# Weak Lensing, the tSZ Effect, and Deep Learning

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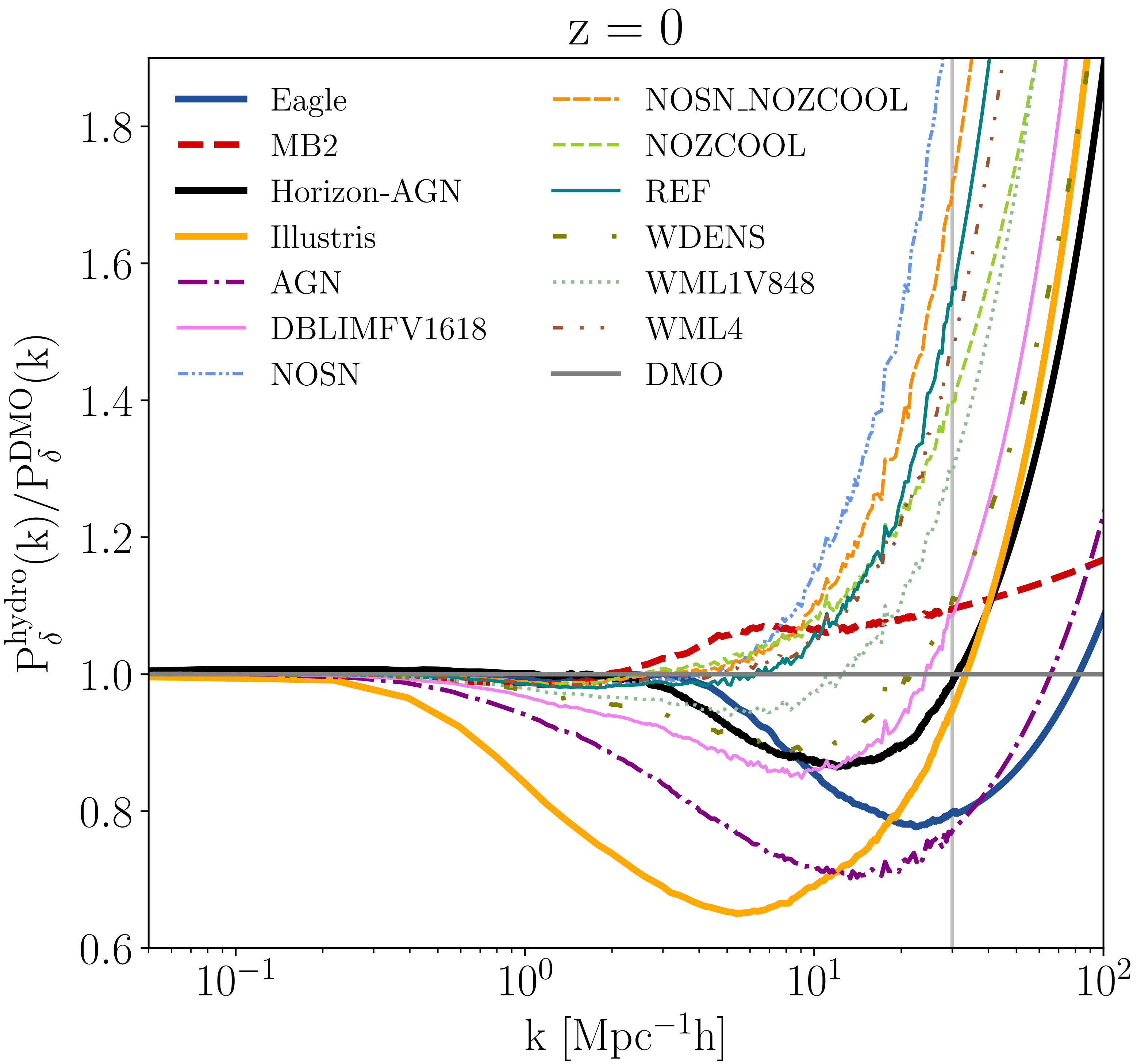
# Weak lensing

**Weak lensing probes the total matter distribution**

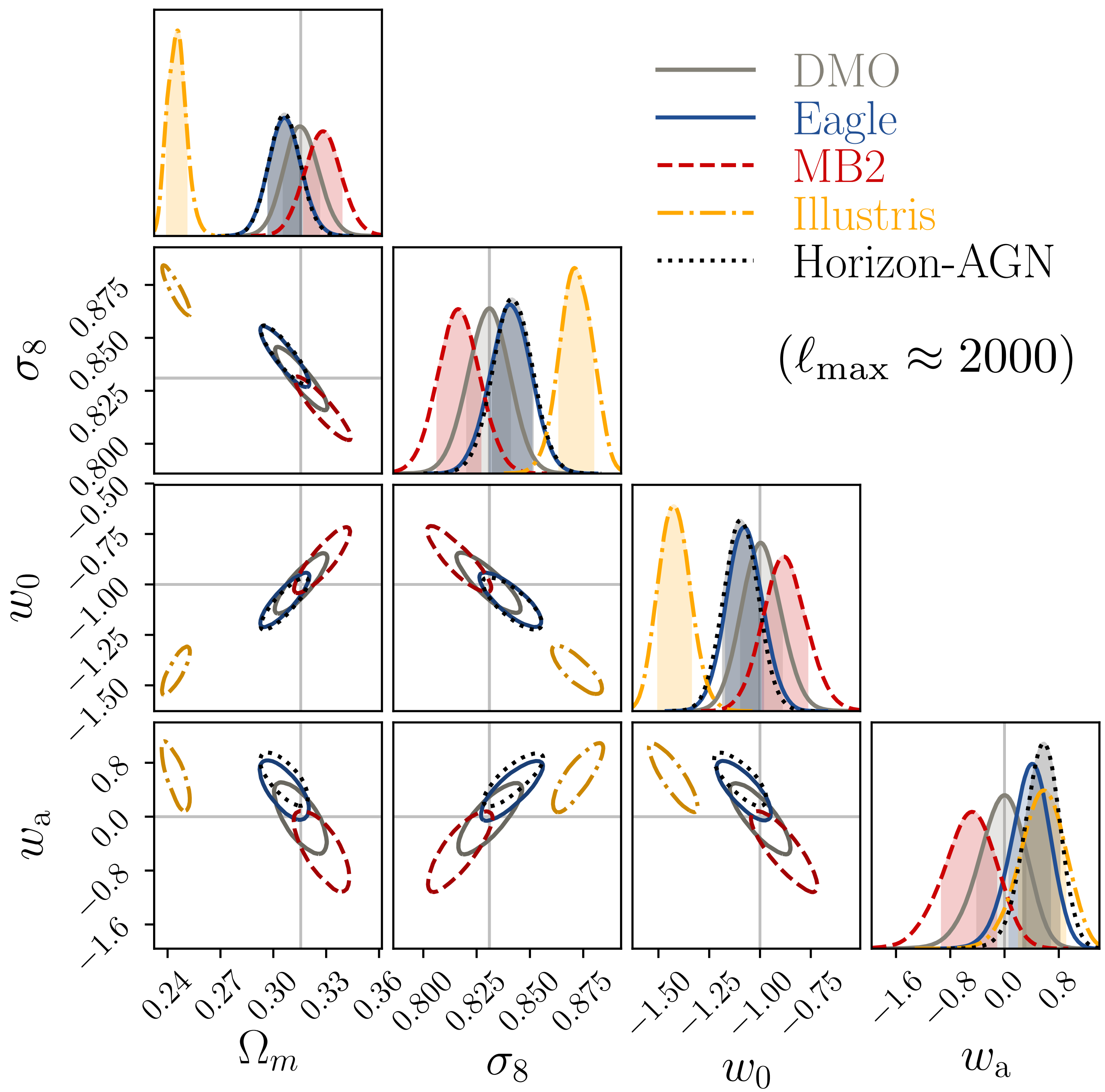
- ~80% of matter is dark matter
- ~20% is baryons
- If we want to constrain ΛCDM, we need to understand the 20% of baryons
- Baryons are complicated!

# Effect of baryons on the matter power spectrum




Huang+ 2018

# Effect on cosmological parameters



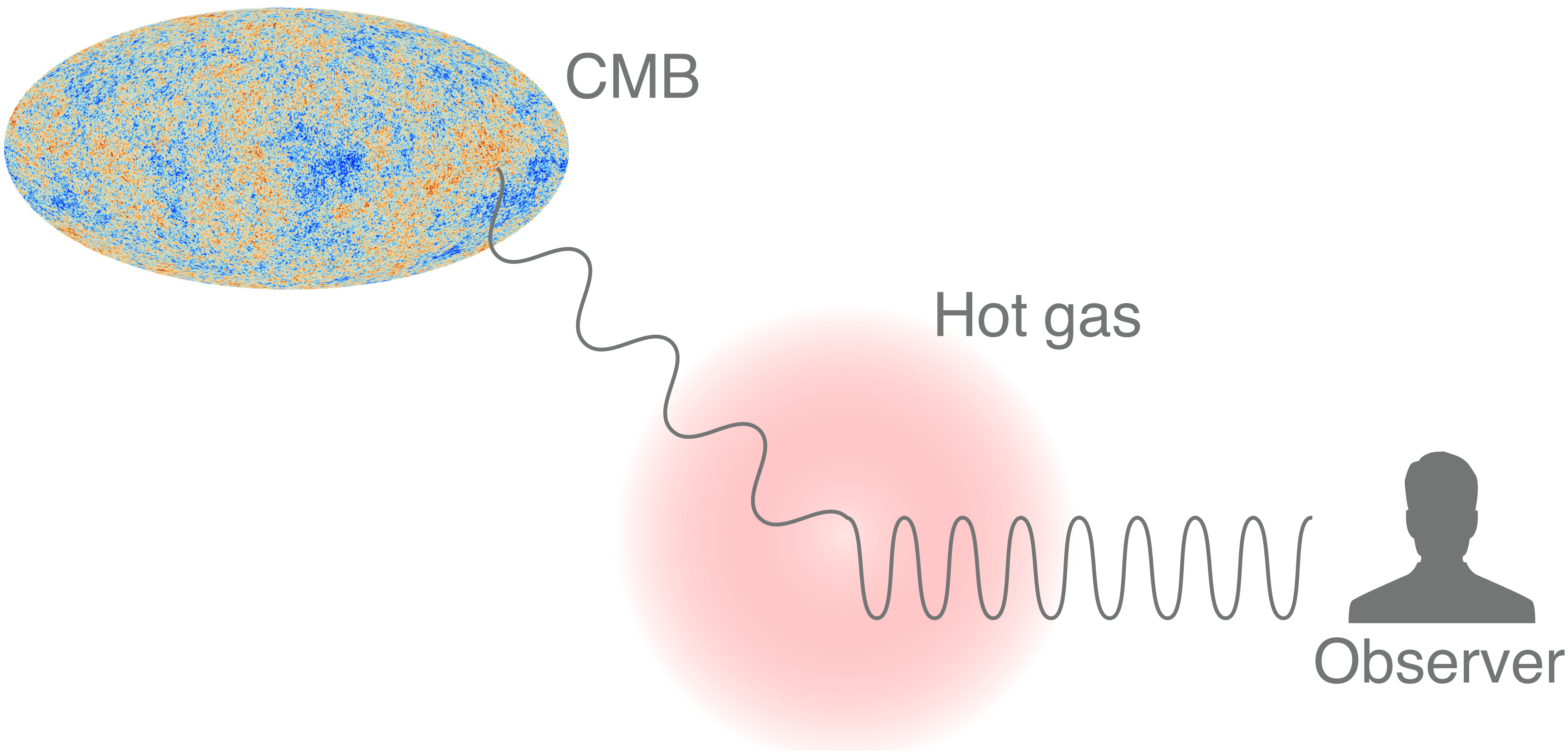

Huang+ 2018

# Effect on cosmological parameters

## Account for baryons

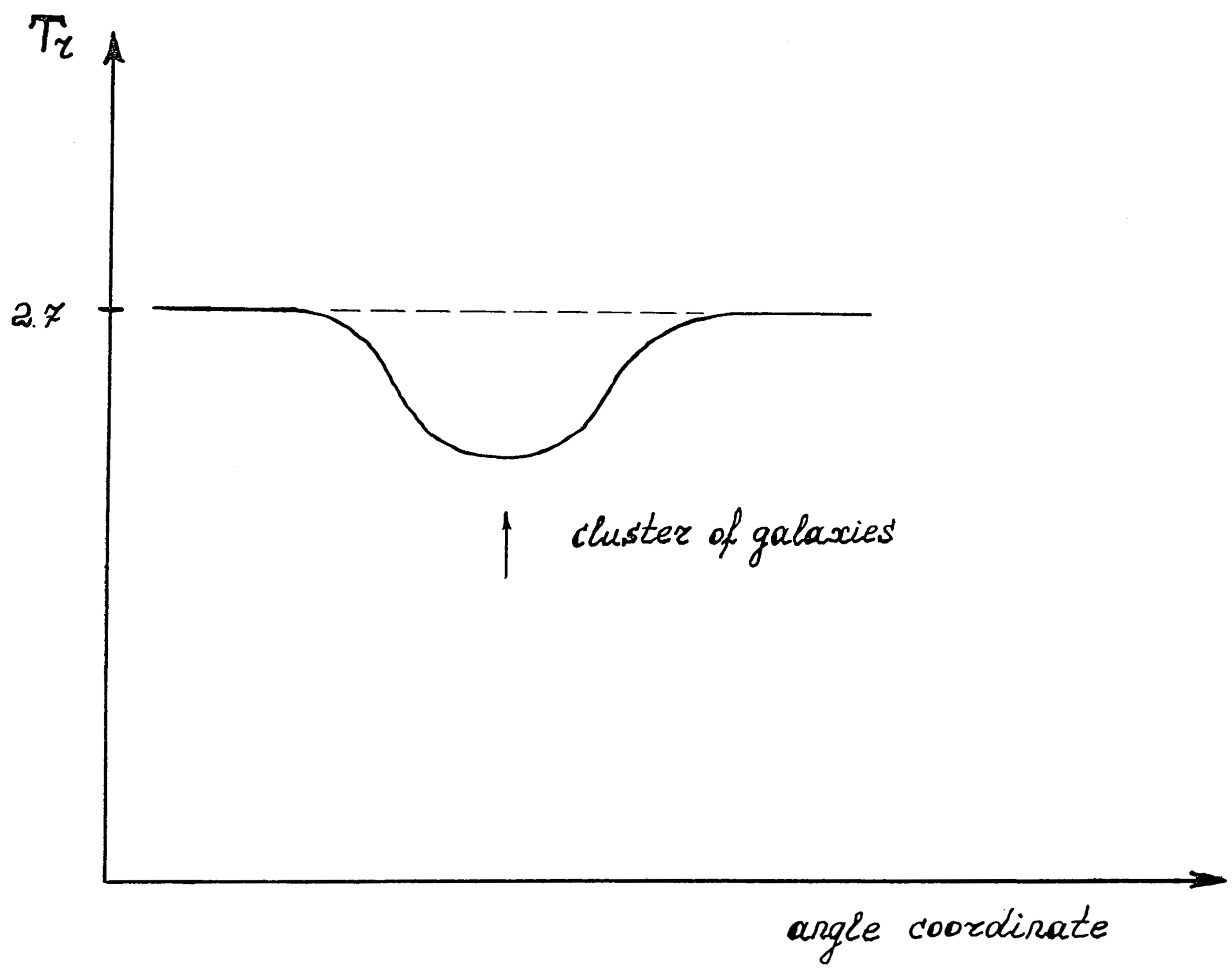
- Throw out data
- Model & marginalise
  - Need priors
    - Need observations of distribution of baryons

# Thermal Sunyaev-Zel'dovich Effect



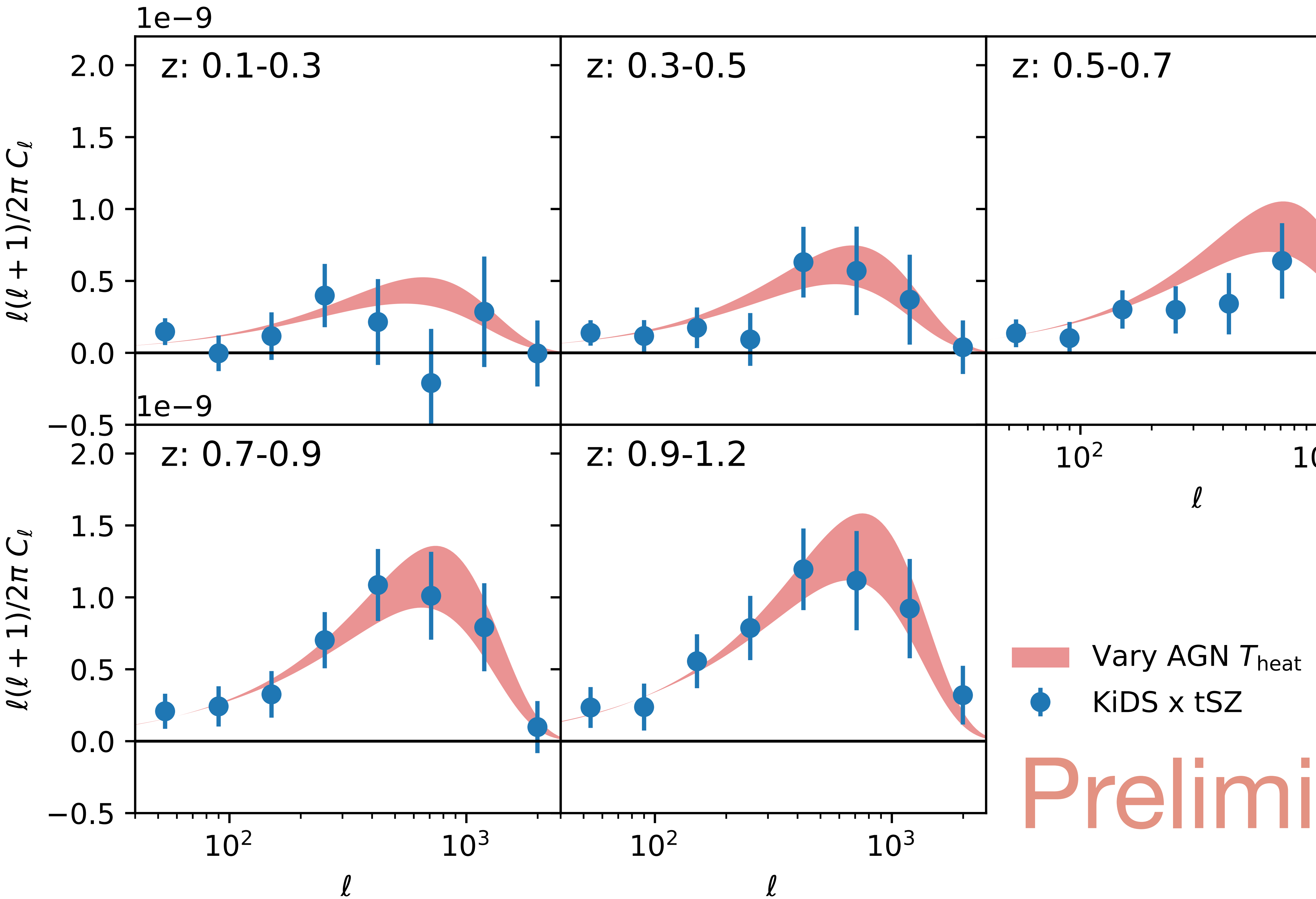
# tSZ effect

## "Shadow" on the CMB



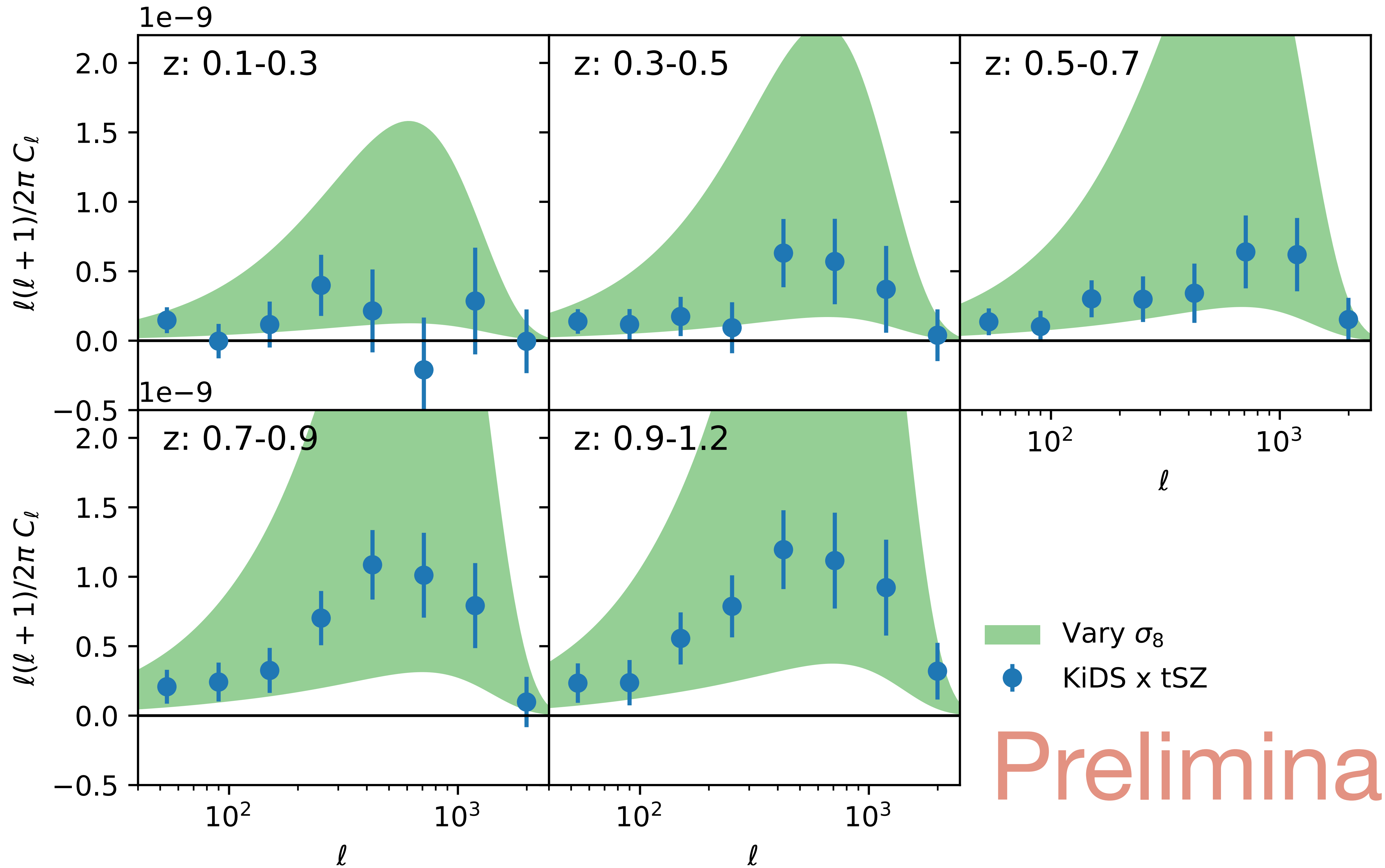

Sunyaev, Zel'dovich 1972

# Cross-correlate tSZ with lensing (Planck x KiDS-1000)




Preliminary!

# Cosmology dependence?




Preliminary!

# Effect on cosmological parameters

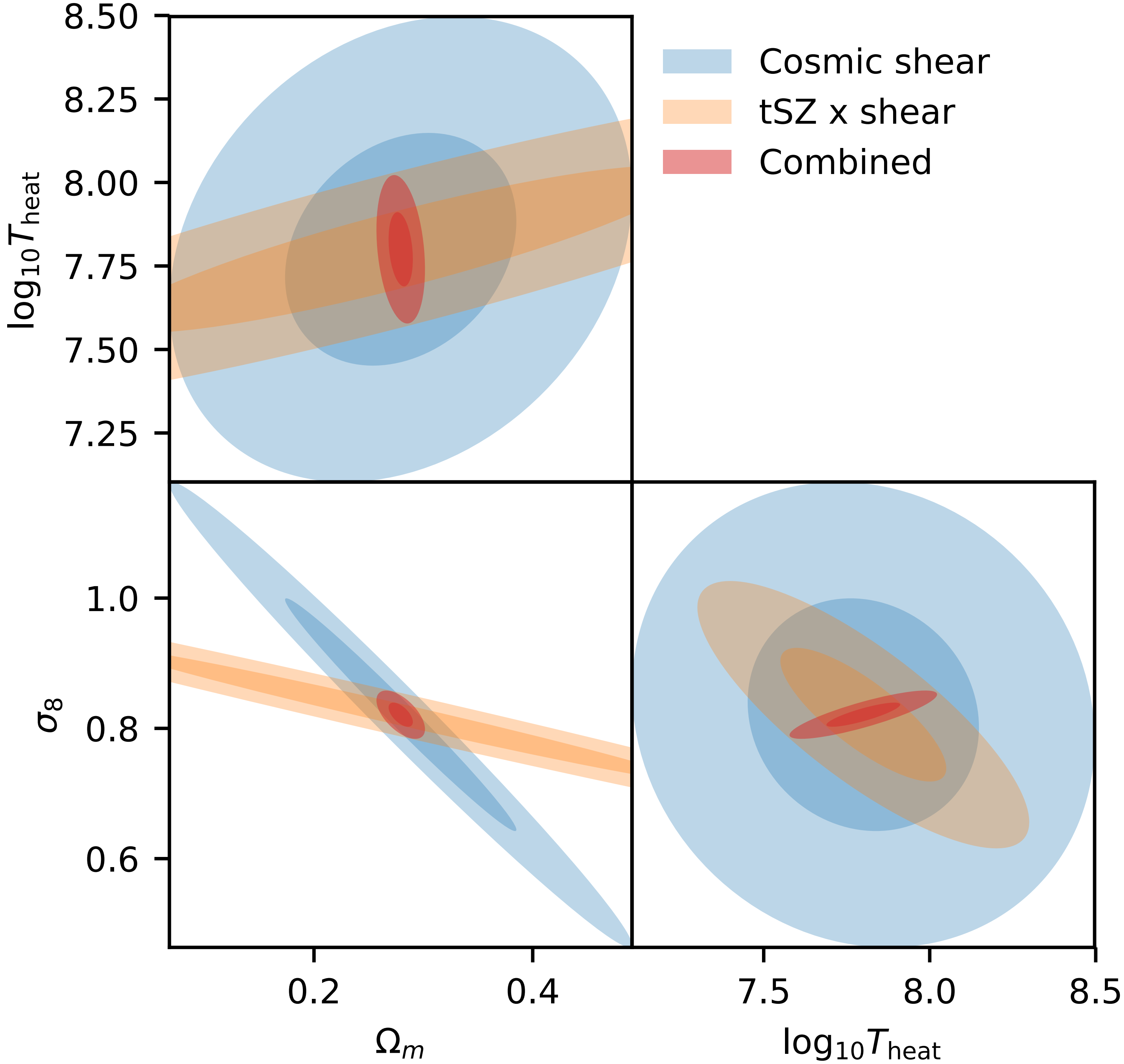
## Account for baryons

- Throw out data
- Model & marginalise
  - Need priors
    - Need observations of distribution of baryons

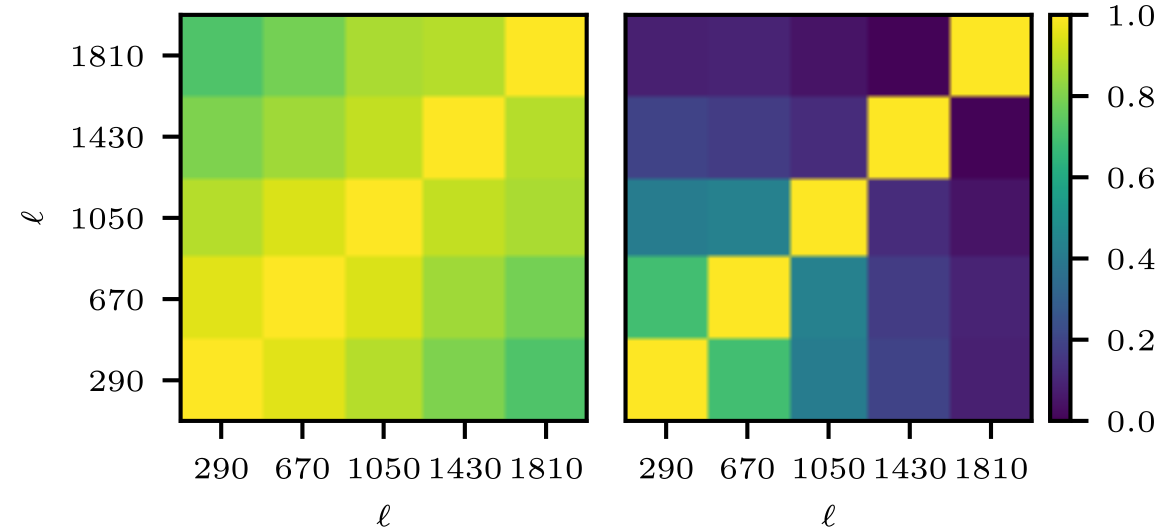
## Use baryons for cosmology

- Joint analysis of lensing and tSZ

# Joint analysis of lensing, tSZ



# Covariances




## Analytic

- Gaussian insufficient
- Modelling uncertain

## Simulations

- O($10^3$) hydrosims for tSZ+lensing is expensive

## Internal

- Non-trivial to do correctly

# Why are hydro sims hard?

## Feedback couples large and small scales

- Simulating large and small scales at the same time is hard
- We don't care about the small scales
- Is there an effective mapping from dark matter to the large-scale gas distribution?

# Simulation data

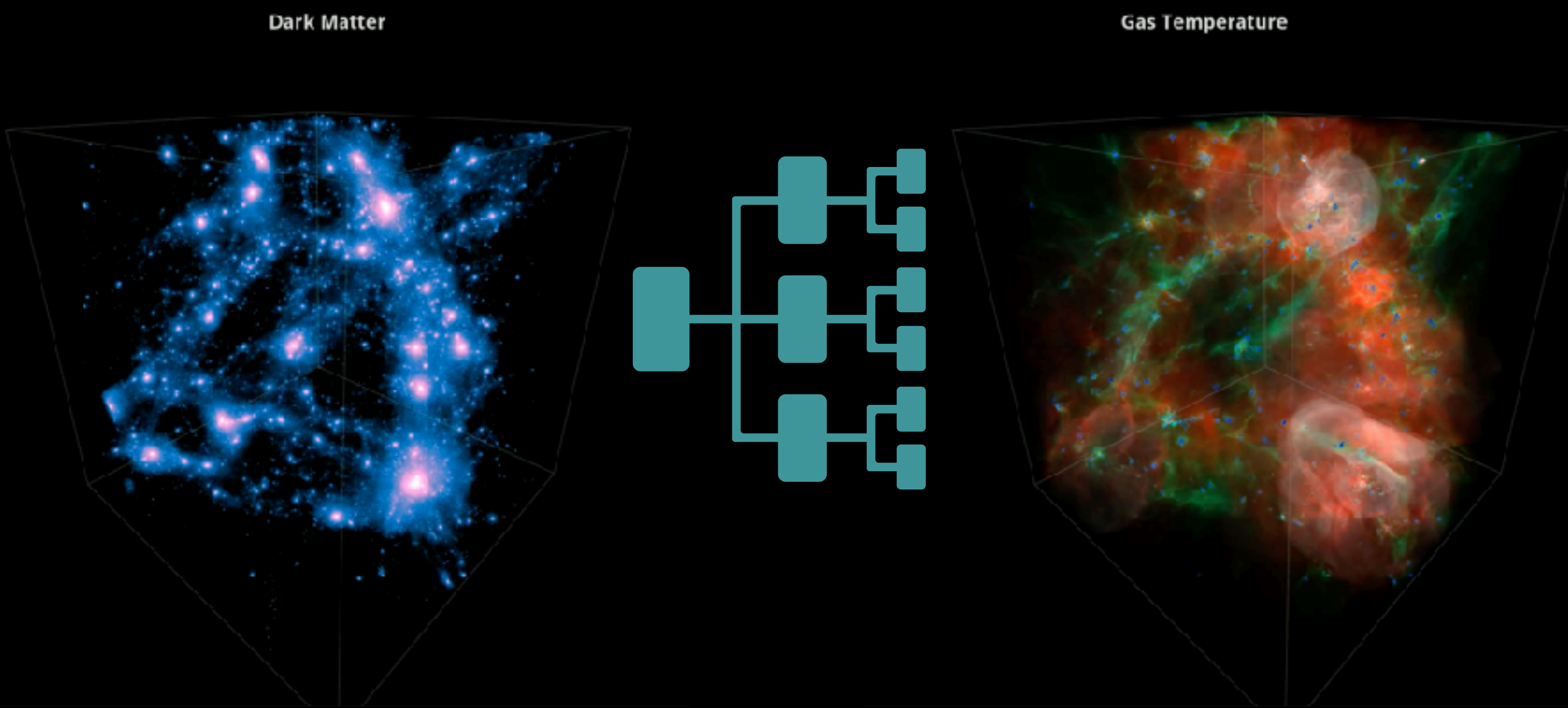
SLICS

- N-body simulation for covariance estimation
- 505 Mpc/h box size
- ~1000 independent volumes

BAHAMAS

- Hydrodynamical simulation
- 400 Mpc/h box size
- 3 independent volumes

# Use machine learning?




Vogelsberger+2004

Karras+ 2018

Zhu+2017

# Deep generative models

## Variational auto-encoder (VAE)

- Probabilistic description
- Easy to train
- Can predict variance of output

## Generative adversarial network (GAN)

- Tends to give better results
- Training is harder; often unstable

# Conditional Variational Auto-Encoder (CVAE)

## Basic problem: given dark matter, sample pressure

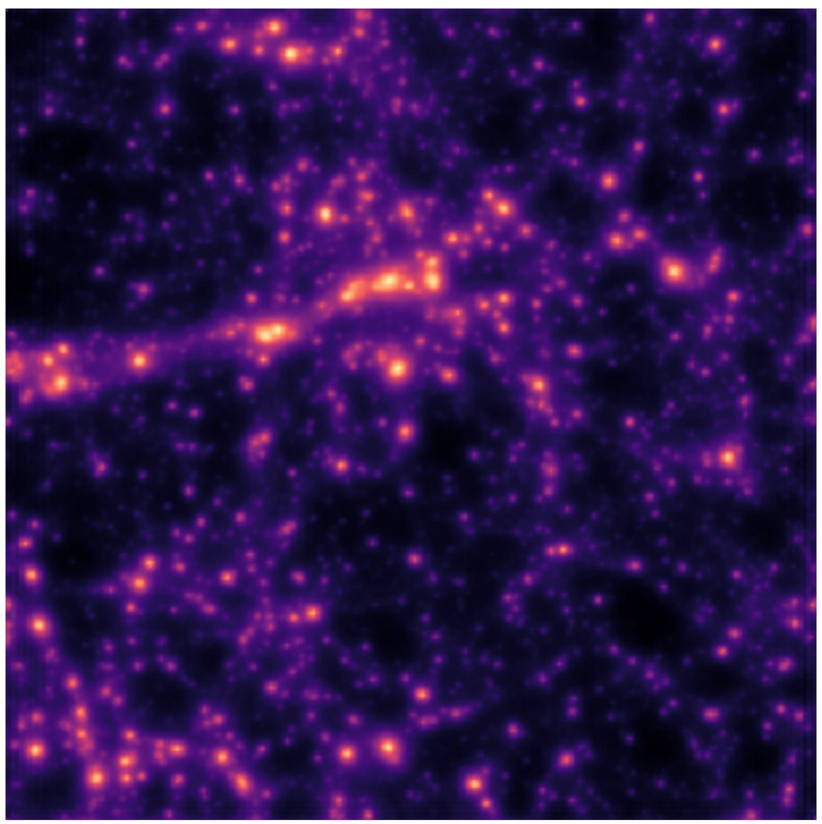
- x is pressure, y is dark matter
  - $x \sim p(x|y)$

## Introduce latent variable z

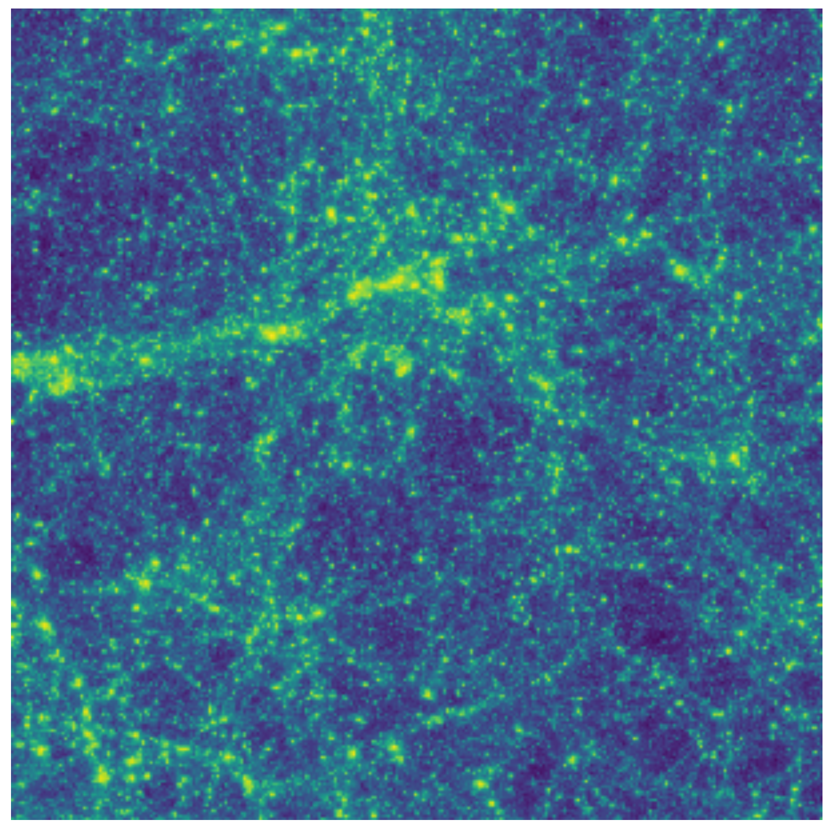
- $p(x|y) = \int \mathrm{d}z \; p(x,z|y) = \int \mathrm{d}z \; p(x|y,z)p(z|y)$
- Infinite mixture model

# Results

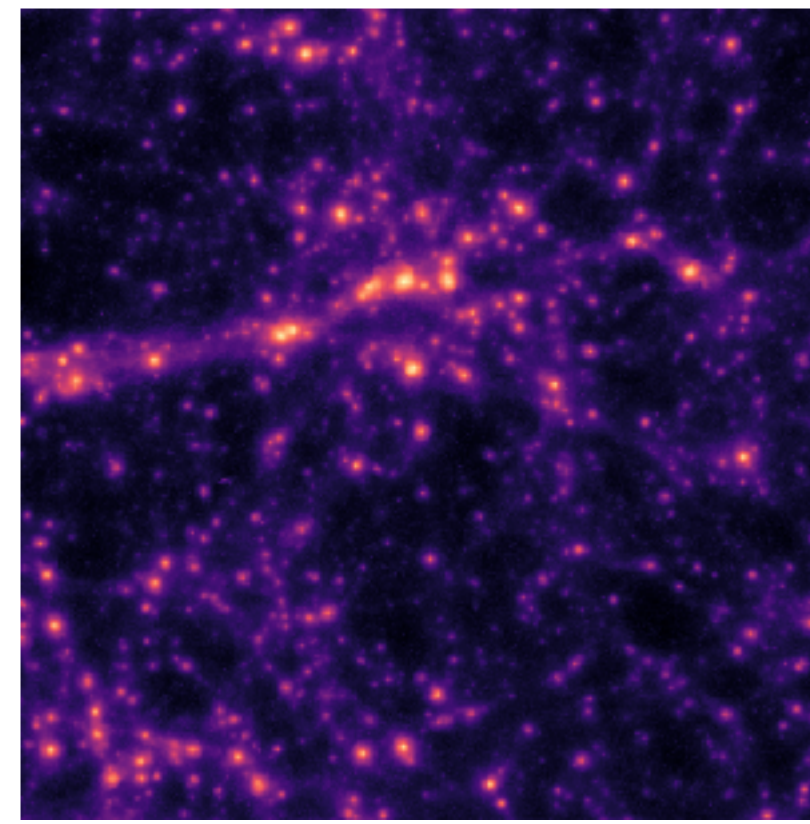
Pressure (fake)



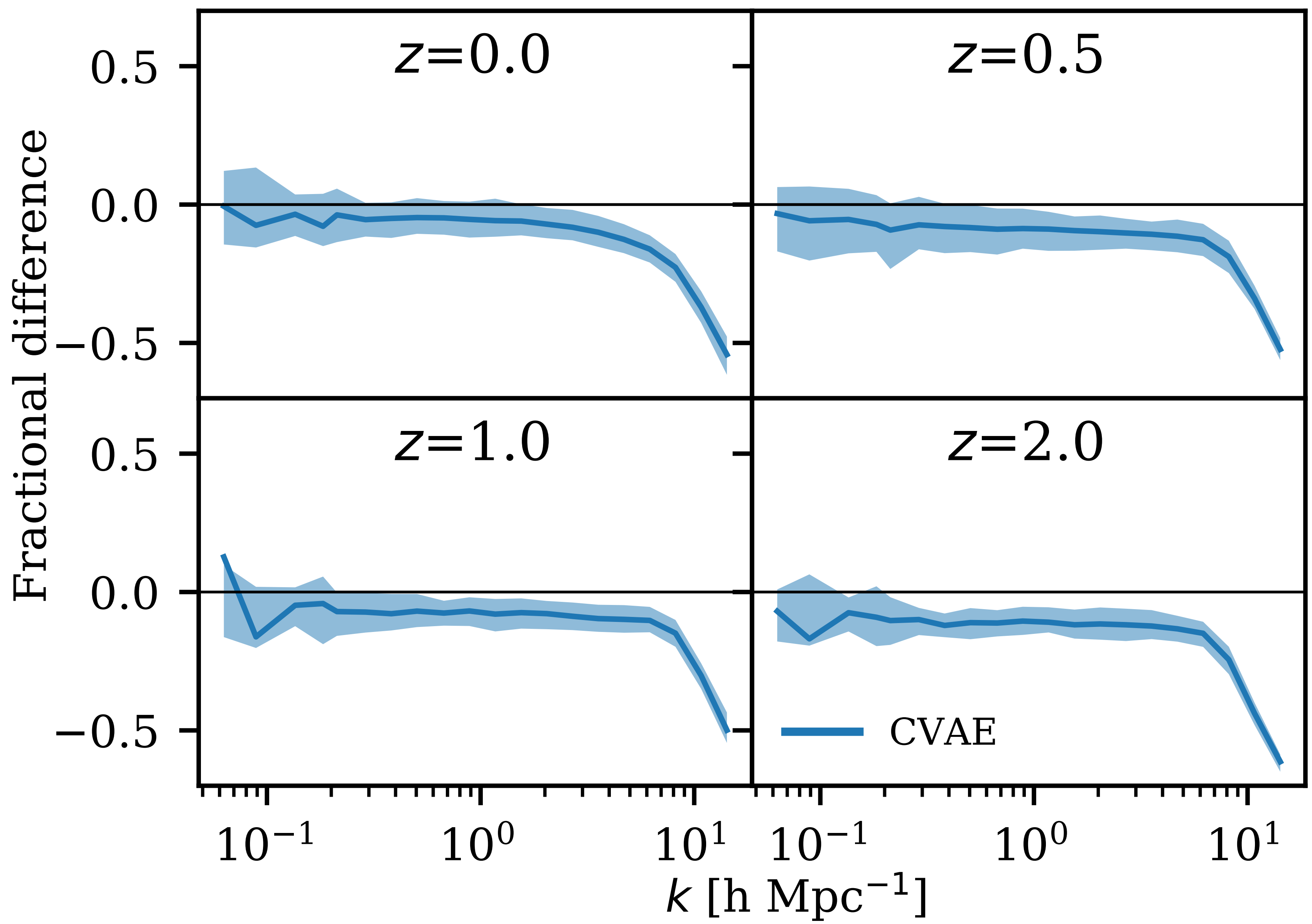
Dark matter (input)



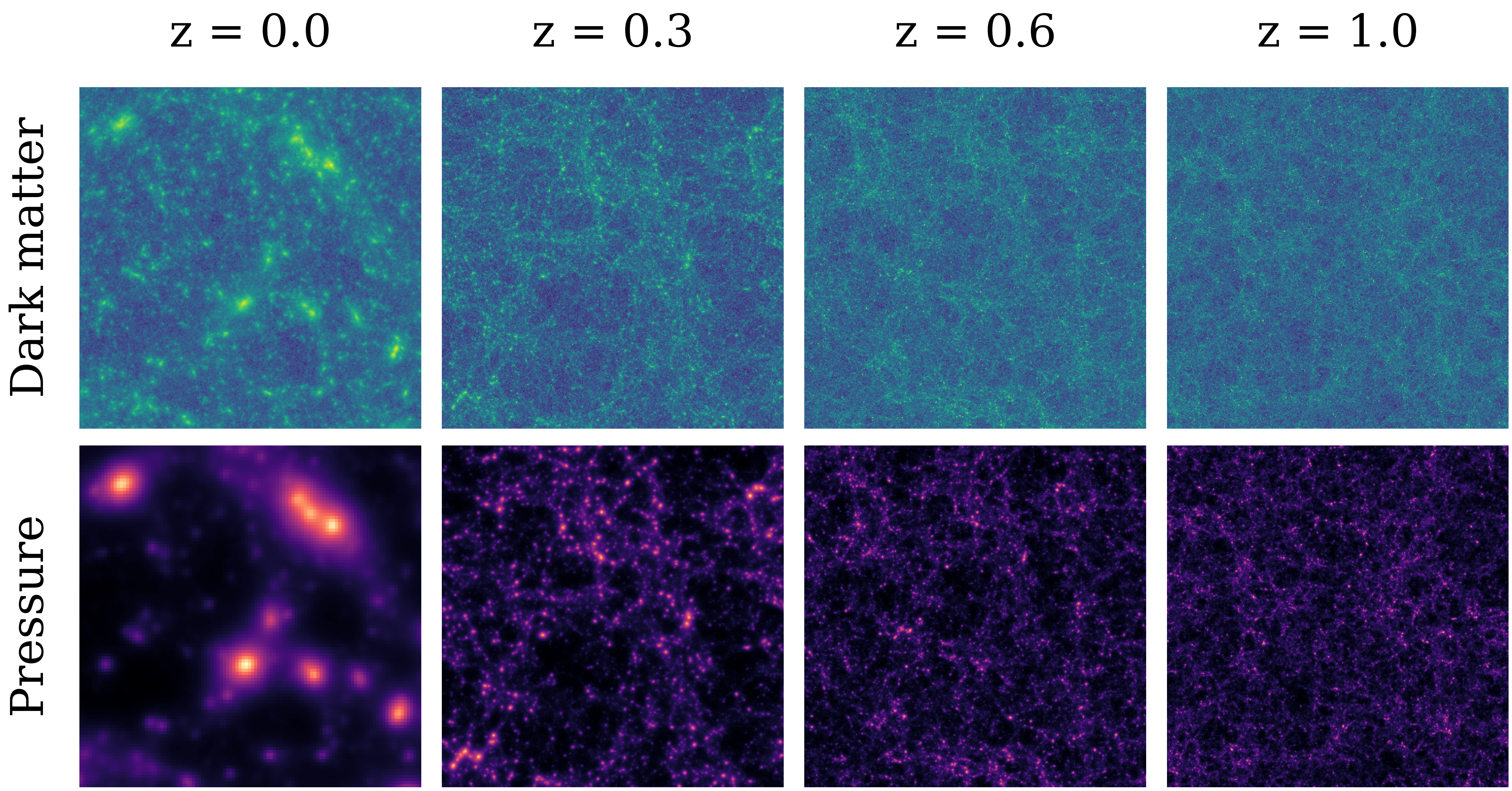
Pressure (truth)



# Cross-power spectra

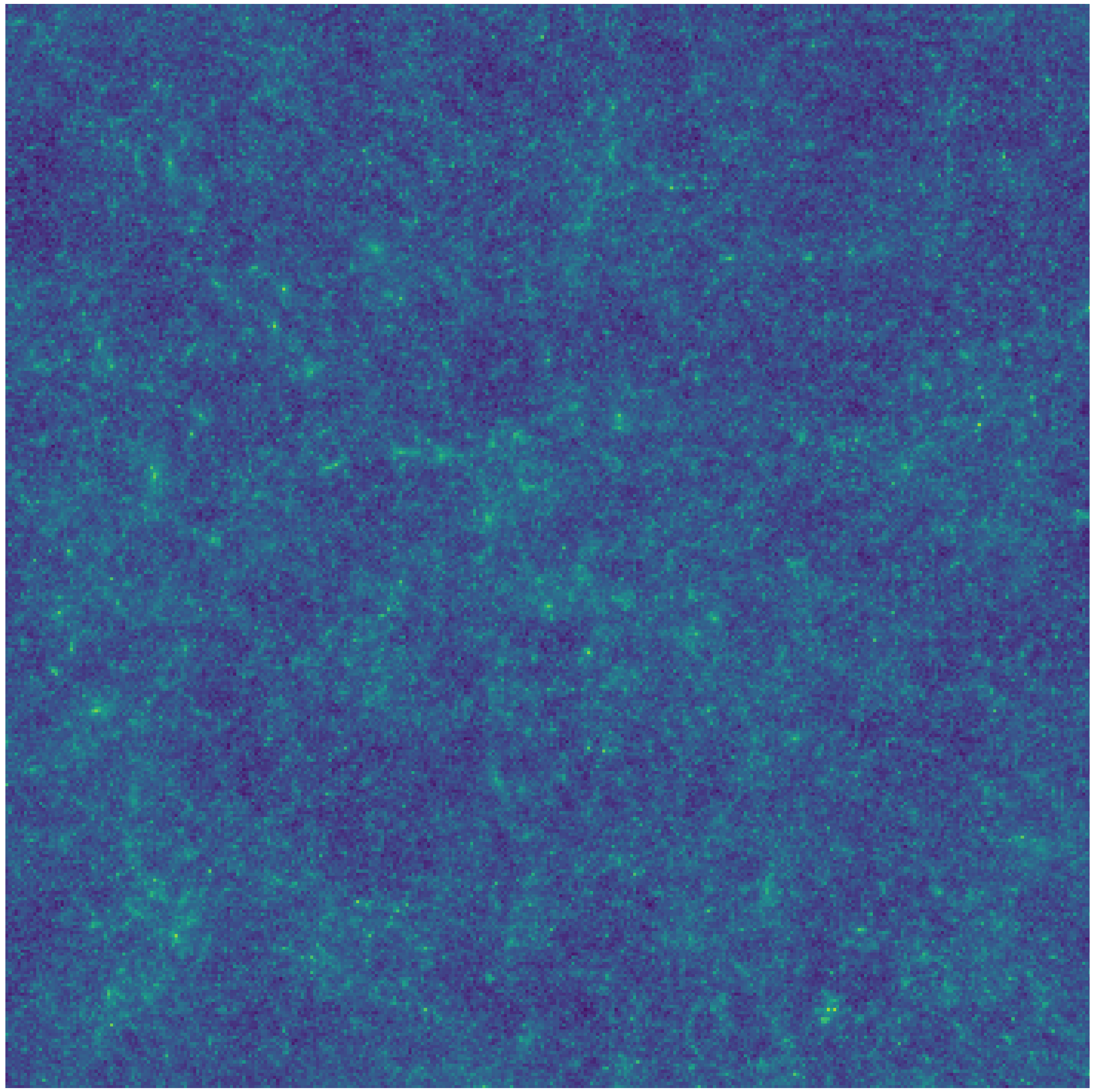


# Paint on SLICS

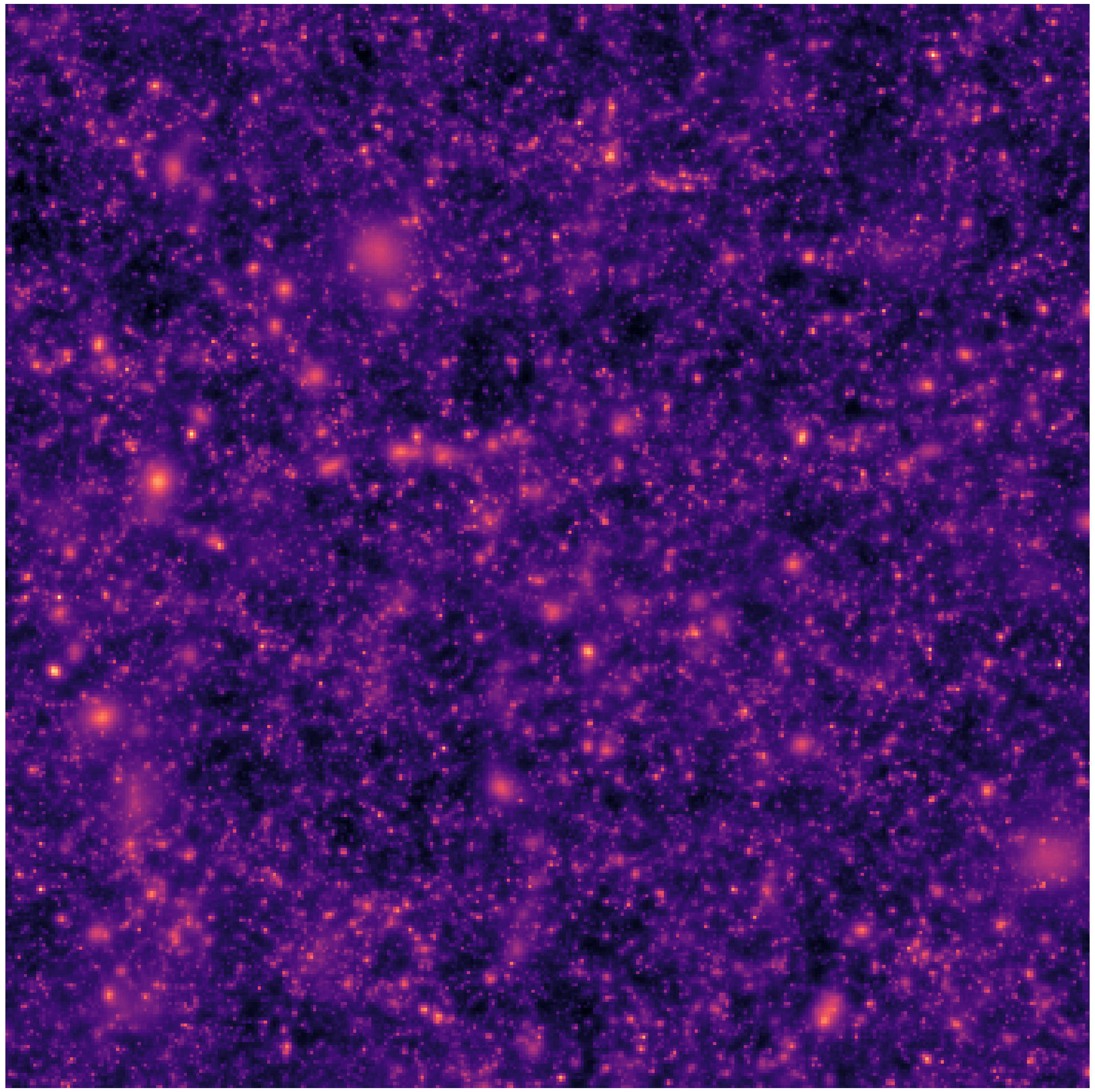


# Convergence vs Compton-y

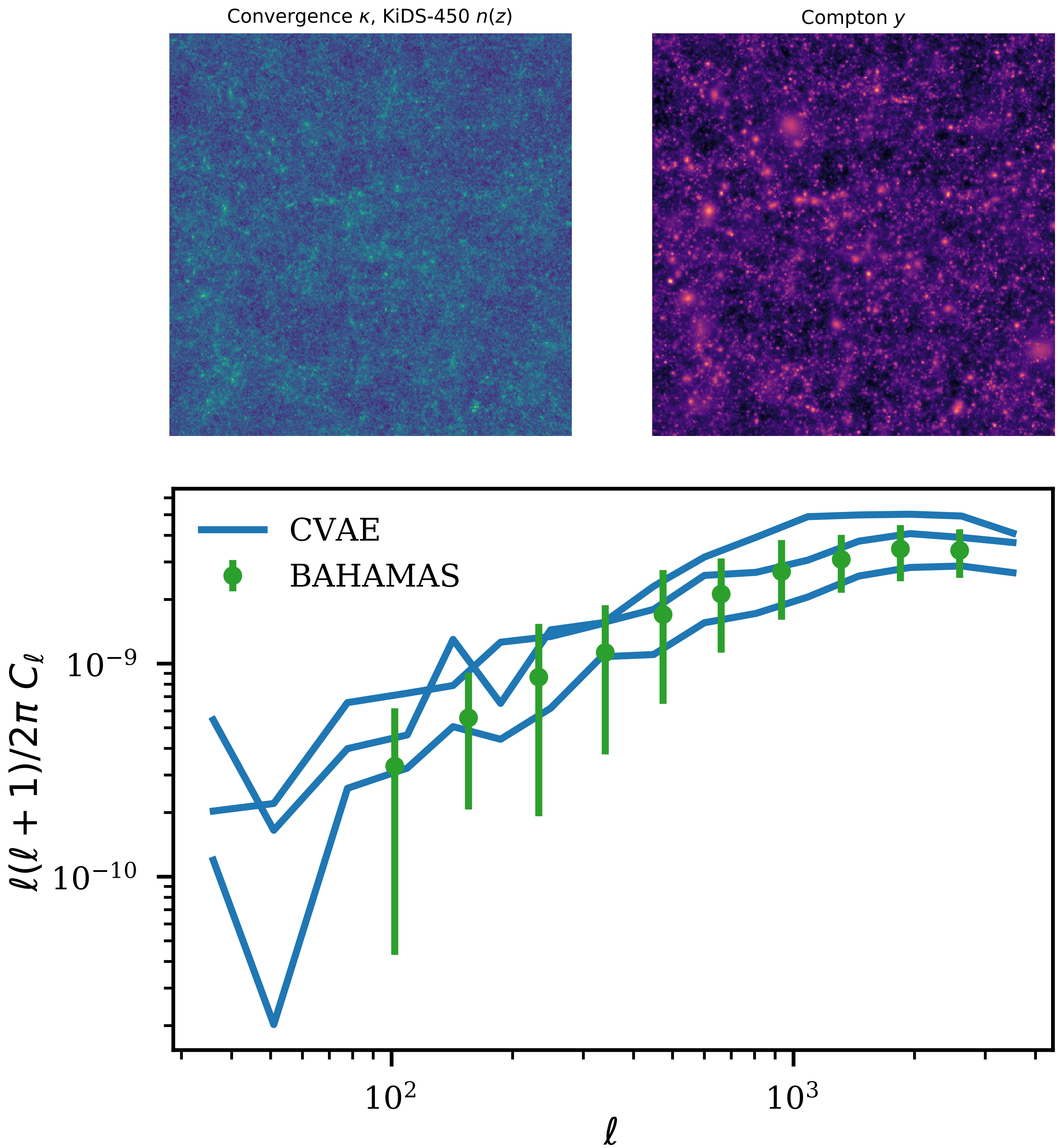
Convergence $\kappa$, KiDS-450 $n(z)$



Compton $y$



# Convergence vs Compton-y



# Summary

Baryons need to be accounted for if we want to fully exploit weak lensing data

Baryons hold cosmological information themselves

Deep generative models are powerful tools to bridge the gap between N-body and hydrosims

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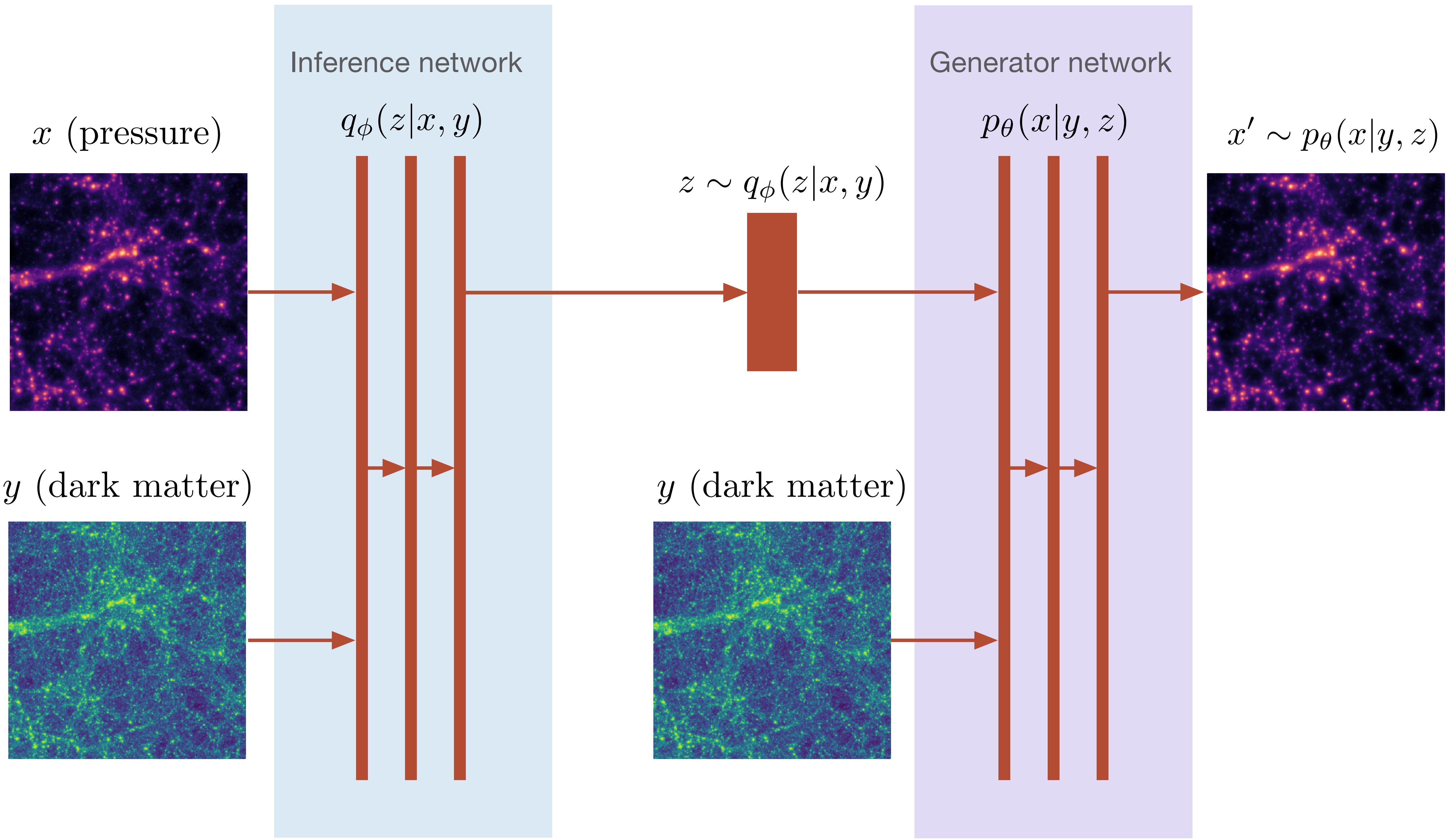
# Conditional Variational Auto-Encoder (CVAE)

## Variational lower bound

- $\log p(x|y) \geq \underbrace{-\mathbb{D}_{\mathrm{KL}}(q_\phi(z|x,y)||p_{\theta_1}(z|y))}_{\text{KL-term}} + \underbrace{\mathbb{E}_{z\sim q_\phi(z|x,y)}[\log p_{\theta_2}(x|y,z)]}_{\text{Reconstruction}}$

- $q_\phi(z|x,y)$ , $p_{\theta_1}(z|y)$, and $p_{\theta_2}(x|y,z)$ can be expressed as neural networks
- Can be efficiently optimised

# Conditional Variational Auto-Encoder (CVAE)



# Simulation data

## SLICS

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- 505 Mpc/h box size
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## BAHAMAS

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# Simulation data

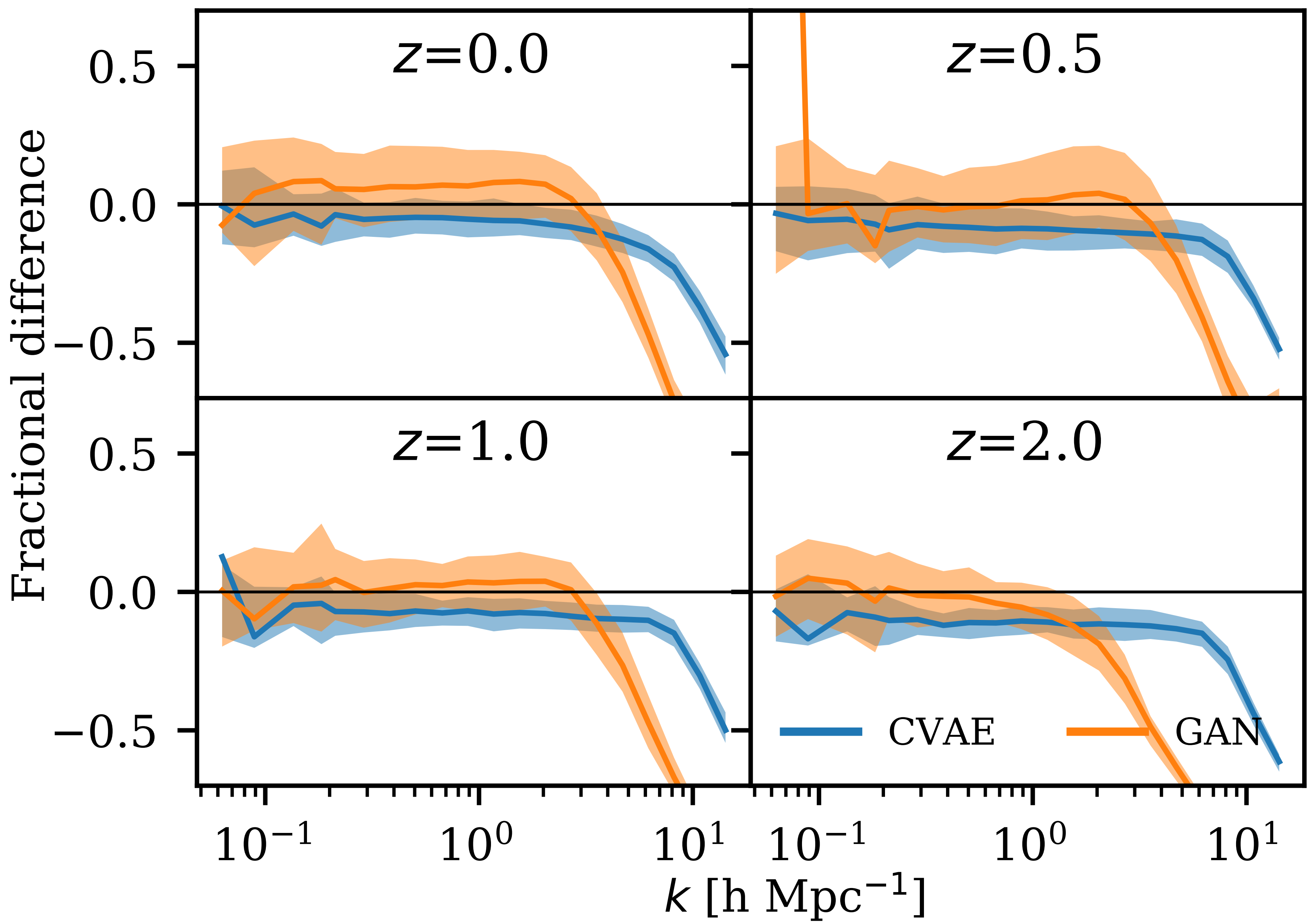
## SLICS

- No particle snapshots
- Mass sheets corresponding to 252 Mpc/h thick slices
- Not a problem; lensing and tSZ are projected quantities

## BAHAMAS

- Create 250 Mpc/h thick slices
- Form combinations of 150 Mpc/h and 100 Mpc/h slices
- ~50k samples per redshift

# CVAE vs CGAN


z=0.0
z=0.5
z=1.0
z=2.0
0.5
0.0
−0.5
Fractional difference
$10^{-1}$
$10^{0}$
$10^{1}$
$k$ [h Mpc$^{-1}$]
CVAE
GAN