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DeepMass
Deep learning dark matter map reconstructions from DES weak lensing data

Niall Jeffrey

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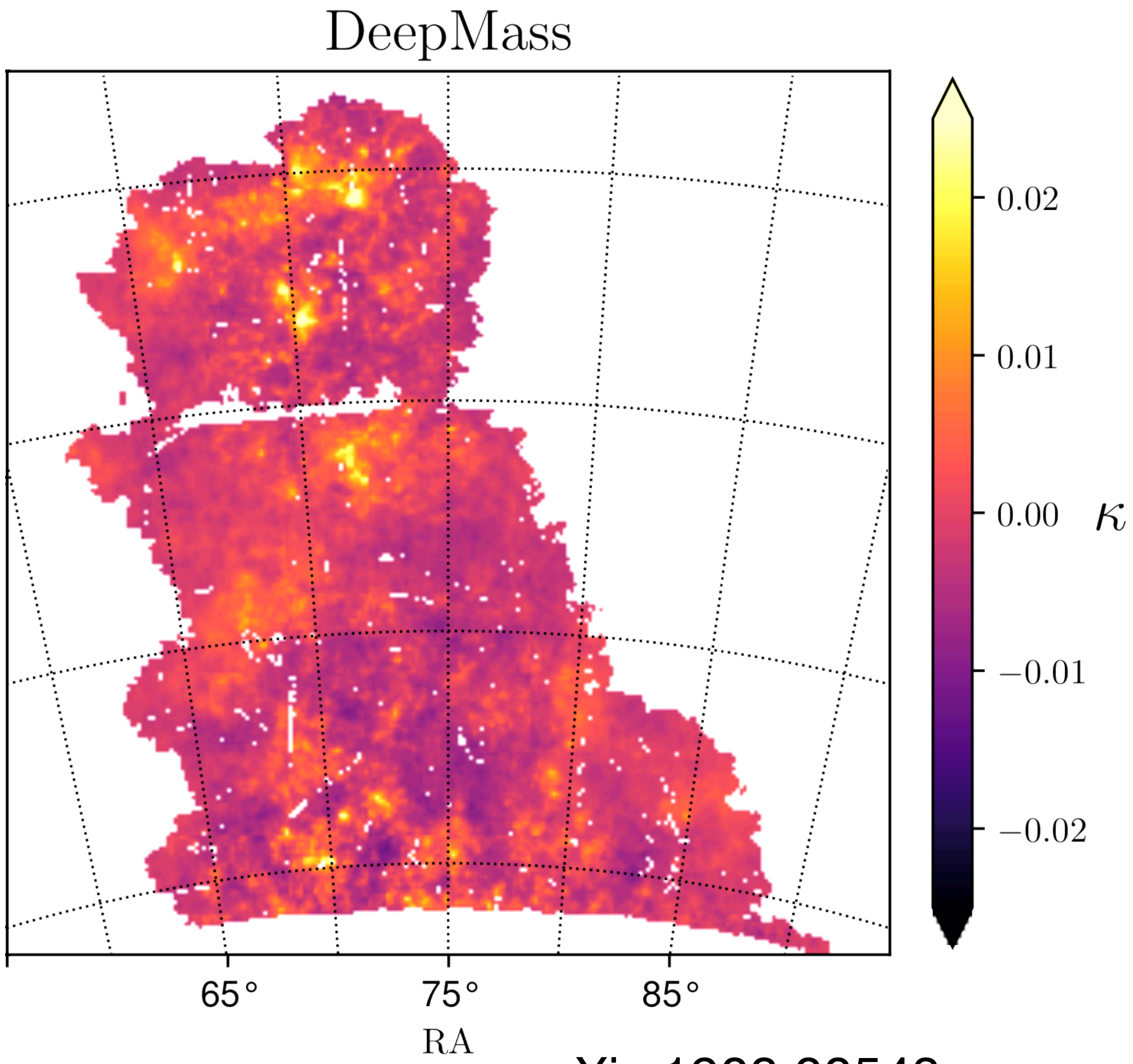

arXiv:1908:00543

Outline

1. Weak lensing map reconstruction
2. Deep learning a Bayesian estimate
3. Dark Energy Survey results
4. New results:
   DeepMass and the CMB

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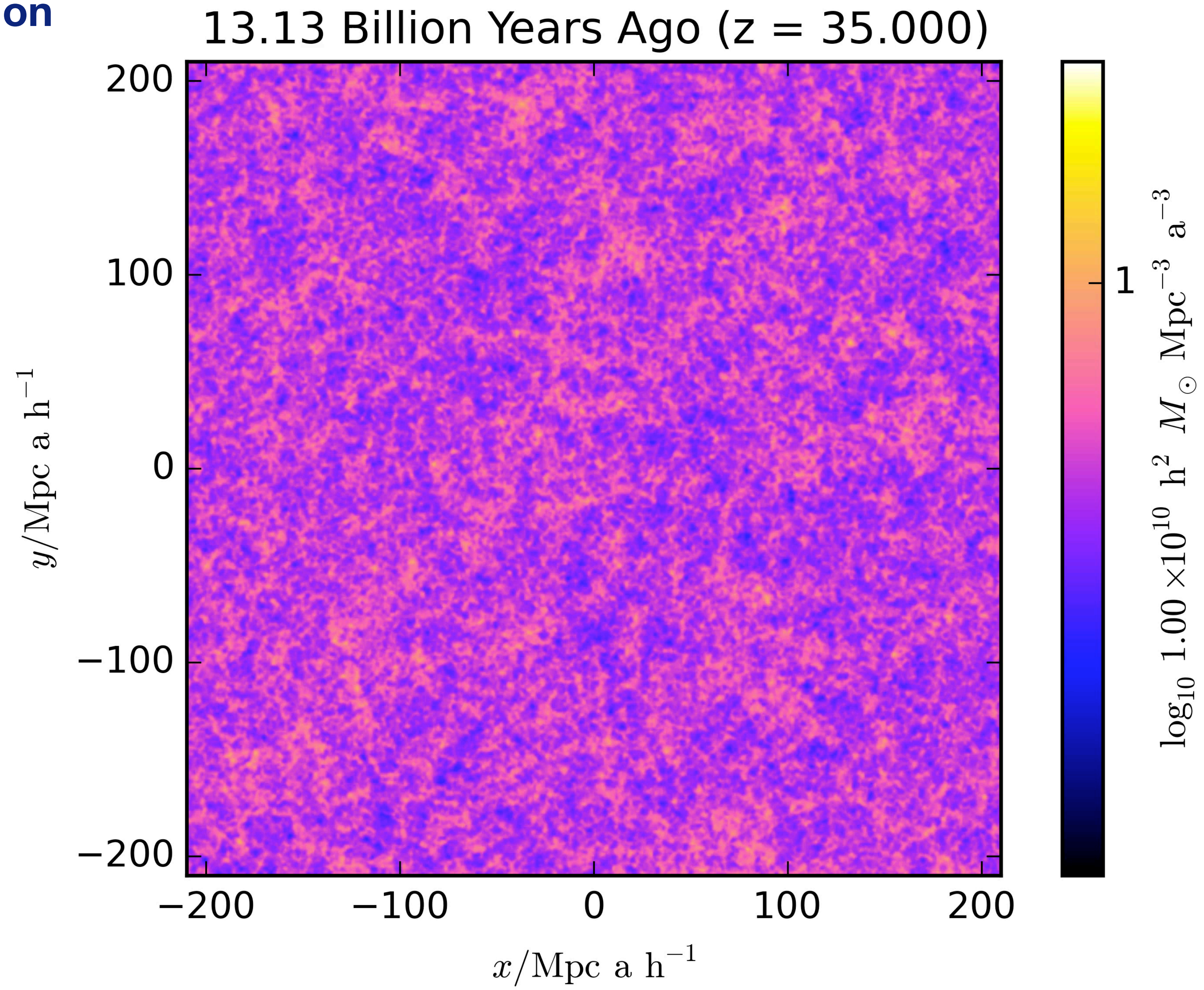
01

Weak lensing mass maps

Growth of structure

L-PICOLA simulation



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(*Using “lens_your_face”- provided by A. Leonard)

Mass mapping

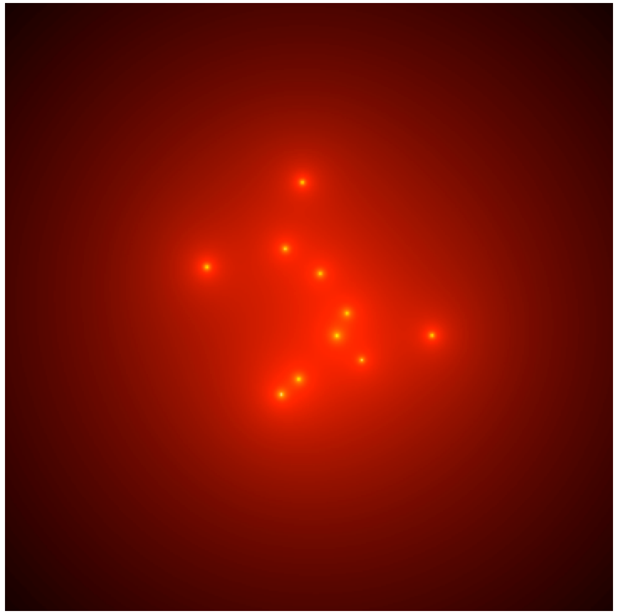
Weak gravitational lensing

I. Galaxy shape encoded in the shear: $\boldsymbol{\gamma}$

II. Weighted projected density is convergence: $\boldsymbol{\kappa}$

III. Objective: use observed $\boldsymbol{\gamma}$ from galaxies to reconstruct $\boldsymbol{\kappa}$

DATA



CONVERGENCE

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Mass mapping

Linear data model

$$\boxed{\gamma = \mathbf{A}\kappa + \mathbf{n}}$$

DATA

LINEAR TRANSFORM

SIGNAL

(MASS MAP)

SHAPE NOISE

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Mass mapping

Linear data model

$$\boxed{\gamma = \mathbf{A}\kappa + \mathbf{n}}$$

DATA

LINEAR TRANSFORM

SIGNAL

(MASS MAP)

SHAPE NOISE

Kaiser-Squires 1993 Estimator

$$\boxed{\hat{\gamma}(\vec{l}) = \pi^{-1}\hat{\mathcal{D}}(\vec{l})\hat{\kappa}(\vec{l})}$$

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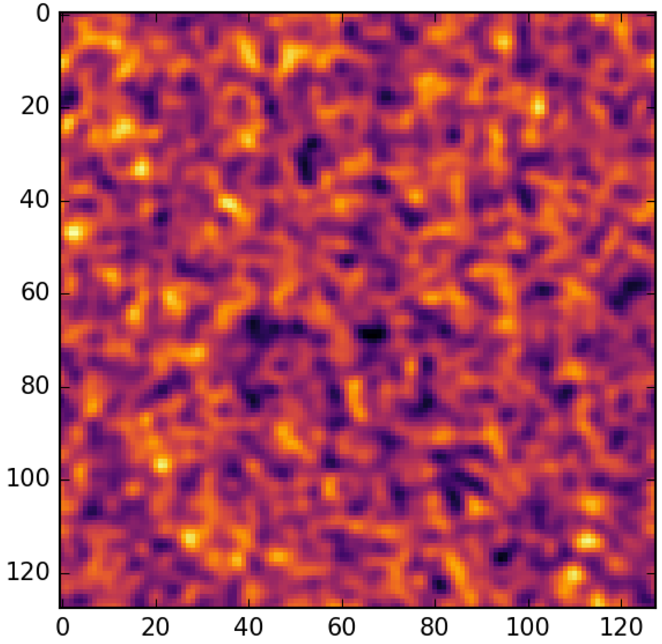
Mass mapping inference

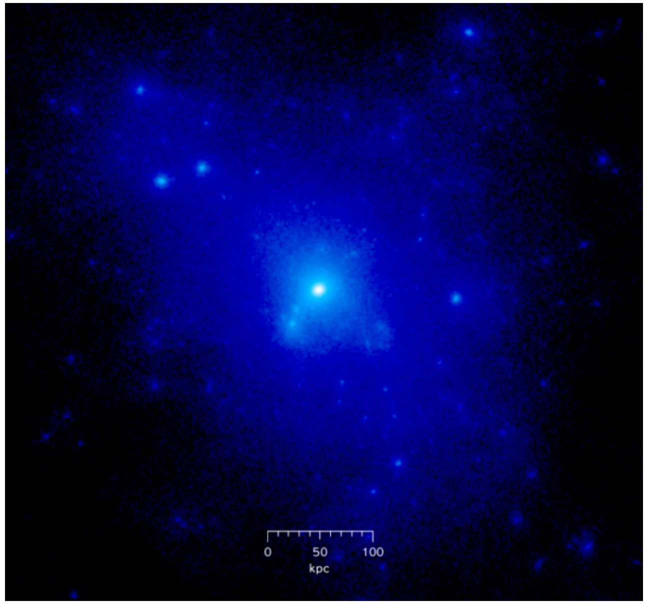
Bayesian “*maximum a posteriori*"

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

Gaussian Random Field?



Dark Matter Halos?



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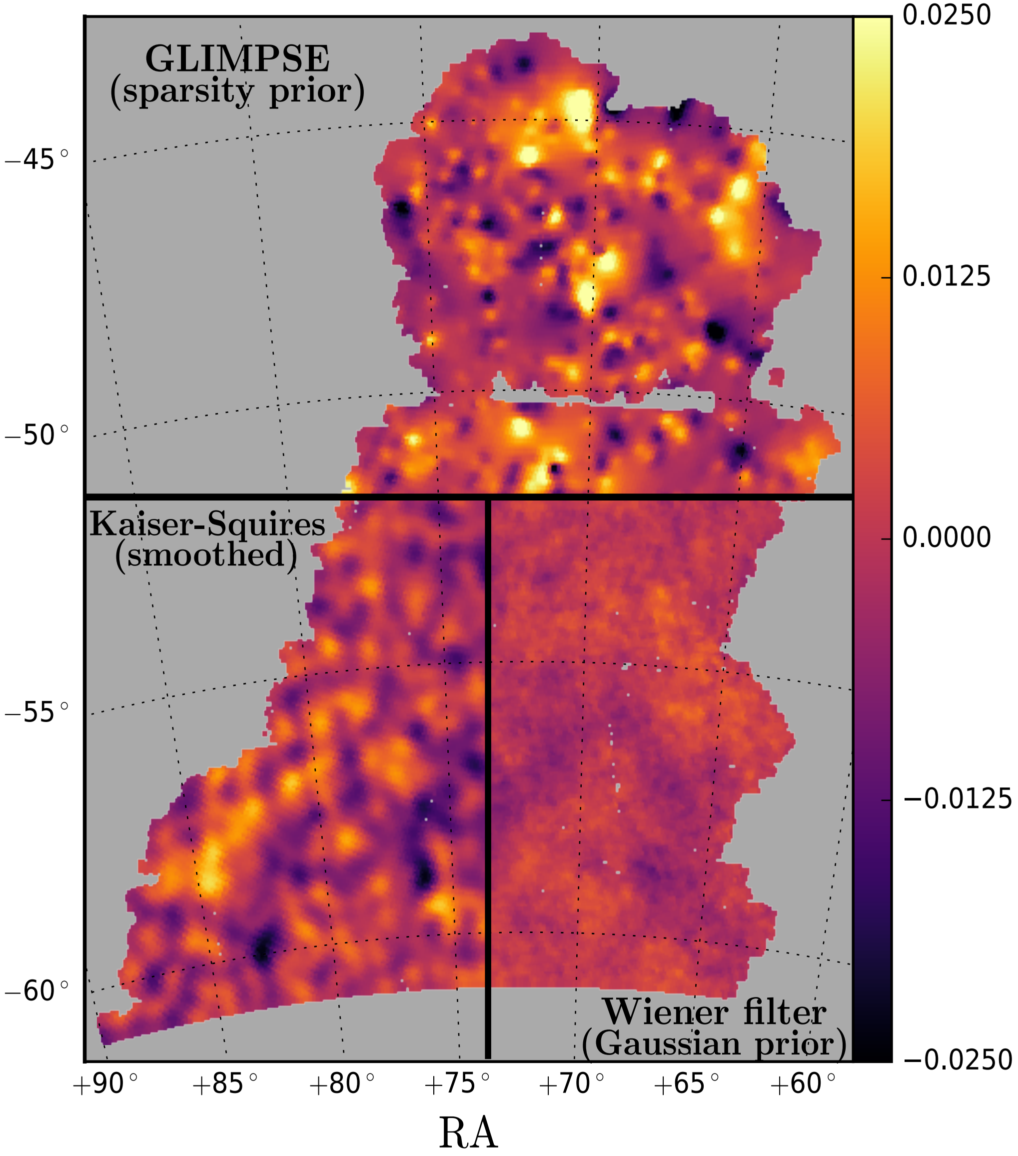
Approximate priors

DES SV results

I. Improved accuracy:
   i. Gaussian prior (Wiener filter)
   ii. “Halo-model" sparsity prior (GLIMPSE)

II. Sparsity prior increases peaks statistic signal-to-noise (up to x9)



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The perfect prior?

No closed-form probability distribution of the matter field for the late Universe…

$$P(\kappa | \theta, \mathcal{M})$$

Parameters

Cosmological model

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The perfect prior?

But, we can sample from the prior distribution…

$$P(\kappa|\theta, \mathcal{M})$$

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The perfect prior?

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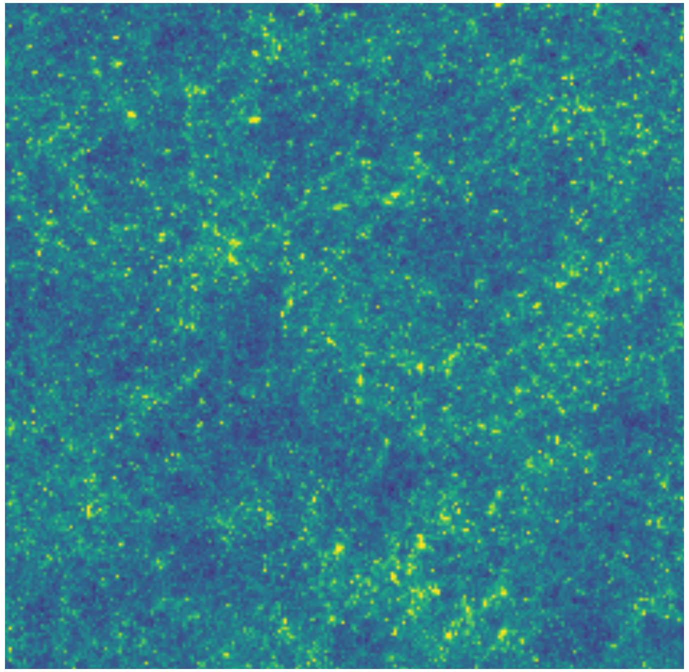

simulated convergence map

$$P(\kappa|\theta, \mathcal{M})$$

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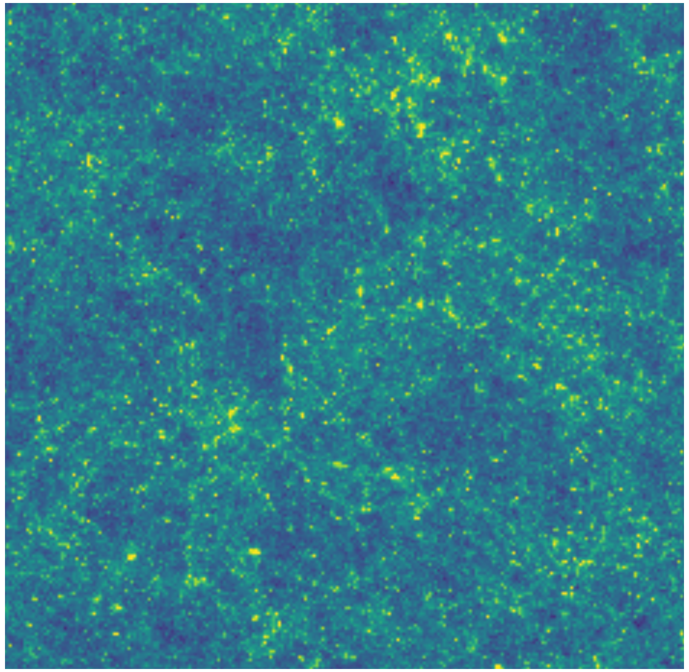

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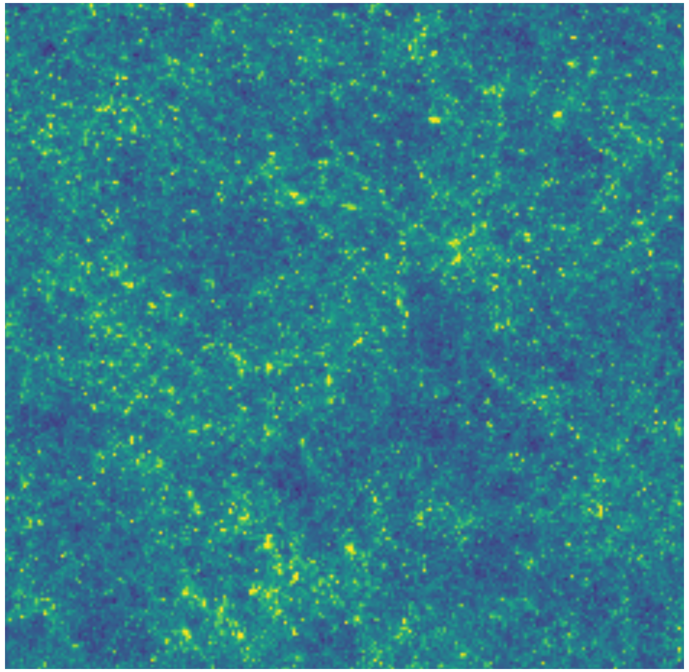

$$\longleftarrow P(\kappa|\theta, \mathcal{M})$$

simulated convergence map

02 Deep learning a Bayesian estimate

Mean posterior estimate
Deep learning framework

I. We seek to approximate the mean posterior:

$$\hat{\kappa} = \mathscr{F}_{\Theta}(\gamma) = \int \kappa \, P(\kappa | \gamma) \, \mathrm{d}\kappa$$

II. This is achieved by minimising:

$$J(\Theta) = || \mathscr{F}_{\Theta}(\gamma) - \kappa_{\mathrm{true}} ||_2^2$$

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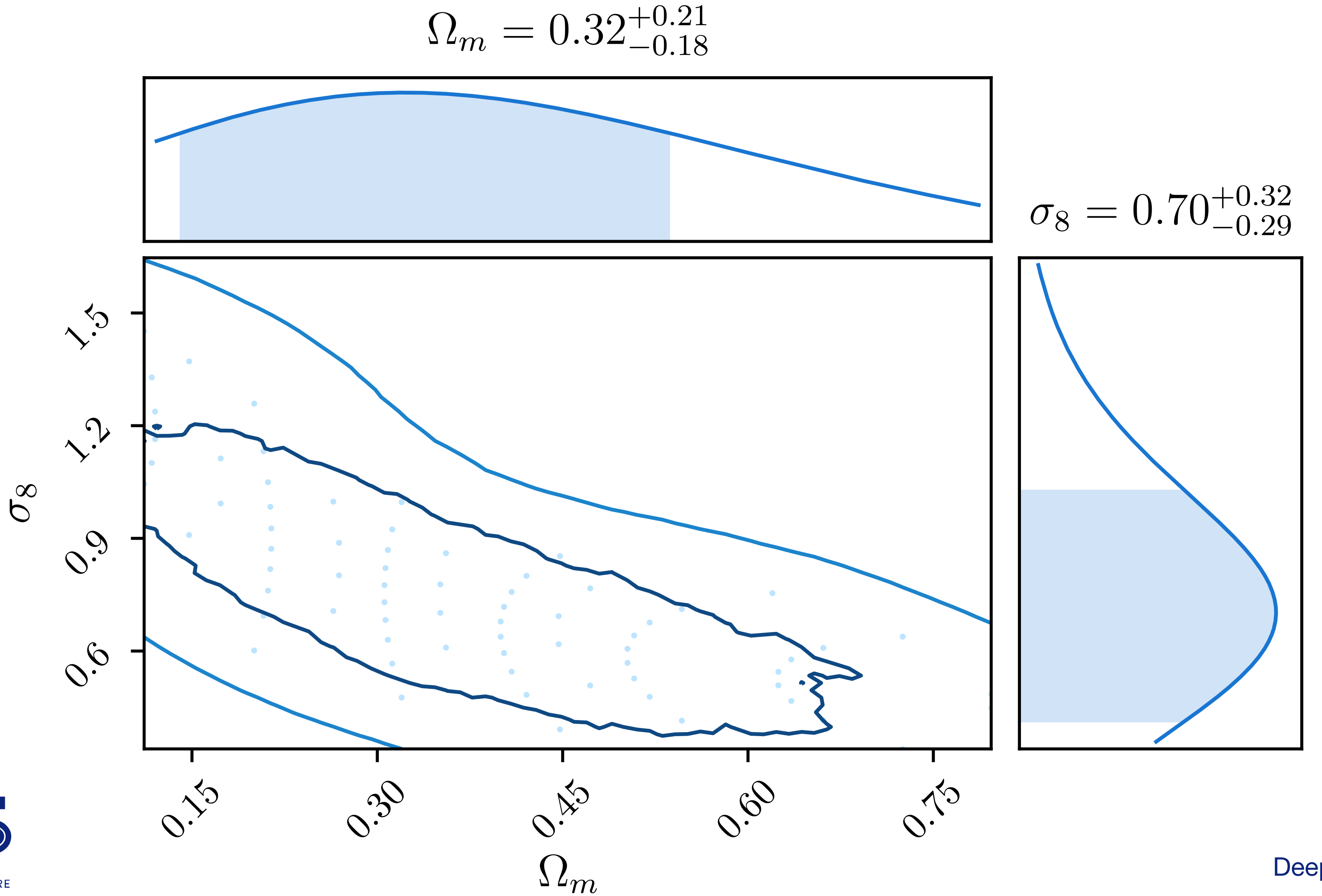
Step 1

Sample simulations from prior $P(\theta)$



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Step 2
Learn the unknown function

$$\hat{\kappa} = \mathscr{F}_{\Theta}(\gamma)$$

I. Approximate function as a Convolutional Neural Network (CNN)

II. Unknown parameters Θ are mainly convolution filters

III. Minimise $J(\Theta)$ using 3×10^5 {clean map, noisy data} realisations

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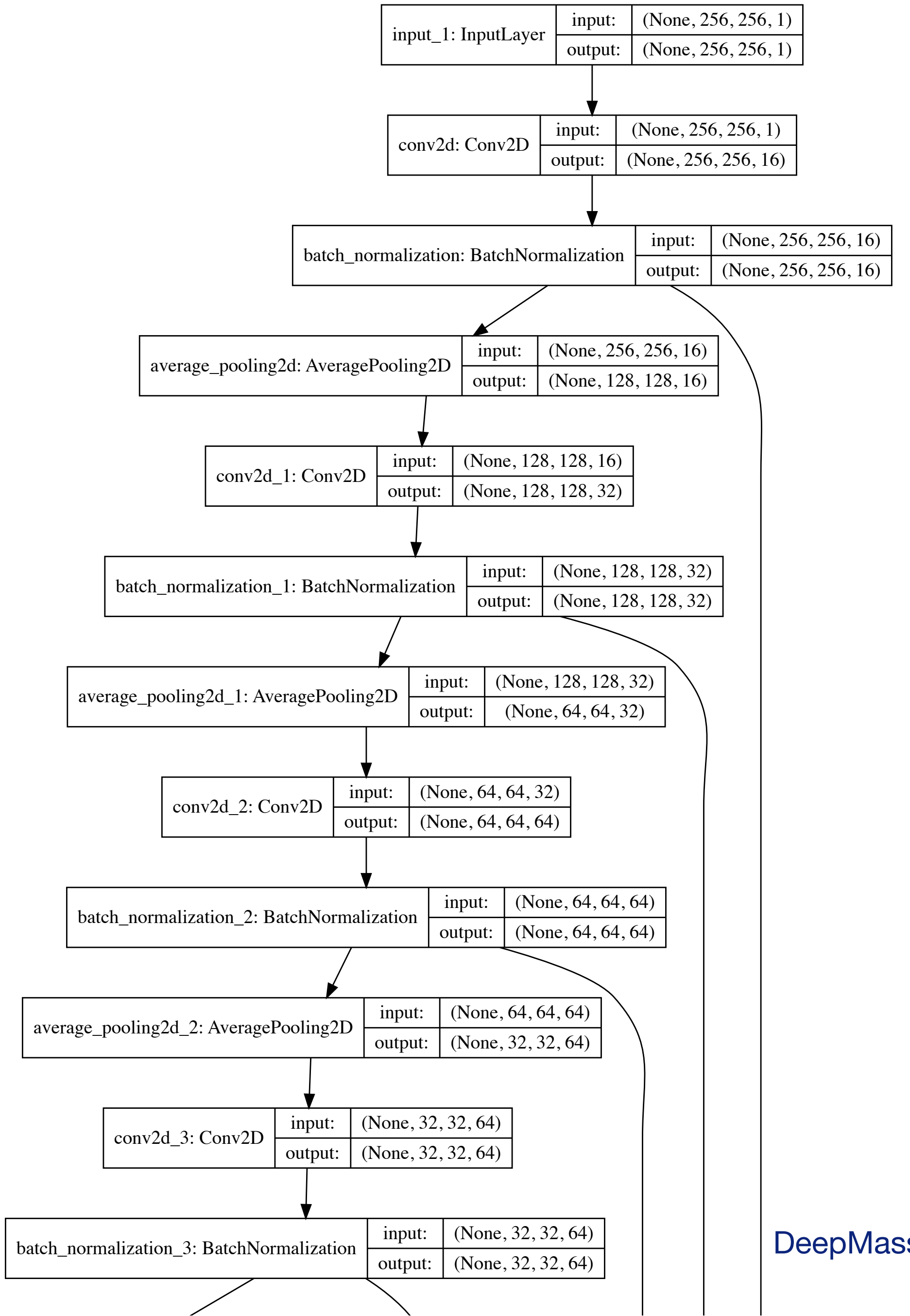
DeepMass architecture: U-Net

Expanding and contracting paths

I. Hierarchy of downsampling i.e. “pooling”

II. Increasing filter “receptive area”

III. Multiscale filters



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03 Results with Dark Energy Survey data

Dark Energy Survey

SV weak lensing data

I. Ground based 5-band photometric survey (just completed 6 years)

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

III. 1.6 million background galaxies with $0.6 < z < 1.2$ in this sample

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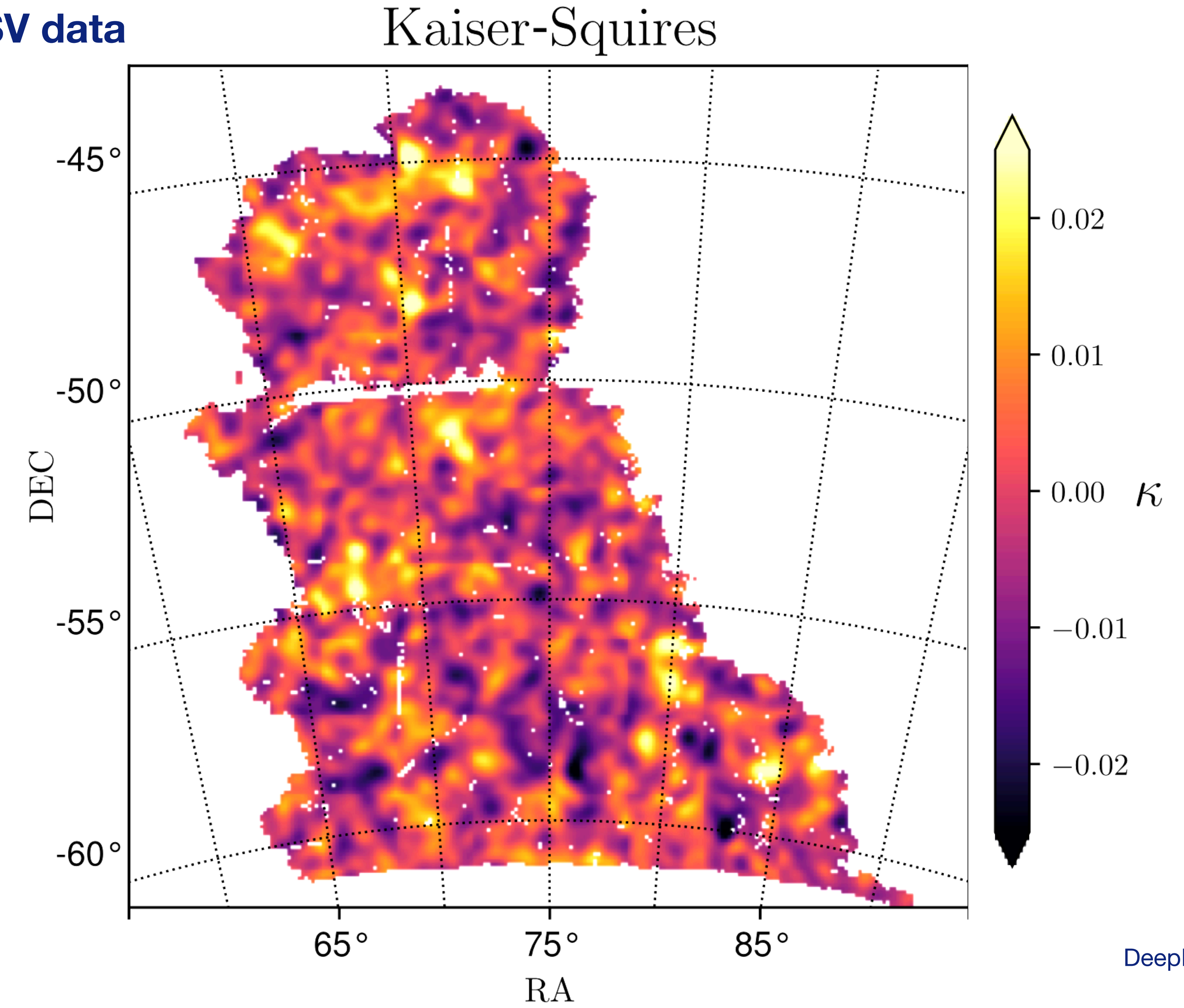
Results

Dark Energy Survey SV data



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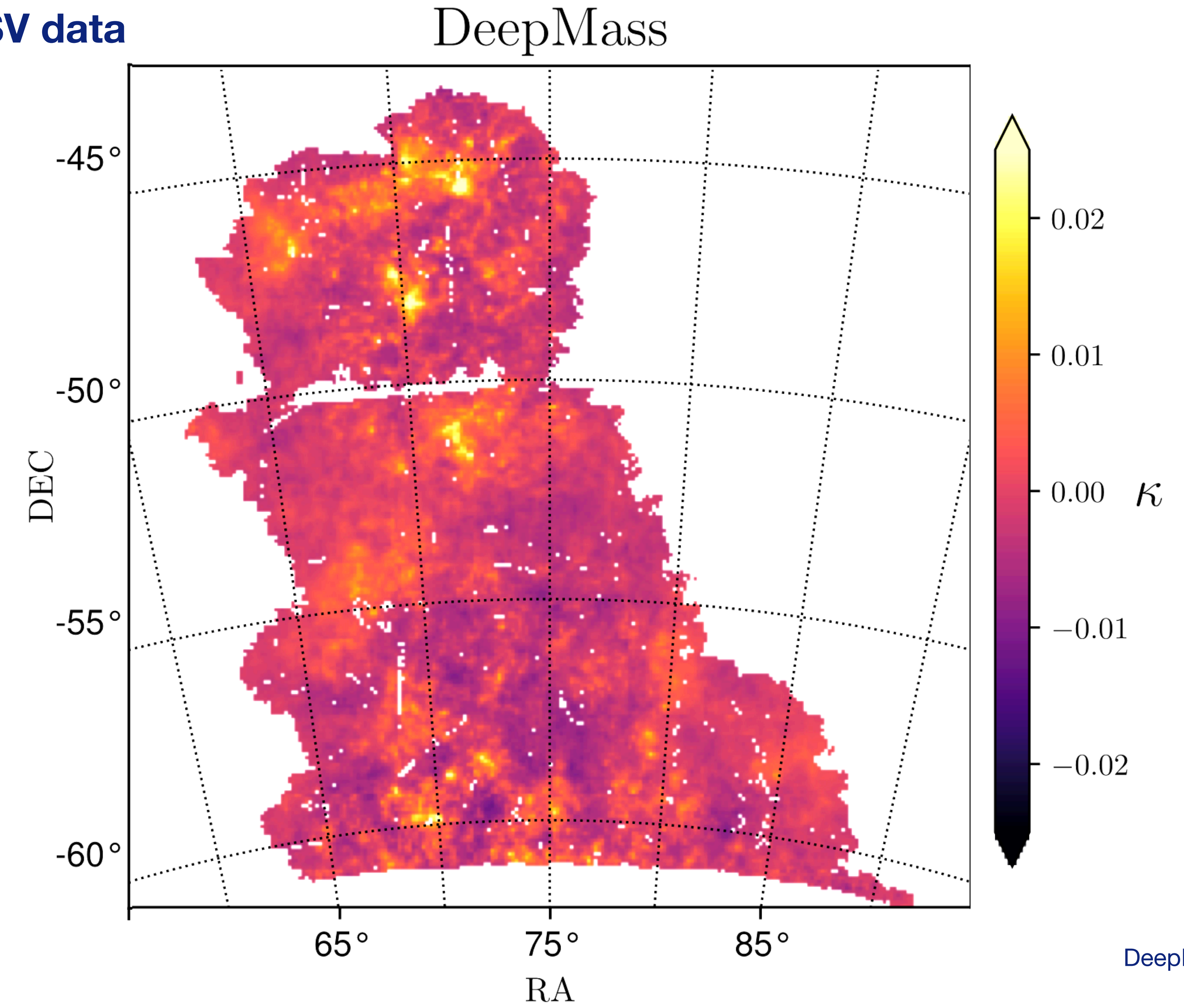
Results

Dark Energy Survey SV data



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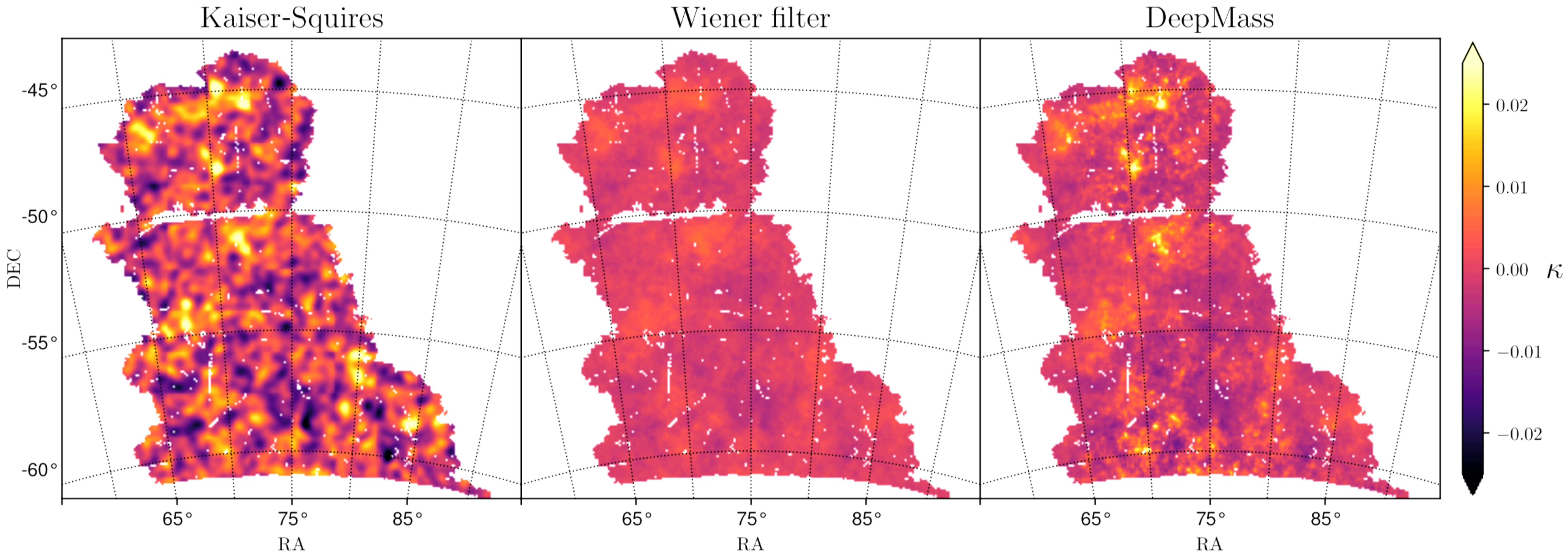

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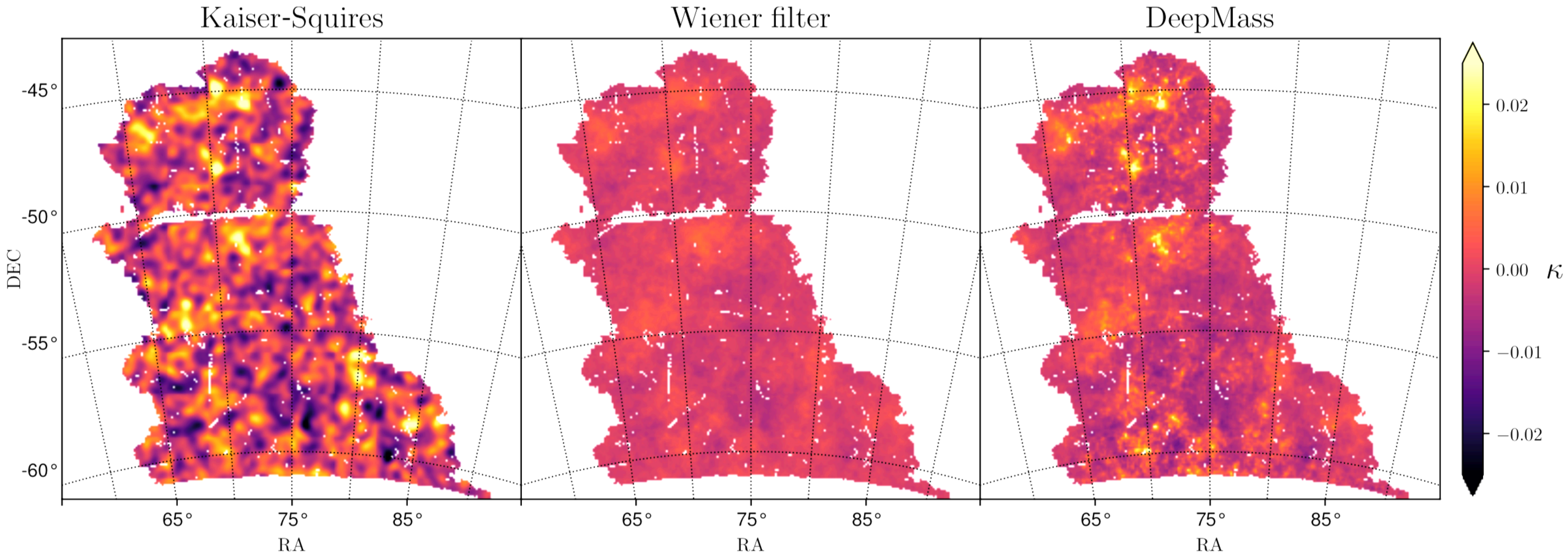

I. Wiener filter is optimal linear MSE filter

II. 8000 sample maps not used for training

III. **DeepMass improves MSE by 11% compared to Wiener**

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04

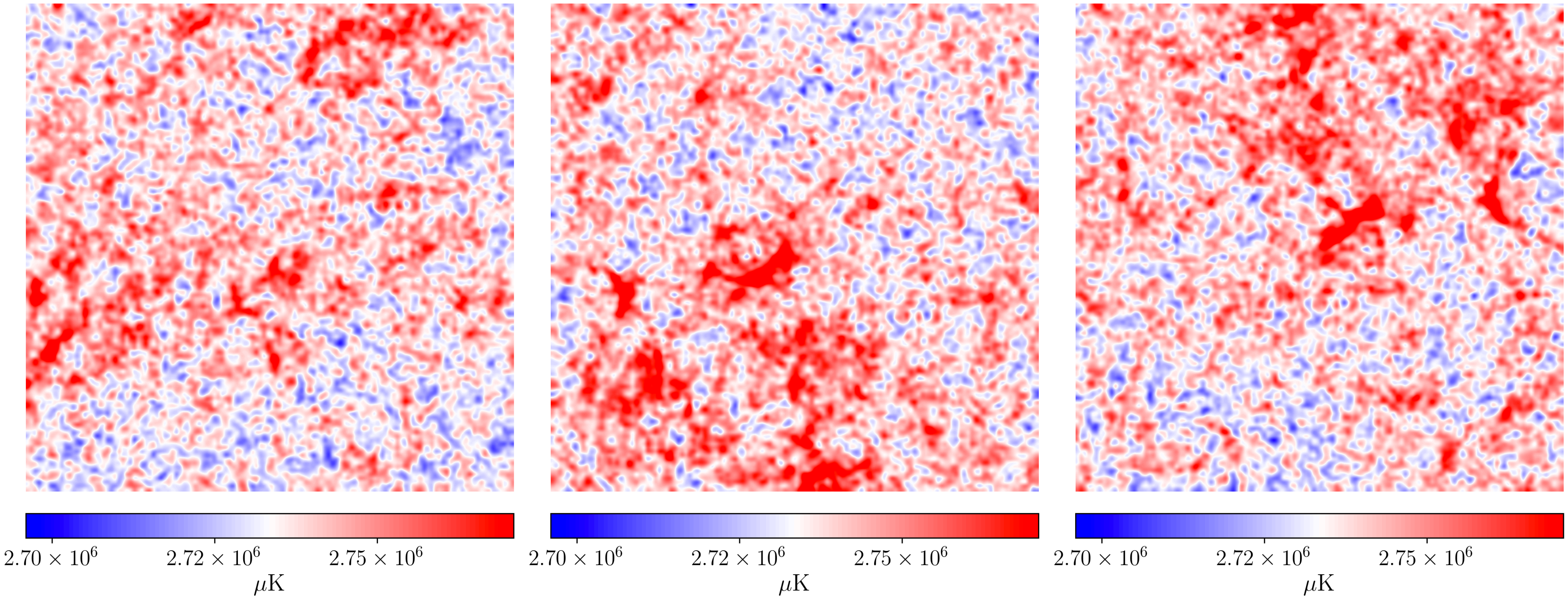
DeepMass and the CMB

(Preliminary)

DeepMass as general tool

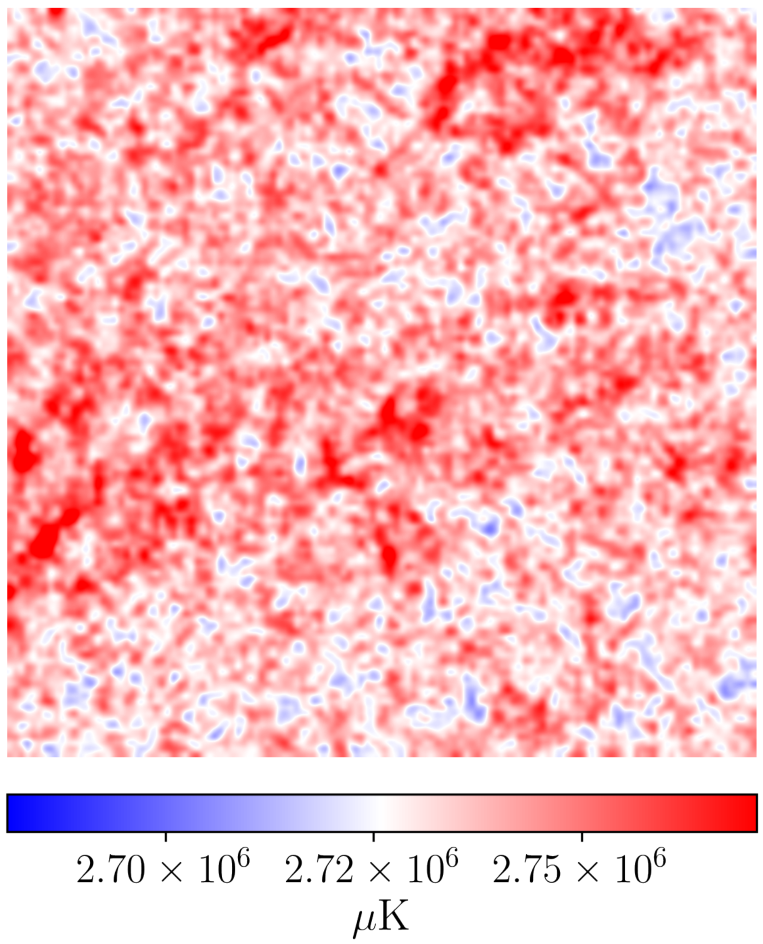
I. If observations can be modelled, DeepMass recovers the signal

II. Example, synthesise CMB foreground data: *(See Francois Boulanger's talk)*



DeepMass: CMB T foreground removal
(preliminary)

Simulated observed data



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DeepMass: CMB T foreground removal
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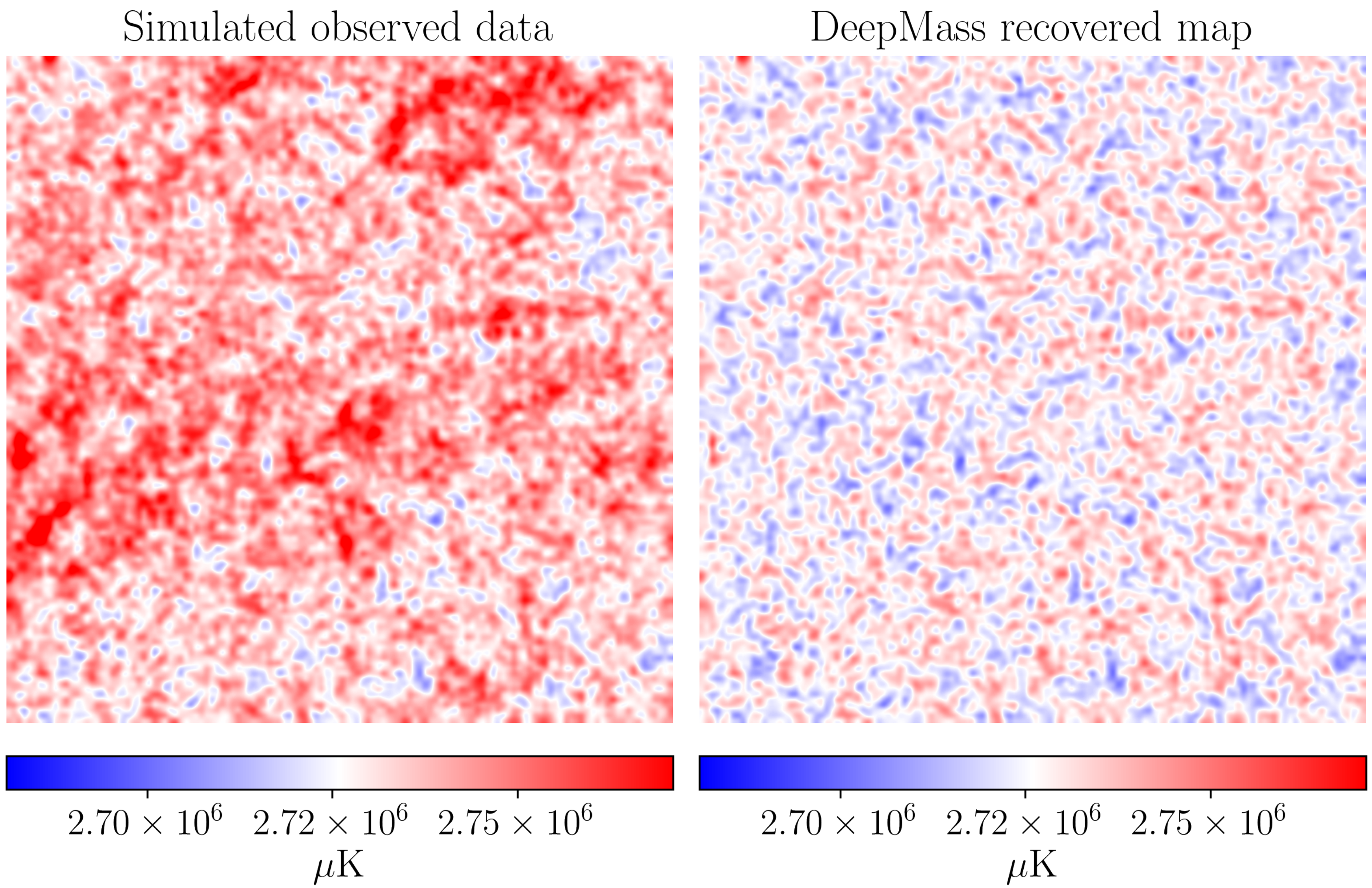

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DeepMass: CMB T foreground removal
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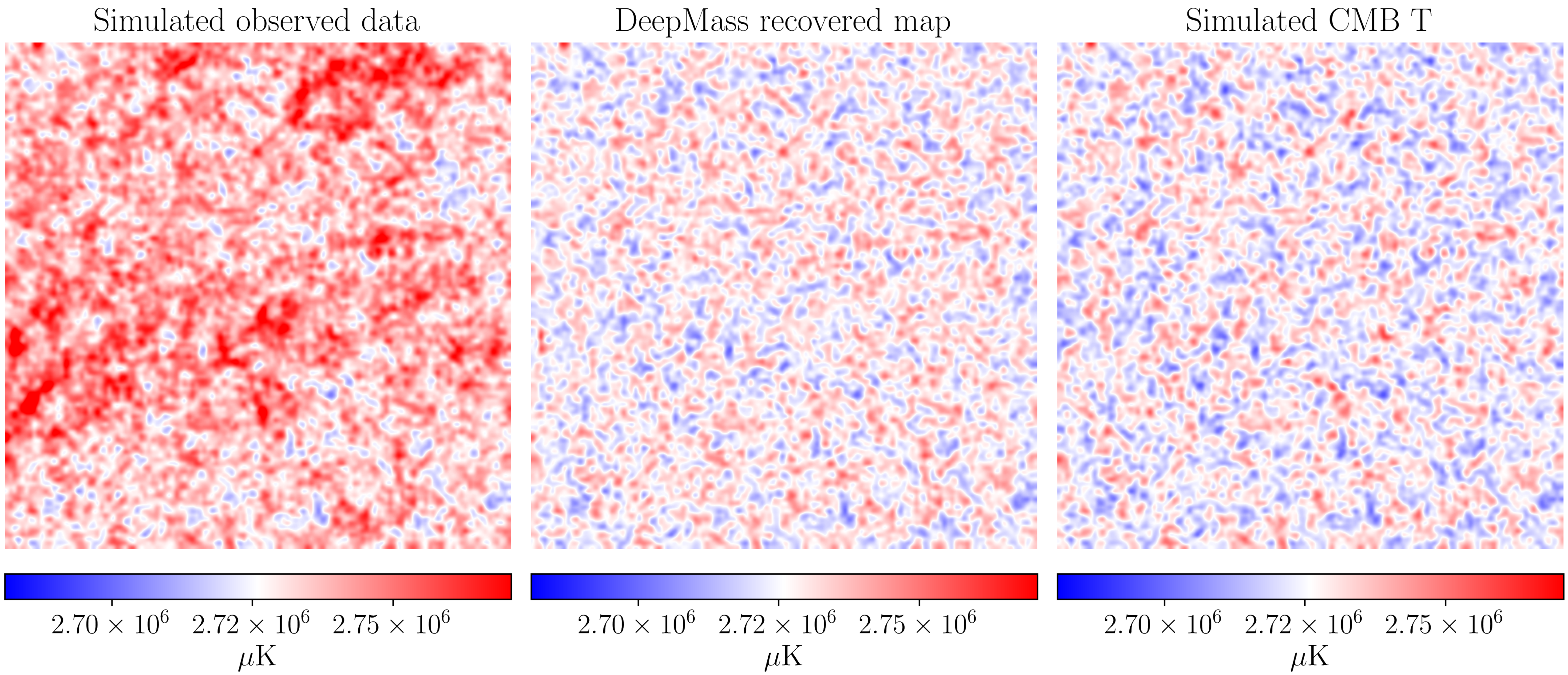

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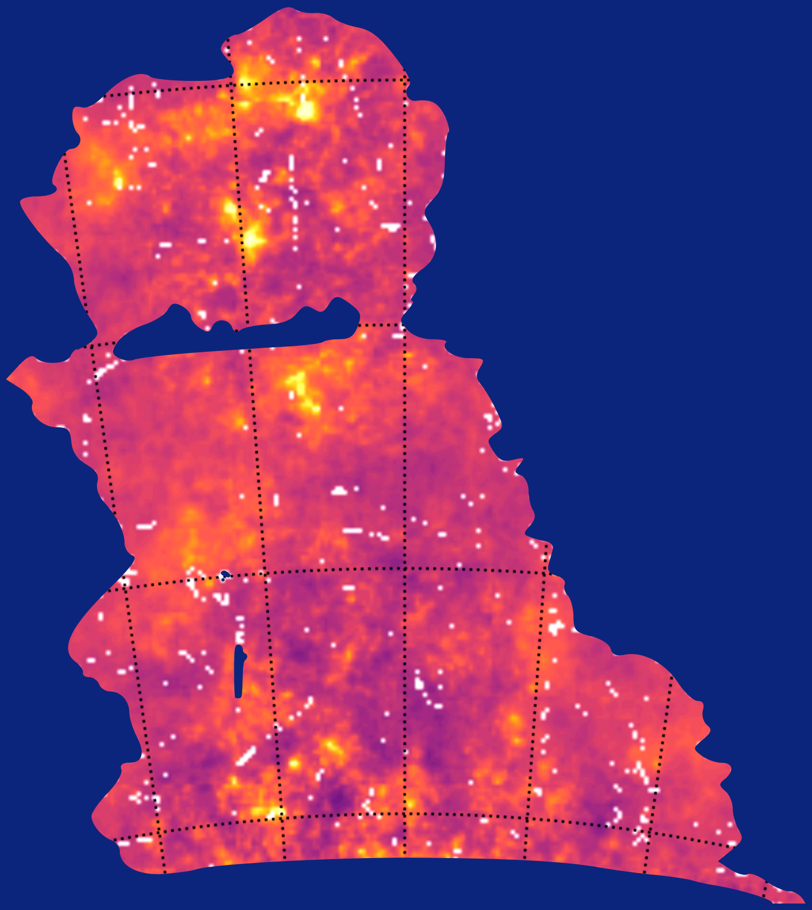
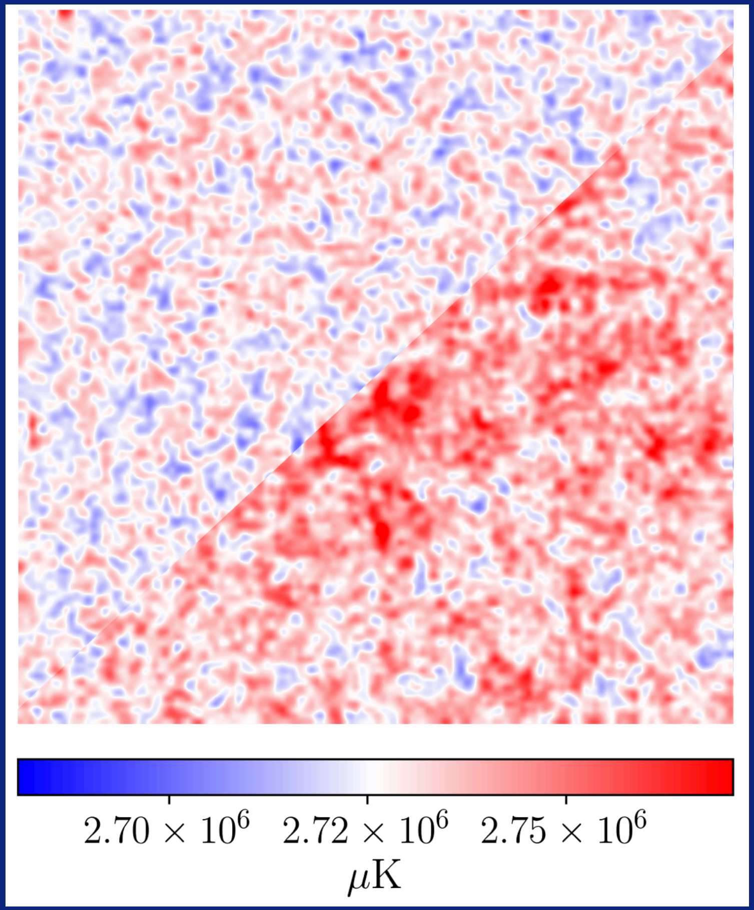
github.com/NiallJeffrey/DeepMass



Merci !



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