Galactic Alchemy I:

Domain Transfer with Generative AI for Hydrodynamical Simulations

SKA research at
Zurich University of Applied Sciences (ZHAW)

Centre for Artificial Intelligence (CAI)
Institute for Business Information Technology (IWI)

Sept 4, 2024

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Slides On My Website

https://phdenzel.github.io/

Outlook

- Motivation
- Multi-domain galaxy image dataset
- Generative Deep Learning
- Results
- Next steps

Motivation

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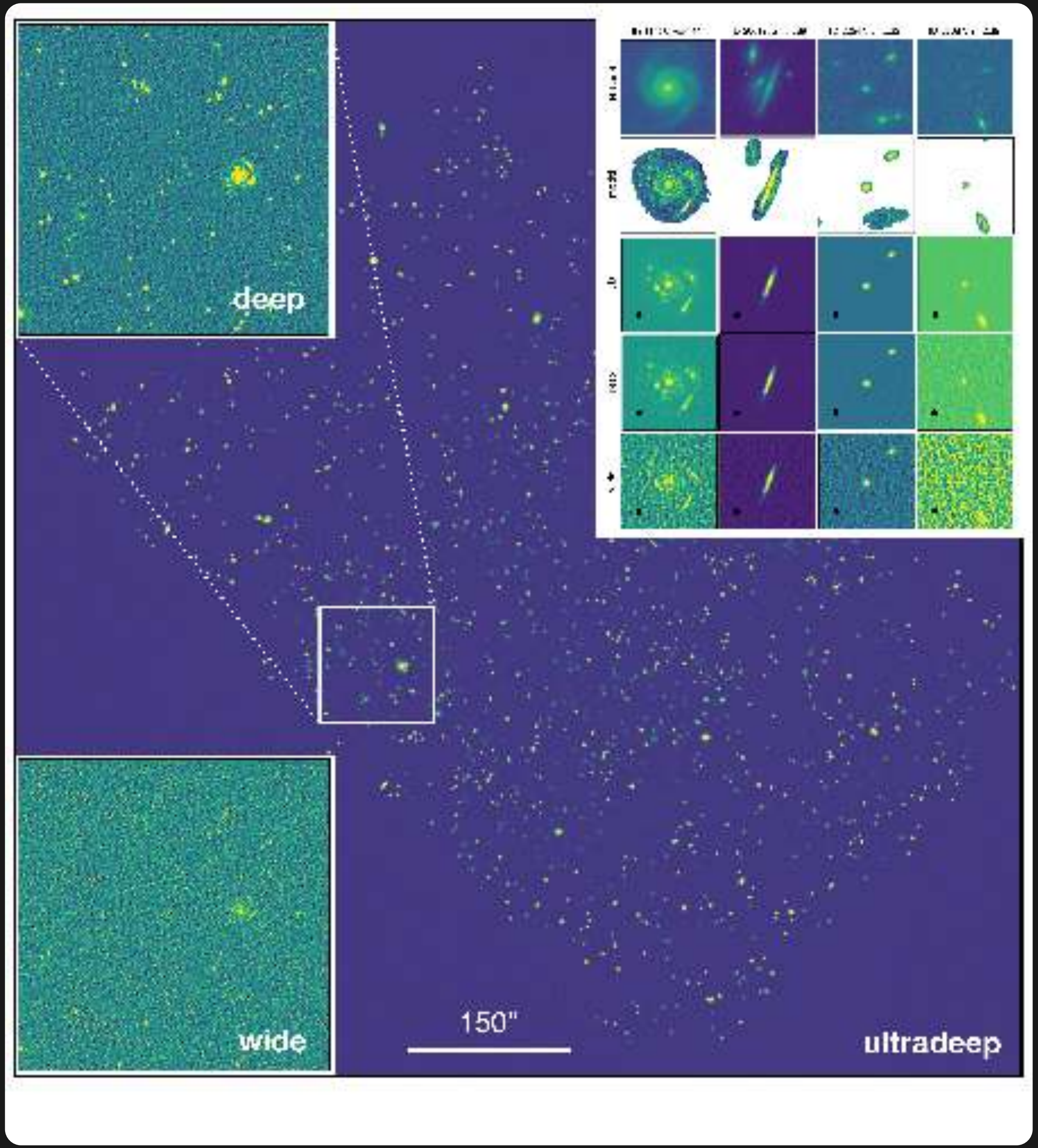
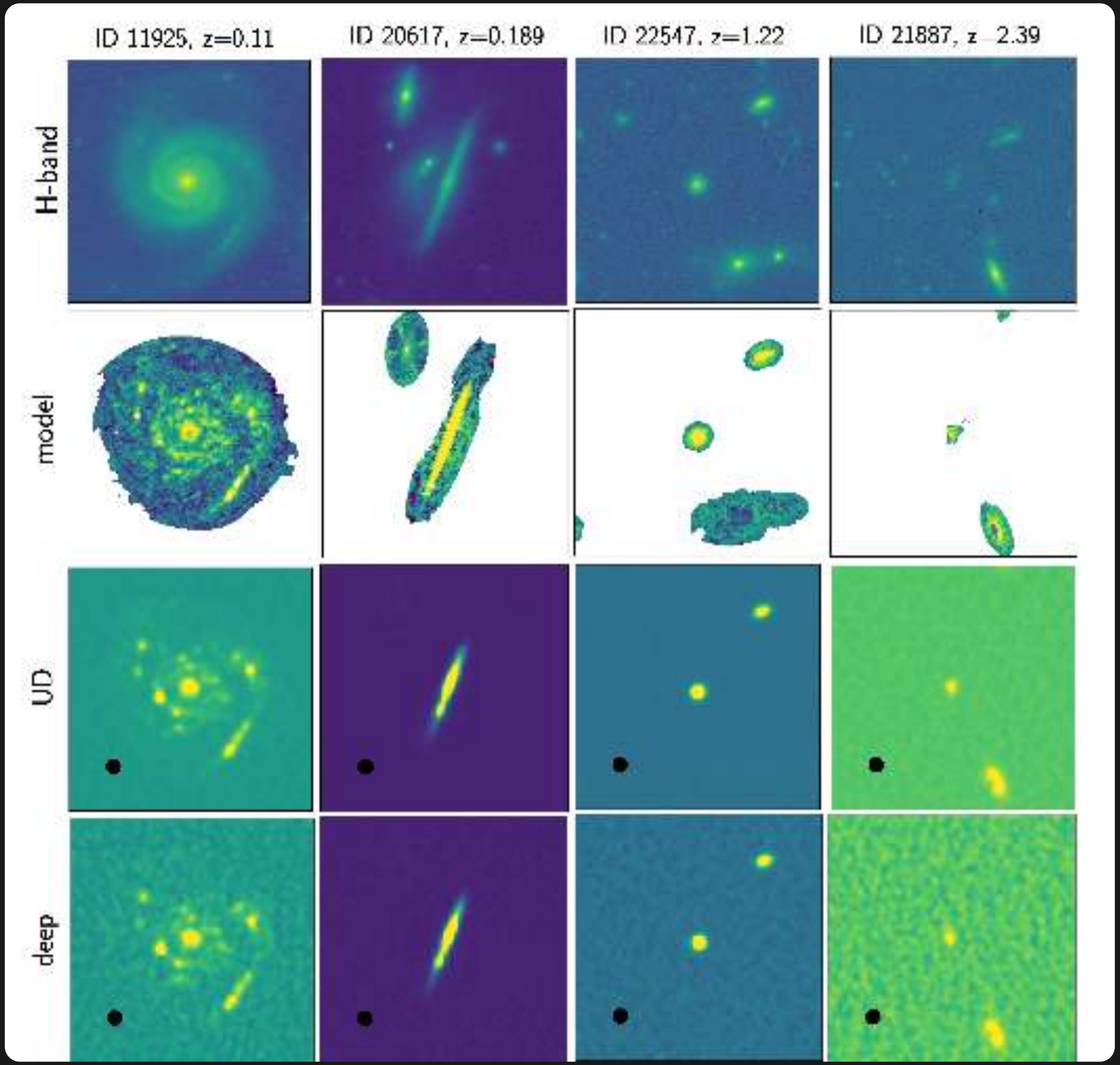
- SKA-MID (0.35 GHz - 15 GHz, lower redshifts):
  - between 0.04" - 0.70" resolution (with baseline ~ 150km)
  - significant substructure in flux distributions
  - enable new perspective on star-formation as well as AGN

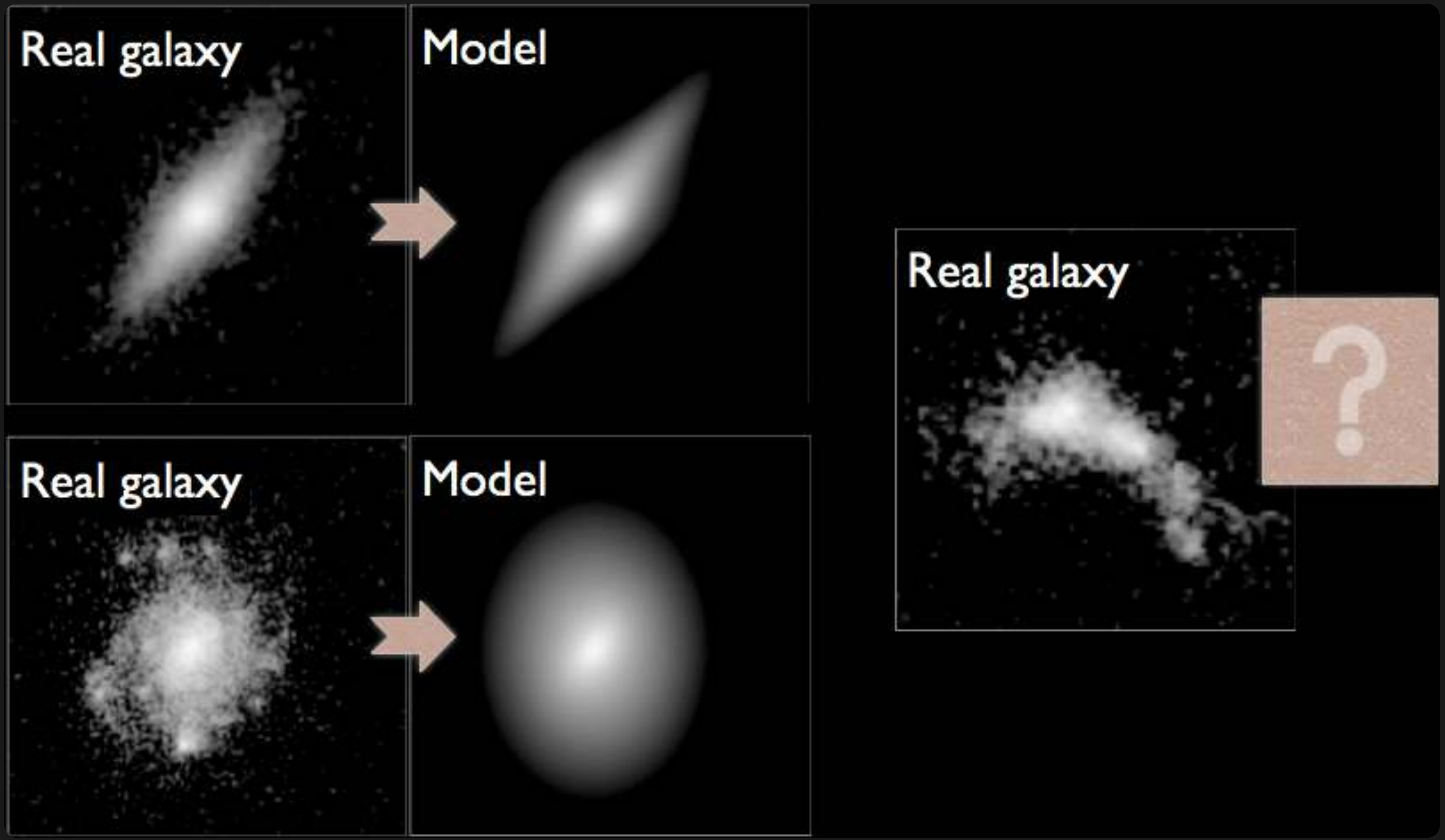


simulation of ~0.04 deg^2 region of GOODS-North by Coogan et al. (2023)



zoom of previous figure Coogan et al. (2023)

The old way of modelling galaxies



Mandelbaum et al. (2014)

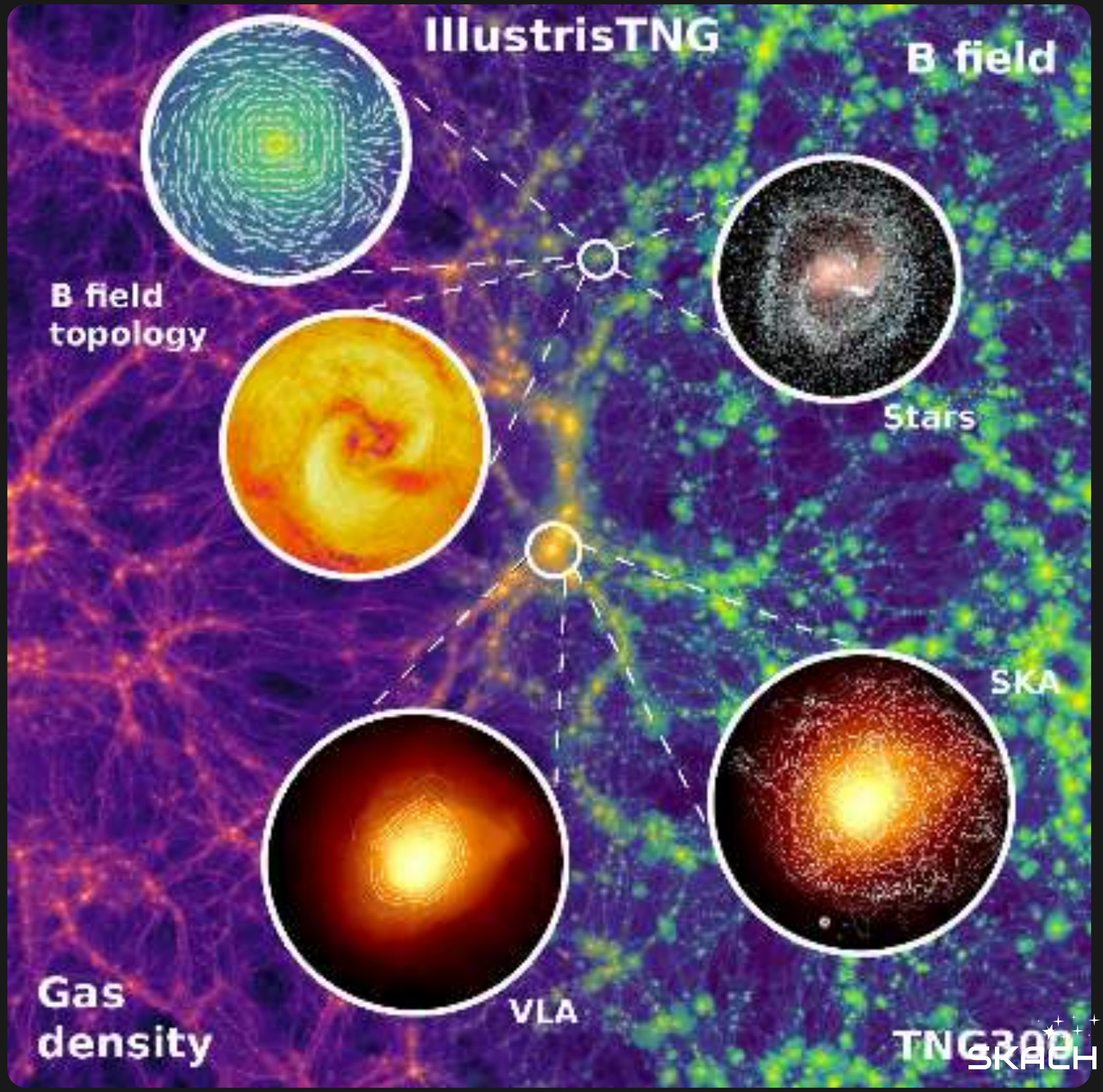
What problems come with this

- simple models work for simple galaxies, but we will often see:
  - no more blobs, no more Gaussian signals
- not physical models:
  - difficult to infer physical properties
- galaxy modelling has to evolve:
  - e.g., with data-driven methods

More advanced models

IllustrisTNG simulations

- complex, realistic models
- self-consistent dynamics
- physics: on a wide range of scales
- implicit models:
    - what if we want to fit them to an observation?



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Multi-Domain Galaxy Image Dataset

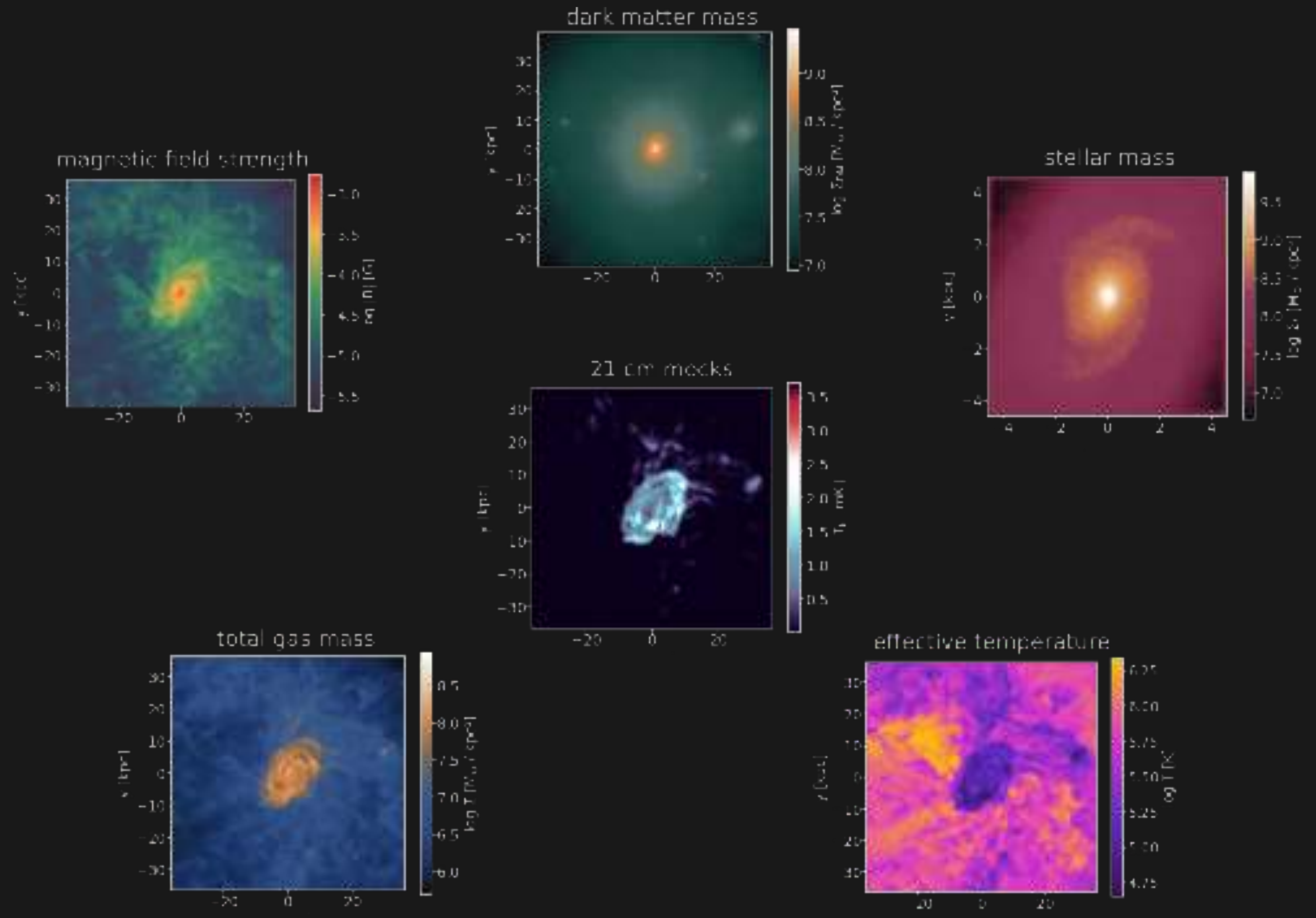
Our goal:

> *"Infuse deep learning map-to-map translation models with the physical model from simulations."*

- Question: can we infer unseen properties in observations?

Dataset from IllustrisTNG

- projected TNG50-1 galaxies
- 6 domains: dark-matter, stars, gas, HI, temperature, magnetic field
  - 21cm mocks following Villaescusa-Navarro et al. (2018)
  - Karabo mock upgrade coming soon
- ~ 2'000 galaxies, 6 snapshots, 5 rotations in 3D, ~ 360'000 images
- each galaxy $\geq$ 10'000 particles
- scale: 2 baryonic half-mass radii



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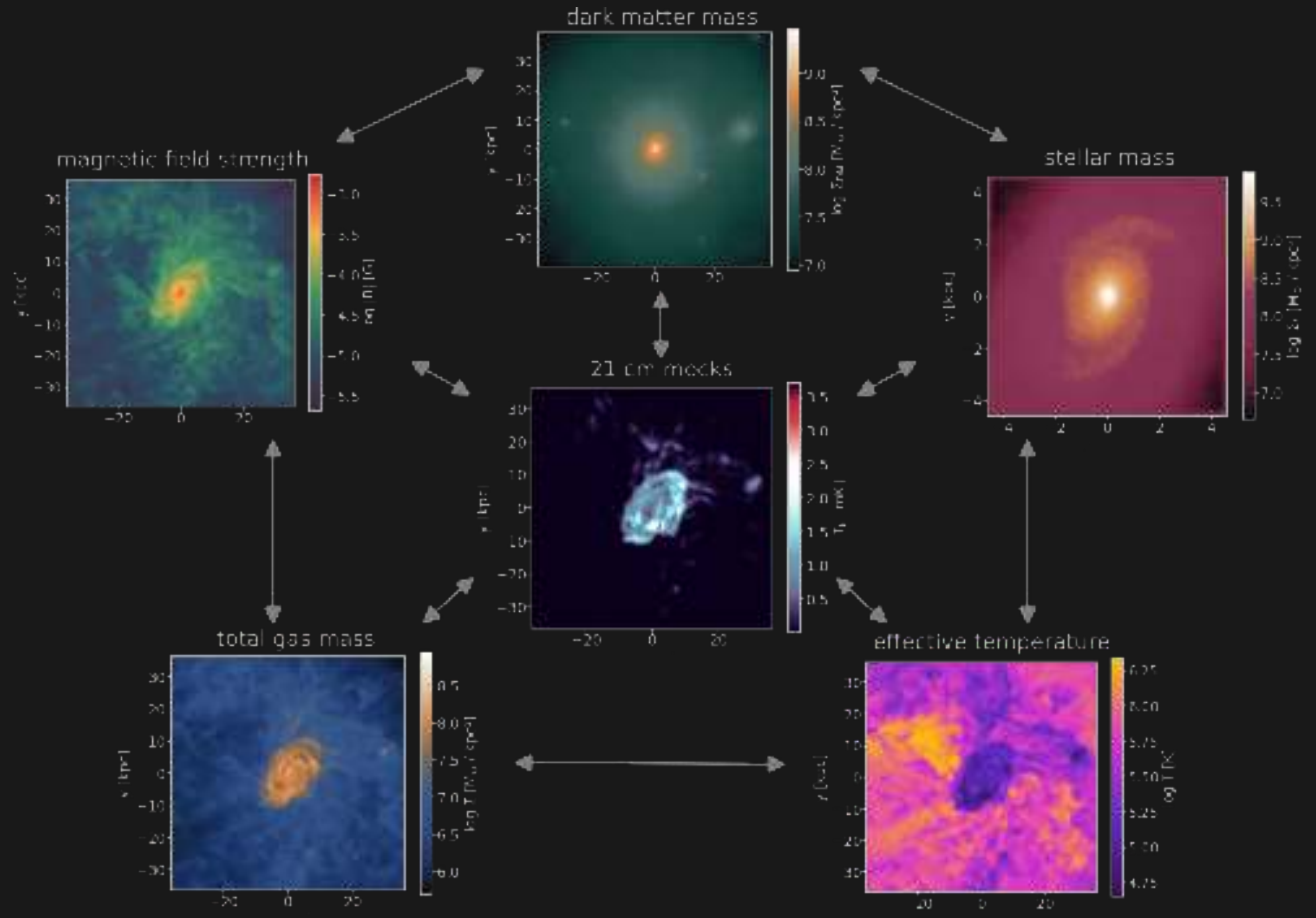

Generative Deep Learning

- *Image-to-image translation* solves the inverse problem:
  $y = Ax + b$
- in Bayesian terms: $p(x|y) \propto p(y|x)\ p(x)$
- $p(y|x)$ is the data likelihood including the physics
- $p(x)$ is our prior knowledge on the solution.
- MAP solution: $\hat{x} = \arg\max_x \log p(y|x) + \log p(x)$
- explicitly sampling from the posterior distribution is difficult and expensive!

Generative Deep Learning architectures

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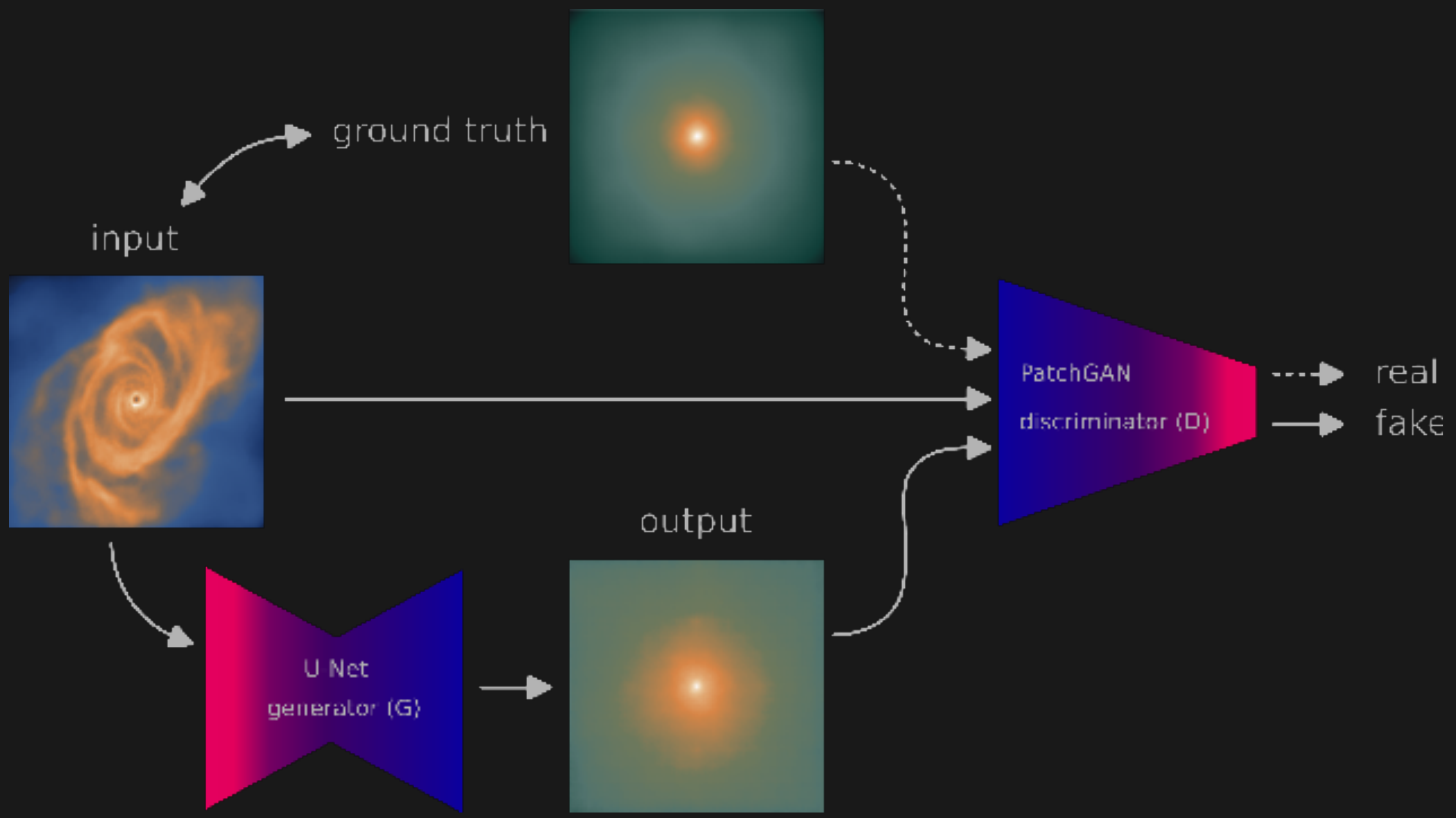
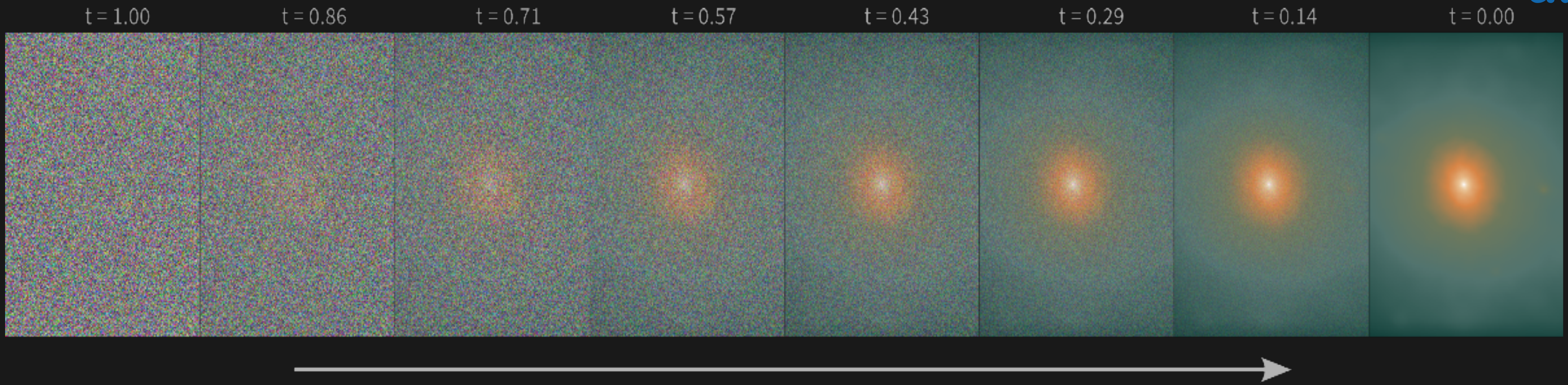
cGANs



pix2pix scheme

DDPM



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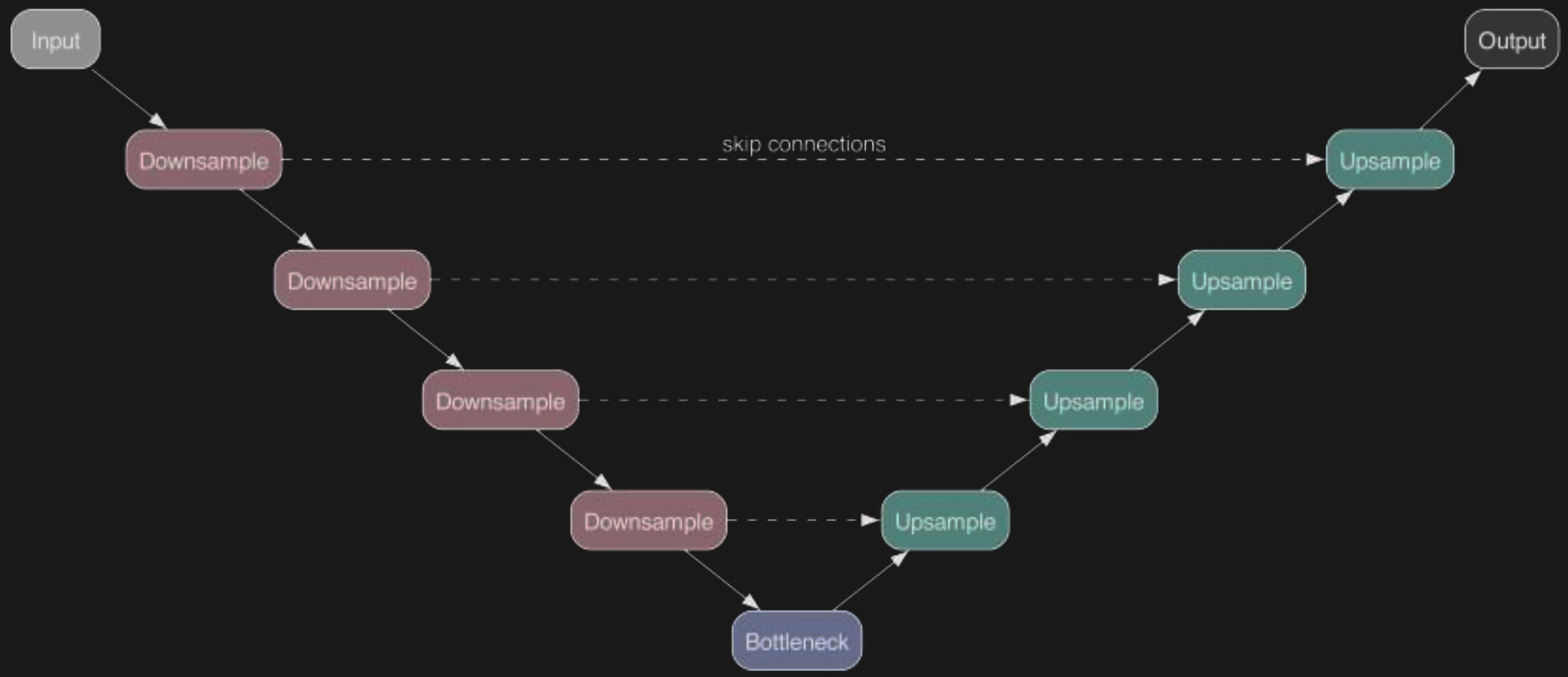
Main component: U-Net

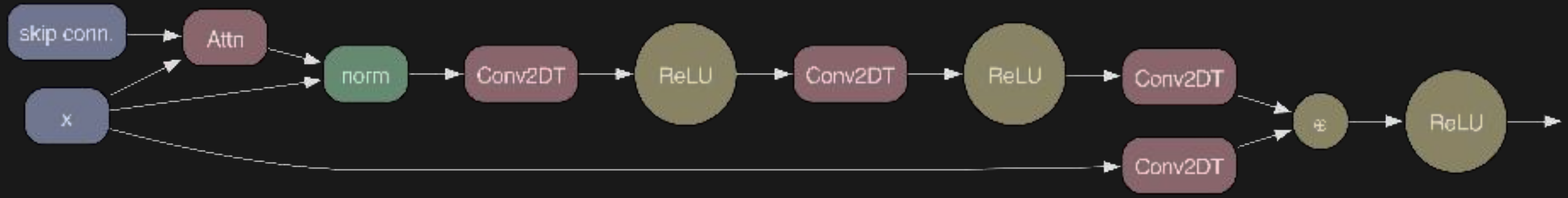


U-Net following Ronneberger et al. (2015)

Essential changes to U-Net blocks

> *"Attention is (almost) all you need!"*

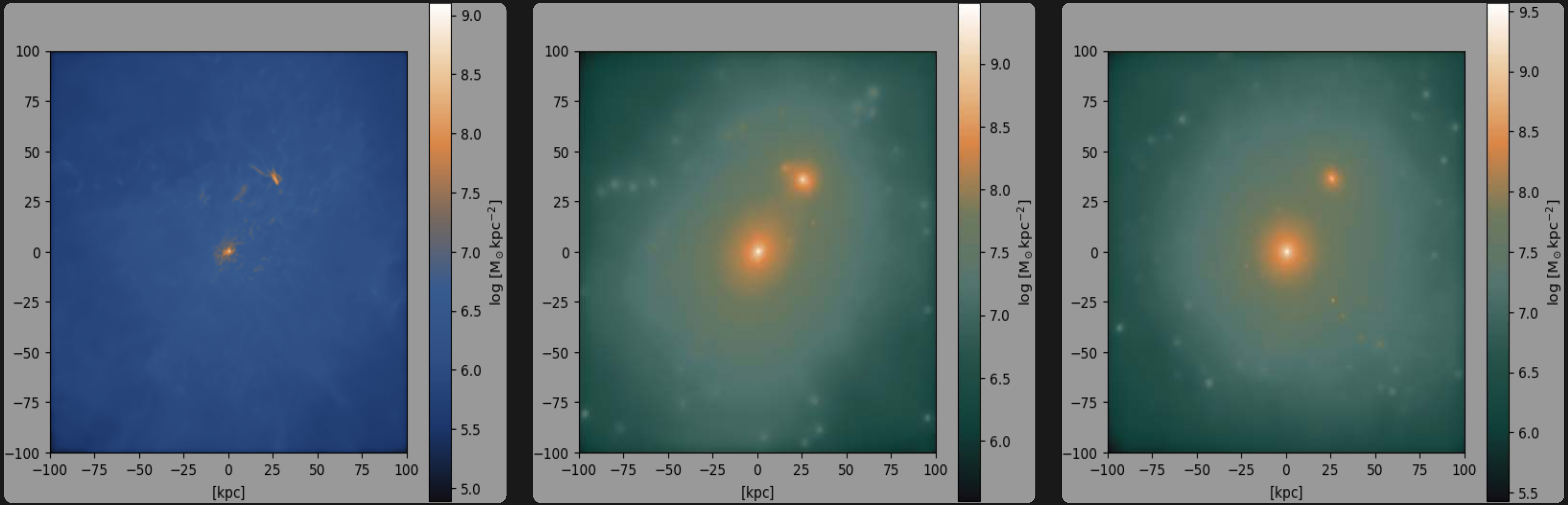
- for better feature selection



Results

- all evaluated on a hold-out set
- still somewhat preliminary…

Gas ⟶ DM: Massive halo

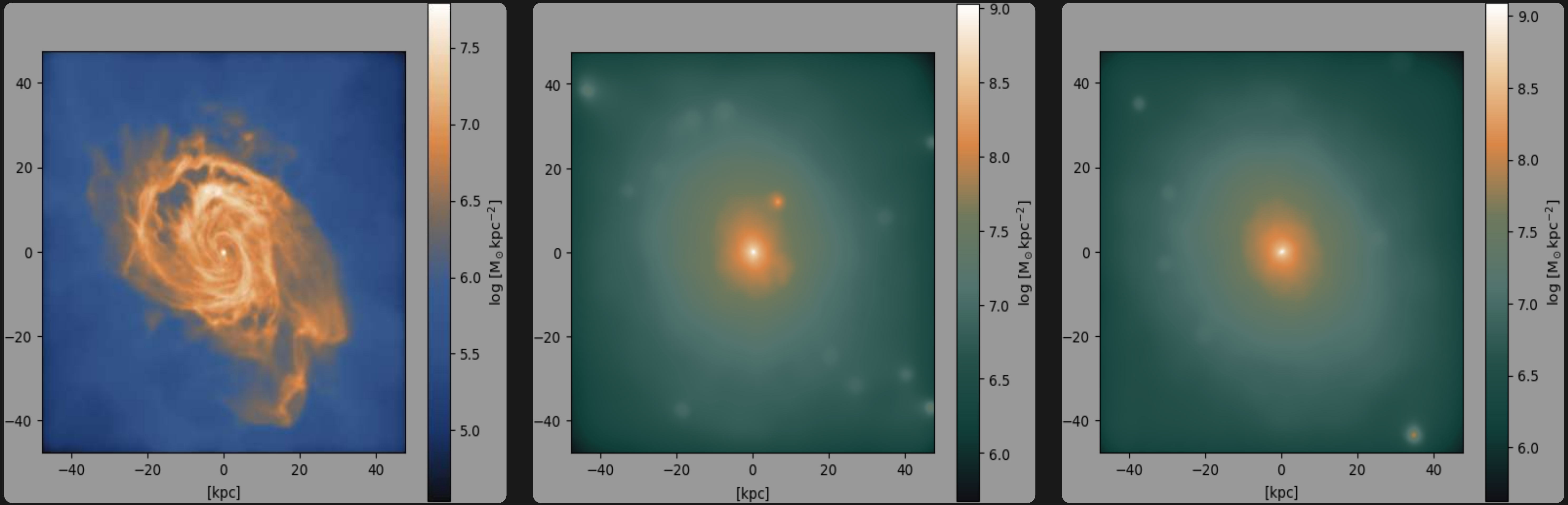


Input

Output (pix2pix with Attention U-Net)

Ground truth

Gas ⟶ DM: Spiral galaxy

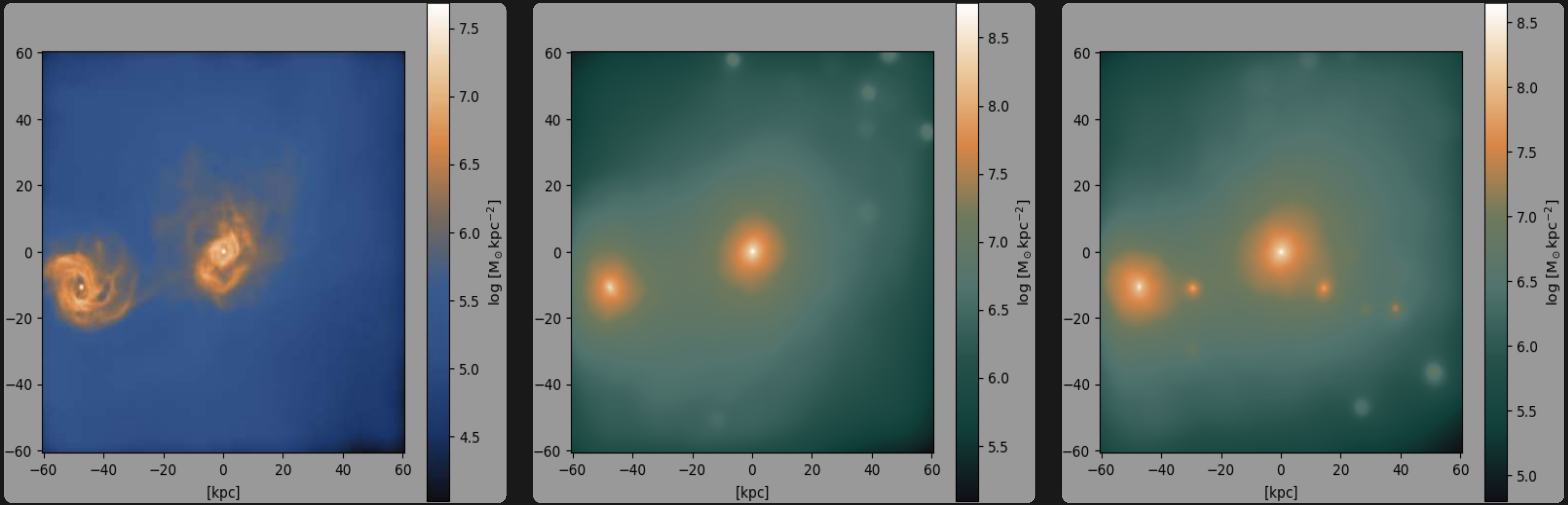


Input

Output (pix2pix with Attention U-Net)

Ground truth

Gas ⟶ DM: Merger

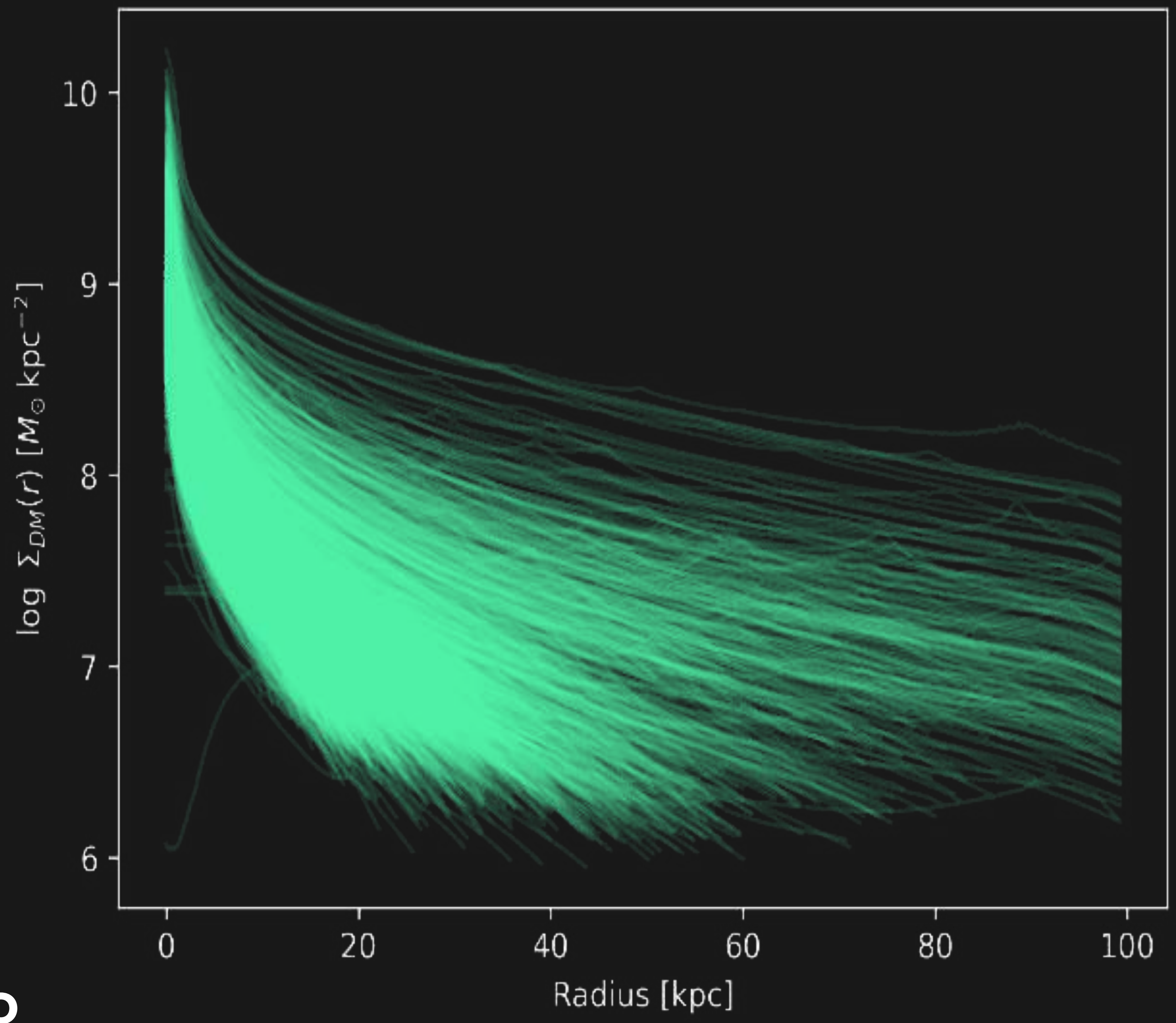


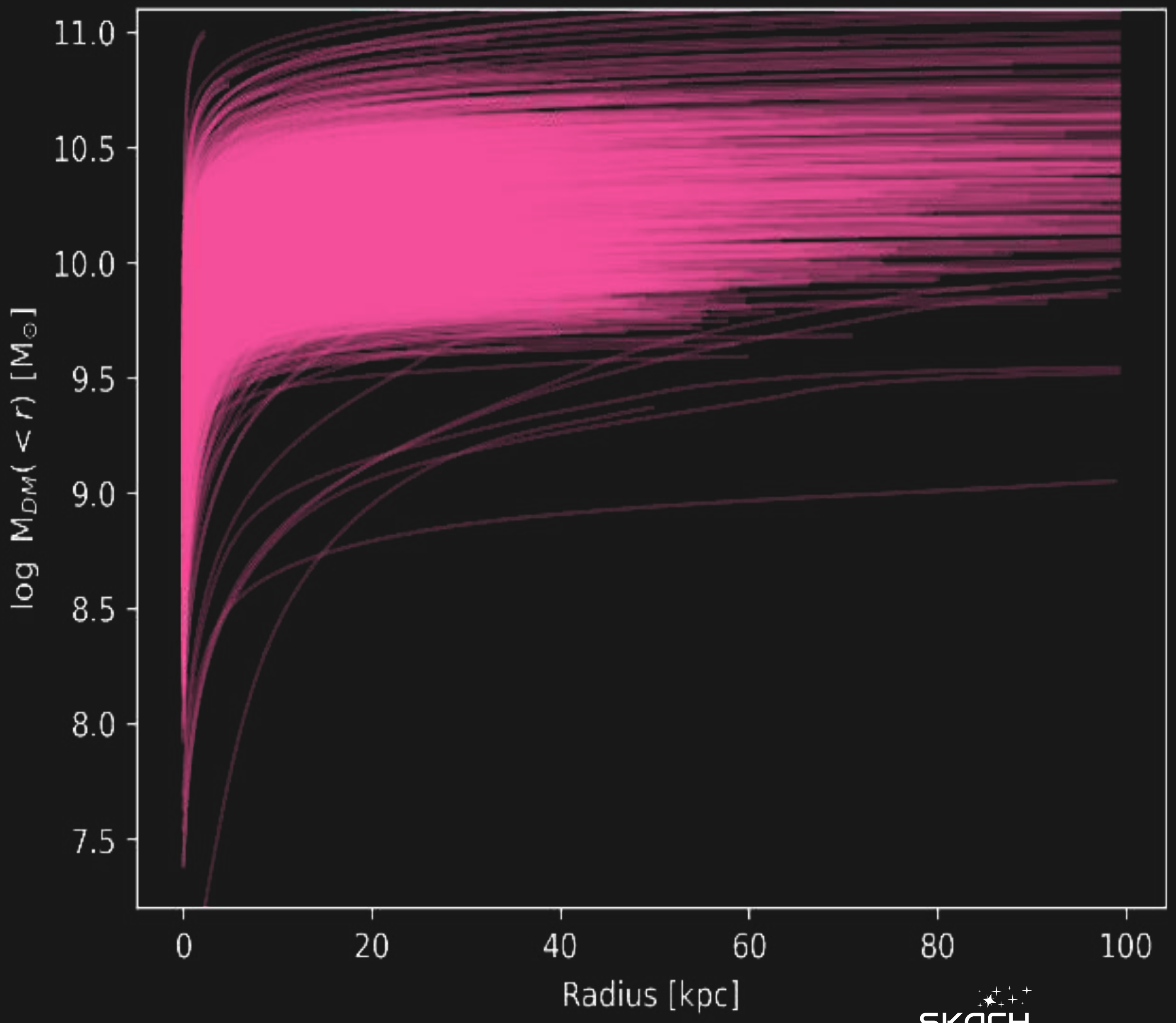
Input

Output (pix2pix with Attention U-Net)

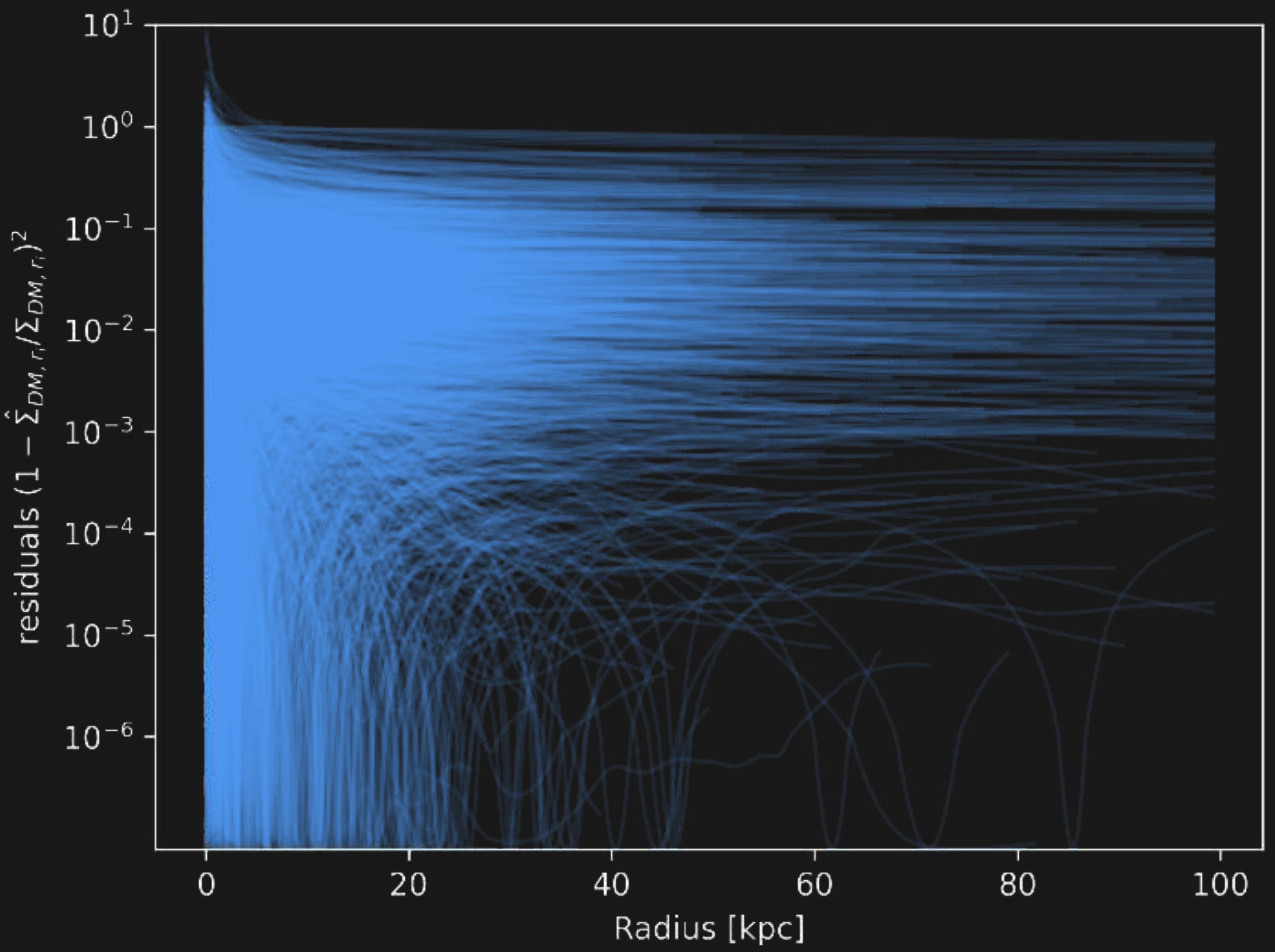
Ground truth

Profiles of DM column density





Profile residuals



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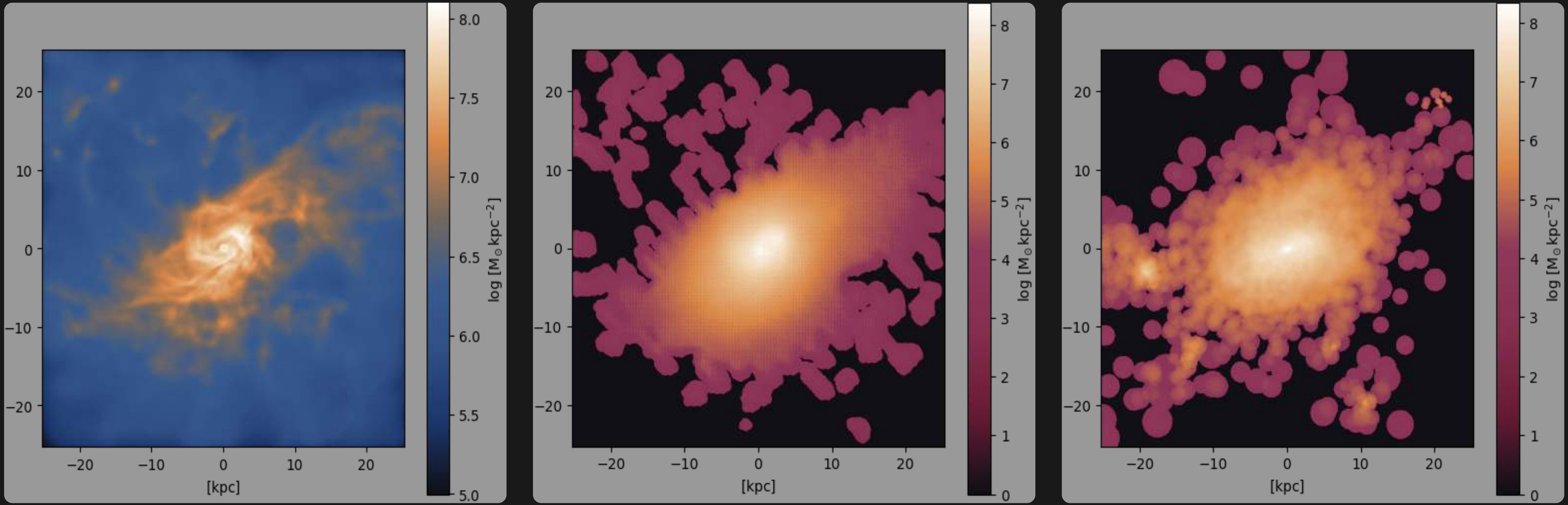
Gas ⟶ stars: High turbulence

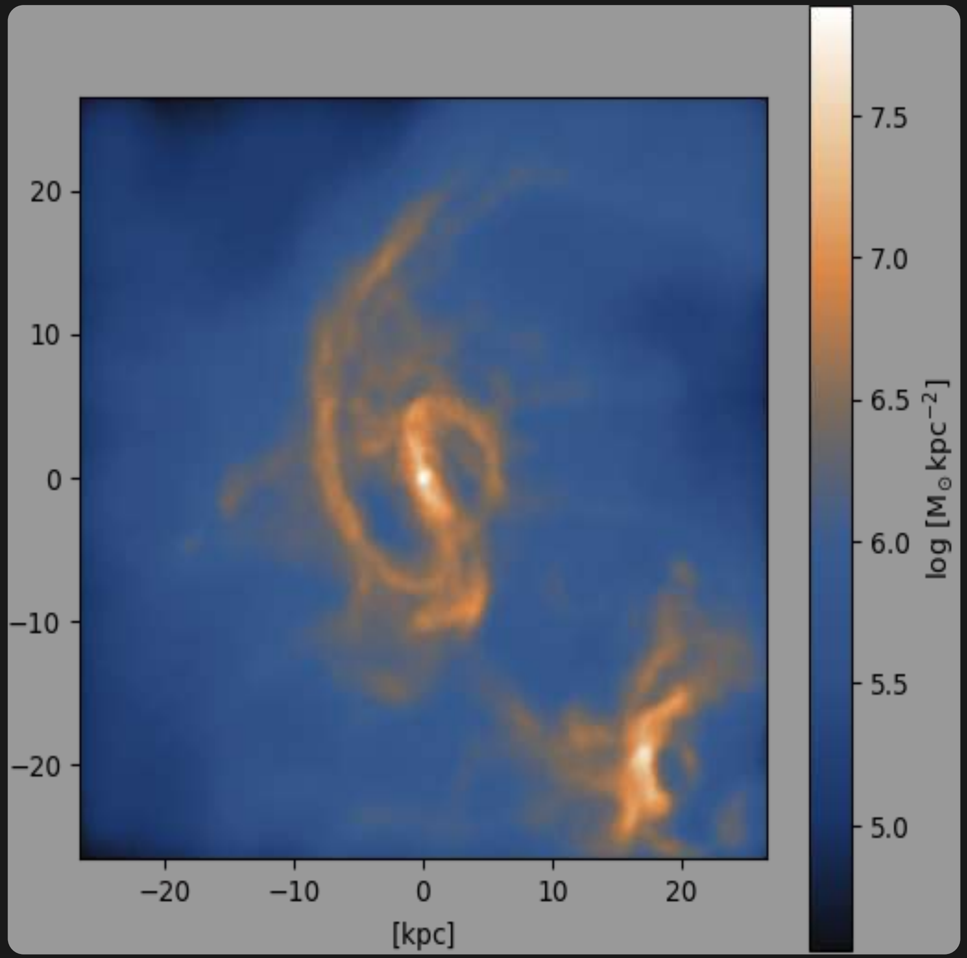


Input

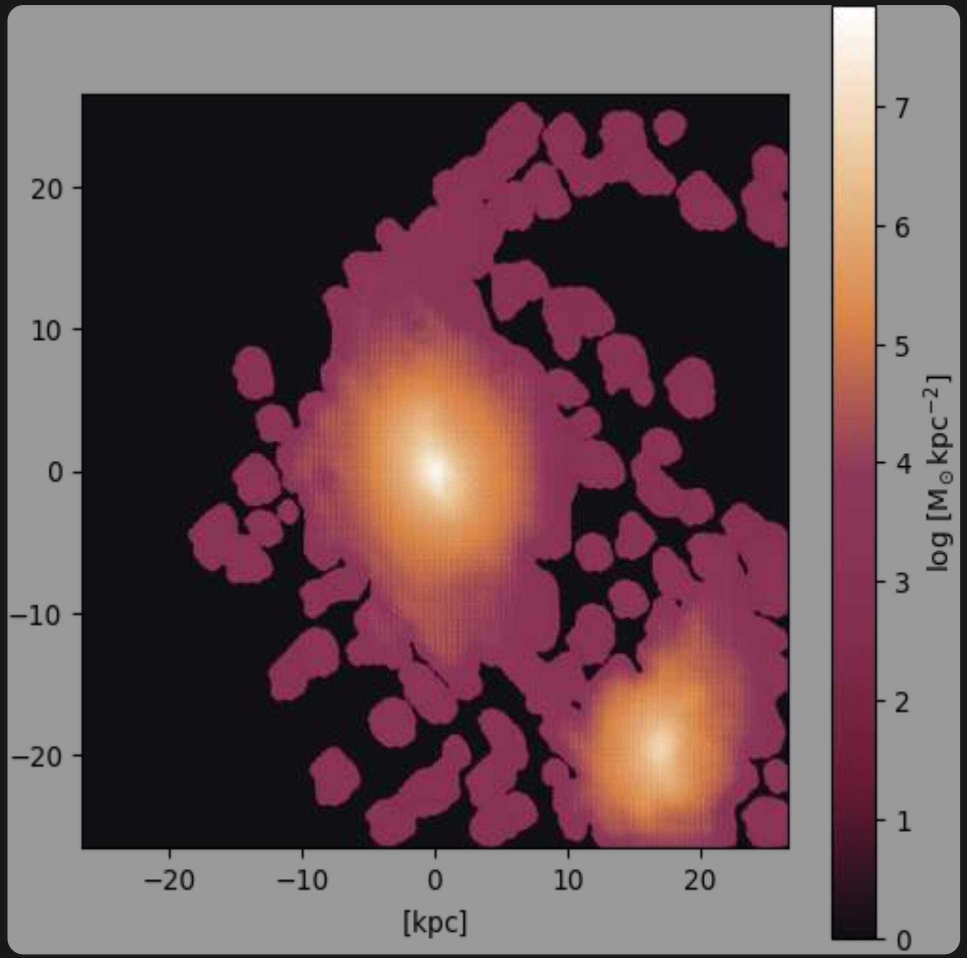
Output (pix2pix with Attention U-Net)

Ground truth

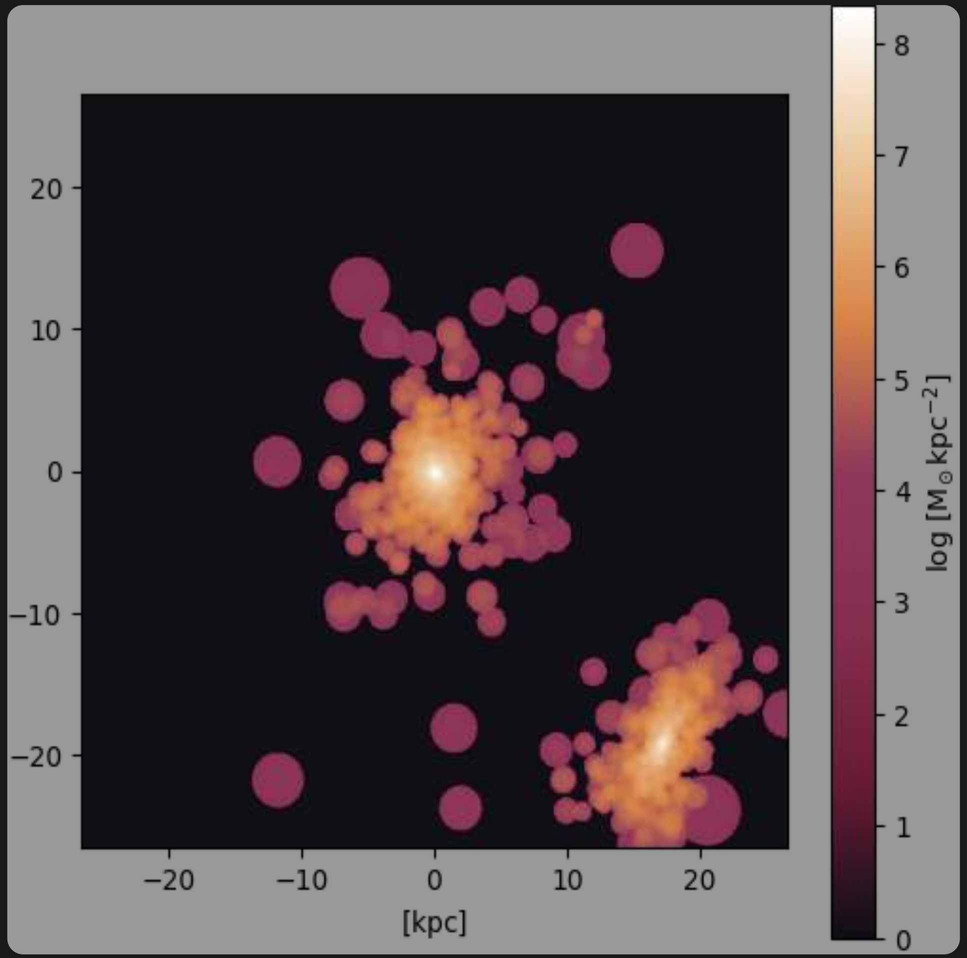
Gas ⟶ stars: Mergers



Input

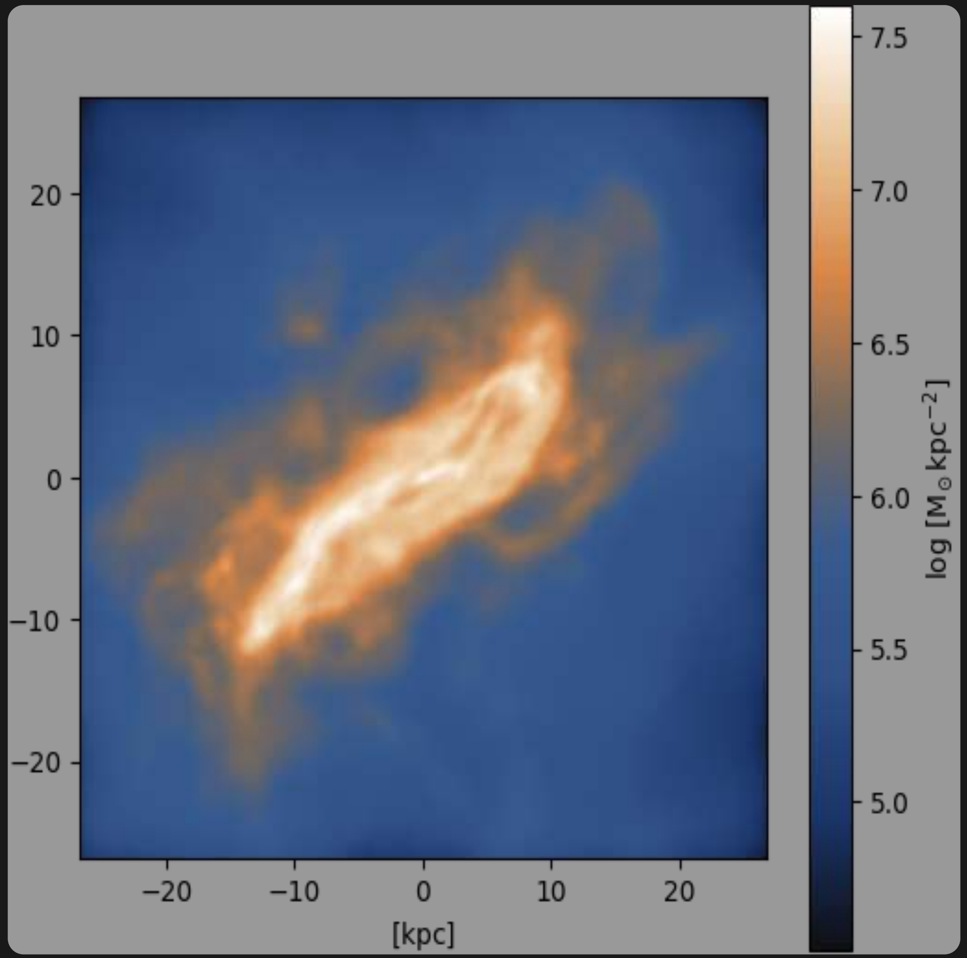


Output (pix2pix with Attention U-Net)

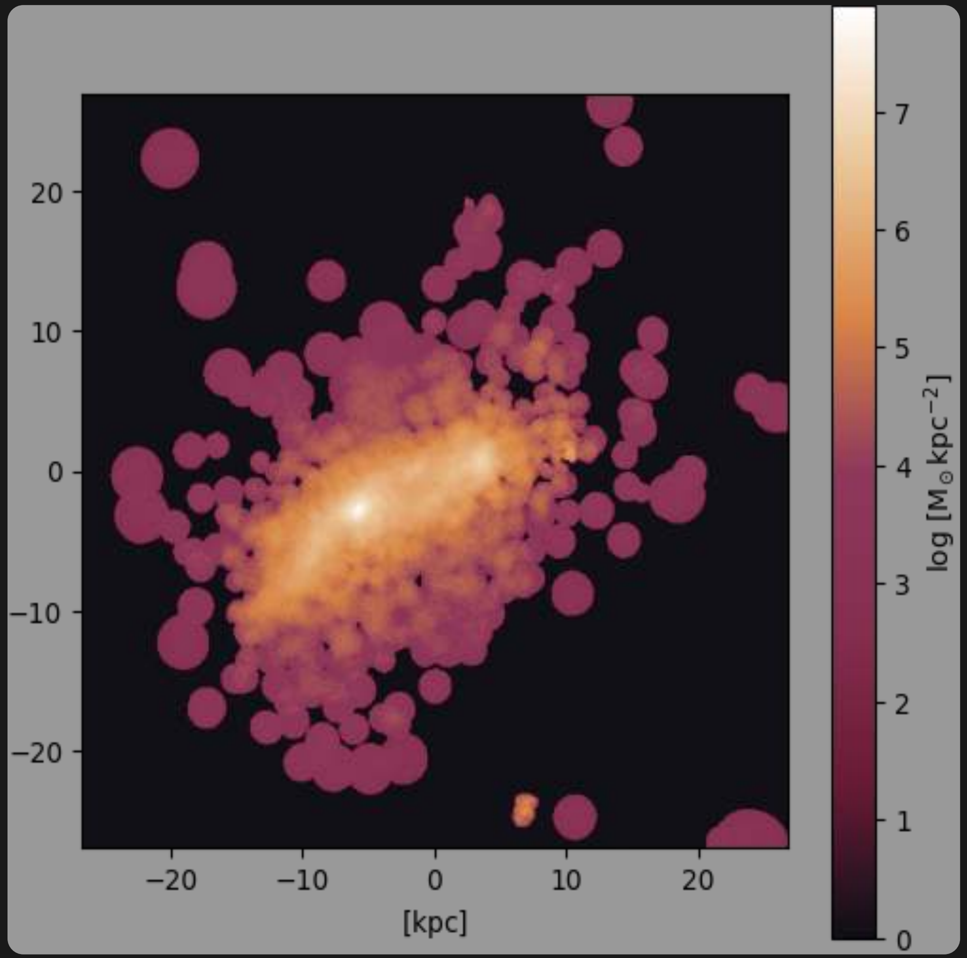


Ground truth

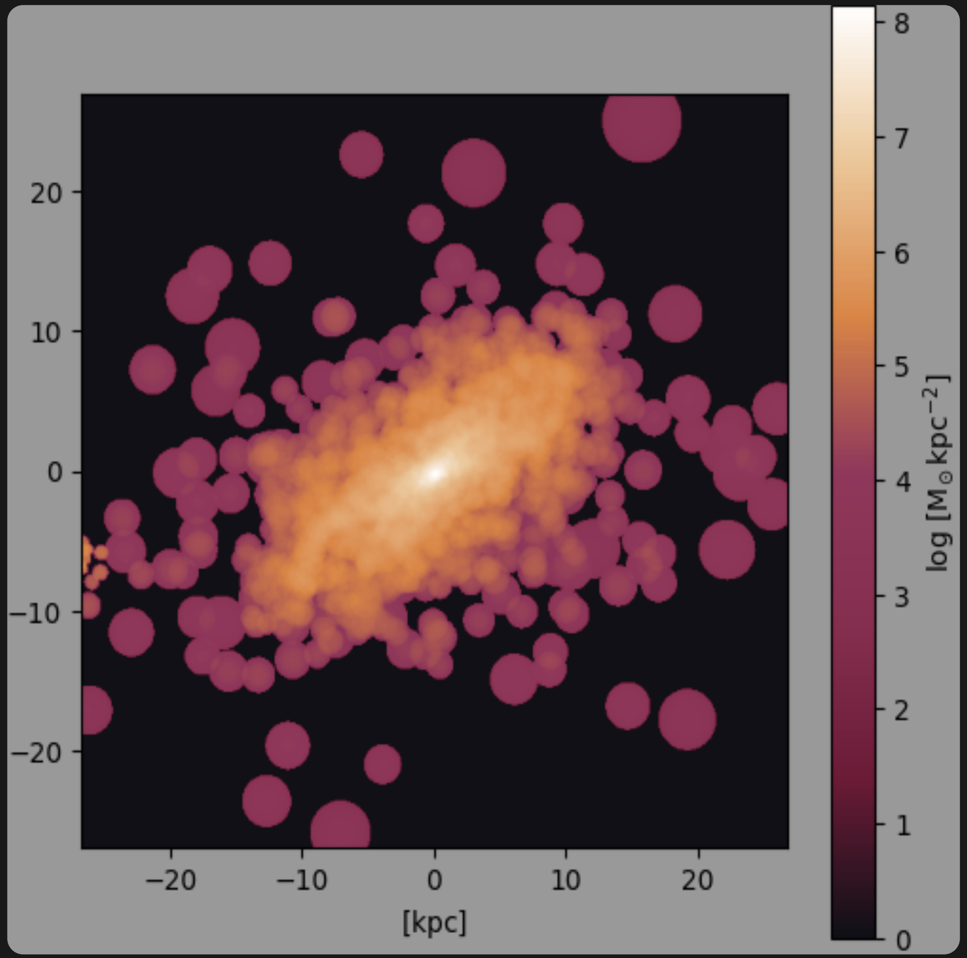
Gas ⟶ stars: Irregular shape



Input

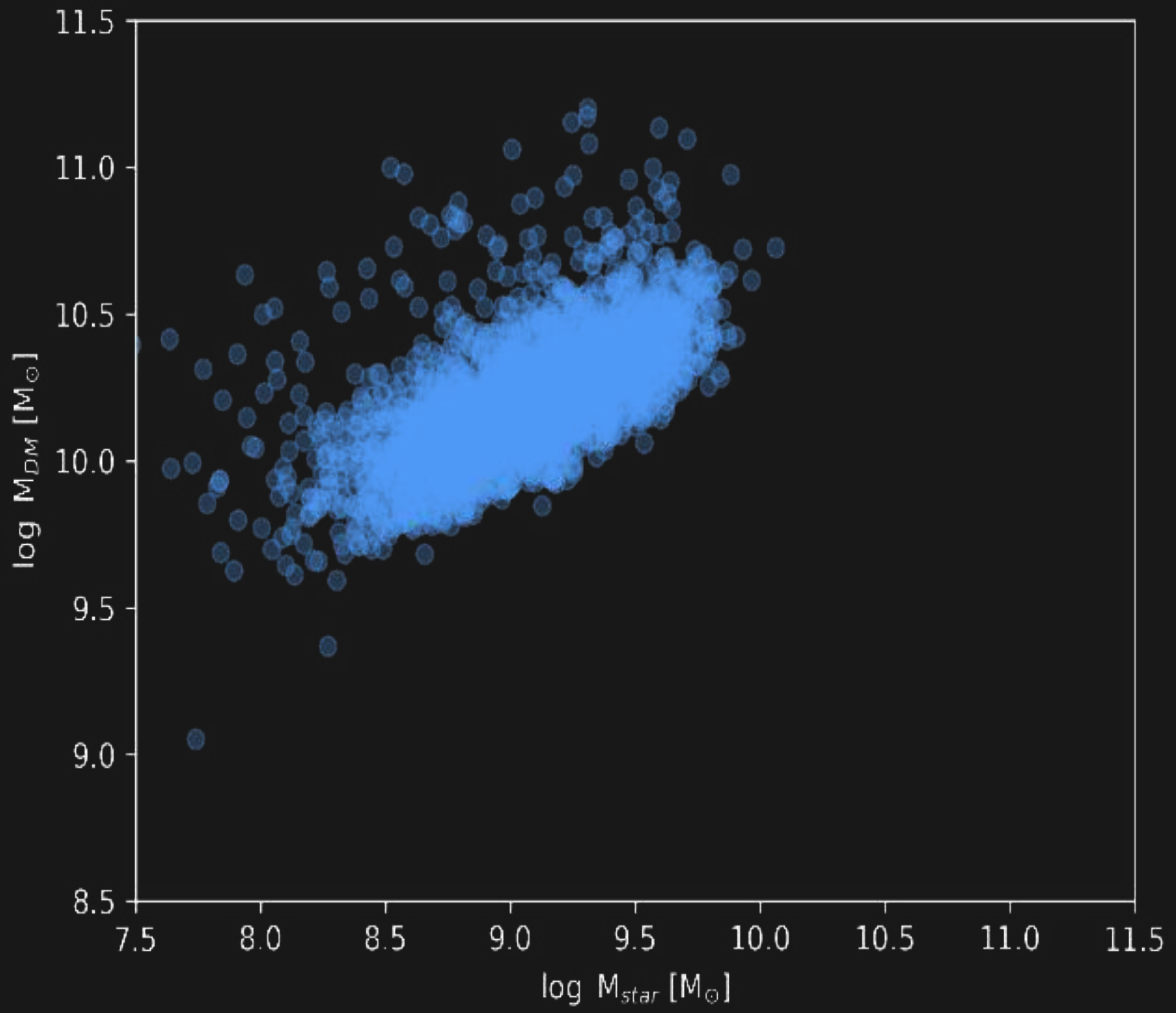


Output (standard DDPM)

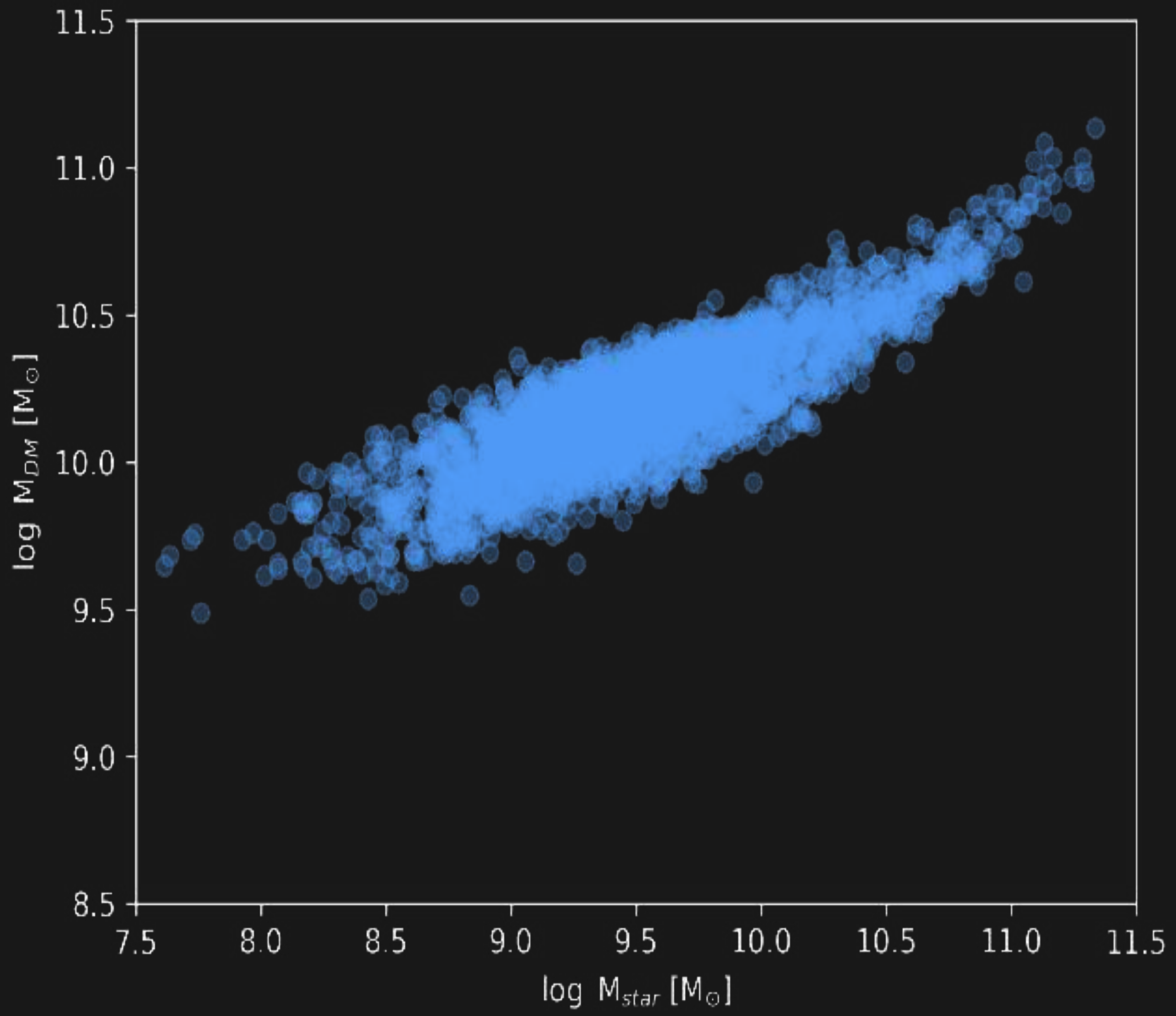


Ground truth

"Abundance matching"

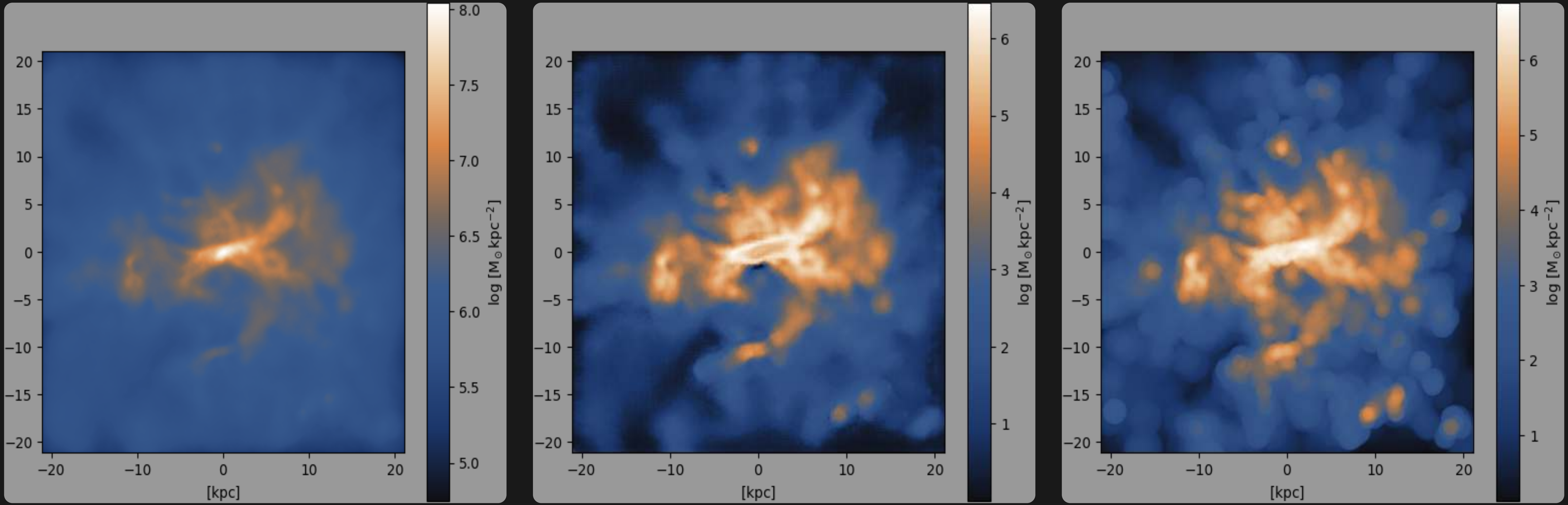


model using pix2pix+Attention



data

Gas ⟶ HI

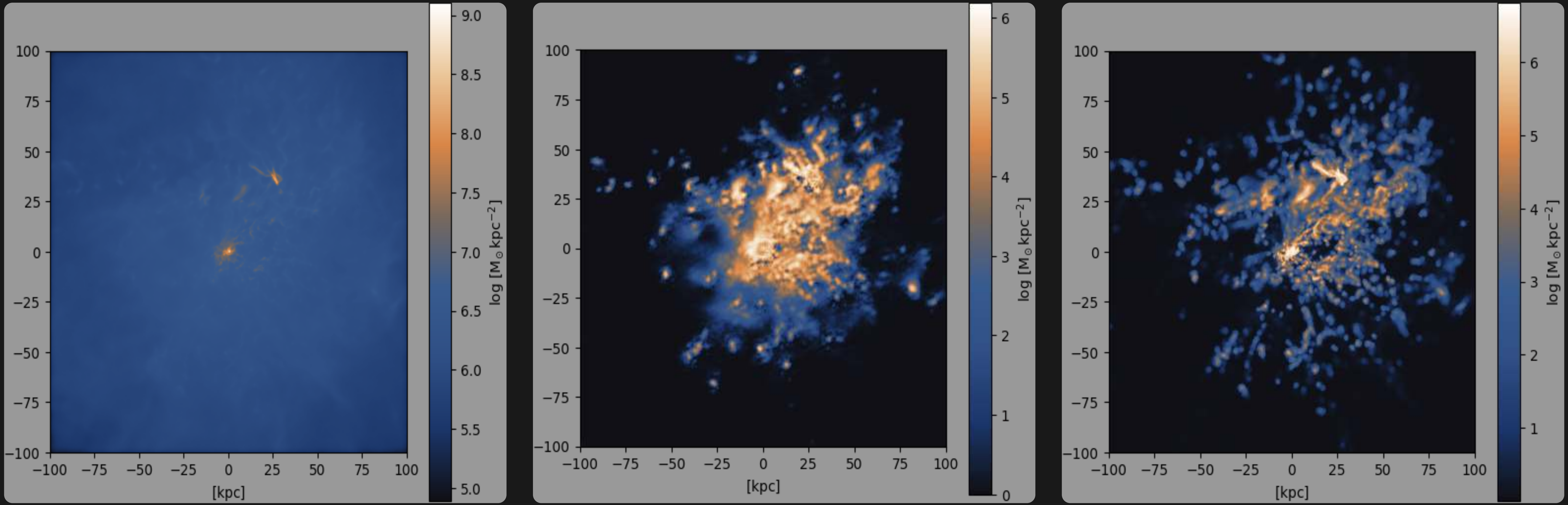


Input

Output (pix2pix with Attention U-Net)

Ground truth

Gas ⟶ HI: Massive halo



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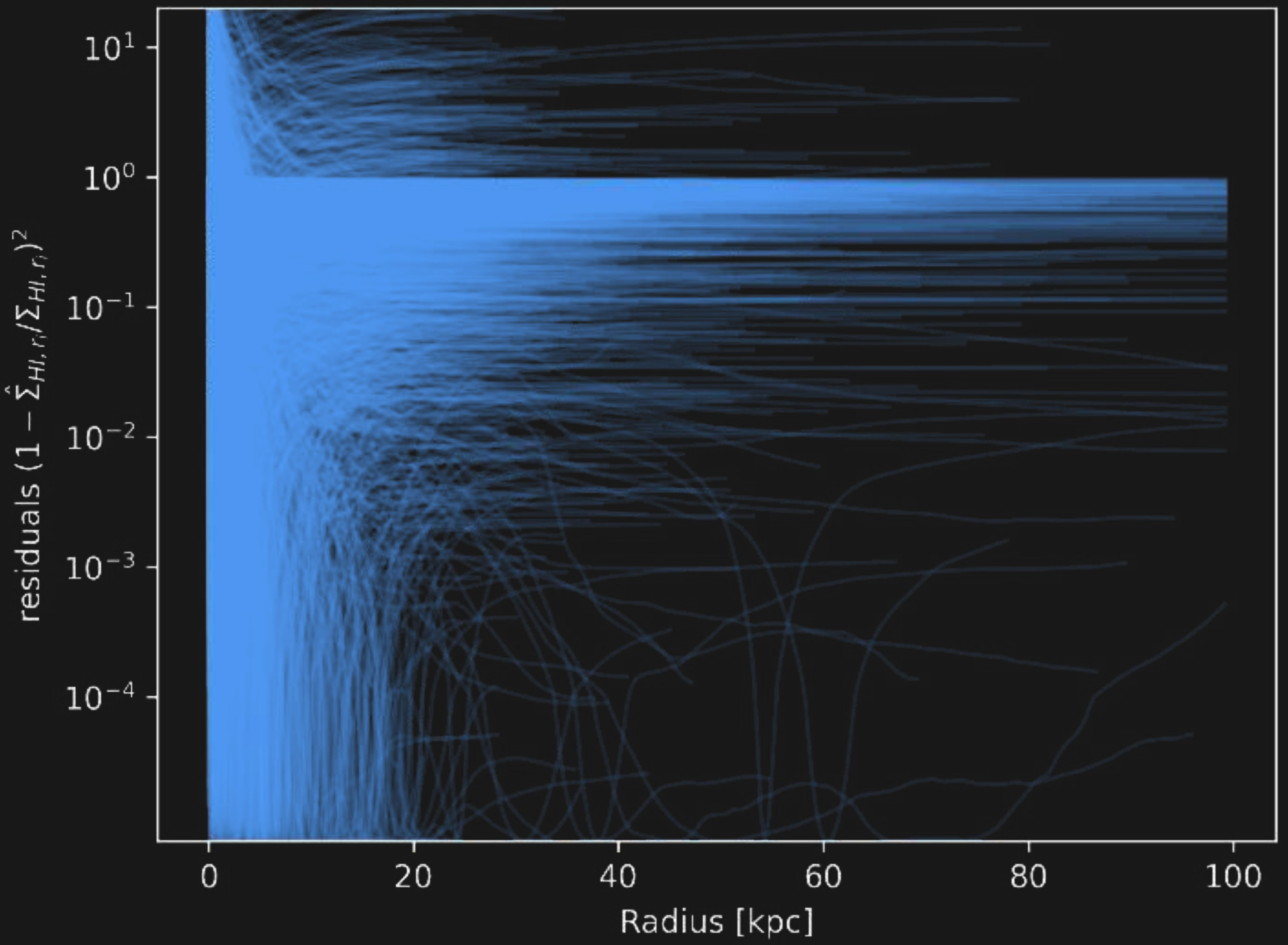
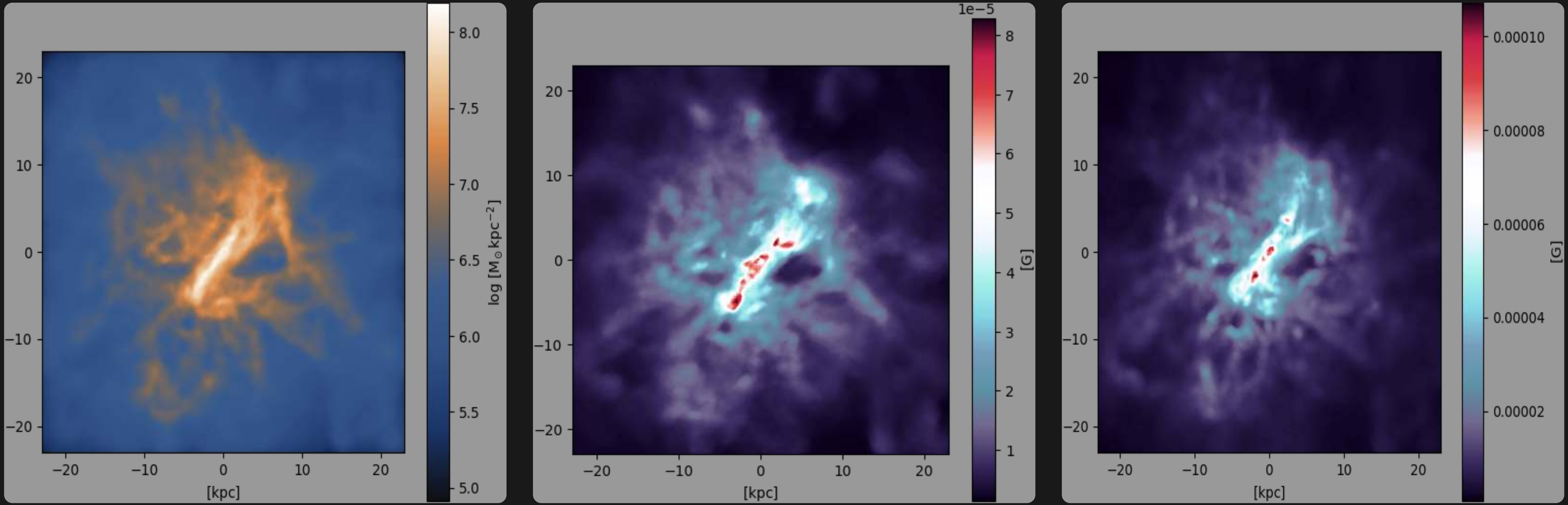
Ground truth

Profile residuals



Gas ⟶ B-field:



Input

Output (pix2pix with Attention U-Net)

Ground truth

Next Steps

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- test more architectures
- improve observation mocks using Karabo
- analogue with point clouds in 3D
    - problem: scaling to larger clouds

Contact

https://phdenzel.github.io/

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References

- simulations: IllustrisTNG project
- SKA-MID simulation: Coogan et al. (2023)
- 21cm mocks: Villaescusa-Navarro et al. (2018)
- cGAN: Isola et al. (2016)
- DDPM: Ho et al. (2020)
- InDI: Delbracio & Milanfar (2023)
- SDM: Song et al. (2021)
- DiM: Teng et al. (2024)

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