From Cosmic Shear to Subhalo Detection:

Leveraging Simulation-Based Inference for Precision Cosmology

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MPA Garching

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Euclid consortium

KiDS Kilo-Degree Survey

Institute for Computational Cosmology

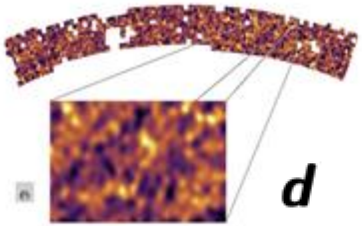
Durham Centre for Extragalactic Astronomy

Durham University

UK Space Agency

UK Research and Innovation

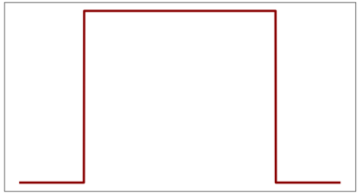
Recipe for Cosmological Inference



d

Data

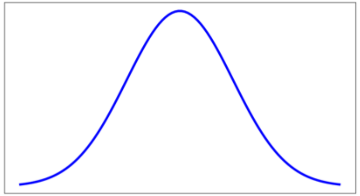
$P(\theta)$



θ

Prior

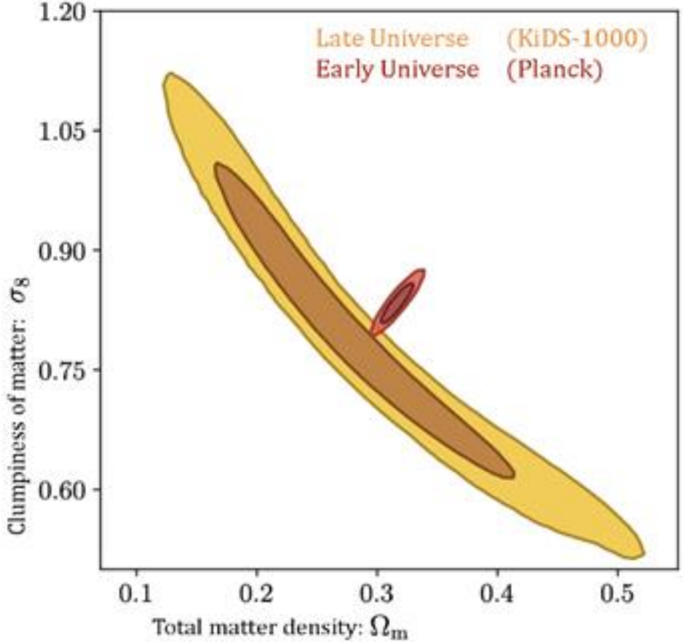
$P(d|\theta)$



d

Likelihood

$P(\theta|d)$: **Posterior**

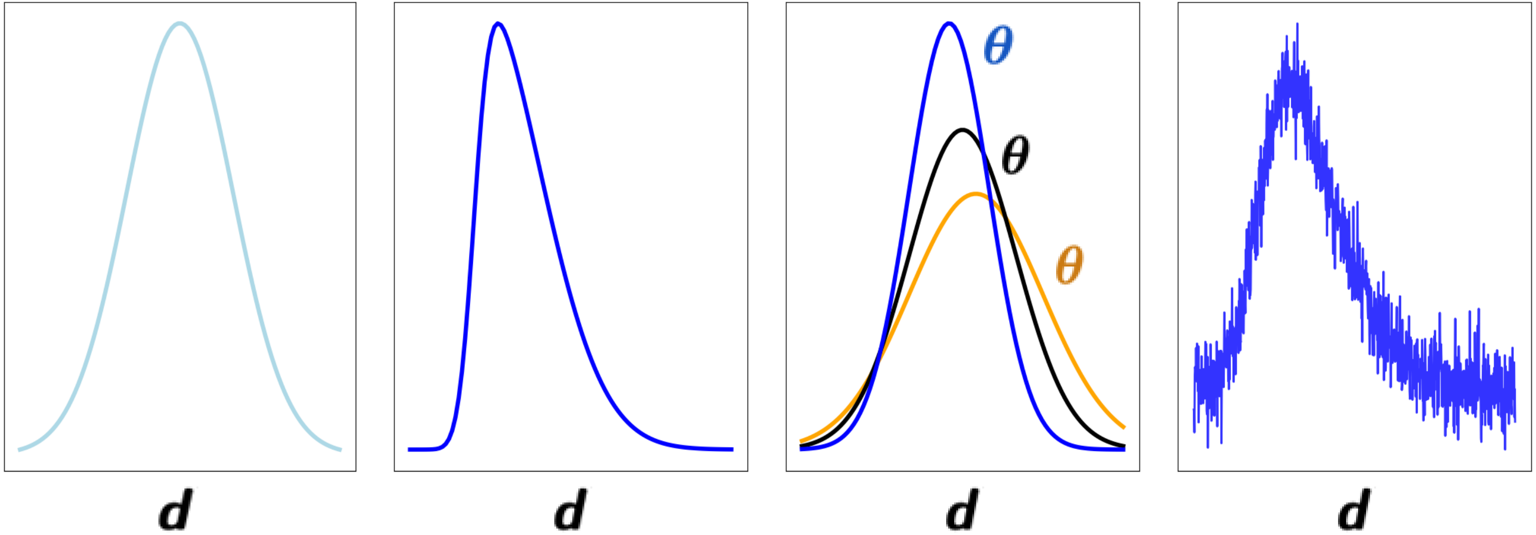


Model: ΛCDM

Modelling Likelihoods

Given a model!

$P(\boldsymbol{d}|\boldsymbol{\theta})$



Analytic	**Biased**	**Signal-dependent uncertainty**	**Intractable**
e.g.	e.g.	e.g.	e.g.
$P(d \mid \theta) \propto e^{-(d-\mu)^2}$	Instrumental systematics	Cosmic variance	Non-trivial selection functions

Bayes' Theorem

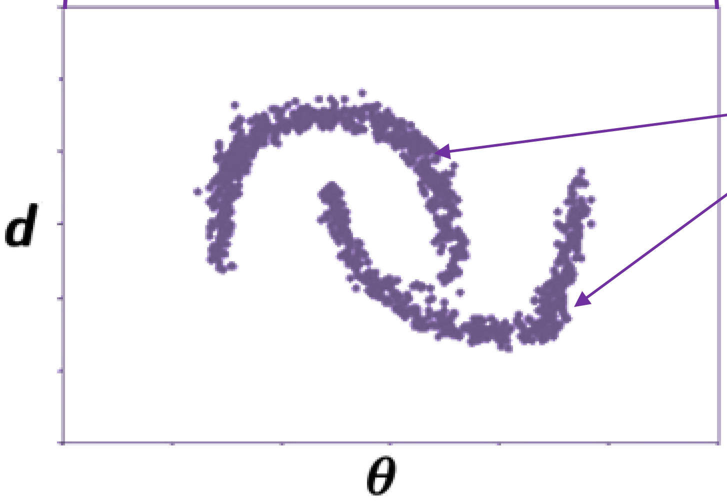
Posterior **Likelihood** Prior **Joint probability**

$$P(\boldsymbol{\theta}|\boldsymbol{d}) = \frac{P(\boldsymbol{d}|\boldsymbol{\theta}) \cdot P(\boldsymbol{\theta})}{P(\boldsymbol{d})} \propto P(\boldsymbol{\theta}, \boldsymbol{d}) \cdot P(\boldsymbol{\theta})$$

$\boldsymbol{\theta}$: Model parameters

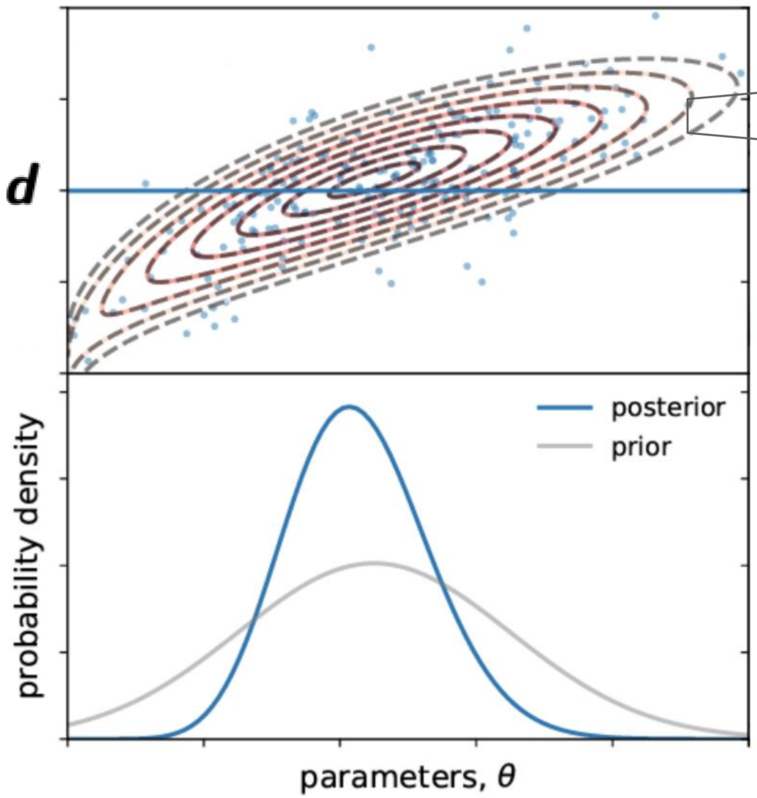
$\boldsymbol{d}$: Data

Simulation-based or **likelihood-free** or **implicit likelihood inference**



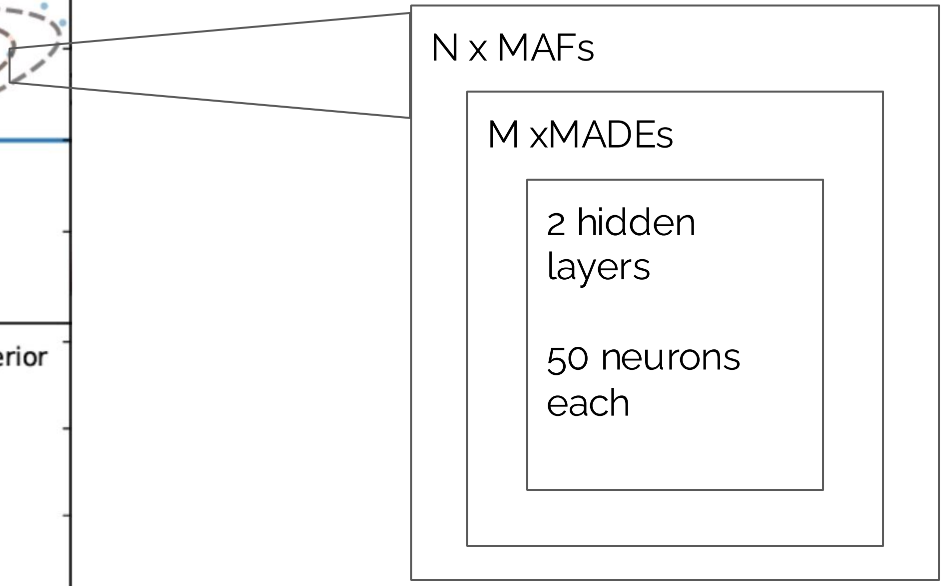
Populate with **simulations** given a model

Neural Density Estimation



Alsing et al. (2019), MNRAS, 488(3), 4440-4458.

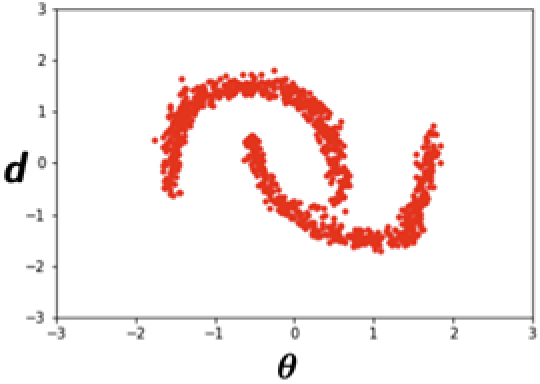
Ensemble of NDEs



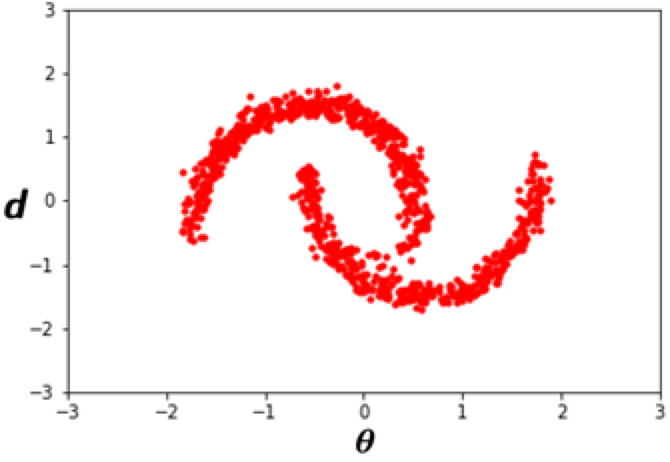
→ N x M x |$\boldsymbol{d}$| multivariate Gaussians, P($\boldsymbol{d}$|$\boldsymbol{\theta}$, $\mathbf{w}$)

Masked Autoregressive Flows

$P(\theta, \boldsymbol{d})$
from simulations

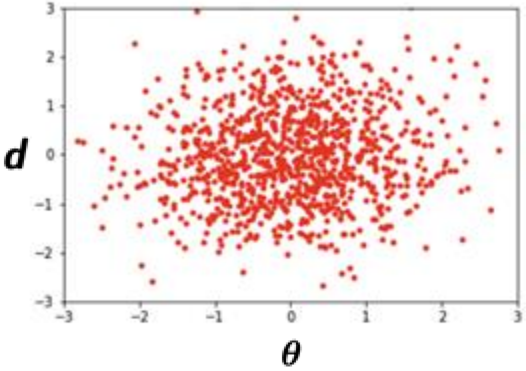


Learn transformations
to



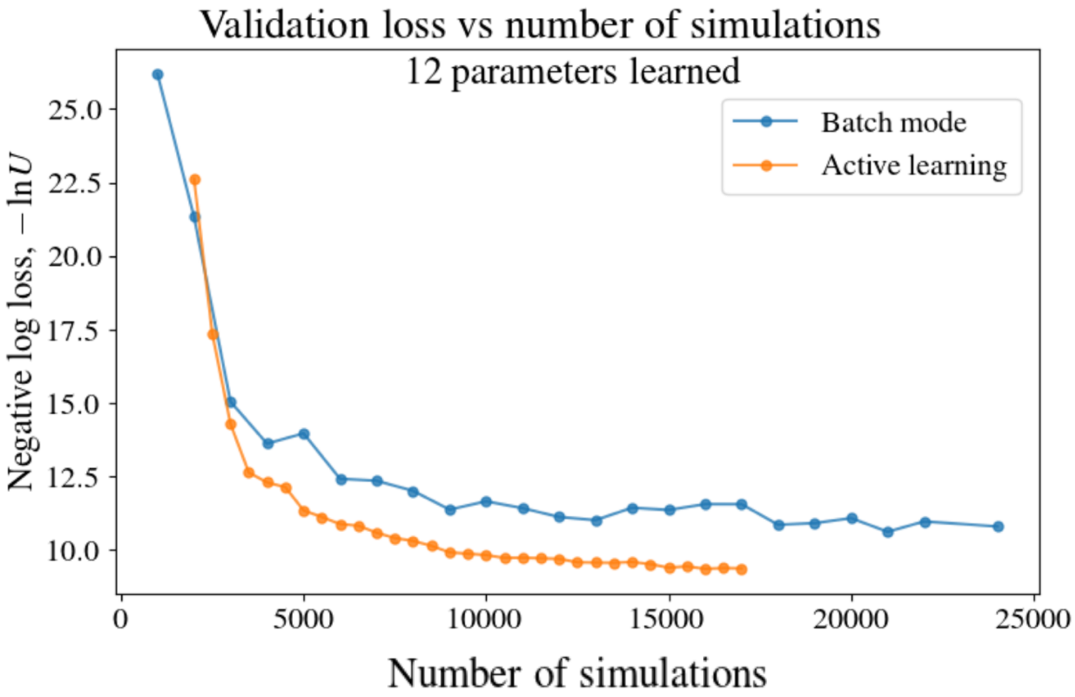
Credit: Eric Jang

Gaussian
distribution



Invertible

Masked Autoregressive Flows



Lin, von Wietersheim-Kramsta, et al. (2022), MNRAS 524(4), pp. 6167-6180

Cosmic Shear
& Large-Scale Structure

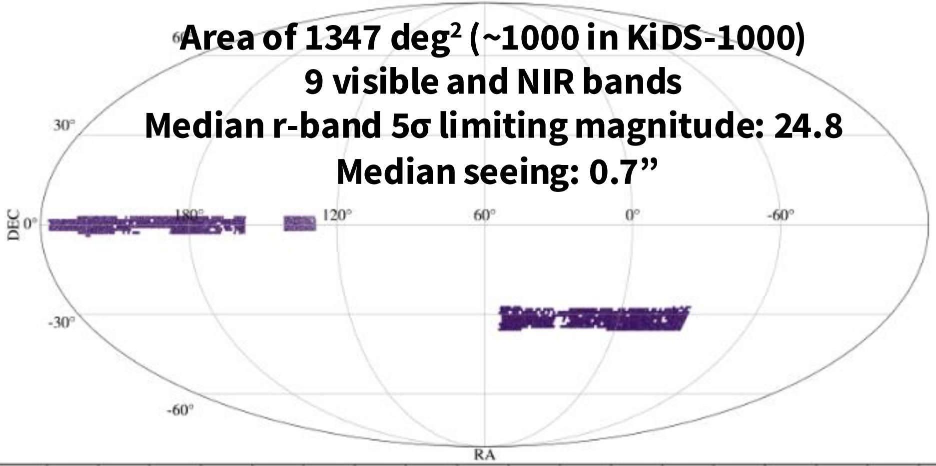
In collaboration with K. Lin, N. Tessore, B. Joachimi, A. Loureiro, R. Reischke, A.H. Wright

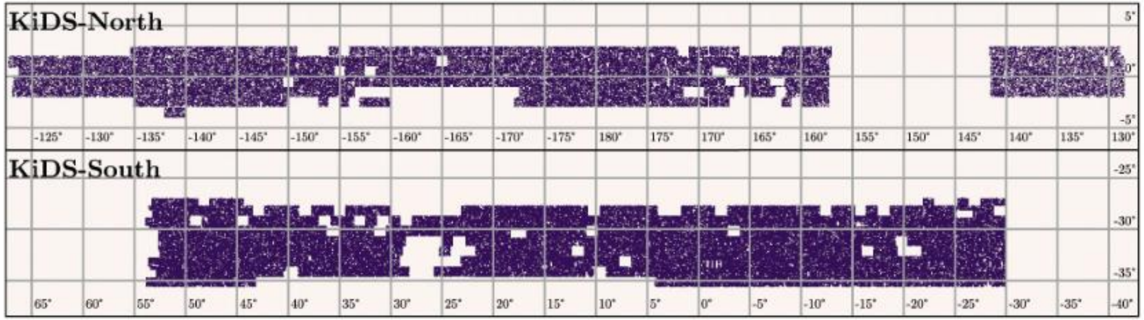
von Wietersheim-Kramsta, Lin et al. (2024), A&A 694, A223.

Kilo-Degree Survey

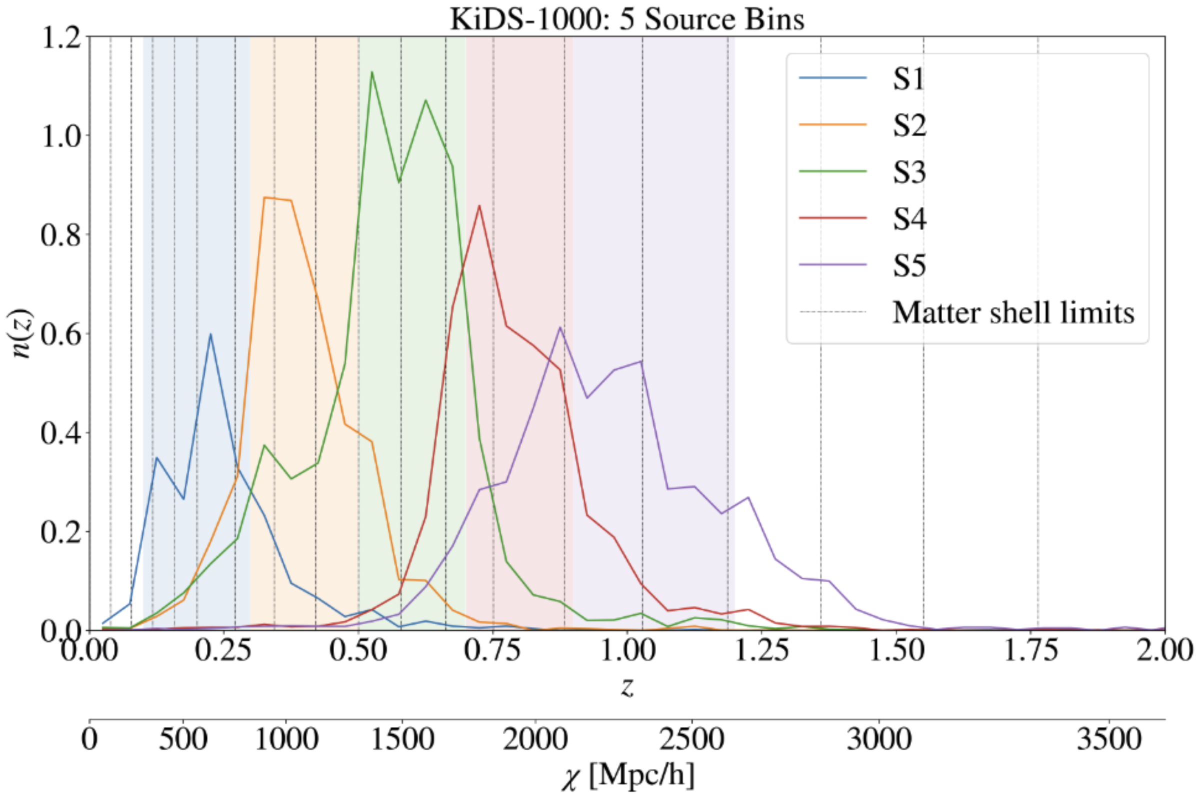
ESO VLT Survey Telescope

Area of 1347 deg^2 (~1000 in KiDS-1000)
9 visible and NIR bands
Median r-band 5σ limiting magnitude: 24.8
Median seeing: 0.7”



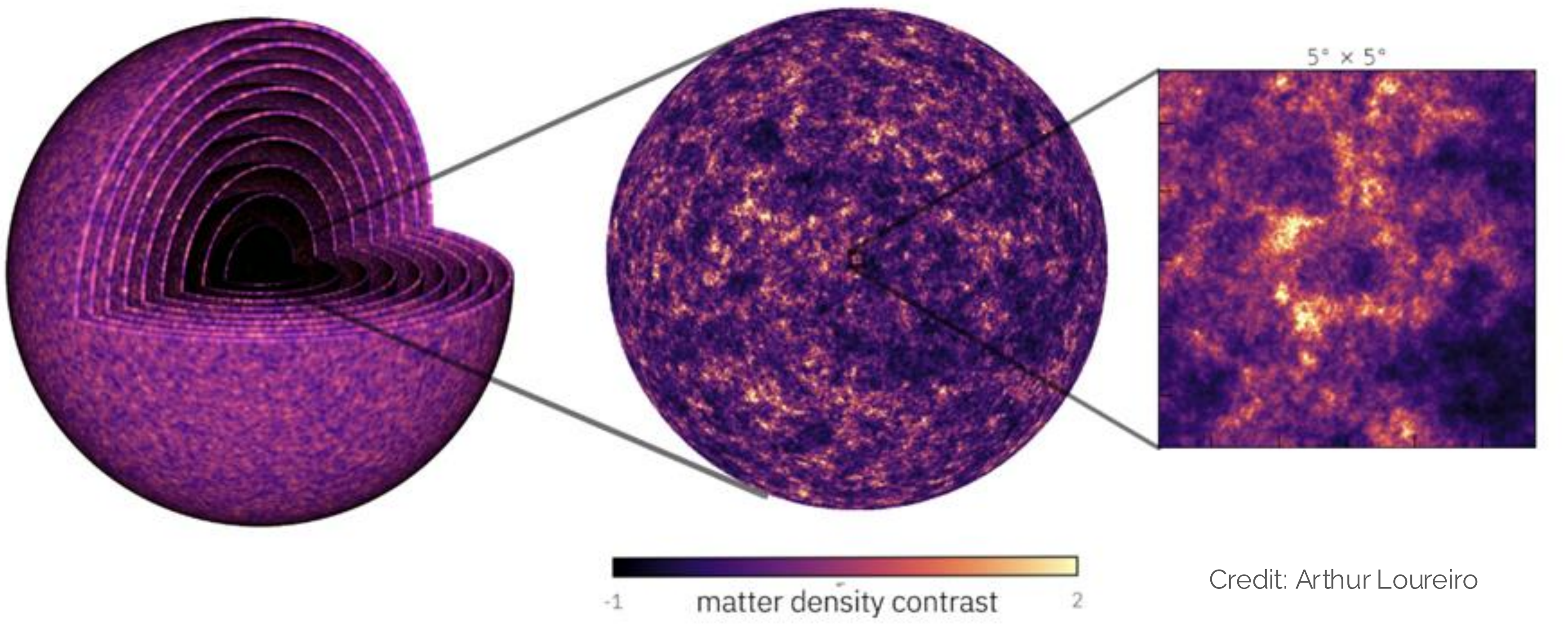


Harnessing the Photometric Uncertainties



Simulating Large-Scale Structure

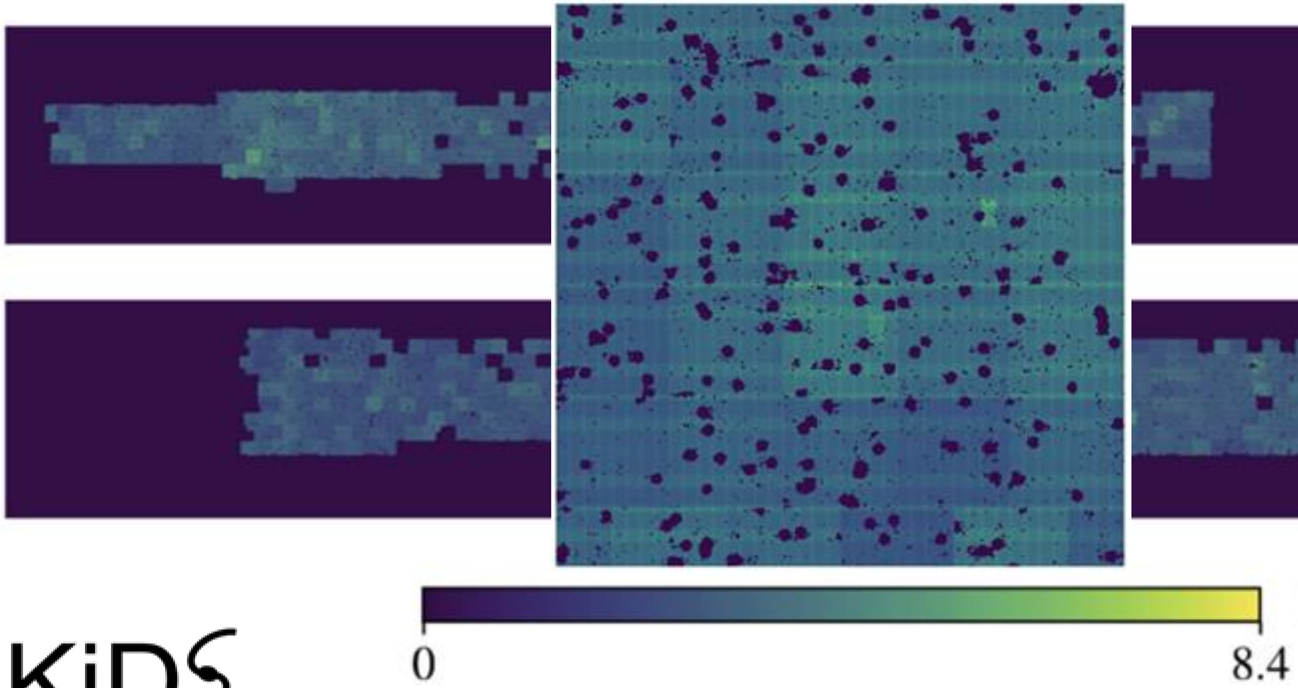
GLASS: Generator for Large Scale Structure



Credit: Arthur Loureiro

Tessore, et al. (2023), OJA 6 (March).

Realistic Selection and Systematics



(Galaxy selection)

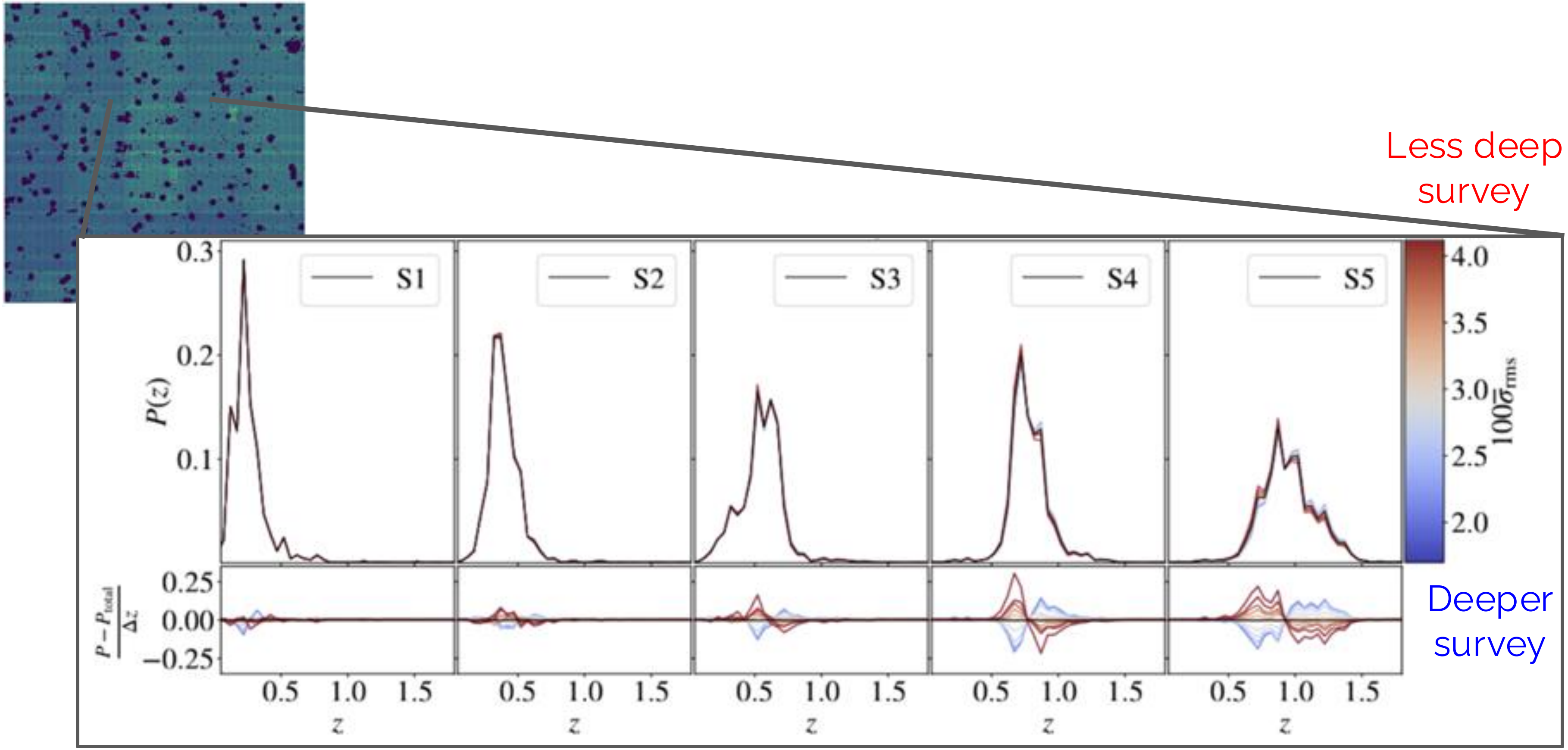
KiDS
Kilo-Degree Survey

Deeper survey

Less deep survey

von Wietersheim-Kramsta, Lin et al. (2024), A&A 694, A223.

Depth and Galaxy Redshift



Sampling Galaxies

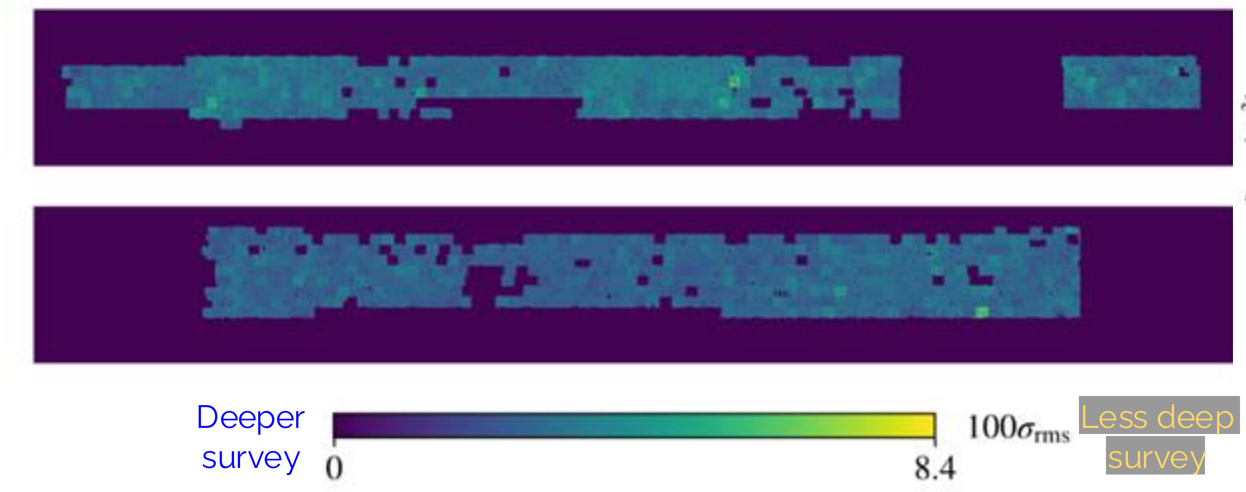
Shell

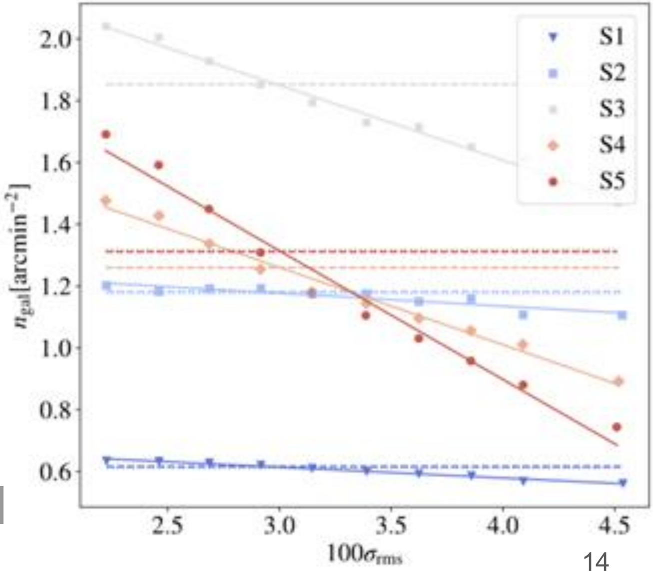
Tomographic bin

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

Pixel

Galaxy density (variable depth)



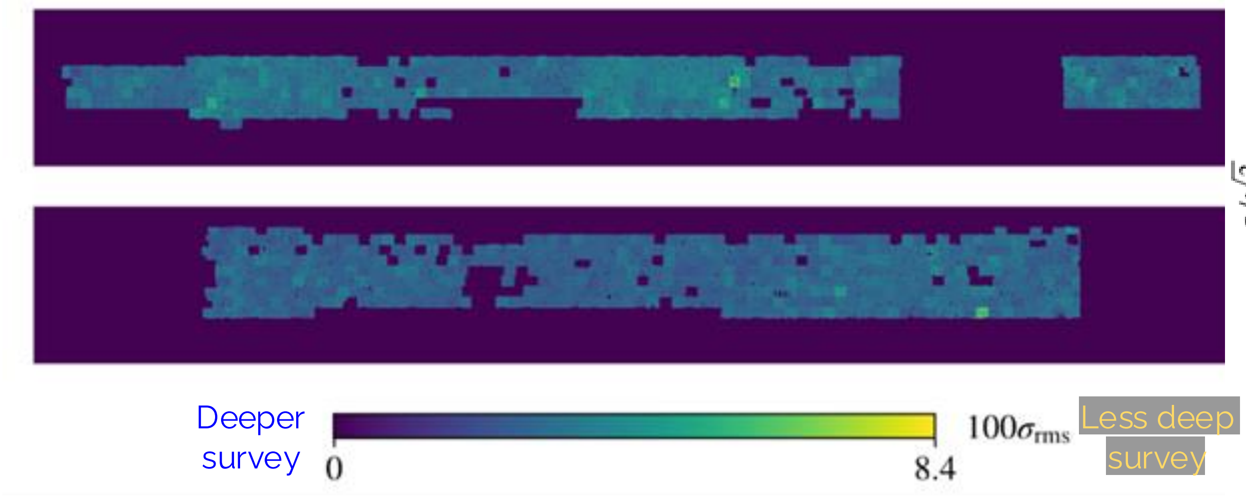


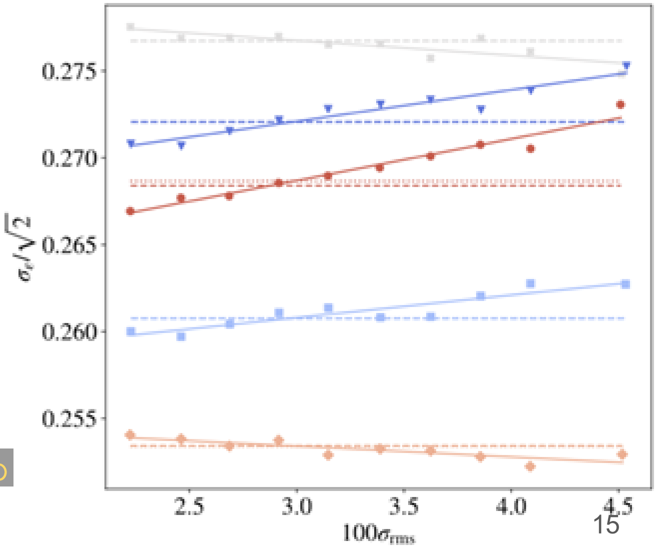
Galaxy Shapes

Reduced shear

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

Intrinsic shapes
(variable depth)





Shear Biases

Pixel

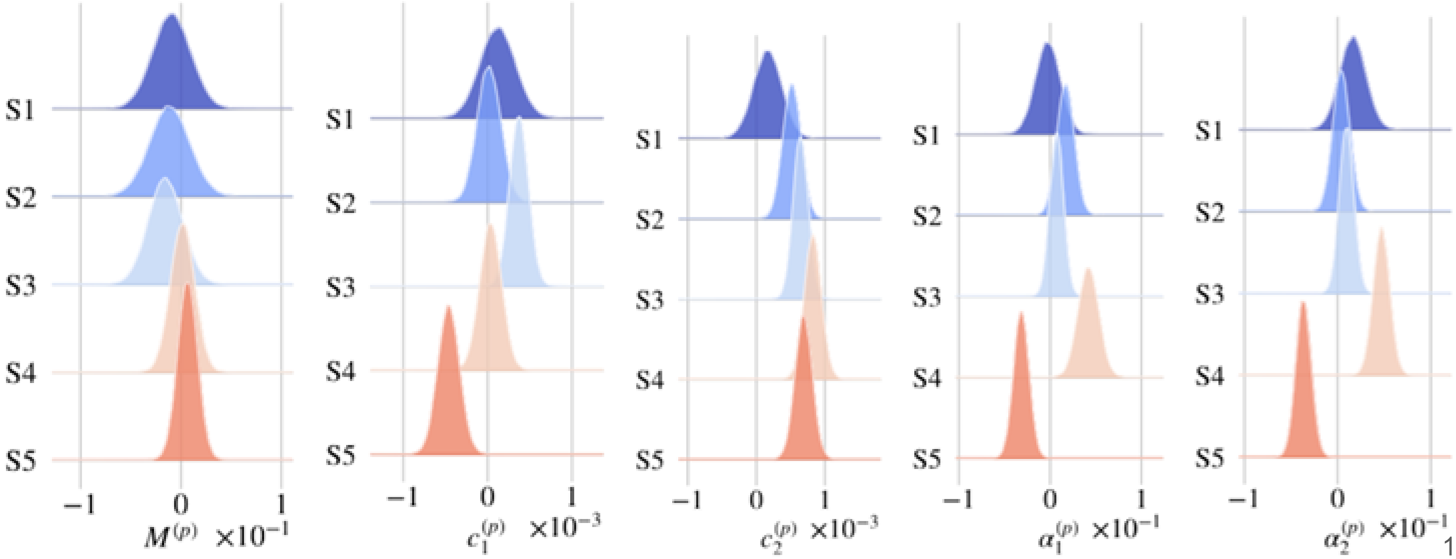
$$\epsilon_{\rm obs}(p, m; \Theta) = \left(1 + M^{(p)}\right)\epsilon_{\rm lensed}(\Theta) + \alpha^{(p)}\epsilon_{\rm PSF}(m) + \underbrace{\cancel{\beta^{(p)}\delta\epsilon_{\rm PSF}}}_{0} + c^{(p)}$$

Tomographic bin

Multiplicative shear bias

PSF shear bias

Additive shear bias



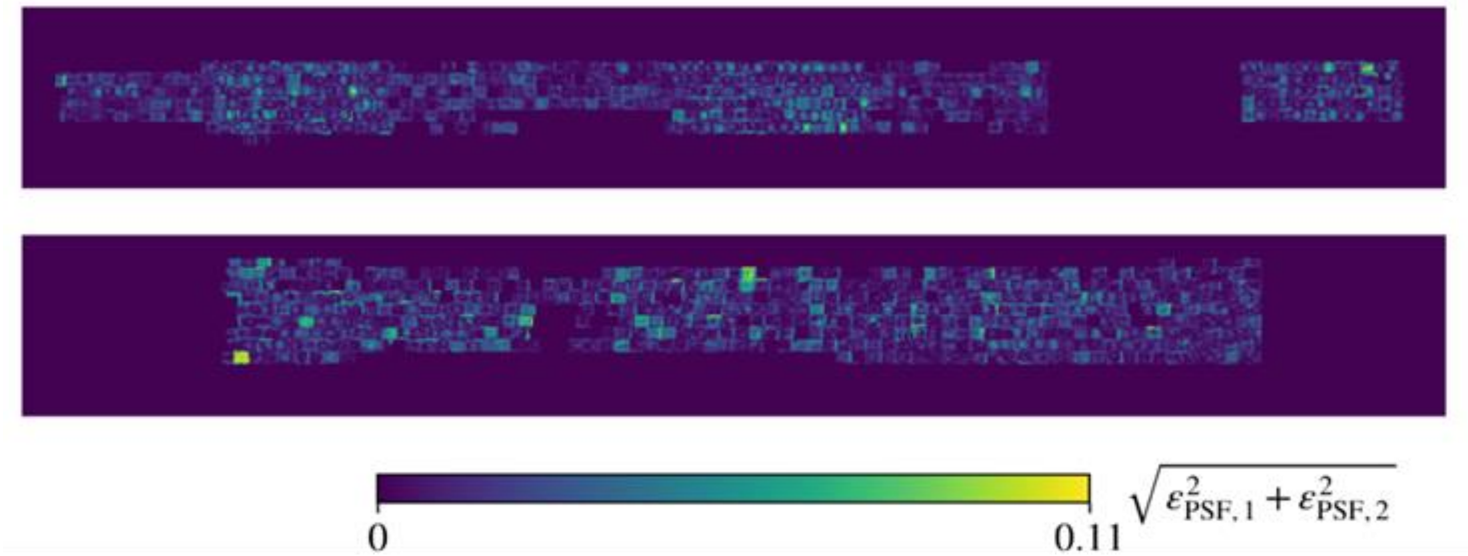
PSF Residuals

Pixel

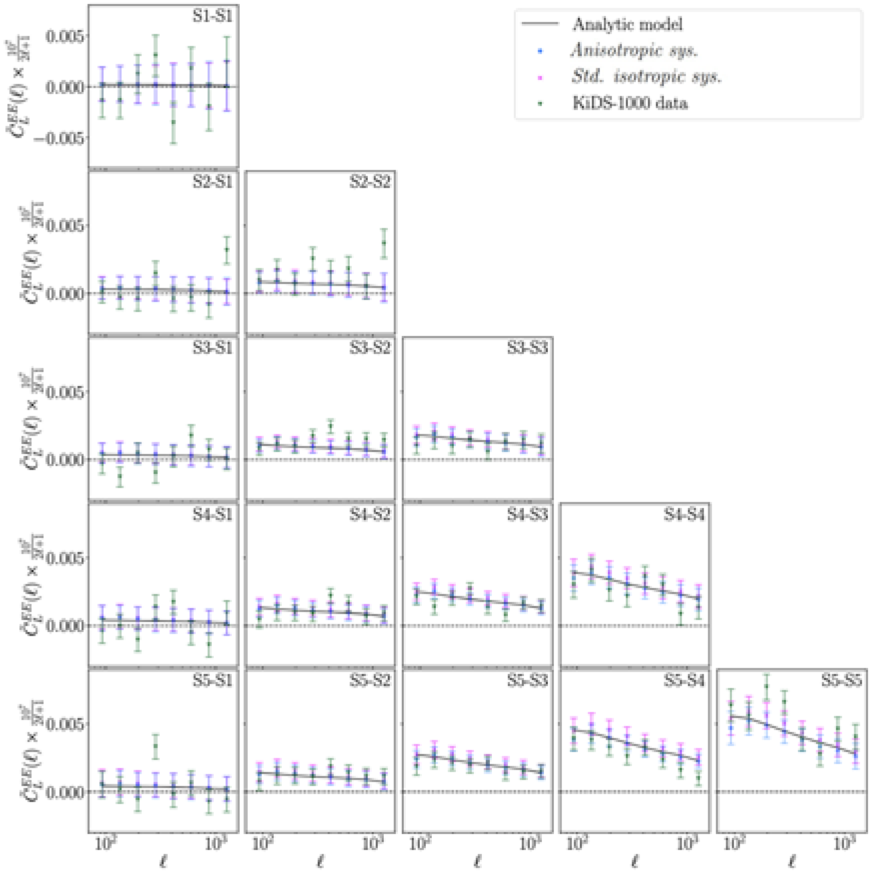
$$\epsilon_{\mathrm{obs}}(p, m; \Theta) = \left(1 + M^{(p)}\right)\epsilon_{\mathrm{lensed}}(\Theta) + \alpha^{(p)}\epsilon_{\mathrm{PSF}}(m) + \underbrace{\cancel{\beta^{(p)}\delta\epsilon_{\mathrm{PSF}}}}_{0} + c^{(p)}$$

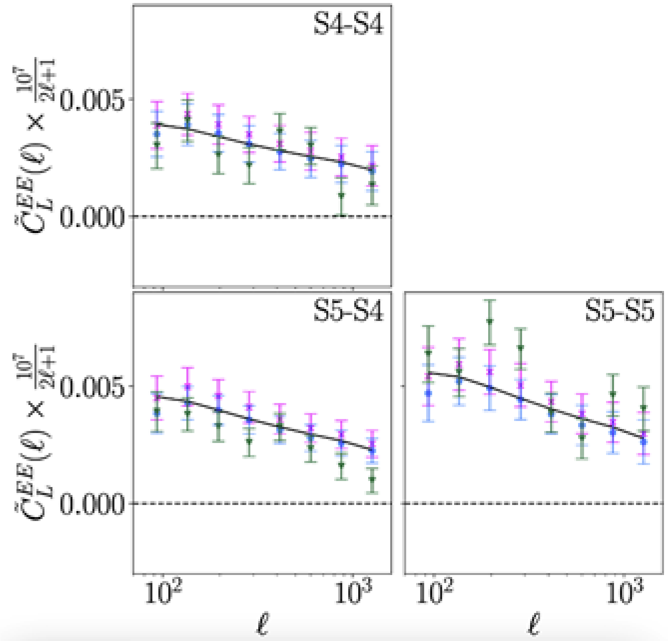
Tomographic bin

PSF shear bias

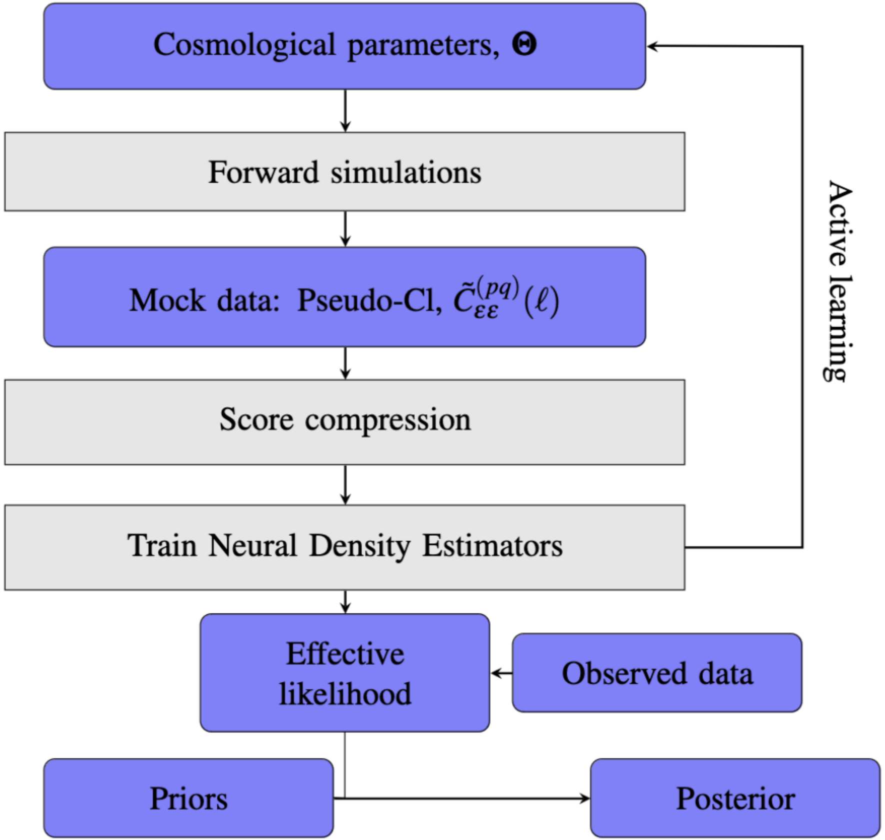


Summary: Angular Power Spectra/Pseudo-Cls

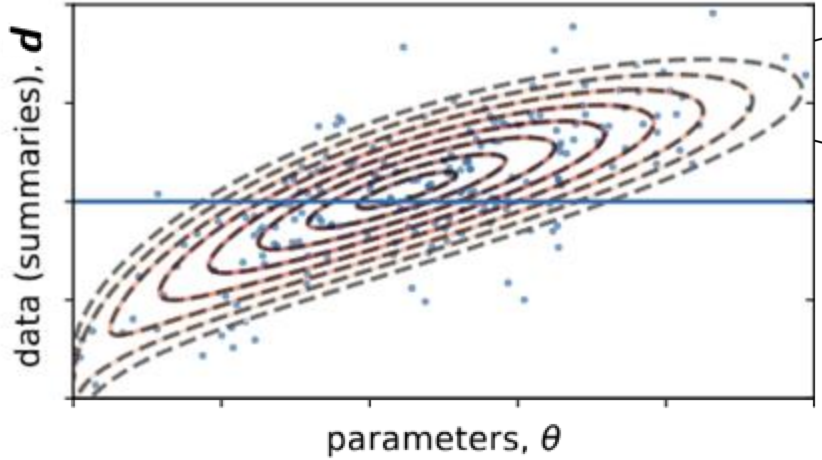




SBI: Sequential NDE

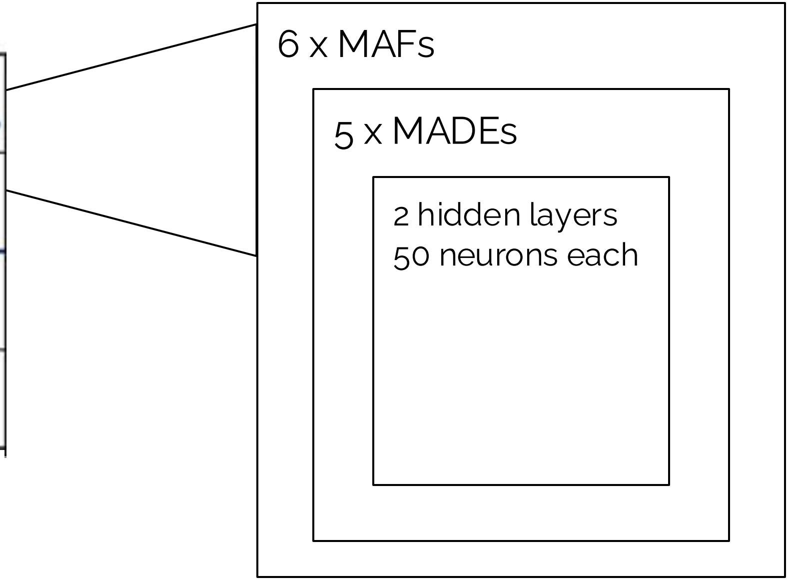


SBI: Neural Likelihood Estimation



Varying **32 parameters**
18,000 simulations

Ensemble of 5 NDEs

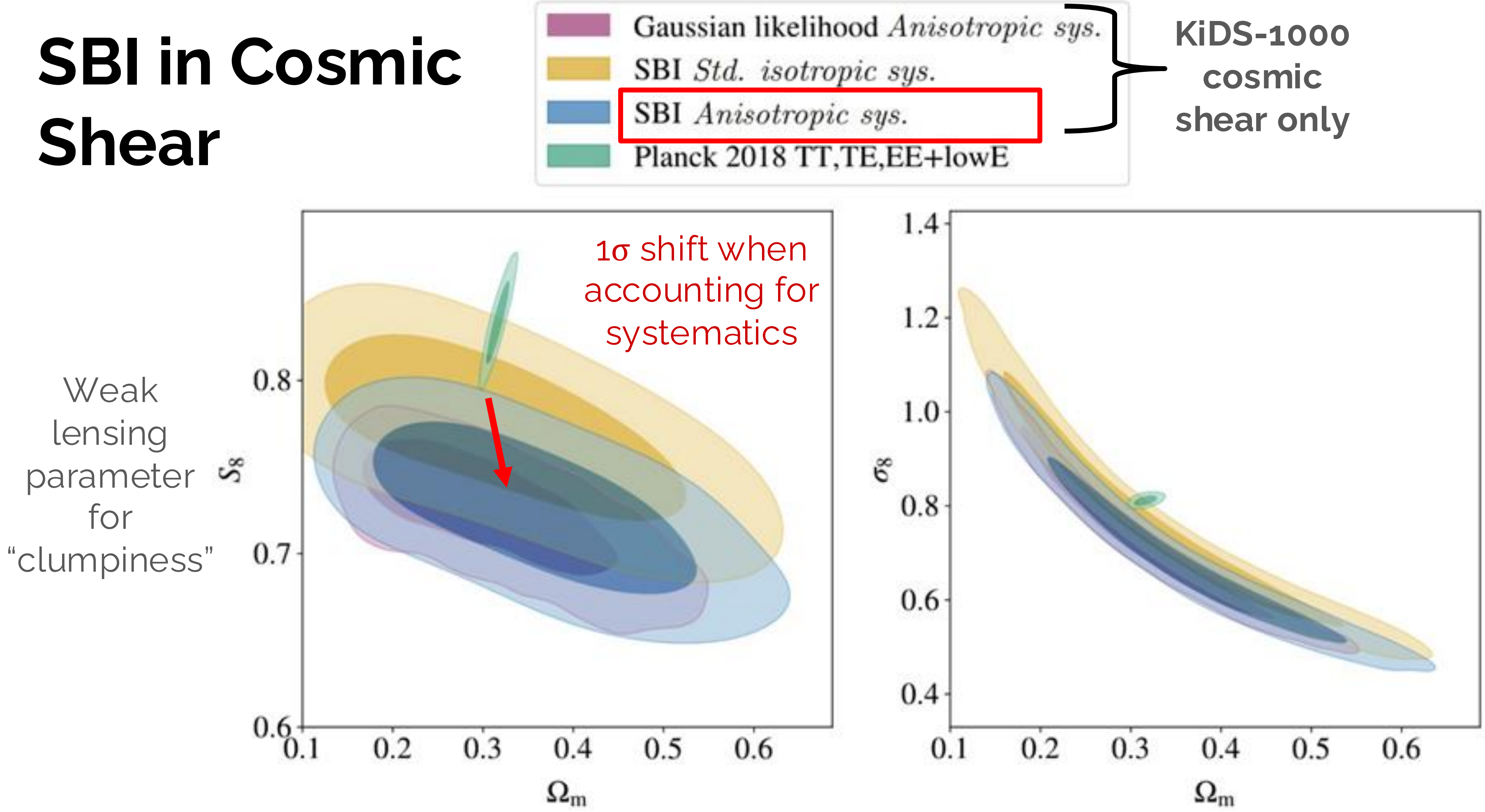


→ 6 x 5 x |**d**| multivariate Gaussians,
P(**d**|$\boldsymbol{\theta}$, **w**)

5 cosmological + 7 nuisance + 25 pre-marginalised parameters

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	$\boldsymbol{\delta}_z$	Gaussian	$\mathcal{N}(\mathbf{0}, \boldsymbol{C}_z)$	$\mathbf{0}$
Multiplicative shear bias	$M^{(p)}$	Gaussian	$\mathcal{N}(\overline{M}^{(p)}, \sigma_M^{(p)})$	$\overline{M}^{(p)}$
Additive shear bias	$c_{1,2}^{(p)}$	Gaussian	$\mathcal{N}(\overline{c}_{1,2}^{(p)}, \sigma_{c_{1,2}}^{(p)})$	$\overline{c}_{1,2}^{(p)}$
PSF variation shear bias	$\alpha_{1,2}^{(p)}$	Gaussian	$\mathcal{N}(\overline{\alpha}_{1,2}^{(p)}, \sigma_{\alpha_{1,2}}^{(p)})$	$\overline{\alpha}_{1,2}^{(p)}$

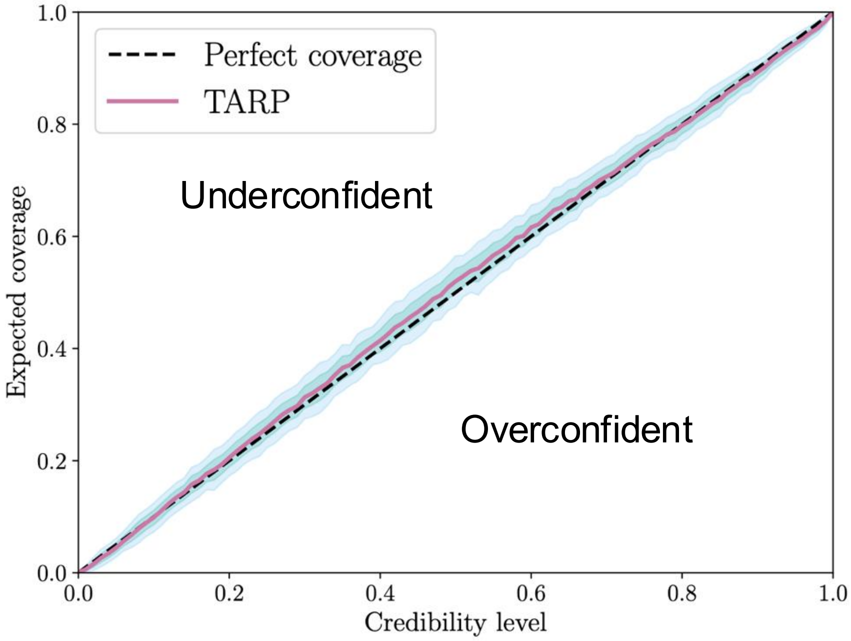
SBI in Cosmic Shear



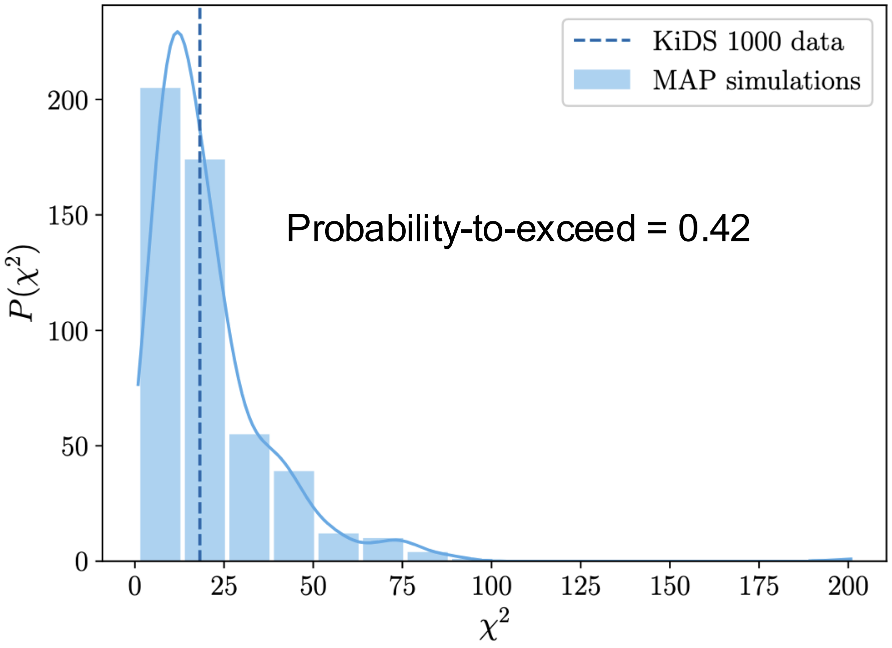
von Wietersheim-Kramsta, Lin et al. (2024), A&A 694, A223.

SBI: Accuracy Testing

Agreement between learnt posterior & forward model

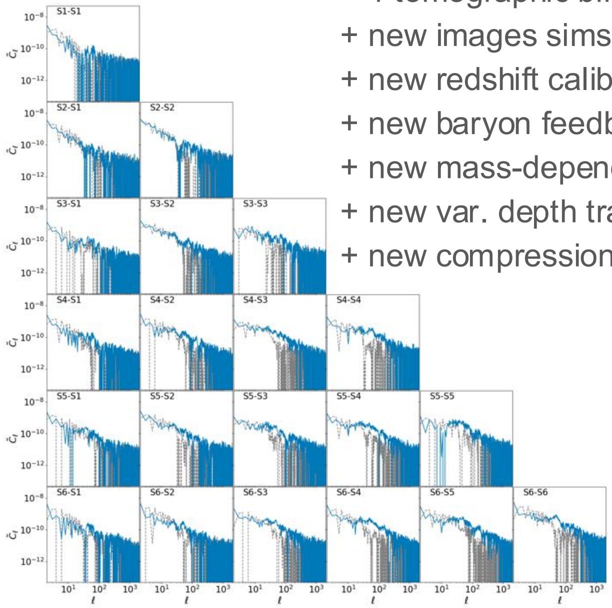


How likely is the real data given the model?



Extensions to KiDS-SBI

KiDS-SBI with KiDS-Legacy

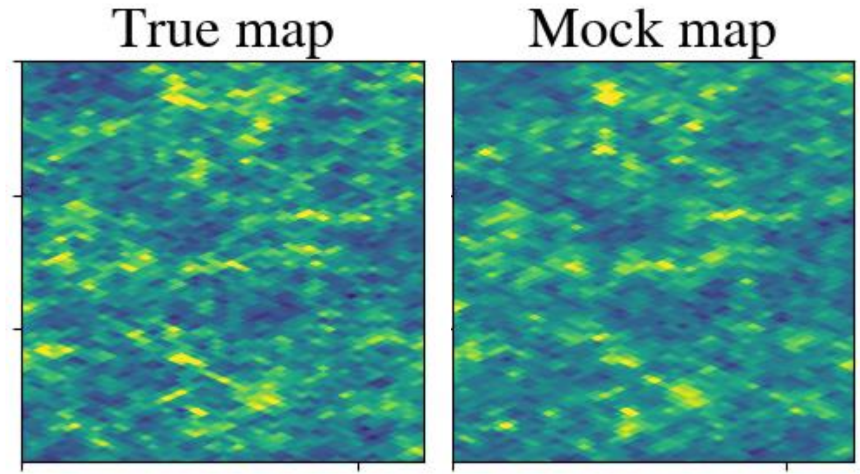


+ extra 350 deg^2
+ 1 extra i-band pass
+ 1 tomographic bin
+ new images sims for calib.
+ new redshift calibration
+ new baryon feedback model
+ new mass-dependent IAs model
+ new var. depth tracer
+ new compression

Lin, von Wietersheim-Kramsta, et al. (in prep.)

3x2pt analysis (shear x clustering)

Forward simulating galaxy bias



von Wietersheim-Kramsta, et al. (in prep.)

Takeaways from Cosmic Shear

SBI allows for uncertainty propagation of **arbitrary complexity**

Including a **realistic systematics and selections** is important (it can shift S_8 1σ lower!)

Modelling the noise correctly is just as important as the signal (if not more!)

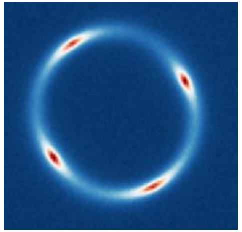
von Wietersheim-Kramsta, Lin et al. (2024), A&A 694, A223.

Galaxy-Scale Strong Lenses for Subhalo Detection

In collaboration with R. Massey, Q. He, J. Nightingale, A. Robertson, A. Amvrosiadis, L. Fung, S. Lange, C. Frenk, S. Cole, R. Li, et al.

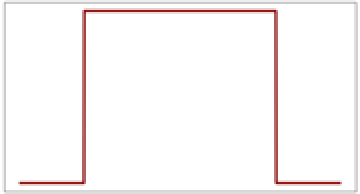
Recipe for Inference

$\boldsymbol{d}$



Data

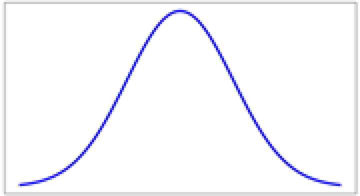
$P(\theta)$



$\boldsymbol{\theta}$

Prior

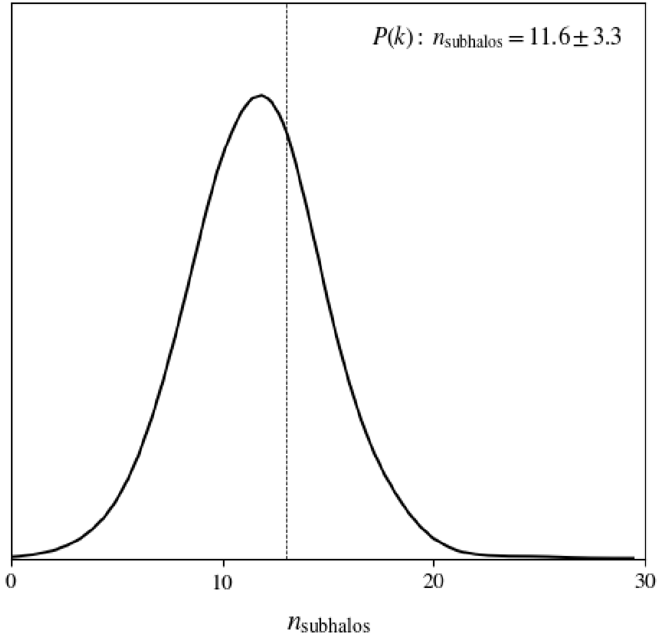
$P(\boldsymbol{d}|\boldsymbol{\theta})$



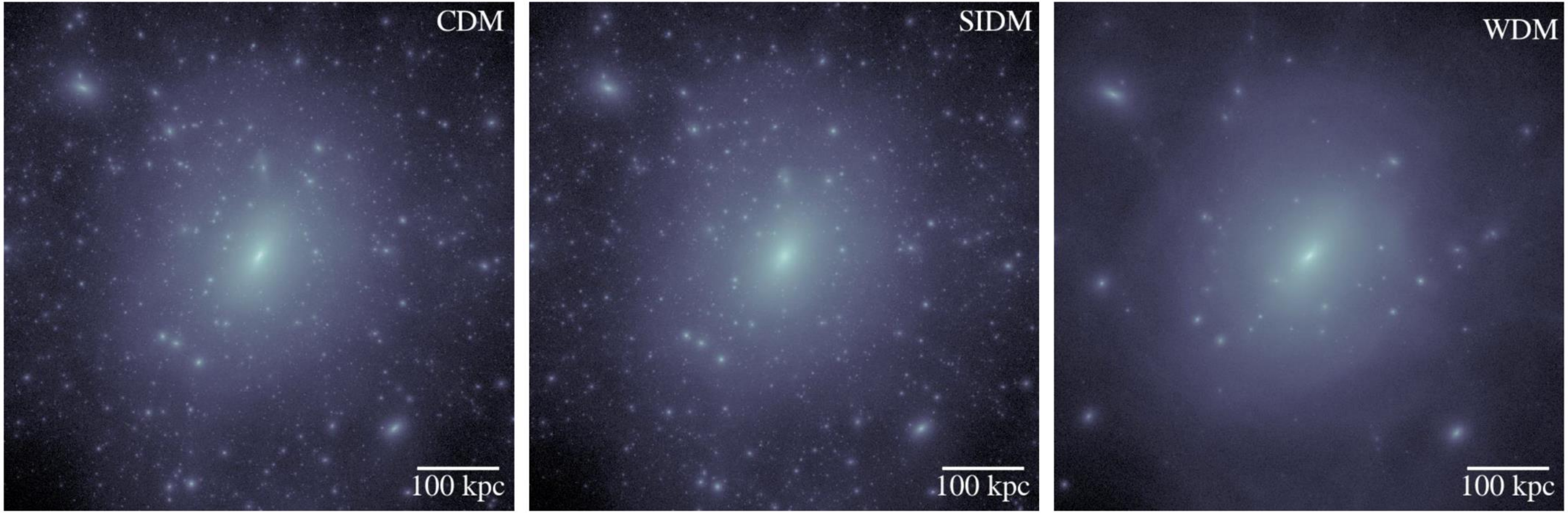
$\boldsymbol{d}$

Likelihood

$P(\boldsymbol{\theta}|\boldsymbol{d})$ **: Posterior**



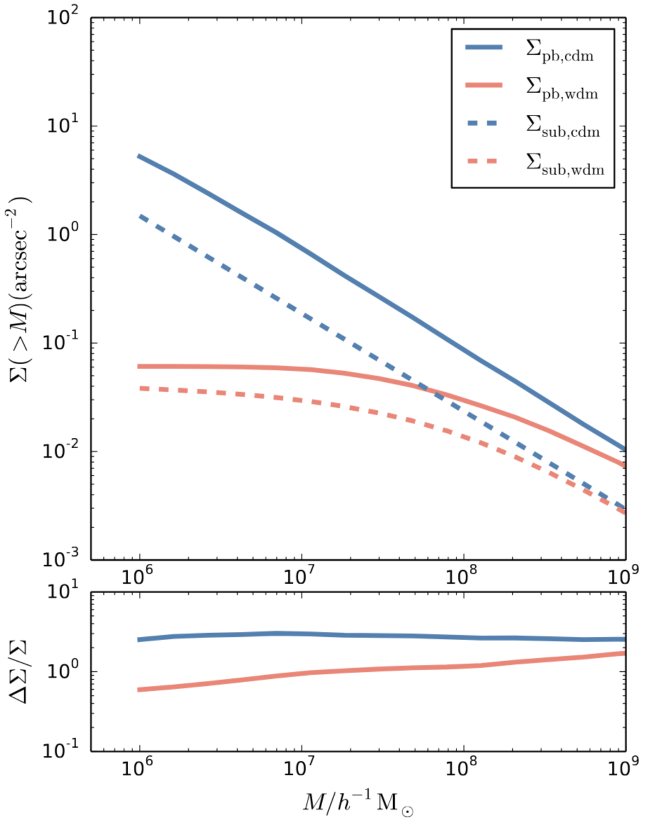
Substructure & the Nature of Dark Matter



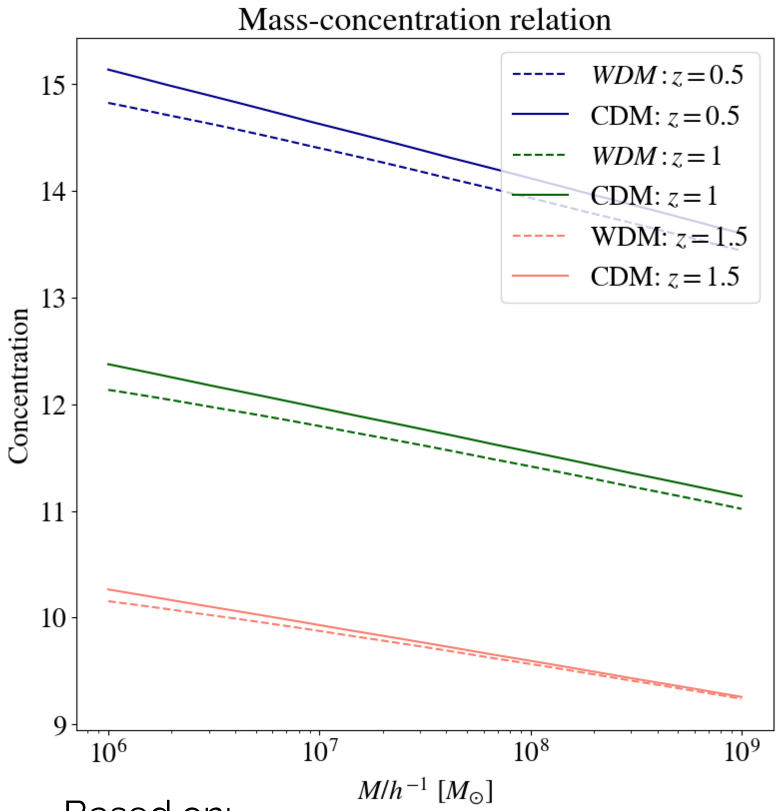
Bullock & Boylan-Kolchin (2017), ARA&A, 55:343-387.

Forward Modelling: Substructure

Number densities of **perturbing interlopers and subhaloes**



Li et al. (2016), MNRAS, 468(2), 1426-1432.



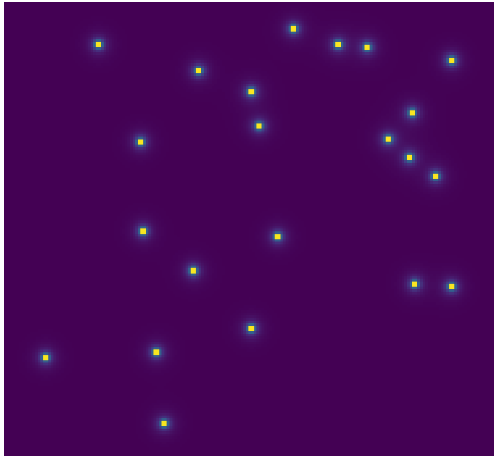
Based on:
Ludlow et al. (2016), MNRAS, 460(2), 1214-1232.

Forward Modelling: Galaxy-Scale Lens

Source:
- Elliptical Core-Sersic
- $z = 1$

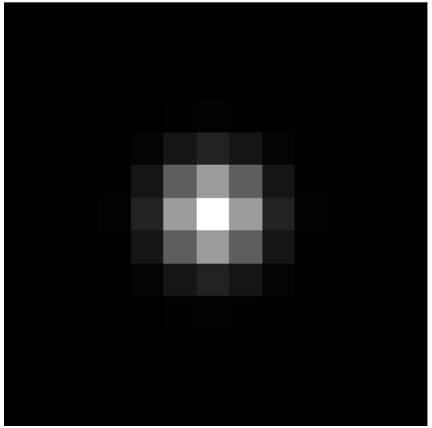
Lens:
- Power law mass
- $z = 0.5$
- No external shear

Perturbers:
- Warm Dark Matter
- Truncated NFW mass
- $M_{hf} = 10^7$
- $\mathbf{n_{subhalos}} \in [0, 30]$



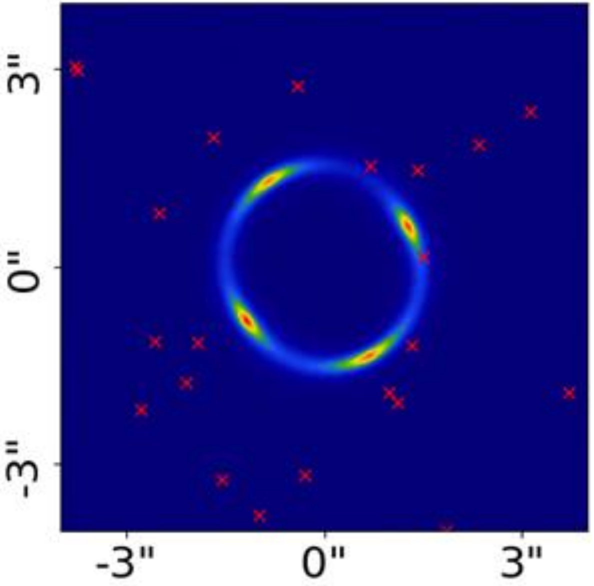
He et al. (2022), MNRAS, 511(2), 3046-3062.

Observational Effects
(HST-like)
- Exposure = 8000s
- Sky background = 0.1
- Pixel scale = 0.05”
- $\boldsymbol{\sigma}_{PSF}$ = 0.05”
- + Poisson noise



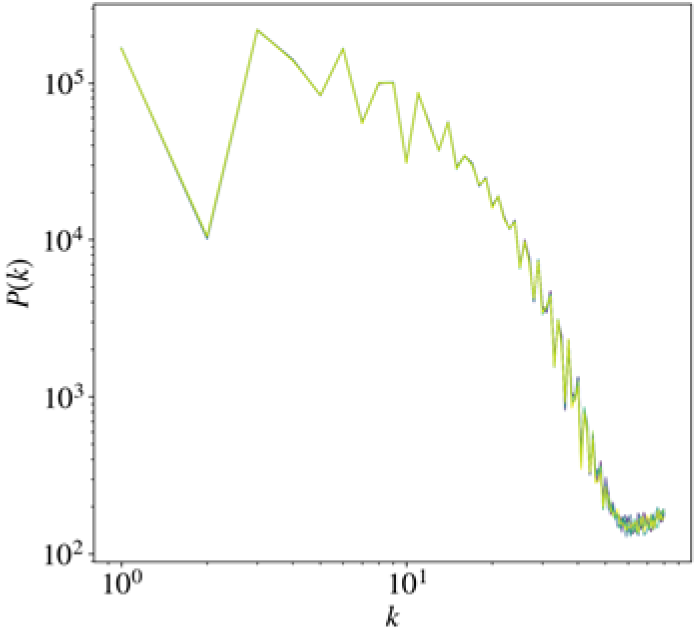
Forward Modelling: Compression

AutoLens: Mock Observation



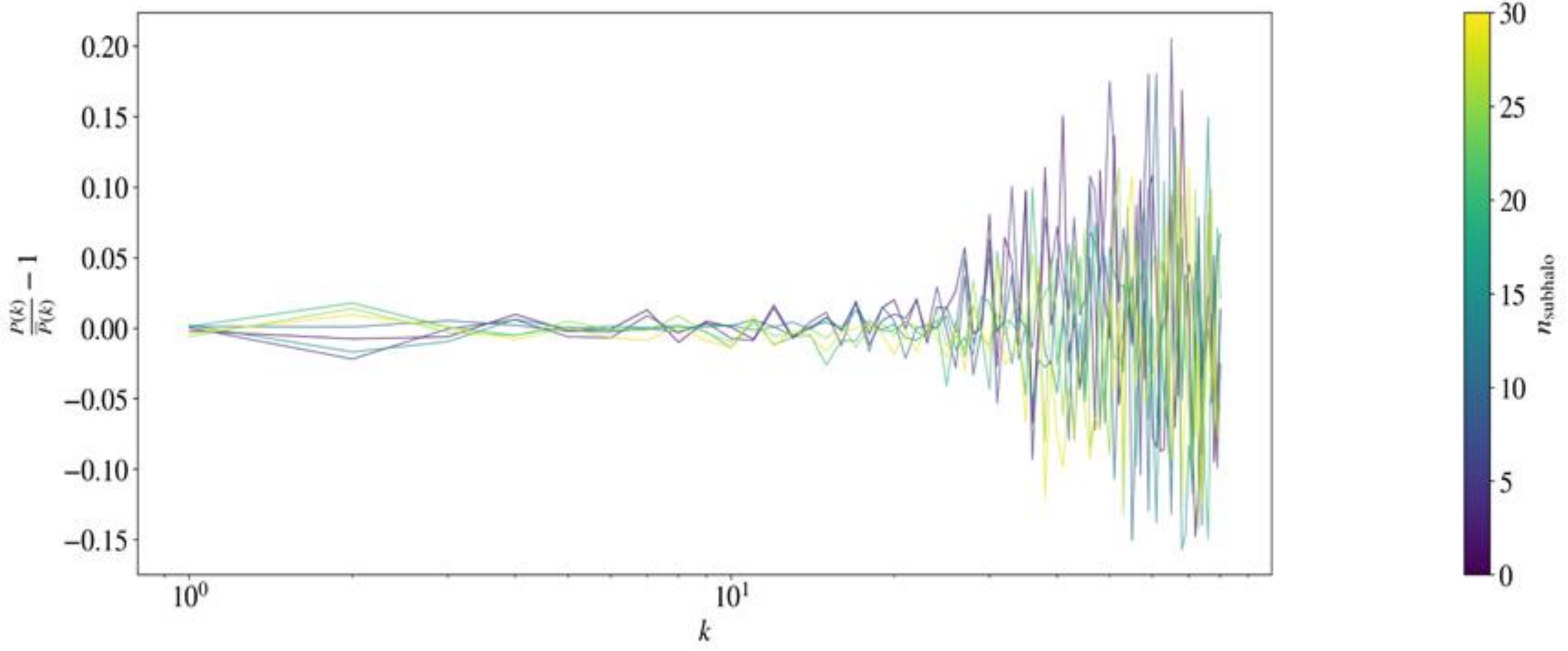
Nightingale et al., (2021), JOSS, 6(58), 2825

Compression/summary statistic: P(k)



RINSE & REPEAT 1000 TIMES!

Forward Modelling: Compression



SBI: Neural Posterior Estimation

Ensemble of 2 NDEs

2 x MAFs

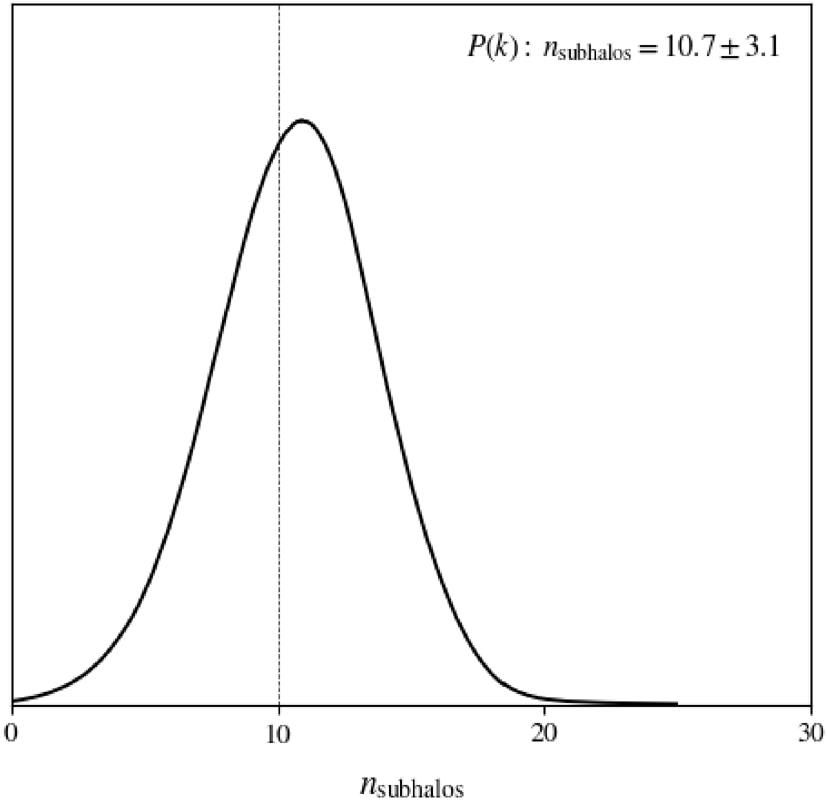
5 x MADEs

2 hidden layers

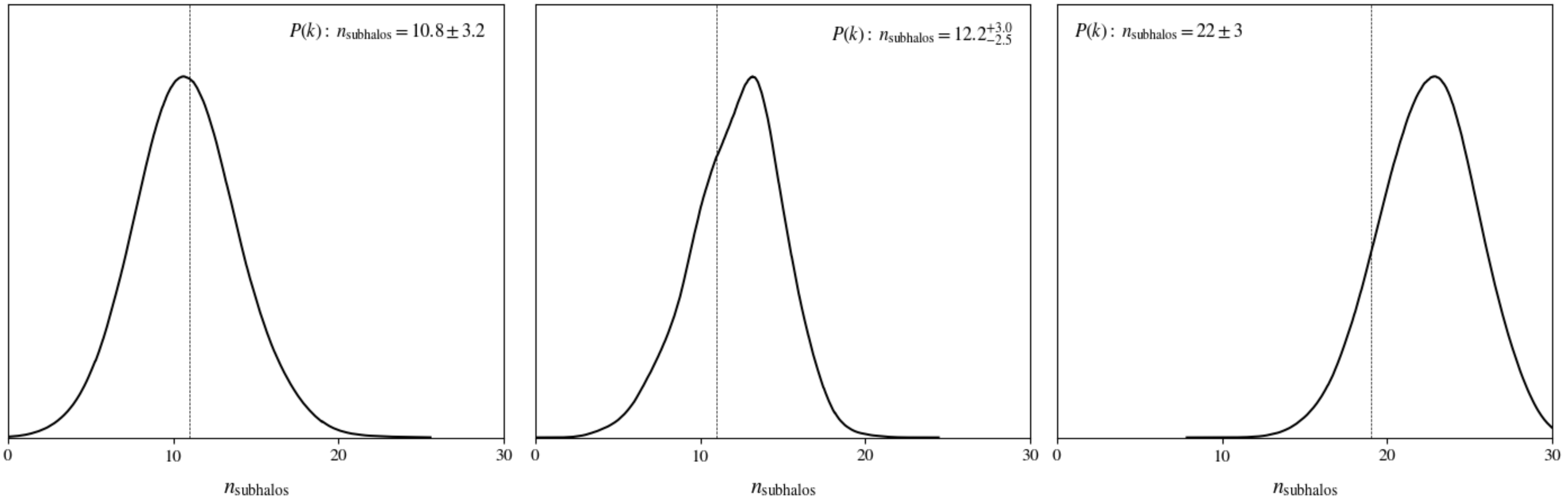
50 neurons each

Varying **1 parameter**

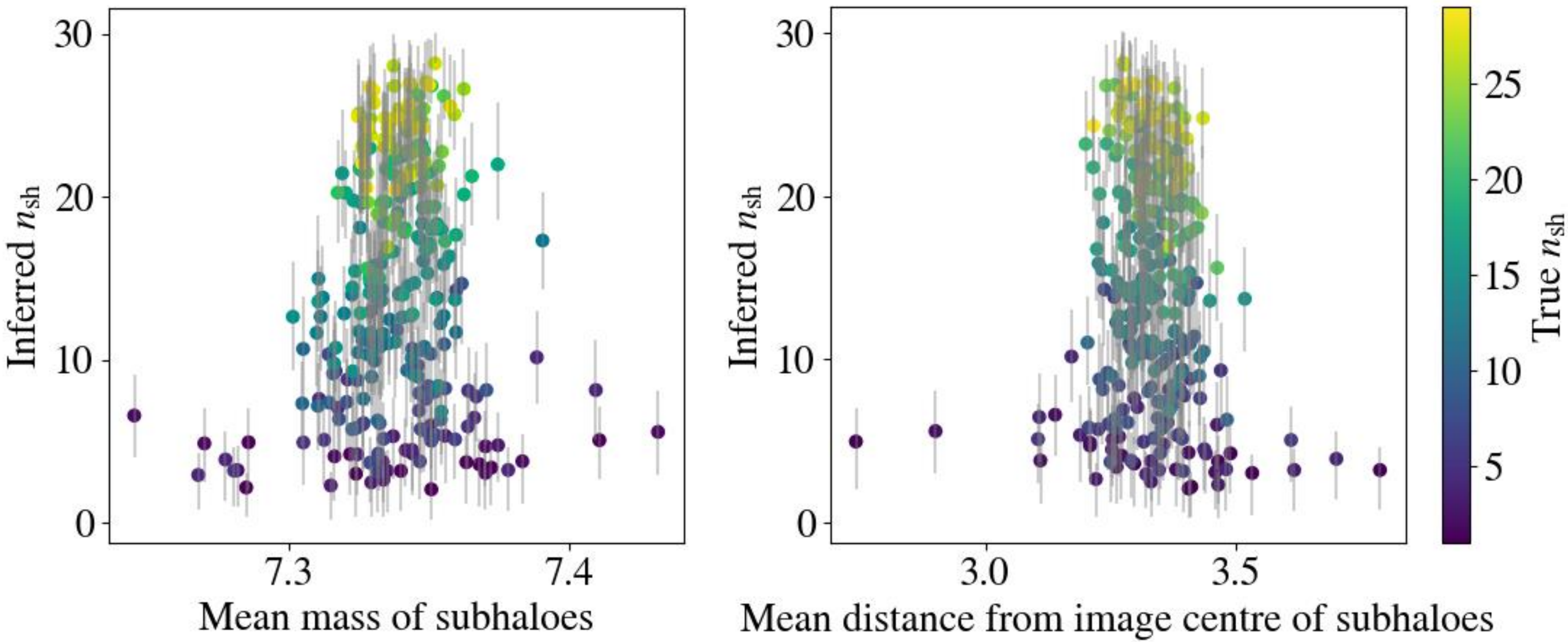
1,000 simulations



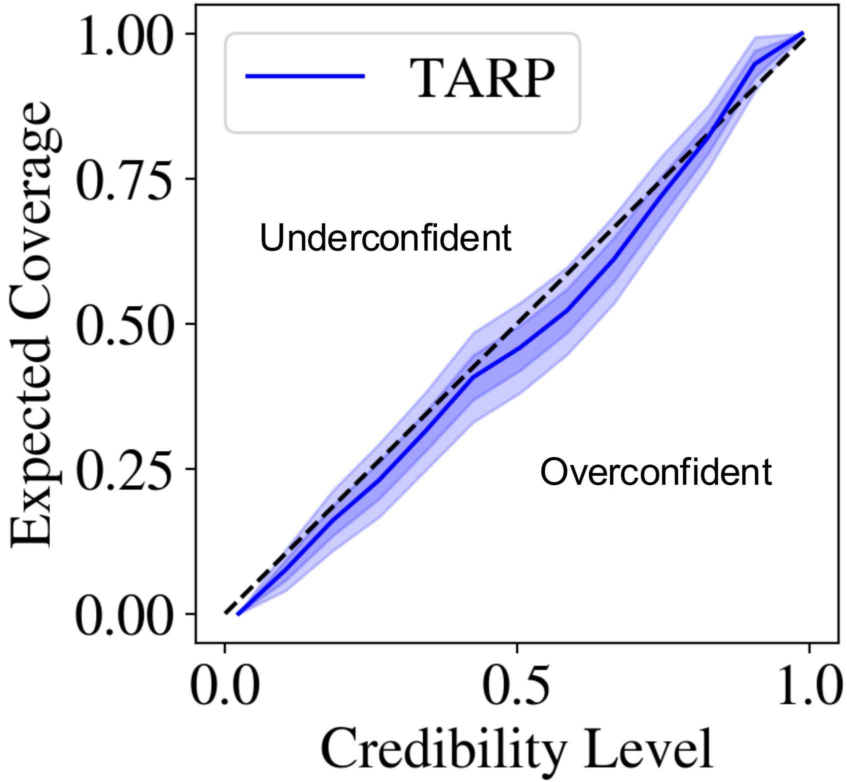
SBI: Neural Posterior Estimation



SBI: Robustness



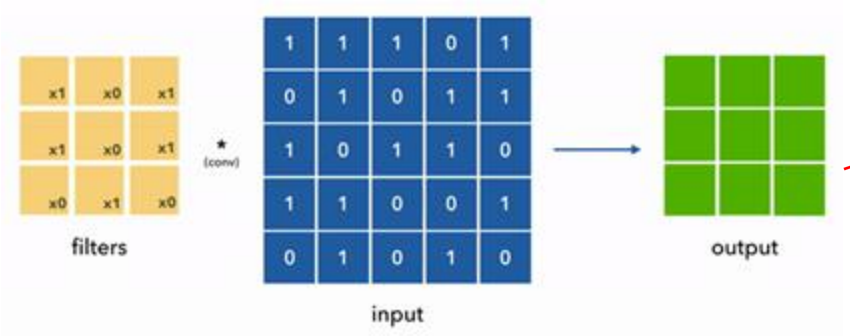
SBI: Coverage



SBI: Other Compressions

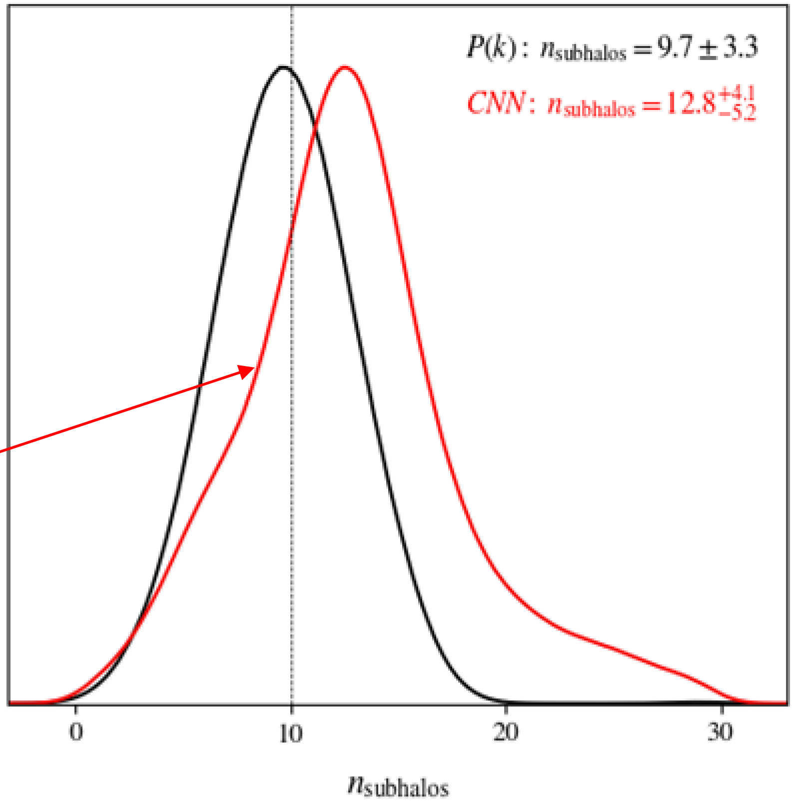
Other compression schemes/summary statistics:

Convolutional Neural Networks



Learn weights based on all simulated images

Convolutional layer

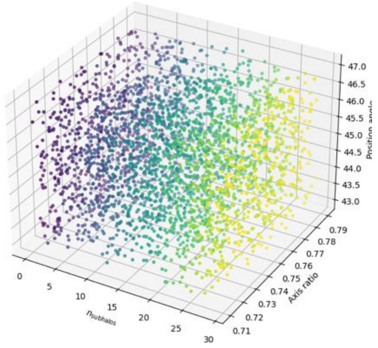


Conclusions & Outlooks

SBI can incorporate complexities into lens model inference

$t \rightarrow \theta$

We accurately and robustly recover subhalo counts → M_{hf}

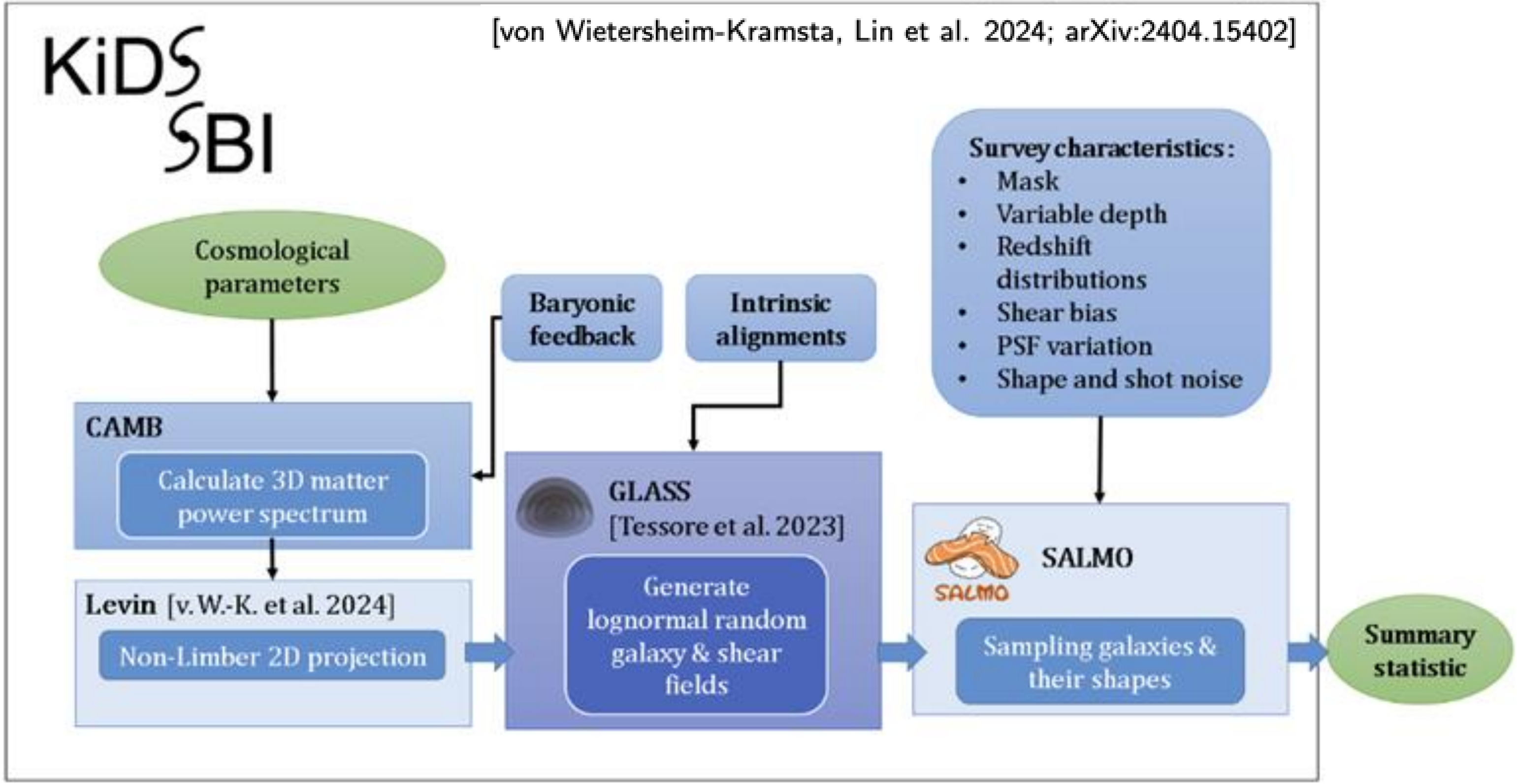


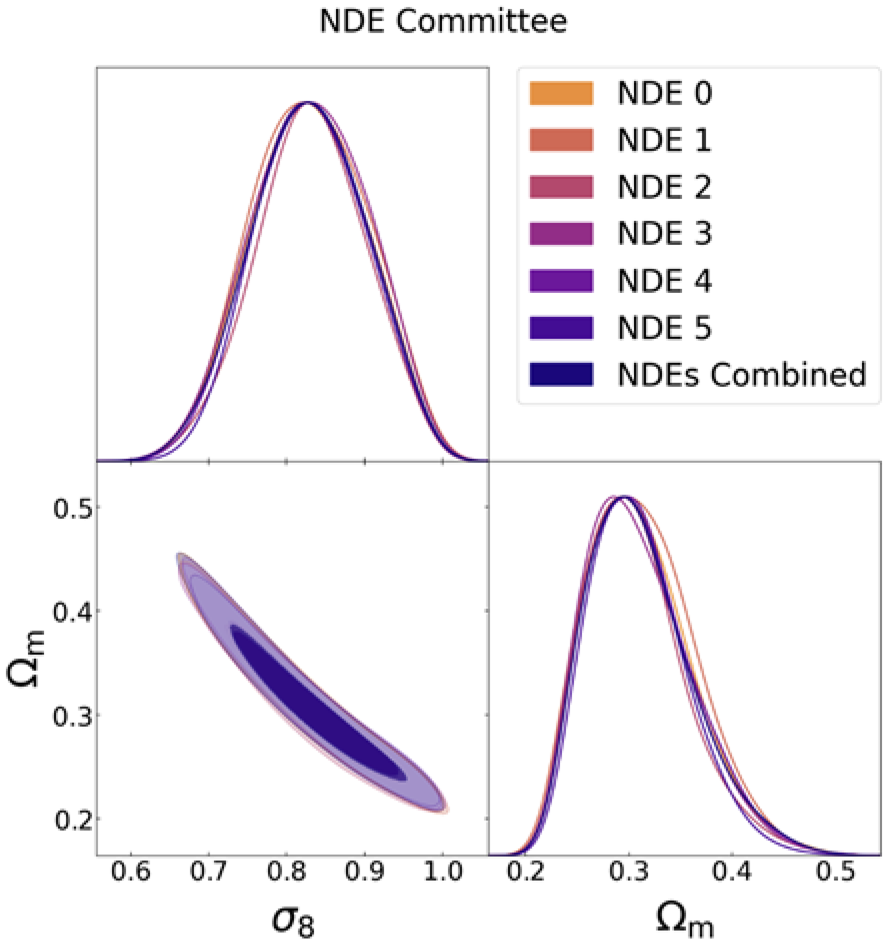
Plans:

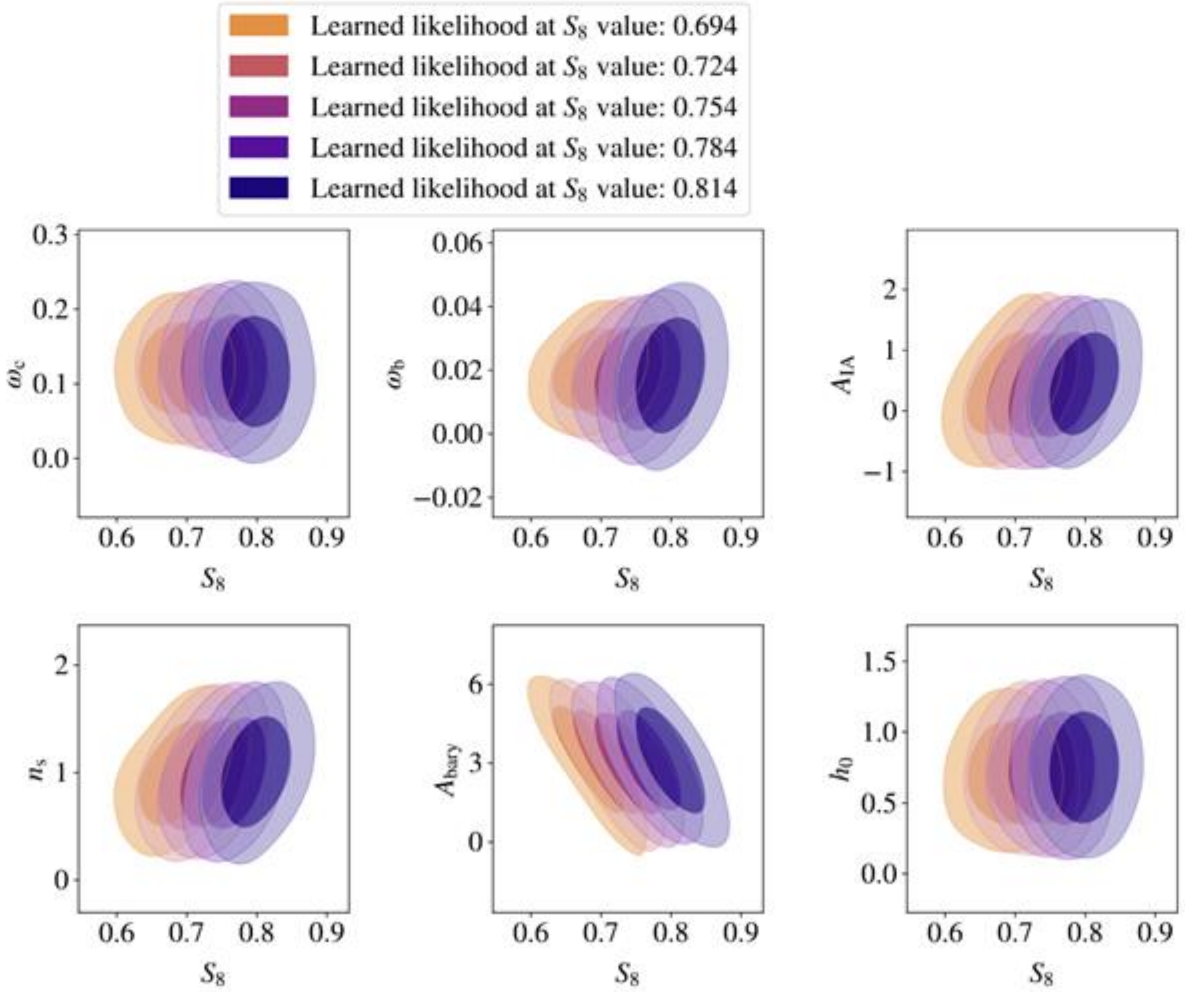
- Scale up to higher-dimensional parameter space
- Add realism and additional dark matter models (SIDM)

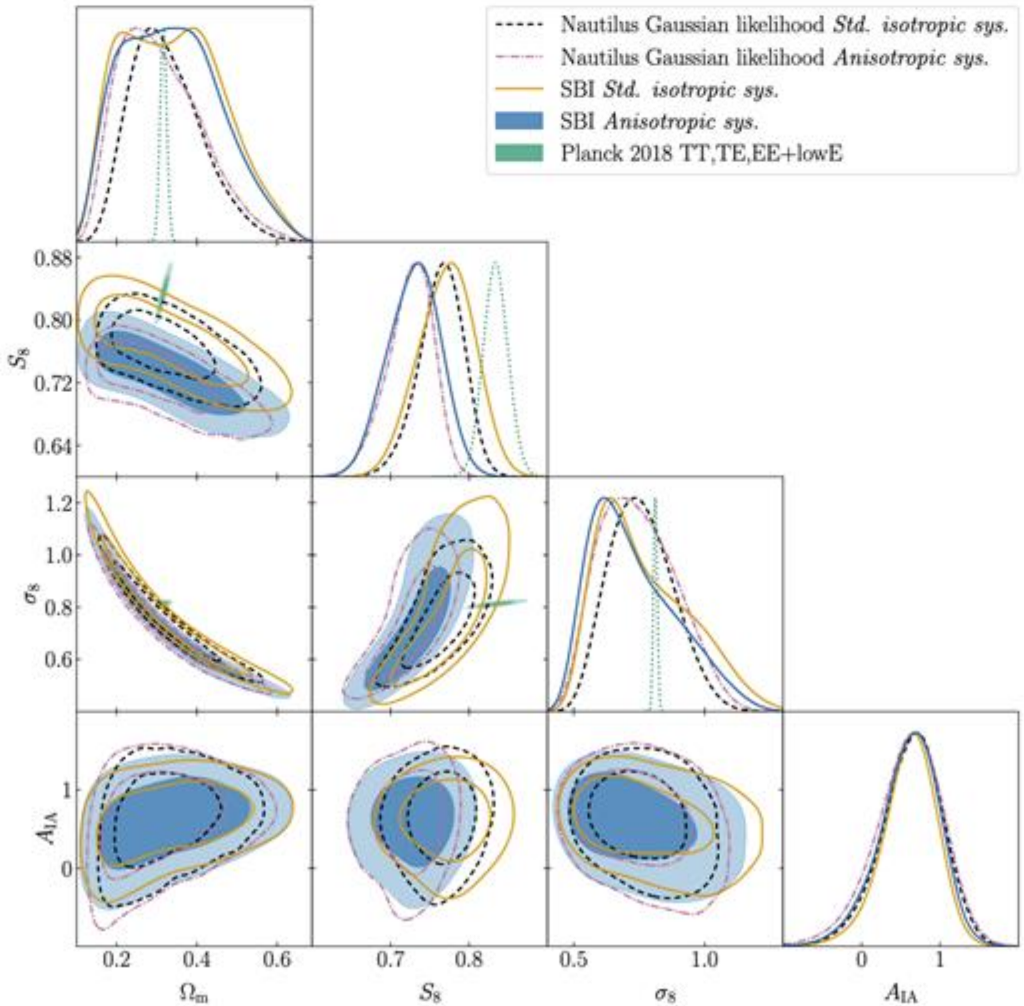
Appendix

Forward Simulations




NDE Committee
NDE 0
NDE 1
NDE 2
NDE 3
NDE 4
NDE 5
NDEs Combined
0.5
0.4
0.3
0.2
Ω_m
0.6
0.7
0.8
0.9
1.0
σ_8
0.2
0.3
0.4
0.5
Ω_m


Learned likelihood at S_8 value: 0.694
Learned likelihood at S_8 value: 0.724
Learned likelihood at S_8 value: 0.754
Learned likelihood at S_8 value: 0.784
Learned likelihood at S_8 value: 0.814
ω_c
ω_b
A_{IA}
n_s
A_{bary}
h_0
S_8



Nautilus Gaussian likelihood *Std. isotropic sys.*
Nautilus Gaussian likelihood *Anisotropic sys.*
SBI *Std. isotropic sys.*
SBI *Anisotropic sys.*
Planck 2018 TT,TE,EE+lowE
S_8
σ_8
A_{IA}
Ω_{m}