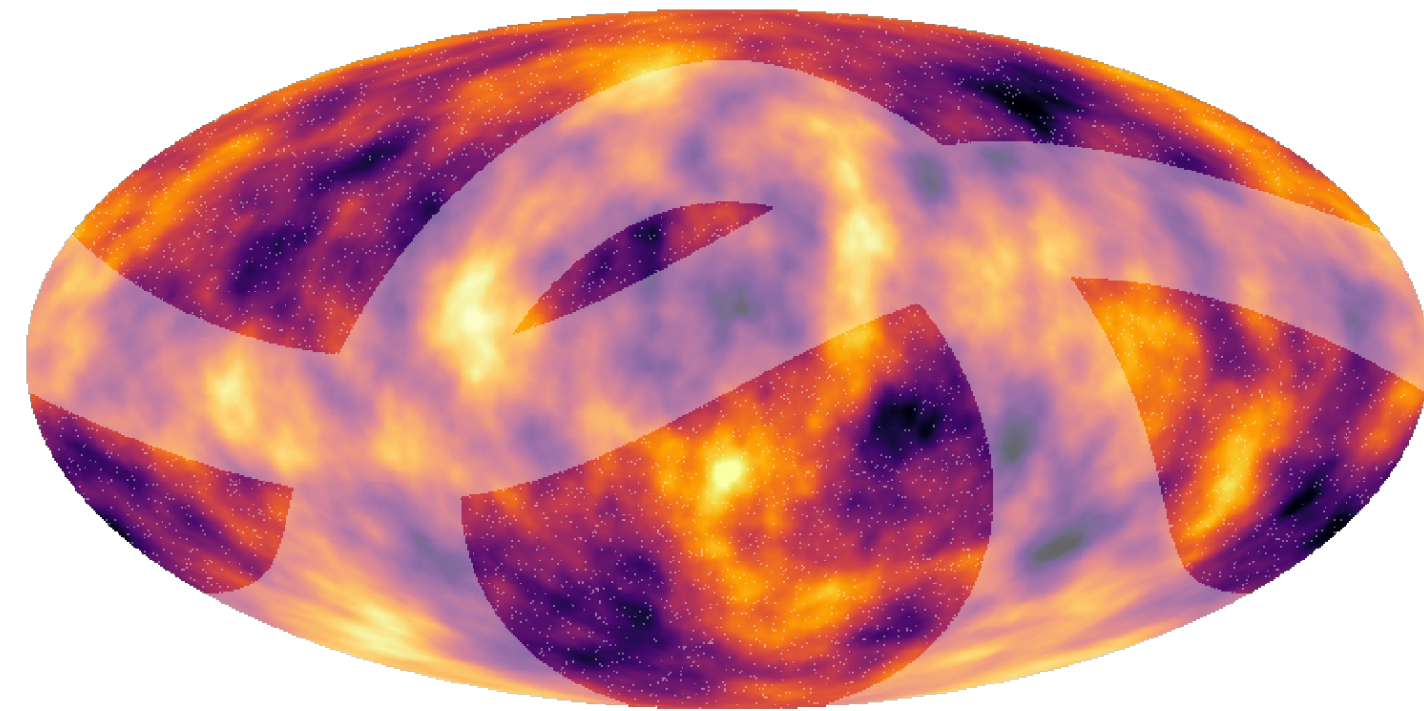


Sellentin,
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Almanac

**Field Level Inference of Full-Sky Cosmological Fields
and Angular Power Spectra**

Dr. Arthur Loureiro @ Statistical Challenges in 21st Century Cosmology
(Oskar Klein Centre, Stockholm University & Imperial College London)

The Almanac Team



Dr Arthur Loureiro
(Also visiting researcher at ICIC)



Prof. Alan Heavens



Prof. Elena Sellentin



Dr. Lorne Whiteway



Prof. Andrew Jaffe



Javier S. Lafaurie



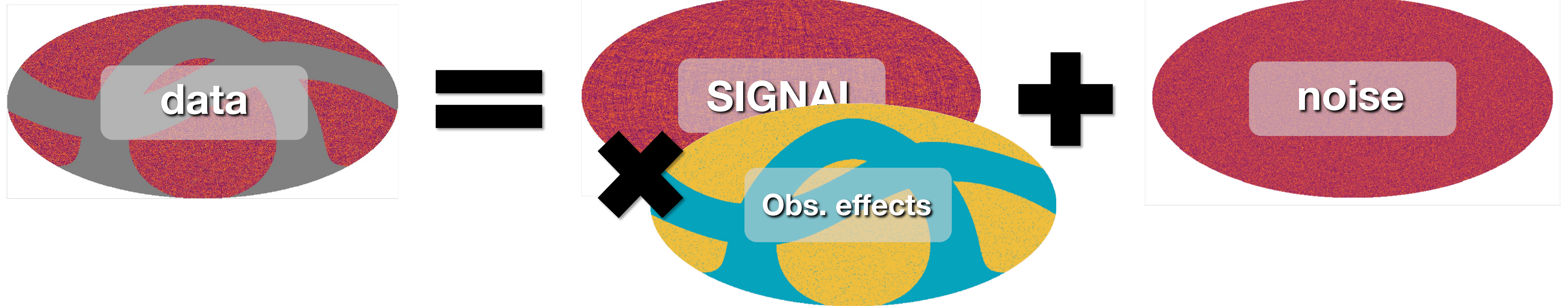
Kutay Nazli



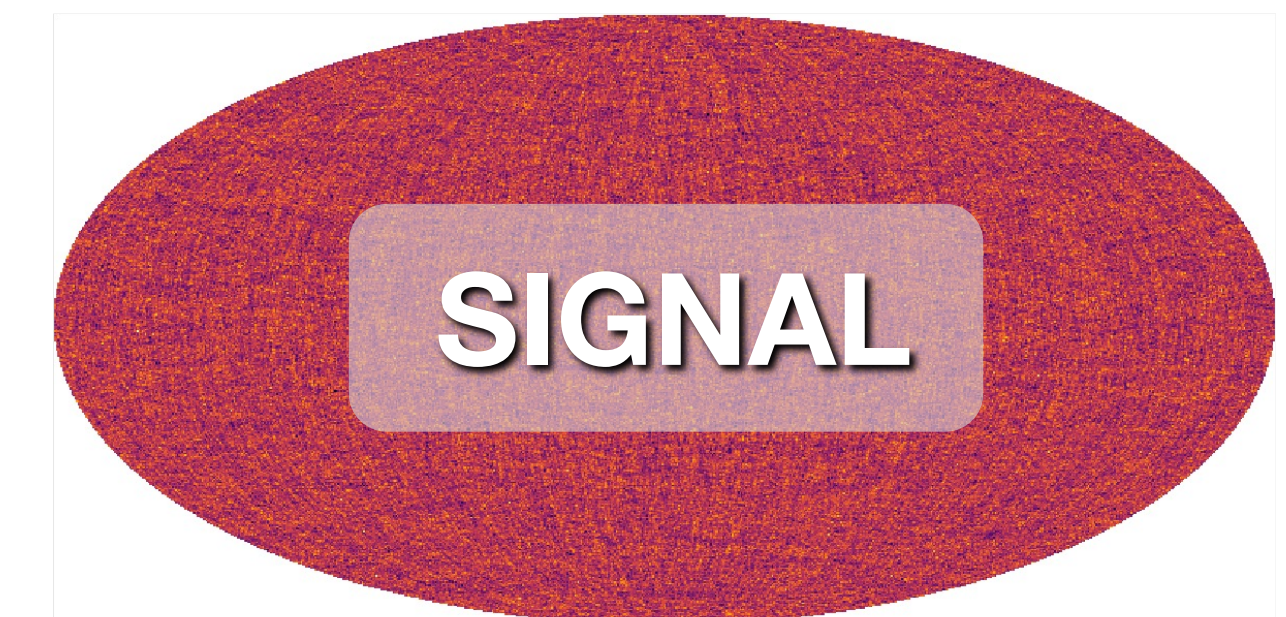
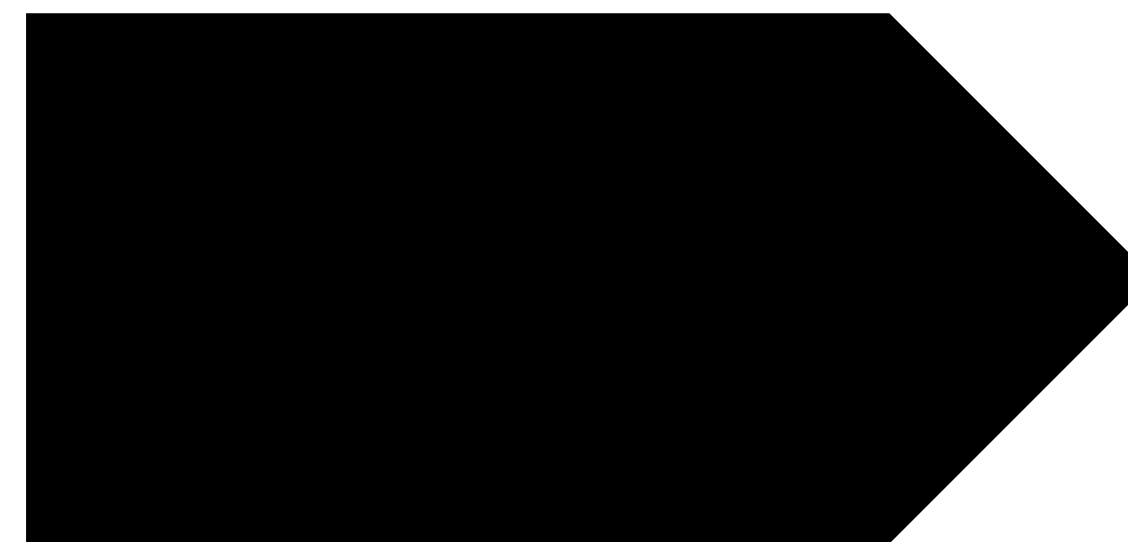
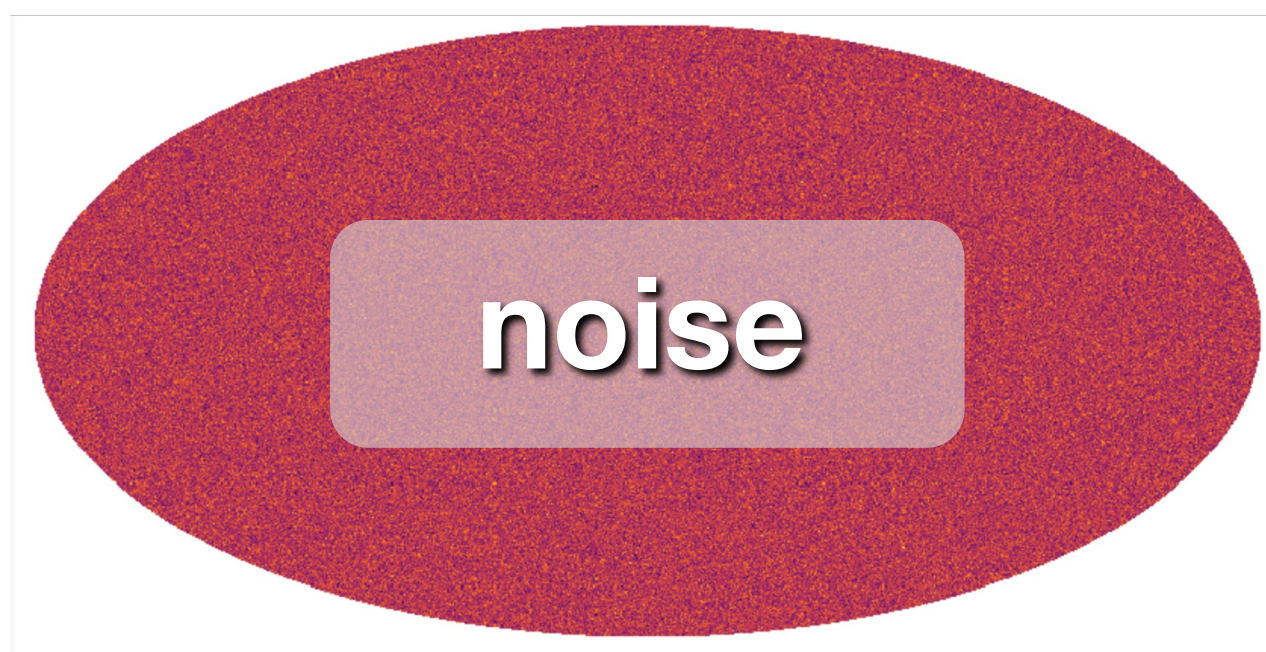
Almanac uses a highly optimised sampler to obtain full-sky, model-independent, de-noised samples for maps of cosmological fields and their angular power spectra.

Real data is incomplete and noisy

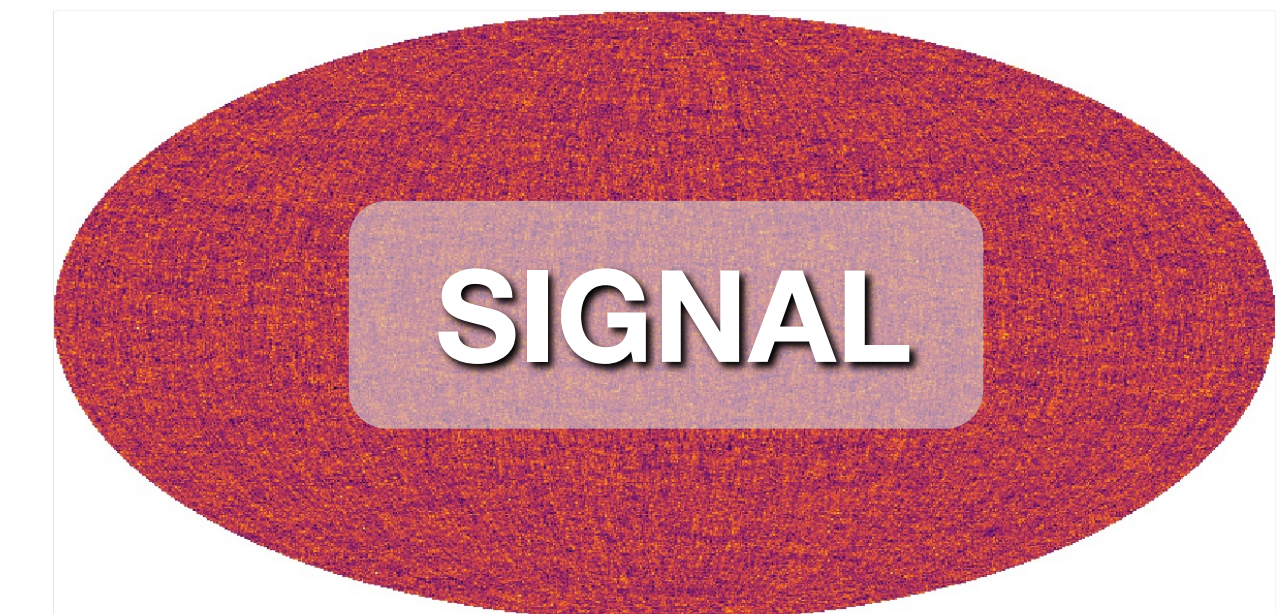
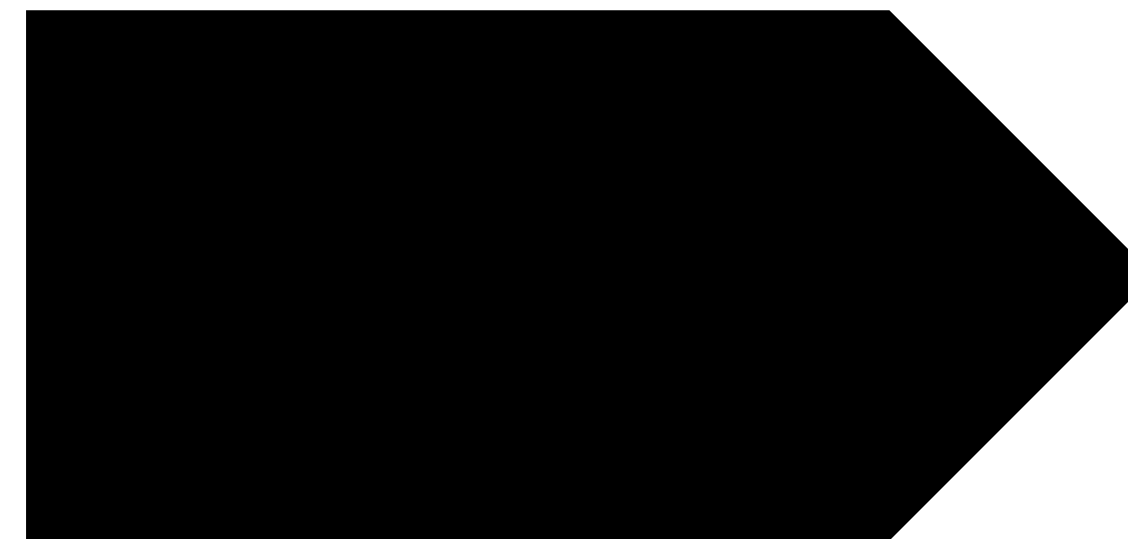
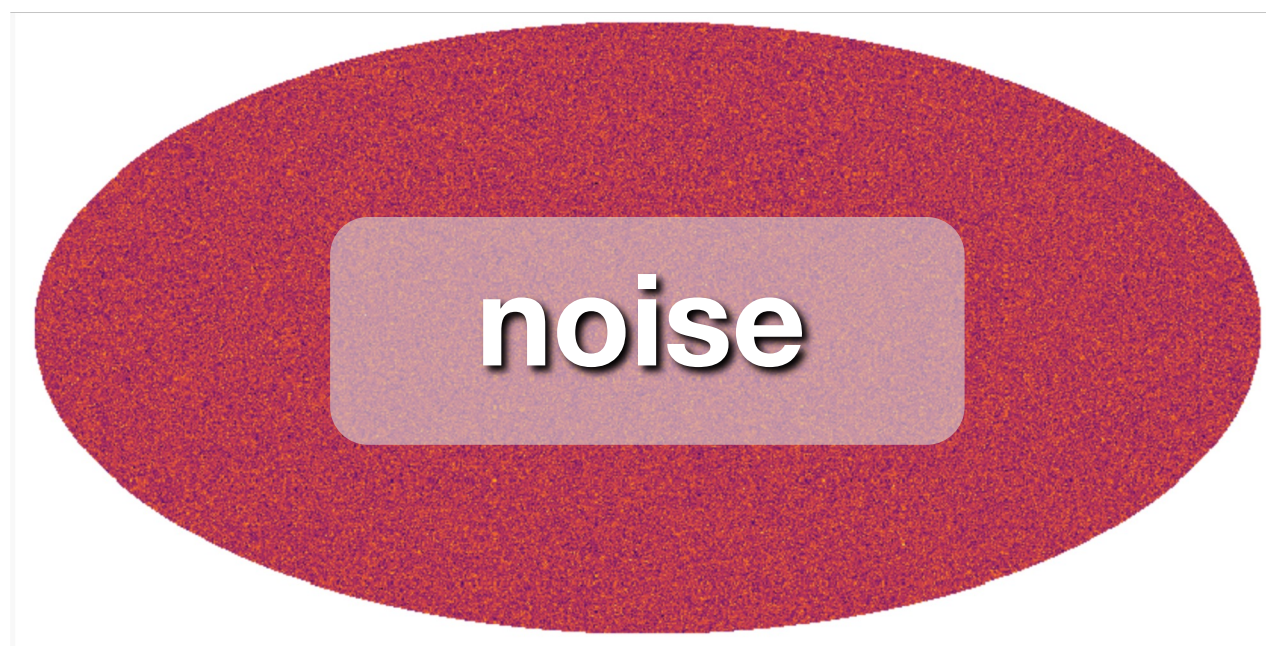
The signal we are interested is affected



Real data is incomplete and noisy



Real data is incomplete and noisy



Almanac can obtain posteriors for

- The denoised full sky signal maps
- The full sky angular power spectra

In a model-independent and unbiased way!

Almanac

Spin-0 and Spin-2 Cosmological Fields

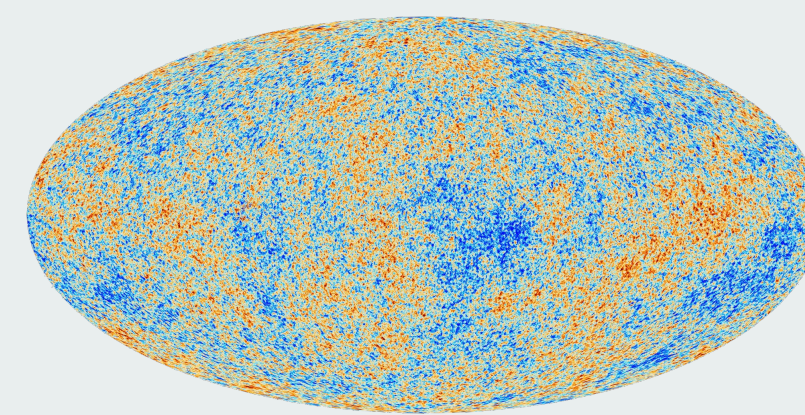
An arbitrary spin- s field can be represented in the basis of spin- s spherical harmonics

$$f(\hat{n}) = \sum_{\ell m} f_{\ell m} {}_s Y_{\ell m}(\hat{n})$$

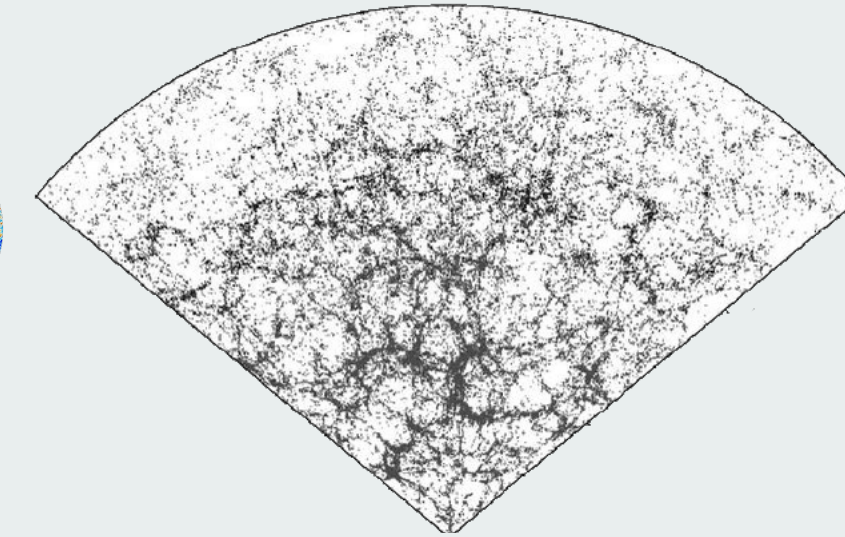
And covariance

$$\mathbf{C} \equiv \langle f_{\ell m} f_{\ell' m'}^* \rangle \delta_{\ell \ell'} \delta_{m m'}$$

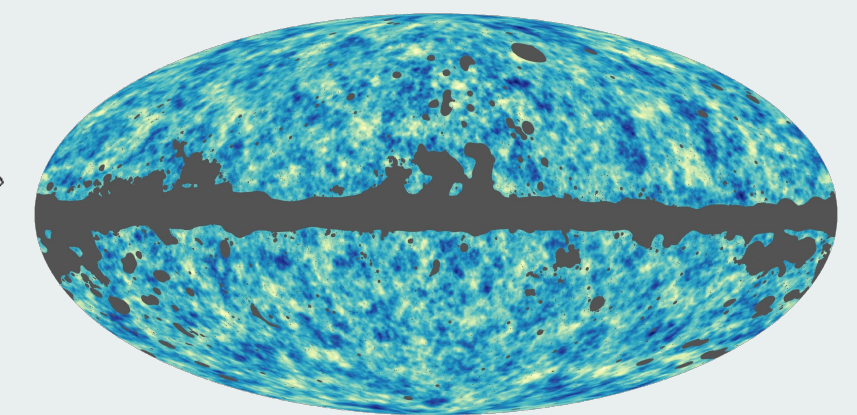
Spin-0 Fields



CMB Temperature

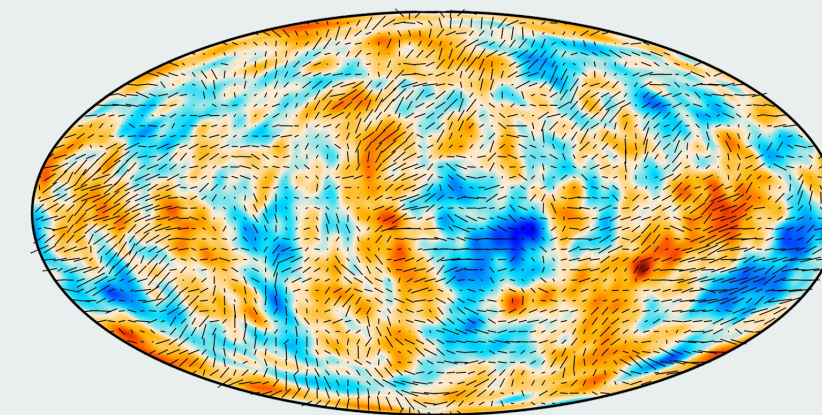


Galaxy Clustering

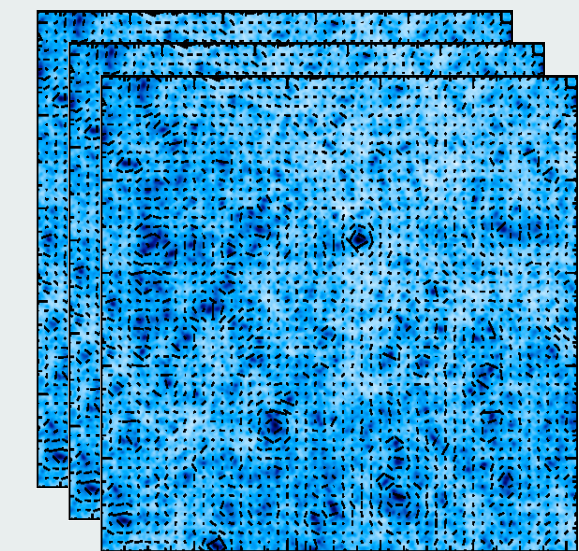


Lensing Convergence

Spin-2 Fields



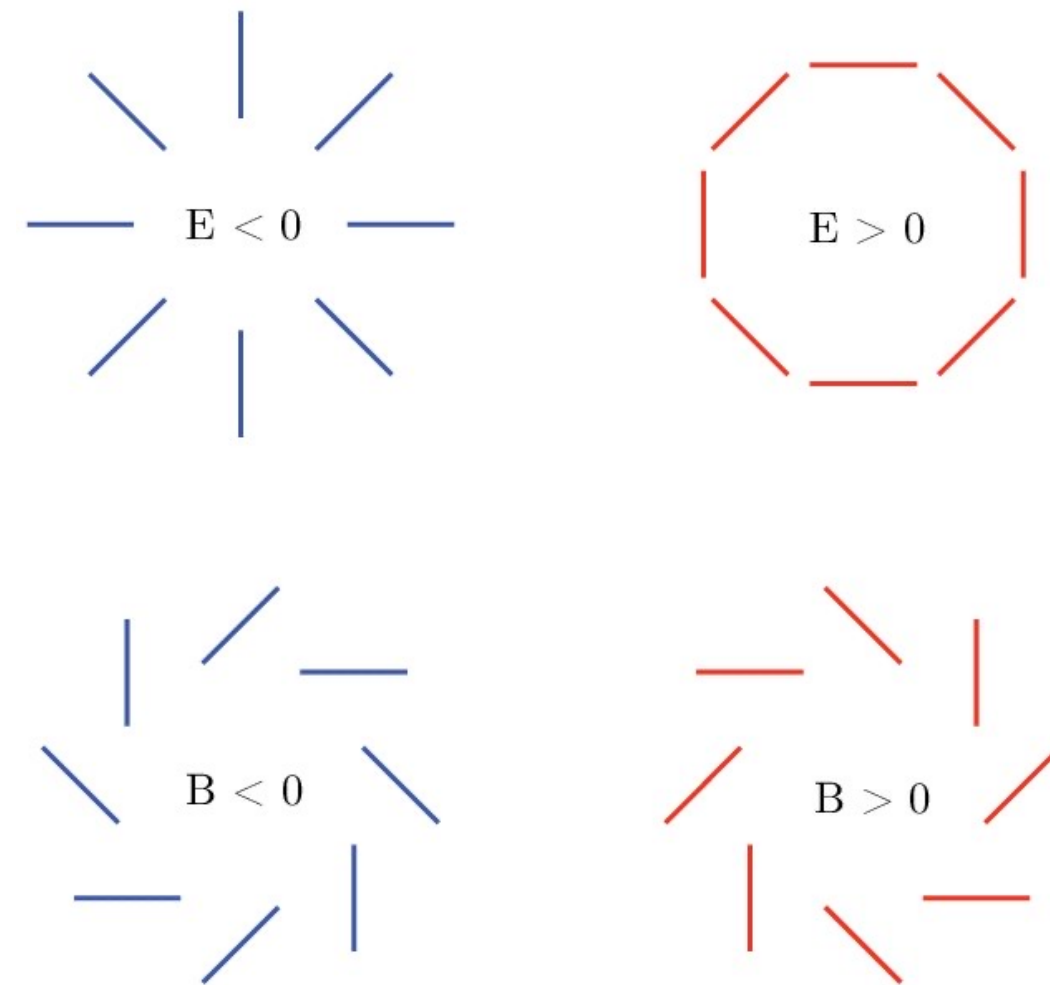
CMB Polarisation



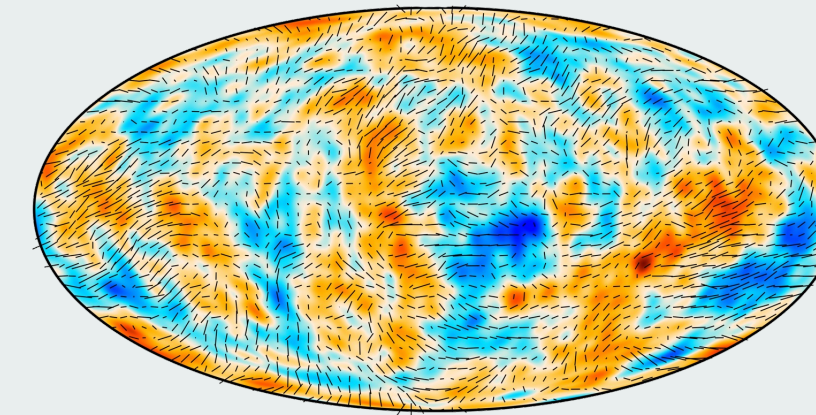
Cosmic Shear

Spin-2 Data

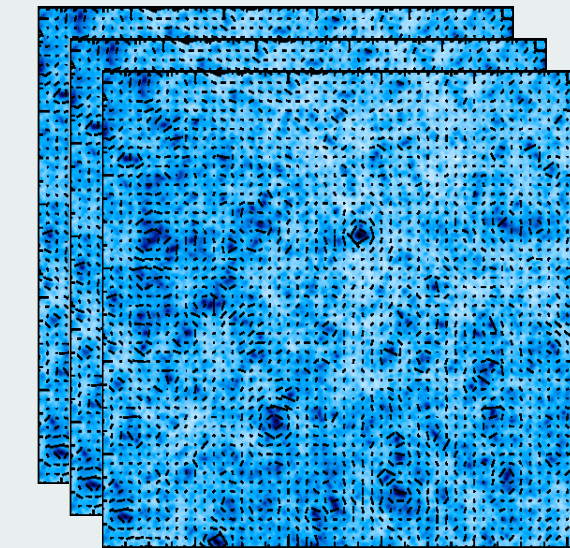
Ambiguous modes due to masking of the data



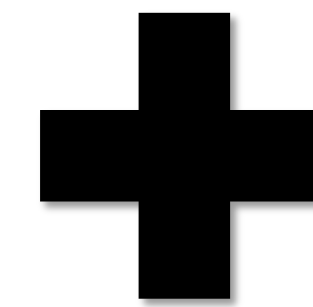
Spin-2 Fields



CMB Polarisation



Cosmic Shear



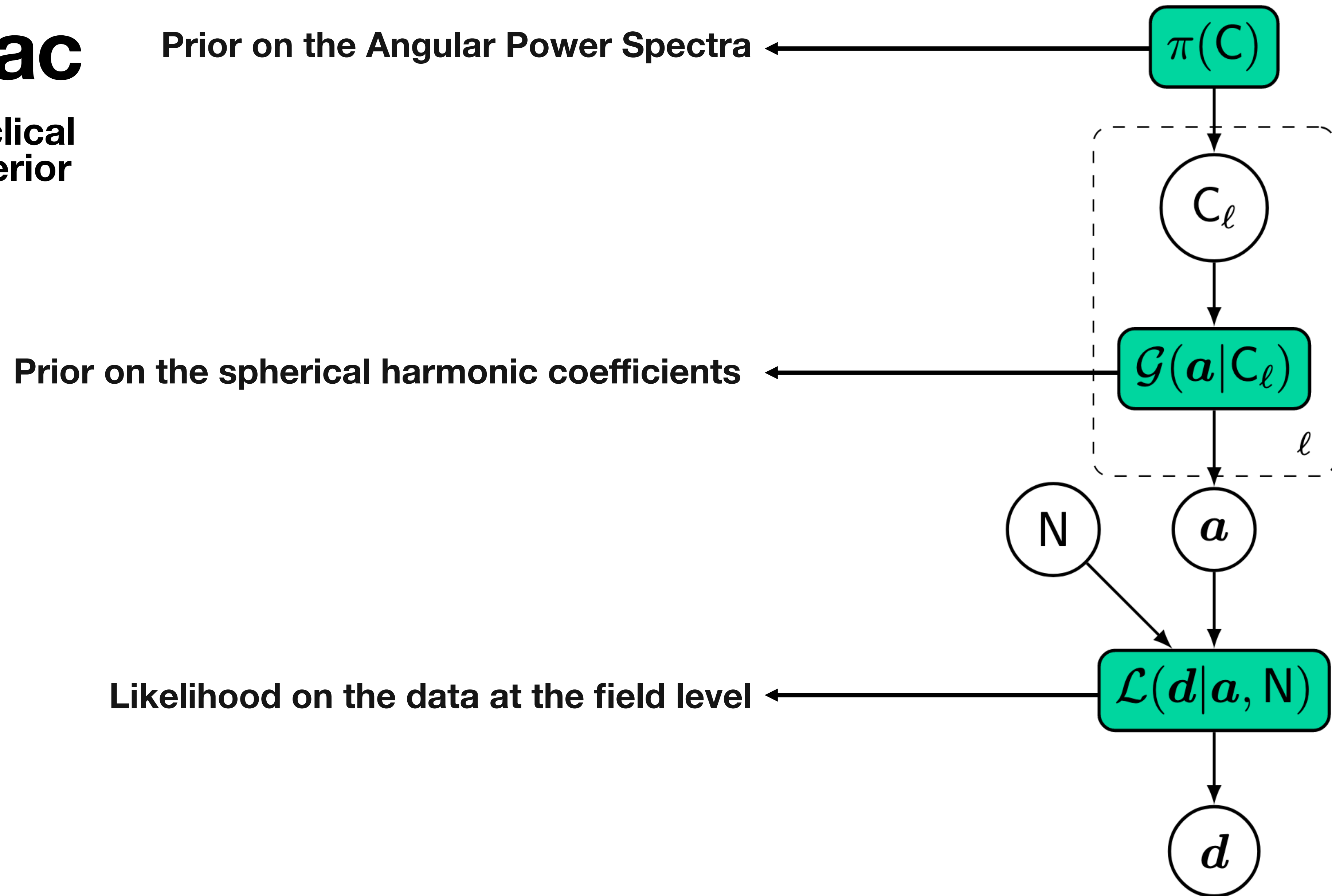
$$\tilde{E}_{\ell m} = \sum_{\ell' m'} (E_{\ell' m'} W_{\ell \ell' m m'}^+ + B_{\ell' m'} W_{\ell \ell' m m'}^-)$$

$$\tilde{B}_{\ell m} = \sum_{\ell' m'} (B_{\ell' m'} W_{\ell \ell' m m'}^+ - E_{\ell' m'} W_{\ell \ell' m m'}^-),$$

Lewis, Challinor & Turok, 2002

Almanac

Directed Acyclical Graph & posterior



Almanac

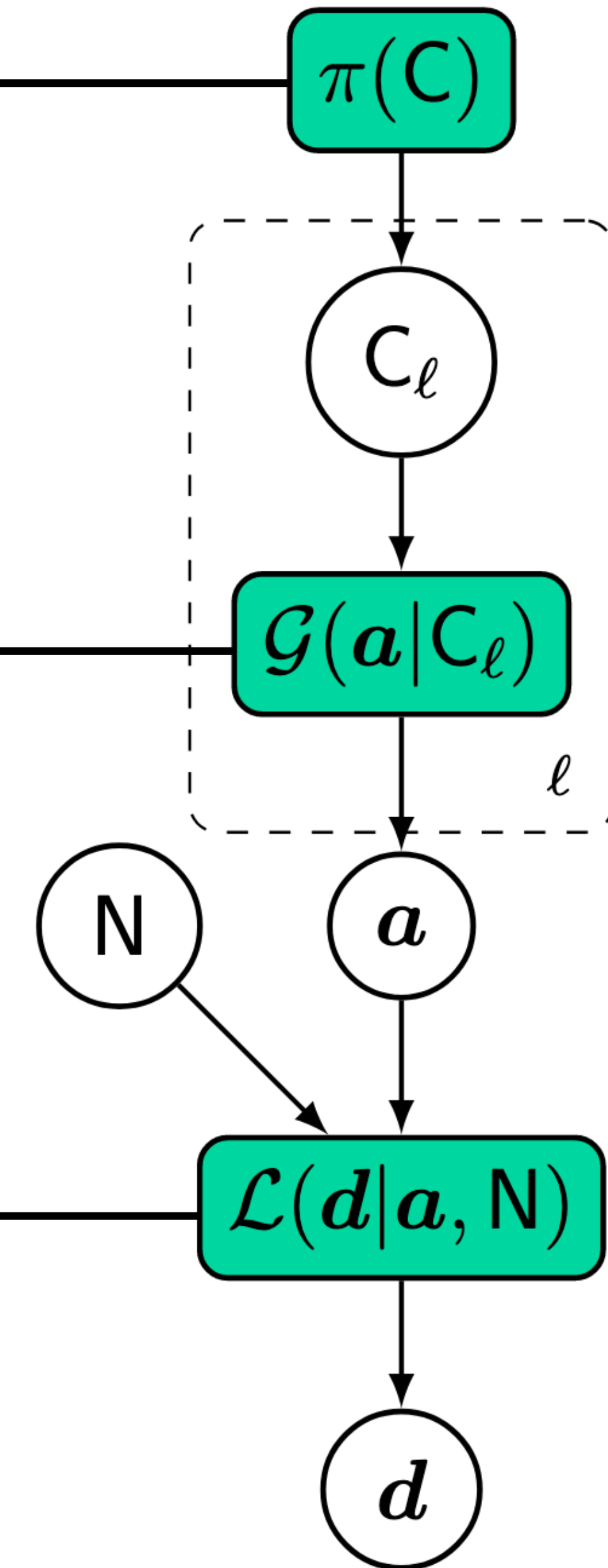
Directed Acyclical Graph & posterior

$$\pi(\mathbf{C}) = |\mathbf{C}|^q$$

$$\mathcal{G}(\mathbf{a}|\mathbf{C}) = \frac{1}{\sqrt{|2\pi\mathbf{C}|}} \exp\left(-\frac{1}{2}\mathbf{a}^T\mathbf{C}^{-1}\mathbf{a}\right)$$

$$\mathcal{L}(\mathbf{d}|\mathbf{a}, \mathbf{N}) \propto \exp\left[-\frac{1}{2}(\mathbf{d} - \mathbf{Y}\mathbf{a})^T\mathbf{N}^{-1}(\mathbf{d} - \mathbf{Y}\mathbf{a})\right]$$

Posterior: $\mathcal{P}(\mathbf{C}, \mathbf{a}|\mathbf{d}, \mathbf{N}) \propto \mathcal{L}(\mathbf{d}|\mathbf{a}, \mathbf{N})\mathcal{G}(\mathbf{a}|\mathbf{C})\pi(\mathbf{C})$



Almanac

Directed Acyclical Graph & posterior

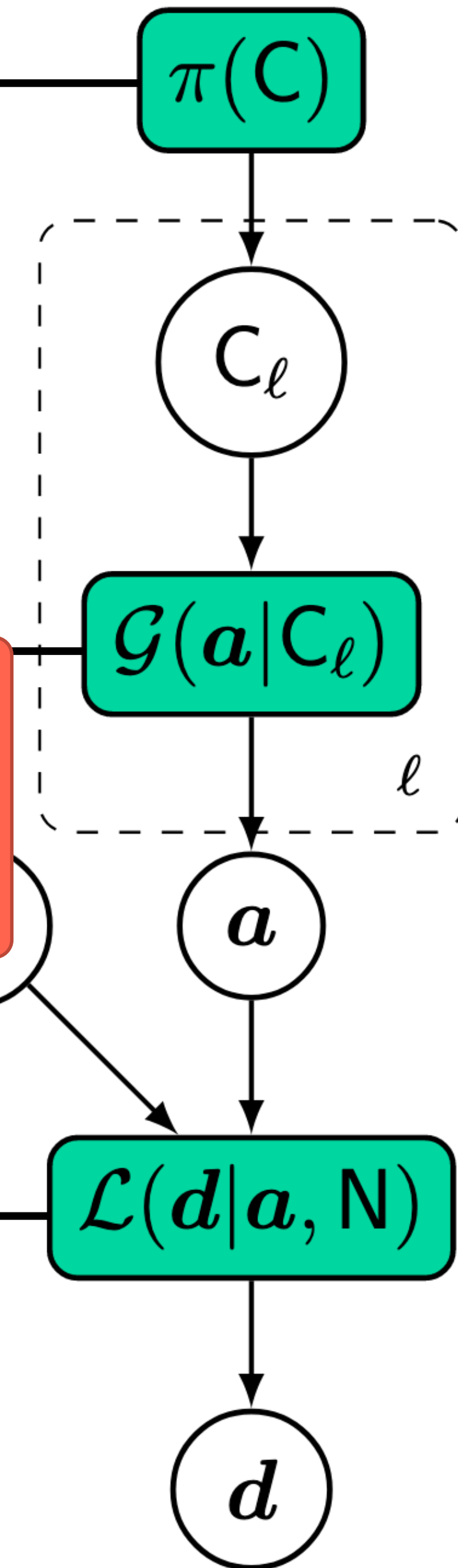
$$\pi(\mathbf{C}) = |\mathbf{C}|^q$$

$$\mathcal{G}(\mathbf{a}|\mathbf{C}) = \prod_{\ell=1}^L \mathcal{G}(\mathbf{a}_\ell | \mathbf{C}_\ell)$$

Gaussian Prior DOES NOT mean a Gaussian posterior!!!

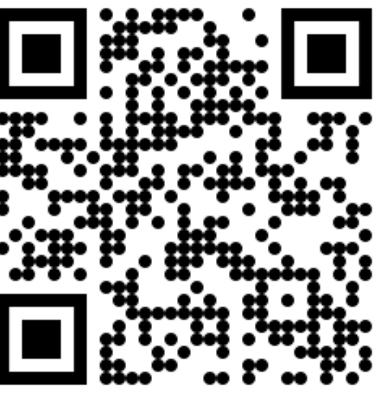
$$\mathcal{L}(\mathbf{d}|\mathbf{a}, \mathbf{N}) \propto \exp \left[-\frac{1}{2} (\mathbf{d} - \mathbf{Y}\mathbf{a})^T \mathbf{N}^{-1} (\mathbf{d} - \mathbf{Y}\mathbf{a}) \right]$$

Posterior: $\mathcal{P}(\mathbf{C}, \mathbf{a}|\mathbf{d}, \mathbf{N}) \propto \mathcal{L}(\mathbf{d}|\mathbf{a}, \mathbf{N}) \mathcal{G}(\mathbf{a}|\mathbf{C}) \pi(\mathbf{C})$

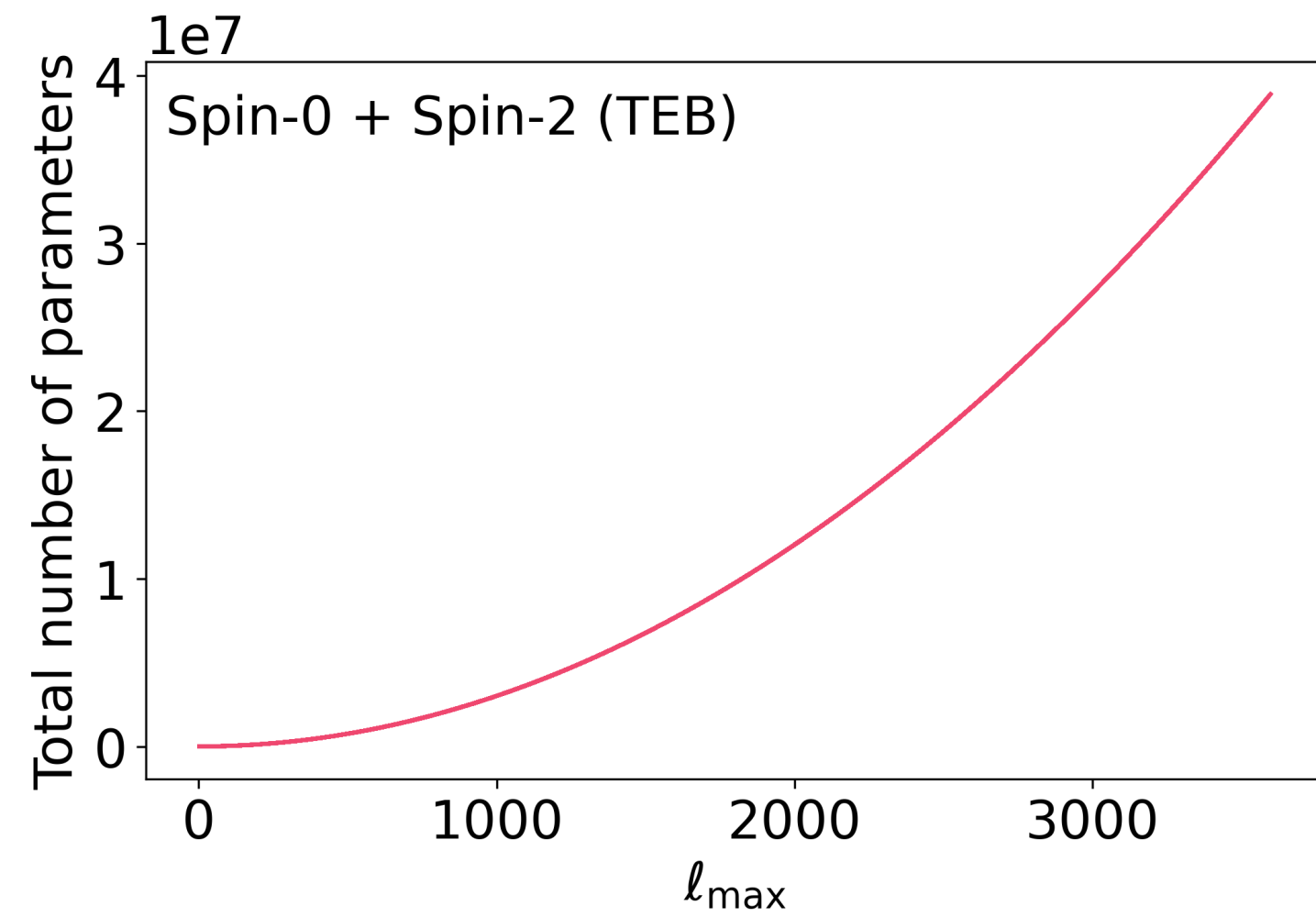


Almanac

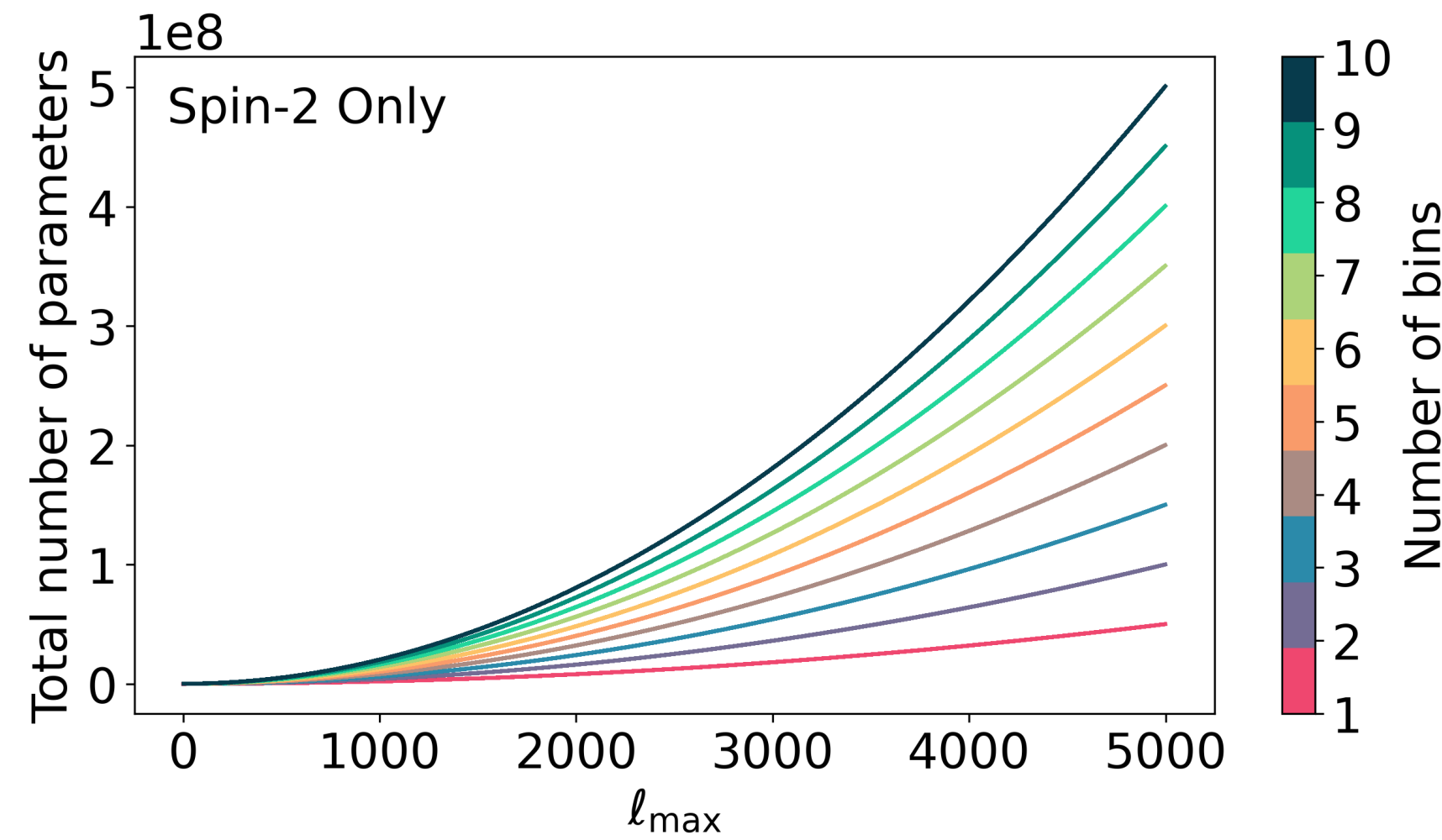
Number of free parameters



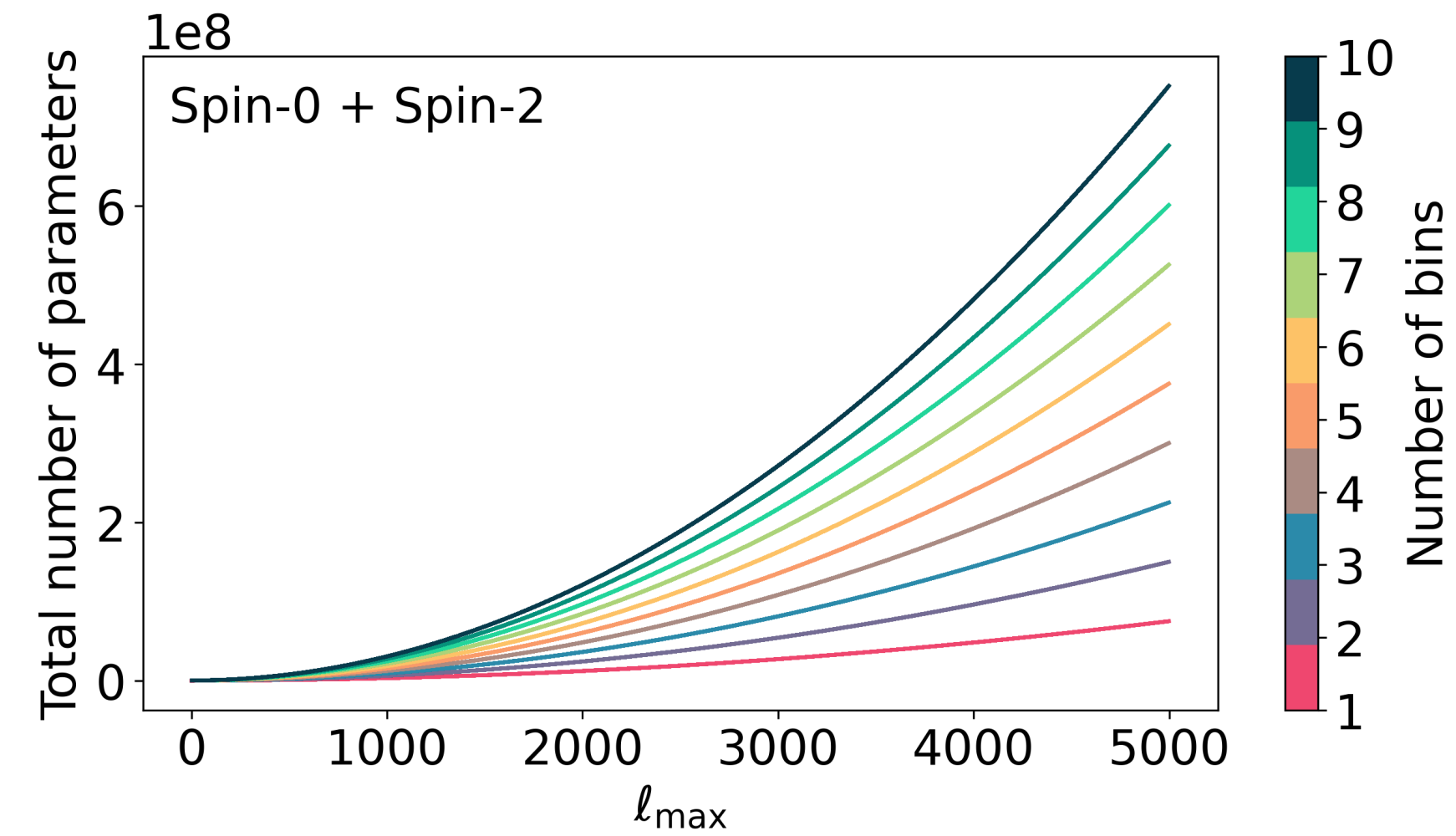
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Loureiro et. al, 2023



CMB Temperature + Polarisation



Stage-IV Cosmic Shear

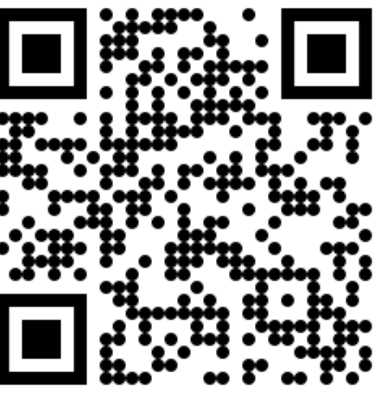


Stage-IV 3x2pt

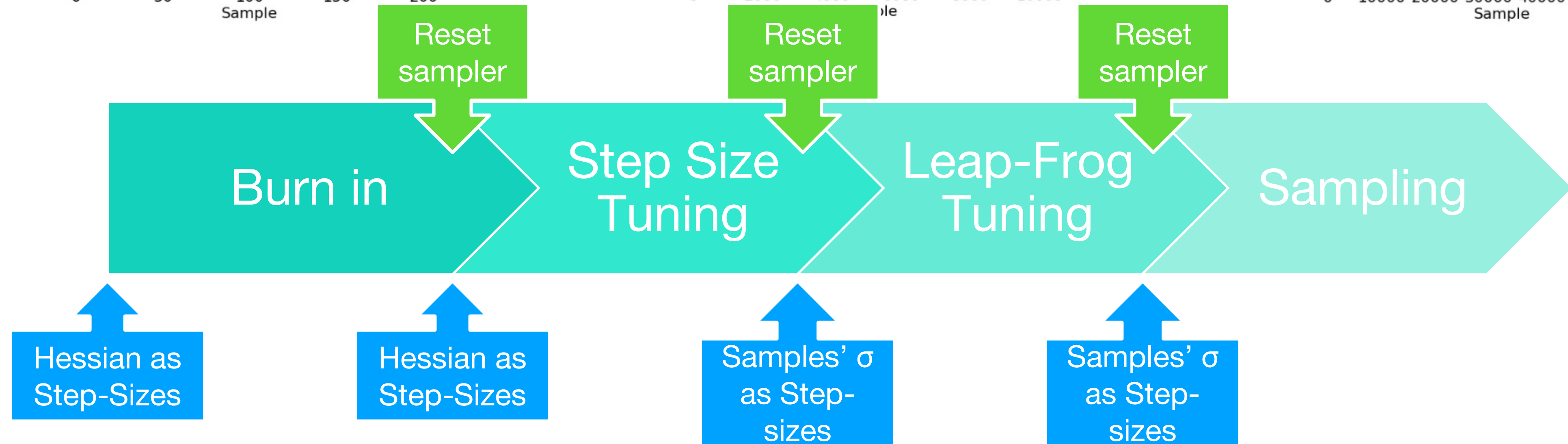
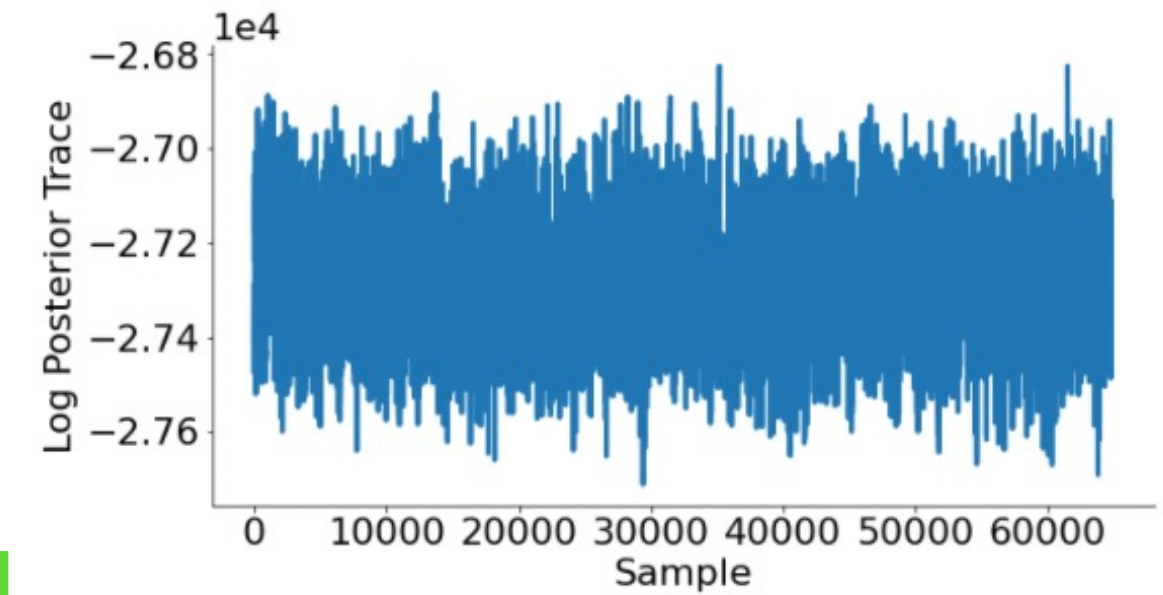
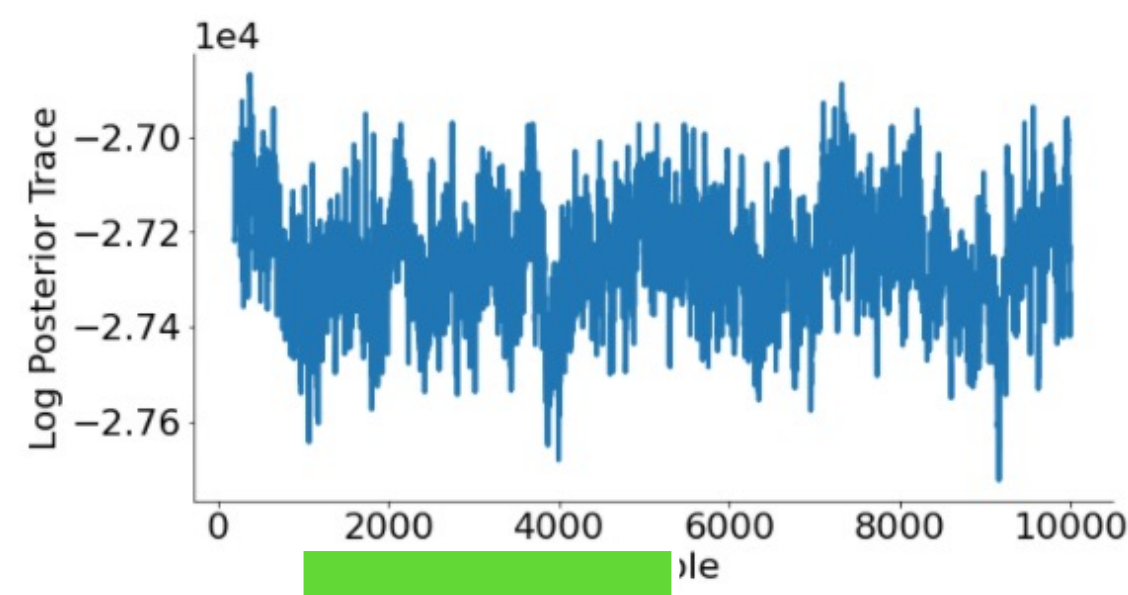
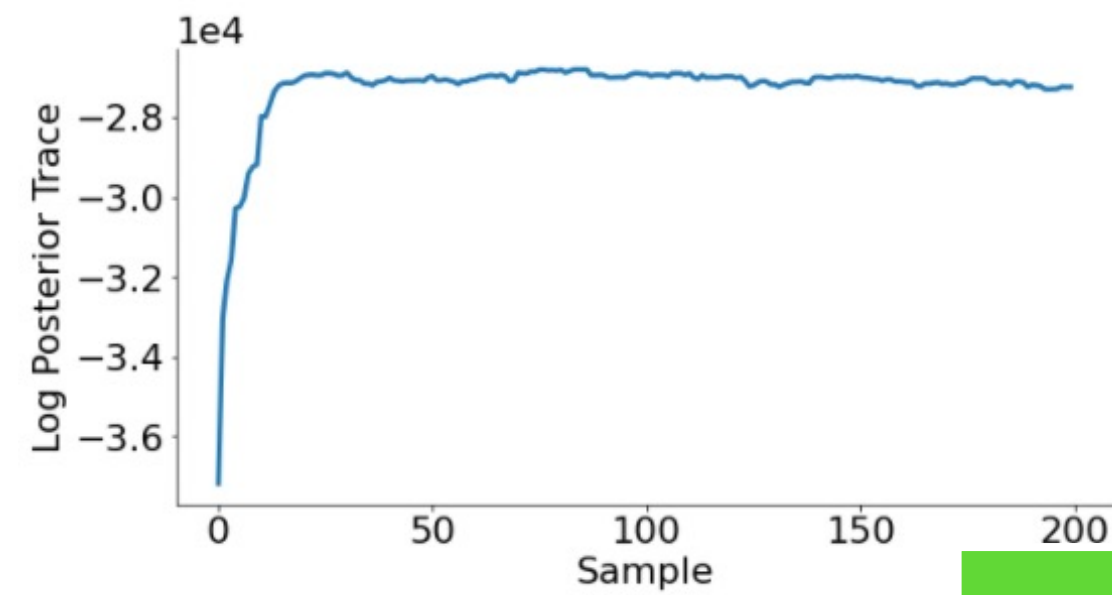
Our current state-of-the-art run has 16.8 Million free parameters!

Tuned HMC

Three phase tuning



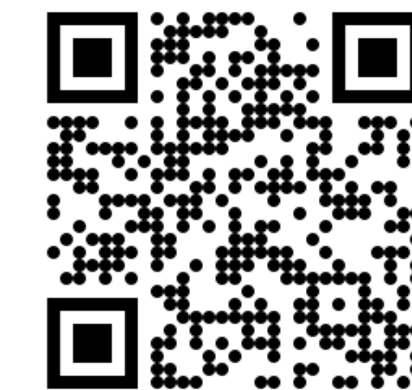
Sellentin,
Loureiro et. al, 2023



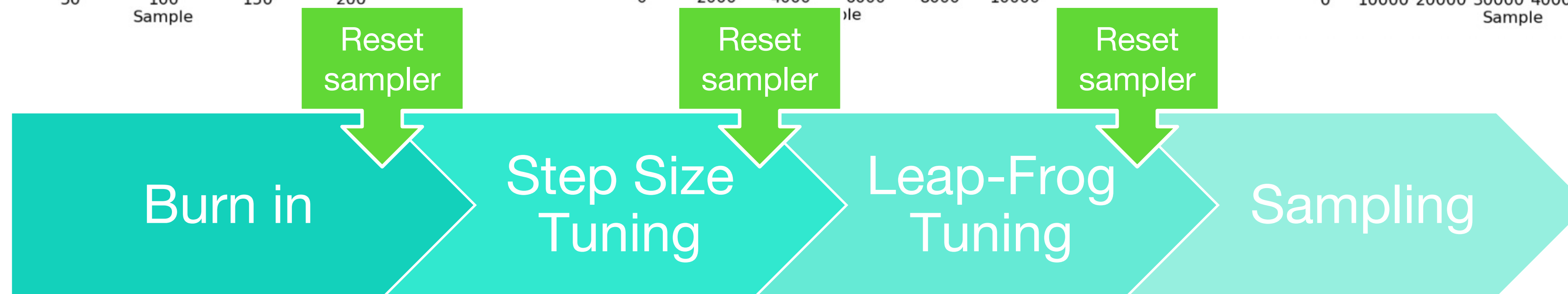
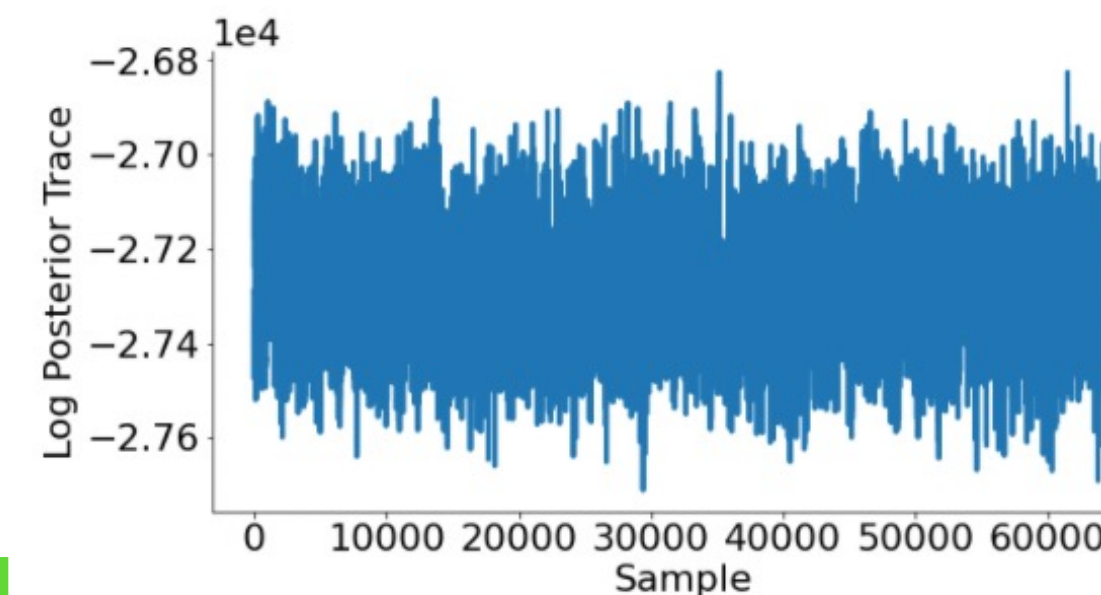
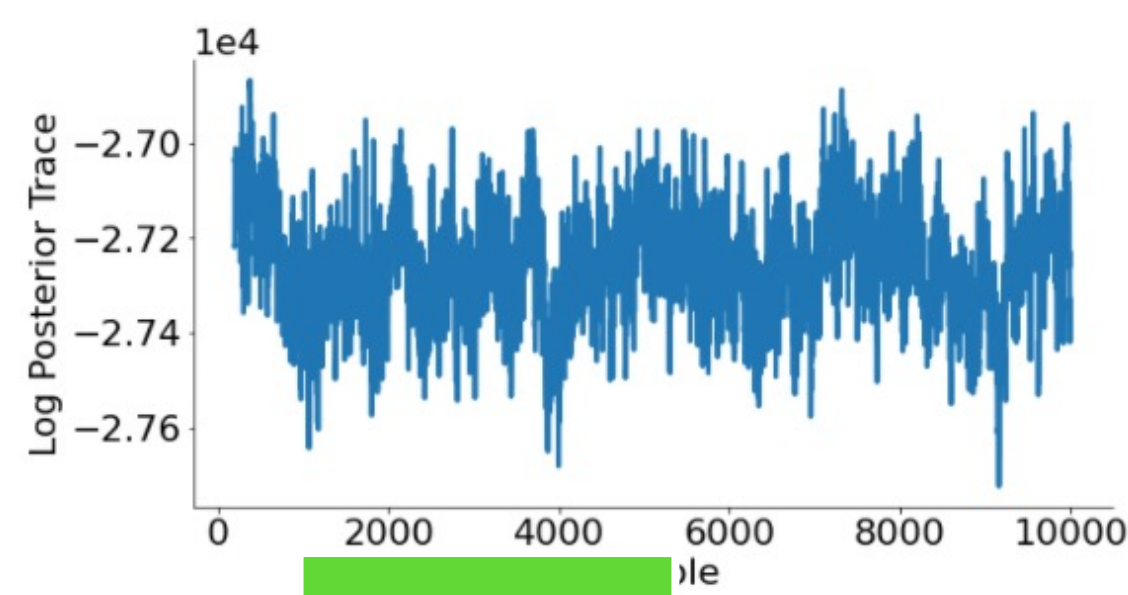
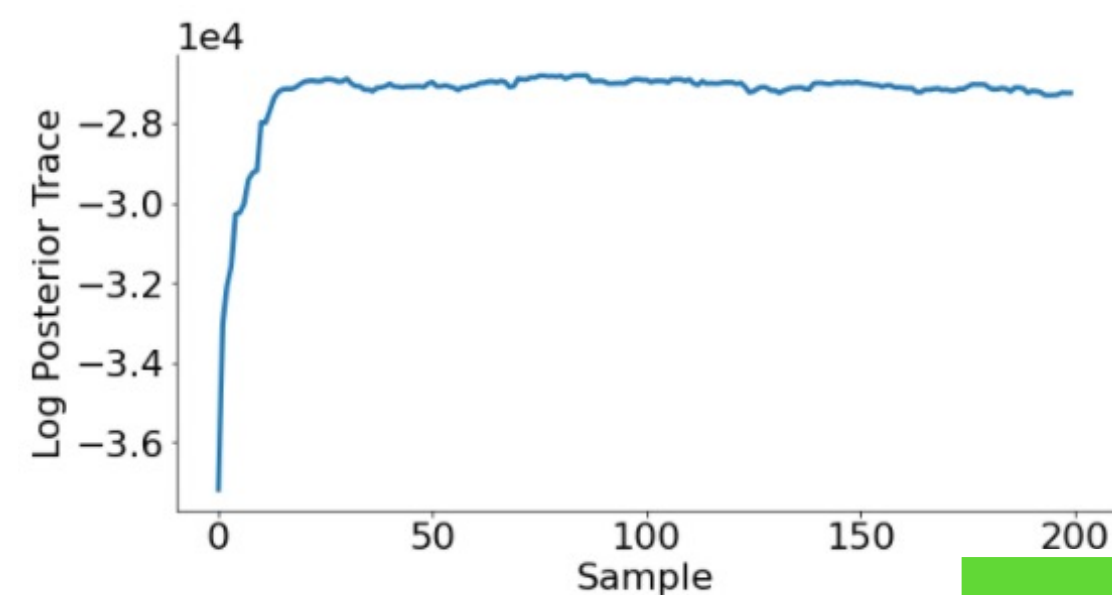
$$\mathcal{E} = \eta \left(\frac{\partial^2 \psi}{\partial \mathbf{x}^2} \right)^{-1/2}$$

Tuned HMC

Three phase tuning



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Hessian as
Step-Sizes

Hessian as
Step-Sizes

Samples' σ
as Step-
sizes

Samples' σ
as Step-
sizes

$$\mathcal{E} = \eta \left(\frac{\partial^2 \psi}{\partial \mathbf{x}^2} \right)^{-1/2}$$

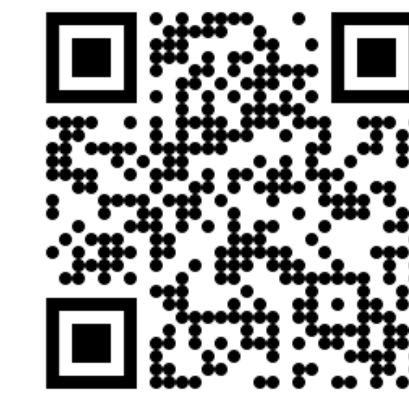


Prof. Elena Sellentin

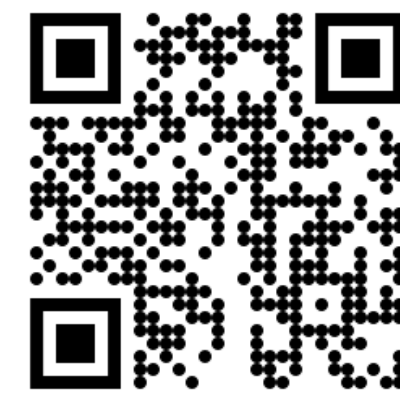


Dr. Lorne Whiteway

Coordinate System comparison

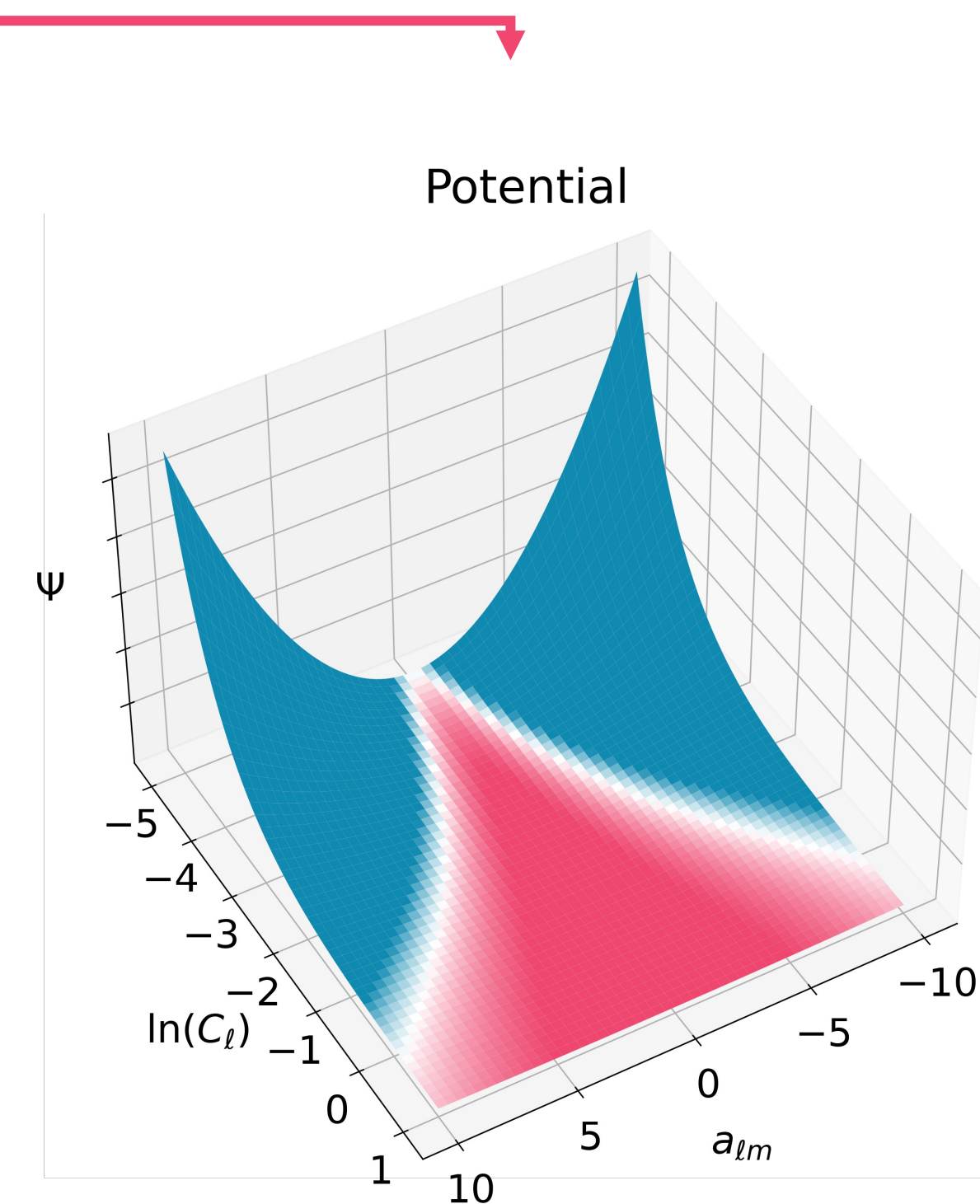
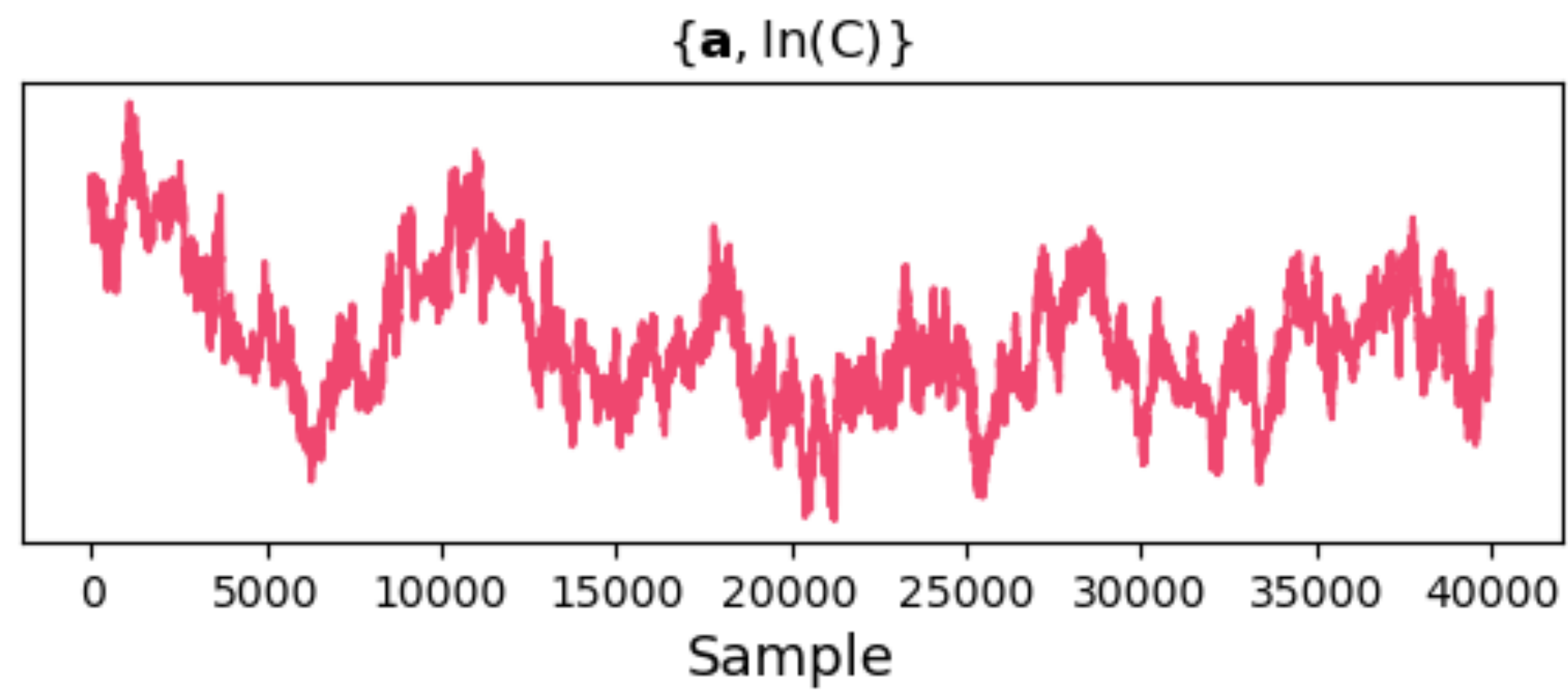


Sellentin, Loureiro
et. al, 2023

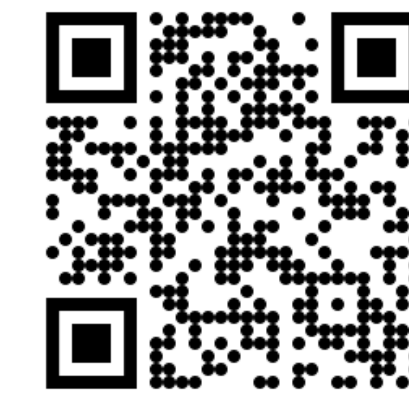


Loureiro et. al, 2023

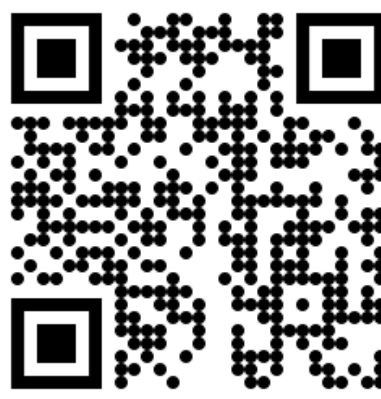
ψ - Negative Log-Posterior Trace



Coordinate System comparison



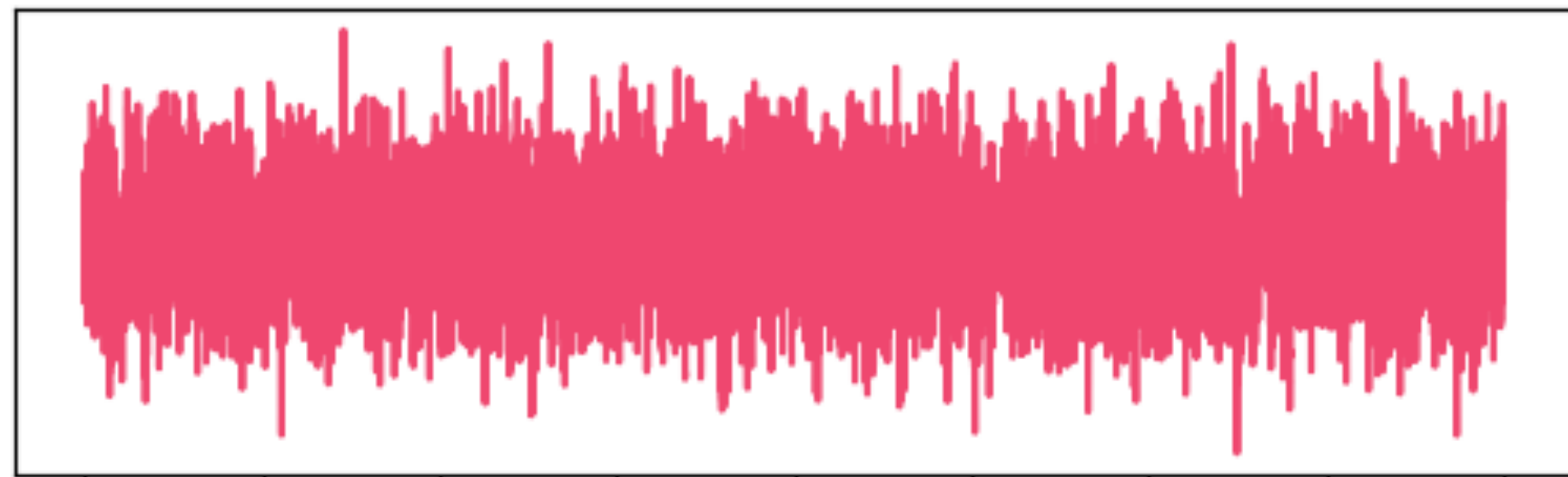
Sellentin, Loureiro et. al, 2023



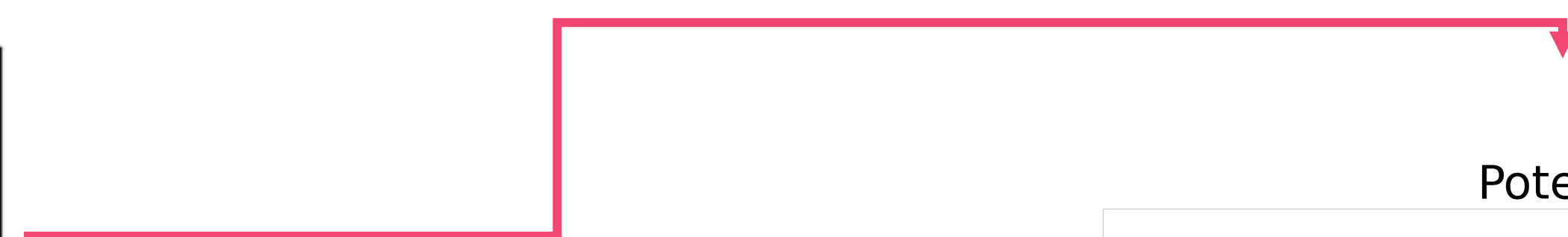
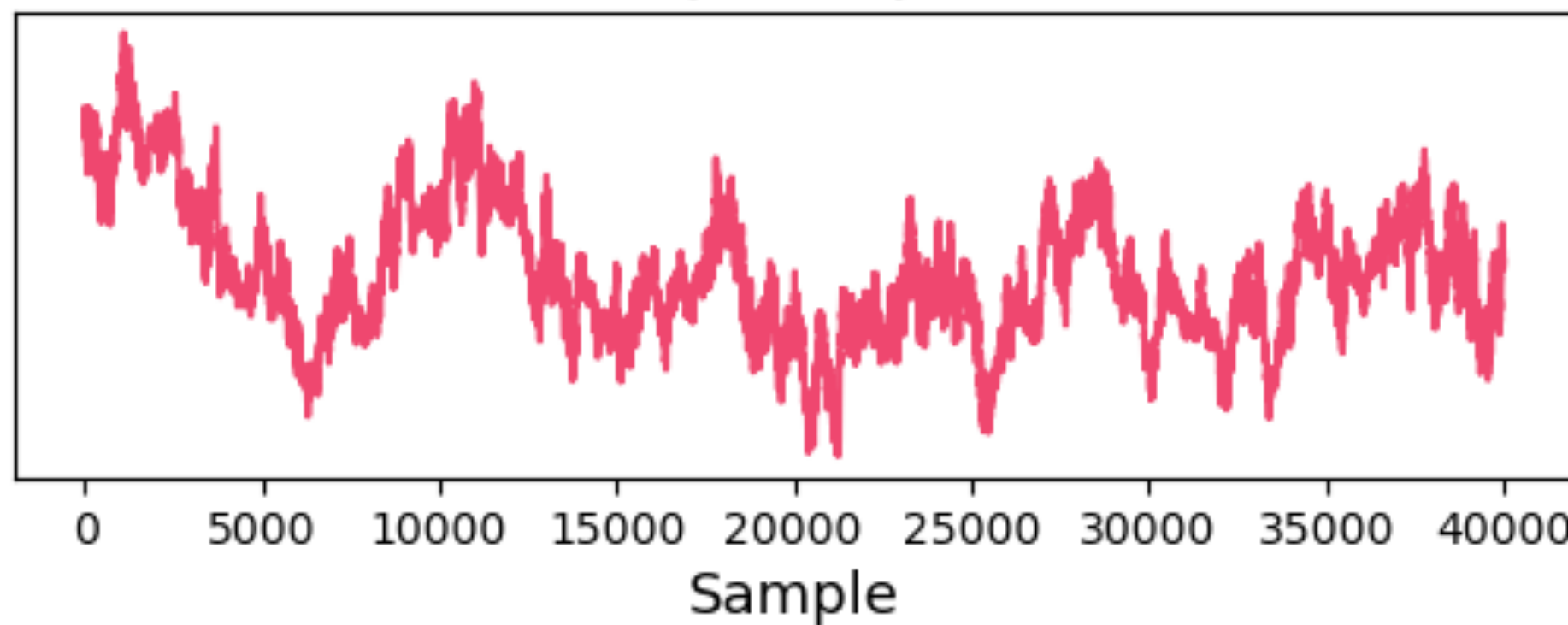
Loureiro et. al, 2023

ψ - Negative Log-Posterior Trace

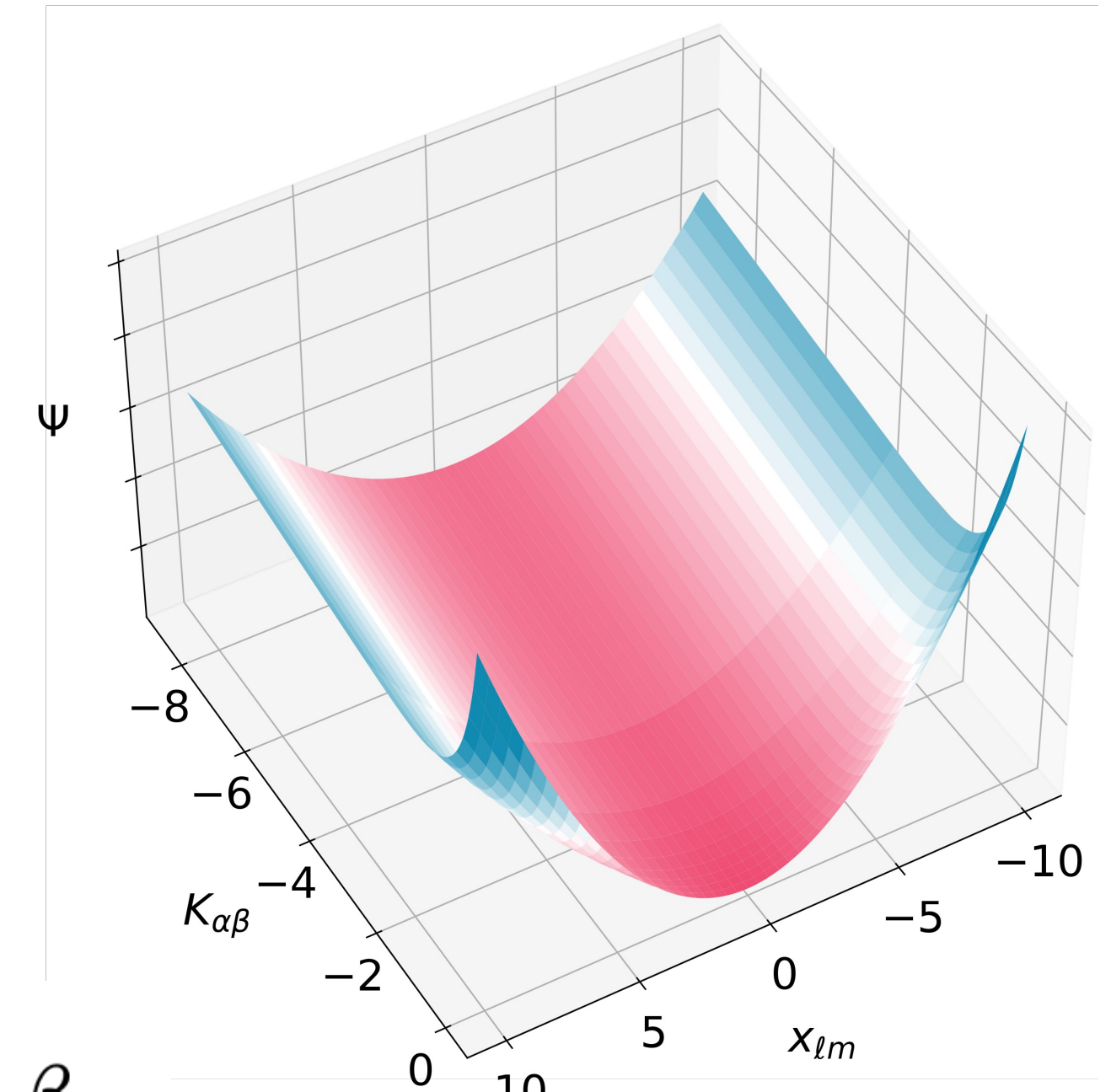
$\{\mathbf{x}, K\}$



$\{\mathbf{a}, \ln(C)\}$



Potential



New Coordinate System:

$$\mathbf{x} = \mathbf{L}^{-1} \mathbf{a}$$

$$K_{\alpha\beta} = \begin{cases} \ln(L_{\alpha\beta}) & \text{if } \alpha = \beta, \\ L_{\alpha\beta} & \text{otherwise.} \end{cases}$$

Test Cases & Results

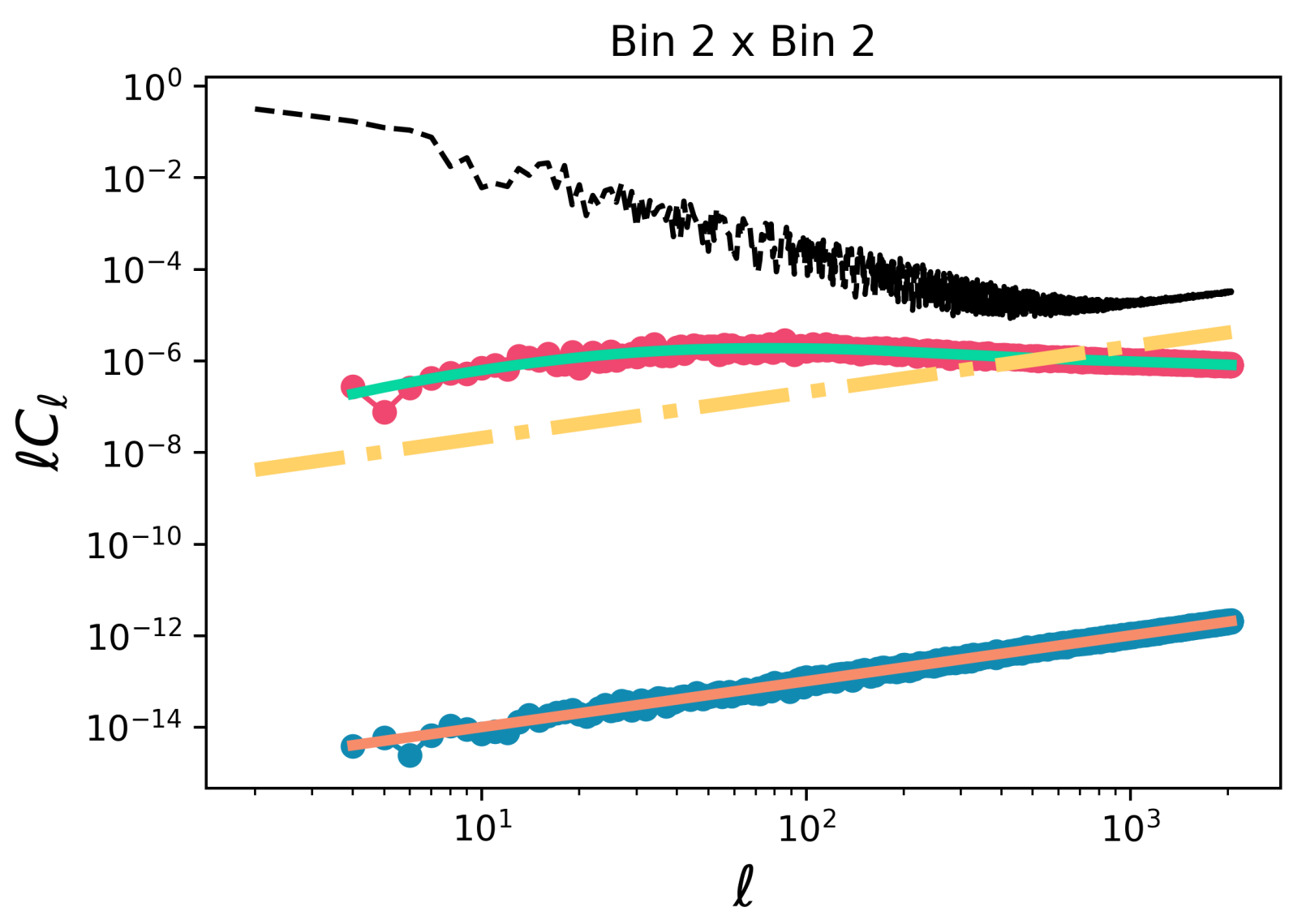
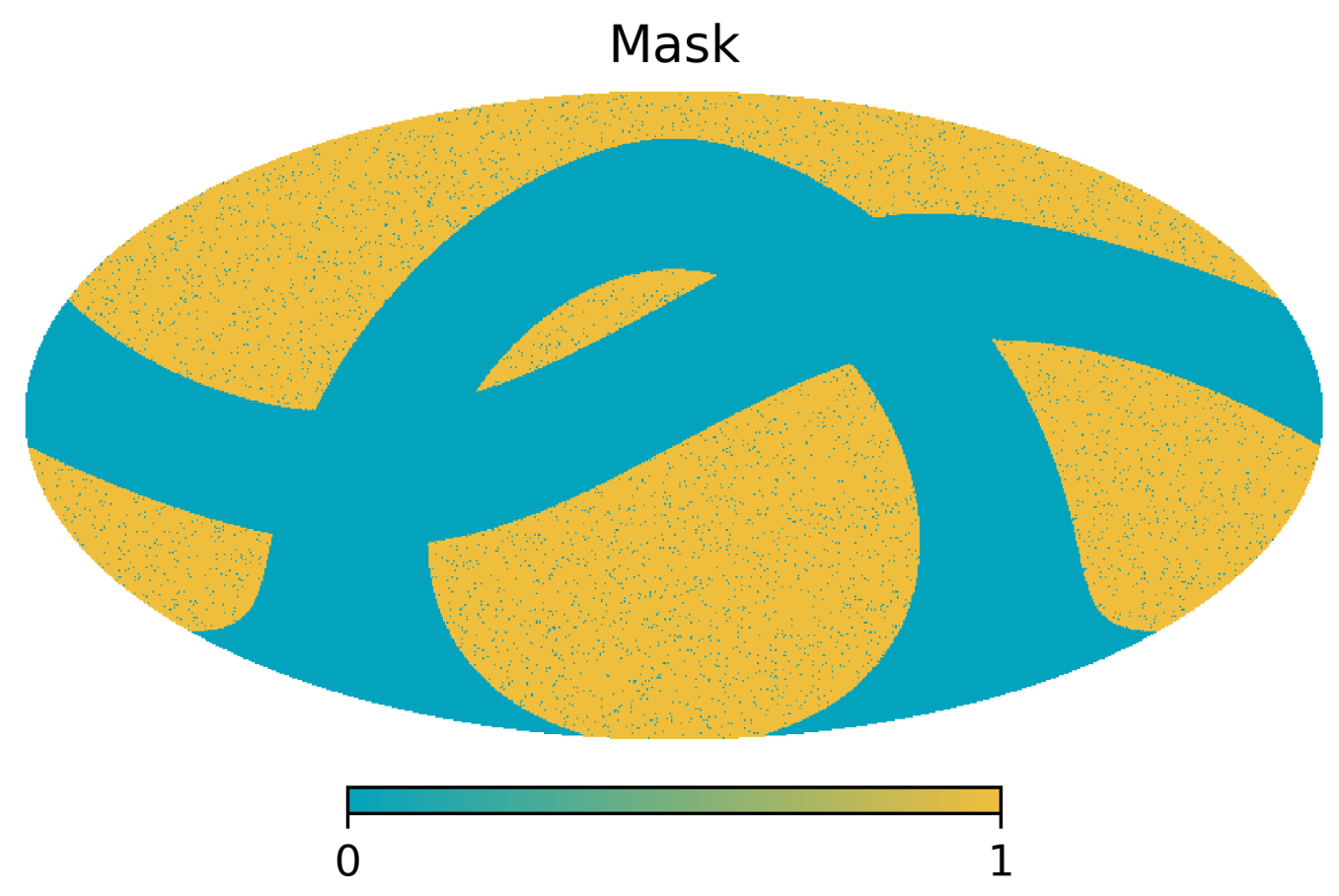
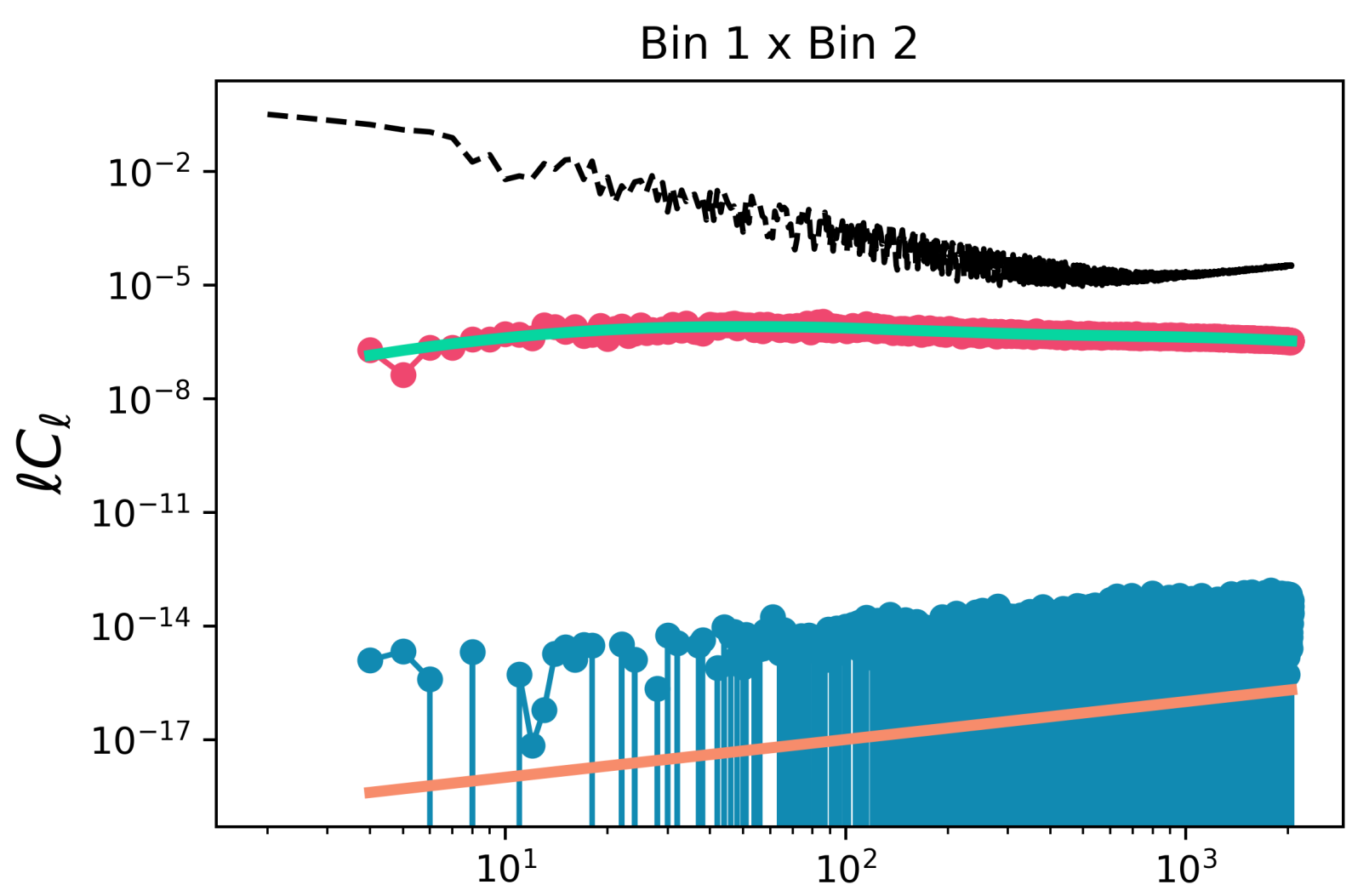
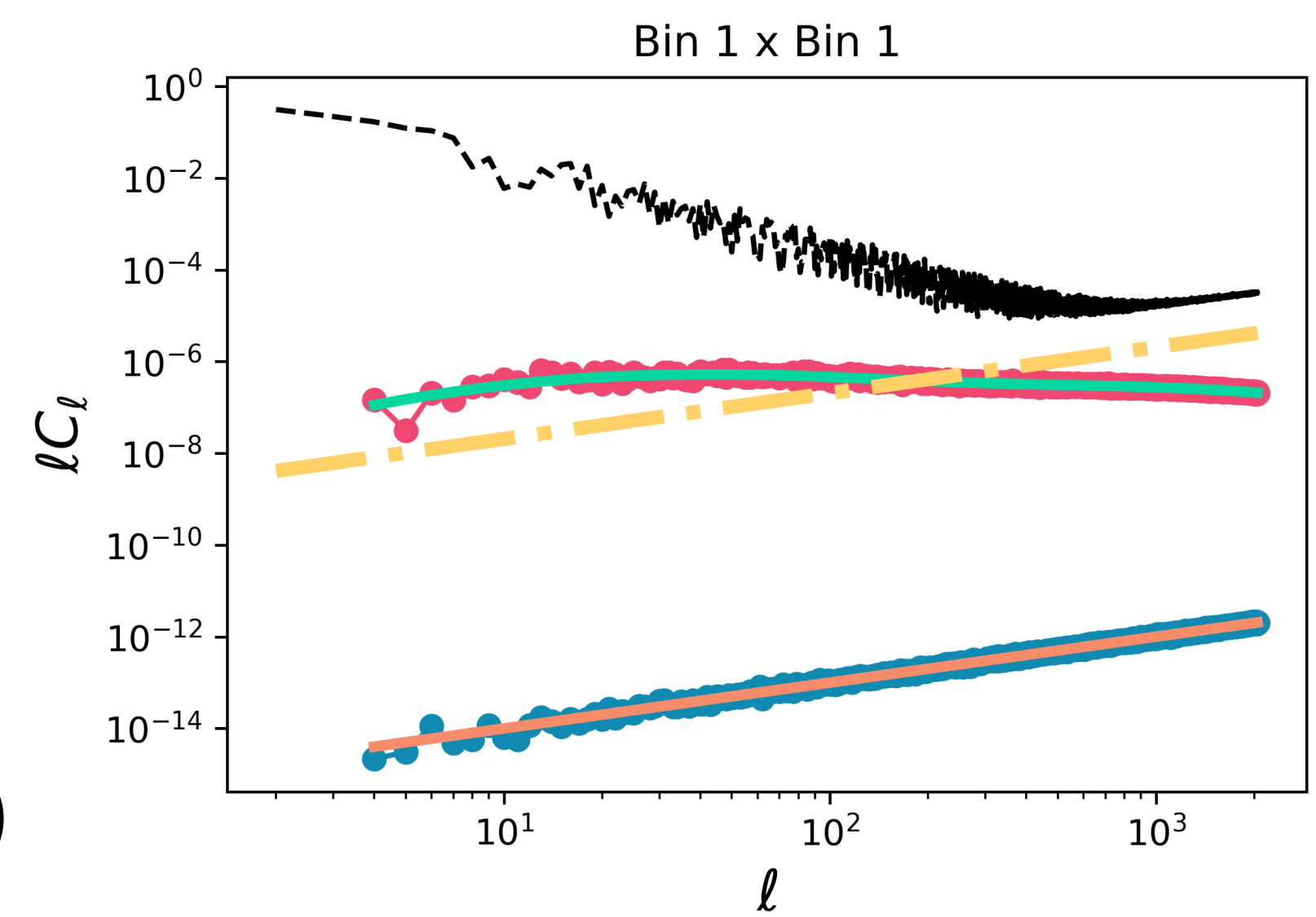
Weak Lensing & CMB Temperature and Polarisation



Weak Lensing

Euclid-like case

- Multipoles: 4, 2048
- $N_{\text{side}} = 1024$ (12.5M pixels)
- 2 tomographic bins for a spin-2 field is 50.3M pixels!
- **16.8 Million free parameters; ~20k are C_ℓ**

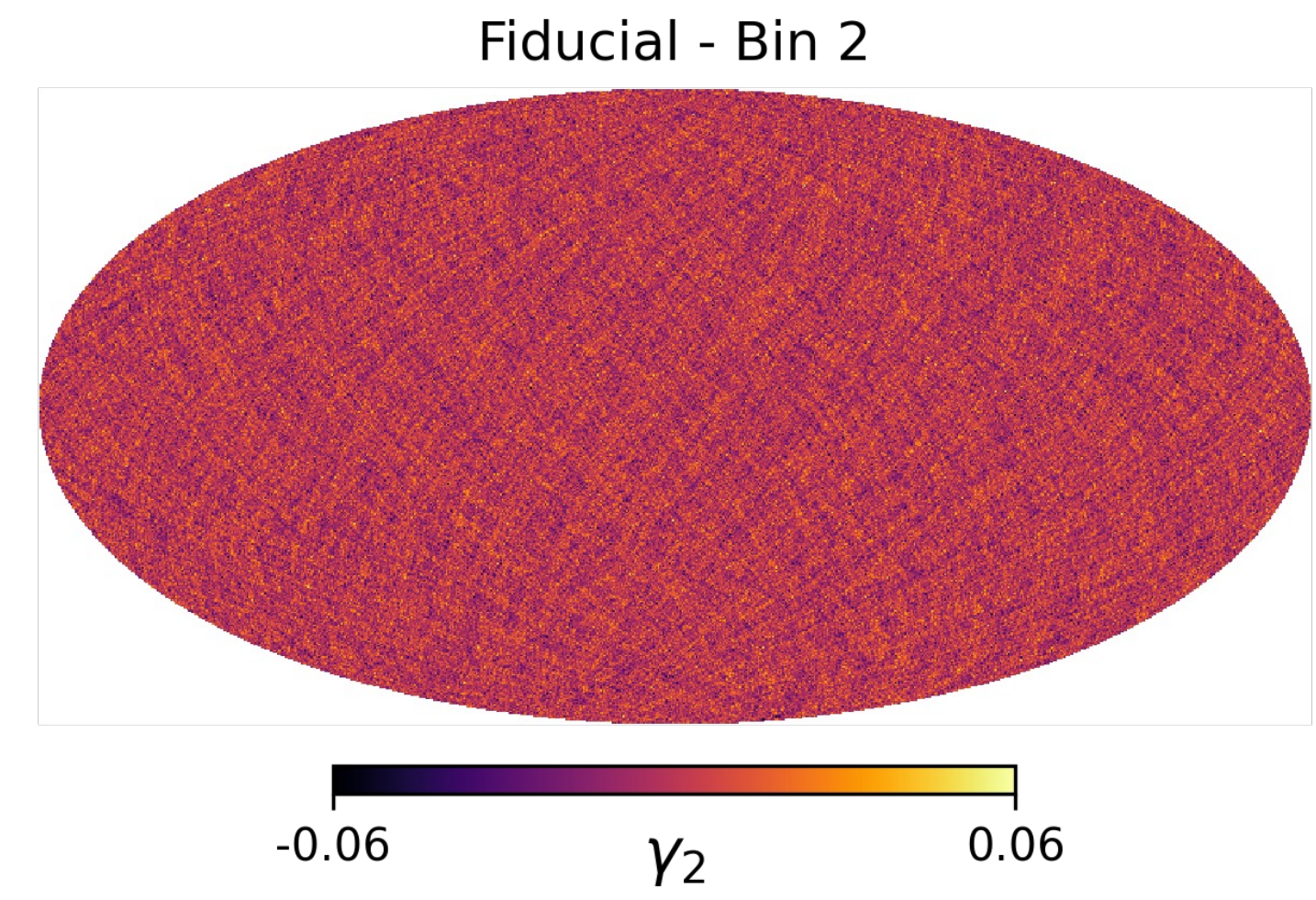
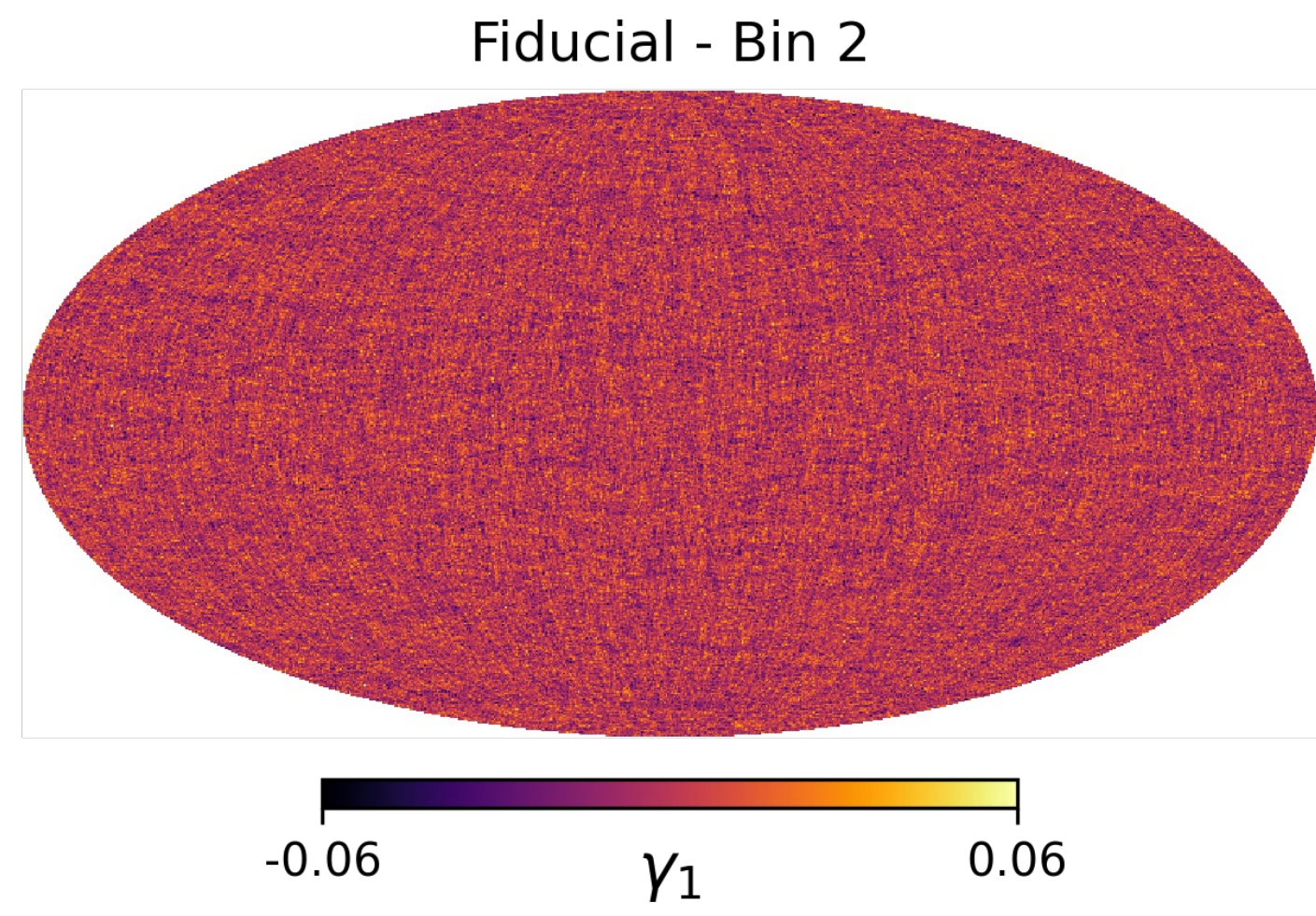
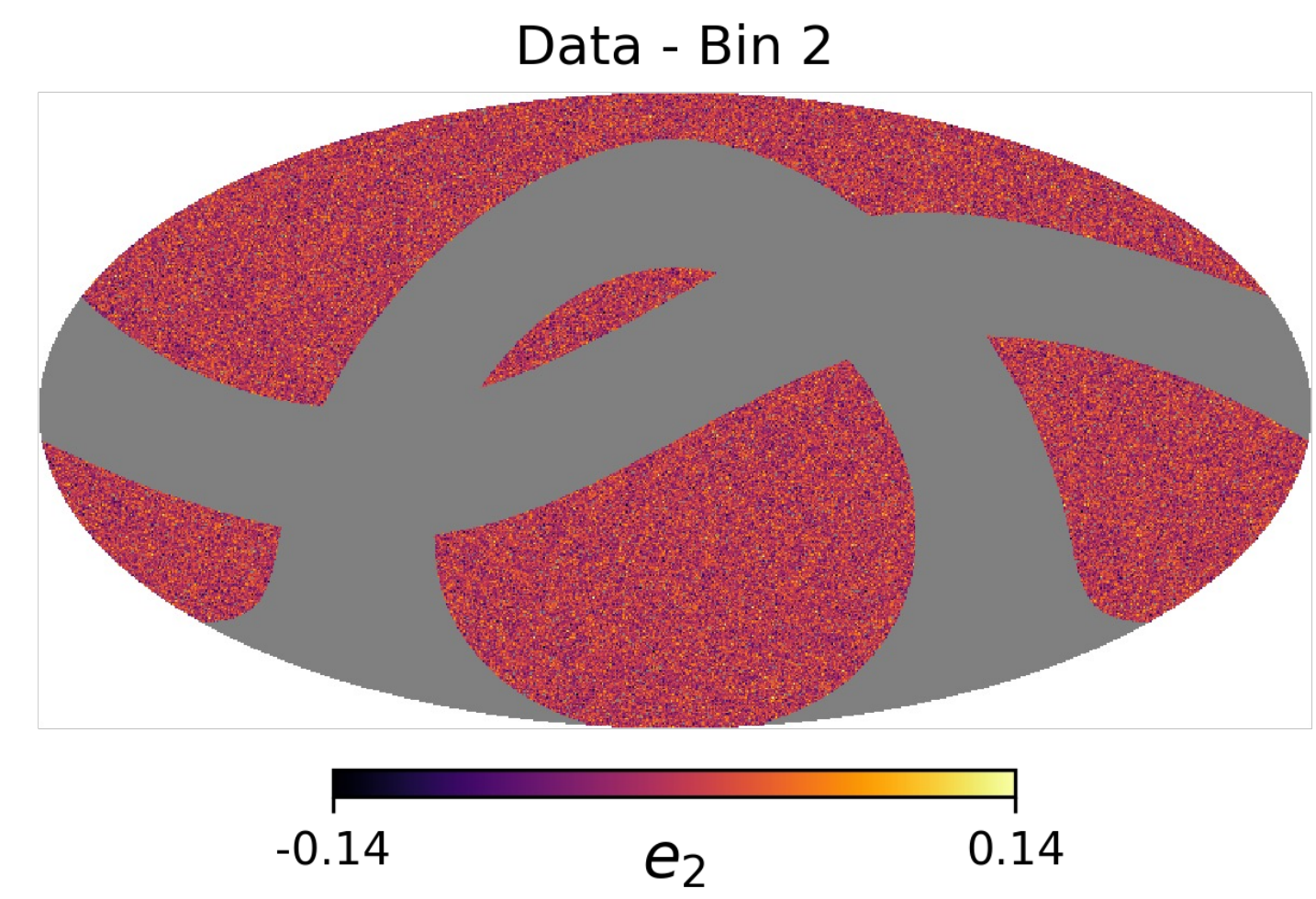
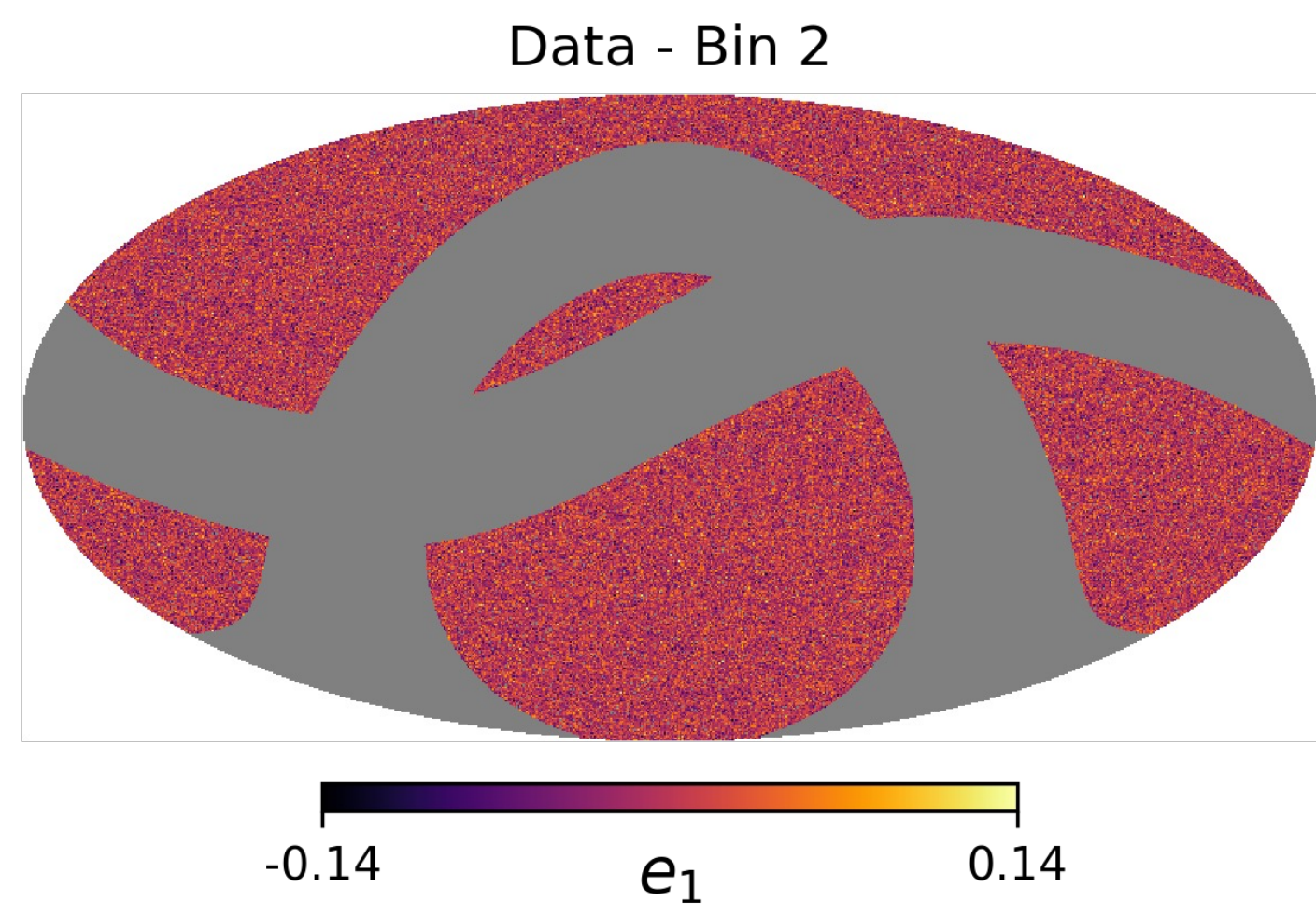




Weak Lensing

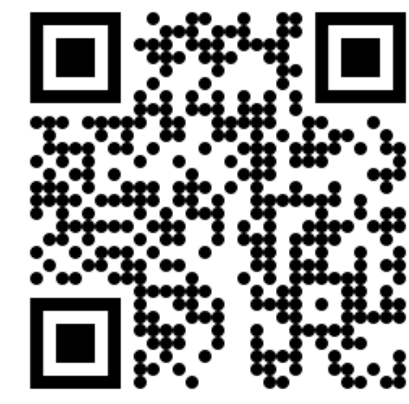
Euclid-like case

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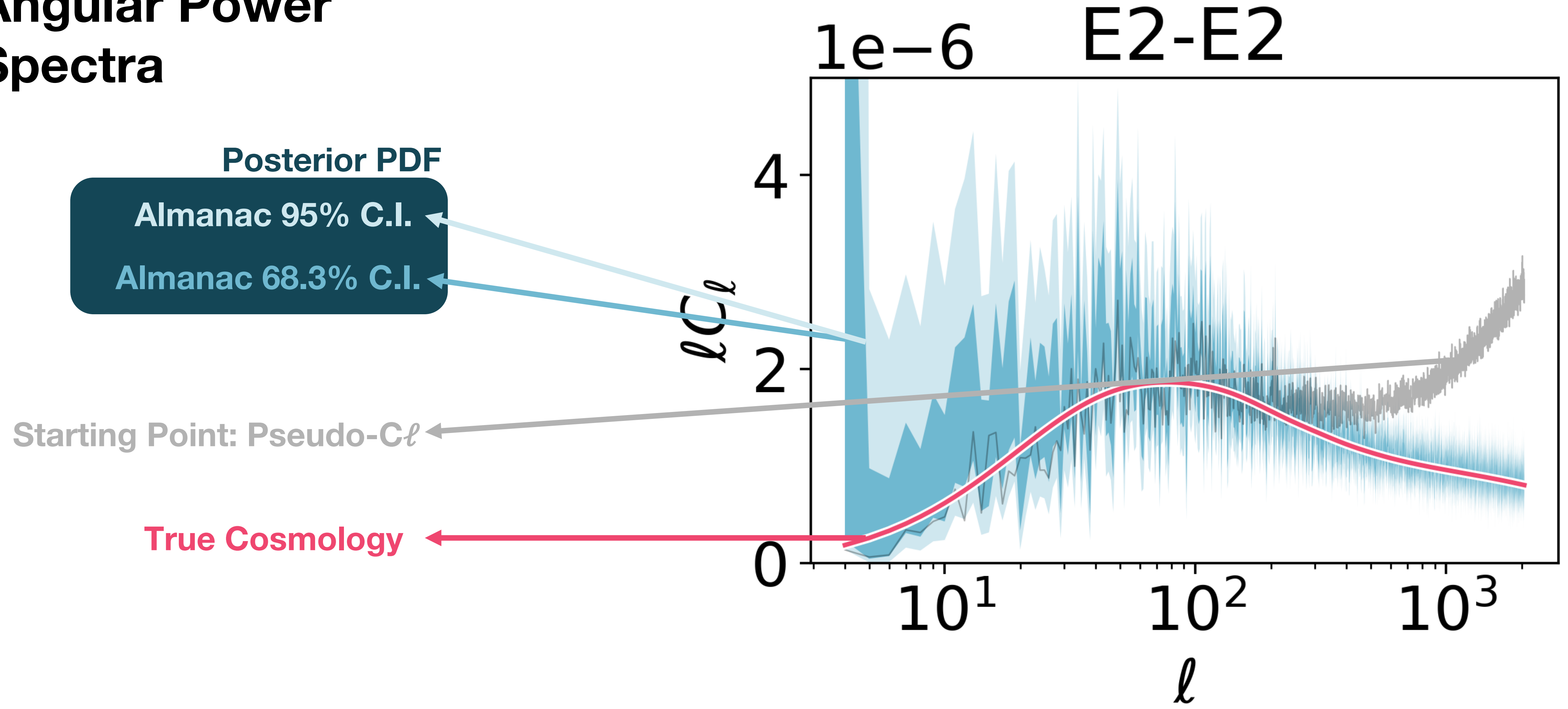


Weak Lensing



Loureiro et. al, 2023

Angular Power Spectra



Posterior PDF
Almanac 95% C.I.
Almanac 68.3% C.I.

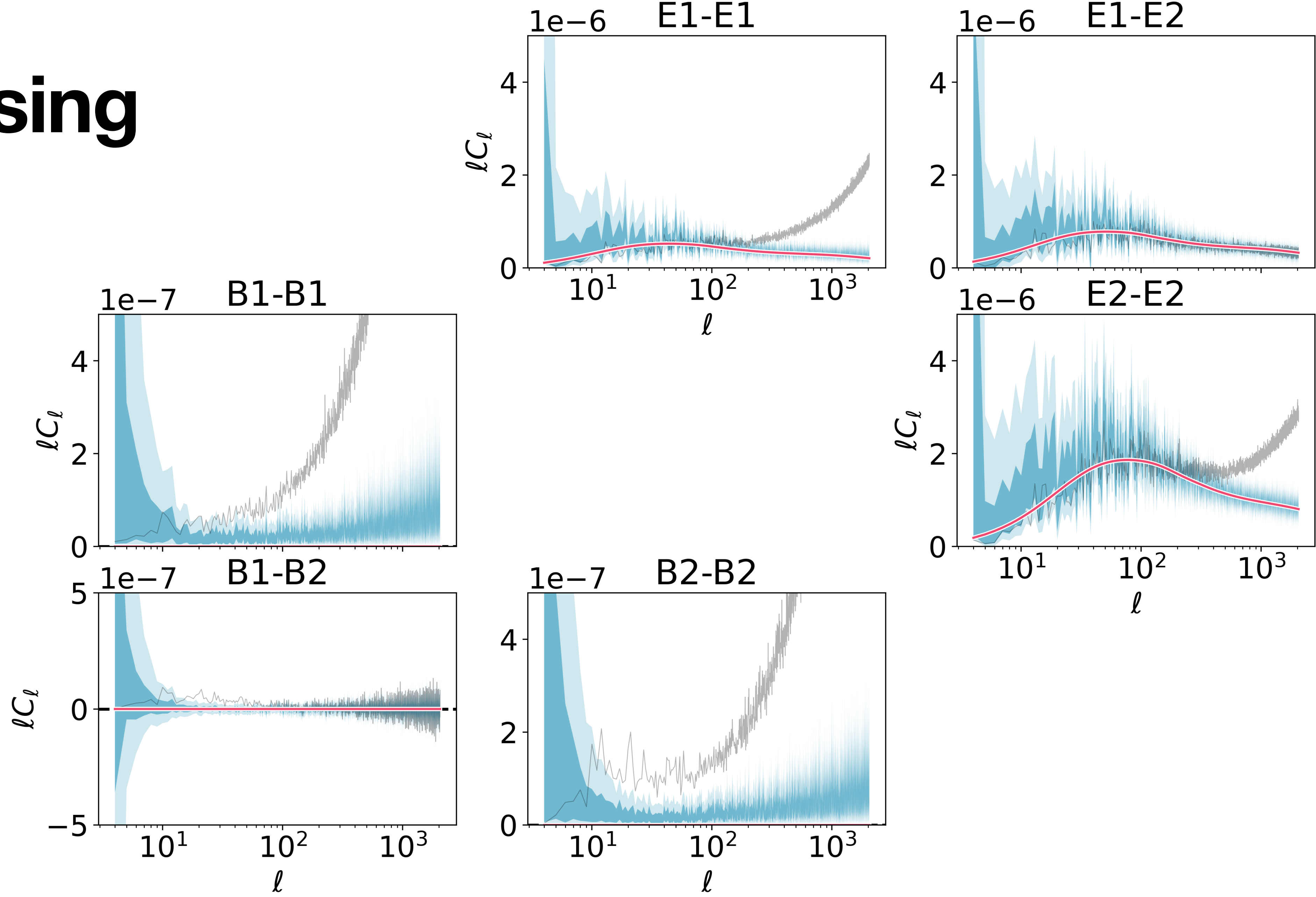
Starting Point: Pseudo- Cl

True Cosmology



Weak Lensing

Angular Power Spectra

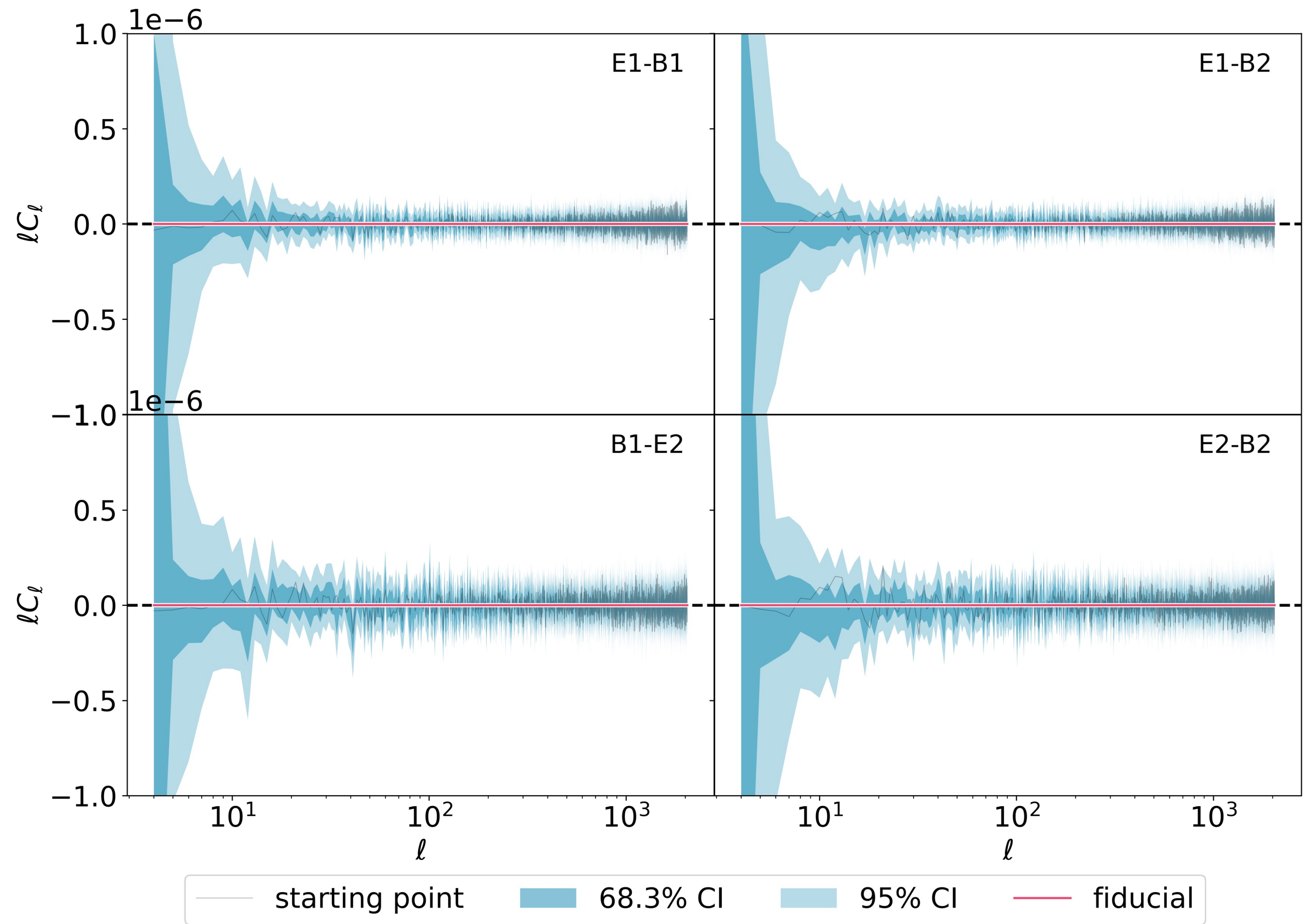


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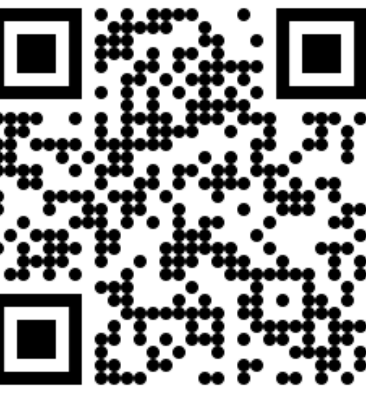




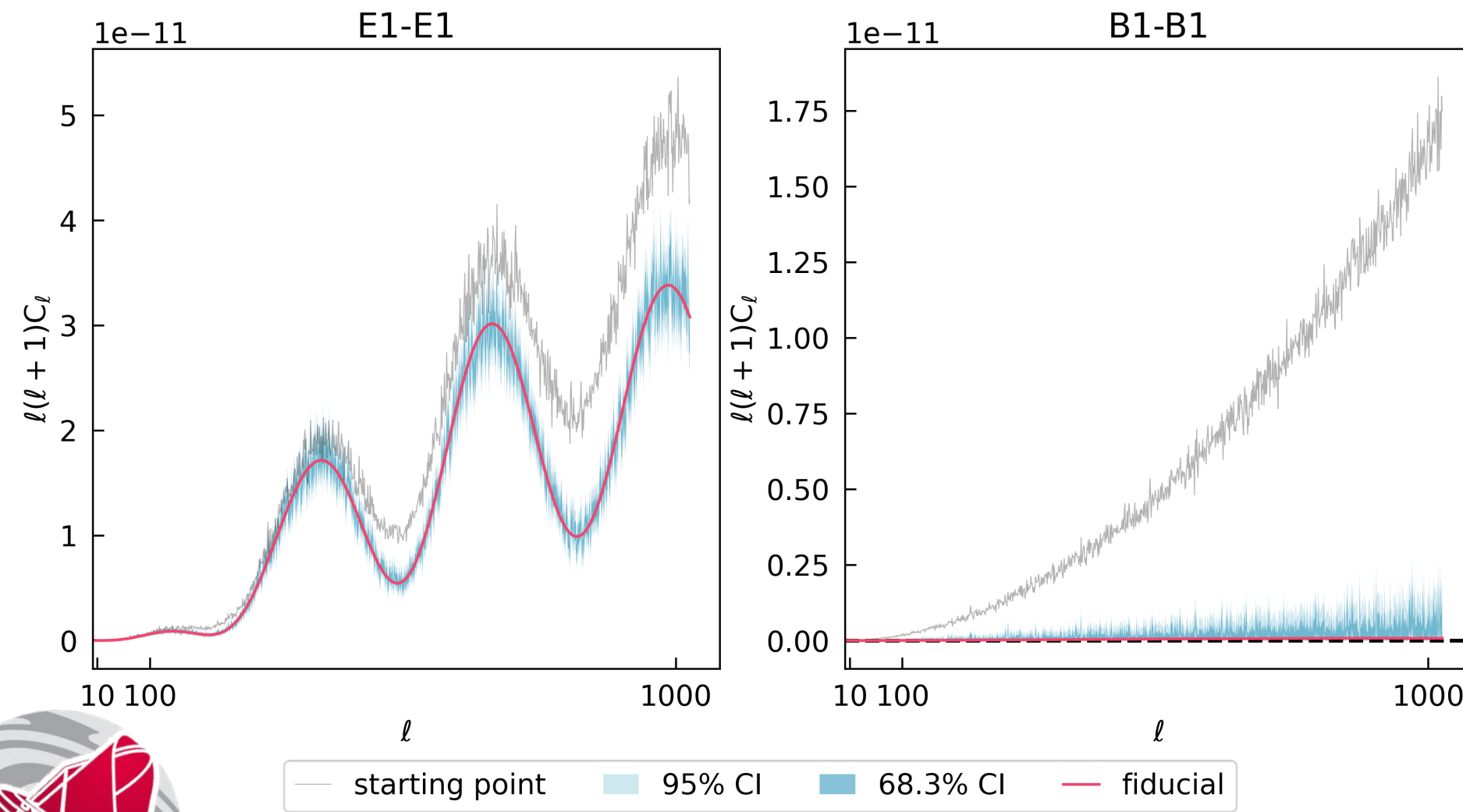
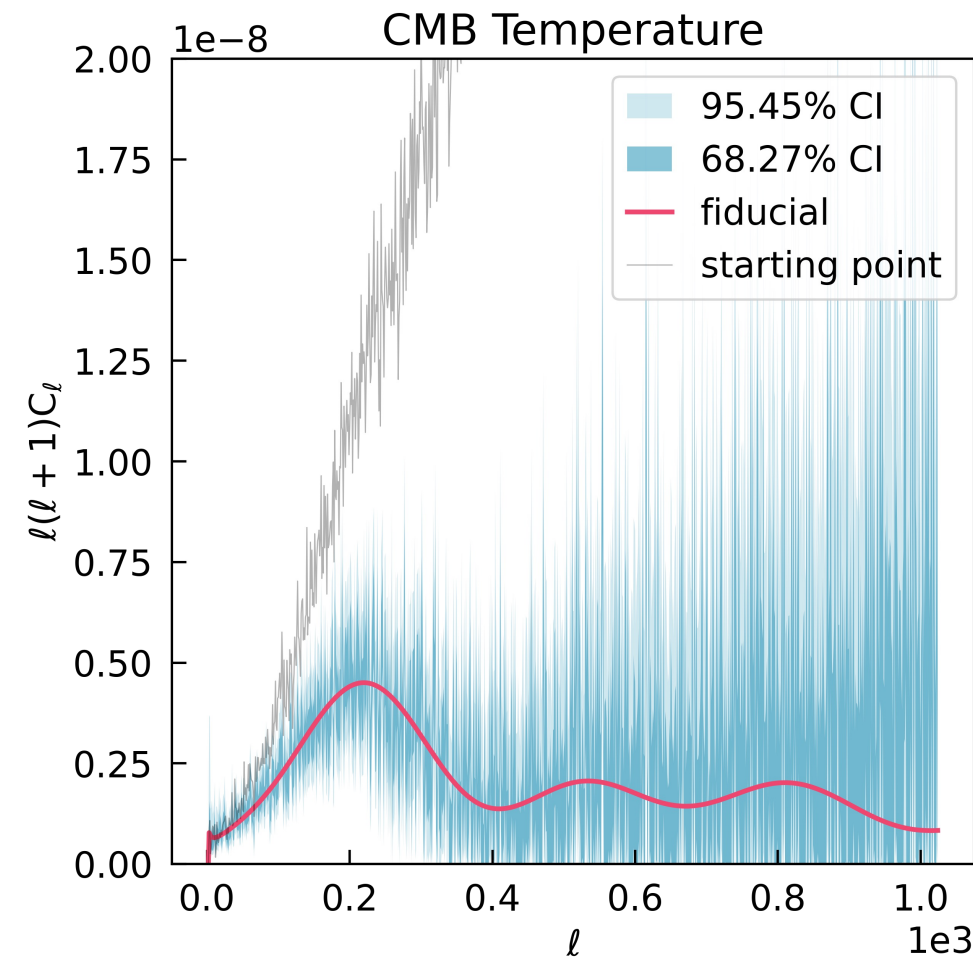
Weak Lensing Angular Power Spectra



CMB Angular Power Spectra



Sellentini,
Loureiro et. al, 2023

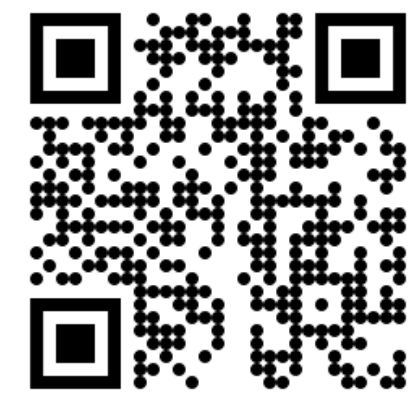


CMB Temperature & Polarisation

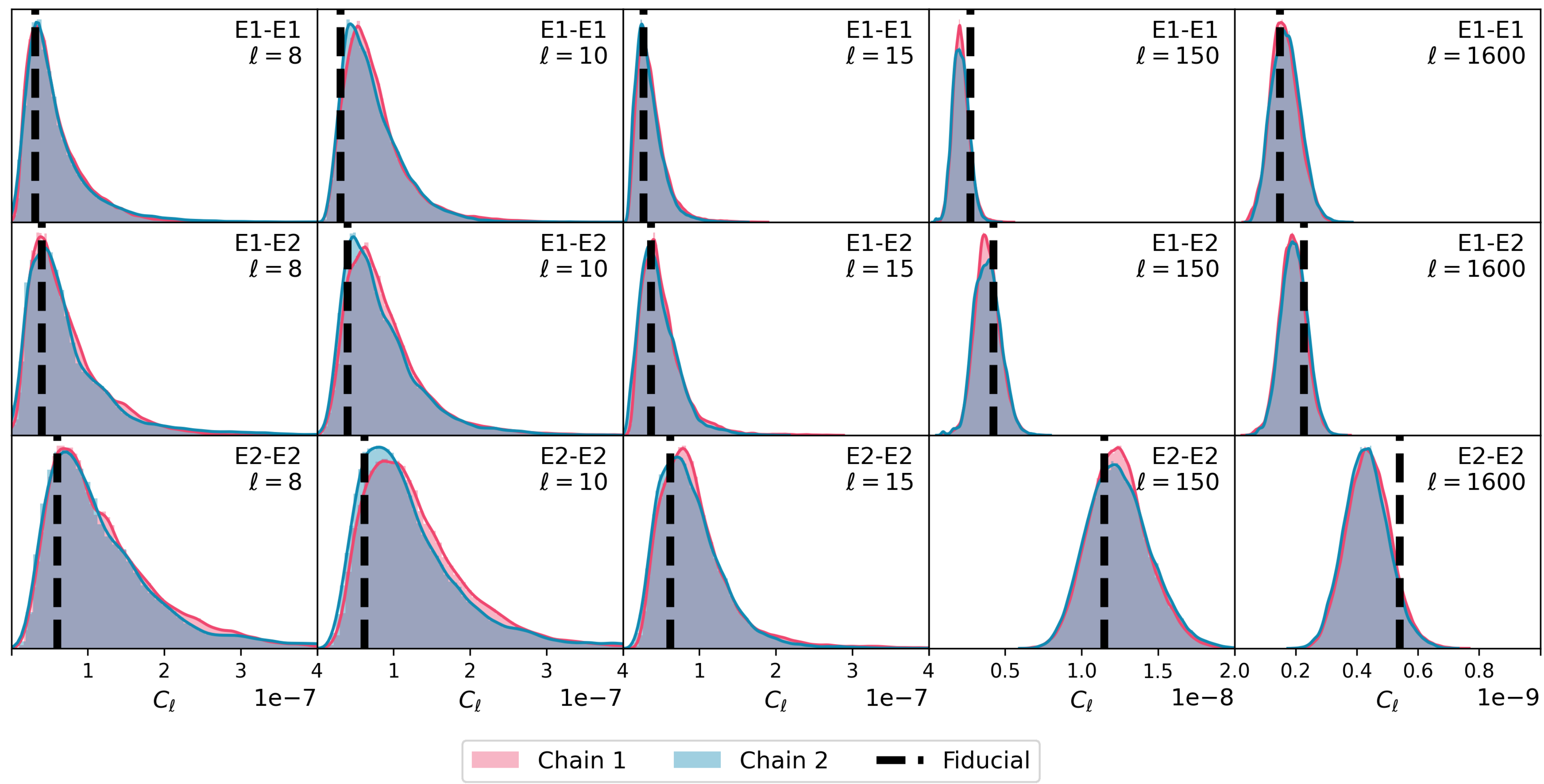


Weak Lensing

Angular Power Spectra

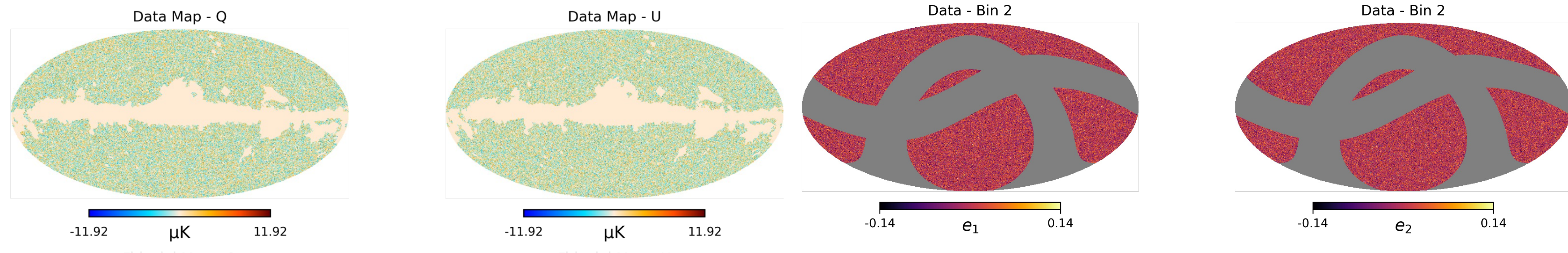


Loureiro et. al, 2023



Partial Sky E/B-Leakage

A Spin-2 problem for CMB Polarisation and Weak Lensing

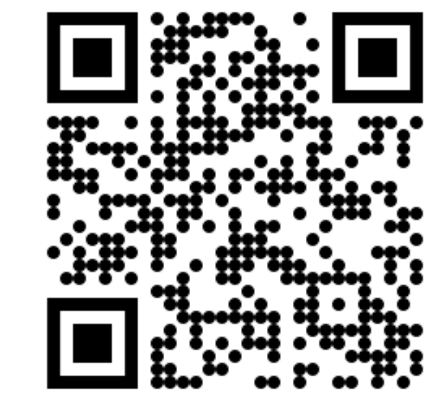


$$\tilde{E}_{\ell m} = \sum_{\ell' m'} (E_{\ell' m'} W_{\ell \ell' m m'}^+ + B_{\ell' m'} W_{\ell \ell' m m'}^-)$$
$$\tilde{B}_{\ell m} = \sum_{\ell' m'} (B_{\ell' m'} W_{\ell \ell' m m'}^+ - E_{\ell' m'} W_{\ell \ell' m m'}^-),$$

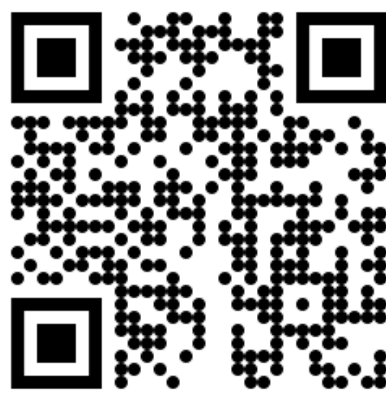
Lewis, Challinor & Turok, 2002

Partial Sky E/B-Leakage

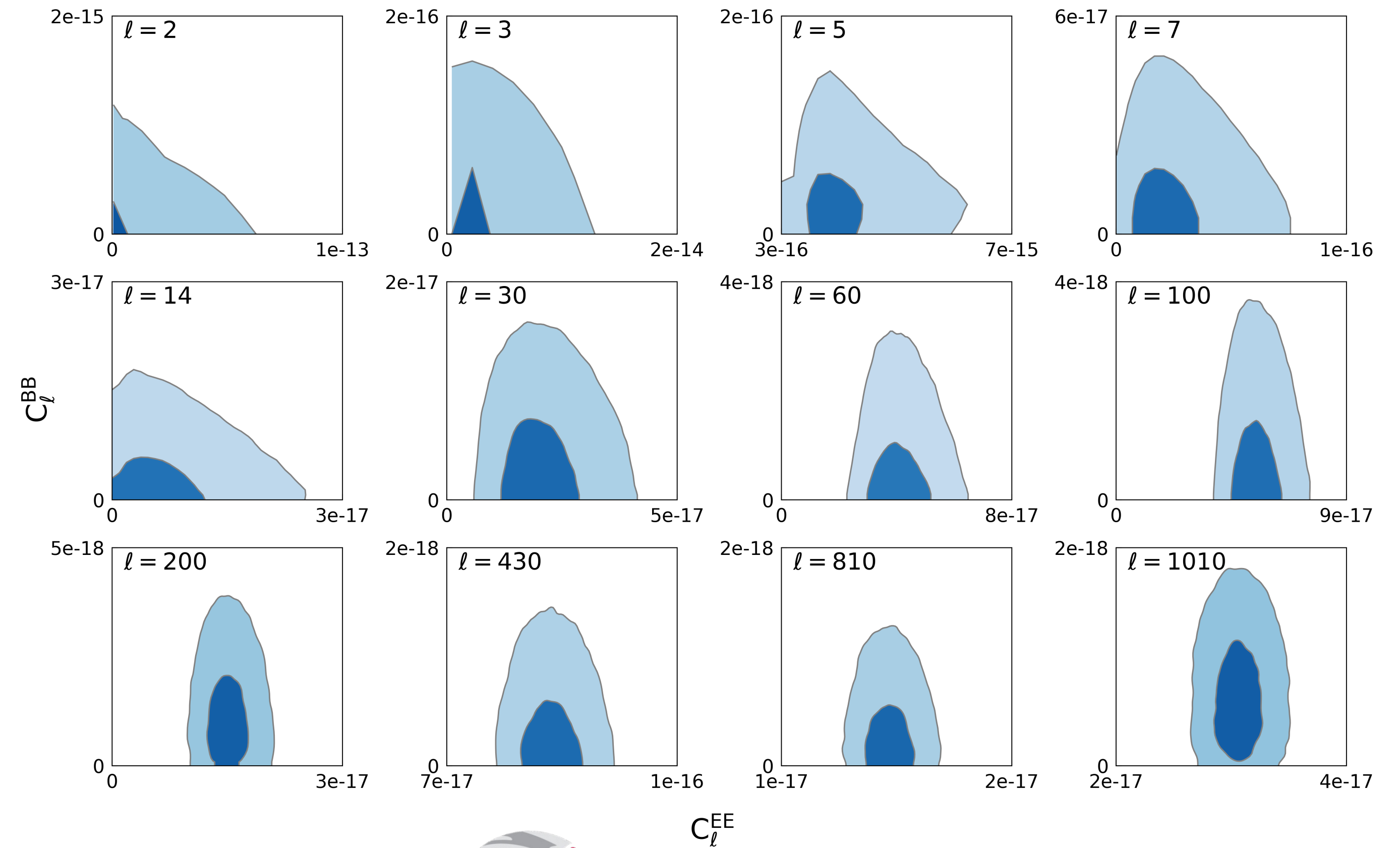
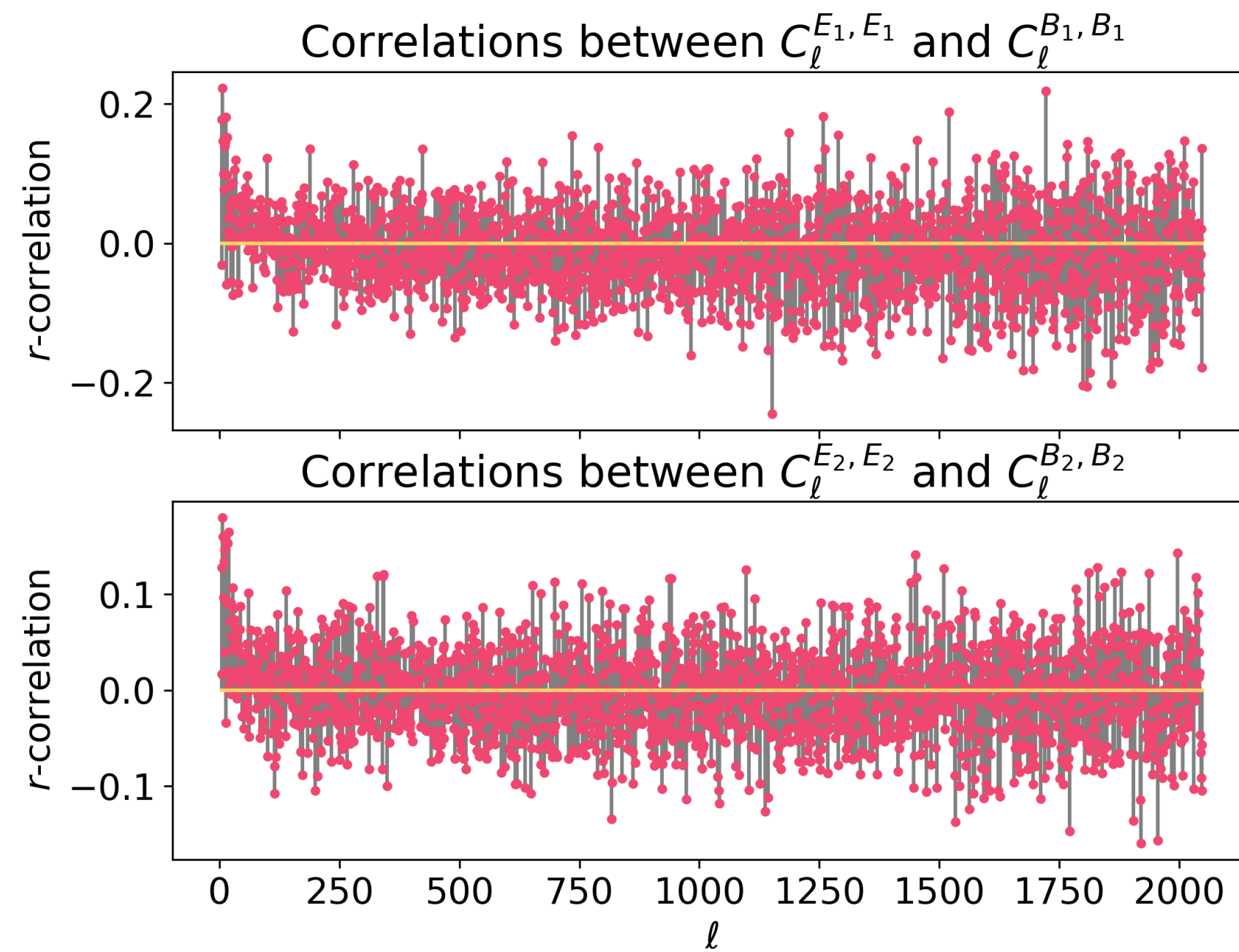
No longer an issue with Almanac



Sellentin,
Loureiro et. al, 2023



Loureiro et. al, 2023



Euclid-like tomographic Weak Lensing



CMB Polarisation

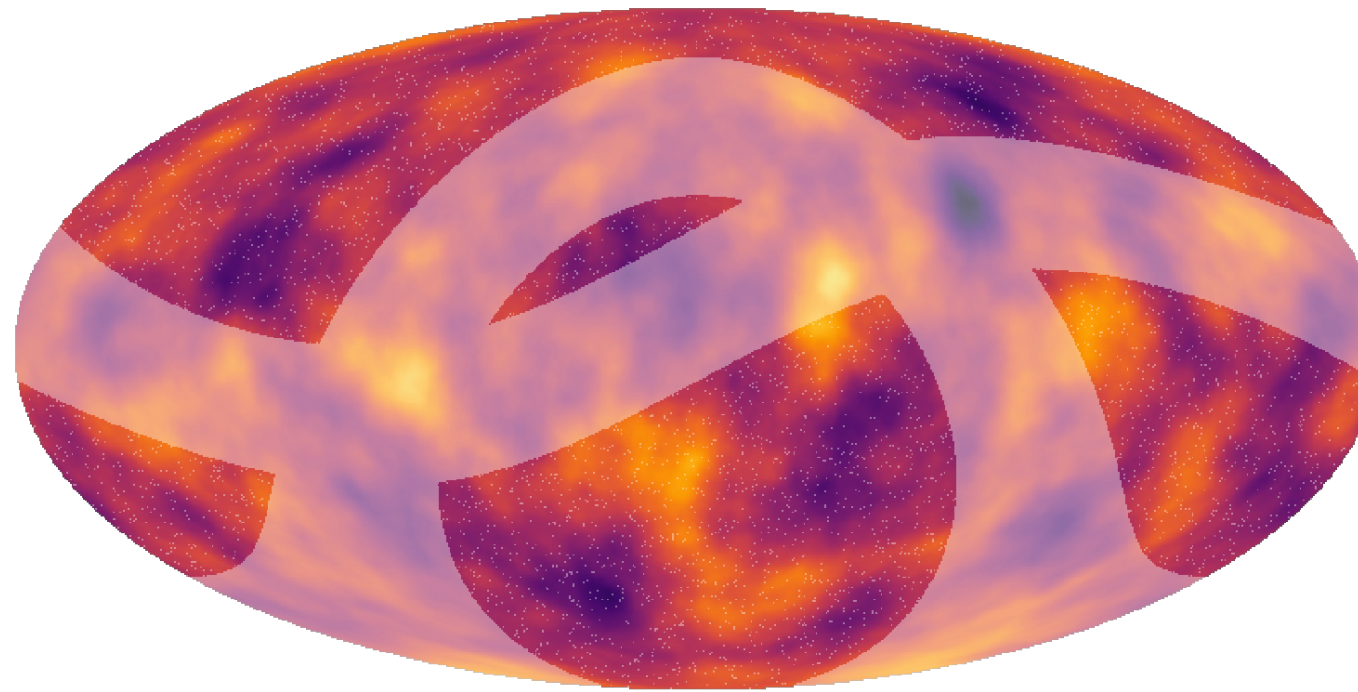


Weak Lensing

Reconstructed Lensing Potential

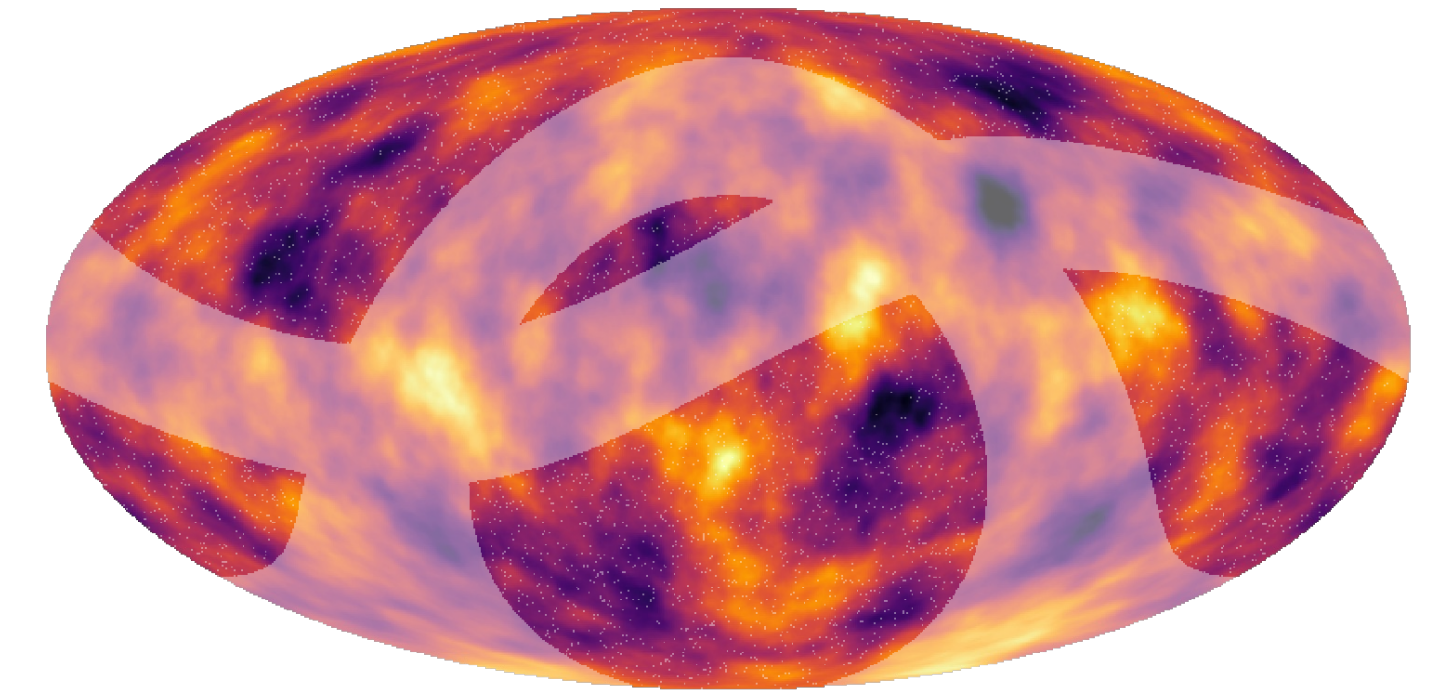
$$\tilde{\Psi}_{lm} = \frac{2}{l(l+1)} \kappa_{lm}$$

Ground Truth - Bin 1



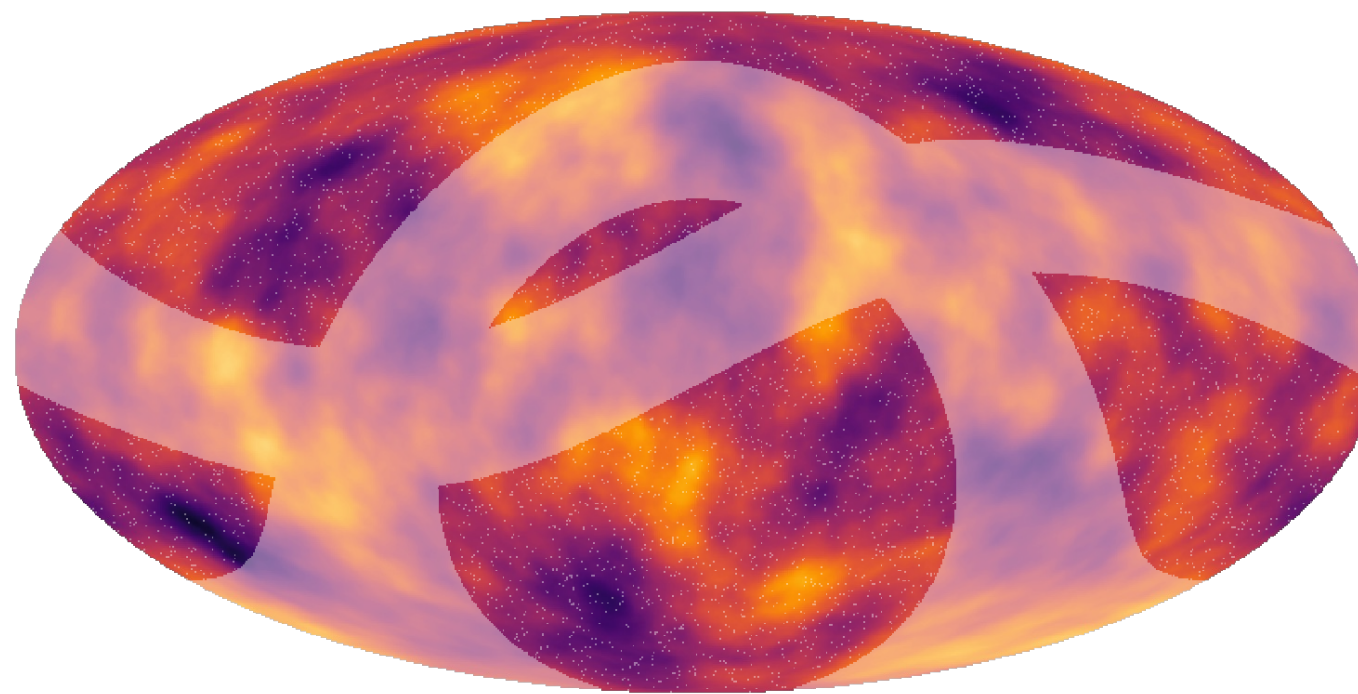
Lensing potential

Ground Truth - Bin 2



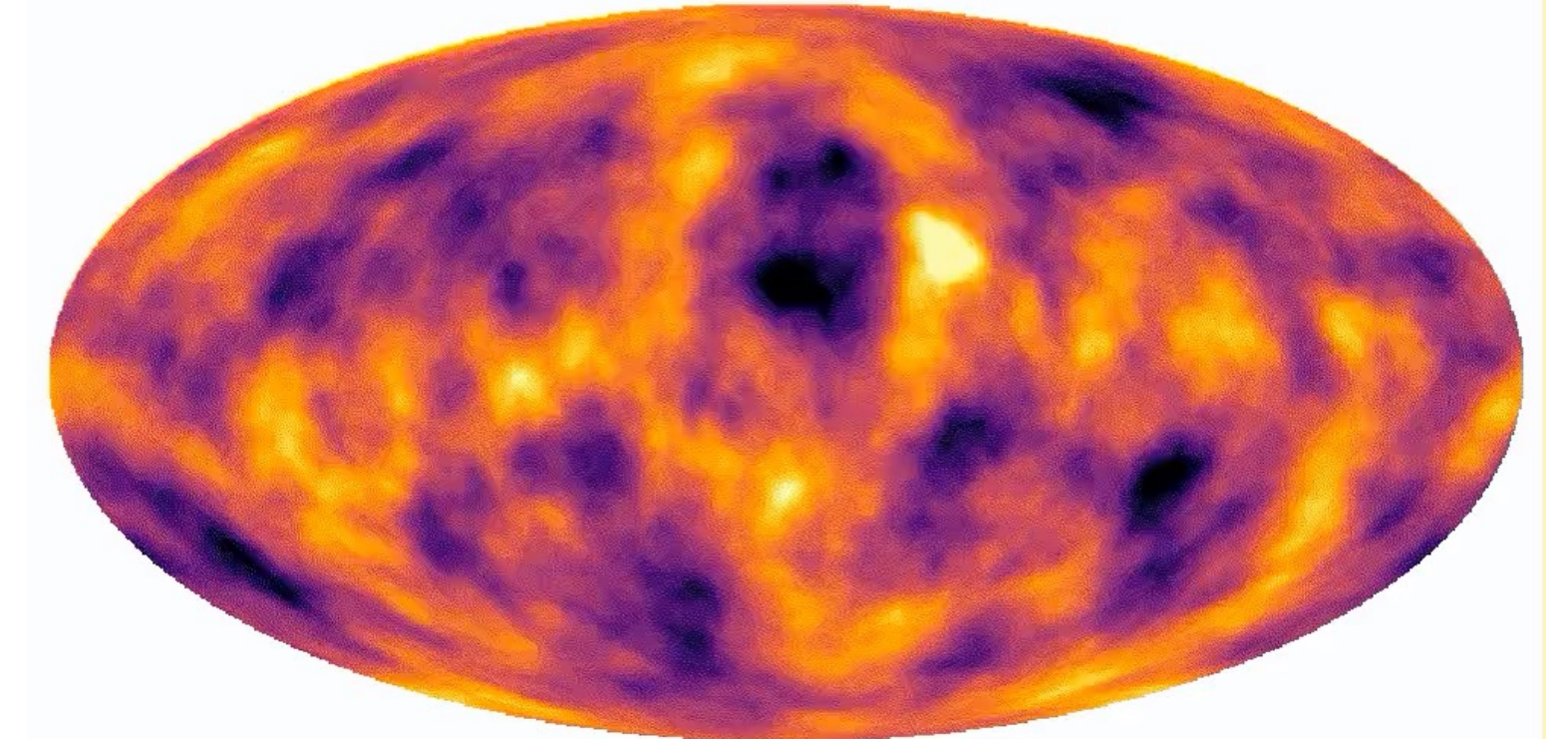
Lensing potential

Typical Sample Map from Almanac- Bin 1



Lensing potential

Bin 2 - Lensing Potential



Lensing potential



Loureiro et. al, 2023

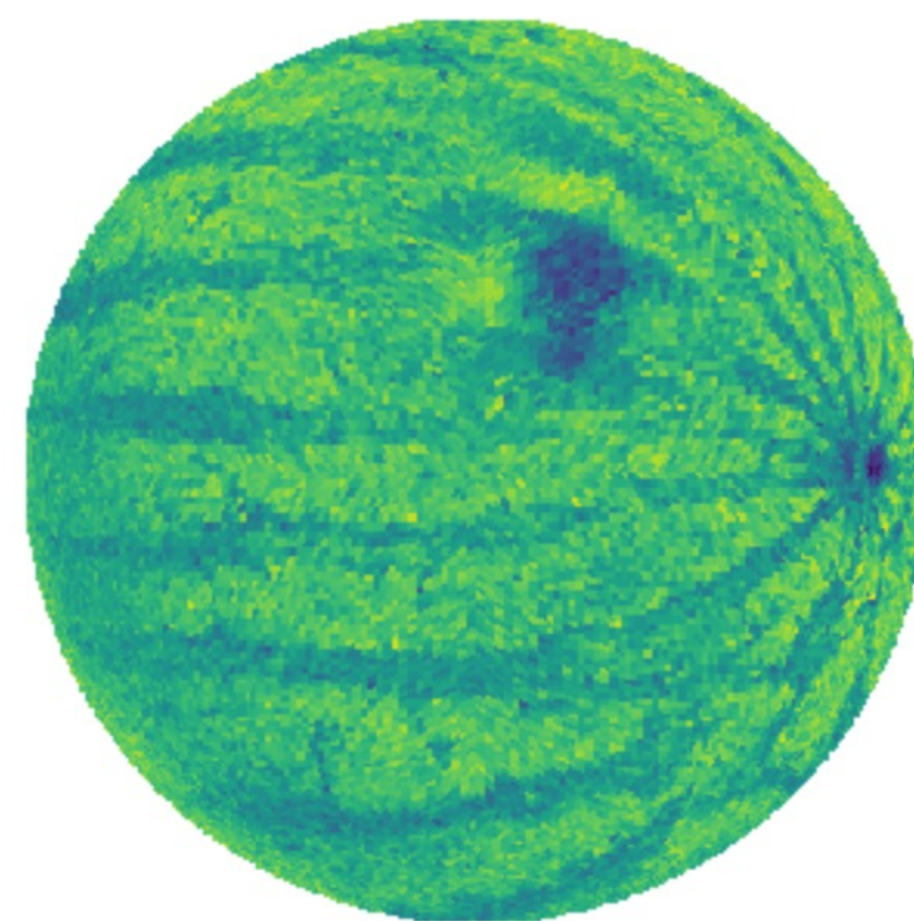


The maps are not necessarily gaussian!

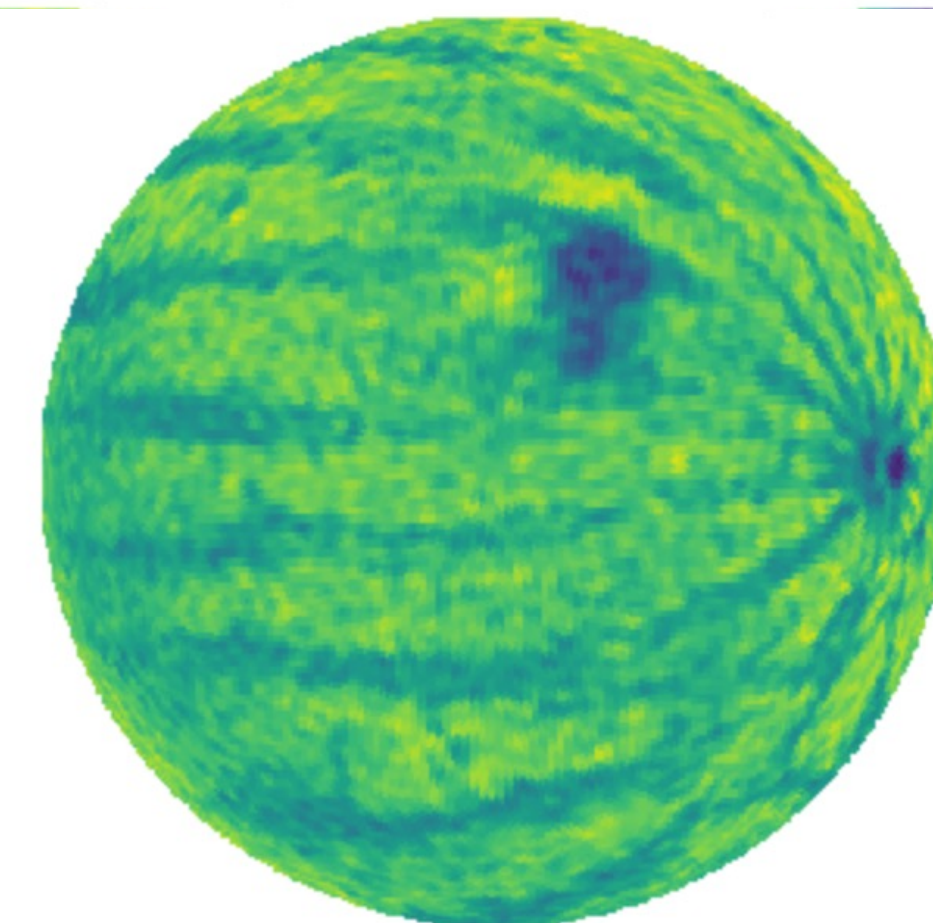
Gaussian prior \neq Gaussian Posterior

Half a watermelon is “famously non-gaussian”*

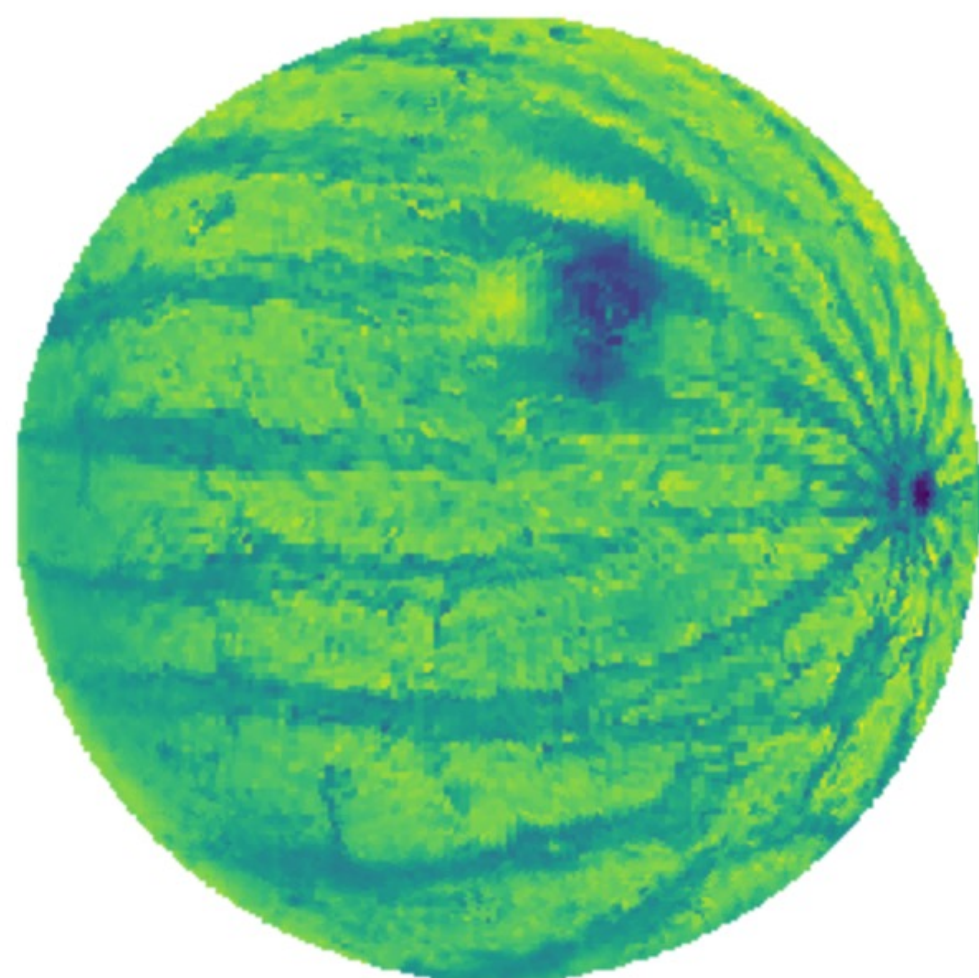
Noisy Watermelon Overdensity



Typical Sample for Watermelon Overdensity



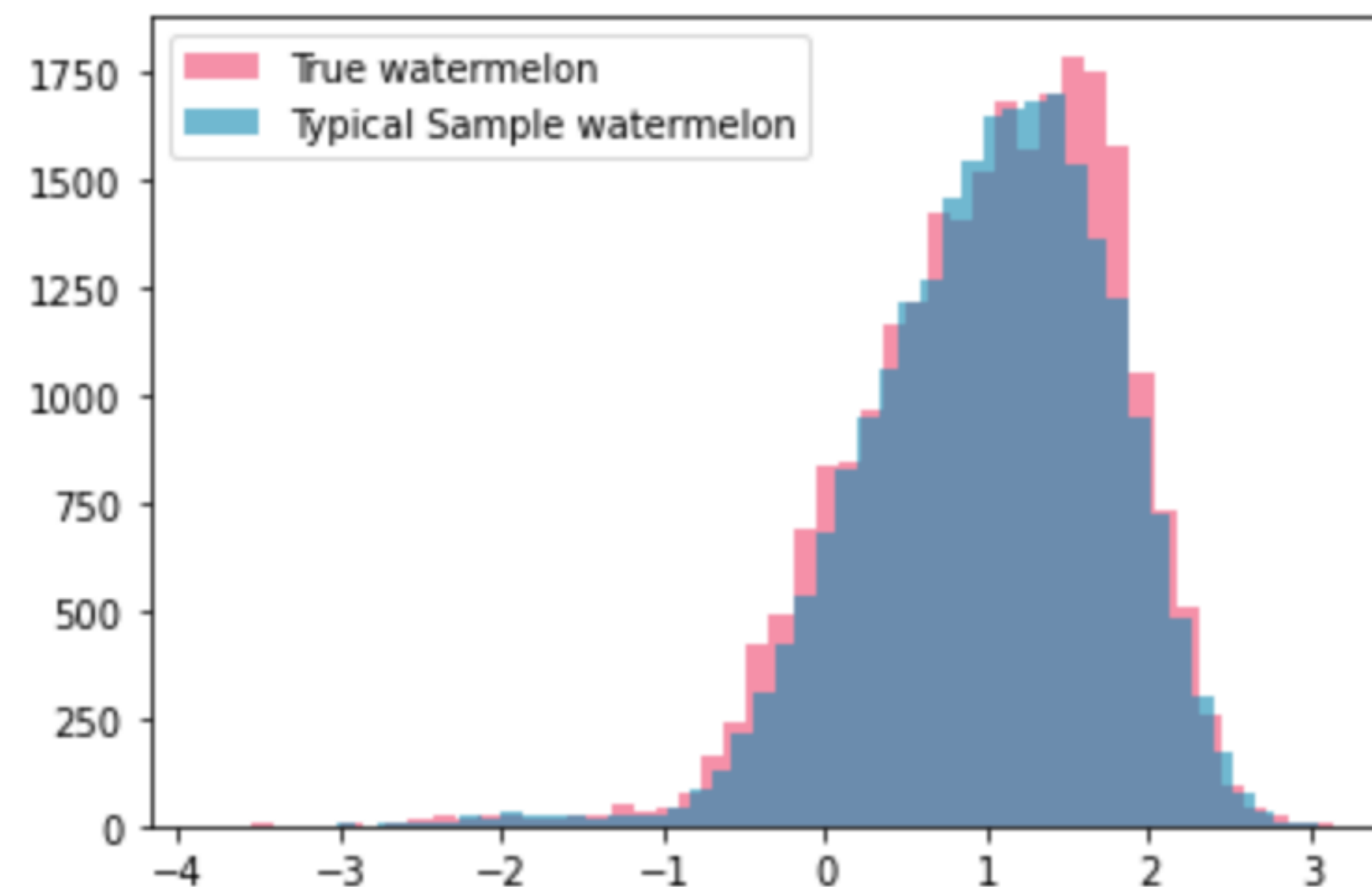
Watermelon Overdensity



-3.82784

3.13873

Original Watermelon Healpix Map



δ_{pixel}

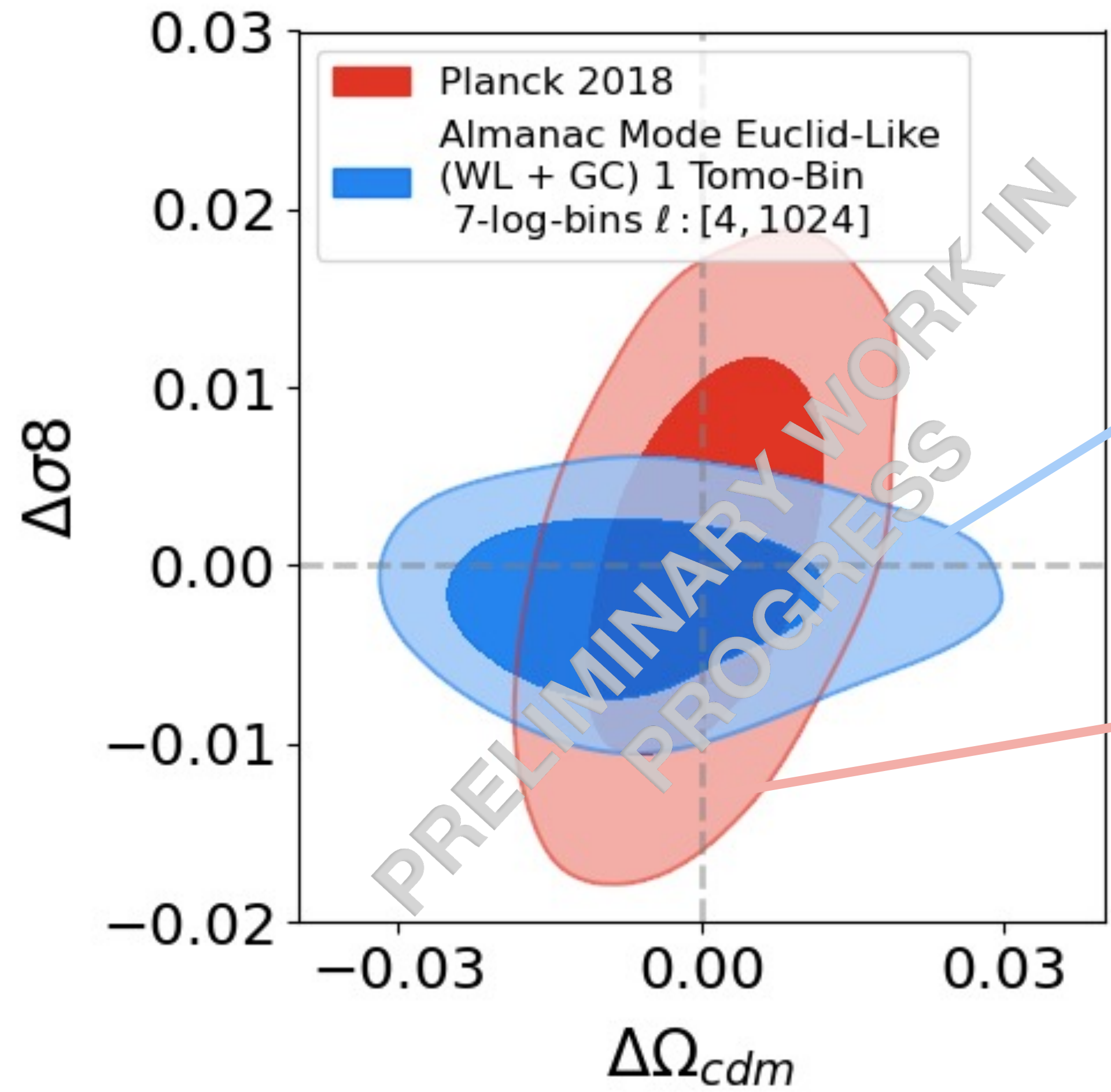
Extracting Cosmology

Using point estimates and normalizing flows



Cosmology with point estimates

Work lead by PhD Candidate Javier Lafaurie



- Using Almanac Post. Mode and Covariance:**
- Sampling $\sigma_8, \Omega_{\text{cdm}}, \Omega_b, h, n_s$
 - Other parameters fixed
 - Single redshift bin, 1 out of 10 (more coming!)
 - Weak Lensing + Galaxy Clustering
 - Gaussian covariance: $\mathcal{P}(\theta|d) \propto \mathcal{L}(d|\theta)\pi(\theta)$

Full Planck 2018

⚠ This is an illustrative comparison ; parameter spaces are different (for now)! ⚠

Cosmology with Normalising Flows

Work lead by PhD Candidate Kutay Nazli



DELUGE: Normalizing flows to model non-Gaussian posteriors
Adapting normalizing flows to high-dimensions to model ALMANAC's posterior

Abstract

- Context: Analyzing the shape distortions of galaxies on large scales due to weak lensing (WL) allows for statistical analysis of the shear field, which measures the overdensities of matter in the universe. Thus, weak lensing shear fields and their power spectra can be used to constrain the values of multiple cosmological parameters, such as Ω_m , σ_8 and H_0 . These observables can be modeled independently of assumed cosmological models, allowing for a flexible complement to the current probes.
- Aims: Currently, to model the full posterior distributions of the E-modes of the power spectra of the weak lensing shear field obtained from the ALMANAC [1, 2] Bayesian hierarchical model (BHM) using normalizing flows.
- Methods: Within this framework, the analytically unknown posteriors of the power spectrum are iteratively mapped to known probability distributions via variable transformations learned by neural networks. This enables the generation of new data, probability calculation and parameter inference.
- Results: At the current stage, the method of learning posterior distributions of ALMANAC binned into up to 400 bins produces remarkable agreement in the 1-dimensional and 2-dimensional marginals. More holistic tests show that better agreement in the full posterior space requires further training and fine tuning.

ALMANAC: Sampling the WL power spectrum

Below, 1-dimensional marginal samples of the WL power spectrum for 2 Euclid tomographic bins from 2 separate chains of ALMANAC presented in [2]. It shows very clearly that for low l , the posteriors are significantly non-Gaussian for both auto-correlations and the cross-correlation.

ALMANAC is a modified Hamiltonian Monte Carlo-based code for signal extraction of power spectra and maps on the sphere [1]. It allows for cosmology agnostic sampling of the power spectrum C of the weak lensing (WL) shear field defined by its spherical coefficients a . It evaluates the following posterior:

$$P(C, \vec{a} | \vec{d}, N) \propto \mathcal{L}(\vec{d} | \vec{a}, N) g(\vec{a} | C) \pi(C)$$

In the case of spin-weight 2 fields such as WL, ALMANAC infers E- and B-mode power spectra and parity-splitting E/B power by sampling the full posteriors [1] rather than using point estimates. The non-Gaussianity observed in these full posteriors necessitates the methods employed in this work.

Normalizing Flows

1-dimensional marginals of ALMANAC's posterior are non-Gaussian. Thus fitting a multivariate Gaussian to this posterior would ultimately bias the preceding inference. To avoid this, it is possible to model the full posterior using normalizing flows without making assumptions about the true function. The above figure explains the concept of normalizing flows. The data distribution is normalized through consecutive application of diffeomorphisms $f_n(z; \theta_n)$, where θ_n denote function parameters learned by neural network NN. Then, the relation between Gaussian variable z_n and data x is:

$$\vec{z}_n = f_n \circ f_{n-1} \circ f_{n-2} \circ \dots \circ f_2 \circ f_1(\vec{x})$$

Requiring invertibility allows for generation of samples of data never-before-seen:

$$\vec{x} = f_1^{-1} \circ f_2^{-1} \circ f_3^{-1} \circ \dots \circ f_{n-1}^{-1} \circ f_n^{-1}(\vec{z}_n)$$

Even though there are many candidates for suitable diffeomorphisms, this work uses rational quadratic splines and ELU-decomposed linear transformations. Finding the best function parameters θ_n is possible through minimizing the approximate reverse Kullback-Leibler divergence:

$$L = -\frac{1}{N} \sum_{i=1}^N \left(\log p(\vec{z}_i) + \log \left| \det \frac{df_1(\vec{z}_i)}{d\vec{x}} \right| + \dots + \log \left| \det \frac{df_n(\vec{z}_i)}{dz_{n-1}} \right| \right)$$

DELUGE: NF for WL power spectrum

Above flowchart illustrates the components of DELUGE. The individual components are implemented as follows:

- Data Preparation: A PyTorch-based class allows for the preparation of data for flow model training including options for binning, slicing, normalization and memory mapping for extremely large training sets.
- HPO: Hyperparameter optimization is handled using the new industry standard Optuna [3]. A wrapper around Optuna allows for saving of a desired number of best models to be saved for further training.
- Training: The normalizing flows used are from the normalflows [4] package. A custom flow architecture is built around the individual flow transformations to allow the further implementation of loss function engineering and optimization.
- Ensemble: All the trained models are ensemble to reduce the training-induced random noise effects.
- Parameter Inference: The resulting ensemble model can be evaluated on many theory power spectra in parallel in a matter of seconds to produce posterior plots.

DELUGE: Early results

Below: The cumulative buildup of samples in ALMANAC and in normalizing flow models as a function of distance from the maximum-a-posteriori in 100-dimensions. The smaller panel displays the difference in the number of samples accumulated. The difference needs to be accounted for correct cosmological parameter contours.

Above: 10-dimensional corner plot showing a fraction of the full 100-dimensional ALMANAC to normalizing flows comparison between samples drawn from both over-plotted. The agreement is to the point that it is near impossible to distinguish the ALMANAC contours in black behind the flow contours in red.

References

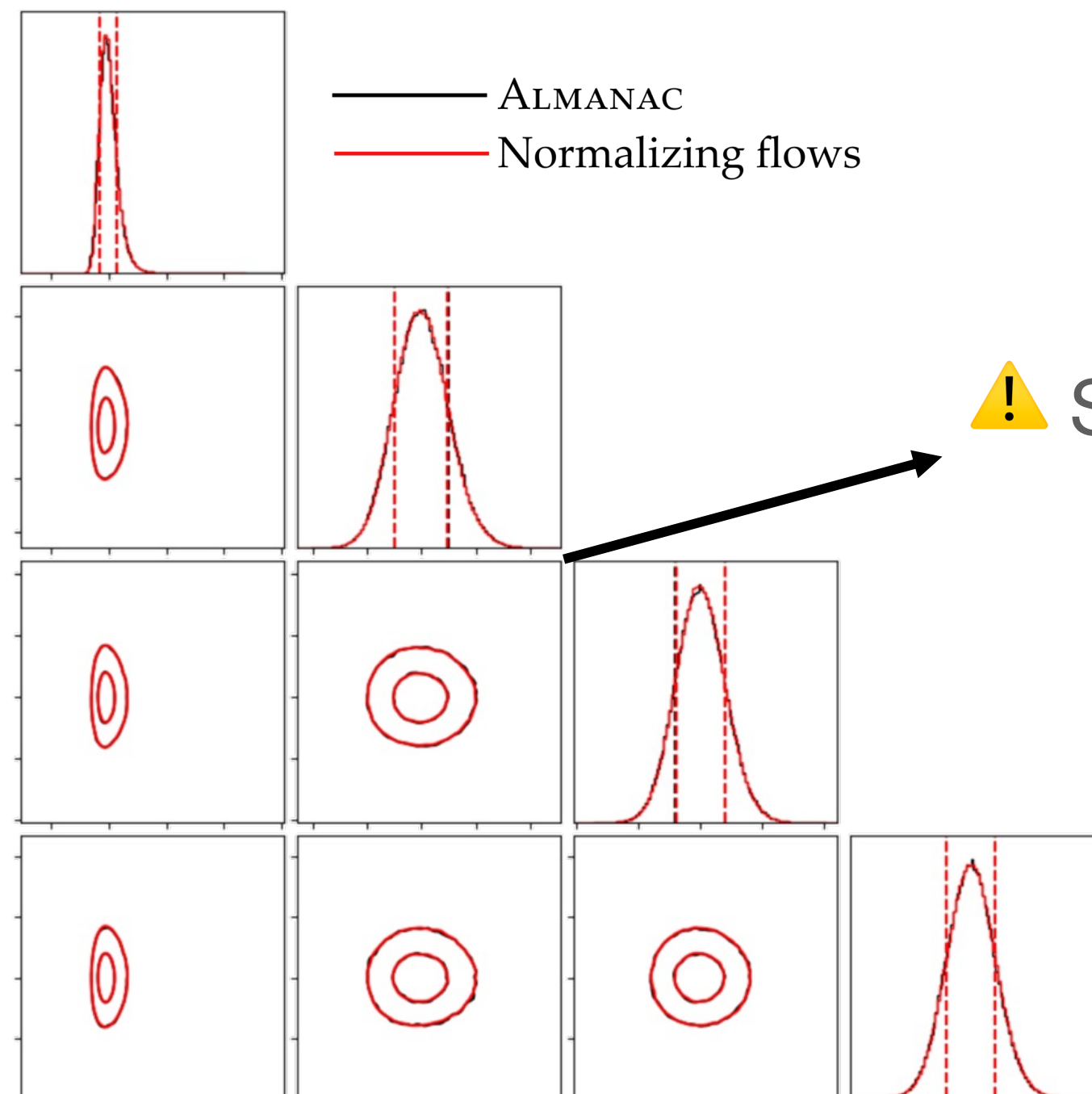
[1] E. Seldner, A. Loureiro, I. Whiteley et al. 2023. ALMANAC: MCMC-based signal extraction of power spectra and maps on the sphere. The Open Journal of Astrophysics, Vol. 6, id. 10. <https://doi.org/10.1051/olj/2023/6/10>

[2] E. Seldner, I. Whiteley, E. Seldner et al. 2023. ALMANAC: Weak Lensing power spectra and map inference on the masked sphere. The Open Journal of Astrophysics, Vol. 6, 2023. <https://doi.org/10.1051/olj/2023/6/20>

[3] Takuya Akiba, Shunta Noma, Yoshino Tanaka, Takuma Ohta, and Masamichi Yamada. 2019. Optuna: A Next-generation Hyperparameter Optimization Framework. In IJCAI.

[4] H. Singer et al. (2022). normalflows: A PyTorch Package for Normalizing Flows. Journal of Open Source Software, 5(9), 5361. <https://doi.org/10.21105/joss.05361>

Goal: to obtain a normalising flow representing the full non-gaussian posterior of Almanac angular power spectra



! Showing her just a small subsection !
of the 20k dimensional space!

Check out Kutay's poster and chat with him for more!

A stylized map of the sky showing survey paths and data points. The map is dark with numerous small white dots representing stars or galaxies. Overlaid on this are several paths: orange lines forming a grid-like pattern, blue lines forming a more irregular, winding pattern, and clusters of orange and blue dots. The map is partially cut off on the right side.

Summary

- Almanac uses one of the most optimized samplers to simultaneously sample full-sky cosmological signal fields and their angular power spectra!
- Almanac produces data products that are model-independent: we can use them to test Λ CDM, wCDM, w_0w_a CDM, that weird cosmological model from Penrose... anything!
- We can already achieve the expected scales for Stage-IV Weak Lensing surveys with accuracy and precision!

Next:

- Applications to Stage III Survey Data
- Cosmological analysis from point estimates (Javier Lefaurie)
- Cosmological analysis using normalising flows (Kutay Nazli)
- Primordial non-gaussianities with Weak Lensing Fields

Interested?

Come talk to us here!



That's me,
(obviously...)



Prof. Elena Sellentin



Kutay Nazli



Prof. Alan Heavens

