

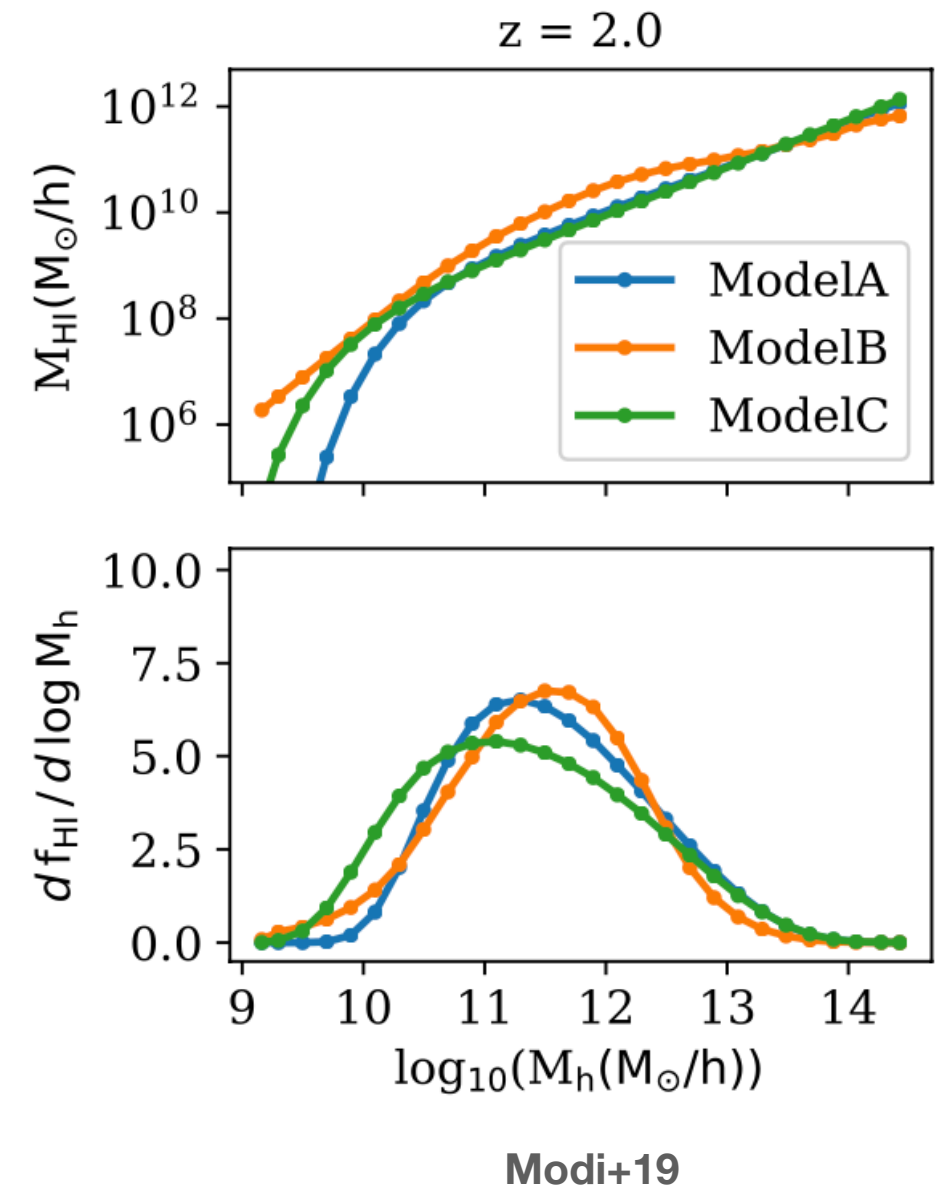
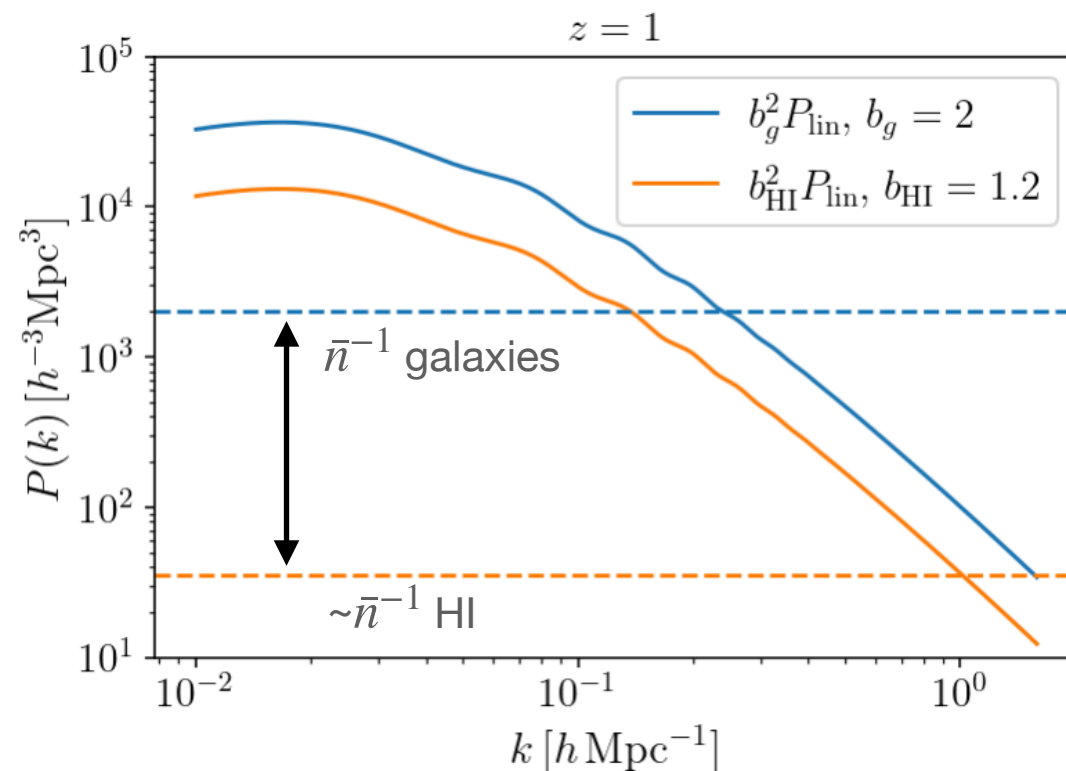
Improving HI cosmology analysis: Fisher forecasts & Machine Learning

[Andrej Obuljen \(UZH\)](#)

w/ S. Foreman, M. Simonović, F. Villaescusa-Navarro et al.

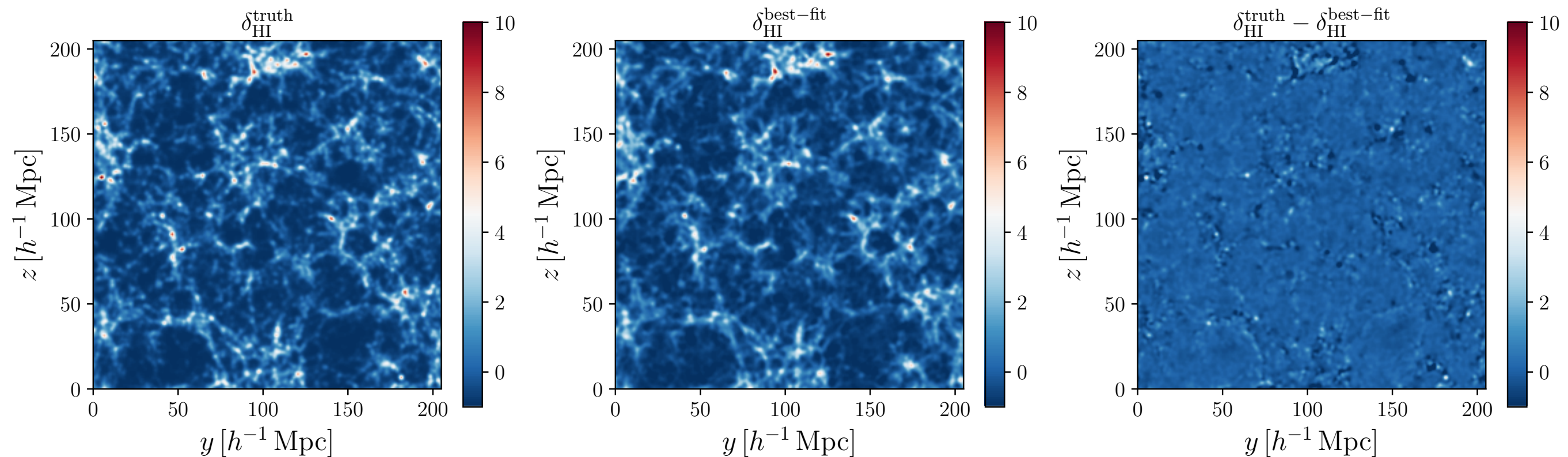
Why is HI great for cosmology?

- HI signal from numerous lower halo masses $\sim 10^{11} M_{\odot}/h$
- Low sampling noise / shot-noise!
- Shot-noise limiting factor for galaxy clustering (Kobayashi+22)



HI: simulations vs theoretical model

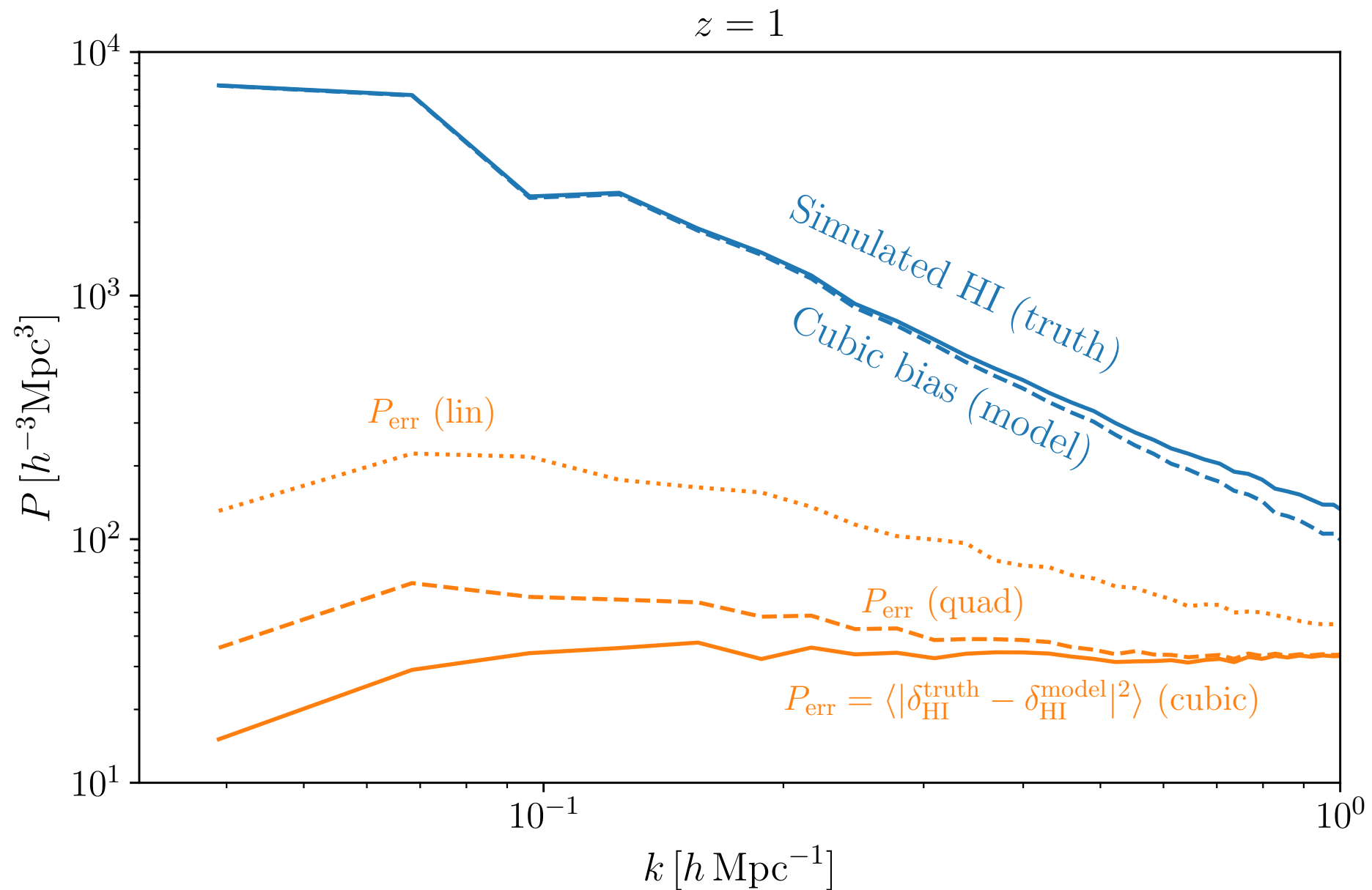
$$\delta_{\text{HI}}(\mathbf{k}) = \beta_1(k)\tilde{\delta}_1(\mathbf{k}) + \beta_2(k)\tilde{\delta}_2^\perp(\mathbf{k}) + \beta_{\mathcal{G}_2}(k)\tilde{\mathcal{G}}_2^\perp(\mathbf{k}) + \beta_3(k)\tilde{\delta}_3^\perp(\mathbf{k}) + \dots + \text{noise}$$



Slice depth 20 Mpc/h, smoothed 1 Mpc/h Gaussian

Simulated HI vs theoretical model

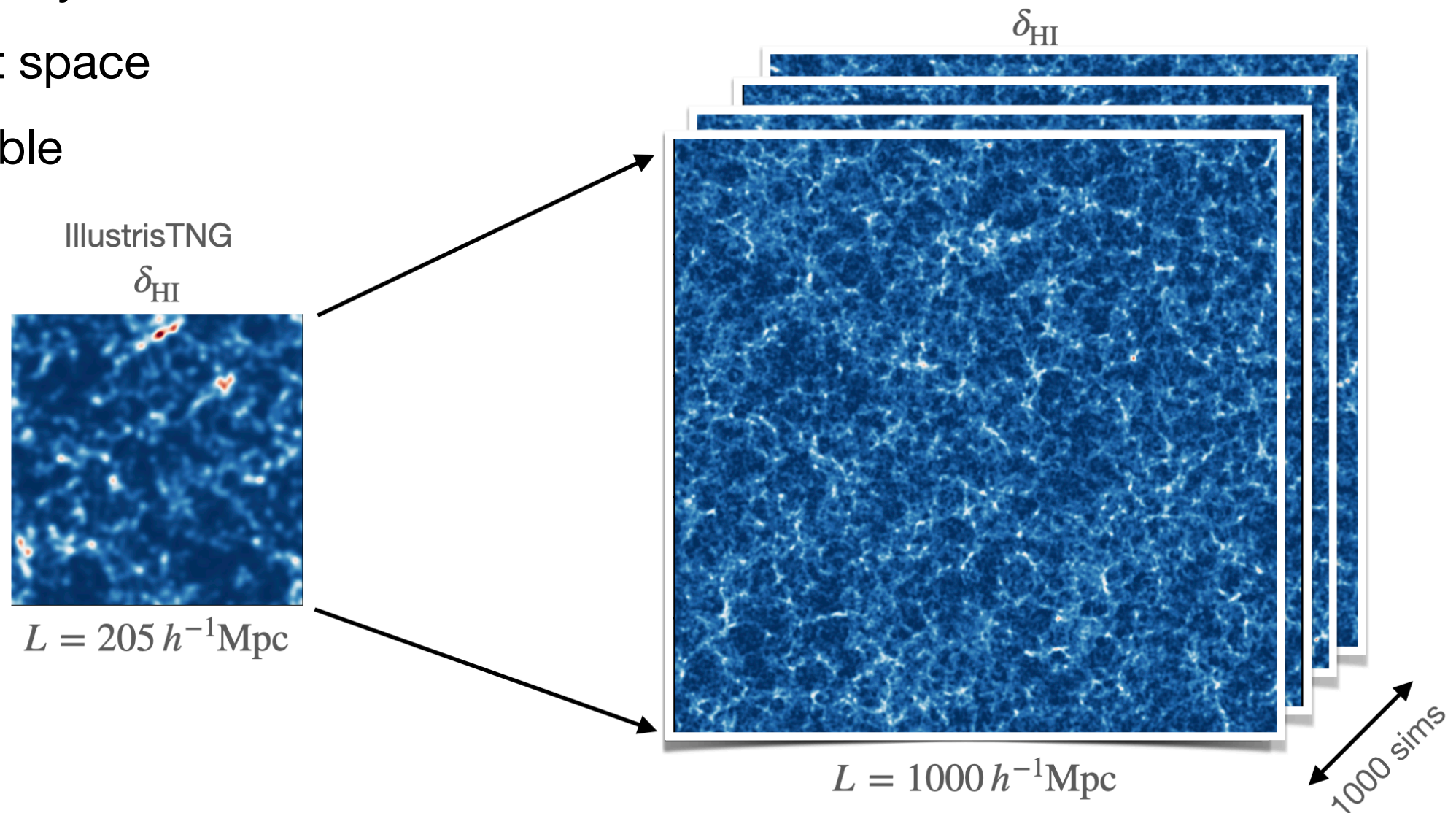
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Hi-Fi mocks

https://github.com/andrejobuljen/Hi-Fi_mocks

- Generate fast 3D HI field-level mocks
- Tuned to TNG HI clustering at $z=[0-5]$
- Extendable to any volume!
- Real & redshift space
- Publicly available



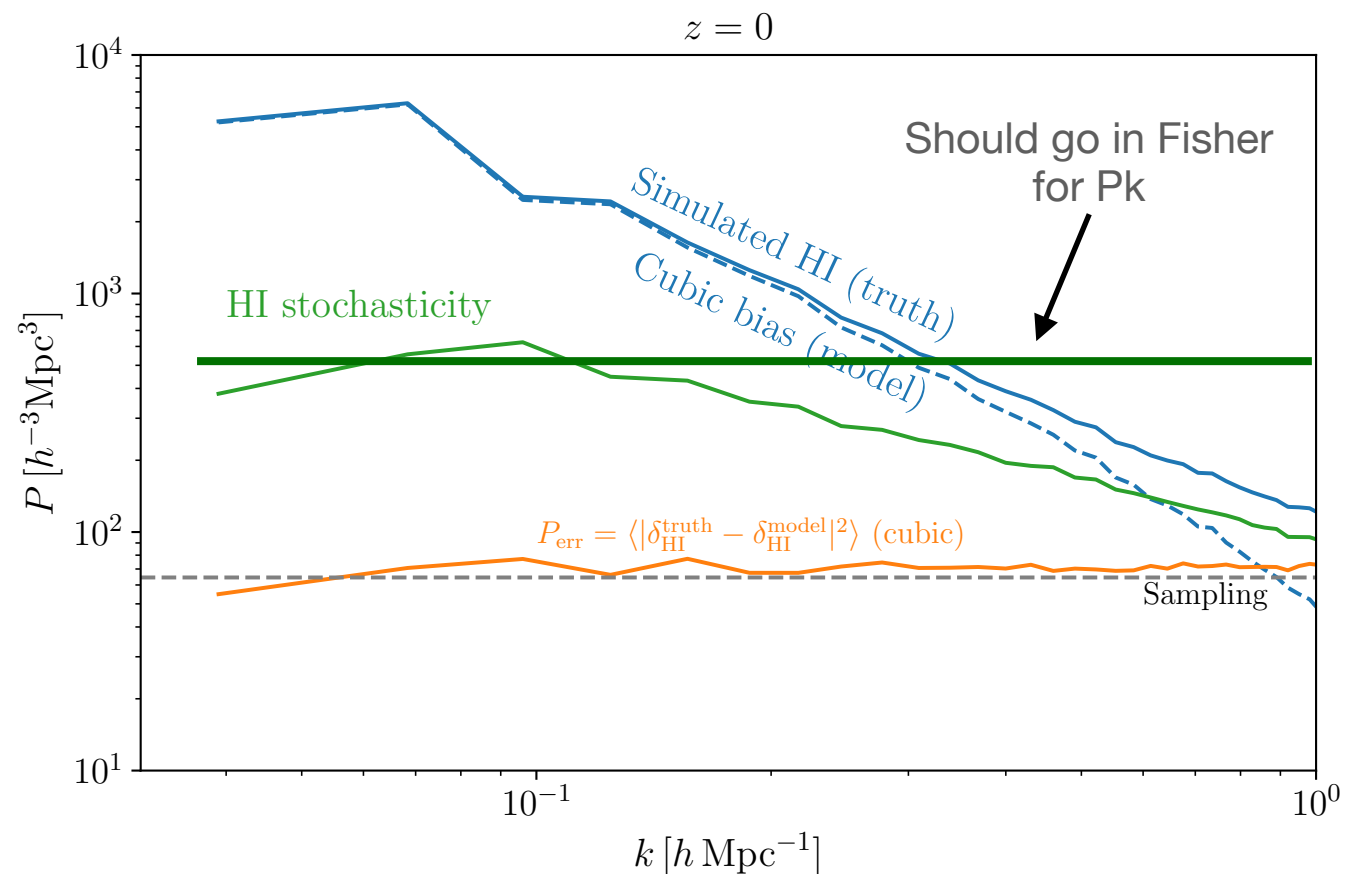
HI noise properties

- HI stochasticity: $\langle |\delta_{\text{HI}}^{\text{truth}} - b_1 \delta_{\text{m}}|^2 \rangle$

- Two contributions:

$$\delta_{\text{HI}}(\mathbf{k}) - \beta_1 \tilde{\delta}_1(\mathbf{k}) = \beta_2 \tilde{\delta}_2^\perp(\mathbf{k}) + \beta_{\mathcal{G}_2} \tilde{\mathcal{G}}_2^\perp(\mathbf{k}) + \dots + \epsilon$$

- In contrast to galaxies, higher order terms dominate sampling noise for HI
- Degenerate with sampling noise
- Fisher forecasts for Pk typically assume sampling noise (optimistic)
- Field-level may do better, even on linear scales!
- Improvement proportional to $|b_2|$

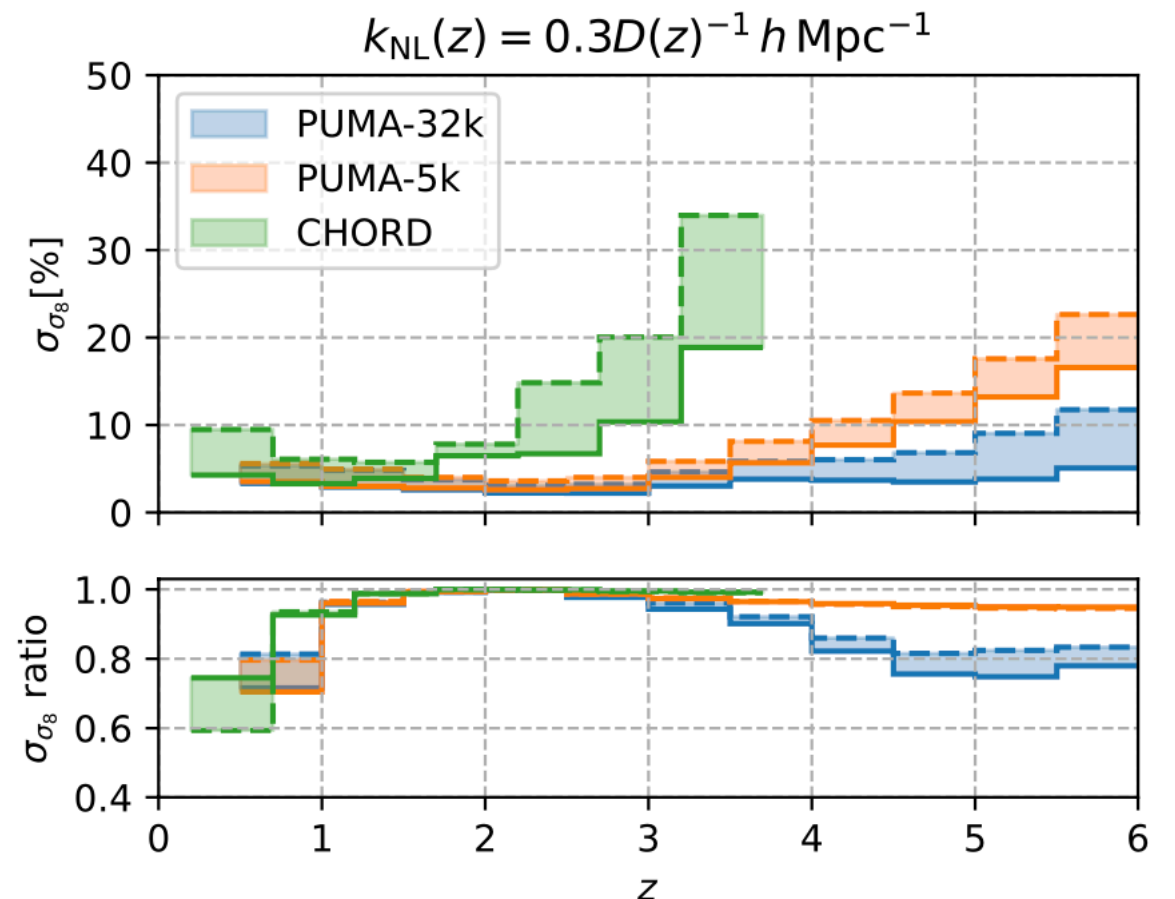
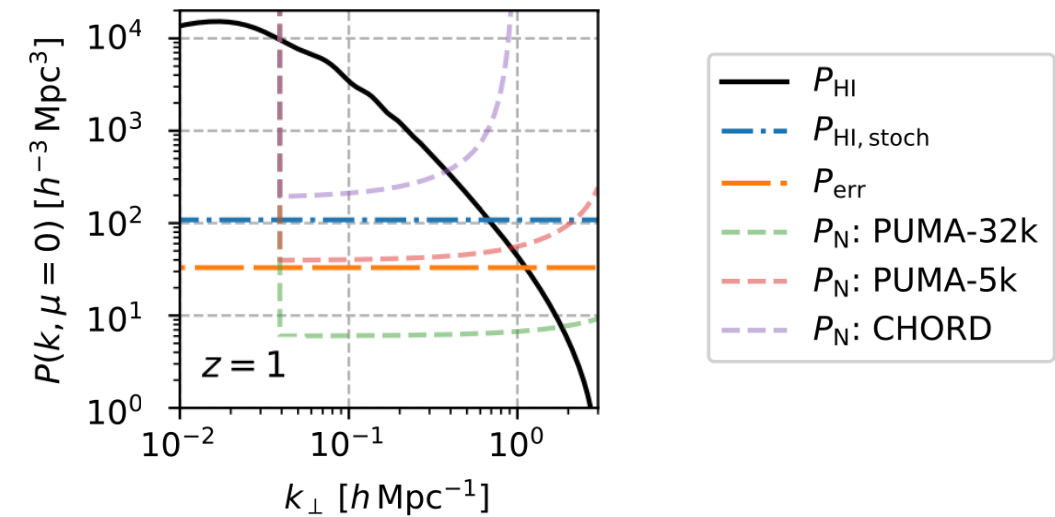


Field-level vs Pk

How big is the improvement?

w/ S. Foreman & M. Simonović 2405.18559

- Fisher forecasts with (un)realistic noise levels
- Two forecast sets:
 1. remove $\langle \delta^2 \delta^2 \rangle$ from covariance
 2. keep it in the covariance
- Mimic FL vs Pk analysis on large scales
- **~20%** improvement on cosmological parameters given **current** thermal noise

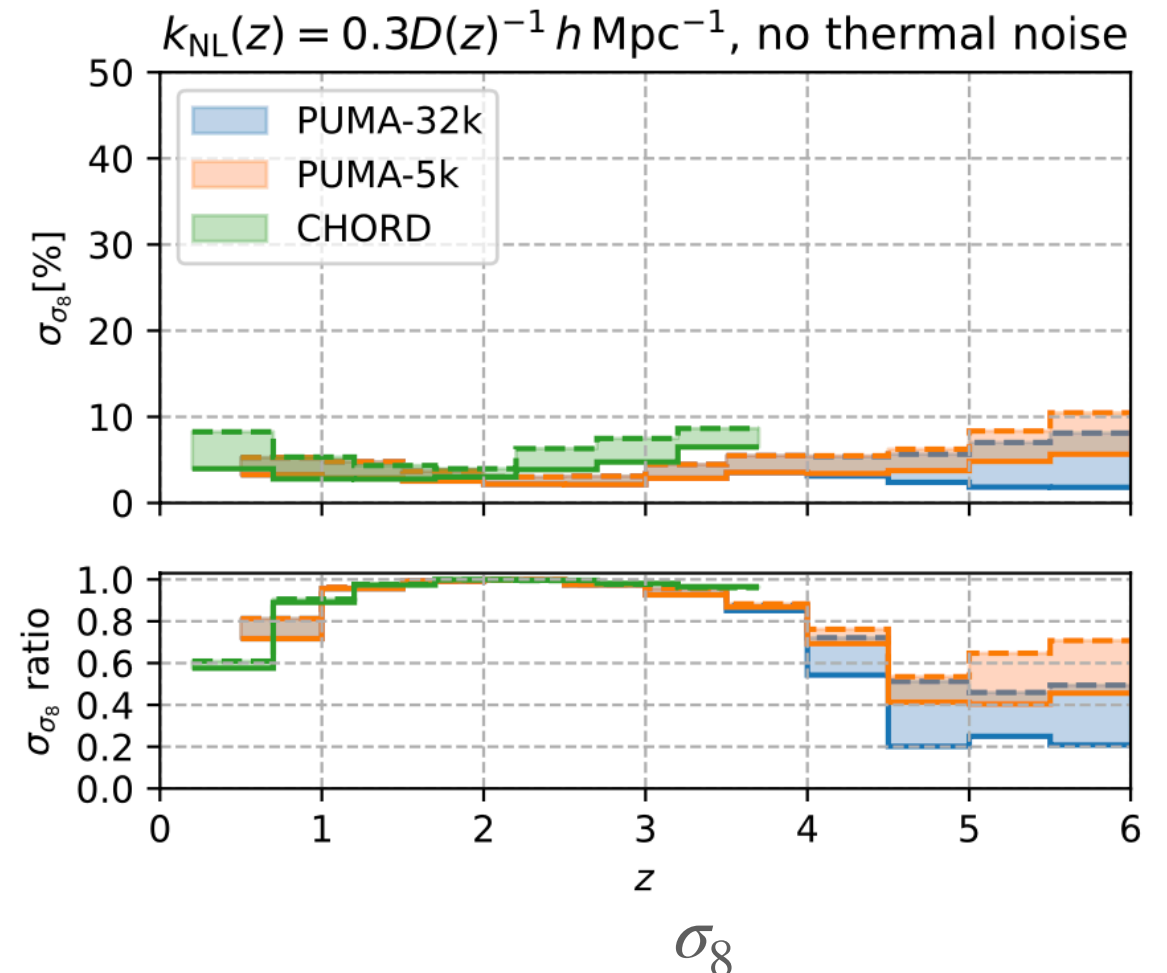
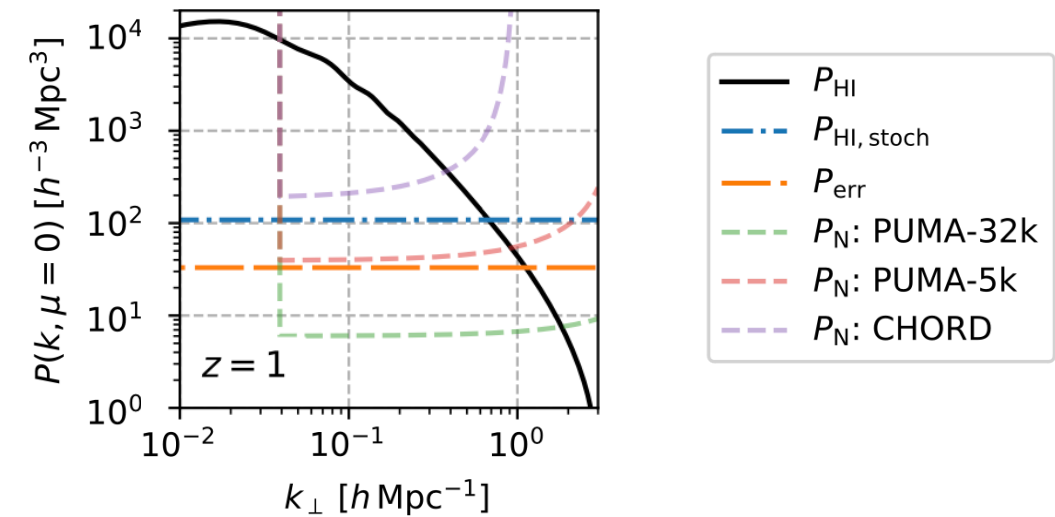


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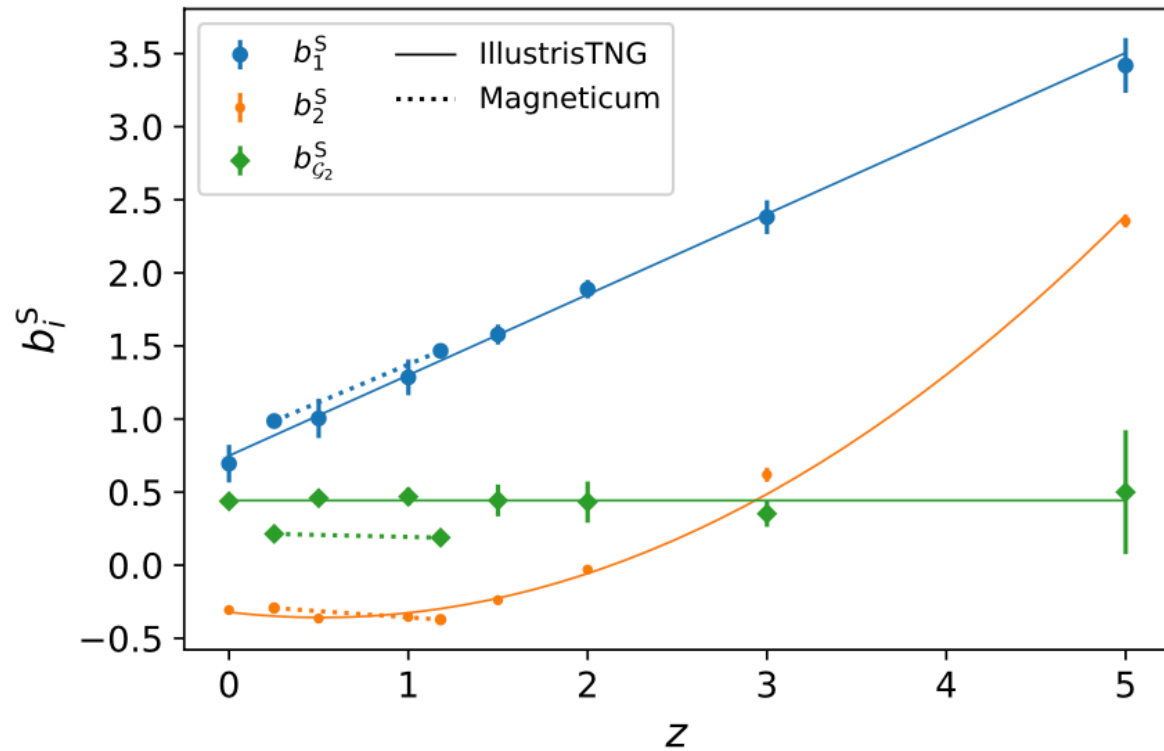
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- Two forecast sets:
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- **~50%** improvement on cosmological parameters given **no thermal** noise



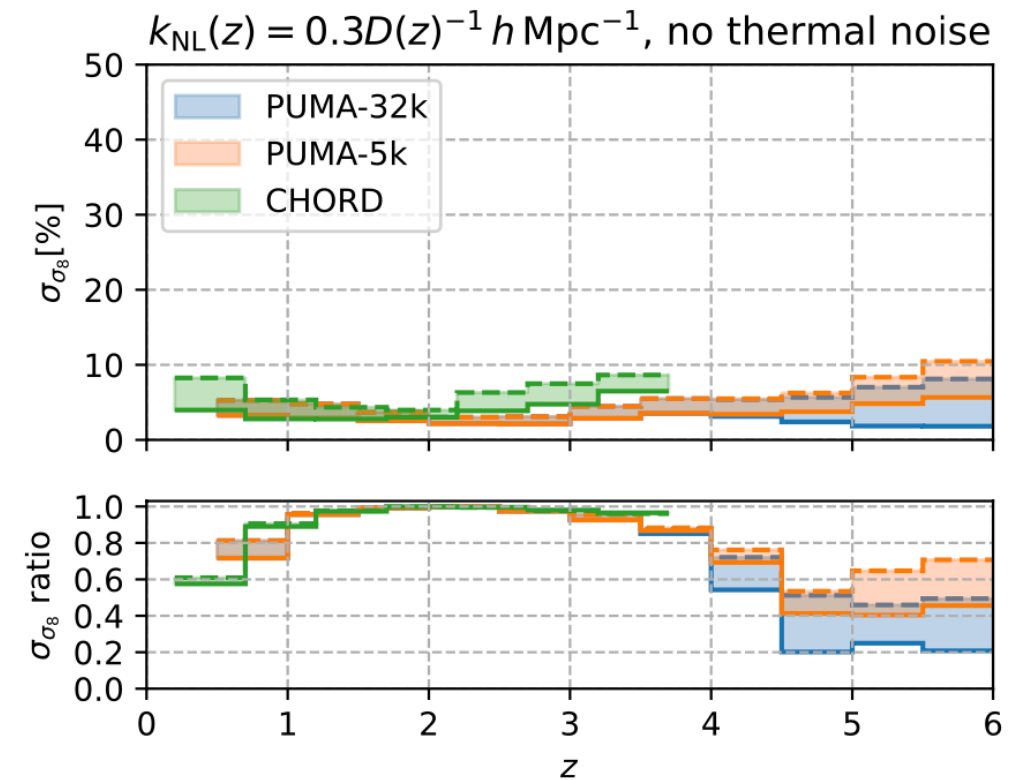
Field-level vs Pk

How big is the improvement?

- No improvement when $b_2 = 0$



Constraints on σ_8



Field-level vs Pk

How big is the total improvement?

‘Planned’ thermal noise levels ~20%

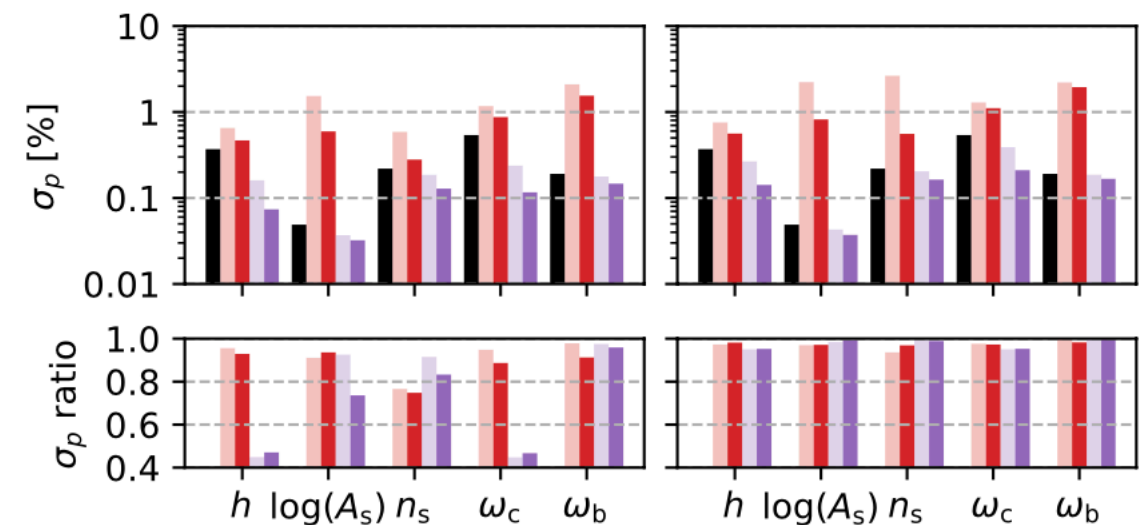
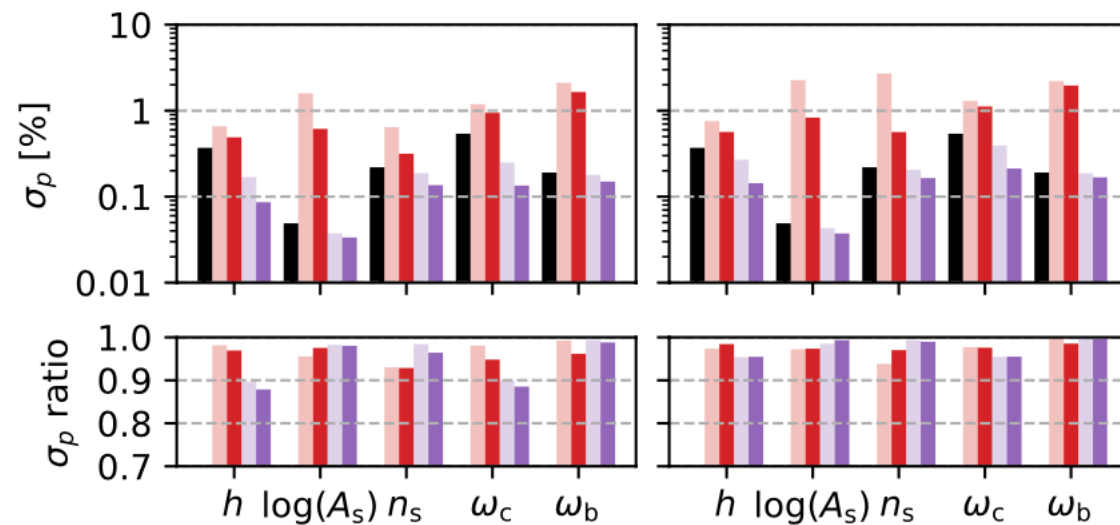
No thermal noise ~50%

$$k_{\text{NL}}(z) = 0.3D(z)^{-1} h \text{ Mpc}^{-1} \quad k_{\text{NL}}(z) = 0.4h \text{ Mpc}^{-1}$$

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PUMA-32k

PUMA-32k, no thermal noise



HI bias & stochasticity fitting functions

arXiv:2405.18559

- HI biases:

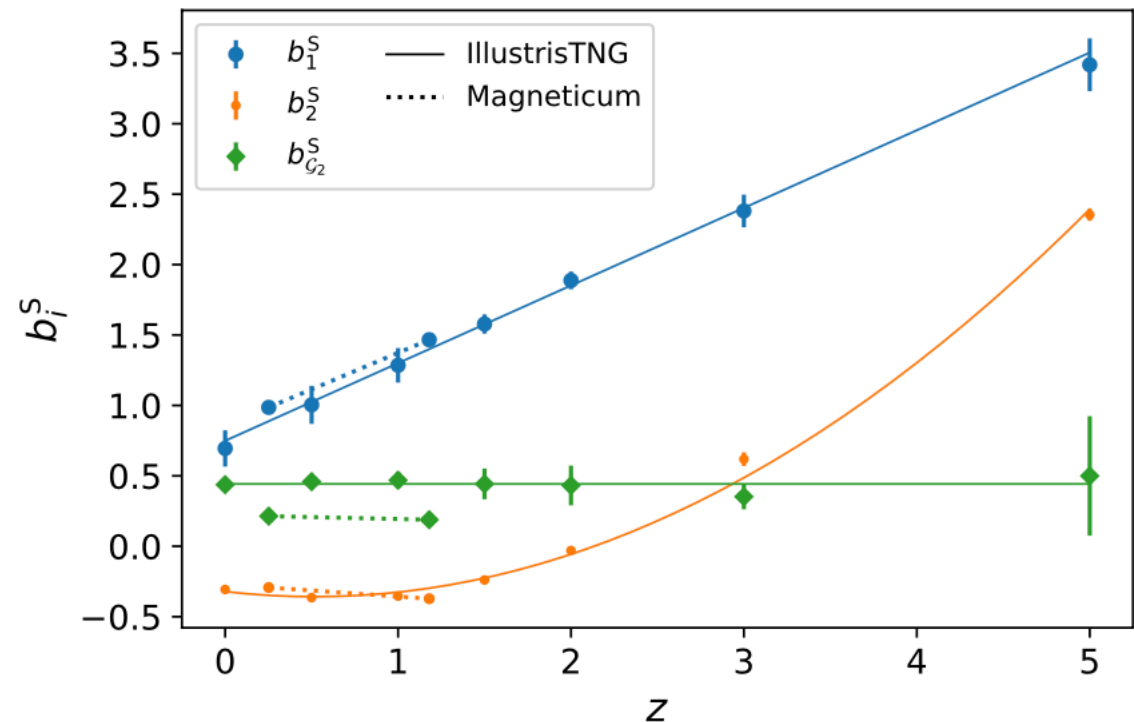
$$b_1^E(z) = 0.75 + 0.55z,$$

$$b_2^E(z) = -0.64 - 0.28z + 0.28z^2,$$

$$b_{G_2}^E(z) = 0.23 - 0.16z,$$

- HI stochasticity:

$$P_{\text{stoch}}^{(k \rightarrow 0)}(z) = \begin{cases} 471 - 485z + 132z^2, & \text{if } z \leq 2 \\ -33 + 31z, & \text{if } 2 < z \leq 5 \end{cases}$$



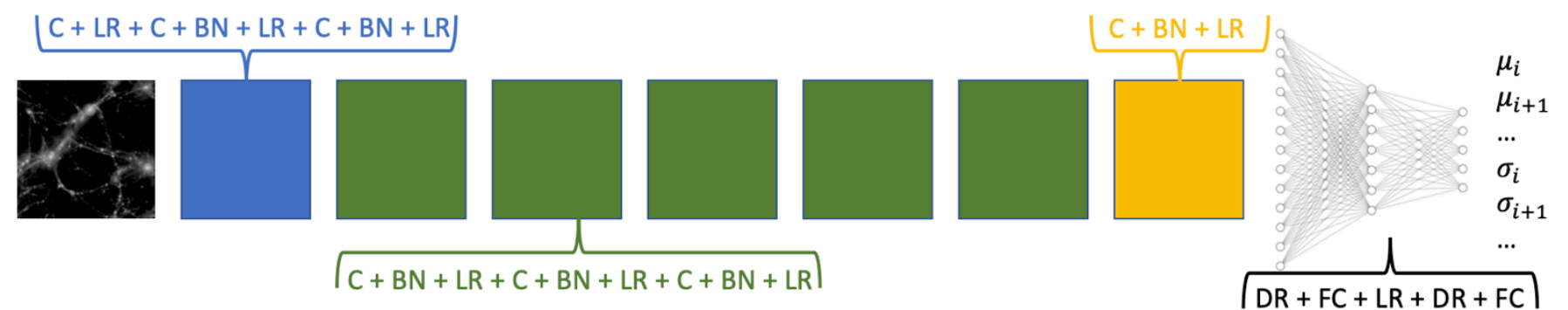
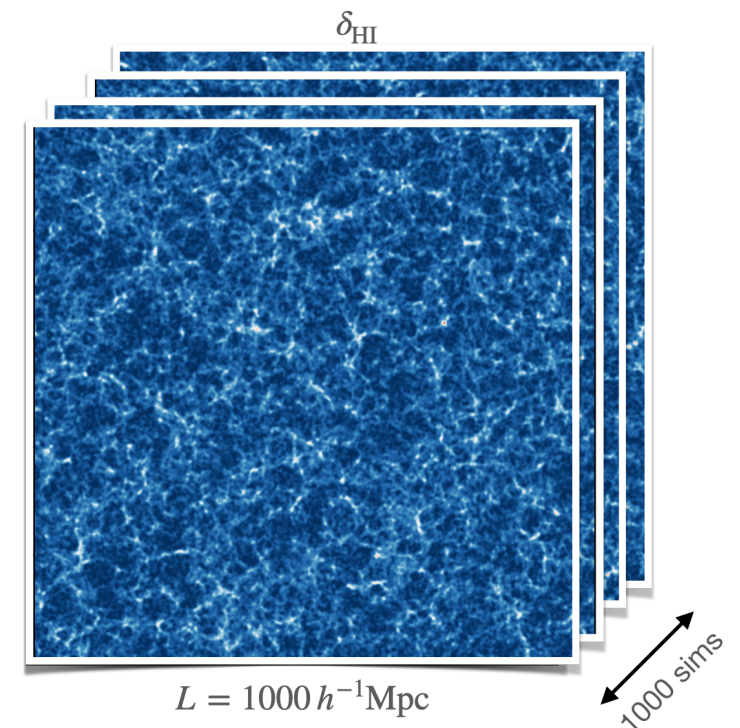
Some messages

- Clear motivation to go beyond P_k , even on large scales
- Large gains from future surveys with more optimal data analysis
- For current surveys gains small due to large thermal noise...
- HI sampling noise is ideal thermal noise target, not stochasticity
- Our estimates conservative, field-level analysis will do better

HI field-level inference with CNNs

w/ F. Villaescusa-Navarro in prep.

- Likelihood-free inference using ML on large boxes
- Train convolutional neural networks on 1000 Hi-Fi mocks ($L=1\text{Gpc}/h$) following [2109.09747](https://arxiv.org/abs/2109.09747)
- Dataset of 24000 HI maps, varying: cosmology, biases & initial conditions
- We test different scale cuts, different HI simulations and other redshifts
- We compare to P_k analysis

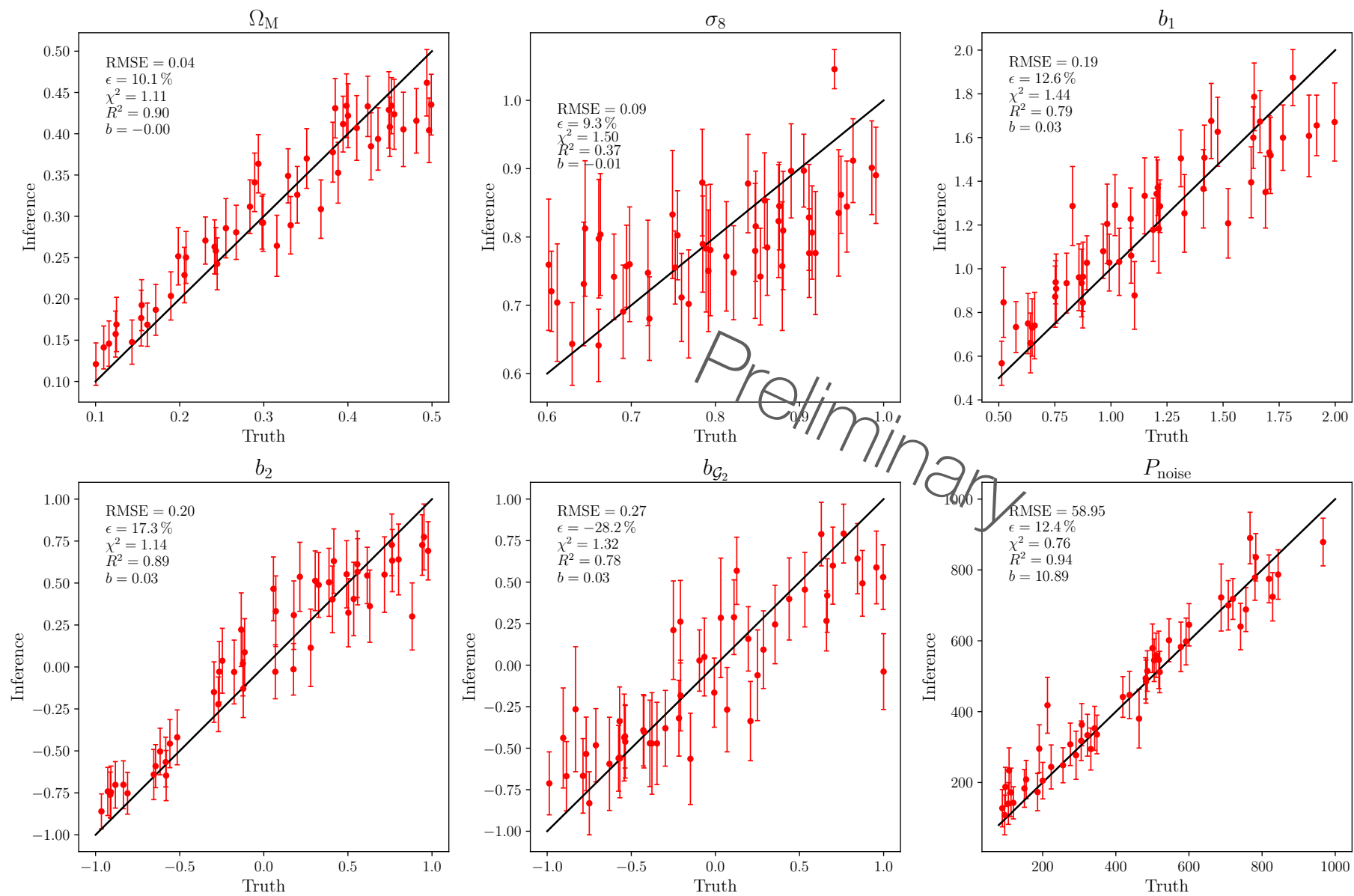


C = Convolutional layer
 BN = Batchnorm layer
 LR = LeakyReLU activation layer
 DR = Dropout
 FC = Fully connected layer

HI field-level inference with CNNs

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Field-level

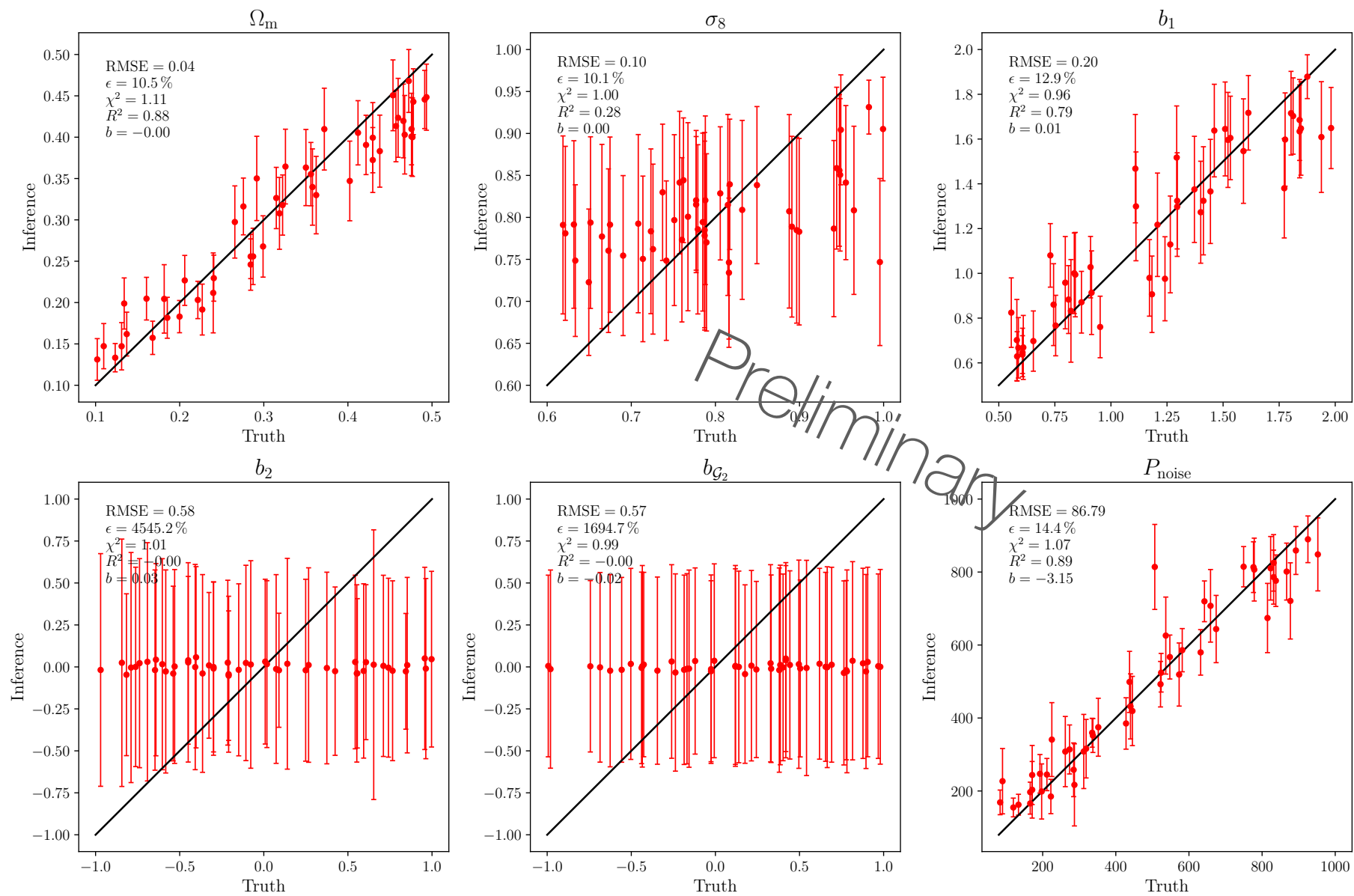


kmax=0.4 h/Mpc

HI field-level inference with CNNs

w/ F. Villaescusa-Navarro in prep.

Power spectrum



kmax=0.4 h/Mpc

Conclusions

- HI dense tracer with very low sampling (shot) noise
- HI clustering well captured by perturbation theory
- We provide code to generate fast HI mocks (Hi-Fi mocks)
- For dense tracers like HI, power spectrum is suboptimal
- Field-level analysis breaks these degeneracies and provides better constraints on cosmology even on large scales!
- For ideal instruments, the improvement can be at least 50%