# Towards robust Bayesian inference (**`ROBIN`**) using physics-informed priors from cosmological simulations

**Ludvig Doeser,** Simon Ding, Guilhem Lavaux, Jens Jasche

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Oskar Klein centre

Stockholms Universitet

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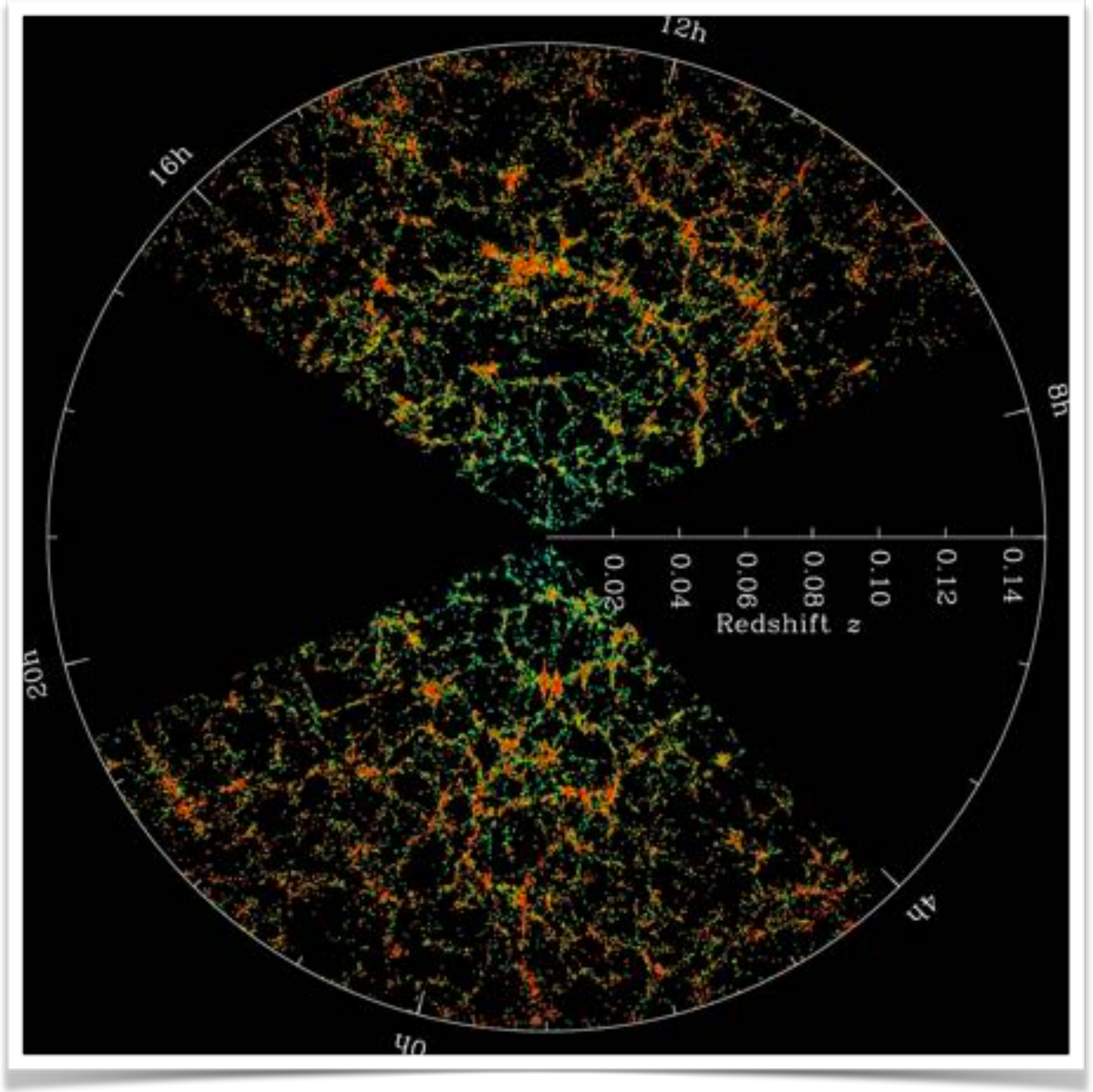
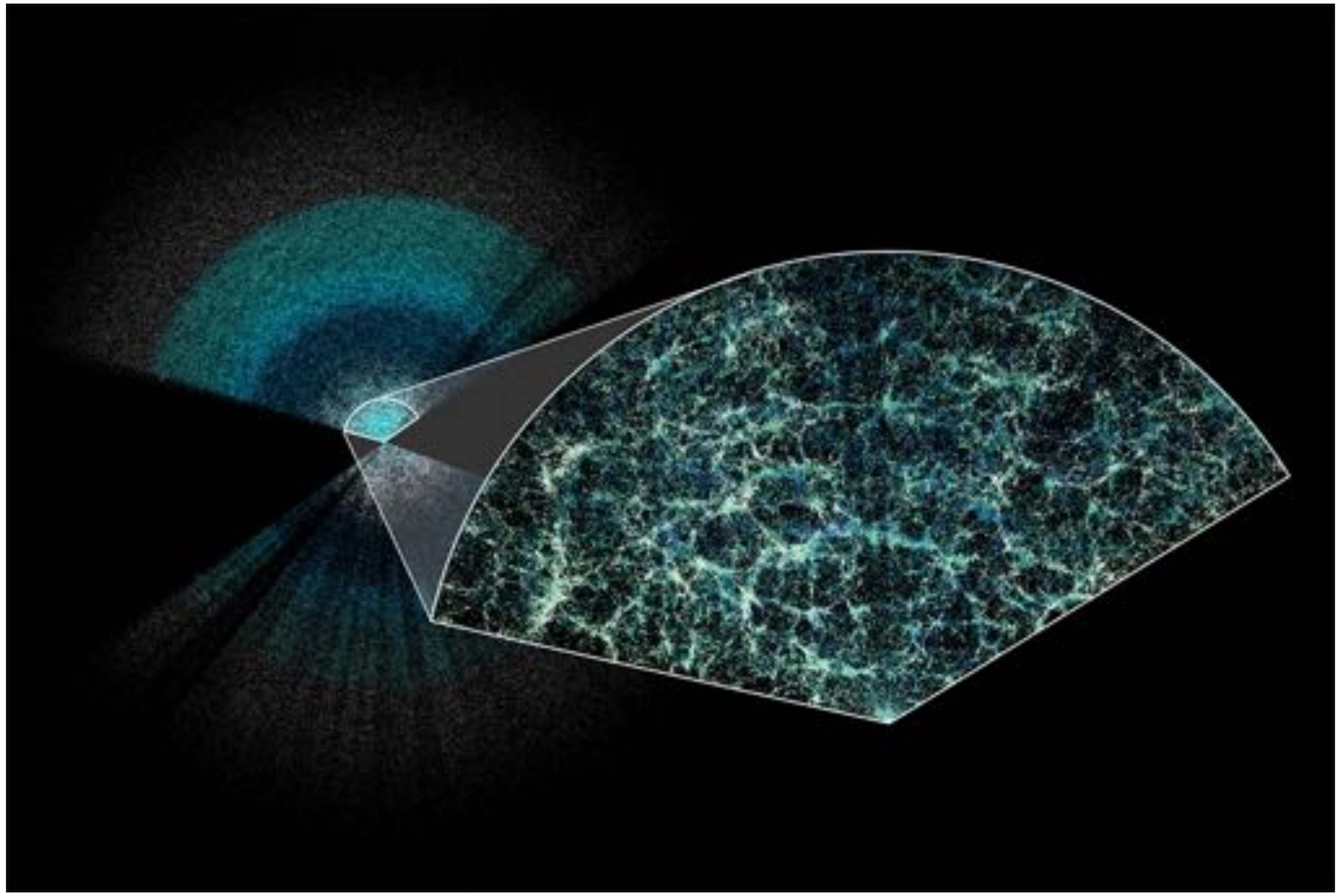
# **Aim:** Cosmological inference with the large-scale structure

- **Data:** Galaxy redshift surveys; unprecedented amount of data with Stage IV-surveys




**SDSS**



Credit: Claire Lamman/DESI collaboration

**DESI**

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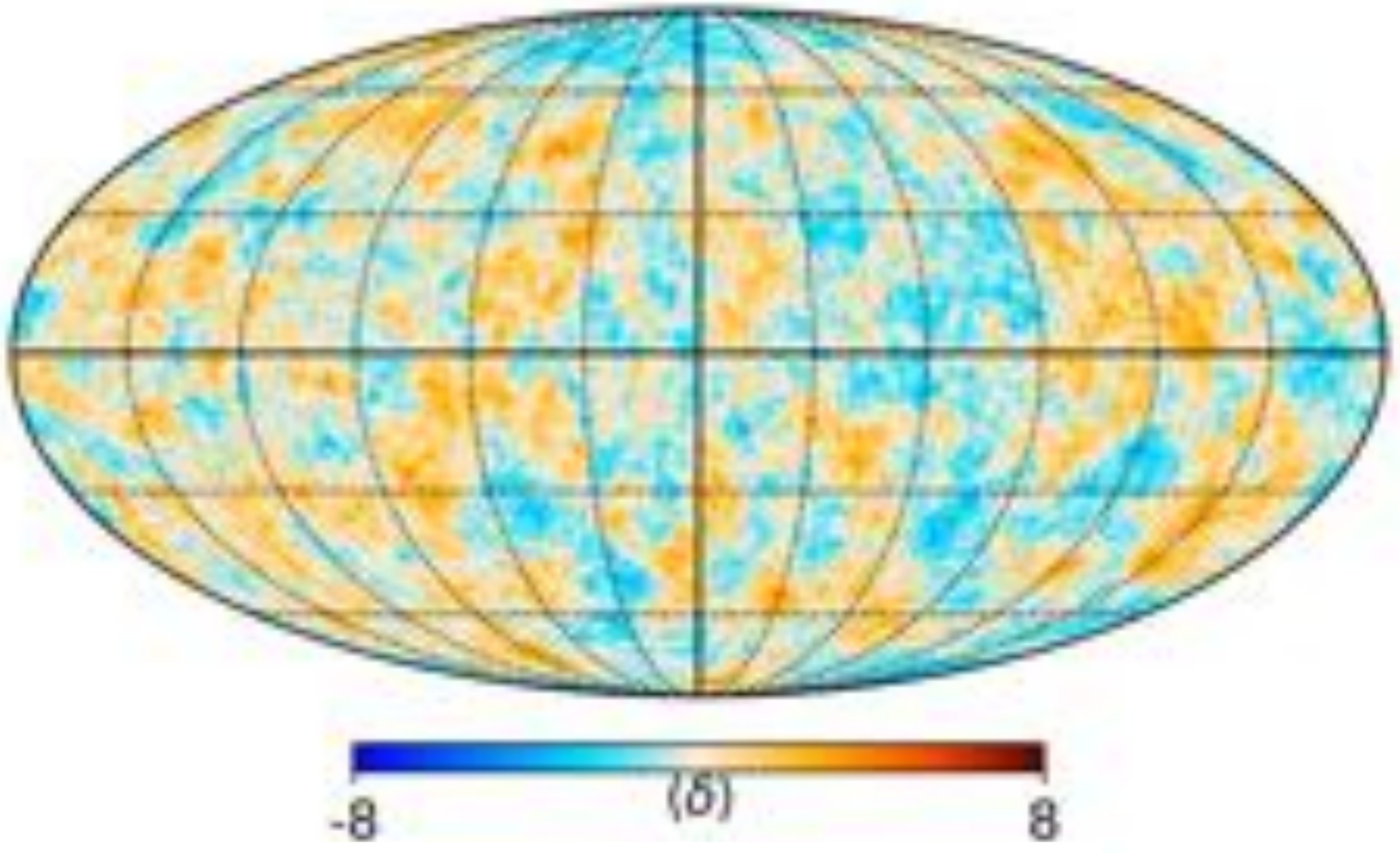
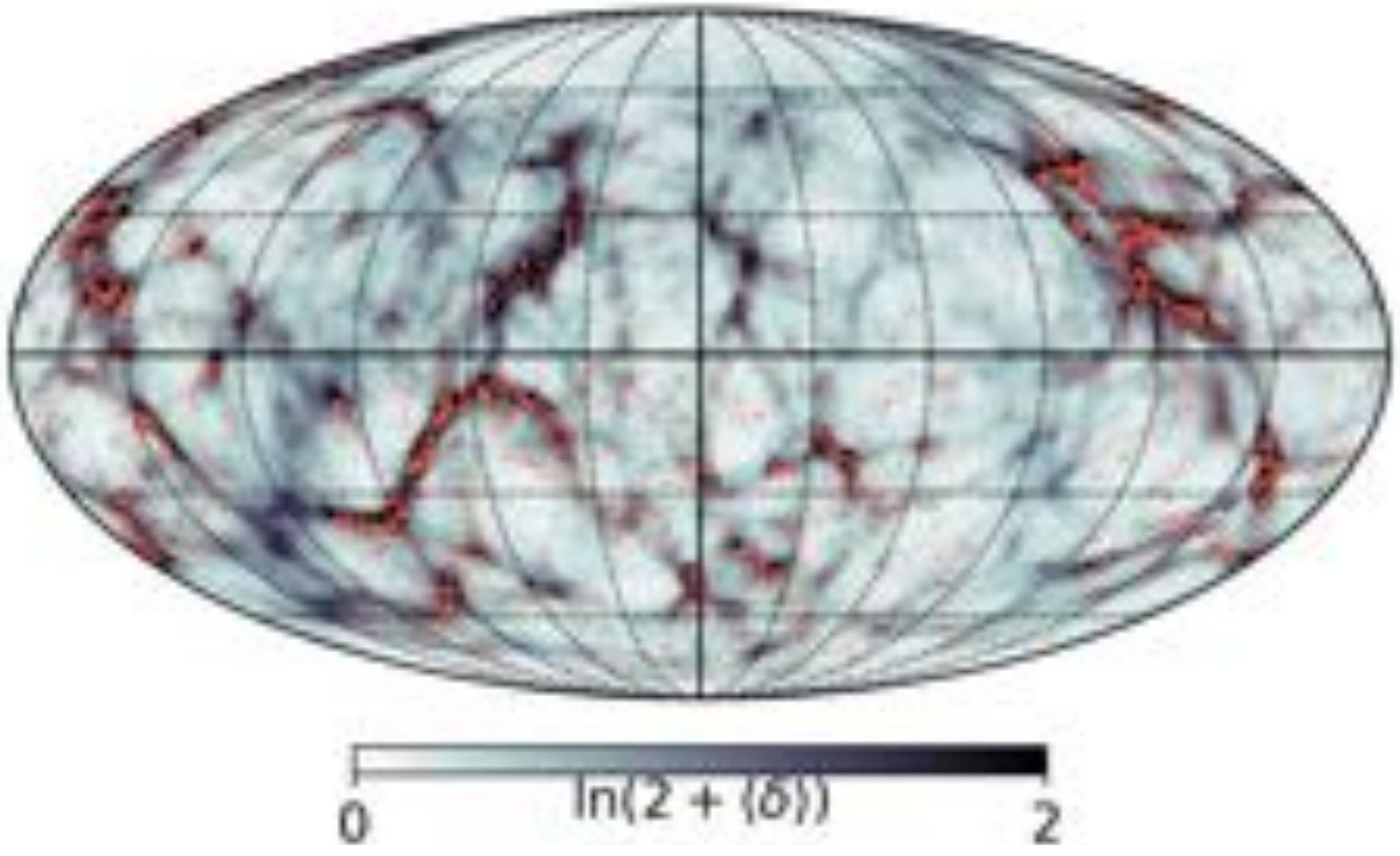
- **Optimal information extraction*:** Field-level analysis see e.g. Jasche & Lavaux 2019, * Leclercq & Heavens 2021




Inferred primordial density field




Inferred evolved density field + observed galaxies

Jasche & Lavaux 2019

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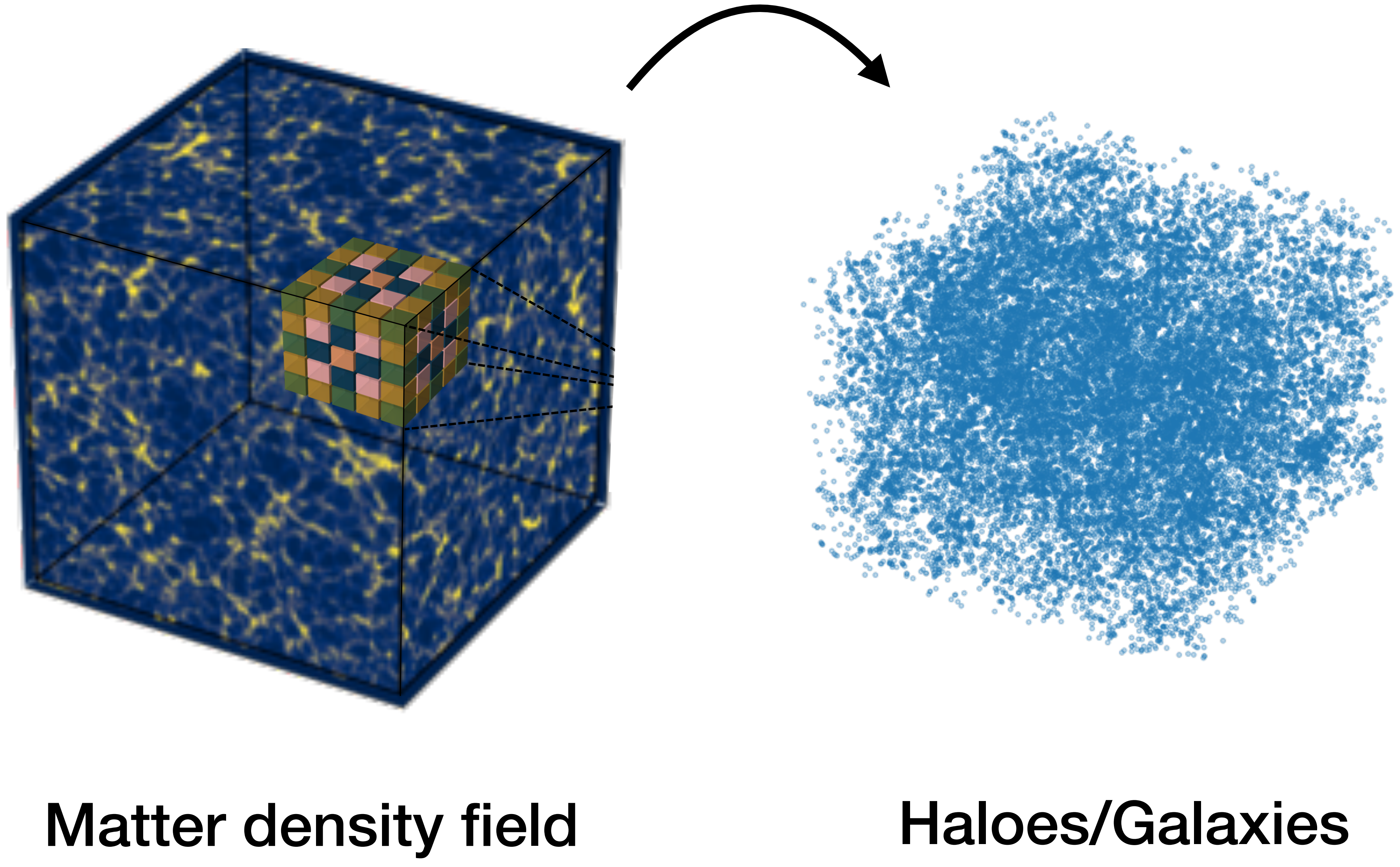
- **Bottleneck:** **Galaxy bias model:** Challenging at the field-level
  - Local bias insufficient, e.g. Bartlett, Ho, & Wandelt 2024
  - Resort to ML models, e.g. Doogesh et al 2018, Charnock et al 2019

* Leclercq & Heavens 2021




Ding et al 2024 (in prep)

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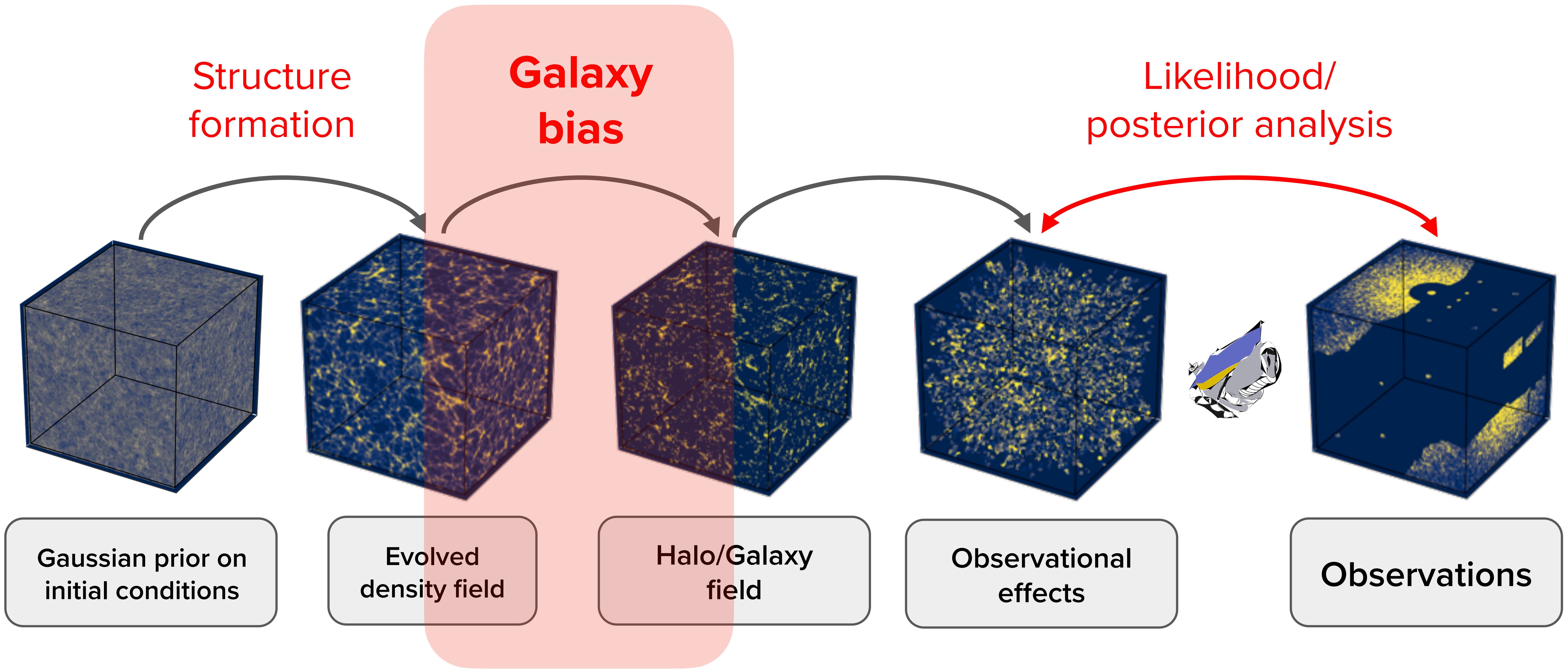
  - Local bias insufficient, e.g. Bartlett, Ho, & Wandelt 2024
  - Resort to ML models, e.g. Doogesh et al 2018, Charnock et al 2019
  - Training neural galaxy bias model on the fly (zero-shot) as pre-training locks to specific simulations
  - Only have one Universe! Data not enough to constrain both physics and neural network parameters
- **Solution: Incorporate physics constraints by imposing knowledge from simulations**
  - Use physics-informed prior to guide/regularize neural network parameter exploration

**Model agnostic approach**

# Field-level inference with BORG



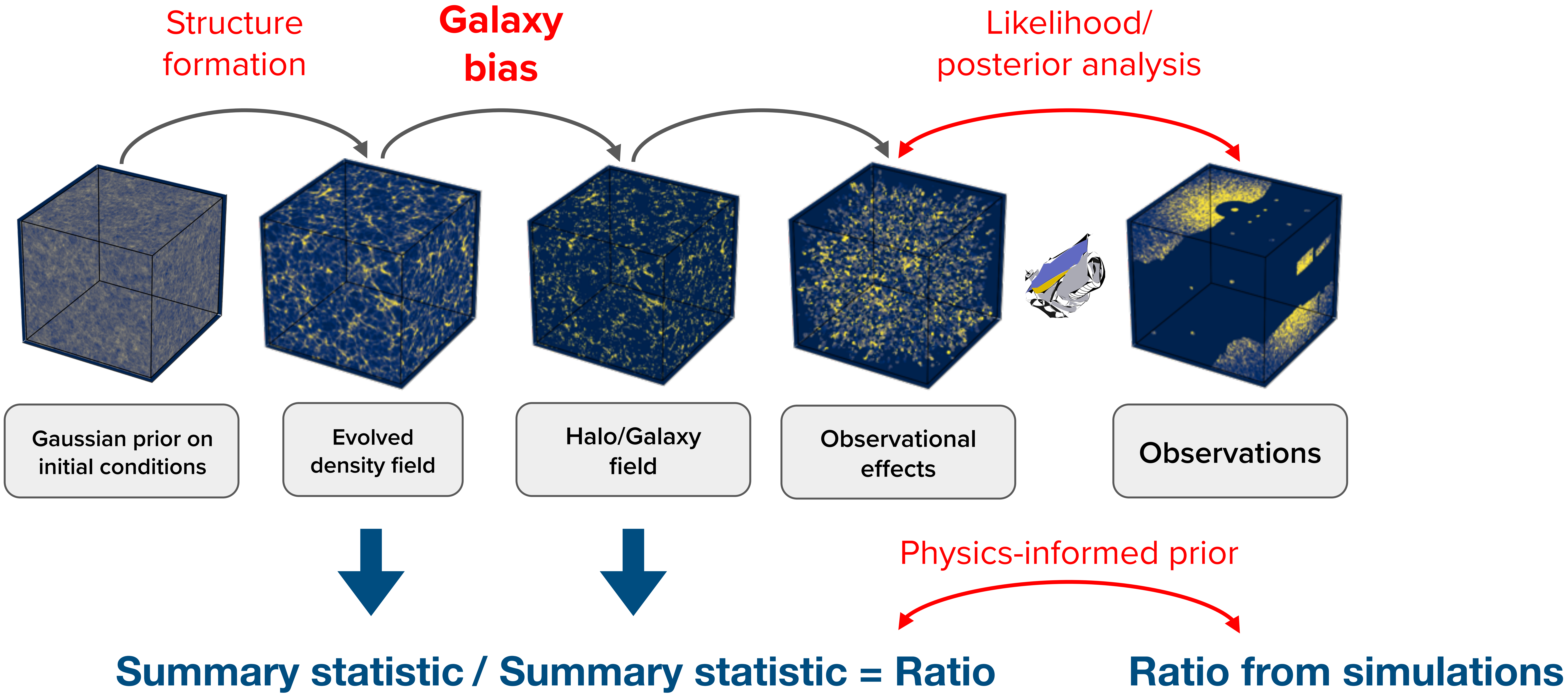

- Hierarchical Bayesian framework
- **Differentiable** data model at the field level
- Non-compressed exploration of posterior of initial conditions

Jasche & Wandelt 2014,
Jasche, Leclercq, & Wandelt 2015,
Jasche & Lavaux 2019

**Bayesian Origin Reconstruction from Galaxies**
https://www.aquila-consortium.org/

# **ROBIN** at field-level using **physics-informed prior**

**RObust Bayesian INference**



# Distilling knowledge from simulations

**From inferring the bias parameters $\alpha$ from data $d$ alone**

$$\pi(\alpha \mid d) = \frac{\pi(d \mid \alpha)\boxed{\pi(\alpha)}}{\pi(d)}$$

**to also constrain with $\boxed{\text{physics-informed prior } r}$**

$$\pi(\alpha \mid d, r) = \frac{\pi(d, r \mid \alpha)\pi(\alpha)}{\pi(d, r)} = \frac{\pi(d \mid \alpha)}{\pi(d)} \frac{\pi(r \mid \alpha)\pi(\alpha)}{\pi(r)} = \frac{\pi(d \mid \alpha)\boxed{\pi(\alpha \mid r)}}{\pi(d)} \propto \pi(d \mid \alpha)\underline{\pi(r \mid \alpha)}\pi(\alpha)$$

Bayes Law

Conditional Independence

Bayes Law

ROBIN likelihood

**New likelihood term $\pi(r \mid \alpha)$**

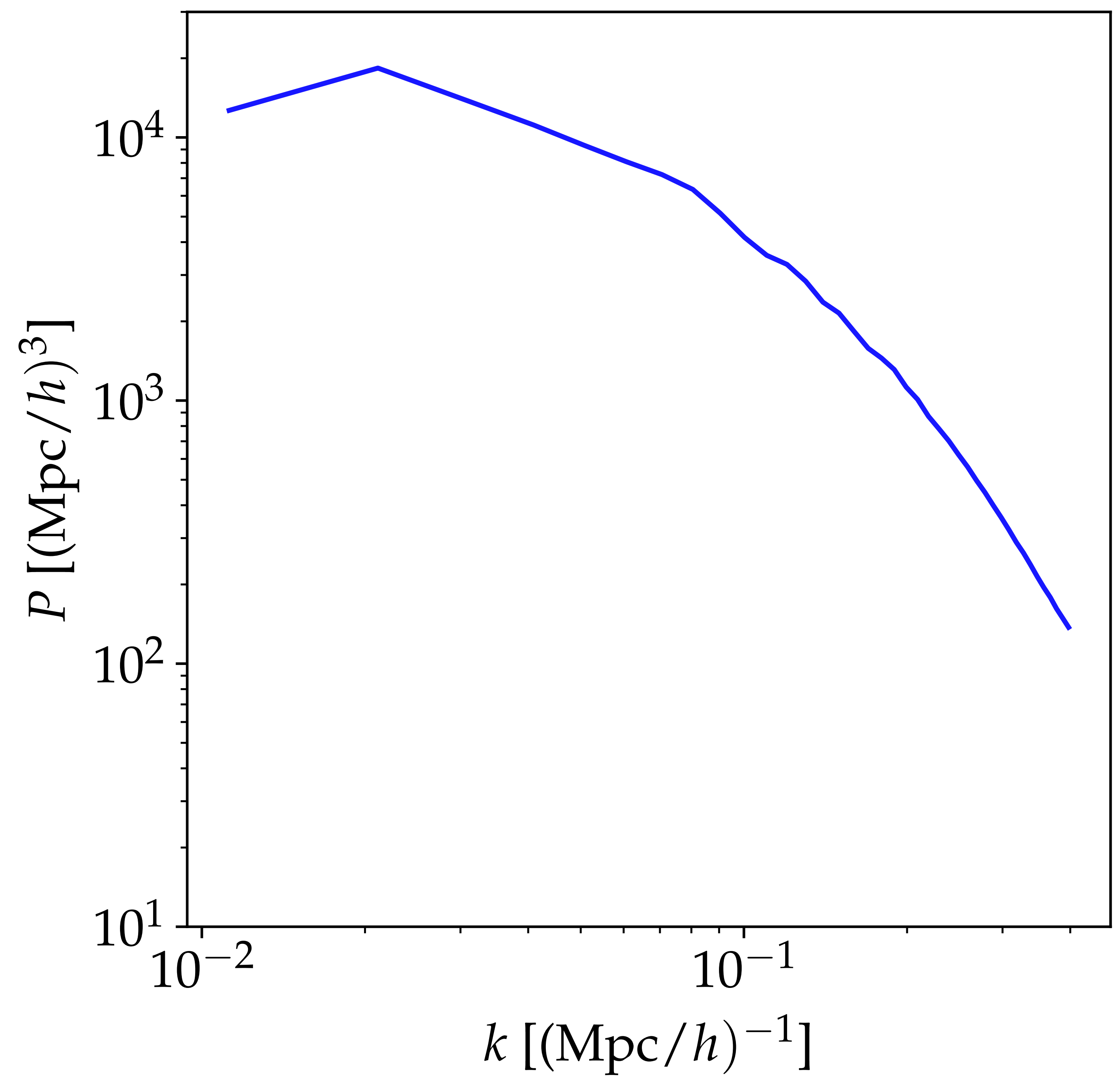
- Can pick any statistics; for proof-of-concept pick power spectrum ratio:

$$r = \frac{P_\mathrm{m}(k)}{P_\mathrm{h}(k)}$$

# Proof of concept with power-spectrum ratio

$$r = \frac{P_m(k)}{P_h(k)}$$

**Matter density field**

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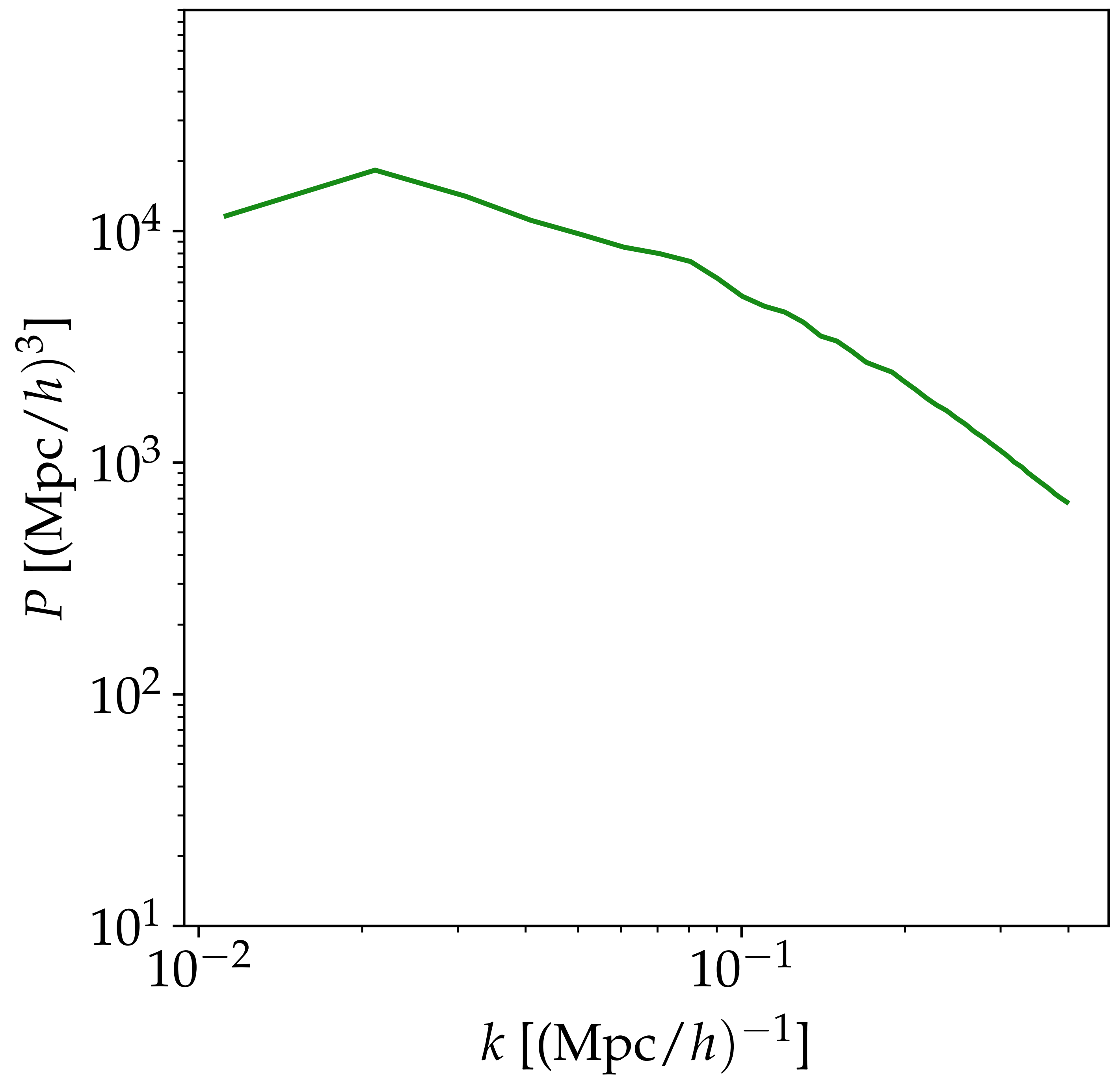
**Haloes**

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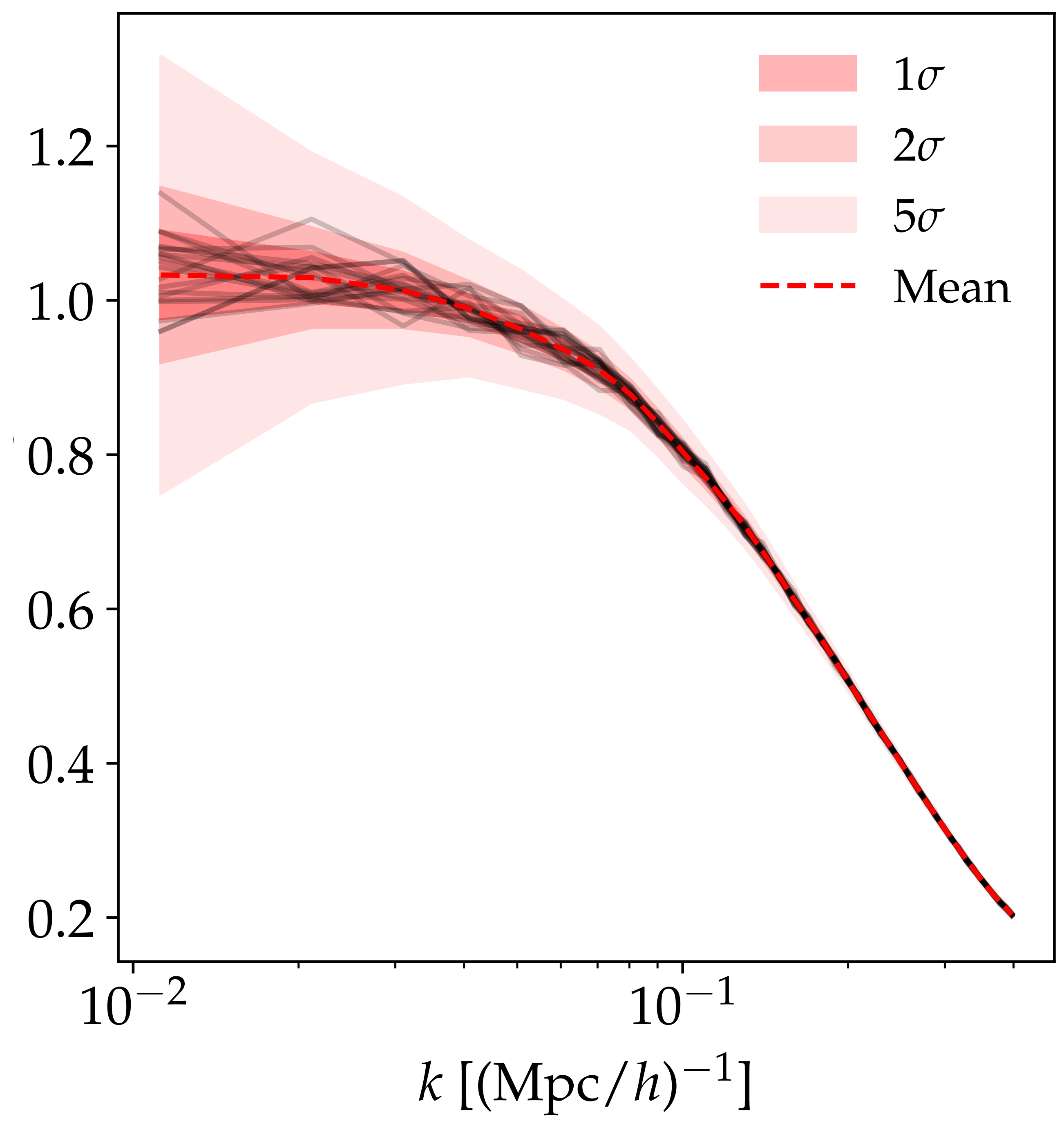
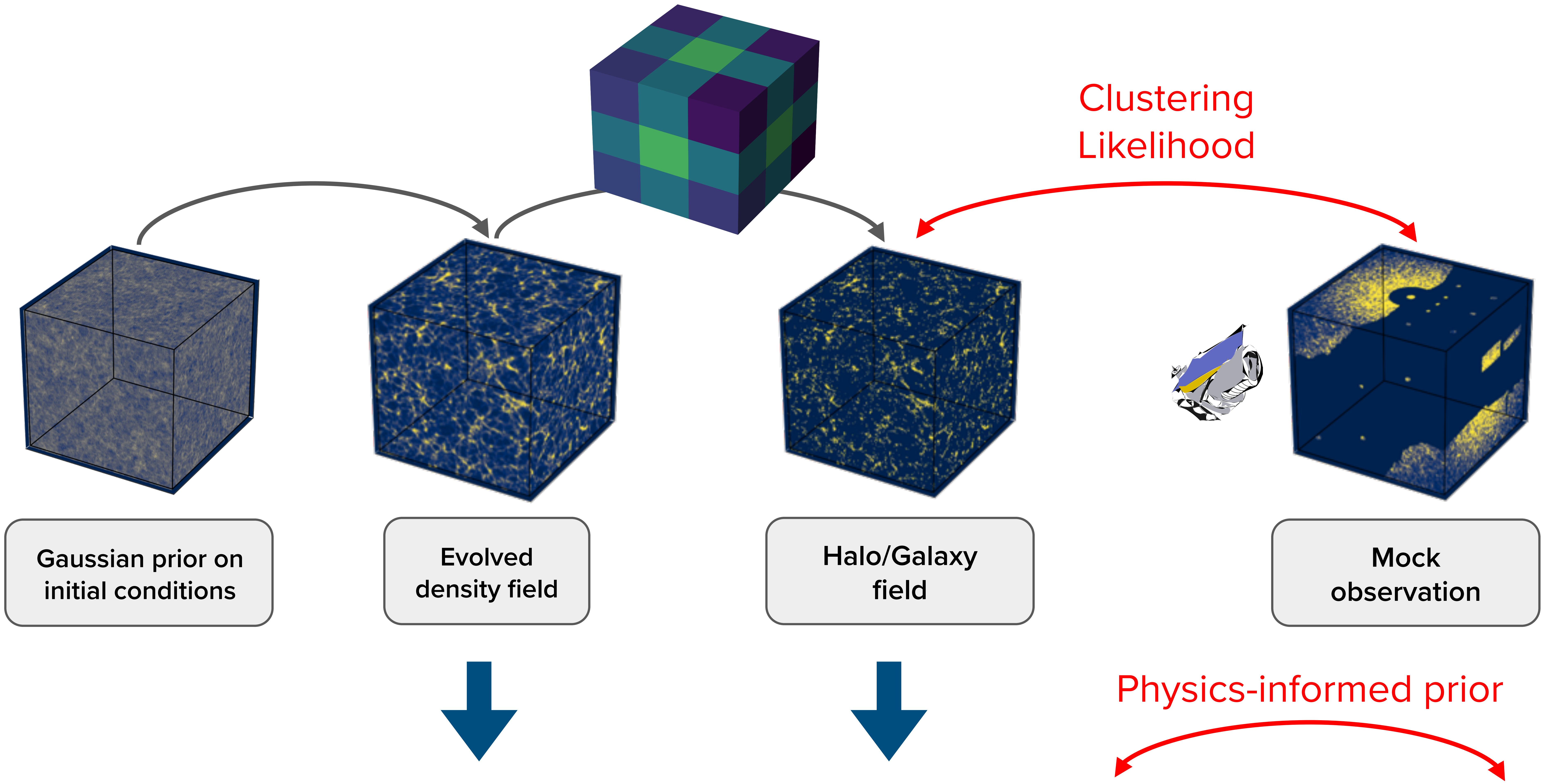


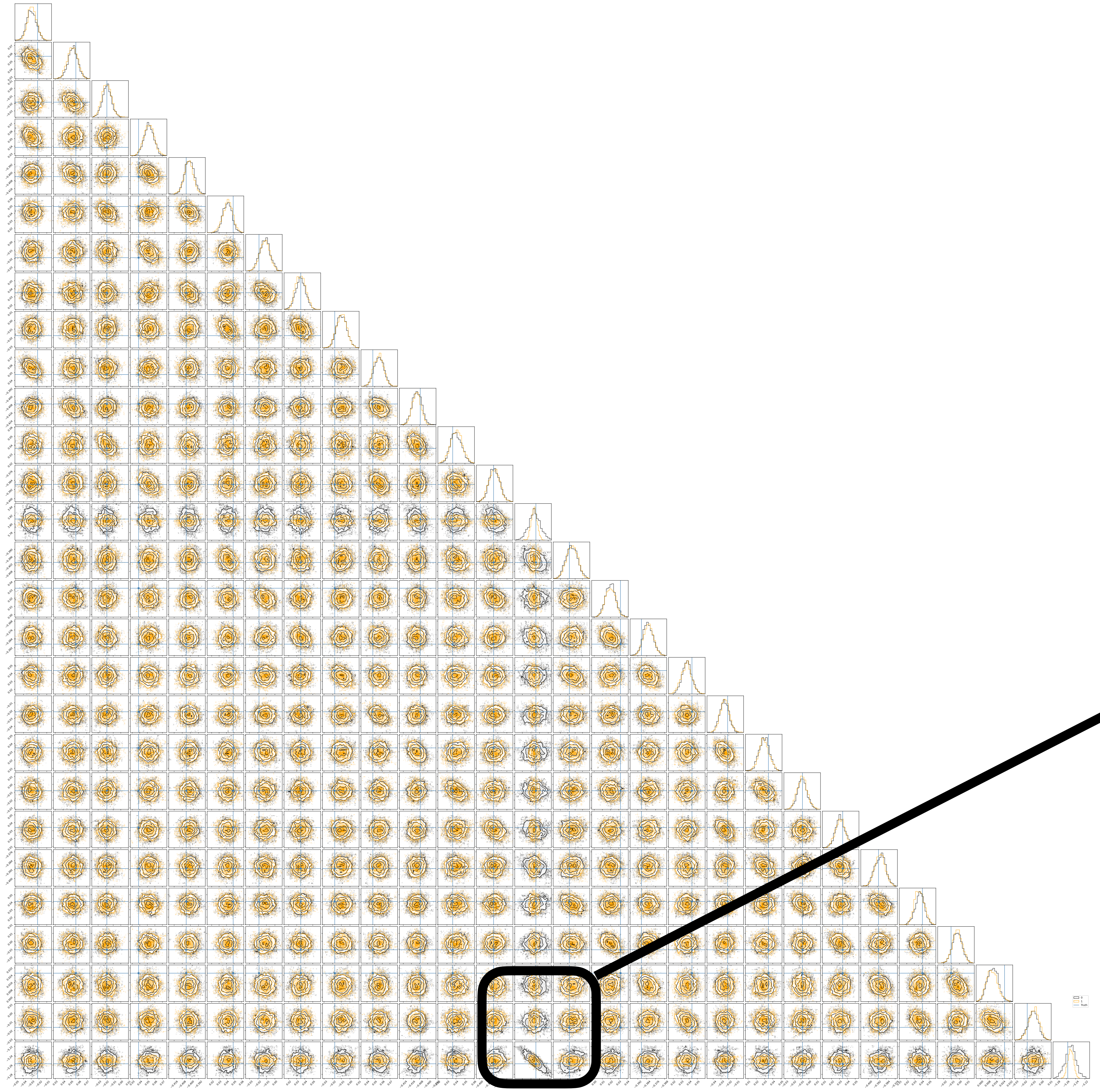
# Application using 28-parameter CNN halo bias model

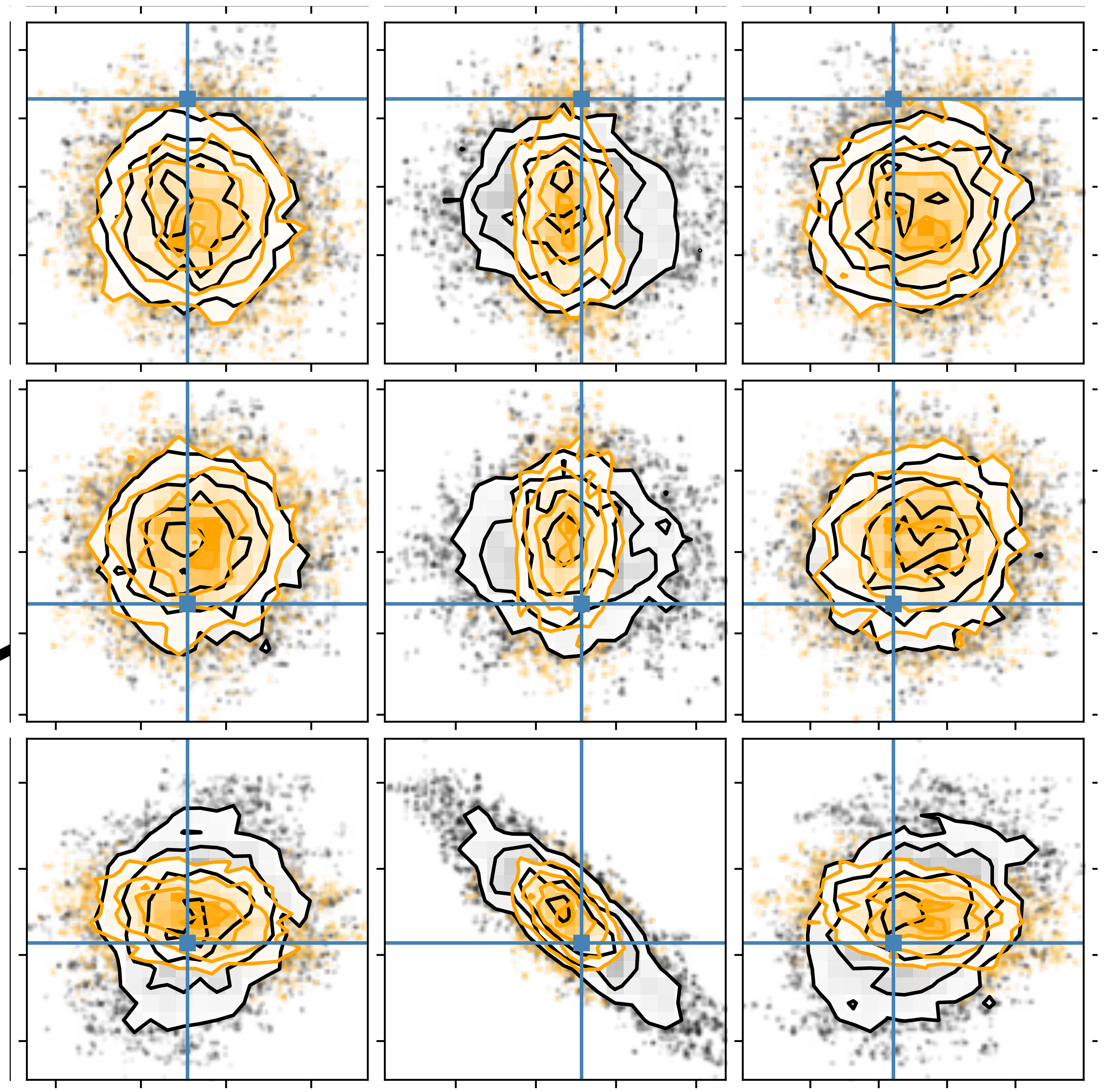



**Power spectrum / Power spectrum = Ratio**

**Ratio from simulations**

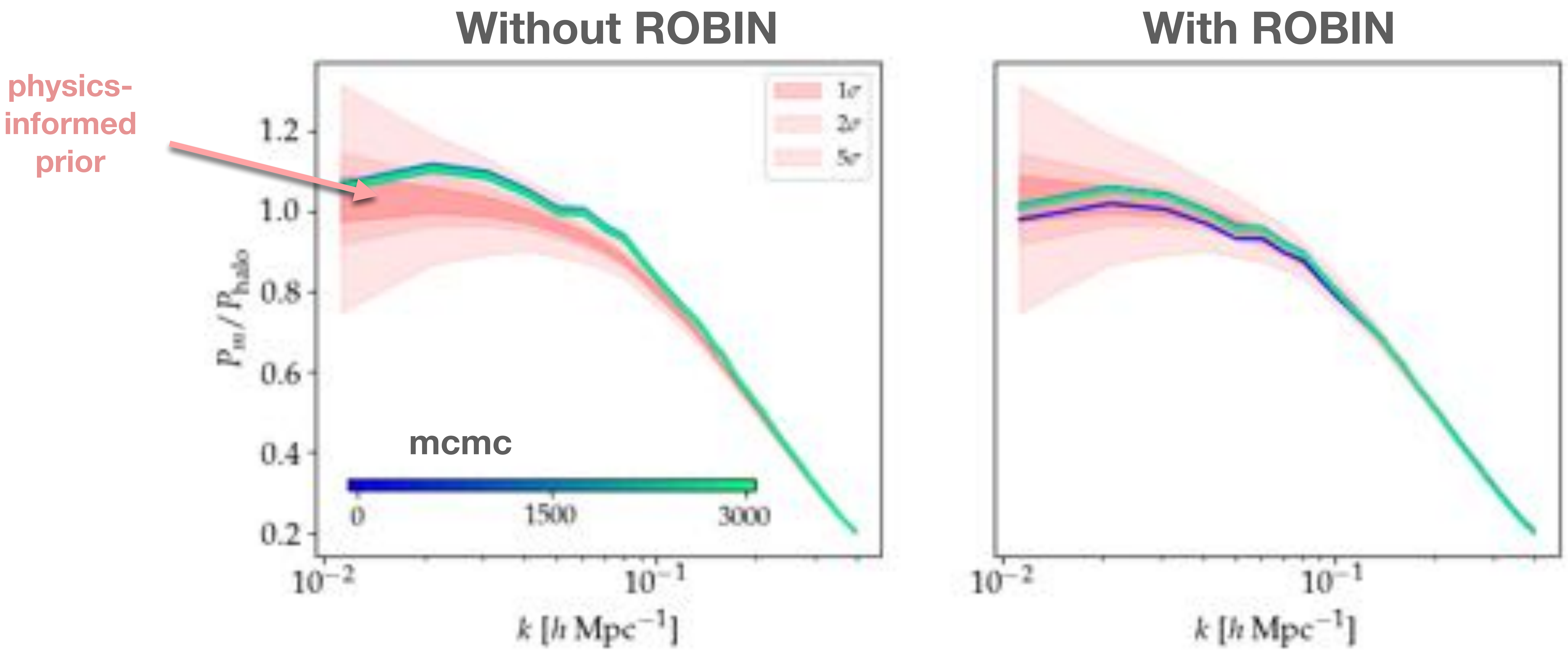
# **Result:** constraining parameter space for efficient exploration





**Without ROBIN** **With ROBIN**

# **Result:** joint inference of initial conditions and bias parameters



# Summary & Conclusions

Towards robust Bayesian inference (ROBIN) using physics-informed priors from cosmological simulations

**Accurately modelling galaxy bias at the field-level is challenging**

- Field-level inference offers information optimality
- Over-parameterised neural galaxy bias models at the field-level promising path forward

**ROBIN: Principled way of incorporating simulation knowledge into inference**

- Physics-informed prior incorporated through power spectrum ratio
- Model agnostic: works for any bias model

**Enabling zero-shot learning**

- Direct inference of un-trained neural networks possible
- Demonstrated to constrain physical parameter region during inference