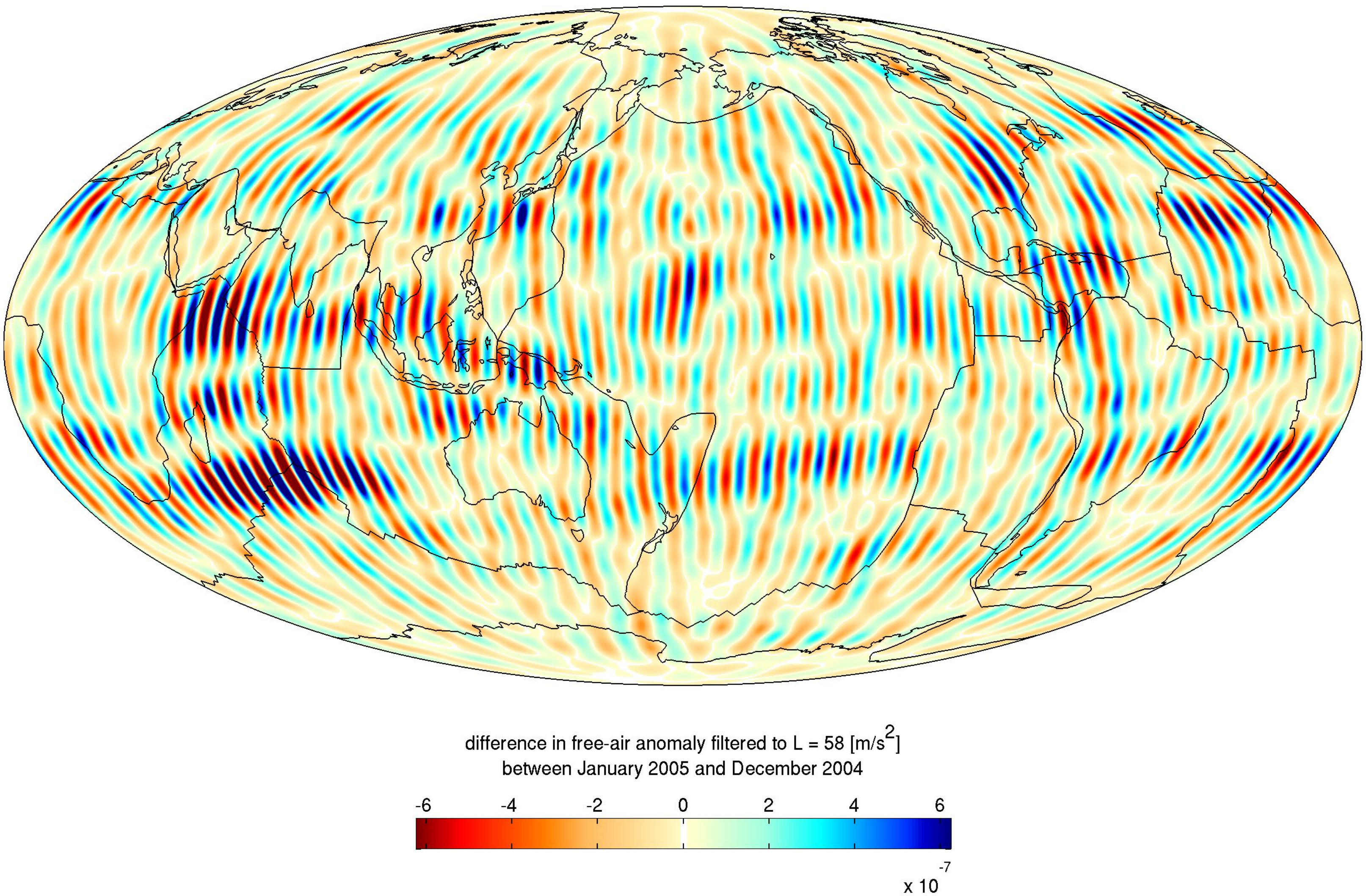


Earthquakes are small (even large ones)



Difference Jan 2005 – Dec 2004



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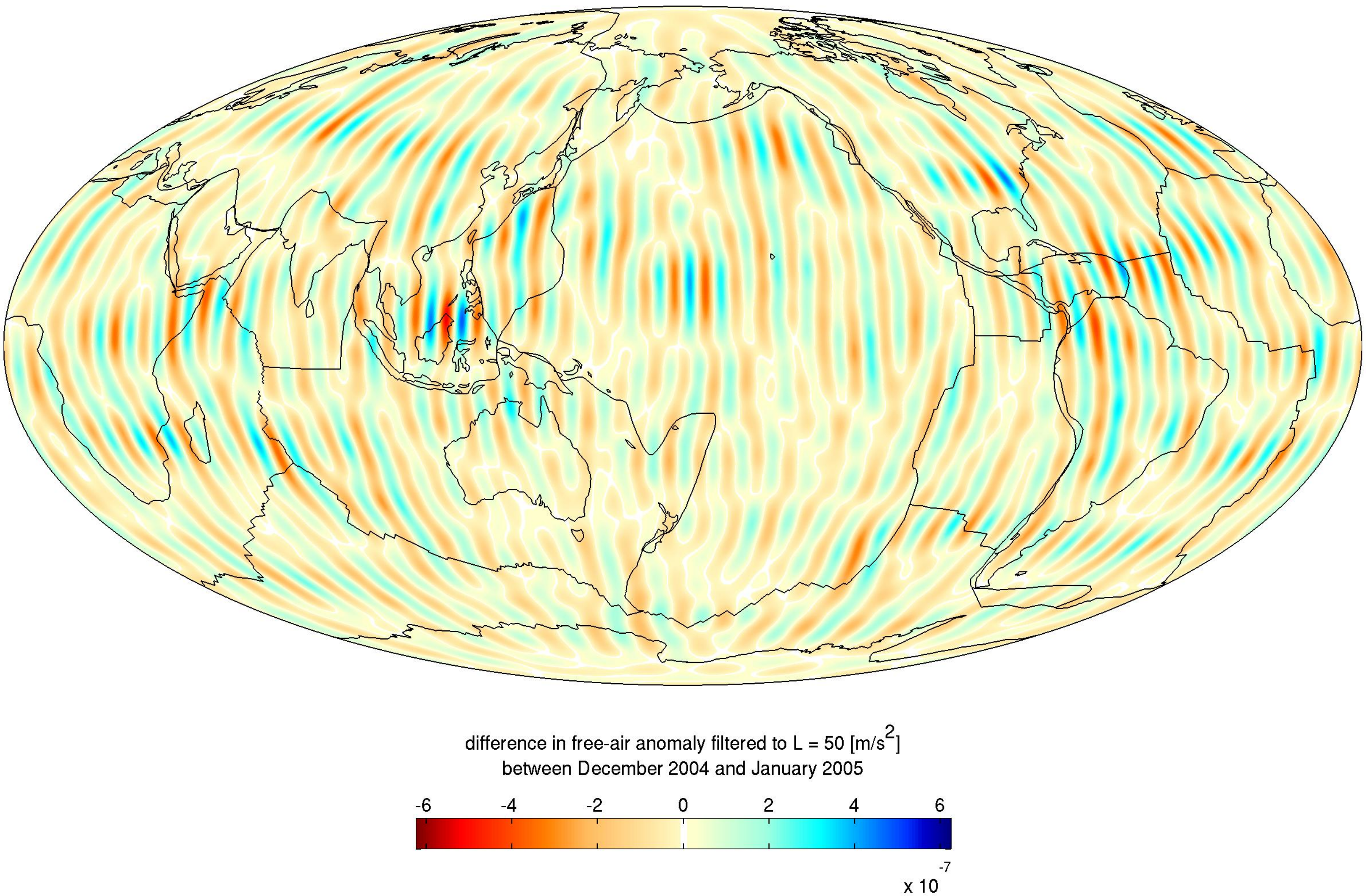

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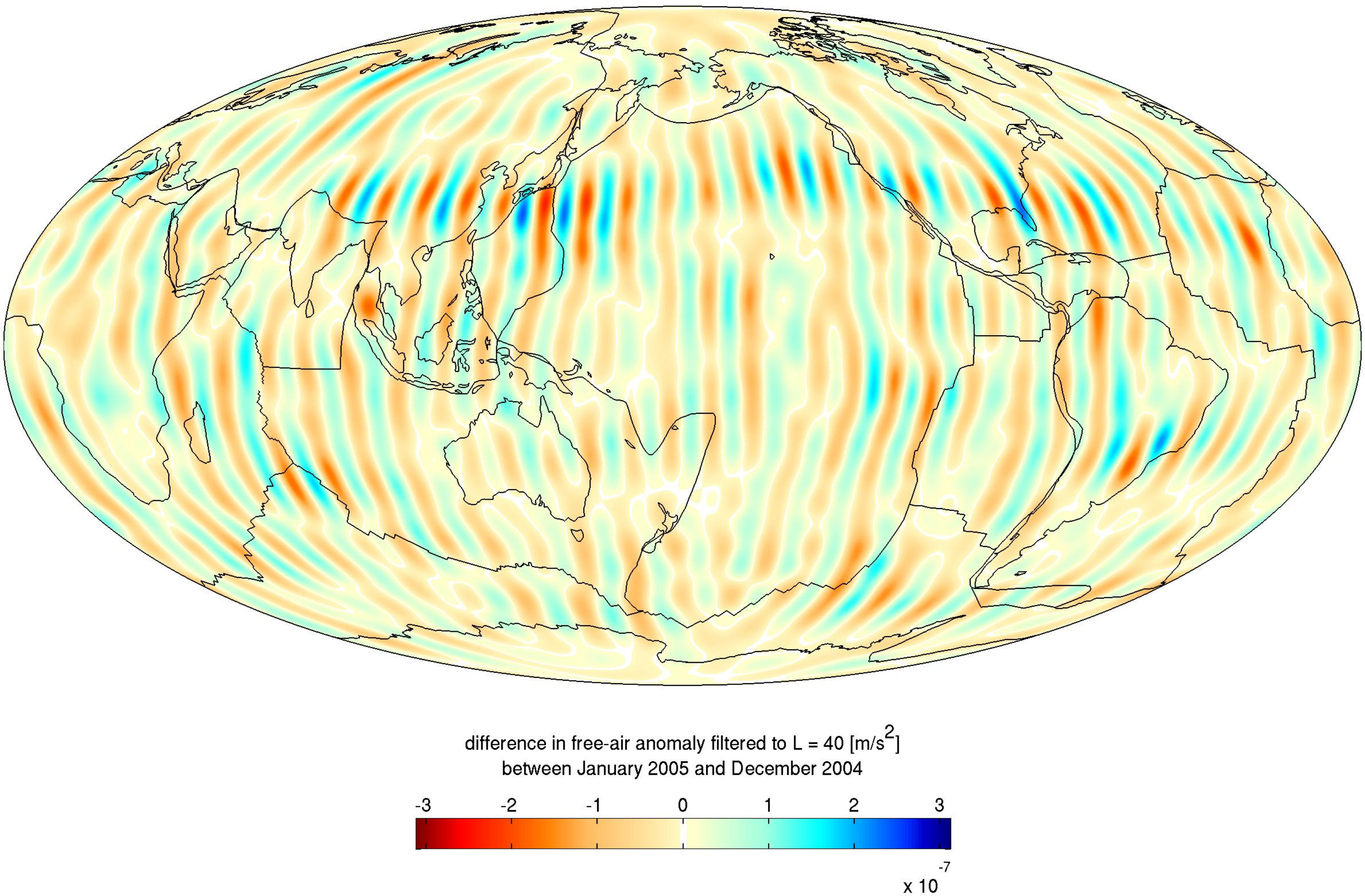

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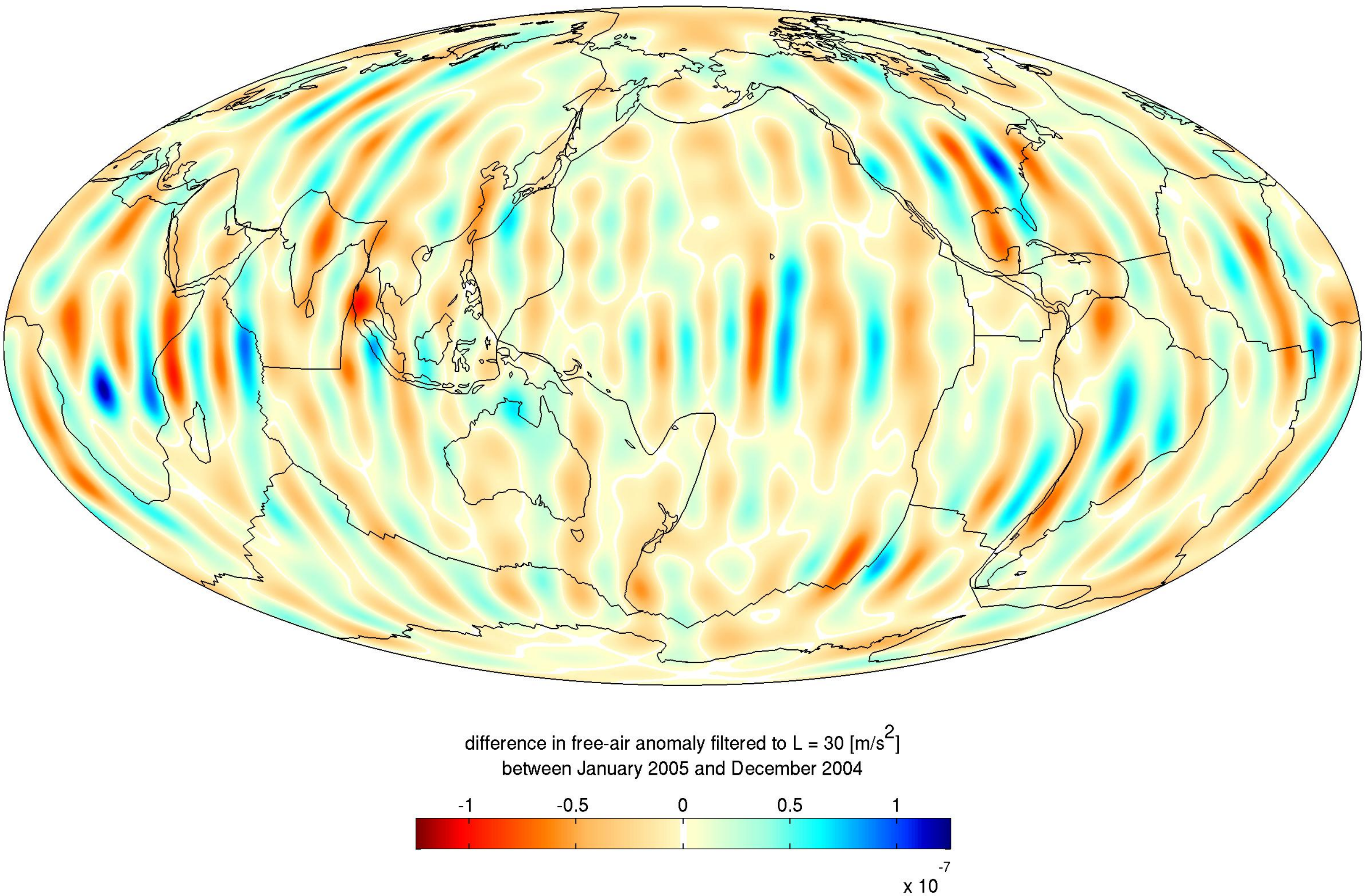

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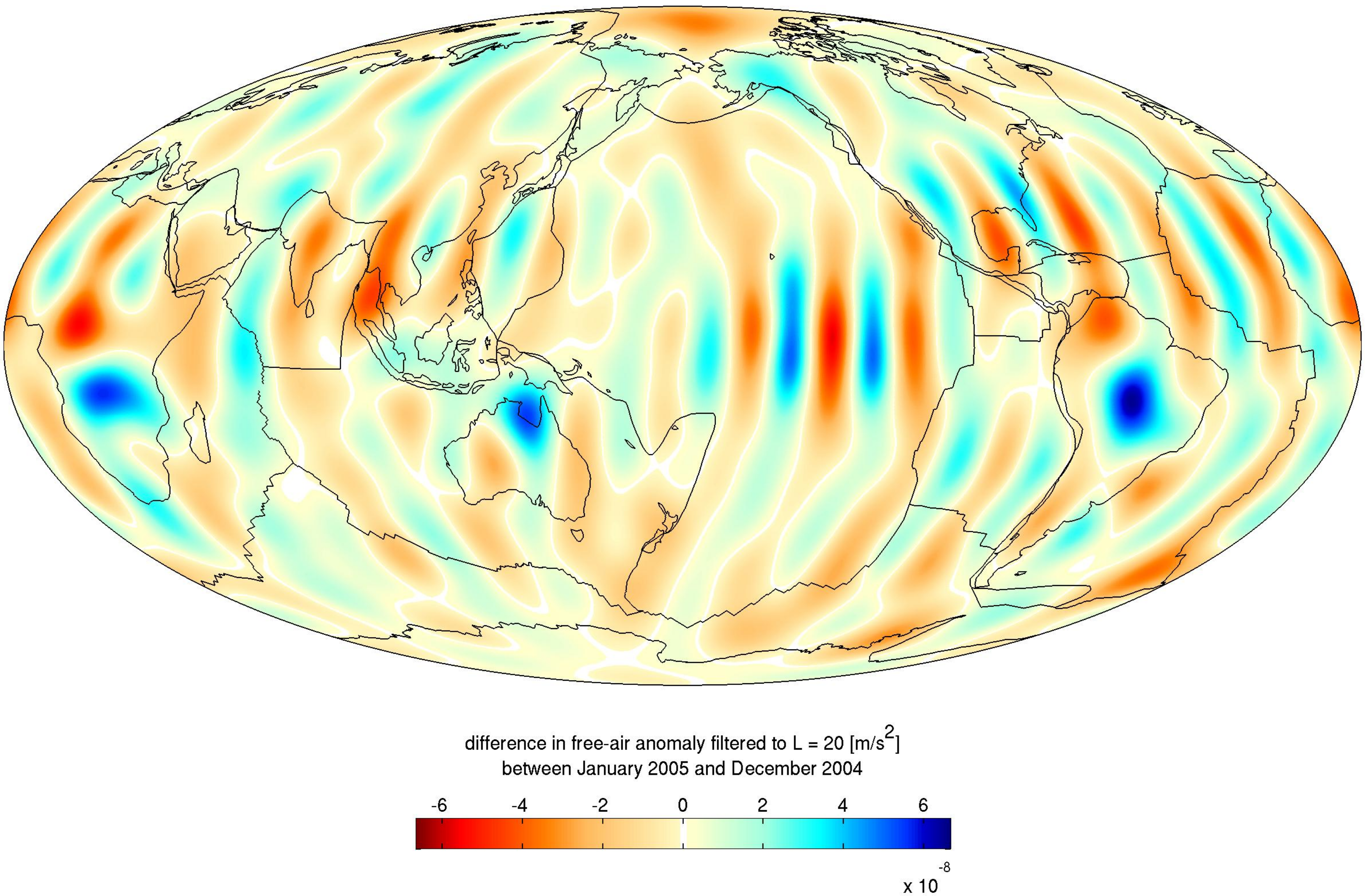

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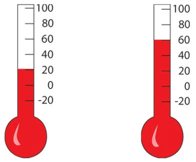

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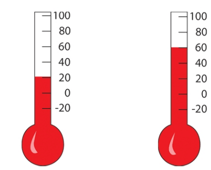

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  Aware of the huge challenges to beat elevated noise levels at small spatial footprints, the community has developed a multitude of **filtering** methods to **enhance signal-to-noise ratios** and, in particular, to eliminate the prominent effect of the satellite orbits on the behavior of the solutions (**destriping**).

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- Authors *disagree* on matters as fundamental as the **choice of basis** to represent the solution. Pixels? Mascons? Spherical harmonics? How do these choices influence the results?

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We may assume that $n(\mathbf{r})$ is **zero-mean** and **uncorrelated** with the signal,

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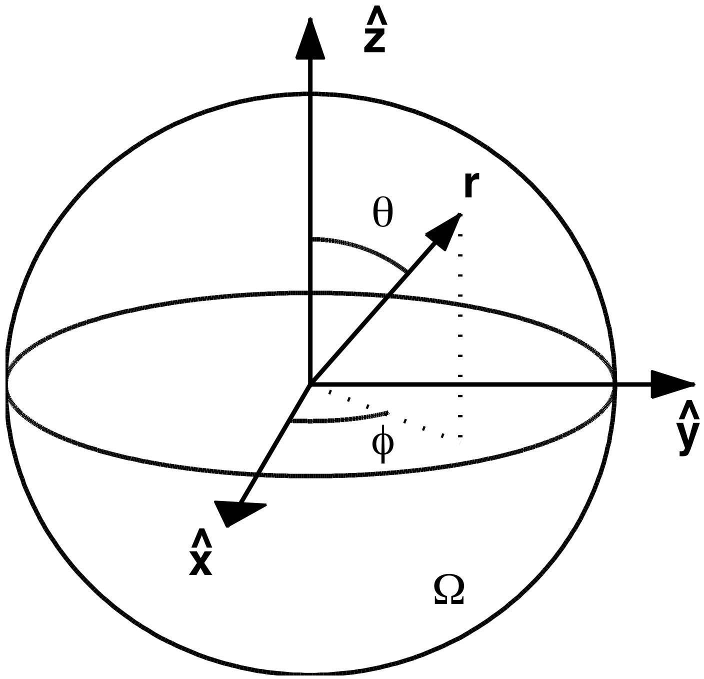
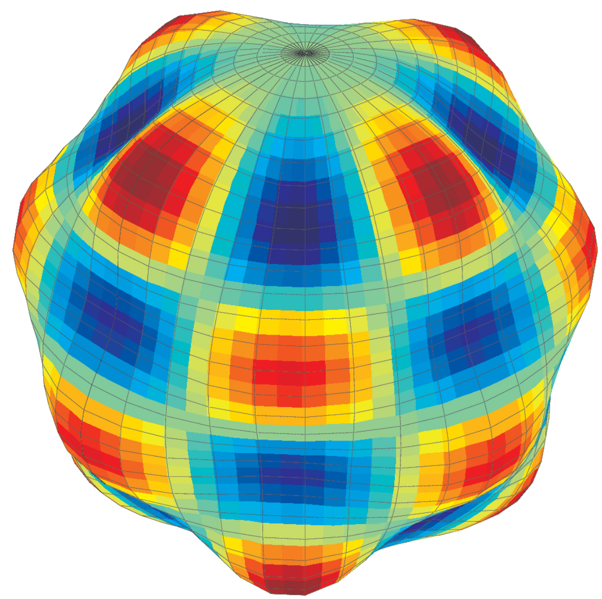
To honor the spherical shape of the Earth,

we work in the **spherical-harmonic** basis.

Spherical harmonics

Scalar signals $s(\mathbf{r})$ modeled on a unit sphere Ω:





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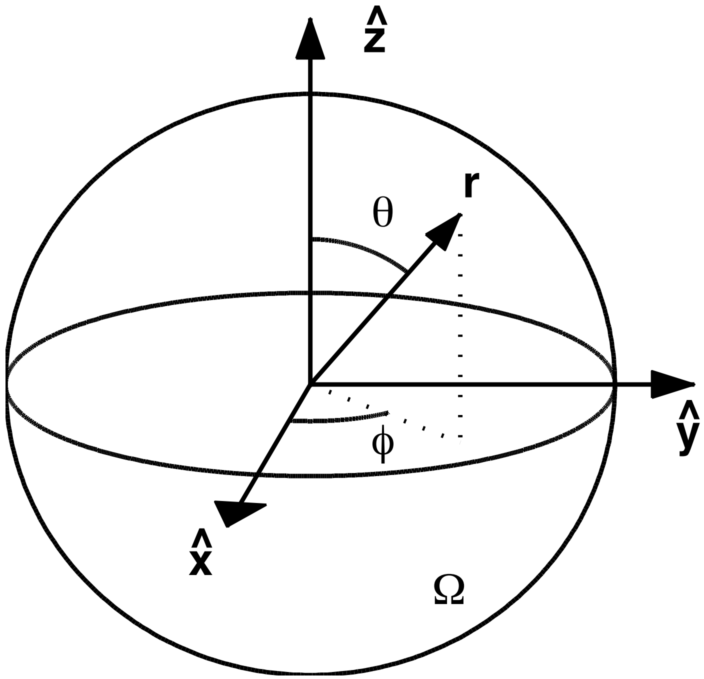

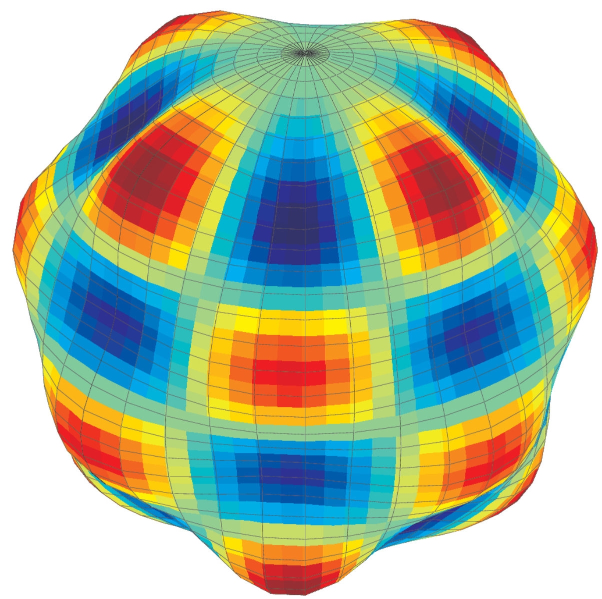

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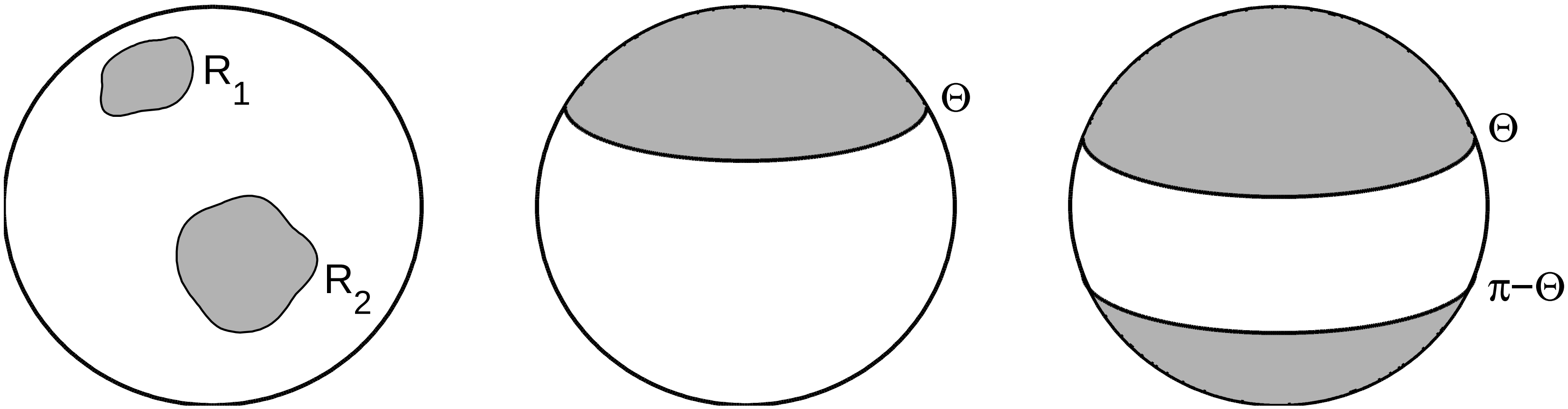

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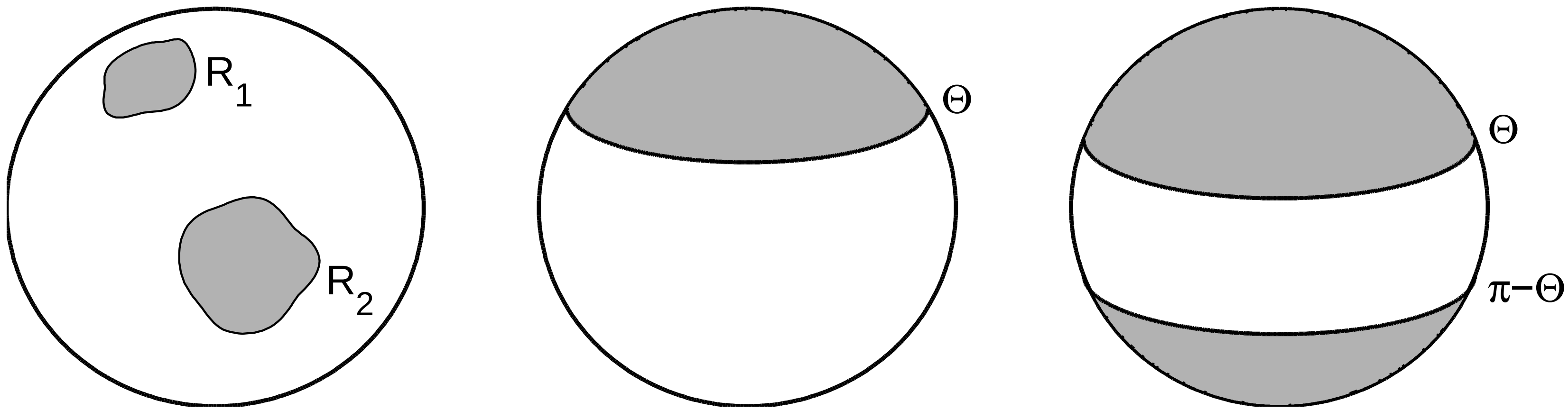

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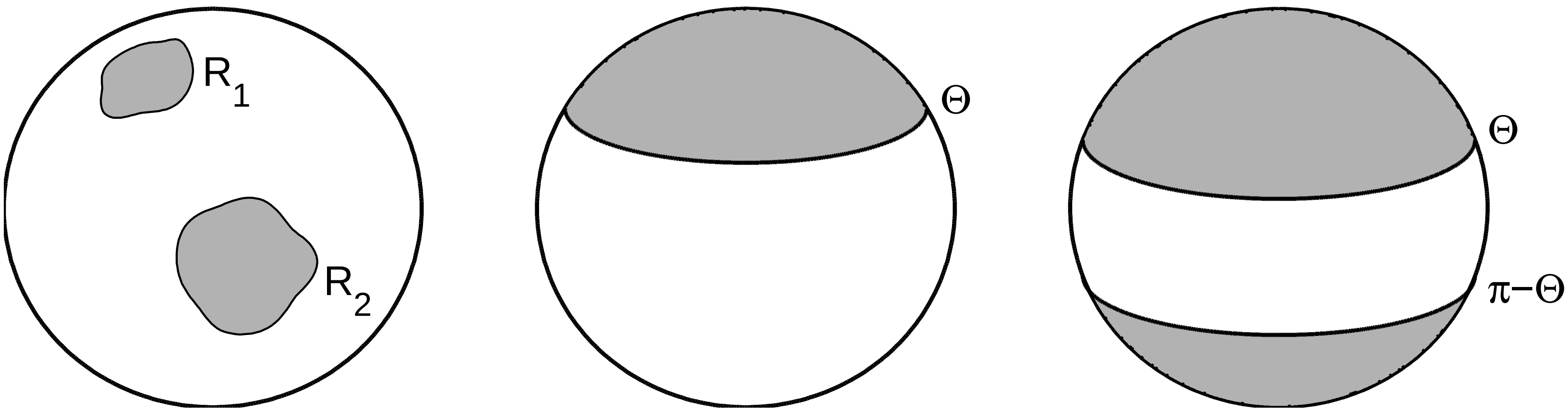

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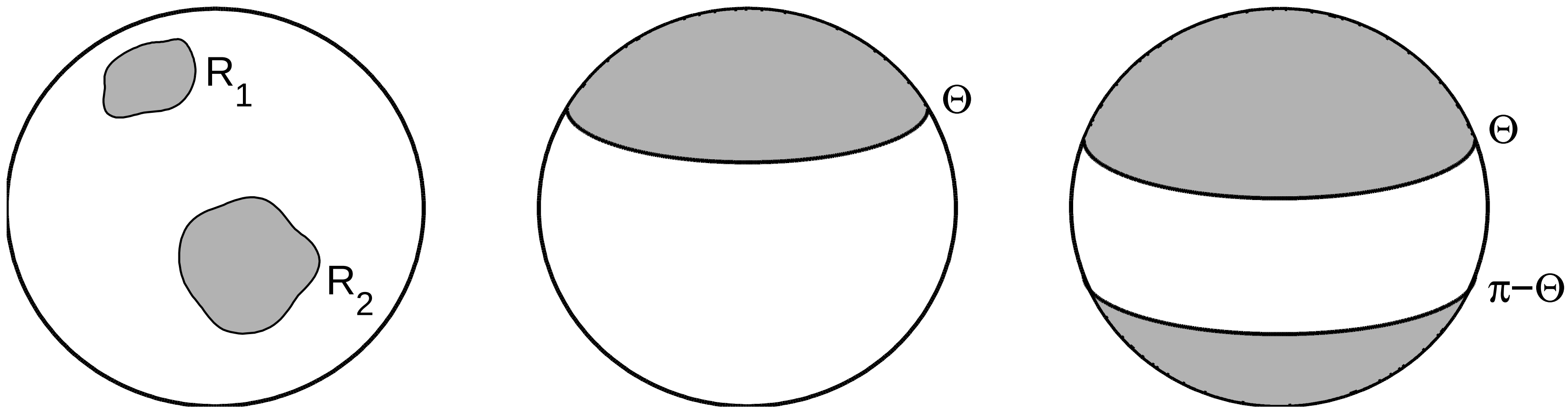

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These new, **doubly orthogonal**, functions are called **Slepian functions**, $g(\mathbf{r})$.

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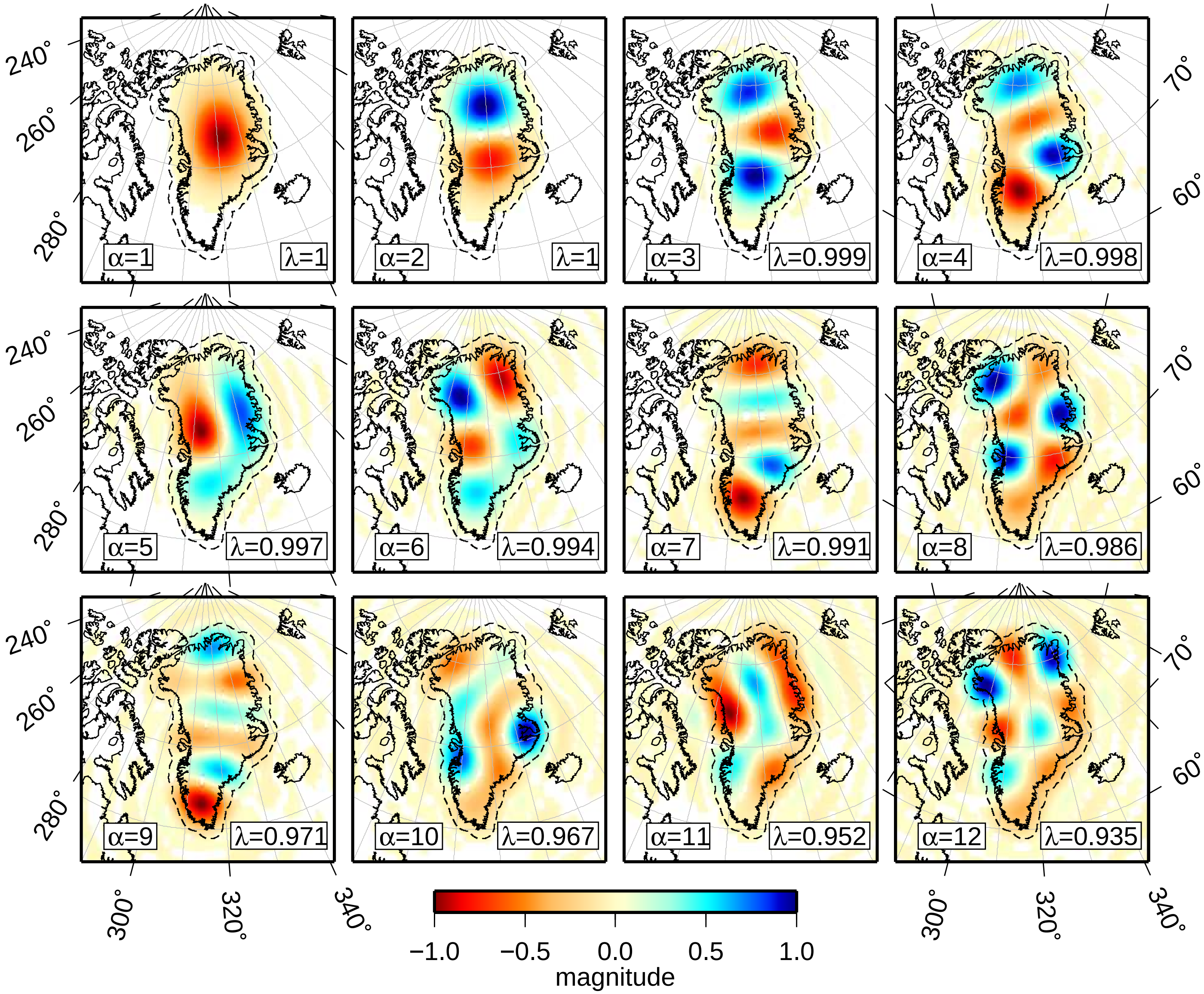
Voilà! We have *concentrated* a poorly localized basis of $(L+1)^2$ functions, Y_{lm}, both *spatially* and *spectrally*, to a new basis with only about K functions, g.

Slepian functions for Greenland, $L = 60$



Harig & Simons, PNAS 2012

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4. In this philosophy, the signal is **projected** onto the basis in which signal-to-noise ratios are maximized, and all subsequent estimates take the full spatial and spectral noise **covariance** into account.

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1. Learn as much as possible about the **noise** and the structure of the **signal**. More than likely, this is an **iterative** procedure.

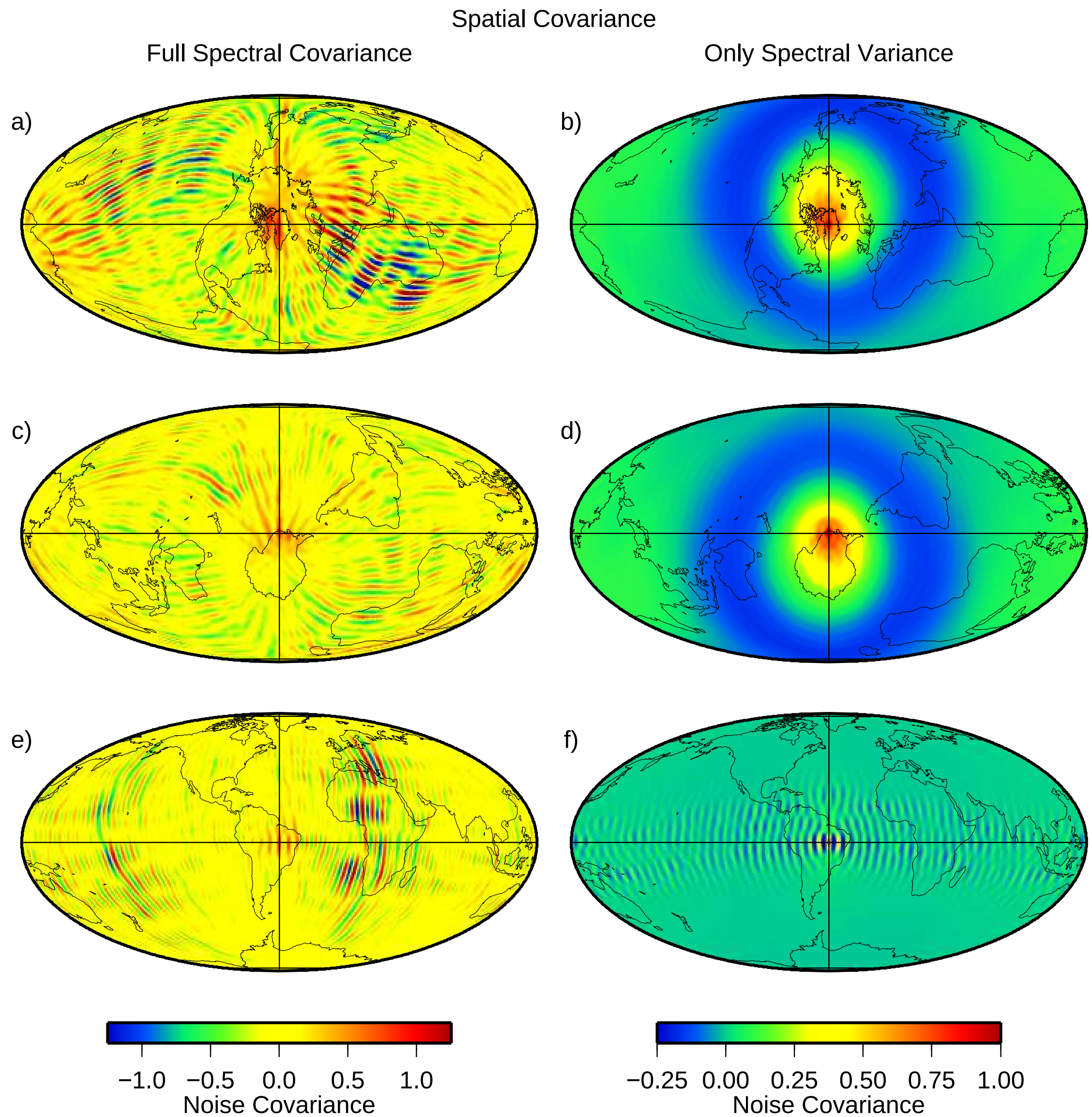
2. Design basis functions **appropriate for the region** of interest. Slepian functions are **optimal** for this type of problem in multiple respects.

3. Experiment with the **bandwidth** L of the signal as considered, allow for small **buffers** outside the region of interest. Monitor the statistics.

4. In this philosophy, the signal is **projected** onto the basis in which signal-to-noise ratios are maximized, and all subsequent estimates take the full spatial and spectral noise **covariance** into account.

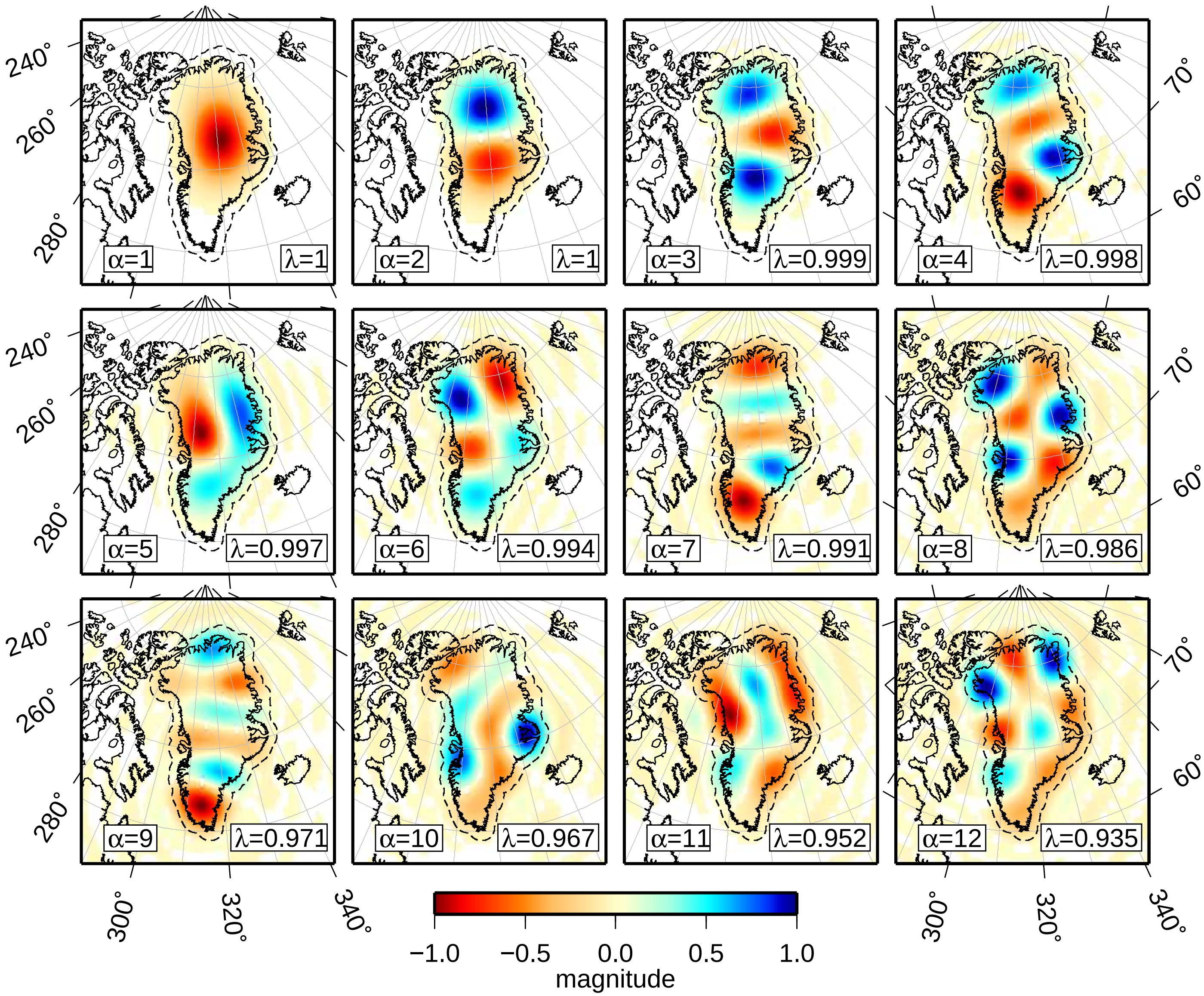
5. This is *very* different from most other approaches, though in spirit, it is *identical* to the stuff Slepian, Shannon and Wiener figured out in the 1950s.

I. Look at the noise (in the pixel basis)



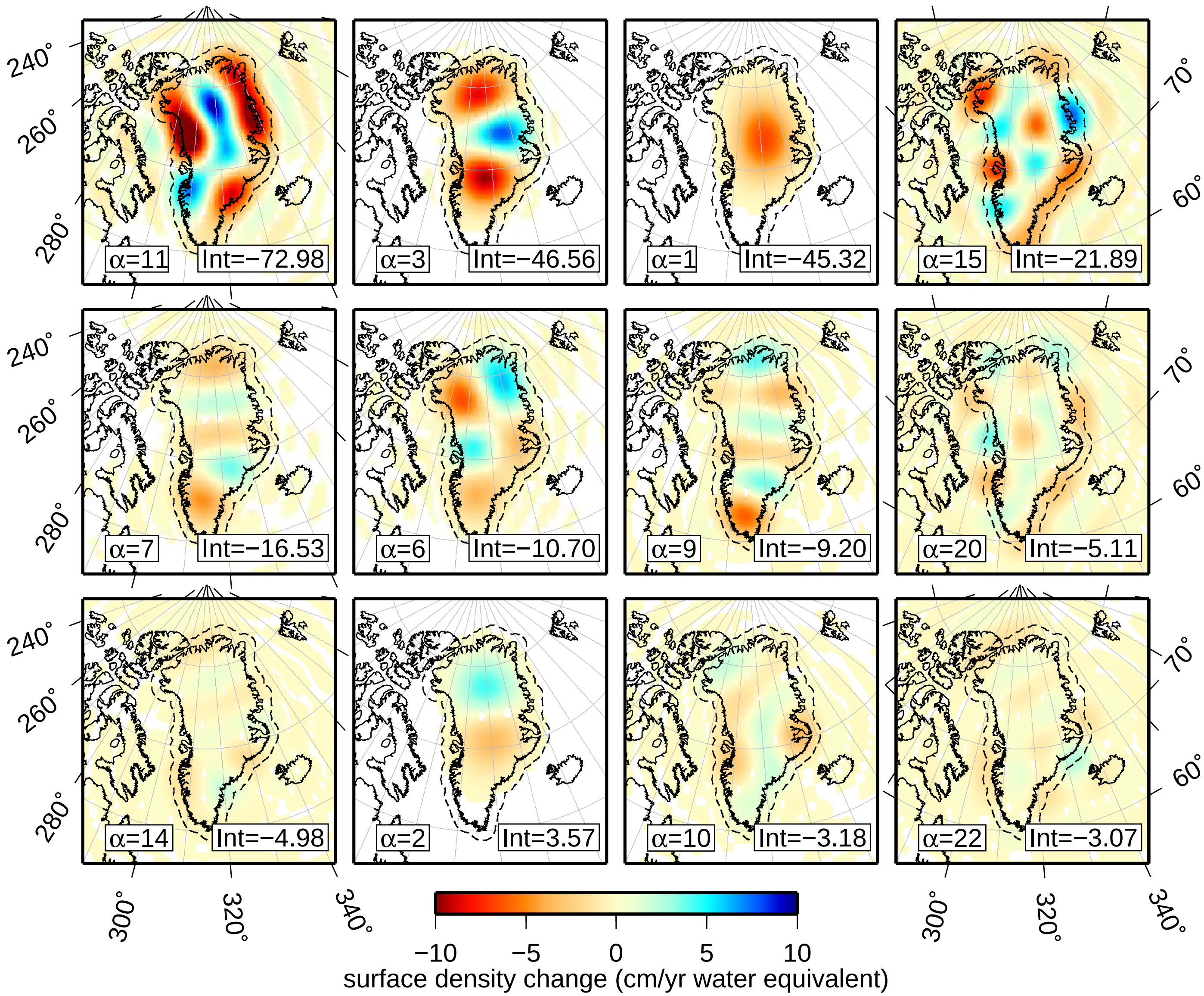
Harig & Simons, PNAS 2012

II. Construct an appropriate basis



Harig & Simons, PNAS 2012

III. Project the signal onto the new basis



Harig & Simons, PNAS 2012

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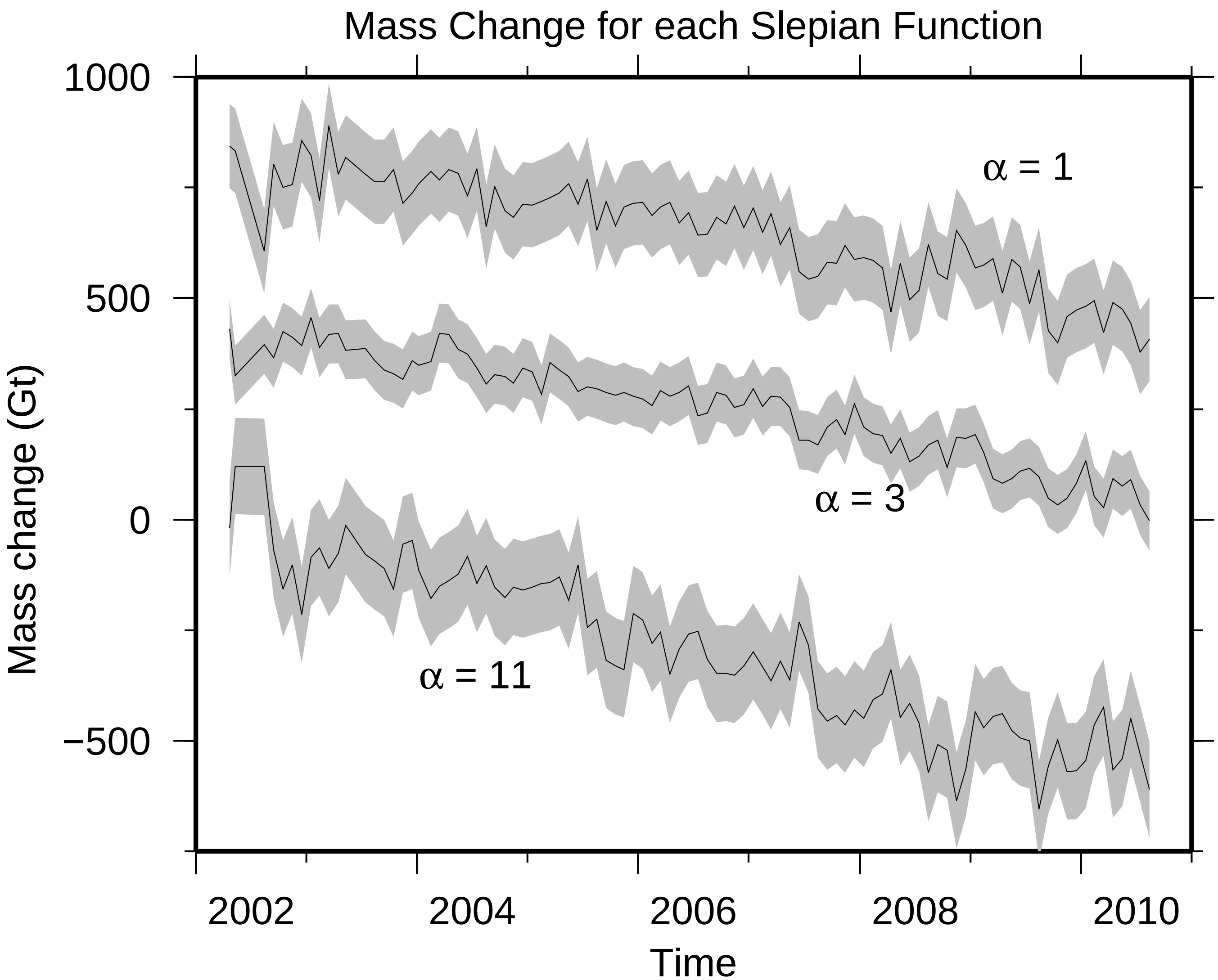
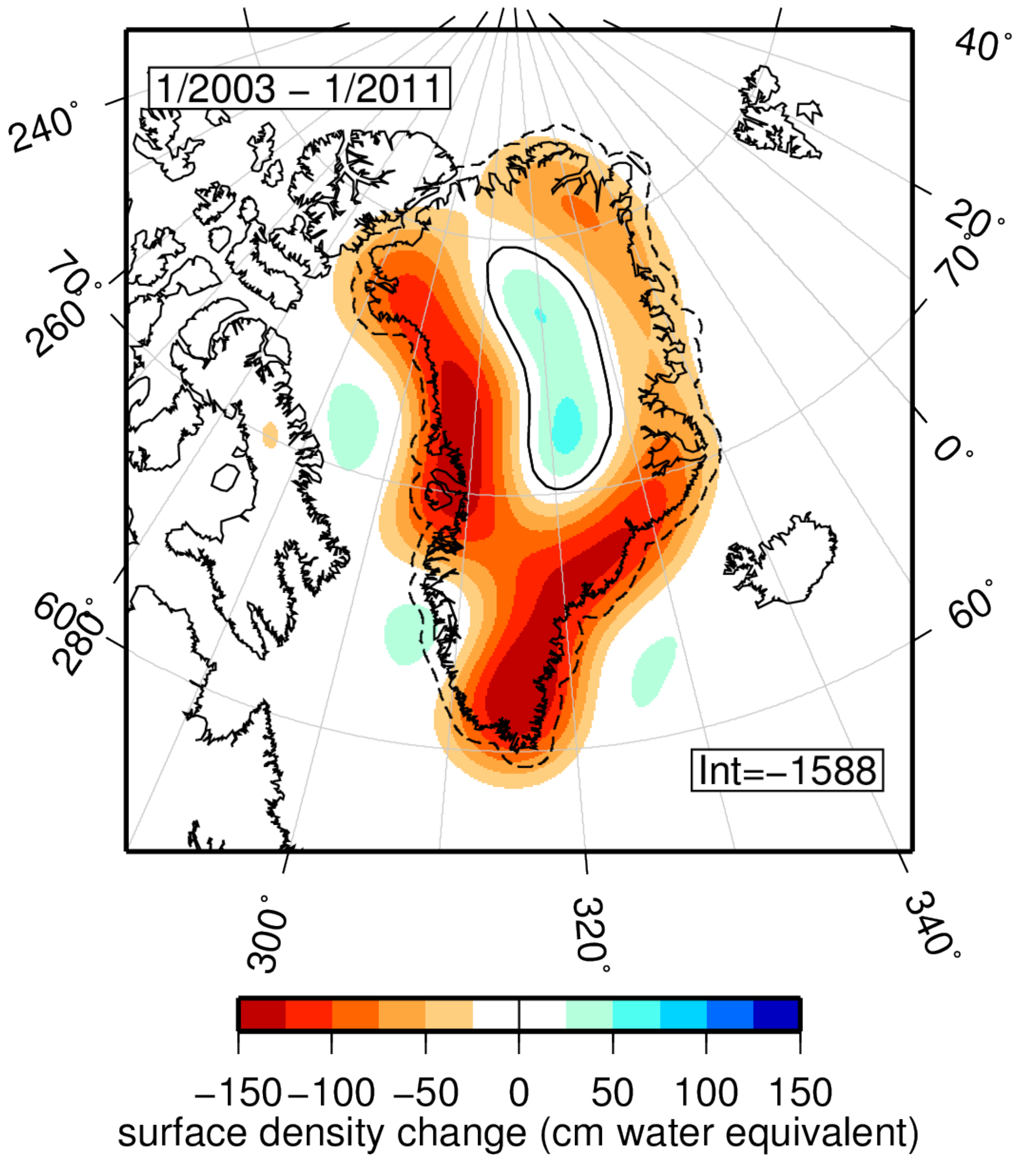


Harig & Simons, PNAS 2012

IV. Construct the final total estimate



Harig & Simons, PNAS 2012

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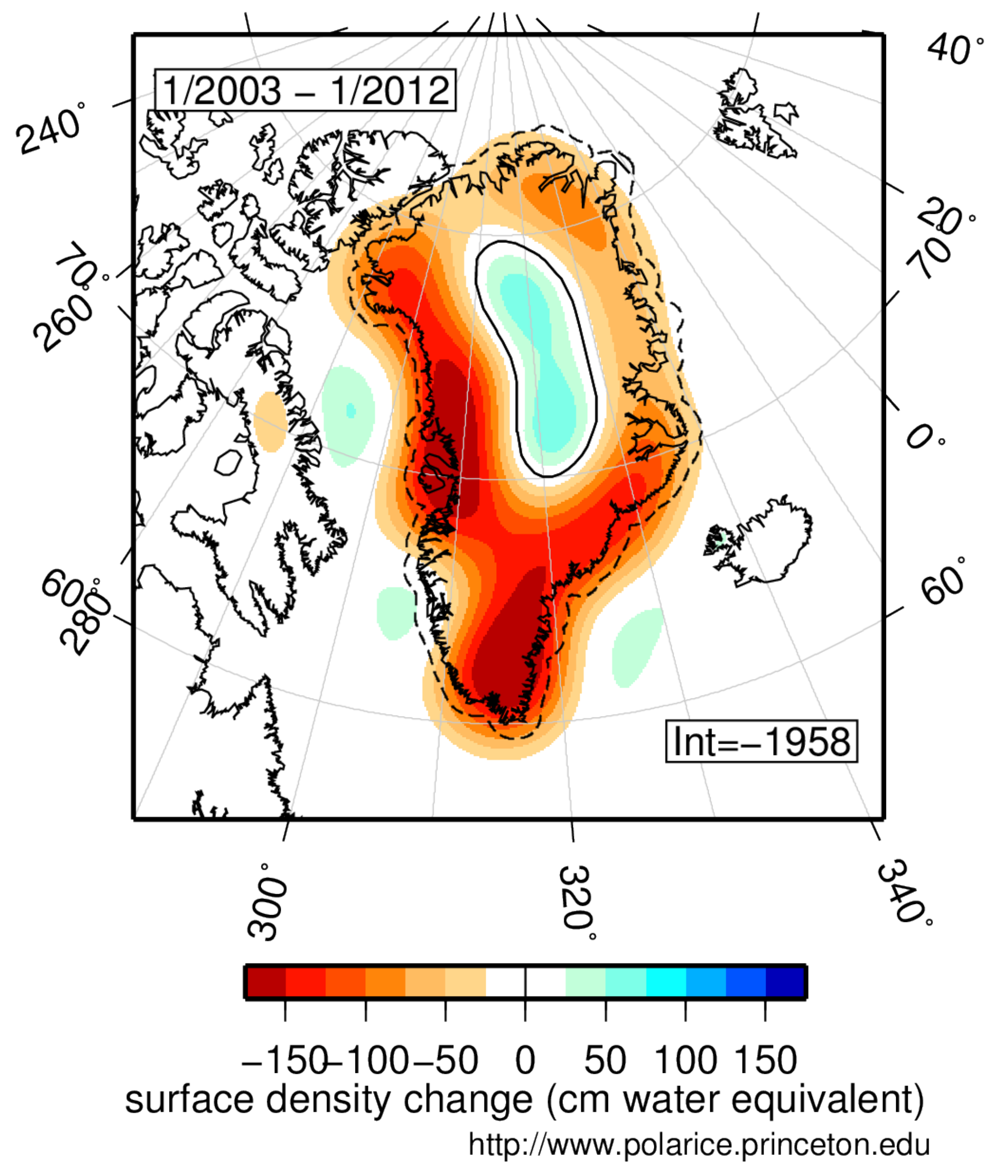
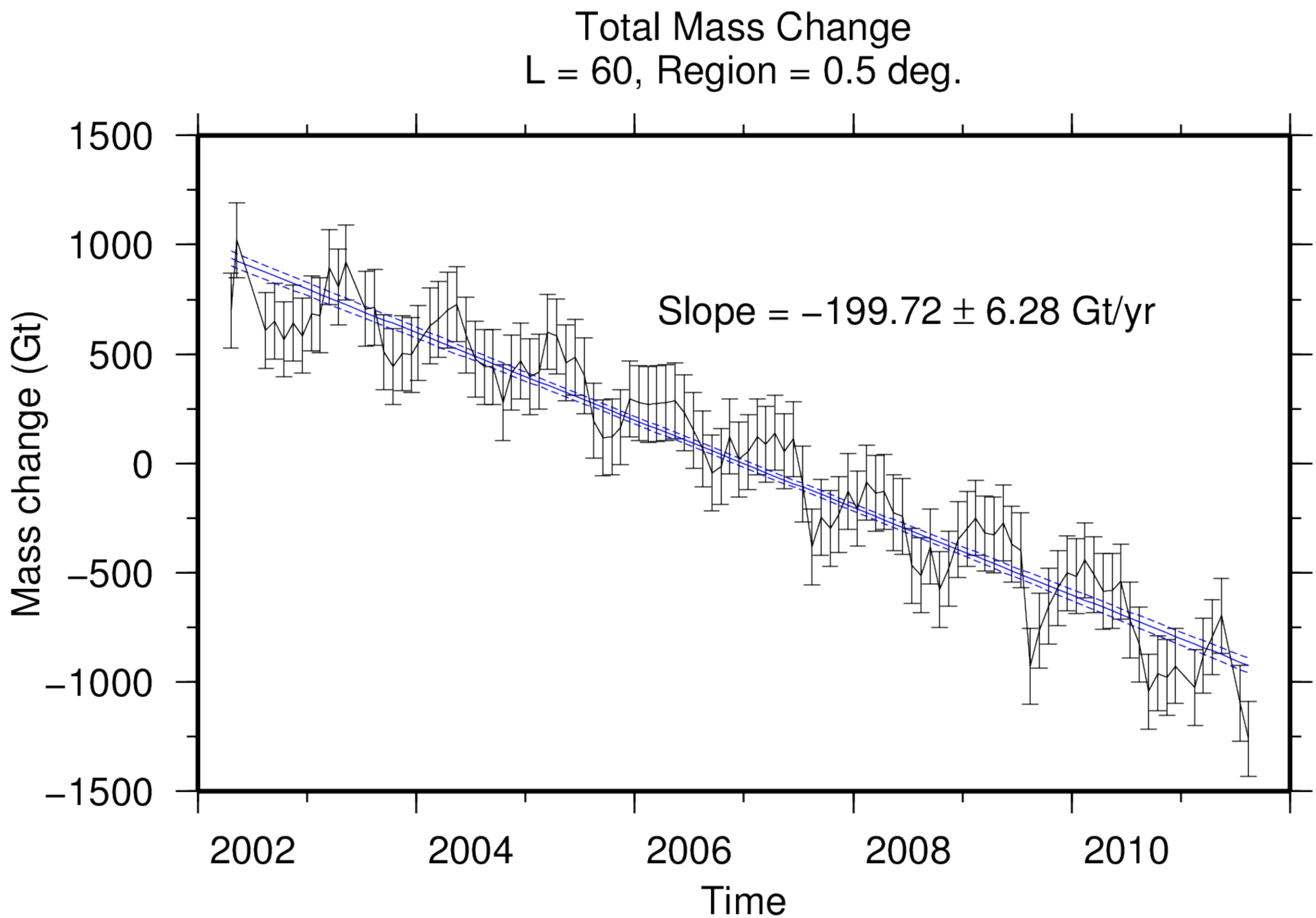


Harig & Simons, PNAS 2012

IV. Invert for the total budget (if you must)



Harig & Simons, PNAS 2012

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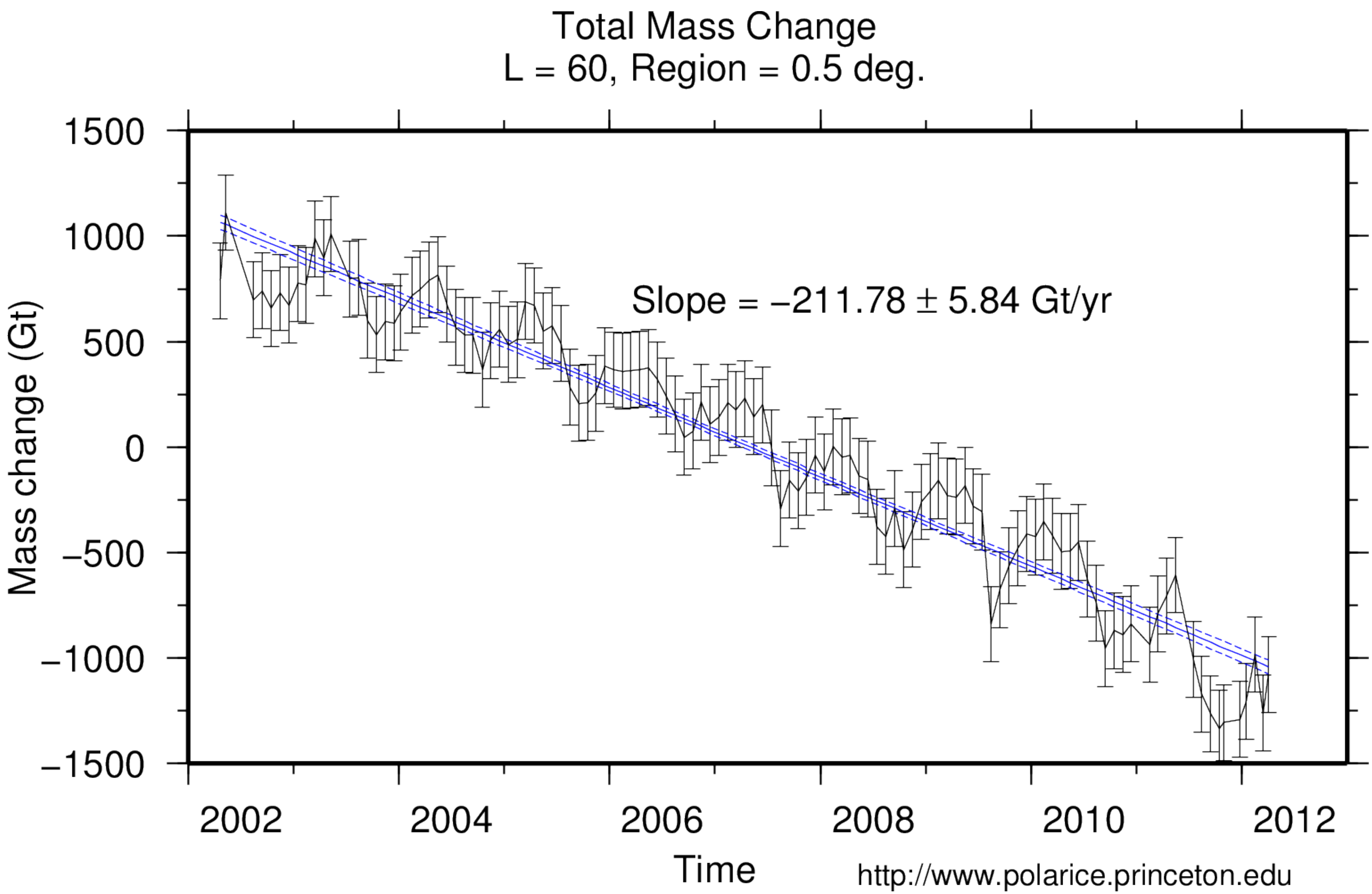

Harig & Simons, PNAS 2012

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- Modeling by Slepian functions requires very few *ad hoc* assumptions. Moreover, in addition to regional mass-average estimates, we get **maps**.
- Maps of the time-averaged mass loss show a marked concentration at the **outlet glaciers**. Observed rates compare well with GPS surveys.

Common problems

Planetary gravity/magnetic field: **Problem 1**

Given $d(\mathbf{r})$ and $\langle n(\mathbf{r})n(\mathbf{r}')\rangle$, estimate the signal $s(\mathbf{r})$ at **source level**:

$$\hat{s}(\mathbf{r}) = \sum_{\alpha=1}^{J} \hat{s}_\alpha g_\alpha(\mathbf{r}), \tag{1}$$

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Also: *Cosmic Microwave Background radiation*: **Problem 2**

Given $d(\mathbf{r})$ and $\langle n(\mathbf{r})n(\mathbf{r}')\rangle$, and assuming the universe behaves as

$$\langle s_{lm}\rangle = 0 \quad \text{and} \quad \langle s_{lm}s^*_{l'm'}\rangle = S_l\,\delta_{ll'}\delta_{mm'}, \tag{2}$$

estimate the **power spectral density** S_l, for $0 \le l < \infty$.

Dahlen & Simons, GJI 2008

Quadratic spectral estimators

Whole-sphere ... *unattainable*

$$\hat{S}_l^{\mathrm{WS}} = \frac{1}{2l+1} \sum_m \left| \int_\Omega d(\mathbf{r})\, Y_{lm}^*(\mathbf{r})\, d\Omega \right|^2 - \text{noise correction.} \tag{3}$$

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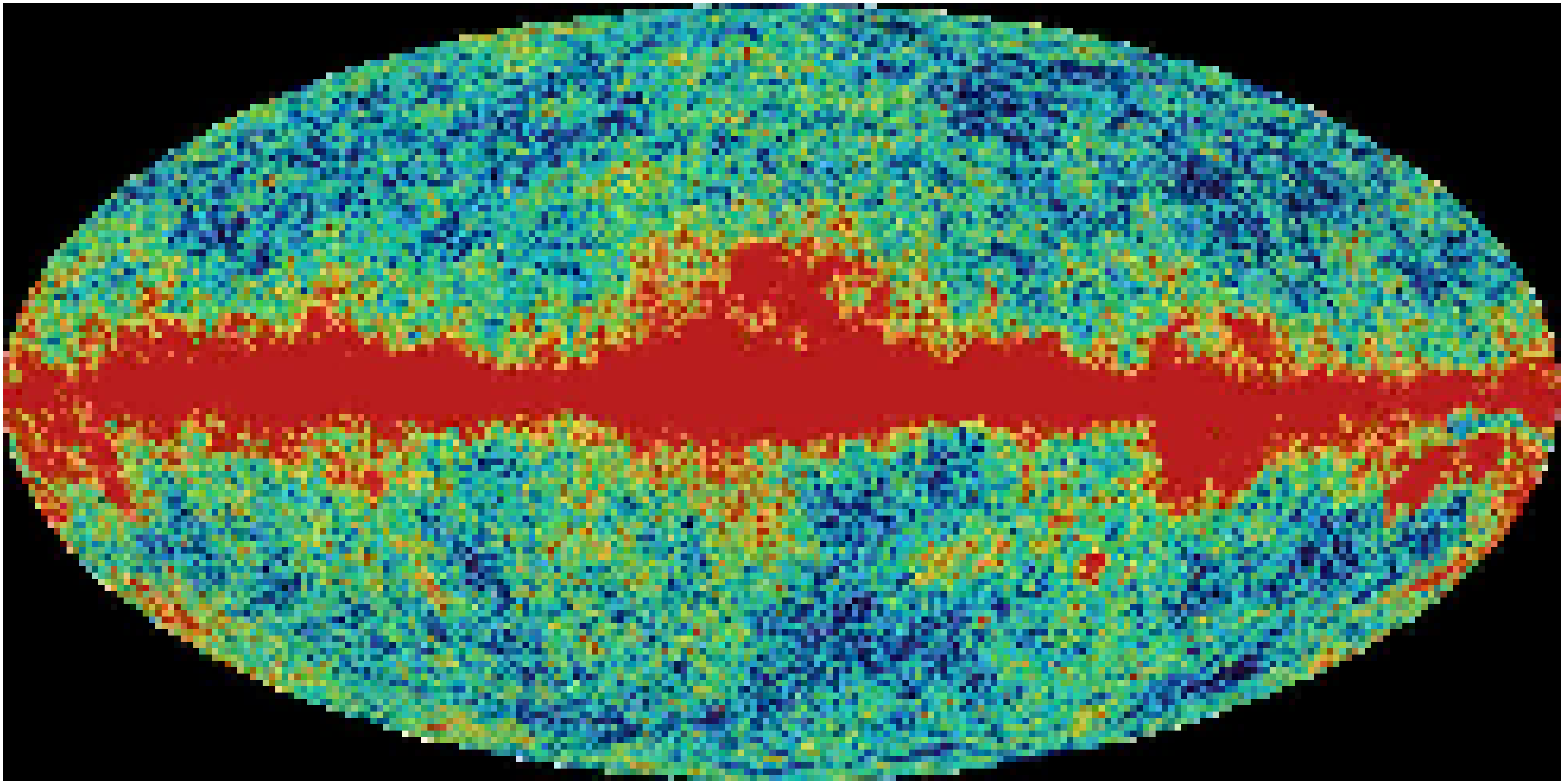
Multiple-taper ... *bandlimited bias, lower variance, easily implemented*

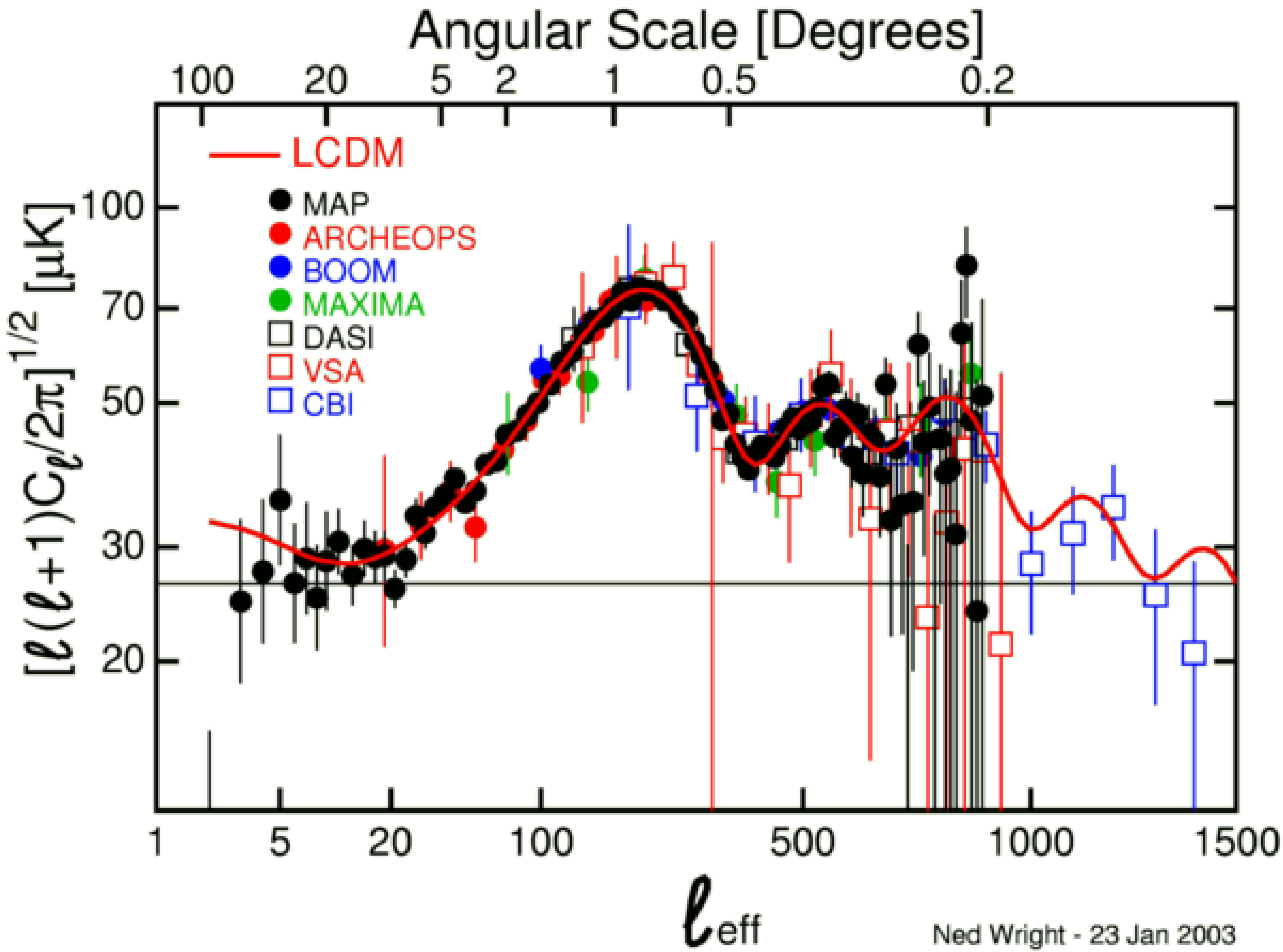
$$\hat{S}_l^{\mathrm{MT}} = \frac{1}{N} \sum_\alpha \lambda_\alpha \hat{S}_l^{\alpha}. \tag{6}$$

Dahlen & Simons, GJI 2008

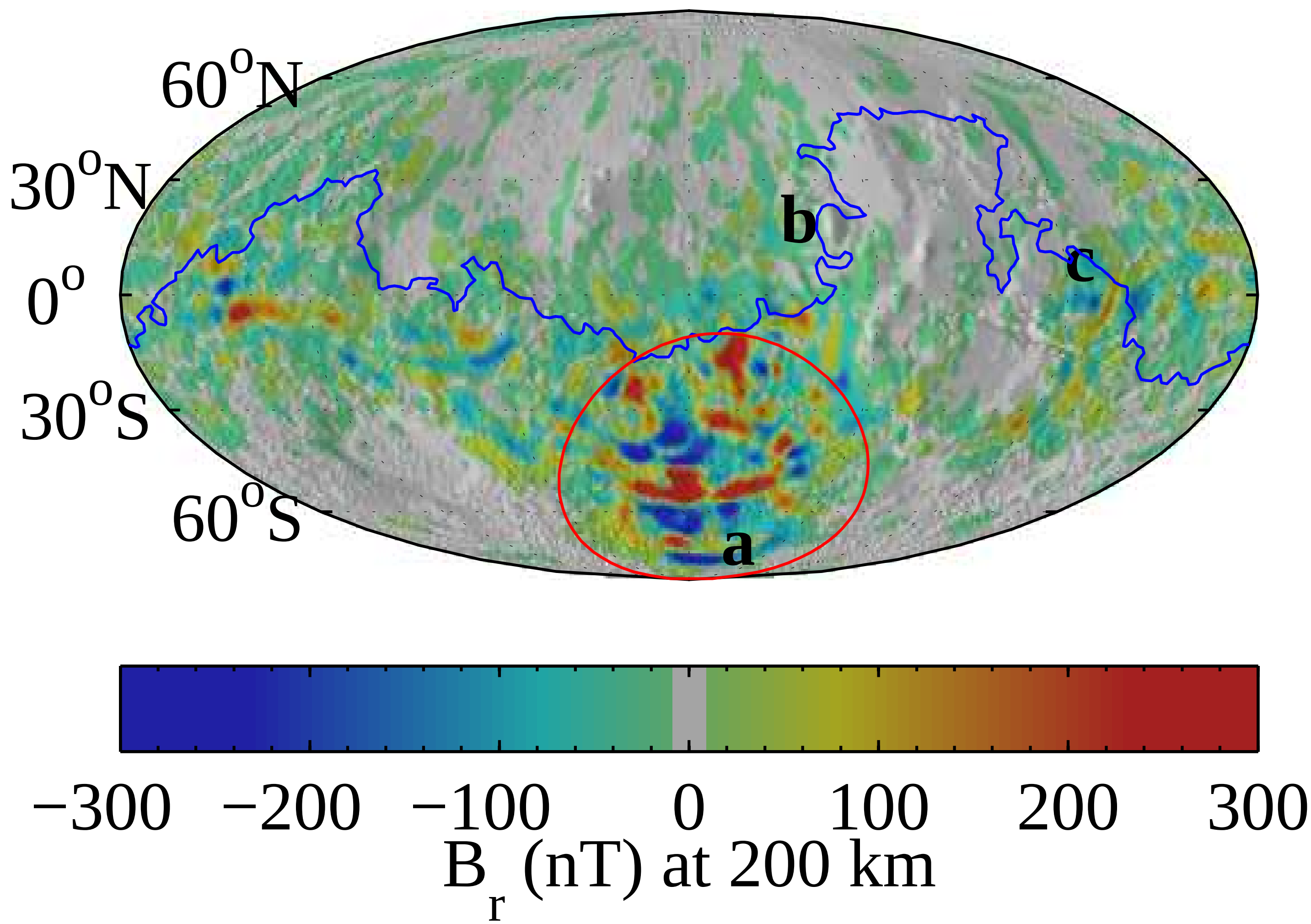
WMAP & Cosmic Background Radiation — 1



WMAP & Cosmic Background Radiation — 2

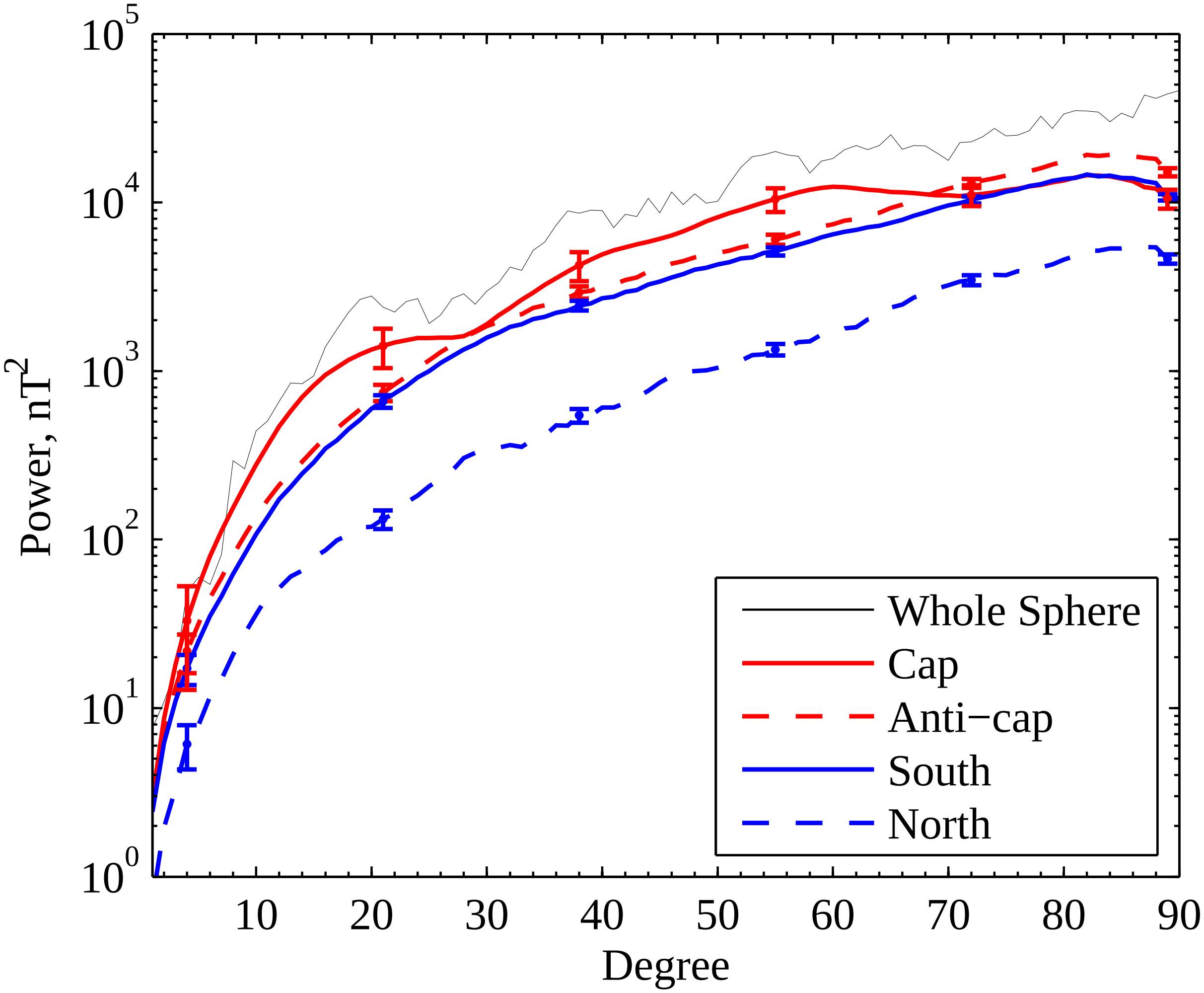


Mars' radial magnetic field



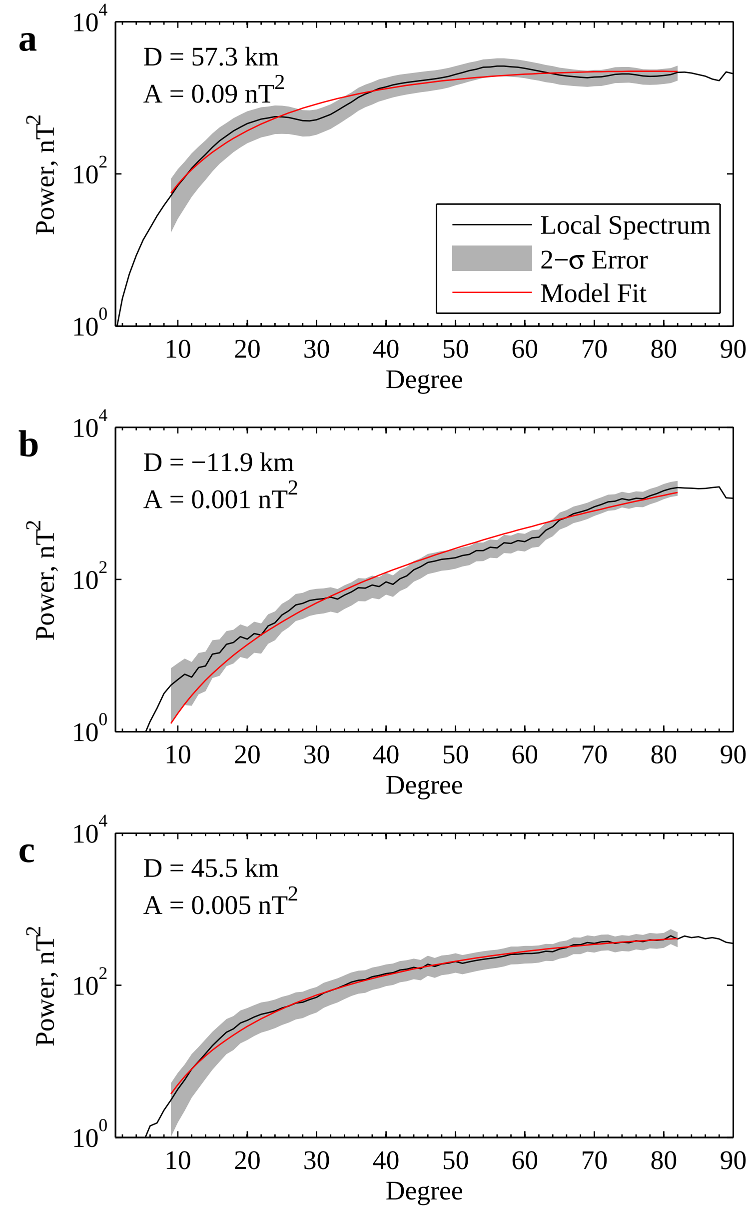
Lewis & Simons, GRL 2012

Mars' magnetic field: Power spectral density



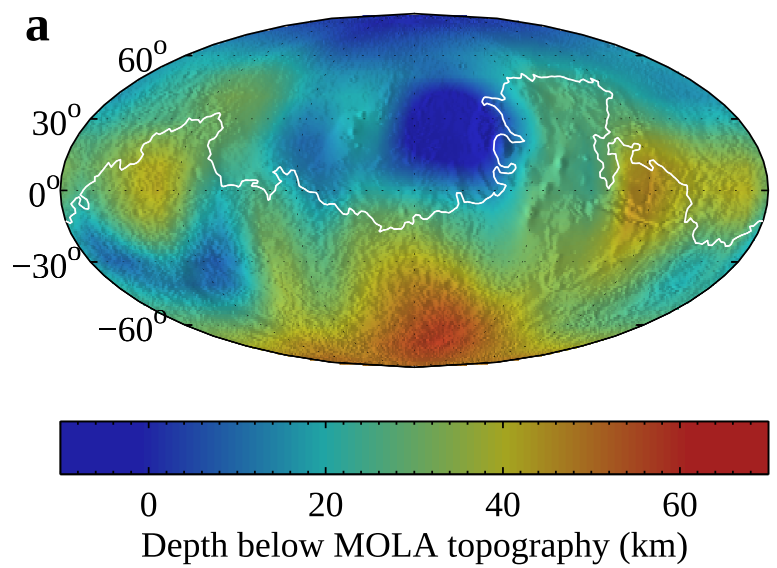
Lewis & Simons, GRL 2012

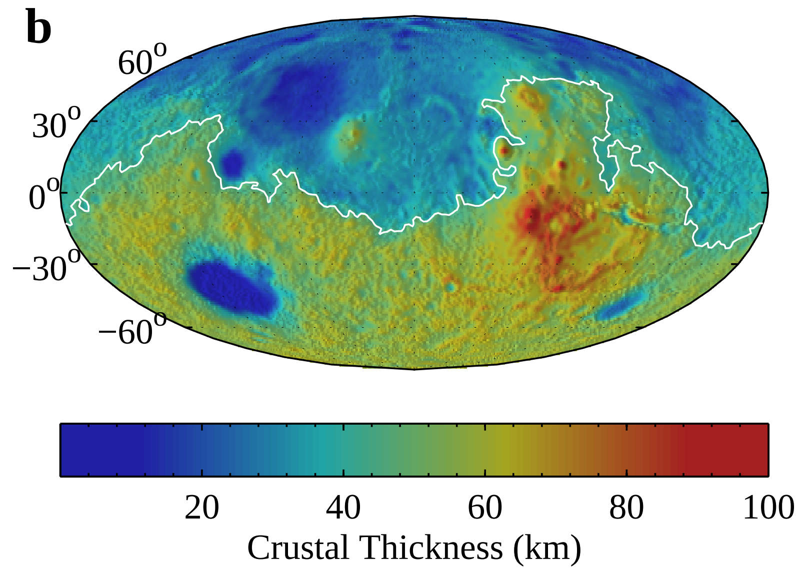
Mars: Magnetic strength vs decorrelation depth



Lewis & Simons, GRL 2012

Mars: Decorrelation depth vs crustal thickness





Lewis & Simons, GRL 2012

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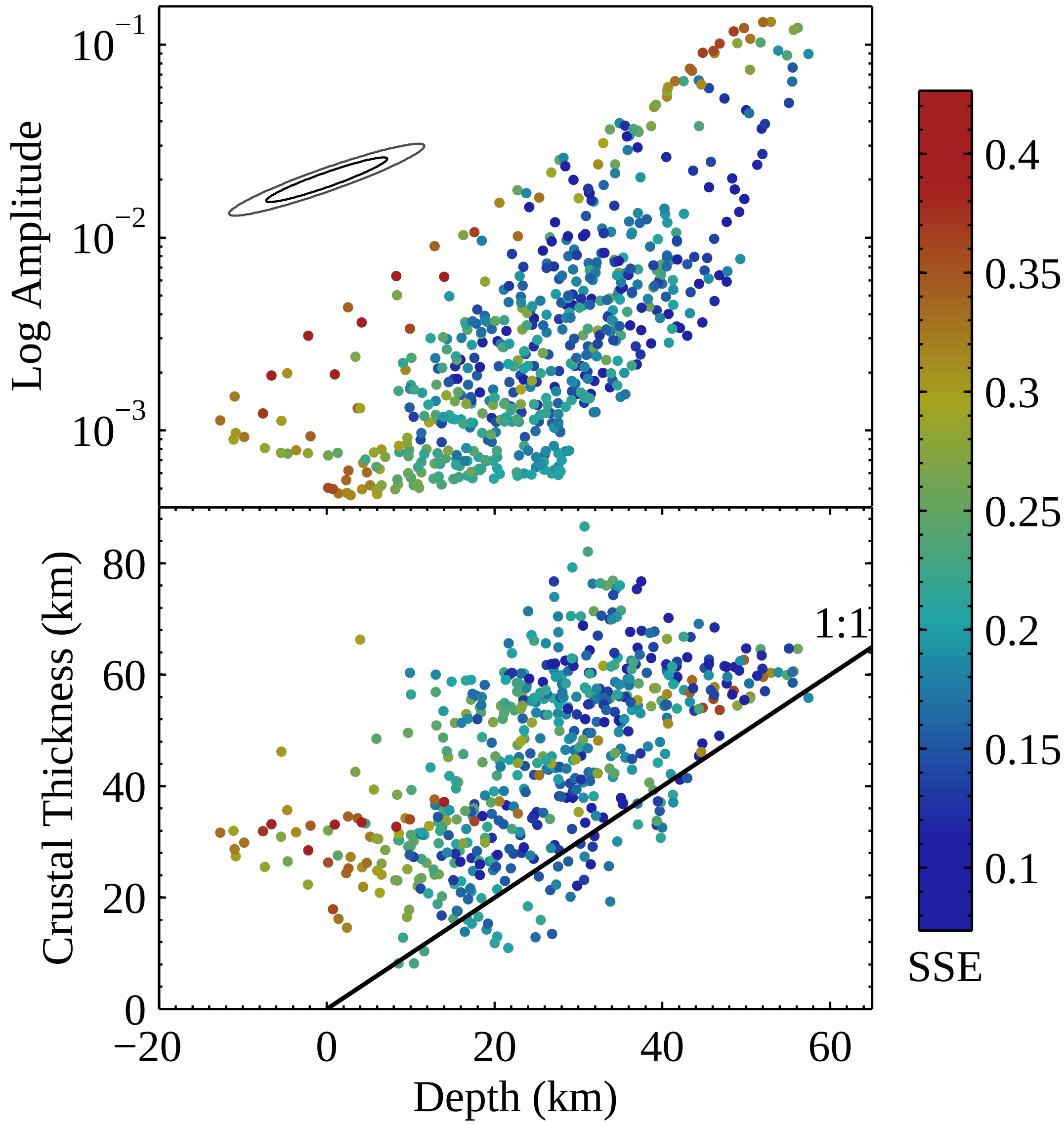

Lewis & Simons, GRL 2012

Conclusions

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- A **power-spectral analysis** of the **Martian magnetic field** reveals that for much of the planet **local source models** provide much better fits to the data than is captured by a global model.
- The **correlation** of magnetic **source depths and strengths** with independent **crustal thickness** estimates indicates that a significant fraction of the martian crustal column may contribute to the observed field, as would be consistent with an **intrusive magmatic origin**.