# Maximum-likelihood Theory for the Inversion of Gravity and Topography

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# Topography



# The free-air gravity anomaly



# The Bouguer-air gravity anomaly



## The standard model



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# The lithosphere is two differential equations

#### **Surface loading**

Surface-loading topography  $\mathcal{H}_{11}$  is in instantaneous **elastic** balance with the subsurface topography  $\mathcal{H}_{12}$ , according to the **biharmonic equation**:

$$\left(\nabla^4 + \frac{g\Delta_2}{D}\right) \mathcal{H}_{12}(\mathbf{x}) = -\frac{g\Delta_1}{D} \mathcal{H}_{11}(\mathbf{x}).$$
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Similarly, subsurface-loading topography  $\mathcal{H}_{22}$  is balanced at the surface by  $\mathcal{H}_{21}$  following the same equation:

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We want to find D, the **flexural rigidity**.

Thus the **free-air anomaly**  $d\mathcal{G}_{ij}(\mathbf{k})$  due to the topographic perturbation  $d\mathcal{H}_{ij}(\mathbf{k})$ , at the *j*th interface resulting from the *i*th loading process, is given by

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The **Bouguer gravity anomaly** is calculated from the free-air anomaly by subtracting the gravitational effect from the observable surface topography  $d\mathcal{H}_{o1}(\mathbf{k})$ ,

$$d\mathcal{G}_{\circ 2}(\mathbf{k}) = d\mathcal{G}_{12}(\mathbf{k}) + d\mathcal{G}_{22}(\mathbf{k}).$$
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## The standard model — again



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- We only observe the *sum of the outputs*.

- We allow ourselves to assume a certain **proportionality** between the powerspectral densities of the inputs:  $f^2$ .
- We specify a joint structure to the initial inputs that also allows for their **correlation**: *r*.

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Define the **admittance**:

$$Q_{\circ}'(\mathbf{k}) = \frac{\langle d\mathcal{G}_{\circ 2}(\mathbf{k}) \, d\mathcal{H}_{\circ 1}^{*}(\mathbf{k}) \rangle}{\langle d\mathcal{H}_{\circ 1}(\mathbf{k}) \, d\mathcal{H}_{\circ 1}^{*}(\mathbf{k}) \rangle}.$$

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Define the **coherence-squared**:  $\gamma_{\circ}^{\prime 2}(\mathbf{k}) = \frac{|\langle d\mathcal{G}_{\circ 2}(\mathbf{k}) \, d\mathcal{H}_{\circ 1}^{*}(\mathbf{k}) \rangle|^{2}}{\langle d\mathcal{H}_{\circ 1}(\mathbf{k}) \, d\mathcal{H}_{\circ 1}^{*}(\mathbf{k}) \rangle \langle d\mathcal{G}_{\circ 2}(\mathbf{k}) \, d\mathcal{G}_{\circ 2}^{*}(\mathbf{k}) \rangle}.$   $\mathcal{H}_{\circ 1}$  is the "visible topography" and  $\mathcal{G}_{\circ 2}$  the "Bouguer gravity anomaly".

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The forward model is a very doable function of D,  $f^2$ , and r.

#### Admittance and Coherence — II



#### Admittance and Coherence — III



## **Measurements of coherence**



## **Measurements of admittance**





100

150

and an average loading and standard deviation resulting from the 100 analyses for analysis was 1000 Histograms of 100 Bouguer coherence and  $\times$  1000 km. Output  $T_e$  is the mean ratio of j The 20, of window size used 40, synthetic and 80 data km

70 100 Te (km)

150

1000x1000 km

50

1000x1000 km

20

зд

40

50

Free Air Admittance

Bouguer Coherence

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and  ${f S}$  is something that we can perfectly well calculate within the model.

$$\mathbf{S} = S_{11} \begin{pmatrix} \boldsymbol{\xi}^2 + f^2 \Delta_1^2 \Delta_2^{-2} & -\Delta_1 \Delta_2^{-1} \boldsymbol{\xi} - f^2 \Delta_1^3 \Delta_2^{-3} \boldsymbol{\phi} \\ -\Delta_1 \Delta_2^{-1} \boldsymbol{\xi} - f^2 \Delta_1^3 \Delta_2^{-3} \boldsymbol{\phi} & \Delta_1^2 \Delta_2^{-2} + f^2 \Delta_1^4 \Delta_2^{-4} \boldsymbol{\phi}^2 \end{pmatrix} \boldsymbol{\xi}^{-2},$$

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Note that the forms for admittance and coherence are ratios of the terms in this variance matrix. In our formulation, we simply retain the individual terms, which lead to Gaussian forms, rather than forming the spectral ratios, which don't.

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 Assuming isotropy, we choose a three-parameter Matérn form for the initial driving loads. Anisotropy is next. Now we can form the **log-likelihood** of observing  $\mathbf{H}$  under their being given by a loading process  $S_{11}$  and a lithospheric response characterized by D and  $f^2$ :

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The **maximum-likelihood** is the **best**, minimum-variance, unbiased estimate of the new (three lithospheric, three spectral) parameter vector:

$$\boldsymbol{\theta} = [D \ f^2 \ r \ \sigma^2 \ \nu \ \rho]^T.$$

## The (isotropic) Matérn spectral class





MLE Simulations with  $\Delta_1 = 2670$ ;  $\Delta_2 = 630$  kg m<sup>-3</sup>;  $z_2 = 35$  km; 64x64 grid; 1280x1280 km

# **Does it work? Trade-offs**



## **Does it work? Modeling the residuals**



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- The *full* problem: **anisotropic** inputs, **anisotropic** responses, **multilayer** systems... is still out there.
- The connections in marrying **deterministic** forward models with **stochastic** inputs and observables are fruitful and widespread.

• Reducing gravity and topography to **coherence** or **admittance** estimated at a handful of wavenumbers, and then inverting for rigidity D and loading ratio  $f^2$  is a *very* non-optimal thing to do. A **robust method** keeps the power of the abundance of data by forming a **Whittle maximum-likelihood estimator**.

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- Simulations verify that the estimates are normally distributed, and unbiased and closely track the variance predicted by the **fully analytic theory**, which is minimized. Confidence intervals are symmetric, and covariance between the estimated D and  $f^2$  is small. Though no longer needed, predicting admittance and coherence in retrospect vastly tightens their error bars.

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- Our current method successfully takes into account *r*-correlated loads, small data sets, irregular domains. **Anisotropy** in both the loading and the response is further down the line. *Then*, the statistics will be interesting.