

KiDS SBI

Simulation-Based Inference of KiDS-1000 Cosmic Shear

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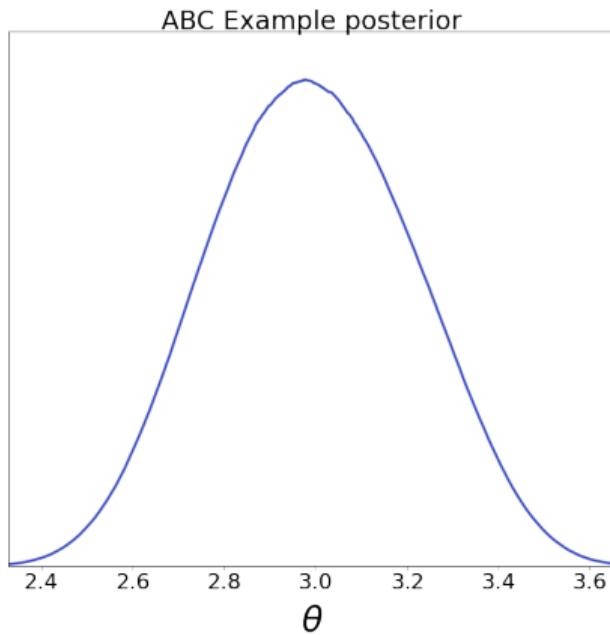
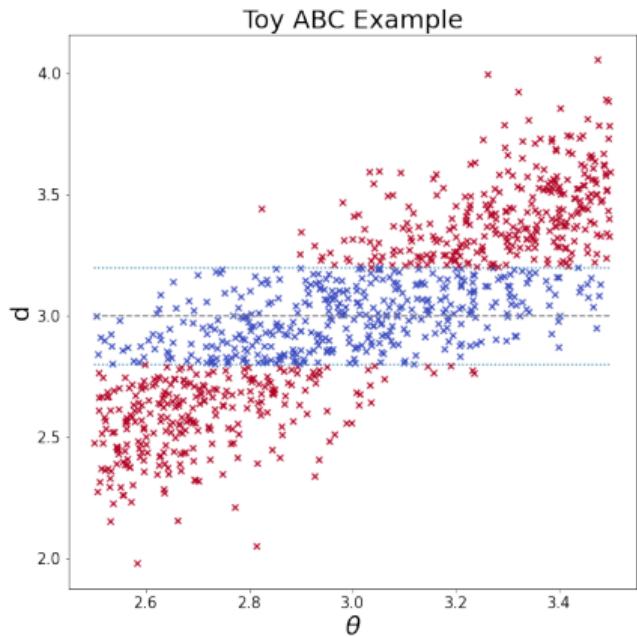
Simulation-Based Inference (SBI)

A.k.a. likelihood-free or implicit likelihood inference

- Signal and noise modelling as complex as simulations can be.
- Likelihood can take an arbitrary form (non-Gaussian).
- Full Bayesian uncertainty propagation from measurements to parameters.
- Number of simulations required similar to the number needed for numerical covariances [Lin et al. 2022; arxiv:2212.04521].

SBI: Approximate Bayesian Computation

$$P(\theta|\mathbf{d}) = \frac{P(\mathbf{d}|\theta) \cdot P(\theta)}{P(\mathbf{d})} \propto P(\theta, \mathbf{d}) \cdot P(\theta) \quad (1)$$



SBI: Density Estimation

$$P(\theta|\mathbf{d}) = \frac{P(\mathbf{d}|\theta) \cdot P(\theta)}{P(\mathbf{d})} \propto P(\theta, \mathbf{d}) \cdot P(\theta) \quad (2)$$

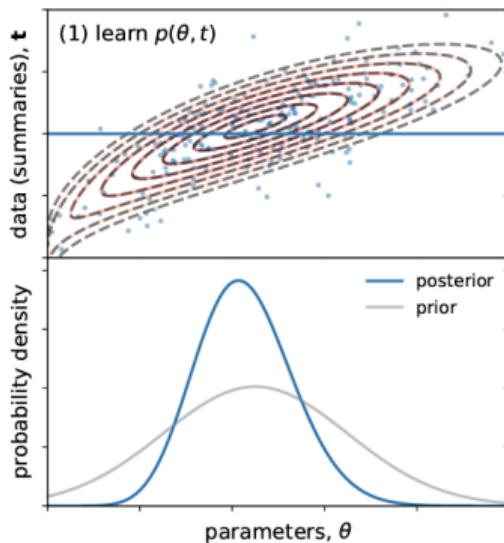
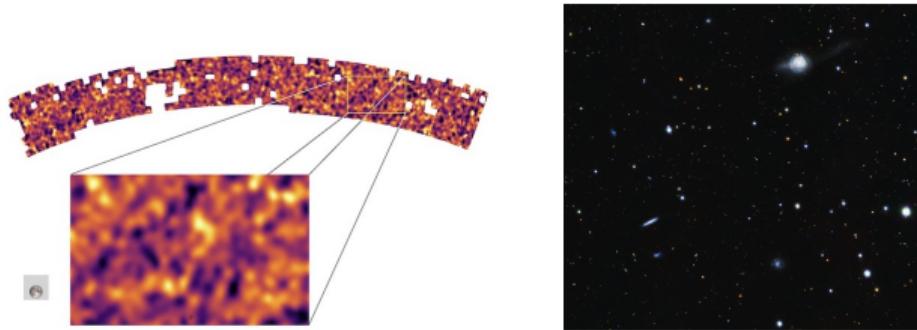
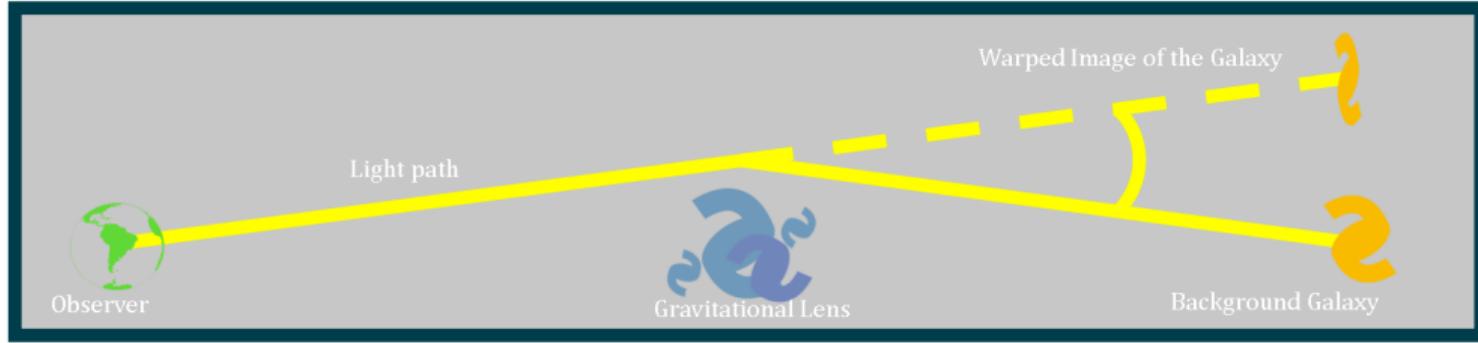


Figure: [Alsing et al. 2019]

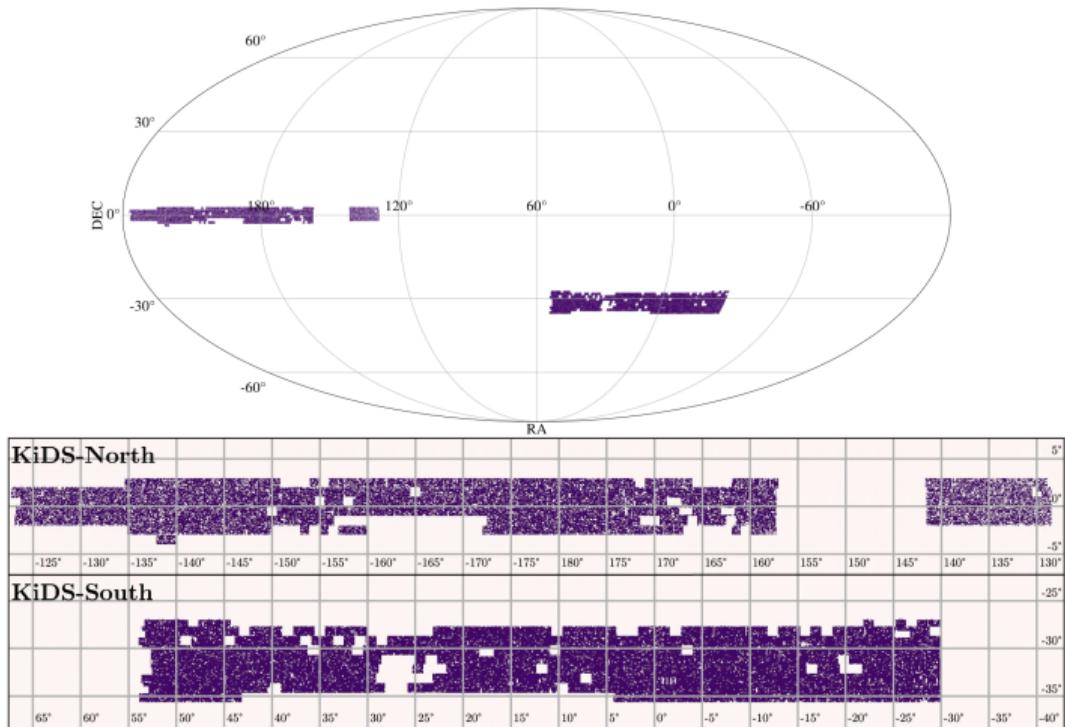
Weak Gravitational Lensing



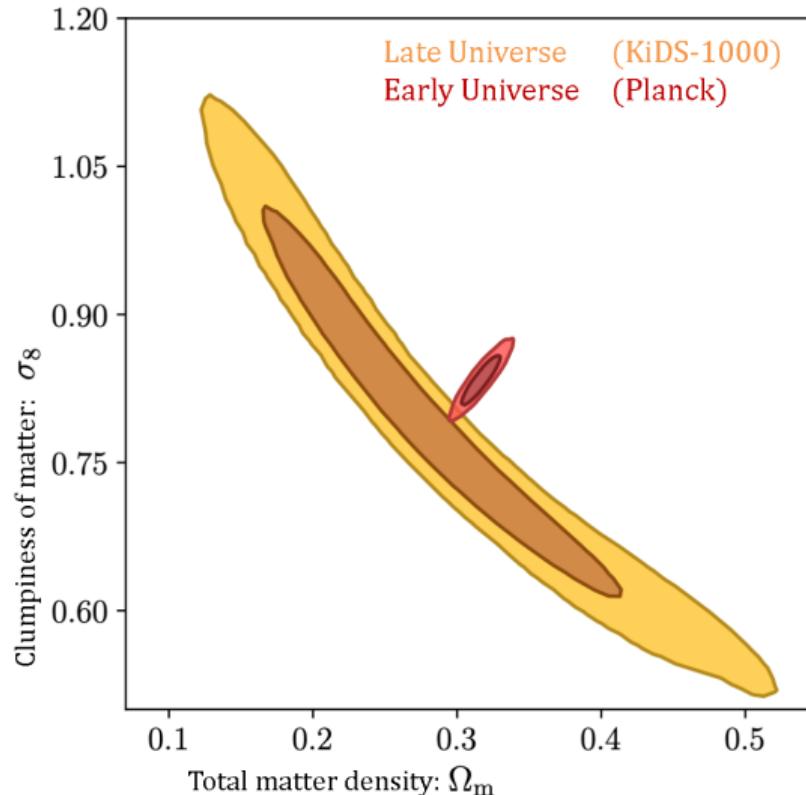
Kilo-Degree Survey: KiDS-1000



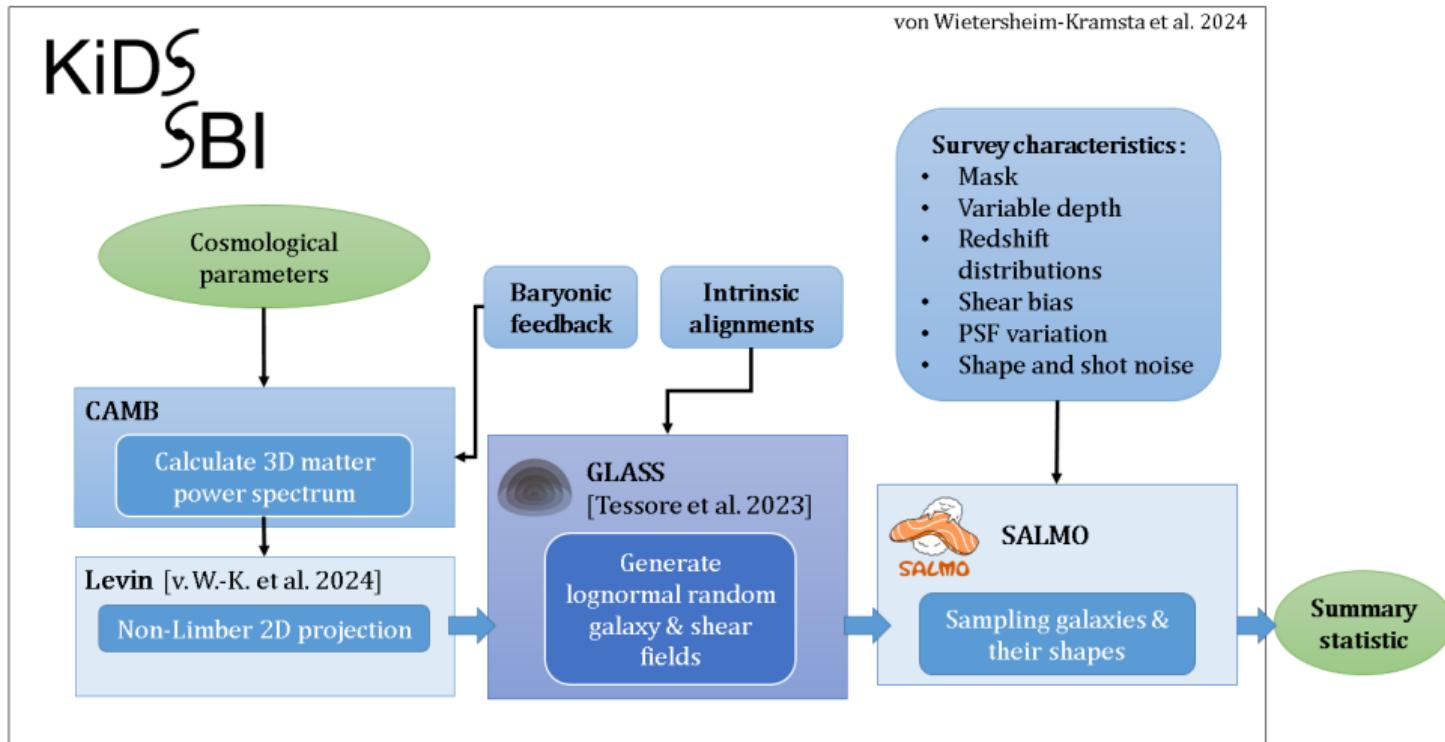
Credit: A. Tudorica



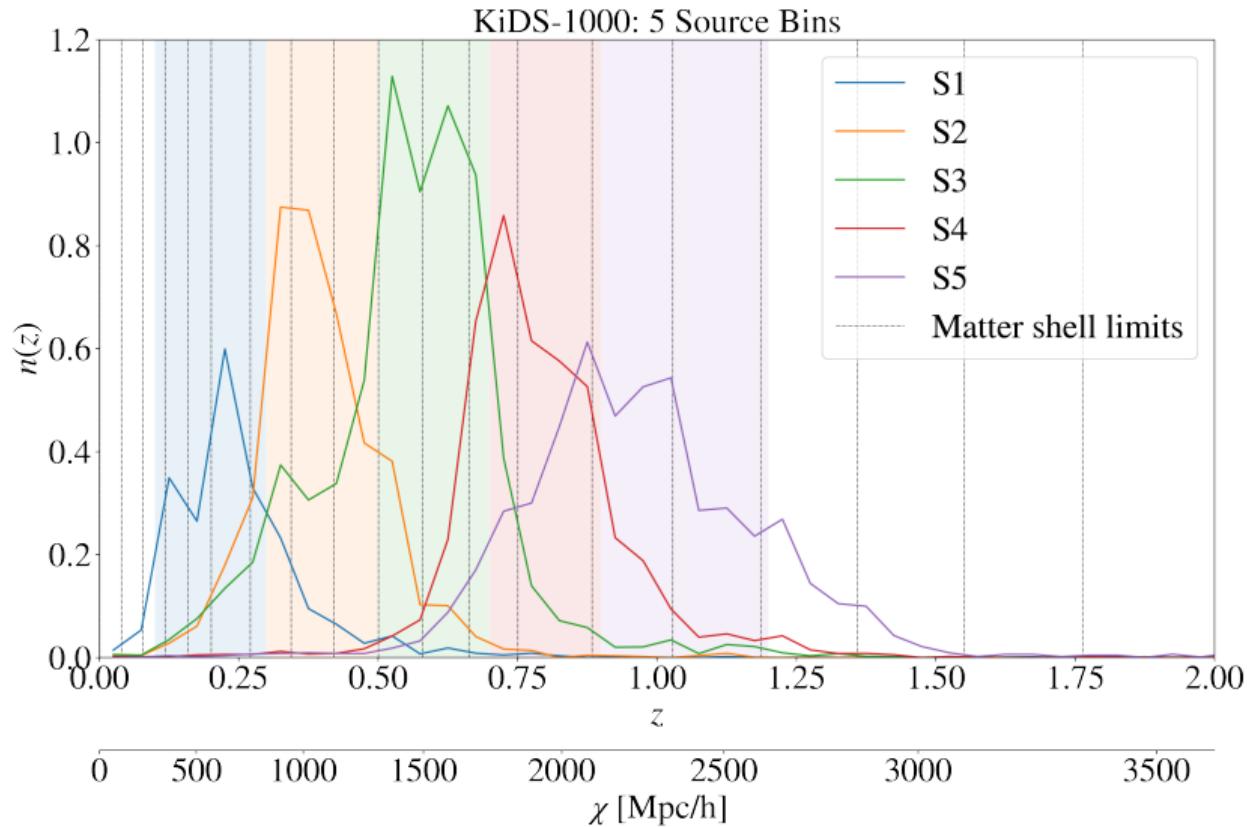
Previous KiDS-1000 Cosmic Shear Results



Forward-Simulation Pipeline



Geometry of the simulations & tomography



Geometry of the simulations

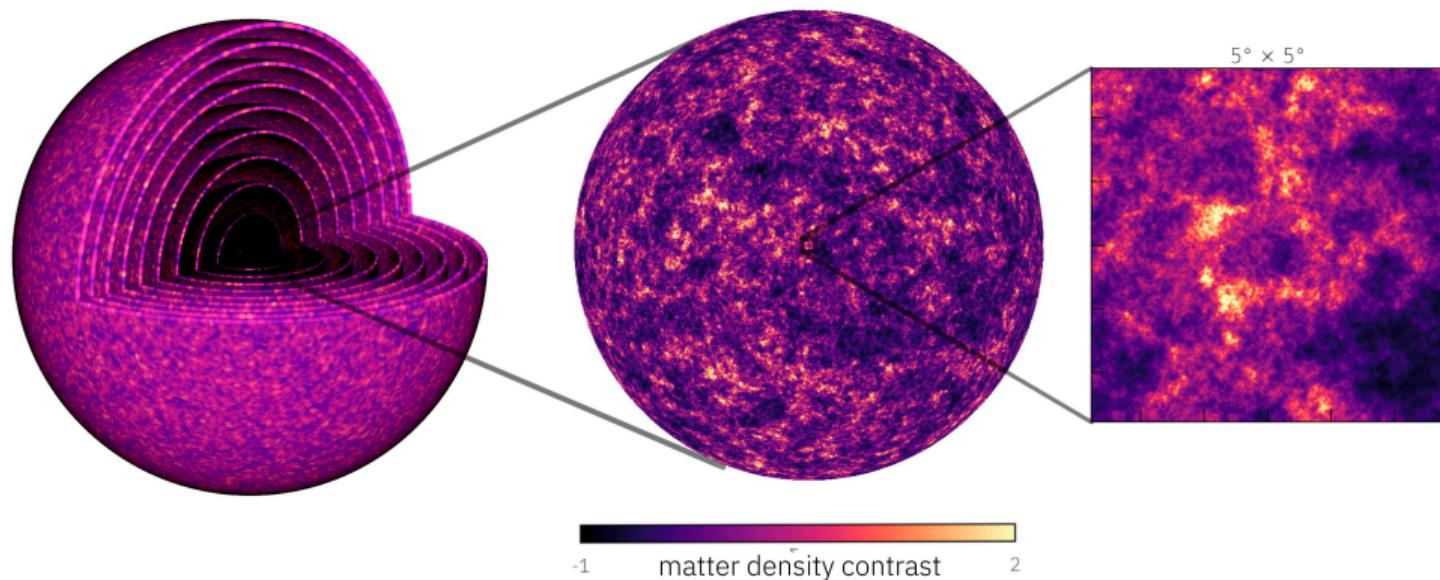
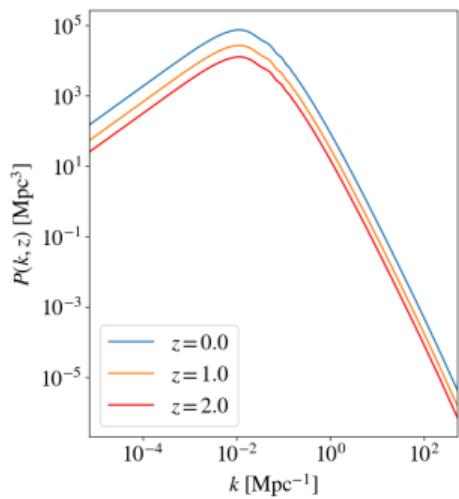
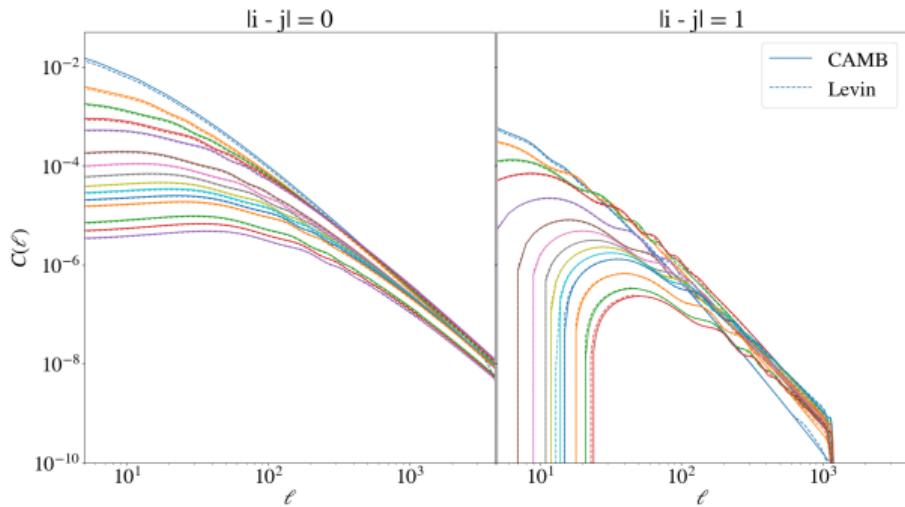


Figure: [Tessore et al. 2023; arxiv:2302.01942]

Non-Limber Projection: Levin

$$C_{\delta\delta}^{(ij)}(\ell) = \frac{2}{\pi} \int d\chi W^{(i)}(z[\chi]) \int d\chi' W^{(j)}(z'[\chi]) \int dk k^2 P(k, z[\chi], z'[\chi]) j_\ell(k\chi) j_\ell(k\chi') \quad (3)$$



GLASS: Generator of Large Scale Structure

$$C_{\delta\delta}^{(ij)}(\theta) = \langle \delta^{(i)}(\theta) \delta^{(j)*}(\theta) \rangle \quad (4)$$

$$\kappa(\theta, z) = \frac{3\Omega_m}{2} \int_0^z dz' \frac{f_k(z') [f_k(z') - f_k(z)]}{f_k(z)} \frac{1+z'}{E(z')} \delta(\theta, z') \quad (5)$$

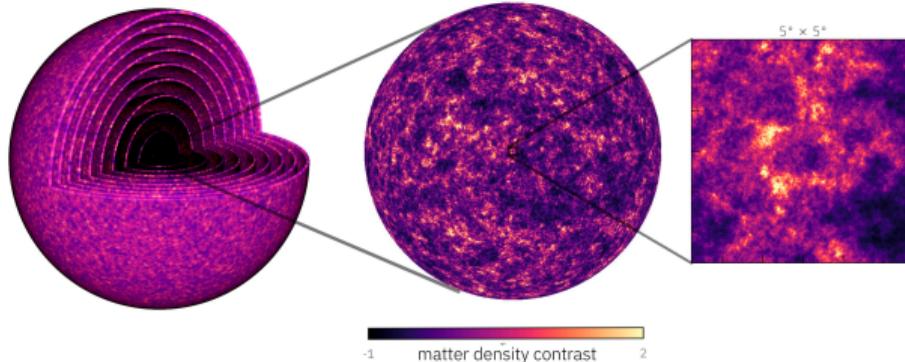
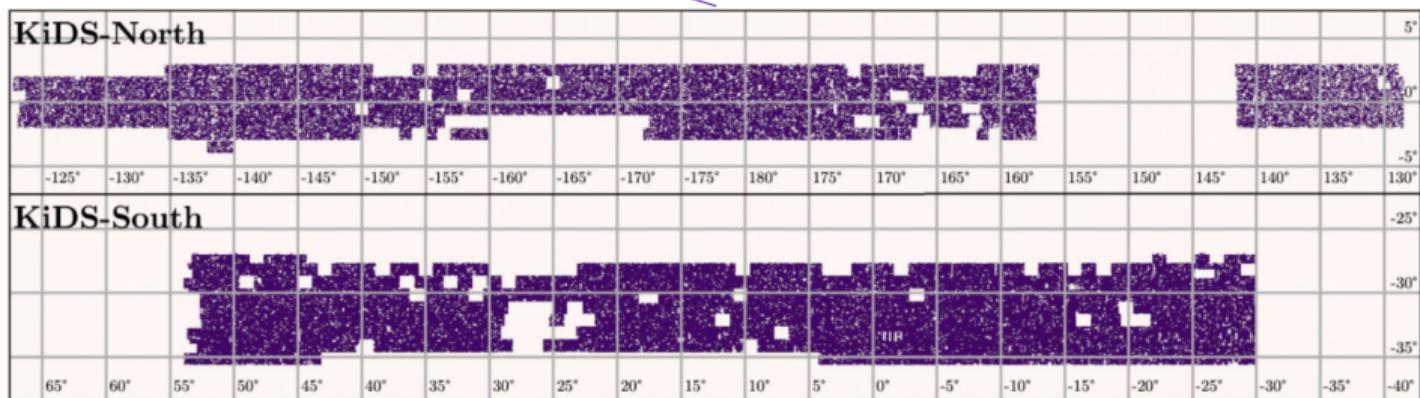


Figure: [Tessore et al. 2023; arxiv:2302.01942]

Galaxy Positions & Survey Characteristics

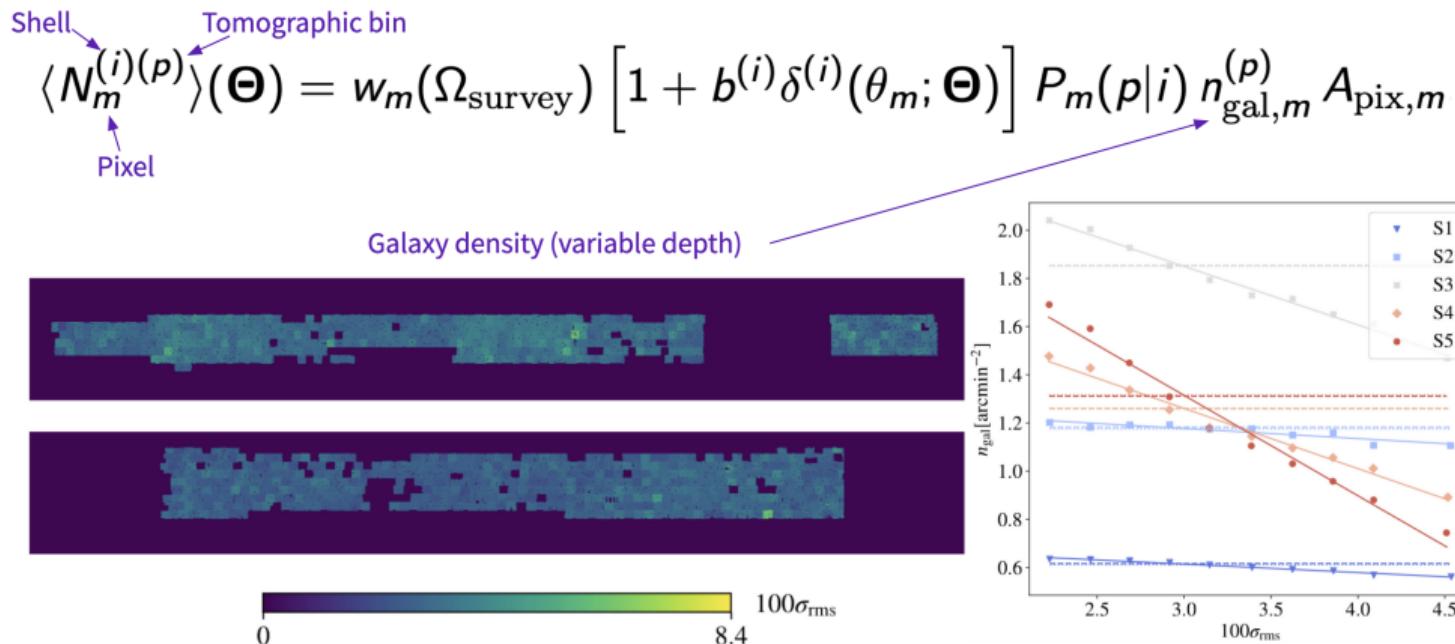
$$\langle N_m^{(i)(p)} \rangle(\Theta) = w_m(\Omega_{\text{survey}}) \left[1 + b^{(i)} \delta^{(i)}(\theta_m; \Theta) \right] P_m(p|i) n_{\text{gal},m}^{(p)} A_{\text{pix},m}$$

Annotations: Shell, Tomographic bin, Pixel, Mask.



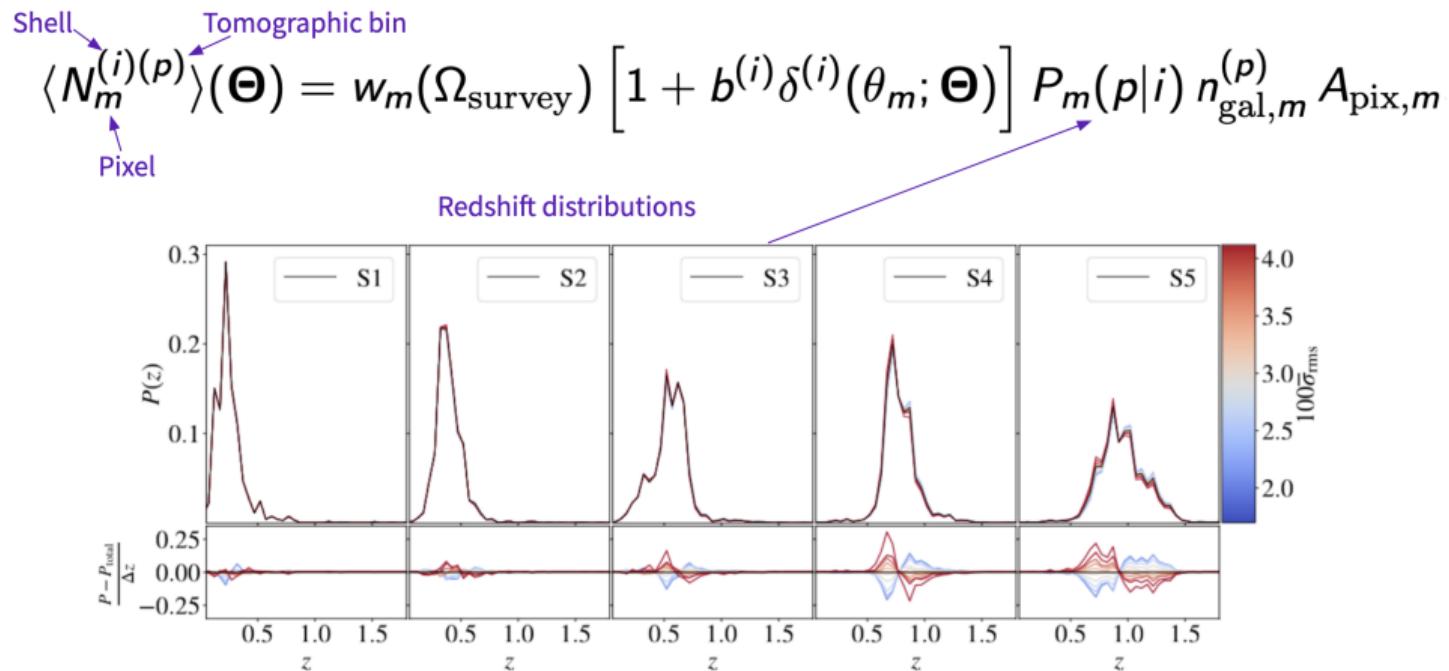
[von Wietersheim-Kramsta, Lin et al. 2024; arXiv:2404.15402]

Galaxy Positions & Survey Characteristics



[von Wietersheim-Kramsta, Lin et al. 2024; arXiv:2404.15402]

Galaxy Positions & Survey Characteristics



[von Wietersheim-Kramsta, Lin et al. 2024; arXiv:2404.15402]

Variable Depth

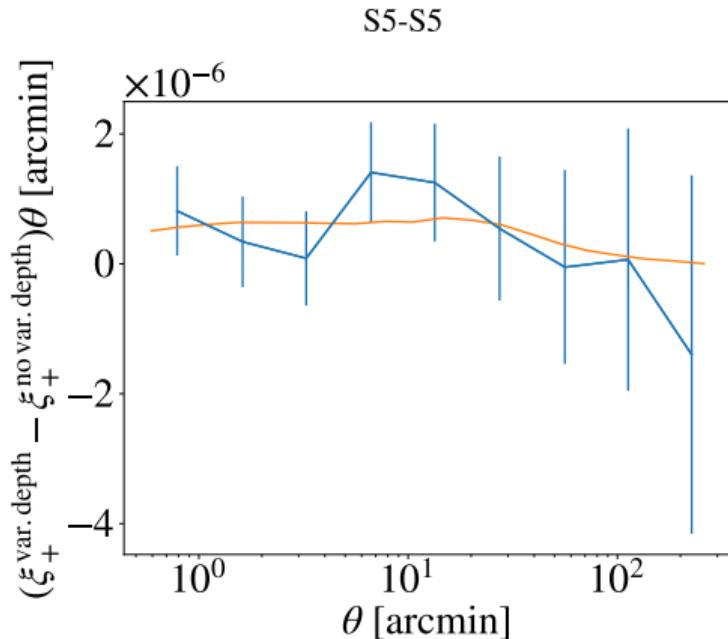
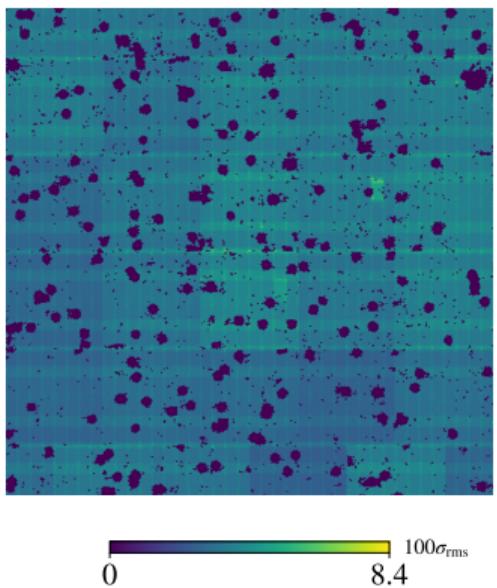
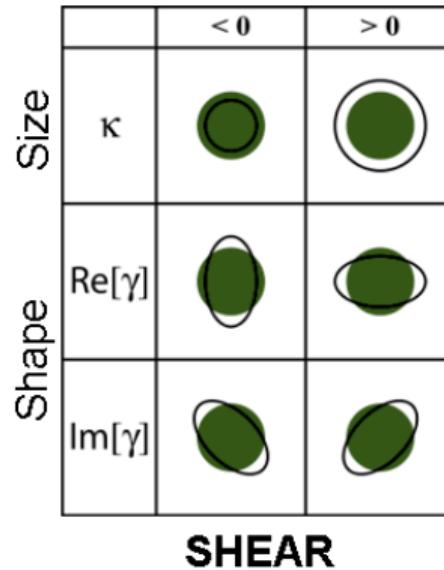


Figure: Orange: theory [Heydenreich et al. 2020; arXiv:1910.11327]. Blue: forward-simulations.

Cosmic Shear & Galaxy Shapes

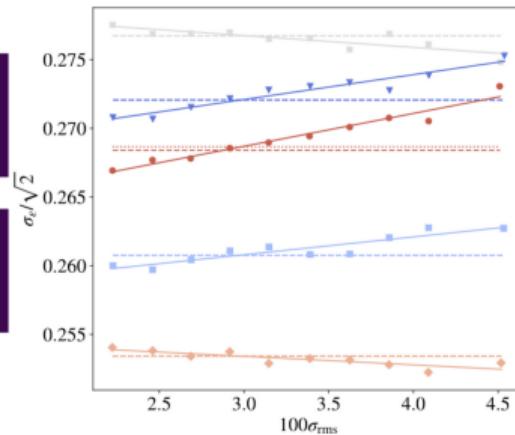
$$g(\Theta) = \frac{\gamma(\Theta)}{1 - \kappa(\Theta)} \quad (6)$$



Galaxy Shapes & Survey Characteristics

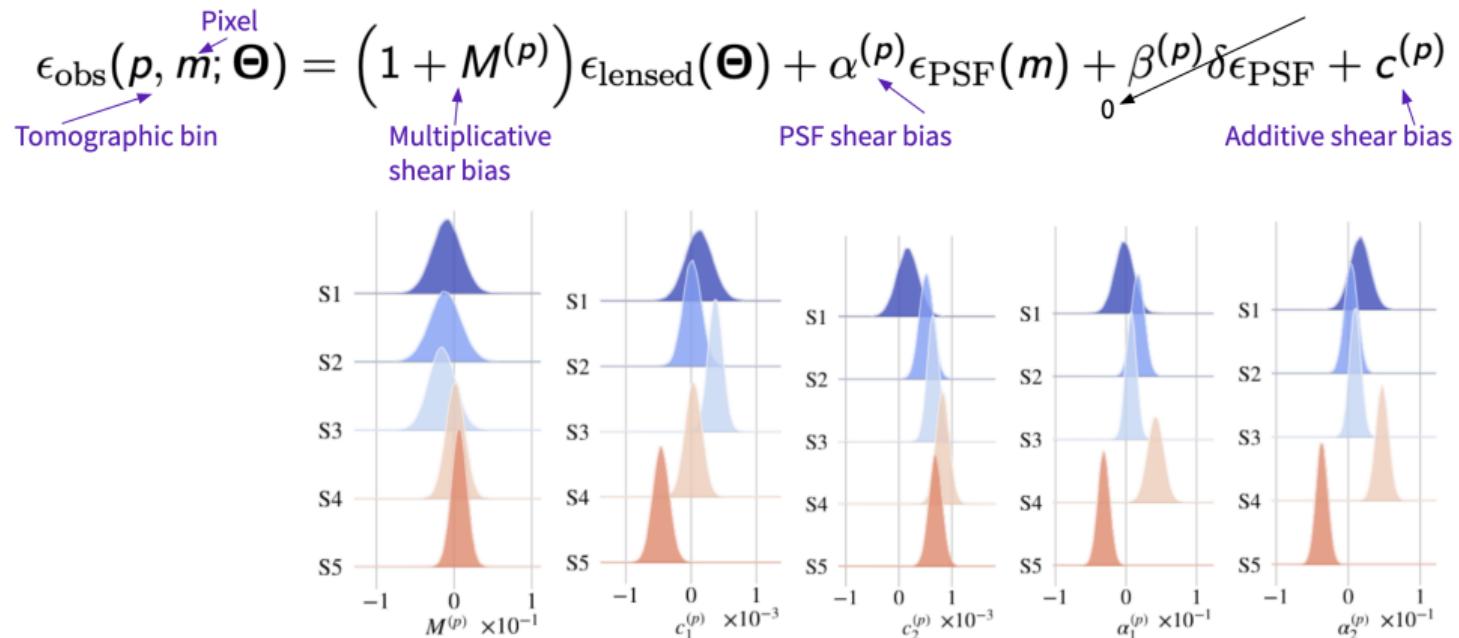
$$\epsilon_{\text{lensed}}(\Theta) = \frac{\epsilon_{\text{int}} + g(\Theta)}{1 + g^*(\Theta)\epsilon_{\text{int}}}$$

Reduced shear
Intrinsic shapes
(variable depth)



[von Wietersheim-Kramsta, Lin et al. 2024; arXiv:2404.15402]

Galaxy Shapes & Survey Characteristics

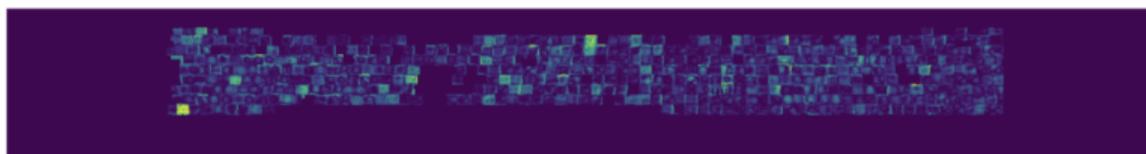


[von Wietersheim-Kramsta, Lin et al. 2024; arXiv:2404.15402]

Galaxy Shapes & Survey Characteristics

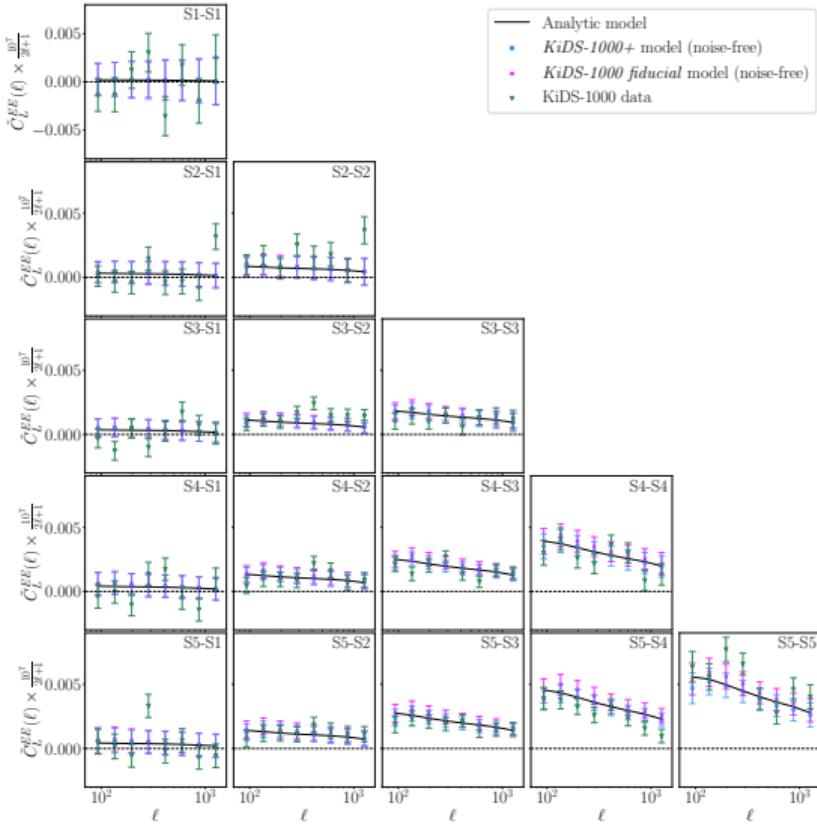
$$\epsilon_{\text{obs}}(p, m; \Theta) = (1 + M^{(p)}) \epsilon_{\text{lensed}}(\Theta) + \alpha^{(p)} \epsilon_{\text{PSF}}(m) + \beta^{(p)} \delta \epsilon_{\text{PSF}} + c^{(p)}$$

Pixel
Tomographic bin
PSF shear bias
0

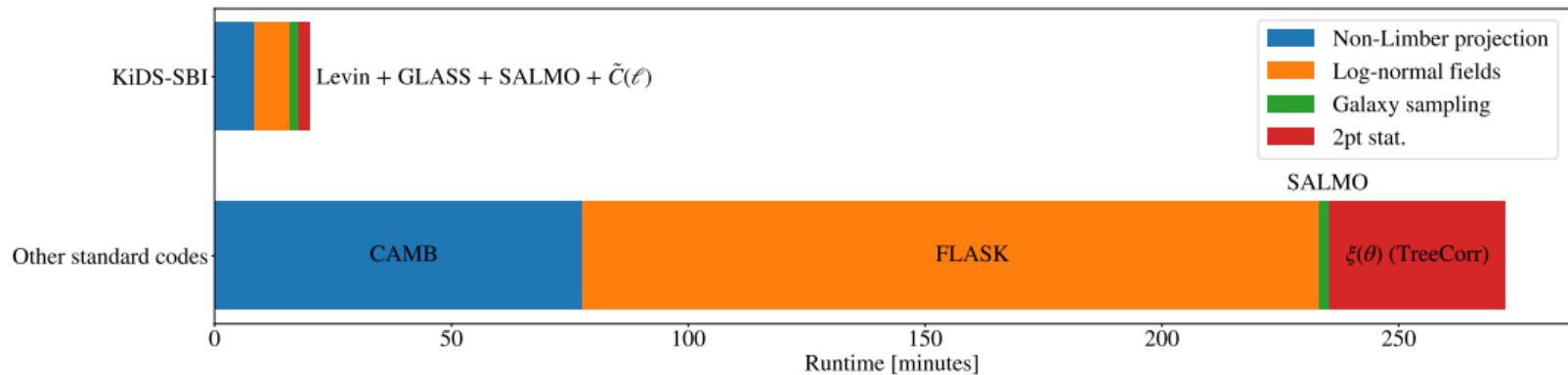


[von Wietersheim-Kramsta, Lin et al. 2024; arXiv:2404.15402]

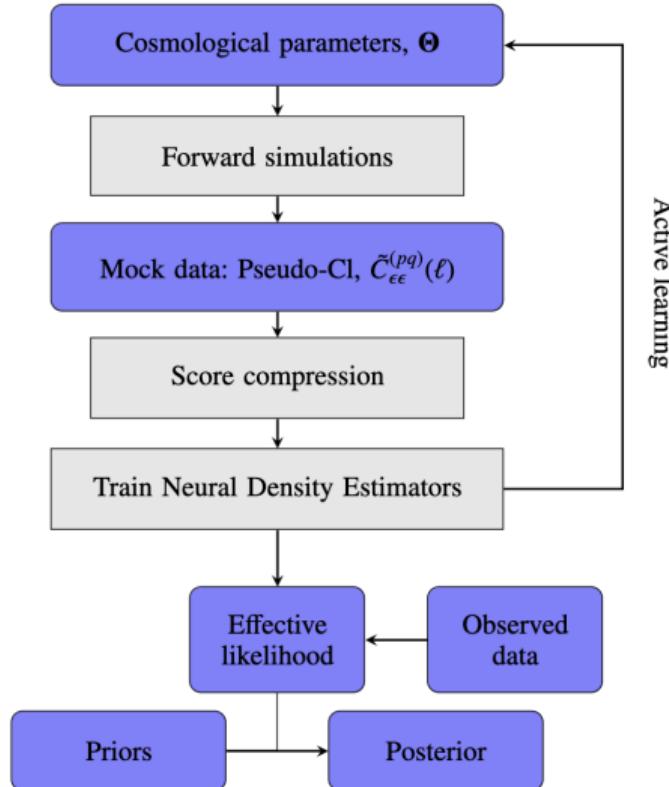
Measurement: Pseudo Angular Power Spectra



Forward-simulations Speed



[von Wietersheim-Kramsta, Lin et al. 2024; arXiv:2404.15402]



KiDS-SBI: Parameters and Priors

Parameter	Symbol	Prior type	Prior range	Fiducial
Density fluctuation amp.	S_8	Flat	[0.1, 1.3]	0.76
Hubble constant	h_0	Flat	[0.64, 0.82]	0.767
Cold dark matter density	ω_c	Flat	[0.051, 0.255]	0.118
Baryonic matter density	ω_b	Flat	[0.019, 0.026]	0.026
Scalar spectral index	n_s	Flat	[0.84, 1.1]	0.901
Intrinsic alignment amp.	A_{IA}	Flat	[-6, 6]	0.264
Baryon feedback amp.	A_{bary}	Flat	[2, 3.13]	3.1
Redshift displacement	δ_z	Gaussian	$\mathcal{N}(\mathbf{0}, \mathbf{C}_z)$	$\mathbf{0}$
Multiplicative shear bias	$M^{(p)}$	Gaussian	$\mathcal{N}(\bar{M}^{(p)}, \sigma_M^{(p)})$	$\bar{M}^{(p)}$
Additive shear bias	$c_{1,2}^{(p)}$	Gaussian	$\mathcal{N}(\bar{c}_{1,2}^{(p)}, \sigma_{c_{1,2}}^{(p)})$	$\bar{c}_{1,2}^{(p)}$
PSF variation shear bias	$\alpha_{1,2}^{(p)}$	Gaussian	$\mathcal{N}(\bar{\alpha}_{1,2}^{(p)}, \sigma_{\alpha_{1,2}}^{(p)})$	$\bar{\alpha}_{1,2}^{(p)}$

[von Wietersheim-Kramsta, Lin et al. 2024; arXiv:2404.15402]

KiDS-SBI: Score Compression

Further massive compression from summary statistics to reduce dimensionality via score compression [Alsing et al. 2018]

$$\mathcal{L} = \mathcal{L}_* + \delta\theta^T \nabla \mathcal{L}_* - \frac{1}{2} \delta\theta^T \mathbf{J}_* \delta\theta, \quad (7)$$

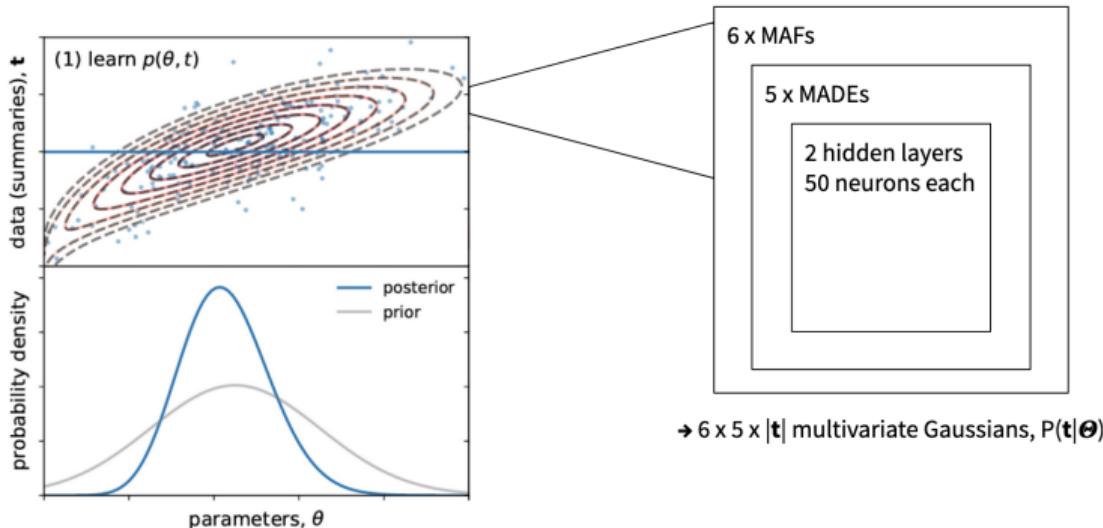
$$\mathbf{t} = \nabla \mu^T \mathbf{C}^{-1} (\mathbf{d} - \mu). \quad (8)$$

The score compression is repeated after an initial SBI which refines the fiducial parameter estimate.

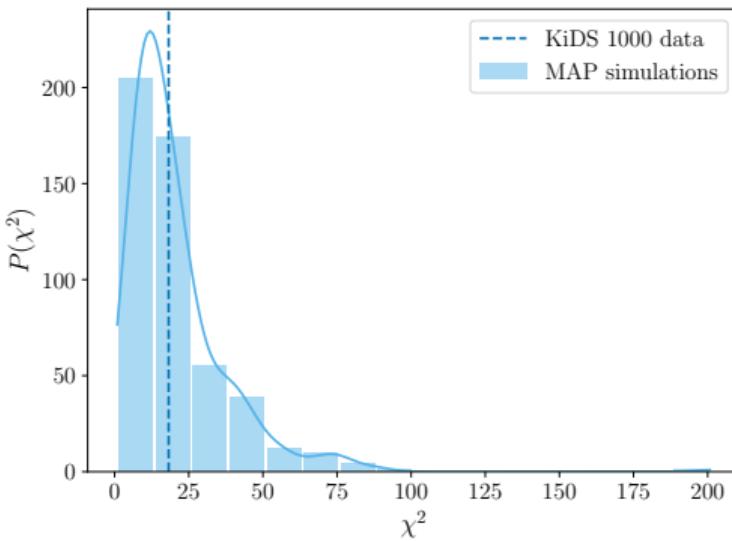
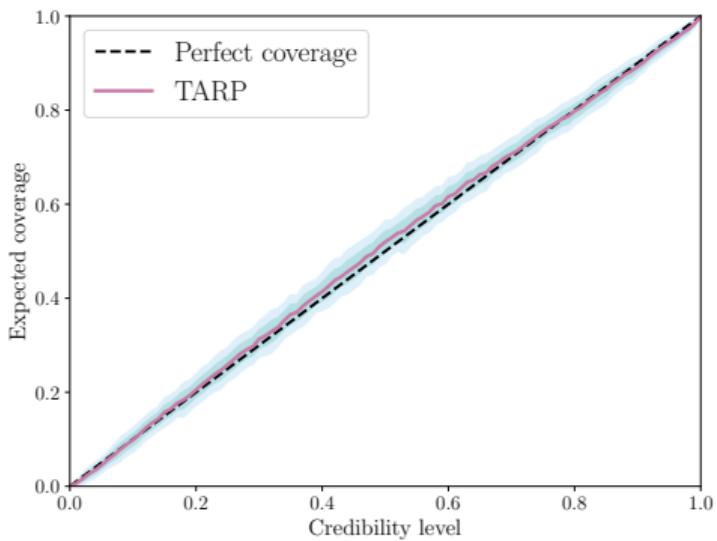
KiDS-SBI: Neural Likelihood Estimation (DELFI)

An ensemble of six independent Masked Autoregressive Flows (MAFs) is combined to characterise the likelihood

$$p(\mathbf{t}|\theta; \mathbf{w}) = \prod_{\alpha=1}^{N_{\text{NDEs}}} \beta_\alpha p_\alpha(\mathbf{t}|\theta; \mathbf{w}) \quad (9)$$



Internal Consistency & Goodness-of-Fit



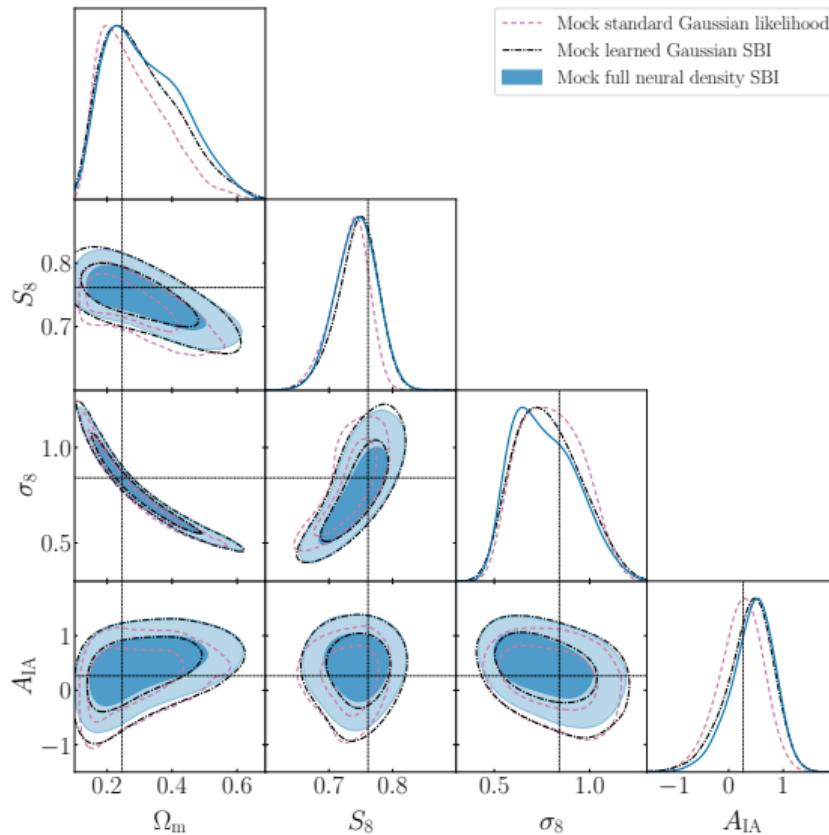
[von Wietersheim-Kramsta, Lin et al. 2024; arXiv:2404.15402]

KiDS-SBI: Mock Analysis

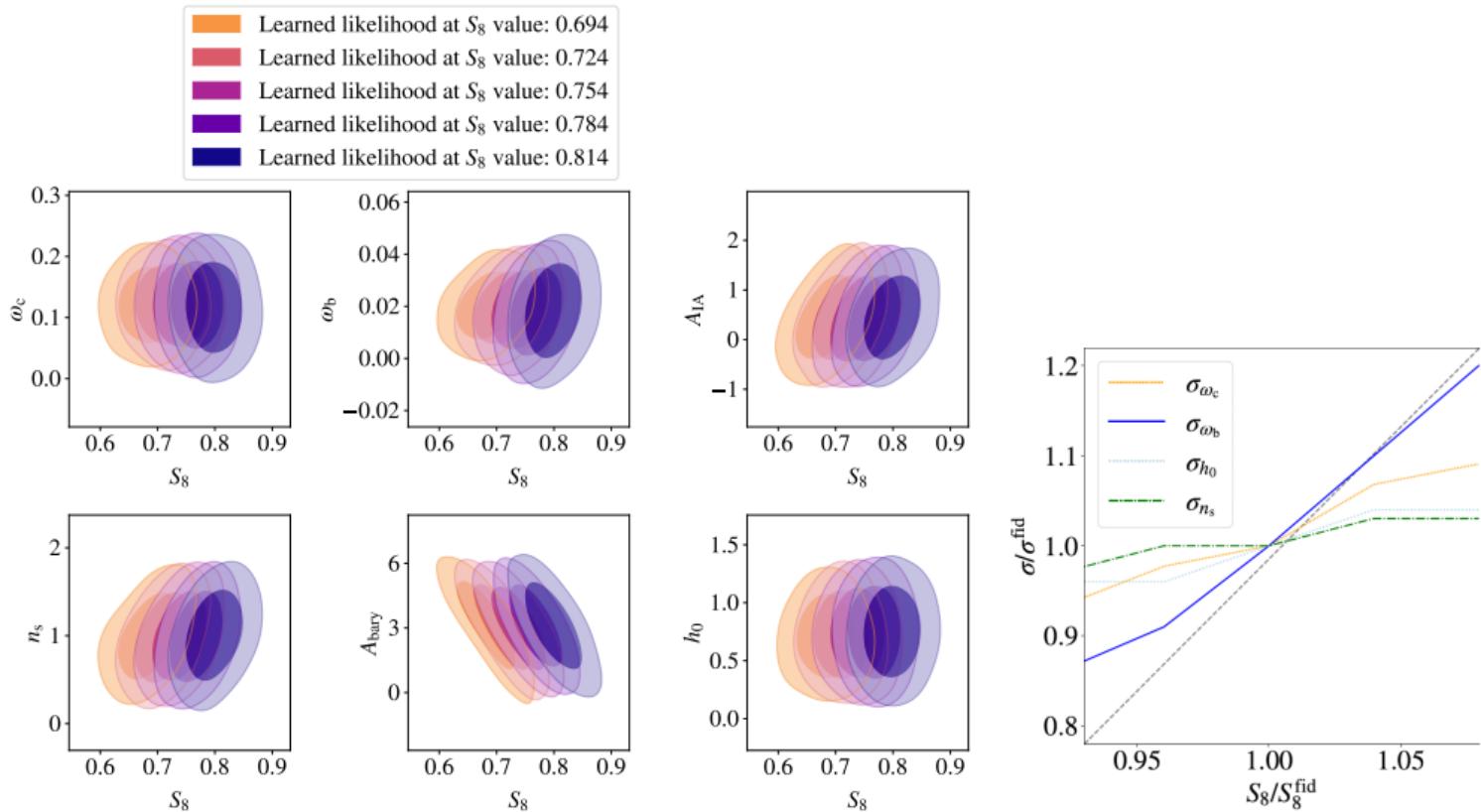
Compare different types of inferences:

- “Standard” Gaussian likelihood assumption with a fixed covariance matrix
- SBI with a learned multivariate Gaussian (MDN)
⇒ Gaussian likelihood with a parameter-dependent covariance matrix
- **Full neural density SBI** (ensemble of MAFs)
⇒ non-Gaussian likelihood with a parameter-dependent covariance matrix

KiDS-SBI: Mock Analysis



S_8 -dependent Uncertainty

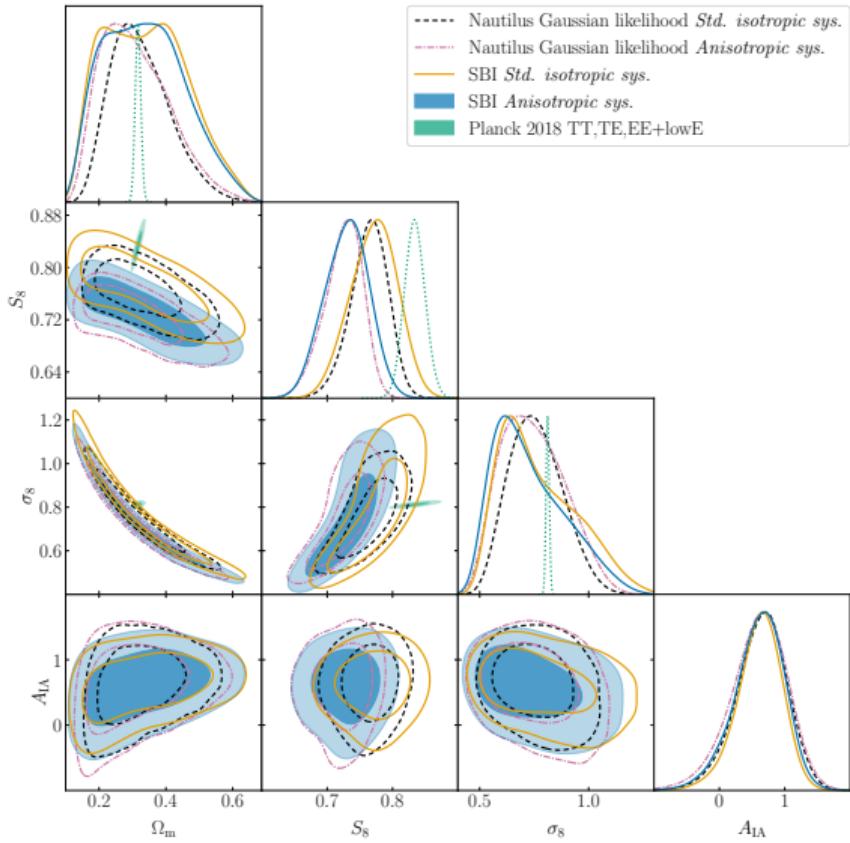


KiDS-SBI: Forward Models

Two main models:

- **“Standard” isotropic systematics model :**
galaxy selection function isotropic in each tomographic bin
- **Anisotropic systematics model :**
anistropic galaxy selection (position, shapes and redshift)
+ anisotropic PSF distortions

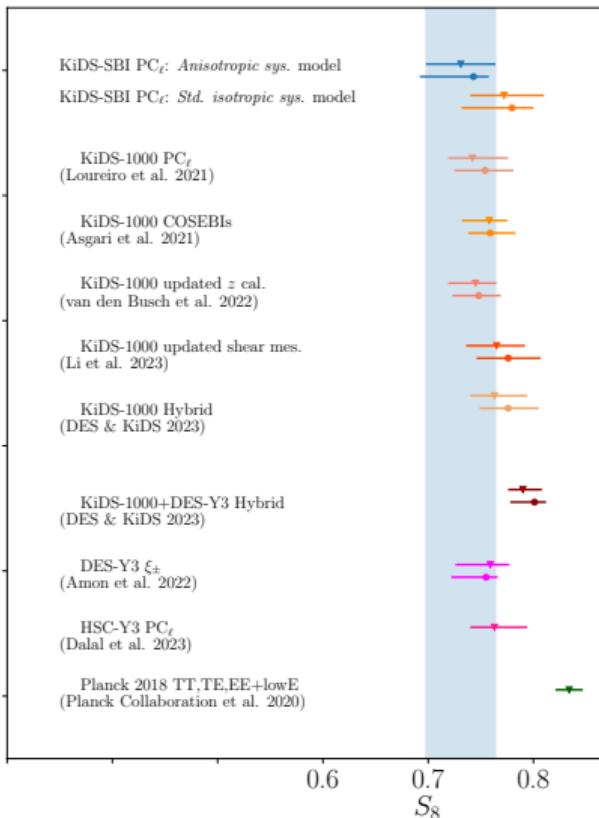
Cosmological Results for Flat Λ CDM



$$S_8 = 0.731 \pm 0.033$$

$$S_8 = 0.772^{+0.038}_{-0.032}$$

Cosmological Results for Flat Λ CDM



KiDS-SBI: Conclusions

- SBI is a powerful tool to rigorously conduct cosmological inference and model testing
- We report $S_8 = 0.731 \pm 0.033$ which is in 2.9σ tension with Planck 2020
- Neglecting variable depth and shear biases can bias S_8 by approx. 5%
- Cosmic shear likelihood is consistent with a Gaussian
- Its covariance is measurably cosmology-dependent (cosmic variance)
⇒ uncertainty on S_8 is 10% higher

[von Wietersheim-Kramsta, Lin et al. 2024; arXiv:2404.15402]

Questions?

References

-  Niall Jeffrey, Justin Alsing, François Lanusse (2020)
Likelihood-free inference with neural compression of DES SV weak lensing map statistics
MNRAS Volume 501, Issue 1, February 2021, Pages 954–969.
-  Arthur Loureiro, et al. (2021)
KiDS & Euclid: Cosmological implications of a pseudo angular power spectrum analysis of KiDS-1000 cosmic shear tomography
arxiv 2110.06947v1 .
-  David Levin (1994)
Fast integration of rapidly oscillatory functions
JCAM Volume 67, Issue 1, 20 February 1996, Pages 95-101.

References



Justin Alsing et al. (2019)

Fast likelihood-free cosmology with neural density estimators and active learning

Monthly Notices of the Royal Astronomical Society Volume 488, Issue 3, September 2019, Pages 4440–4458.



Justin Alsing et al. (2018)

Massive optimal data compression and density estimation for scalable, likelihood-free inference in cosmology

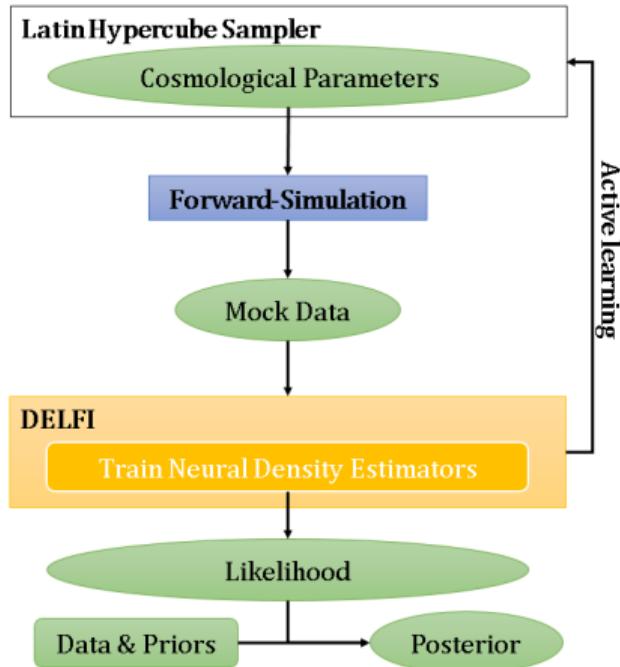
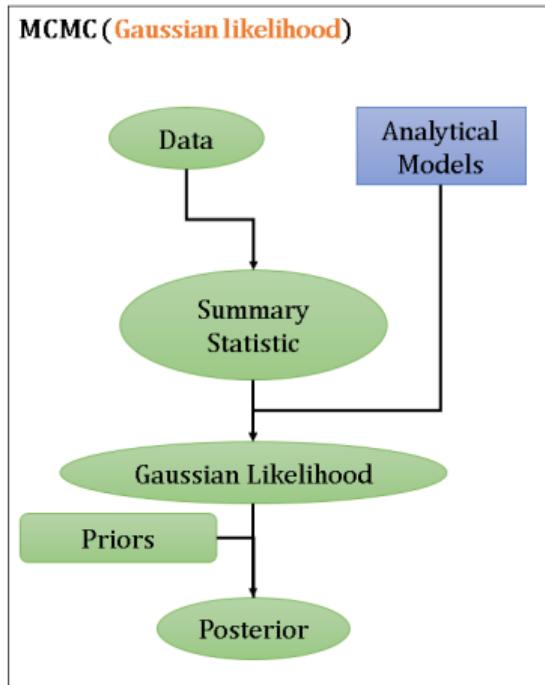
Monthly Notices of the Royal Astronomical Society Volume 477, Issue 3, July 2018, Pages 2874–2885.

Appendices A - Pipeline Setup

- Shear-shear weak lensing from KiDS-1000 using pseudo-Cl_s
- Latin hypercube of cosmology values as simulation input

Parameter	Symbol	Prior type	Prior range	Fiducial
Density fluctuation amp.	S_8	Flat	[0.1, 1.3]	0.76
Hubble constant	h_0	Flat	[0.64, 0.82]	0.767
Cold dark matter density	ω_c	Flat	[0.051, 0.255]	0.118
Baryonic matter density	ω_b	Flat	[0.019, 0.026]	0.026
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Multiplicative shear bias	$M^{(p)}$	Gaussian	$\mathcal{N}(\bar{M}^{(p)}, \sigma_M^{(p)})$	$\bar{M}^{(p)}$
Additive shear bias	$c_{1,2}^{(p)}$	Gaussian	$\mathcal{N}(\bar{c}_{1,2}^{(p)}, \sigma_{c_{1,2}}^{(p)})$	$\bar{c}_{1,2}^{(p)}$
PSF variation shear bias	$\alpha_{1,2}^{(p)}$	Gaussian	$\mathcal{N}(\bar{\alpha}_{1,2}^{(p)}, \sigma_{\alpha_{1,2}}^{(p)})$	$\bar{\alpha}_{1,2}^{(p)}$

Appendices A - Pipeline Setup



Appendices B - Compression and DELFI

- A stack of NDEs are used in DELFI

$$p(\mathbf{t}|\theta; \mathbf{w}) = \prod_{\alpha=1}^{N_{\text{NDEs}}} \beta_\alpha p_\alpha(\mathbf{t}|\theta; \mathbf{w}), \quad (10)$$

- A mixture of Gaussian Mixture Density Networks (MDNs) and Masked Autoregressive Flows (MAFs) are employed in this ensemble
- Further massive compression from summary statistics to reduce dimensionality via score compression

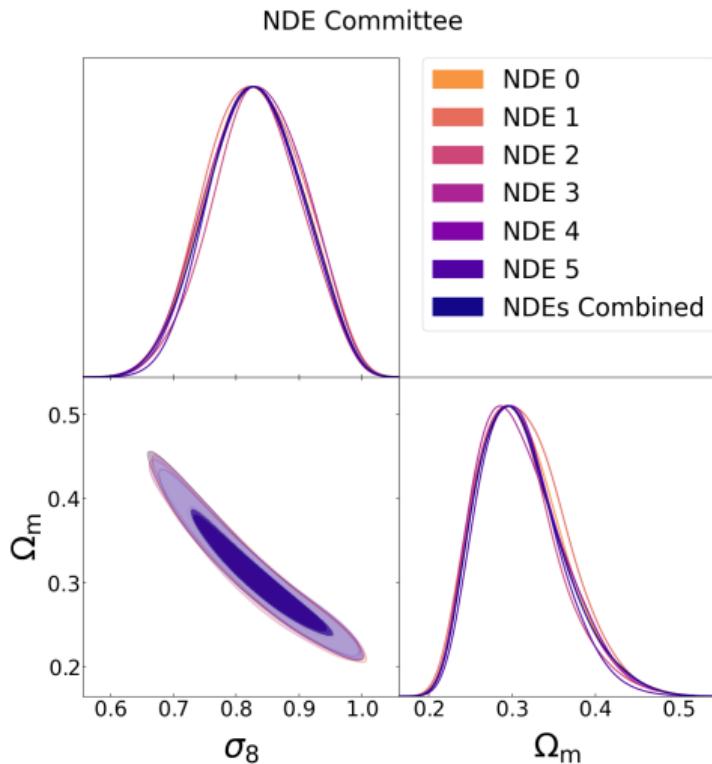
$$\mathcal{L} = \mathcal{L}_* + \delta\boldsymbol{\theta}^T \nabla \mathcal{L}_* - \frac{1}{2} \delta\boldsymbol{\theta}^T \mathbf{J}_* \delta\boldsymbol{\theta}, \quad (11)$$

$$\mathbf{t} = \nabla \boldsymbol{\mu}^T \mathbf{C}^{-1} (\mathbf{d} - \boldsymbol{\mu}), \quad (12)$$

- Remap this to a MLE estimate via the Fisher matrix

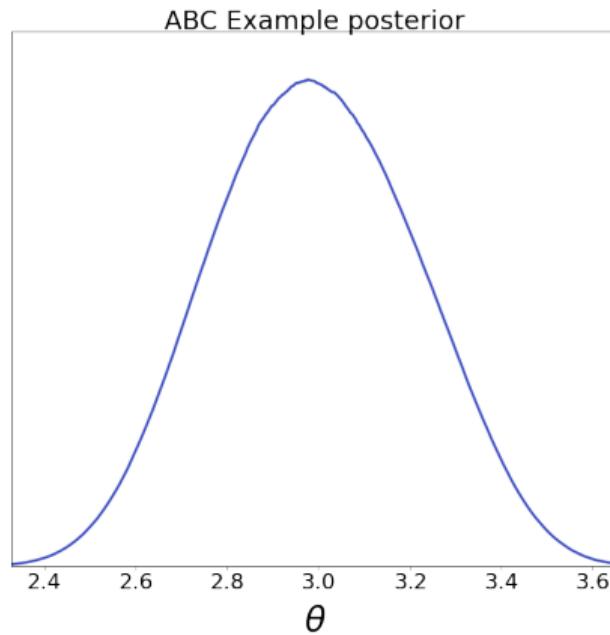
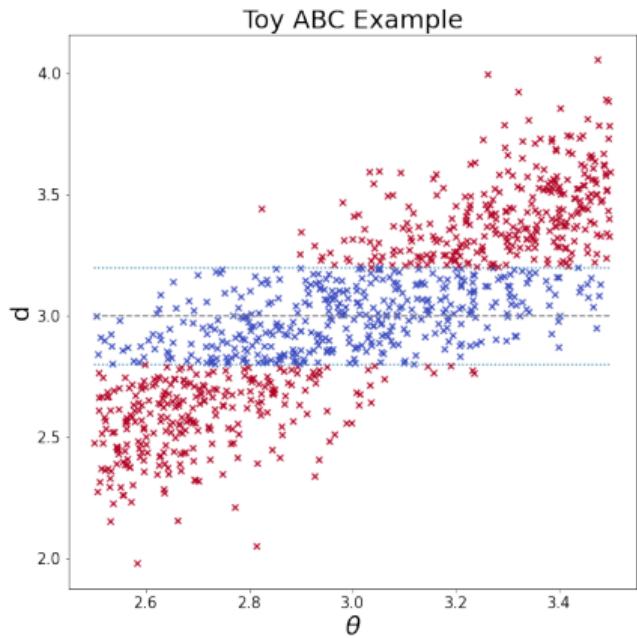
$$\hat{\boldsymbol{\theta}} = \boldsymbol{\theta}_* + \mathbf{F}_*^{-1} \nabla \mathcal{L}_* = \boldsymbol{\theta}_* + \mathbf{F}_*^{-1} \mathbf{t}_*, \quad (13)$$

Appendices C - PyDELFI



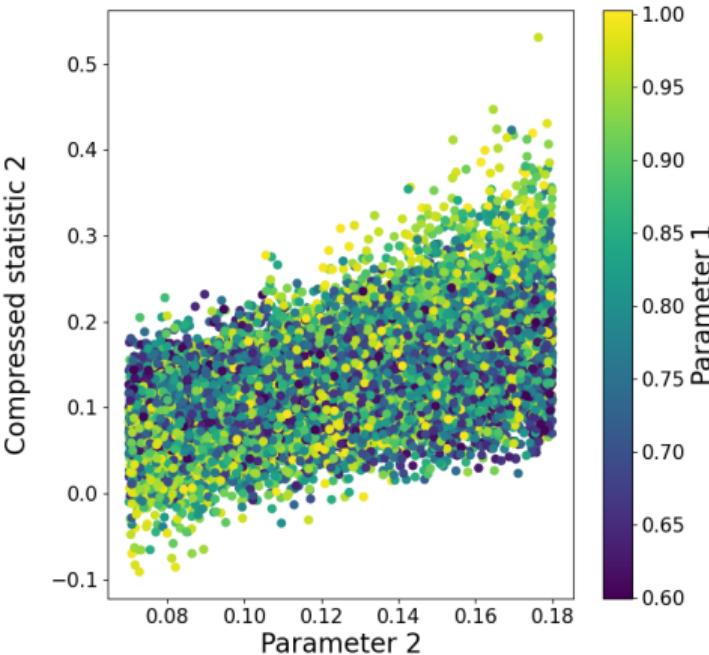
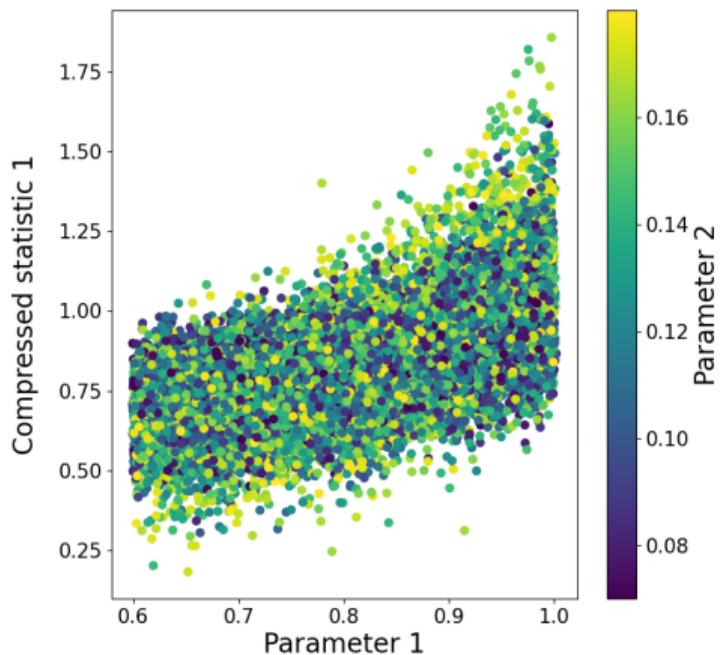
Appendices D - SBI - ABC

$$P(\theta|\mathbf{d}) = \frac{P(\mathbf{d}|\theta) \cdot P(\theta)}{P(\mathbf{d})} \quad (14)$$

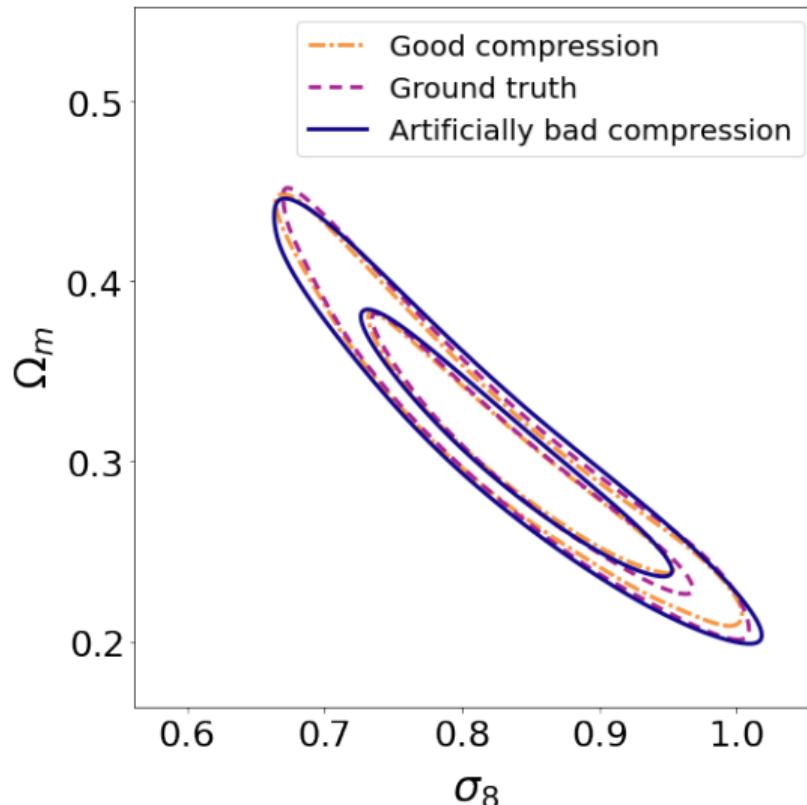


Appendices E - Score Compression

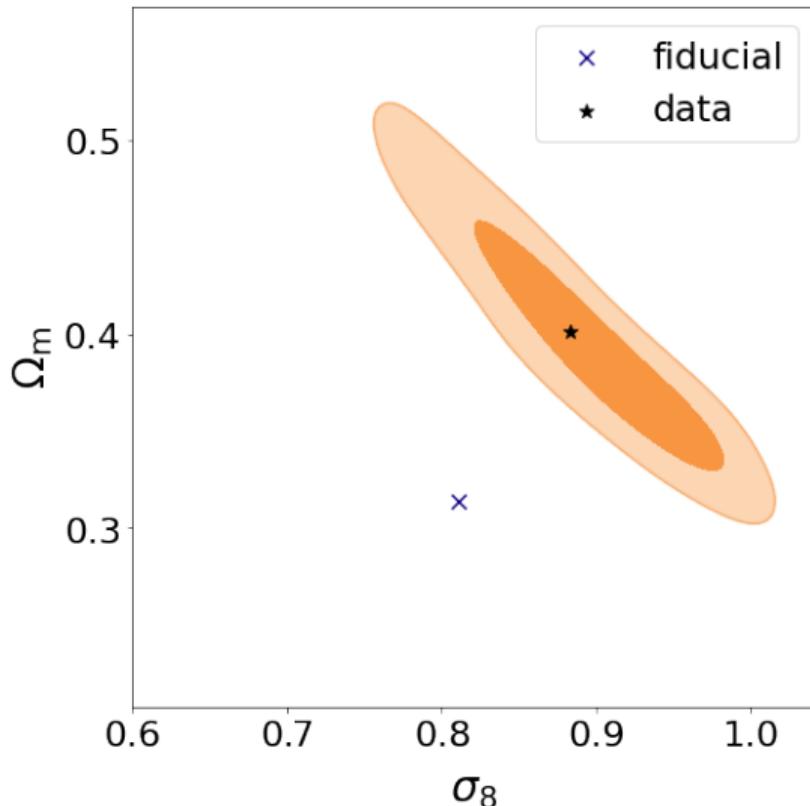
Linearly score compressed data vs. parameters



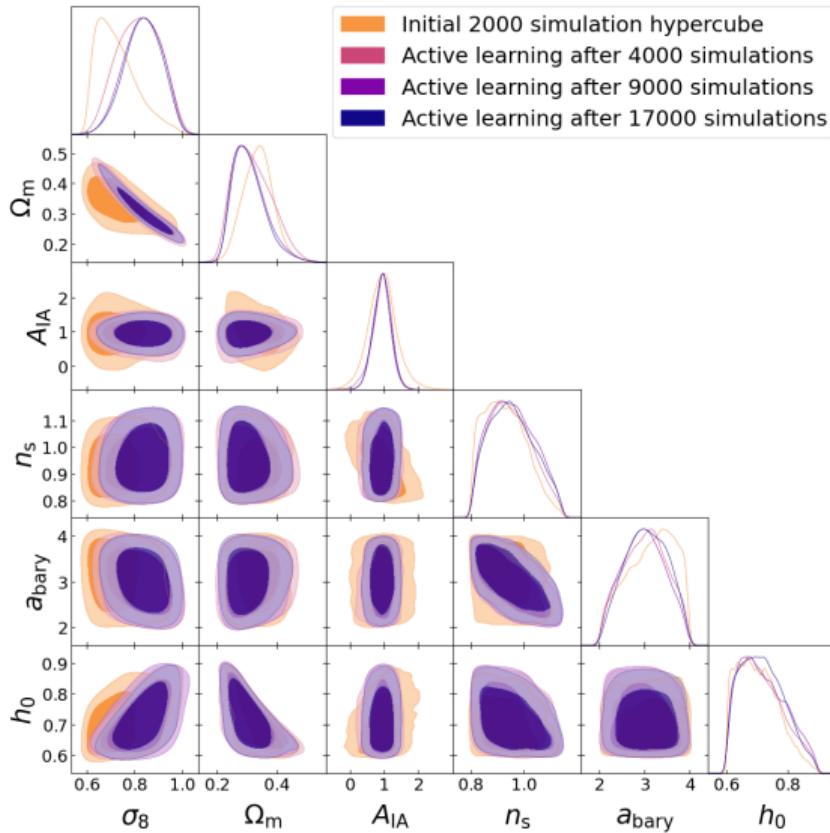
Appendices F - Sensitivity to Compression



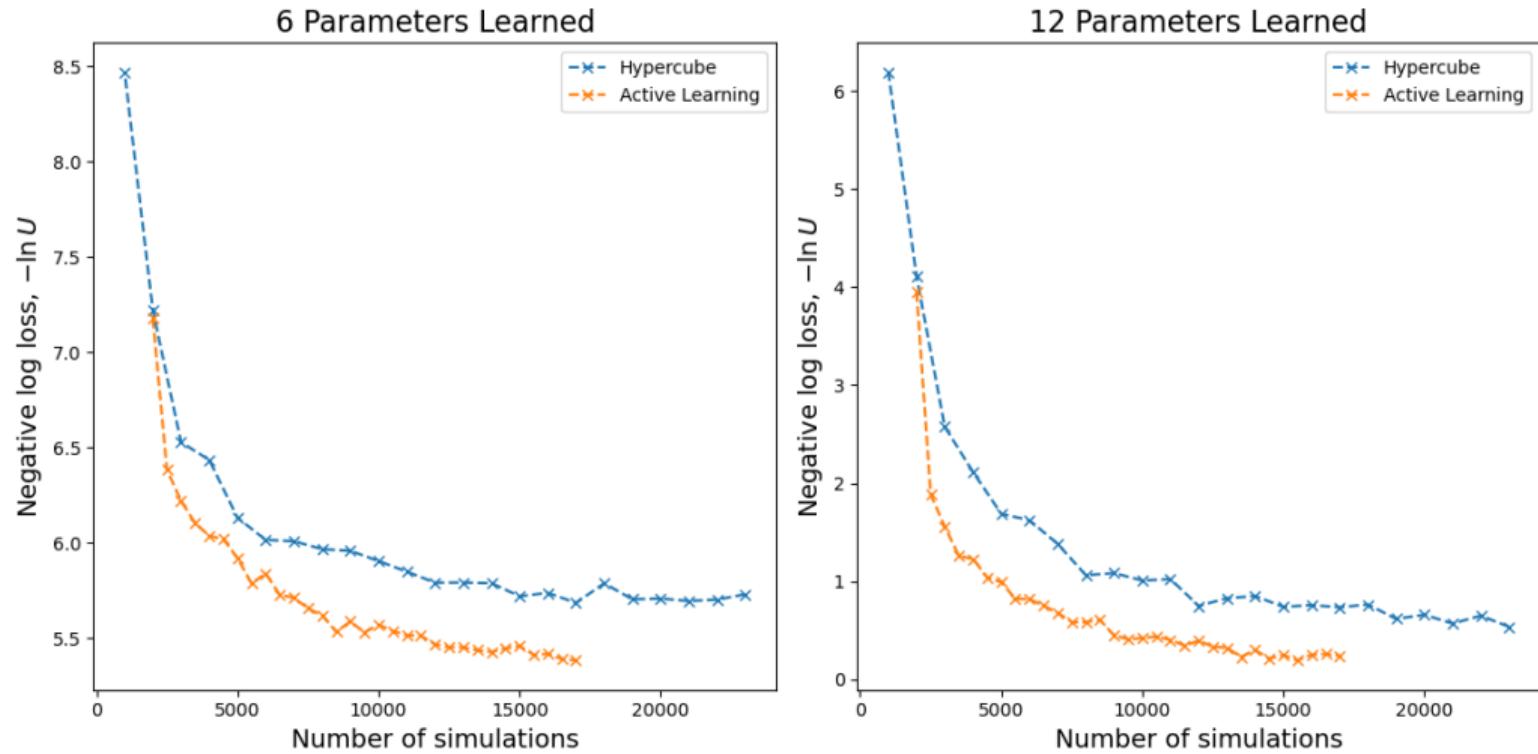
Appendix G - Sensitivity to Fiducial Cosmology



Appendix H - Active Learning

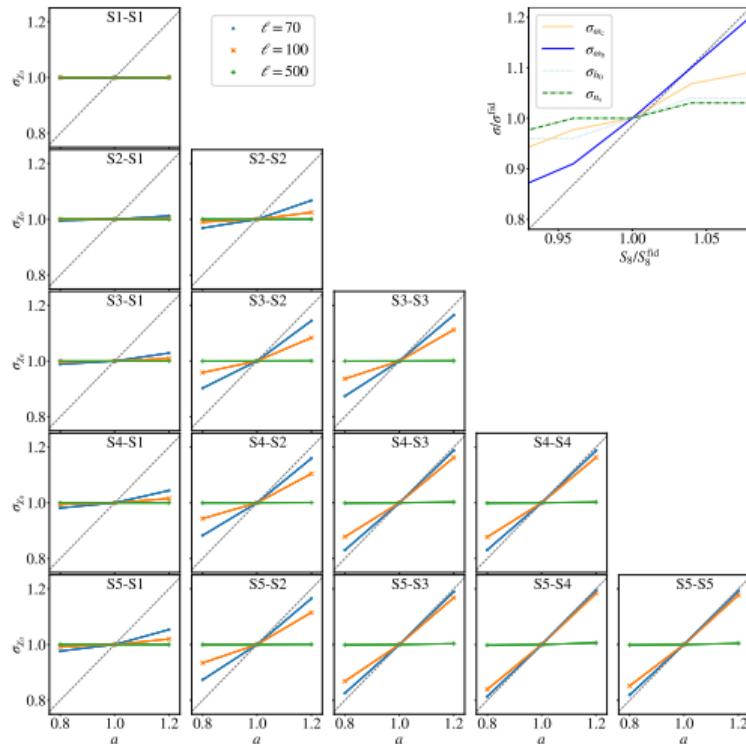


Appendix I - Simulation Number Sufficiency

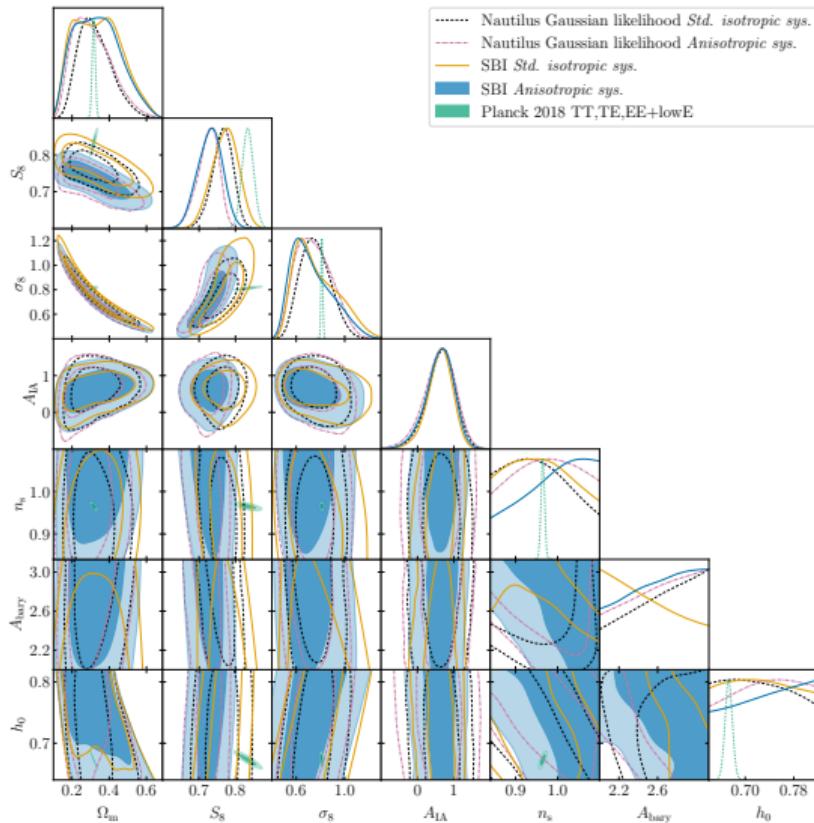


Appendix J - S_8 -dependent Uncertainty from Theory

Scaling of the analytical Gaussian likelihood in KiDS-1000 if $C_{\text{scaled}}^{(ij)}(\ell) = a C^{(ij)}(\ell)$



Appendix J - Full Posterior



Appendix K - Signal Test

