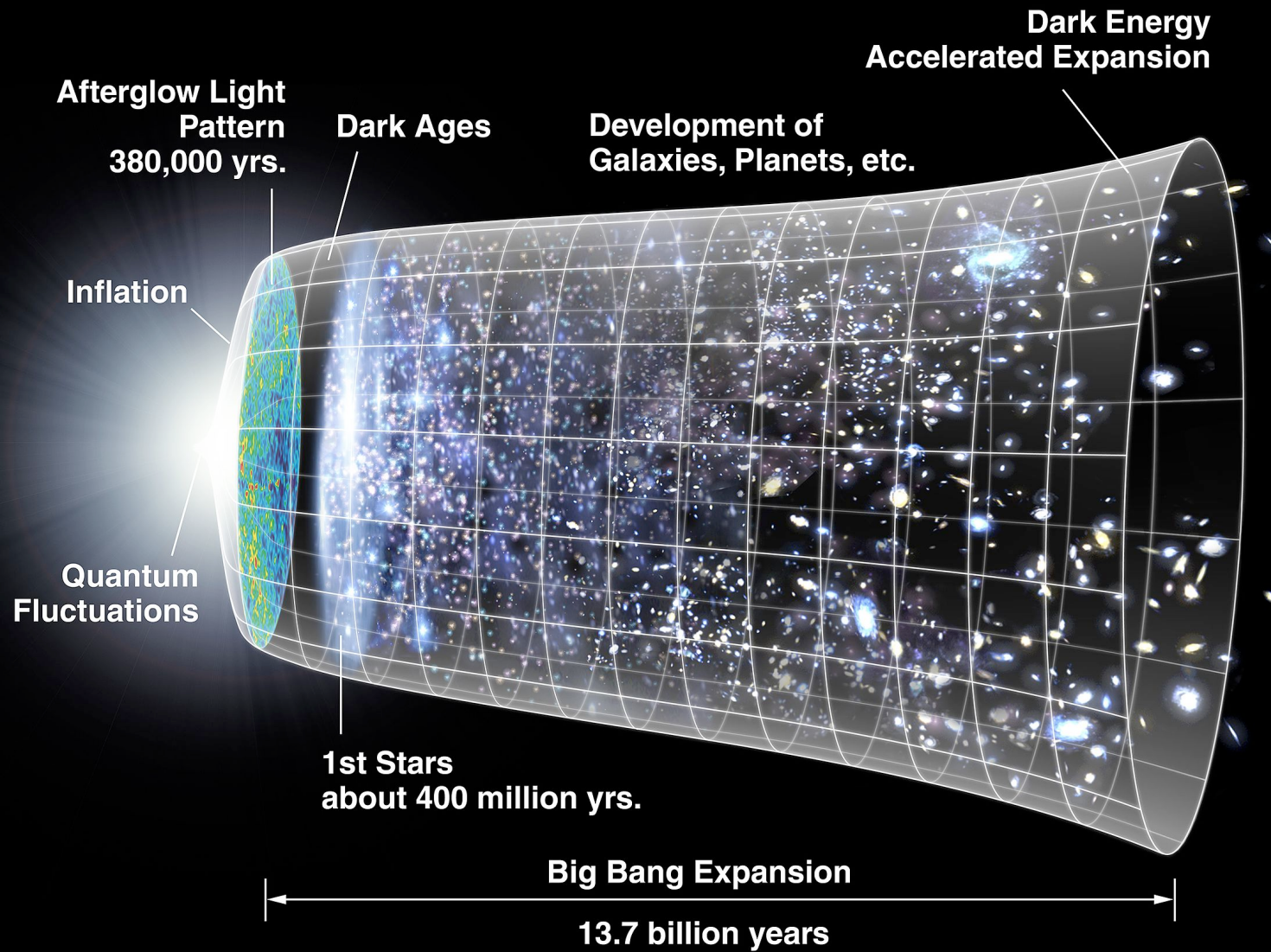


AI Foundation Models for Large-Scale Structure Cosmology



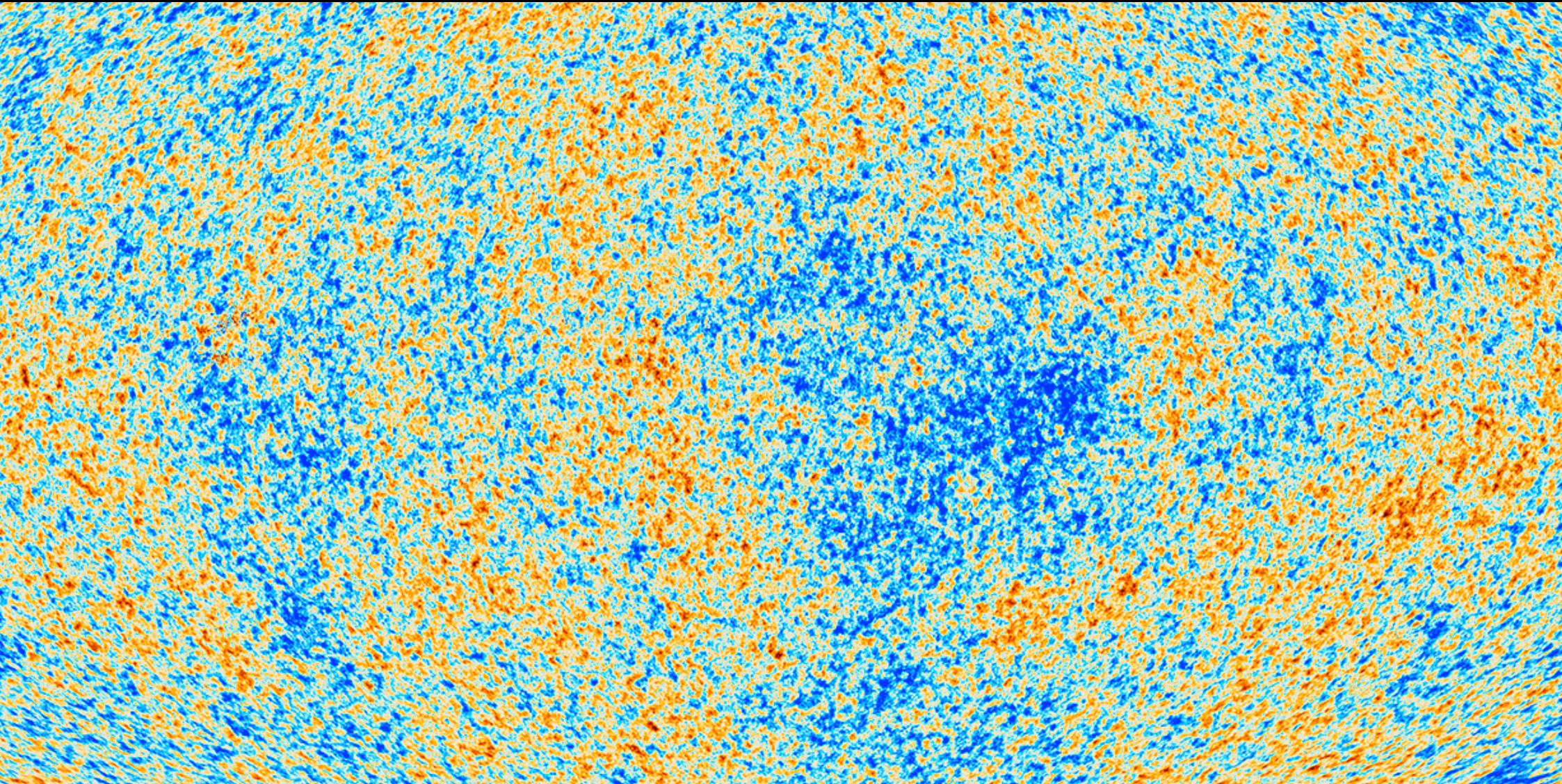
**Tomasz Kacprzak (University of Applied Sciences Northwestern Switzerland FHNW
AI+Astronomy, EPFL, 1 April 2026**

The Expanding Universe

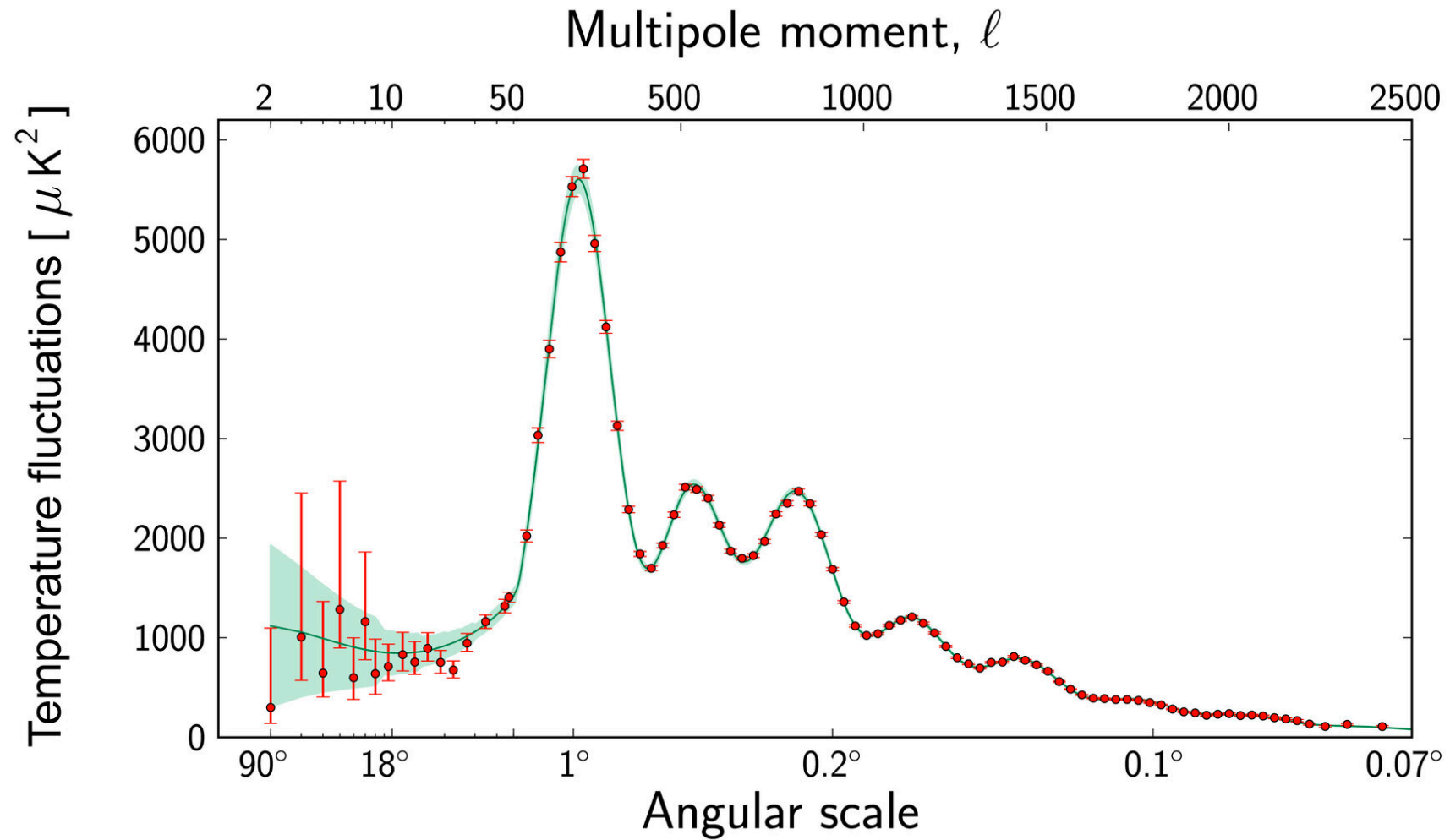


Cosmic Microwave background

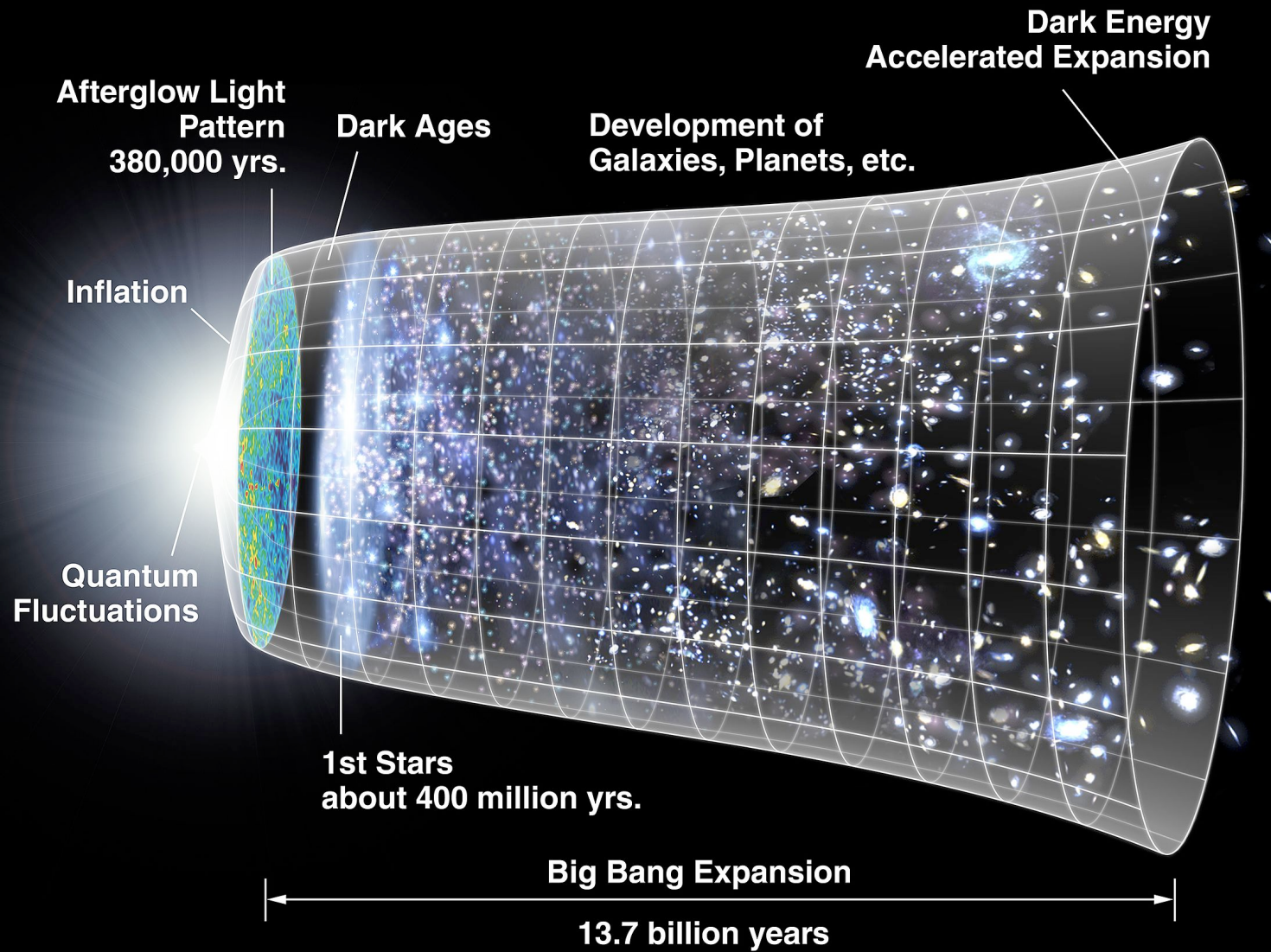
Linear density fluctuations



Temperature Power Spectrum of the Cosmic Microwave Background



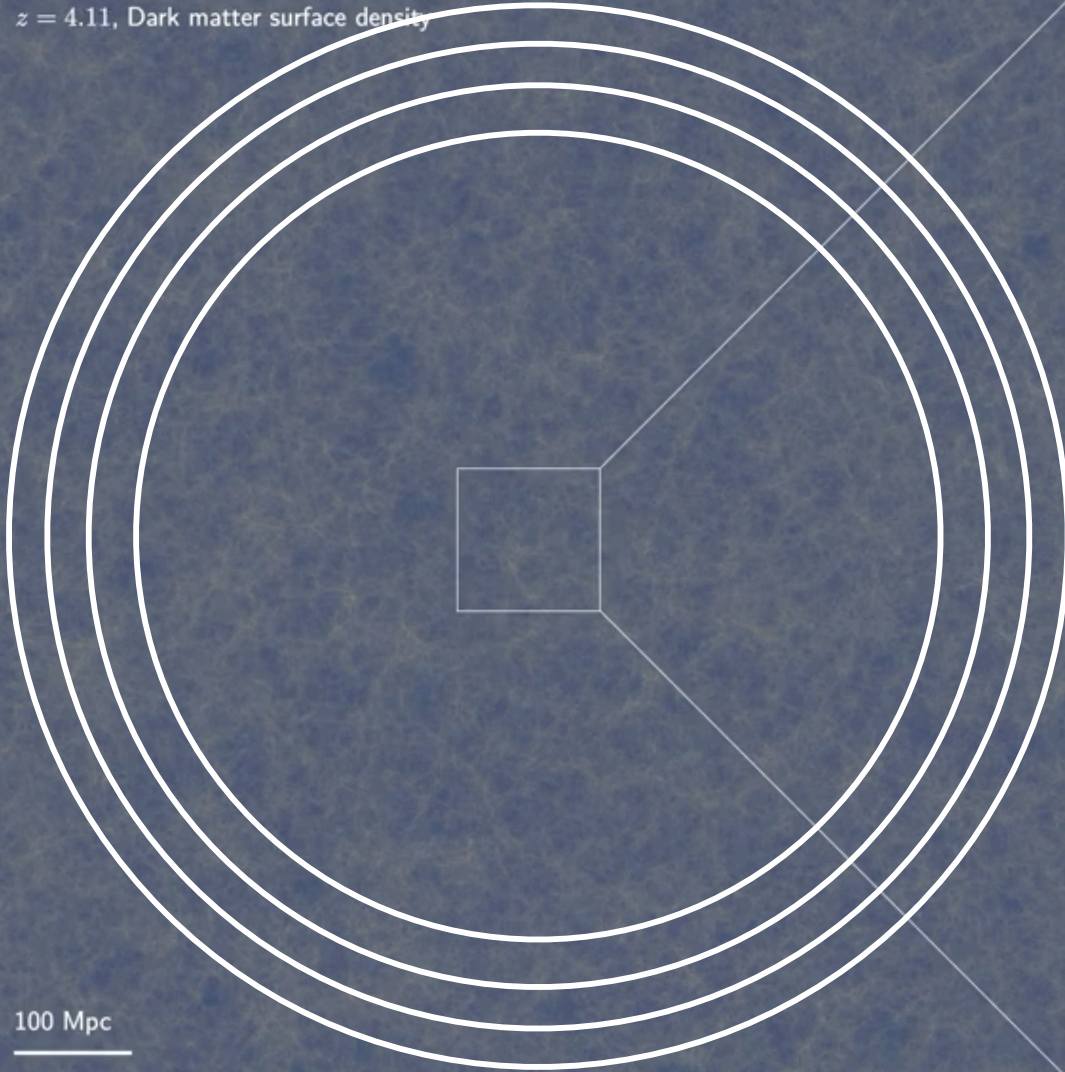
The Expanding Universe



Large-scale matter distribution in the universe

Matter distribution evolves under laws of gravity and expansion of the universe

$z = 4.11$, Dark matter surface density



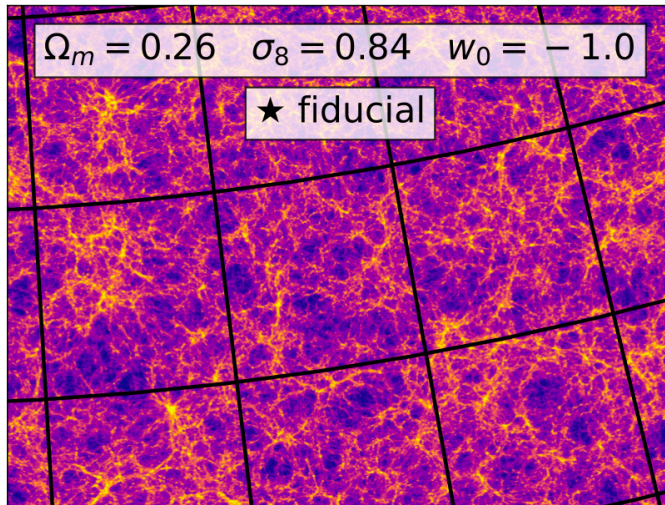
10 Mpc

FLAMINGO
Virgo Consortium



Dark matter distributions carries information about cosmological parameters

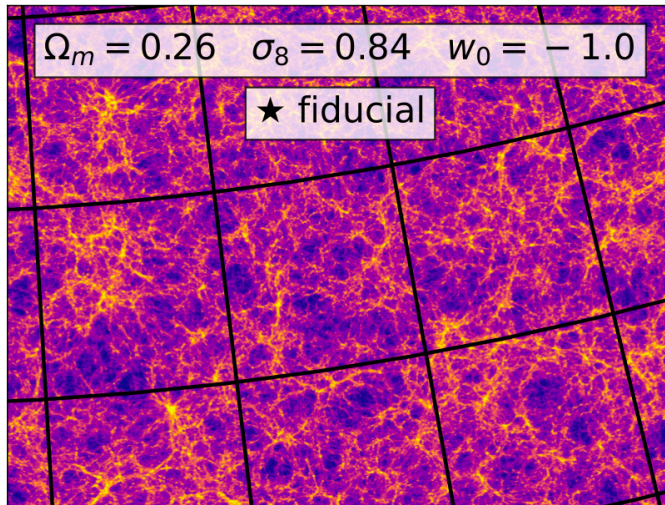
Dark energy density Ω_Λ , dark matter density Ω_m , such that $\Omega_\Lambda + \Omega_m = 1$



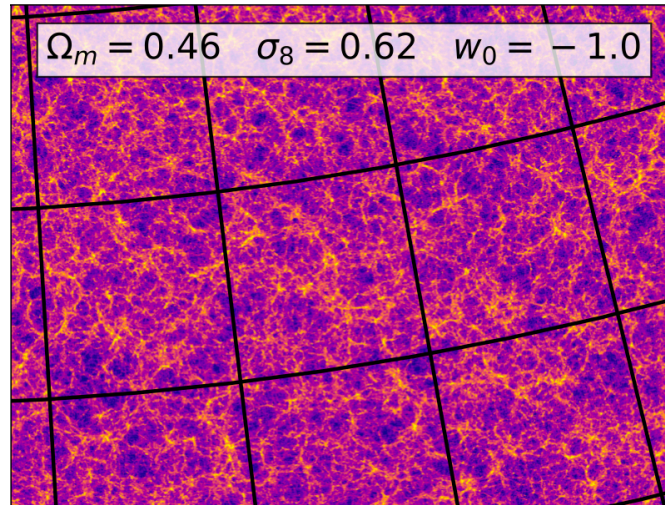
best-fitting today ★

Dark matter distributions carries information about cosmological parameters

Dark energy density Ω_Λ , dark matter density Ω_m , such that $\Omega_\Lambda + \Omega_m = 1$

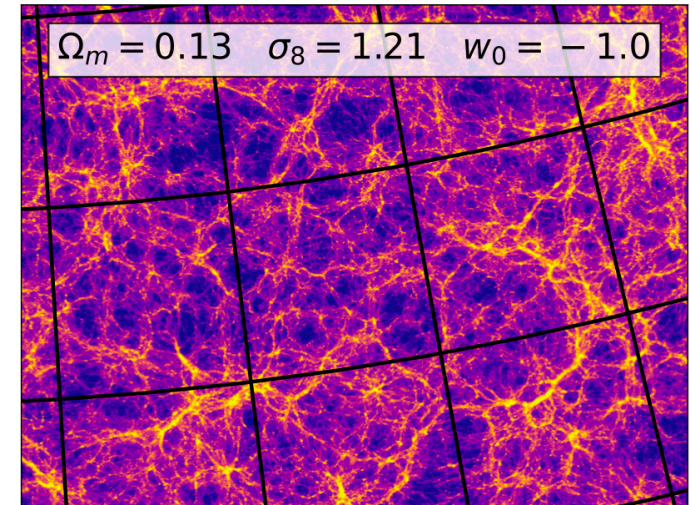


best-fitting today ★



high matter density

$\Omega_m \uparrow$, $\Omega_\Lambda \downarrow$



high dark energy

$\Omega_m \downarrow$, $\Omega_\Lambda \uparrow$

Testing Cosmological Models

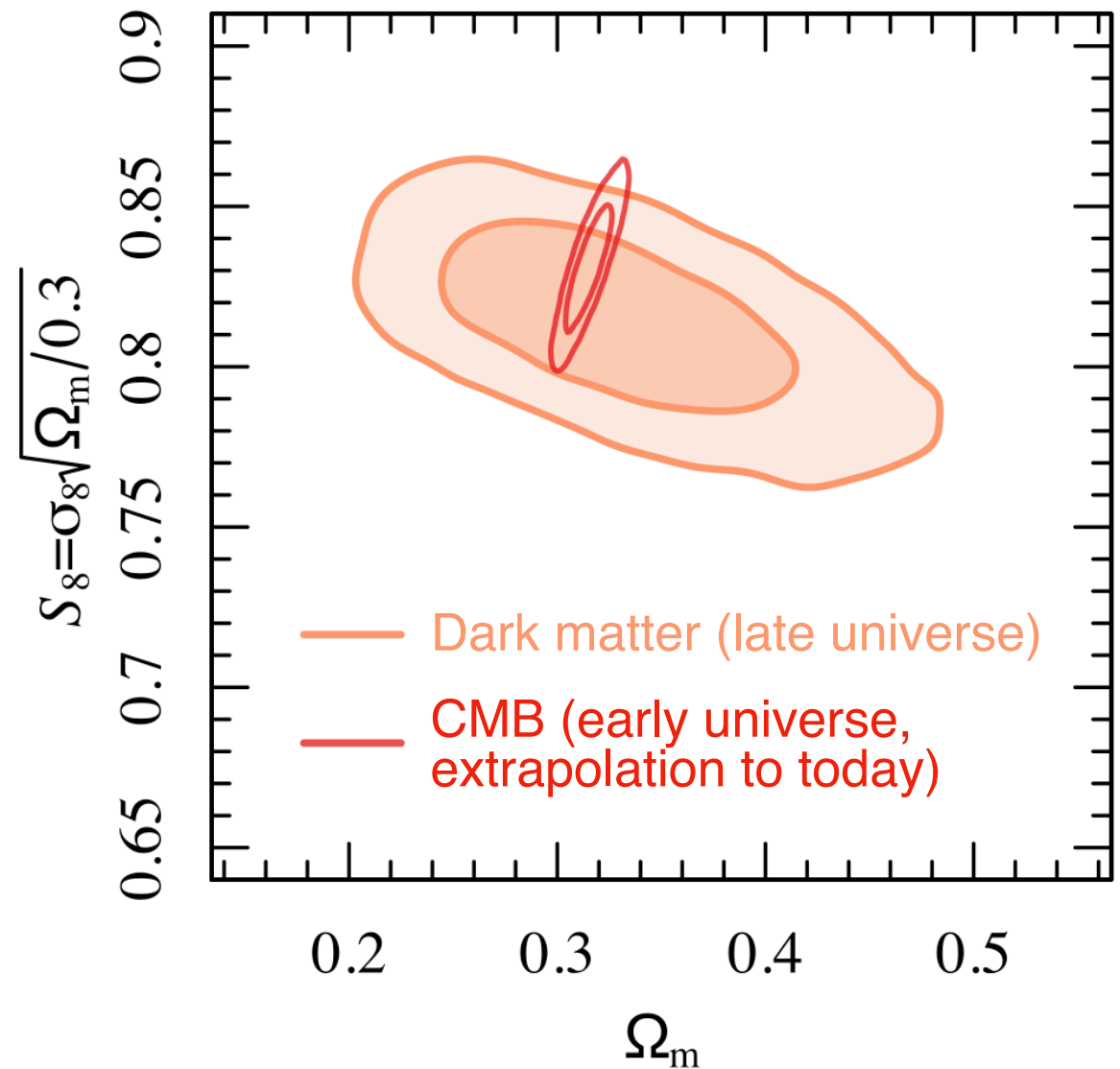
Two parameters of interest at the moment:

- Ω_m : fraction of dark matter in the universe today
- σ_8 : clustering strength, nuisance parameter

Consistency between early and late universe models is a powerful method to test our cosmological models. Possible discrepancies can stem from:

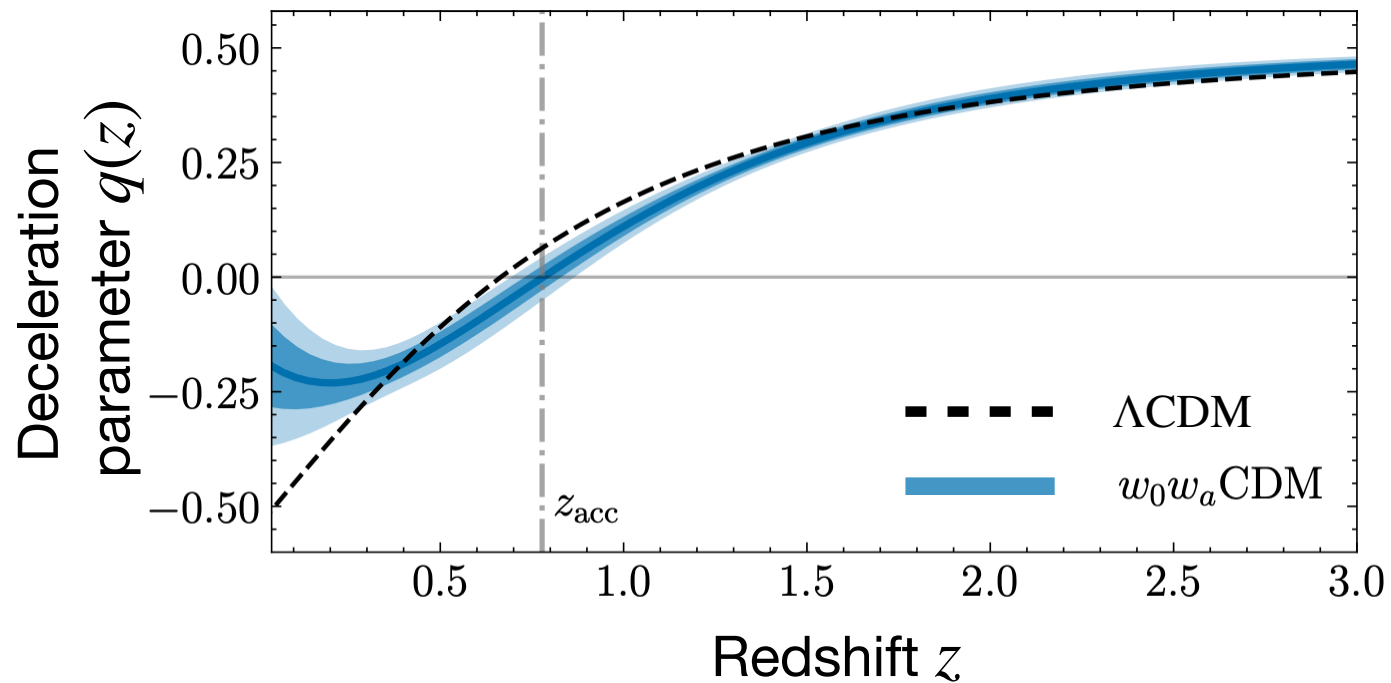
- It can be a sign of missing physics in our cosmological model
- Our understanding of the nature of gravity and cosmic acceleration is may wrong
- Measurement systematics and theoretical modelling errors

★ We need to increase the precision of measurements to test the laws of physics at cosmological scales



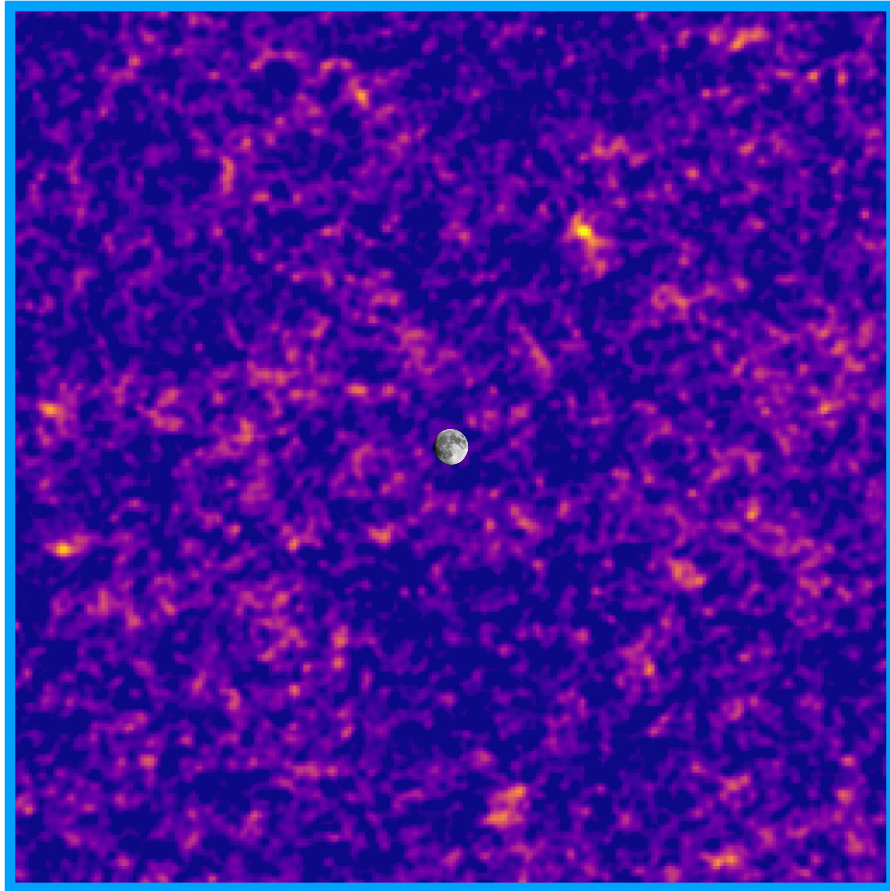
Evolving Dark Energy?

★ Latest DESI results give a hint of time evolution of dark energy, pointing towards expansion of space being more complicated than a cosmological constant Λ .

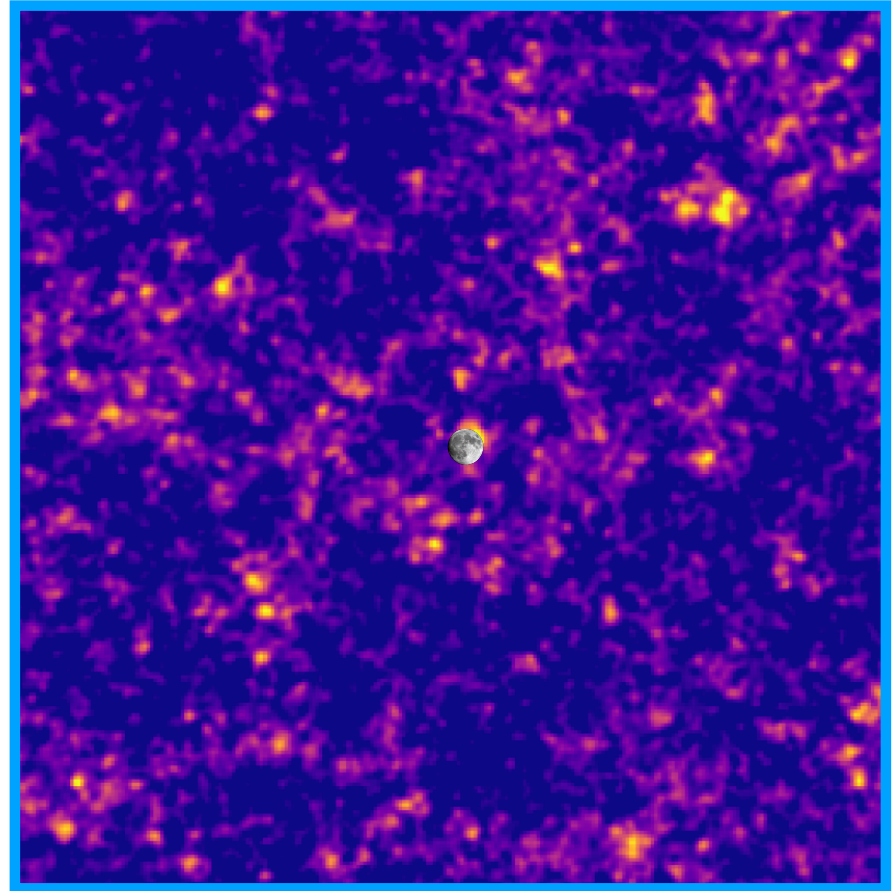


LSS Probes: Projected Matter Distributions

Example: weak lensing maps

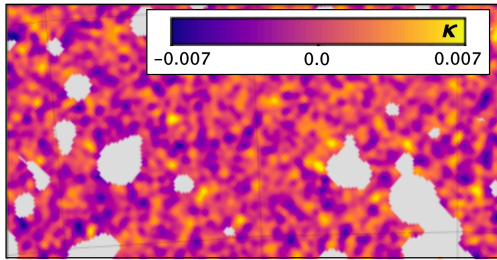


low σ_8 low Ω_m



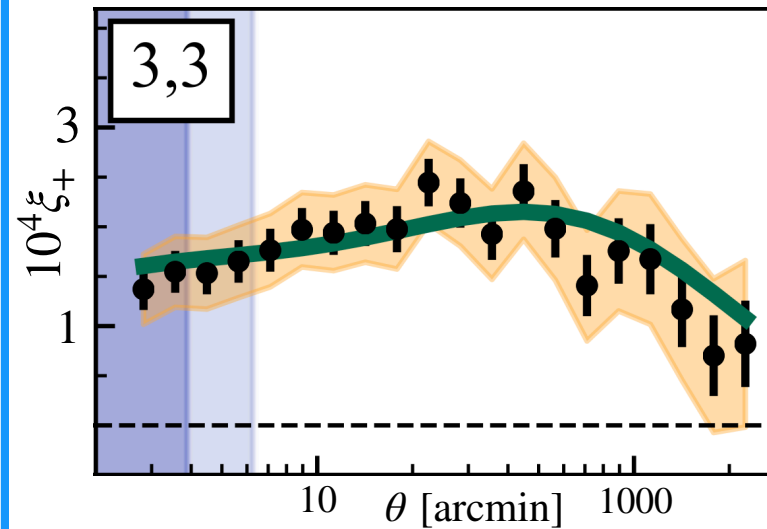
high σ_8 high Ω_m

LSS observations

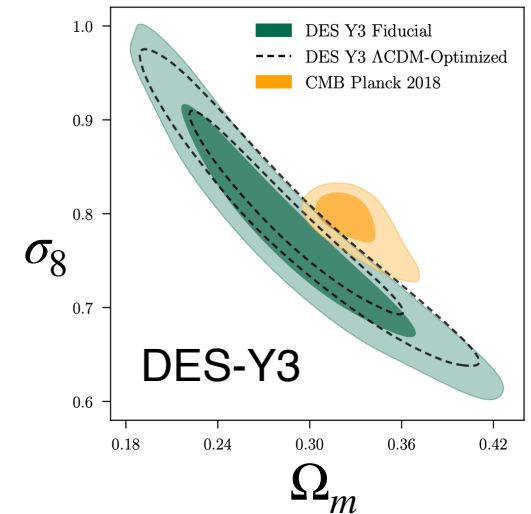


Traditional Inference with 2-pt Functions

statistics: 2pt functions



parameter

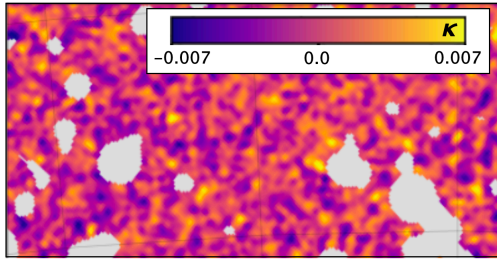


$$C_l = \frac{9}{16} \left(\frac{H_0}{c} \right)^4 \Omega_m^2 \int_0^{\chi_h} d\chi \left[\frac{g(\chi)}{ar(\chi)} \right]^2 P \left(\frac{l}{r}, \chi \right)$$

theory prediction: analytical

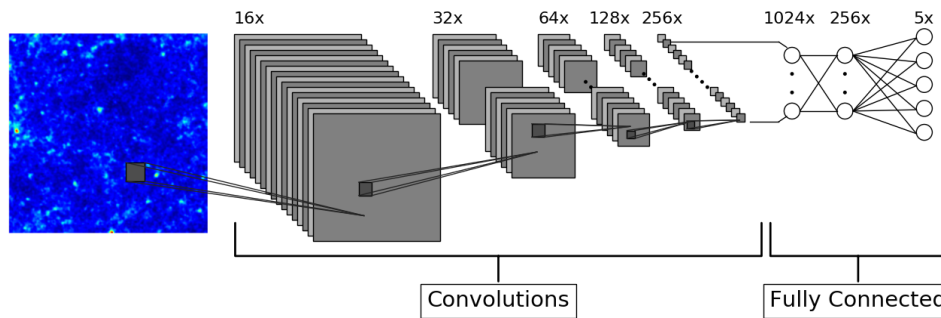
Amon+DES Collab. 2021, 2105.13543

LSS observations

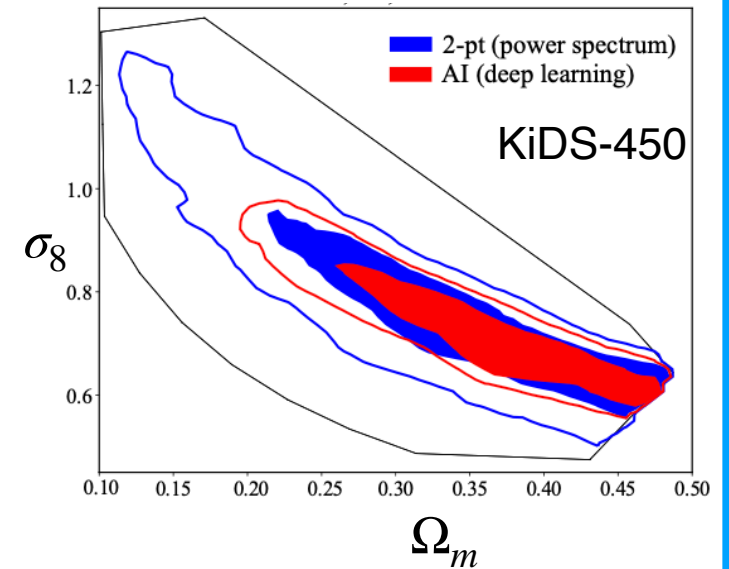


Simulation-Based Inference with Deep Learning

statistics: deep convolutional network

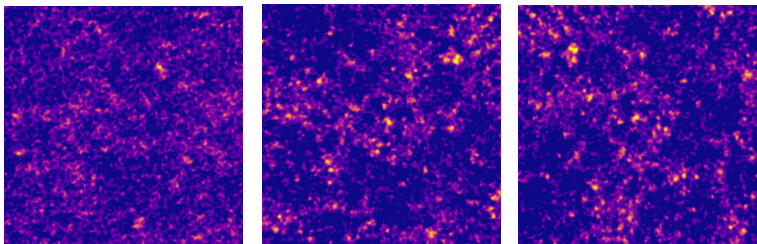


parameter measurement

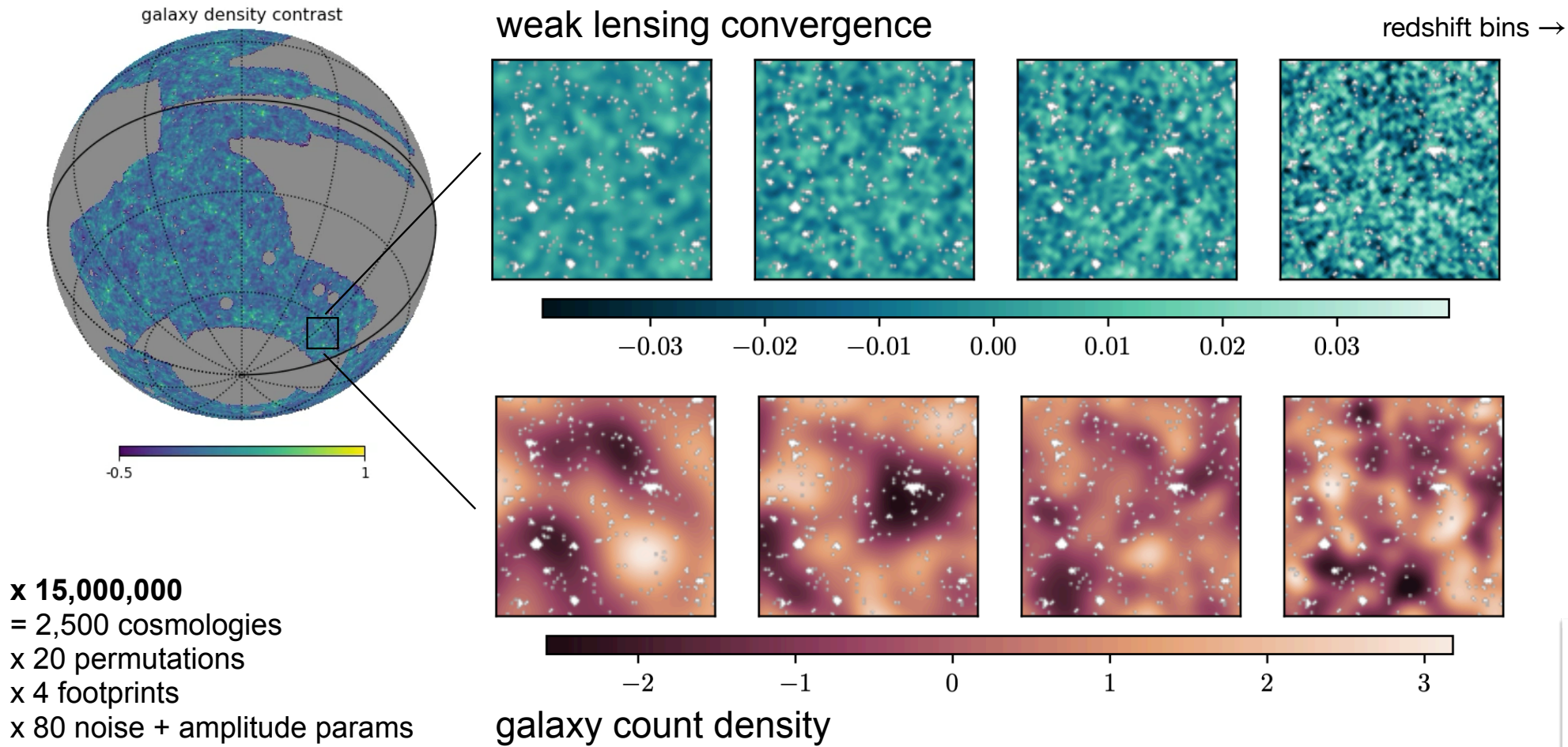


Fluri, TK, et al. 1906.03156

theory prediction: simulations



Simulations-Based Inference in Dark Energy Survey

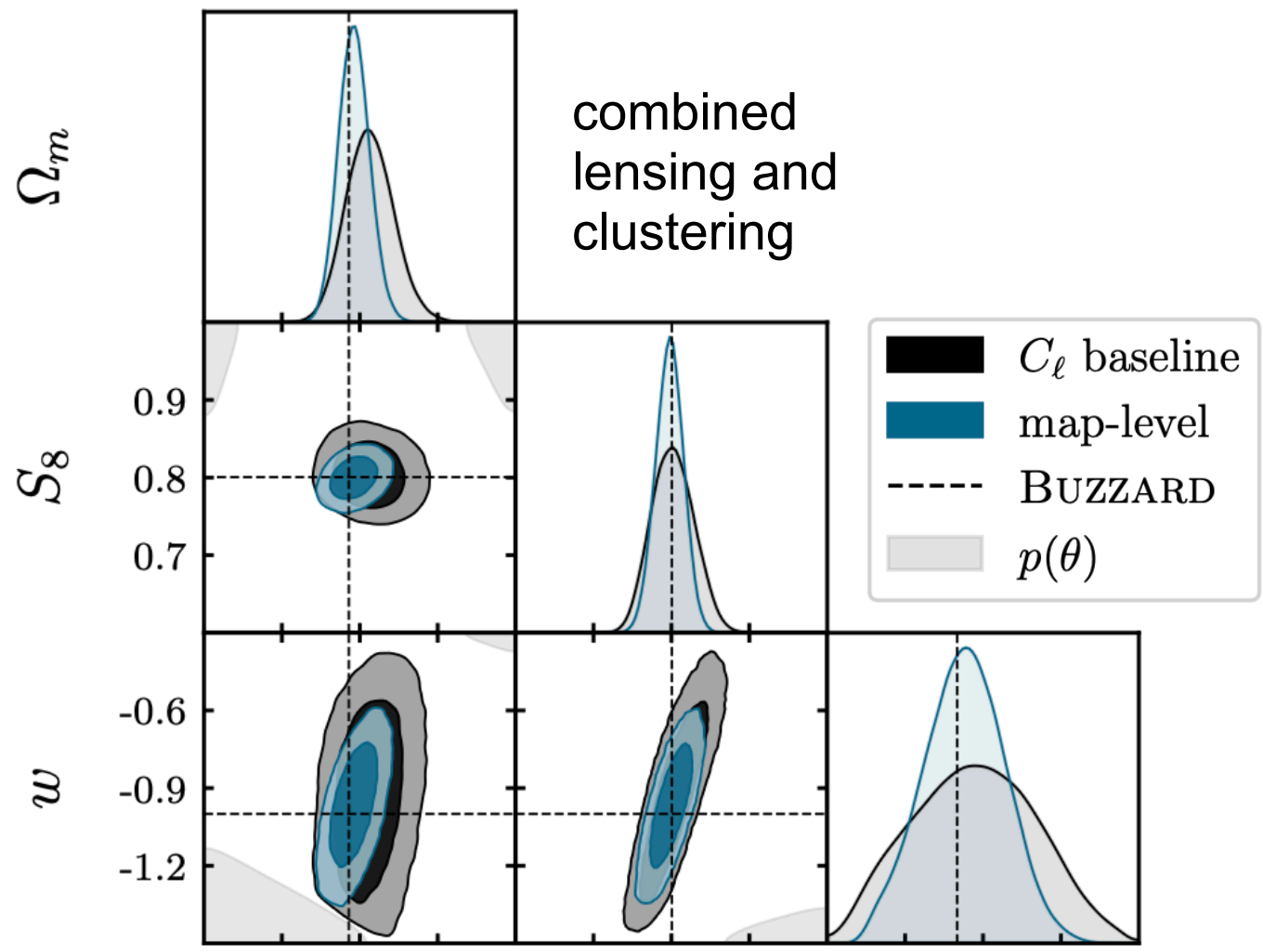


x 15,000,000
= 2,500 cosmologies
x 20 permutations
x 4 footprints
x 80 noise + amplitude params
→ ~ 15 TB

By Arne Thomsen (ETHZ)

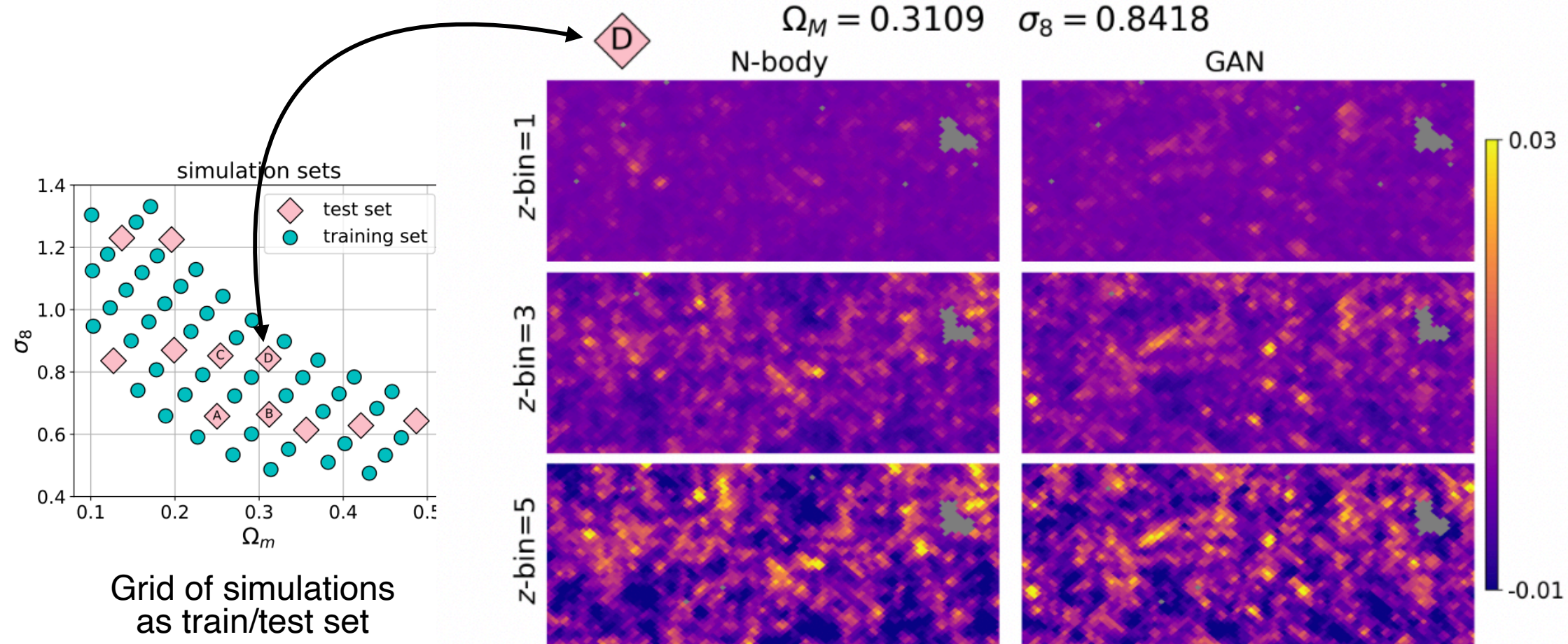


Preliminary results (Buzzard): Maps vs. 2-point statistics



★ increase in
constraining power by
 $> 2 \times$

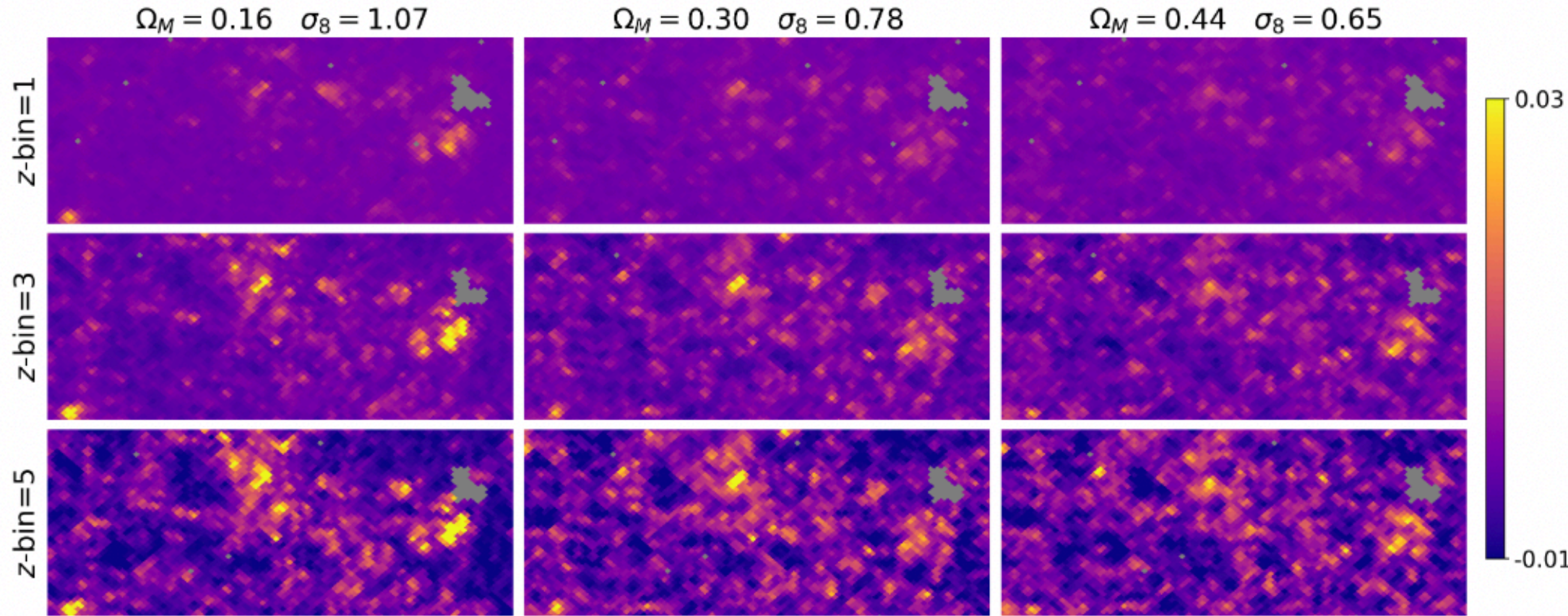
KiDS-1000 mass map emulator



Visual comparison between original N-body and GAN maps

Very fast generator publicly available: <https://tfhub.dev/cosmo-group-ethz/models/kids-cgan/1>

KiDS-1000 mass map emulator

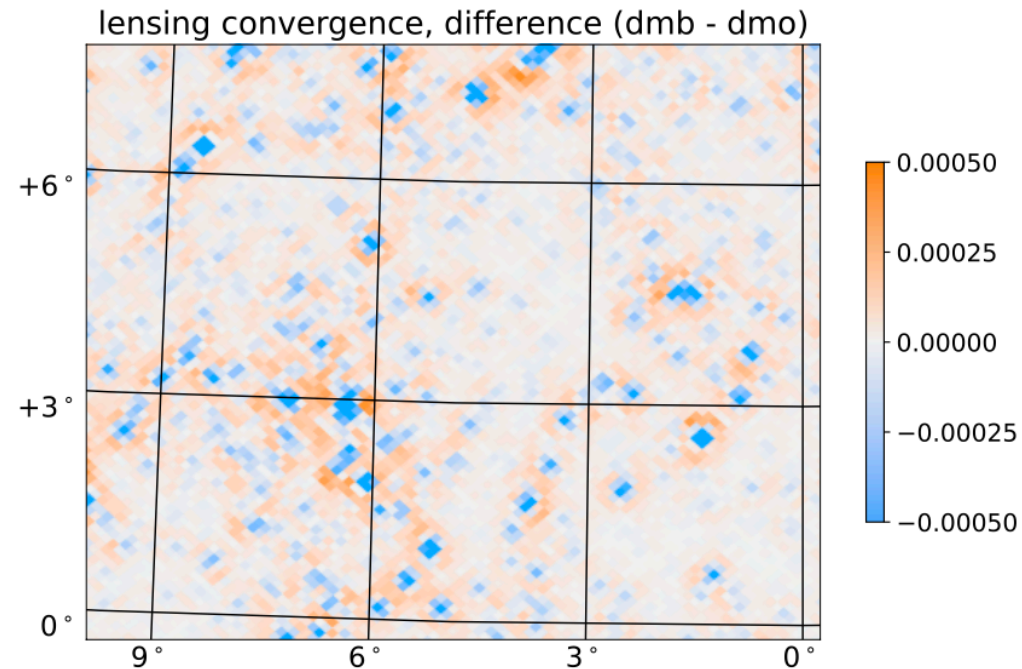
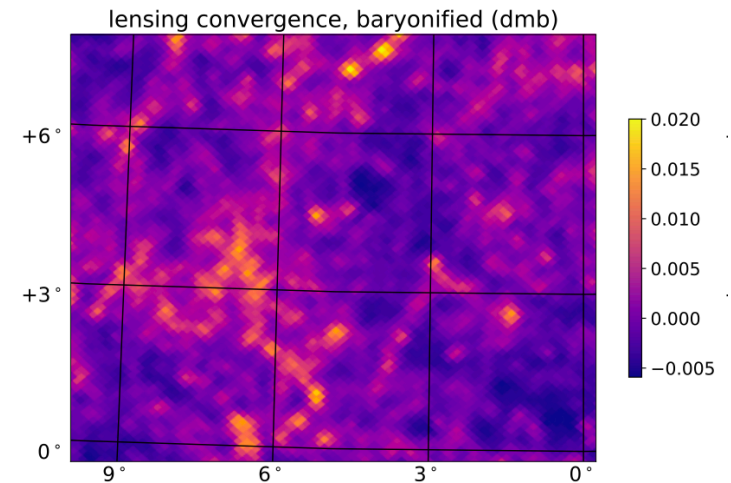


The generated maps are differentiable with respect to the input cosmological parameters
Very good agreement on power spectra and non-Gaussian summary statistics

Baryon feedback modeling in CosmoGridV1

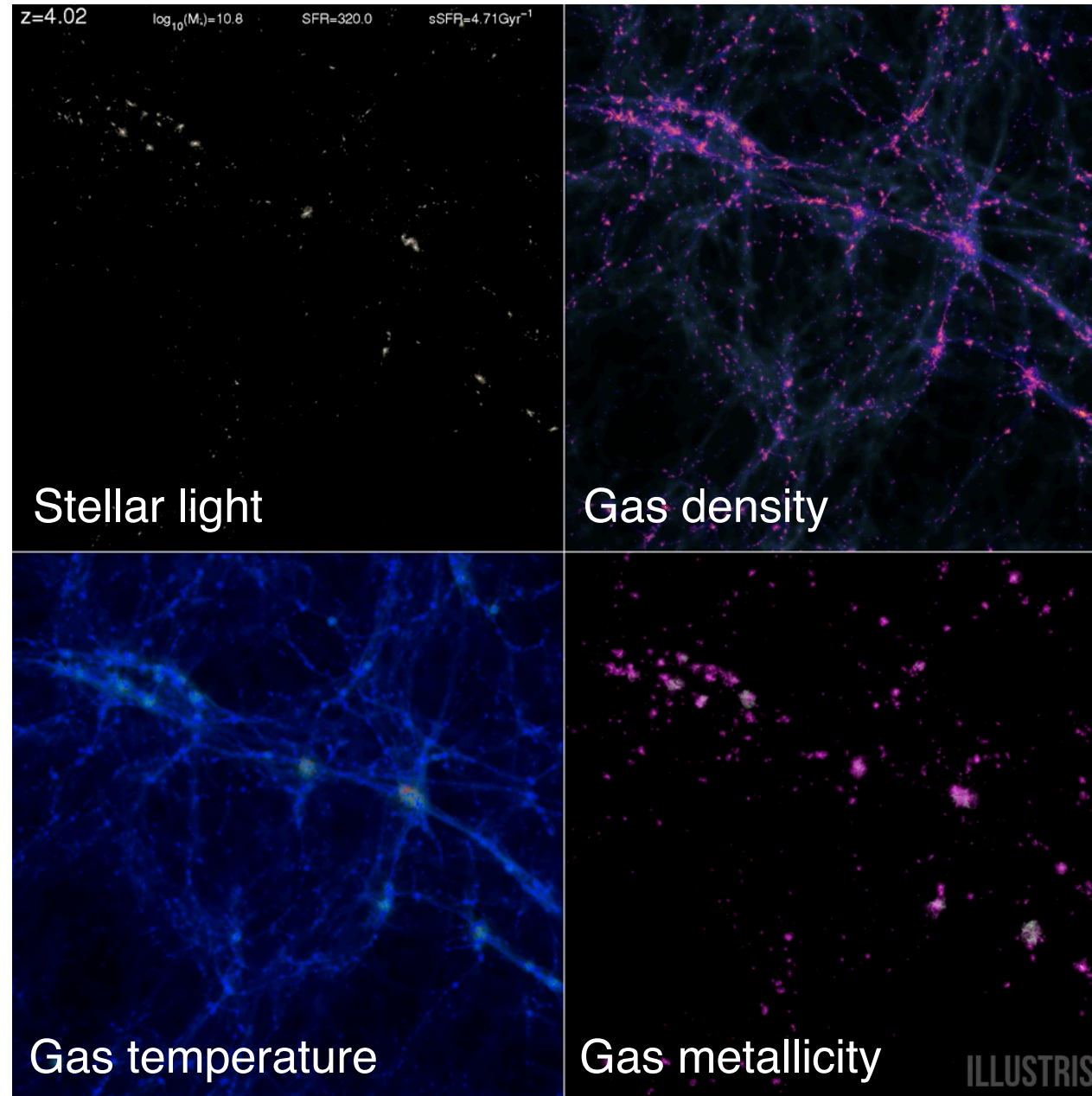
TK, Fluri, Schneider, Refregier, Stadel 2209.04662

- Baryon feedback effects change the distribution of dark matter on small scales
- Different approaches for modeling on the map level:
 1. Hydrodynamical simulations: very expensive, good realism
 2. Semi-analytical models: mid-expensive, reasonable realism
 3. Baryon Correction Model (BCM): doable, but limited realism
- No community consensus which hydrodynamical model is correct
- CosmoGridV1 uses BCM with broad parameter priors

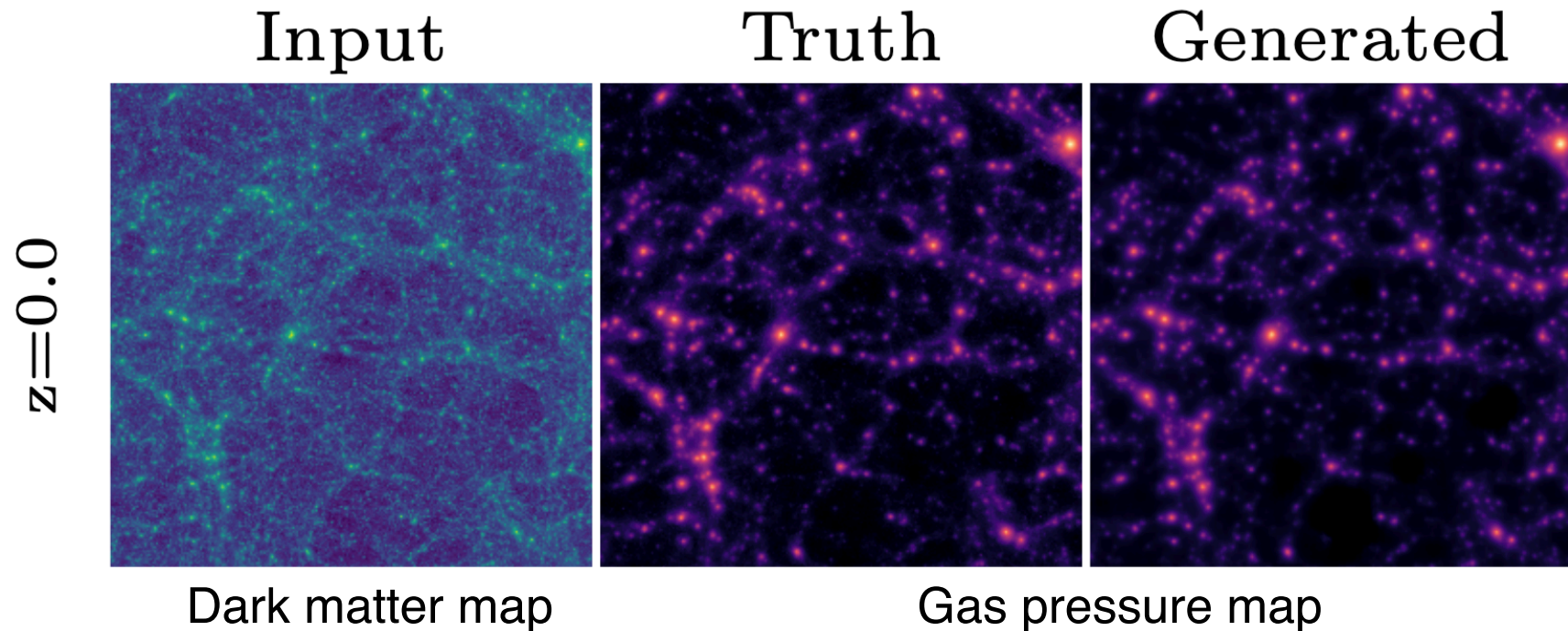


Multiple observables

- Large-scale structure is observable through different probes:
- 2D galaxy positions, dark matter distribution: optical surveys
- 3D galaxy positions: spectroscopic surveys
- Gas distribution and temperature: X-ray telescopes
- Galaxy colors: optical surveys
- CMB temperature and polarization: CMB telescopes



“Painting with baryons: augmenting N-body simulations with gas using deep generative models”



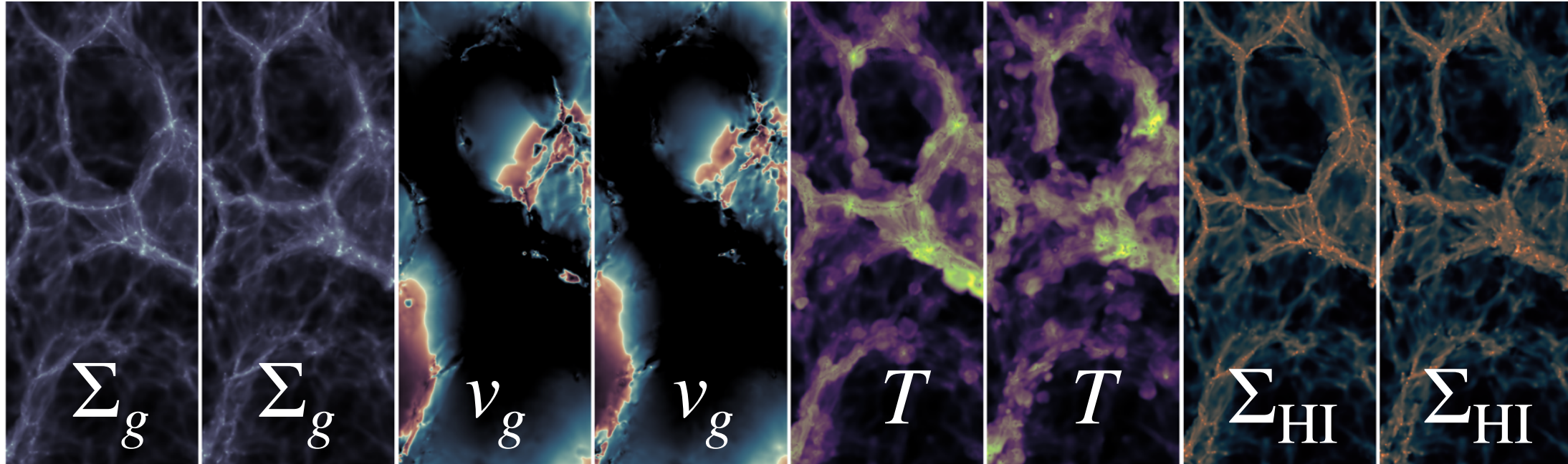
- Using expensive hydrodynamical simulations to create gas pressure maps for the corresponding dark matter maps
- Using Generative Adversarial Nets and Variational Autoencoders to create the gas pressure maps **based on the dark matter map only**

[Troester et al. 2019, 1903.12173](#)

Emulating baryons from dark matter across cosmic time with deep modulation networks

Sim

Emu



Σ_g Total gas surface density [$M_\odot / kpc^2$]

v_g Radial (i.e. line-of-sight velocity) of total gas [km/s],

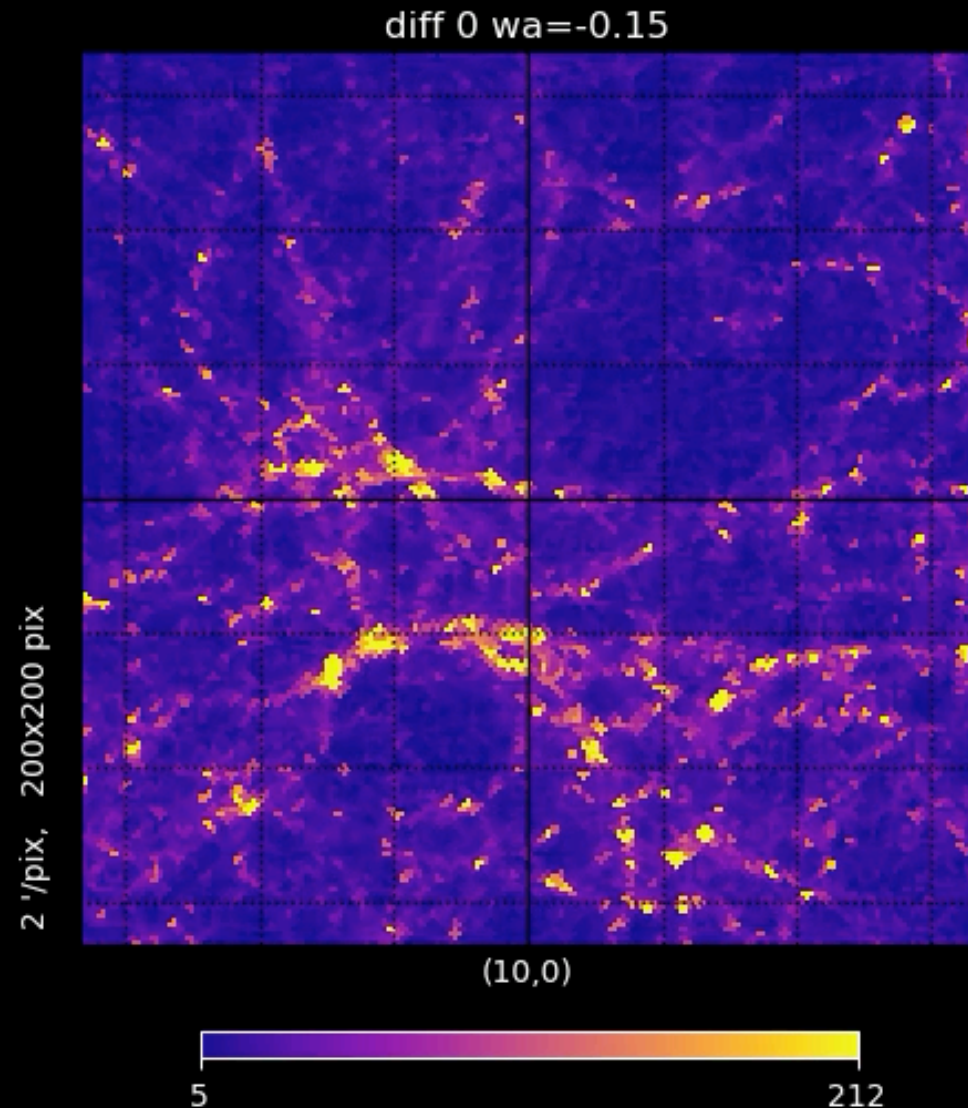
T Gas temperature [K],

Σ_{HI} HI surface density [$M_\odot/pc^2$]

Mauro Bernadrini et al, 2502.1587

Rapid testing of dark energy models on map-level

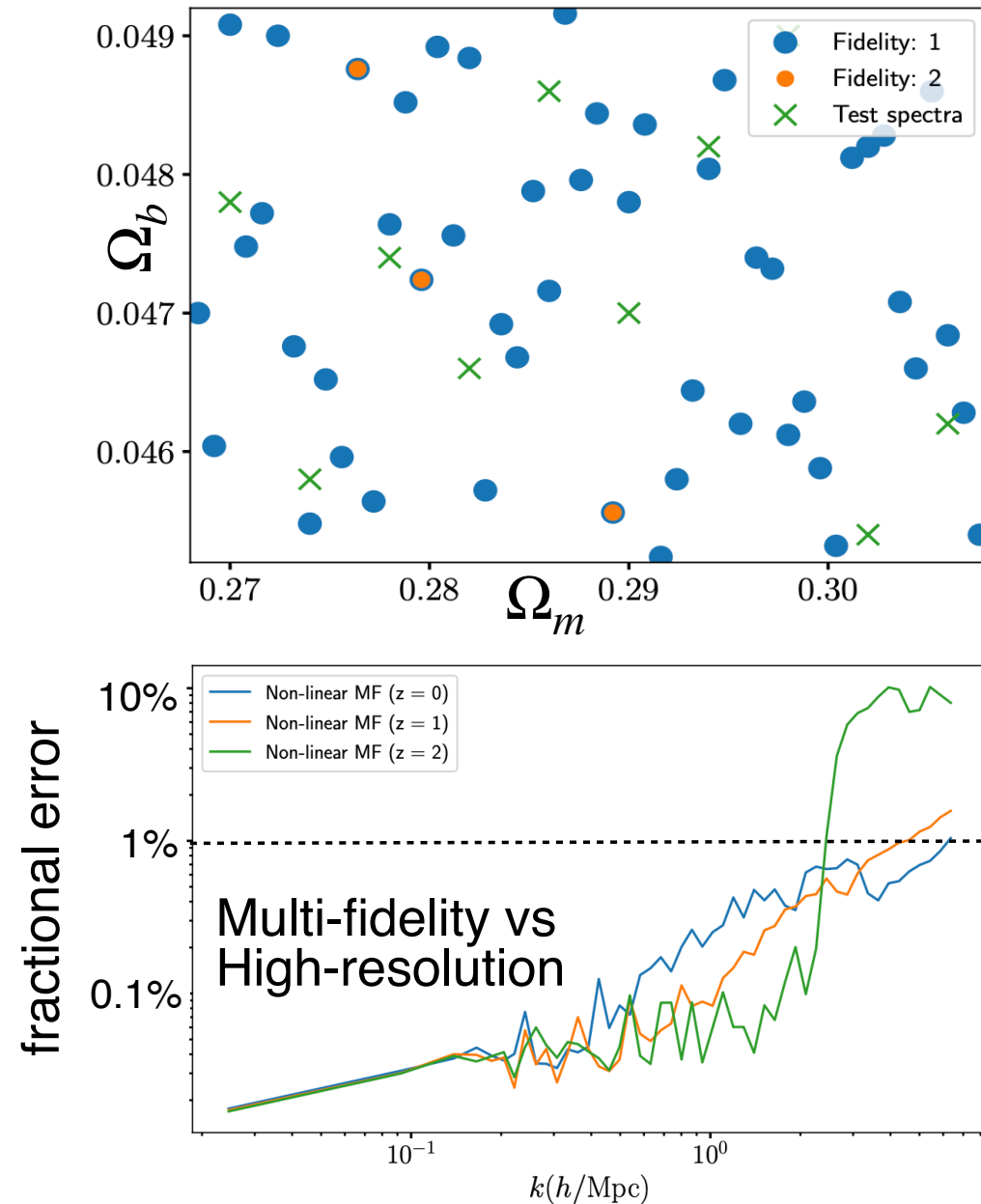
- “Exotic physics” simulations are quite expensive as we do as it is risky to invest engineering efforts to optimize their codes
- Solution: use generative AI model!
- Train a foundation model on standard cosmology simulations, e.g. CosmoGridV1
- Create a small number of “exotic physics” simulations with matched initial conditions
- Train a foundation model adapter to learn how to convert the “standard” to “exotic”
- Deploy adapter on the full grid
- Repeat for many “exotic” models, detect some with sufficient statistical significance
- In case of a detection, run full simulation grid with expensive simulations, if needed
- MSc project Noor Schepers



Data Science Challenge: simulations-based inference with multi-fidelity simulations

- Goal: build simulations for AI-based map-level inference that include realistic small scale effects
- Problem: small hydro-simulations are expensive, cosmological-scale hydro-sims are out of our current reach
- Idea: combine expensive small scale simulations with cheap large scale simulation
- This technique is called **multi-fidelity** and has recently been demonstrated on the level of summary statistics (power spectra)
- **Challenge:** build AI systems that can learn from small-scale simulations and correctly “augment” large scale simulations and produce consistent probe maps for SBI
- Possible answers: foundation models

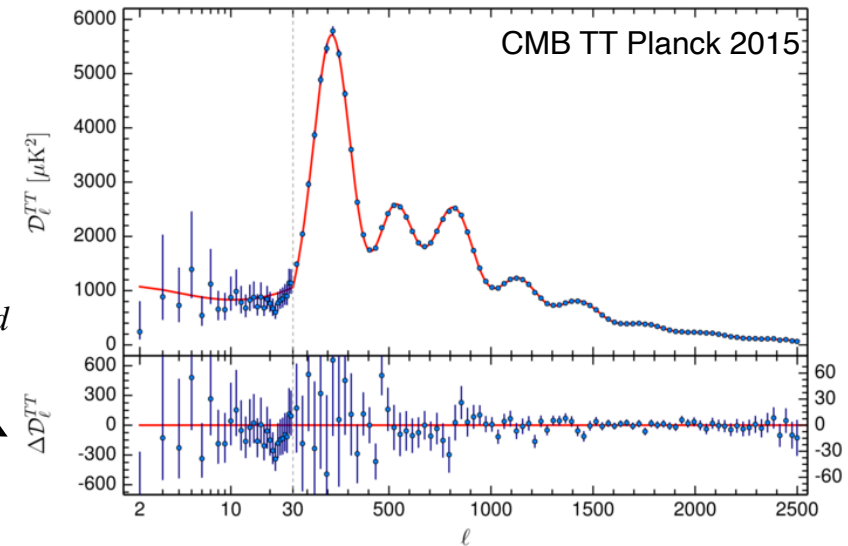
MF Ho, Bird, Shelton 2021 2105.01081



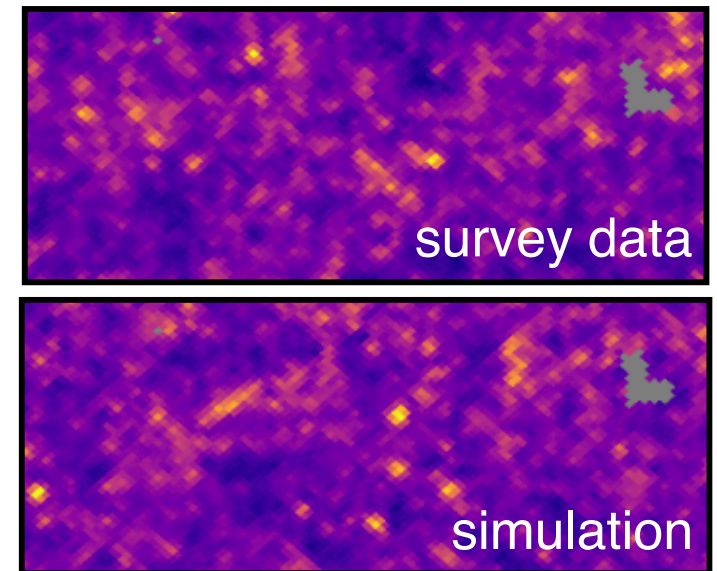
Data Science Challenge: map-level goodness of fit

- Goal: simulations-based inference without bias stemming from a wrong simulation model
- In traditional inference with summaries, simple metrics exist to quantify this, simplest being the reduced χ^2
- Problem: how to evaluate goodness of fit for a 1m-dimensional map vector
- No established methods existing yet
- Possible approach: decompose data and check stability of results:
 - different areas of the survey
 - scale decomposition: naturally included in normalizing flows (Dai Seljak 2023 2306.04689)
- Another proposed method: foundation models

Distribution of residuals tells us about goodness of fit, for example χ^2_{red}



How to quantify goodness of fit for stochastic maps?



Practical Application of AI Foundation Models for LSS Cosmology

Modify simulations
with baryon
feedback

Modify simulations
to include new dark
energy models

Constrain
cosmological
parameters from
projected probes

Predict simulations
across modalities:
e.g. dark matter $\rightarrow$
gas temperature

Create goodness-of-
fit maps of the
measured maps

Multi-fidelity, multi-
resolution stitching

