Rosseland
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A Neural Network Approach to 3D NLTE Radiative Transfer

Bruce Chappell, Tiago M. D. Pereira
Rosseland Centre for Solar Physics, University of Oslo
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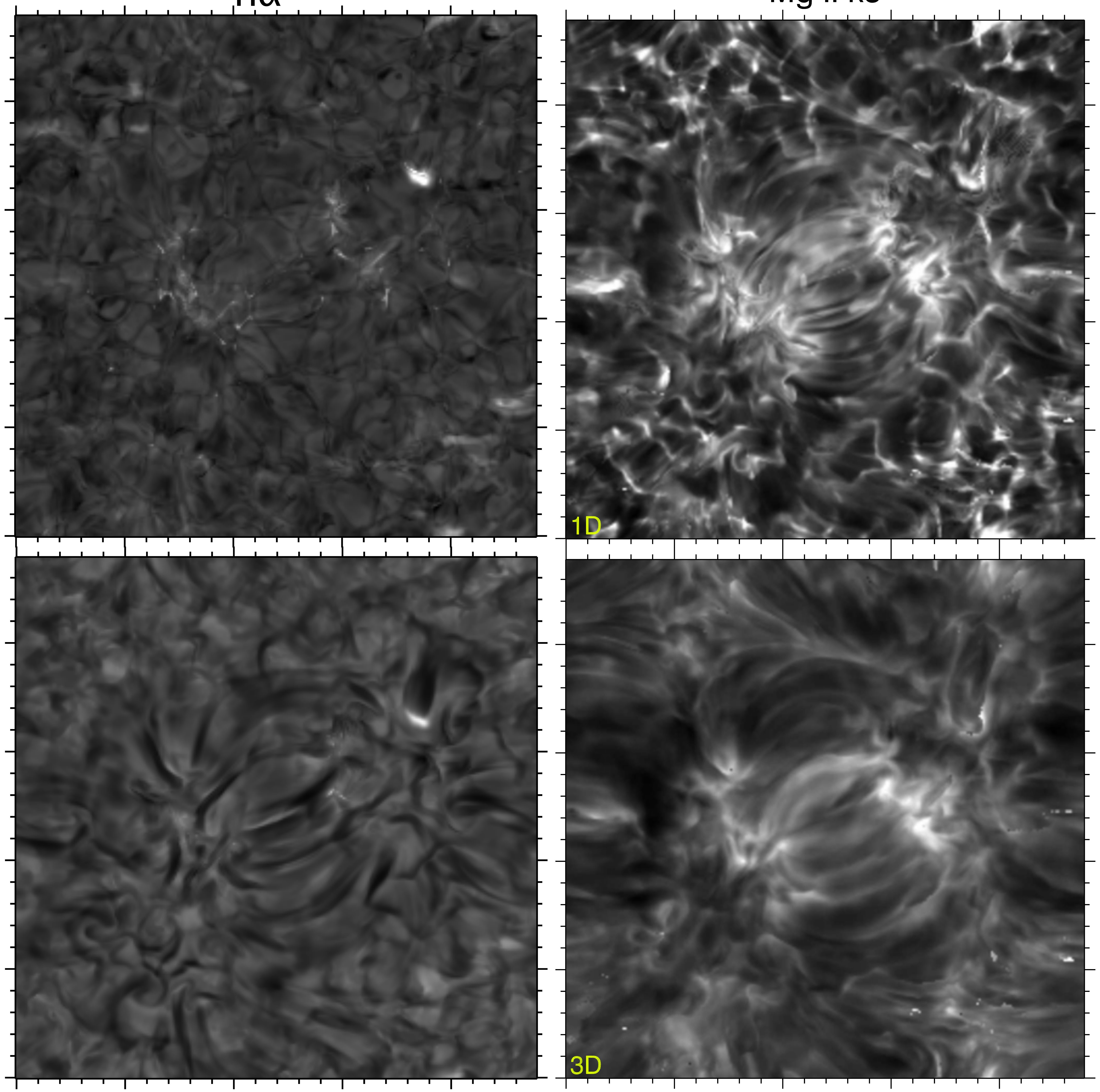
Why 3D non-LTE Radiative Transfer?

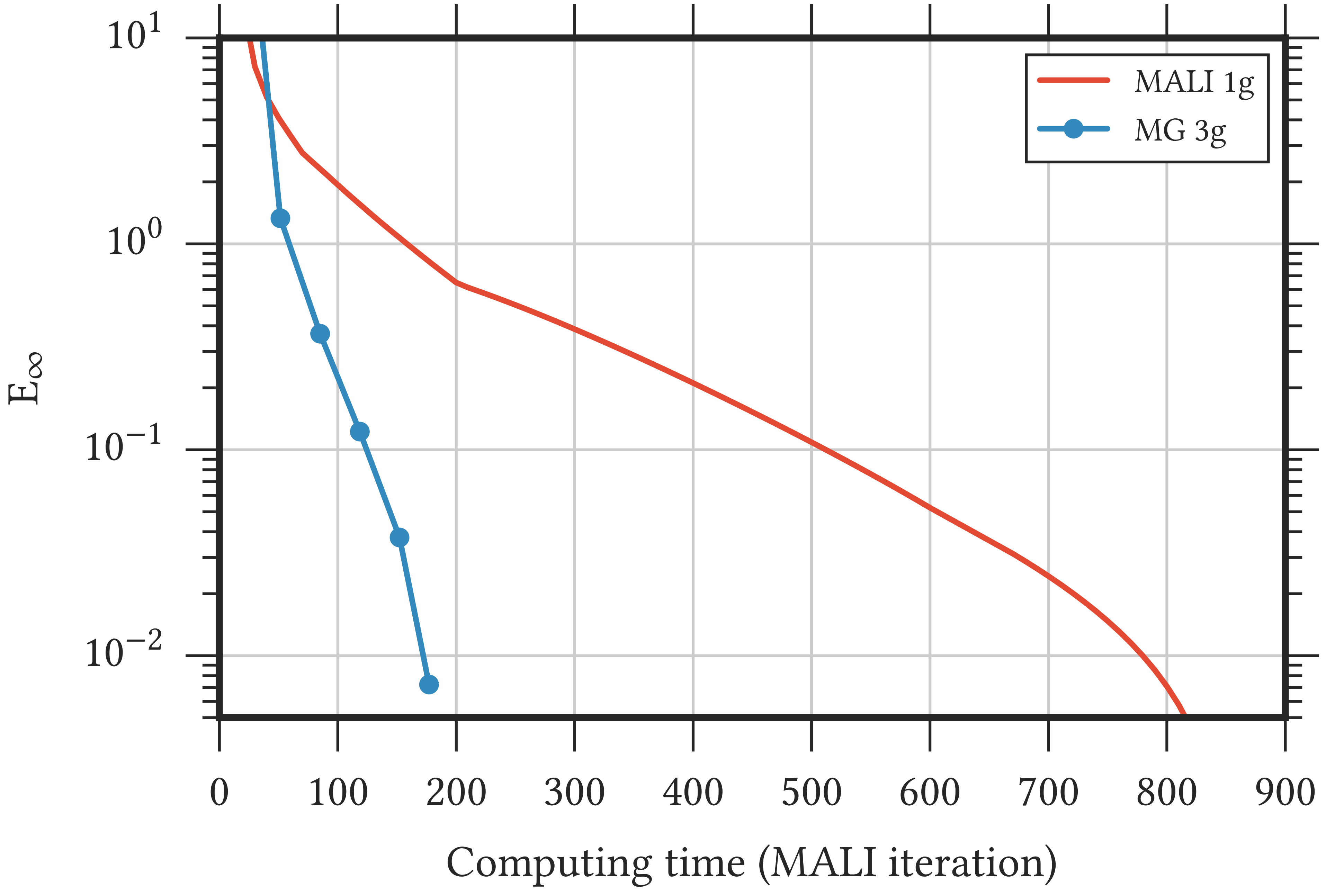
Hα | Mg II k3

1.5D

3D



Leenaarts et al. (2012, ApJ 749) | Leenaarts et al. (2013, ApJ 772)



Bjørgen & Leenaarts (2017, A&A 599)

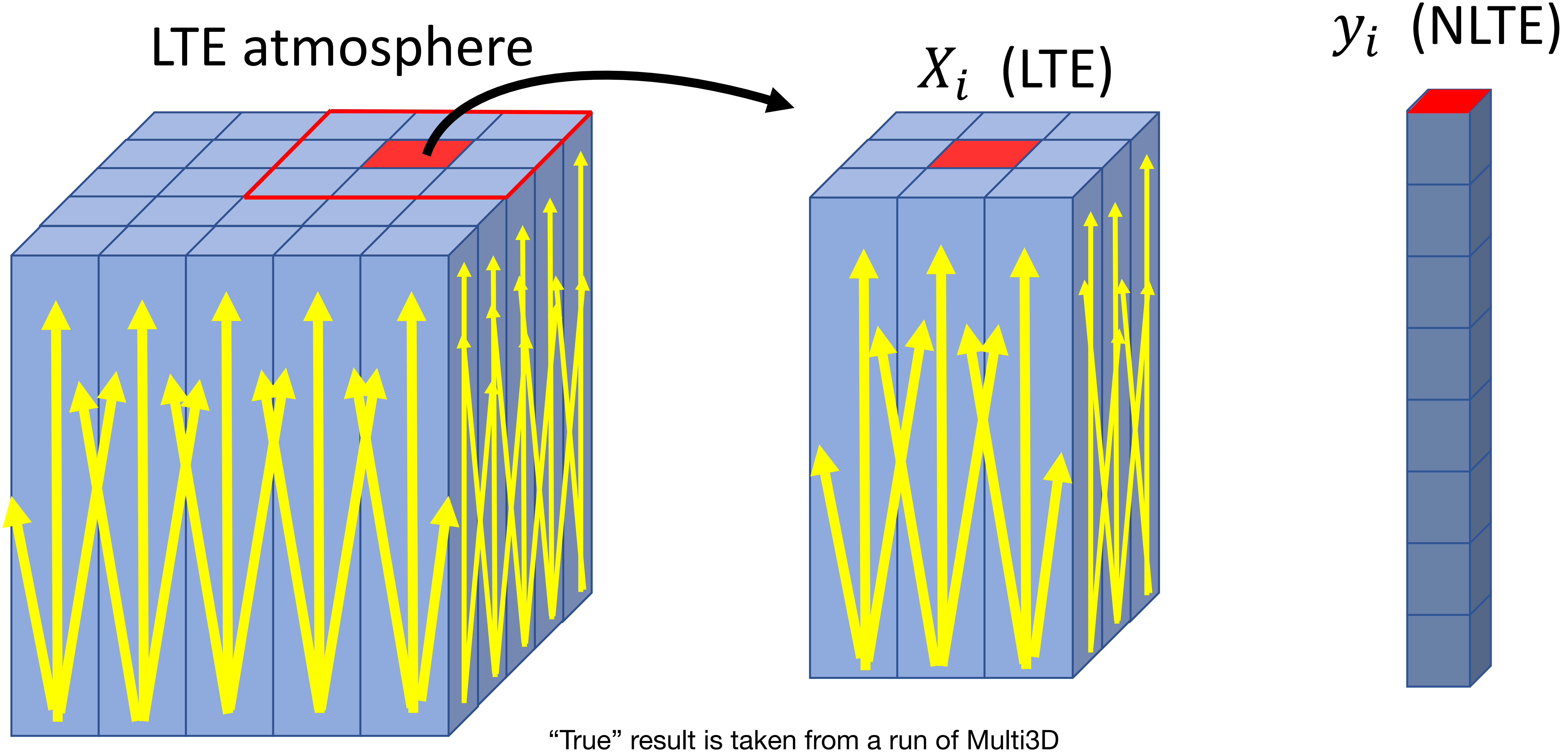
Full 3D NLTE calculations very expensive. Many iterations, hundreds of thousands of CPU-hours.

3D effects can be important in the cores of strong lines, 1.5D (column-by-column) radiative transfer is not enough.

SunnyNet

We consider not just 1 to 1 pixel mapping, but input is 3D, so we surround the pixel of interest by neighbouring columns, to account for inclined rays. Window size can be adjusted.

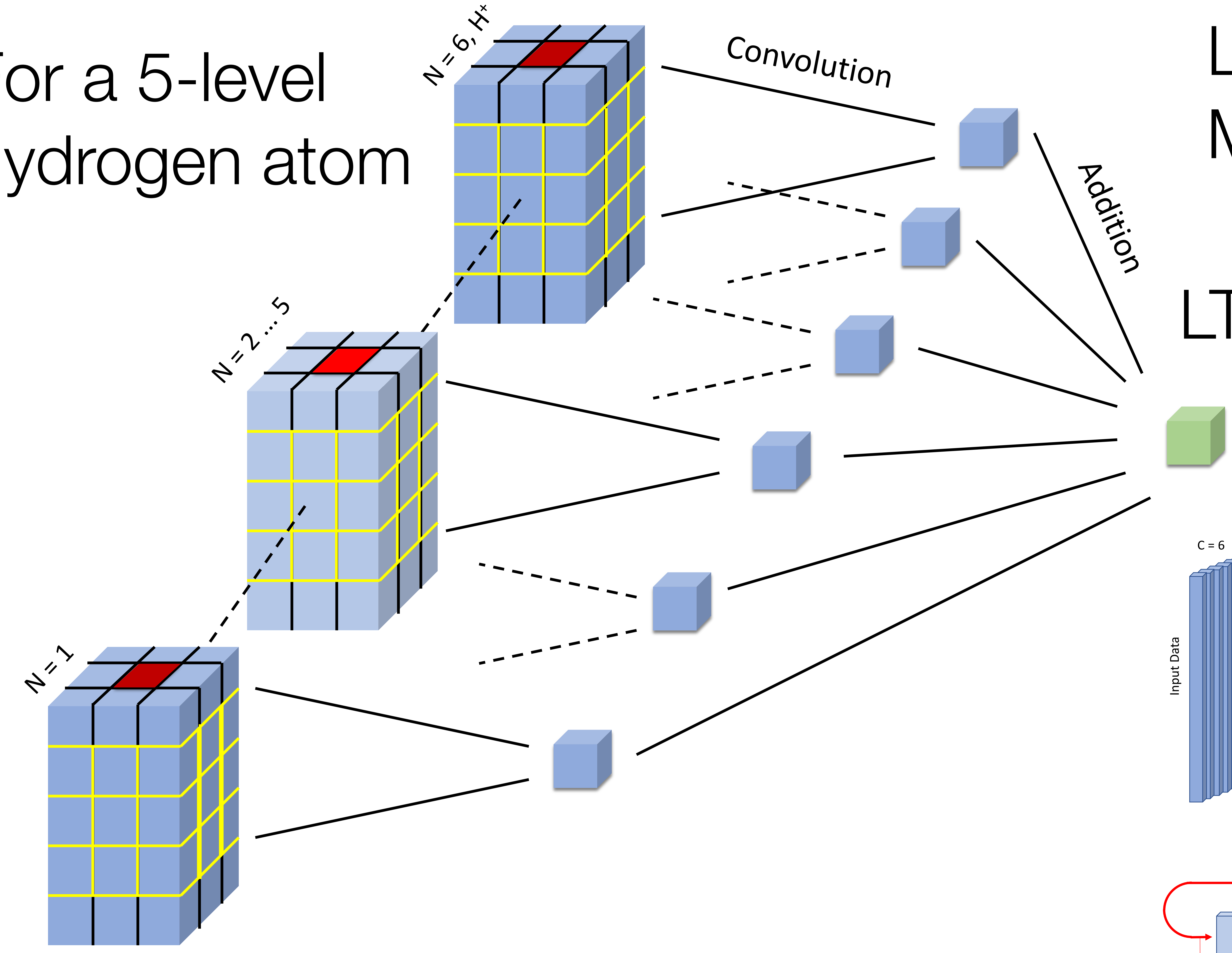
Goal is to learn final spectra from simulations, but SunnyNet learns mapping from LTE to NLTE populations of a given model atom. This allows later computation of any spectral line in the model, for any viewing angle (in CRD).



"True" result is taken from a run of Multi3D

Input is LTE populations, output NLTE populations

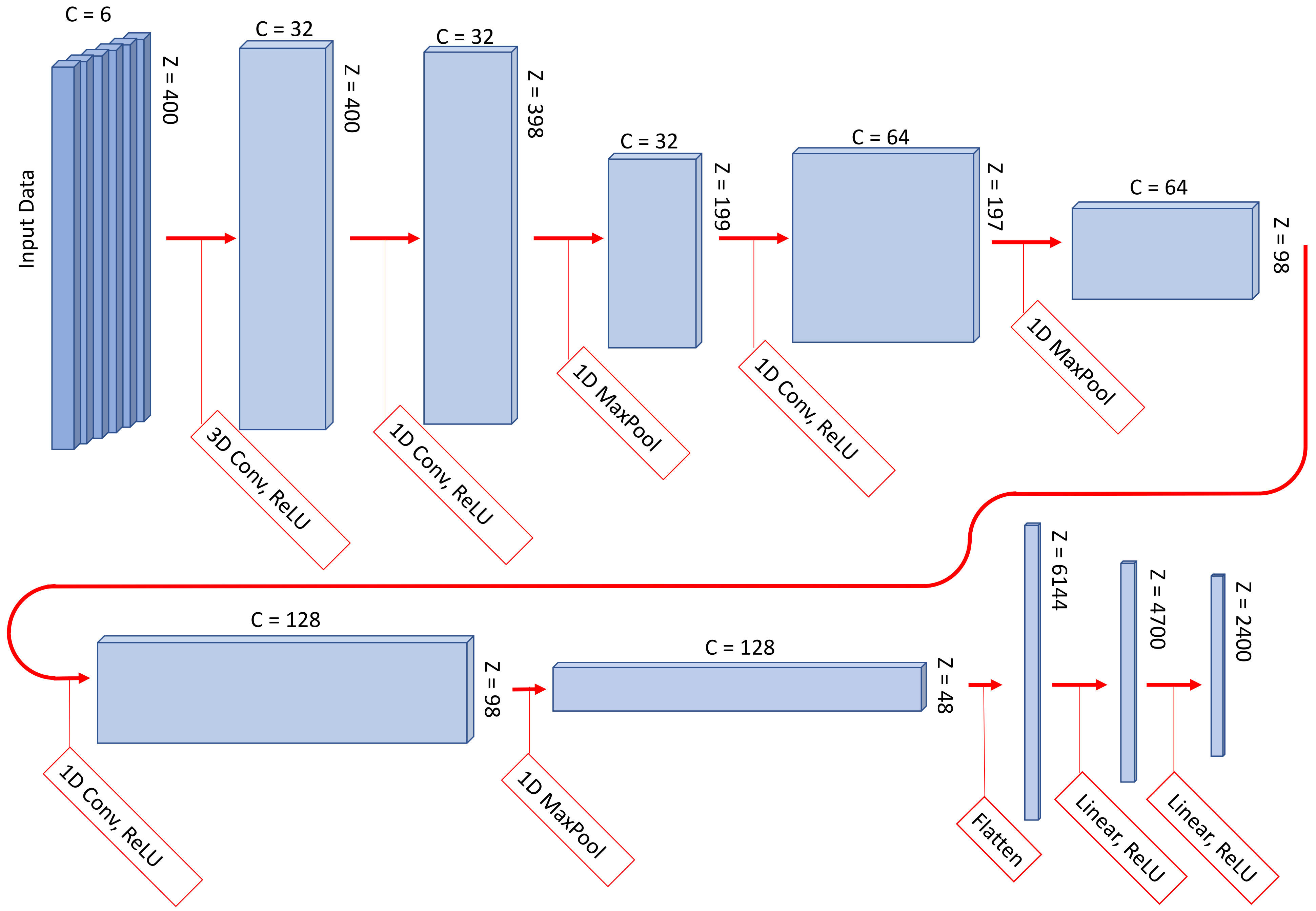
For a 5-level hydrogen atom



Learn “true” result from Multi3D calculations

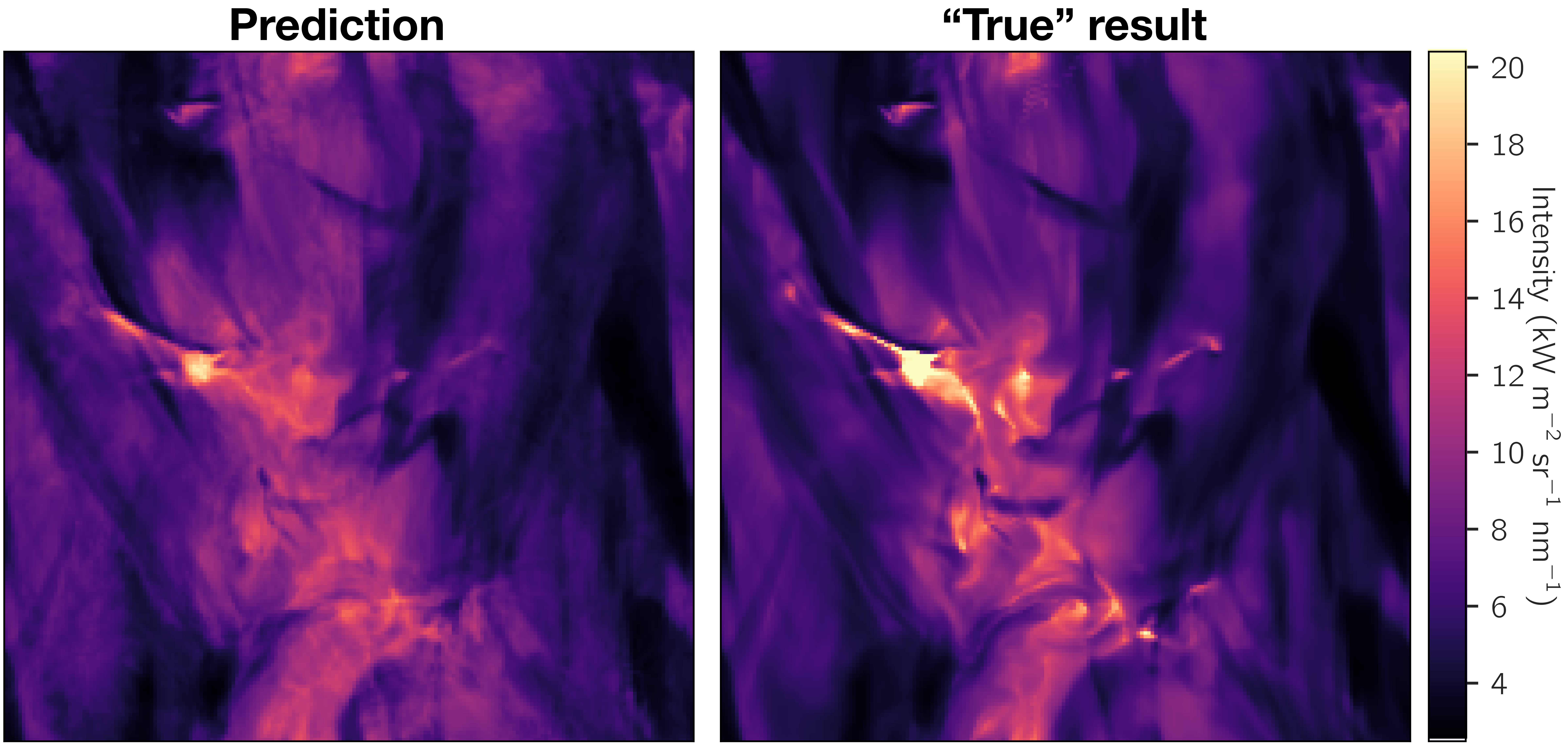
LTE pops → NLTE pops

From NLTE populations we then calculate the synthetic spectra.




Prediction
"True" result
Enhanced Network simulation
Hα core
Hα wing
5 Mm
Intensity (kW m^{-2} sr^{-1} nm^{-1})
Occurence
n= 1
n= 2
n= 3
n= 6
$|n_{pred} - n_{true}|/n_{true}$
Average Column Mass (kg m^{-2})
n=1
n=2
n=3
n=6

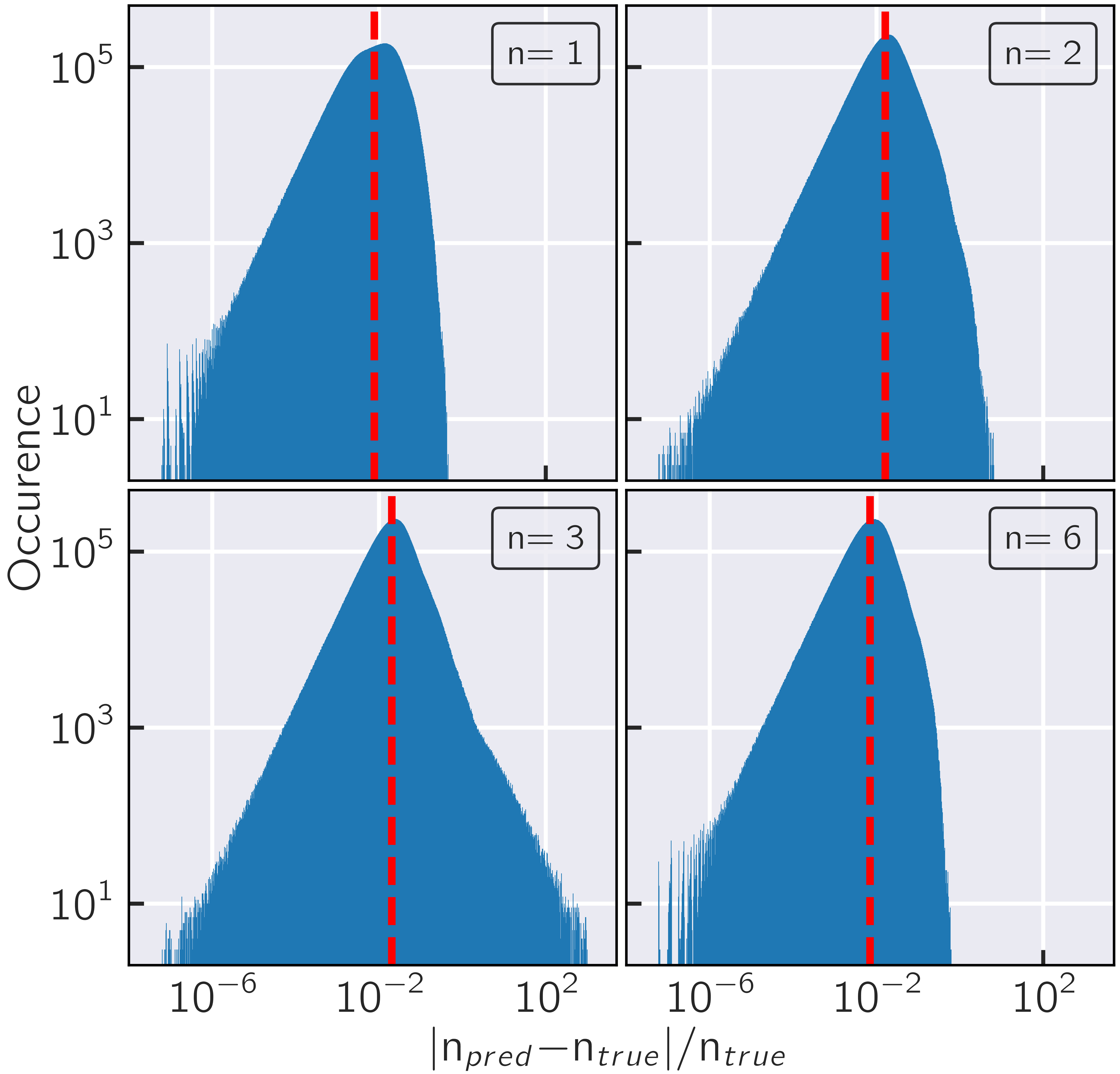
Flaring simulation

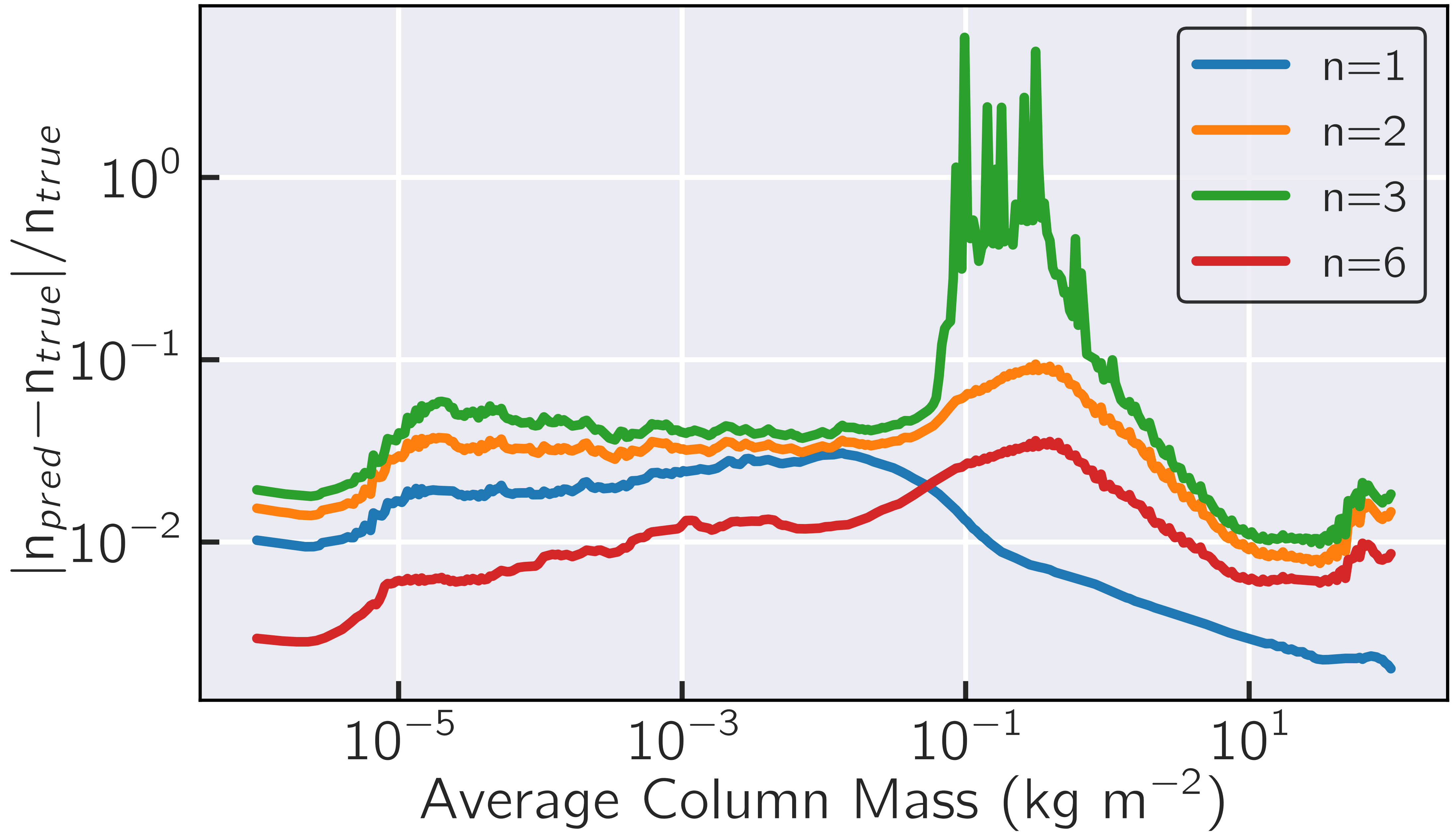


Hα core

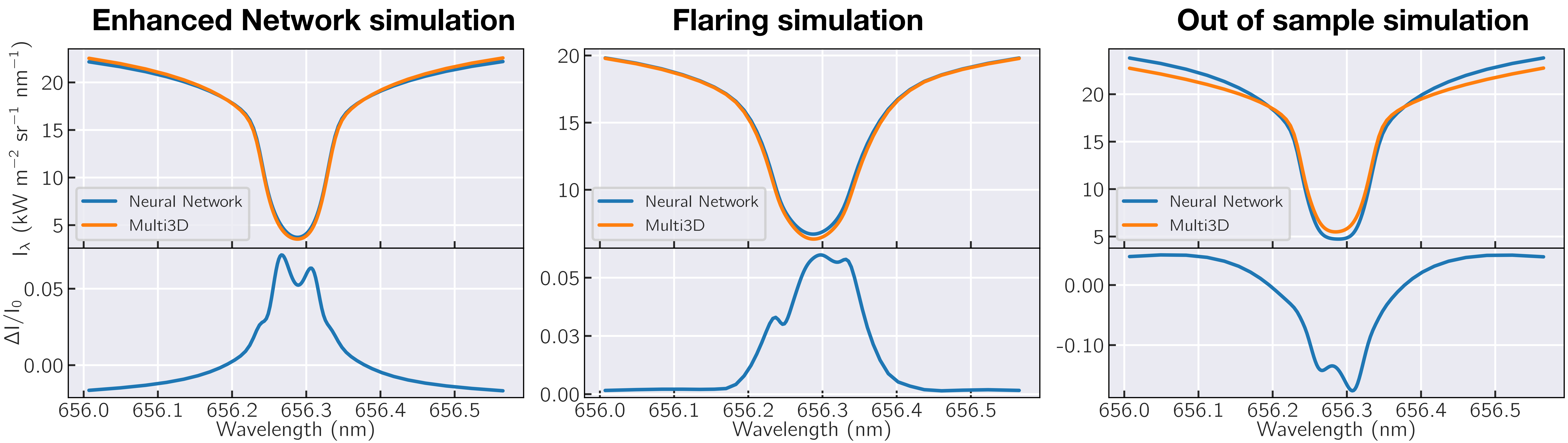
R C S

Flaring simulation





R C S



Training and testing from different snapshots of **same** simulation

Training and testing using **different** simulations (“out of sample”)

- Excellent results based on simple network structure
- GPU-based, PyTorch, speeds up 3D NLTE by 10^5
- Open source, available at https://github.com/bruce-chappell/SunnyNet