ACCELERATE RADIATIVE TRANSFER SIMULATIONS WITH PHYSICS INFORMED NEURAL NETWORKS

EPFL

MASTER'S THESIS

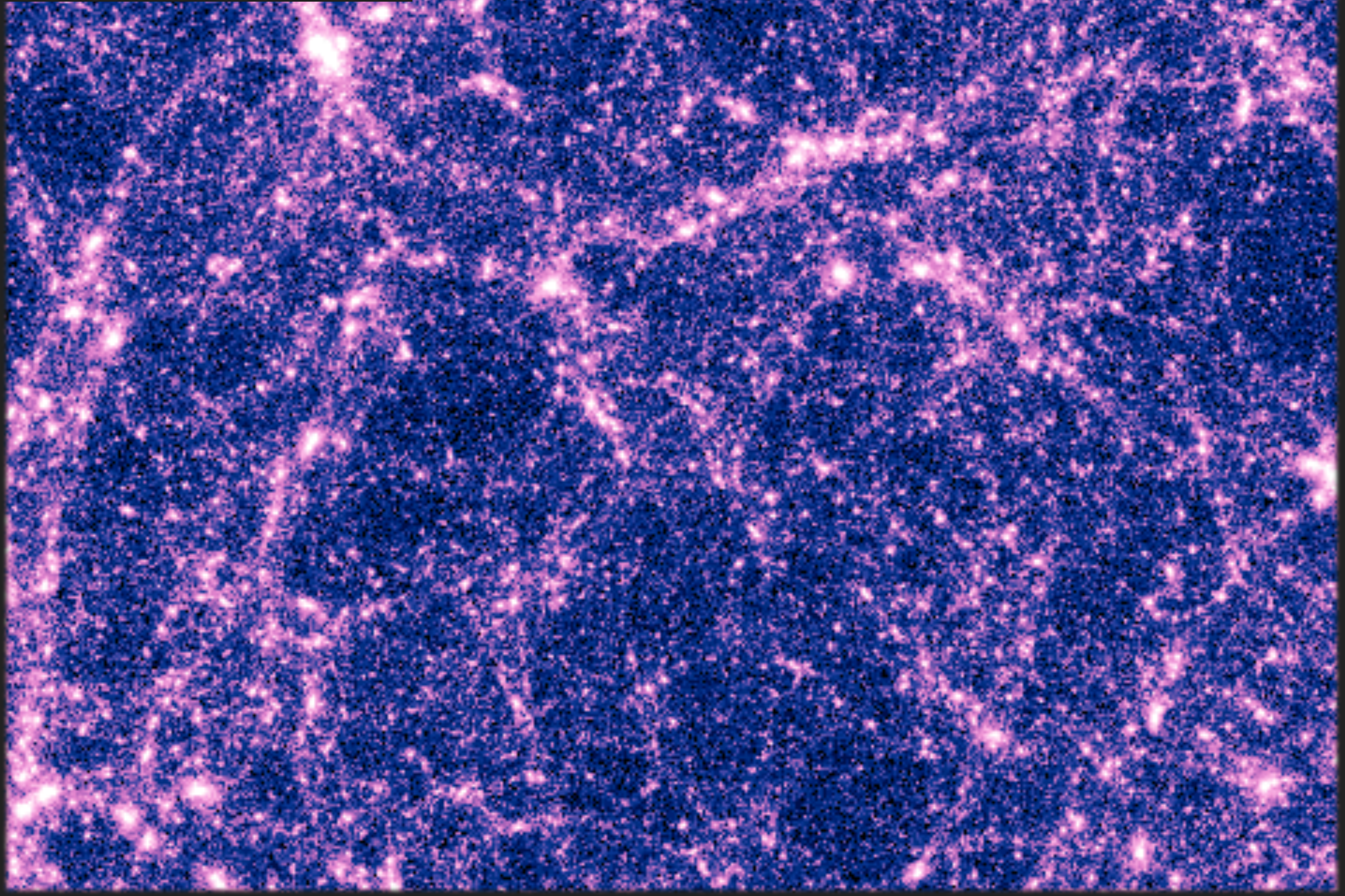
DAMIEN KORBER

UNDER SUPERVISION OF

MICHELE BIANCO

EMMA TOLLEY

JEAN-PAUL KNEIB

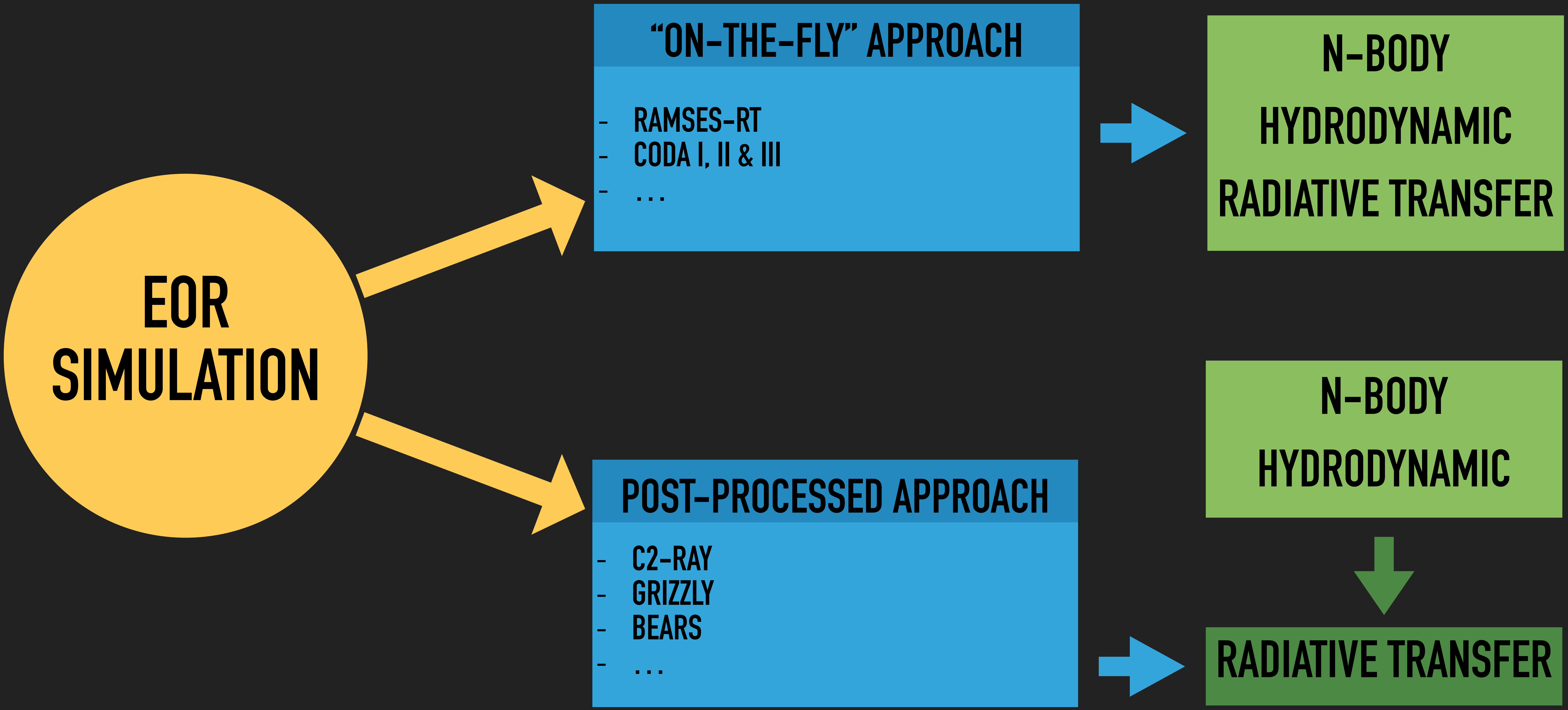


INTRODUCTION

- EoR study is vital for Cosmology
- SKA-Low will allow detailed EoR observations
- Need simulations to compare to SKA observations

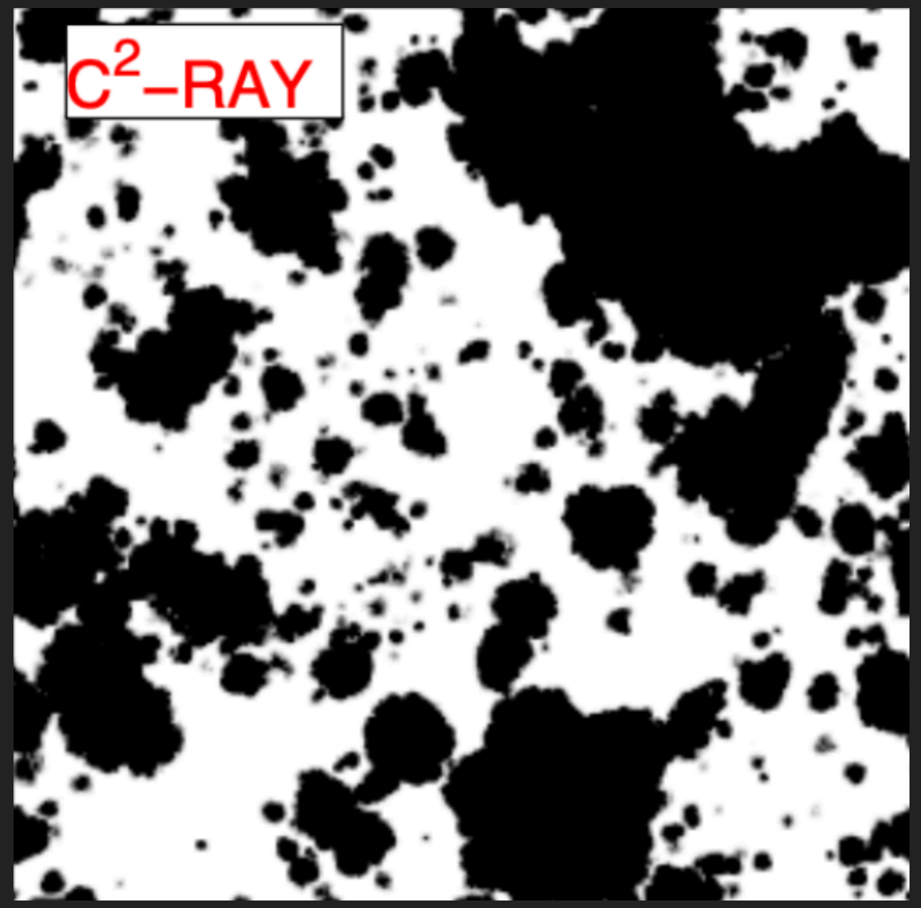
SKA-Low demonstration images. Credit: SKAO (Media Kit)

Reference: SKAO



References: Rosdahl+ (2013); Ocvirk+ (2016, 2020); Lewis+ (2021); Mellema+ (2006); Ghara+ (2018)

- **C^2-Ray**
  - State of the art 3D RT code
  - ✓ Physically motivated results
  - x Very computationally intensive (millions of core-hours)



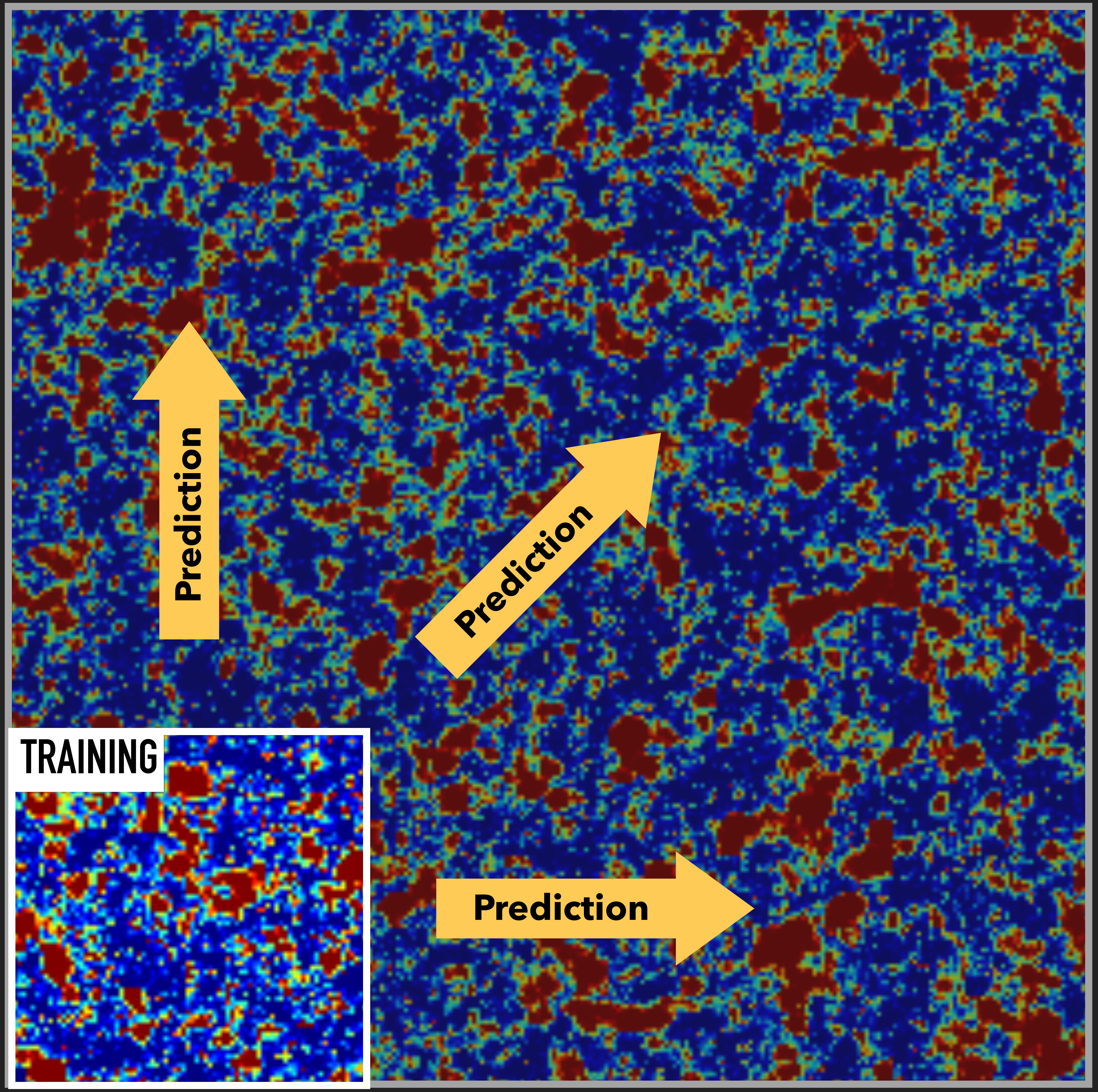
- **Grizzly**
  - 1D RT code
  - x Very approximated but physically motivated results
  - ✓ Light to run (a few core-hours)

References: Mellema+ (2006); Ghara+ (2018)

- **PINION**
  - Train neural network on small C^2-Ray simulation
  - Produce larger scale RT simulations:

    ✓ Faster than C^2-Ray

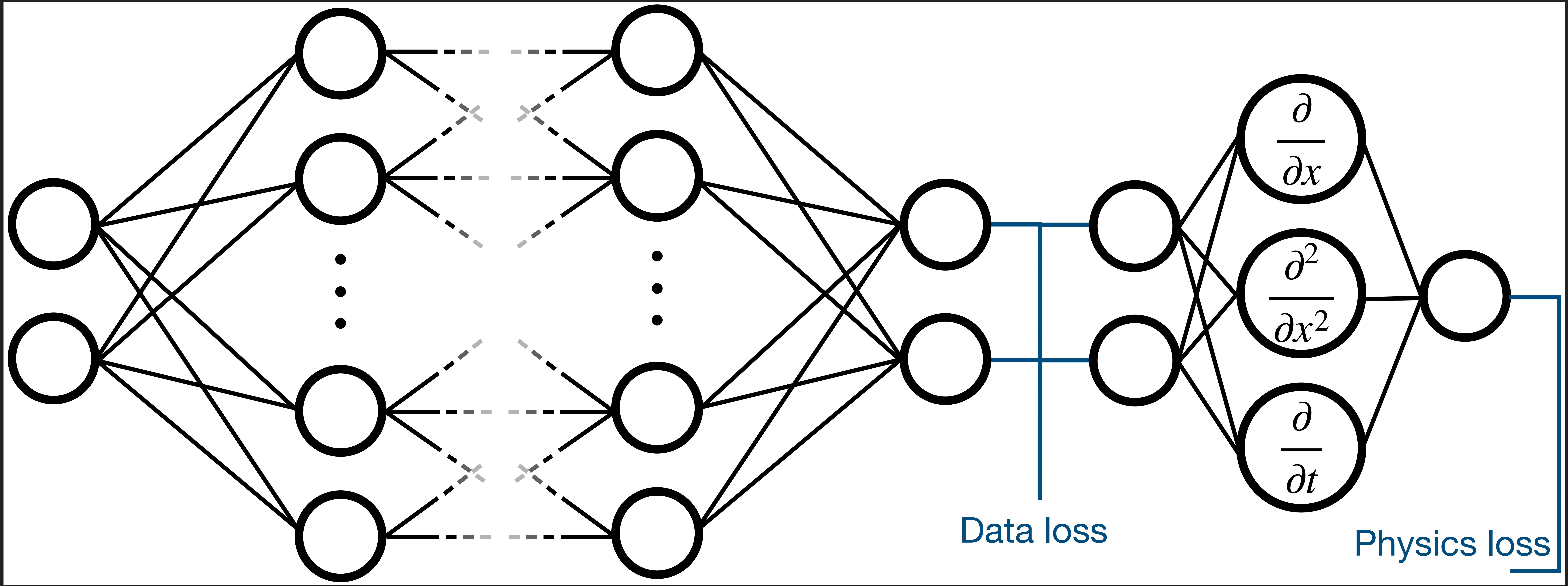
    ✓ As accurately as C^2-Ray



PINION

PHYSICS INFORMED NEURAL NETWORK FOR REIONIZATION

arXiv:2208.13803



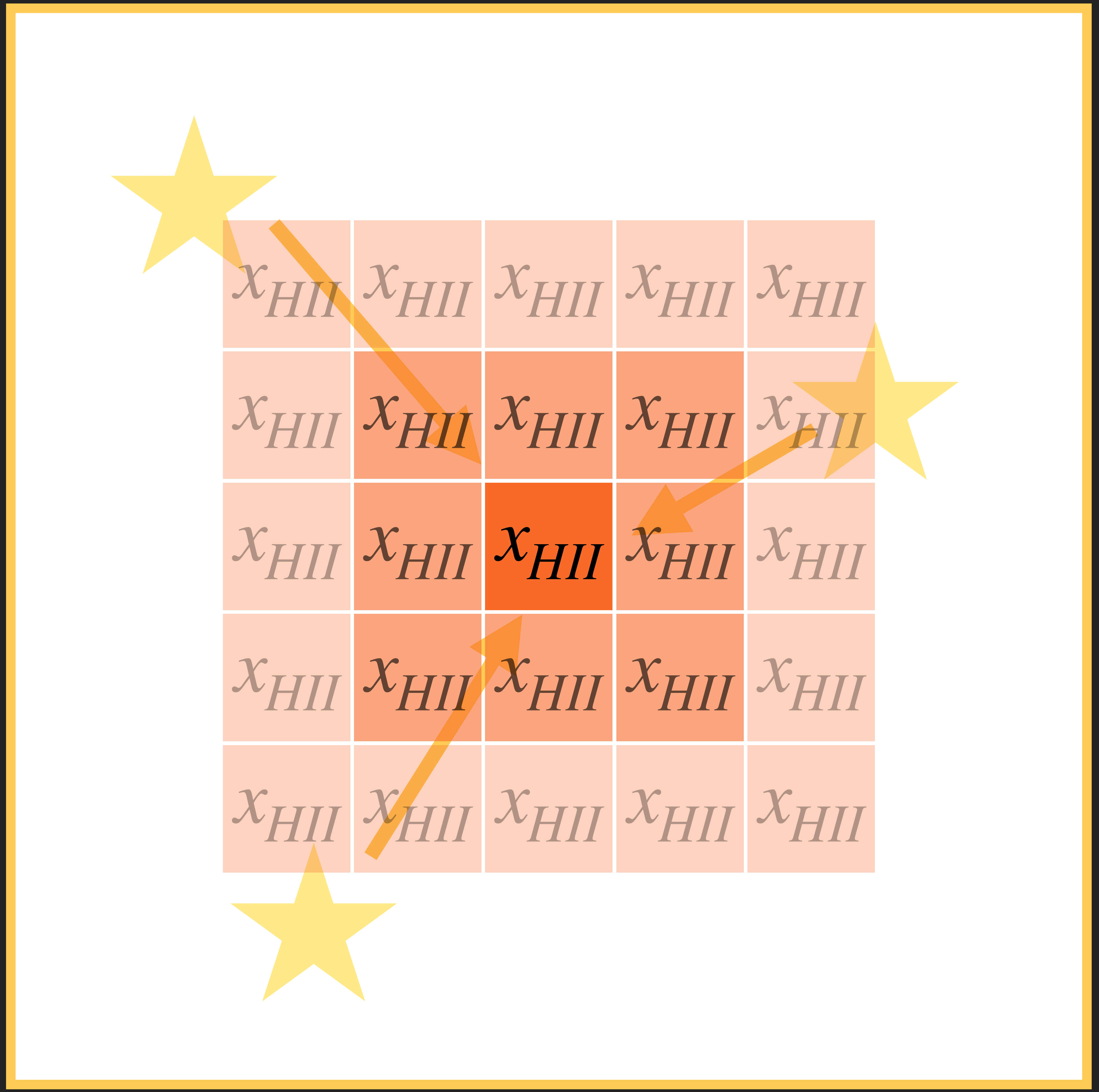
Physics informed neural network with learning bias

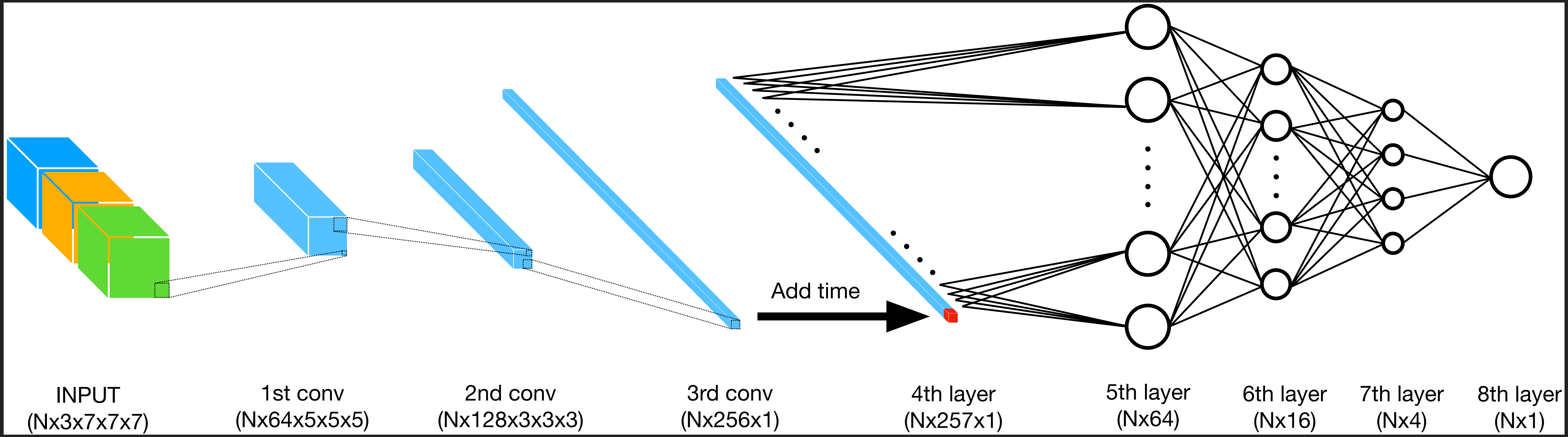
References: Karniadakis+ (2021)

$$\frac{dx_{HII}}{dt} = (1 - x_{HII})\Gamma - \mathscr{C}\alpha_B \bar{n}_H x_{HII}^2$$

THE NETWORK

- We want to predict x_{HII} for every cells
- We expect that the main ionisation effect come from the nearby sources
- To predict one cell, feed the network with the small surrounding volume




Add time
INPUT
(Nx3x7x7x7)
1st conv
(Nx64x5x5x5)
2nd conv
(Nx128x3x3x3)
3rd conv
(Nx256x1)
4th layer
(Nx257x1)
5th layer
(Nx64)
6th layer
(Nx16)
7th layer
(Nx4)
8th layer
(Nx1)

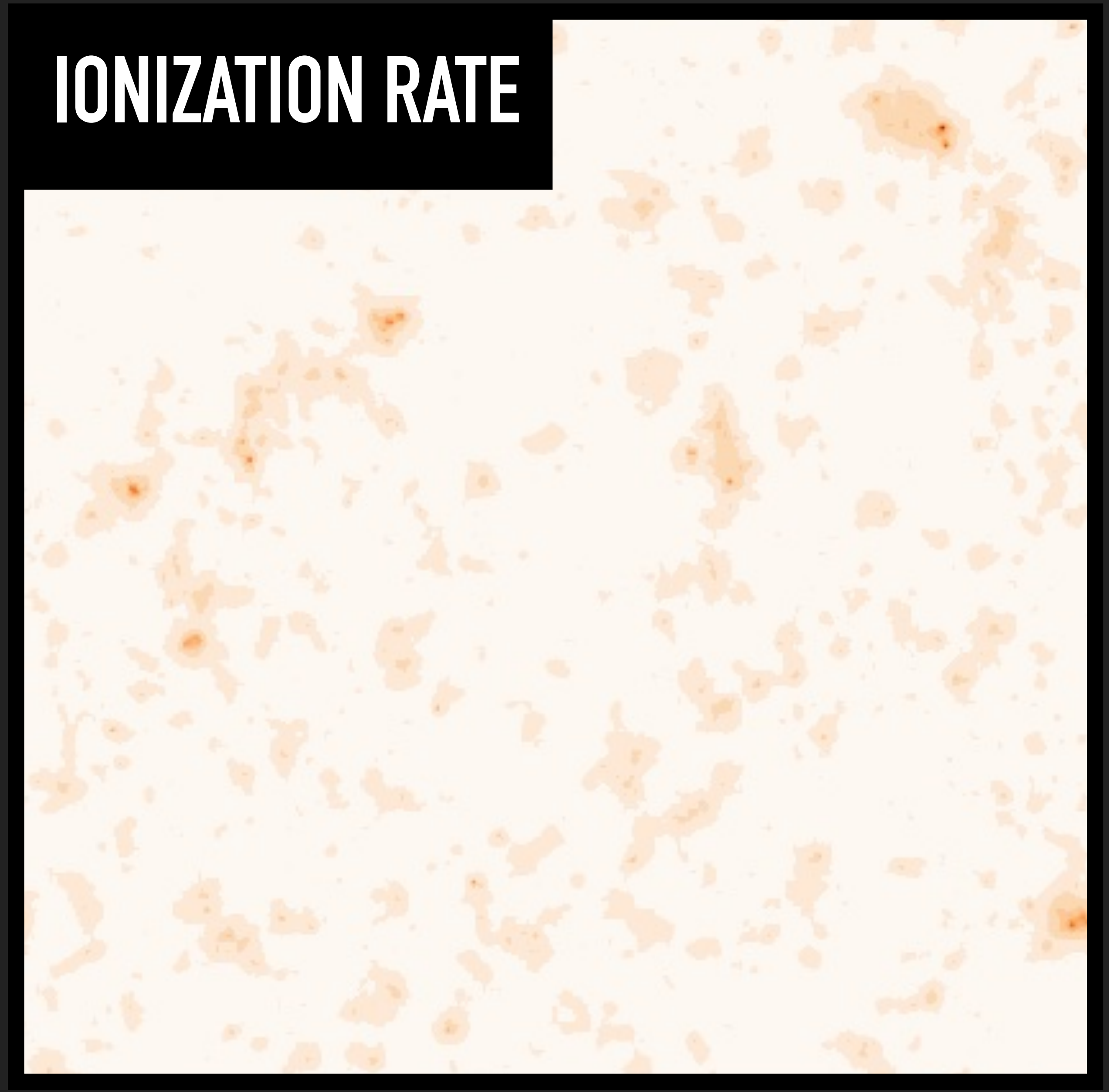
1. Approximate the mean free path of light at each redshift: $\lambda_{\nu_{HI}} \approx \frac{c}{H(z)} \times 0.1[(1+z)/4]^{-2.55}$

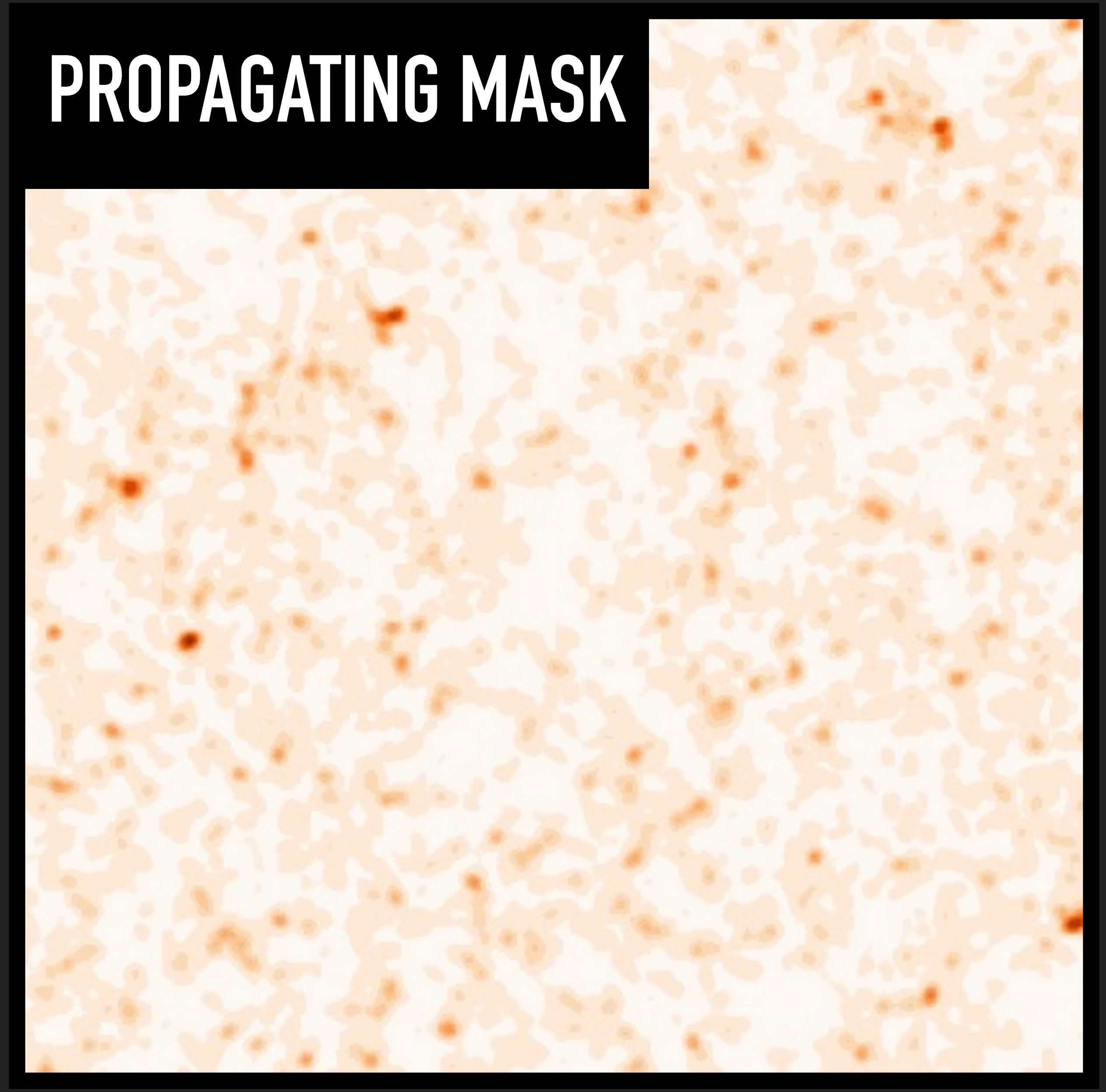
2. Define a spherical kernel of radius $\lambda_{\nu_{HI}}$

3. Convolve cube of sources mass with this kernel

✓ Produces an ***propagating mask***

✓ Similar growth behaviour than ionization rate



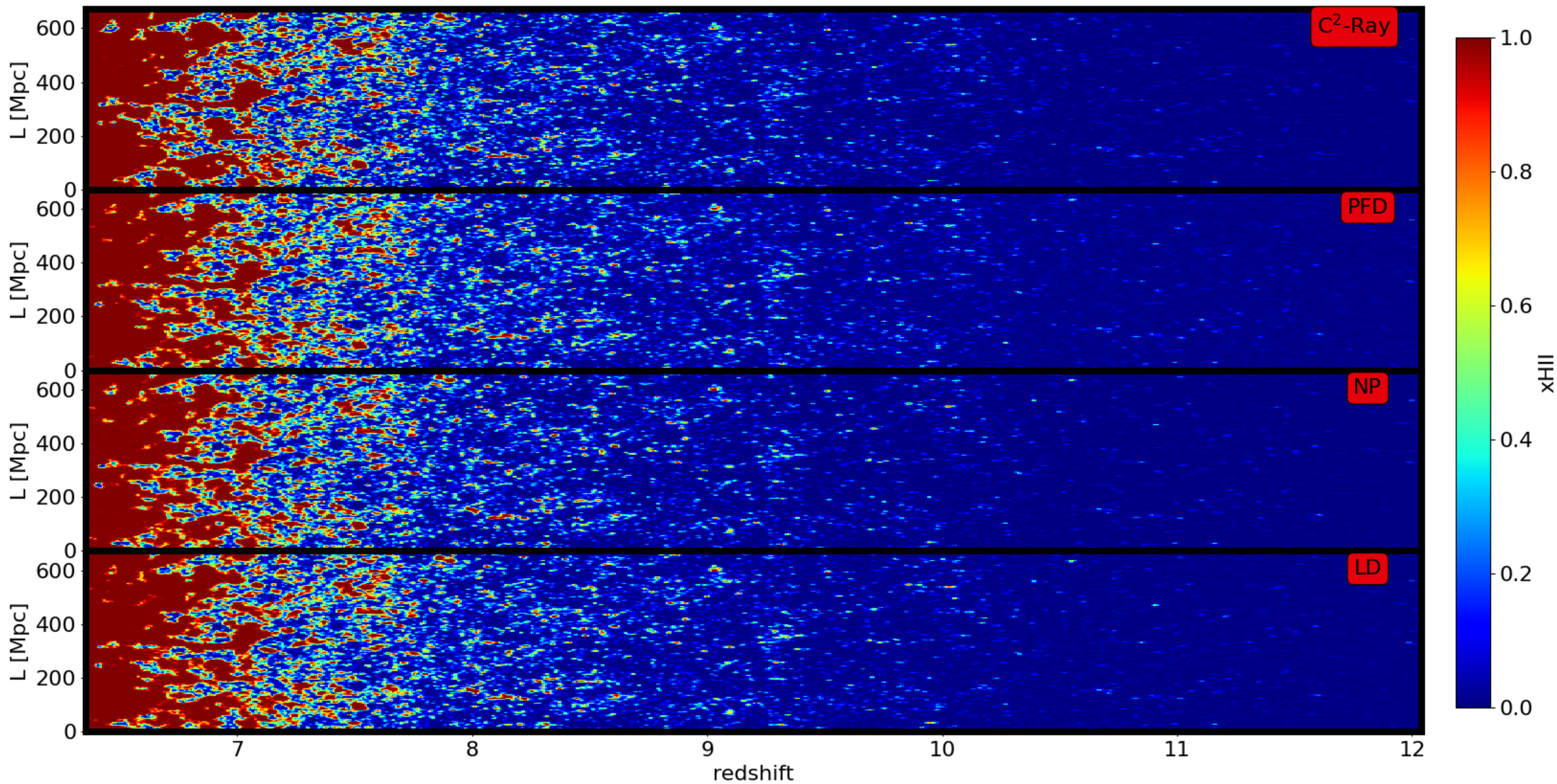


Reference: Choudhury (2009)

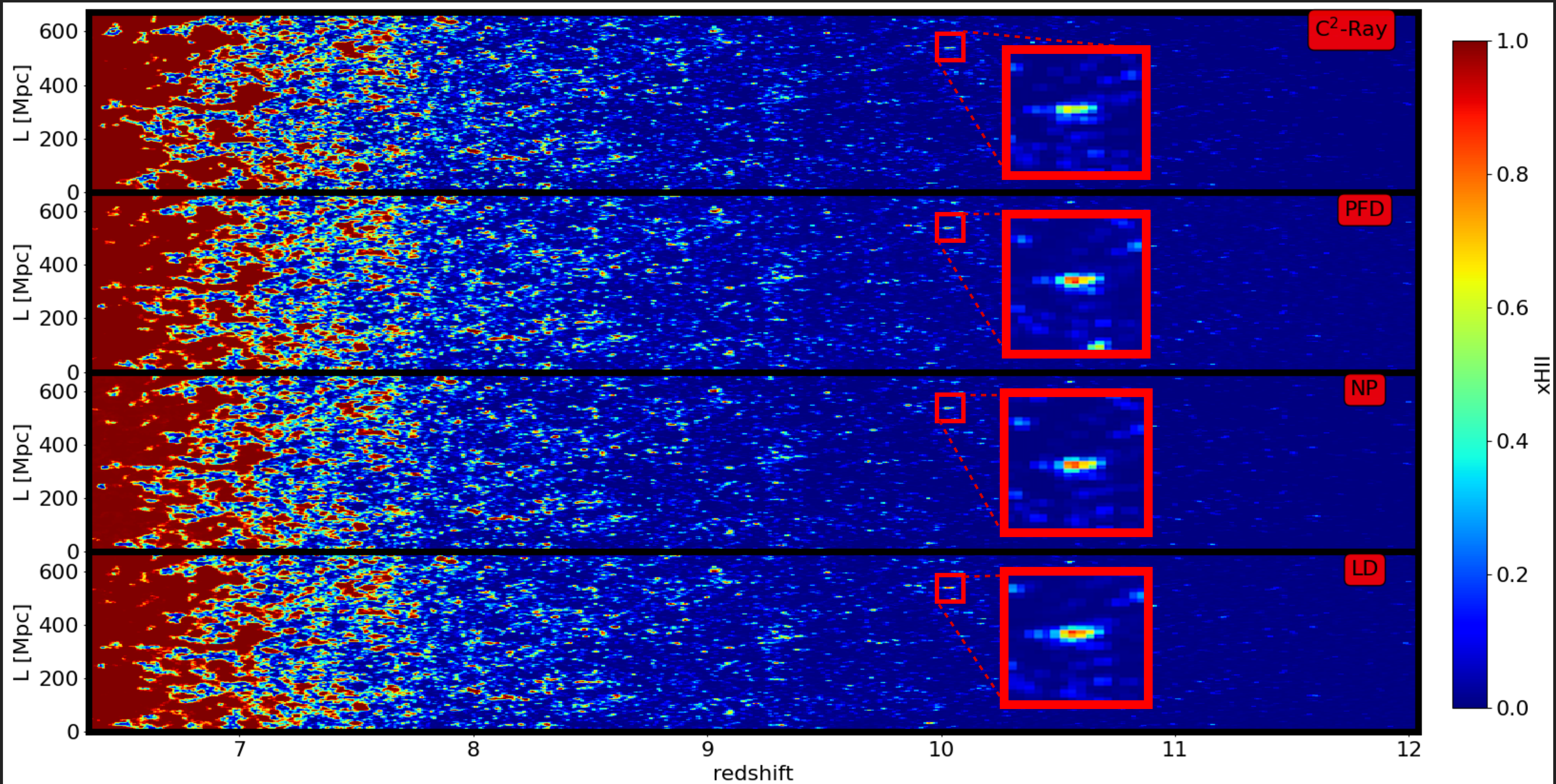
RESULTS

EXPERIMENTS

- Three different trainings scenarios for the same network
  - **PFD** (*Physics and Full Data*): training on the full evolution for the data and with the physics constraint
  - **NP** (*No Physics*): training on the full evolution for the data without the physics constraint
  - **LD** (*Low Data*): training on a limited sample of the evolution of the data and the physics constraint
- Training & predicting take about 85 GPU-hours but is highly parallelizable and can be strongly improved



Light-cone for a slice of x_{HII}



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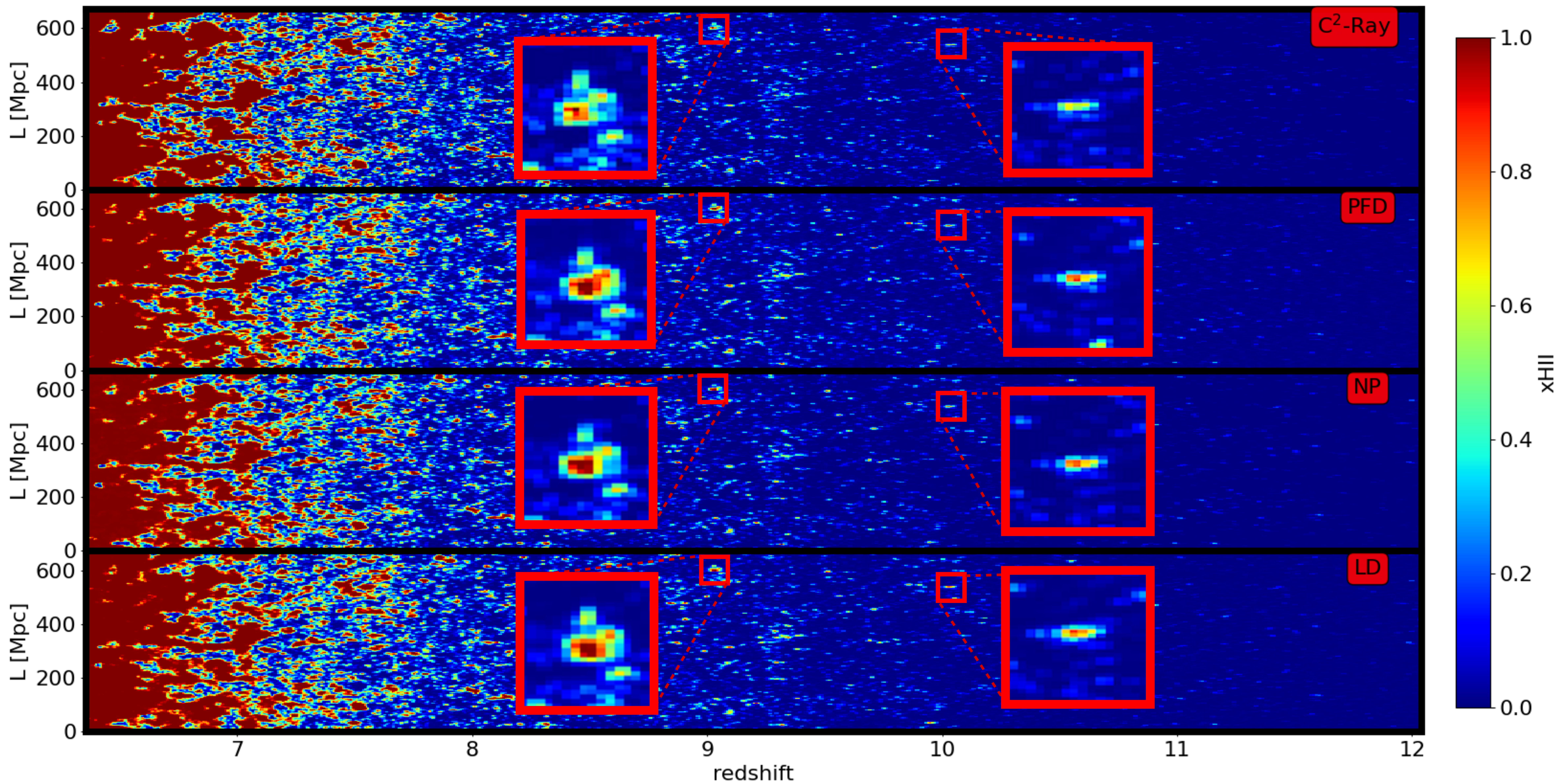

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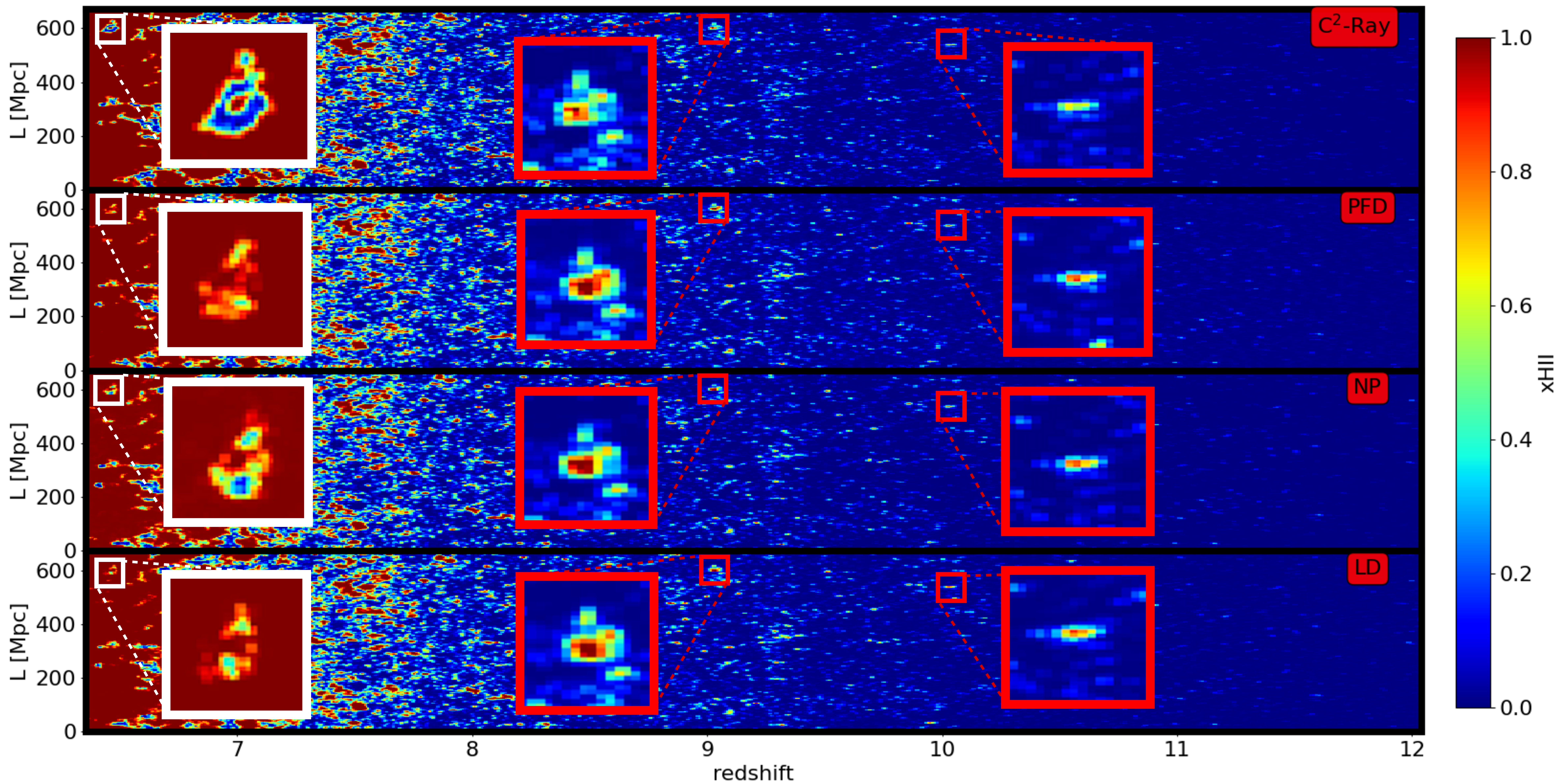
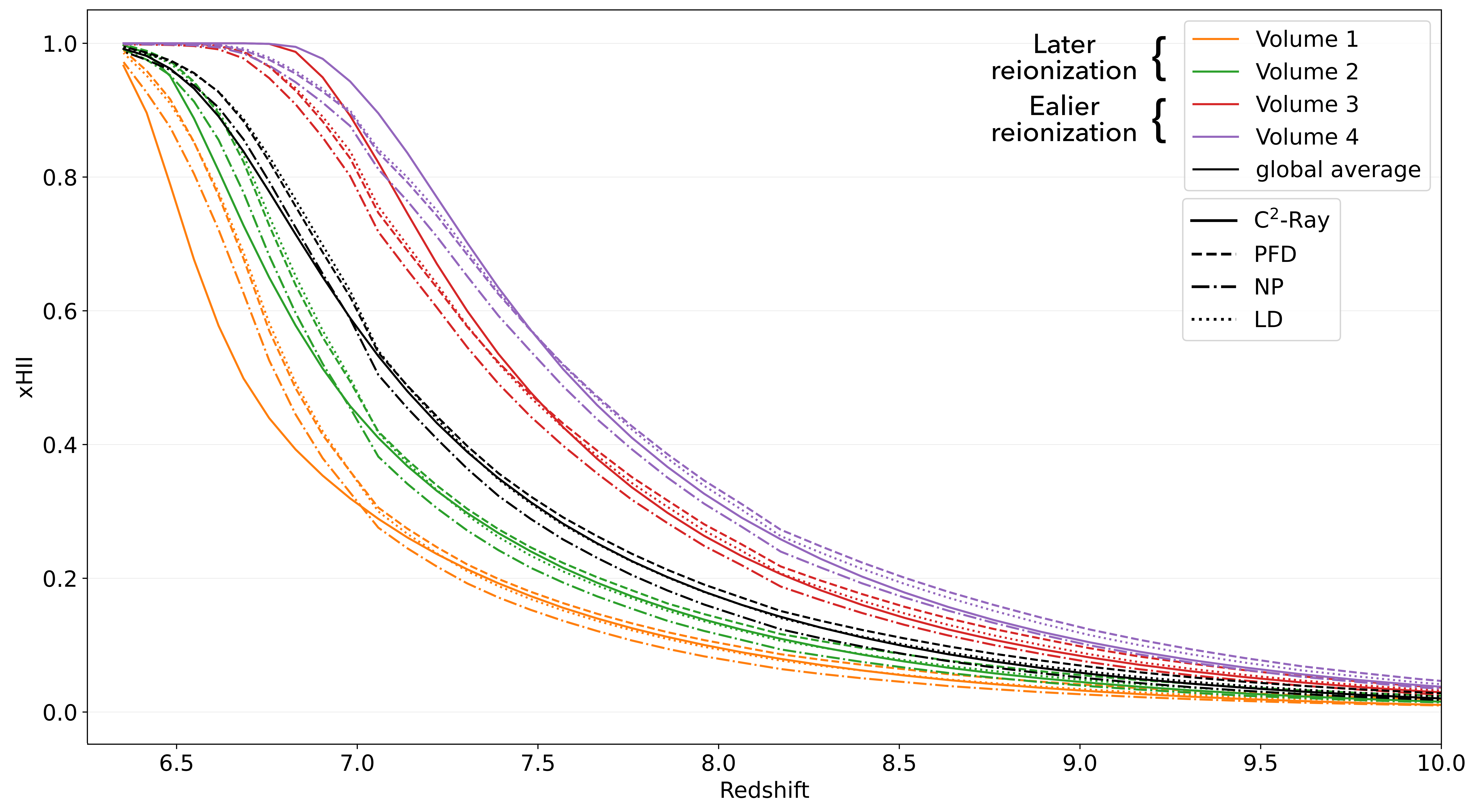
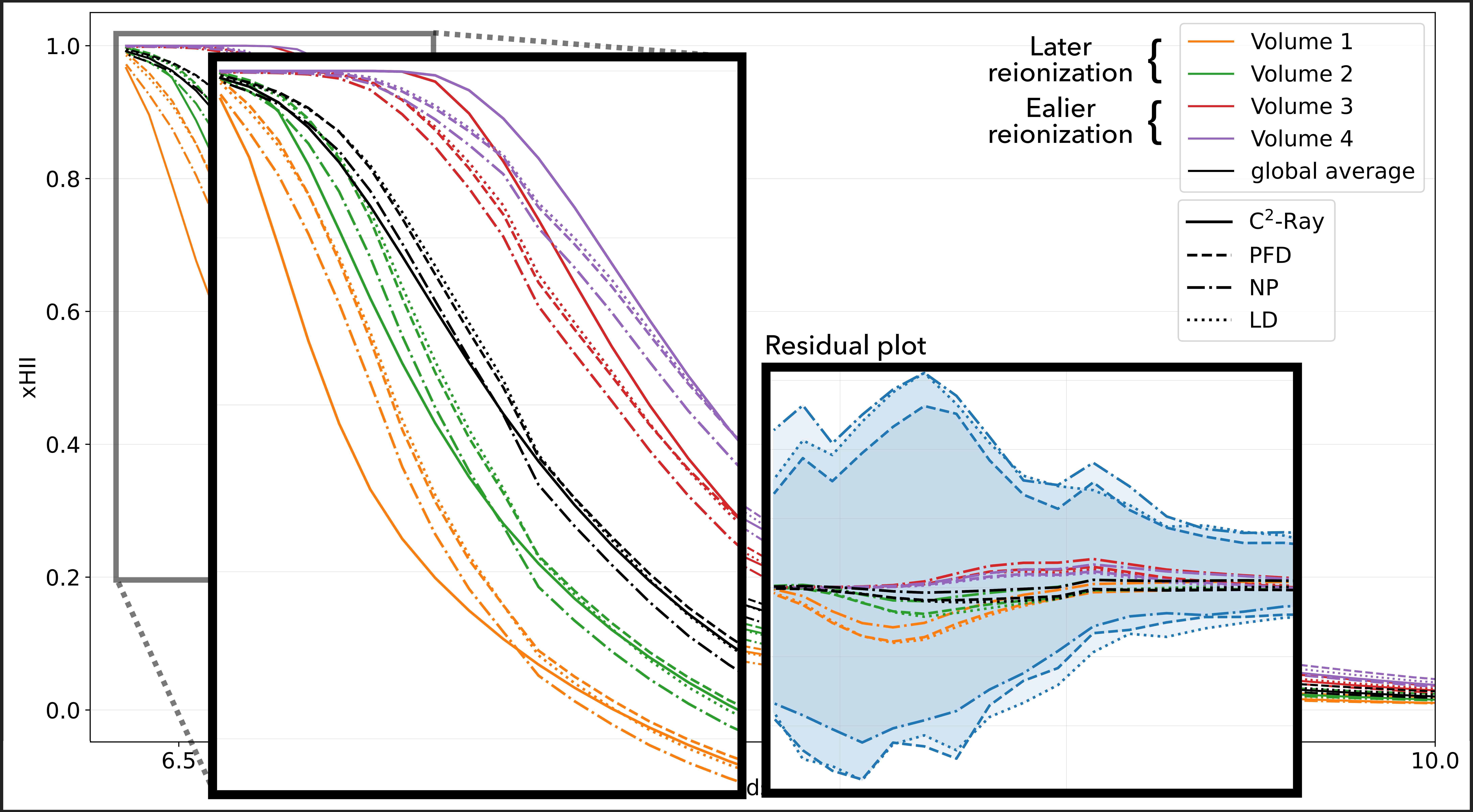


Light-cone for a slice of x_{HII}



Volume averaged evolution of x_{HII} for 5 different cases



Volume averaged evolution of x_{HII} for 5 different cases

CONCLUSION

- ✓ In general, we obtained a good reproduction of the C^2-Ray simulation
- ✓ PINNs help reducing the training supervision
  - LD performs as well as other trainings
  - Fully unsupervised training tested but didn't work
    - Might work with initial condition
- ✓ PINNs help improving the EoR predictions in neural networks
- ✓ PINION is fast for a EoR simulation

➡ Inaccuracies from propagating mask

- Simplest possible model
- over-simplistic

➡ Imbalanced dataset for training

- Induces bias in the prediction

➡ Heavy improvement can be made to the propagating mask

➡ We need a baseline comparison with Grizzly like Ghara+ (2018)

➡ We need to test the up-scaling by training on a small simulation and predicting a large simulation

➡ We are currently publishing results

- Preprint on ArXiv: arXiv:2208.13803

THANK YOU FOR LISTENING!

Damien Korber

damien.korber@protonmail.ch

Michele Bianco

mbianco@protonmail.com

Emma Tolley

emma.tolley@epfl.ch

Jean-Paul Kneib

jean-paul.kneib@epfl.ch

Preprint

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