

# Simulation-Based Inference of KiDS-1000 Cosmic Shear

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KiDS





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# Challenges facing galaxy surveys

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- Galaxy surveys are getting **wider, deeper** and **more precise**.
  - ⇒ Galaxy clustering and weak lensing probes become sensitive to **non-linear scales**
  - ⇒ The S/N becomes high enough that **higher-order statistics** can be measured precisely
  - ⇒ Observational **systematics** begin limiting the precision
- ⇒ "Traditional" signal and noise modelling can become inaccurate/too expensive.

# Simulation-Based Inference (SBI)

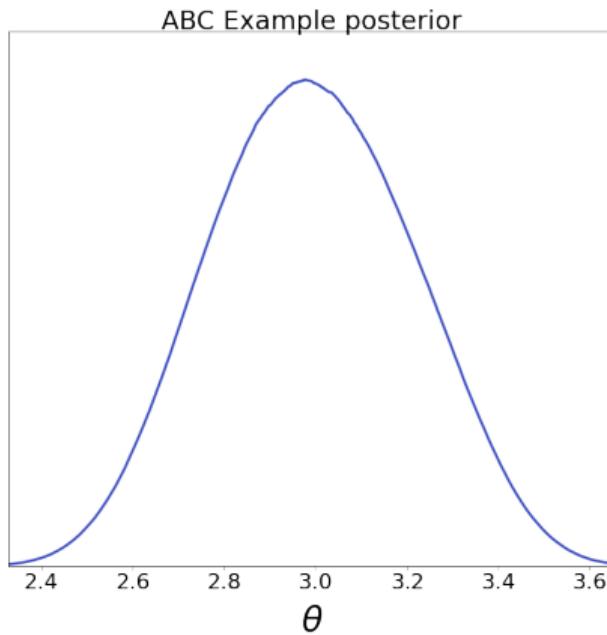
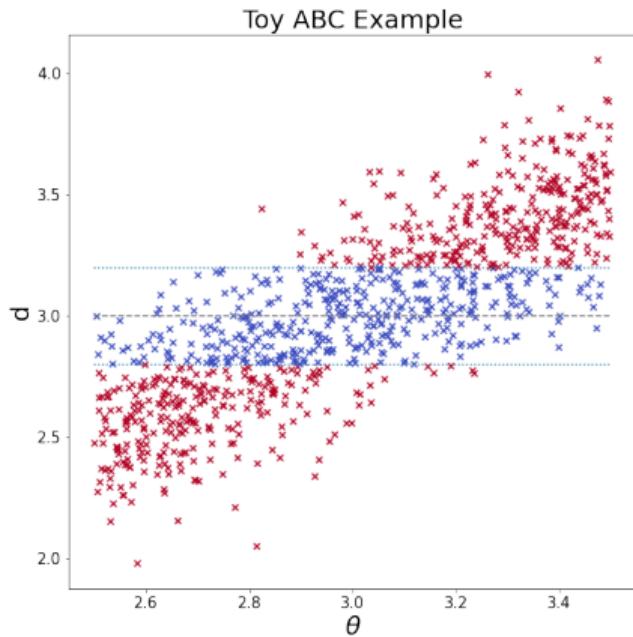
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A.k.a. *likelihood-free* or *implicit likelihood inference*

- 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

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



# SBI: Density Estimation

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

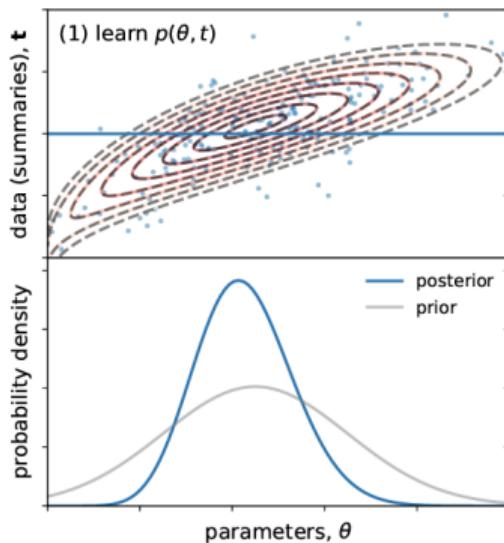
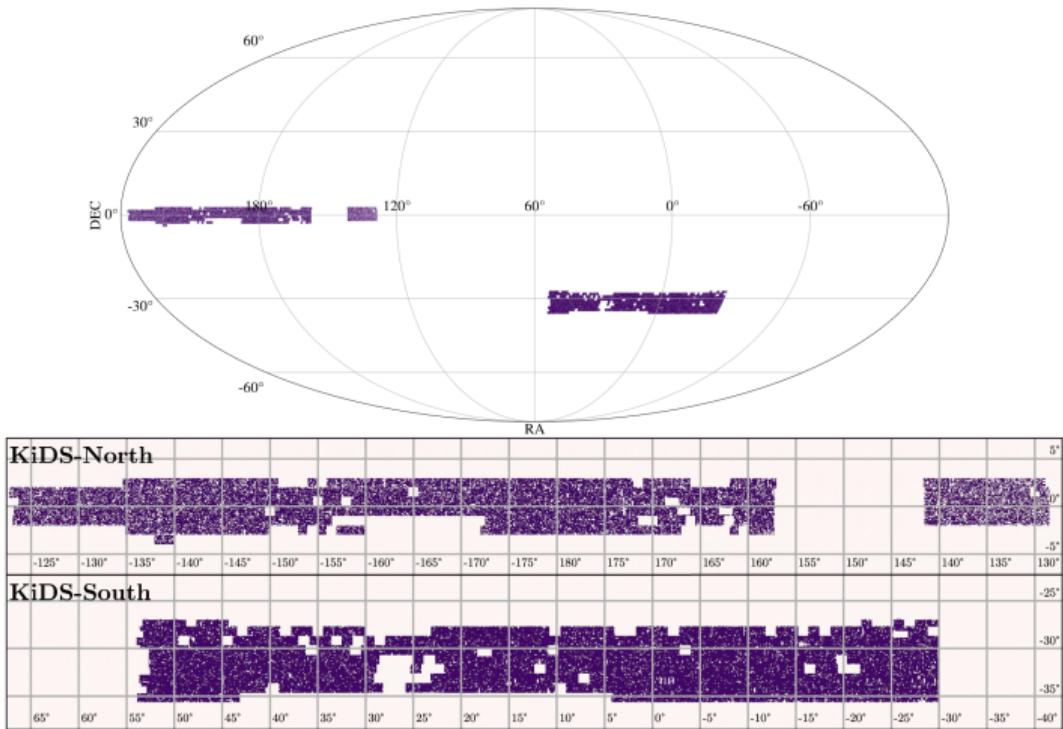
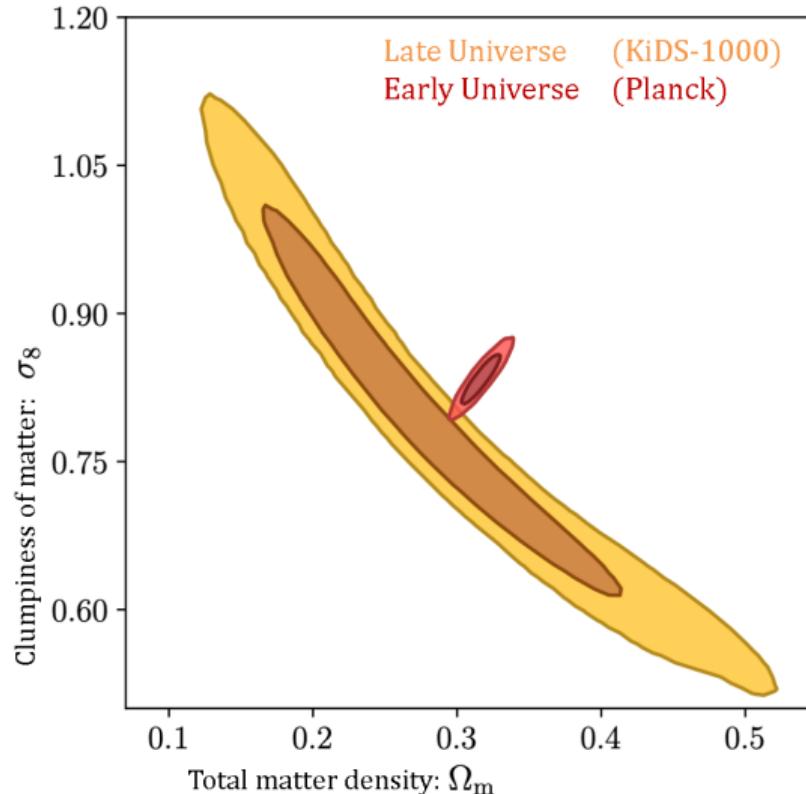


Figure: [Alsing et al. 2019]

# Kilo-Degree Survey: KiDS-1000



# Previous KiDS-1000 Cosmic Shear Results

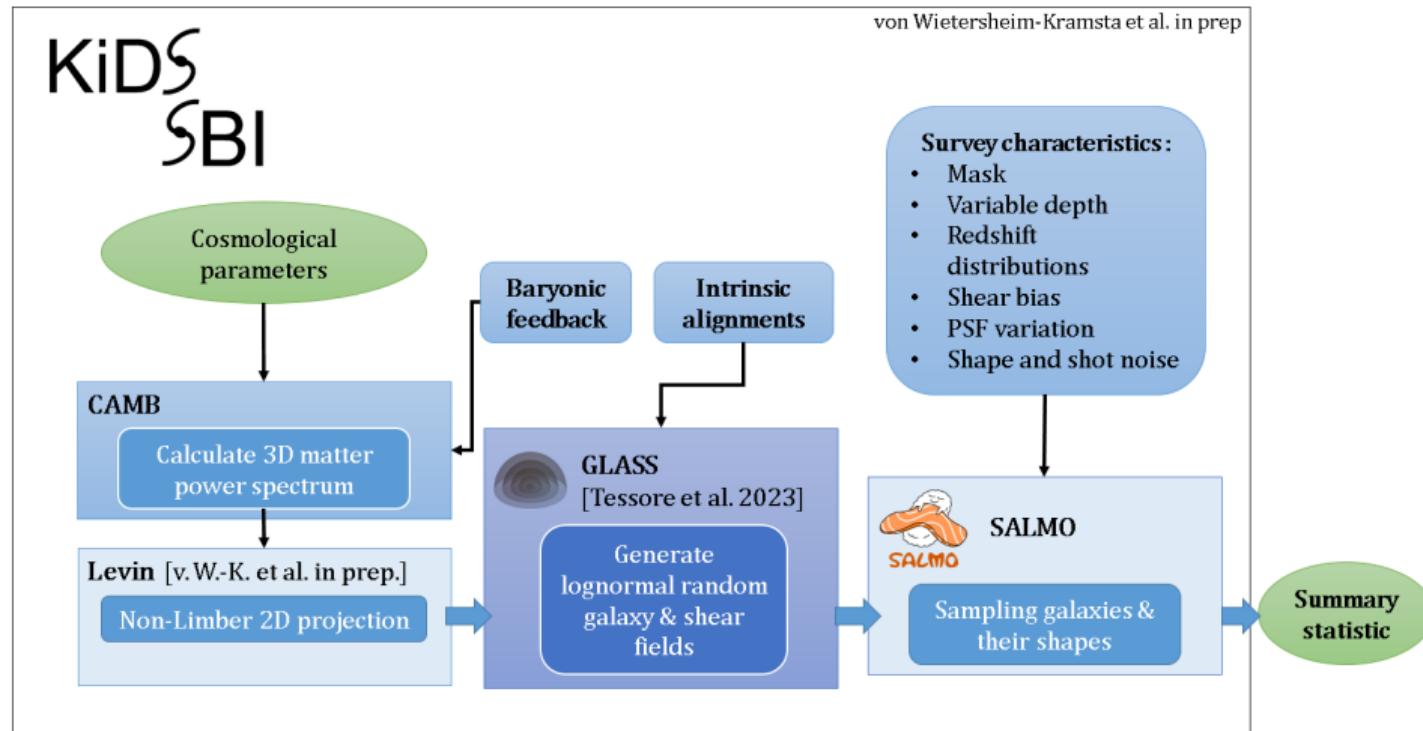


# Requirements for Cosmic Shear Forward-Simulations

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- Physically accurate
  - Require highly resolved matter and shear fields
  - Consideration of relevant systematic effects: baryonic feedback and intrinsic alignments
- Realistic
  - Consideration of survey characteristics
  - Choice of data vector
- Fast
  - Many realisations required for DELFI
- Expandable
  - Future-proof implementations

# Forward-Simulation Pipeline



# Geometry of the simulations

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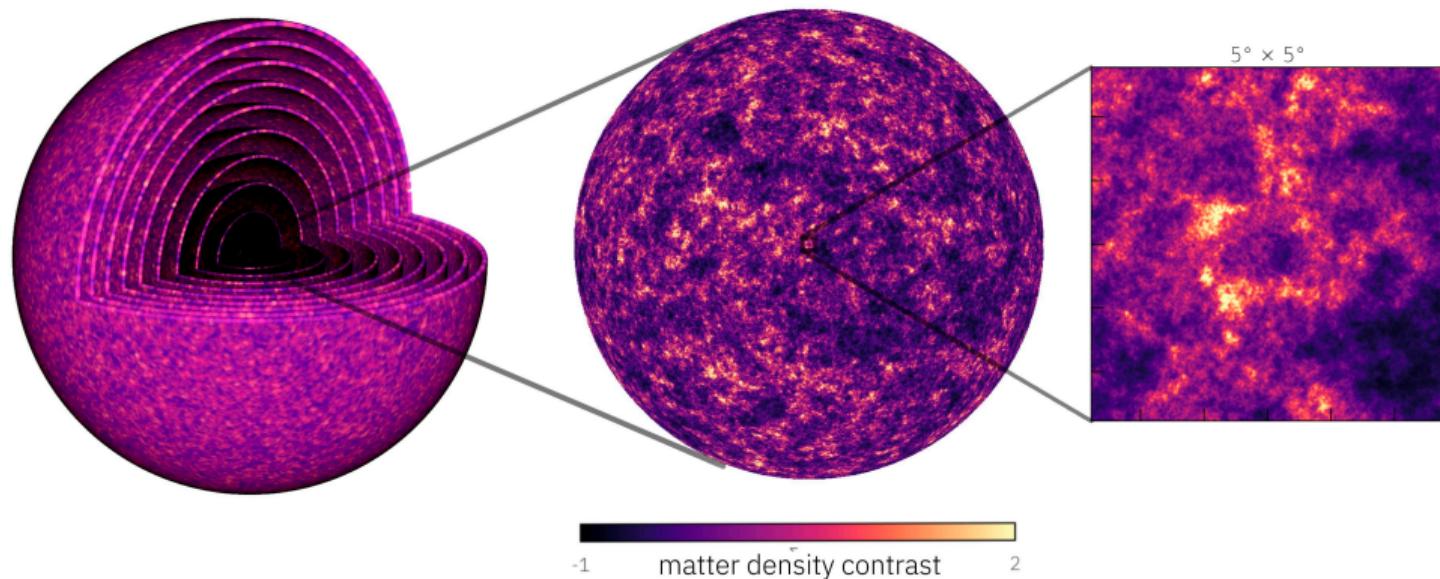
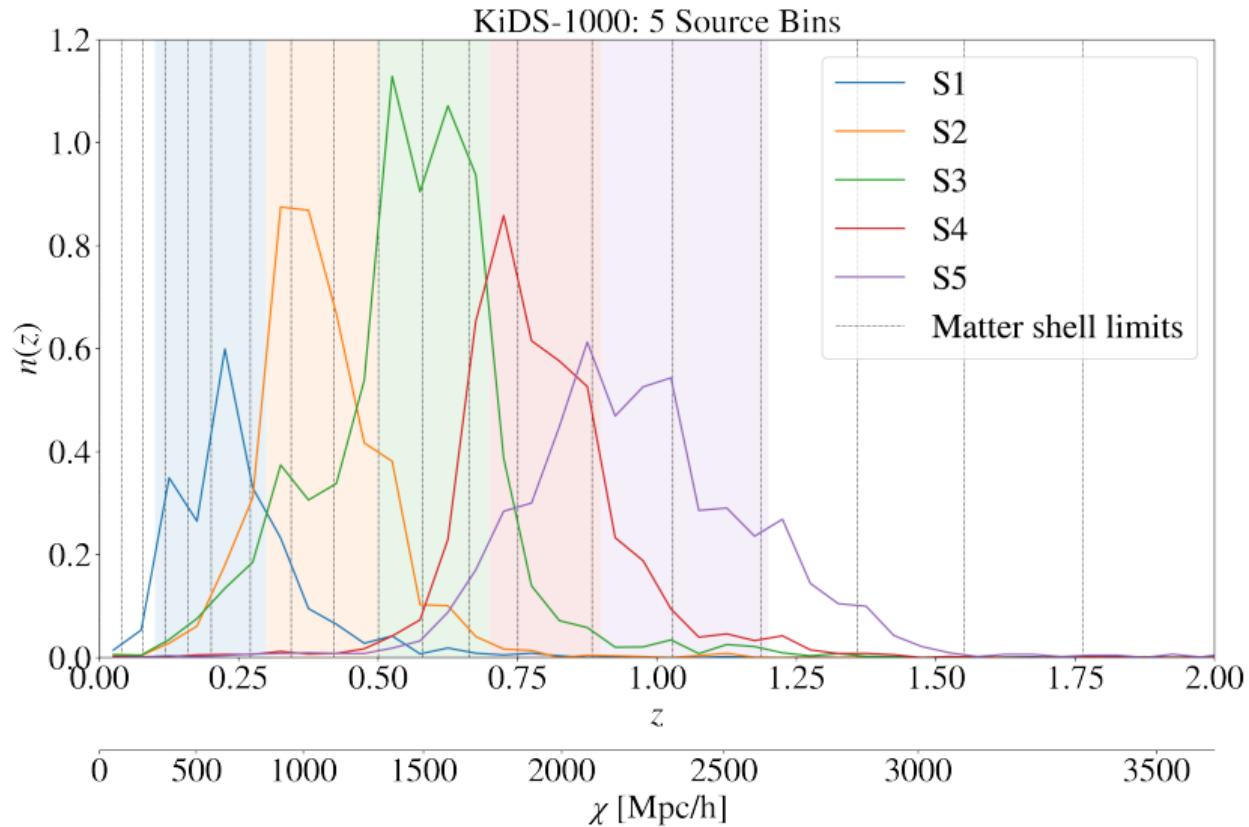
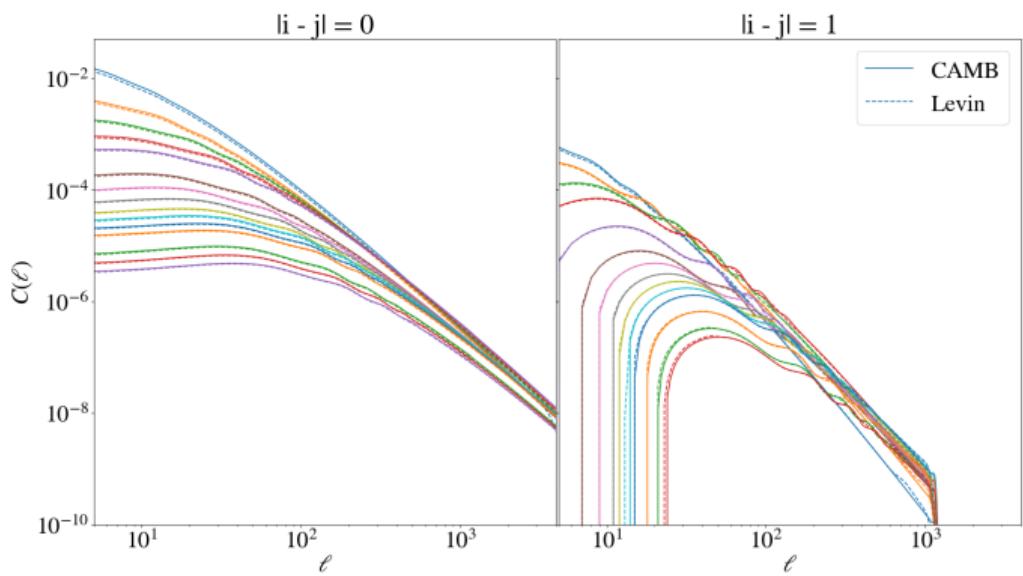
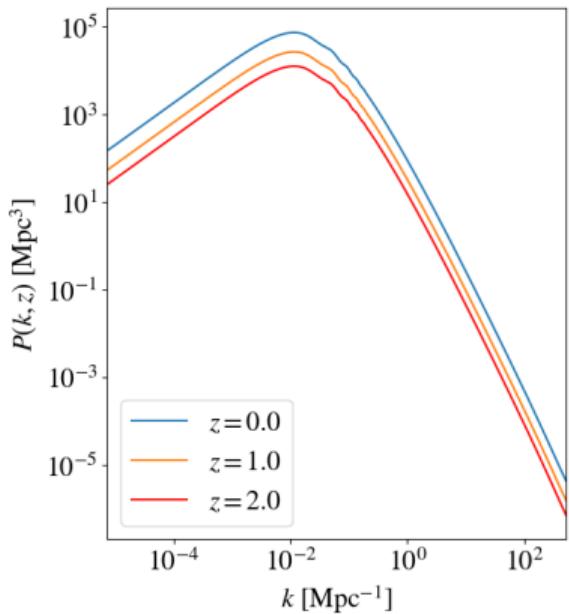


Figure: [Tessore et al. 2023; arxiv:2302.01942]

# Geometry of the simulations



# Non-Limber Projection: Levin



# GLASS: Generator of Large Scale Structure

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$$C_{\delta\delta}^{(ij)}(\theta; \Theta) = \langle \delta^{(i)}(\theta; \Theta) \delta^{(j)*}(\theta; \Theta) \rangle \quad (3)$$

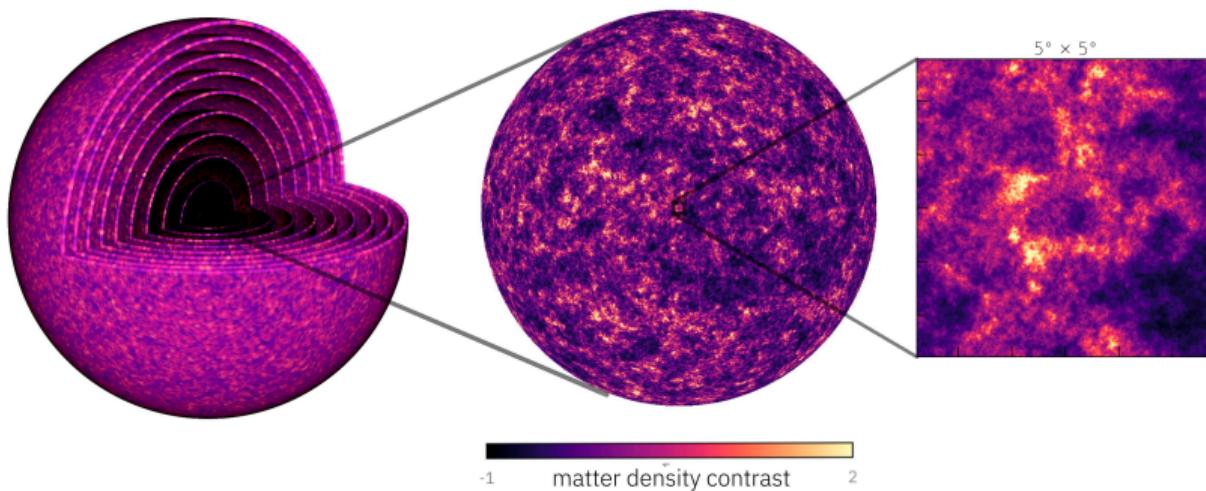


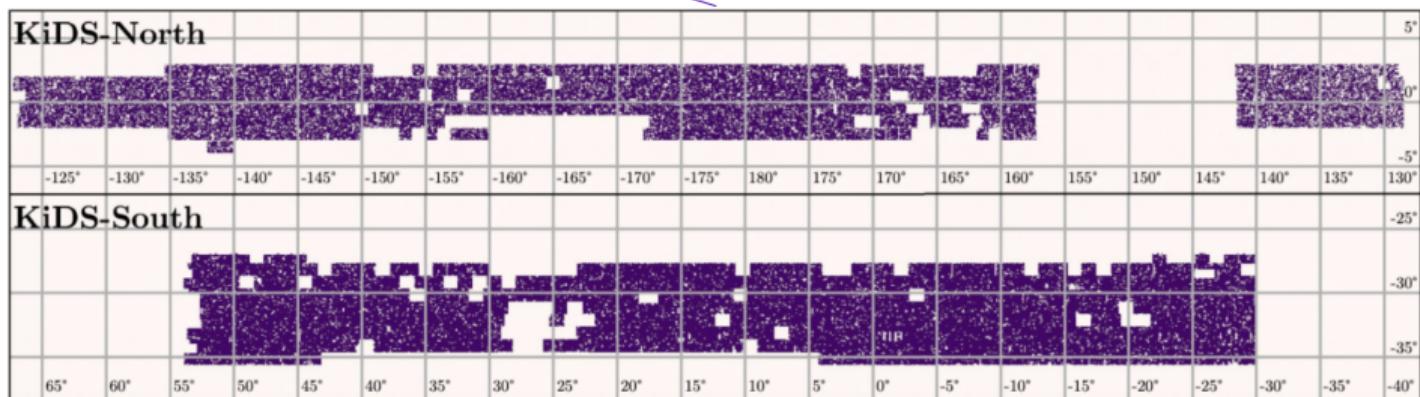
Figure: [Tessore et al. 2023; arxiv:2302.01942]

# Survey Characteristics

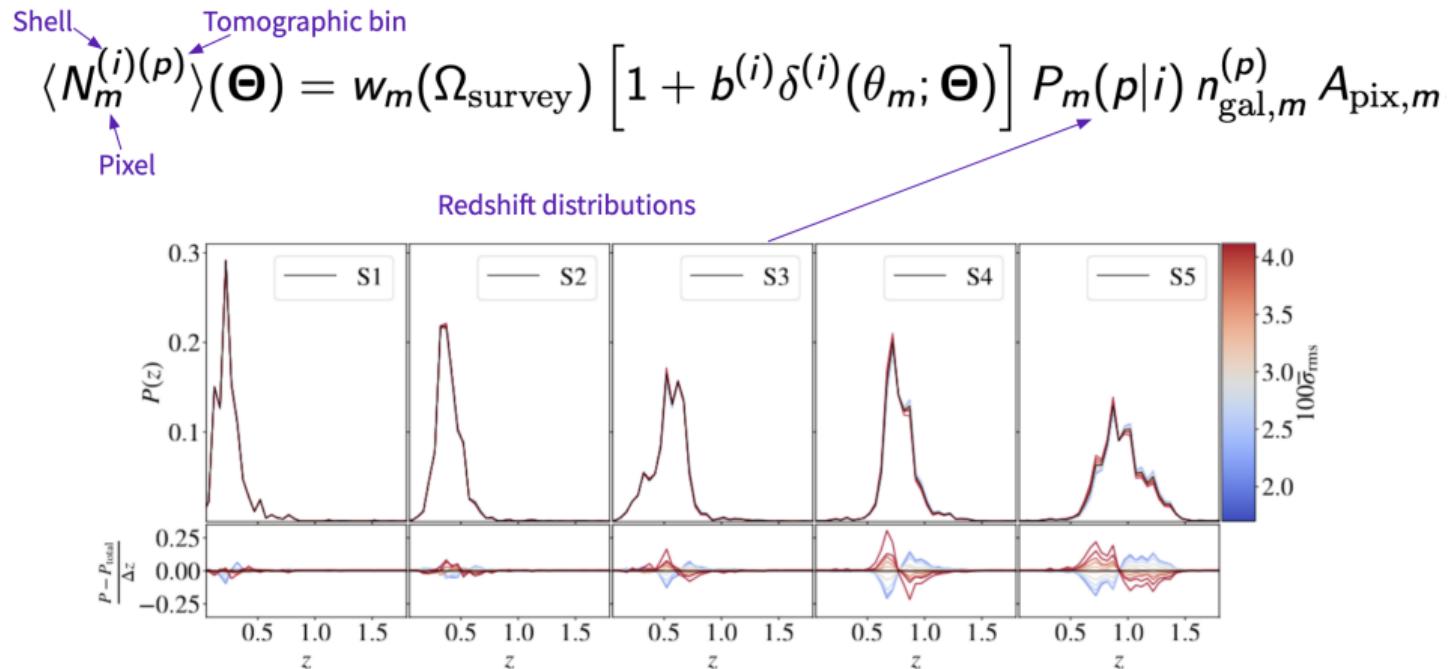
$$\langle N_m^{(i)(p)} \rangle(\Theta) = w_m(\Omega_{\text{survey}}) \left[ 1 + b^{(i)} \delta^{(i)}(\theta_m; \Theta) \right] P_m(p|i) n_{\text{gal},m}^{(p)} A_{\text{pix},m}$$

Annotations:

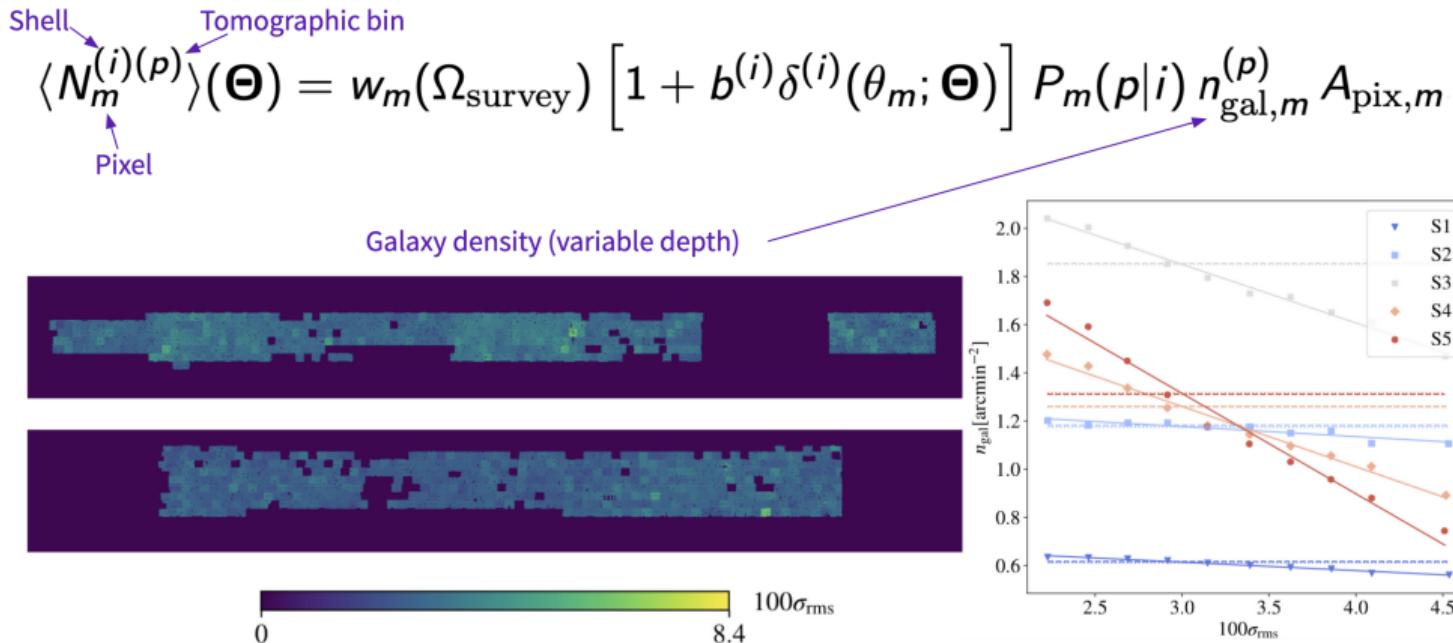
- Shell
- Tomographic bin
- Pixel
- Mask



# Survey Characteristics



# Survey Characteristics



# Variable Depth

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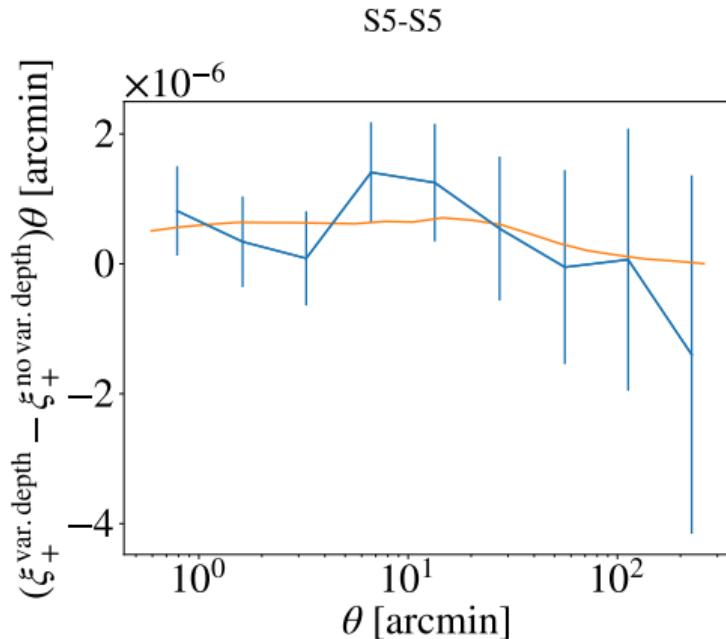
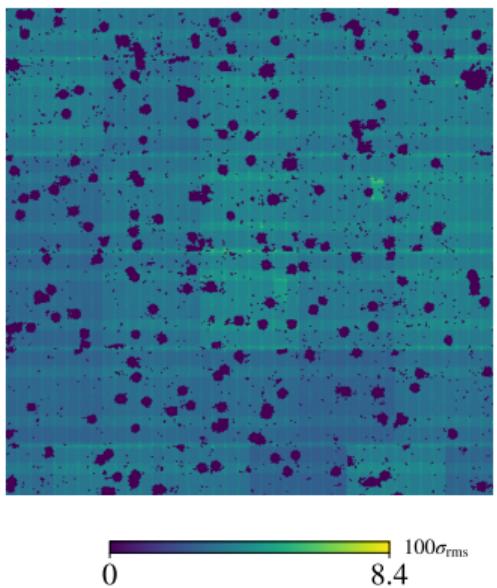
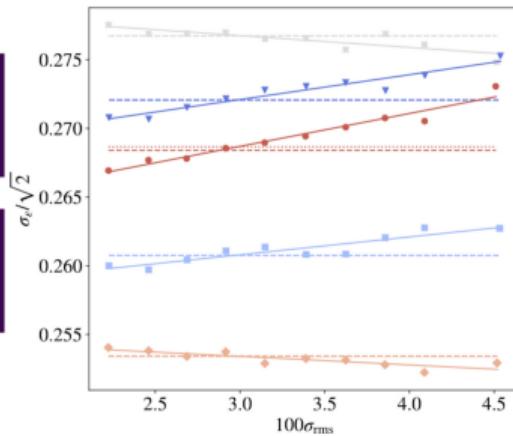


Figure: Orange: theory [Heydenreich et al. 2020; arXiv:1910.11327]. Blue: forward-simulations.

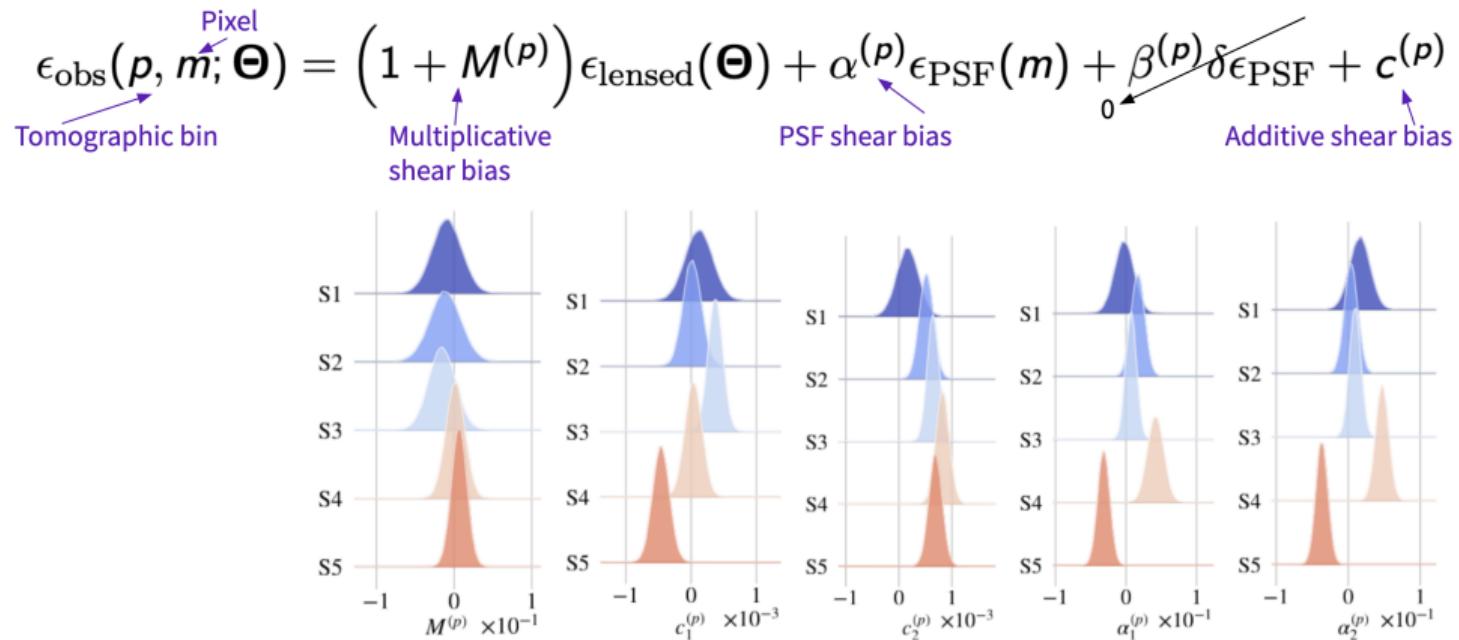
# Survey Characteristics

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

Reduced shear  
Intrinsic shapes  
(variable depth)



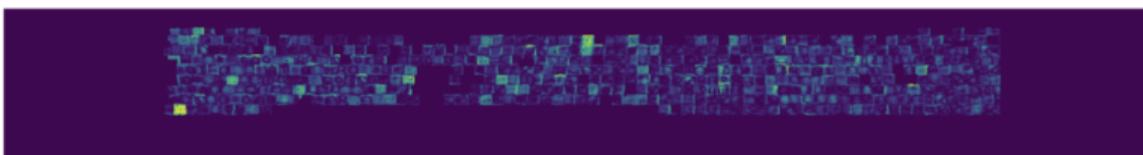
# Survey Characteristics



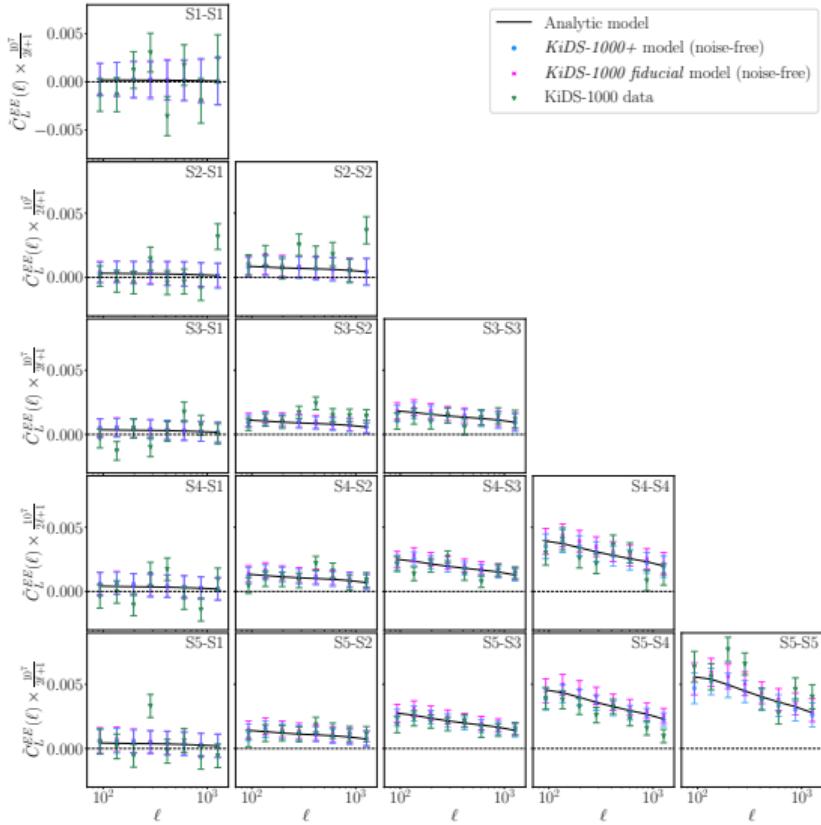
# Survey Characteristics

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

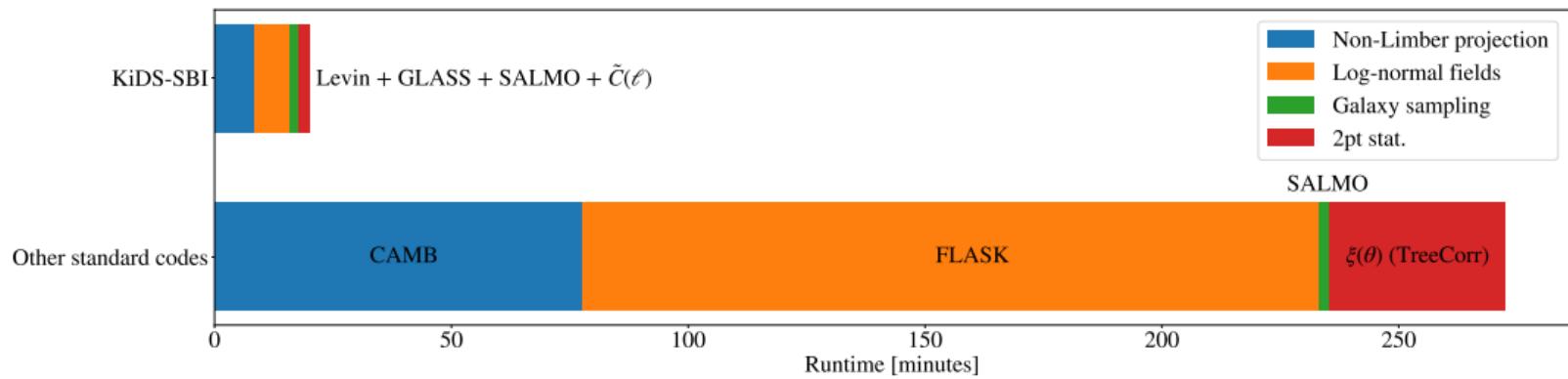
Pixel  
Tomographic bin  
PSF shear bias  
0

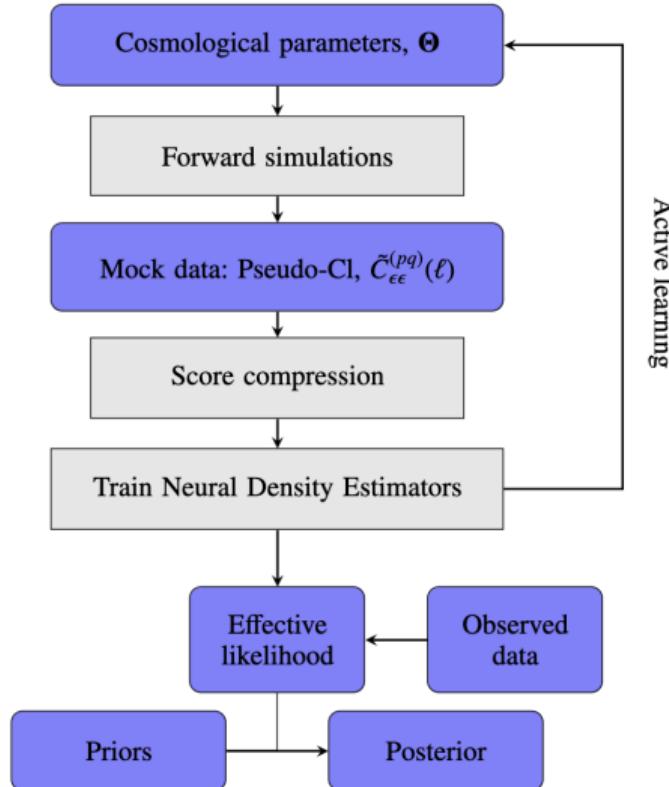


# Measurement: Pseudo-Cl<sub>s</sub>



# Forward-simulations speed



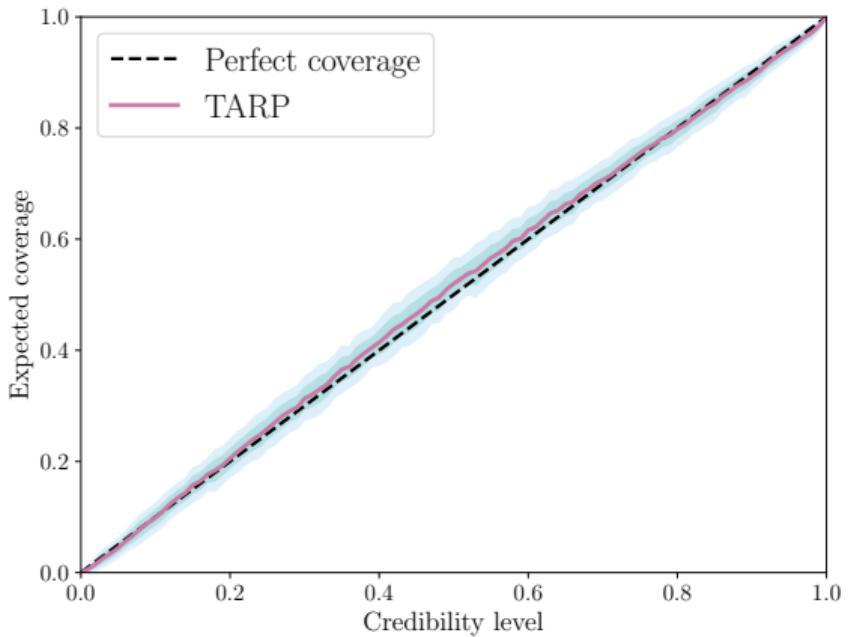
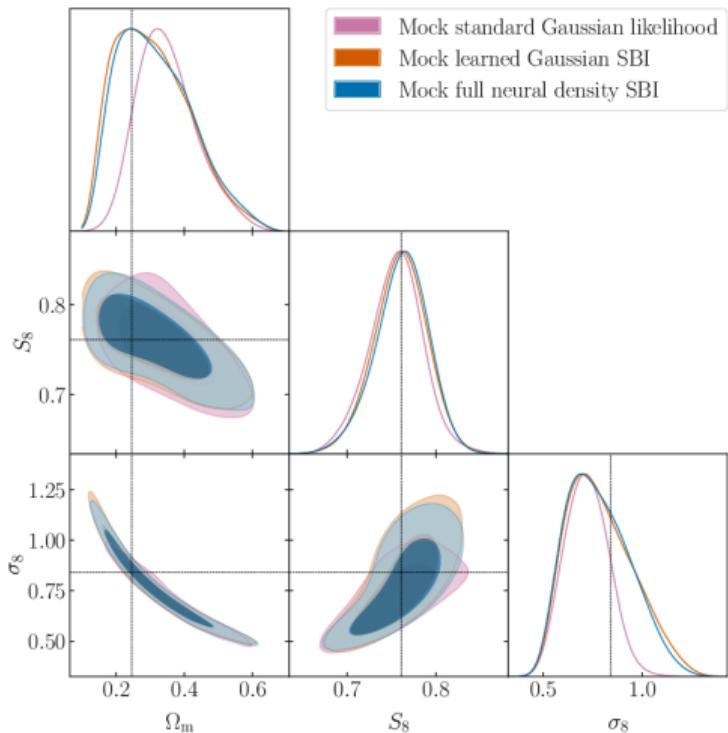


# KiDS-SBI: Parameters and Priors

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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	$\omega_c$	Flat	[0.051, 0.255]	0.118
Baryonic matter density	$\omega_b$	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	$\delta_z$	Gaussian	$\mathcal{N}(\mathbf{0}, C_z)$	$\mathbf{0}$
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	$\mathcal{N}(\bar{\alpha}_{1,2}^{(p)}, \sigma_{\alpha_{1,2}}^{(p)})$	$\bar{\alpha}_{1,2}^{(p)}$

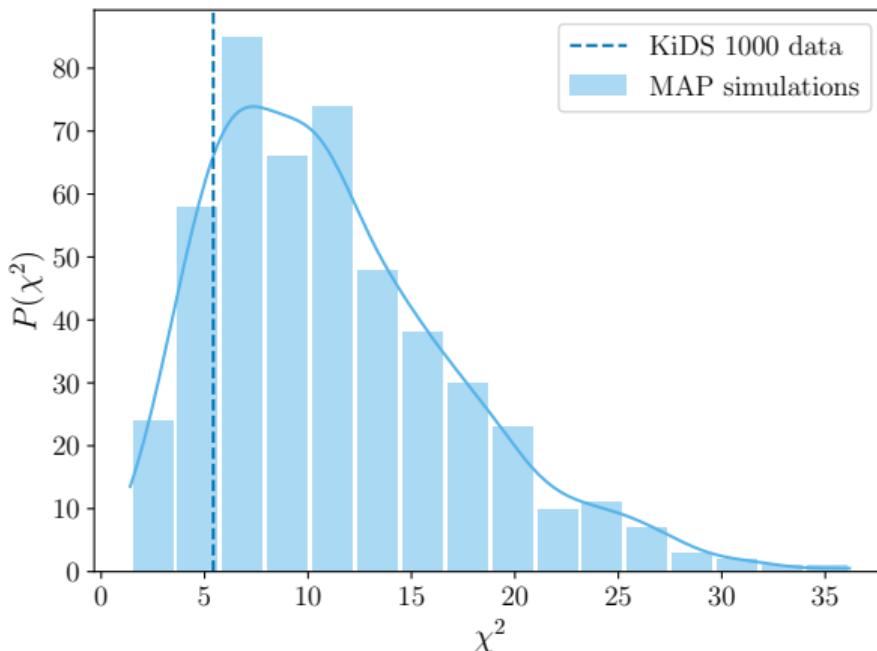
# Internal Consistency



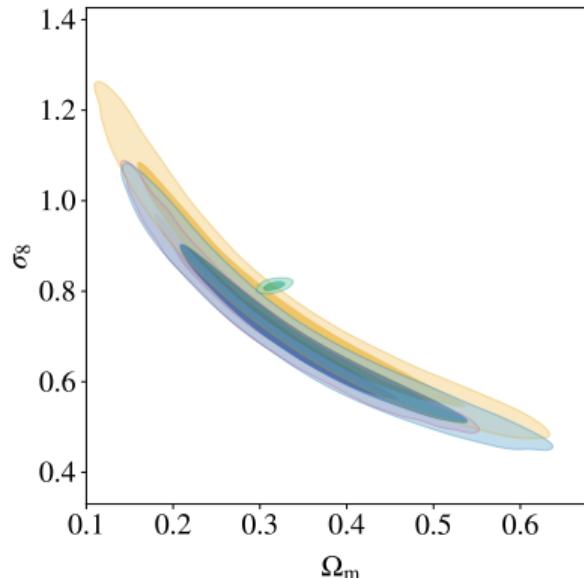
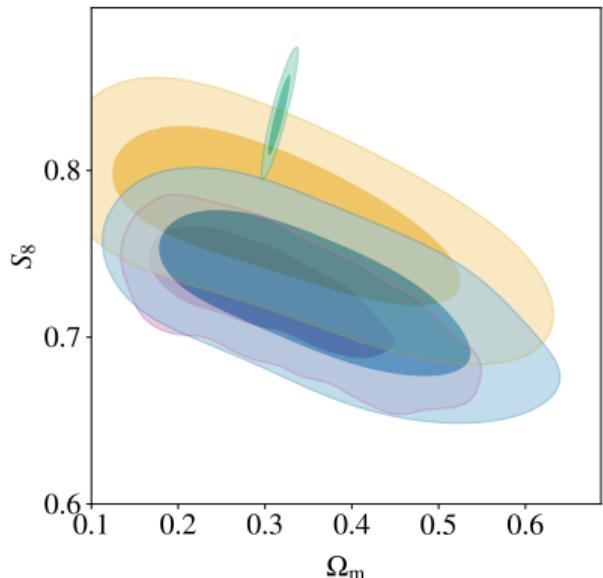
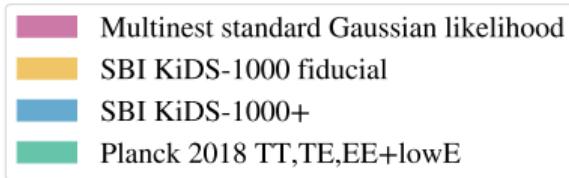
# Goodness-of-Fit in SBI

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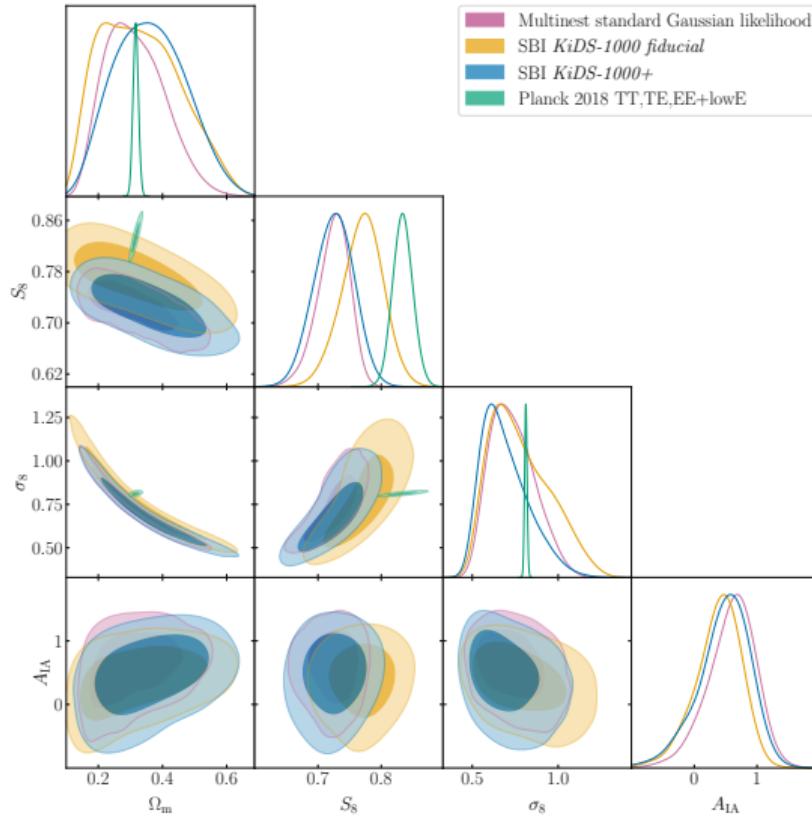
$$\chi^2(\mathbf{t}|\Theta) = (\mathbf{t}_i - \text{E}[\mathbf{t}_*|\Theta_*])^T (\text{Cov}(\mathbf{t}_*|\Theta_*))^{-1} (\mathbf{t}_i - \text{E}[\mathbf{t}_*|\Theta_*]) \quad (4)$$



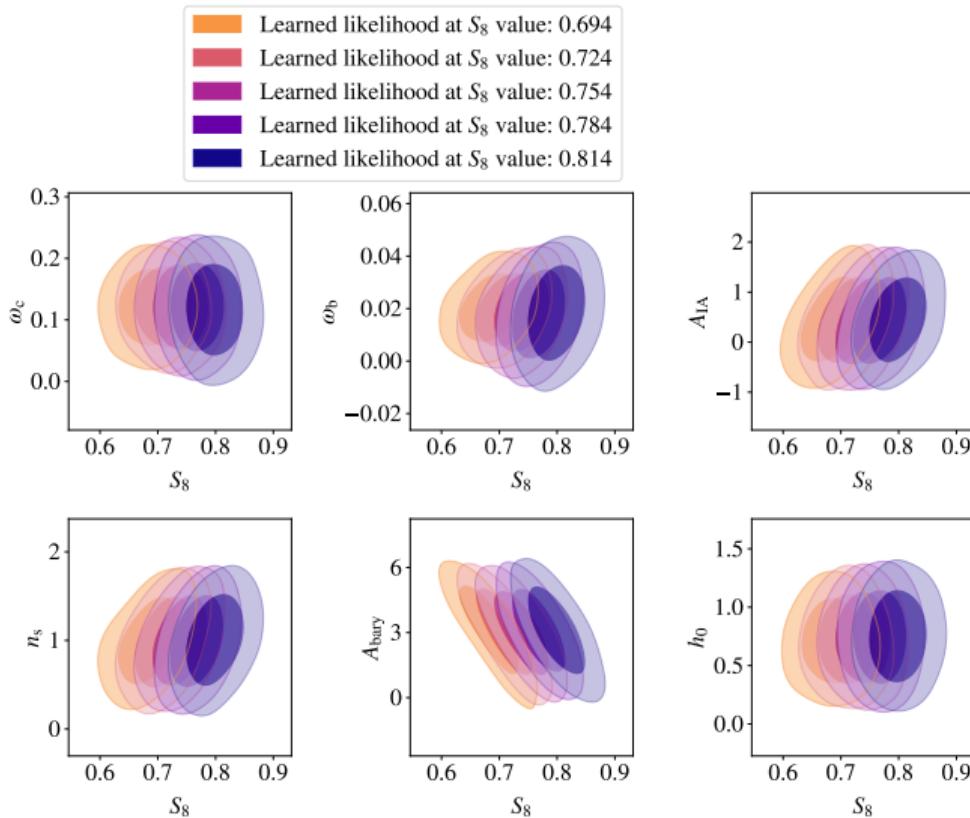
# Posterior Probability



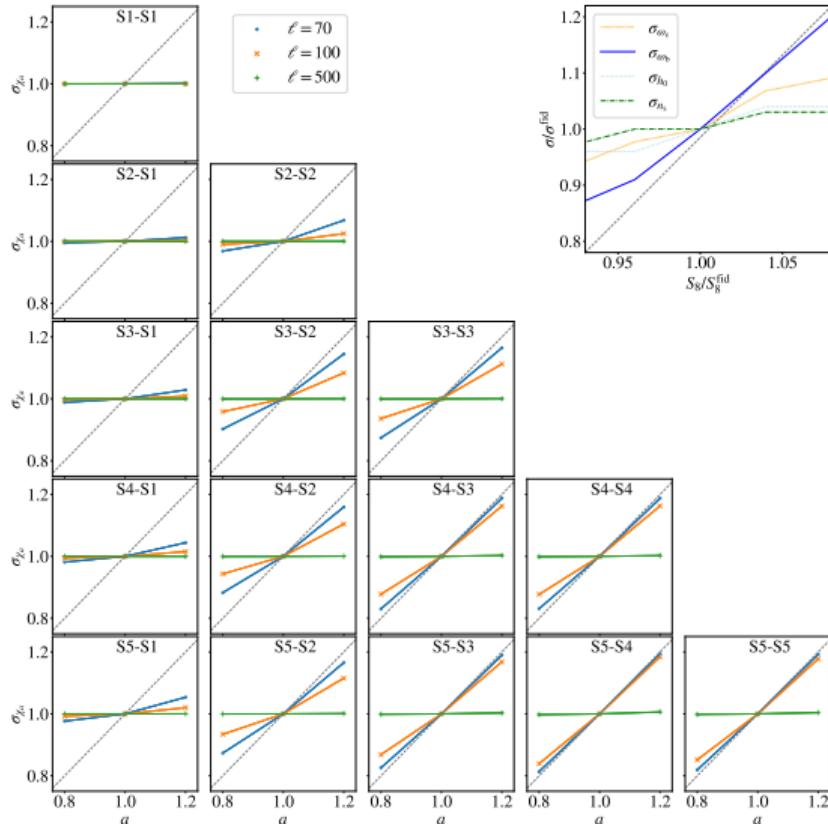
# Posterior Probability



# $S_8$ -dependent Uncertainty



# $S_8$ -dependent Uncertainty from Theory



# KiDS-SBI: Conclusions

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- Neglecting variable depth and shear biases can bias  $S_8$  by approx. 5%
- Cosmic shear likelihood is consistent with a Gaussian, but its covariance is measurably cosmology-dependent (cosmic variance) → uncertainty on  $S_8$  is higher
- **Future:** test different models, apply to 3x2pt analysis, analyse KiDS-Legacy or Euclid, etc.

# Questions?

# References

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-  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

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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

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- Shear-shear weak lensing from KiDS-1000 using pseudo-Cl<sub>s</sub>
- 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	$\omega_c$	Flat	[0.051, 0.255]	0.118
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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 B - Compression and DELFI

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- A stack of NDEs are used in DELFI

$$p(\mathbf{t}|\theta; \mathbf{w}) = \prod_{\alpha=1}^{N_{\text{NDEs}}} \beta_\alpha p_\alpha(\mathbf{t}|\theta; \mathbf{w}), \quad (5)$$

- 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

$$\mathcal{L} = \mathcal{L}_* + \delta\boldsymbol{\theta}^T \nabla \mathcal{L}_* - \frac{1}{2} \delta\boldsymbol{\theta}^T \mathbf{J}_* \delta\boldsymbol{\theta}, \quad (6)$$

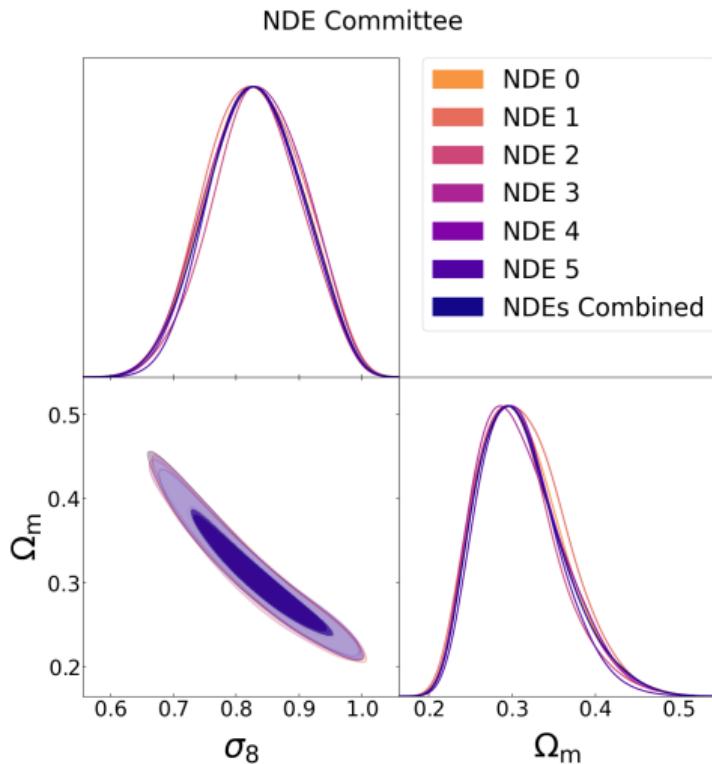
$$\mathbf{t} = \nabla \boldsymbol{\mu}^T \mathbf{C}^{-1} (\mathbf{d} - \boldsymbol{\mu}), \quad (7)$$

- Remap this to a MLE estimate via the Fisher matrix

$$\hat{\boldsymbol{\theta}} = \boldsymbol{\theta}_* + \mathbf{F}_*^{-1} \nabla \mathcal{L}_* = \boldsymbol{\theta}_* + \mathbf{F}_*^{-1} \mathbf{t}_*, \quad (8)$$

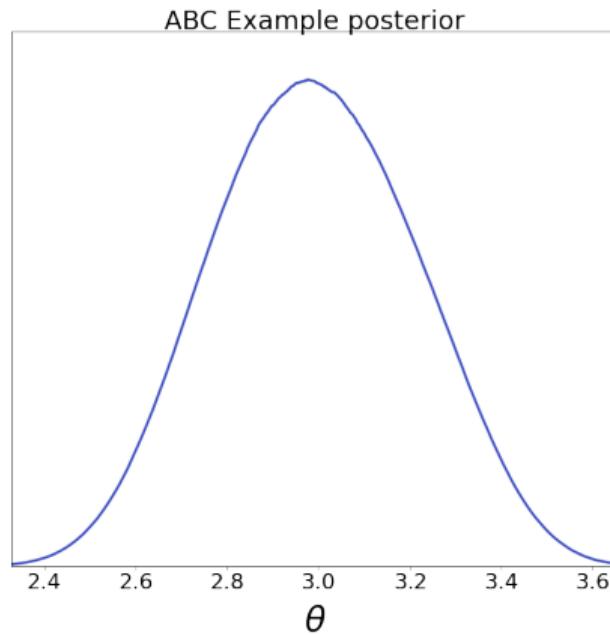
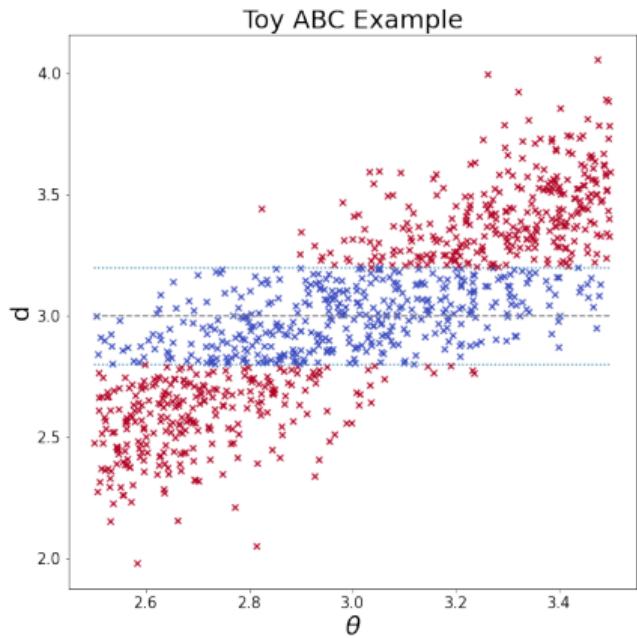
# Appendices C - PyDELFI

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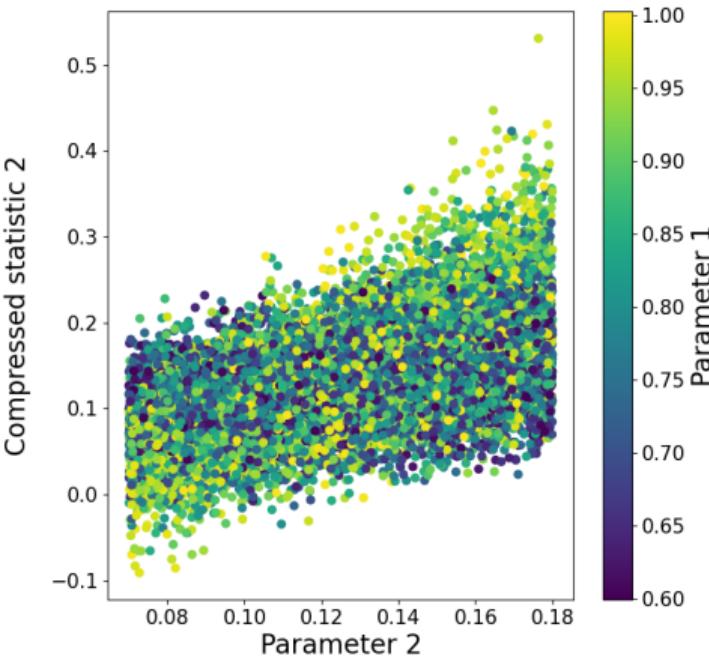
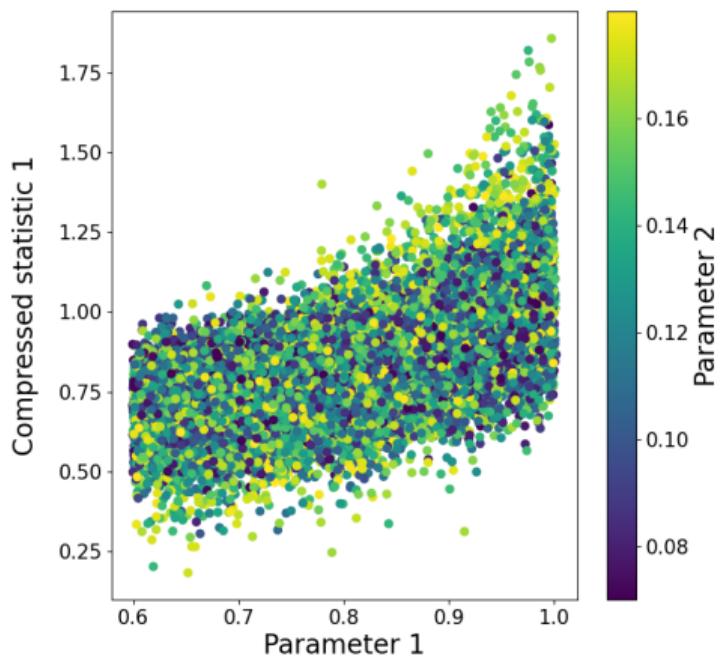
# Appendices D - SBI - ABC

$$P(\theta|\mathbf{d}) = \frac{P(\mathbf{d}|\theta) \cdot P(\theta)}{P(\mathbf{d})} \quad (9)$$



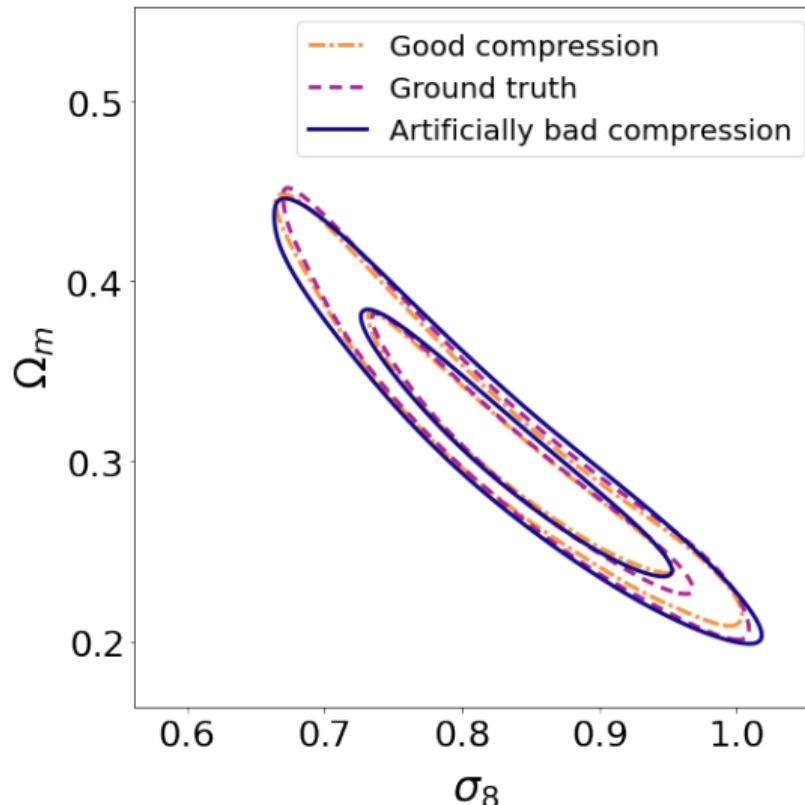
# Appendices E - Score Compression

Linearly score compressed data vs. parameters



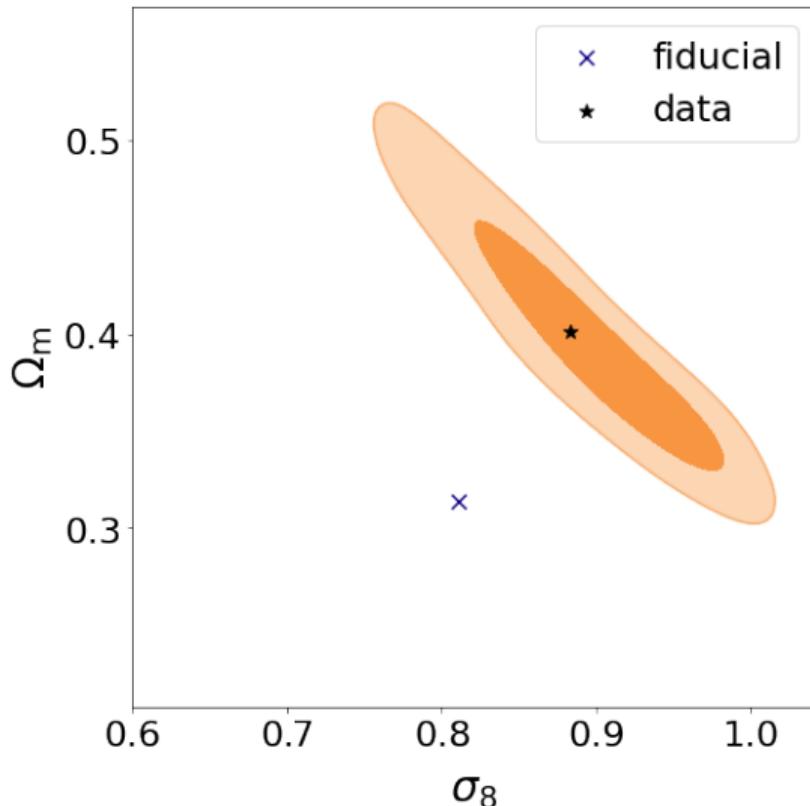
## Appendices F - Sensitivity to Compression

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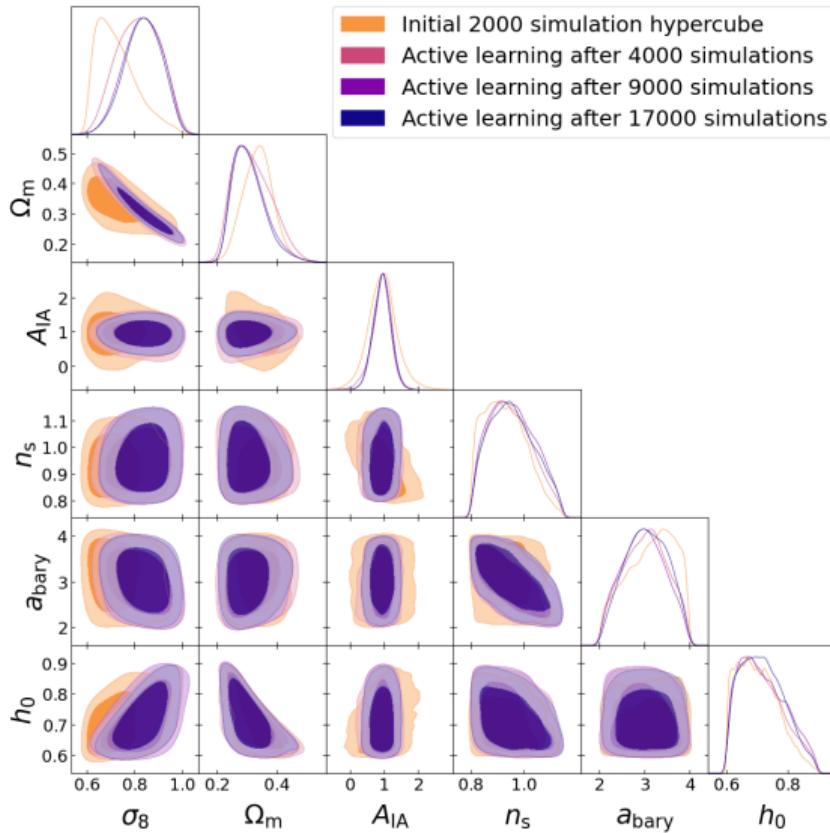


## Appendix G - Sensitivity to Fiducial Cosmology

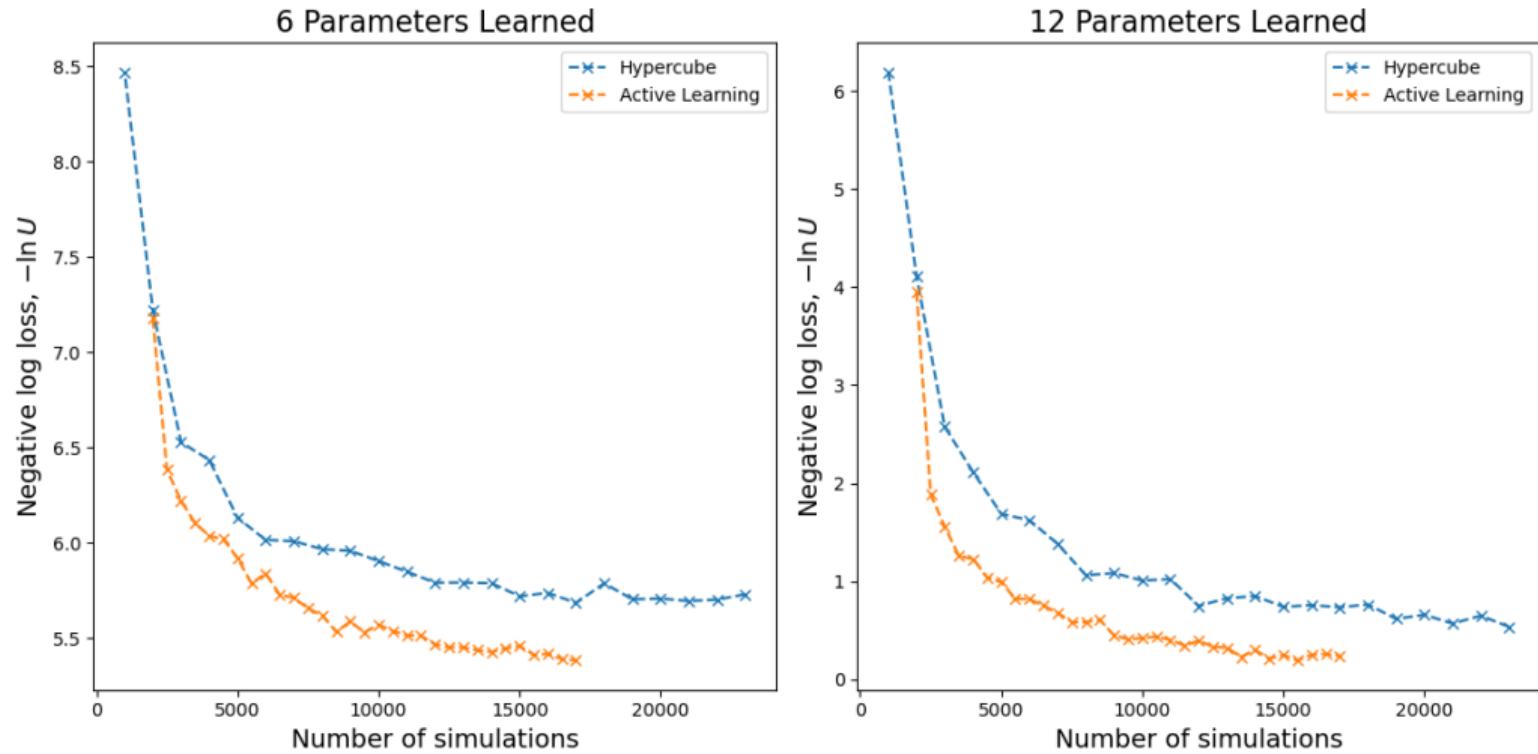
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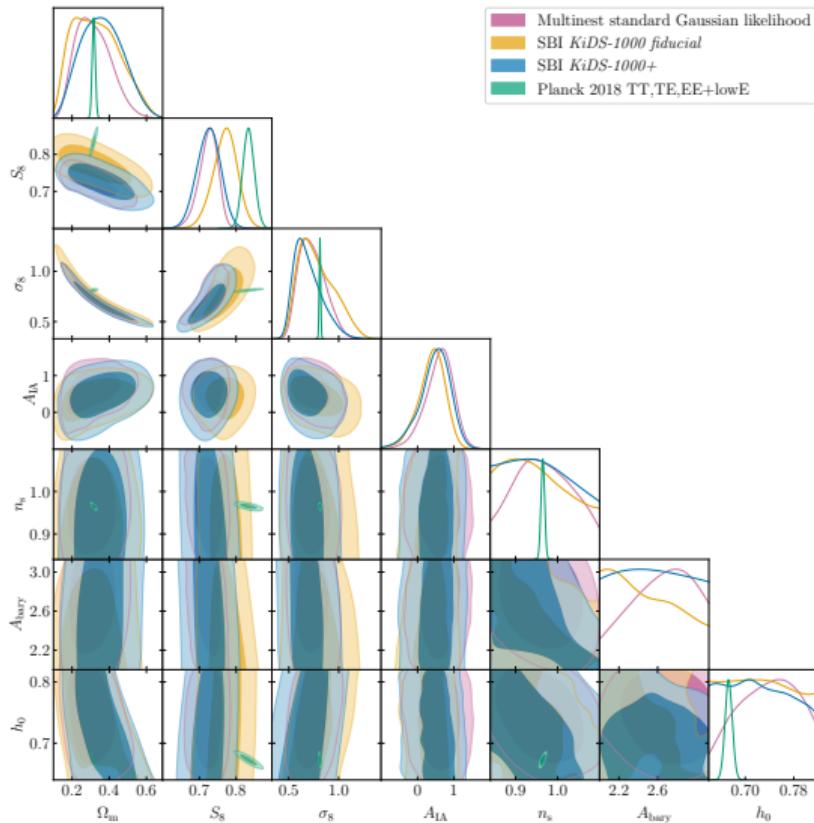
# Appendix H - Active Learning



# Appendix I - Simulation Number Sufficiency



# Appendix J - Full Posterior



# Appendix K - Signal Test

