Field-level inference for weak lensing

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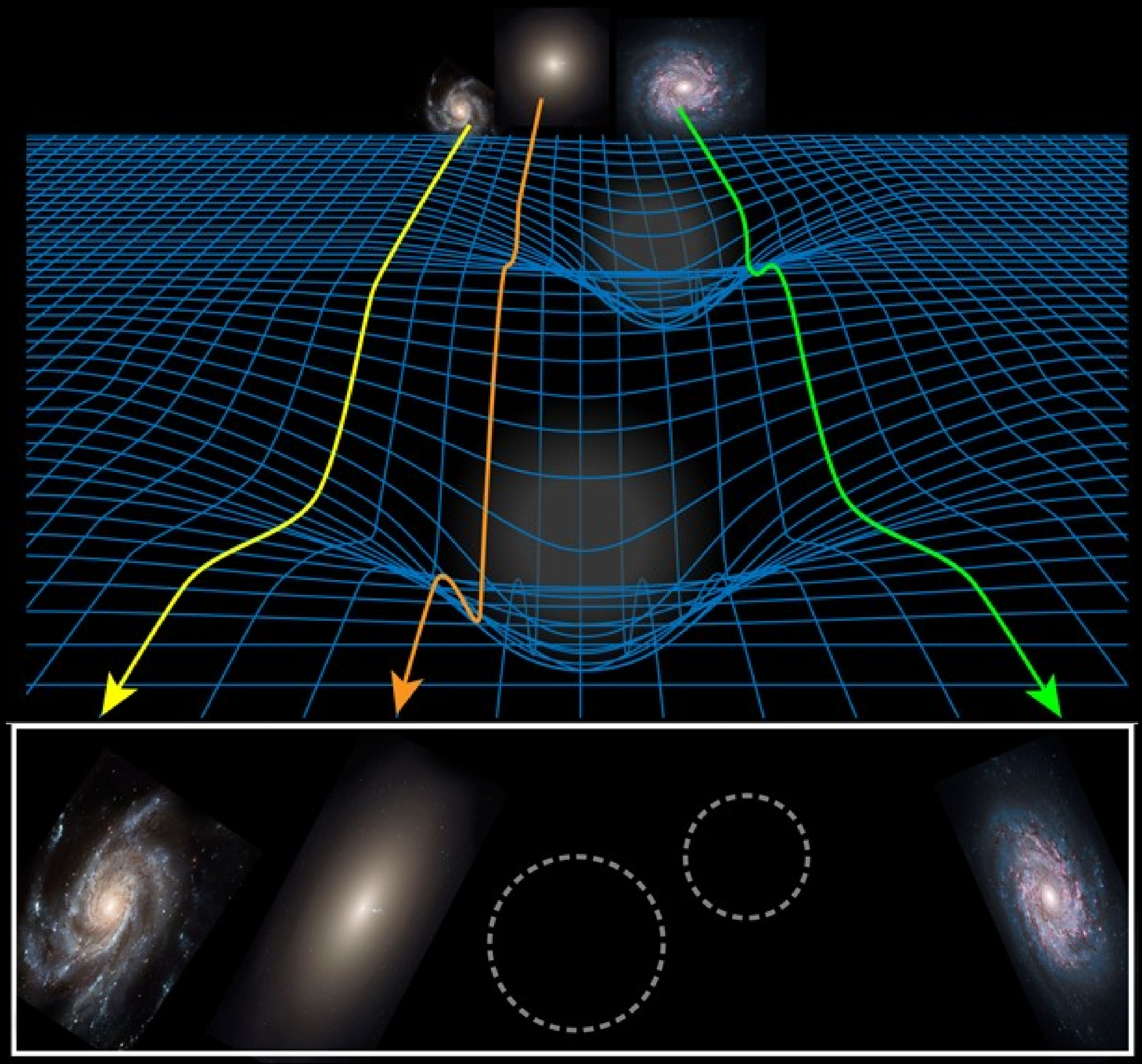
with Alan Heavens, Daniel Mortlock, Guilhem Lavaux, Lucas Makinen

Deep CosmoStat Days – 16/1/2025

Weak gravitational lensing



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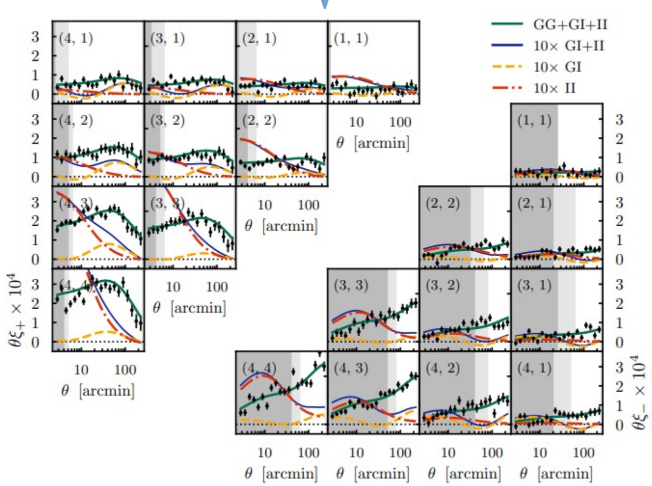
The standard approach to shear analysis

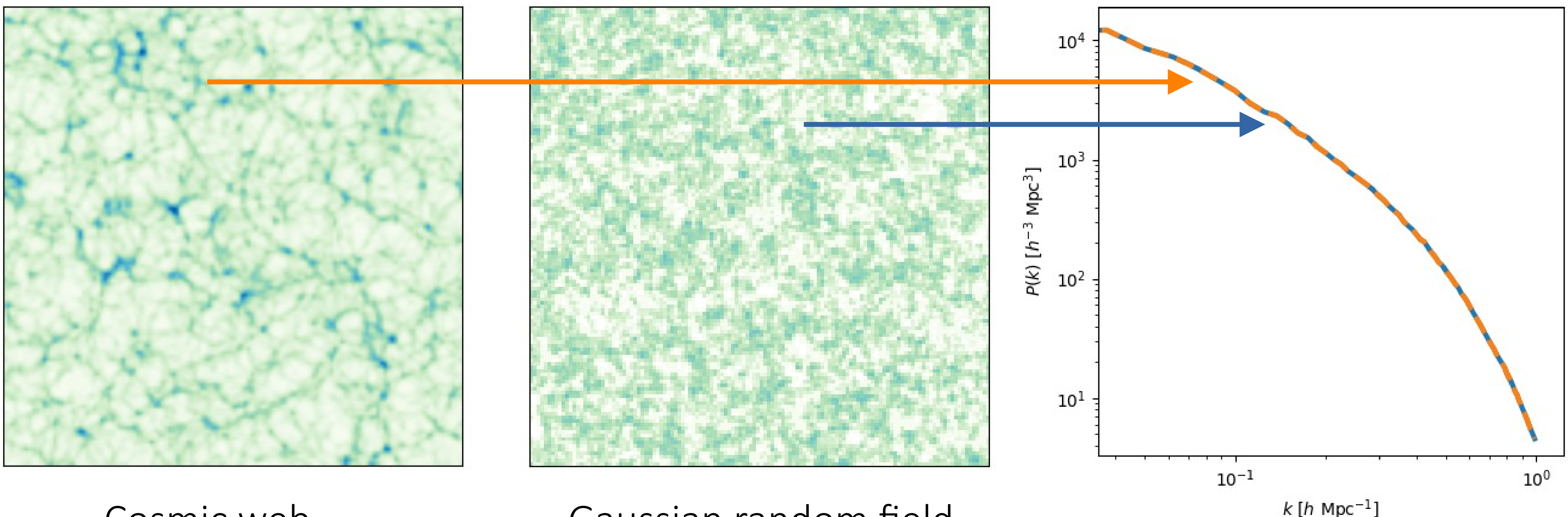
Summarise



Does this capture all the information?

Is the standard approach enough?

The standard approach misses information!



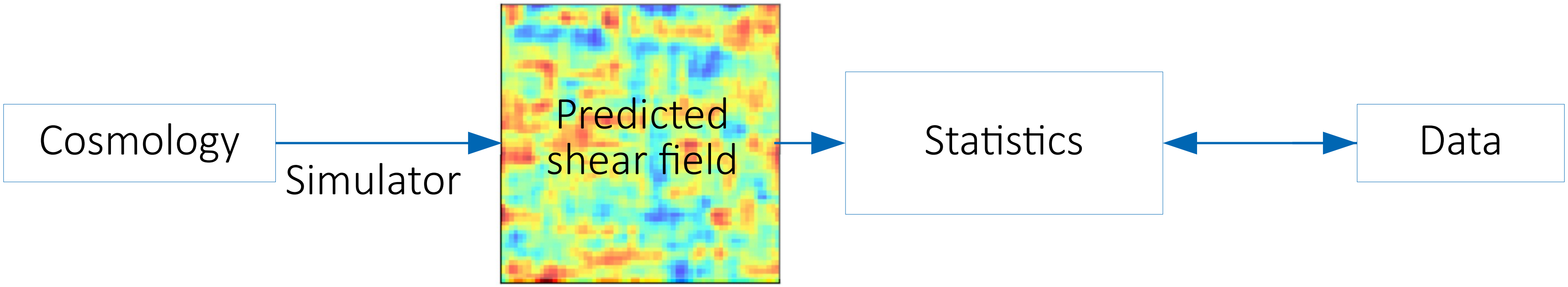
Cosmic web

Gaussian random field

Higher-order statistics: data compression designed to capture non-Gaussian information.

Field-based inference: analysis of pixelised shear maps without compression.

The forward modelling approach



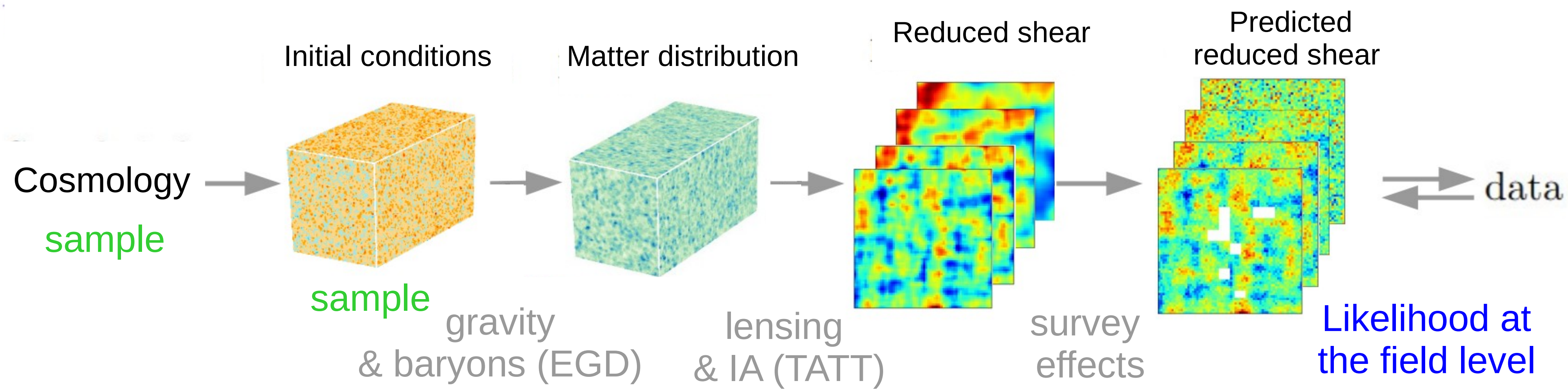
Two approaches:

- **explicit inference** (Bayesian hierarchical model)
  Simulator treated as a probabilitic model and run by the inference framework.
  Constrained simulations.

- **implicit inference** (simulation-based inference, likelihood-free inference)
  Simulator to draw random samples, often before the inference framework.
  Random simulations.

BORG-WL framework: **explicit inference** with a gravity model

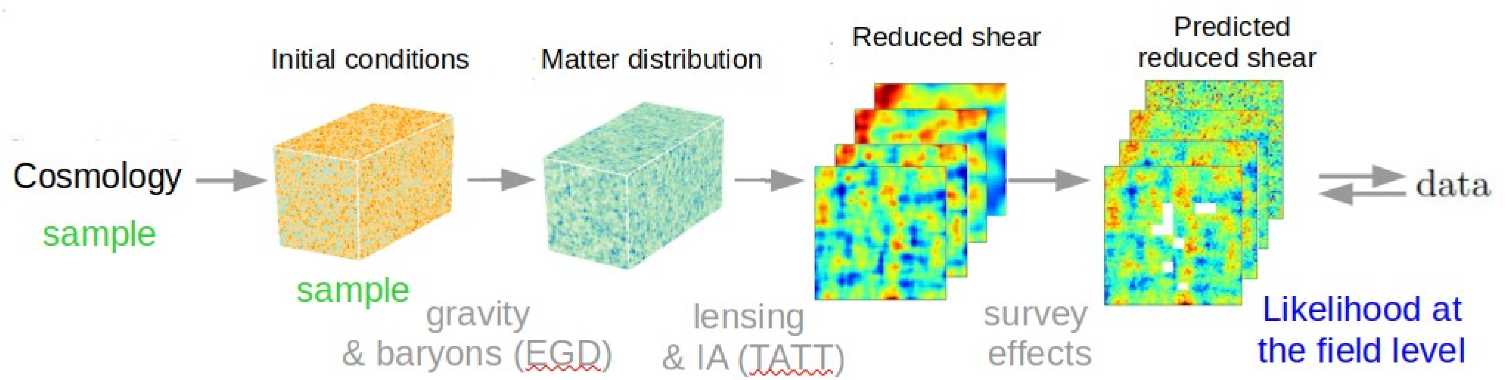
The forward model of BORG-WL



Sensitivity to cosmology:

- Initial matter power spectrum
- Growth of structures
- Geometry

The likelihood



Likelihood: Assuming Gaussian noise in pixelised shear

$$\log \mathcal{L} = -\frac{1}{2} \sum_b \sum_{mn} \frac{(\epsilon^b_{1,mn} - \hat{\epsilon}^b_{1,mn})^2 + (\epsilon^b_{2,mn} - \hat{\epsilon}^b_{2,mn})^2}{\sigma_b^2}$$

Doesn't need covariance matrix! $\sigma_b = \sigma_\epsilon / \sqrt{N_b}$

Getting the full posterior distribution

$$P(\theta, \delta^{\mathrm{ic}} | \hat{\epsilon}) \propto P(\hat{\epsilon}|\epsilon) P(\epsilon|\delta^{\mathrm{ic}}) P(\delta^{\mathrm{ic}}|\theta) P(\theta)$$

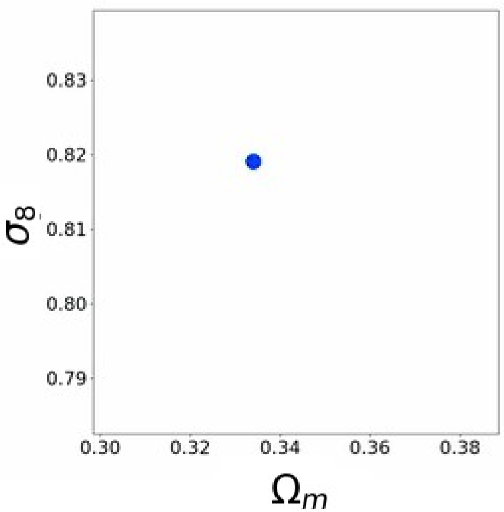
posterior likelihood prior

$$\delta^D \left[\epsilon - \mathcal{F}(\delta^{\mathrm{ic}})\right] \; G(0, S(\theta))$$

forward model prior

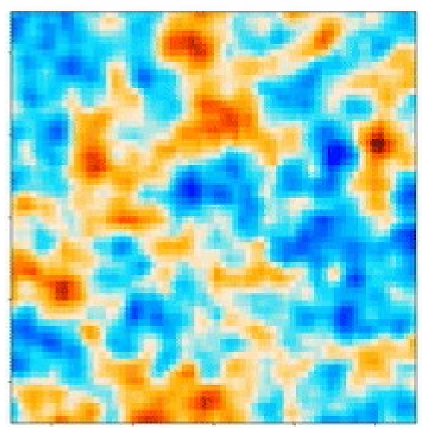
10^7 parameters!

Cosmological parameters



sampled

Primordial fluctuations



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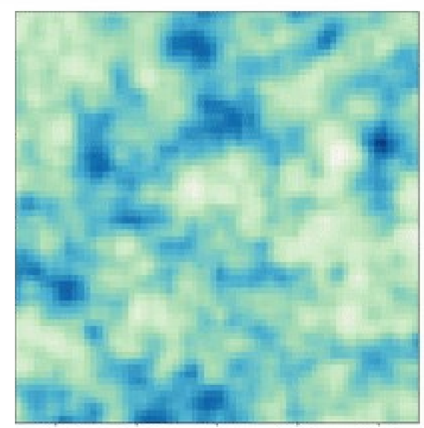
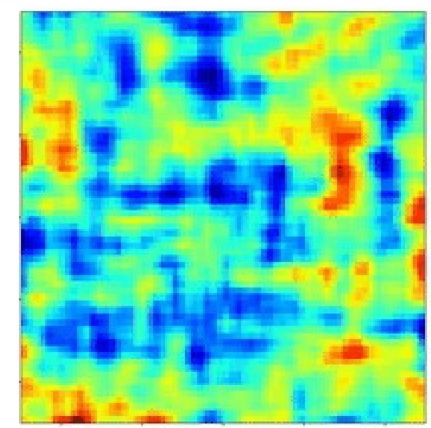
Evolved matter



Predicted lensing



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Sampling in a high-dimensional space

Hamiltonian Monte Carlo
(initial conditions)

Gibbs sampling

Simple MCMC
- cosmological parameters
- IA parameters
- baryon parameters

Addresses curse of dimensionality by:

- exploiting information in gradients

- using conserved quantities

- no analytical derivatives

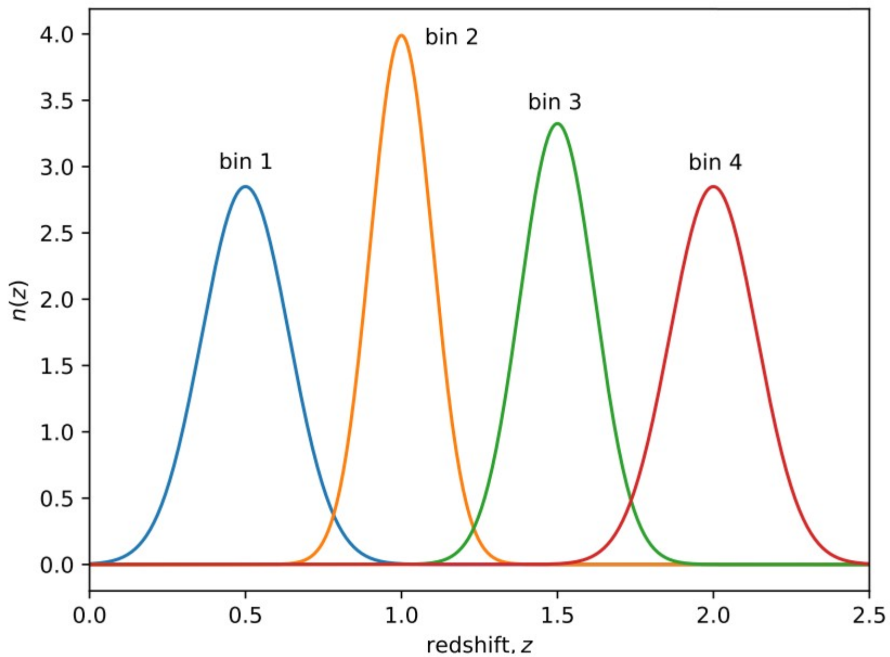
- efficient mass matrix?

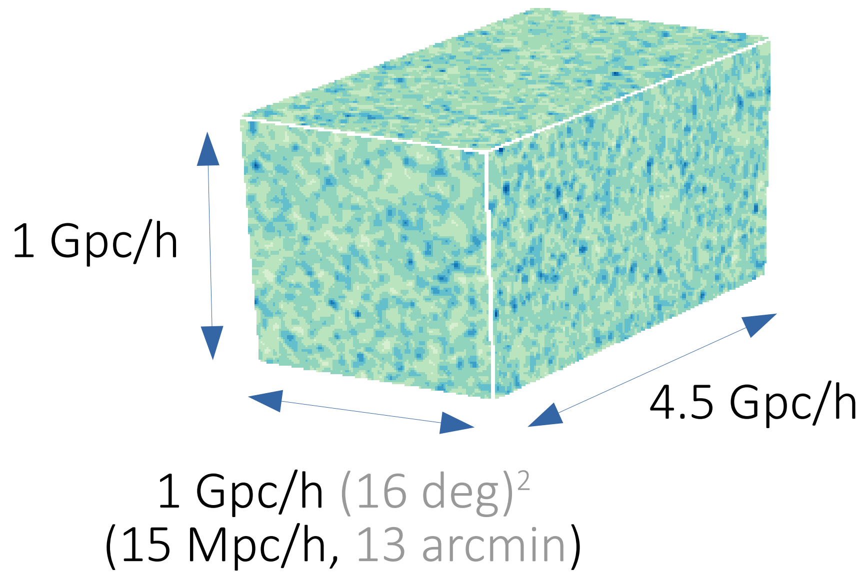
The proof of concept Results with synthetic data

How much do we get from going to the field level?

Simulated data

Tomographic bins





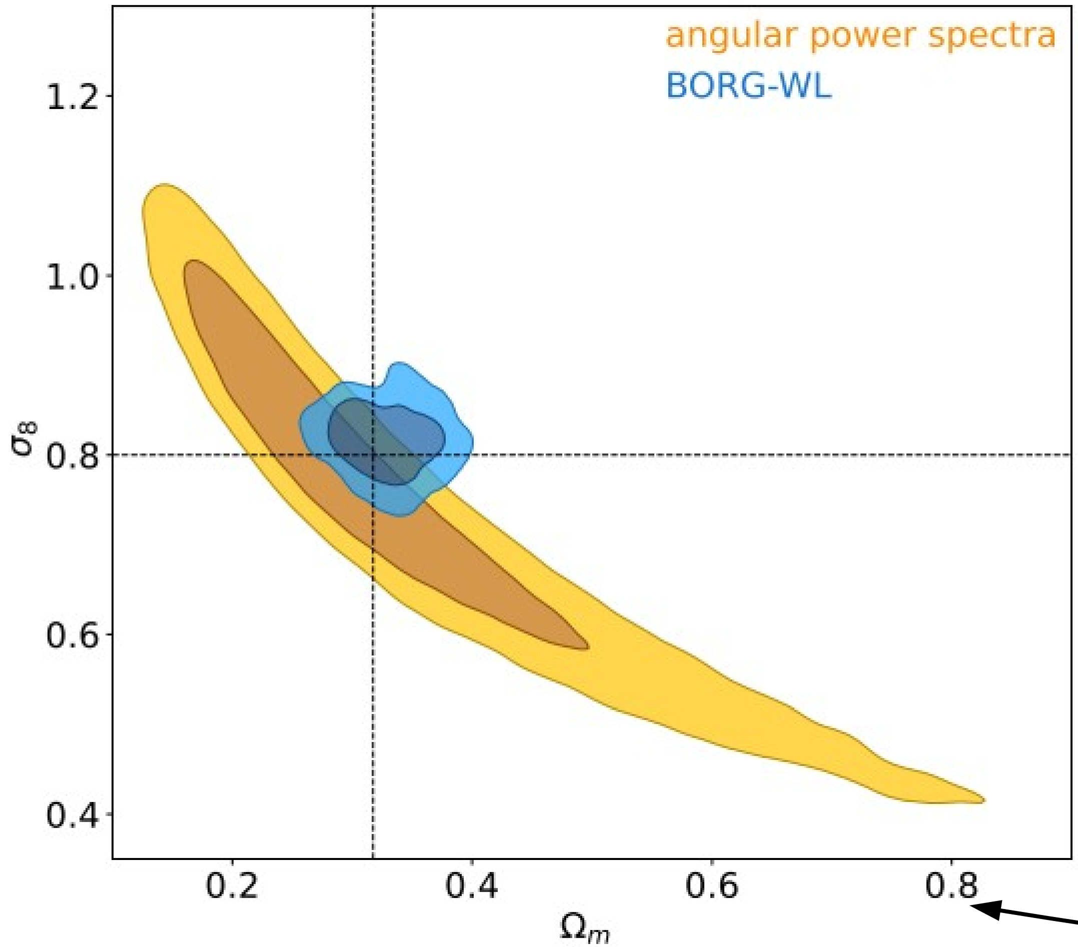
Gravity model: LPT.

Gaussian pixel-noise: 30 sources per square arcmin.

Intrinsic alignment amplitudes: DES values (0.18, 0.8, 0.1)

Comparison of cosmology constraints

marginal error
3 times smaller



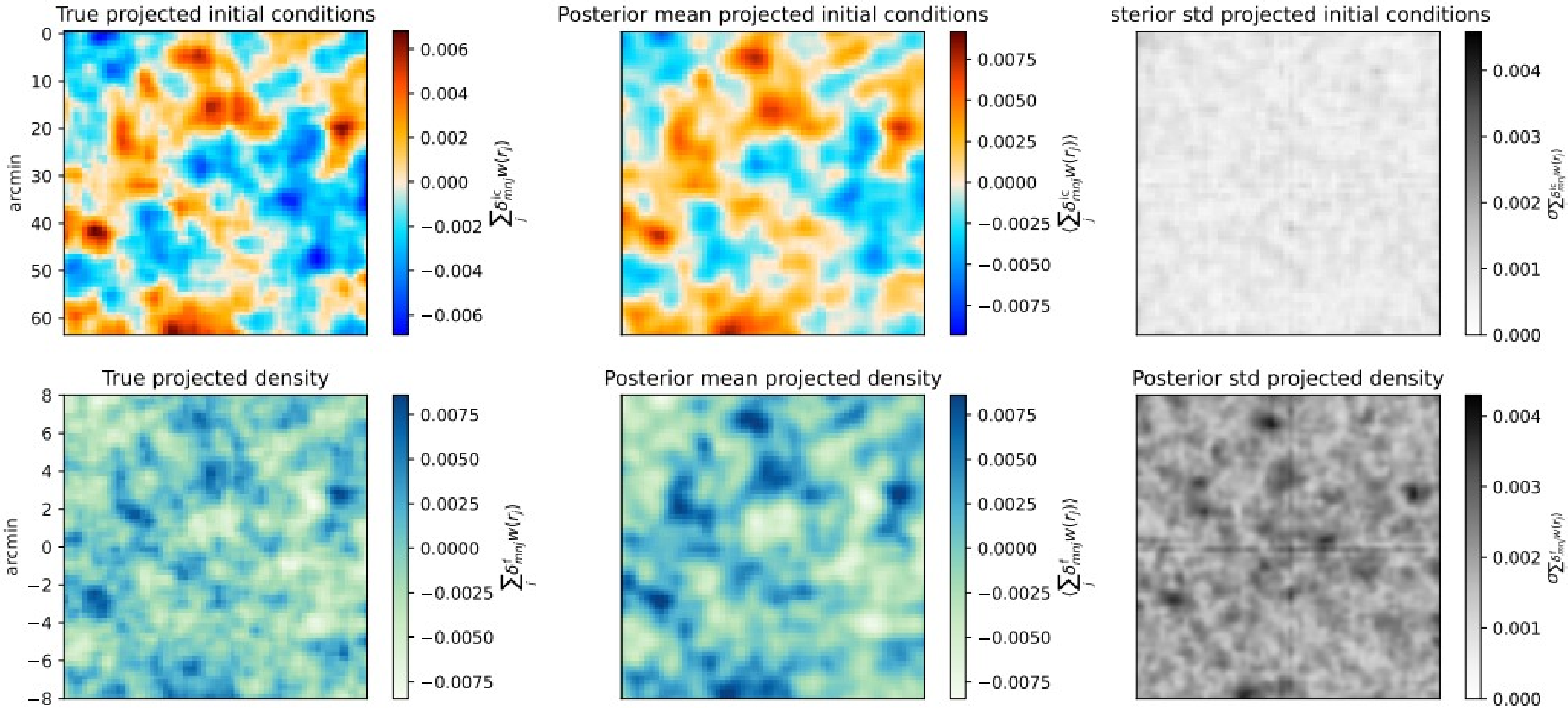
(1 Gpc/h)^2, 4.5 Gpc/h
(16 deg)^2, 13 arcmin
LPT

marginal error
5 times smaller

Field-level approach **lifts degeneracy** by extracting more information from the data

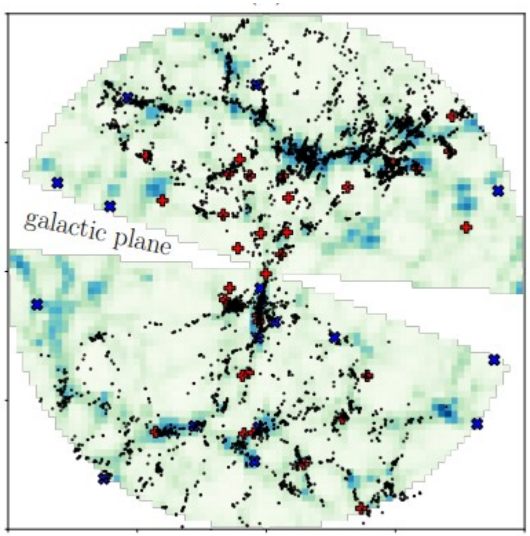
Porqueres+2023

Inferred density fields

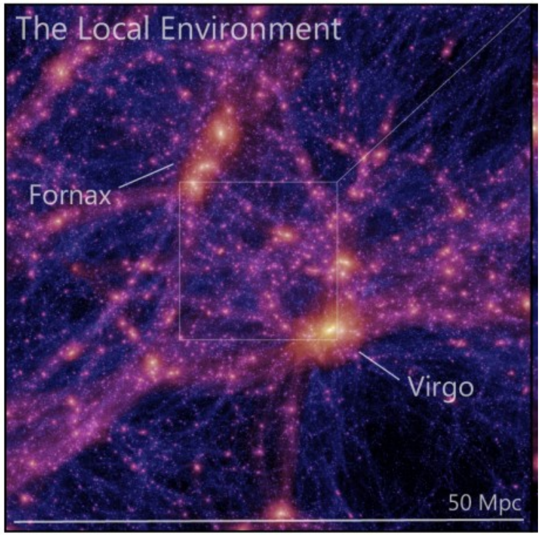


What physics can we do with the density fields?

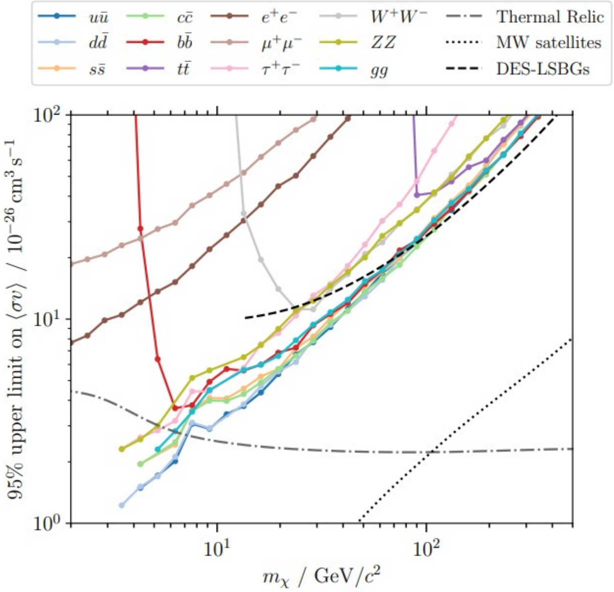
Galaxy or SN evolution
(Porqueres et al. 2017)
(Tsaprazi et al. 2021)



Constrained simulations
(McAlpine et al 2022)



Constrain DM anihilation
(Bartlett et al 2022)



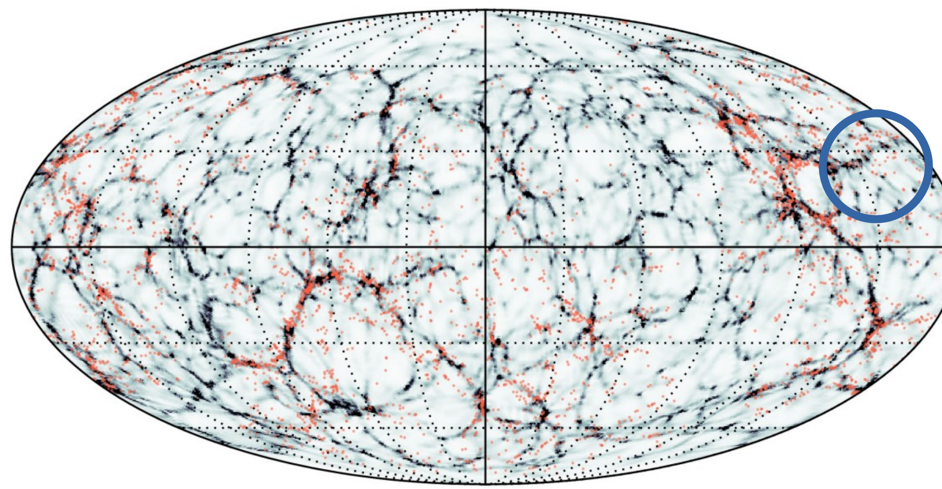
Validation of results with the density fields

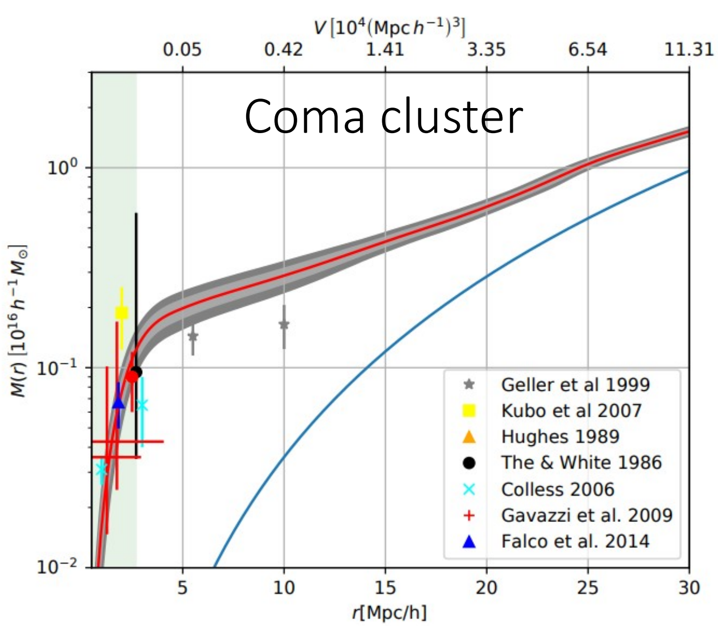
Posterior predictive tests and cross-validation with independent measurements

- do we get the clusters we know are there?

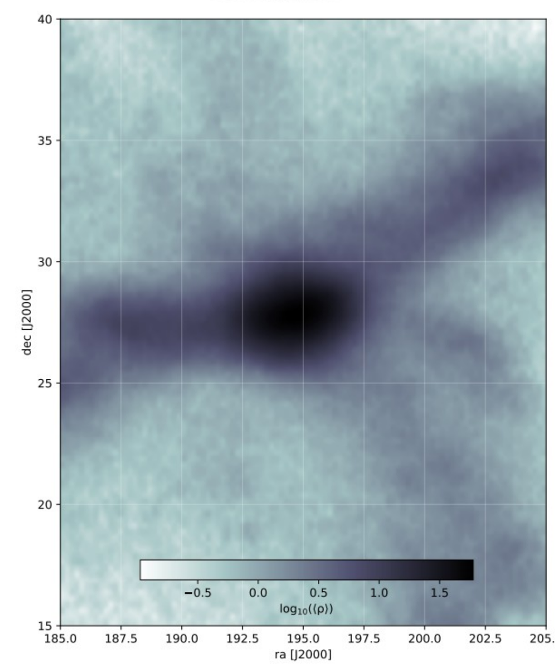
- do we get the expected mass profiles?

- are the inferred IC compatible with CMB?





Jasche & Lavaux 2019



Jasche & Lavaux 2019

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The challenge Getting ready for real data

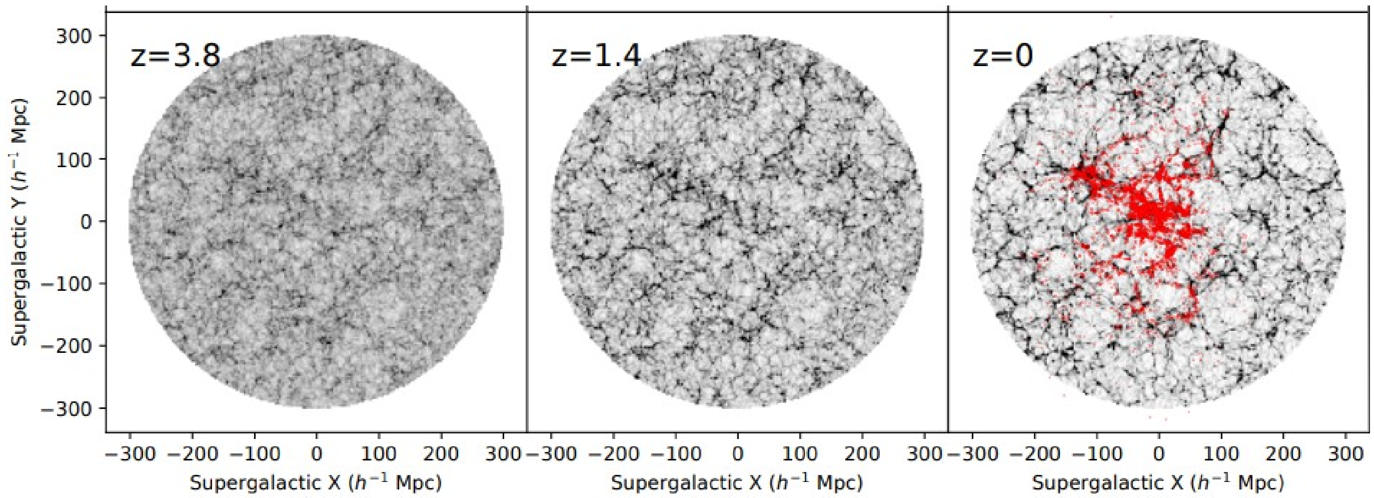
- More realistic gravity model

- Modelling of systematics

- What if the models of systematics are not good enough?

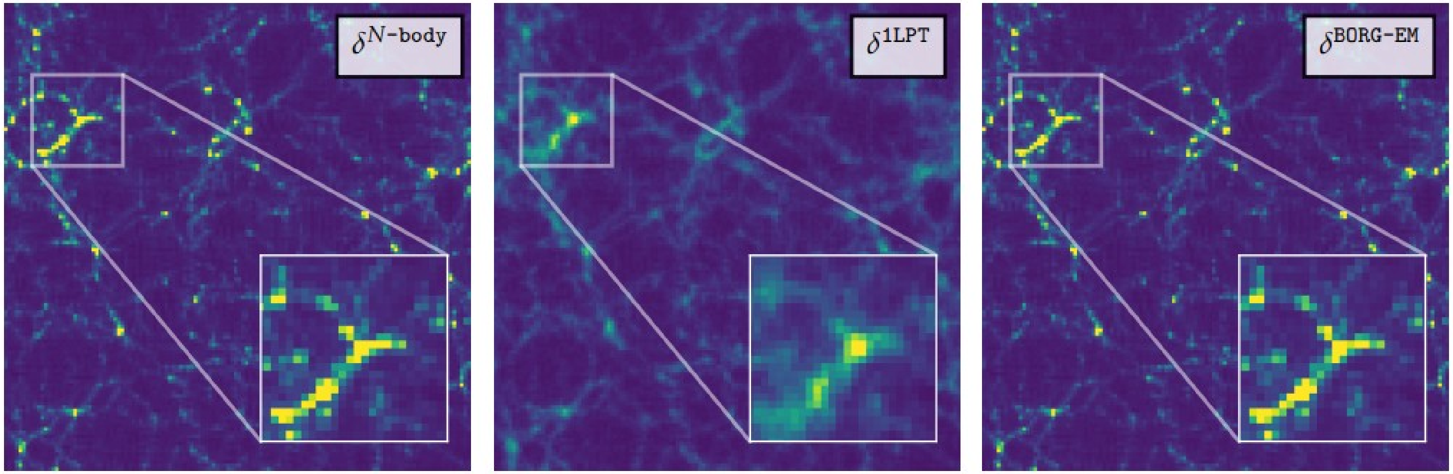
More realistic gravity model: Particle-mesh in BORG

Particle mesh is **ready** and has been **used in real data** BORG analysis (2M++)



Jasche & Lavaux 2019

Particle-mesh emulator: percentage-level agreement



Doeser et al 2023

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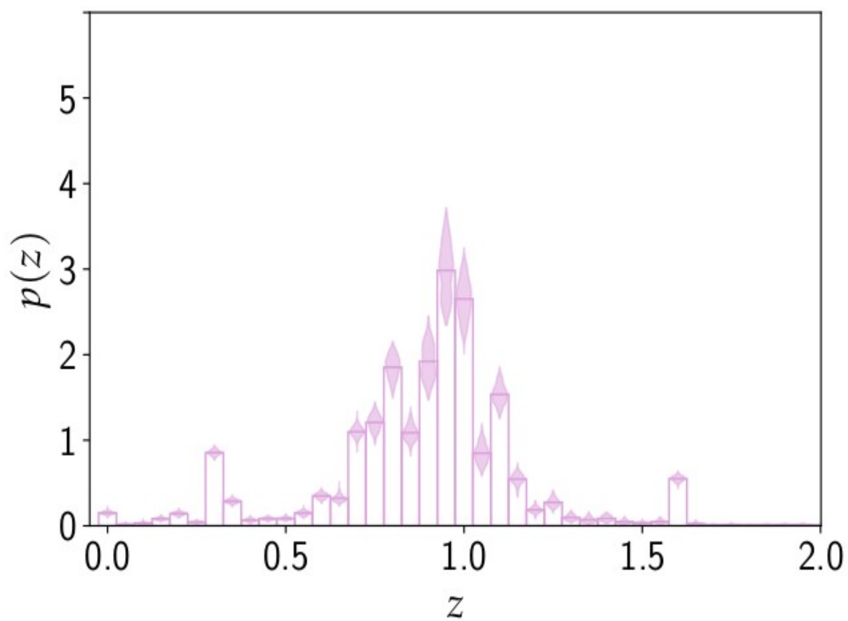
Calibration systematics: robust n(z)

We need to **propagate the redshift uncertainty** to the cosmology results

Bayesian hierarchical model to sample n(z) and marginalise over redshift uncertainties

Using forward model of the photometric fluxes (Leistedt+ 2016)



Kyriacou, Heavens+ in preparation

What if the models of systematics are not good enough?

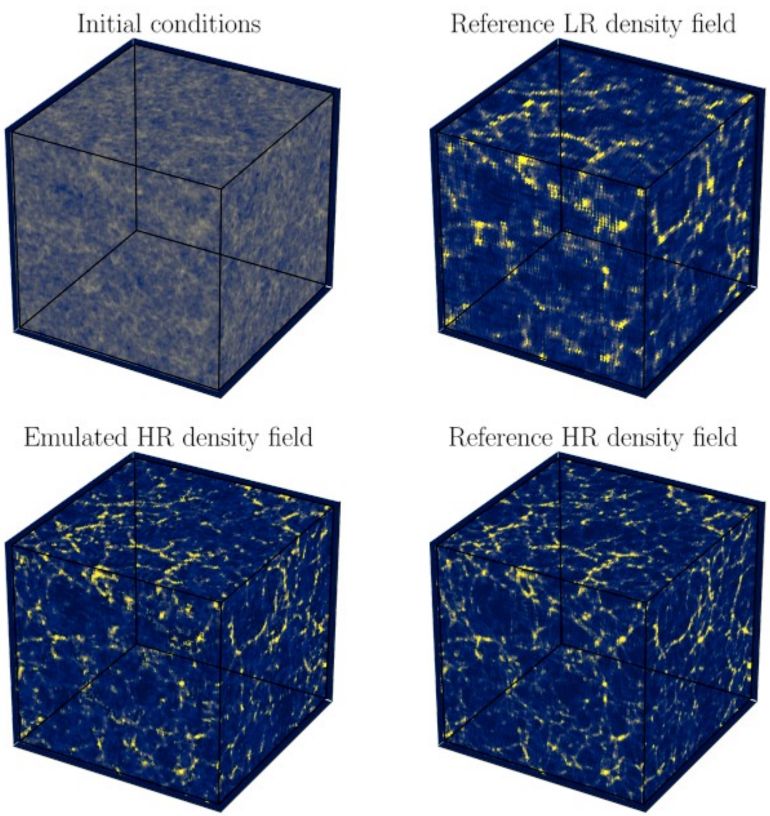
Machine learning can help connecting physical models to data

Neural physical engines (Charnock+ 2019): fully Bayesian way of using NN in MCMC inference

- encoding symmetries to reduce dimensionality

- inferring NN parameters from data. No training data!

An example in BORG: Emulating high resolution N-body



Charnock+ 2019

Summary

- There is more information in the data that the 2-point summary statistics do not capture.
- Field-based approach lifts degeneracy and reduces marginal error up to a factor of 5.
- What’s next?
  Get ready for first real data application