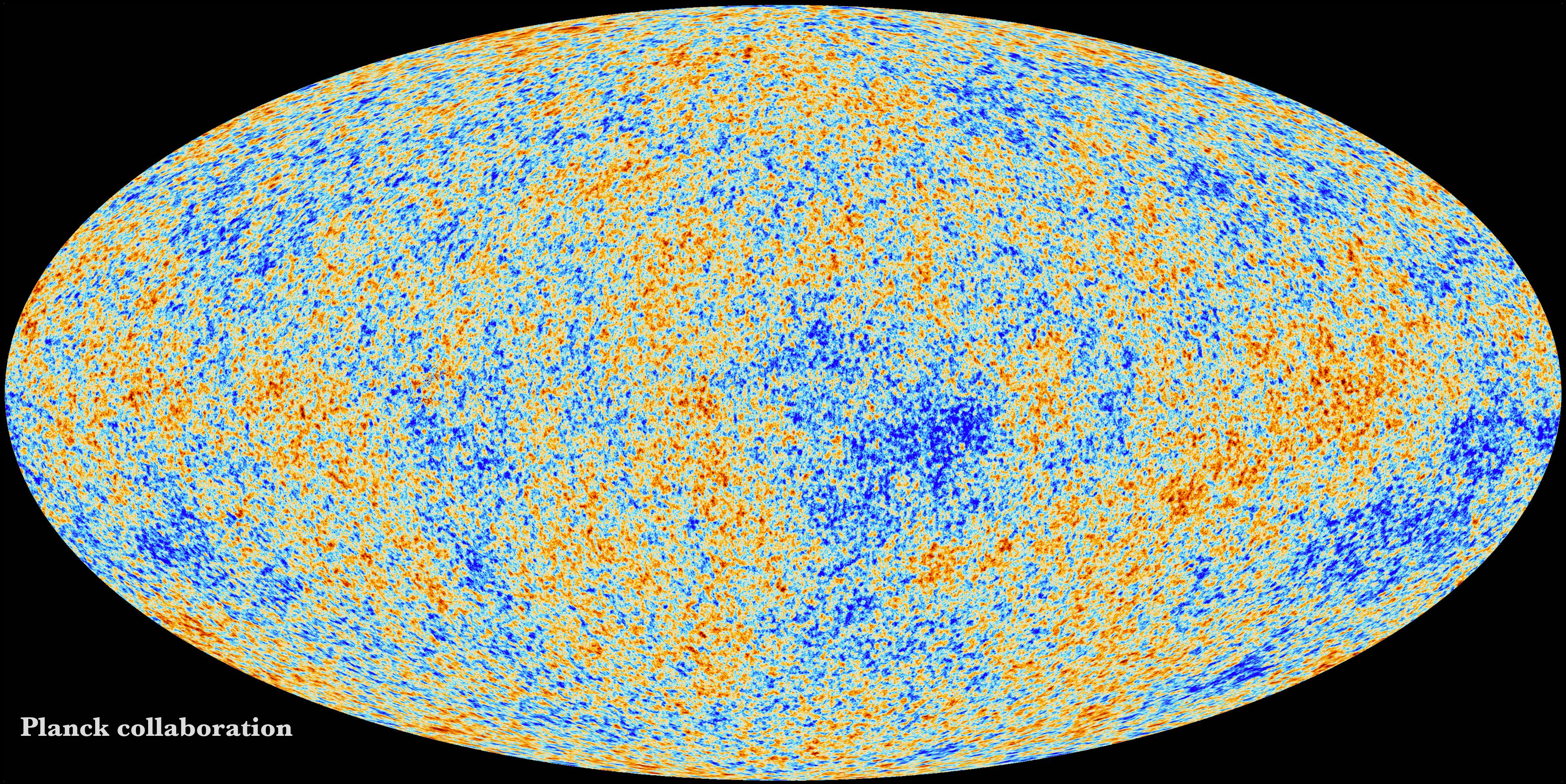
Peculiar velocities in Cosmology

Romain Graziani

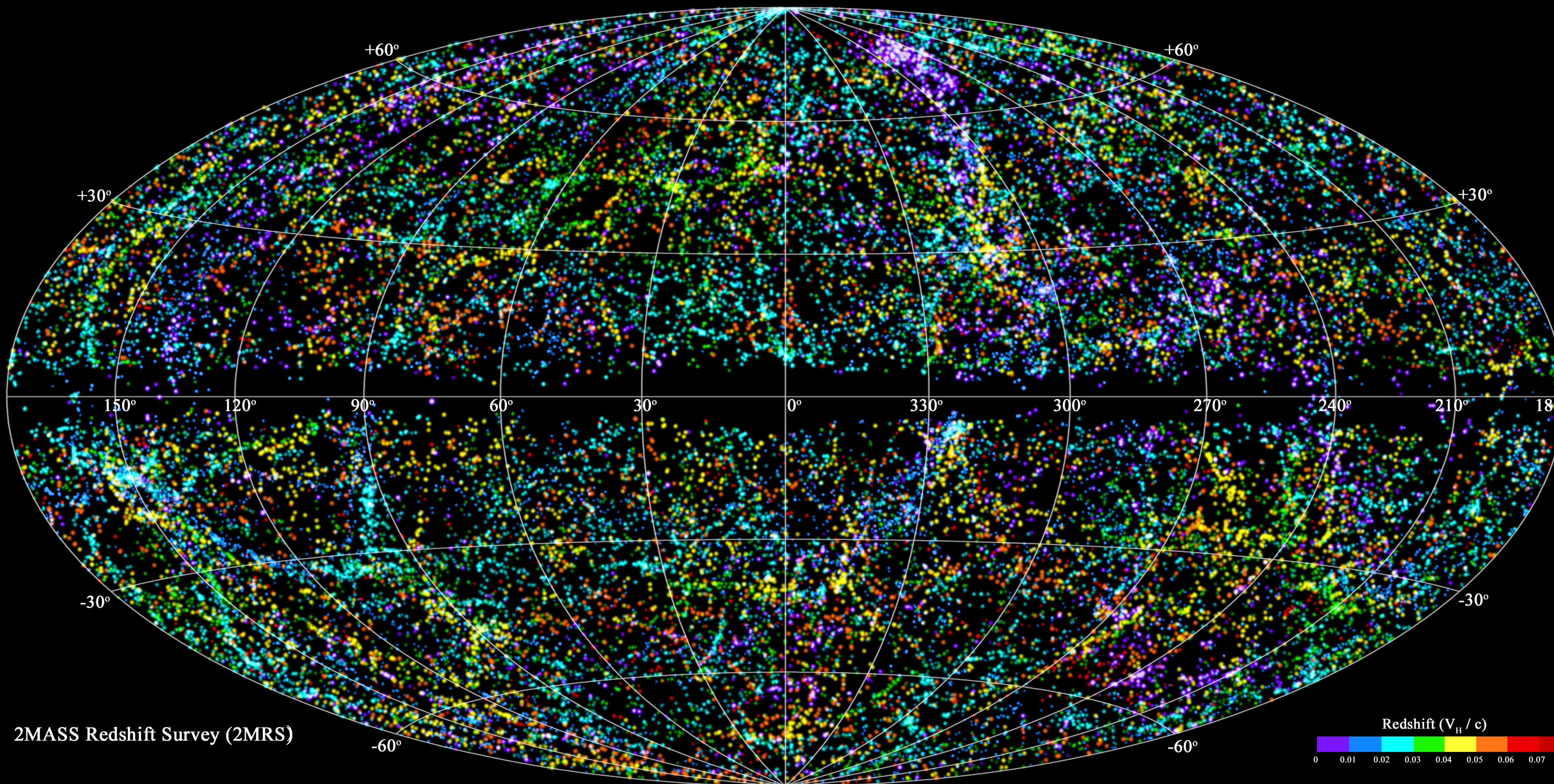
September 27th - LBNL

This project has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement n°759194 - USNAC)



$$z \sim 1100$$

$$t \sim 400\,000\,\mathrm{yr}$$

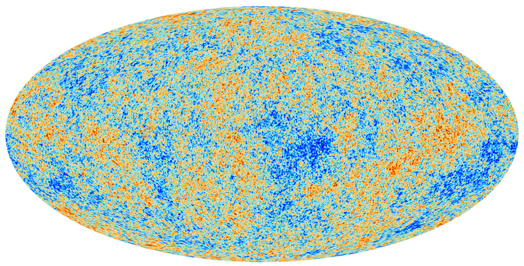


$$z \sim 0$$

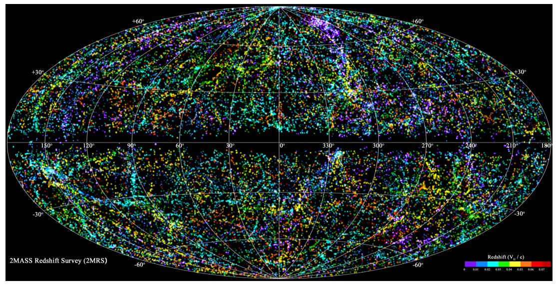
$$t \sim 14 \times 10^9 \text{ yr}$$

Probing our cosmological model

Universe



Cosmology



Probing our cosmological model

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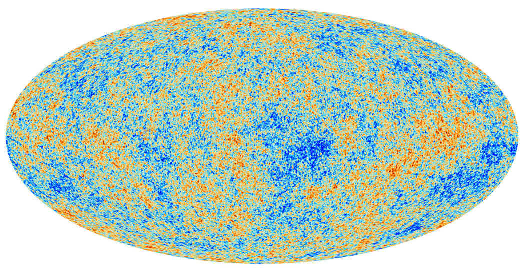
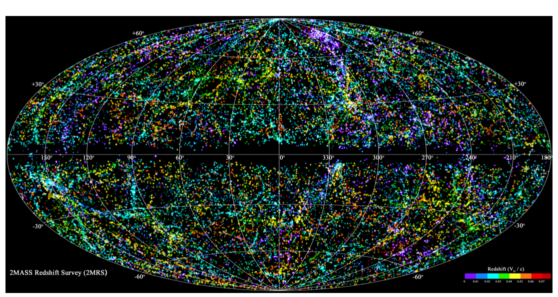


Cosmology



Expansion : H_0

Acoustic scale

LCDM model

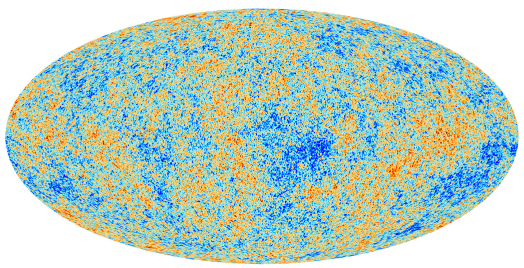
$$67.4 \pm 0.4$$

$\mathrm{km.s^{-1}.Mpc^{-1}}$

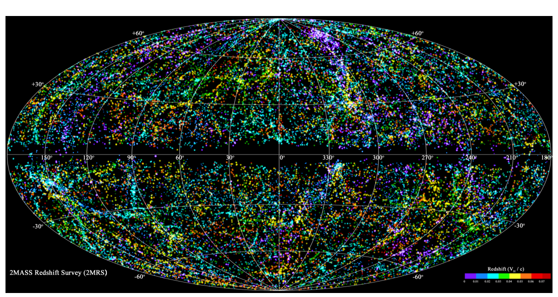
Planck VI. 2018

The Hubble constant tension

Universe



Cosmology



Direct measurement

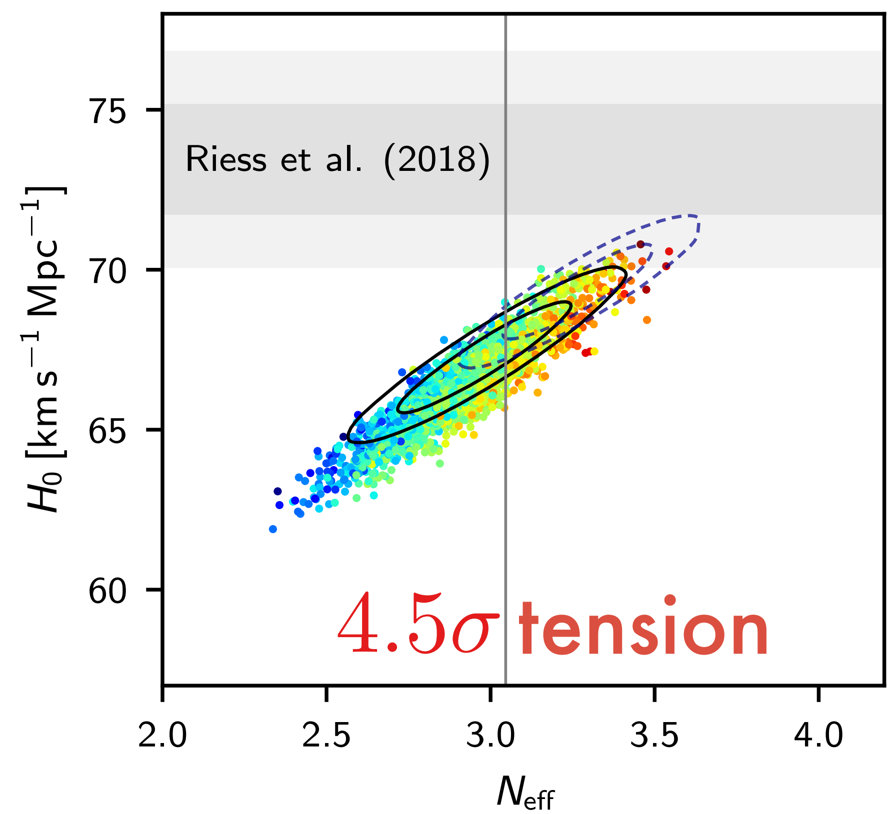
Expansion : H_0

Acoustic scale

LCDM model

$$67.4 \pm 0.4 \ \mathrm{km.s^{-1}.Mpc^{-1}}$$

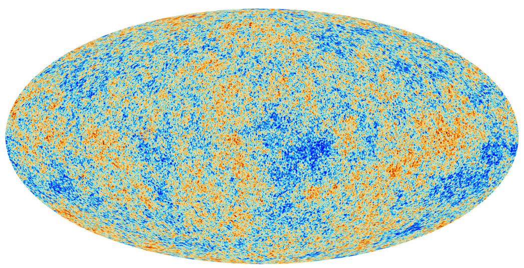
$$74.1 \pm 1.4 \ \mathrm{km.s^{-1}.Mpc^{-1}}$$



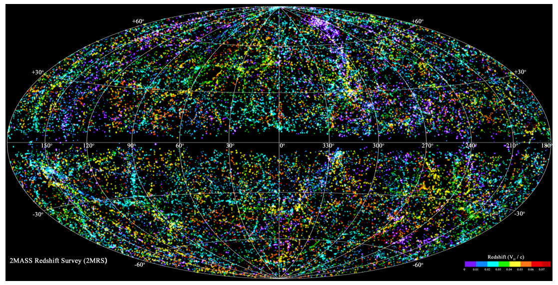
Planck VI. 2018, Riess et al. 2019

Growth rate

Universe



Cosmology



Expansion : H_0

Growth : $f\sigma_8$

$$\Omega_m, \Omega_\Lambda$$

LCDM model

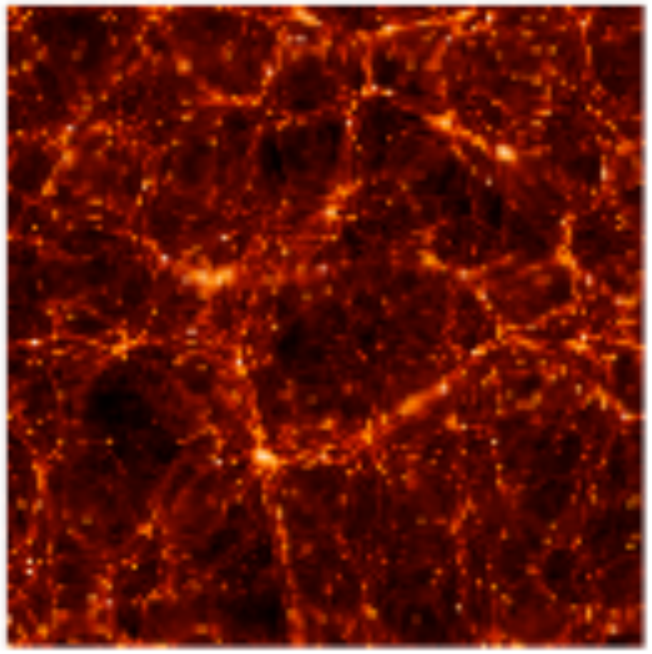
Large Scale Structures
Statistics

Direct measurement ?

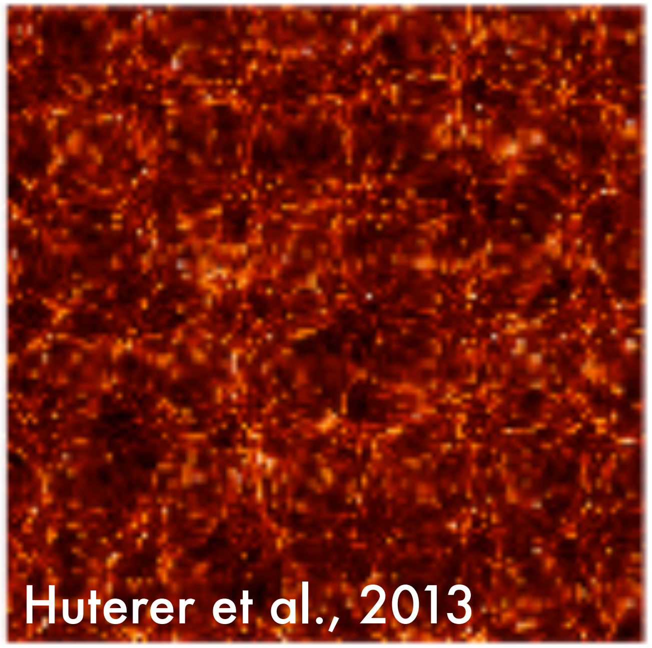
The Local Universe

Simulated Local Universe

$\Omega_m = 0.3$
LCDM



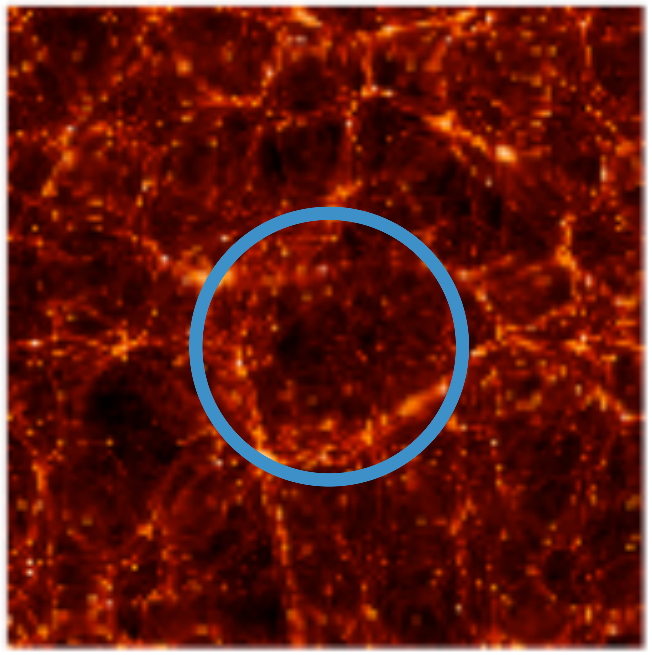
$\Omega_m = 1$
CDM



Density fluctuations

Simulated Local Universe

$\Omega_m = 0.3$
LCDM



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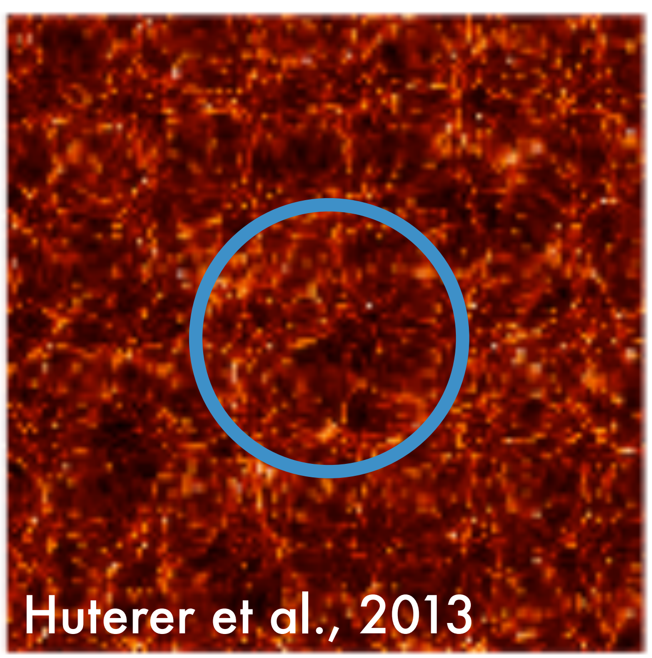


Matter density fluctuations :

$$\sigma_8^2 = \langle \delta^2 \rangle$$

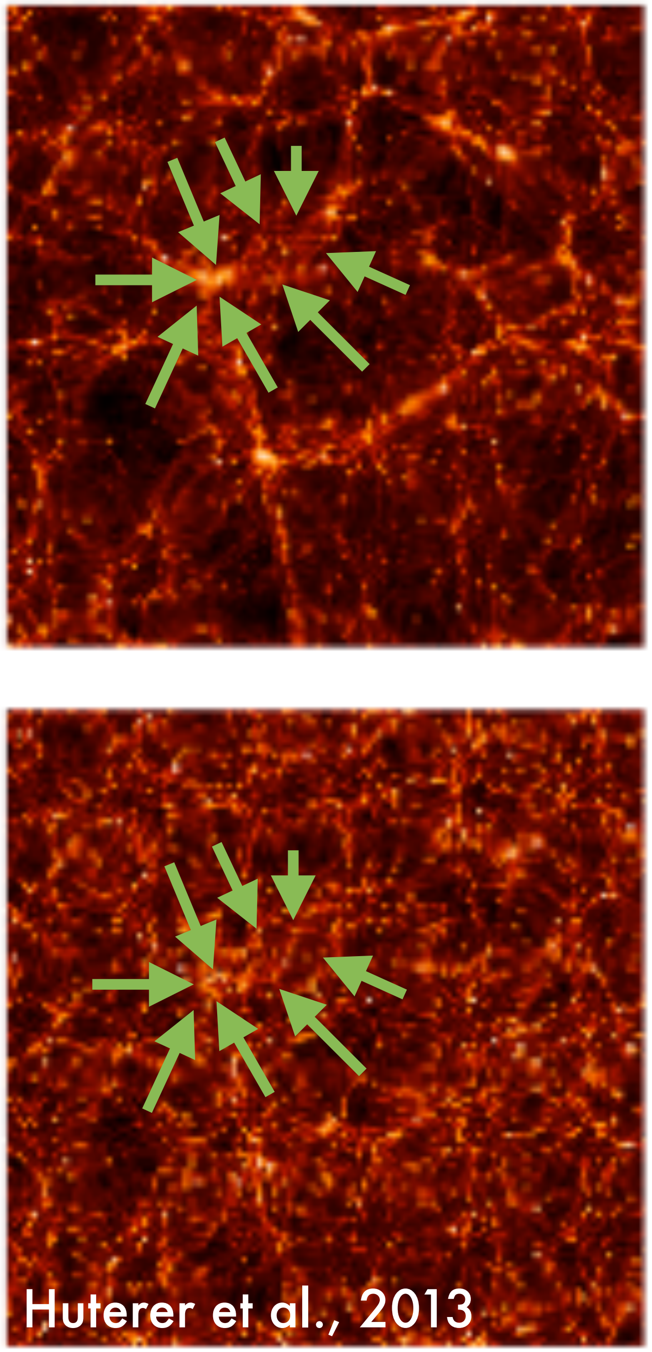
But we don't see dark matter...

Growth rate of structures

Simulated Local Universe

$\Omega_m = 0.3$
LCDM

$\Omega_m = 1$
CDM

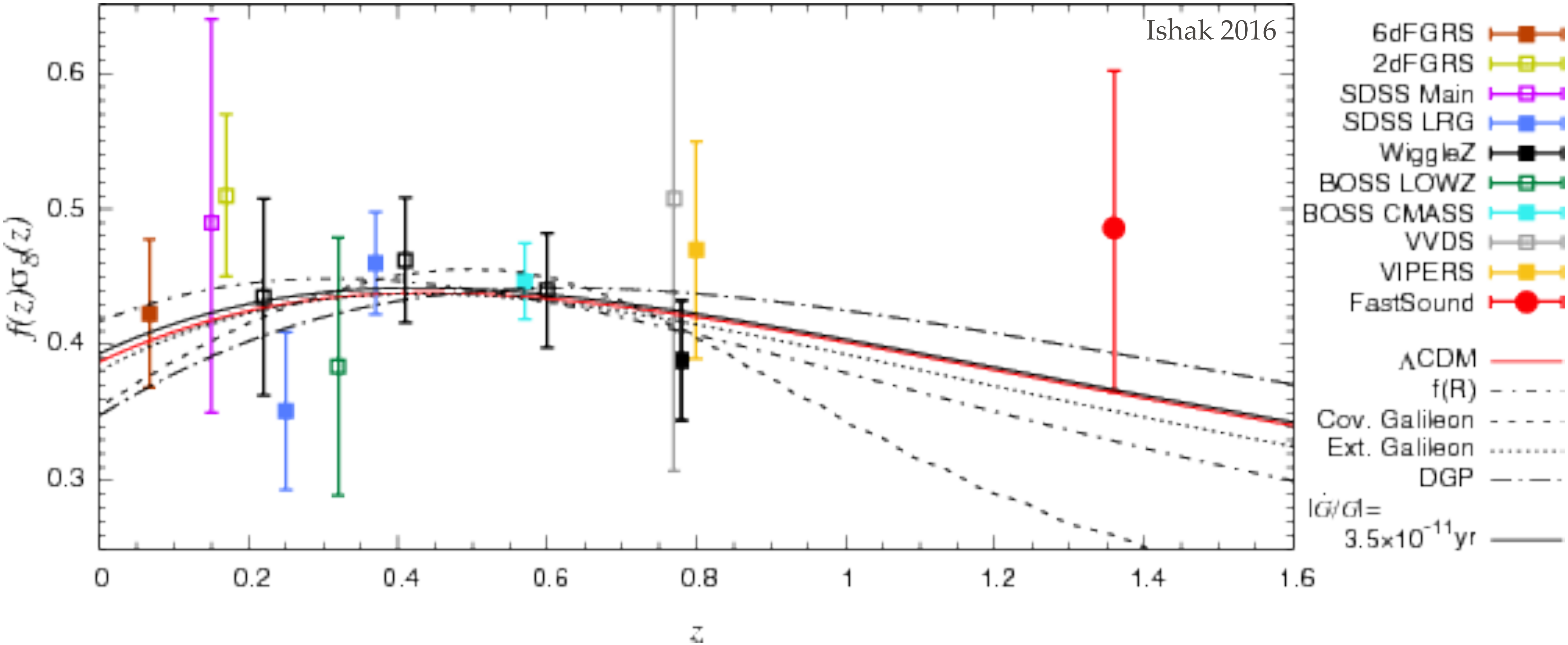


Matter density fluctuations
+
Growth factor

$$(f\sigma_8)^2 = \langle v^2 \rangle$$

Depends on the <u>expansion model</u> **and** <u>gravity</u>

Goal



State of the art: >15% measurement with peculiar velocities

Measuring peculiar velocities

Peculiar velocity measurement

$$1 + z = (1 + \bar{z}) \left(1 + \frac{v^r}{c} \right)$$

Peculiar velocity measurement

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Peculiar velocity

Apparent redshift

Cosmological (expansion) redshift

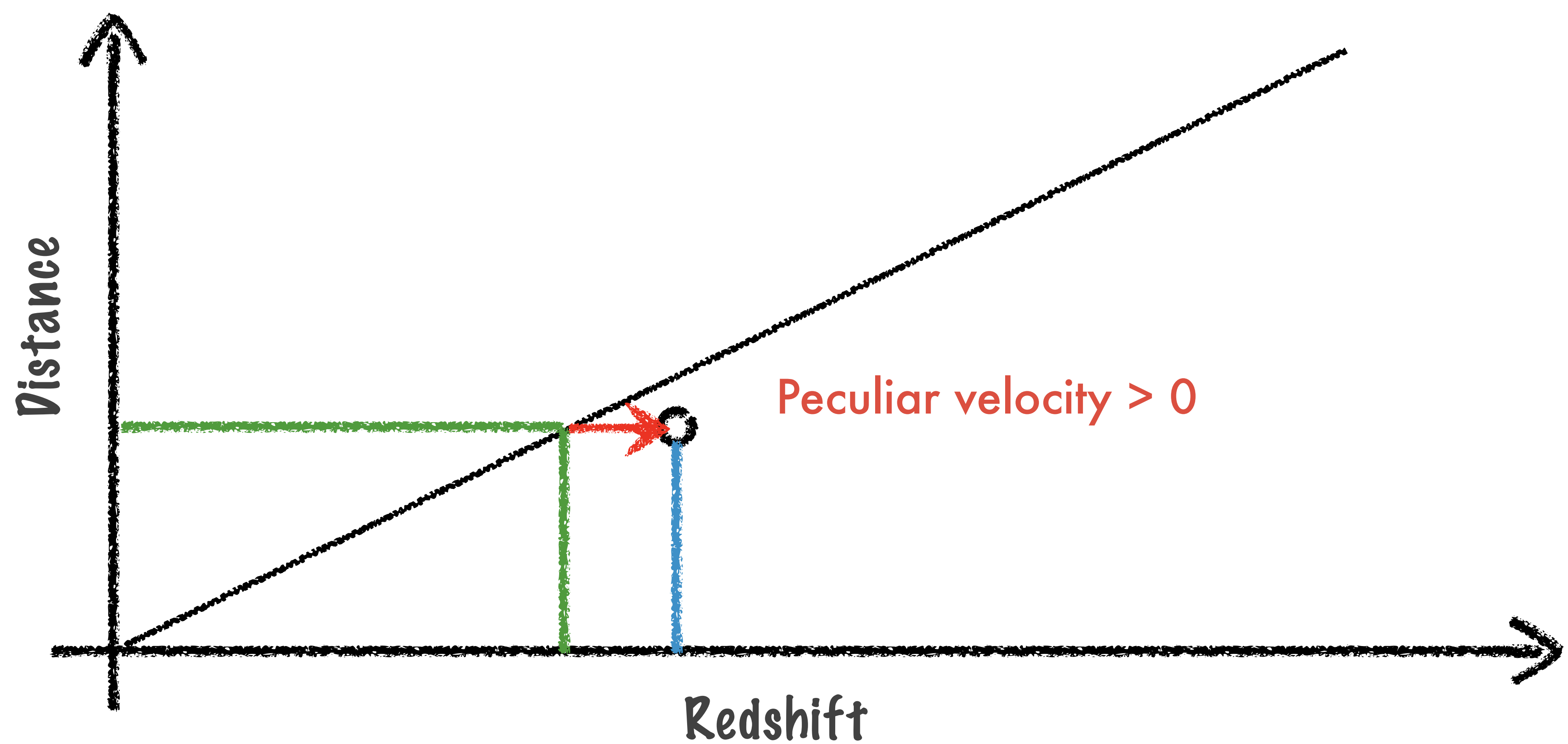
Peculiar velocity measurement

$$1 + z = (1 + \bar{z})\left(1 + \frac{v^r}{c}\right)$$

Apparent redshift (z)

Cosmological (expansion) redshift ($\bar{z}$)

Peculiar velocity (v^r)



The roadmap to peculiar velocities

?

$$1 + z = (1 + \bar{z})\left(1 + \frac{v^r}{c}\right)$$

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$$\mu = 5\log_{10}\frac{d}{10\ \mathrm{pc}} = m - \boxed{M}$$

?

The roadmap to peculiar velocities

$$1 + z = (1 + \bar{z})\left(1 + \frac{v^r}{c}\right)$$

$$\mu = 5\log_{10}\frac{d}{10\ \mathrm{pc}} = m - M$$

?

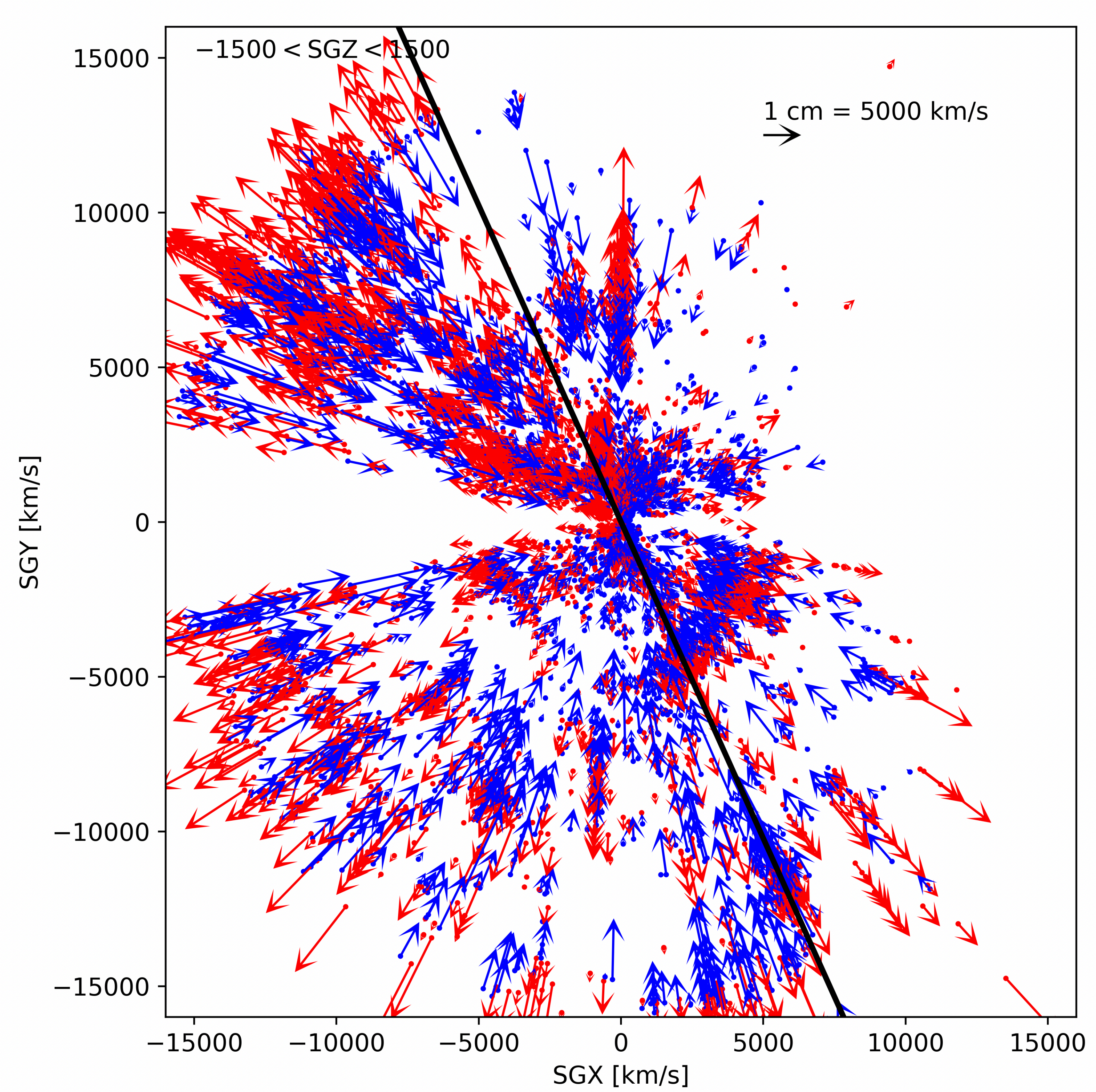
Tully-Fisher Relation	$L \sim V^4$	$\sigma_\mu \sim 0.4$

$z \sim 0.1$

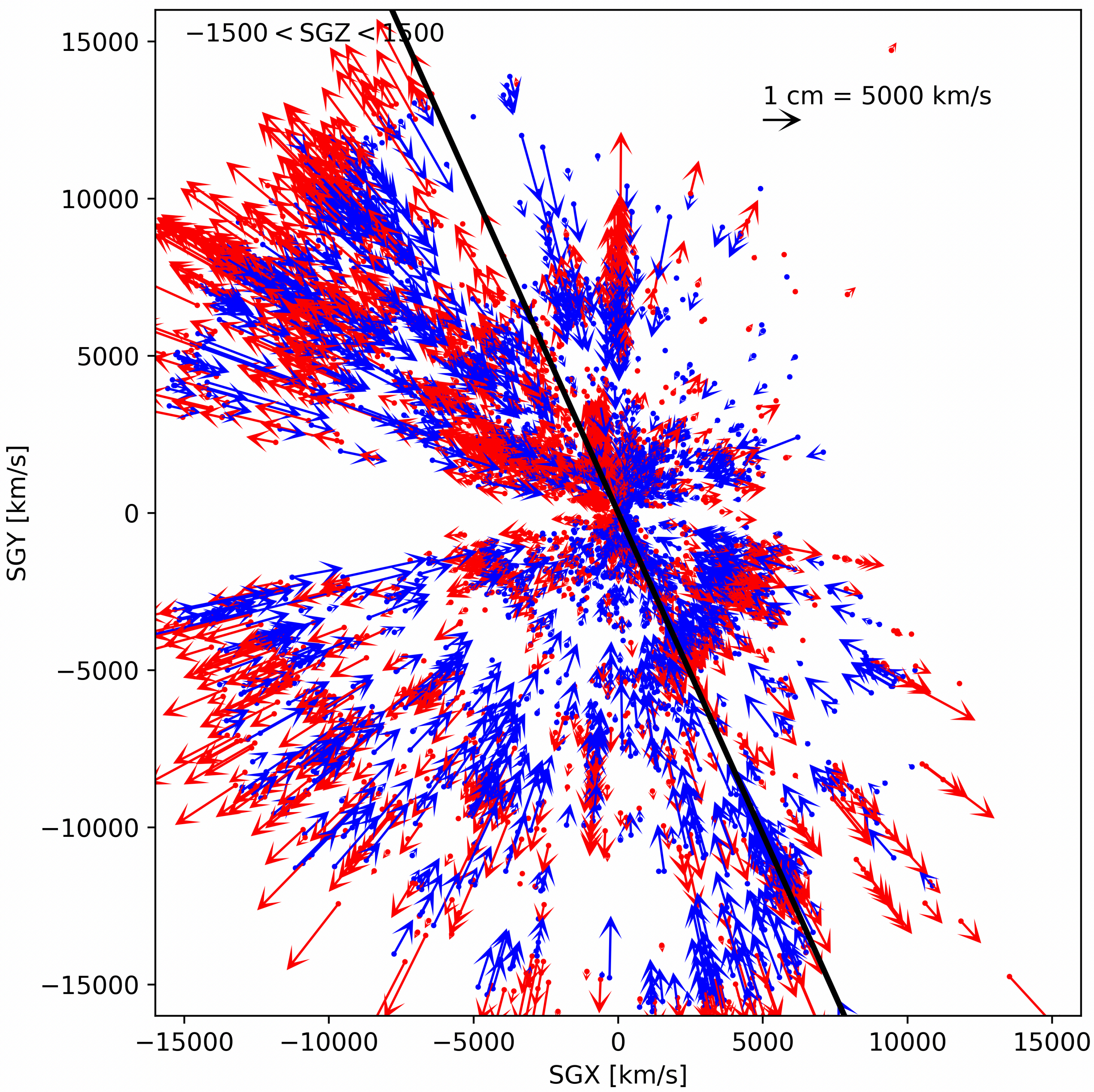
SNeIa	$L \sim \text{constant}$	$\sigma_\mu \sim 0.14$

$z \sim 1$

Radial peculiar velocity measurement : an exemple



Radial peculiar velocity measurement : an exemple

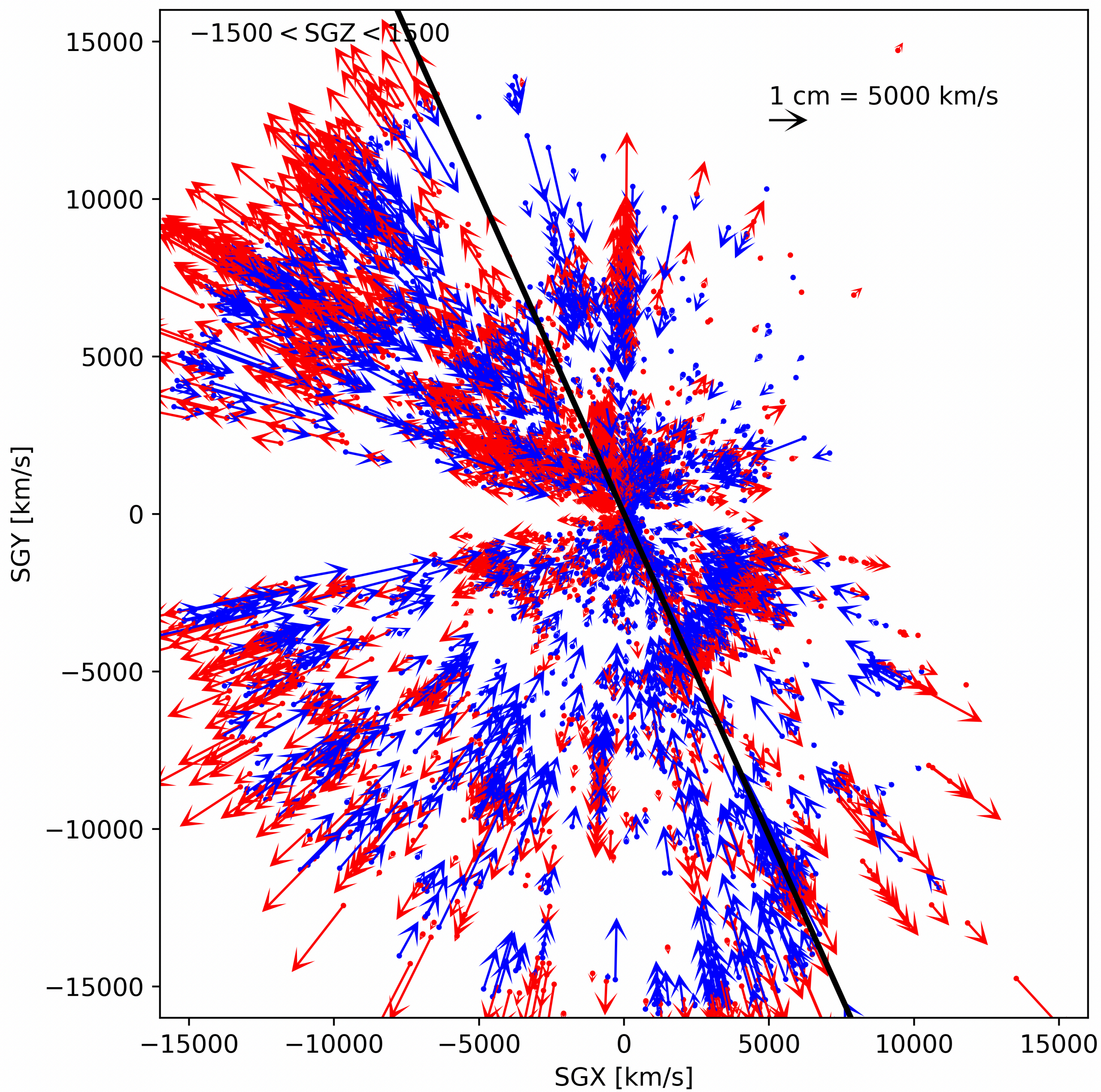


$$d = 100 \pm 20 \text{ Mpc}$$

$$cz = 6500 \text{ km/s}$$

$$v^r = -500 \pm 1400 \text{ km/s}$$

Radial peculiar velocity measurement : an exemple



$$d = 100 \pm 20 \text{ Mpc}$$

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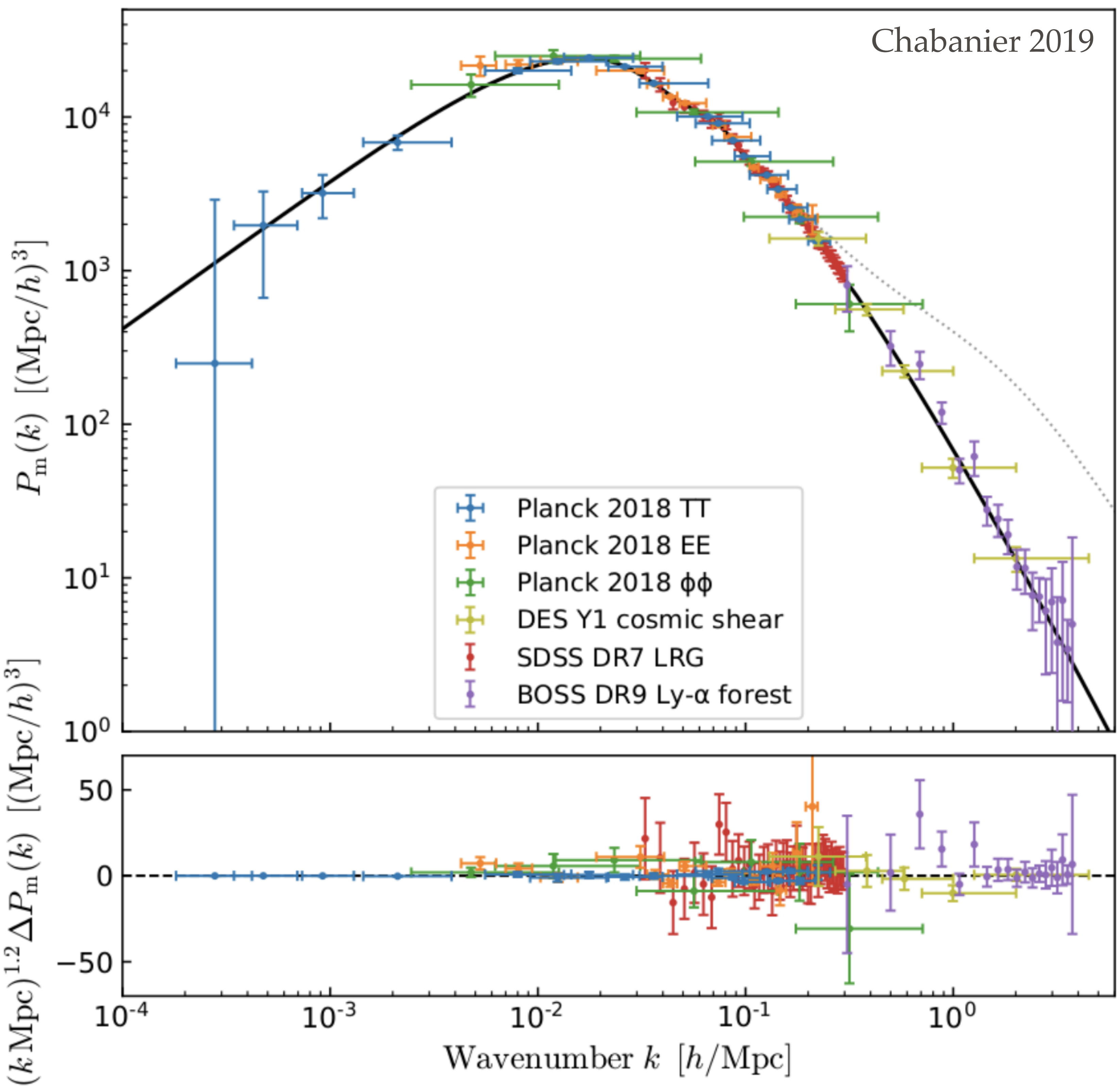
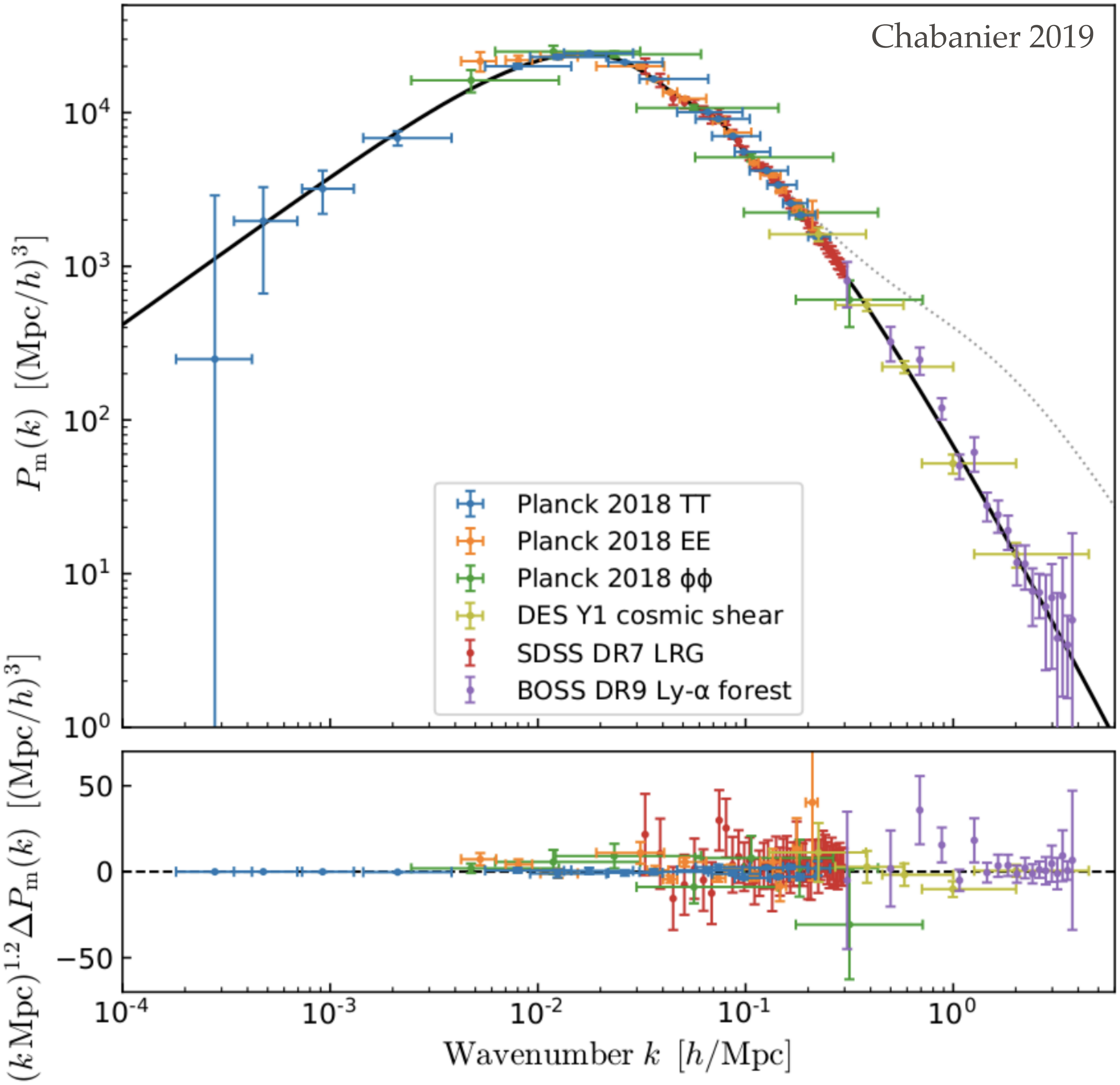
Not enough information?
Be Bayesian!

Power spectrum



$$\langle\delta^2\rangle = \sigma_8^2 P_0(k)$$

Power spectrum

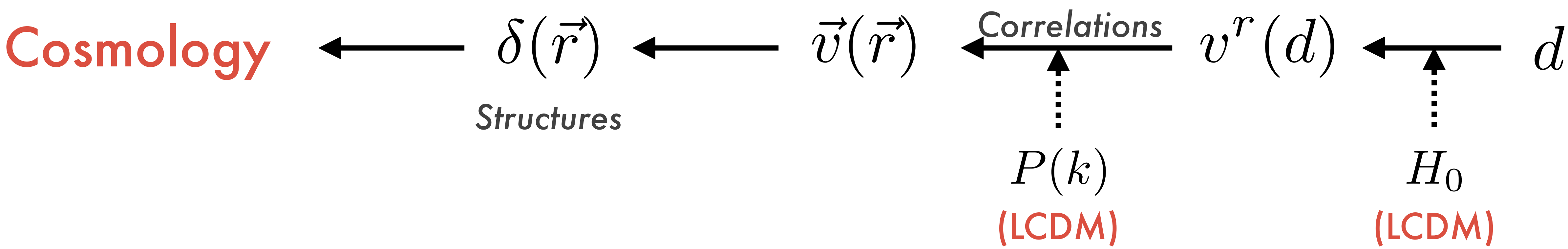


$$\langle \delta^2 \rangle = \sigma_8^2 P_0(k)$$

$$\vec{\nabla}\vec{v} = -H_0 f \delta$$

$$\langle v_\alpha^2 \rangle = (f\sigma_8)^2 \frac{k_\alpha^2}{k^4} P_0(k)$$

Inverse analysis



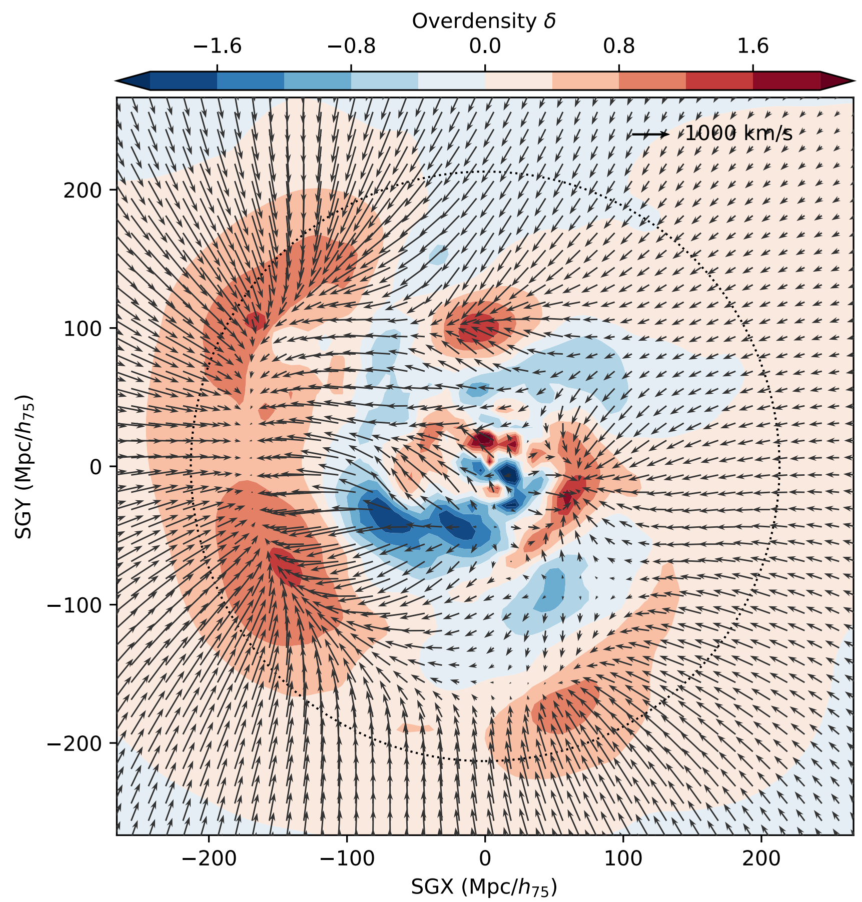
Inverse analysis

Cosmology ← $\delta(\vec{r})$ ← $\vec{v}(\vec{r})$ ← (Correlations) $v^r(d)$ ← d

Structures

$P(k)$ (LCDM) → Correlations

H_0 (LCDM) → $v^r(d)$ ← d



Graziani et al., 2019

Systematic Errors →

- Malmquist bias
- Selection effects
- Error bias
- Density bias
- Covariance bias

Forward modeling

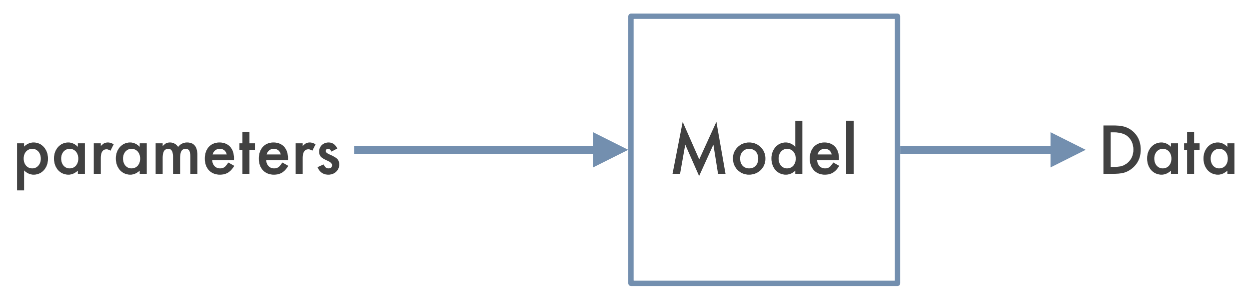
Backward modeling

- Information loss
- Systematics ?
- Hard to estimate covariances

Forward modeling

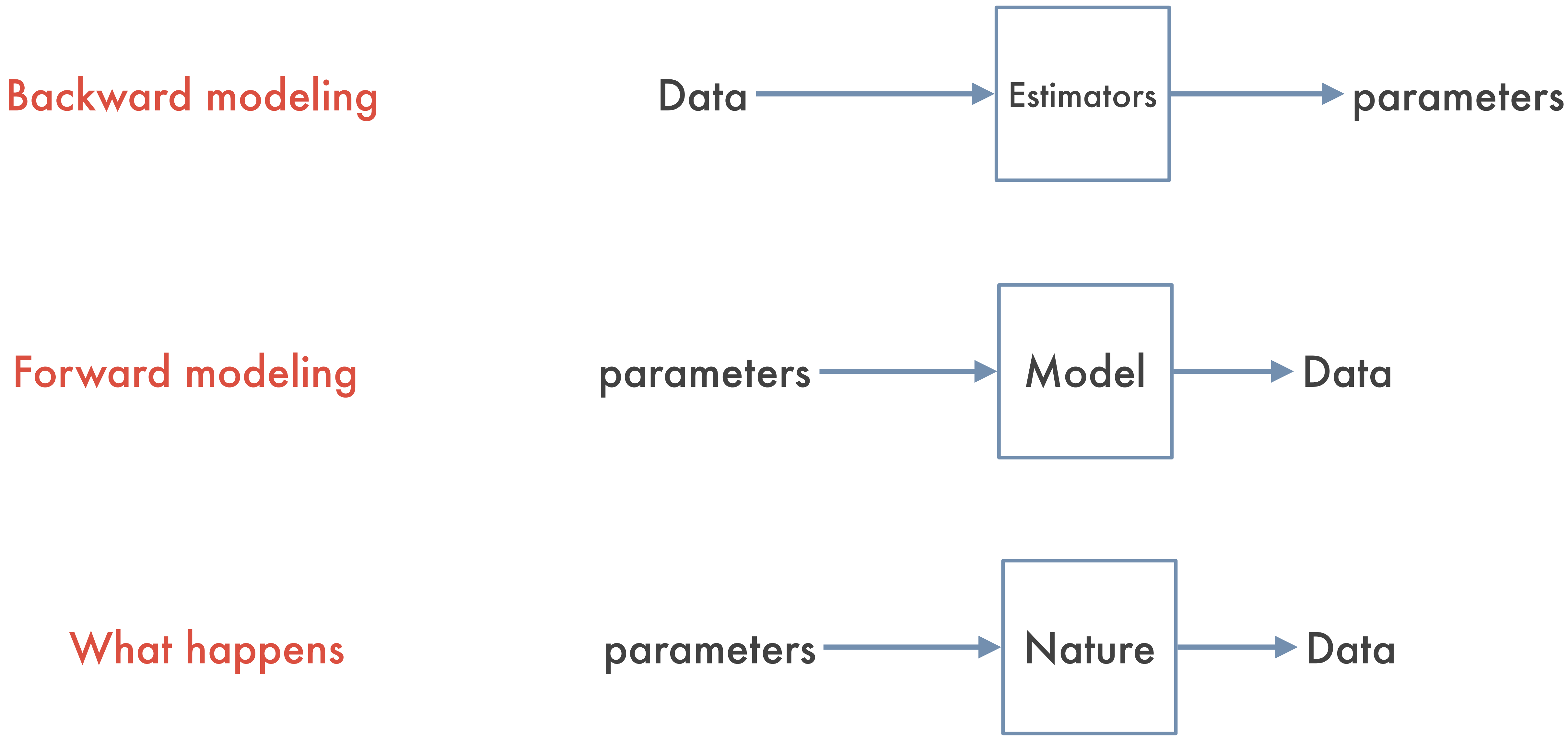
Backward modeling

Forward modeling

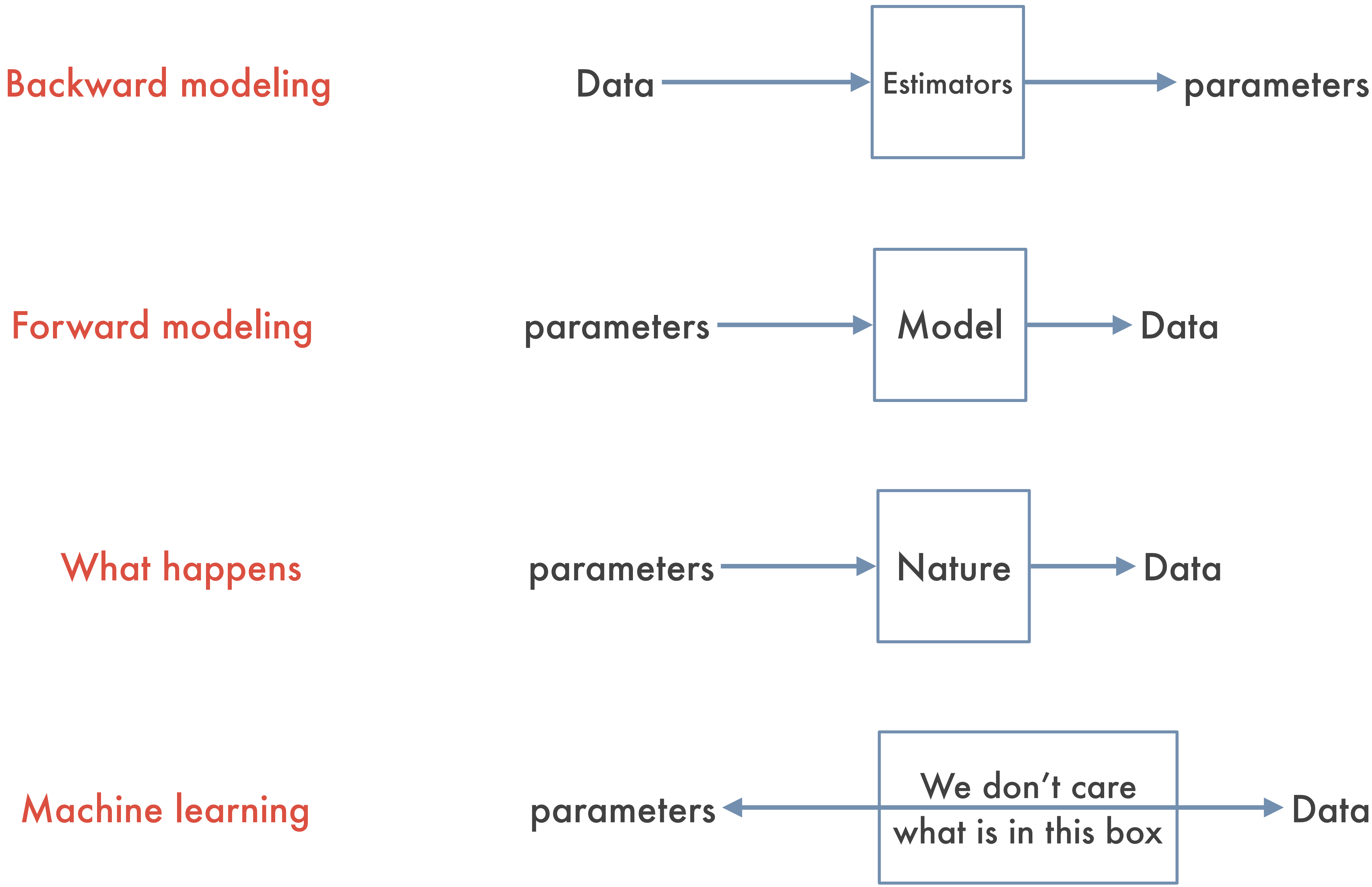


- No convolution of the data
- No need to copy the data
- Numerically expensive

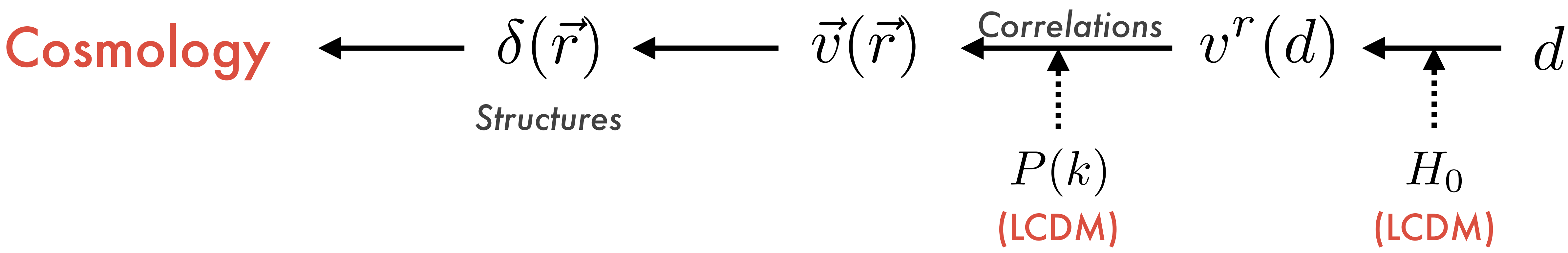
Forward modeling



Forward modeling

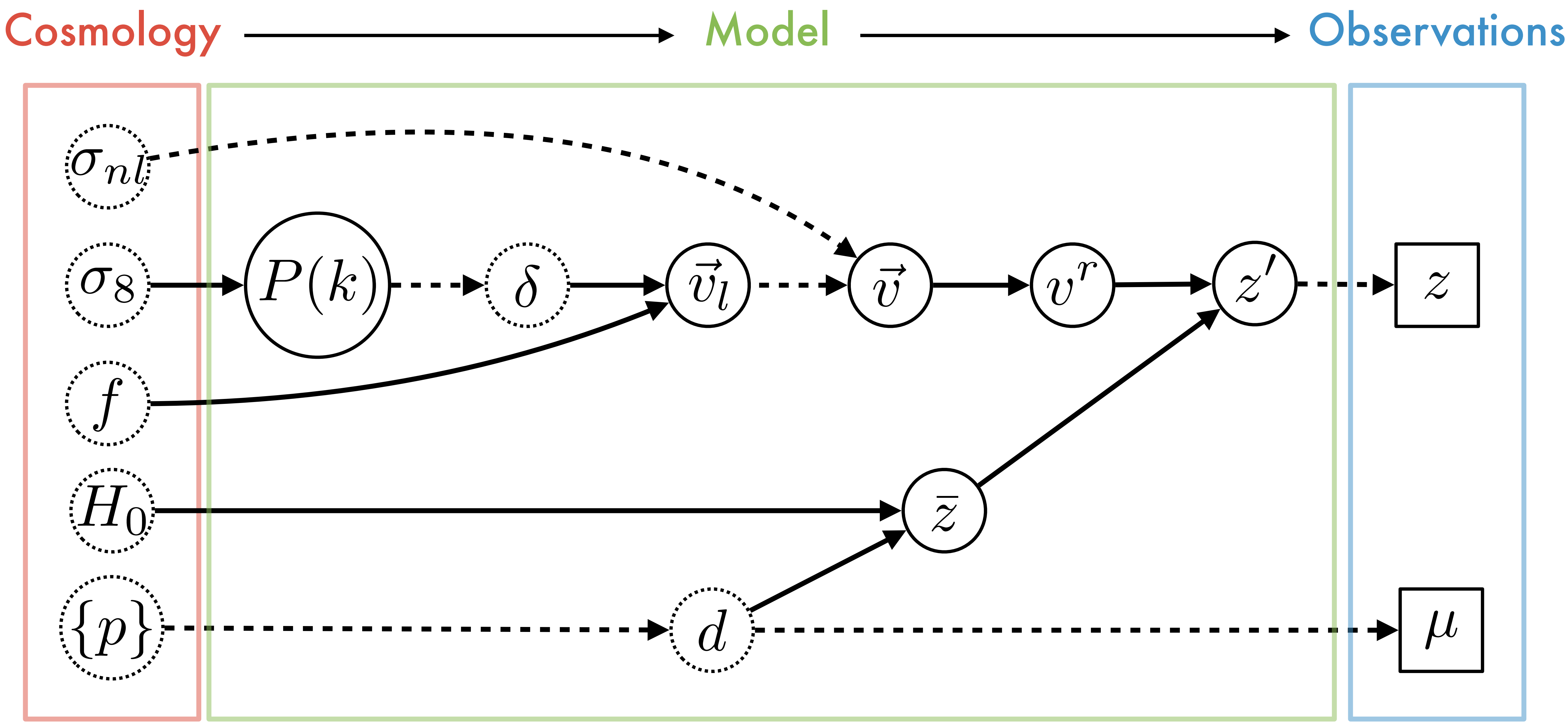


Inverse analysis



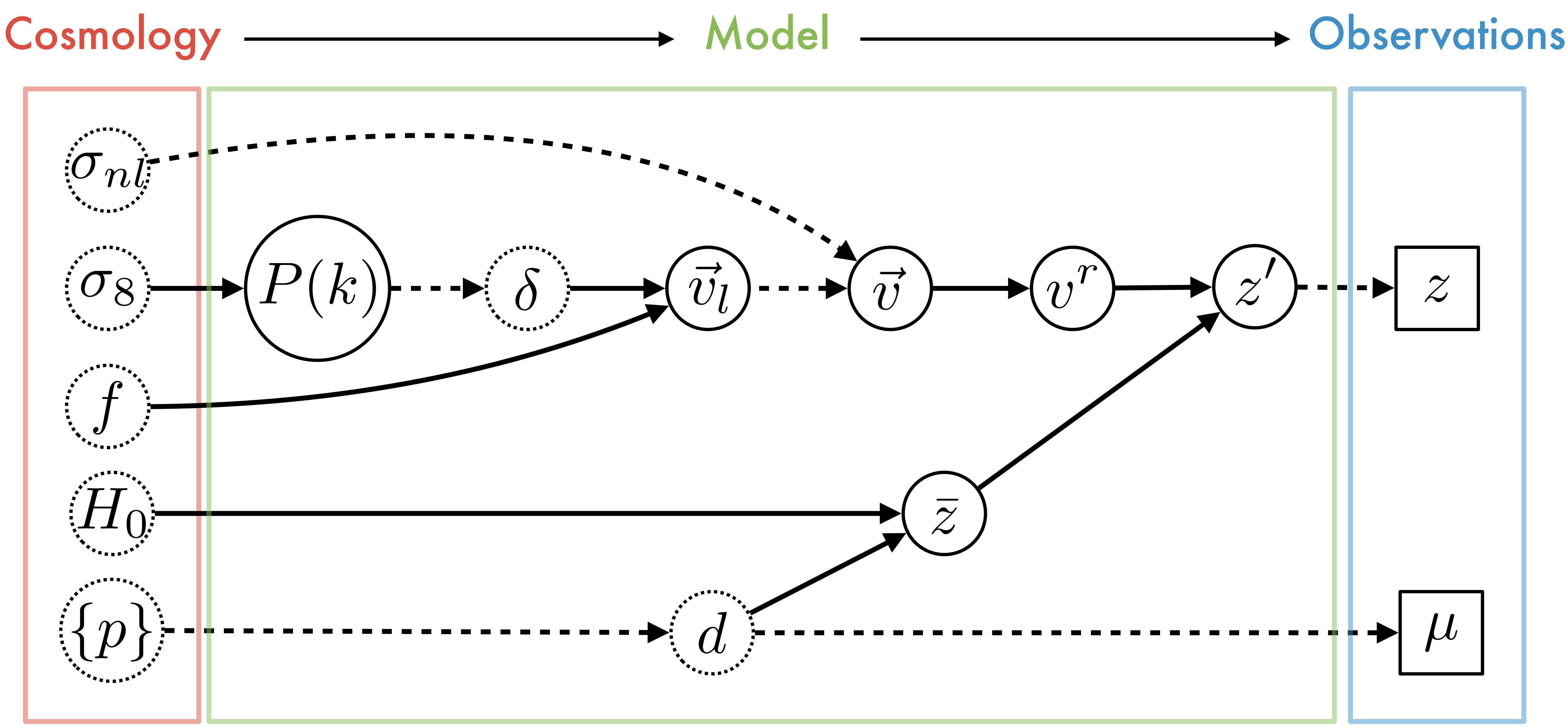
A forward model

Graziani et al., 2019



A forward model

Graziani et al., 2019



- Hierarchical Bayesian model
- Highly modular
- Room for systematics modeling

A forward model

$$\begin{aligned} \mathcal{L} &= \int \mathcal{N}\left(m - M_{SN} - 5\log_{10}\frac{r}{10\ \mathrm{pc}}, \sigma_m\right) \\ &\times \mathcal{N}\left(v^r(z,r) - \boldsymbol{v}_\delta(\boldsymbol{r}), \sigma_{nl}\right) \\ &\times \mathcal{N}\left(\hat{\delta}(\boldsymbol{k}), P(k)\right)\ \mathrm{d}\hat{\delta} \end{aligned}$$

Metropolis Sampling

- Randomly draw a set of parameters
- If the posterior probability is approximately higher than previously, keep this set
- Else, retry

Metropolis Sampling

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Pros	Cons
Converges* to the solution *sometimes	Inefficient in high dimensions
Easy to implement	Inefficient when parameters are correlated
	Inefficient for multi-modal or multi-scale distribution
	Samples are highly correlated

Gibbs Sampling

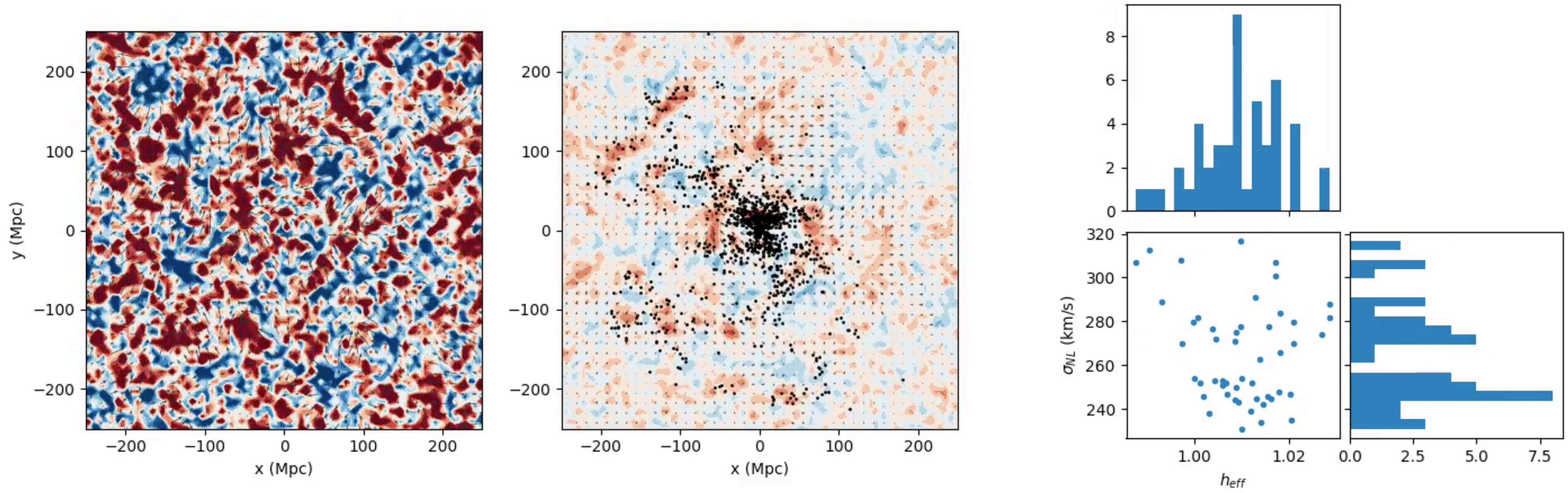
- Draw each parameter from its conditional probability
- Accept all the samples

Gibbs Sampling

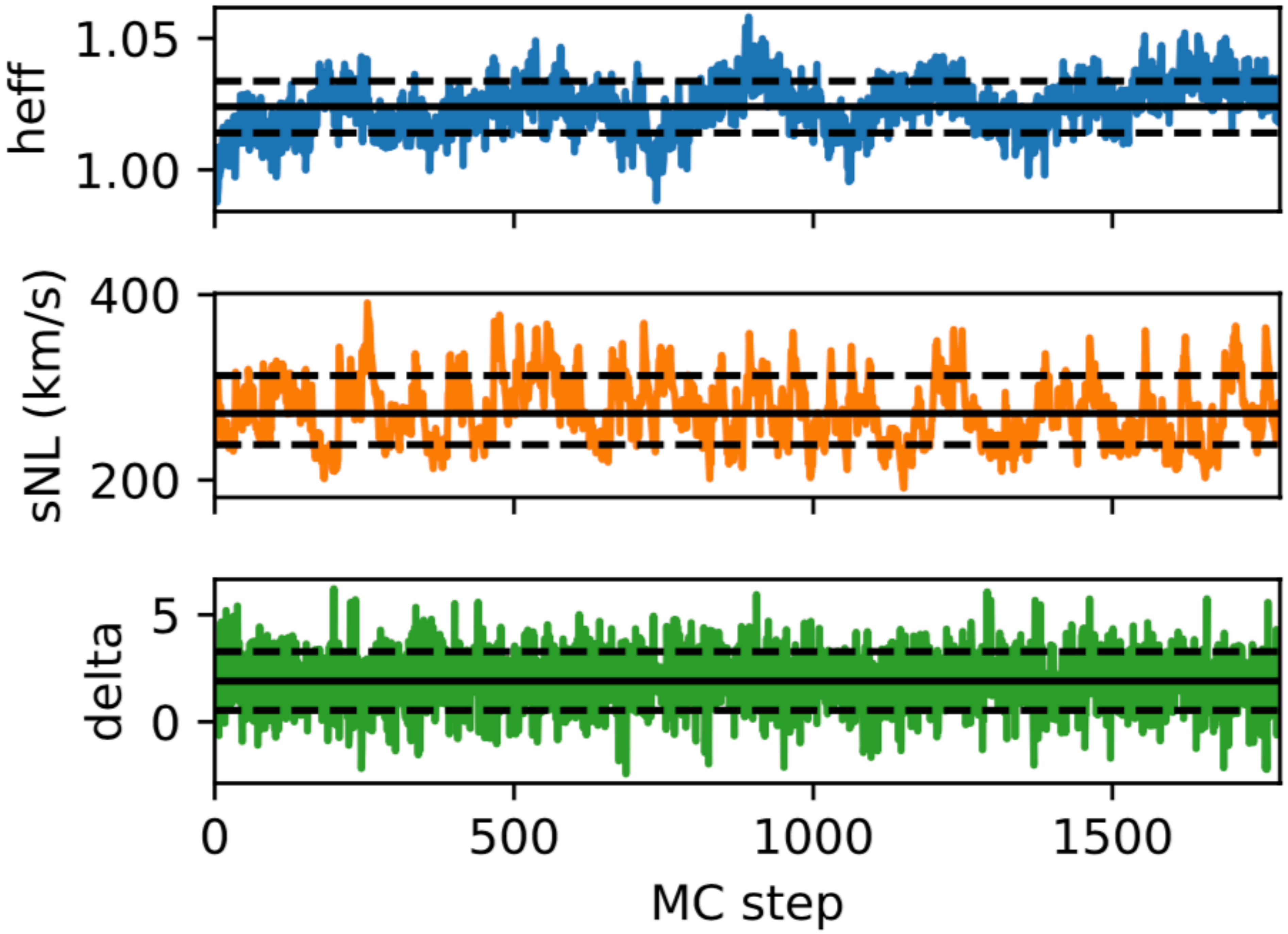
- Draw each parameter from its conditional probability
- Accept all the samples

Pros	**Cons**
Converges* to the solution *always	Need the conditional probability (rare)
Easy to implement	Samples highly correlated
Acceptance rate of 100%	Model dependent

MCMC

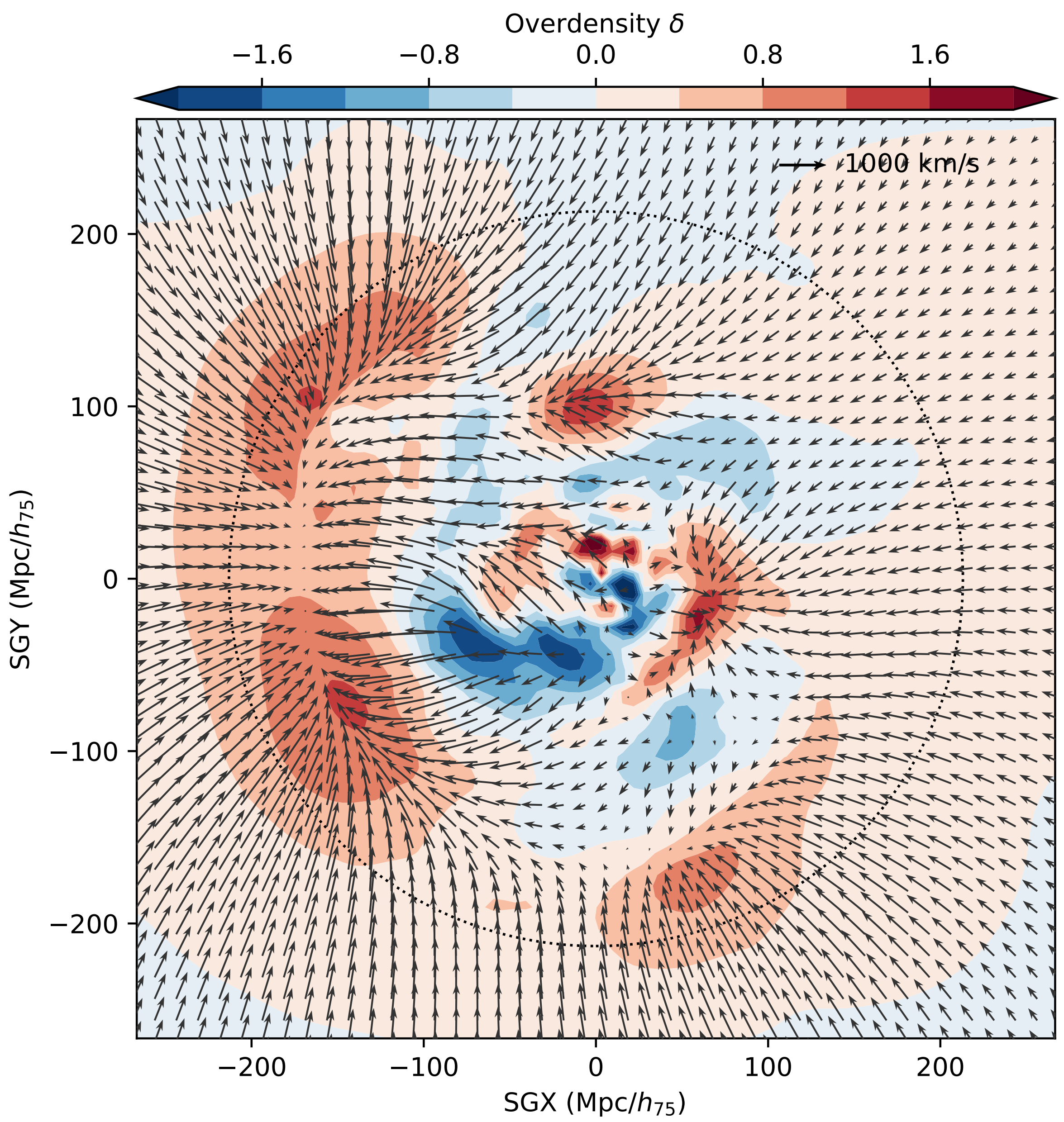


MCMC

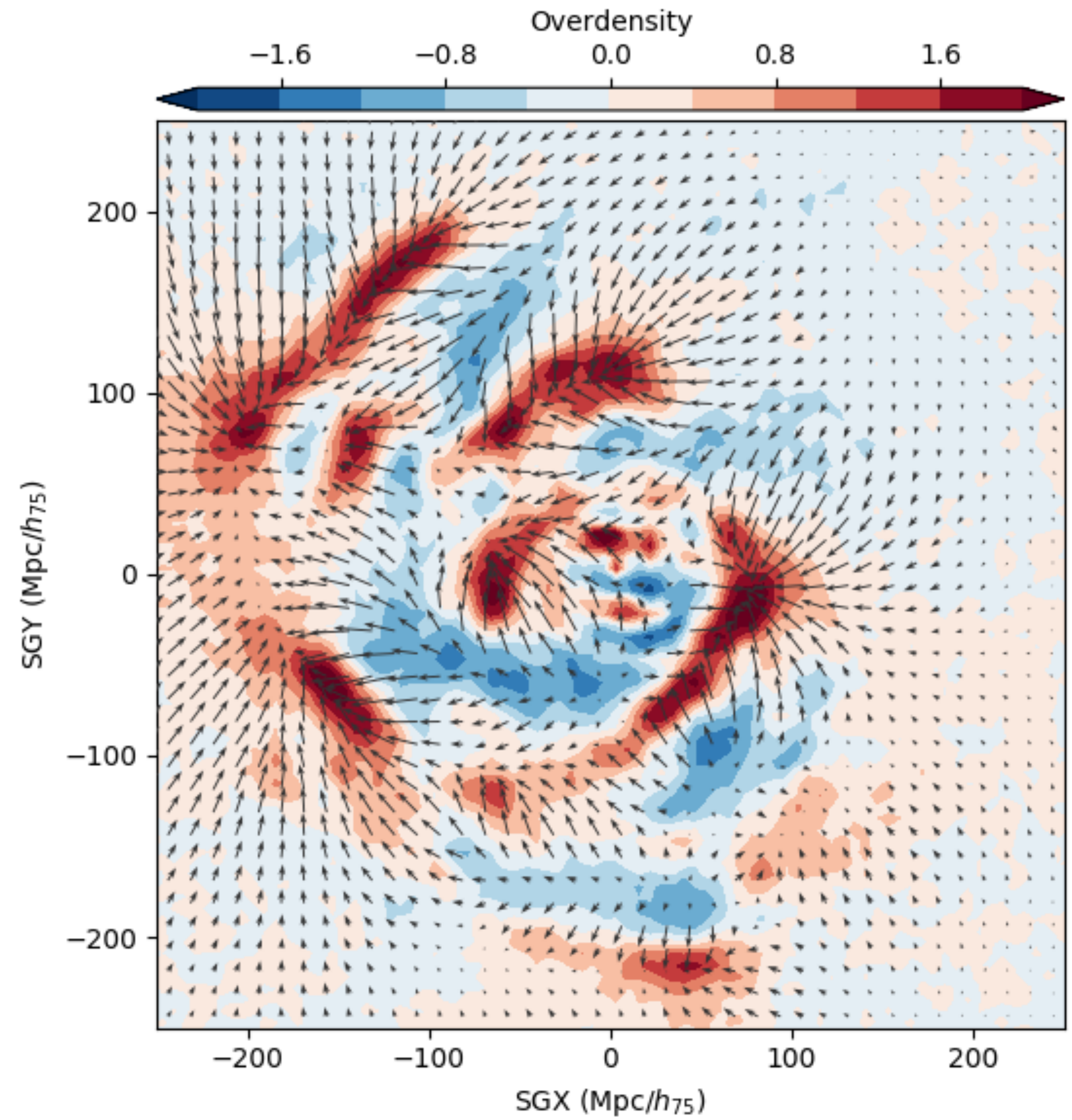


The model applied on galaxy data

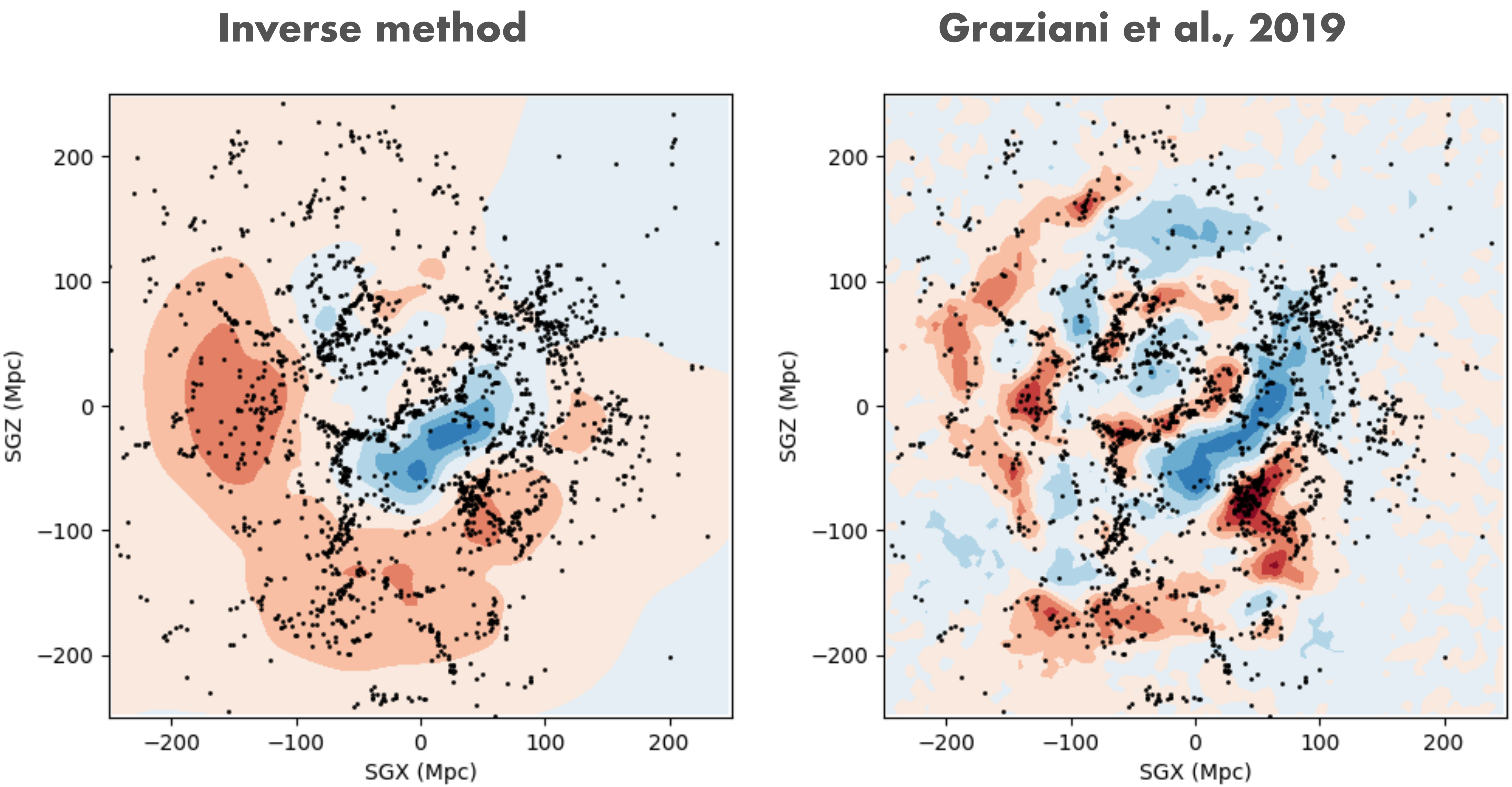
Inverse method



Graziani et al., 2019

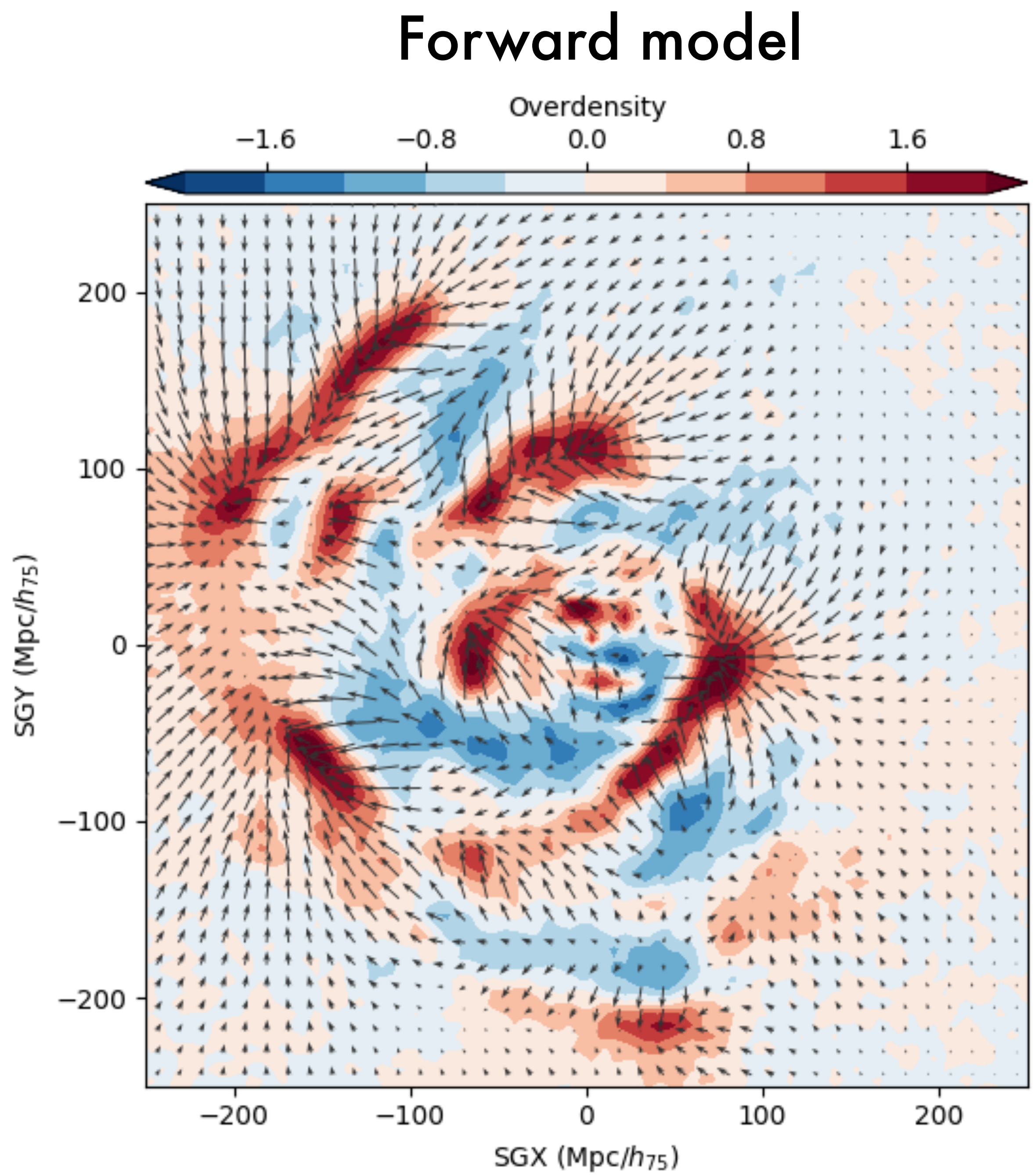


Peculiar velocity field vs galaxy distribution



The model applied on galaxies

Graziani et al. 2019, 1901.01818



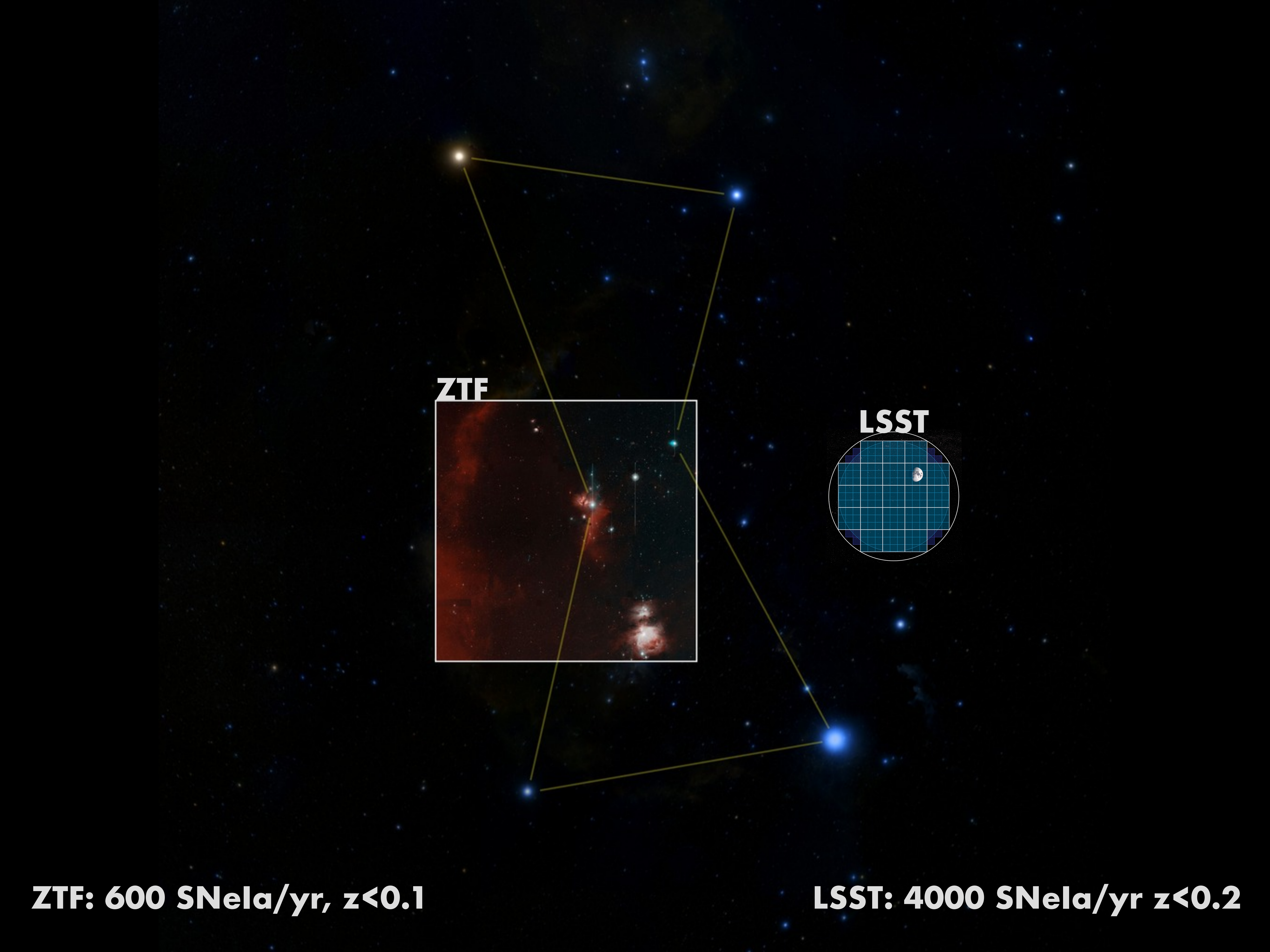
No cosmological parameter fitting because galaxy data are prone to **systematics**

Cosmology

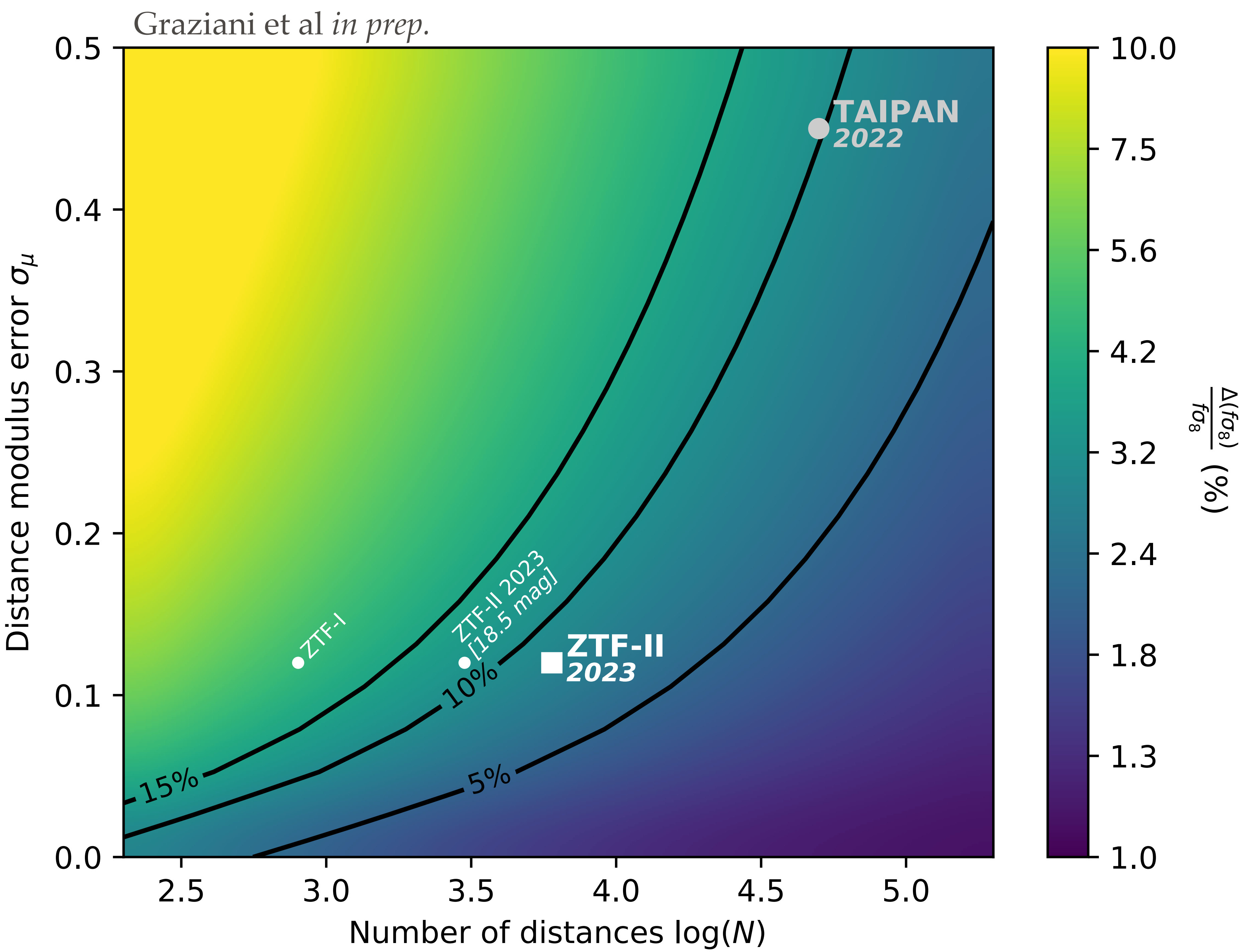
Why SNeIa ?

Graziani et al., *in prep.*
Kim, ..., Graziani,... et al. 2019

- Brightness
- Precision : 1 SNeIa = 15 galaxies
- Systematics studied for cosmology
- Number ?


ZTF
LSST
ZTF: 600 SNeIa/yr, z<0.1
LSST: 4000 SNeIa/yr z<0.2

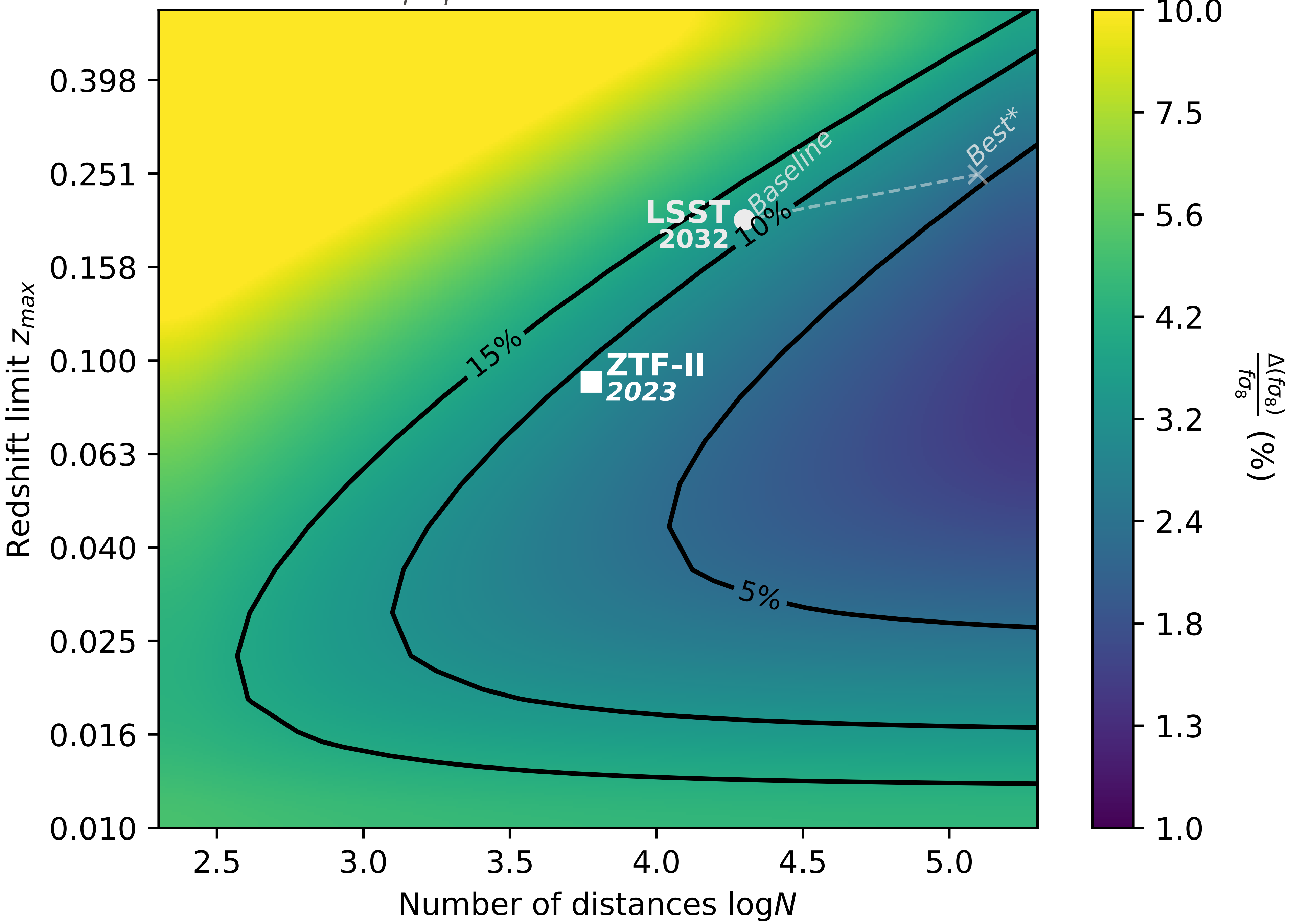
Forecasts



Graziani et al *in prep.*
Distance modulus error σ_μ
Number of distances log(N)
0.0
0.1
0.2
0.3
0.4
0.5
2.5
3.0
3.5
4.0
4.5
5.0
15%
10%
5%
ZTF-I
ZTF-II 2023 [18.5 mag]
ZTF-II 2023
TAIPAN 2022
10.0
7.5
5.6
4.2
3.2
2.4
1.8
1.3
1.0
$\frac{\Delta(f\sigma_8)}{f\sigma_8}$ (%)

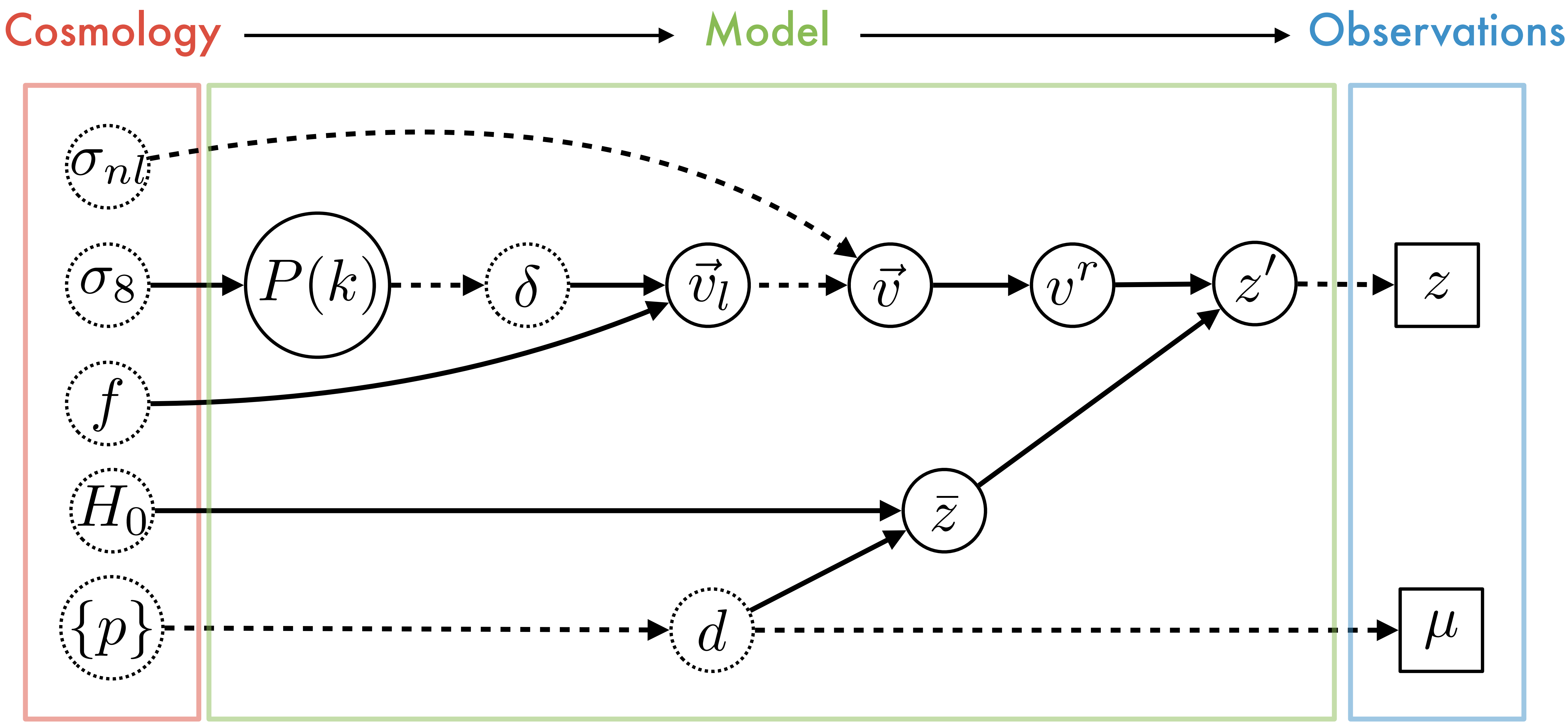
Forecasts

Graziani et al *in prep.*

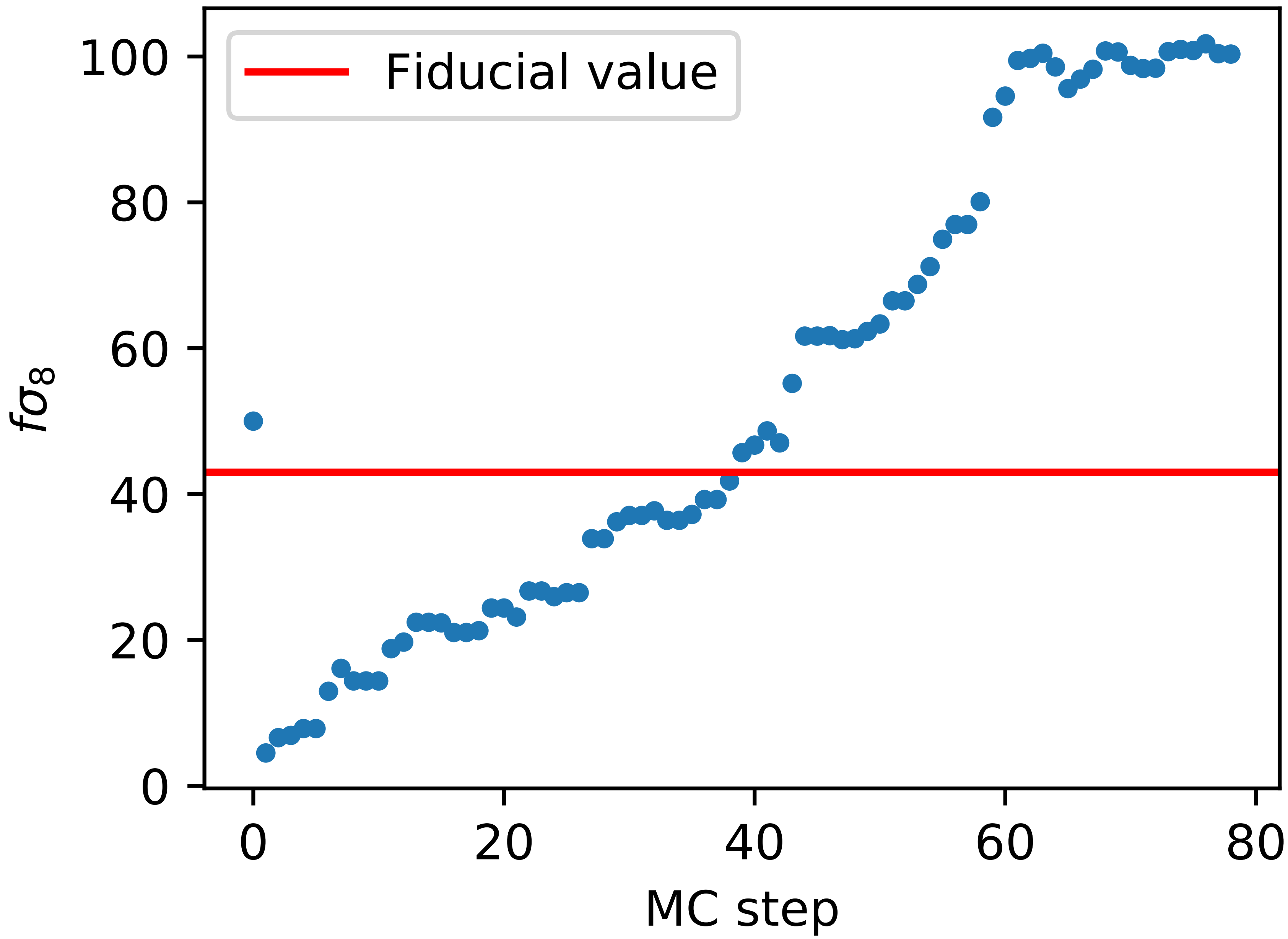


A forward model

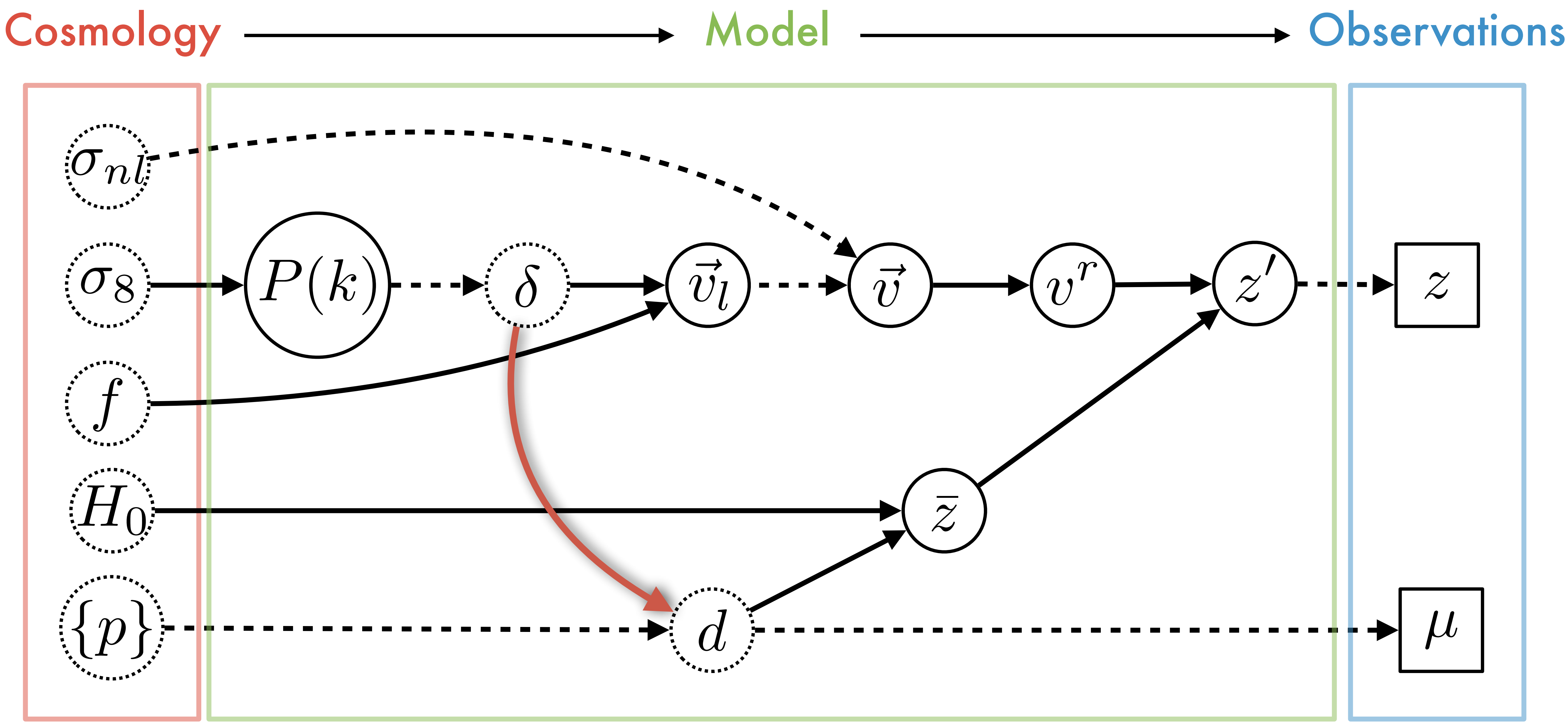
Graziani et al., 2019



Results on mock



Including density correlations



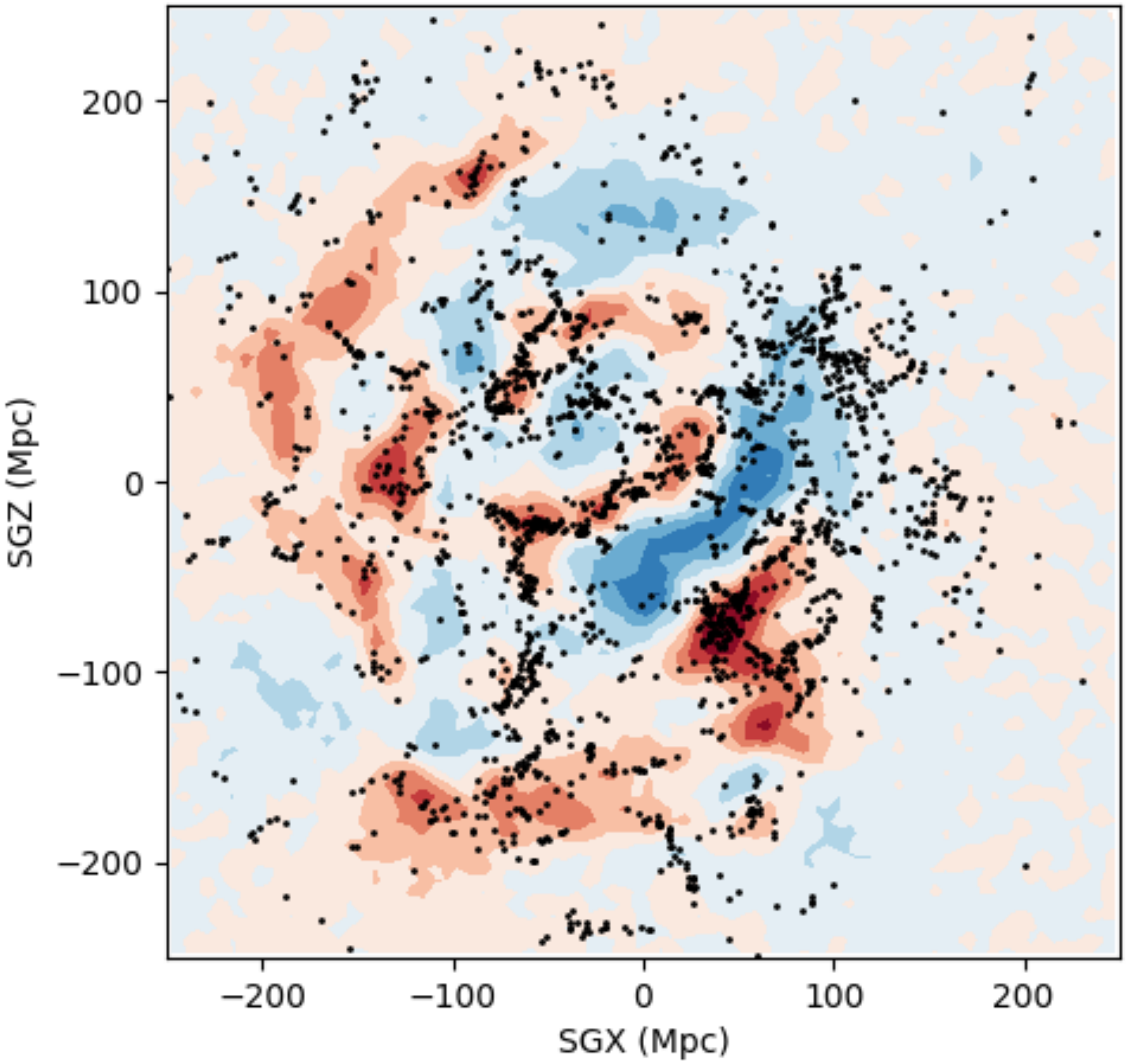
$\mathcal{P}\left(\mathcal{O}|\delta\right)$?

Density model

$$\mathcal{P}\text{oisson}\left(\mathcal{O}|\mathbf{r}\right) \propto n_g(\mathbf{r}) \times \mathrm{e}^{-\int n_g(\mathbf{x})\ \mathrm{d}\mathbf{x}}$$

Density model: Linear bias

$$\mathcal{P}\text{oisson}\left(\mathcal{O}|\mathbf{r}\right) \propto n_g(\mathbf{r}) \times \mathrm{e}^{-\int n_g(\mathbf{x})\ \mathrm{d}\mathbf{x}}$$

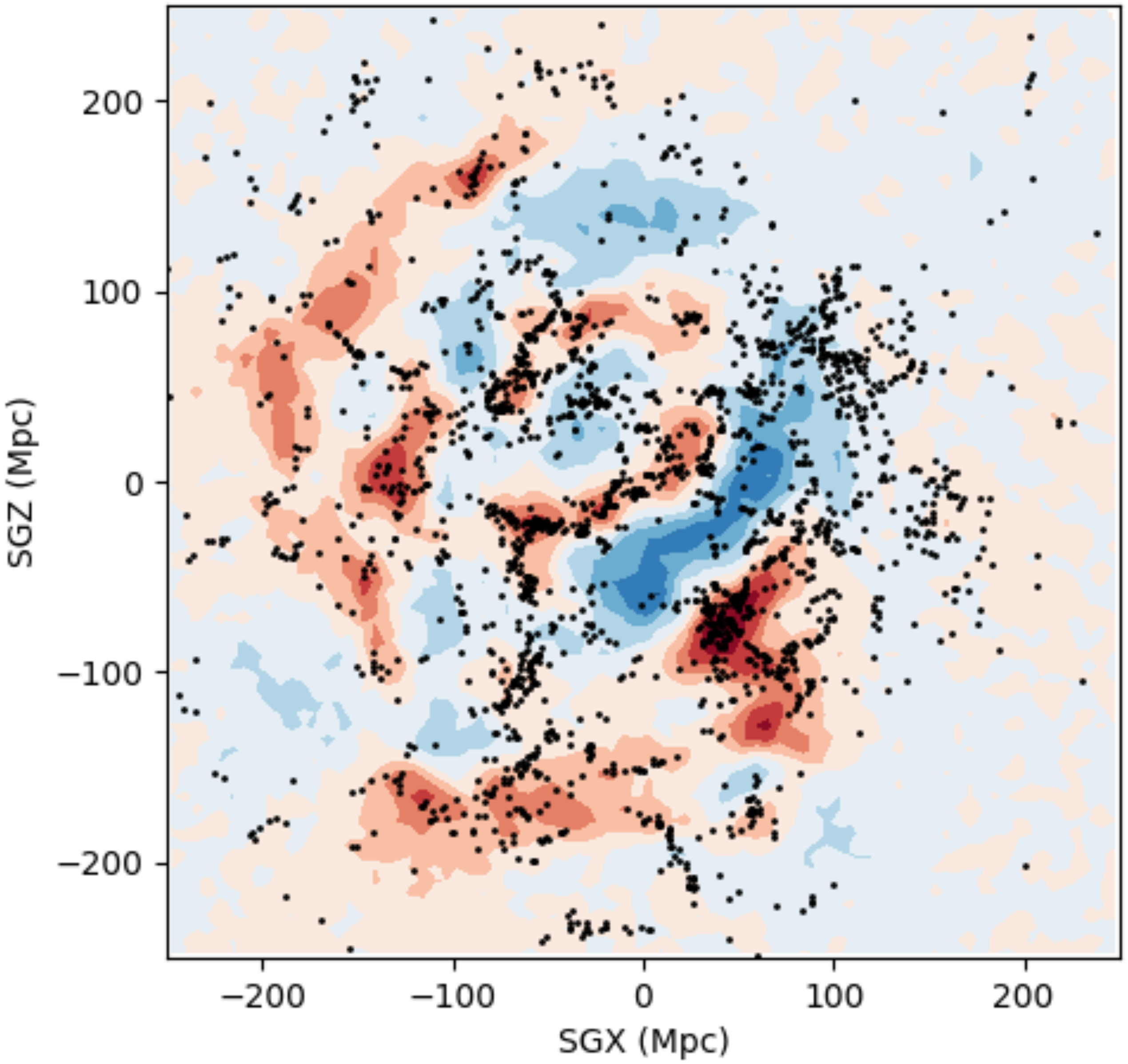


$$n_g = 1 + \delta_g = 1 + b\delta$$

Linear bias

Density model: Non-linear model

$$\mathcal{P}\text{oisson}\left(\mathcal{O}|\mathbf{r}\right) \propto n_g(\mathbf{r}) \times \mathrm{e}^{-\int n_g(\mathbf{x})\ \mathrm{d}\mathbf{x}}$$



$$n_g = 1 + \delta_g = 1 + b\delta$$

Linear bias

$$\delta = f(\delta^L)?$$

Density model: Non-linear model

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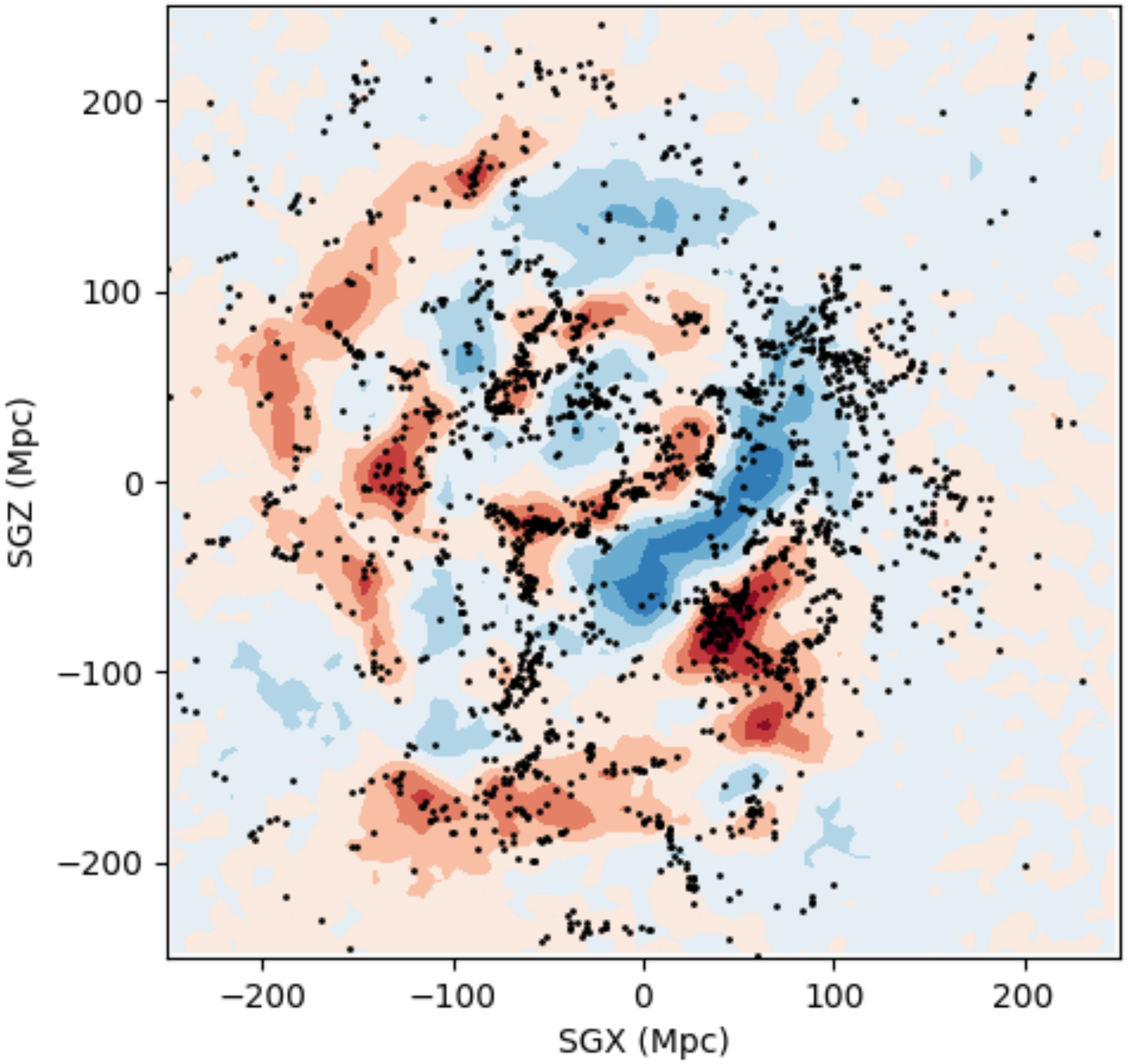

$$n_g = 1 + \delta_g = 1 + b\delta$$

Linear bias

$$\delta = f(\delta^L)?$$

- Eulerian perturbation theory
- Lagrangian perturbation theory
- Effective perturbation theory

Density model: Non-linear model

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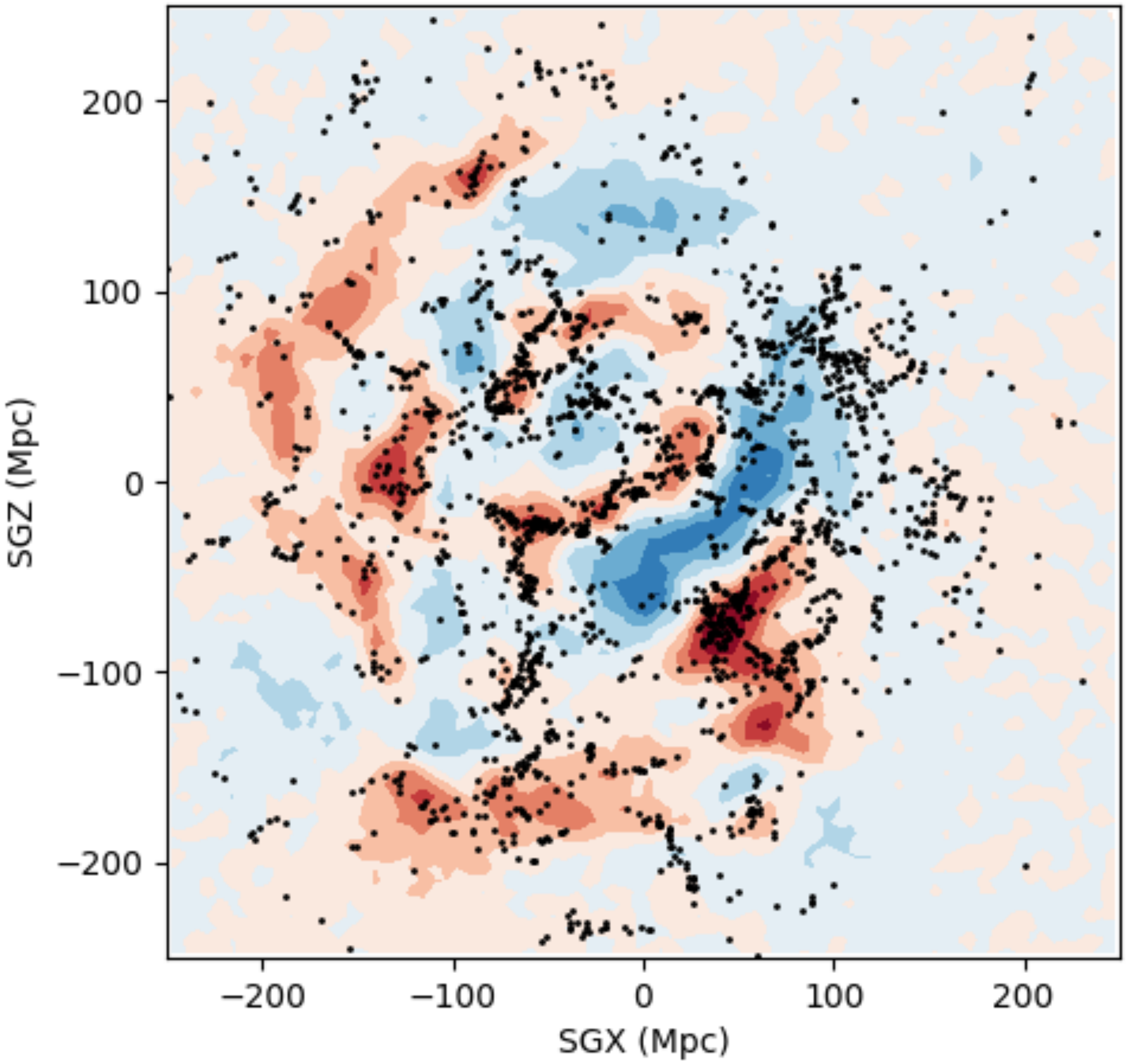

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Linear bias

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- **Eulerian perturbation theory**
- Lagrangian perturbation theory
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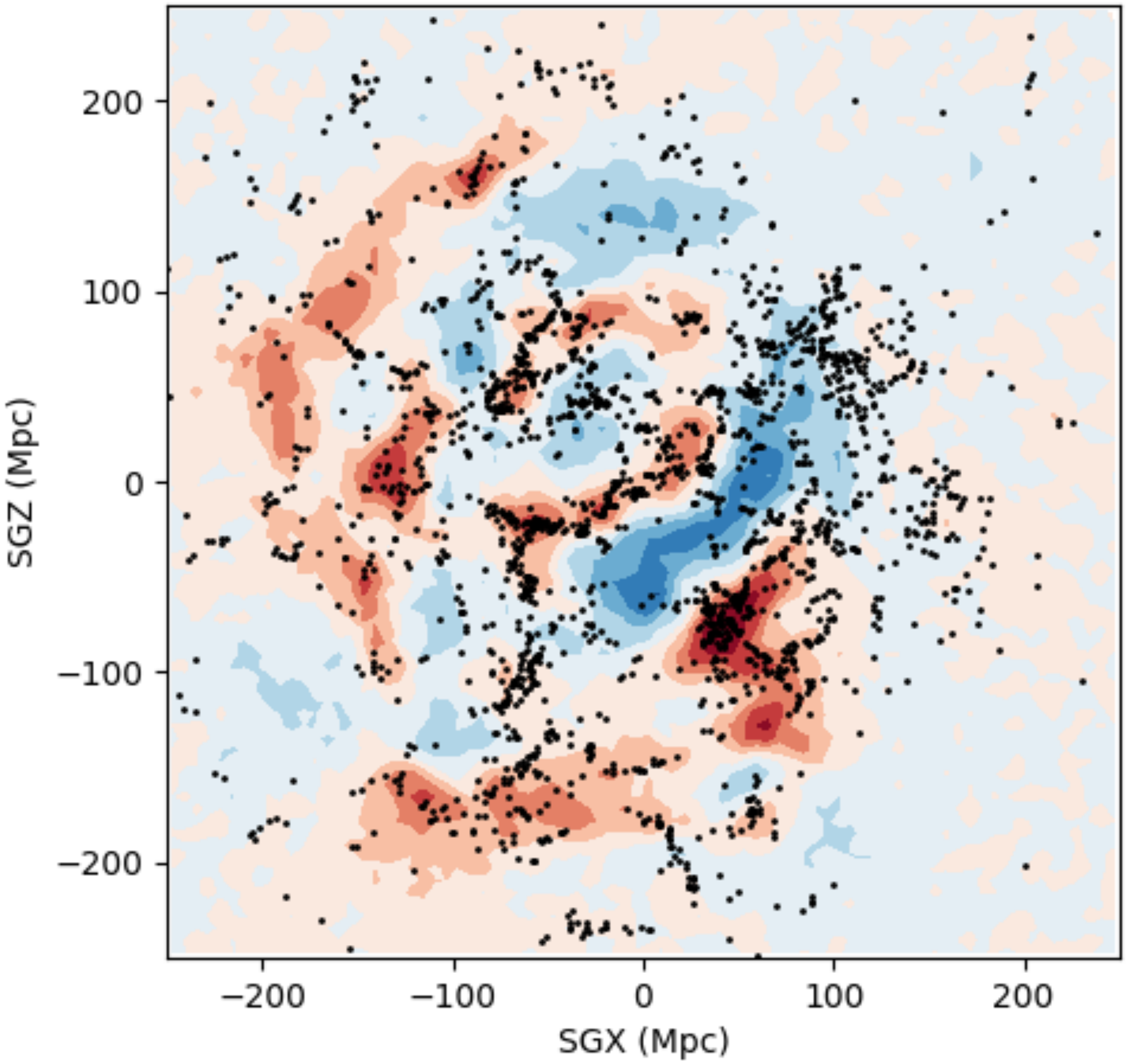

$$n_g = 1 + \delta_g = 1 + b\delta$$

Linear bias

$$n_g = \exp(b\delta^L)$$

(it is positive)

Hamiltonian sampling

- Draw a momentum for each parameter
- Integrate Hamiltonian equation for the parameters and their momenta
- Accept the state

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- Integrate Hamiltonian equation for the parameters and their momenta
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Potential : $\psi = -\ln \mathcal{L}$

Hamiltonian : $H = \sum_i \sum_j \frac{1}{2} p_i \mathbf{M}_{ij}^{-1} p_j + \psi$

Hamilton's equation of motion :

$$\frac{\mathrm{d}x_i}{\mathrm{d}t} = \frac{\partial H}{\partial p_i}$$

$$\frac{\mathrm{d}p_i}{\mathrm{d}t} = -\frac{\partial \psi}{\partial x_i}$$

Hamiltonian sampling

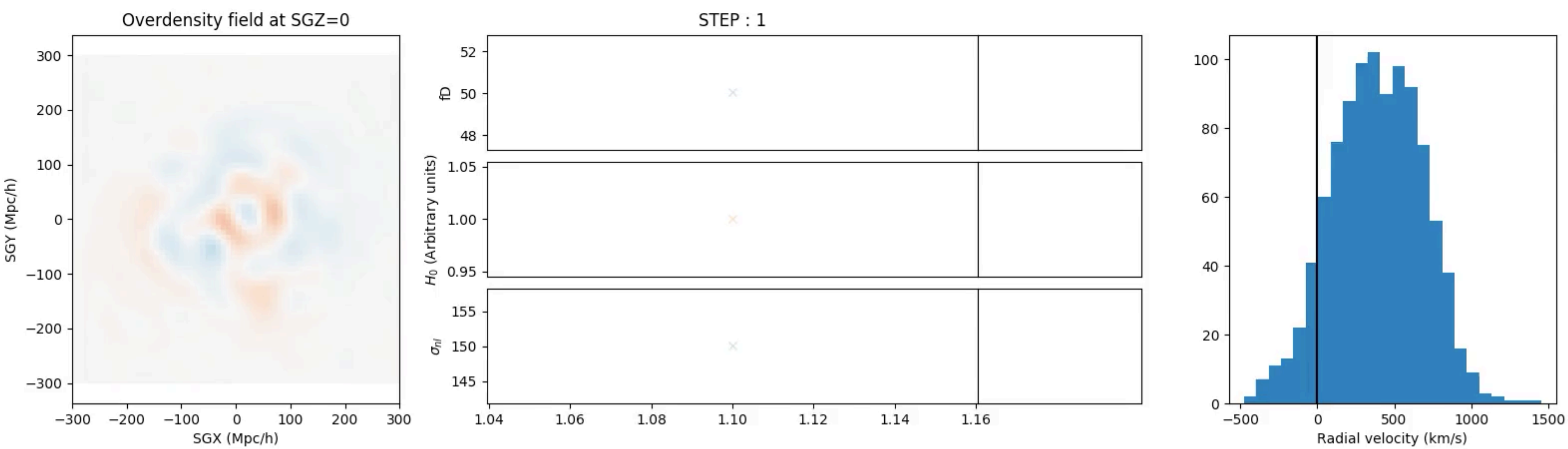
- Draw a momentum for each parameter
- Integrate Hamiltonian equation for the parameters and their momenta
- Accept the state

Pros	**Cons**
Converges to the solution	Hard to implement
Theoretical acceptance rate of 100%	Need to do math
Efficient for high dimensions and correlated models	

Link

Results on mocks

- Mocks based on DM-only simulation
- 1000 SNe at z<0.05
- Observational uncertainty of 0.1mag
- Includes LSST angular mask



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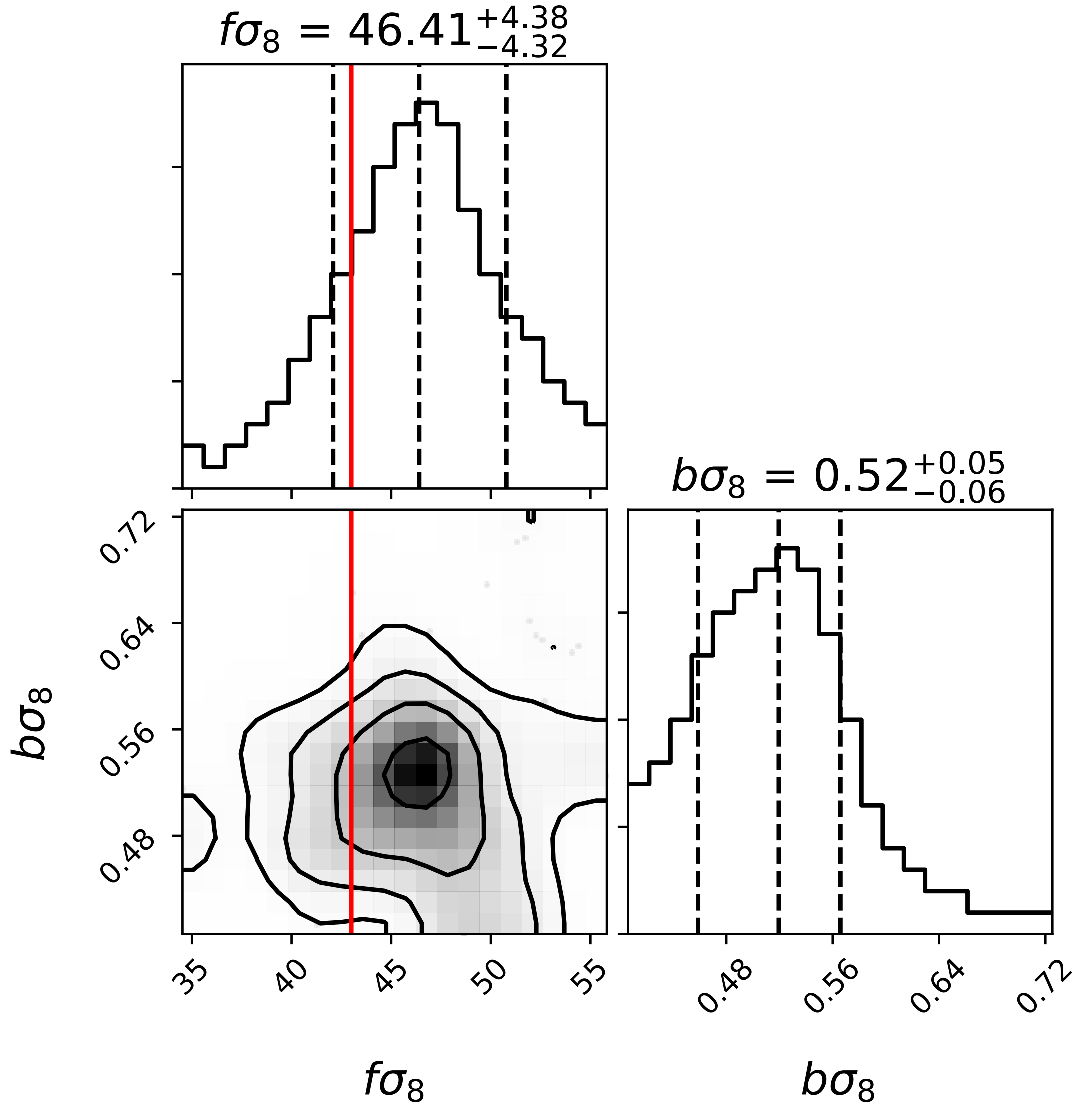

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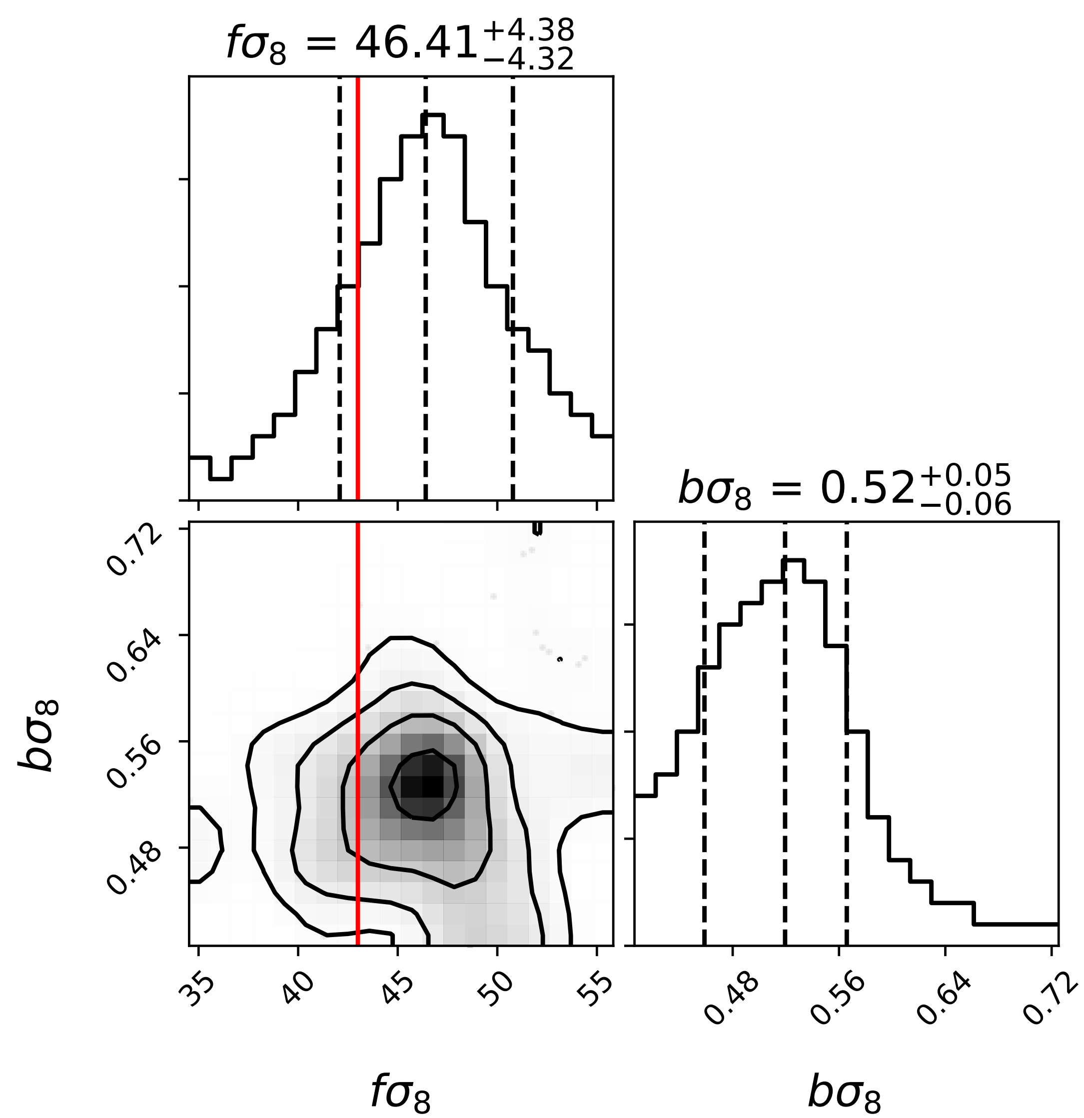
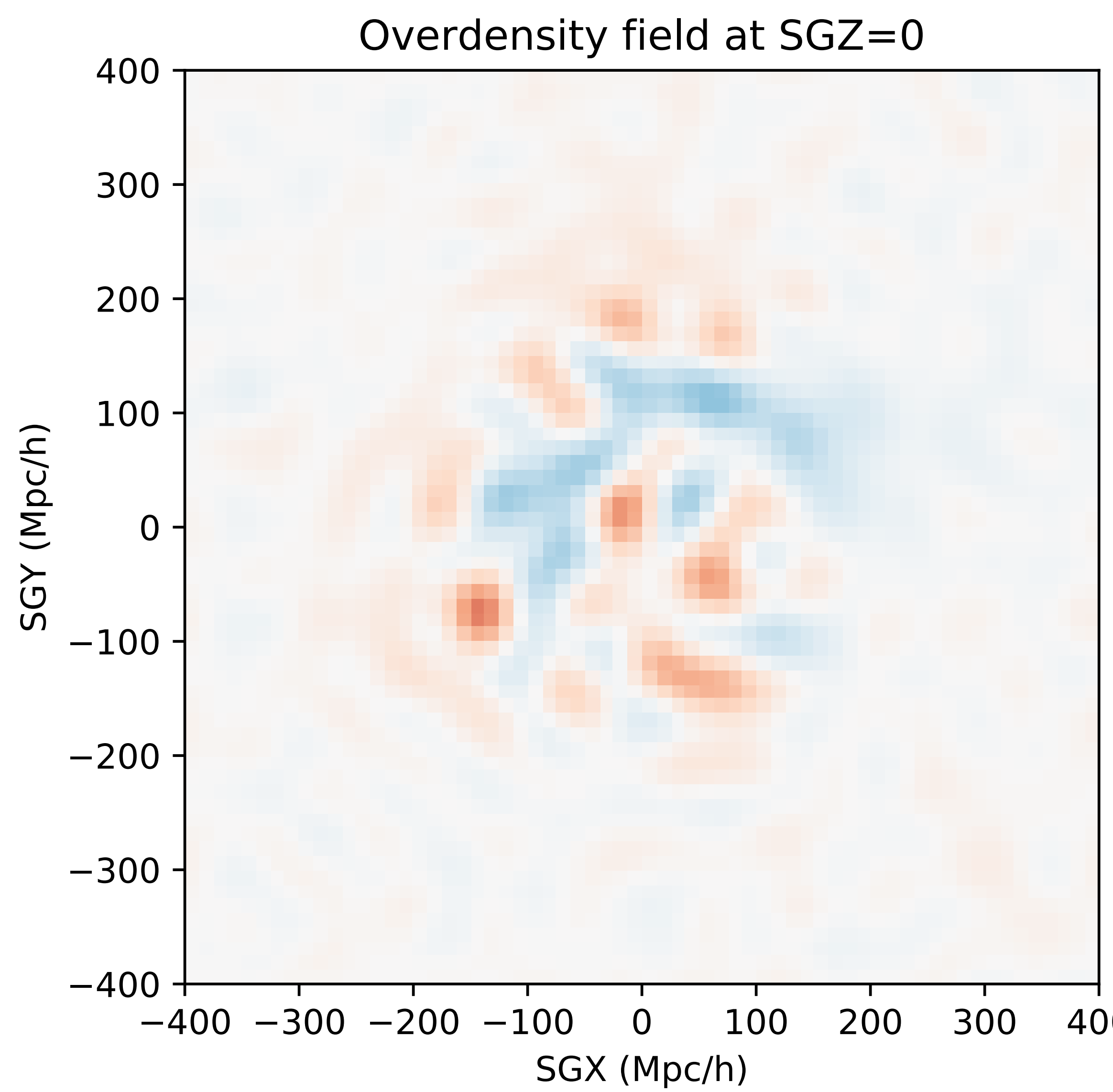
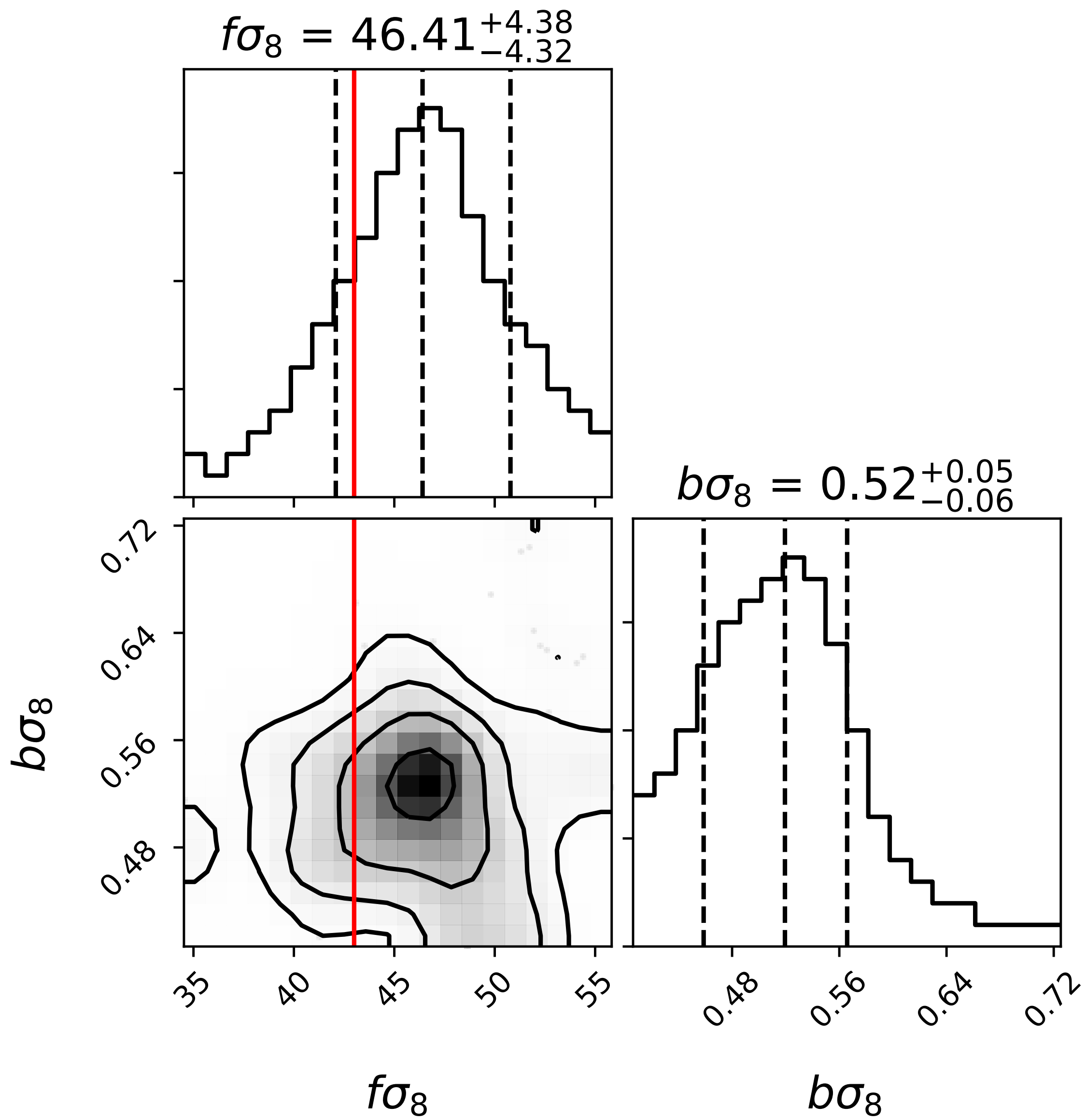


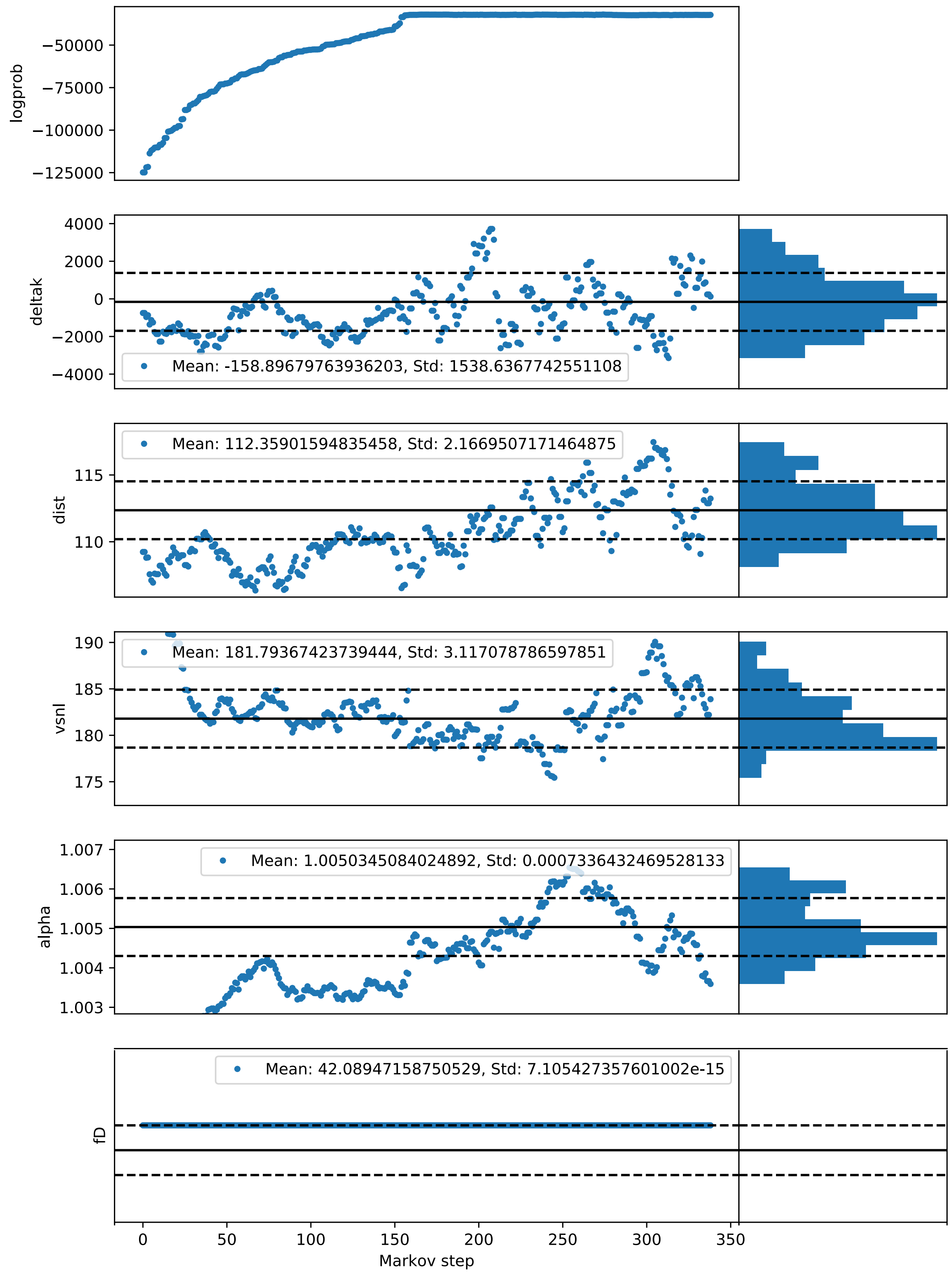


Comments

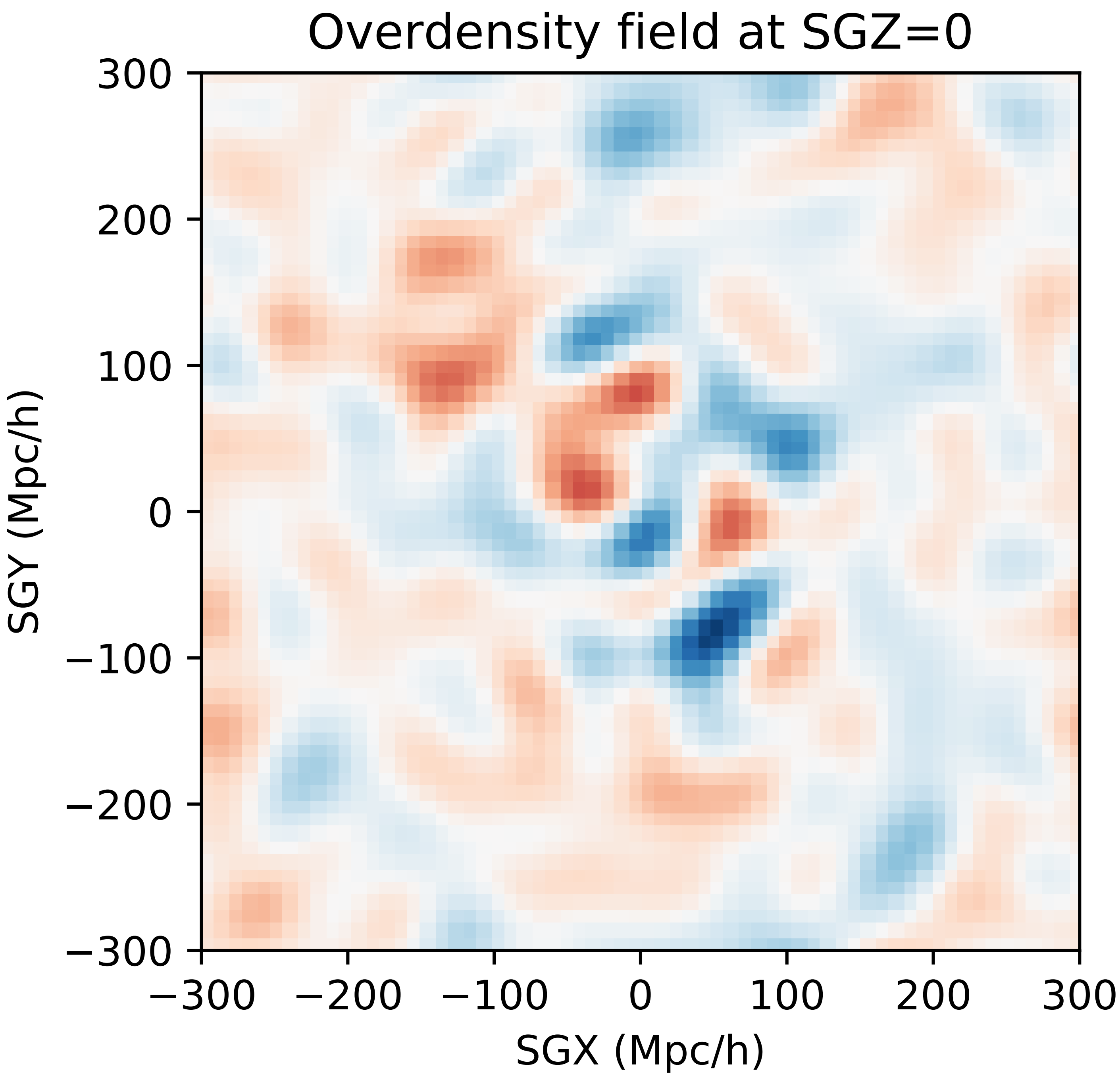
- Peculiar-velocity only Fisher-Matrix error: 6.3 (15%)
- Algorithm converges in approx. few hours
- Need to know the selection function



CF2


logprob
−50000
−75000
−100000
−125000
deltak
4000
2000
0
−2000
−4000
Mean: -158.89679763936203, Std: 1538.6367742551108
dist
115
110
Mean: 112.35901594835458, Std: 2.1669507171464875
vsnl
190
185
180
175
Mean: 181.79367423739444, Std: 3.117078786597851
alpha
1.007
1.006
1.005
1.004
1.003
Mean: 1.0050345084024892, Std: 0.0007336432469528133
fD
Mean: 42.08947158750529, Std: 7.105427357601002e-15
0
50
100
150
200
250
300
350
Markov step

CF2


Overdensity field at SGZ=0
SGY (Mpc/h)
SGX (Mpc/h)
300
200
100
0
−100
−200
−300
−300
−200
−100
0
100
200
300

Take home messages

- We can do maps from peculiar velocities
- We can do cosmology from peculiar velocities
- Know your selection effects