THERE AND BACK AGAIN

RECOVERING AUTOSPECTRA INFORMATION WITH MULTIPLE CROSSCORRELATION MEASUREMENTS

Lisa Mc Bride
LIM 2025

Line Intensity Mapping (LIM)

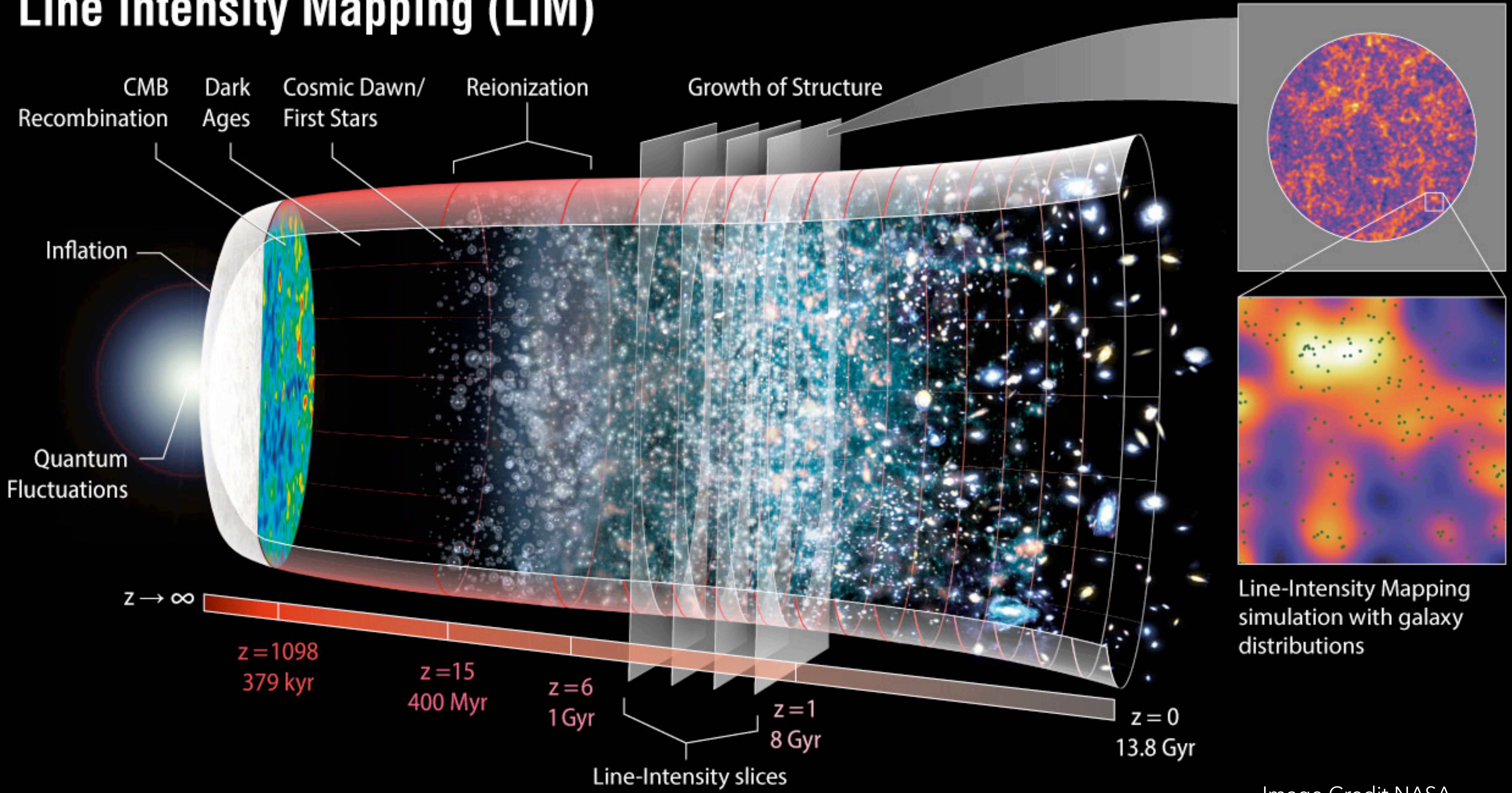

Image Credit NASA

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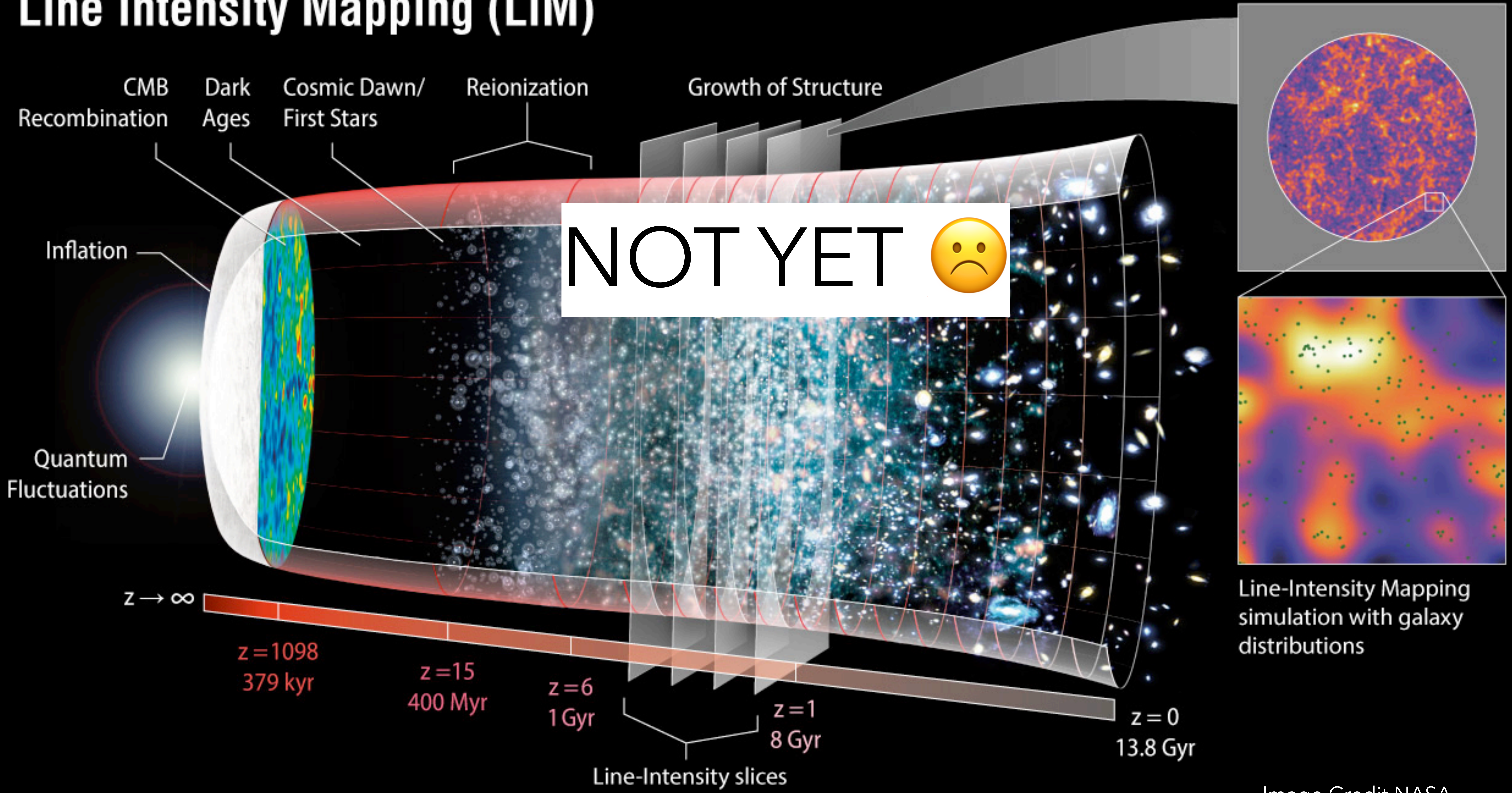

Image Credit NASA

NOT YET ☹️

Still very few auto spectra detections, particularly for 21cm

Image Credit NASA

Can we extract auto spectra information without a direct detection?

THE LINEAR BIASING MODEL

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On large scales, spectral lines are biased tracers of the underlying matter density field

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(power spectrum)

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Measuring the EoR Power Spectrum Without Measuring the EoR Power Spectrum

ANGUS BEANE,[1,2] FRANCISCO VILLAESCUSA-NAVARRO,[1] AND ADAM LIDZ[2]

[1] *Center for Computational Astrophysics, Flatiron Institute, 162 5th Ave., New York, NY 10010, USA*
[2] *Department of Physics & Astronomy, University of Pennsylvania, 209 South 33rd St., Philadelphia, PA 19104, USA*

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Beane et al: arXiv 1811.10609

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Stayed tuned for Adrian and Hannah's talks! 🥳

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LEAST SQUARES ESTIMATORS (LSE)

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a Frequentist estimator that is optimal (minimum variance) and unbiased under certain assumptions

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$$\boxed{\hat{x}} = [\mathbf{A}^T\mathbf{N}^{-1}\boxed{\mathbf{A}}]^{-1}\mathbf{A}^T\boxed{\mathbf{N}^{-1}}\boxed{\mathbf{d}}$$

$$\begin{pmatrix} \hat{\beta}_i \\ \hat{\beta}_j \\ \hat{\beta}_k \\ \hat{P}_m \end{pmatrix} = \begin{pmatrix} \beta_0 \\ \beta_0 P_{jk}/P_{ki} \\ \beta_0 P_{jk}/P_{ij} \\ \frac{P_{ij}P_{ki}}{\beta_0^2 P_{jk}} \end{pmatrix}$$

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$$\boxed{\hat{P}_{ii,\mathrm{B19}} = \frac{P_{ij}P_{ik}}{P_{jk}} \qquad \sigma^2_{P_{ii}} = \left(\frac{\sigma^2_{ij}}{P^2_{ij}} + \frac{\sigma^2_{jk}}{P^2_{jk}} + \frac{\sigma^2_{ik}}{P^2_{ik}}\right) P^2_{ii}}$$

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(1 prior, 1 autocorrelation, 3
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An inverse-variance weighted linear combination of the two types of observations!

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$$\begin{aligned}\ln \hat{P}_{21\mathrm{cm}} = {} & \frac{\tilde{\sigma}_{jl}^2\tilde{\sigma}_{il}^2 + \tilde{\sigma}_{kl}^2\tilde{\sigma}_{il}^2 + \tilde{\sigma}_{kl}^2\tilde{\sigma}_{jl}^2}{\Xi^2} \ln\left(\hat{P}_{\mathrm{B19},ijk}\right) \\ & + \frac{\tilde{\sigma}_{kl}^2\tilde{\sigma}_{jk}^2 + \tilde{\sigma}_{ik}^2\tilde{\sigma}_{jk}^2 + \tilde{\sigma}_{ik}^2\tilde{\sigma}_{kl}^2}{\Xi^2} \ln\left(\hat{P}_{\mathrm{B19},ijl}\right) \\ & + \frac{\tilde{\sigma}_{ij}^2\tilde{\sigma}_{jk}^2 + \tilde{\sigma}_{jl}^2\tilde{\sigma}_{jk}^2 + \tilde{\sigma}_{ij}^2\tilde{\sigma}_{jl}^2}{\Xi^2} \ln\left(\hat{P}_{\mathrm{B19},ikl}\right) \\ & + \frac{\tilde{\sigma}_{ik}^2\tilde{\sigma}_{il}^2}{\Xi^2} \ln\left(\hat{P}_{\mathrm{B19},ijkl}\right) + \frac{\tilde{\sigma}_{ij}^2\tilde{\sigma}_{il}^2}{\Xi^2} \ln\left(\hat{P}_{\mathrm{B19},ikjl}\right) \\ & + \frac{\tilde{\sigma}_{ij}^2\tilde{\sigma}_{ik}^2}{\Xi^2} \ln\left(\hat{P}_{\mathrm{B19},iljk}\right),\end{aligned}$$

$$\Xi^2 \equiv (\tilde{\sigma}_{ij}^2+\tilde{\sigma}_{kl}^2)(\tilde{\sigma}_{ik}^2+\tilde{\sigma}_{il}^2+\tilde{\sigma}_{jk}^2+\tilde{\sigma}_{jl}^2)+(\tilde{\sigma}_{ik}^2+\tilde{\sigma}_{jl}^2)(\tilde{\sigma}_{il}^2+\tilde{\sigma}_{jk}^2)$$

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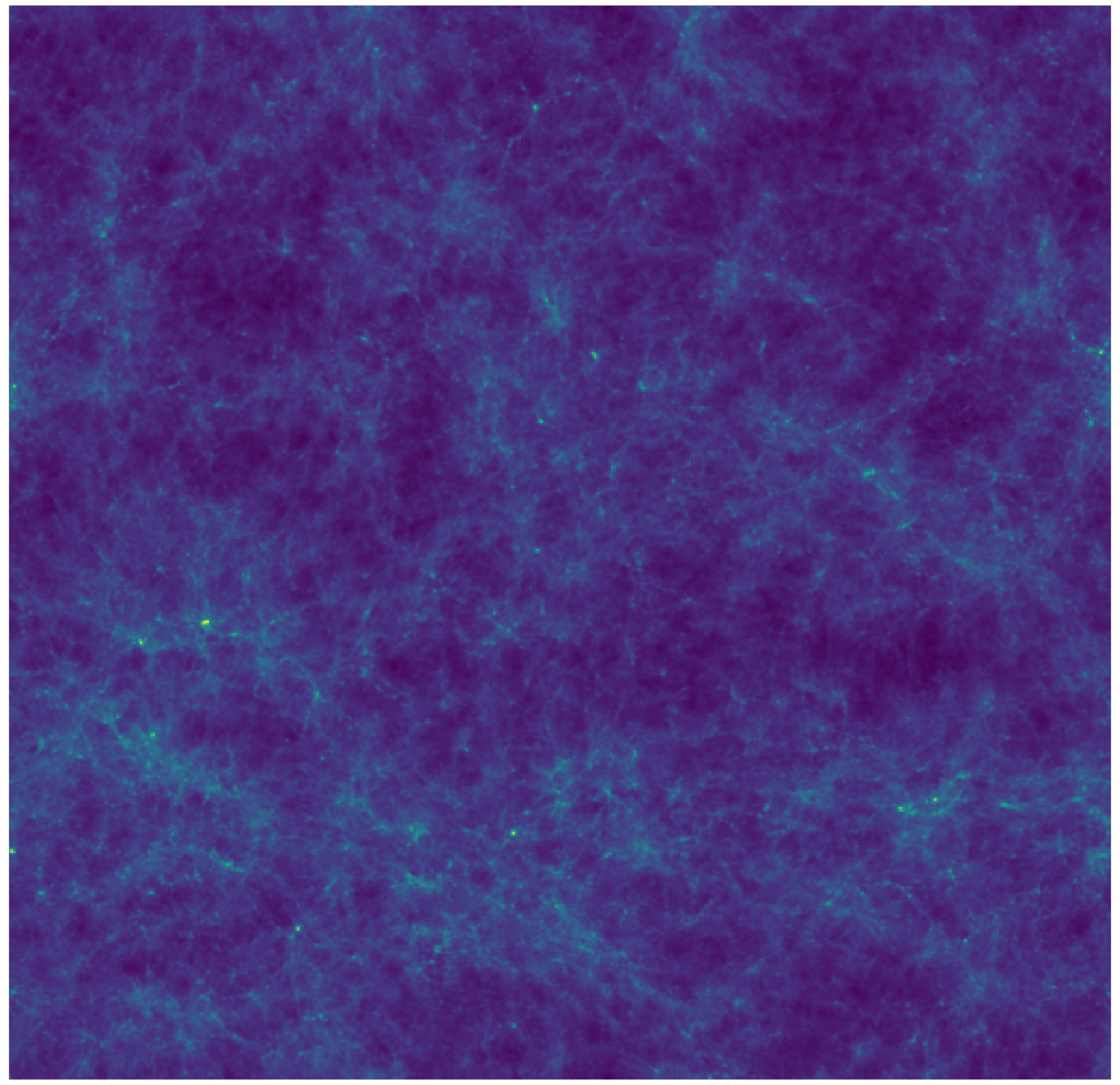

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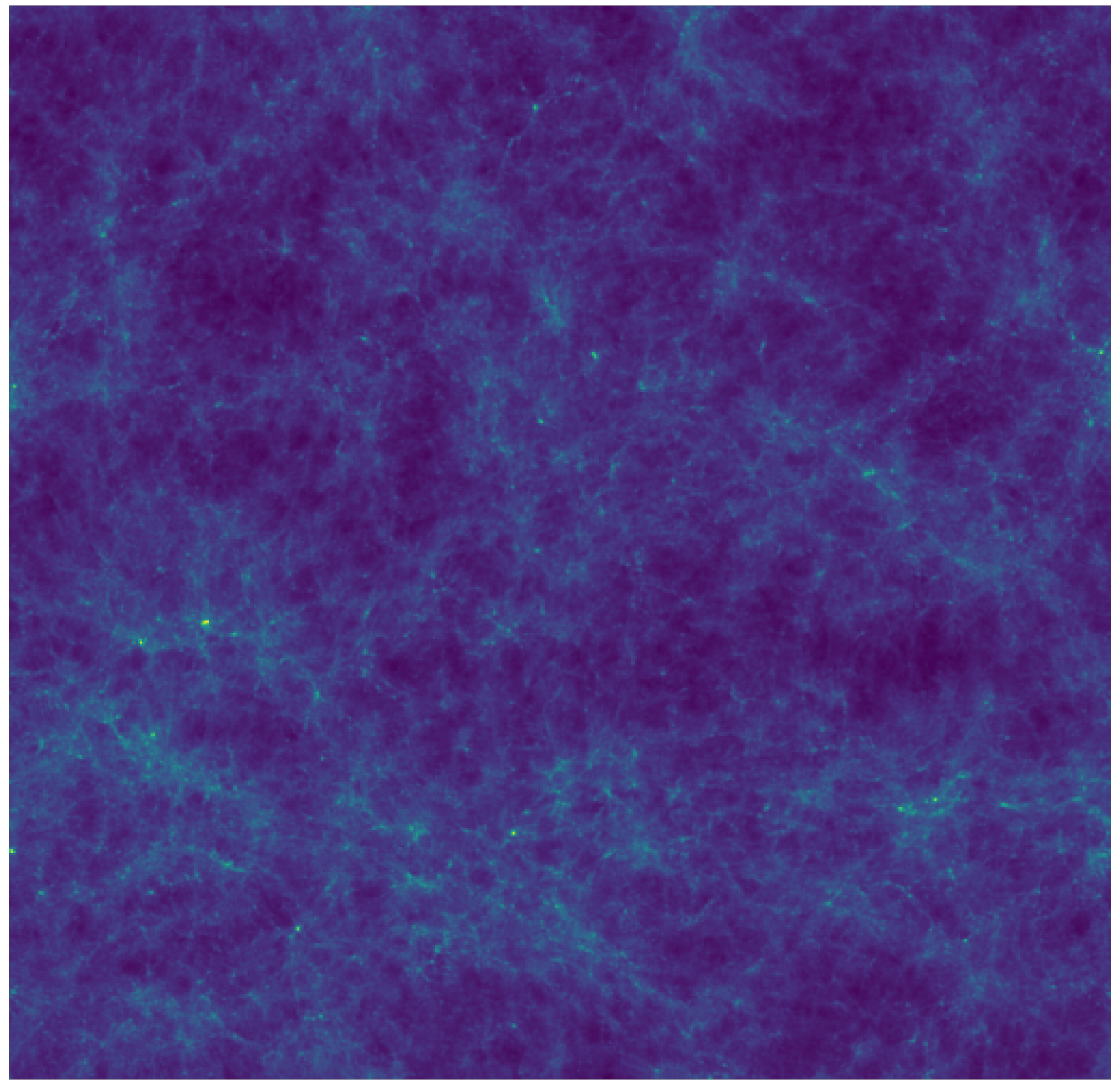
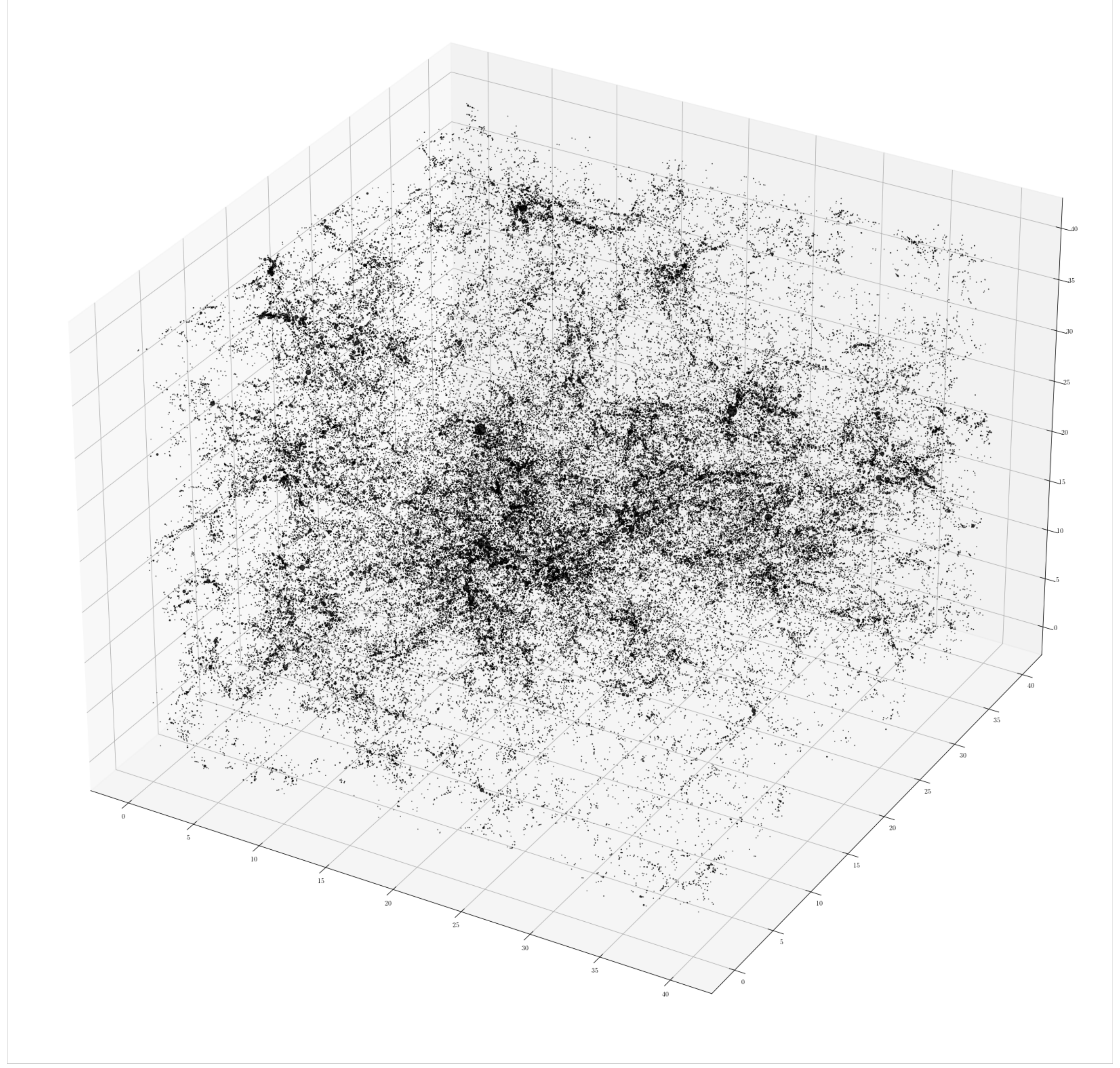


DARK MATTER HALO CATALOG



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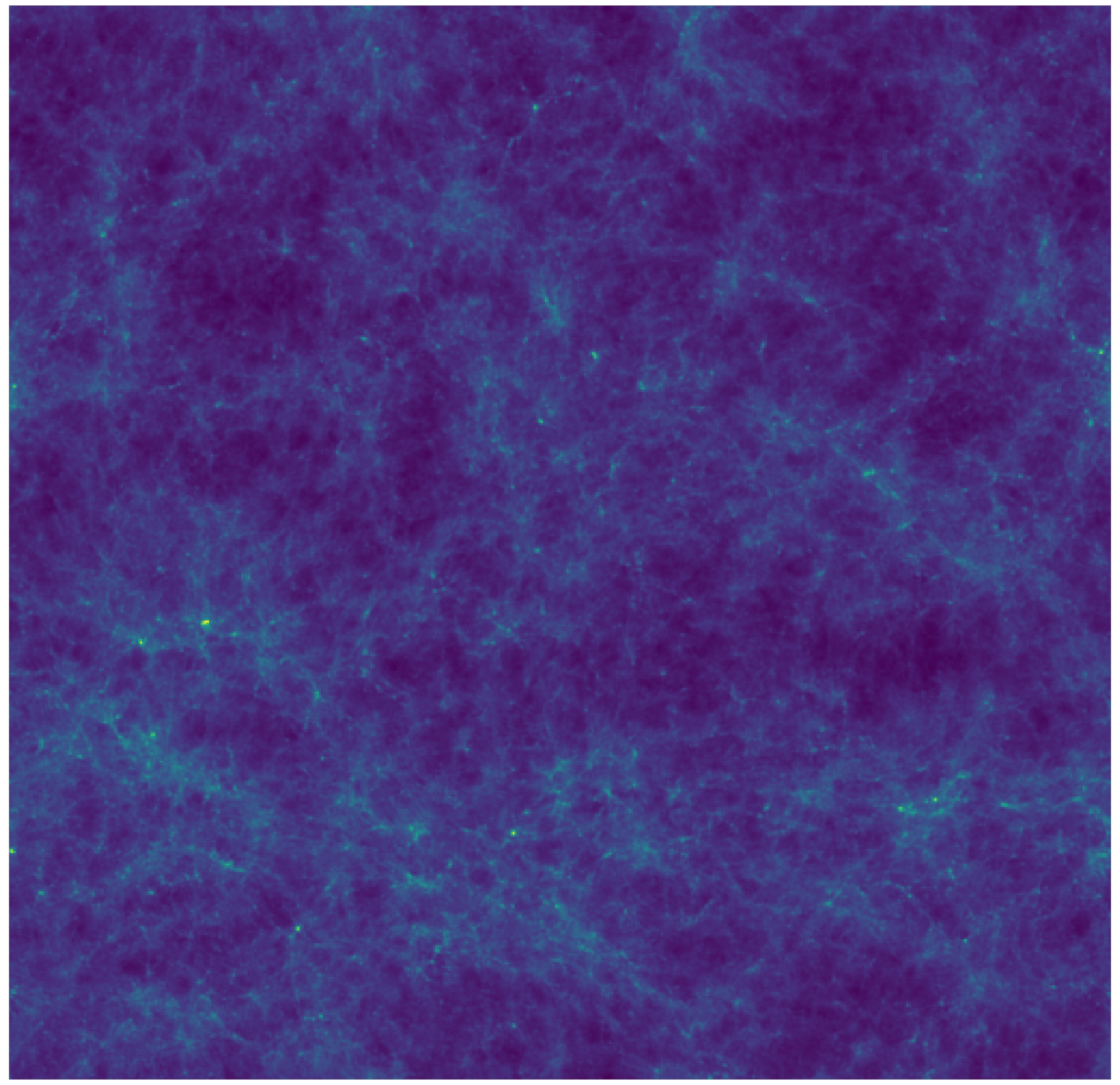

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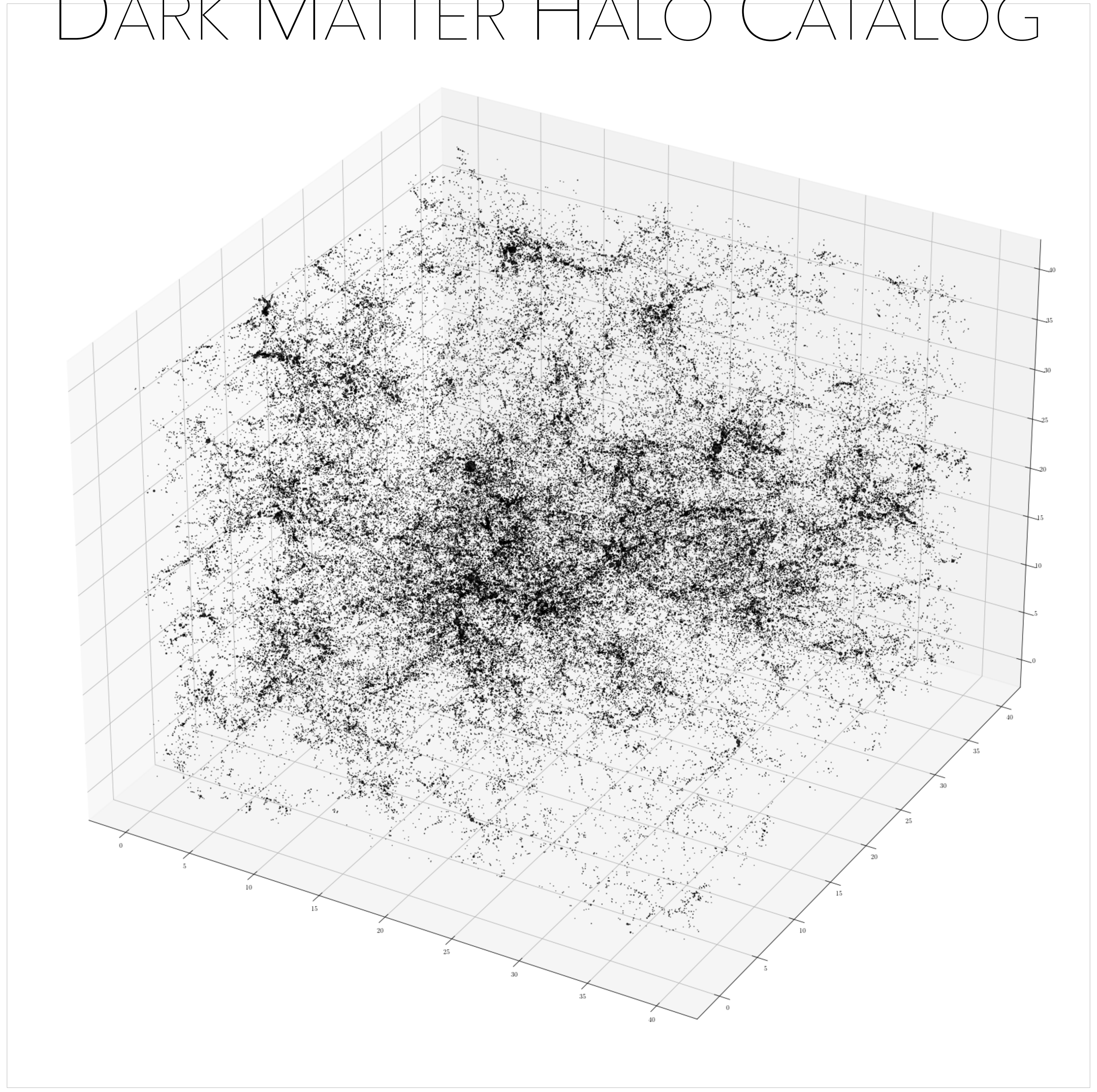

SPECTRAL LINES

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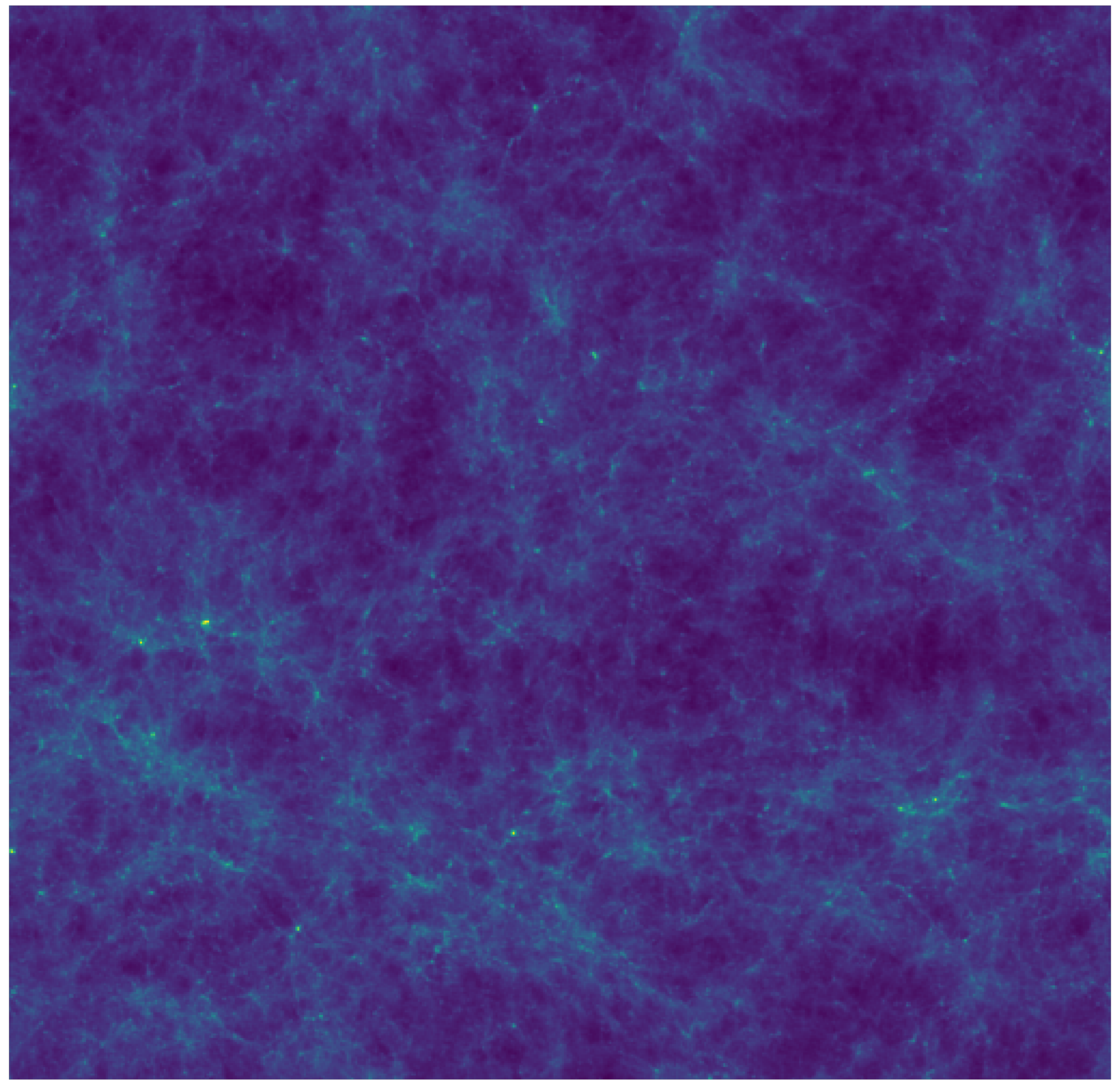
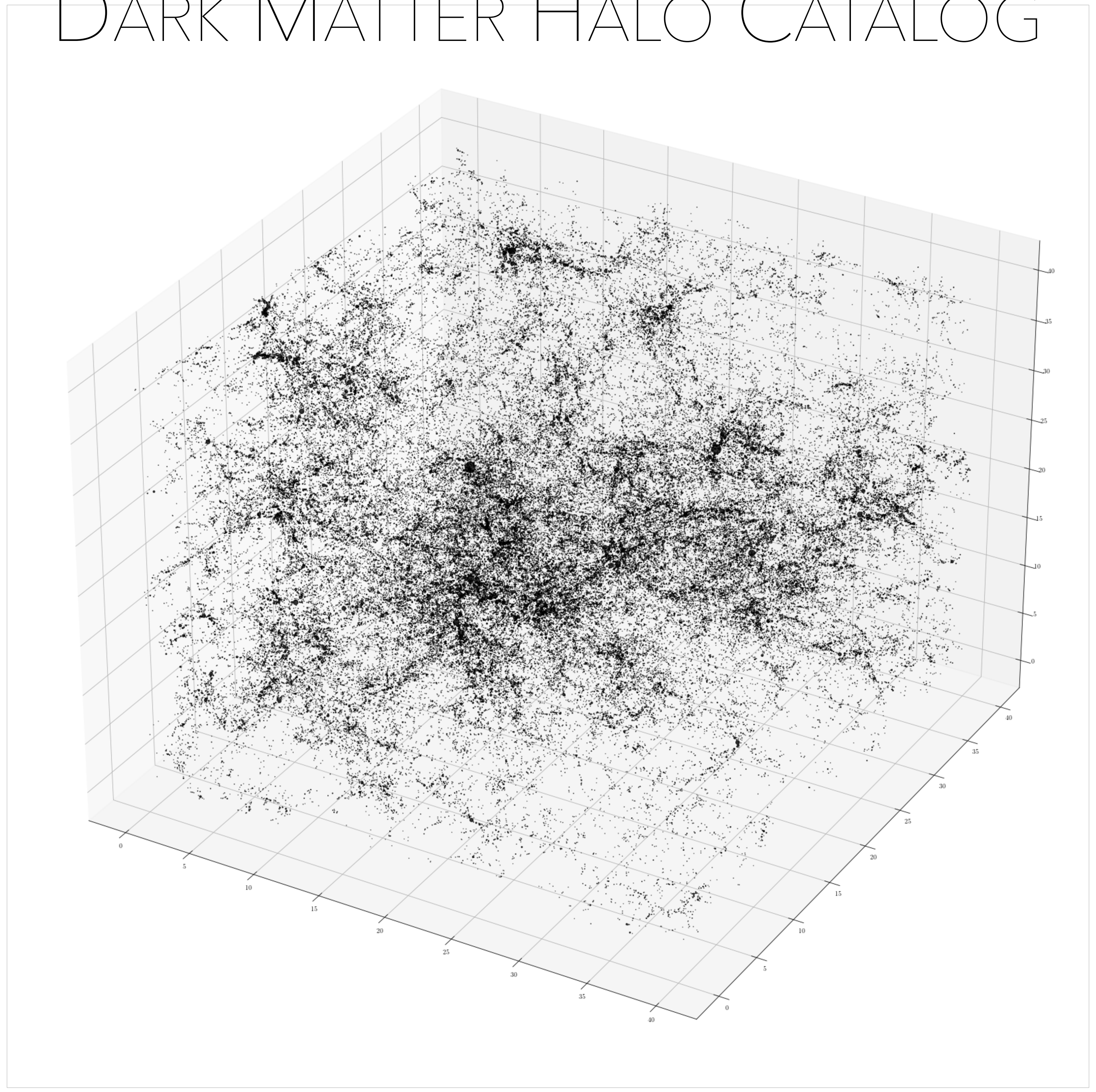
Matter Density Field



Dark Matter Halo Catalog



Spectral Lines

21cm Hyperfine transition of neutral hydrogen. Forms the bulk of the IGM.

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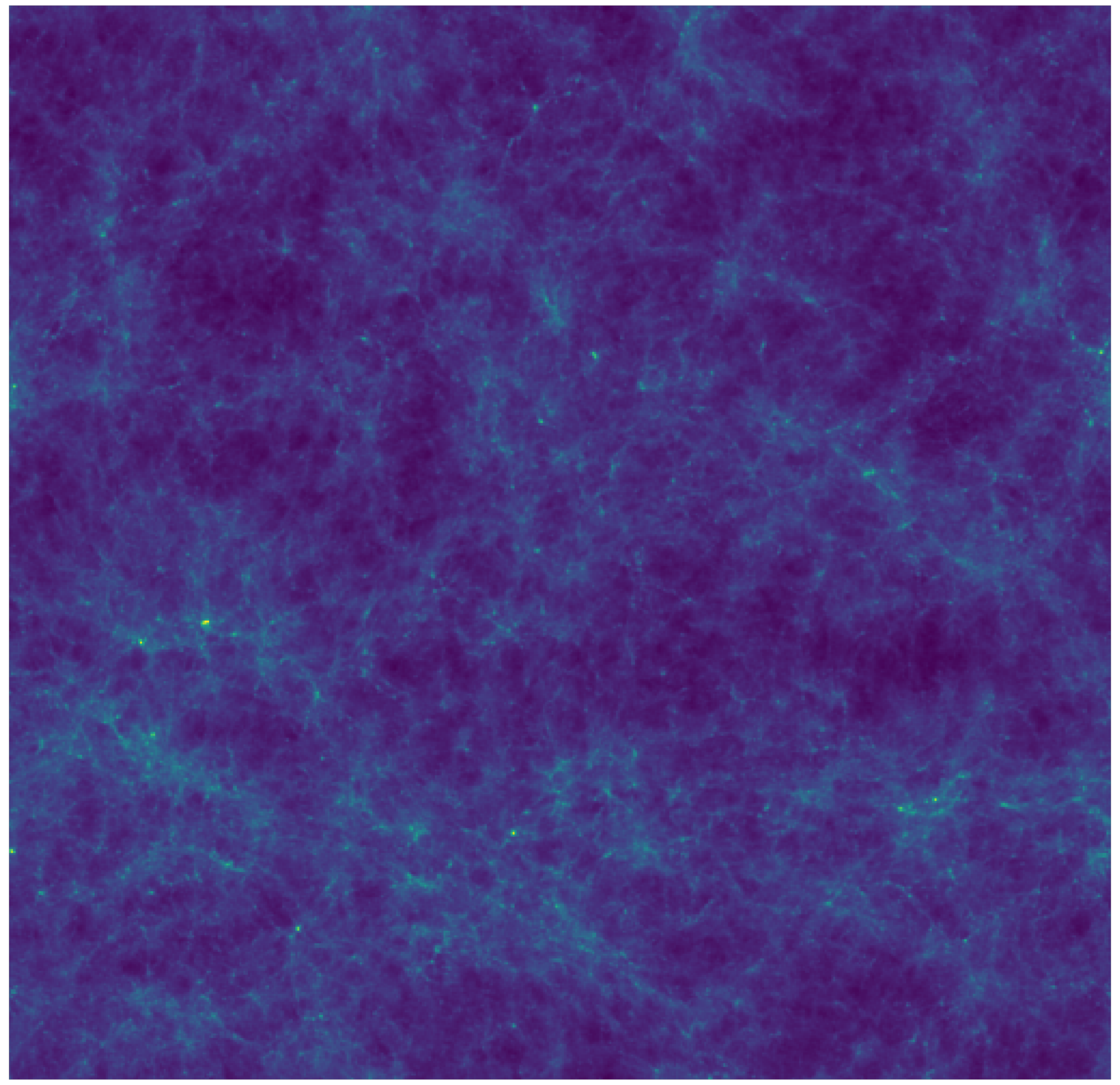

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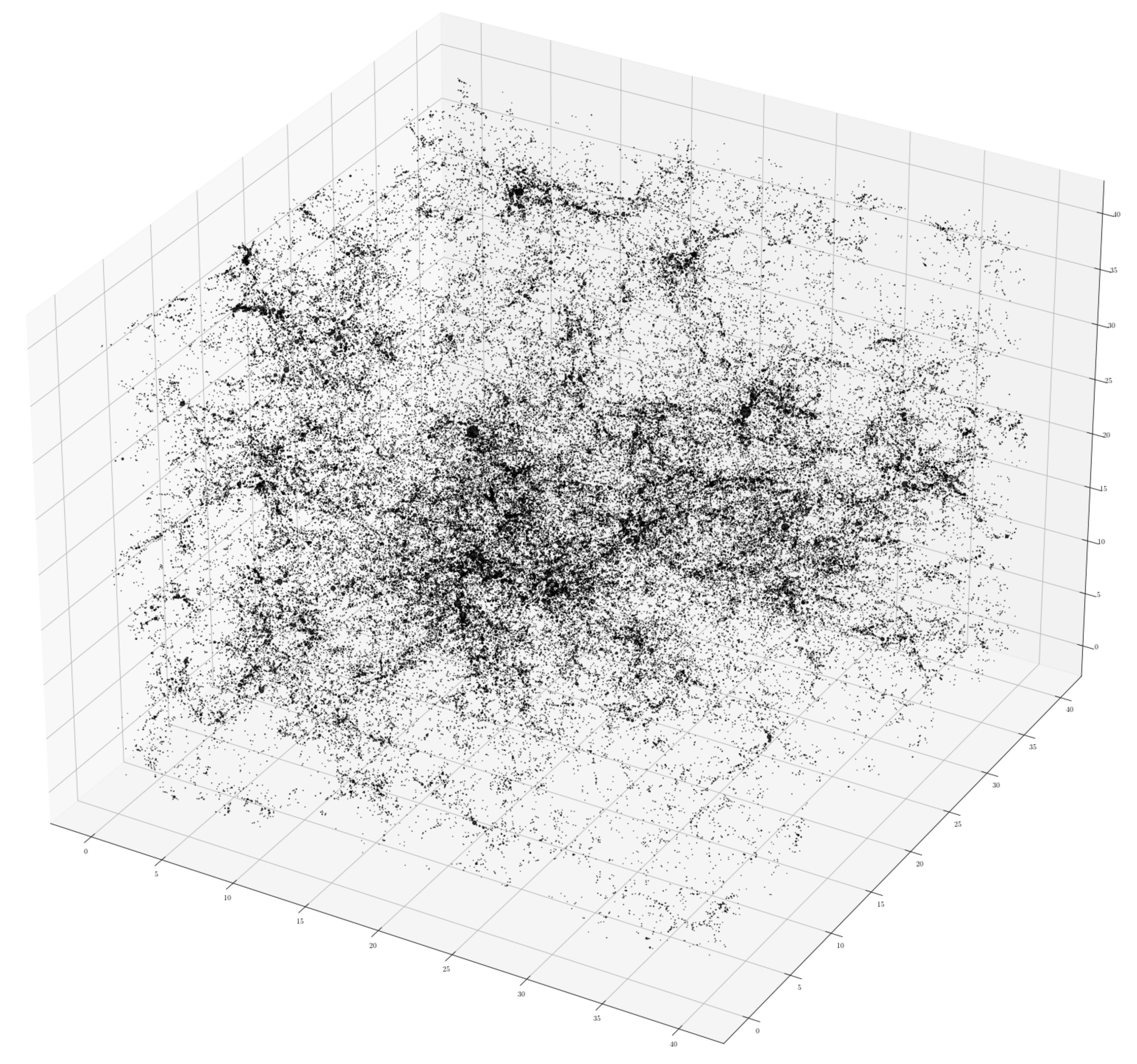

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CII Atomic fine structure line of singly ionized carbon. One of the brightest lines at low-z. ((Croxall et al. 2017; Lapham et al. 2017

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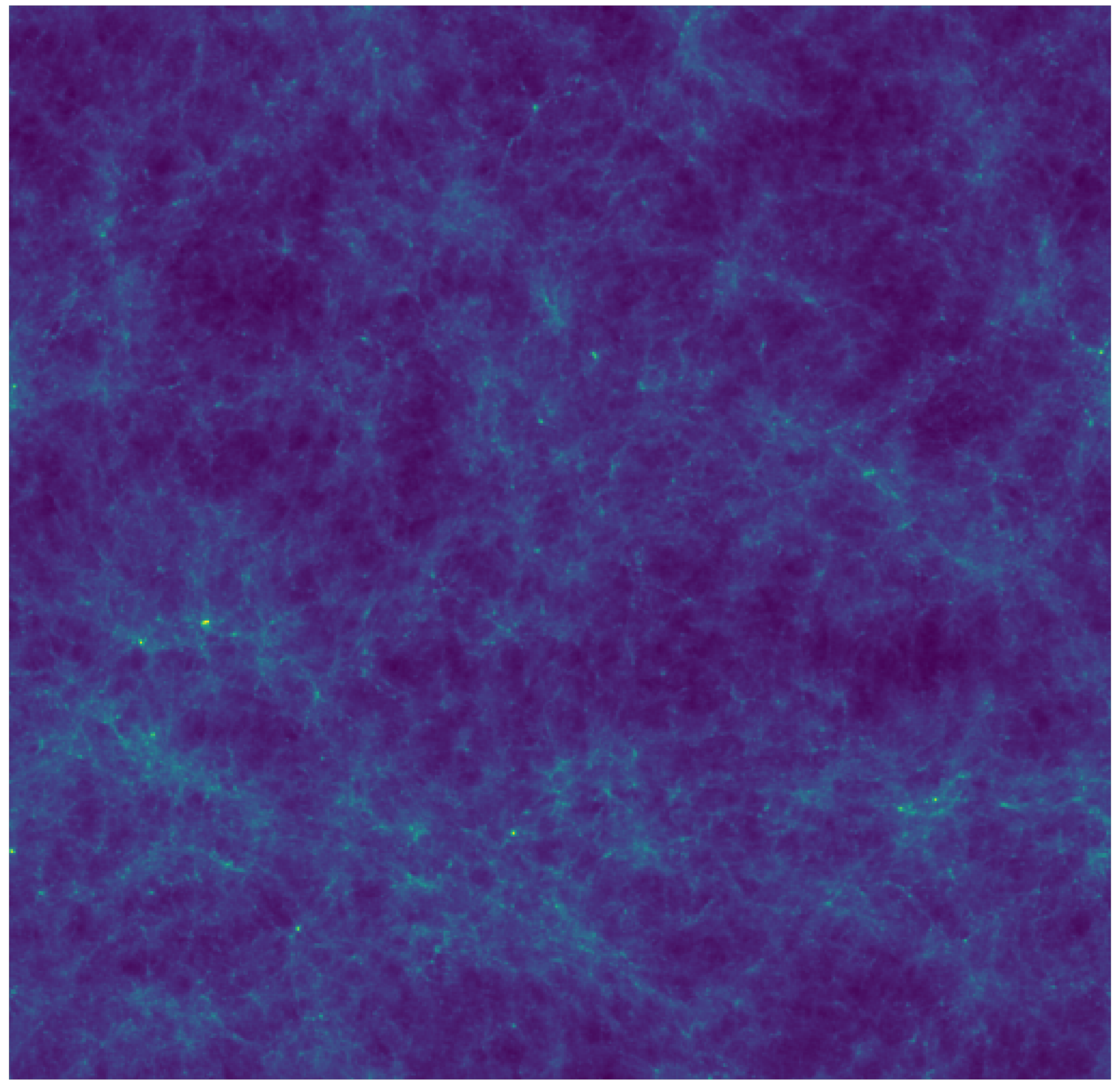

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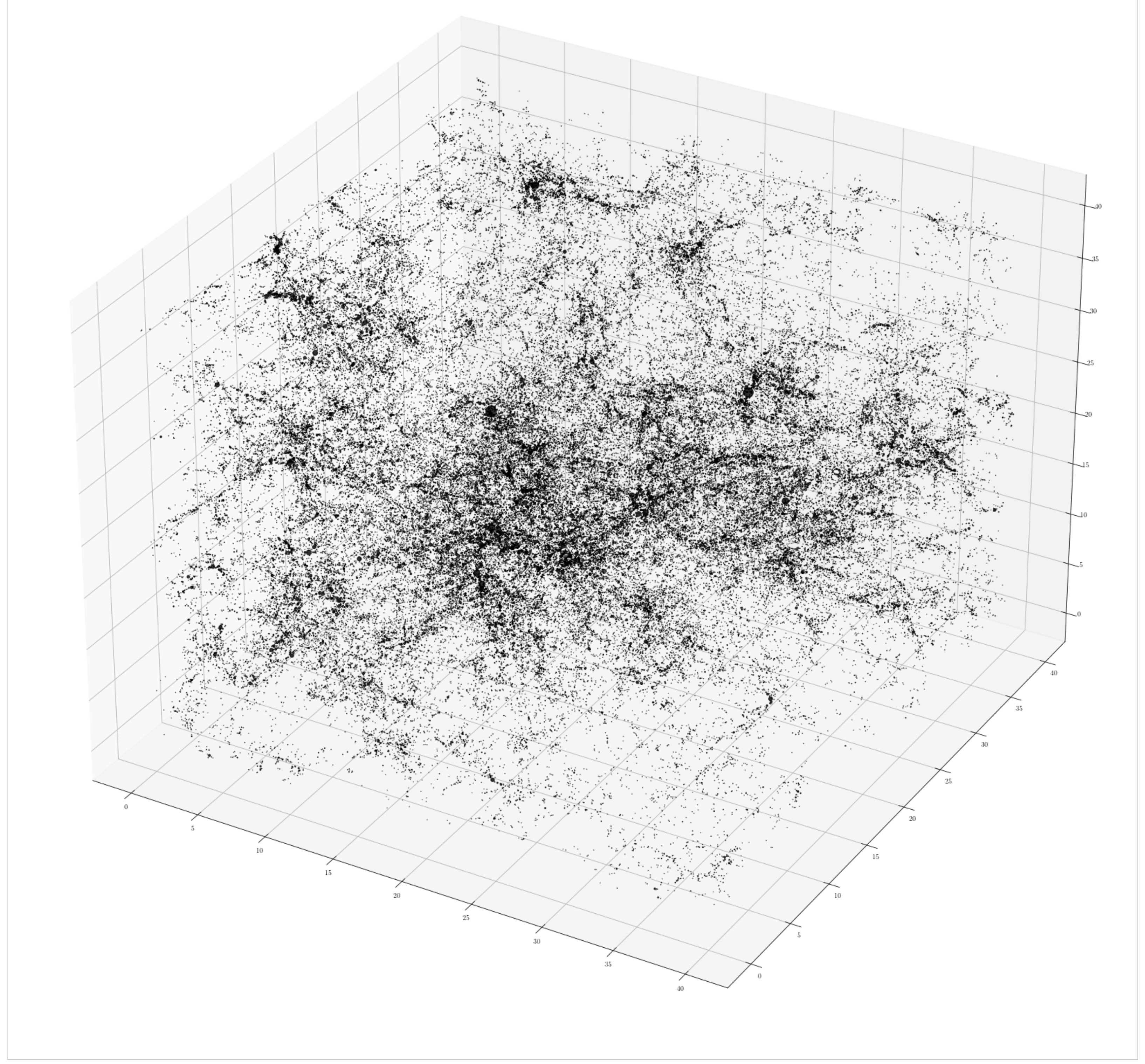

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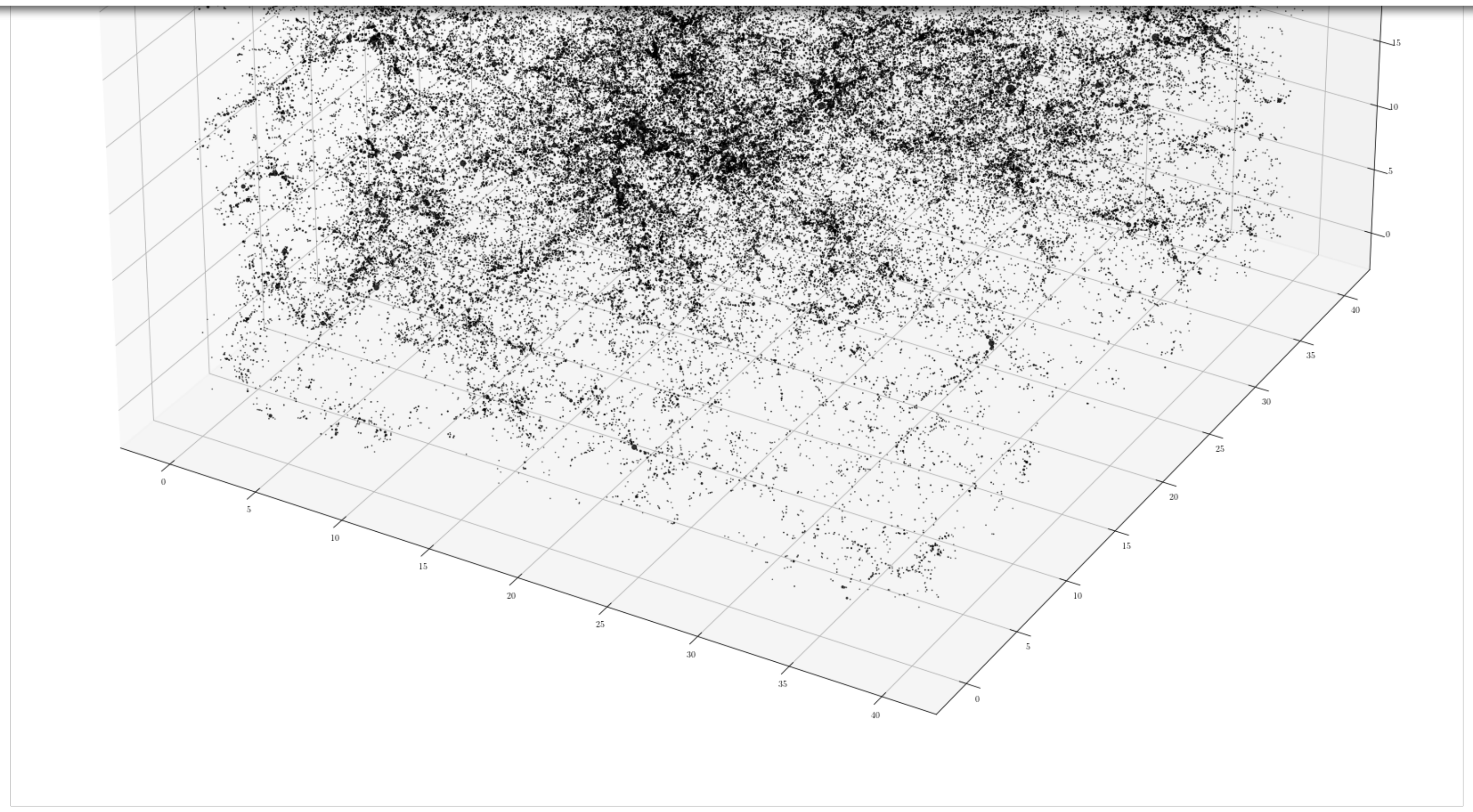
OIII Fine structure lines at 52 μm and 88 μm. Important for cooling molecular gas, and by extension star formation (Schimek et al. 2023; Suzuki et al. 2016).

APPLICATION TO (SIMULATED) DATA

The importance of galaxy formation histories in models of reionization

Jordan Mirocha[1★†] Paul La Plante[2‡] and Adrian Liu[1]
[1]McGill University Department of Physics & McGill Space Institute, 3600 Rue University, Montréal, QC, H3A 2T8, Canada
[2]Department of Astronomy and Radio Astronomy Laboratory, University of California Berkeley, Berkeley, CA 94720, USA



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COSMOLOGICAL SIGNALS

Simulations from Mirocha et al. (2021): arXiv: 2012.09189

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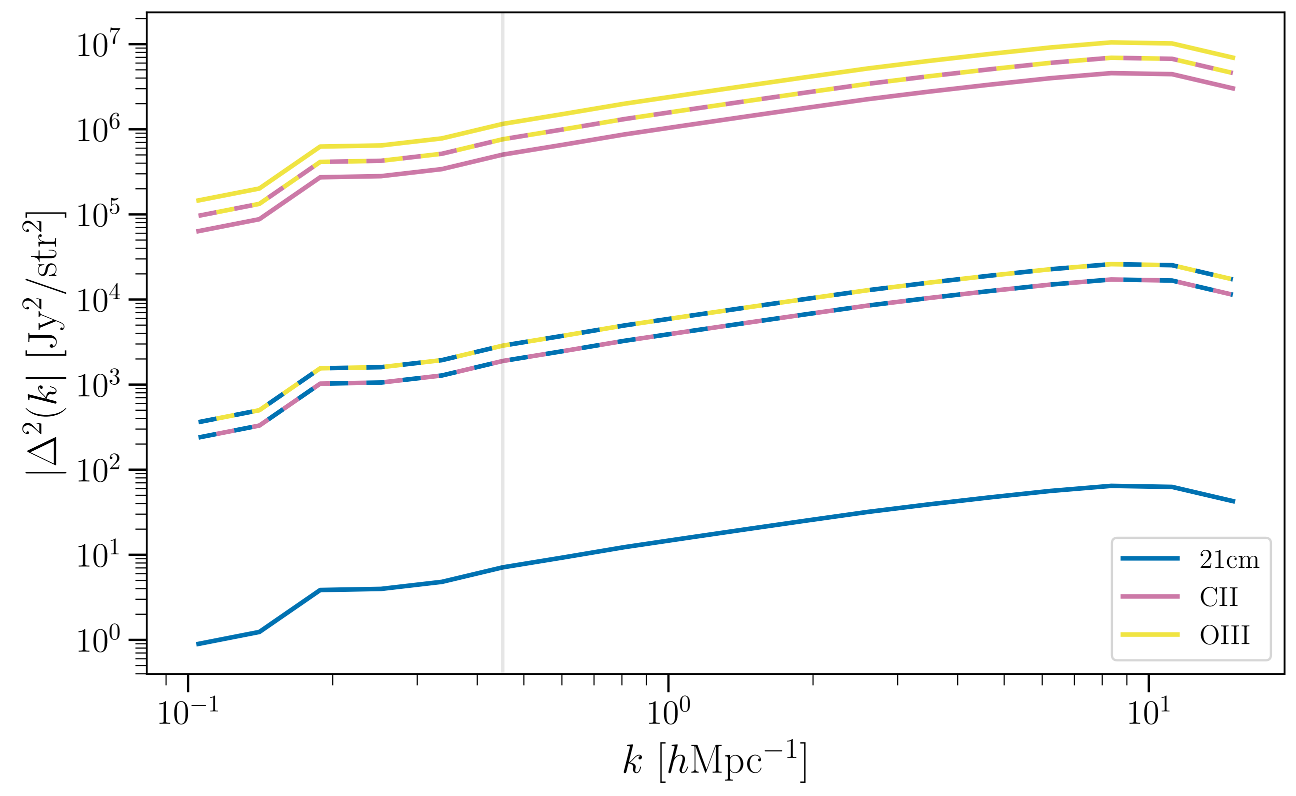

PERFECT TRACER MODEL

Exact match to the linear biasing model

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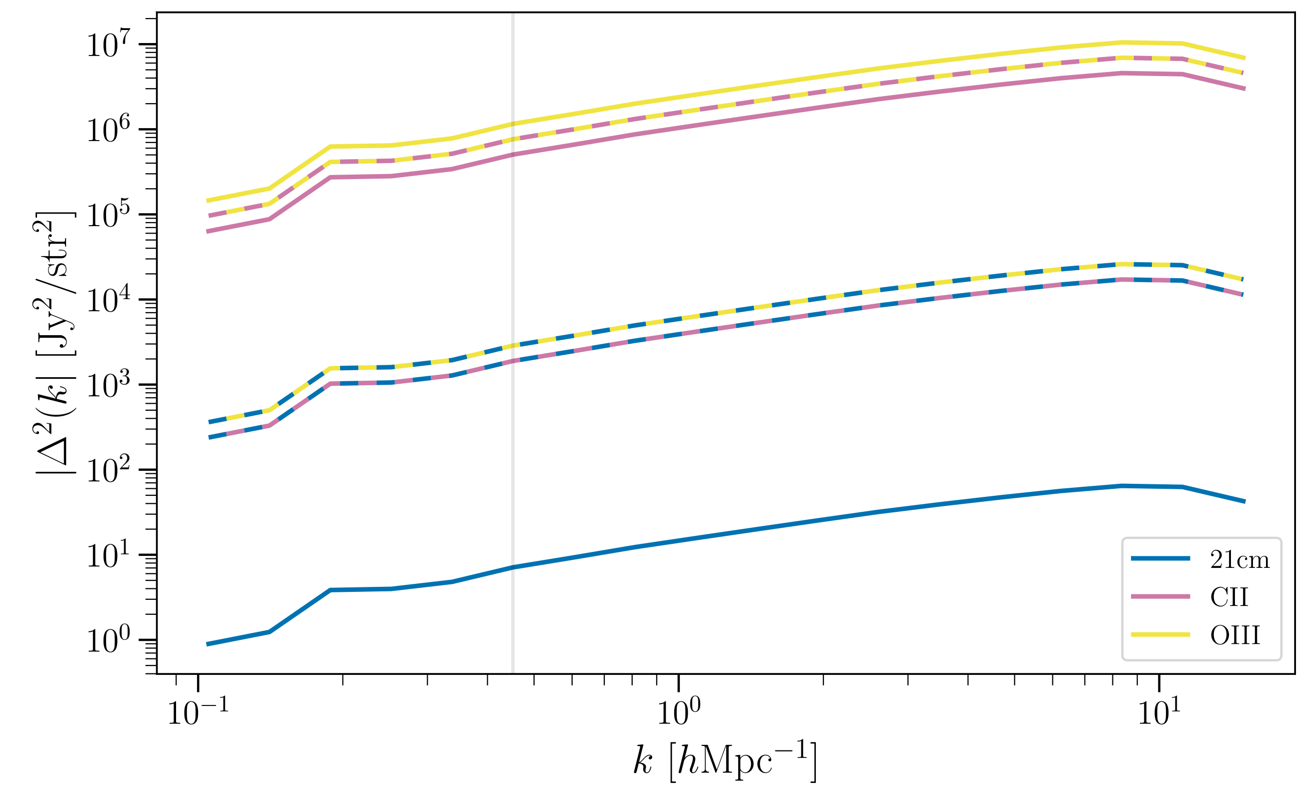

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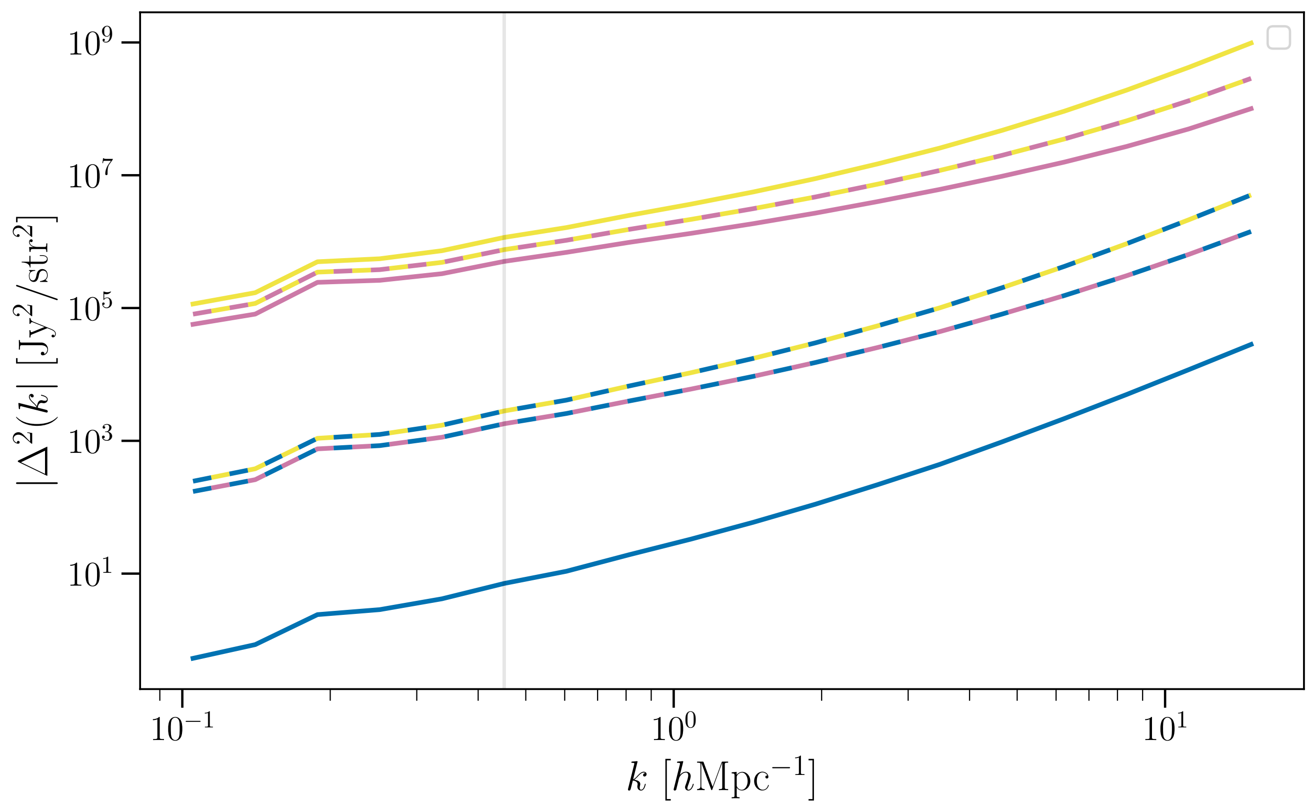


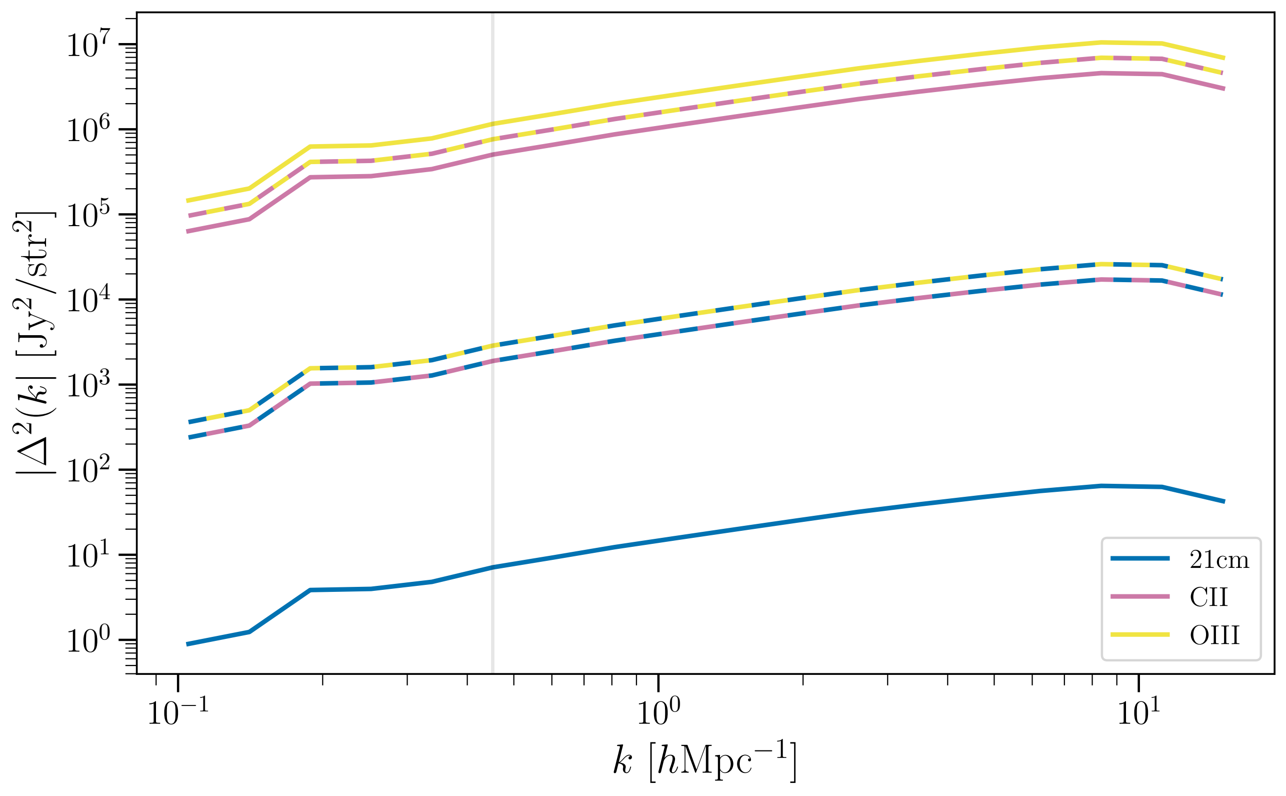
POWER LAW MODEL

Assuming a halo mass-luminosity power law relation

$$L_i(M) = L_{0,i}\left(\frac{M}{M_0}\right)^{\alpha_i}$$

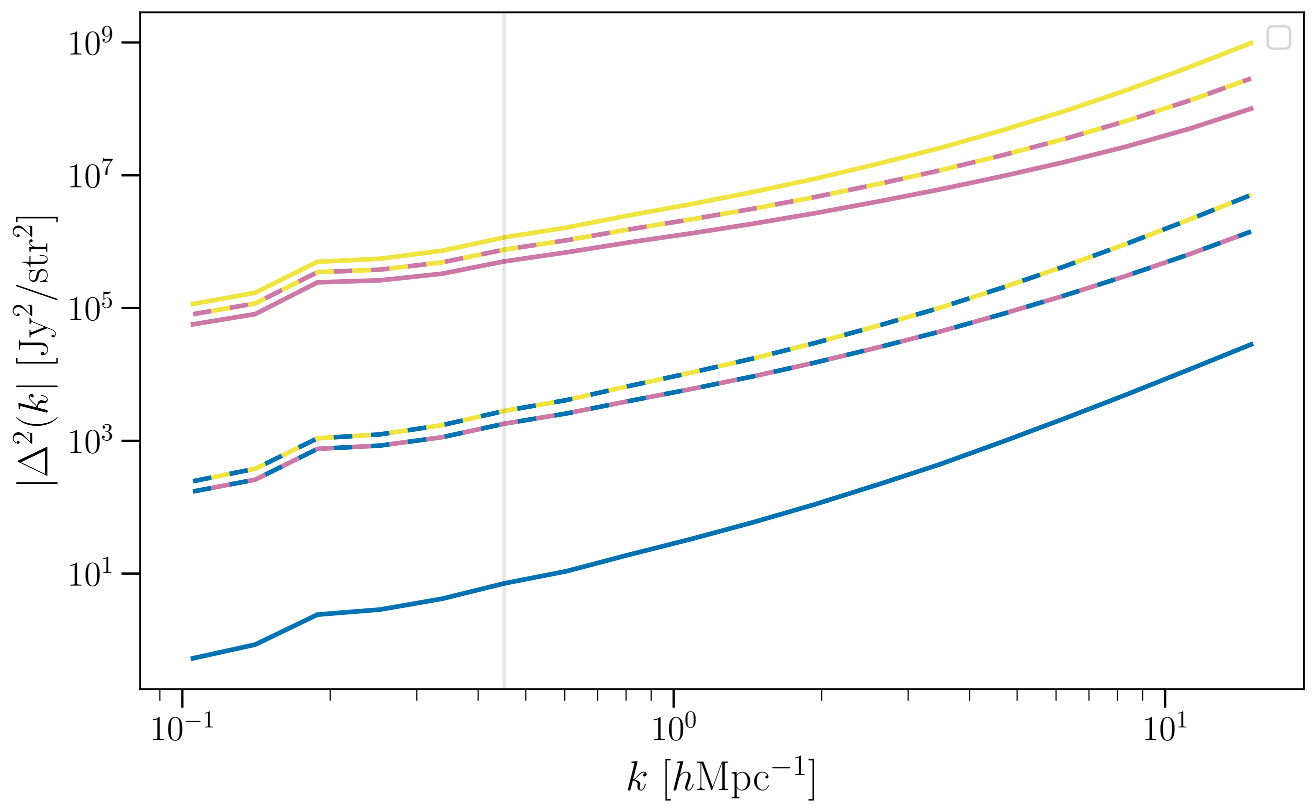
Simulations from Mirocha et al. (2021): arXiv: 2012.09189

COSMOLOGICAL SIGNALS



PERFECT TRACER MODEL

Exact match to the linear biasing model



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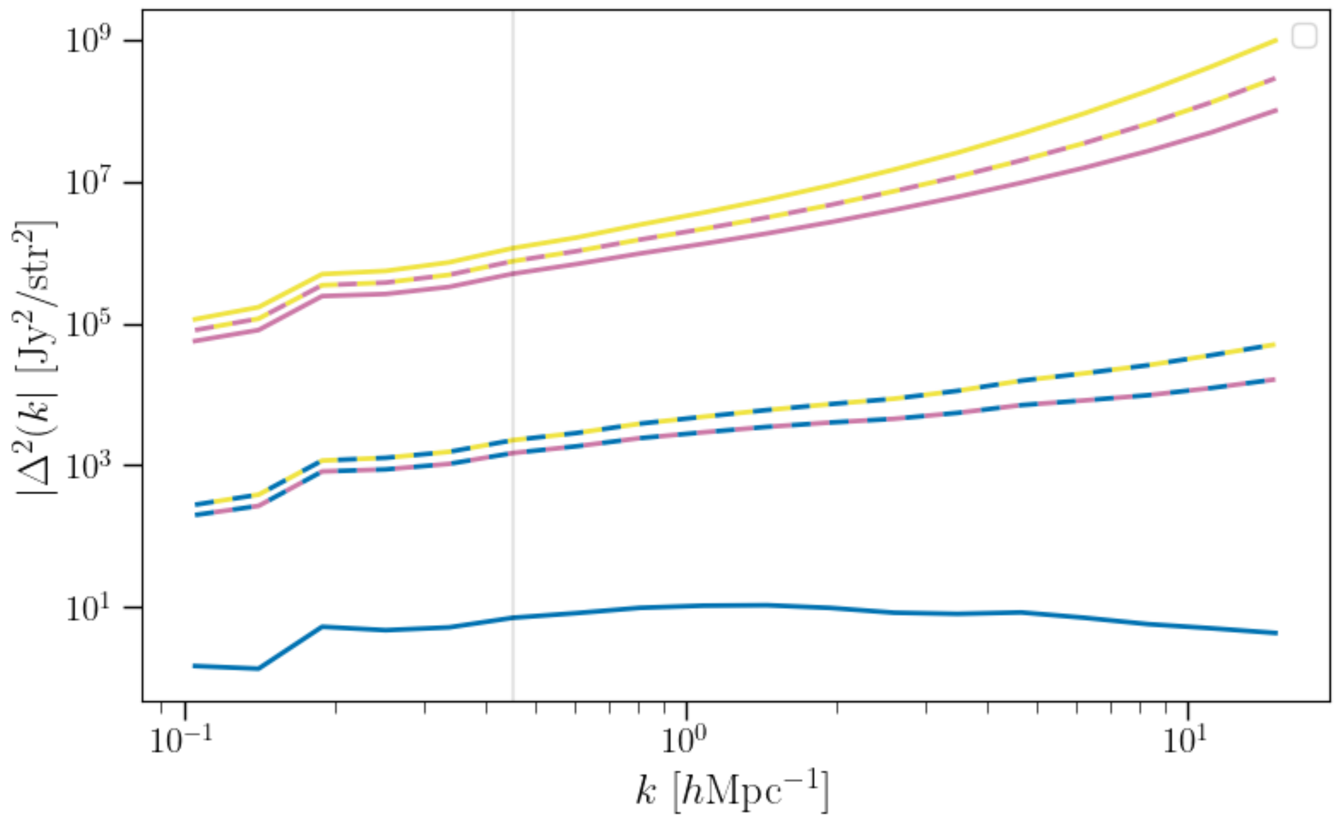
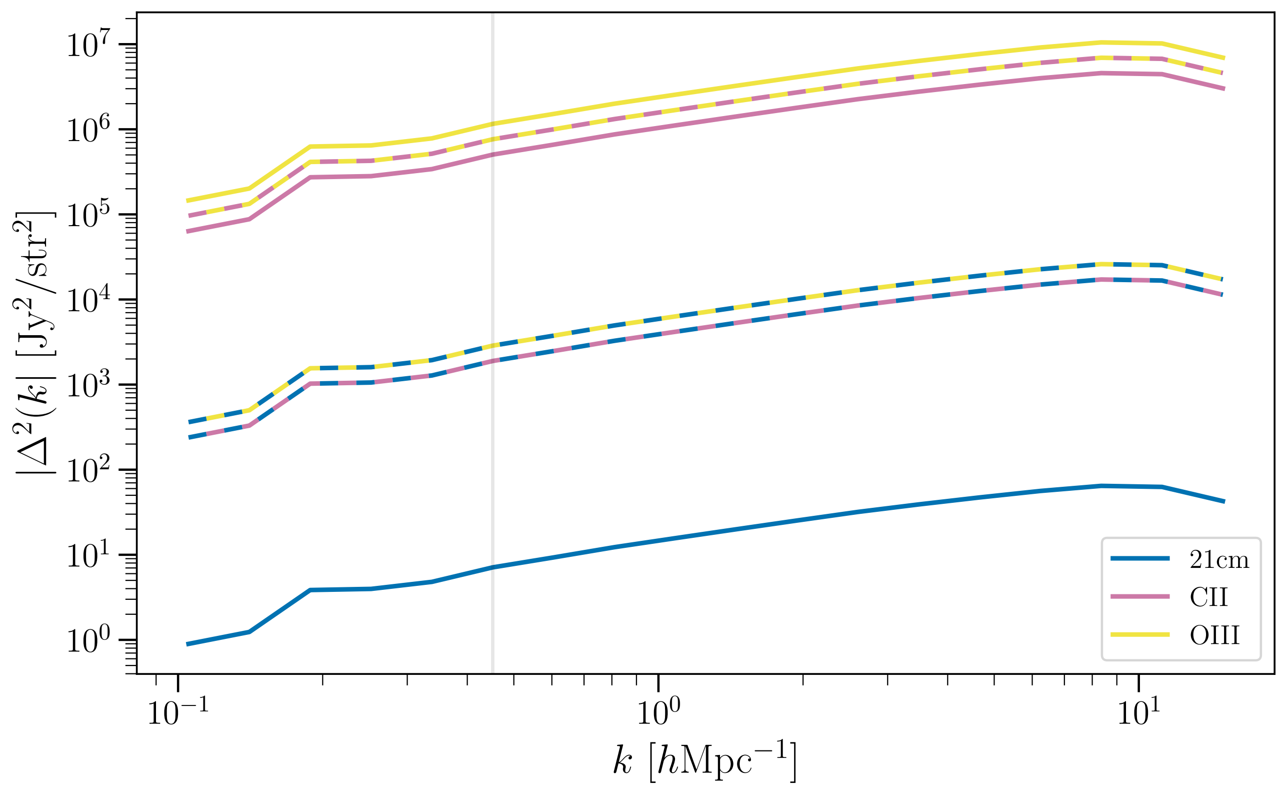


BUBBLE MODEL

Addition of bubble morphology to 21cm model via the `zreion` package.

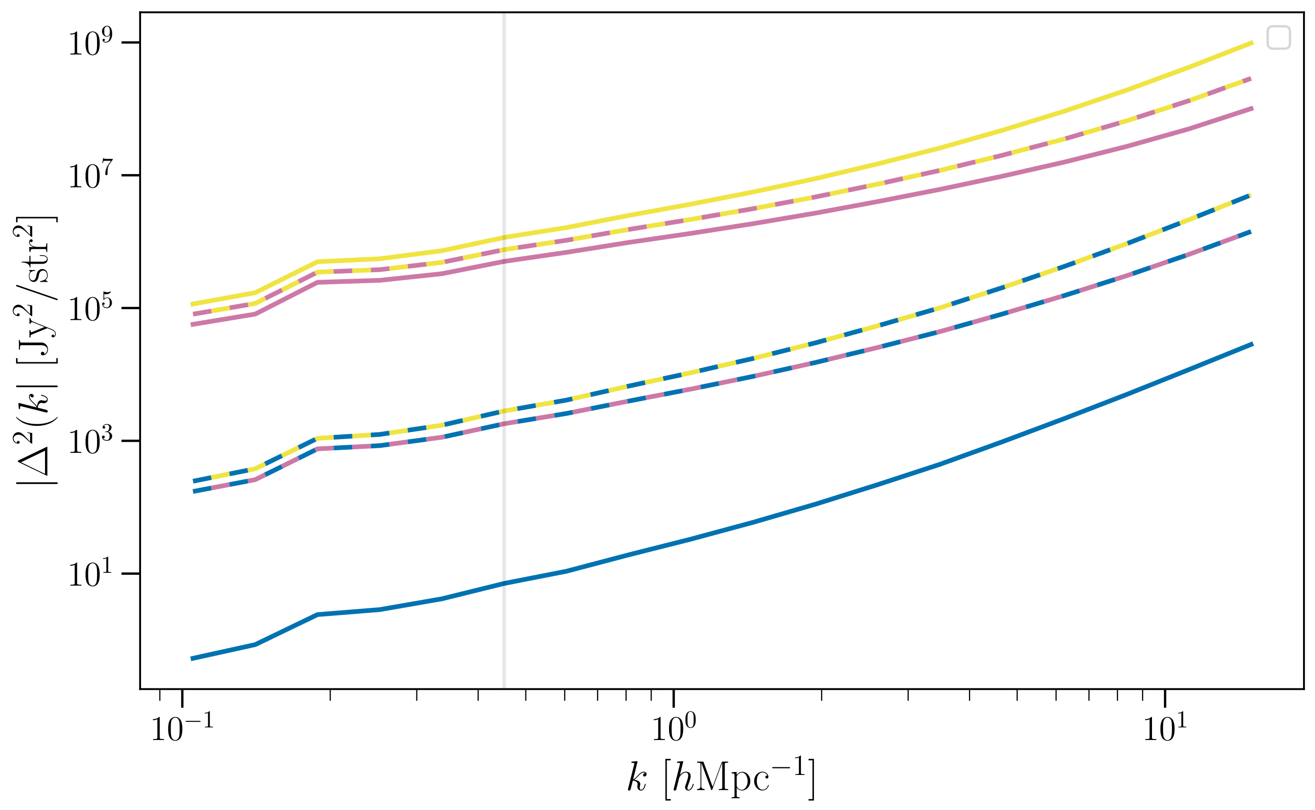
Simulations from Mirocha et al. (2021): arXiv: 2012.09189

COSMOLOGICAL SIGNALS



Perfect Tracer model

Exact match to the linear biasing model



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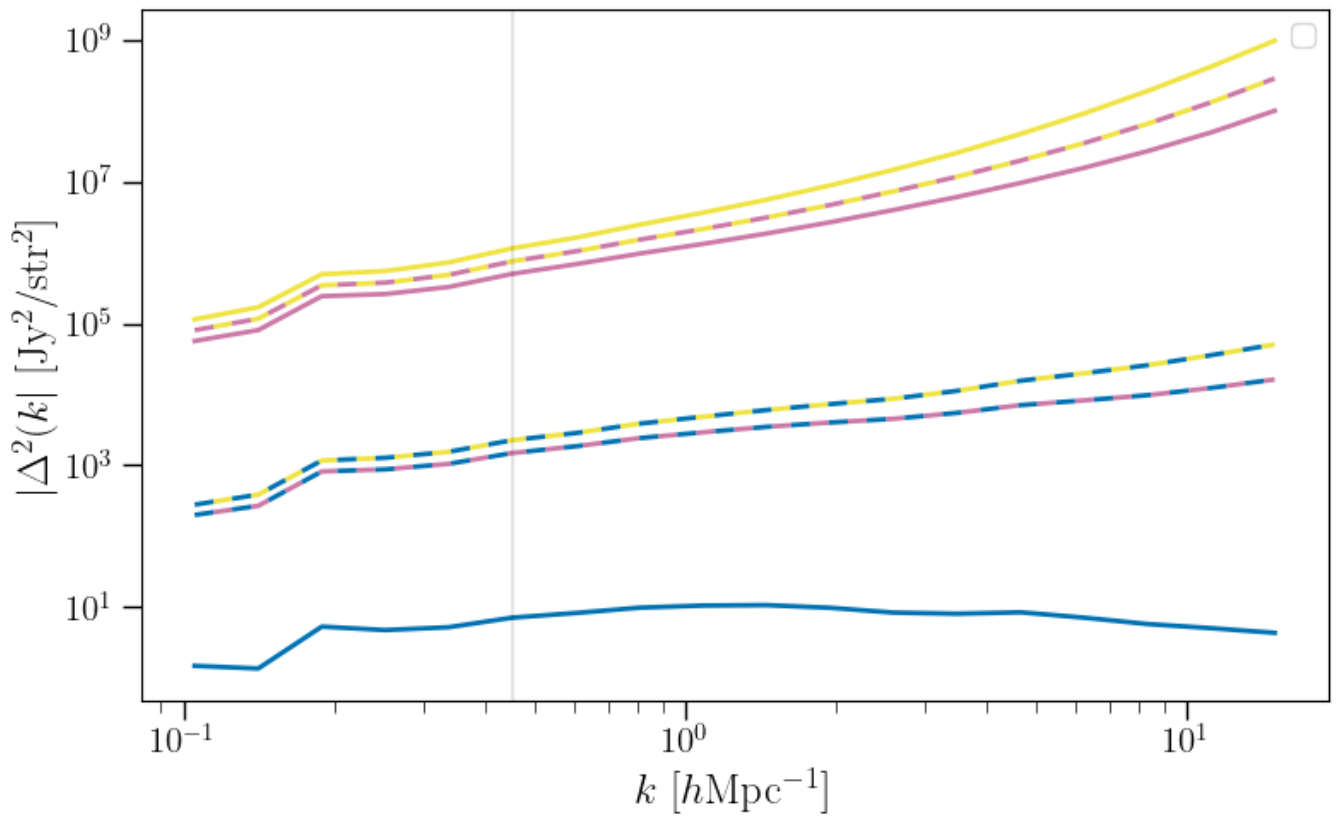

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plaplant / zreion Public

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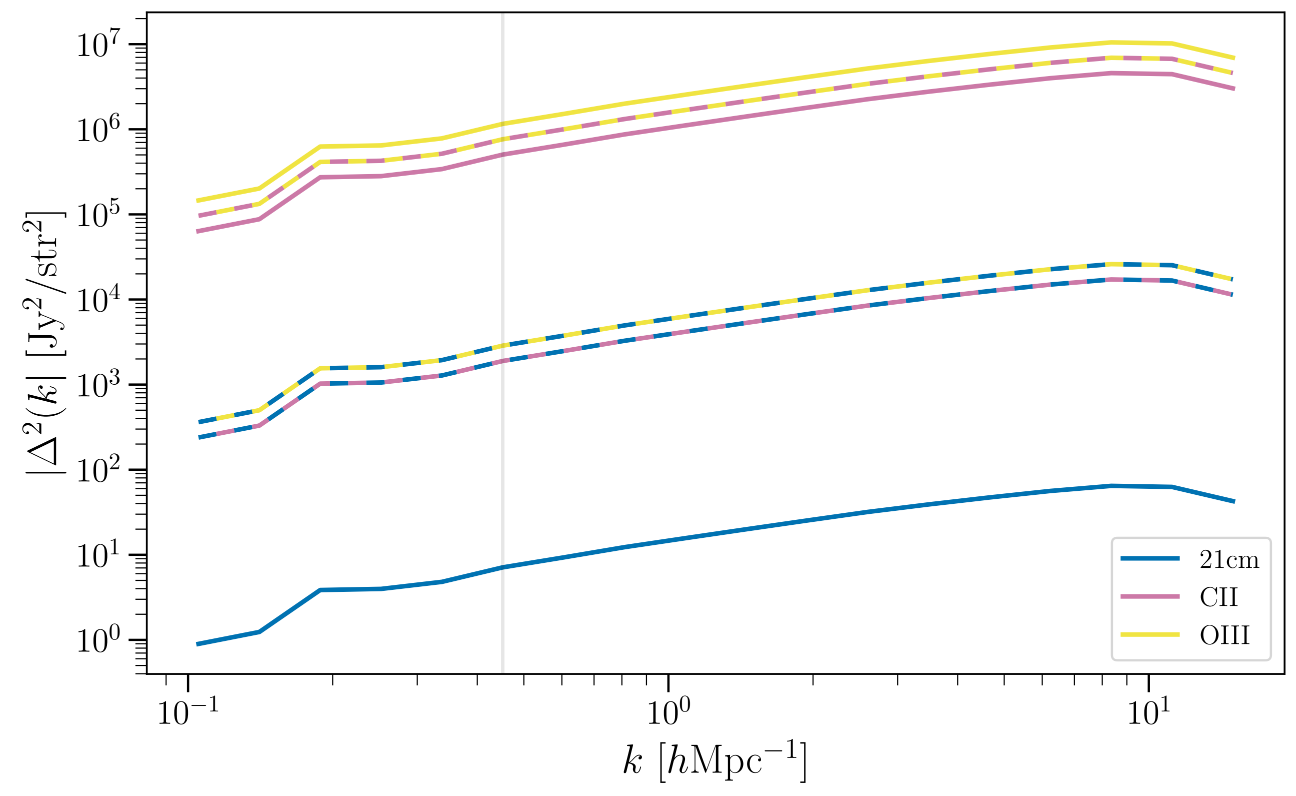

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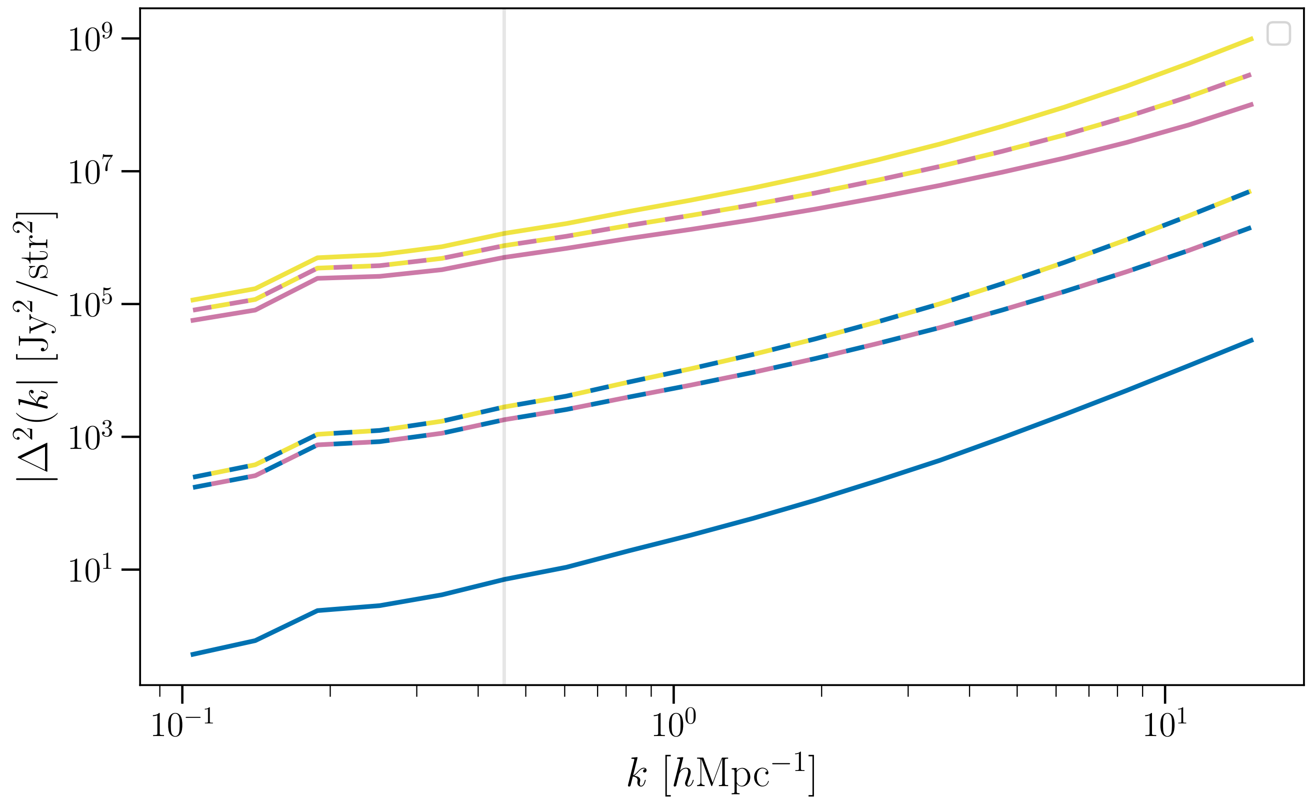

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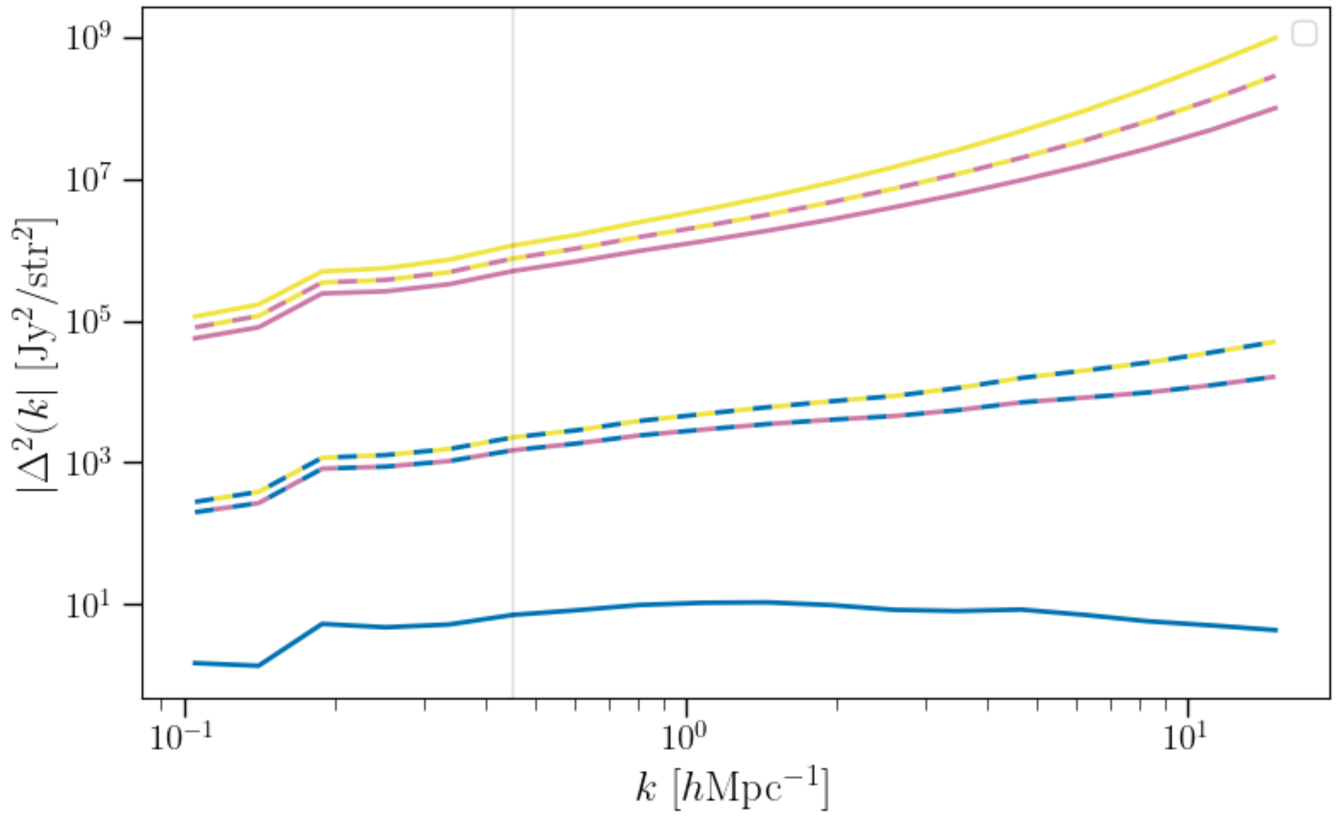


Bubble model

Addition of bubble

REIONIZATION ON LARGE SCALES. I. A PARAMETRIC MODEL CONSTRUCTED FROM RADIATION-HYDRODYNAMIC SIMULATIONS

N. Battaglia[1], H. Trac[1], R. Cen[2], and A. Loeb[3]
[1] McWilliams Center for Cosmology, Wean Hall, Carnegie Mellon University, 5000 Forbes Avenue, Pittsburgh PA 15213, USA
[2] Department of Astrophysical Sciences, Princeton University, Princeton, NJ 08544, USA
[3] Harvard-Smithsonian Center for Astrophysics, Cambridge, MA 02138, USA

plaplant / zreion Public

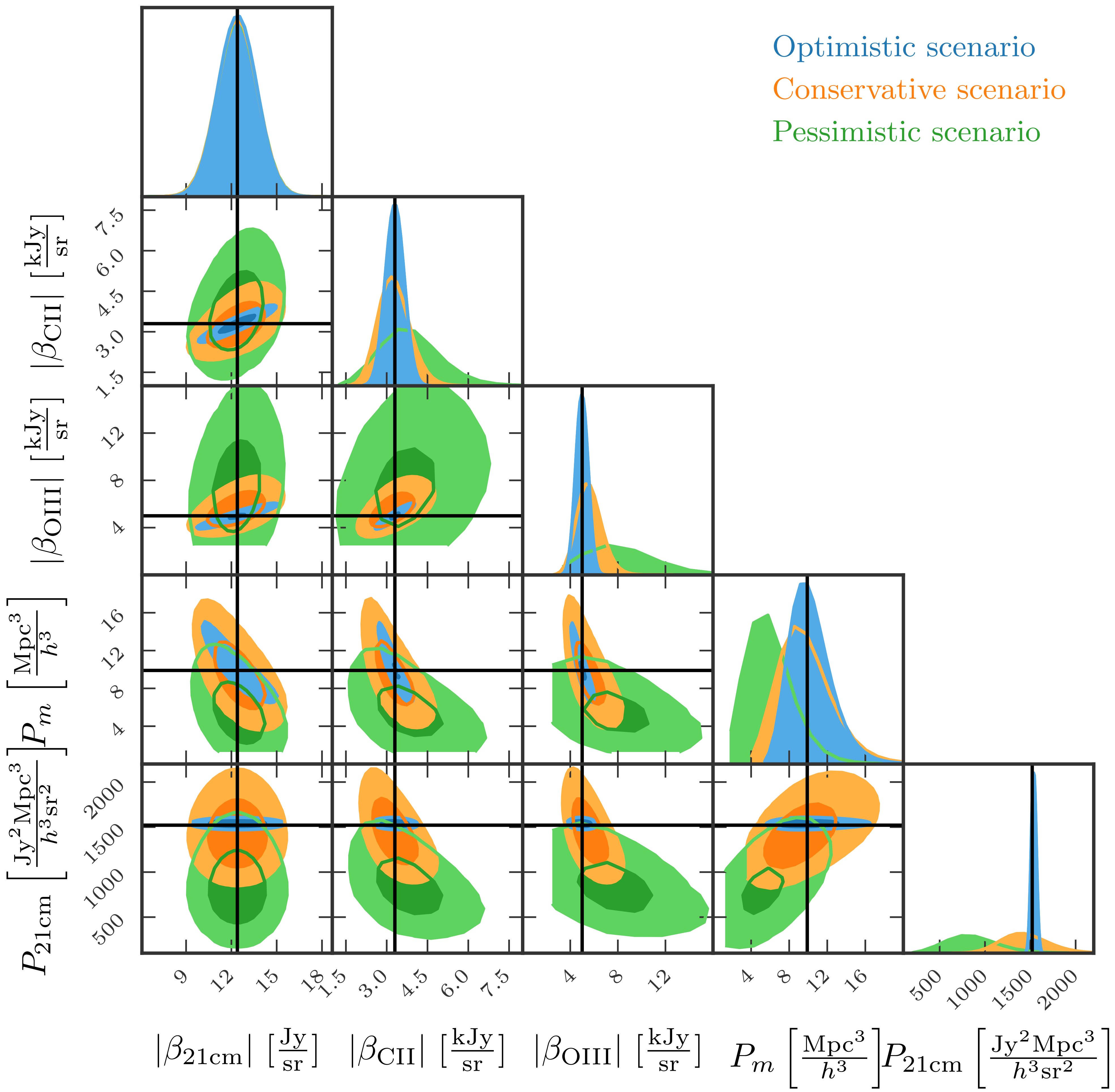
Simulations from Mirocha et al. (2021): arXiv: 2012.09189

arXiv: 1211.2821

RESULTS 1/2

Fitting cosmological signal models

- Optimistic scenario:
  Perfect tracer + 1% fractional noise
- Conservative scenario:
  Power law + 10% fractional noise
- Pessimistic scenario:
  Bubble + 15% fractional noise



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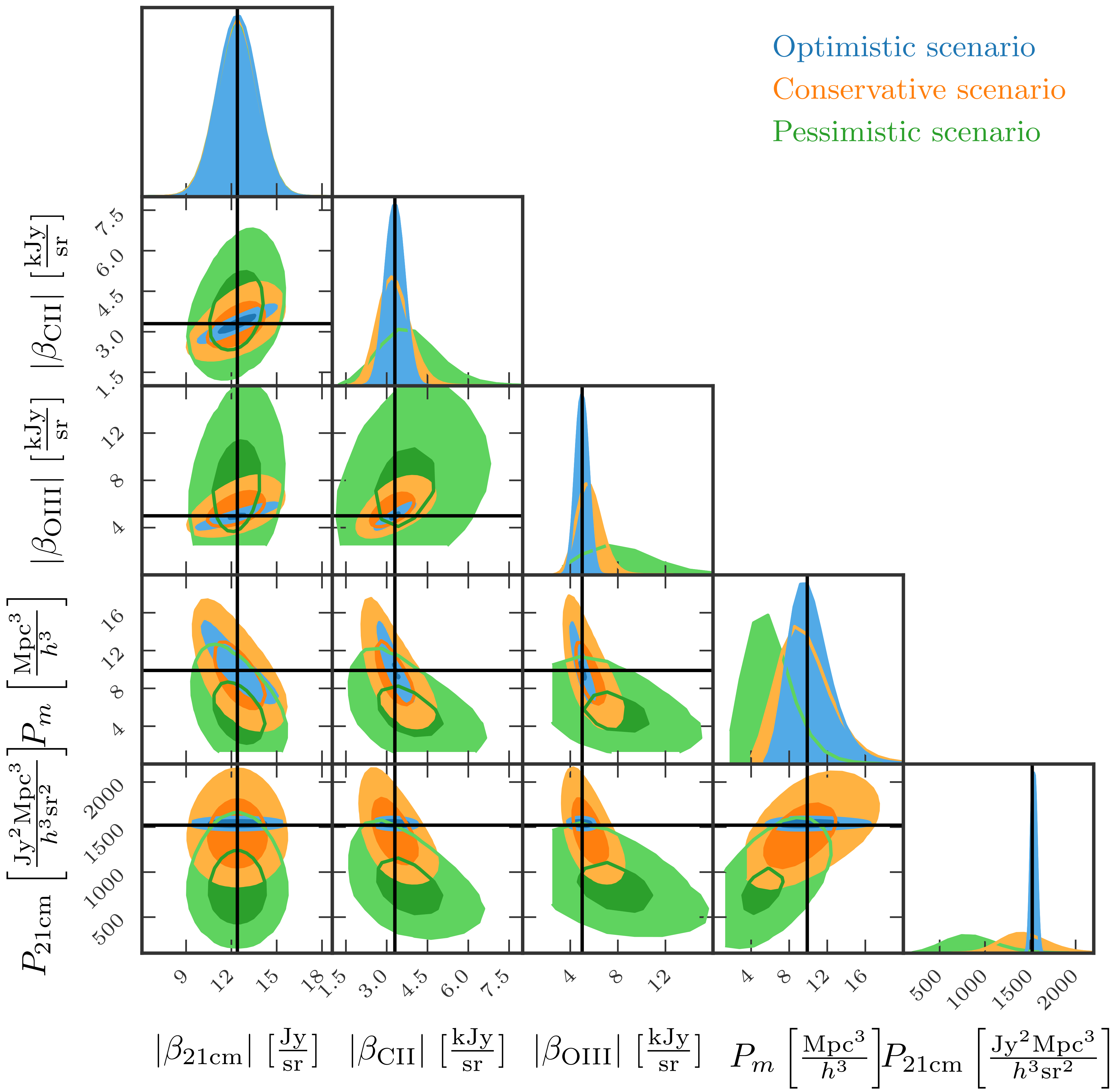

Technique fails for the Bubble model because fields are more decorrelated!

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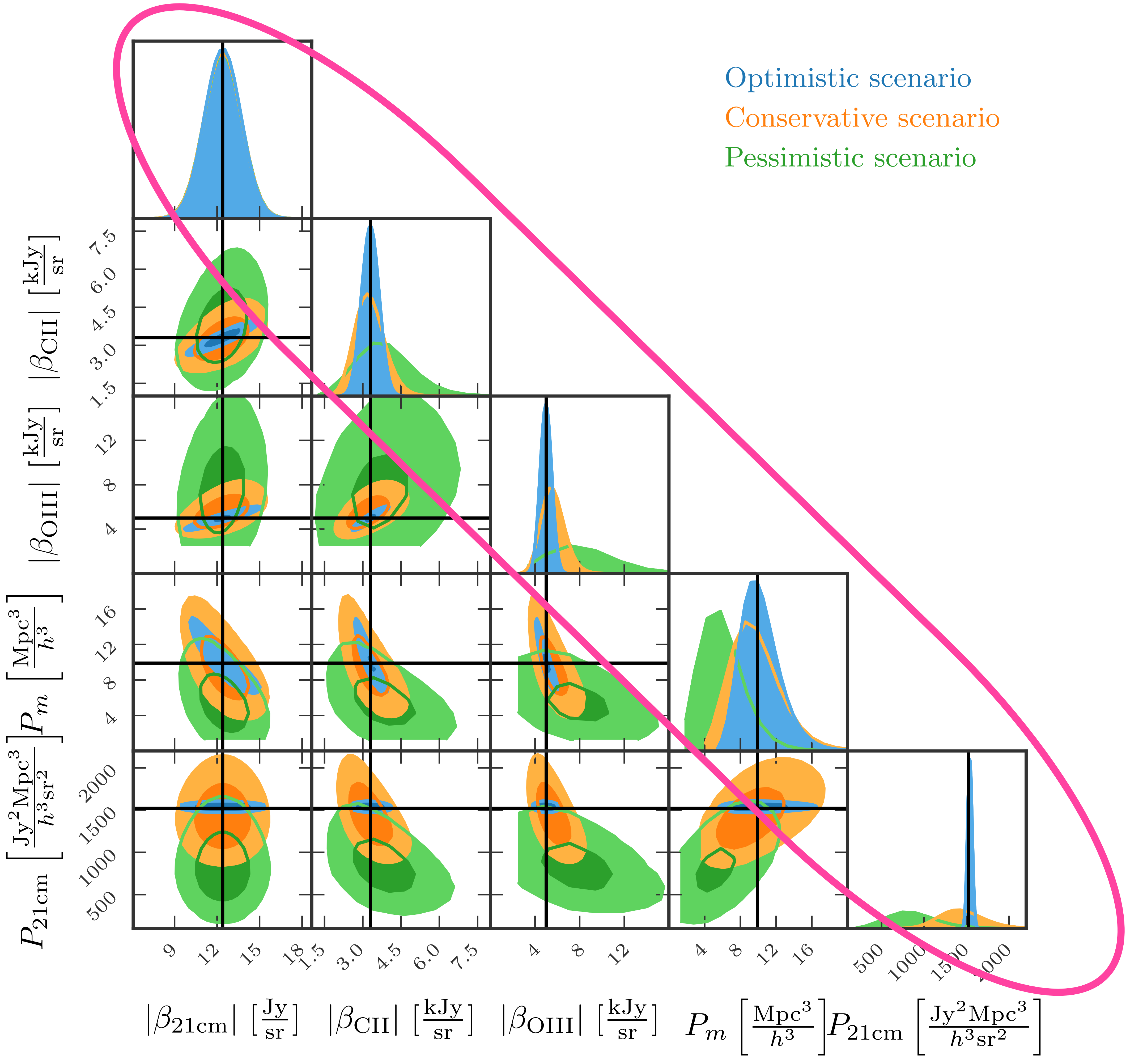

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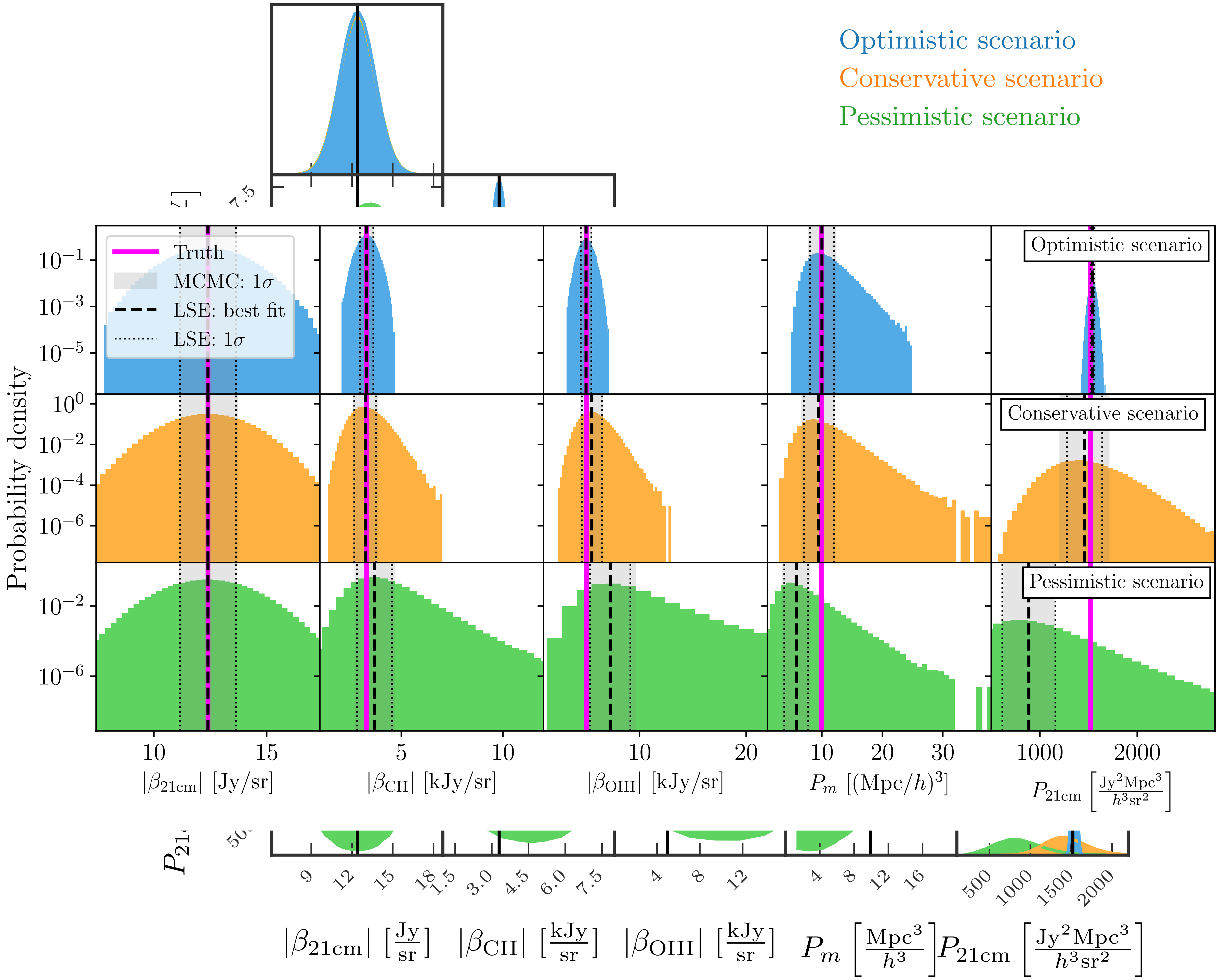

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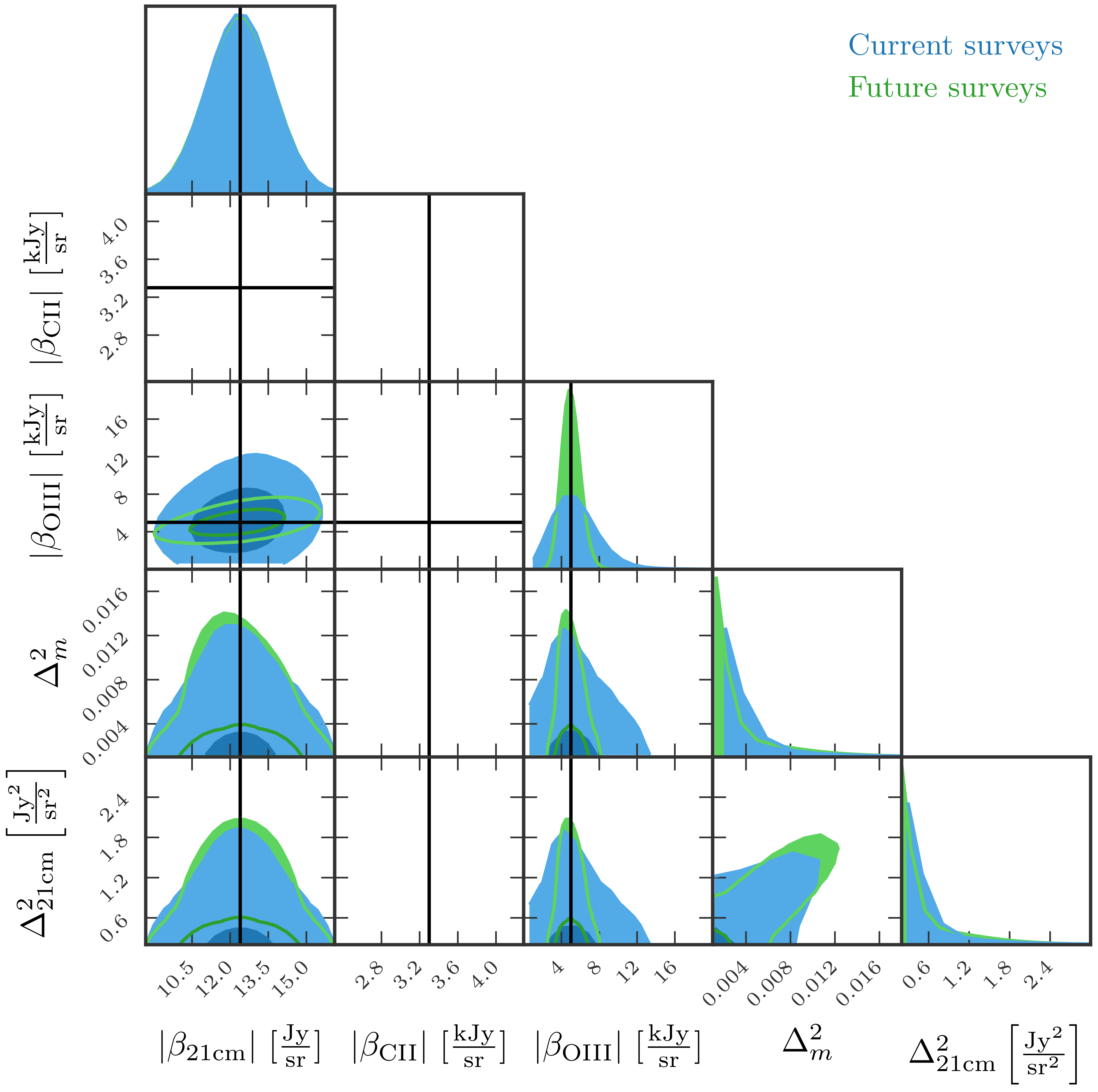
RESULTS 2/2

Fitting current and futuristic surveys

- Current (or upcoming) surveys:
  HERA, FYST-like, EXCLAIM-like

- Futuristic survey:
  improved instrumental specifications

see Padmanabhan et al. (2020):
arXiv: 2105.12148



RESULTS 2/2

Fitting current and futuristic surveys

- Current (or upcoming) surveys:
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- Current (or upcoming) surveys + prior:
  above + additional prior on C[II]
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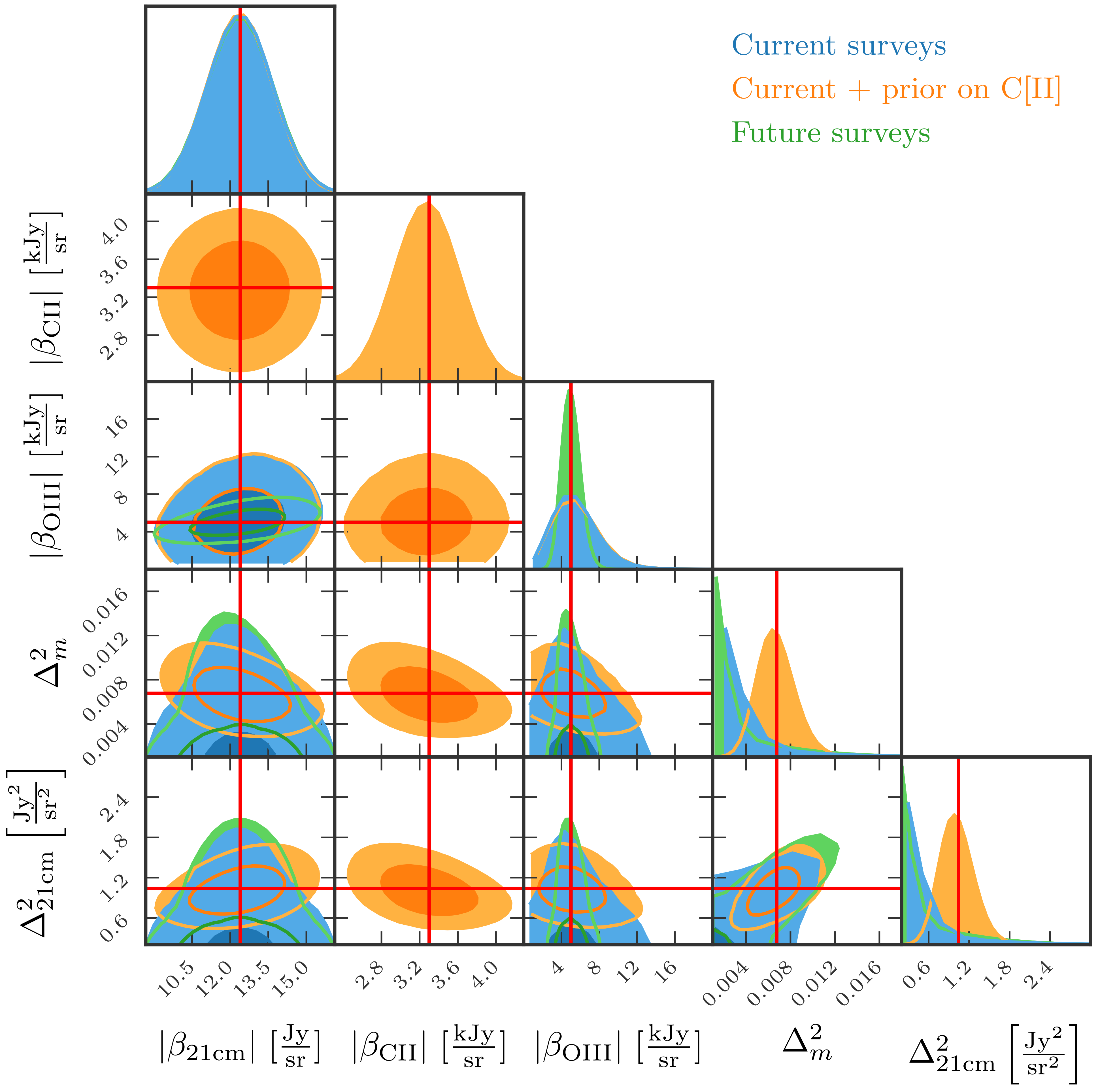

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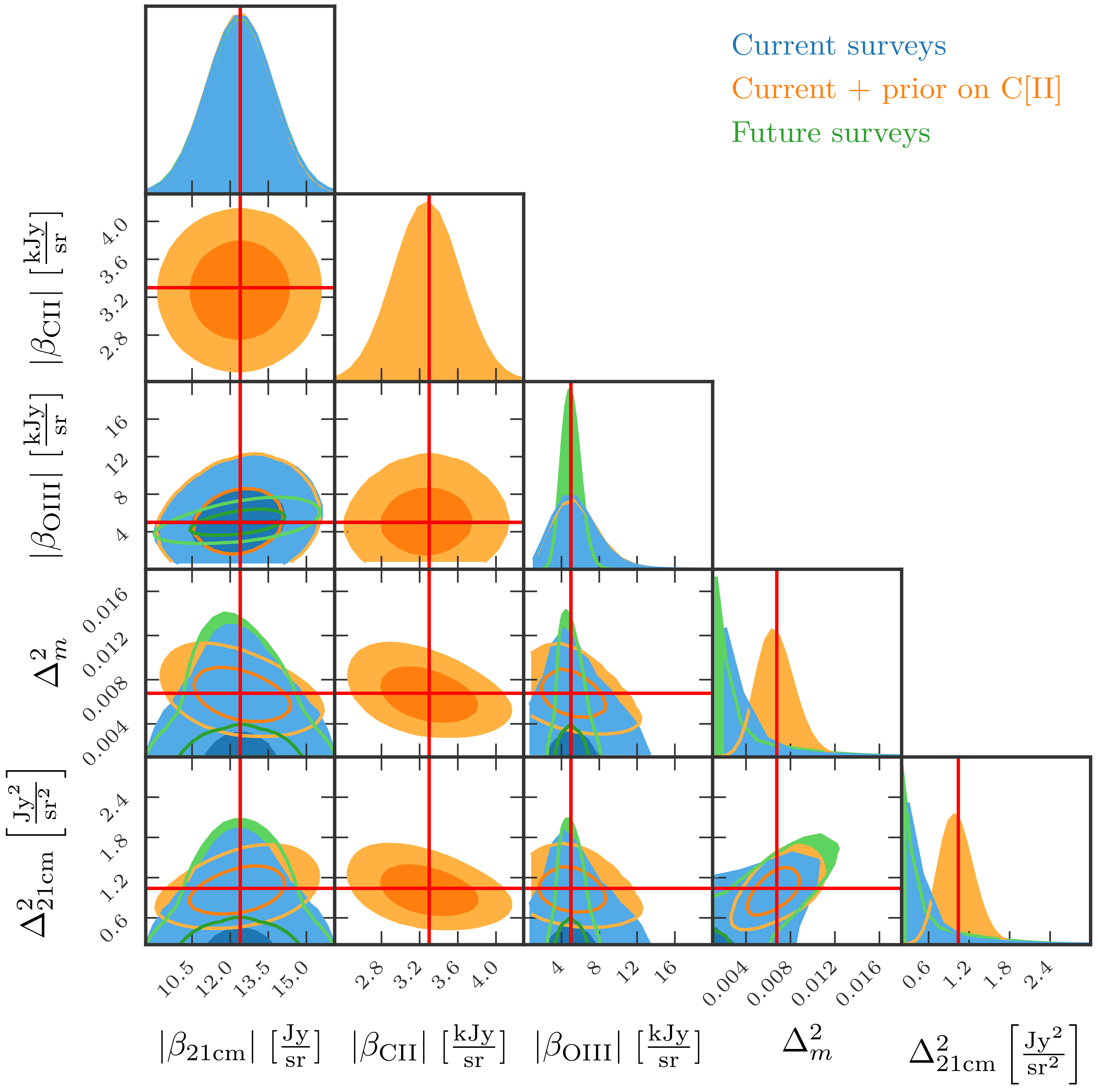

see Padmanabhan et al. (2020):
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Technique fails without additional information because ratios are tricky!

SUMMARY

- On large scales, in the linear biasing regime, it may be possible to reconstruct the 21cm power spectrum from three crosscorrelations. But caution must be taken if …
    - …the three fields are decorrelated with each other
    - …the instrumental noise is large, in particular if one line is very noisy
- However theoretical modeling and simulations can improve…
    - …our understanding of what lines are tracing what underlying fields
    - …the physical constraints on the bias factors, thus improving the priors on the model parameters

arXiv:2308.00749

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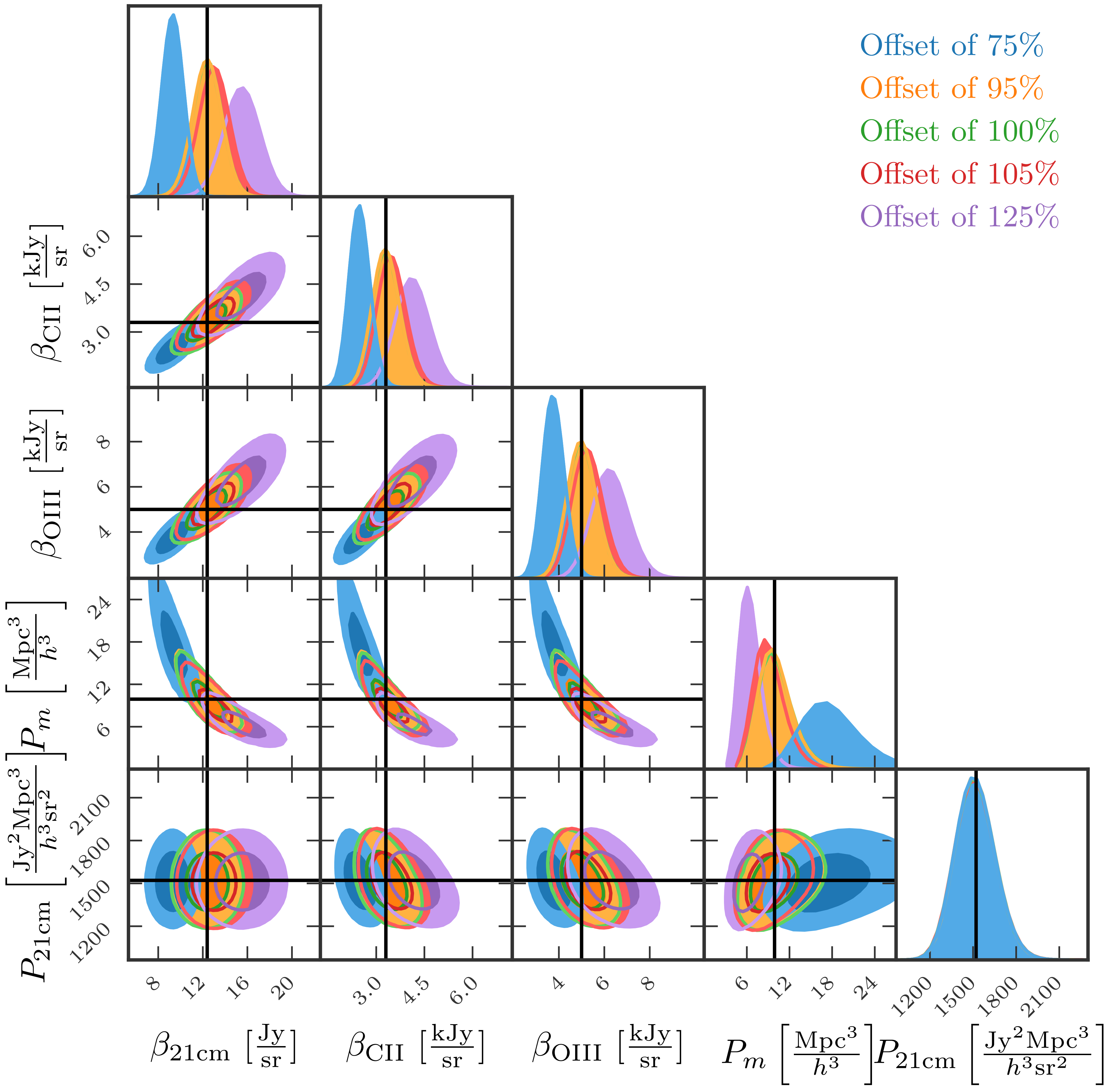
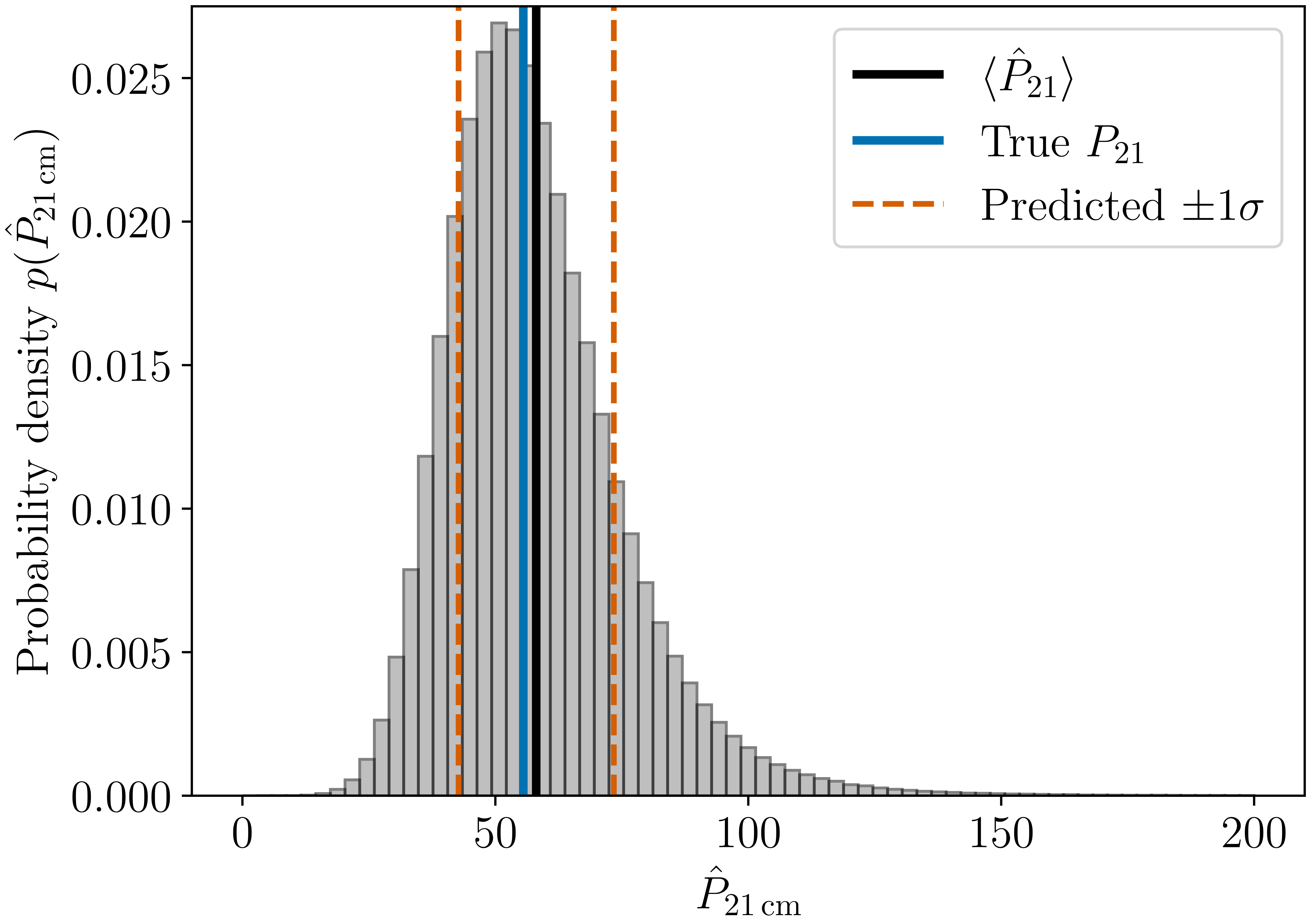
ADRIAN'S TALK NEXT!

arXiv:2308.00749

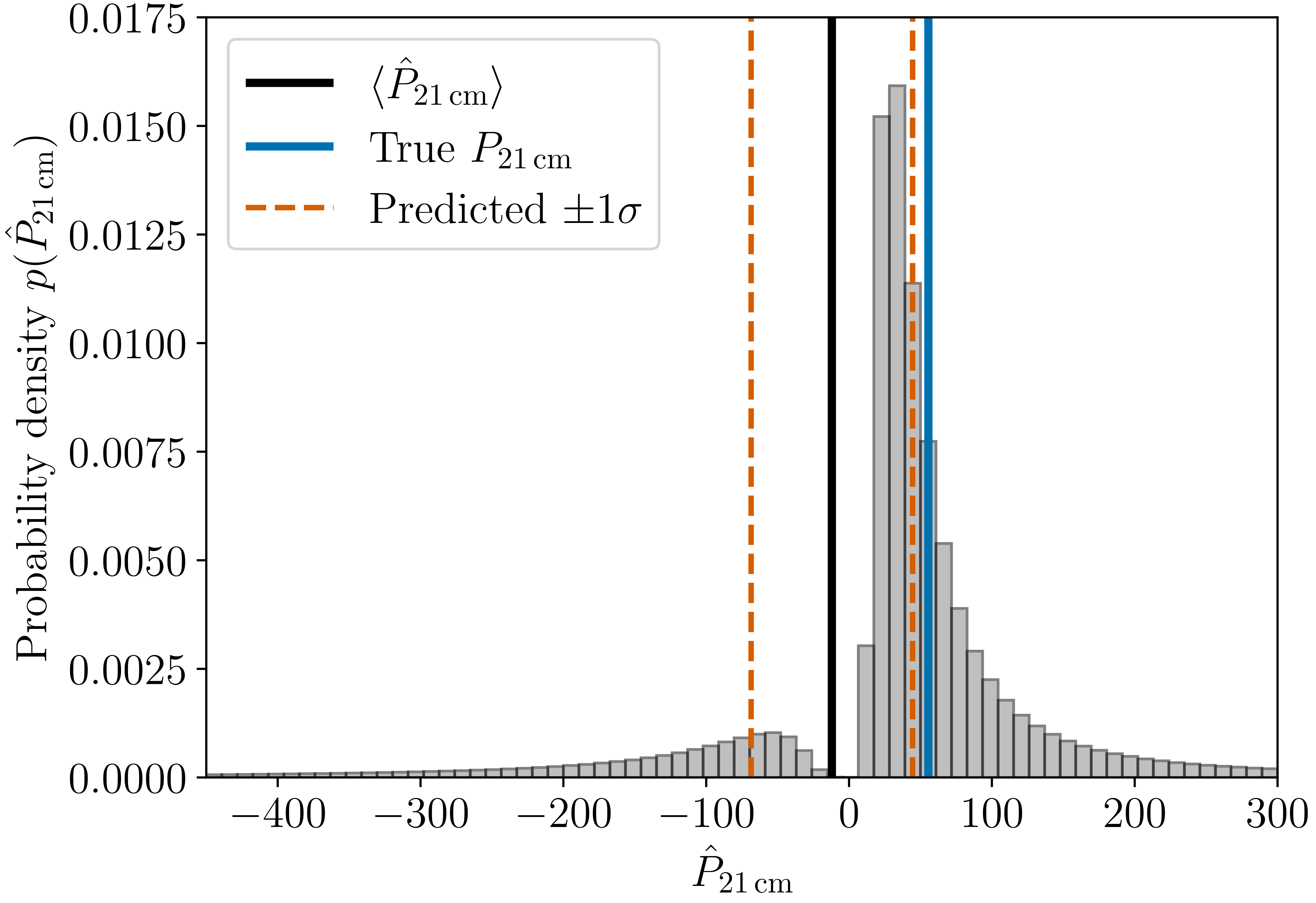
On the importance of priors



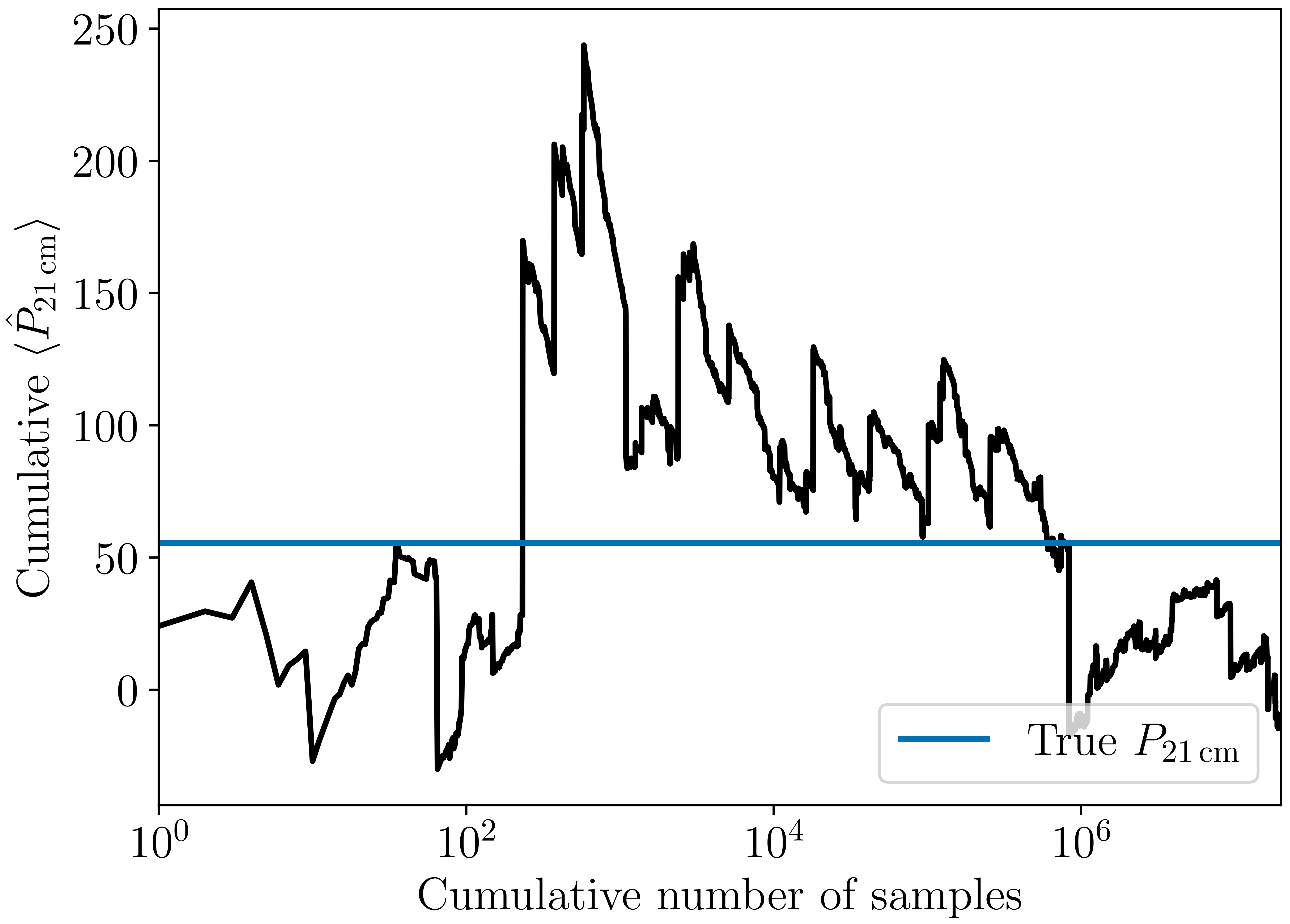
SNEAKY ERROR PROPAGATION 1/3



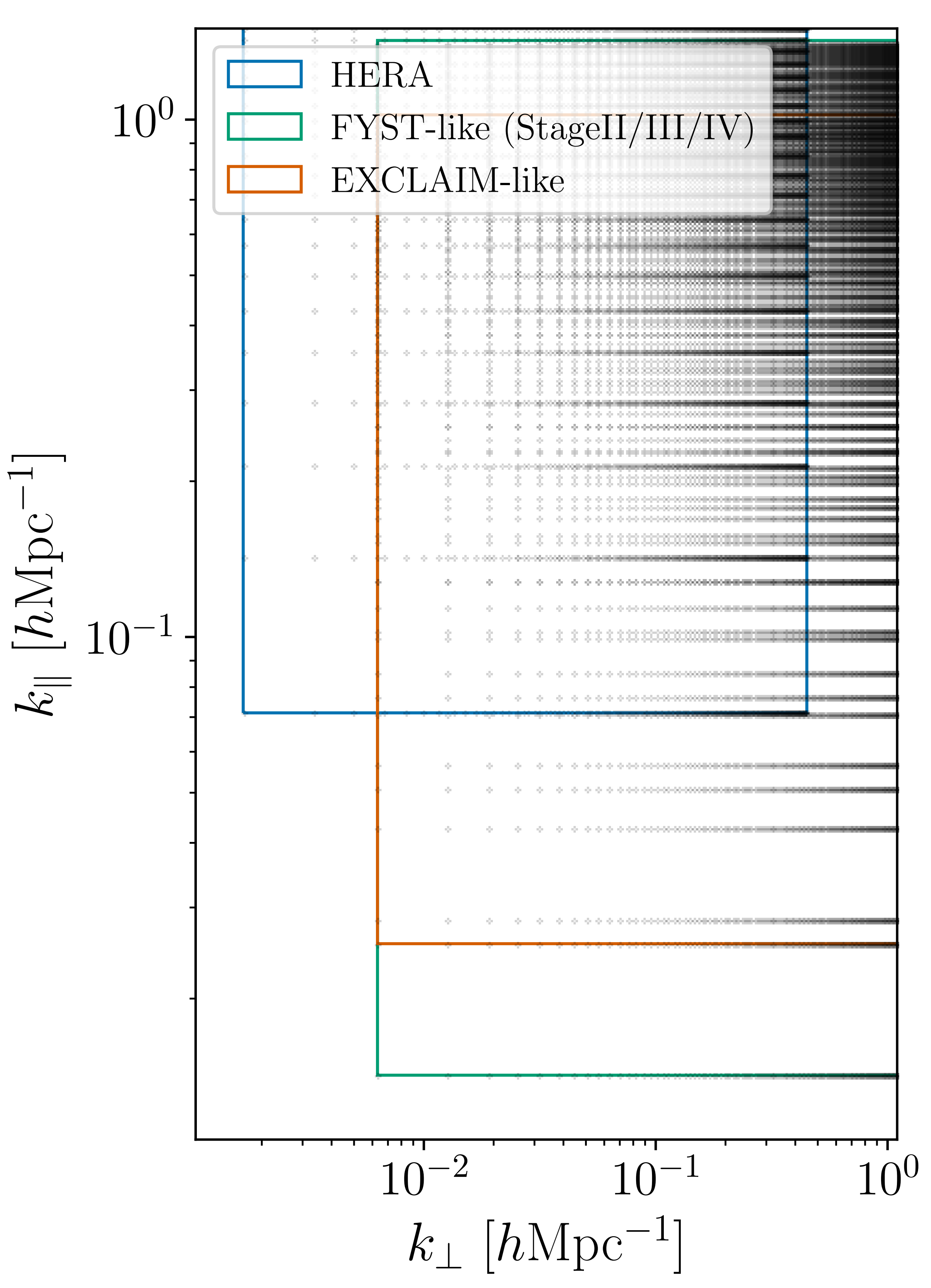
SNEAKY ERROR PROPAGATION 2/3



SNEAKY ERROR PROPAGATION 3/3



CAREFUL IN k-SPACE



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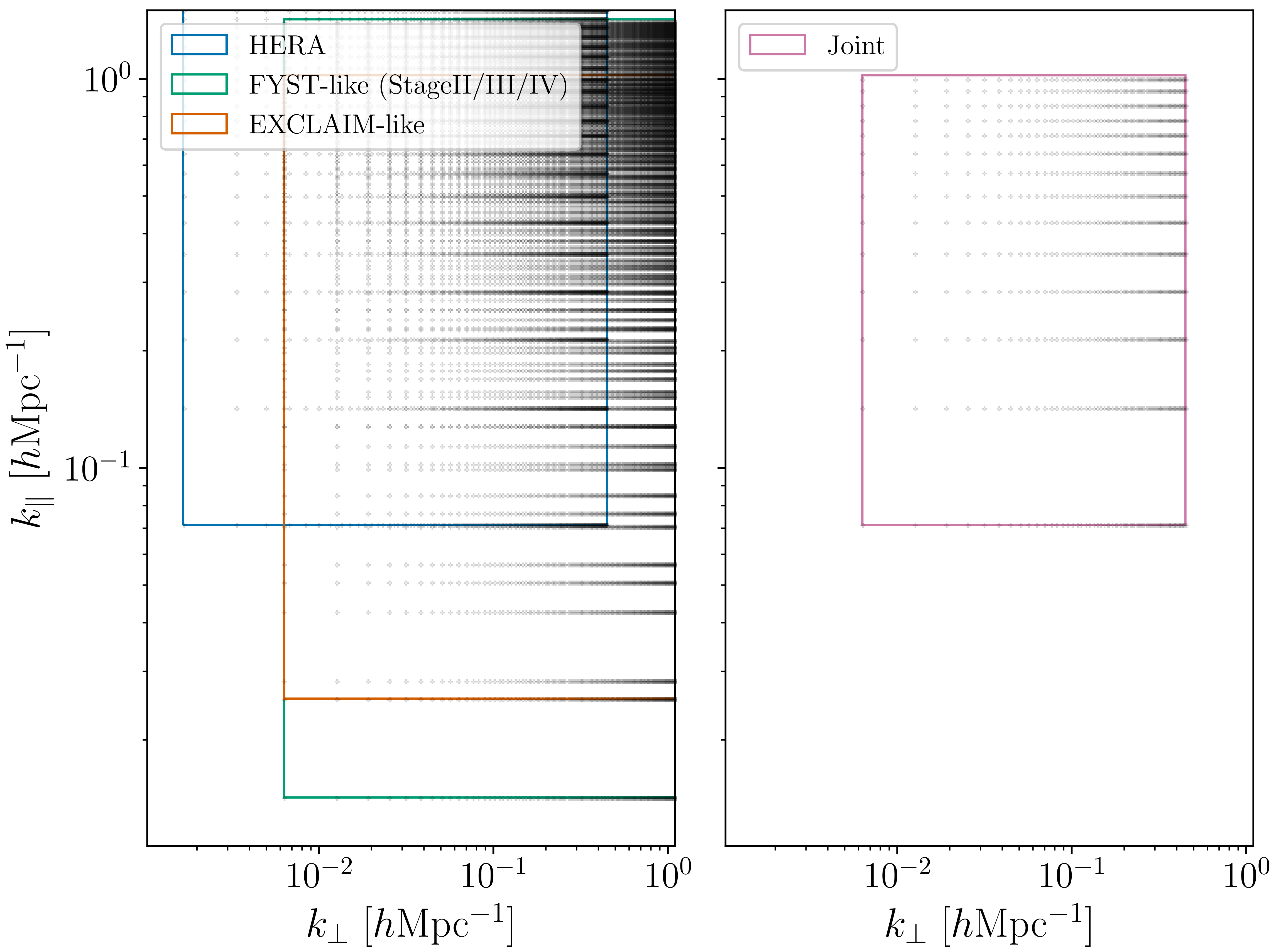
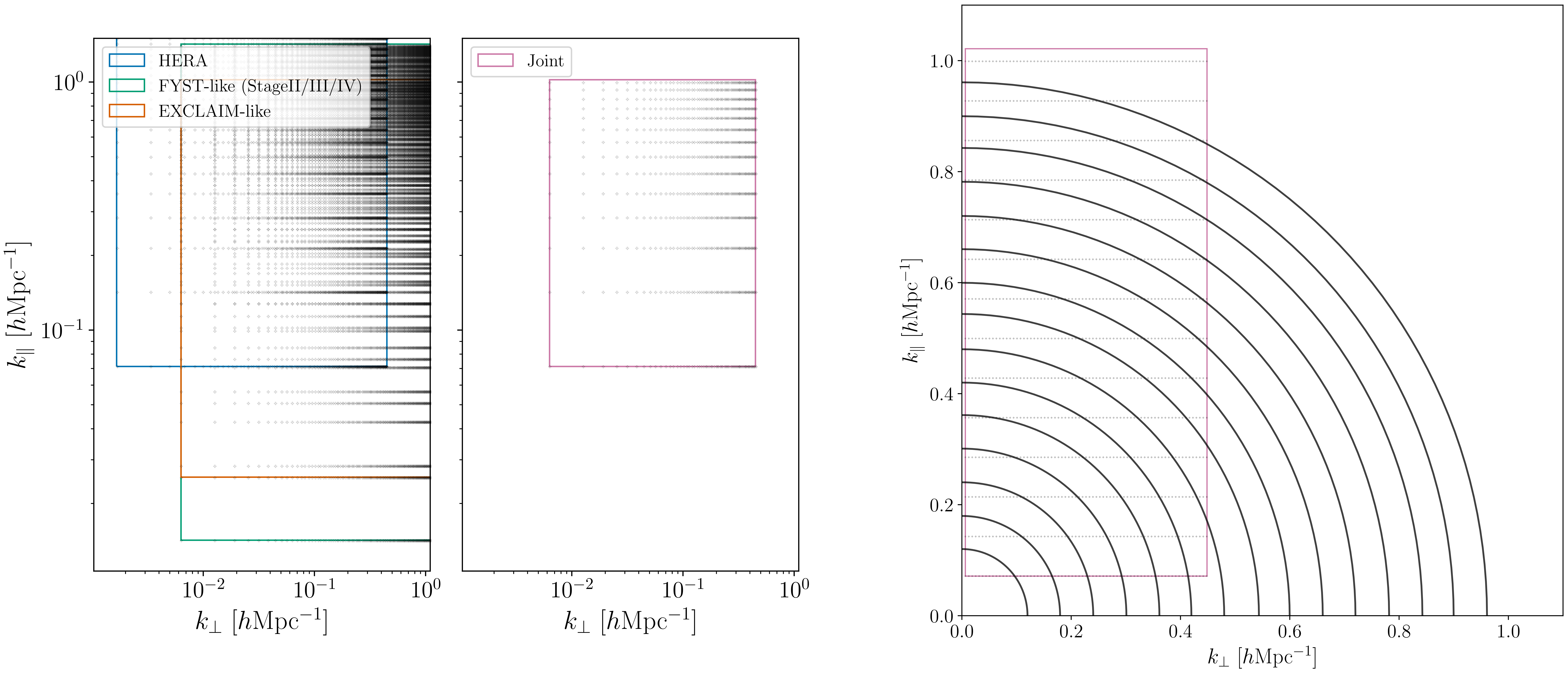
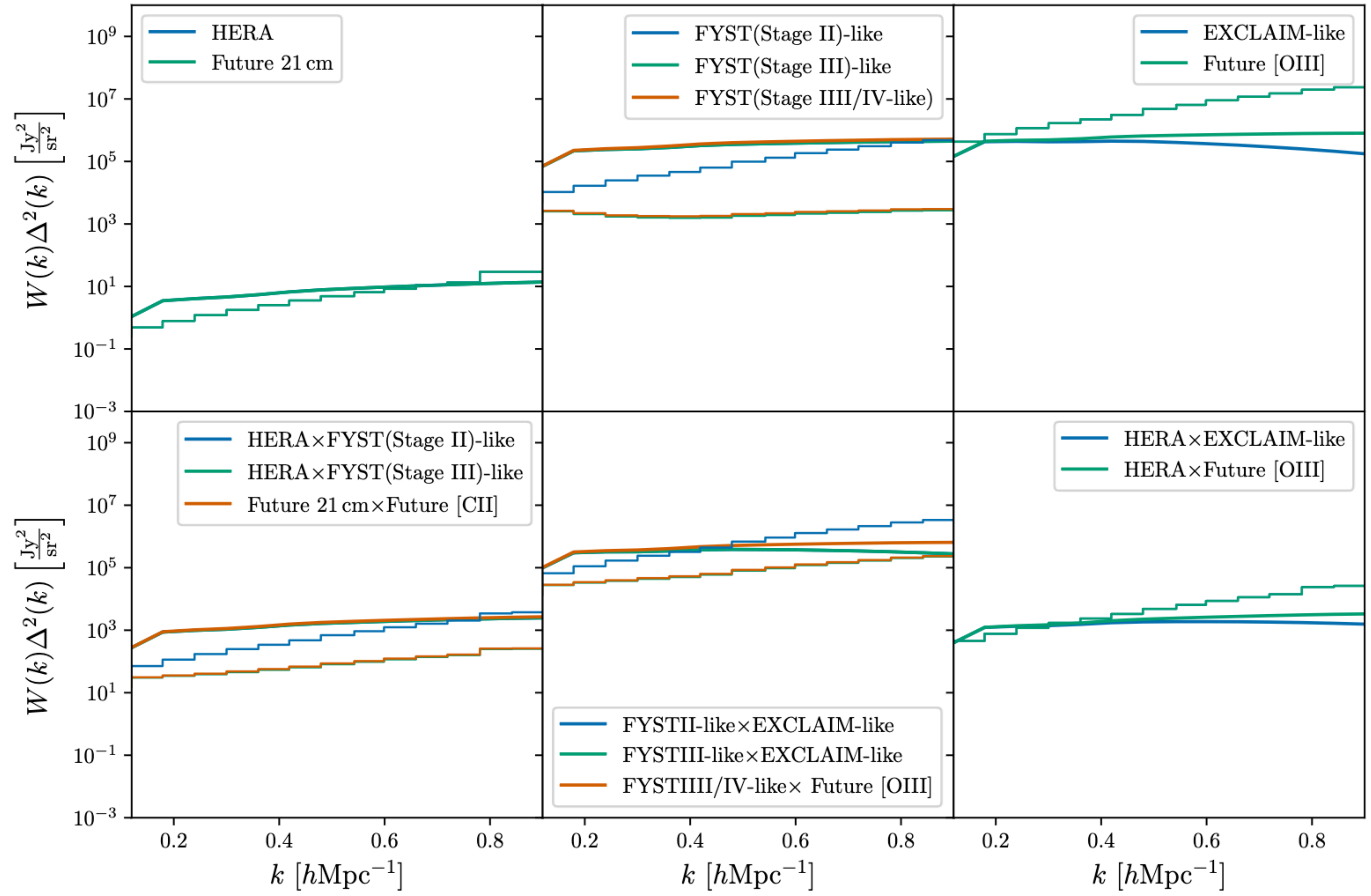


CAREFUL IN k-SPACE

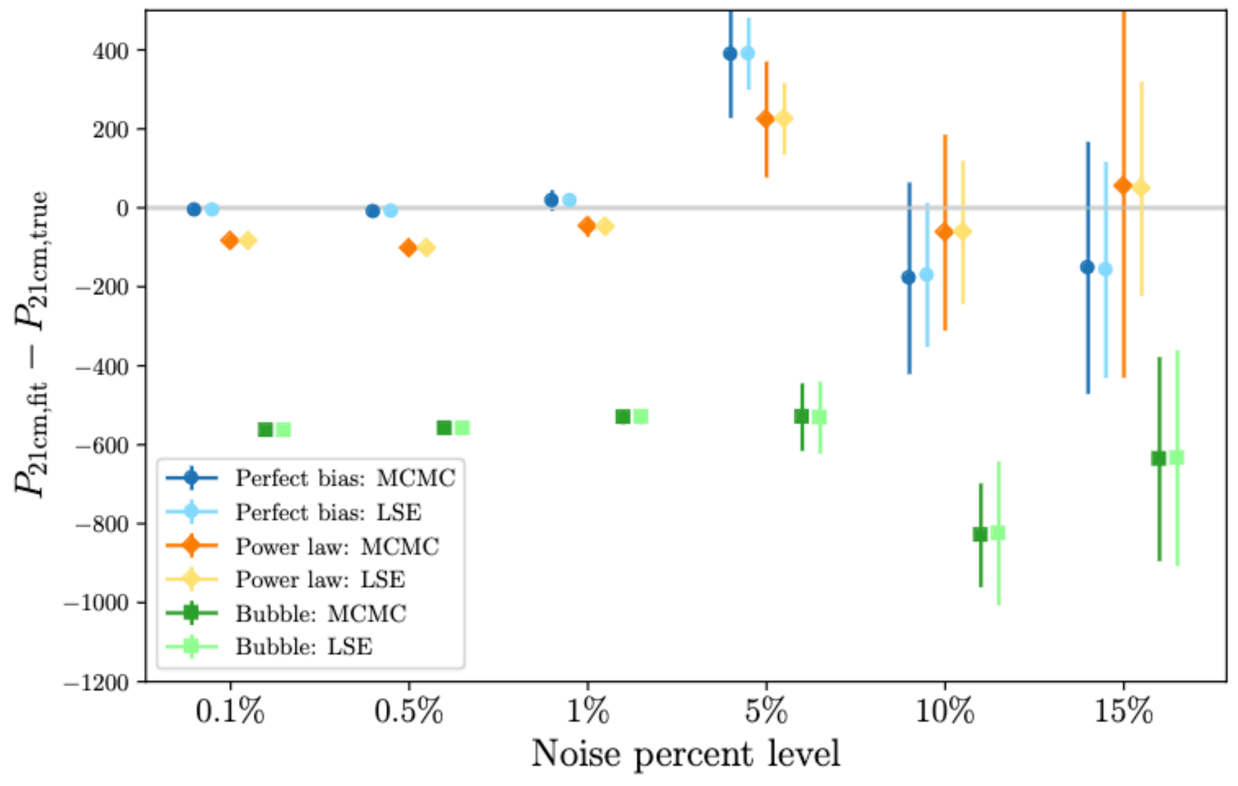


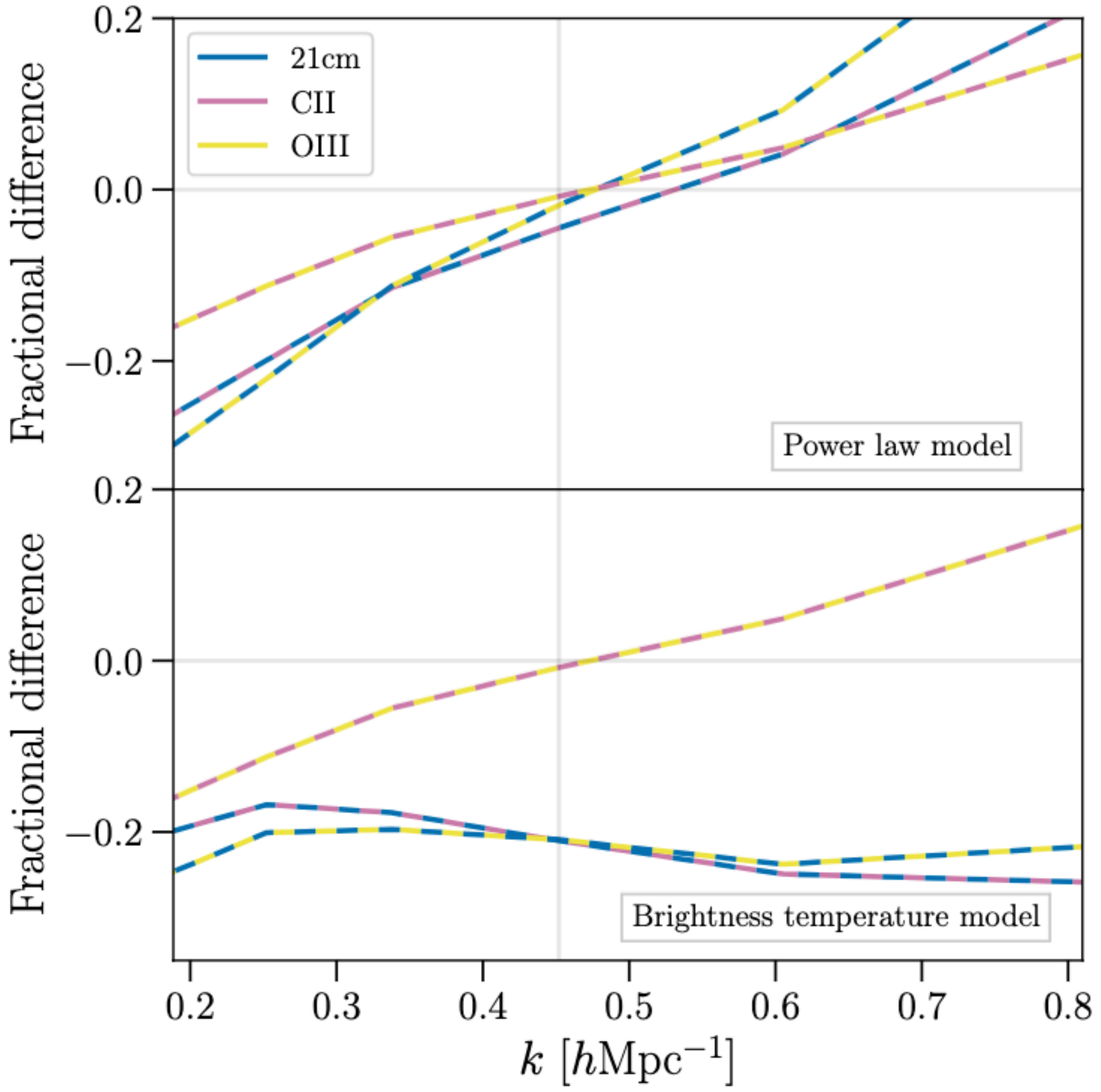
SURVEYS

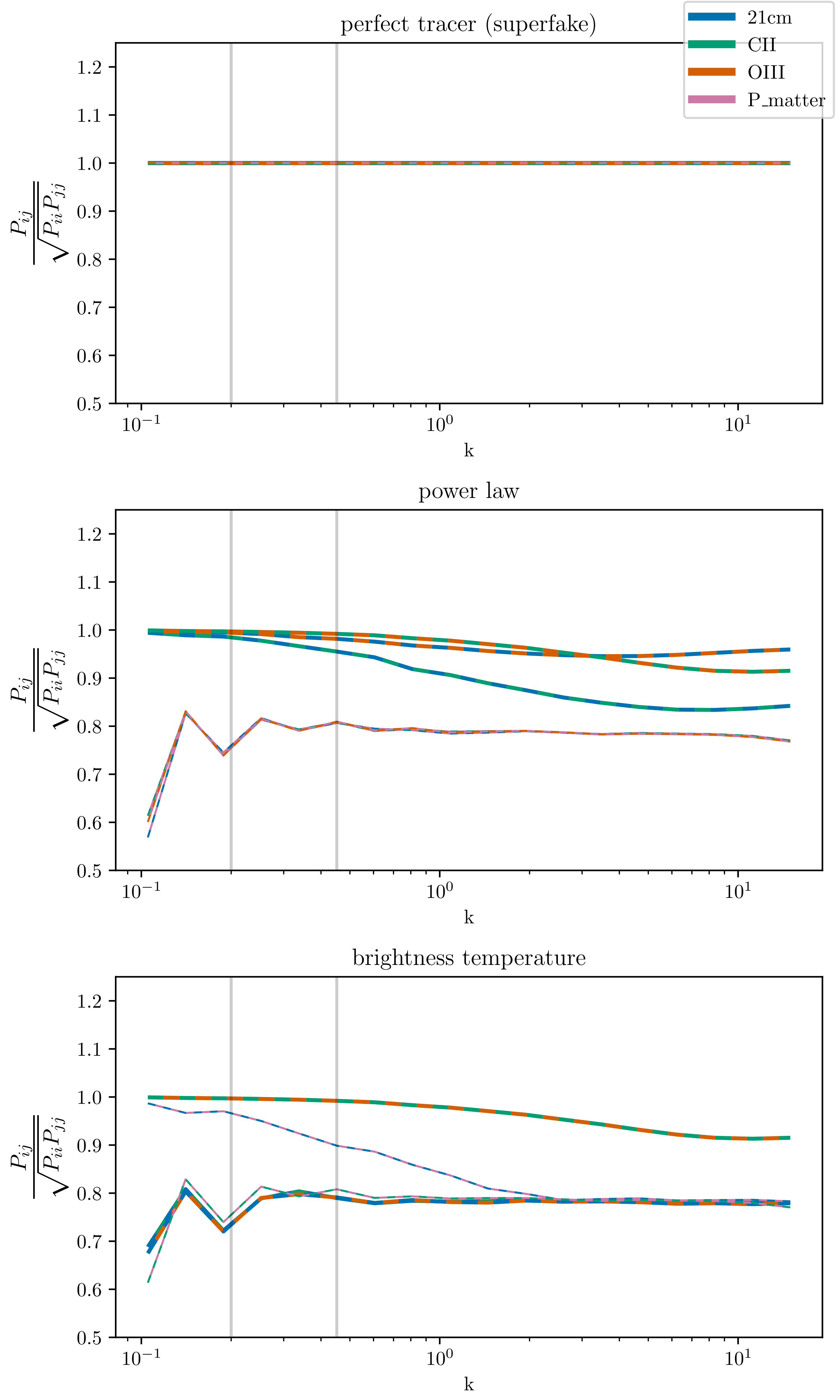


HERA
Future 21 cm
FYST(Stage II)-like
FYST(Stage III)-like
FYST(Stage IIII/IV-like)
EXCLAIM-like
Future [OIII]
HERA×FYST(Stage II)-like
HERA×FYST(Stage III)-like
Future 21 cm×Future [CII]
FYSTII-like×EXCLAIM-like
FYSTIII-like×EXCLAIM-like
FYSTIIII/IV-like× Future [OIII]
HERA×EXCLAIM-like
HERA×Future [OIII]
$W(k)\Delta^2(k)$ $\left[\frac{\mathrm{Jy}^2}{\mathrm{sr}^2}\right]$
k [hMpc^{-1}]

INTRINSIC BIAS

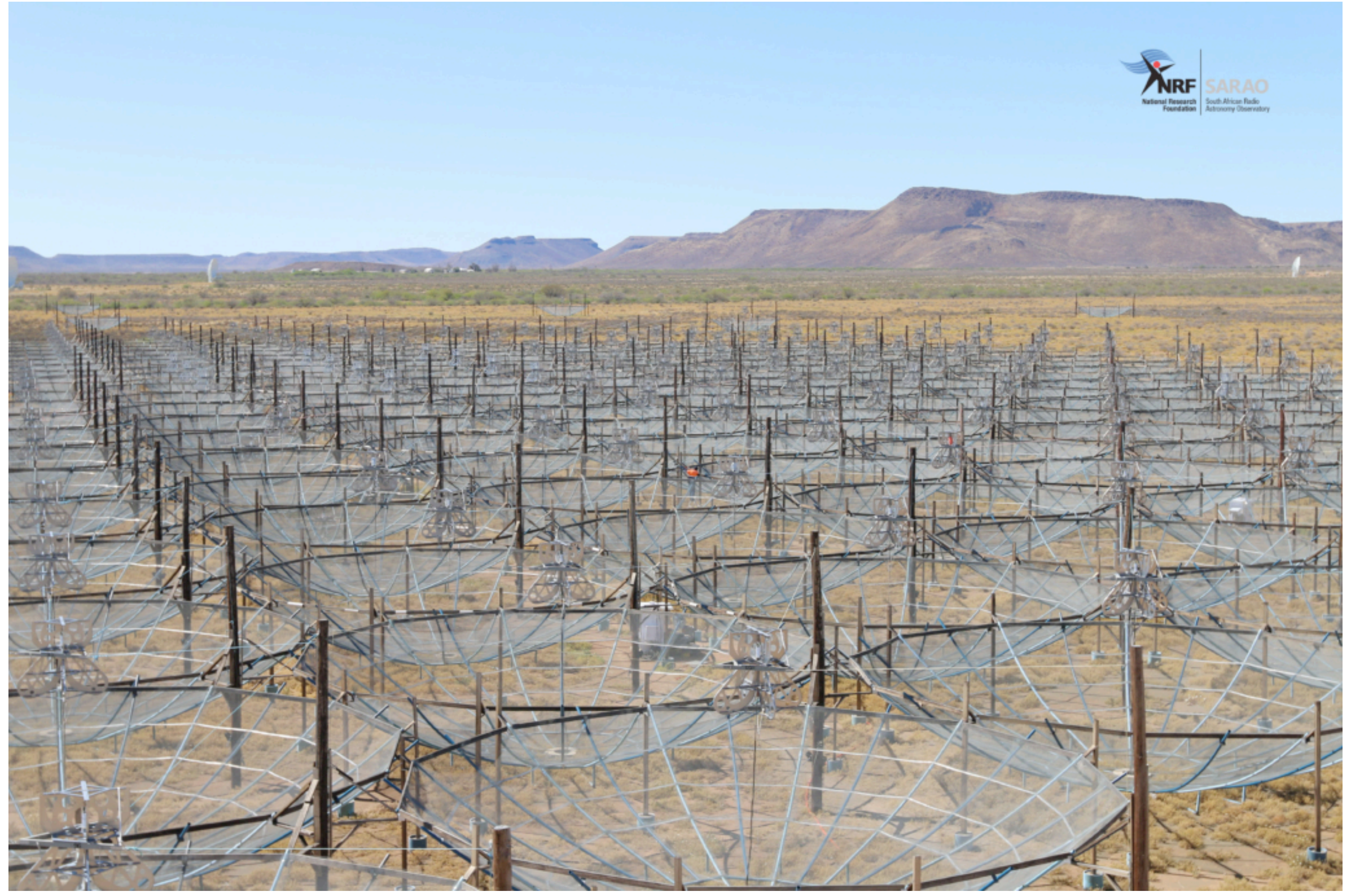






tinder

HERA'S TINDER PROFILE



HERA

Telescope at SARAO

Radio interferometer based in the Karoo Desert in South Africa. Currently responsible for the world's leading upper limits of the P21 at EOR redshifts, but always looking to improve.

Hoping to meet a complementary survey who shares the same values (and sky coverage). Let's crosscorrelate some data and see how it goes. Looking to avoid drama, and foregrounds.