Lifting weak lensing degeneracies with a field-based likelihood

Natalia Porqueres

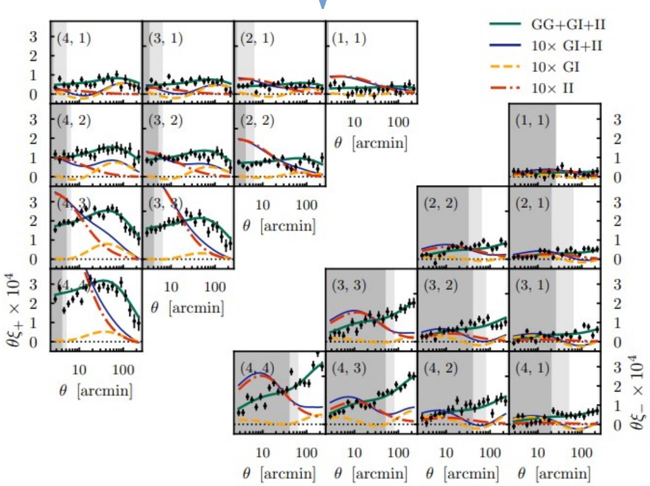
with Alan Heavens, Daniel Mortlock, Guilhem Lavaux, Lucas Makinen

LSS Prague – 28/6/2023

The standard approach to shear analysis

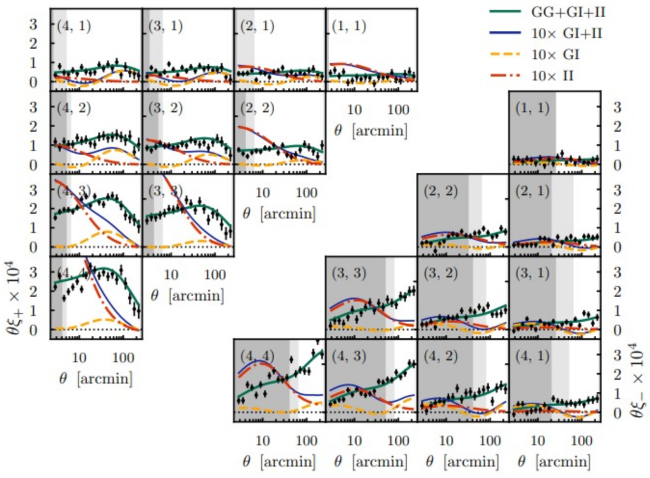
The standard approach to shear analysis

Summarise



The standard approach to shear analysis

Summarise



Does this capture all the information?

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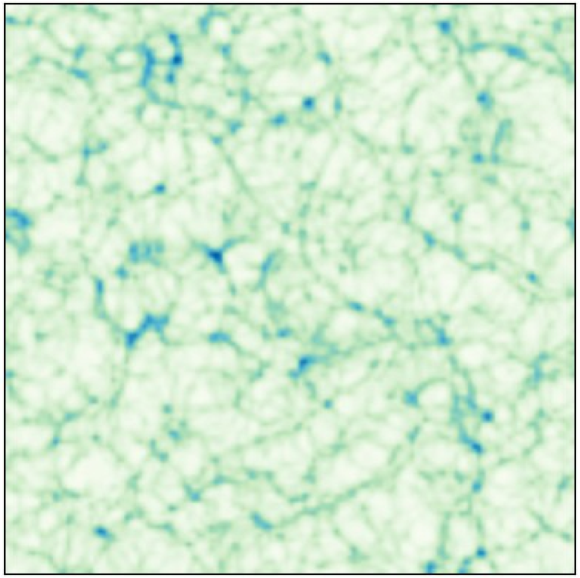
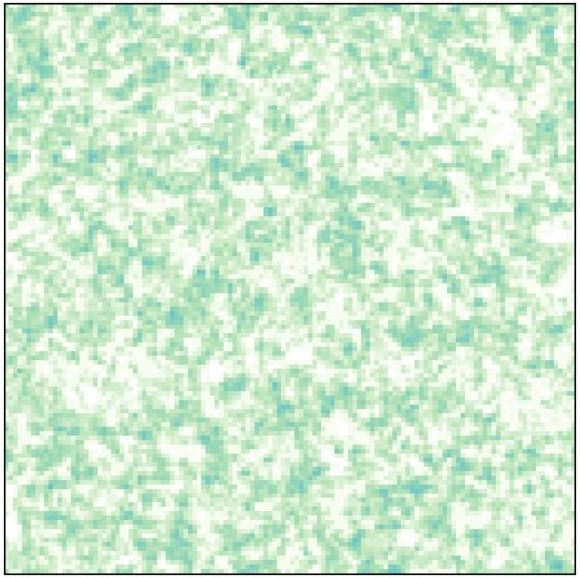
Is the standard approach enough?

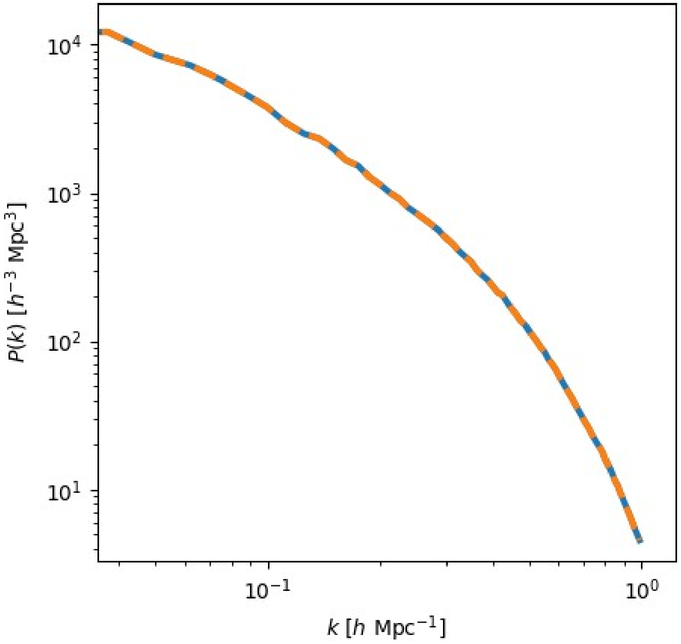
The standard approach misses information!



Cosmic web



Gaussian random field



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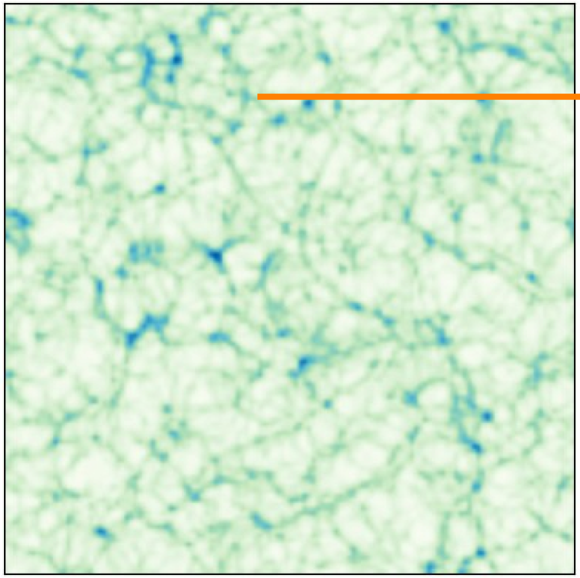

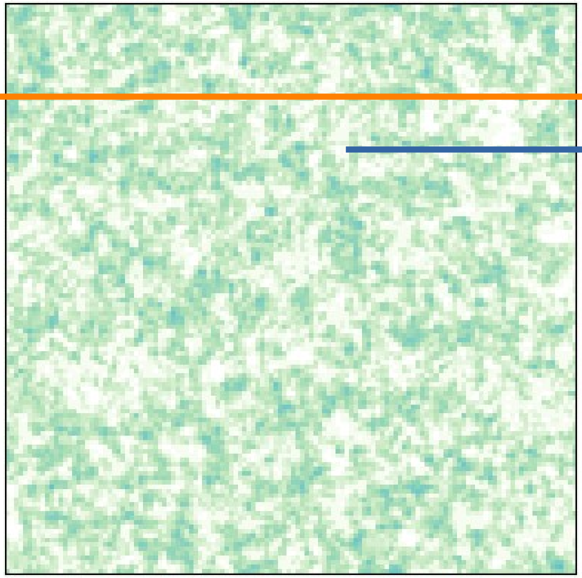

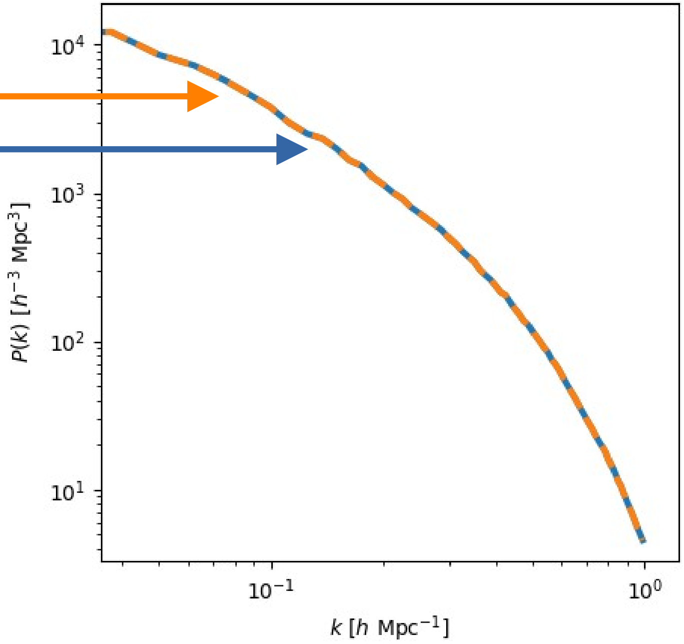

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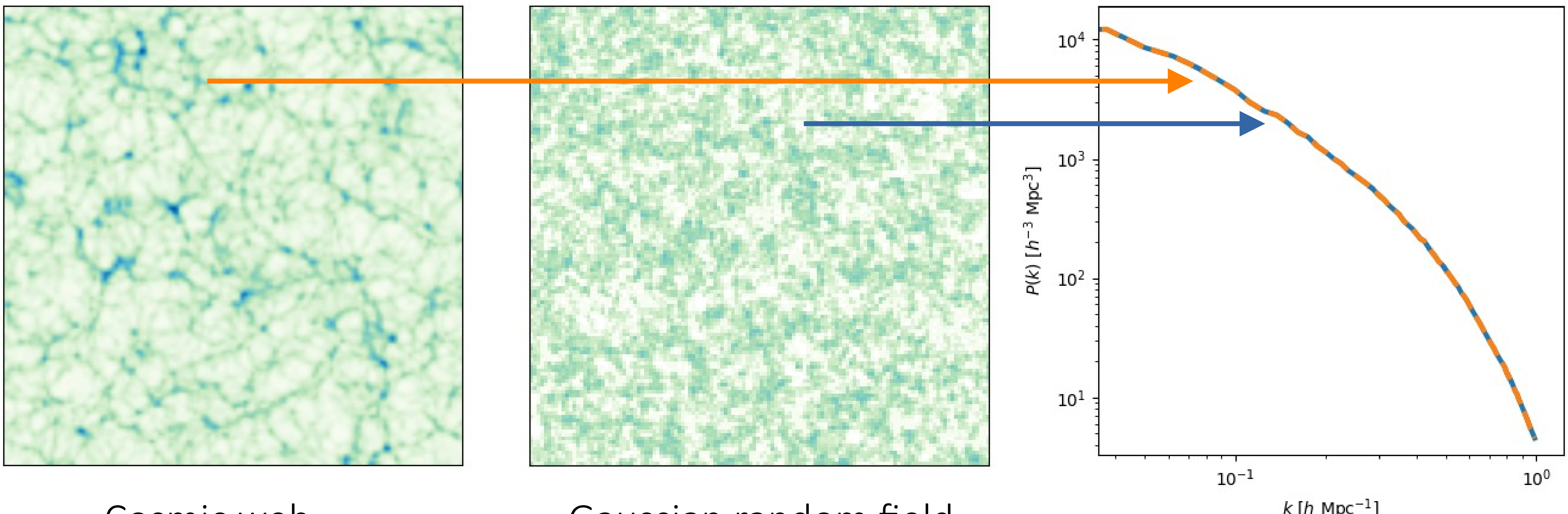

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Gaussian random field

- Higher-order statistics: what are the sampling distributions? And covariance matrix?

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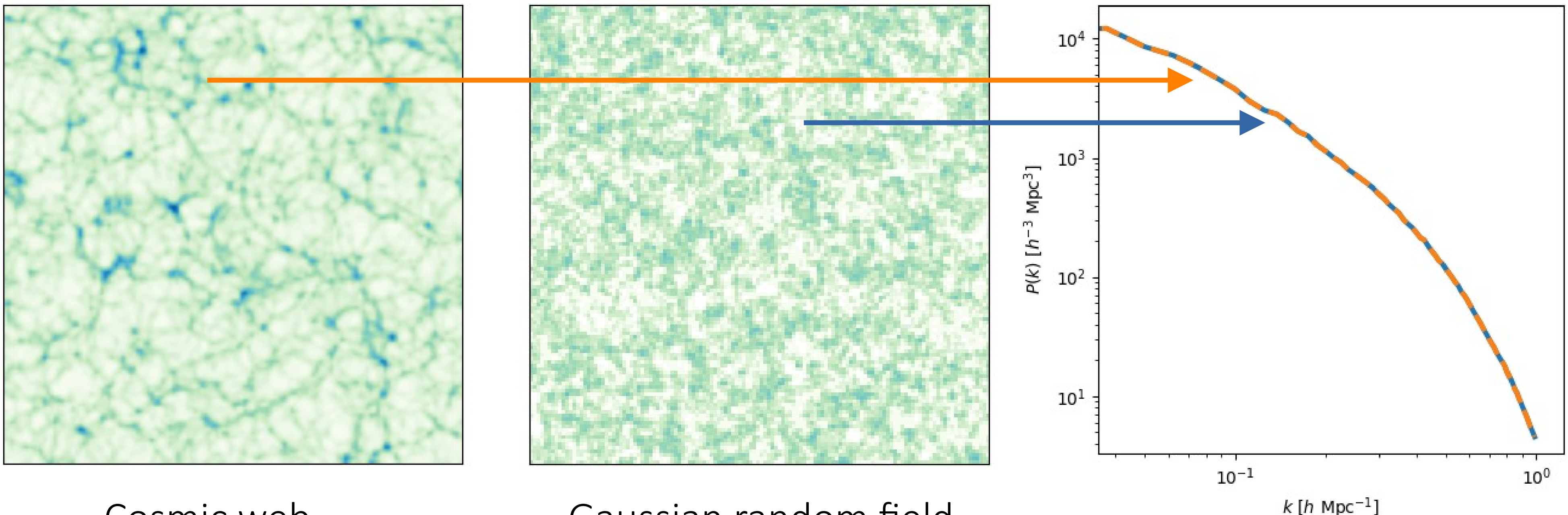


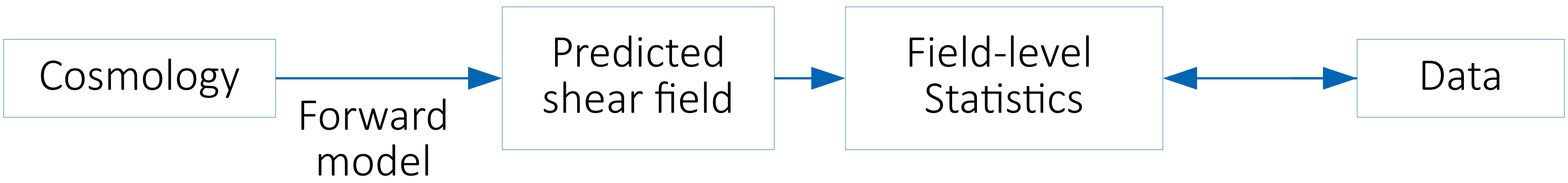
Cosmic web

Gaussian random field

- Higher-order statistics: what are the sampling distributions? And covariance matrix?

- Field-based approach without data compression of the pixelised shear.

The field-level approach



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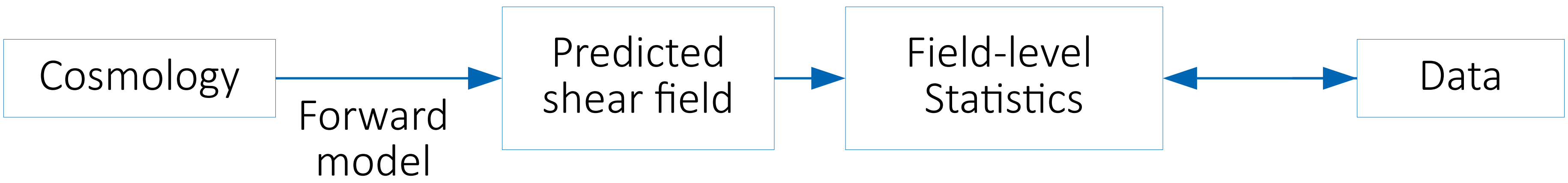
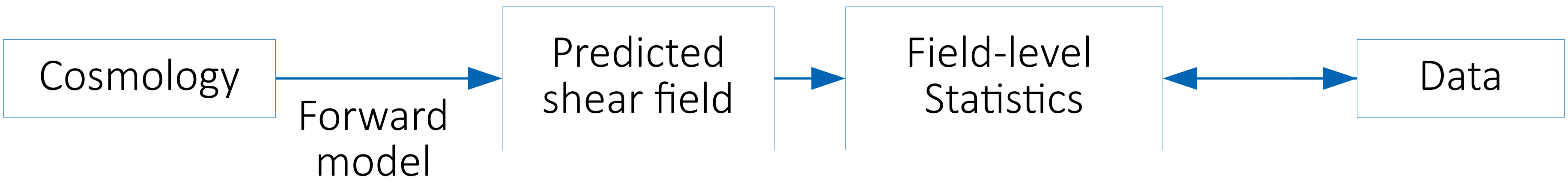


Statistics pixel by pixel can access all the information

The field-level approach



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Probabilistic forward model → Simulations are constrained by the data

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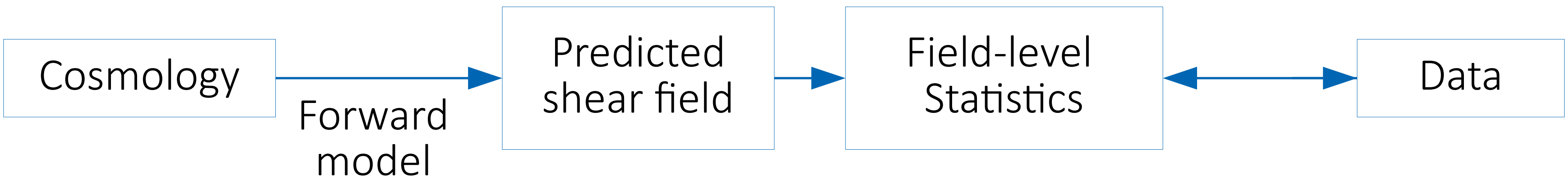

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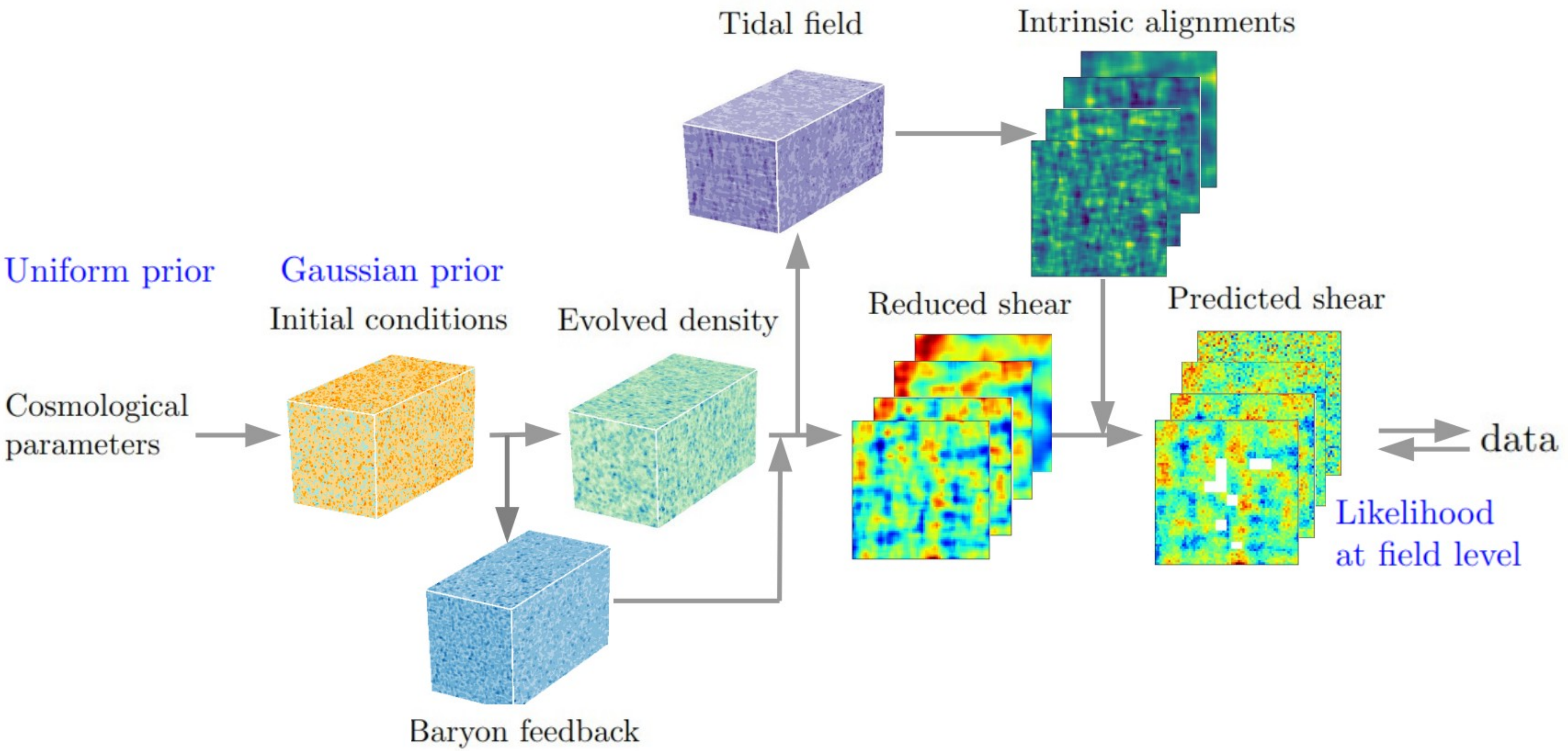
BORG framework: gravity model

The forward model of BORG-WL



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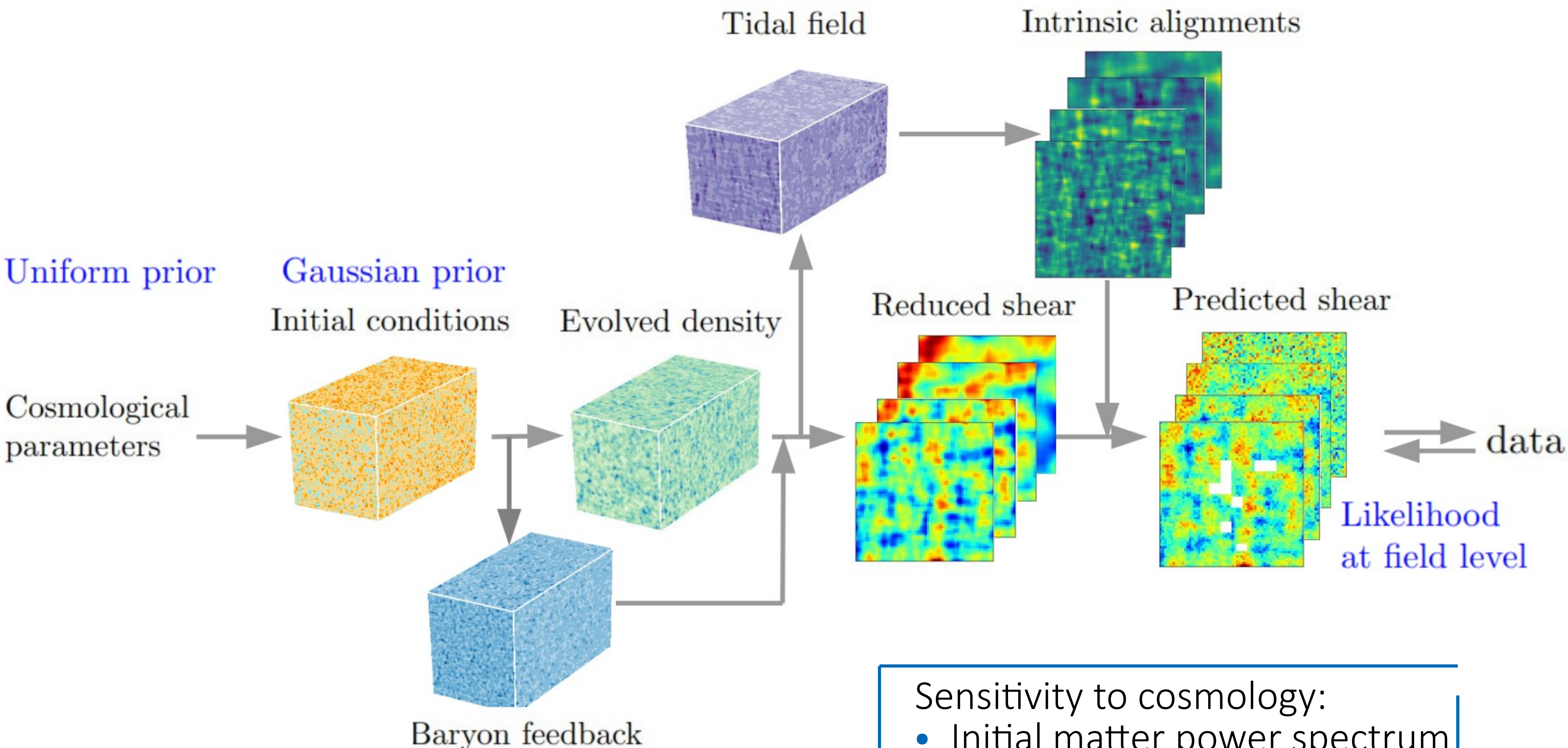
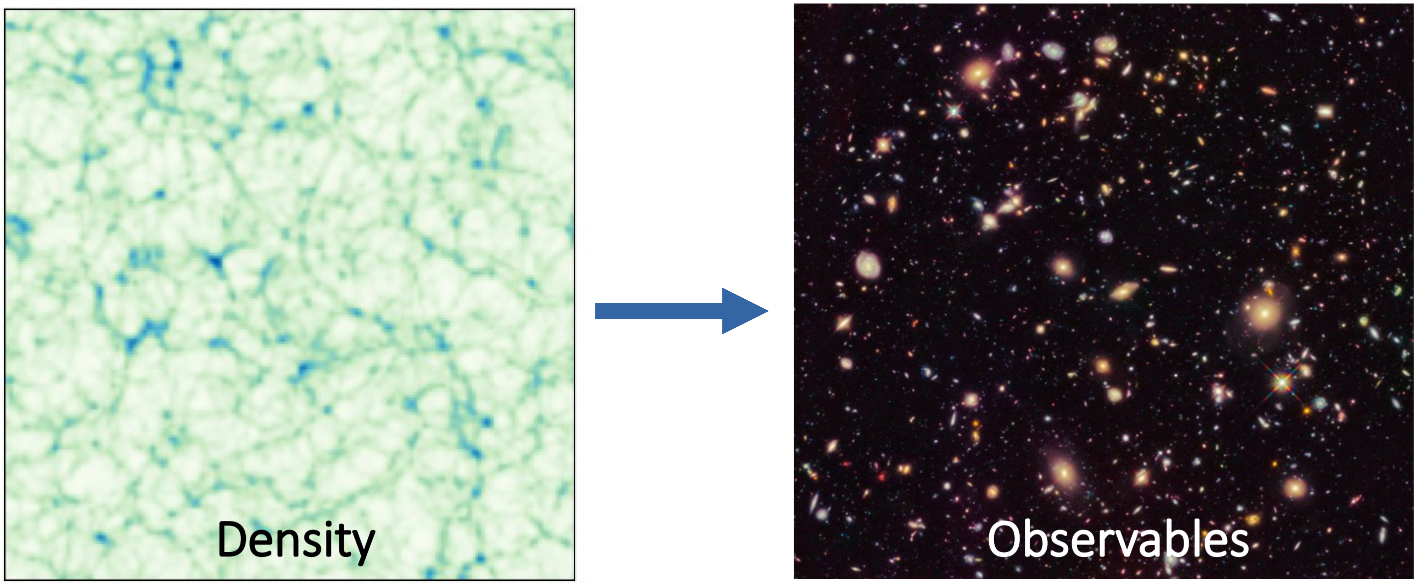


Sensitivity to cosmology:

- Initial matter power spectrum
- Growth of structures
- Geometry

Intrinsic alignments: Tidal alignment and tidal torquing



TATT model includes linear (tidal alignment) and quadratic (tidal torque) terms

$$\gamma_1^{\mathrm{IA}}(\boldsymbol{r},\boldsymbol{\vartheta}) = (C_1 + C_{1\delta}\delta)(s_{xx} - syy) + C_2(s_{xk}s_{xk} - s_{yk}s_{yk})$$
$$\gamma_2^{\mathrm{IA}}(\boldsymbol{r},\boldsymbol{\vartheta}) = 2(C_1 + C_{1\delta}\delta)s_{xy} + 2C_2 s_{xk}s_{yk},$$

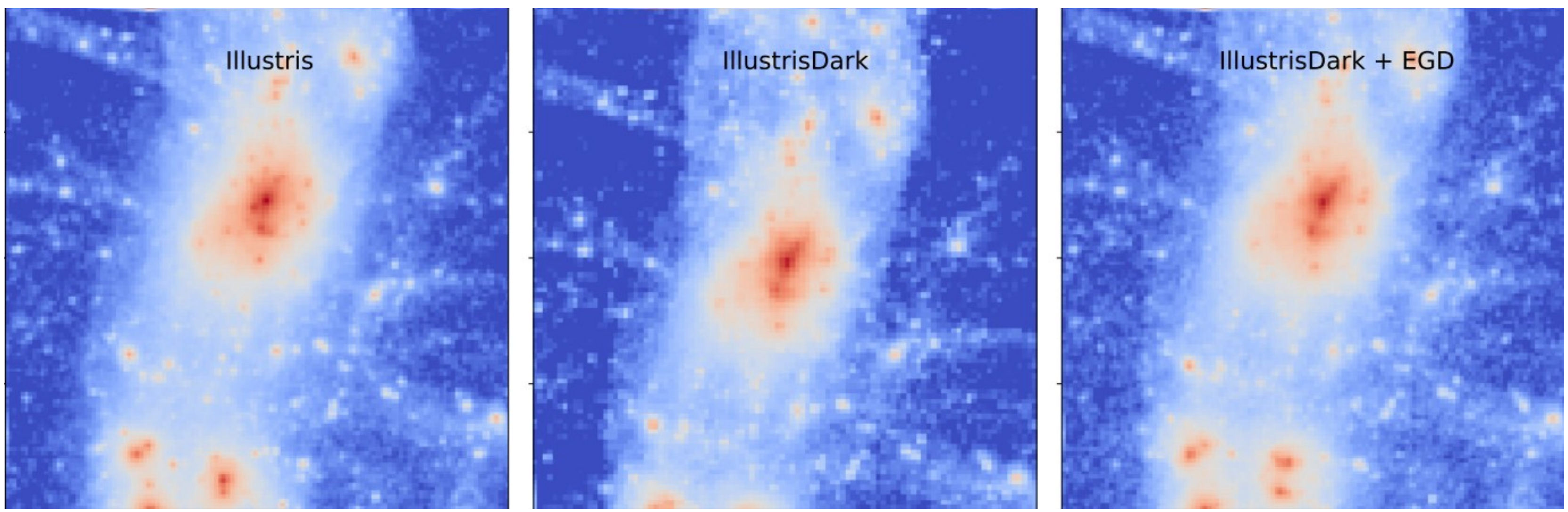
Blazek+ 2017

Baryon feedback: Enthalpy gradient descent model

Displaces dark matter particles with

$$\mathbf{S}_{\text{baryons}} = -\frac{\beta}{H_0^2}\frac{k_B T_0}{\mu}\frac{\gamma}{\gamma-1}\nabla\left[\mathbf{O}_{\mathrm{J}}(1+\delta)\right]^{\gamma-1}$$

Assumes power law equation of state of baryons $T(\delta) = T_0(1+\delta_b)^{\gamma-1}$



Dai & Seljiak, 2018

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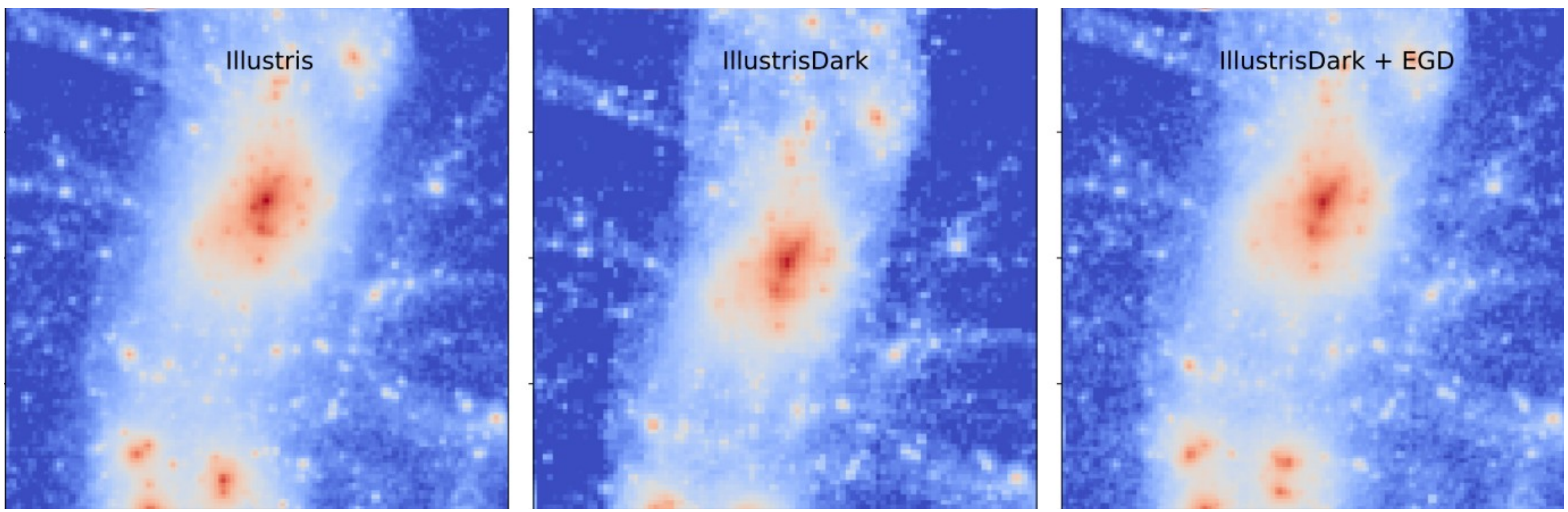

Dai & Seljiak, 2018

- Self calibration of model parameters.

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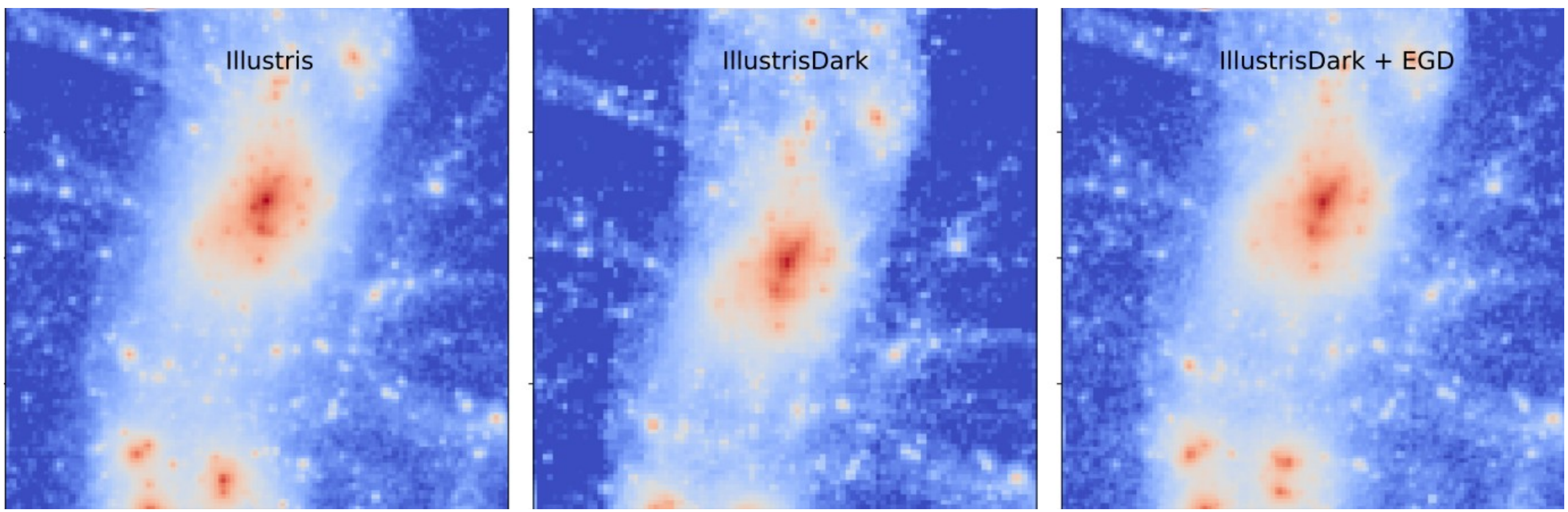

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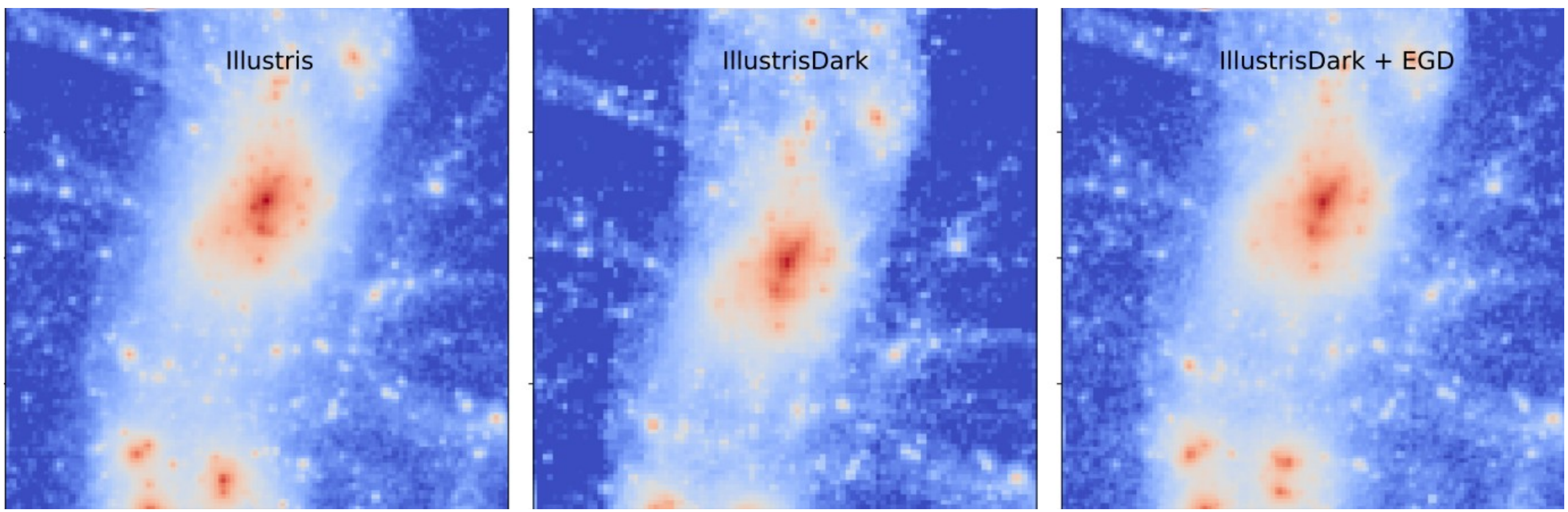


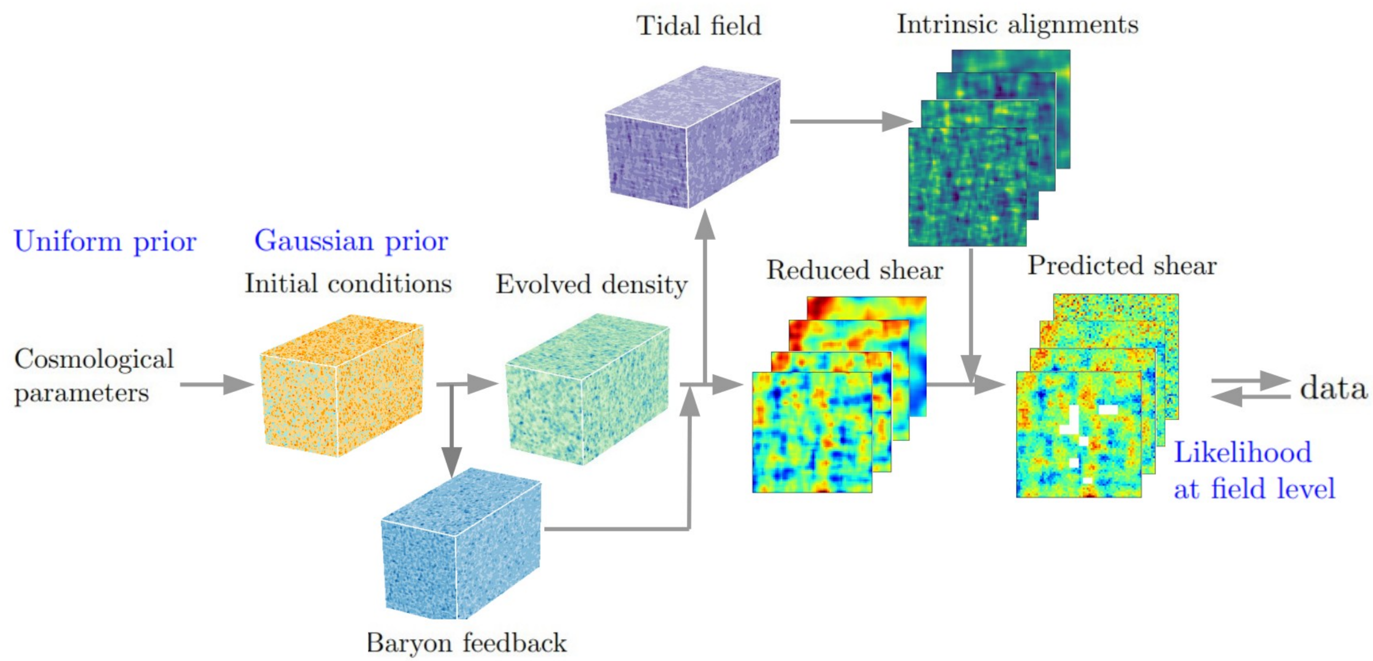
Dai & Seljiak, 2018

- Self calibration of model parameters.

- Displaces particles independently of whether they are in a halo.

- Fully differentiable.

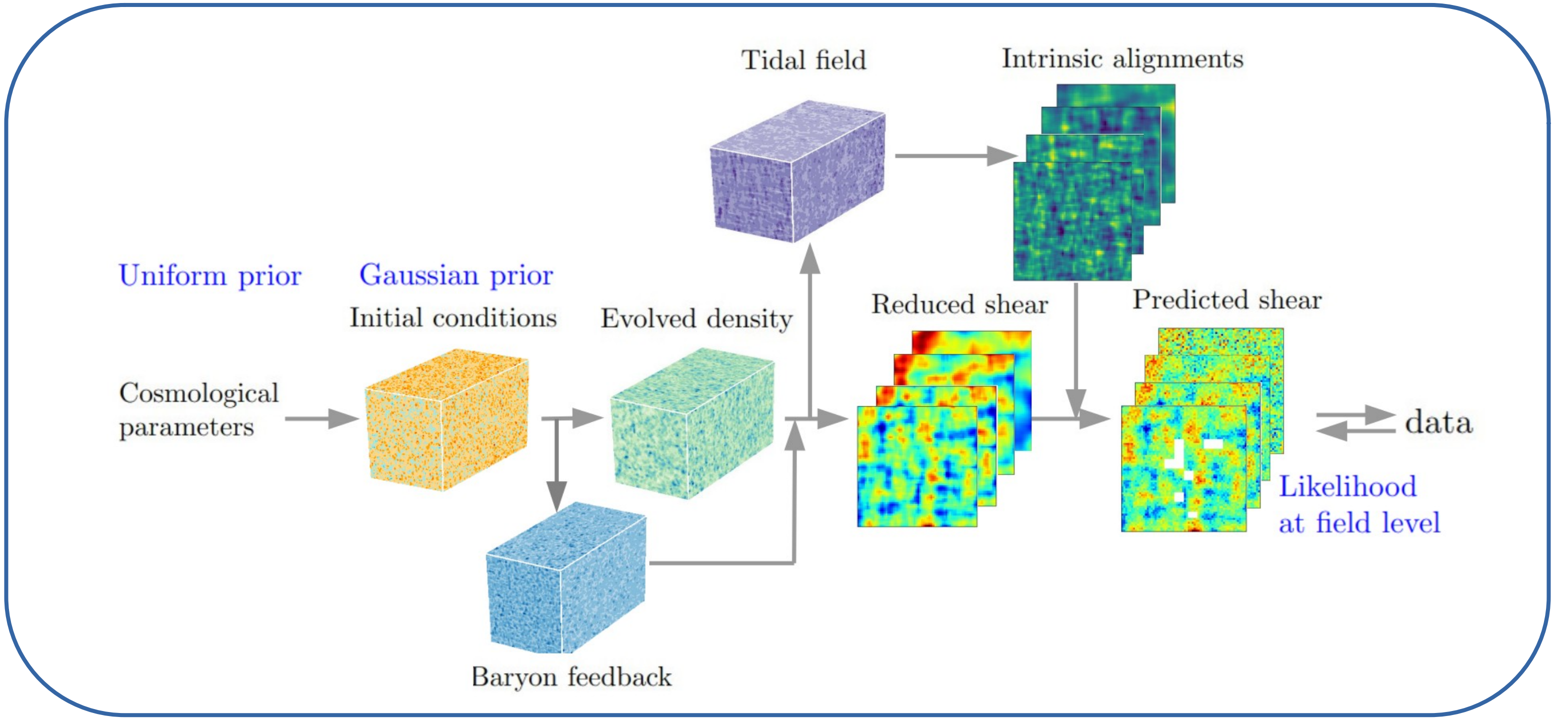
The likelihood



Likelihood: Assuming Gaussian noise in pixelised shear

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

The likelihood



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

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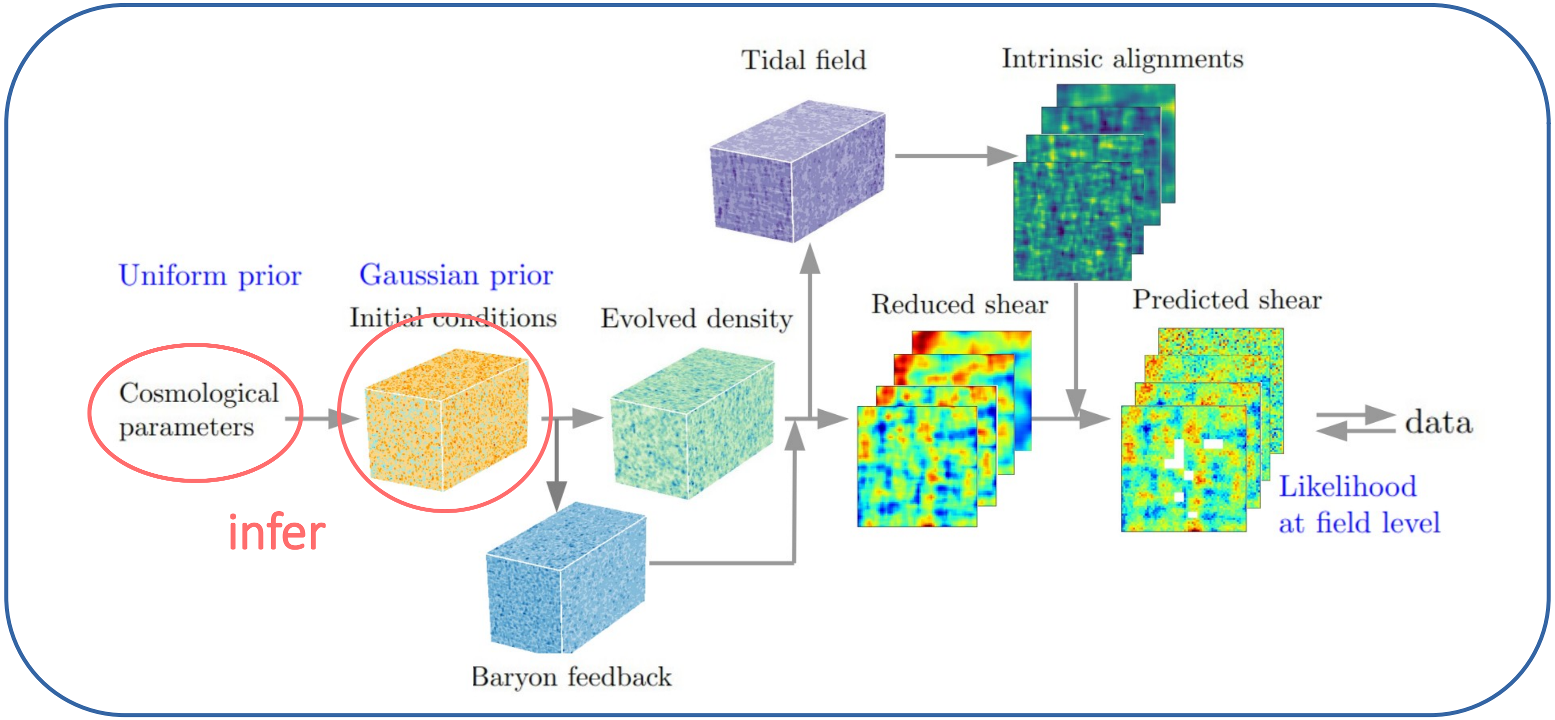

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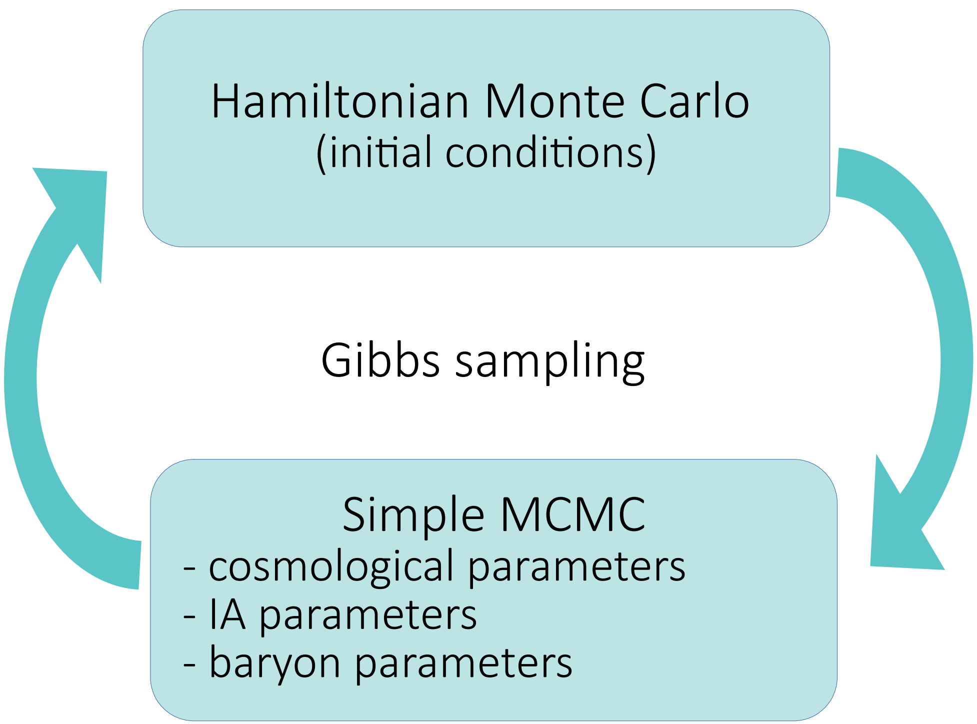
Sampling efficiently in a high-dimensional space



Addresses curse of dimensionality by:

- exploiting information in gradients

- using conserved quantities

The proof of concept Results with synthetic data

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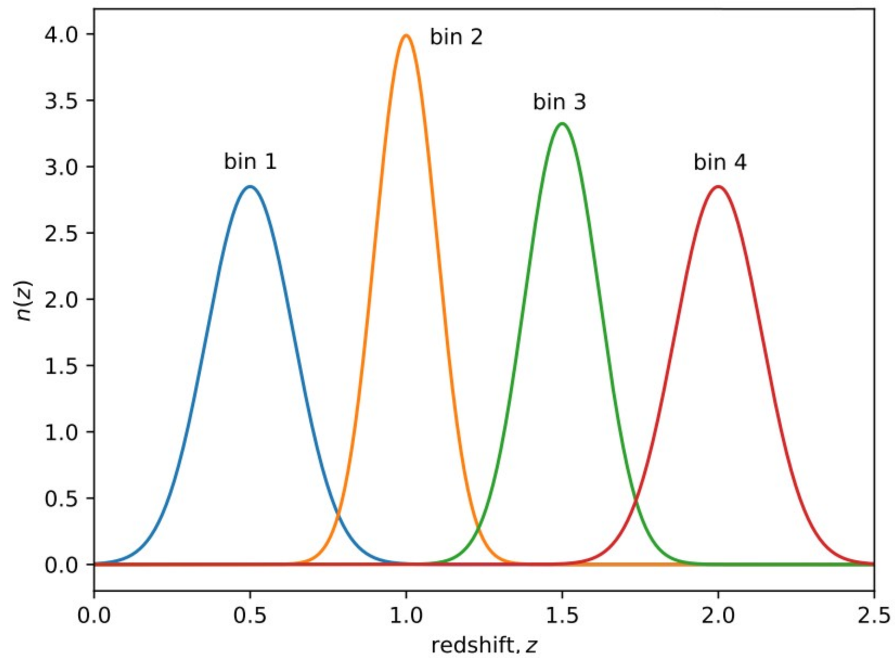
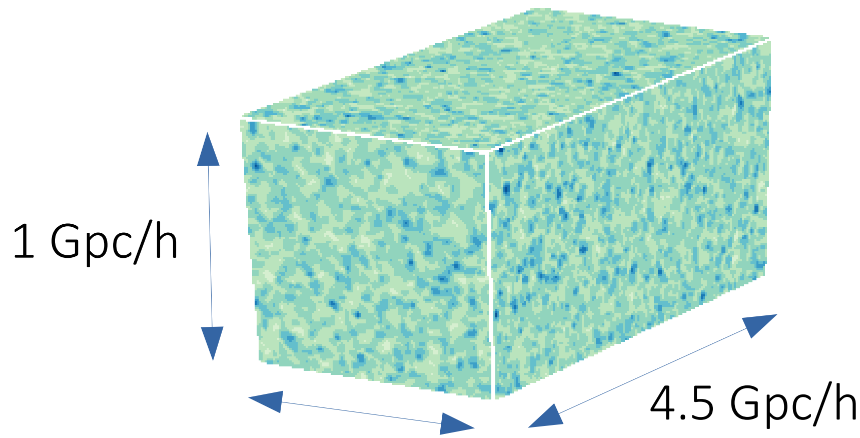
How much do we get from going to the field level?

Simulated data

Tomographic bins





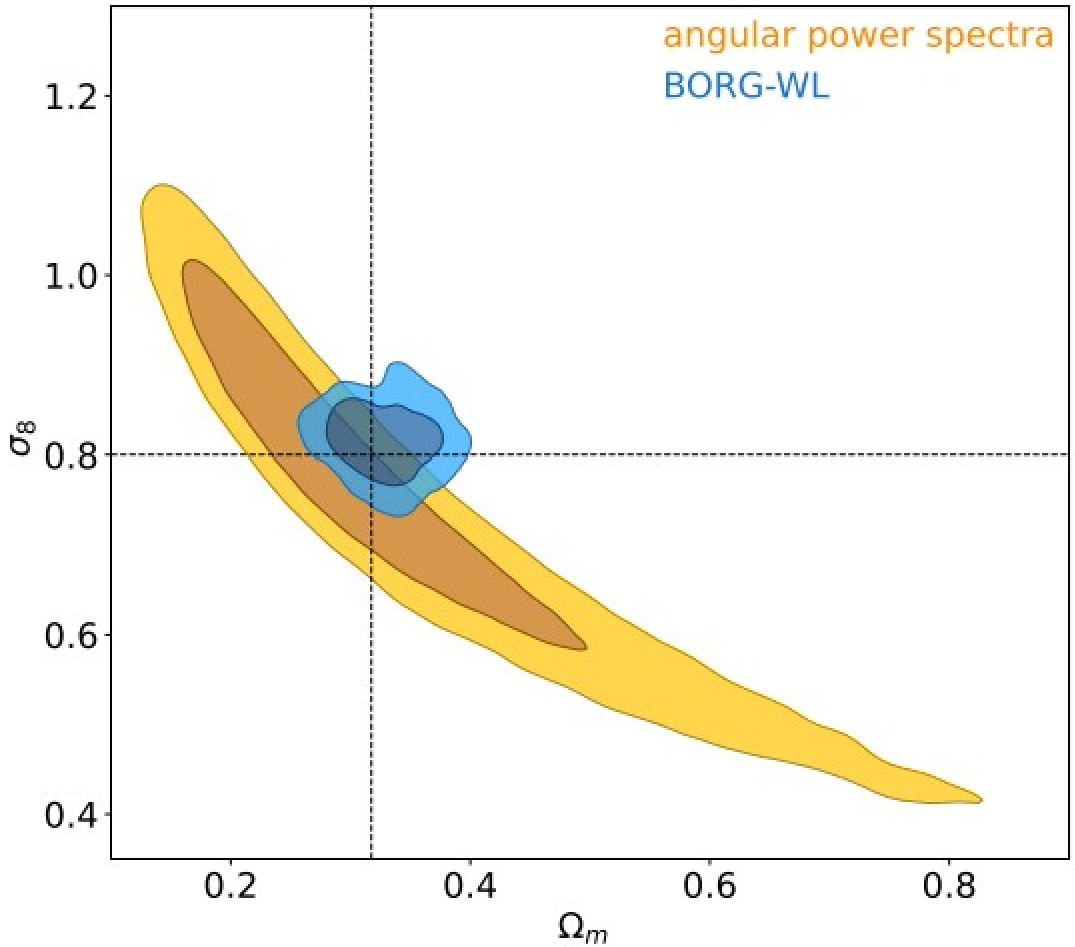
1 Gpc/h (16 deg)^2
(15 Mpc/h, 13 arcmin)

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



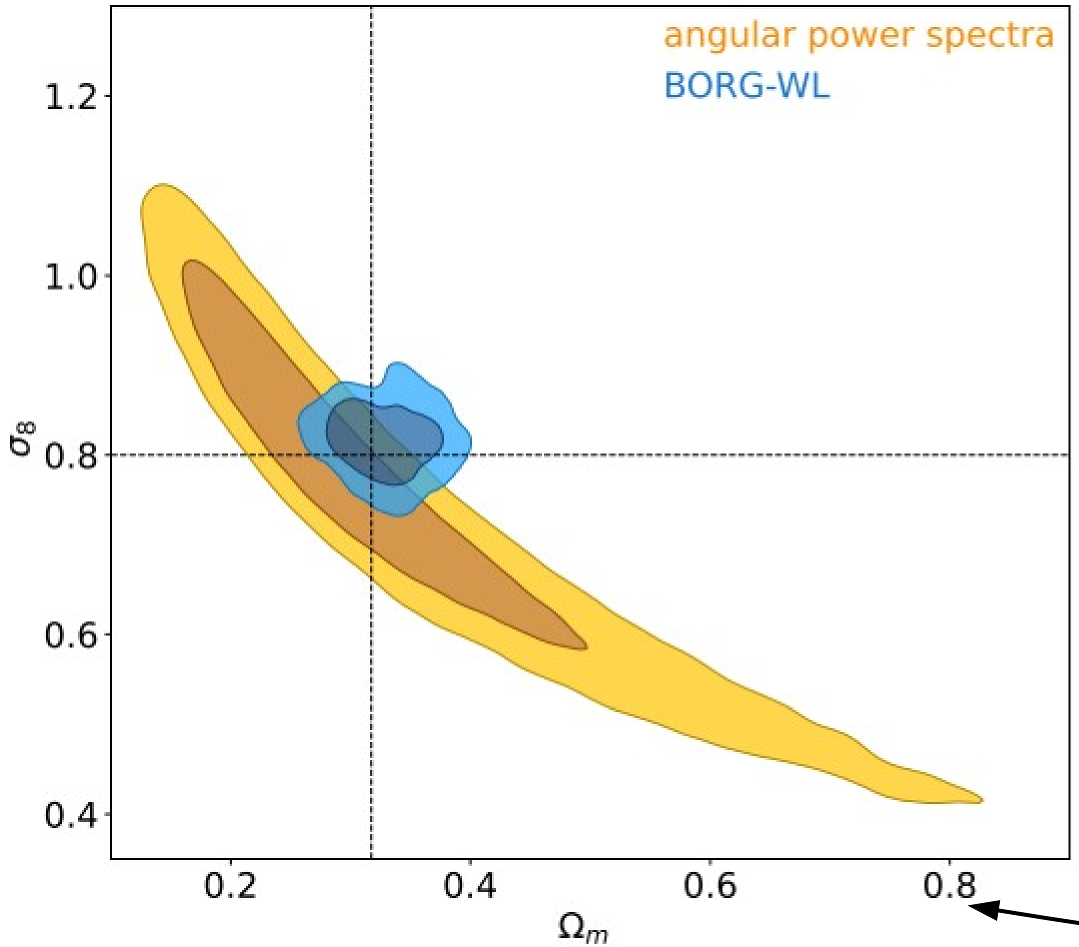
$(1\ \text{Gpc}/h)^2$, 4.5 Gpc/h
$(16\ \text{deg})^2$, 13 arcmin
LPT

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

Porqueres+2023

Comparison of cosmology constraints

marginal error
3 times smaller



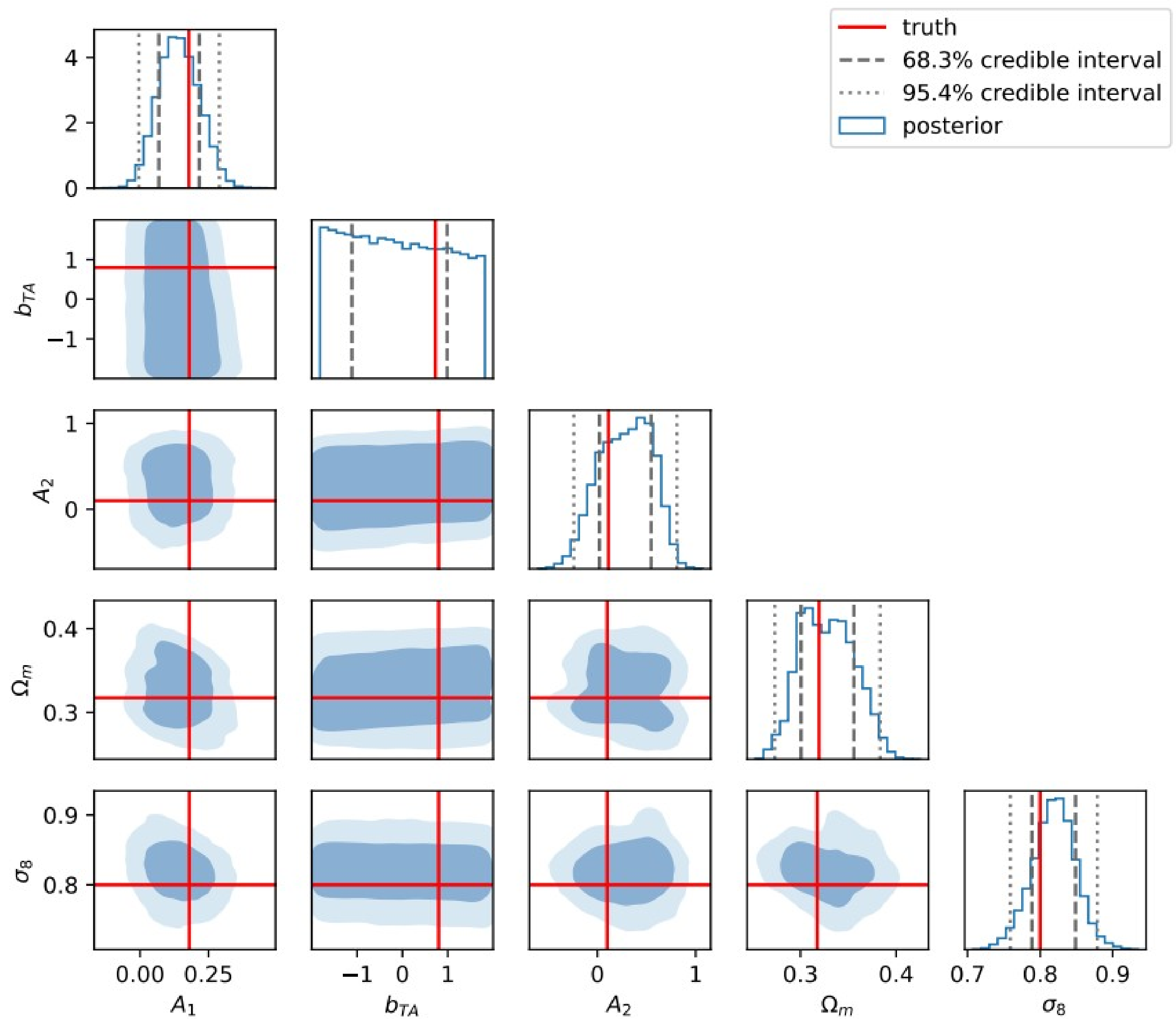
(1 Gpc/h)^2, 4.5 Gpc/h
(16 deg)^2, 13 arcmin
LPT

marginal error
5 times smaller

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

Porqueres+2023

Intrinsic alignment parameters



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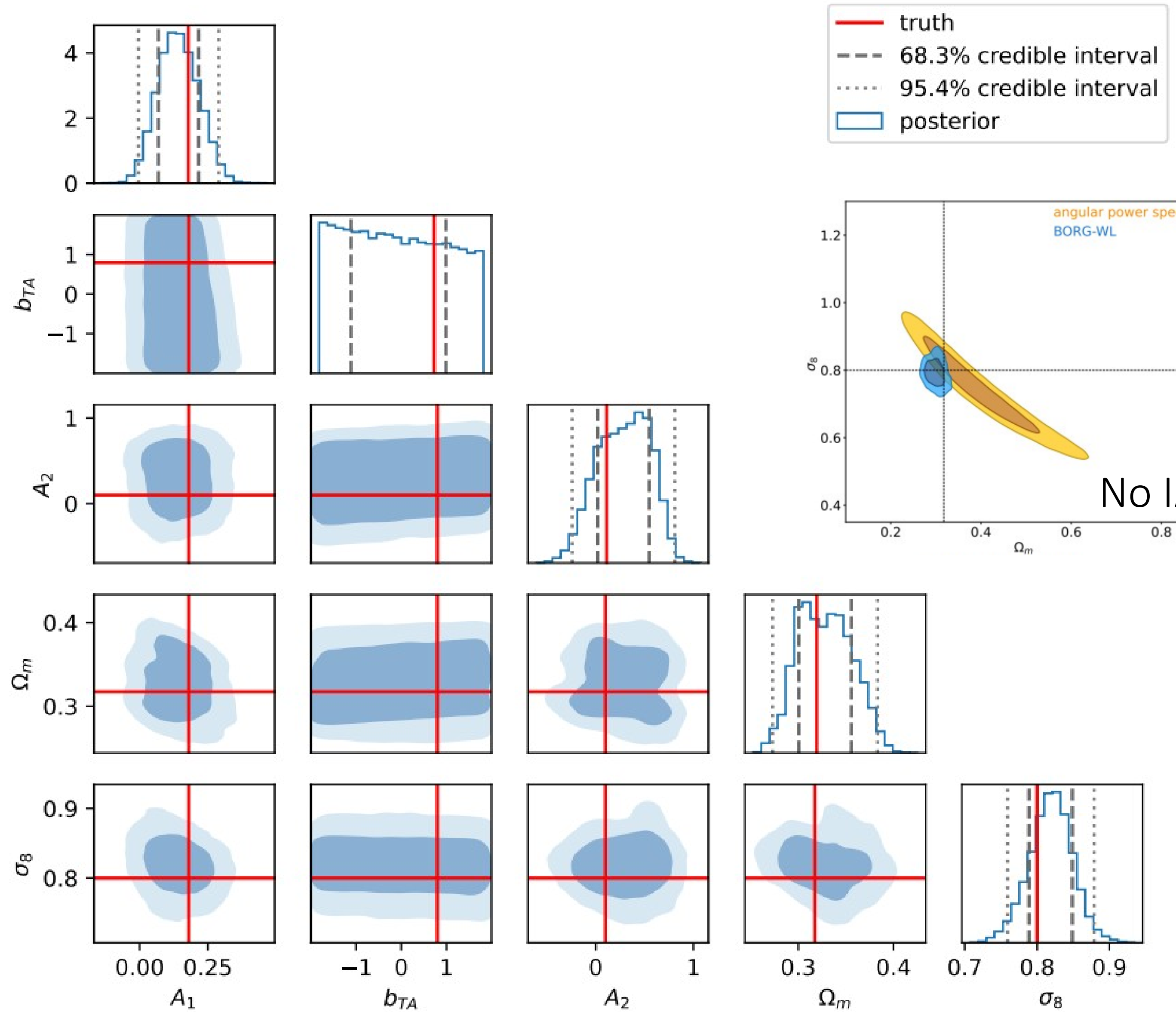
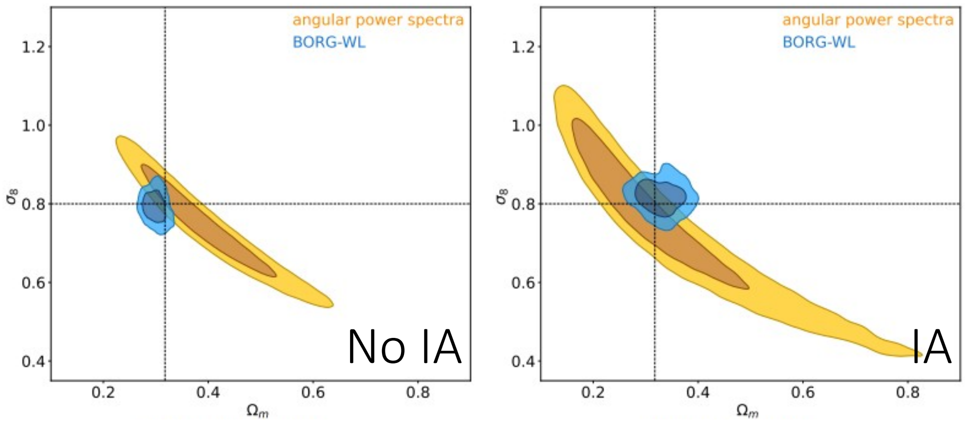
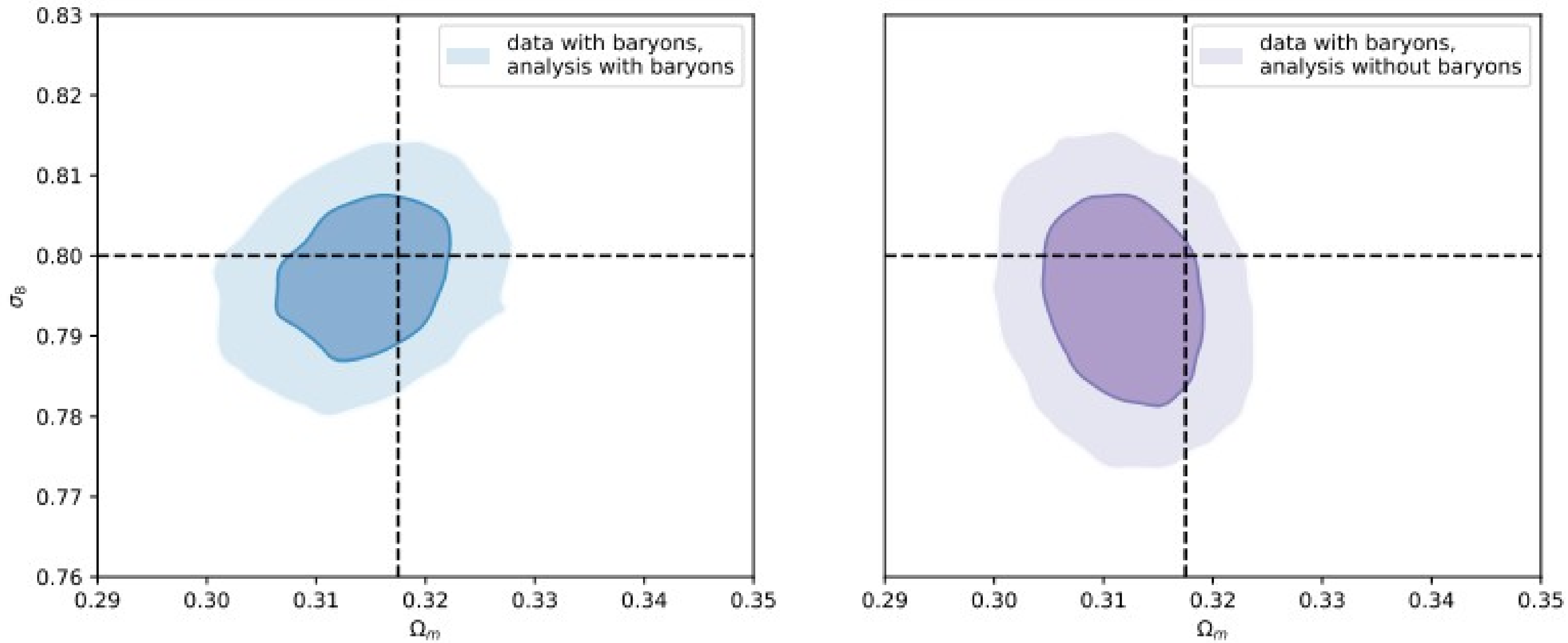




Porqueres+2023

Baryon feedback parameters

(0.1 Gpc/h)^2,2.5 Gpc/h
(3 deg)^2, 5 arcmin
LPT

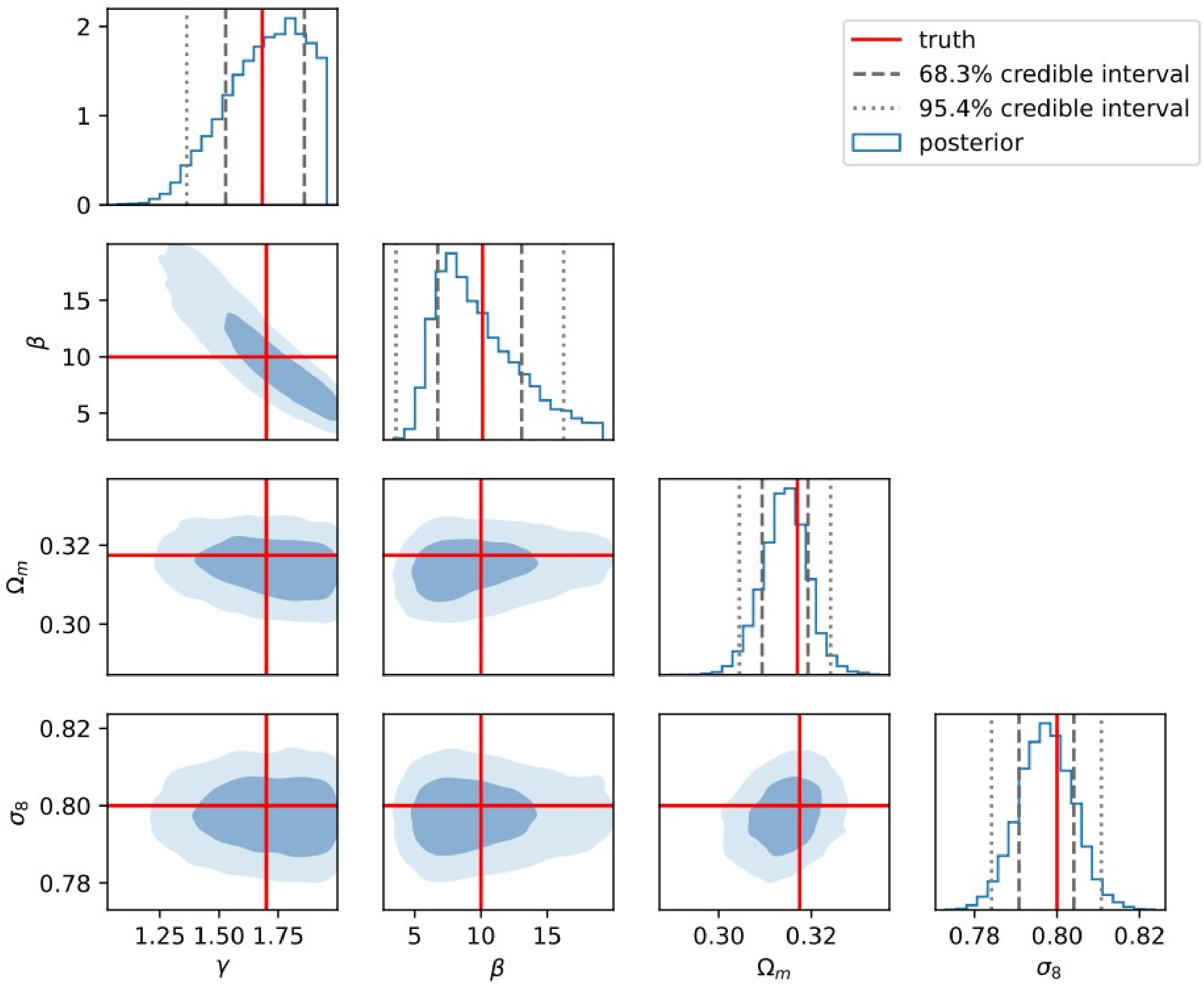


self-consistent

model misspecification

Porqueres+2023

Posterior distribution baryon parameters



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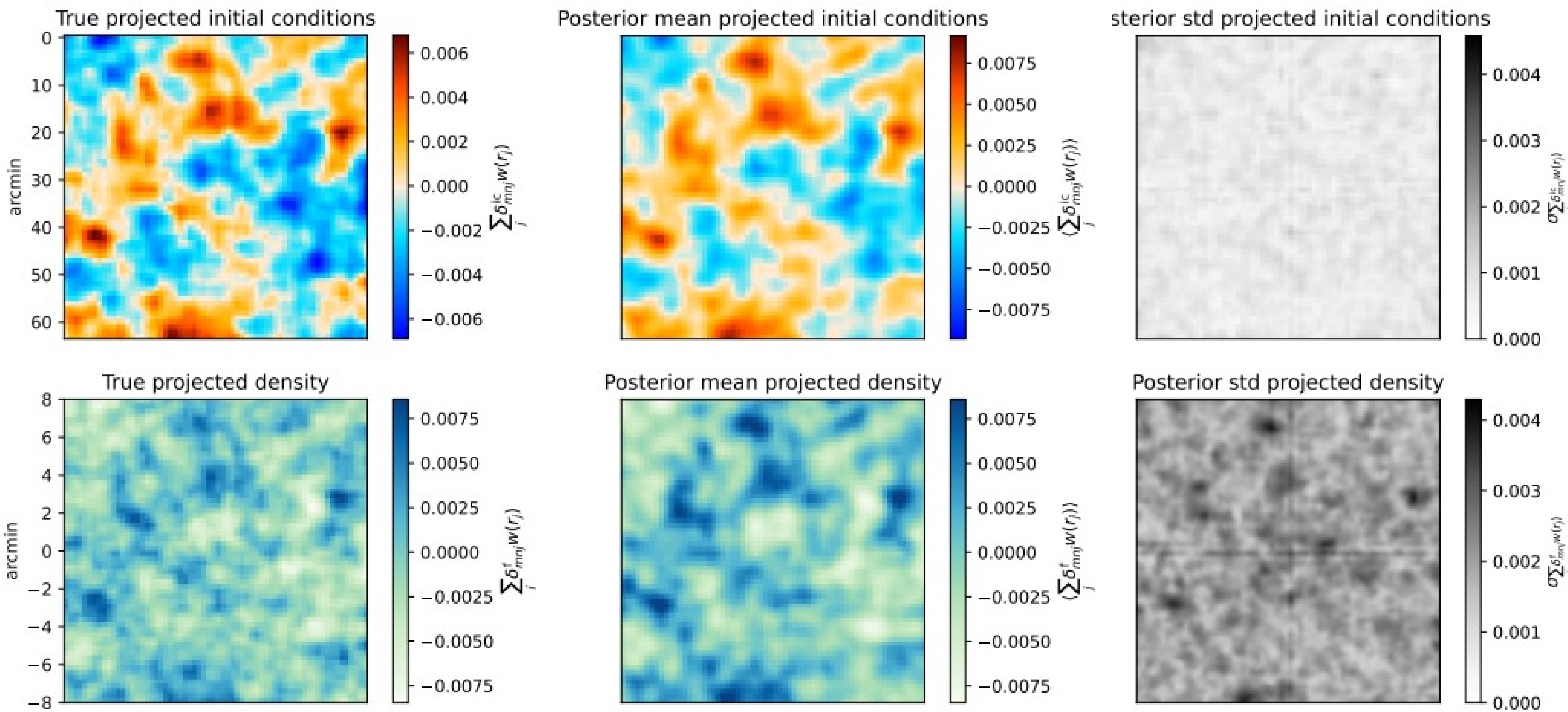
Projection of inferred density fields



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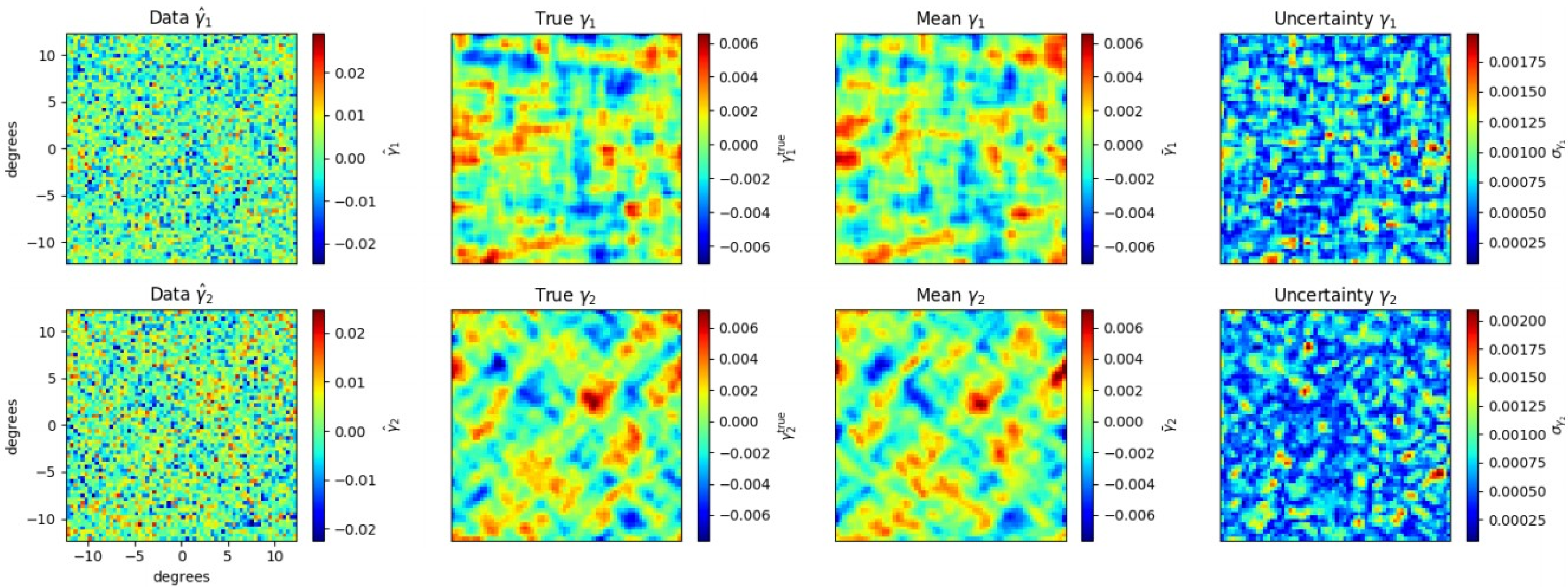
How can we test the results with such high dimensionality?

Posterior predictive tests: Can the inferred quantities explain the data?



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The current state of BORG

Generated data products

Currently supported data

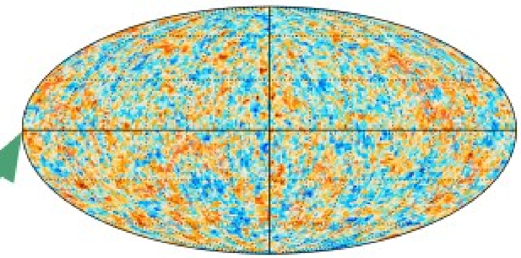
Galaxy clustering
(Jasche et al 2012)

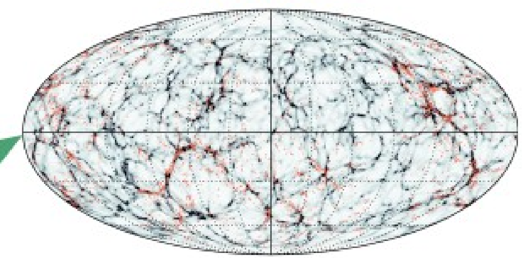
Cosmic shear
(NP et al 2021)

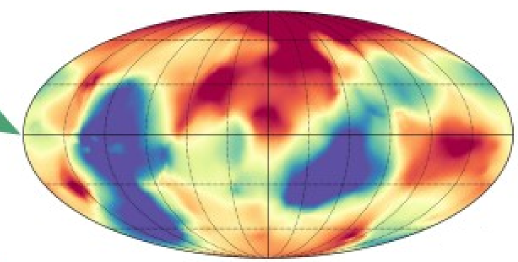
Velocity tracers
(Prideaux et al 2022)

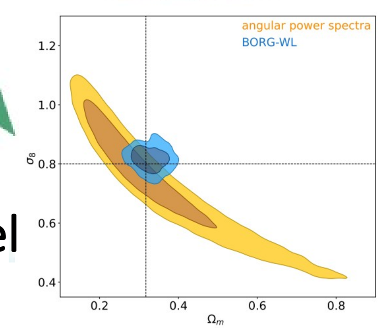
Lyman-α forest
(NP et al 2019)

BORG









Multiple probe analysis will become possible **at field level**

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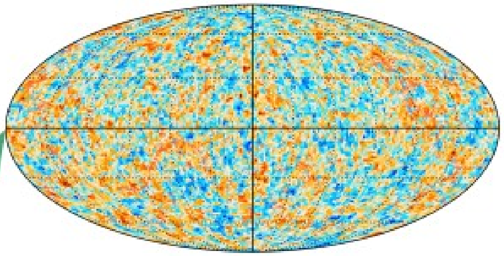

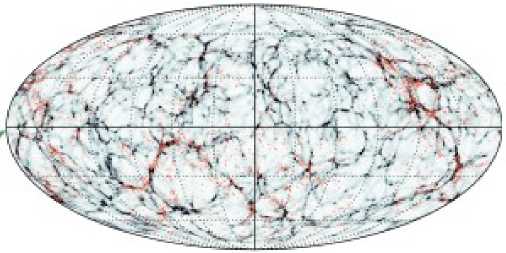

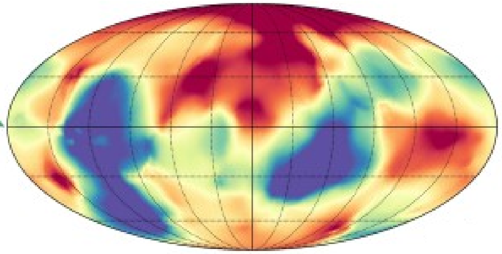

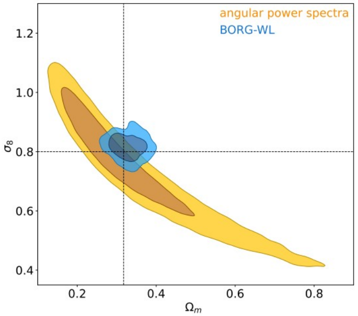

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BORG

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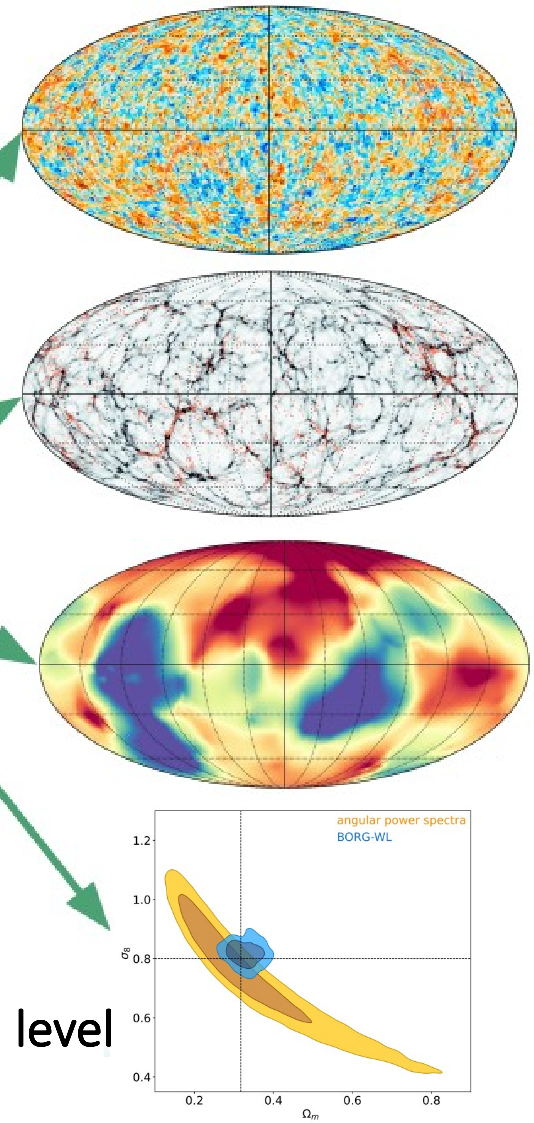

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Real data!

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(Jasche et al 2012)

towards
real data

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(NP et al 2021)

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BORG

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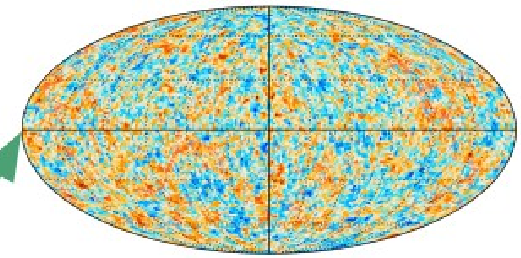
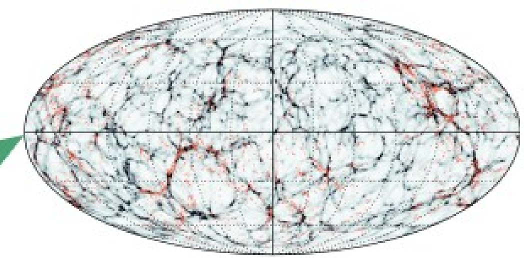
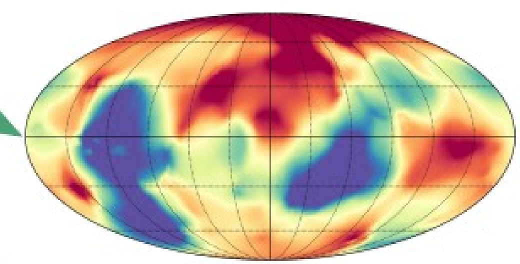
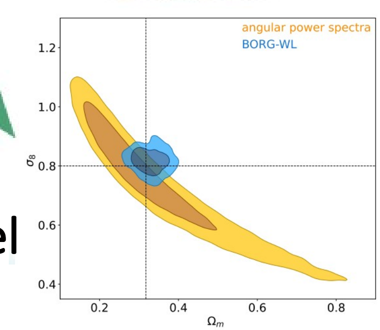








Multiple probe analysis will become possible **at field level**

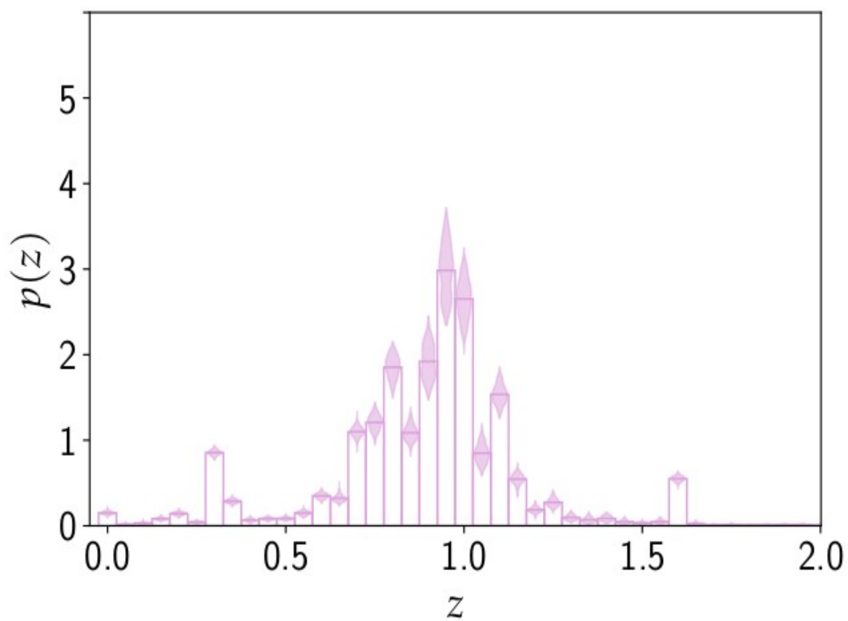
The challenge Dealing with systematics

Calibration systematics: robust n(z)

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

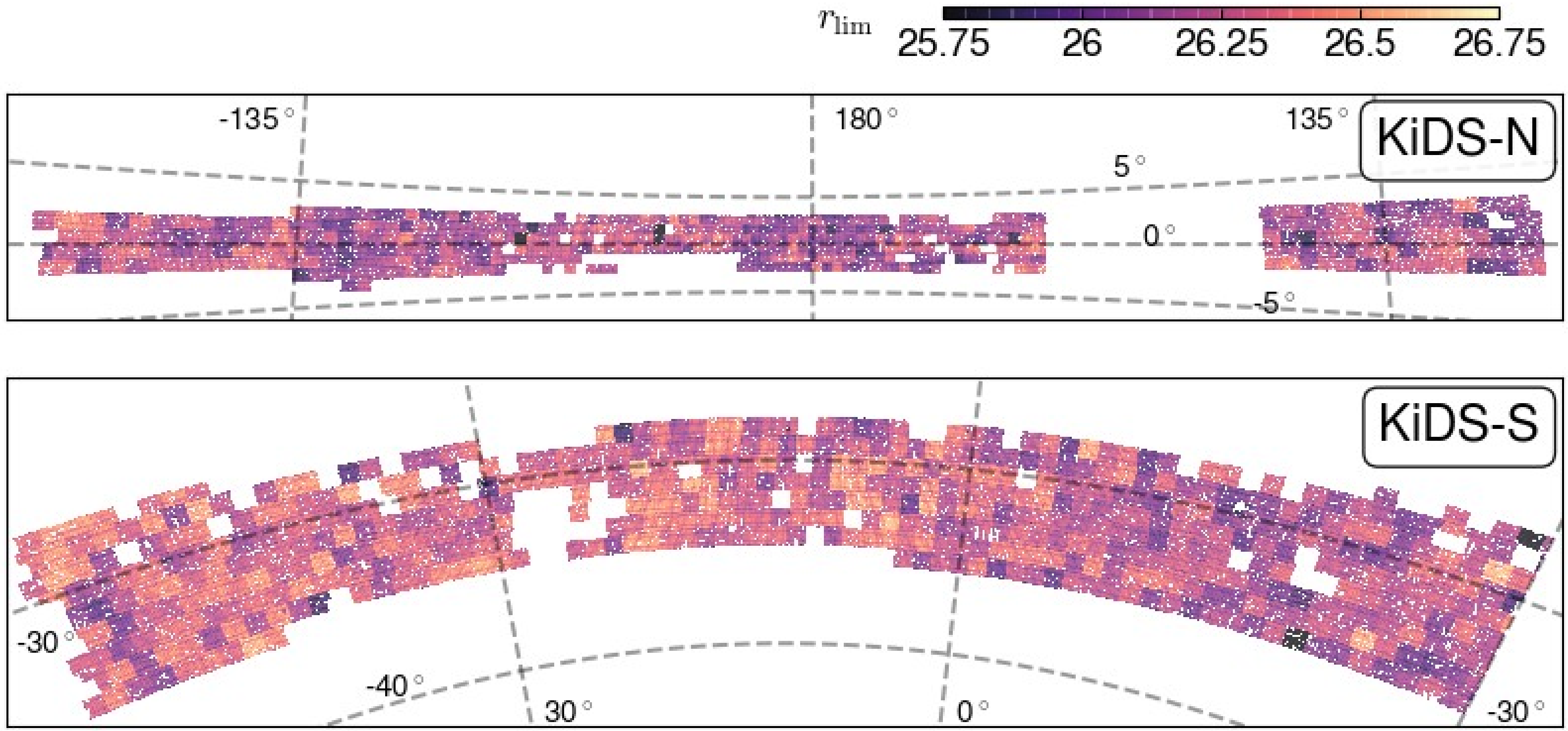
Bayesian hierarchical model to sample n(z) and marginalise over redshift uncertainties

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



Kyriacou, Heavens+ in preparation

Calibration systematics on the sky (survey depth)



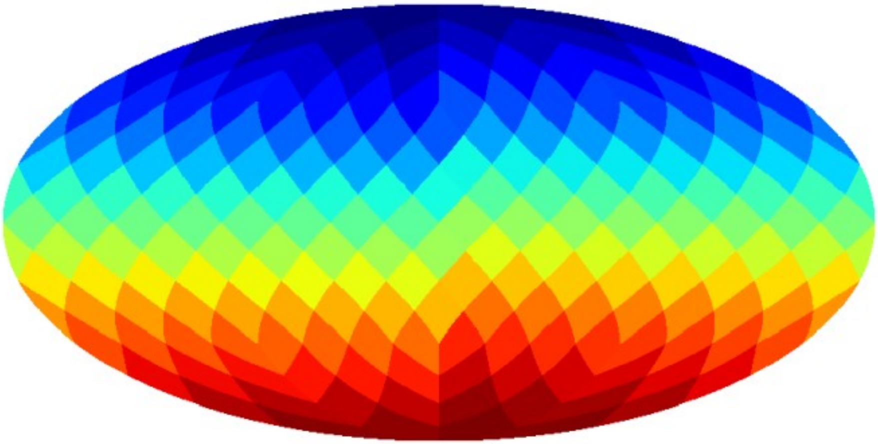
Joachimi+ 2020

- Variable depth
- Variable seeing (PSF)
- Variation in source galaxy and redshift distribution

Unknown systematics

Porqueres+ 2019
Lavaux, Jasche & Leclerq, 2019

Assuming amplitude of patch is unknown



For a Poisson likelihood:

$$P(\{N\}|\{\lambda\}) \propto \prod_{\text{patch}} \prod_{i \in \text{patch}} \left(\frac{\lambda_i}{\sum_{j \in \text{patch}} \lambda_j} \right)^{N_i}$$

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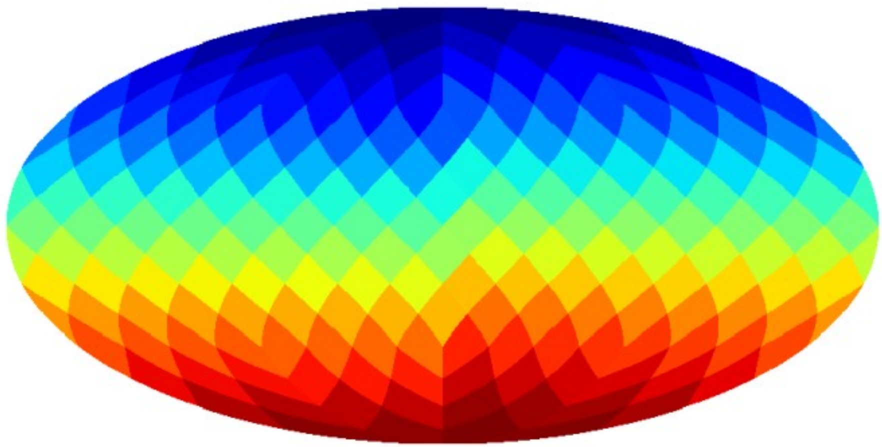
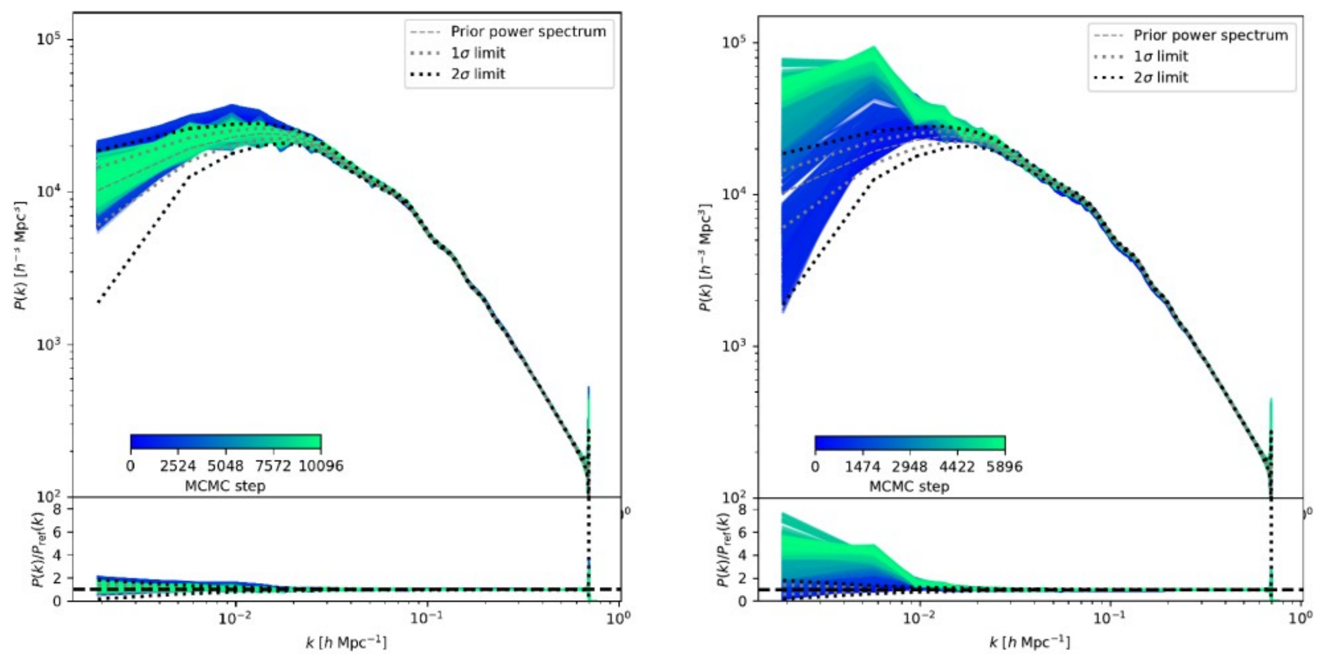
Lavaux, Jasche & Leclerq, 2019

Assuming amplitude of patch is unknown



For a Poisson likelihood:

$$P(\{N\}|\{\lambda\}) \propto \prod_{\text{patch}} \prod_{i \in \text{patch}} \left(\frac{\lambda_i}{\sum_{j \in \text{patch}} \lambda_j} \right)^{N_i}$$



(a) Robust likelihood

(b) Standard Poissonian likelihood

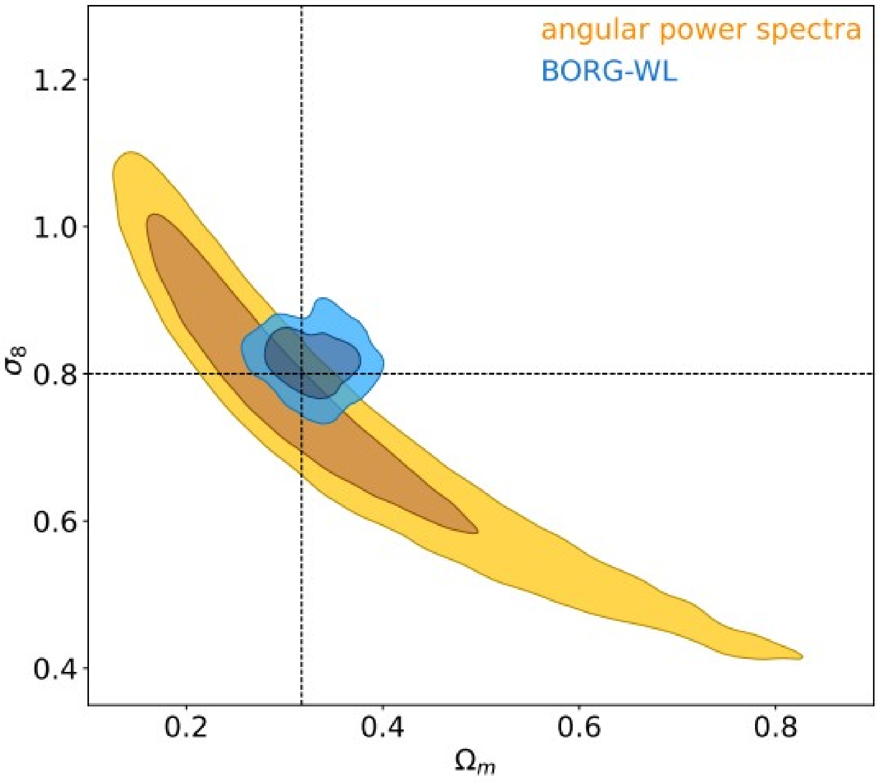
Natalia Porqueres

Summary

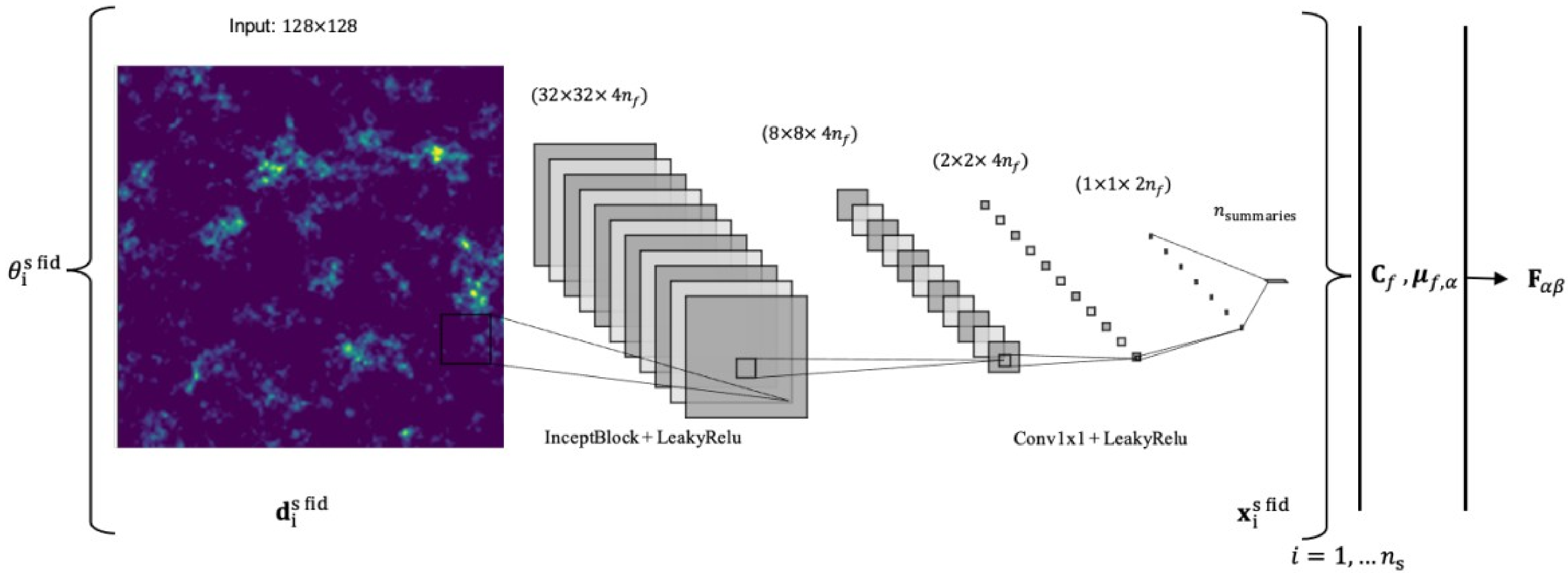
- There is more information in the data that the 2-point summary statistics do not capture.

- Field-based approach lifts degeneracy and reduces marginal error up to a factor of 5.

- What's next?
  First real data analysis with BORG-WL



Can we define a summary that extracts as much information?



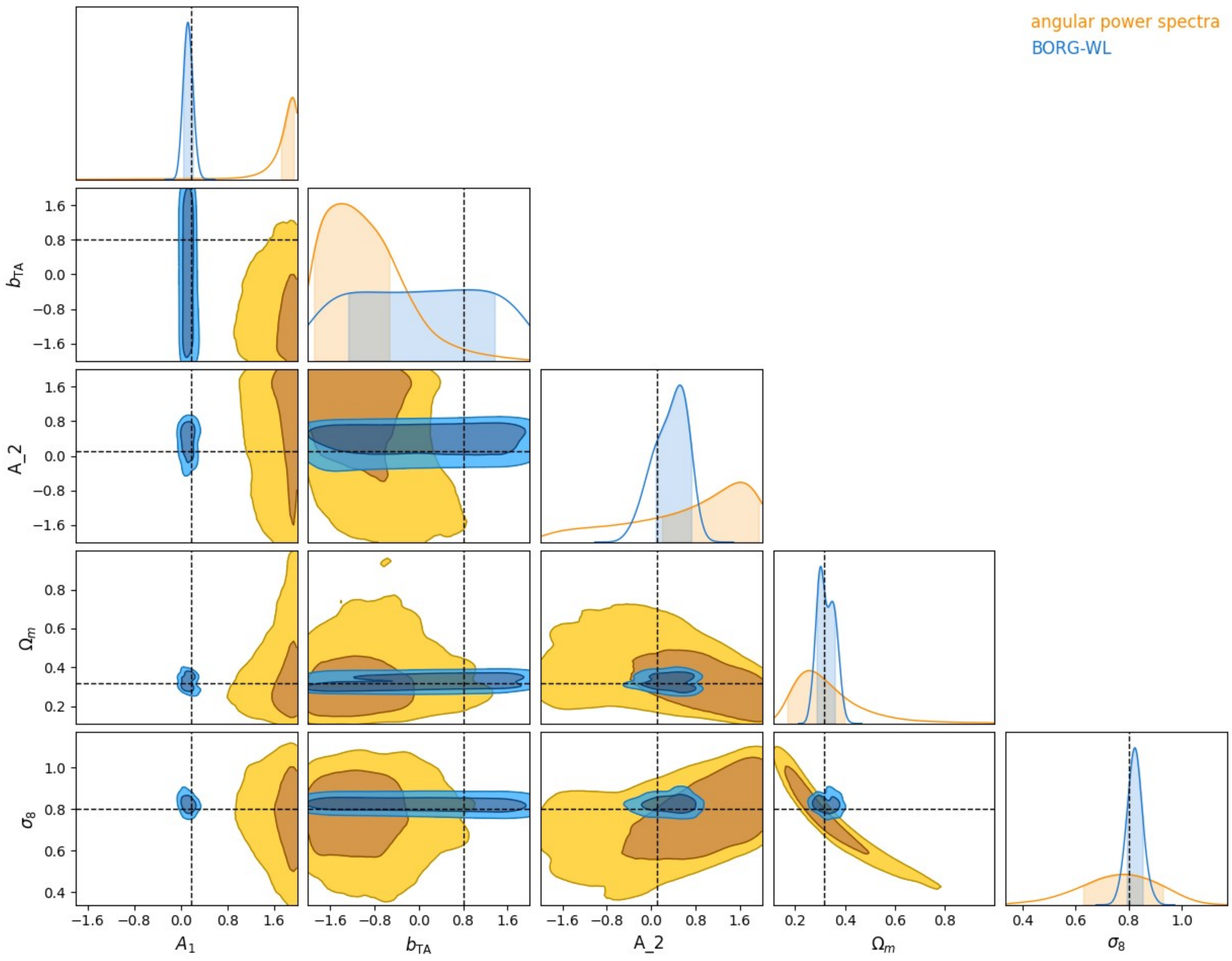
Lucas Makinen
(Imperial College)

Information Maximising Neural Networks (Charnock+2018)

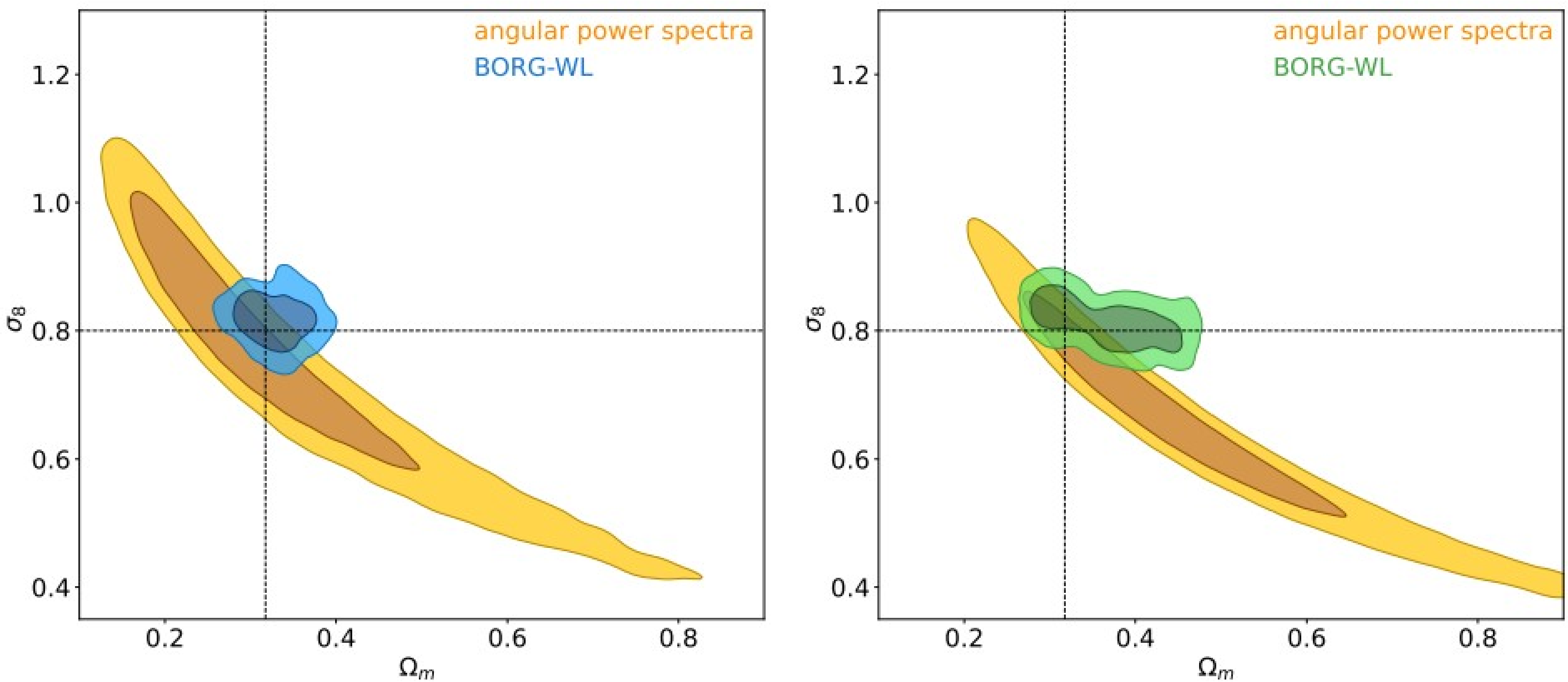
Compress data keeping Fisher matrix intact

$$\mathbf{F}_{\alpha\beta}(\boldsymbol{\vartheta}) = -\left\langle \frac{\partial^2 \ln \mathcal{L}(\mathbf{d}|\boldsymbol{\vartheta})}{\partial\vartheta_\alpha \partial\vartheta_\beta} \right\rangle \Bigg|_{\boldsymbol{\vartheta}=\boldsymbol{\vartheta}^{\mathrm{fid}}}$$

Posterior distribution Cls vs BORG-WL



Model misspecification intrinsic alignments

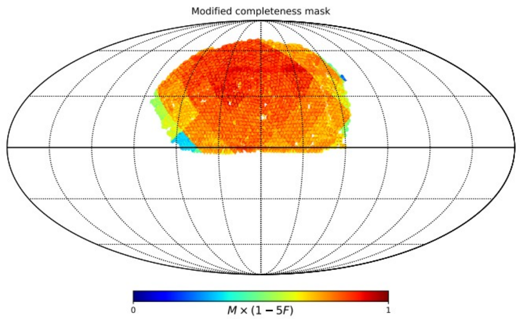


data: TATT, analysis: TATT

data: TATT, analysis: NLA

Robust likelihood

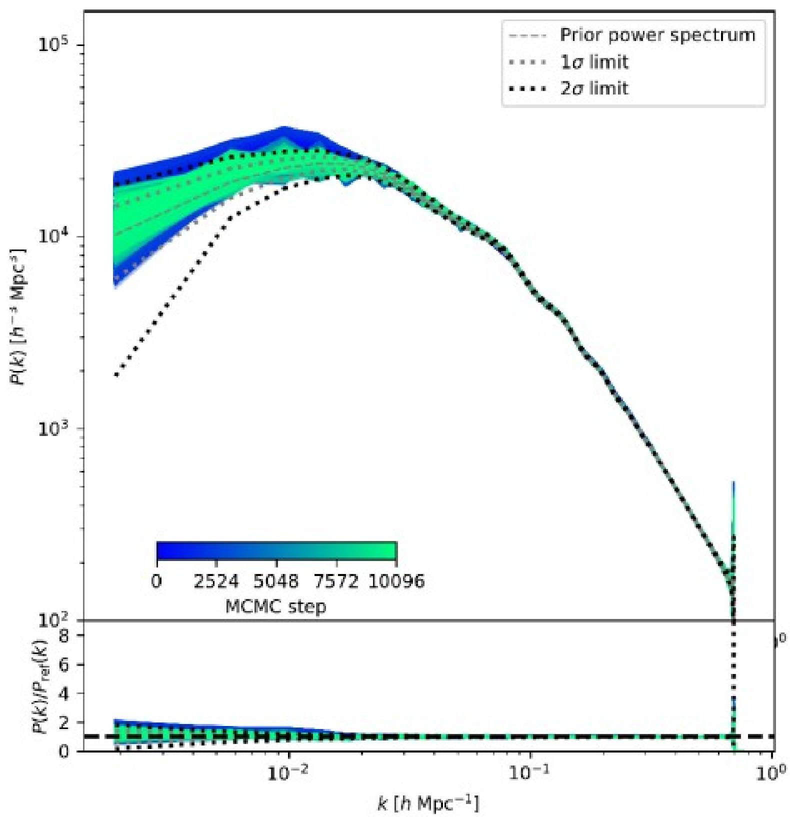
(Porqueres, Ramanah, Jasche, Lavaux, 2018)



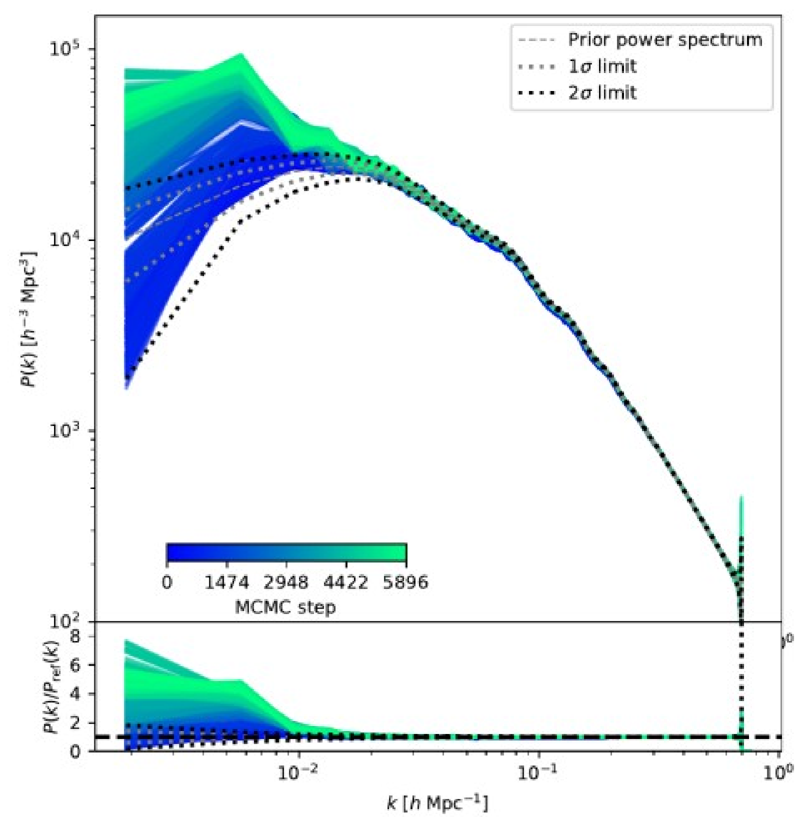
$$\lambda_c = A_c \bar{\lambda}_c$$

$$\downarrow$$

$$P(N|\lambda) = \prod_i \frac{e^{-\lambda_i}(\lambda_i)^{N_i}}{N_i!}$$



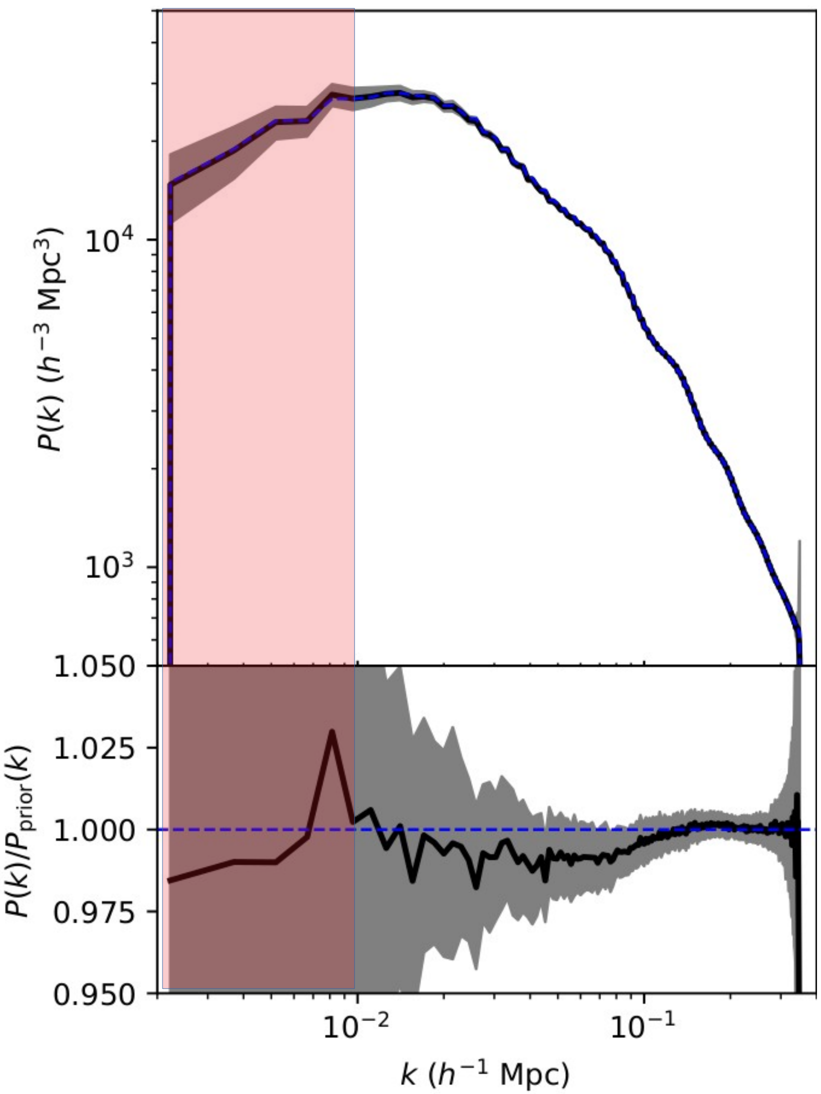
(a) Robust likelihood

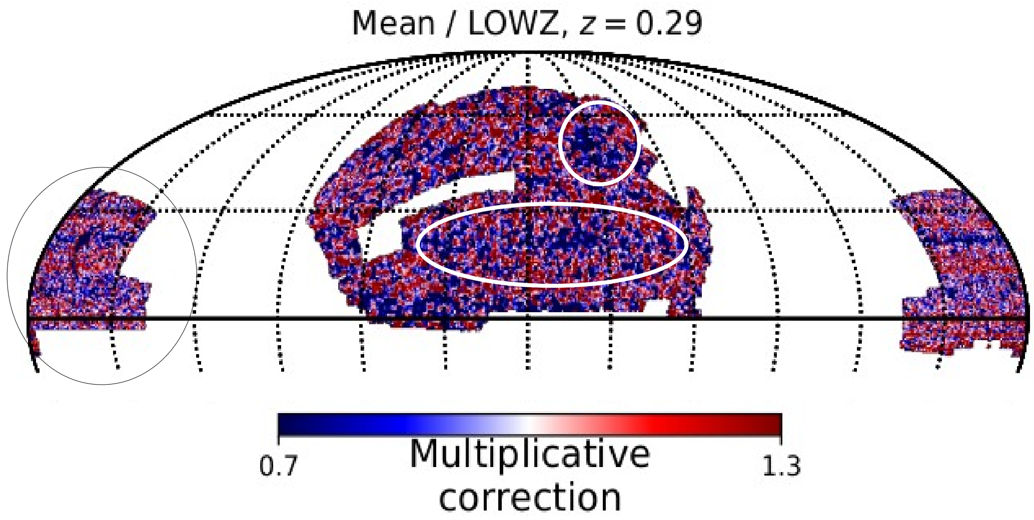


(b) Standard Poissonian likelihood

Robust likelihood: SDSS-III analysis

(Lavaux, Jasche, Leclercq, 2019)





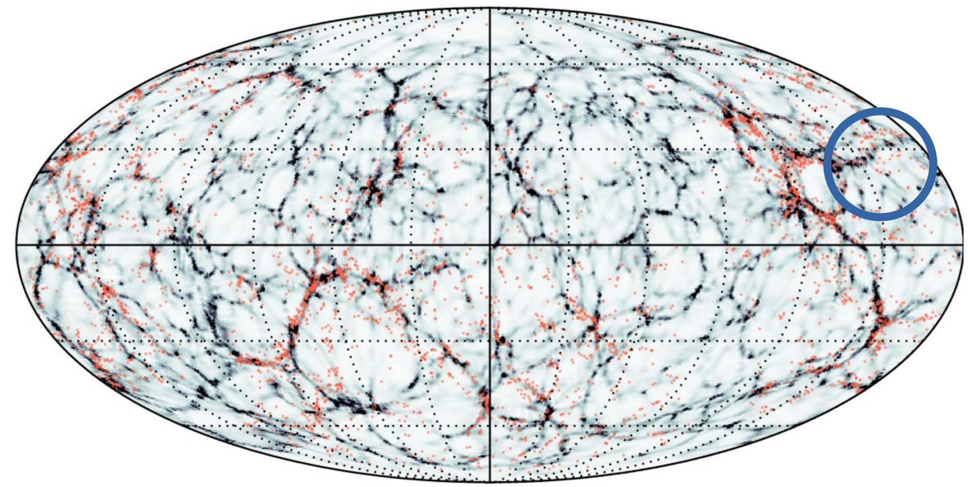
Validating the results of a real data analysis

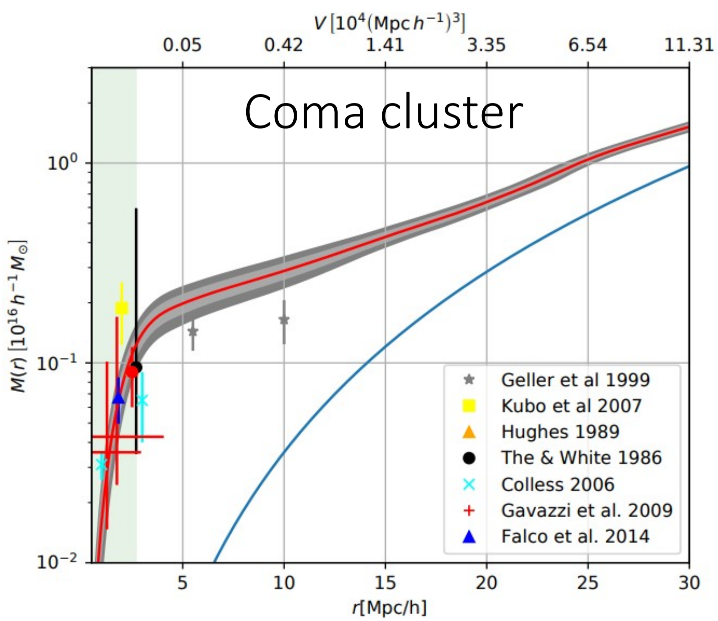
Posterior predictive tests and cross-validation with independent measurements

- do we get the clusters we know are there?

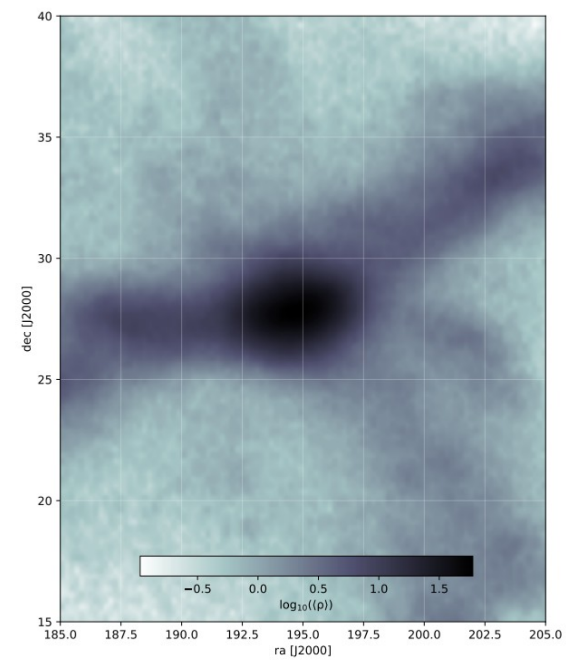
- do we get the expected mass profiles?

- are the inferred IC compatible with CMB?





Jasche & Lavaux 2019

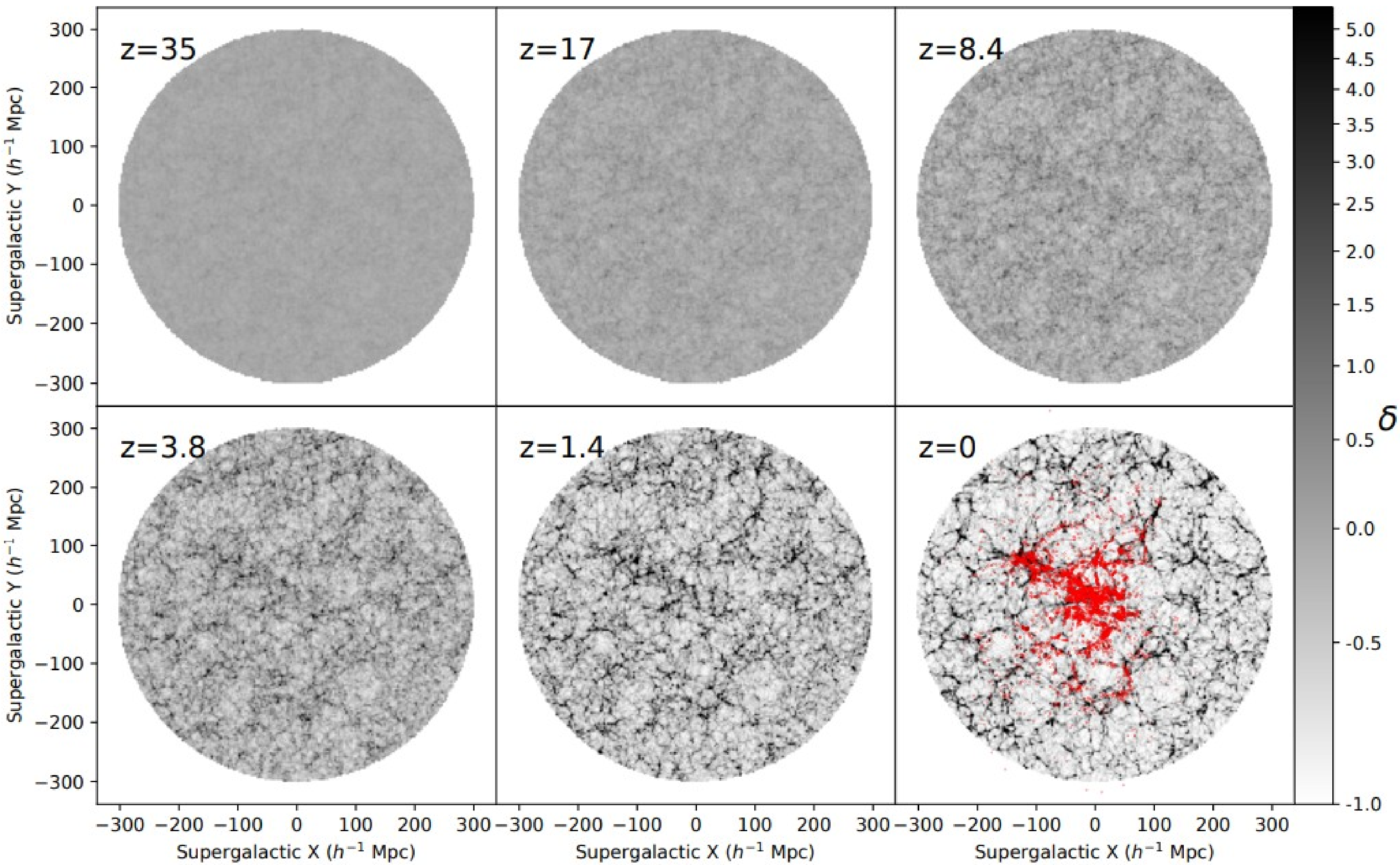


Jasche & Lavaux 2019

Natalia Porqueres

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

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What if the models of systematics are not good enough?

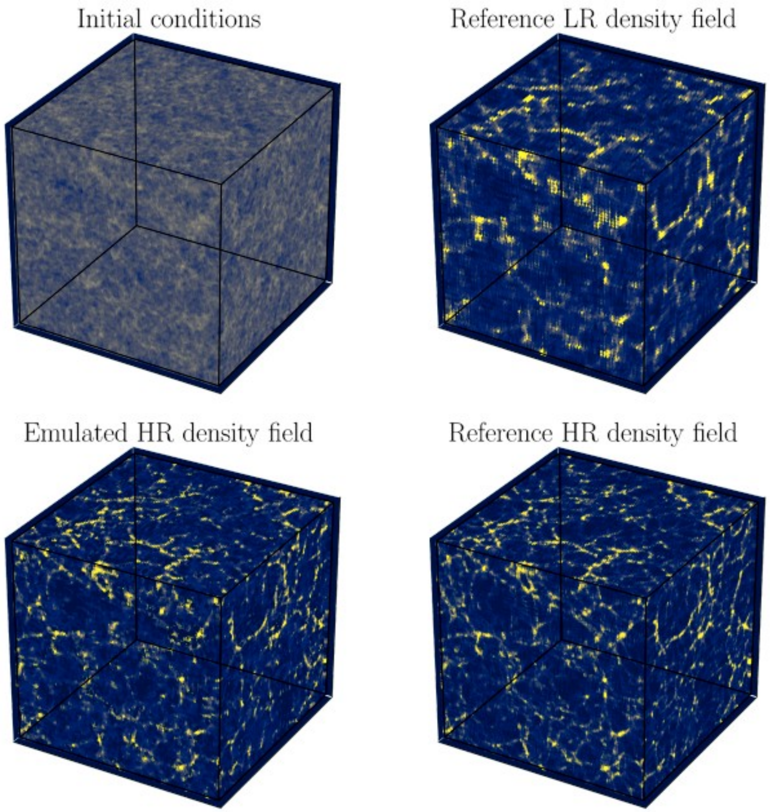
Machine learning can help connecting physical models to data

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



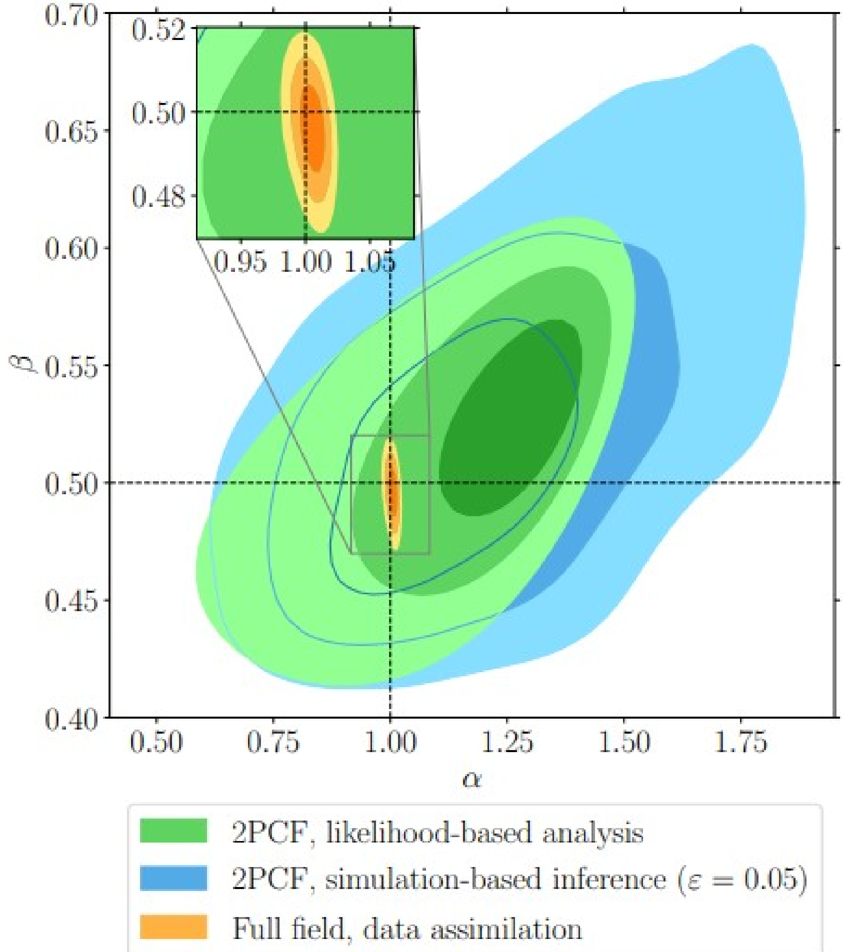
Charnock+ 2019

Table of cosmological constraints

	Power spectra	BORG-WL	
Ω_{m}	$0.3^{+0.5}_{-0.2}$	$0.34^{+0.07}_{-0.05}$	Factor 5
σ_8	$0.6^{+0.4}_{-0.3}$	$0.79^{+0.11}_{-0.11}$	Factor 3
S_8	$0.80^{+0.15}_{-0.10}$	$0.83^{+0.10}_{-0.10}$	Factor 1.2

Where does the information come from?

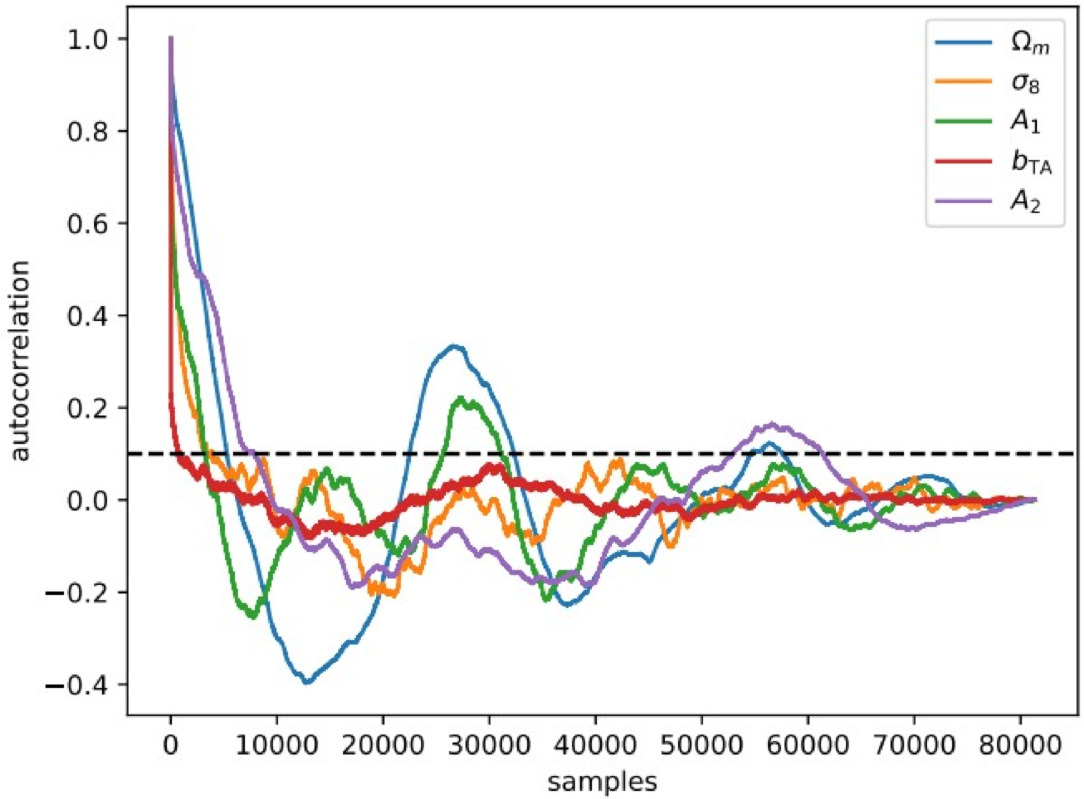
For a log-normal field:



Field-based approach: **more precise** for even nearly Gaussian fields.

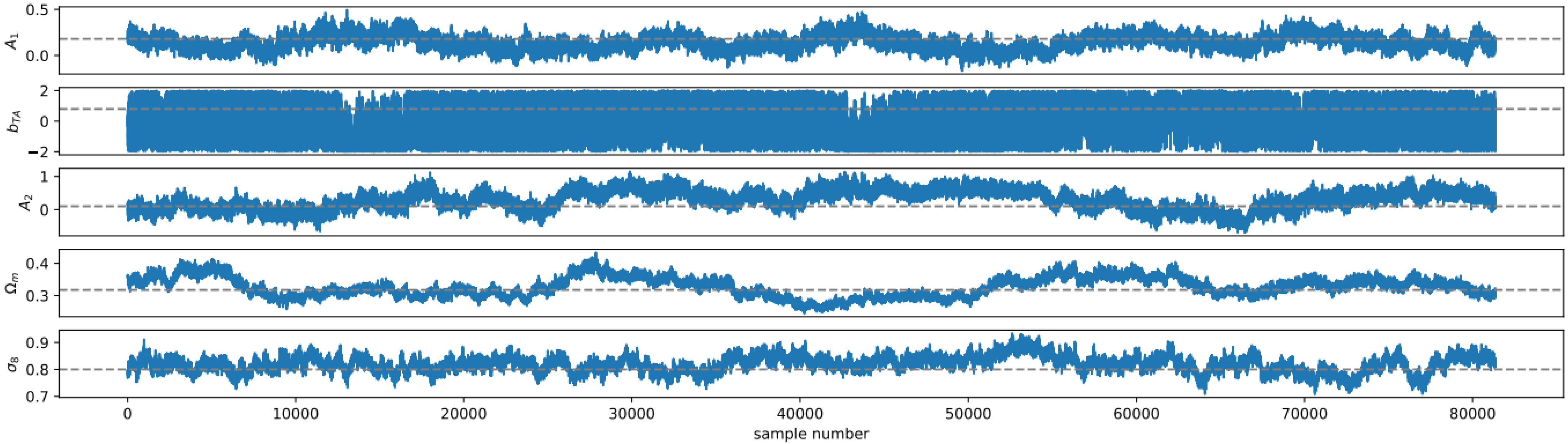
Leclercq & Heavens (2021)

Convergence test and correlation length



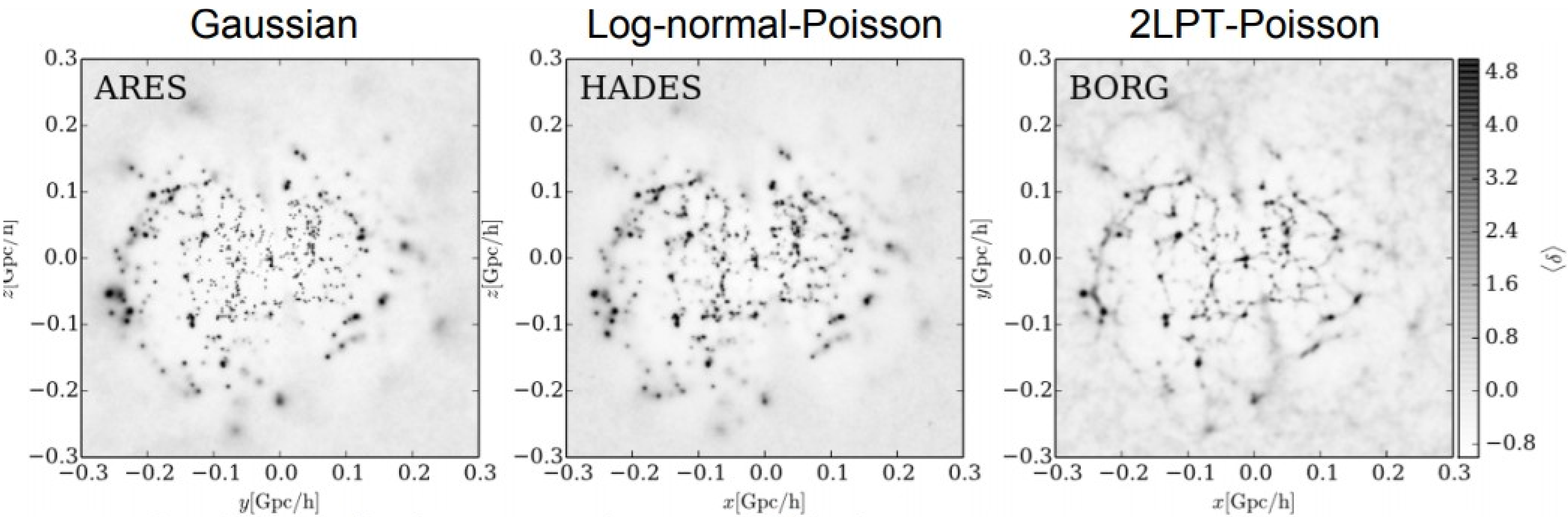
Gelman-Rubin test < 1.04 for all cosmological parameters

Trace plots



A_1
0.5
0.0
b_{TA}
2
0
−2
A_2
1
0
Ω_m
0.4
0.3
σ_8
0.9
0.8
0.7
0
10000
20000
30000
40000
50000
60000
70000
80000
sample number

Comparison between field-based approaches (J. Jasche)



a.k.a: Wiener-filtering
Zaroubi et al. 1994
Erdogdu et al. 2004
Kitaura & Ensslin 2008
Grannet et al. 2015

log-normal-filtering

Kitaura 2010
Jasche & Kitaura 2010

Jasche&Wandelt 2012

Which scheme performs best?

Ask the data!

$$A_{ij} = \ln\left(\mathcal{P}(d|\delta_i)\right) - \ln\left(\mathcal{P}(d|\delta_j)\right)$$

	ARES	HADES	BORG
ARES	0	-219580.31	-383482.25
HADES	219580.31	0	-163901.94
BORG	383482.25	163901.94	0.

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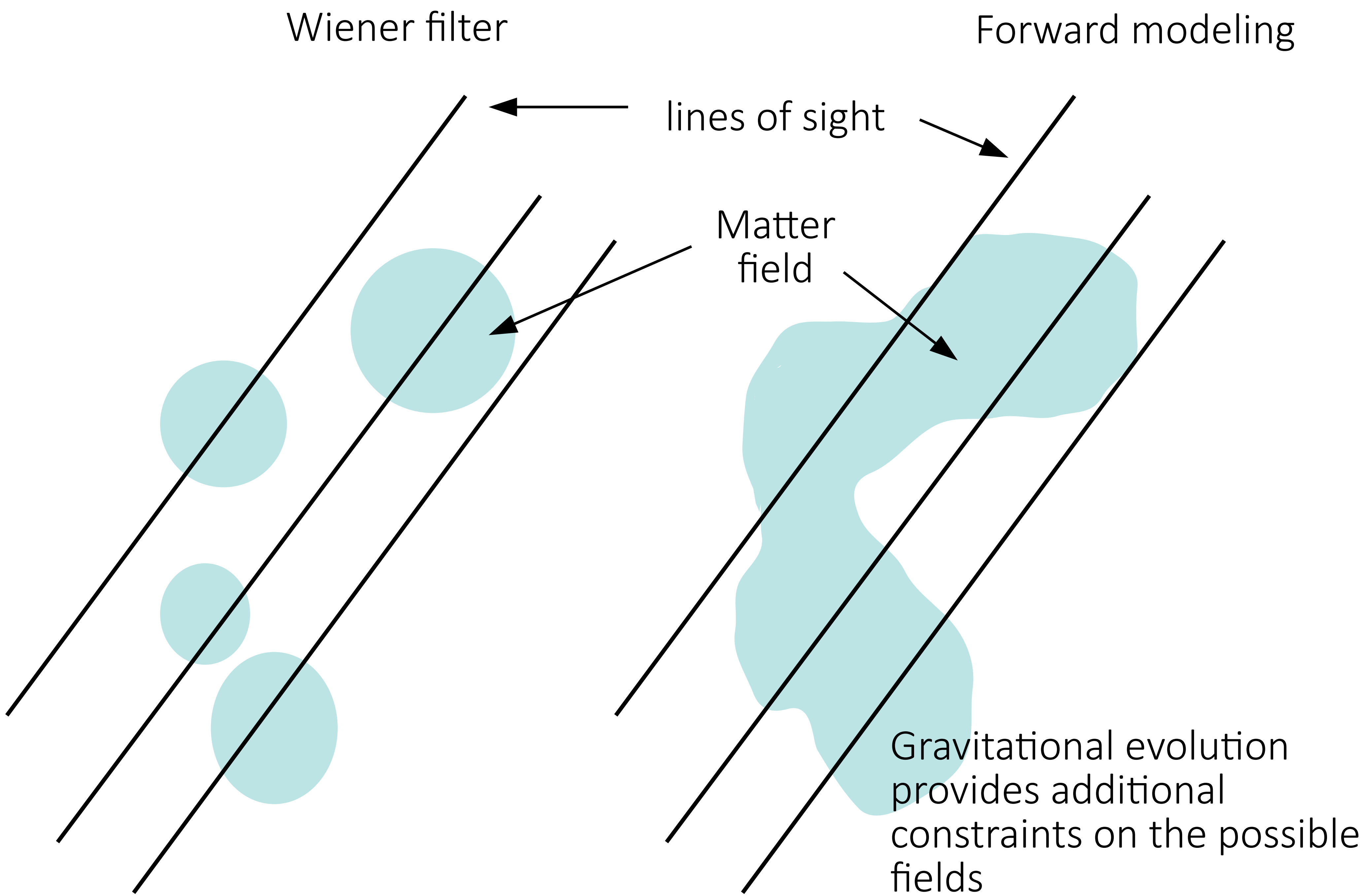


Natalia Porqueres

Hamiltonian Monte Carlo

Define potential $\psi = -\ln(P(x))$

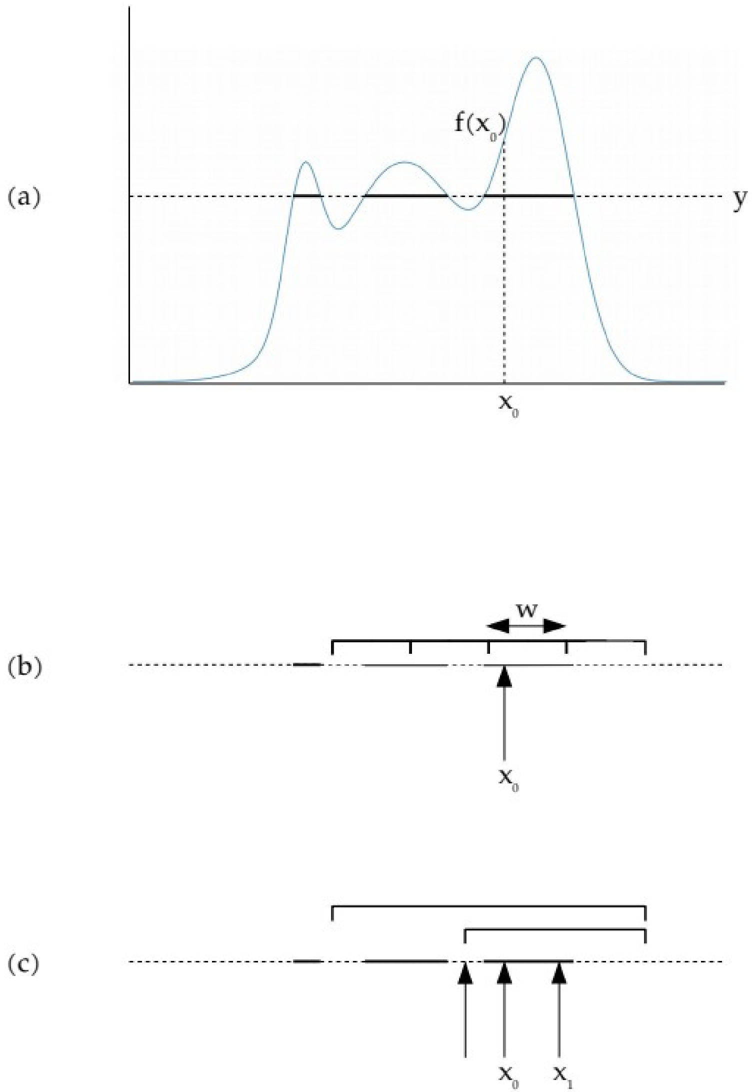
Define Hamiltonian $H = \frac{1}{2}\mathbf{p}^T\mathbf{M}^{-1}\mathbf{p} + \psi(x)$

Use mechanics:

$$(x, p) \longrightarrow \boxed{\begin{aligned} \frac{d\mathbf{x}}{dt} &= \frac{\partial H}{\partial \mathbf{p}} = \mathbf{M}^{-1}\mathbf{p} \\ \frac{d\mathbf{p}}{dt} &= -\frac{\partial H}{\partial \mathbf{x}} = -\frac{\partial \psi(x)}{\partial \mathbf{x}} \end{aligned}} \longrightarrow (x', p')$$

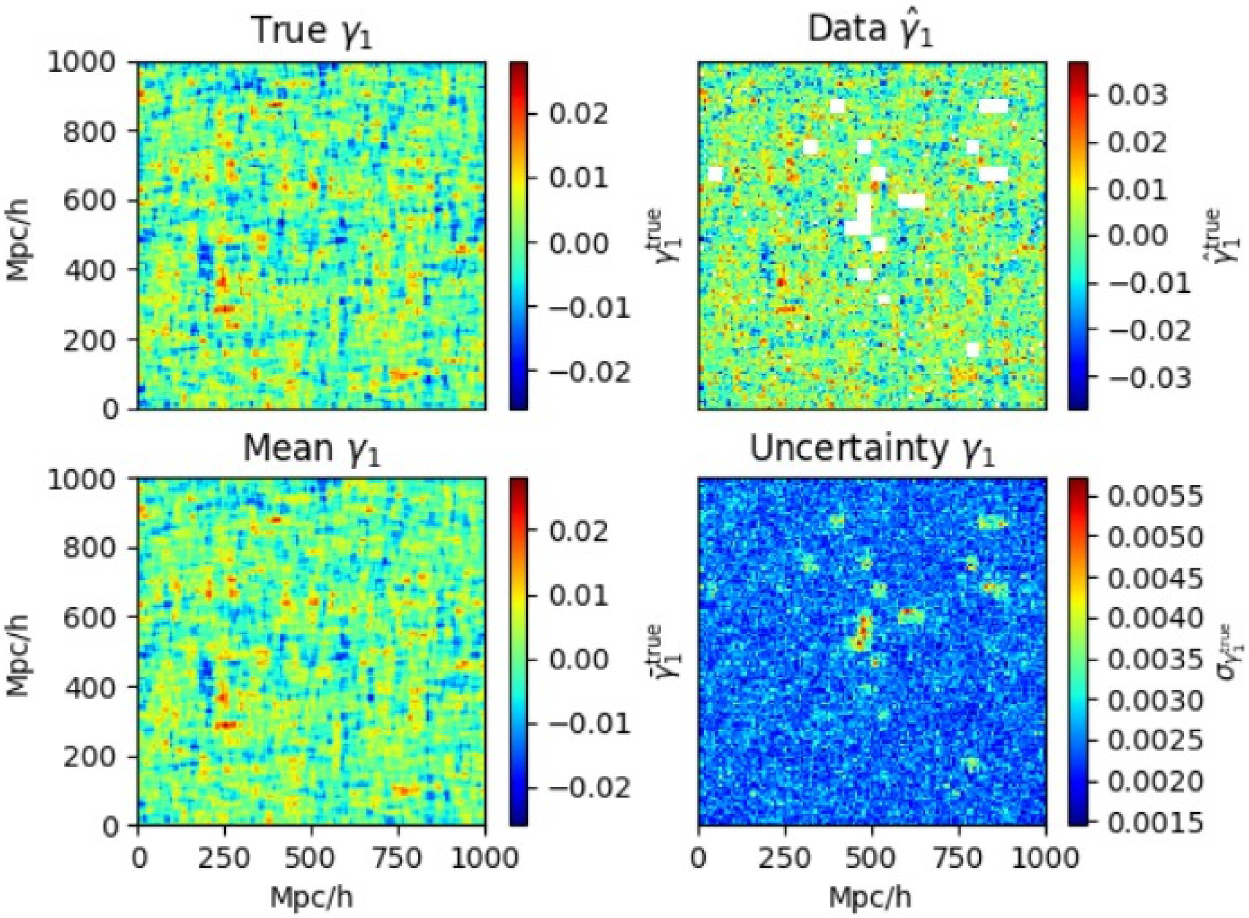
Randomise momentum and accept $\alpha = \min[1, e^{-(H-H')}] = 1$

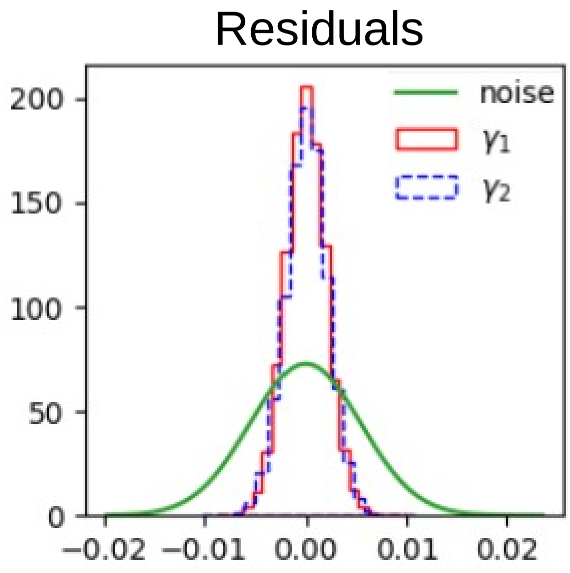
Slice sampler



MCMC algorithm

Test with mask

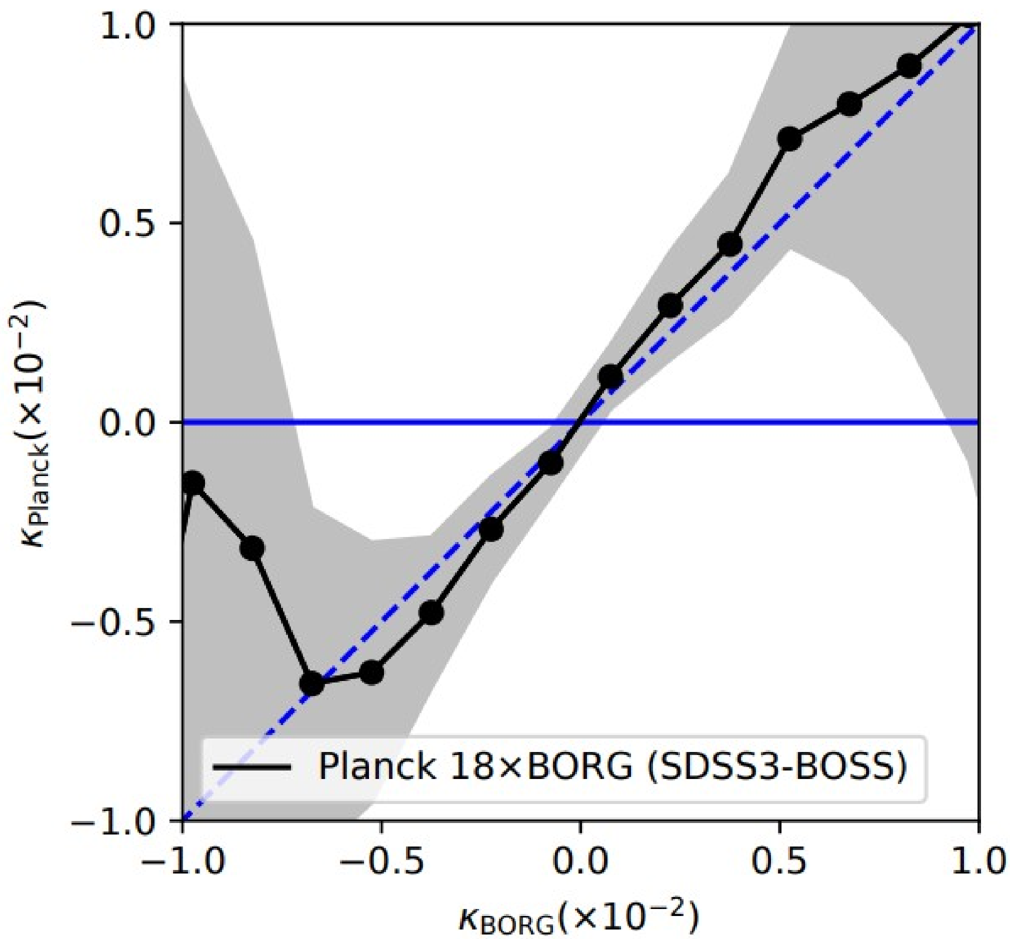




Inferred quantities explain data to sub-noise level

CMB lensing

(Lavaux, Jasche & Leclercq, 2019)



SDSS-III/BOSS

Sampling efficiently in a high-dimensional space

Hamiltonian Monte Carlo
- density field

Slice sampler
- cosmological parameters
- nuisance parameters
- systematics

Define potential $\psi = -\ln(P(x))$

Hamiltonian $H = \frac{1}{2}\mathbf{p}^T\mathbf{M}^{-1}\mathbf{p} + \psi(x)$

Use mechanics to solve a statistical problem:

$$\frac{d\mathbf{x}}{dt} = \frac{\partial H}{\partial \mathbf{p}} = \mathbf{M}^{-1}\mathbf{p}$$

$$\frac{d\mathbf{p}}{dt} = -\frac{\partial H}{\partial \mathbf{x}} = -\frac{\partial \psi(x)}{\partial \mathbf{x}}$$

Addresses curse of dimensionality by
- exploiting information in gradients
- using conserved quantities

The challenge for upcoming surveys

Upcoming surveys will provide large volumes of **high-quality data**.

→ unprecedented statistical power.

→ great potential for discoveries.

But…

→ existing methods are reaching their limits.

→ good control of systematics becomes paramount.

We need **new data analysis techniques** to fully realise the potential of these surveys.

- Higher-order statistics: what are the sampling distributions? And covariance matrix?
- Field-based approach without data compression of the pixelised shear.