Map-based cosmology inference with lognormal cosmic shear maps

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Cosmology from Home, 2021

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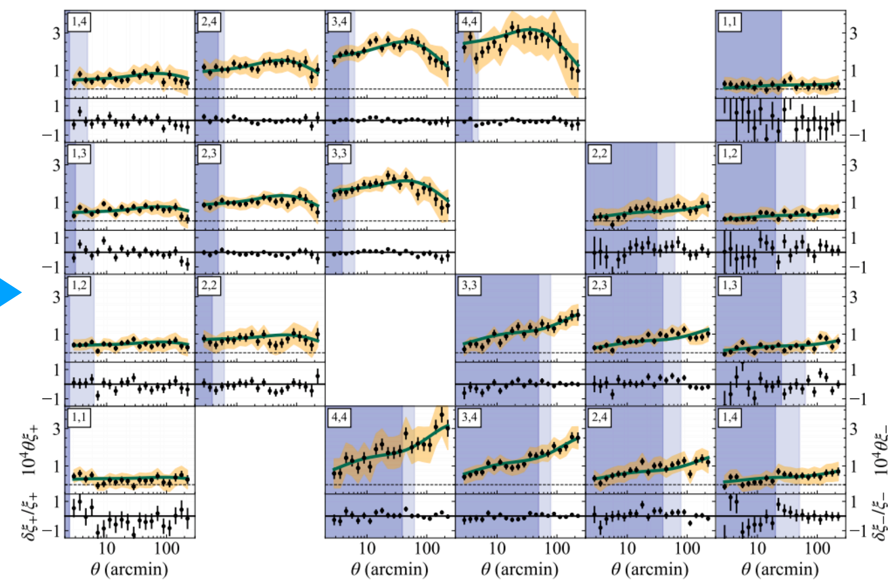
Cosmological parameters from weak lensing

Galaxy shapes

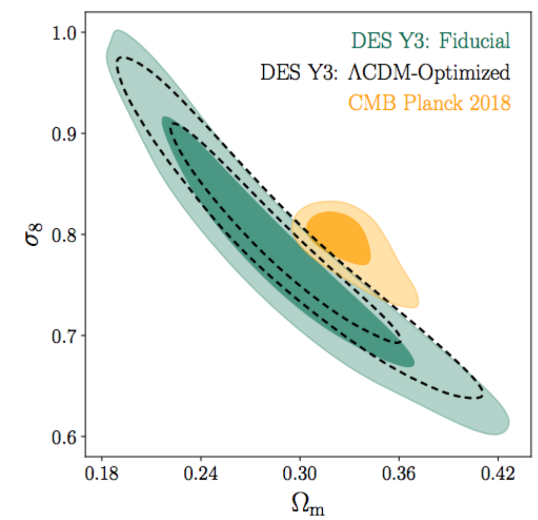
Summarize

DES-Y3 correlation functions



Compare model prediction + systematics

Cosmology contours



- *2 pt functions capture all the information for a Gaussian field*
- *Gravitational structure formation induces non-Gaussianity*
- *Potentially much more information in the NG statistics*

Images: NASA/ESA, DES

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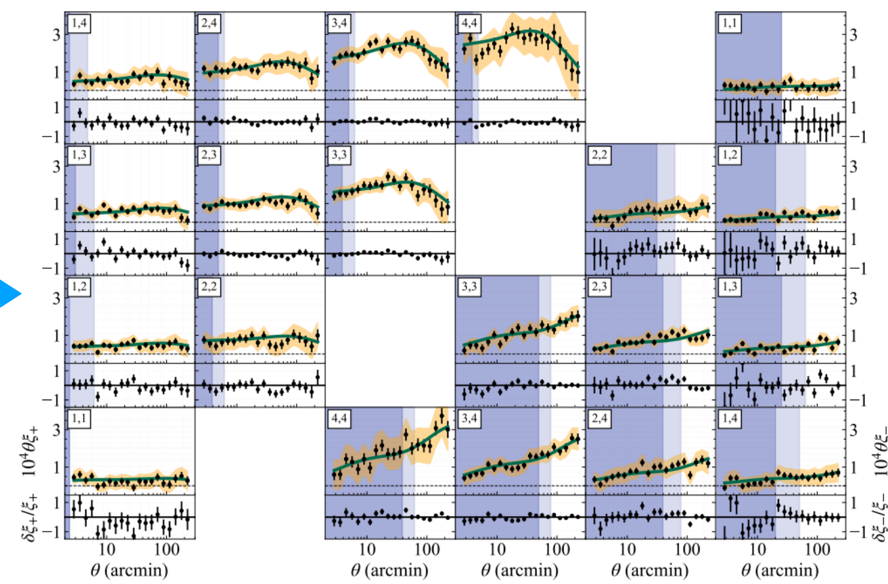
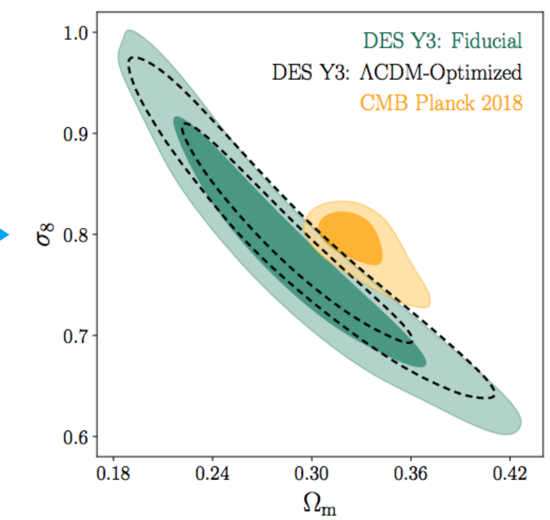
Summarize

DES-Y3 correlation functions



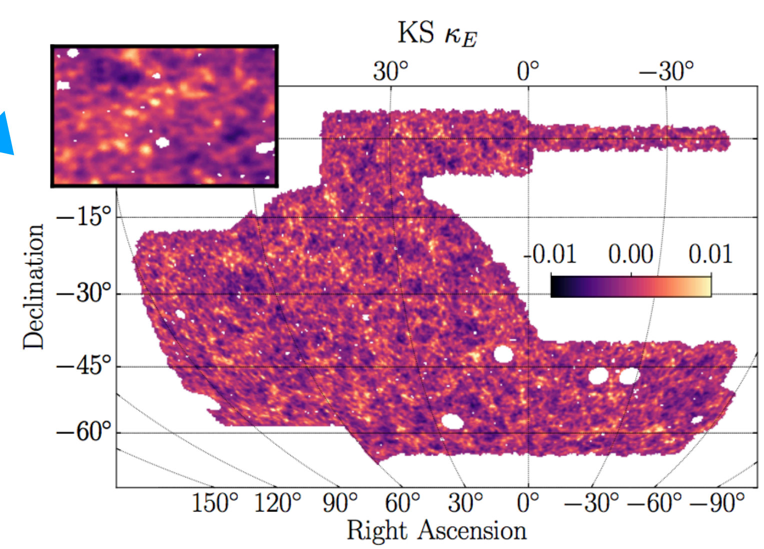
Compare model prediction + systematics

Cosmology contours



Mass mapping algorithm

Mass maps



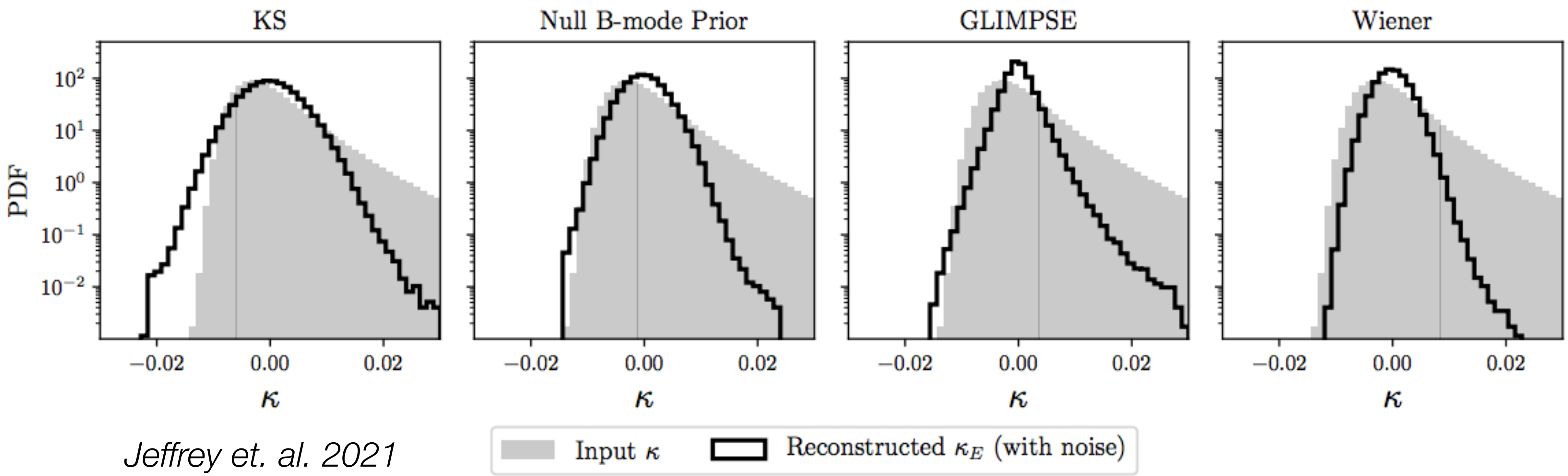
Summarize

NG summary statistics, e.g, peak counts, 1 pt. PDF, Minkowski functional, ….

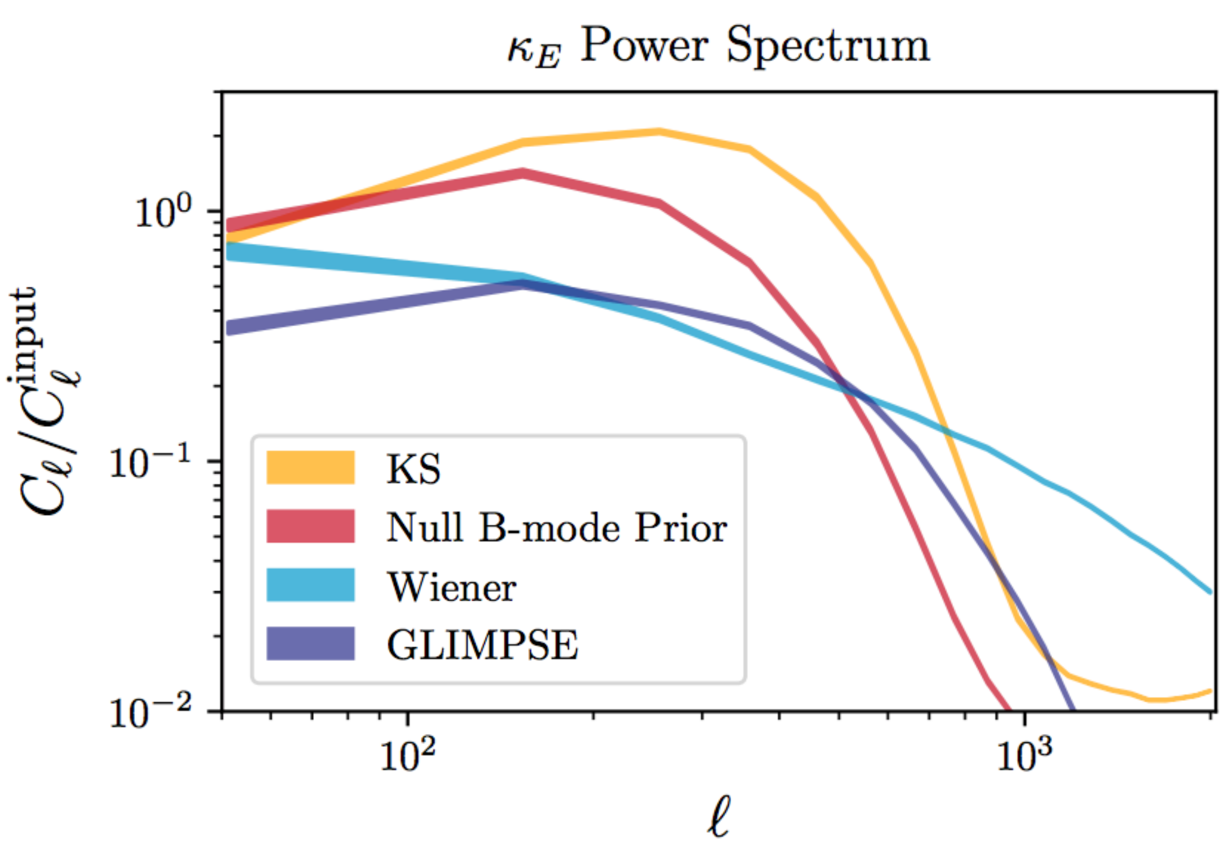
Compare model prediction + systematics

Images: NASA/ESA, DES

Mass mapping algorithms



Jeffrey et. al. 2021
DES-Y3 mass maps



Drawbacks of mass mapping algorithms:

- Wrong statistics
- Correlations between different redshift bins are not considered
- No uncertainty estimates

Map-based inference

Galaxy shapes

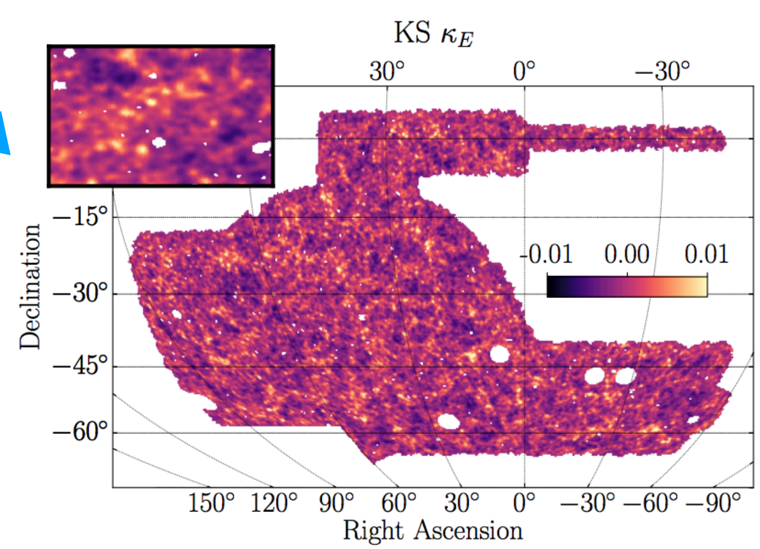
Can we have a unified framework to simultaneously make (improved) mass maps and constraint cosmological parameters?

If we had the probability distribution for the full field, $P(\kappa \,|\, \Theta)$, we can capture ***all*** *the available information in the maps*

Mass mapping algorithm

Improved algorithm

Mass maps

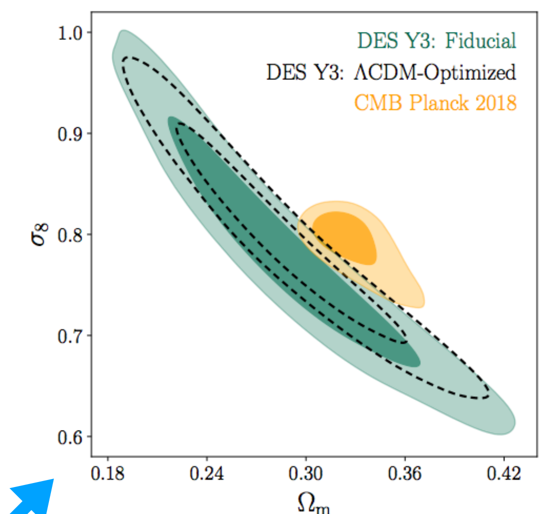


Compare at field level

Summarize

NG summary statistics, e.g, peak counts, 1 pt. PDF, Minkowski functional, ….

Cosmology contours

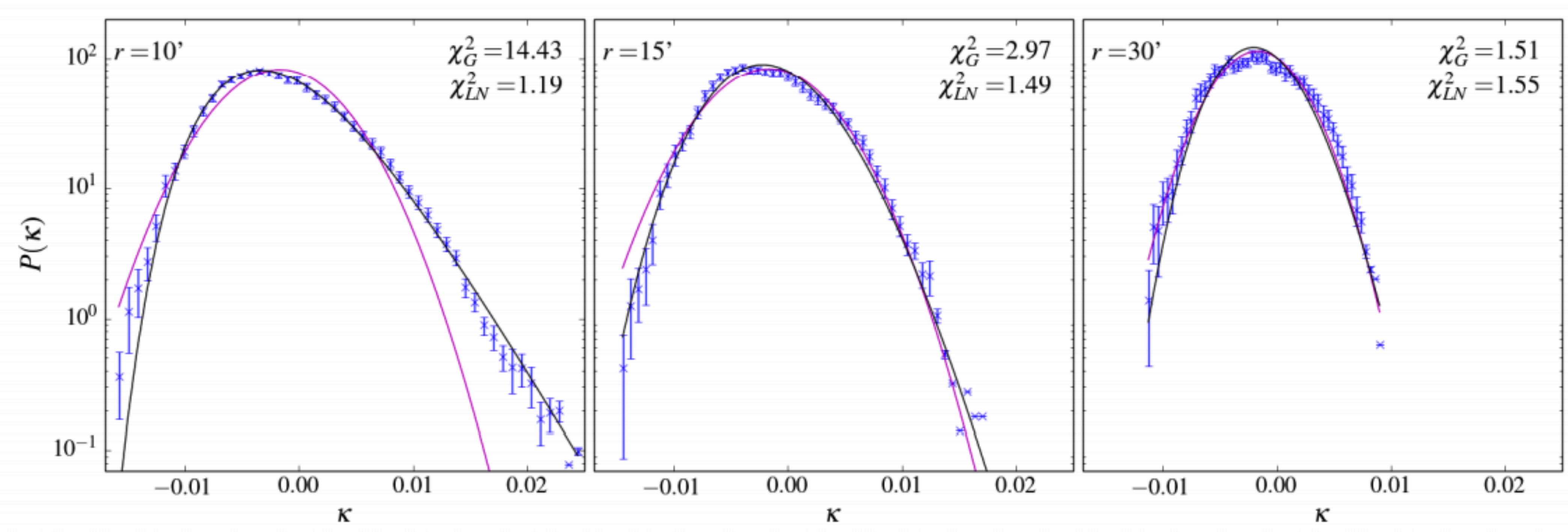


Compare model prediction + systematics

Images: NASA/ESA, DES

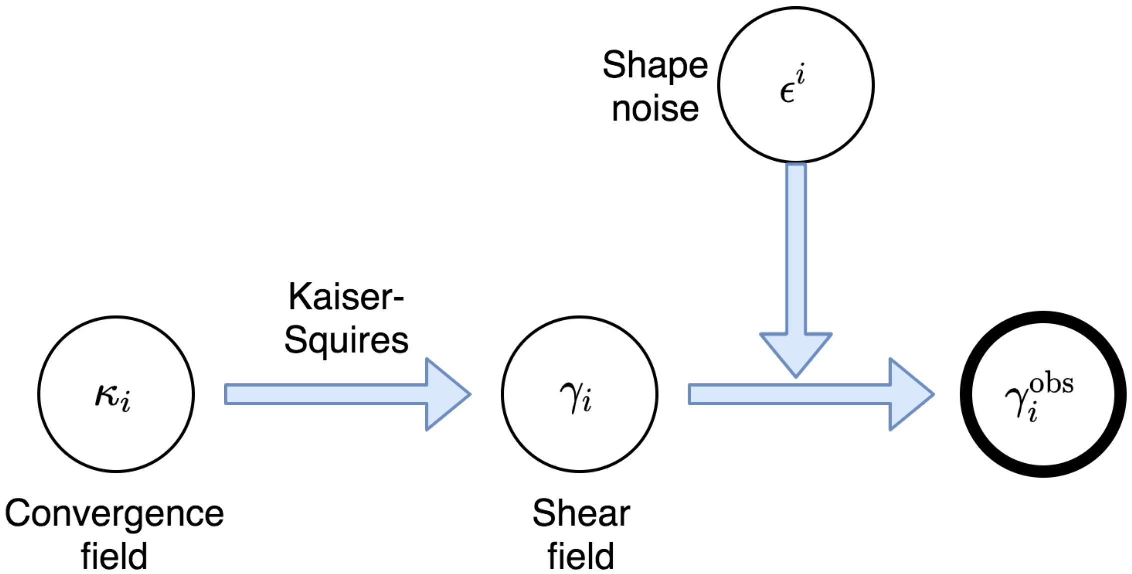
Lognormality of convergence field

- 3D density field can be modelled with a lognormal distribution *(Coles & Jones 93)*. Can enforce $\delta > -1$
- The convergence field can be well described by a multivariate lognormal field. Used for state-of-the art mocks.
- Captures the (correlated) 2 point and 1 point statistics of the map very well.



Clerkin et. al., 2017

Forward modelled mass mapping



Likelihood:

$$L(\kappa_i) \propto \prod_{i=1}^{N_{pix}} \exp\left[-\frac{1}{2}\frac{(\gamma_i(\kappa) - \gamma_i^{obs})^2}{2\sigma_\epsilon^2}\right]$$

Bayes Theorem: $P(\kappa_i | \gamma_i^{obs}) \propto P(\gamma_i^{obs} | \kappa_i) P(\kappa_i)$

Prior:

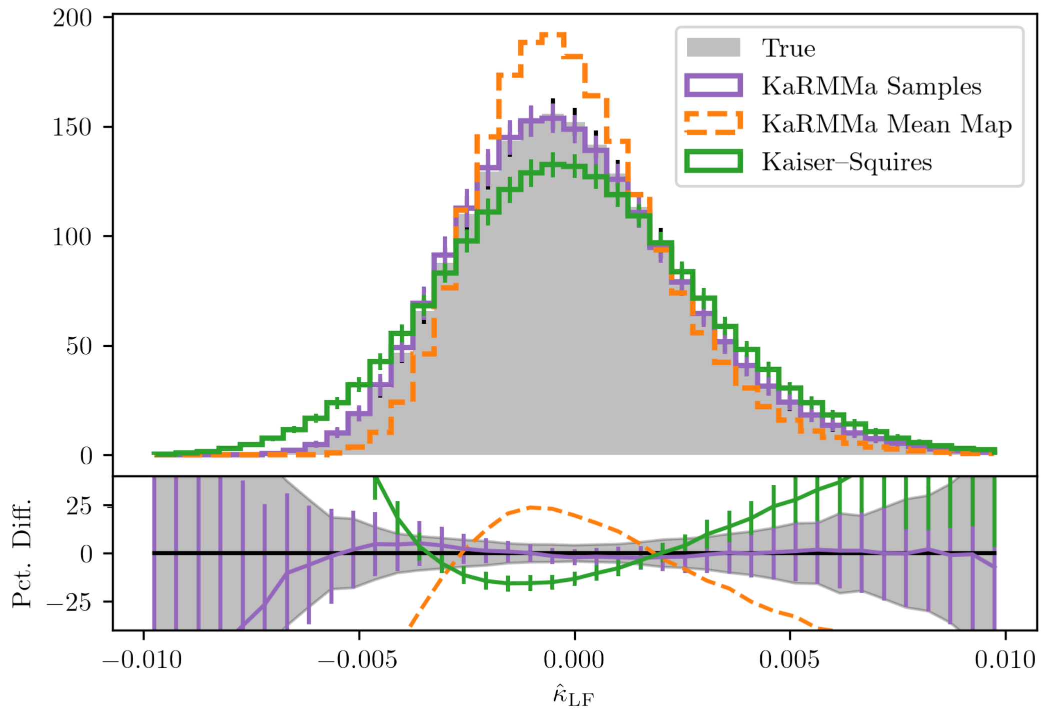
Sensible prior on the κ field, e.g, Lognormal prior

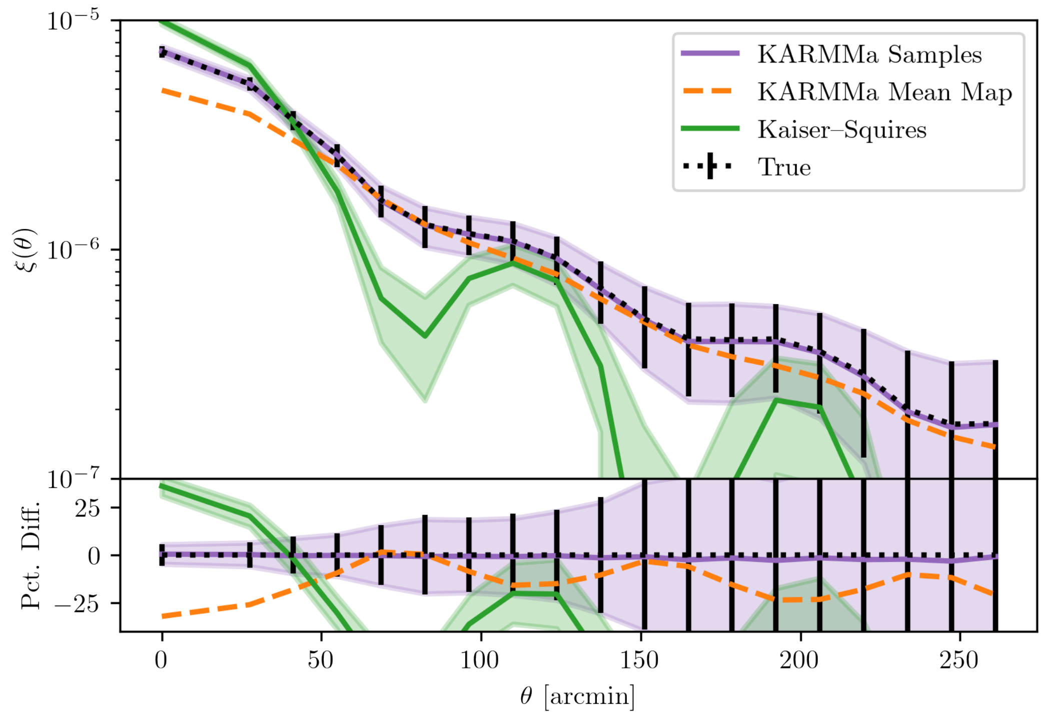
- *Treat κ_i as parameters to be inferred*
- *Very high $(N_{bins} \times N_{pix})$ dimensional parameter space.*
- *We can sample from the posterior using HMC*

- *Other forward modelled methods:*
  - *Weak lensing (Alsing et. al. 2017, Porqueres et. al. 2021)*
  - *CMB delensing (Millea et. al. 2020)*
  - *3D IC reconstruction (Jasche, et. al. 2013, Modi et. al., 2018, …)*
  - *many more…*

KaRRMa mass mapping algorithm

- KaRRMa: Kappa Reconstruction for Mass Mapping (arXiV: 2105.14699)
- Forward-modelled reconstruction with lognormal prior on convergence field
- Recovers the correct one-point and two-point functions in the mass maps





Fiedorowicz et. al. (2105.14699)

Going beyond KaRRMa

- In KaRRMa, parameters are κ values in pixel in real space $\implies$ dense covariance matrix $\implies$ Prohibitive memory requirement.
- Tomographic mass mapping. Include cross redshift bin correlations in the mass mapping algorithm.
- Sample cosmology simultaneously.

Going beyond KaRRMa

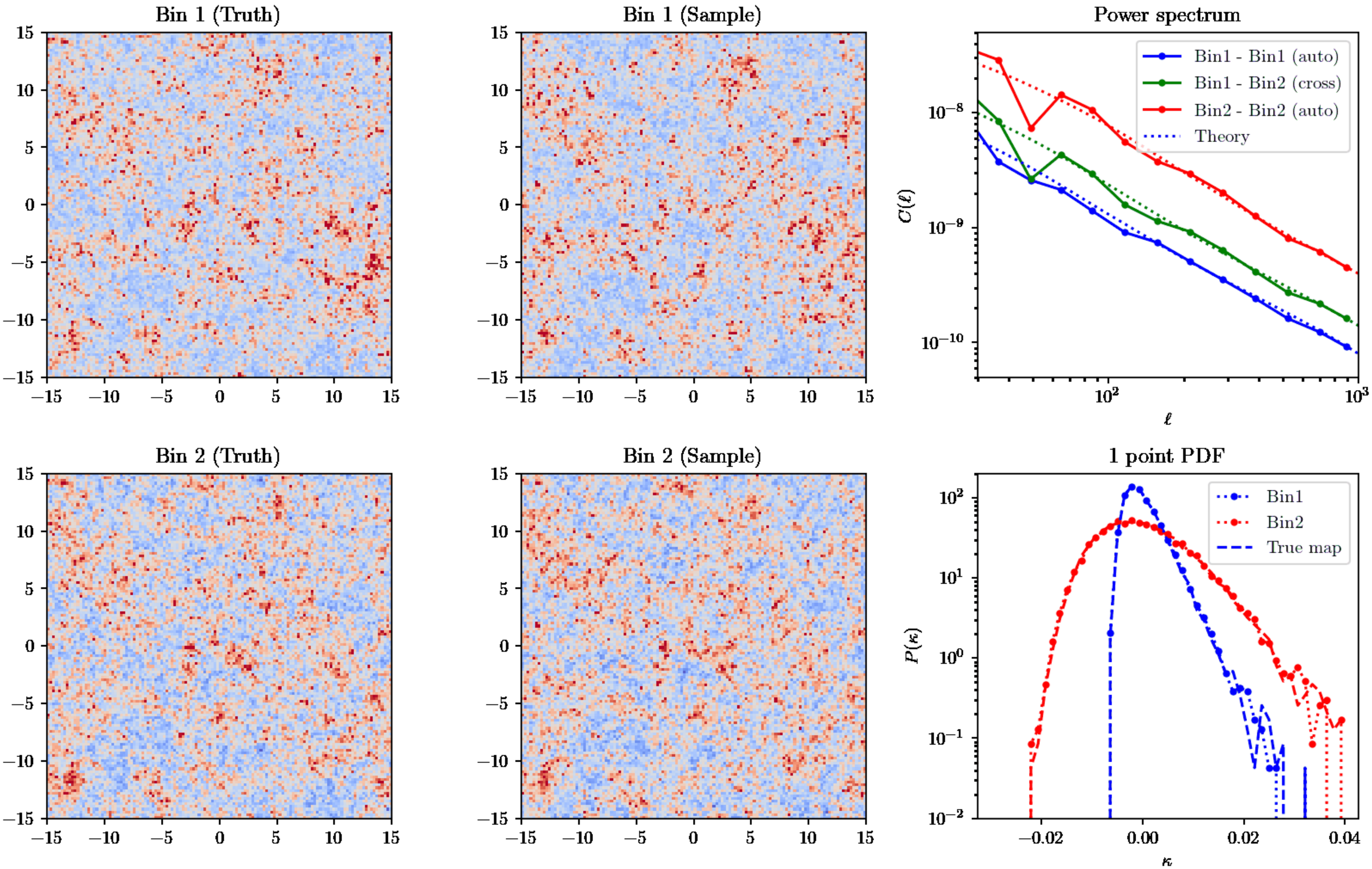
- In KaRRMa, parameters are κ values in pixel in real space $\implies$ dense covariance matrix $\implies$ Prohibitive memory requirement.

$$P(\kappa_i) \propto \exp\left[-\frac{1}{2}\kappa_i C^{-1} \kappa_j \right]$$

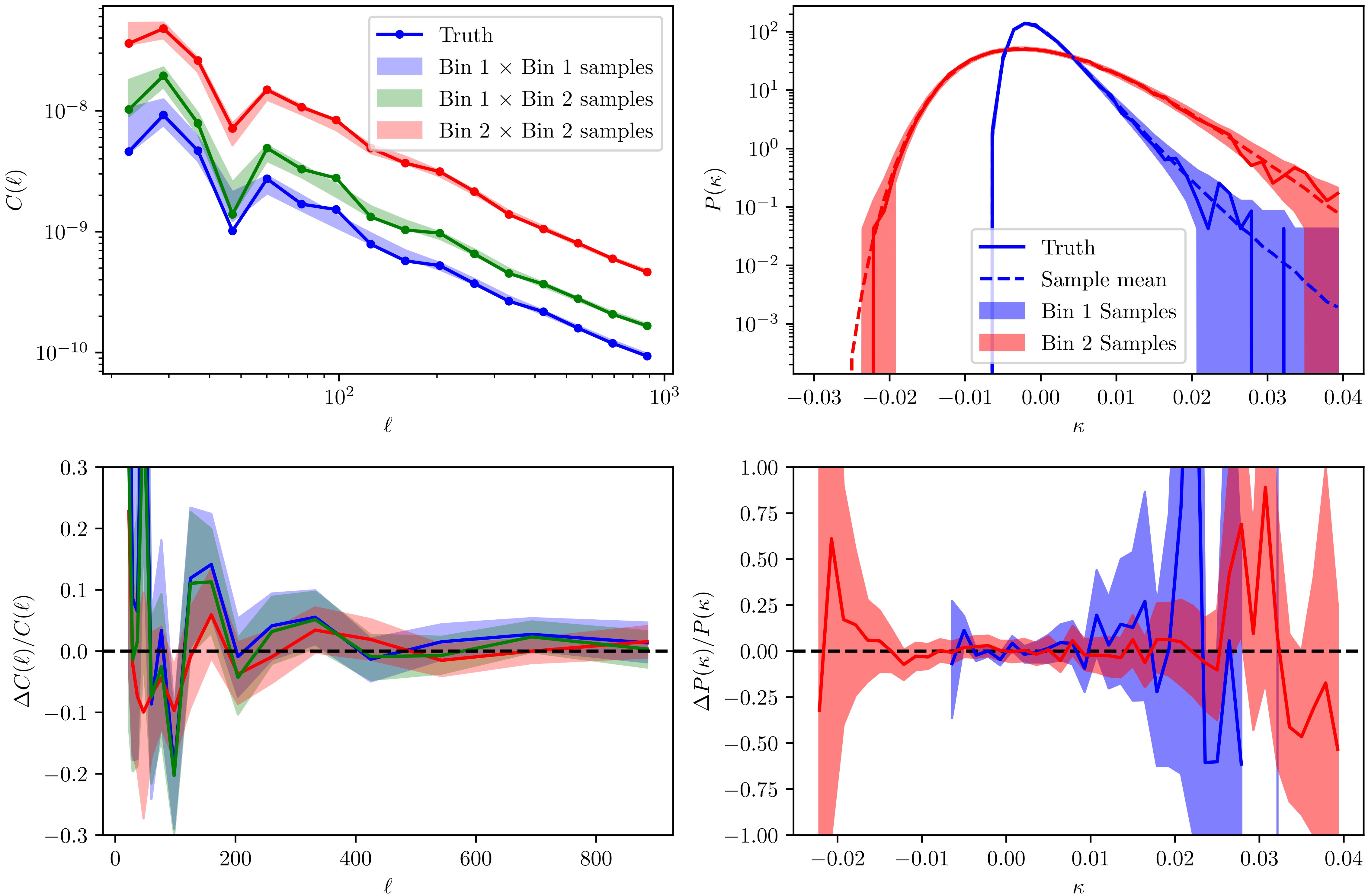
  - If κ_i are the convergence value in real space, C is dense ($N_{pix} \times N_{pix}$ independent values)
  - For Gaussian fields, in Fourier/harmonic space, C is diagonal (N_{pix} independent values)

✦ *Solution*: Sample Fourier/harmonic modes

Map sampling



Summary statistics of the maps



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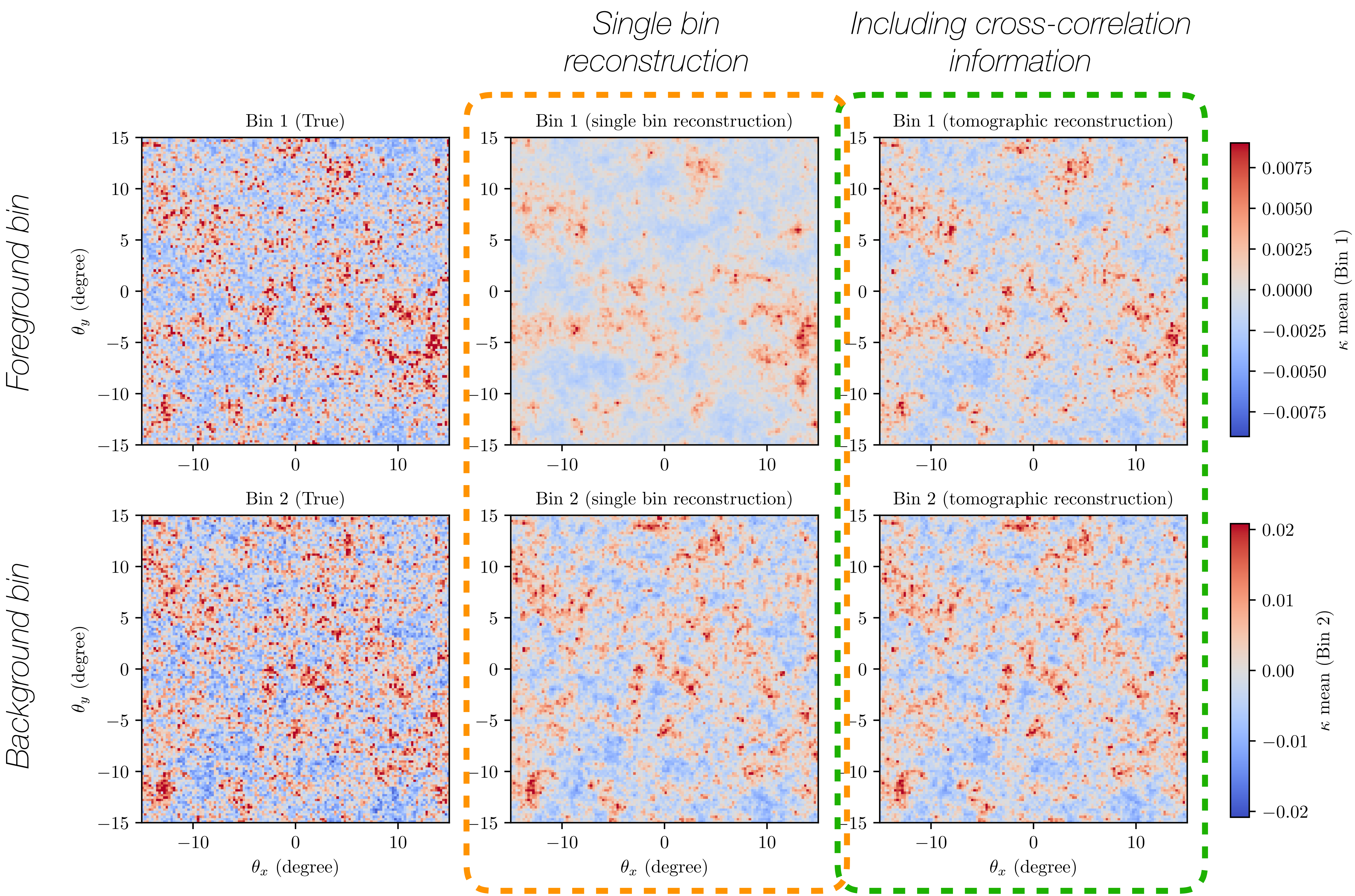
Including correlations in mass mapping



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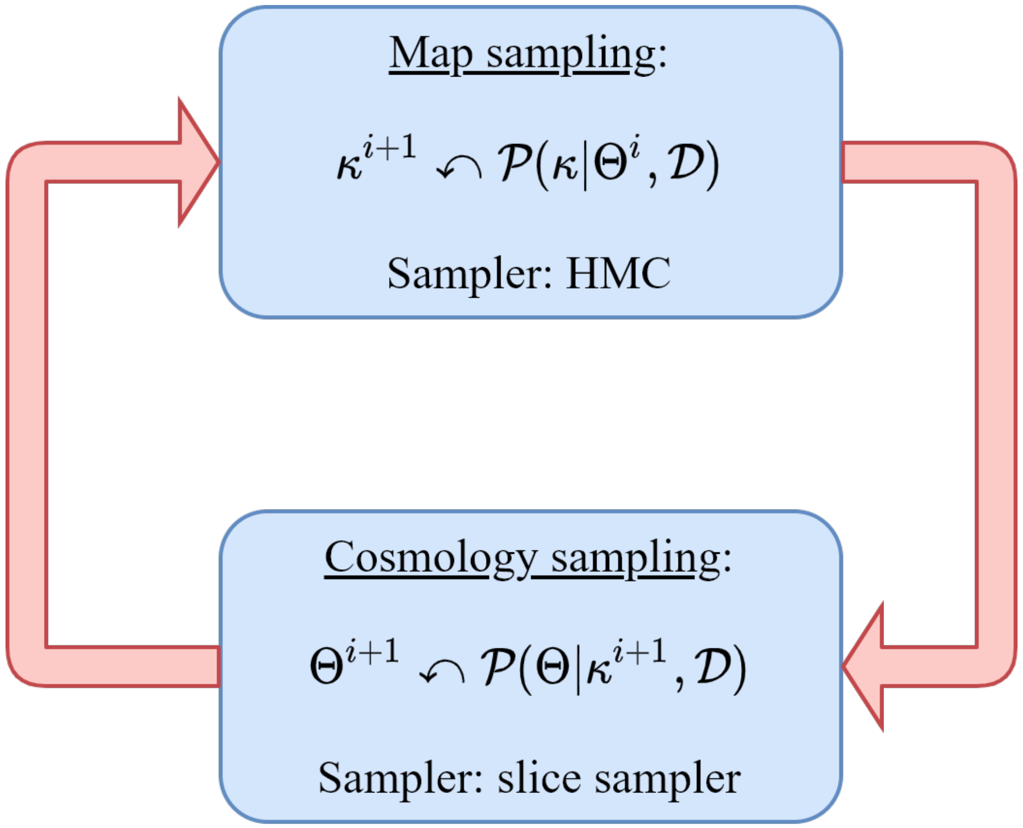


Forecasts for future surveys

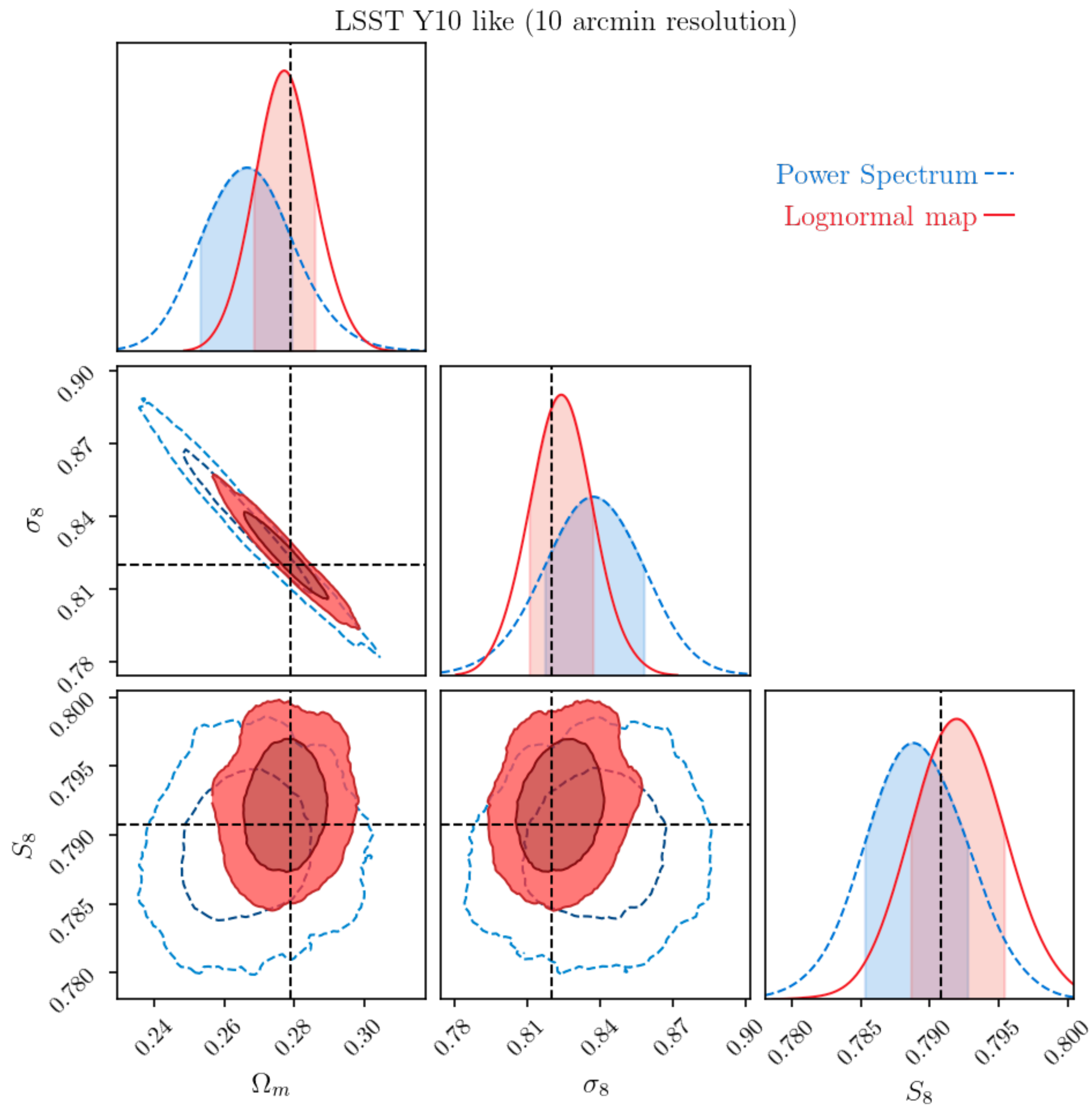
LSST-Y10 like $n(z)$

5 bin tomography

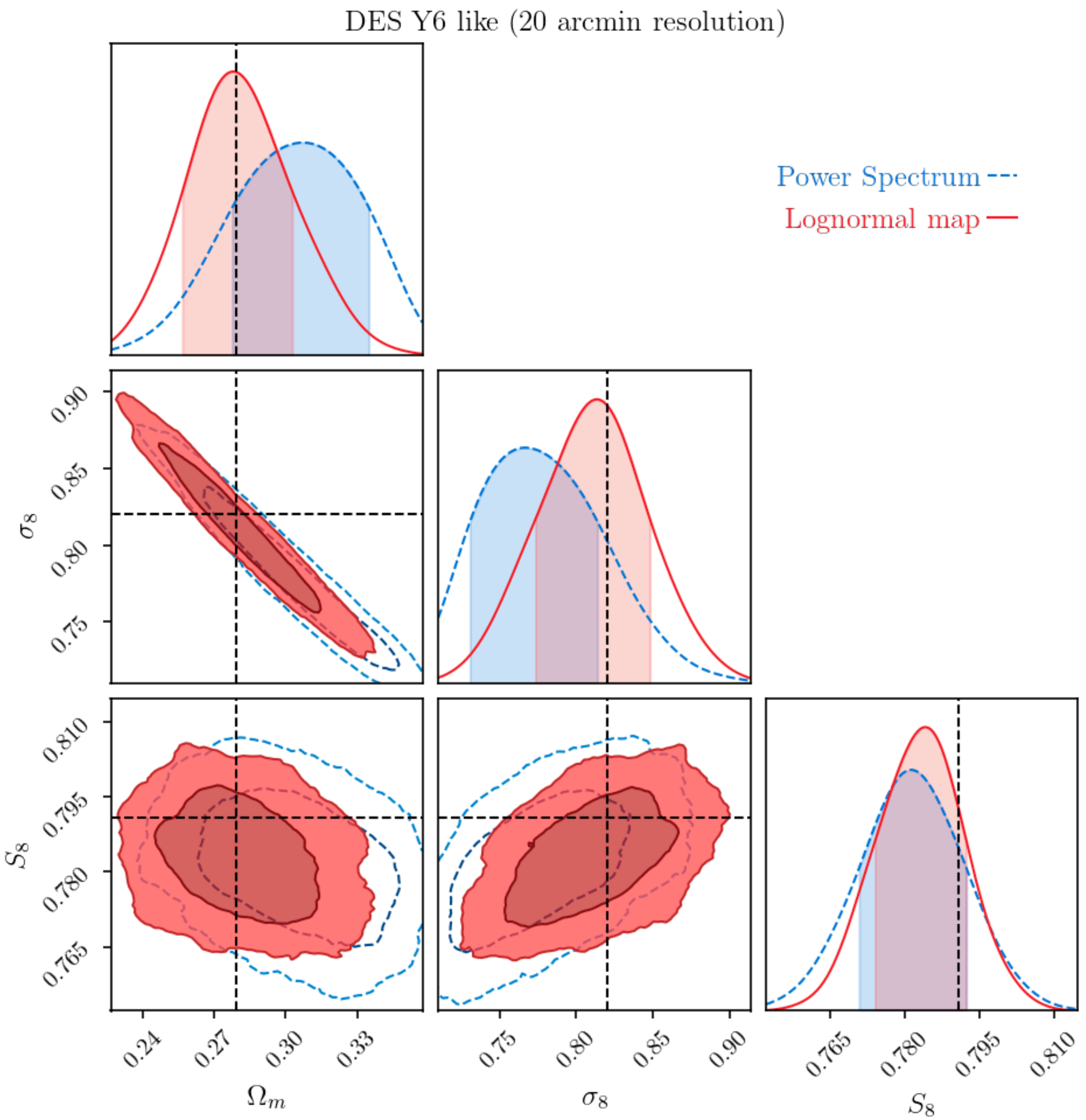
Resolution: 10 arcminute)

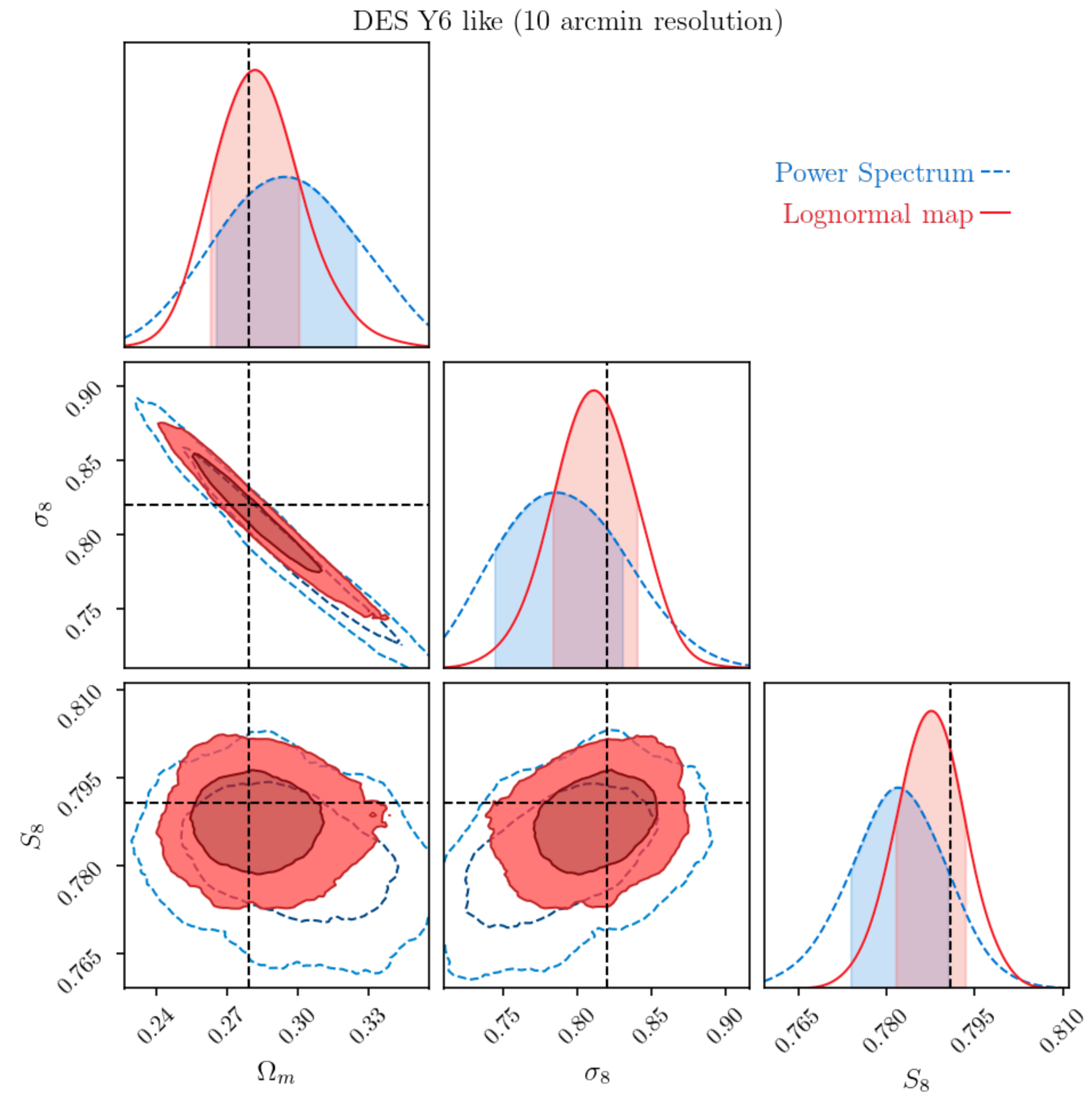
Area ~ 1000 sq degrees

- σ_8-Ω_m *Figure of merit gain:* $> 90\,\%$
- S_8 *gain:* $\sim 20\,\%$ *improvement*



Forecasts for future surveys (resolution effect)

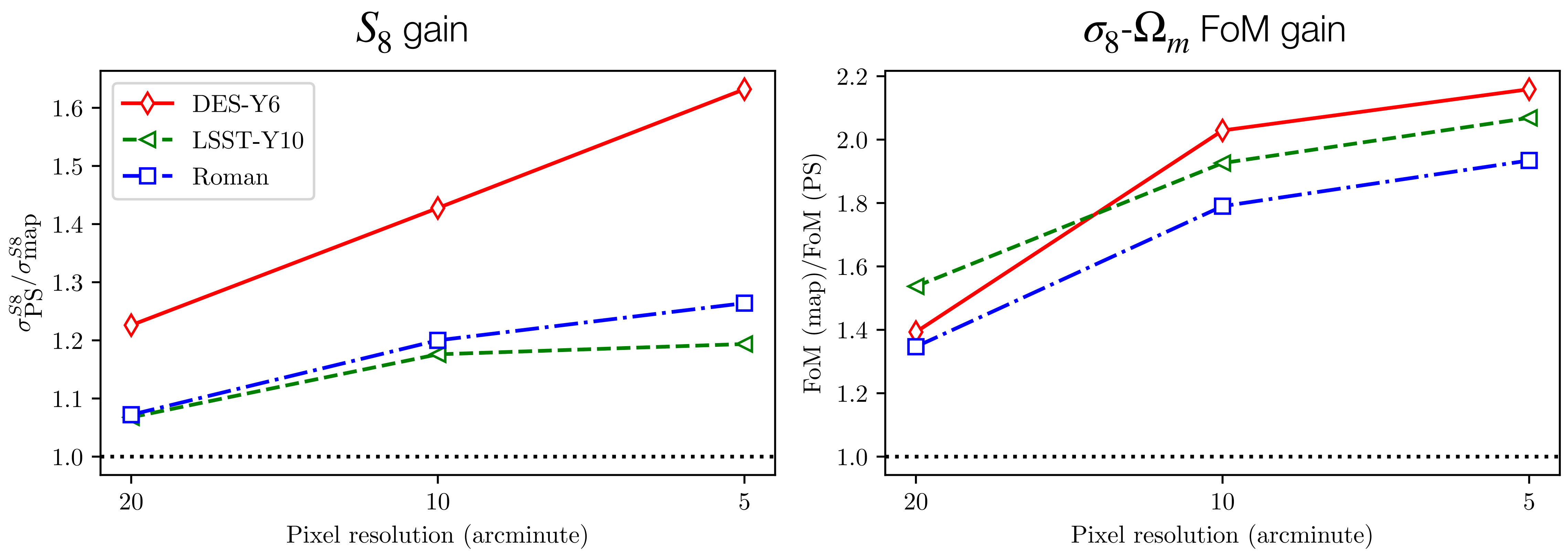




FoM gain: 40 %
S_8 *gain:* 20 %

FoM gain: 100 %
S_8 *gain:* 40 %

Forecasts for future surveys



- Substantial improvement over power spectrum inference for all surveys at all resolution.

- Breaks Ω_m-σ_8 degeneracy

- ~ 2 times improvement over power spectrum in the Ω_m-σ_8 figure of merit at 5 arc minute resolution for all surveys.

Outlook

- Map-based inference with lognormal maps gives us a principled way to infer cosmological parameters from weak lensing datasets.
- $\sim 2\times$ improvement in σ_8-Ω_m Figure of merit for future surveys by including the non-Gaussian information
- Provides a way for combining other probes, e.g, 2D galaxy clustering/CMB lensing/tSZ/any other correlated maps at the map level
- Can be used for uncertainty quantification in cross-correlation studies

Thank you!