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DE L'ÉCOLE NORMALE SUPÉRIEURE

DES Year 3: Curved-sky weak lensing mass map reconstruction and applications

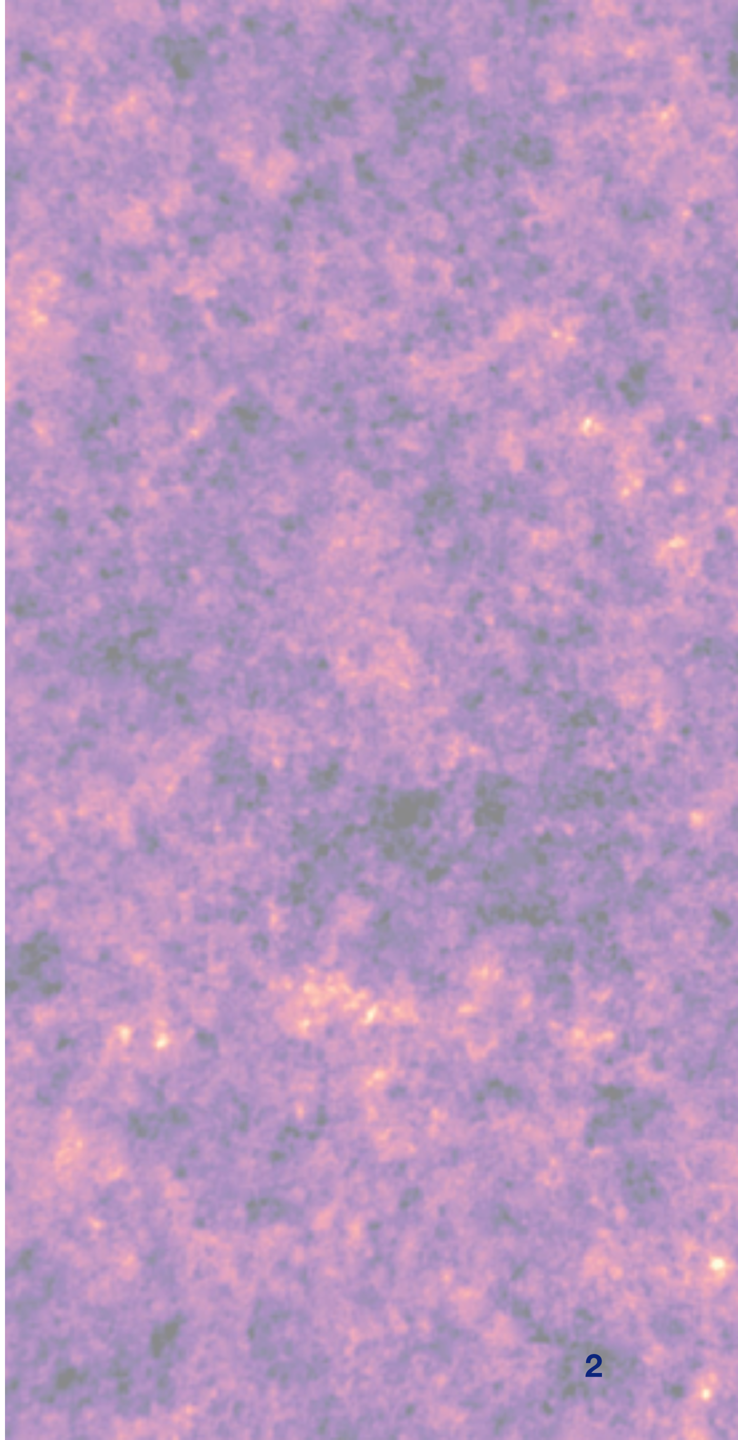
Niall Jeffrey

(DES Collaboration)

ENS | PSL UNIVERSITÉ PARIS · cnrs · SORBONNE UNIVERSITÉ · Université de Paris

Outline

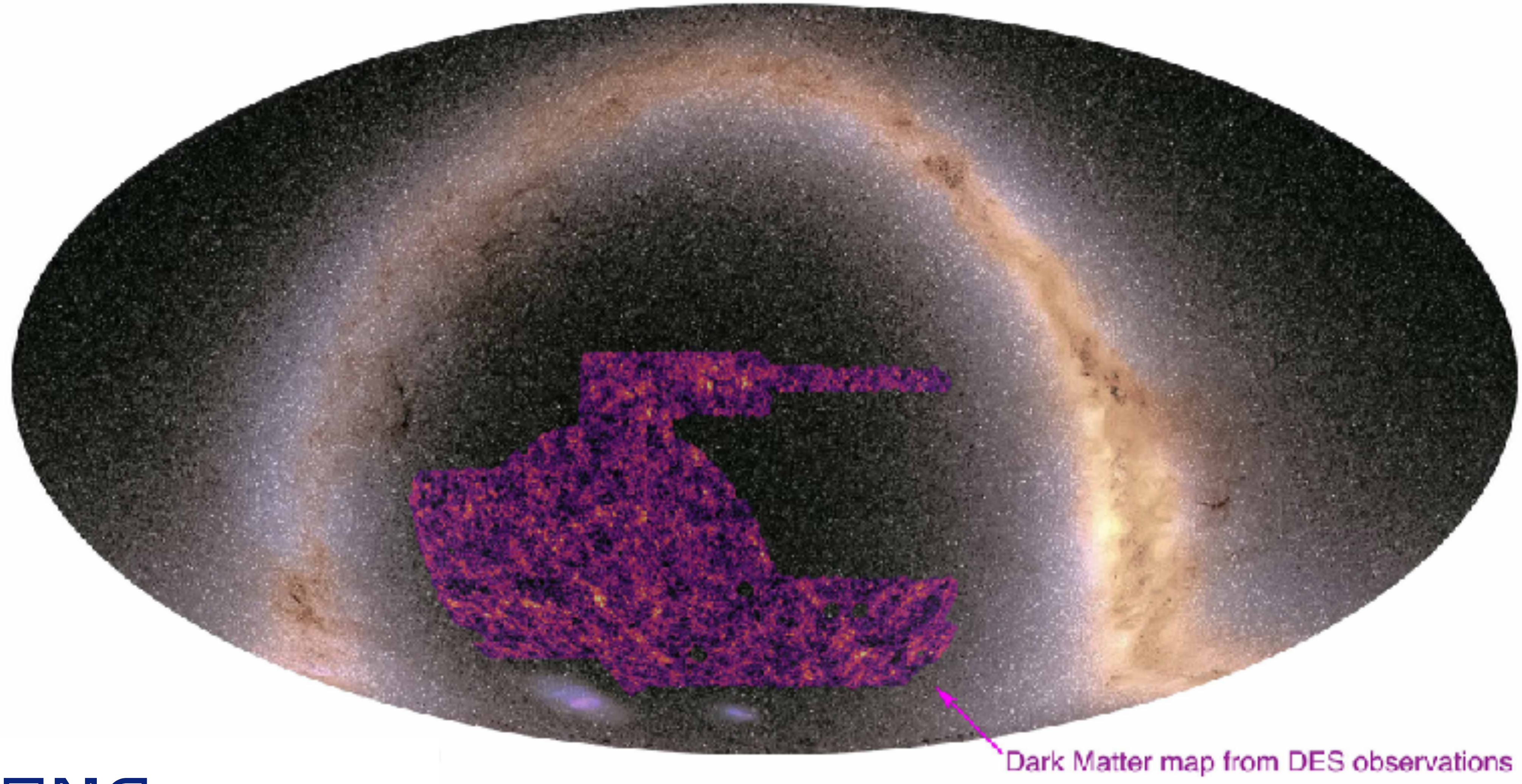
1. DES Year 3: weak lensing mass maps
2. Applications: Cosmic Web
3. Applications: Beyond 2-point
4. Future: Deep learned priors & likelihood-free inference



01

DES Year 3: weak lensing mass maps

Largest ever Dark Matter map from galaxy lensing



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Dark Energy Survey

Weak lensing data

I. Ground based 5-band photometric survey

II. Completed 6 years of observations

III. Over 100 million source galaxies in Y3

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Bayesian Mass Mapping

$$p(\kappa|\gamma, \mathcal{M}) = \frac{p(\gamma|\kappa, \mathcal{M})\ p(\kappa|\mathcal{M})}{p(\gamma|\mathcal{M})}$$

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Bayesian Mass Mapping

SHEAR DATA

$$p(\kappa|\gamma, \mathcal{M}) = \frac{p(\gamma|\kappa, \mathcal{M})\ p(\kappa|\mathcal{M})}{p(\gamma|\mathcal{M})}$$

UNKNOWN MAP

ASSUMPTIONS

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Bayesian Mass Mapping

Maximum posterior

$$\hat{\boldsymbol{\kappa}} = \arg\max_{\boldsymbol{\kappa}} \; \log p(\boldsymbol{\gamma}|\boldsymbol{\kappa}, \mathcal{M}) + \log p(\boldsymbol{\kappa}|\mathcal{M})$$

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Bayesian Mass Mapping

Prior choice?

$$\log p(\boldsymbol{\kappa}|\mathcal{M})$$

?

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Kaiser-Squires

$$p(\boldsymbol{\gamma}|\boldsymbol{\kappa}) = \frac{1}{\sqrt{(\det 2\pi \mathbf{N})}} \exp\left[-\frac{1}{2}(\boldsymbol{\gamma} - \mathbf{A}\boldsymbol{\kappa})^{\dagger}\, \mathbf{N}^{-1}(\boldsymbol{\gamma} - \mathbf{A}\boldsymbol{\kappa})\right]$$

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Kaiser-Squires

$$p(\boldsymbol{\kappa}) \propto 1$$

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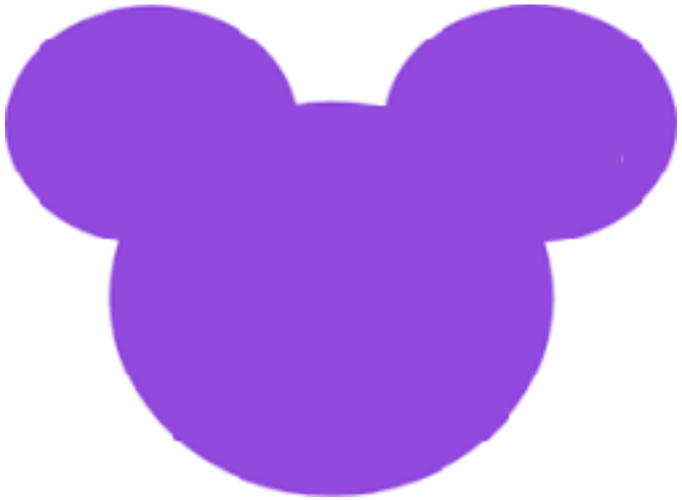

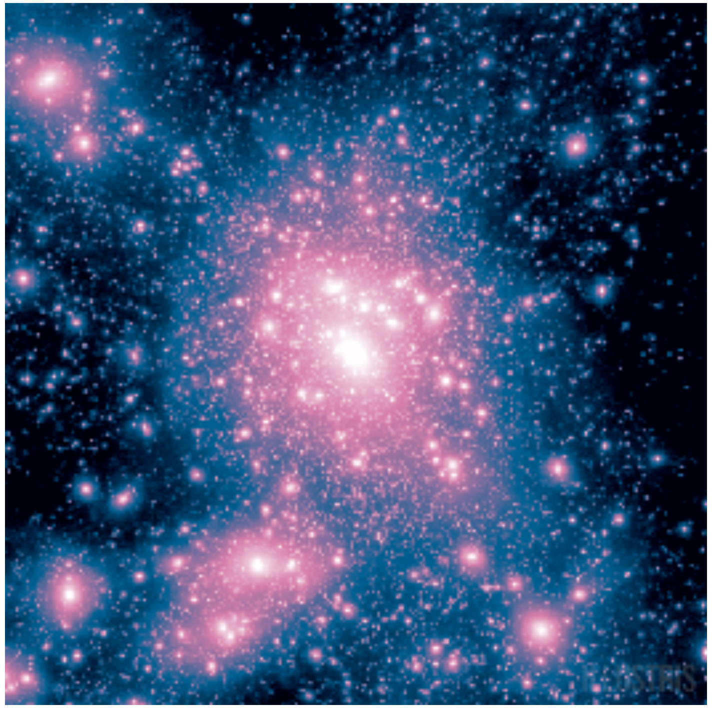

Null B-mode

Give zero probability to maps with imaginary values

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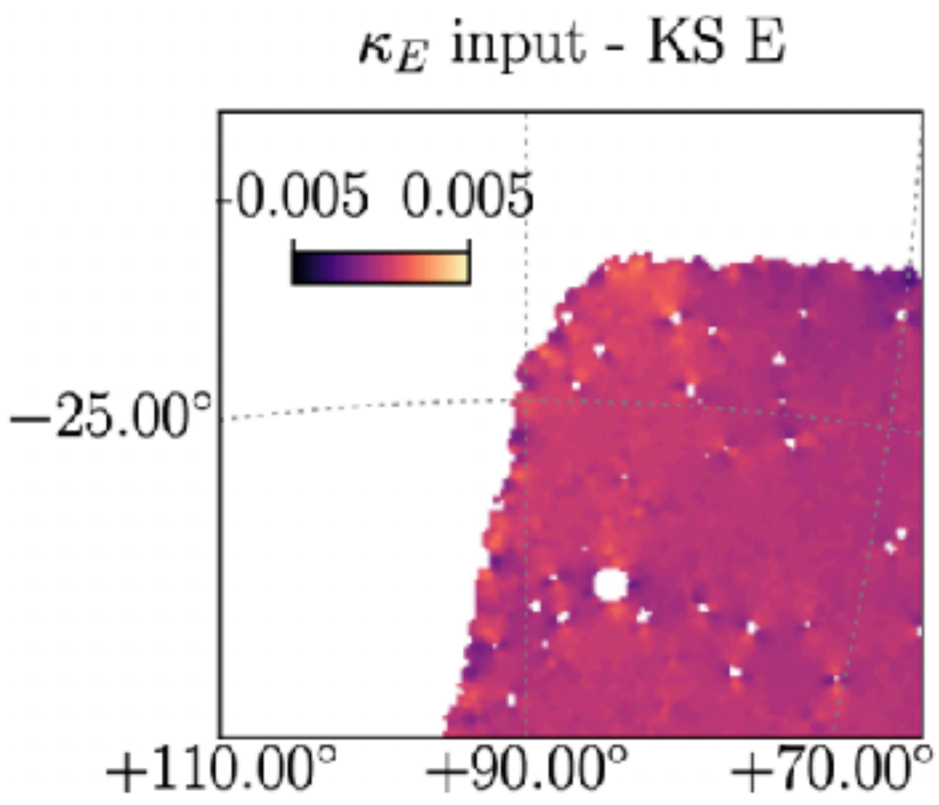
Give zero probability to maps with imaginary values

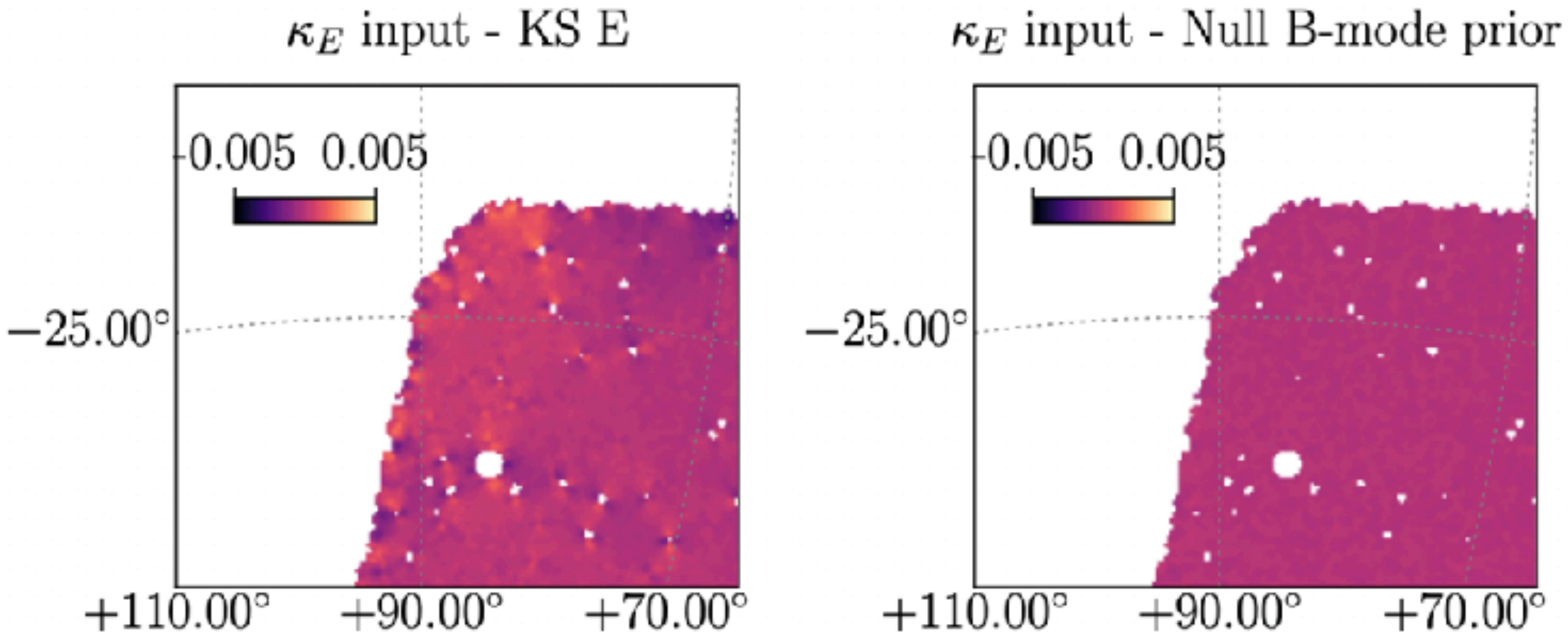
$$-\log p(\boldsymbol{\kappa}) = i_{\mathrm{Im}(\boldsymbol{\kappa})=0} \ + \ \mathrm{c}$$

Null B-mode



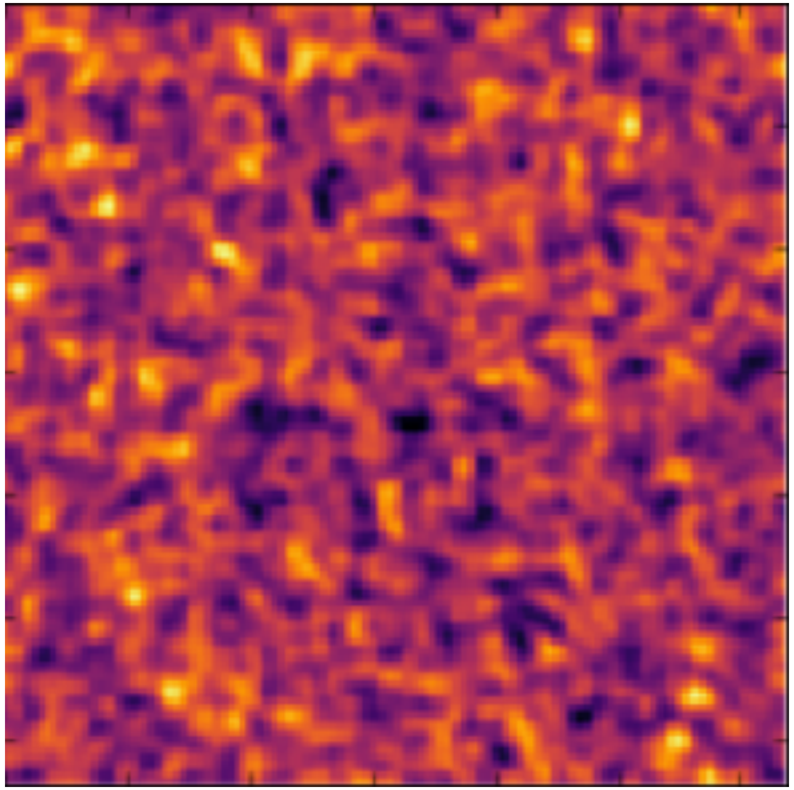
Give zero probability to maps with imaginary values

Null B-mode



Give zero probability to maps with imaginary values

Gaussian & Sparsity priors



Wiener filter/posterior

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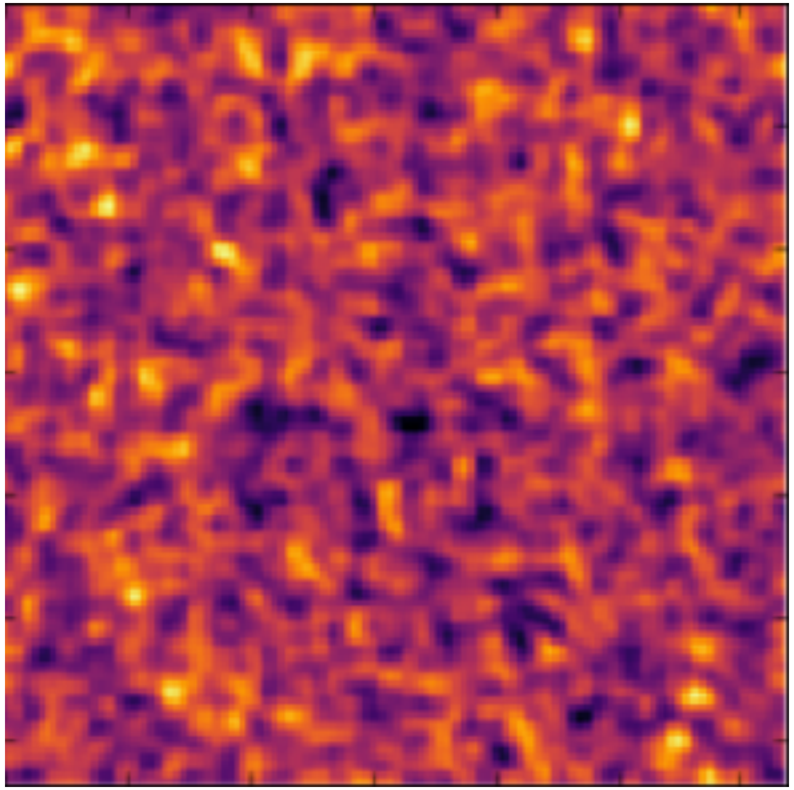
Gaussian & Sparsity priors



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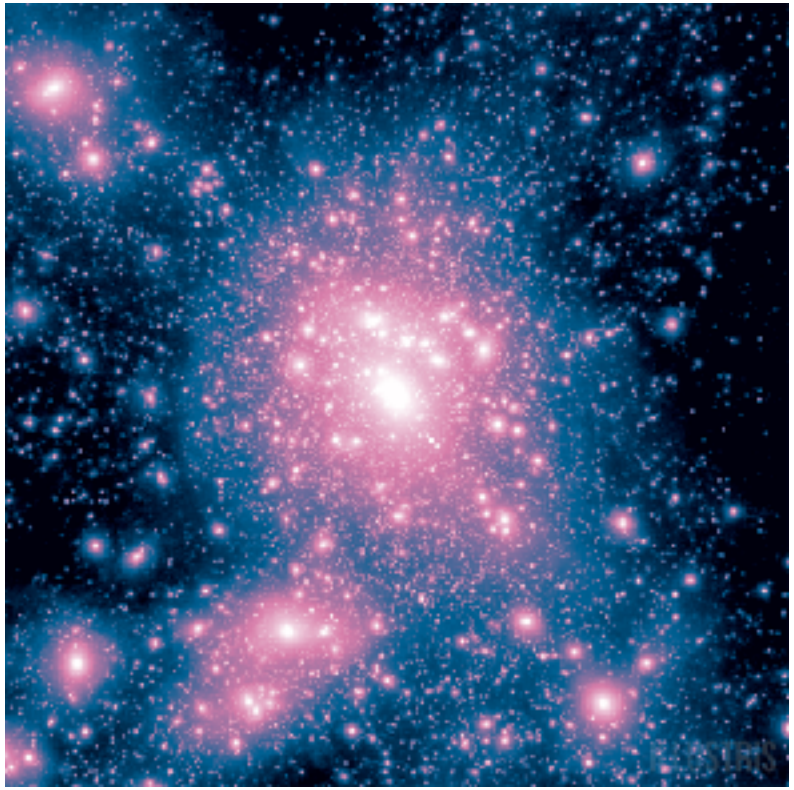

Halo-model wavelet prior

GLIMPSE

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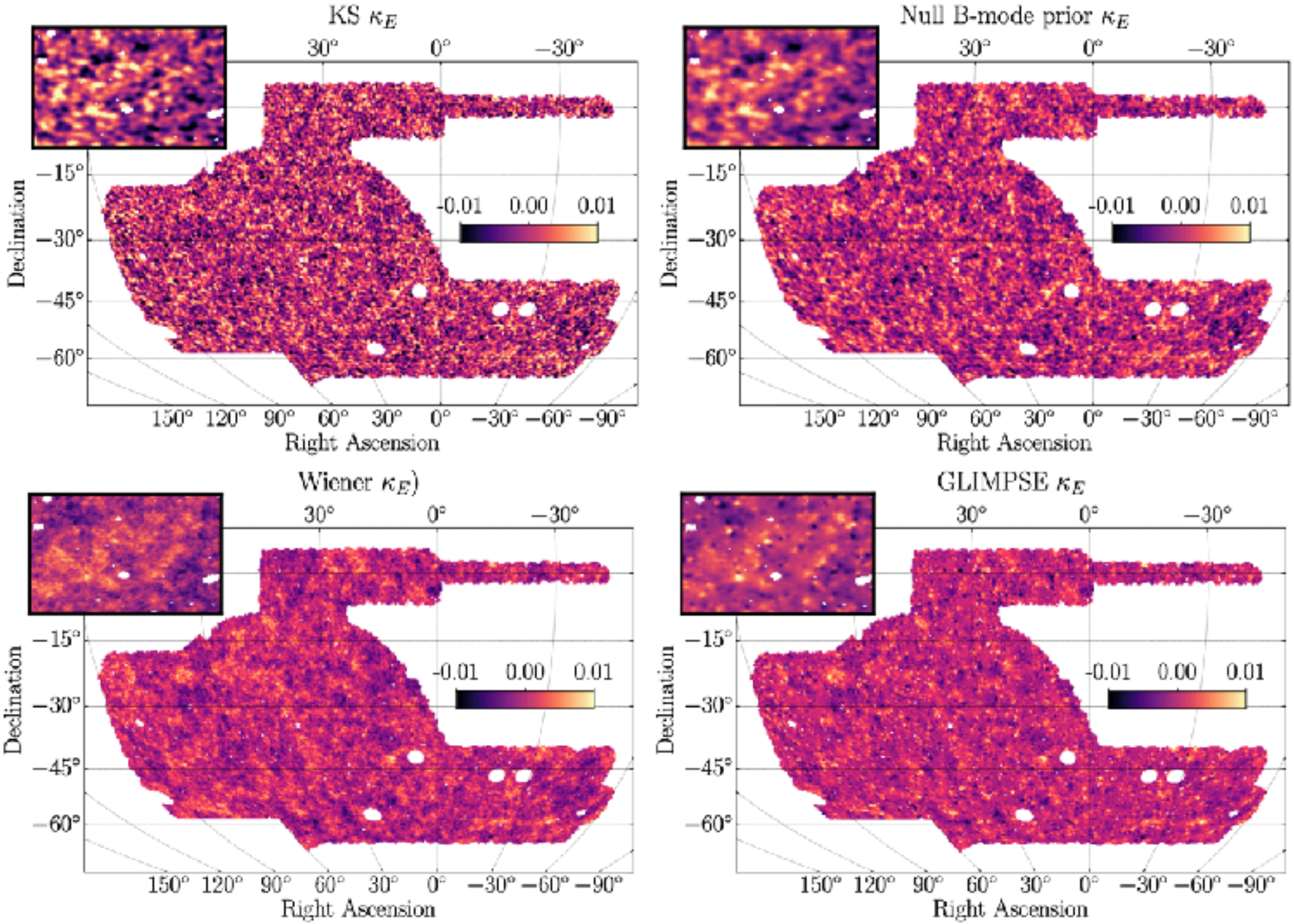
Results

Results



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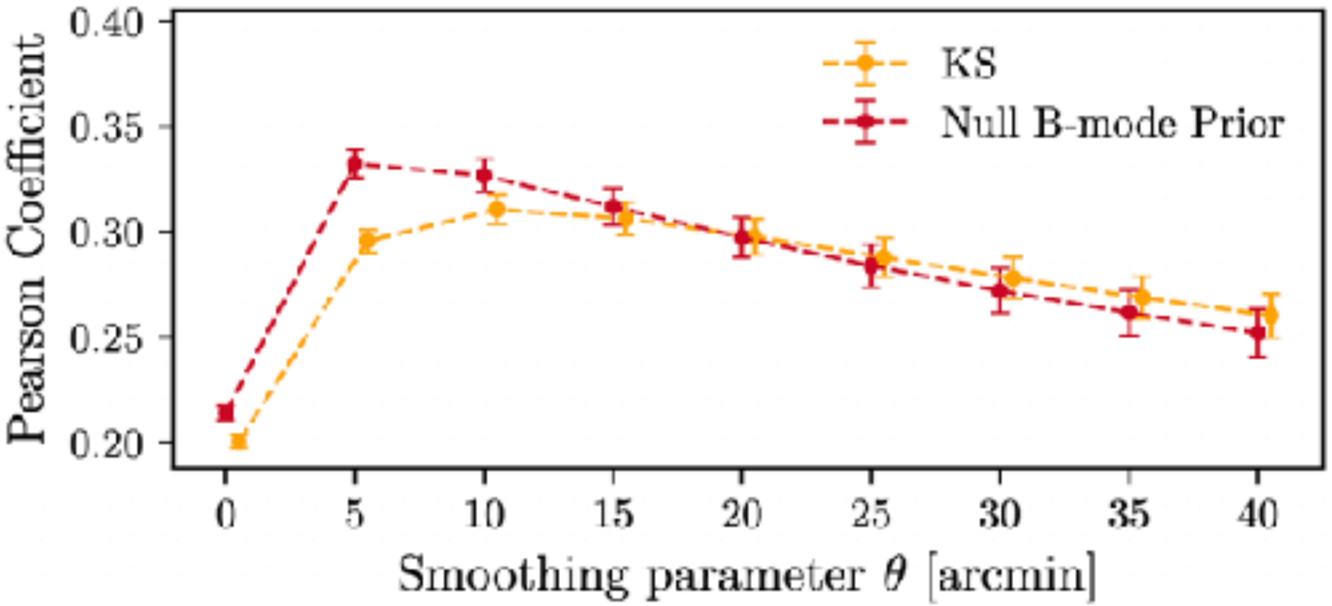
Validation on simulations

Validation on simulations



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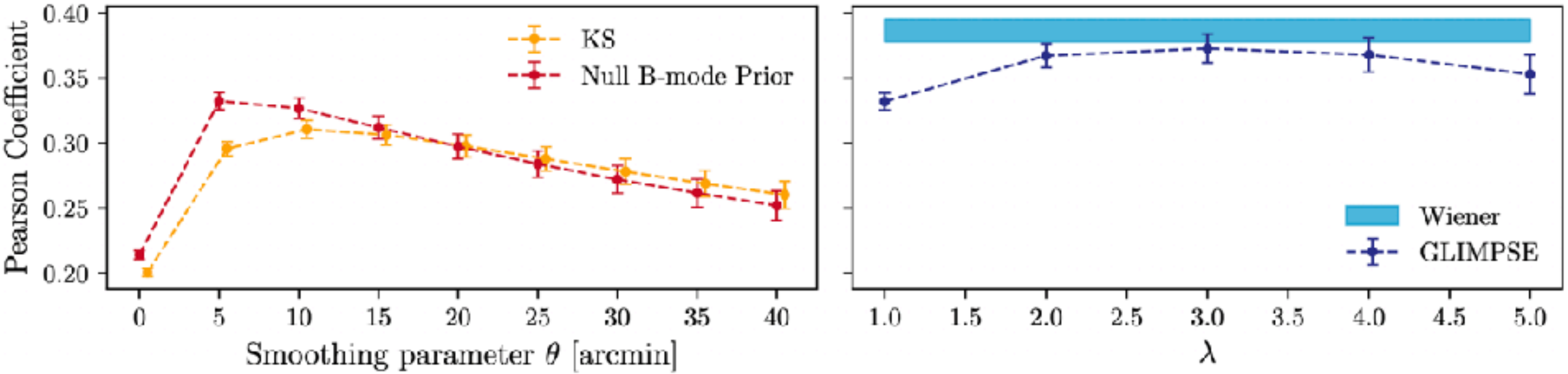
Validation on simulations



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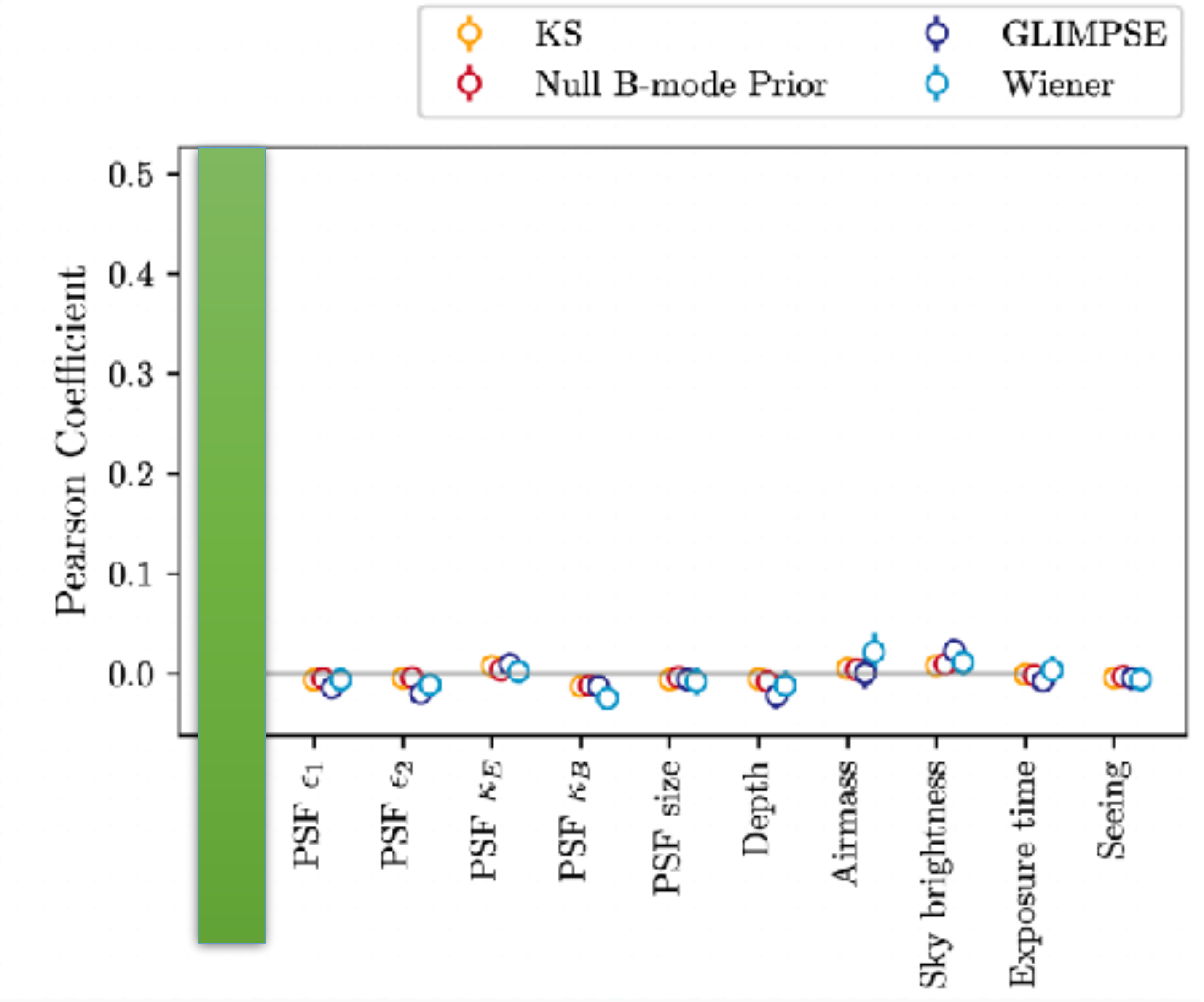
02

Applications: Cosmic web

Foreground correlations



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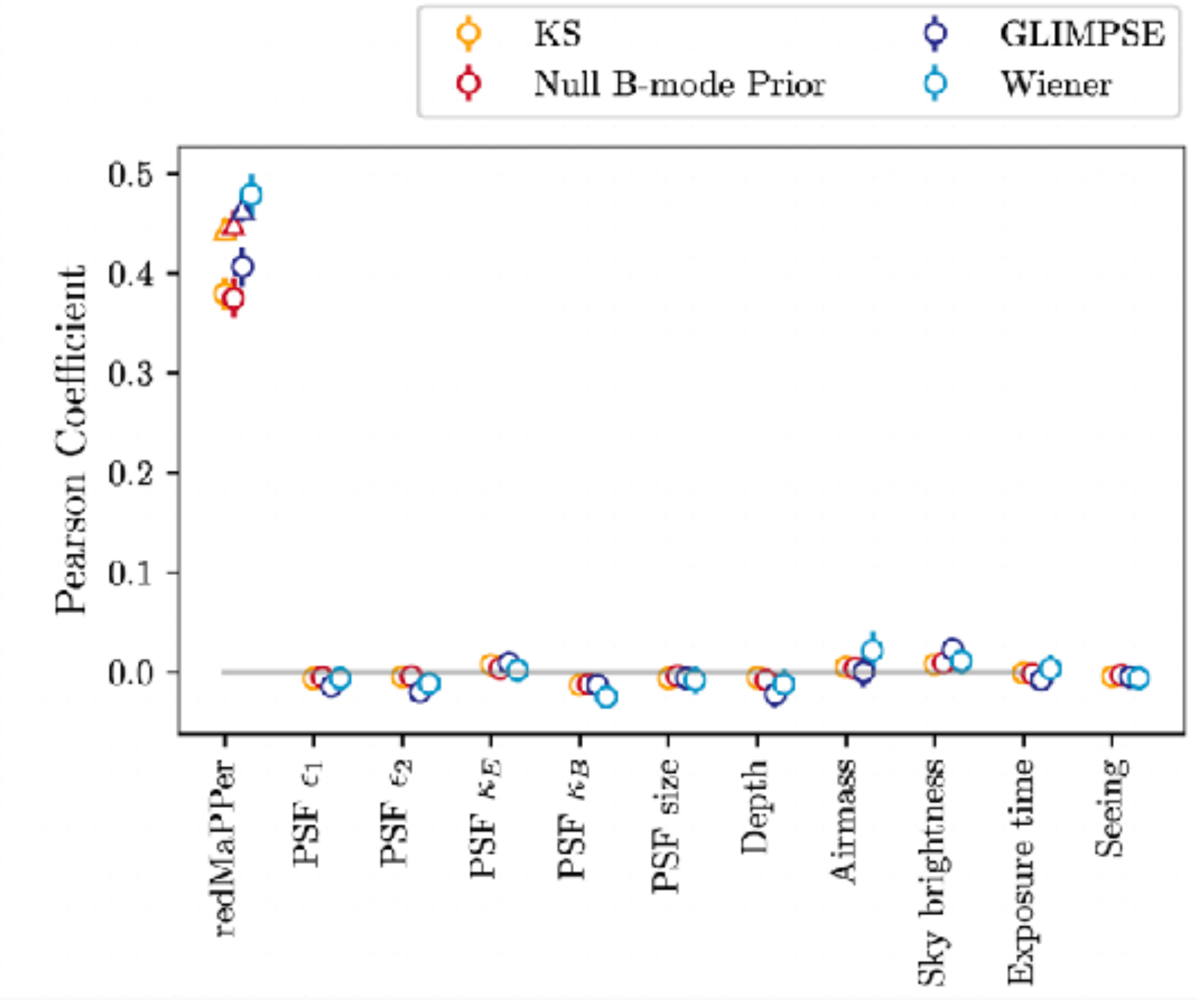
Foreground correlations



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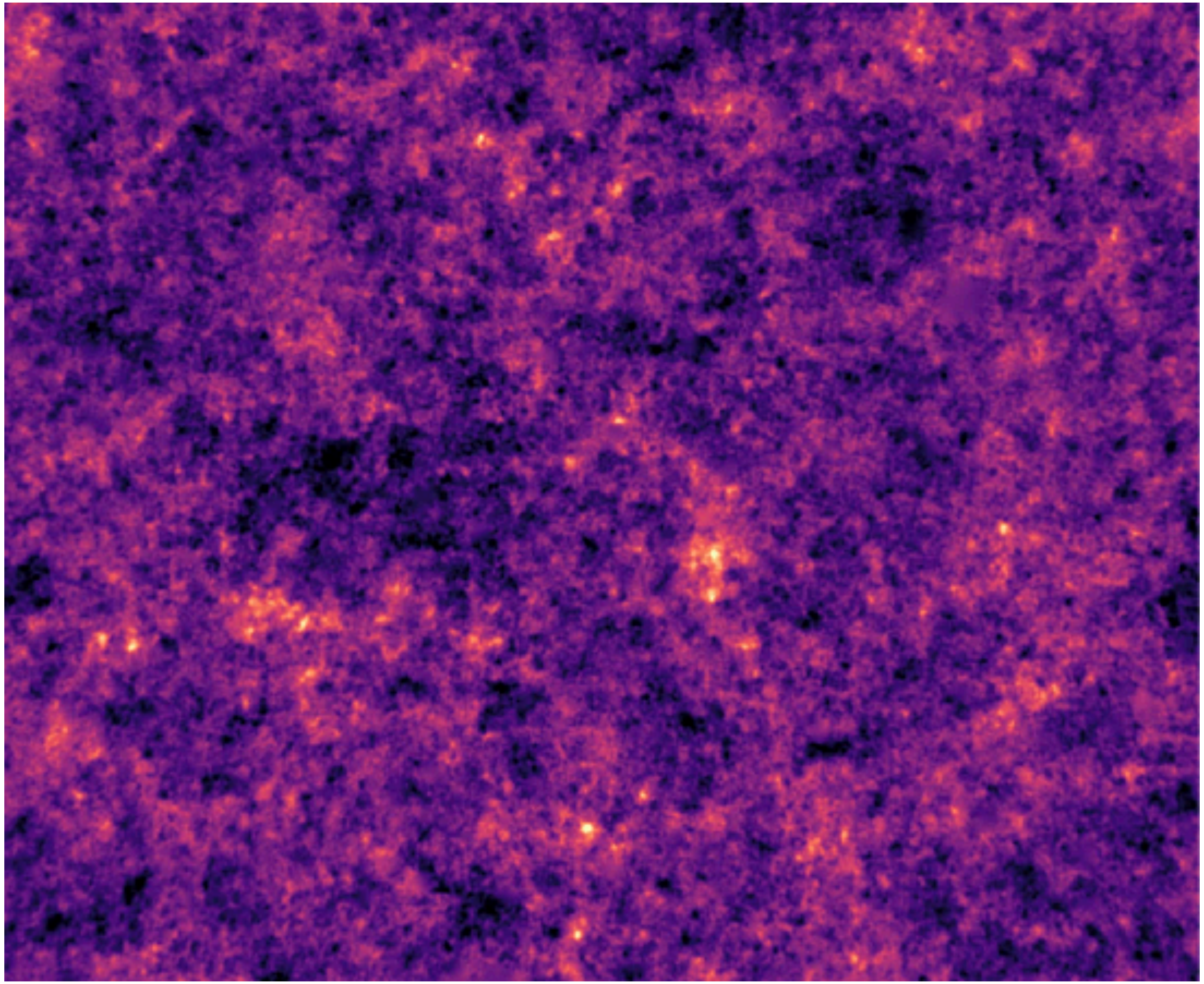
Cosmic Voids



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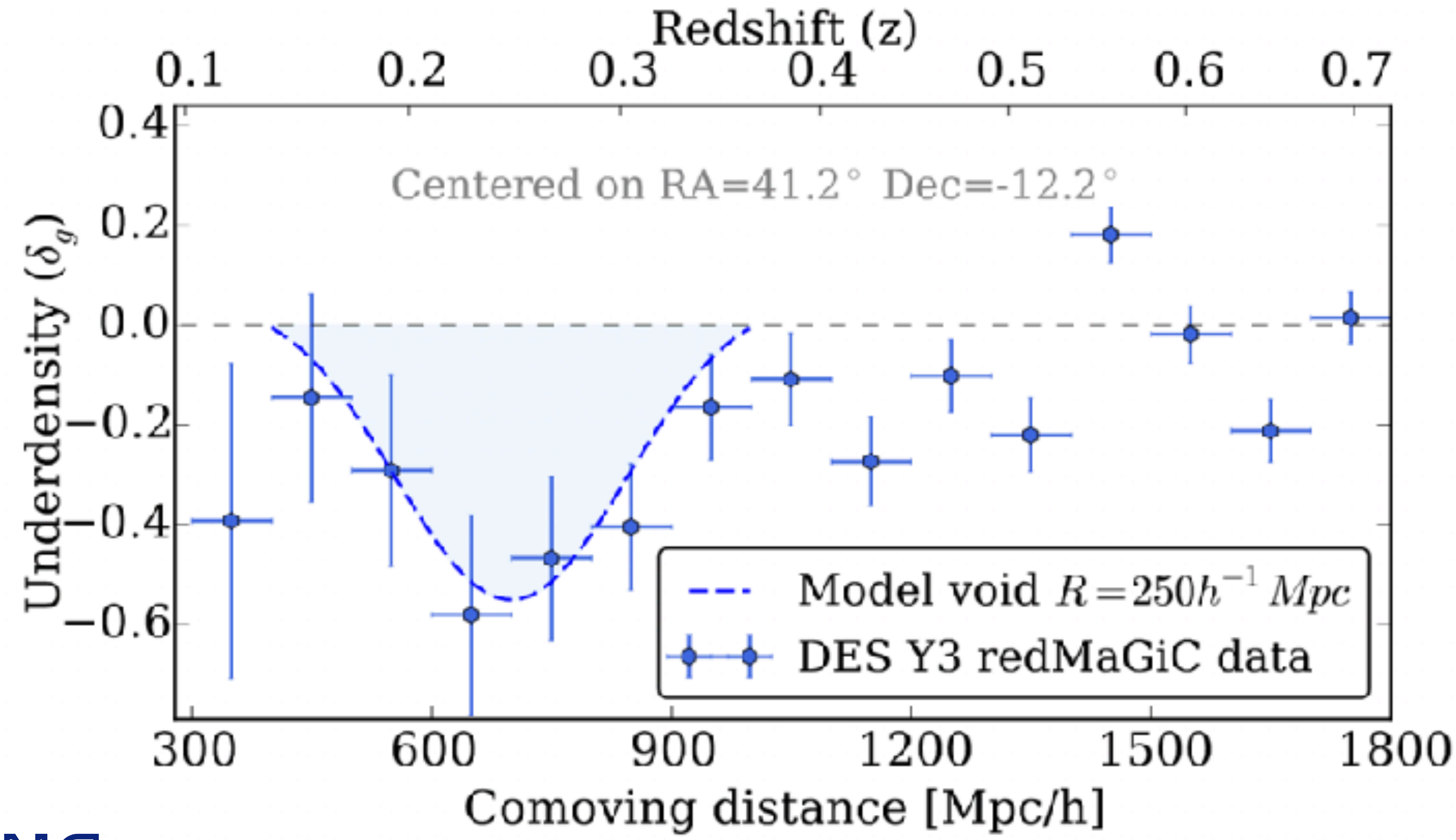
“Vole” line-of-sight



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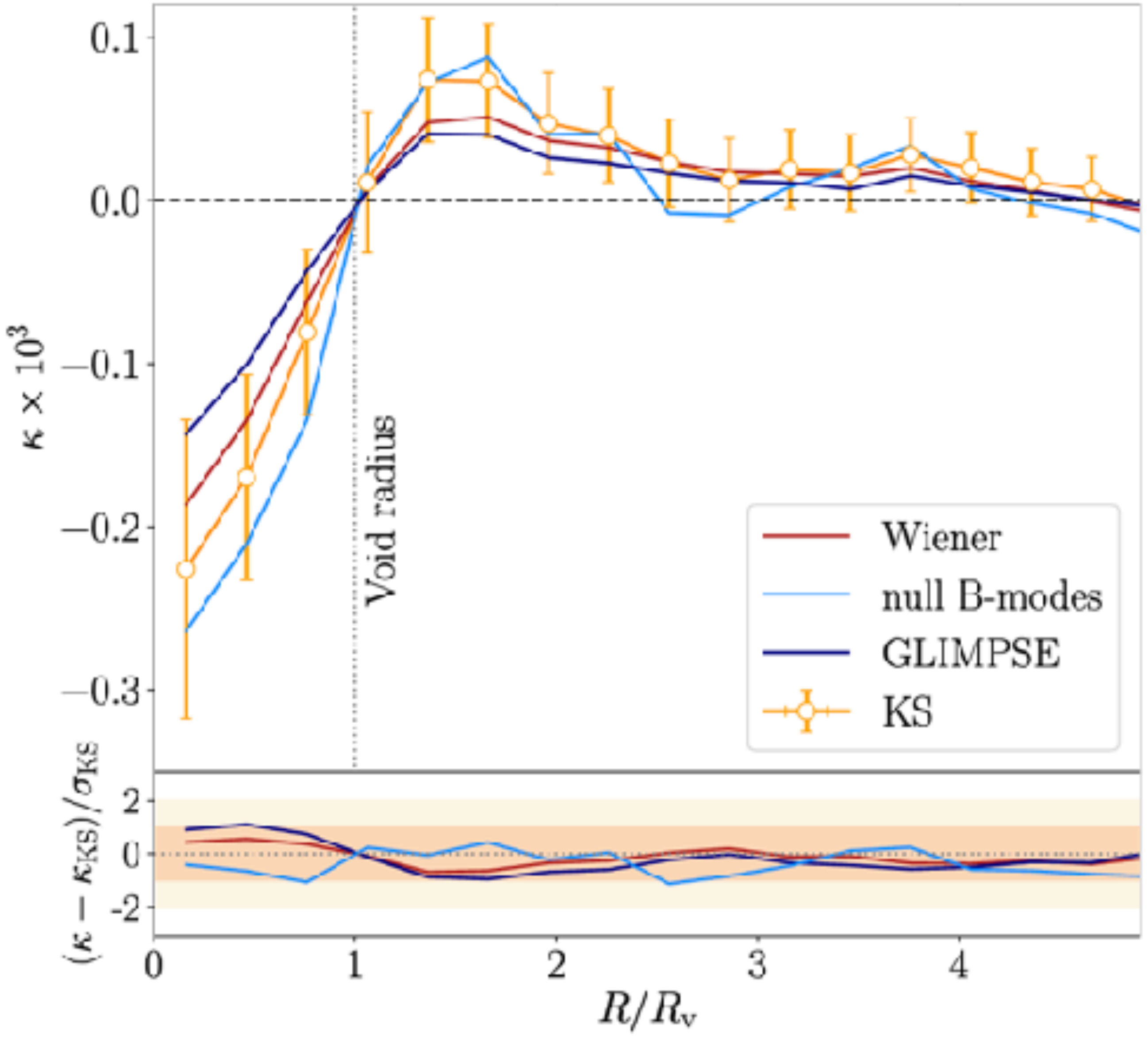
Cosmic Void profiles



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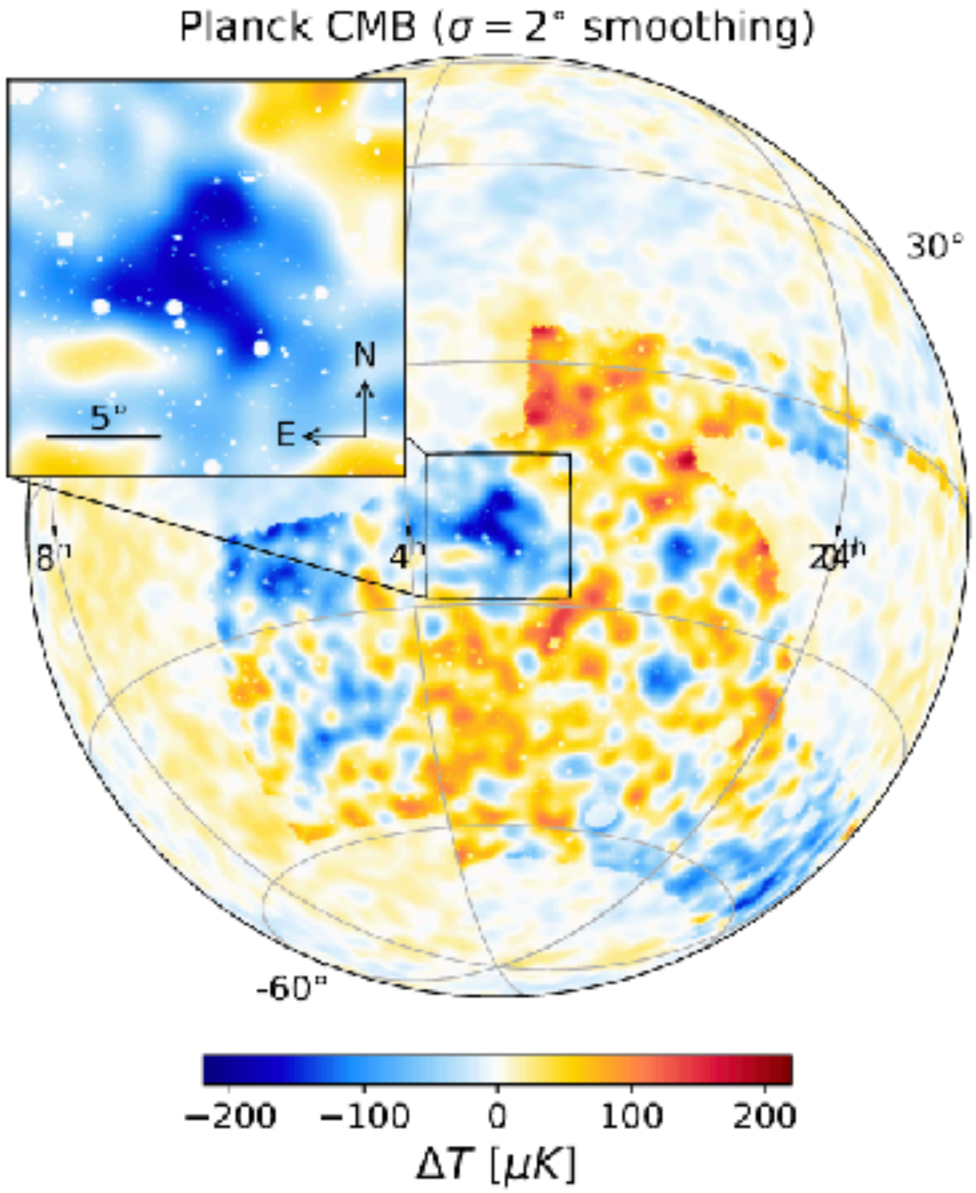
CMB Cold Spot

(A. Kovacs in prep.)



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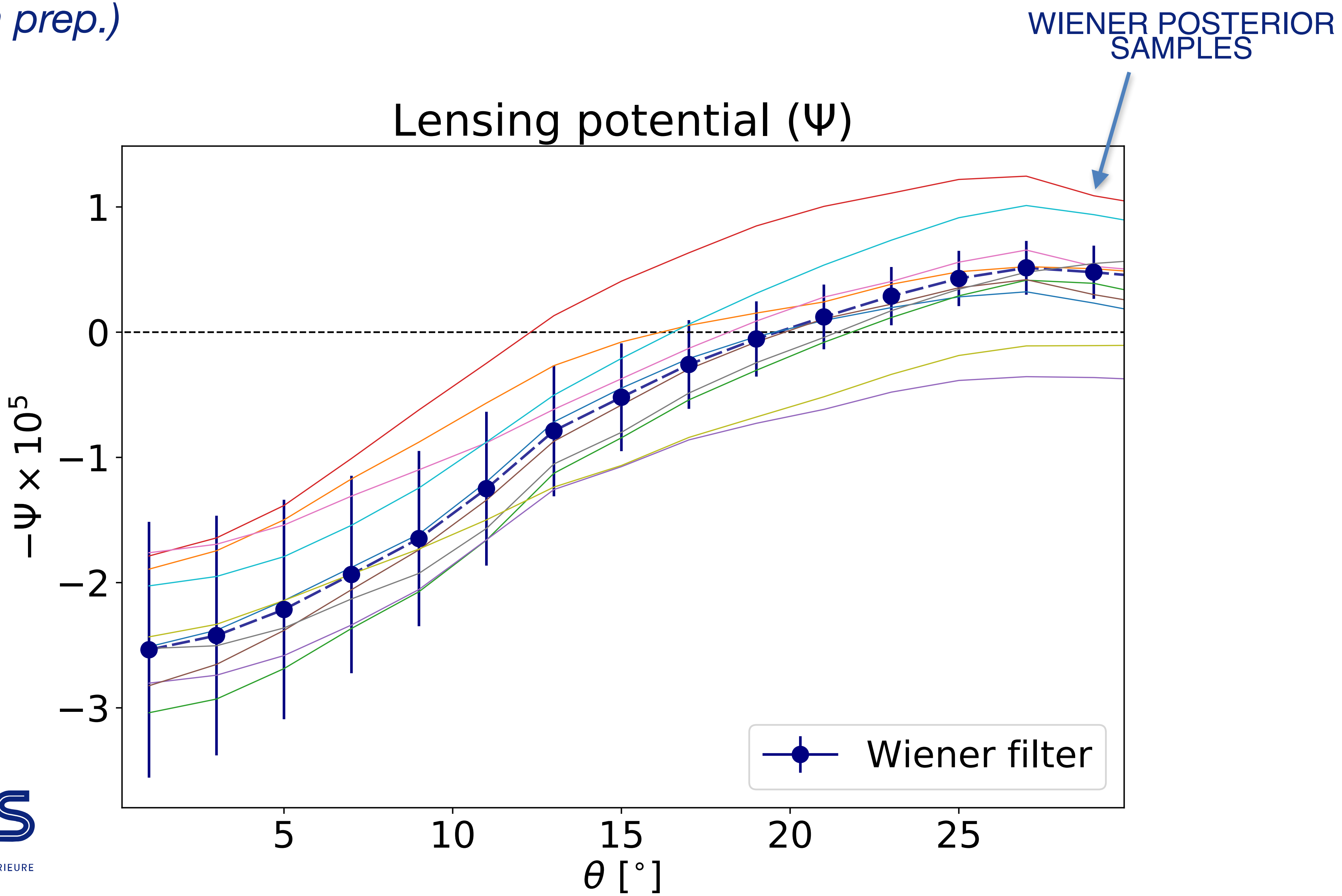

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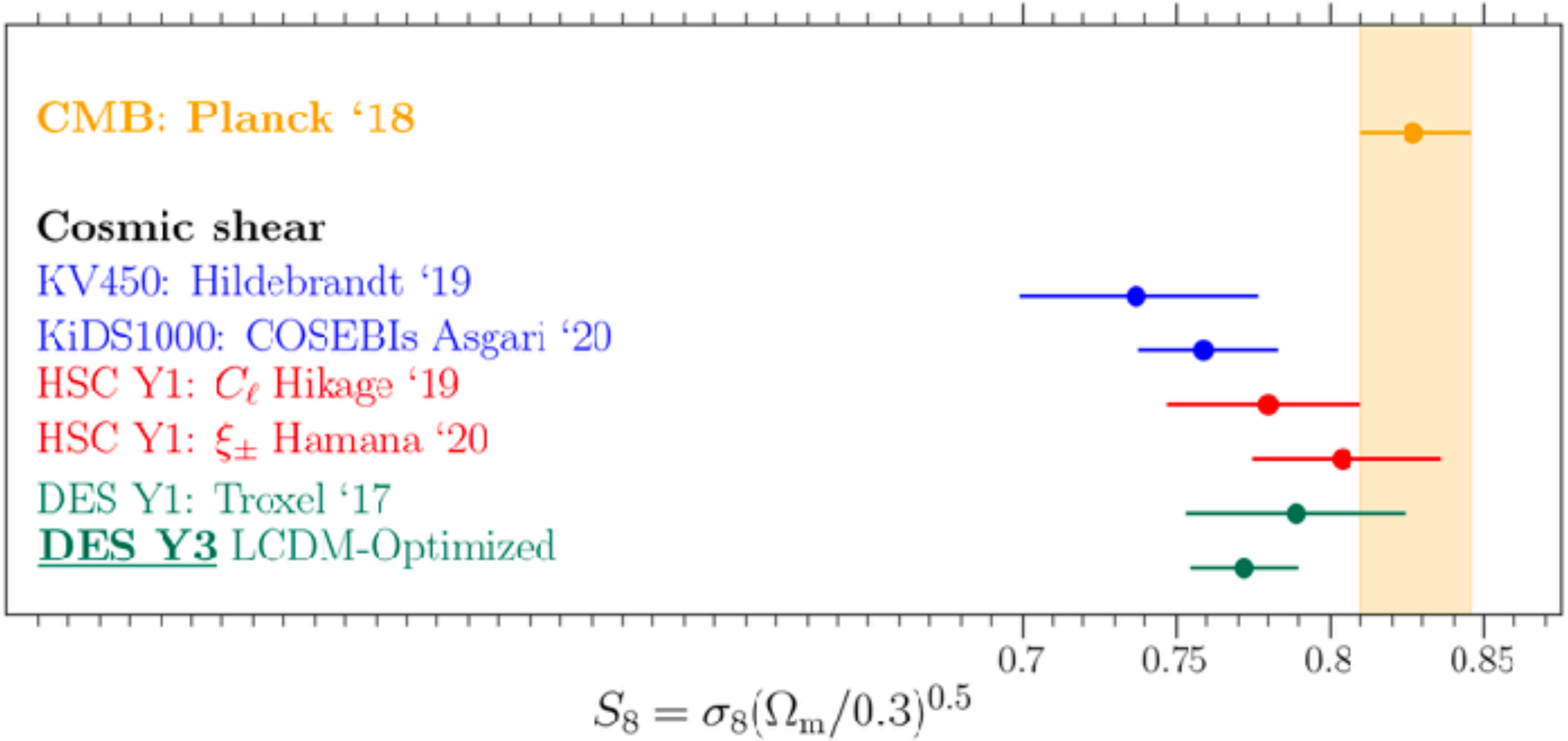
Applications: Beyond 2-point

Lensing is low?



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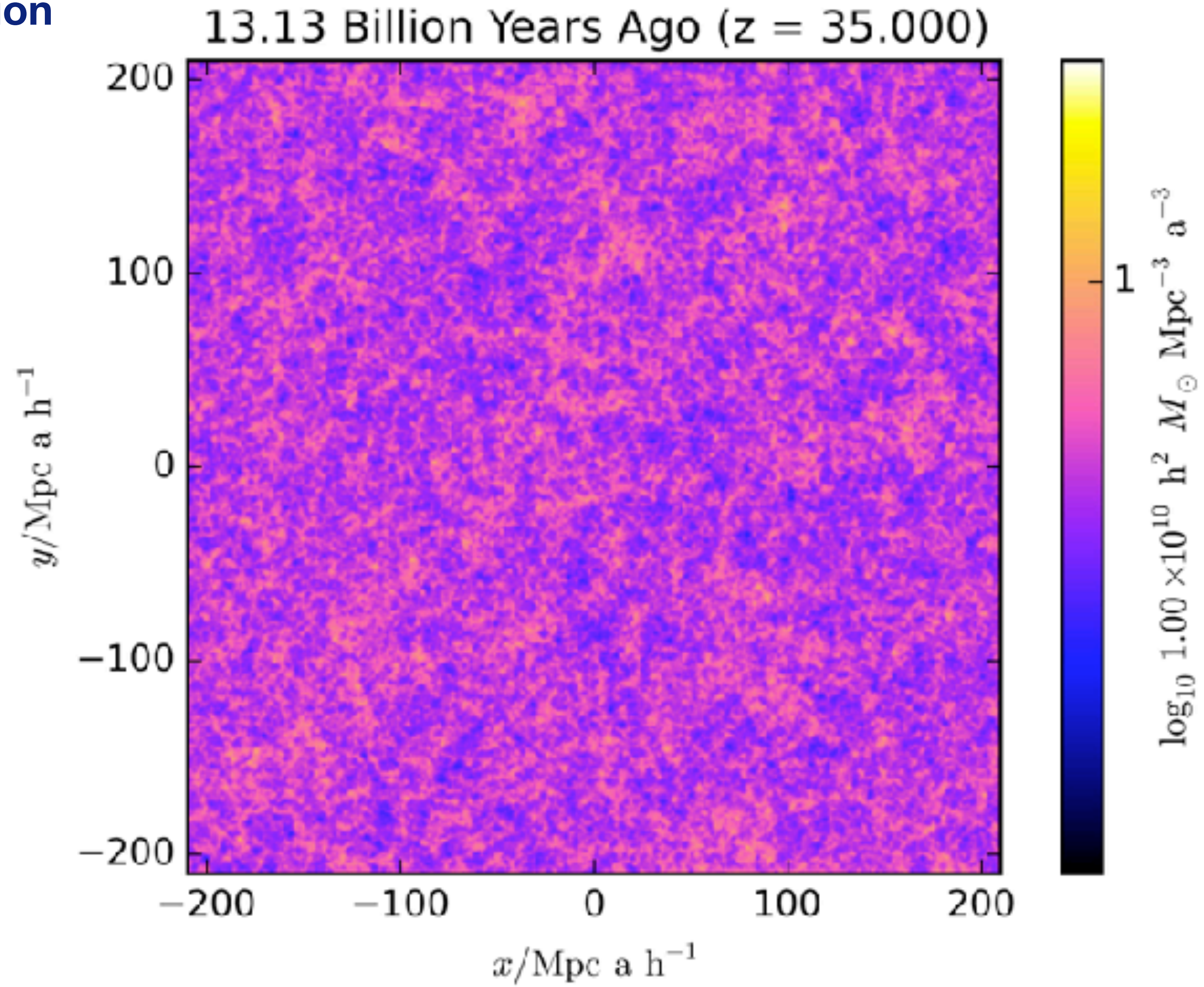
Growth of structure

L-PICOLA simulation



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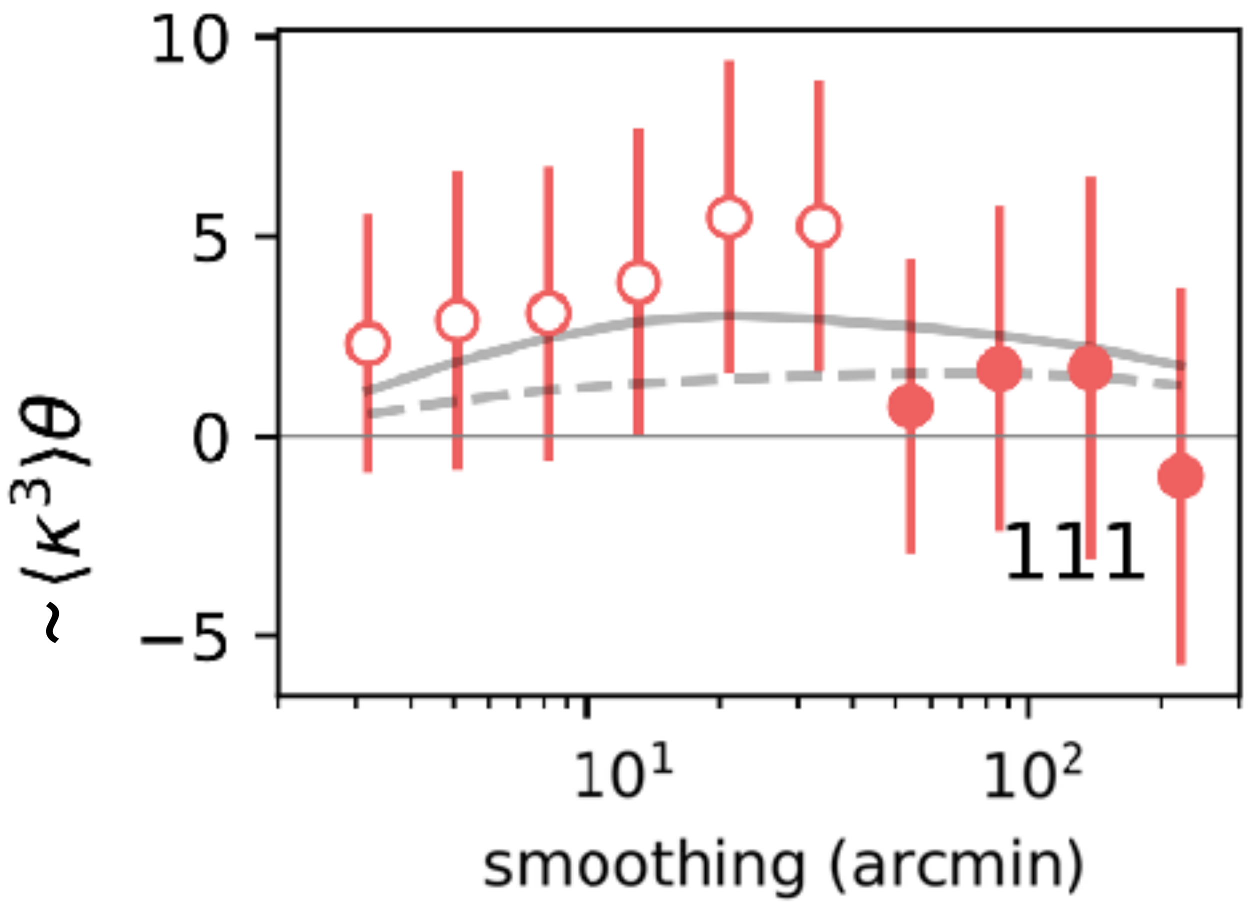
Higher-order moments

Blinded! (Gatti et al. in prep.)



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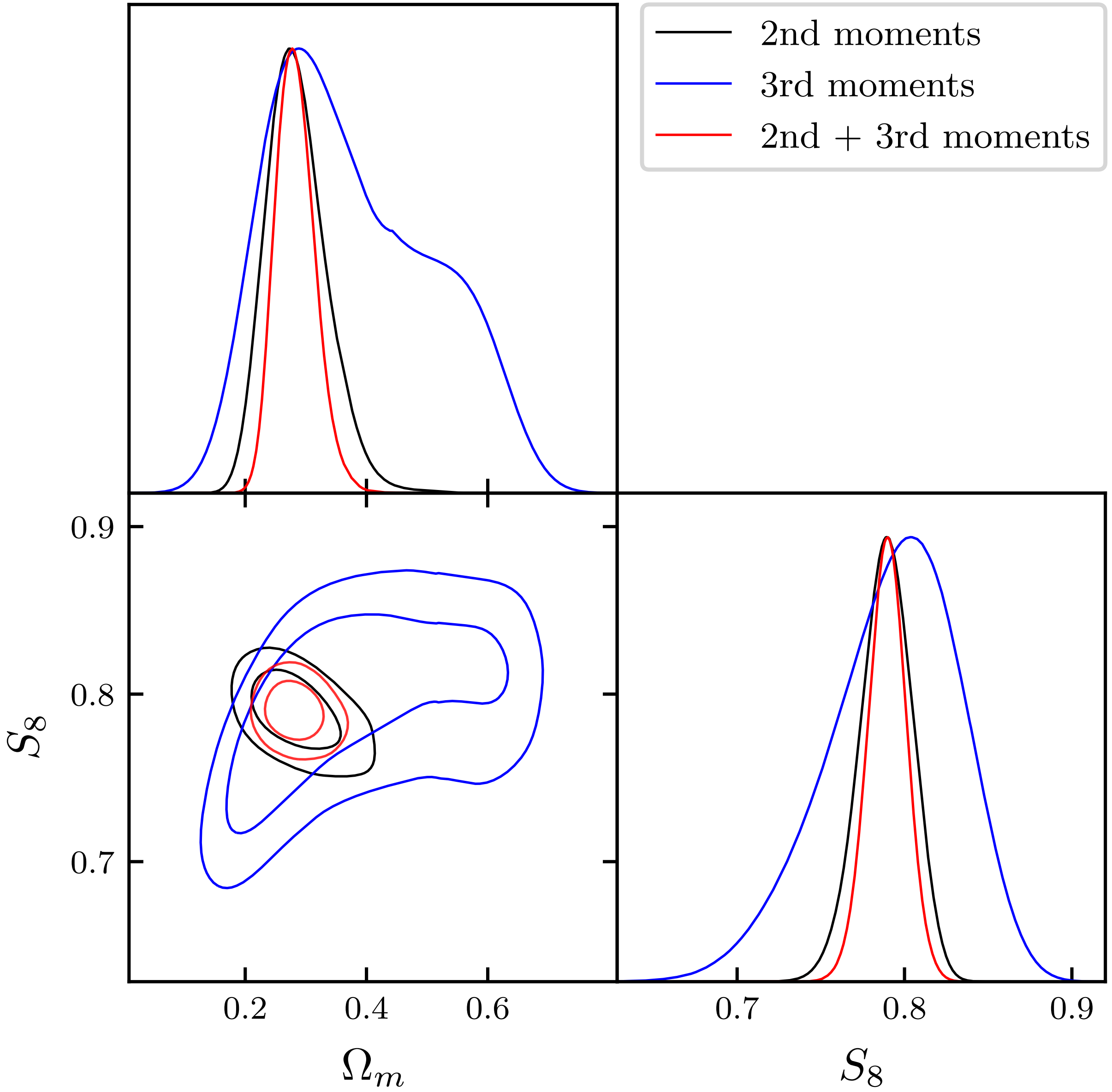

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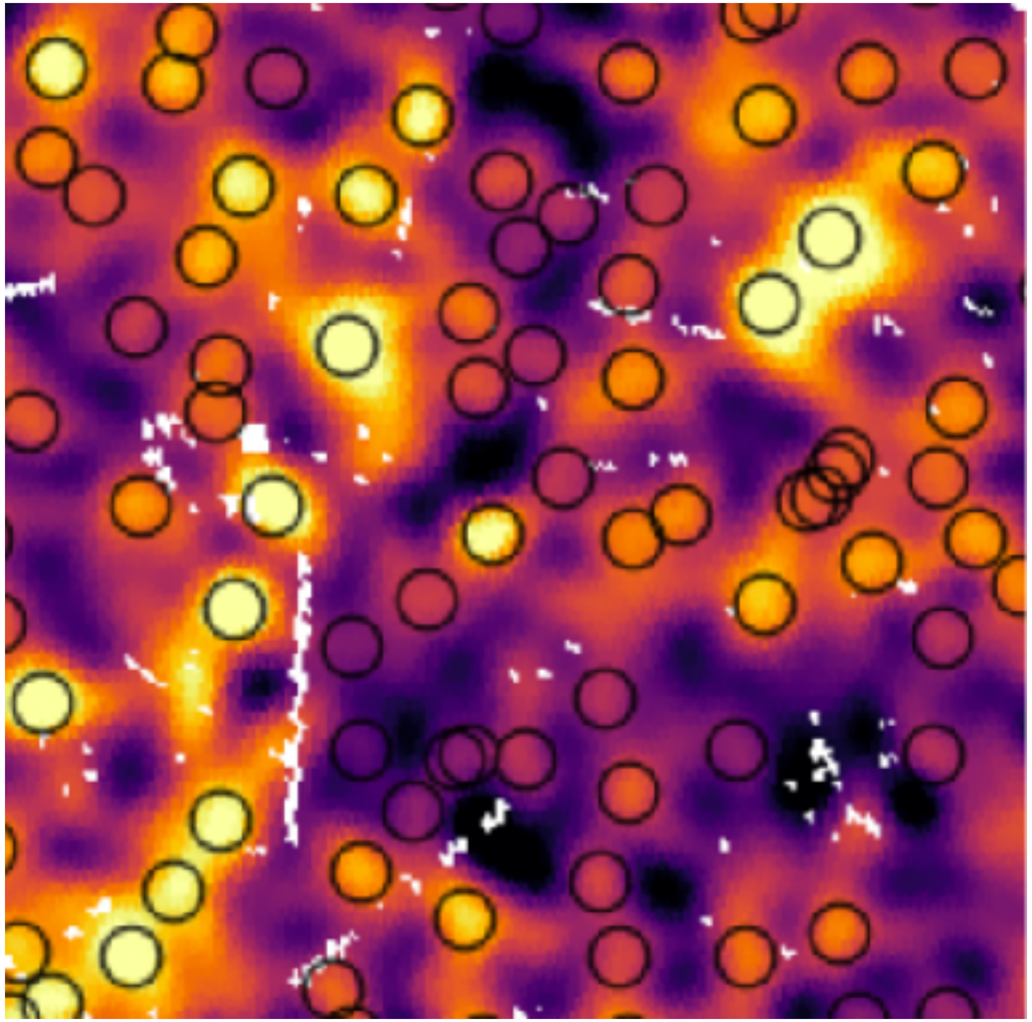
Inference with peak count emulator

Blinded! (Zuercher et al. in prep.)



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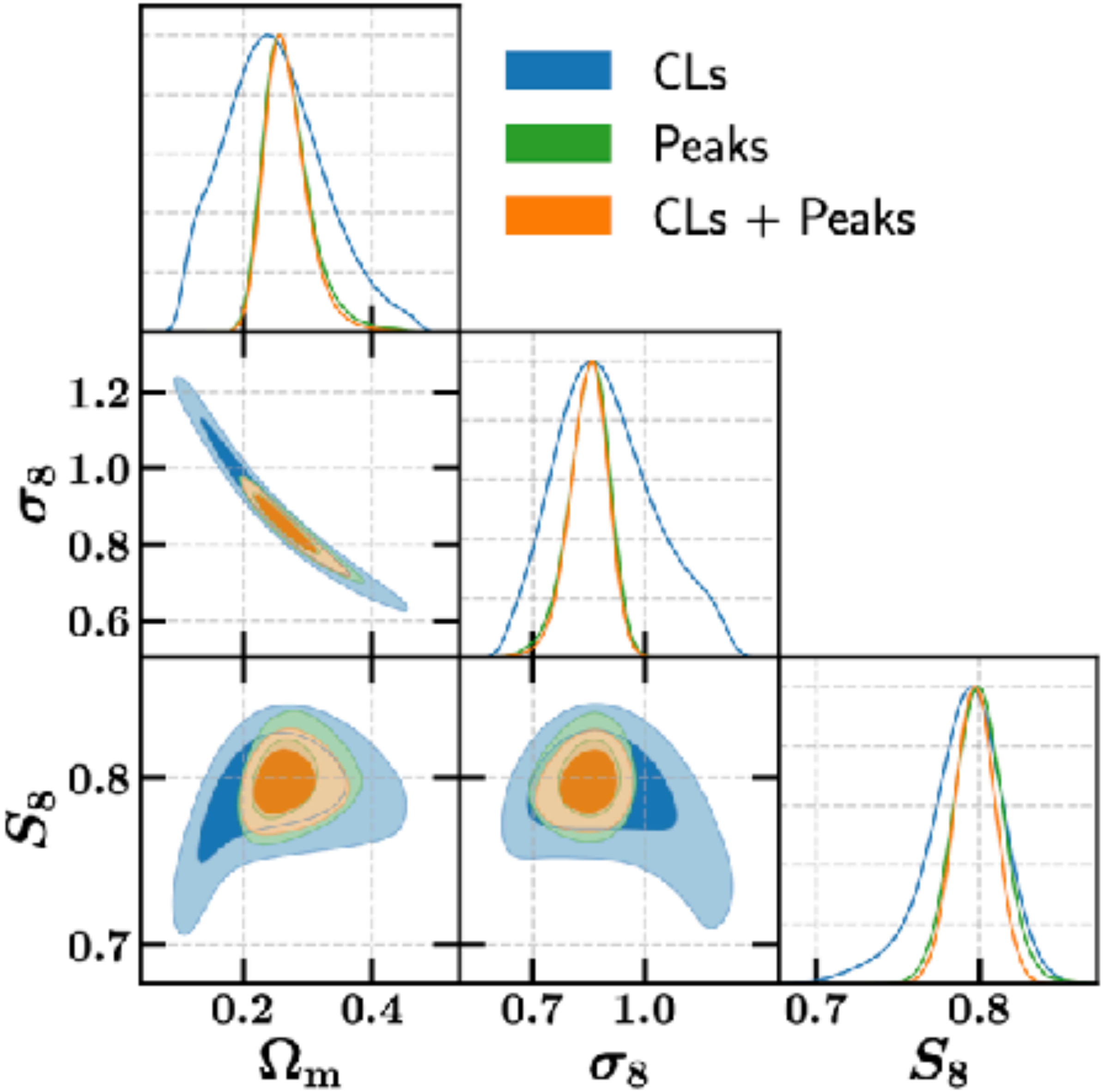

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04

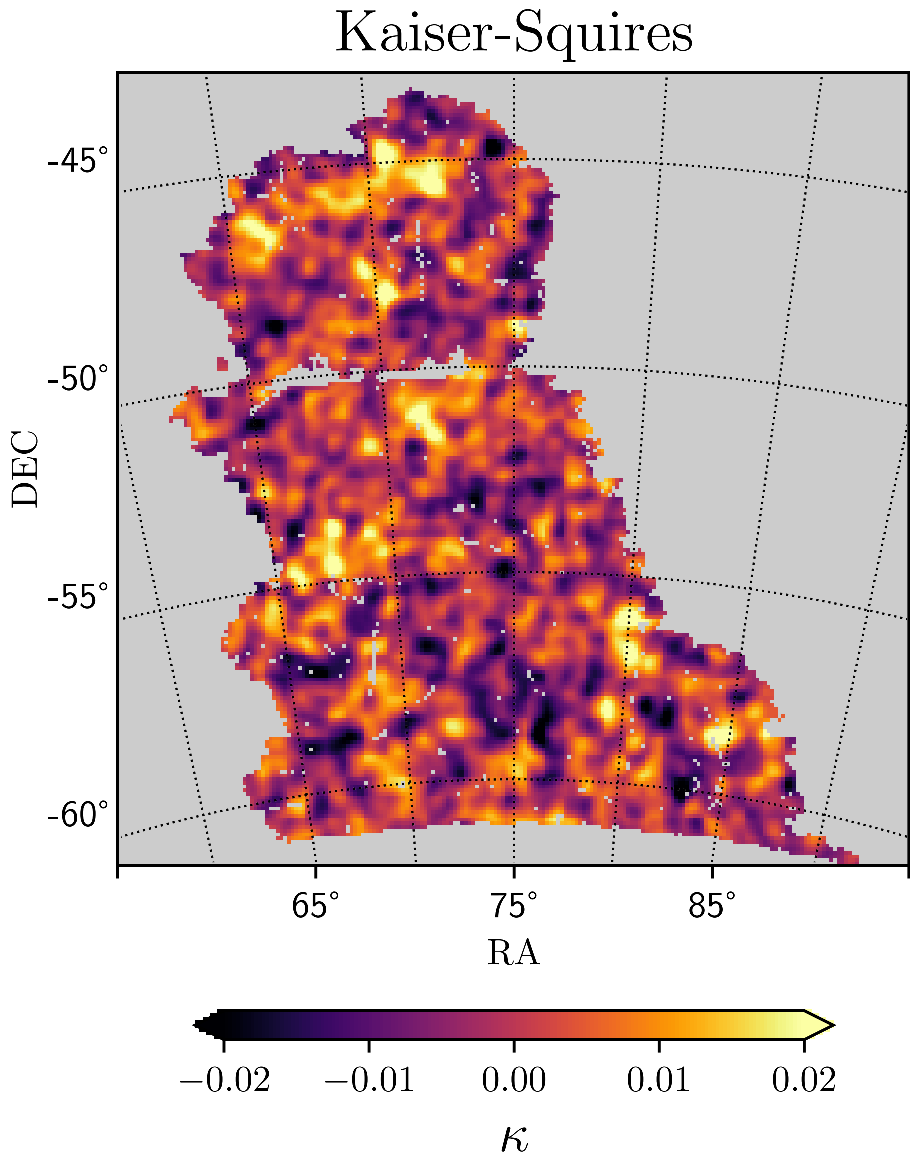
Future:
Deep learned priors & likelihood-free inference

Weak lensing mass maps

NJ, Lanusse, Lahav, Starck 1908.00543

Weak lensing mass maps

NJ, Lanusse, Lahav, Starck 1908.00543



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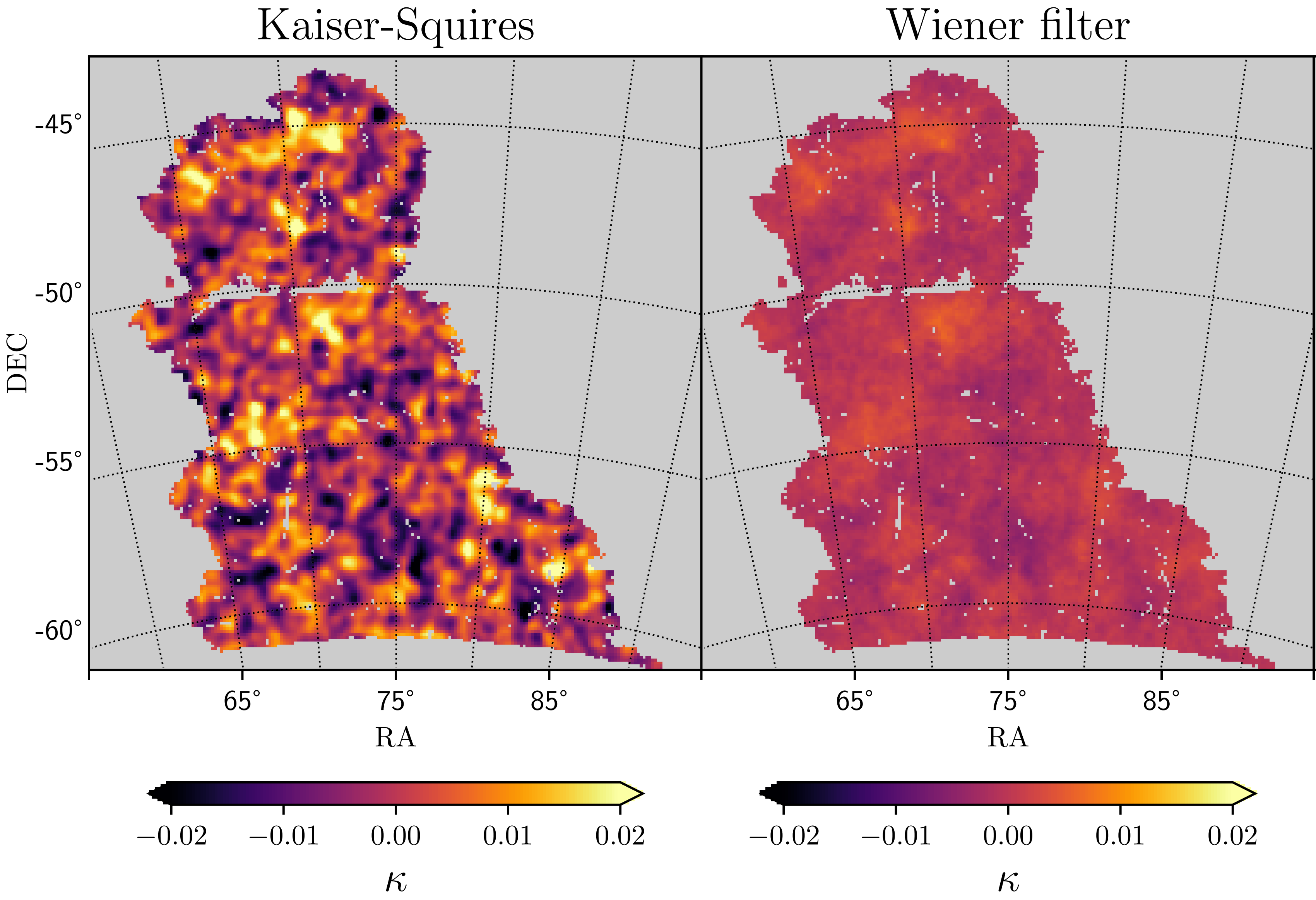

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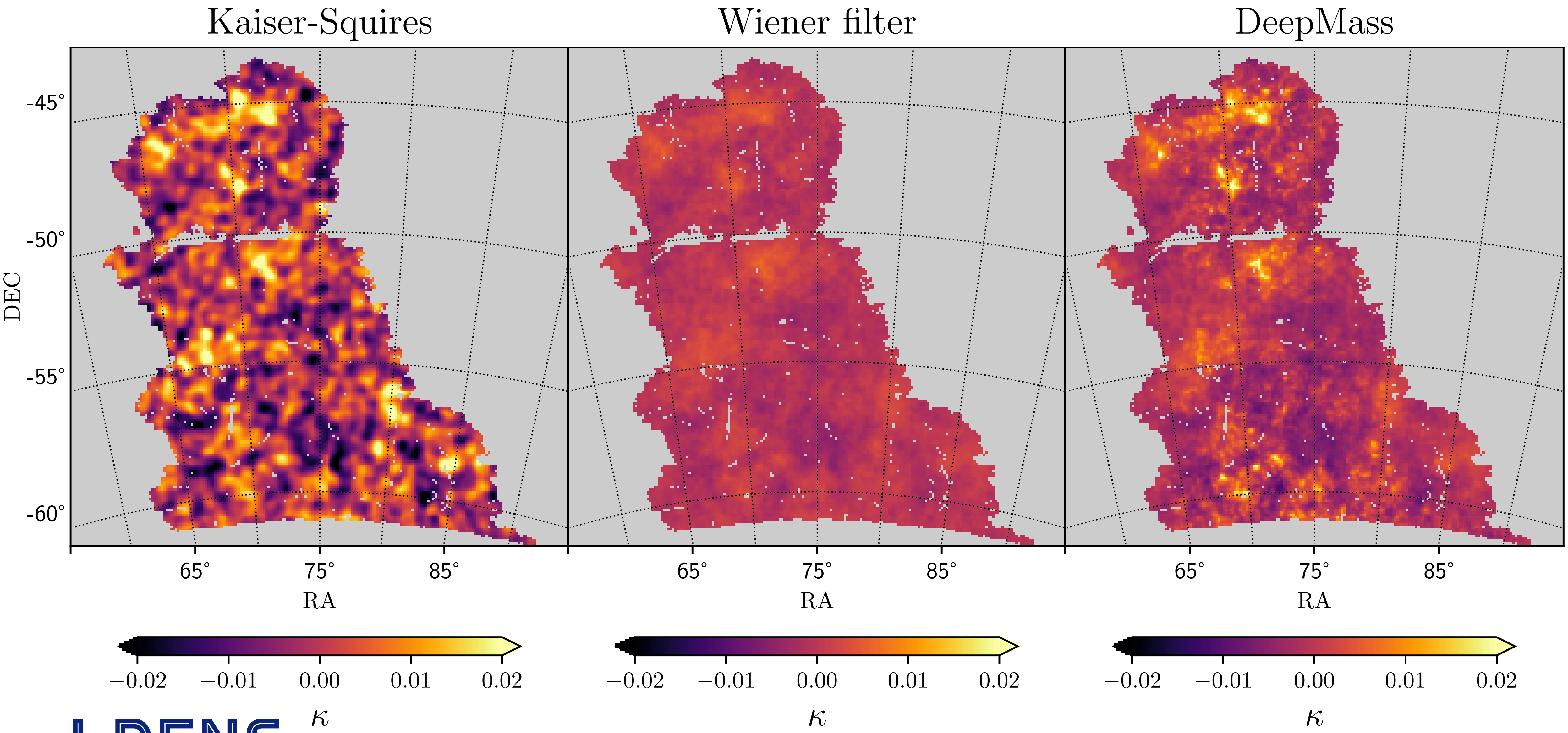

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Parameter inference

1. Observed "data" summary statistic d_o

2. Unknown parameters θ of a given model

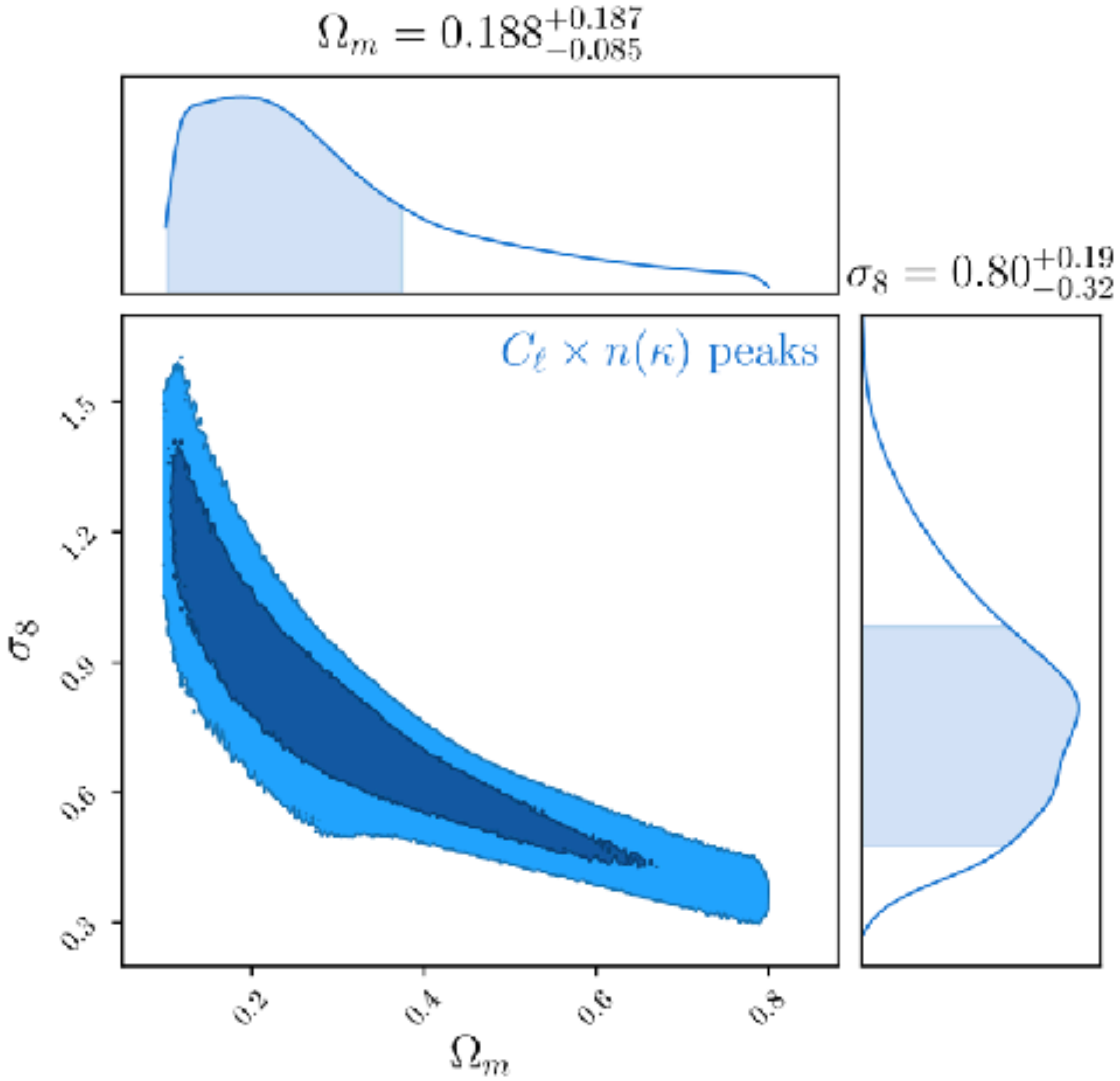
$$p(\theta \,|\, d_o) \propto p(d_o \,|\, \theta)\; p(\theta)$$

LIKELIHOOD

PRIOR

Posterior with learned likelihood:

NJ, Alsing, Lanusse 2009.08459



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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

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Forward modelled mock data

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

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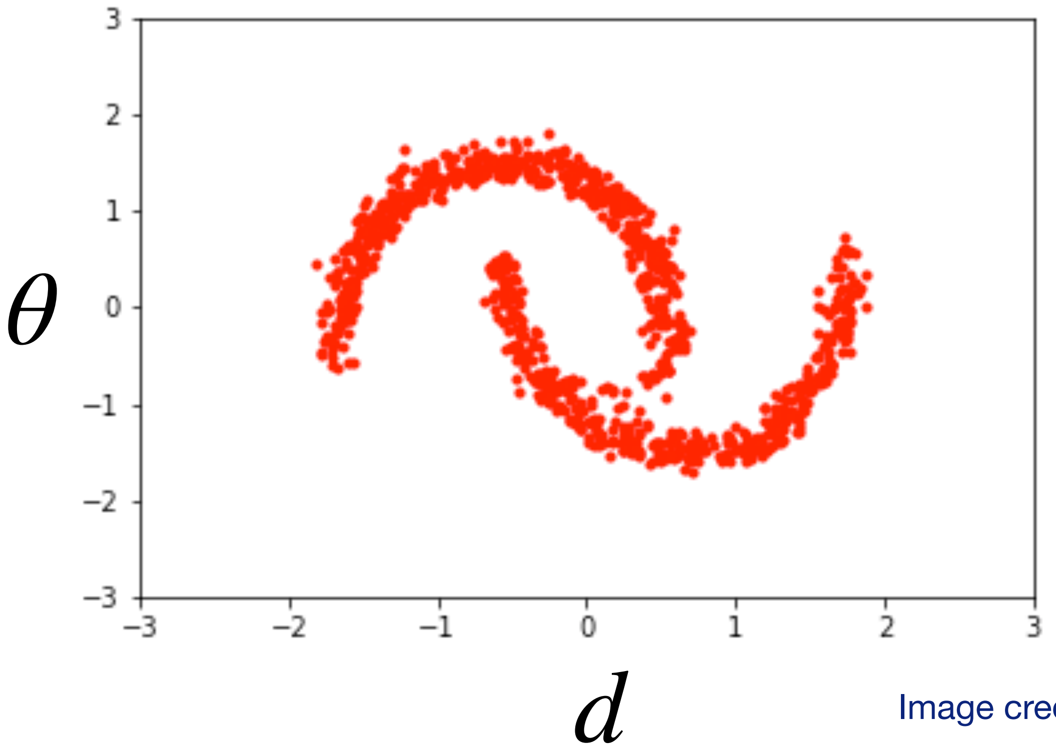

Image credit: Eric Jang

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Forward modelled mock data

$$P(d, \theta)?$$

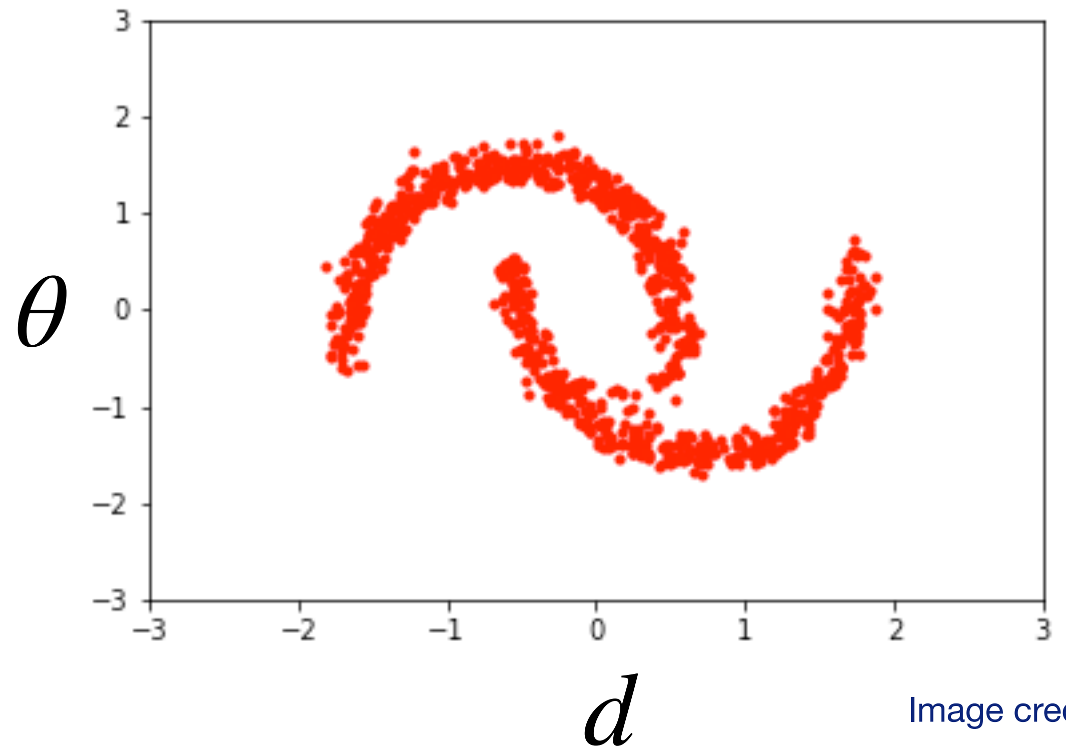
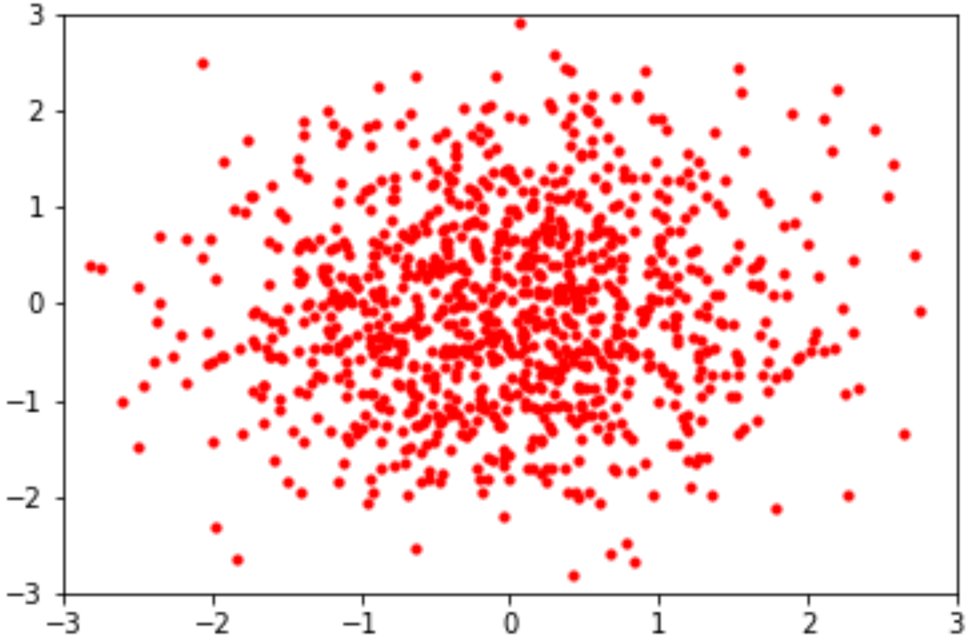


Image credit: Eric Jang

Neural density estimation

Normalizing flow from simple known distribution



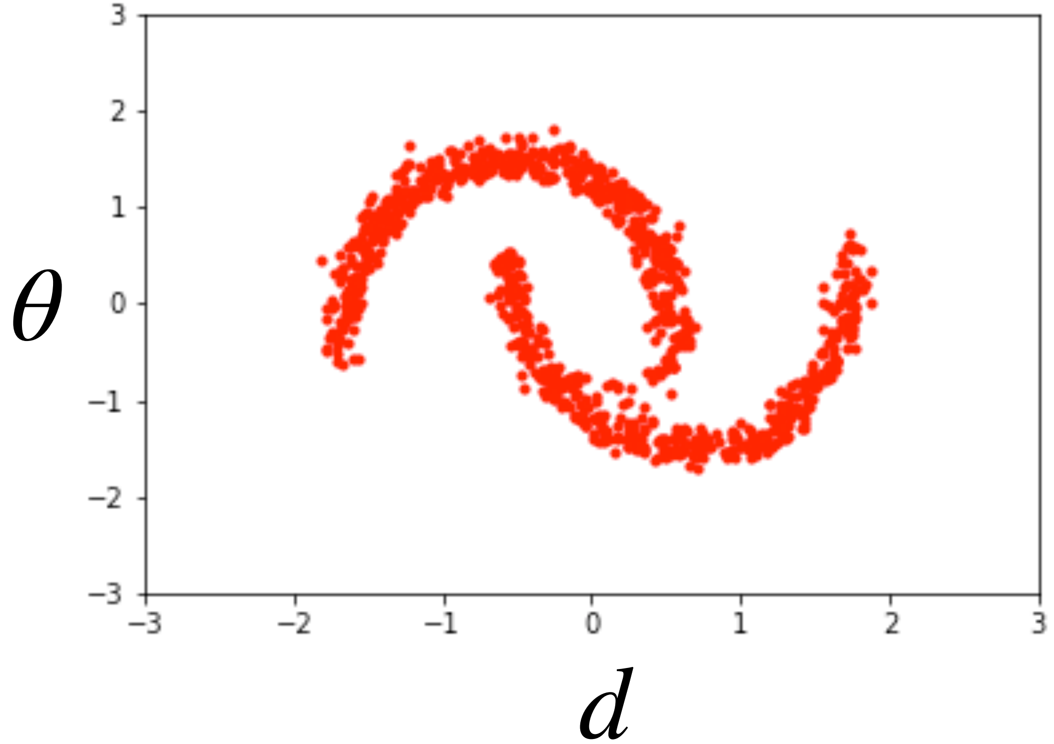


Image credit: Eric Jang

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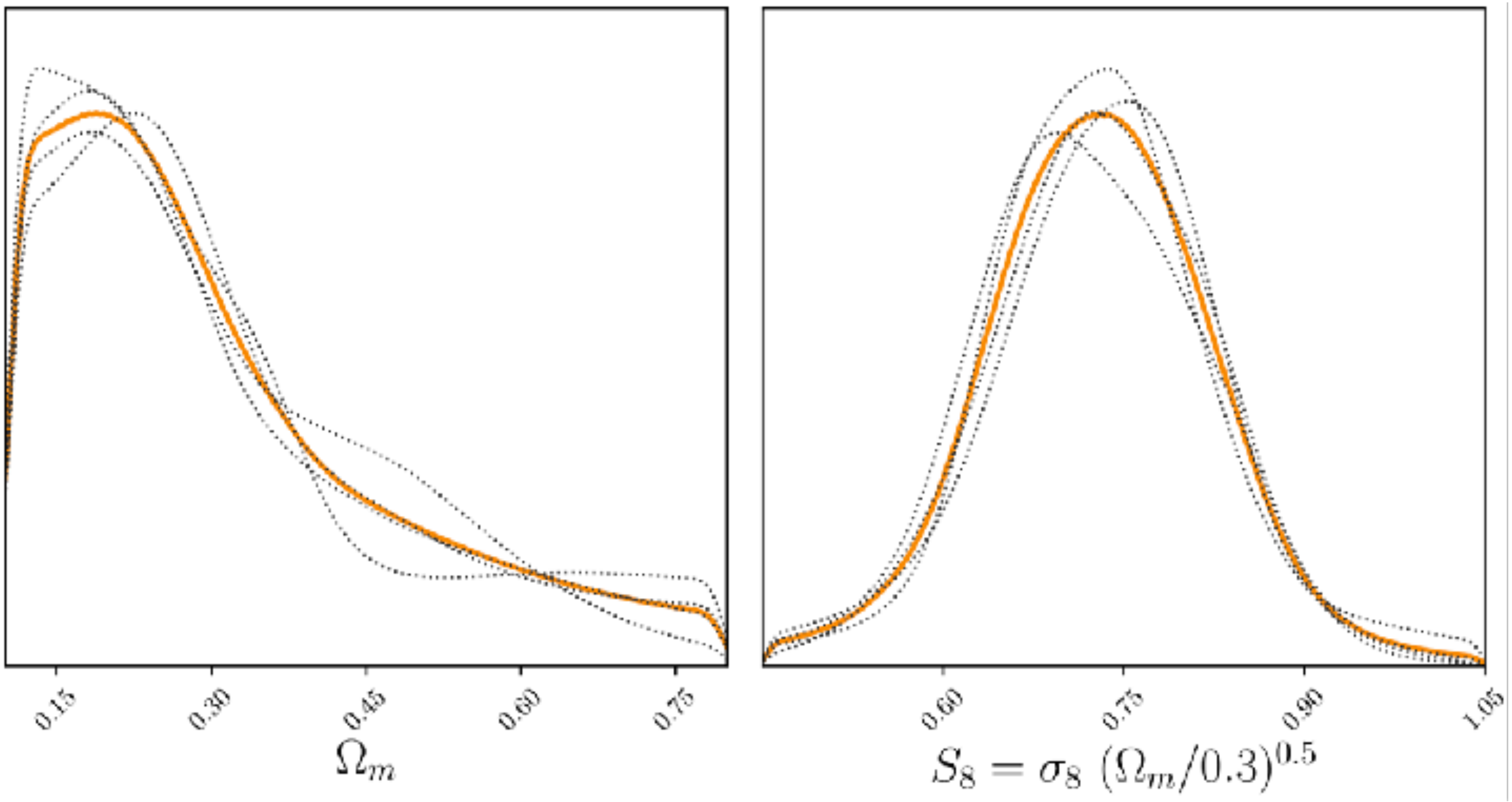
Density estimation validation:



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Deep convolutional compression of maps:

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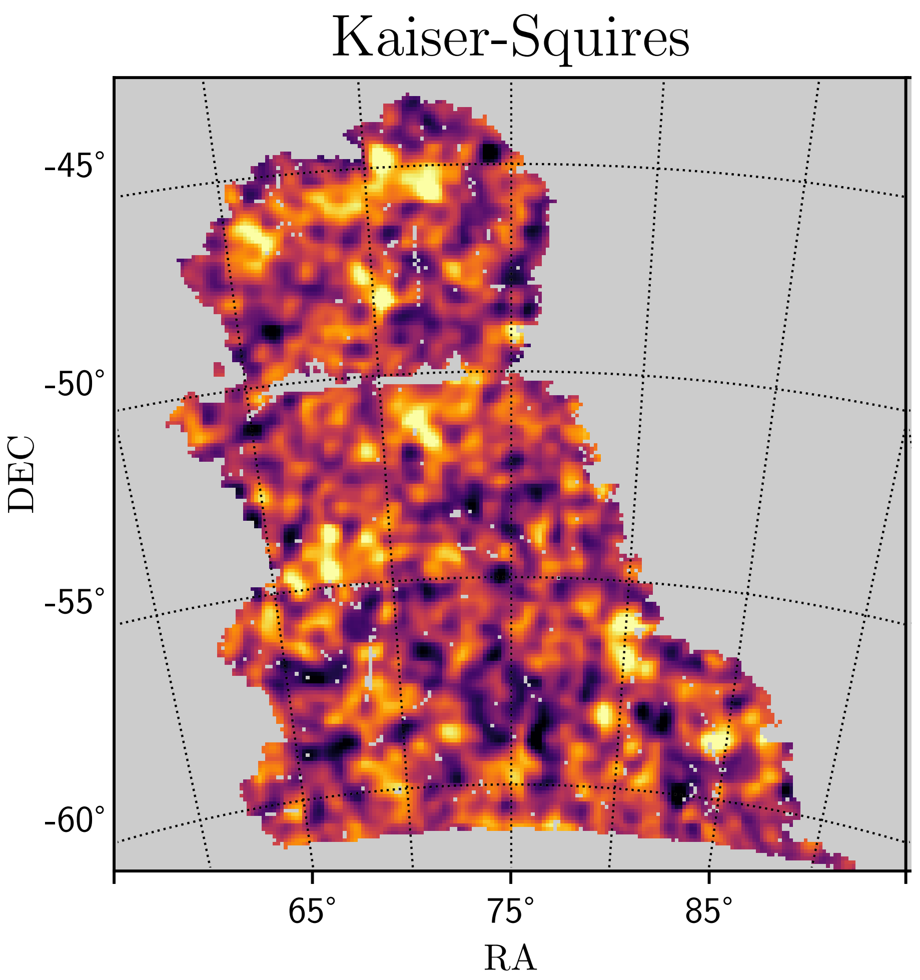

$$\mathbf{t} = F(\text{map})$$

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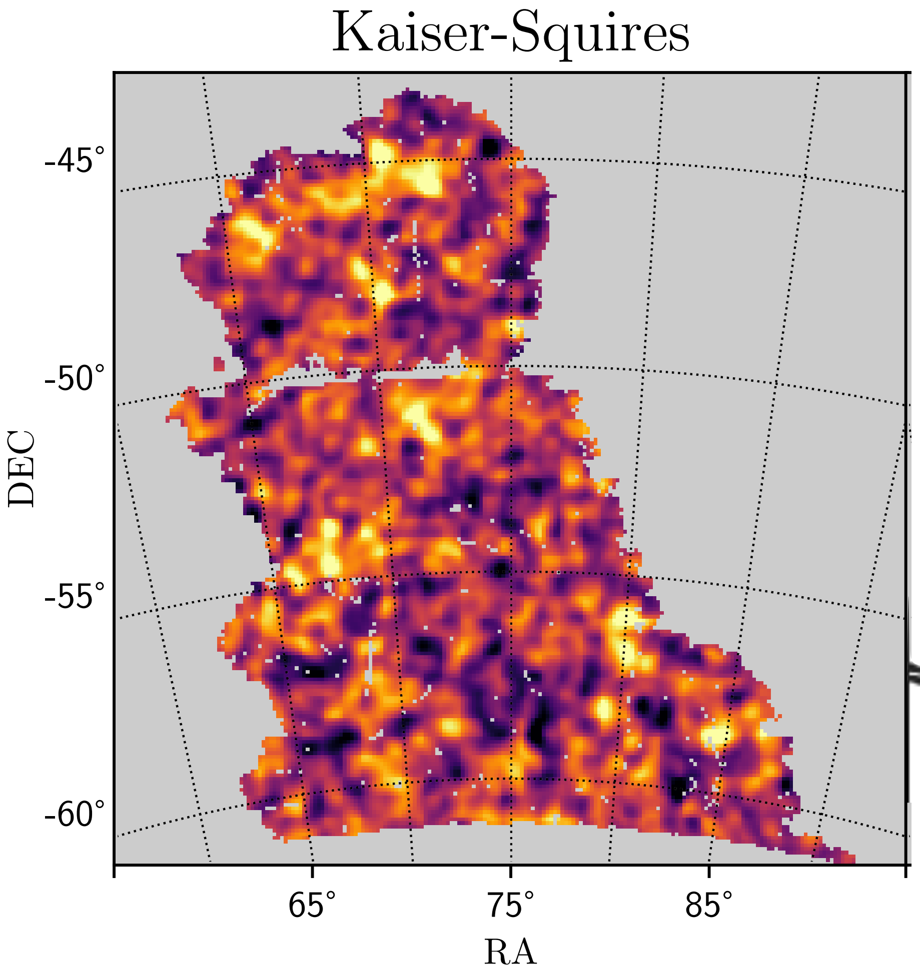
Deep convolutional compression of maps:



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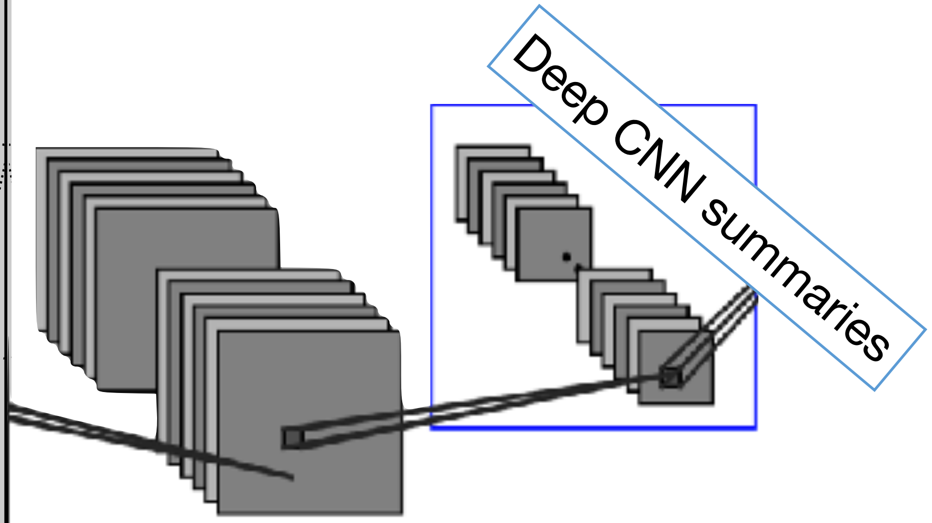

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Deep convolutional compression of maps:

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

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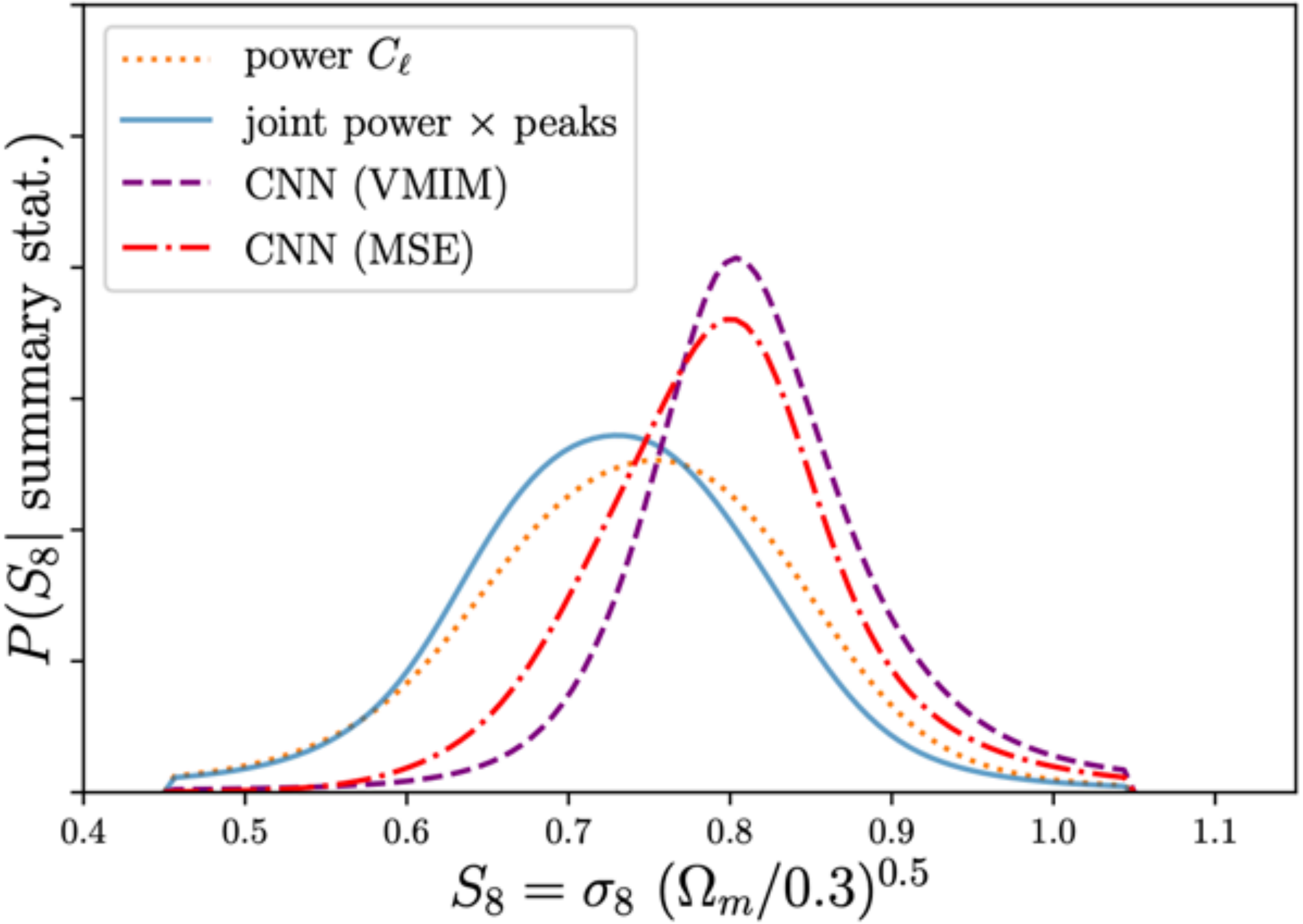
$$\mathbf{t} = F(\mathrm{map})$$

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

Deep convolutional compression of maps:



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NJ, Alsing, Lanusse 2009.08459

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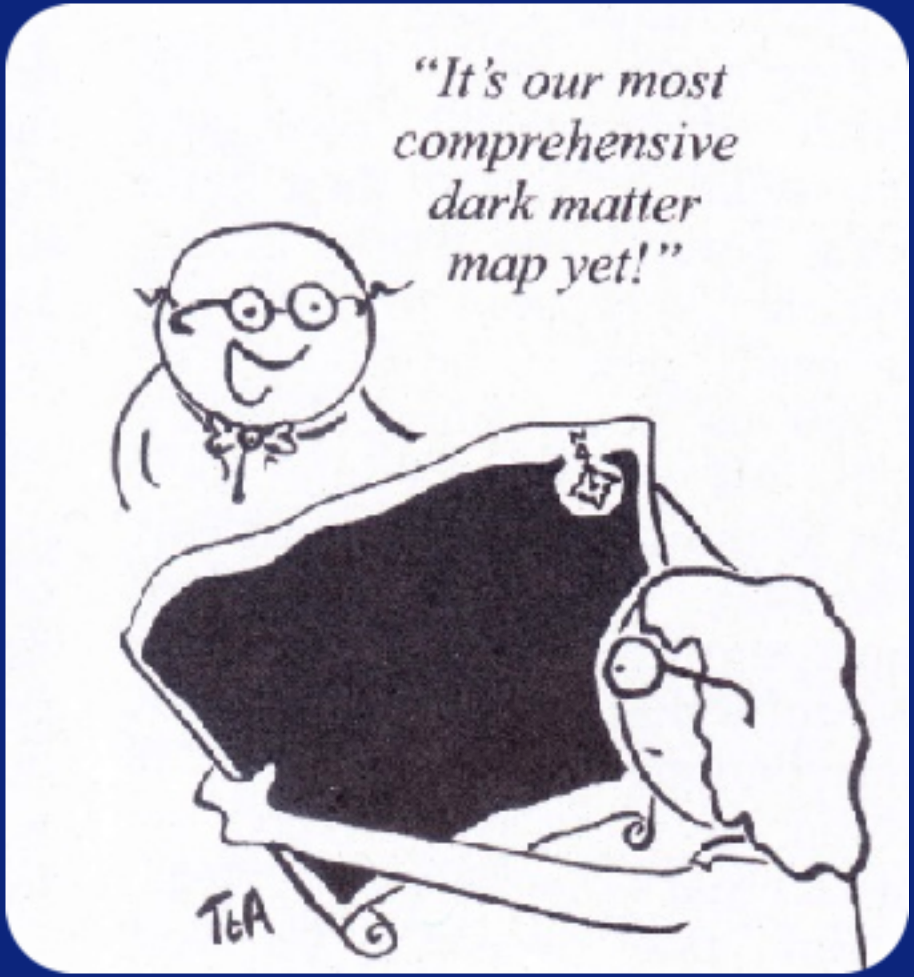
Merci !



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