

# **Deciphering the dynamical Universe via non-linear Bayesian inference**

Jens Jasche

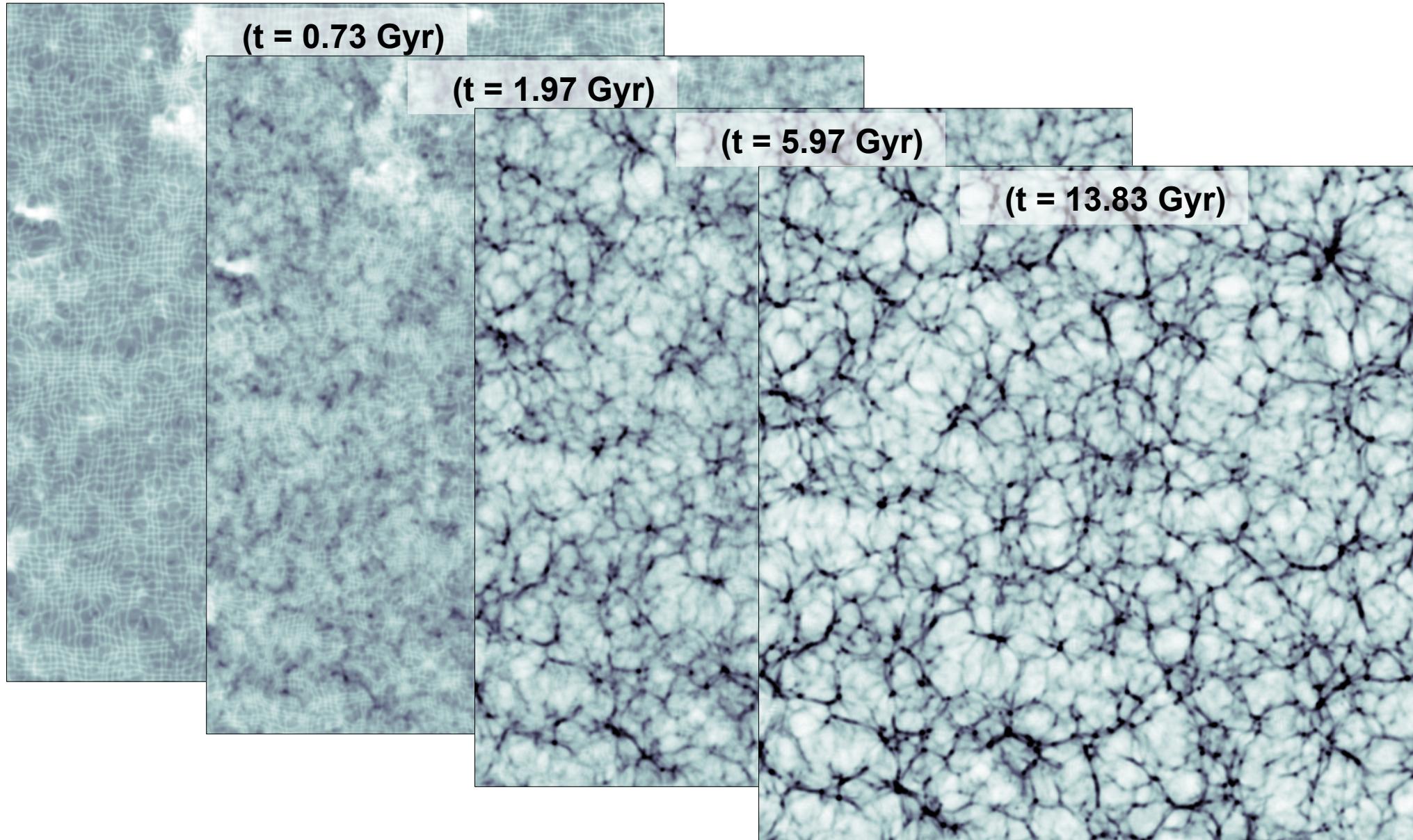
Guilhem Lavaux, Florent Leclercq,  
Benjamin Wandelt

Statistical challenges for large-scale structure in the era of LSST  
Oxford, 18 April 2018



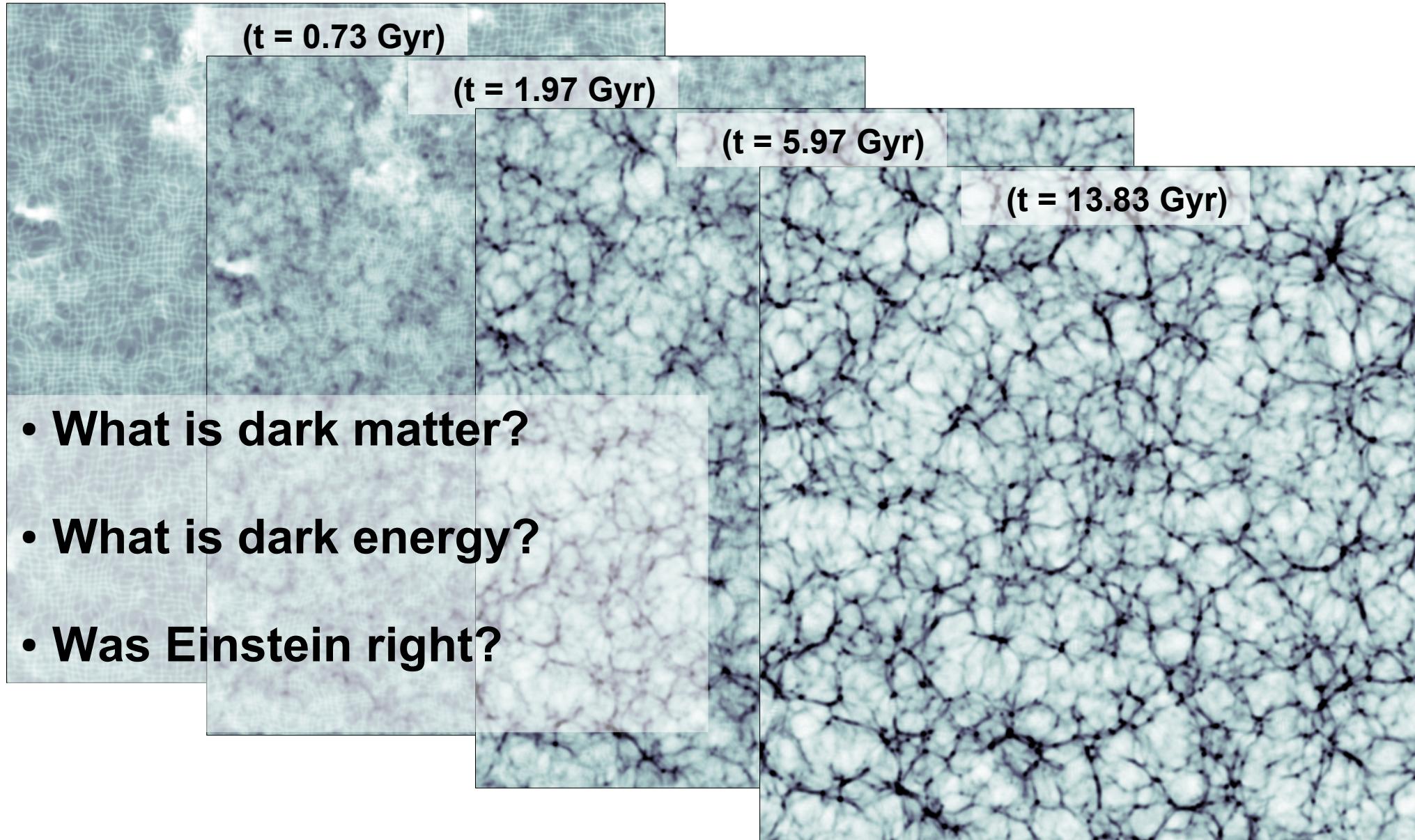
# The cosmic large scale structure...

... A source of knowledge!



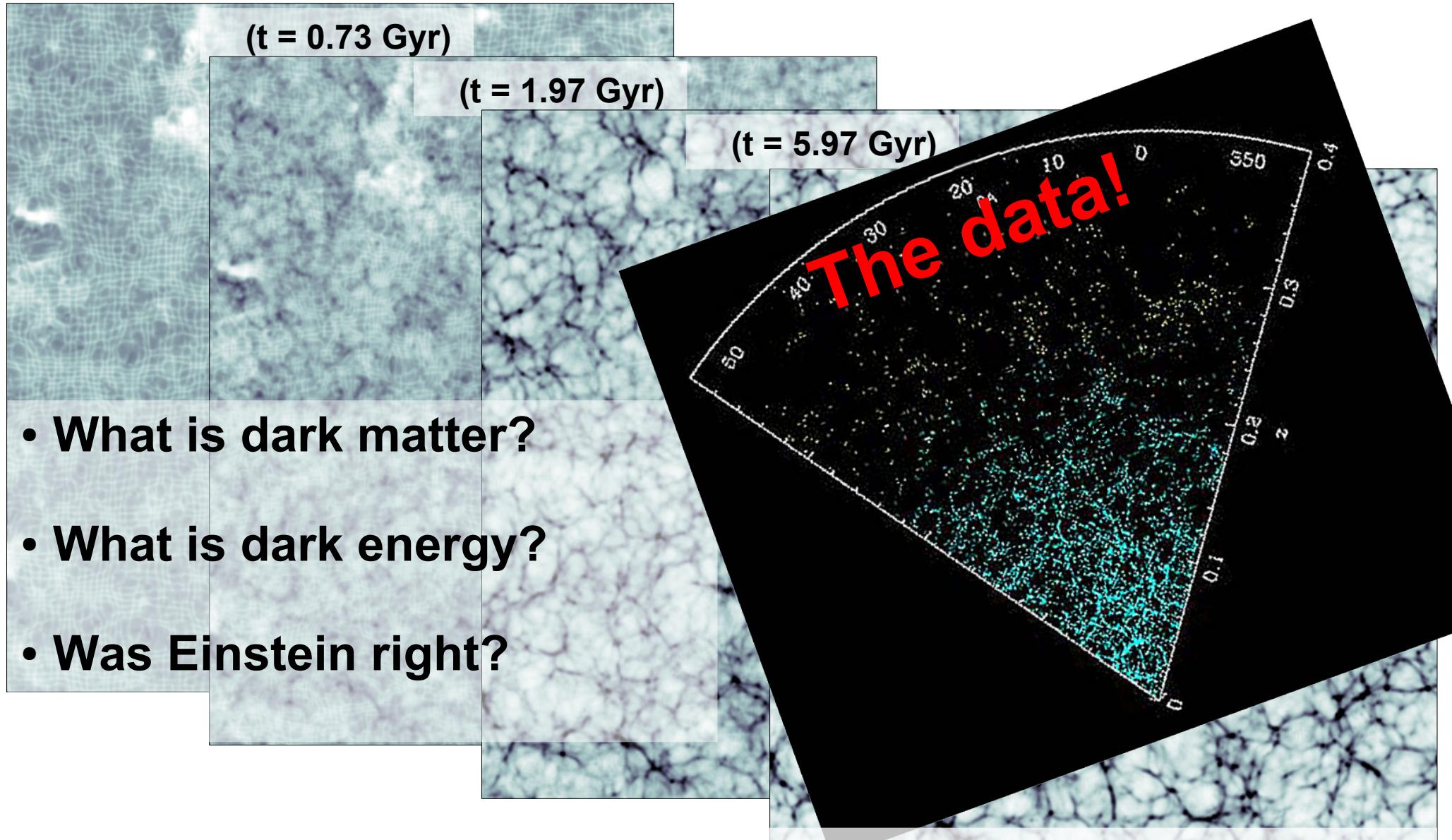
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# Bayesian Statistics

“If your experiment needs statistics, you ought to do a better experiment.”

*Lord Ernest Rutherford*

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Reasoning under uncertainty

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Reasoning under uncertainty

- Bayesian Statistics



$$\mathcal{P}(s|d) = \mathcal{P}(s) \frac{\mathcal{P}(d|s)}{\mathcal{P}(d)}$$

# Bayesian Statistics

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*Lord Ernest Rutherford*

## Reasoning under uncertainty

- Bayesian Statistics



$$\mathcal{P}(s|d) = \mathcal{P}(s) \frac{\mathcal{P}(d|s)}{\mathcal{P}(d)}$$

Get a computer representation of the full posterior distribution!

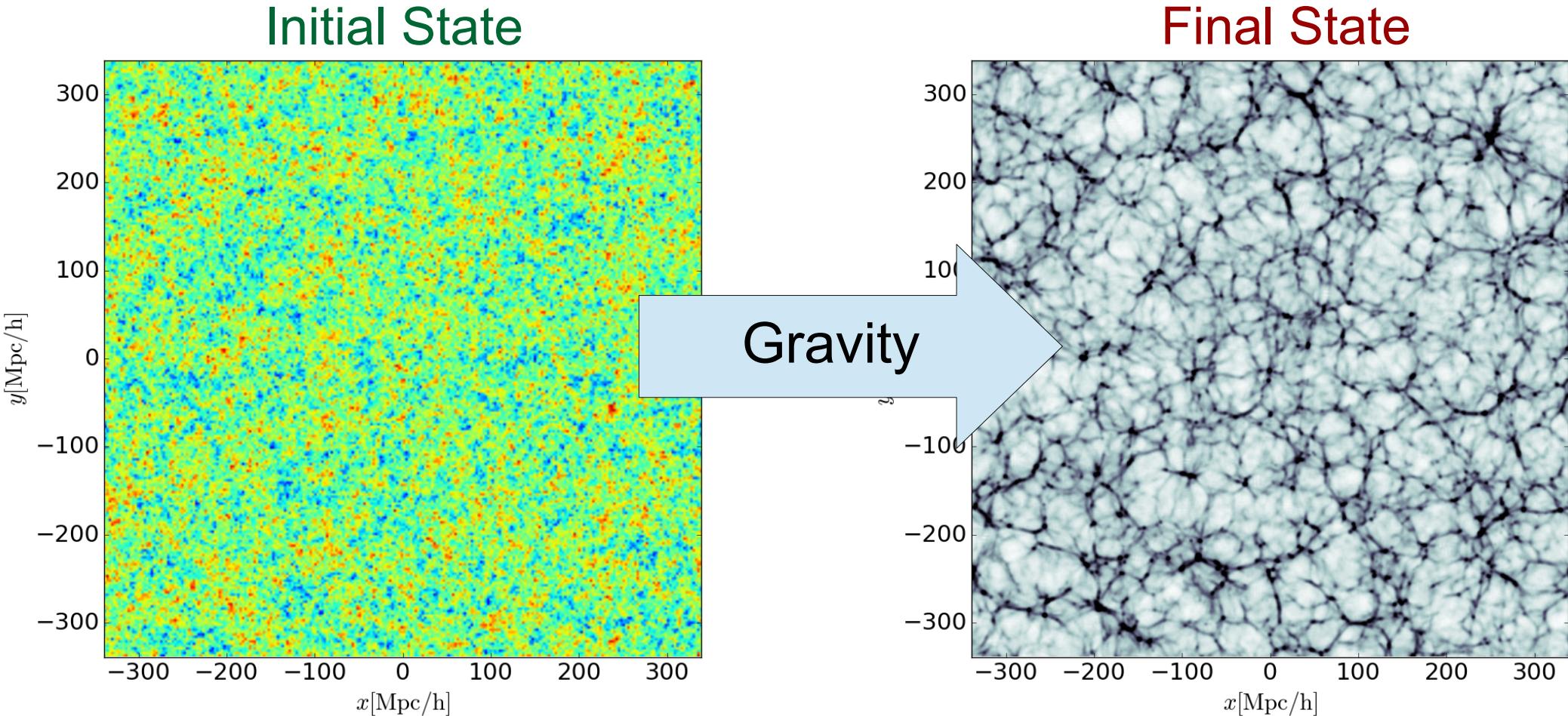
- Model tests
- Parameter studies
- Report statistical summaries
- Non-linear and Non-Gaussian uncertainty propagation

# Motivation

Bayesian physical inference

Jasche, Wandelt (2013)

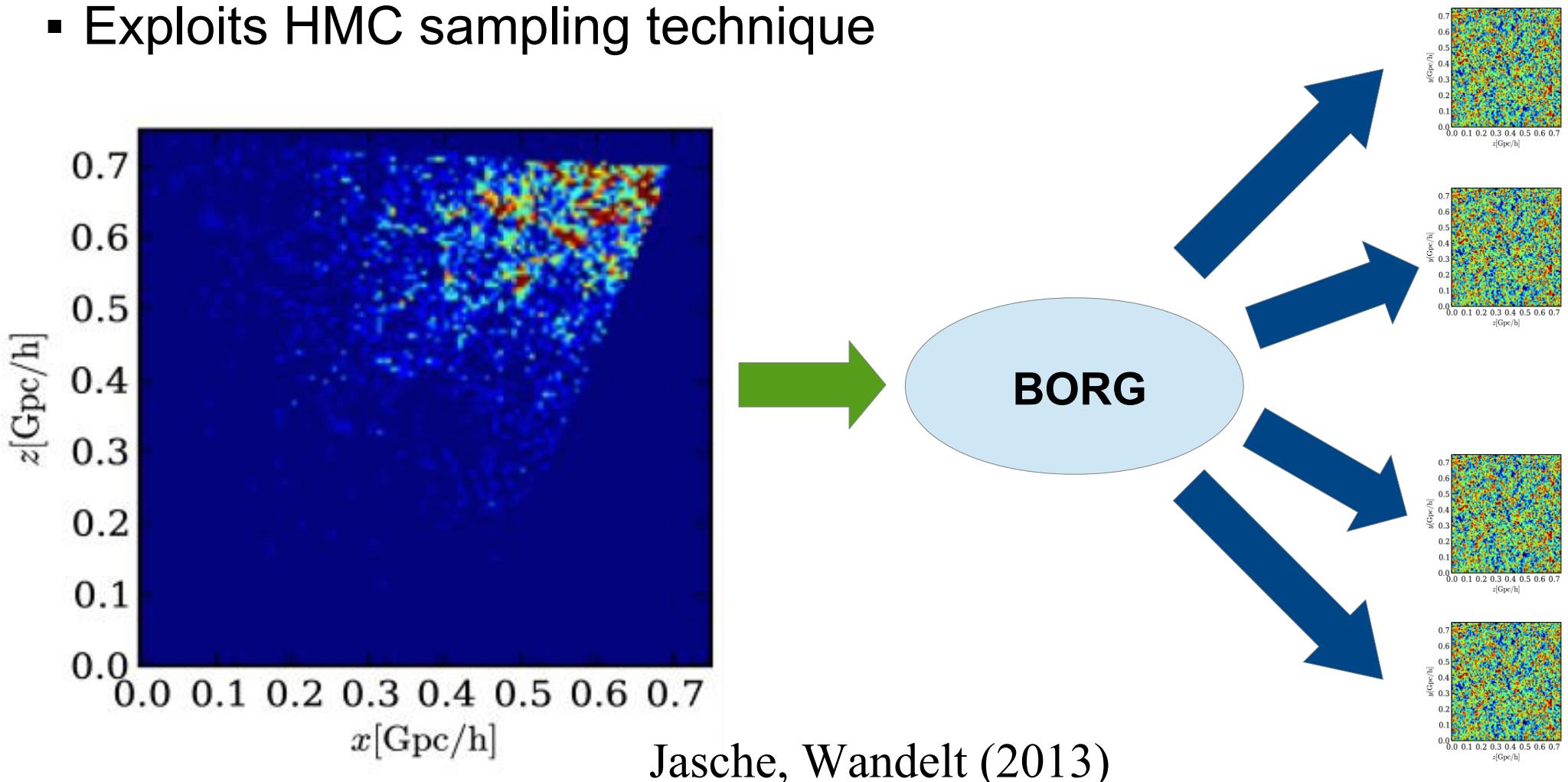
- Statistically complex final state
- Statistically simple initial state
- Solve inverse Problem via forward modeling



# Bayesian Inference of initial conditions

## BORG (Bayesian Origin Reconstruction from Galaxies)

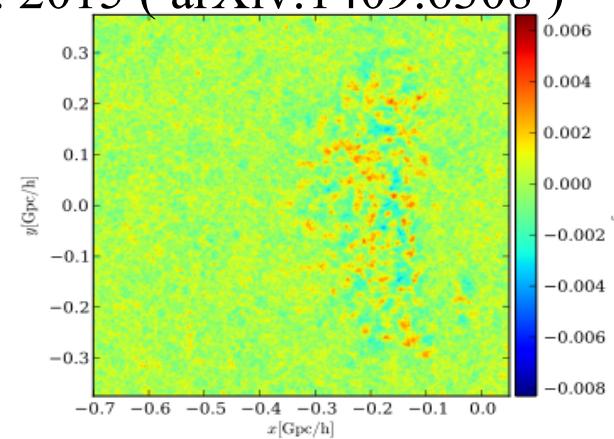
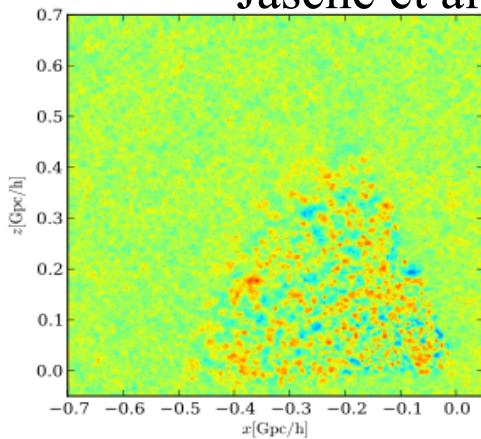
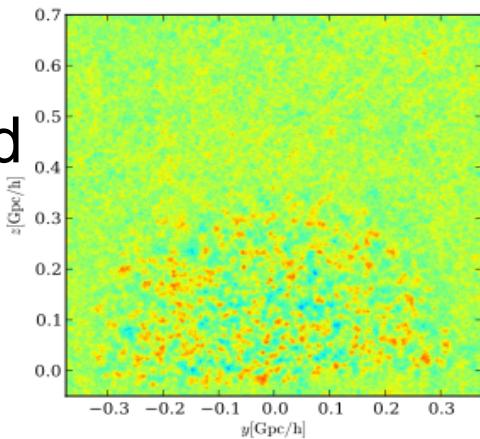
- Uses dynamical LSS model (2LPT, PM) within Likelihood
- Solves a statistical initial conditions problem
- Exploits HMC sampling technique



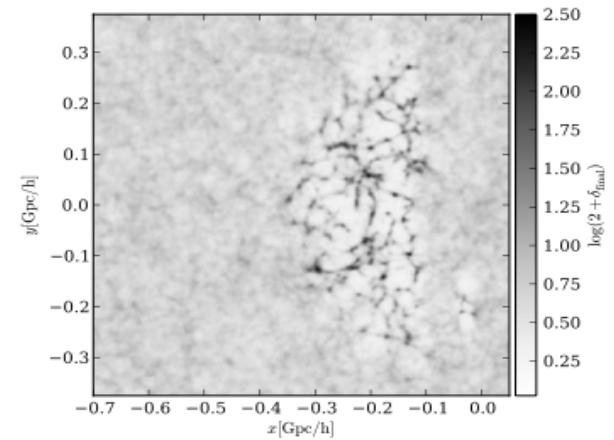
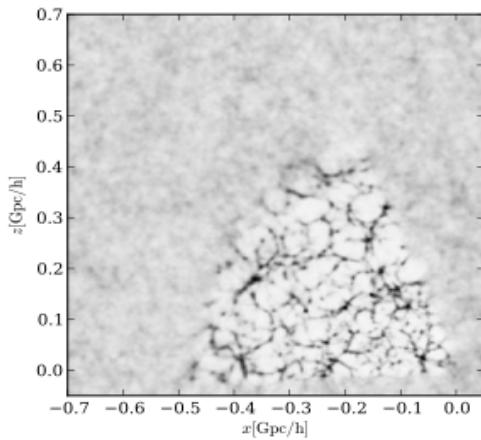
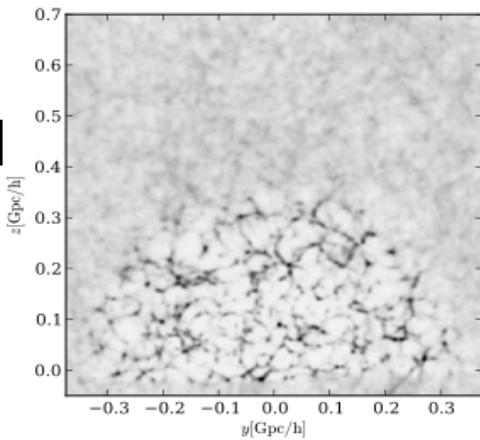
Jasche, Wandelt (2013)

# Bayesian analysis of the SDSS DR7

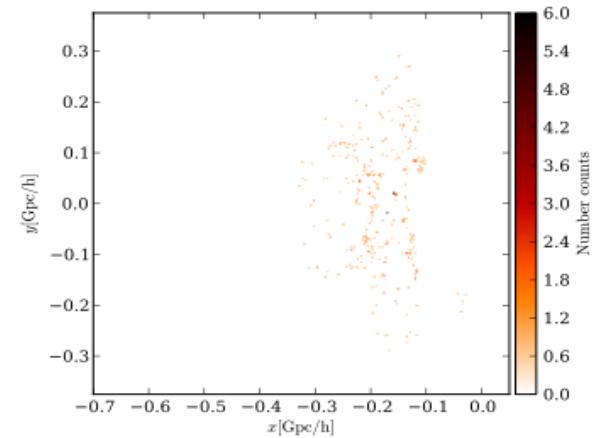
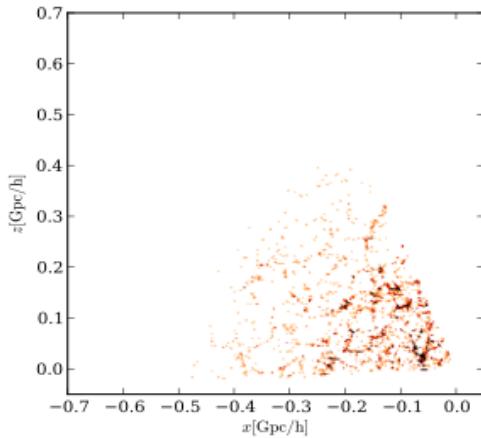
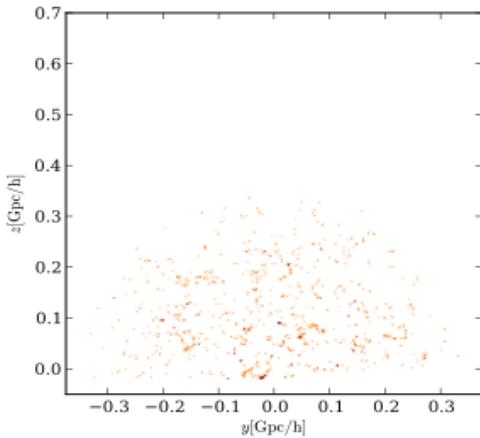
Initial density field  
 $z \sim 1000$



final density field  
 $z=0$



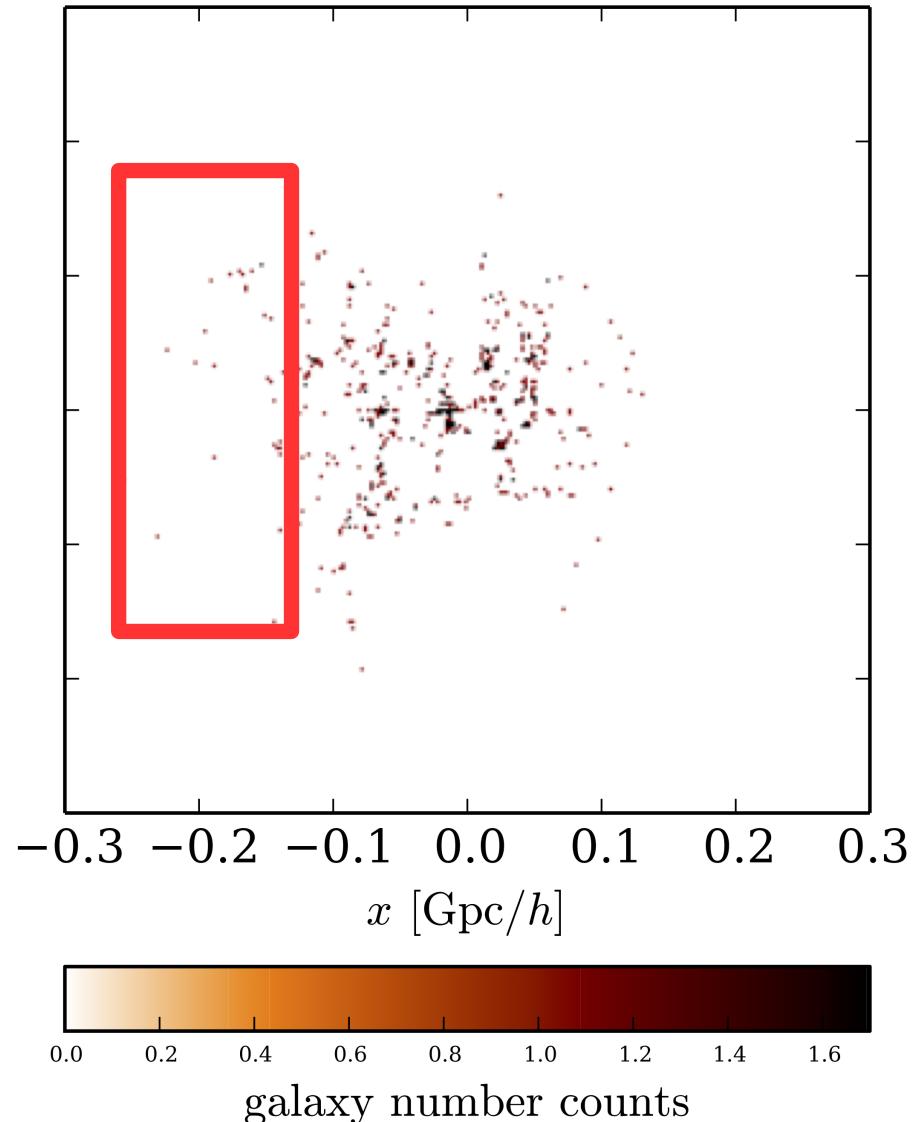
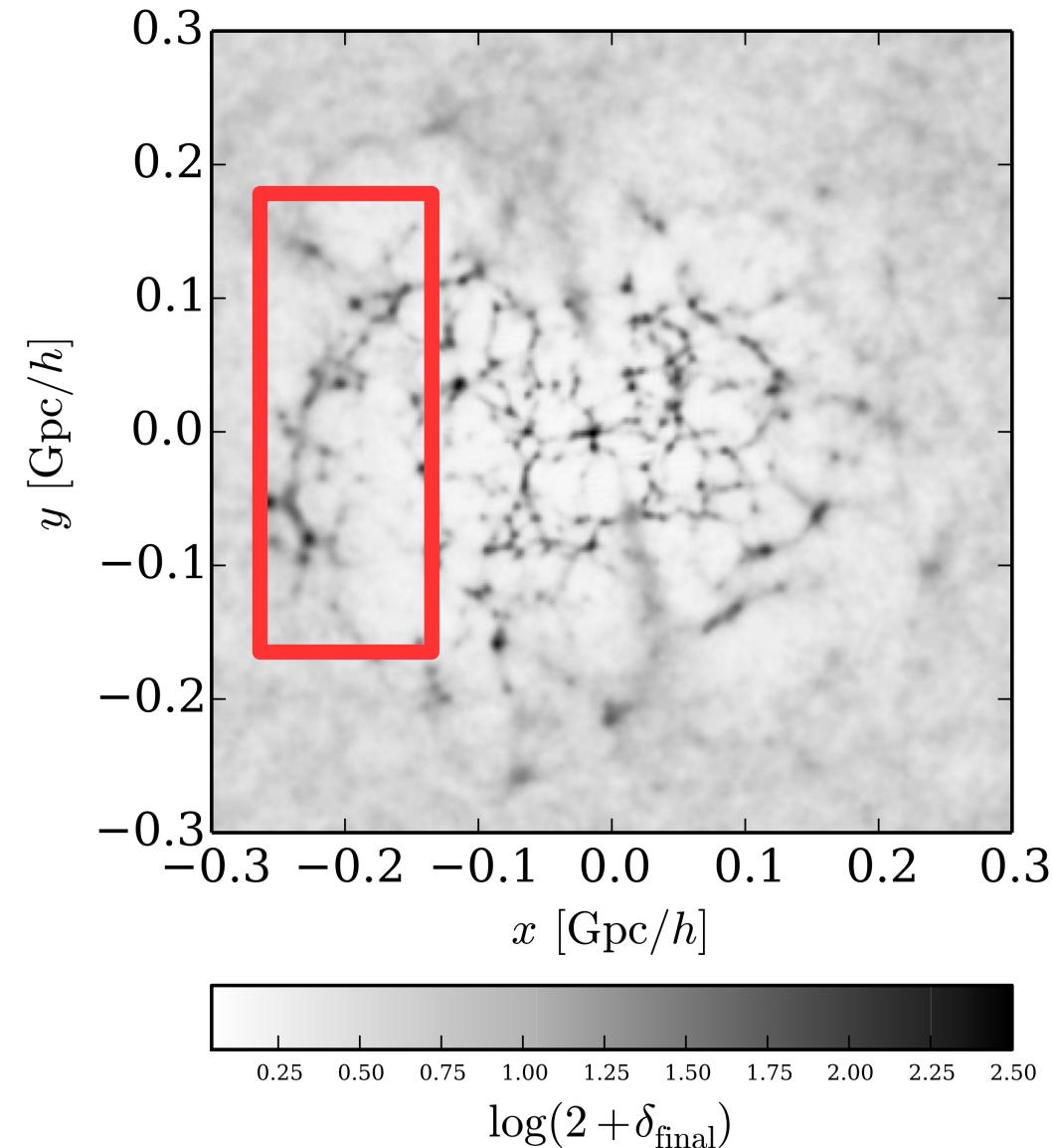
SDSS  
number counts  
 $z=0$



Jasche et al. 2015 ( arXiv:1409.6308 )

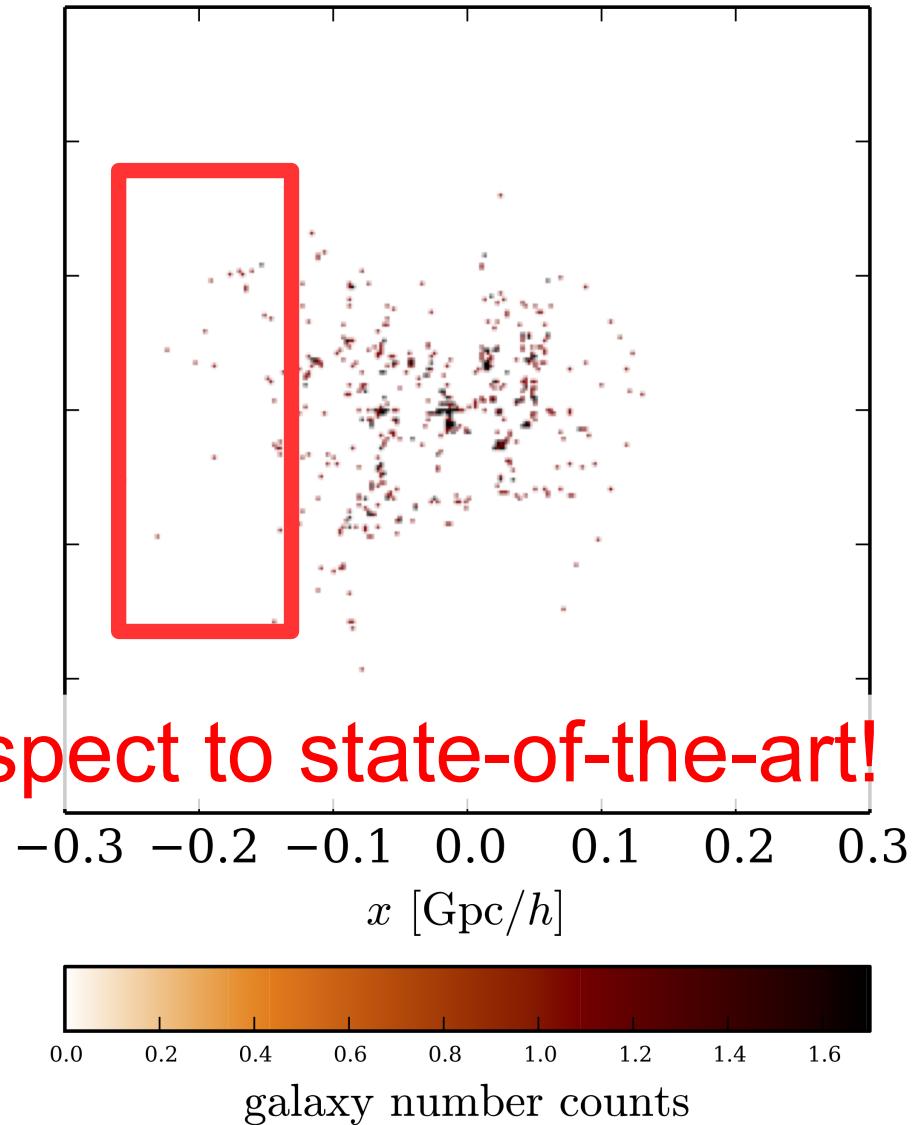
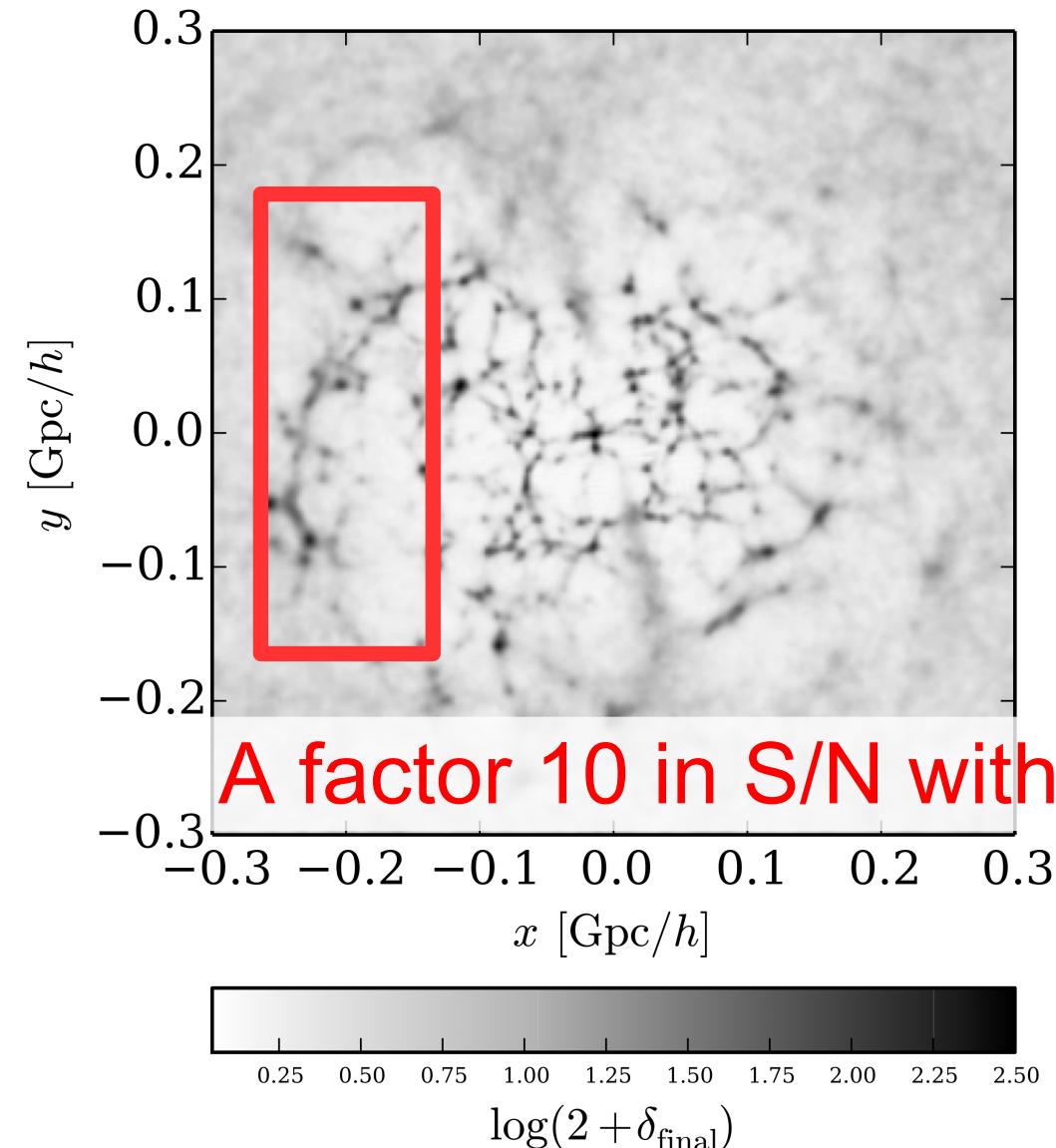
# The LSS in noisy regimes

Recovering the Sloan Great Wall in 2M++ data



# The LSS in noisy regimes

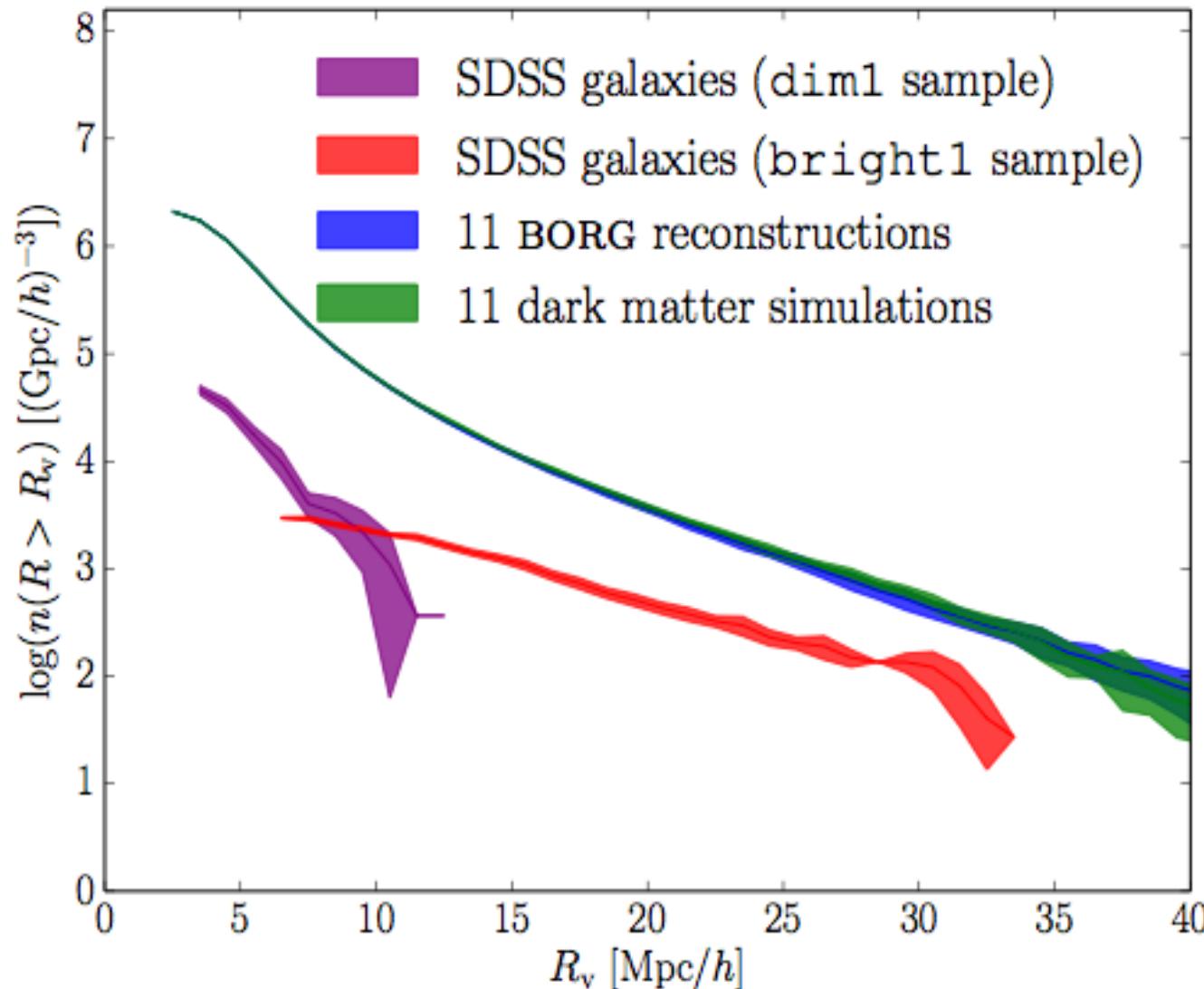
Recovering the Sloan Great Wall in 2M++ data



A factor 10 in S/N with respect to state-of-the-art!

# Dark matter voids in the SDSS

## Cumulative void number functions

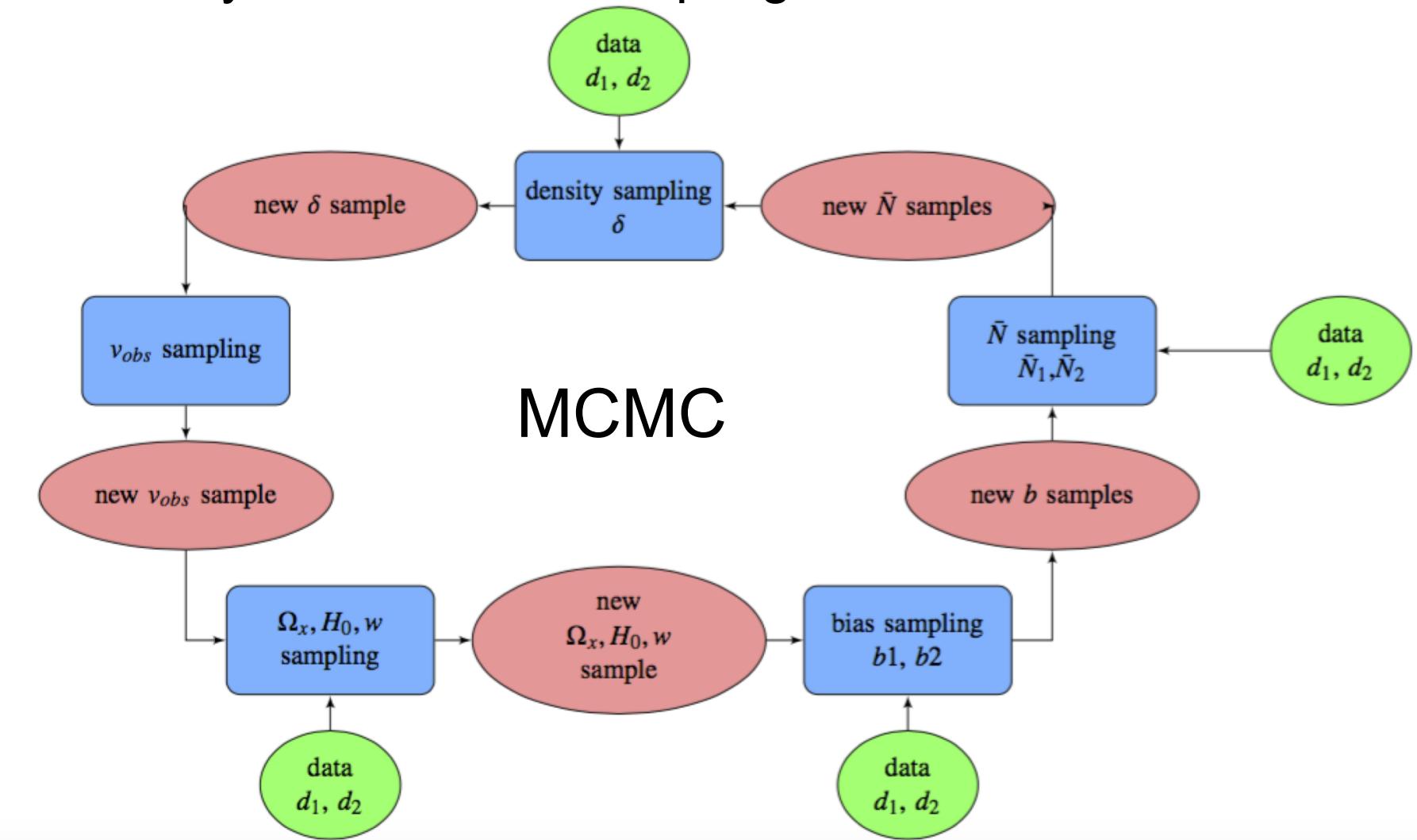


Leclercq et al. 2015 (arXiv:1410.0355)

# BORG<sup>3</sup>: A Modular statistical programing engine

Build flexible data models

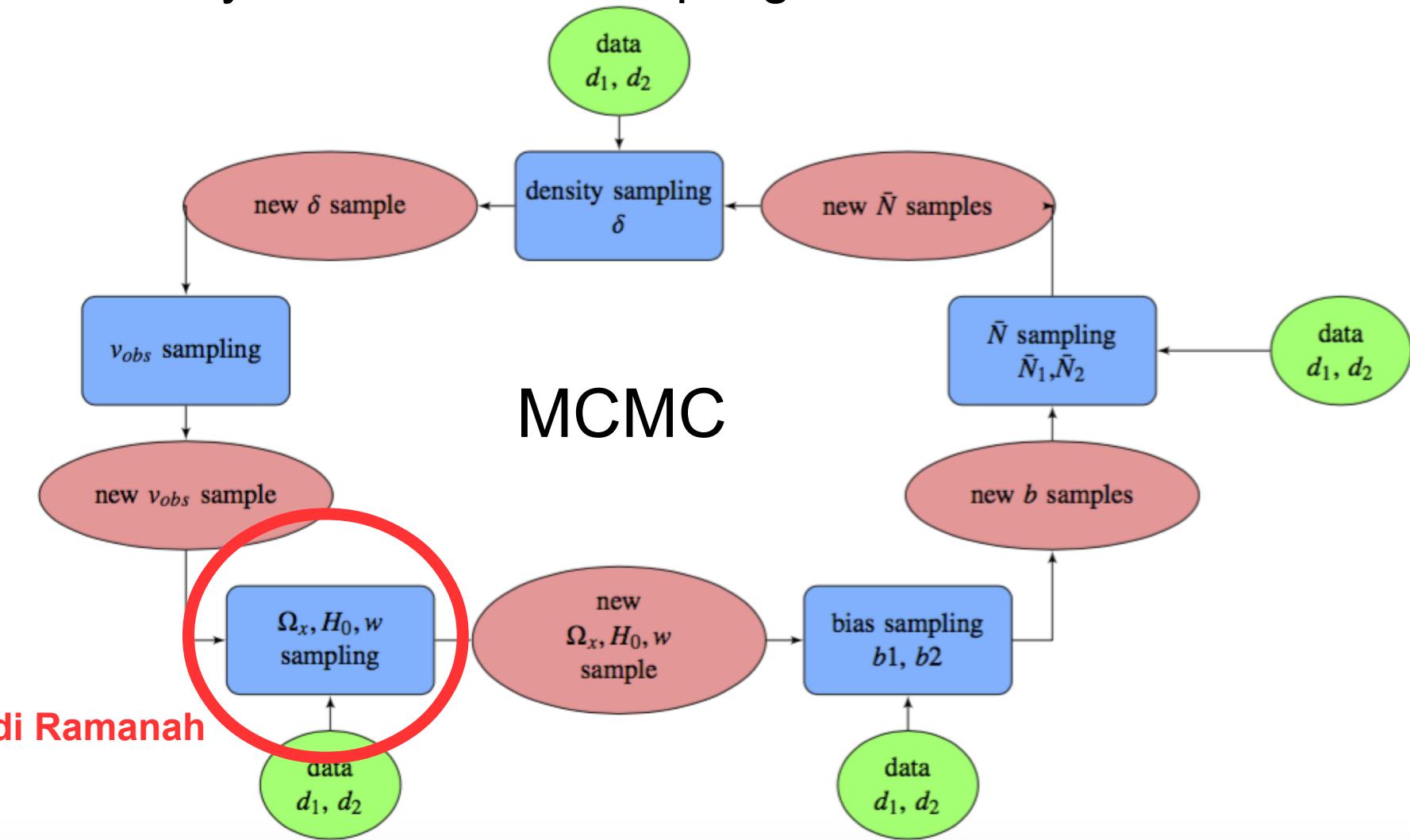
- Hierarchical Bayes and block sampling



# BORG<sup>3</sup>: A Modular statistical programing engine

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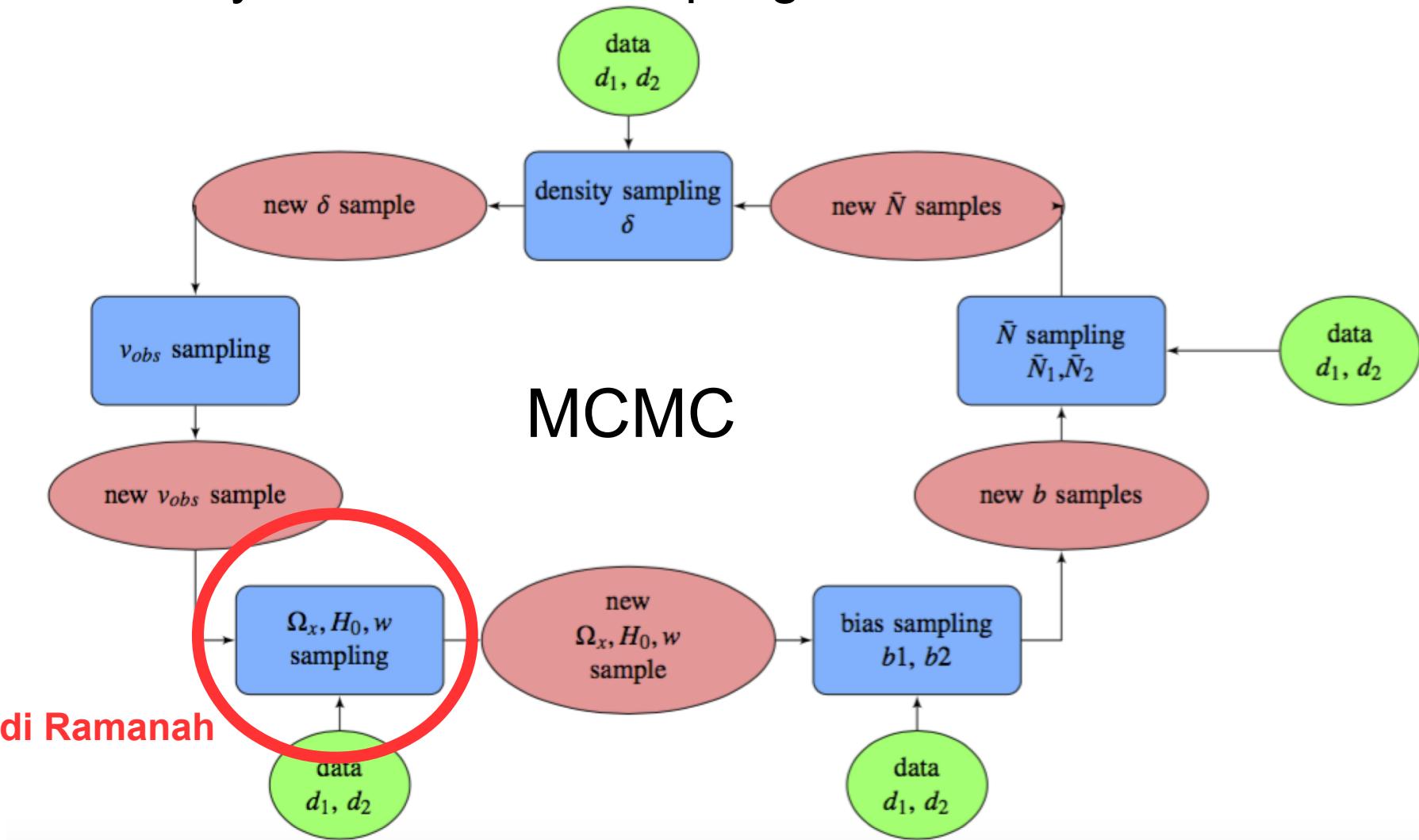
- Hierarchical Bayes and block sampling



# BORG<sup>3</sup>: A Modular statistical programing engine

Build flexible data models

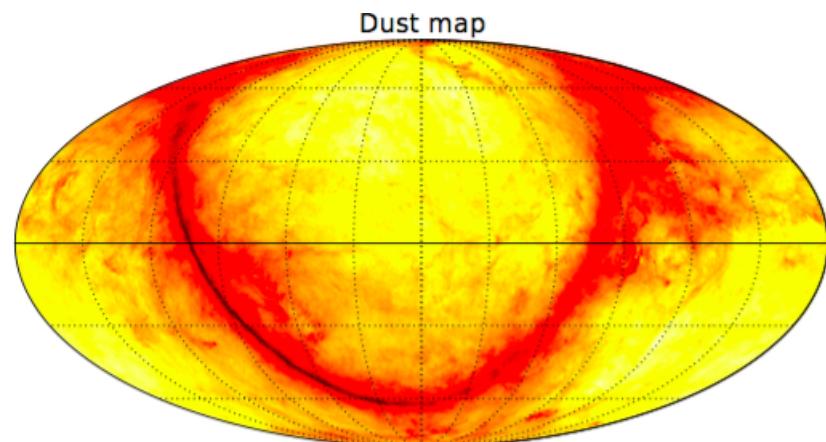
- Hierarchical Bayes and block sampling



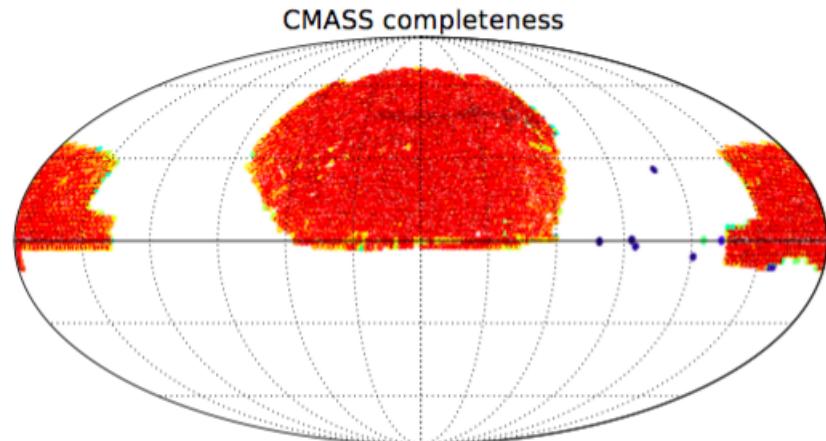
Marginalize out nuisance parameters.

# Foreground contaminations

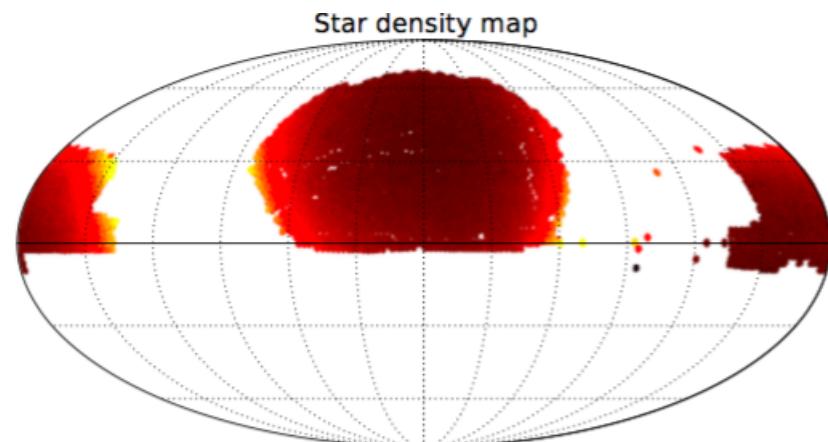
Foreground effect contaminate the inference ( see e.g. Leistedt & Peiris (2014))



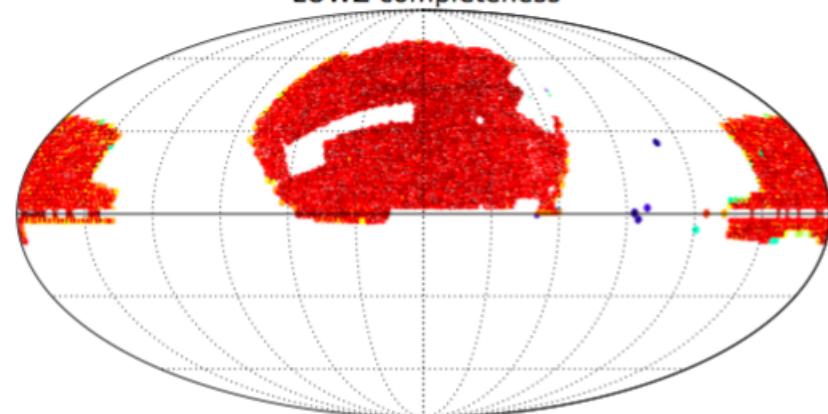
-2.7       $\log_{10}(E(B-V))$       1.8



0      completeness      1



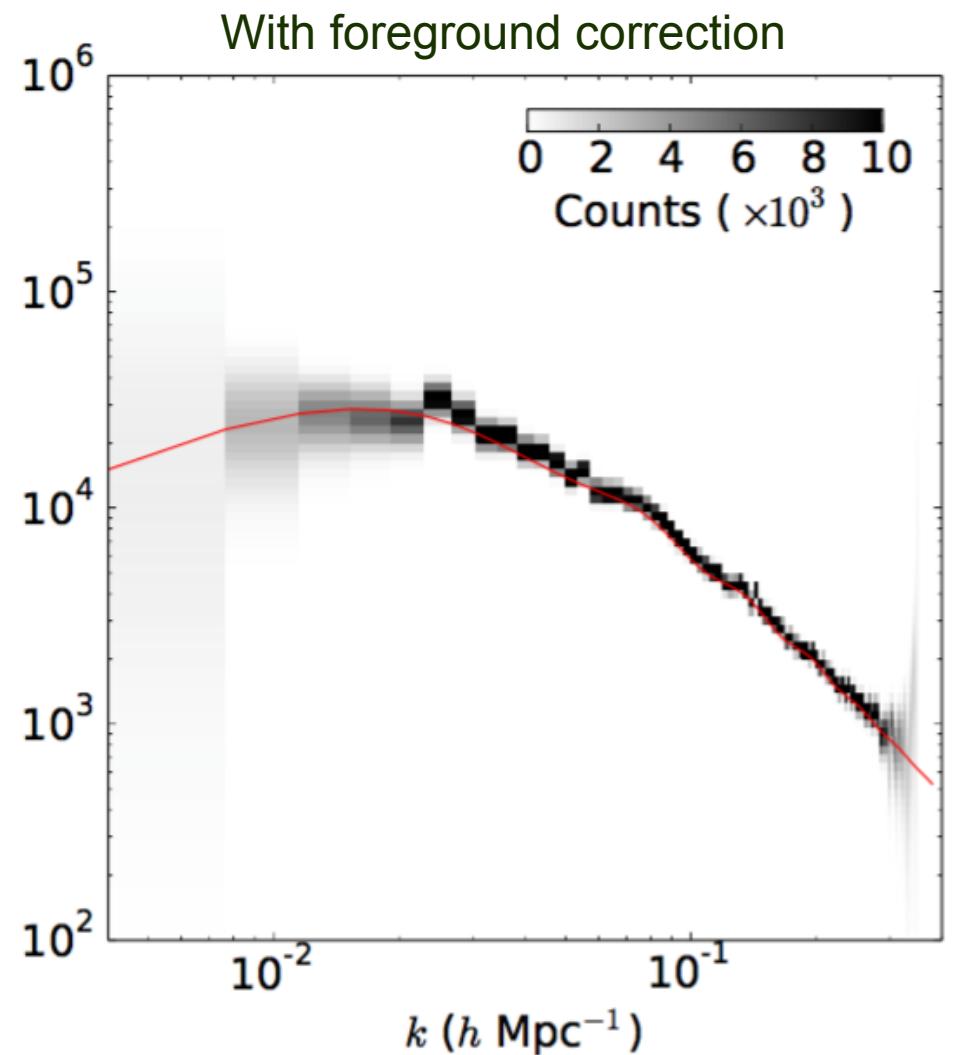
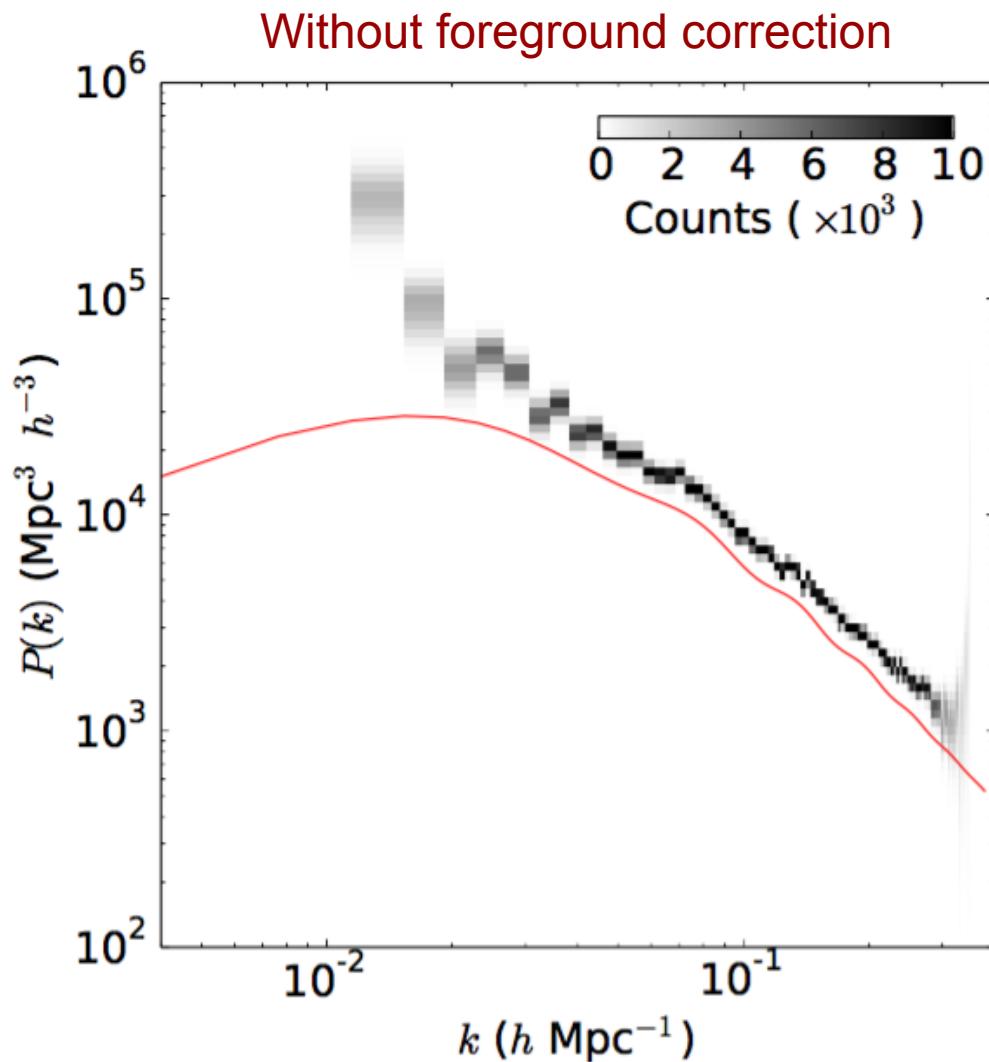
0      ( $\times 10^6$  stars/steradian)      6



0      completeness      1

# Foreground contaminations

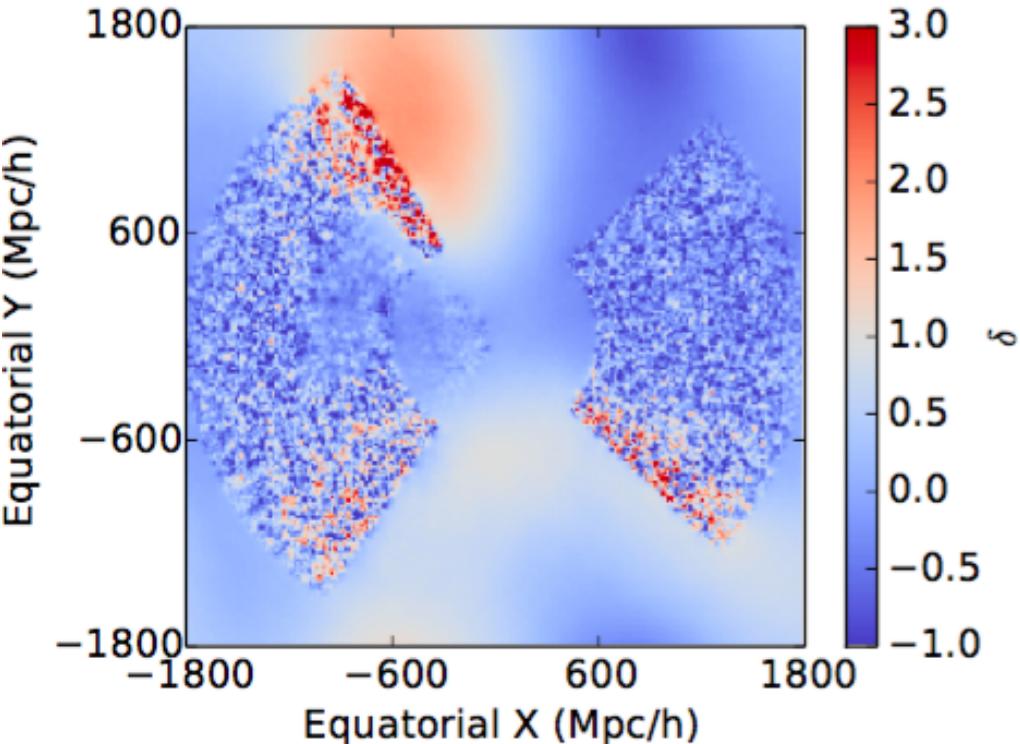
Mock data emulating LOWZ + CMASS



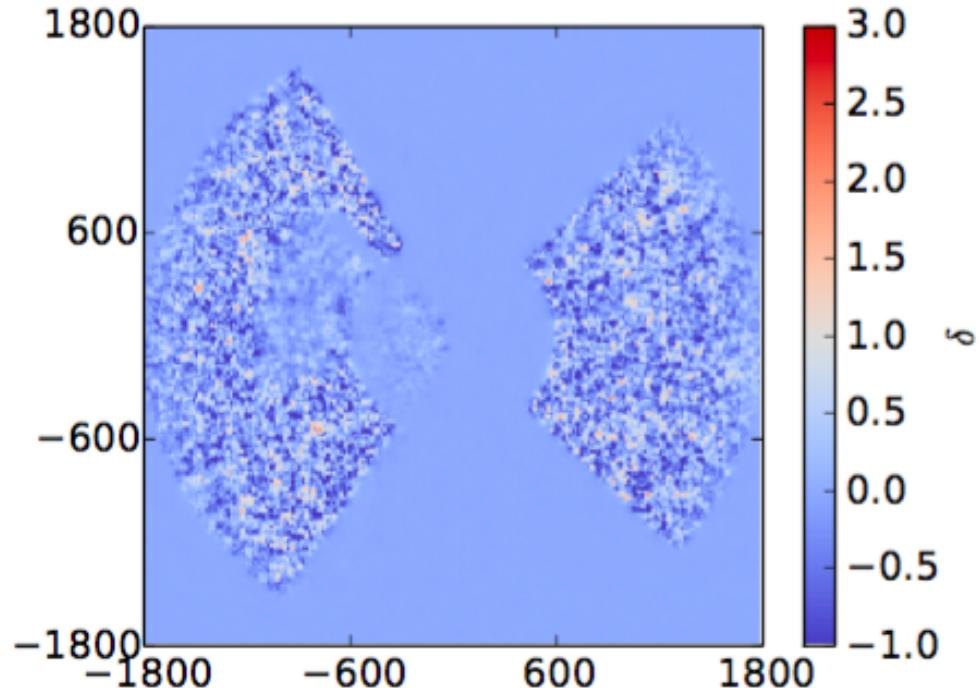
# Foreground contaminations

Mock data emulating LOWZ + CMASS

Without foreground correction



With foreground correction



Use inferred 3D density field as diagnostics.

# Photometric redshift uncertainties

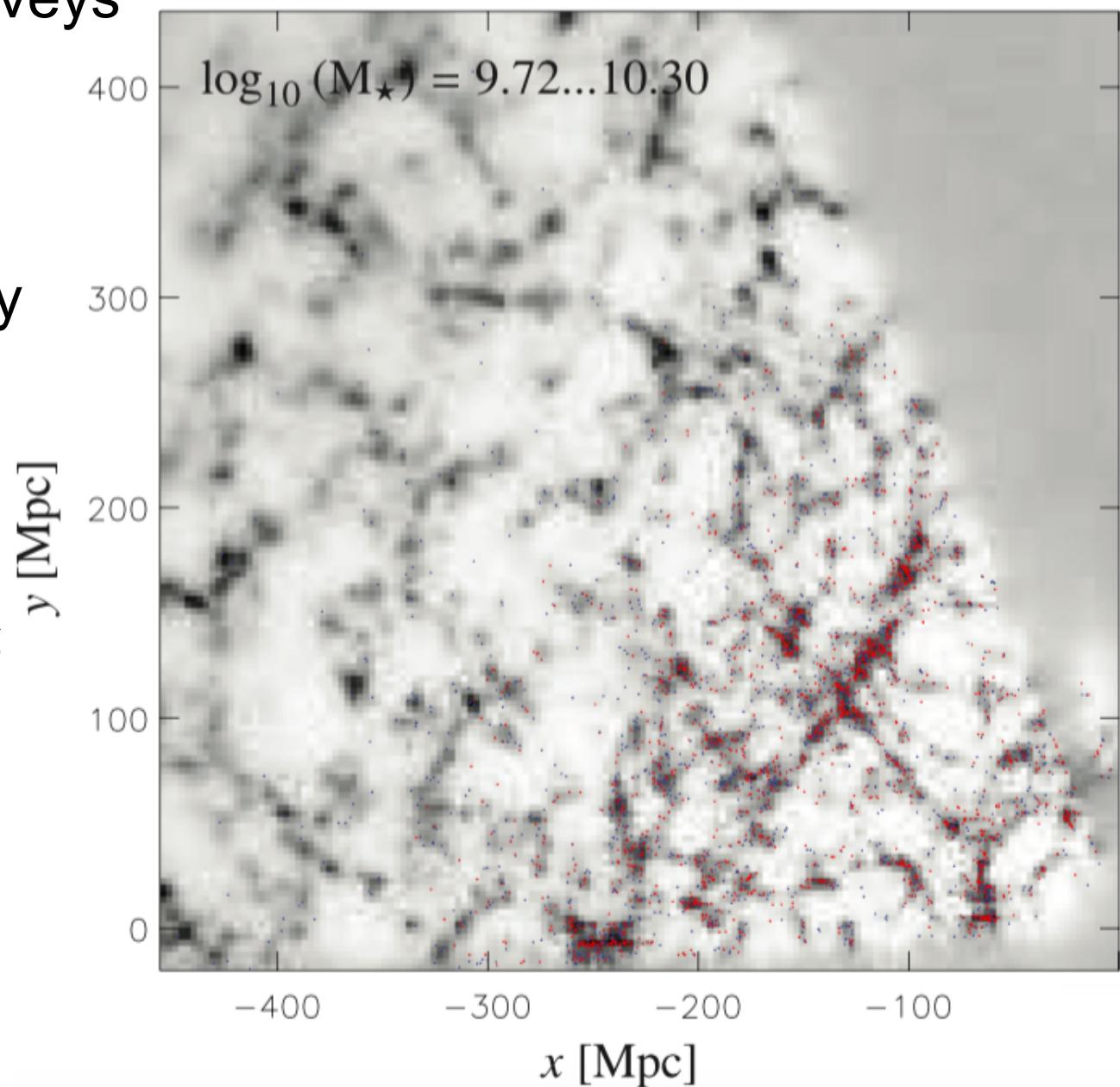
## Photometric redshift surveys

- Deep volumes
- Millions of galaxies
- Low redshift accuracy

**affects density fields  
and  
cosmological analyses**

See e.g. Blake, Bridle 2005

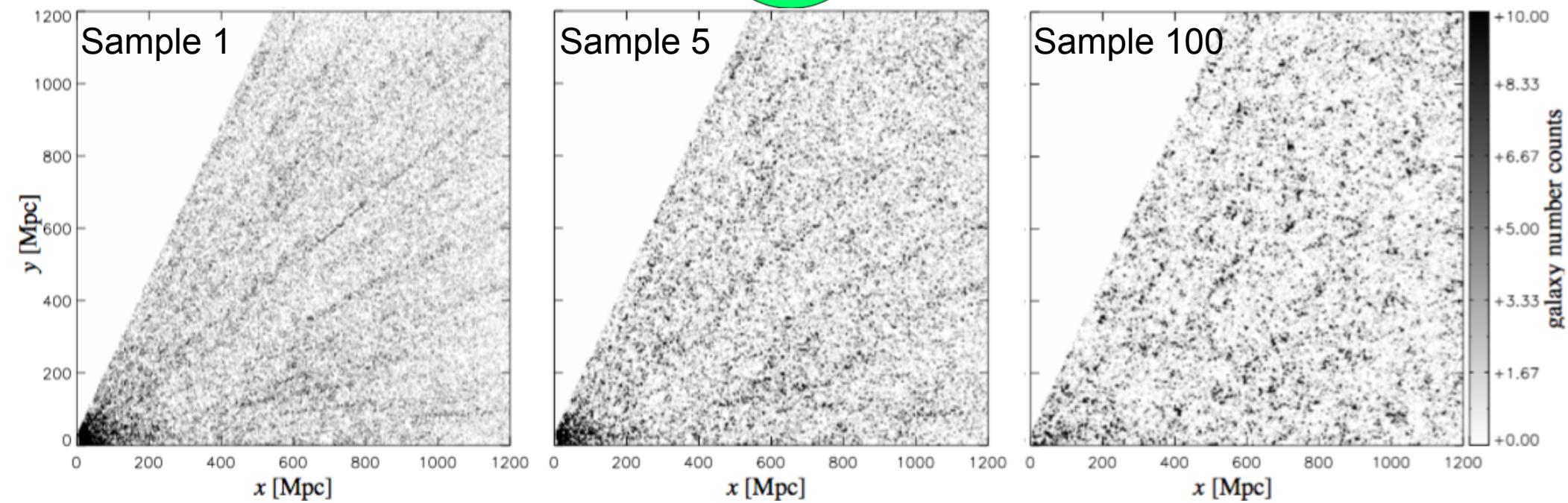
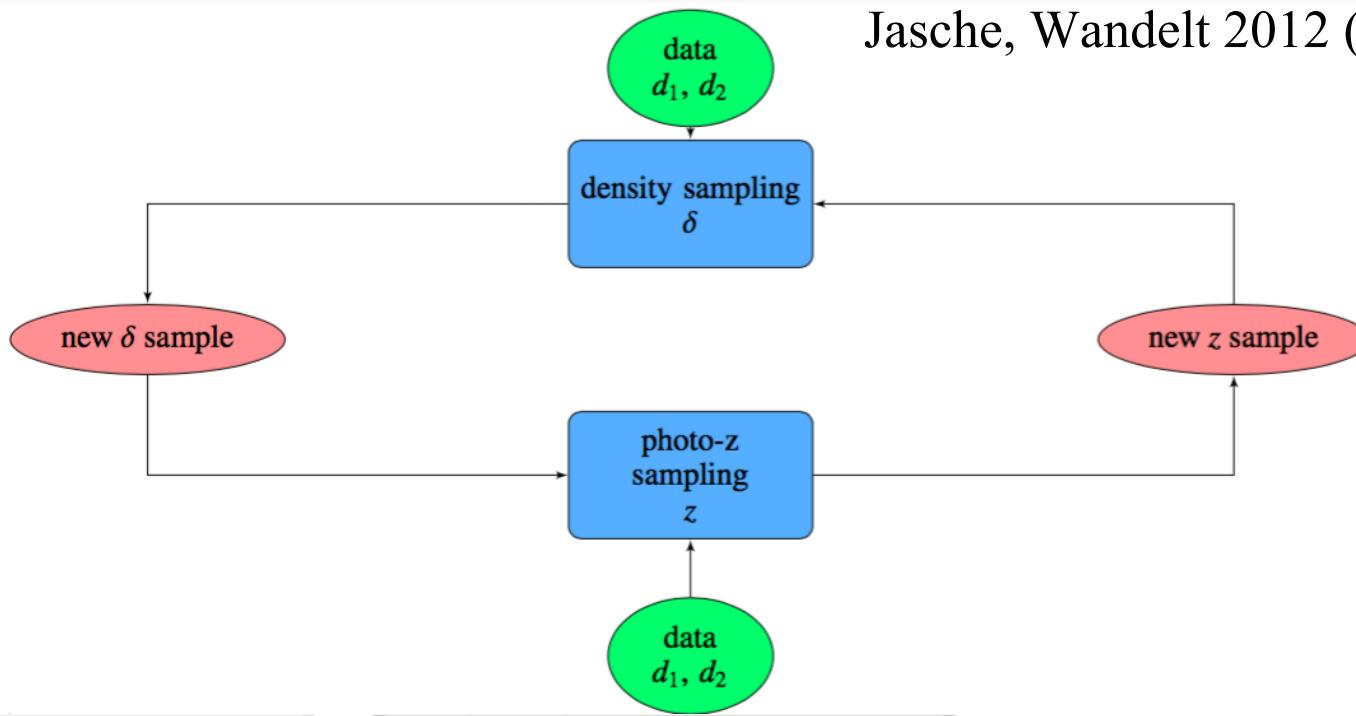
**But:  
Galaxies trace the  
matter distribution!!**



Jasche et al 2010 (arXiv:0911.2498)

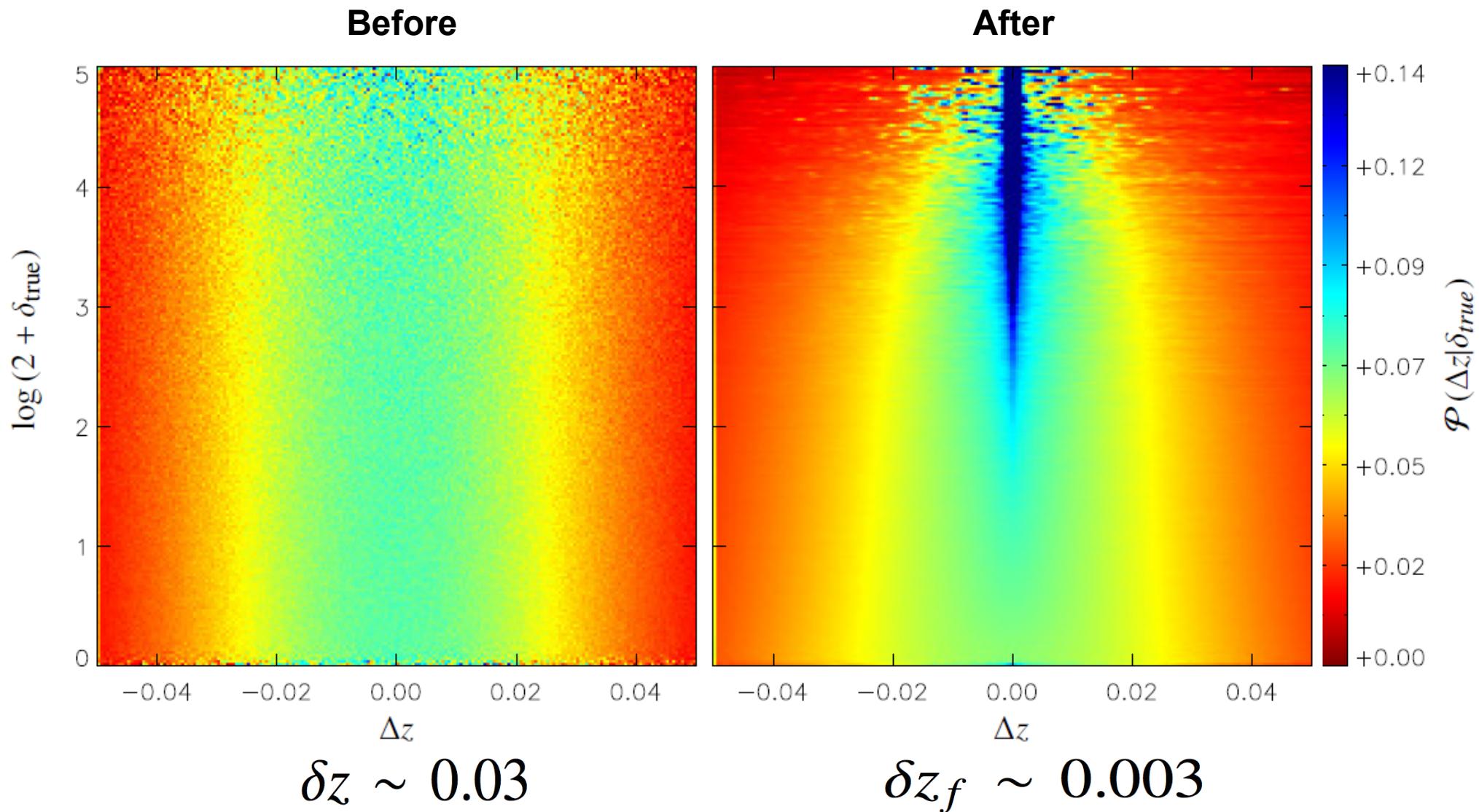
# Photo-z sampling

Jasche, Wandelt 2012 (arXiv:1106.2757)



# Photo-z sampling

Application to mock data

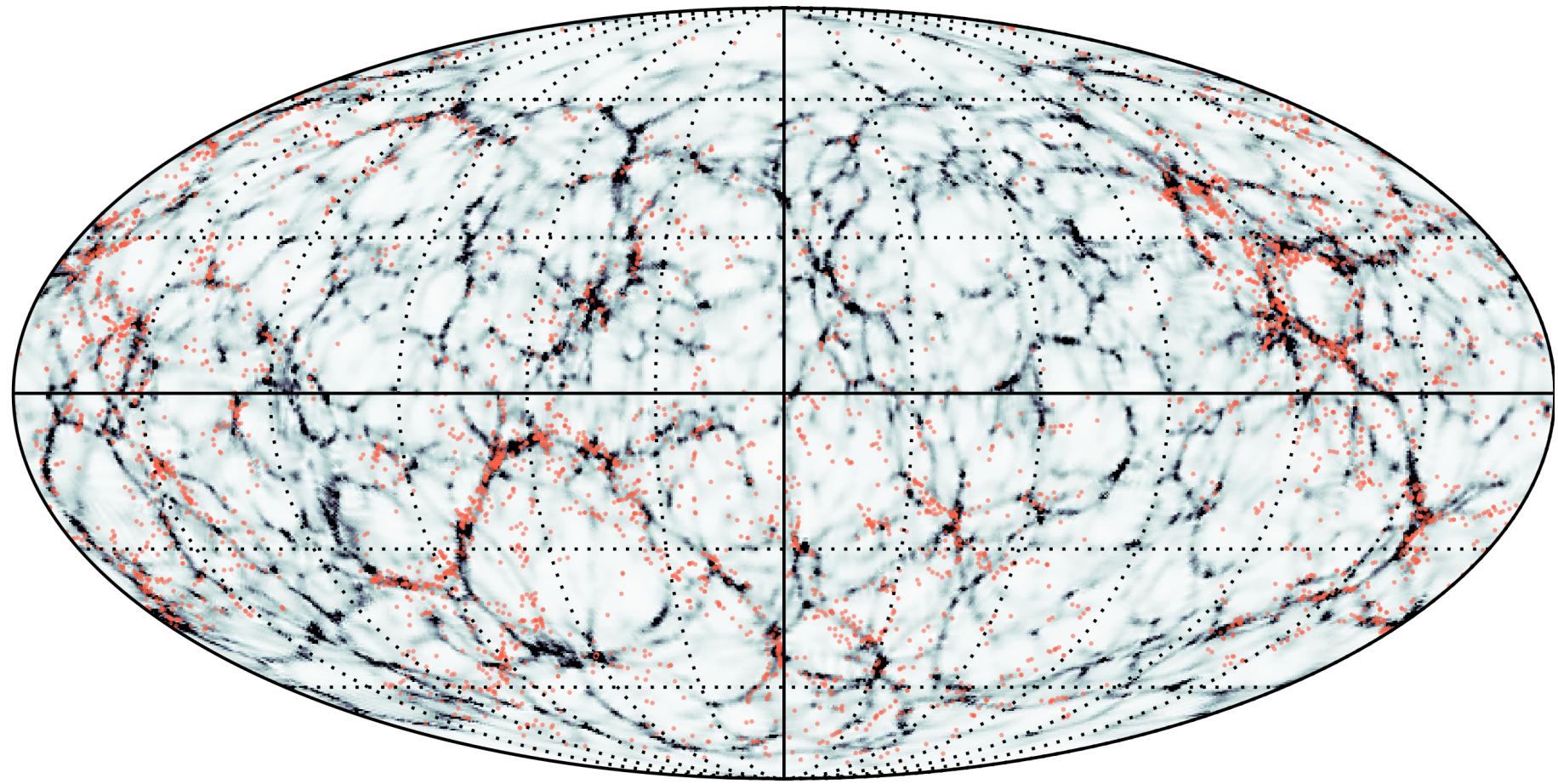


Jasche, Wandelt 2012 (arXiv:1106.2757)

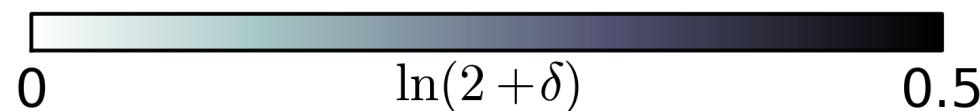
# The non-linear LSS of our Universe

Preliminary work!

Final conditions inferred from 2M++ data



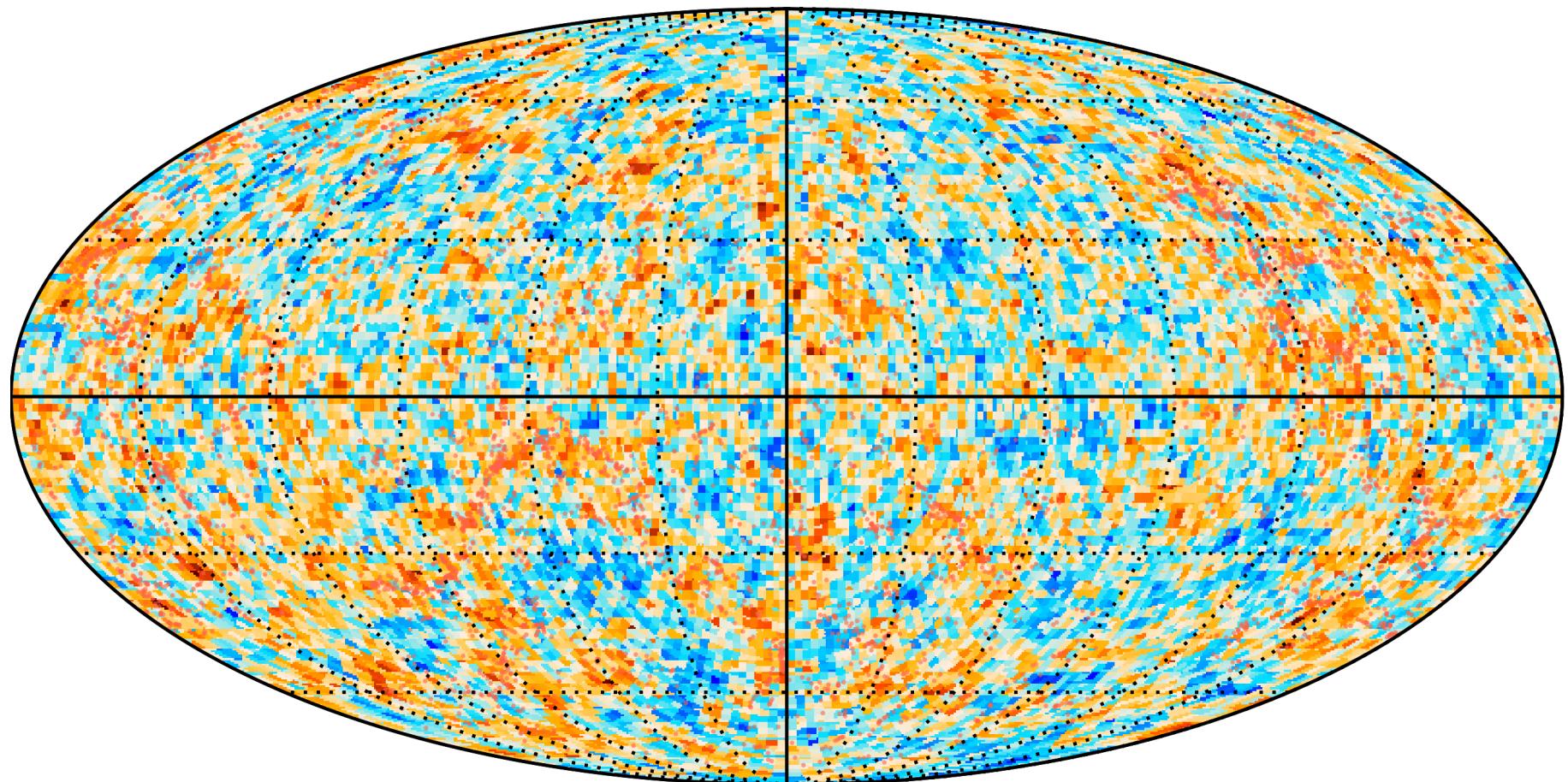
Jasche & Lavaux 2018 (in prep)



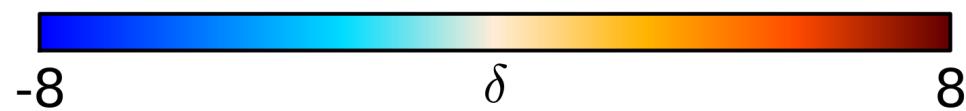
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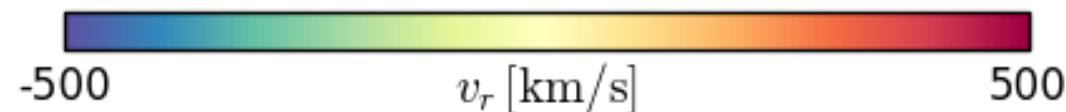
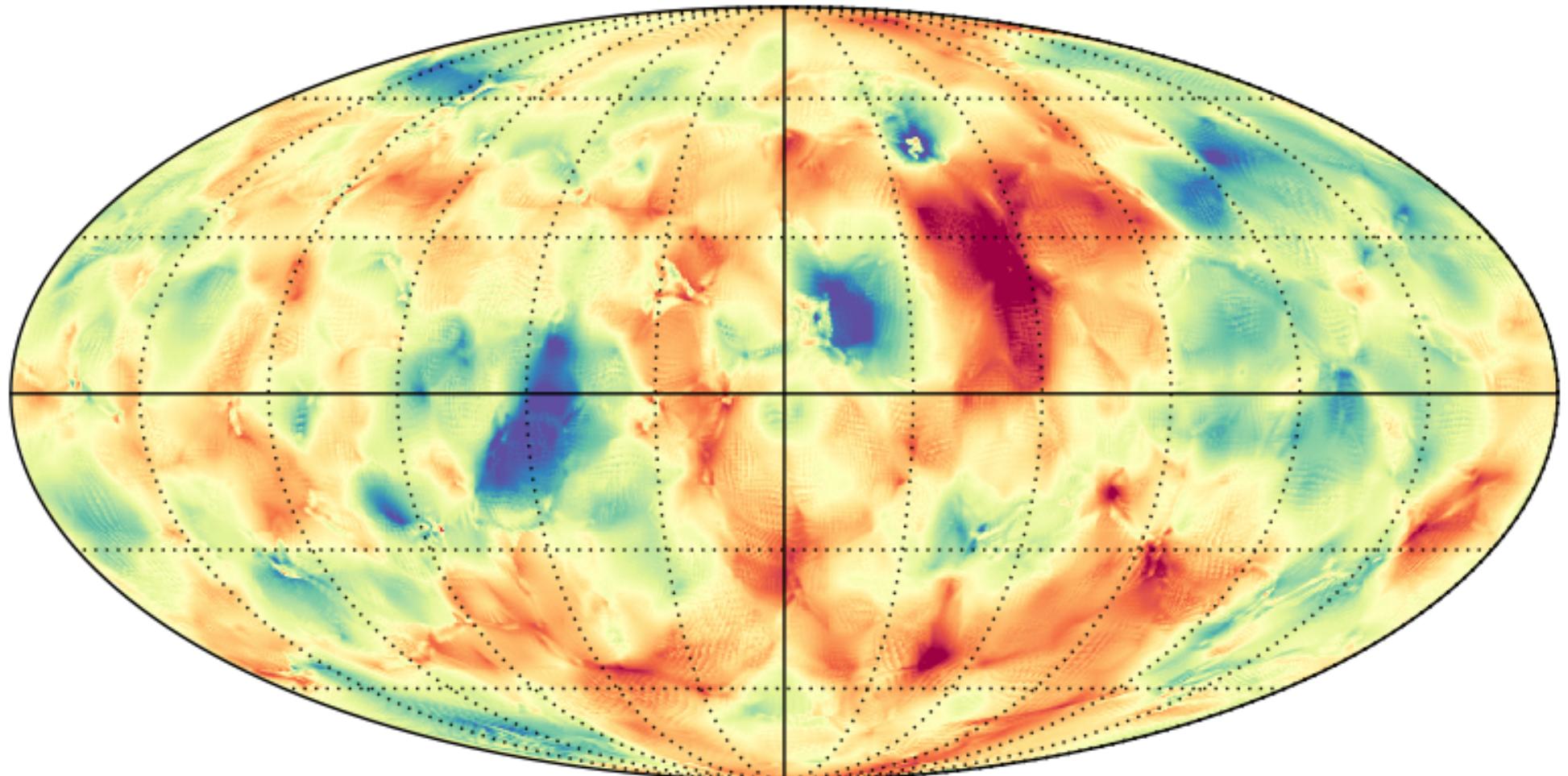
Jasche & Lavaux 2018 (in prep)



# Peculiar velocities and the Hubble flow

Preliminary work!

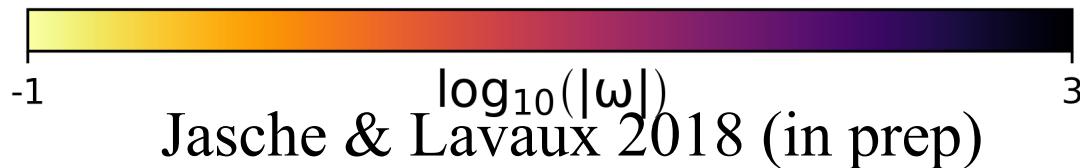
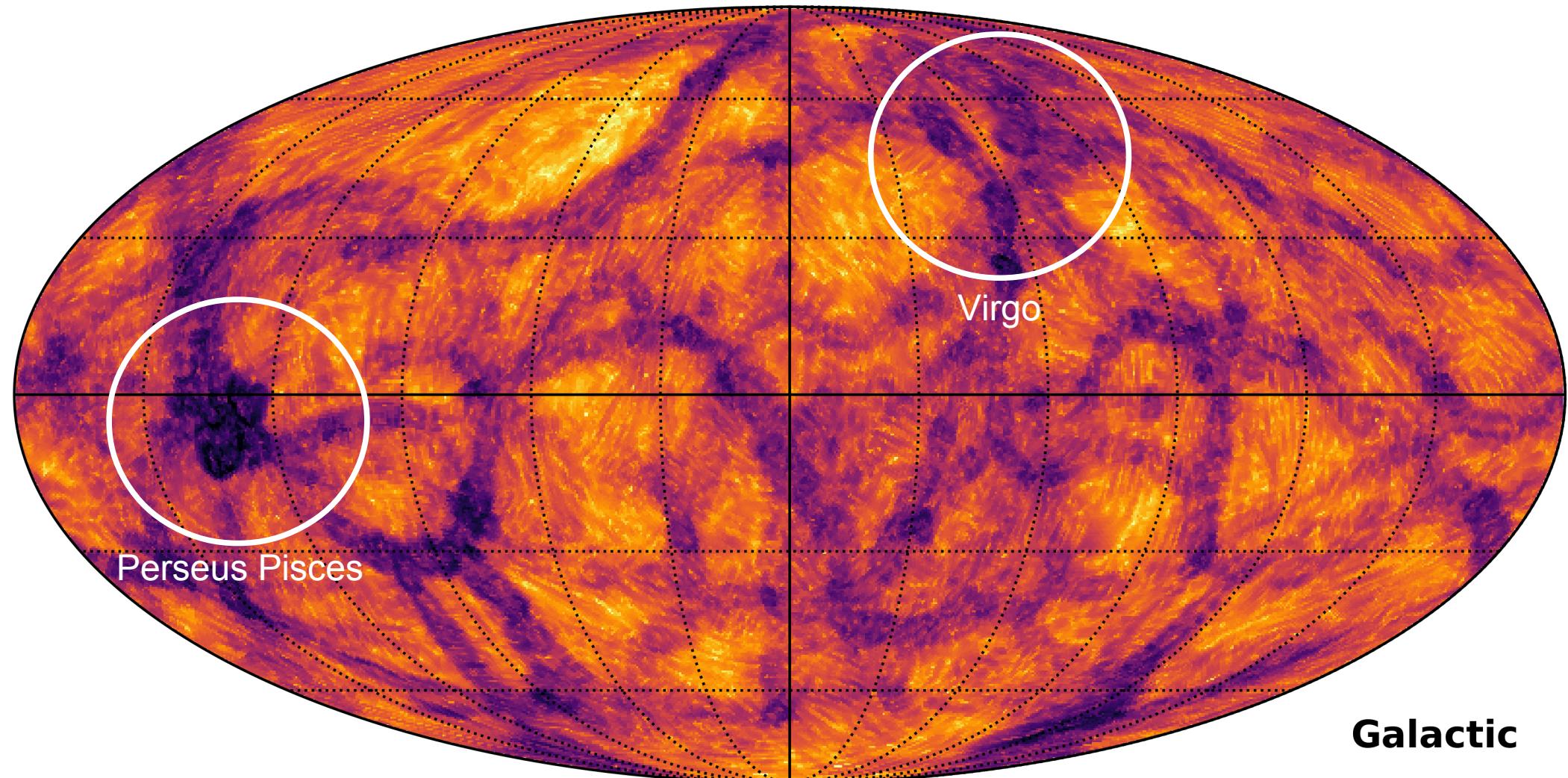
$$96.77 \text{ [Mpc/h]} < r < 106.45 \text{ [Mpc/h]}$$



Jasche & Lavaux 2018 (in prep)

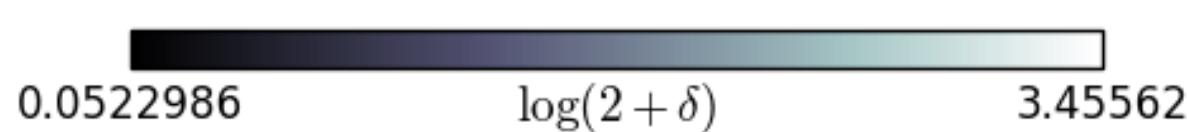
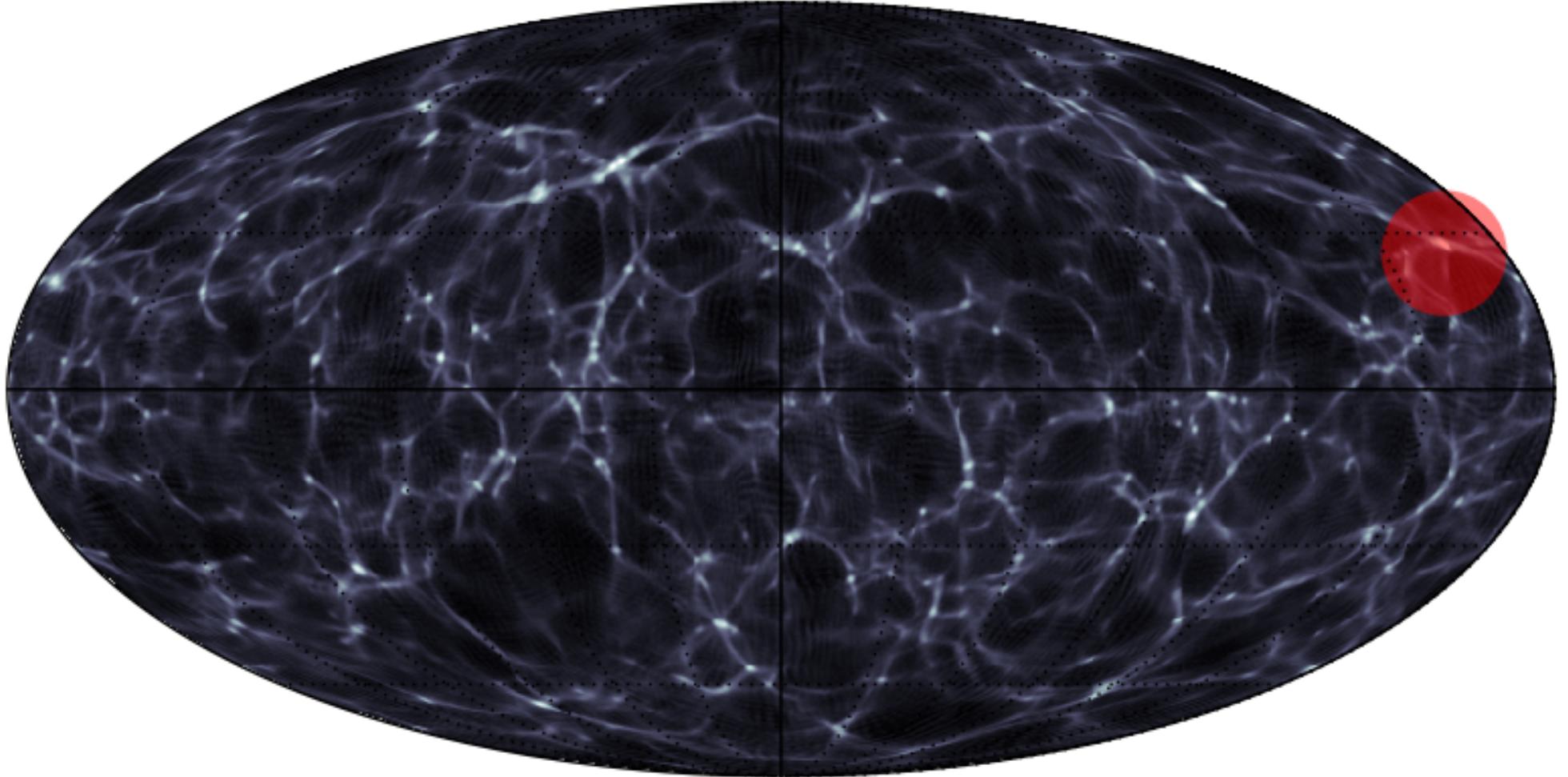
# Vorticity of the velocity field

Preliminary work!



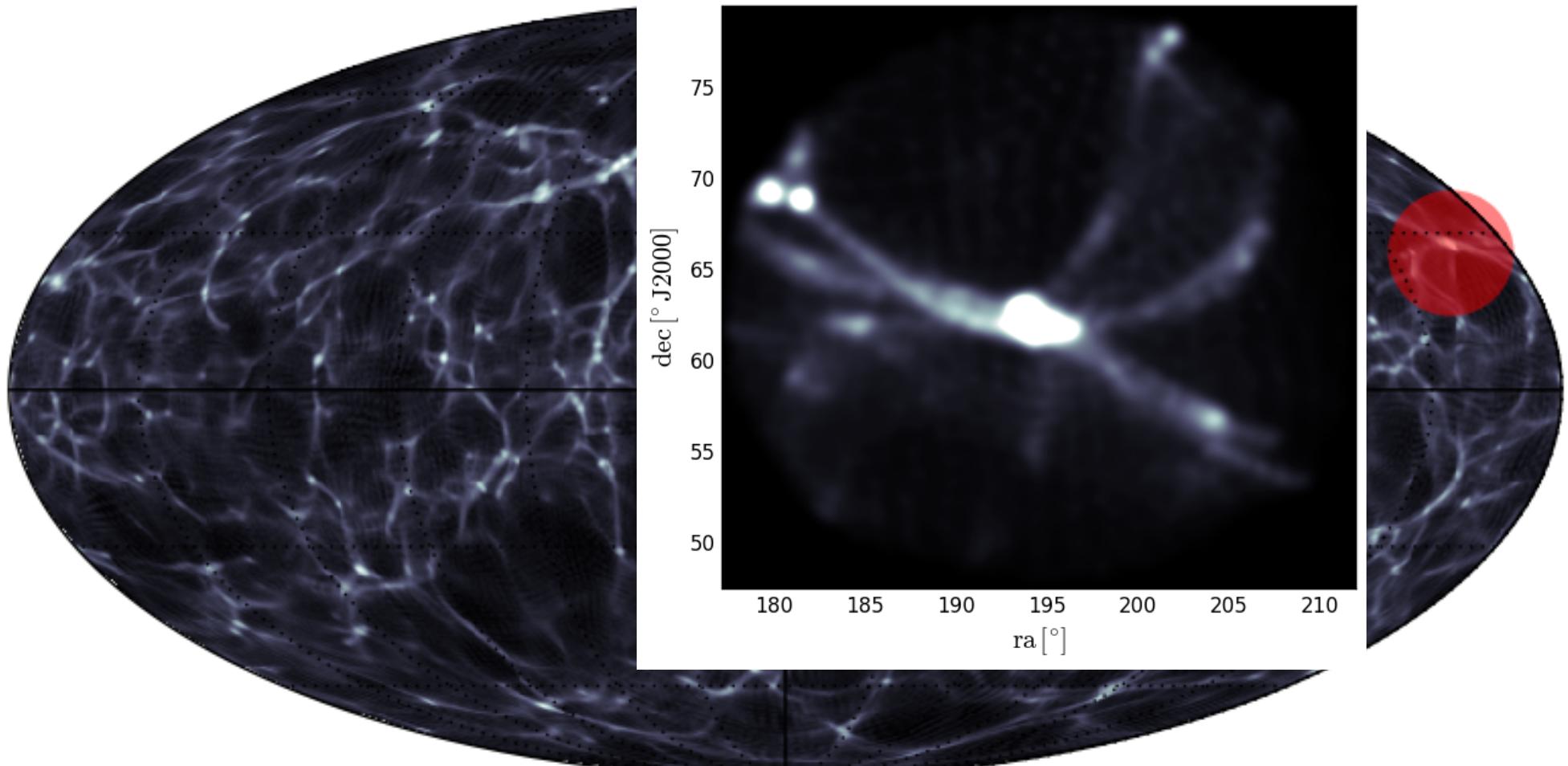
# The Coma Cluster

$52 \text{ [Mpc/h]} < r < 92 \text{ [Mpc/h]}$



# The Coma Cluster

$52 \text{ [Mpc/h]} < r < 92 \text{ [Mpc/h]}$



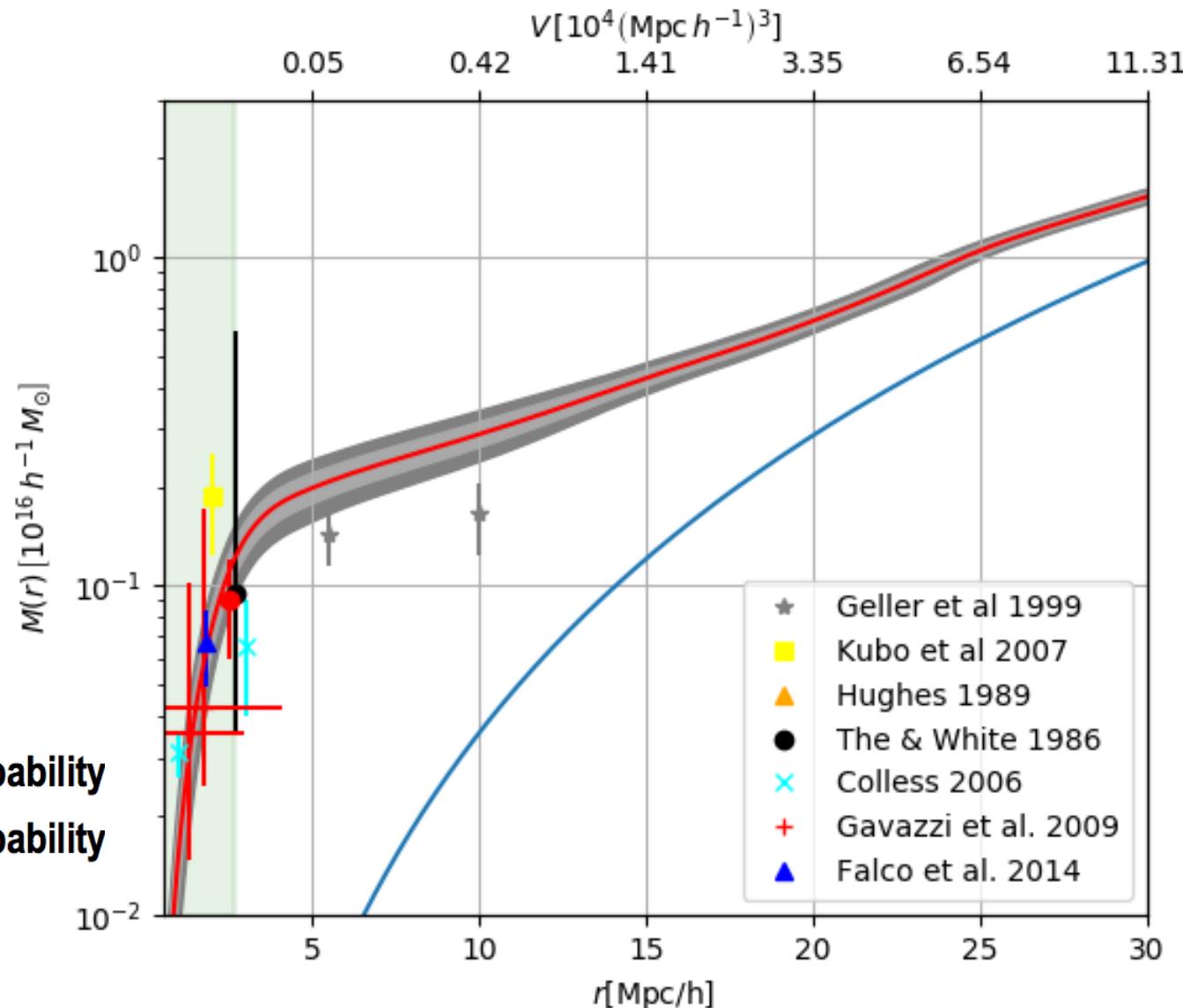
0.0522986

$\log(2 + \delta)$

3.45562

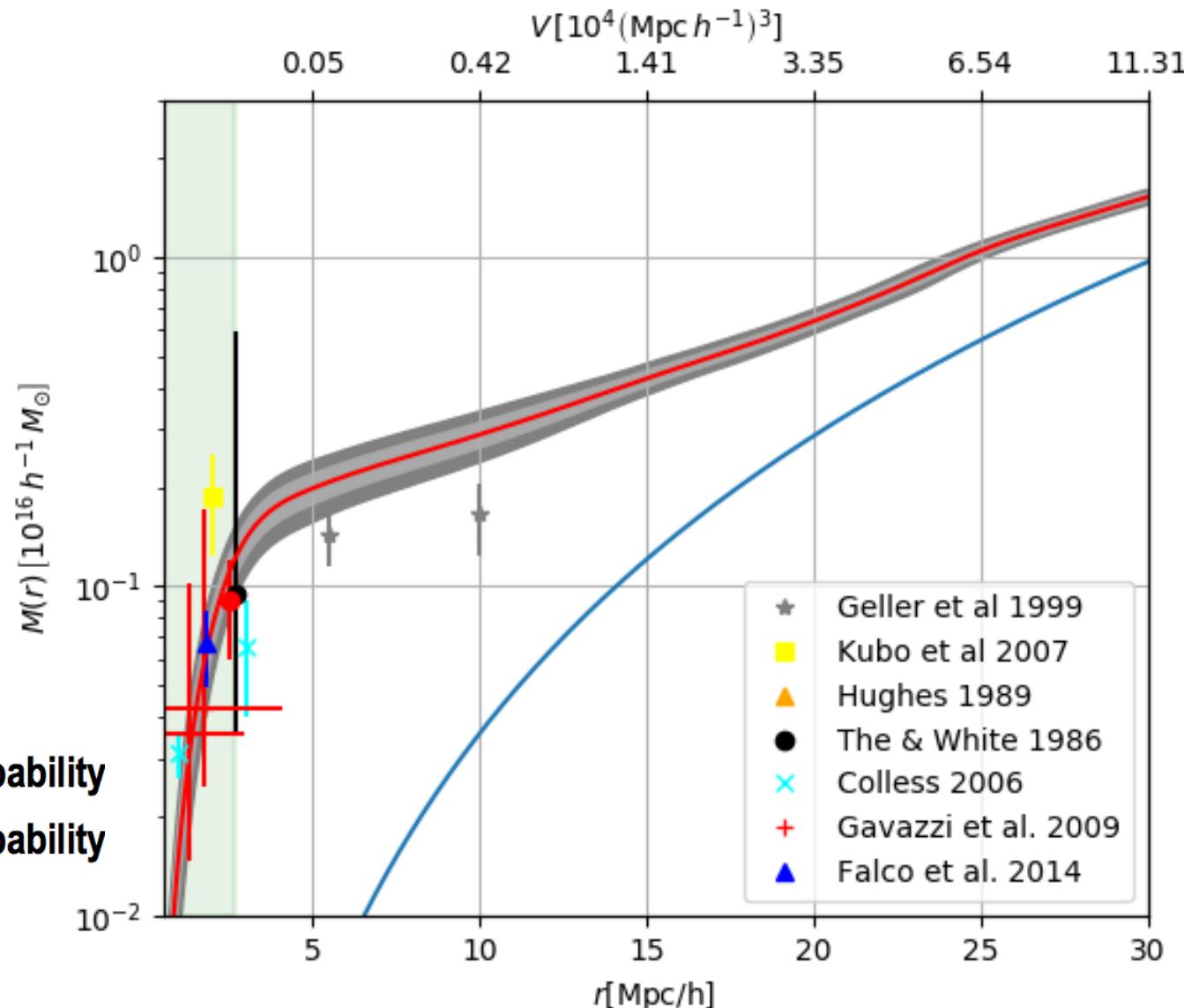
# Coma mass profile

Lavaux & Jasche 2018 in prep.



# Coma mass profile

Lavaux & Jasche 2018 in prep.



Also see talk by Guilhem Lavaux

# Summary & Conclusion

BORG combines physical modeling with data science:

- Dynamical modeling accounts for non-Gaussian statistics
- Flexible data modeling via HMC and block sampling
- Solves complex high dimensional statistics problems
- Improves photo-z estimates

Scientific results:

- Characterization of initial conditions
- Accurate & Detailed reconstructions of the DM field
- Complementary mass estimates
- Dynamical reconstructions (velocity + vorticity)
- **We arrive at a consistent dynamical picture of our Universe**

# The end...

## Thank You!

### **Selected Bibliography:**

**Jasche**, J. & Kitaura, F. S. *MNRAS* **407**, 29–42 (2010).

**Jasche**, J., Kitaura, F. S., Li, C. & Enßlin, T. A. *MNRAS* **409**, 355–370 (2010).

**Jasche**, J. & Wandelt, B. D. *MNRAS* **425**, 1042–1056 (2012).

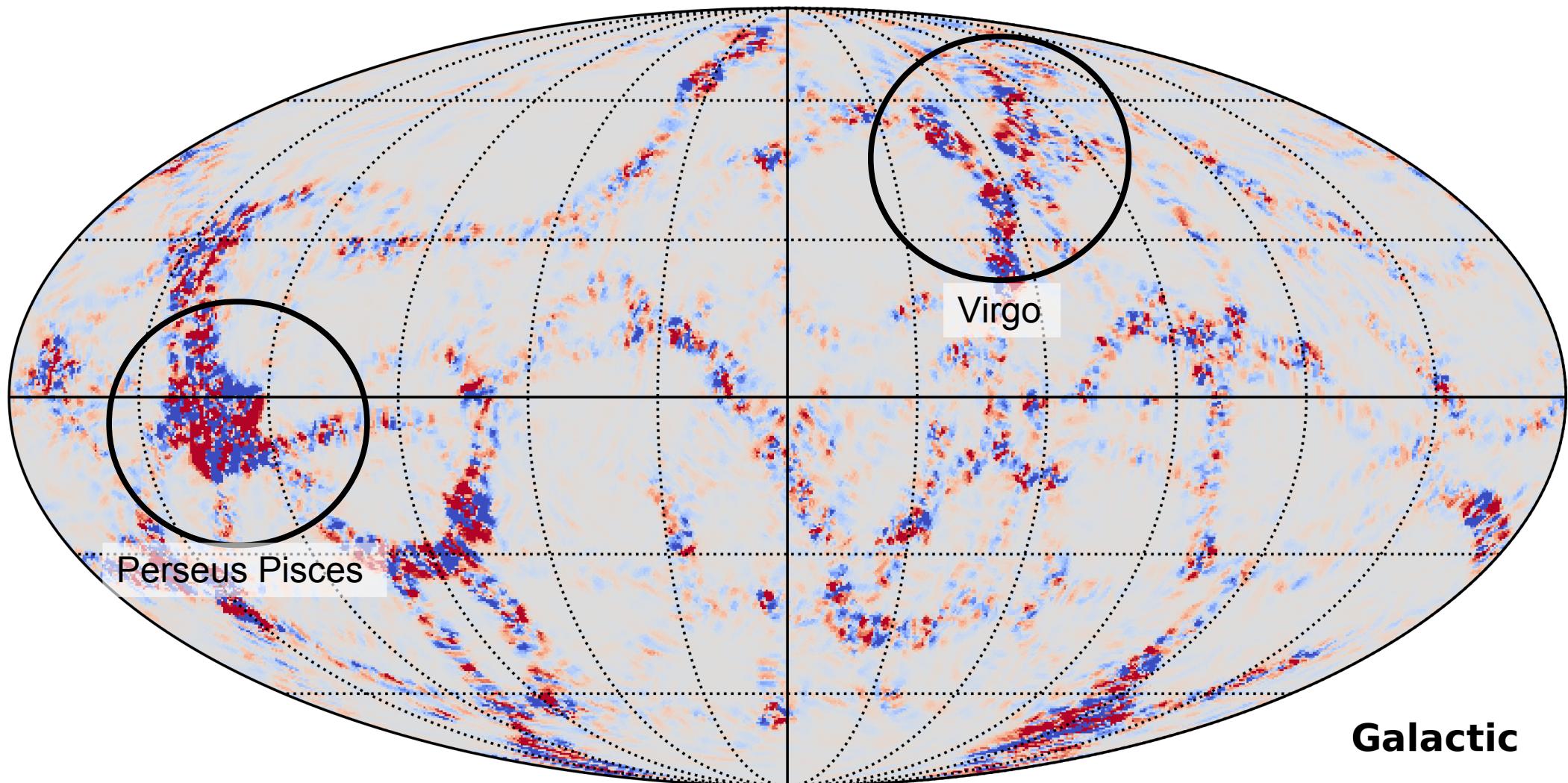
**Jasche**, J. & Wandelt, B. D. *MNRAS* **432**, 894–913 (2013).

**Jasche**, J., Leclercq, F. & Wandelt, B. D. *JCAP* **01**, 036 (2015).

Lavaux, G. & **Jasche**, J. *MNRAS* **455**, 3169–3179 (2016).

# Vorticity of the velocity field

Preliminary work!



-50       $\omega_{\text{los}}$       50

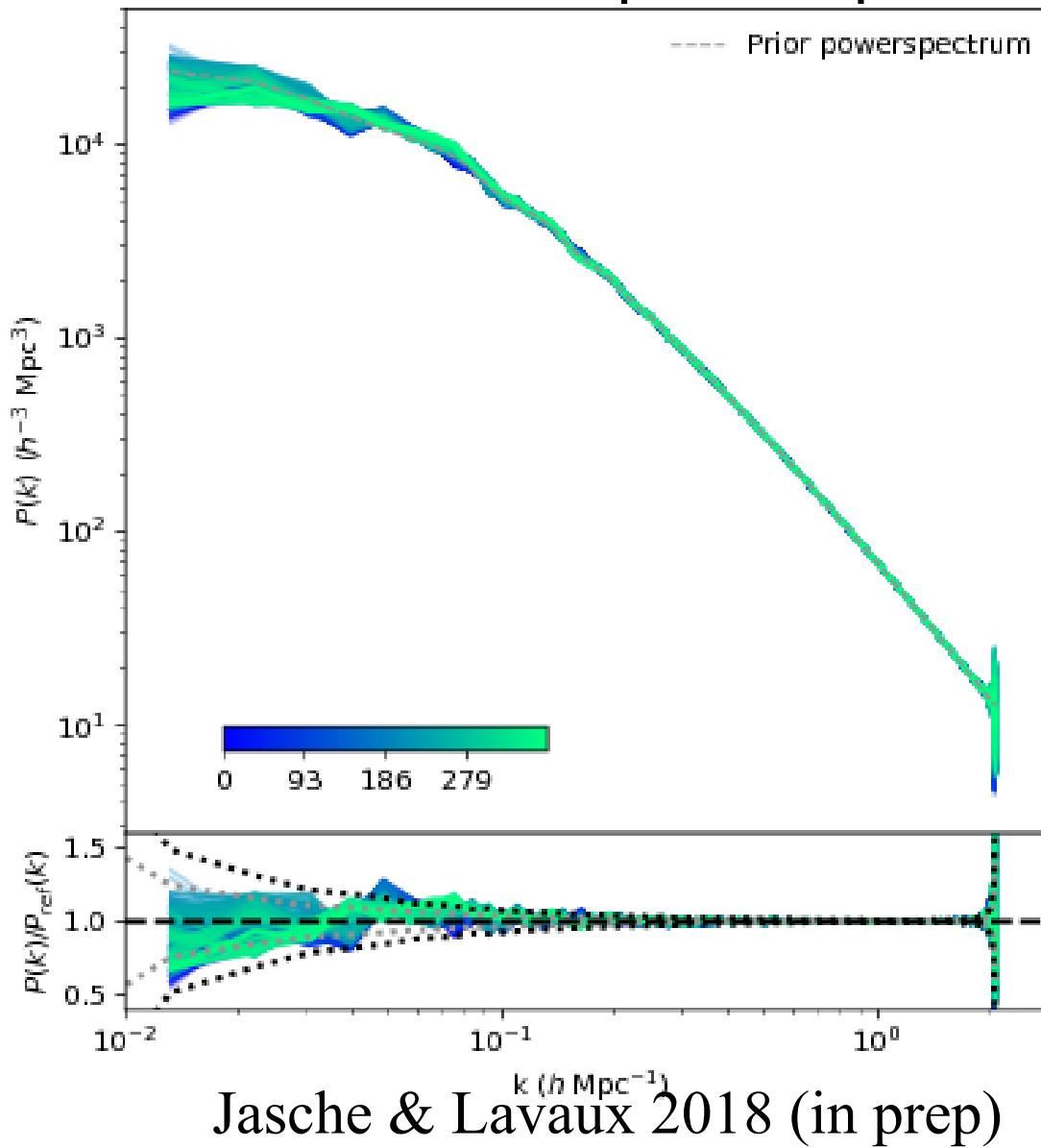
Jasche & Lavaux 2018 (in prep)

# The non-linear LSS of our Universe

Preliminary work!

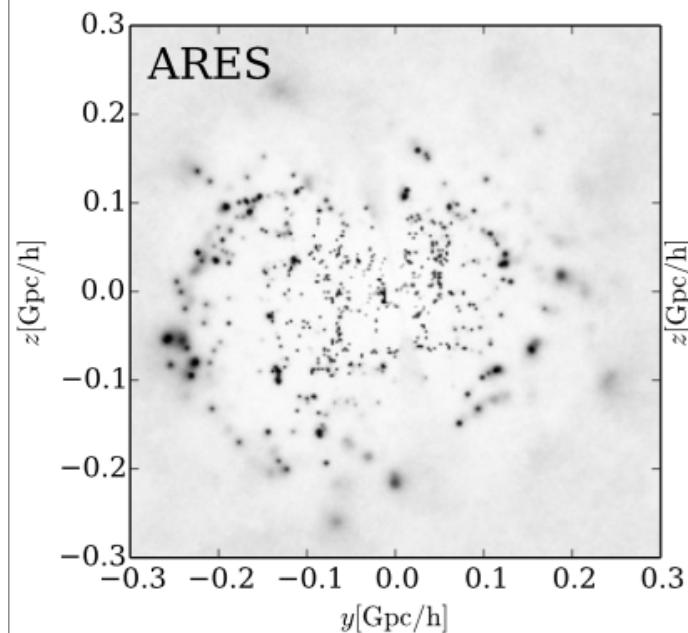
Consistency check

- Posterior estimate of the initial power-spectrum



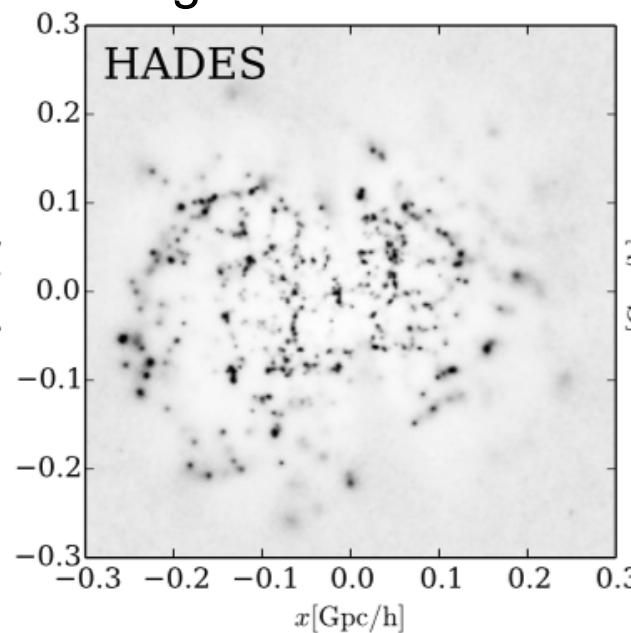
# Comparing inference schemes

Gaussian



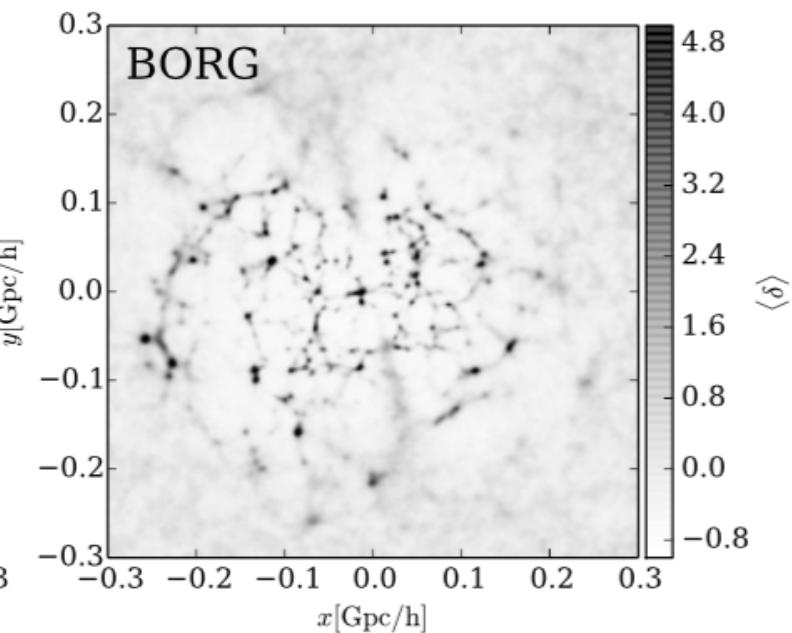
a.k.a: Wiener-filtering  
Zaroubi et al. 1994  
Erdogdu et al. 2004  
Kitaura & Ensslin 2008  
Grannet et al. 2015

Log-normal-Poisson



log-normal-filtering  
Kitaura 2010  
Jasche&Kitaura 2010

2LPT-Poisson



Jasche&Wandelt 2012

Which scheme performs best?

Ask the data!

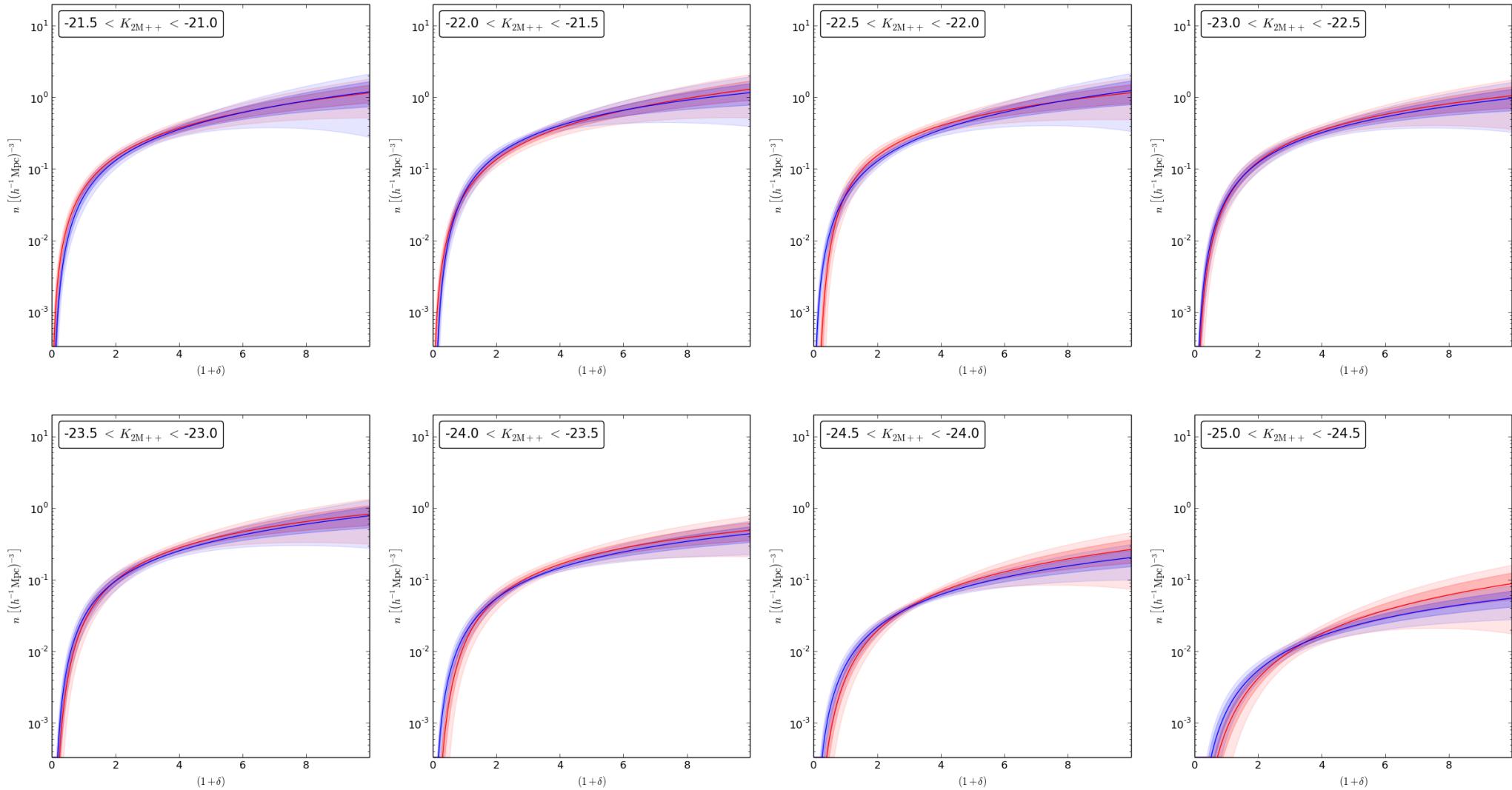
$$A_{ij} = \ln(\mathcal{P}(d|\delta_i)) - \ln(\mathcal{P}(d|\delta_j))$$

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

Jasche & Lavaux (in prep)

# Astrophysics: The galaxy bias

Jasche & Lavaux 2018 (in prep)



**Bias model: local generalized power-law**

$$n^g(\delta, \bar{N}, \beta, \rho_g, \epsilon_g) = \bar{N} (1 + \delta)^\beta e^{-\rho_g (1 + \delta)^{-\epsilon_g}}$$

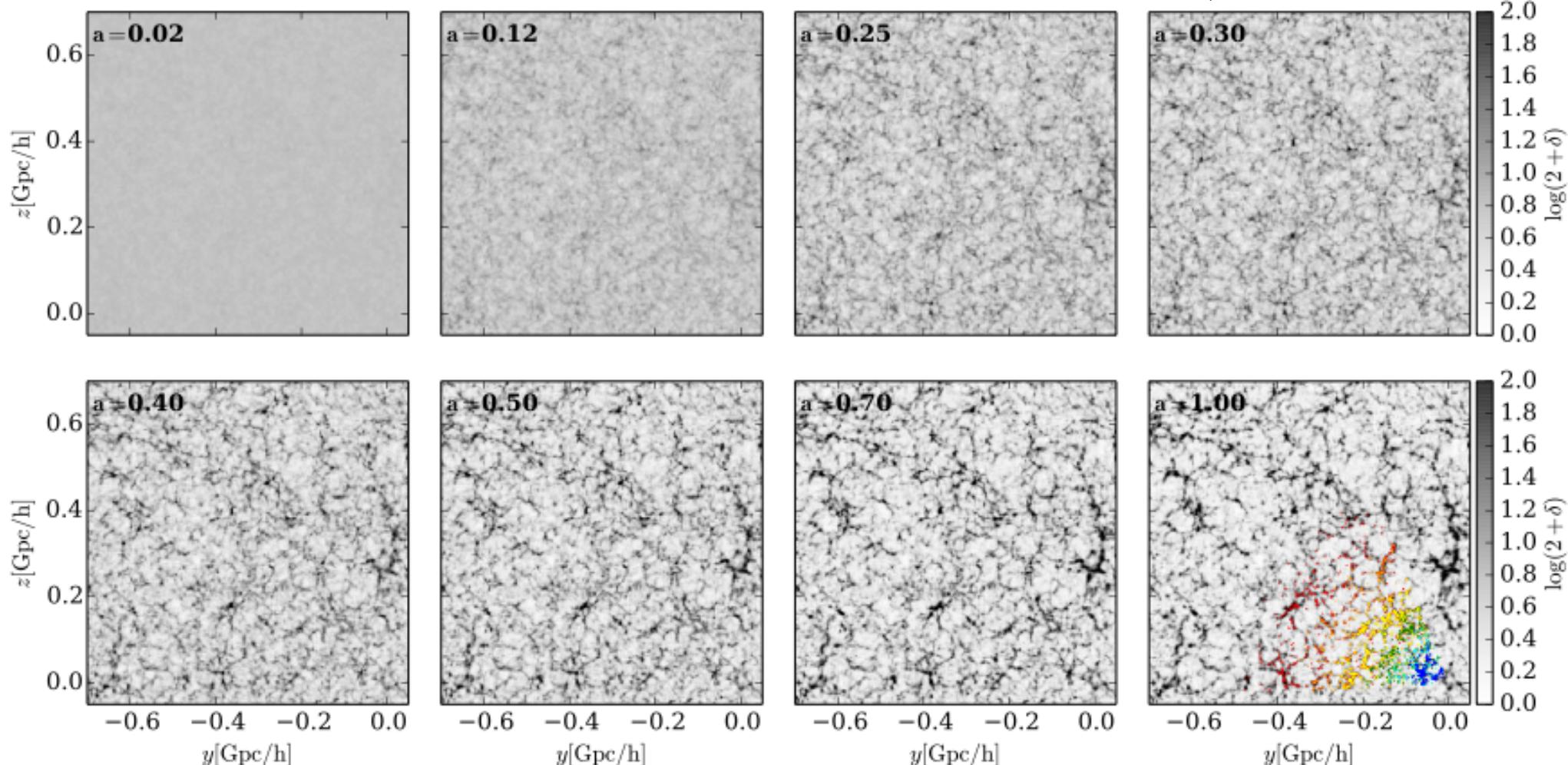
Neyrinck et al. 2014

# Reconstructing formation histories

## Dynamic Information

- Plausible LSS formation history

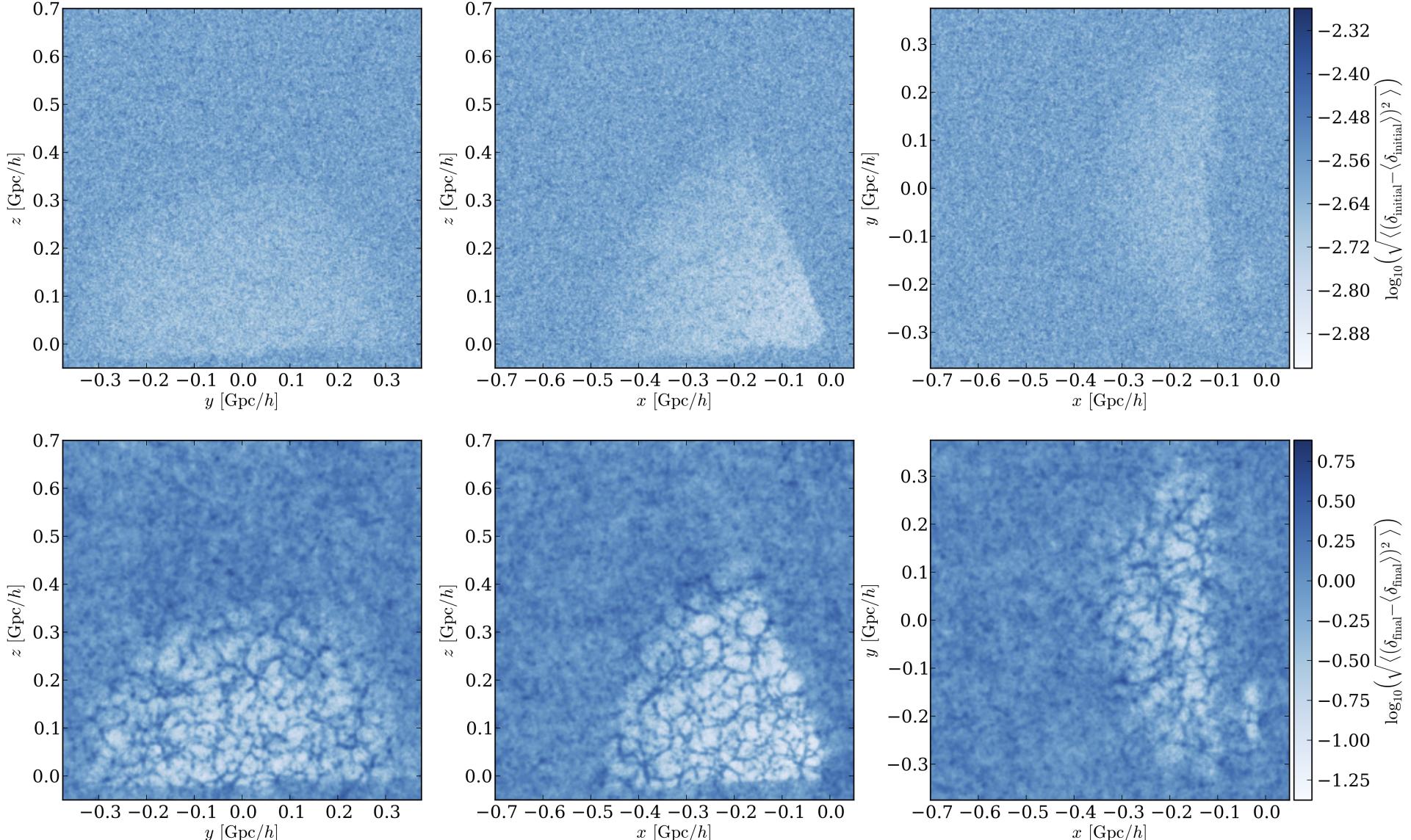
Jasche et al. 2015 ( arXiv:1409.6308 )



# Bayesian analysis of the SDSS DR7

## Uncertainty quantification

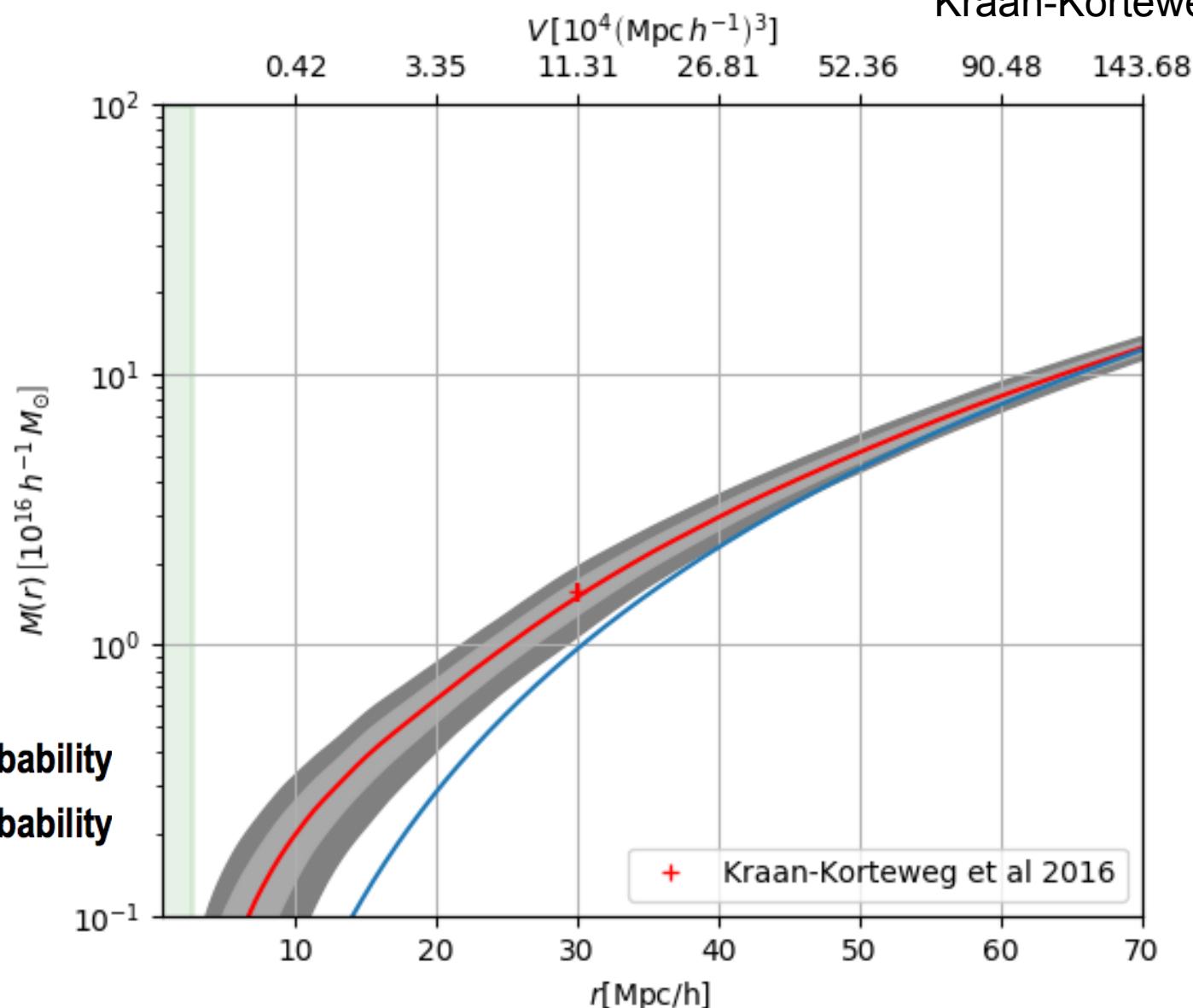
- Voxel-wise standard deviations for initial and final states



# Mass of Vela Supercluster

2016 Discovery of a supercluster in the ZOA in Vela

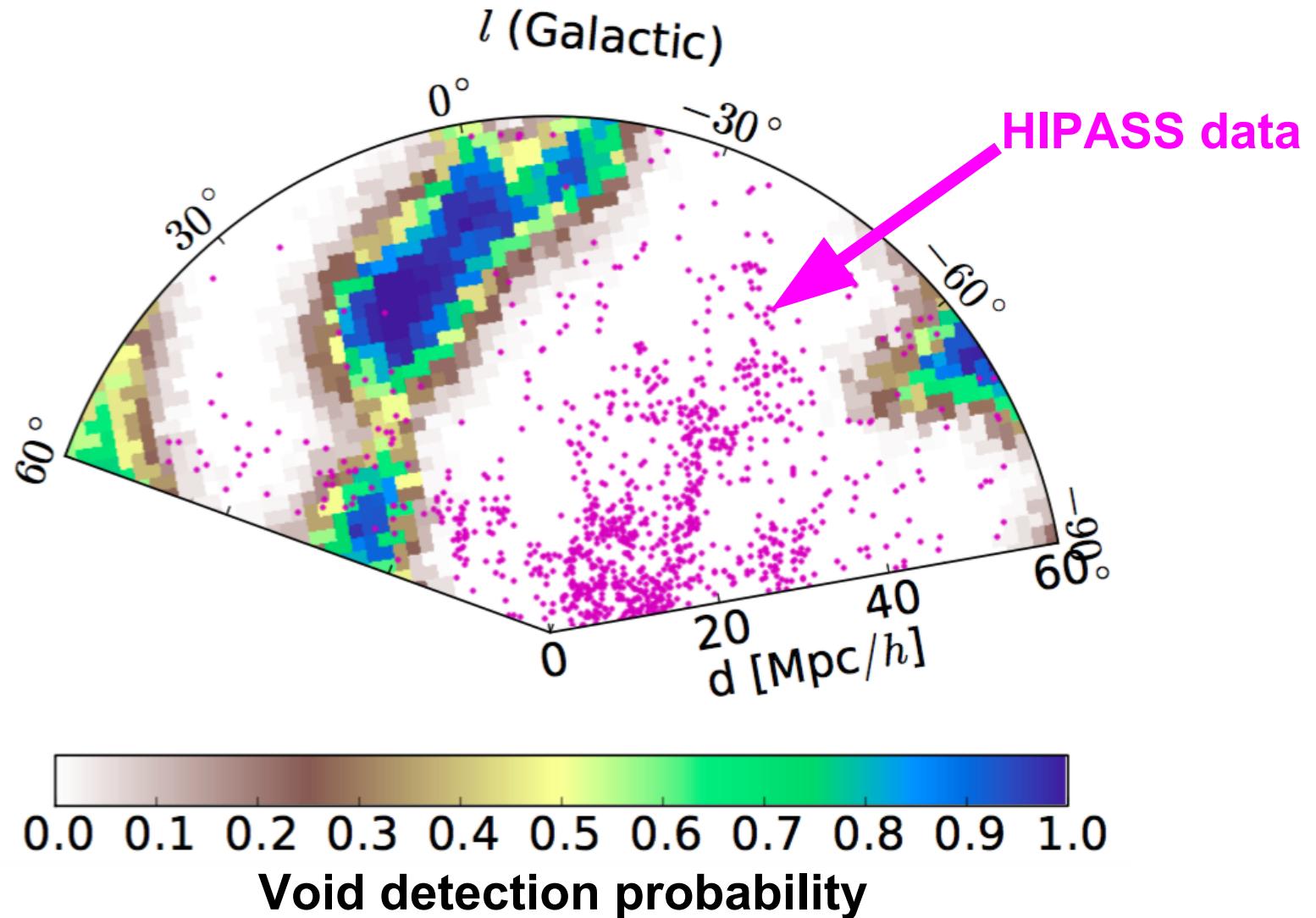
Kraan-Korteweg et al 2016



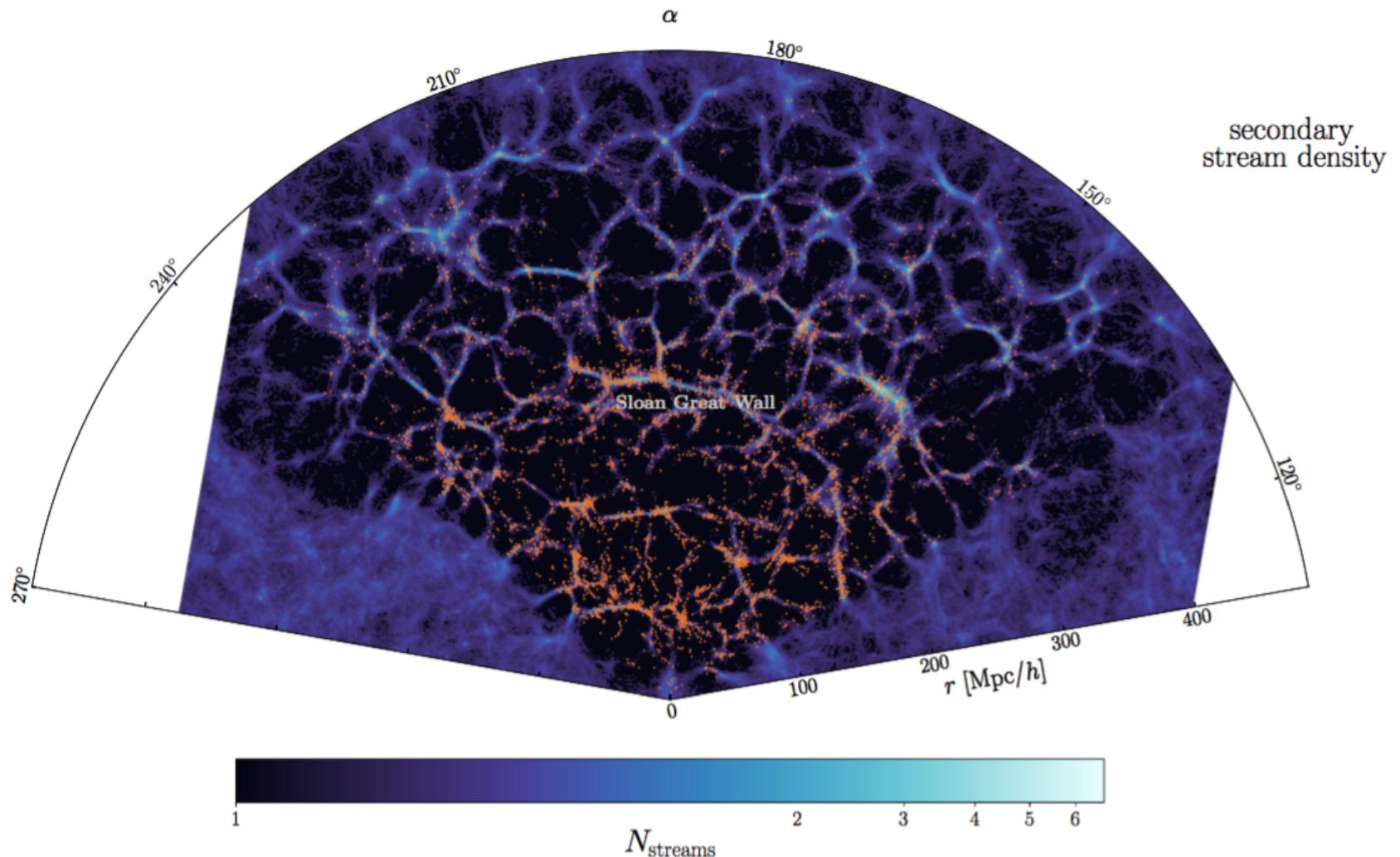
Lavaux & Jasche 2018 in prep.

# Detecting the local void

Testing with complementary HI data (HIPASS, Meyer et al. 2014 ):

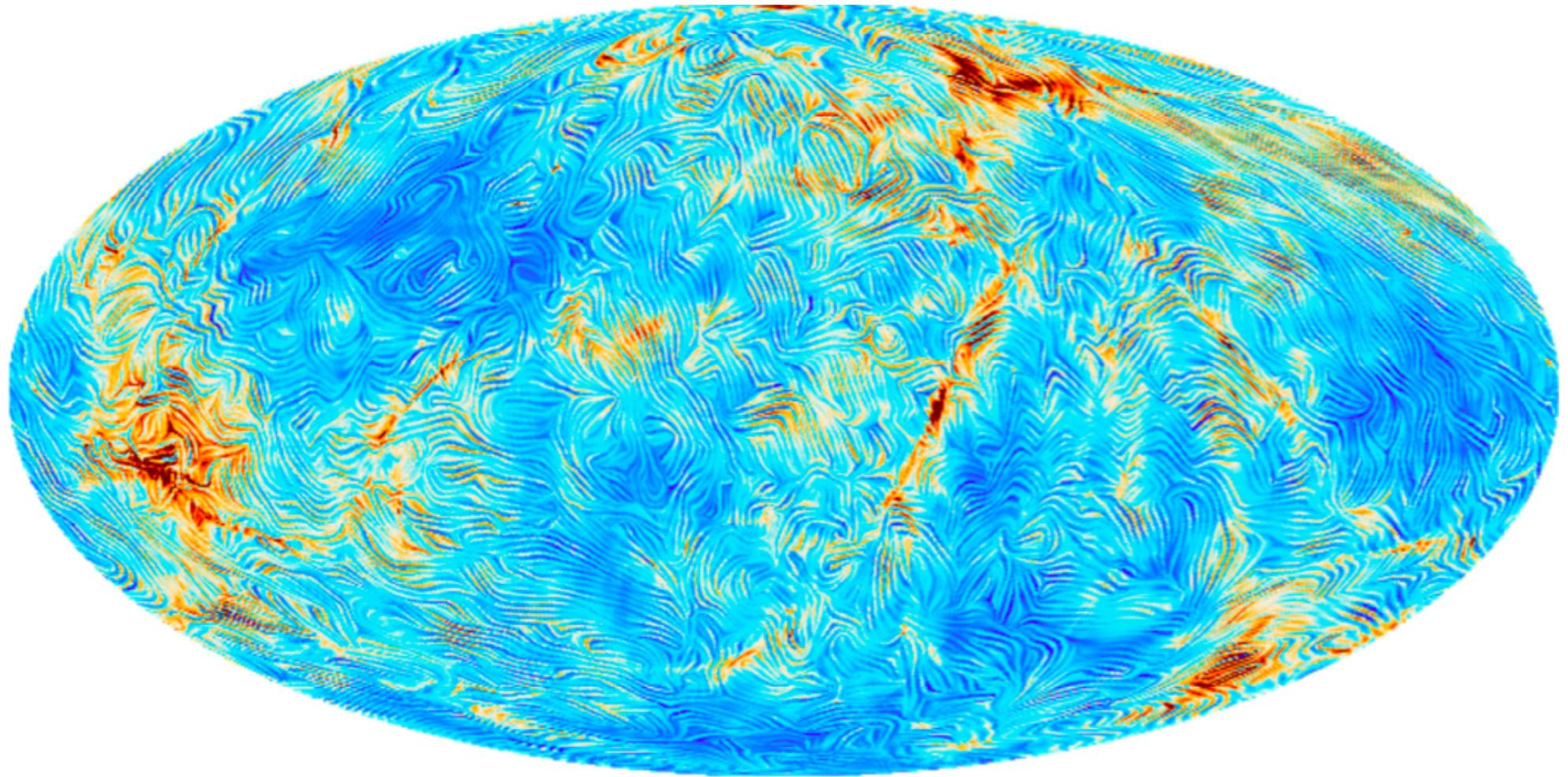


# The Future: Stream densities



# Remnants of primordial Magnetic fields

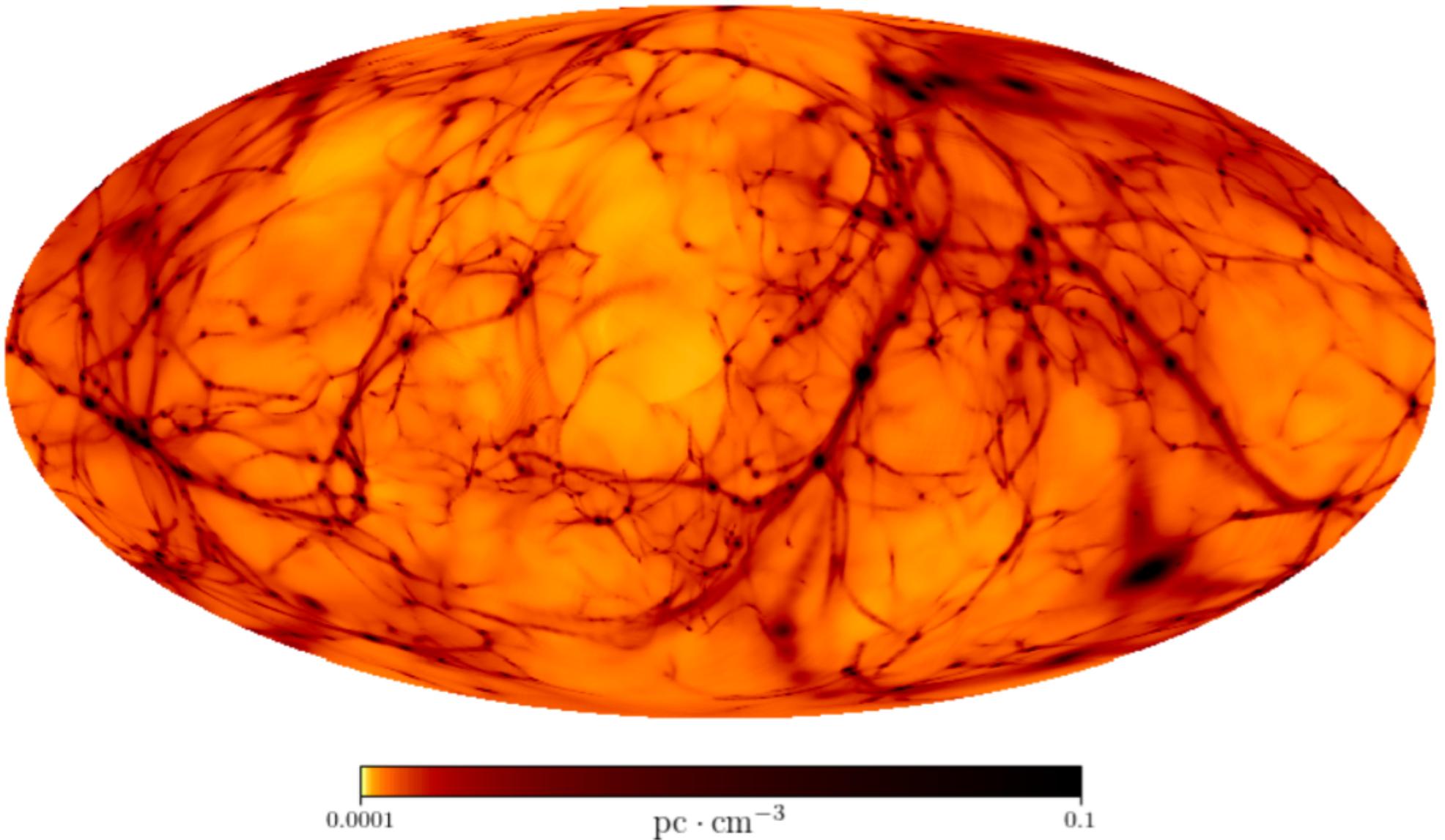
- Generate primordial MF via Harrison mechanism
- Evolve with MHD sim (ENZO)



Hutschenreuter et al. 2018 ( arXiv:1803.02629 )

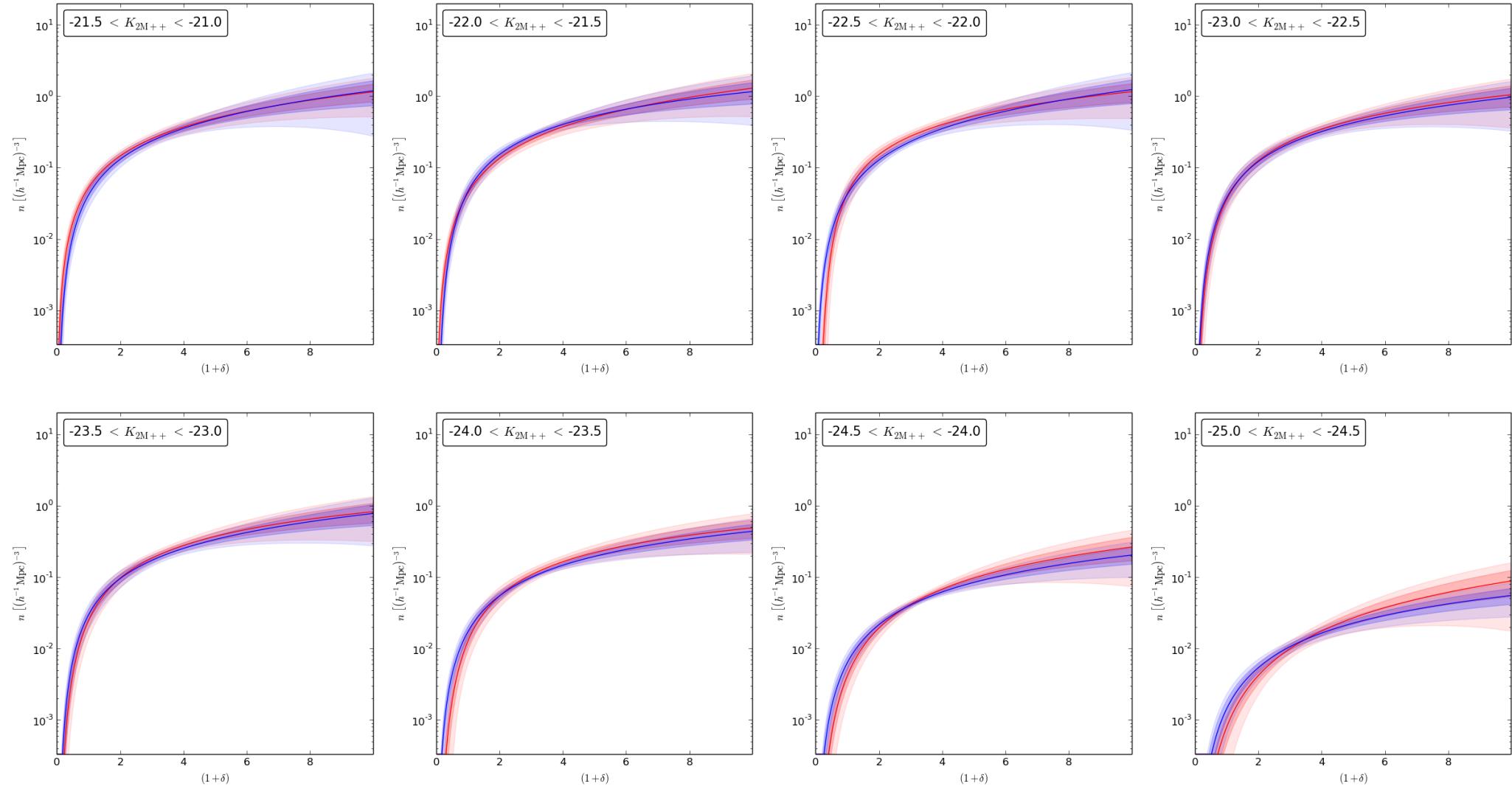
# Remnants of primordial Magnetic fields

- Electron dispersion measure



Hutschenreuter et al. 2018 ( arXiv:1803.02629 )

# Astrophysics: The galaxy bias



# Detecting the local void

Analyzing the 2M++ galaxy survey (Lavaux et al. 2011):

