

# LPENS

LABORATOIRE DE PHYSIQUE  
DE L'ÉCOLE NORMALE SUPÉRIEURE

## Single frequency CMB B-mode inference with realistic foregrounds from a single training image

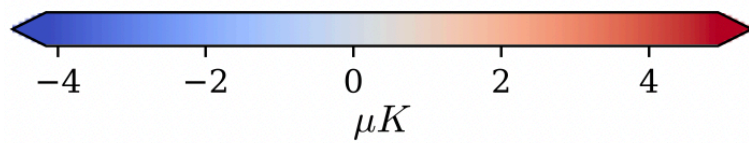
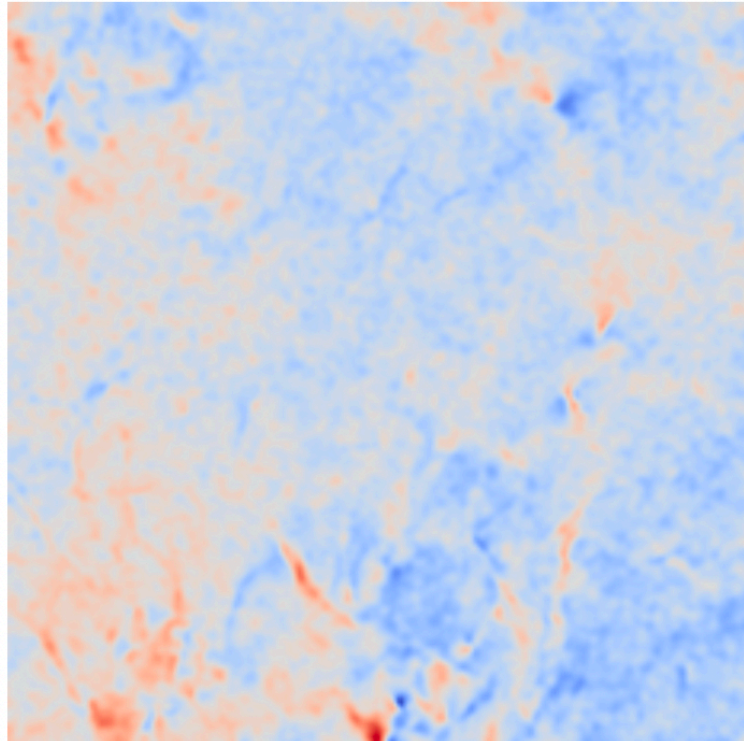
**Niall Jeffrey**

*François Boulanger, Benjamin Wandelt,  
Bruno Regaldo-Saint Blancard, Erwan Allys, François Levrier*



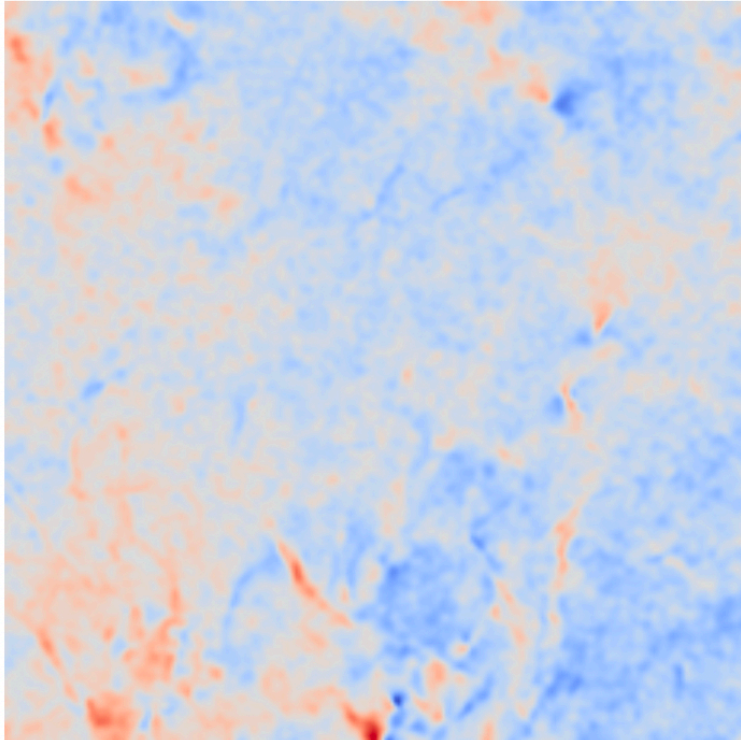
# B-mode inference

B-mode data

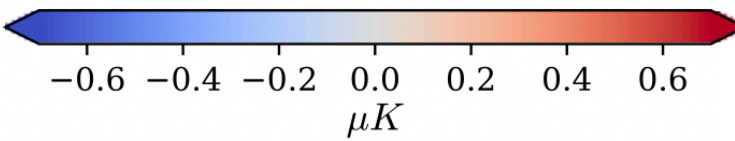
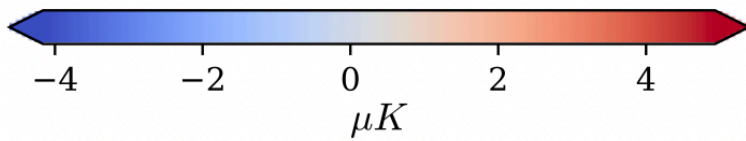
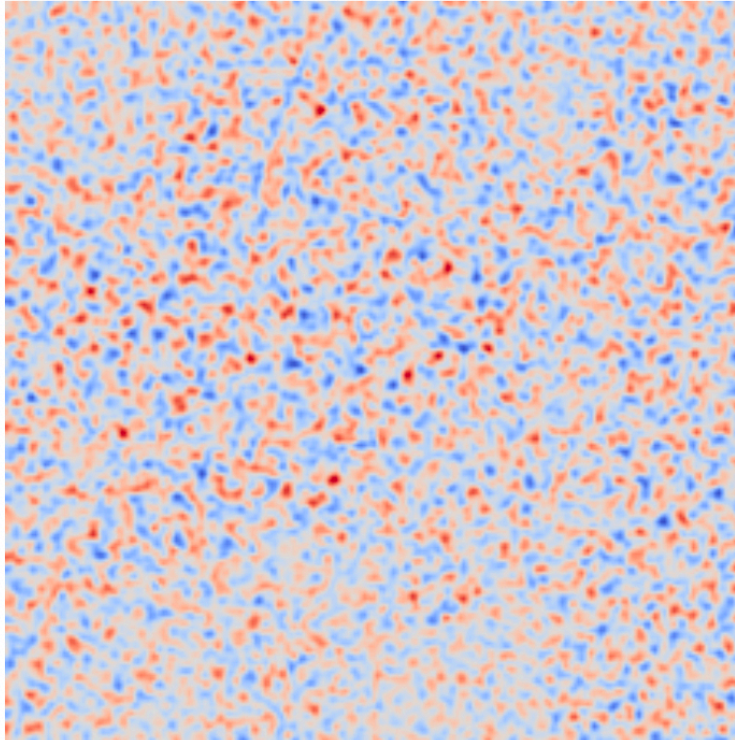


# B-mode inference

B-mode data



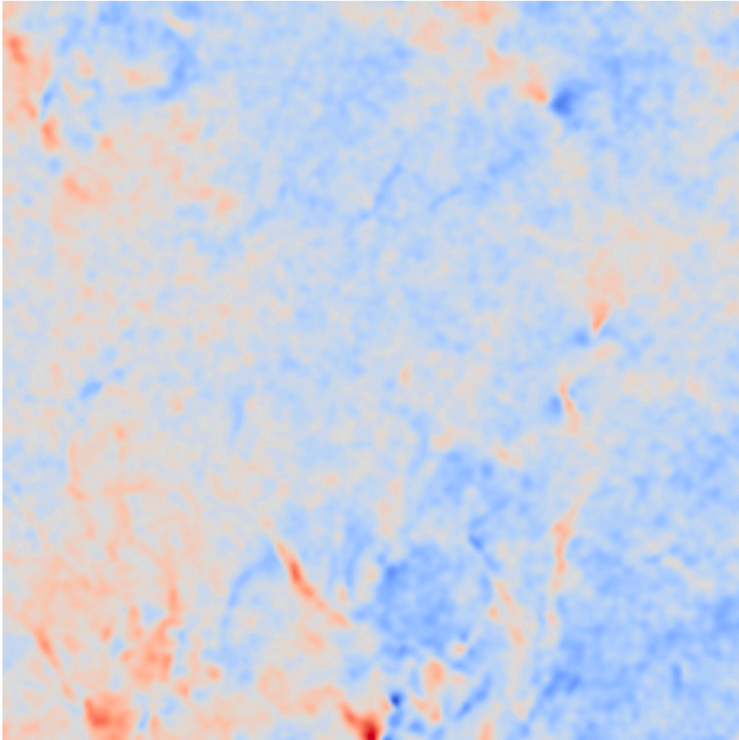
Posterior mean



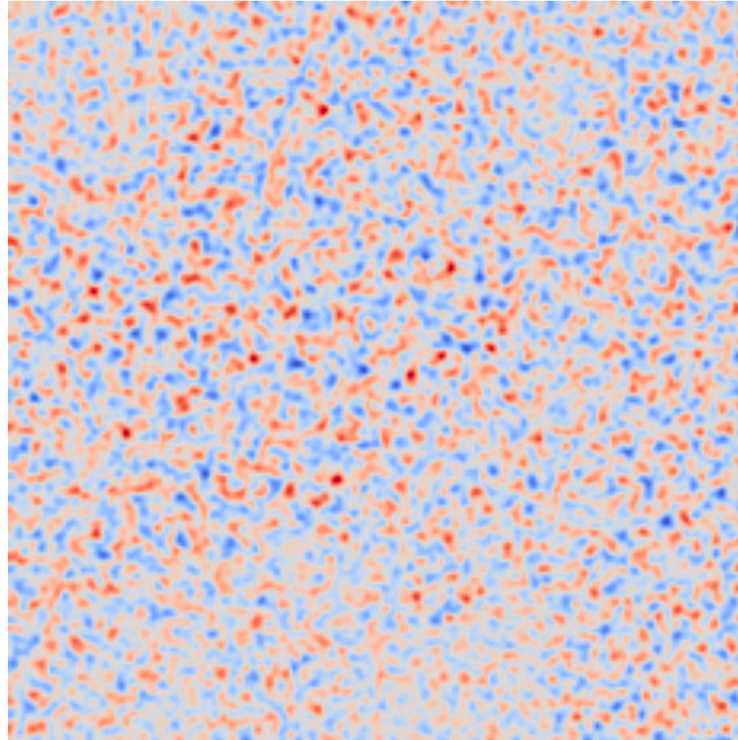


# B-mode inference

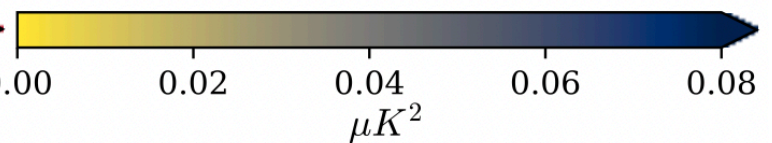
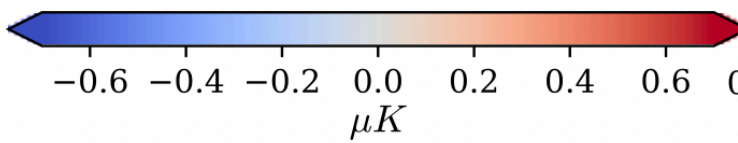
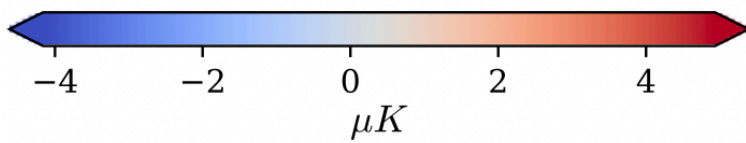
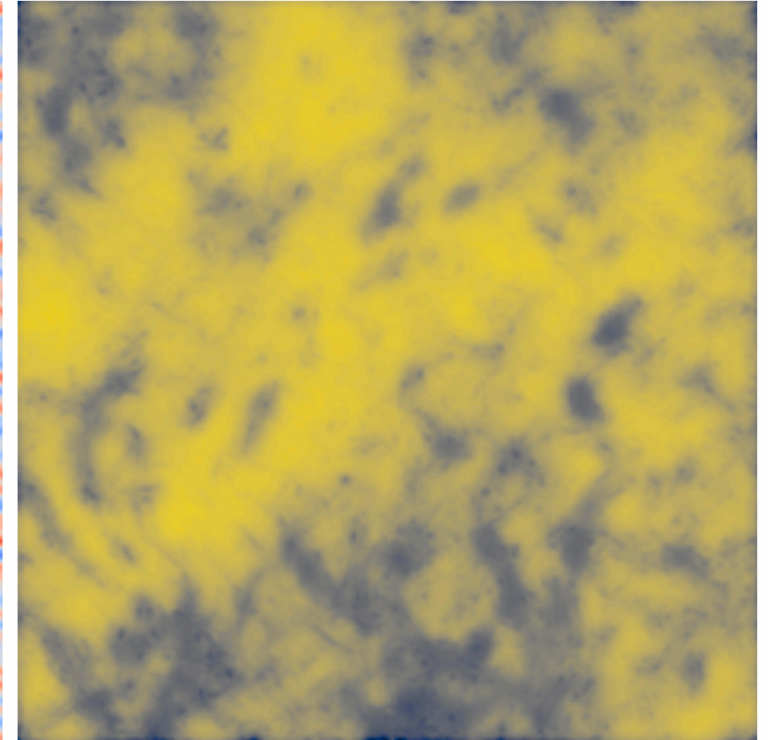
B-mode data



Posterior mean



Posterior marginal variance





# Outline

1. *High-dimensional likelihood-free inference*
2. *Realistic forward model*
3. *Posterior validation*

01

*High-dimensional likelihood-free:*  
**Moment Networks**

# Parameter inference

1. Possible “data”  $\mathbf{d}$
2. Unknown parameters:  $\mathbf{S}$  signal

$$p(\mathbf{s} | \mathbf{d}) \propto p(\mathbf{d} | \mathbf{s}) p(\mathbf{s})$$



# Moment Network: *side-step density estimation problem*

NJ & Wandelt 2011.05991

# Moment Network: *side-step density estimation problem*

- I. Hierarchy of Networks
- II. Optimization objective use square loss

$$J_0 = \int \|\mathbf{s} - \mathcal{F}(\mathbf{d})\|^2 p(\mathbf{d}, \mathbf{s}) \, d\mathbf{d} \, d\mathbf{s}$$

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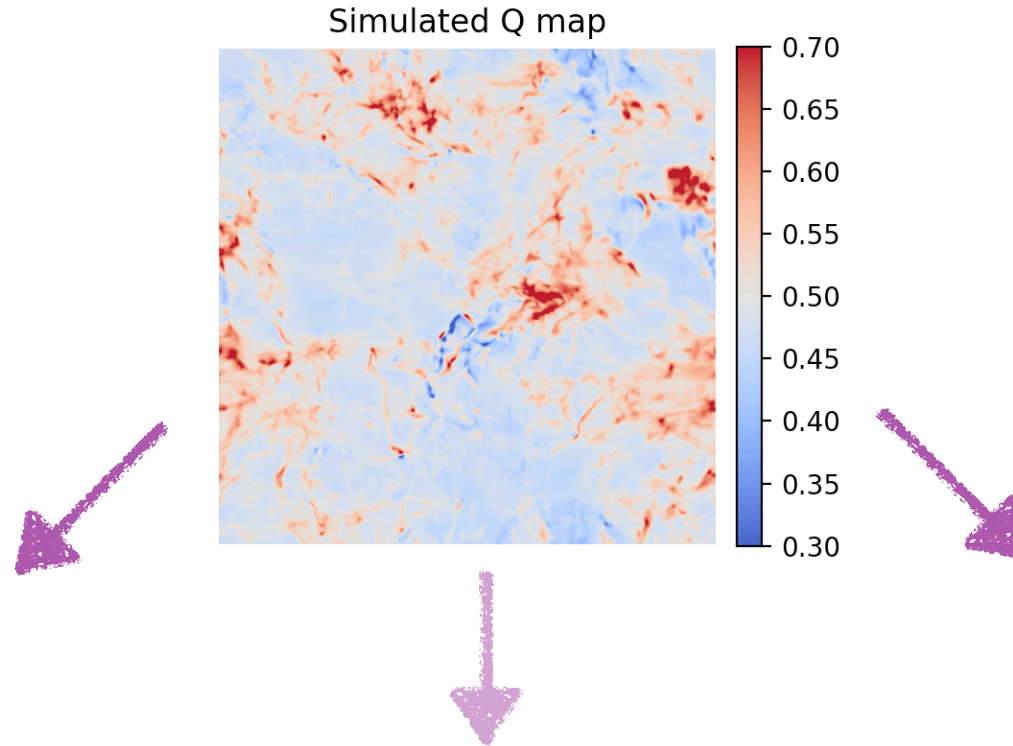
$$J_1 = \int \left\| (\mathbf{s} - \mathcal{F}_{\text{fixed}}(\mathbf{d}))^2 - \mathcal{G}(\mathbf{d}) \right\|^2 p(\mathbf{d}, \mathbf{s}) \, d\mathbf{d} \, d\mathbf{s}$$



02

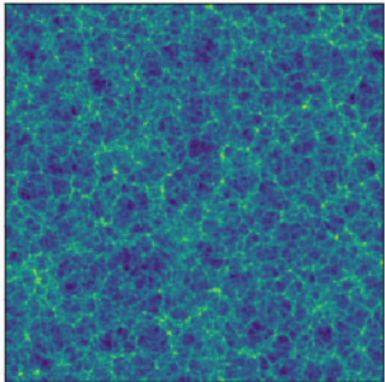
*Forward model &  
B-mode inference*

# Generative model for data?



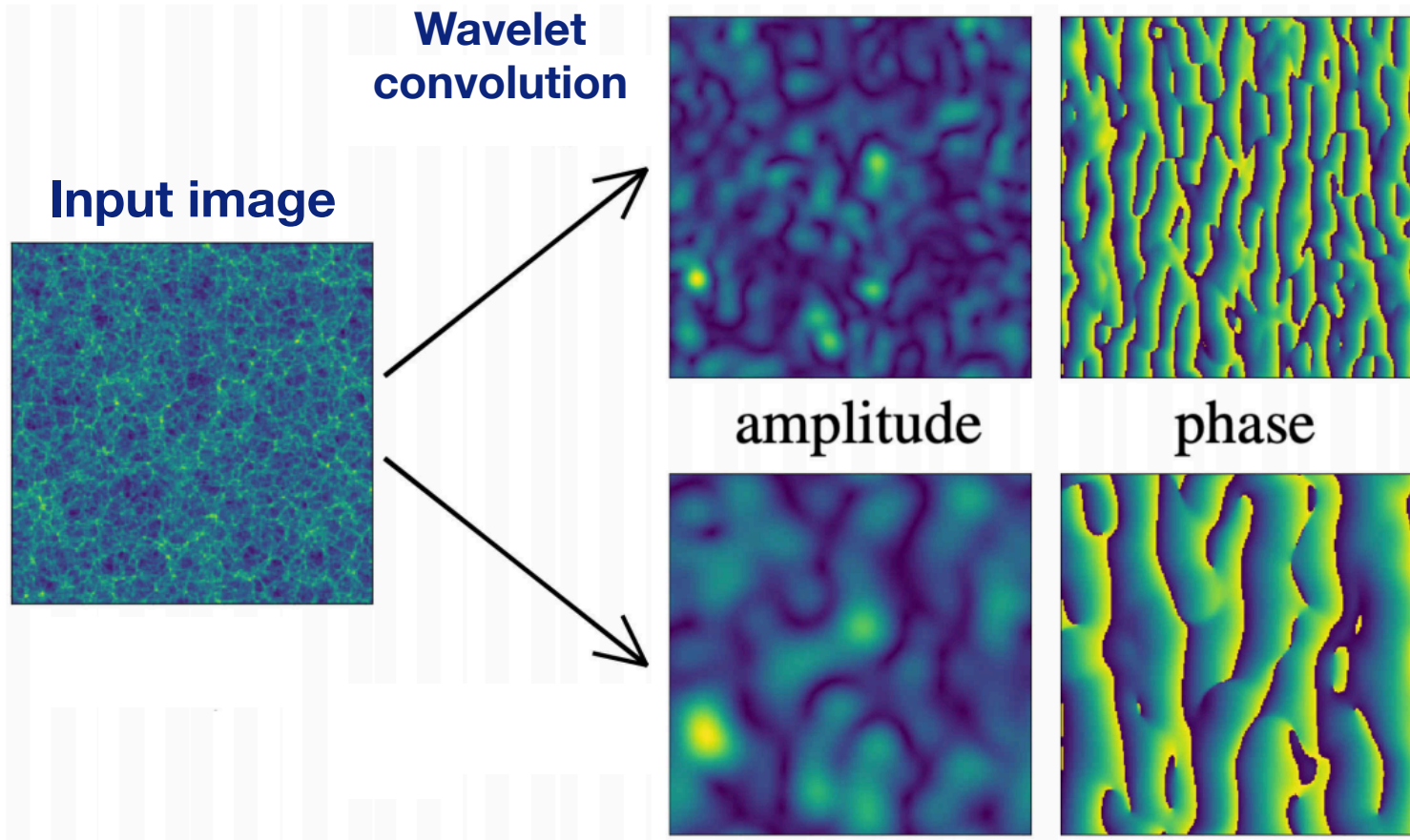
# Wavelet Phase Harmonics

Input image

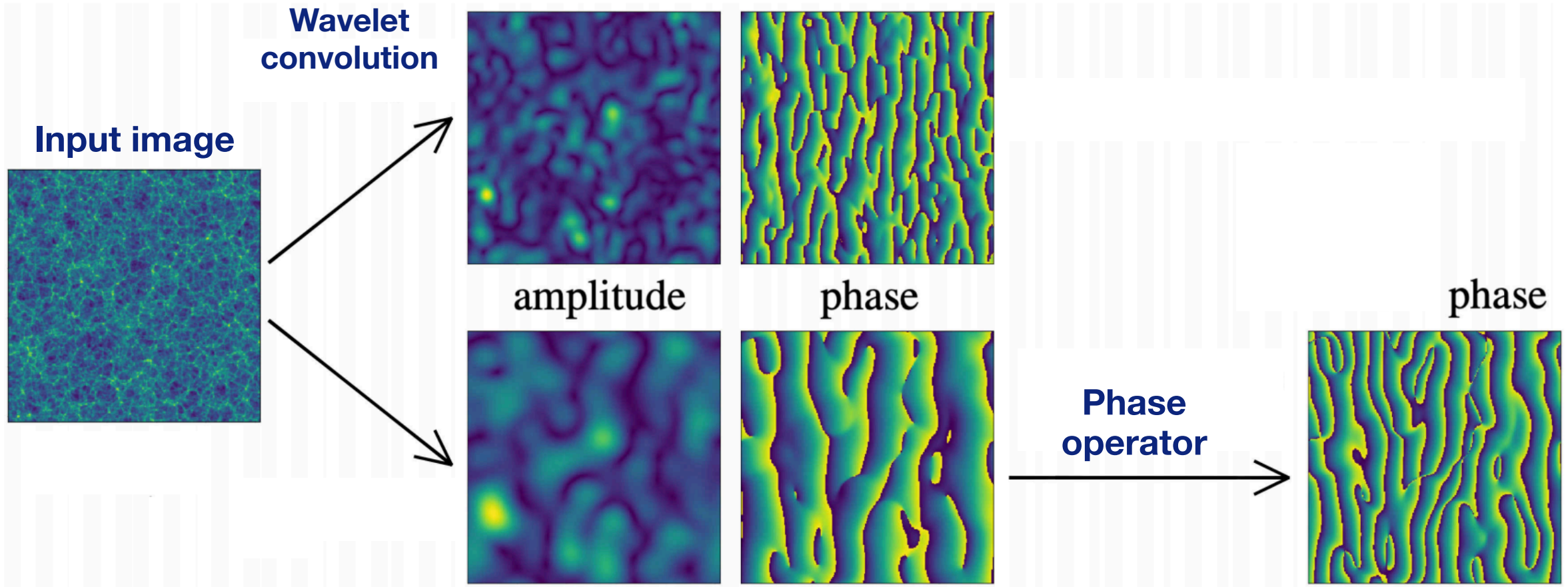




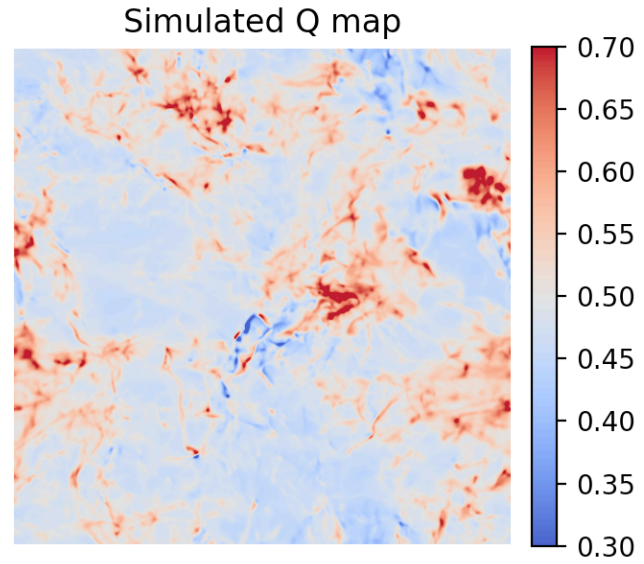
# Wavelet Phase Harmonics



# Wavelet Phase Harmonics

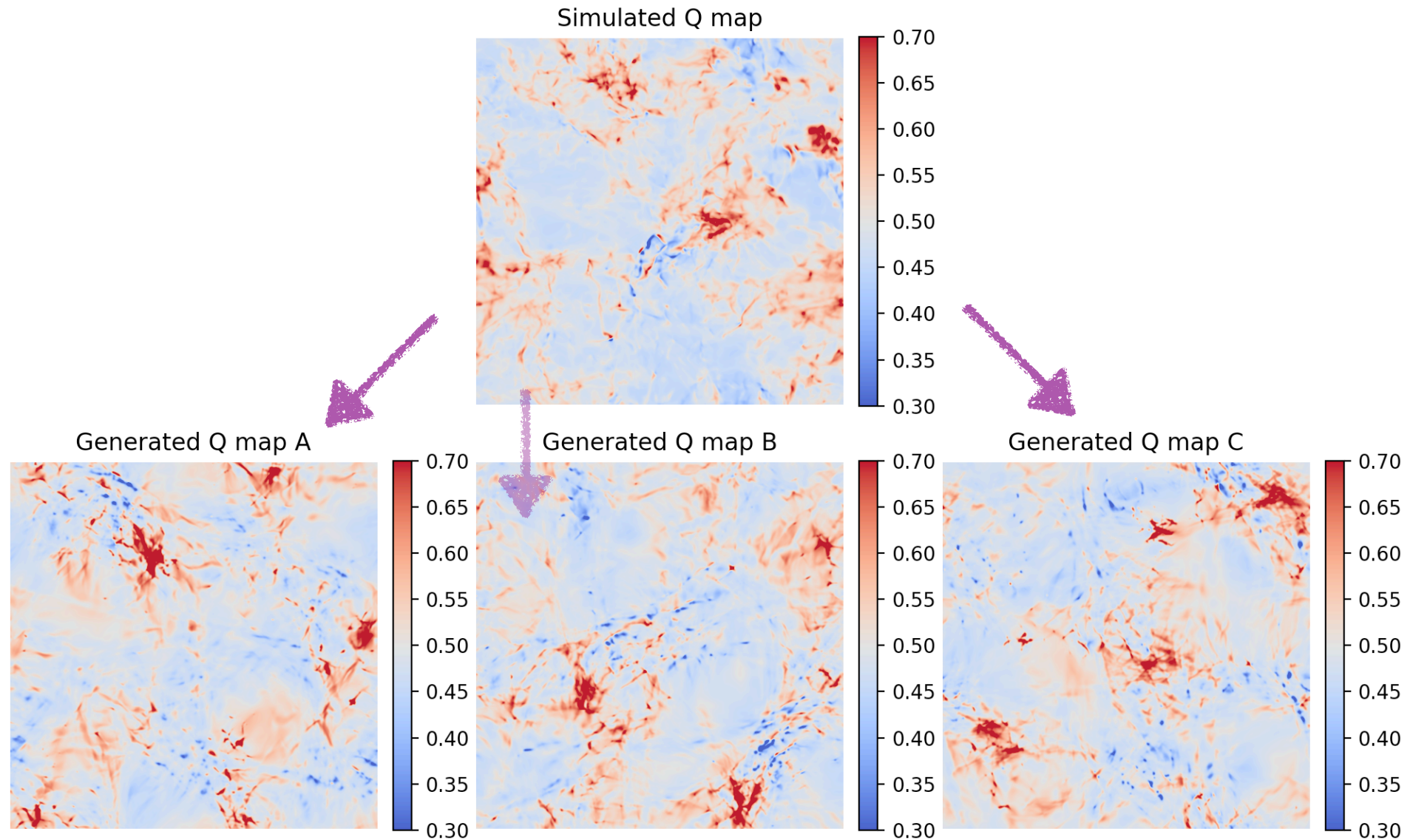


# Generative model for data



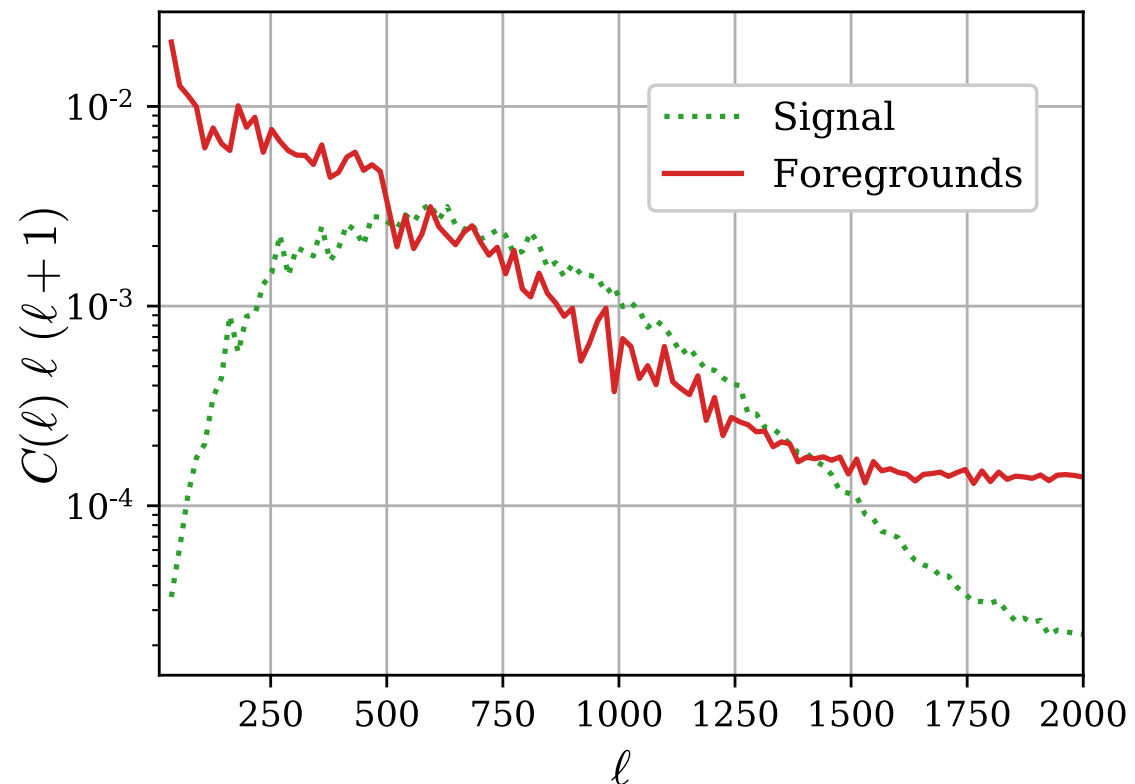


# Generative model for data



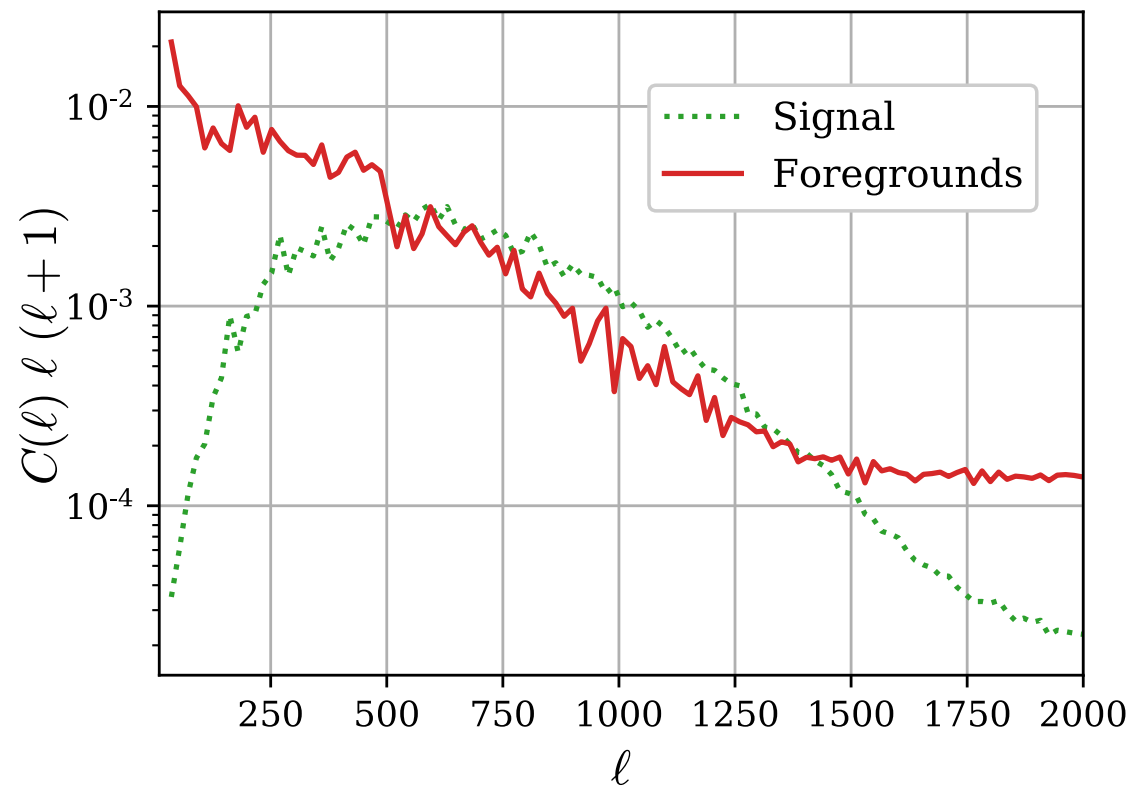
# Model parameters from prior

Validation data example "A"  
(signal dominated  $\ell \sim 1000$ )

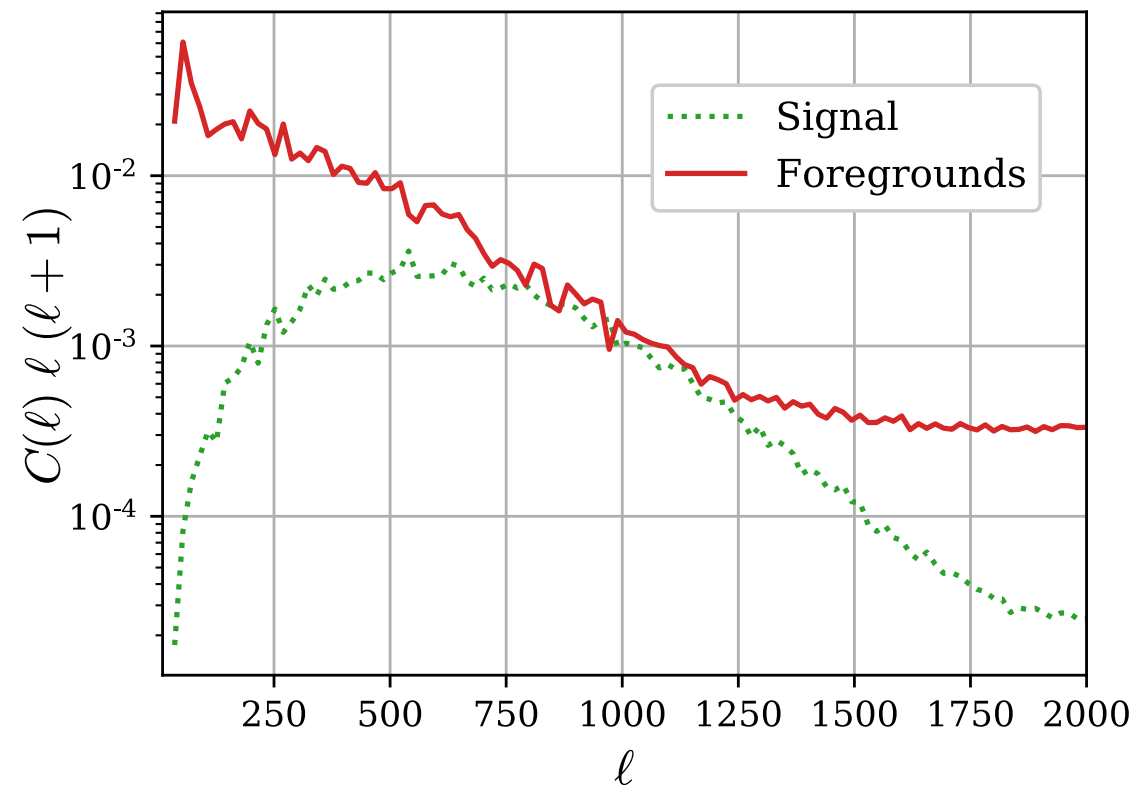


# Model parameters from prior

Validation data example "A"  
(signal dominated  $\ell \sim 1000$ )



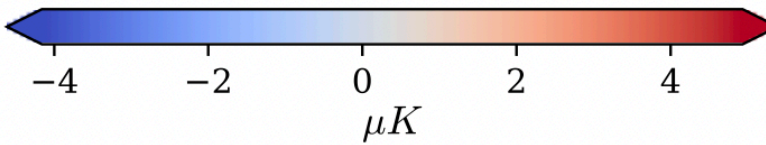
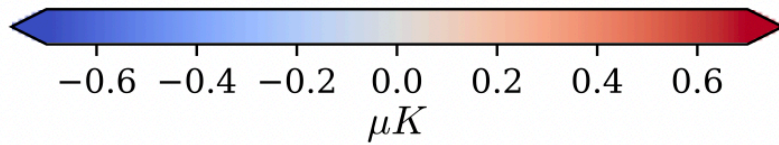
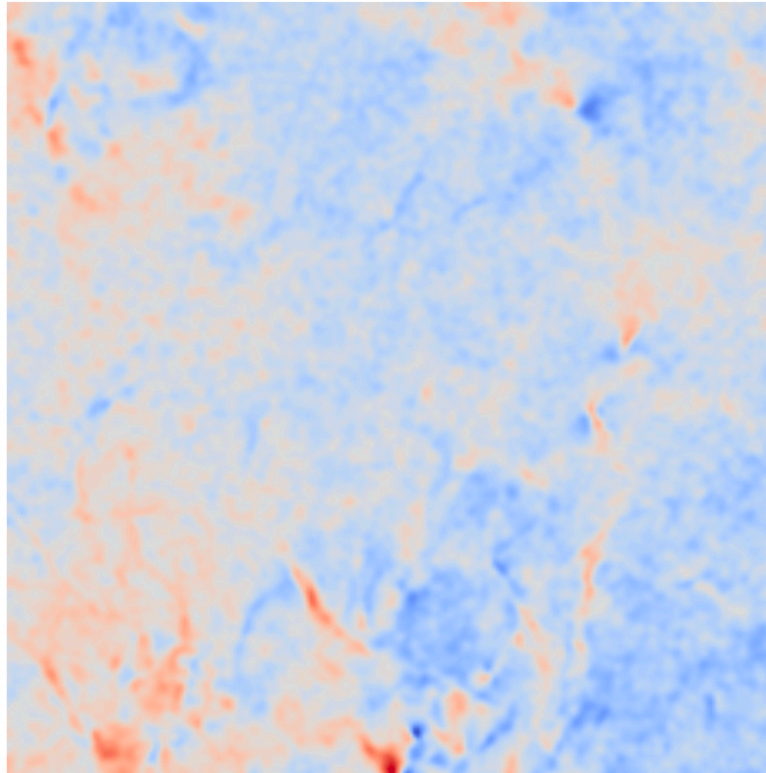
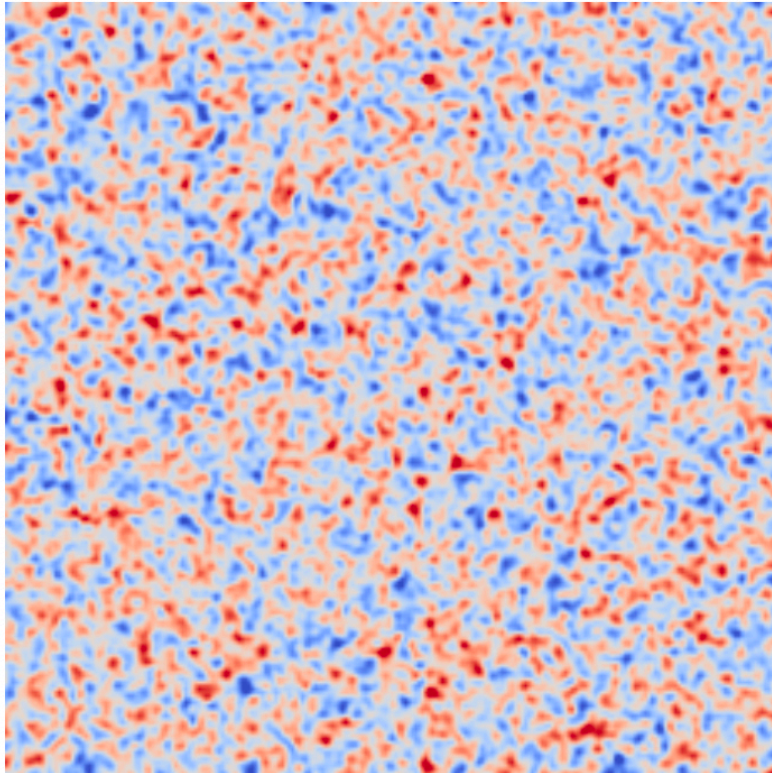
Validation data example "B"  
(foreground dominated  $\ell \sim 1000$ )



# B-mode inference

B-mode truth

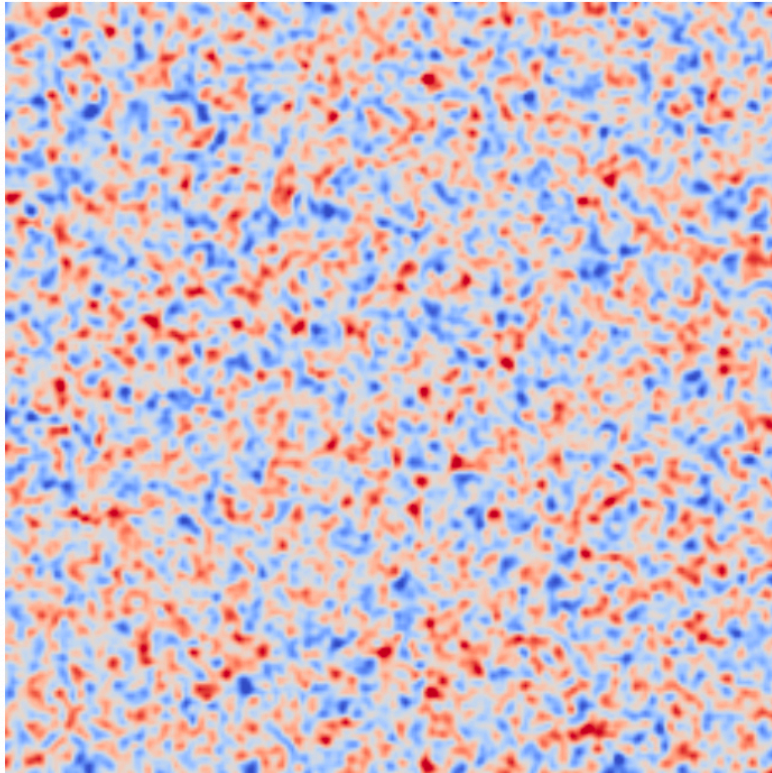
B-mode data



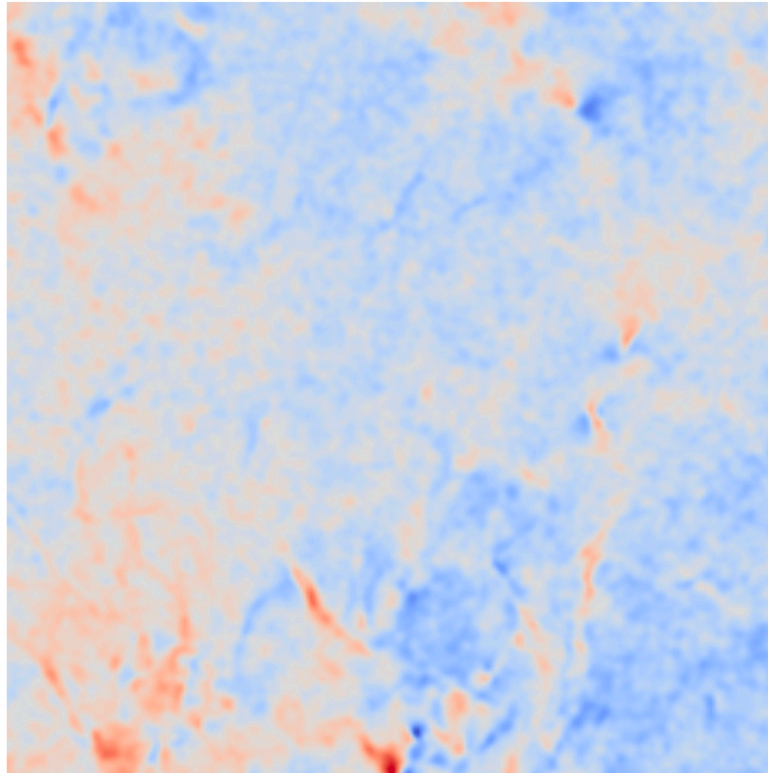


# B-mode inference

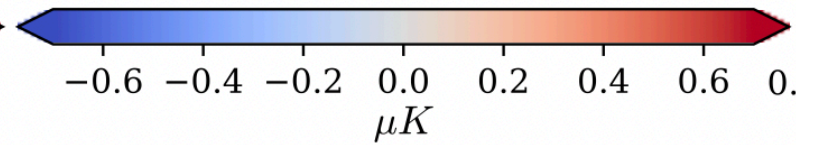
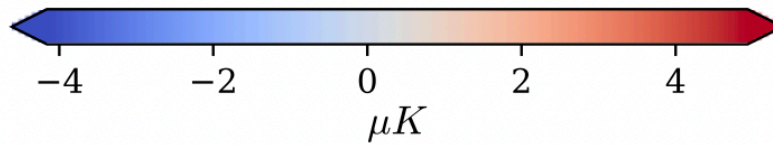
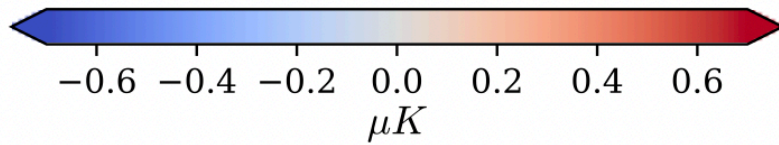
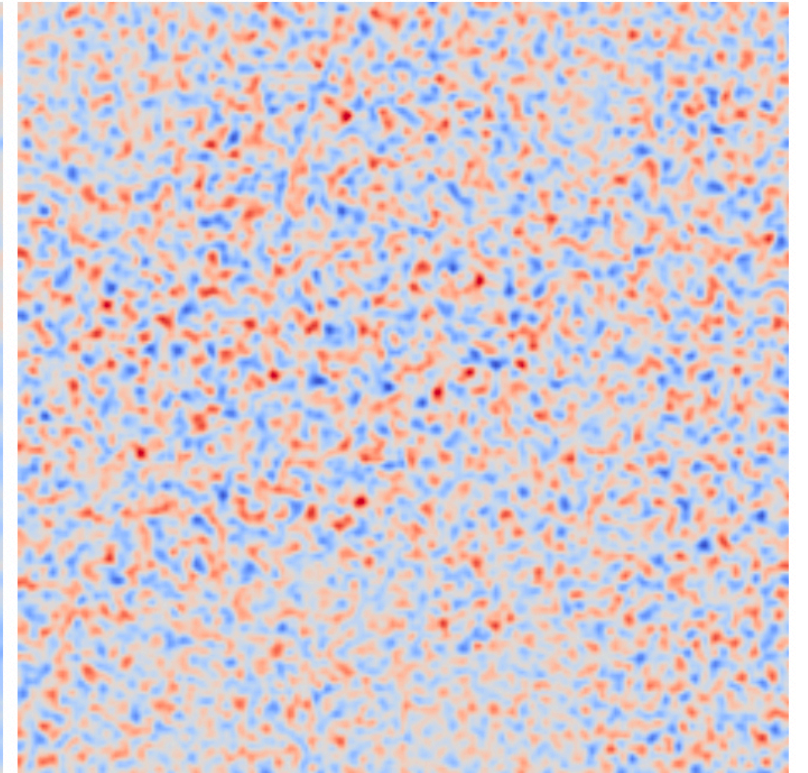
B-mode truth



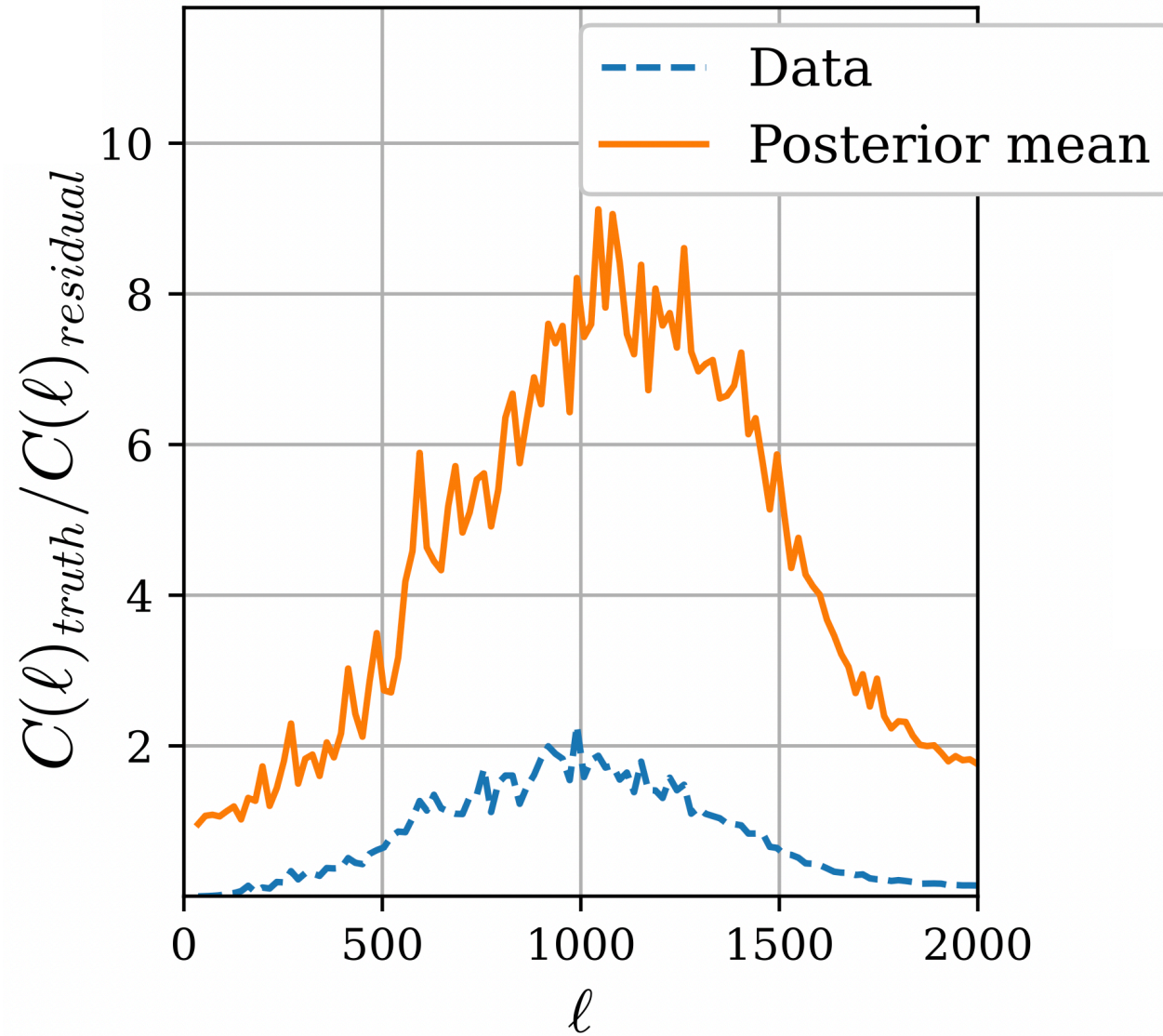
B-mode data



Posterior mean



# Recovered “signal-to-noise”



03

*Posterior validation*

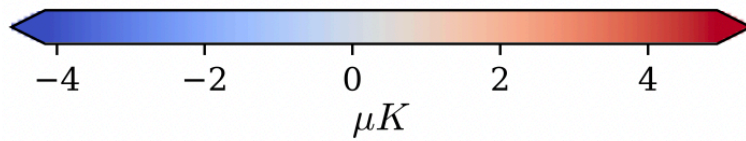
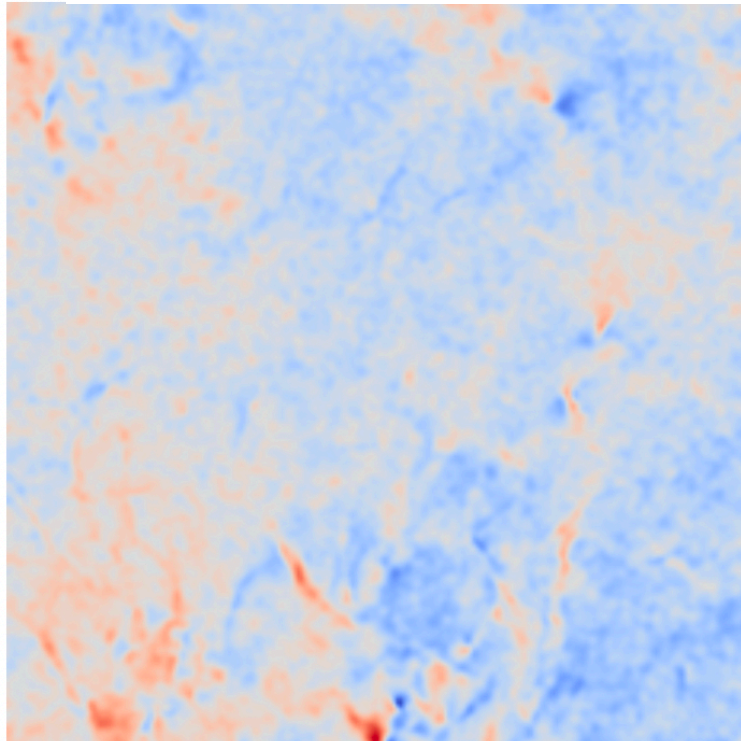


**How can we test the posterior?**

**What does the “wrong” answer look like...**

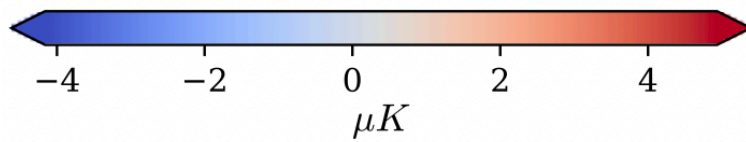
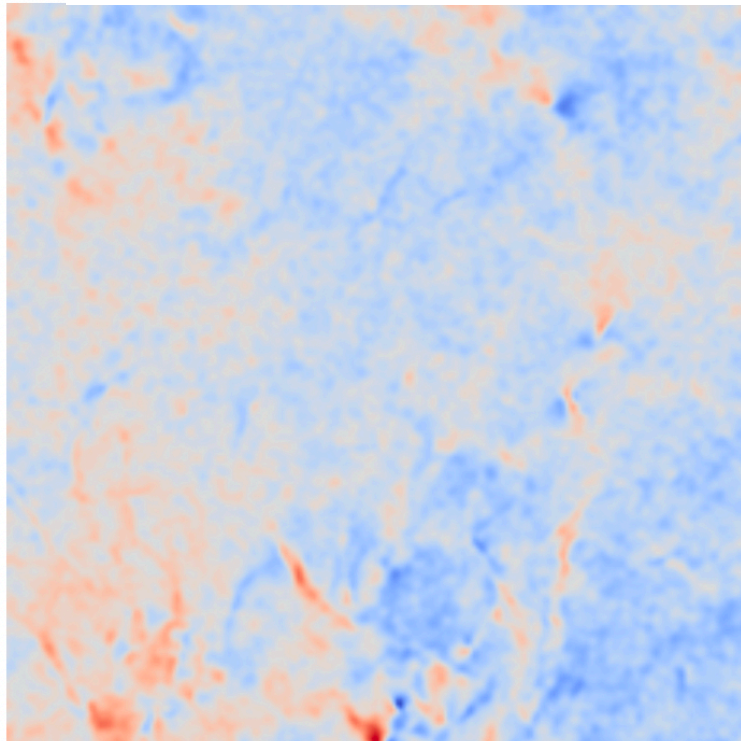
# Naive Gaussian model:

B-mode data

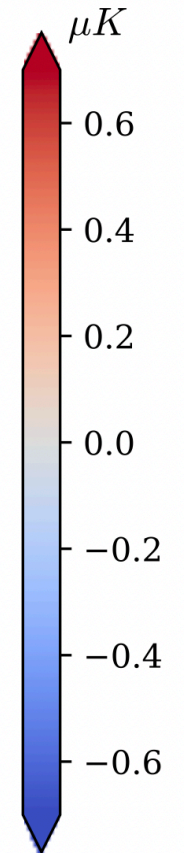
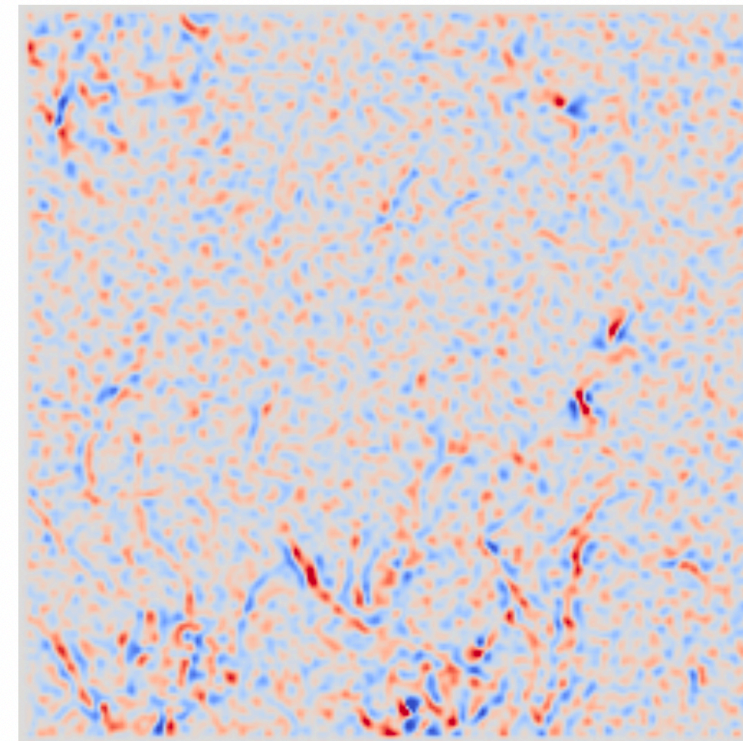


# Naive Gaussian model:

B-mode data



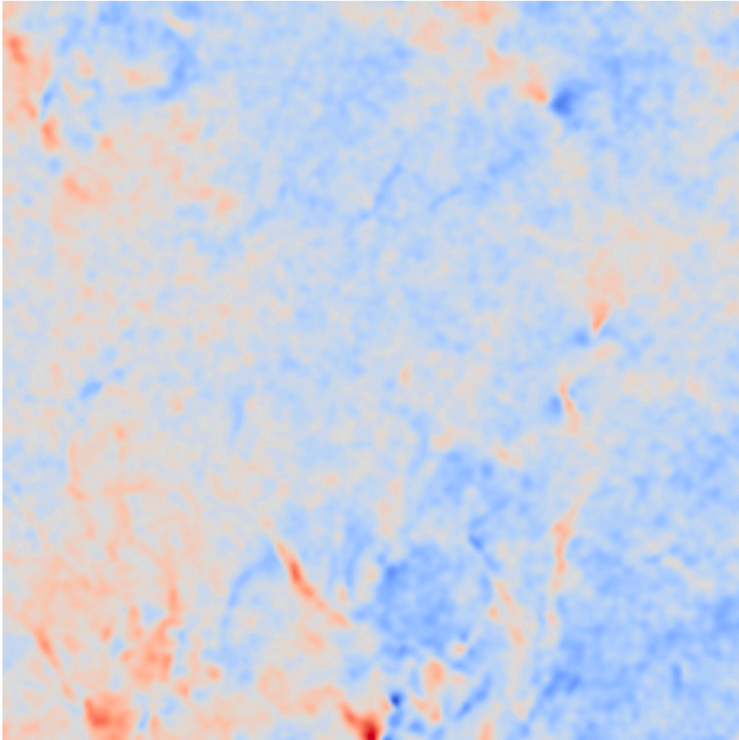
Posterior mean



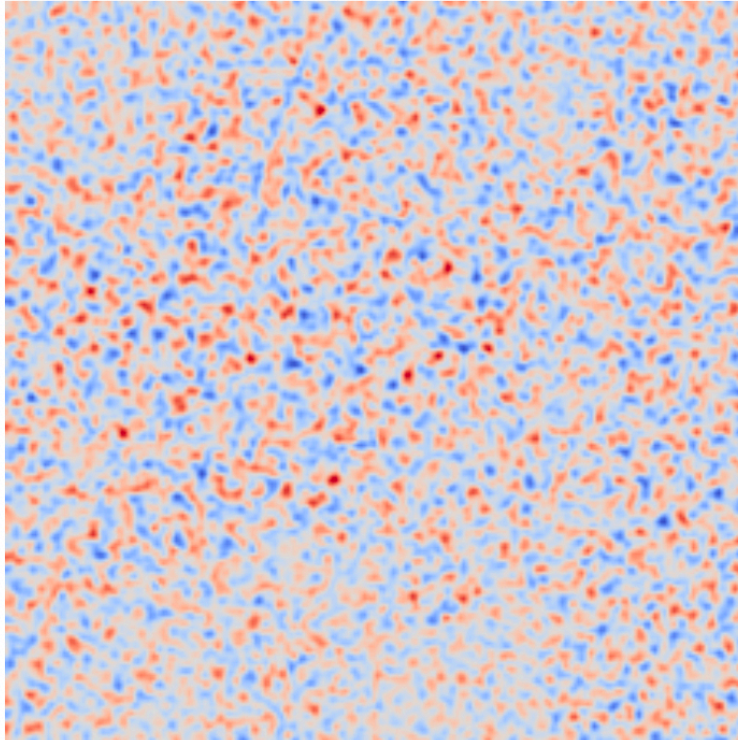


# Validation of posterior

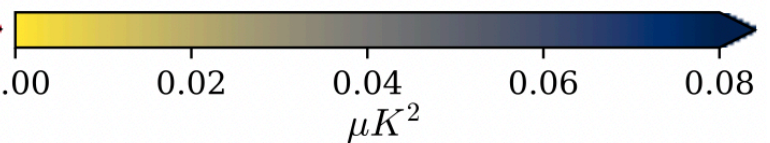
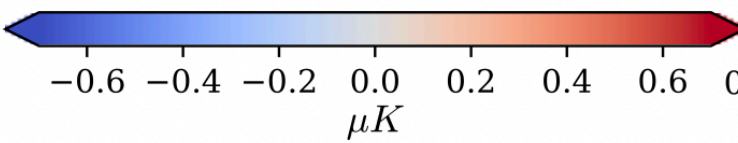
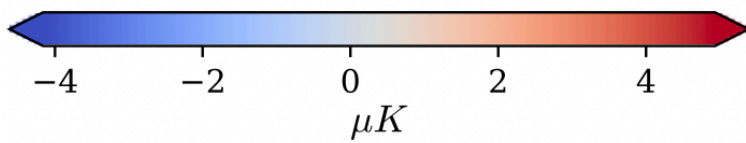
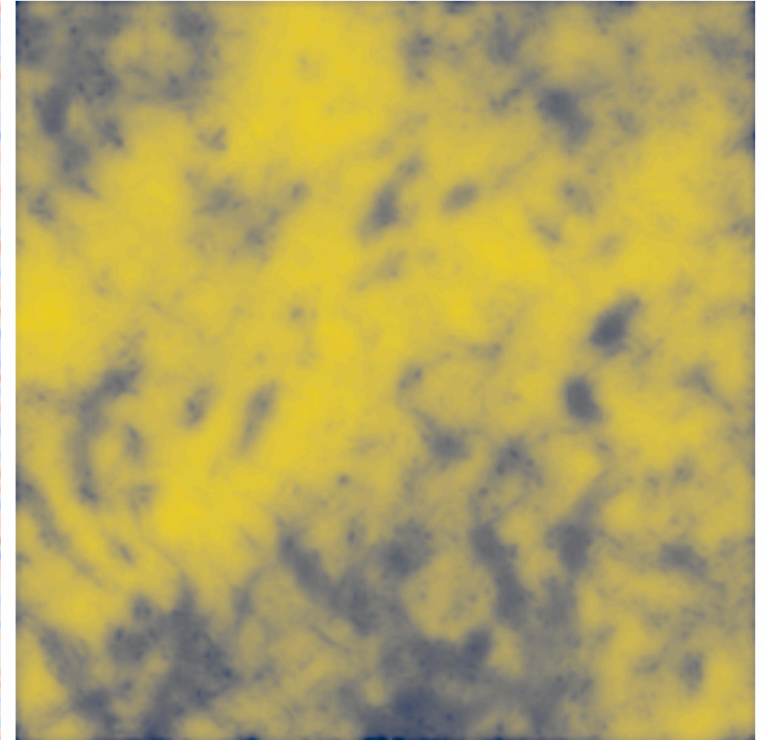
B-mode data



Posterior mean



Posterior marginal variance



# Rescaled residuals

$$(\mu_B - s_B) / \sigma_B$$

POSTERIOR  
MEAN



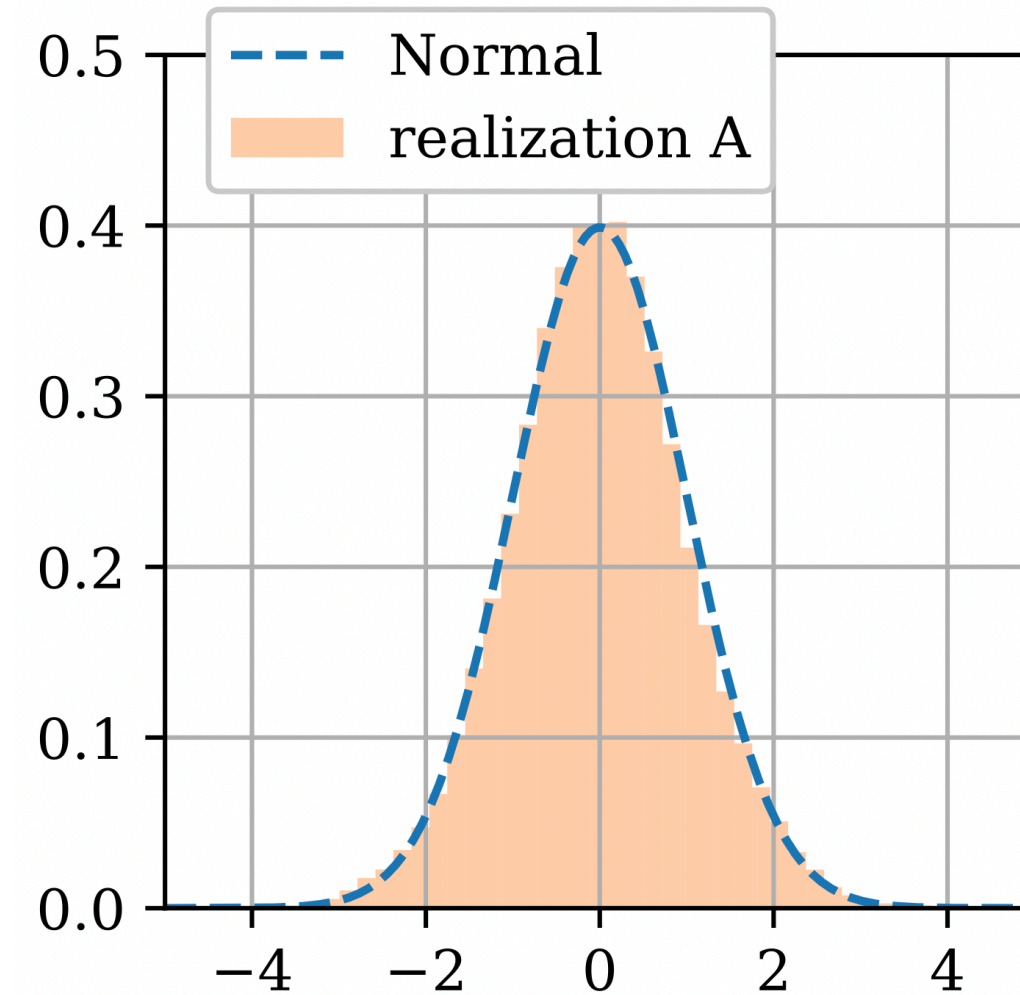
TRUE PIXEL  
VALUE



POSTERIOR  
VARIANCE

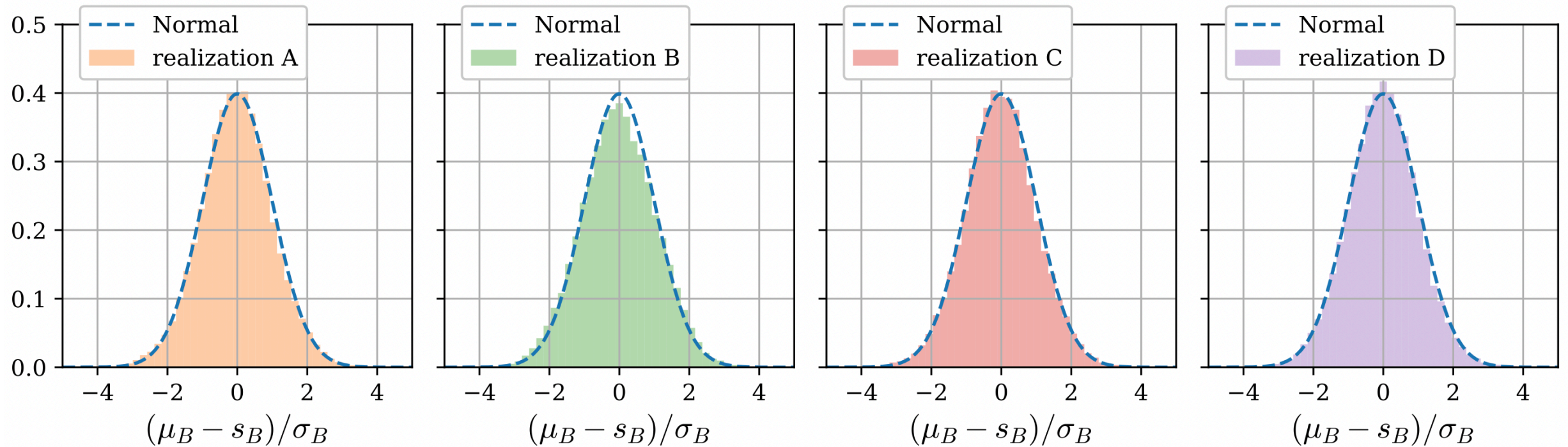


# Rescaled residuals

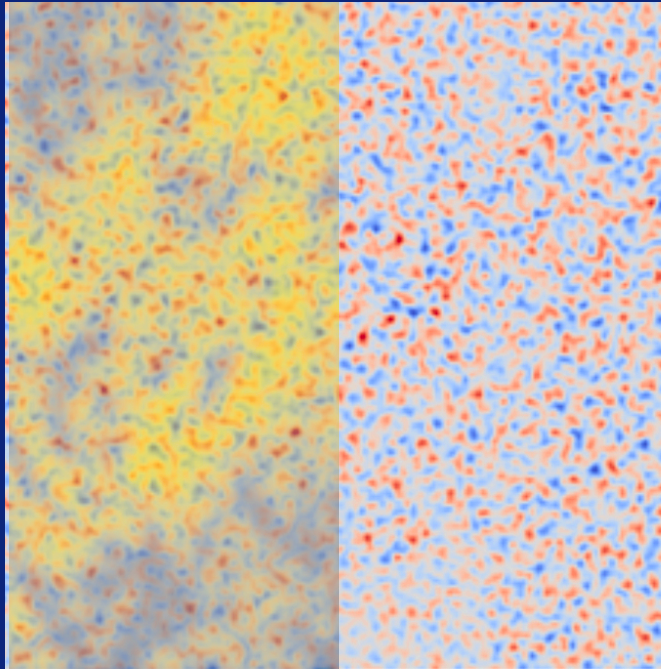


$$(\mu_B - s_B) / \sigma_B$$

# Posterior estimates are excellent:







# Merci !

