



**UNIVERSITÀ
DEGLI STUDI
DI TRIESTE**



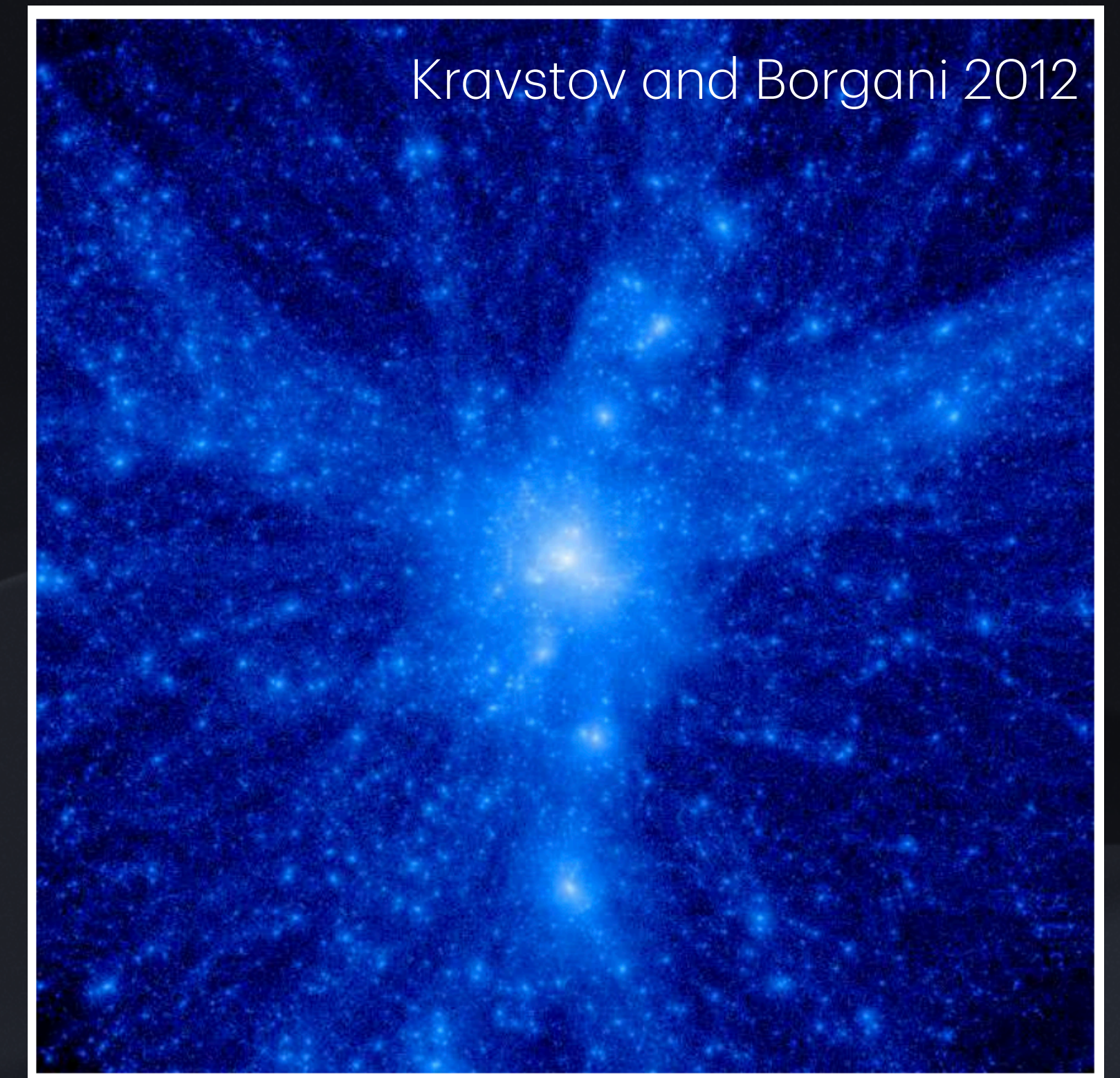
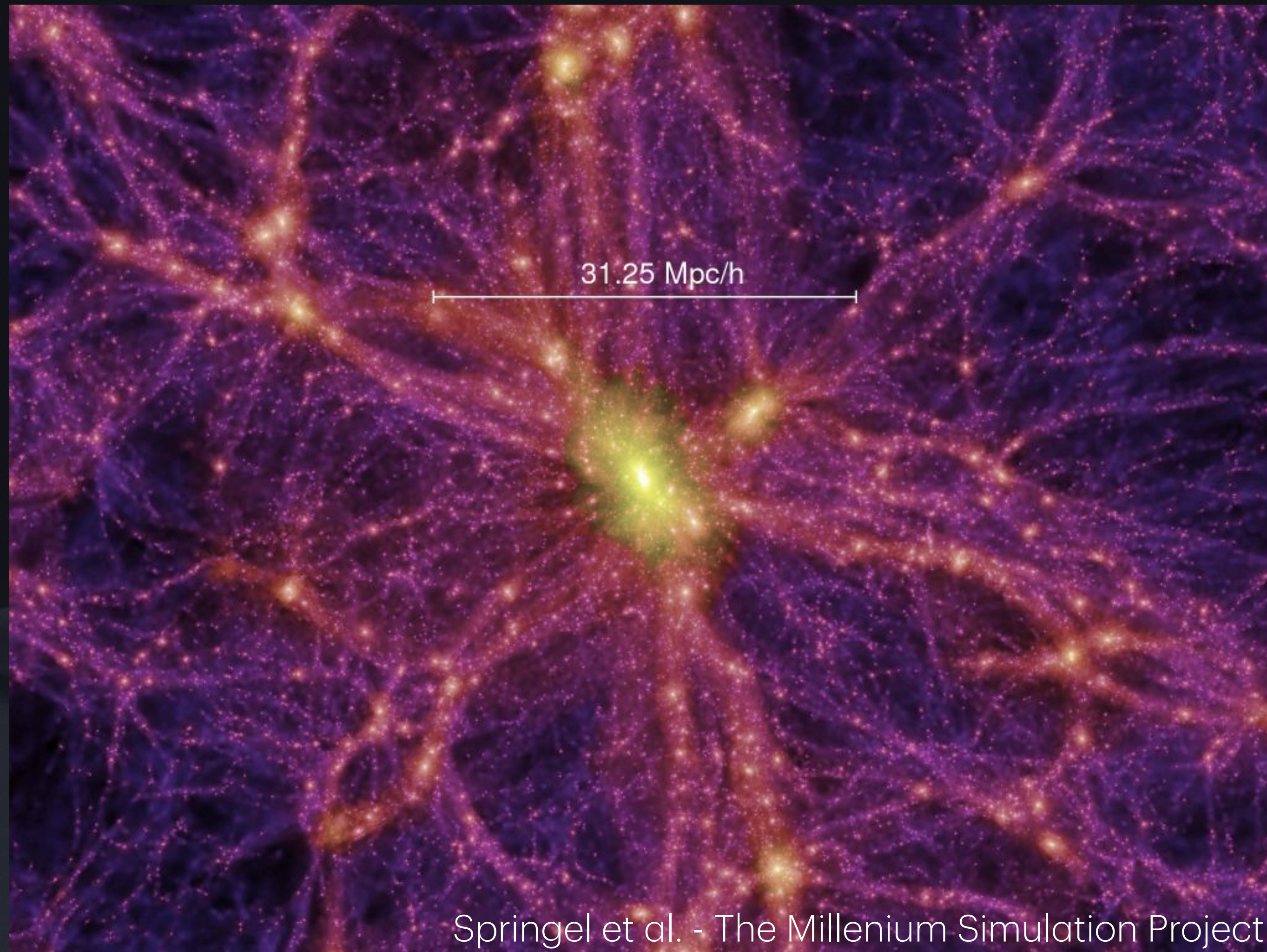
INAF
OSSERVATORIO
ASTRONOMICO
DI TRIESTE

Deep Generative Priors for Interferometry

Non-parametric forward modeling of the Sunyaev-Zeldovich effect

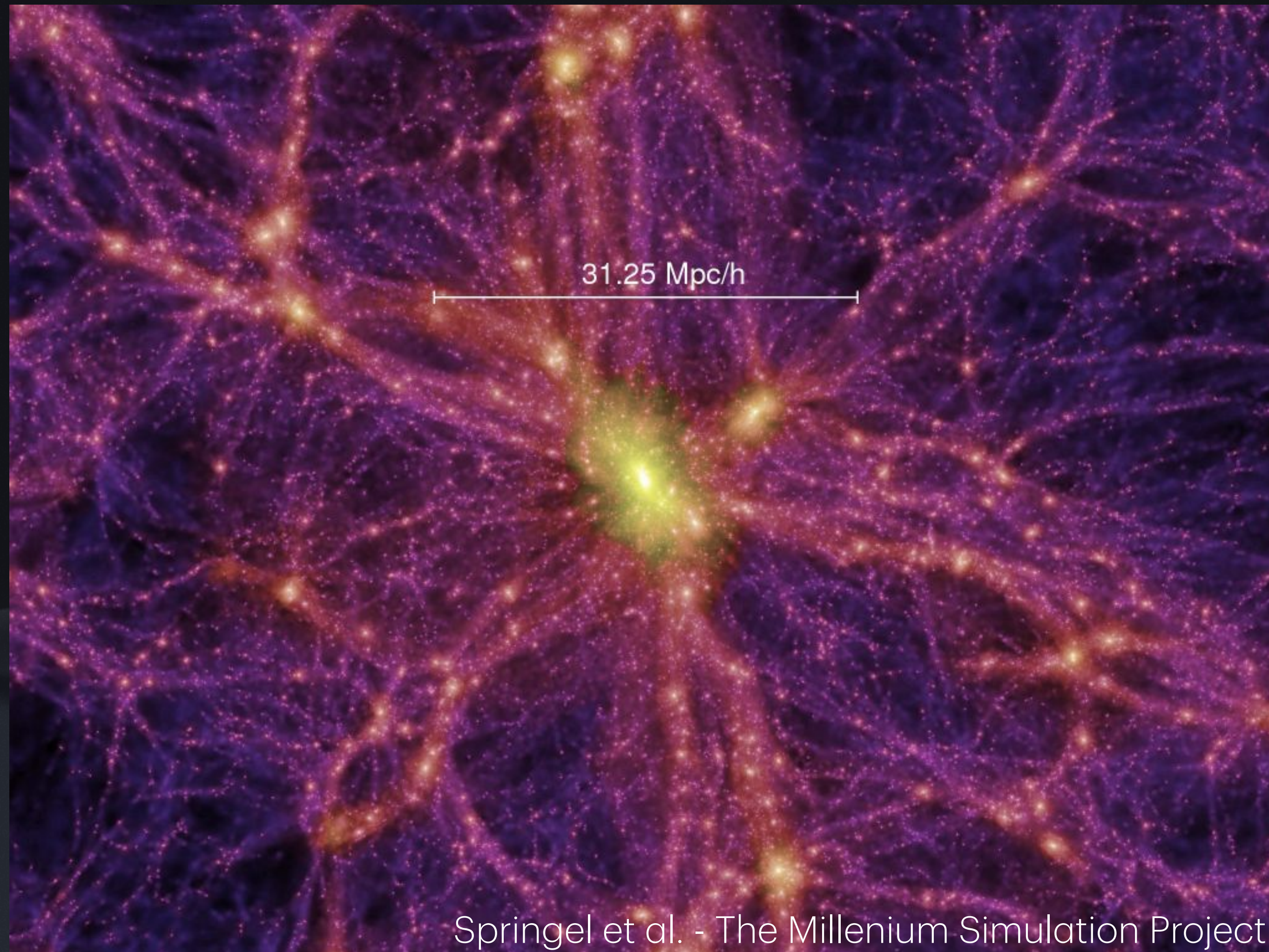
Galaxy Clusters

Extreme environments at the nodes of the Cosmic Web



Galaxy Clusters

Extreme environments at the nodes of the Cosmic Web

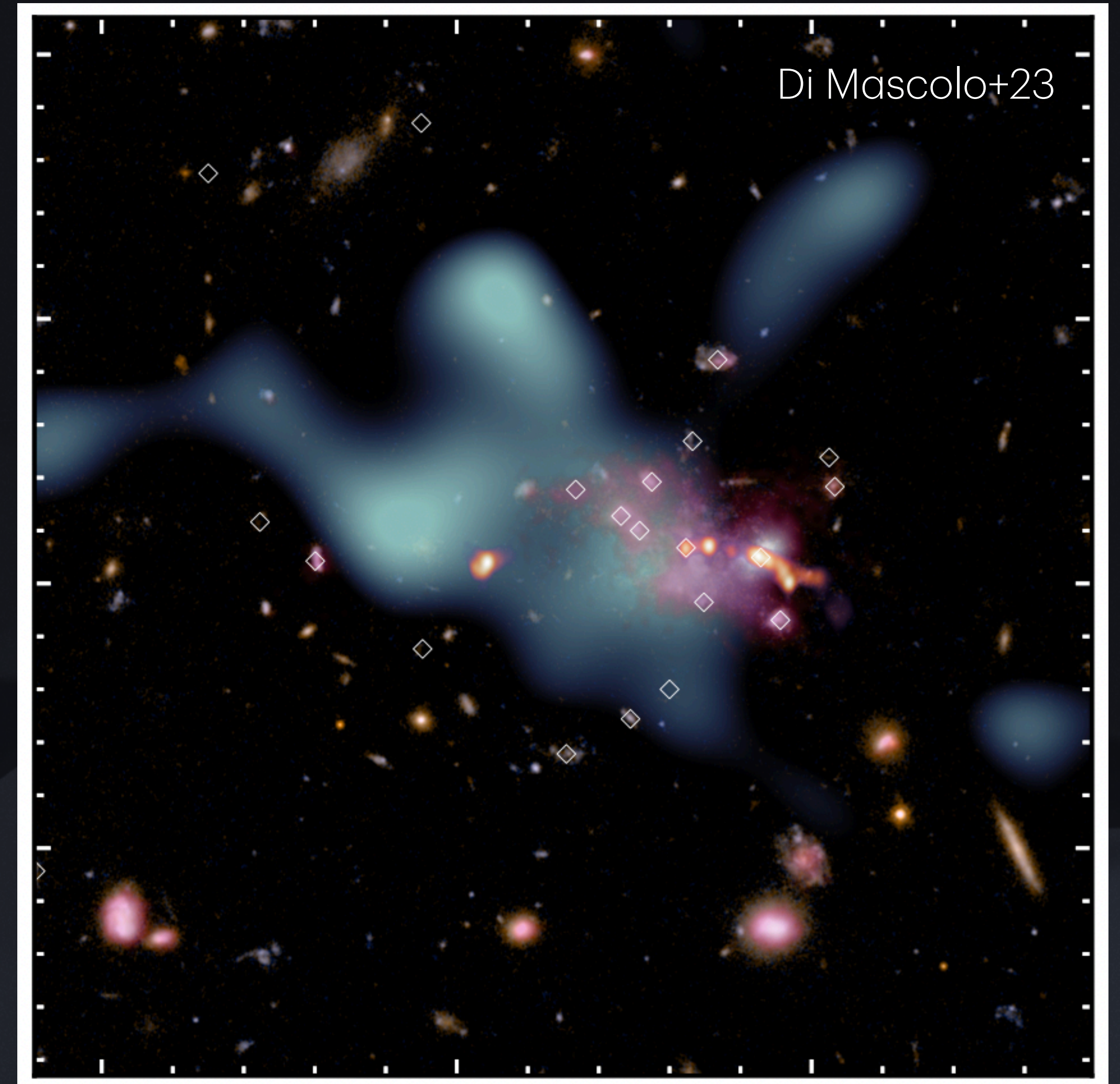


Kravstov and Borgani 2012

- Cosmology
Tracking their abundance and mass evolution over time
- High-energy laboratories
Vast amounts of Dark Matter and plasma. They can be used also to put constraints on neutrino masses.

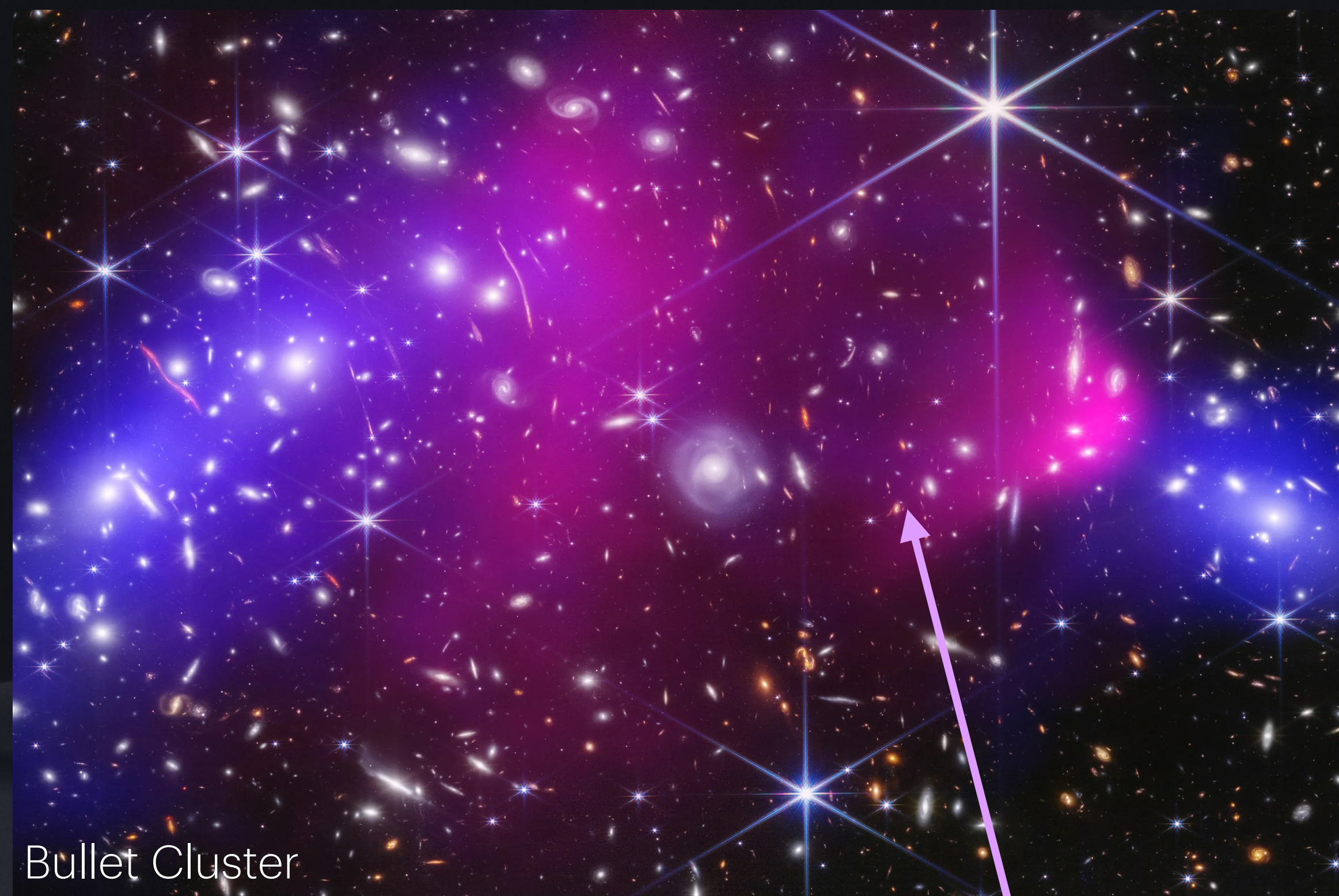
Galaxy Clusters

Multi wavelength view

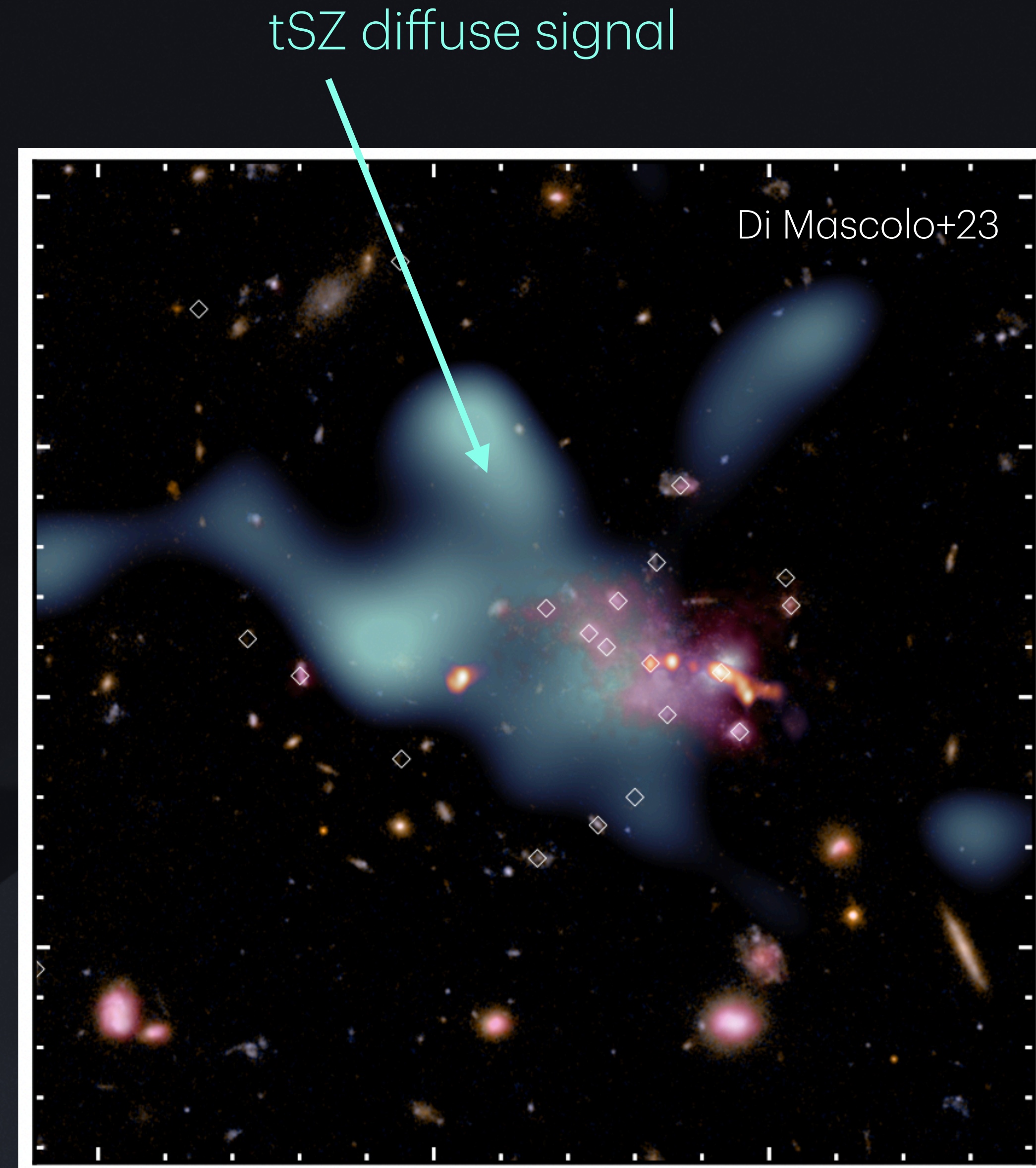


Galaxy Clusters

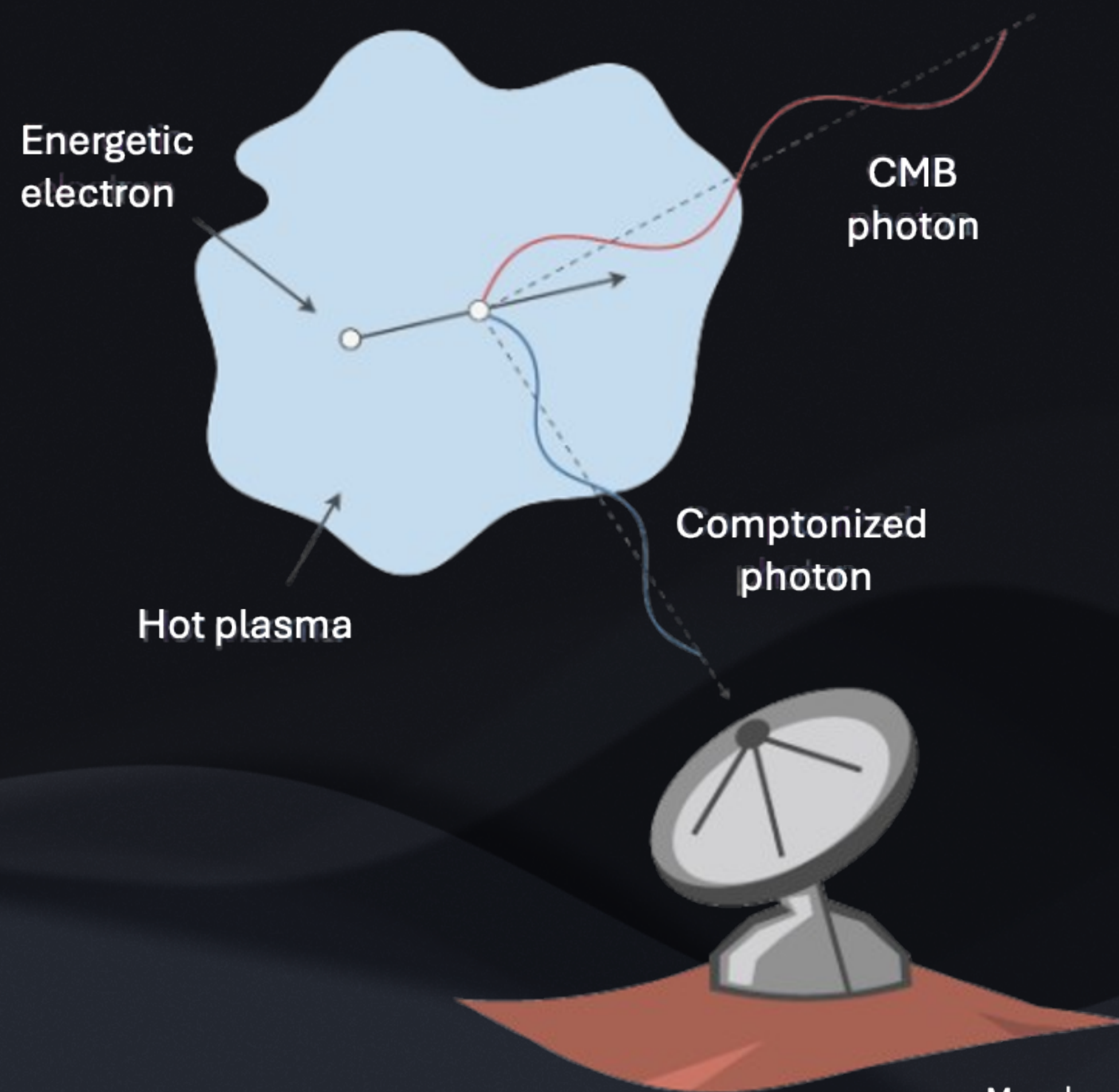
Multi wavelength view



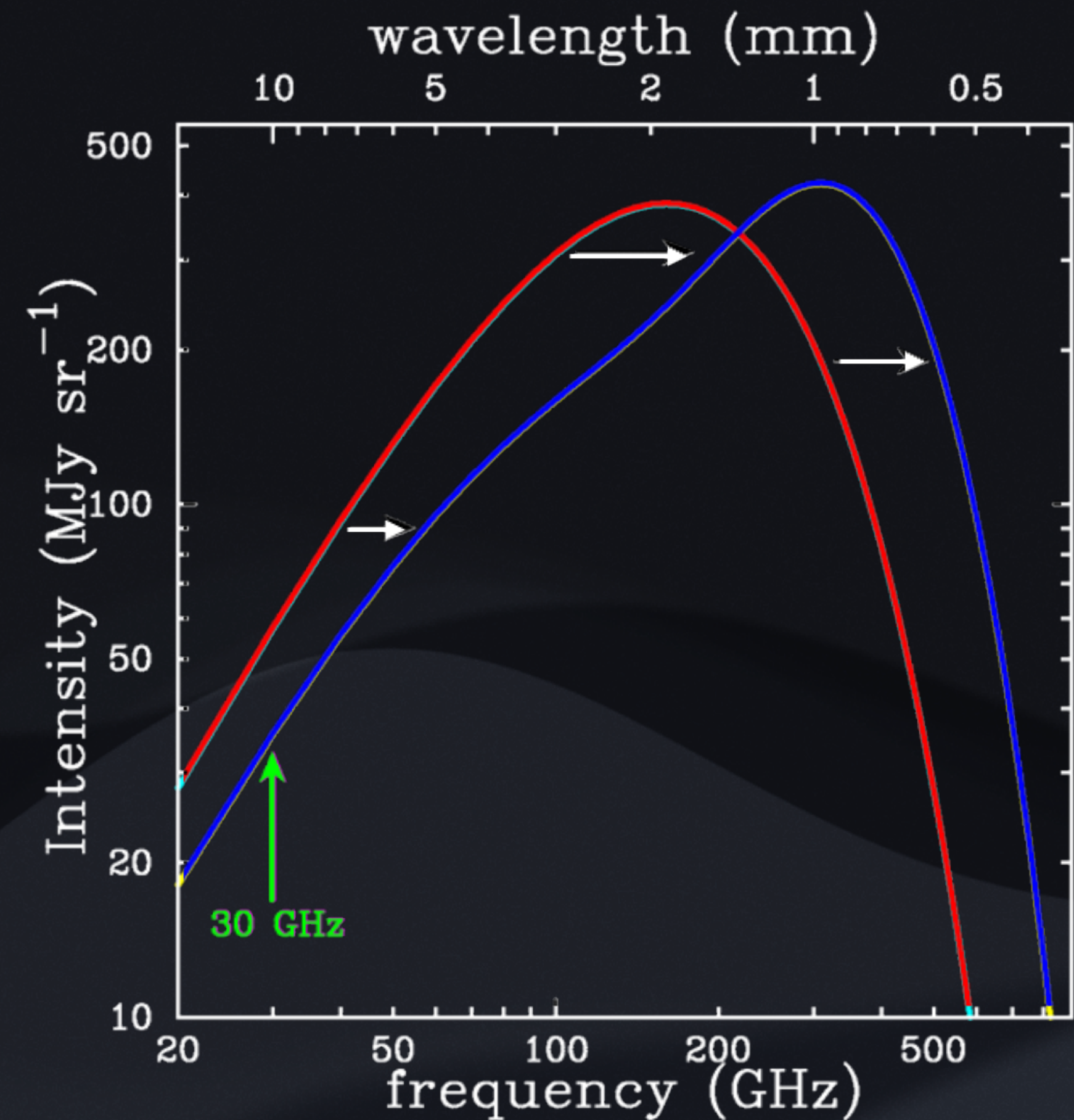
X-Ray emission



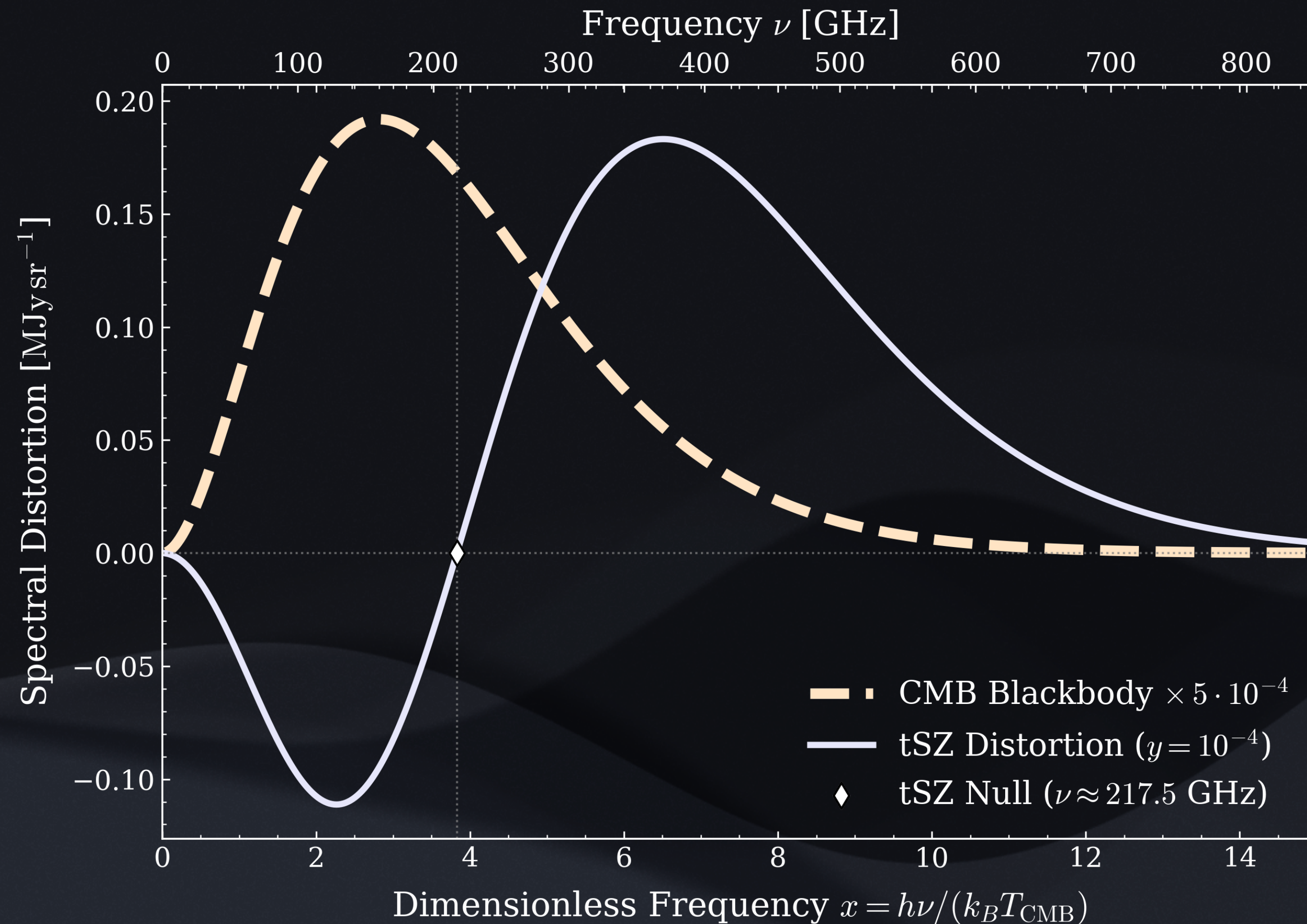
The thermal Sunyaev-Zeldovich effect



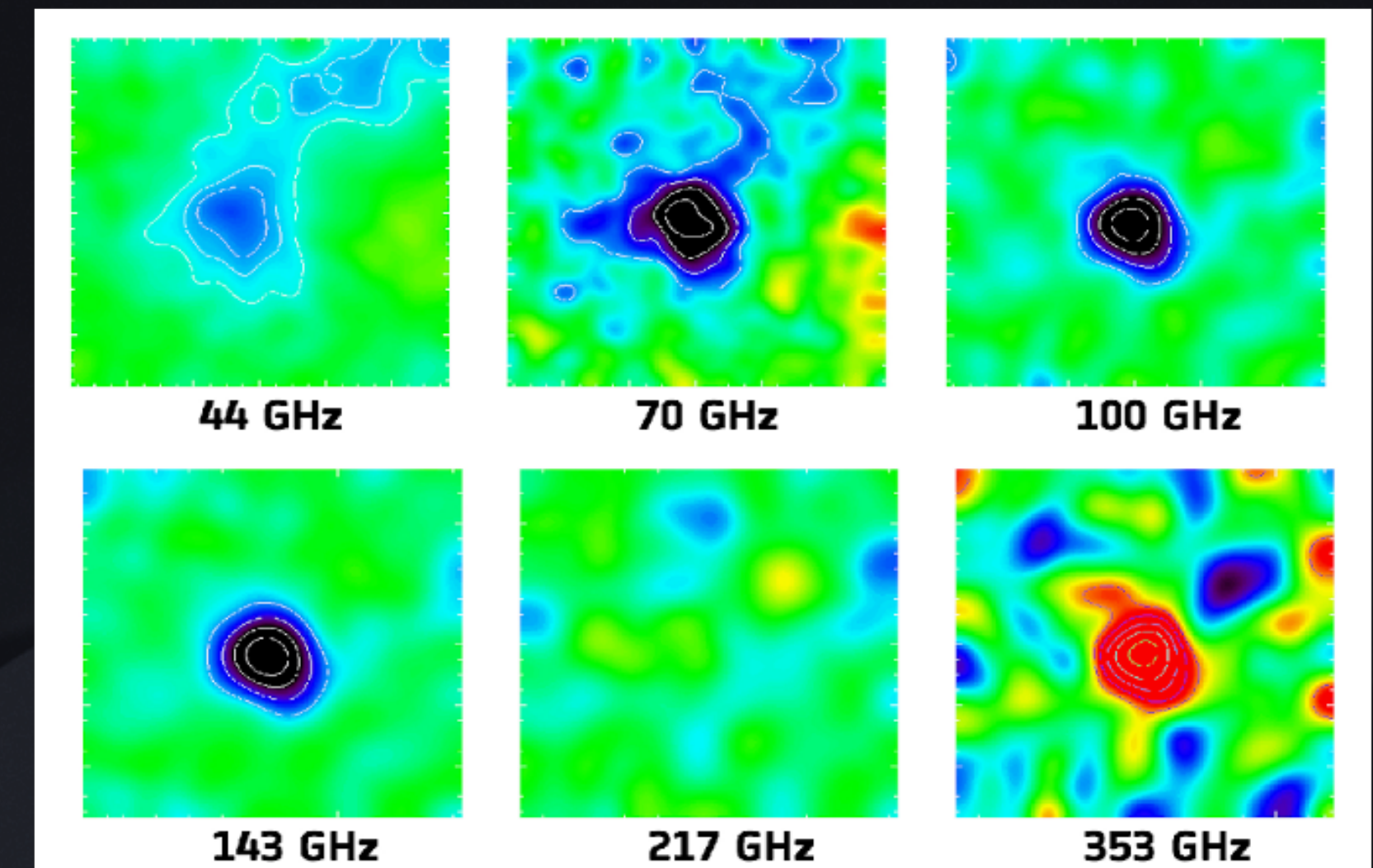
Mroczkowski et al. 2020



The thermal Sunyaev-Zeldovich effect



$$\frac{\Delta T_{\text{CMB}}}{T_{\text{CMB}}} \approx y \frac{x^4 e^x}{(e^x - 1)^2} \left(x \frac{e^x + 1}{e^x - 1} - 4 \right) = y f(x)$$



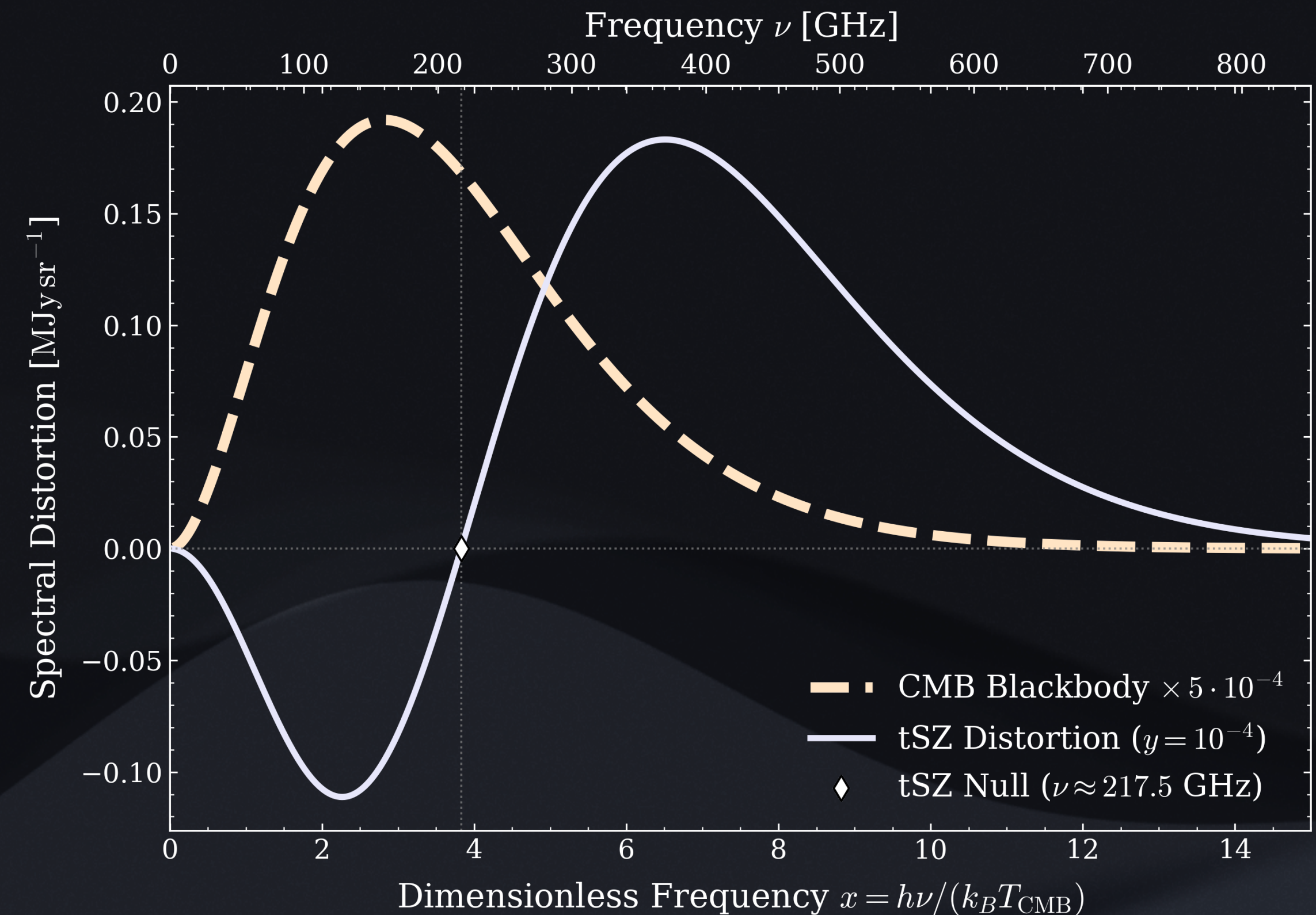
Sequence of observation of the Abell 2319 cluster made with Planck (credits: ESA/LFI & HFI Consortia).

tSZ effect

High resolution observations

$$M_{500} = 10^{14} M_{\odot} \quad z = 1,00 \quad r_{500} \simeq 40 \text{ arcsec}$$

$$R = 1,22 \frac{\lambda}{D} \longrightarrow D = 1,22 \frac{0,002 \text{ m}}{2 \times 10^{-5} \text{ rad}} \simeq 122 \text{ m}$$



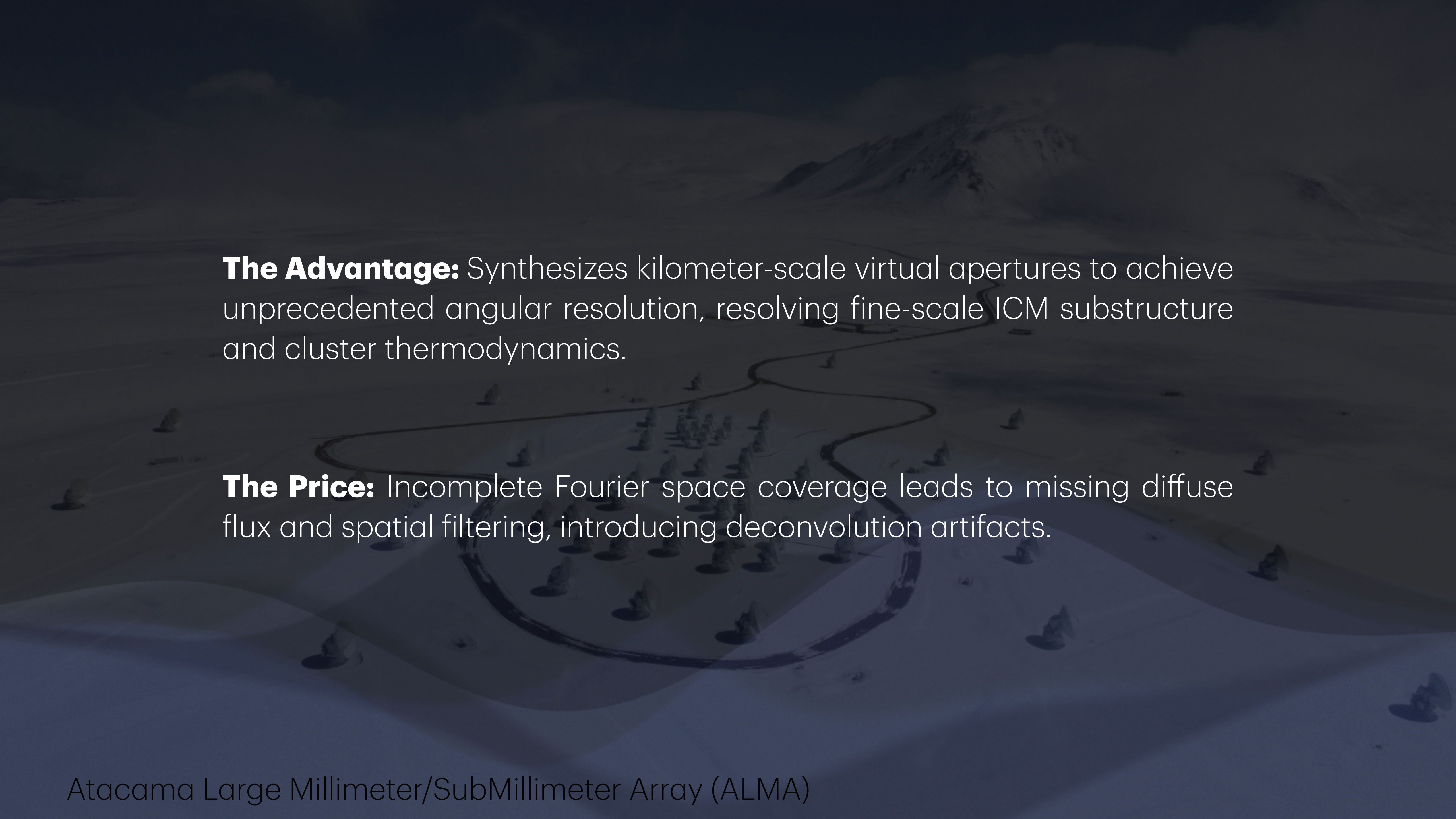


Atacama Large Millimeter/Submillimeter Array (ALMA)



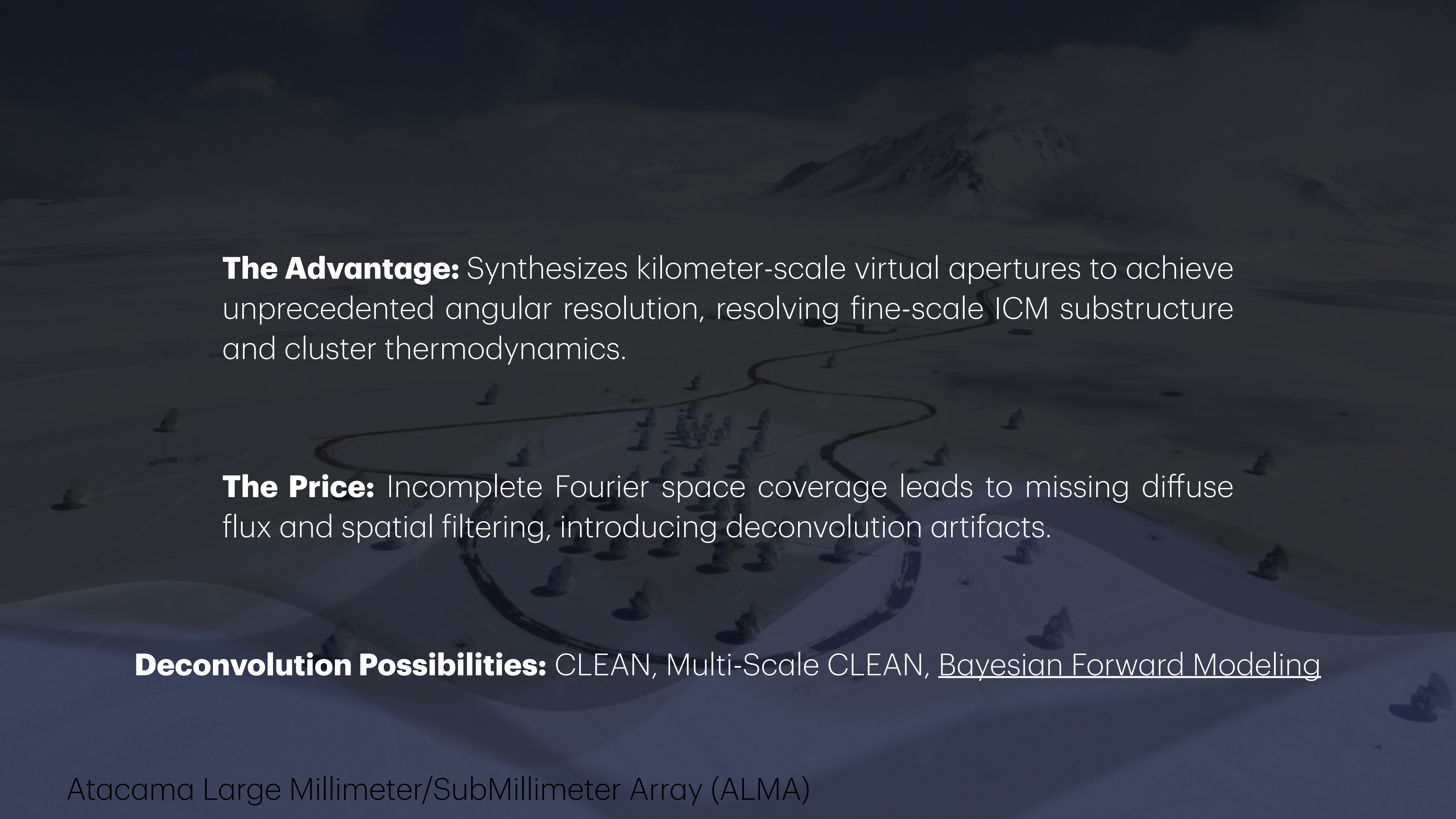
Longest Baseline

Atacama Large Millimeter/Submillimeter Array (ALMA)

An aerial photograph of the Atacama Large Millimeter/Submillimeter Array (ALMA) in a desert landscape. The image shows a large number of radio telescope dishes arranged in a circular pattern, with a winding road or path cutting through the center. The background features rolling hills and mountains under a clear sky.

The Advantage: Synthesizes kilometer-scale virtual apertures to achieve unprecedented angular resolution, resolving fine-scale ICM substructure and cluster thermodynamics.

The Price: Incomplete Fourier space coverage leads to missing diffuse flux and spatial filtering, introducing deconvolution artifacts.

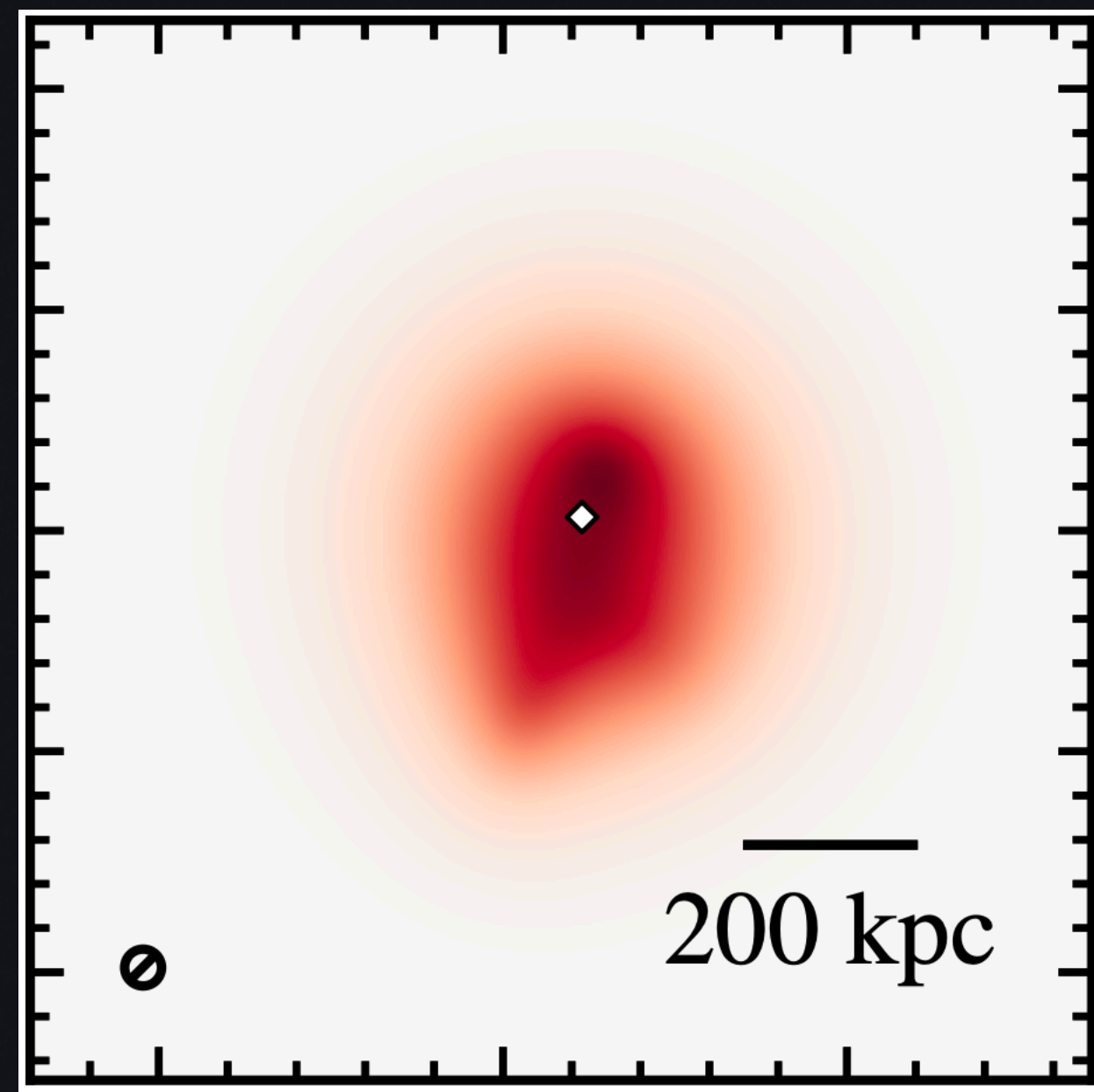
An aerial photograph of the Atacama Large Millimeter/Submillimeter Array (ALMA) in a desert landscape. The image shows a large number of radio telescope dishes arranged in a semi-circular pattern, with a winding road or path cutting through the desert floor. The background features rolling hills and mountains under a clear sky.

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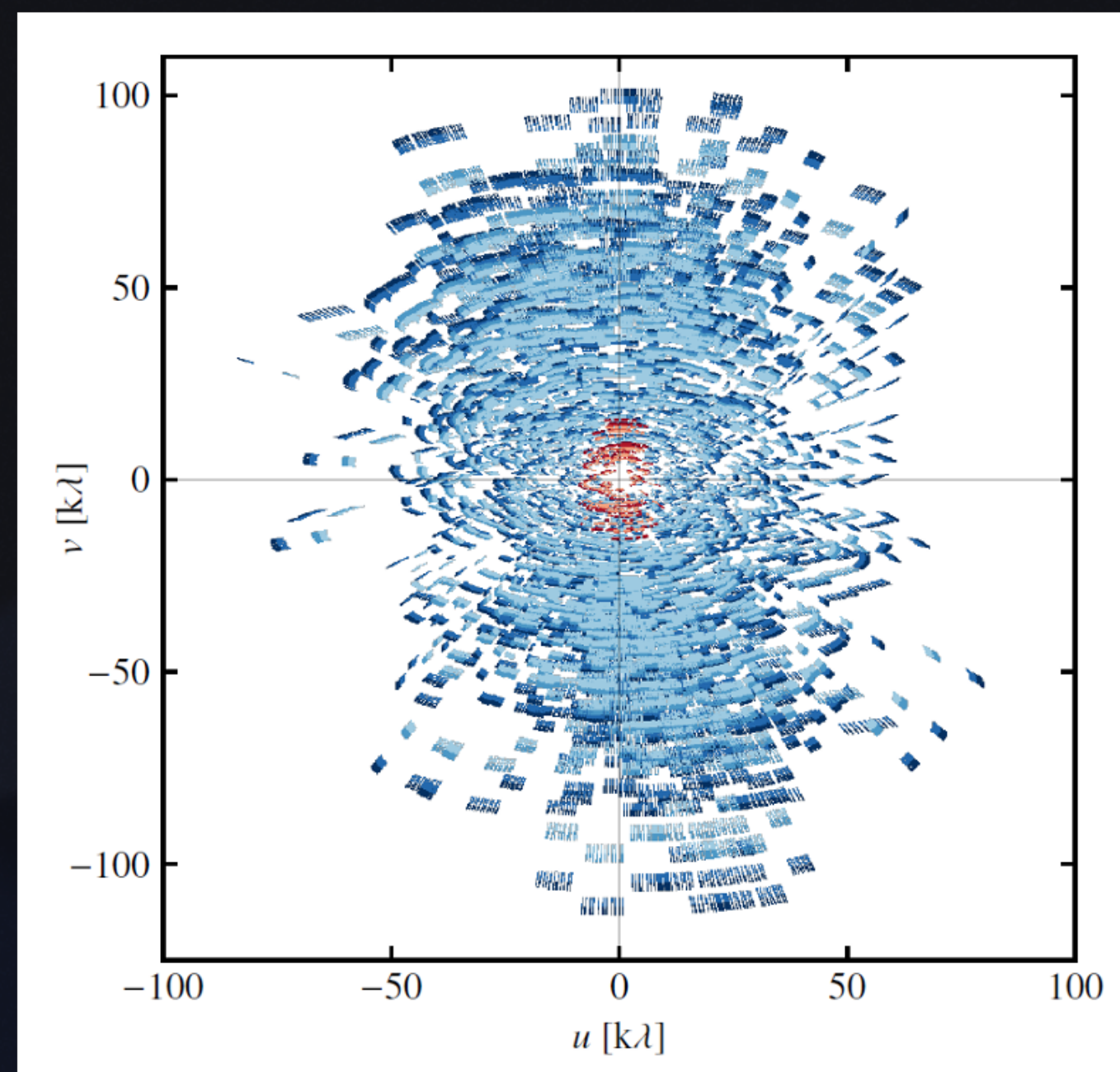
Deconvolution Possibilities: CLEAN, Multi-Scale CLEAN, Bayesian Forward Modeling

Clean Model that depends on some parameters θ



Di Mascolo in prep.

FFT

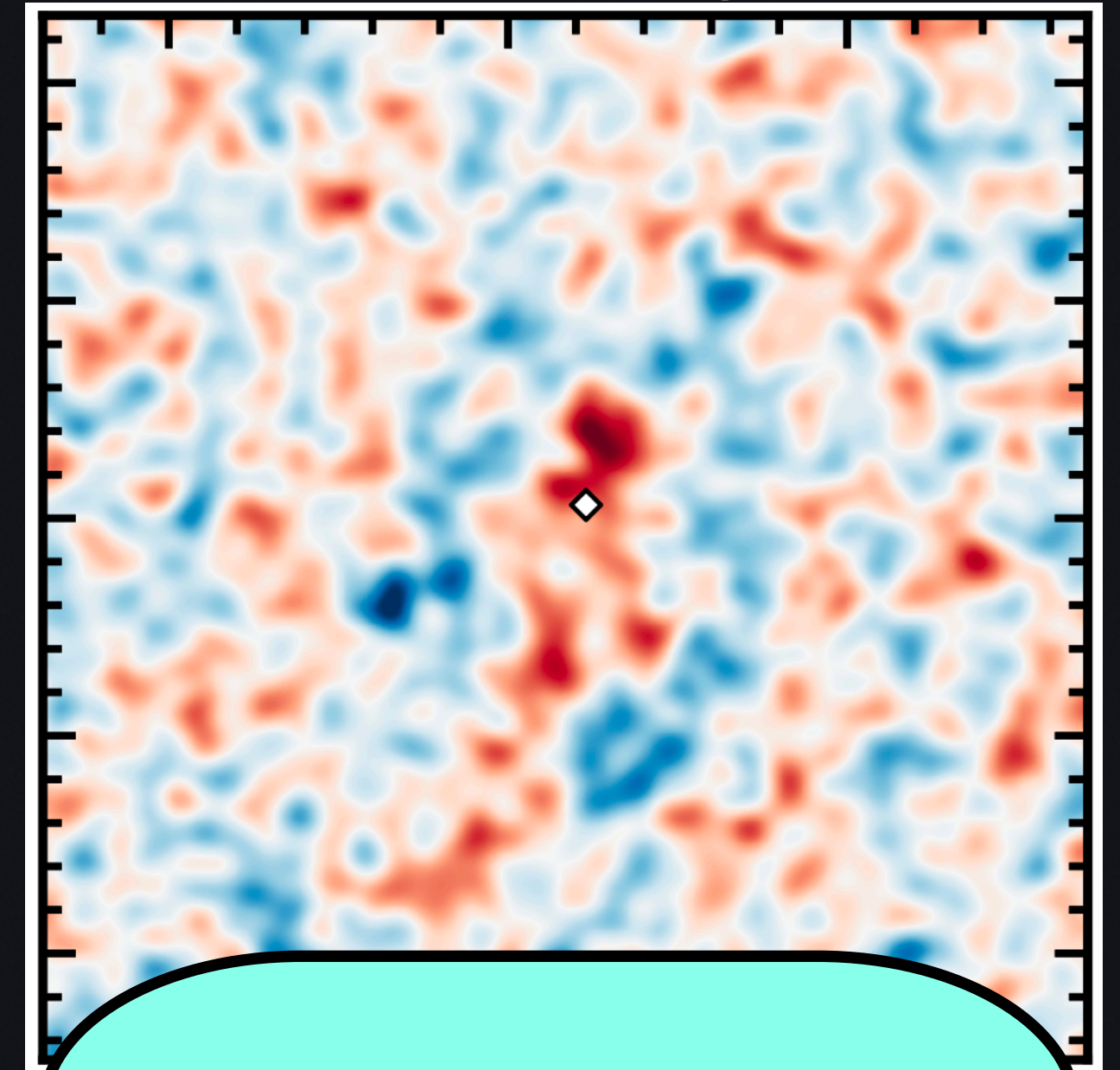


Sampled Visibilities

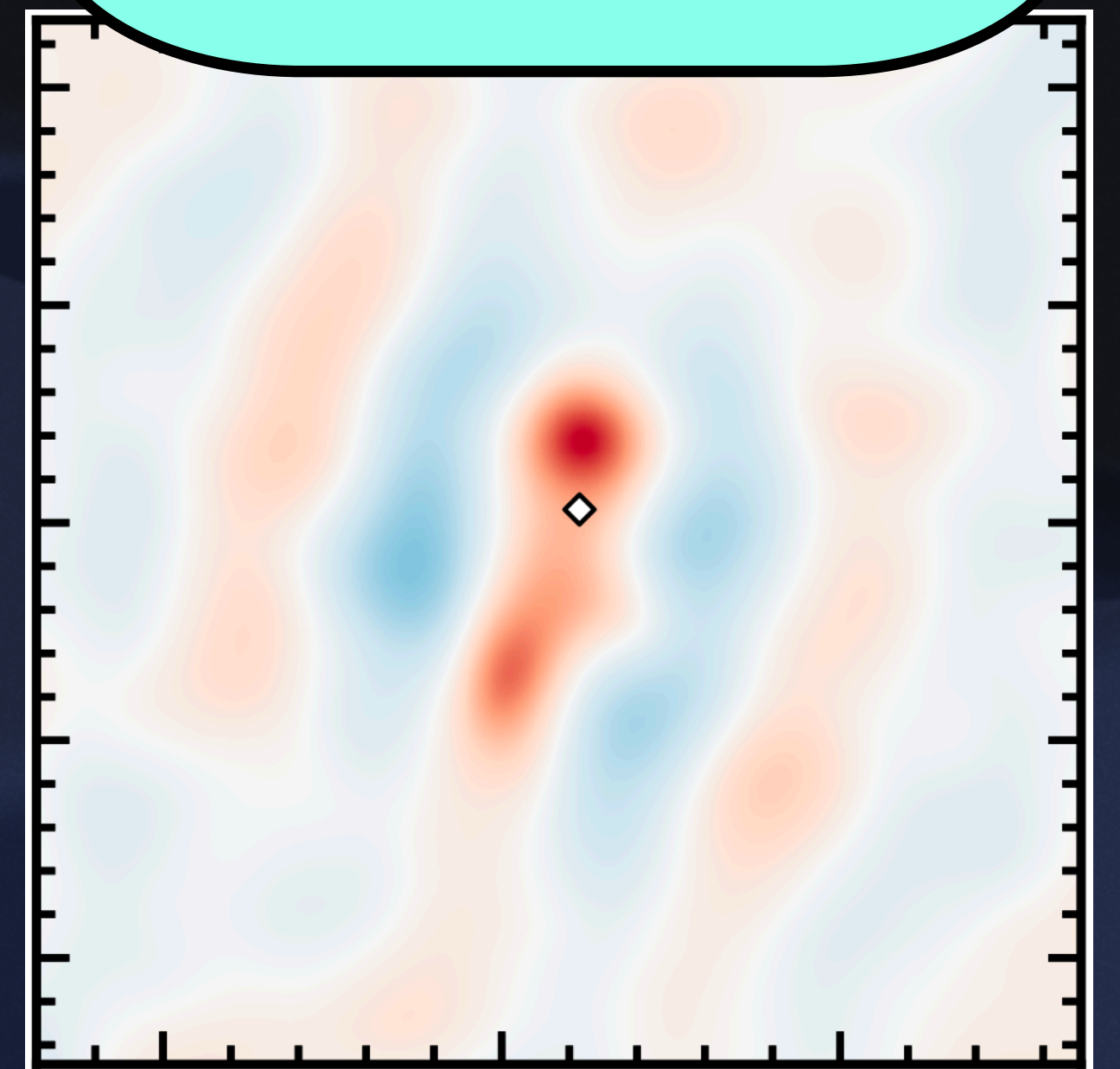
iFFT

iFFT

Dirty Image



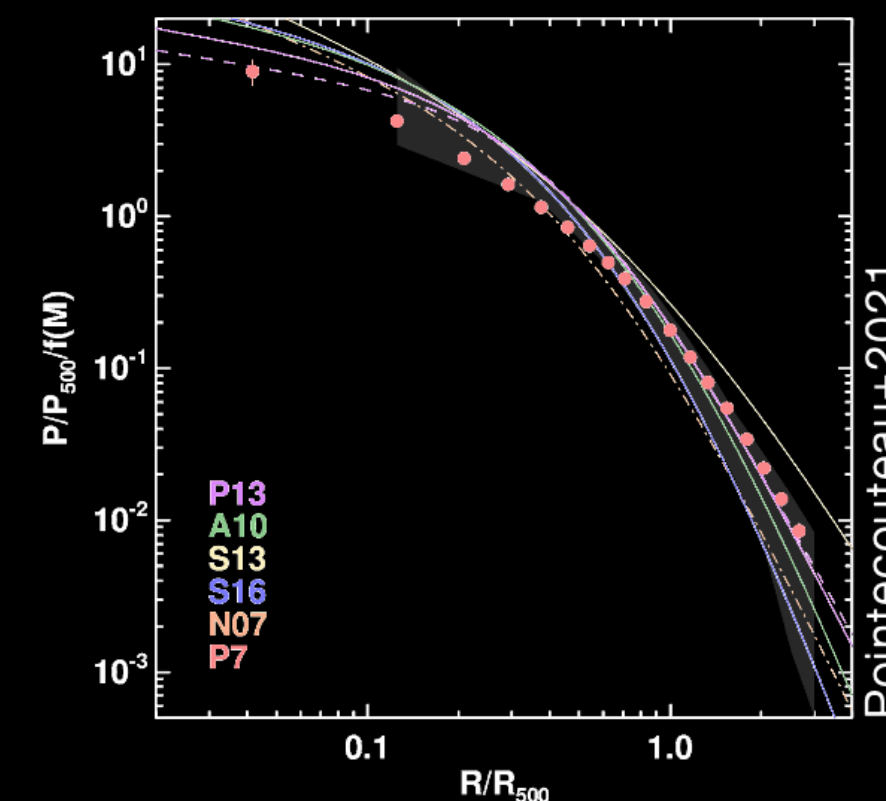
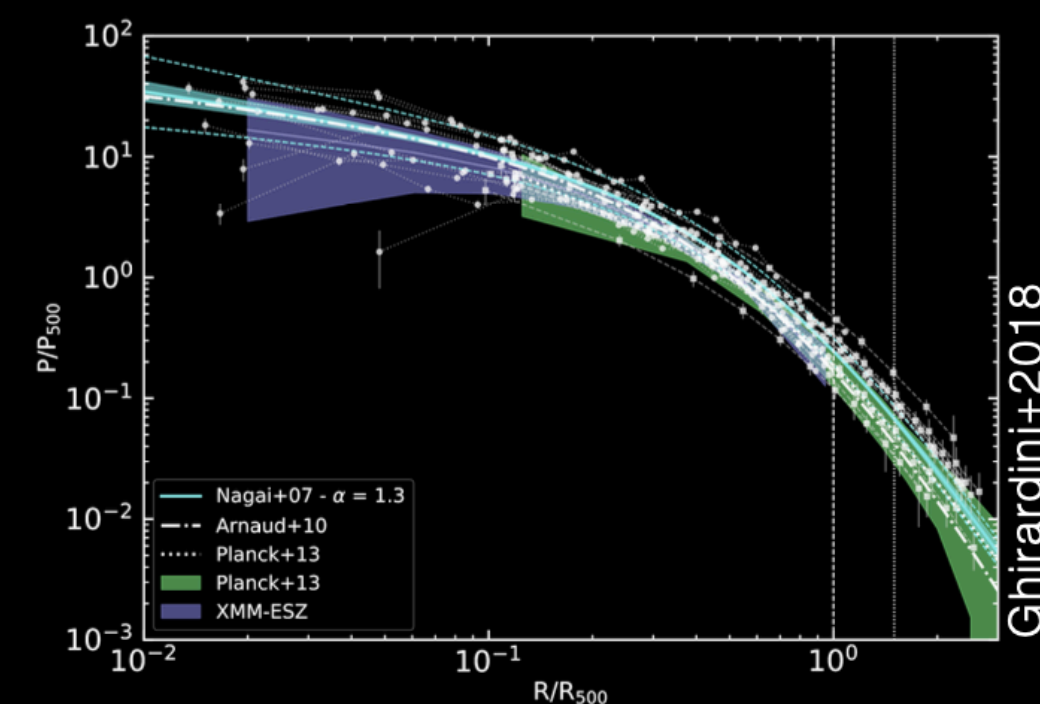
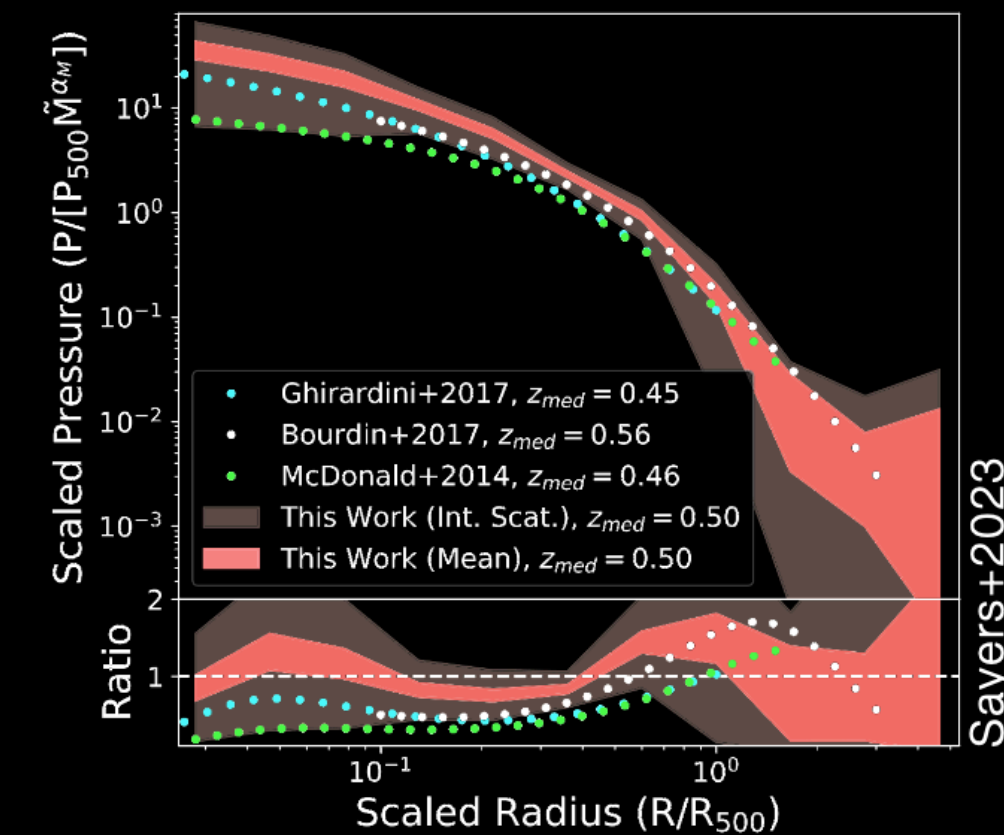
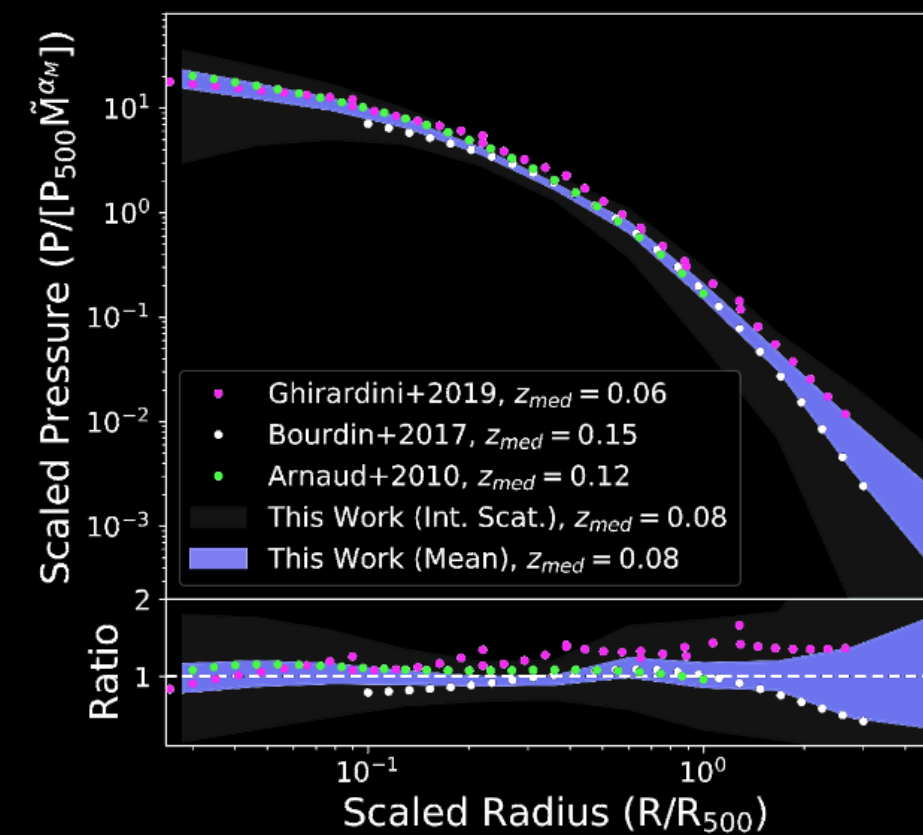
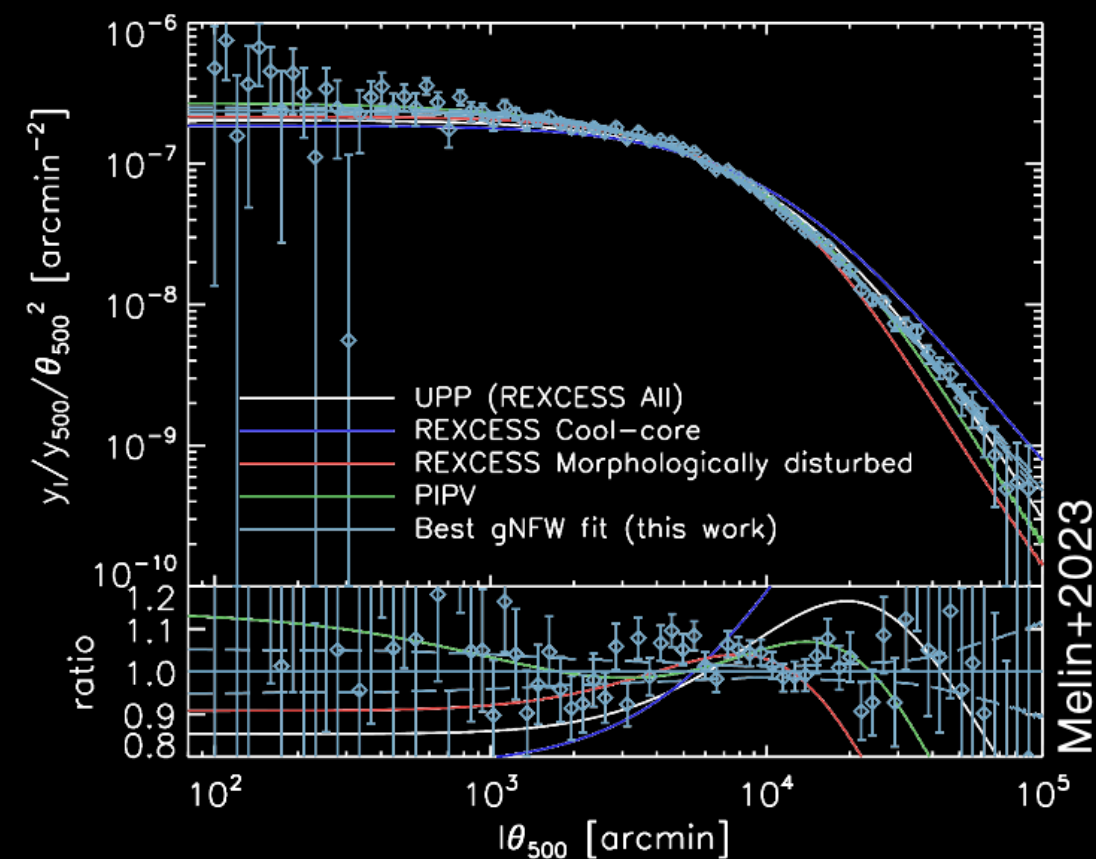
Likelihood(Data| θ)



Limitations of the approach

Many models, all one dimensional

Many clusters ... one pressure profile



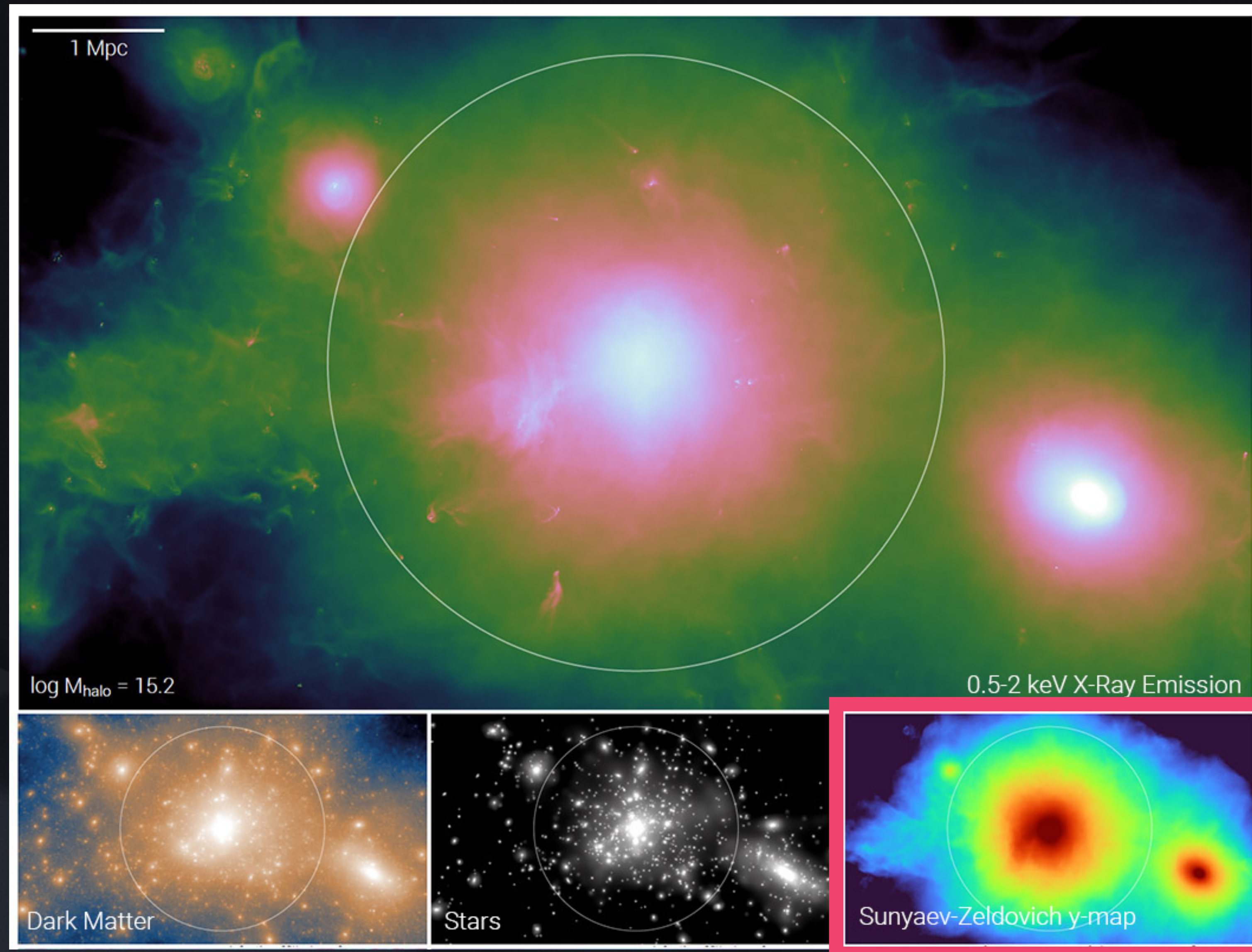
Courtesy of Luca Di Mascolo

“All clusters follow the A10,
no cluster is an A10”

Speaker in the TRACING COSMIC EVOLUTION WITH GALAXY CLUSTERS V conference

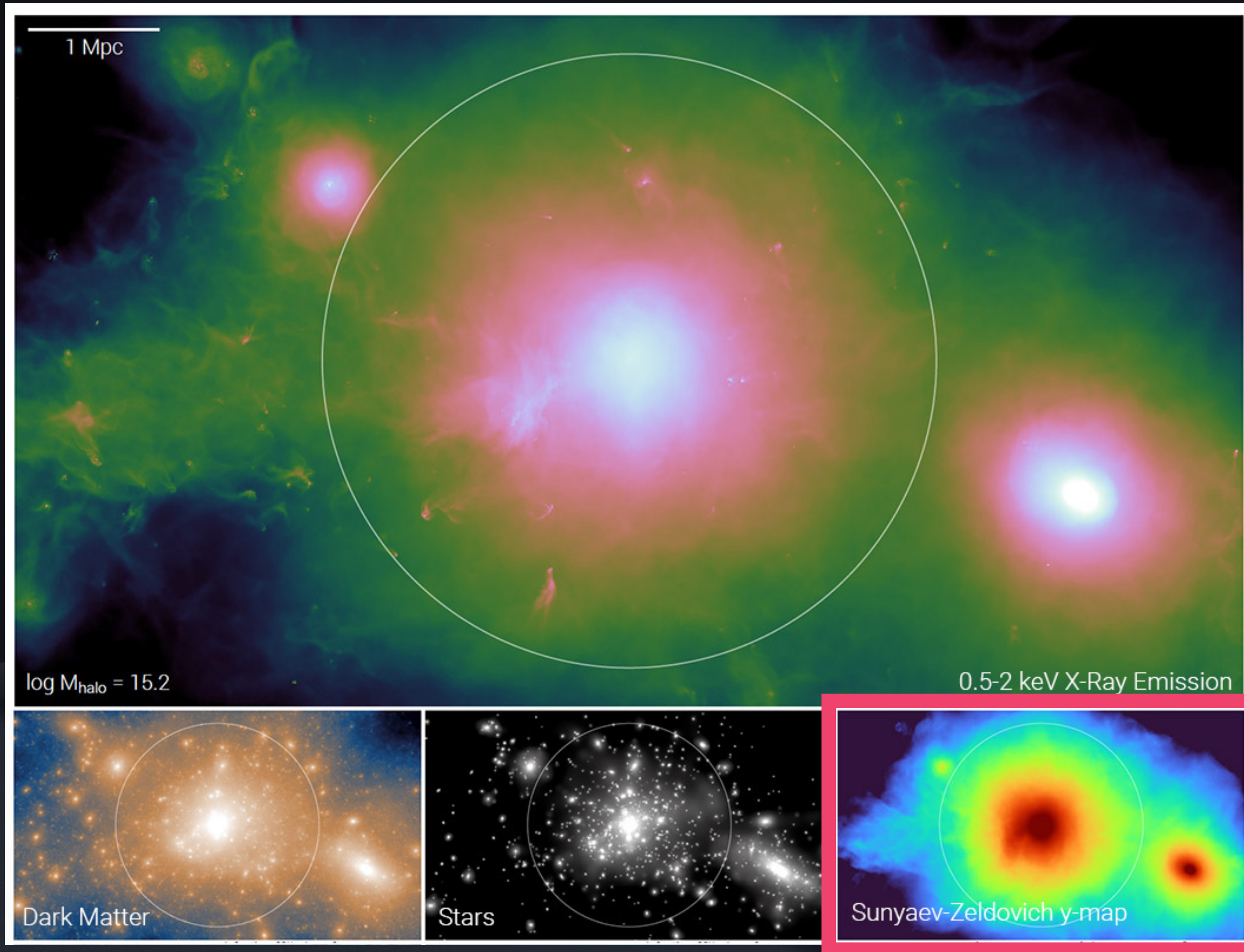
Rigid symmetry assumptions (spherical/elliptical); unable to capture complex ICM dynamics
(mergers, shocks, filaments, and substructures).

Cosmological Hydrodynamical Simulations



TNG-Cluster
Illustris TNG suite

Cosmological Hydrodynamical Simulations



Built a dataset of **3,026 Compton-y maps** coming from Magneticum, TNG-Cluster and The300 simulations suites.

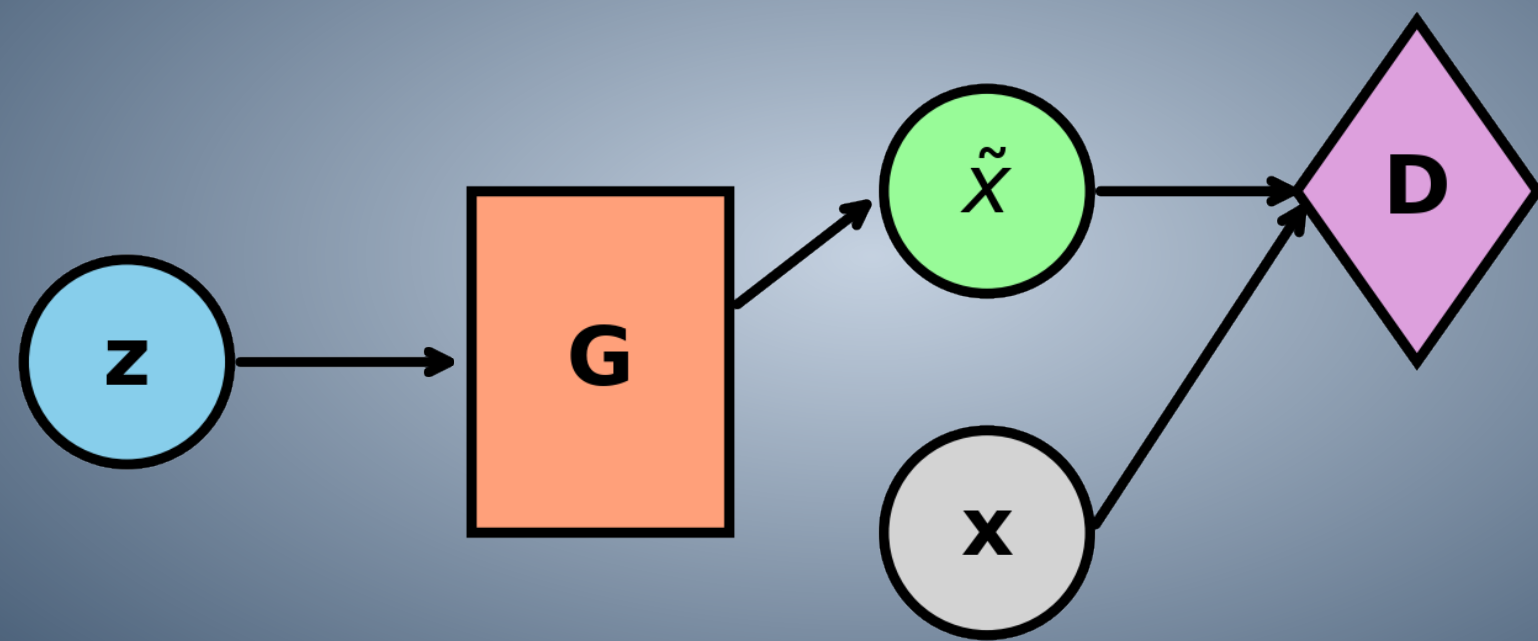
Fixed map size of $\pm 2 \times R_{200}$

TNG-Cluster
Illustris TNG suite

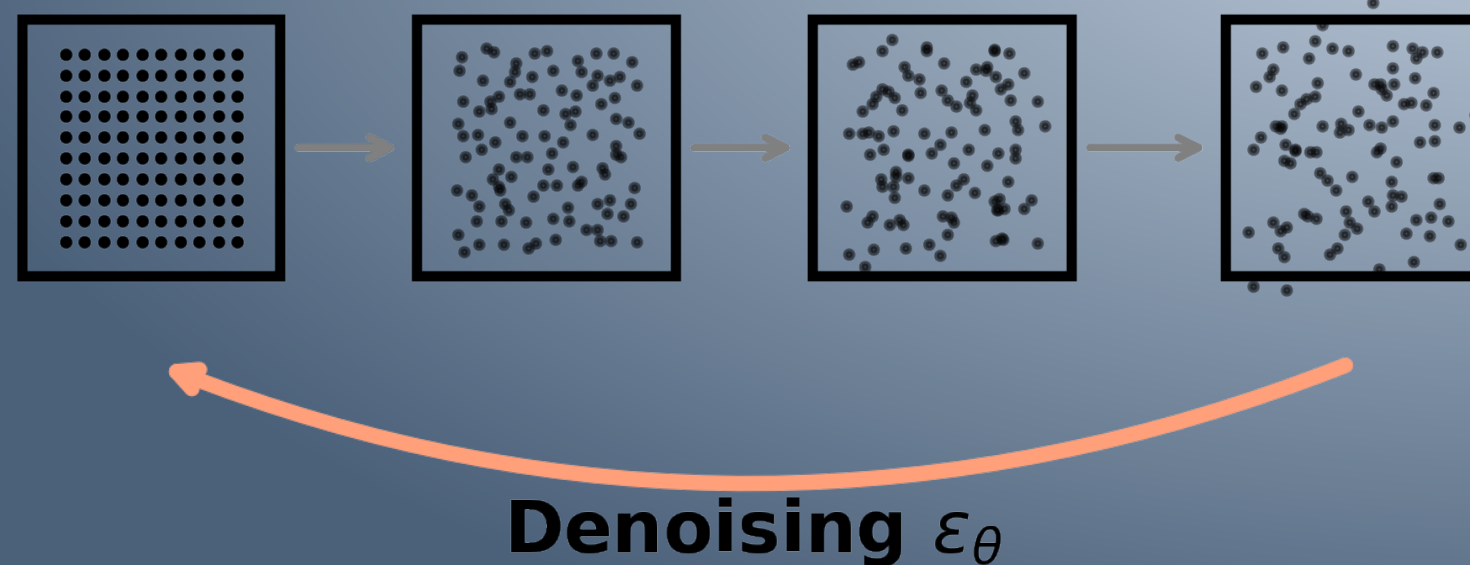
Generative Machine Learning Models

The zoo of Generative Models

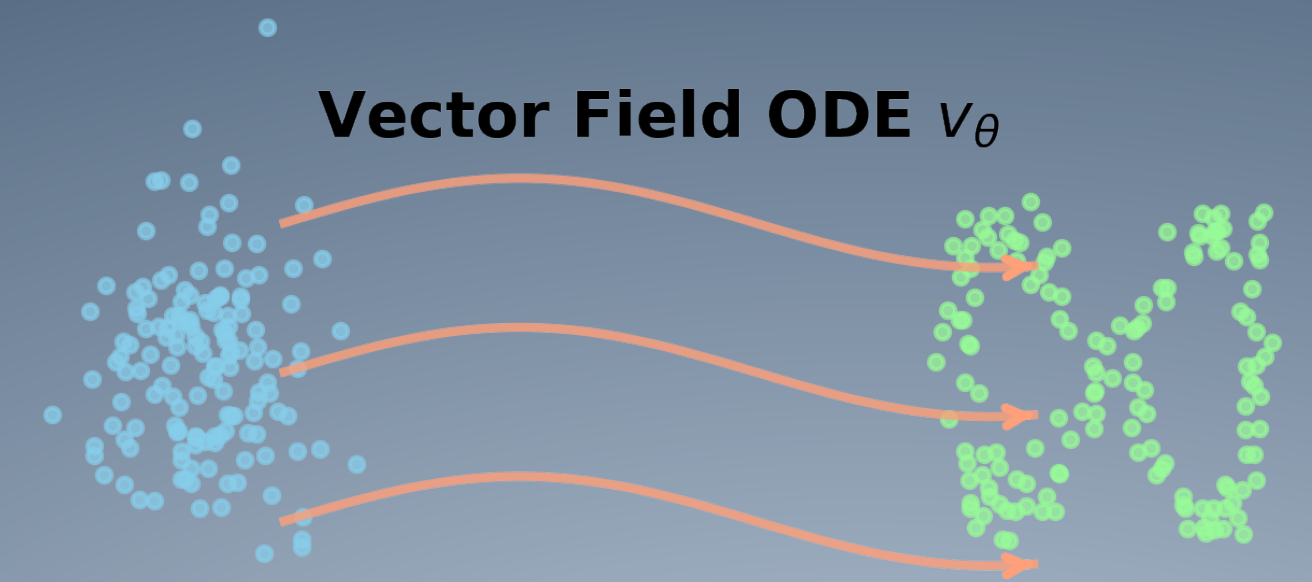
Generative Adversarial Networks **GANs**



Diffusion Models

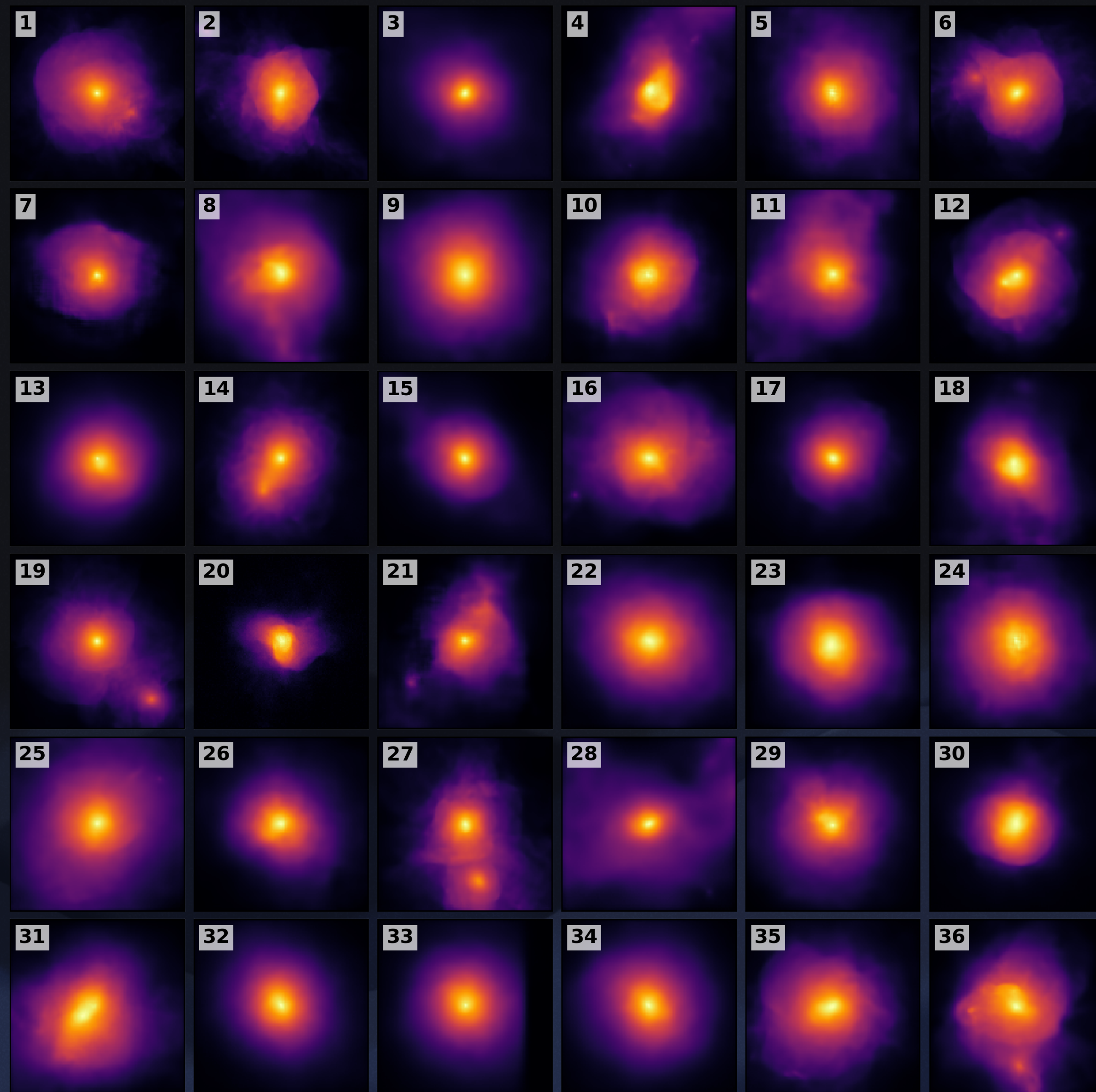


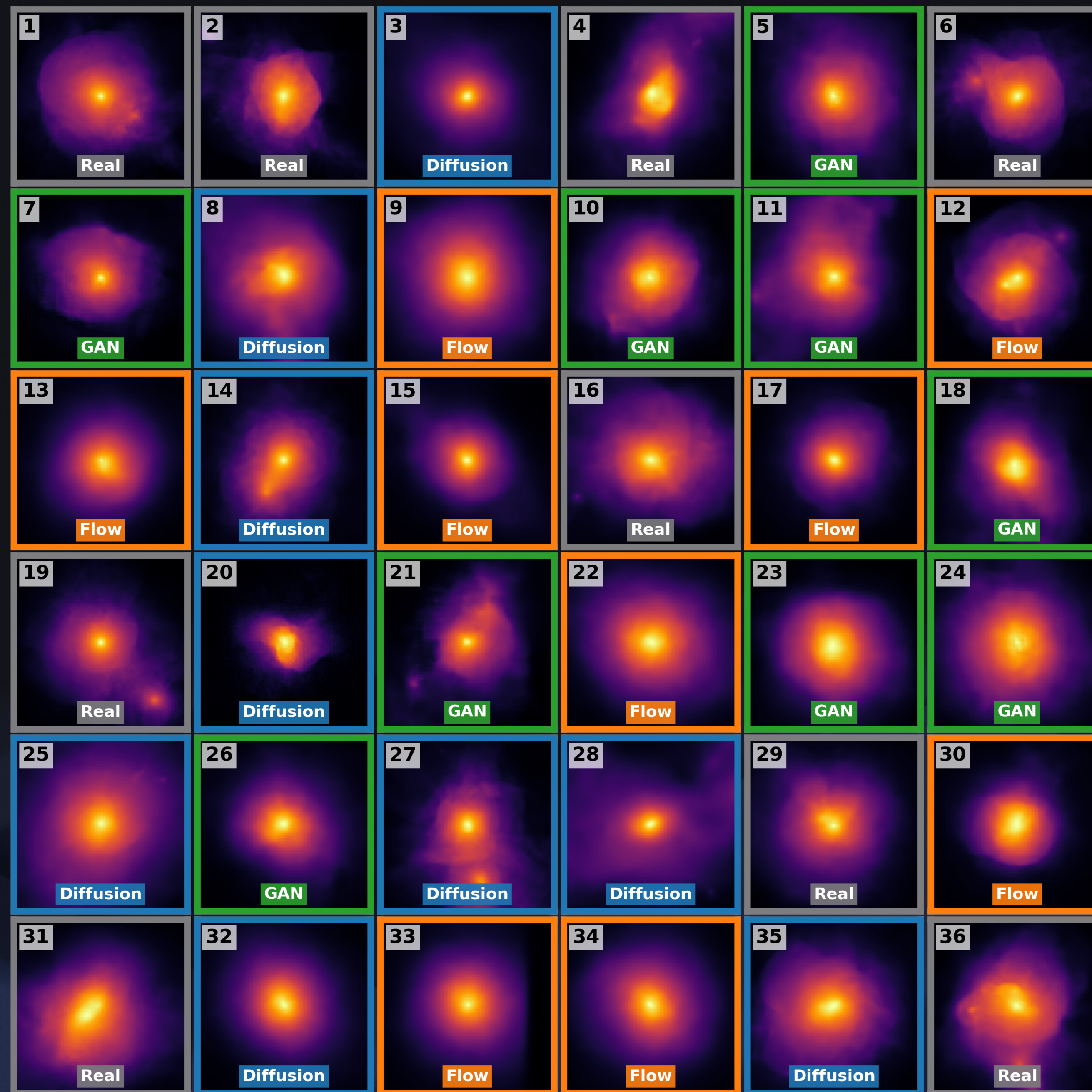
Flow Matching Models



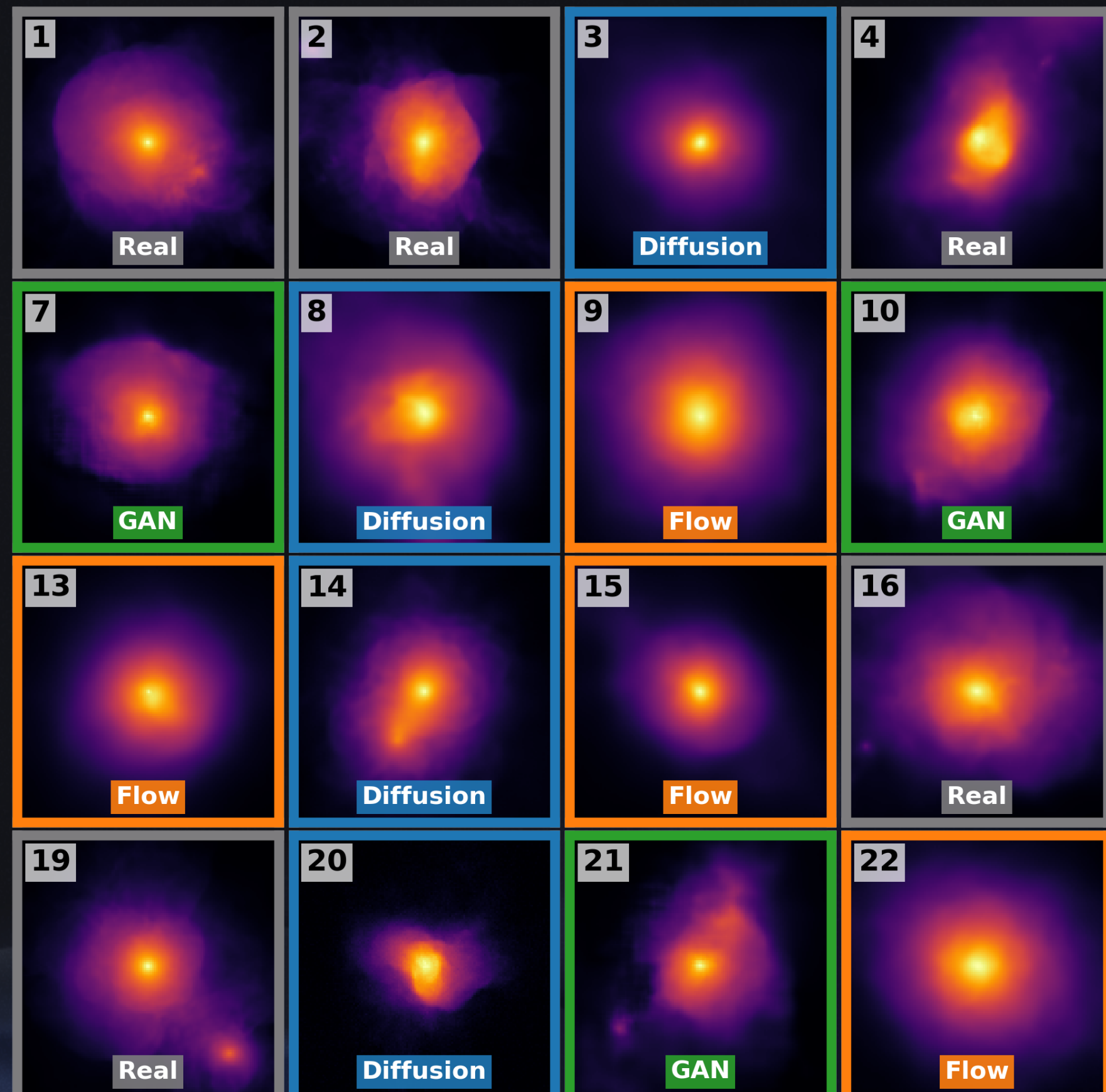
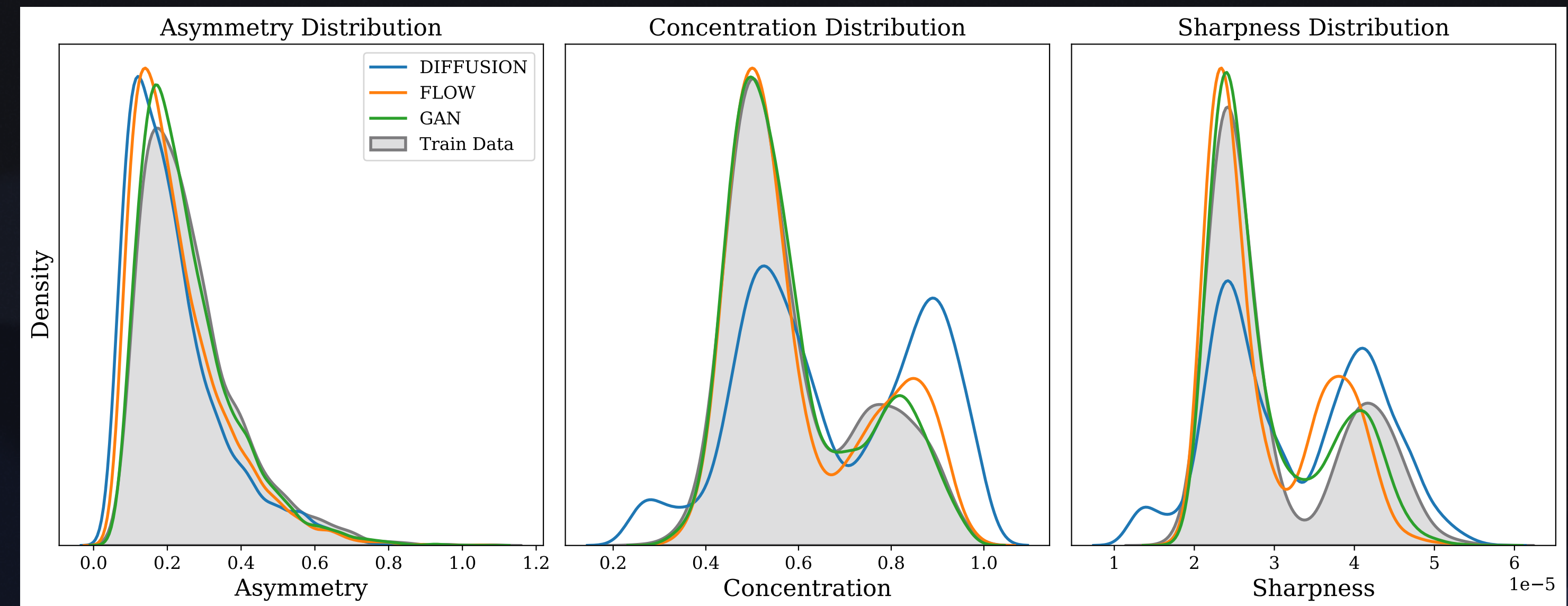
- Target resolution: 128 x 128 pixels;
- Conditional generation on cluster mass M_{200} ;

- Dynamic Range Transformation: $y(x; k, \epsilon) = k \log_{1/\epsilon} \left(\frac{x + \epsilon}{\epsilon} \right)$.



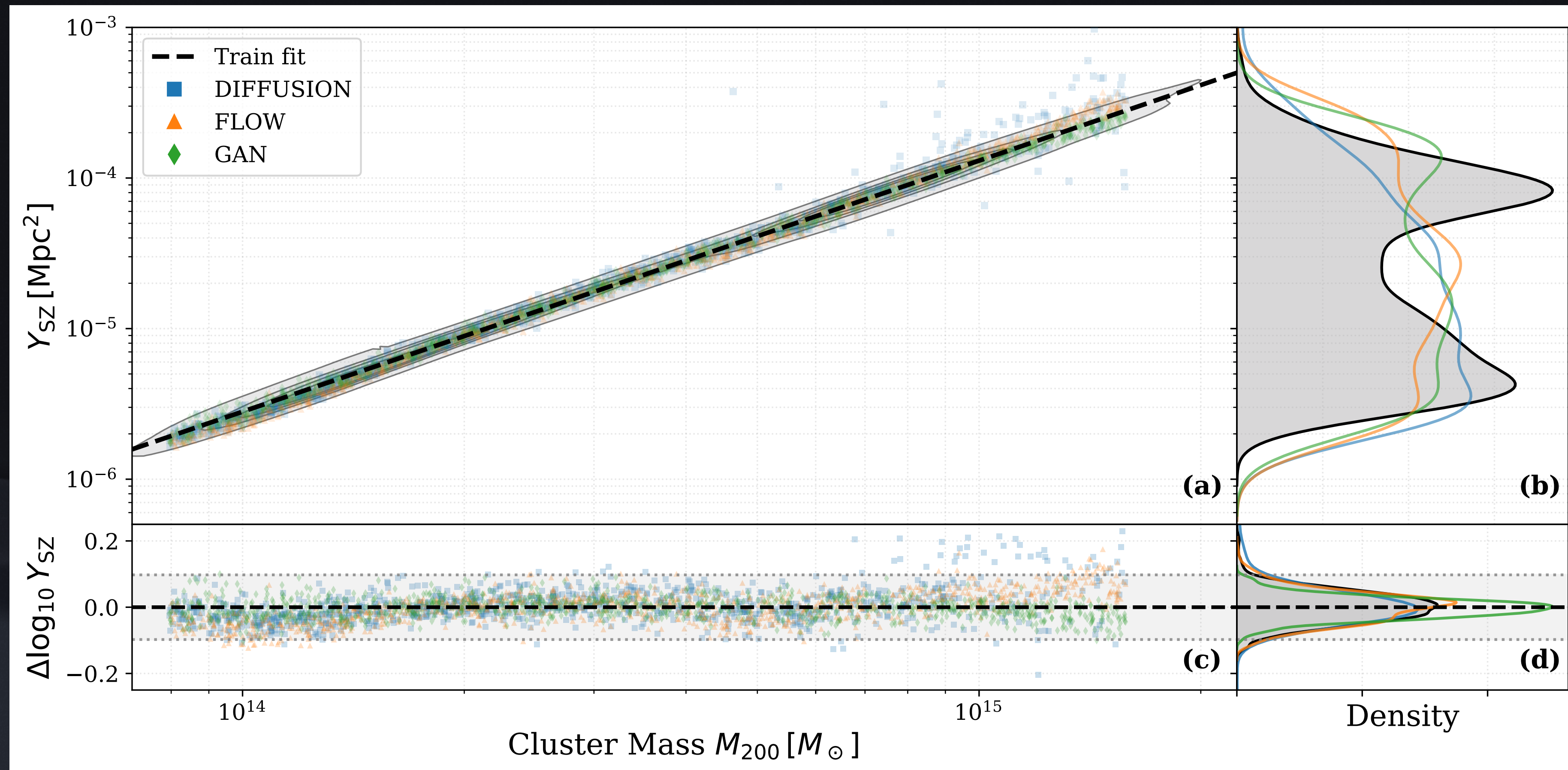


Perform visual inspection and checking population morphological properties.



Physical Conditioning

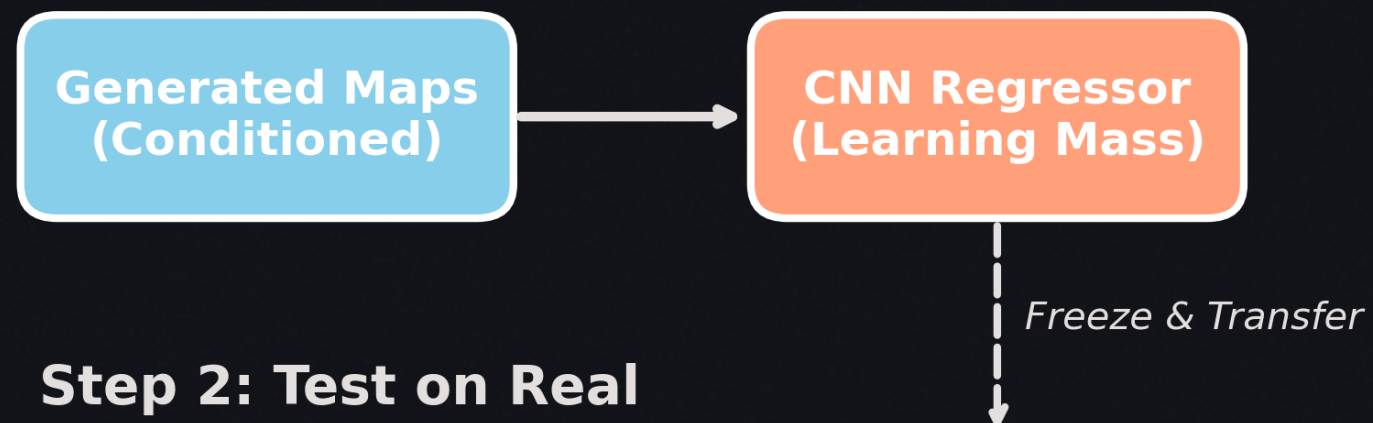
We condition the generation on Cluster Mass. Does the model learn the physics or just copy textures?
Integrated Y_{SZ} vs. M_{200} relation.



Physical Conditioning

We condition the generation on Cluster Mass. Does the model learn the physics or just copy textures?
Train on Synthetic Test on Real (TSTR)

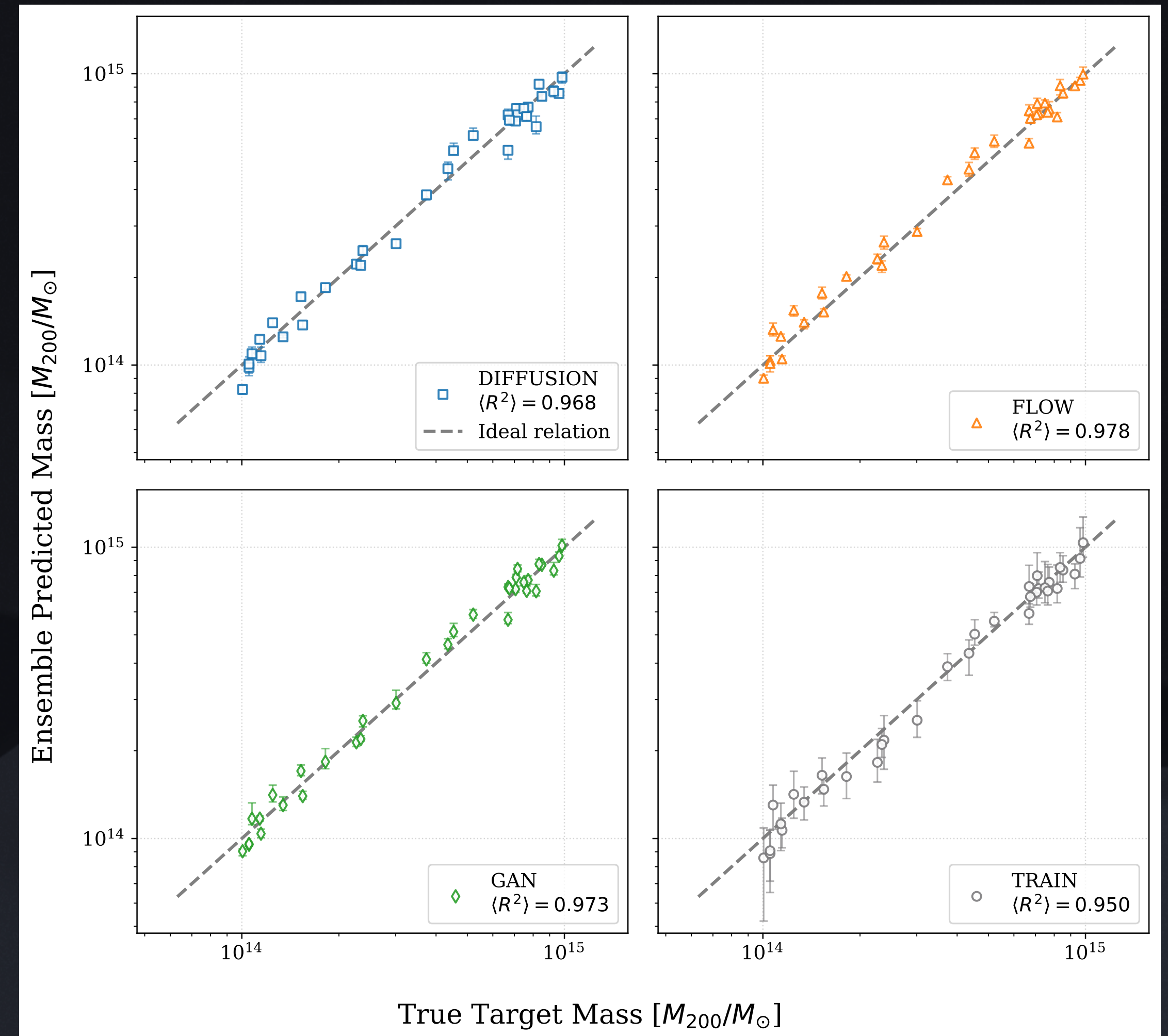
Step 1: Train on Synthetic



Step 2: Test on Real



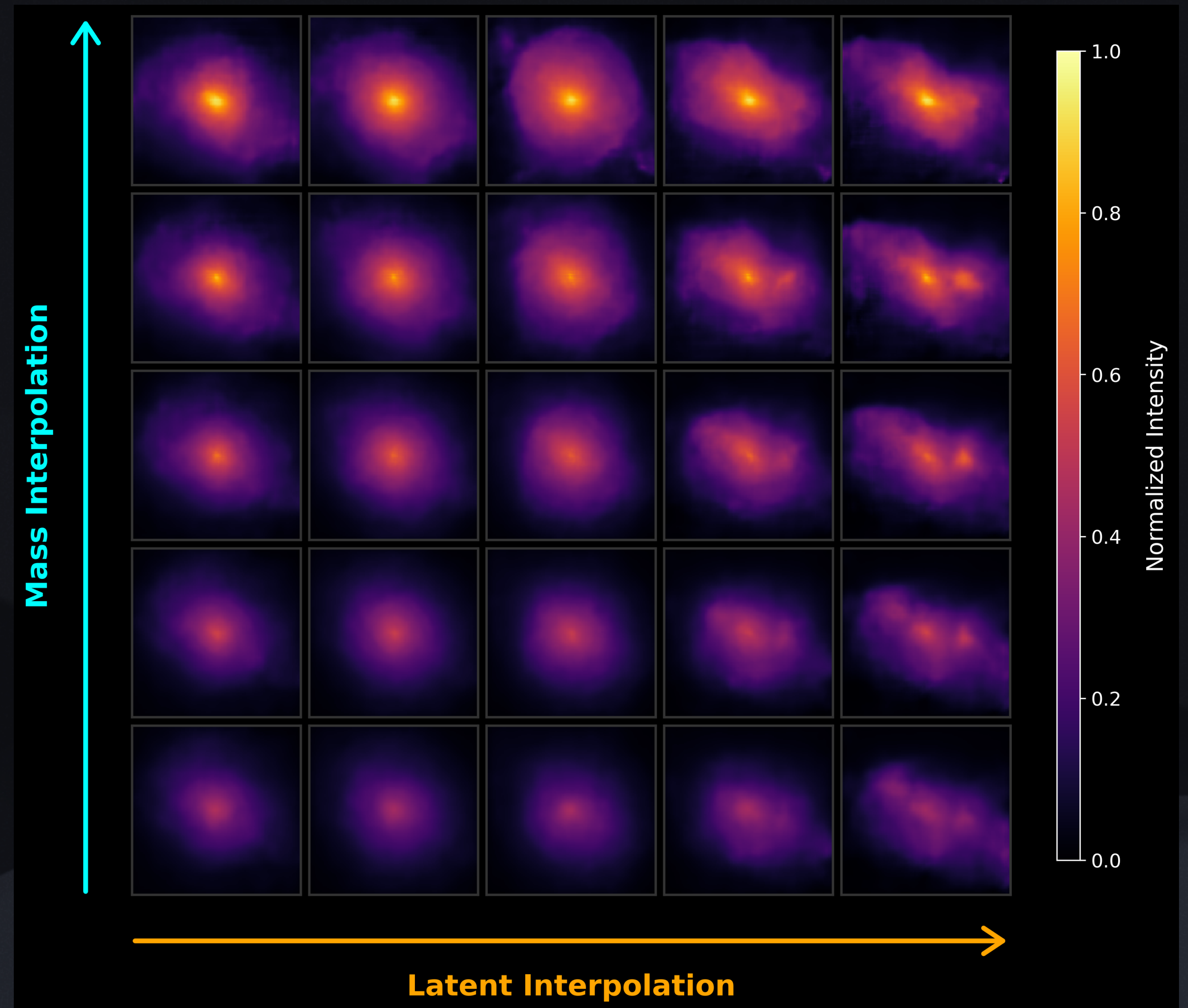
Generative models outperform the raw training set by acting as smooth manifold interpolators, reducing sensitivity to outliers.



Generalization Capabilities

Latent space Interpolation

- **Beyond Memorization:** smooth transition between generated samples prove the model has learned the underlying physical manifold.
- **Why it matters for Inference:** a continuous, well-behaved latent space is strictly required to efficiently sample the posterior distribution during Bayesian inference.



Bayesian Visibility Modeling via Hydrodynamical Priors

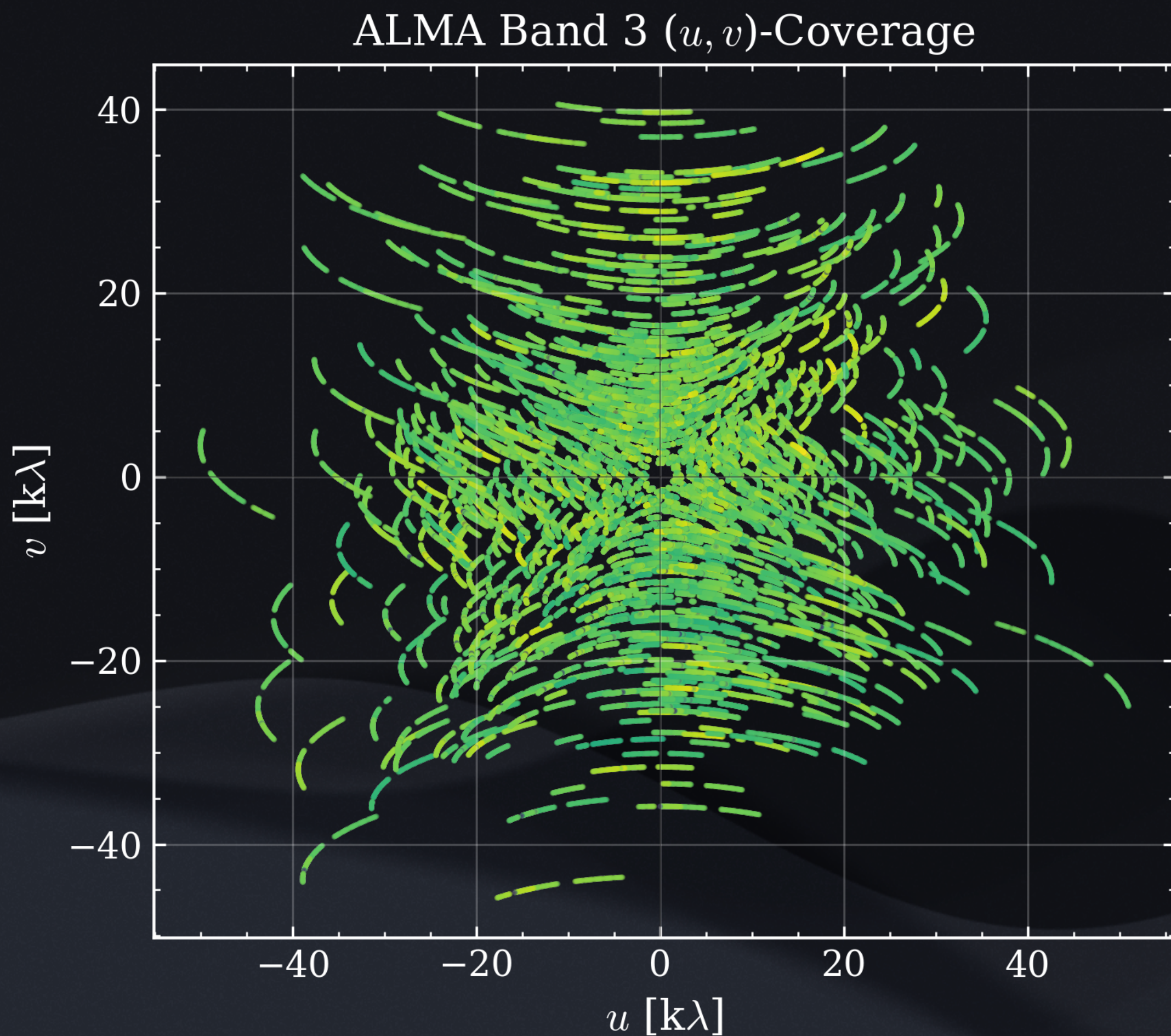
Bayesian Forward Modeling

Leveraging the exact Gaussian Likelihood in visibility domain

- All tested generative architectures **successfully reproduce population statistics and mass-scaling relations**;
- Score- & Flow-Based Models yield higher image fidelity and comprehensive manifold coverage, making them naturally suited for Simulation-Based Inference (SBI) applications;
- Since the interferometric (u, v) likelihood is exact and analytic, **the single-step forward pass of a GAN generator enables computationally tractable MCMC/HMC sampling**.

Inferring the Morphology of a Cluster

Application to a mock target with realistic uv coverage and noise levels

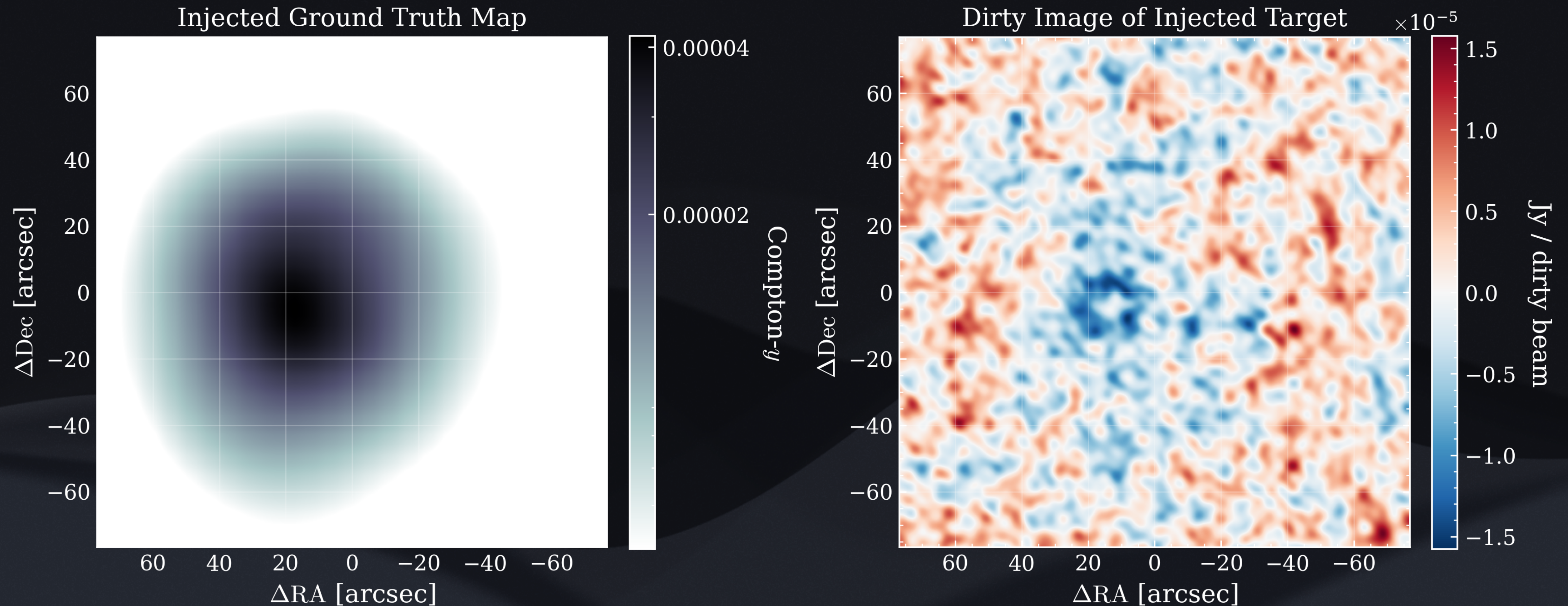


1. Sample latent $\vec{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{1})$ and conditioning $\mathbf{M}_{200}$.
2. Invert dynamic range to recover physical Compton- y values, rescale map extent to angular size using redshift and apply primary beam attenuation.
3. Compute 2D Fourier Transform and interpolate at the exact observed baseline coordinates.
4. Compute the likelihood for real and imaginary part

$$\ln p(V_{\text{obs}} | \mathbf{z}, \mathbf{M}_{200}) = -\frac{1}{2} \sum_k \frac{|V_{\text{obs}}(u_k, v_k) - \mathcal{V}_{\text{model}}(u_k, v_k)|^2}{\sigma_k^2}$$

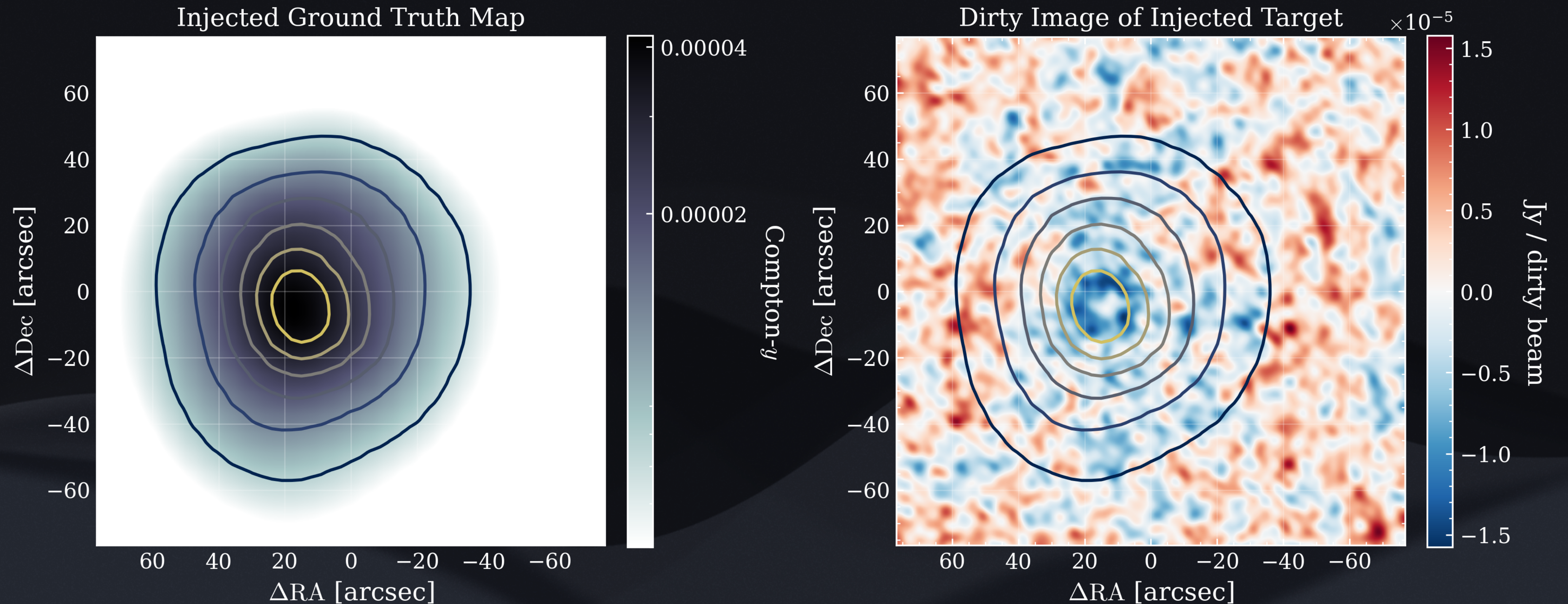
Inferring the Morphology of a Cluster

Injected target



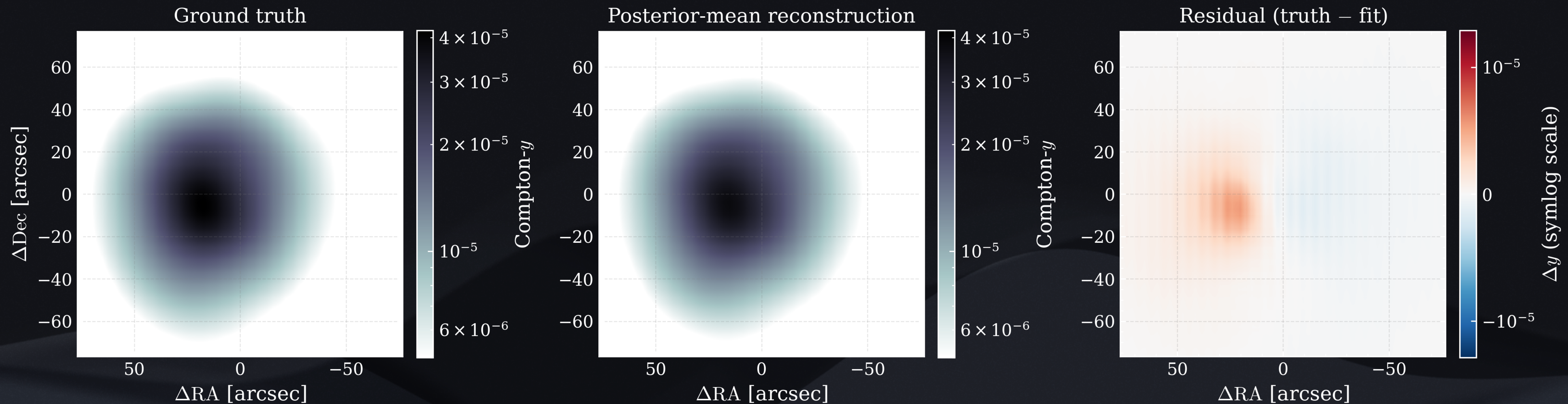
Inferring the Morphology of a Cluster

Ground Truth with overlaid posterior median contours



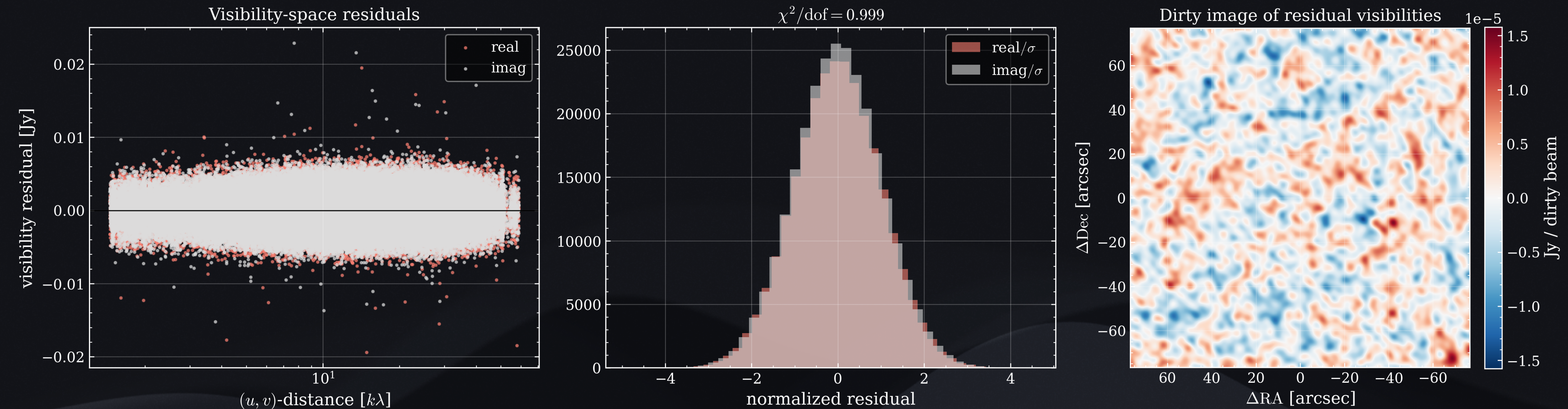
Inferring the Morphology of a Cluster

Residuals Image Space



Inferring the Morphology of a Cluster

Residuals Visibility space



- Visibility space residuals centered on zero with no systematic structure;
- No leftover structure in the dirty image of the residuals.

Conclusions

Recap and Future steps

- Trained, validated, and benchmarked **multiple generative architectures** (PG-WGAN, Diffusion, Flow Matching) **conditioned on cluster mass** (M_{200}). **Confirmed physical fidelity** through morphological metrics, Y_{SZ} vs. M_{200} scaling relation and TSTR validation.
 - **Successfully embedded the generative prior into a forward-modeling pipeline** evaluating the exact (u,v)-plane Gaussian likelihood and demonstrated **robust posterior exploration and parameter recovery** using Nested Sampling.
-
- Next Steps & Real Data Deployment:
 - Application to Real Observations: expanding across multiple spectral windows and incorporating simultaneous point-source modeling to deploy the pipeline on archival interferometric cluster datasets.