Constraining Reionization Morphology and Source Properties with 21cm-Galaxy Cross-Correlation Surveys

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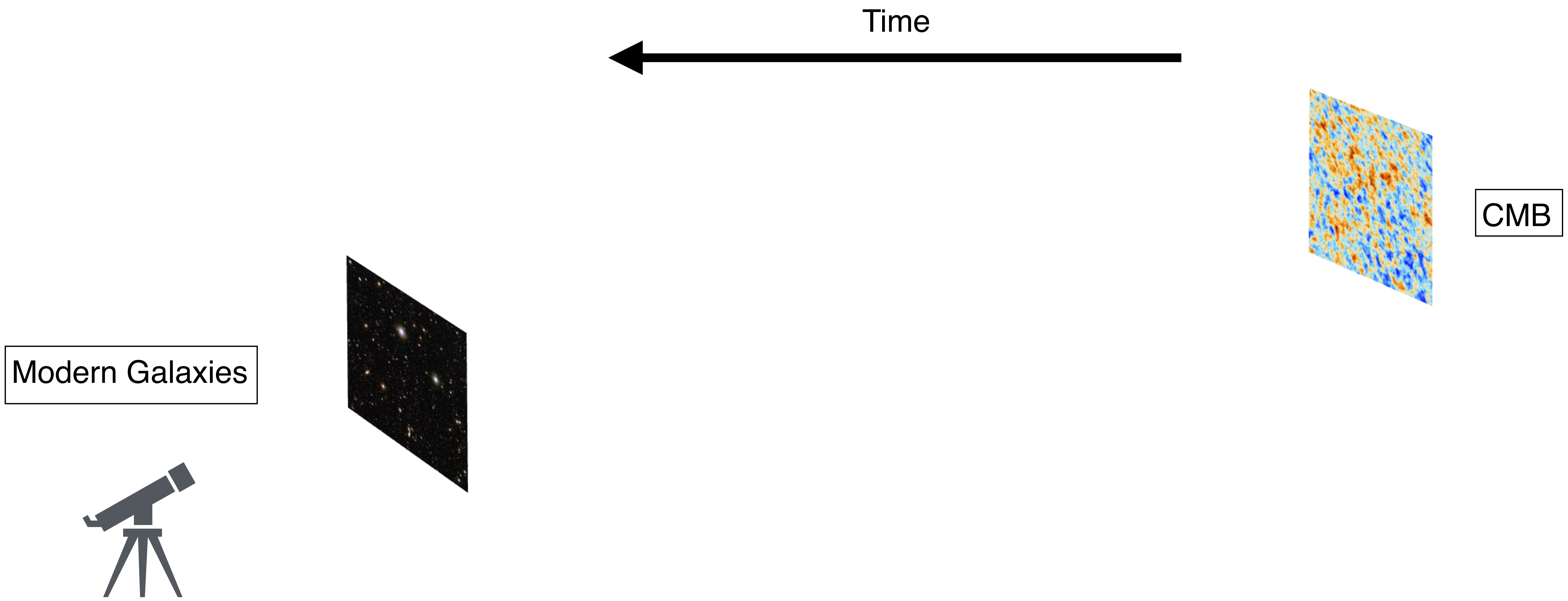
Main Collaborators: Dr. Anne Hutter, Dr. Caroline Heneka

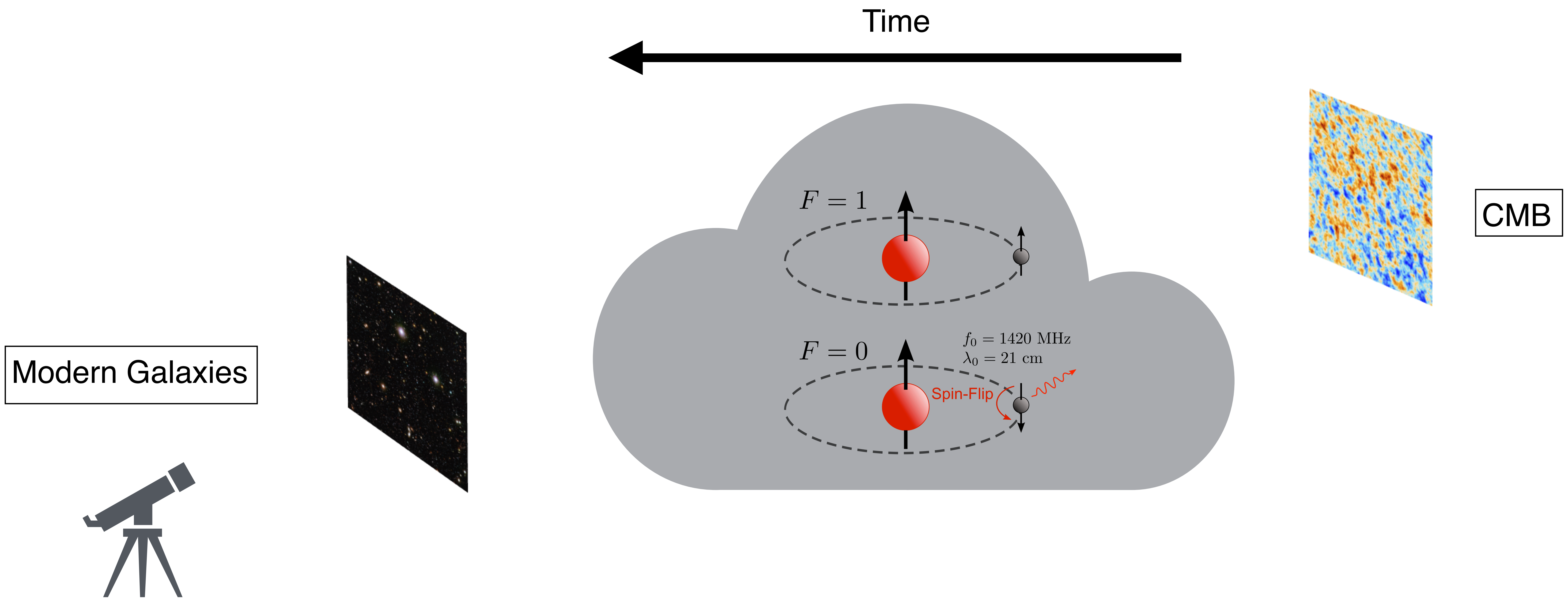
Cosmology in the Alps
18.03.2026

Image Credit: DALL·E 3

21cm-Galaxy Synergies

Introduction

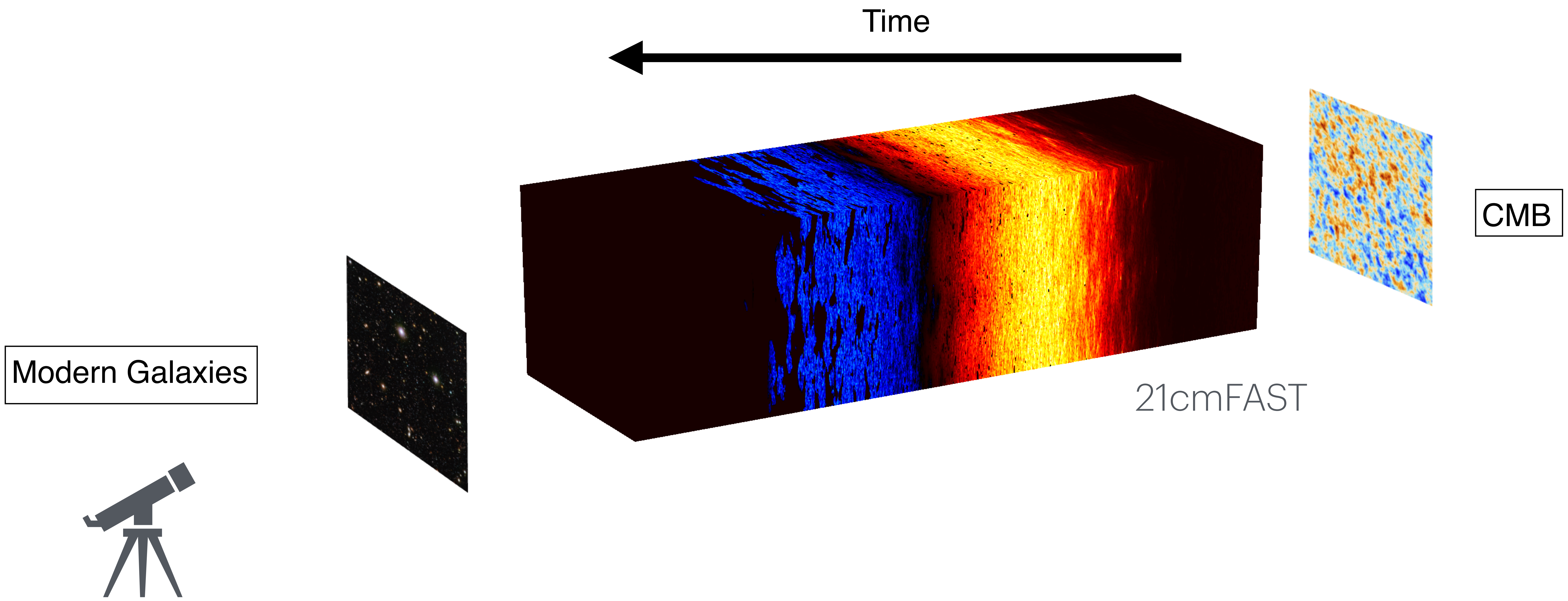




Time
Modern Galaxies
$F = 1$
$F = 0$
$f_0 = 1420$ MHz
$\lambda_0 = 21$ cm
Spin-Flip
CMB

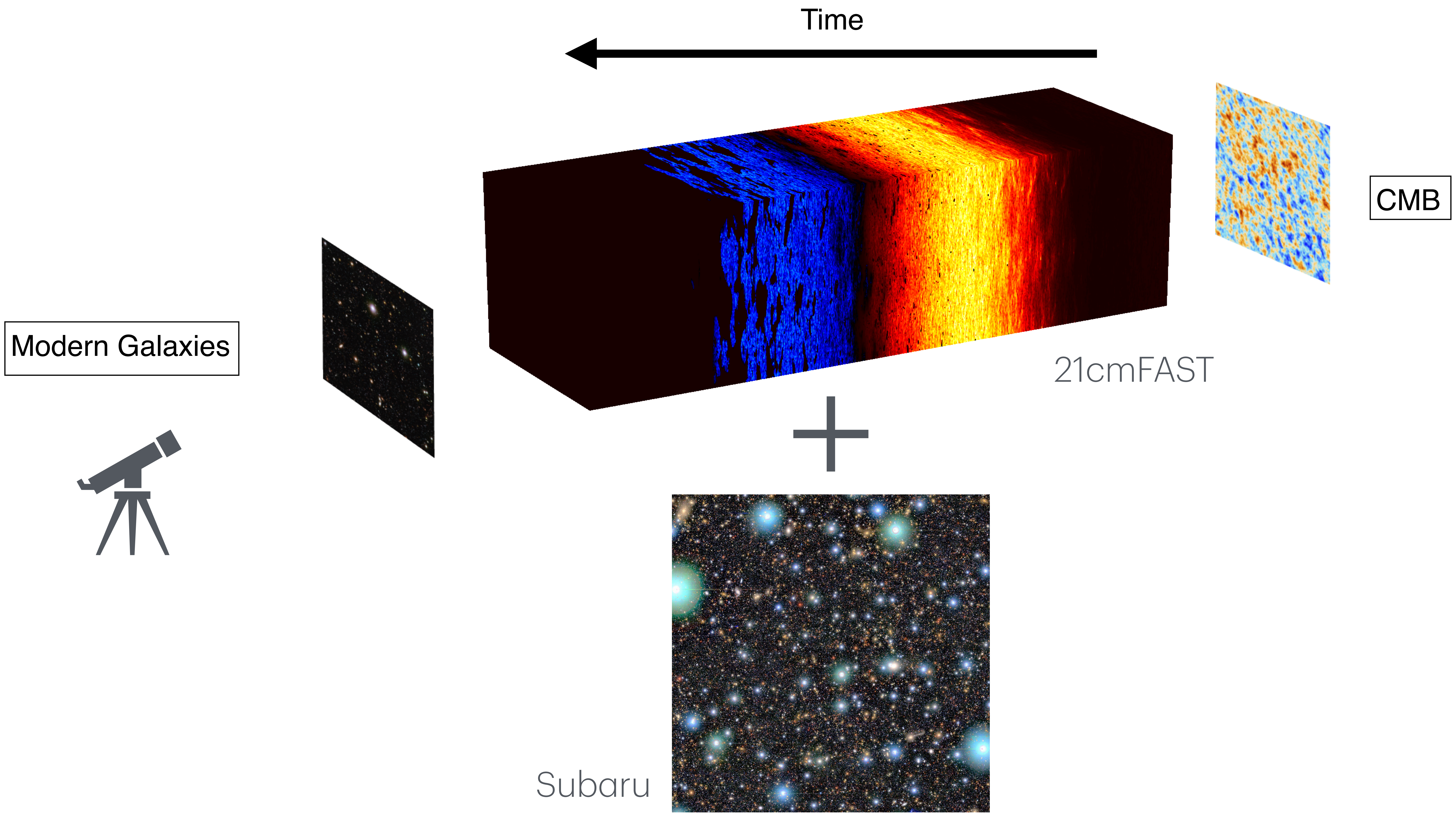
21cm-Galaxy Synergies

Introduction



21cm-Galaxy Synergies

Introduction



21cm-Galaxy Synergies

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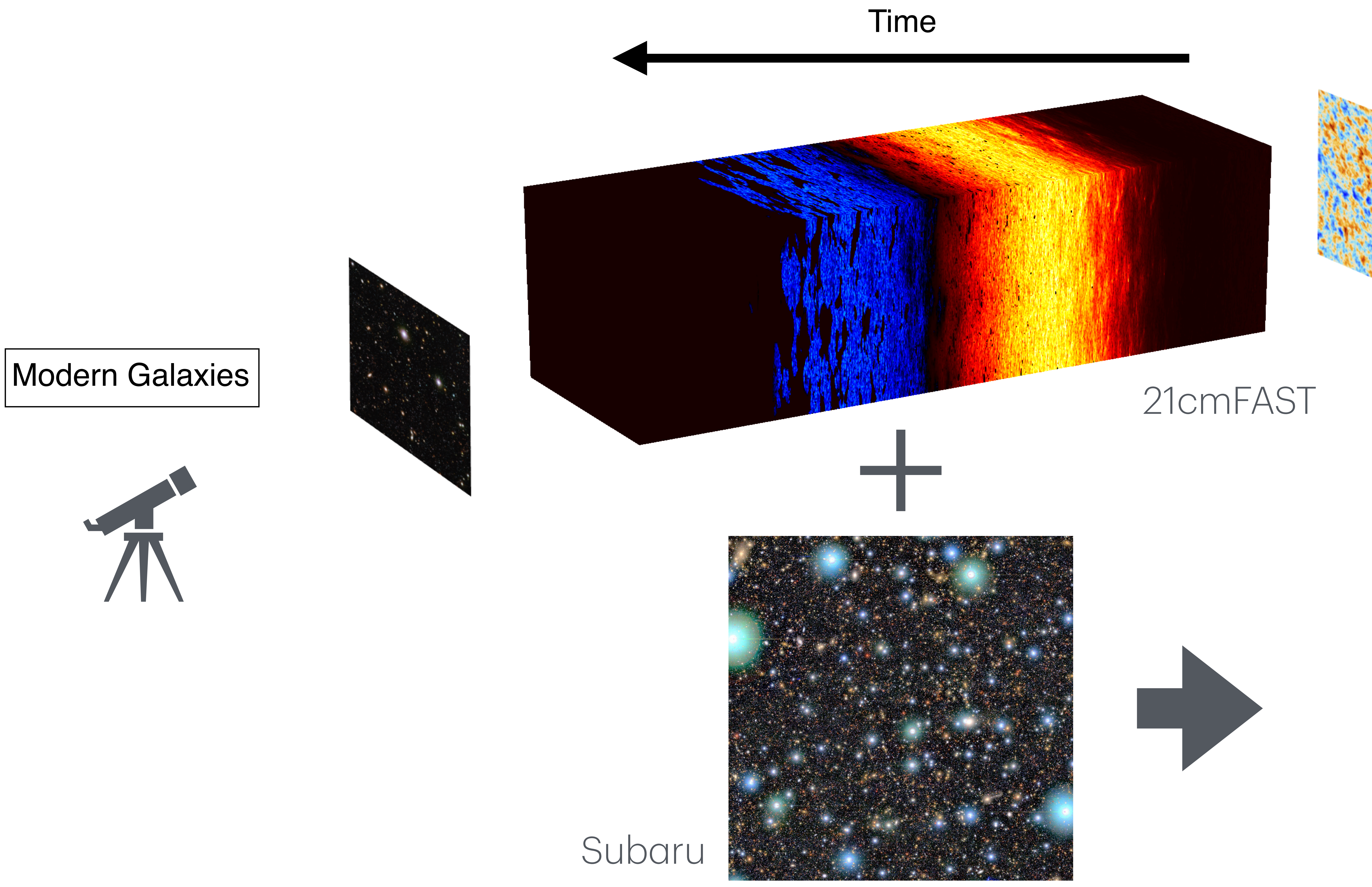
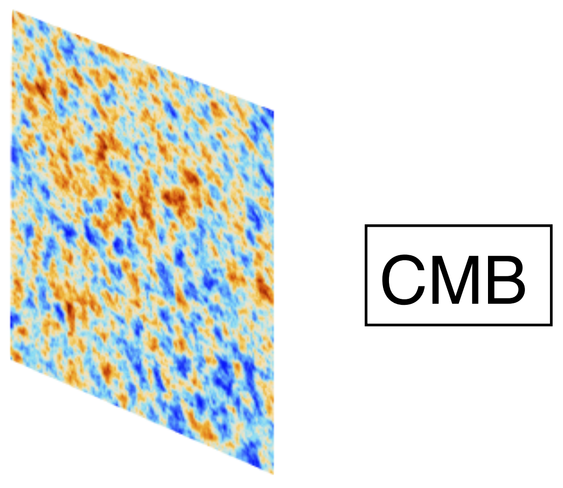




What do we learn by adding cross correlations?

- tighter constraints on global reionization parameters?

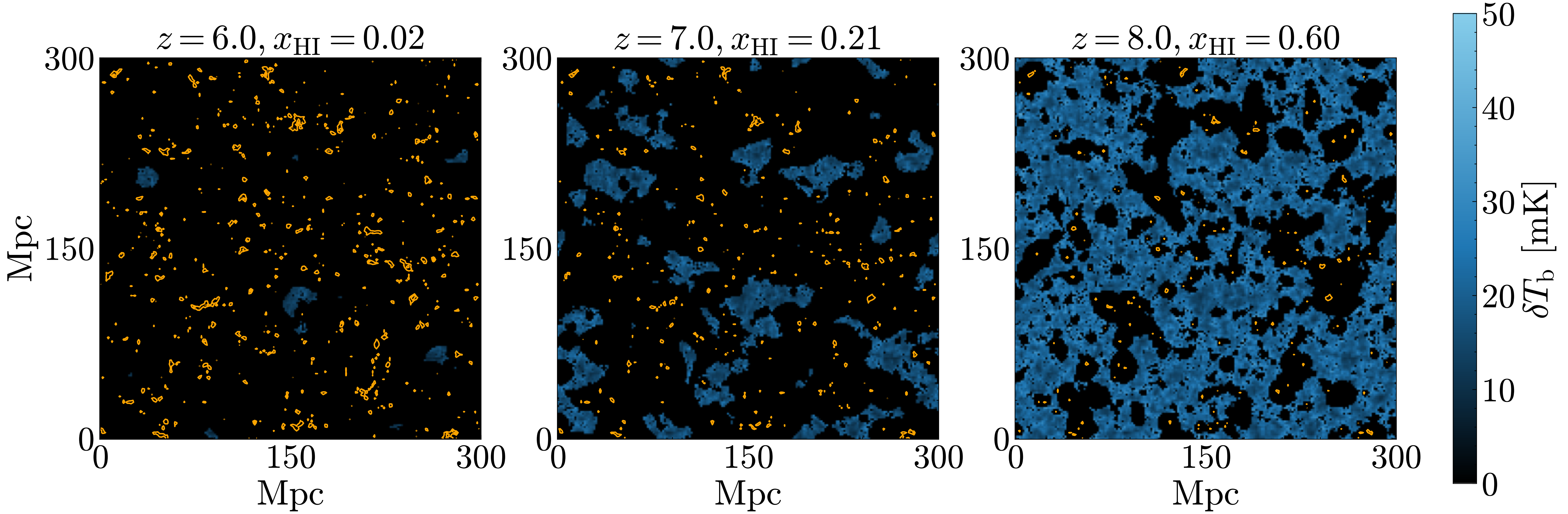
$$\{x_{\mathrm{HI}}, \langle 1 + \delta_{\mathrm{HI}} \rangle\}$$

- source properties?

$$\{f_{*,10}, f_{\mathrm{esc},10}, \alpha_*, \alpha_{\mathrm{esc}}\}$$

21cm-Galaxy Synergies

Forward model

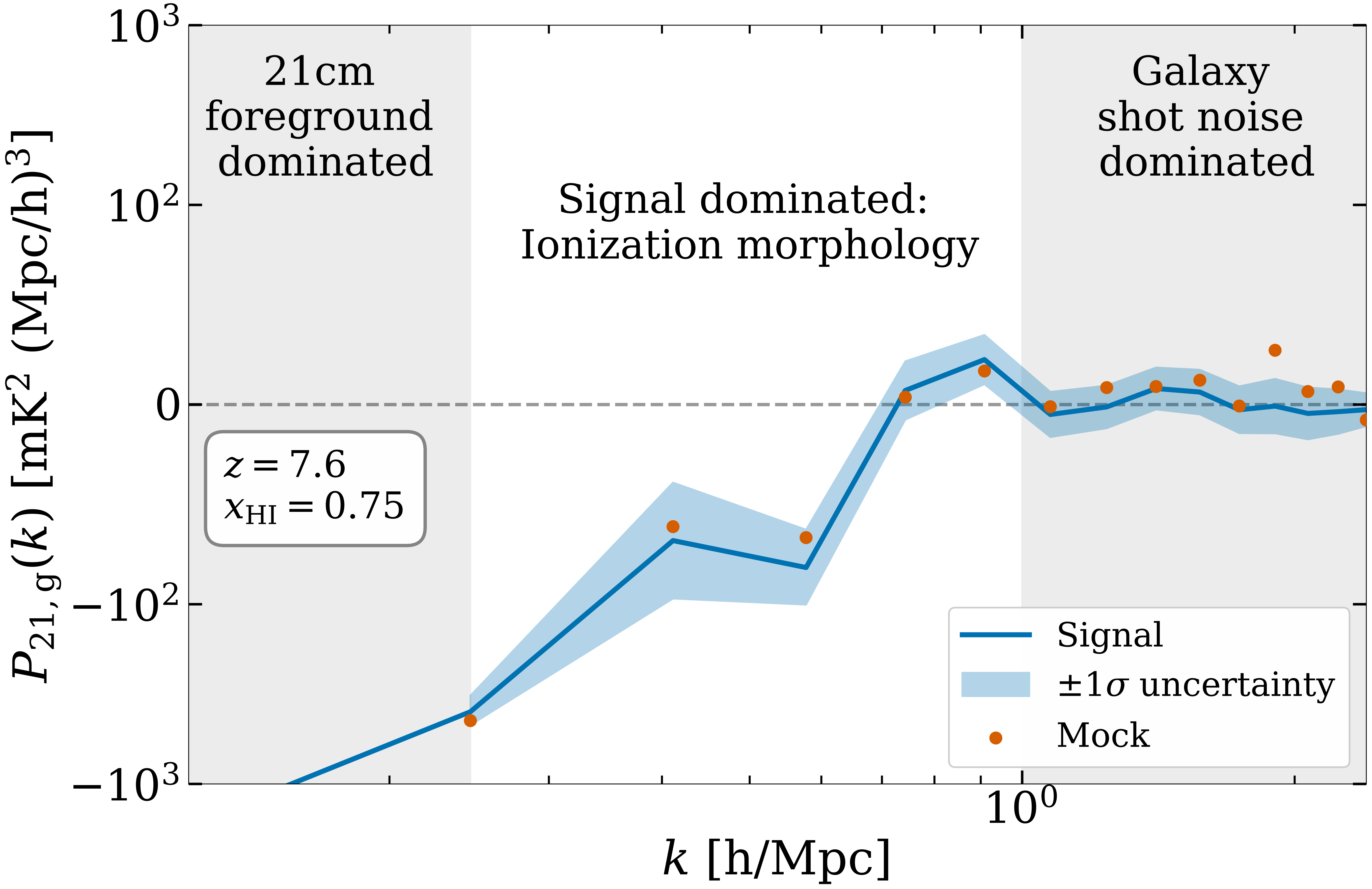


→ consistent simulation of halo and 21cm fields (`21cmFASTv4`)

→ varying random seed and $\{f_{*,10}, f_{\rm esc,10}, \alpha_*, \alpha_{\rm esc}\}$

21cm-Galaxy Synergies

Forward model



Model based on Hutter & Heneka 2025

- 21cm: 100h SKA-Low AA*
- foreground avoidance
- Survey geometry, redshift precision
- Galaxy selection effects (halo mass)

$$(\mathrm{FOV}, \sigma_z, M_{\mathrm{h,min}})$$

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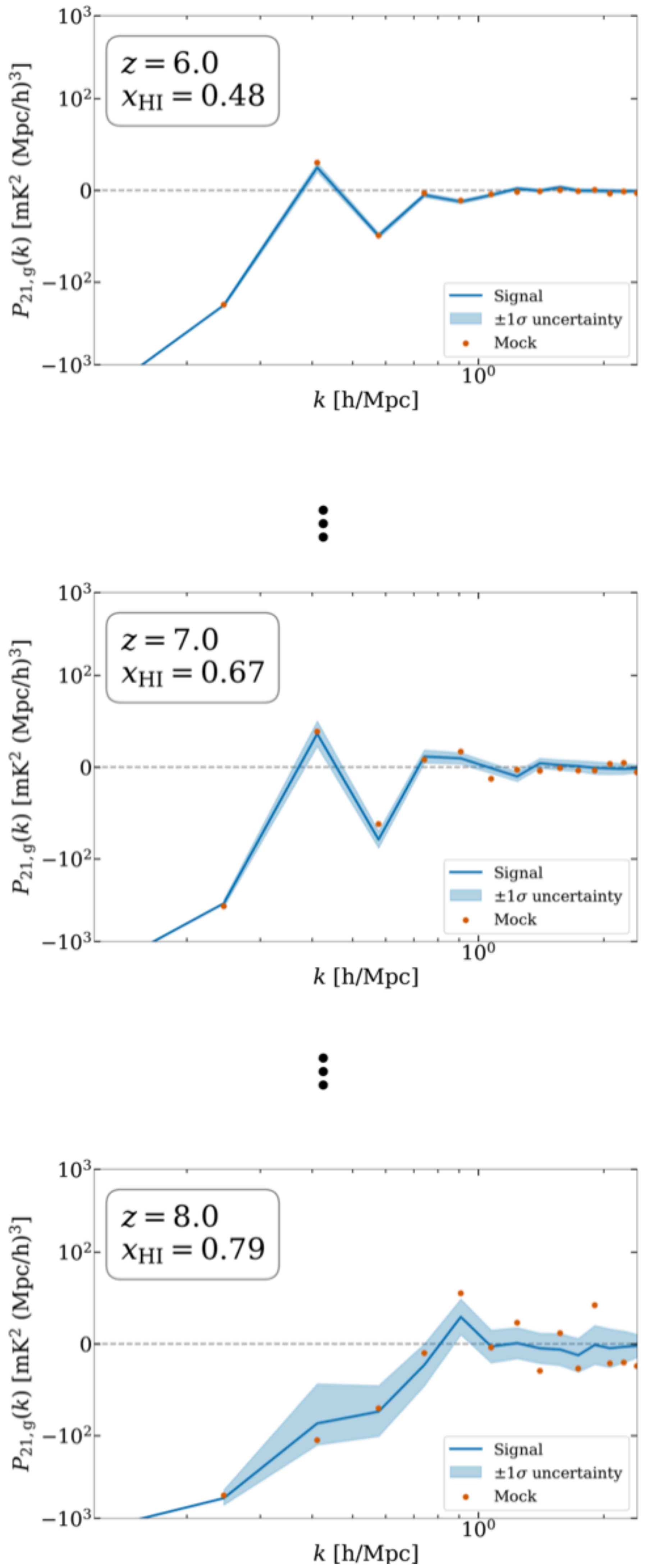
Simulation-based inference (SBI)

EoRFlow



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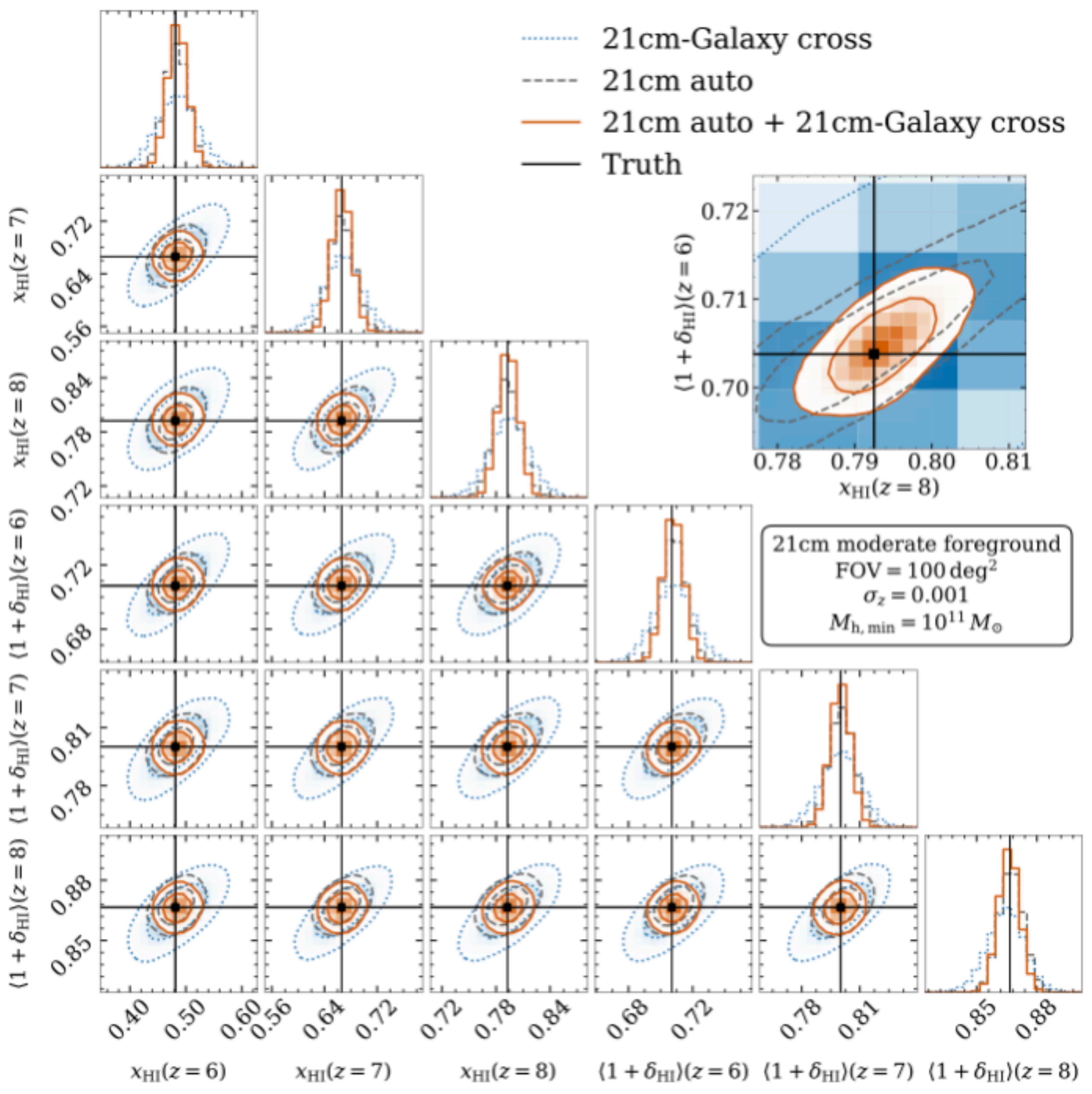

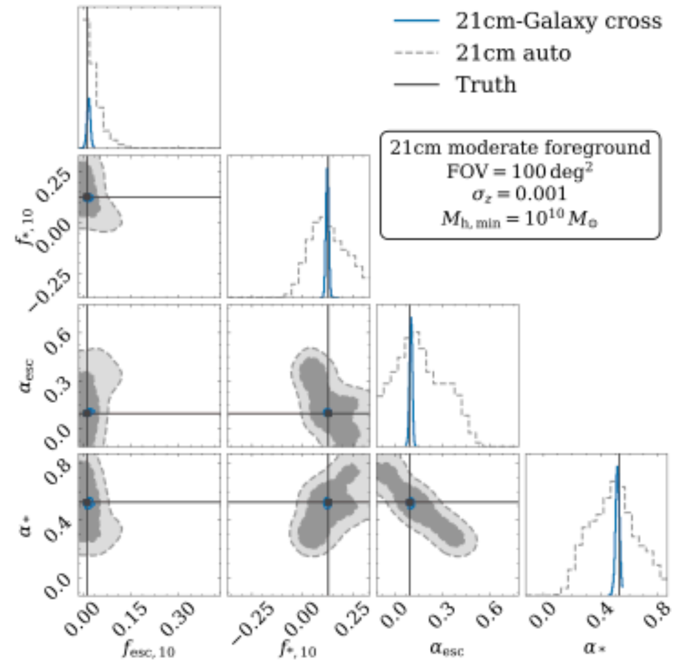

arXiv:2506.19925
JCAP10(2025)039

7 redshifts in z=[6,8]
Training set: ~9000
Test set: 1000

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Simulation-based inference (SBI)

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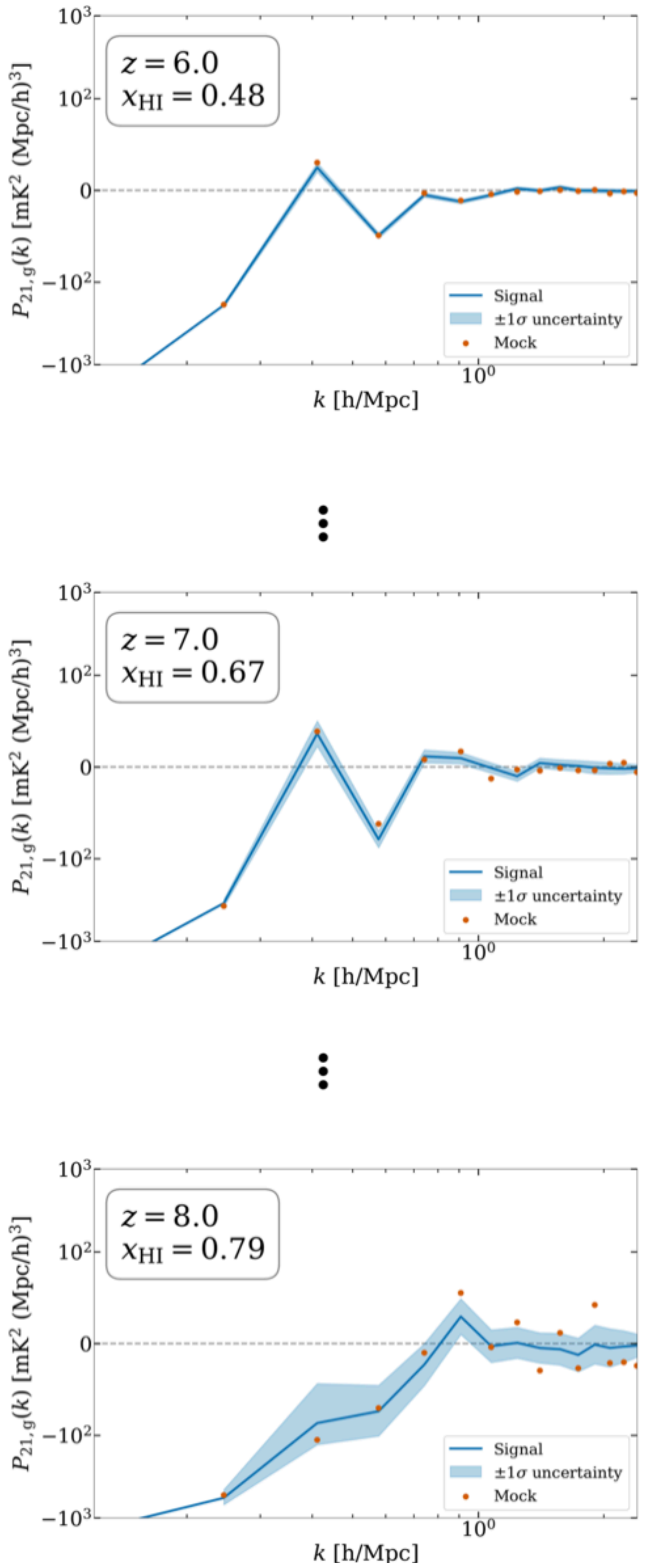
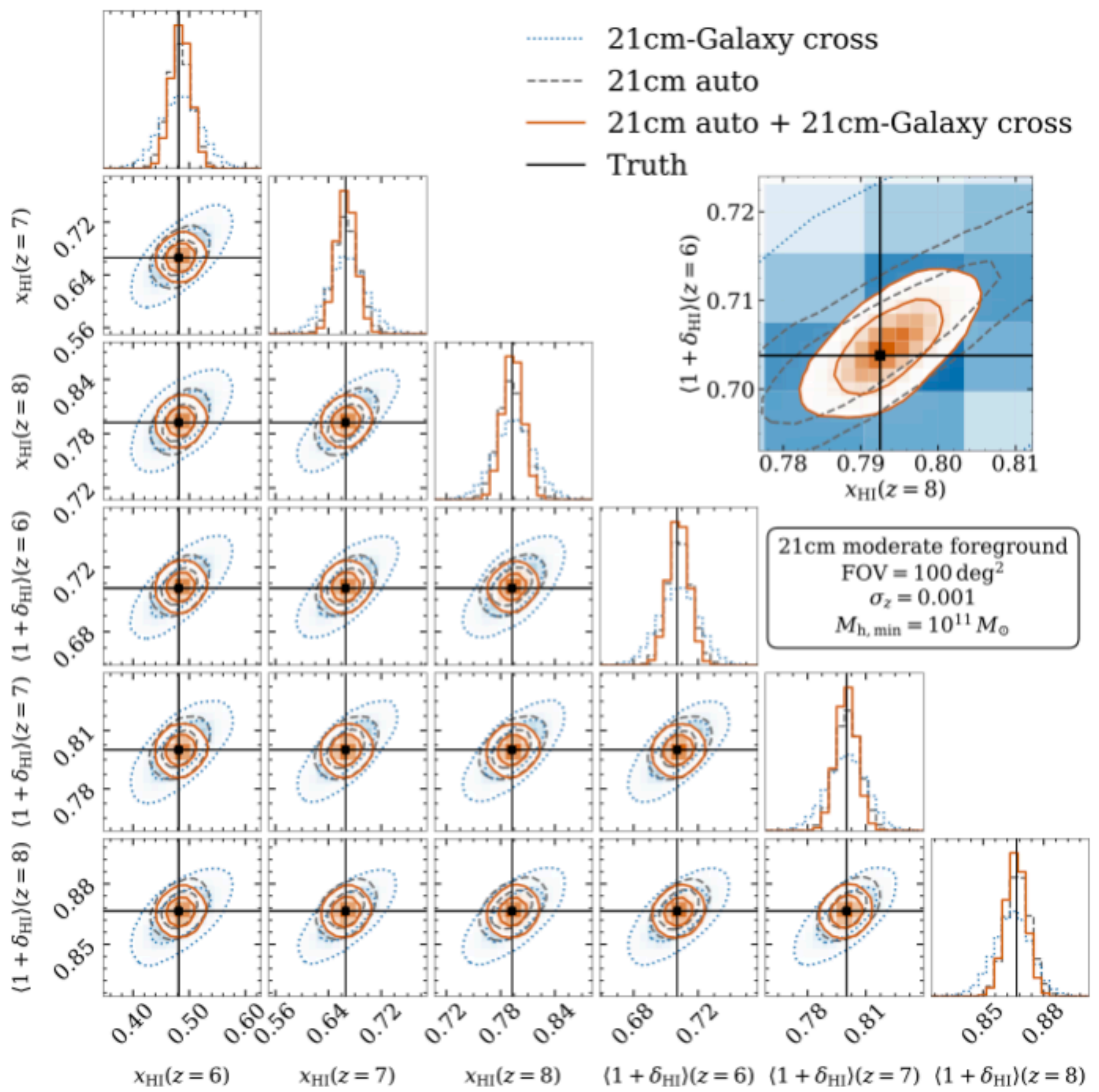
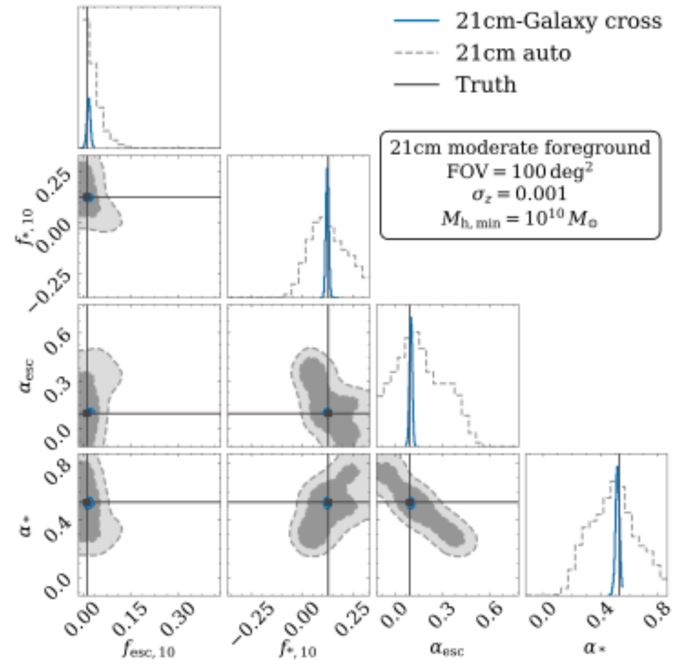


EoRFlow

1) $\{x_{\rm HI}, \langle 1+\delta_{\rm HI}\rangle\}$



2) $\{f_{*,10}, f_{\rm esc,10}, \alpha_*, \alpha_{\rm esc}\}$



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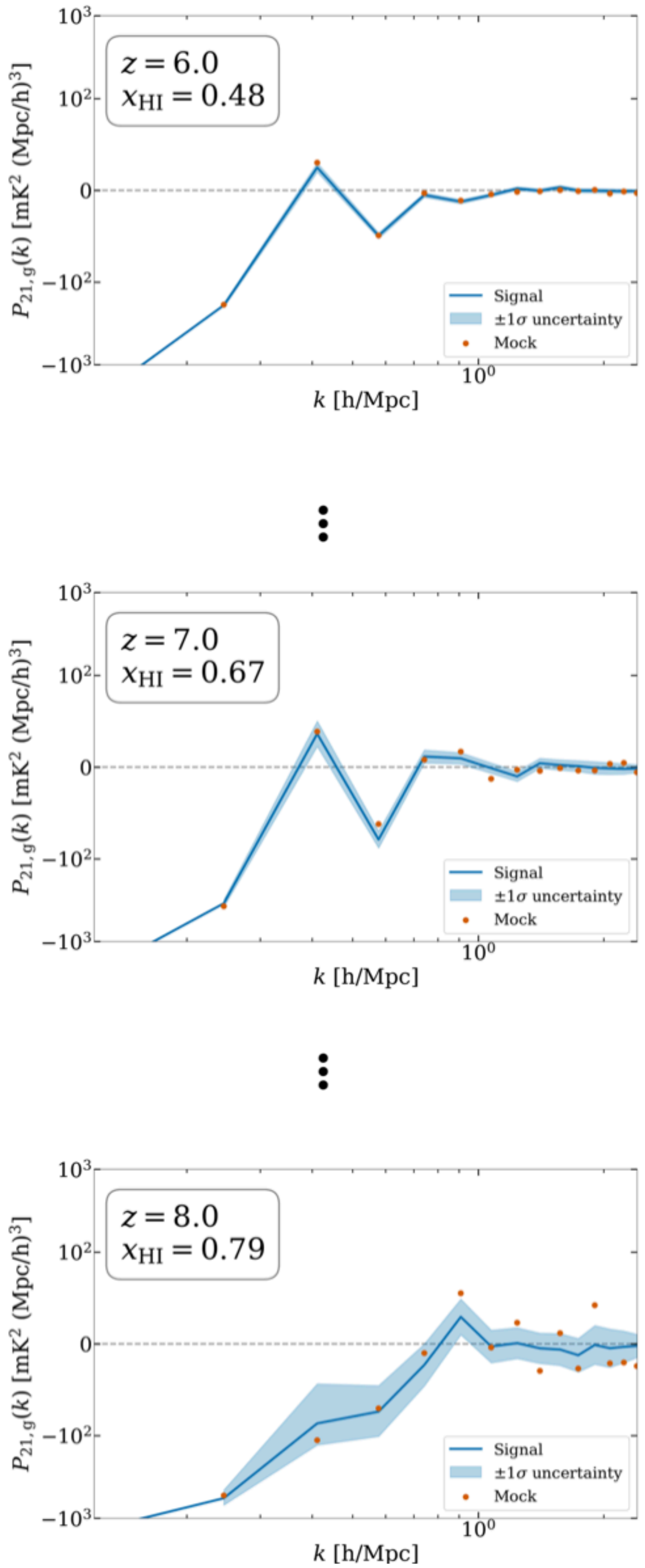

$$\boxed{1)\quad \{x_{\rm HI}, \langle 1+\delta_{\rm HI}\rangle\}}$$

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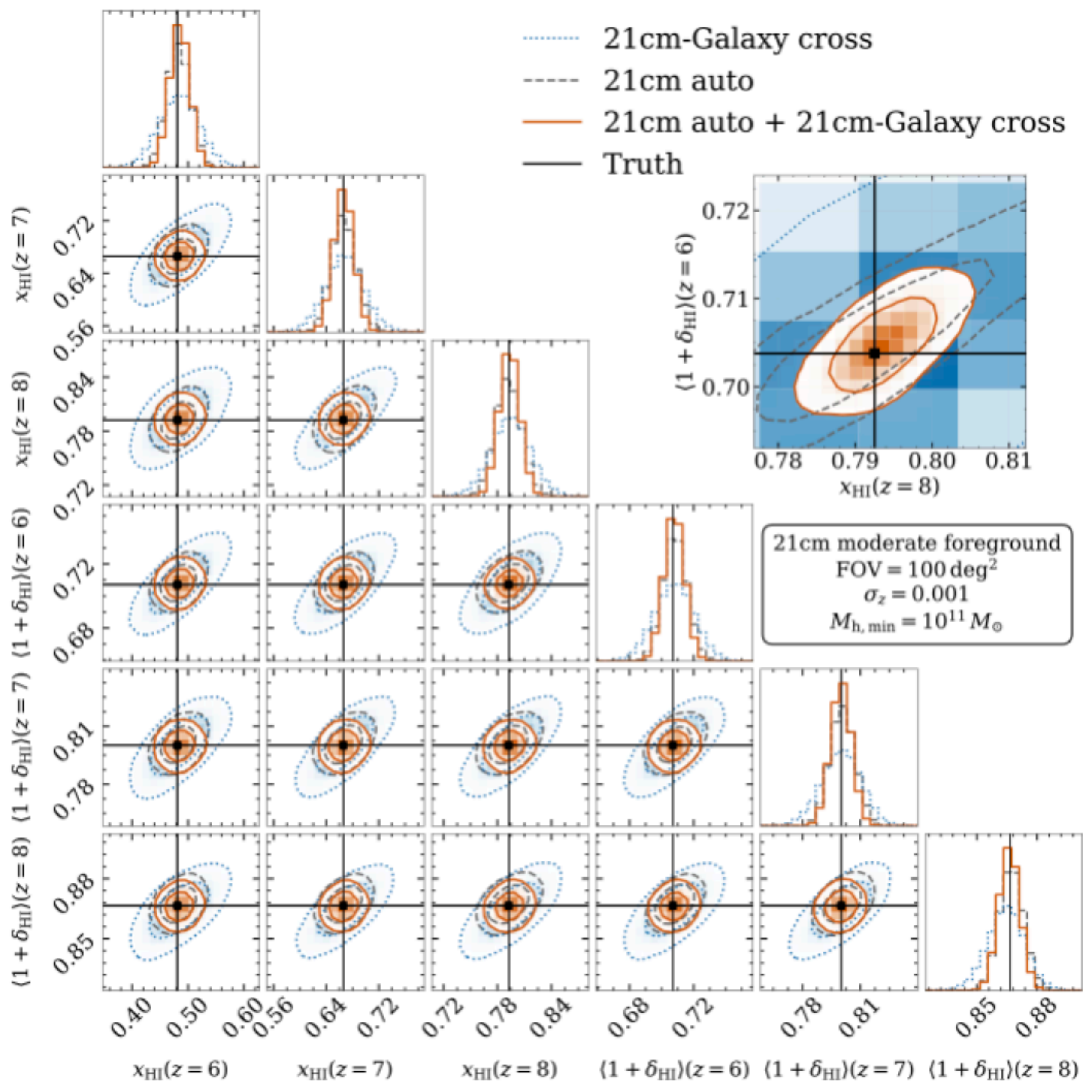

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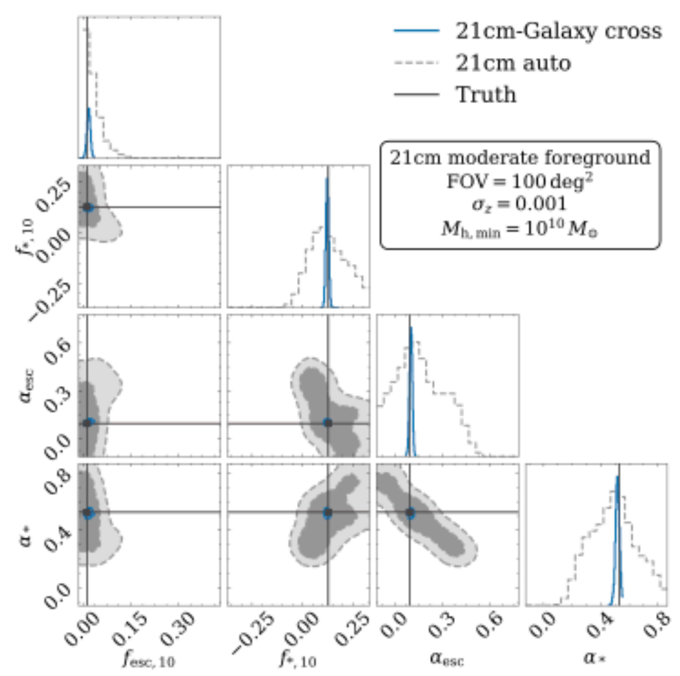

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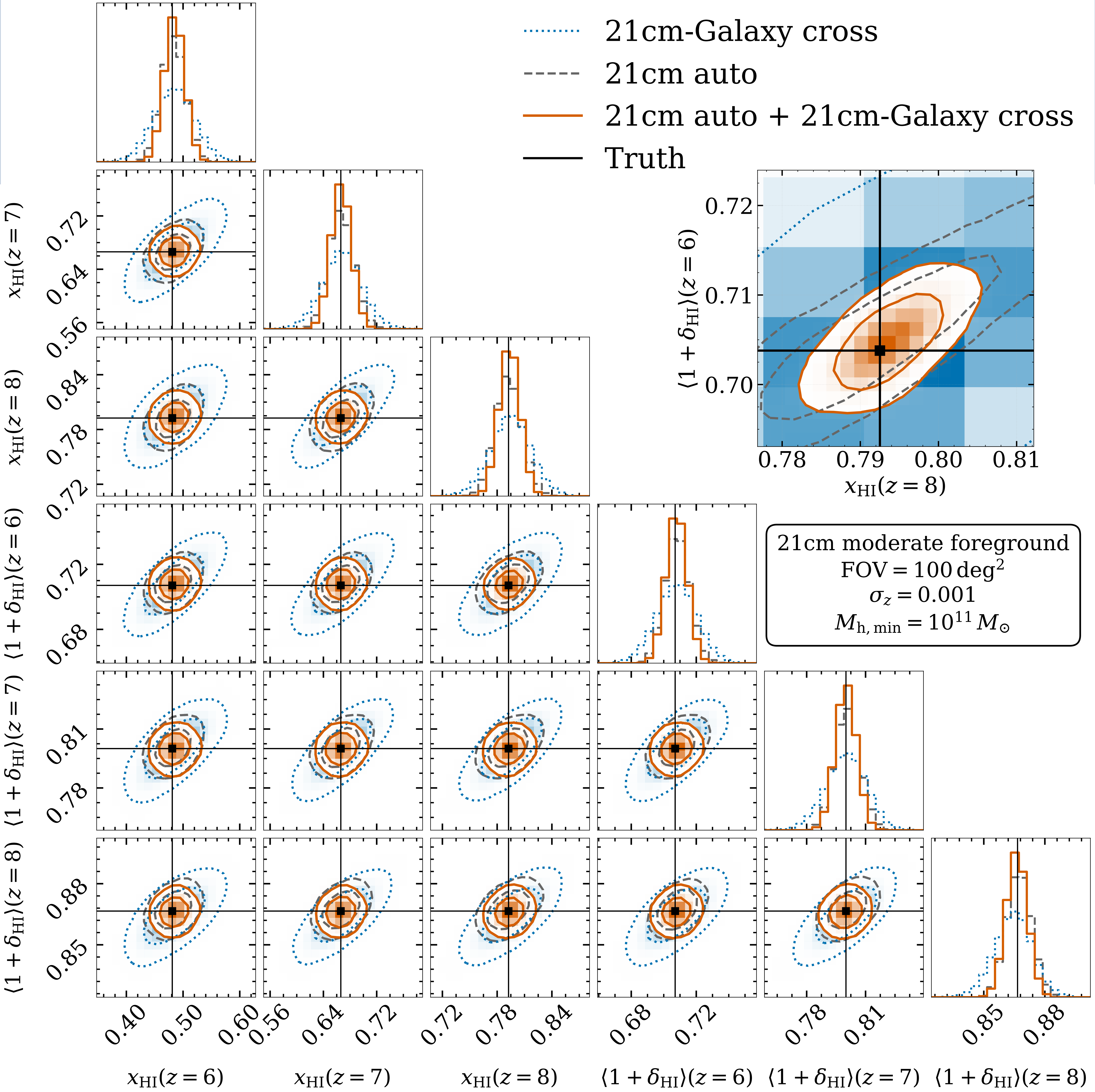
Inference

Global EoR properties



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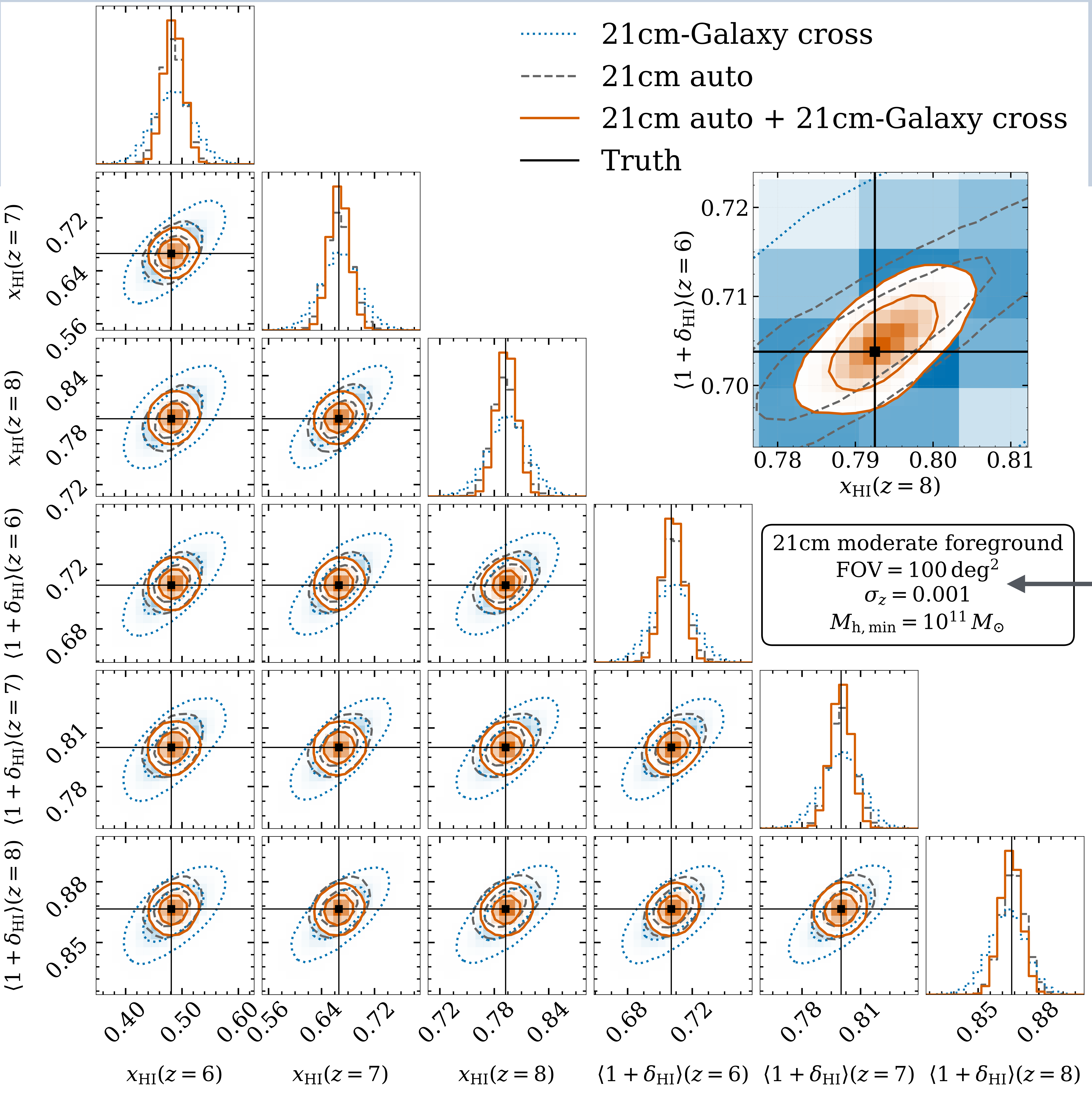

SKA x WST survey

$\left(L_{\mathrm{Ly}\alpha} \approx 10^{42.3} \mathrm{erg\ s^{-1}}\right)$

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Inference

Implications for observational programs

Pietschke et al. 2026

Inference

Implications for observational programs

$\left(L_{\mathrm{Ly}\alpha} \approx 10^{41},\ 10^{41.8},\ 10^{42.3}\ \mathrm{erg\,s^{-1}}\right)$

1. vary survey parameters

Parameter	**Values**
FOV[deg^2]	[5, 10, 100]
σ_z	[0.001, 0.01, 0.1]
$M_{\mathrm{h,min}}[\mathrm{M}_\odot]$	$[10^{10}, 10^{10.5}, 10^{11}]$

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Inference

Implications for observational programs

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2. recreate data and train on cross-power
   (fixed network!)

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$$\mathrm{PV} = \frac{\sigma_{\text{posterior}}}{\sigma_{\text{prior}}} \in (0,1]$$

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$$\mathrm{PV} = \frac{\sigma_{\text{posterior}}}{\sigma_{\text{prior}}} \in (0,1]$$

4. average over several network runs
   (epistemic noise)

Parameter	Values
FOV[deg^2]	[5, 10, 100]
σ_z	[0.001, 0.01, 0.1]
$M_{\mathrm{h,min}}[\mathrm{M}_\odot]$	[10^{10}, $10^{10.5}$, 10^{11}]

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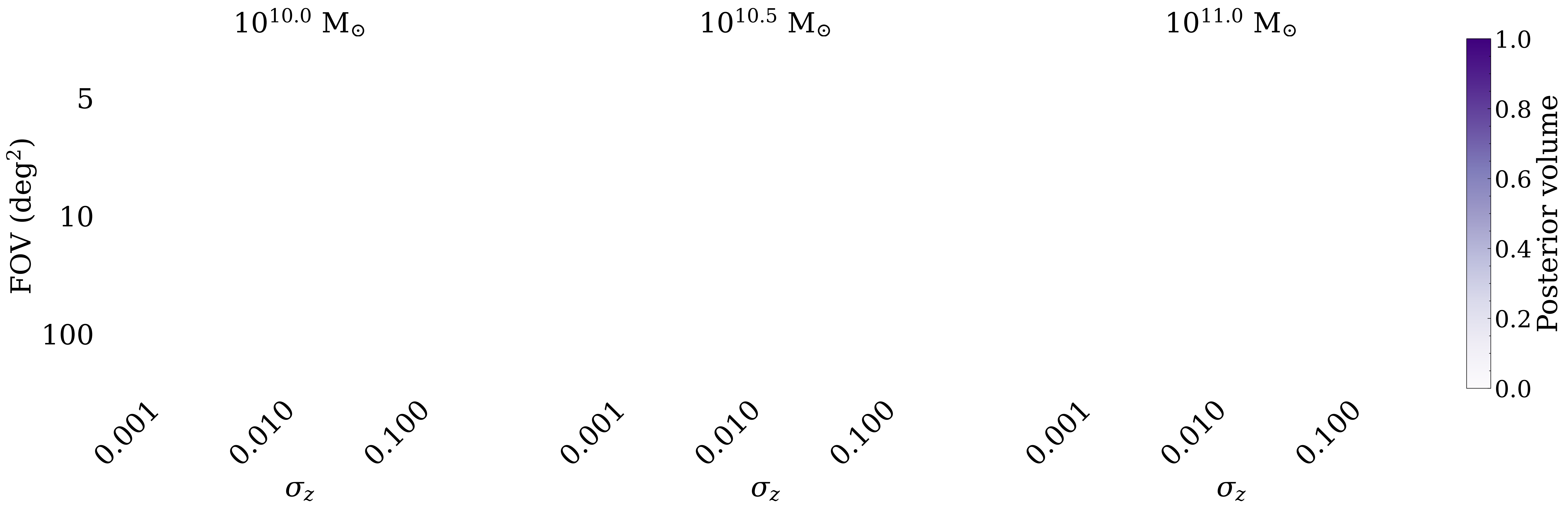

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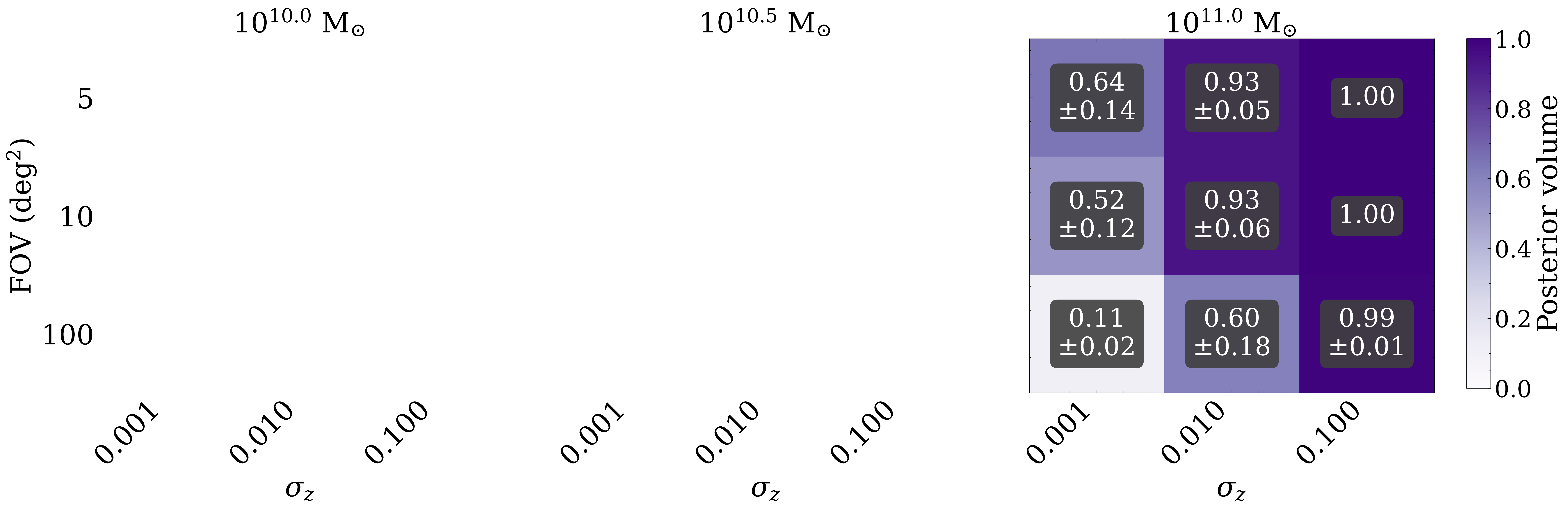

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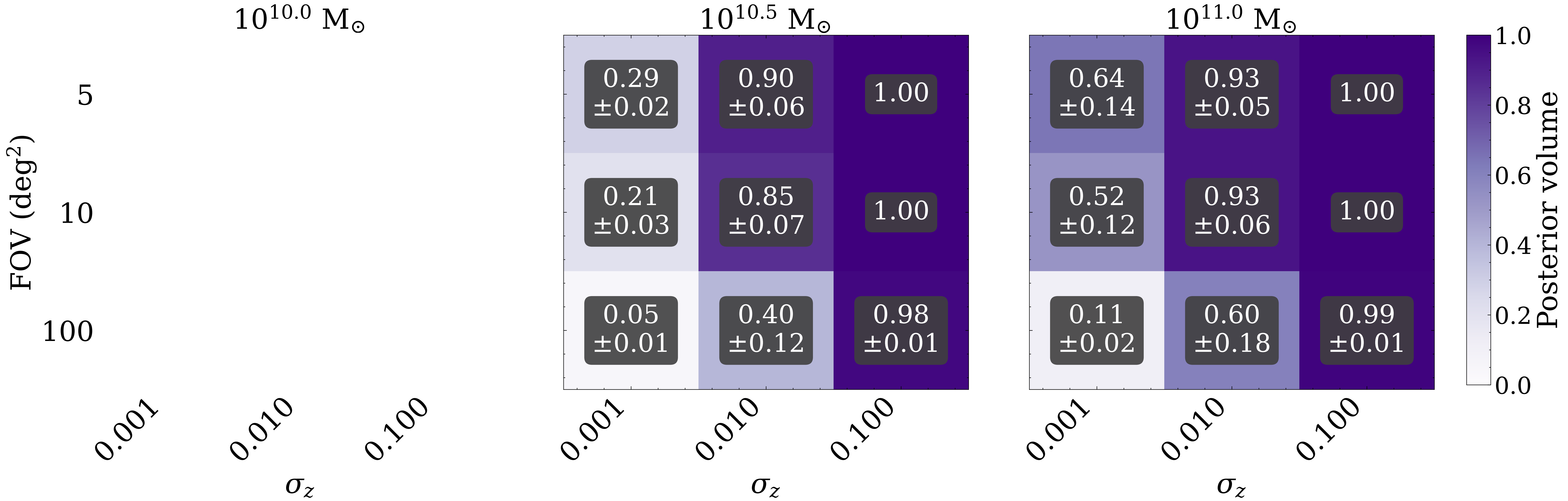

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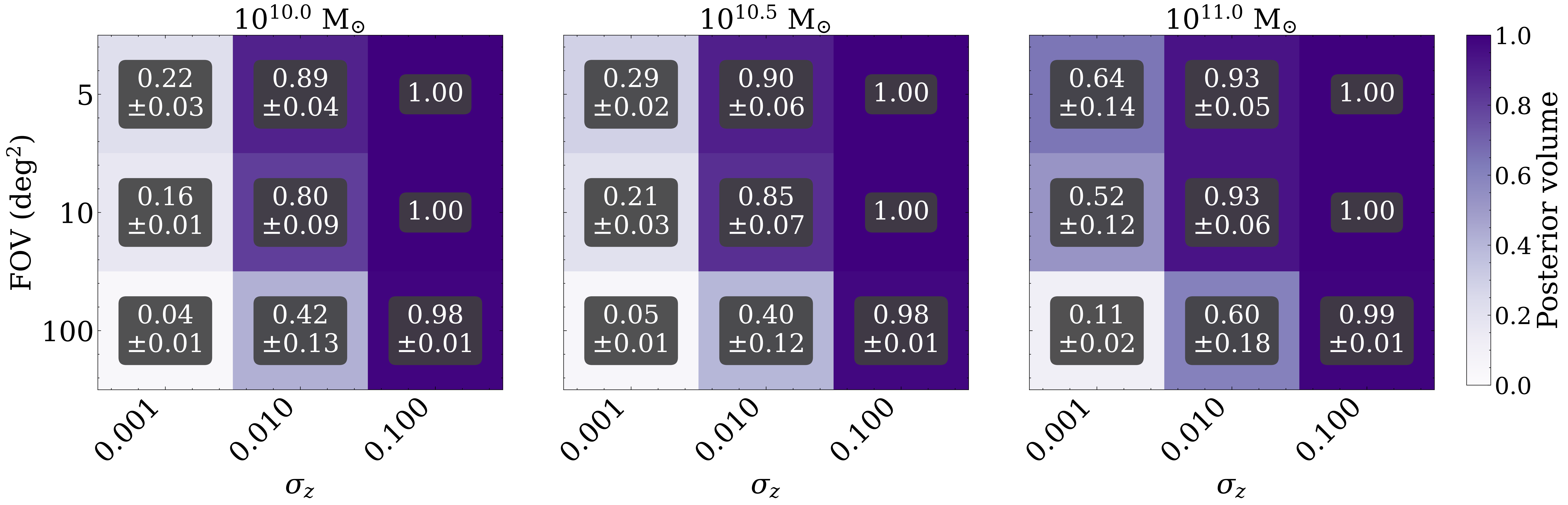

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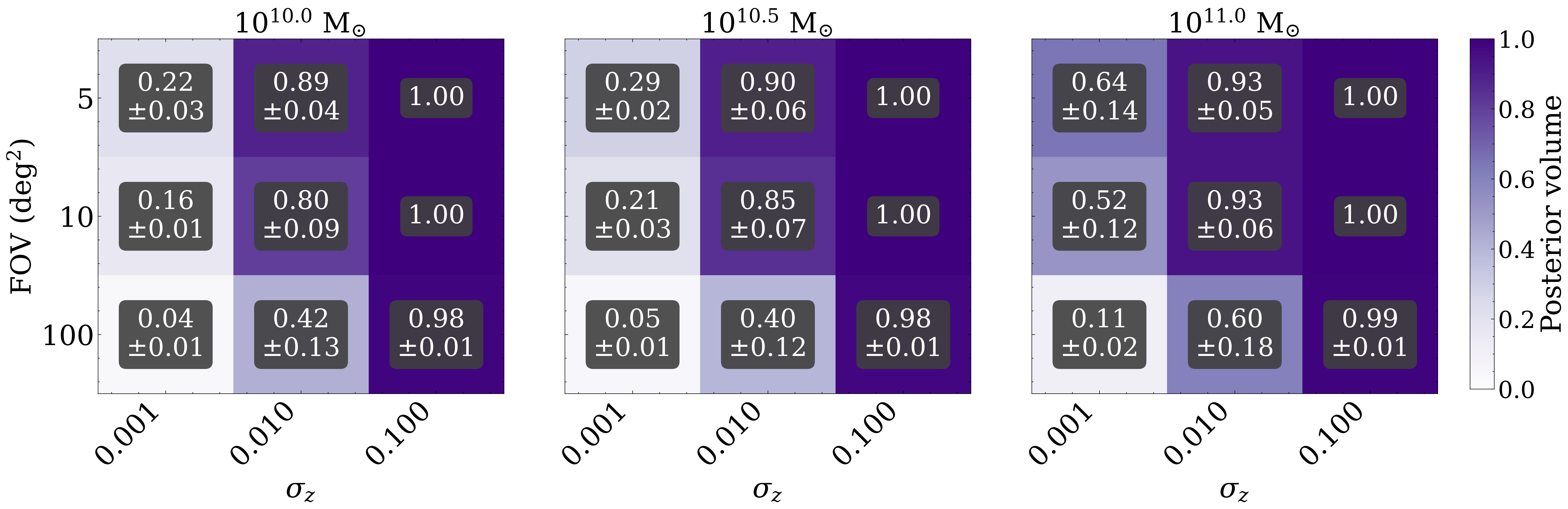

→ **redshift uncertainty crucial**

→ **deeper surveys are worth it!**

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Inference

EoR source properties

Can we learn source properties?

$$\{f_{*,10}, f_{\mathrm{esc},10}, \alpha_*, \alpha_{\mathrm{esc}}\}$$

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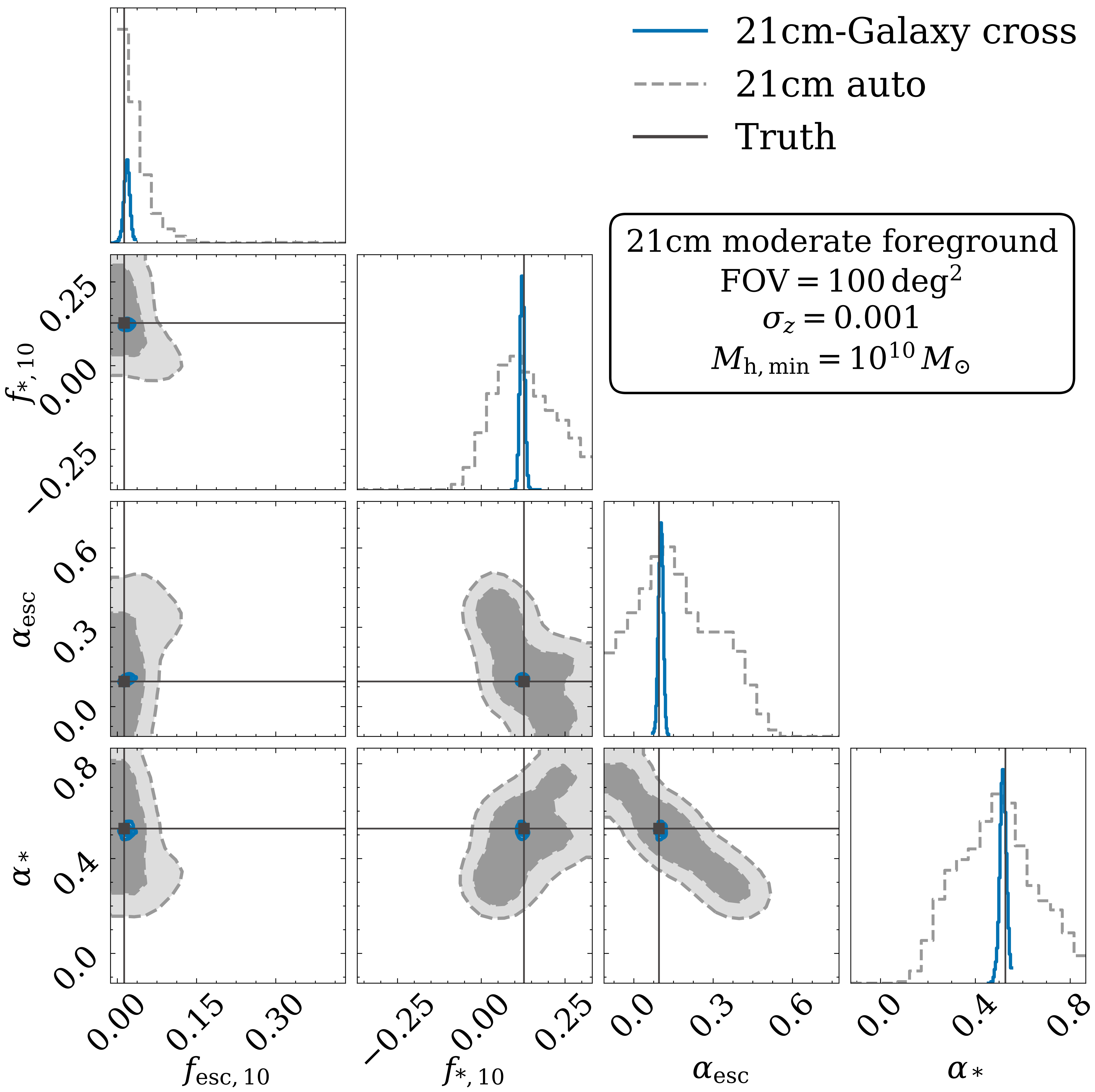
$\left(L_{\mathrm{Ly}\alpha} \approx 10^{41} \mathrm{erg\,s}^{-1}\right)$



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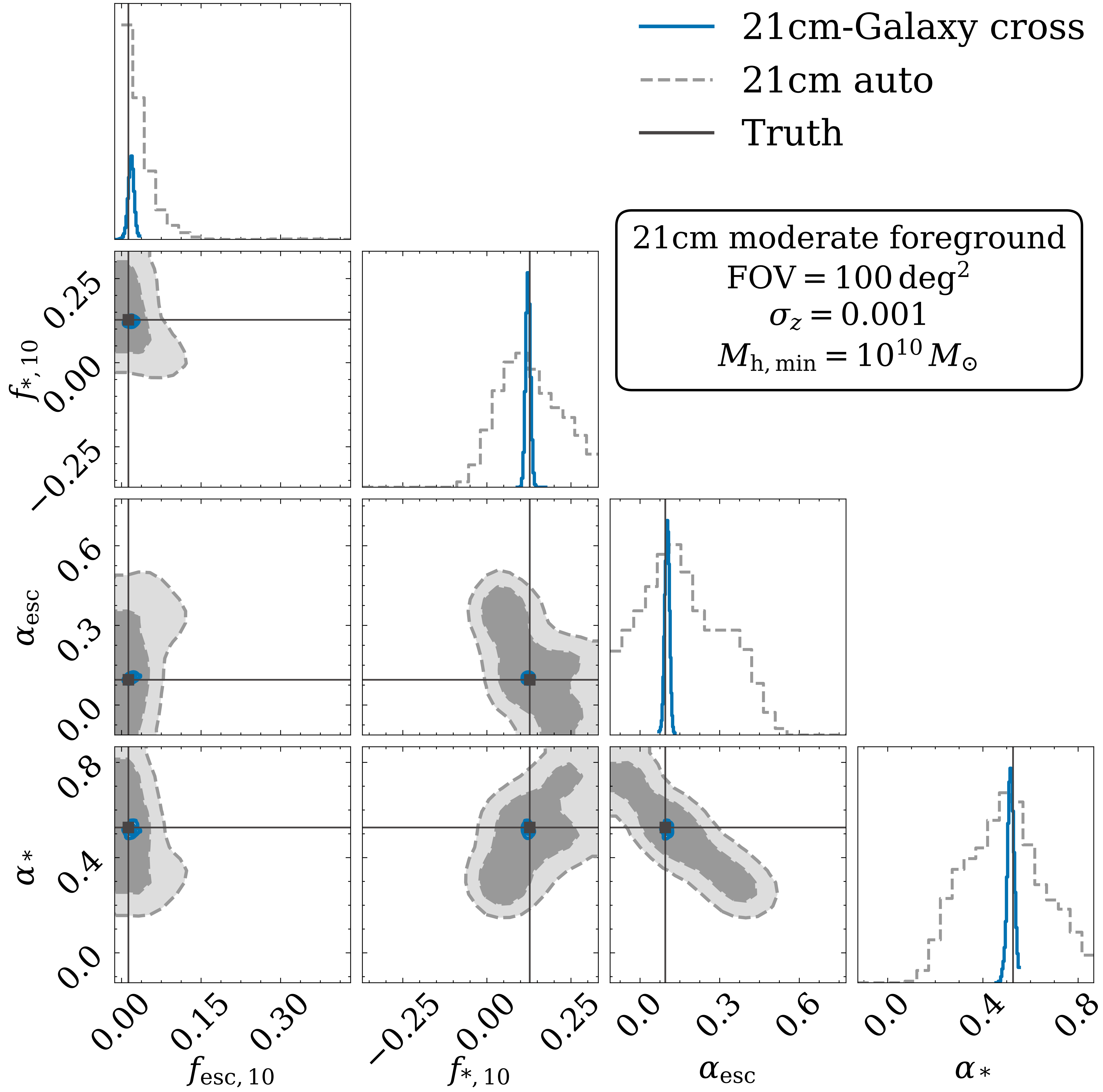

Can we learn source properties?

$\{f_{*,10}, f_{\mathrm{esc},10}, \alpha_*, \alpha_{\mathrm{esc}}\}$

→ Cross-power enables constraints on reionization source properties!

But we need deep enough surveys..

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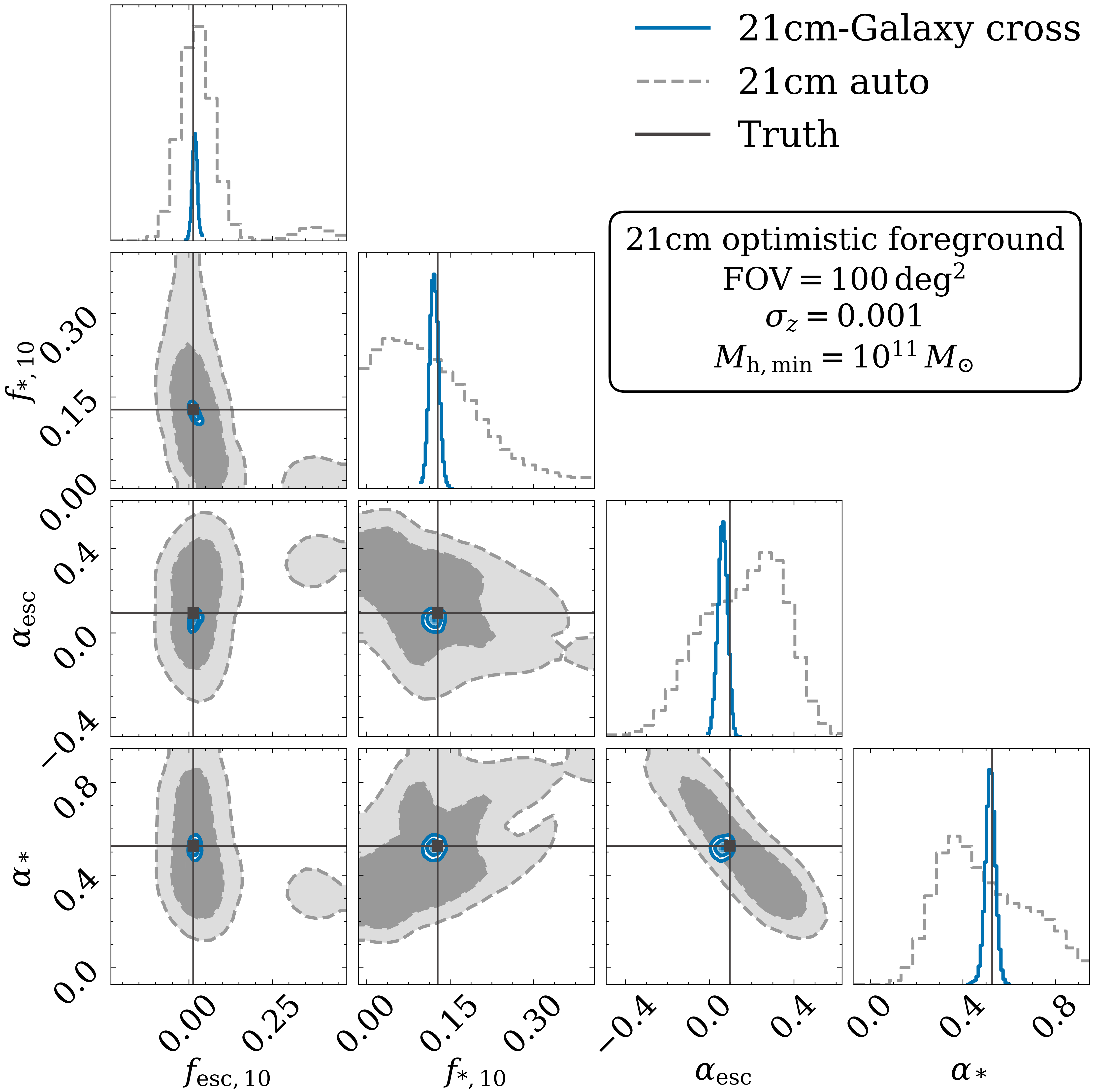
Inference

EoR source properties

$\left(L_{\mathrm{Ly}\alpha} \approx 10^{42.3} \mathrm{erg\ s^{-1}}\right)$



Can we learn source properties?

$\{f_{*,10}, f_{\mathrm{esc},10}, \alpha_*, \alpha_{\mathrm{esc}}\}$

→ Cross-power enables constraints on reionization source properties!

OR foreground removal!

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Take-Home messages

Email: pietschke@thphys.uni-heidelberg.de

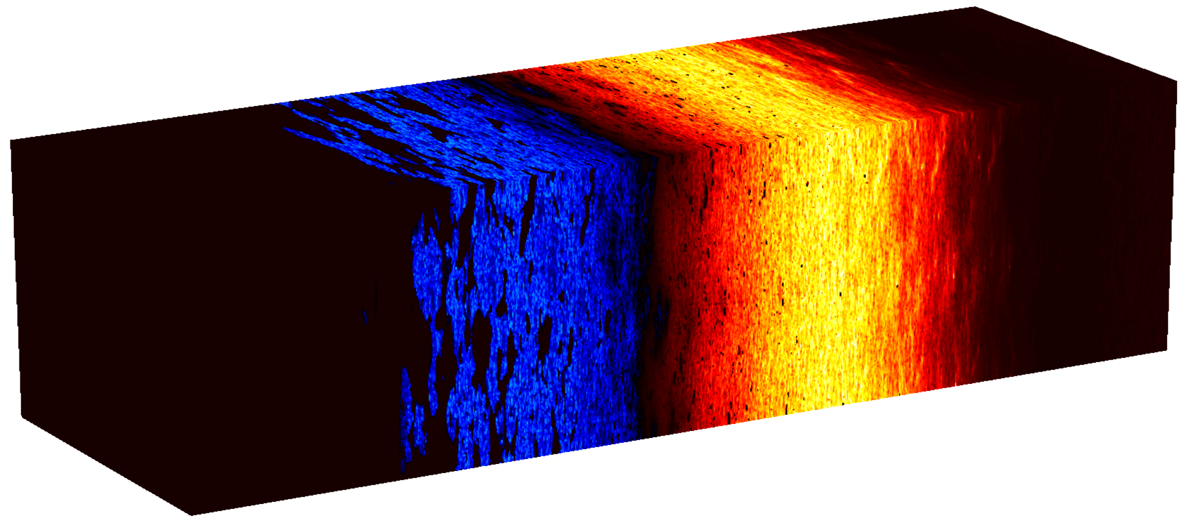
21cm-Galaxy surveys...

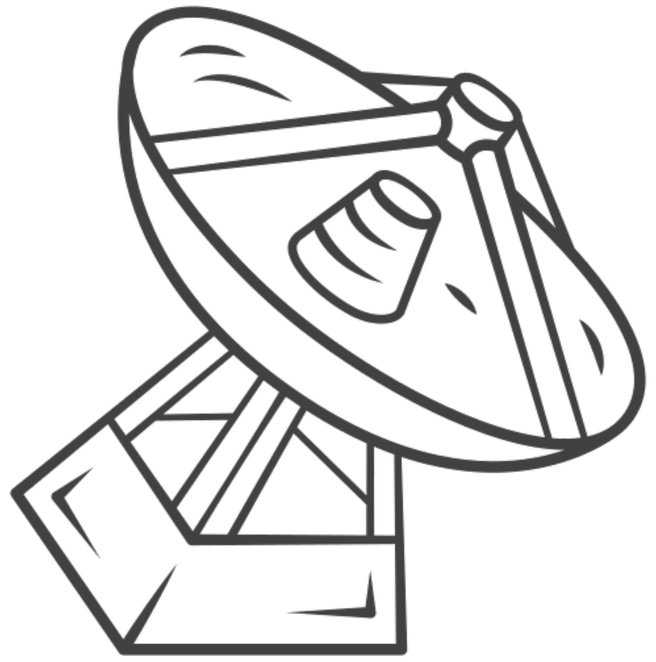
1. **enhance** 21cm-only constraints of global EoR parameters

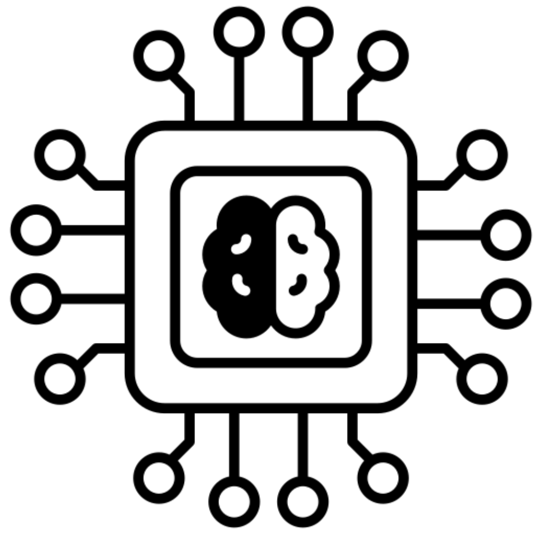
2. **enable** constraints of reionization source properties

3. require **precise** redshift measurements

4. should be **deep** enough for max scientific return







arXiv: 2601.18627

Additional slides

Simulation-based inference

EoRFlow

Training

Inference

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Simulation-based inference

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Model Parameters

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Simulation-based inference

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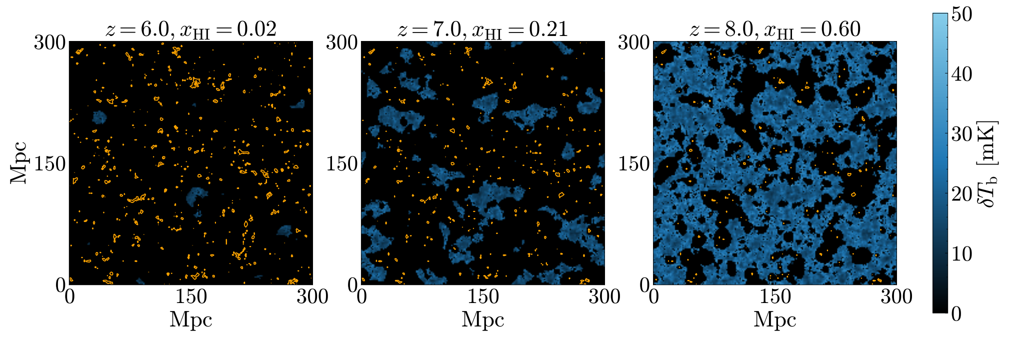
Model Parameters

↓

Simulator



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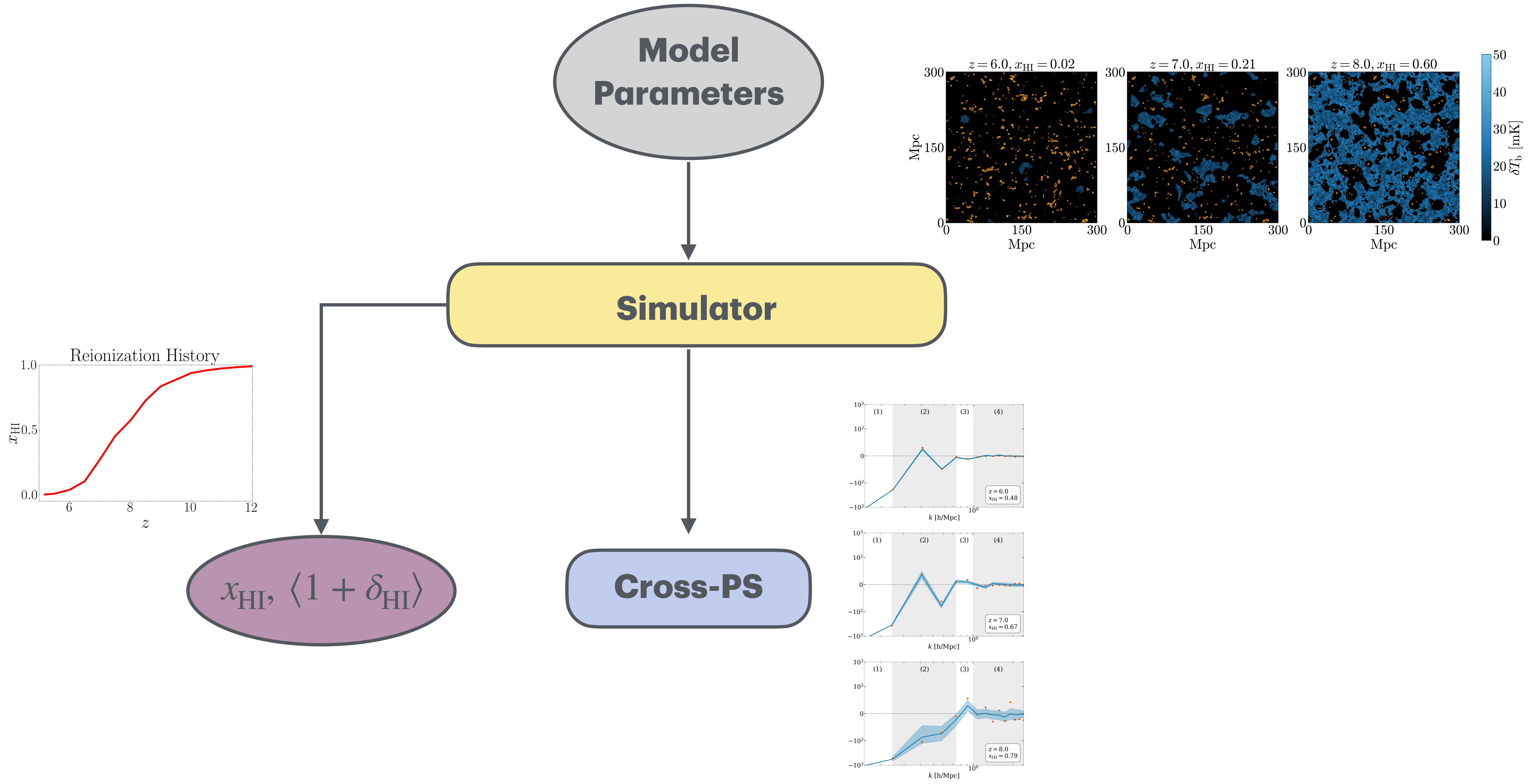

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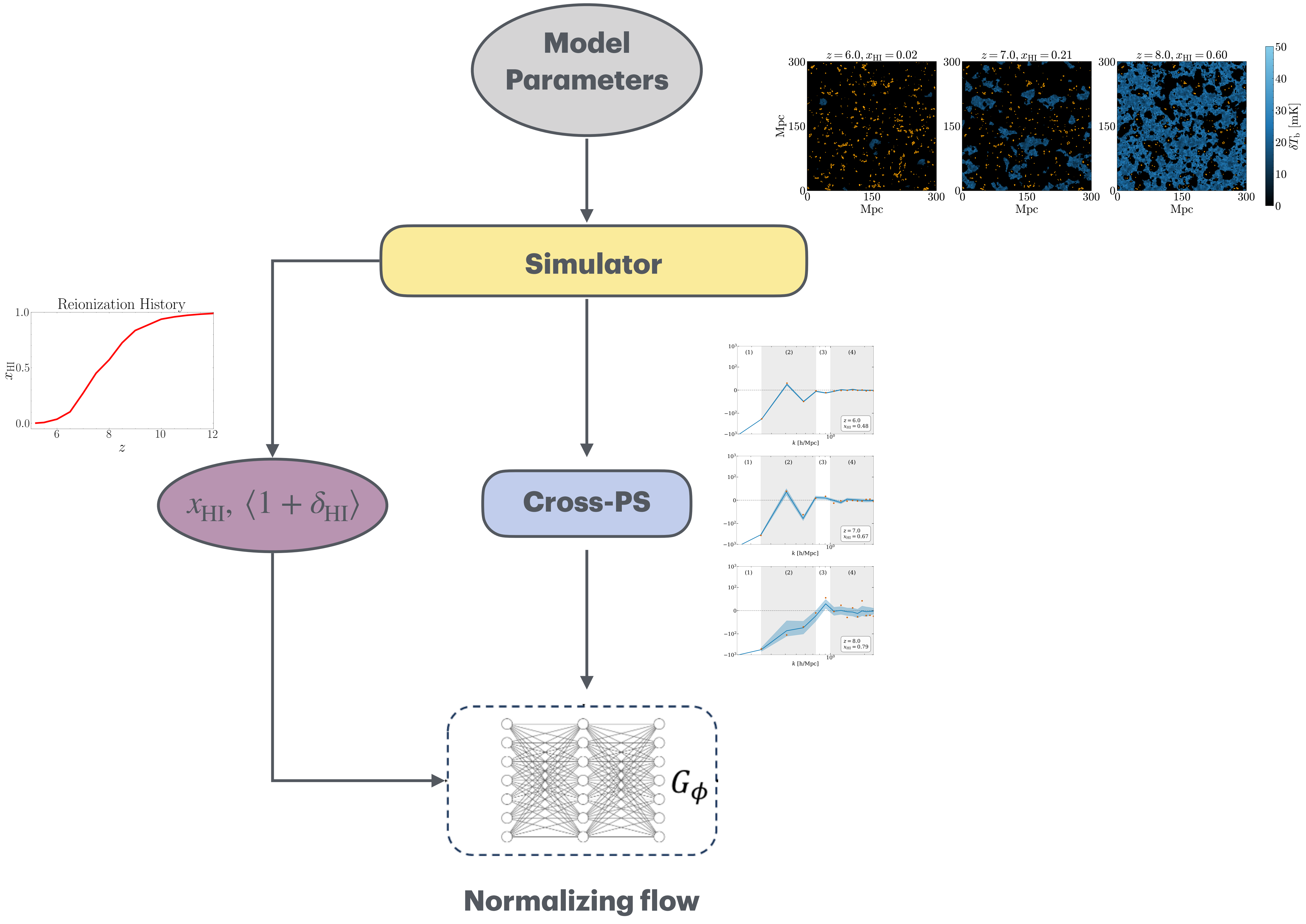

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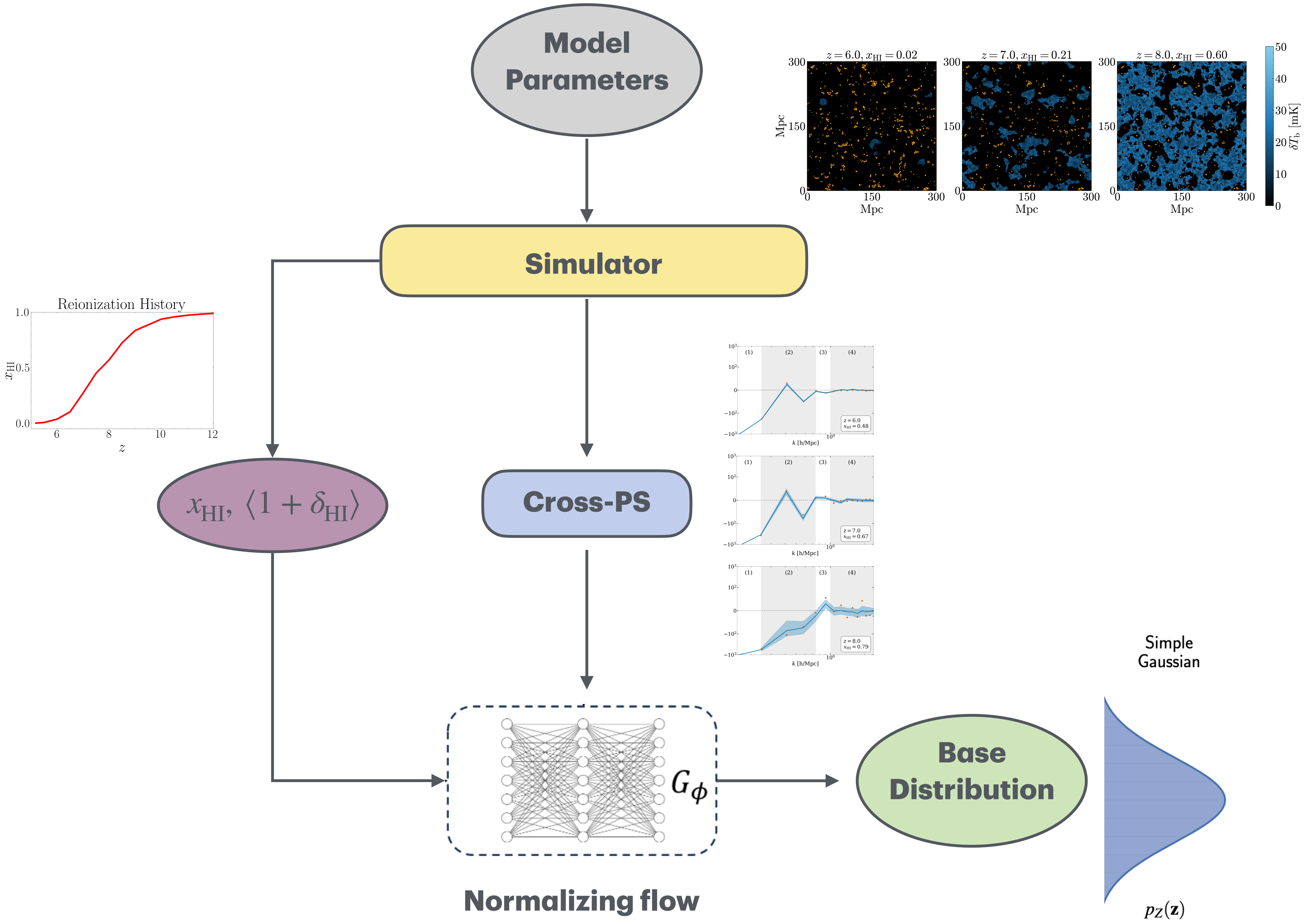

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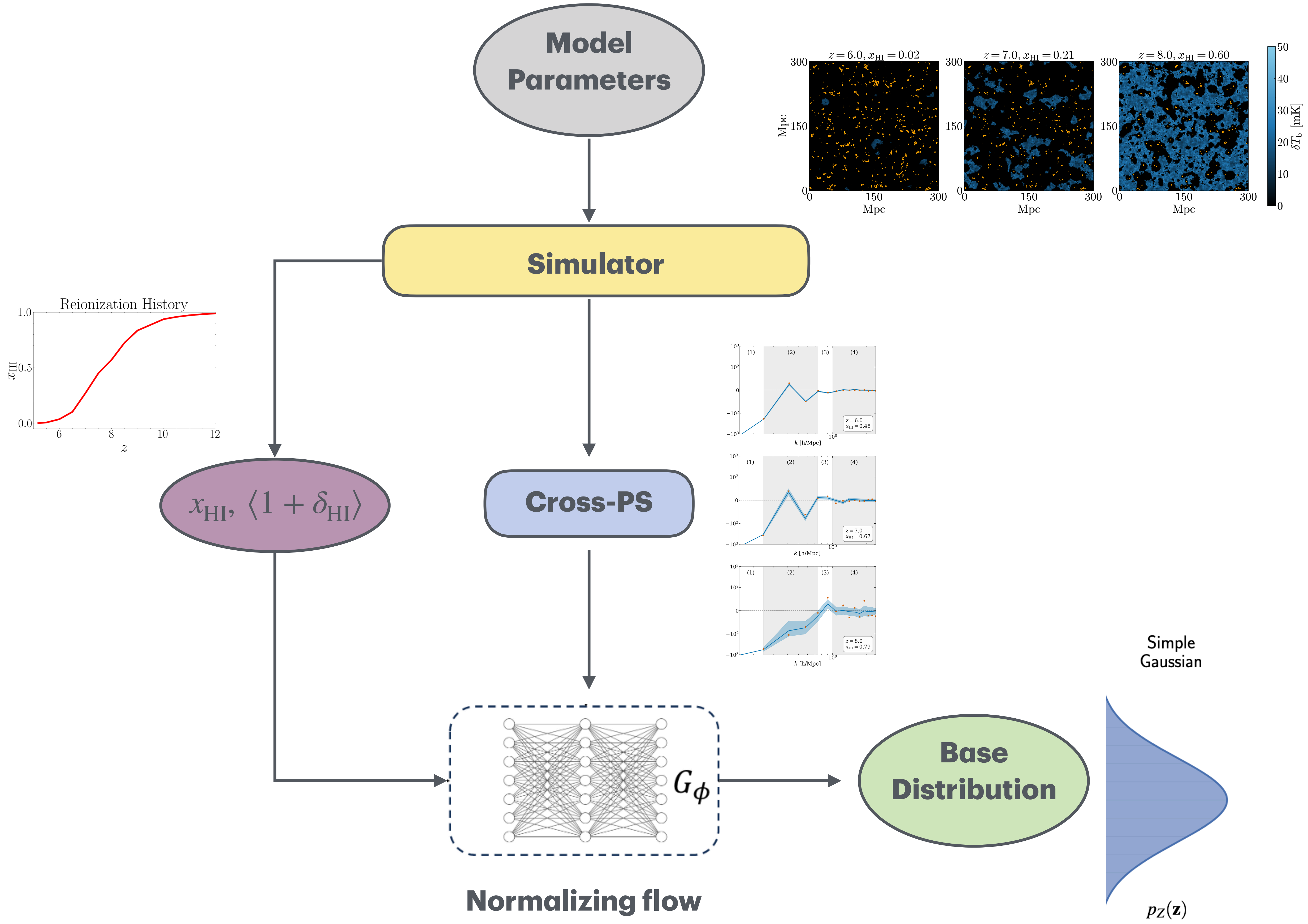

Inference

The universe

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Simulation-based inference

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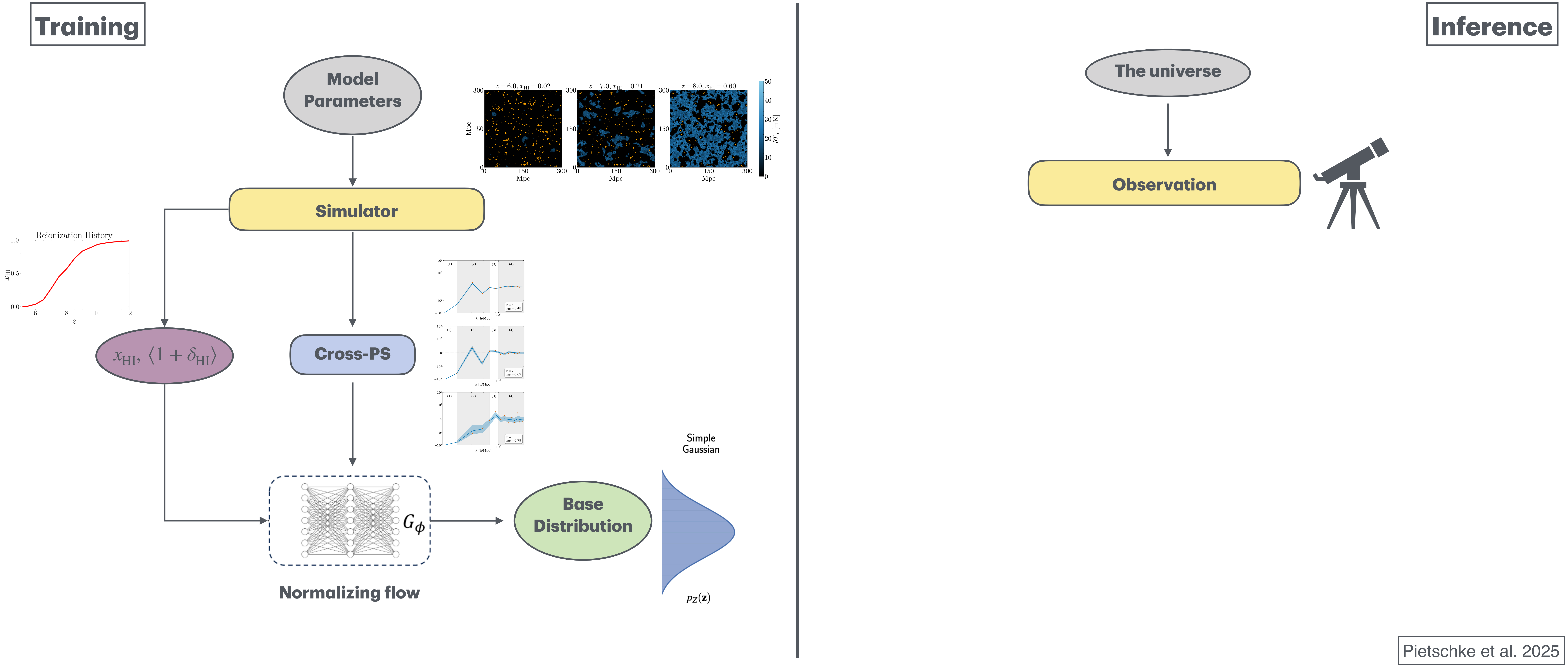

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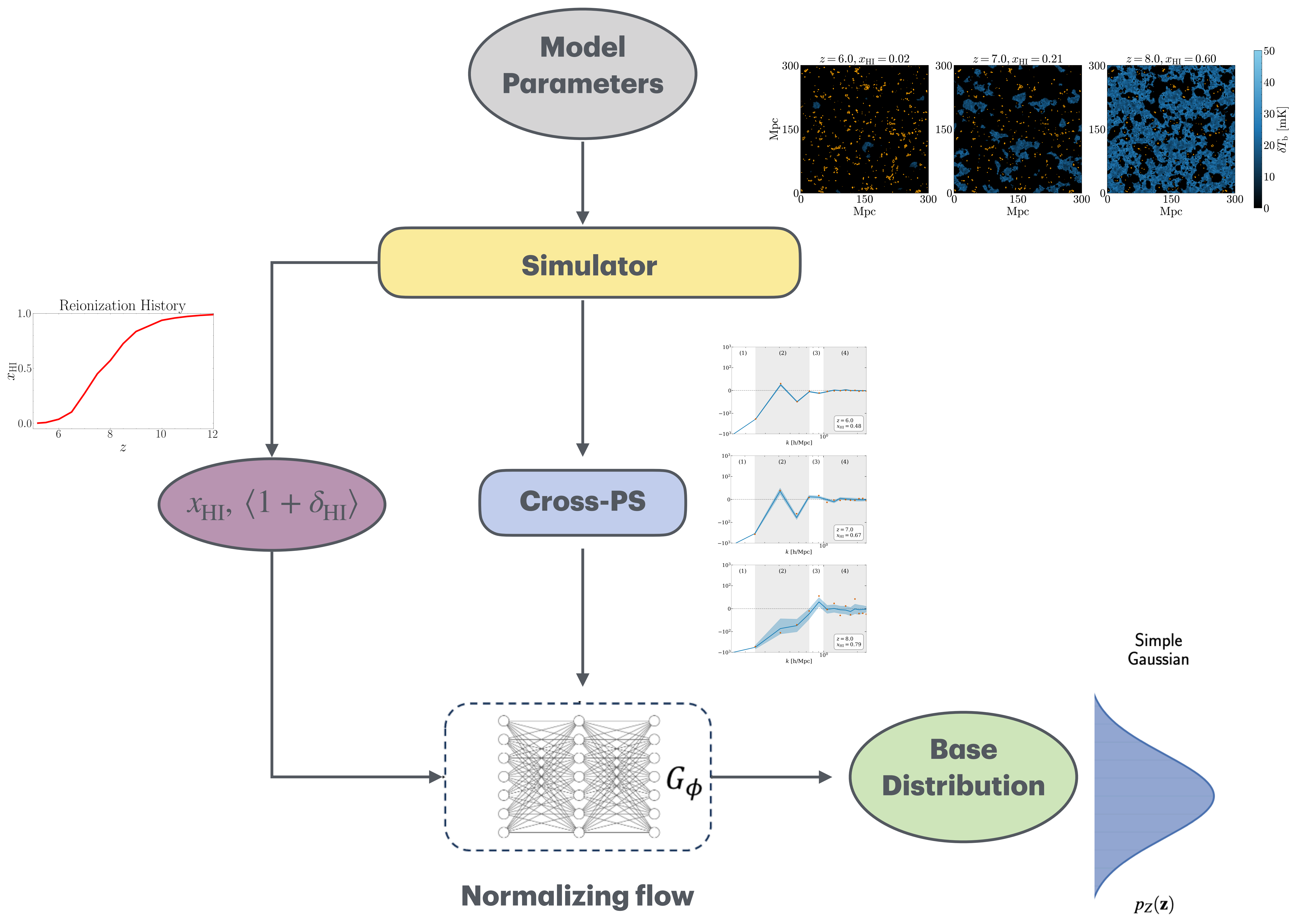
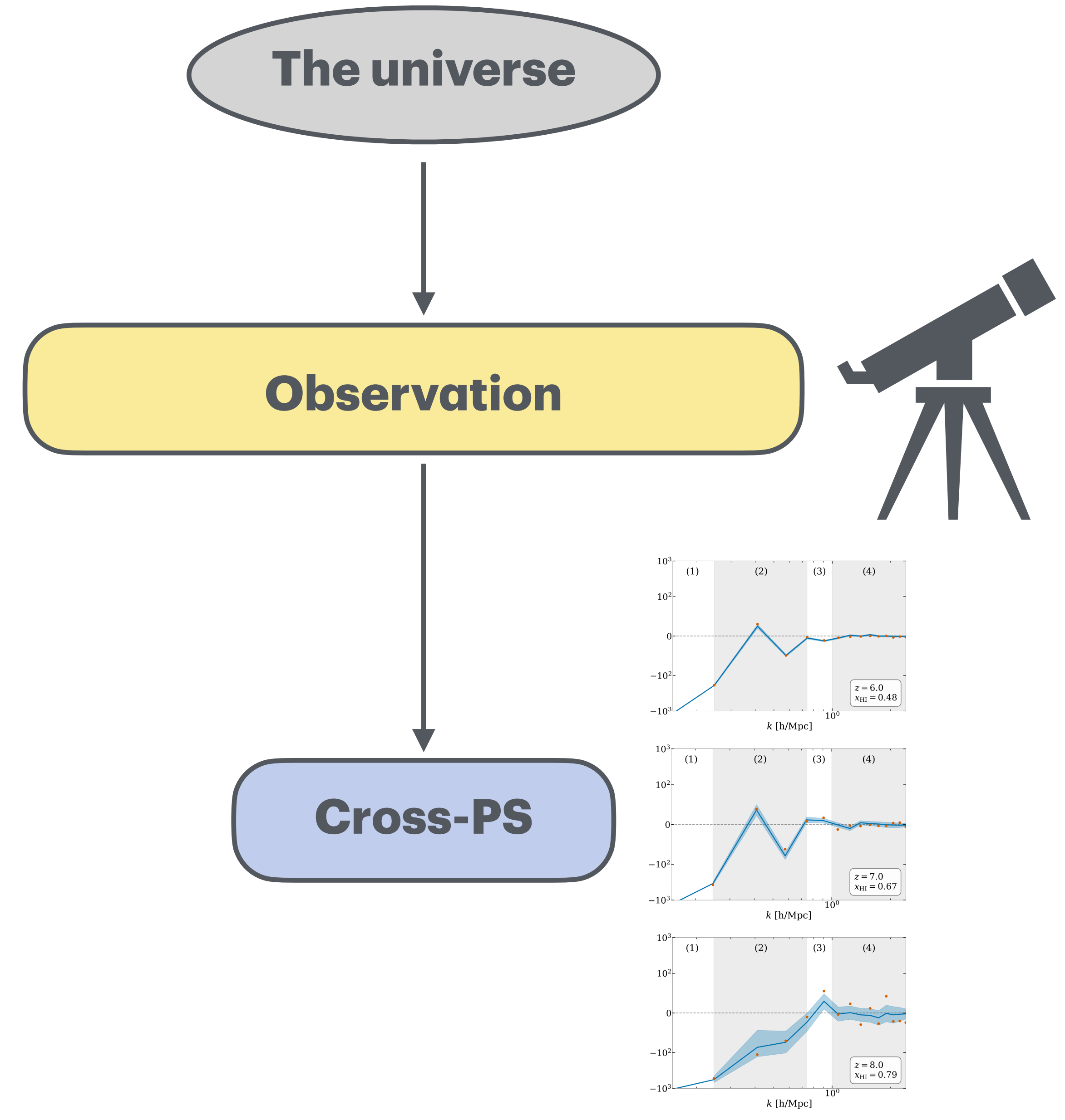


Inference



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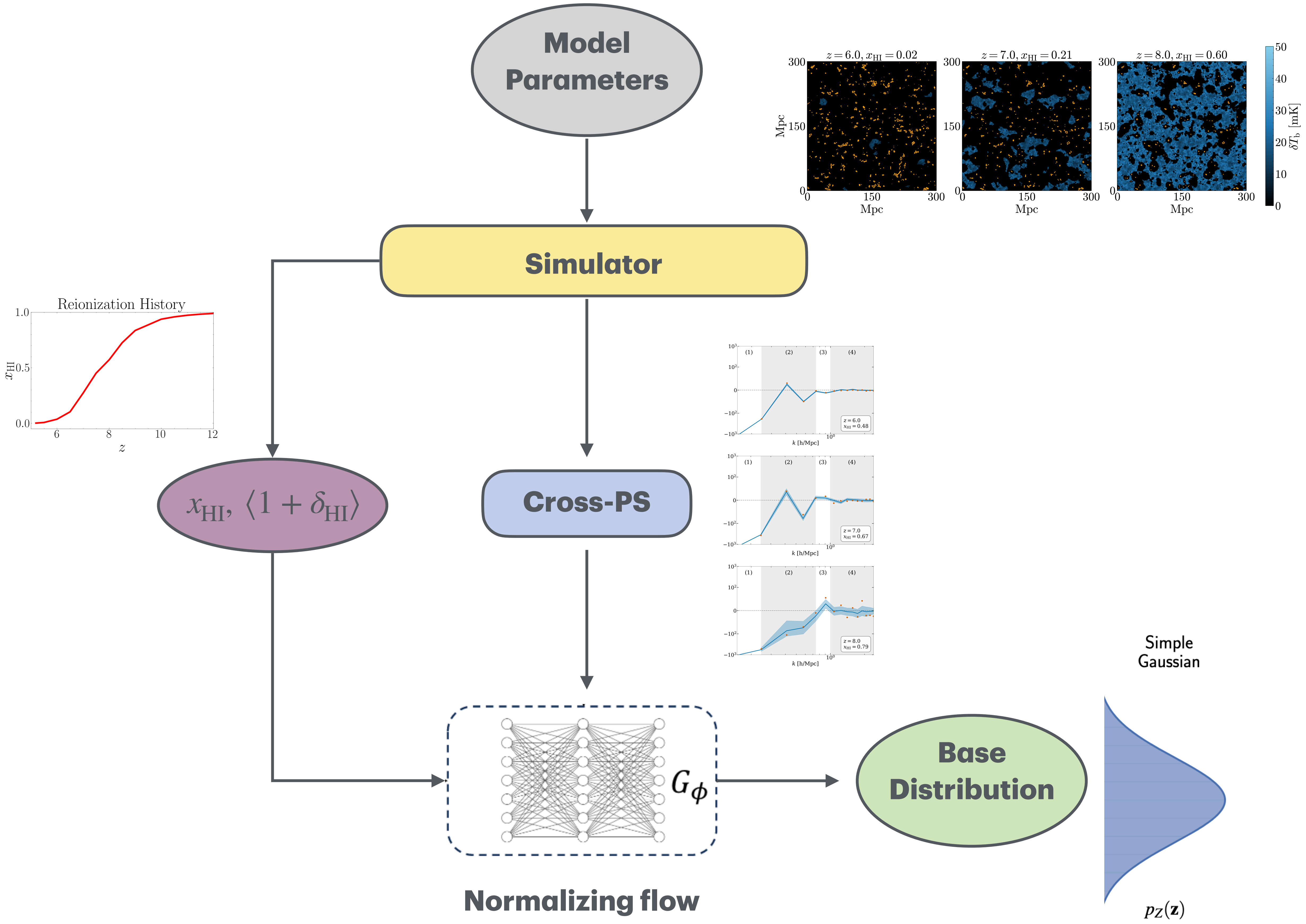
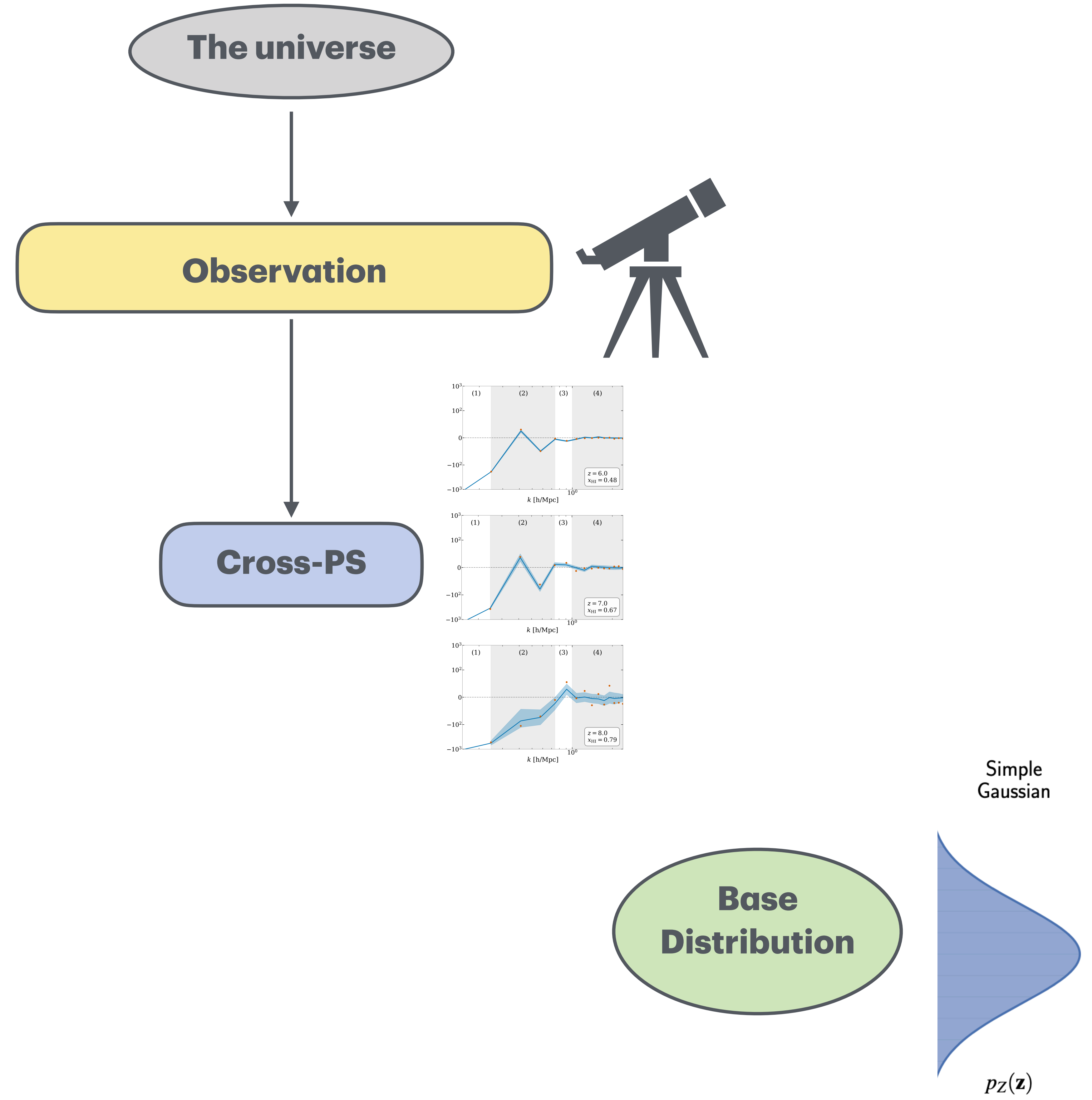


Inference



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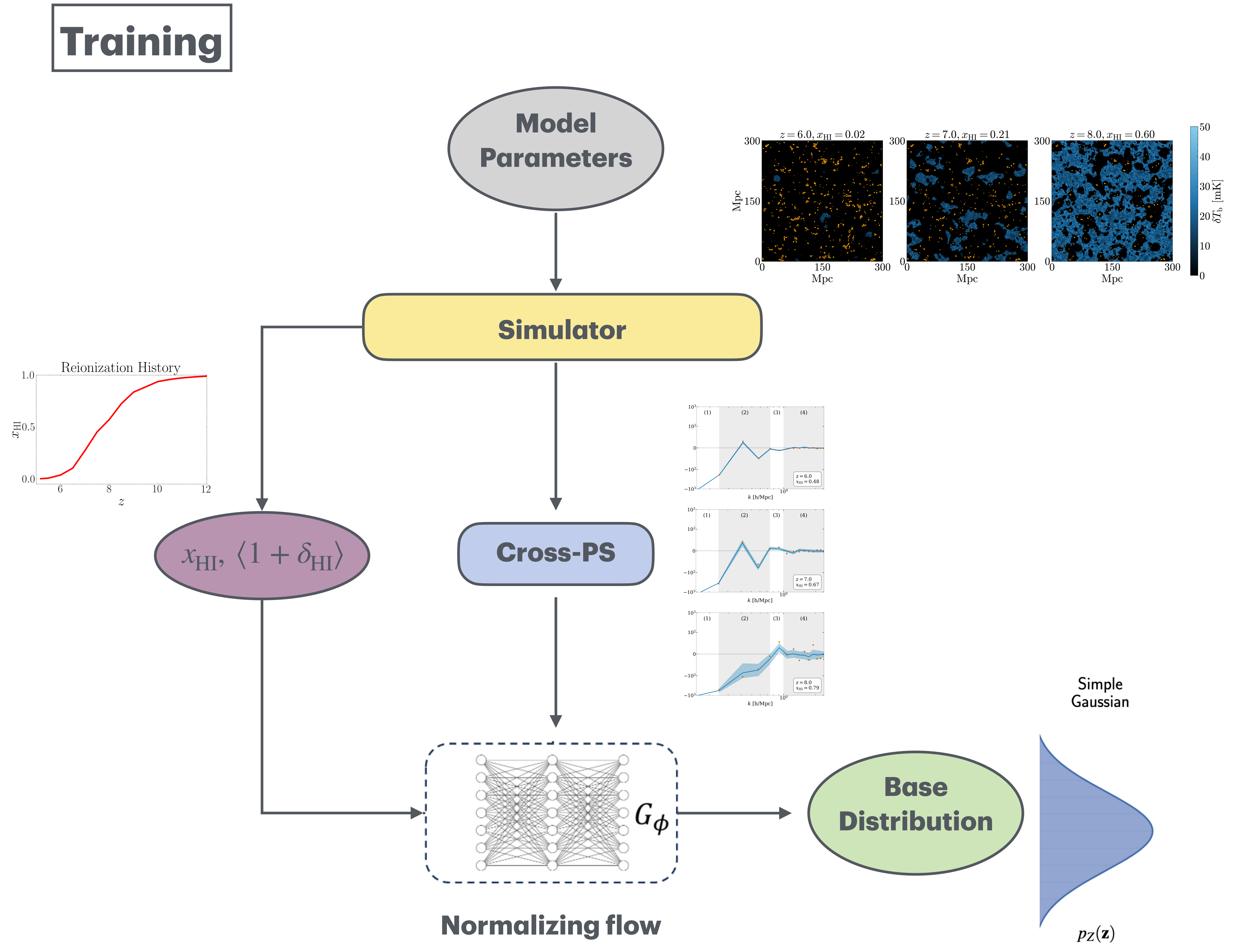

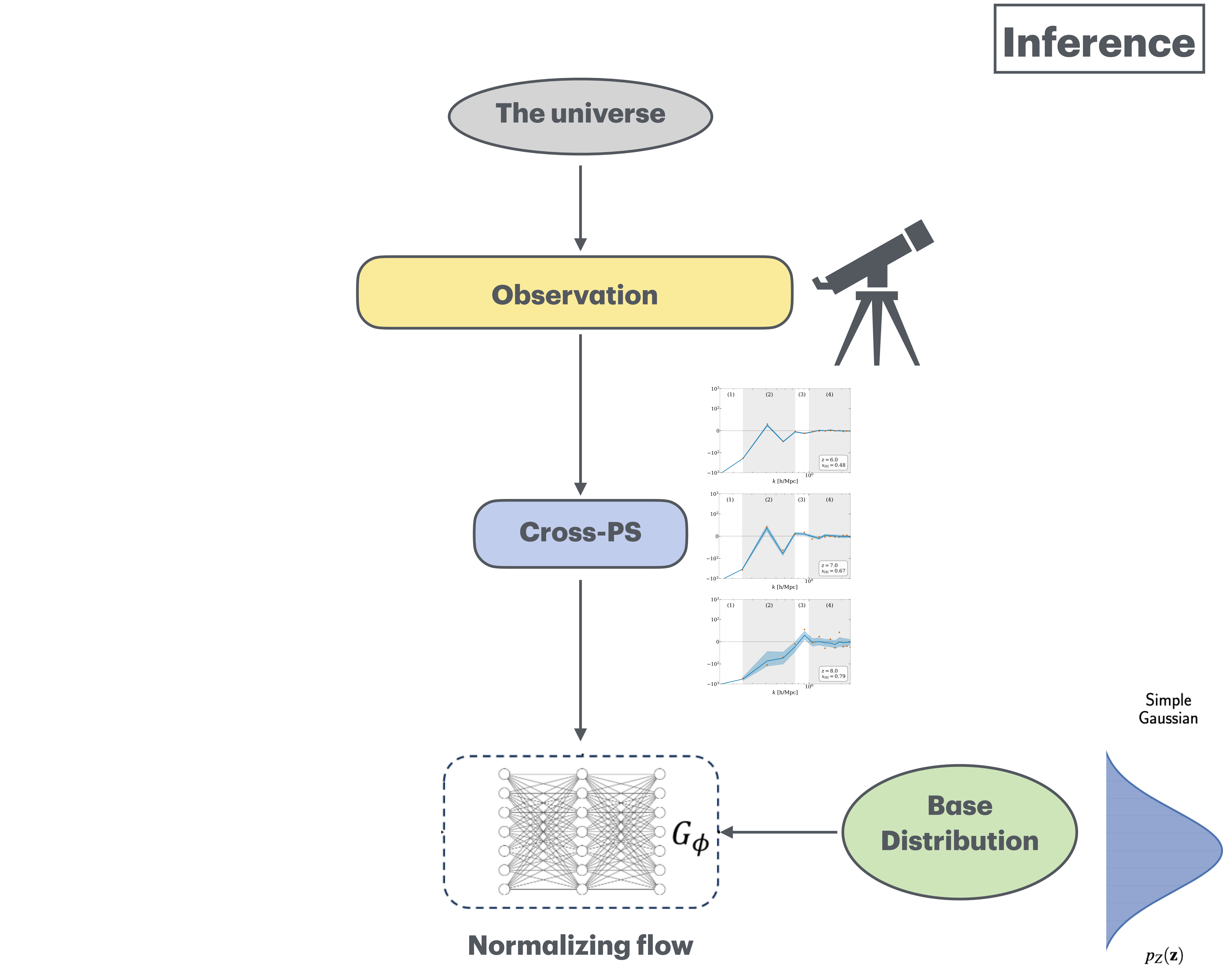

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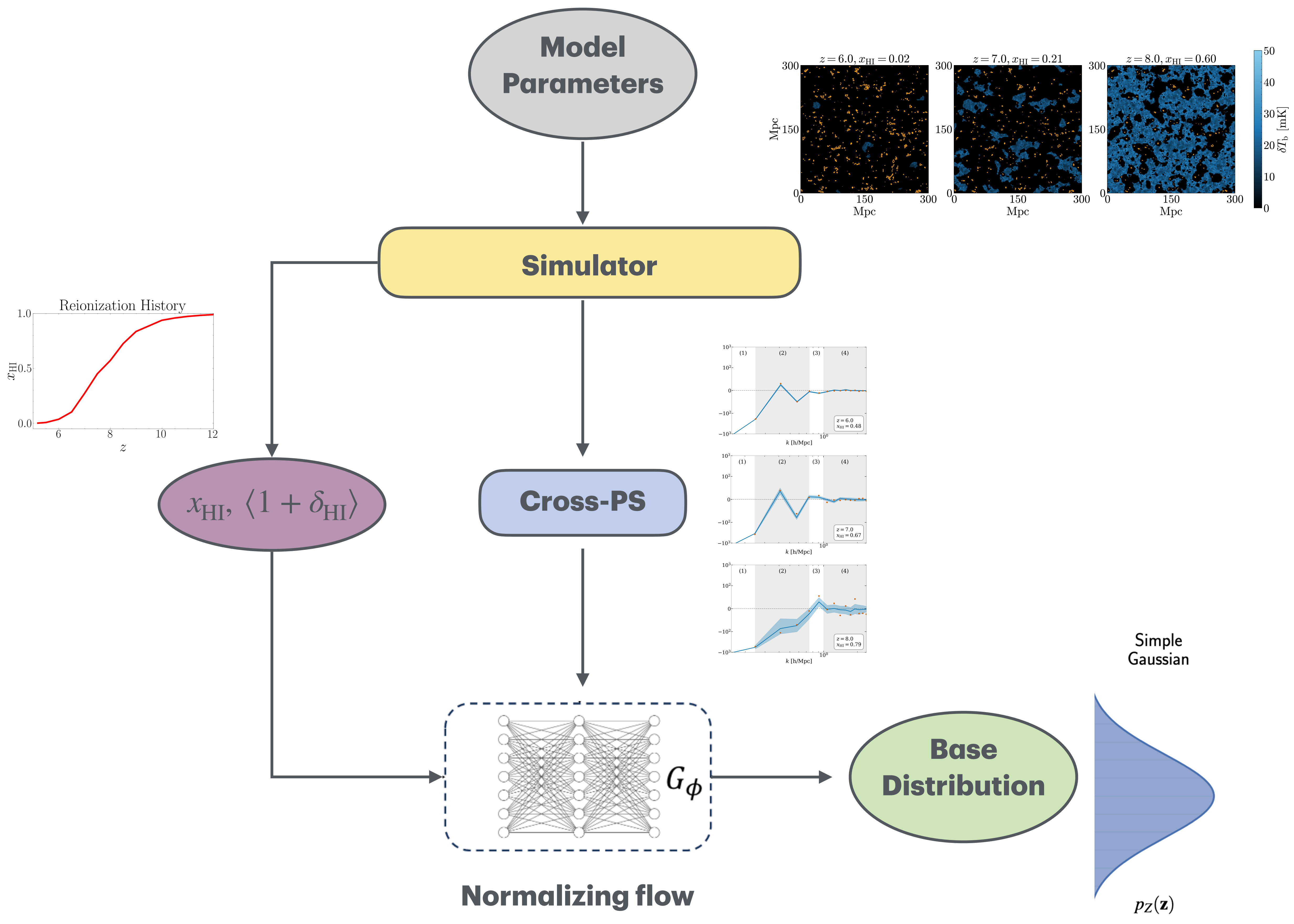

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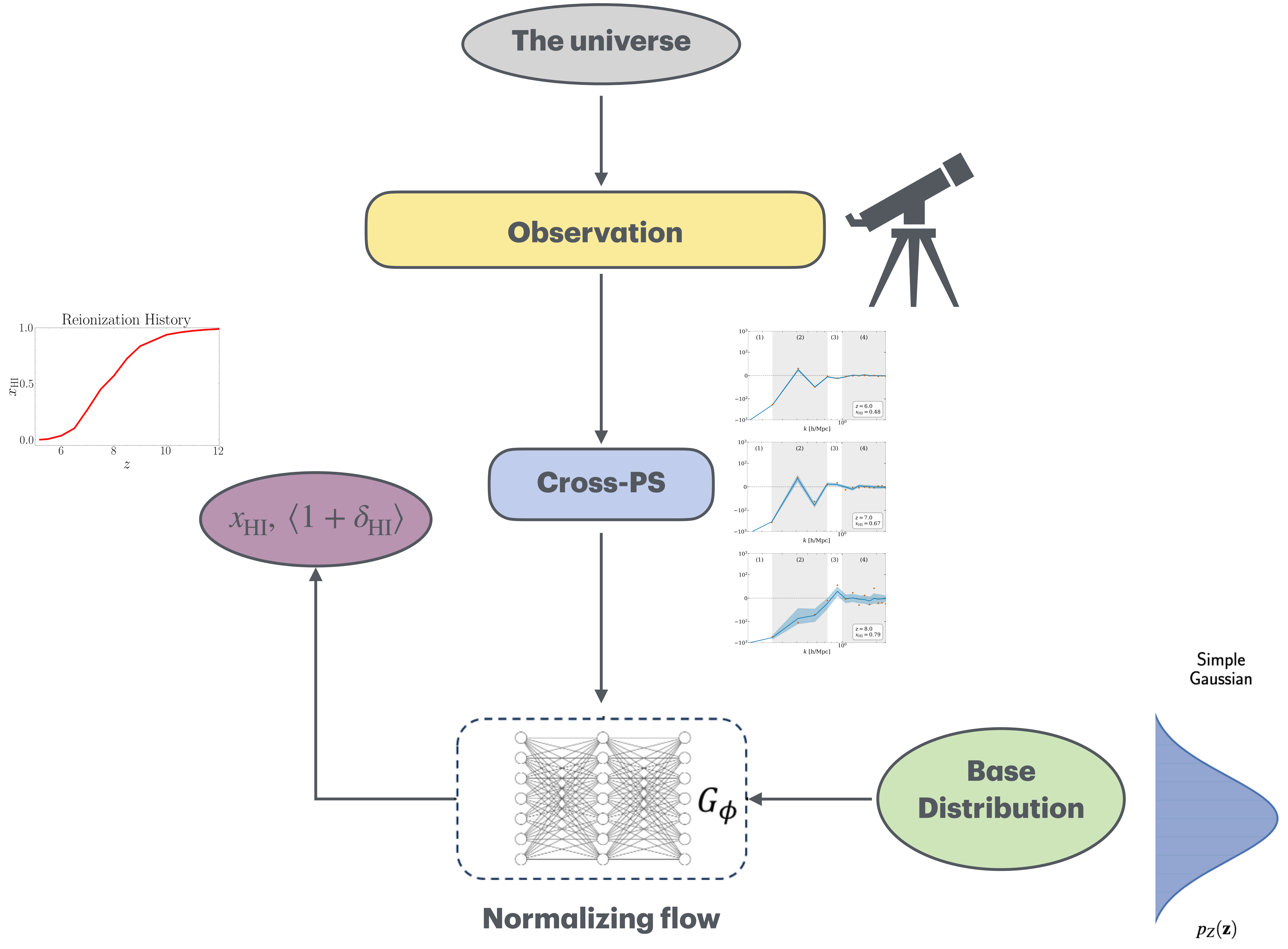

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Normalizing Flows

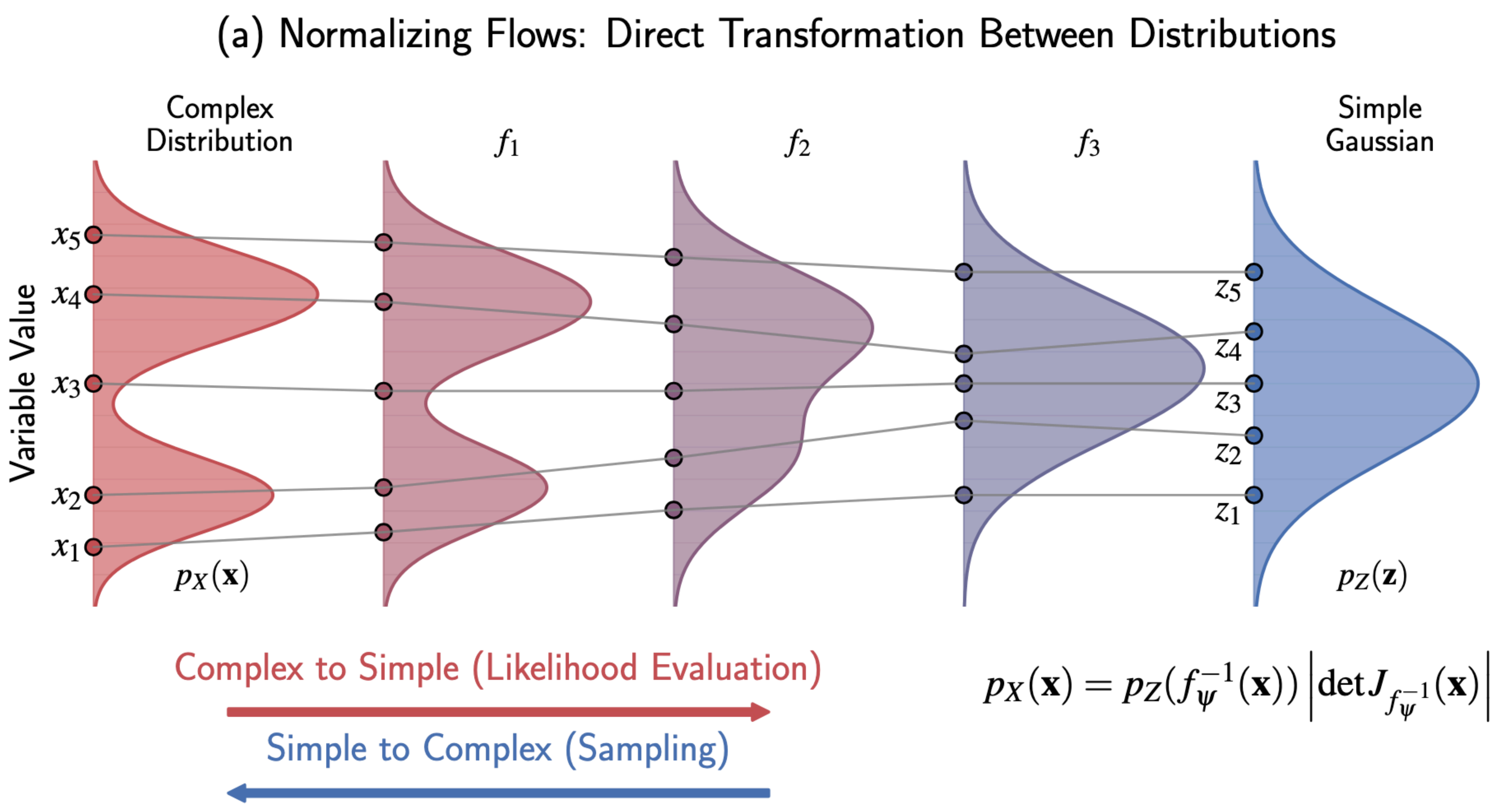
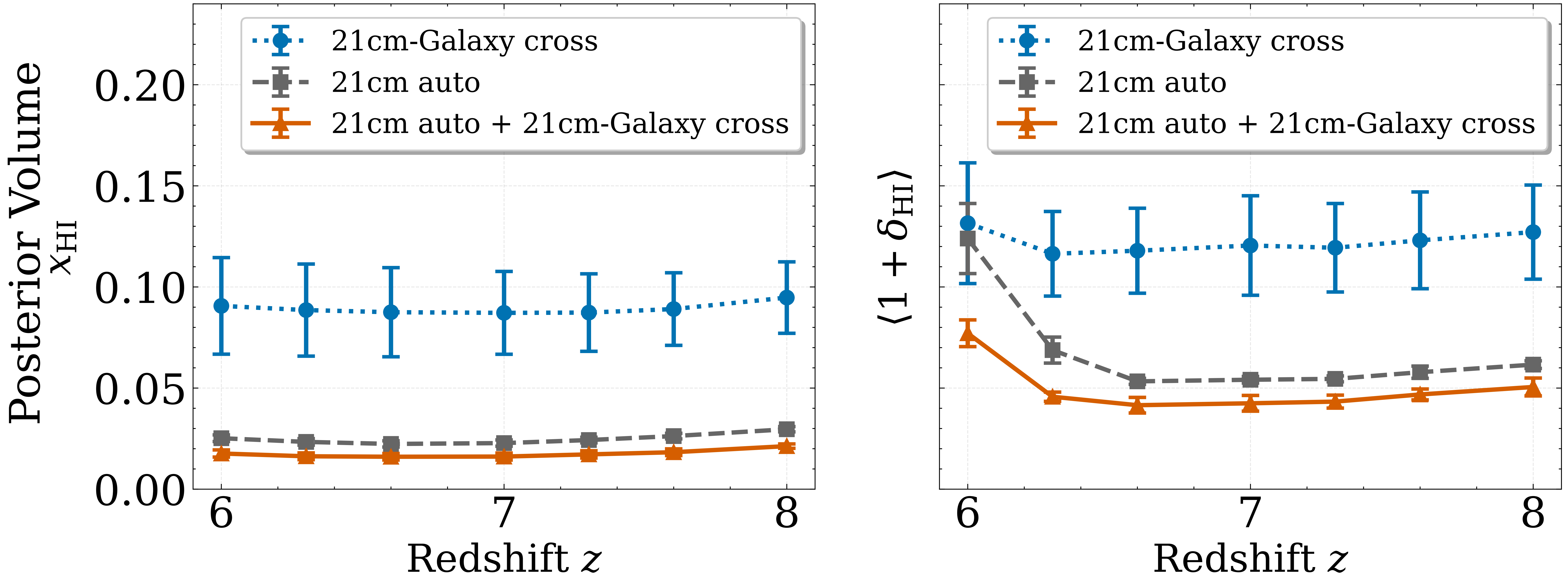


Image Credit: "Deep Learning in Astrophysics" Yuan-Sen Ting

Inference

Global EoR properties



21cm-Galaxy enhances (already strong) auto-power constraints!

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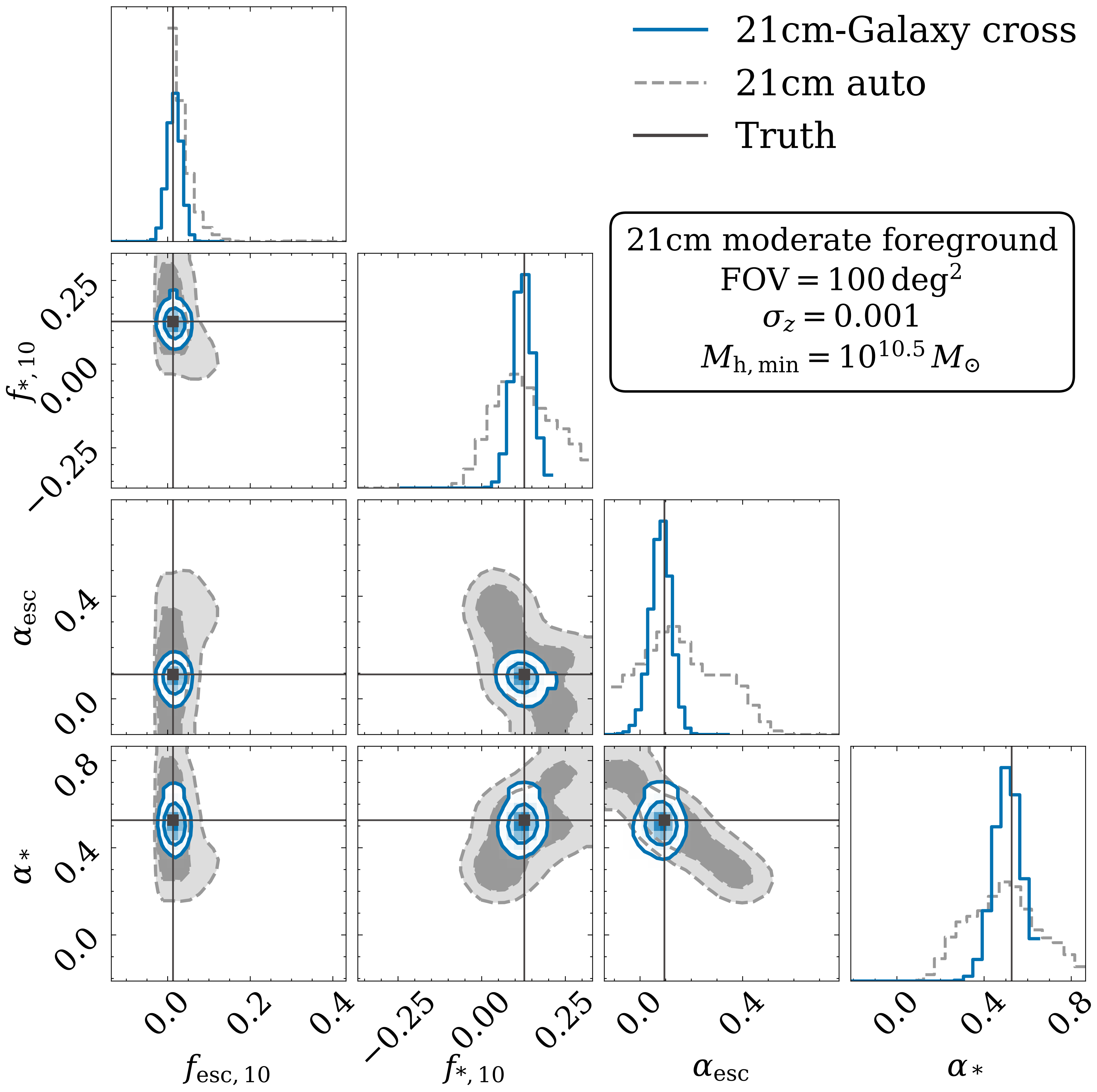
Inference

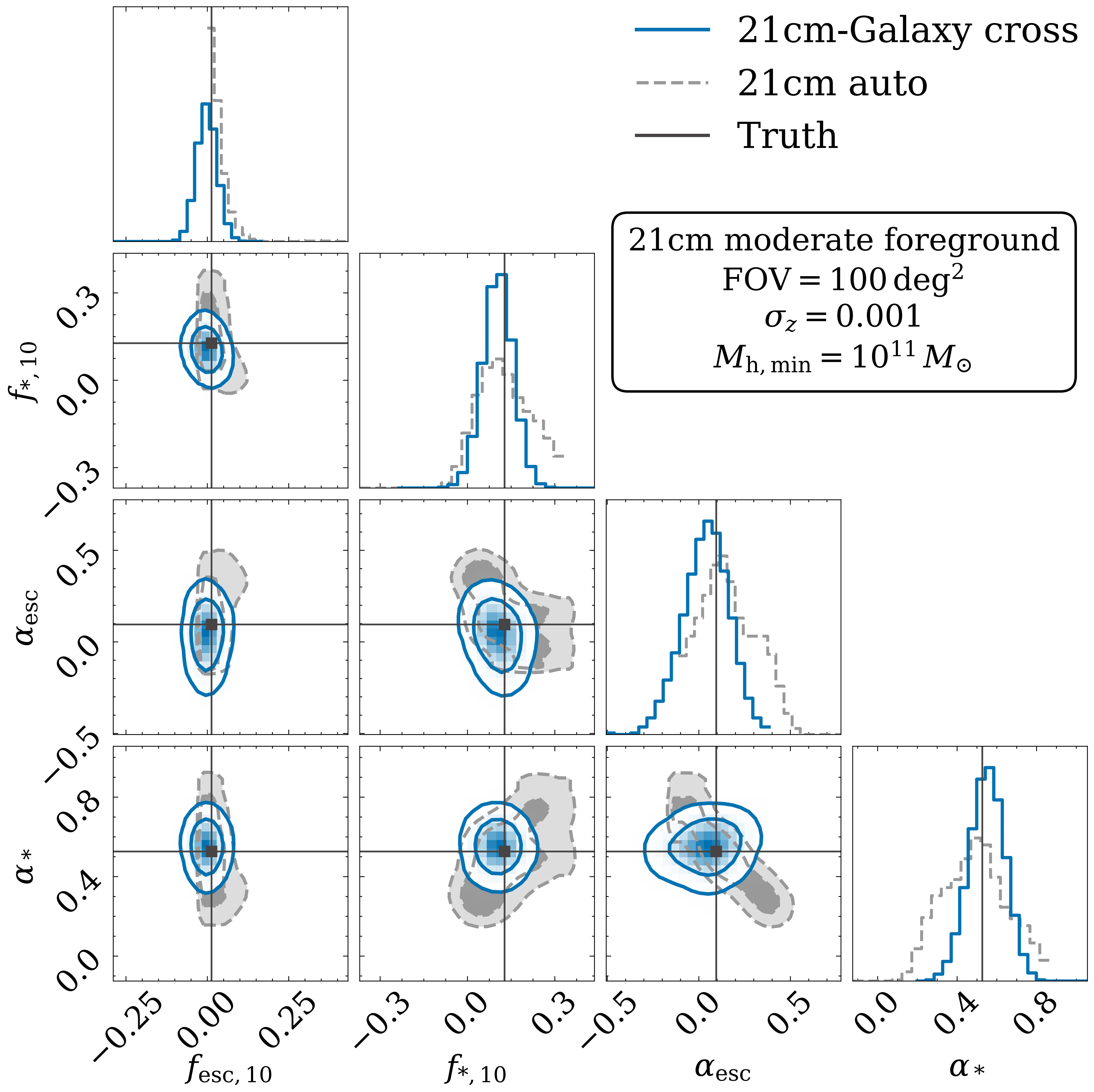
EoR source properties

$f_{*,10}, f_{\mathrm{esc},10} \in [0.005, 0.5] \quad \alpha_* \in [-0.3, 0.9] \quad \alpha_{\mathrm{esc}} \in [-0.8, 0.5]$

$L_{\mathrm{Ly}\alpha} \approx 10^{41.8} \mathrm{erg\,s^{-1}}$



$L_{\mathrm{Ly}\alpha} \approx 10^{42.3} \mathrm{erg\,s^{-1}}$



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Inference

Future surveys

Survey	FOV[deg^2]	σ_z	$L_{\mathrm{Ly}\alpha}[\mathrm{erg\ s}^{-1}]$
WST	100	0.001	$10^{42.3}$
PFS	10	0.001	$10^{42.5}$
Roman	5-10	0.003	$10^{42.8}$

$$10^{42.3}\ \mathrm{erg\,s^{-1}} \approx 11^{11} \mathrm{M}_{\odot}$$

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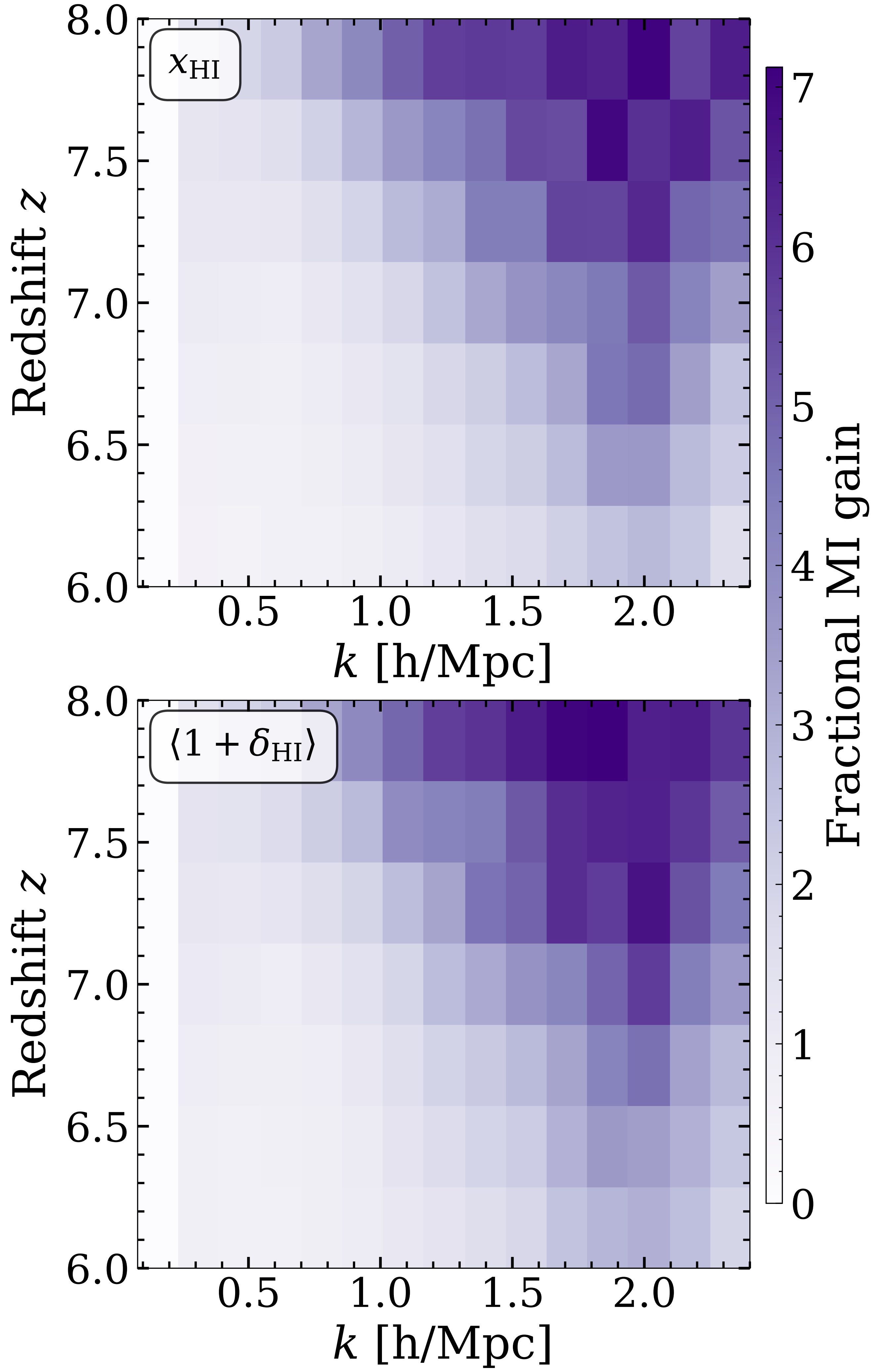
Inference

Where is the information?



Mutual information:
"Information gain by observing Cross, given Auto"

Cross-Power adds mainly
- on smaller scales
- at higher redshifts

Pietschke et al. 2026

Inference

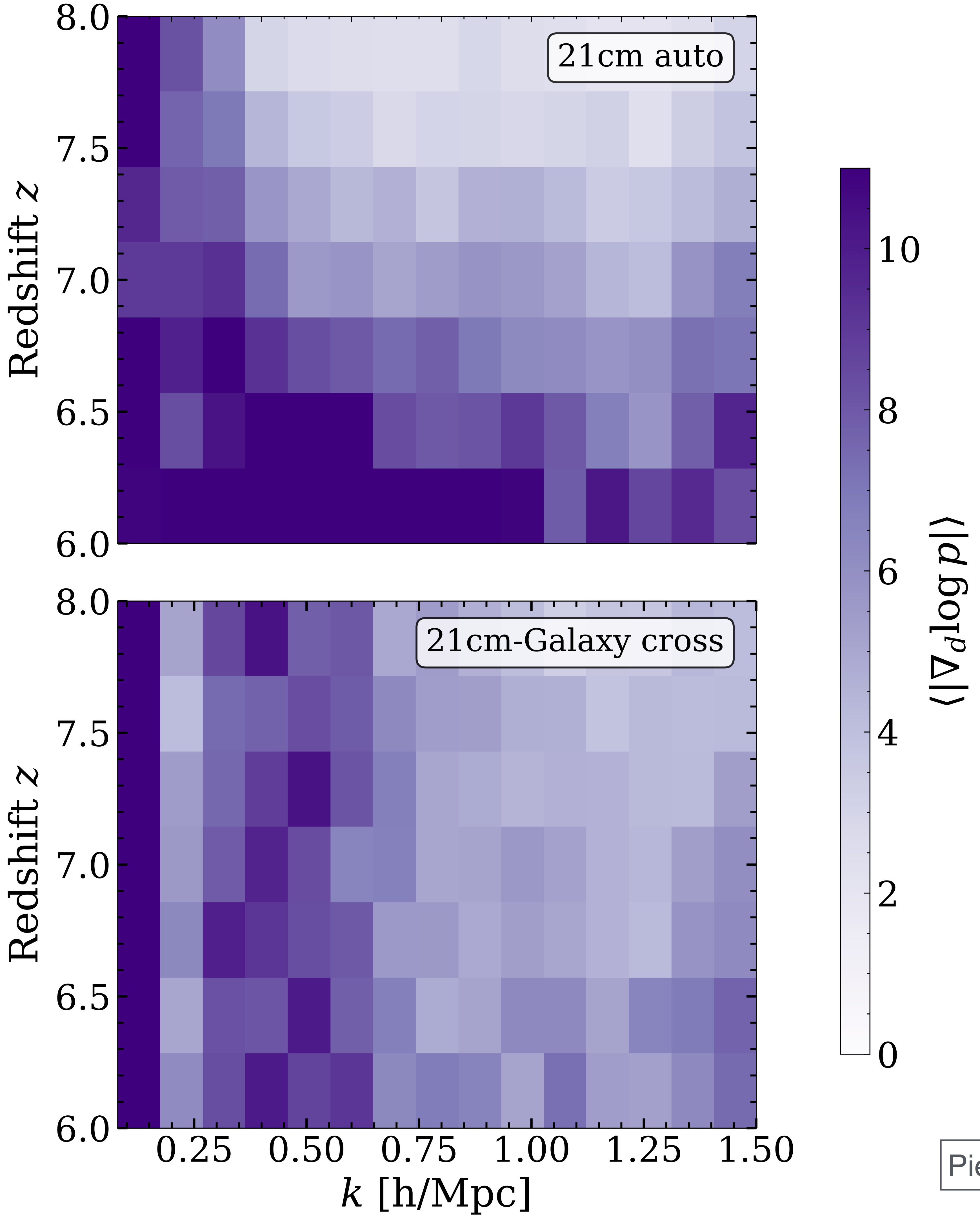
Where is the information?

Saliency:
"Where does the network look?"

21cm auto:
- network attends to low-z

21cm-Galaxy cross:
- attention is spread across all z

(Note: this is architecture dependent!)



Pietschke et al. 2026

Mapping the universe in 21cm

Global evolution

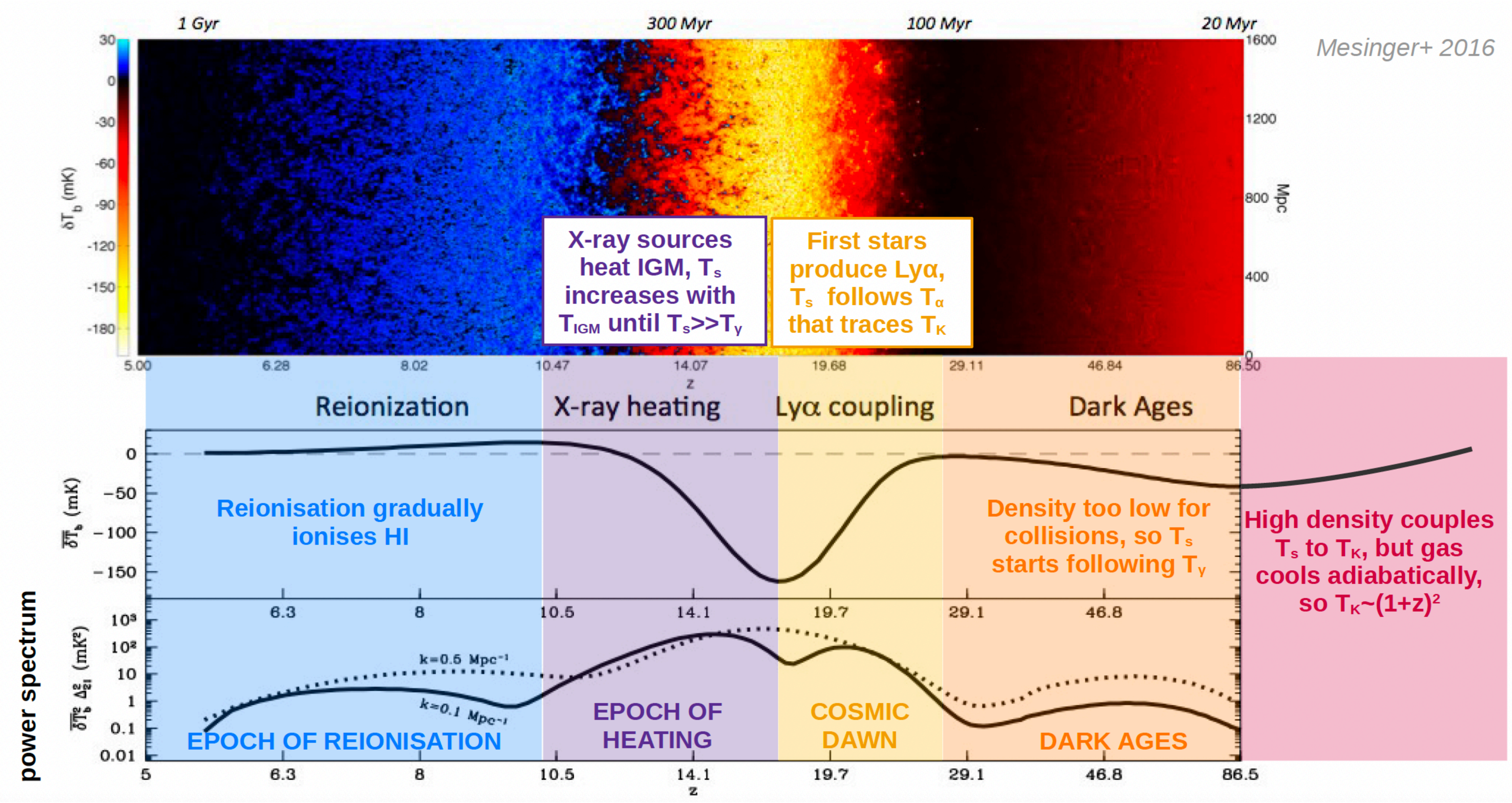


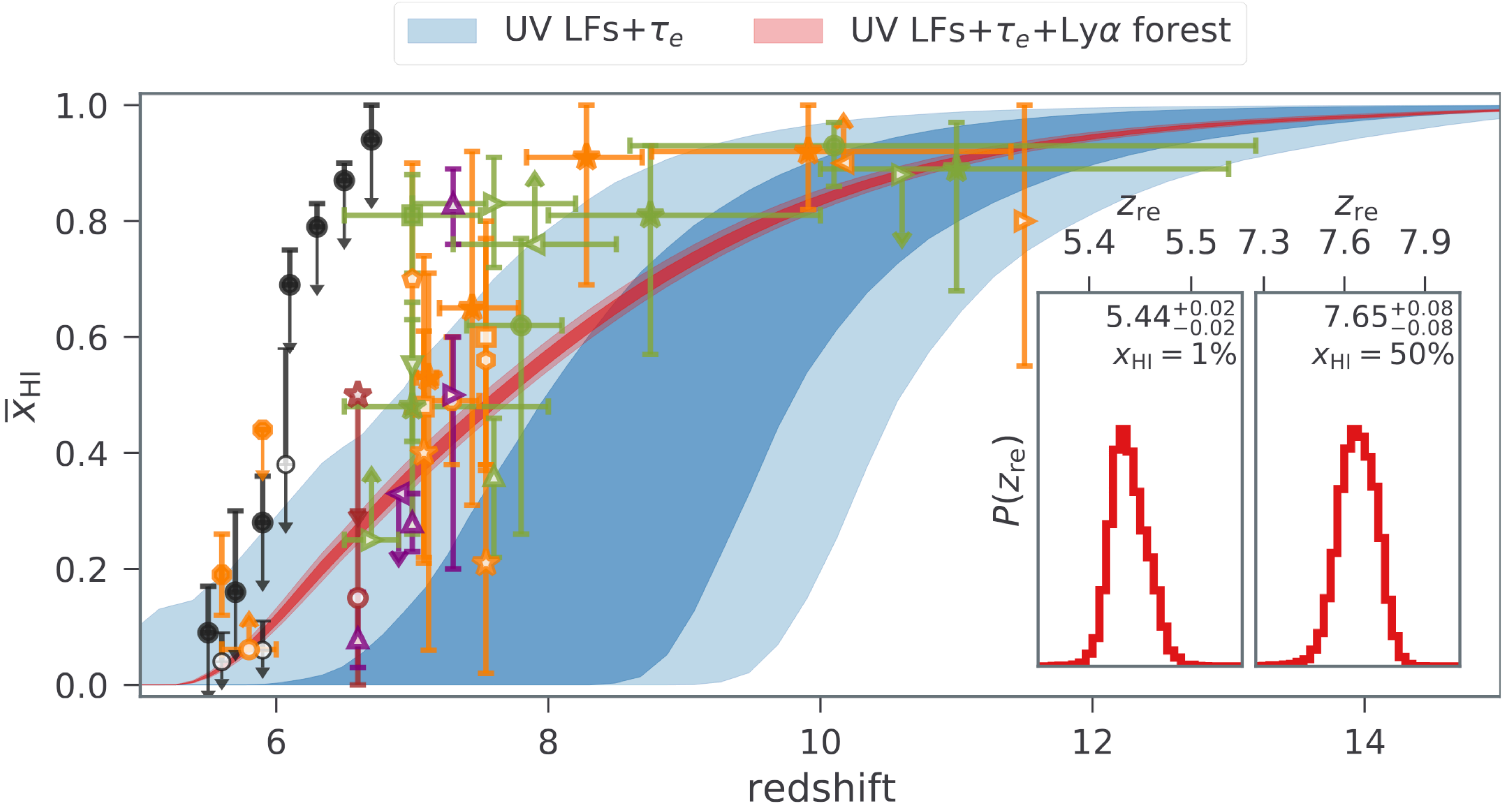
Image Credit: Anne Hutter

The Epoch of Reionization

What we know so far

- Model dependent, indirect probes

→ we need a direct tracer of the IGM!



Qin et al. 2025