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High-dimensional likelihood-free inference: weak gravitational lensing

2009.08459
2011.05991

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(with Justin Alsing, Francois Lanusse, Benjamin Wandelt)

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Outline

1. Weak lensing map statistics
2. Density-estimation likelihood-free inference
3. Dark Energy Survey SV results
4. High-dimensional inference
5. Cosmic Microwave Background foregrounds

01

Weak lensing mass map statistics

Dark Energy Survey

SV weak lensing data

I. Ground based 5-band photometric survey

II. Science Verification (SV) data <5% of final coverage, but final depth

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Weak lensing mass maps

NJ, Lanusse, Lahav, Starck 1908.00543

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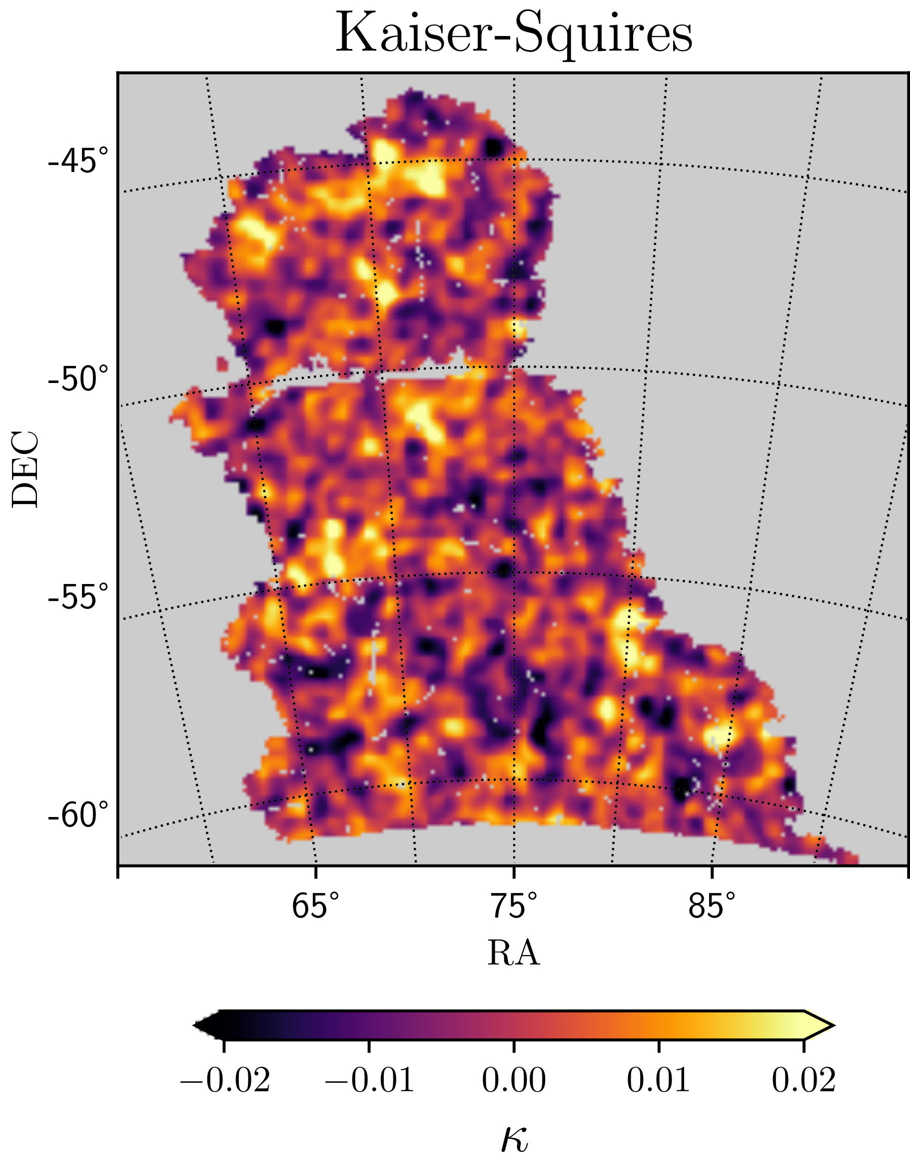

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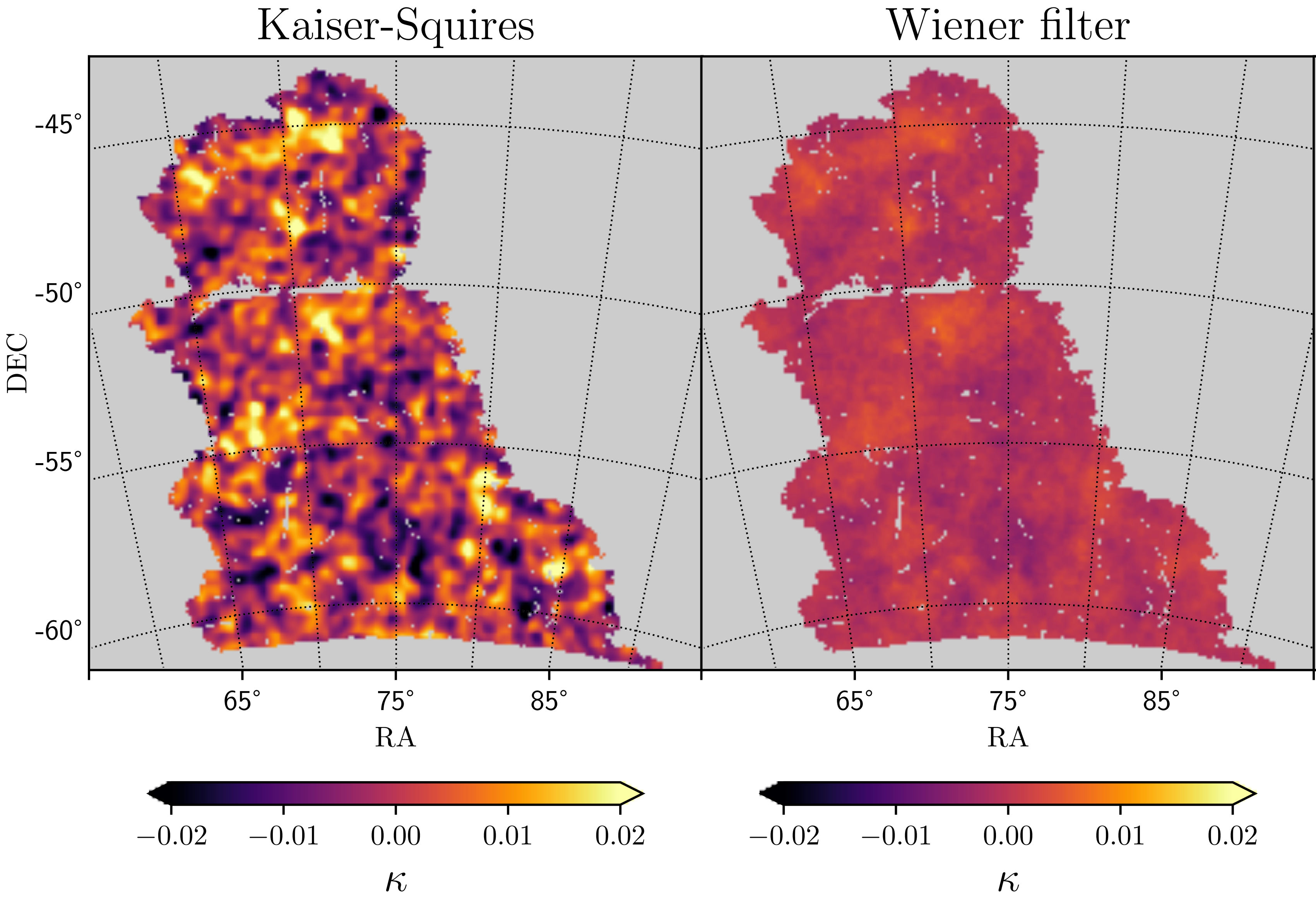

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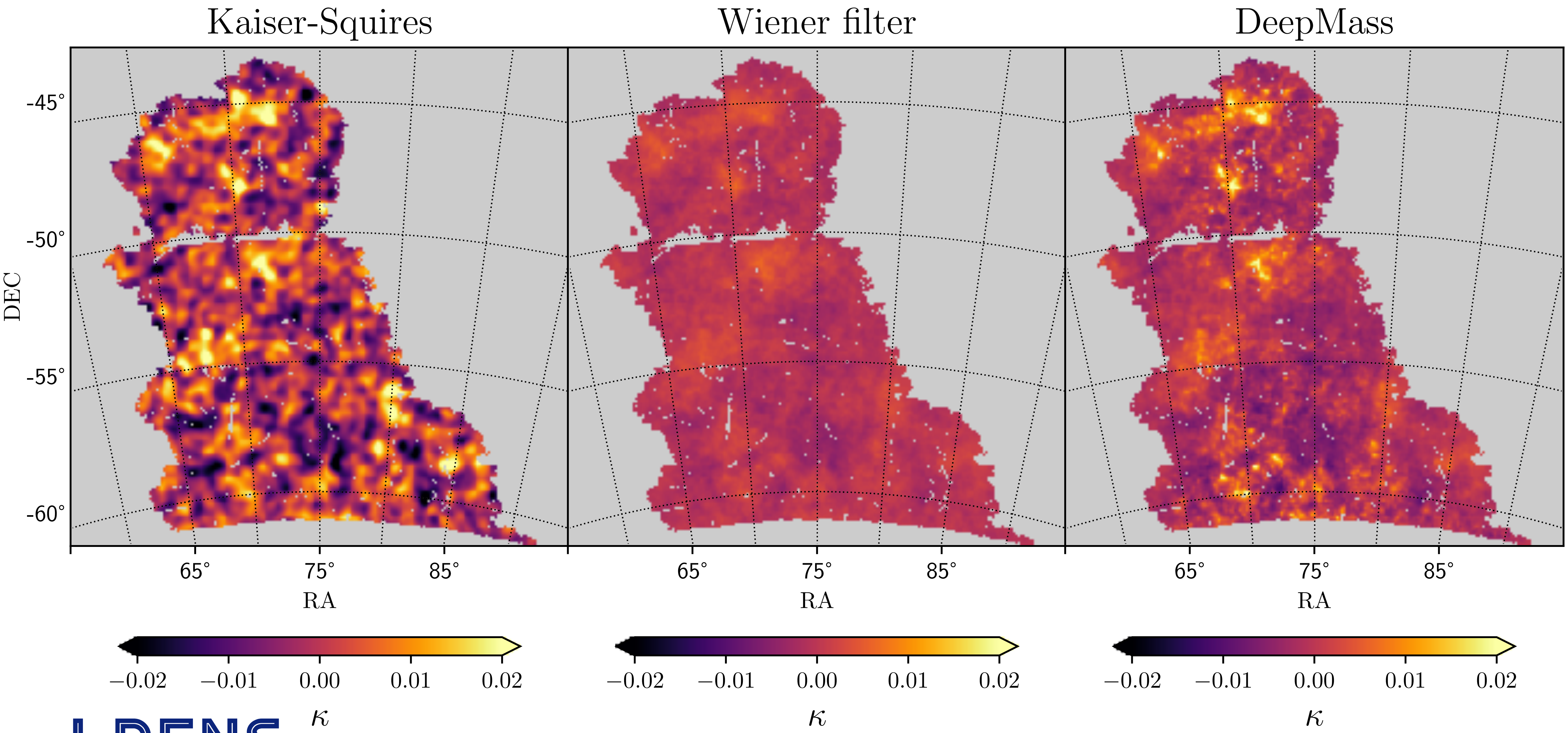
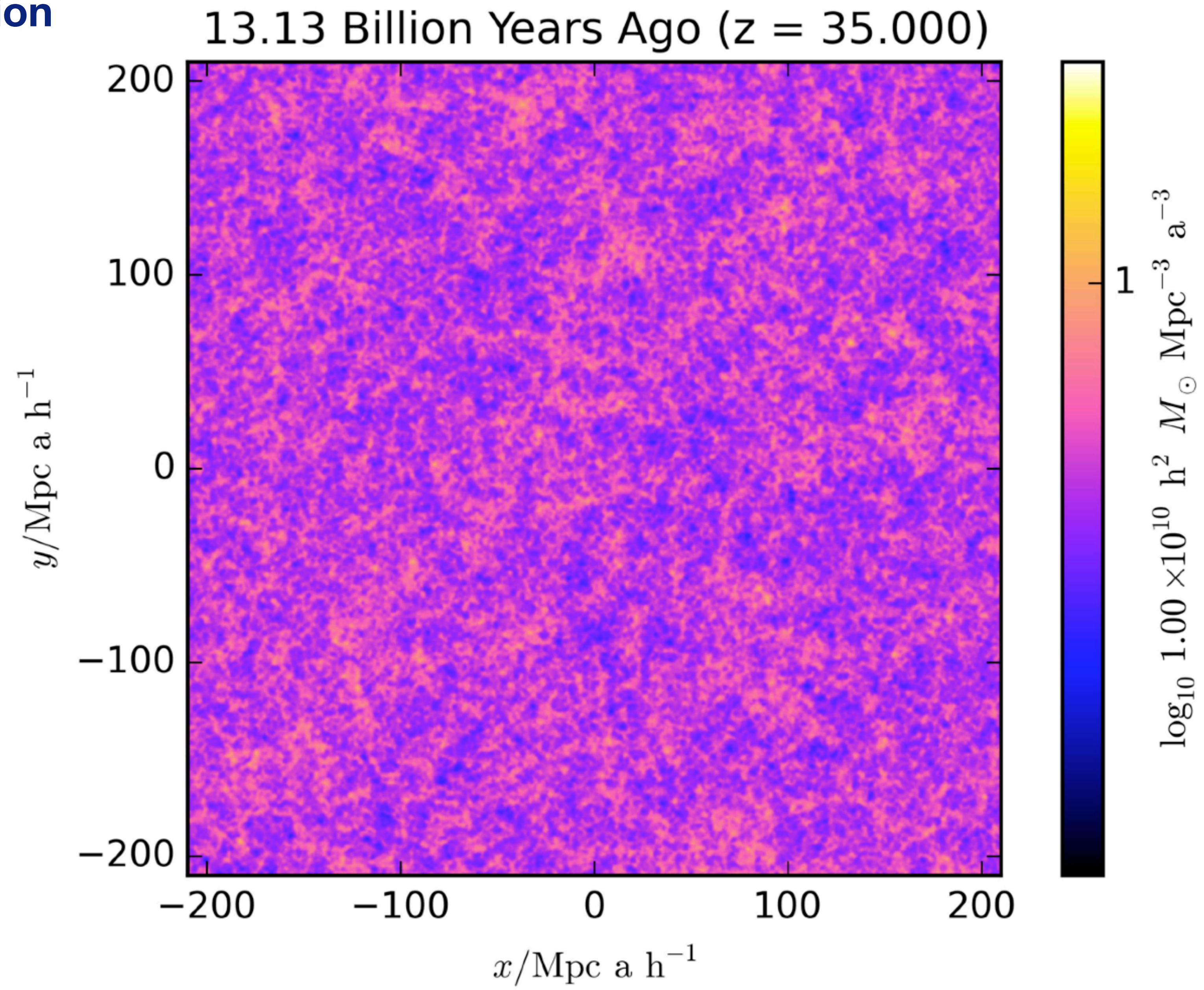


Growth of structure

L-PICOLA simulation



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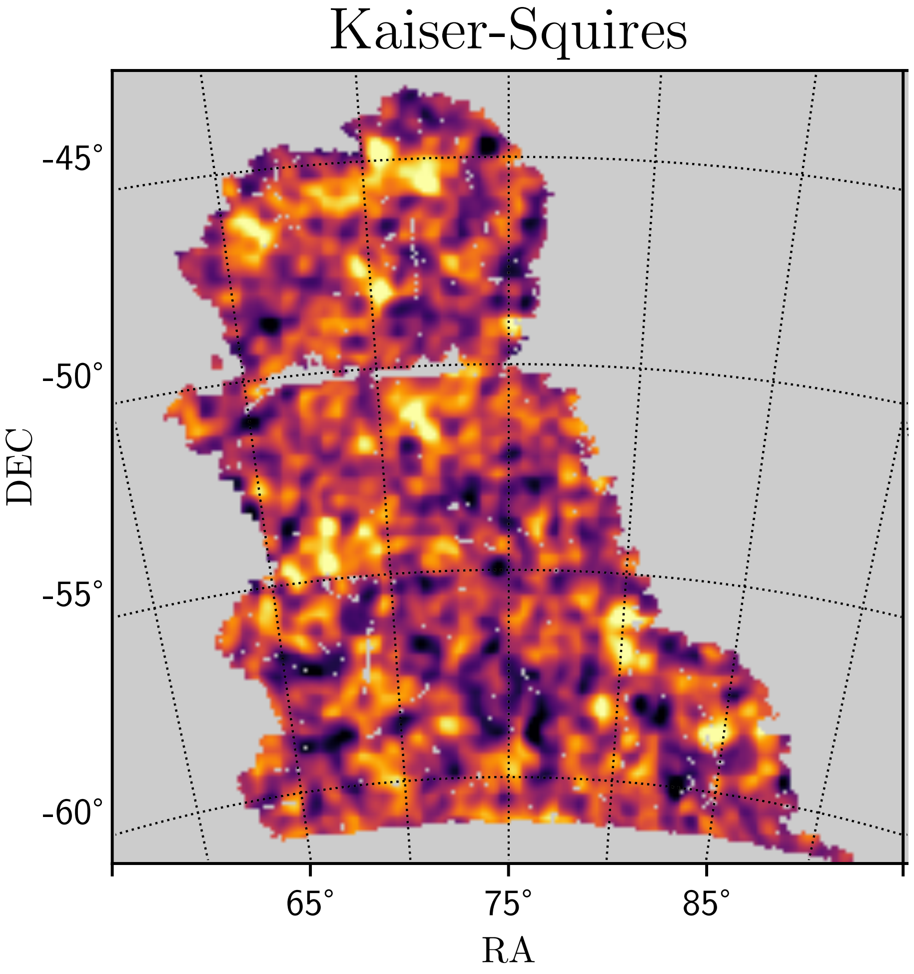
Weak lensing map summary statistics



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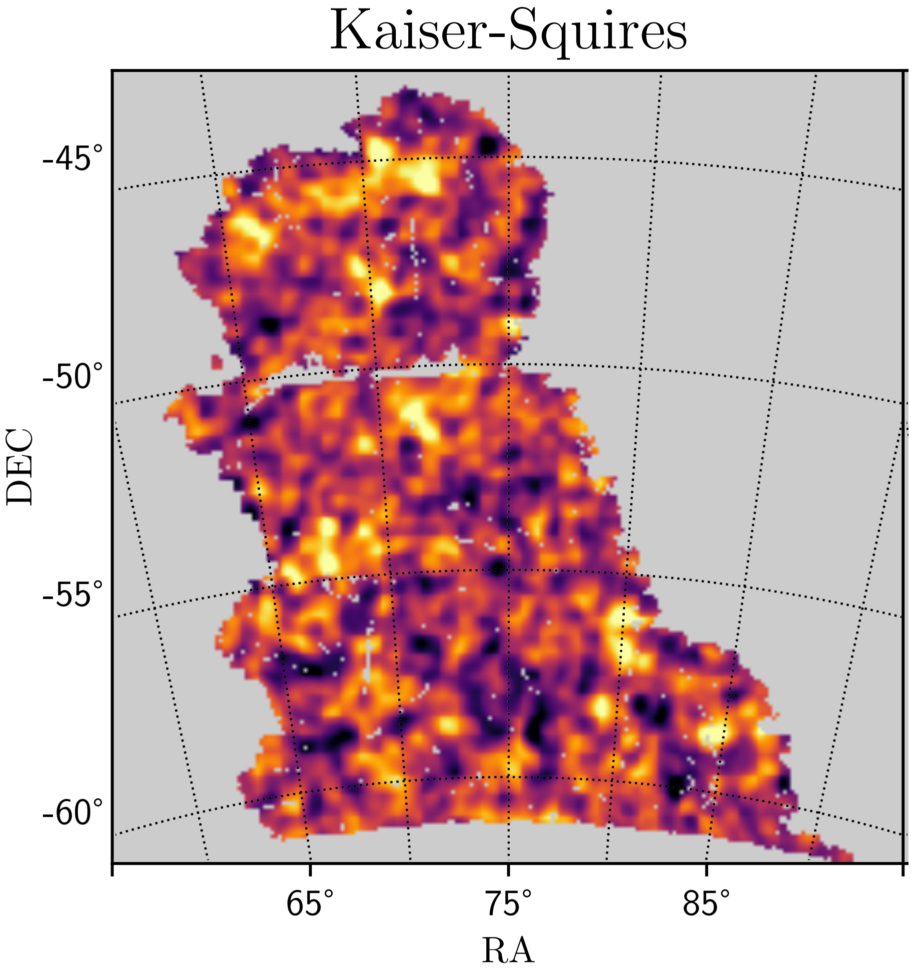

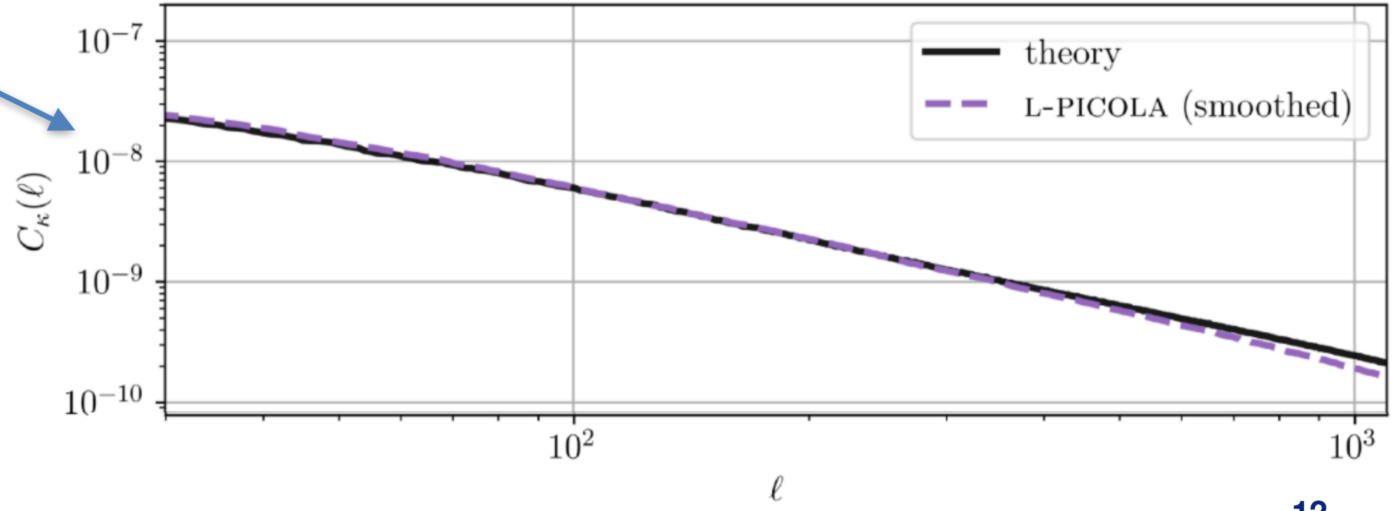

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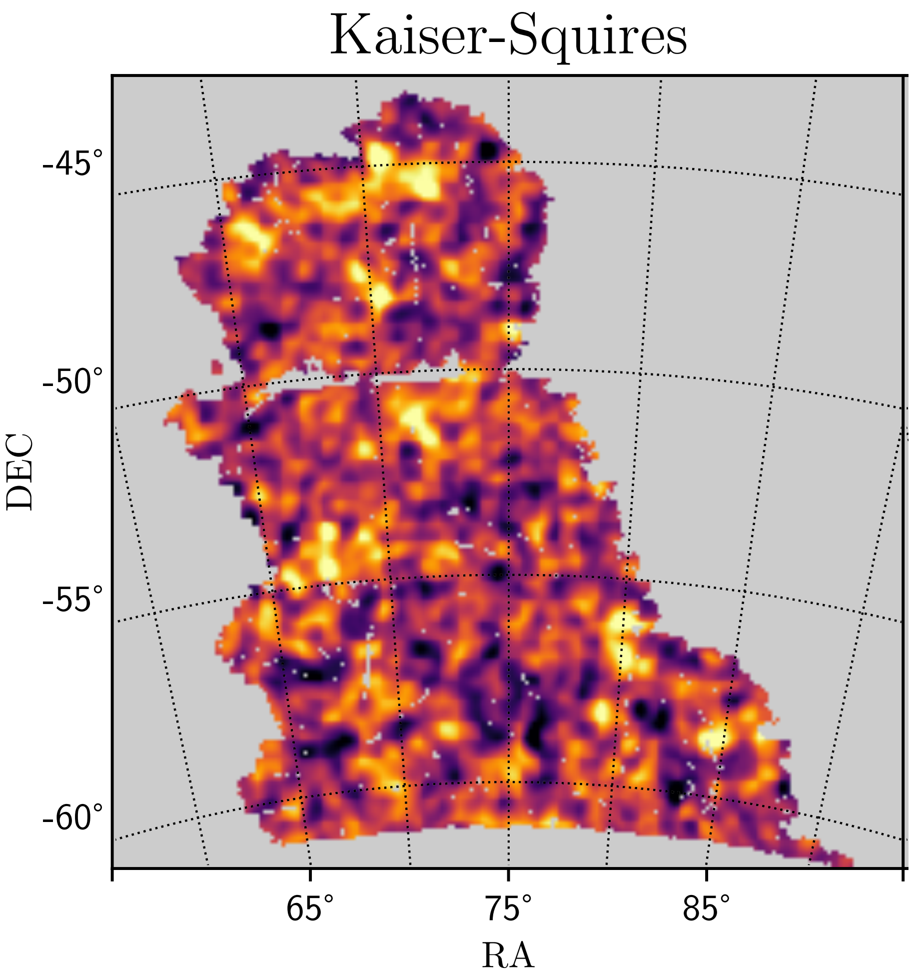
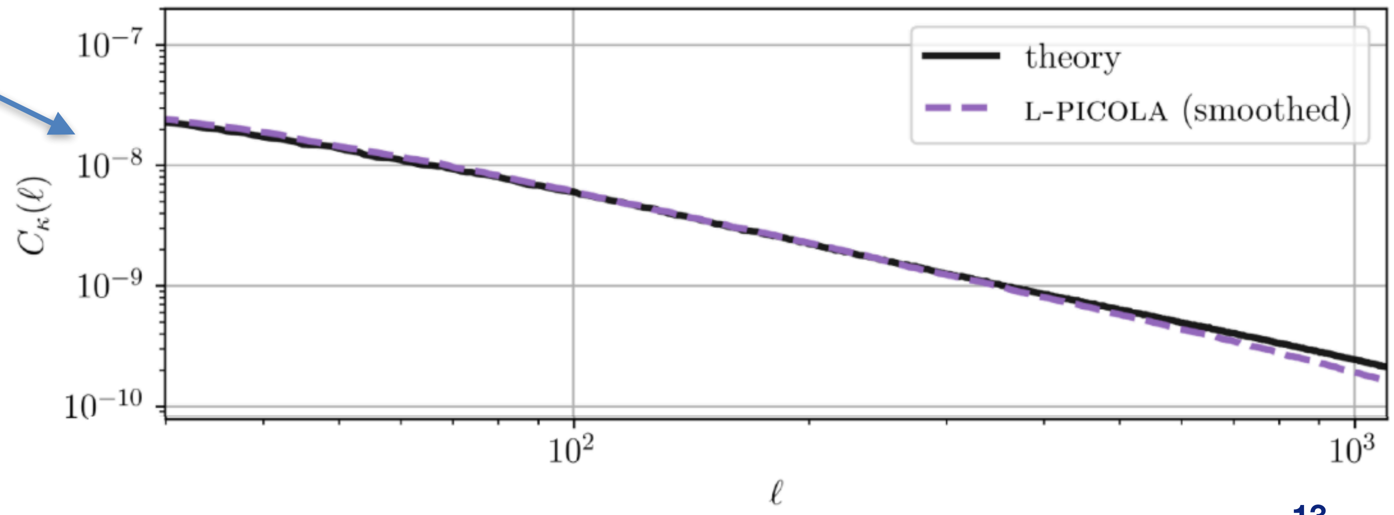
Weak lensing map summary statistics





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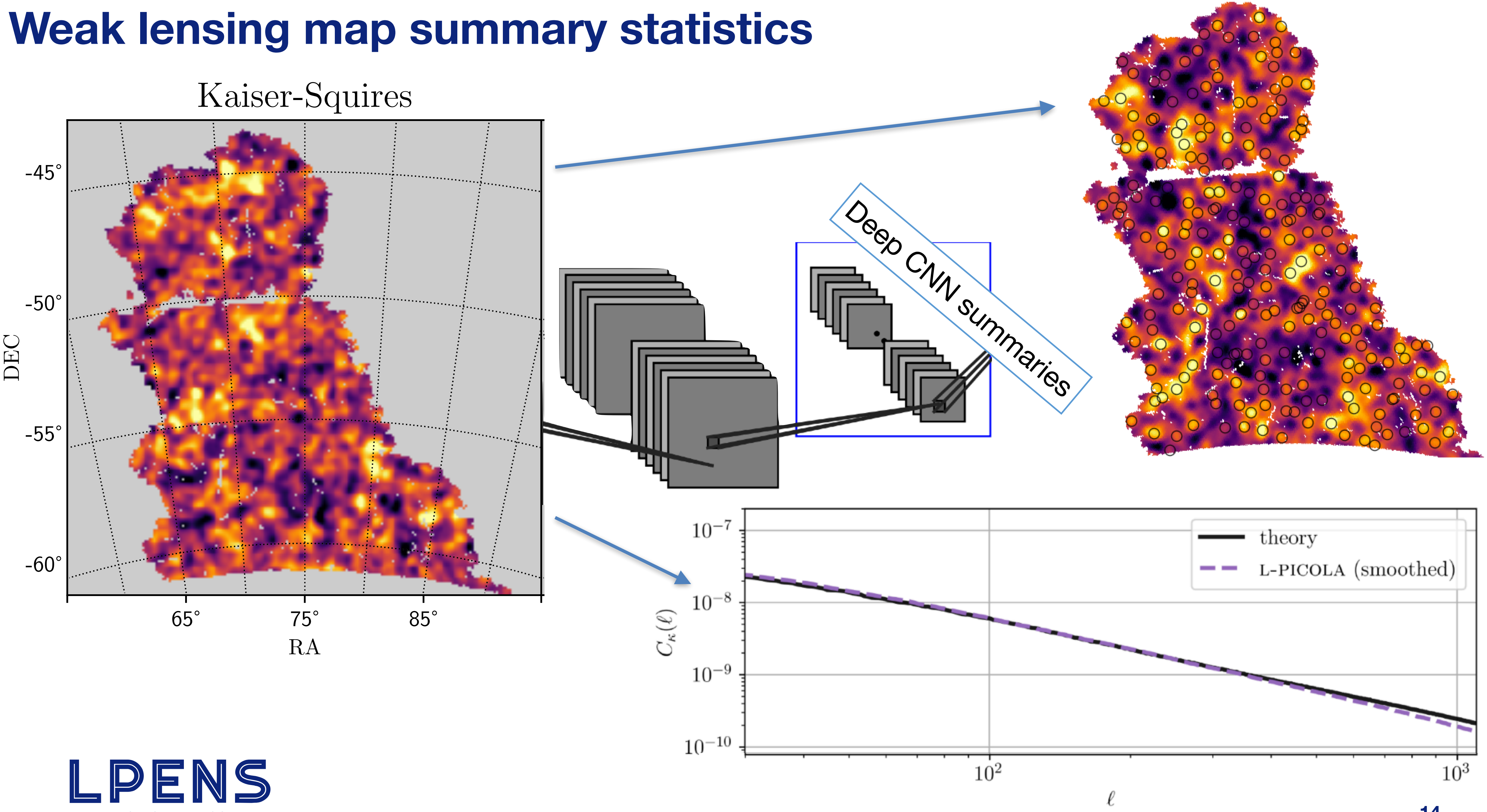

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Parameter inference

1. Observed “data” summary statistic d_o

Parameter inference

1. Observed "data" summary statistic d_o

2. Unknown parameters θ of a given model

$$P(\theta | d_o) \propto \underbrace{P(d_o | \theta)}_{\text{LIKELIHOOD}} \; \underbrace{P(\theta)}_{\text{PRIOR}}$$

02

Density-estimation likelihood-free inference $P(d \mid \theta)$

Step 1
Forward modelled mock data

$$\{\mathbf{d}_i, \theta_i\}$$

I. $\mathbf{d}_i$ are simulated data vector summary statistics (inc. noise)

II. Draw $\mathbf{d}_i$ from the distribution $P(\mathbf{d} \,|\, \theta_i)$ by running a simulation

III. Compress data using fixed compression method to get $\{\mathbf{t}_i, \theta_i\}$

Step 2
Reduce the data dimensionality

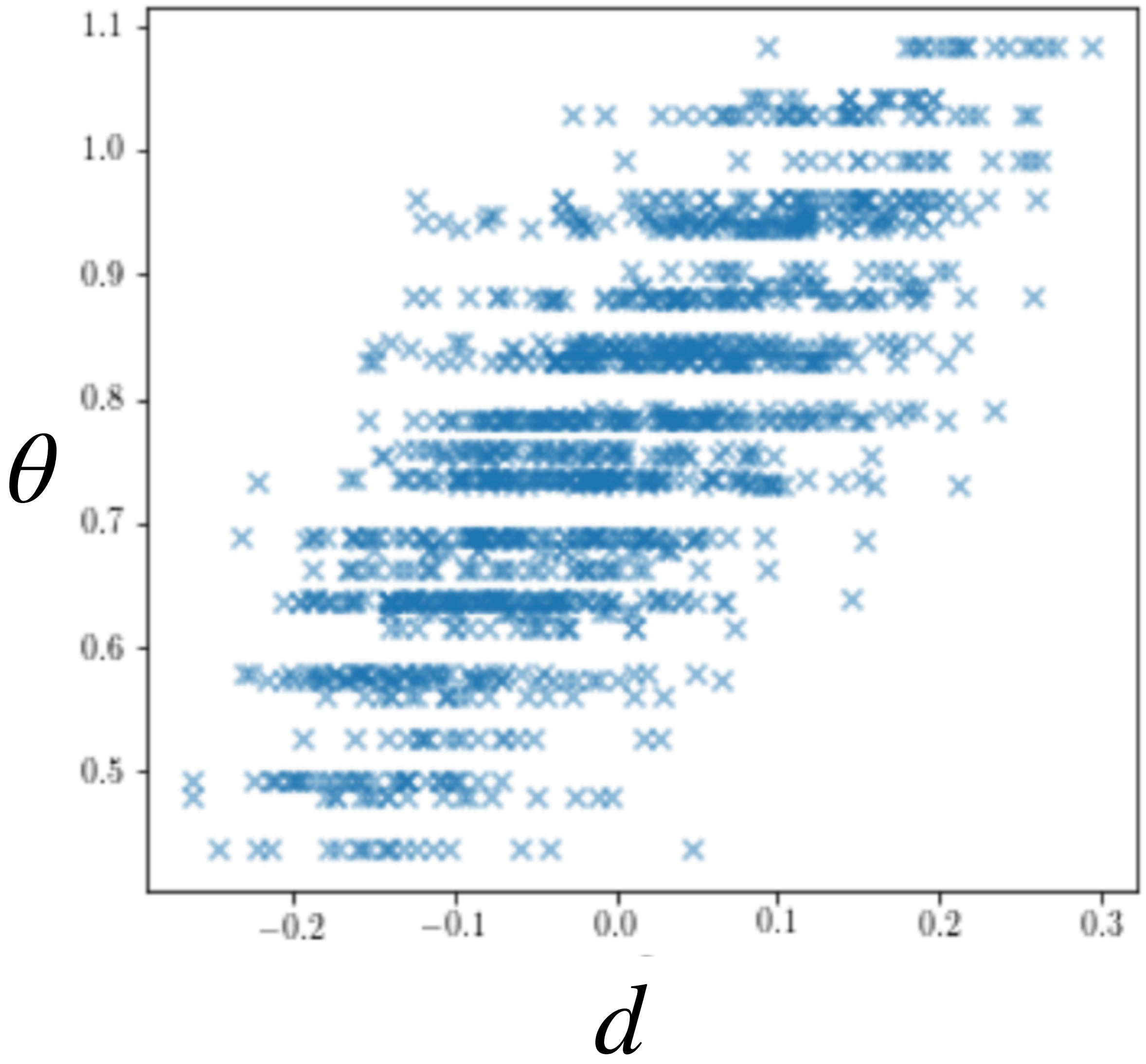
$$\mathbf{t} = F(\mathbf{d})$$

I. For Gaussian likelihoods the compression must be linear

II. With LFI we can use neural compression

Step 3
Density Estimation

Density estimation



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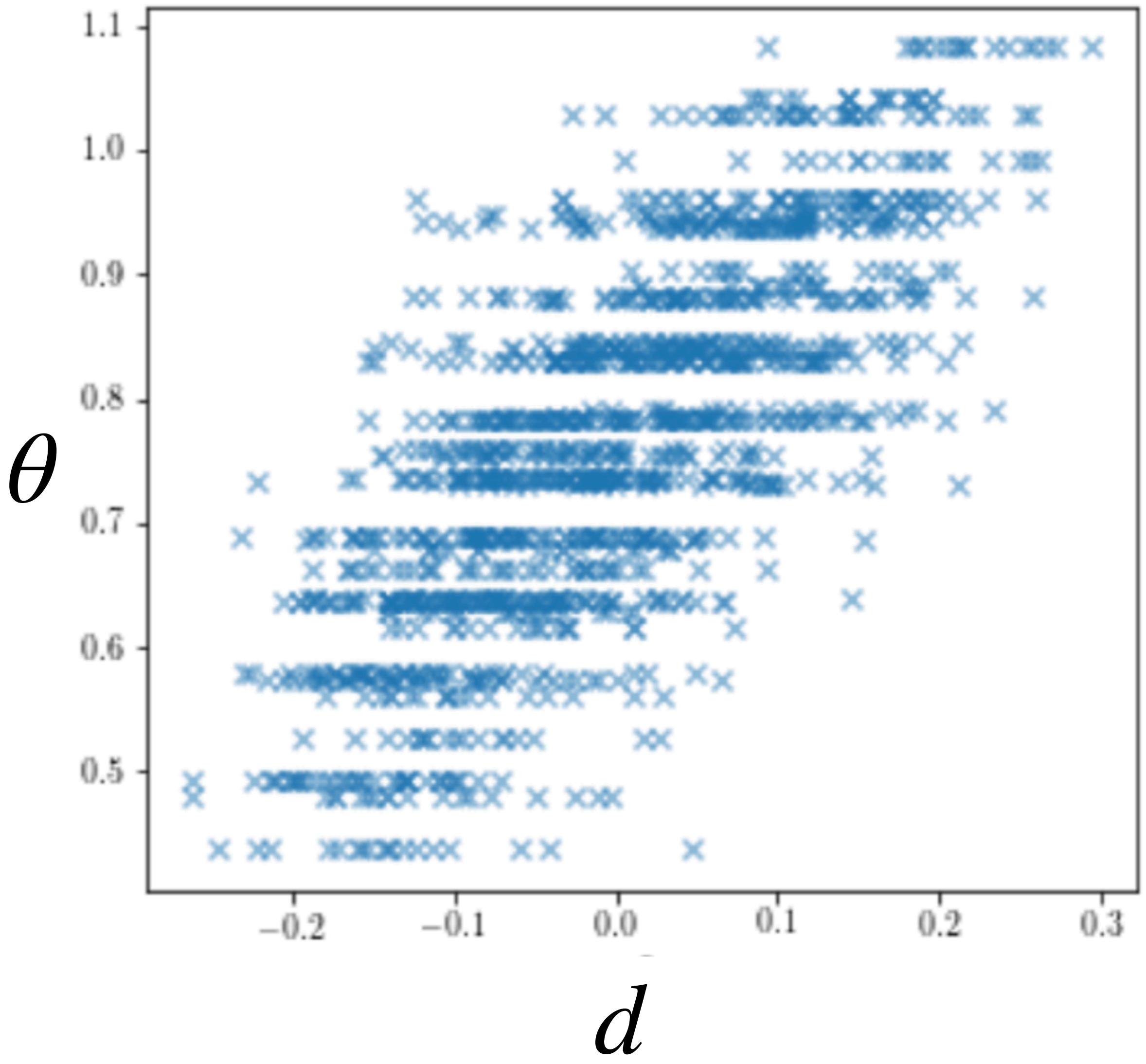
Density estimation

$$P(d, \theta) \quad \text{or} \quad P(d \mid \theta)$$



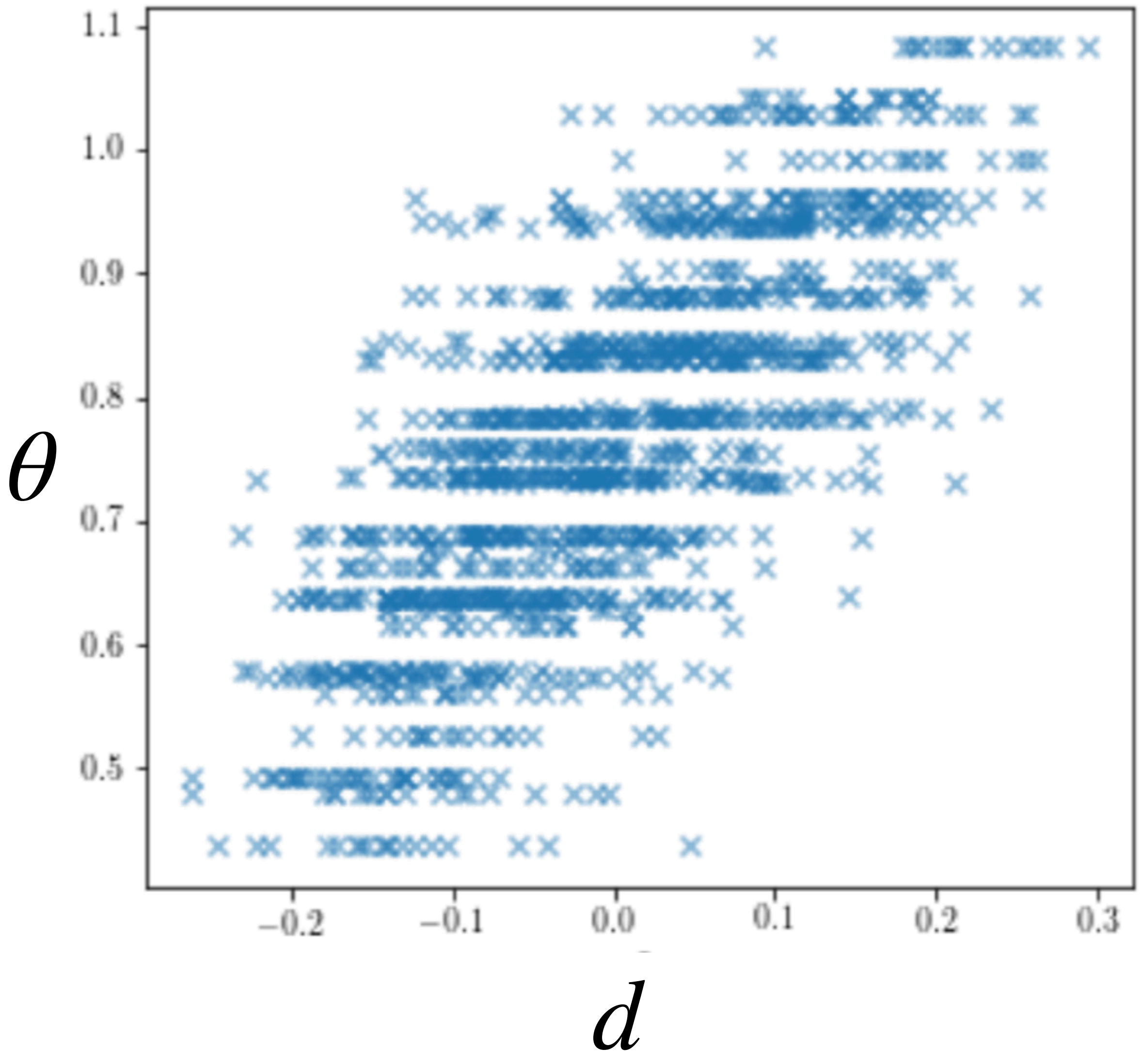
Compression

$$P(d, \theta) \quad \text{or} \quad P(d\,|\,\theta)$$

1. Can compress the data to the dimension of the parameters:

$$\mathbf{t} = F(\mathbf{d})$$

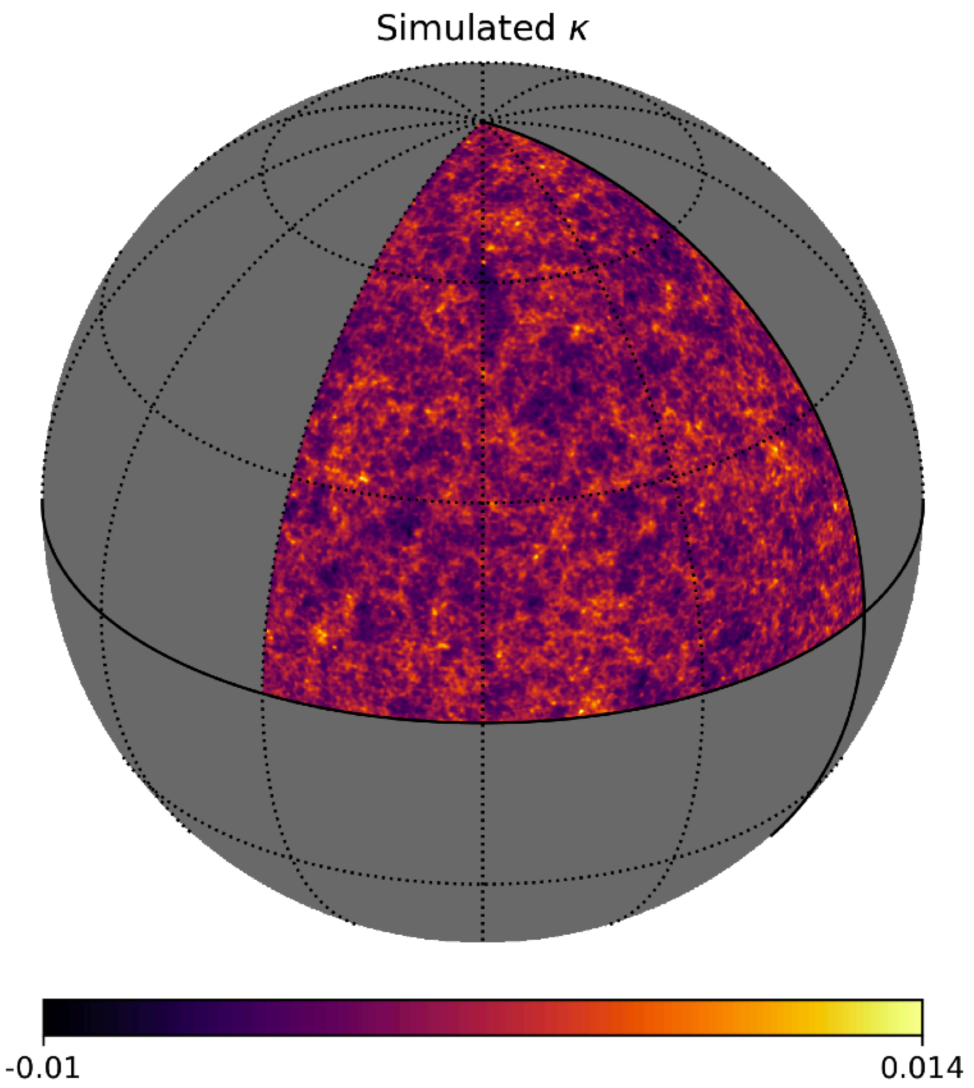
3. Poor compression will lead to larger scatter and worse constraints.



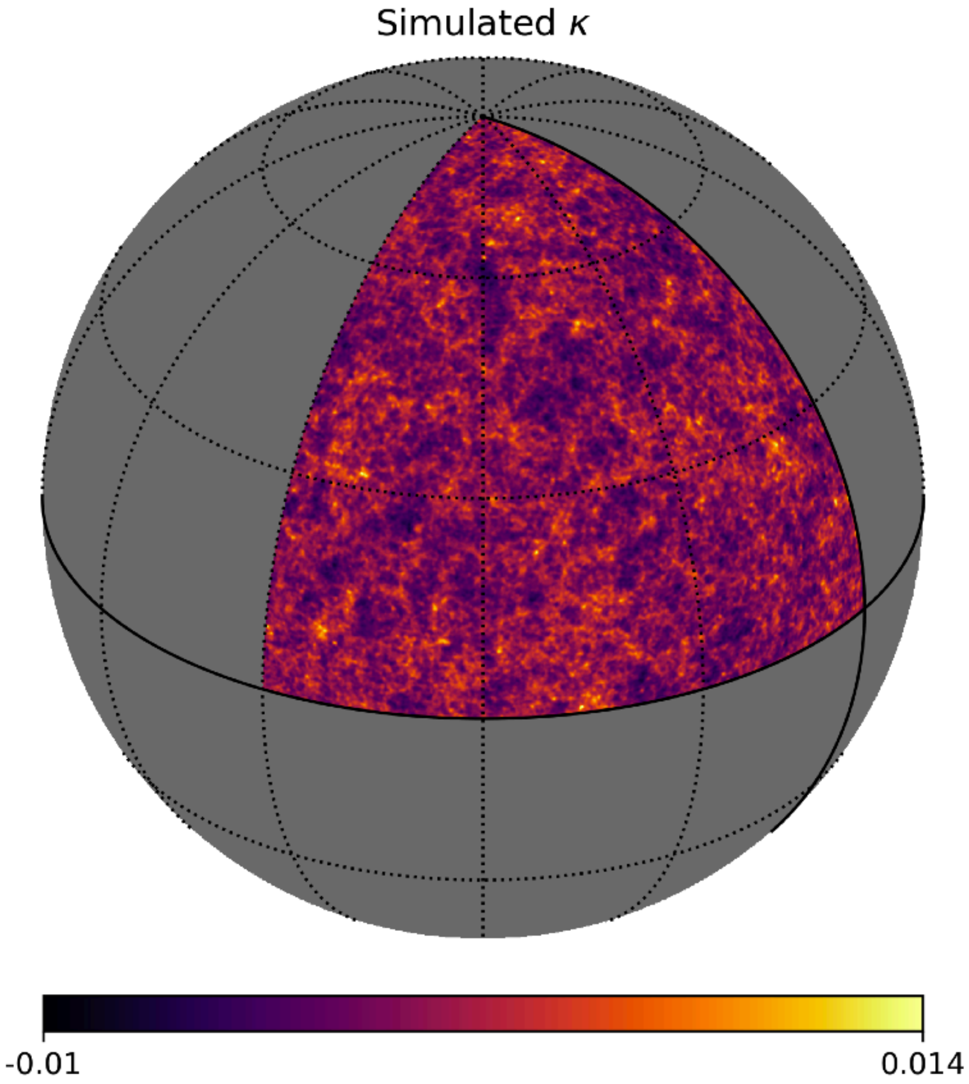
03

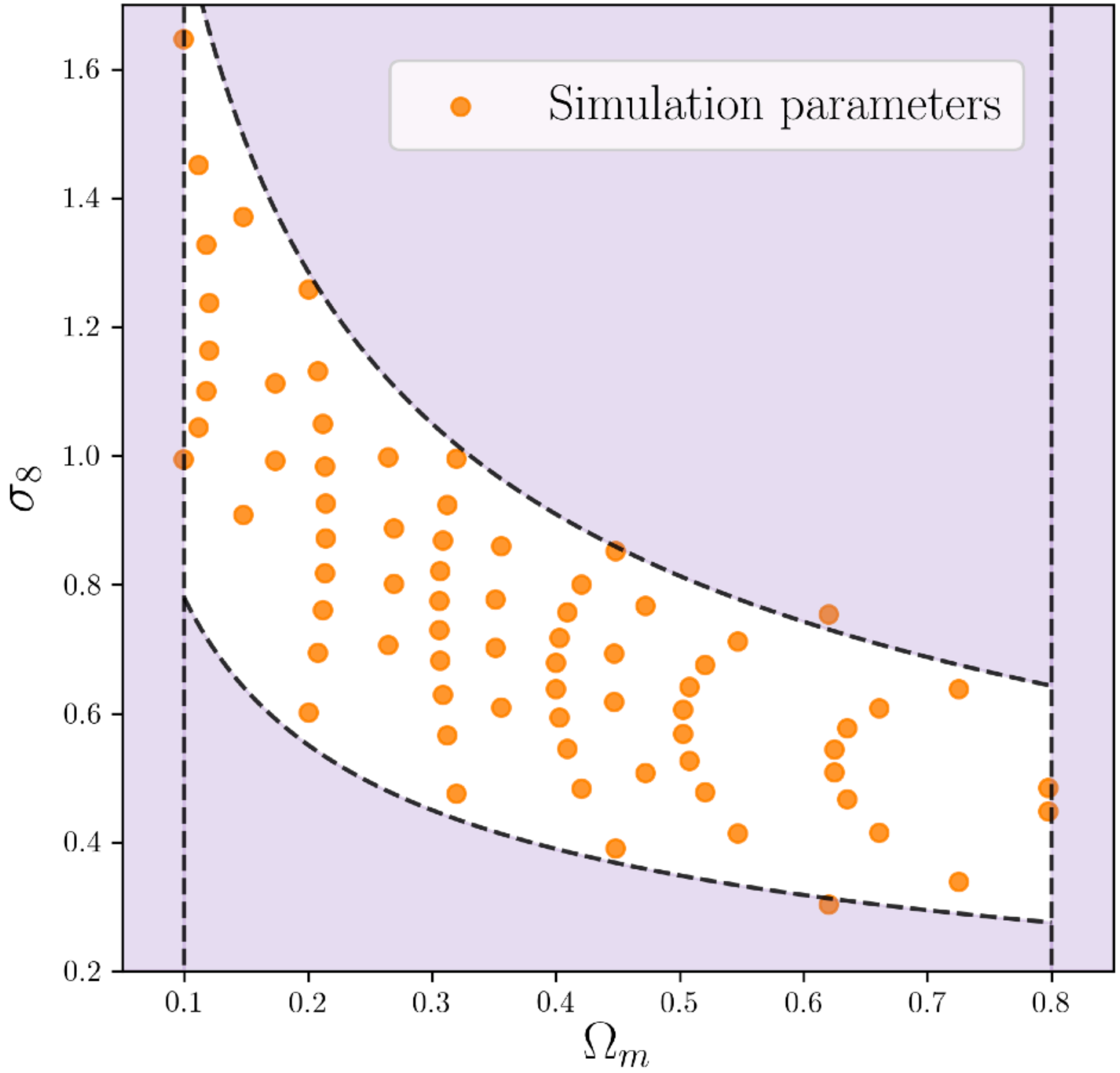
DES SV Results

Run simulations with different cosmologies



Run simulations with different cosmologies





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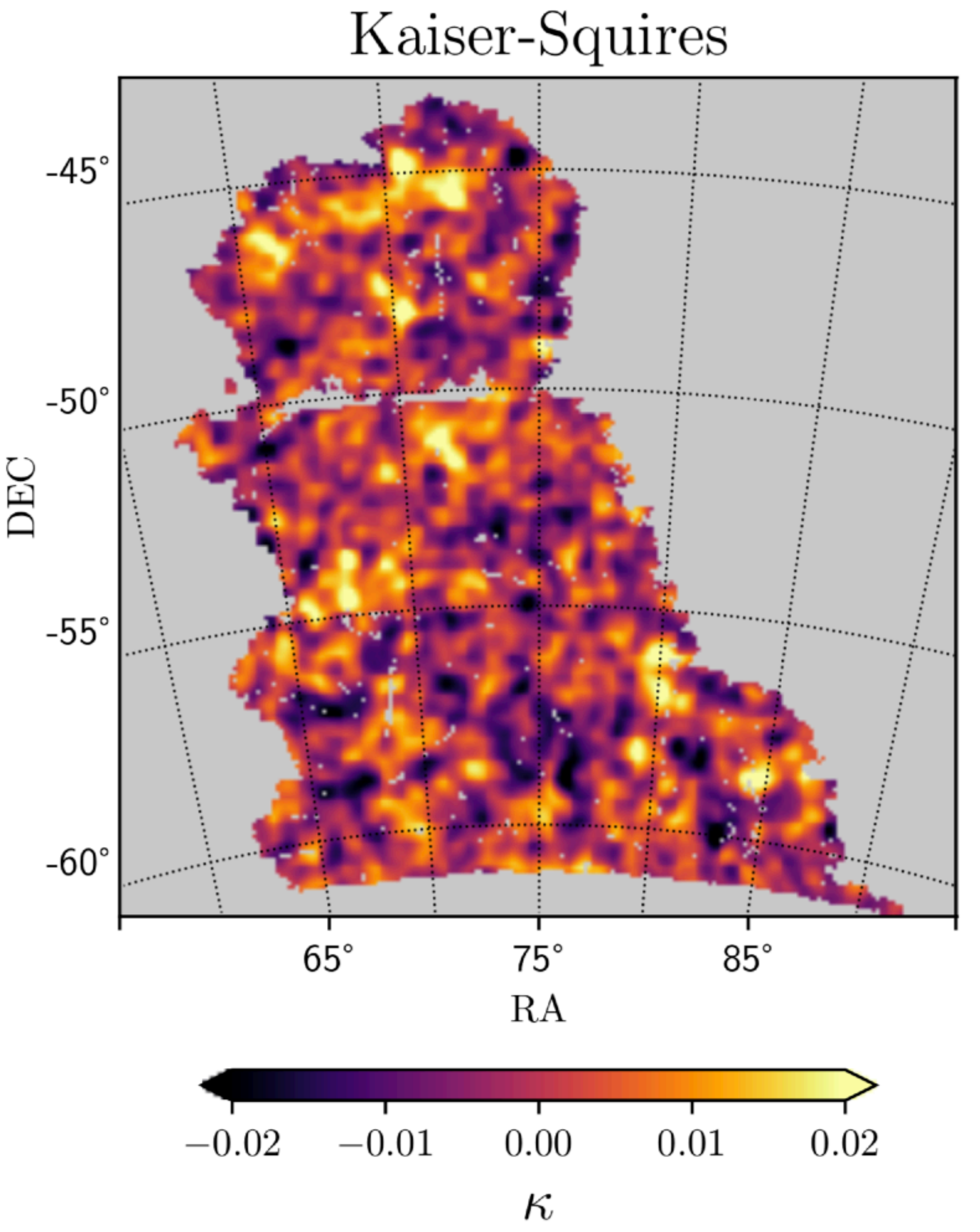
Realistic mock data maps



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Evaluate posterior with learned likelihood:

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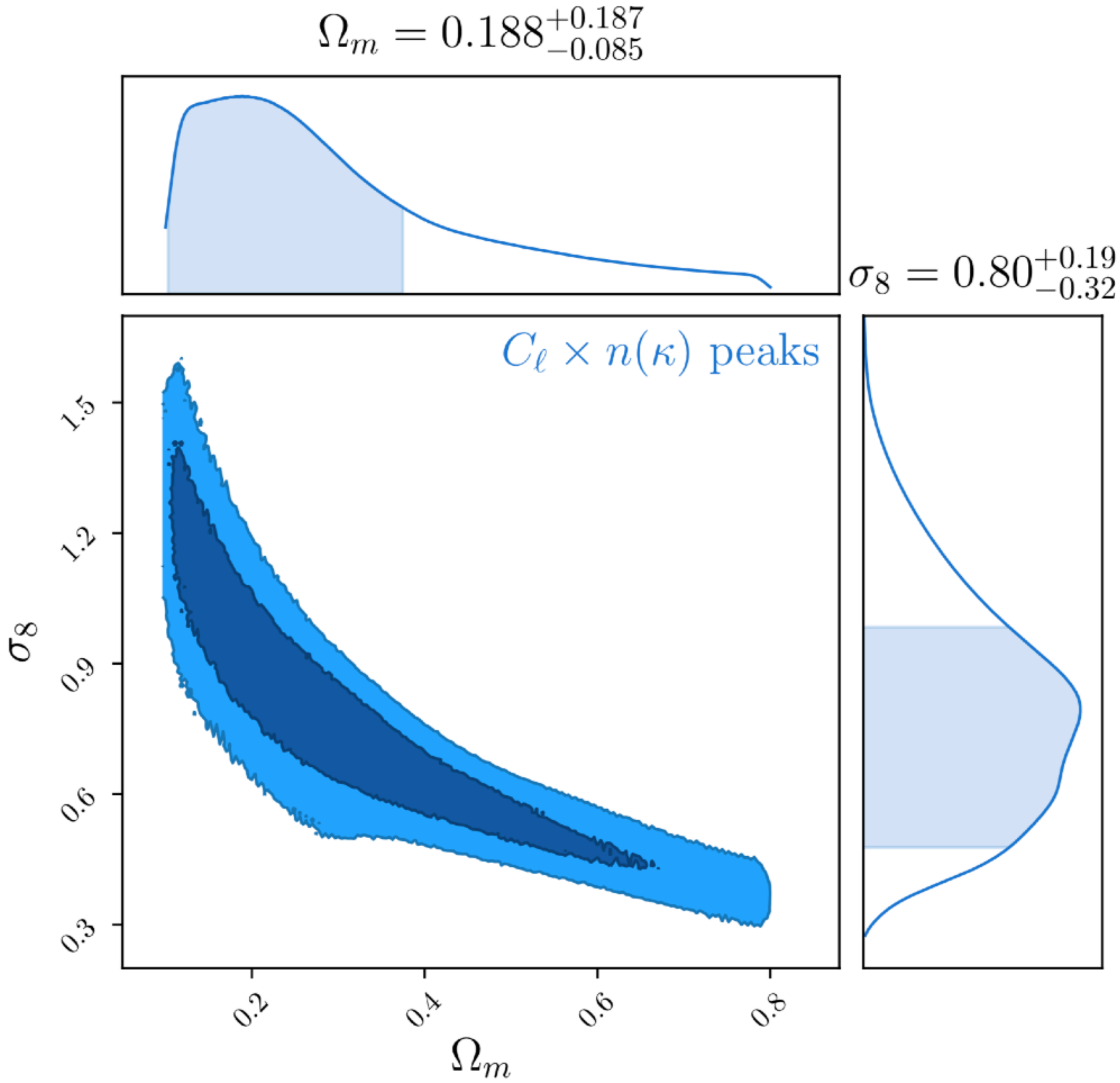

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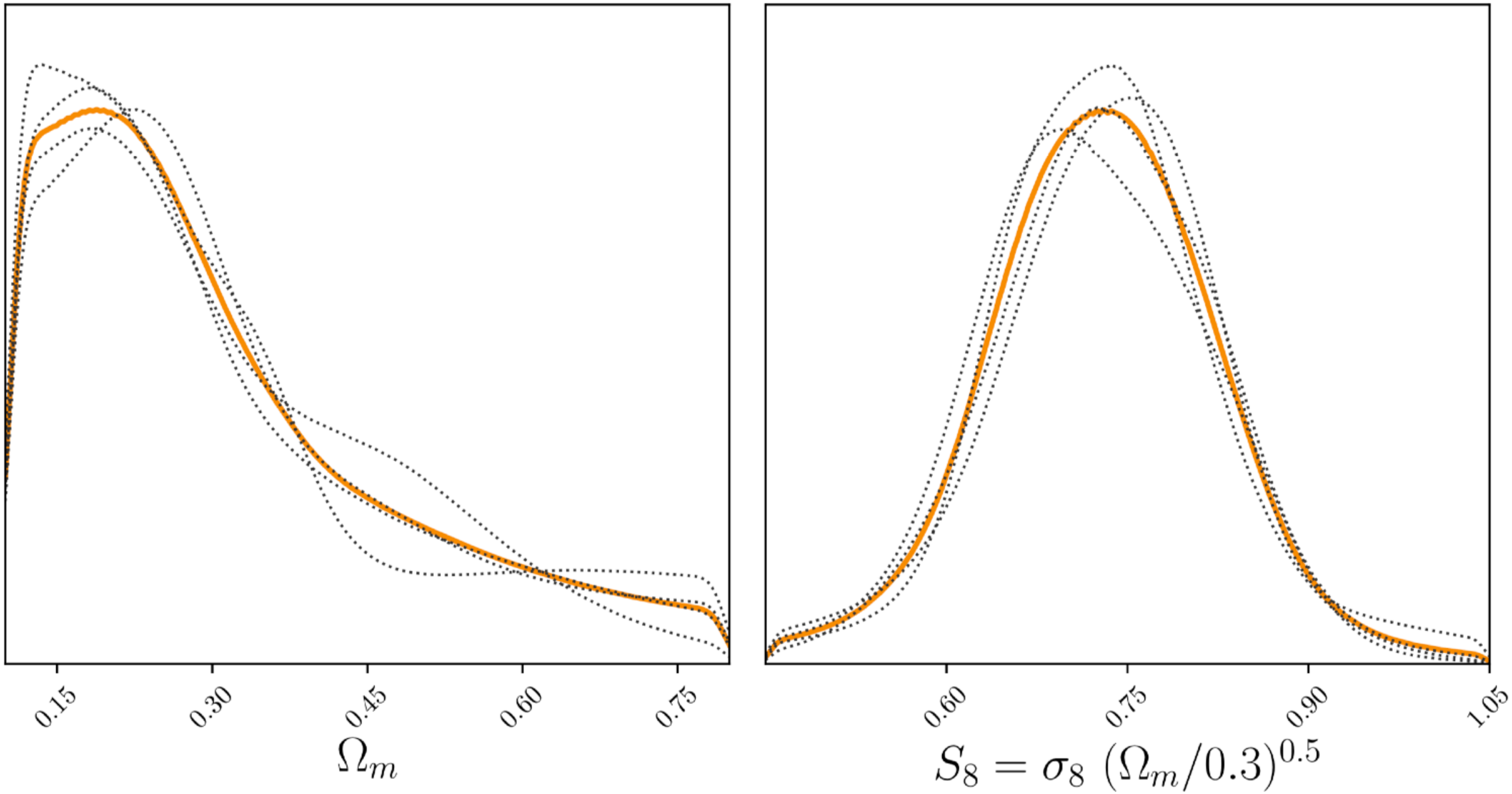
Density estimation validation:



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Deep convolutional compression of maps:

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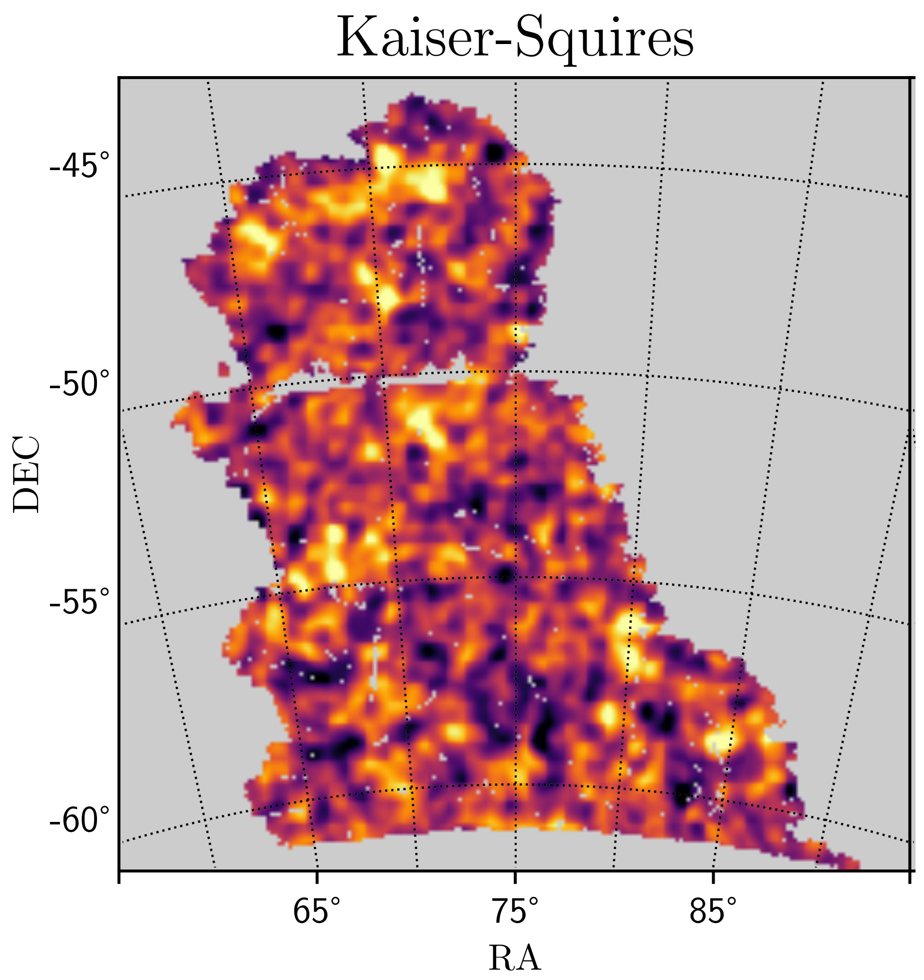

$$\mathbf{t} = F(\mathrm{map})$$

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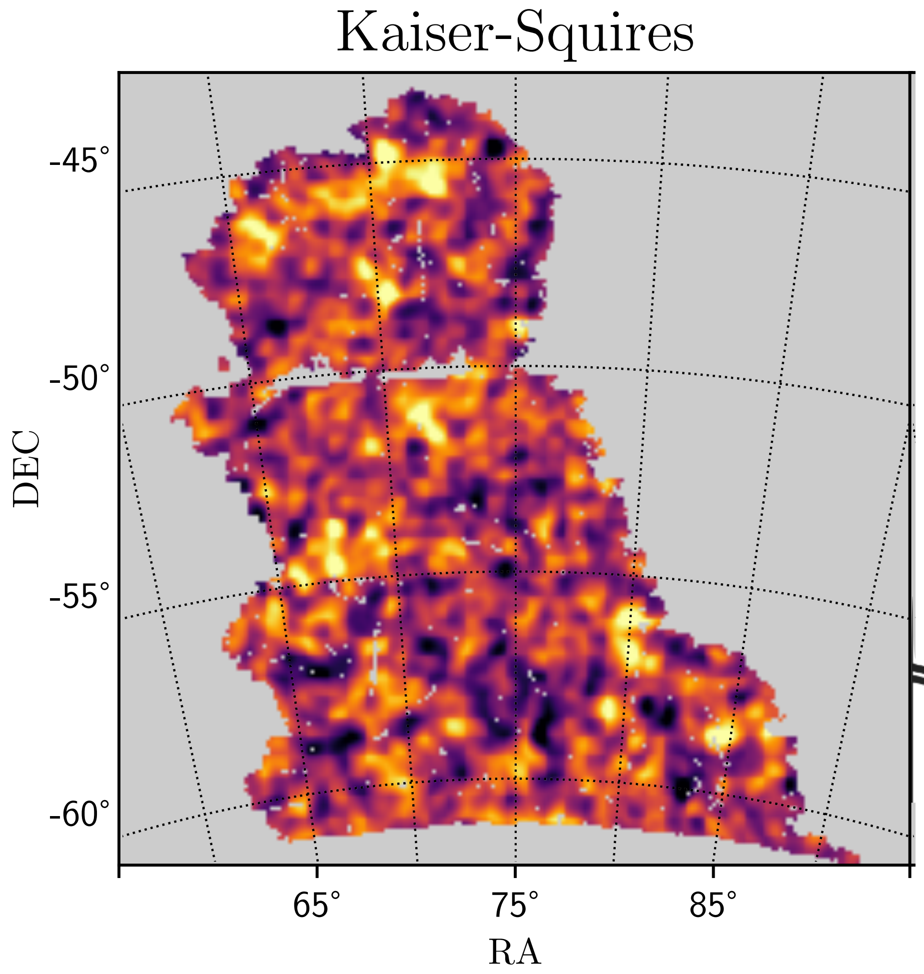
Deep convolutional compression of maps:



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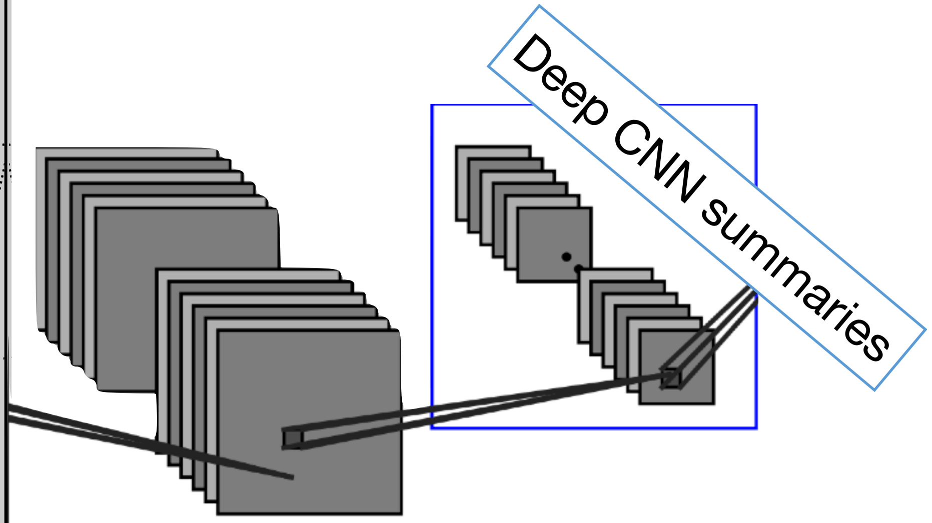

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Deep convolutional compression of maps:

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Deep convolutional compression of maps:

$$\mathbf{t} = F(\mathrm{map})$$

$$I(\mathbf{t}, \boldsymbol{\theta}) = D_{\mathrm{KL}}(p(\mathbf{t}, \boldsymbol{\theta}) \parallel p(\mathbf{t})p(\boldsymbol{\theta}))$$

Deep convolutional compression of maps:

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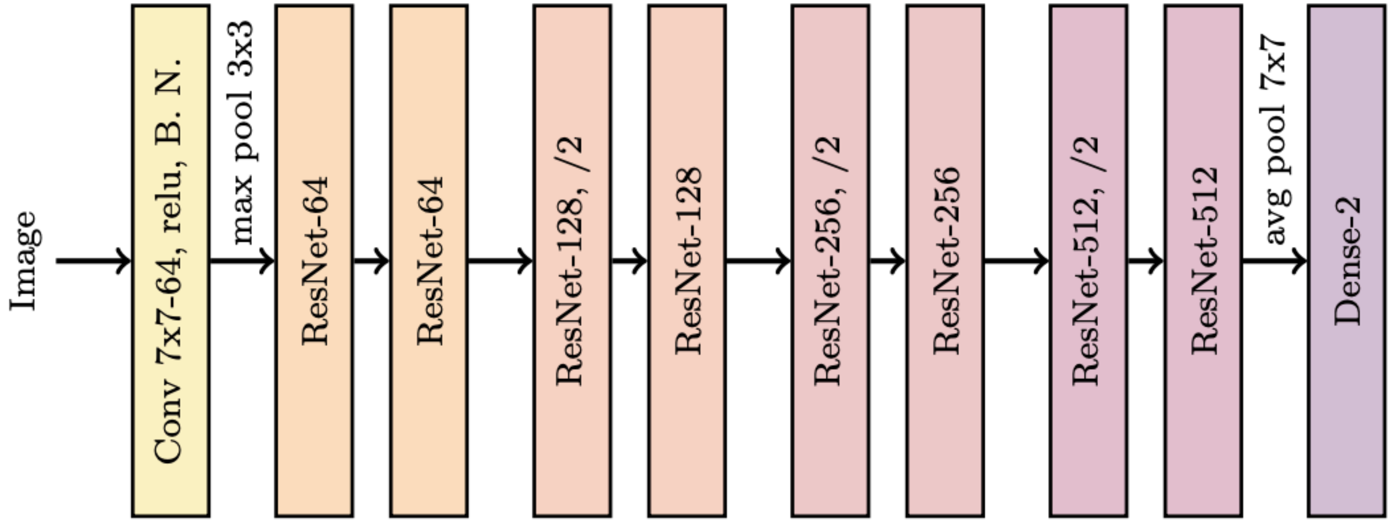

$$I(\mathbf{t}, \boldsymbol{\theta}) = D_{\mathrm{KL}}(p(\mathbf{t}, \boldsymbol{\theta}) \parallel p(\mathbf{t})p(\boldsymbol{\theta}))$$

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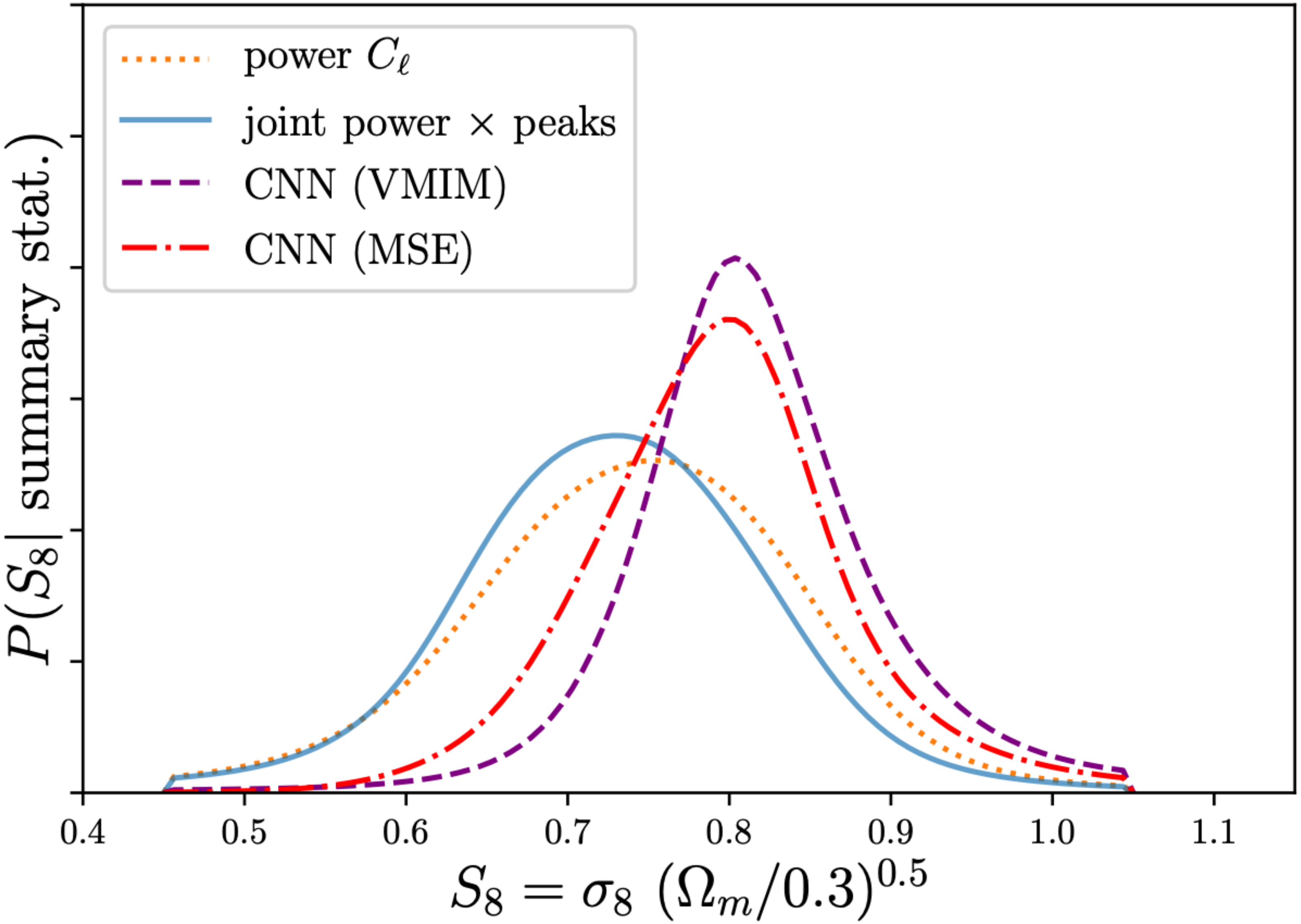

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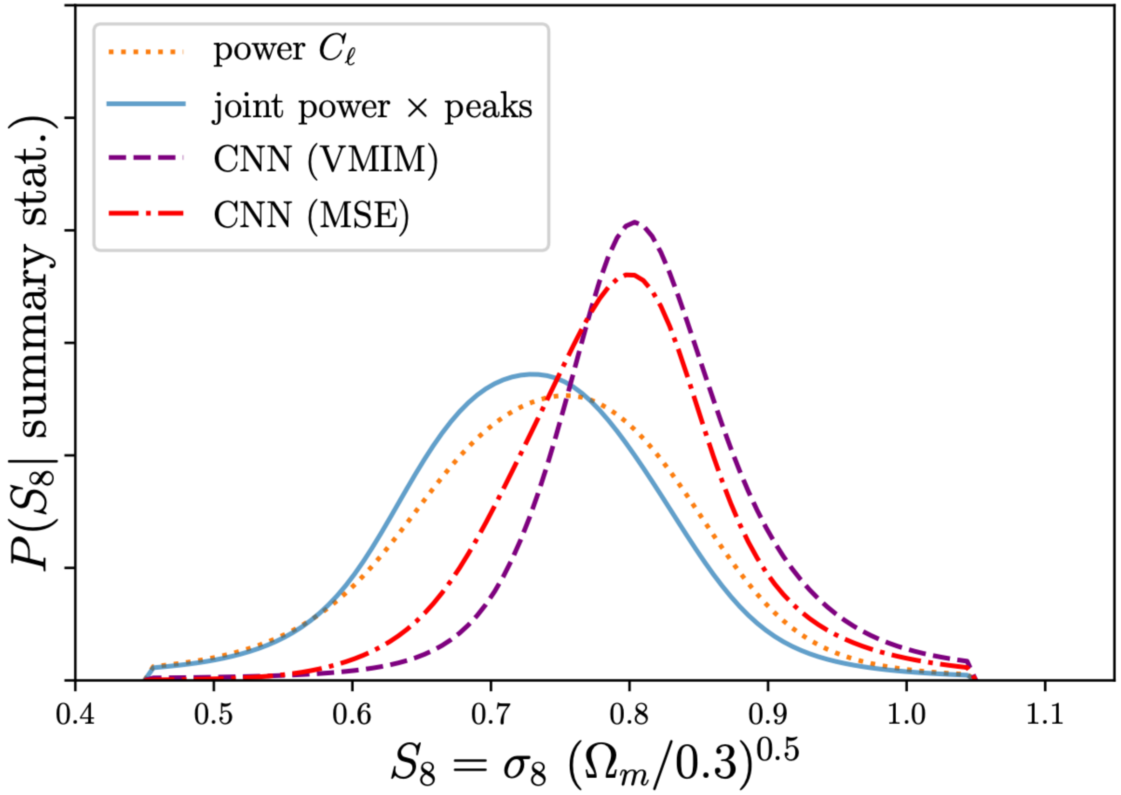
DES SV results:

- Validation: forward model
- Validation: probability density
- Deep convolutional compression



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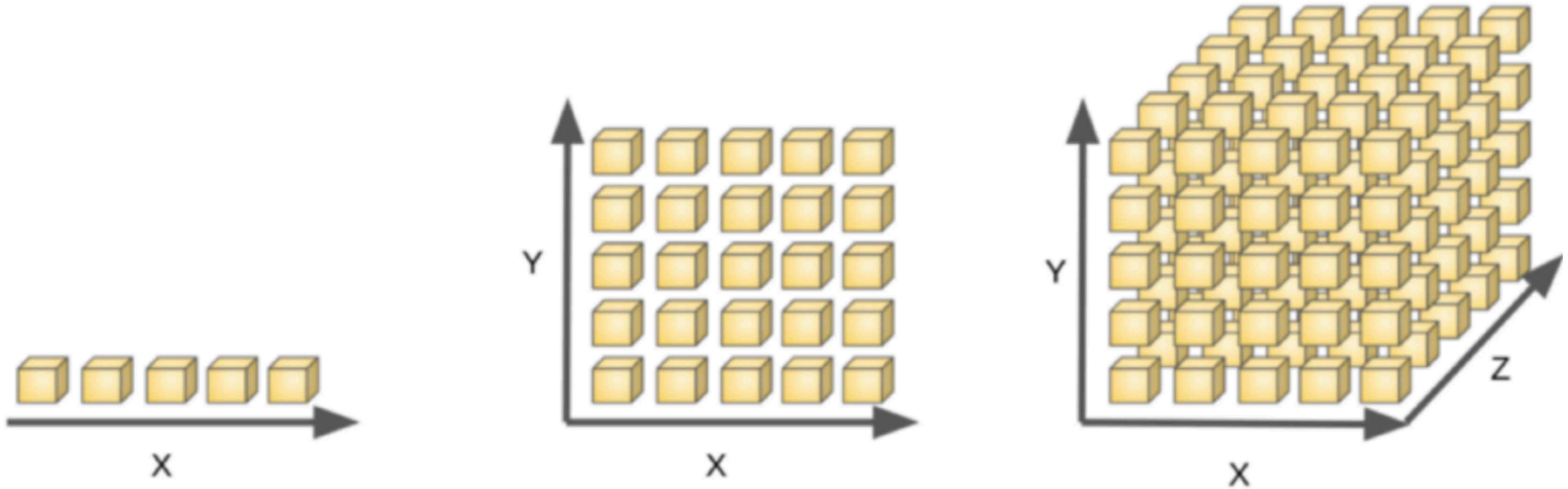
04

High-dimensional inference

Problem: curse of dimensionality

I. High dimension D of $\boldsymbol{\theta}$?

II. Number of mock data scales N^D



Marginal posterior density estimation

$$\boldsymbol{\theta} = [\alpha, \beta]$$

$$p(\alpha, \beta | \boldsymbol{x}_{obs}) = \int p(\alpha, \beta, \boldsymbol{\theta}' | \boldsymbol{x}_{obs})\, \mathrm{d}\boldsymbol{\theta}'$$

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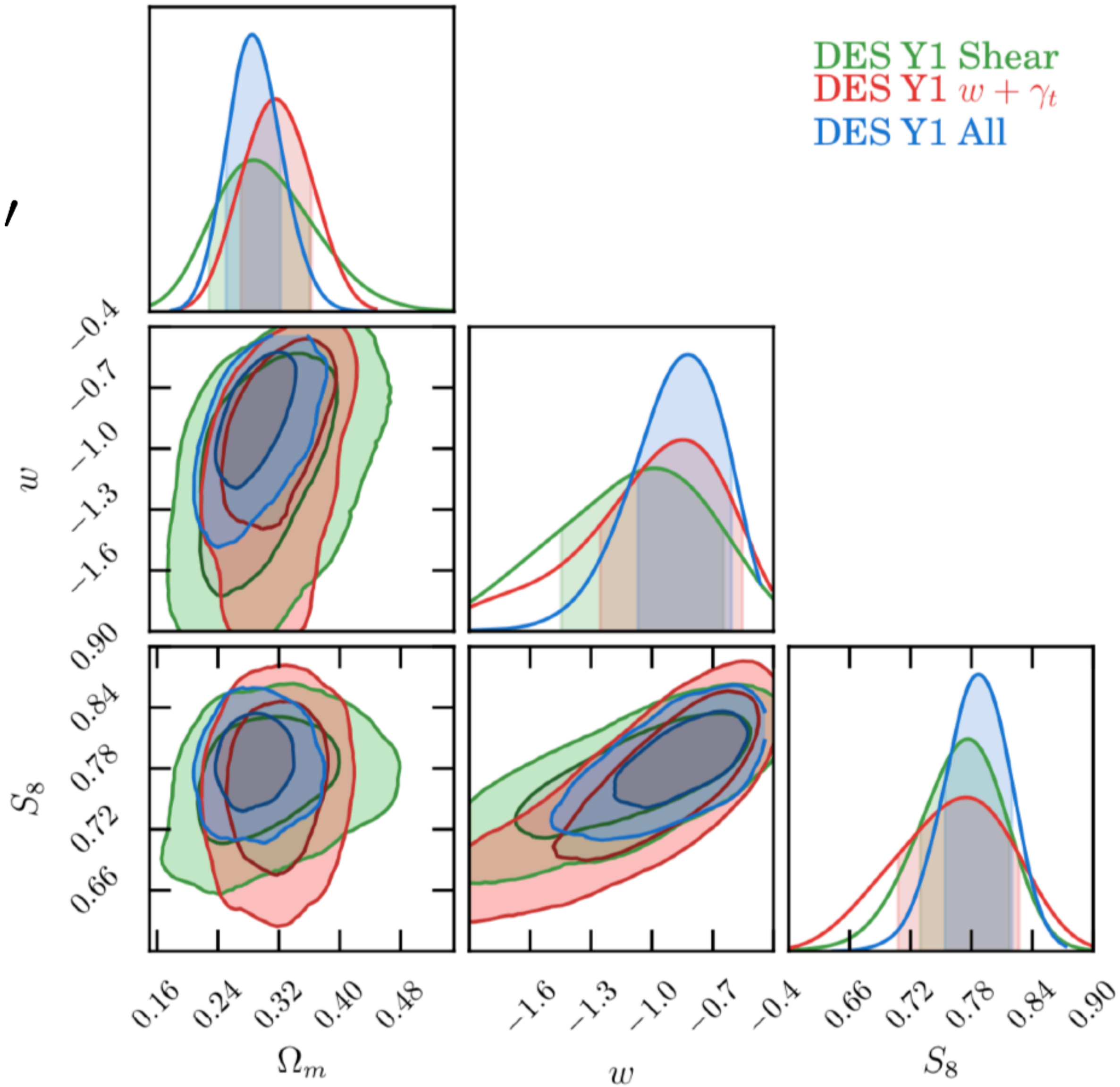
Marginal posterior density estimation

$$p(\alpha, \beta | \boldsymbol{x}_{obs}) = \int p(\alpha, \beta, \boldsymbol{\theta}' | \boldsymbol{x}_{obs}) \, \mathrm{d}\boldsymbol{\theta}'$$



Marginal flow

I. Draw full parameter space from prior $\boldsymbol{\theta}_i \sim p(\boldsymbol{\theta})$

II. Draw simulations $\mathbf{x}_i \sim p(\mathbf{x} \,|\, \boldsymbol{\theta}_i)$

III. Objective between subsets of parameters, e.g.

$$U(\boldsymbol{\varphi}) = -\sum_{i=1}^{N} \log q(\alpha_i, \beta_i | \boldsymbol{x}_i; \boldsymbol{\varphi})$$

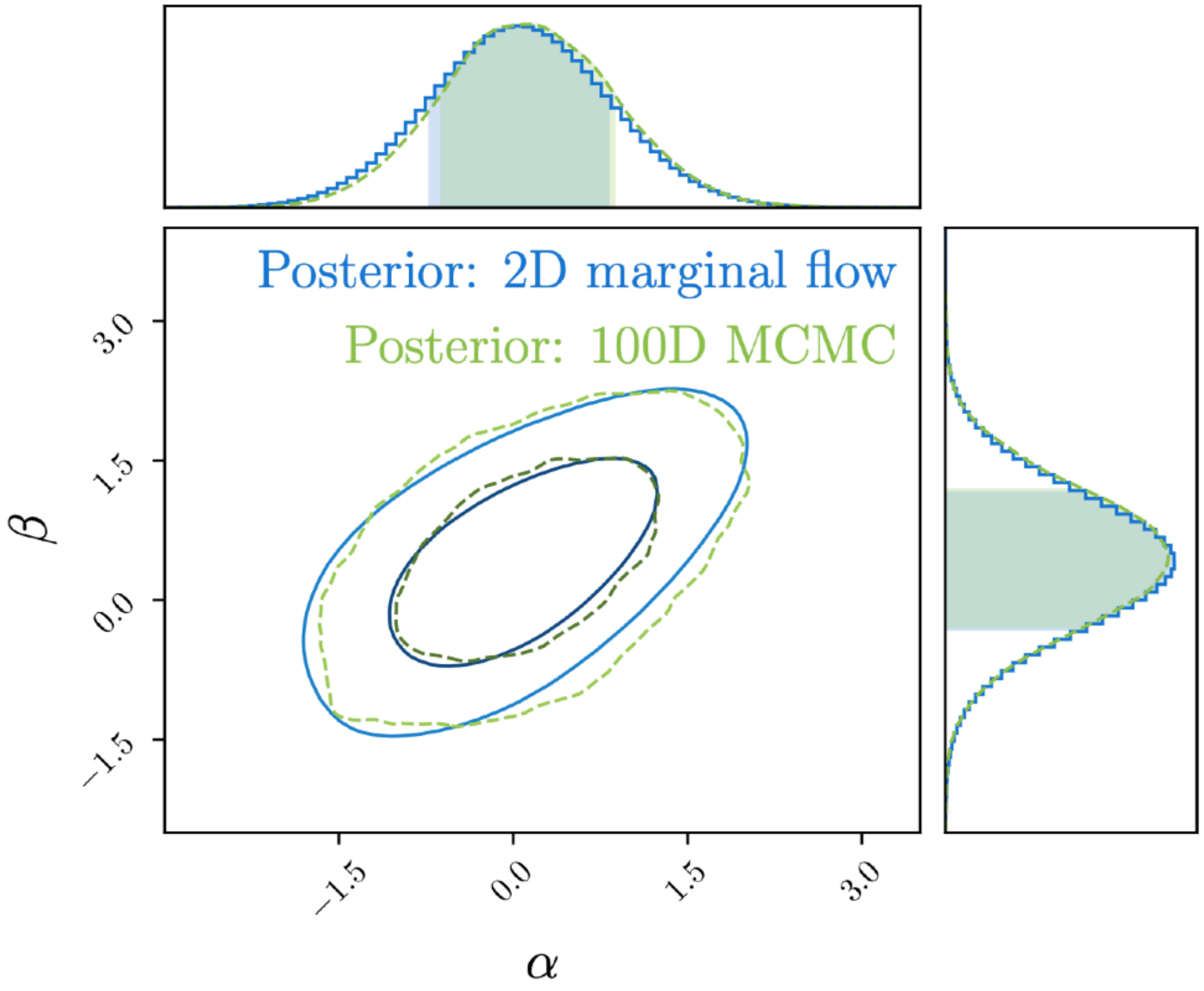
IV. Other parameters are explicitly marginalised away

Marginal flow vs MCMC

I. 100-parameter model

II. 10^7 MCMC samples

III. 8×10^4 simulations for marginal flow



Moment Network:
side-step density estimation problem

I. Network takes the data as input: $F(\mathbf{x})$

II. Train with an L2 loss

$$J_0 = \int ||\boldsymbol{\theta} - \mathcal{F}(\boldsymbol{x})||^2 p(\boldsymbol{x}, \boldsymbol{\theta}) \, \mathrm{d}\boldsymbol{x} \, \mathrm{d}\boldsymbol{\theta}$$

III. The optimal network is the posterior mean $F(\mathbf{x}_o) = \int p(\boldsymbol{\theta} \,|\, \mathbf{x}_o) \, \mathrm{d}\boldsymbol{\theta}$

Moment Network: level 2

I. Network takes the data as input: $G(\mathbf{x})$

II. Optimization objective

$$J_1 = \int ||(\boldsymbol{\theta} - \mathcal{F}_{\mathrm{fixed}}(\boldsymbol{x}))^2 - \mathcal{G}(\boldsymbol{x})||^2 p(\boldsymbol{x}, \boldsymbol{\theta}) \; \mathrm{d}\boldsymbol{x} \; \mathrm{d}\boldsymbol{\theta}$$

III. Estimate mean, variance and covariance (and higher-moments) of marginal

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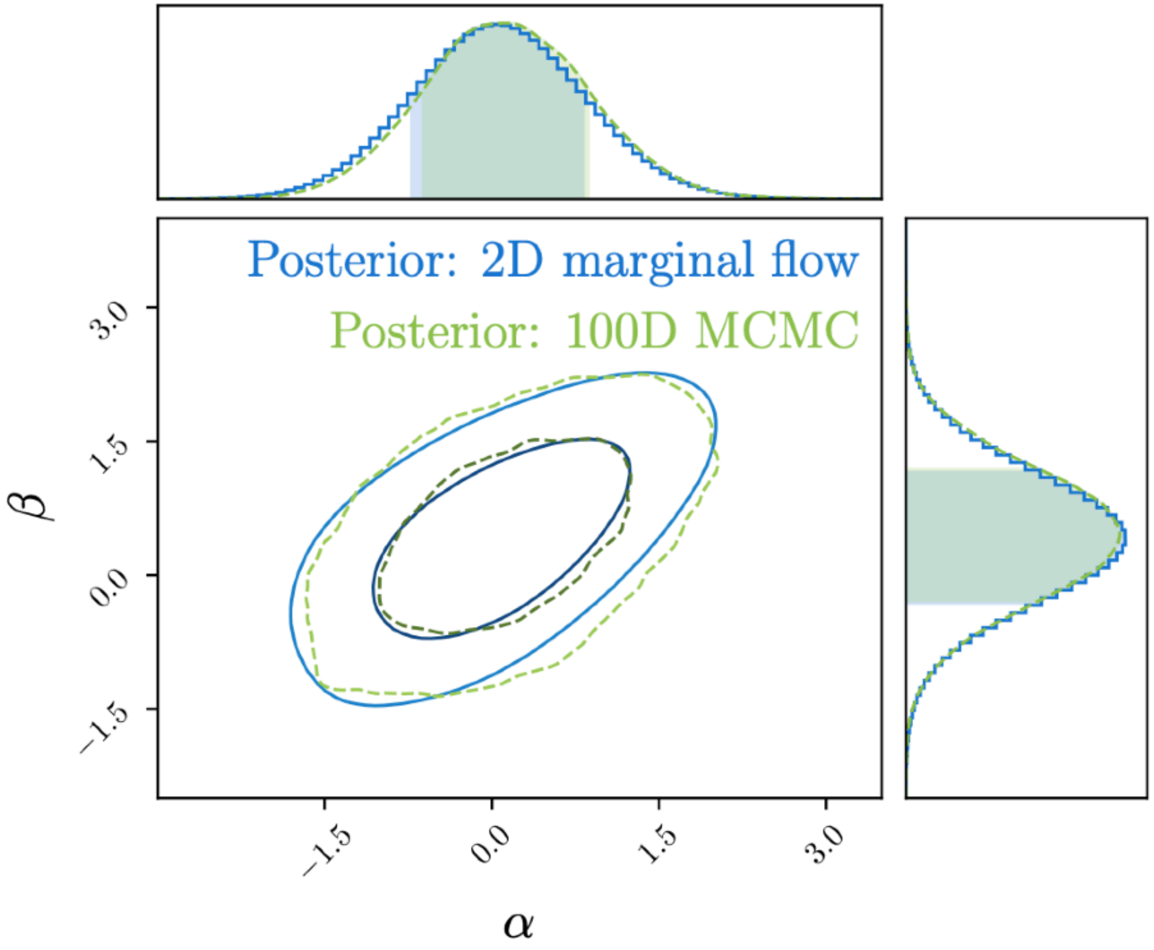
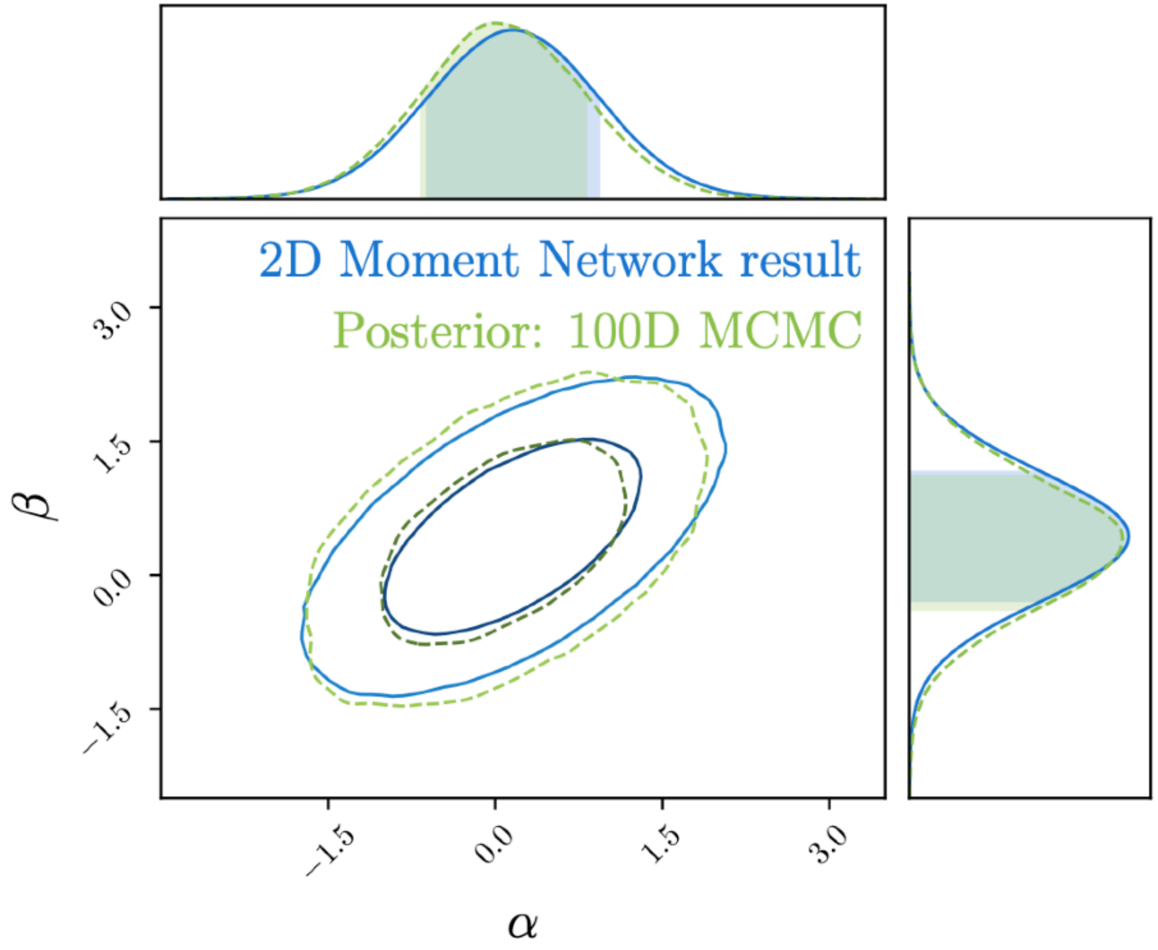
Marginal Flow & Moment Network vs MCMC





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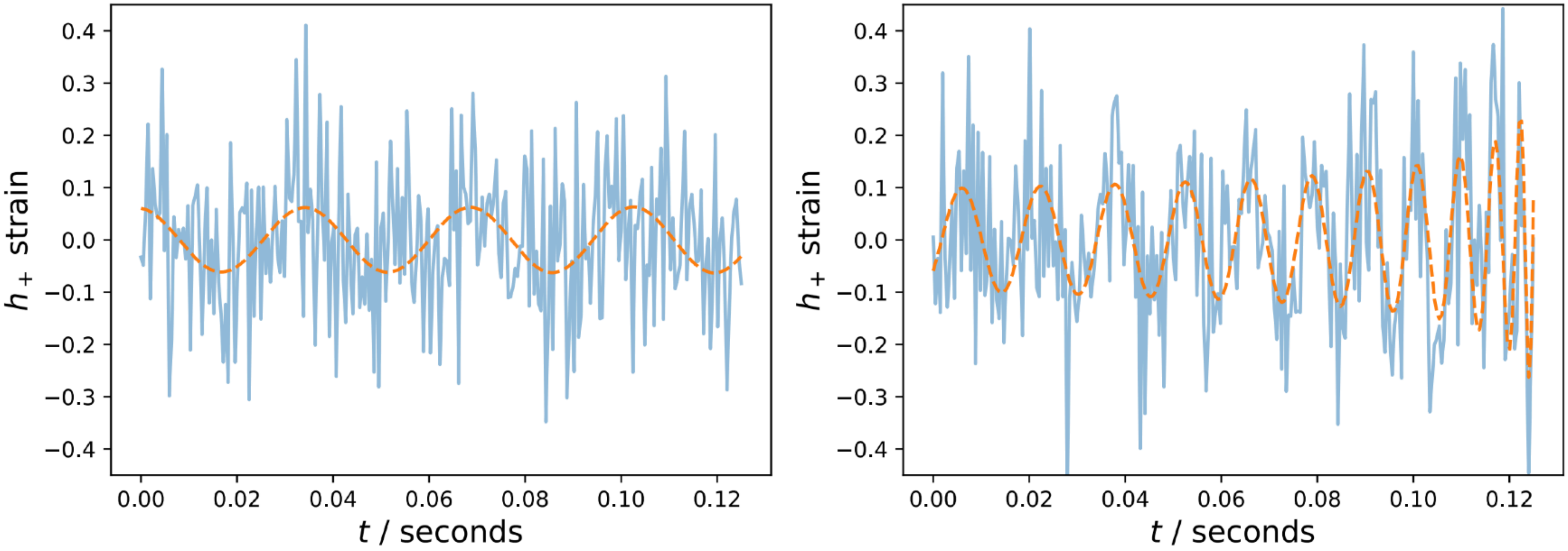
Gravitational wave example



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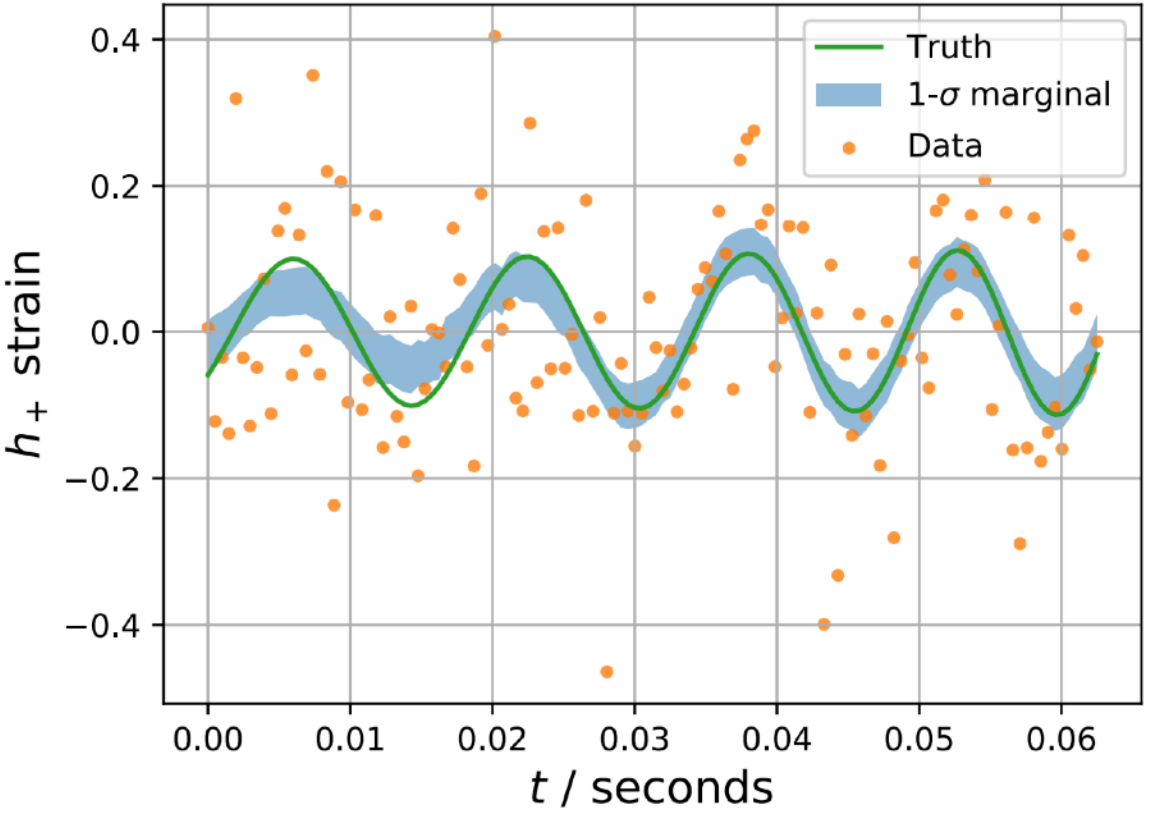

I. Moment Network posterior mean and variance

II. Marginal per parameter h_+

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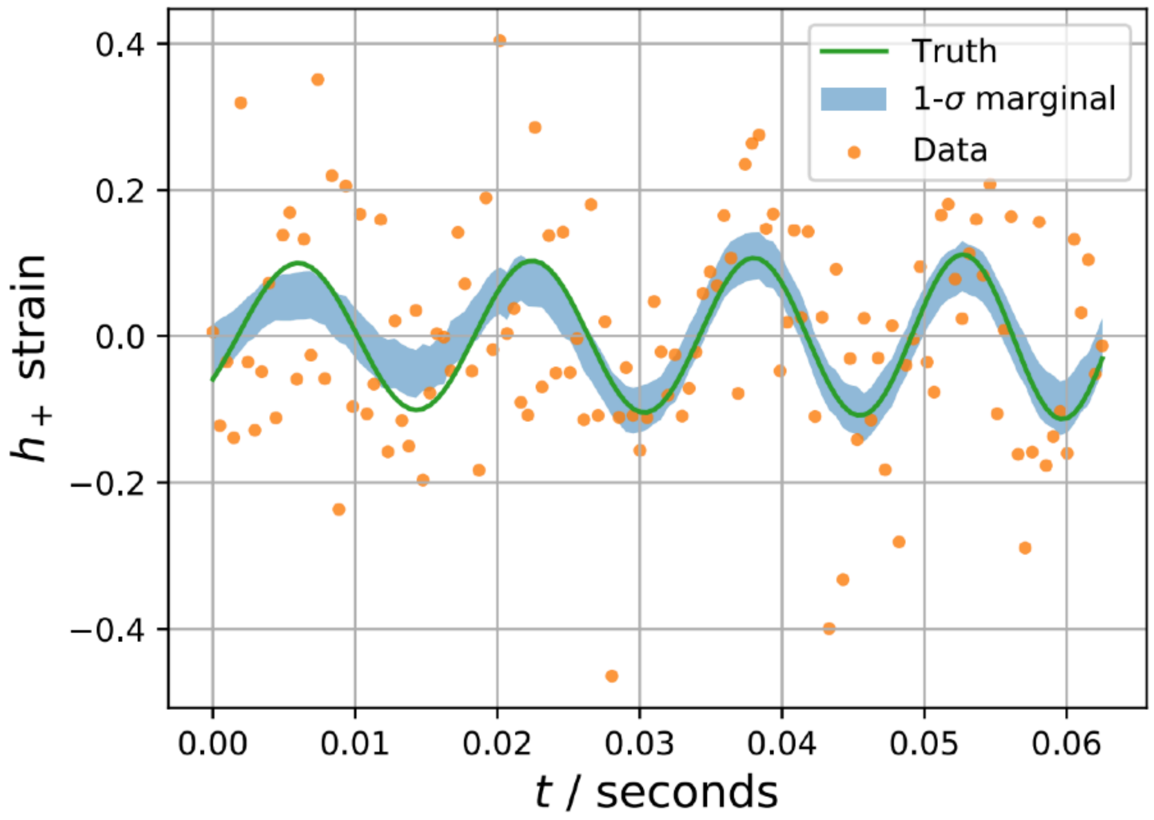
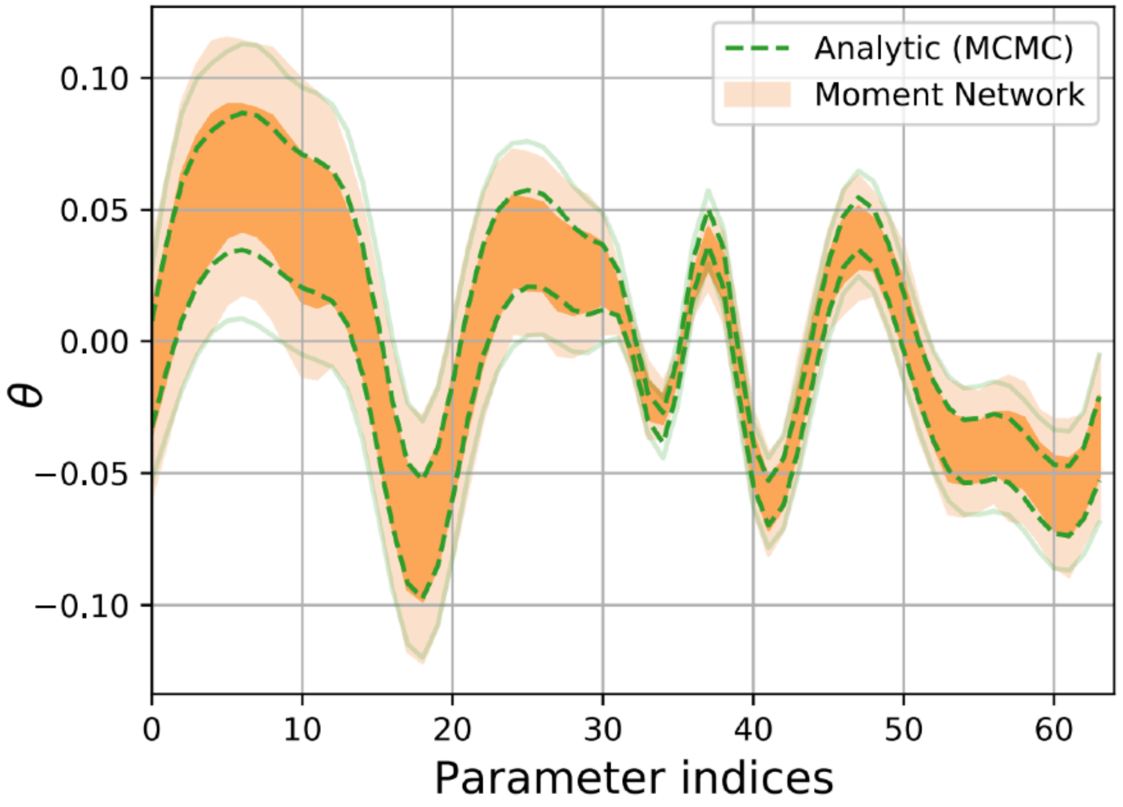
Gravitational wave example





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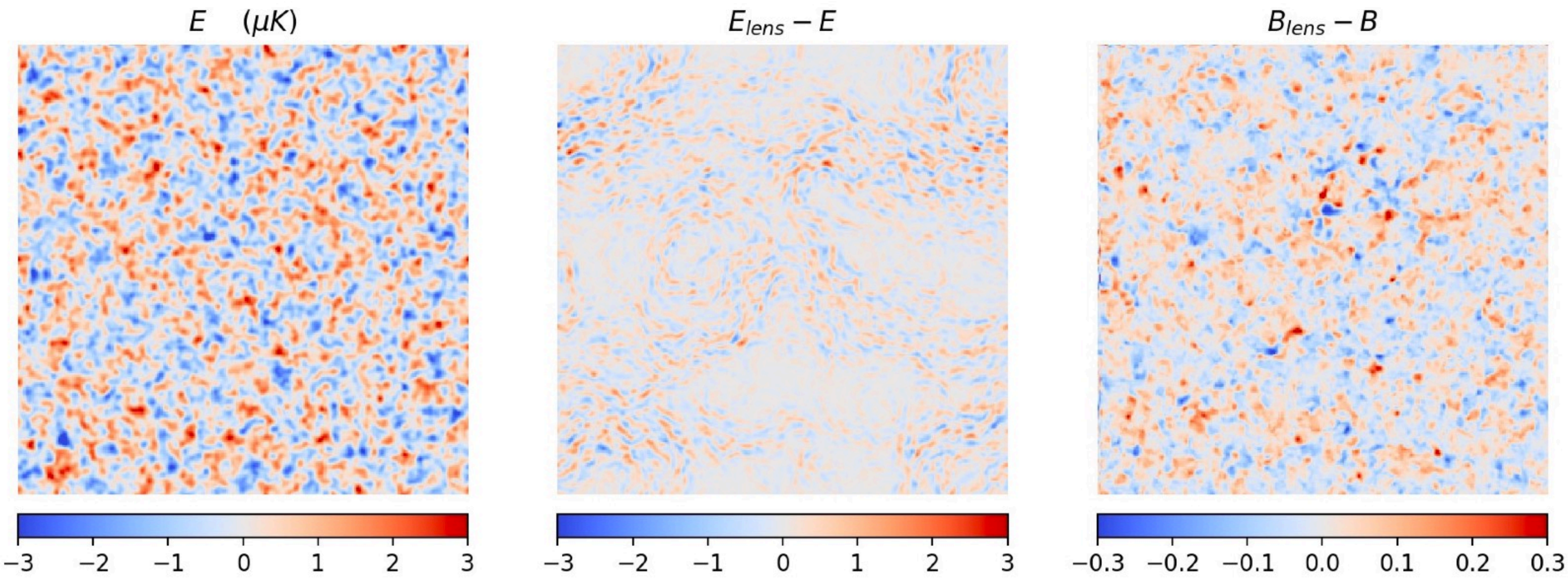
05 CMB modelling with foregrounds

Search for primordial B-modes



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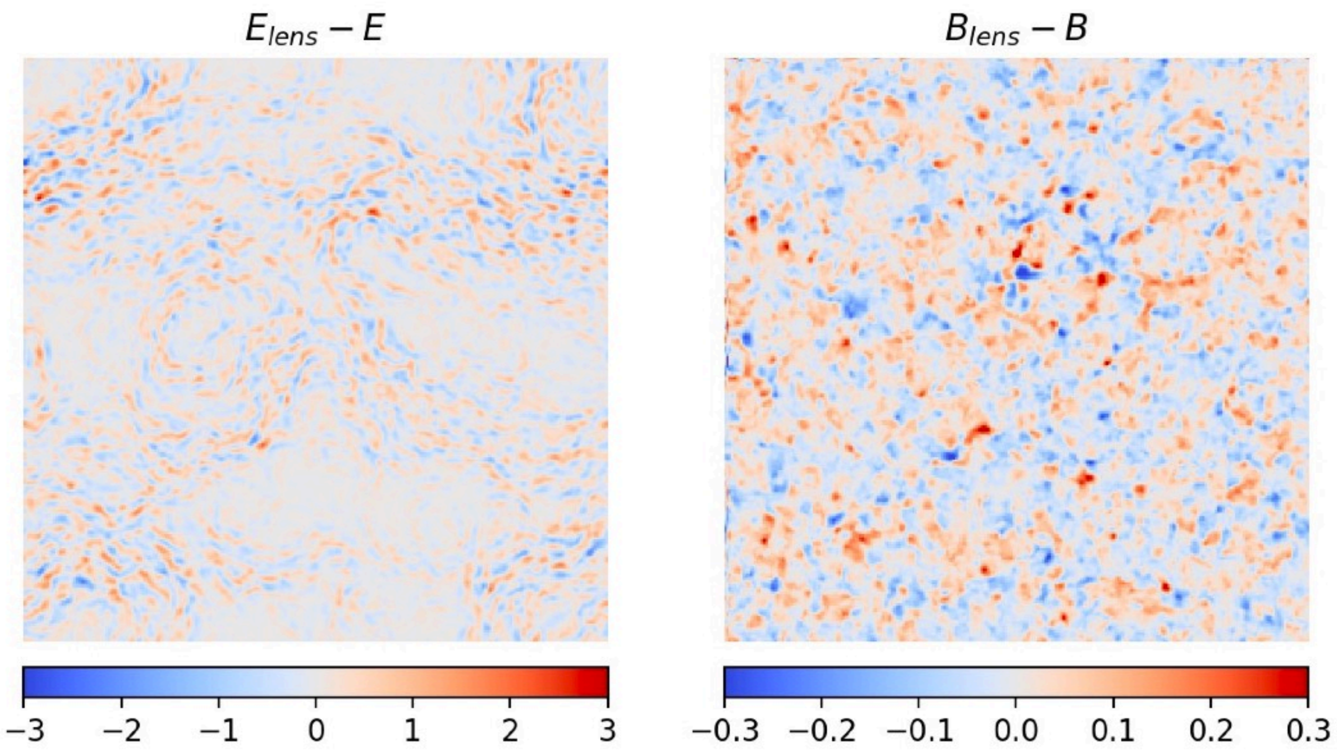

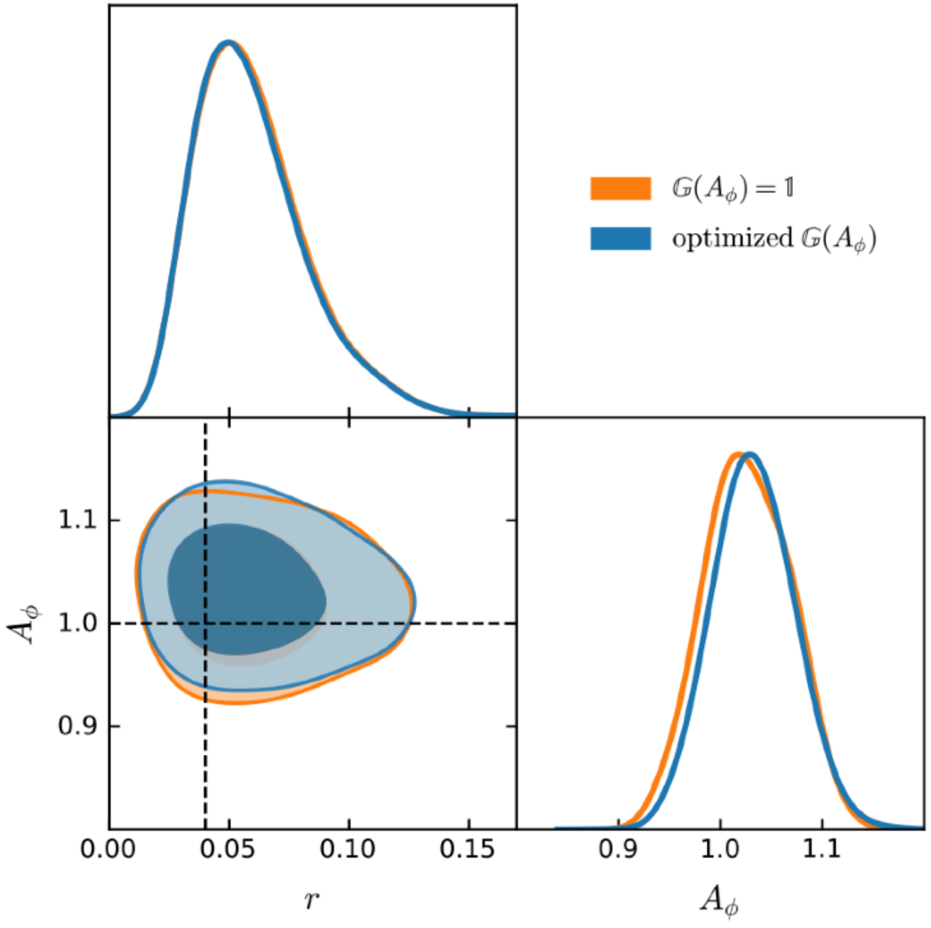

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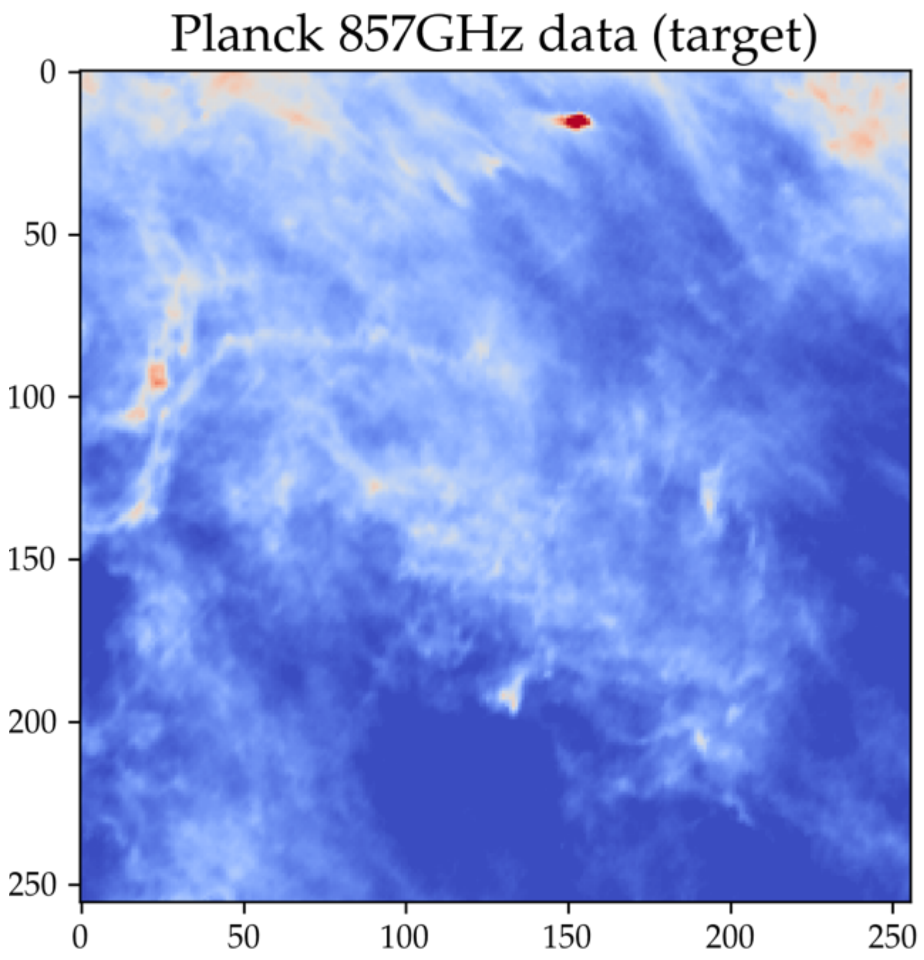
Search for primordial B-modes



Dust foreground T

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Generative models?

Generative models?

Generative models?

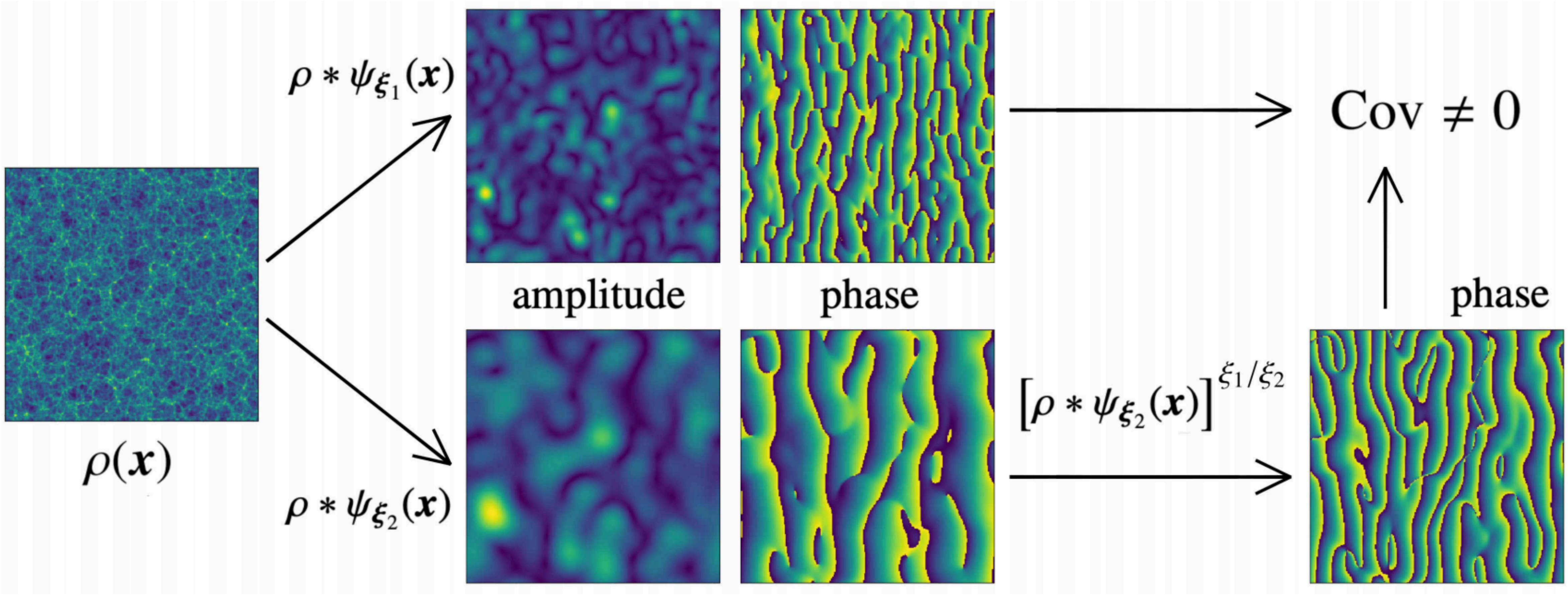
I. Generative adversarial network

II. Requires large training sets

III. Data and simulations not available for foregrounds

Wavelet Phase Harmonics $\phi(\mathbf{x})$

(adapted from Allys++ 2006.06298)



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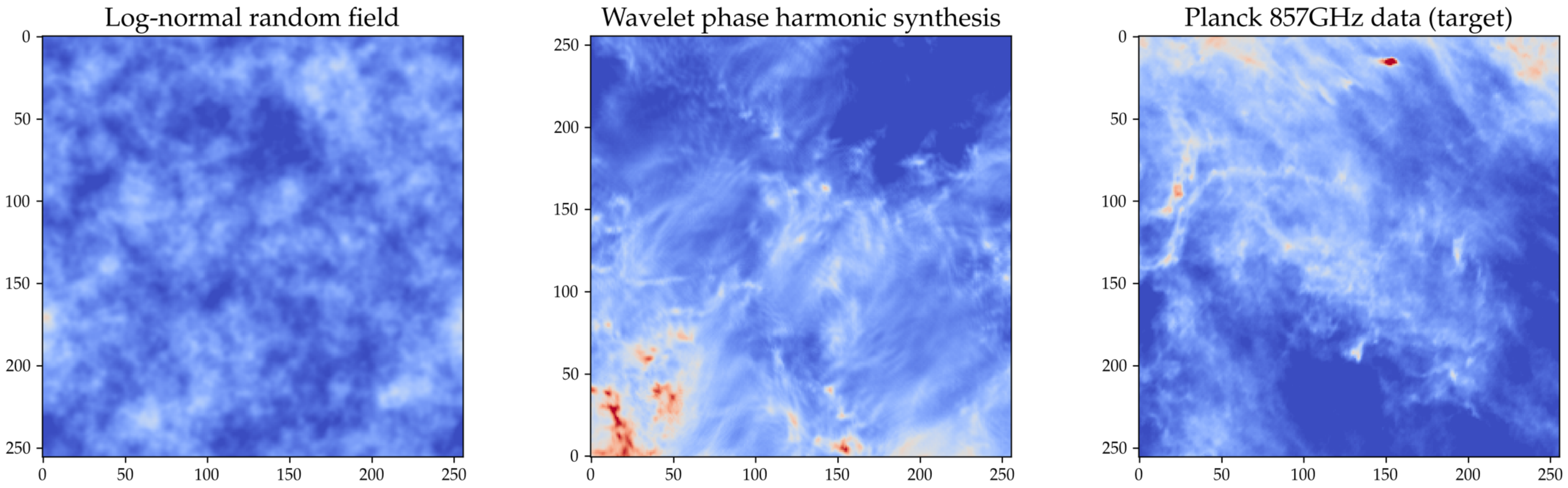
Generative model from single training example



Phase harmonic model for denoising
Polarized dust denoising 353 GHz Planck

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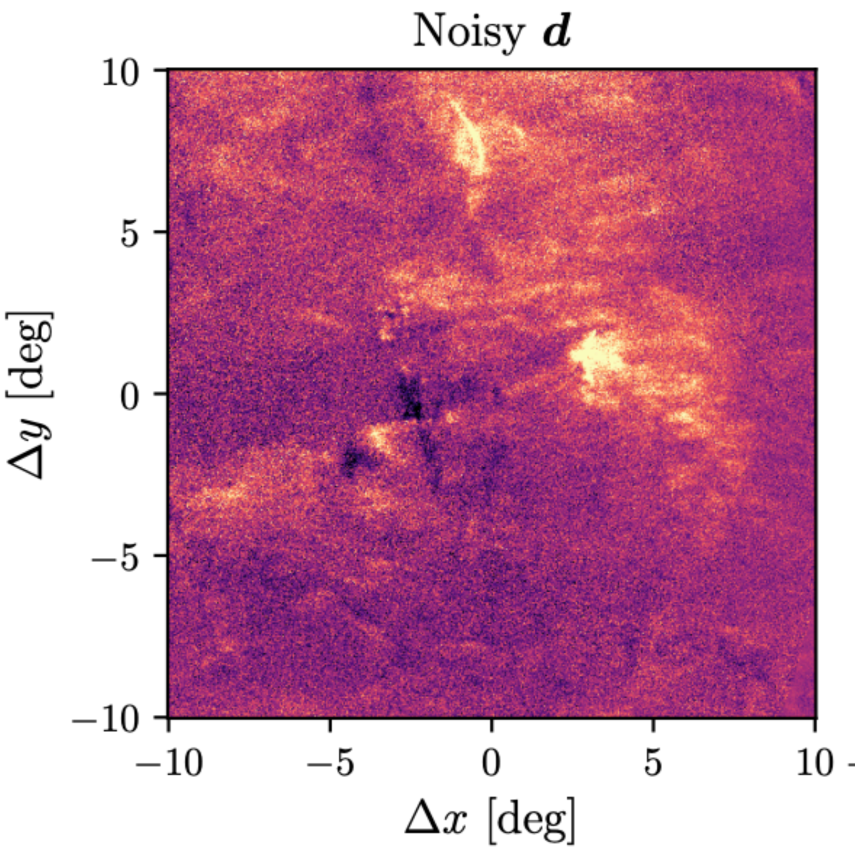

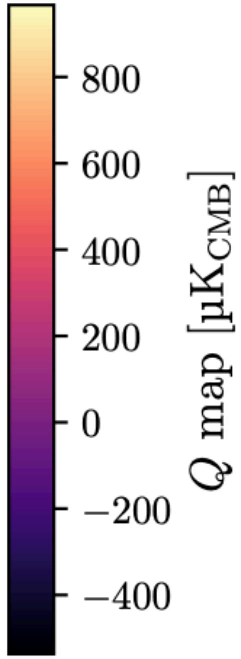

Regaldo-Saint Blancard++ (NJ) 2102.03160

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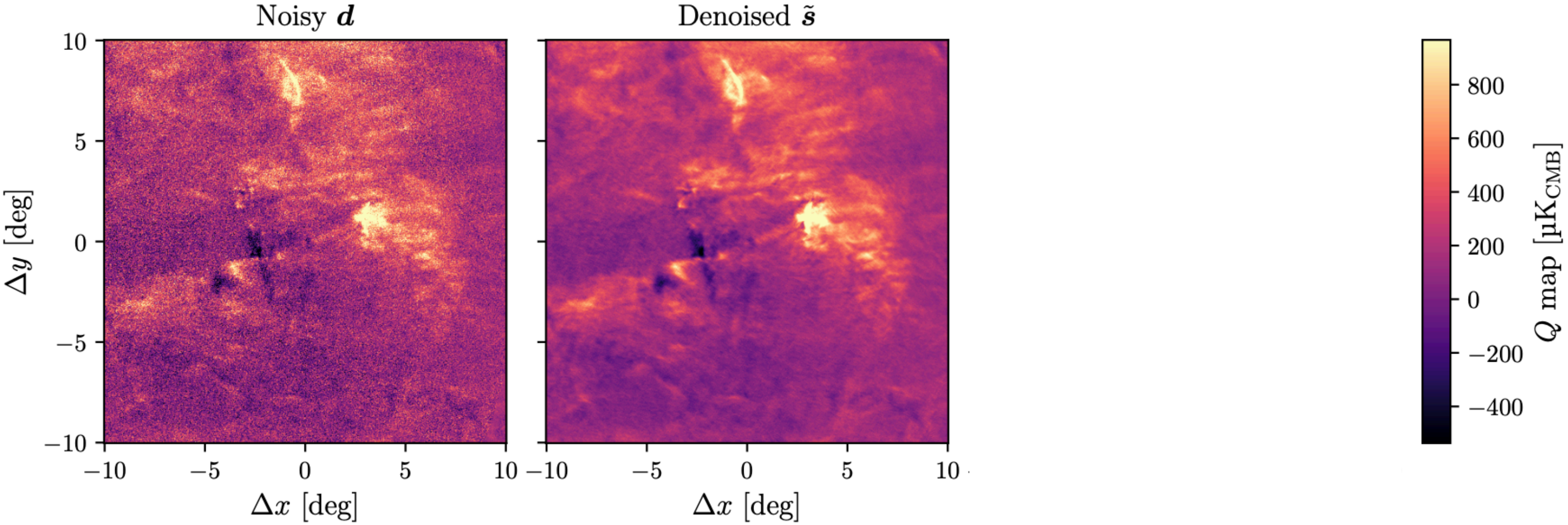
Phase harmonic model for denoising

Polarized dust denoising 353 GHz Planck



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Phase harmonic model for denoising

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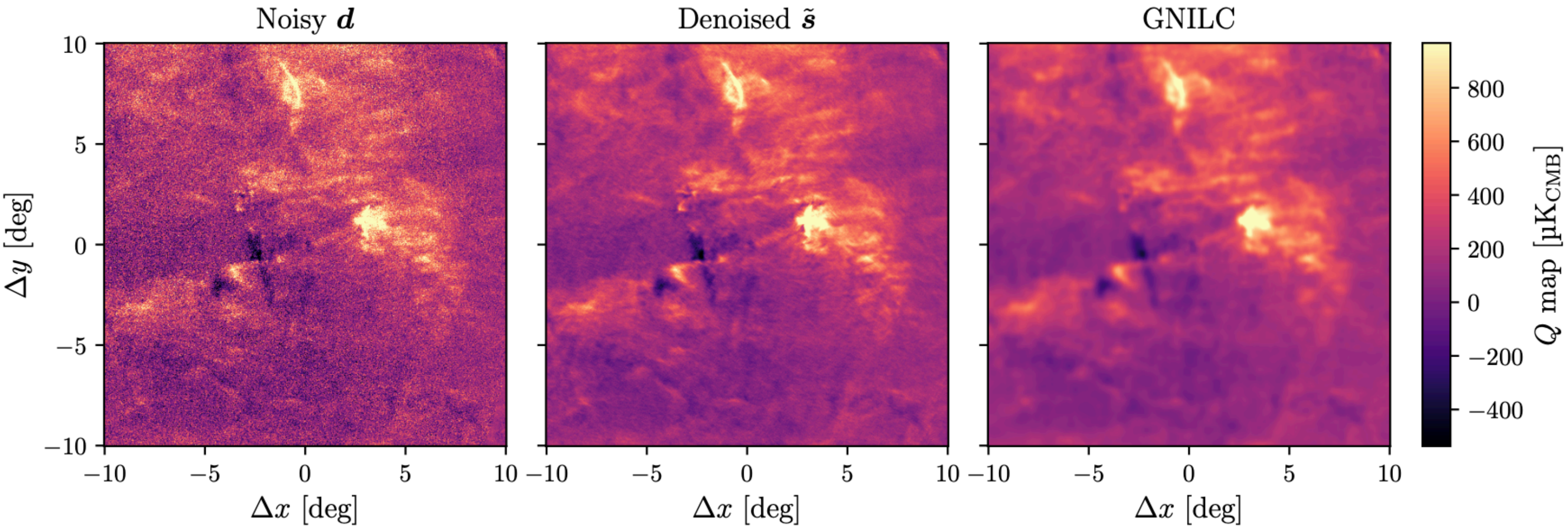

Regaldo-Saint Blancard++ (NJ) 2102.03160

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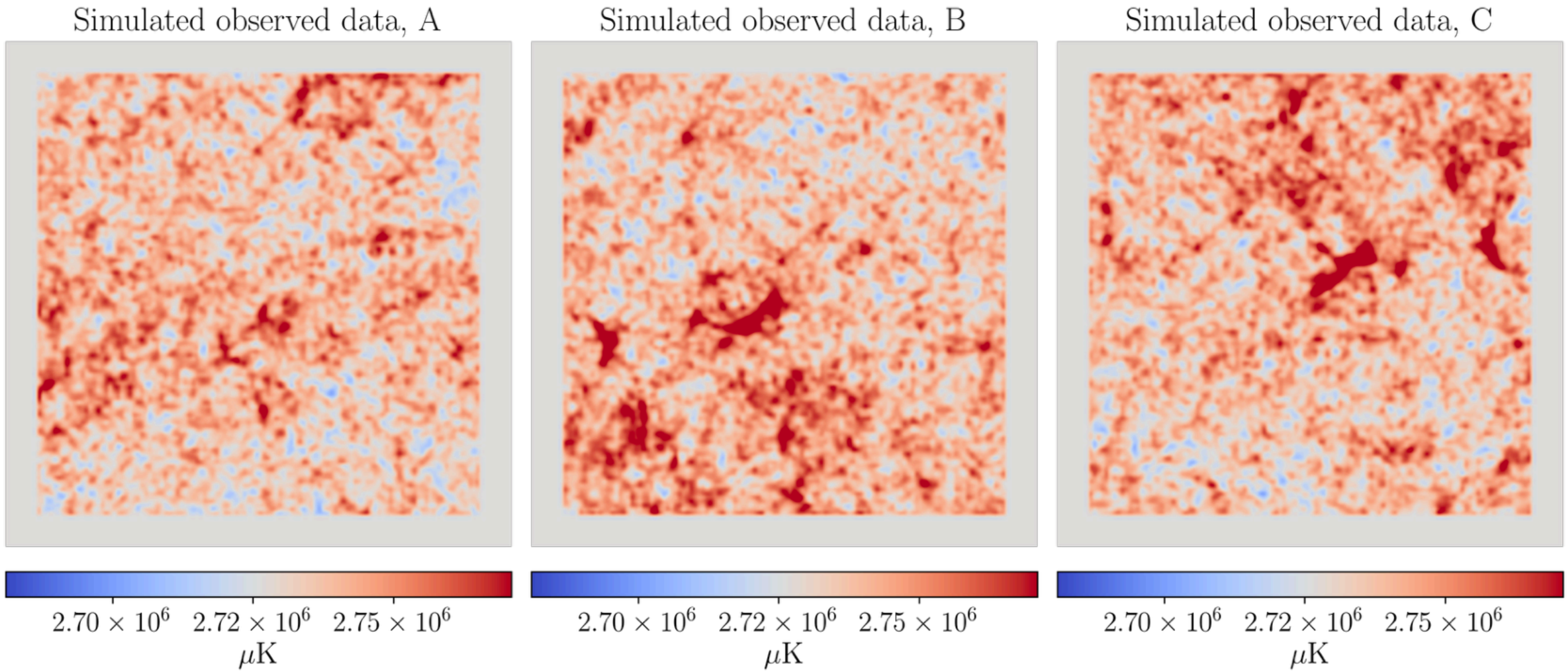
Map inference with Moment Network:
Foreground simulation



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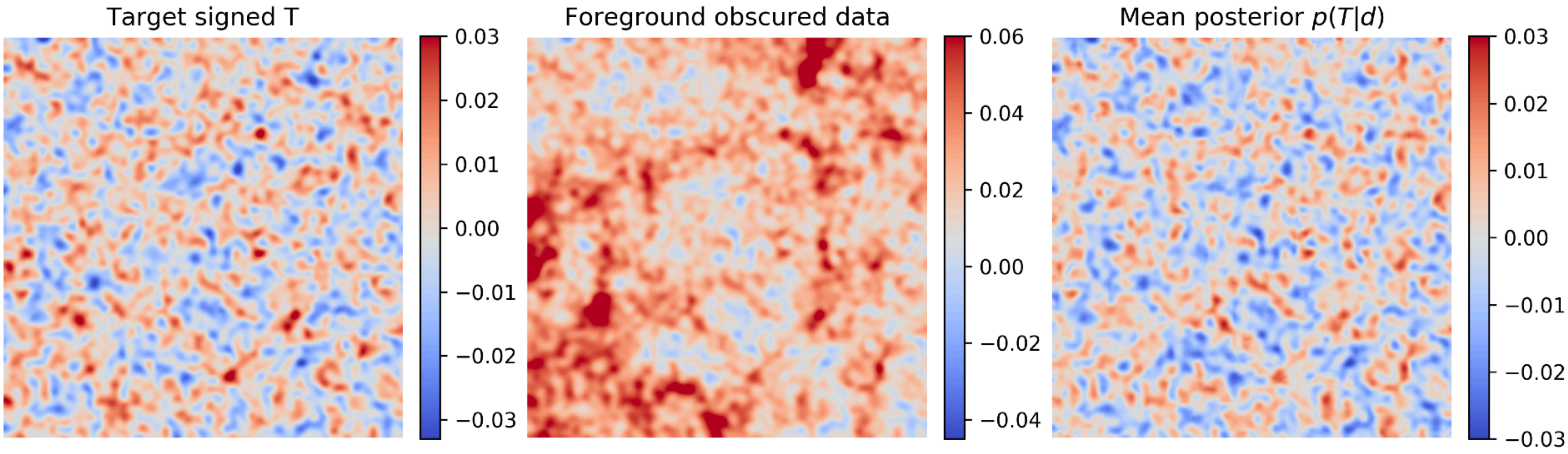
Map inference with Moment Networks:
Bayesian high-dimensional inference



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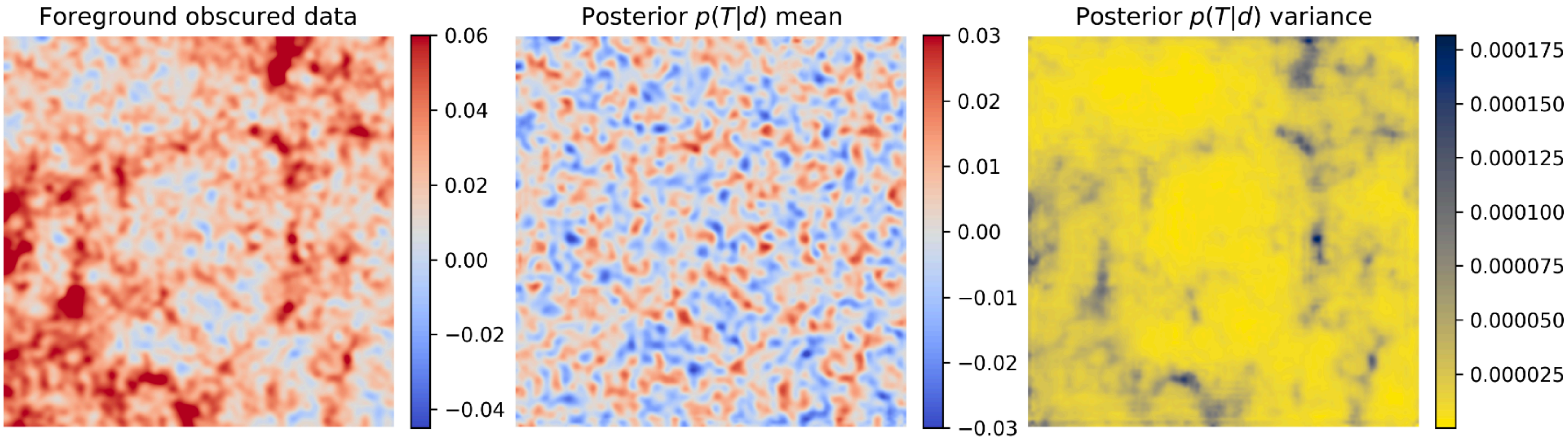

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