Part I

Analytic method for power spectrum covariance:

speedup by four orders of magnitude

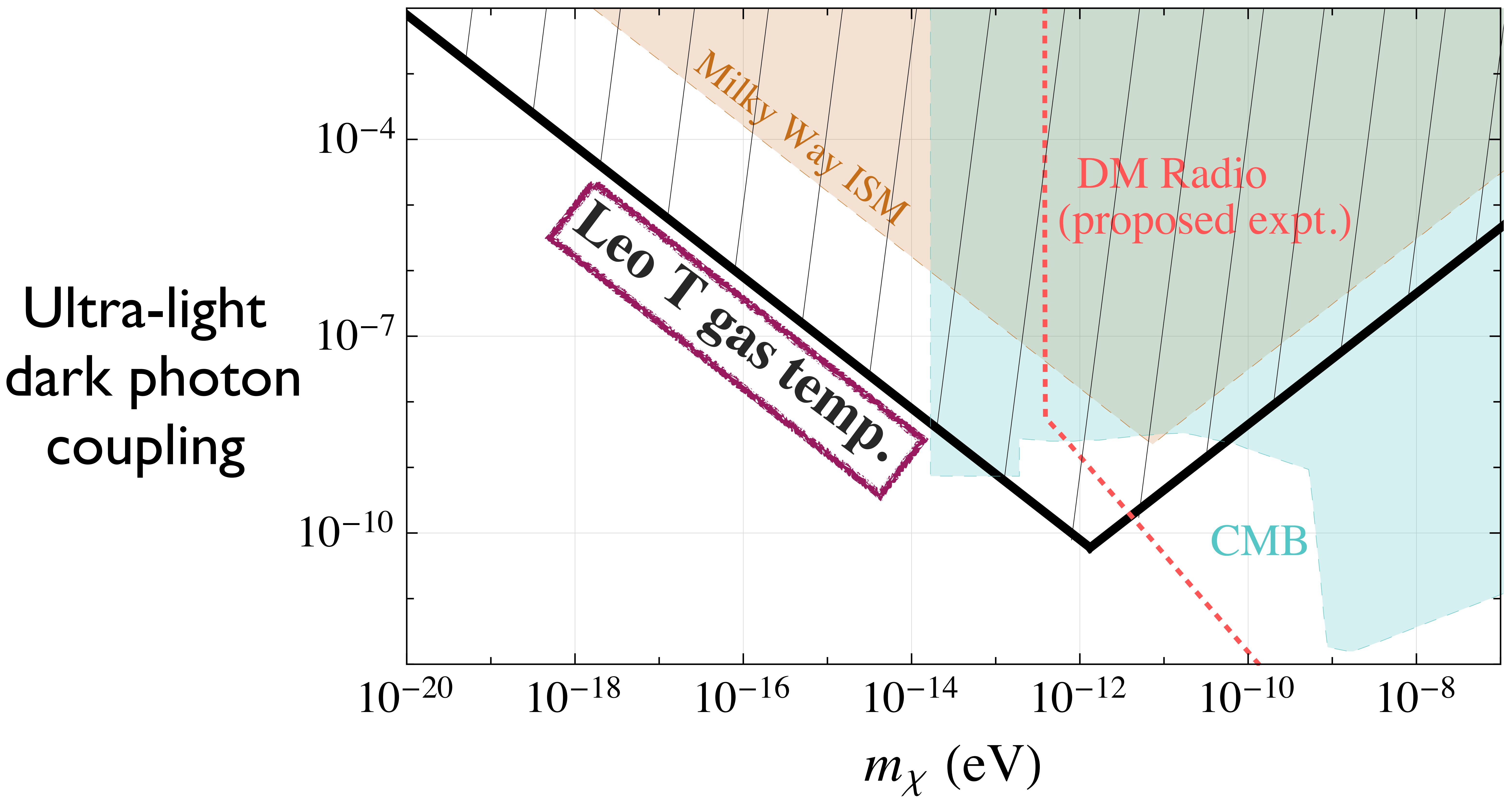
(Jay) Digvijay Wadekar

New York University

DW, R. Scoccimarro, 2019
DW, M. Ivanov, R. Scoccimarro, 2020

Research overview

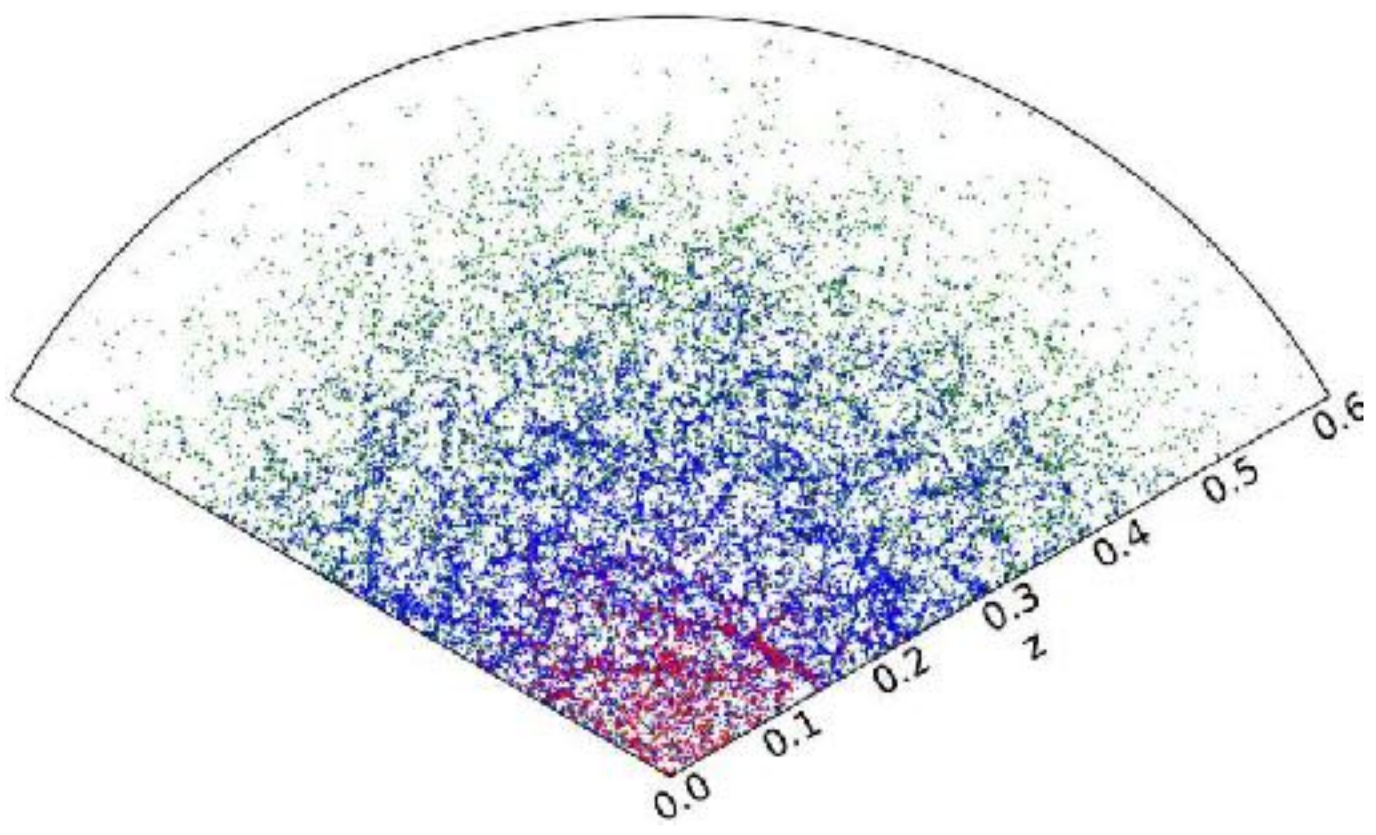
- **Gas-rich dwarf galaxies:**
  - A new probe of alternatives to cold dark matter (CDM)

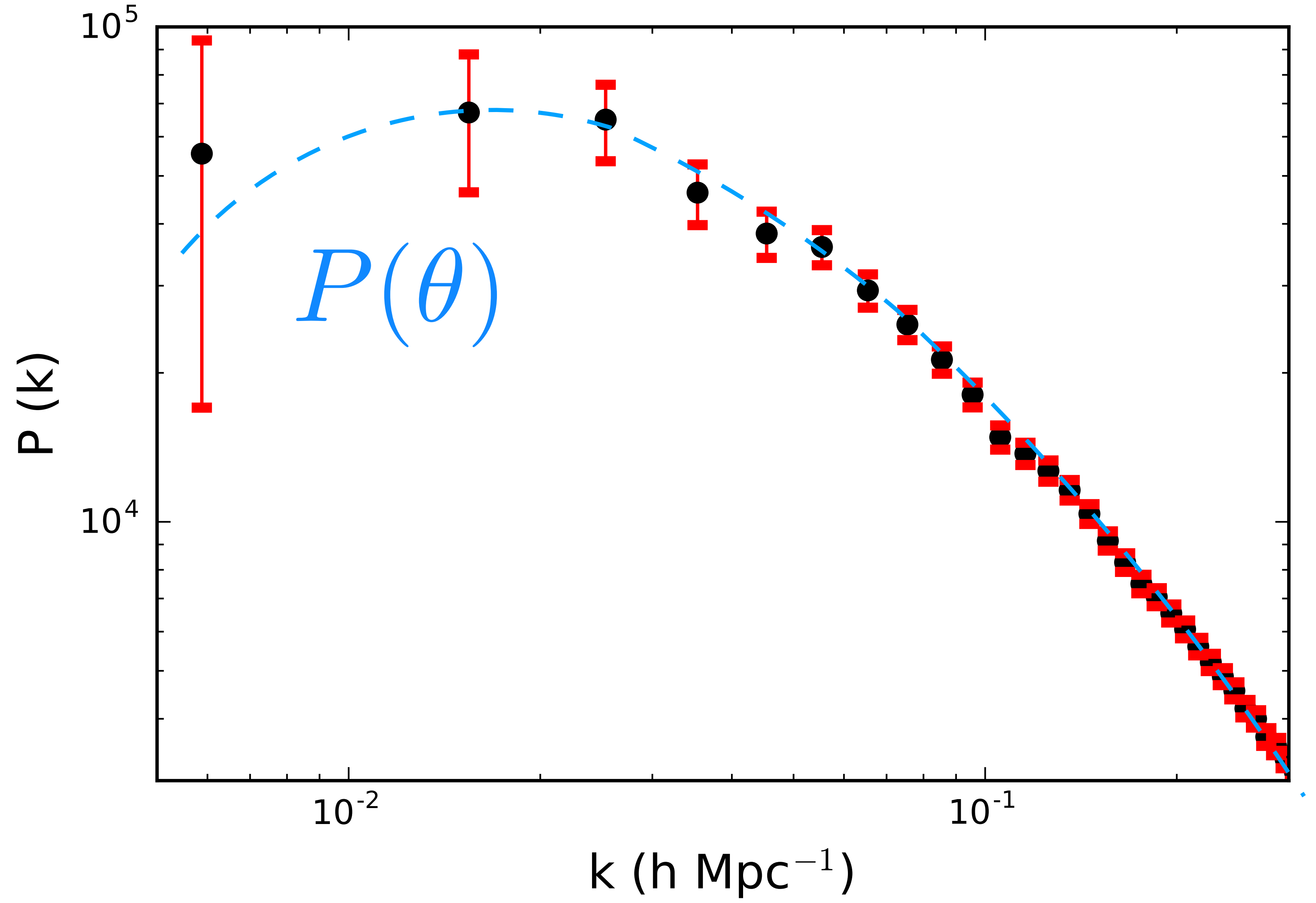


DW & G. Farrar 19

Farrar, .., DW et al. 19

Galaxy power spectrum covariance

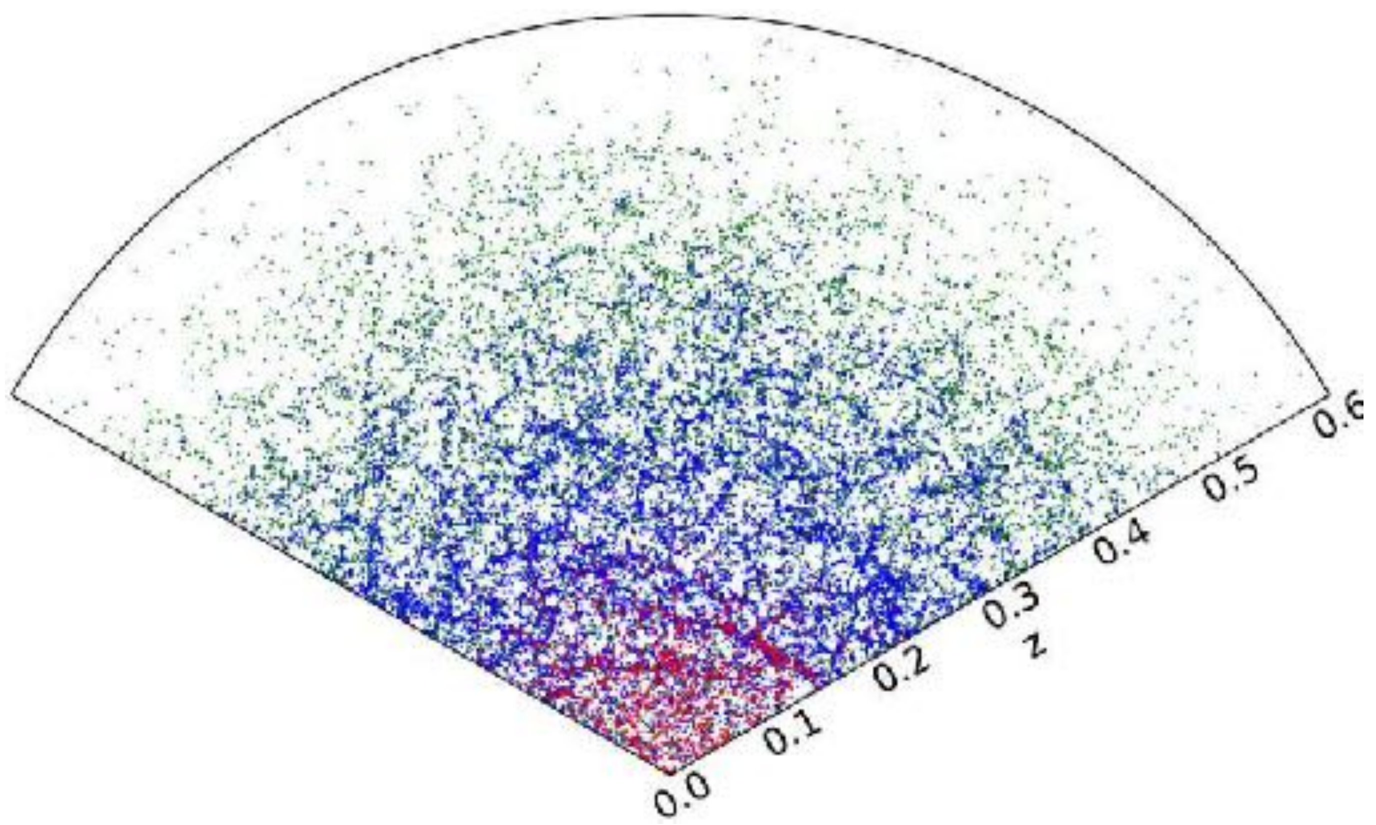


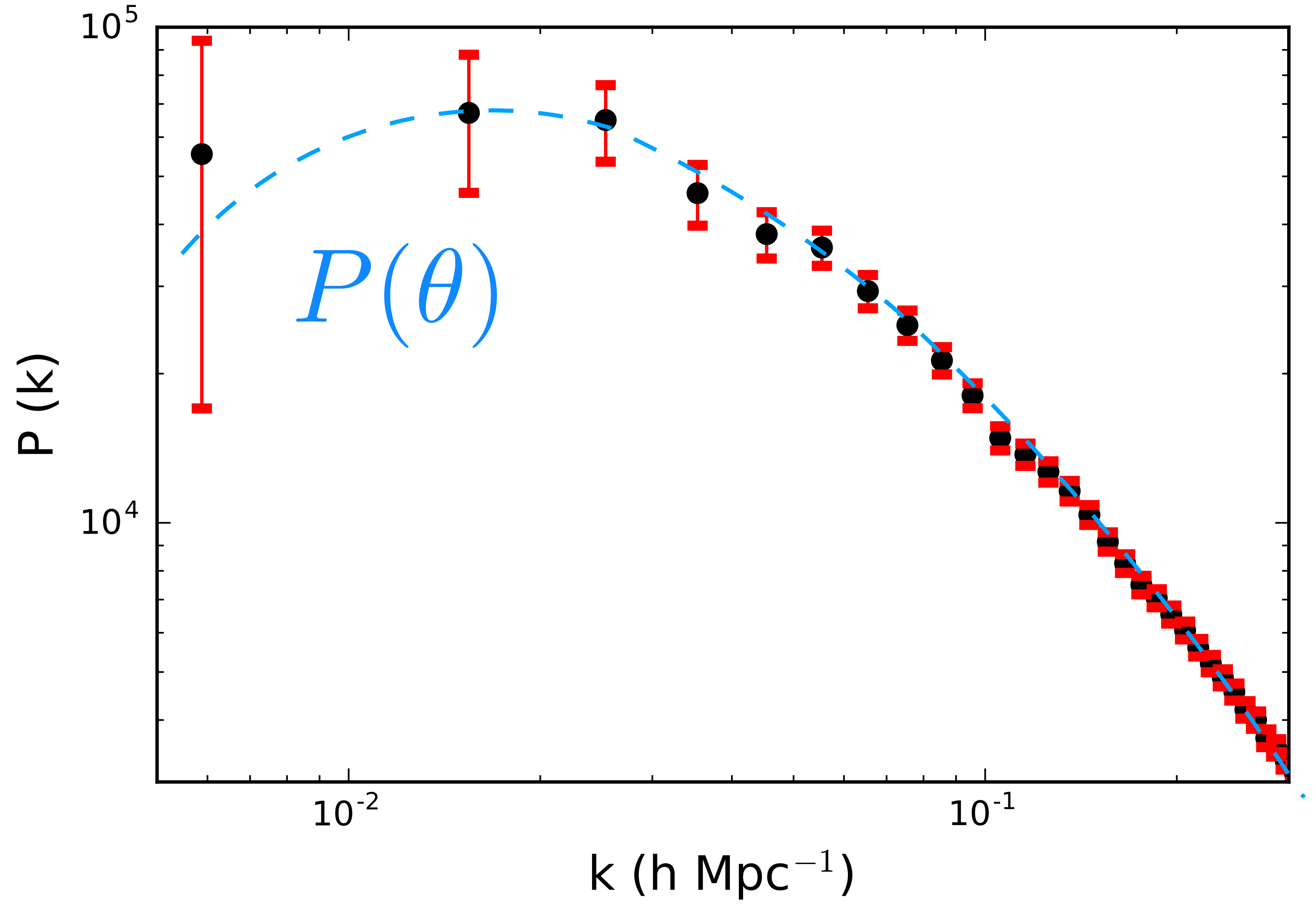


$$\begin{Bmatrix} H_0 \\ \sum m_\nu \\ \Omega_m \\ \ldots \end{Bmatrix}$$

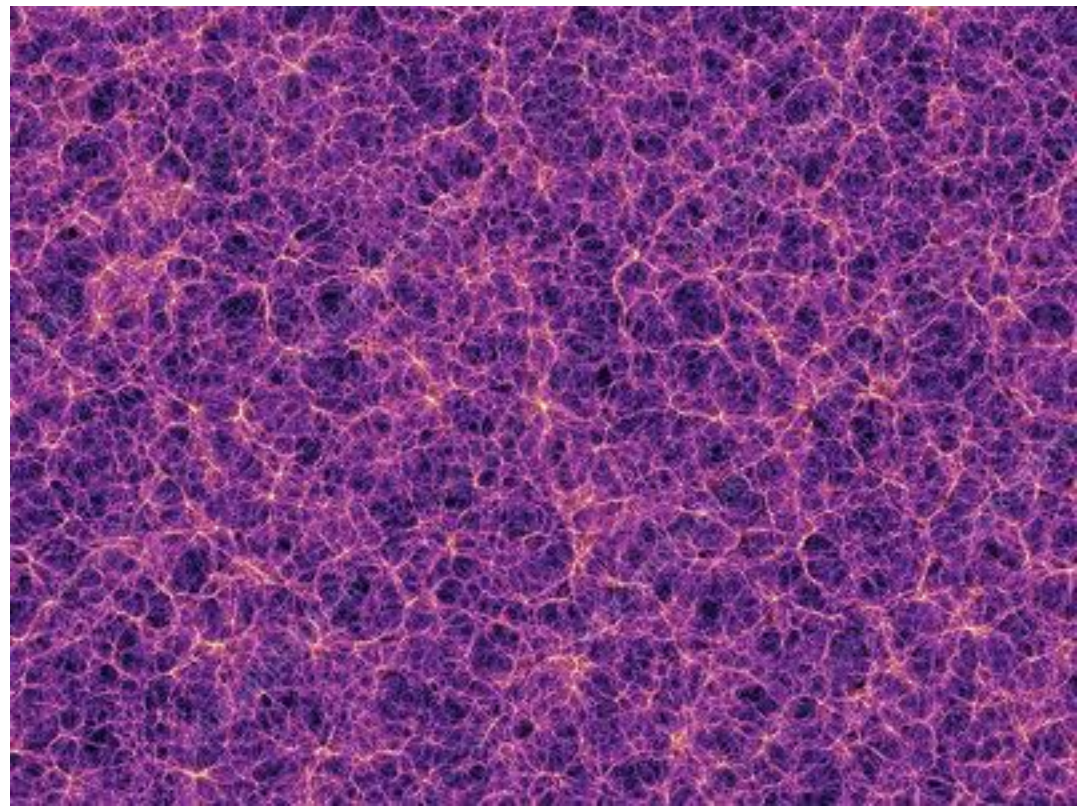
$$p(P_d|\theta) = \frac{1}{(2\pi)^{n/2}\sqrt{\det C(\theta)}} \exp\left[-\frac{1}{2}(P_d - P(\theta))^T C(\theta)^{-1}(P_d - P(\theta)) \right]$$

Galaxy power spectrum covariance





$$H_0$$
$$\left\{ \begin{matrix} \sum m_\nu \\ \Omega_m \end{matrix} \right\}$$
$$\ldots.$$



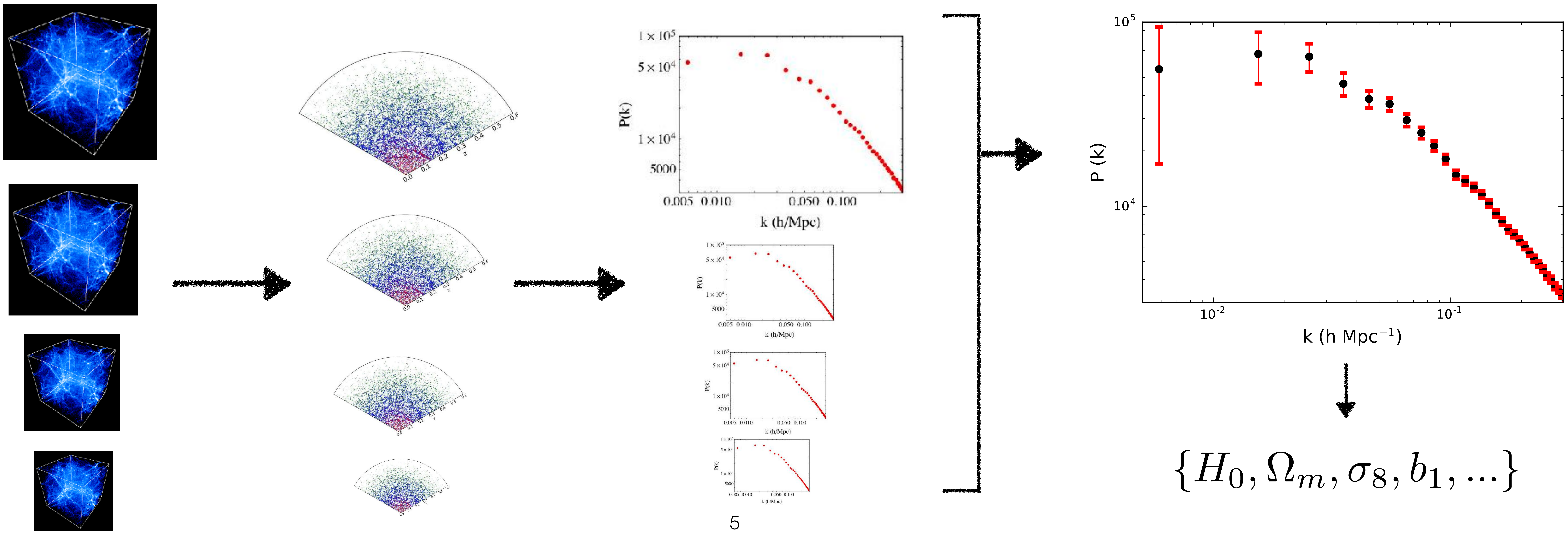
Initial conditions ??

Covariance from mock catalogs

- Need to simulate mock surveys (~ thousands)

$$C_{1,2} = \frac{1}{N_{\rm mock} - 1} \sum_{i=1}^{N_{\rm mock}} (\hat{P}_i(k_1) - \bar{P}(k_1))(\hat{P}_i(k_2) - \bar{P}(k_2))$$

~$\mathcal{O}$ (Gpc)³



$$\{H_0, \Omega_m, \sigma_8, b_1, ...\}$$

Covariance from mock catalogs

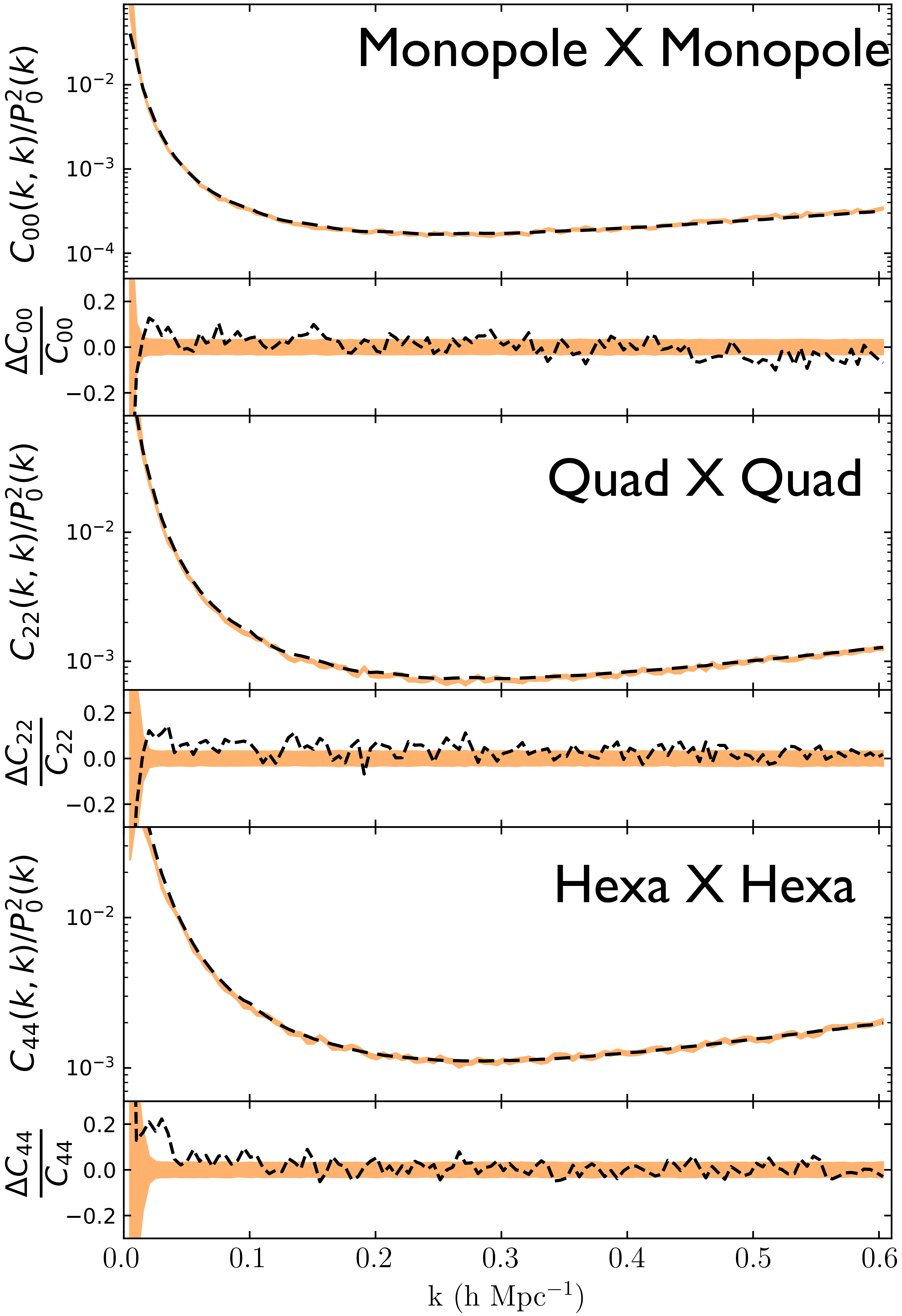
- As survey volume increases, mock catalogs become tougher to simulate (DESI, Rubin observatory)

- Dependence of covariance on cosmology and bias parameters is computationally prohibitive

$$p(P_d|\theta) = \frac{1}{(2\pi)^{n/2}\sqrt{\det C(\theta)}} \exp\left[-\frac{1}{2}(P_d - P(\theta))^T C(\theta)^{-1}(P_d - P(\theta))\right]$$

- Mocks suffer from sampling noise
  - Need to artificially inflate constraints

Results

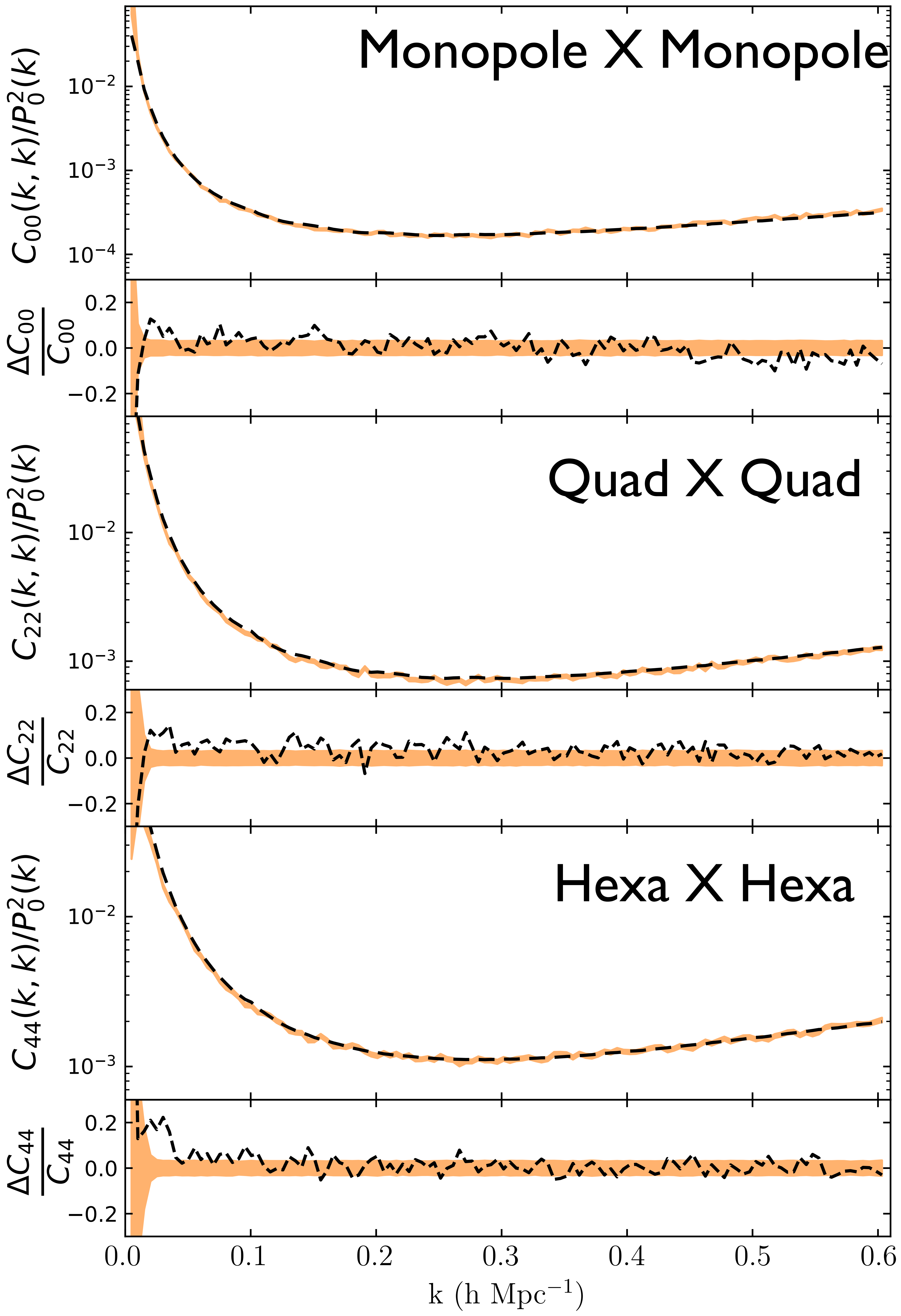


Our analytic method

Patchy Mocks
(state-of-the-art mocks used for SDSS BOSS parameter estimation)

DW & Scoccimarro 19

Results



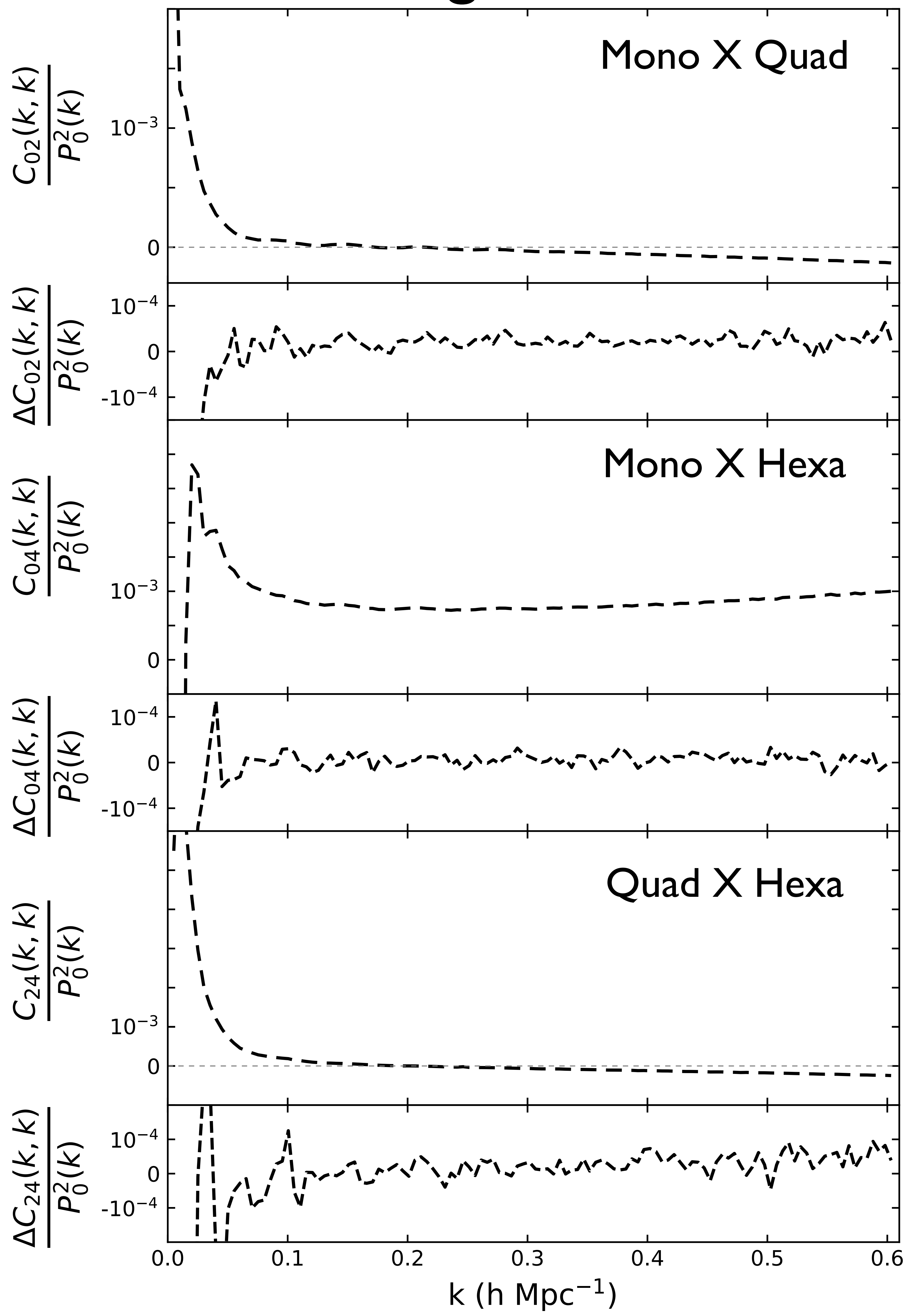
- - - - - ***Our analytic method (MINUTES)***

—— Patchy Mocks ***(MONTHS)*** (state-of-the-art mocks used for SDSS BOSS parameter estimation)

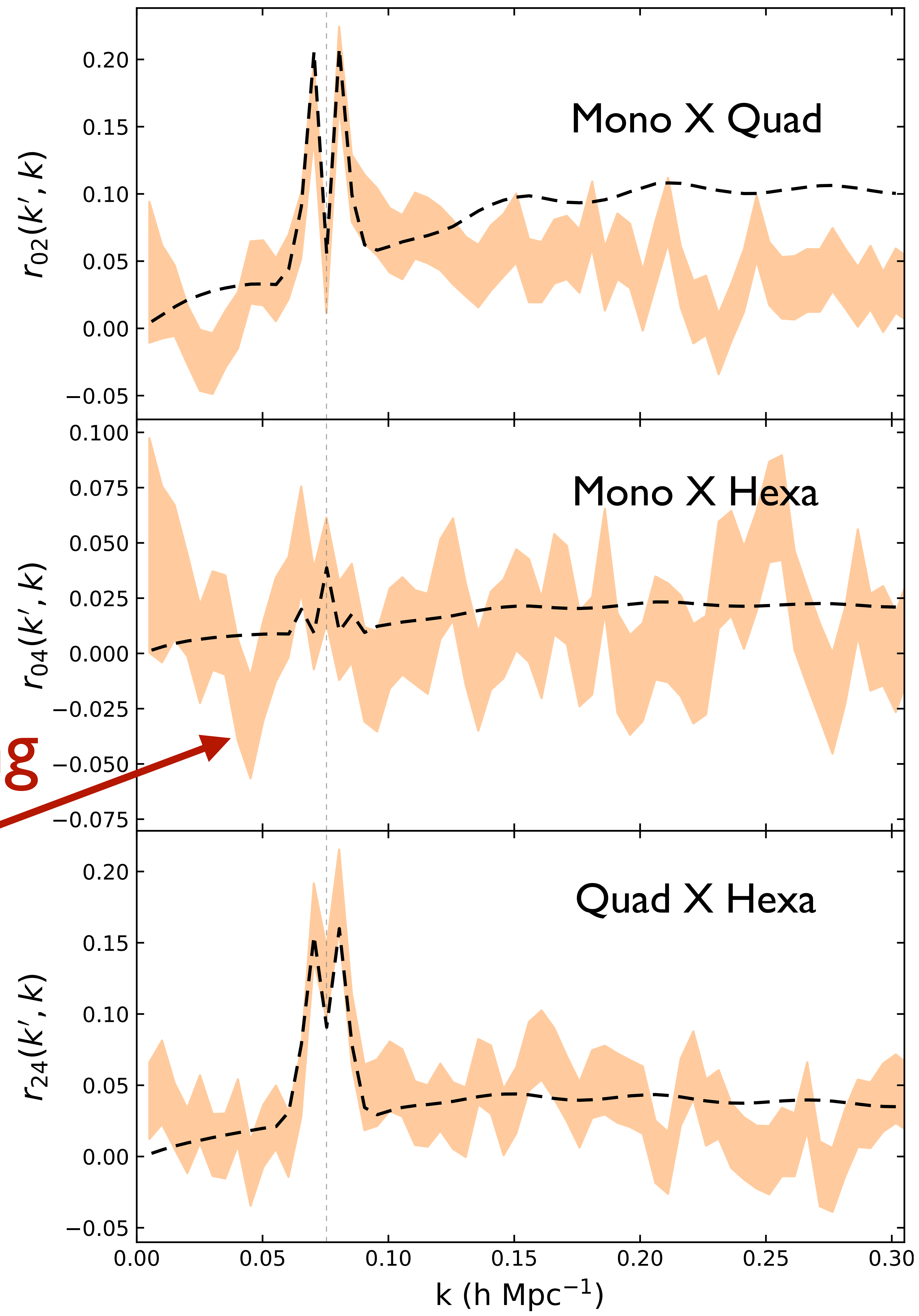
DW & Scoccimarro 19

Cross-covariance

Diagonals

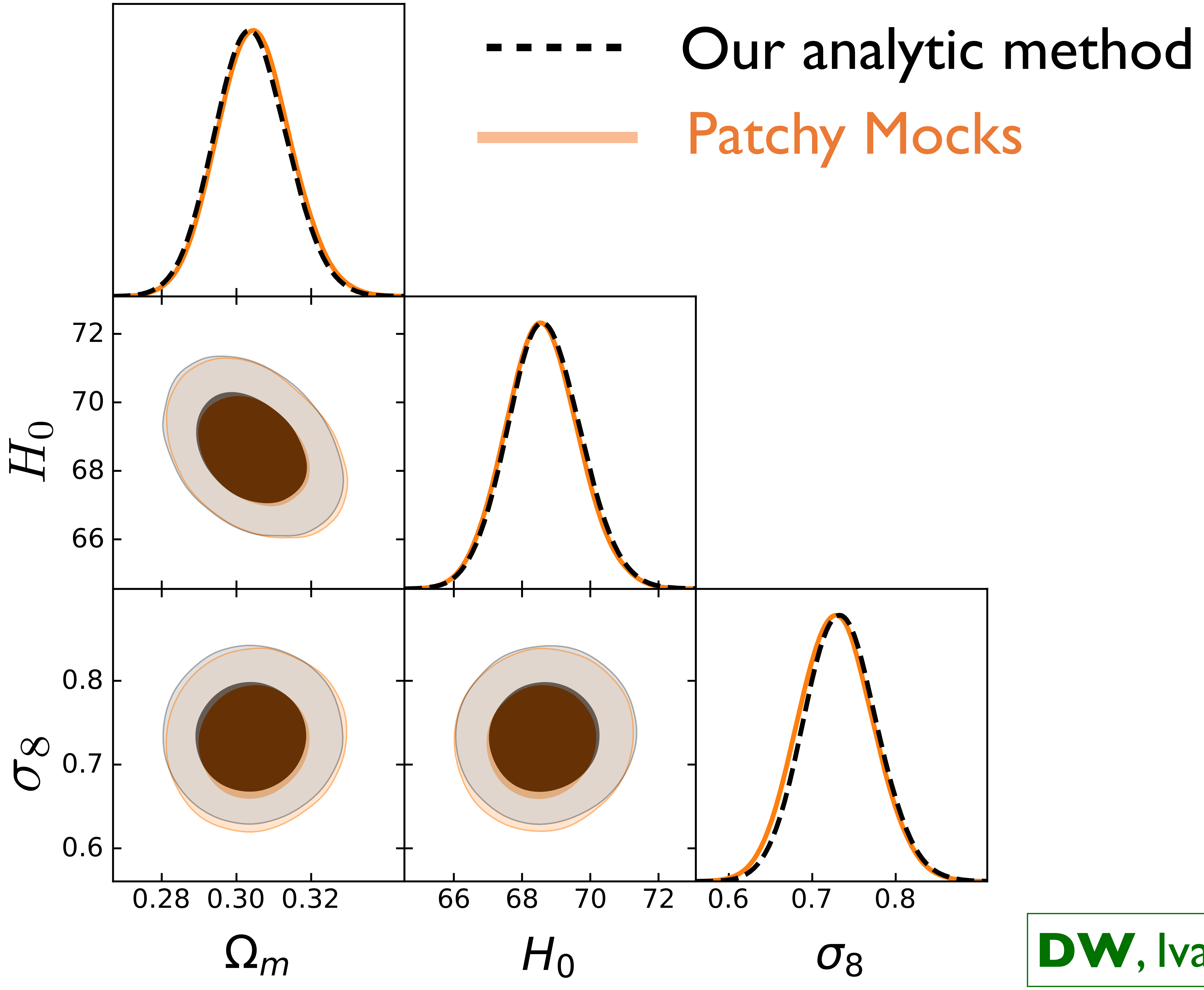


Row of matrix



Large sampling noise with 2048 mocks

Results: BOSS DR12 full-shape analysis



➡ Based on BOSS analysis pipeline of

Ivanov, Simonovic, Zaldarriaga, JCAP 20

Philcox et al. 2020

Ivanov et al 2020 (CLASS-PT)

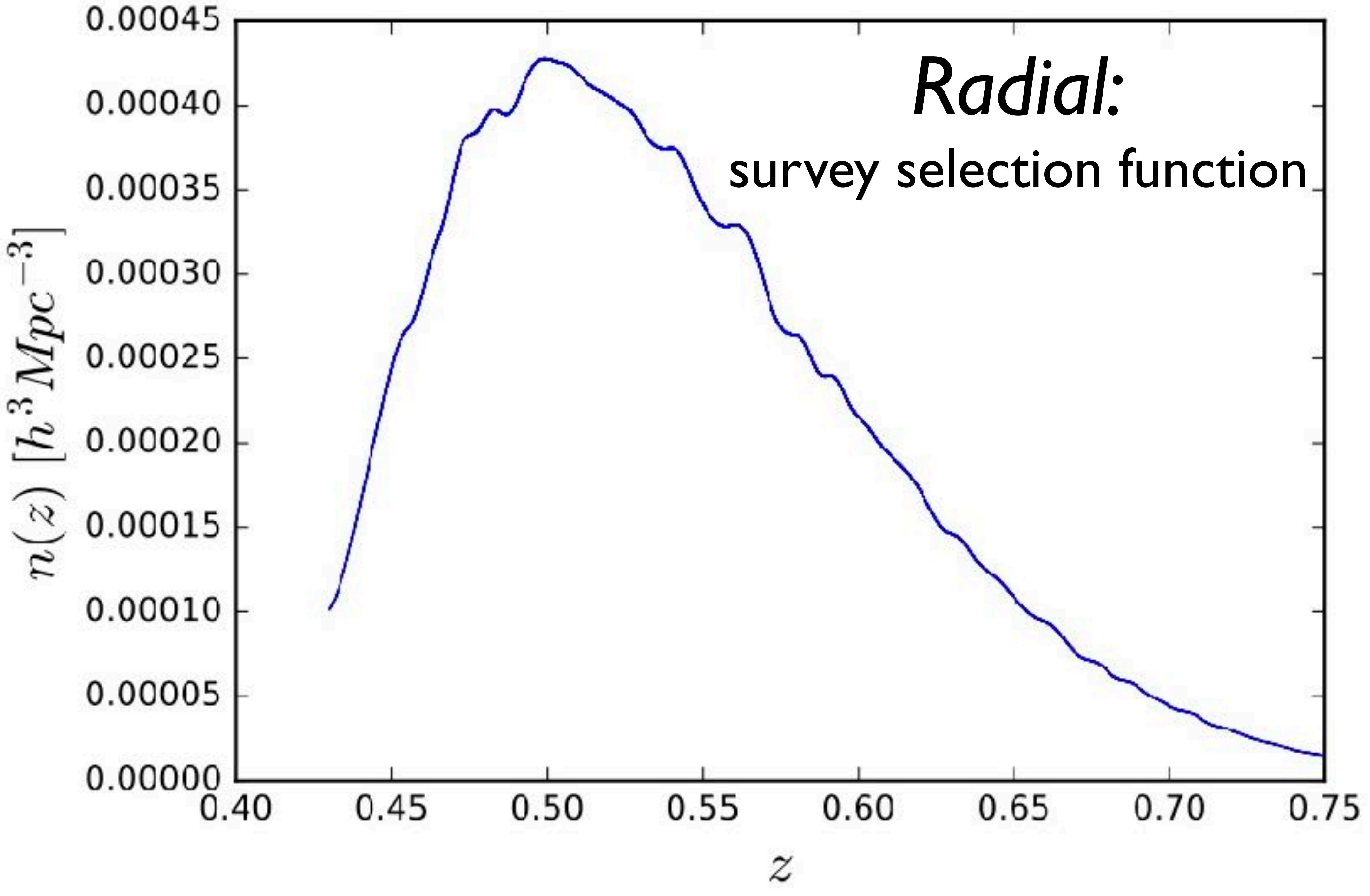
DW, Ivanov & Scoccimarro, 2020a

What are the challenges to analytically calculate the covariance?

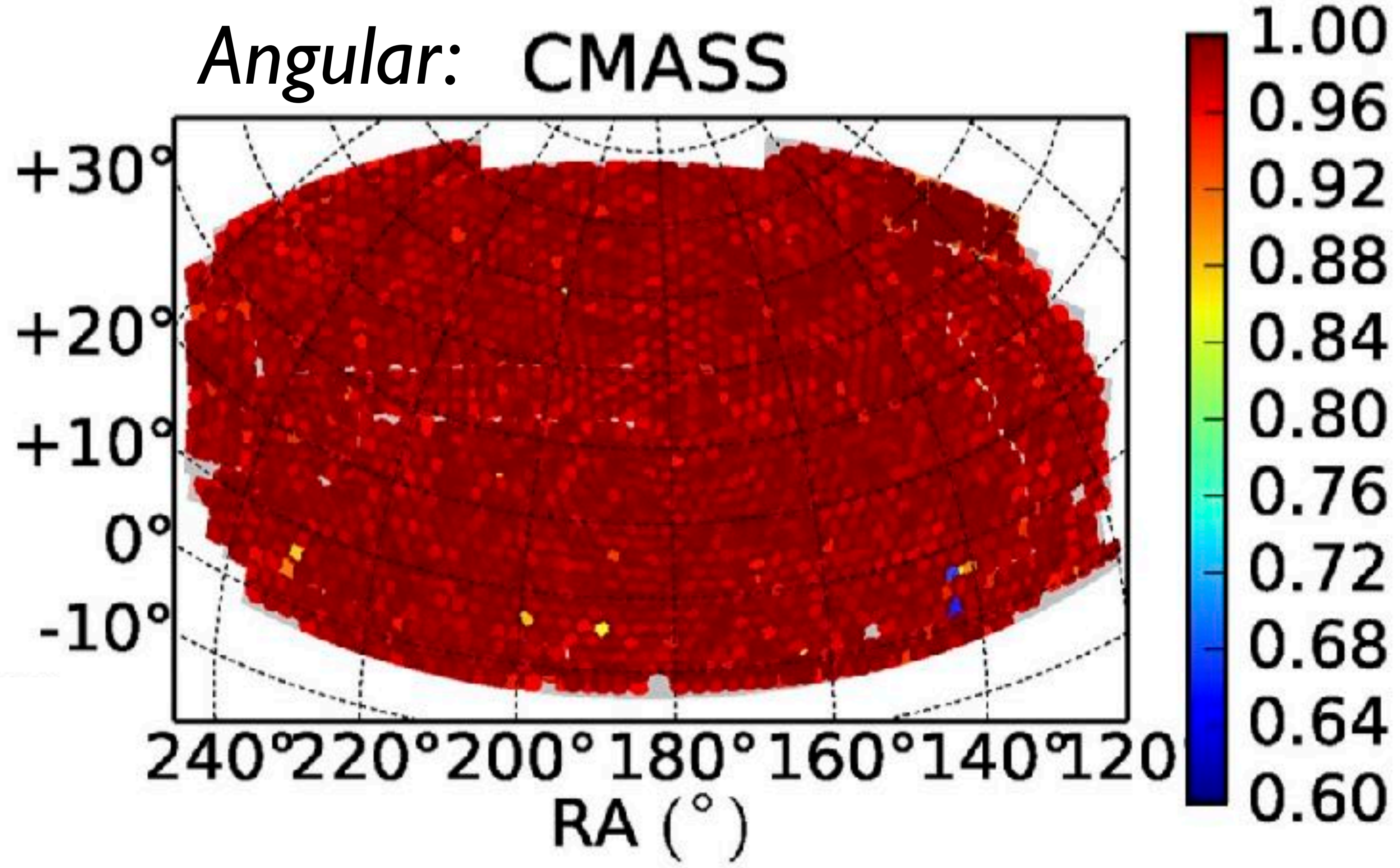
Challenge I:
Highly non-trivial survey window

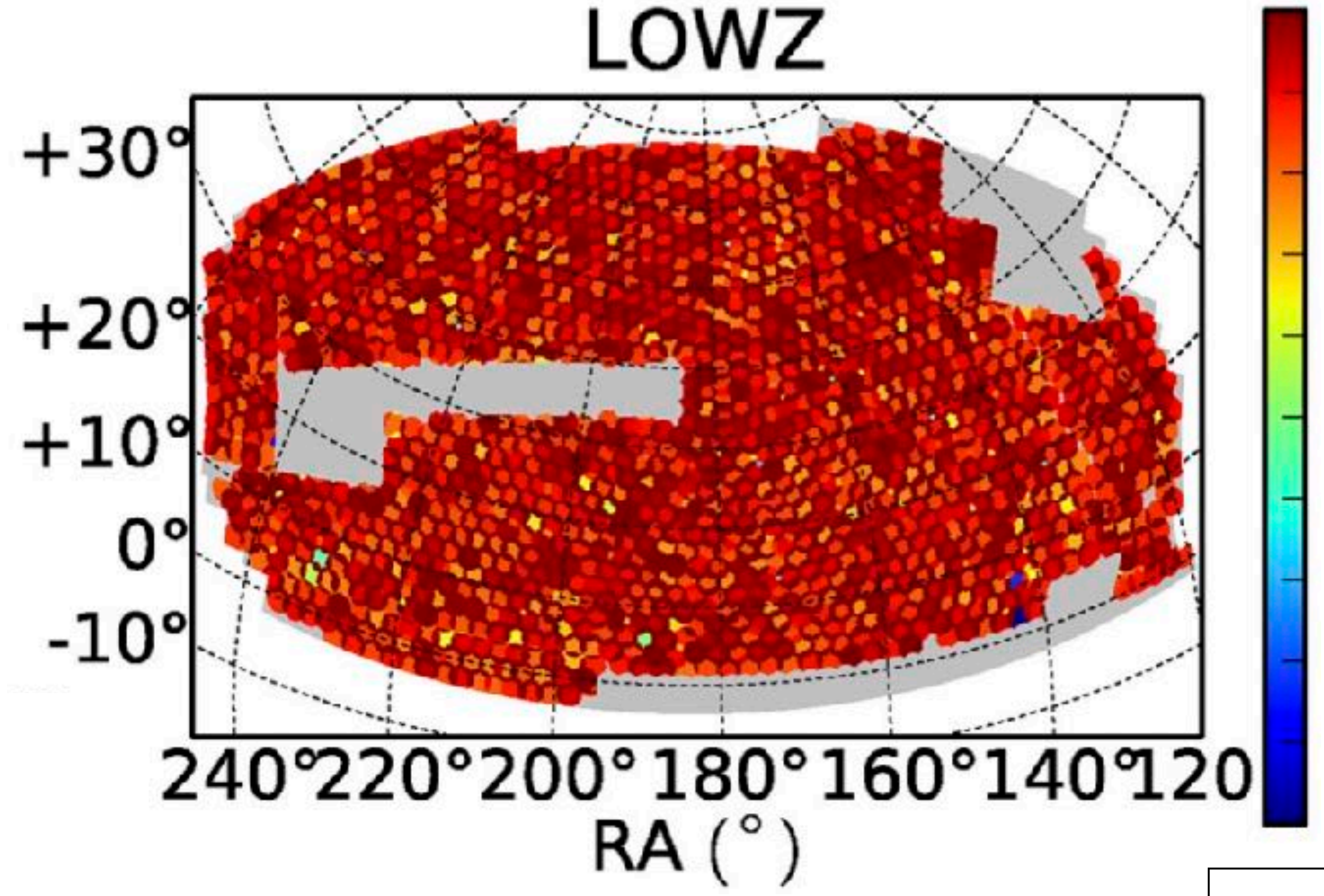
$$\delta_W(\mathbf{x}) \equiv W(\mathbf{x})\delta(\mathbf{x})$$

Radial:
survey selection function



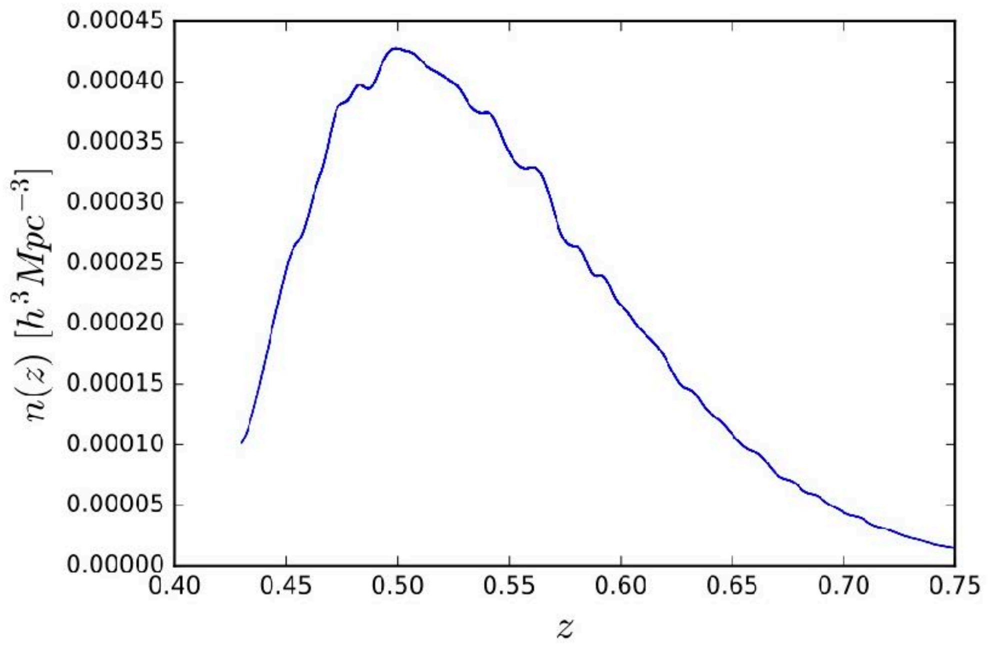
Angular:

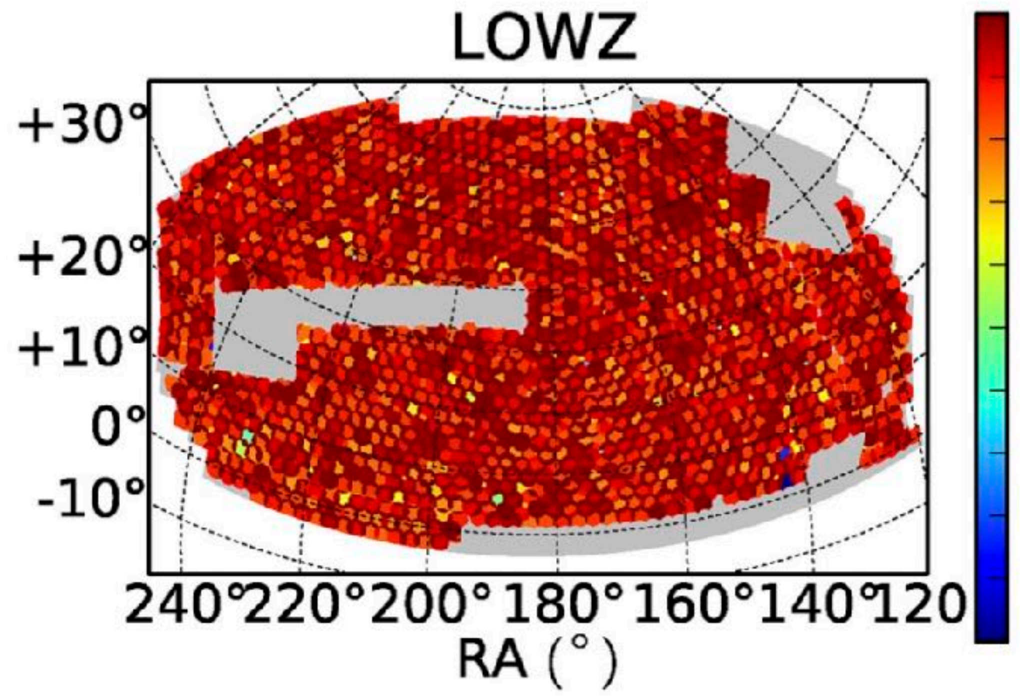




Reid et al. 2015

Survey window enters covariance





$$C(k_1, k_2) = \langle \hat{P}(k_1)\hat{P}(k_2)\rangle - \langle \hat{P}(k_1)\rangle\langle \hat{P}(k_2)\rangle$$

$$\begin{aligned}
\langle \hat{P}(k_1)\hat{P}(k_2)\rangle =& \frac{1}{V_2^2}\int_{\hat{\mathbf{k}}_1,\hat{\mathbf{k}}_2} \langle \delta_W(\mathbf{k}_1)\delta_W(-\mathbf{k}_1)\delta_W(\mathbf{k}_2)\delta_W(-\mathbf{k}_2)\rangle \\
=& \frac{1}{V^2}{}_2 \int_{\hat{\mathbf{k}}_1,\hat{\mathbf{k}}_2,\mathbf{p}_1,\mathbf{p}_1',\mathbf{p}_2,\mathbf{p}_2'} W(\mathbf{k}_1 - \mathbf{p}_1)W(-\mathbf{k}_1 - \mathbf{p}_1')W(\mathbf{k}_2 - \mathbf{p}_2)W(-\mathbf{k}_2 - \mathbf{p}_2') \\
& \times \langle \delta(\mathbf{p}_1)\delta(\mathbf{p}_1')\delta(\mathbf{p}_2)\delta(\mathbf{p}_2')\rangle
\end{aligned}$$

18 dimensional integral

Solution: separate clustering and window terms

Contains all dependence on cosmology and bias parameters

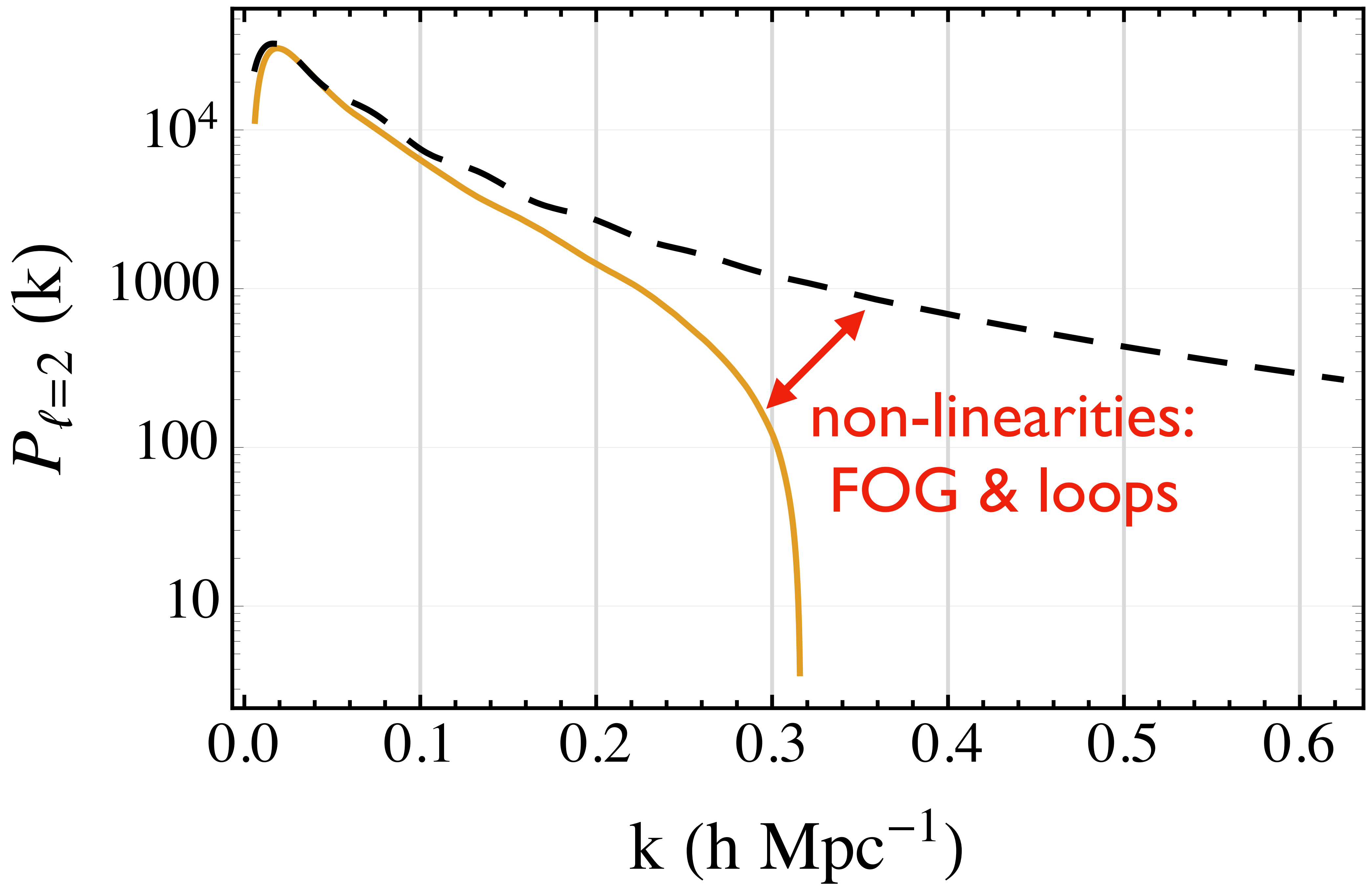
$$\mathbf{C}^{\mathrm{G}}_{\ell_1\ell_2}(k_1,k_2) \simeq \sum_{\ell_1',\ell_2'} \boxed{P_{\ell_1'}(k_2)P_{\ell_2'}(k_1)} \left\{ \frac{(2\ell_1+1)(2\ell_2+1)}{\mathrm{I}_{22}^2} \int_{\hat{\mathbf{k}}_1,\hat{\mathbf{k}}_2,\mathbf{x}_1,\mathbf{x}_2} W_{22}(\mathbf{x}_1)W_{22}(\mathbf{x}_2)\, e^{-i(\mathbf{x}_1-\mathbf{x}_2)\cdot(\mathbf{k}_1-\mathbf{k}_2)} \right.$$

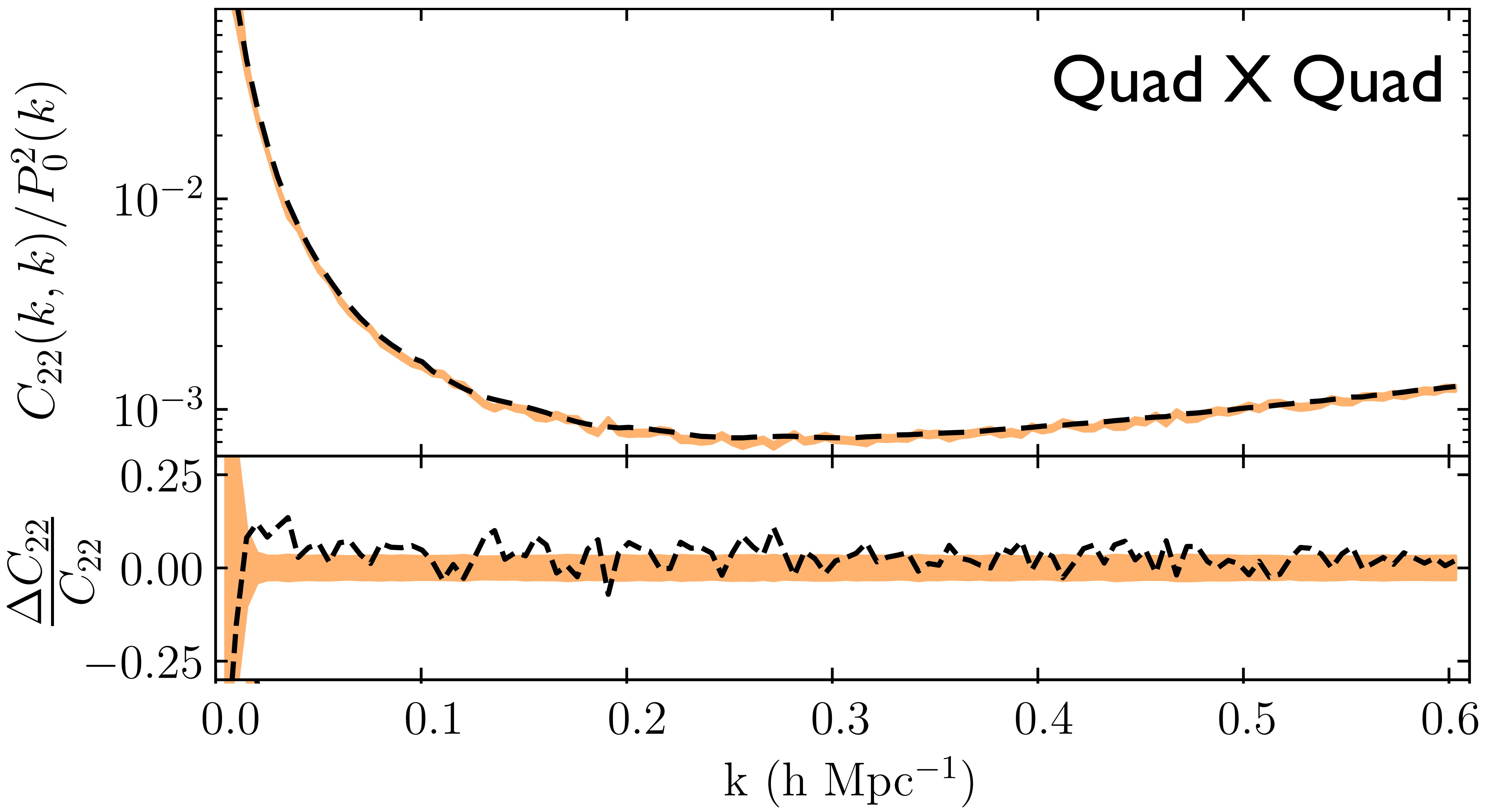
$$\left. \times \mathcal{L}_{\ell_1}(\hat{\mathbf{x}}_1\cdot\hat{\mathbf{k}}_1)\mathcal{L}_{\ell_1'}(\hat{\mathbf{x}}_1\cdot\hat{\mathbf{k}}_1)\mathcal{L}_{\ell_2'}(\hat{\mathbf{x}}_2\cdot\hat{\mathbf{k}}_2)\Big[\mathcal{L}_{\ell_2}(\hat{\mathbf{x}}_2\cdot\hat{\mathbf{k}}_2)+\mathcal{L}_{\ell_2}(\hat{\mathbf{x}}_1\cdot\hat{\mathbf{k}}_1)\Big] \right\}$$

{ Computed from survey random catalog }

See also: Li et al. 19

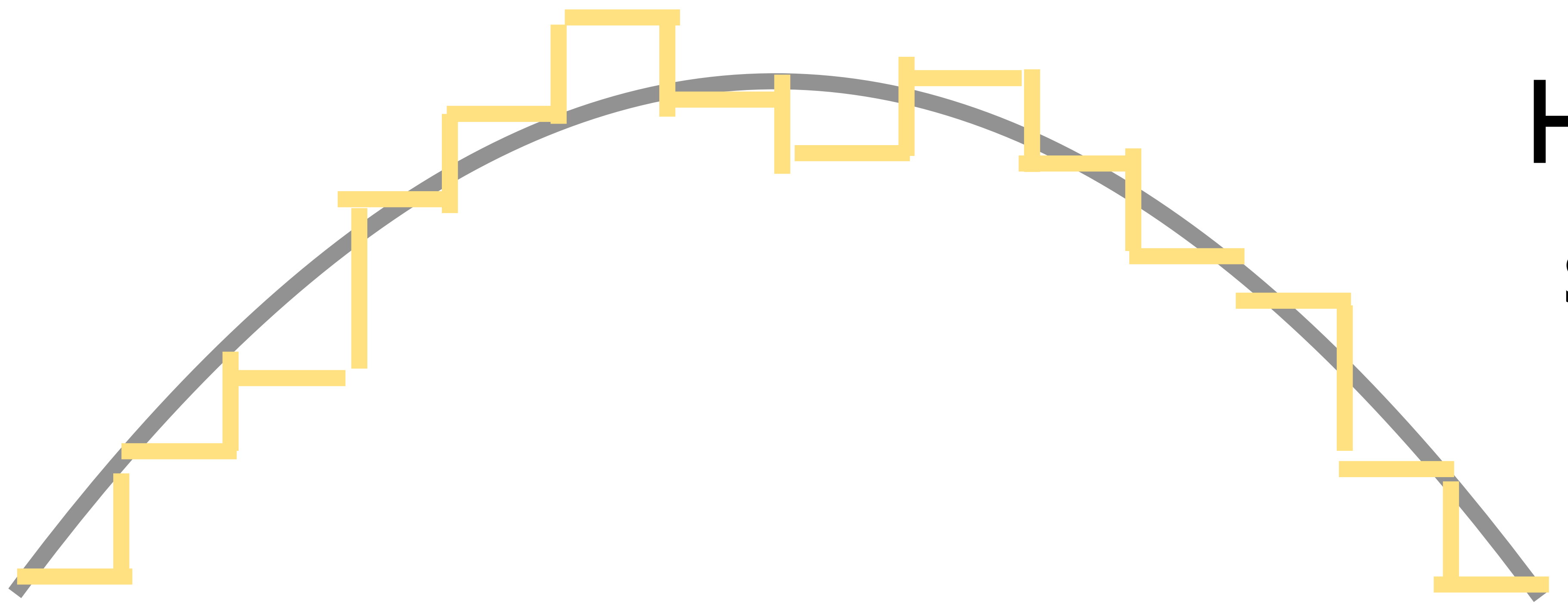
Challenge II:
Analytic modeling in the non-linear regime



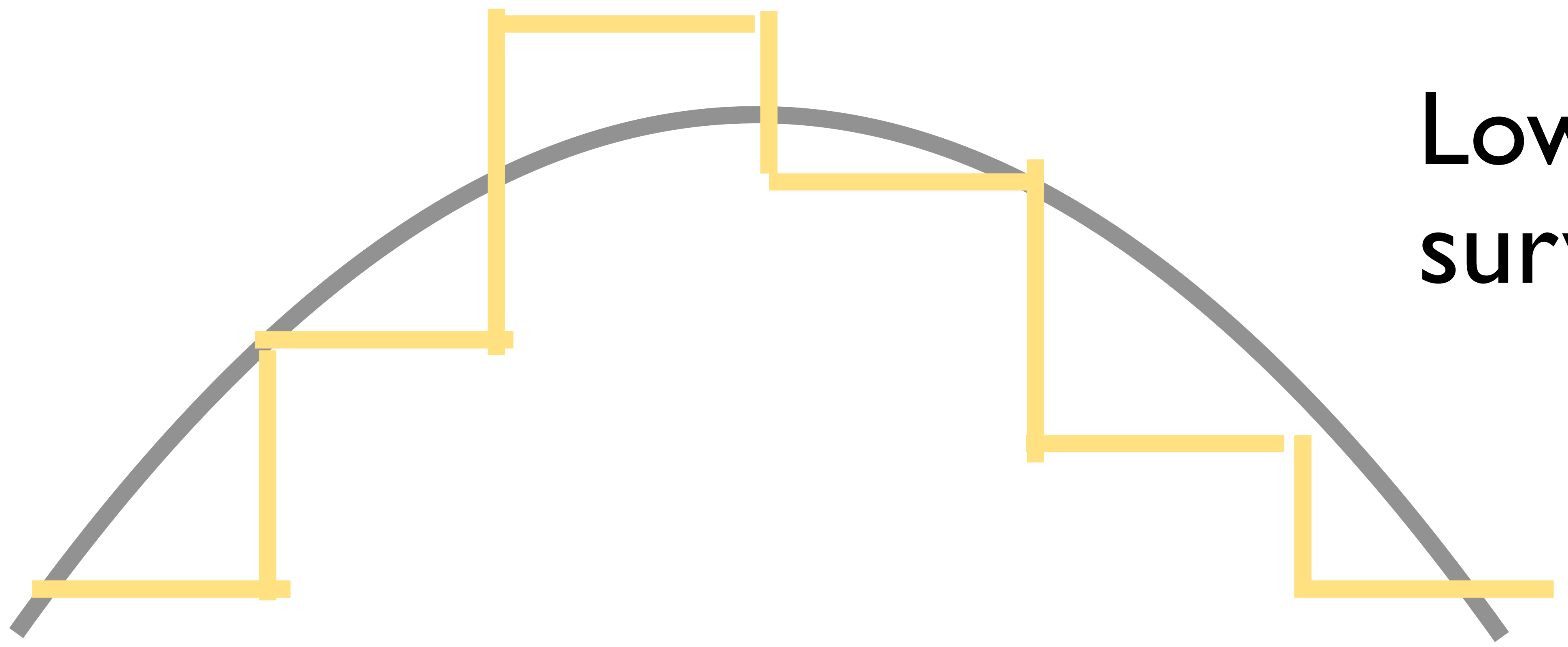


Analytic covariance works
very well at high-k.
WHY!?

Why does analytic work in the non-linear regime?



High $\bar{n}$ survey



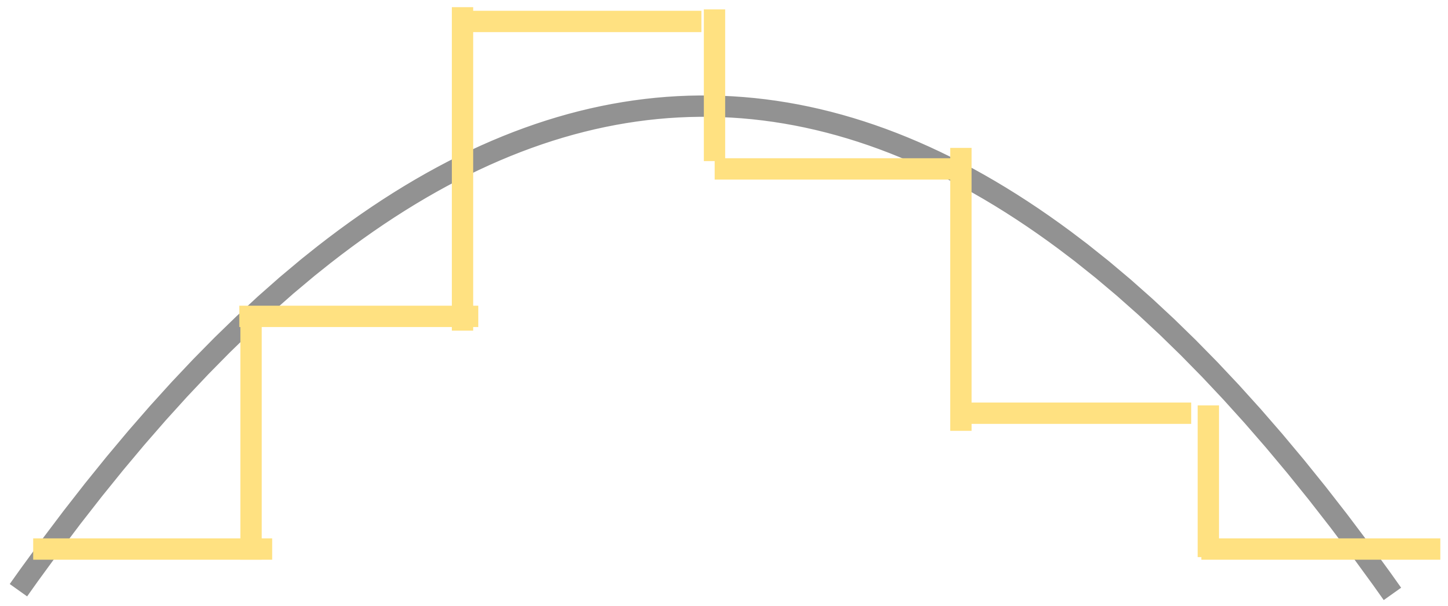
Low $\bar{n}$ survey

- Poisson fluctuations dominate the error bars at small scales:

✓ Can be well modeled analytically

Why does analytic work in the non-linear regime?

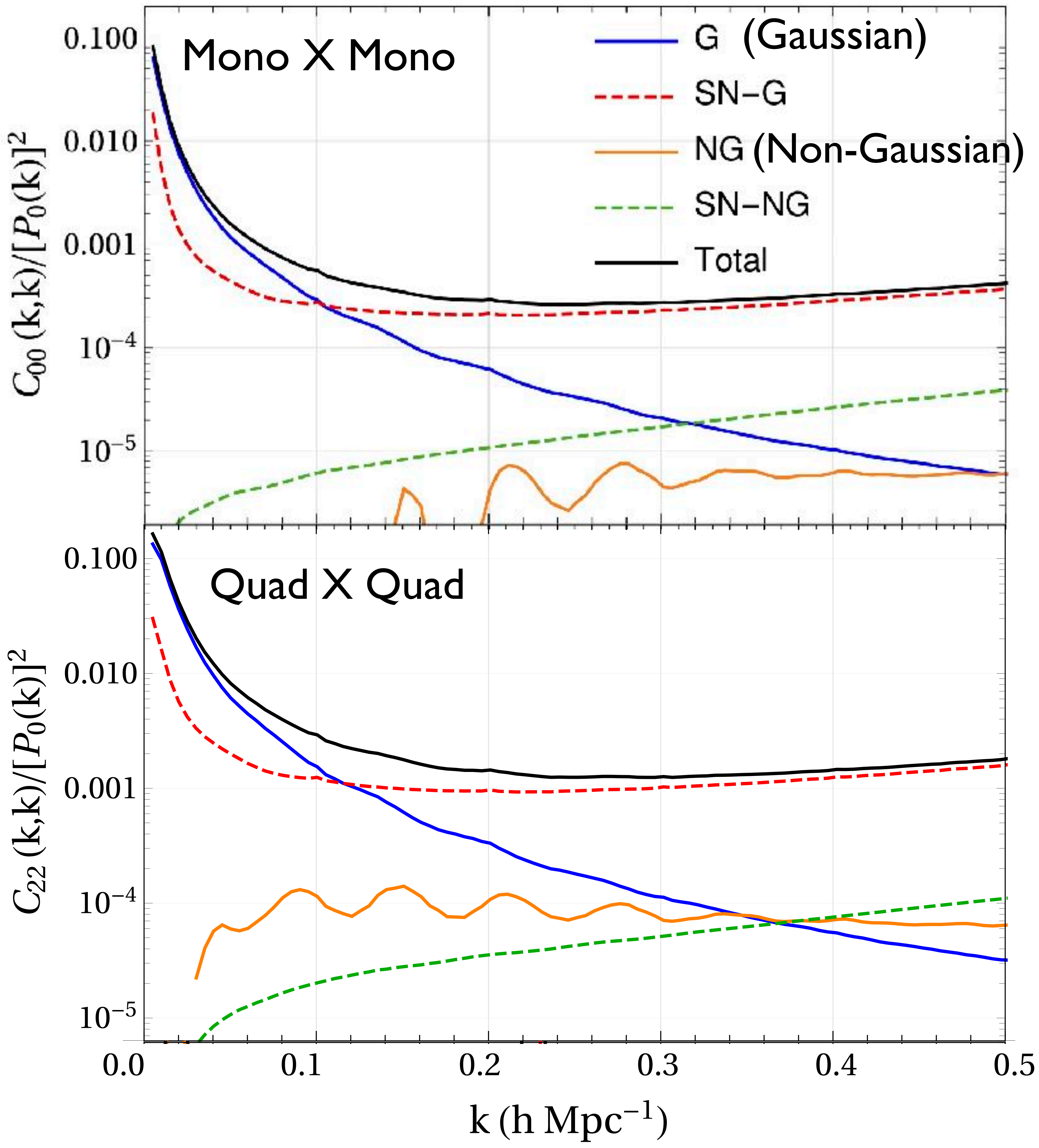
Shot noise (dashed) dominates at high-k



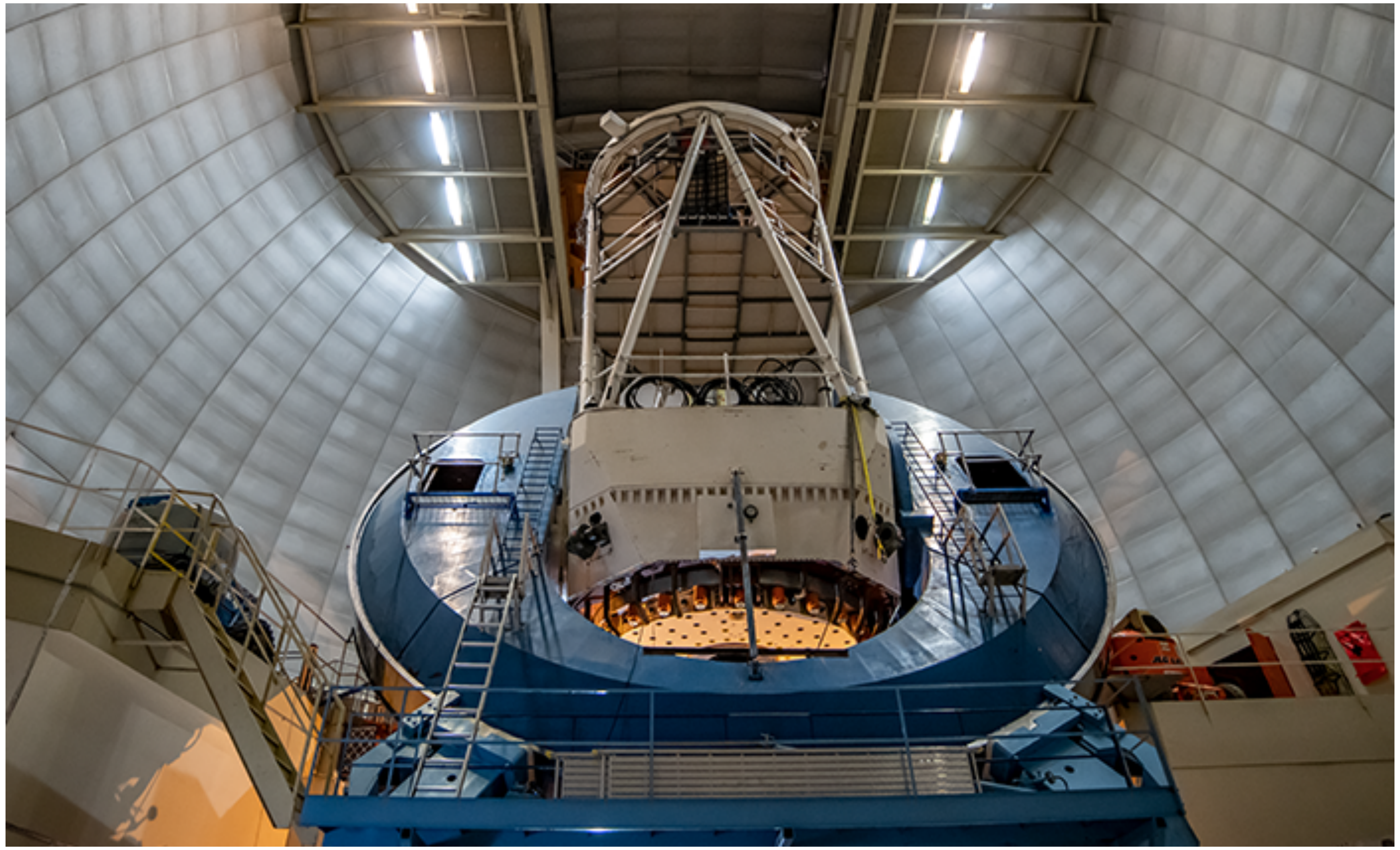
$$\mathbf{C}(k_1,k_2) = \langle \delta(k_1)\delta(-k_1)\delta(k_2)\delta(-k_2)\rangle - \langle \delta(k_1)\delta(-k_1)\rangle\langle \delta(k_2)\delta(-k_2)\rangle$$

$$\mathbf{C}^{\mathrm{G}}(k_1,k_2) \simeq 2\,\langle \delta(k_1)\delta(-k_2)\rangle\,\langle \delta(k_2)\delta(-k_1)\rangle$$

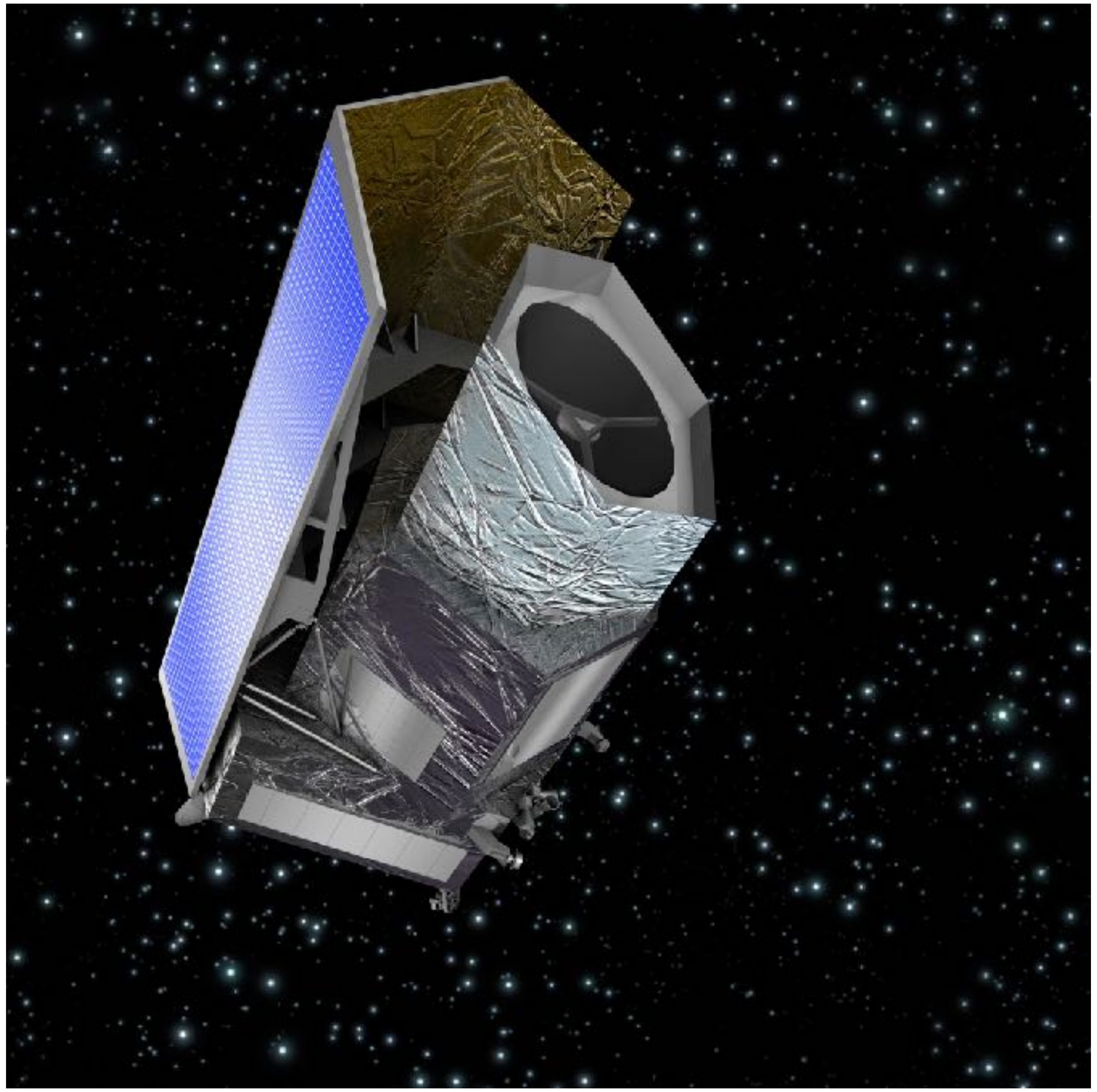
$$\mathbf{C}^{\mathrm{NG}}(k_1,k_2) = \langle \delta(k_1)\delta(-k_2)\delta(k_2)\delta(-k_1)\rangle_c$$



Will analytic cov. work at non-linear scales for upcoming surveys?



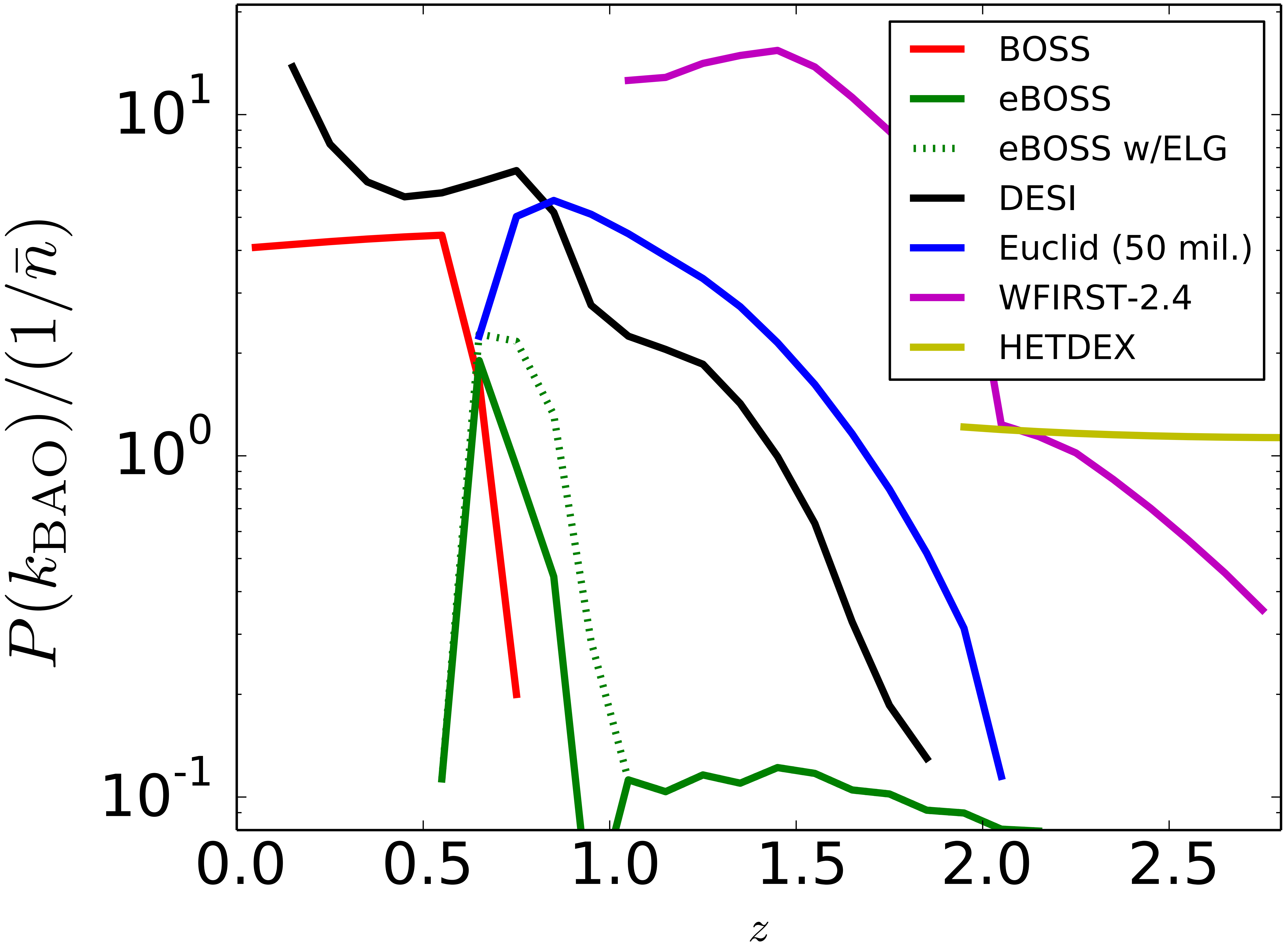
DESI



Euclid

Yes, should work at non-linear scales for upcoming surveys

- Shot noise level of upcoming surveys is comparable to BOSS



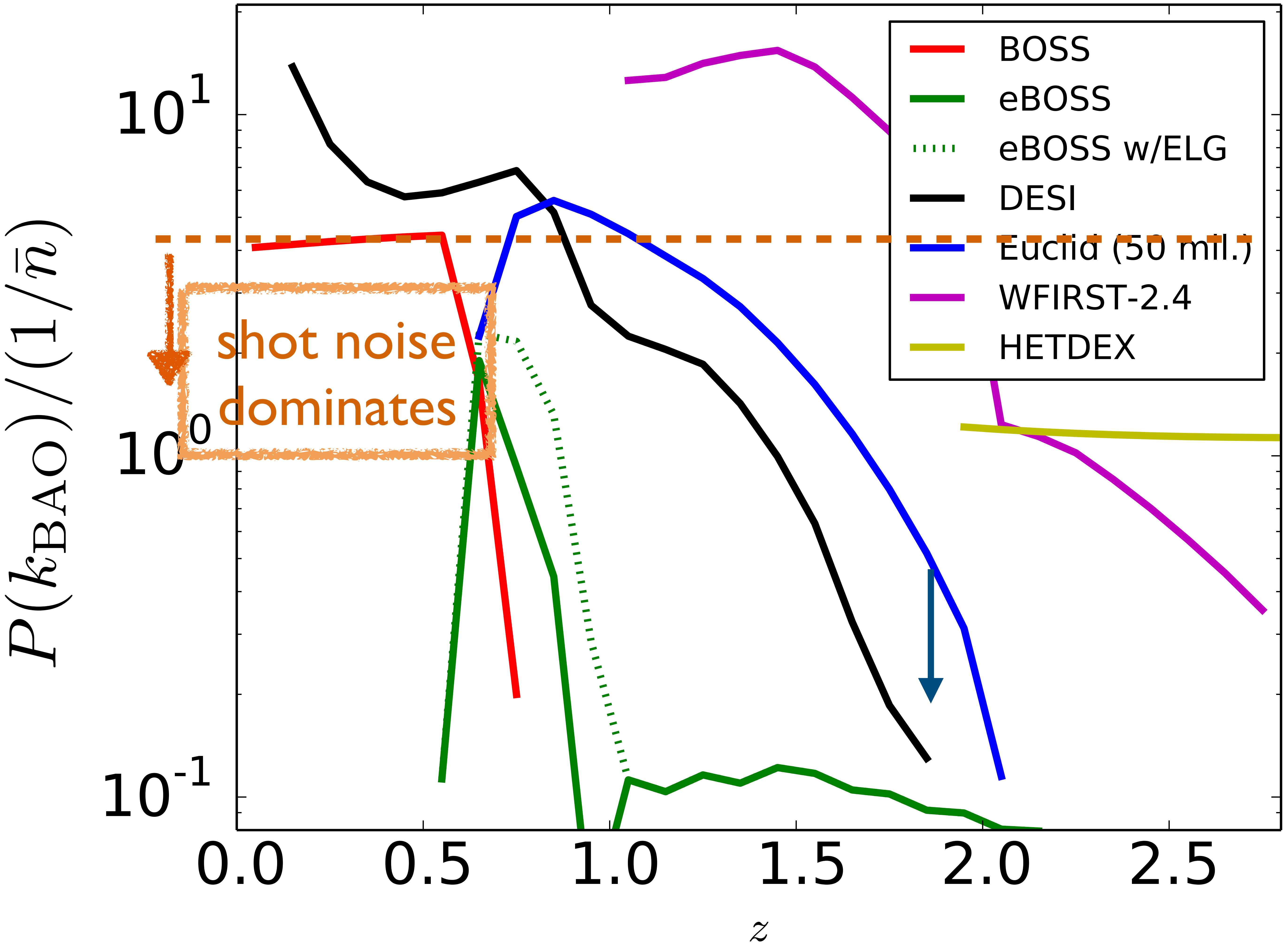
Font-Ribera et al. 2014

Yes, should work at non-linear scales for upcoming surveys

- Shot noise level of upcoming surveys is comparable to BOSS

↓

✓ Shot noise will dominate covariance for upcoming surveys



Font-Ribera et al. 2014

Analytic covariance is crucial for going beyond a 2-point analysis

✓ Number of k-bins in power spectrum ~100

◉ Number of triangles in bispectrum (3-pt) ~6000
- Bottleneck for BOSS (Gil-Marin et al 17 could only use ~800 triangles)

- Number of mock simulations: $\mathcal{O}(1000)$
- For low sampling noise:

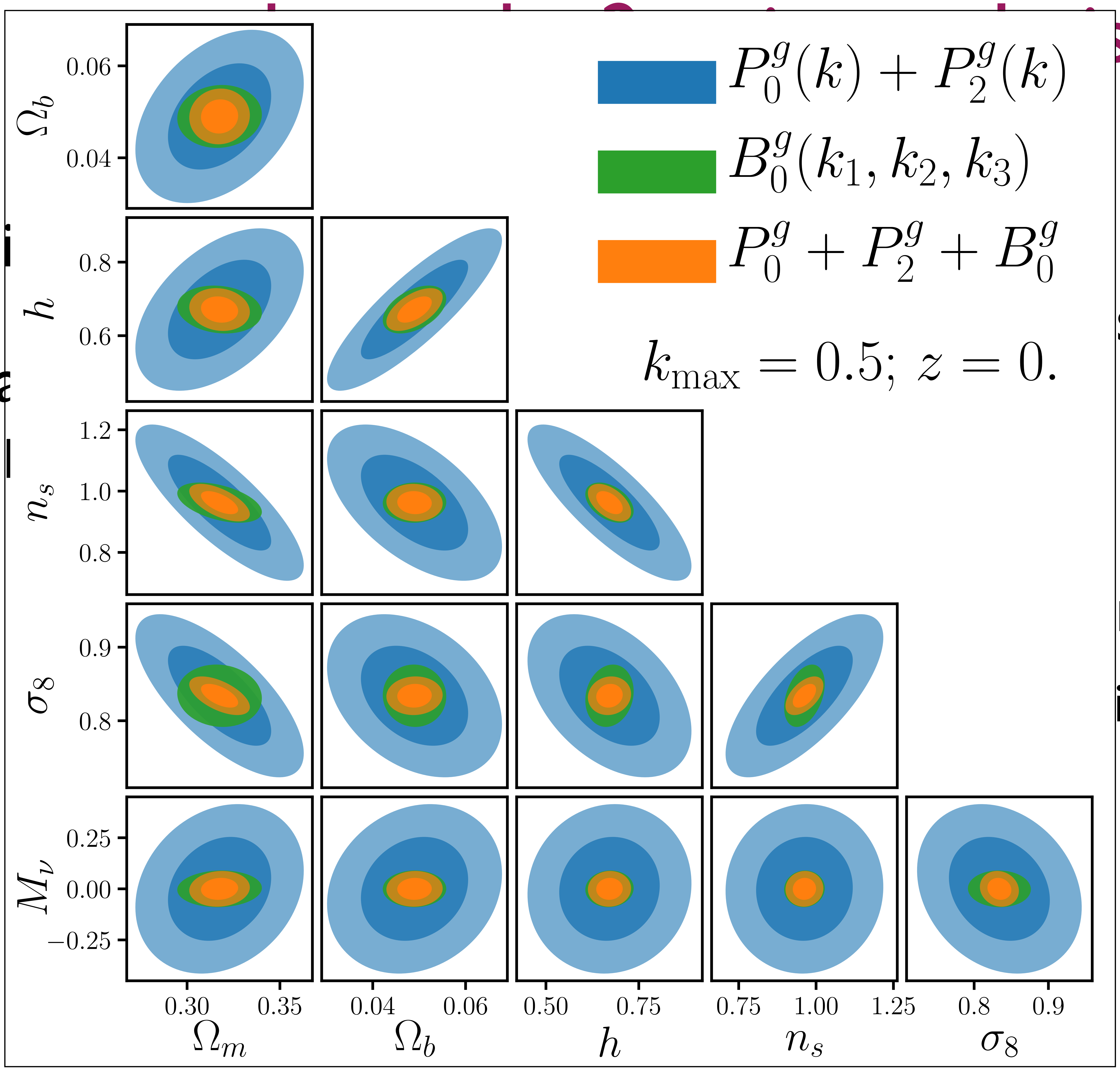
size of data vector $\ll$ no. of mocks

Analytic covariance is crucial for going

✓ Number of k-bi

◉ Number of tria

- Bottleneck for l
  (Gil-Marin et al



Number of mock simulations:
$\mathcal{O}(1000)$

For low sampling noise:

ize of data vector $\ll$ no. of mocks

C. Hahn et al. 2020

Analytic covariance is crucial for going beyond a 2-point analysis

✓ Number of k-bins in power spectrum ~100

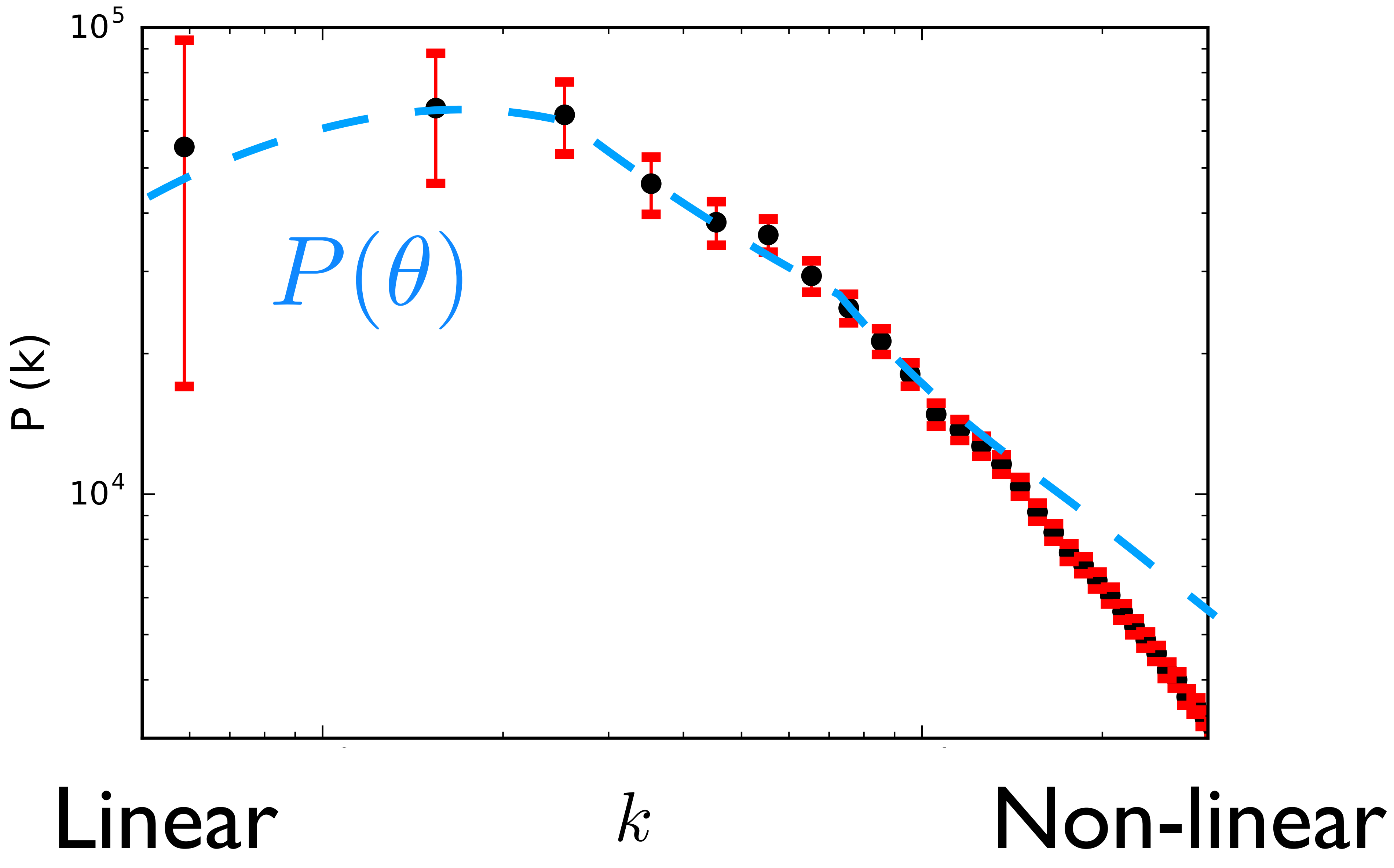
◉ Number of triangles in bispectrum (3-pt) ~6000
- Bottleneck for BOSS
  (Gil-Marin et al 17 could only use ~800 triangles)

➡ Also important for other areas with high-dimensionality of the covariance matrix:
for e.g., 3x2pt analysis in photometric surveys
or combining cluster counts with correlation fns

- Number of mock simulations: $\mathcal{O}(1000)$
- For low sampling noise:

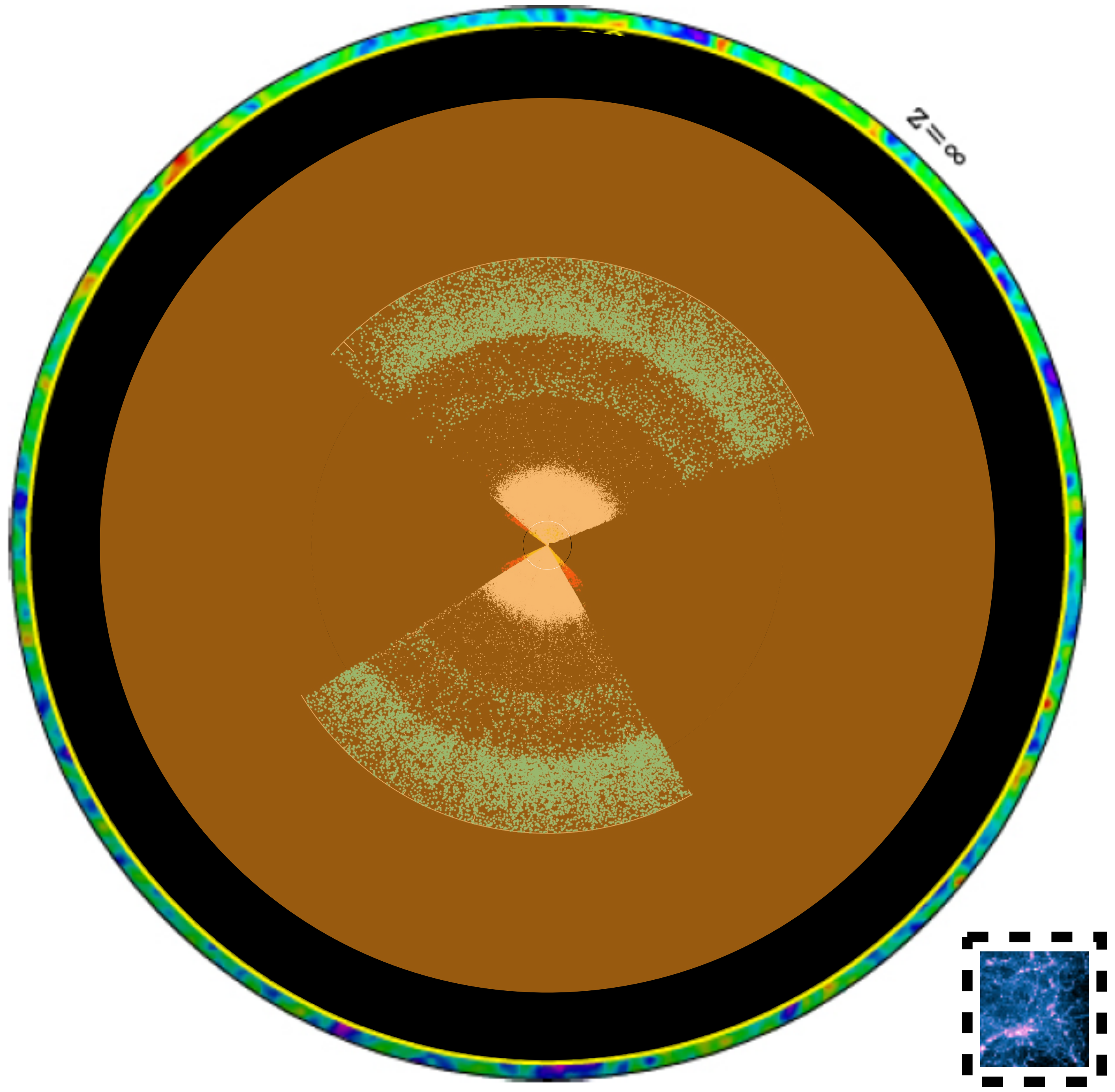
size of data vector $\ll$ no. of mocks

Part II
Machine learning for emulating hydrodynamic simulations



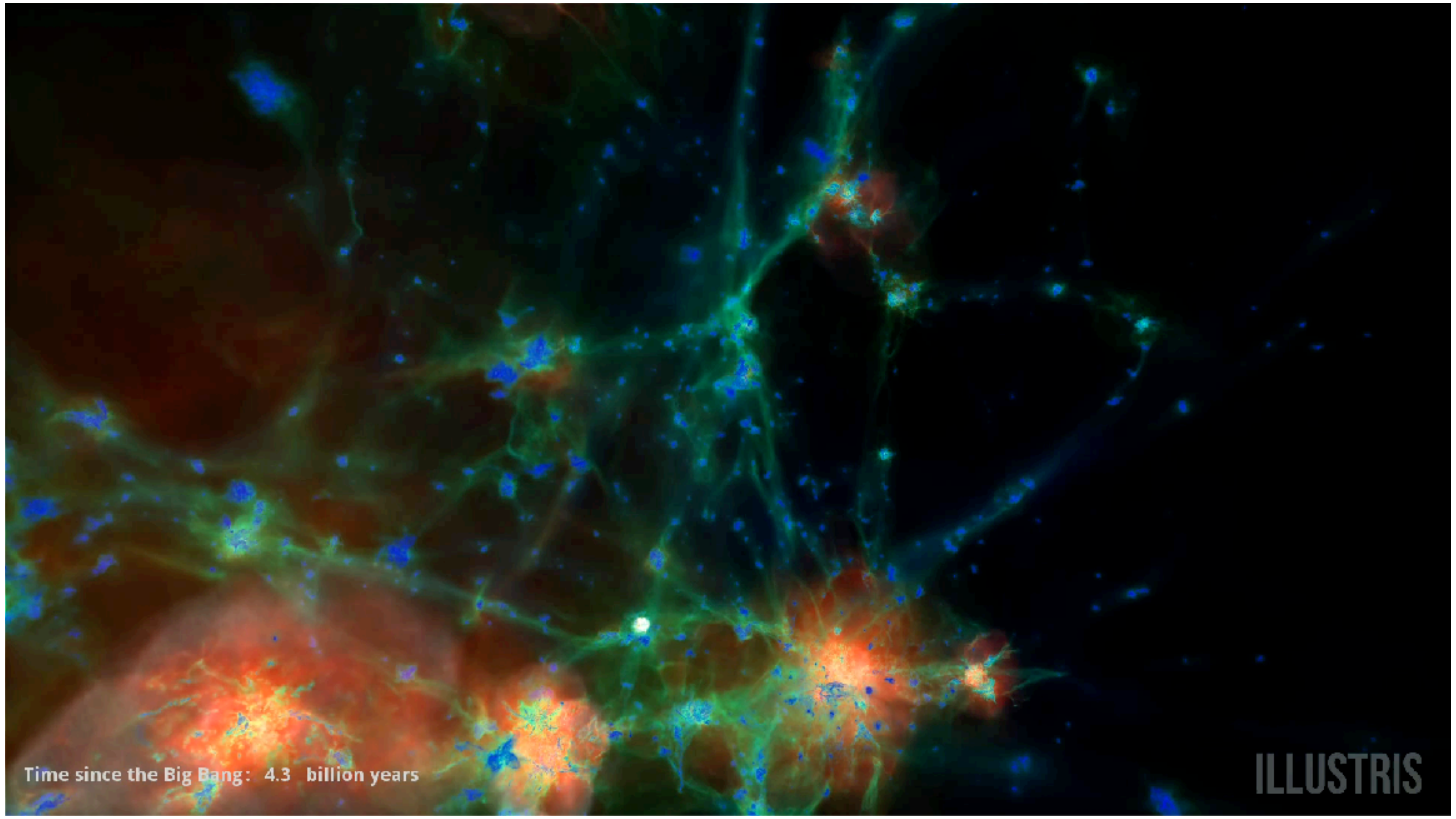
DW, Paco Villaescusa-Navarro, Shirley Ho & Laurence Perrault-Levasseur
(aXiv:2007.10340 & aXiv:2012.00111)

Emulation of hydro sims for future surveys

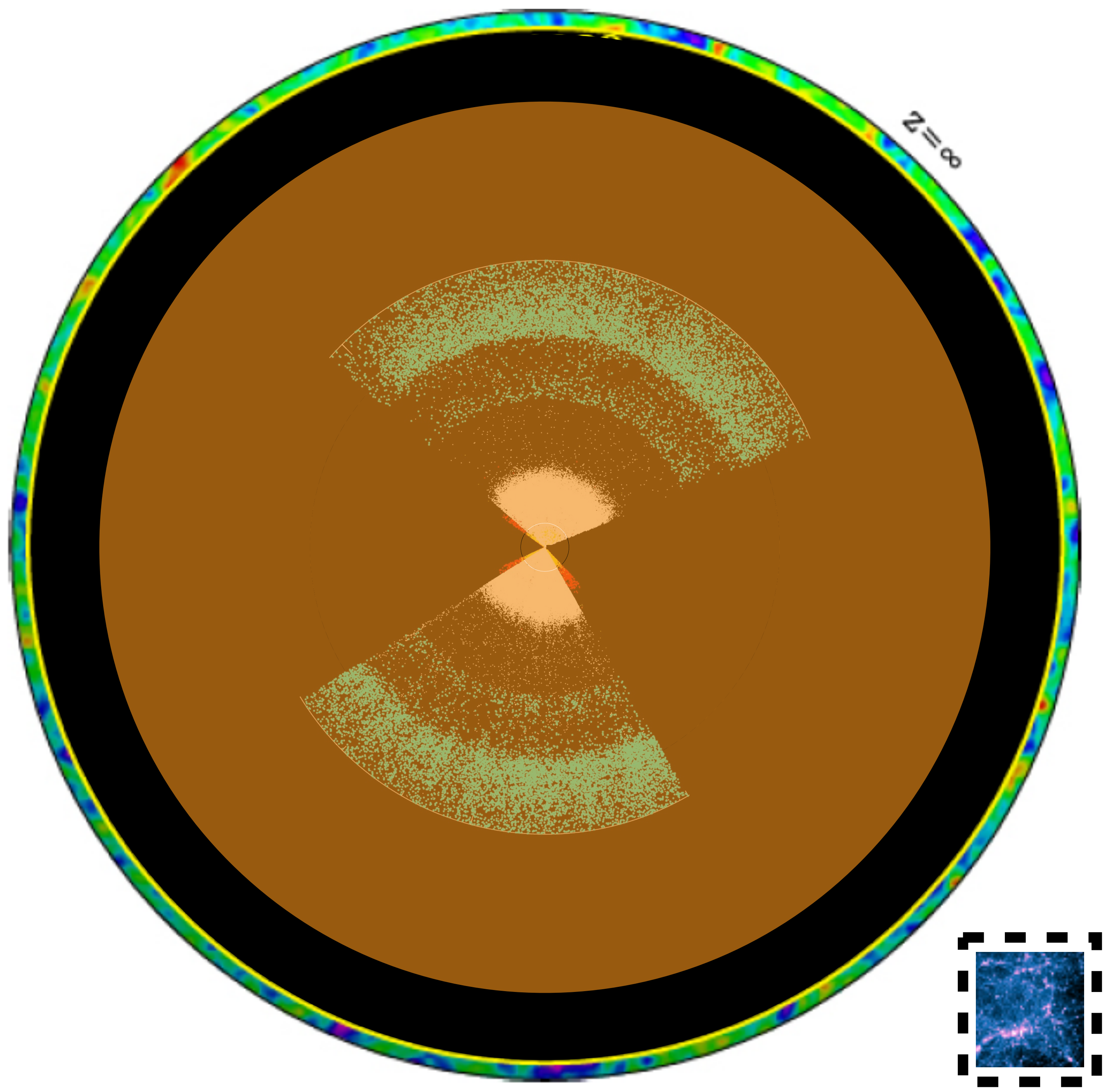


- Volume of upcoming surveys like DESI: ~$\mathcal{O}$ (10-100 Gpc^3)

- Hydro sims are expensive: ~10 million CPU hours for (0.001 Gpc^3)

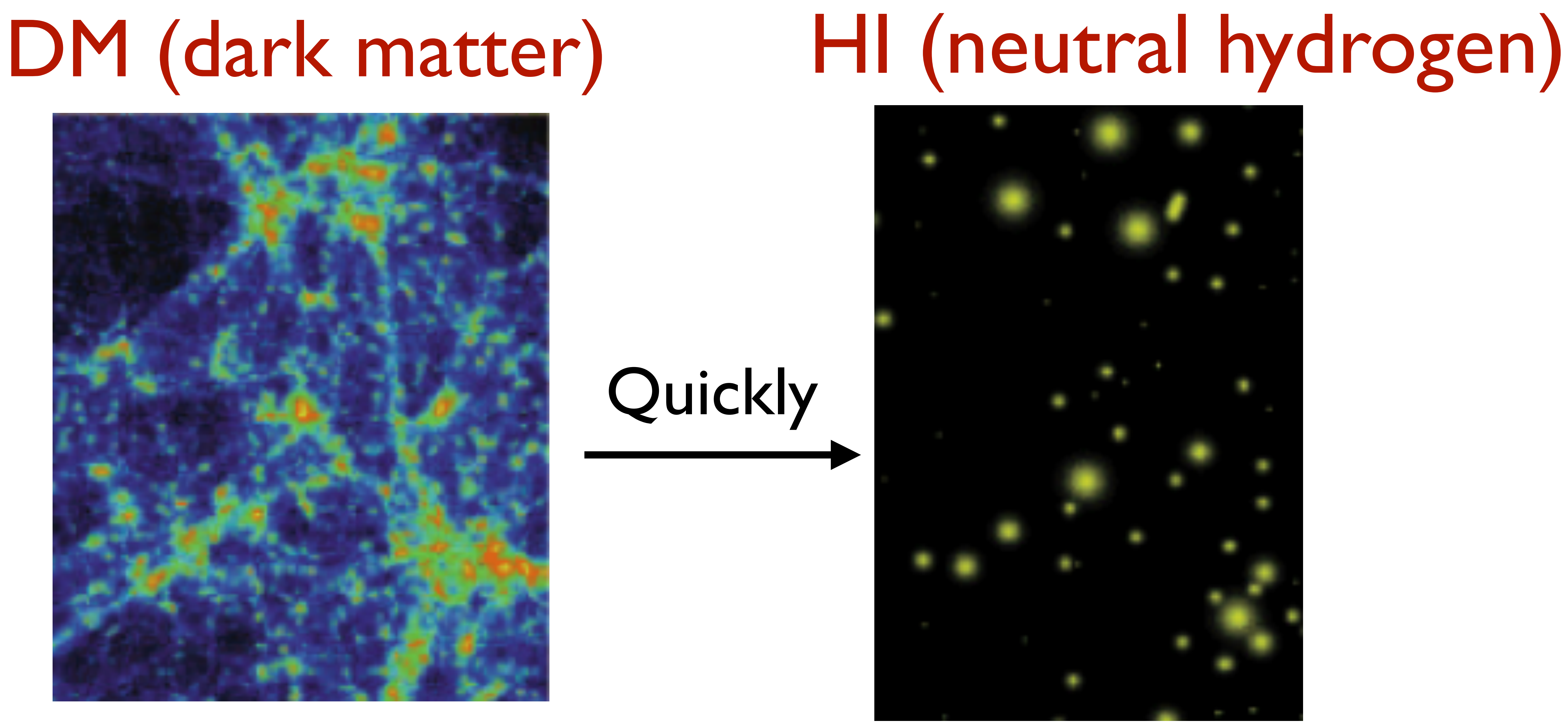


Emulation of hydro sims for future surveys



- Volume of upcoming surveys like DESI: ~$\mathcal{O}$ (10-100 Gpc^3)

- Hydro sims are expensive: ~10 million CPU hours for (0.001 Gpc^3)

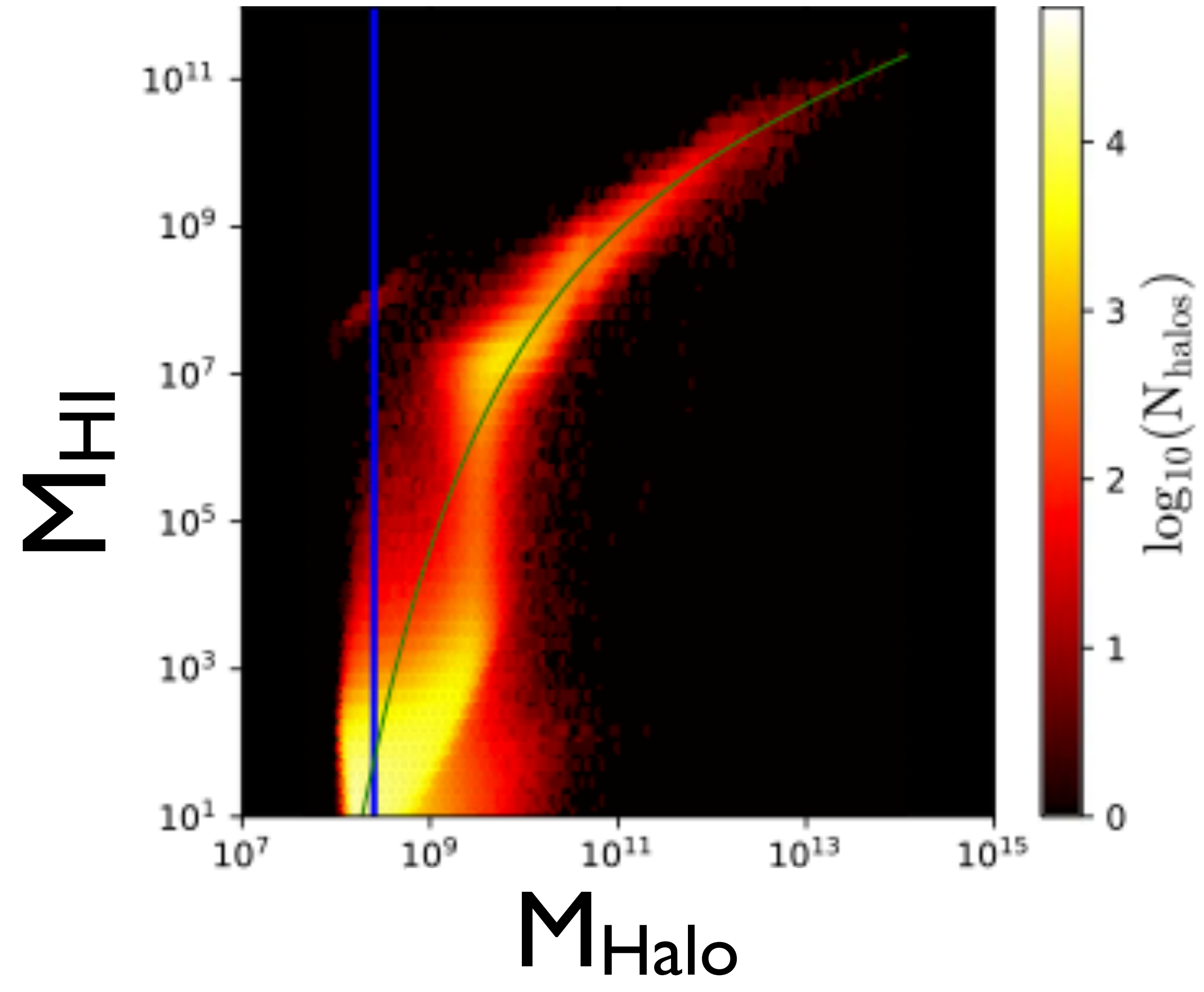


HOD: (Halo Occupation Distribution)

- Identify DM halos
- Fill HI using:

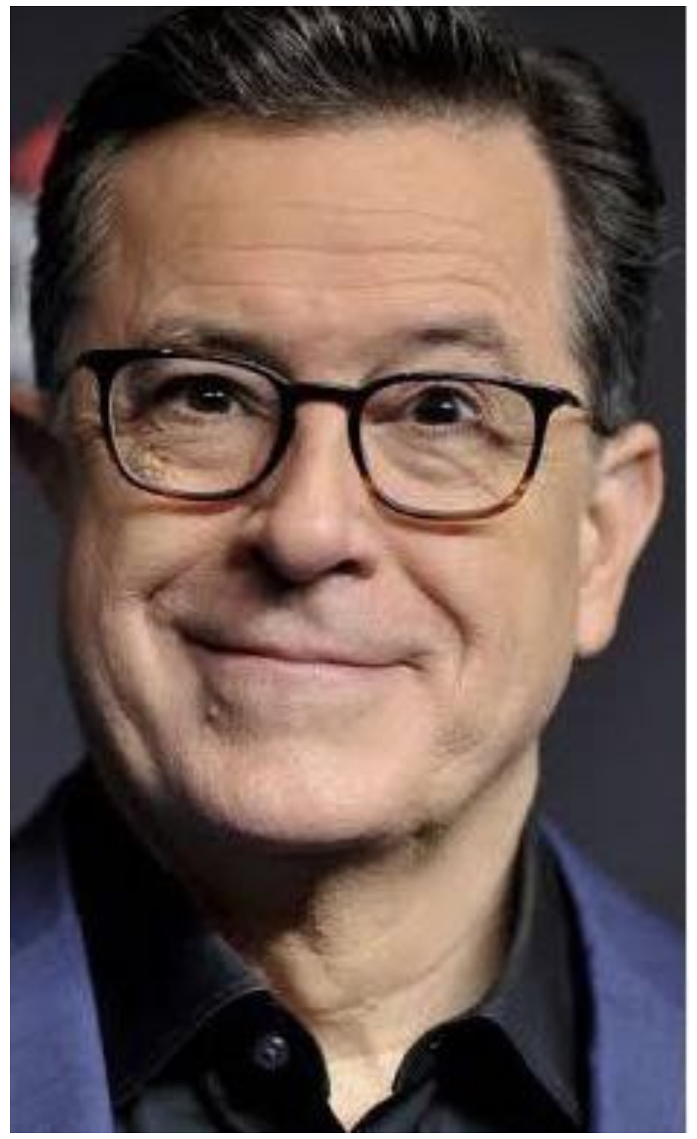
$$M_{HI} = f\,(\,M_{halo}\,)$$

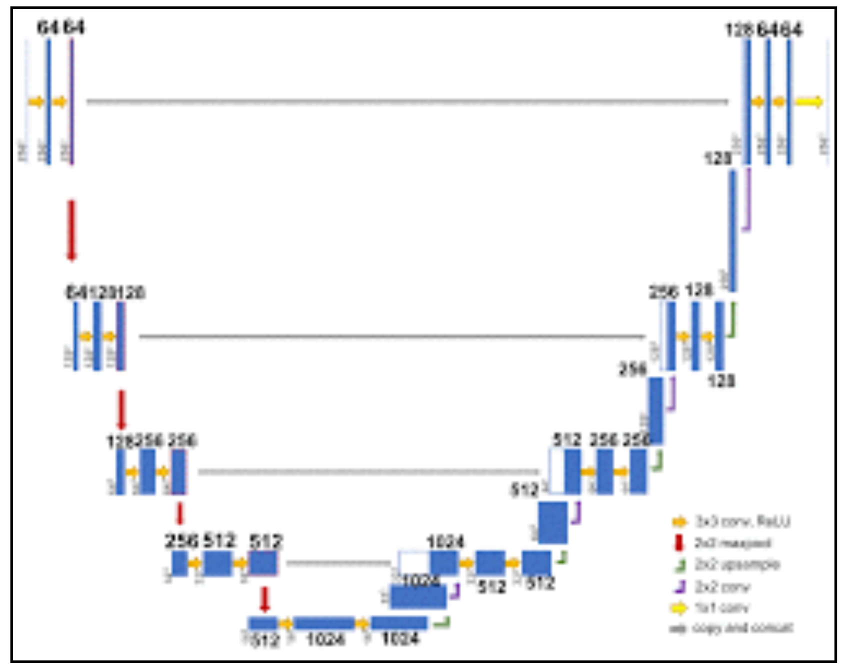
- assembly history, environmental info. neglected



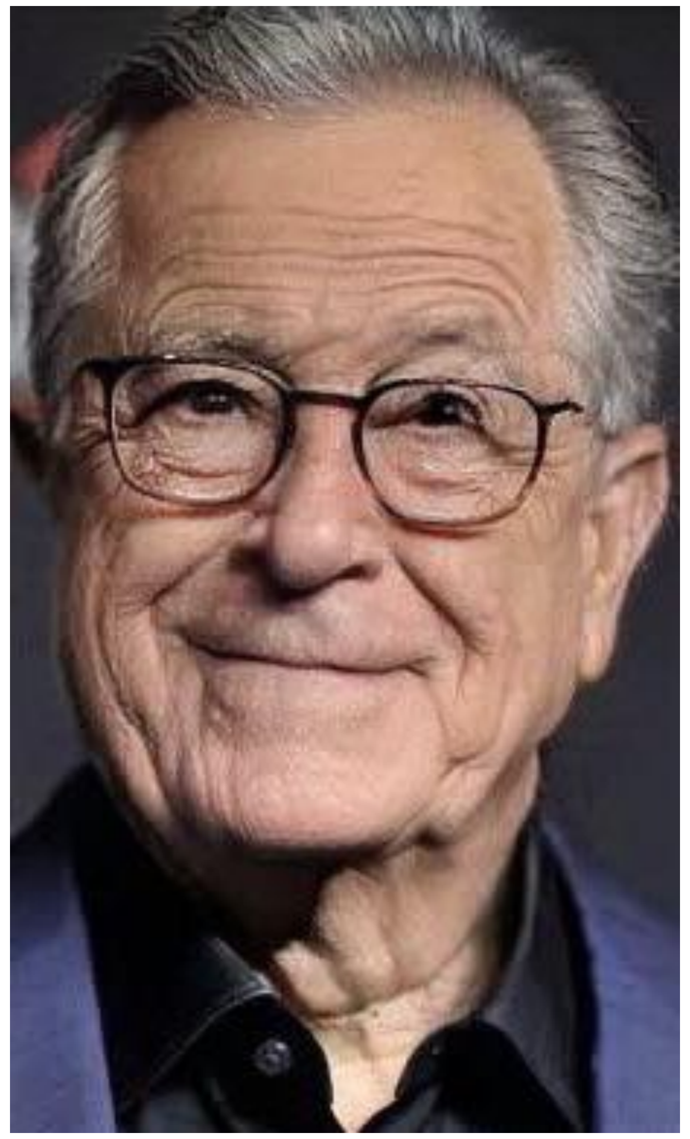
Neural networks: universal approximators

z_1



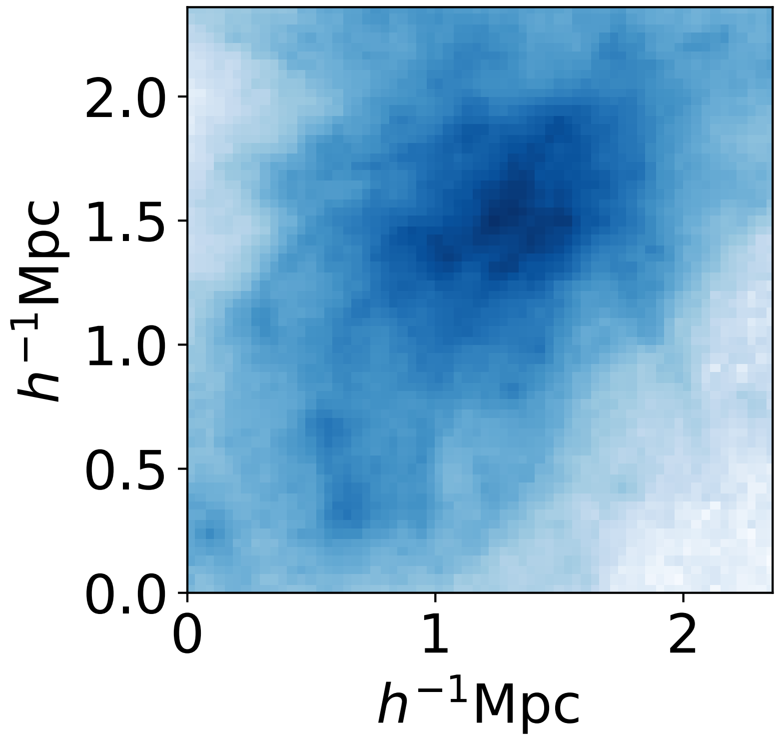


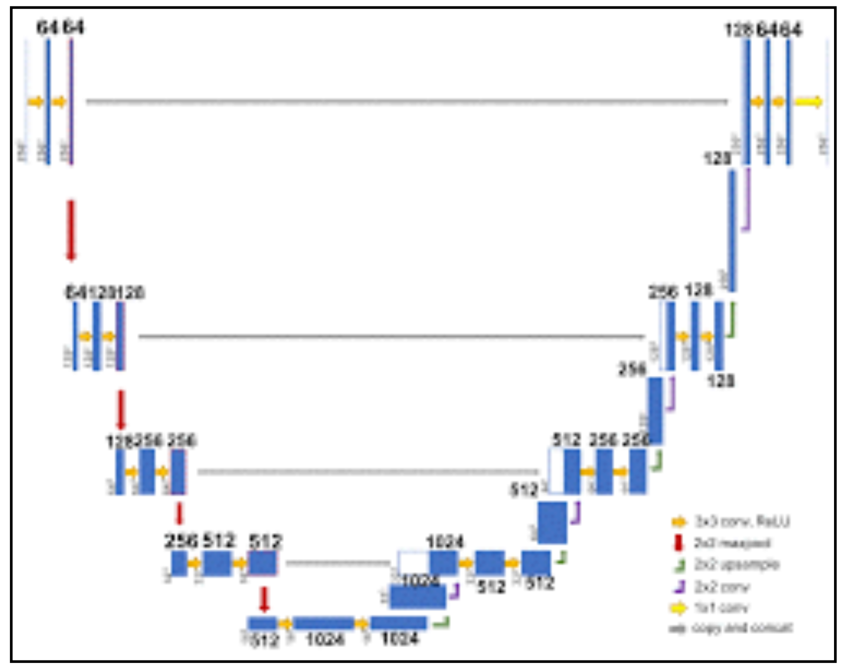
z_2



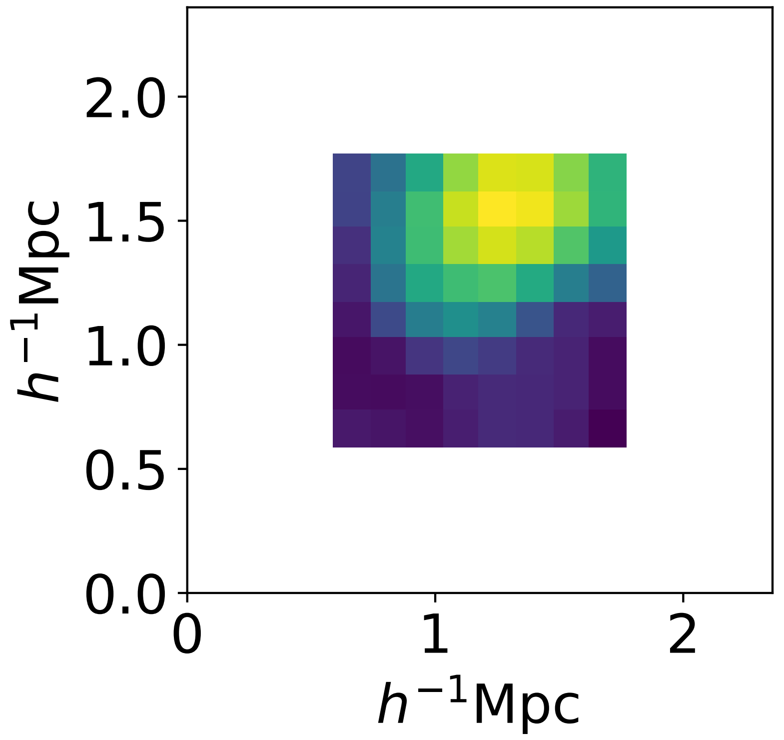
(faceapp)

DM





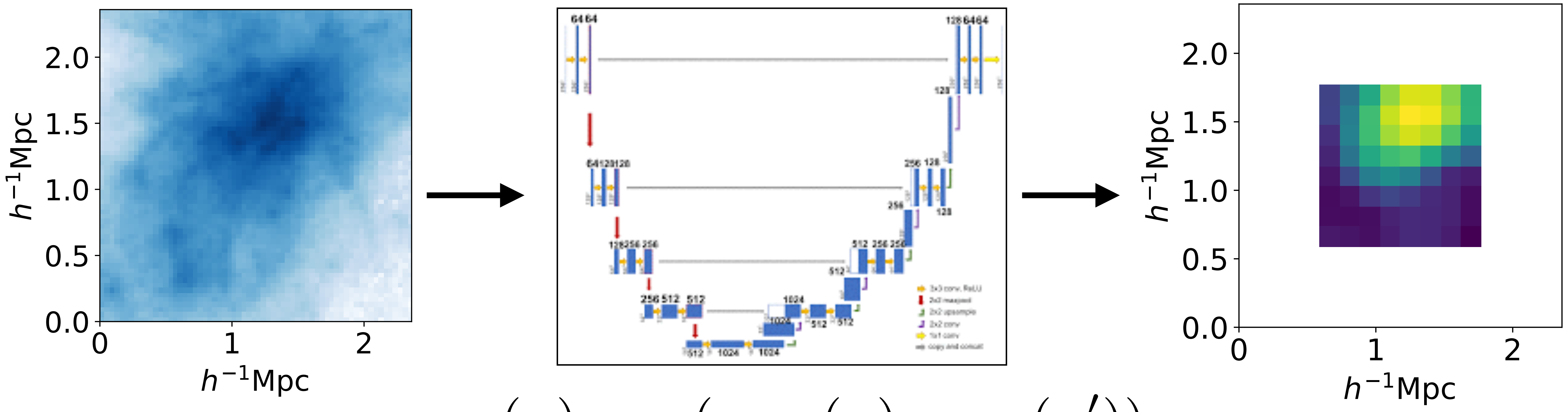
HI



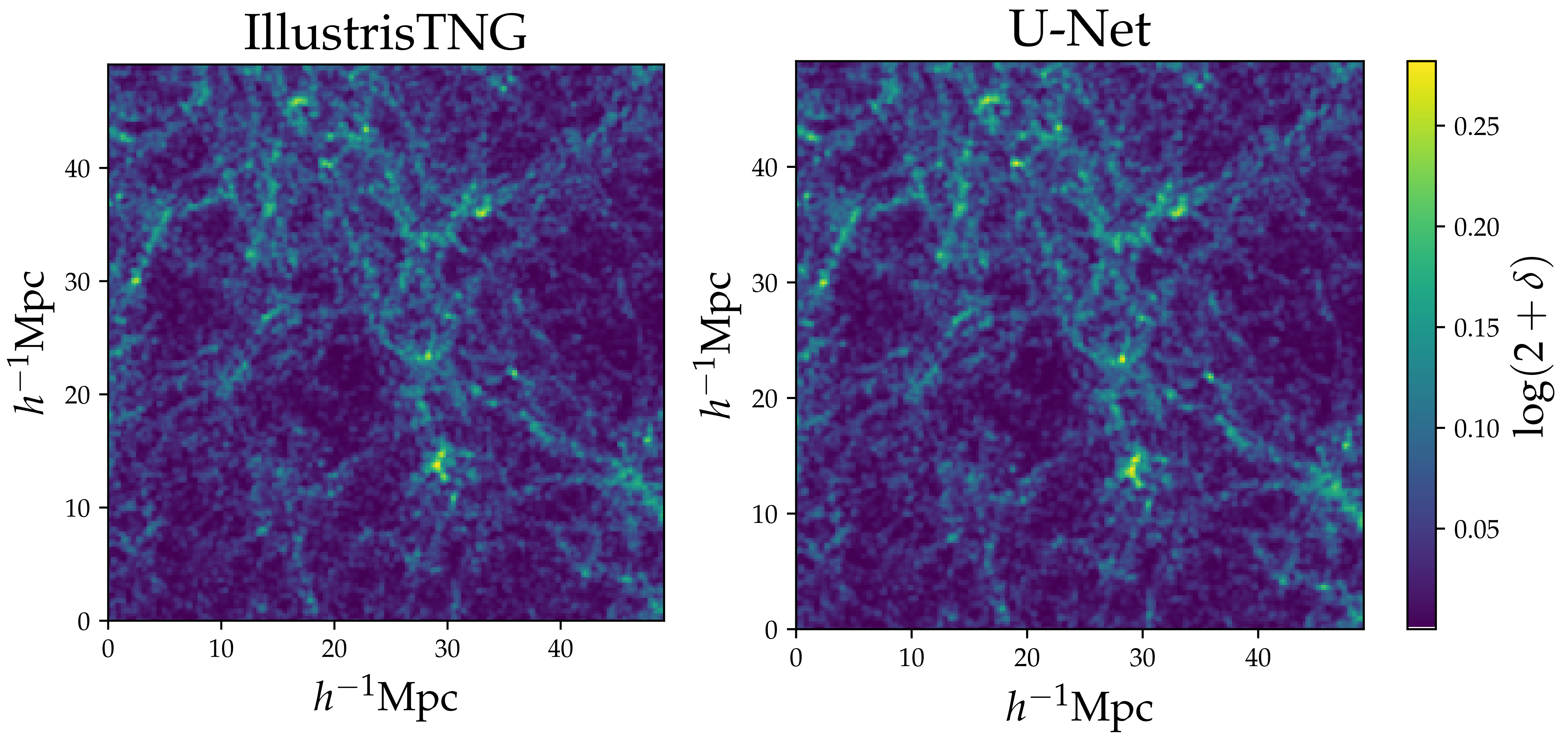
$$\rho_{\mathrm{HI}}(\mathbf{x}) = g\left(\rho_{\mathrm{DM}}(\mathbf{x}), \rho_{\mathrm{DM}}(\mathbf{x}')\right)$$

Neural networks as emulators

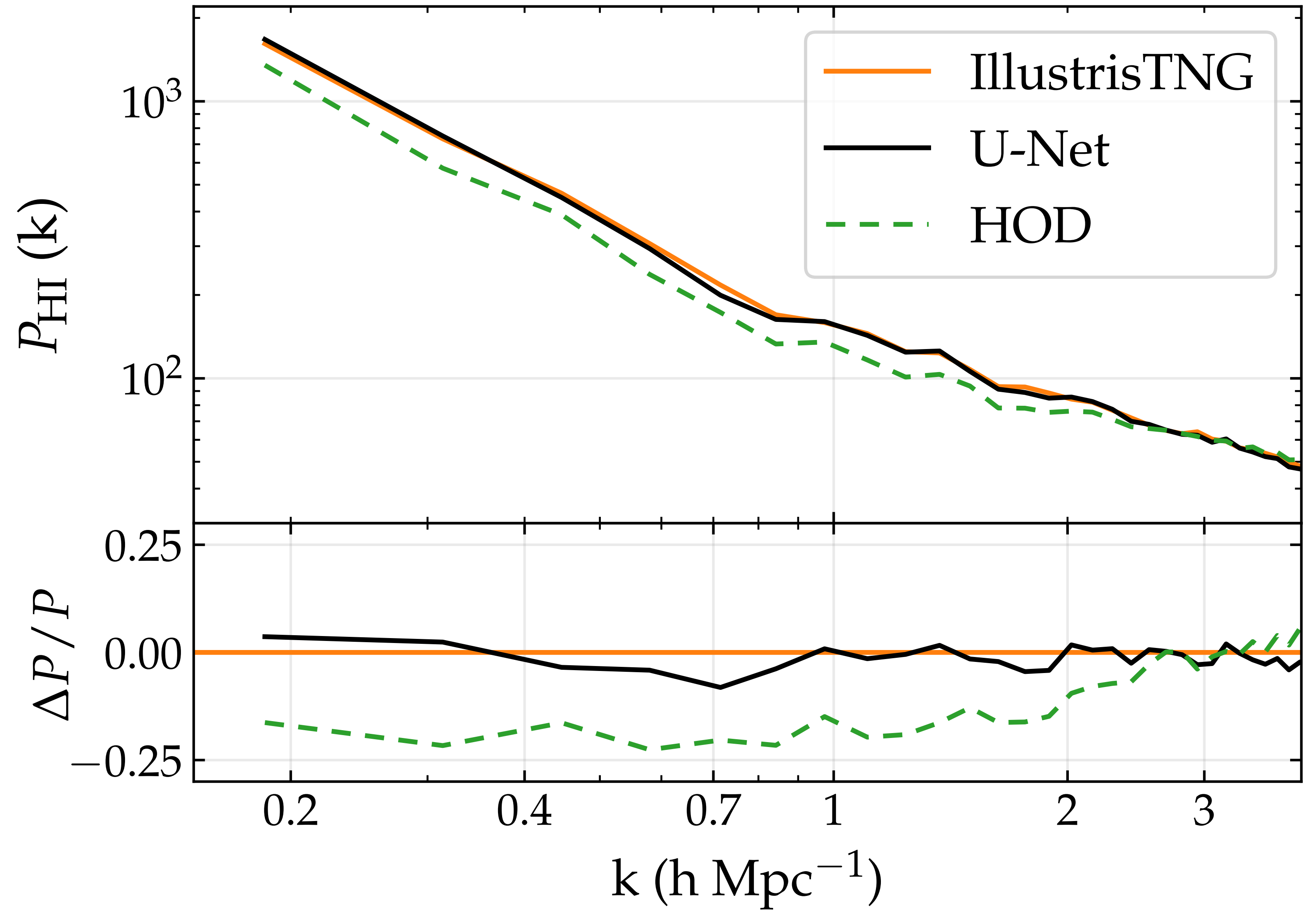
DM HI



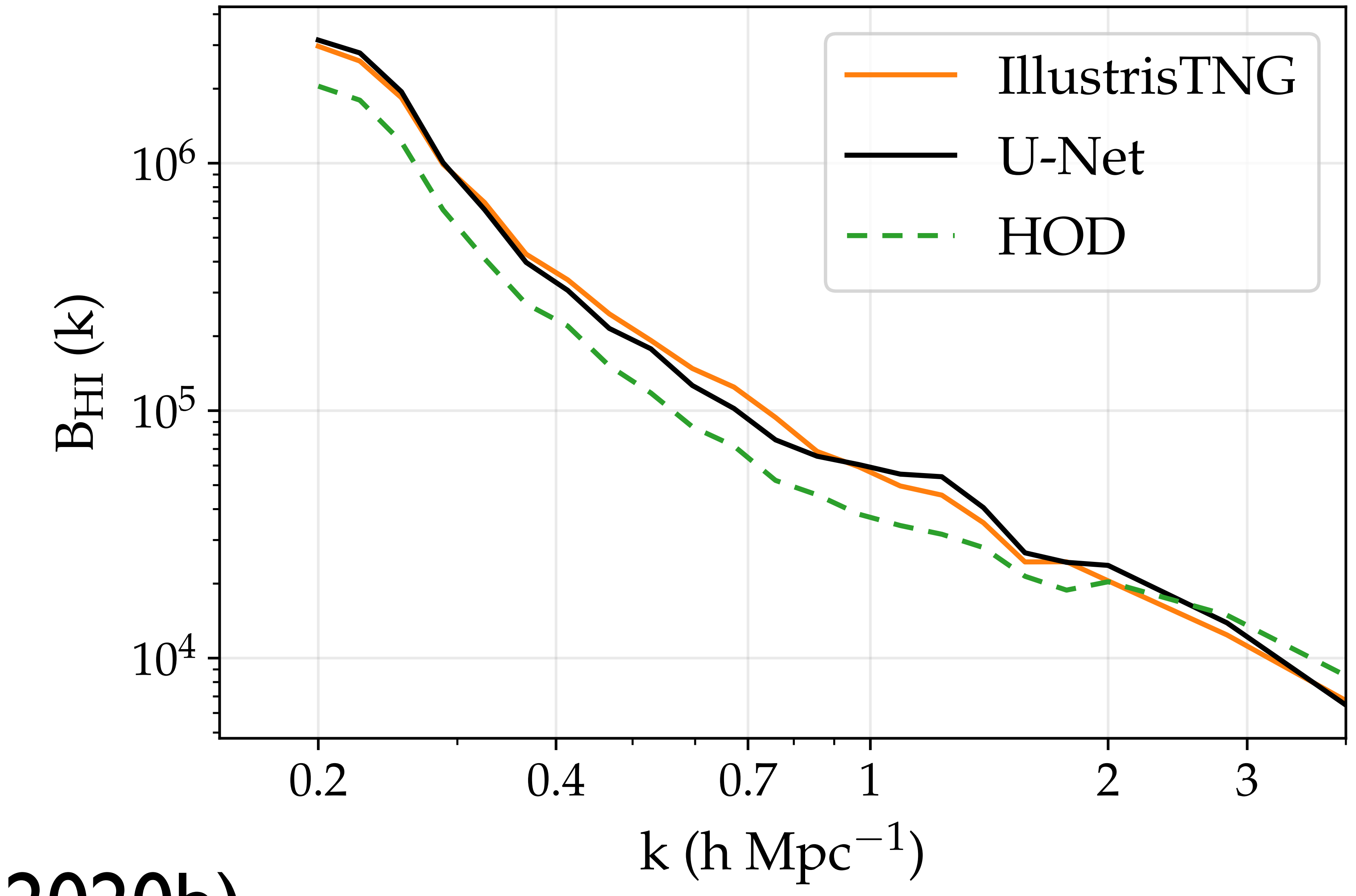
$$\rho_{\rm HI}(\mathbf{x}) = g\left(\rho_{\rm DM}(\mathbf{x}), \rho_{\rm DM}(\mathbf{x}')\right)$$



Power spec. (2 pt)

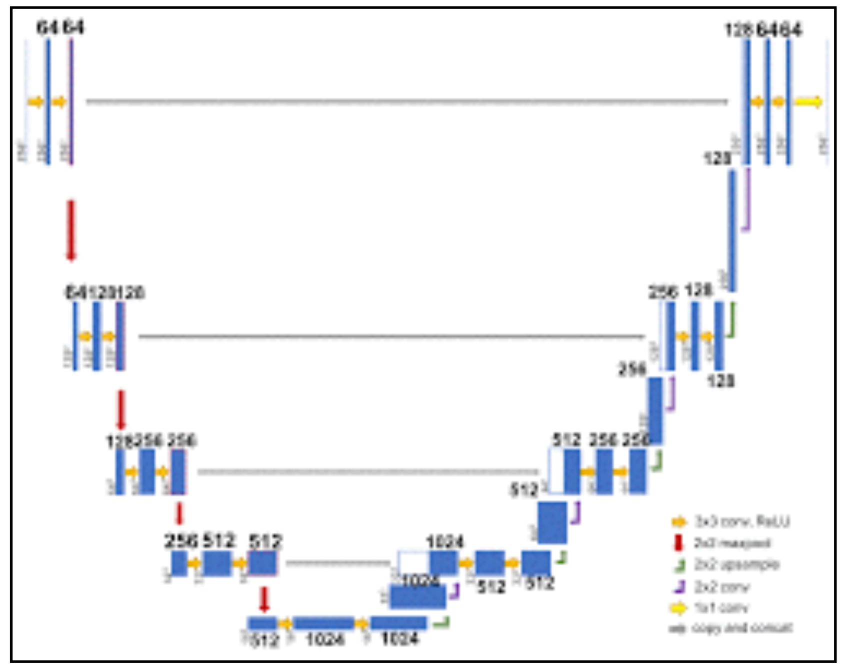


Bispectrum (3 pt)

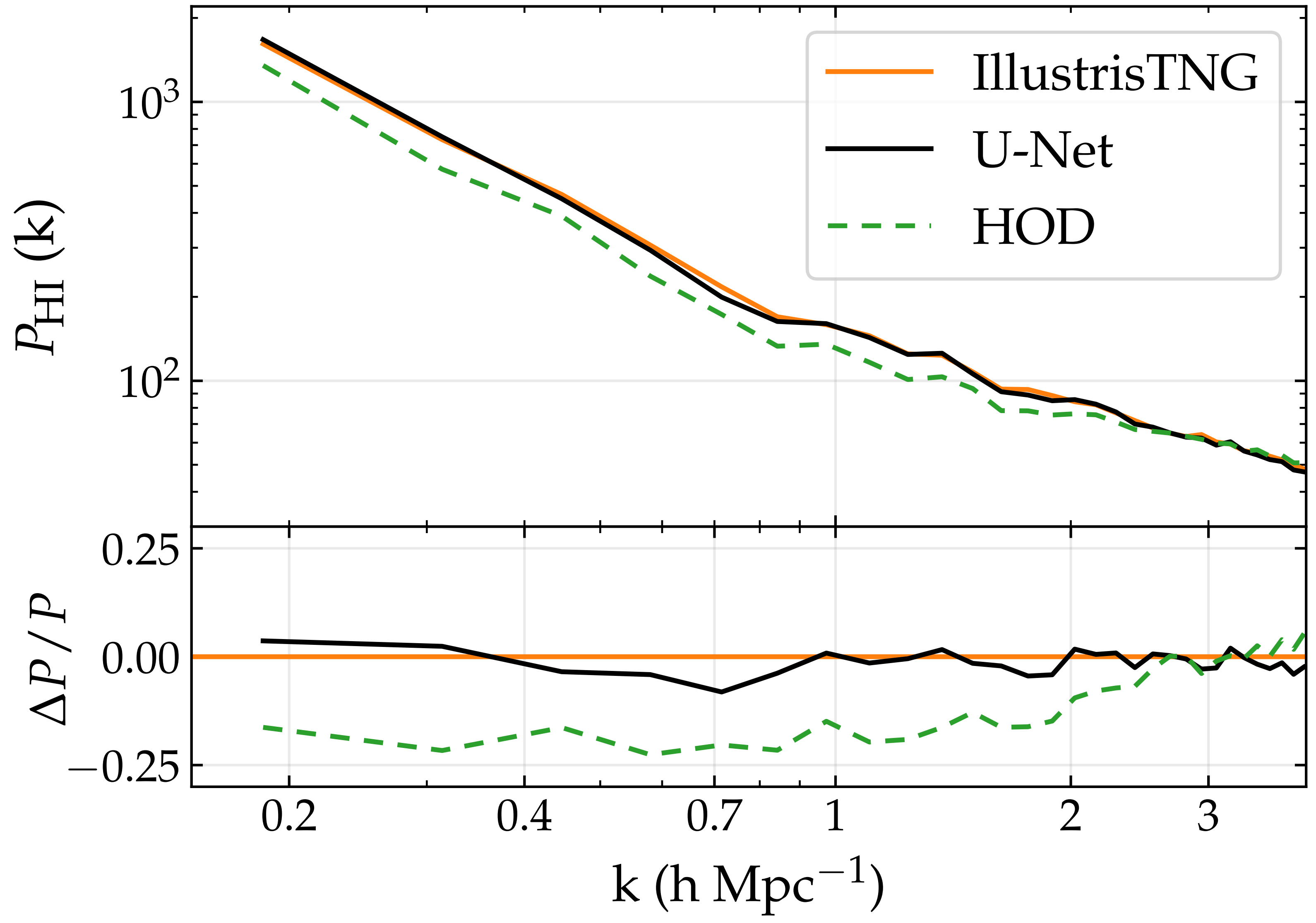


(DW et al. 2020b)

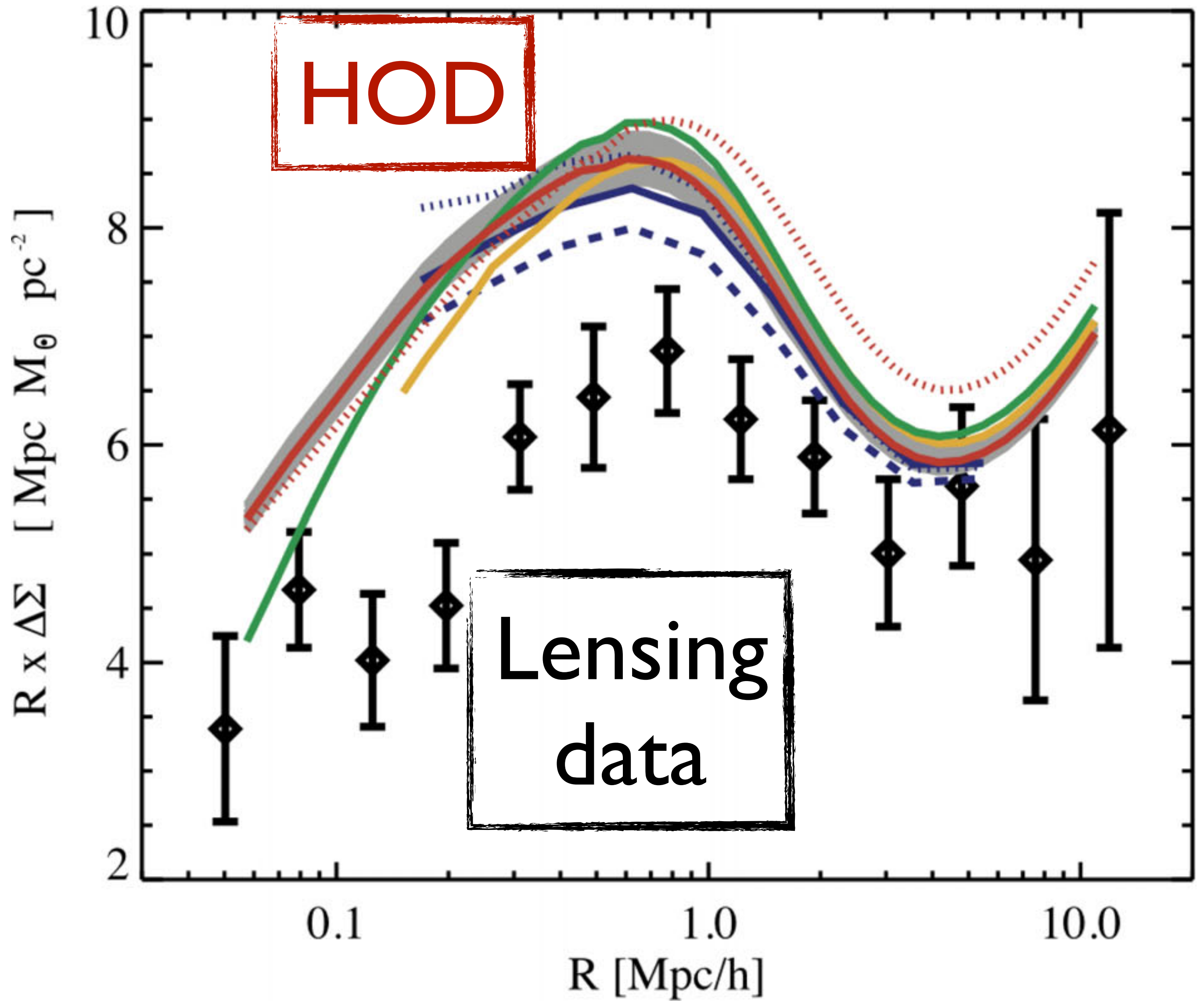
Can we interpret what the network has learnt?



Power spec. (2 pt)



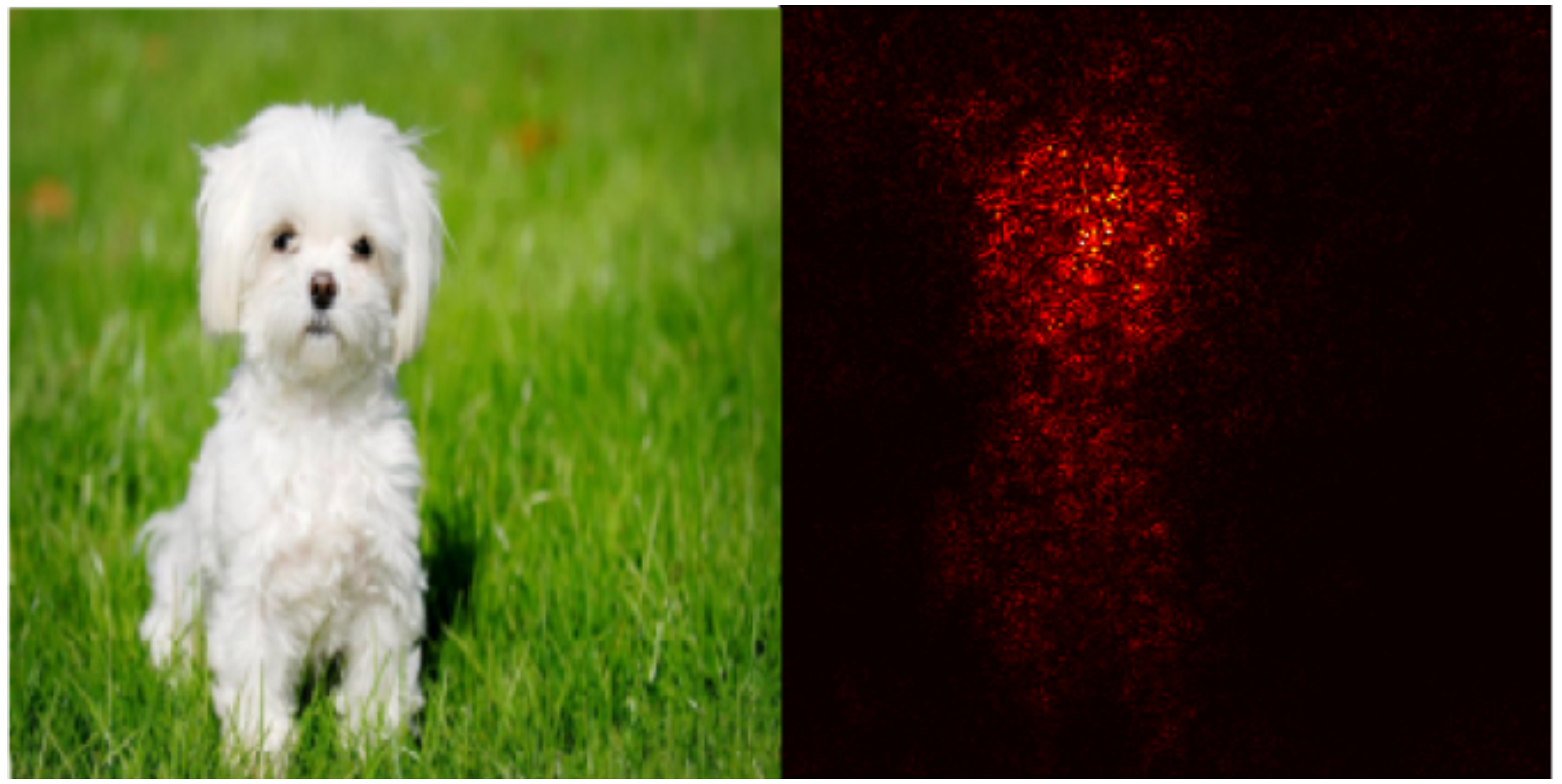
HI

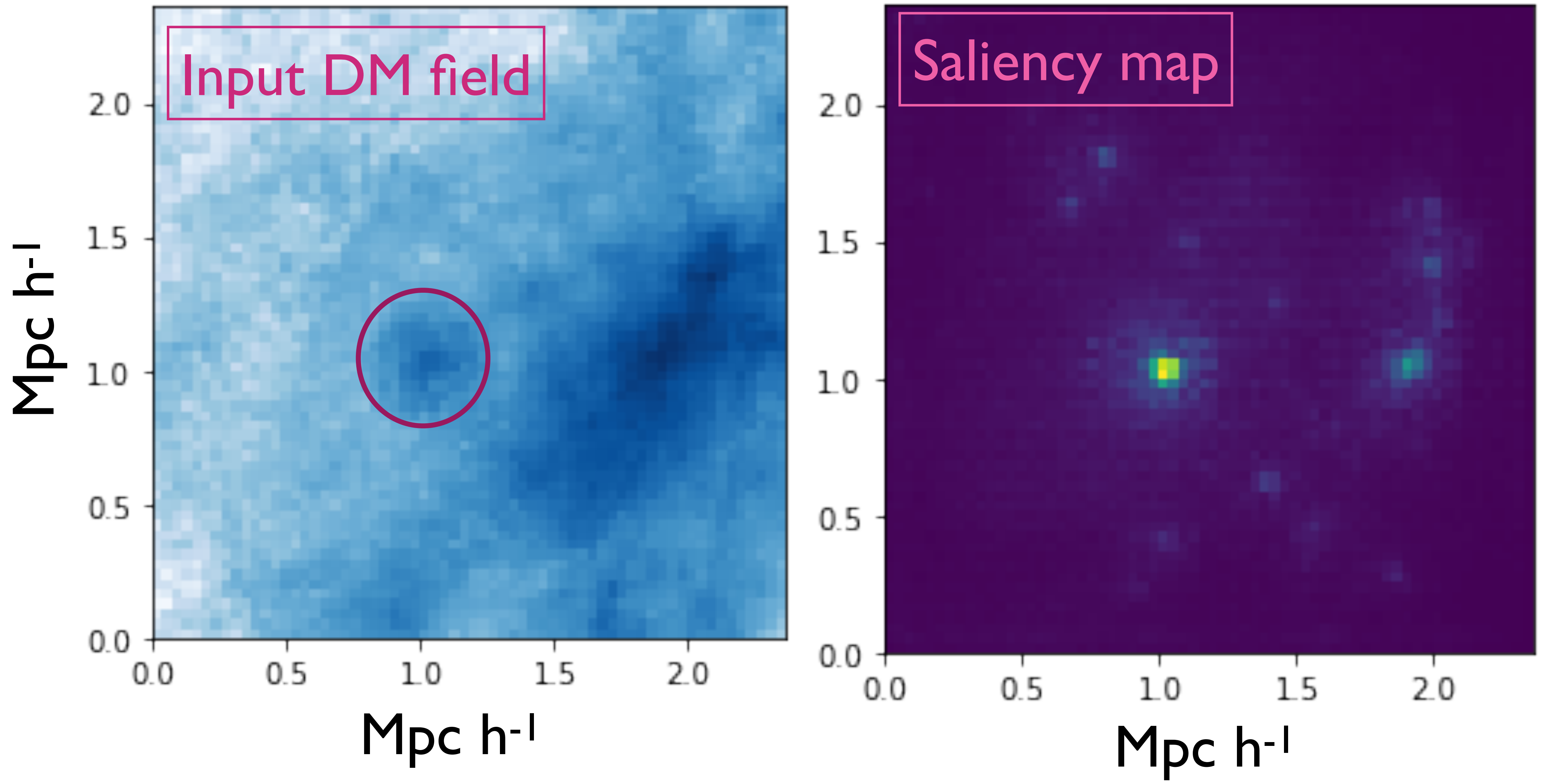


Galaxies from SDSS-CMASS

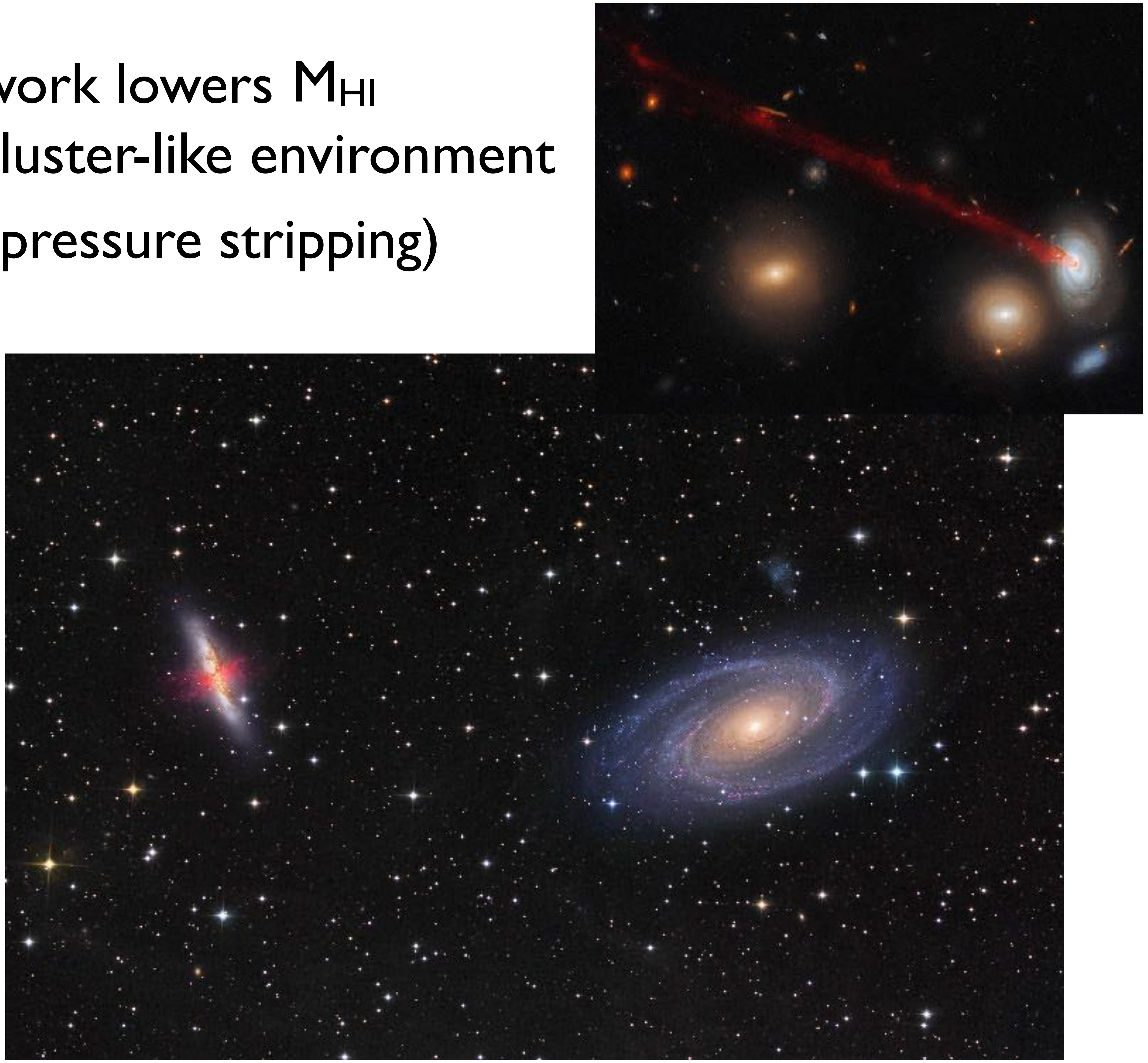
"Lensing is low" problem (Leauthaud et al. 17)

Network has learnt to include env. info





- Network lowers M_{HI}
  in a cluster-like environment
  (ram pressure stripping)

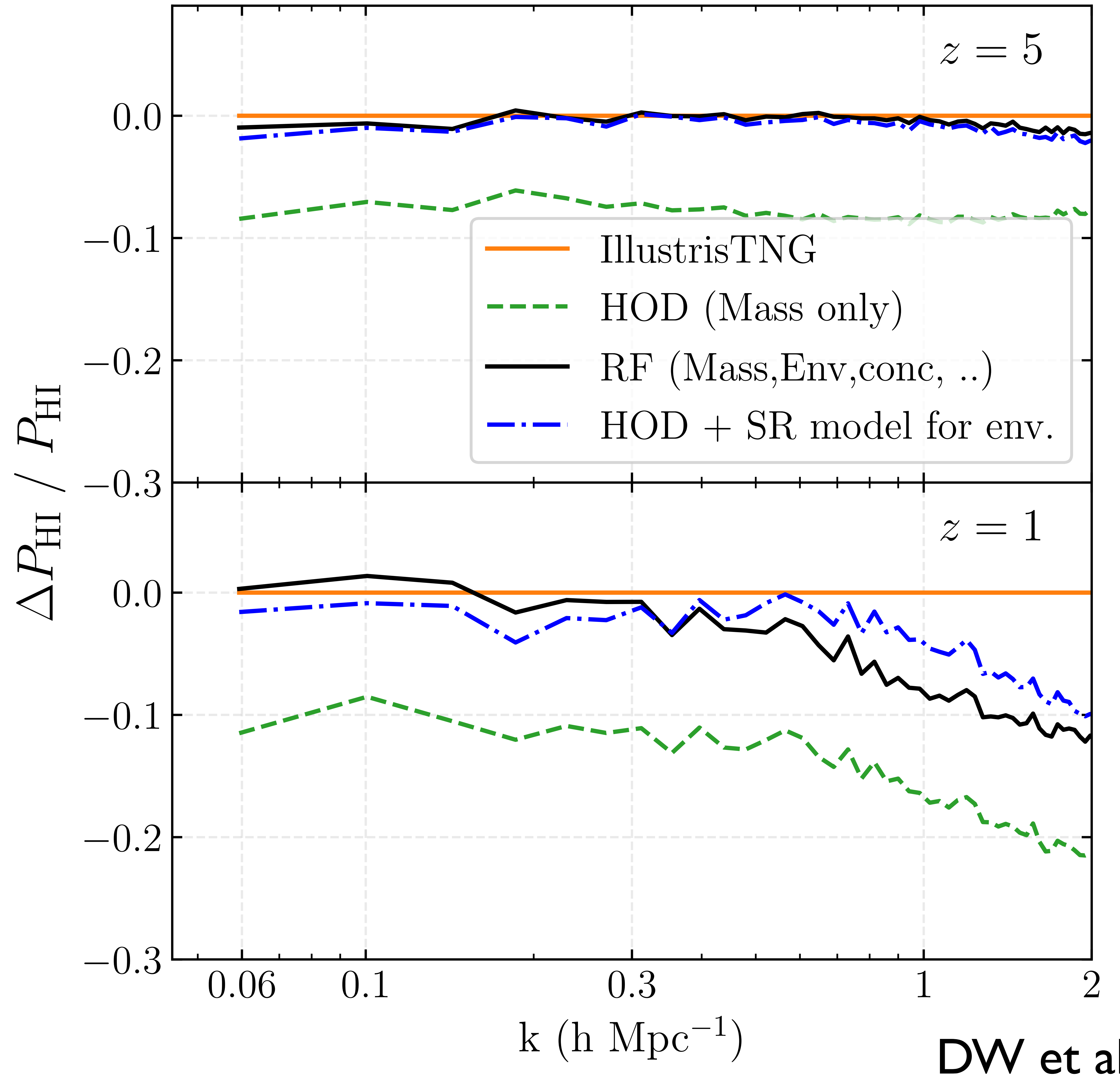


Alternate approach : Modeling the halo HI mass with symbolic regression

HI mass of halo = f (halo mass, ?)

- Halo env. overdensity (R)
- Env. anisotropy (R)
- Halo concentration
- Halo spin
- Halo assembly history
- Halo shape
- Velocity dispersion anisotropy
- …., …., ….

Results: Modeling the halo HI mass with symbolic regression



DW et al. 2020c

Env. overdensity at 0.5 Mpc

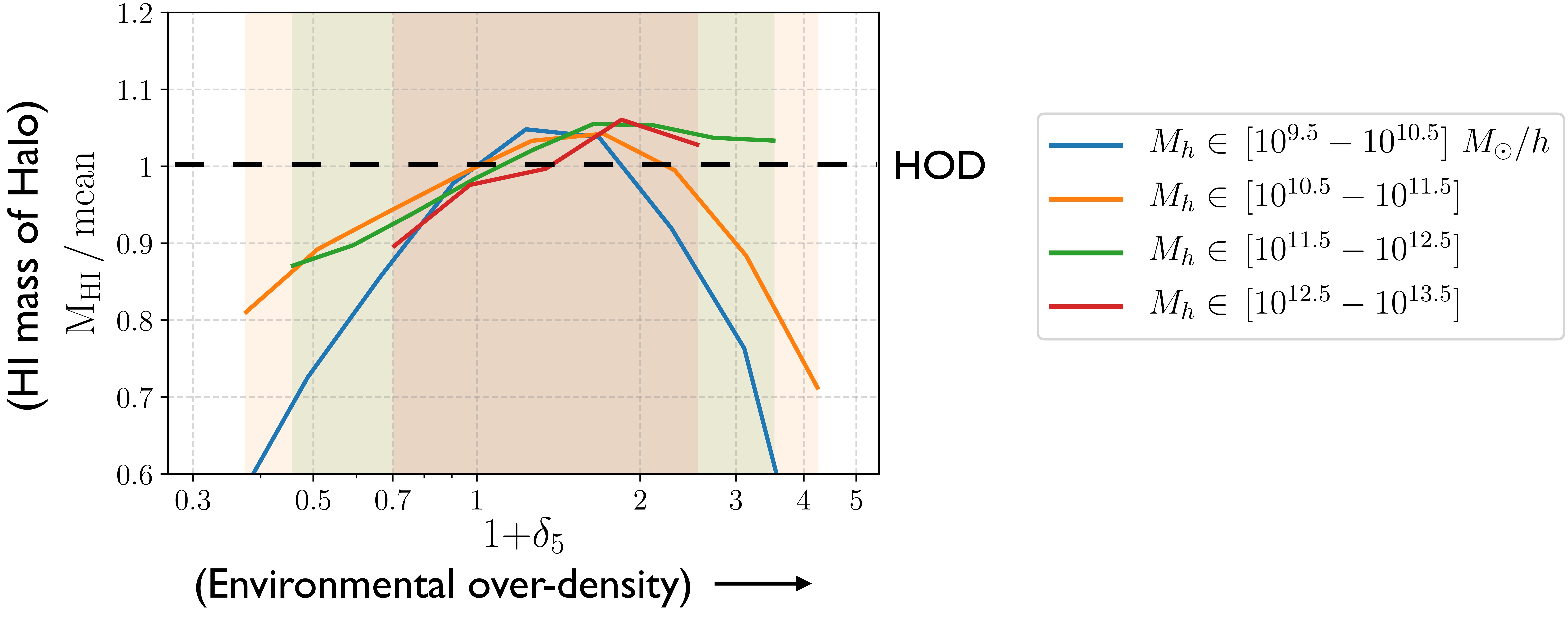
Env. anisotropy

$$z = 5: \quad \frac{M_{\rm HI}}{M_{\rm HOD}} = 0.95 + \alpha'_{0.5}\,\delta'_{0.5}\,(\alpha'_{0.5} + \delta'_{0.5})$$

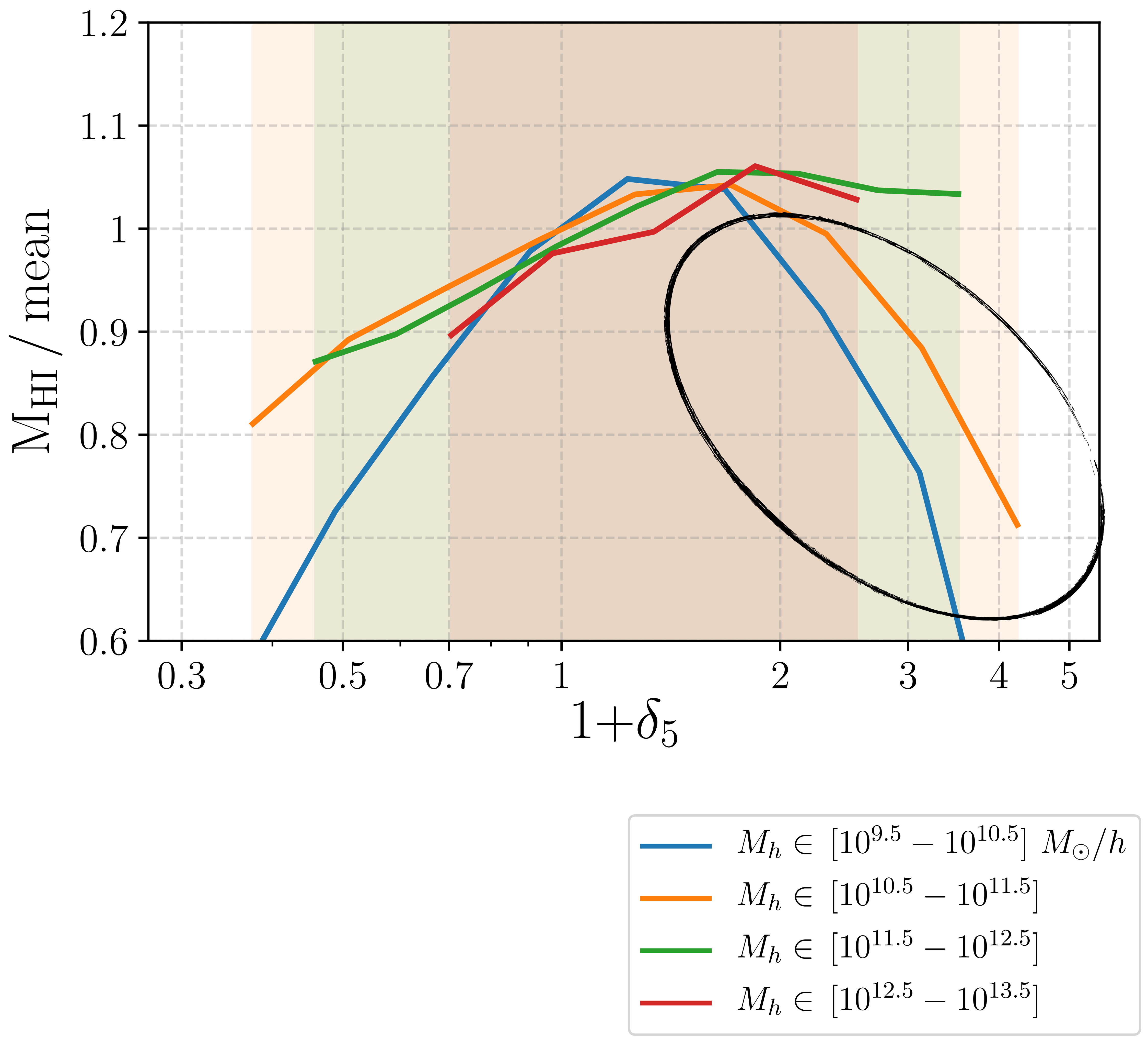
$$z = 1: \quad \frac{M_{\rm HI}}{M_{\rm HOD}} = 0.8 + 1.4\,\alpha'_{0.5} m_{10} - 0.6\,(\alpha'^2_{0.5} m^2_{10} + \alpha'_{0.5}\delta'_5)$$

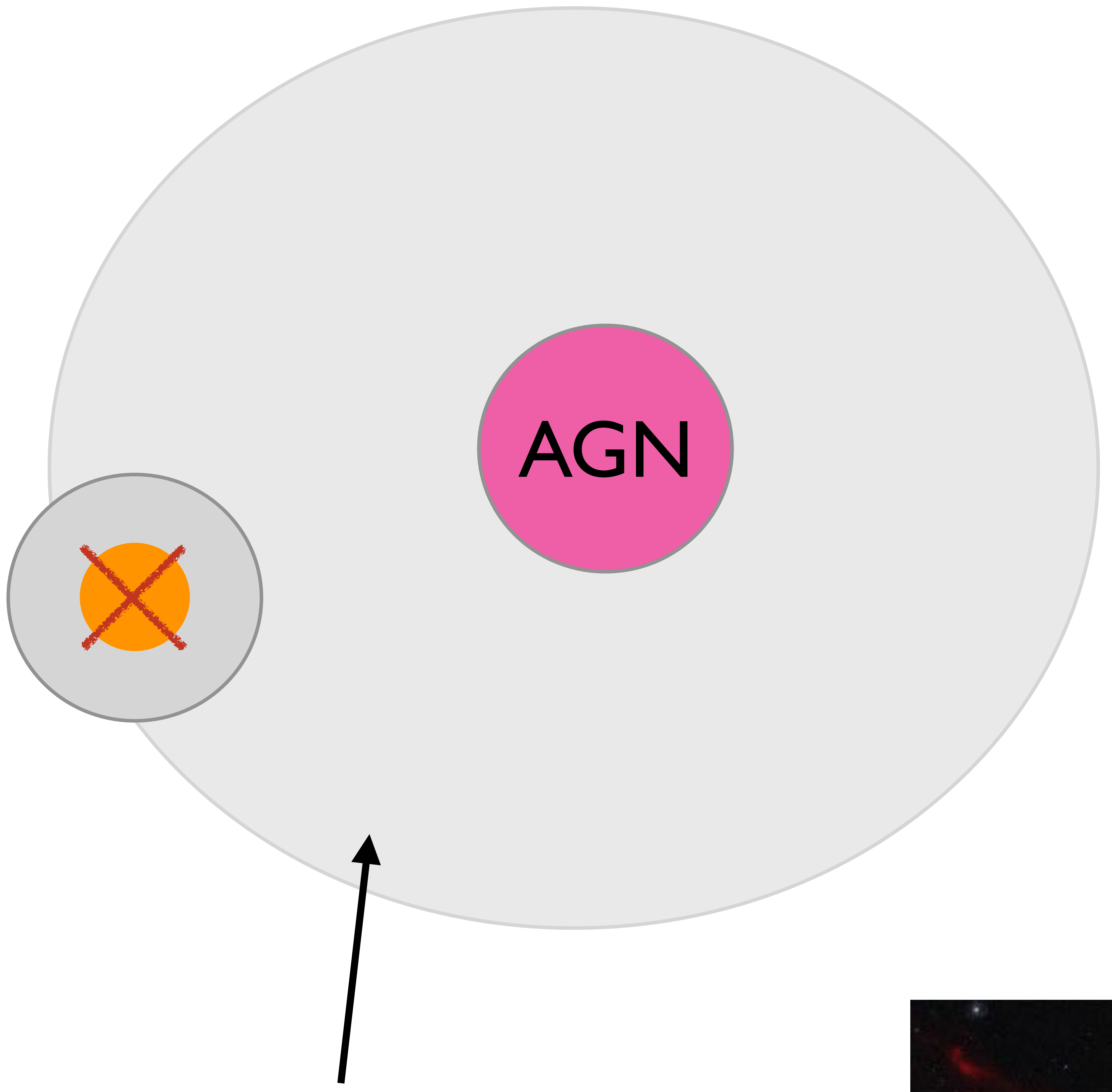
(https://github.com/MilesCranmer/PySR)

Understanding the effect of halo environment on HI: Why don't baryons just follow dark matter?

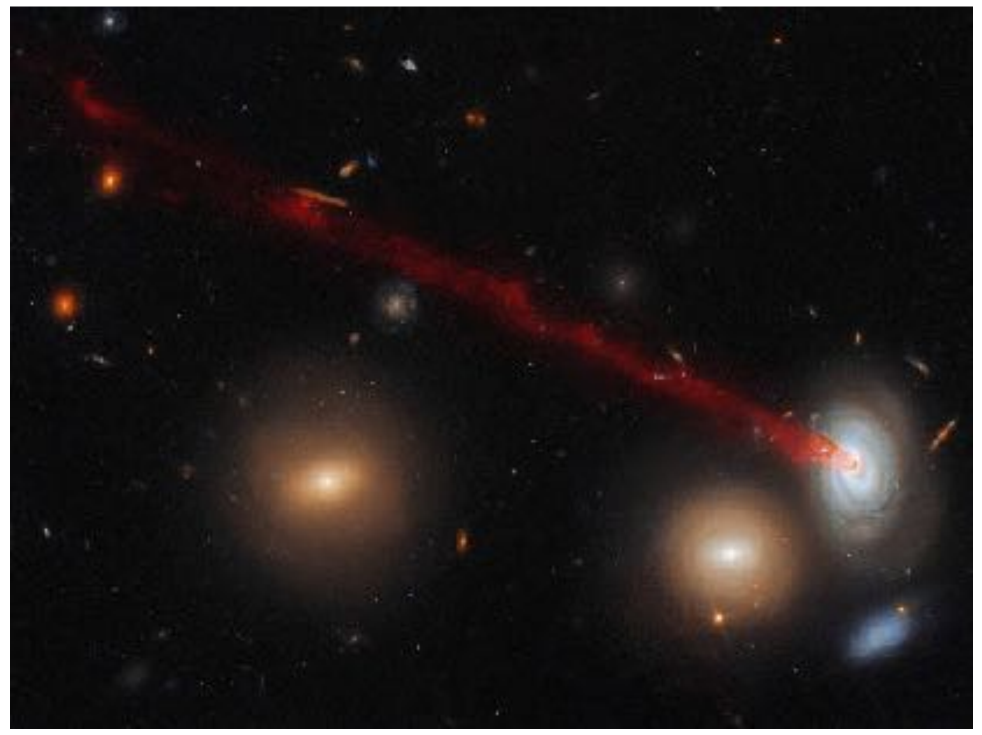


Understanding the effect of halo environment on HI: Don't baryons just follow dark matter?

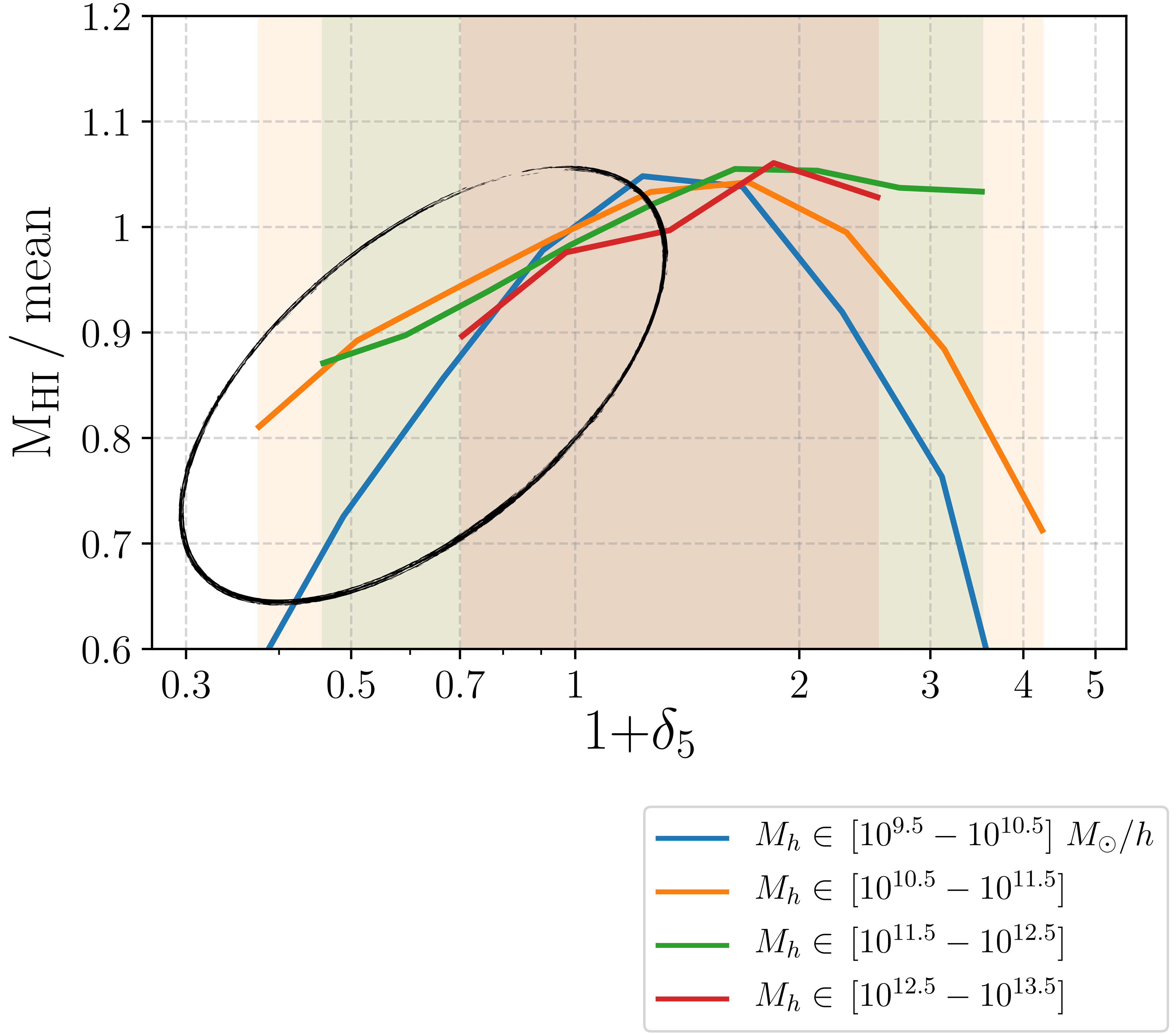


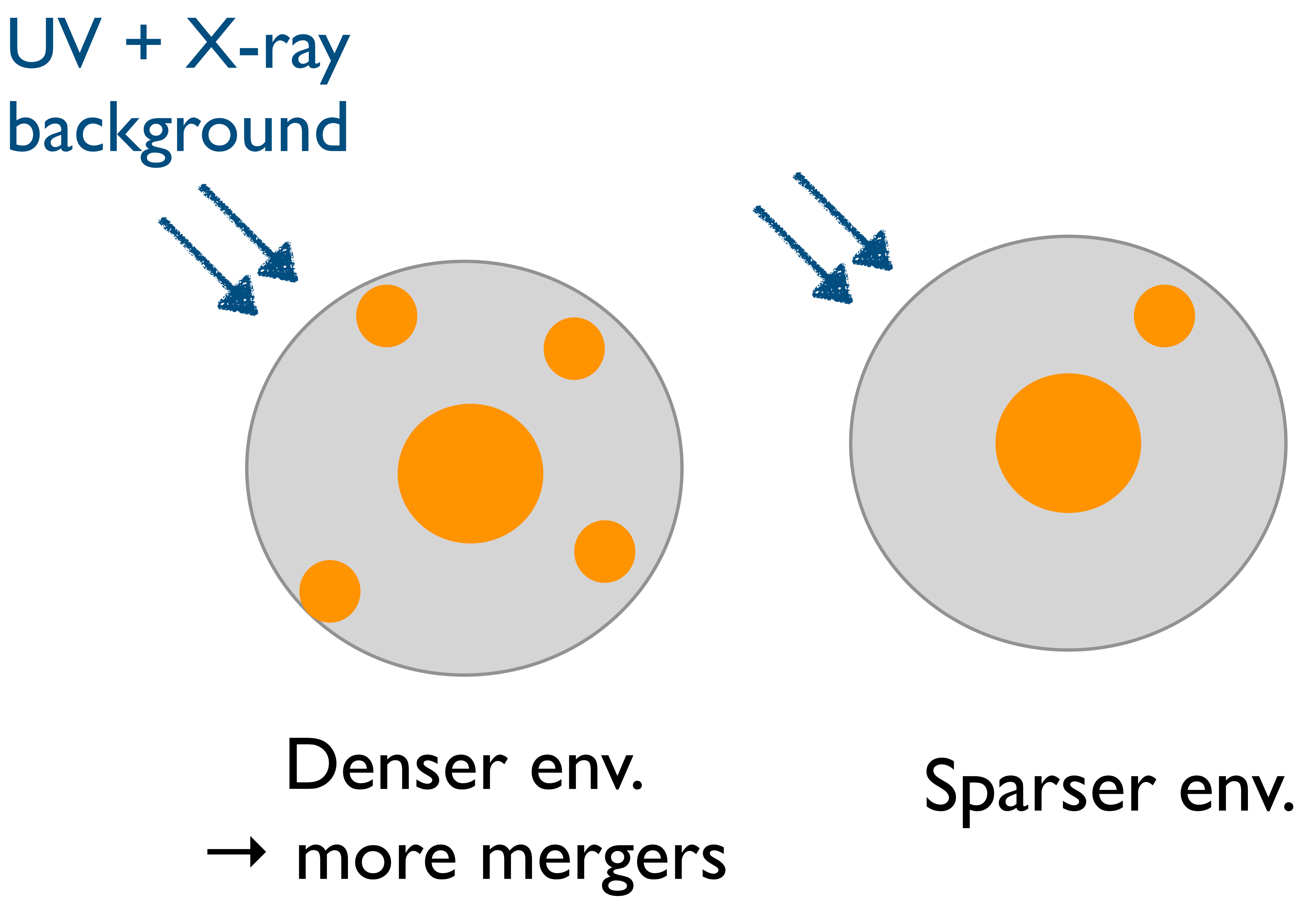


Denser env.: Ionized medium
(ram pressure stripping)



Understanding the effect of halo environment on HI: Don't baryons just follow dark matter?





Future work

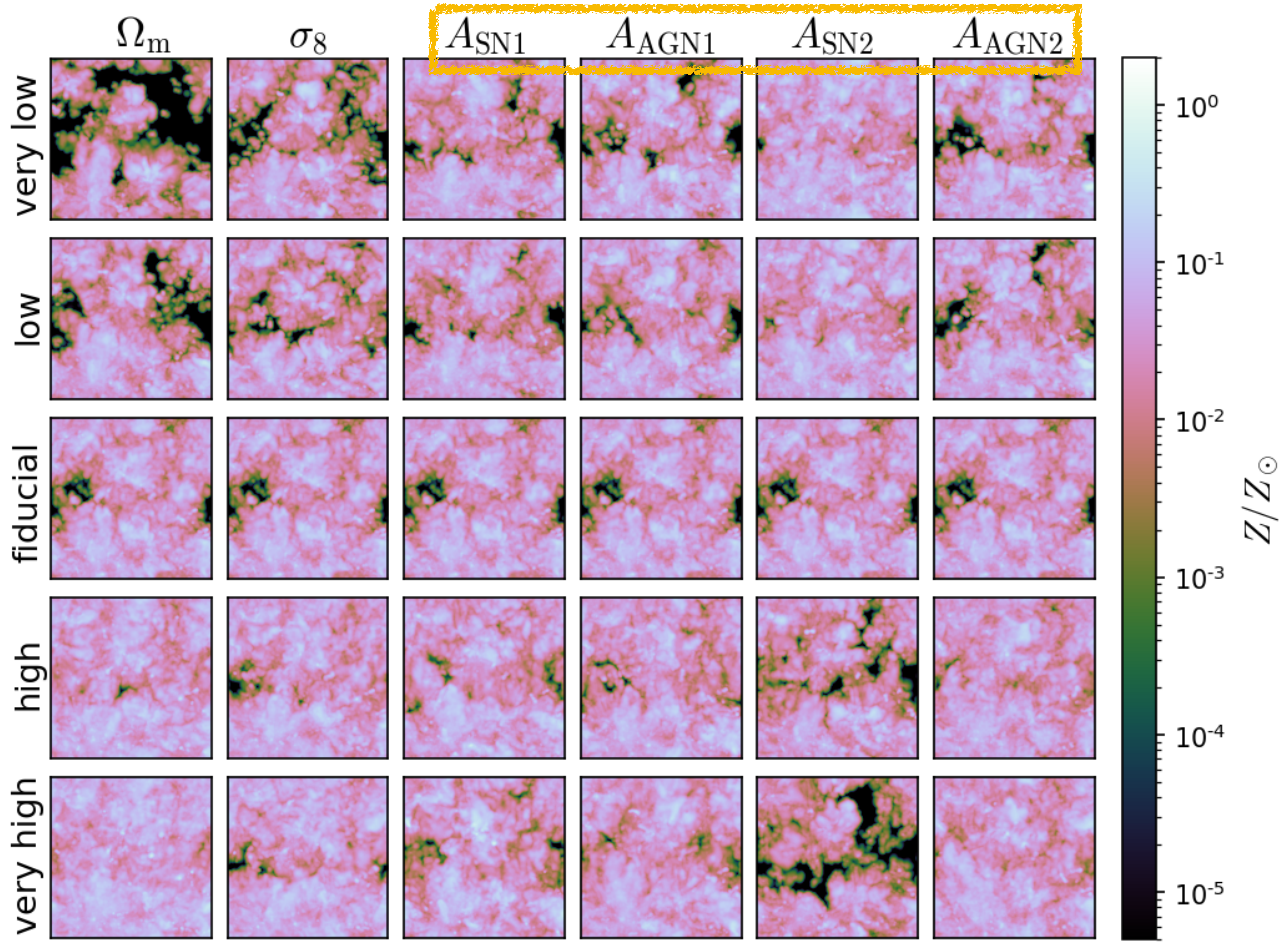
Baryonic content of a halo = f (halo mass, ?)

- No. of galaxies (ELGs for DESI)
- Electron pressure (SO, CMB-S4)

- Halo env. overdensity (R)
- Env. anisotropy (R)
- Halo concentration
- Halo spin
- Halo assembly history
- Halo shape
- Velocity dispersion anisotropy
- …., …., ….

Future work: checking robustness of our results to baryonic feedback

Baryonic feedback parameters



CAMELS

➡2,184 Full hydrodynamic simulations

(Villaescusa-Navarro, .., DW, et al. 2020)

Summary

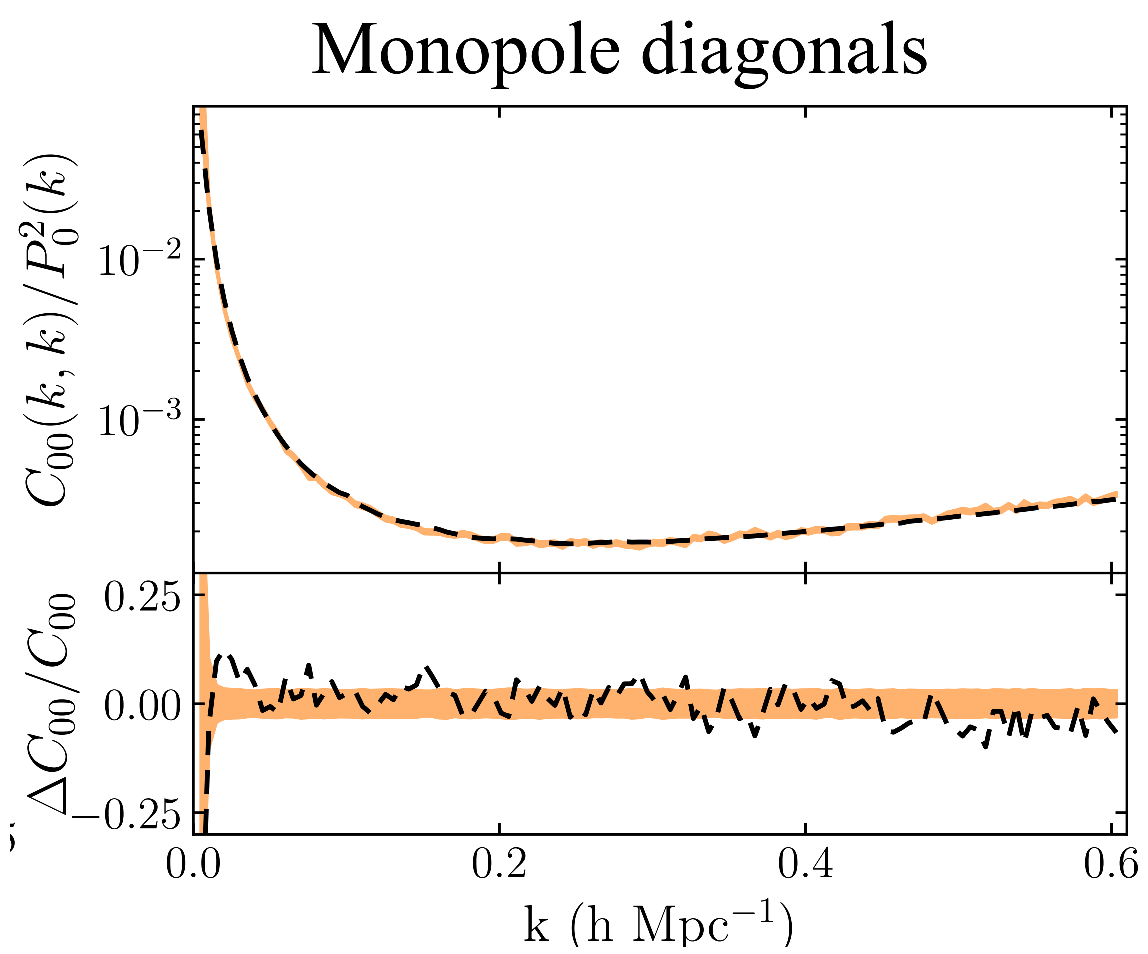
★ Analytic covariance is an excellent complement to mock simulations for DESI and Euclid

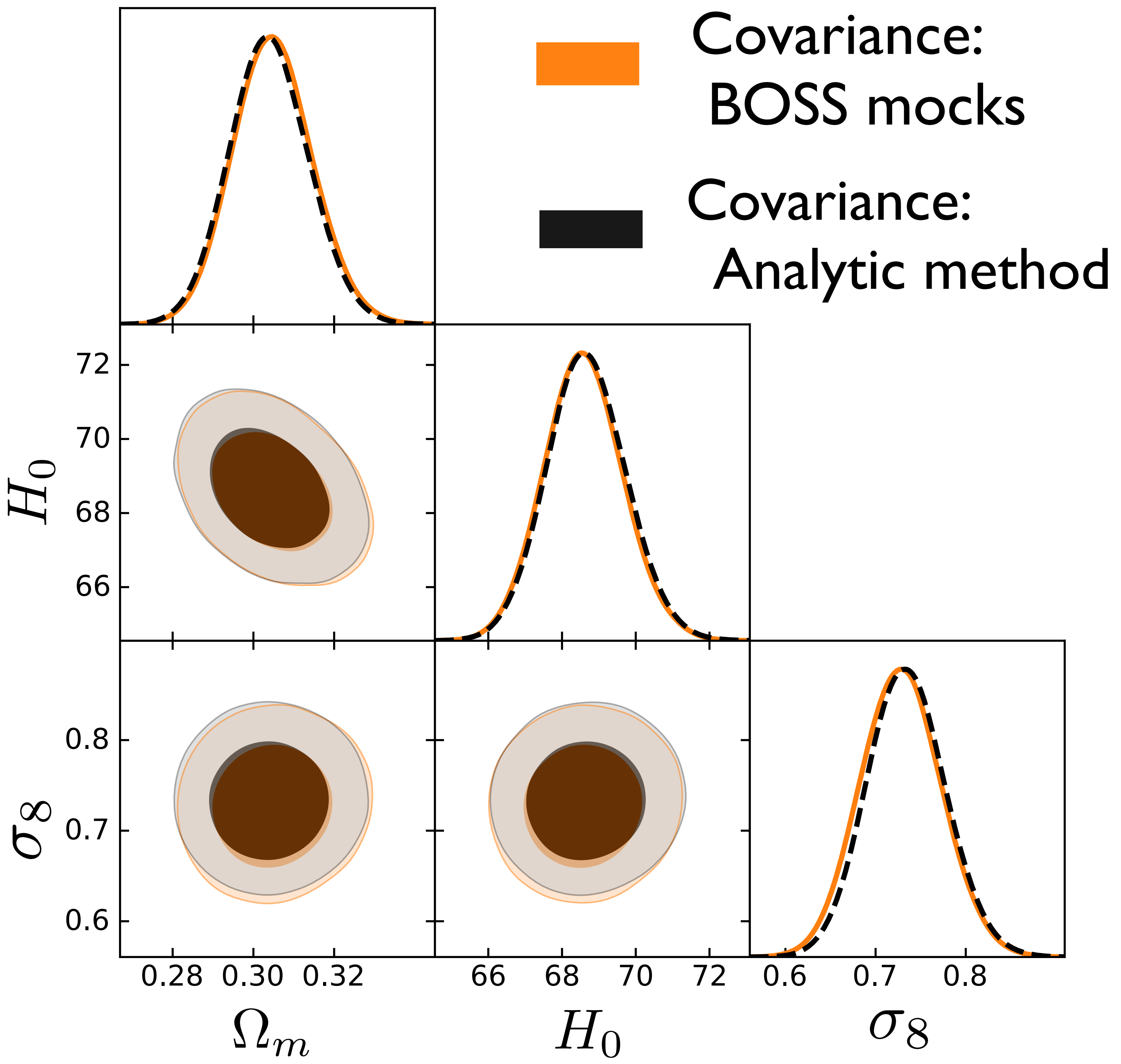
1. Very good agreement with the state-of-the-art mocks up to non-linear scales

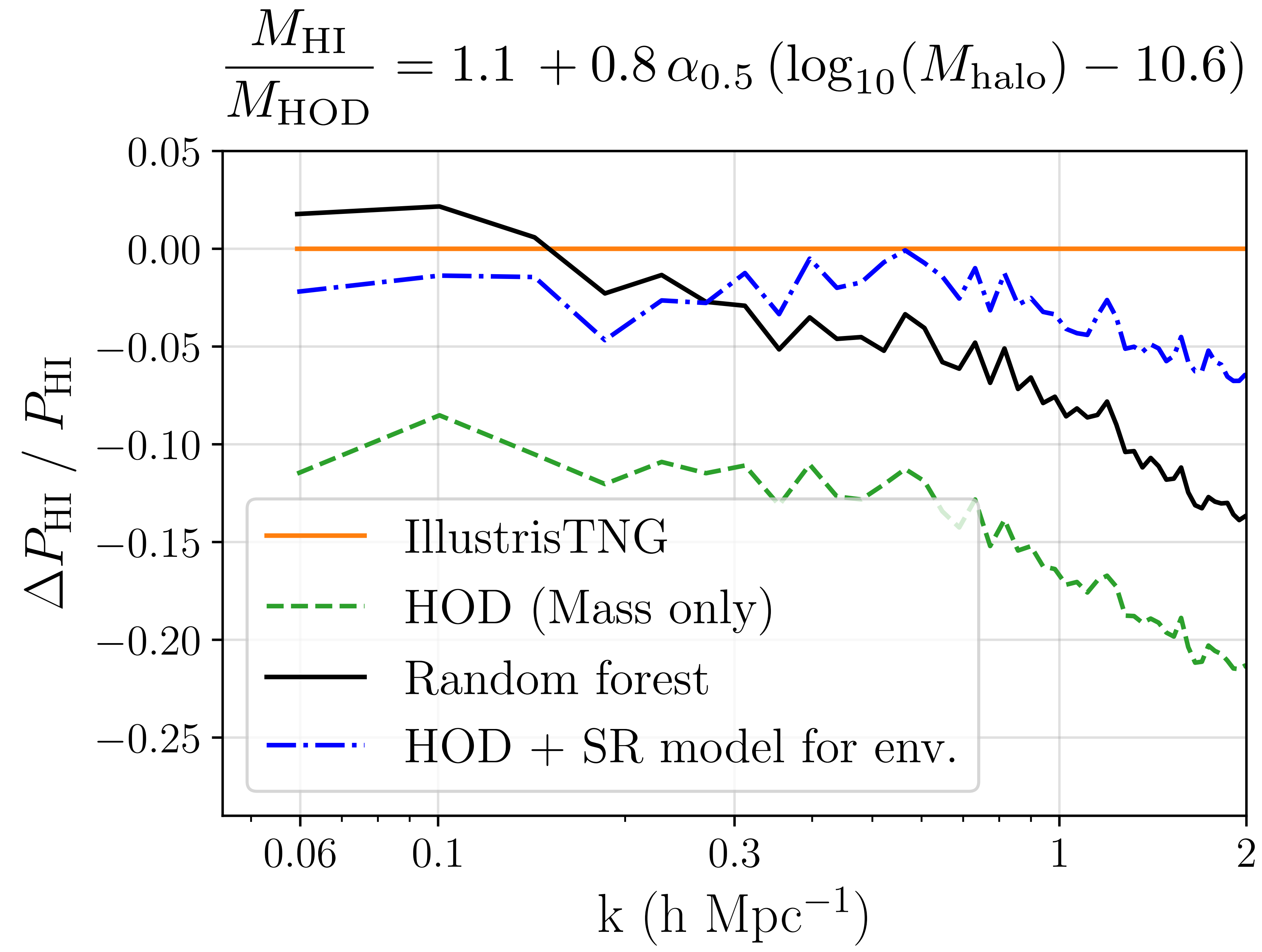
2. Immense computational speedup ($\sim 10^4$)

3. Reduces systematic error budget of constraints

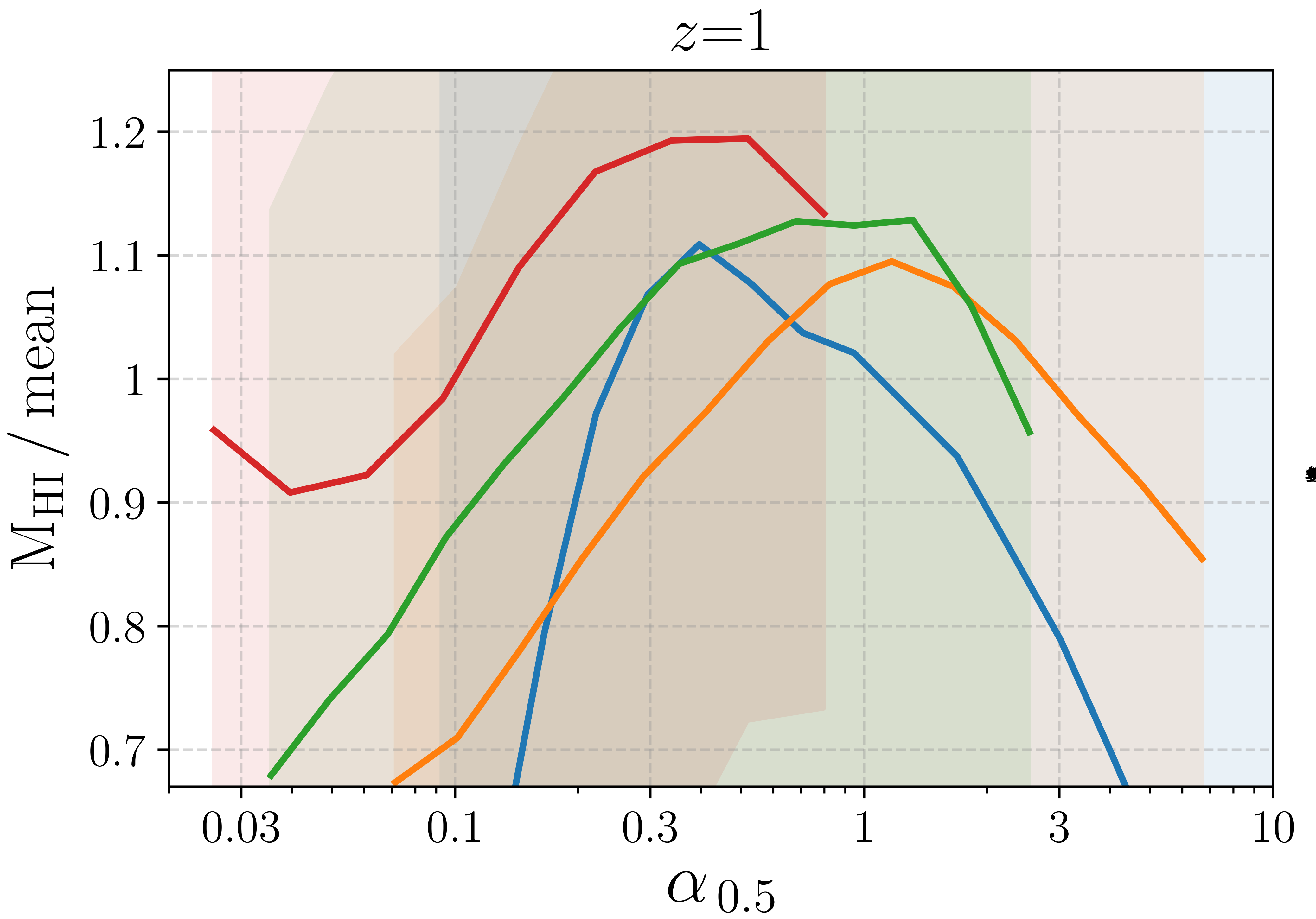
★ Machine learning can be used to emulate hydro sims and make accurate synthetic maps needed for upcoming LSS surveys

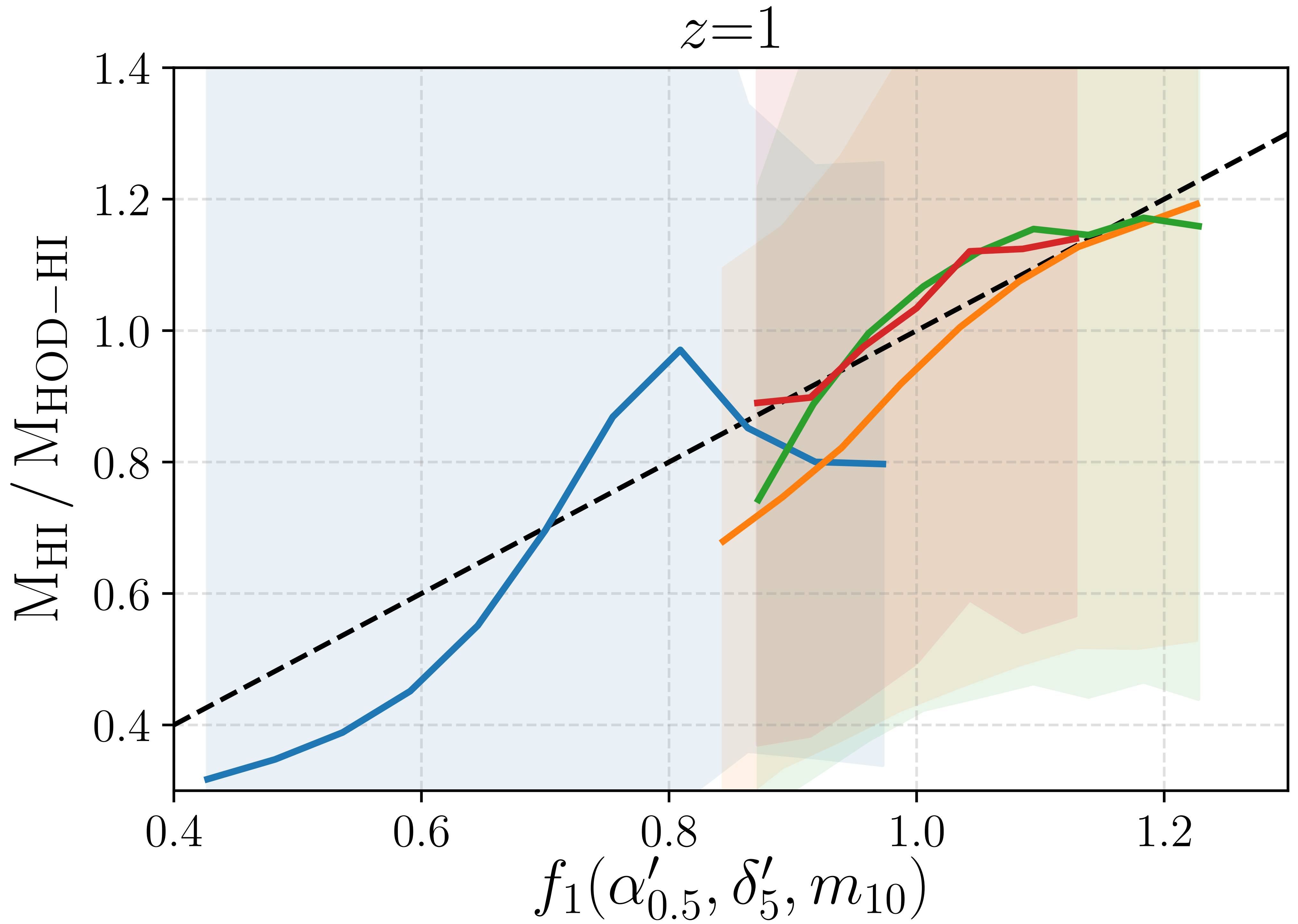






Modeling the environment effect : symbolic regression



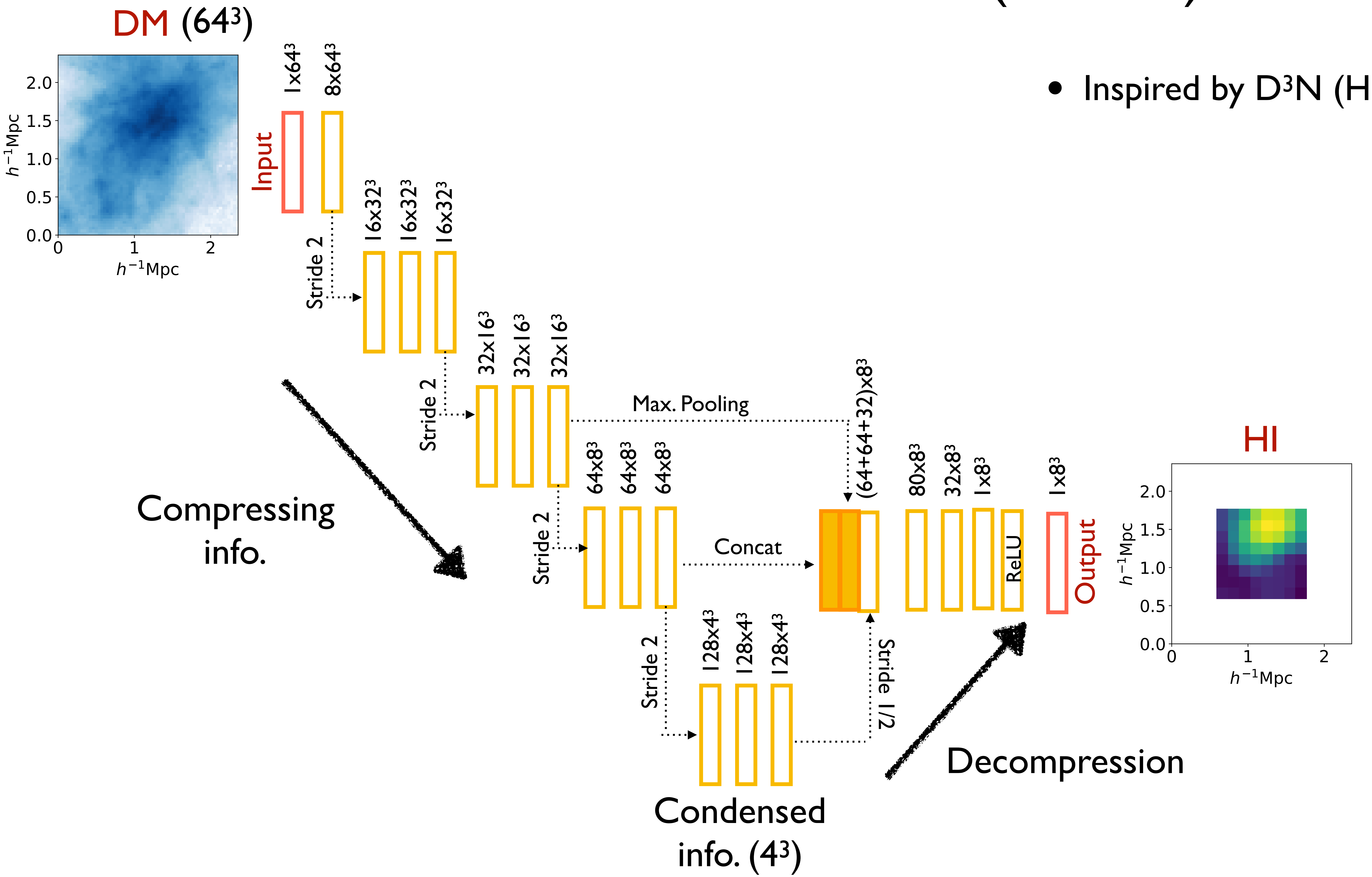


$$z = 1 : \frac{M_{HI}}{M_{HOD}} = \underbrace{0.8 + 1.4\,\alpha'_{0.5} m_{10}}_{\text{Linear trend}} \; \underbrace{- 0.6\,(\alpha'^2_{0.5} m^2_{10} + \alpha'_{0.5}\delta'_5)}_{\text{Quadratic cutoff}}$$

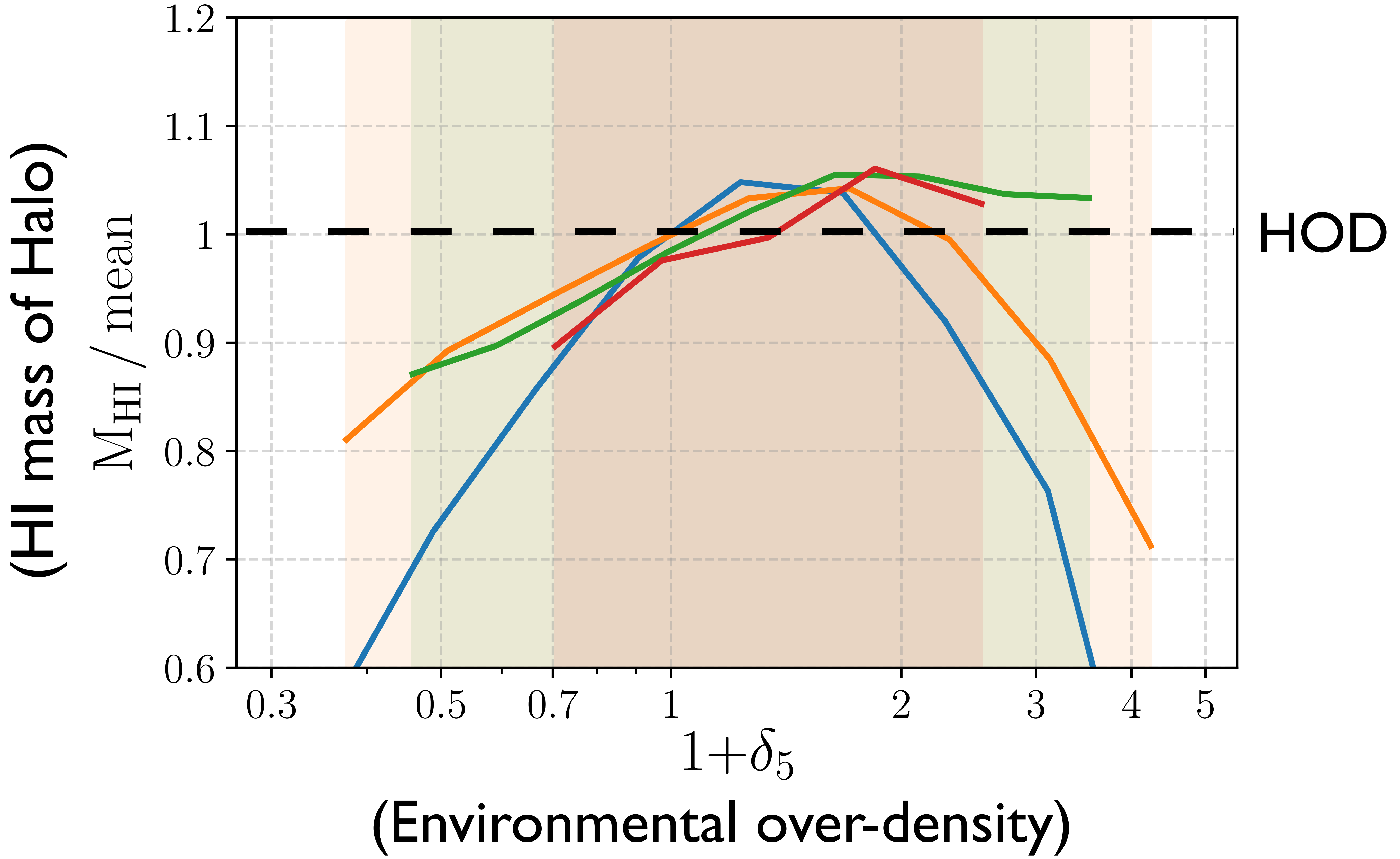
(due to ionizing feedback)

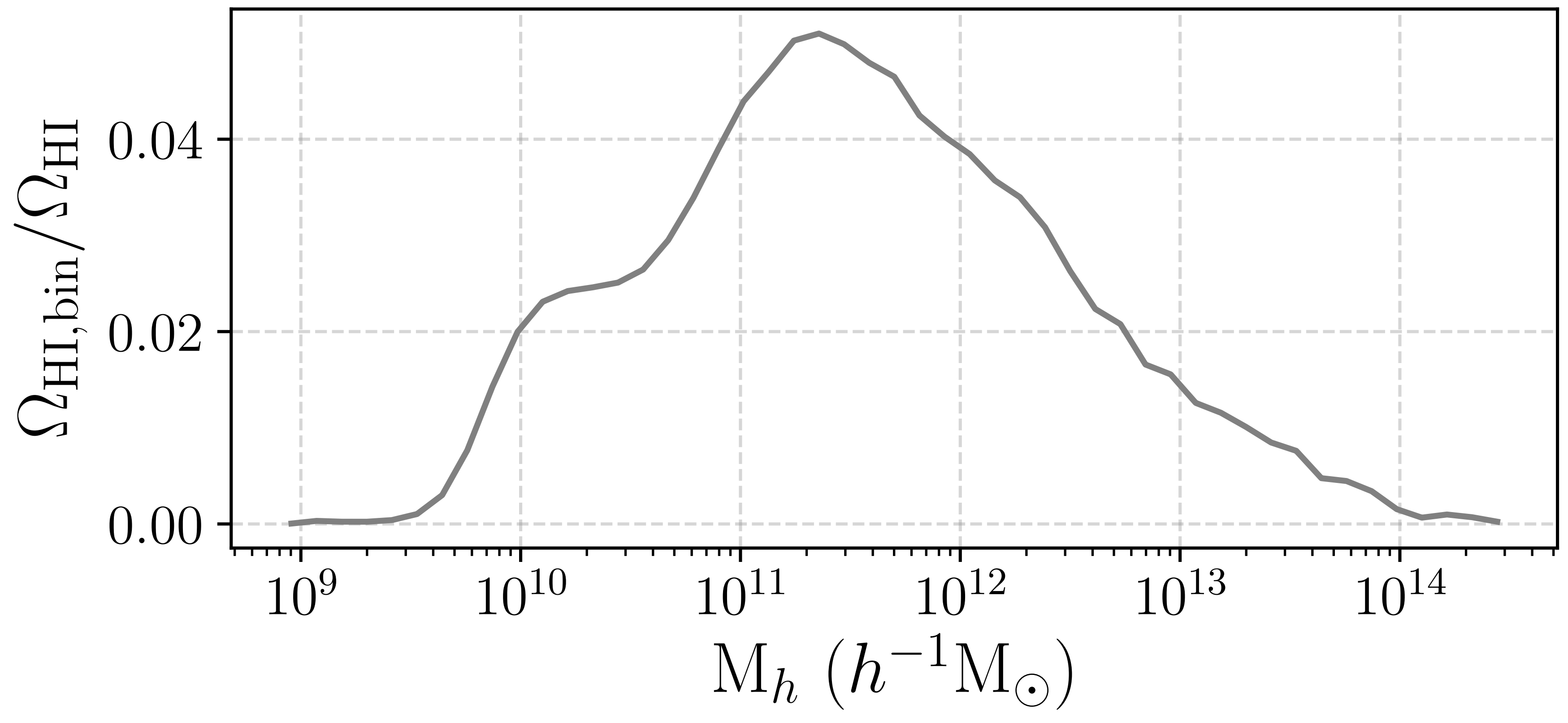
Our NN architecture (U-Net)

- Inspired by D³N (He et al 2019)



Effect of environment is stronger for low-mass halos





Low mass halos are imp for HI surveys

Tidal anisotropy parameter (Paranjape et al 2018)

$$q_R^2 \equiv \frac{1}{2}\left[(\lambda_2 - \lambda_1)^2 + (\lambda_3 - \lambda_1)^2 + (\lambda_3 - \lambda_2)^2\right]$$

$$\alpha_R \equiv \sqrt{q_R^2}/(1 + \delta_R)$$

Non local bias

$$s_{ij}^2 = 2q^2/3$$

In plots: $\alpha'_R \equiv \log(1 + \alpha_R)$

$$\delta'_R \equiv \log(2 + \delta_R)$$