



Stockholm
University



Bayesian field-level inference of primordial non-Gaussianity

Adam Andrews

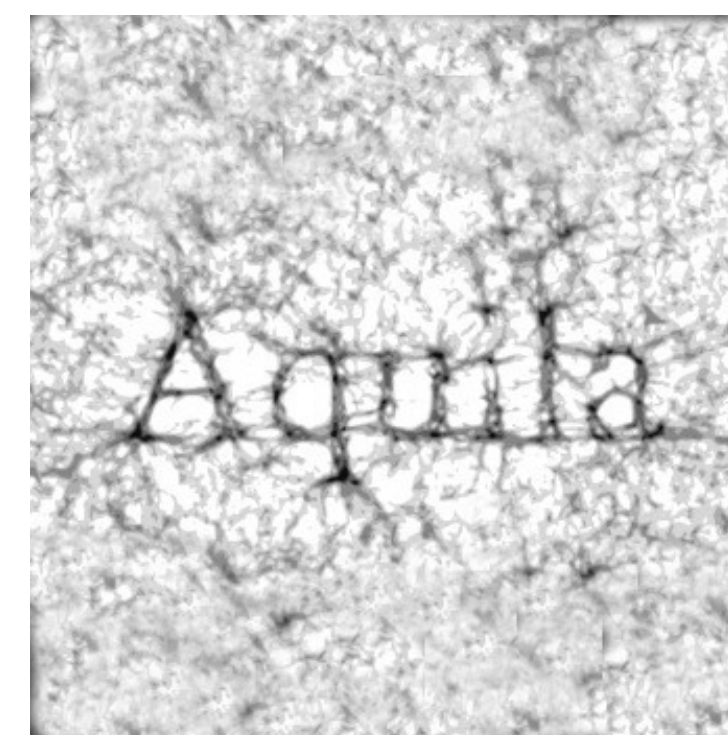
Jens Jasche, Guilhem Lavaux, Fabian Schmidt

arxiv: 2203.08838



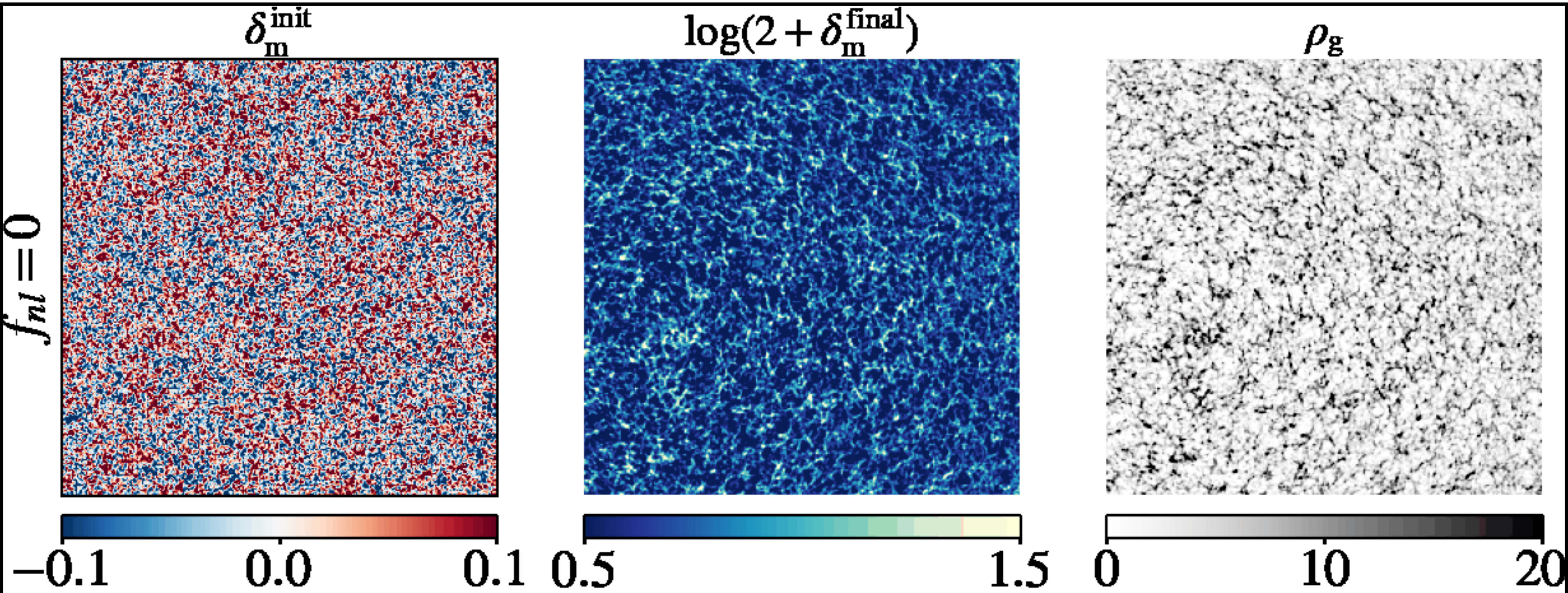
Cosmos Klein
centre

**A Cosmic Window to Fundamental Physics:
PNG Workshop
September 22nd 2022**

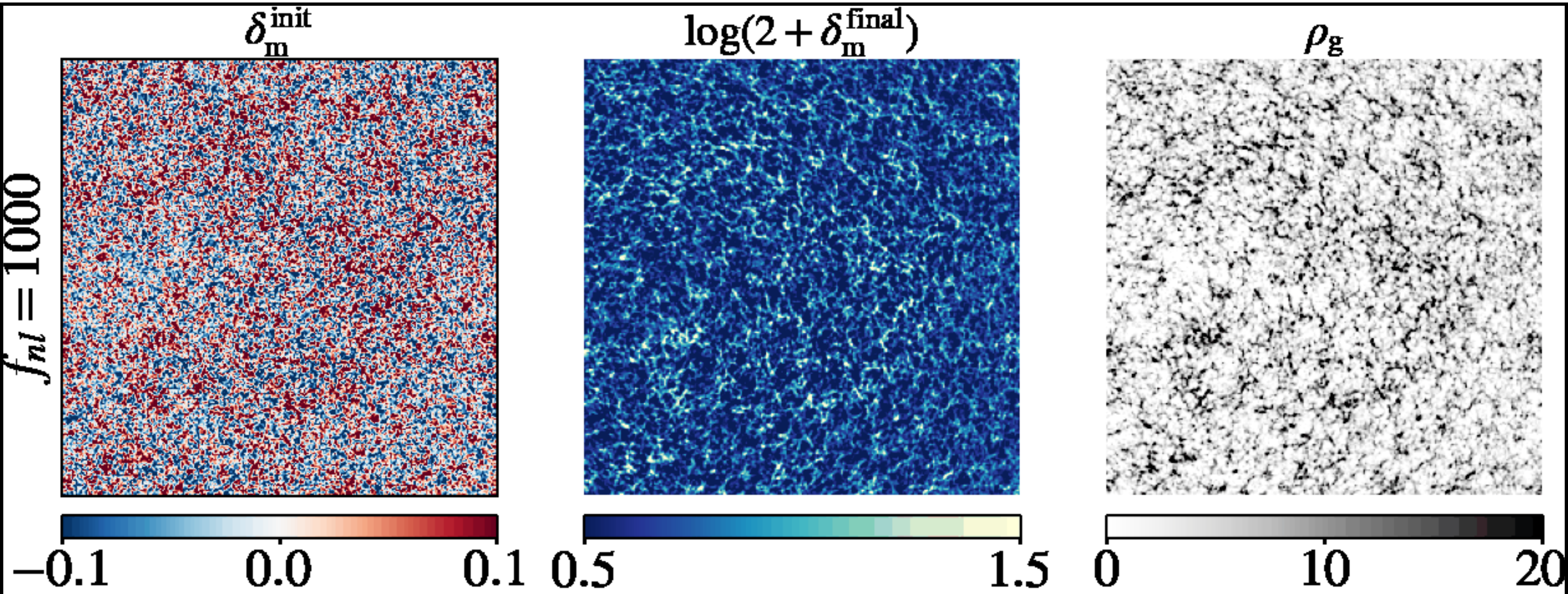


How does f_{nl} affect the cosmic matter field?

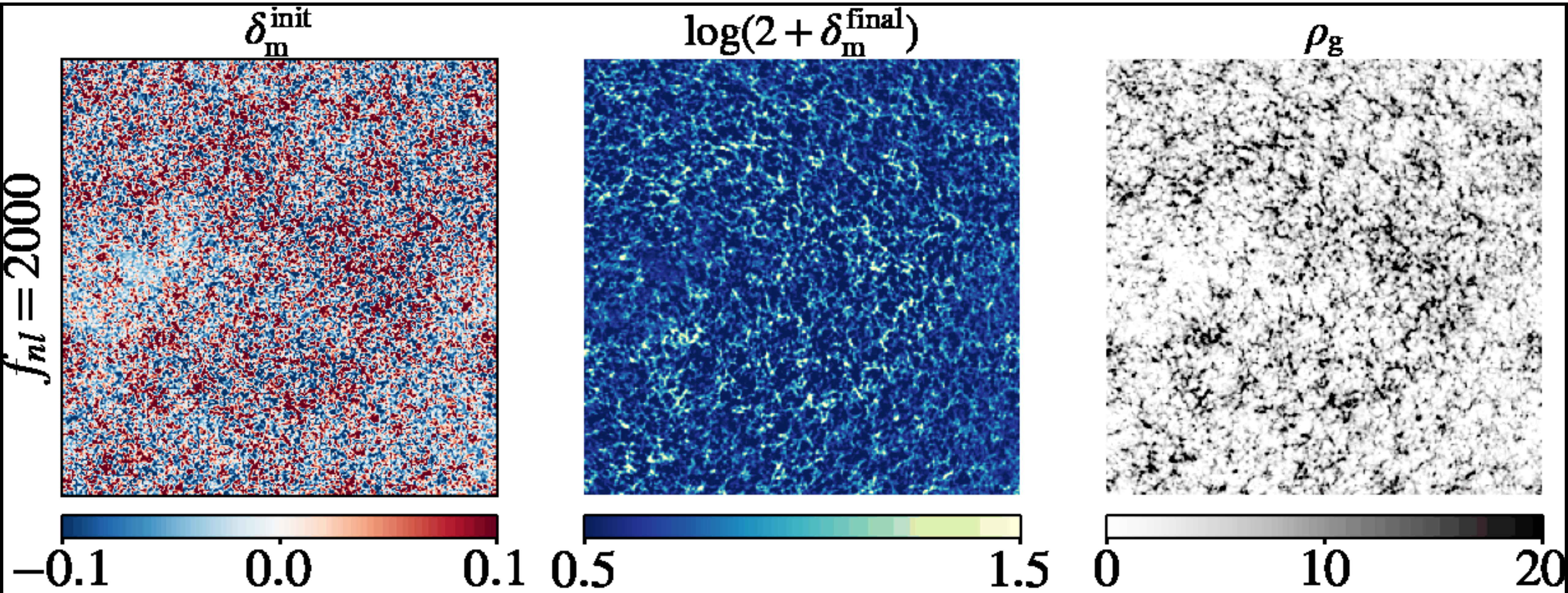
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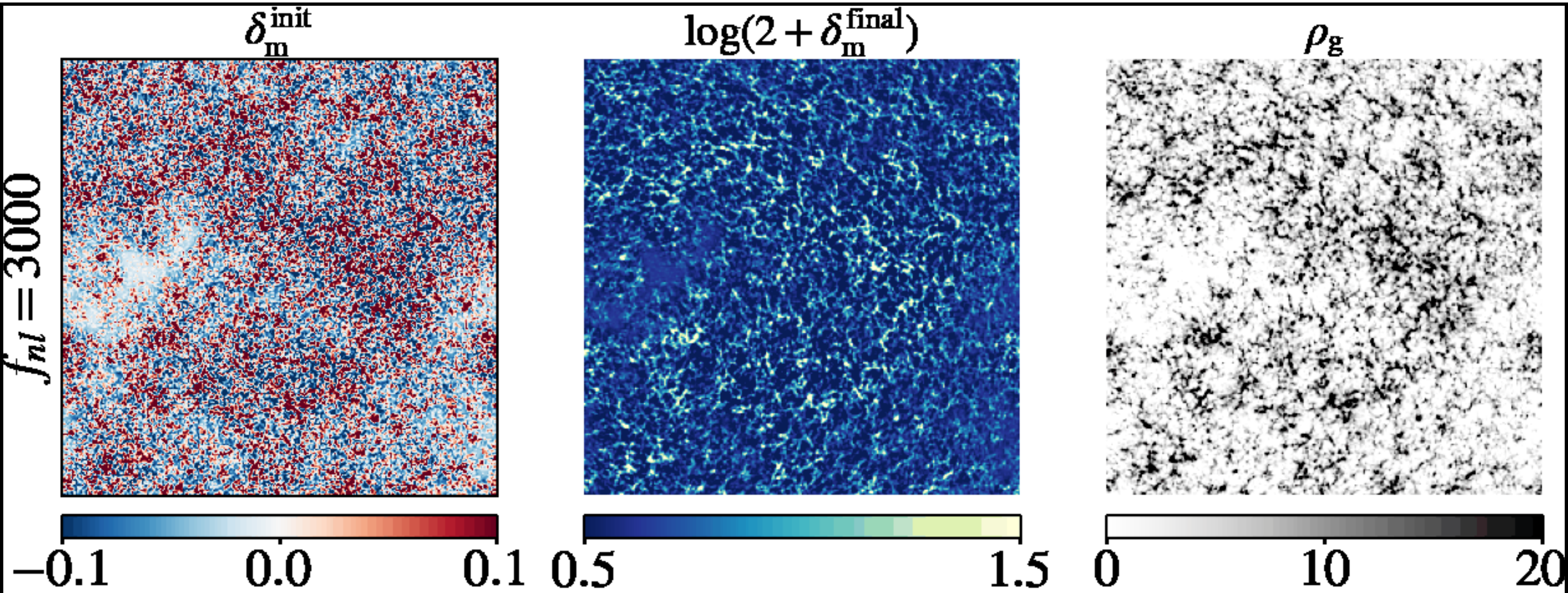
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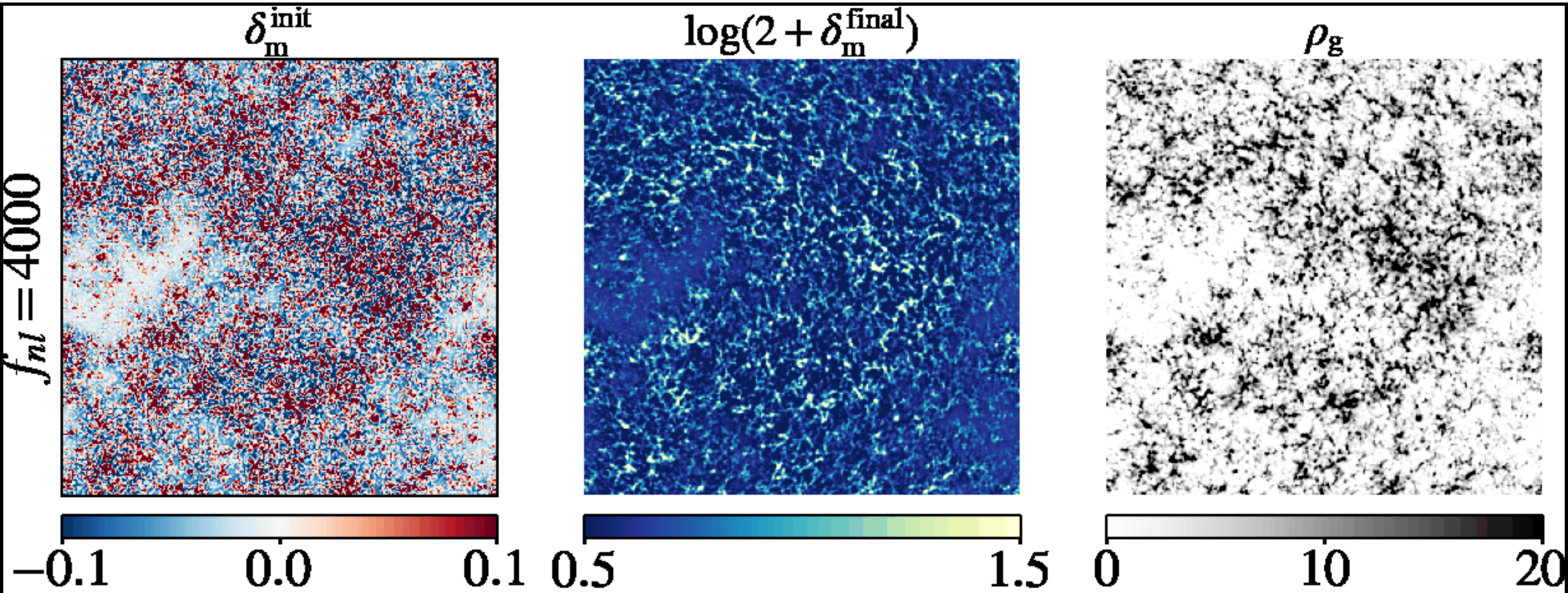
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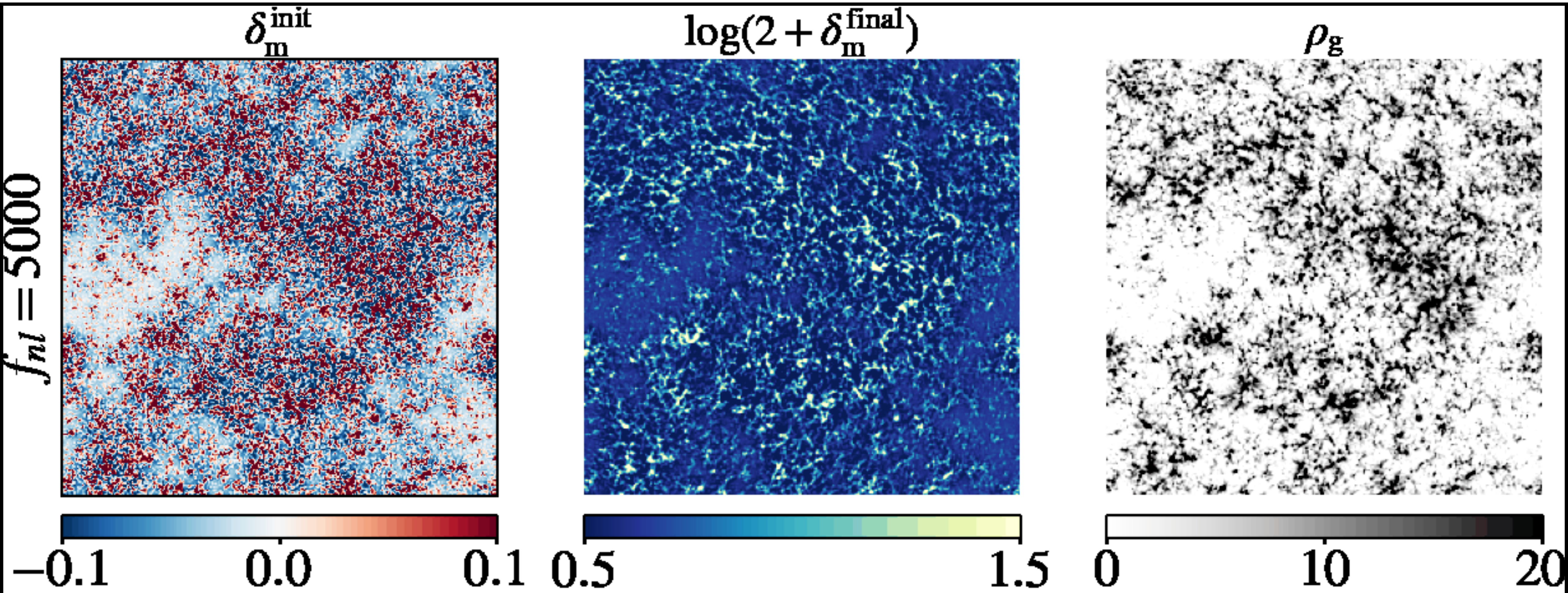
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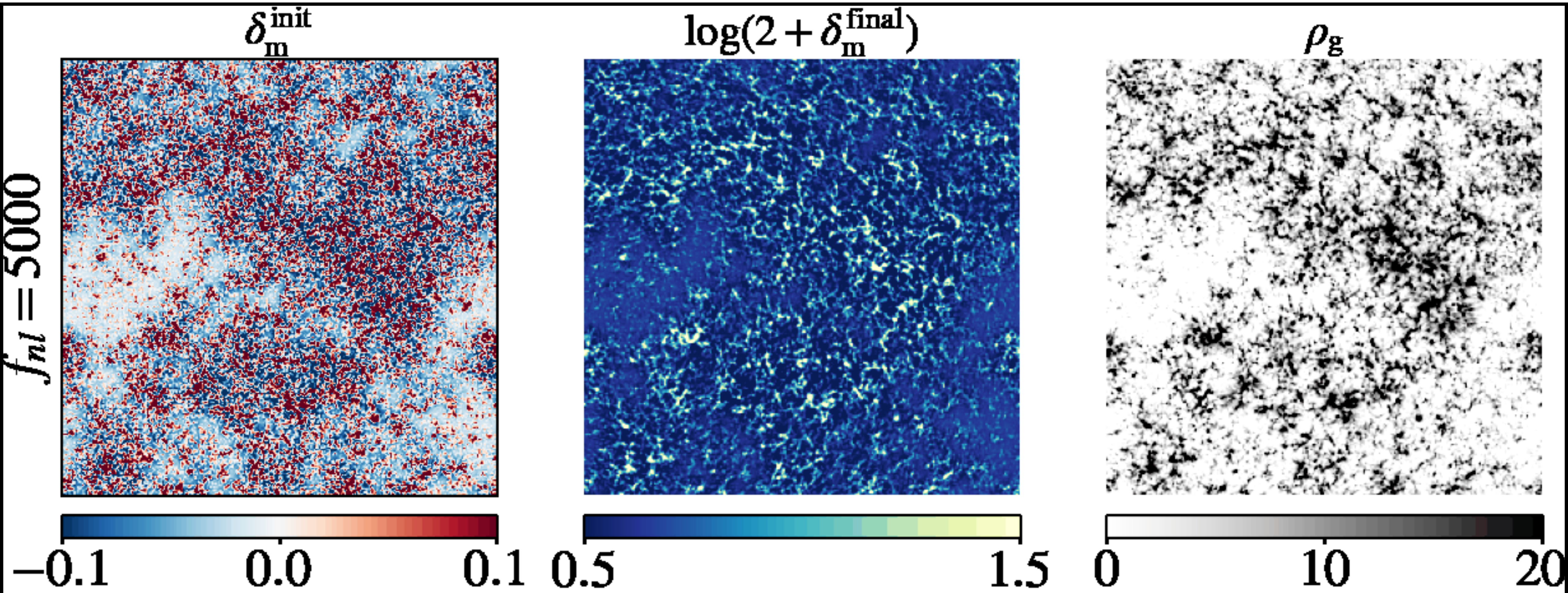
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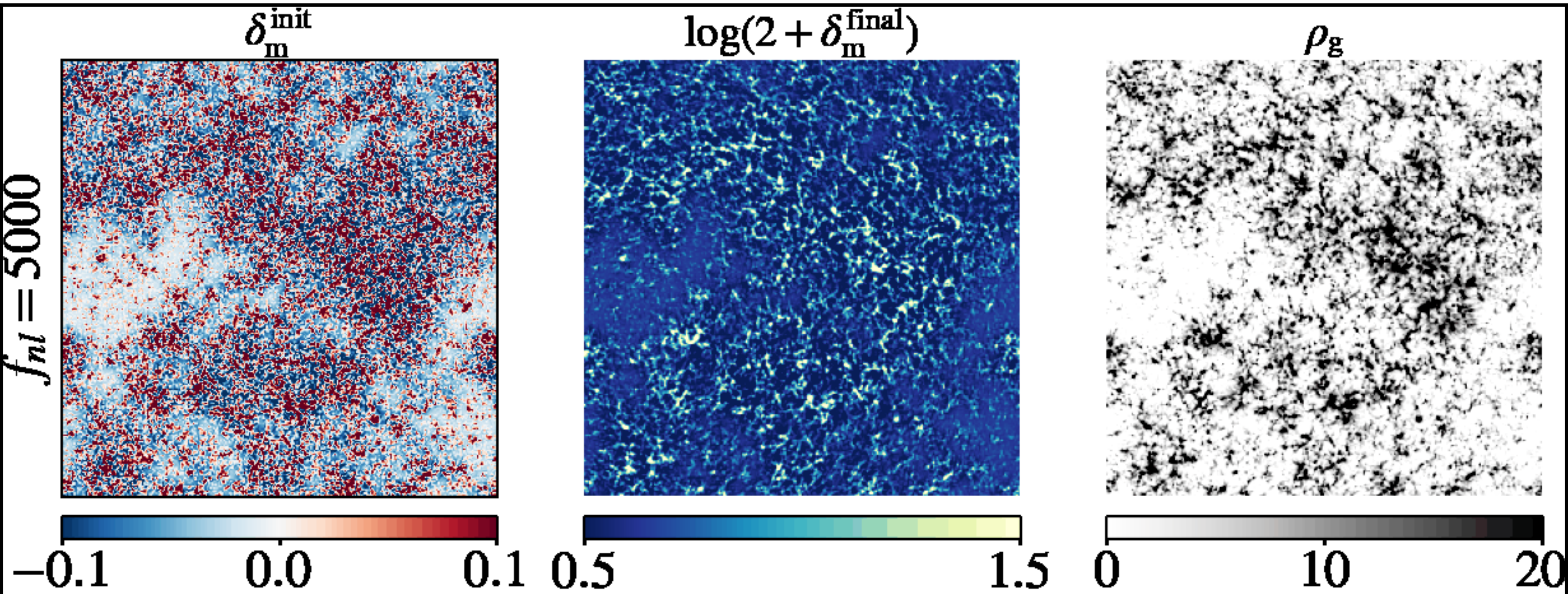


How does f_{nl} affect the cosmic matter field?



Summary statistics:

How does f_{nl} affect the cosmic matter field?



Summary statistics:

Goal: *Fit the full cosmic field*

Field-level inference

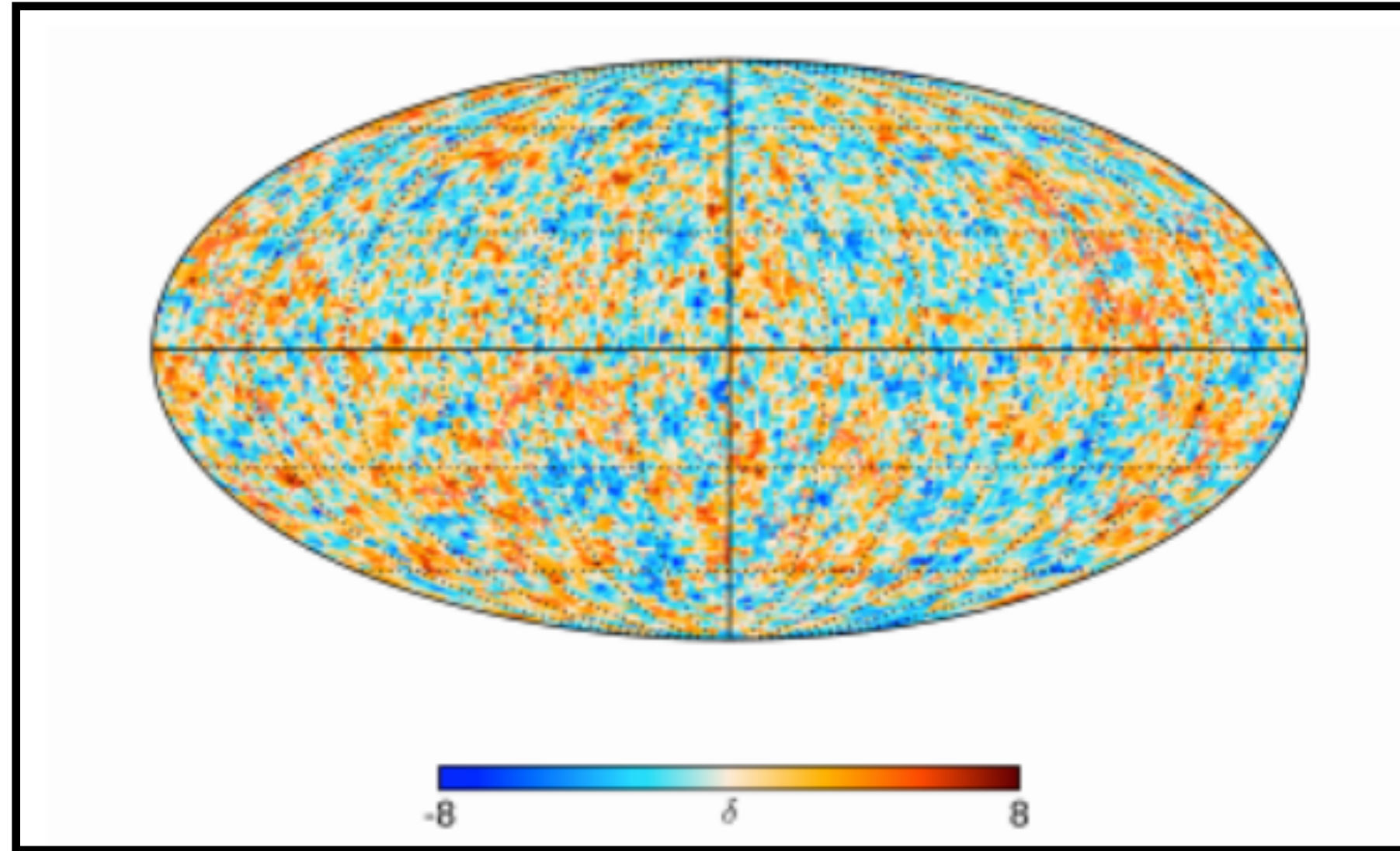
1) Forward model

2) Statistical inference

Field-level inference

1) Forward model

INITIAL FIELD

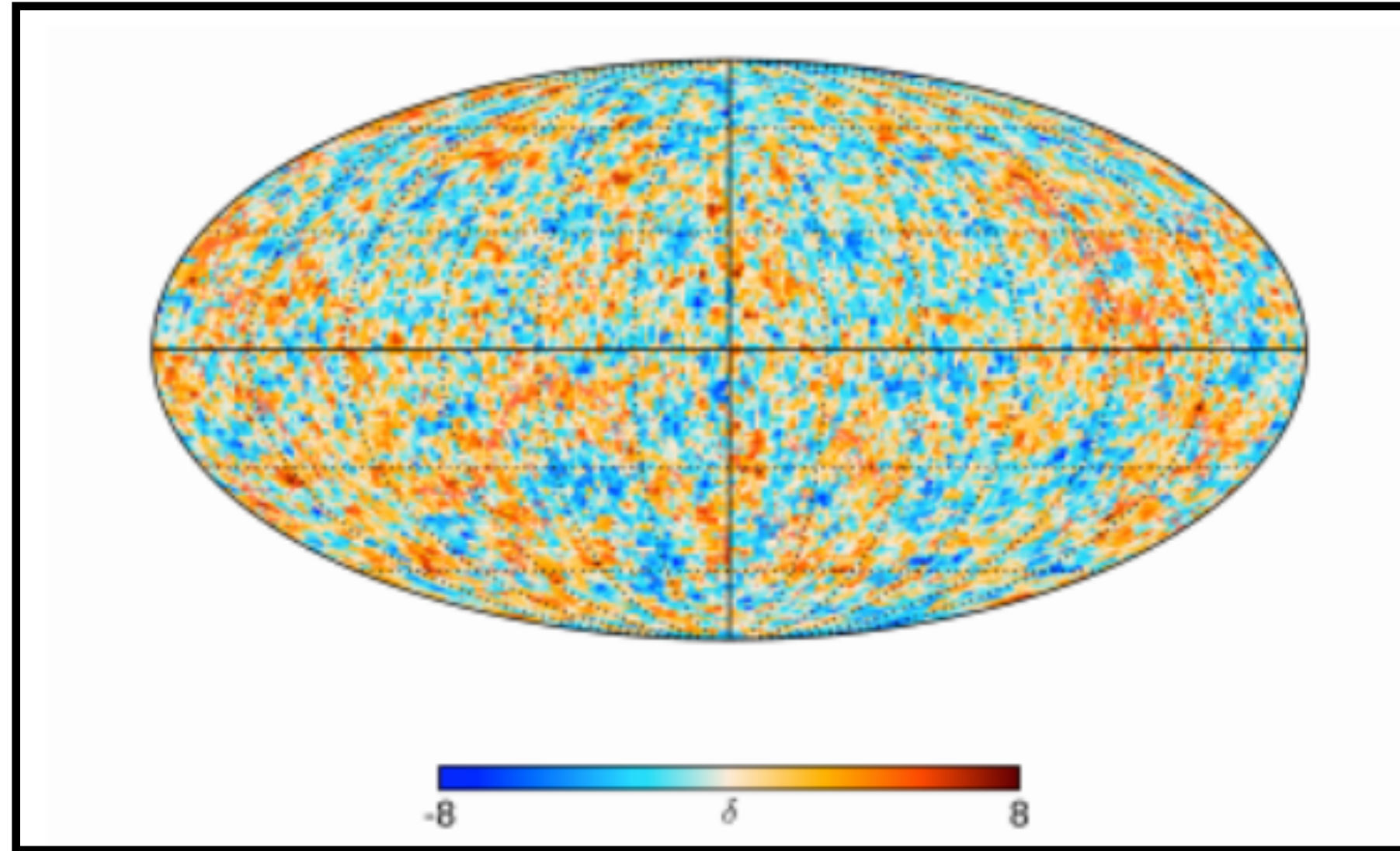


2) Statistical inference

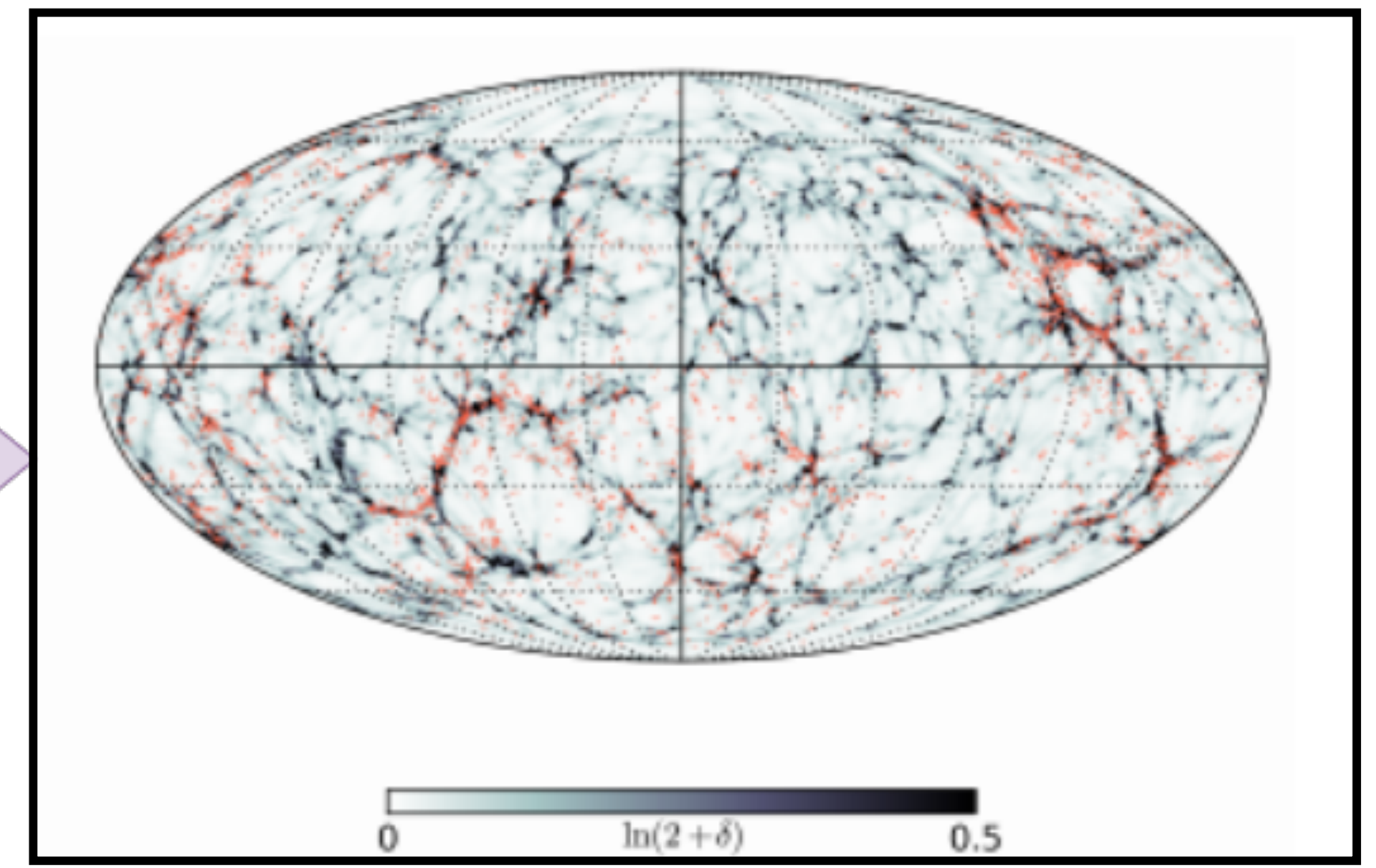
Field-level inference

1) Forward model

INITIAL FIELD



FINAL FIELD

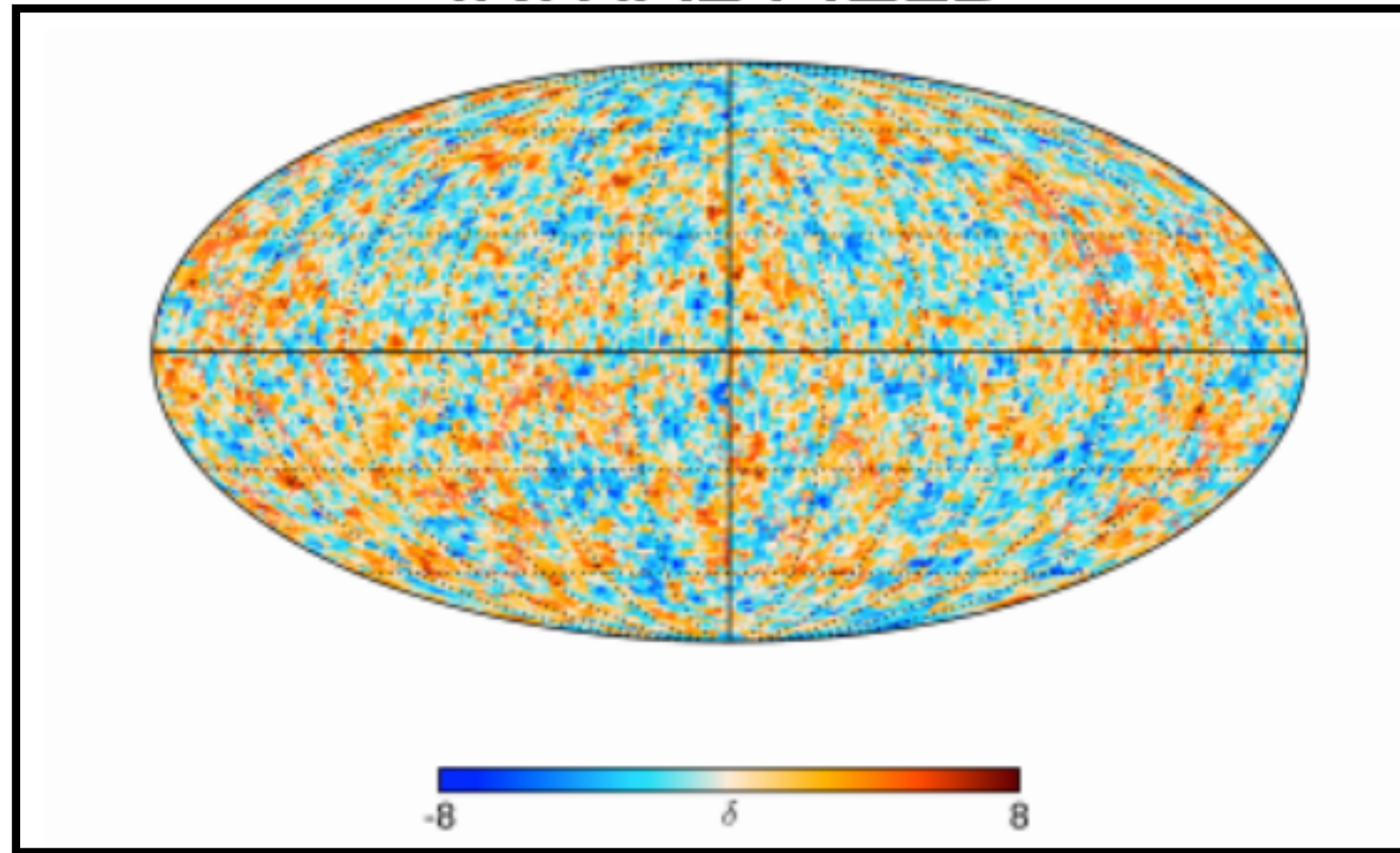


2) Statistical inference

Field-level inference

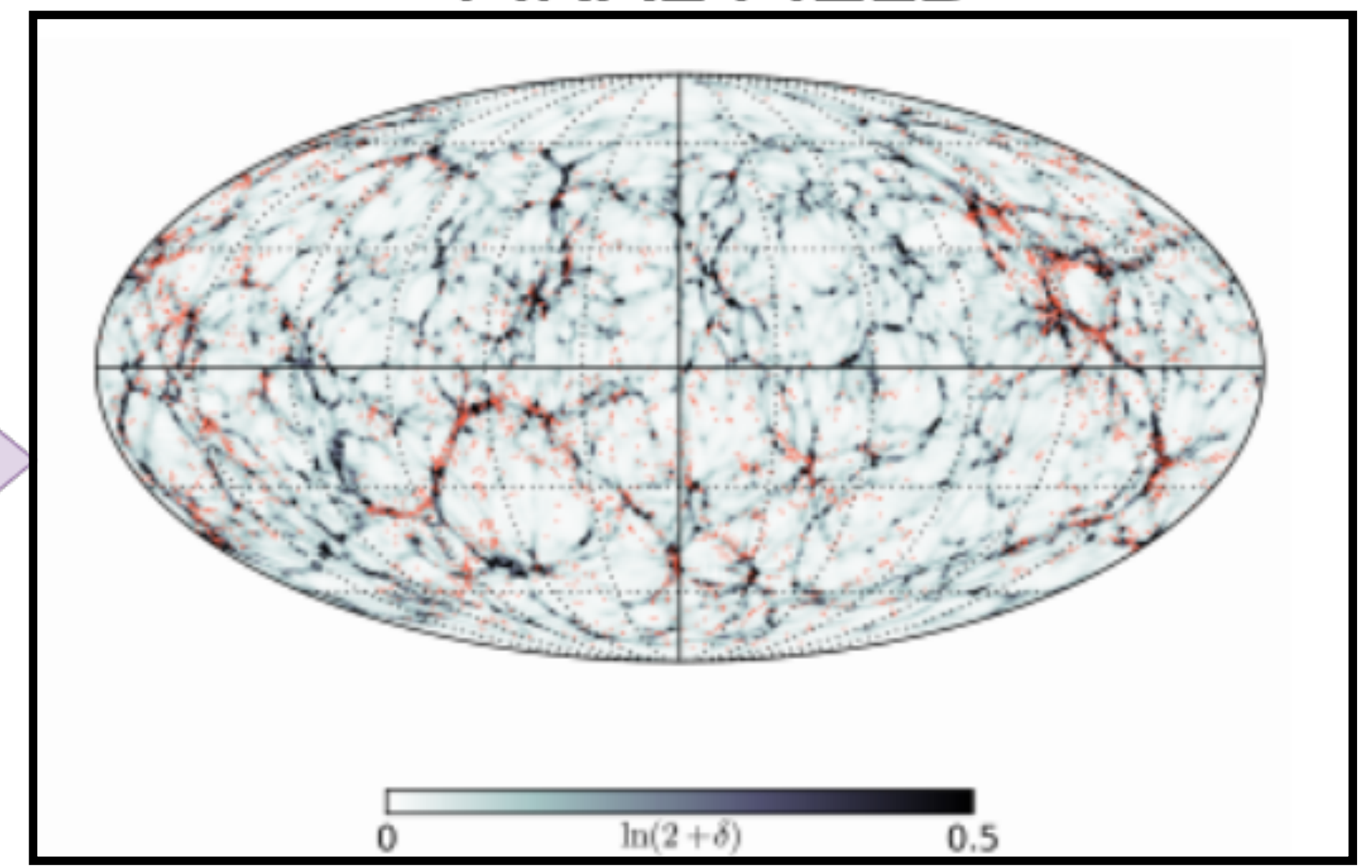
1) Forward model

INITIAL FIELD



Fully differentiable

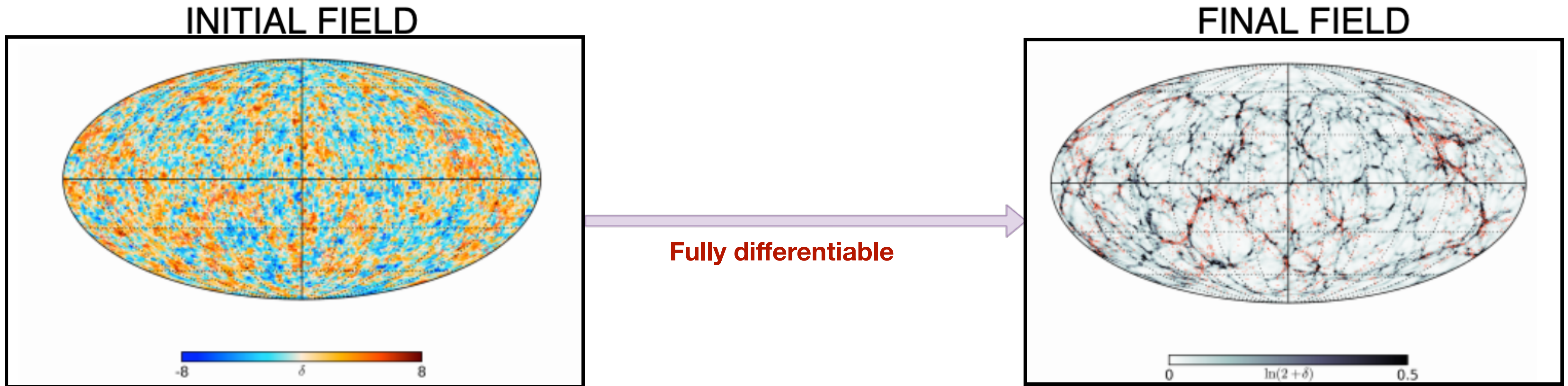
FINAL FIELD



2) Statistical inference

Field-level inference

1) Forward model



2) Statistical inference

Sample from the posterior:

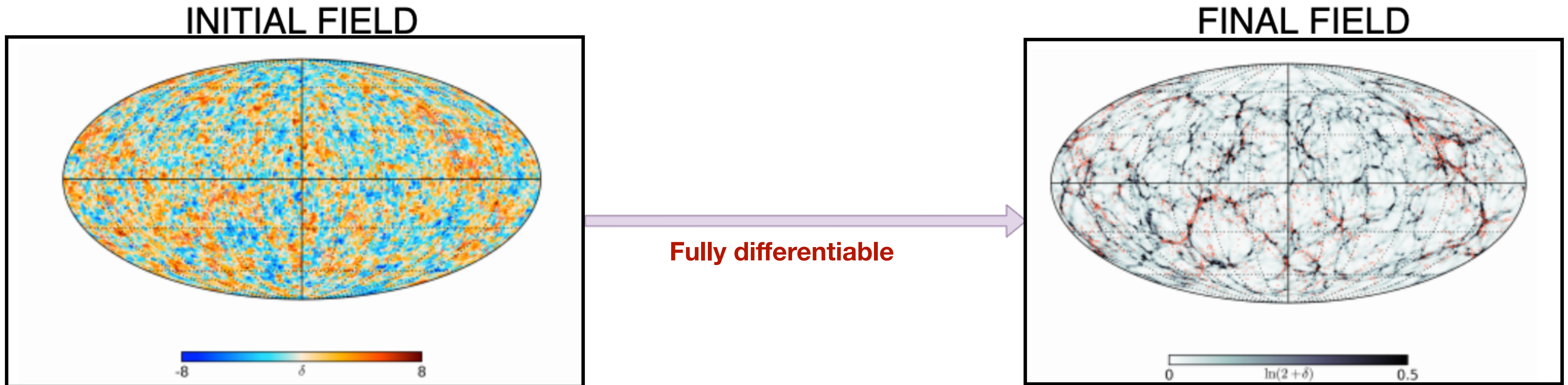
$$\epsilon^N, f_{\text{nl}}^N, \{b_i\}^N \sim \mathcal{P}(\epsilon, f_{\text{nl}}, \{b_i\} | N_g^0)$$

Gaussian Likelihood:

$$\ln \left[\pi \left(N_{g,p}^0 | N_{g,p}, \sigma_g \right) \right] = C - \frac{1}{2} \sum_{p=0}^{P-1} \left(\frac{N_{g,p}^0 - N_{g,p}}{\sigma_g} \right)^2$$

Field-level inference

1) Forward model



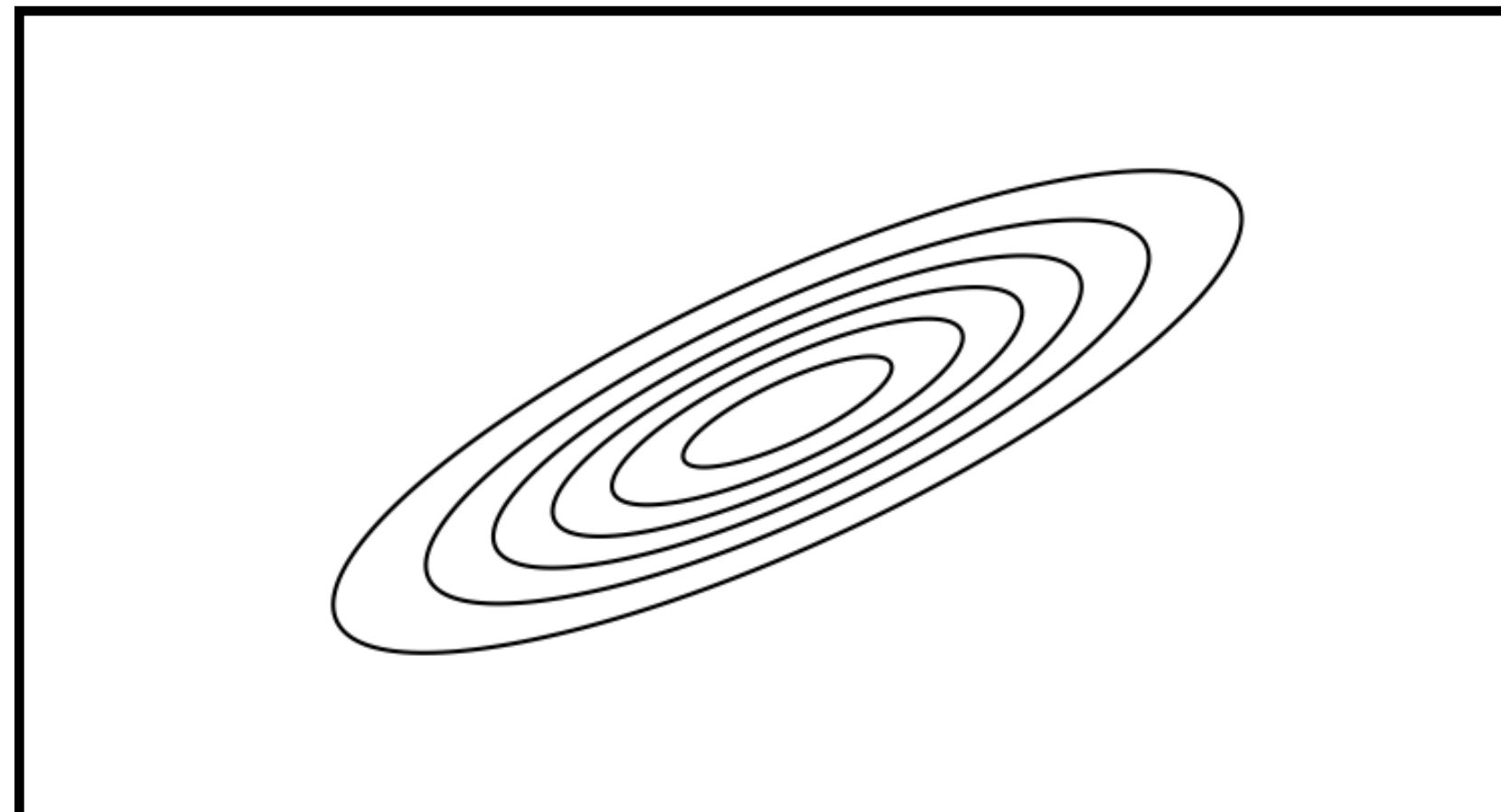
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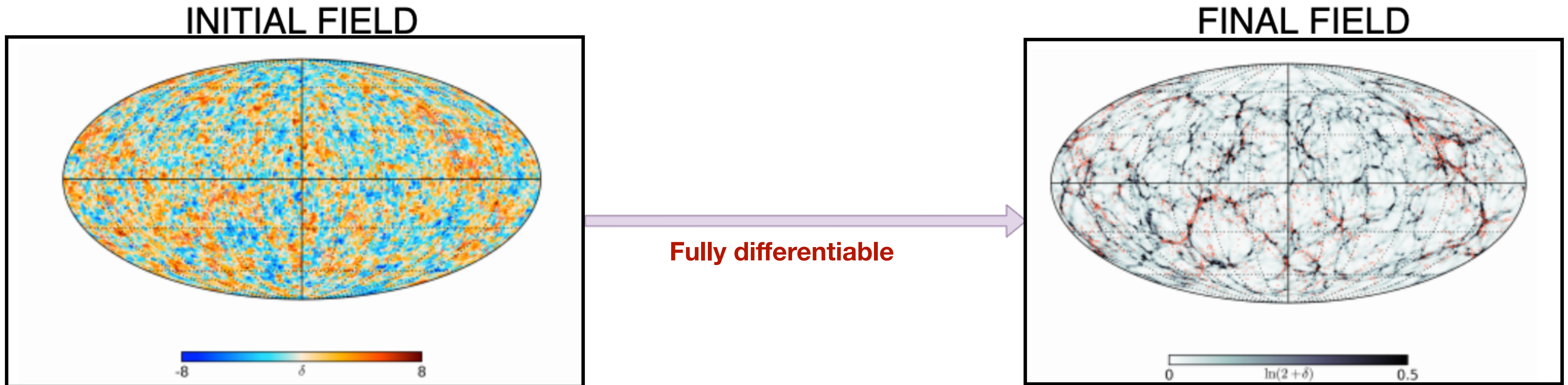
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Field-level inference

1) Forward model



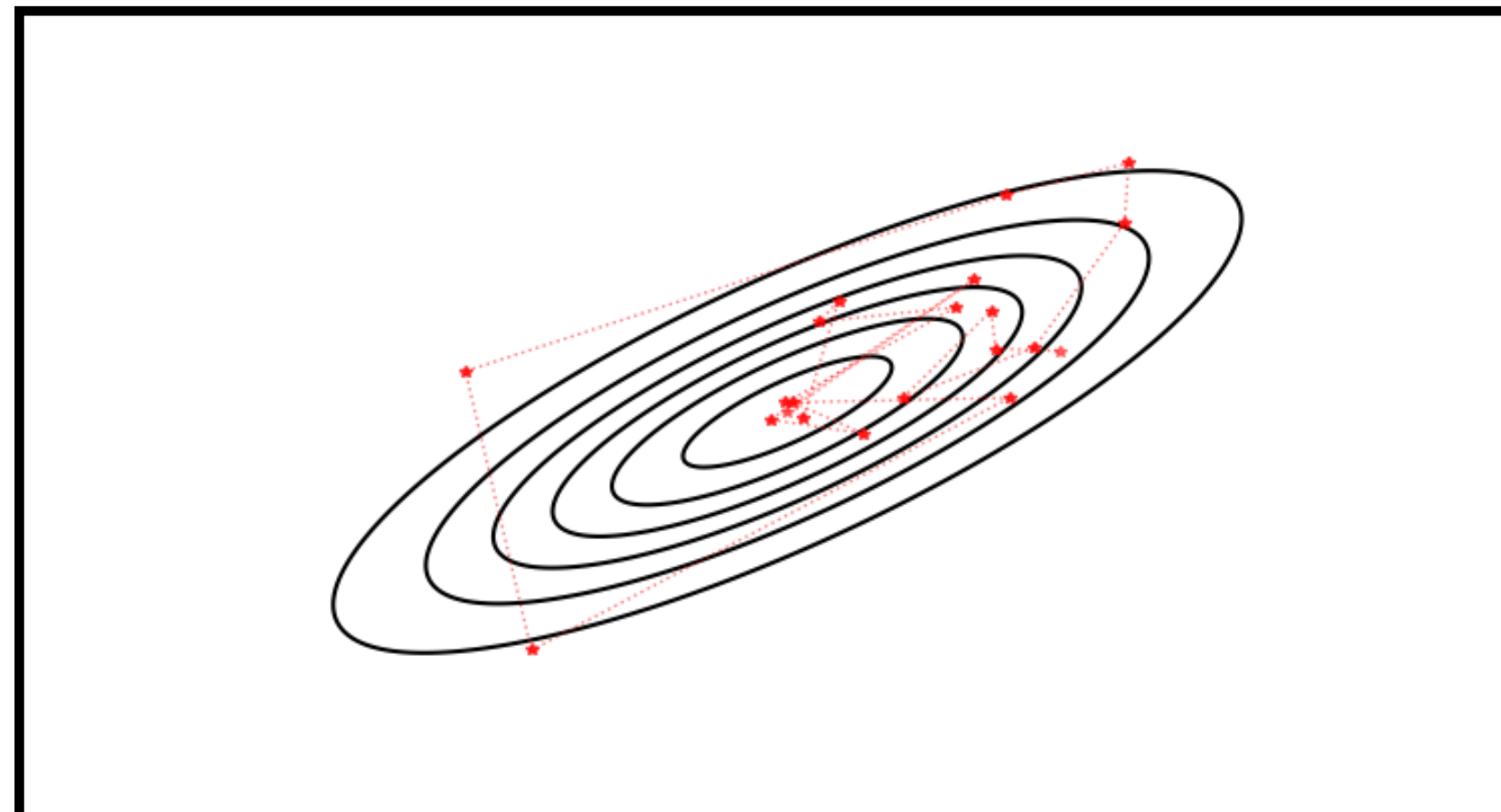
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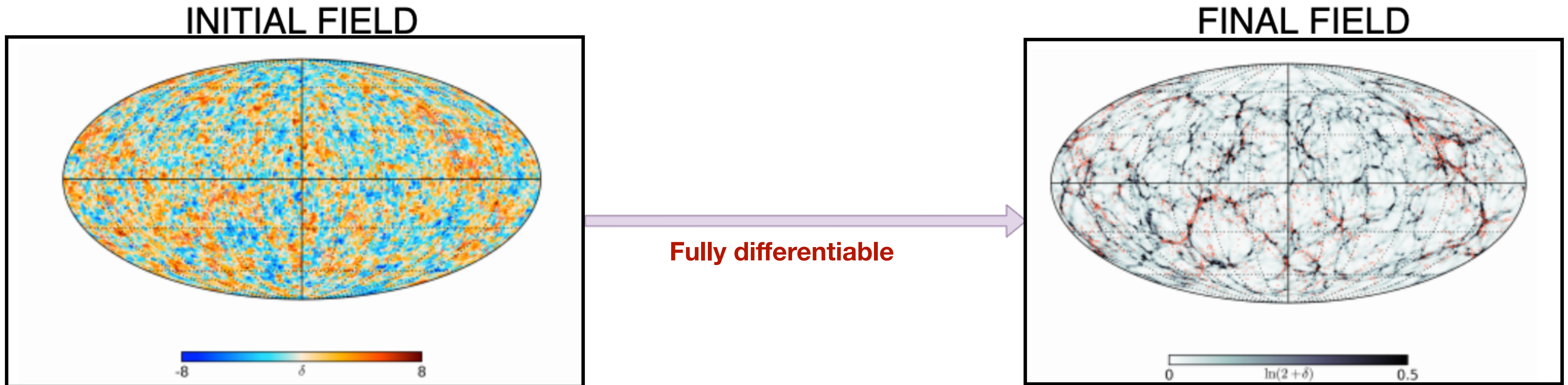
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Field-level inference

1) Forward model



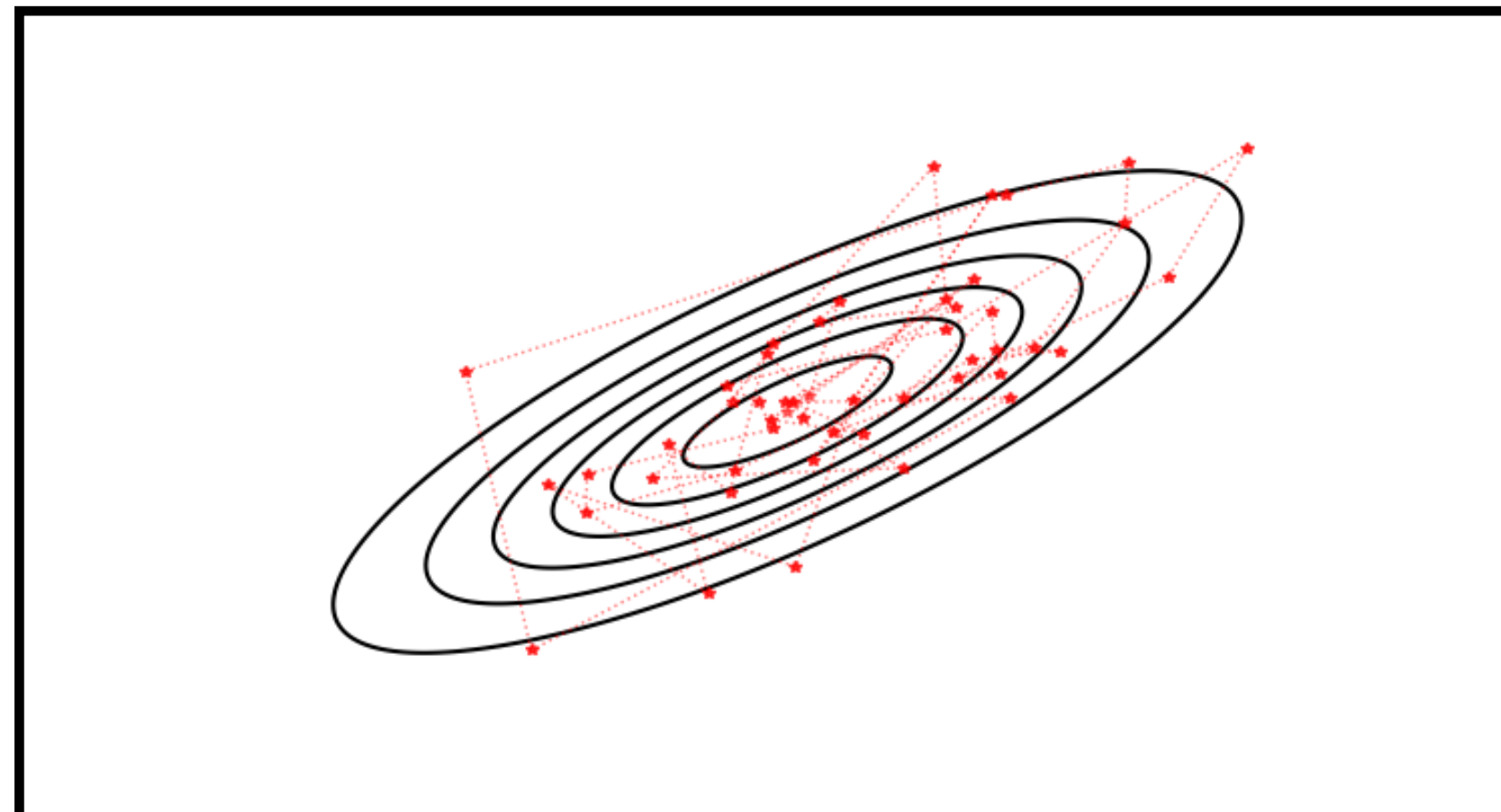
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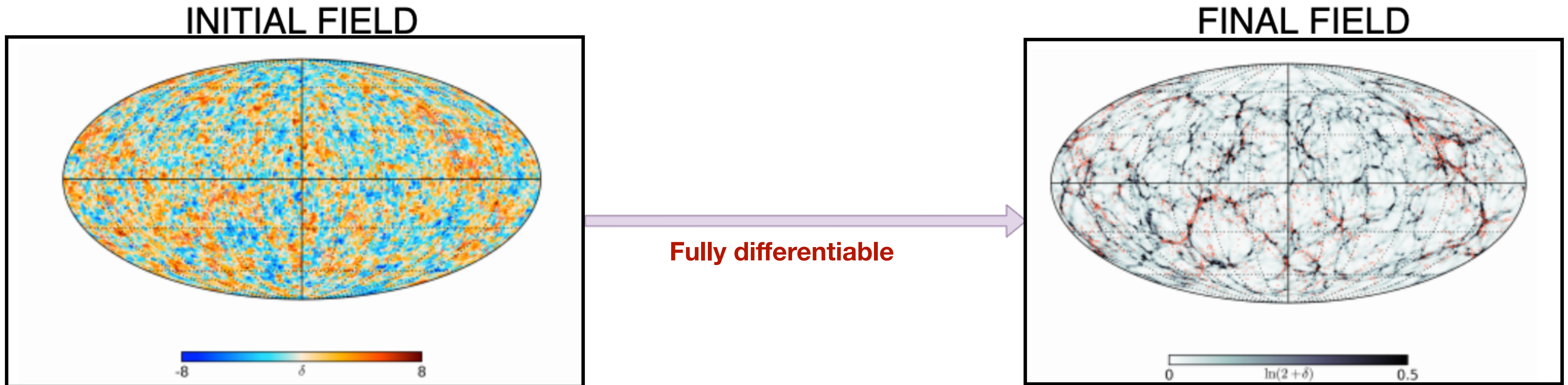
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Field-level inference

1) Forward model



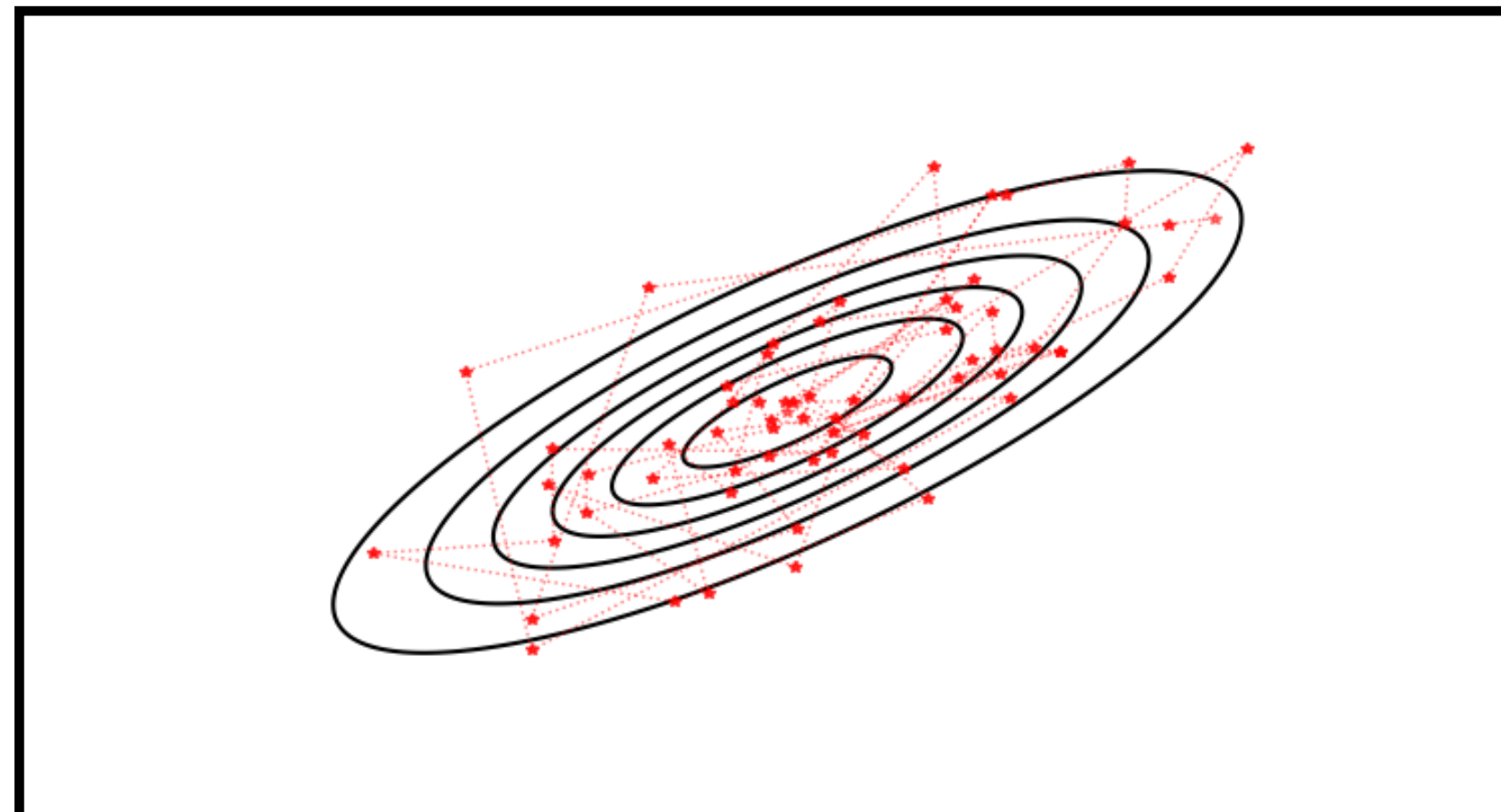
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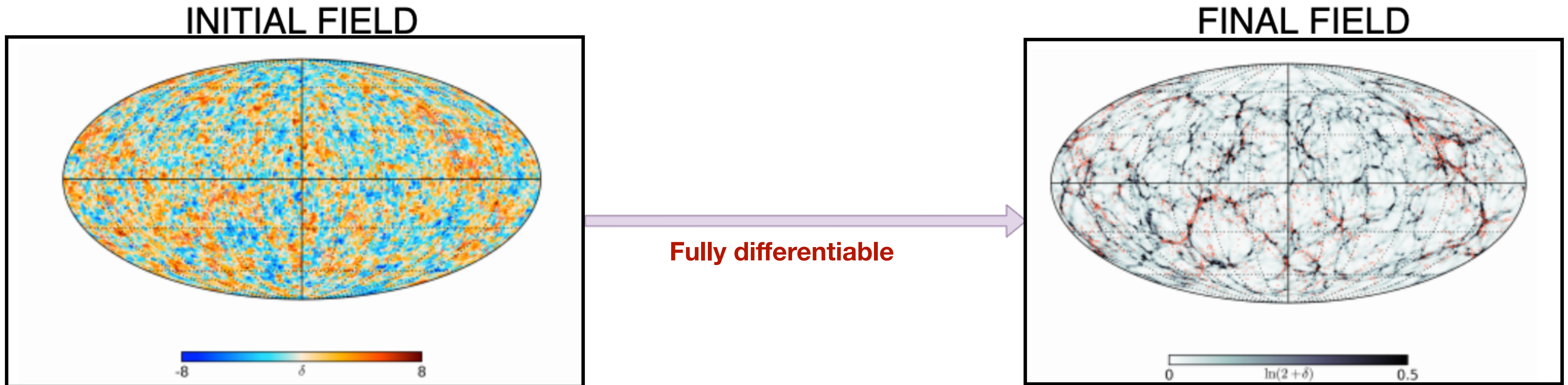
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Field-level inference

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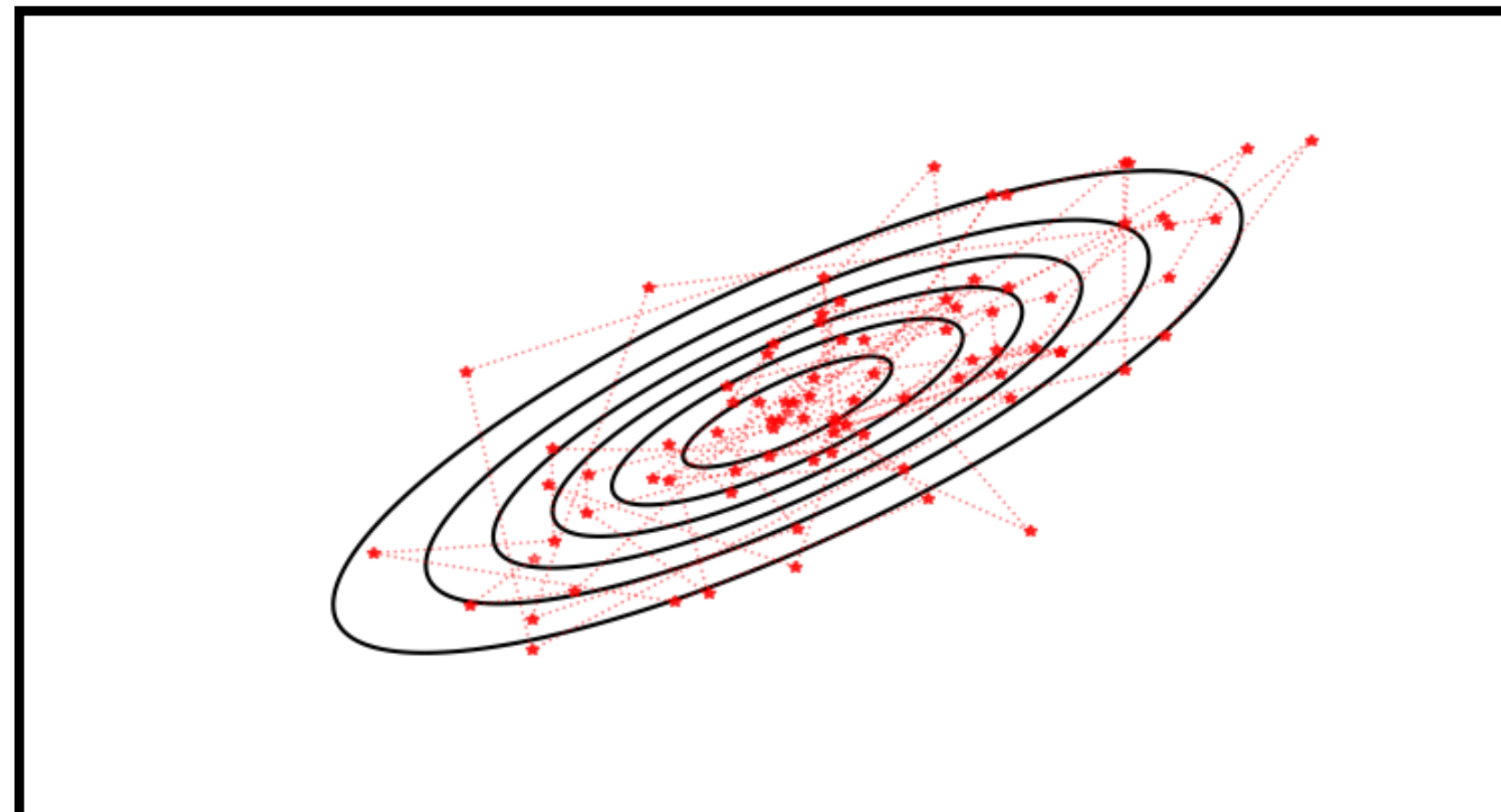
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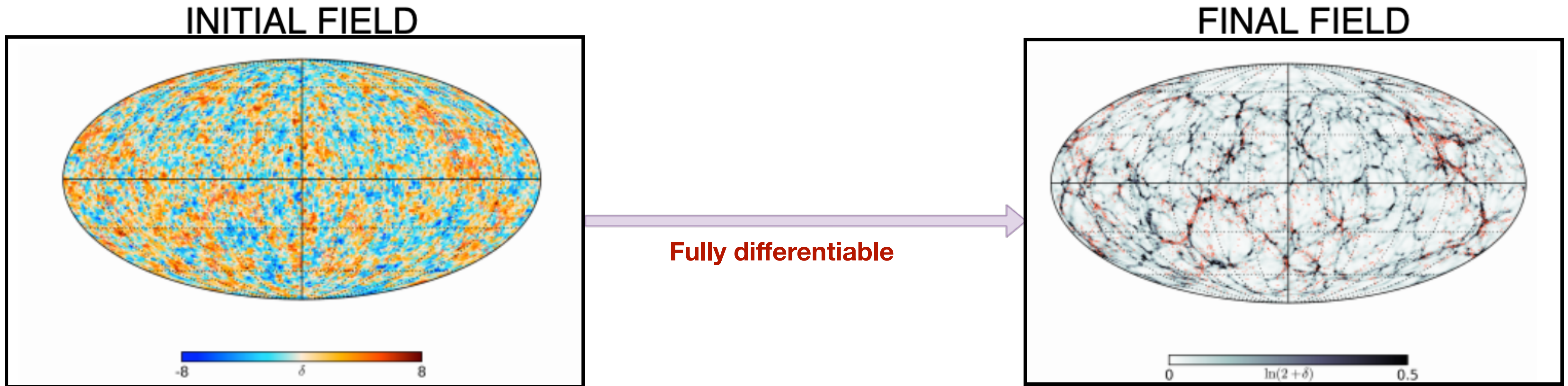
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Field-level inference

1) Forward model



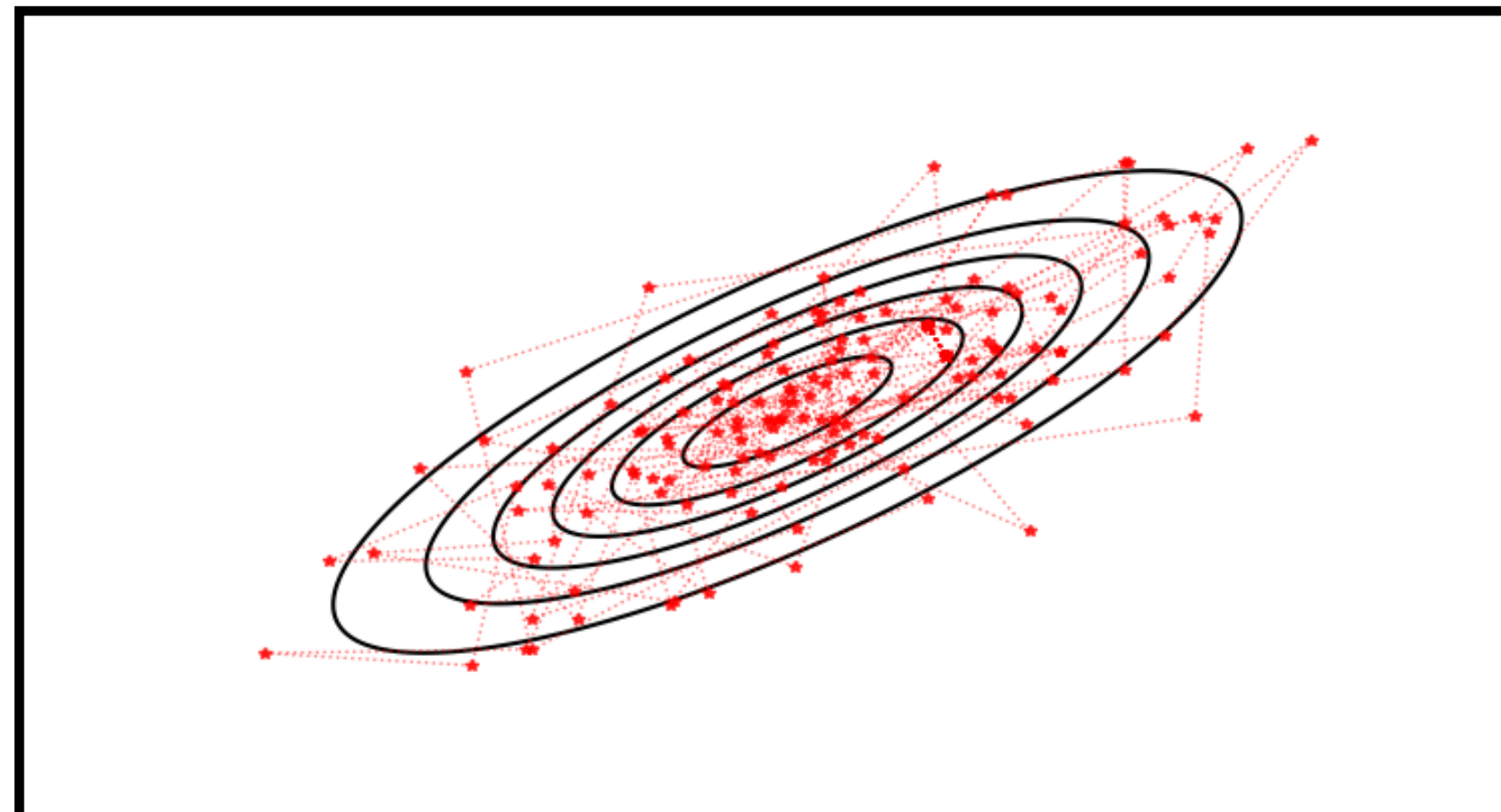
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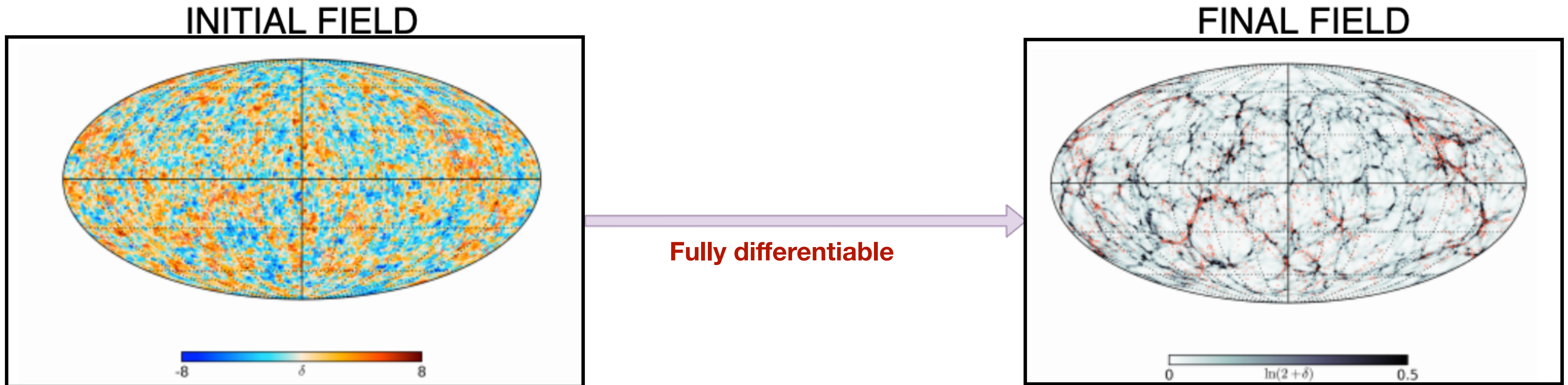
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Field-level inference

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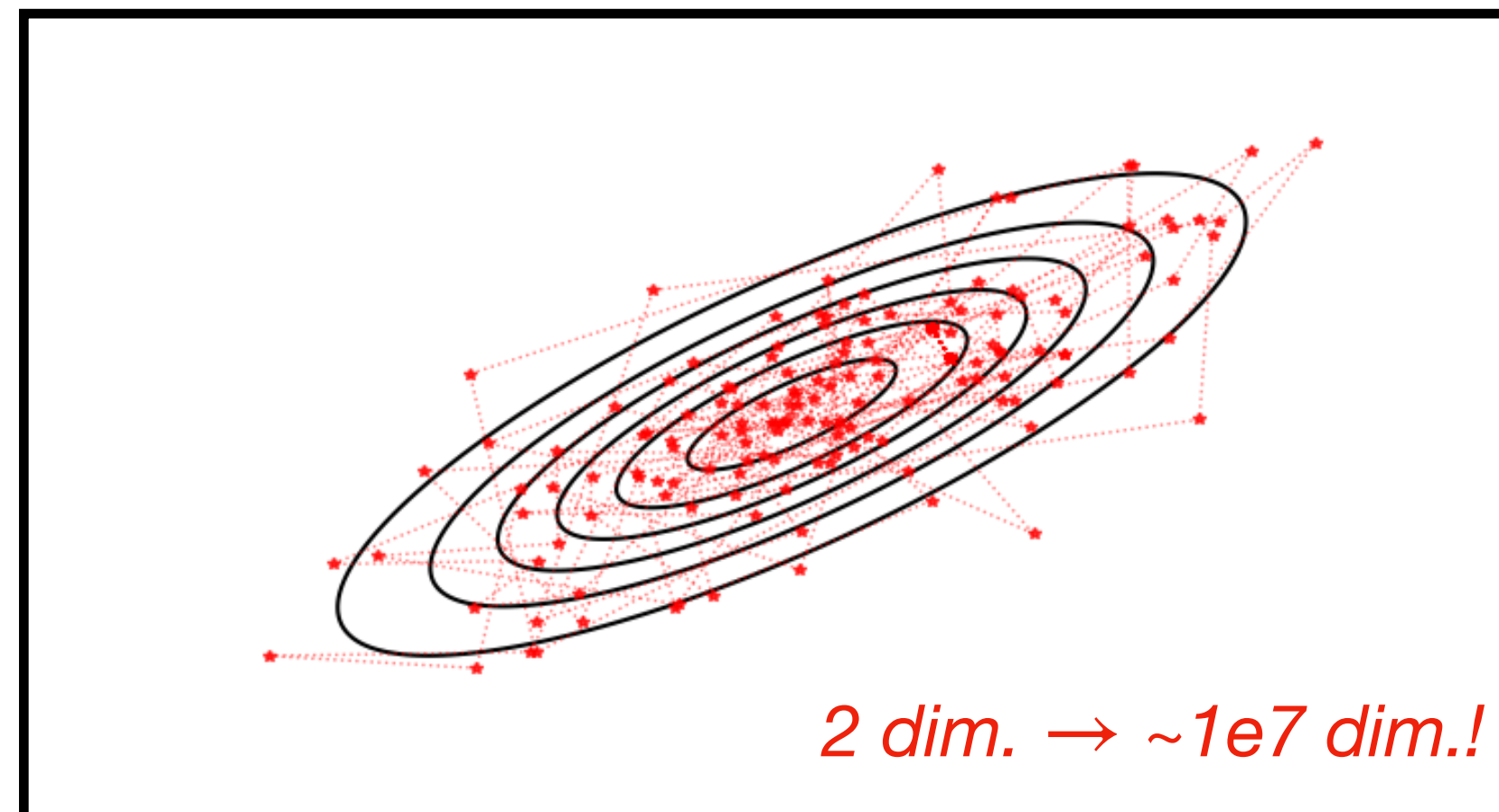
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Field-level inference

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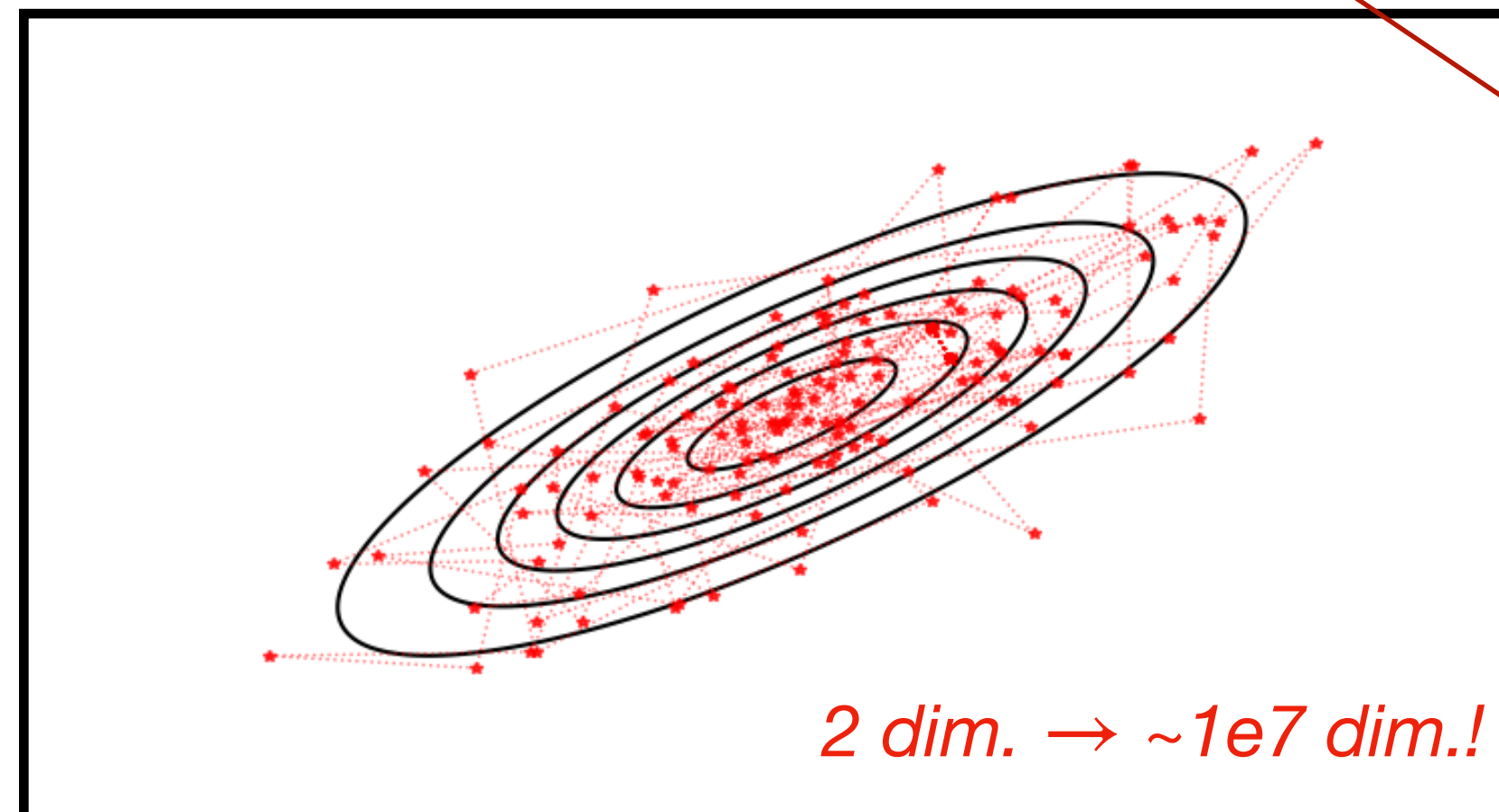
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2 dim. \rightarrow $\sim 1e7$ dim.!

- Go beyond summary statistics
- Handle survey systematics
- Combine multiple probes of PNG
- Cosmic variance cancellation & Super-sample variance

Field-level inference

1) Forward model



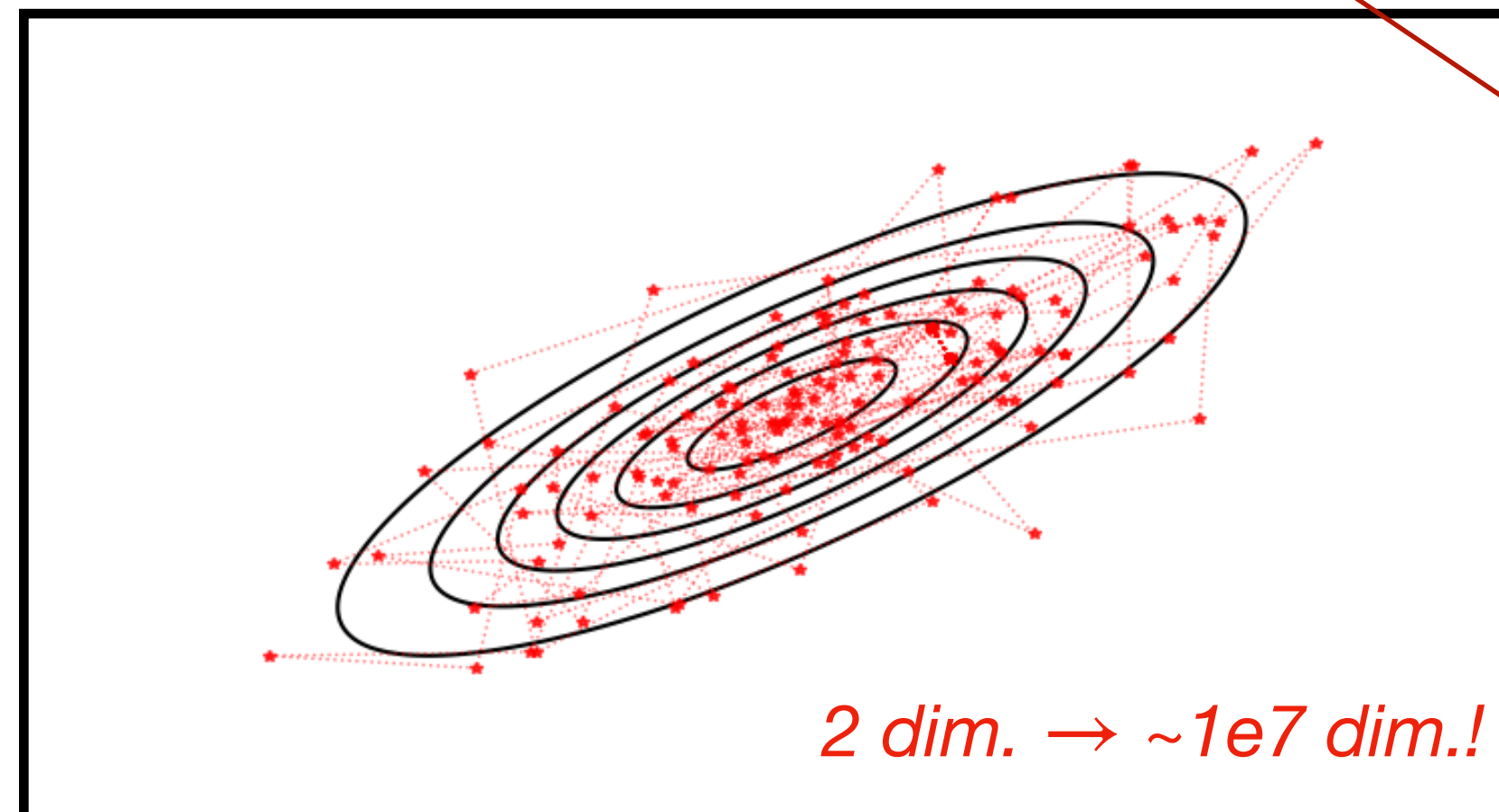
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See Anže's talk

Field-level inference

1) Forward model



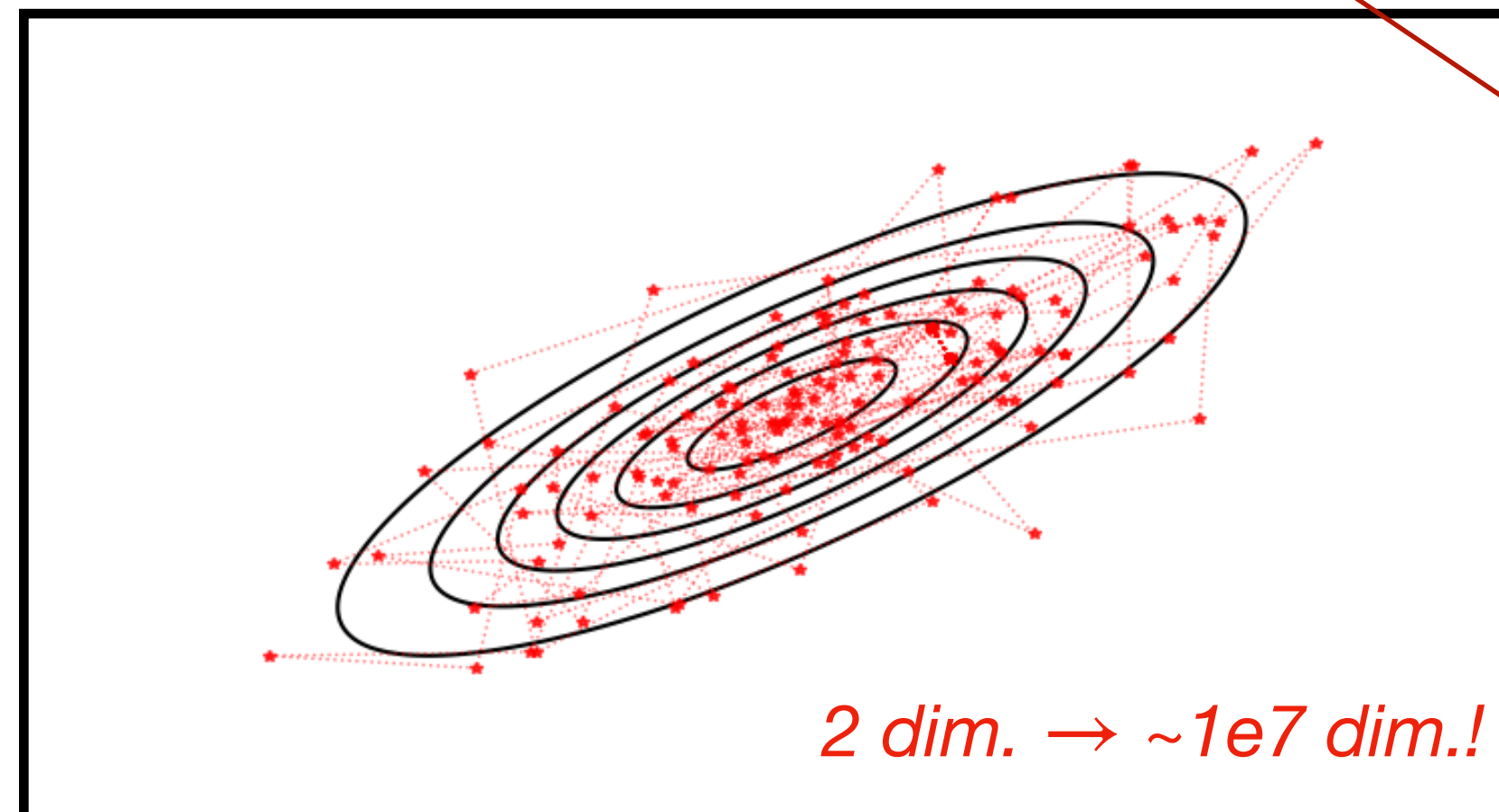
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See Anže's talk

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

Mock data test

Mock data test

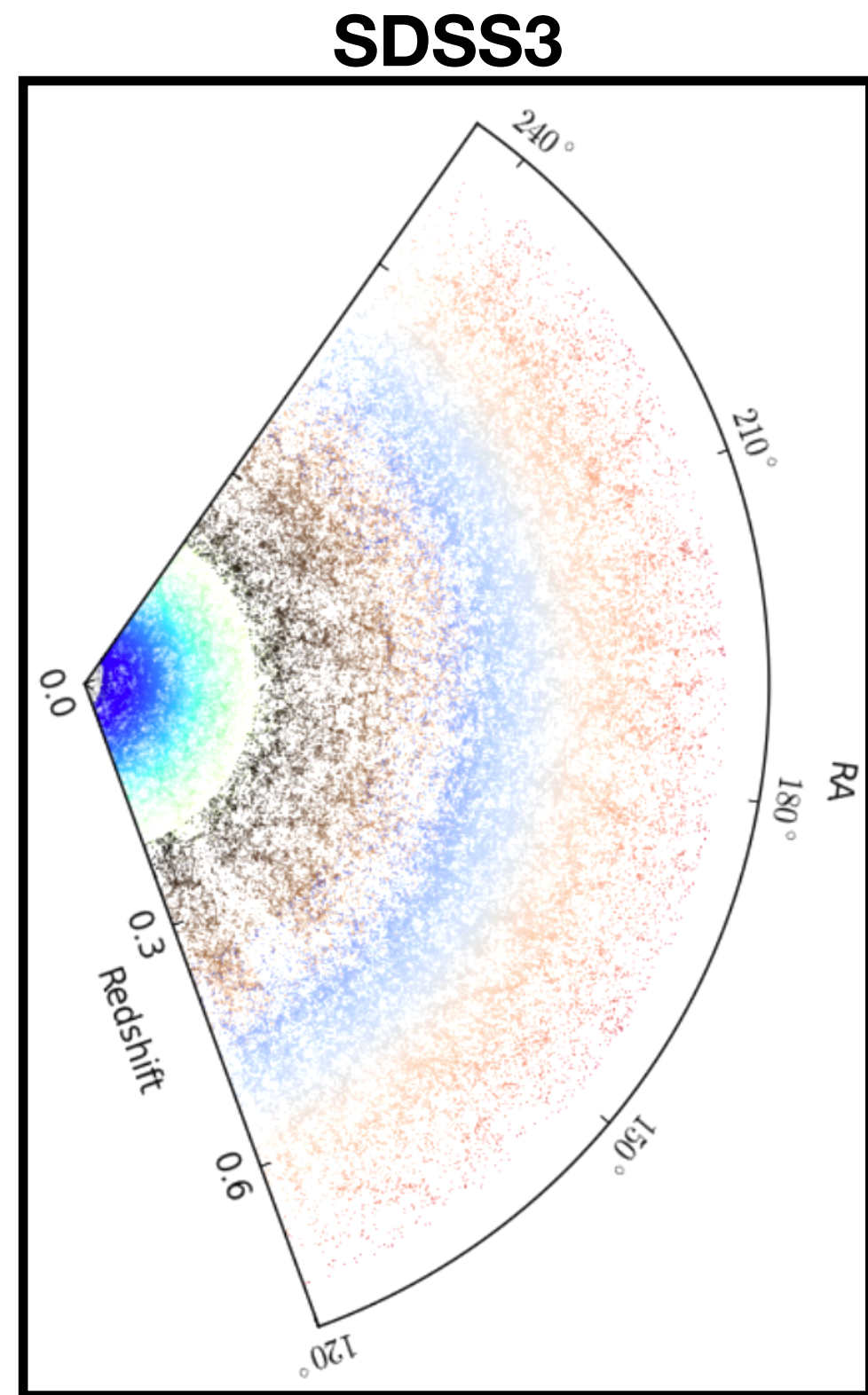
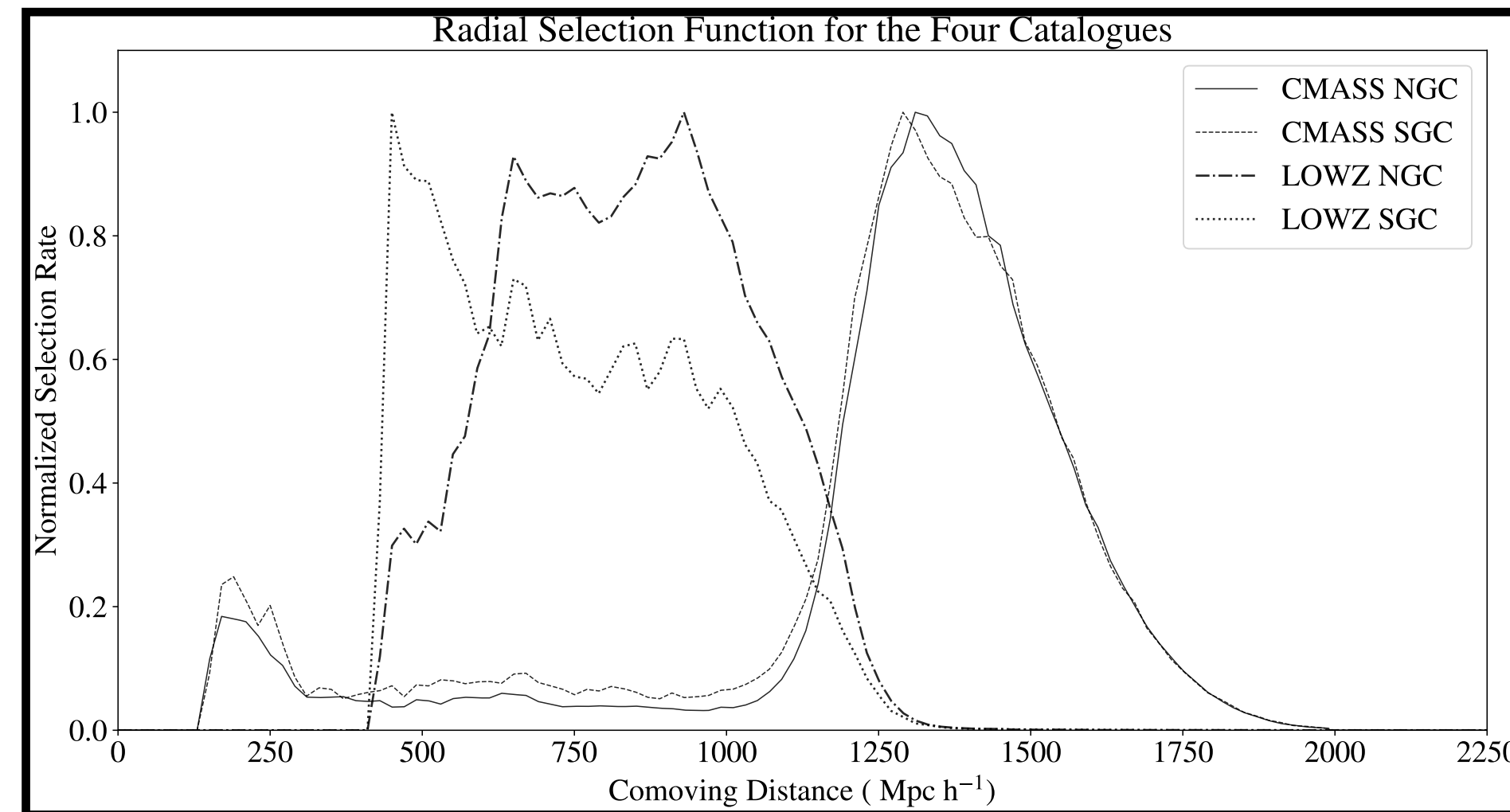
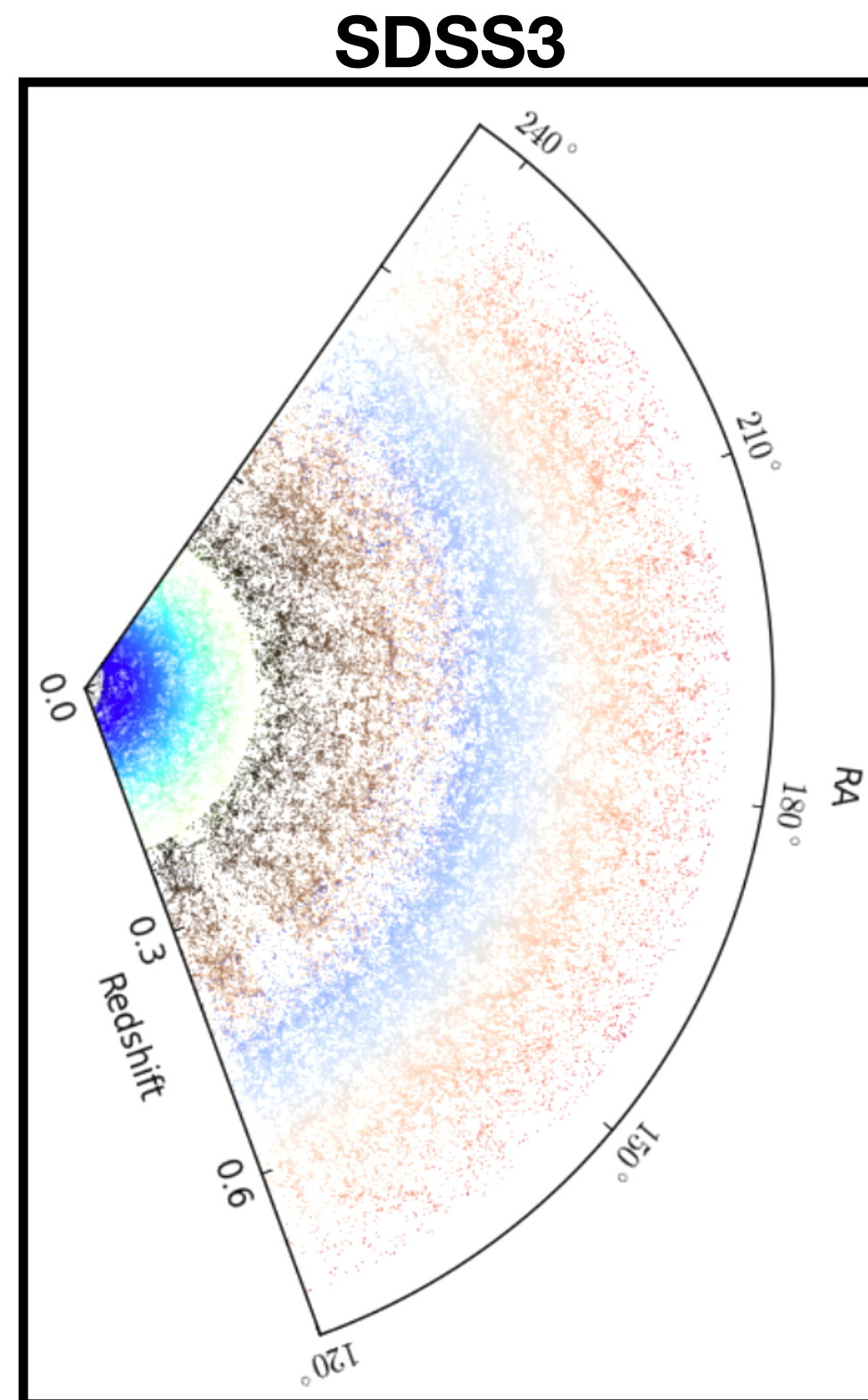


Figure Credit: Guilhem Lavaux

Mock data test

Radial Selection

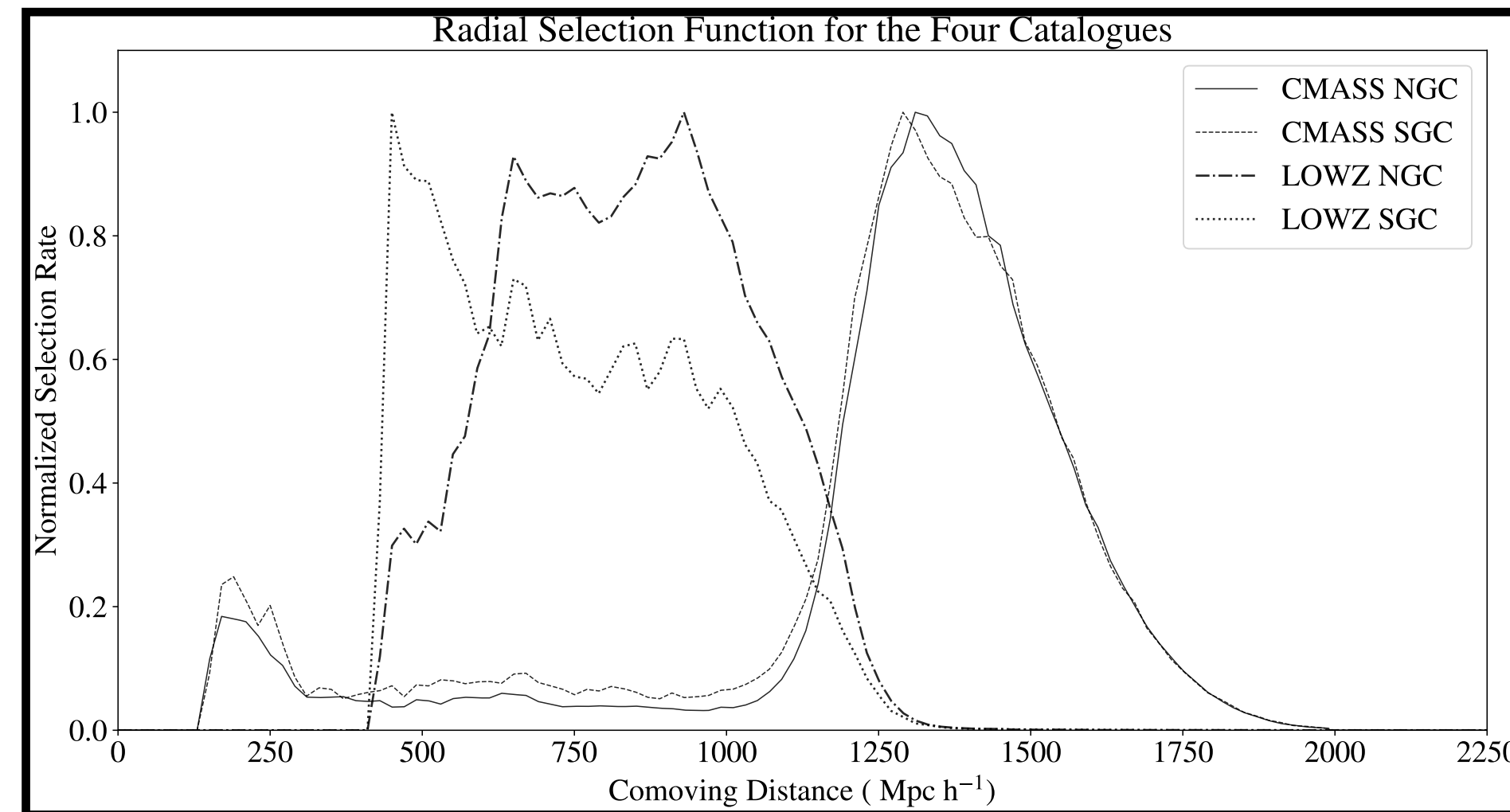
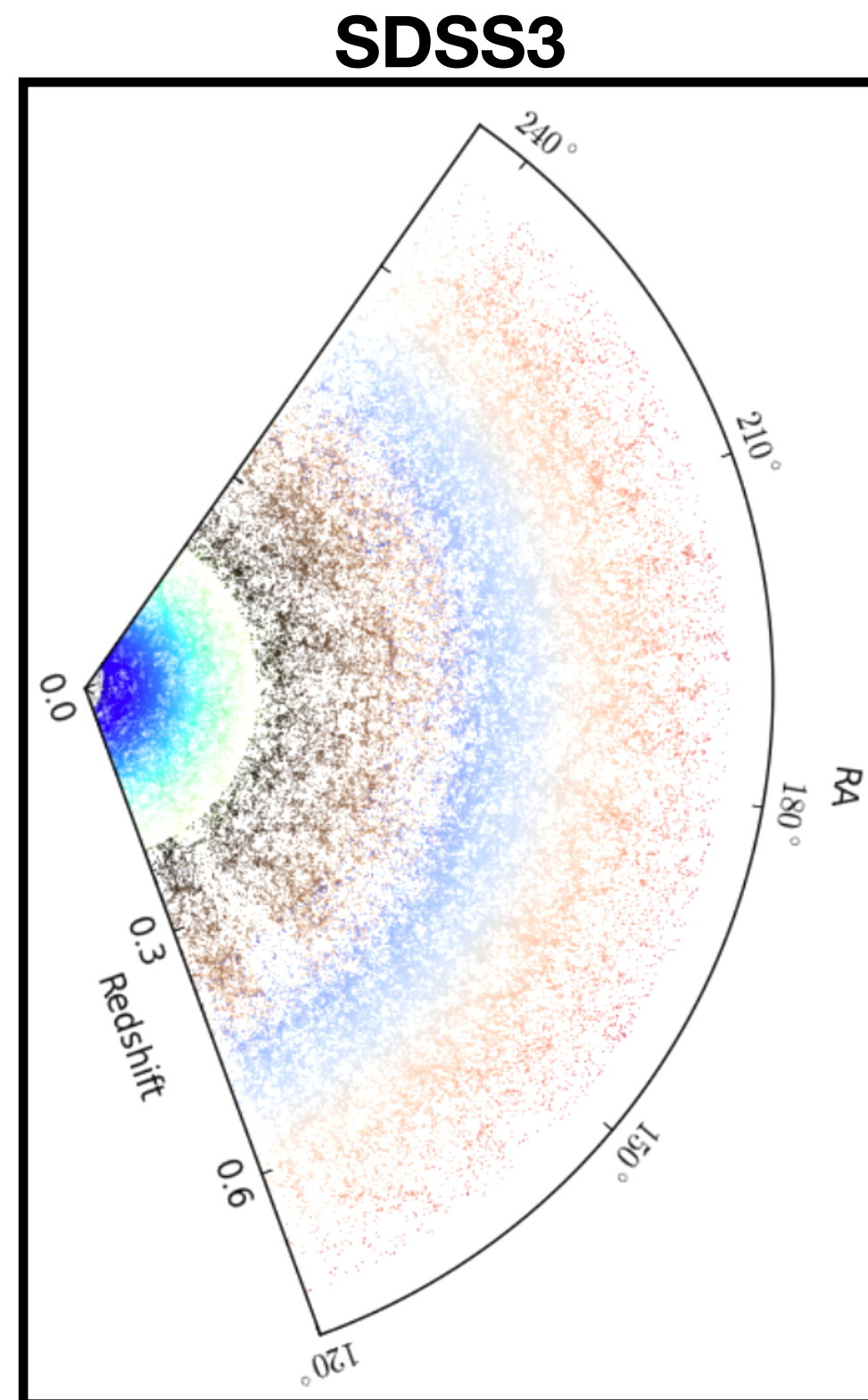


Andrews et al. 2022

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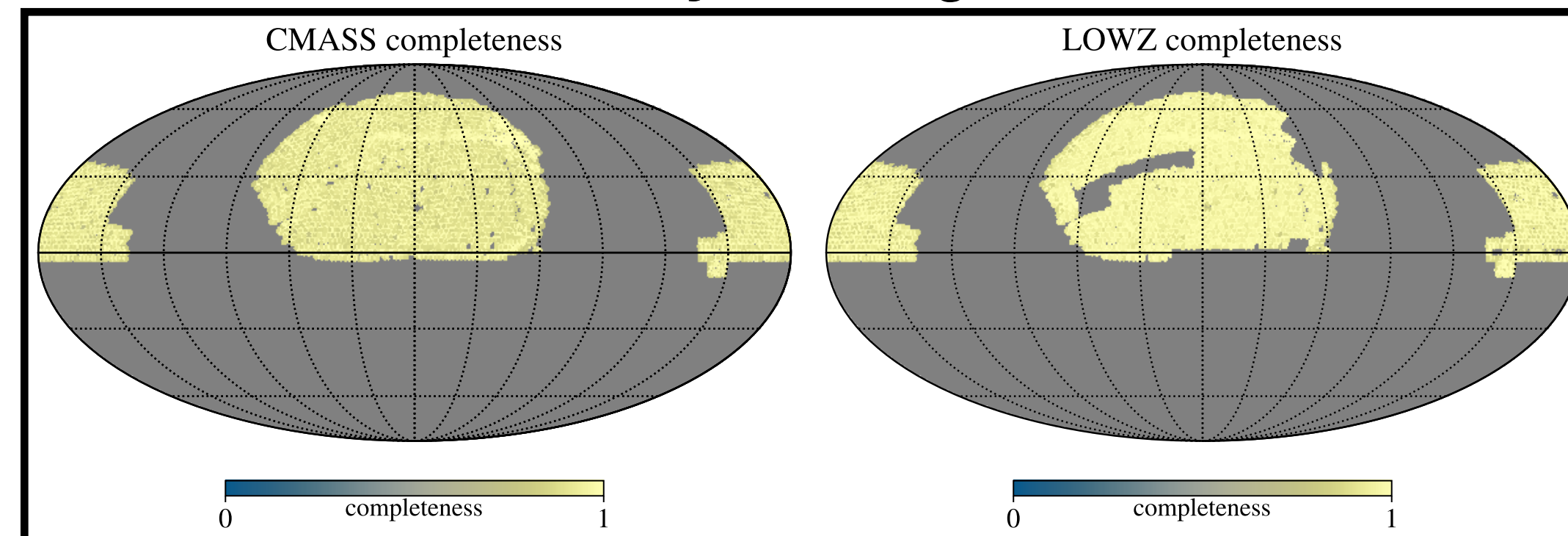
Mock data test

Radial Selection



Andrews et al. 2022

Sky Coverage

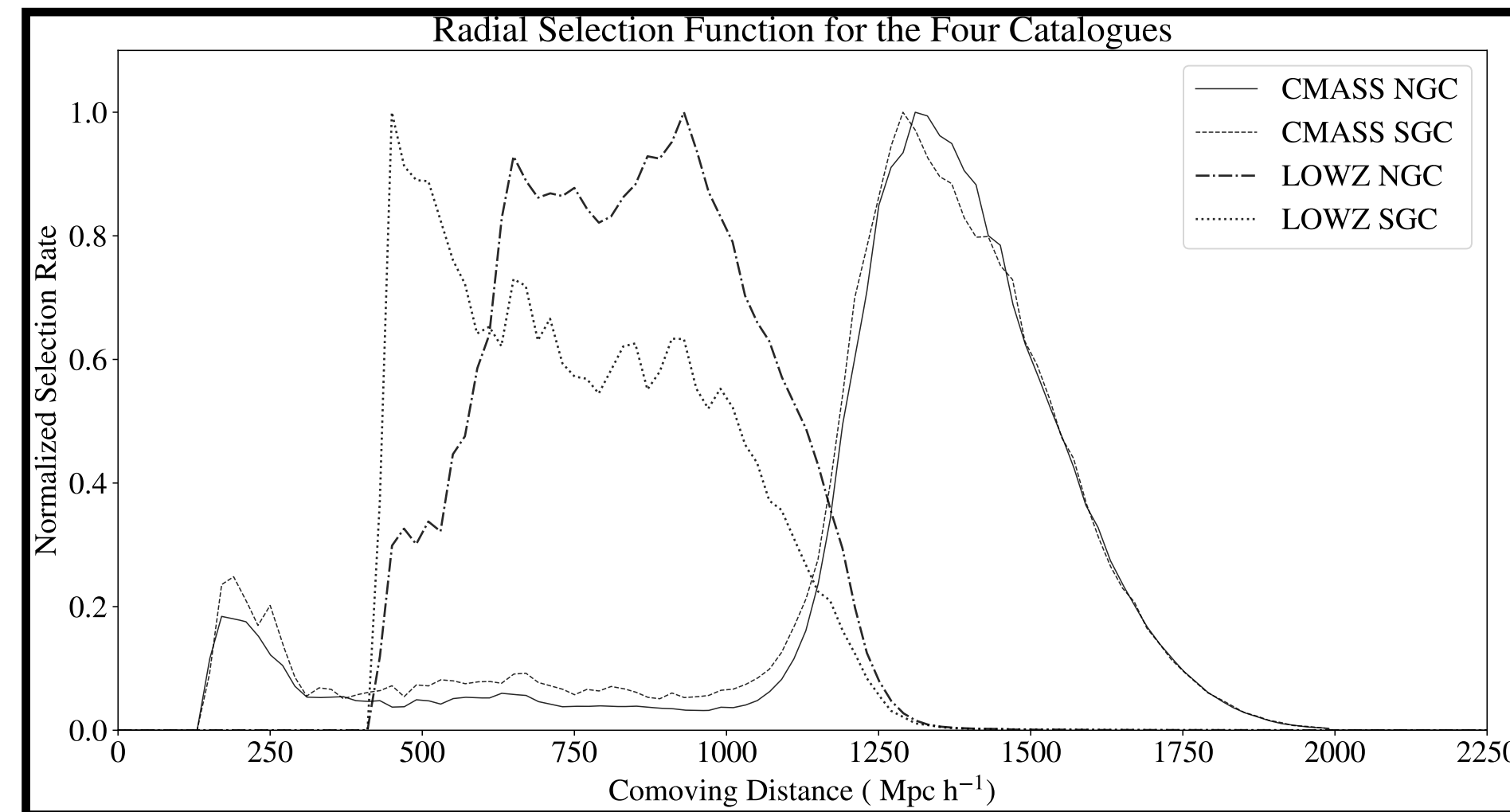
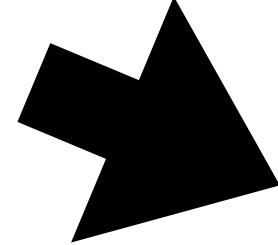
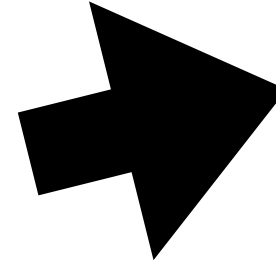
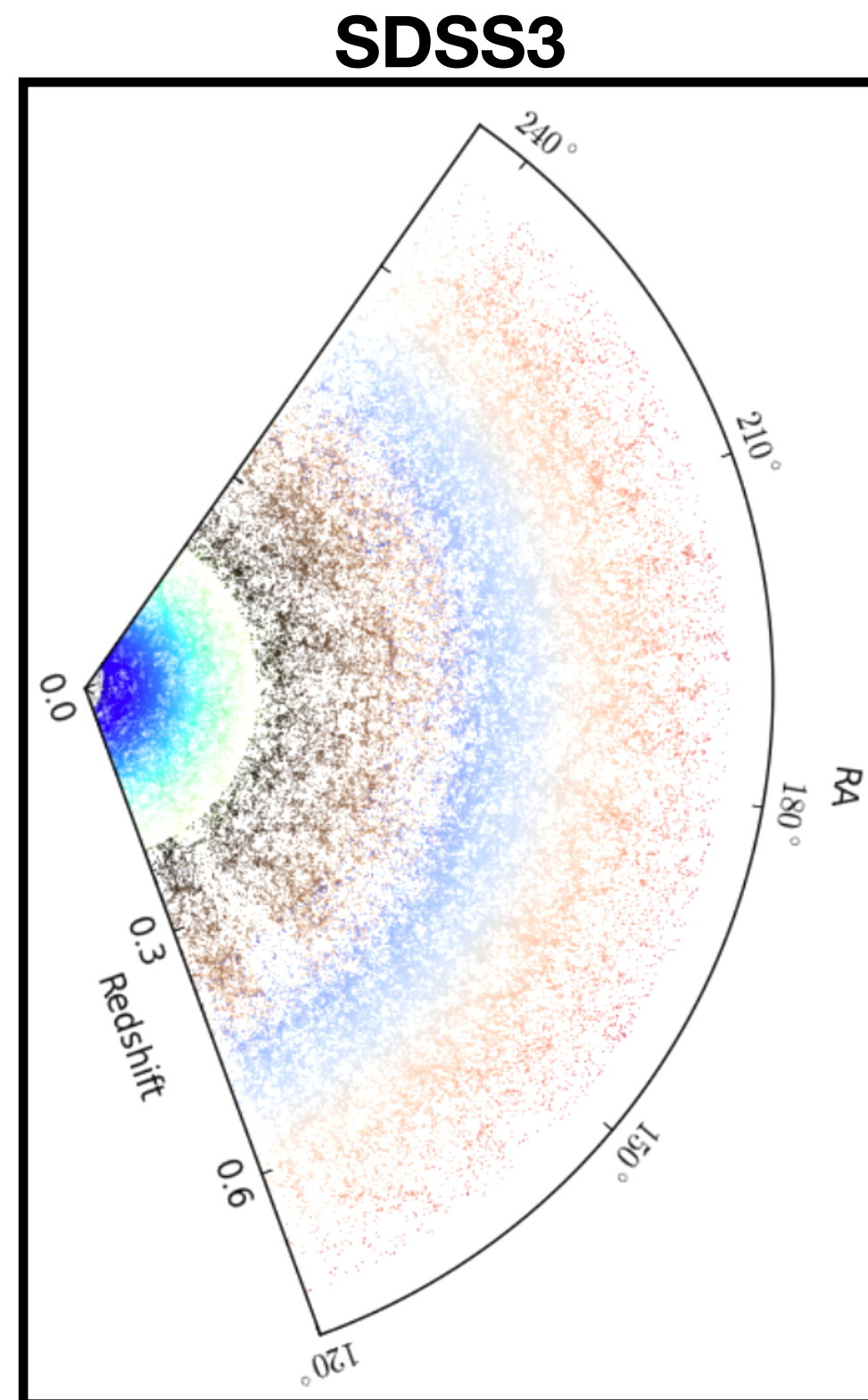


Andrews et al. 2022

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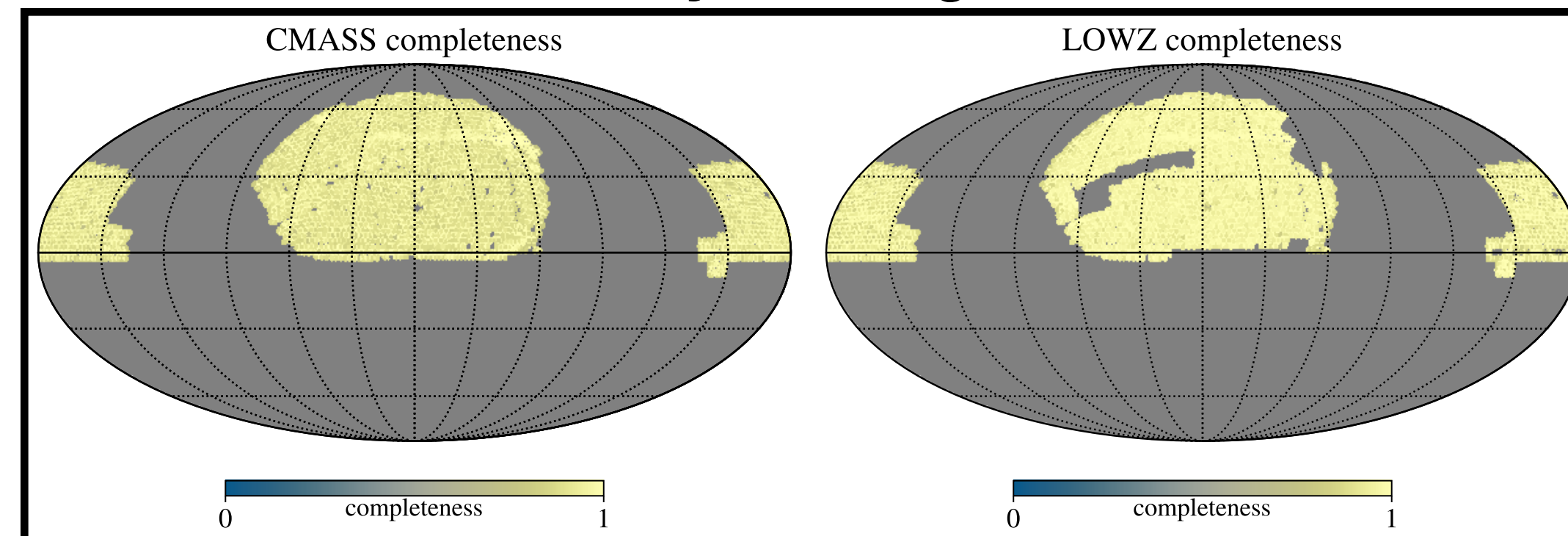
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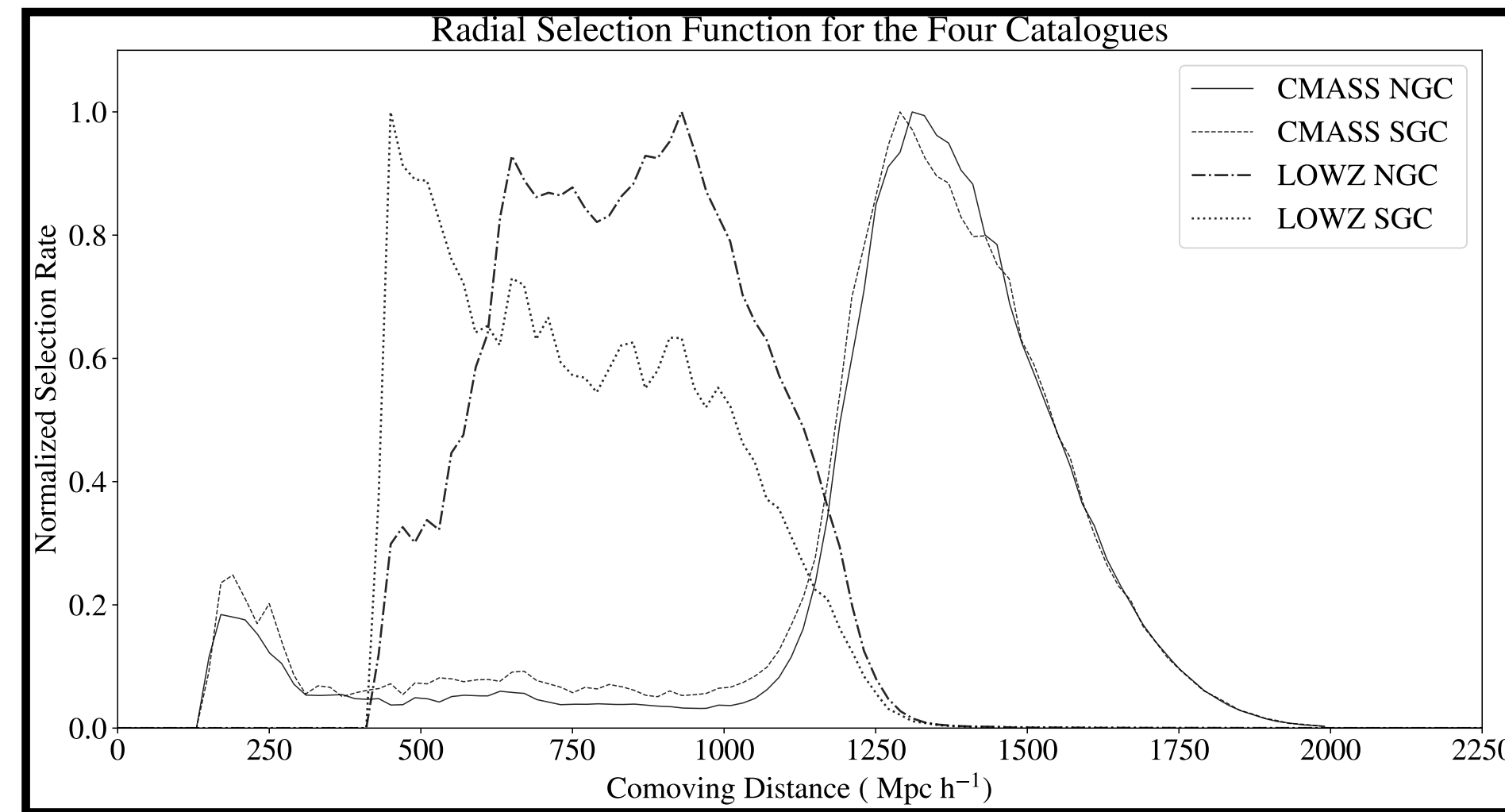
Andrews et al. 2022

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$$f_{nl} = 5$$

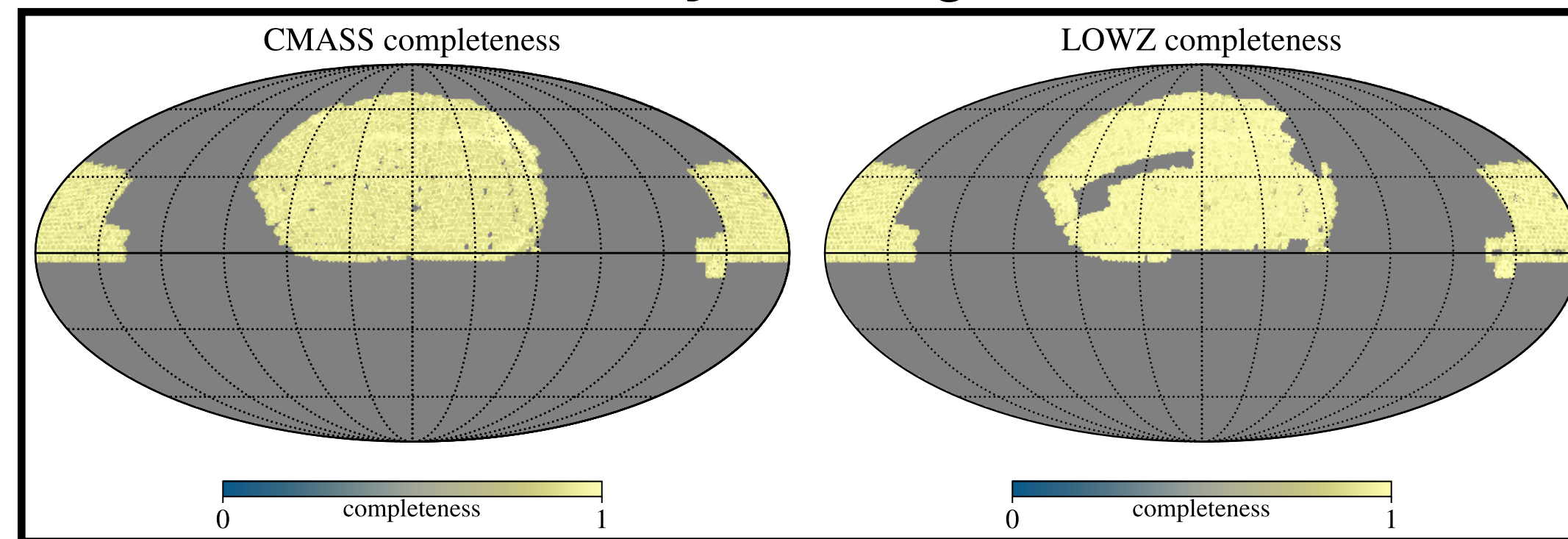
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Andrews et al. 2022

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Andrews et al. 2022

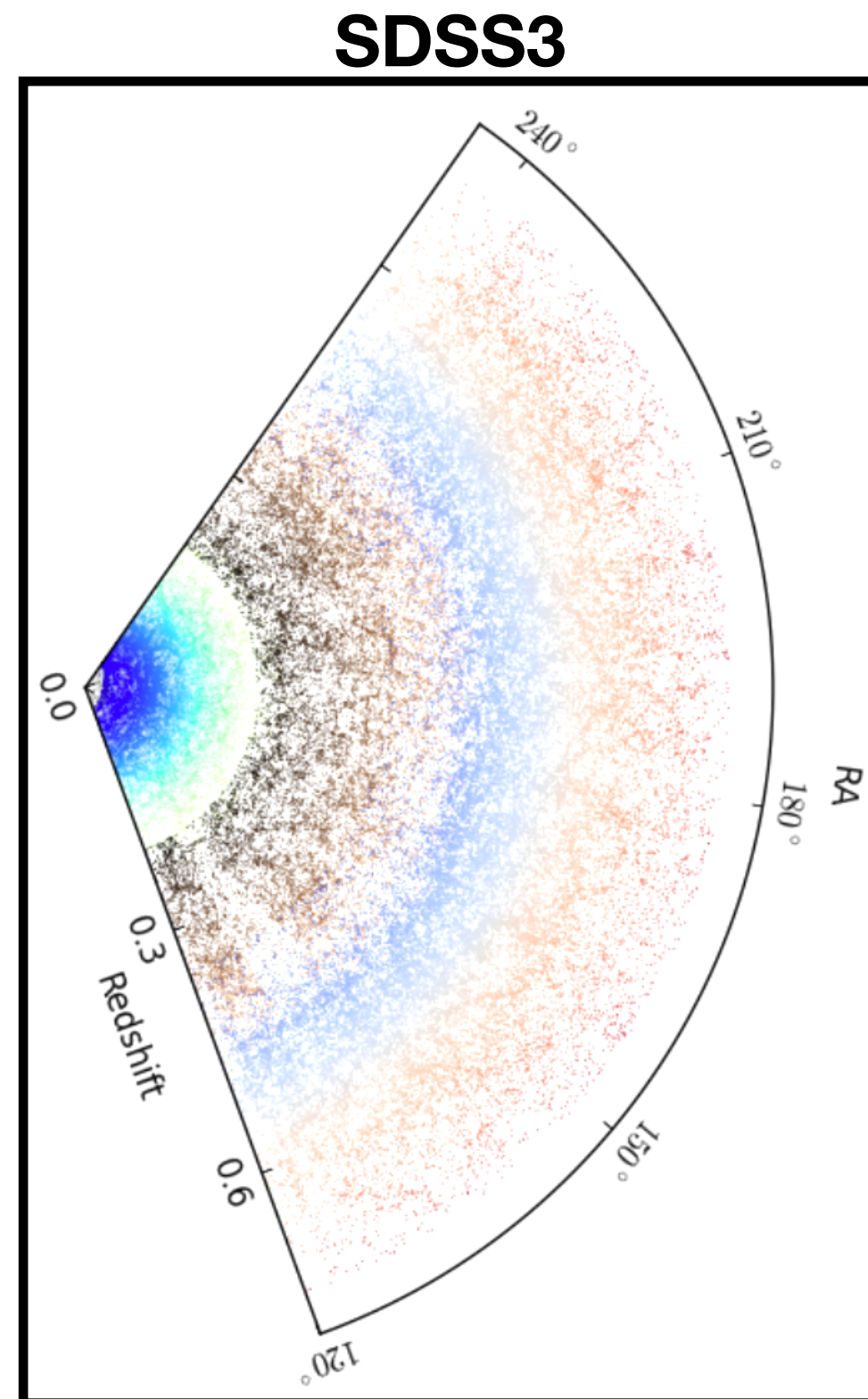
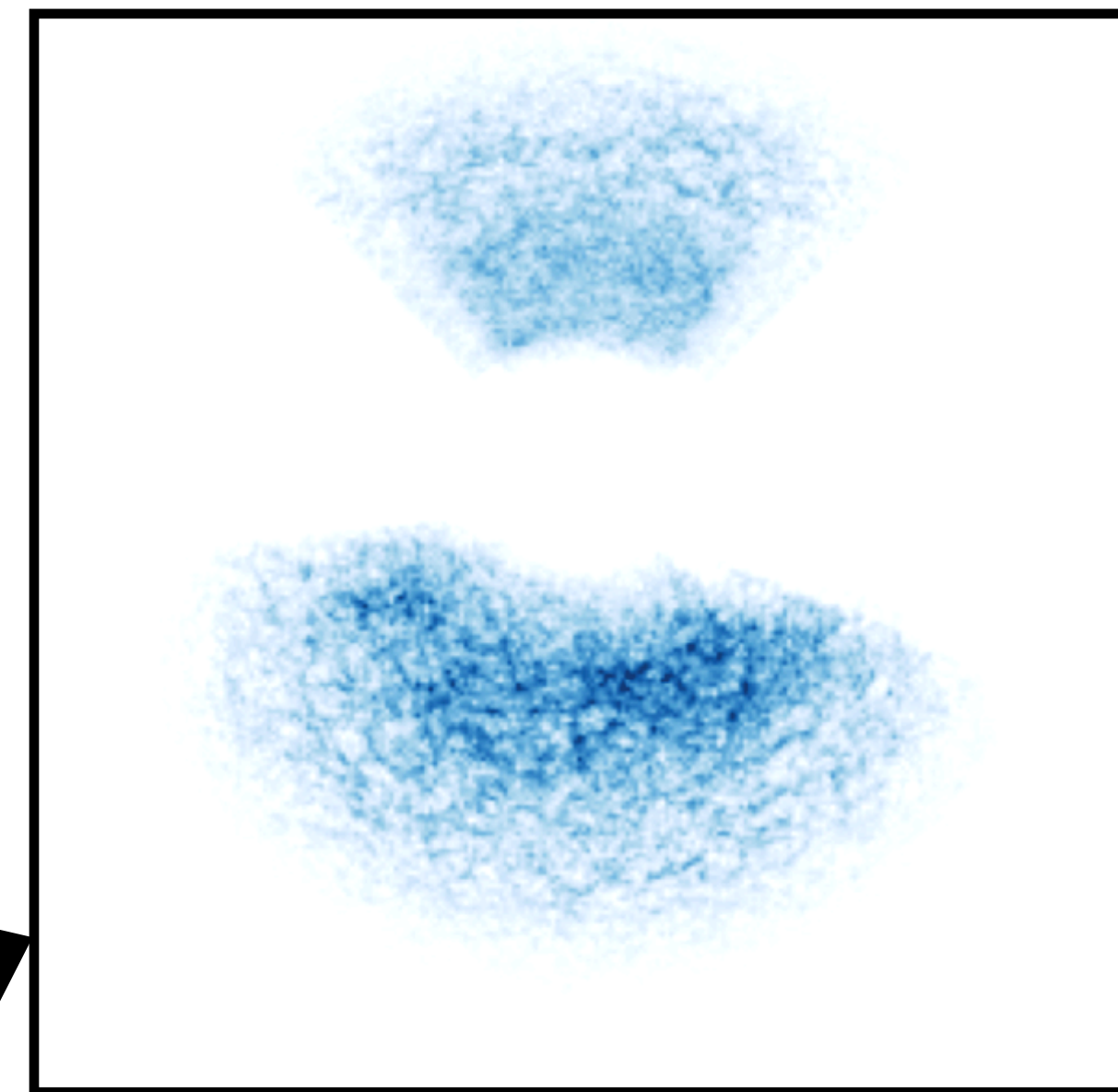


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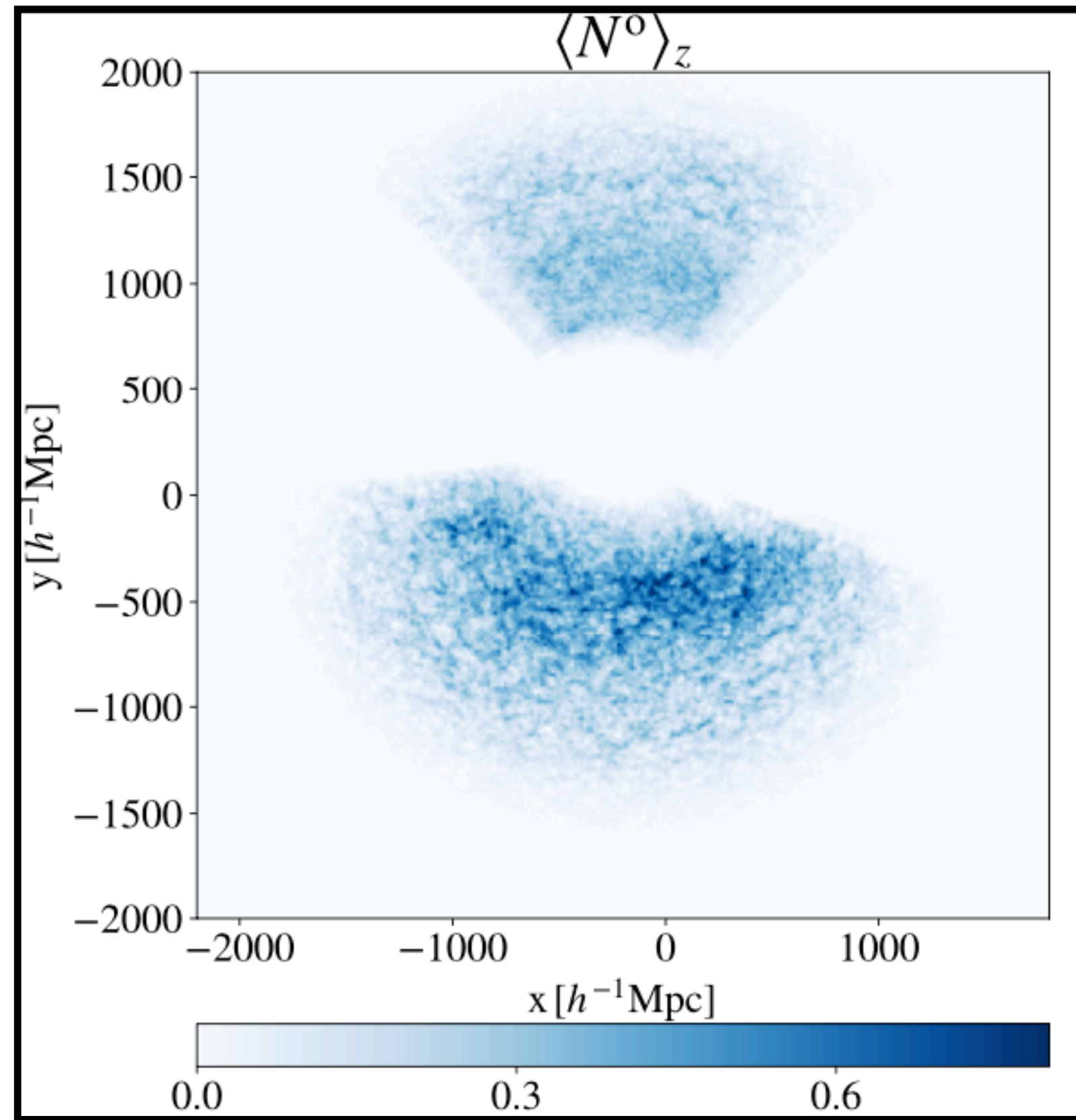
Mock Data



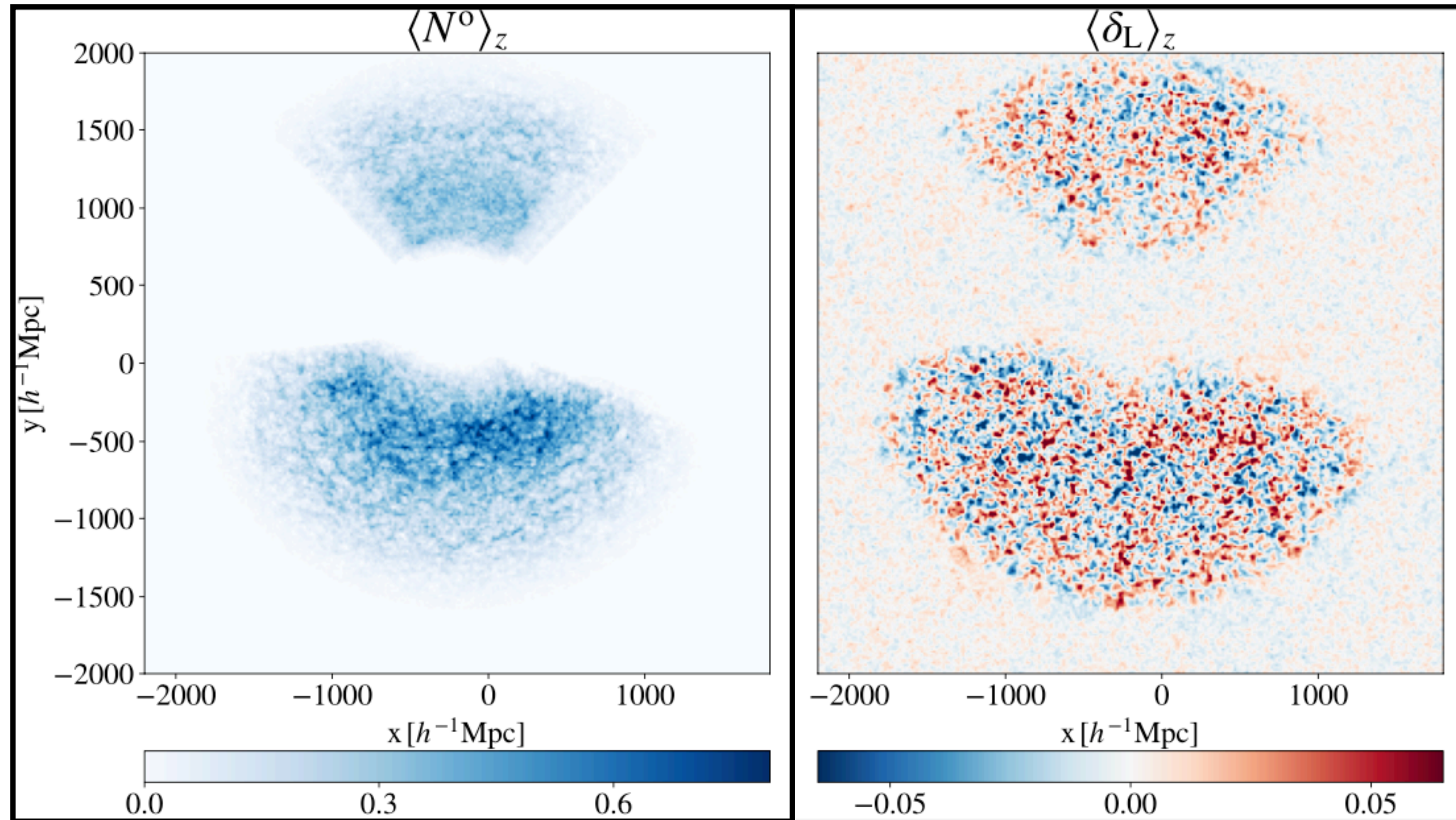
$f_{nl} = 5$

Inferring the density field

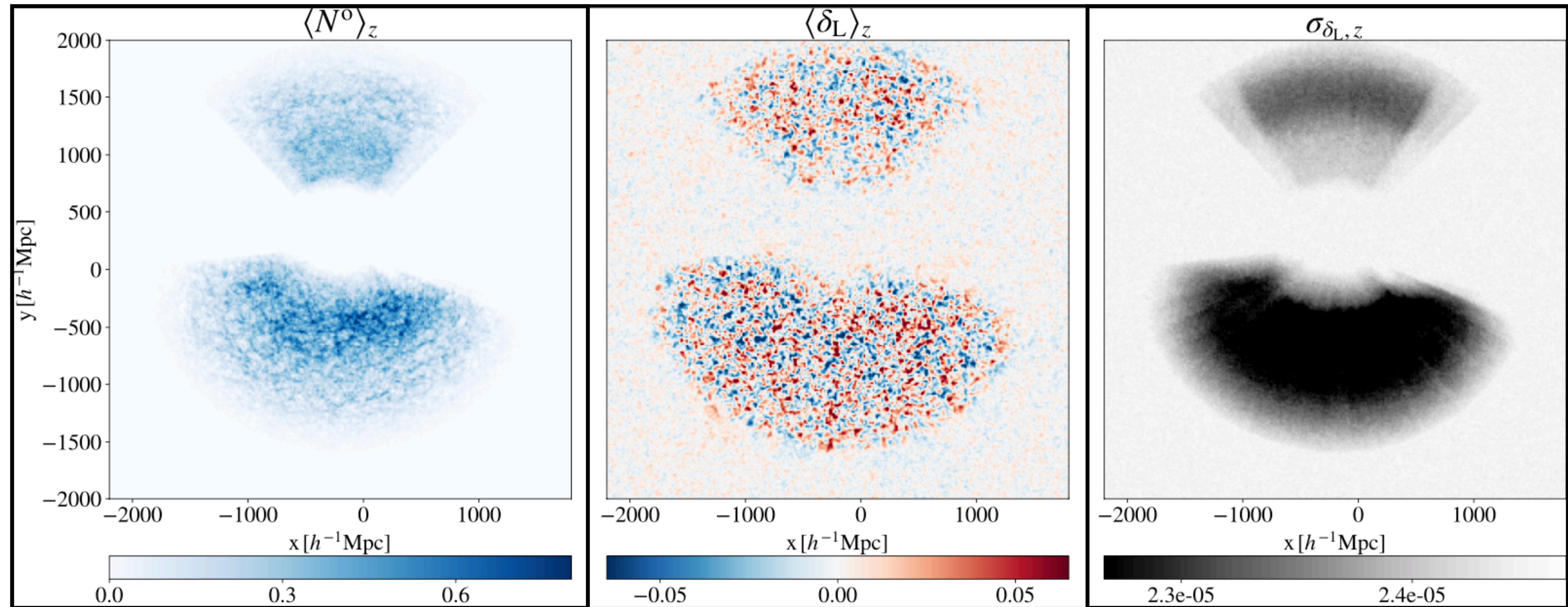
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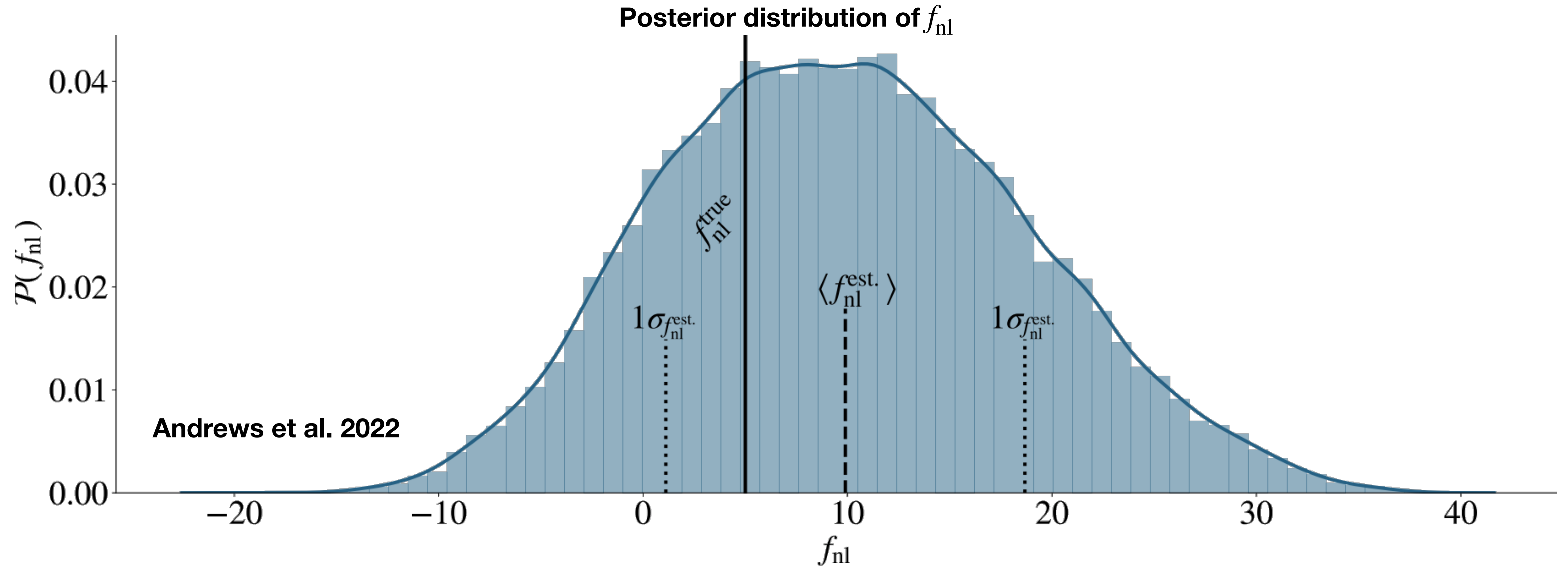


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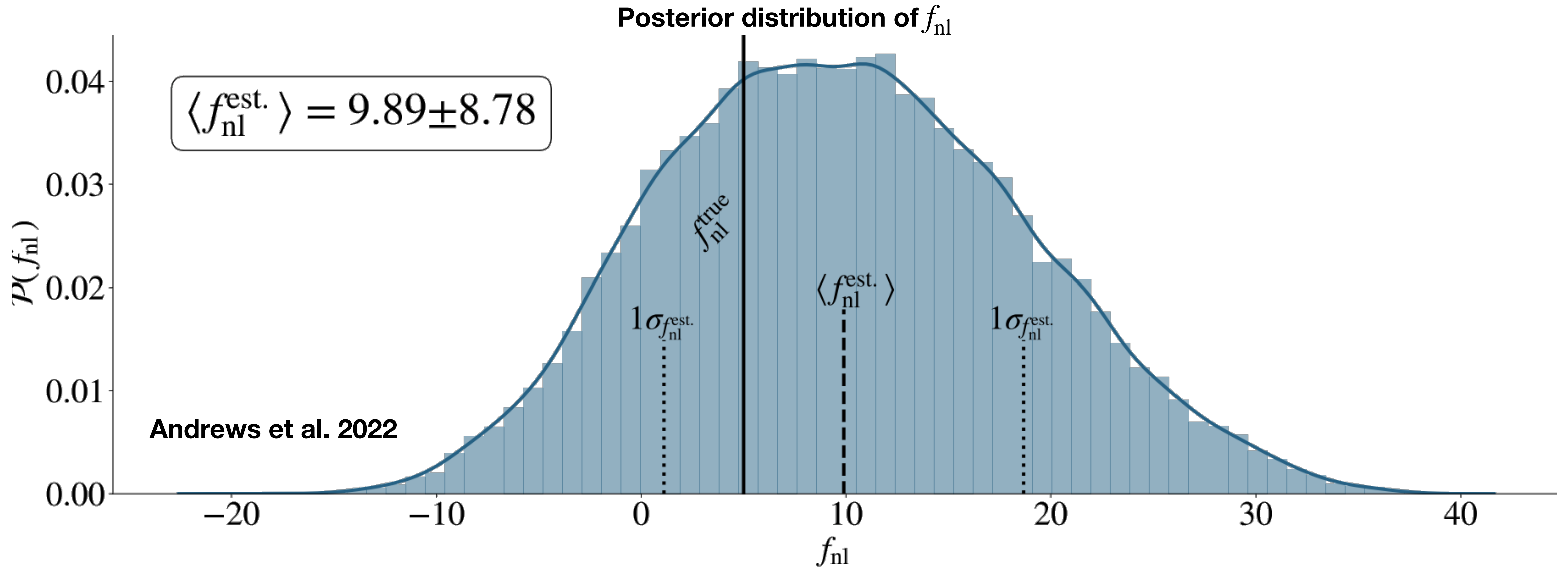


SDSS Mock Test: Main result

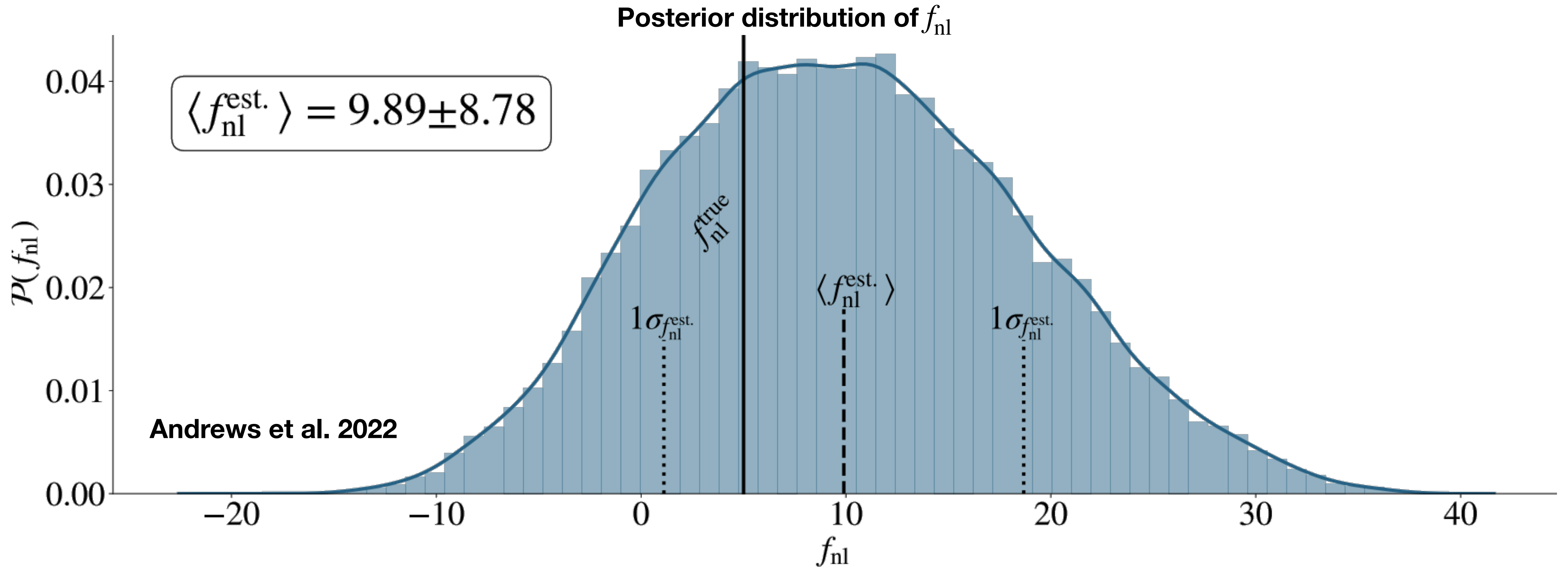
SDSS Mock Test: Main result



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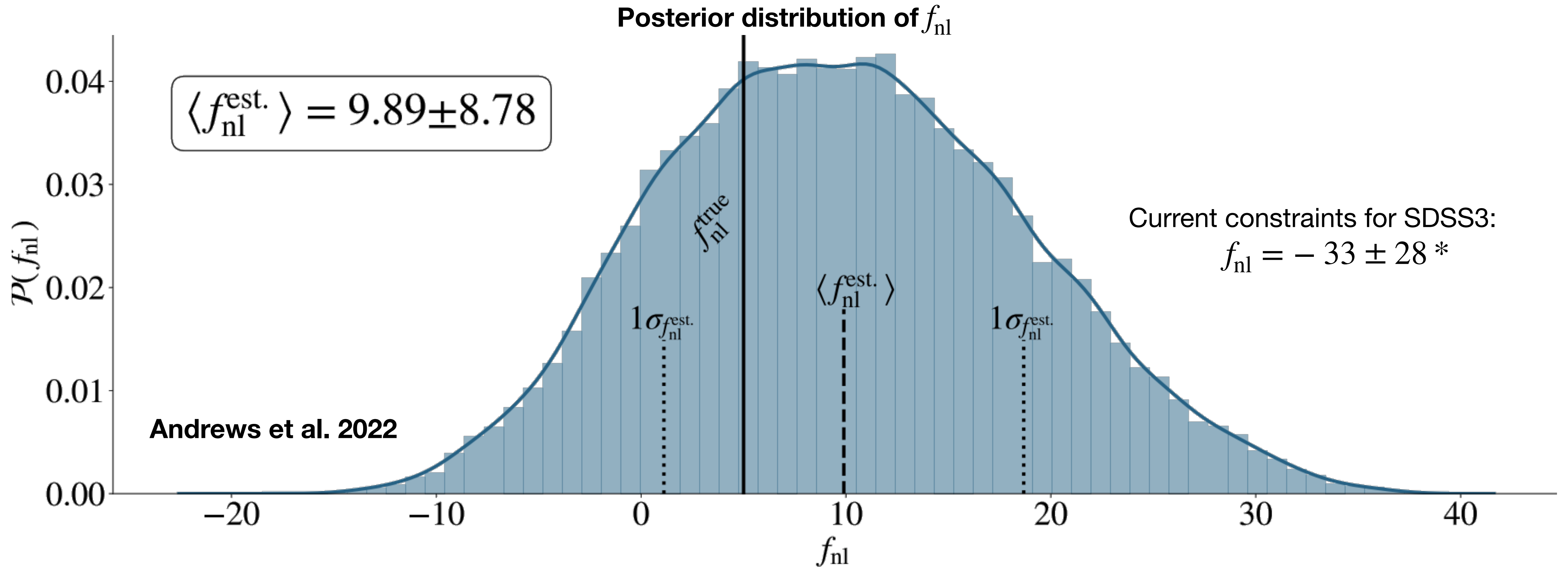


SDSS Mock Test: Main result



Full statement on the information content available in the data!

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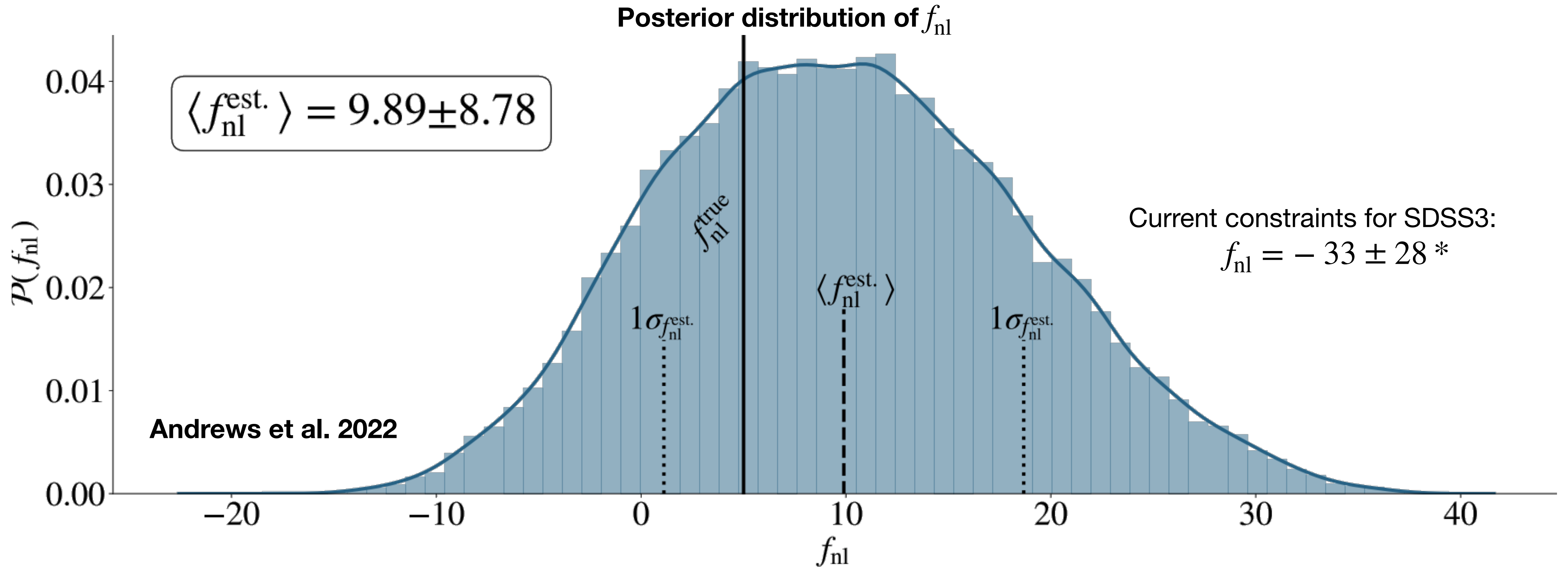


Full statement on the information content available in the data!

See Oliver's talk

*Cabass et al. 2022

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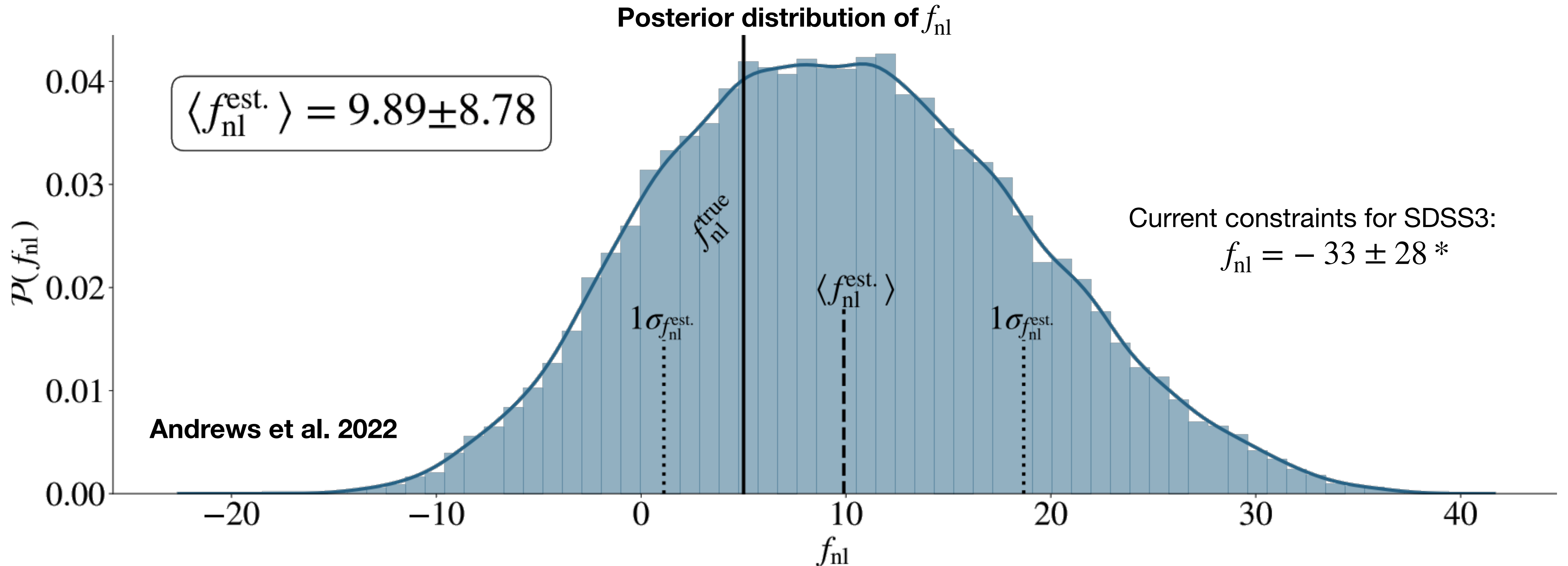
However...

missing realistic survey systematics (Ashley's and Eva's talks)

See Oliver's talk

*Cabass et al. 2022

SDSS Mock Test: Main result



Full statement on the information content available in the data!

However...

missing realistic survey systematics (Ashley's and Eva's talks)

fixed $p=1$ (Alex's talk and yesterday's discussion)

See Oliver's talk

*Cabass et al. 2022

Opportunities for field-level inference

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Handle survey systematics?

Opportunities for field-level inference

Handle survey systematics?

-Physics informed model

Opportunities for field-level inference

Handle survey systematics?

-Physics informed model

-Integrate out unphysical signals

Opportunities for field-level inference

Handle survey systematics?

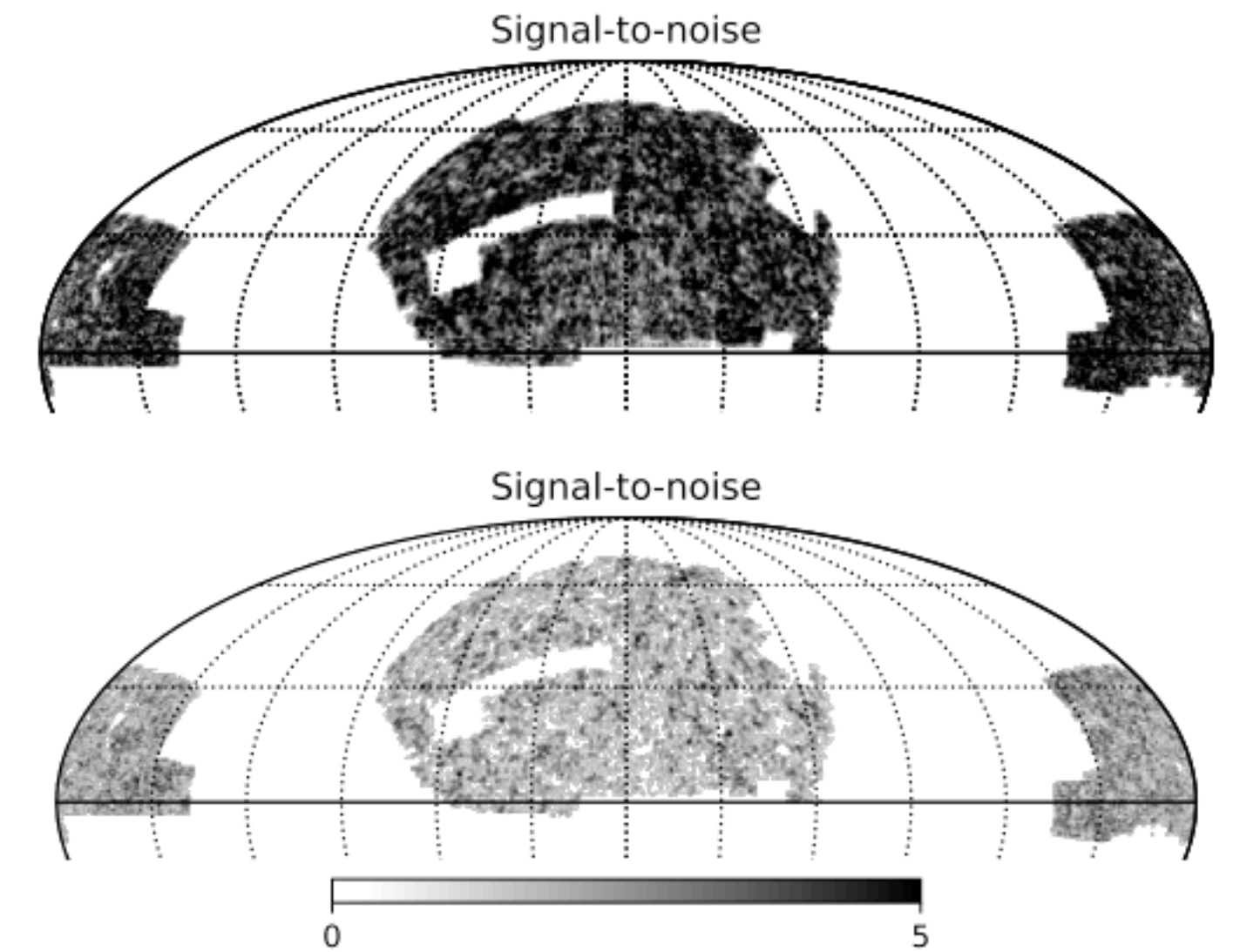
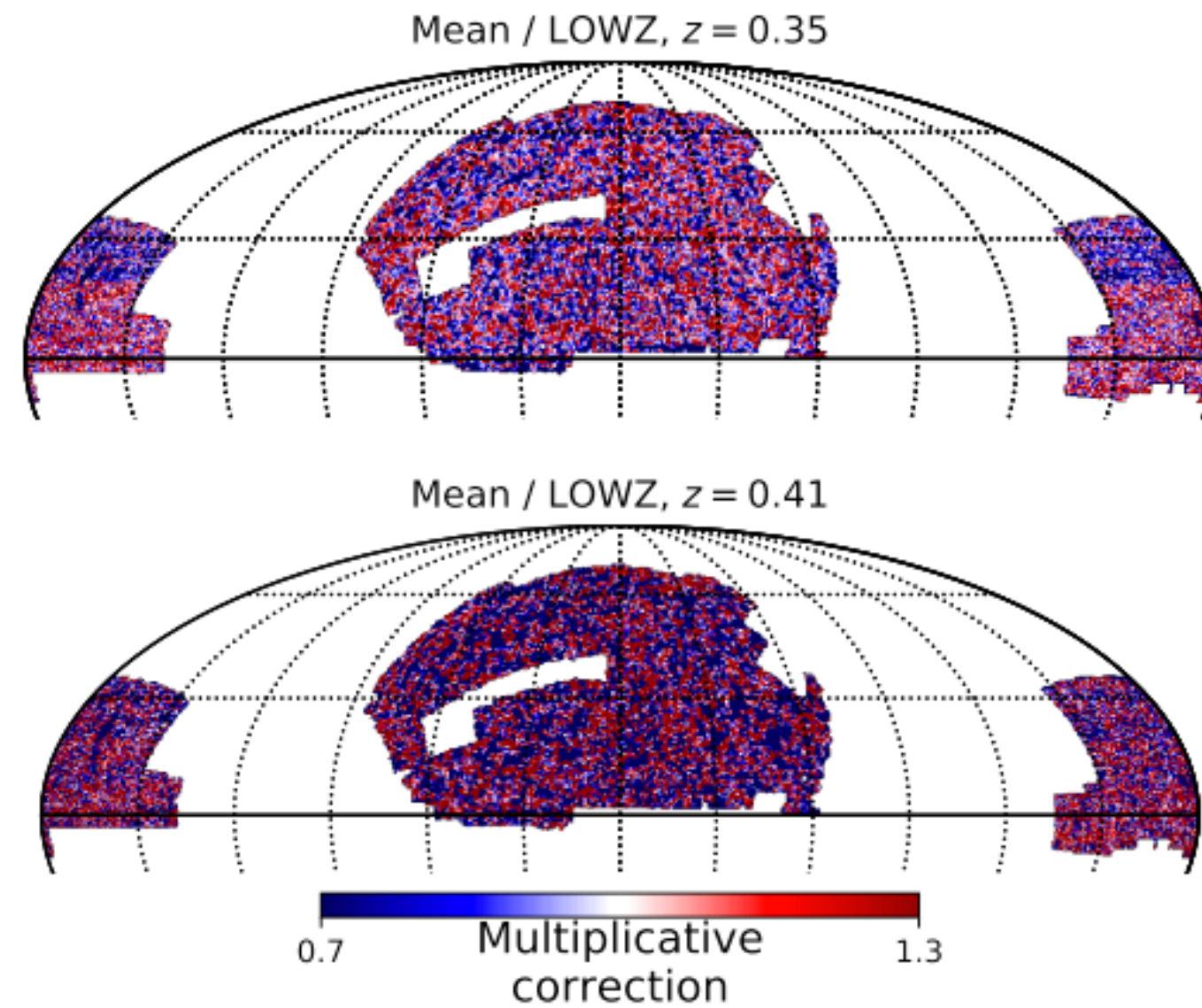
-Physics informed model

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-Go back and check:

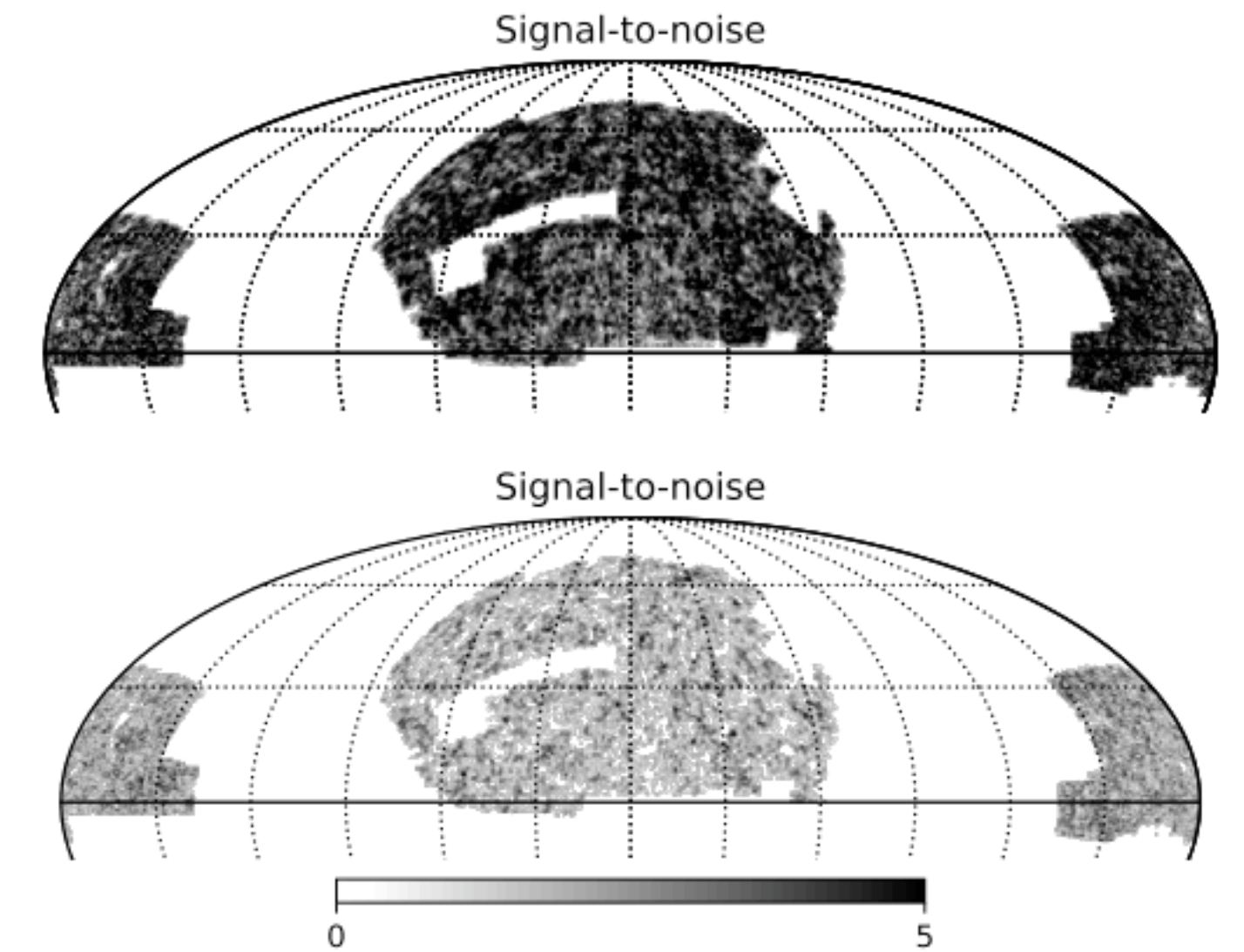
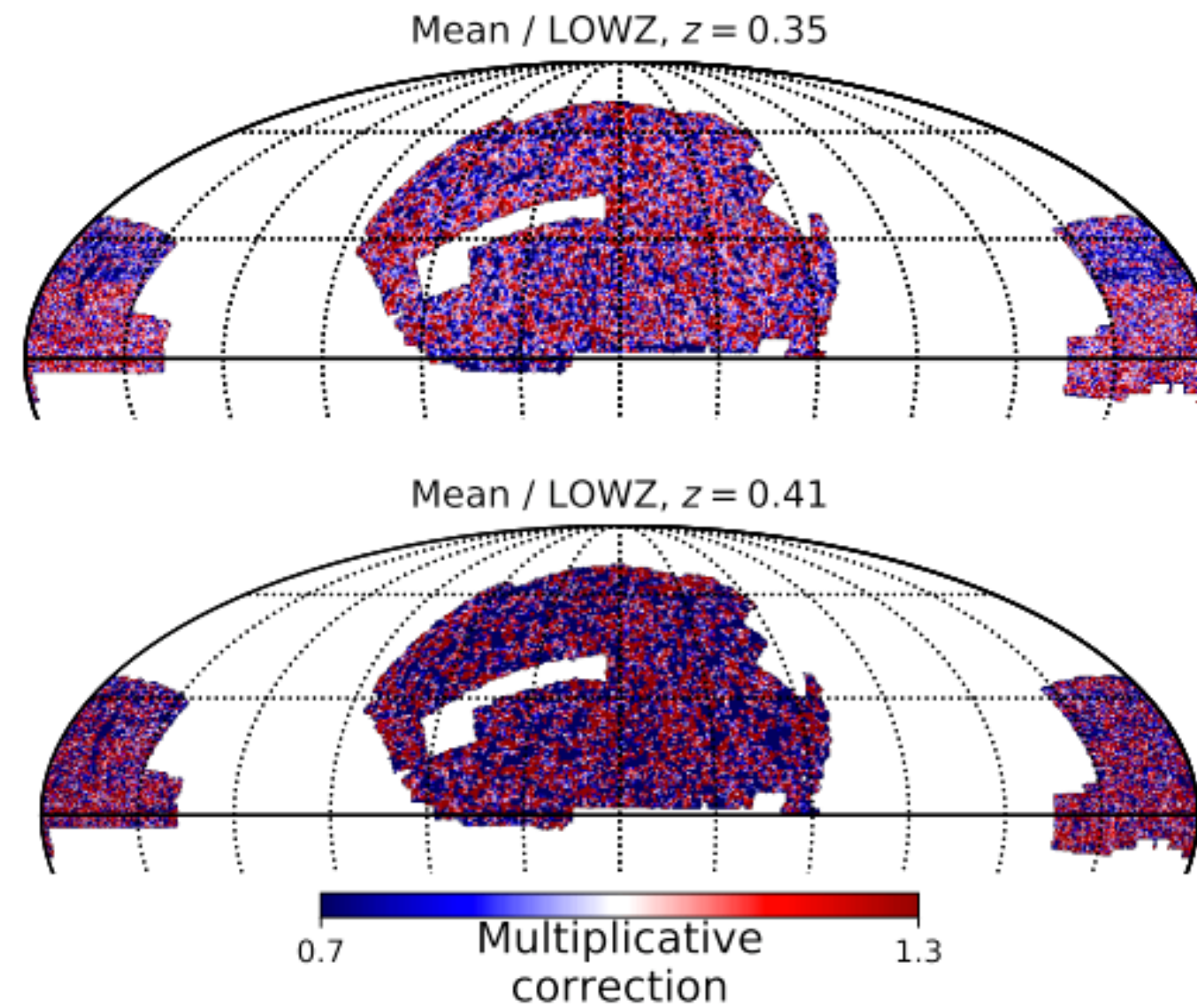
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- Handle survey systematics?
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Opportunities for field-level inference

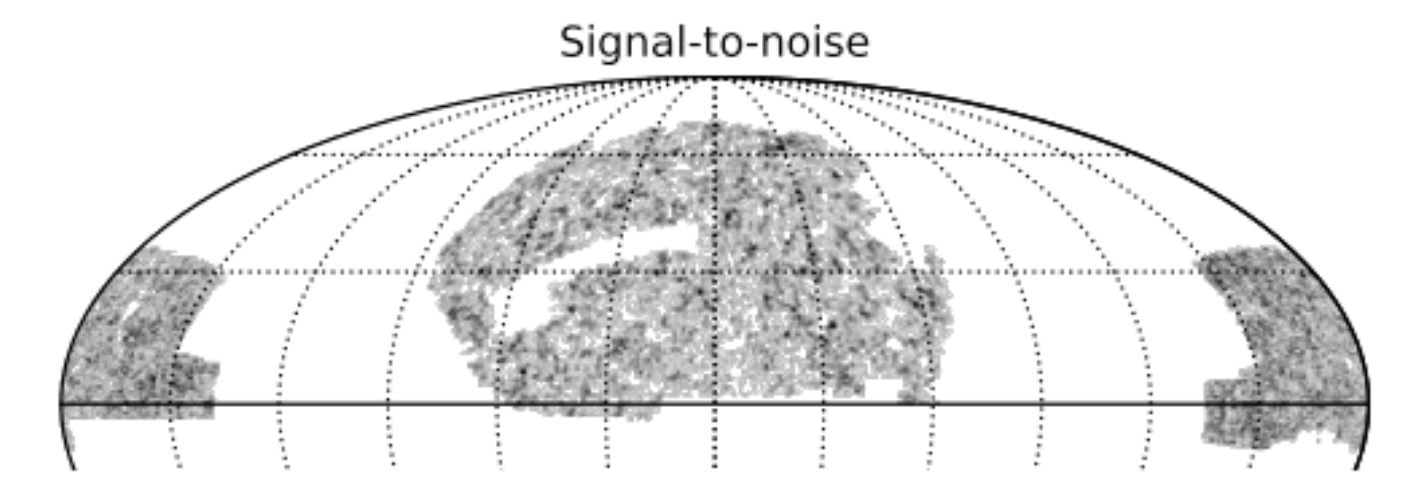
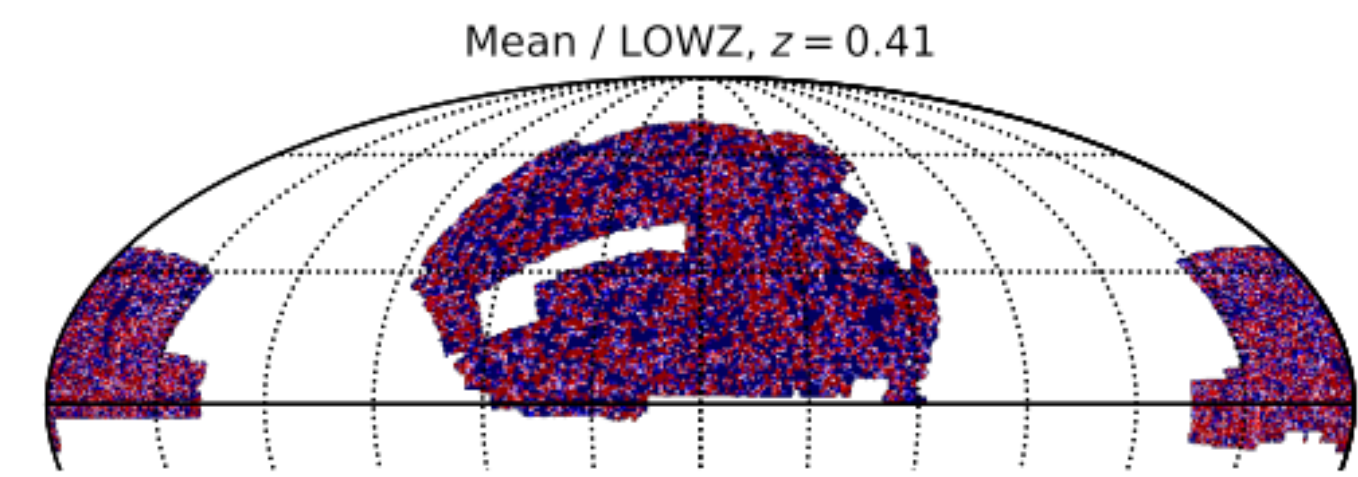
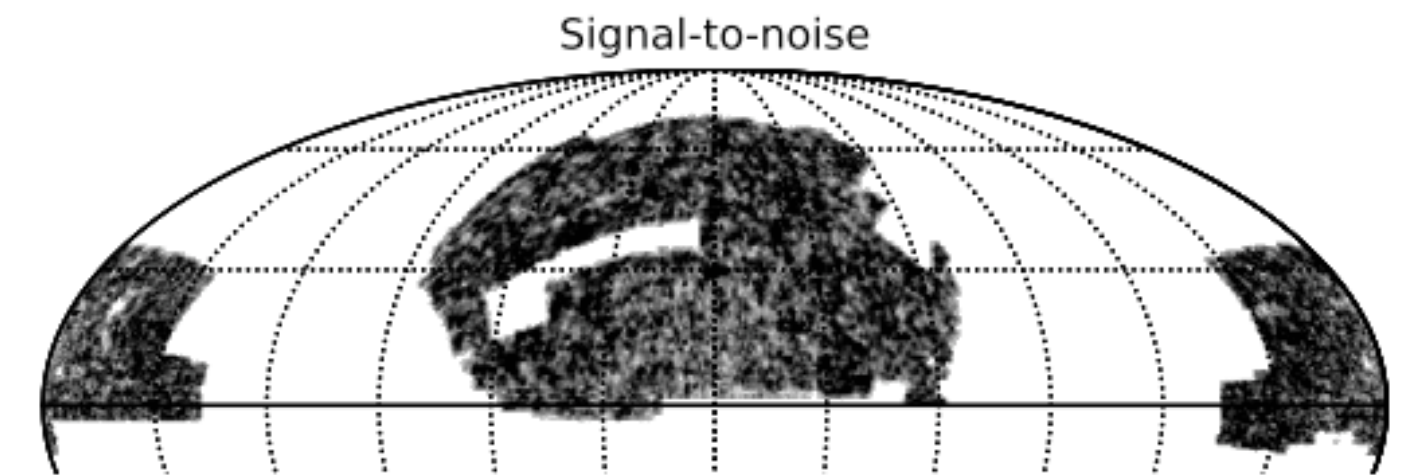
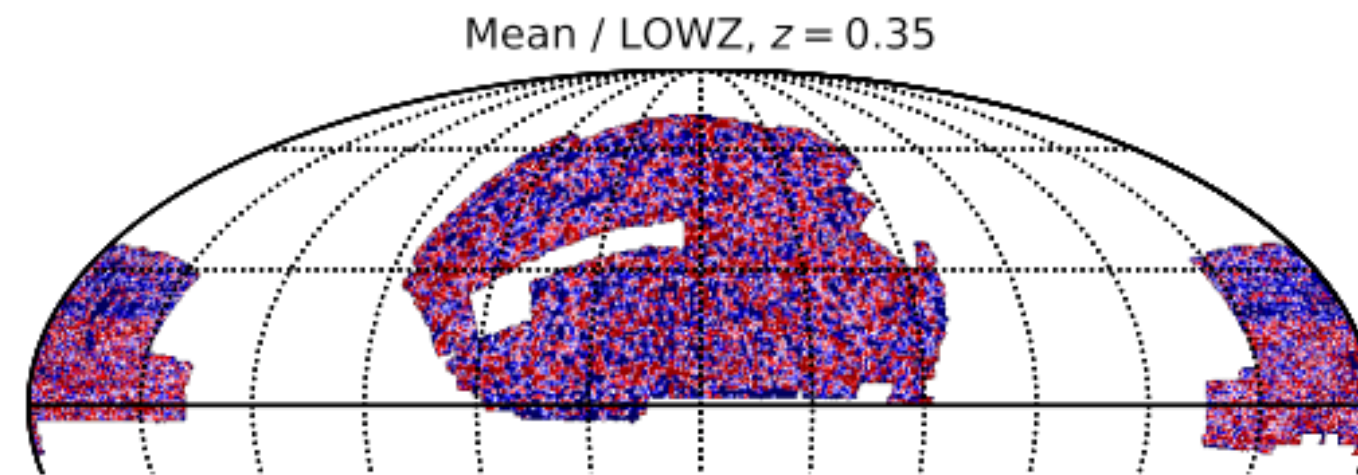
- Handle survey systematics?
-Physics informed model
-Integrate out unphysical signals
-Go back and check:



Where to point of new discoveries?

Opportunities for field-level inference

- Handle survey systematics?
 - Physics informed model
 - Integrate out unphysical signals
 - Go back and check:

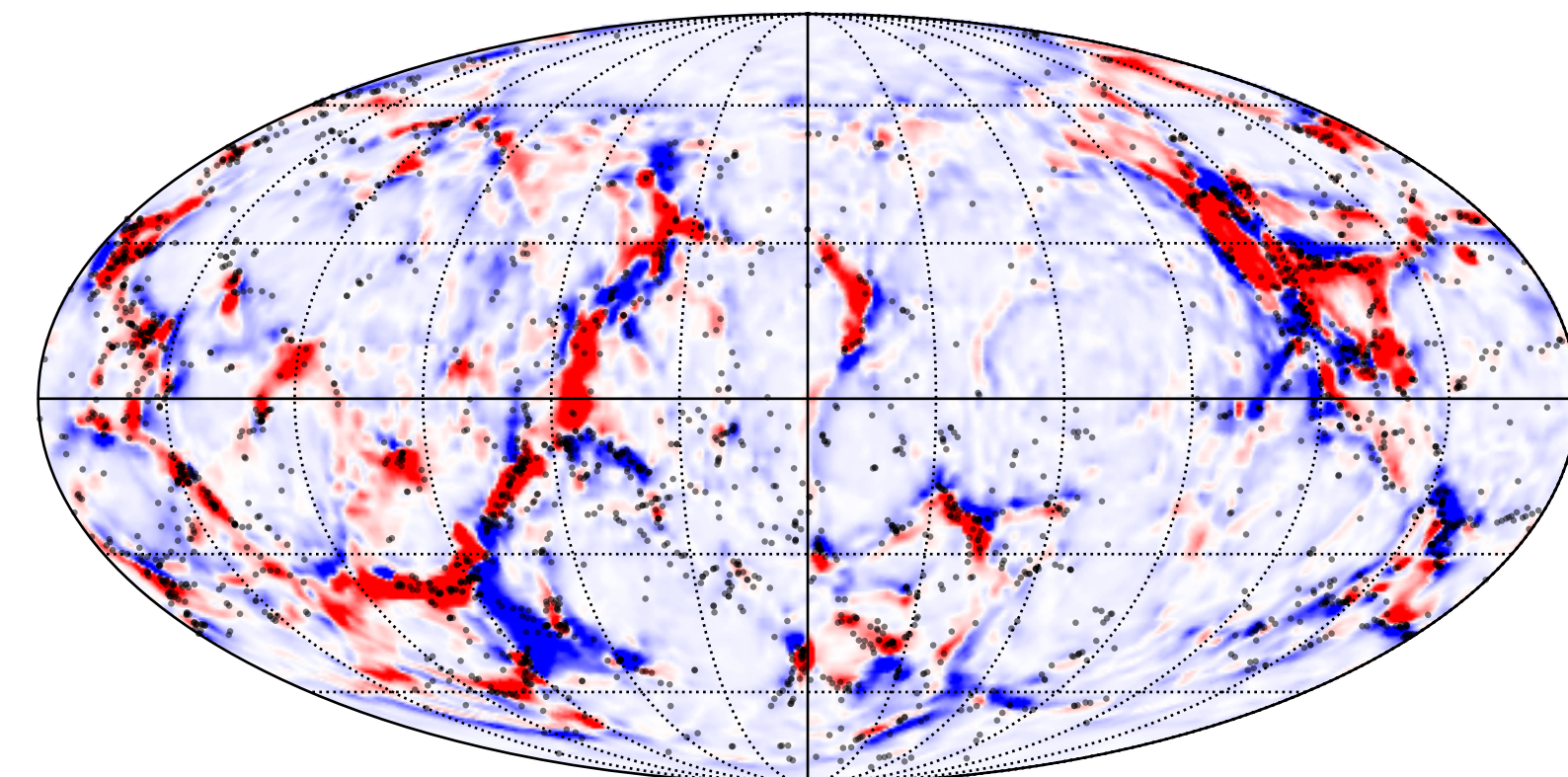
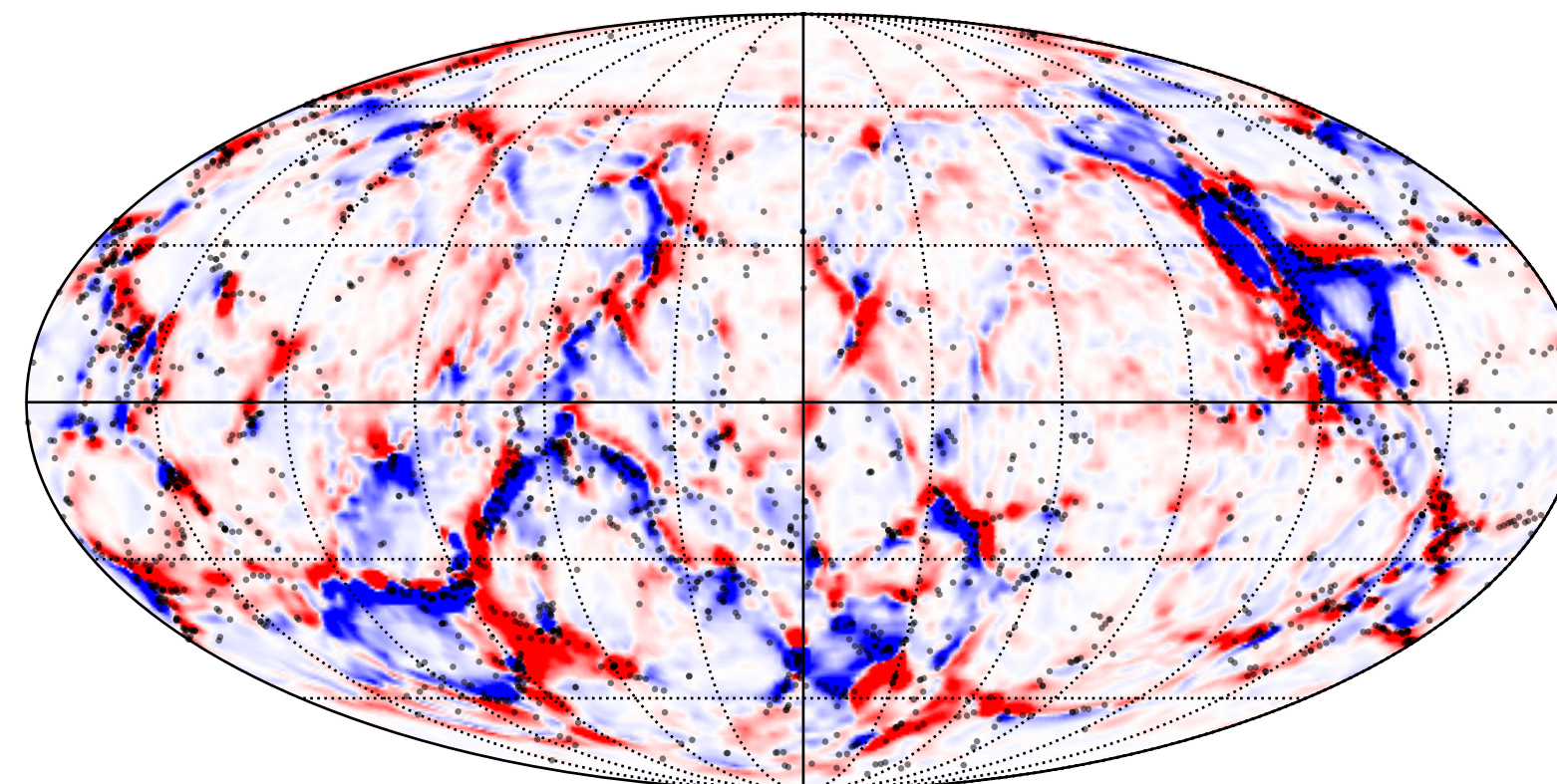


0.7 Multiplicative correction 1.3

0 5

Ω_m sensitivity map

σ_8 sensitivity map



-5 $\Delta_\delta/\Delta\Omega_m$ 5

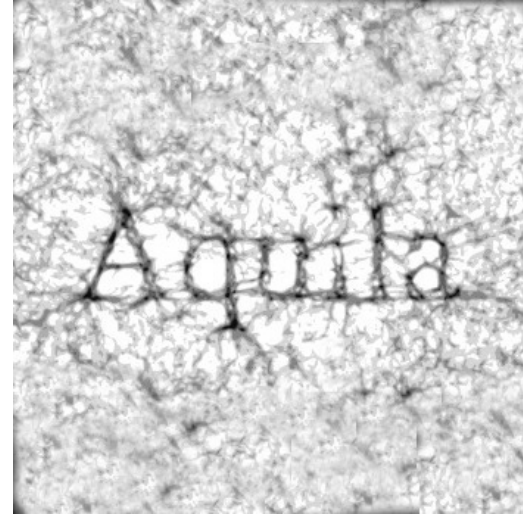
-5 $\Delta_\delta/\Delta\sigma_8$ 5

Where to point of new discoveries?

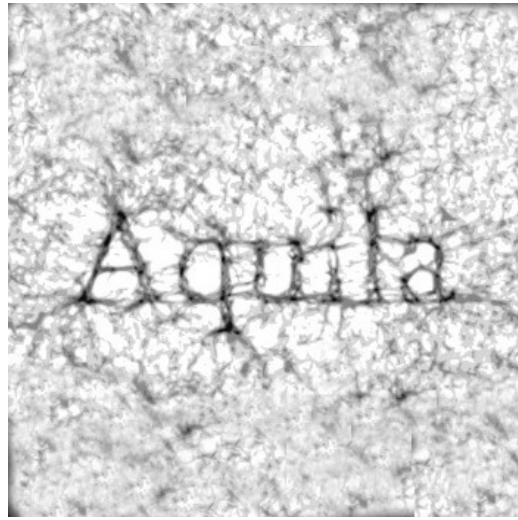


Summary

arxiv: 2203.08838
adam.andrews@fysik.su.se

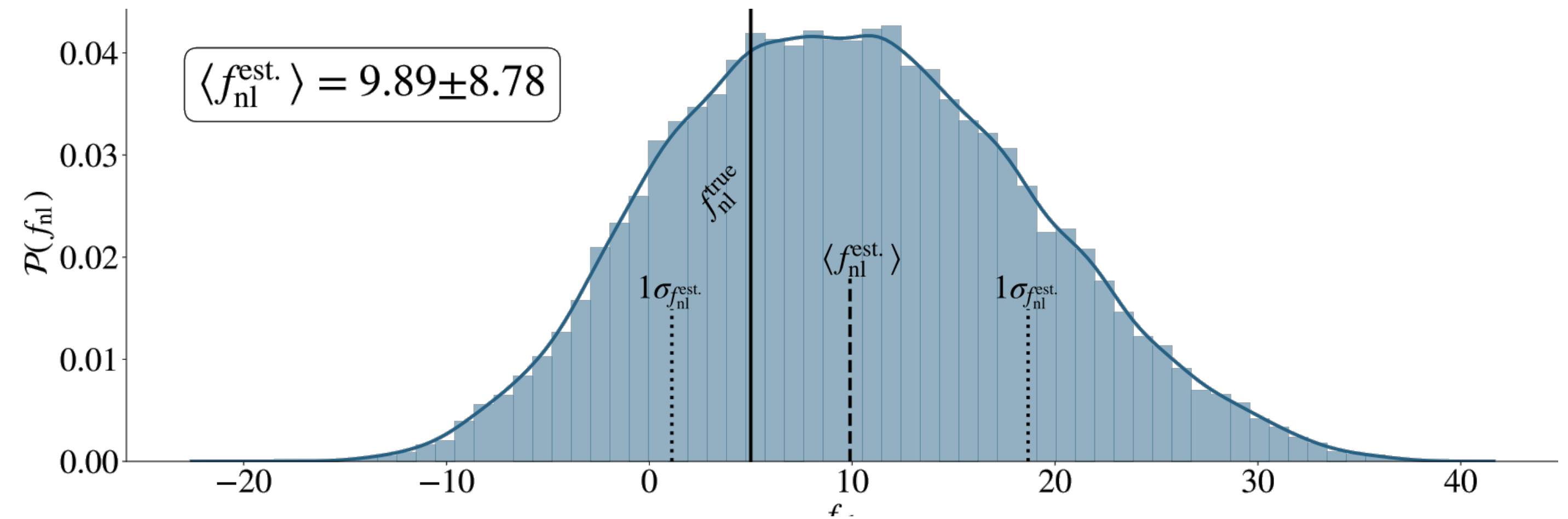


Summary

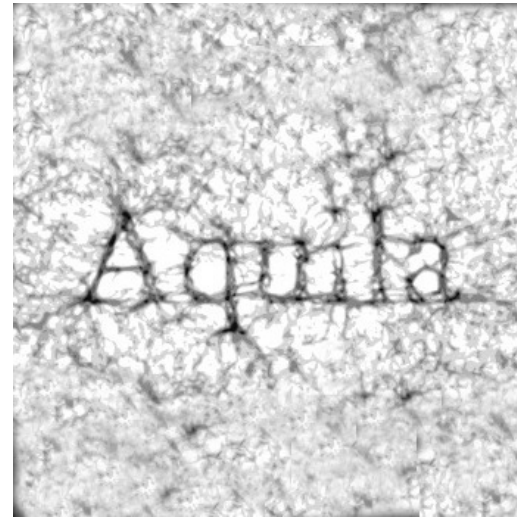


1. Developed a field-level inference which constrains $\sigma_{f_{\text{nl}}} \approx 9$ (68%) on SDSS3-like data

Posterior distribution of f_{nl}

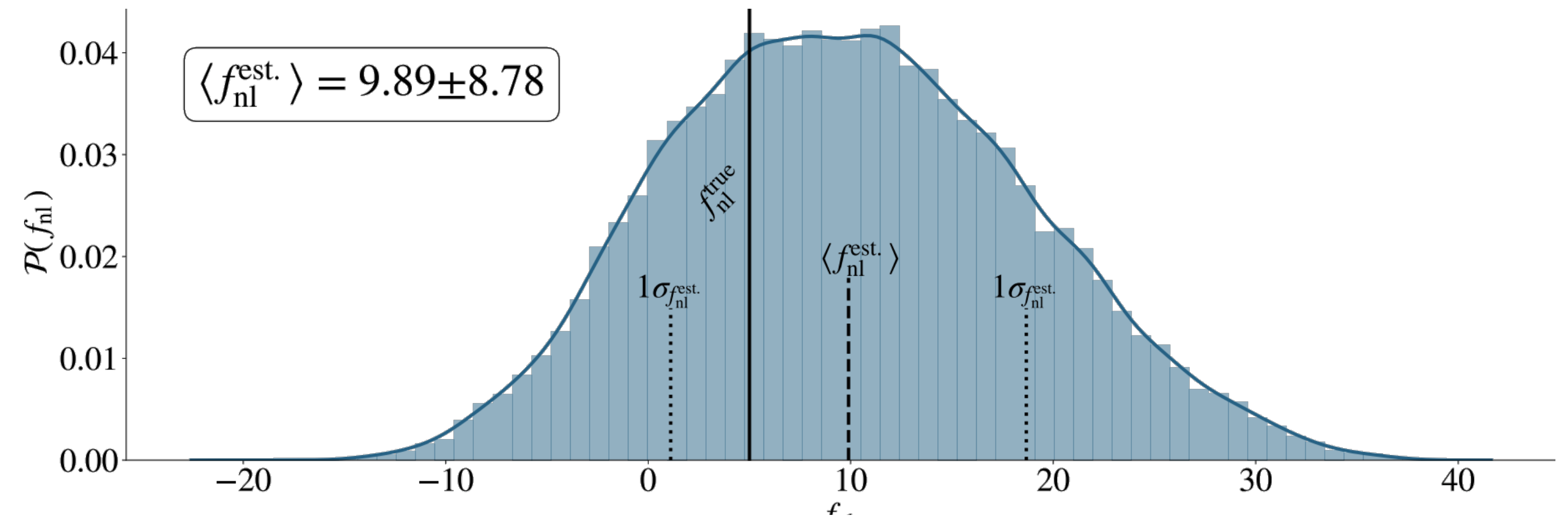


Summary

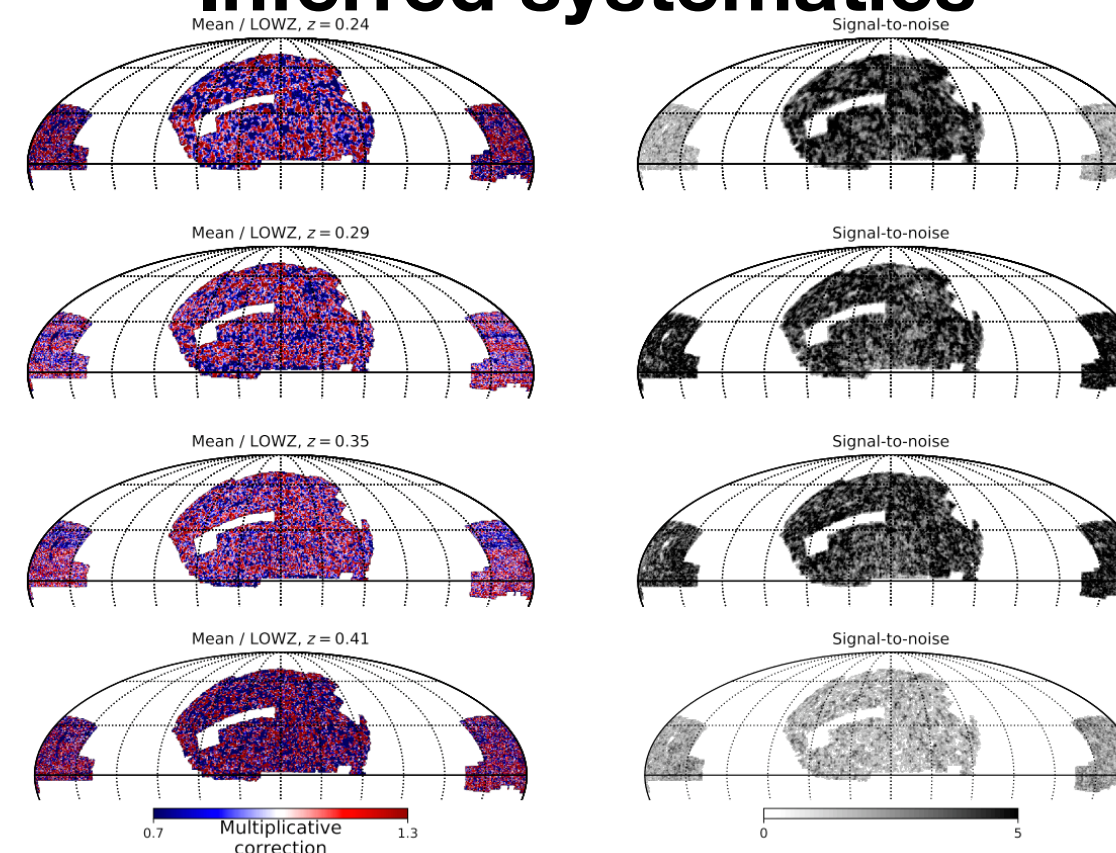


1. Developed a field-level inference which constrains $\sigma_{f_{nl}} \approx 9$ (68%) on SDSS3-like data
2. Opportunity to include systematic effects into analysis

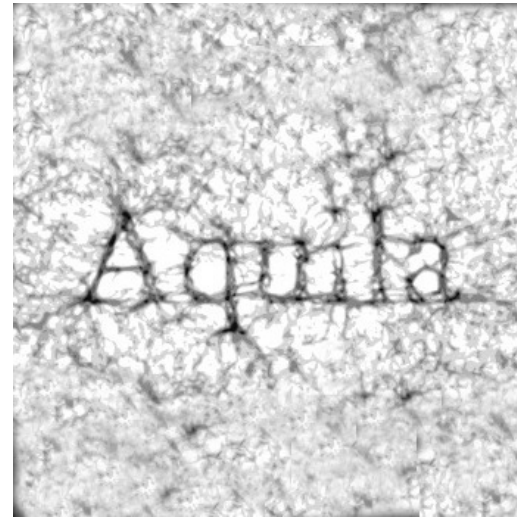
Posterior distribution of f_{nl}



Inferred systematics

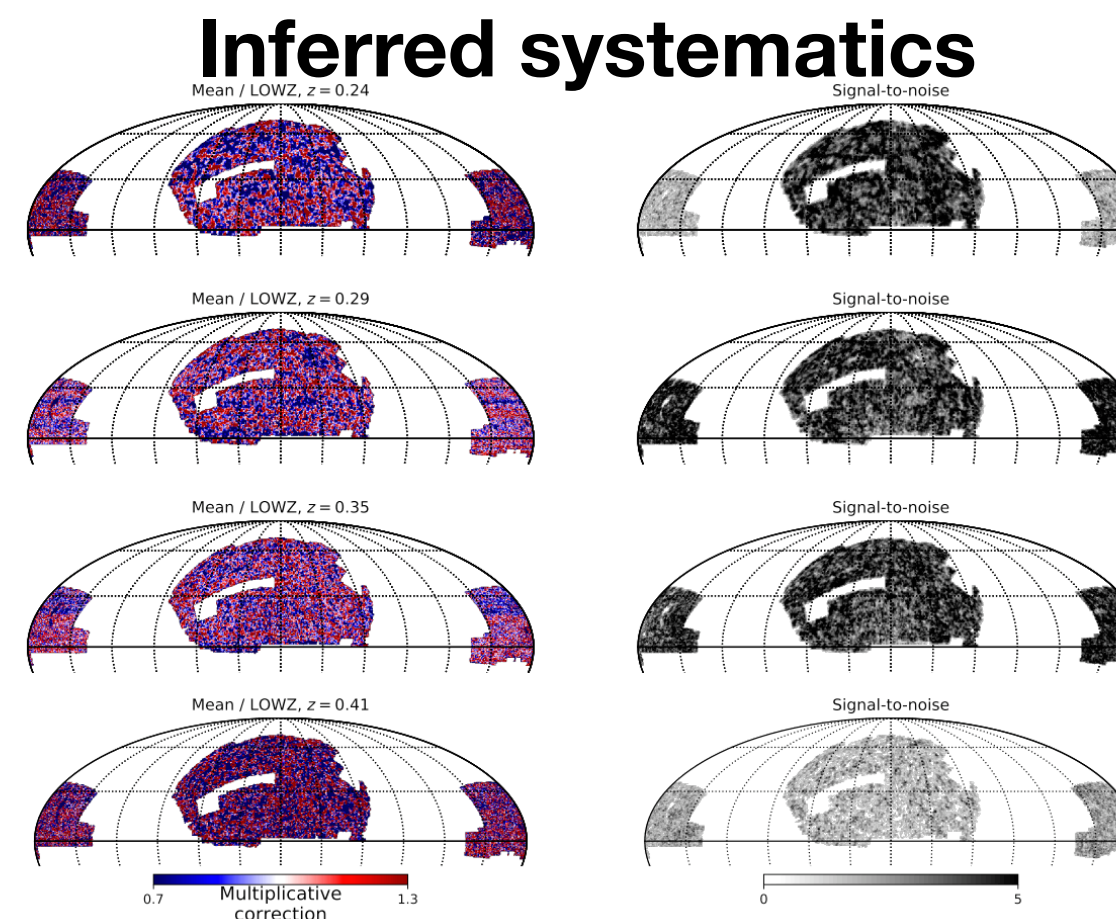
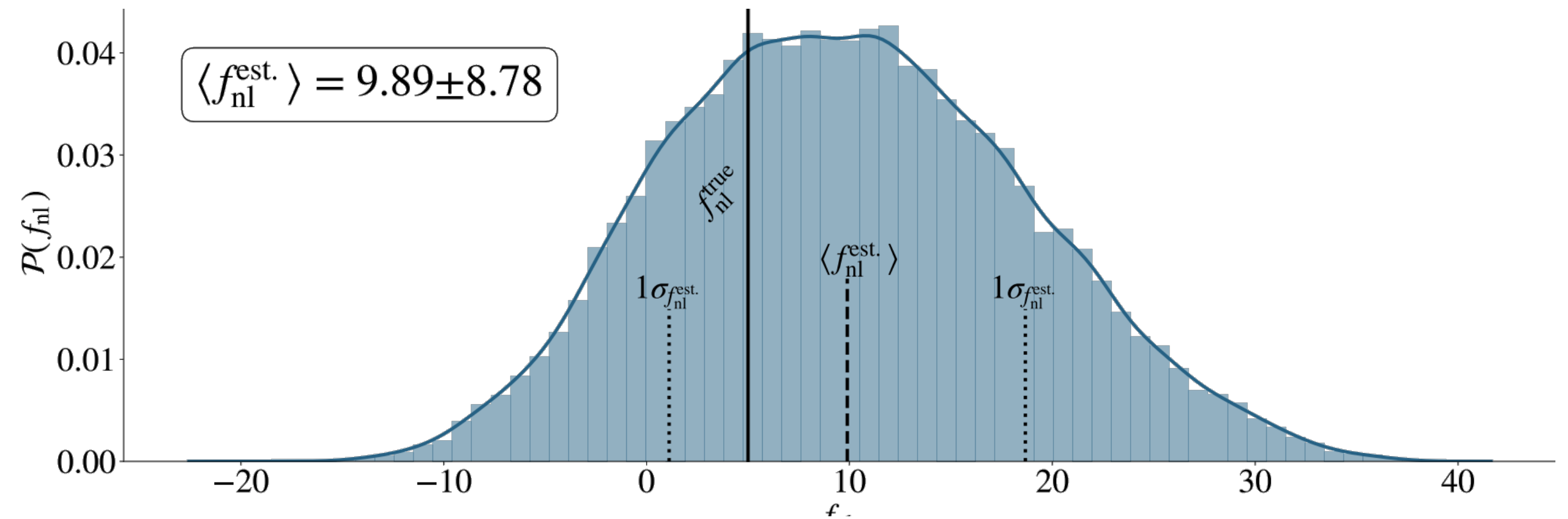


Summary

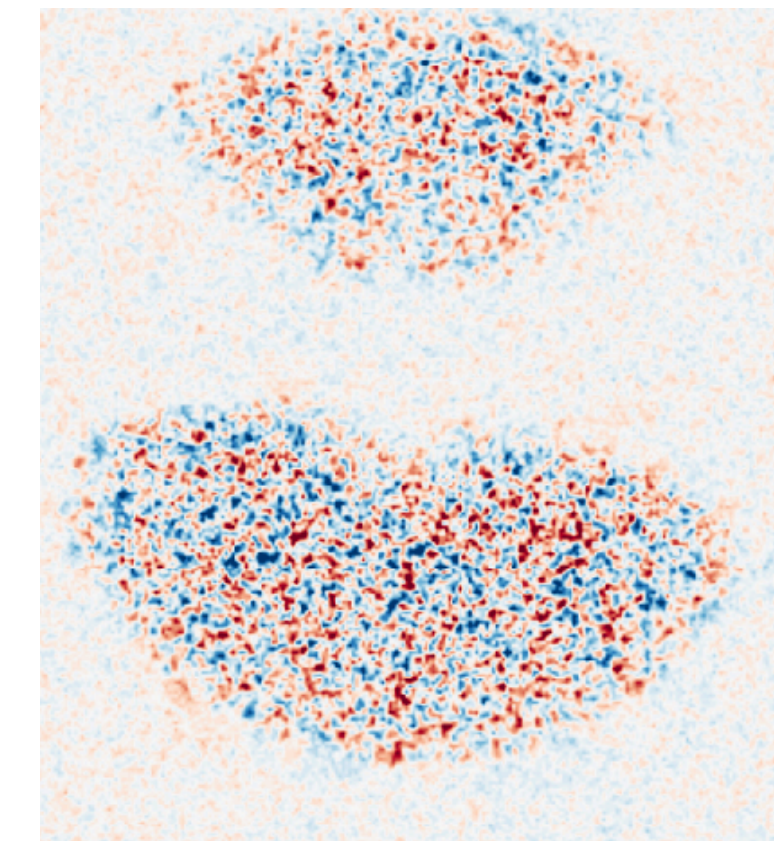


1. Developed a field-level inference which constrains $\sigma_{f_{nl}} \approx 9$ (68%) on SDSS3-like data
2. Opportunity to include systematic effects into analysis
3. Additional data products

Posterior distribution of f_{nl}

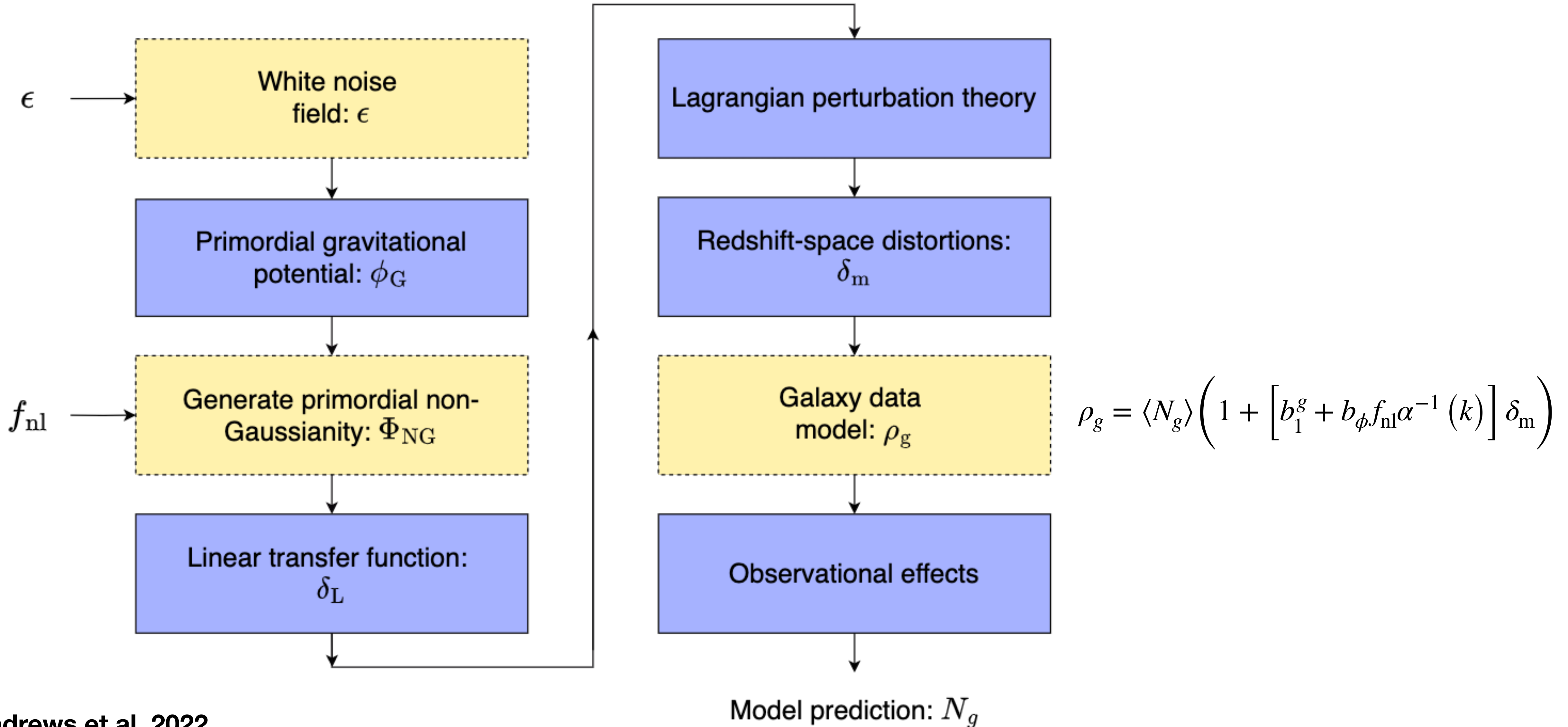


Inferred Density Field

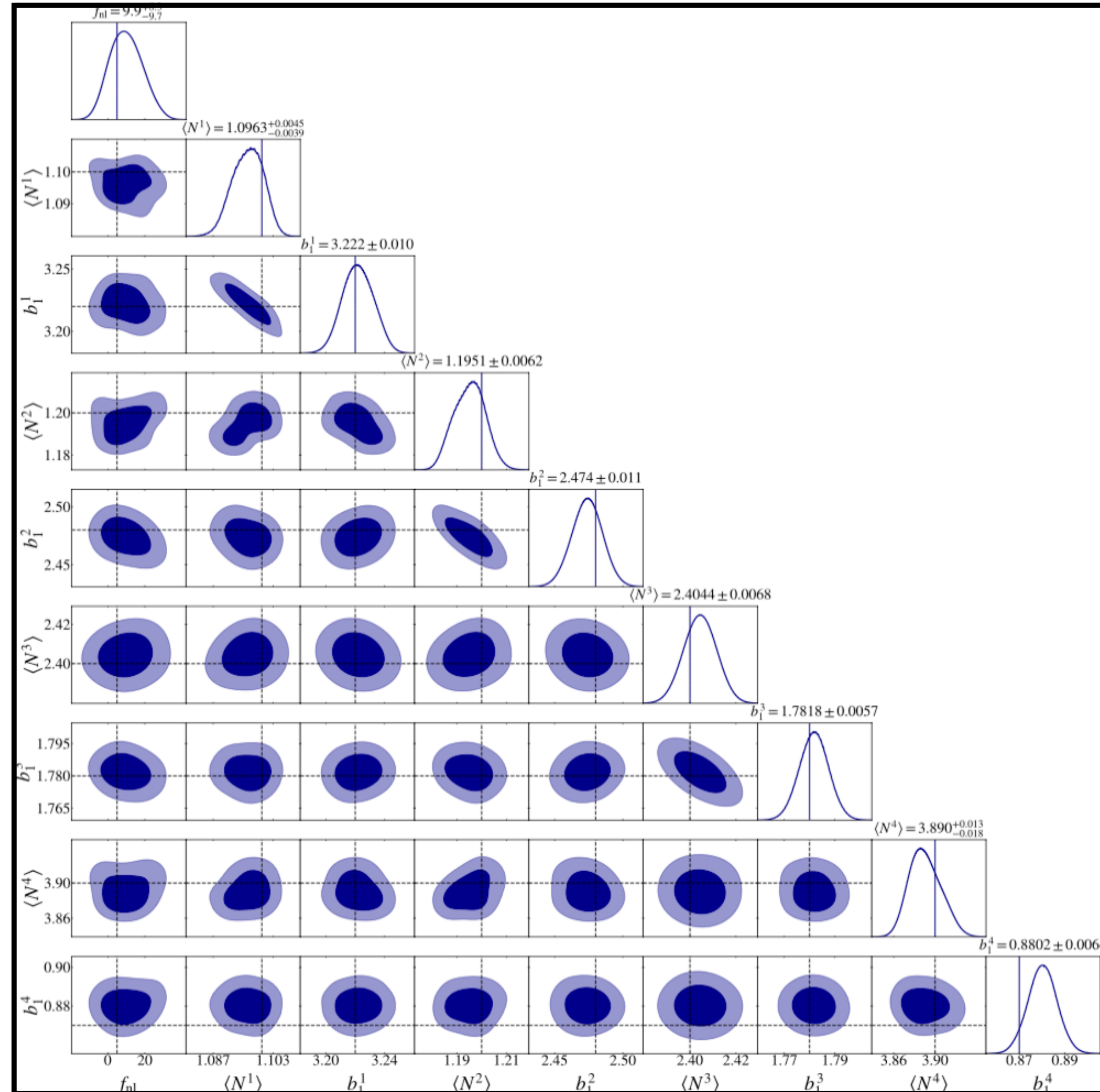


Appendix

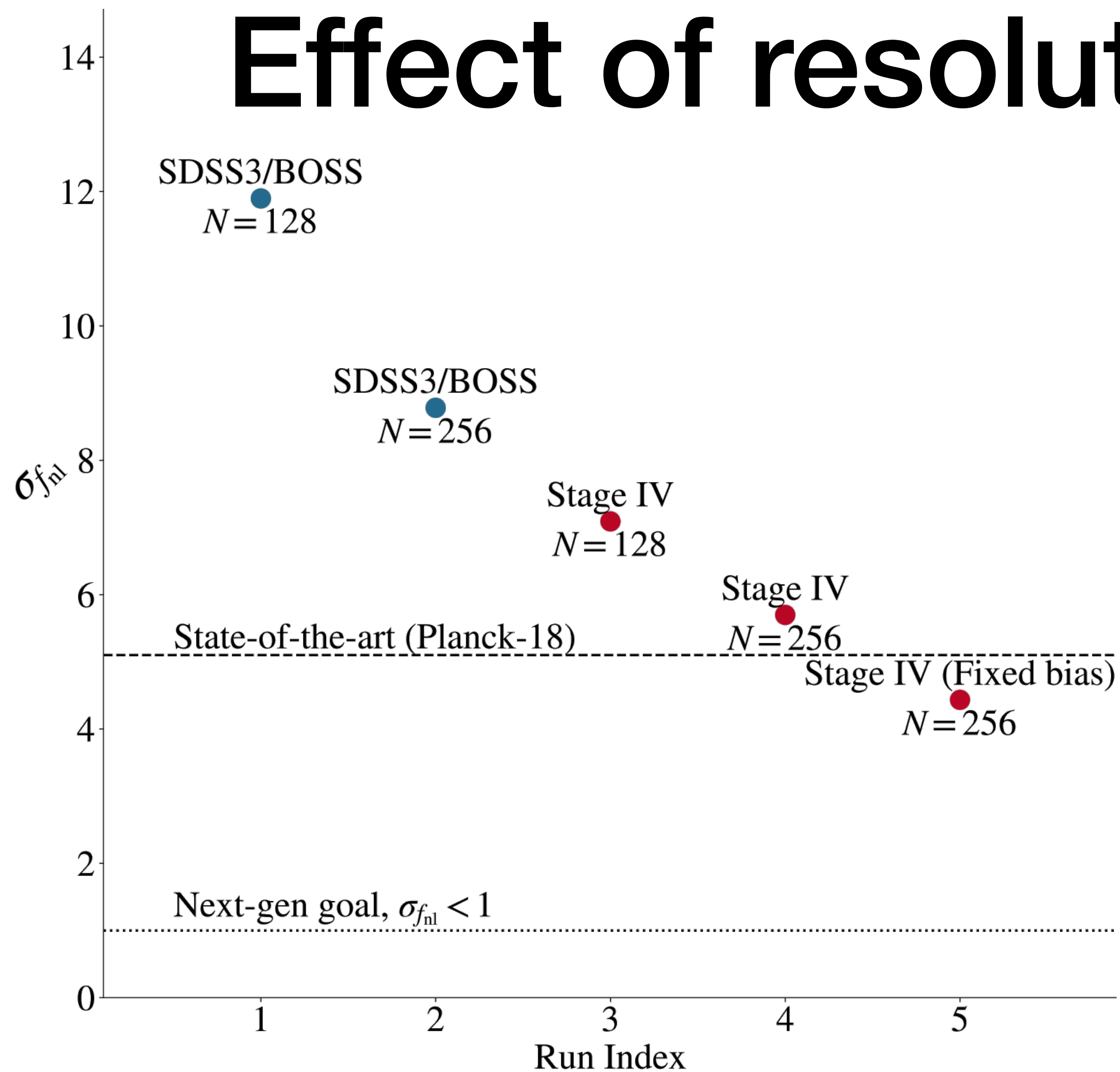
The Physics model



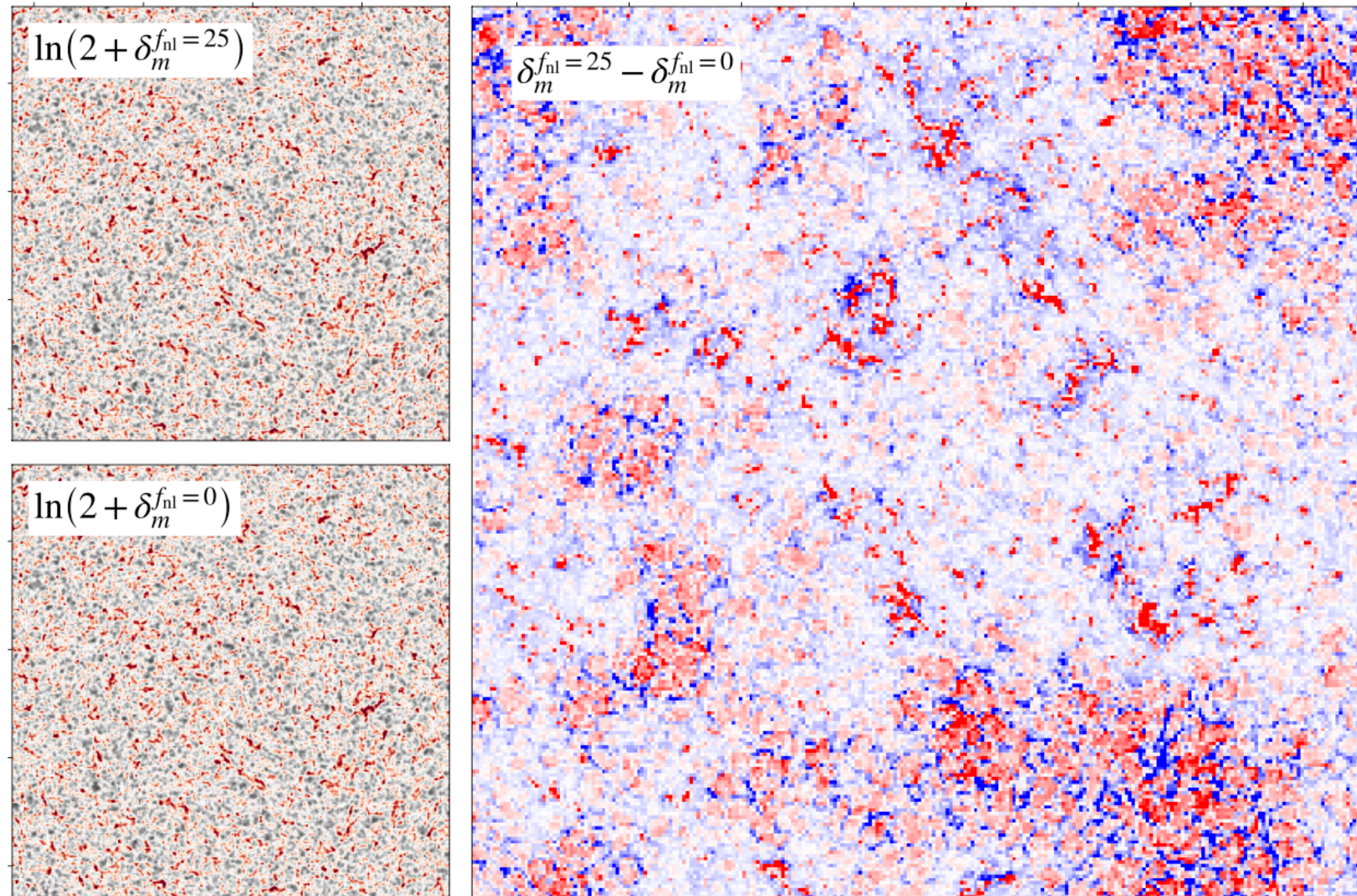
Marginalising out bias parameters



Effect of resolution increase



Effect of Primordial Non-Gaussianity



Statistical sampling (BORNG)

