Understanding Circumgalactic Medium through Extended Lyα Halos:

Emulating Surface Brightness Profiles through Gaussian Process Regression

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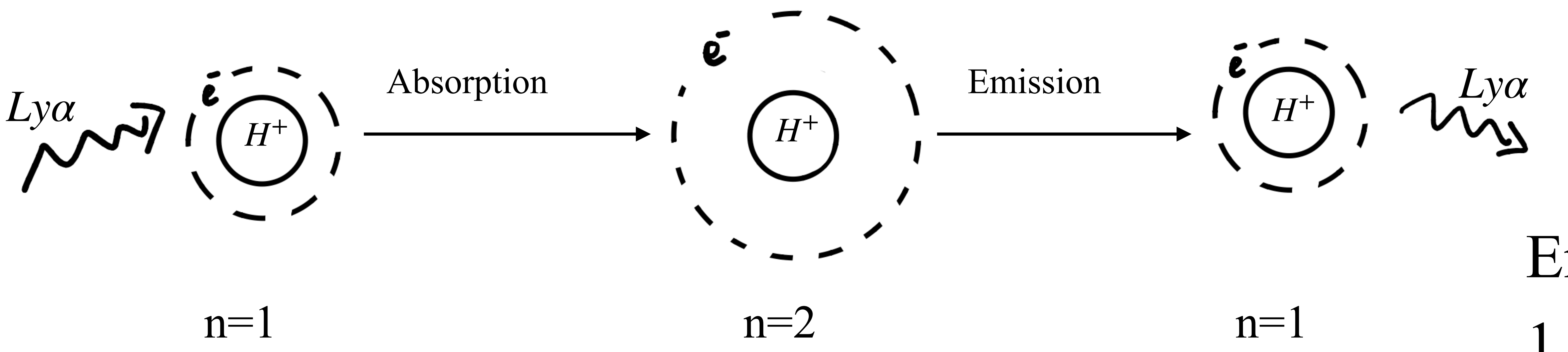
Resonant Scattering

Neutral Hydrogen: n=2 to n=1, $\lambda = 1216$Å



Emitted photons have:

1. Different wavelengths
2. Different direction

Gas ionization state

$$d\tau = n\sigma ds$$

"Interaction Probability"

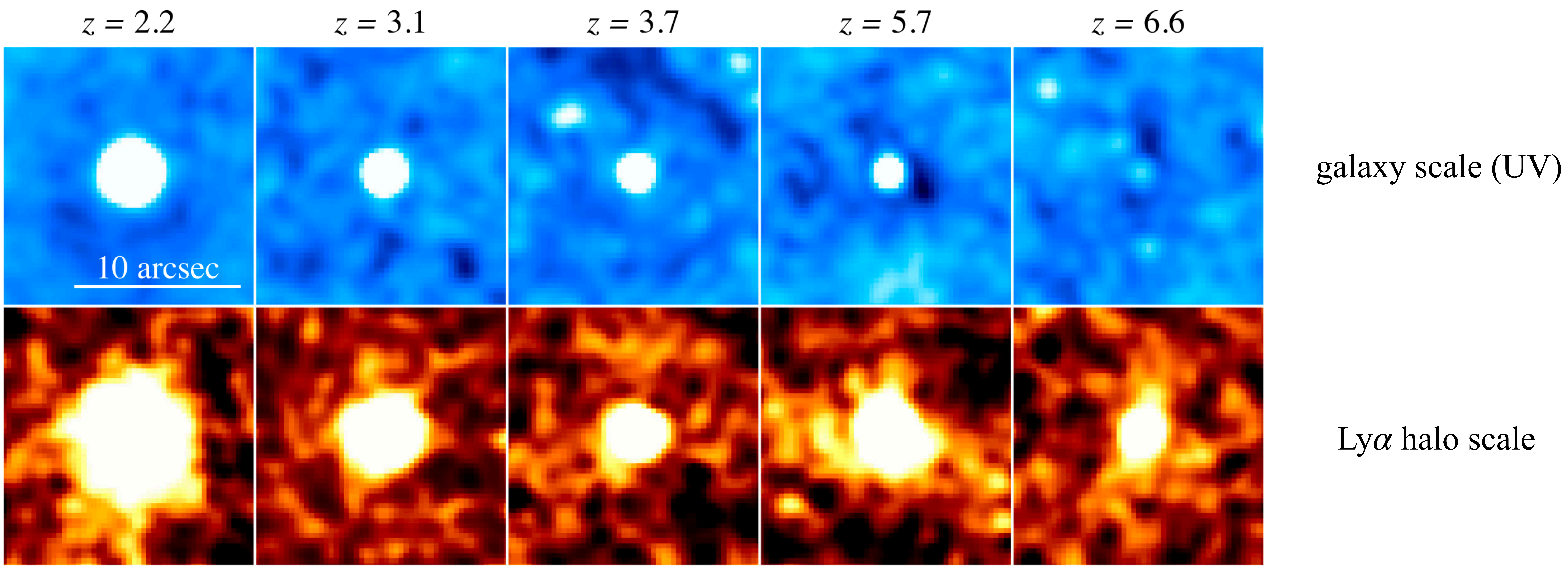
HI gas density

Cross Section

HI gas temperature

HI gas velocity

Extended Lyα halos



Momose+2014

Simulation Setup

Gas density:

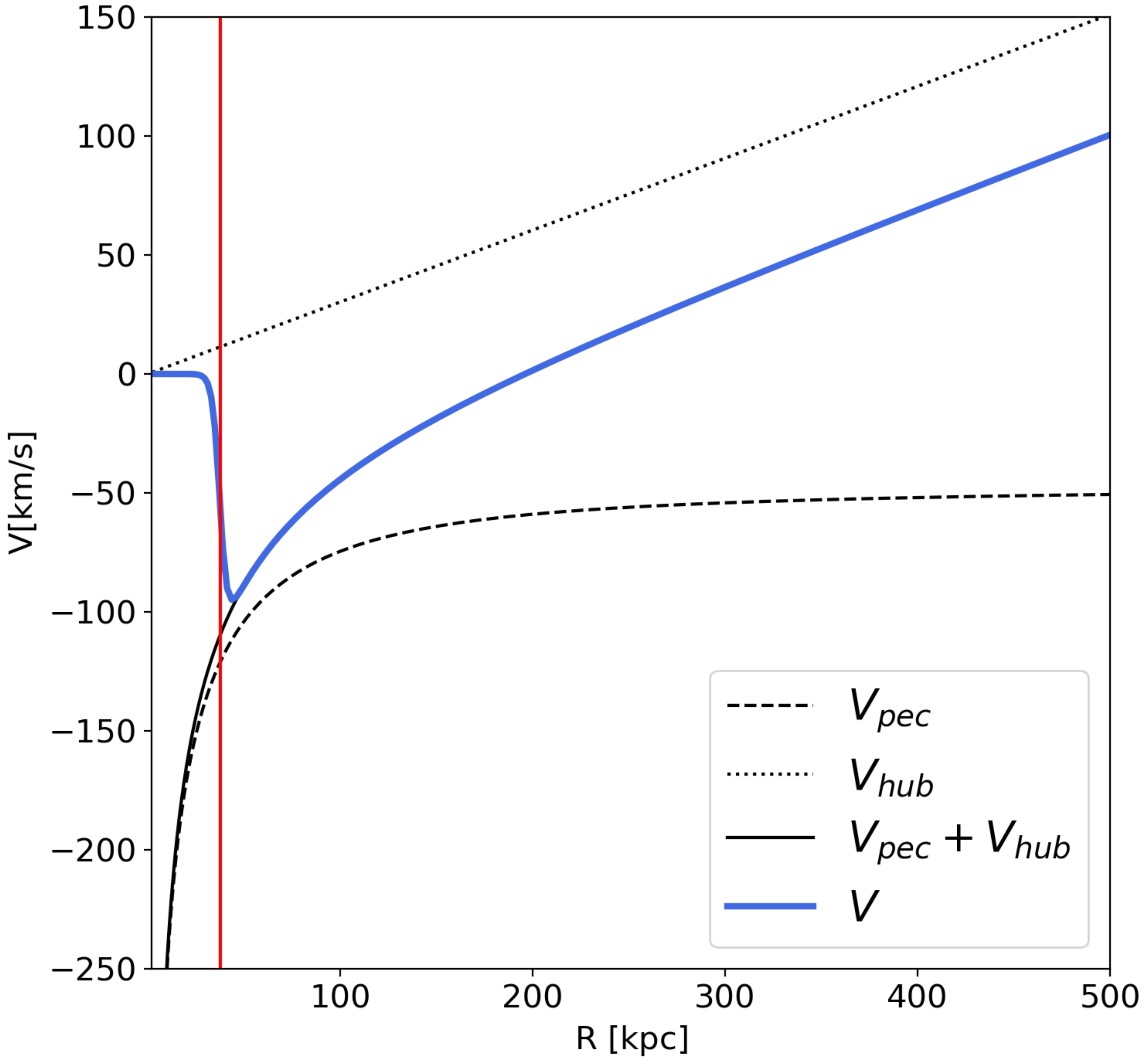
$$\rho = \frac{\rho_0}{(\frac{cr}{R_{vir}} + 0.75)(\frac{cr}{R_{vir}} + 1)^2}$$

Gas ionization state:

- Solved through ionization-recombination equilibrium
- Ionization source: 1. escaping ionizing photons from central star formation; 2. UV background

Gas temperature: 10000 K

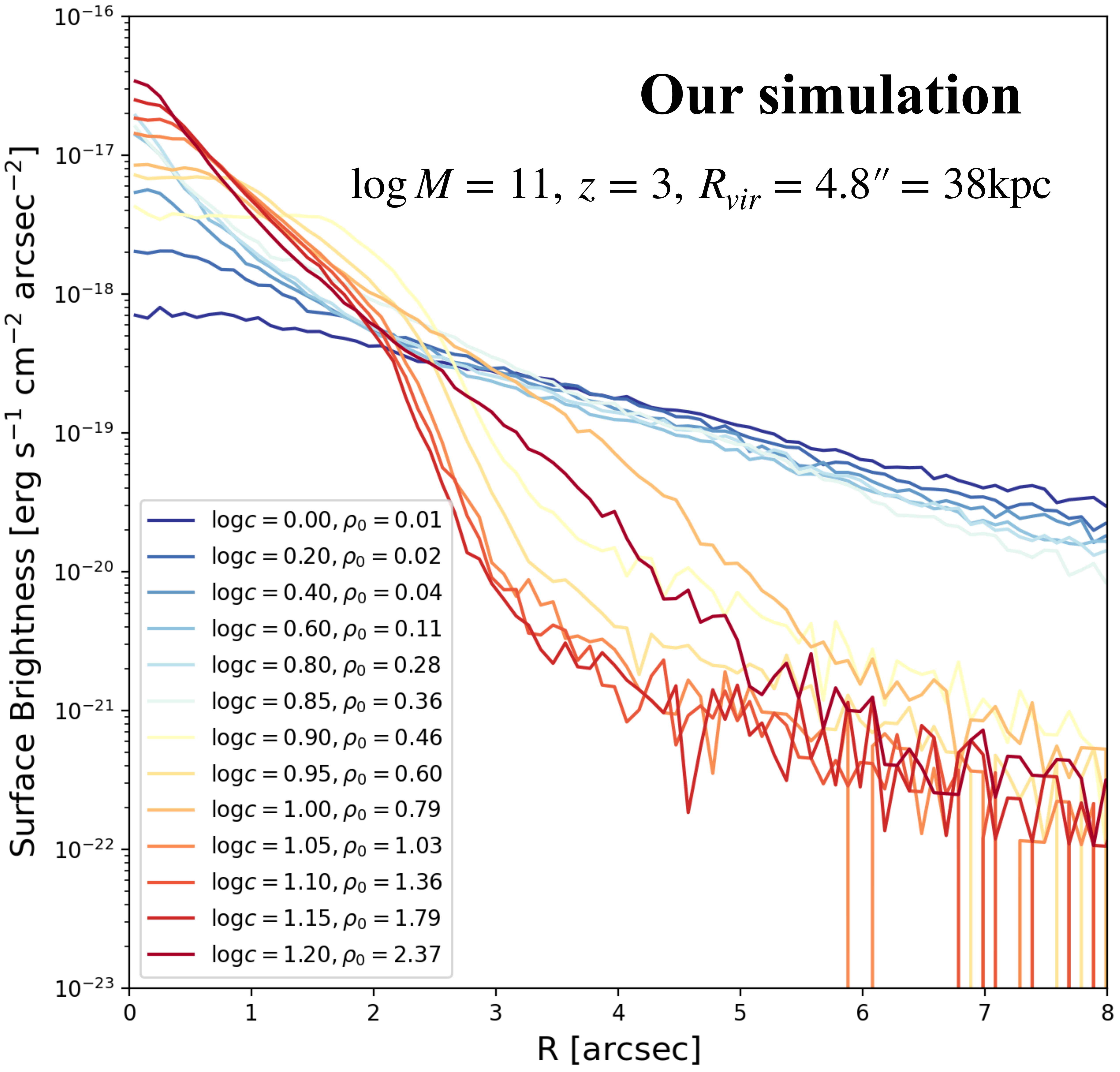
Gas velocity:

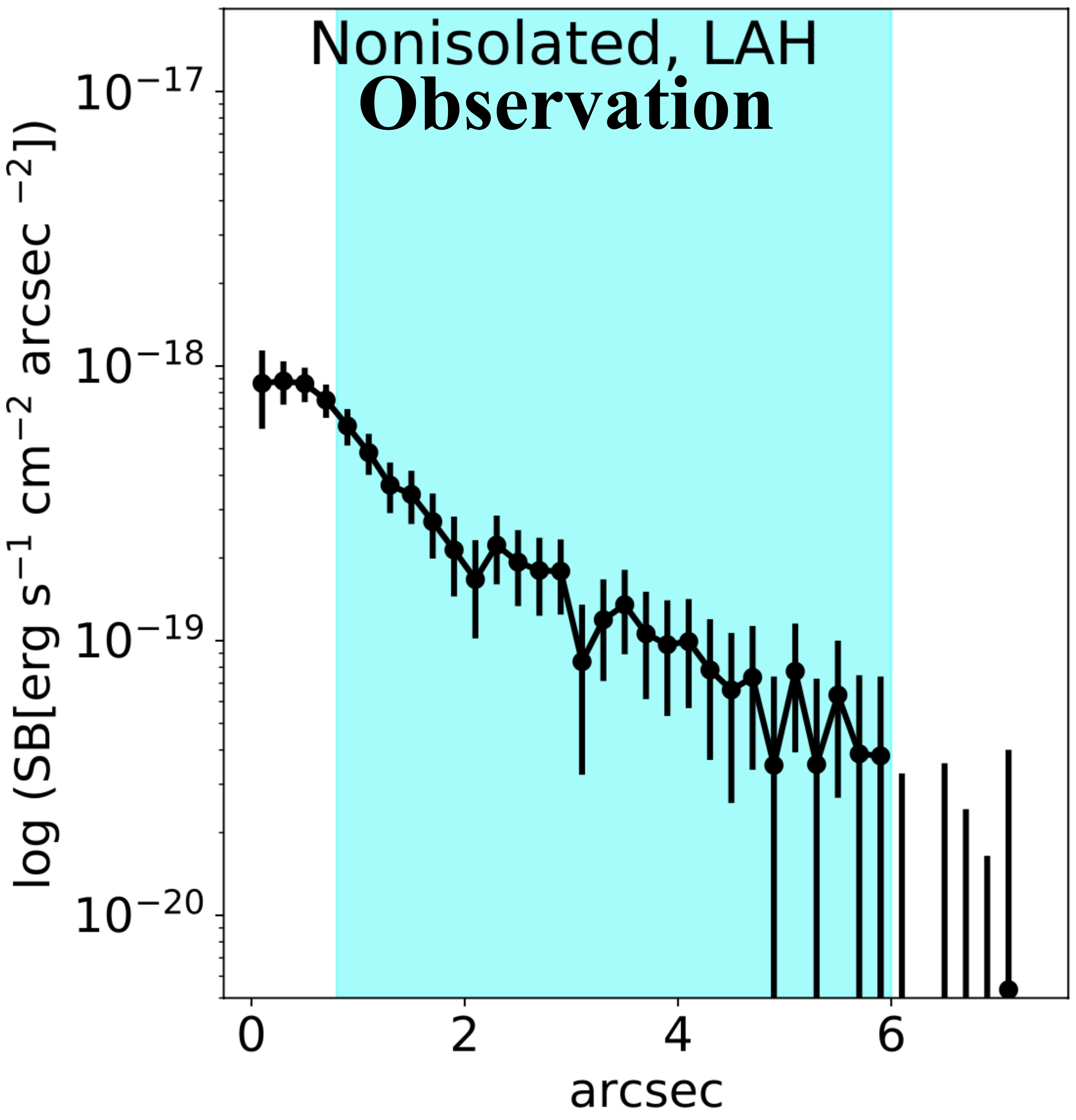


Simulation processes:

- Launch Lyα photons in the center.
- Trace their evolution until escaping simulation boundary. (spherical system).

Surface Brightness Profiles





Kusakabe+2022

GPR Emulator

$$p(y_1, \ldots y_n) = \frac{1}{(2\pi)^{\frac{n}{2}}\sqrt{|\boldsymbol{\Sigma}|}} \exp\left[-\frac{1}{2}\mathrm{Tr}\left((\mathbf{y}-\mu)^T\boldsymbol{\Sigma}^{-1}(\mathbf{y}-\mu)\right)\right]$$

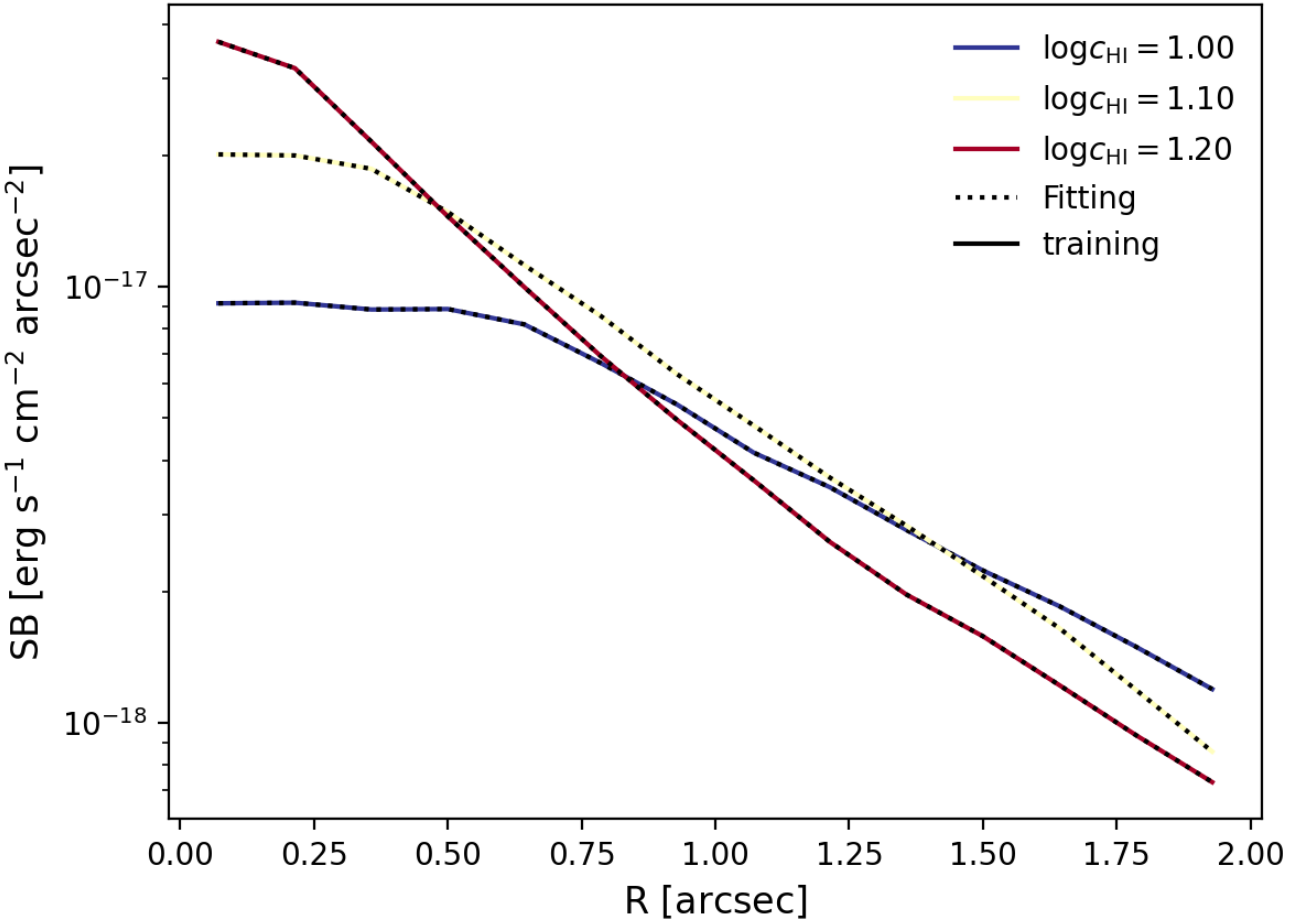
$$\sigma_{ij} = k[(a_i, b_i \ldots), (a_j, b_j, \ldots)] = \exp\left(-\frac{(a_i - a_j)^2 + (b_i - b_j)^2 + \ldots}{2l^2}\right)$$

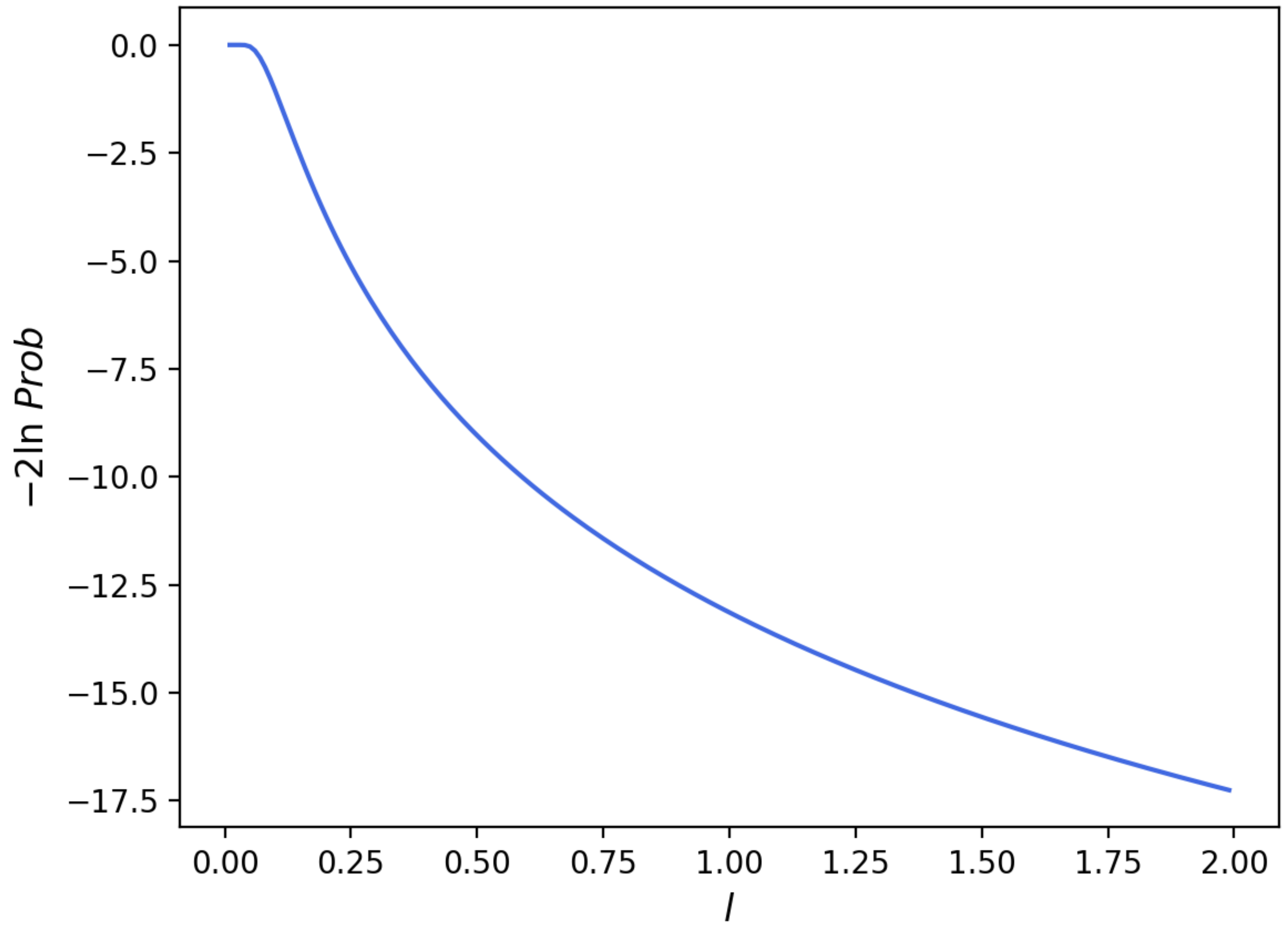
$$\mathbf{y_p} = K_{pt}K_{tt}^{-1}\mathbf{y_t} \qquad \mathrm{var} = K_{pp} - K_{pt}K_{tt}^{-1}K_{tp}$$

$$-2\ln p \propto \ln|K_{tt}| + \mathrm{Tr}\left[(\mathbf{y}-\mu)^T K_{tt}^{-1}(\mathbf{y}-\mu)\right]$$

$$\left[\begin{array}{c|c} K_{tt} & K_{tp} \\ \hline K_{pt} & K_{pp} \end{array}\right]$$

GPR Emulator

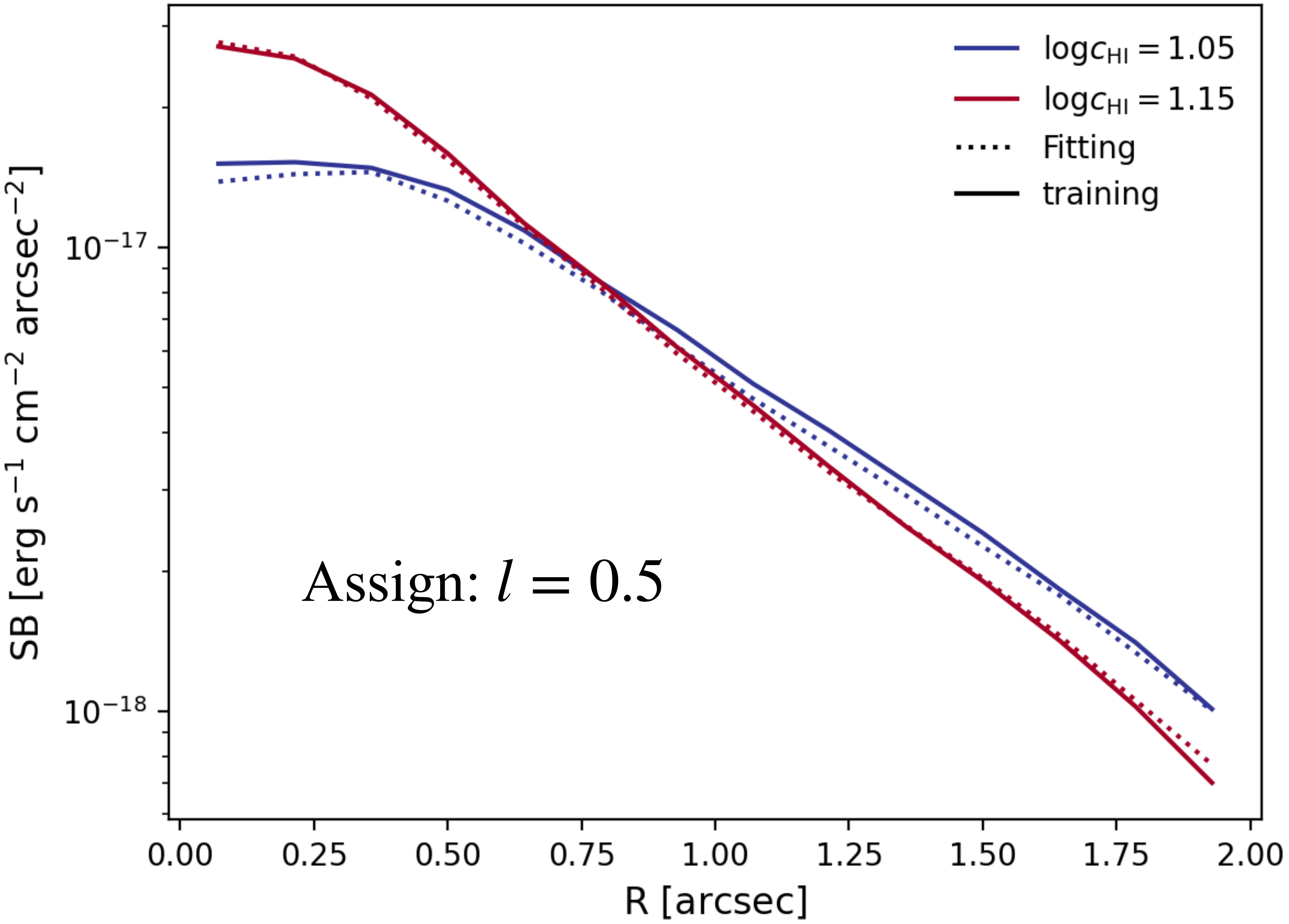




×: training; @: prediction

$\log c_{HI}$	1.00	1.05	1.10	1.15	1.20
	×	@	×	@	×

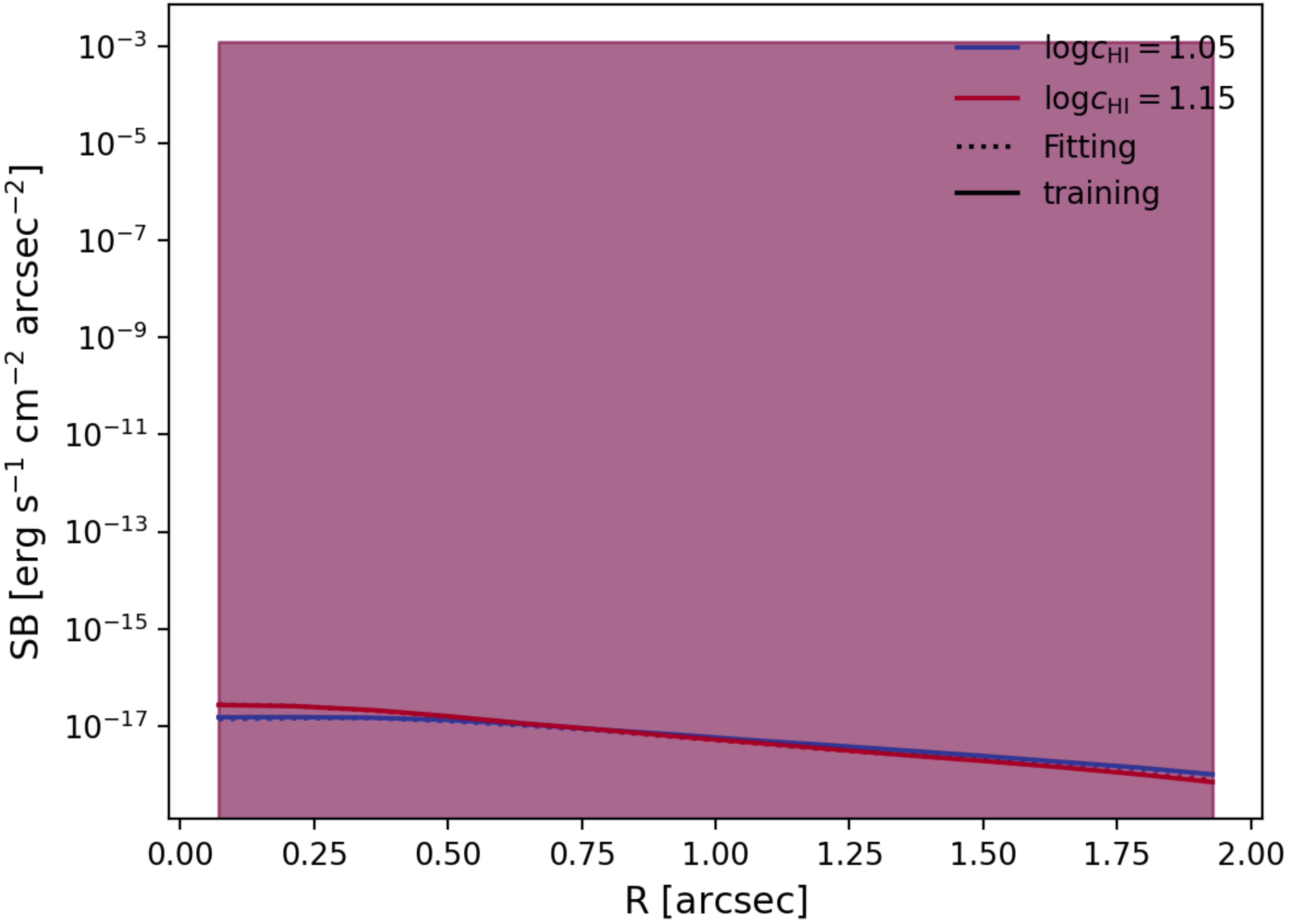
GPR Emulator



×: training; @: prediction

$\log c_{HI}$	1.00	1.05	1.10	1.15	1.20
	×	@	×	@	×

GPR Emulator

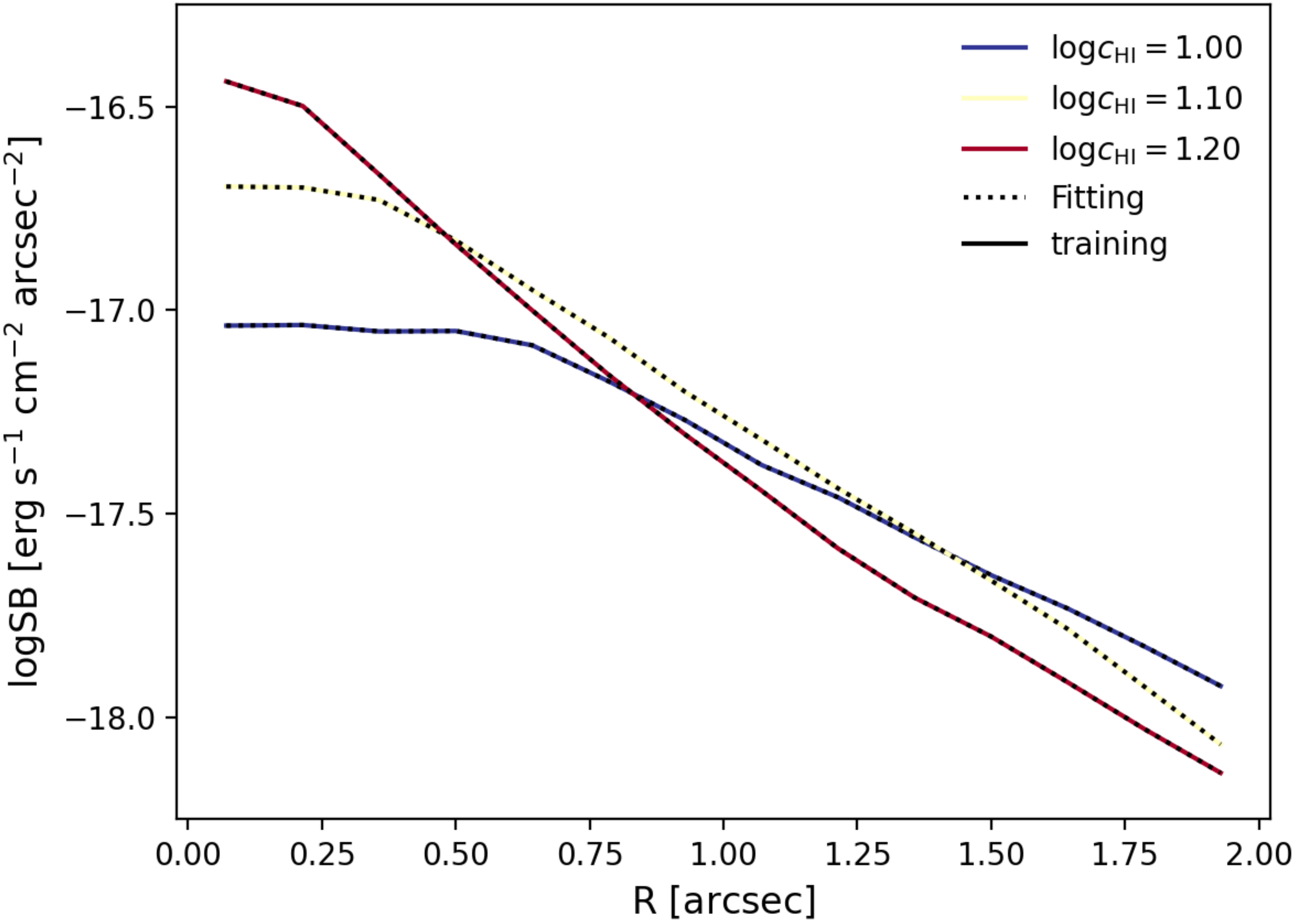


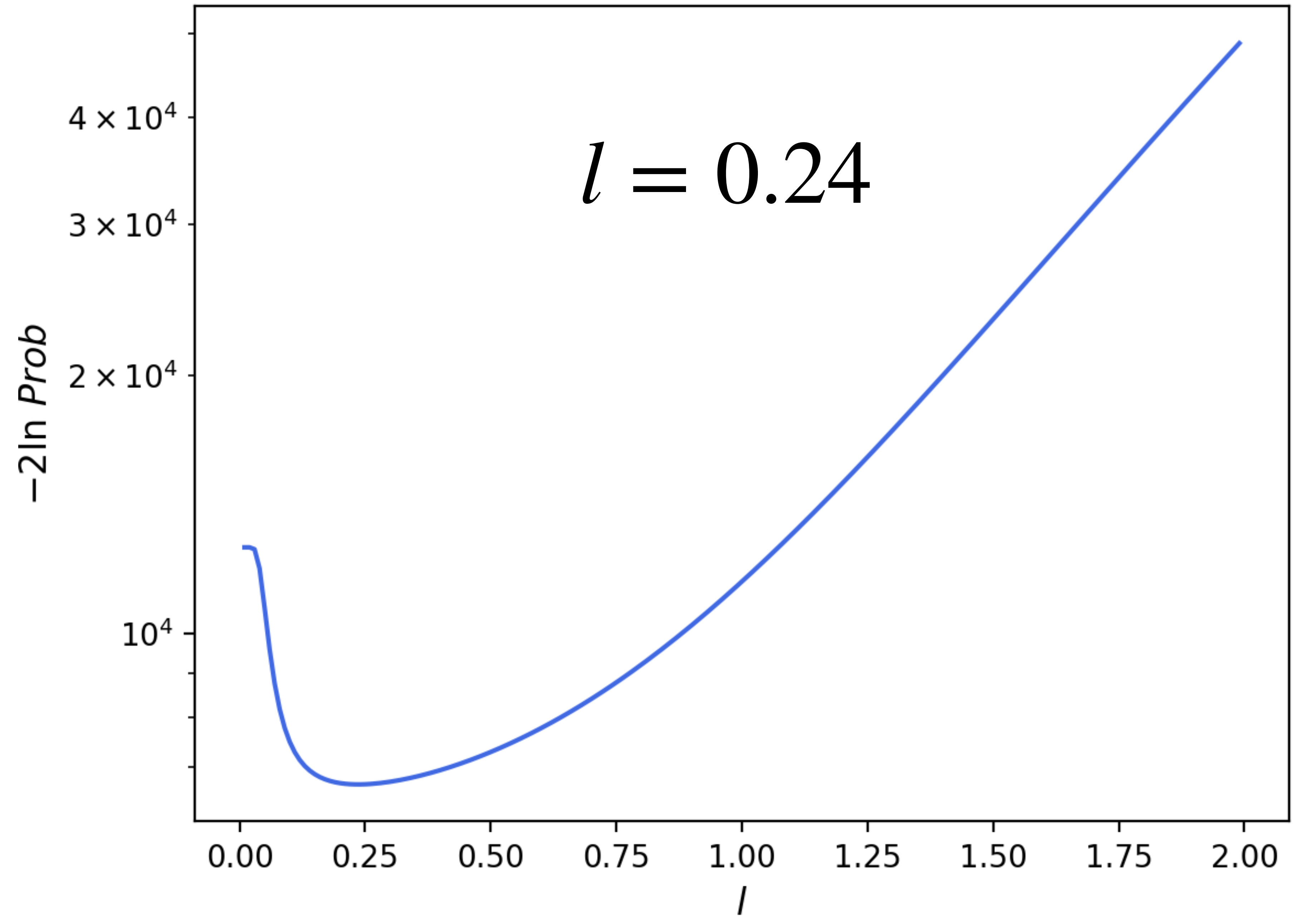
- We may not be able to optimize scale factor, even we can fit the data.
- The predicted variance can tell us whether our Gaussian Process Regression works.

×: training; @: prediction

$\log c_{HI}$	1.00	1.05	1.10	1.15	1.20
	×	@	×	@	×

GPR Emulator

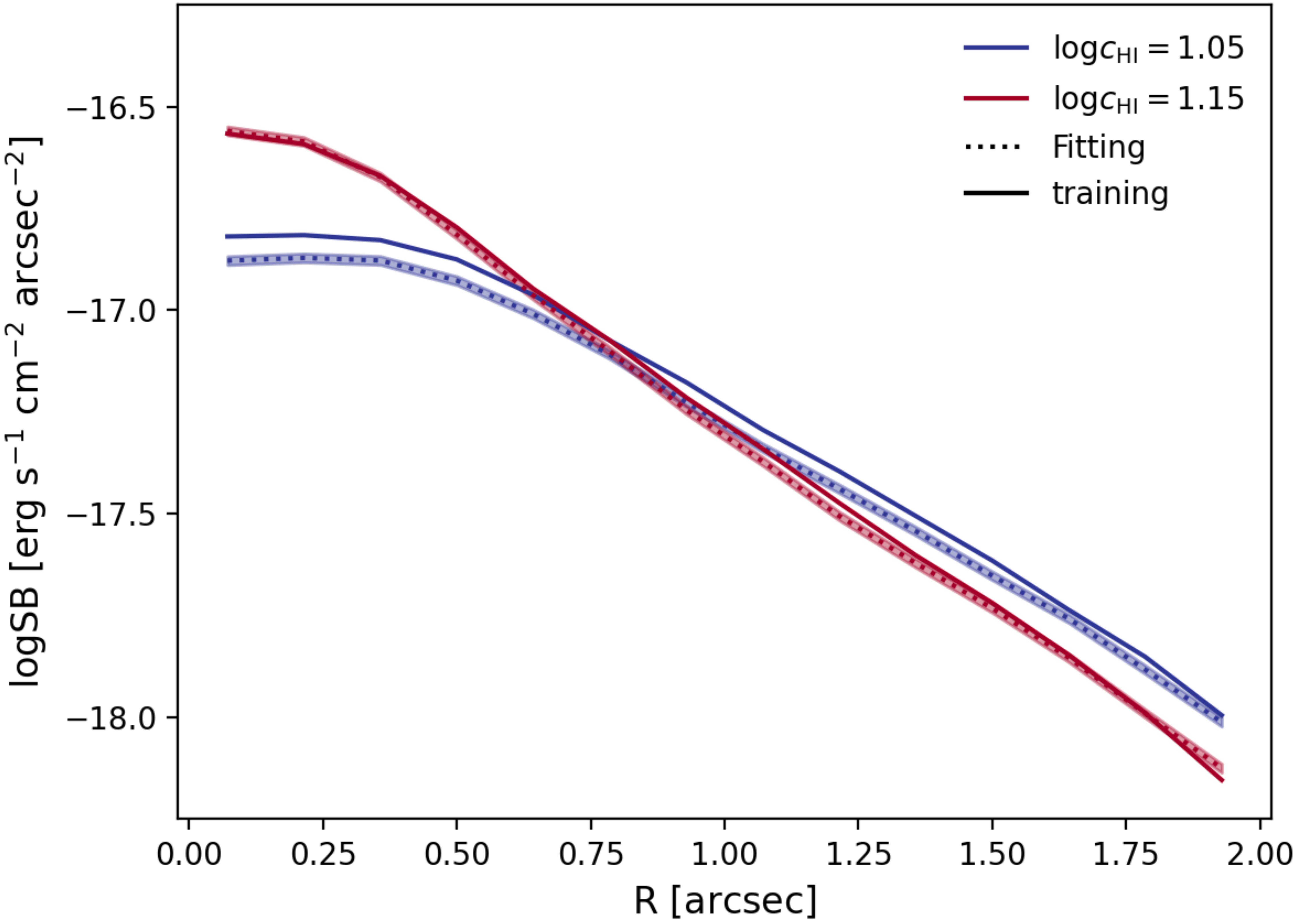




×: training; @: prediction

$\log c_{HI}$	1.00	1.05	1.10	1.15	1.20
	×	@	×	@	×

GPR Emulator

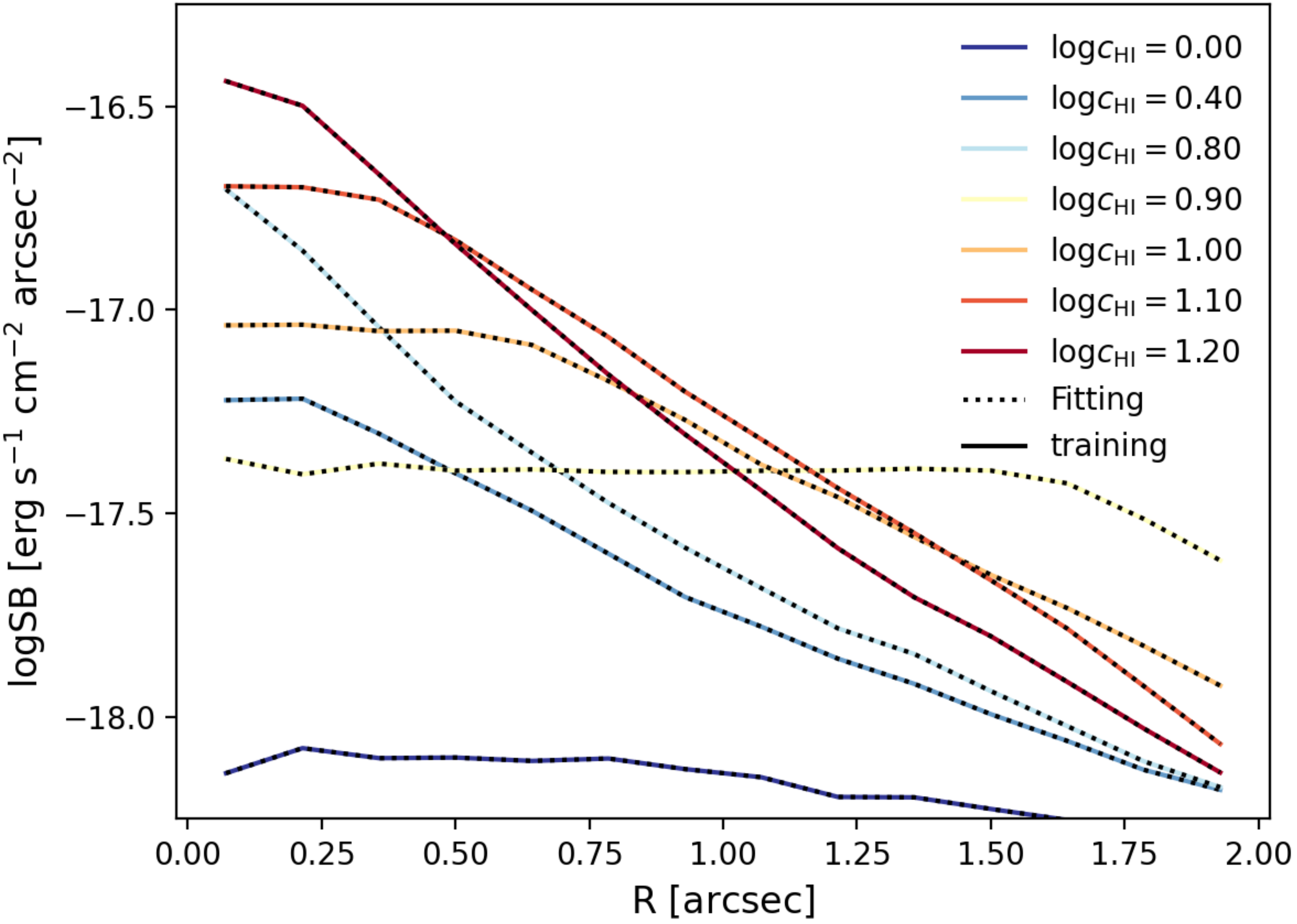


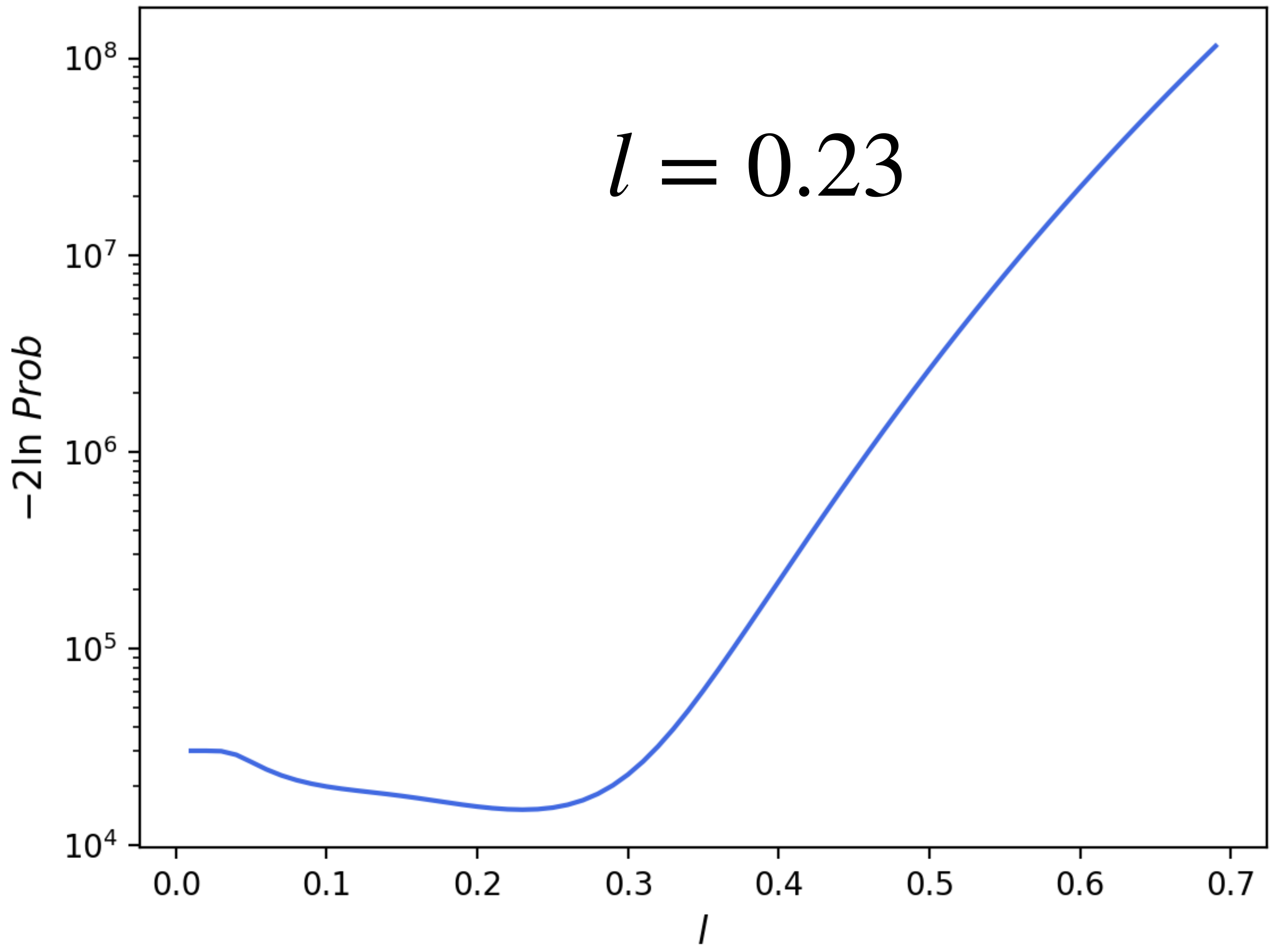
- We may need to process training data before using GPR.
- We have a robust way to estimate scale factor.

×: training; @: prediction

$\log c_{HI}$	1.00	1.05	1.10	1.15	1.20
	×	@	×	@	×

GPR Emulator

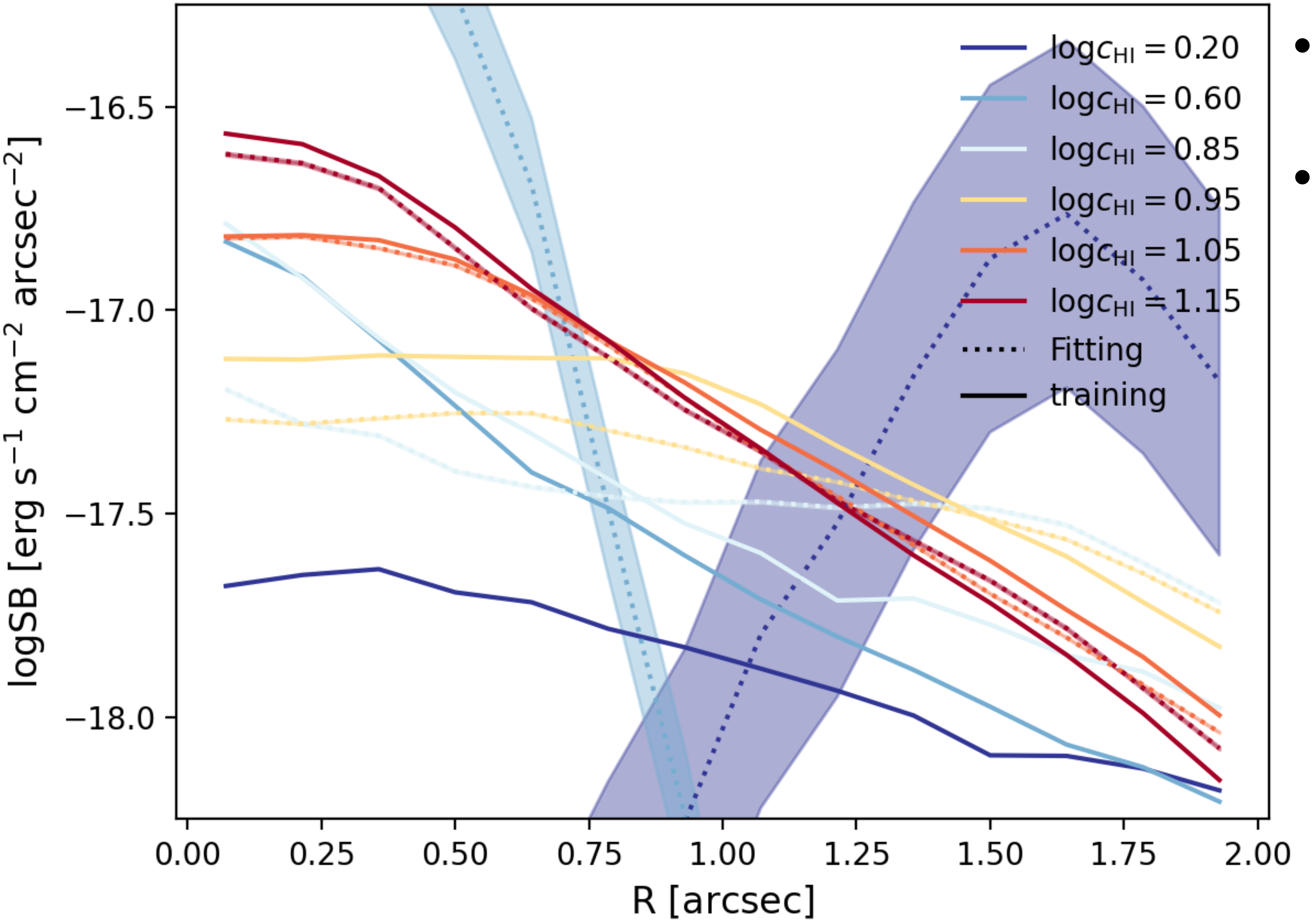




×: training; @: prediction

$\log c_{HI}$	0.0	0.2	0.4	0.6	0.8	0.85	0.9	0.95	1.0	1.05	1.1	1.15	1.2
	×	@	×	@	×	@	×	@	×	@	×	@	×

GPR Emulator

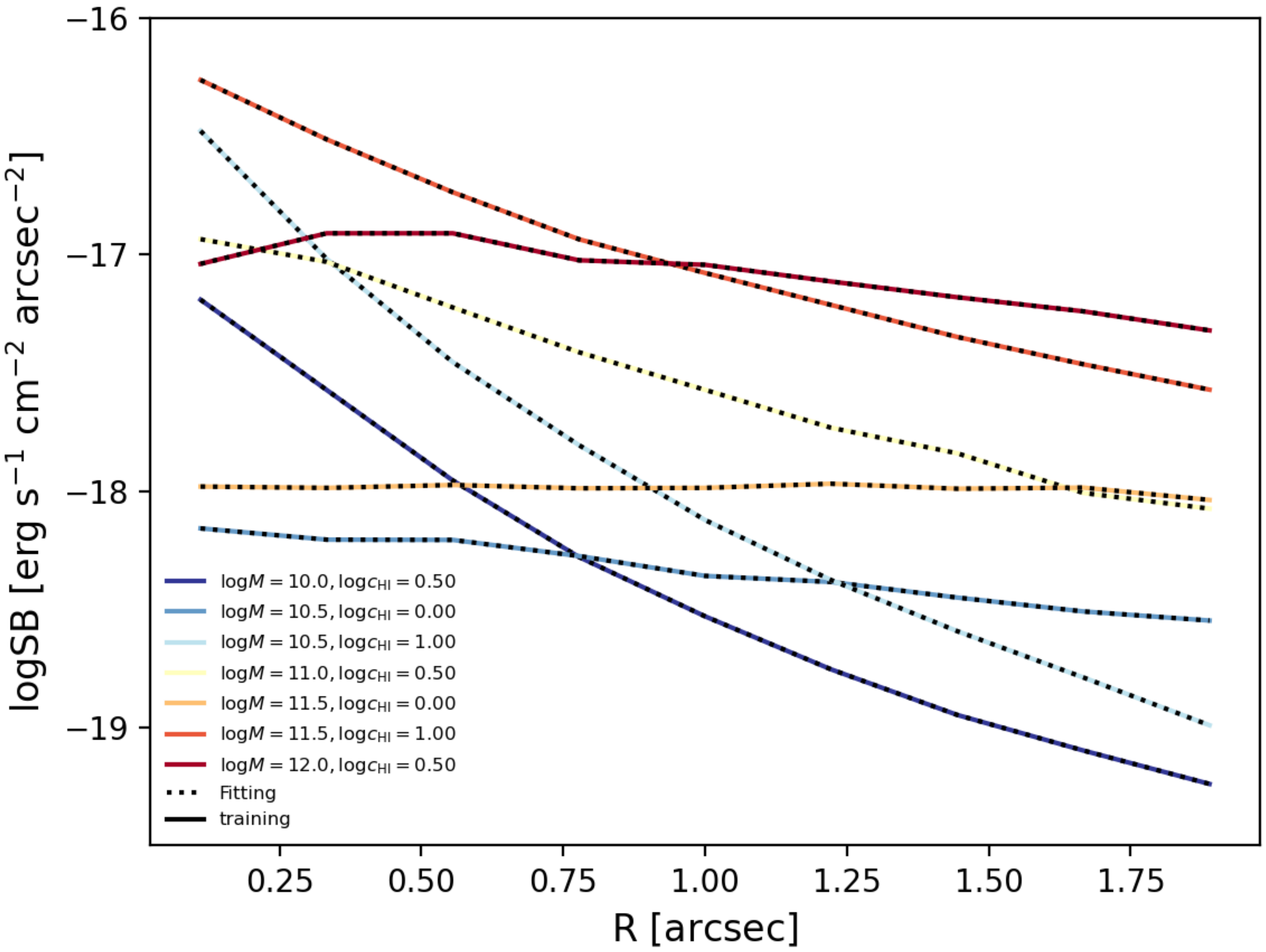


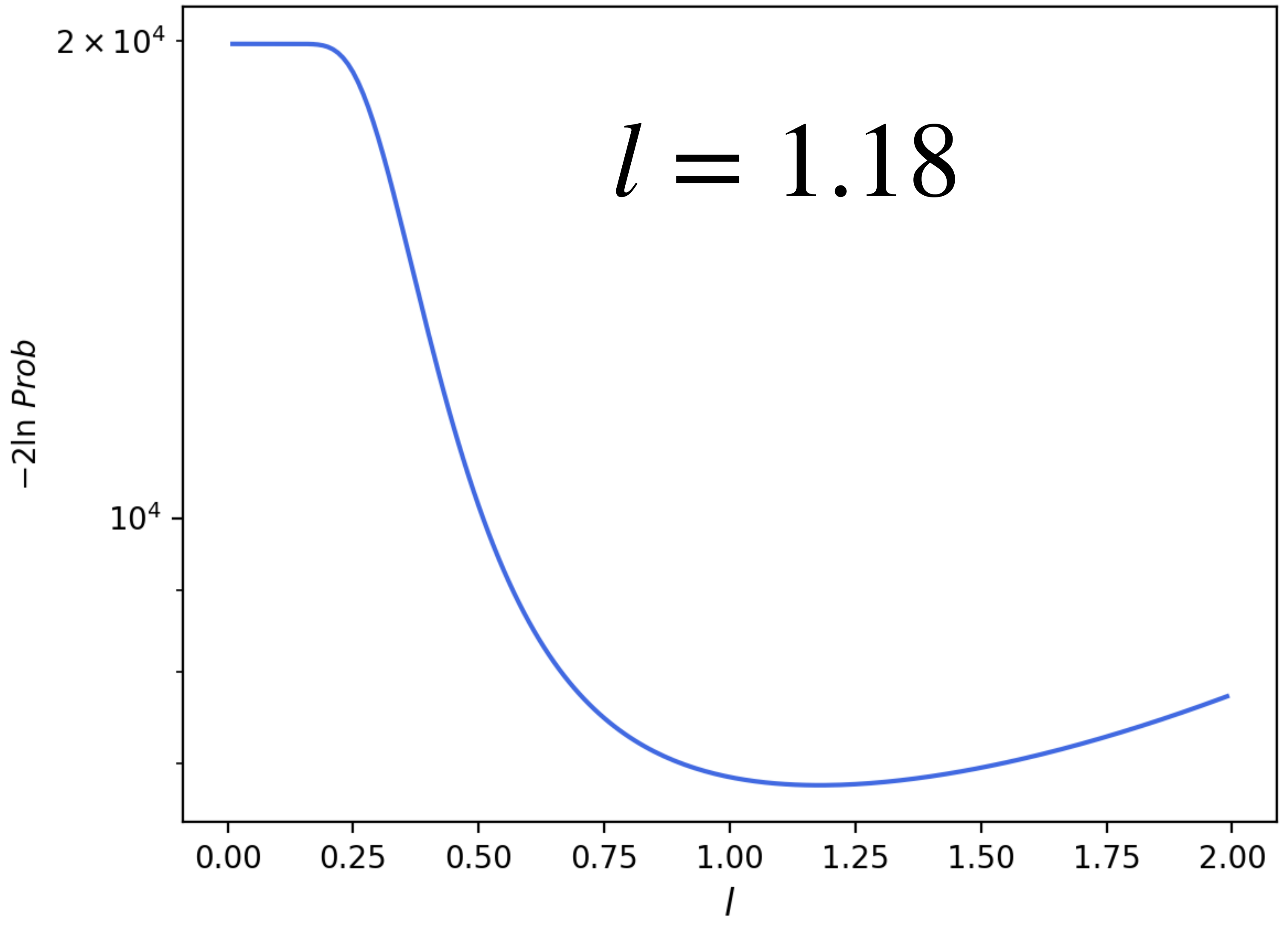
- Small predicted variance can't guarantee that the model works.
- Optimized scale factor can't guarantee that the model works.

×: training; @: prediction

$\log c_{HI}$	0.0	0.2	0.4	0.6	0.8	0.85	0.9	0.95	1.0	1.05	1.1	1.15	1.2
	×	@	×	@	×	@	×	@	×	@	×	@	×

GPR Emulator

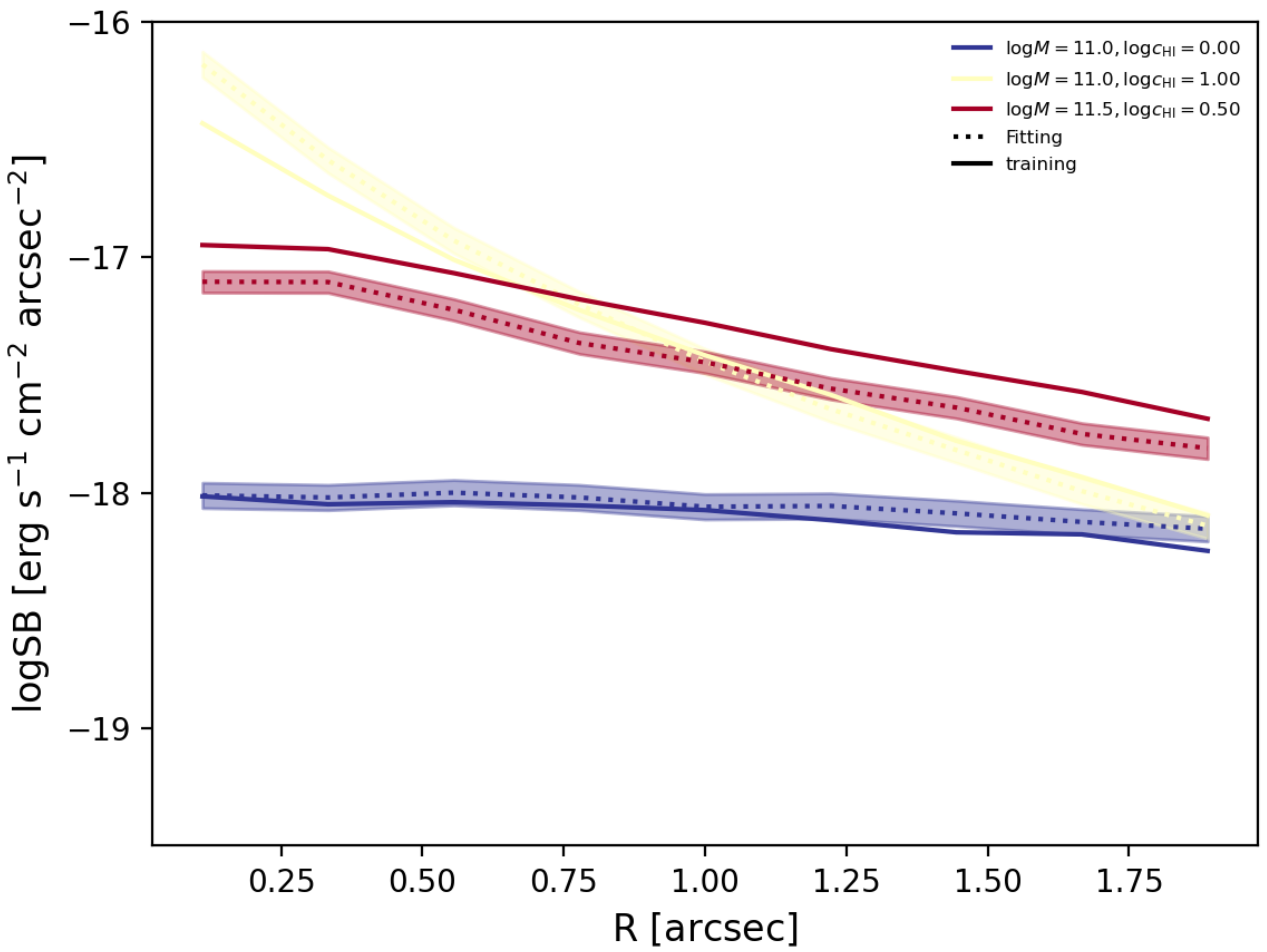




×: training; @: prediction

$\log c_{HI}$ \ $\log M$	10.0	10.5	11.0	11.5	12
0.0	@	×	@	×	@
0.5	×	@	×	@	×
1.0		×	@	×	

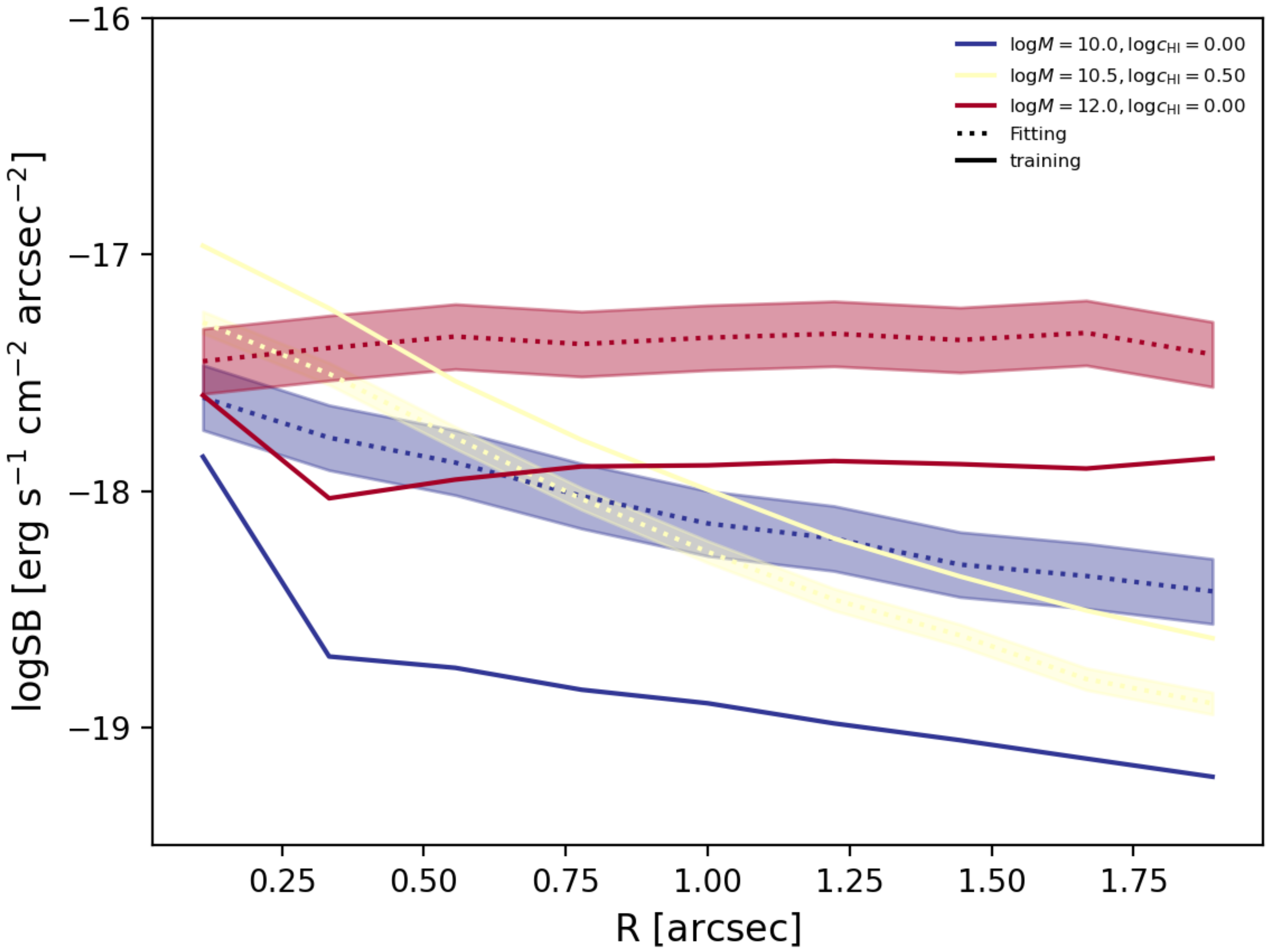
GPR Emulator



×: training; @: prediction

log M / log c_{HI}	10.0	10.5	11.0	11.5	12
0.0	@	×	@	×	@
0.5	×	@	×	@	×
1.0		×	@	×	

GPR Emulator



- We need to design training parameters that properly represent the whole parameter space.

×: training; @: prediction

$\log M$ \ $\log c_{HI}$	10.0	10.5	11.0	11.5	12
0.0	@	×	@	×	@
0.5	×	@	×	@	×
1.0		×	@	×	

Possible Improvement

1. Process SB profiles before fitting.
2. Build up different GPR emulators at different locations.
3. Include more scale parameters.
4. Modify kernels.