

Inference from Cosmology

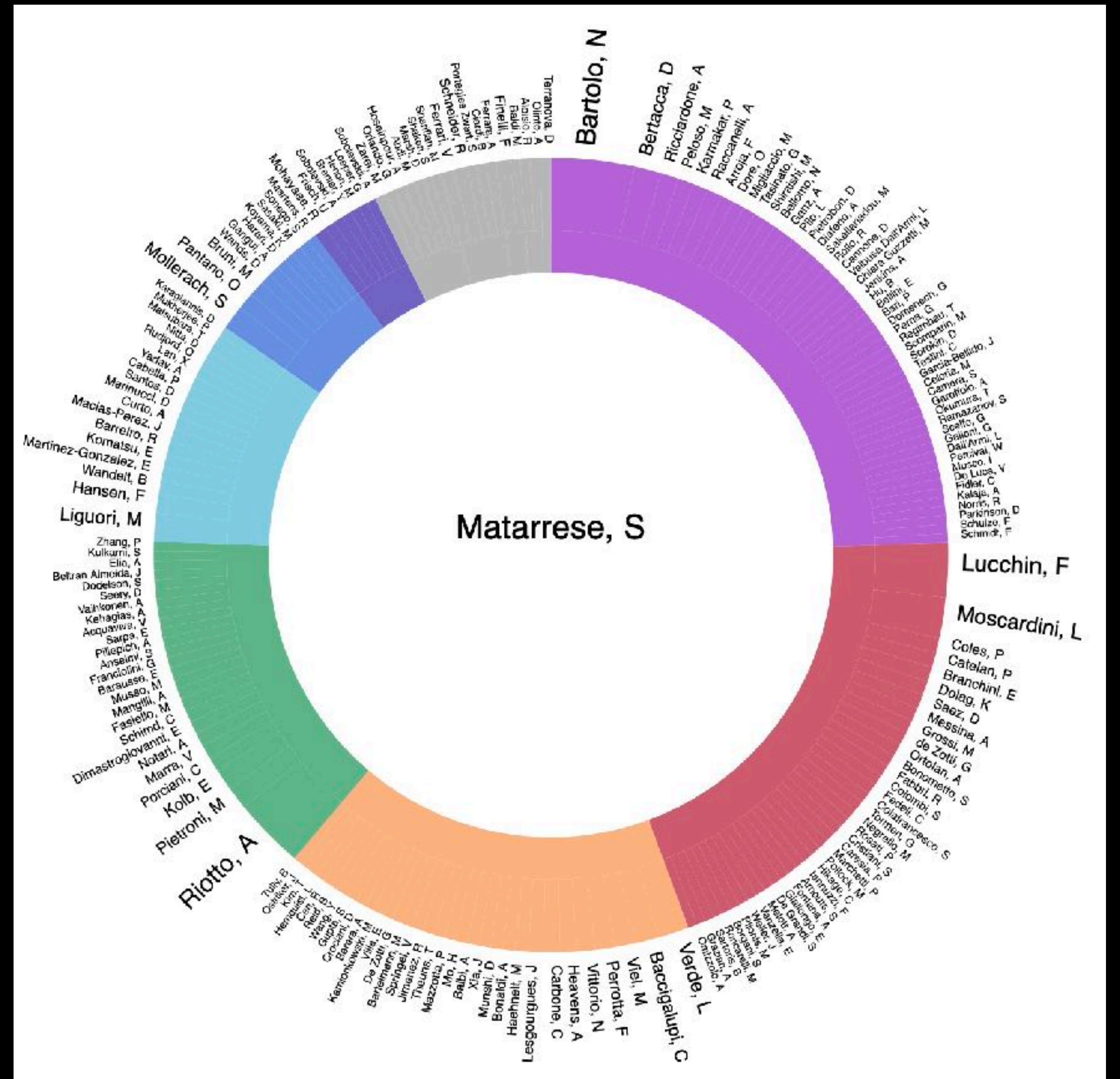
Celebrating Sabino's retirement



Alan Heavens 10 September 2025. Fiera di Primiera

Sabino's career

- 606 publications
- 114,608 citations
- Sabino is beginning to show promise
- “Across decades of pioneering research, mentorship, and scientific engagement, Sabino Matarrese has not only advanced cosmology from theory to observatory but has also shaped the careers of the next generation of scientists—truly a career worthy of celebration.”



Peter Coles: “Me and Lauro on the left with Sabino laughing at us.”



"As usual"

Inference from Cosmology

General methods:

- Classical summary statistics (power spectra, correlation functions)
- Simple, easy, sometimes wrong. Systematics can be very hard
- Bayesian Hierarchical Models
- Often the only way to compute the likelihood. Some systematics easy. High barrier to entry
- AI methods (simulation-based inference)
- Very flexible. Needs very good and fast simulator. Something of an art

Bayesian context

$$p(\theta | d) = \frac{p(d | \theta) p(\theta)}{p(d)} \quad \theta = \text{parameters}; \quad d = \text{data}$$

- $p(\theta | d)$: Posterior - the goal of a Bayesian analysis
- $p(d | \theta)$: Likelihood (or sampling distribution)
- $p(\theta), p(d)$: Prior, Bayesian Evidence

Bayesian hierarchical modeling of cosmological surveys

- Dataset is huge!
- How do we compute the posterior $p(\theta | \text{data})$ for cosmological parameters θ ?

- First, introduce the map and (optionally) marginalise over it:

$$p(\theta | \text{data}) = \int p(\theta, \text{map} | \text{data}) d(\text{map})$$

- $p(\theta, \text{map} | \text{data}) \propto p(\text{data} | \text{map}, \theta) p(\text{map} | \theta) p(\theta)$

Field-level likelihood

Theory

Prior

Very high-dimensional problem (millions), to sample map and parameters.

Techniques: Hamiltonian Monte Carlo, Gibbs, slice sampling

BORG nonlinear gravity model



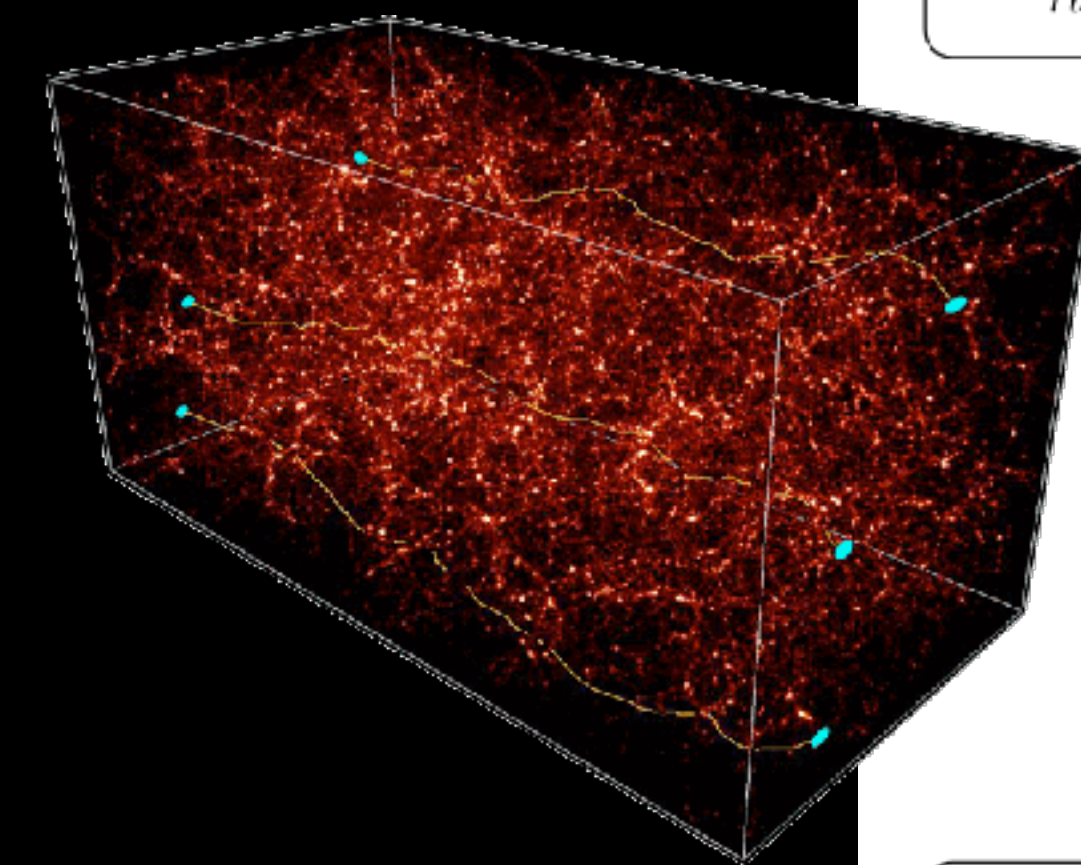
Natalia Porqueres

$$p(\text{map} | \theta) = p(\text{map} | \text{ICs}, \theta) p(\text{ICs} | \theta)$$

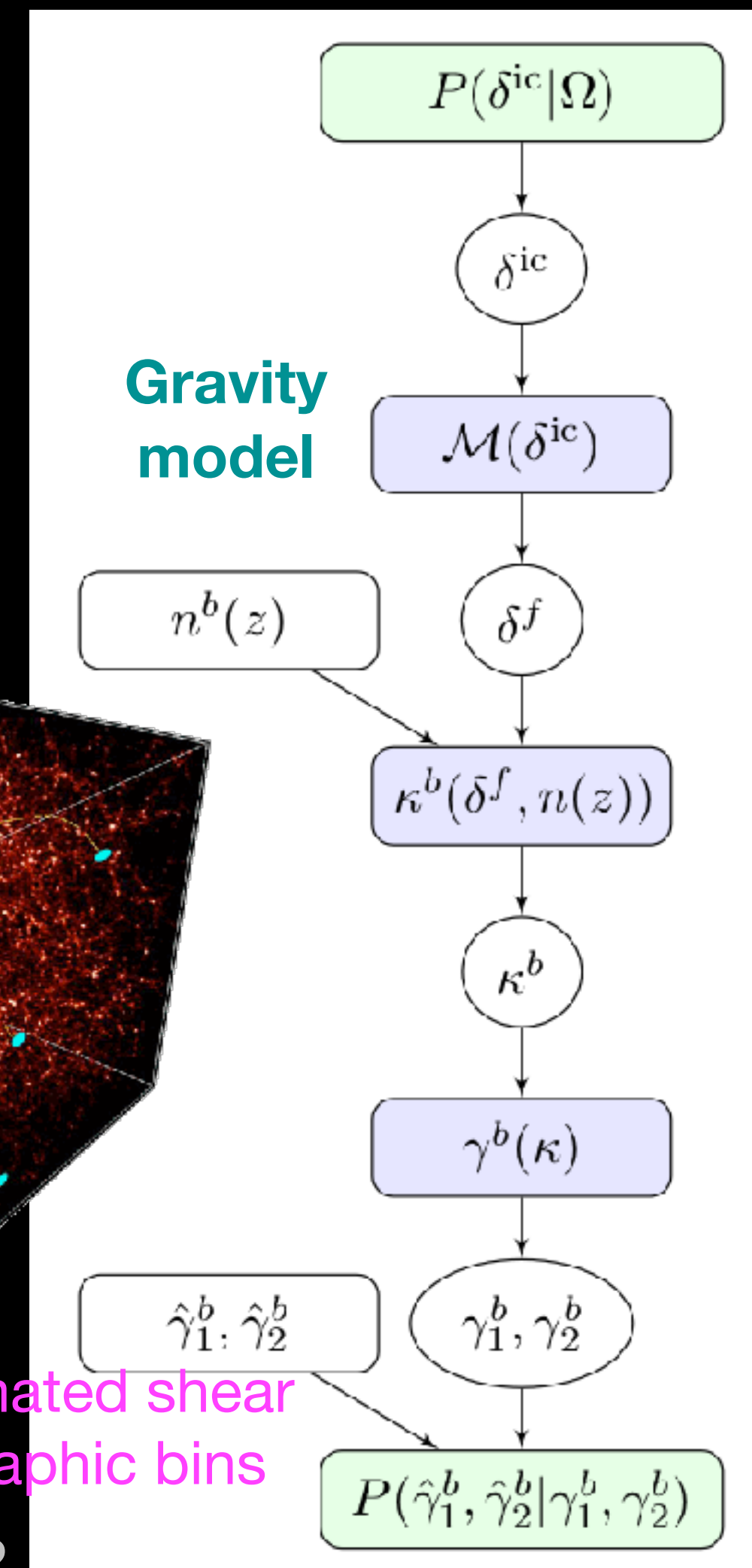
Gravity model:
LPT, PM

Gaussian - and
known power spectrum

- Sample 3D primordial density field (Gaussian!)
- Gravity model (LPT or PM) evolves to the present day
- Density field determines the shear field in tomographic bins
- Apply the likelihood to galaxies (or shear) at the field level
- WL: samples cosmological parameters as well as initial conditions
 - box size changes
 - growth rate changes



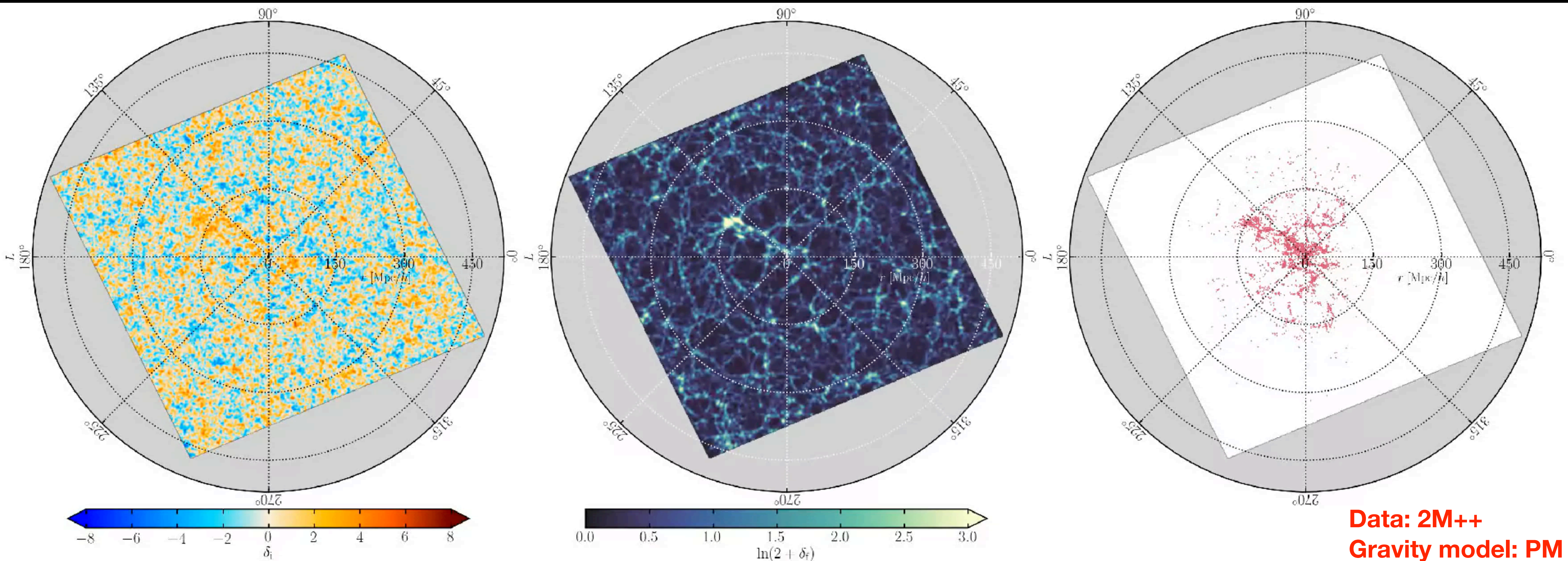
S. Colombi



Data: estimated shear
in tomographic bins



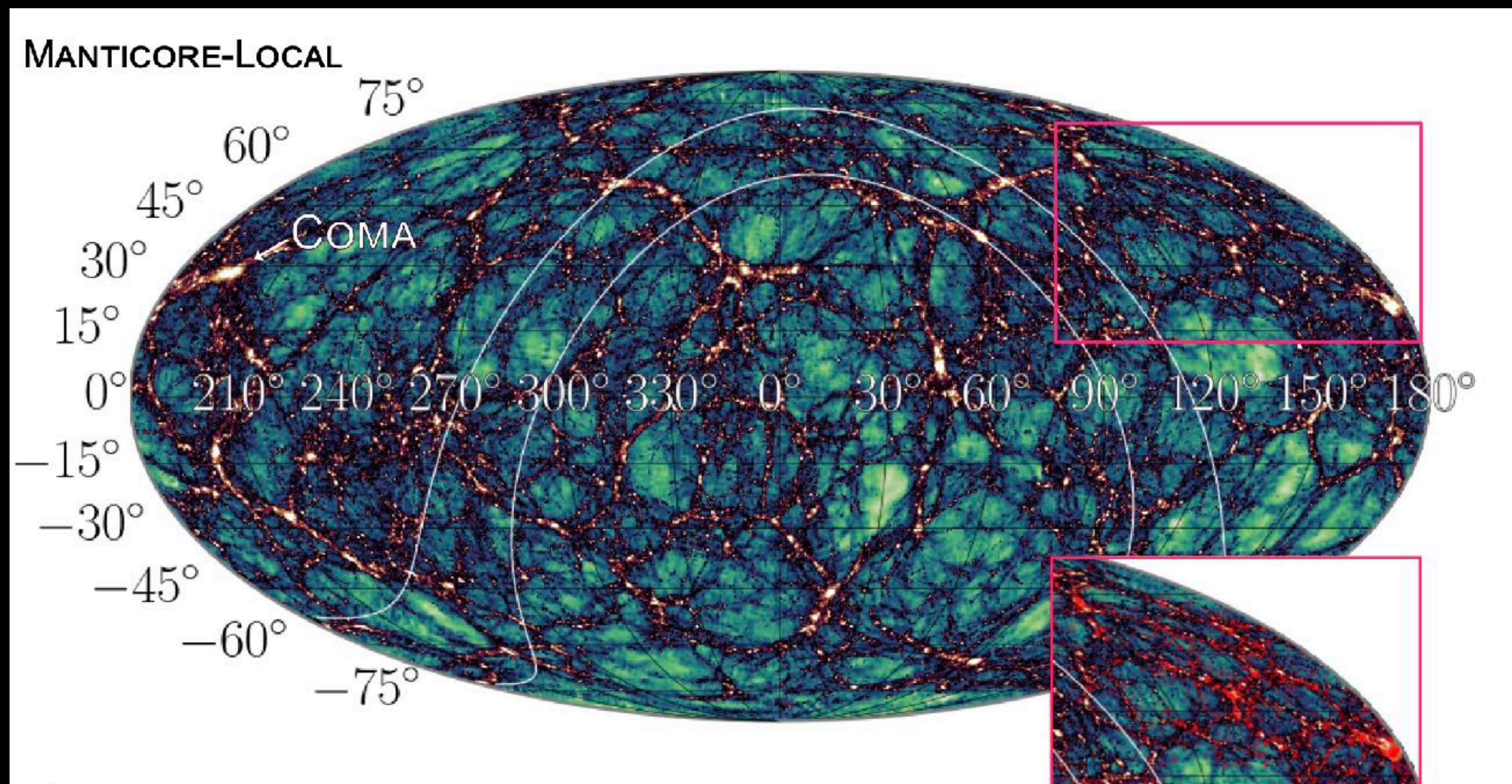
BORG (Bayesian Origin Reconstruction from Galaxies)



Aquila Consortium Credit: Florent Leclercq

Manticore-Local

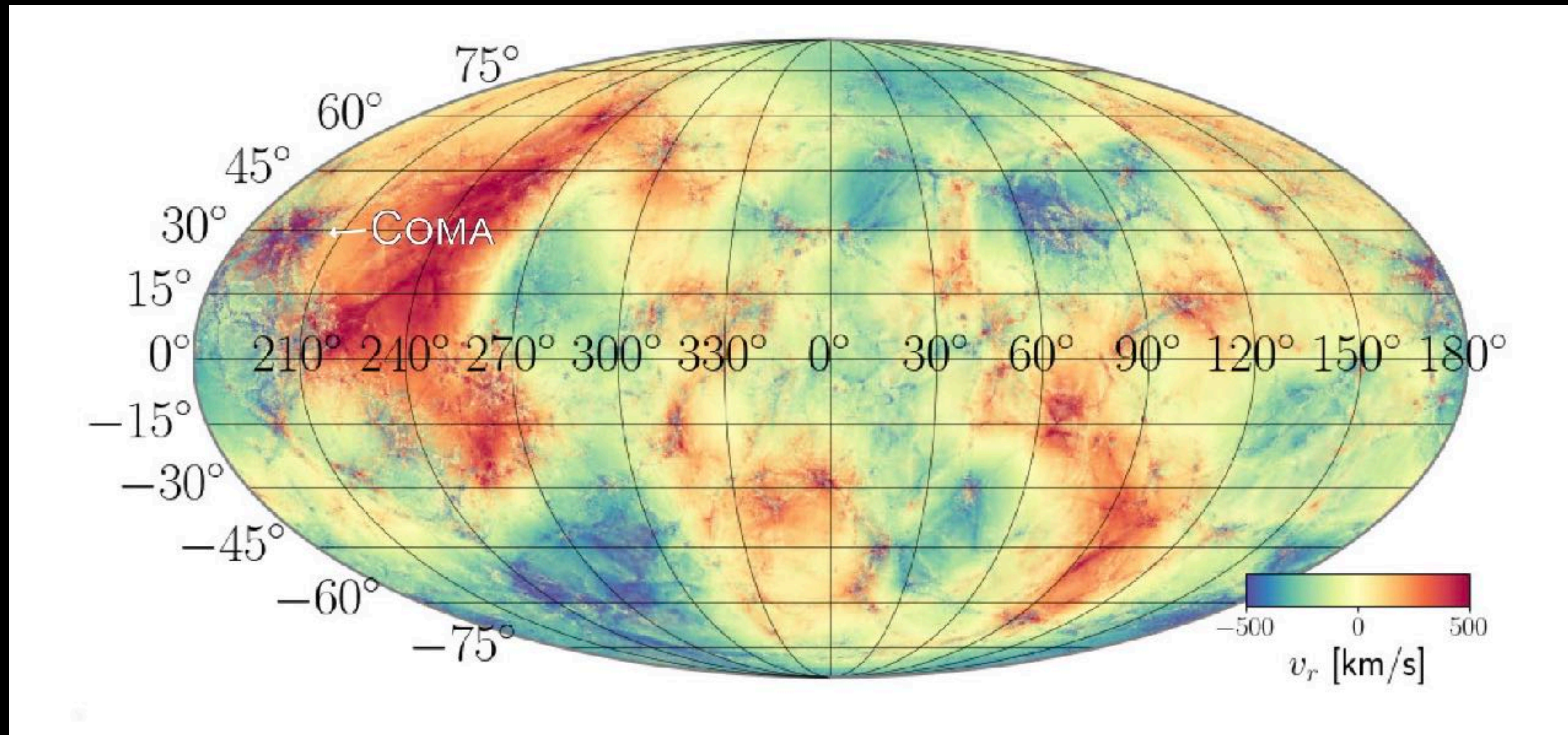
Matter density field



McAlpine et al. 2505.10682

Manticore-Local

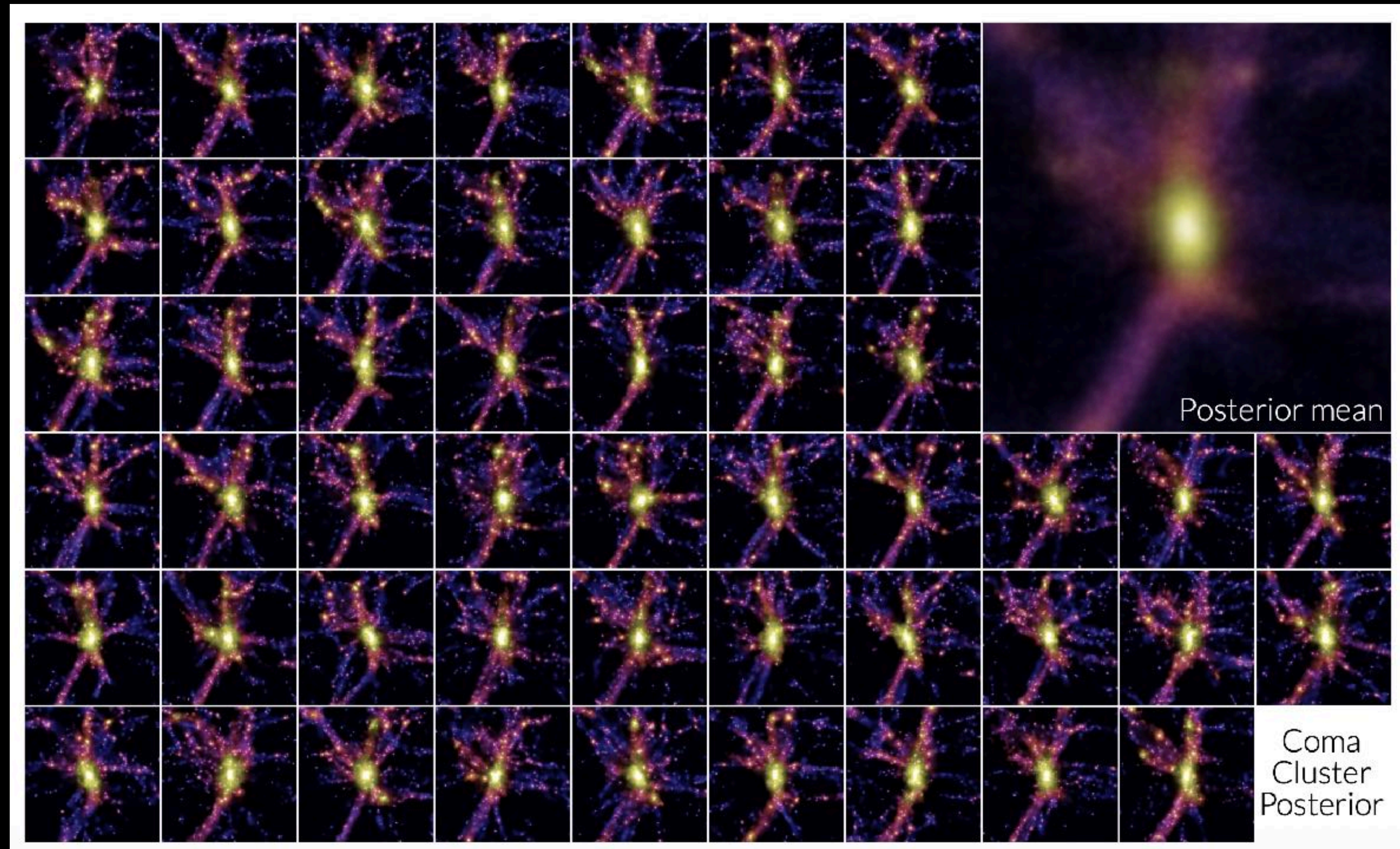
Radial peculiar velocity field



McAlpine et al. 2505.10682

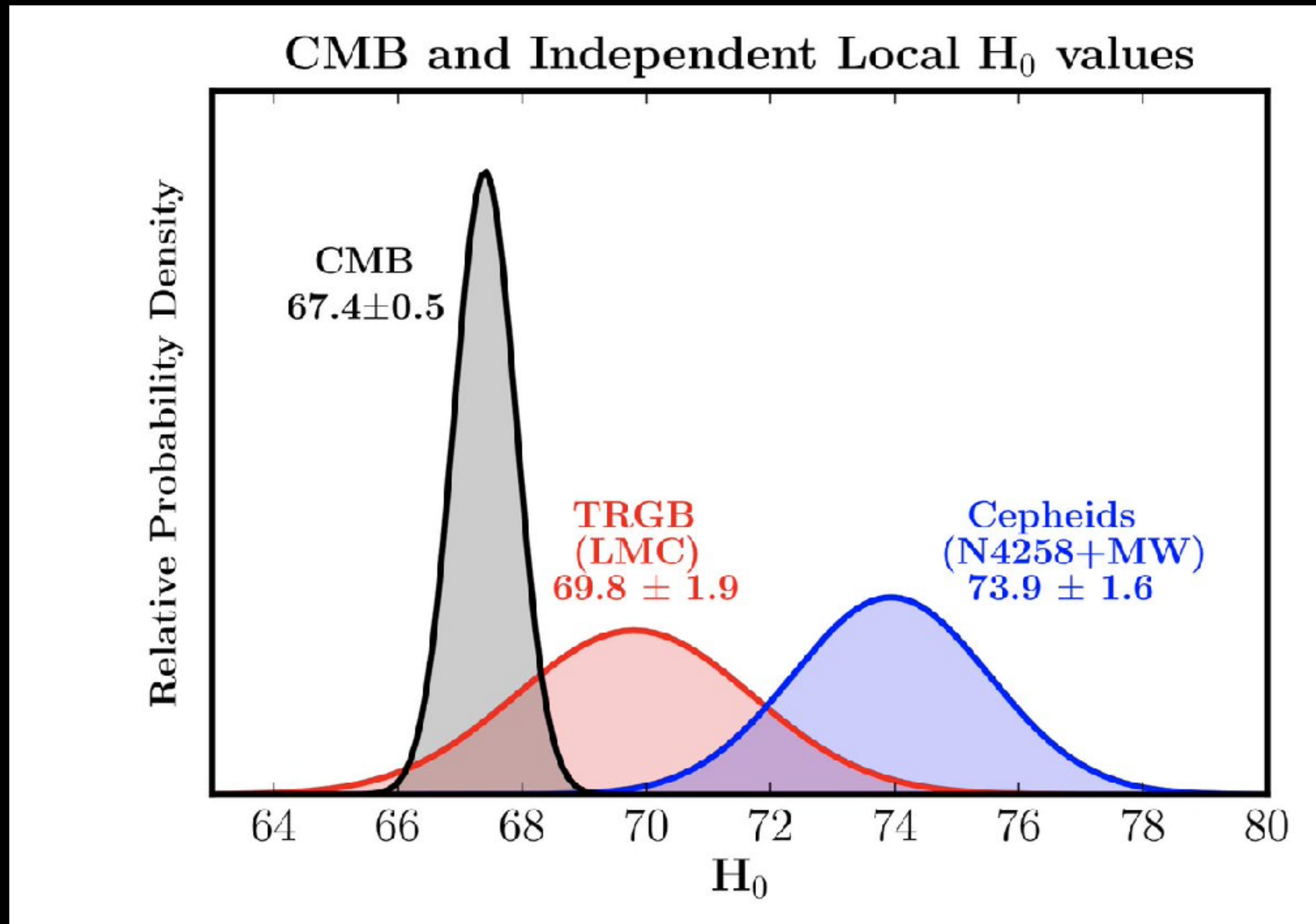
Manticore-Local

Coma samples



McAlpine et al. 2505.10682

Hubble tension

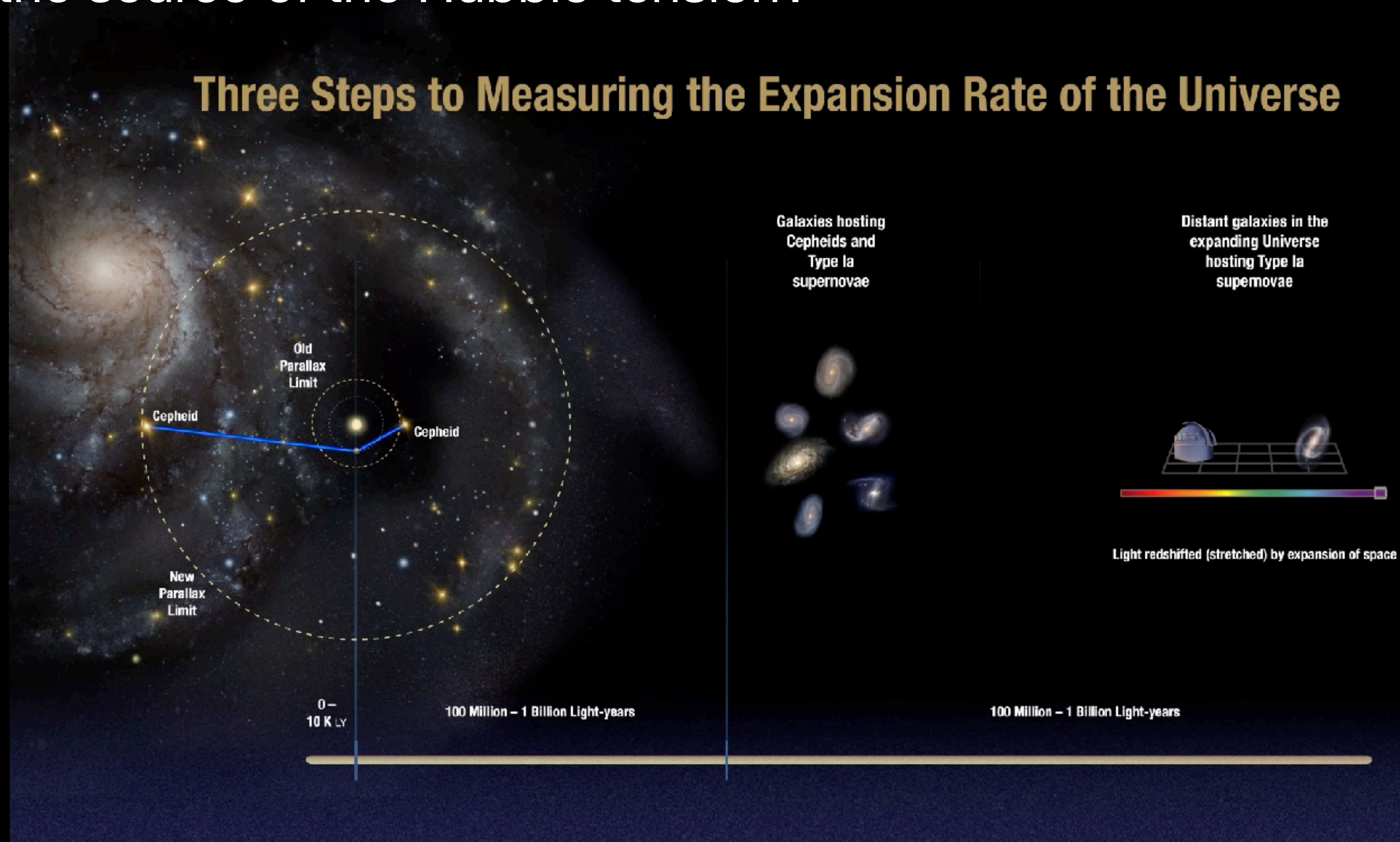


Freedman et al 2019

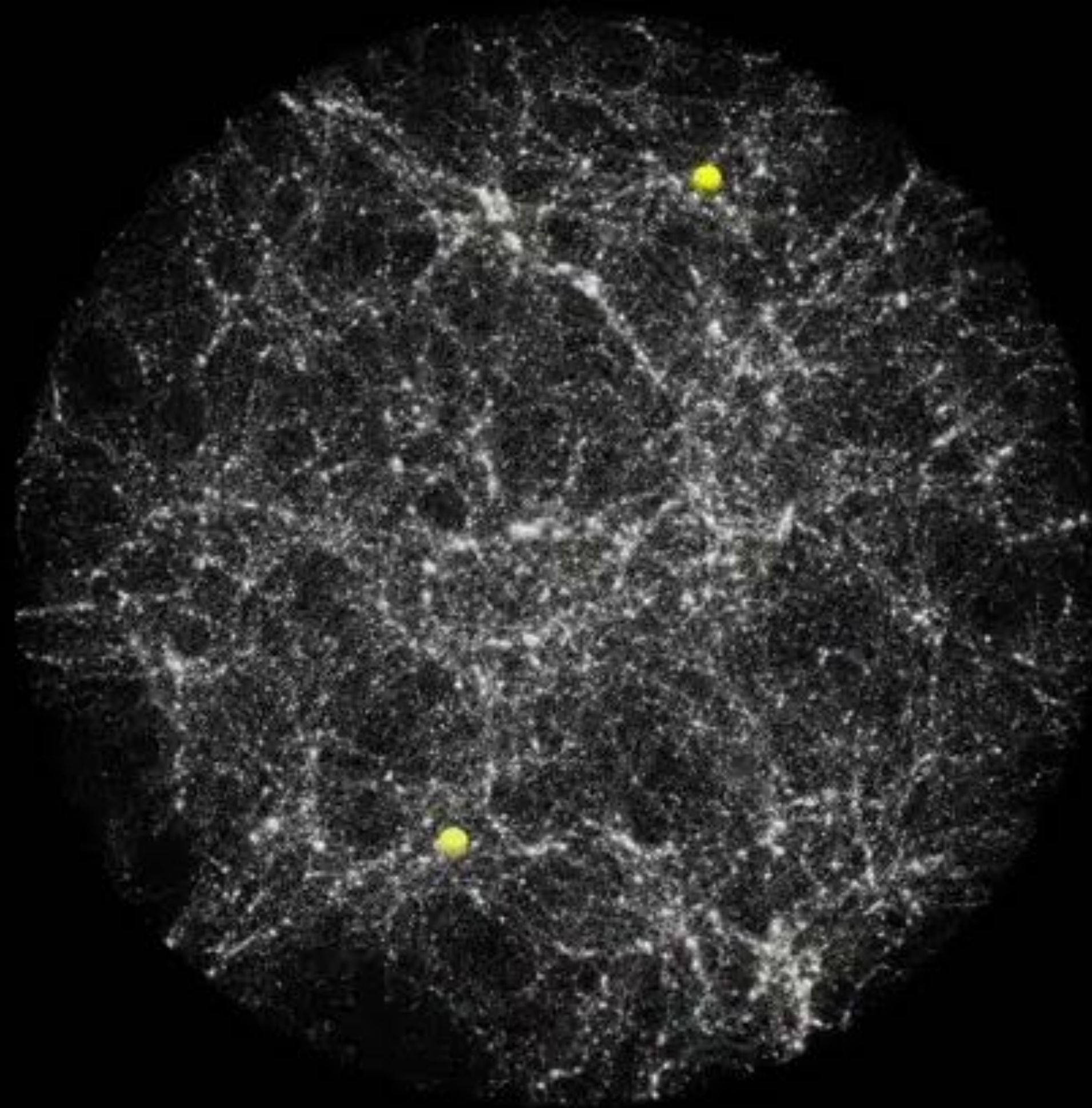
Hubble tension

Stistalek et al. in preparation

What is the source of the Hubble tension?



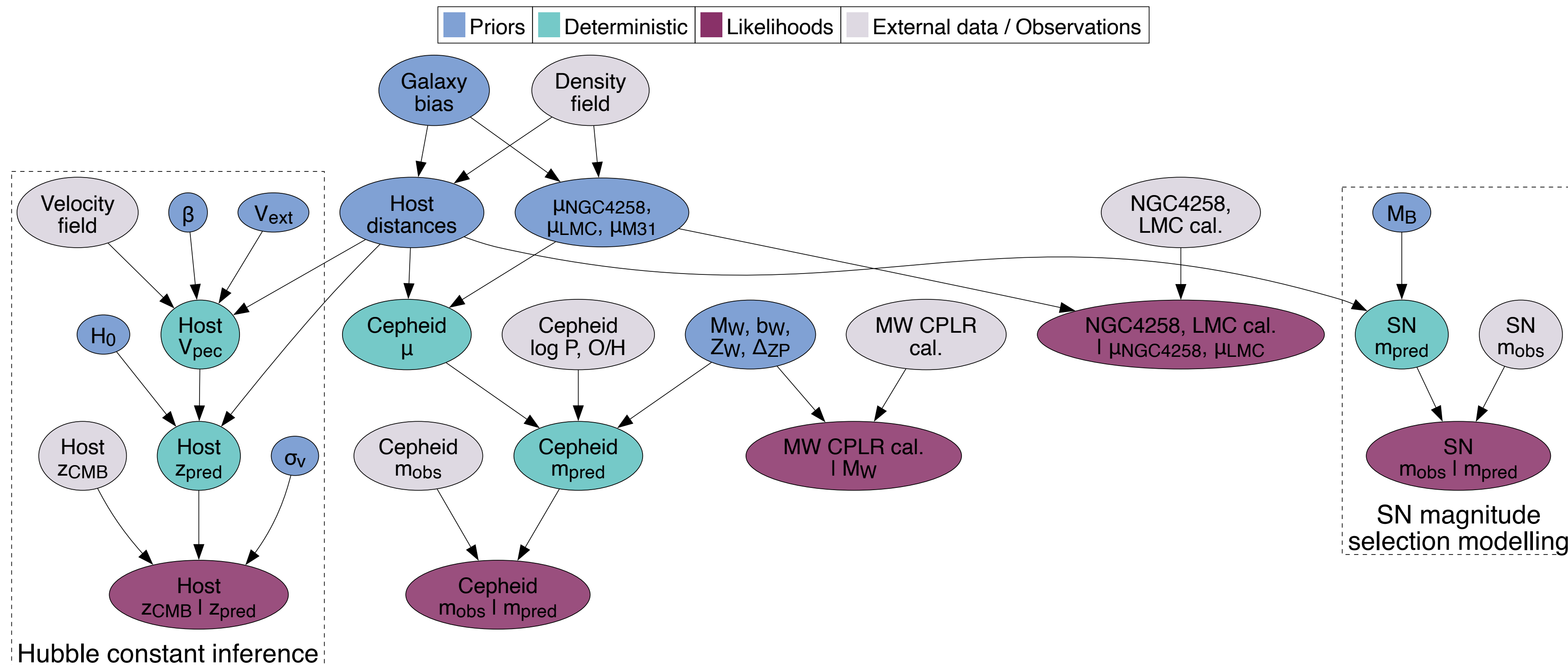
Supernova hosts



Animation by
Eleni Tsaprazi

Bayesian Hierarchical Model

Using Cepheids only



Stistalek et al. in prep.

Bayesian inference

Selection. S = selected

- $p(H_0 | data, S) \propto p(S | H_0)^{-N} p(data, S | H_0)$
- For selection on estimated redshift,
- $p(S | H_0) \propto H_0^{-3}$
- For selection on estimated supernova magnitude $m < m_{lim}$,
- $p(S | H_0) \propto 10^{-0.6(M_B - m_{lim})}$
- Selection matters!

1.8% measurement of H_0 from Cepheids

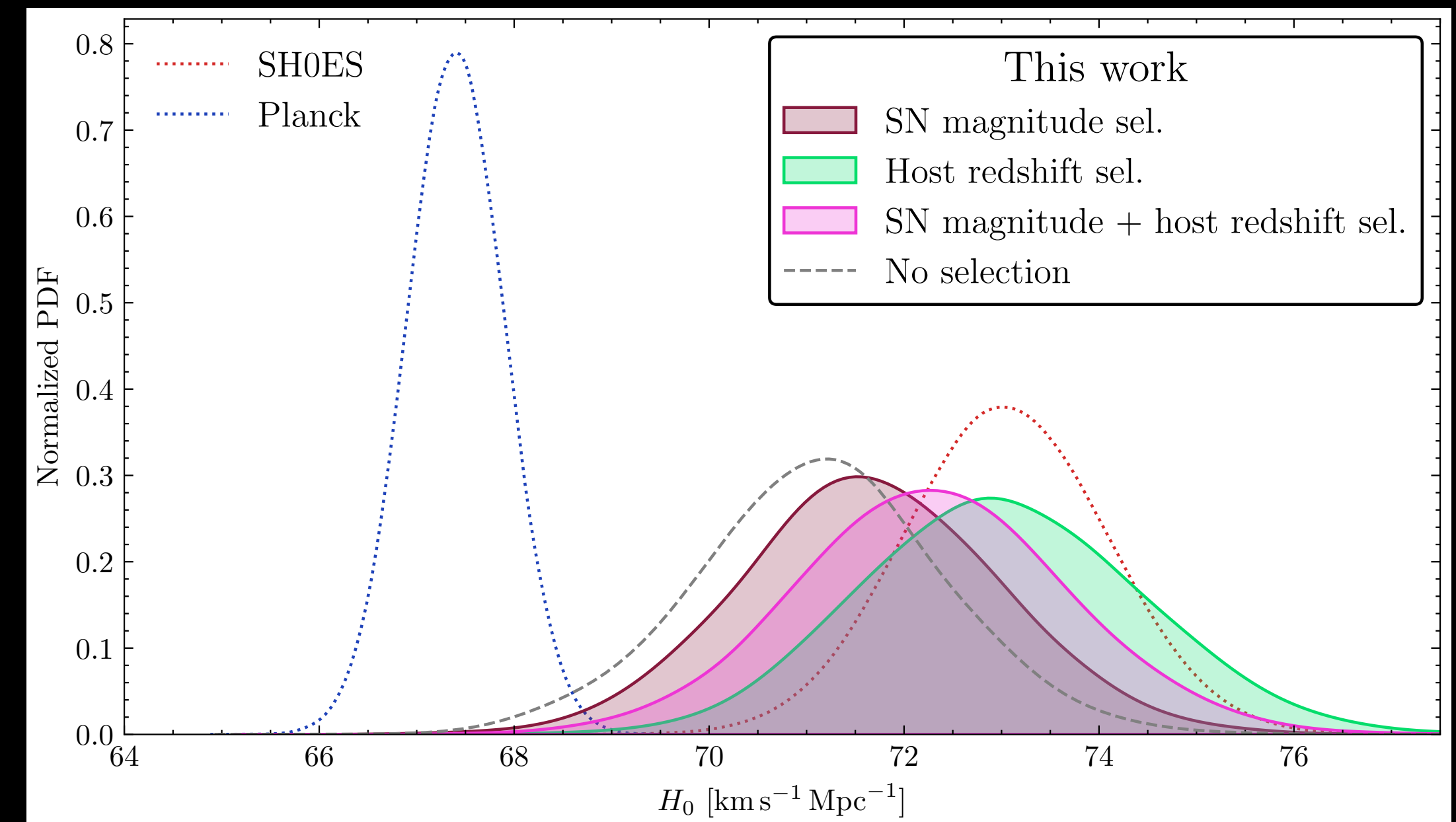


Richard
Stiskalek +
Harry
Desmond++

Eleni
Tsaprazi

35 hosts with SNe, selected (probably) by SN properties

- Uses samples of the Manticore-Local peculiar velocity field, marginalizing over the uncertainty
- Includes selection effects
- Has a physically-motivated prior for the distances (equal volume density)...
- ...modified by overdensity from BORG to avoid inhomogeneous Malmquist bias
- SN not used in likelihood, only in selection



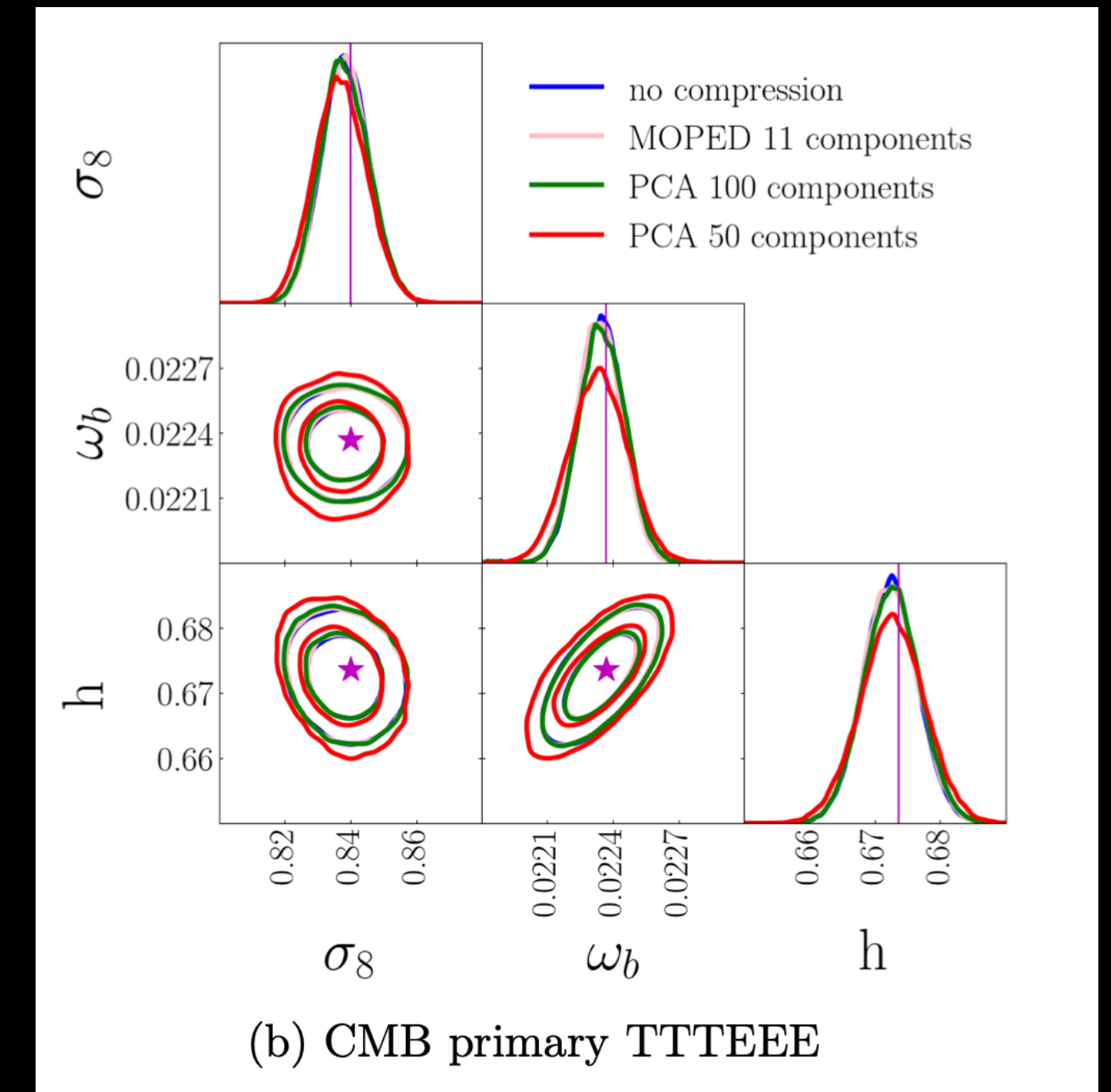
Stiskalek et al. in prep.

$$H_0 = 71.7 \pm 1.3 \text{ km s}^{-1} \text{Mpc}^{-1}$$

Lower H_0 and
~factor 2 smaller
error than
Kenworthy et al.

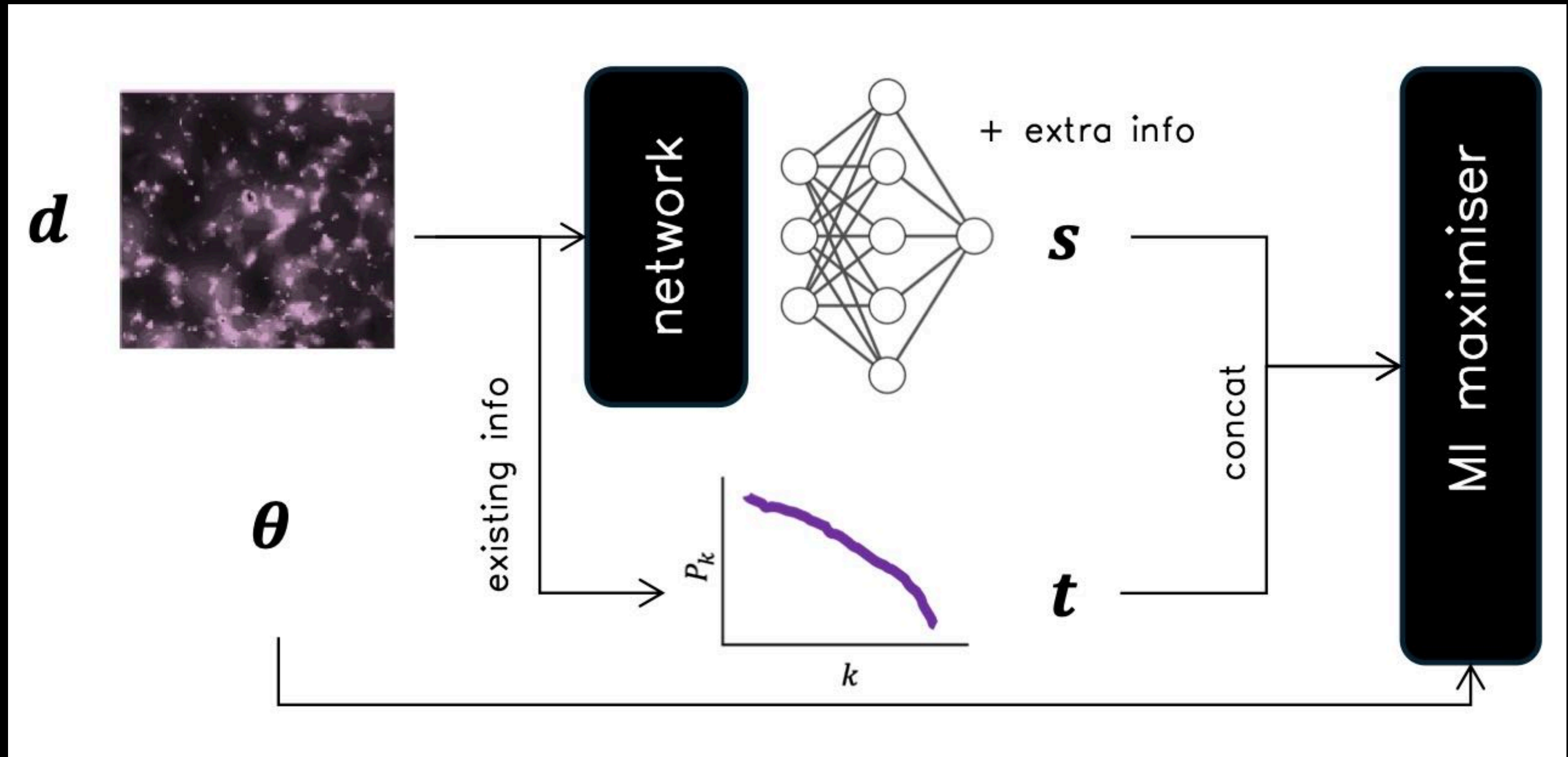
AI alternatives to Bayesian Hierarchical Models

- SBI requires extreme data compression
- Key: find highly-informative, massively compressed summary statistics
- Analytic: e.g. MOPED
- AI: e.g. CNN + NN compression, maximizing Mutual Information



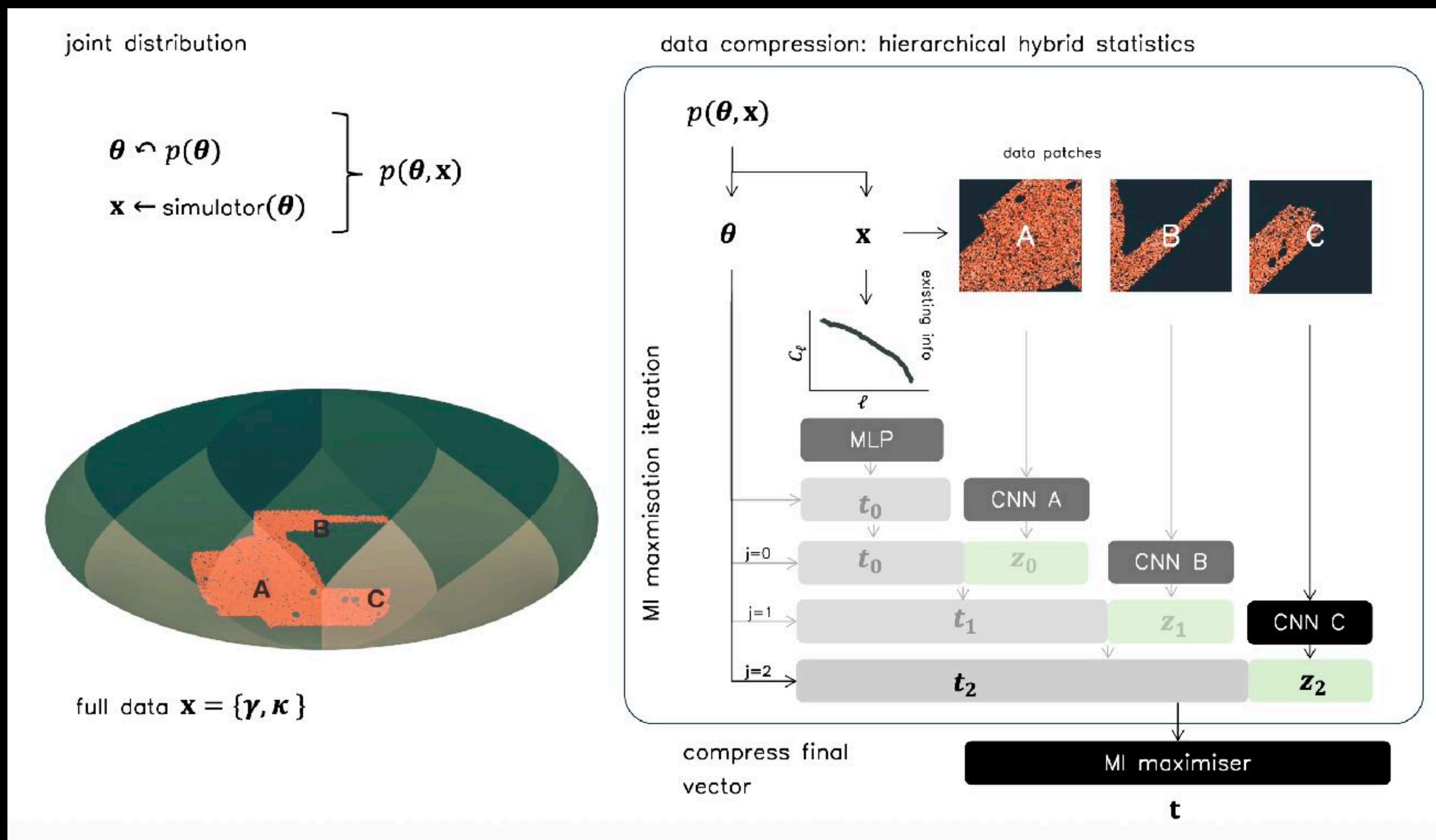
Reeves et al. 2024

Hybrid: power spectrum + field-based NN summaries



Lucas Makinen

Compression of all of DES Y3 to 6 numbers



Analysis of DES cosmic shear data

- Simulated data! Unblinding in a few weeks.

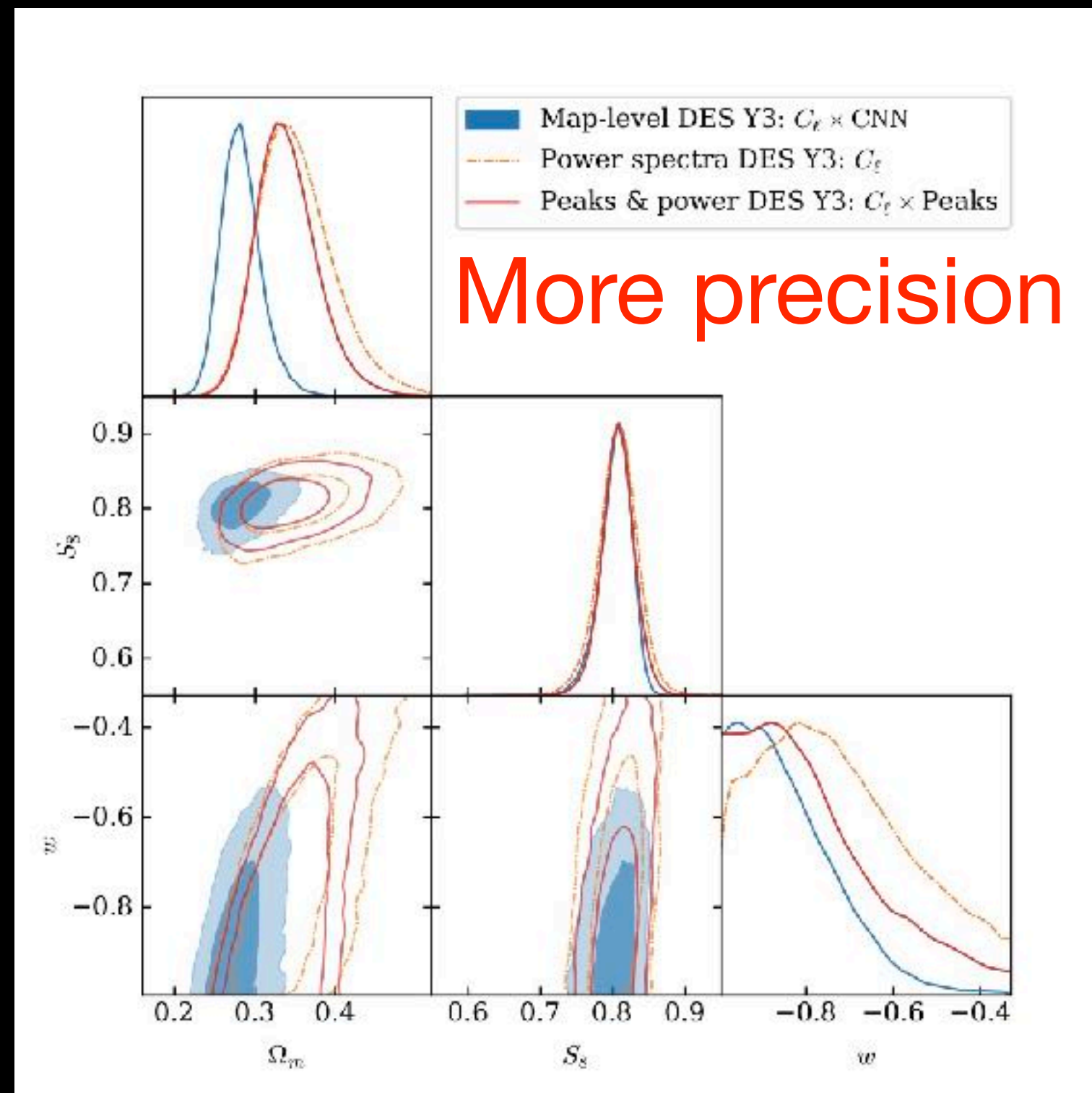


*Lucas Makinen +
Natalia Porqueres*



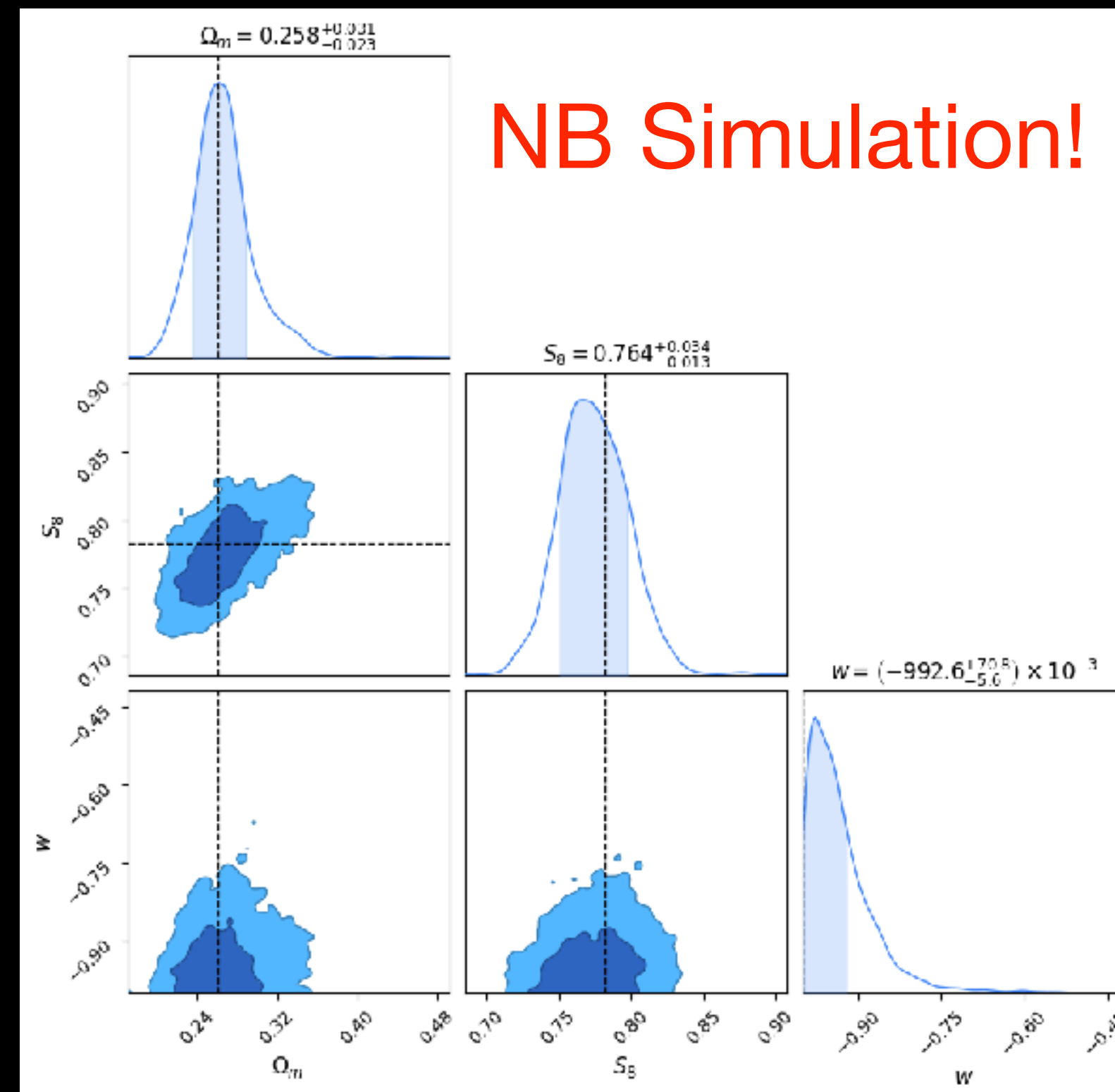
*Josh
Williamson
+Niall
Jeffrey++*

Suboptimal compression



Jeffrey et al 2024

Optimized hybrid statistics



Williamson, Makinen et al in prep.

Conclusions

- Traditional summary statistical inference is approximate
- Bayesian Hierarchical models are often the *only* way to compute the likelihood
- Field-level inference allows ‘all’ the data to be used
- Simulation-based inference can accommodate more complicated systematics
- BHM for Cepheids alone: Hubble tension reduced, using same SH0ES data
 $H_0 = 71.7 \pm 1.3 \text{ km s}^{-1} \text{ Mpc}^{-1}$. Only 2.6σ tension with ACT DR6.
- Hybrid AI summaries + SBI: tight constraint on w from cosmic shear (we hope)
- $w = ???$ Result coming soon!