Bayesian Forward Modeling of Galaxy Surveys

PERSPECTIVES ON LARGE SCALE STRUCTURE,SUMMER WORKSHOP
28-29 June 2023 Prague, Czech Republic

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for
the Aquila Consortium

Aquila UNIVERSITET STOCKHOLMS Oskar Klein centre Knut and Alice Wallenberg Foundation SF Vetenskapsrådet

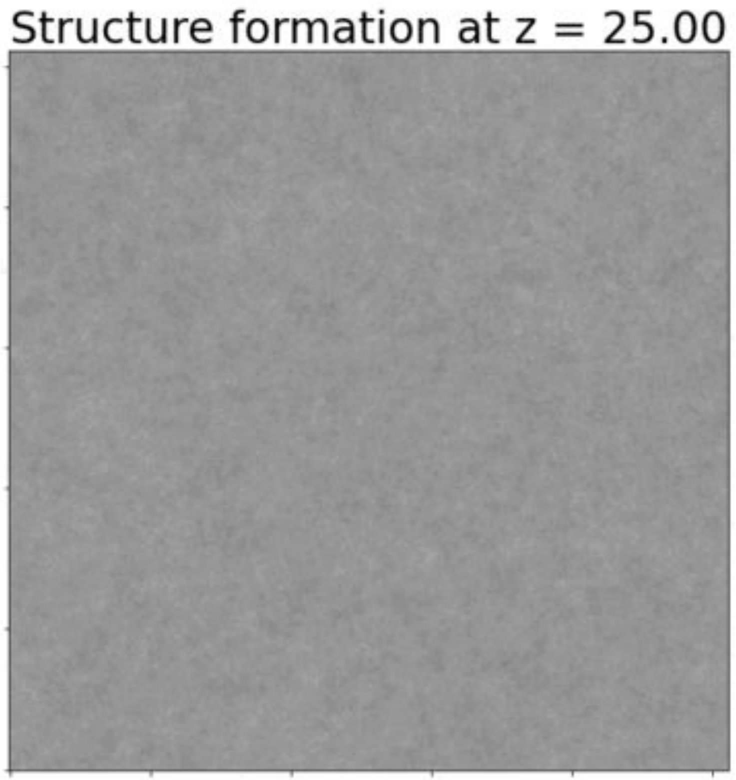
01

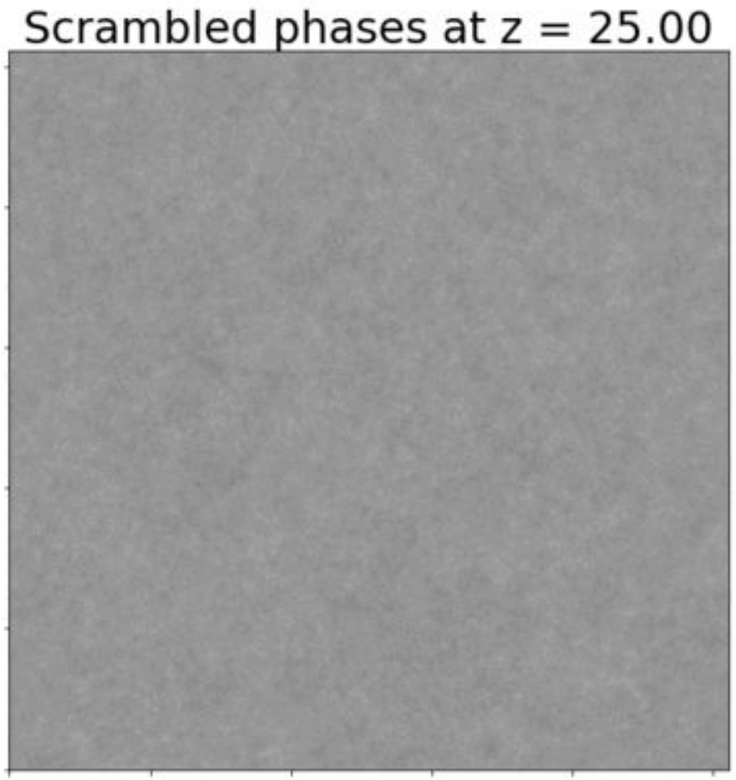
Motivation & Background

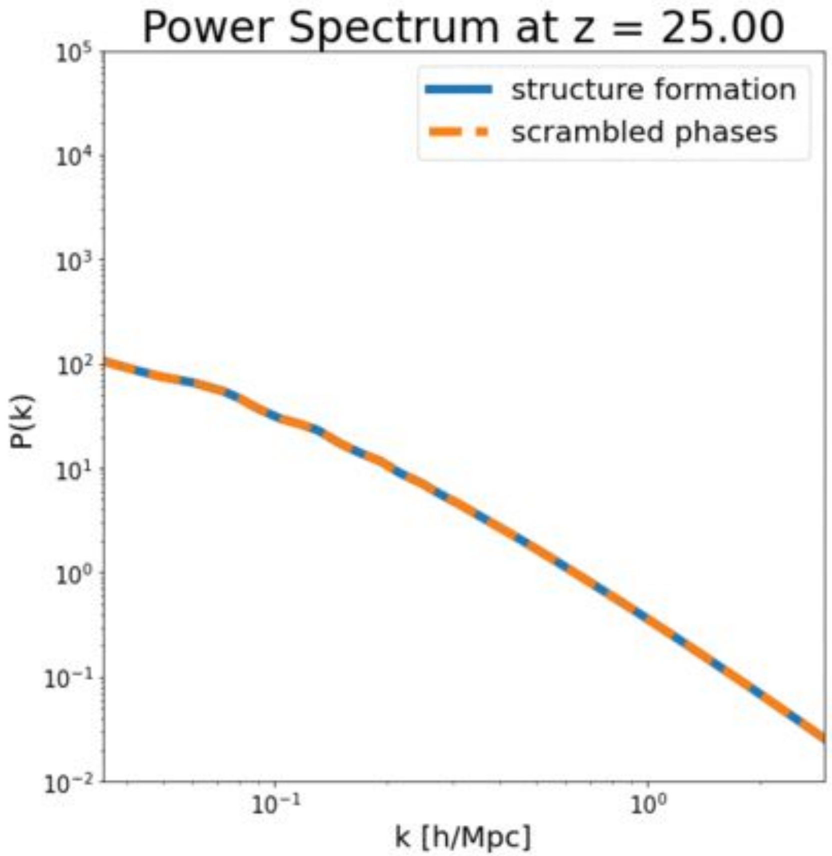
Bayesian forward modeling of
galaxy surveys

The limits of summary statistics

Traditionally cosmic structures are analyzed via summary statistics (mostly 2PT).







There exists no closed form description of the 3D matter distribution:

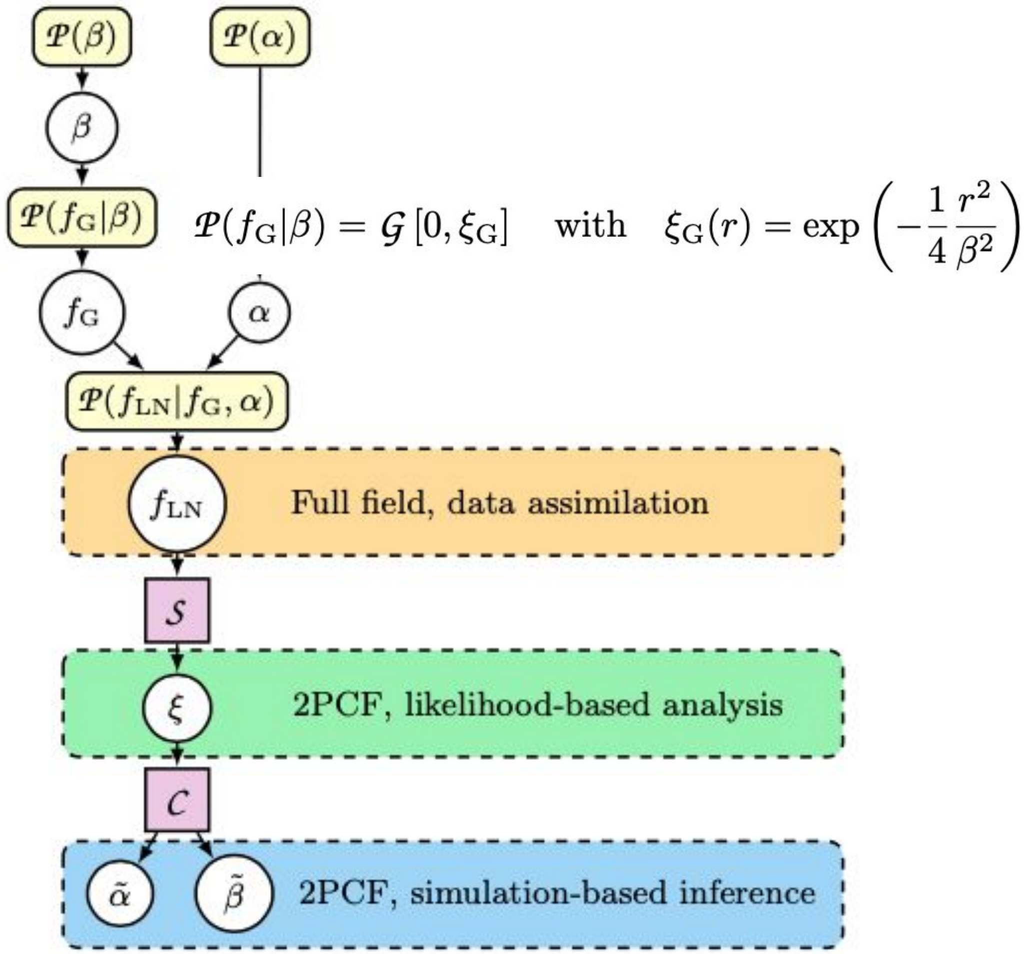
- **The hierarchy of statistical moments is not guaranteed to close (e.g. Carron & Neyrinck 2012)**

Should we rather use the entire field to do cosmology?

What analysis method to choose?

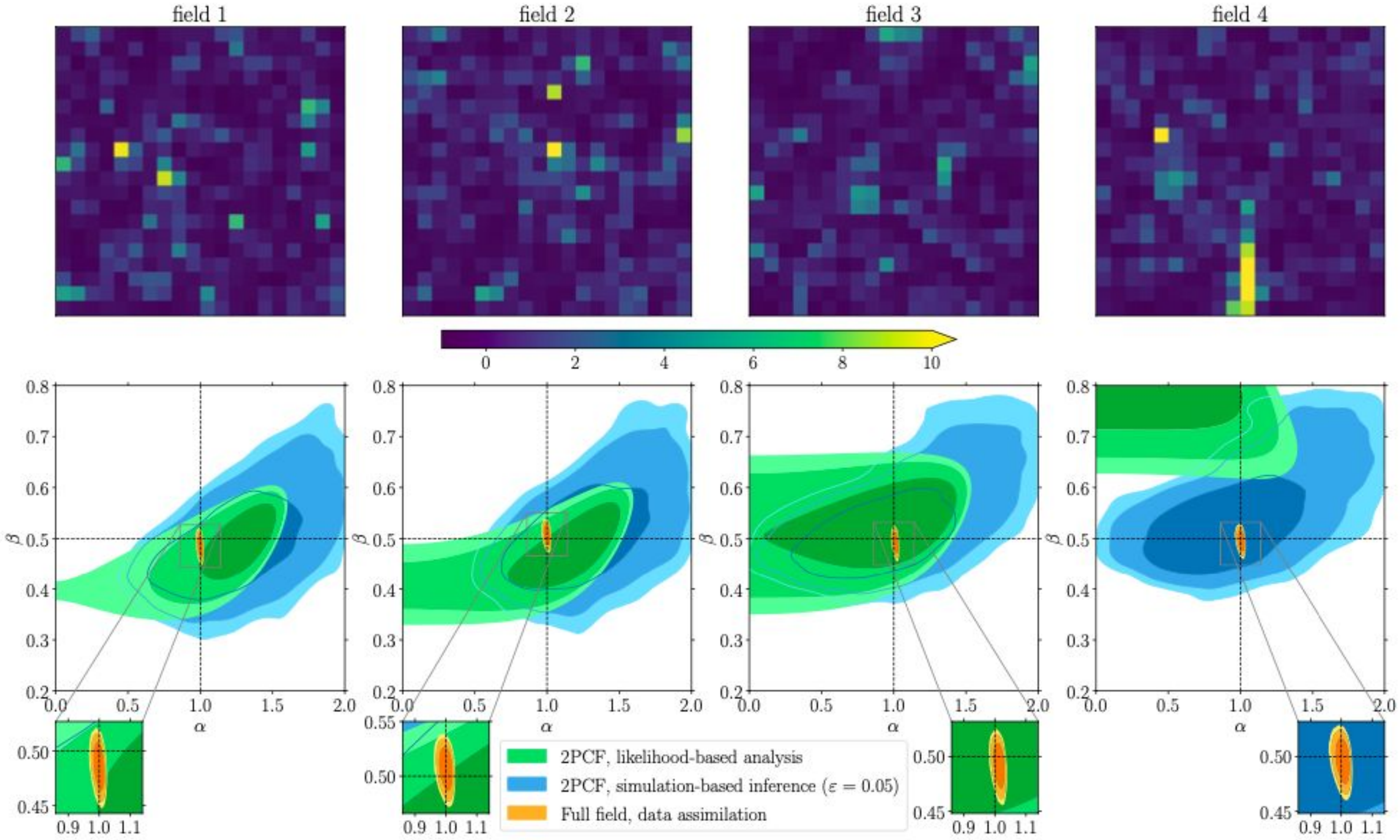
Compare 3 standard approaches:

- **Standard likelihood-based analysis (LBA)** of the two-point correlation function (2PCF), assuming a Gaussian distribution and fixed covariance matrix
- **Simulation-based inference (SBI)**, aka likelihood-free inference, ABC, based on the 2PCF
- **Field level data assimilation (DA)** technique, e.g. Bayesian forward modeling, BORG



Leclercq & Heavens 2021

Beyond summary statistics: Field level inference



Field level inference uses many more constraints of the data! (higher-order statistics)

[Leclercq & Heavens 2021]

(Also see McQuinn (2021))

BORG: Bayesian Physical forward modeling

Prior model

$$\mathscr{P}(\boldsymbol{s}|\boldsymbol{S}) = \frac{\mathrm{e}^{-\frac{1}{2}\boldsymbol{s}^{\mathrm{T}}\boldsymbol{S}^{-1}\boldsymbol{s}}}{\sqrt{\det(2\pi\boldsymbol{S})}}$$

Structure formation model

$$\mathscr{P}(\boldsymbol{\delta}|\boldsymbol{s}) = \prod_i \delta^D\left(\delta_i - G_i(\boldsymbol{s})\right)$$

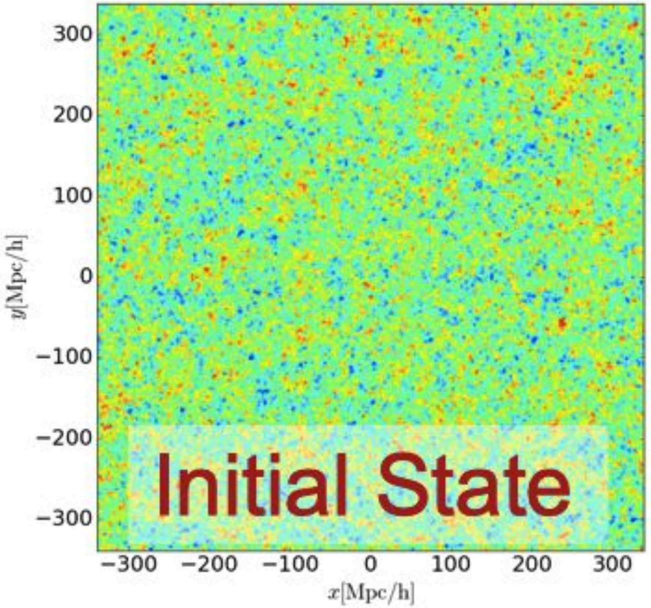
$$\boxed{\begin{aligned} \frac{\mathrm{d}\vec{x}}{\mathrm{d}a} &= \frac{\vec{p}}{\dot{a}a^2} \\ \frac{\mathrm{d}\vec{p}}{\mathrm{d}a} &= -\frac{3}{2}H_0^2\Omega_m\frac{\nabla^2\Phi}{Ha^2} \end{aligned}}$$

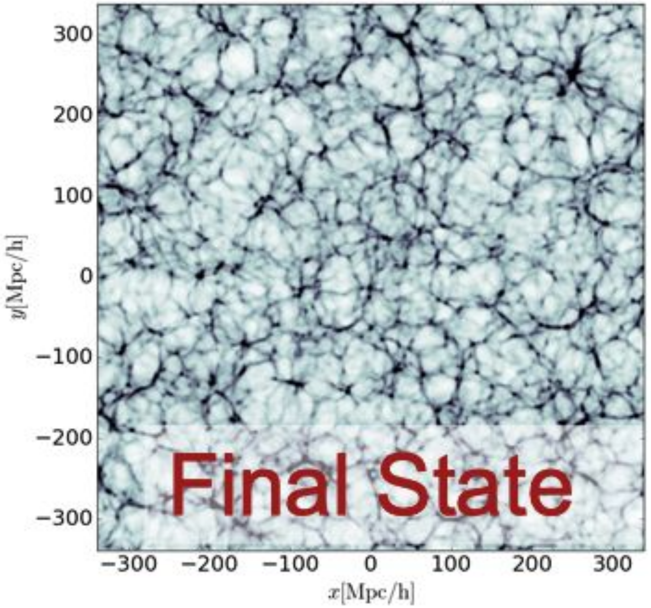
Data model

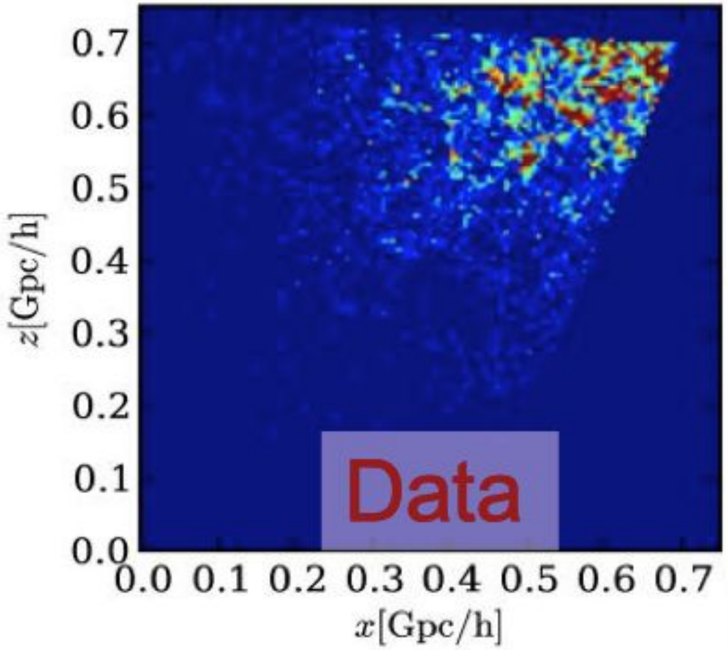
$$\mathscr{P}(\boldsymbol{N}|\boldsymbol{\lambda}(\boldsymbol{\delta})) = \prod_i \frac{\mathrm{e}^{-\lambda_i}\lambda_i^{N_i}}{N_i\,!}$$

Galaxy bias model

See e.g. Neyrinck et al. 2014
Lavaux & Jasche 2016







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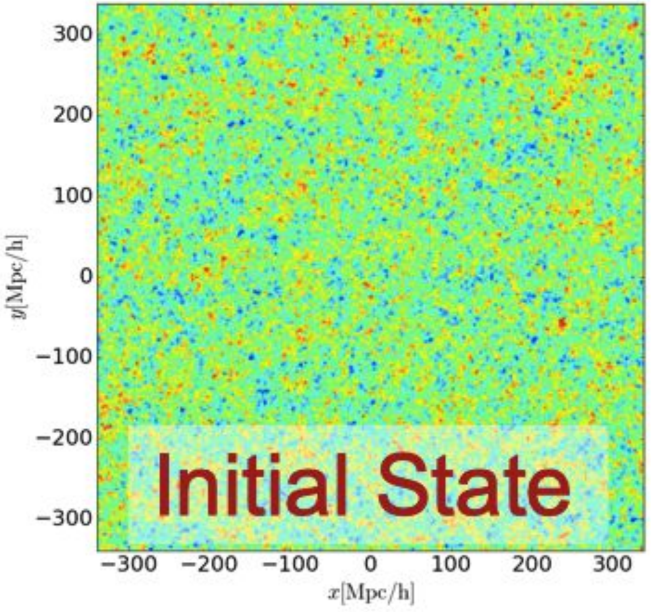
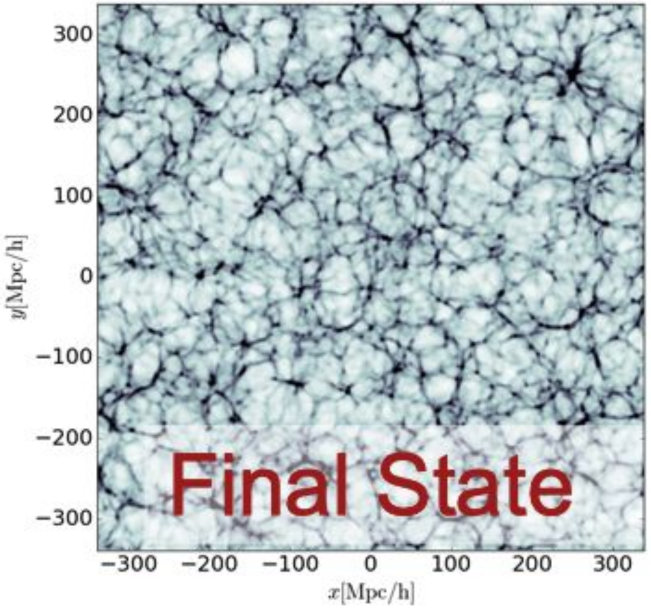
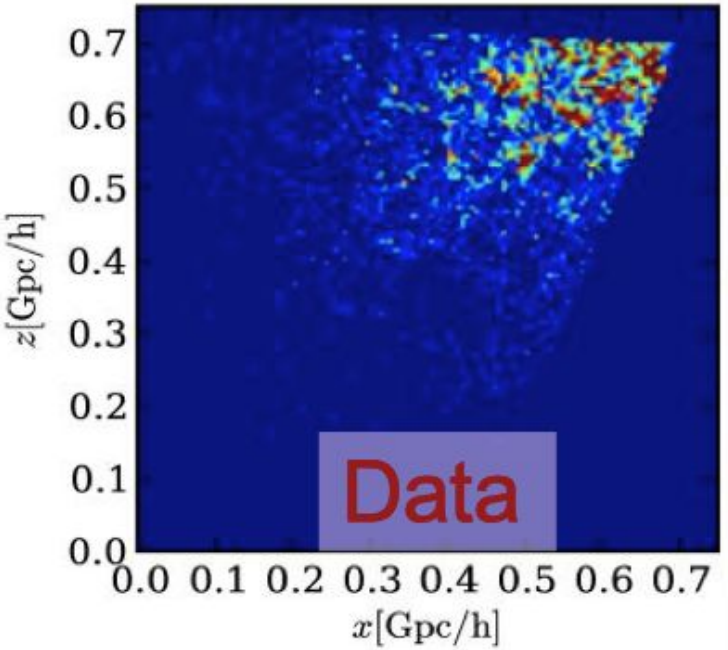
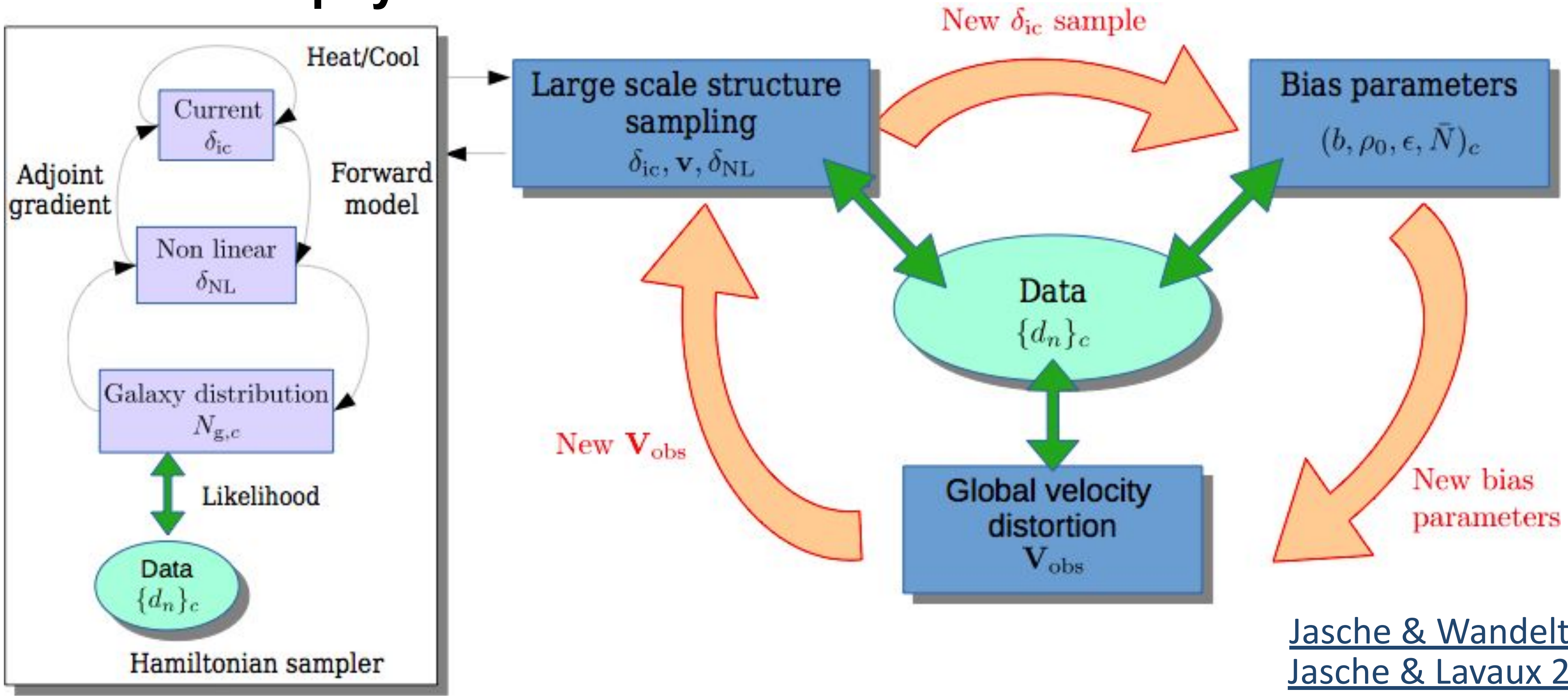






BORG's MCMC framework allows building flexible data models

- Hierarchical Bayes and block sampling
- Efficient Hamiltonian Monte Carlo technique
- **Fully differentiable physics forward model**



Jasche & Wandelt 2014
Jasche & Lavaux 2019

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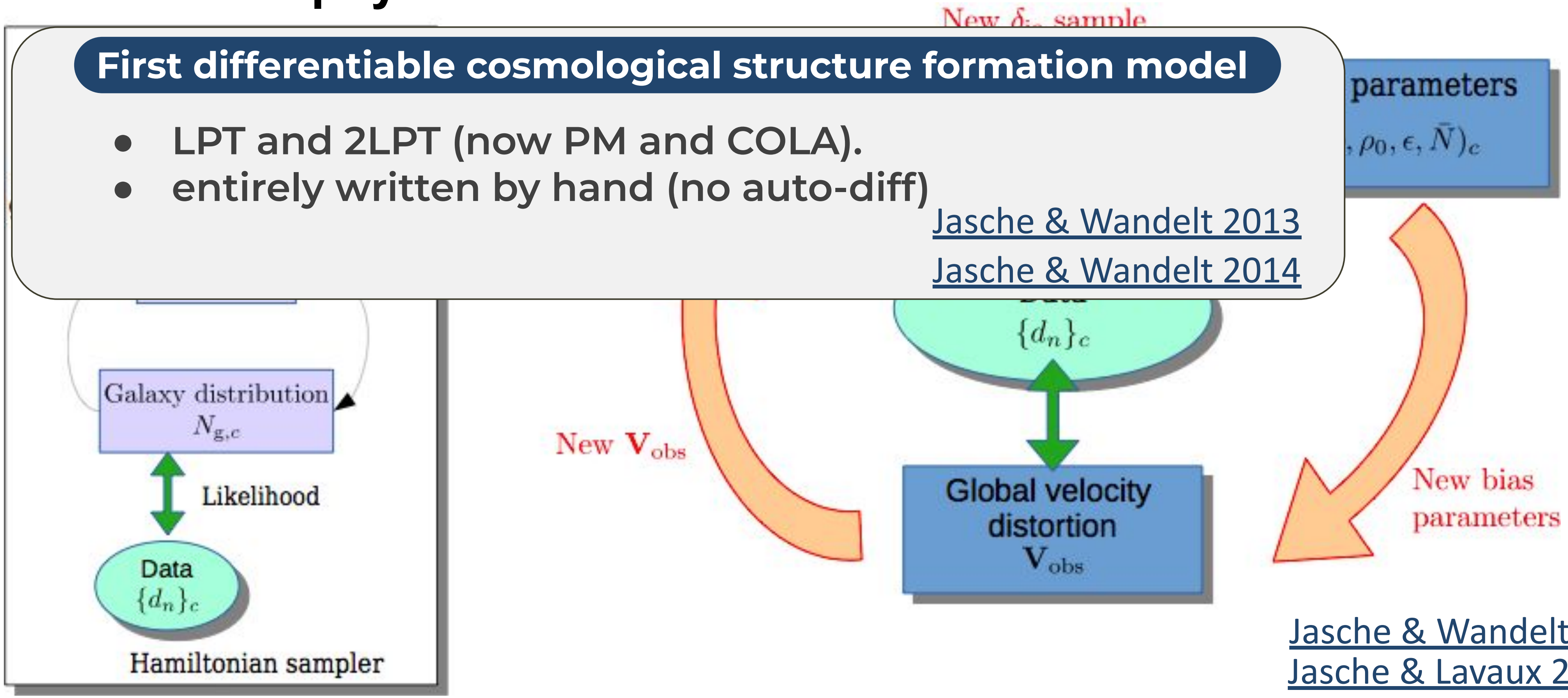


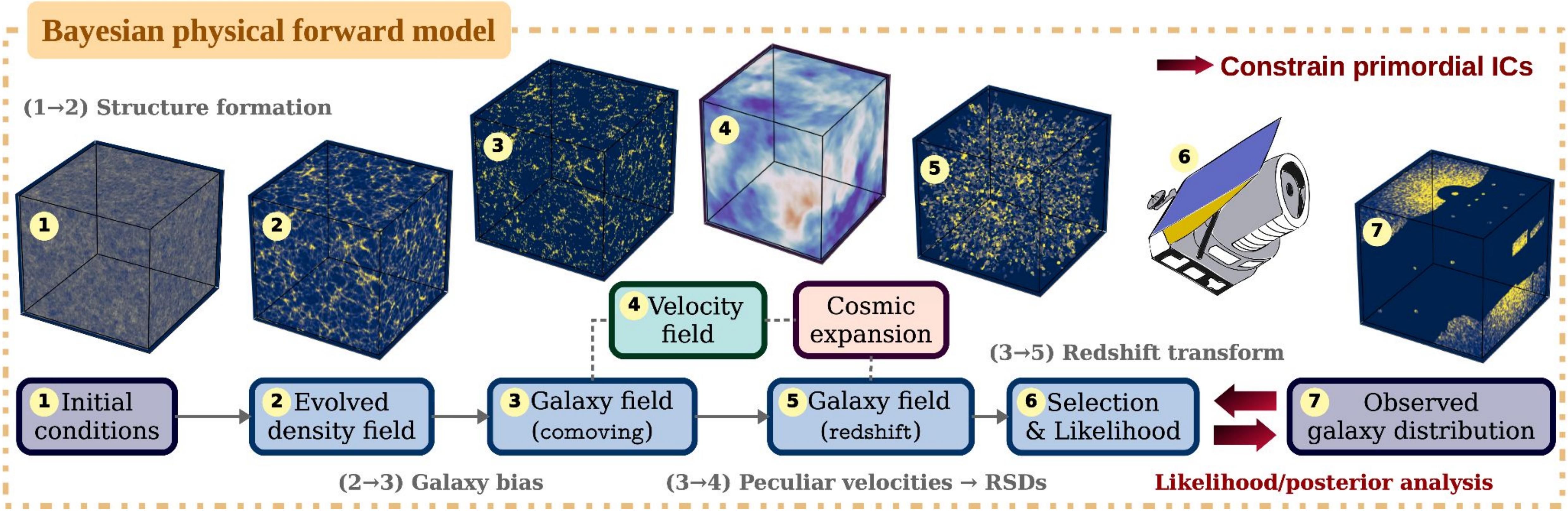
First differentiable cosmological structure formation model

- LPT and 2LPT (now PM and COLA).
- entirely written by hand (no auto-diff)

Jasche & Wandelt 2013
Jasche & Wandelt 2014

Jasche & Wandelt 2014
Jasche & Lavaux 2019

Bayesian Physical forward modeling

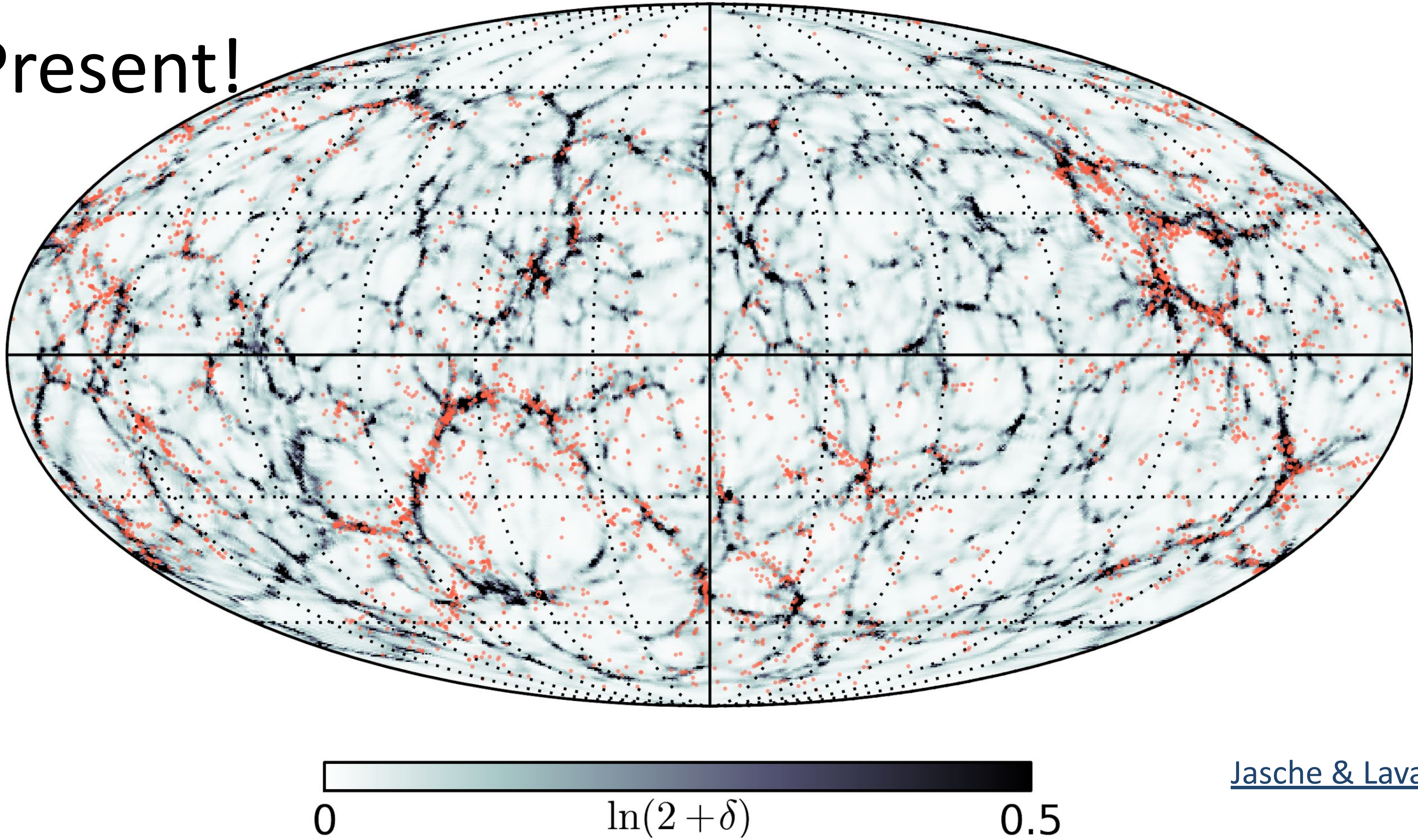


Now several groups are developing Forward Modeling approaches.

Jasche & Wandelt 2014
Wang et al 2014
Jasche, Leclercq, Wandelt 2015
Lavaux & Jasche 2016
Jasche & Lavaux 2019
Kitaura et al 2021
Ata et al 2022
Kostic et al. 2022

Bayesian forward modeling of the 2M++ galaxy compilation (JJ + Guilhem Lavaux)

The Present!



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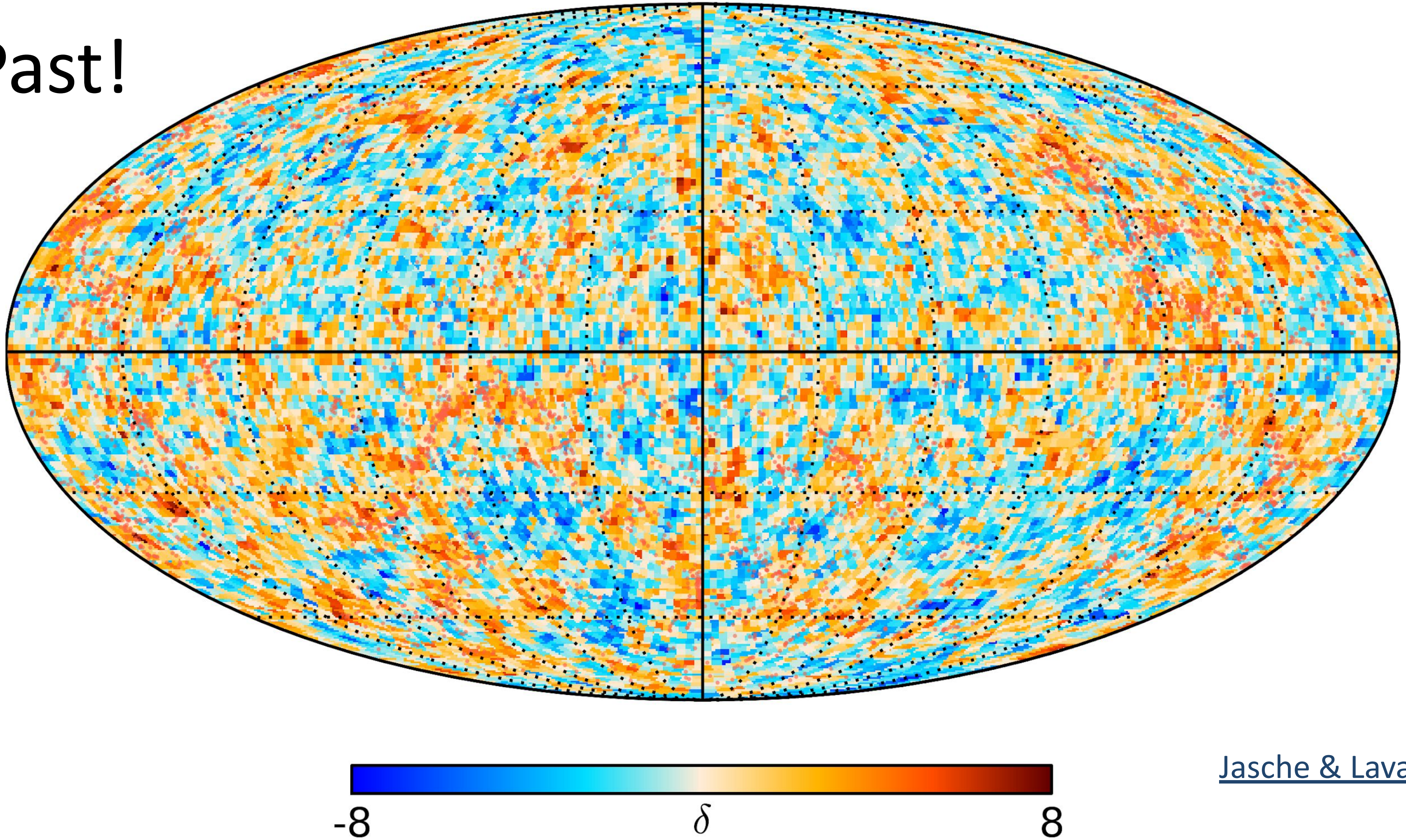
The Past!



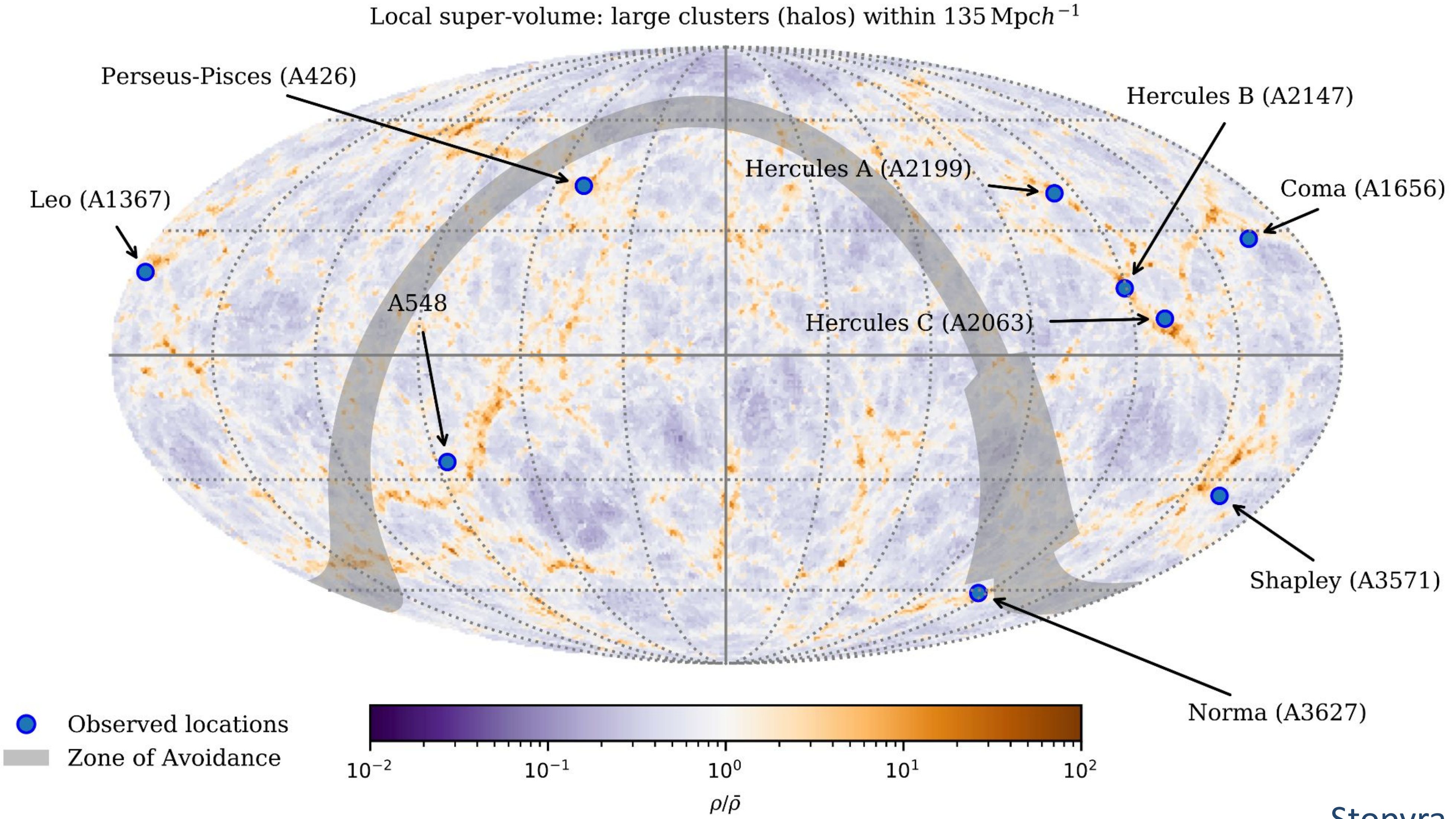
Jasche & Lavaux 2019

02

Measuring Cluster Masses

How rare is the local super volume?

How rare is the local super volume? (Stephen Stopyra)



Stopyra et al 2021

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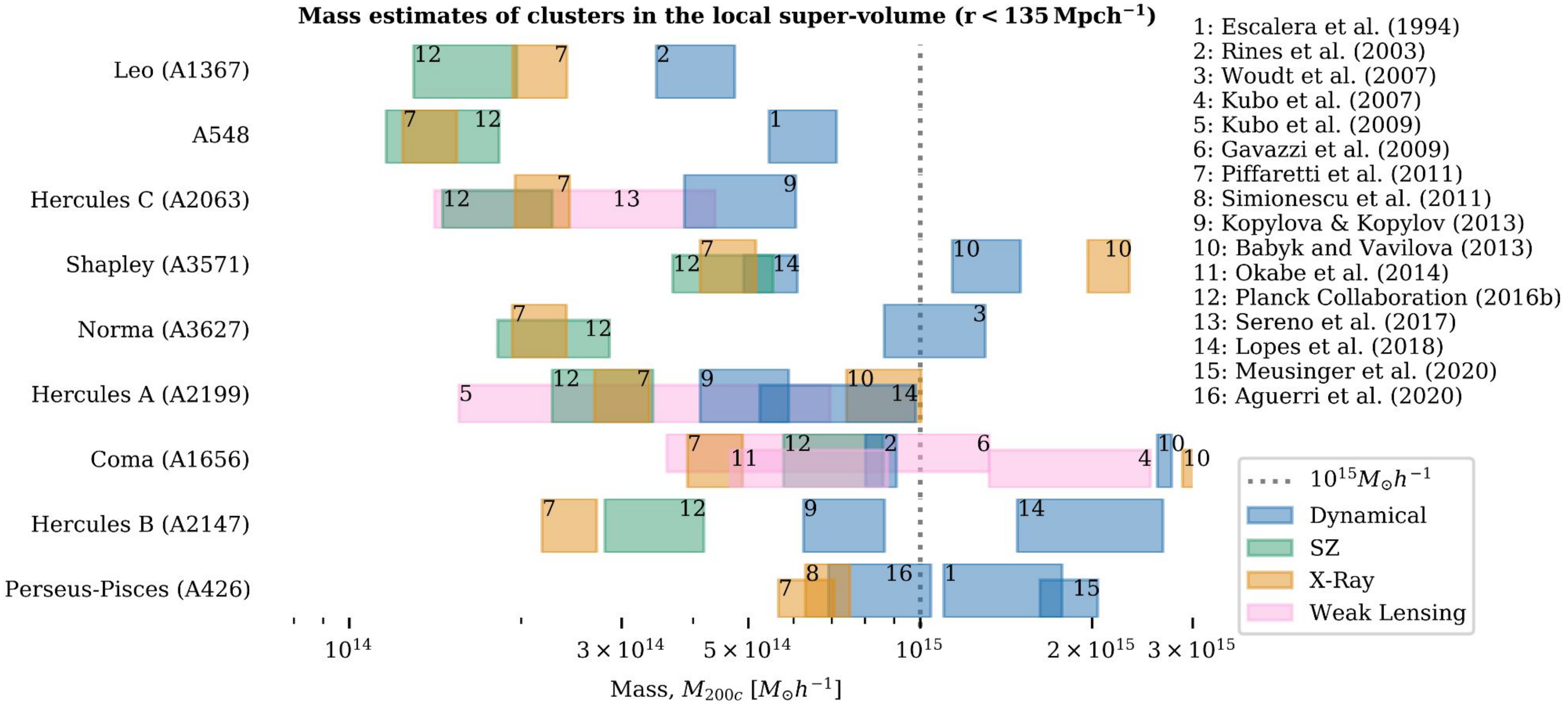


An intriguing situation: Is the local super-volume compatible with ΛCDM or not?

Stopyra et al 2021

How rare is the local super volume? (Stephen Stopyra)

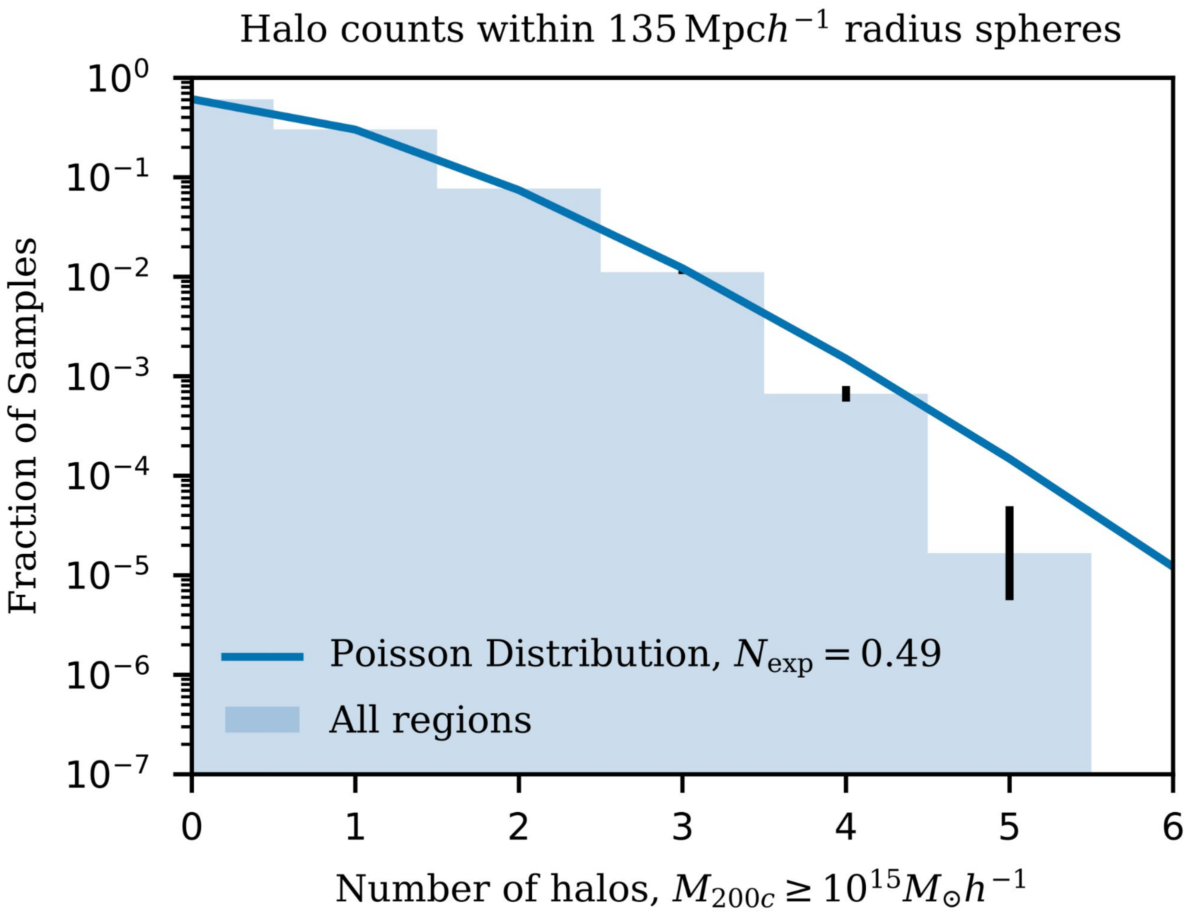
Prevalence of most massive nearby halos:

- Likelihood of finding N clusters with $M_{200c} \geq 10^{15} M_\odot h^{-1}$:

$$\mathcal{L}(N|N_{\mathrm{exp}}) = \frac{N_{\mathrm{exp}}^{N}\, \mathrm{e}^{-N_{\mathrm{exp}}}}{N!}$$

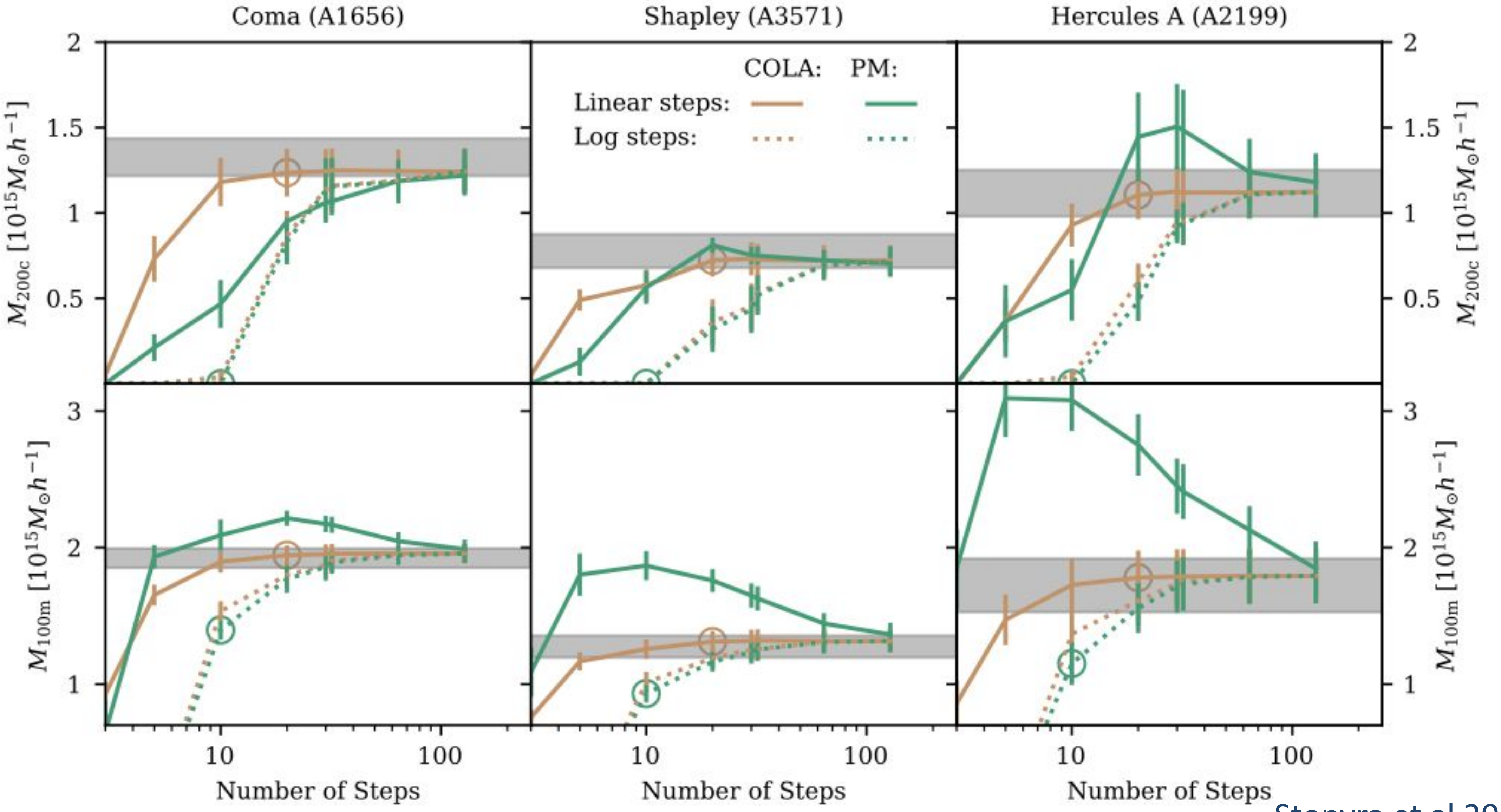
with N_{exp}= 1.

- A few high-mass halos can pose a significant challenge to ΛCDM. [Frenk et al 1990]



[Stopyra et al 2021]

Required simulator accuracy for Massive Cosmic Structures inference (Stephen Stopyra)



Stopyra et al 2023

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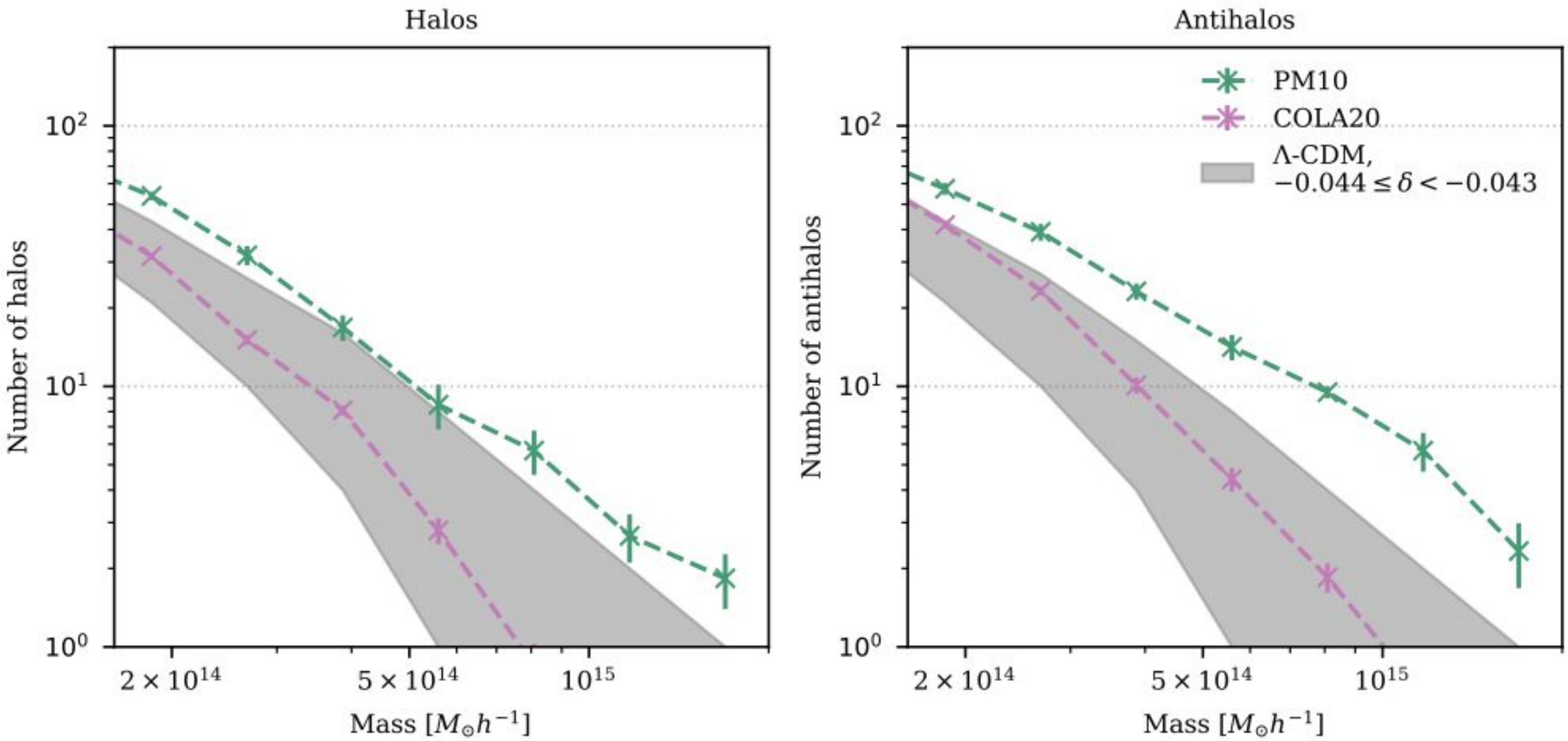

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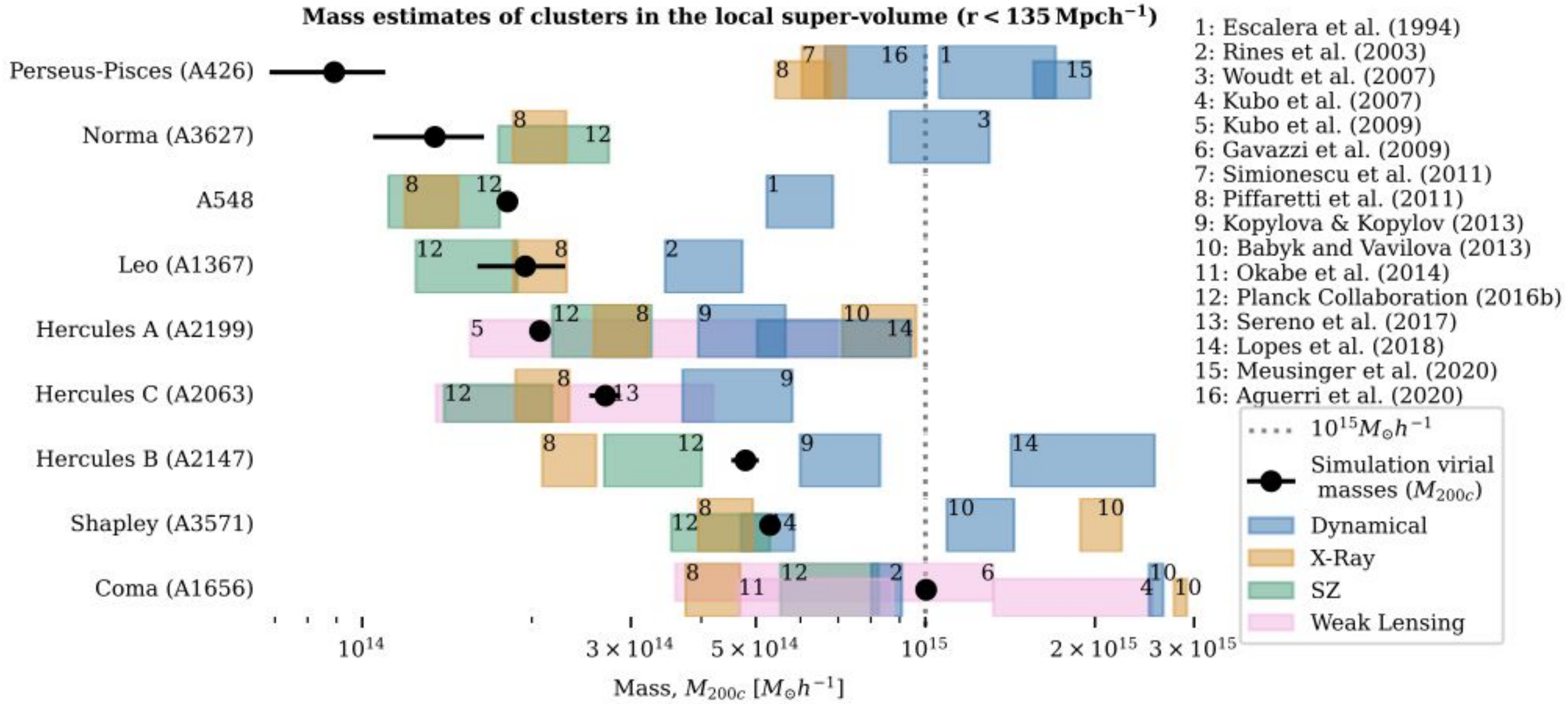


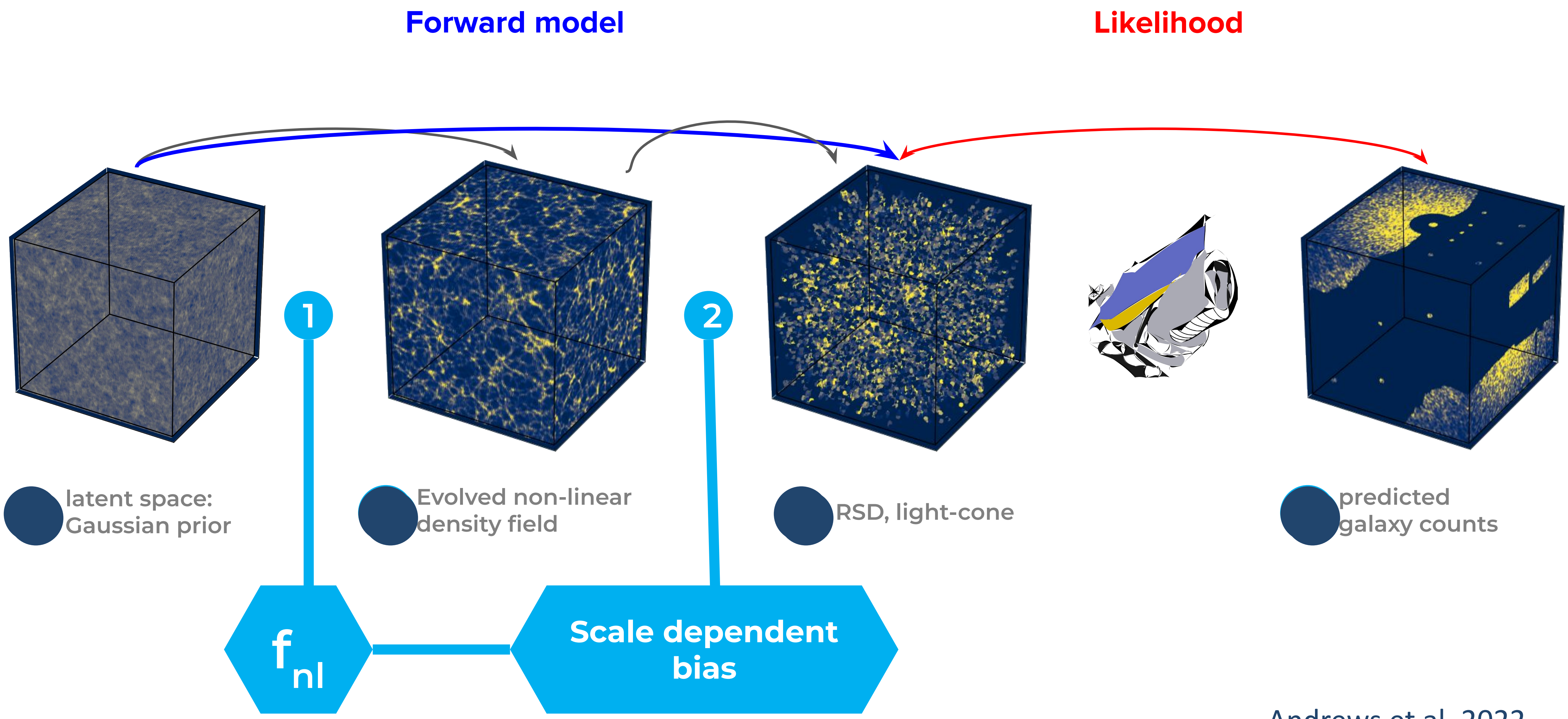
Stopyra et al 2023

03

Testing cosmology

inferring cosmological parameters

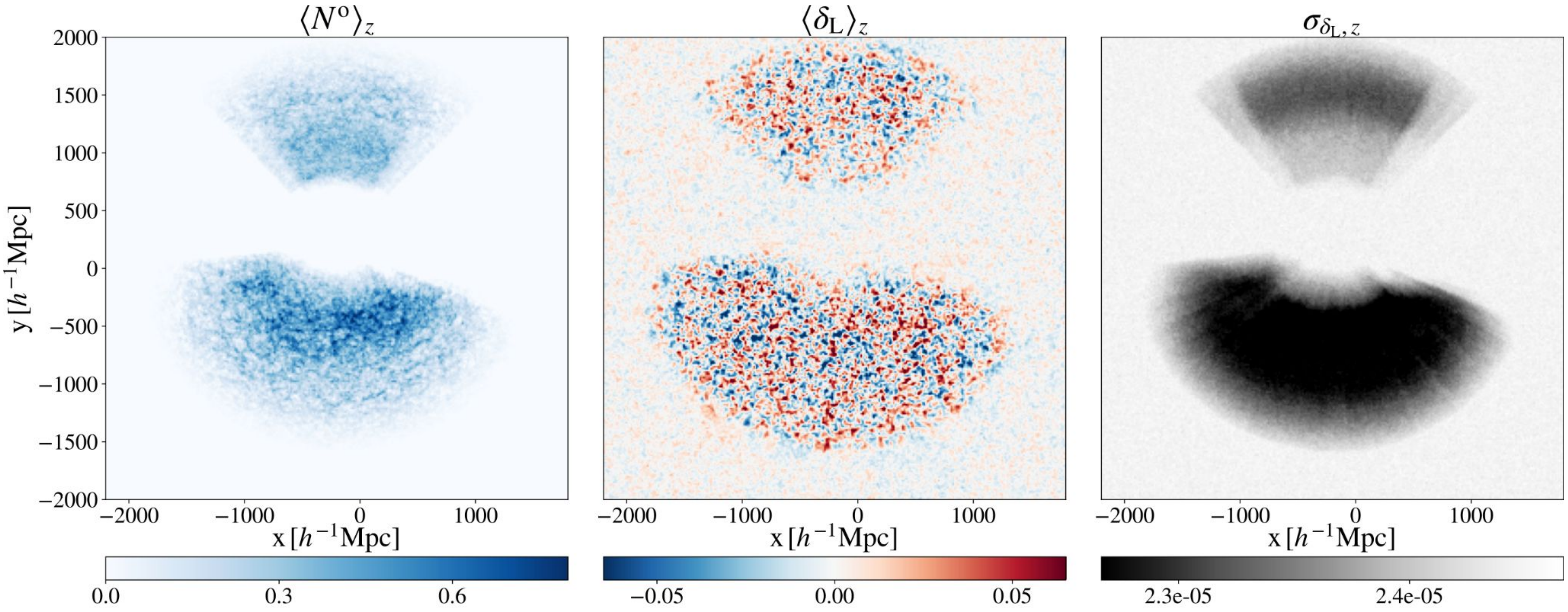
Bayesian forward modeling of Primordial Non-Gaussianity Non-Gaussianity (Adam Andrews)



Andrews et al. 2022

Physical forward modeling of PNG at the level of 3d fields (Adam Andrews)

SDSS3 Mock analysis: Primordial fluctuations field inference from galaxy mock data



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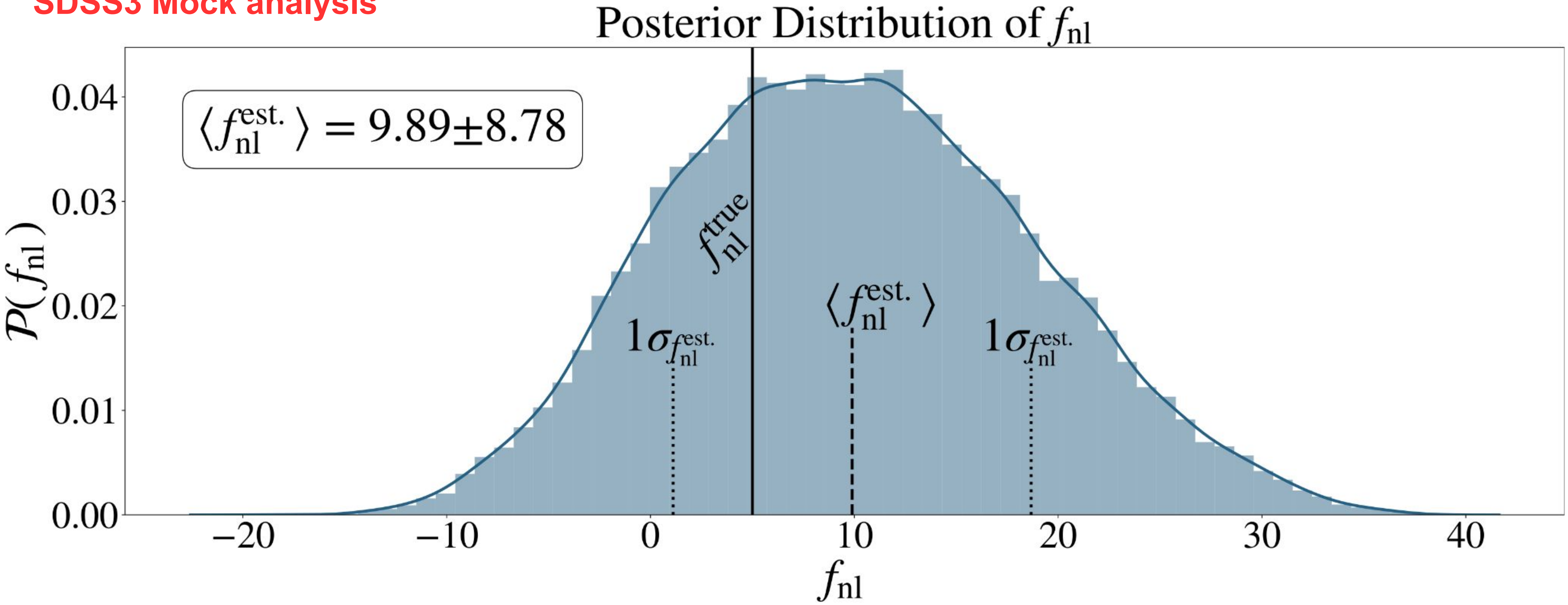
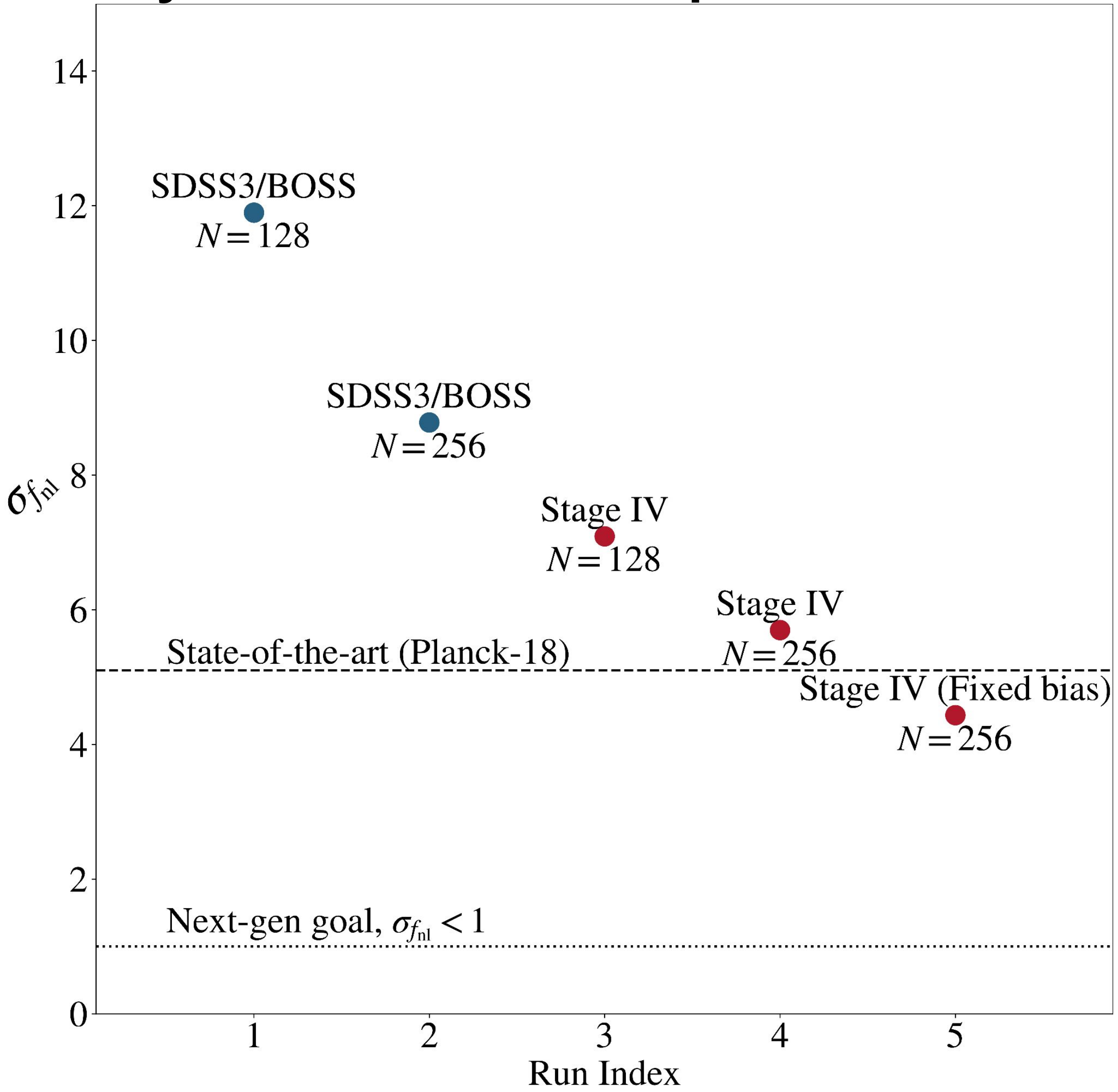


Current state-of-the-art (SDSS3): f_{nl} = -30 ± 29 (D'Amico et al 2022)

Andrews et al. 2022

Physical forward modeling of PNG at the level of 3d fields (Adam Andrews)

Higher resolution of density reconstructions improves PNG constraints.



Andrews et al. 2022

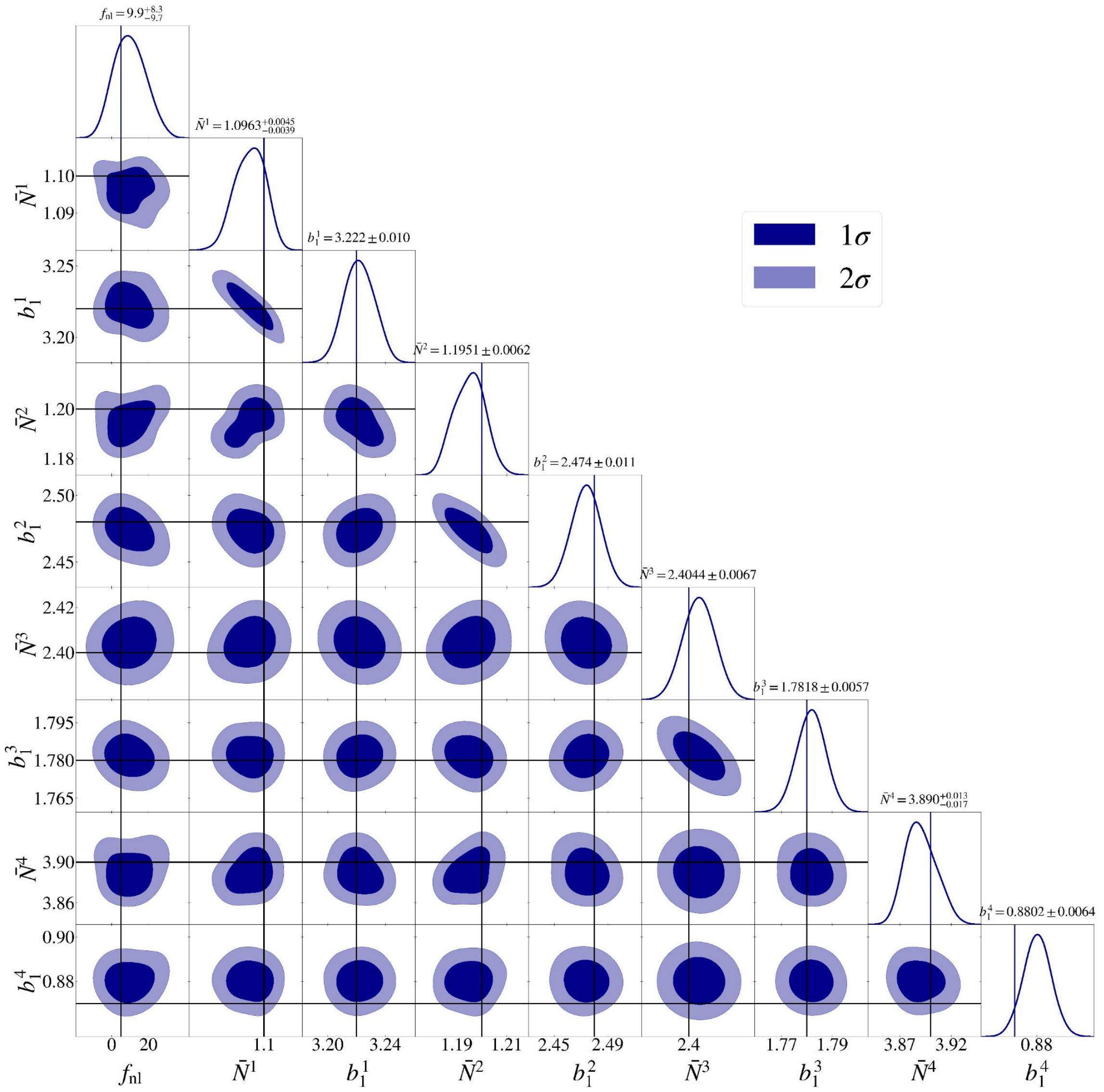
Physical forward modeling of PNG at the level of 3d fields (Adam Andrews)

BORG provides full statistical control

- Covariance matrices of all parameters of the data model
- Marginalizing out nuisance parameters

BORG handles various effects

- Survey Geometries
- Noise
- RSDs
- Light cone effects



Andrews et al. 2022

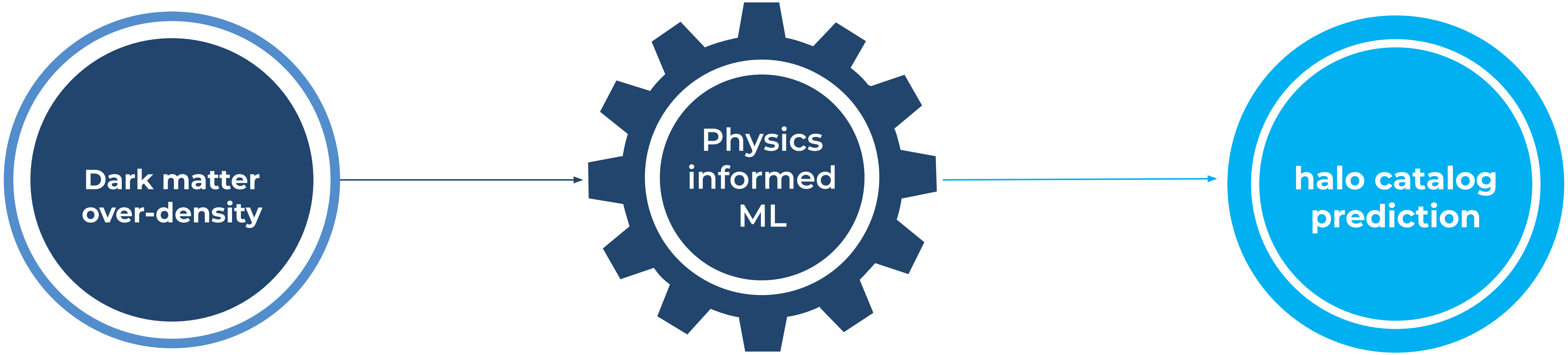
04

Non-linear biases

connecting DM fields with observables

Neural Physical Engine (NPE) (Simon Ding, Tom Charnock)

Preliminary Work!



From approximate simulators e.g. 2LPT

- **Fast & Differentiable**
- **Stochastic**
- **Explainable**
- **17-32 parameters**

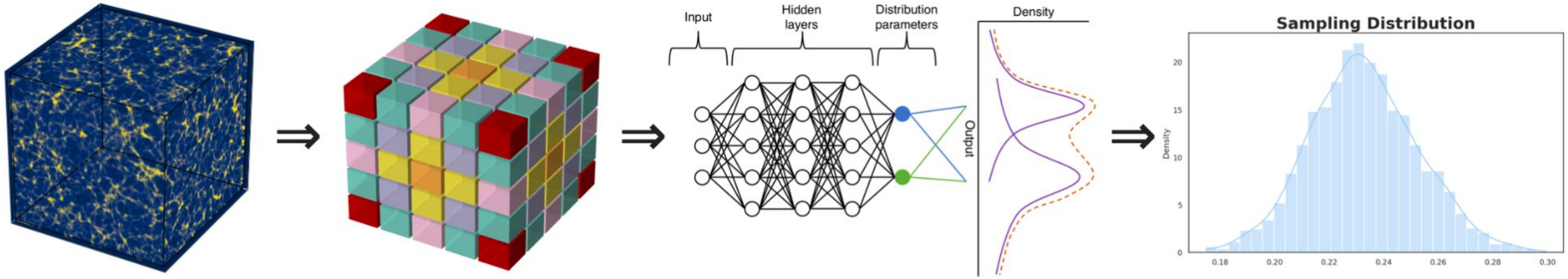
Validation:
- **1pt**
- **2pt**
- **field-level**

Ding et al in prep
Charnock et al 2020

Neural Physical Engine (NPE) (Simon Ding, Tom Charnock)

Preliminary Work!

- Use non-local information
- Use isotropy
- Model non-linearity
- Generative process



$\delta_m(x) \rightarrow$ **Convolve** $\rightarrow$ **Transform** $\rightarrow$ **Sample** $\rightarrow$ $n\left(M|\delta_m(x)\right)$

Ding et al in prep
Charnock et al 2020

credit for slide: Simon Ding

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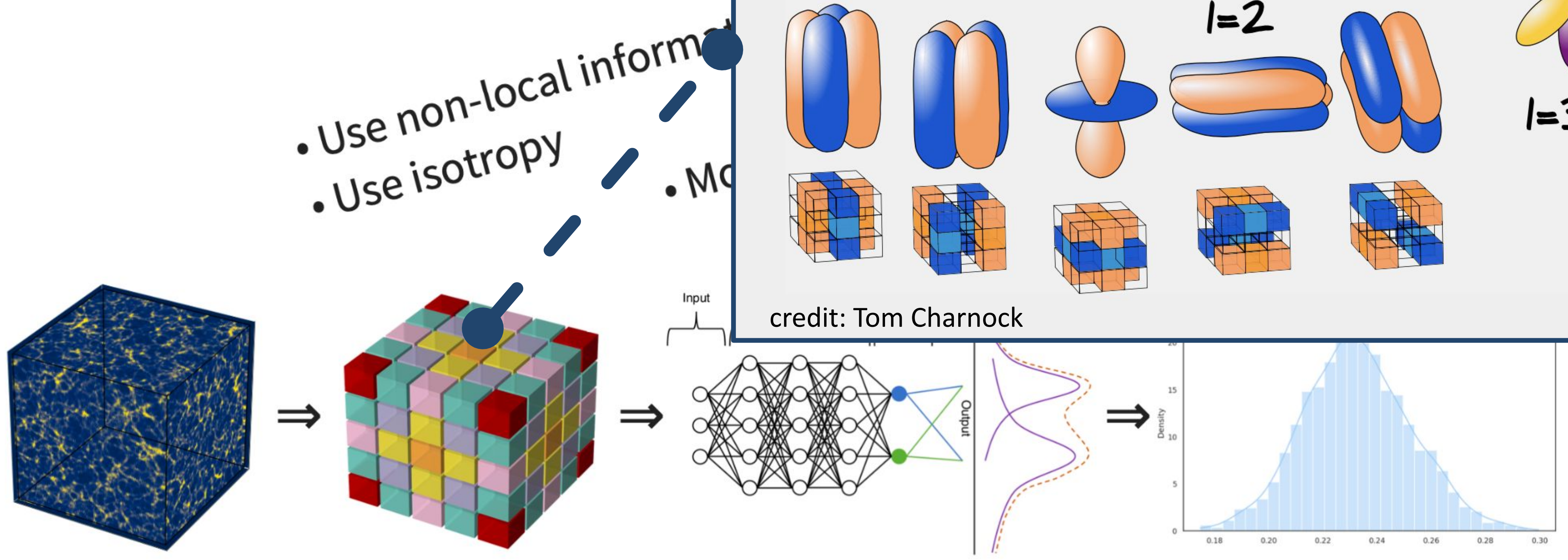

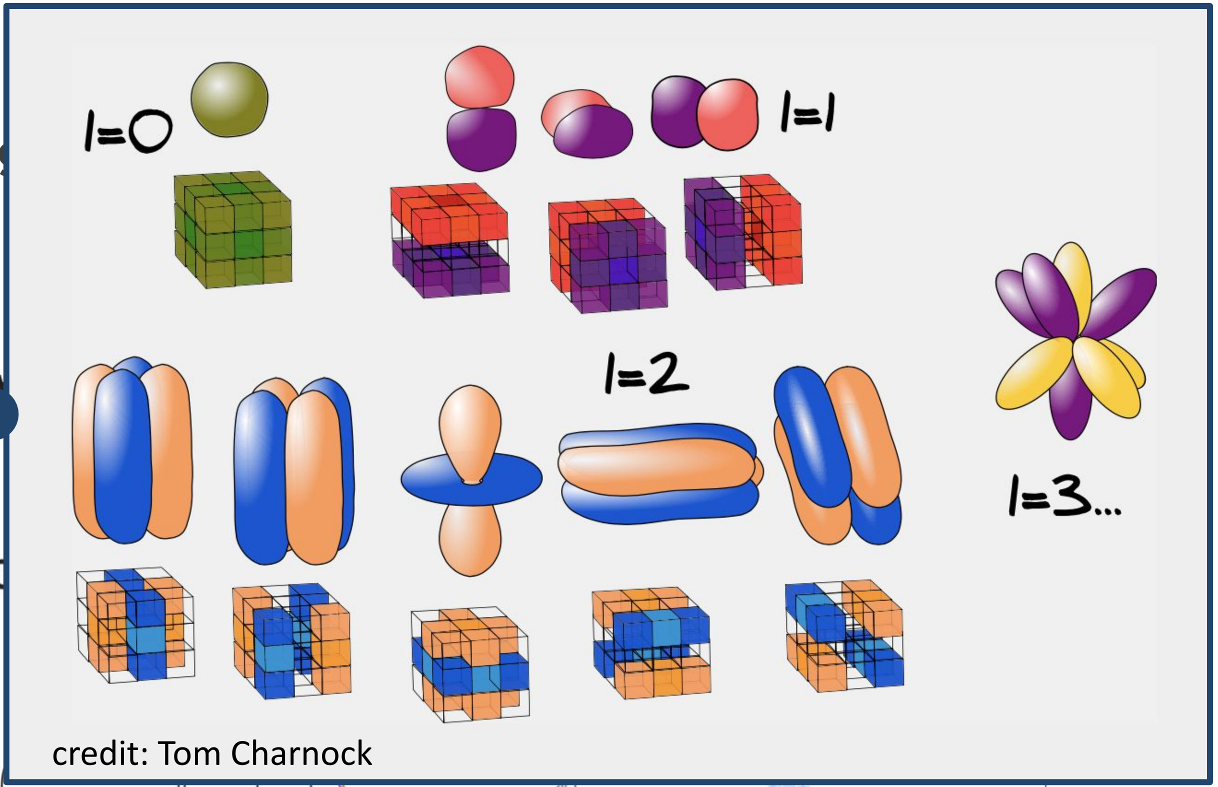

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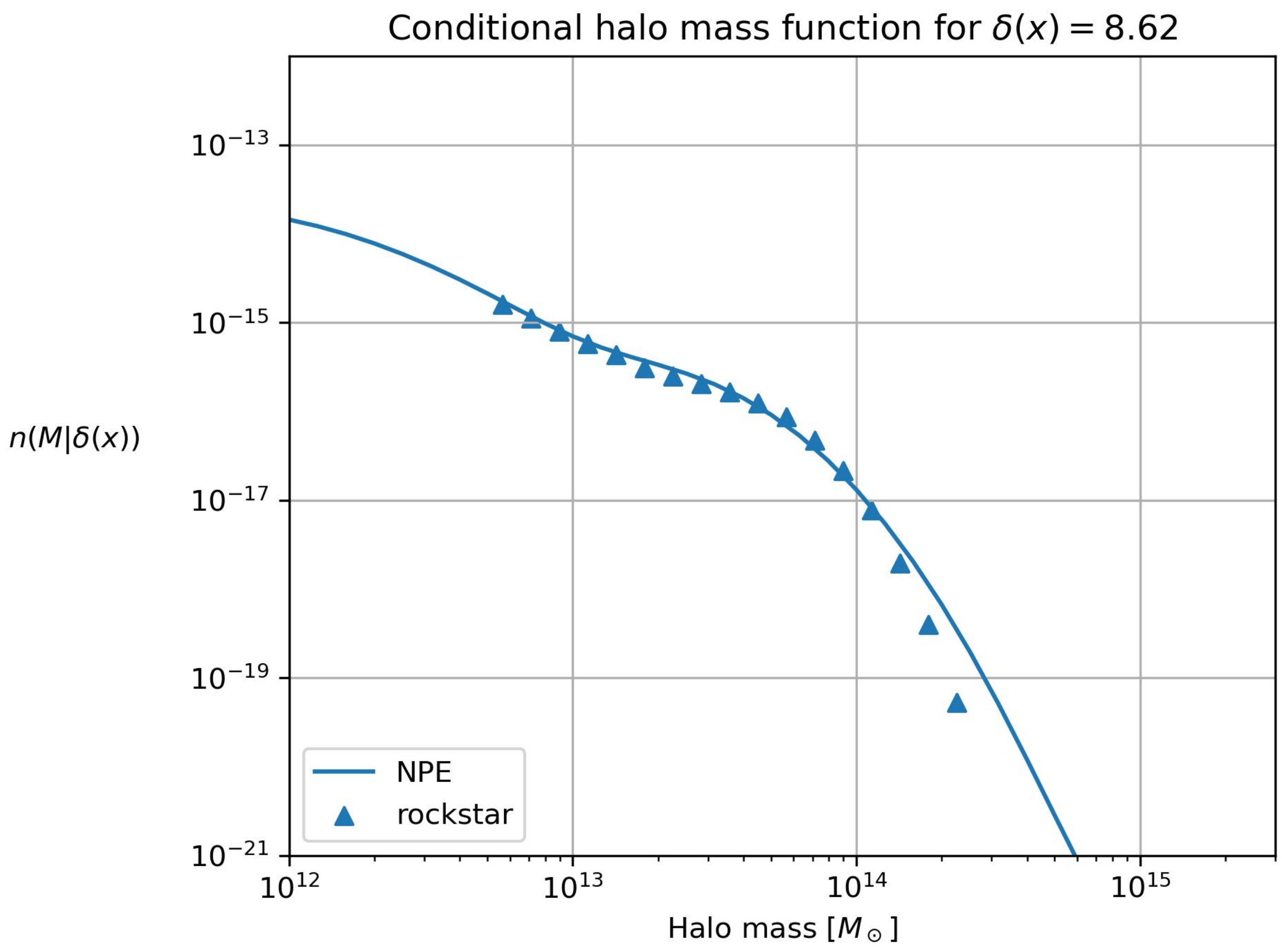

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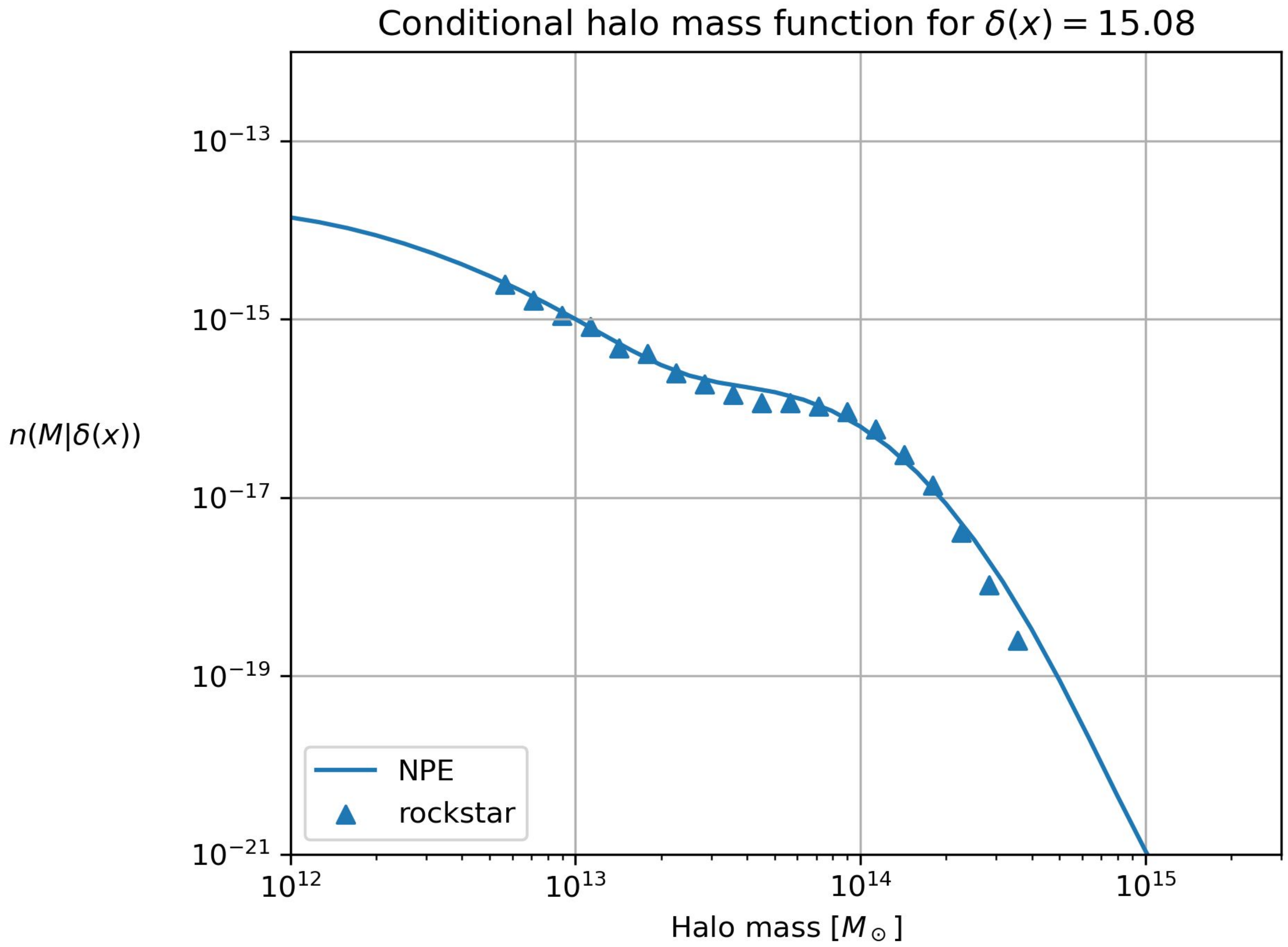

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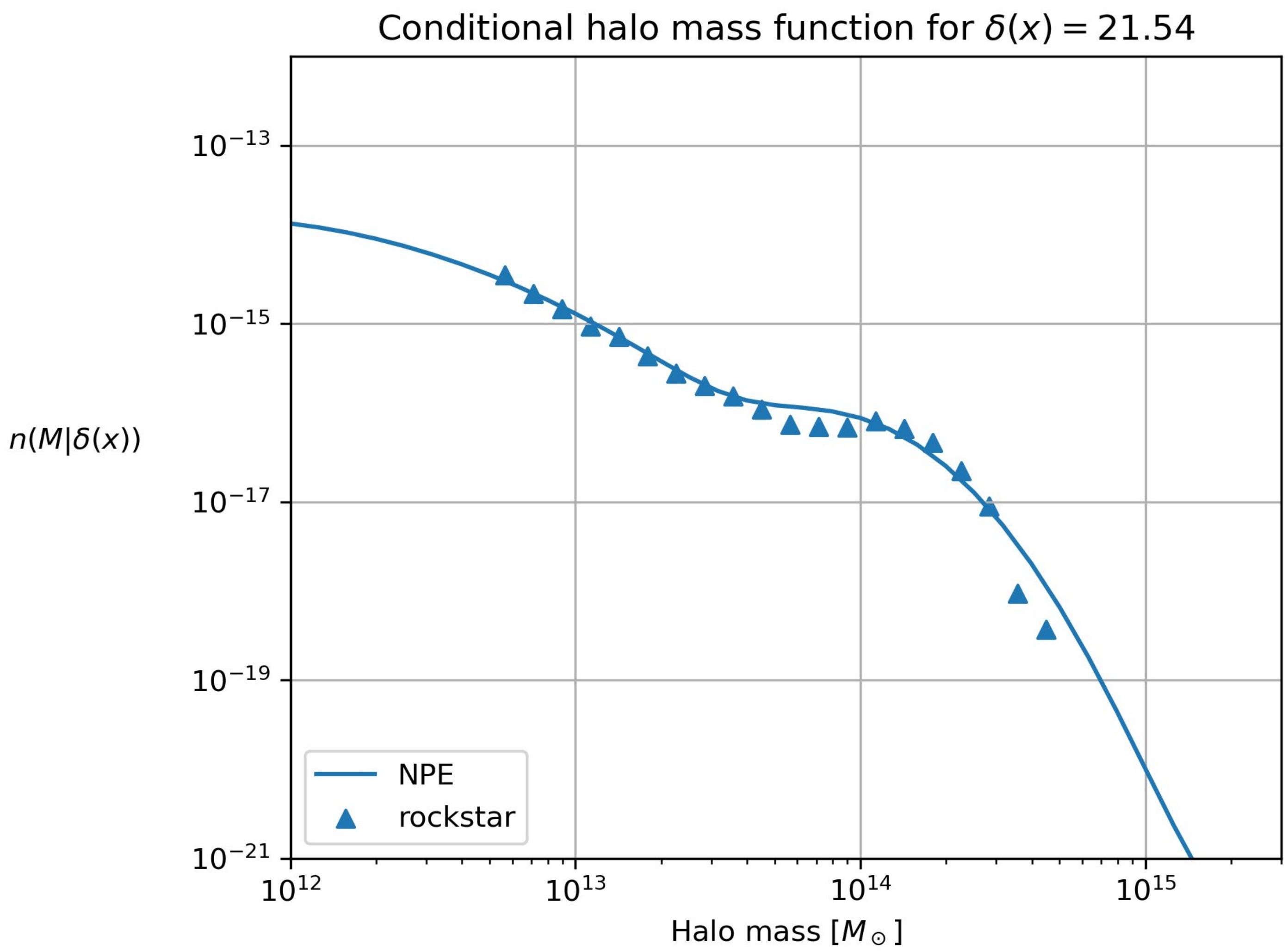

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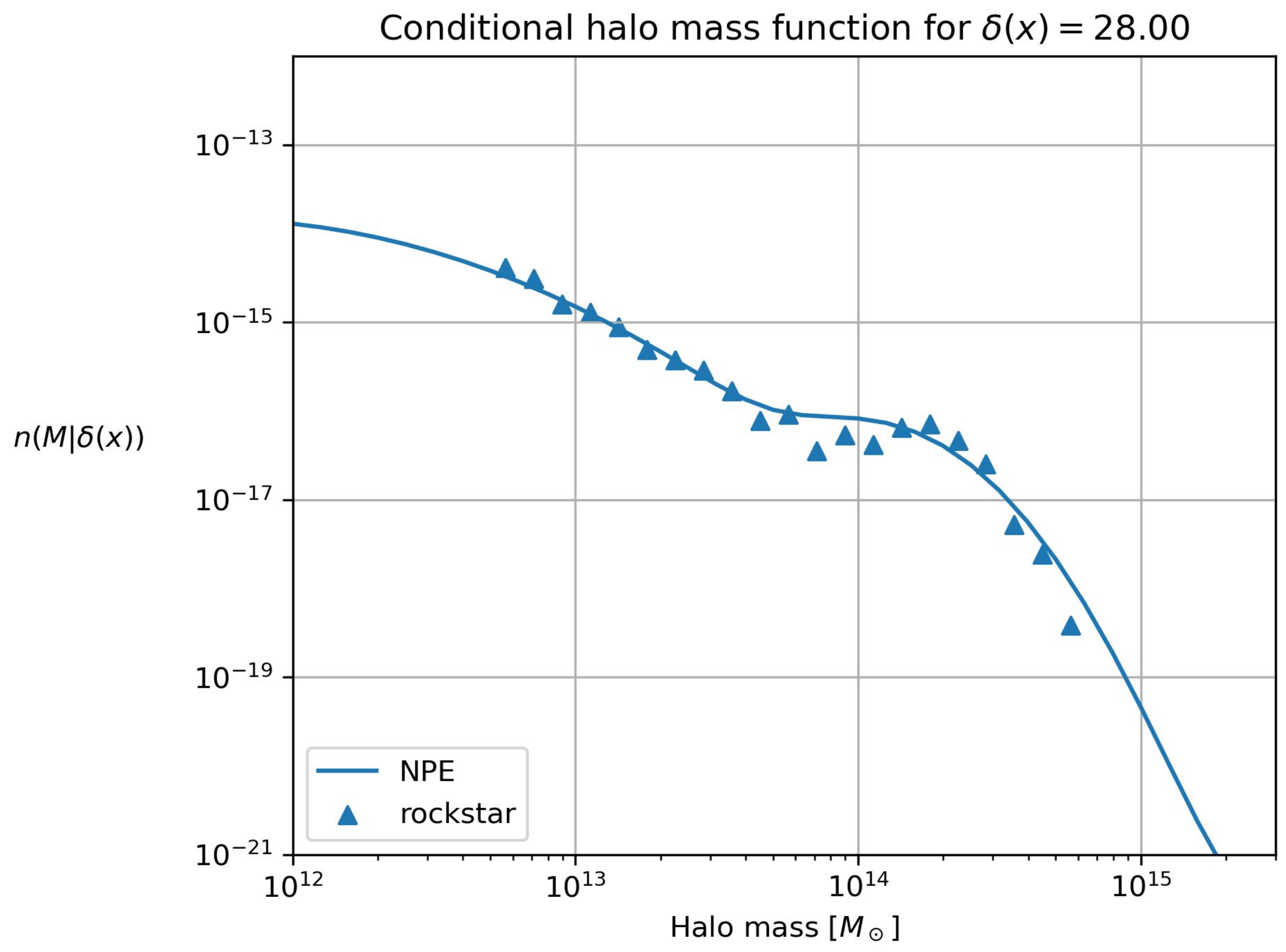

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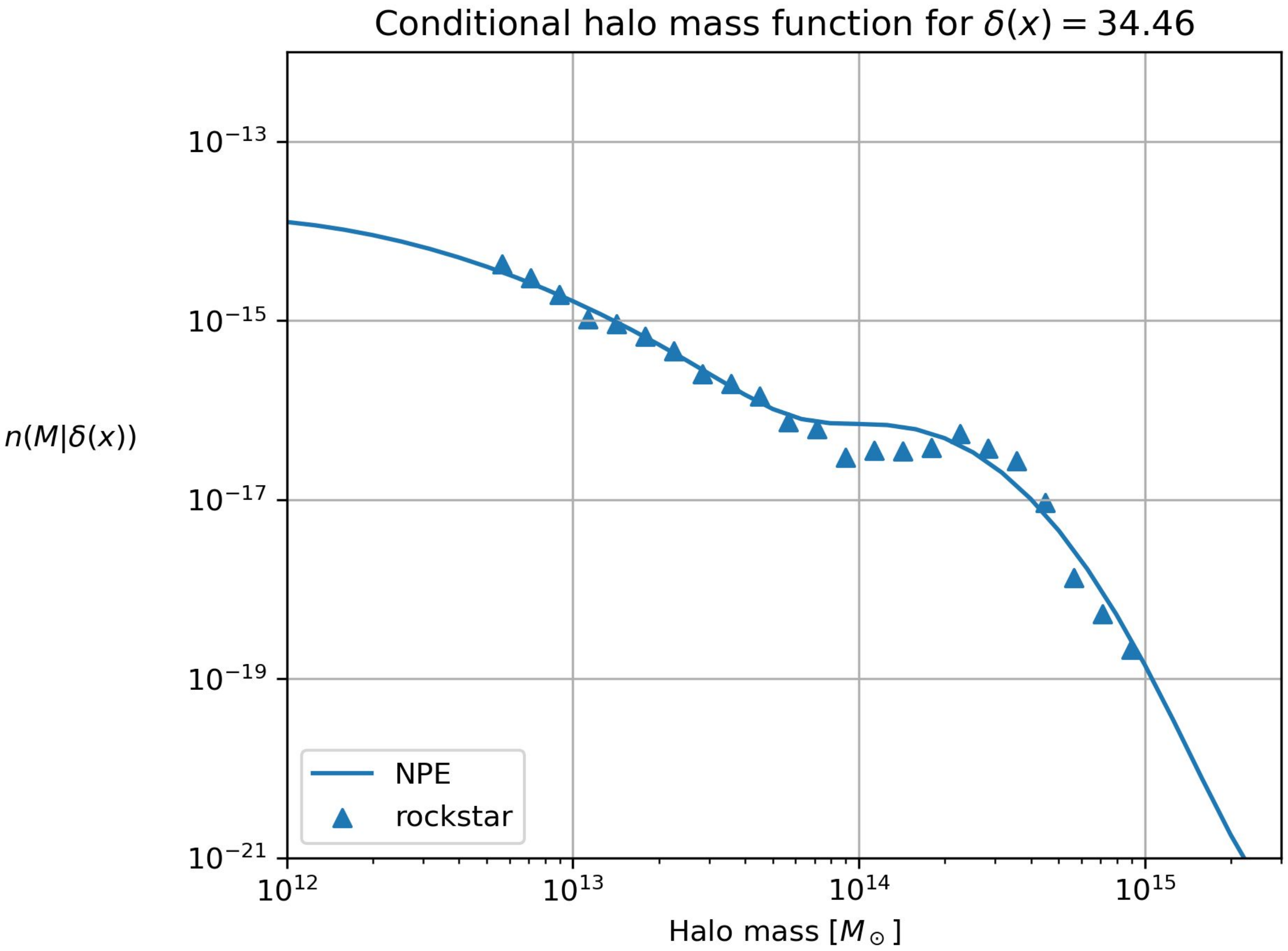

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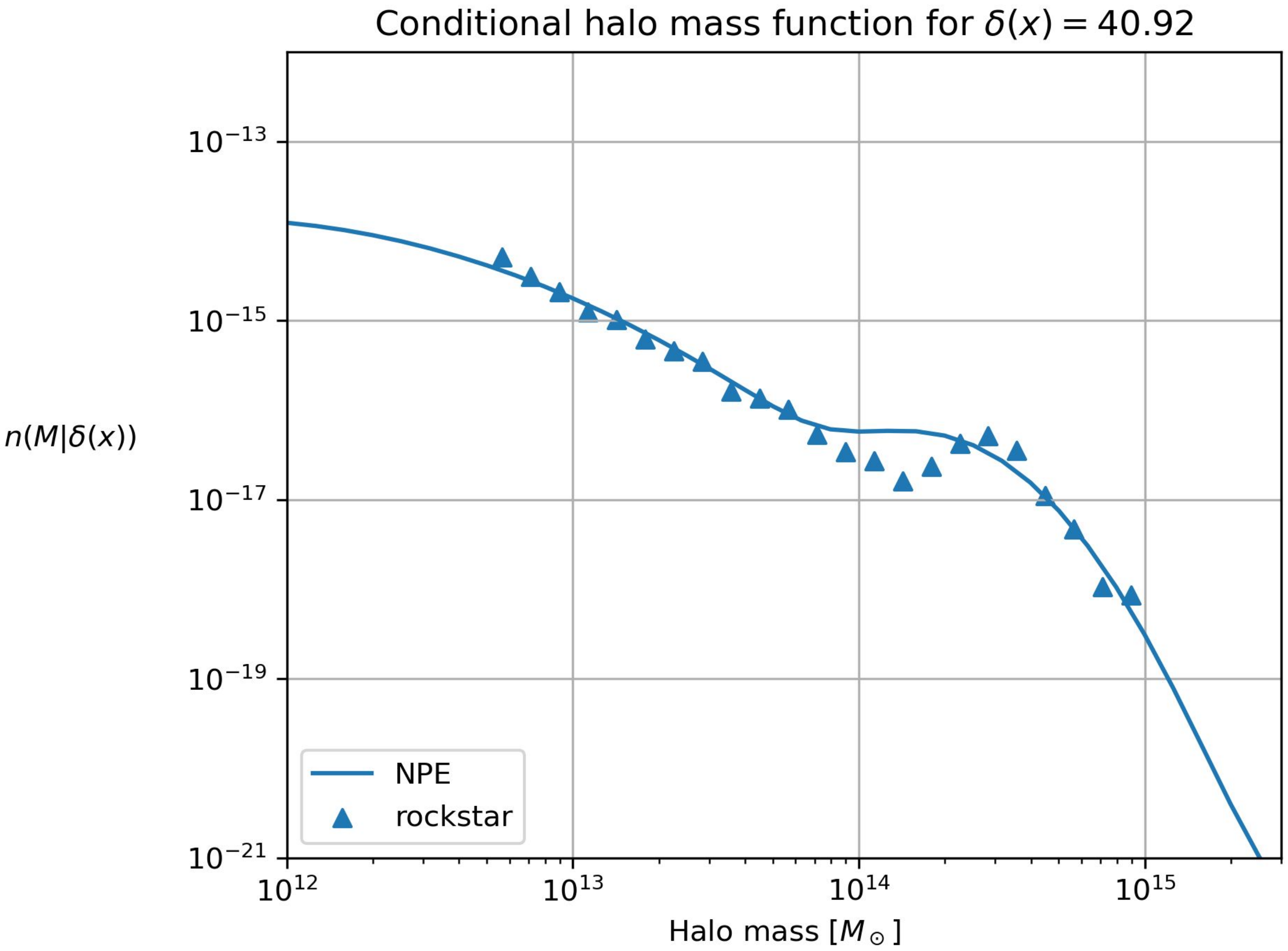

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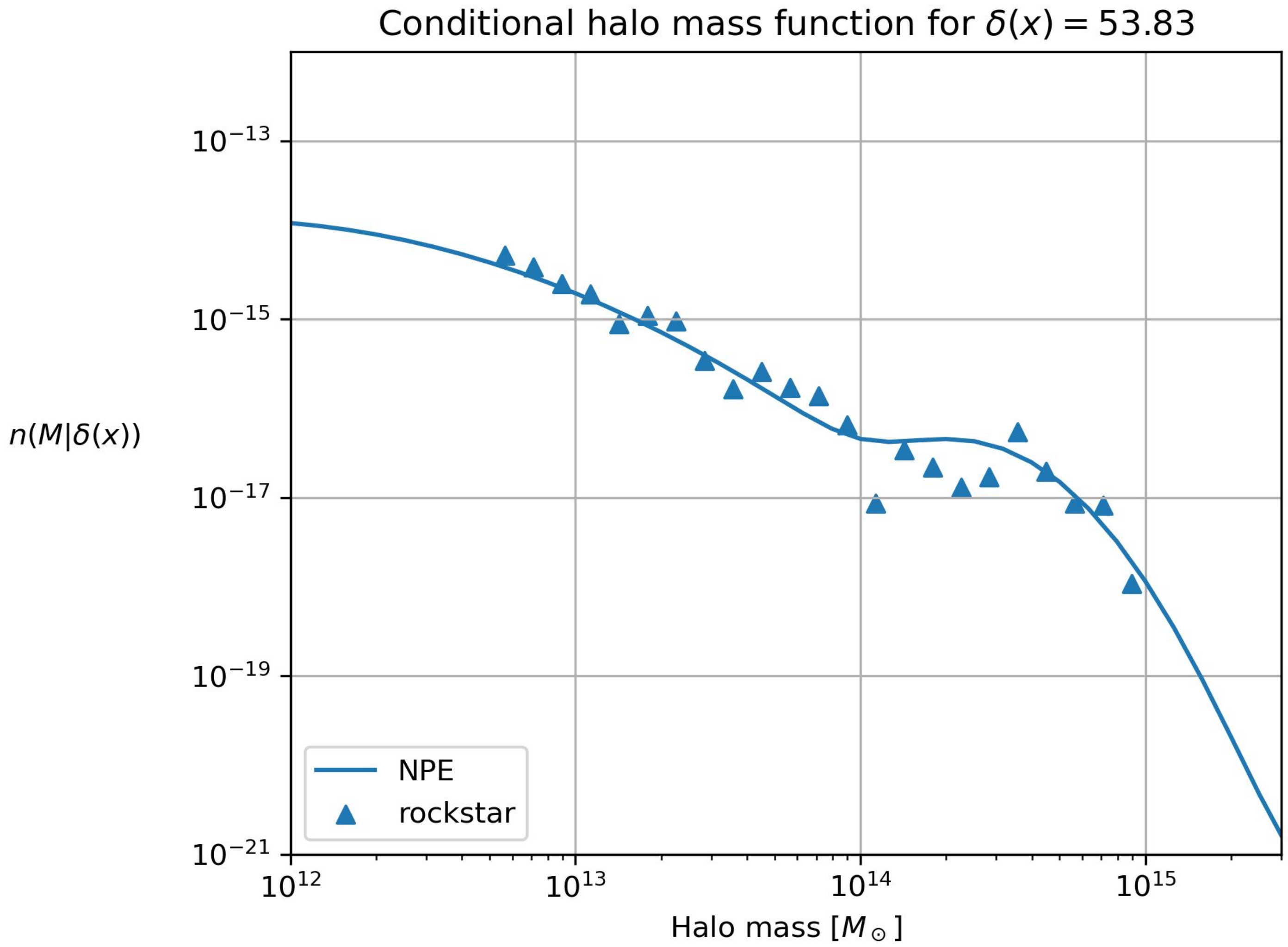

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Charnock et al 2020

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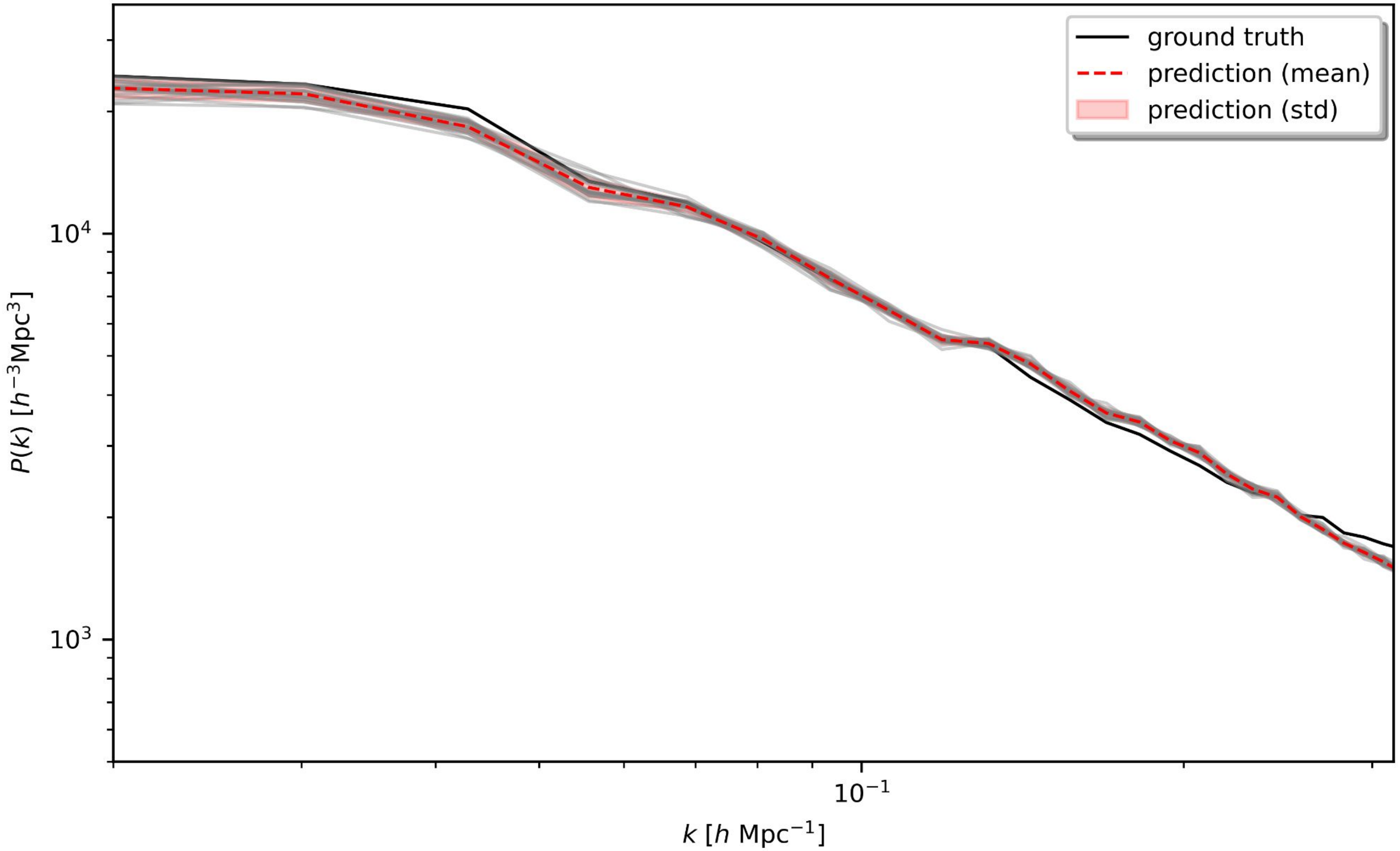
Preliminary Work!

Power spectrum comparison at 10.0 Mpc/h voxel resolution
for halo masses between $3.00e+12M_\odot$ and $9.49e+12M_\odot$



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Charnock et al 2020

credit for slide: Simon Ding

05

SIBELIUS-Dark

Posterior simulations of the Universe

SIBELIUS-DARK: a constrained simulation of the local volume (Stuart McAlpine)

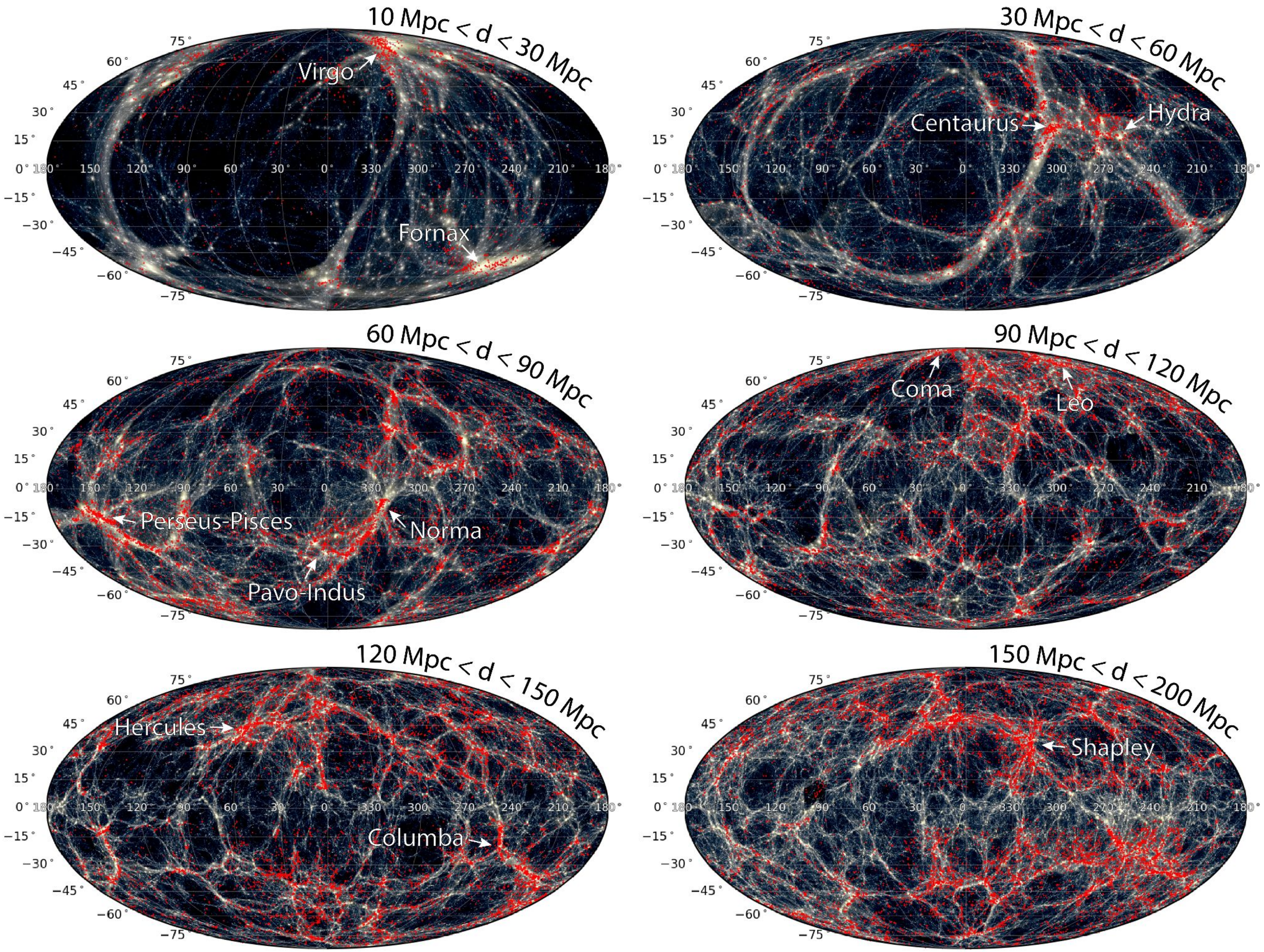
Re-simulate our Nearby Universe (d<200 Mpc)

Constrained Initial conditions

- BORG constraints at scales >3.9 Mpc
- Random fluctuations at scales < 3.9 Mpc
- Add local group candidate

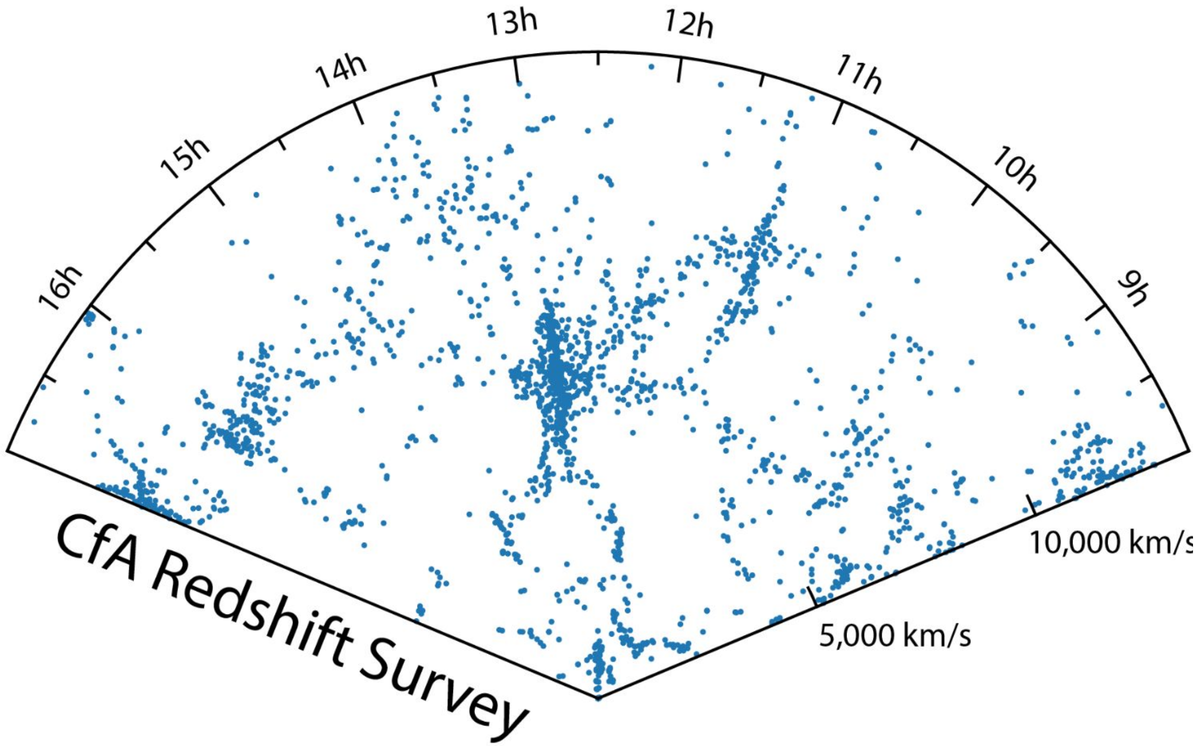
Simulation setup

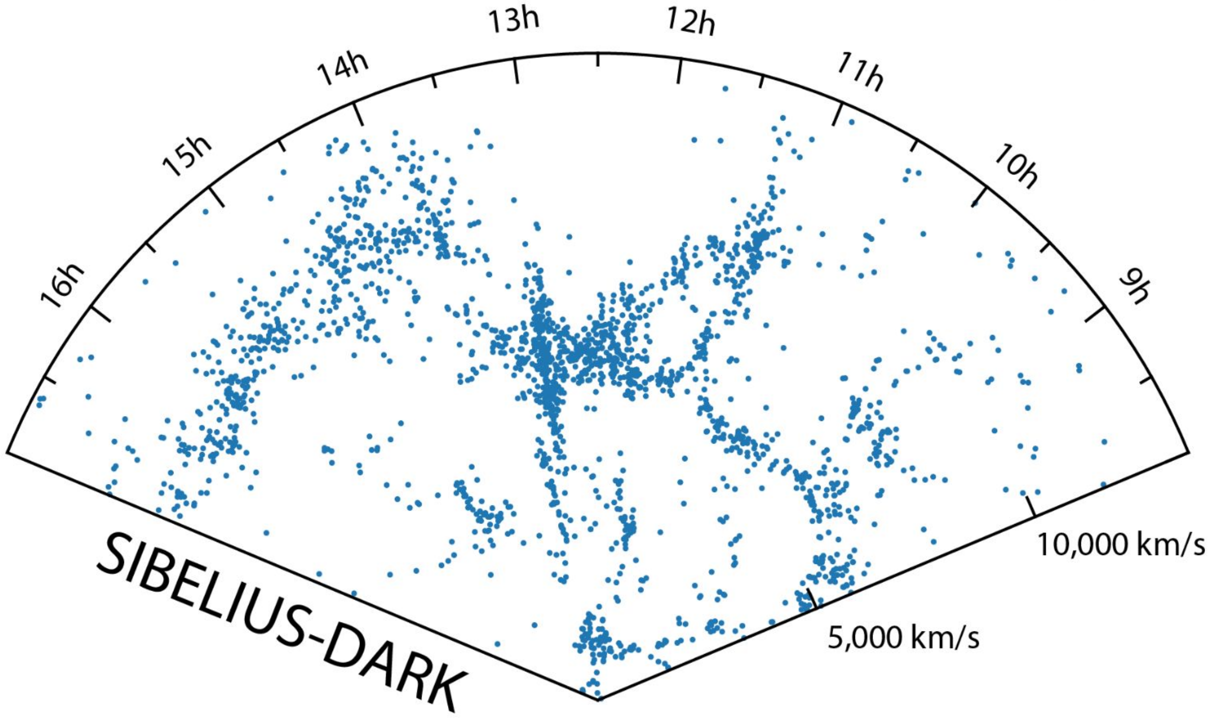
- SWIFT simulation code (Schaller et al 2018)
- Dark Matter Only (DMO)
- L = 1 Gpc
- “Zoom-in” simulation for the inner 200 Mpc
- $N_p^3 = 5078^3$
- 4489 compute cores and 3.5M CPU hours



McAlpine et al 2022

SIBELIUS-DARK: a constrained simulation of the local volume (Stuart McAlpine)





de Lapparent 1986

McAlpine et al 2022

SIBELIUS-DARK: a constrained simulation of the lo

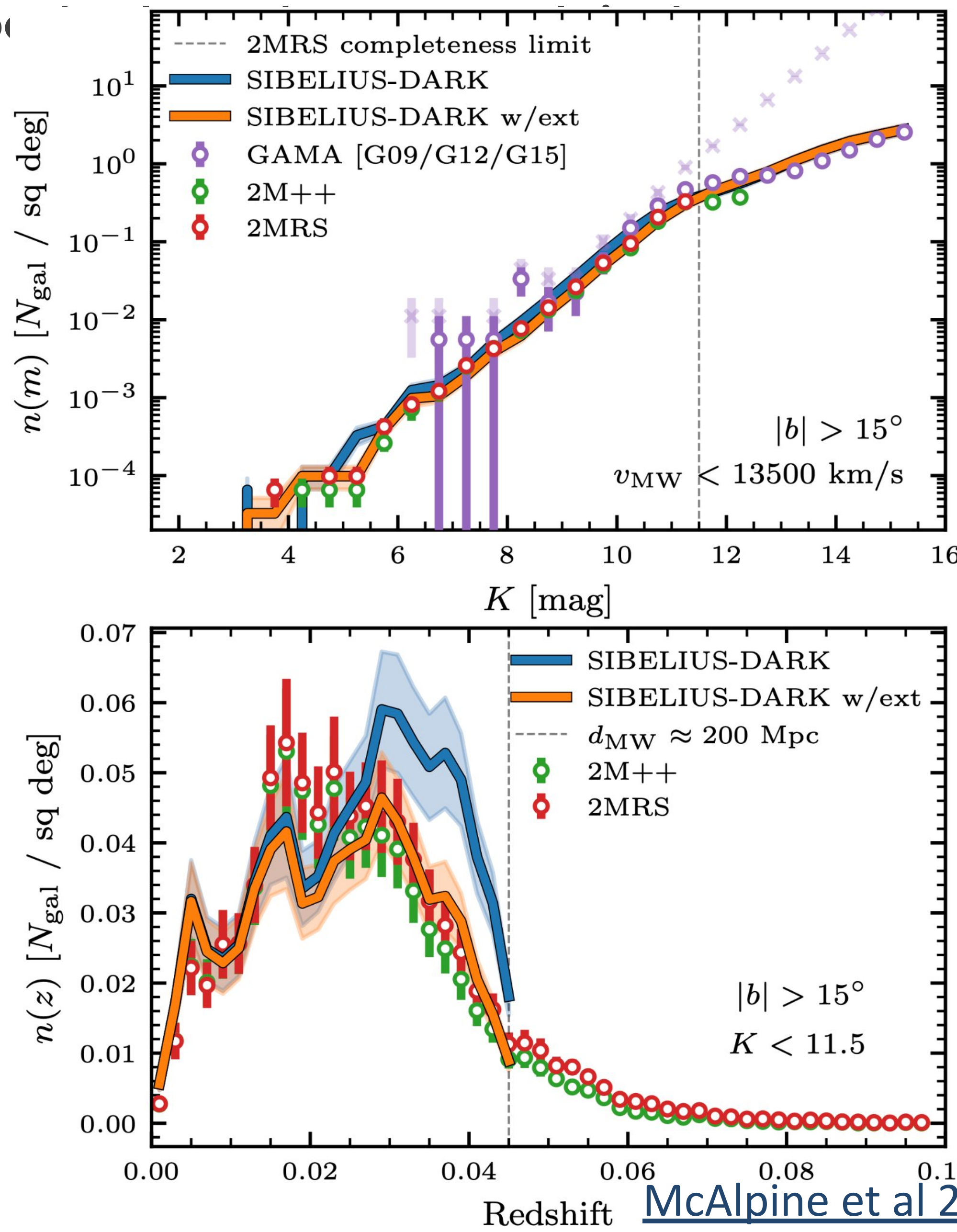
Posterior predictive tests with GALFORM([Lacey et al 2016])

Use **GALFORM** to predict semi-analytic galaxies:

- **SIBELIUS-DARK has a high cadence**

  (200 ‘snapshots’ from $0 < z < 25$)
- **Generate Halo catalogs and Merger trees**

  (22,904,767 halos with mass M >10 $M_{\odot}$)
- **Populate Halos with Galaxies**
- **Account for dust extinction and emission**



[McAlpine et al 2022]

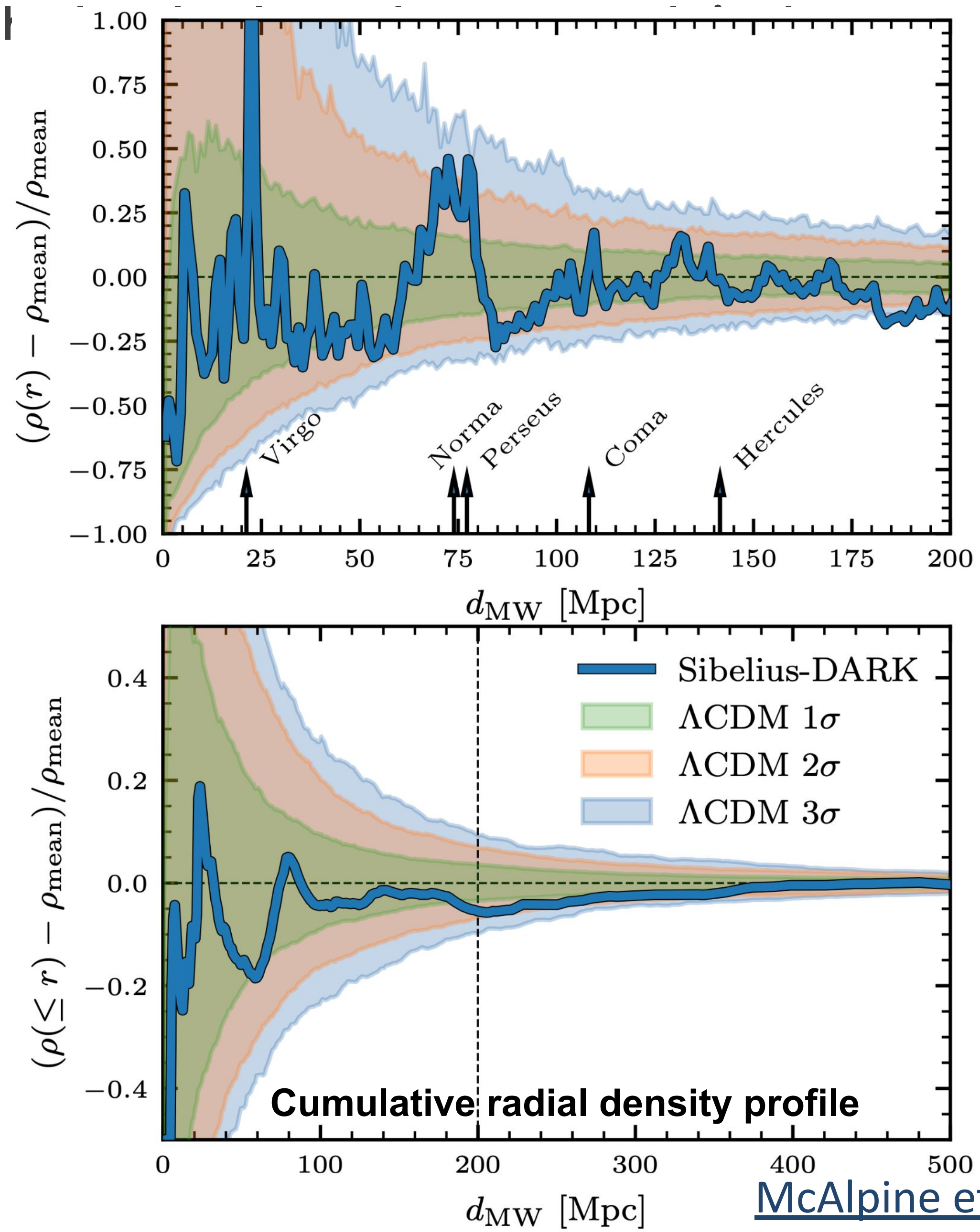
SIBELIUS-DARK: a constrained simulation of th

A local underdensity of 20% of size 150-200 h^{-1} Mpc could alter reported values of H_0 by 5%.

- A 20% large scale underdensity in the galaxy distribution has been reported (see e.g. Whitbourn & Shanks 2014, Böhringer et al 2020, Wong et al 2021).
- Such an underdensity is unlikely in a ΛCDM Universe (e.g. Wu & Huterer 2017, Castello et al 2021).

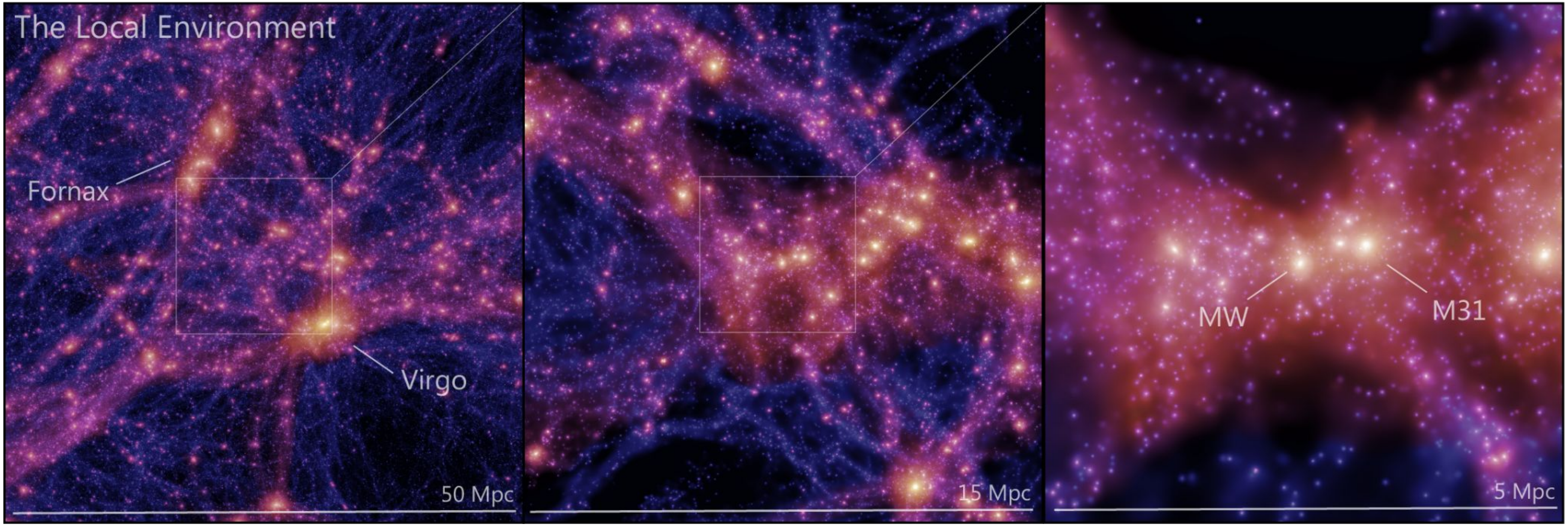
SIBELIUS-DARK finds:

- **No exceptionally large-scale under-density required to reproduce observed galaxy counts.**
- There is a slight 5% underdensity.
- Rare but no challenge for ΛCDM.



McAlpine et al 2022

SIBELIUS-DARK: a constrained simulation of the local volume (Stuart McAlpine)



SIBELIUS-DARK:

is the most comprehensive simulation of the local volume to date.
(For comparison see: Heß et al 2013, Wang et al 2016, Libeskind et al 2020, Sorce et al 2021)

SIBELIUS-DARK data is available at:
https://virgodb.dur.ac.uk/

McAlpine et al 2022

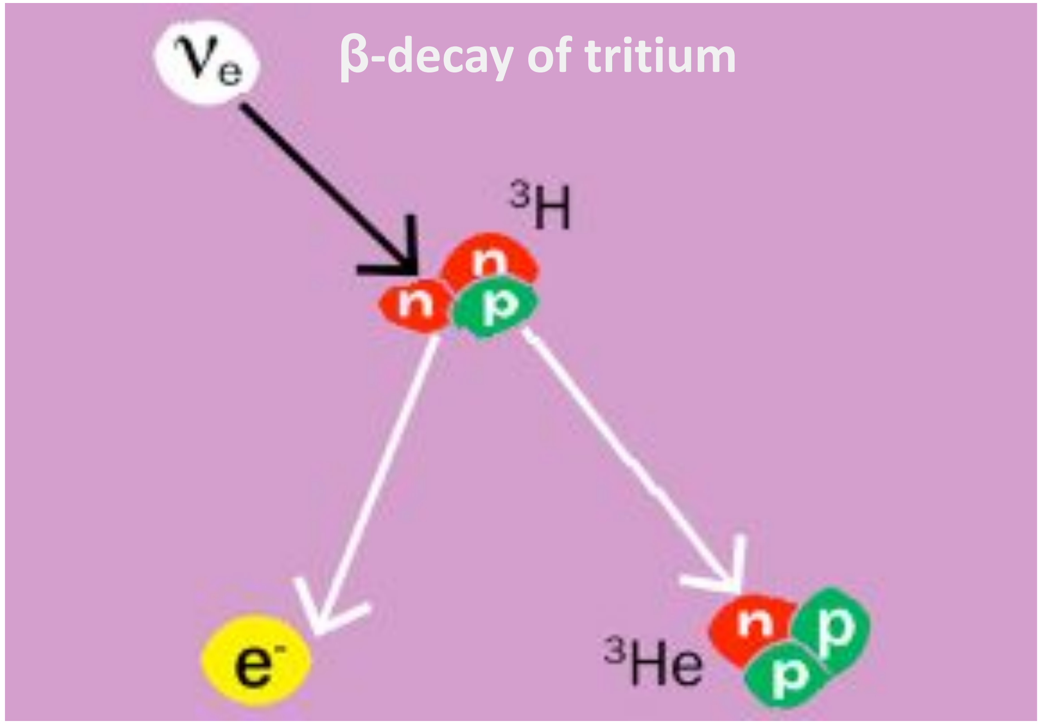
06

Reconstructing anisotropies in the neutrino sky

Preliminary Work!

PTOLEMY: detect CNB by capturing neutrinos through tritium inverse β-decay.

- Event rate depends on the local neutrino number density.
- Some experiments require the dipole moment and consider the velocity of neutrinos in the lab frame.



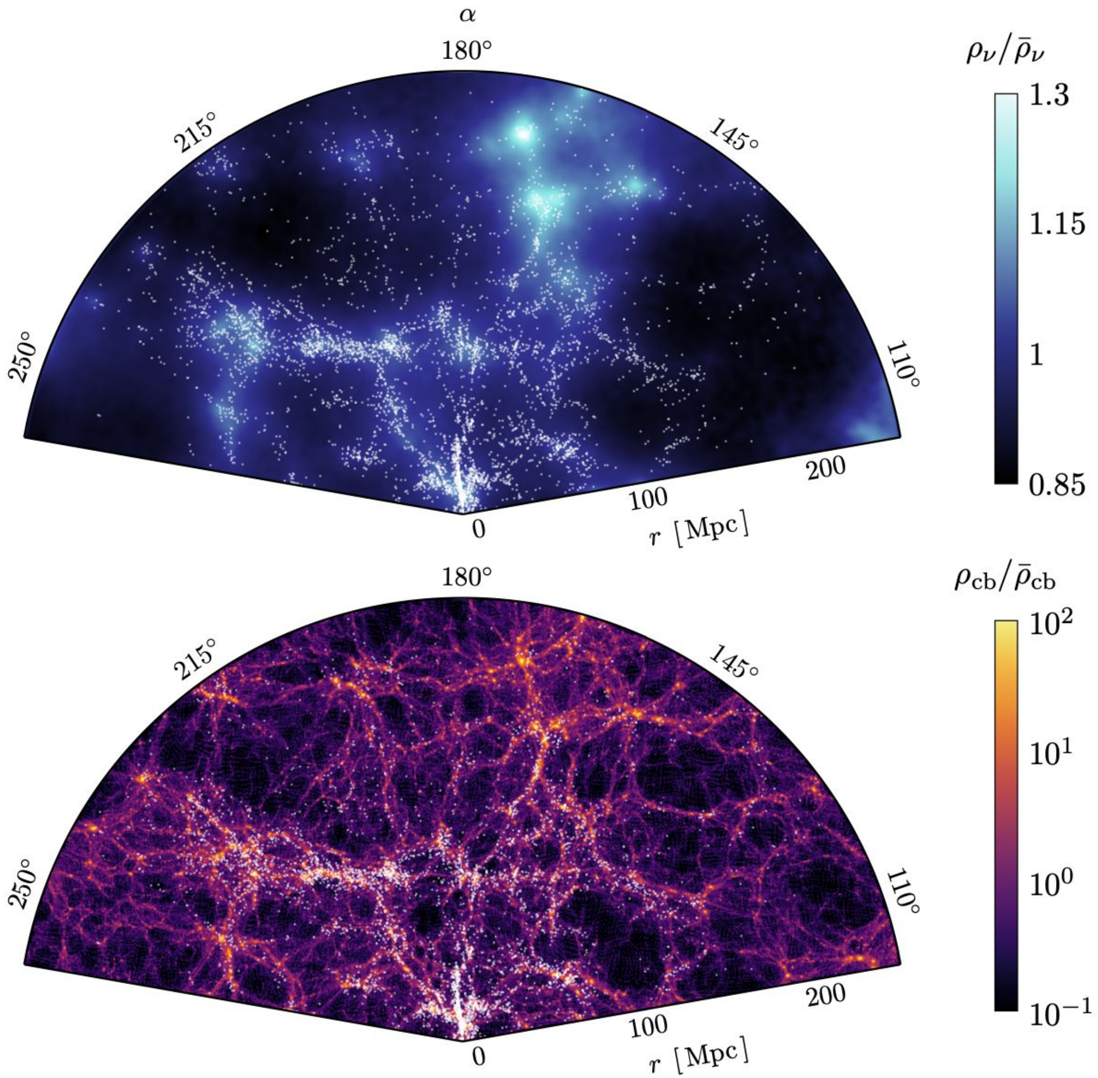
PTOLEMY collaboration 2019

Reconstruction of anisotropies in the neutrino sky (Willem Elbers)

Preliminary Work!

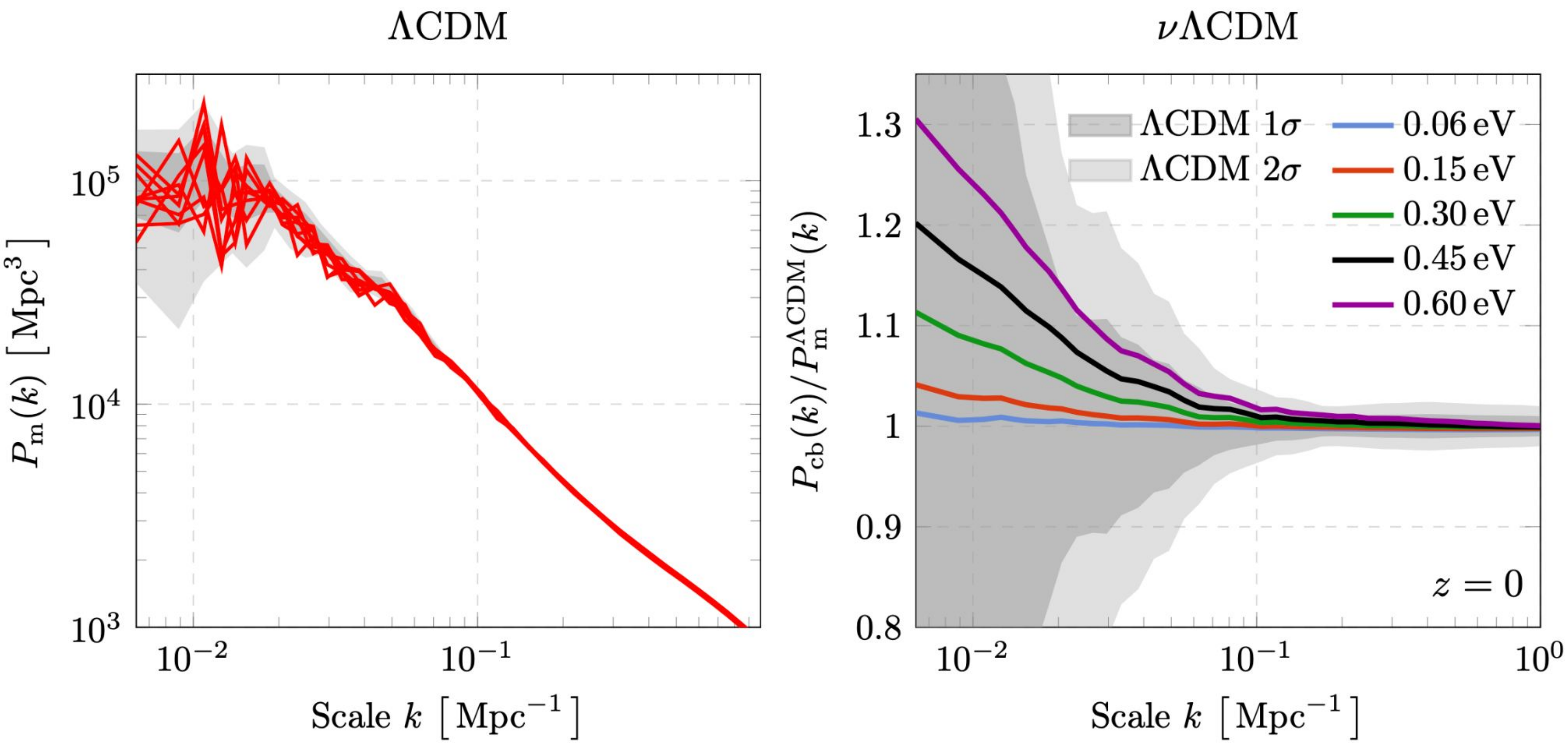
Goal: Determine the prospects of CNB detection

- Posterior simulations to jointly model the evolution of large-scale structures and the neutrino background.
- Non-linear treatment of massive neutrinos, including the gravitational effects of the neutrinos themselves.
- Full scale large-scale distribution of matter within $200h^{-1}$ Mpc
- Compute the expected density, velocity, and direction of relic neutrinos, as well as expected event rates for PTOLEMY.



Elbers et al in prep

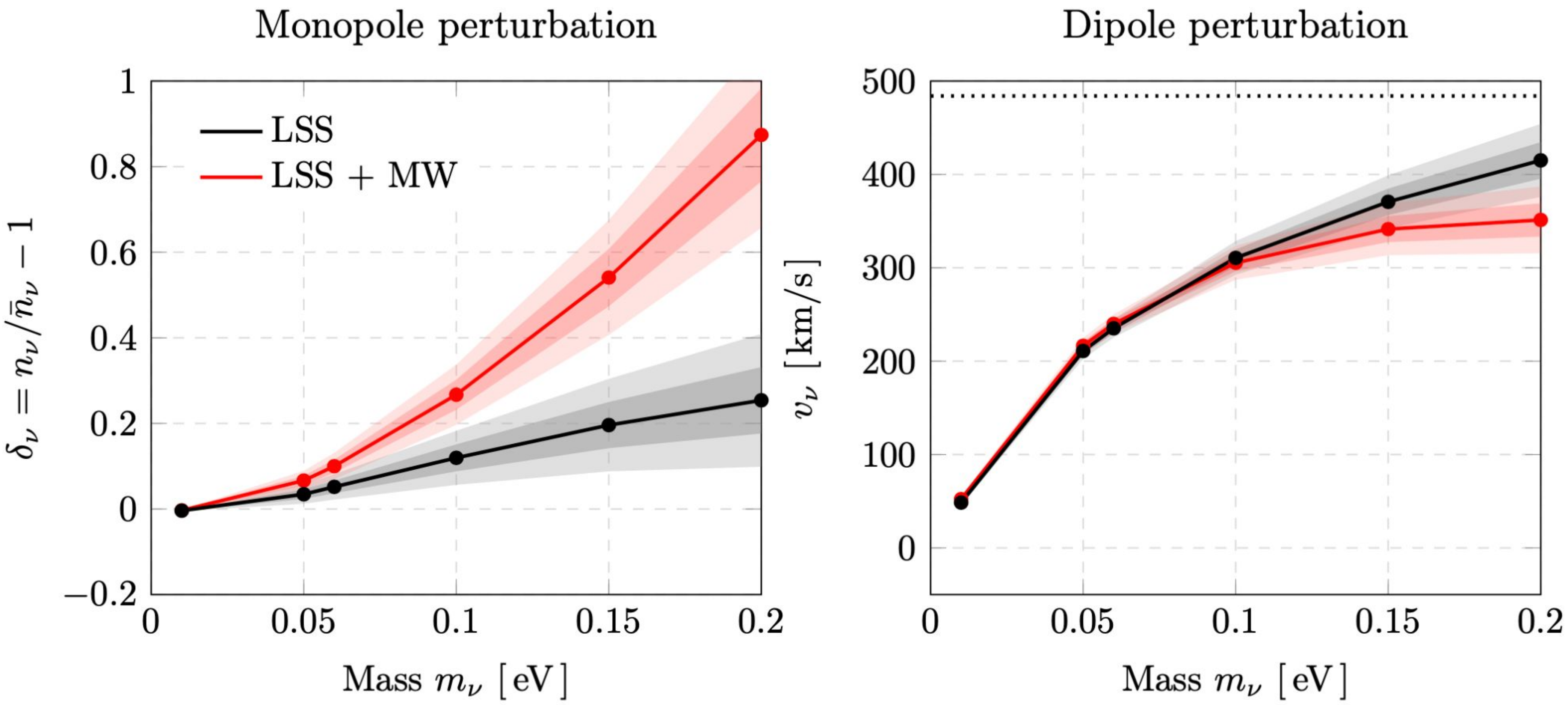
Reconstruction of anisotropies in the neutrino sky (Willem Elbers)



Elbers et al in prep

Reconstruction of anisotropies in the neutrino sky (Willem Elbers)

Preliminary Work!



Elbers et al in prep

Preliminary Work!

Mass m_ν	v_ν [km/s]	l	b
CMB	0	$264°$	$48°$
0.01 eV	48.5 ± 1.5	$267° \pm 3.1°$	$48.7° \pm 0.8°$
0.05 eV	211 ± 4.3	$298° \pm 2.5°$	$48.1° \pm 1.5°$
0.06 eV	235 ± 5.0	$302° \pm 2.6°$	$48.0° \pm 1.8°$
0.10 eV	311 ± 9.0	$311° \pm 3.0°$	$47.5° \pm 2.9°$
0.15 eV	371 ± 14	$318° \pm 3.2°$	$46.6° \pm 4.0°$
0.20 eV	415 ± 20	$322° \pm 3.2°$	$45.5° \pm 4.9°$
Matter	484 ± 88	$344° \pm 11°$	$43° \pm 17°$

Elbers et al in prep

Preliminary Work!

Predicted number of events per year for PTOLEMY

		(LSS)		(LSS + MW)	
$\sum m_\nu$	Ordering	Γ^D_{CNB}	Γ^M_{CNB}	Γ^D_{CNB}	Γ^M_{CNB}
0.06 eV	(NO)	6.86 ± 0.002	8.11 ± 0.004	6.87 ± 0.002	8.12 ± 0.004
0.10 eV	(IO)	4.33 ± 0.04	8.52 ± 0.11	4.45 ± 0.05	8.90 ± 0.12
0.15 eV	(D)	4.24 ± 0.05	8.53 ± 0.12	4.37 ± 0.05	8.92 ± 0.13
0.30 eV	(D)	4.56 ± 0.13	9.07 ± 0.26	5.16 ± 0.14	10.3 ± 0.29
0.45 eV	(D)	4.86 ± 0.22	9.70 ± 0.44	6.26 ± 0.27	12.5 ± 0.54
0.60 eV	(D)	5.10 ± 0.32	10.2 ± 0.63	7.61 ± 0.44	15.2 ± 0.88

Elbers et al in prep

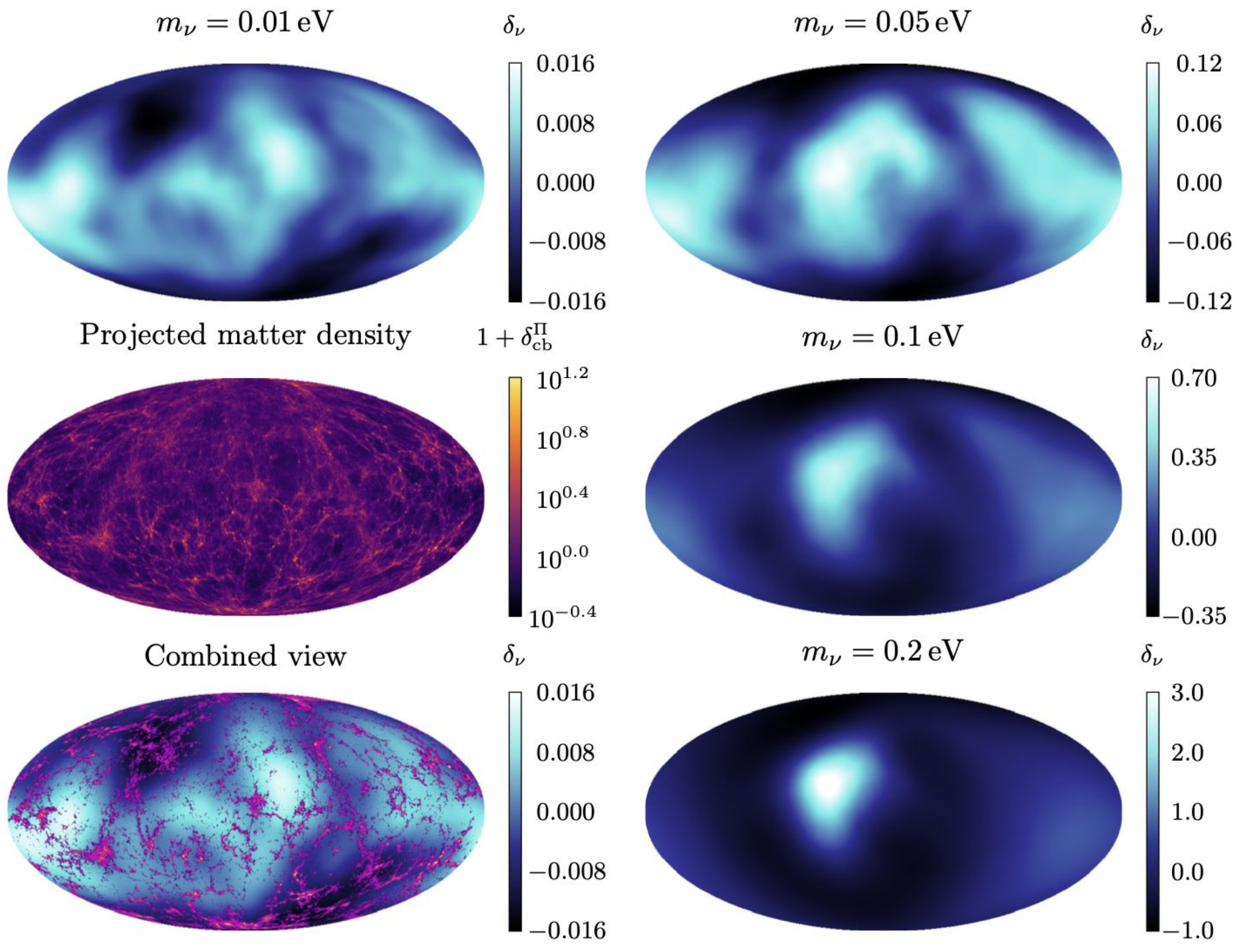
Reconstruction of anisotropies in the neutrino sky (Willem Elbers)

Preliminary Work!

Angular distribution of neutrinos

- Anti-correlated with the projected matter density,
- Capture and deflection of neutrinos by massive structures along the line of sight.

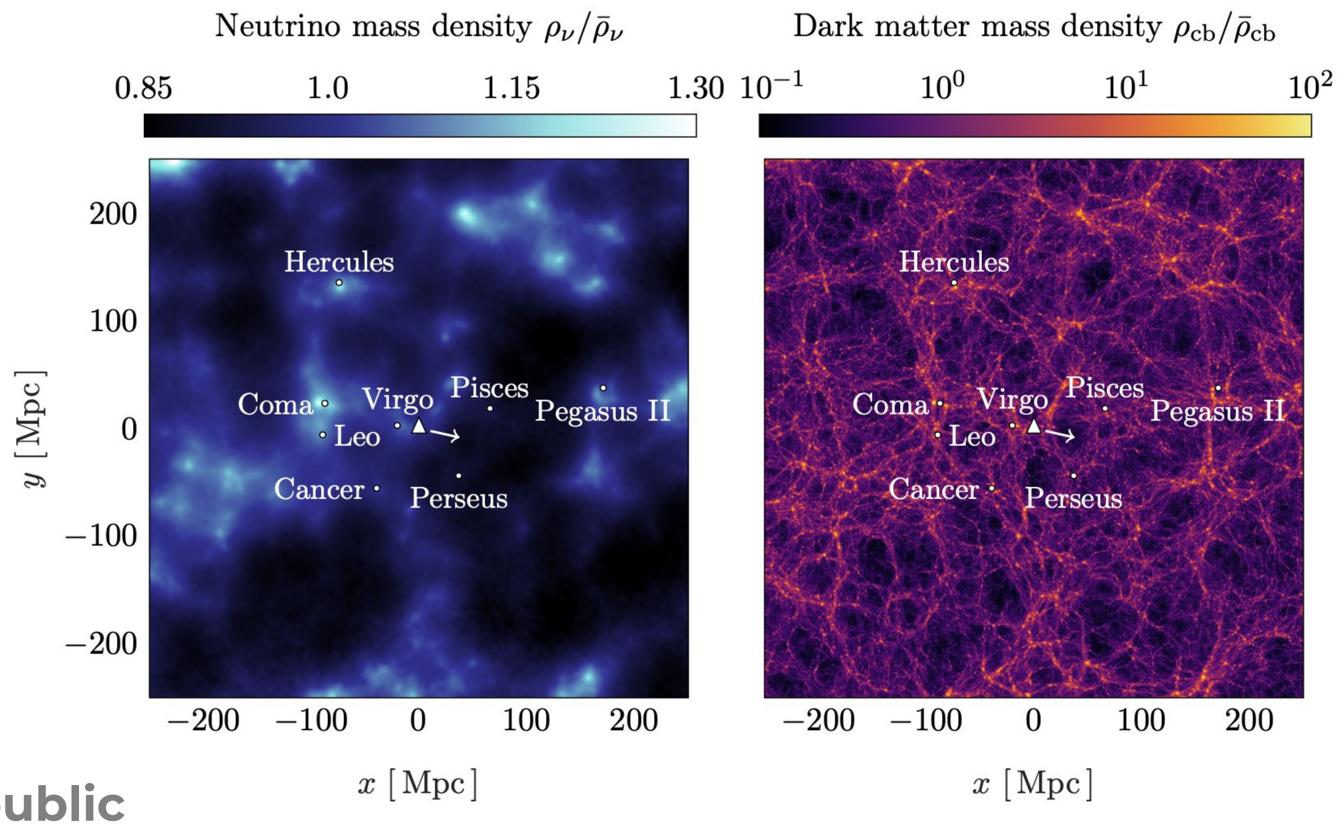
Angular anisotropies in the local neutrino background density



Elbers et al in prep

Reconstruction of anisotropies in the neutrino sky (Willem Elbers)

Preliminary Work!



Data will be public

2 × 9 × 6 simulation files, corresponding

- 2 with and without Milky Way,
- 9 different posterior realizations
- 6 different neutrino masses.

Elbers et al in prep

07

Summary & Conclusion

Summary & Conclusion

1

Physical forward modeling and field-level inference

- Goes beyond summary statistics
- Utilizes all of the data
- Performs causal inferences

2

Improved inferences

- tight constraints of cosmological parameter
- Cluster mass measurements and large scale structure environments
- Detailed insights into galaxy formation

3

Outlook and work needed

- Small-scale galaxy biasing
- Improving inference speed using ML
- Scaling to next-generation galaxy surveys and data volumes
- A complete and joint characterization of the LSS phenomenology

THANKS

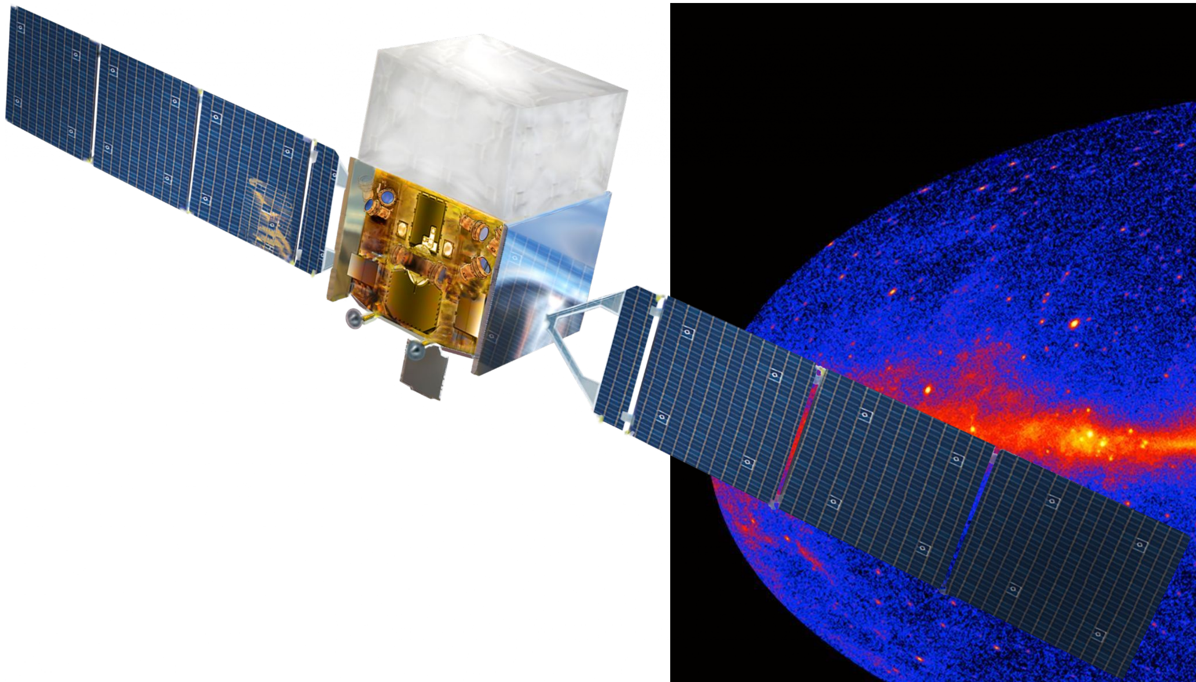
visit us at:
https://aquila-consortium.org/

07 Constraining Fundamental Physics

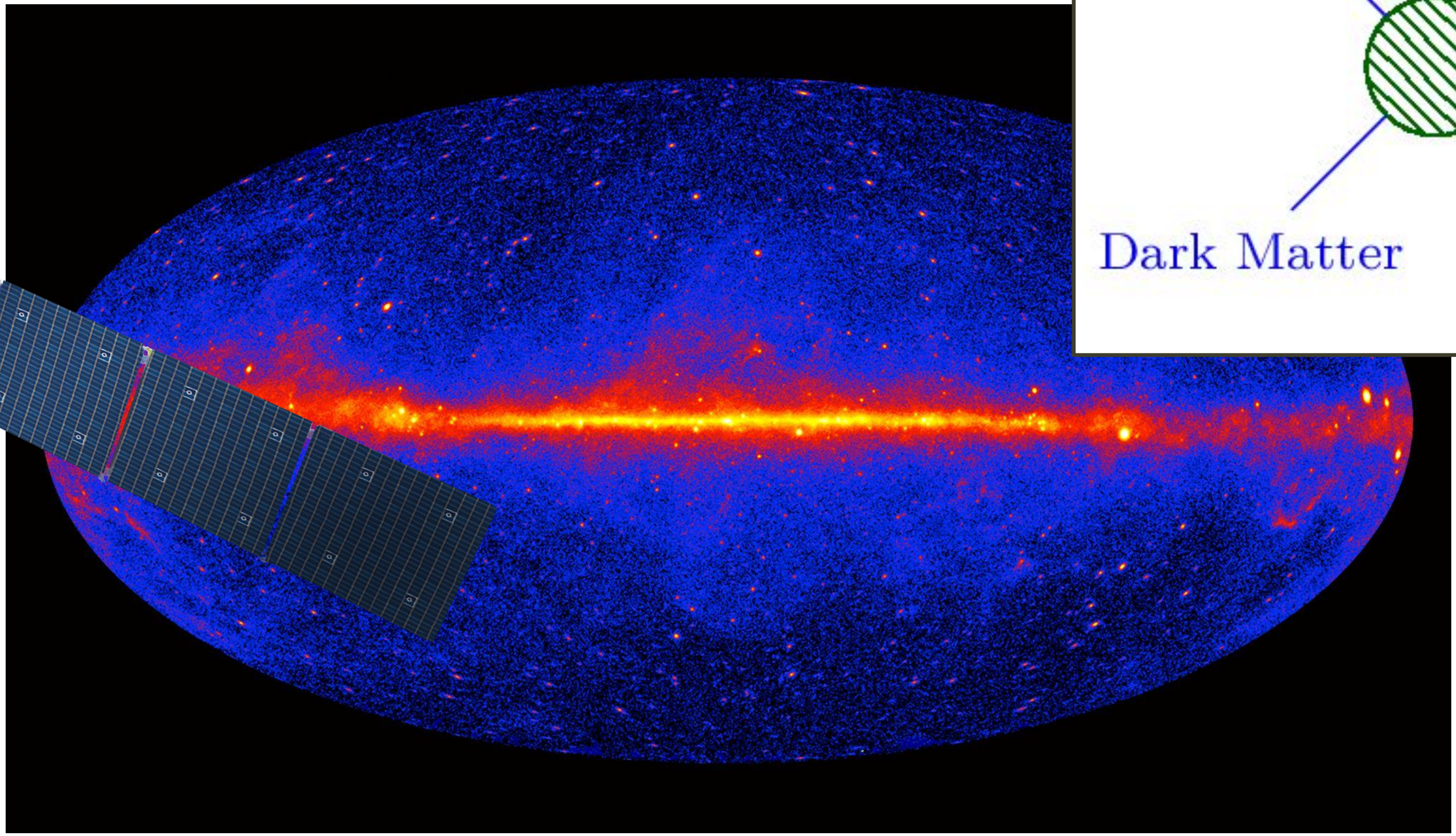
Turning the Universe into a lab

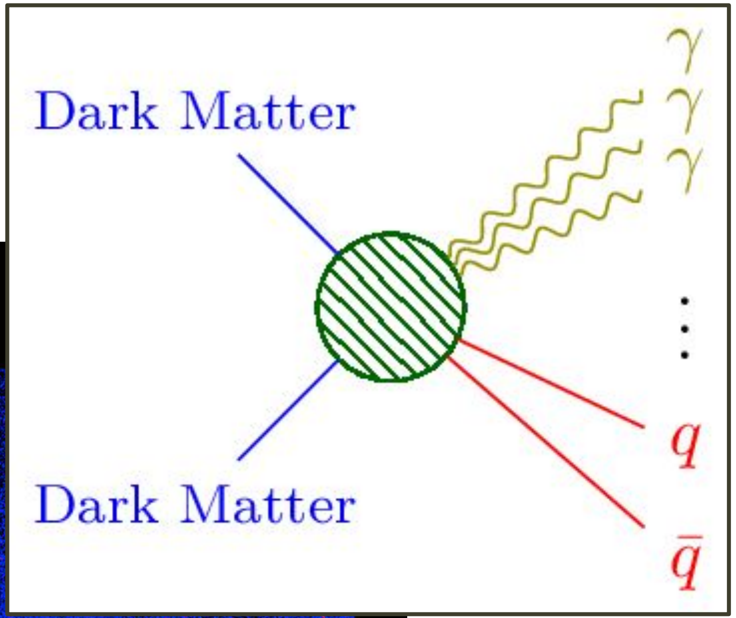
Constraining dark matter annihilation and decay (Deaglan Bartlett & Andrija Kostić)

Fermi Gamma-ray Space Telescope



All-sky Gamma-ray map

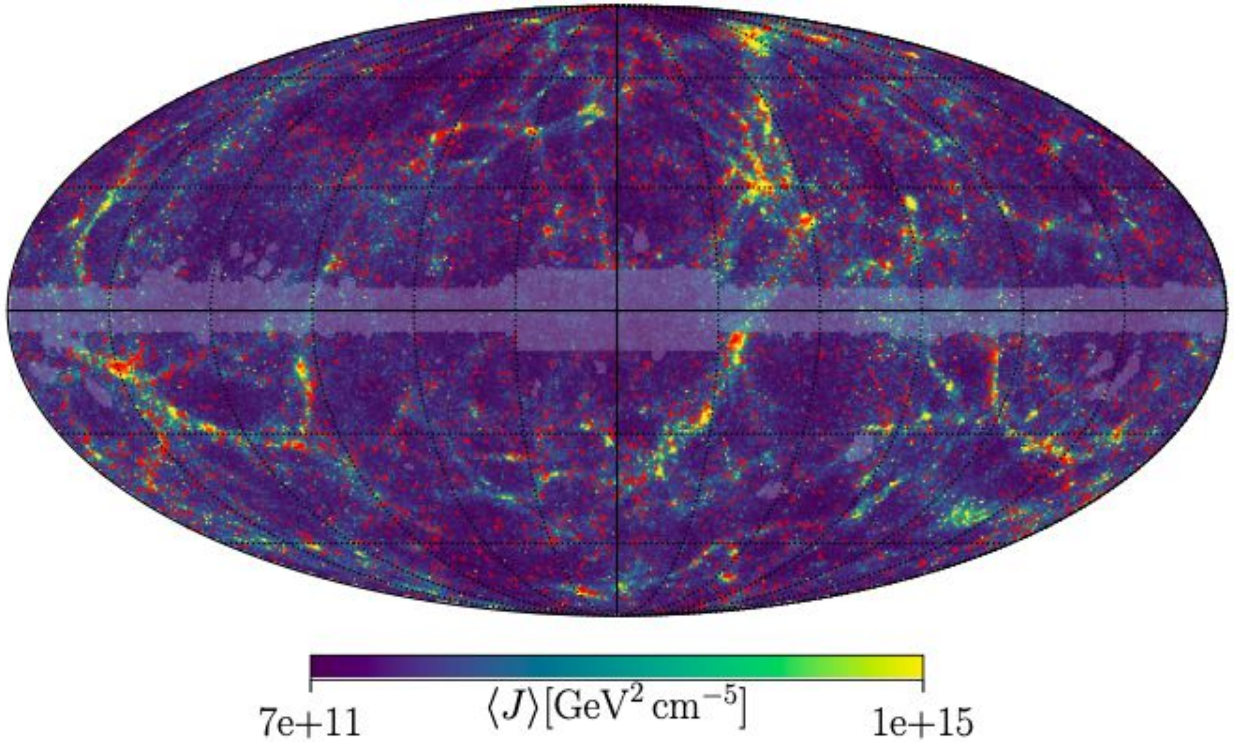




(Image credit: NASA/DOE/Fermi LAT Collaboration)

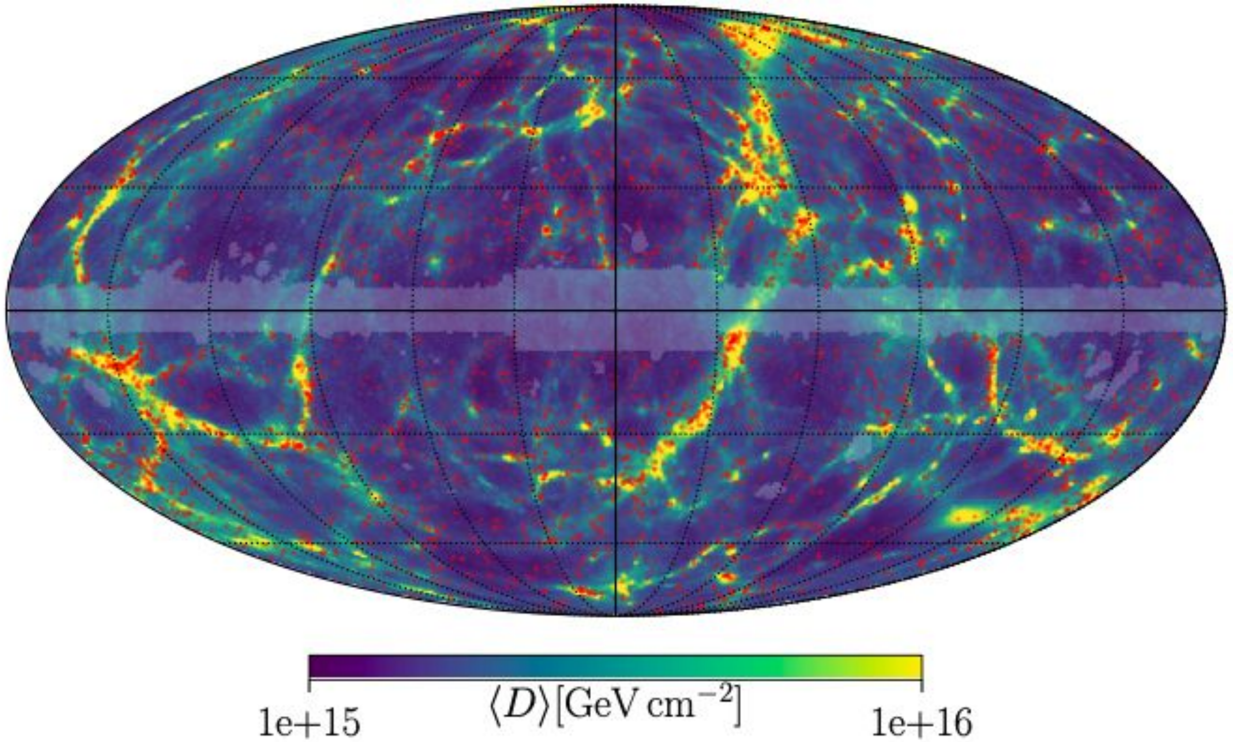
Constraining dark matter annihilation and decay (Deaglan Bartlett & Andrija Kostić)

Dark Matter annihilation



$$\frac{\mathrm{d}J}{\mathrm{d}\Omega} = \int \rho_{\mathrm{DM}}^2 (s, \Omega)\, \mathrm{d}s$$

Dark Matter decay

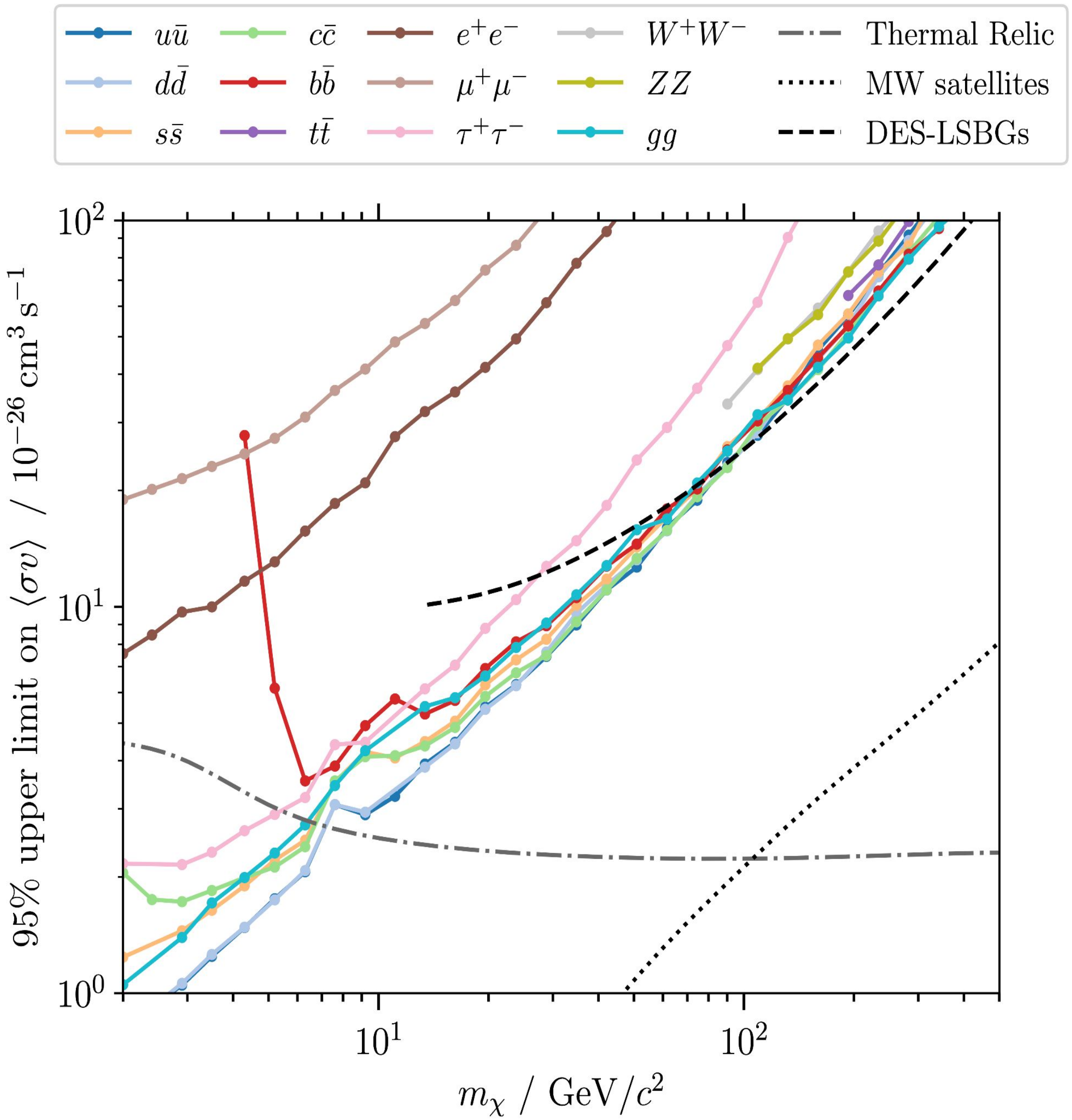


$$\frac{\mathrm{d}D}{\mathrm{d}\Omega} = \int \rho_{\mathrm{DM}} (s, \Omega)\, \mathrm{d}s$$

Bartlett et al 2022

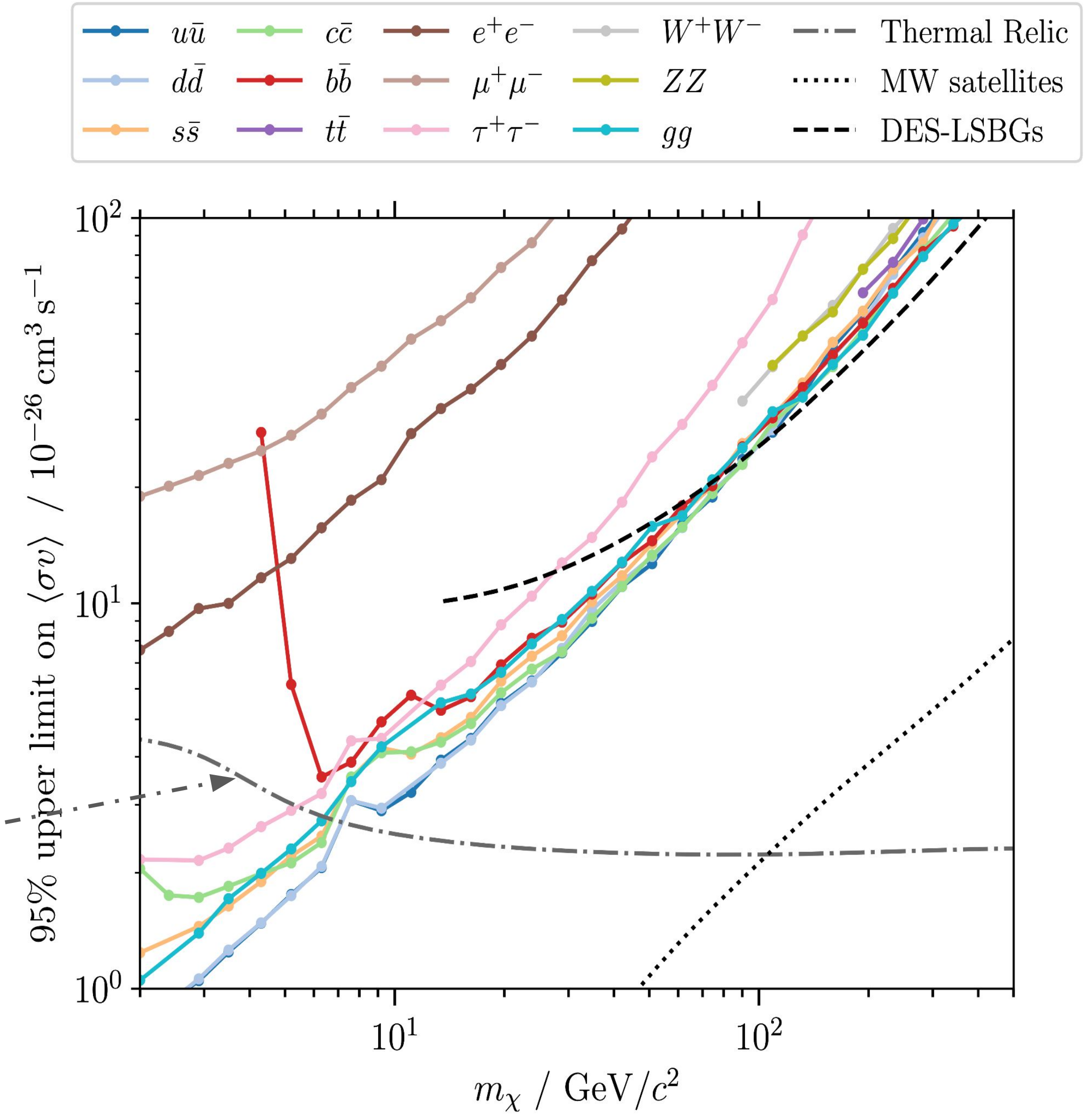
Cuesta et al 2011

Constraining dark matter annihilation and decay (Deaglan Bartlett & Andrija Kostić)



Bartlett et al 2022

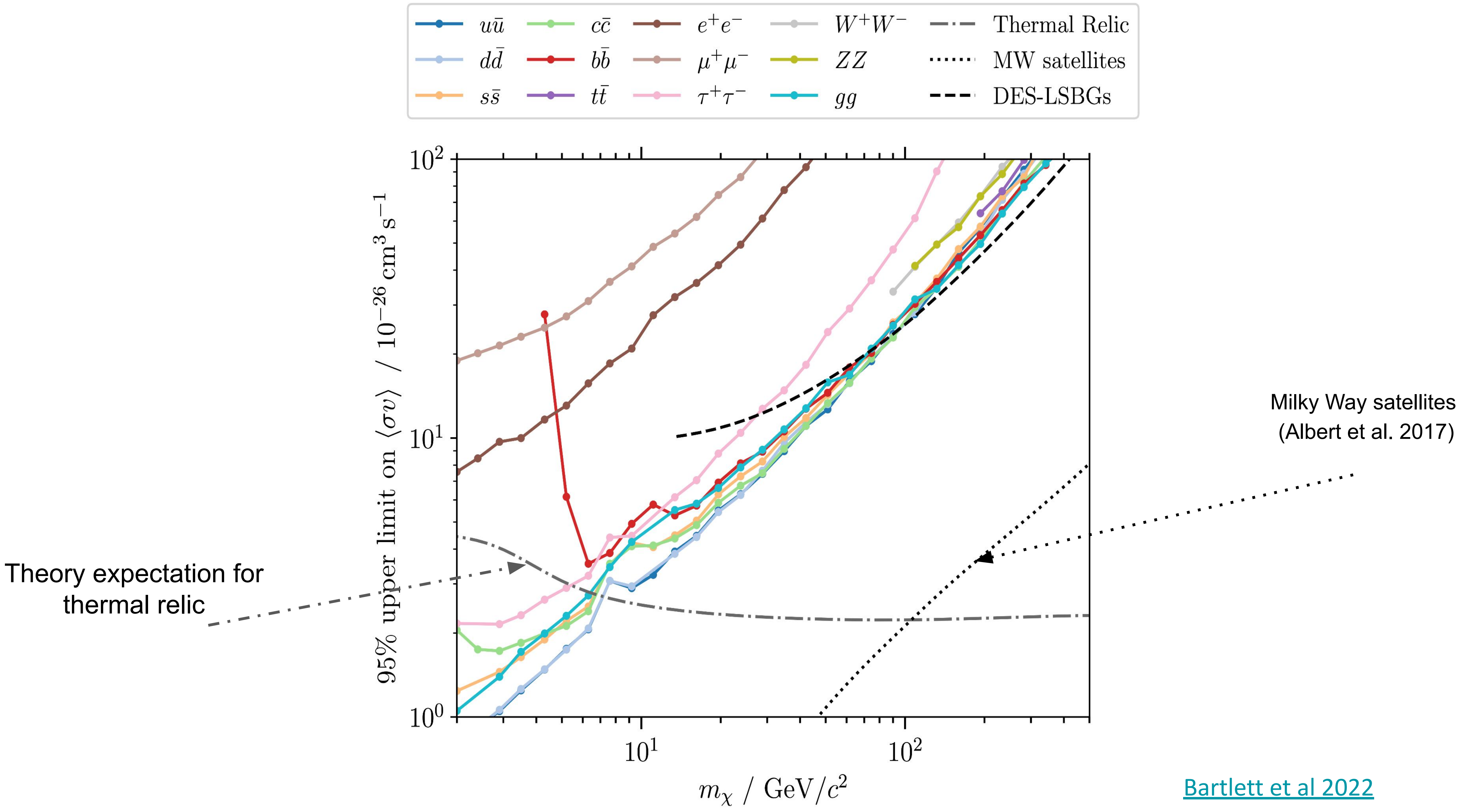
Constraining dark matter annihilation and decay (Deaglan Bartlett & Andrija Kostić)



Theory expectation for thermal relic

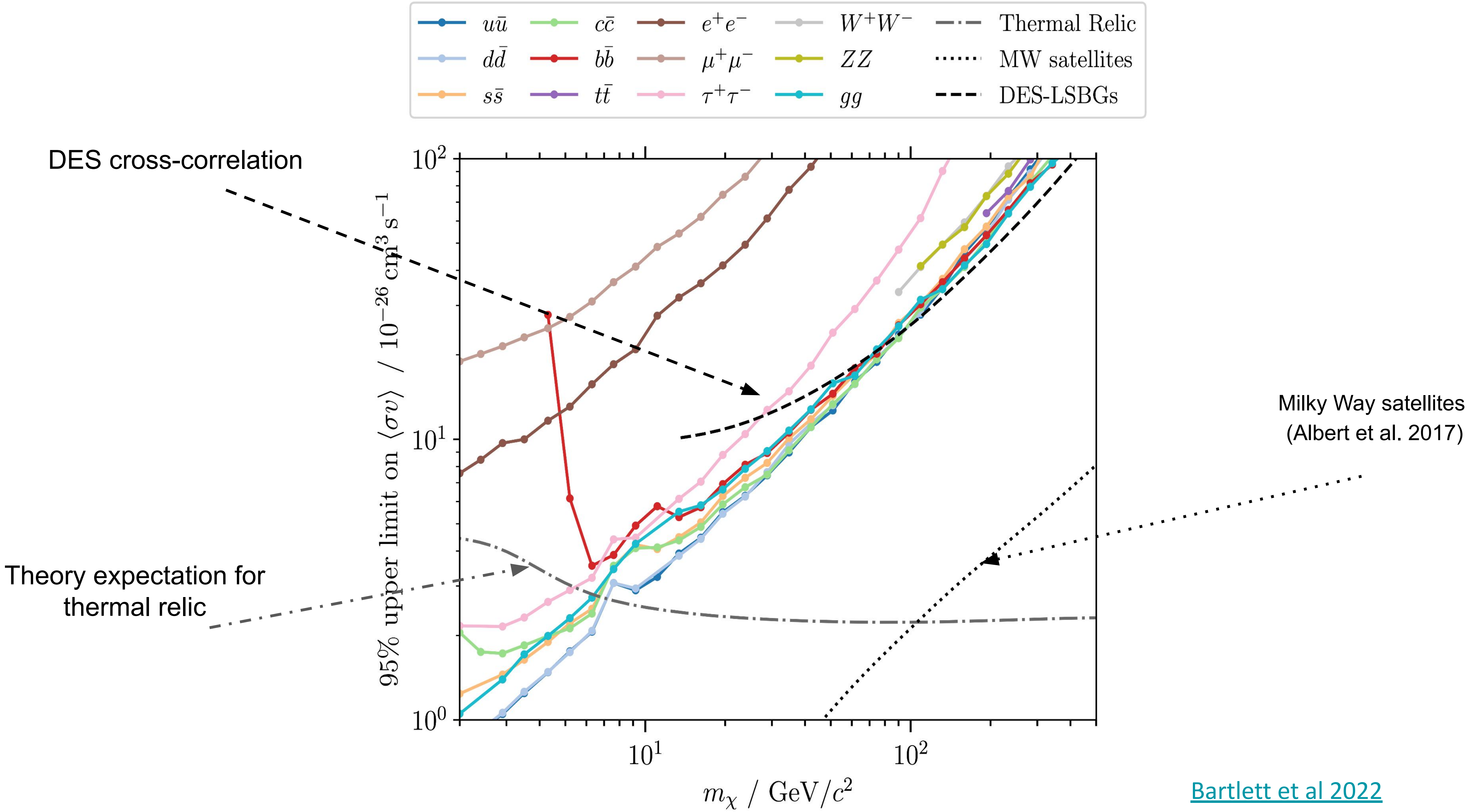
Bartlett et al 2022

Constraining dark matter annihilation and decay (Deaglan Bartlett & Andrija Kostić)



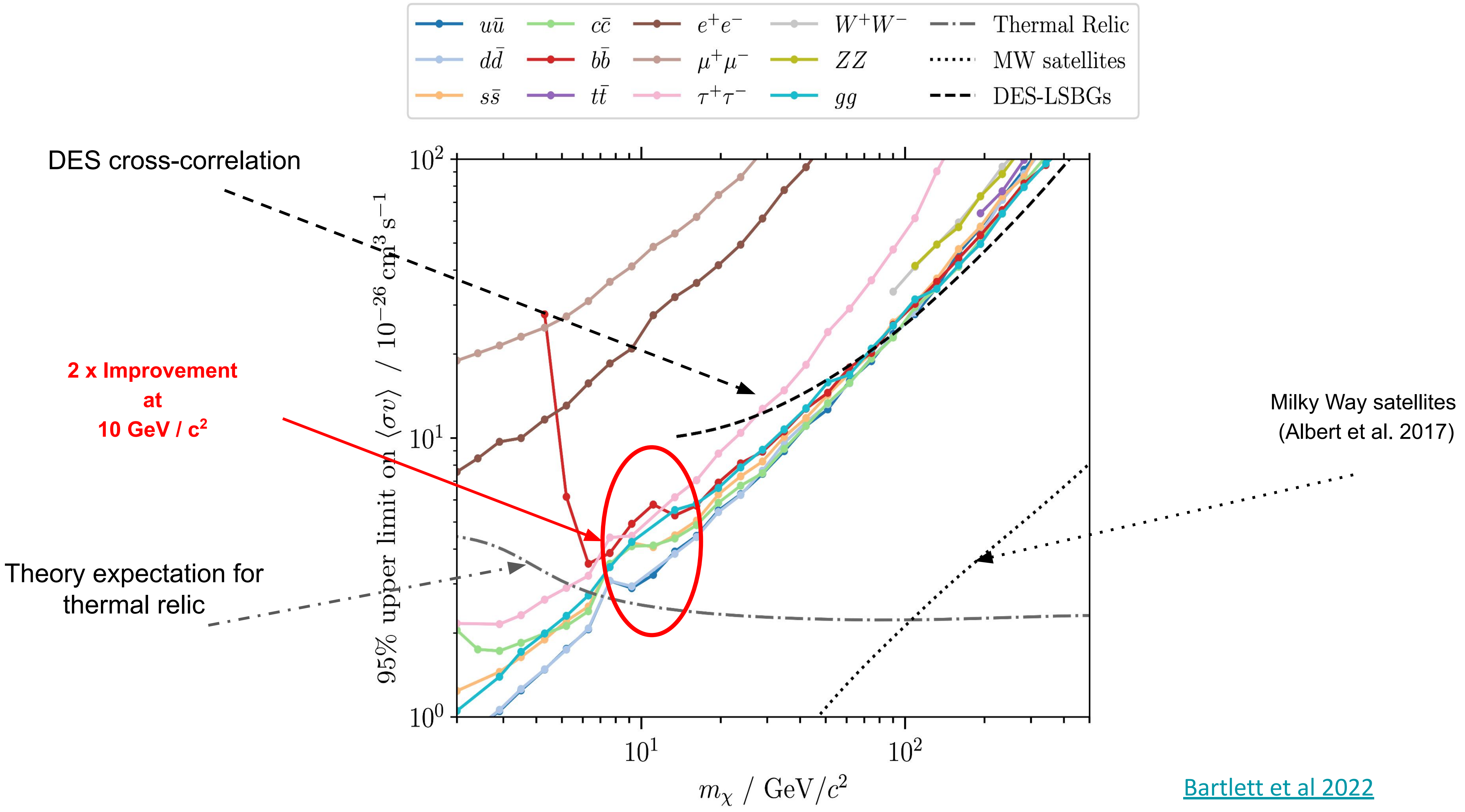
Bartlett et al 2022

Constraining dark matter annihilation and decay (Deaglan Bartlett & Andrija Kostić)



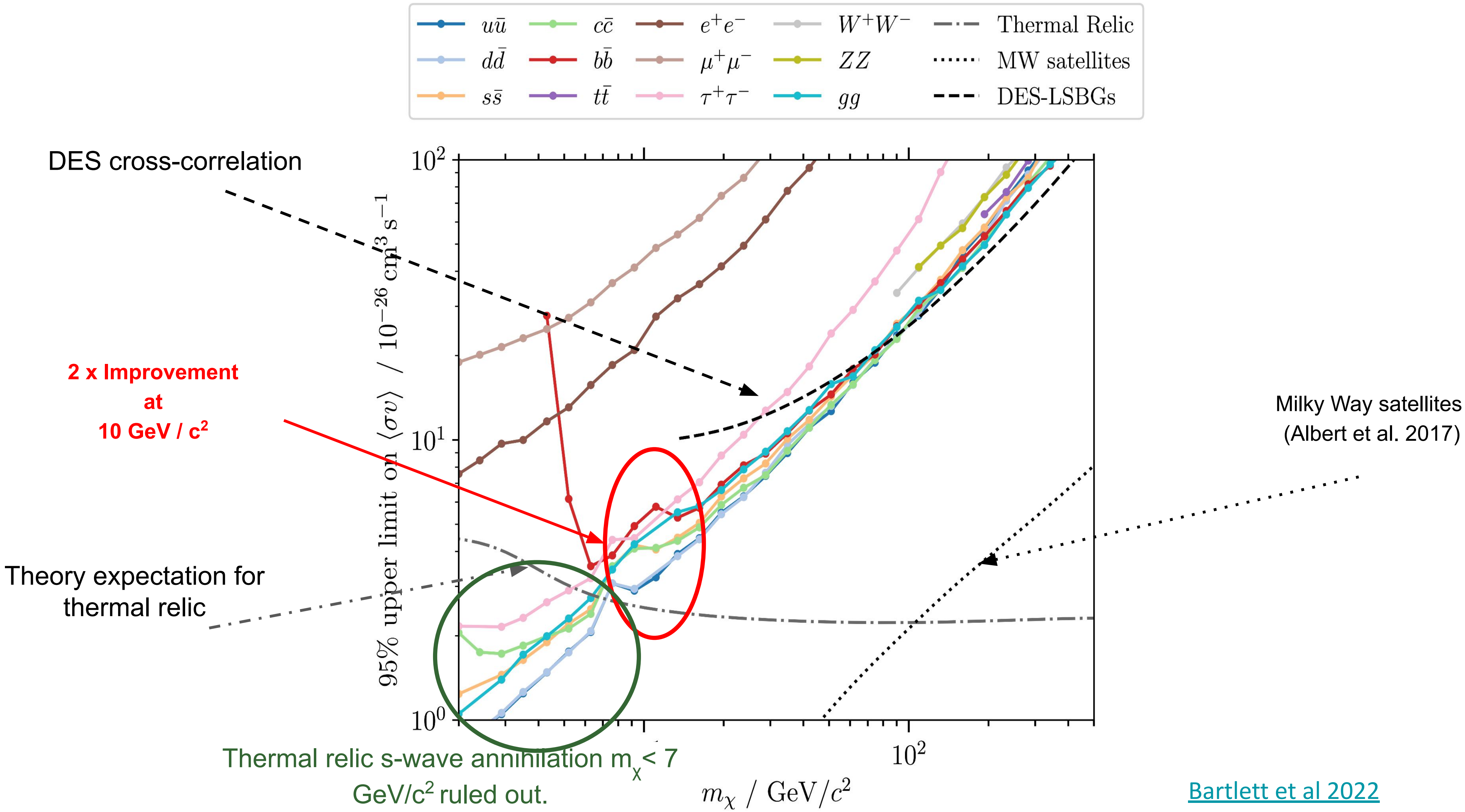
Bartlett et al 2022

Constraining dark matter annihilation and decay (Deaglan Bartlett & Andrija Kostić)



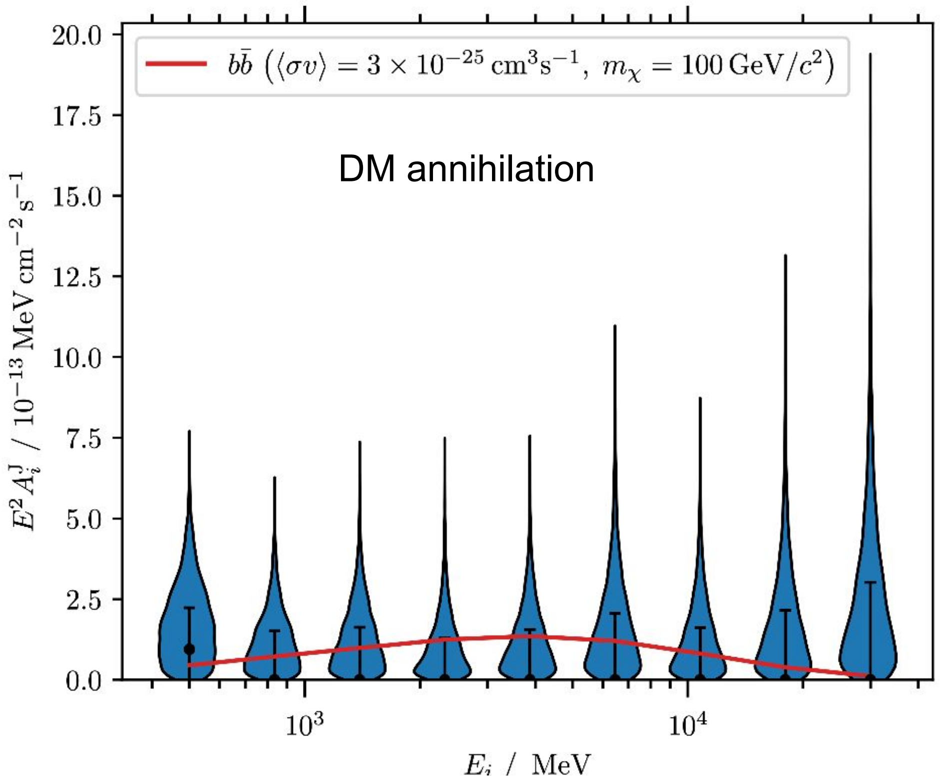
Bartlett et al 2022

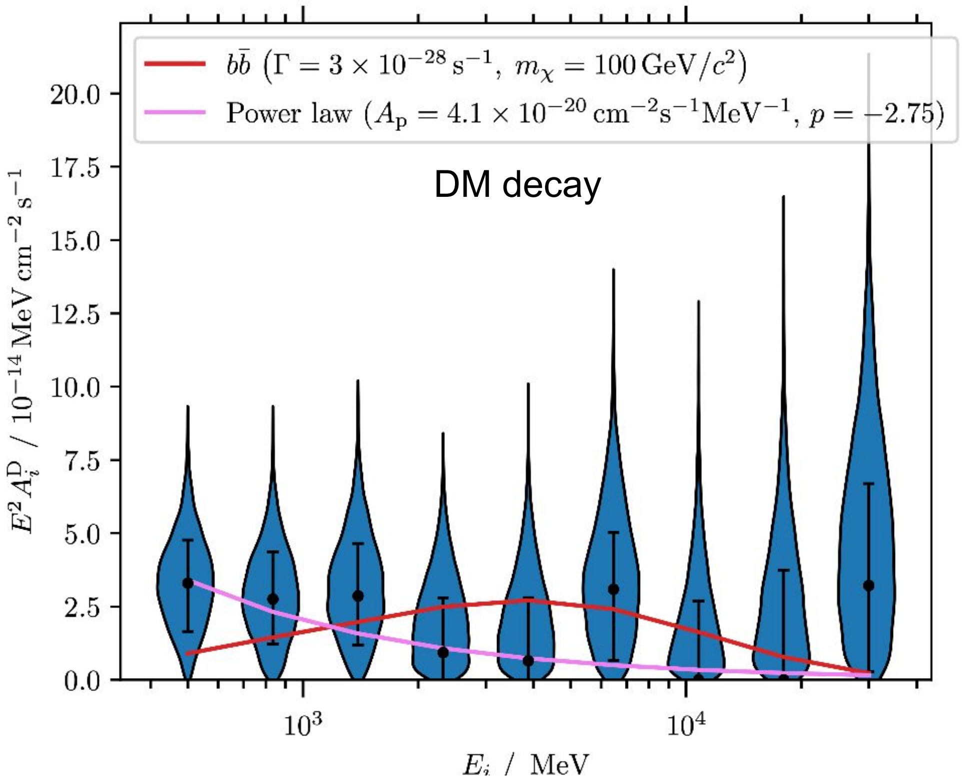
Constraining dark matter annihilation and decay (Deaglan Bartlett & Andrija Kostić)



Bartlett et al 2022

Constraining dark matter annihilation and decay (Deaglan Bartlett & Andrija Kostić)





- We find gamma ray sky contributions correlating spatially with dark matter decay at 3.3σ.
- However, a power-law spectrum likely of baryonic origin, is preferred by the data.

Bartlett et al 2022

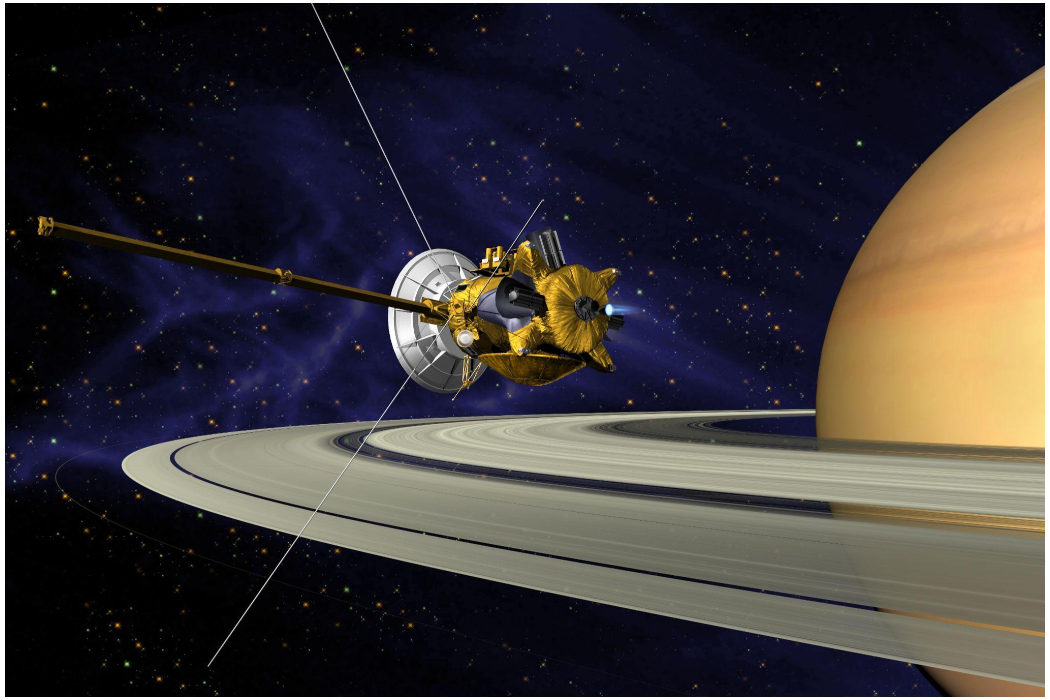
Shapiro time delay - constrain PPN parameter γ

$$\mathrm{d}s^2 = -\left(1 + 2\phi\right)\mathrm{d}t^2 + a^2(t)\left(1 - 2\gamma\phi\right)\mathrm{d}\vec{r}^2$$

$$t = \int_{r_\mathrm{e}}^{r_\mathrm{o}} a(z)\sqrt{\frac{1-2\gamma\phi}{1+2\phi}}\mathrm{d}r$$

$$\approx \int_{r_\mathrm{e}}^{r_\mathrm{o}} a(z)\left(1 - \left(1+\gamma\right)\phi\right)\mathrm{d}r$$

$$= t_0 + t_\mathrm{grav}$$



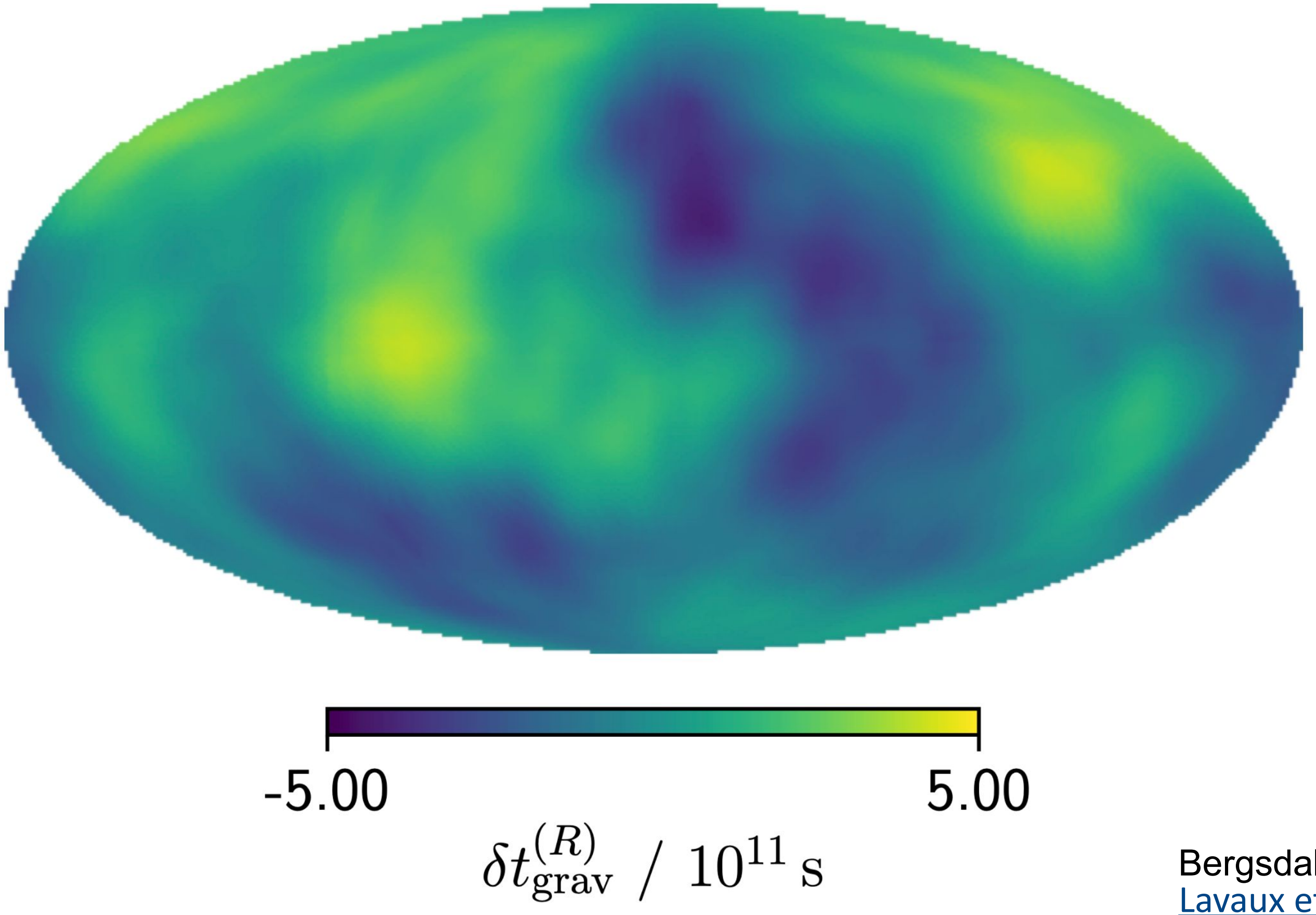
Cassini $(\gamma - 1) = (-0.8 \pm 1.2) \times 10^{-4}$ Bertotti et al 2003

VLBI $(\gamma - 1) < (-2.1 \pm 2.3) \times 10^{-5}$ Titov et al 2018

Bergsdal et al (2019), Bartlett et al 2021

Shapiro time delays predicted by BORG SDSS III DR12 reconstruction

$z = 0.1$



Bergsdal et al (2019), Bartlett et al 2021
Lavaux et al. 2020

Testing Equivalence Principle Violations (Deaglan Bartlett)

Assume the PPN parameter γ to depend on Energy *E*:

$$t_{\mathrm{gra}}(\gamma) = -\frac{1+\gamma(E)}{c^3}\int_{r_e}^{r_0} \phi_0(r) D(z) \mathrm{d}r.$$

If EP is violated then:

- Photons of different Energy have different travel times: ≠1

$$\Delta t_{\mathrm{gra}}^{1,2} = \frac{\gamma(E_1)-\gamma(E_2)}{c^3}\int \phi_0(r) D(z) \mathrm{d}r = \Delta\gamma^{1,2} I_{\mathrm{LOS}}$$

Bergsdal et al (2019), Bartlett et al 2021

Use Gamma Ray Bursts (GRBs):

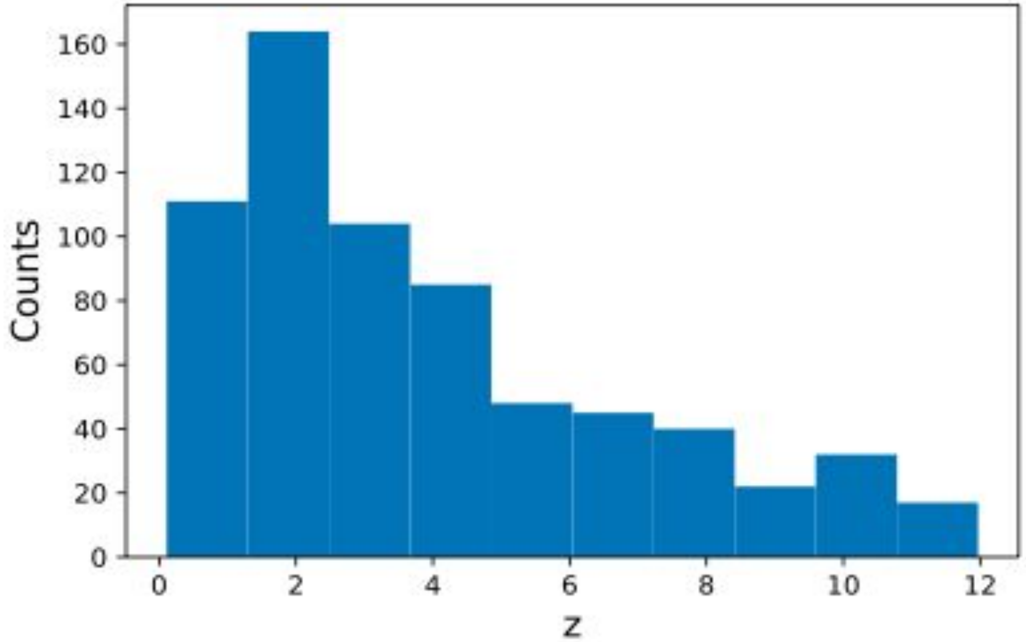
- immensely energetic explosions (e.g. SNe, black holes)
- can last from ten milliseconds to several hours.

Time arrival data for 4 energy channels

Ch 1: 25 - 60 keV
Ch 2: 60 - 110 keV
Ch 3: 110 - 325 keV
Ch 4: > 325 keV

Yu et al (2018, ApJ)

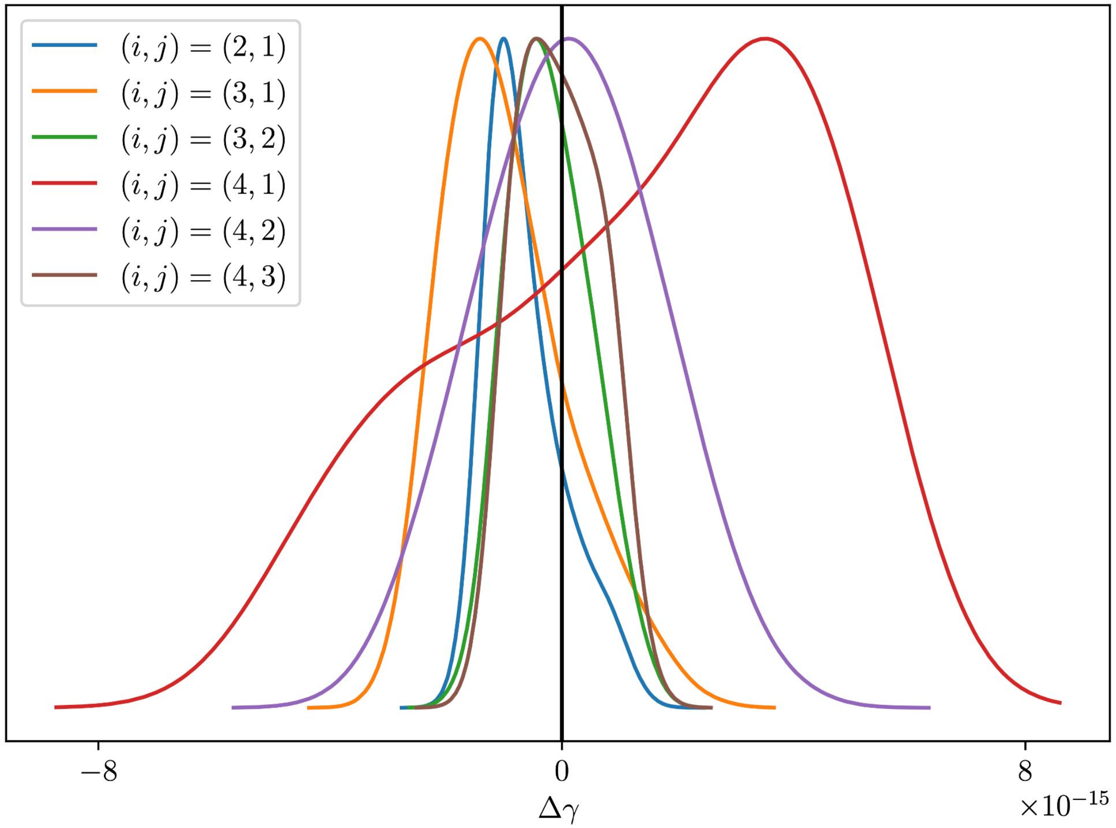
Time delay data (e.g. GRBs)



Equivalence Principle: All photons, irrespective of their energy, should arrive simultaneously!

Testing Equivalence Principle Violations (Deaglan Bartlett)

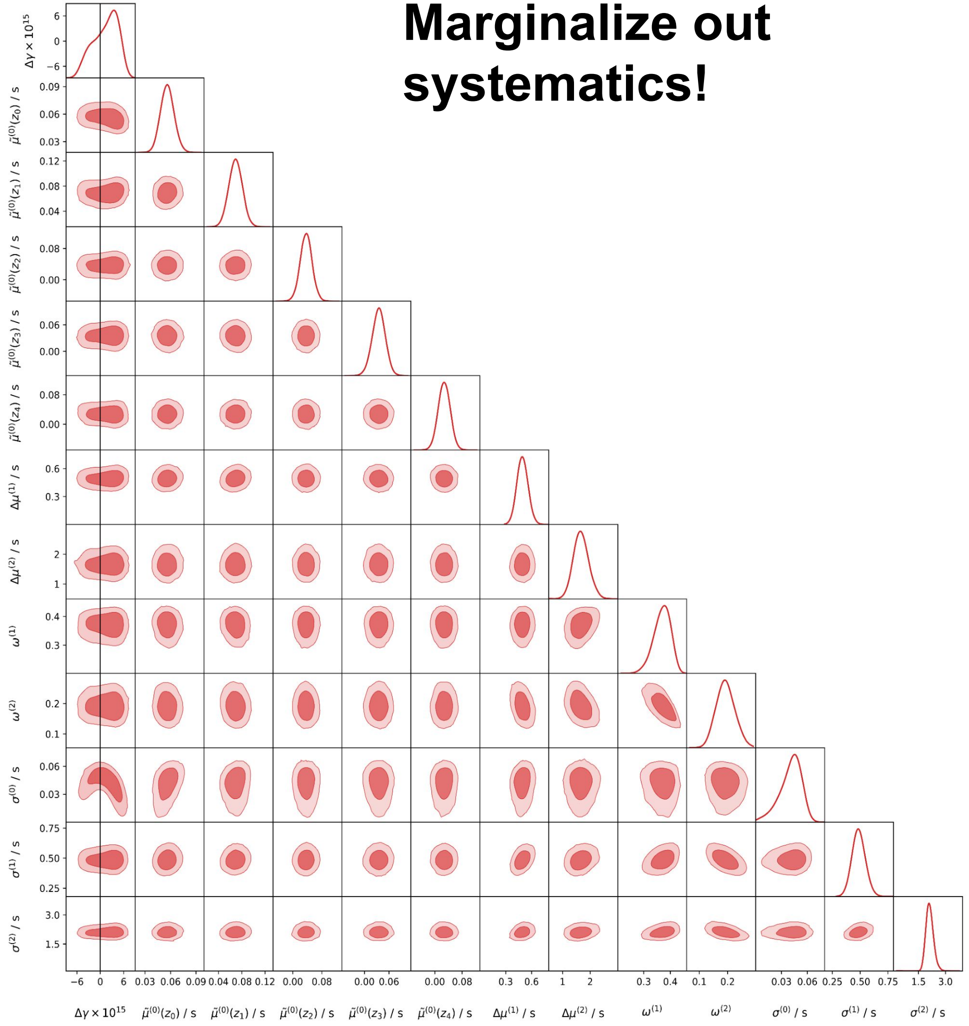
Inferred EP violation



$$\Delta\gamma_{ij} < 3.4 \times 10^{-15}$$

(Also see Nusser (2016), Yu (2018))

Marginalize out systematics!



Bartlett et al 2021

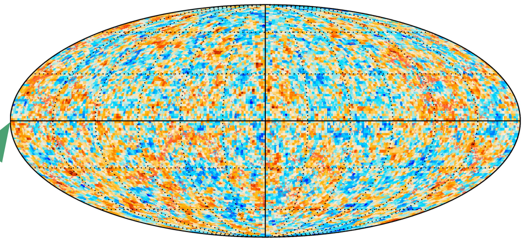
Summary: Current data science capabilities of Aquila

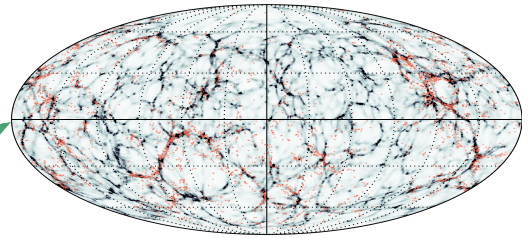
Currently supported data

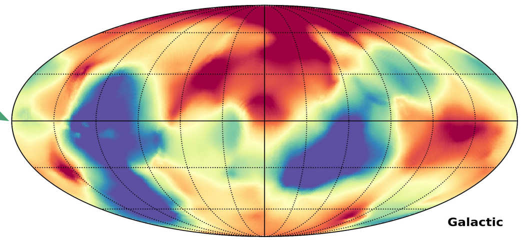
- Galaxy clustering data
- Cosmic shear data
- Velocity tracer data
- Lyman-α data

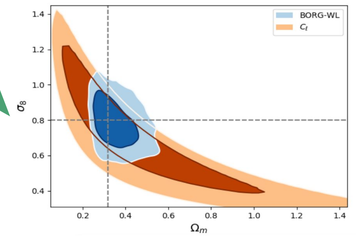
Bayesian forward modeling
Modeling the data e2e at the field level

Generated data products









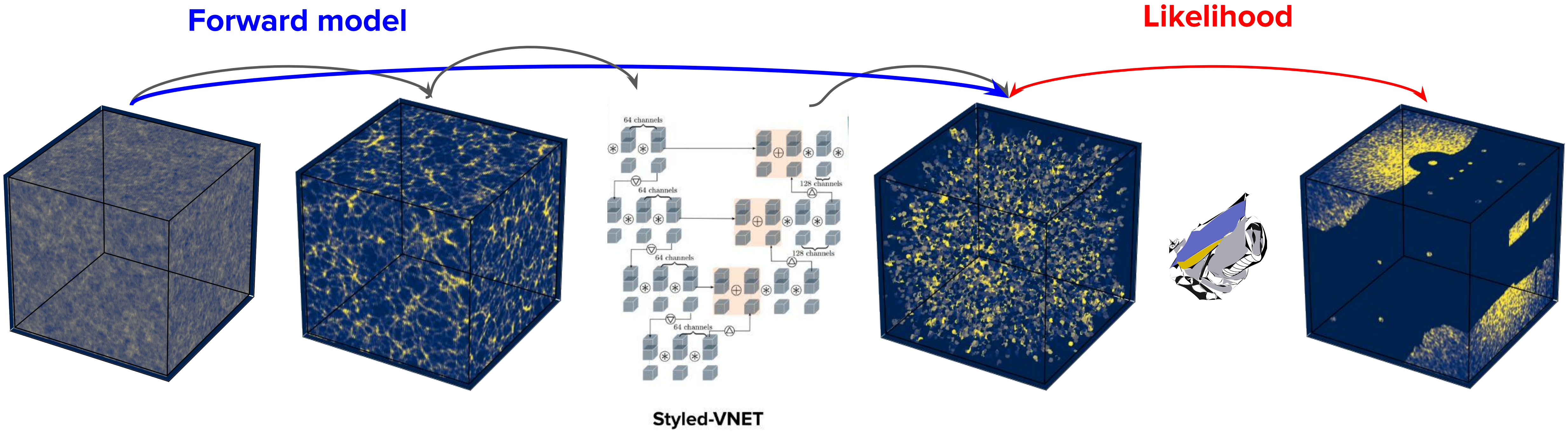
BORG provides:

- Inference of 3d initial conditions
- Full dynamical characterization of cosmic structures
- Improved cosmological parameter inferences
- Rigorous Bayesian uncertainty quantification

BORG + Deep learning Field-Level Emulator (Ludvig Doeser, Drew Jamieson)

Preliminary

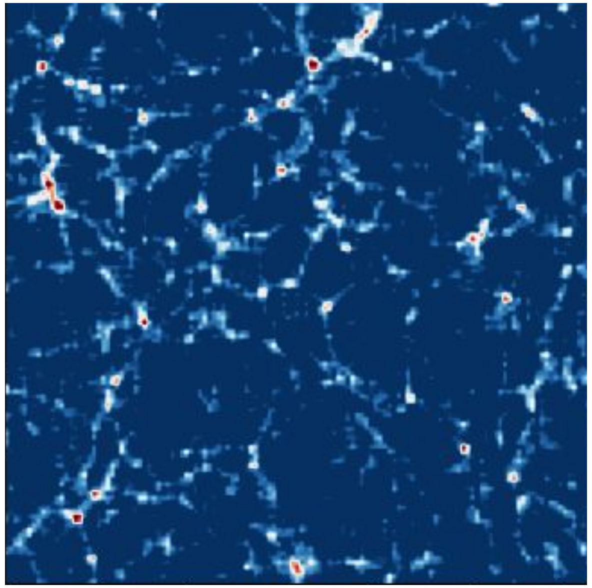
- **Differentiability**
- **Accuracy**
- **Speed**



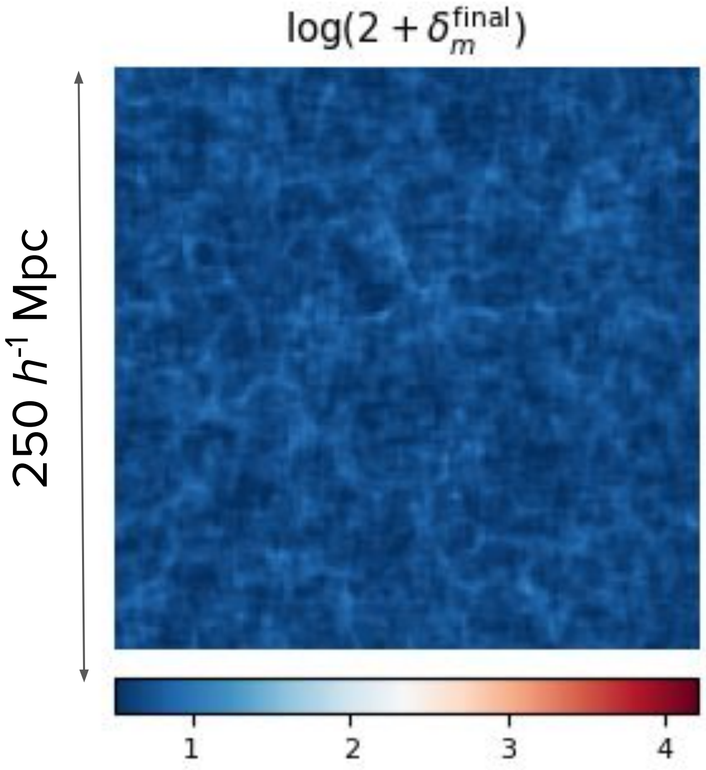
Drew J. et al. (2022): https://arxiv.org/pdf/2206.04594

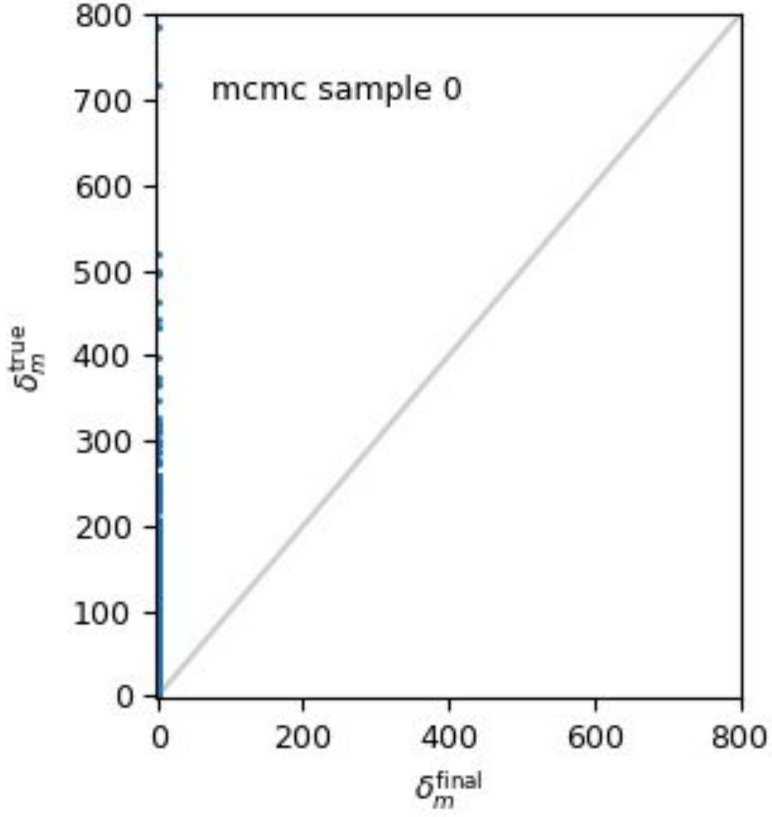
BORG + Deep learning Field-Level Emulator (Ludvig Doeser, Drew Jamieson)

Preliminary



Gadget truth

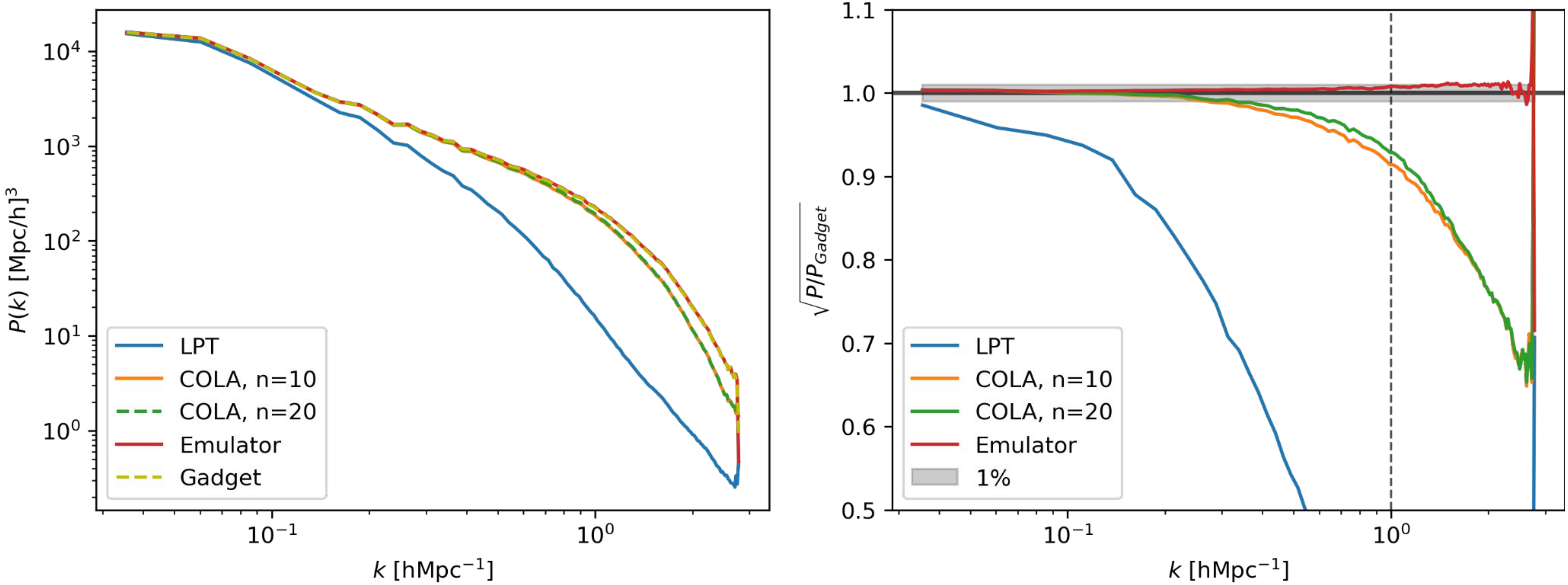




Doeser et al in prep

BORG + Deep learning Field-Level Emulator (Ludvig Doeser, Drew Jamieson)

Preliminary



Doeser et al in prep

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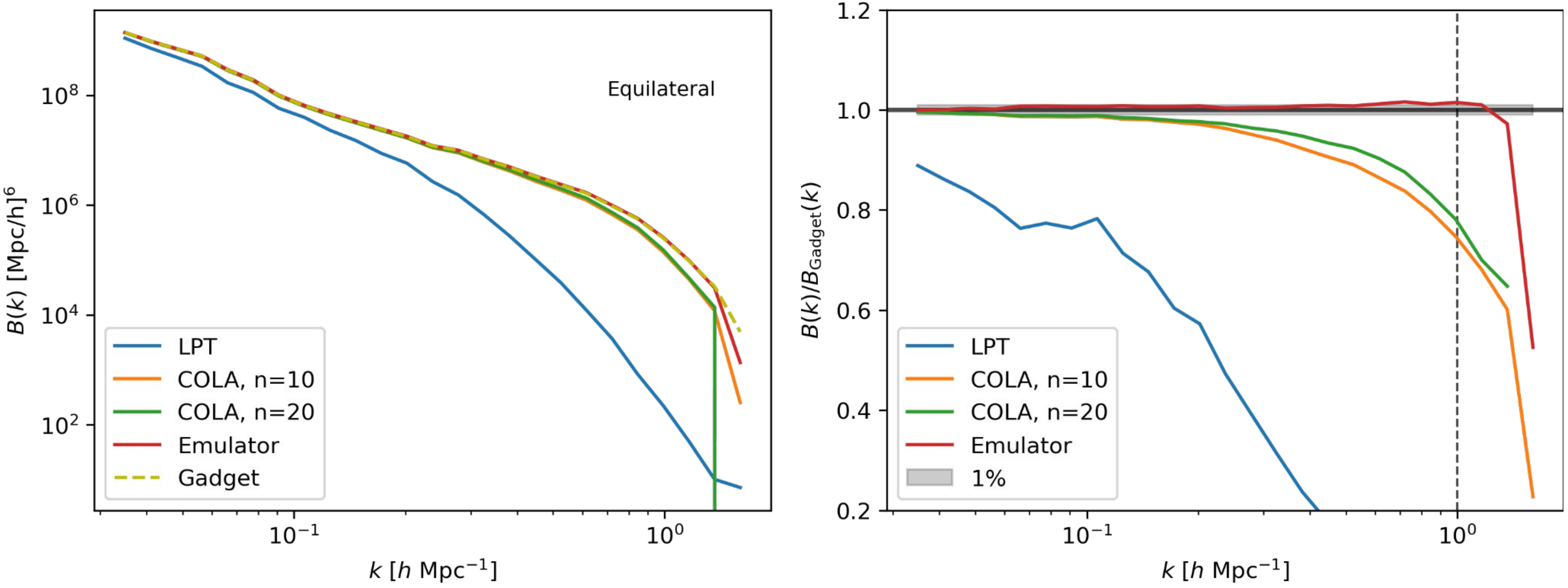
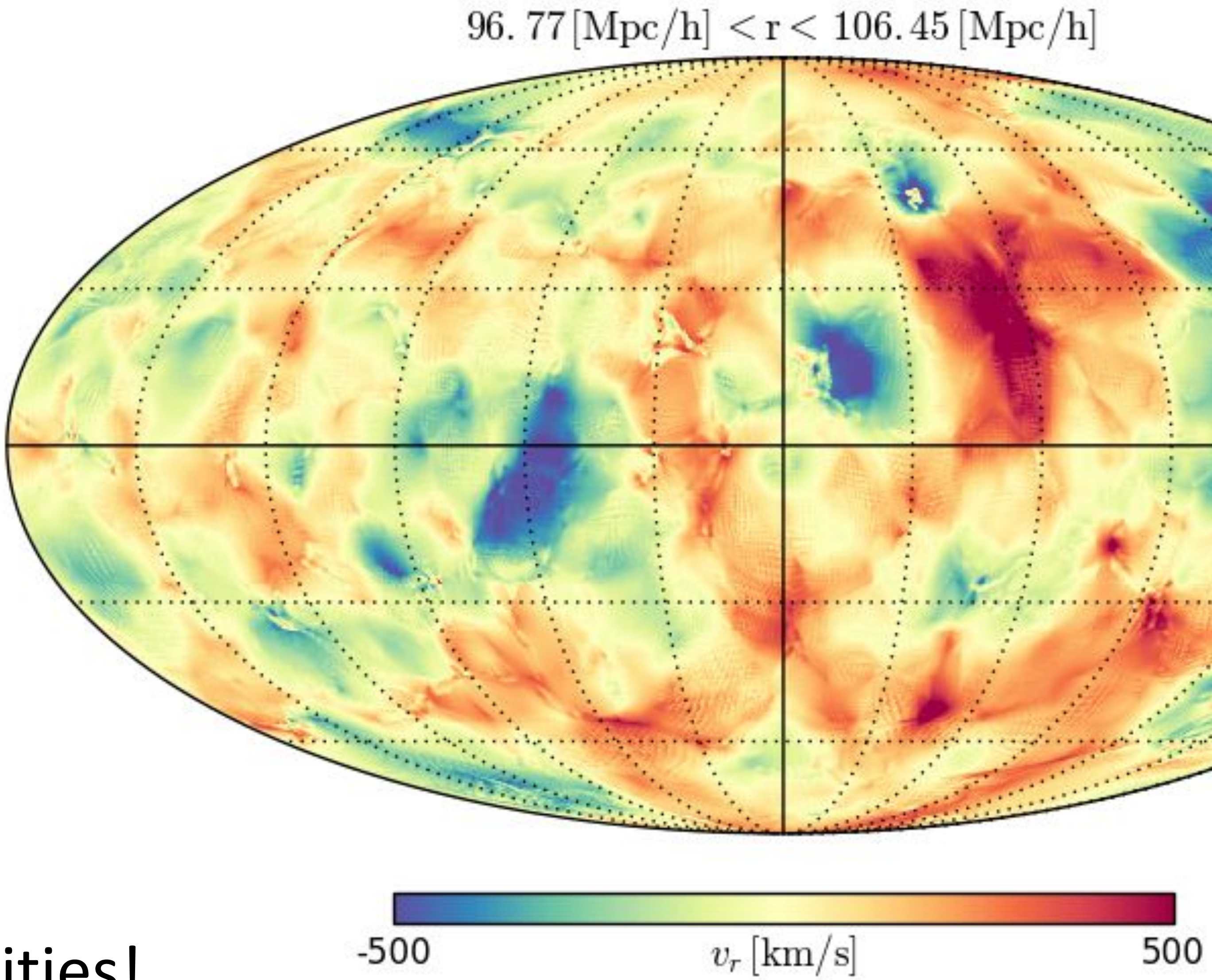
Preliminary



Doeser et al in prep

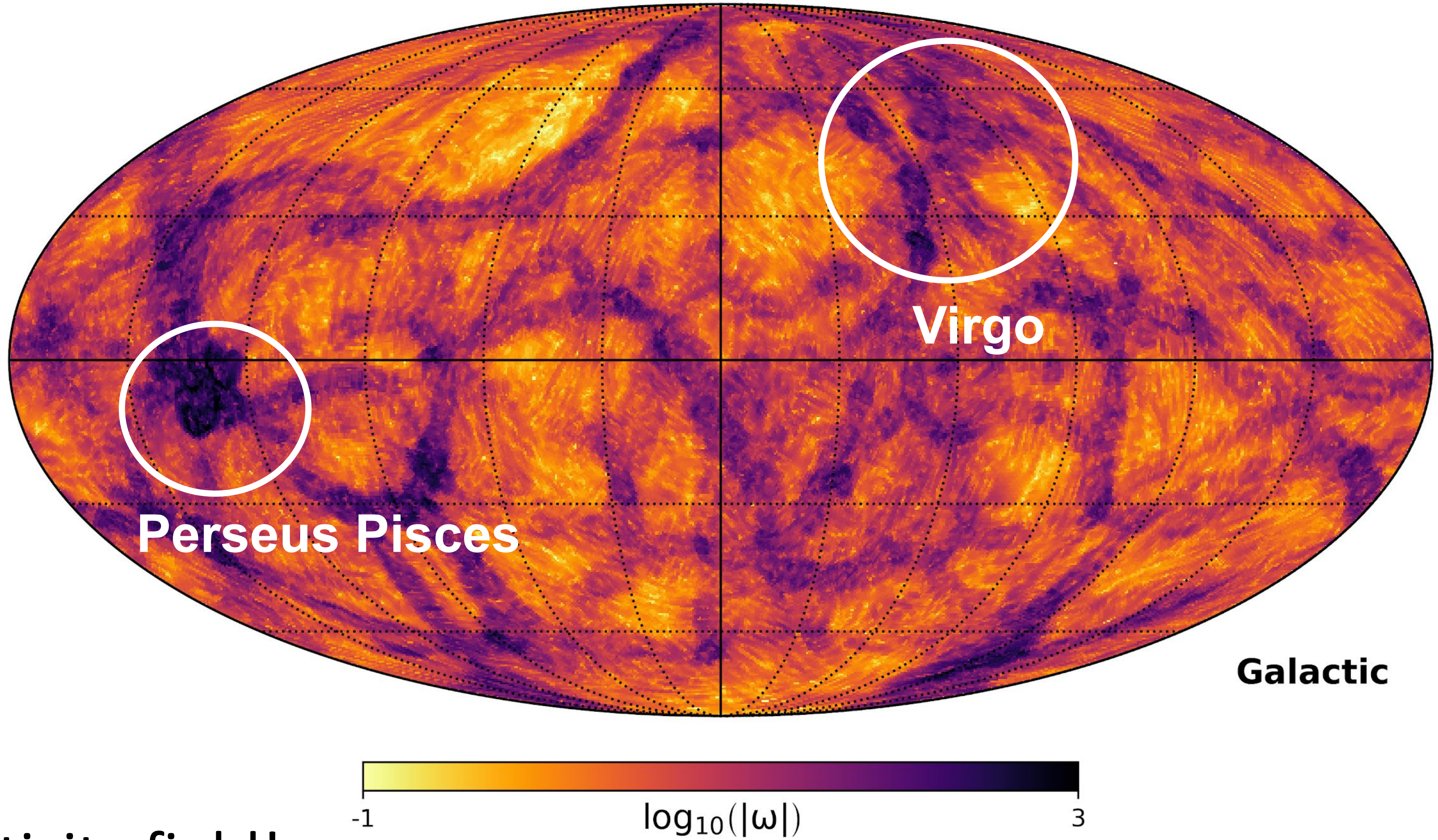
Bayesian forward modeling of the 2M++ galaxy compilation (JJ + Guilhem Lavaux)



Peculiar velocities!

Jasche & Lavaux 2019

Bayesian forward modeling of the 2M++ galaxy compilation (JJ + Guilhem Lavaux)



Velocity vorticity field!

Jasche & Lavaux 2019

05

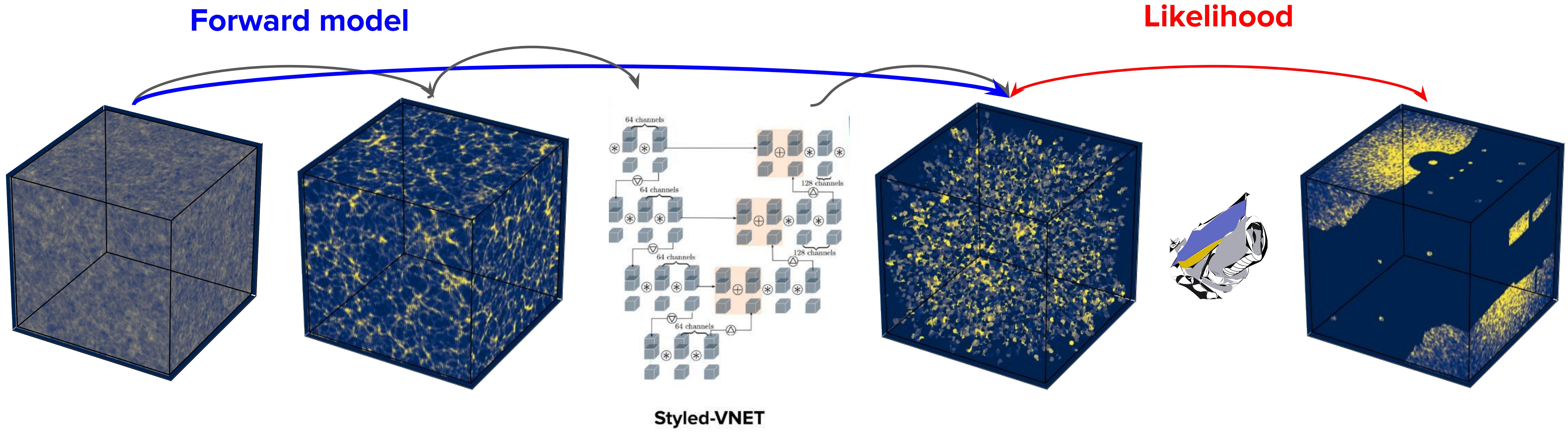
Neural Emulator

Speeding up simulations

BORG + Deep learning Field-Level Emulator (Ludvig Doeser, Drew Jamieson)

Preliminary

- **Differentiability**
- **Accuracy**
- **Speed**



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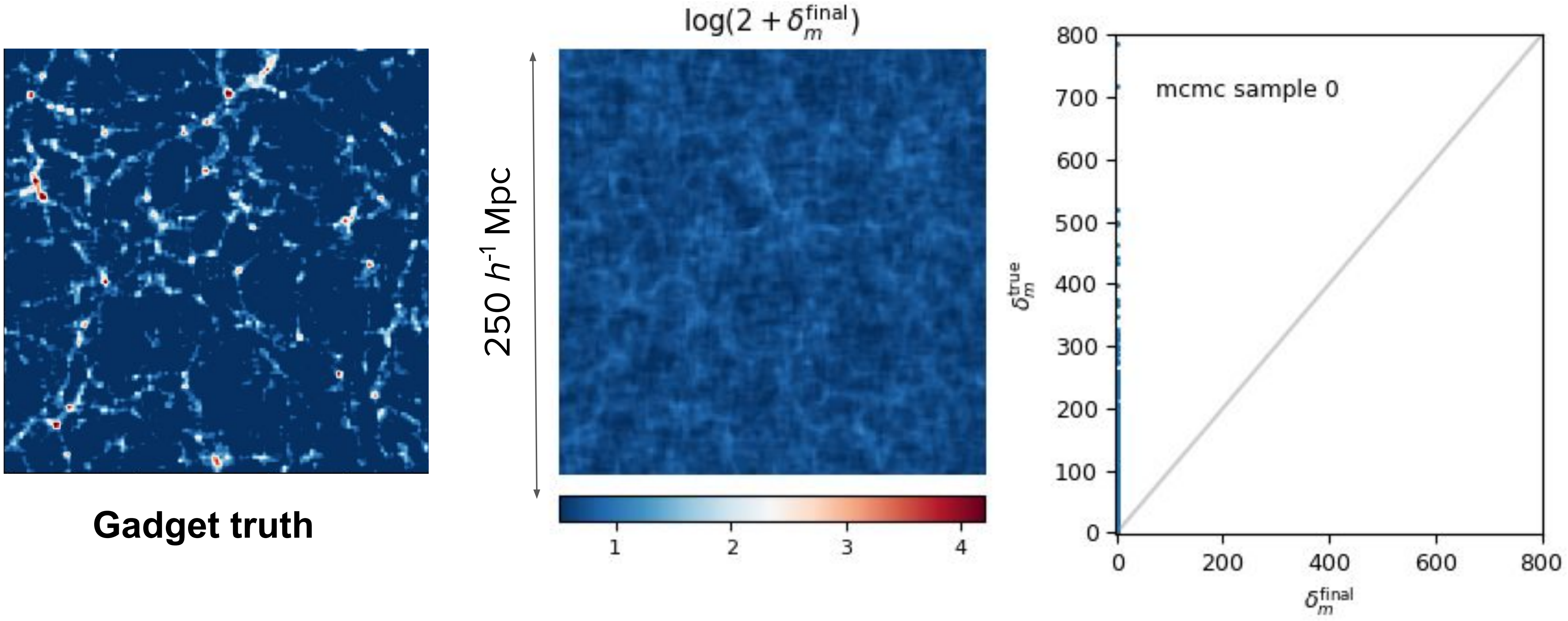

Doeser et al in prep

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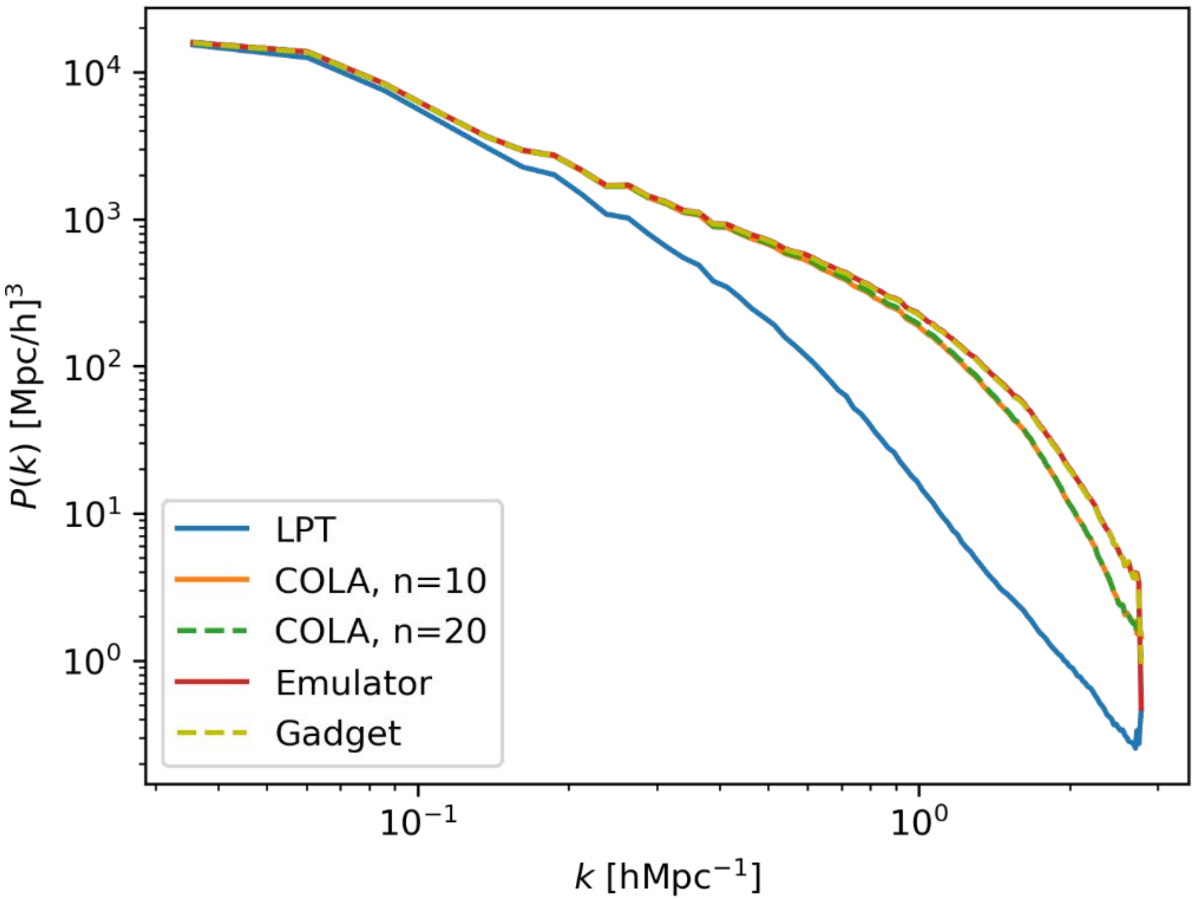

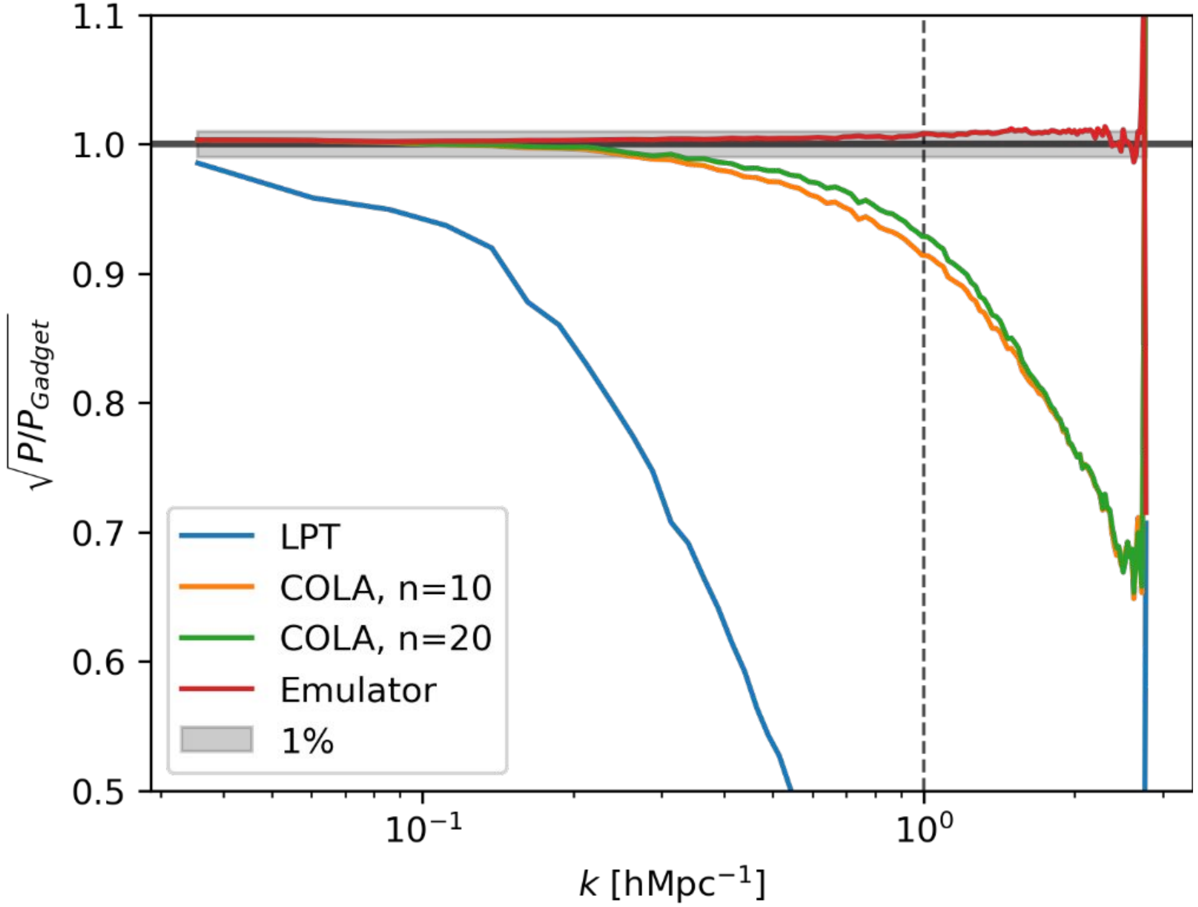

Doeser et al in prep

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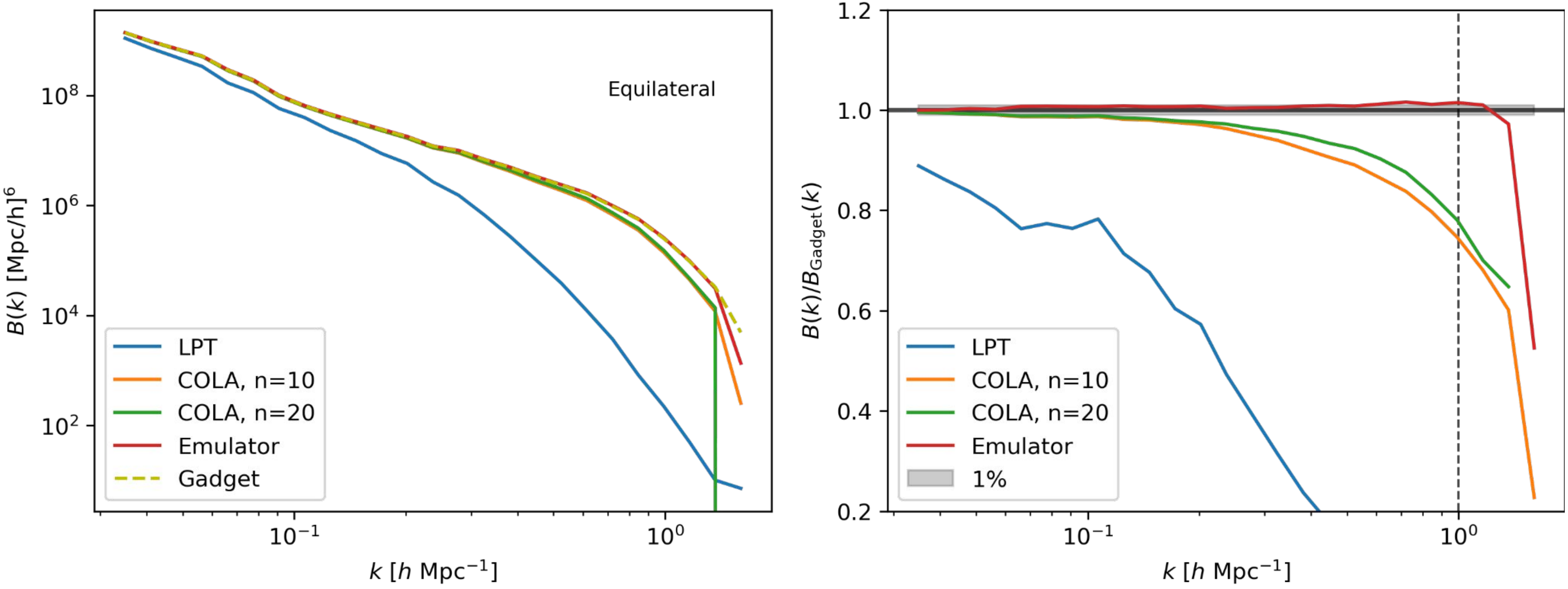


Doeser et al in prep

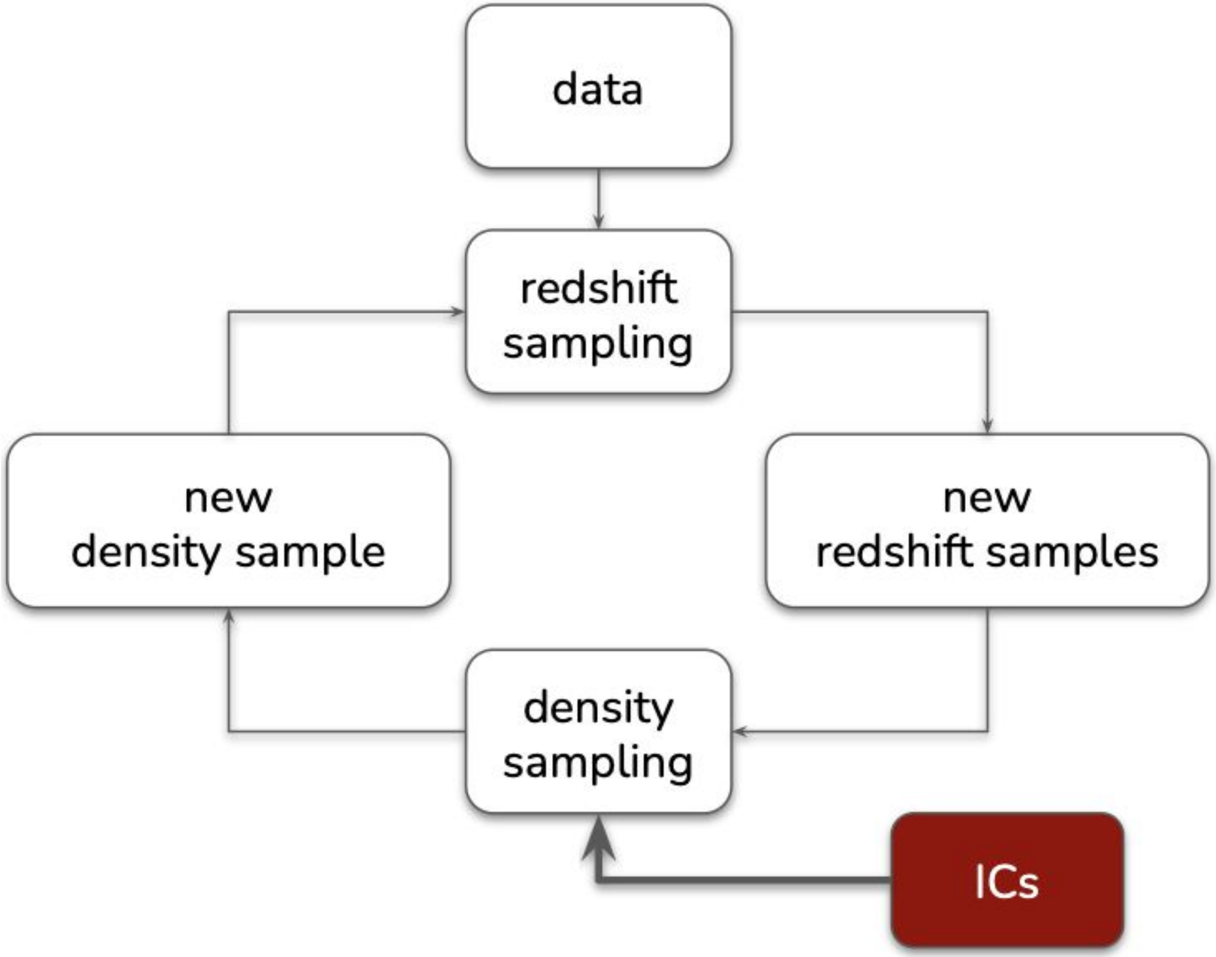
06 Photometric redshift sampling

inferring cosmic structures next-gen surveys

Physics-informed Bayesian correction of photometric redshifts (Eleni Tsaprazi)

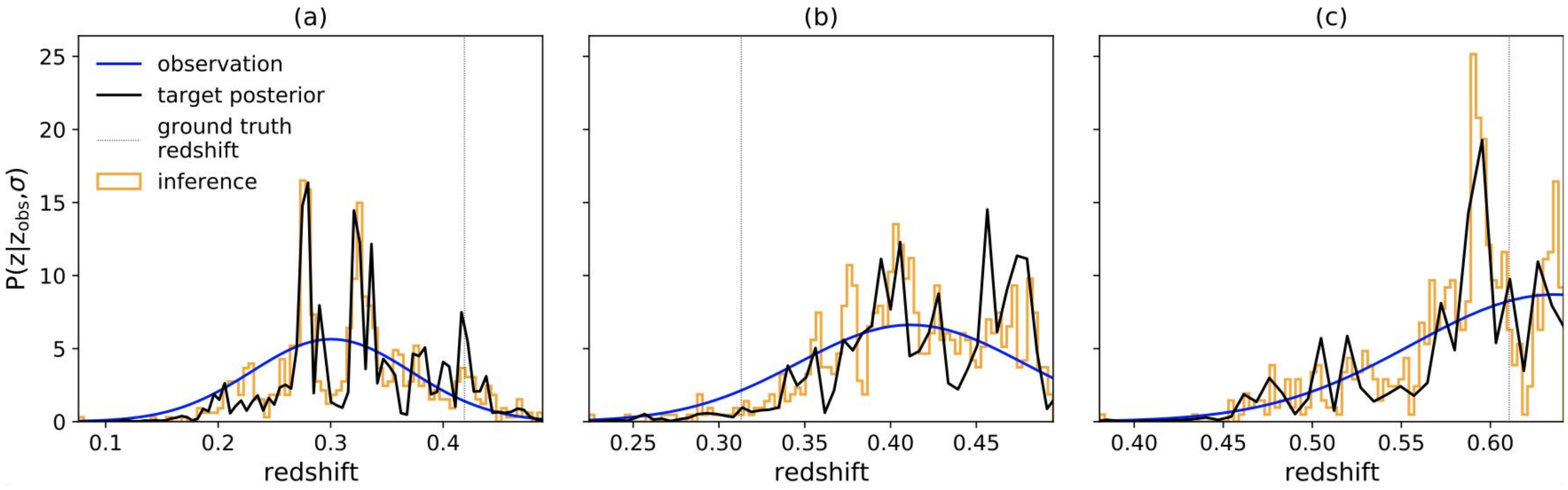
Galaxies trace the cosmic structure

1. **Infer 3D density field**
2. **Update Galaxy positions**



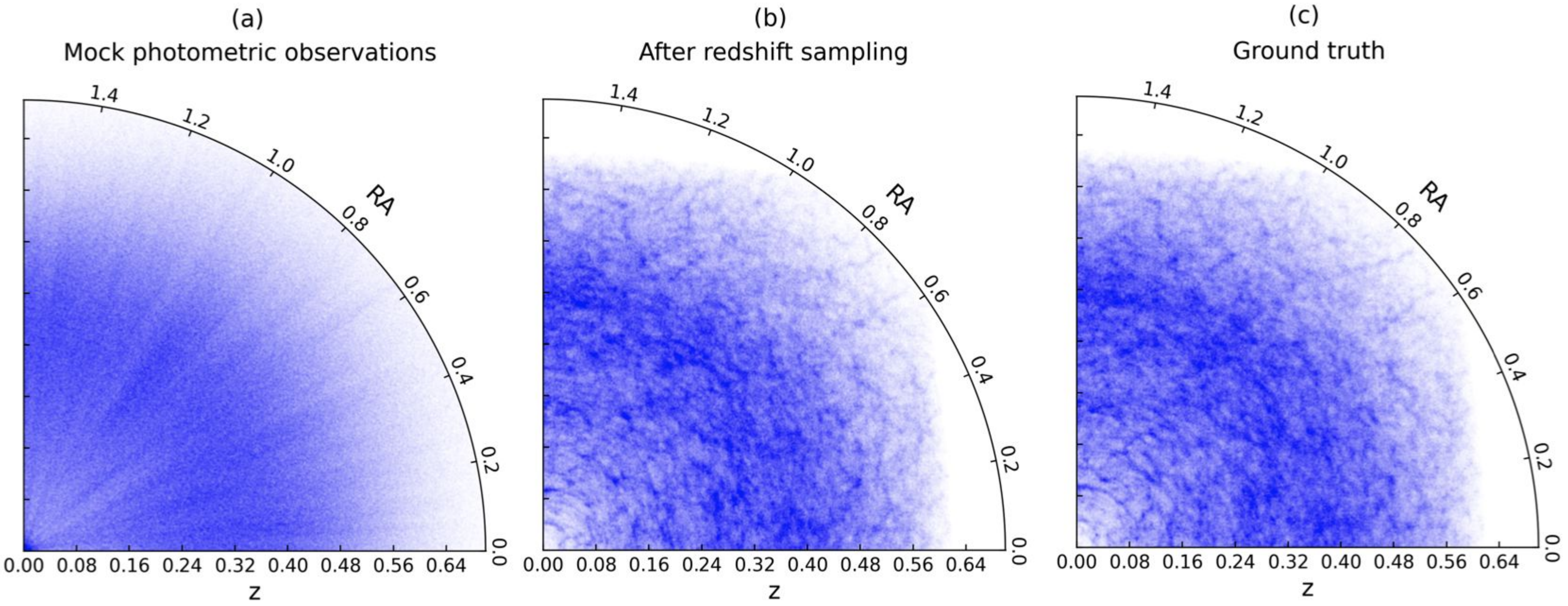
[Jasche & Wandelt 2012](#)
[Tsaprazi et al 2023](#)

Physics-informed Bayesian correction of photometric redshifts (Eleni Tsaprazi)



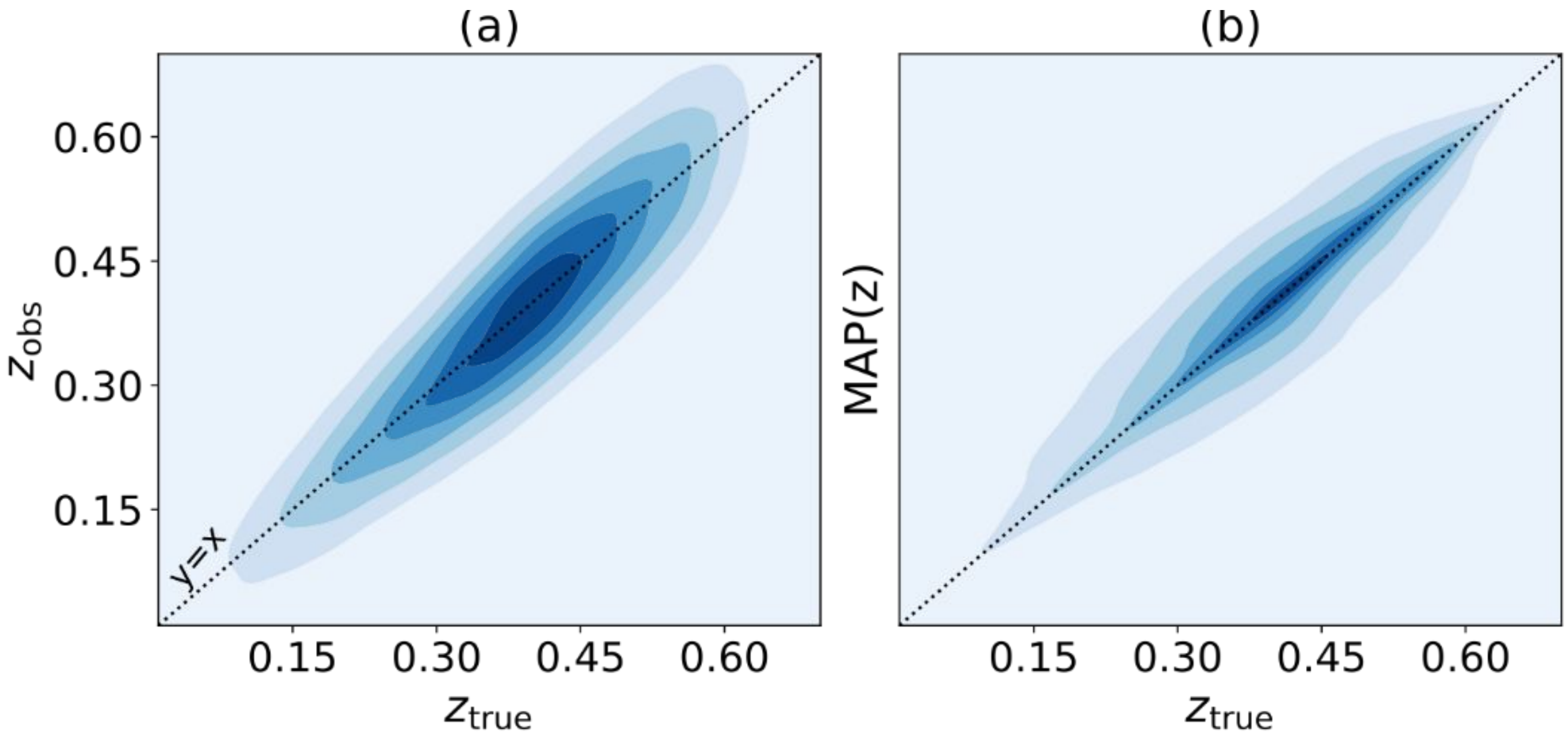
[Tsaprazi et al 2023]

Physics-informed Bayesian correction of photometric redshifts (Eleni Tsaprazi)



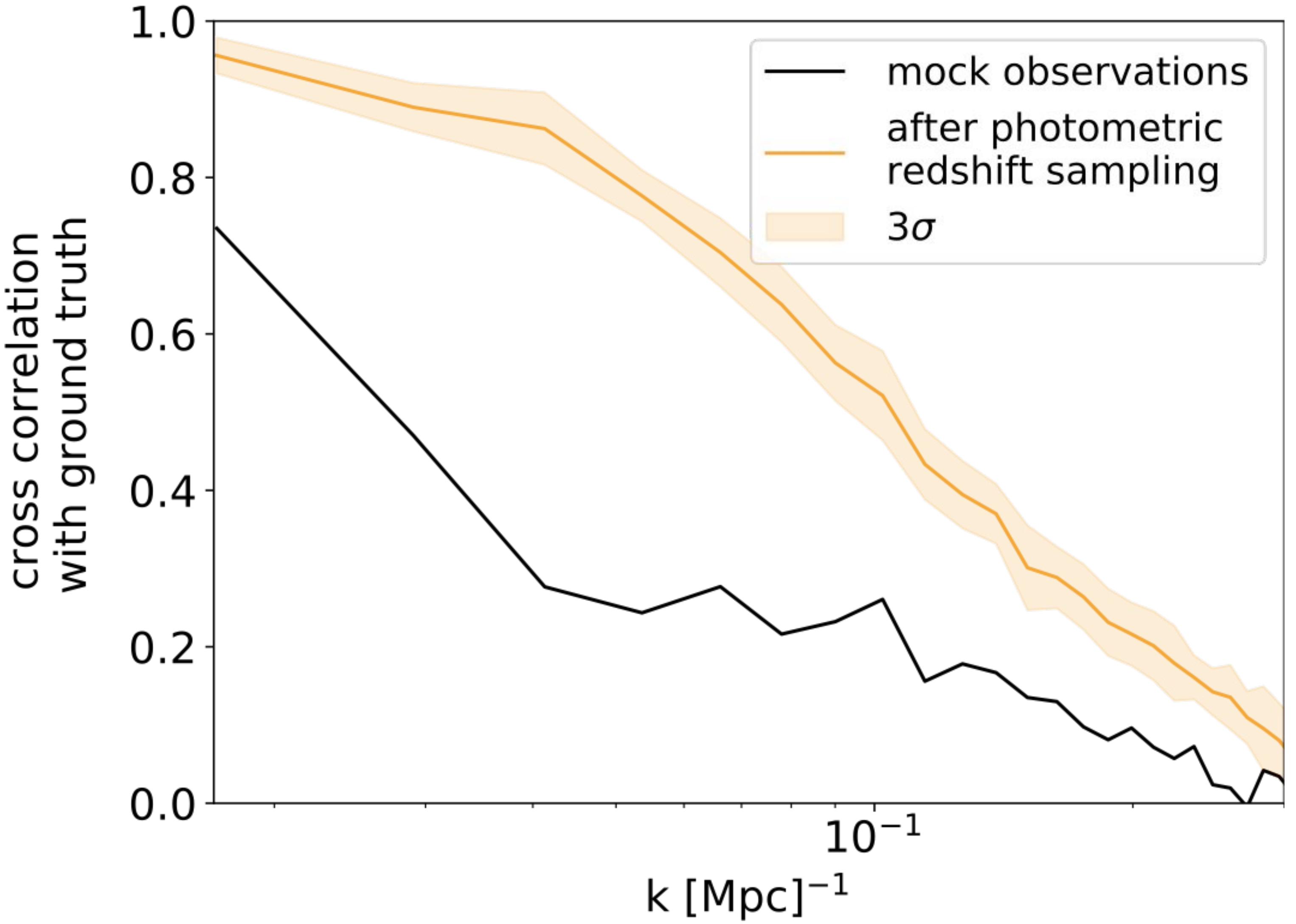
[Tsaprazi et al 2023](#)

Physics-informed Bayesian correction of photometric redshifts (Eleni Tsaprazi)



Tsaprazi et al 2023

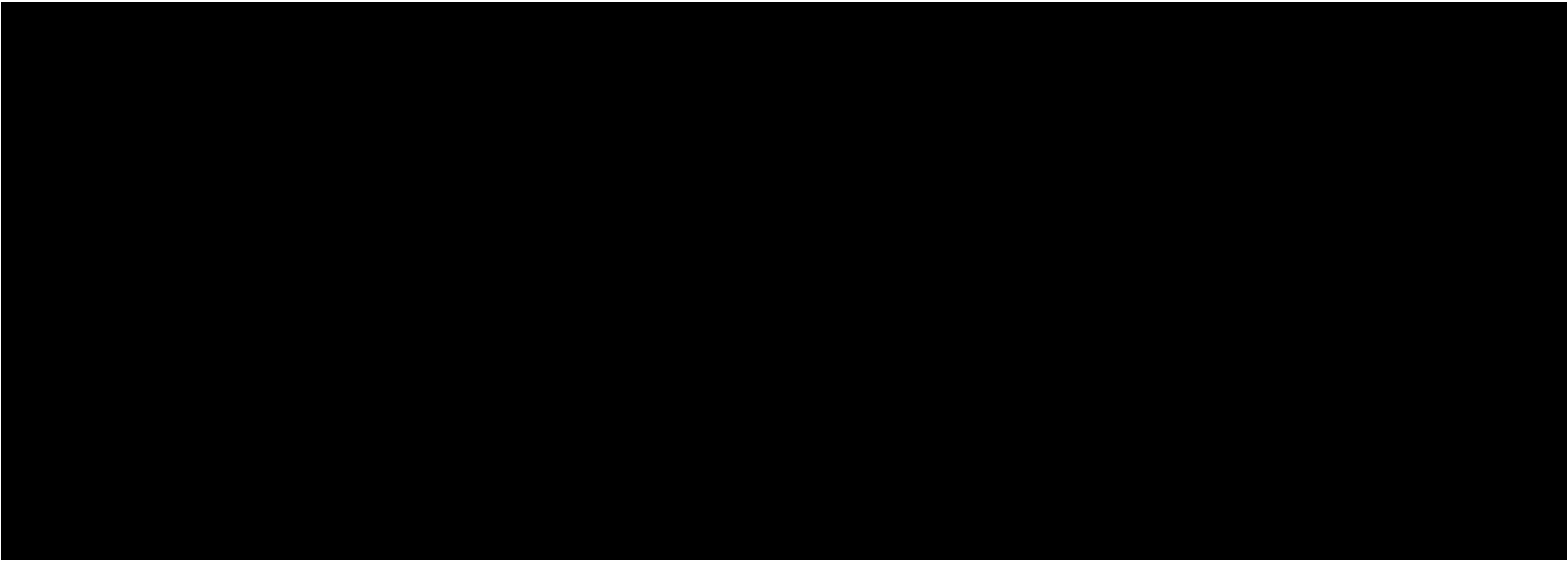
Physics-informed Bayesian correction of photometric redshifts (Eleni Tsaprazi)



Tsaprazi et al 2023

Bayesian forward modeling of the 2M++ galaxy compilation (JJ + Guilhem Lavaux)

A numerical cosmic structure posterior distribution



Movie credit: Florent Leclercq

Leclercq et al 2017

Jasche & Lavaux 2019