Artificial Intelligence: a game-changer for large scale structure cosmology

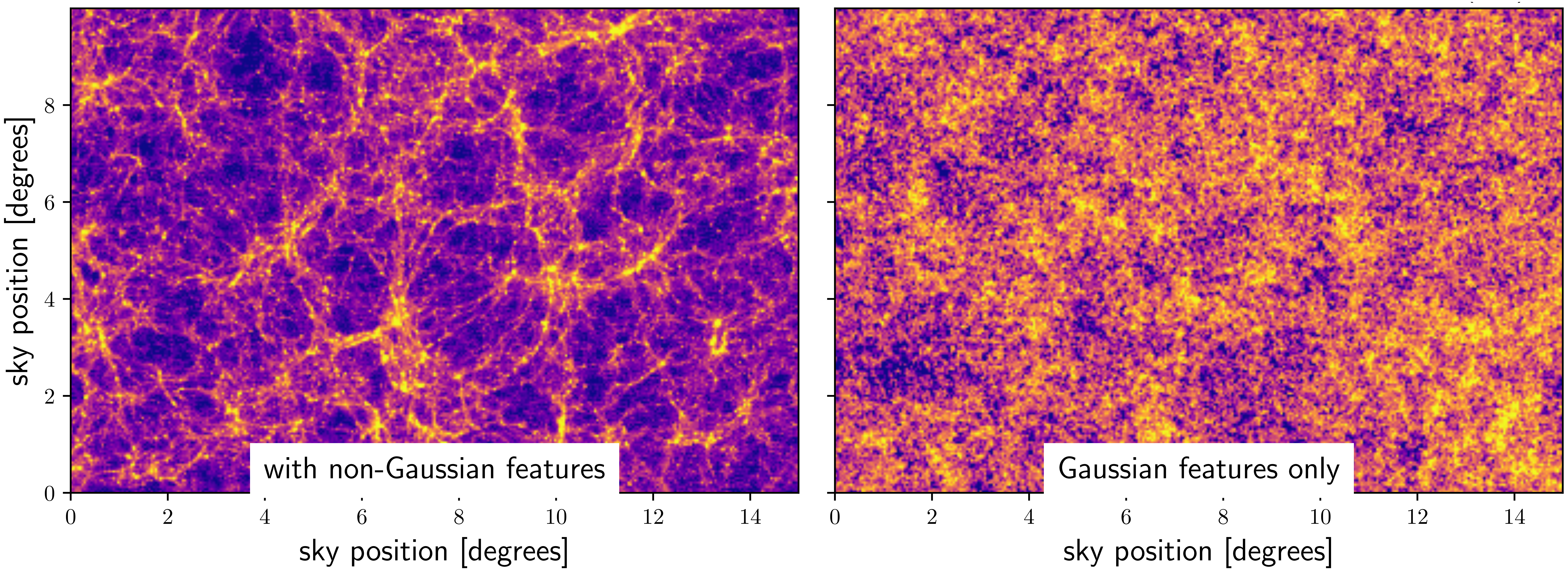
Tomasz Kacprzak (ETH Zurich, Swiss Data Science Center), AstroDeep22, 22/06/2022

Large scale matter distribution in the universe

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

The Millennium Simulation

Large Scale Structure is highly non-Gaussian

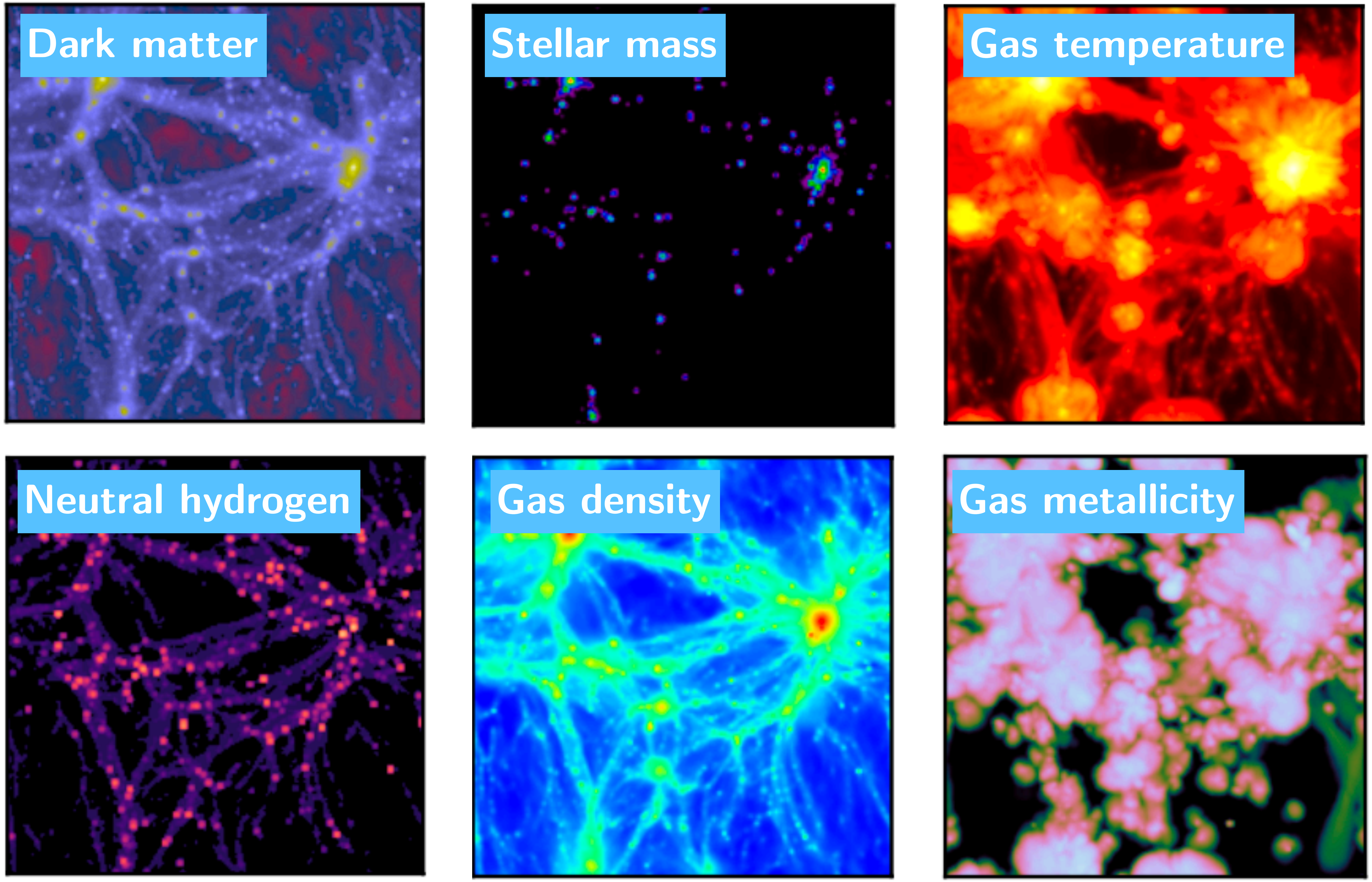


N-body simulation slice

Gaussian Random Field with the same power spectrum as the N-body slice

these maps have the same power spectra

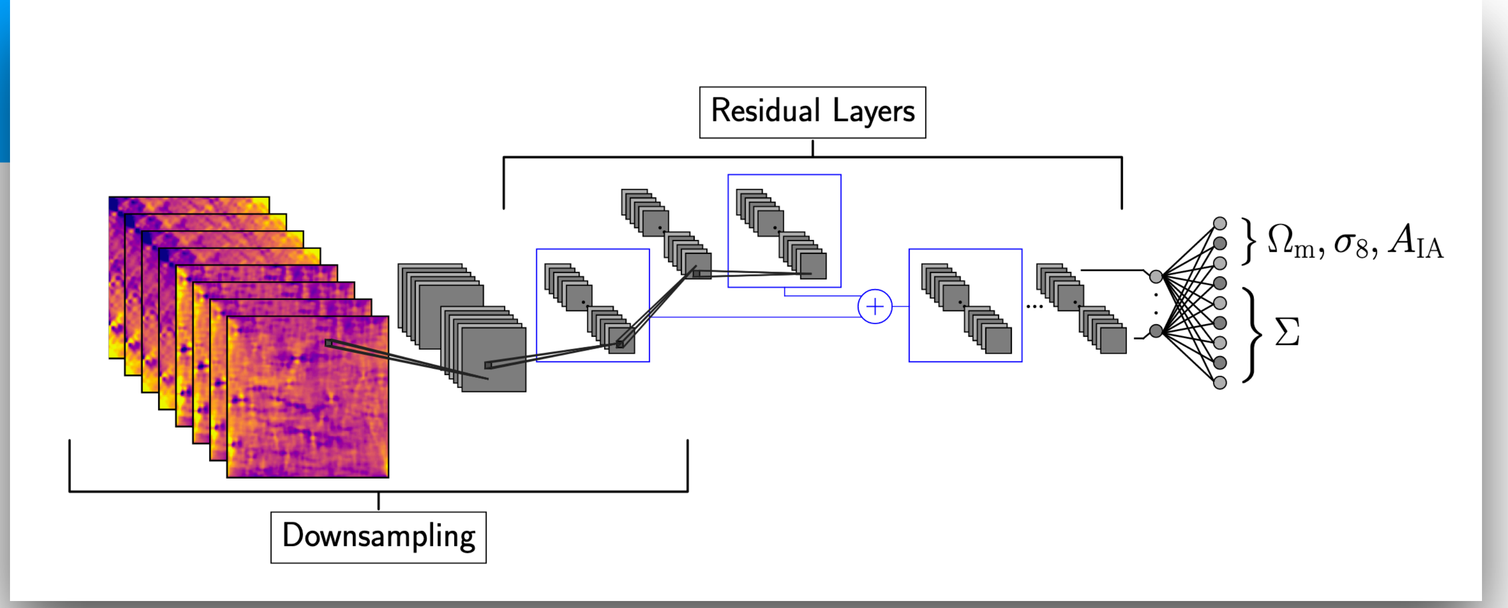
LSS data consists of multiple filelds probed by different observables



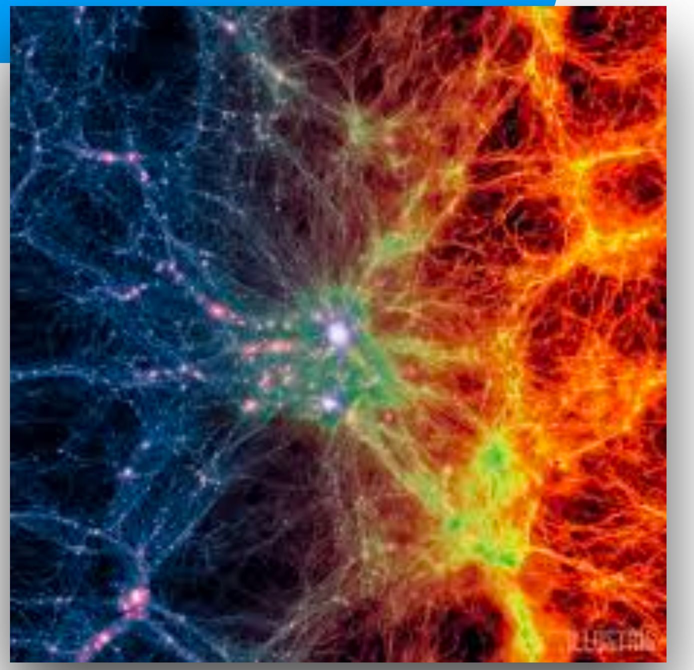
Illustris TNG, Villaescusa-Navarro et al. 2021 2010.00619

How can AI open new possibilities in cosmological analysis of LSS?

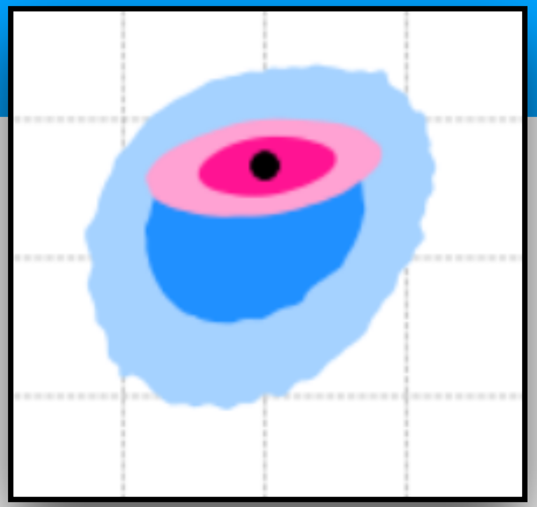
Reaching the information floor of the data



Accelearating simulations



Breaking degeneracies between cosmology and systematics



How can AI open new possibilities in cosmological analysis?

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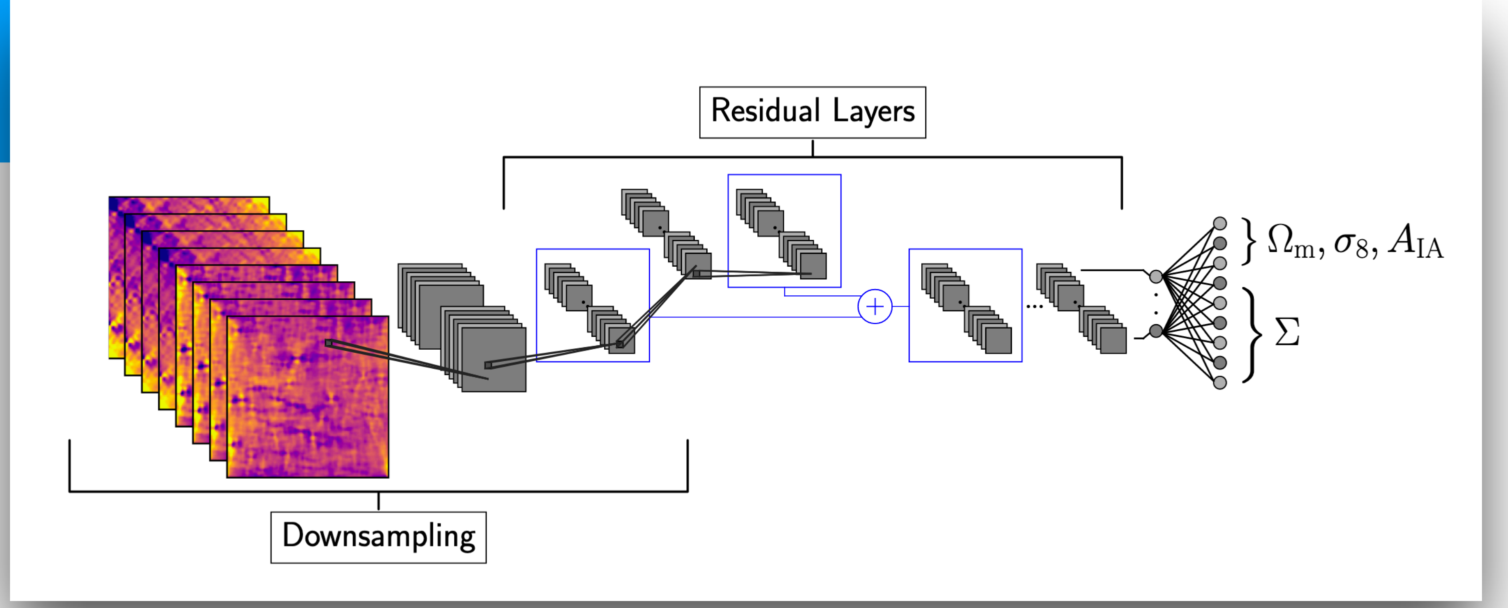

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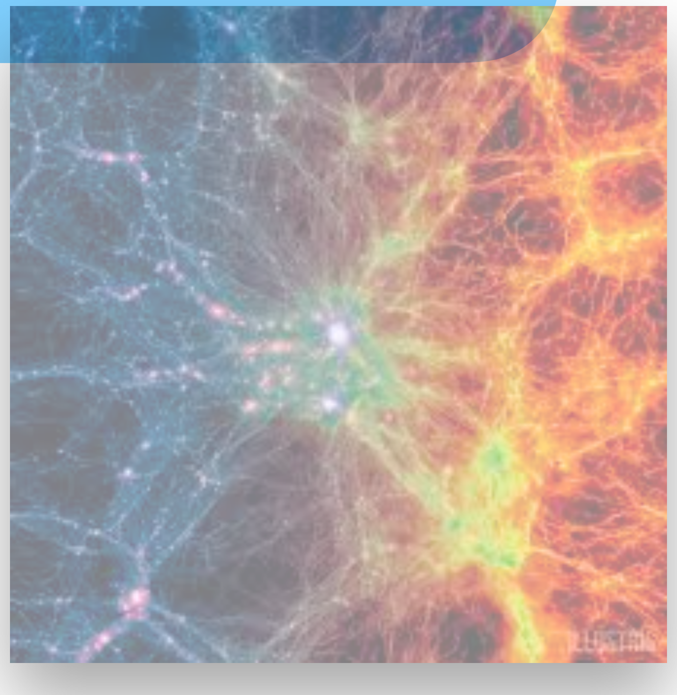

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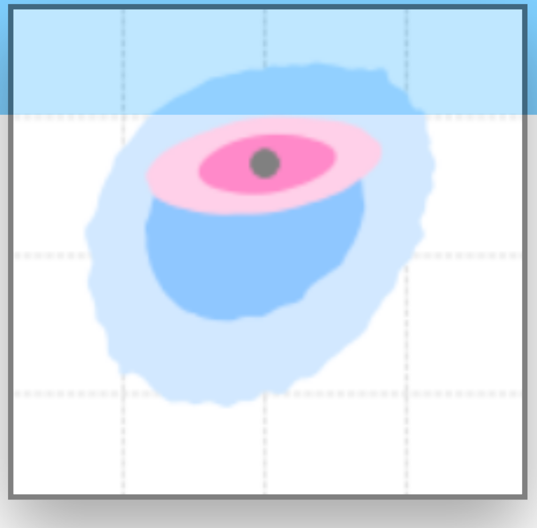
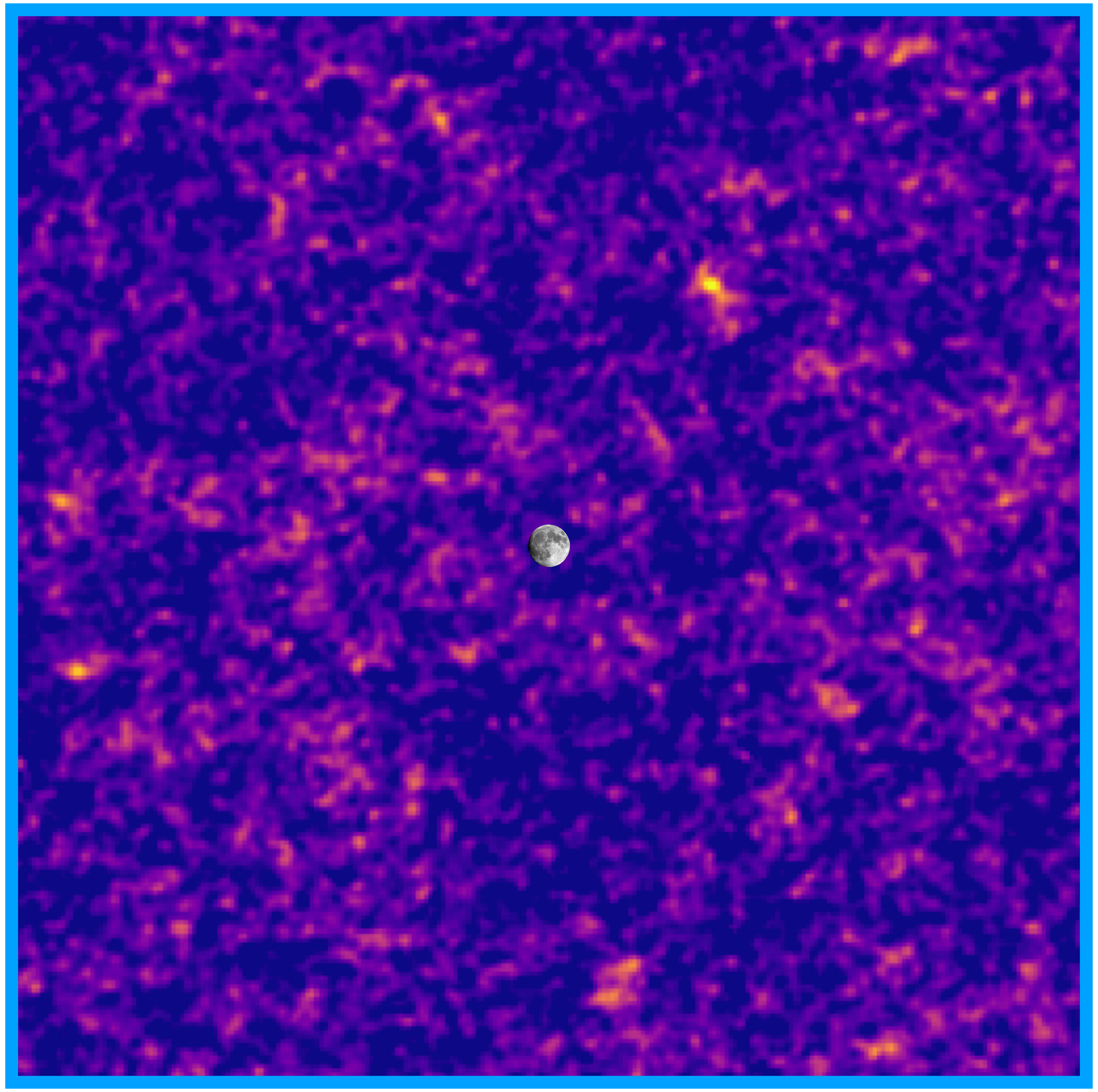
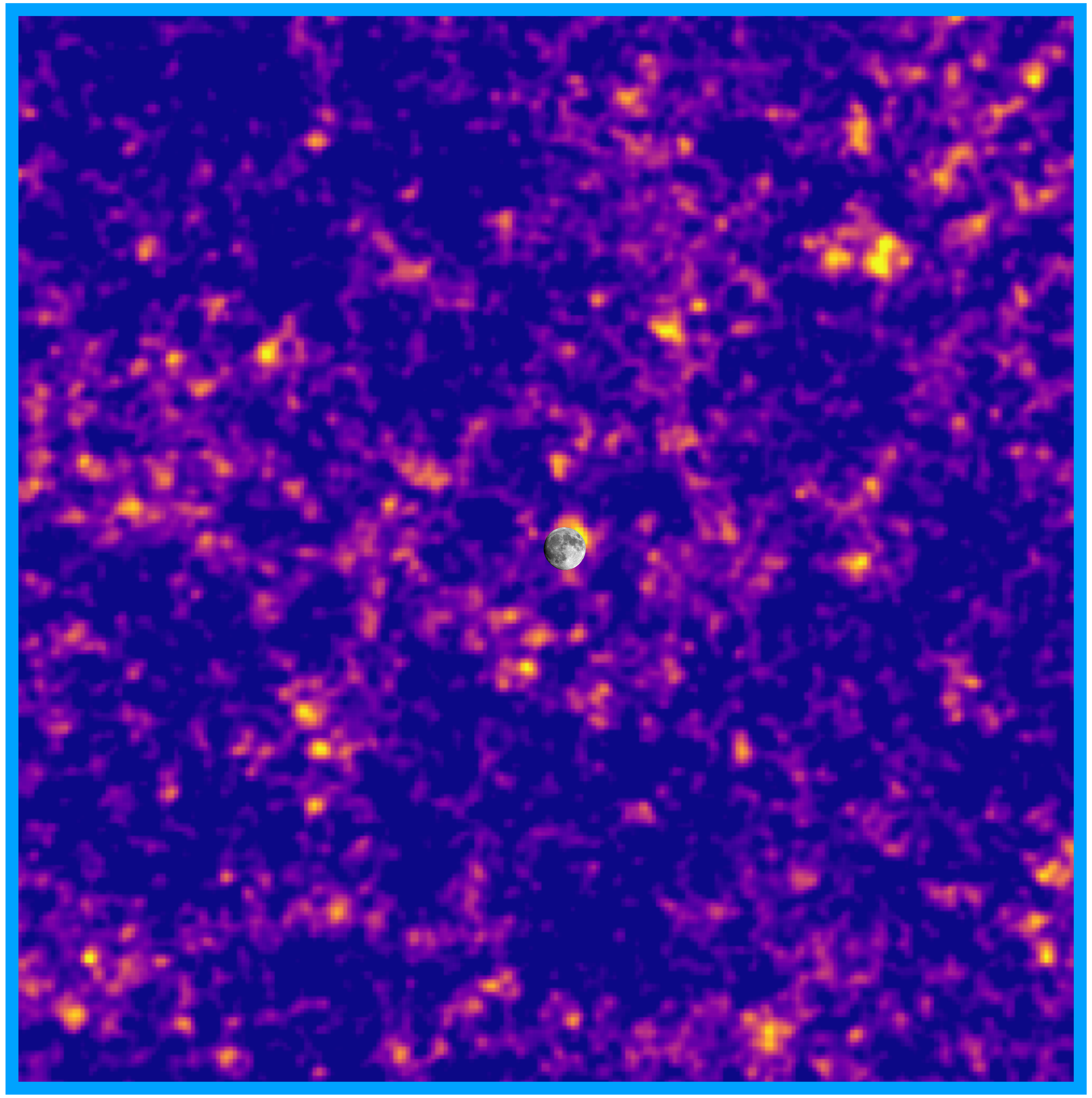


Dark matter mass maps carry information about cosmological parameters

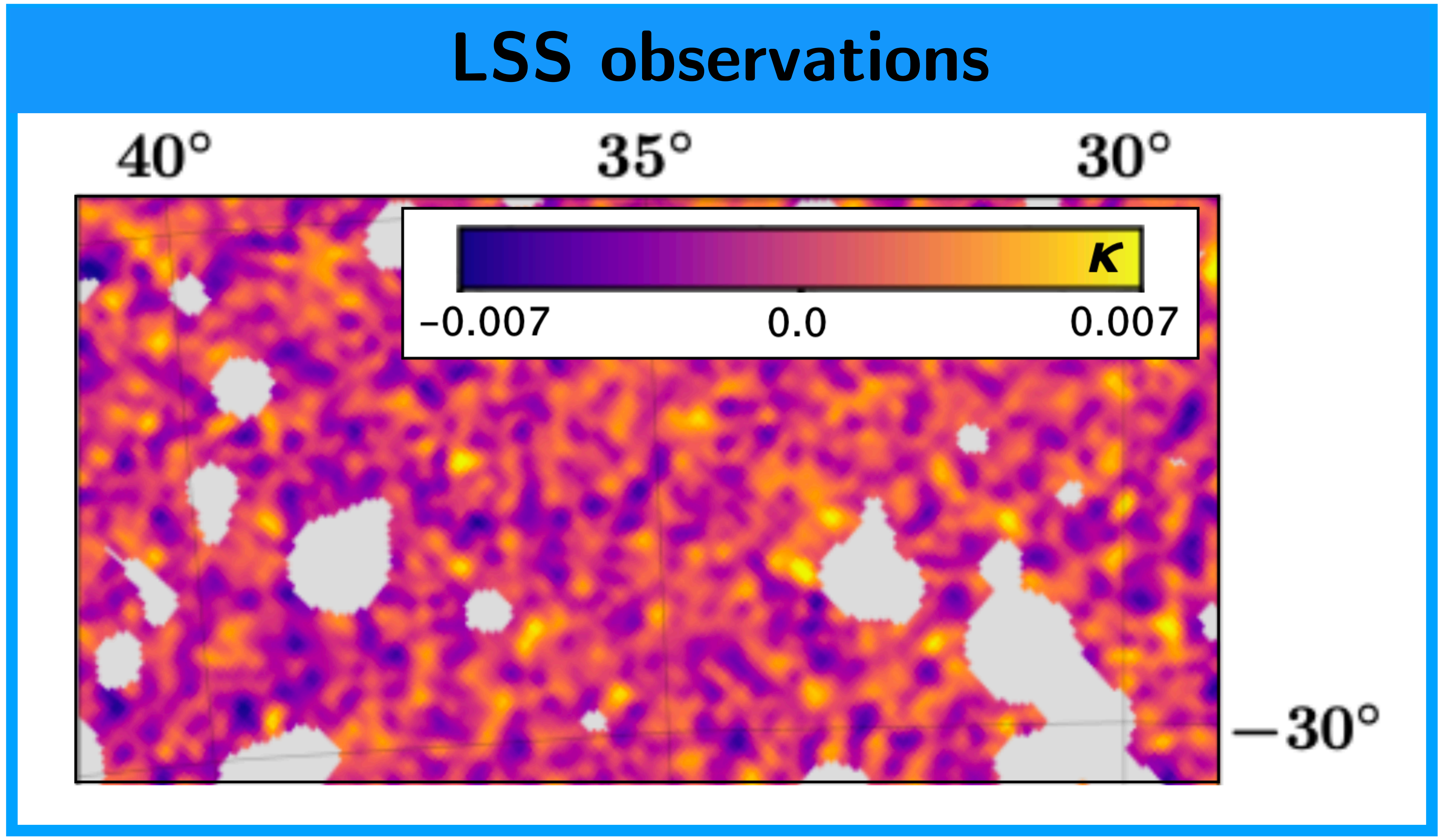


low σ_8 low Ω_m



high σ_8 high Ω_m

Cosmological parameter inference

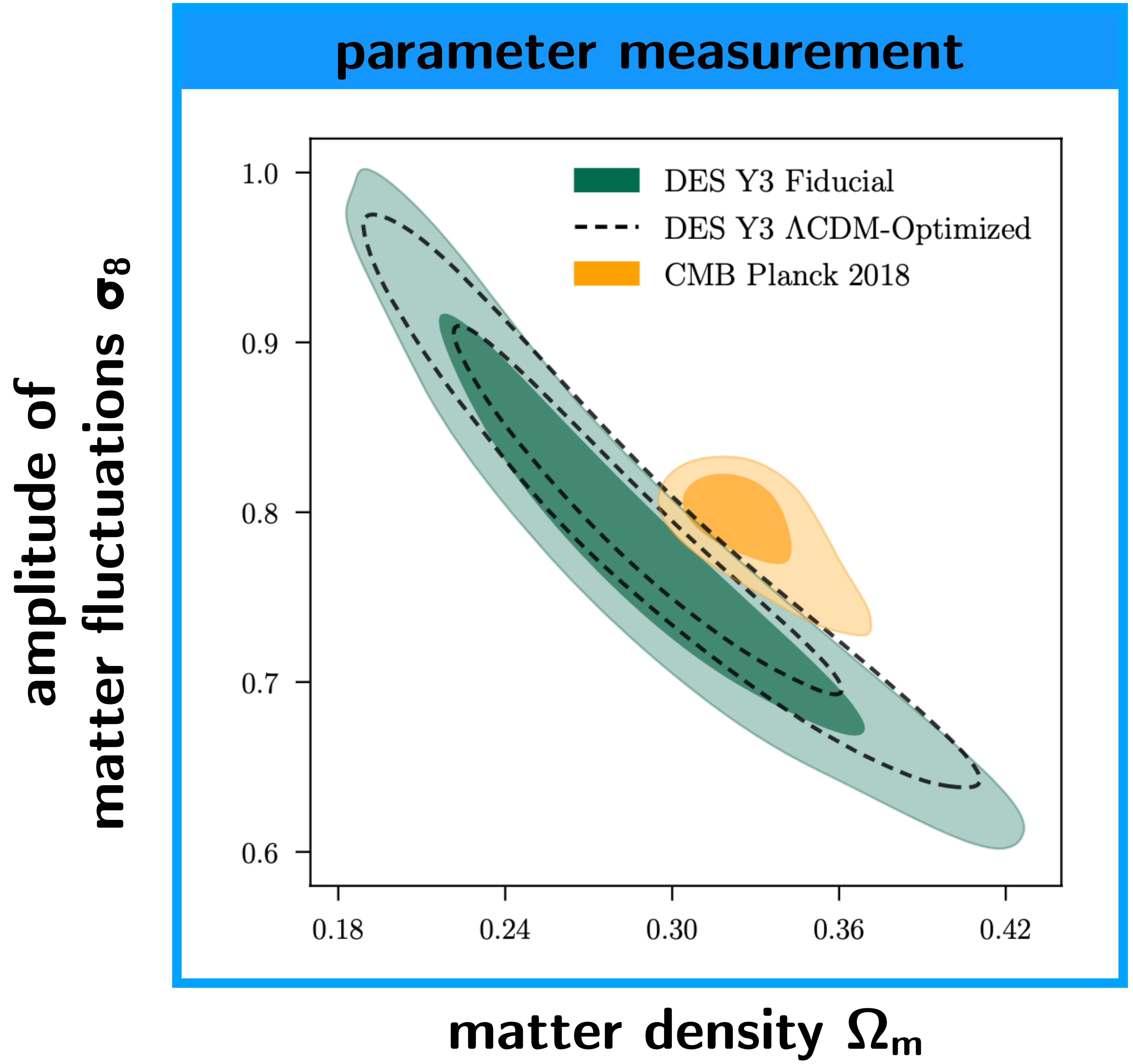


Zuercher, +TK, +DES, 2110.10135

Assume a model with parameters

Assume priors on parameters

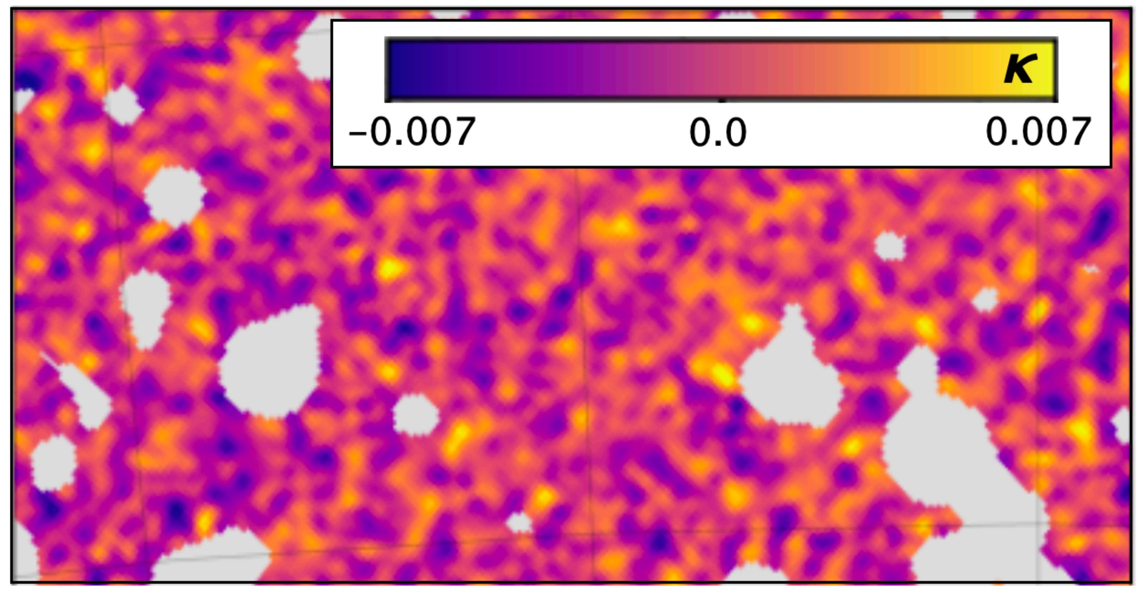
Compare with observations



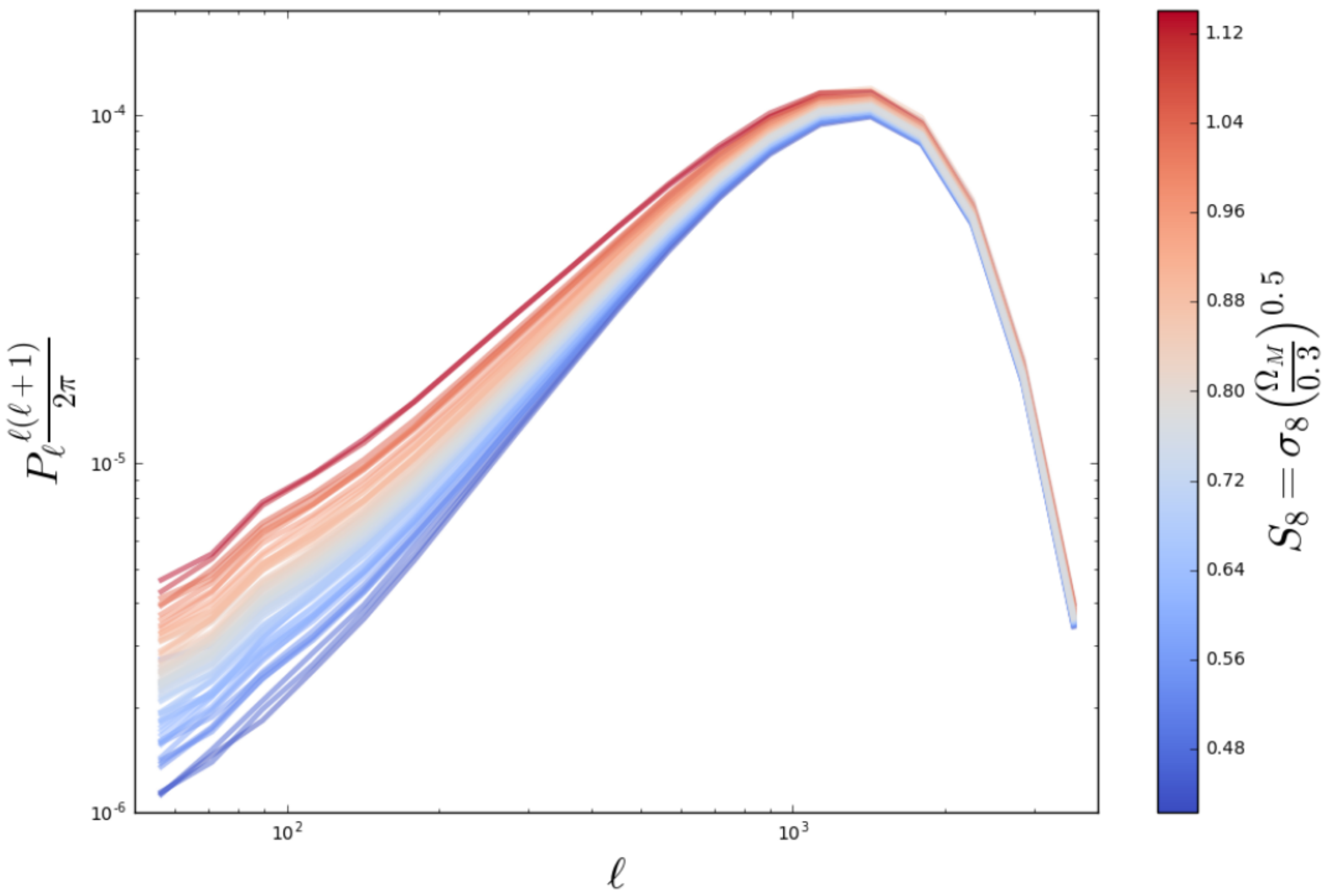
Secco, +DES. +TK, 2105.13544

Traditional inference

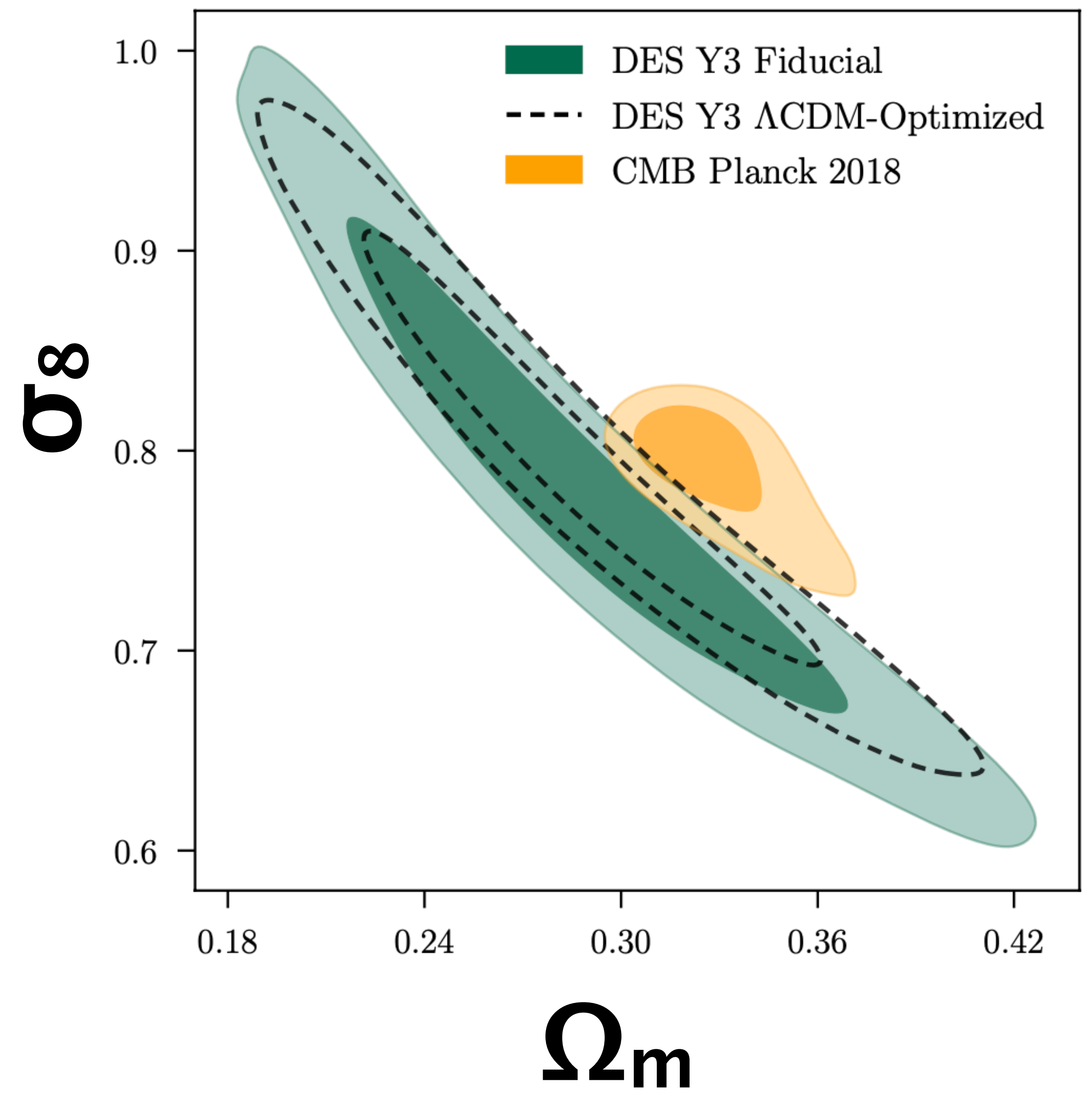
LSS observations



statistics: 2pt functions



parameter measurement



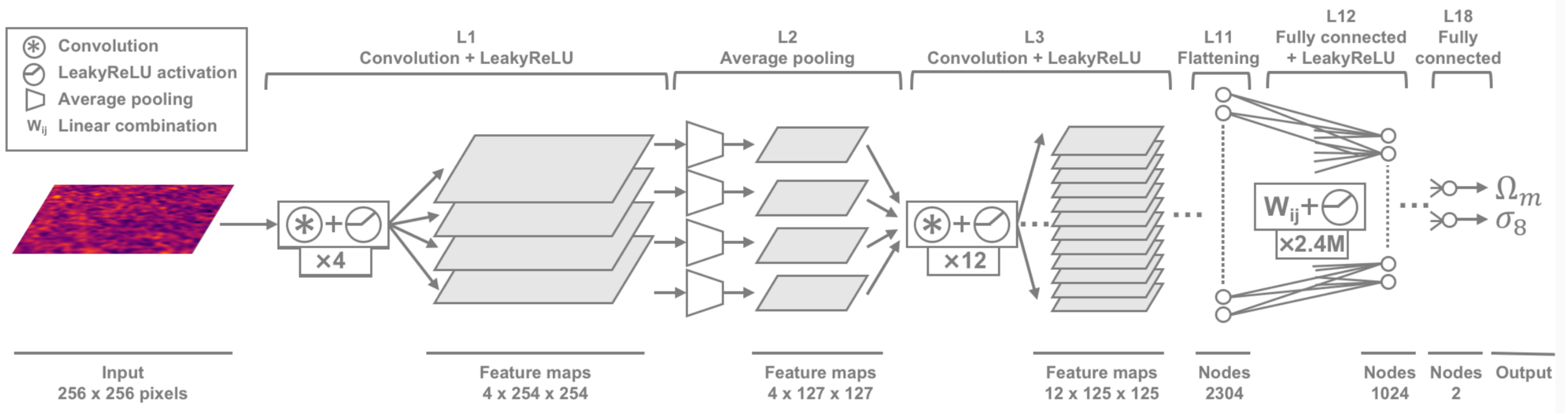
$$C_l = \frac{9}{16} \left(\frac{H_0}{c}\right)^4 \Omega_m^2 \int_0^{\chi_h} d\chi \left[\frac{g(\chi)}{ar(\chi)}\right]^2 P\left(\frac{l}{r}, \chi\right)$$

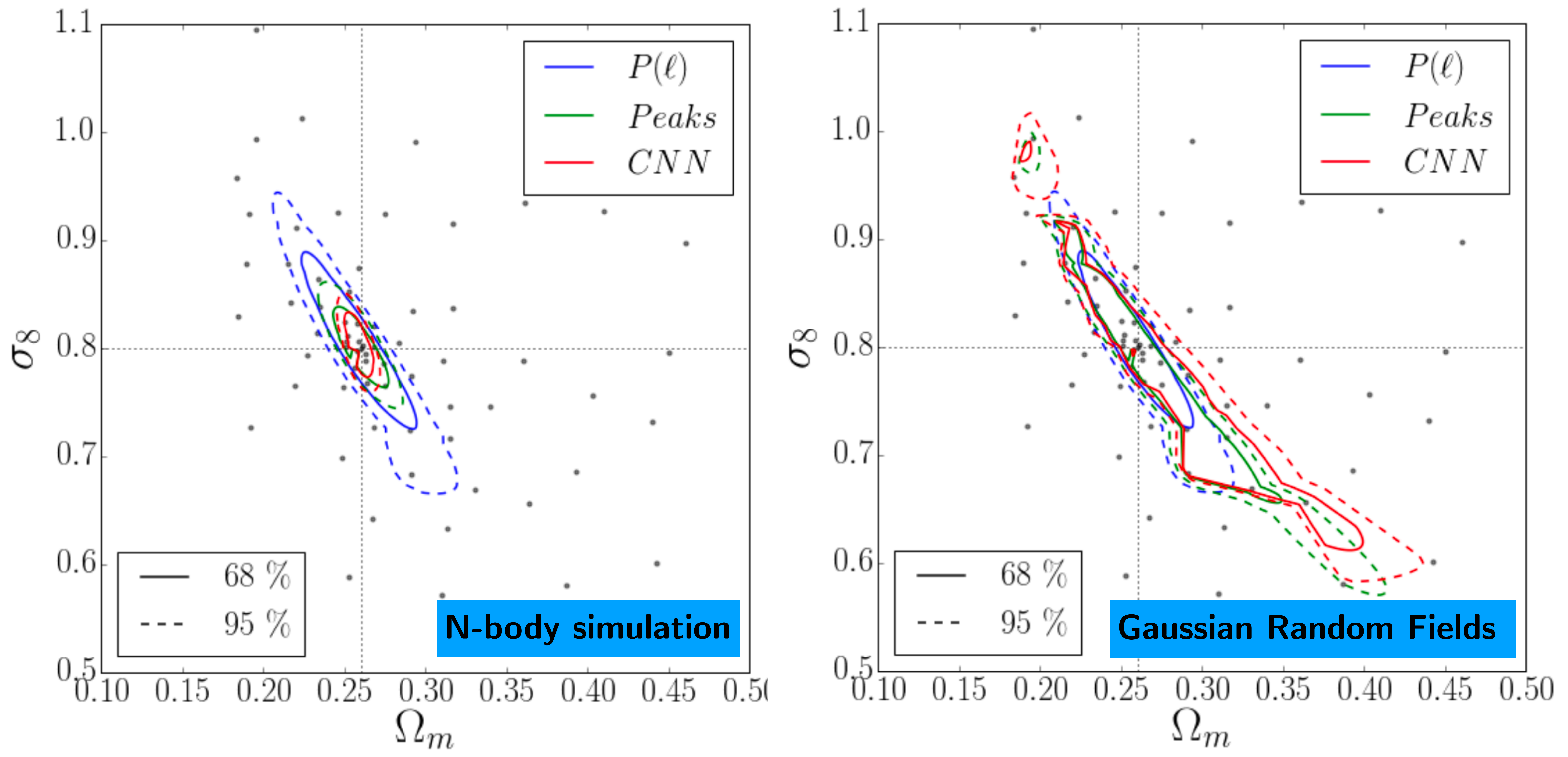
theory prediction: analytical


Inference with Deep Learning
LSS observations
κ
−0.007
0.0
0.007
statistics: deep convolutional network
16x
32x
64x
128x
256x
1024x
256x
5x
Convolutions
Fully Connected
theory prediction: simulations
...
parameter measurement
DES Y3 Fiducial
DES Y3 ΛCDM-Optimized
CMB Planck 2018
σ8
Ωm
1.0
0.9
0.8
0.7
0.6
0.18
0.24
0.30
0.36
0.42

First results for CNN vs 2-pt

- First application of CNNs to weak lensing maps by Schmelzle, +TK, et al. 2017 1707.05167, for a classification problem
- First comparison between CNN and 2-pt by Gupta et al. 2018 1902.03663, noise-free N-body sims
- Greatly improved precision by CNN vs 2-pt
- Same results for CNN as for 2-pt for Gaussian Random Fields → reassuring!



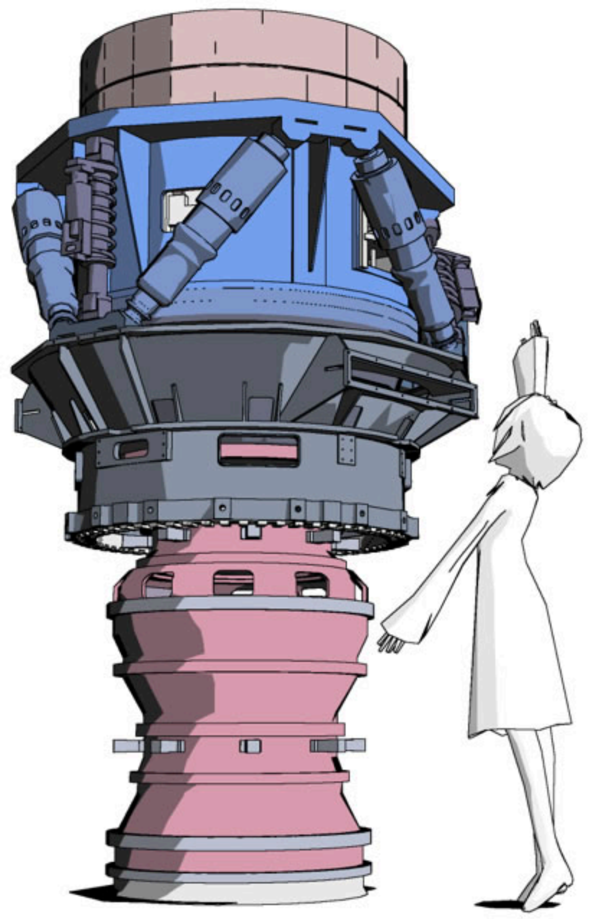


Gupta et al. 2018 1902.03663

How much more information can we gain with deep learning for Stage-III and Stage-IV surveys?

DARK ENERGY SURVEY

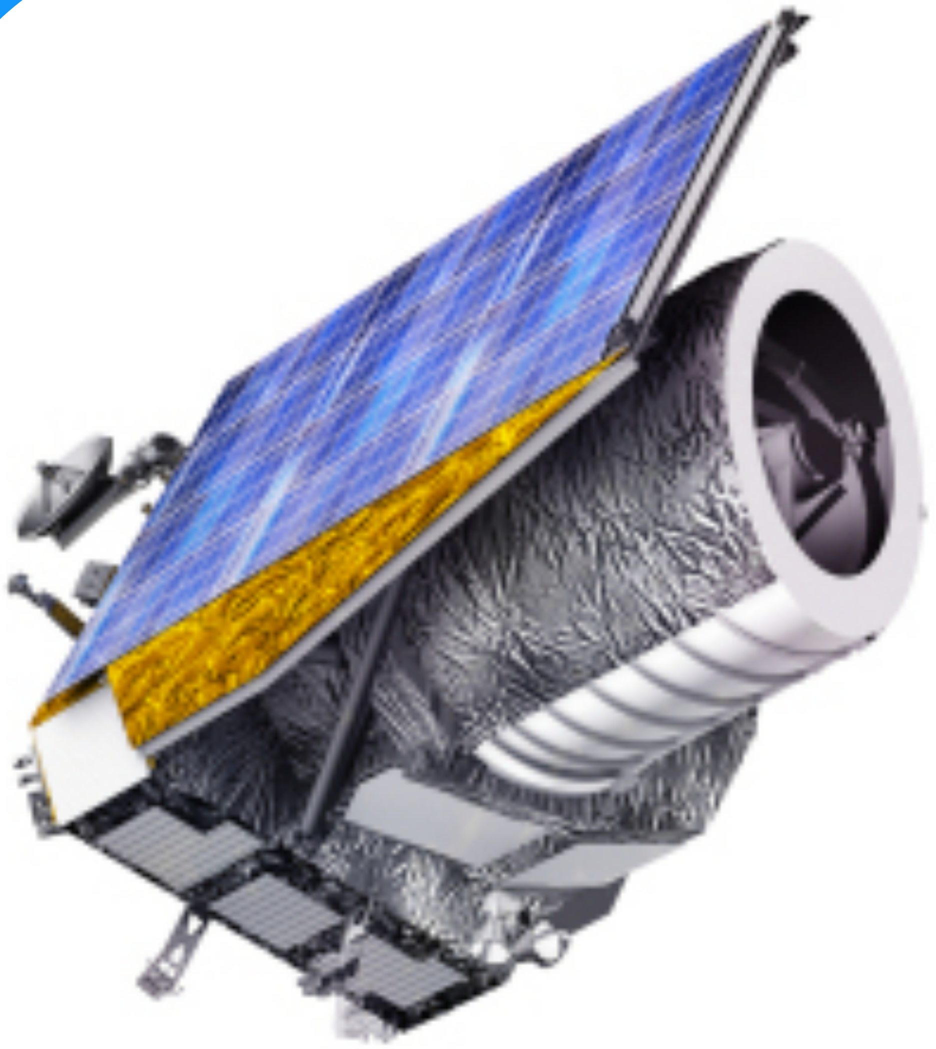
Stage III



Hyper Suprime Cam

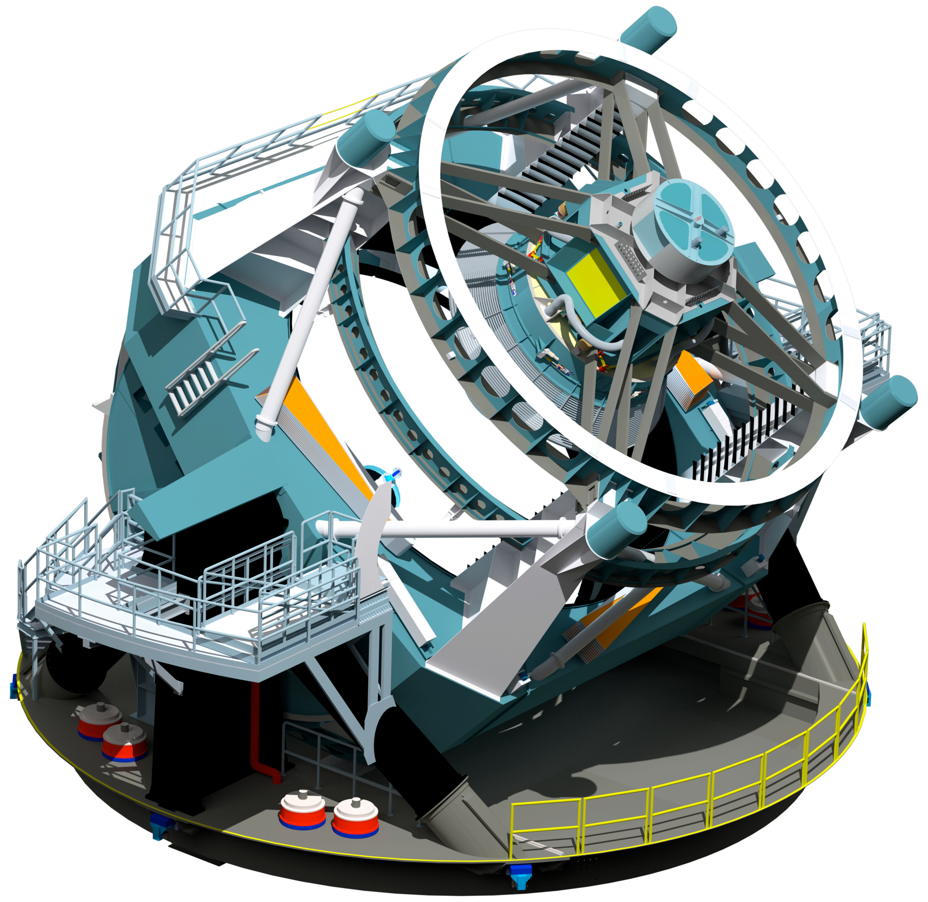
KiDS

Kilo Degree Survey



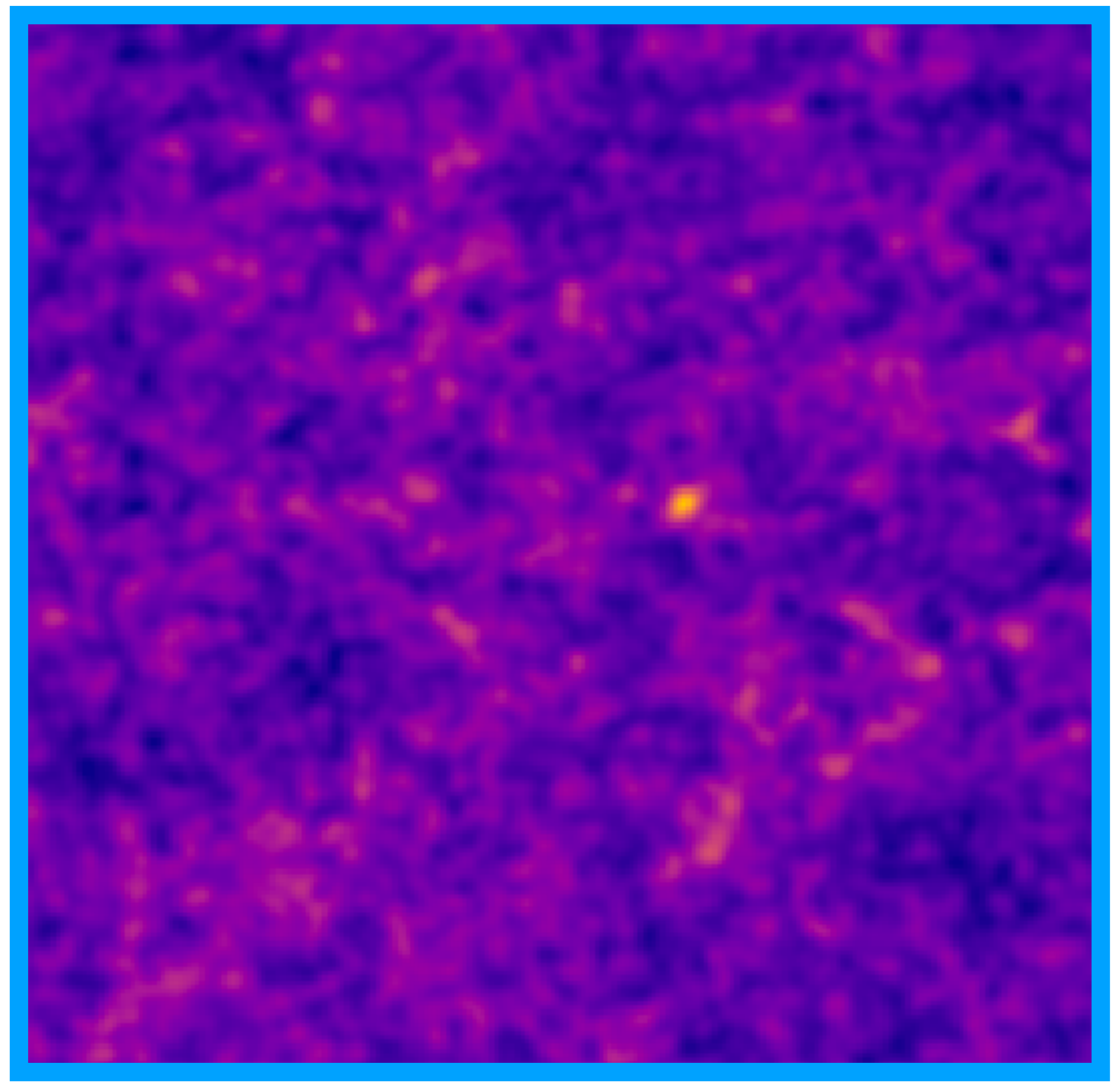
Euclid

Stage IV



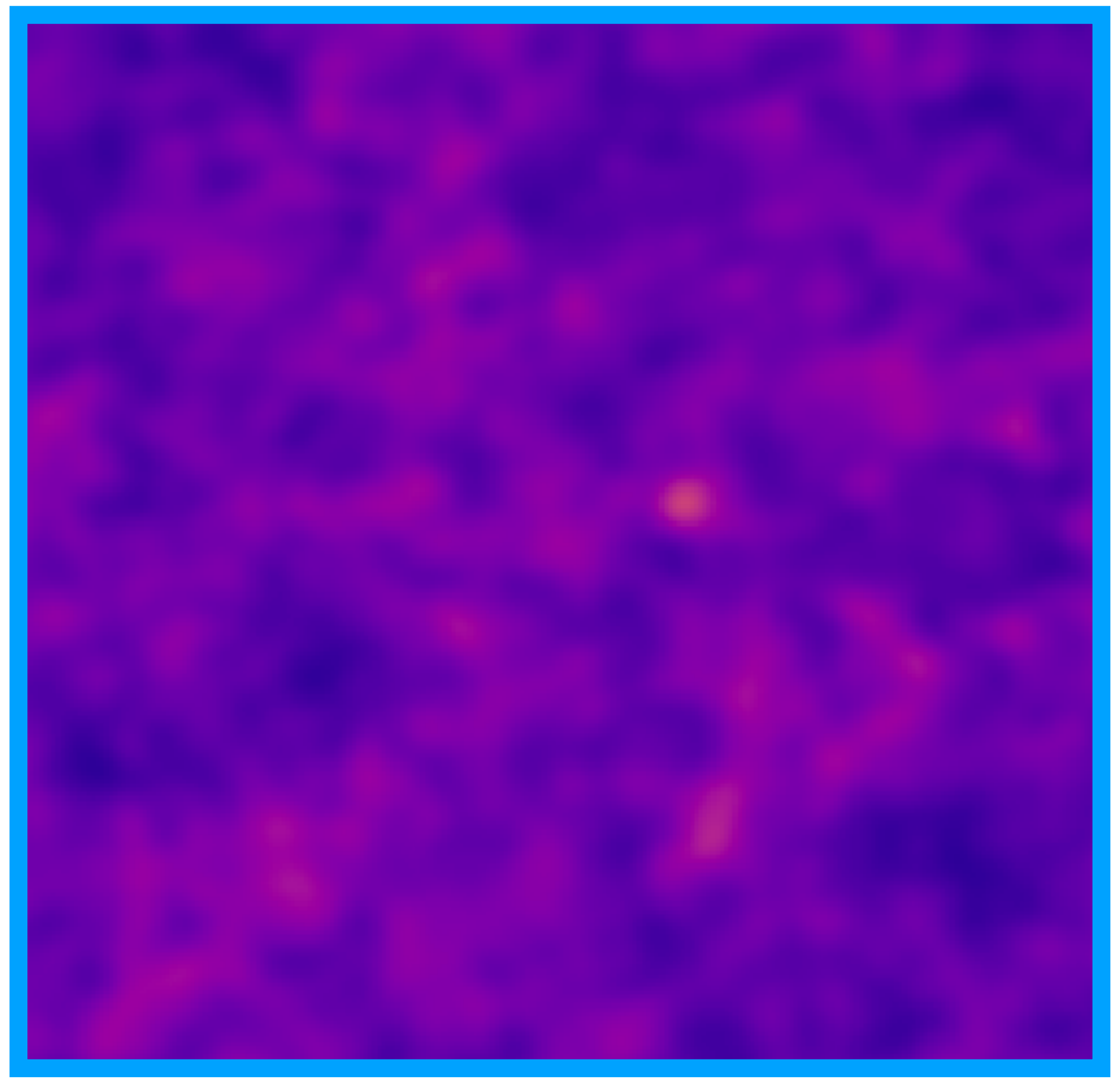
Rubin/LSST

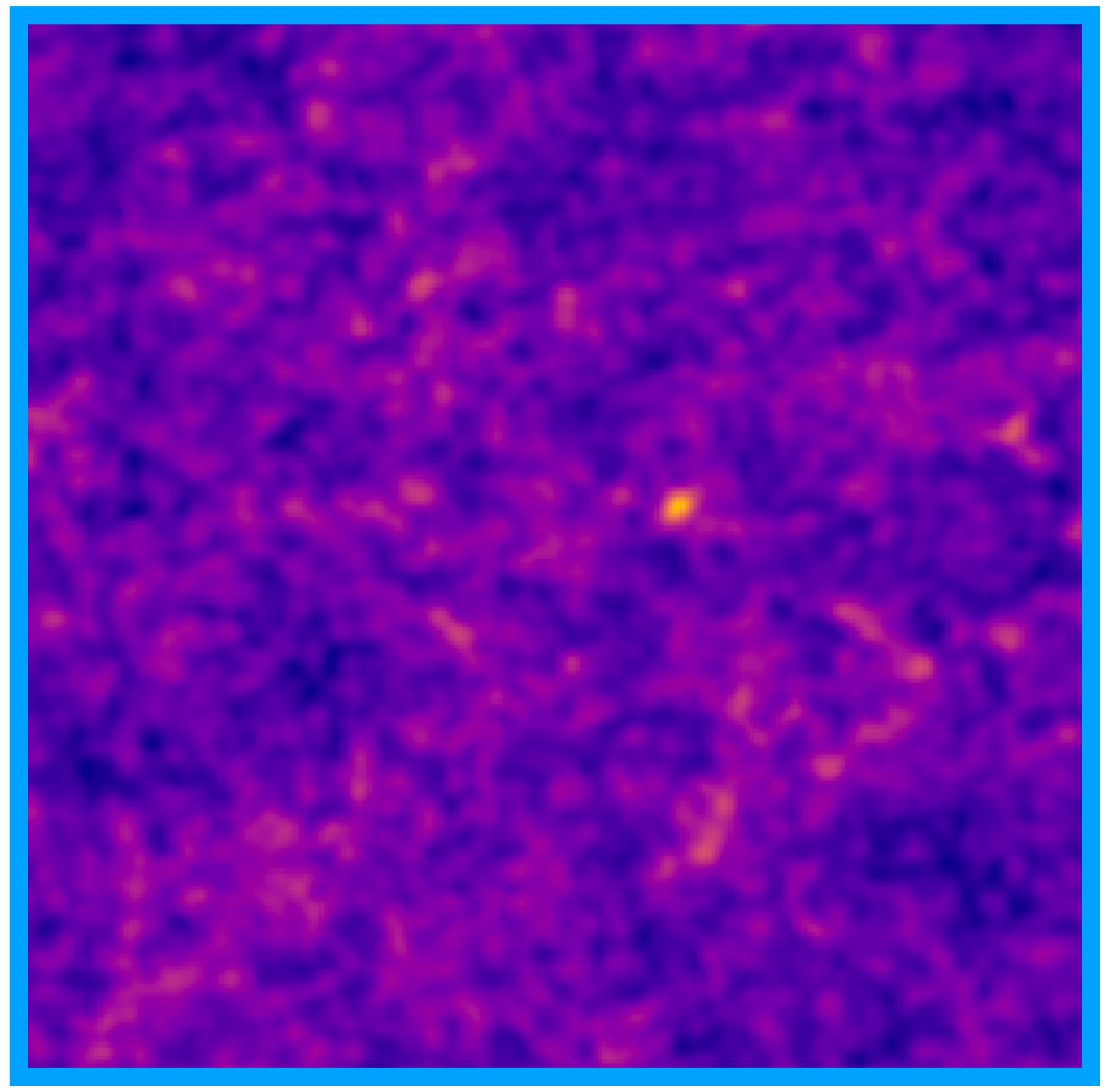
What is the advantage of deep learning for current and upcoming data?



add smoothing →

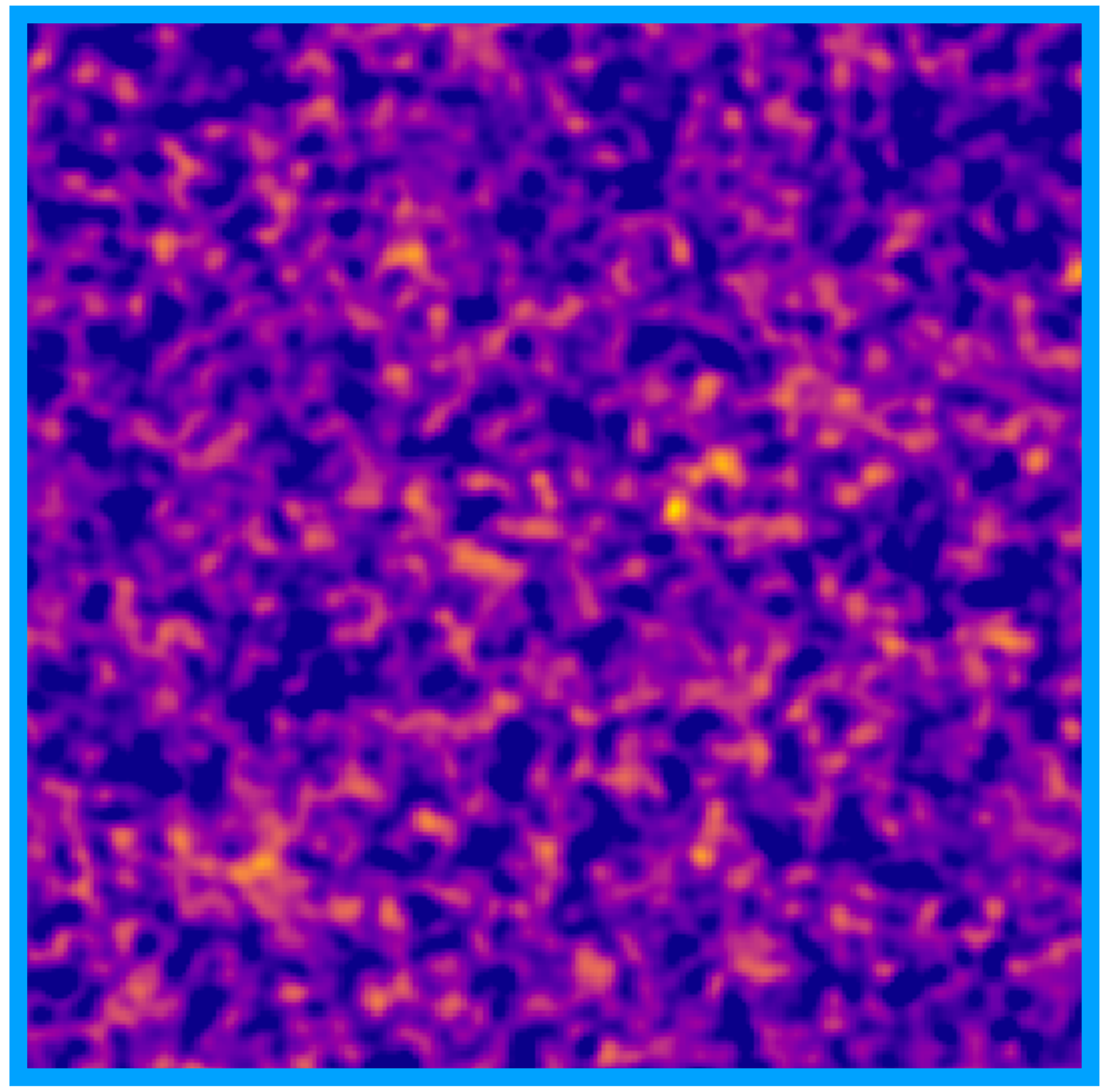
quality of
simulations





add noise →

quality of
observations



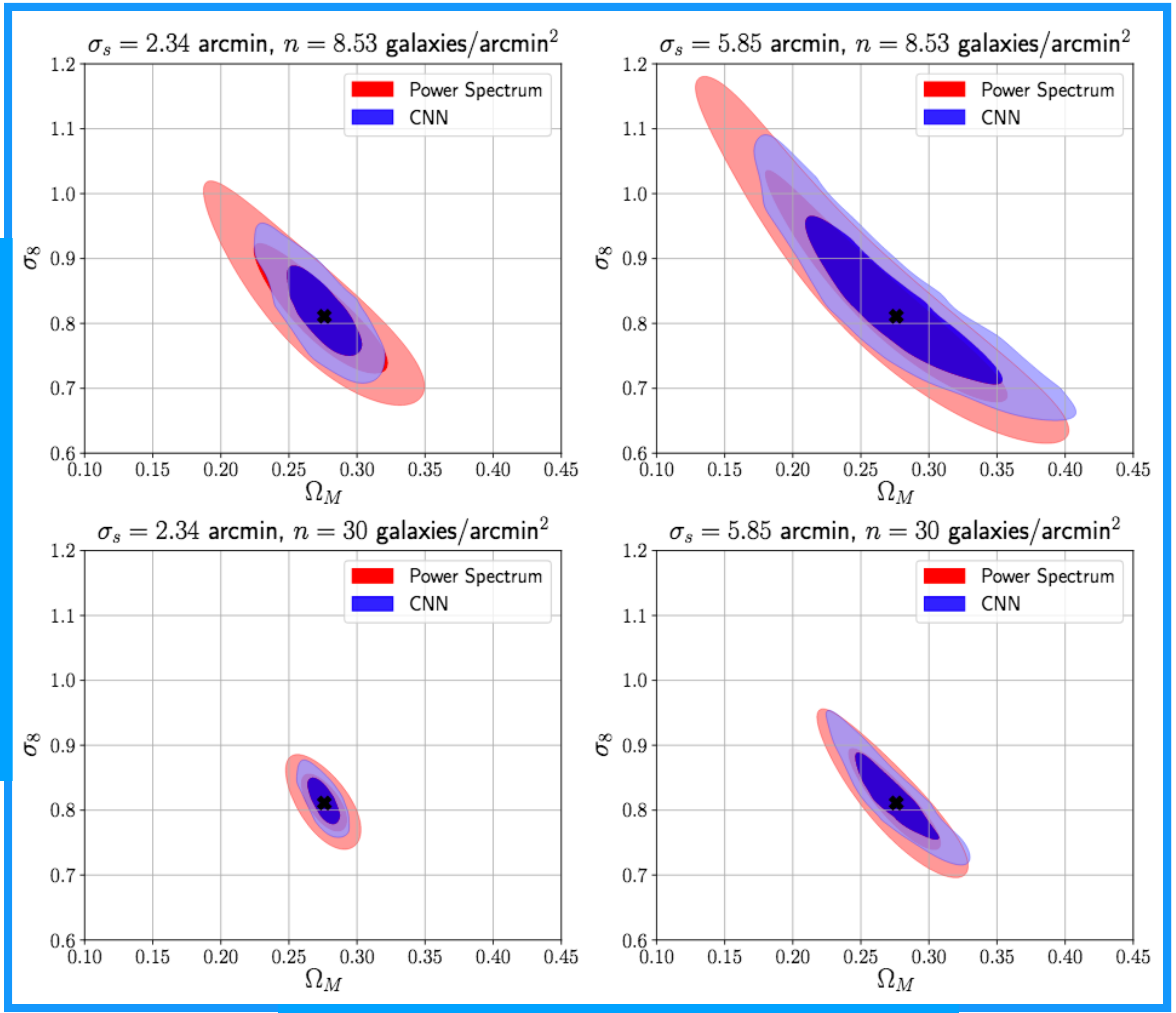
What is the advantage of deep learning for current and upcoming data?

- The advantage of deep learning is preserved for high noise levels
- Advantage of deep learning starts at intermediate scales, around ell < 1000
- This is the regime already affected by baryonic feedback
- The advantage increased greatly if small scales included

DES/KiDS

Euclid/Rubin

increase noise →



increase smoothing→

intermediate scales

large scales

Fluri, TK, et al. 1807.08732

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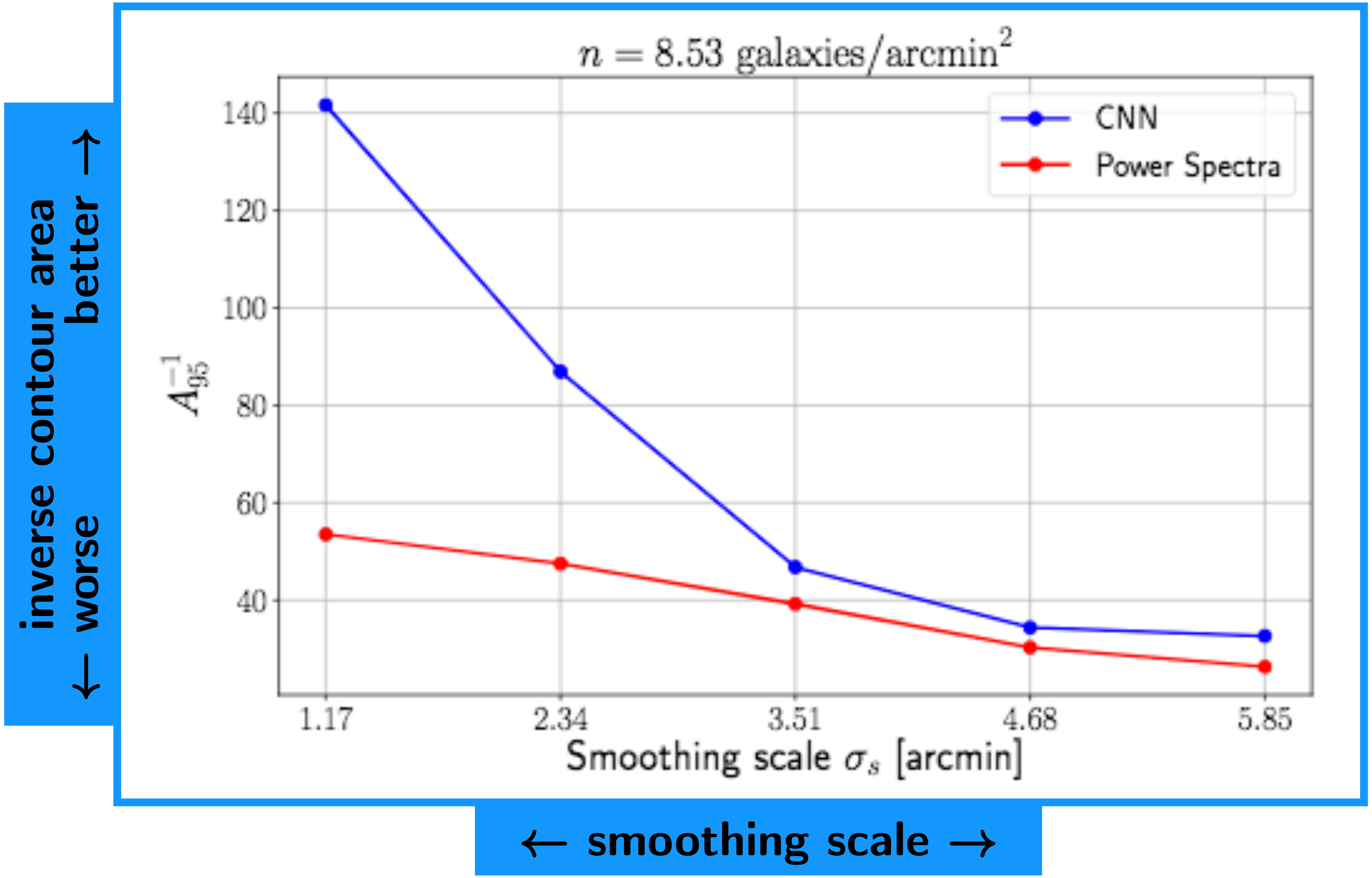
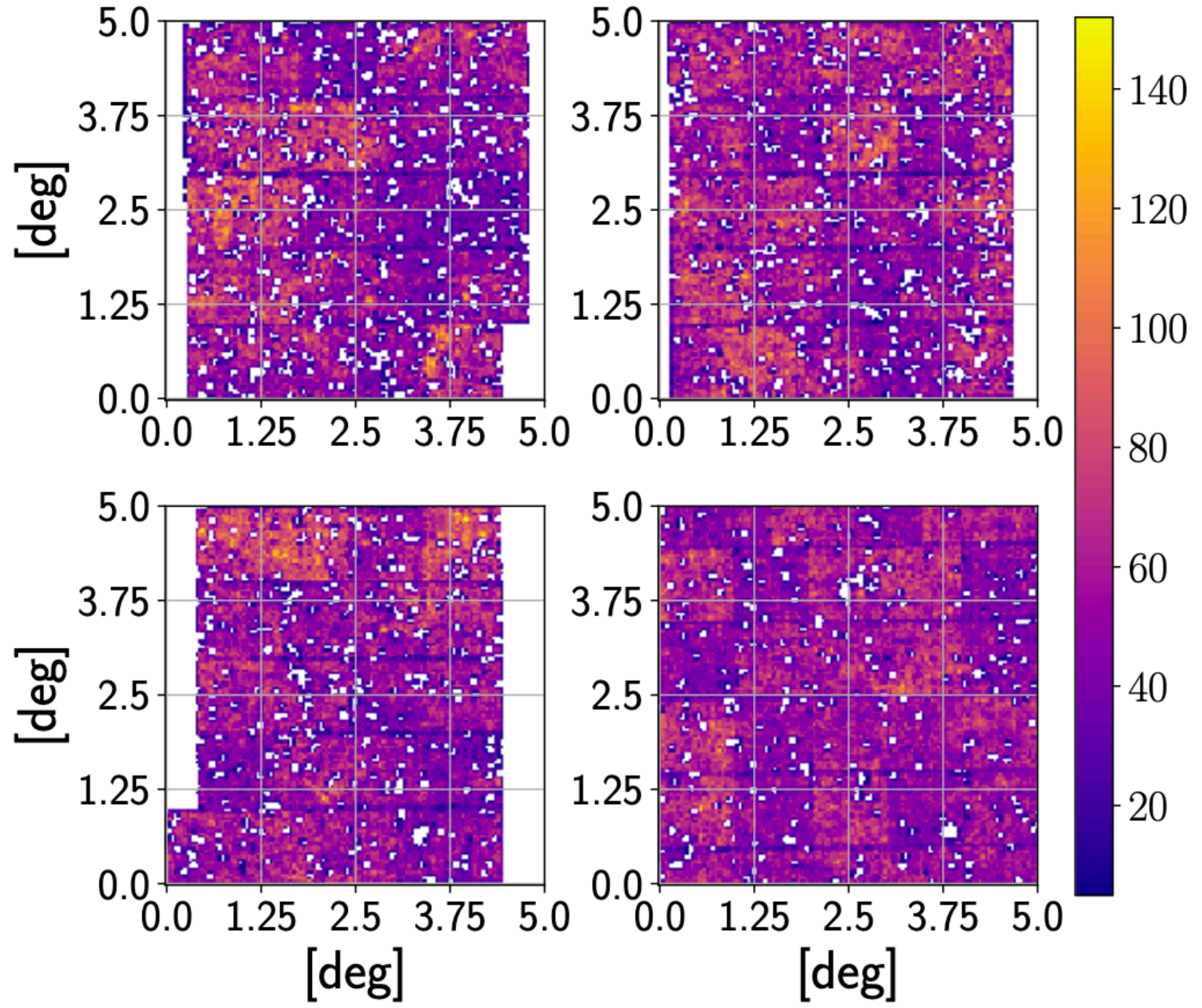
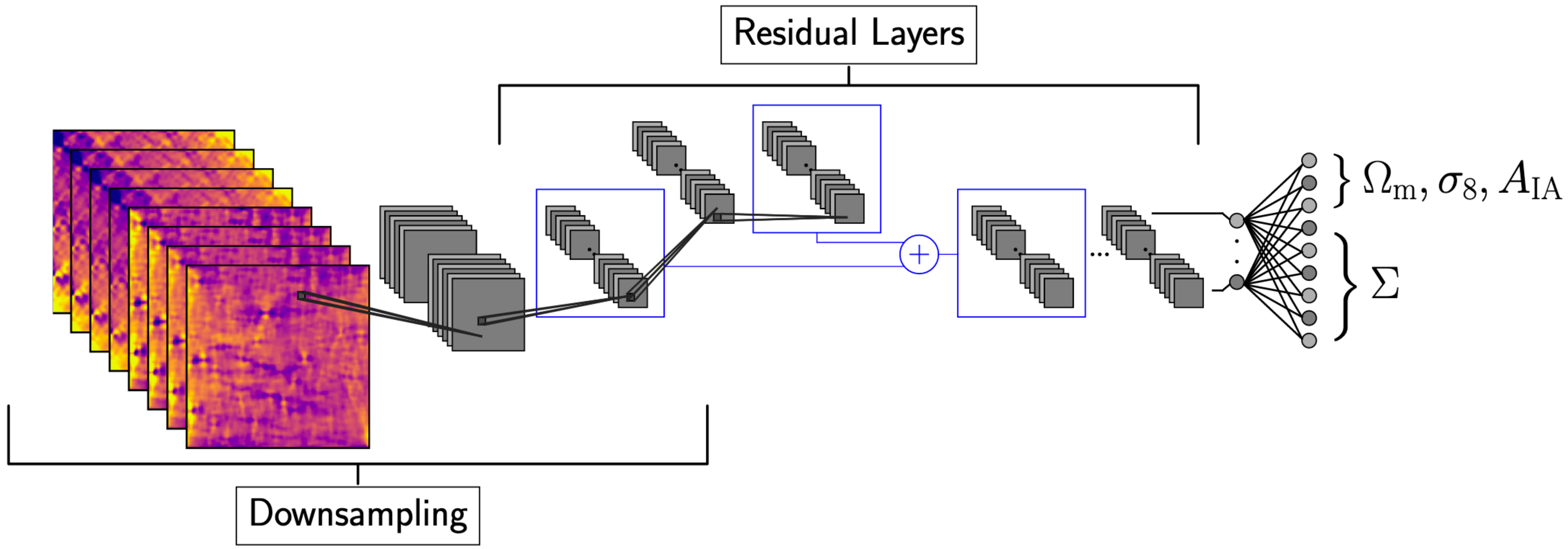


Fluri, TK, et al. 1807.08732

Analysis of KiDS-450 with deep learning





data:
20 x 4 tomographic shear maps

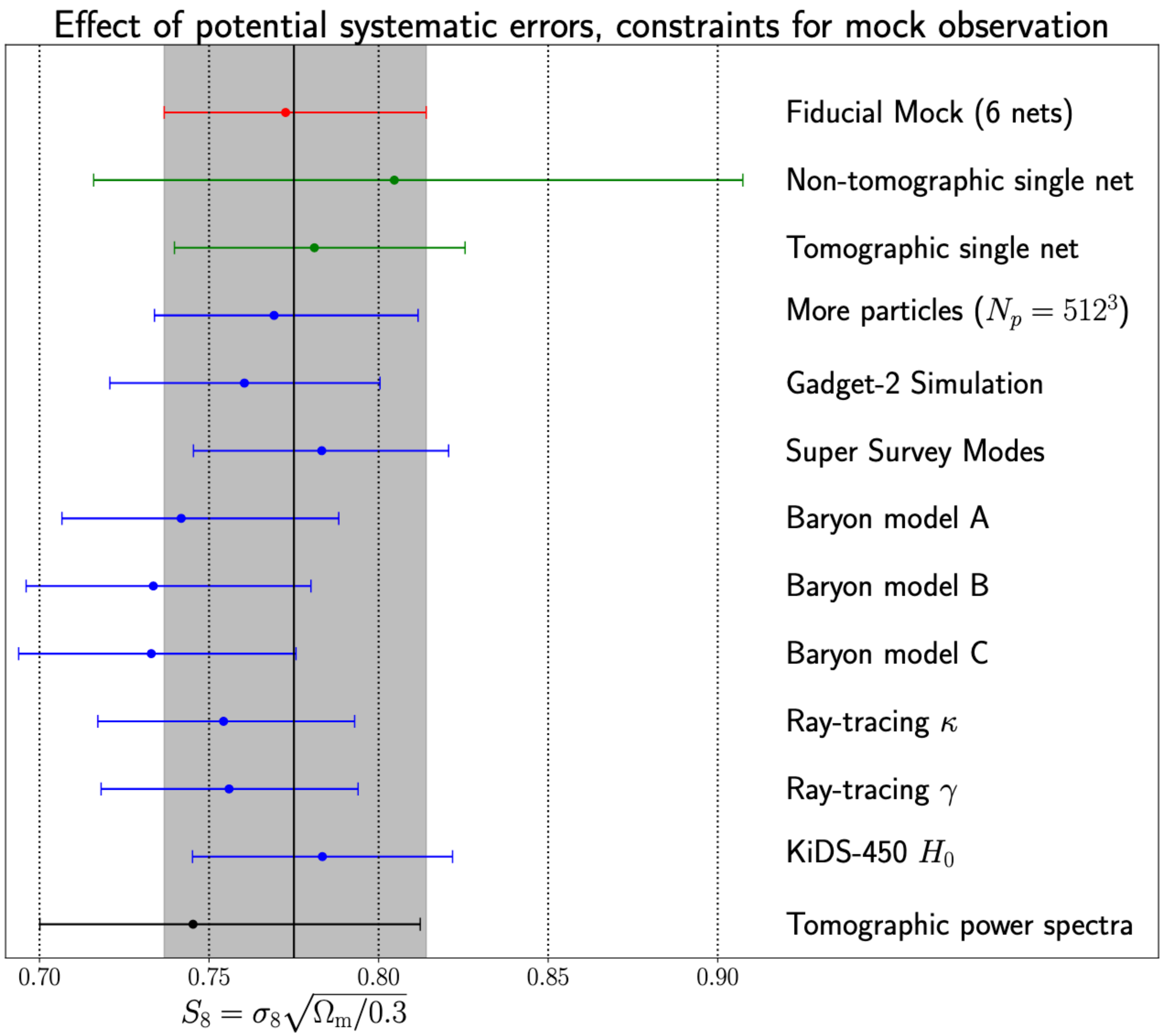
network: 3 parameter output

likelihood analysis

Fluri, TK, et al. 1906.03156

KiDS-450: robustness to simulation details

- With great constraining power comes great systematic responsibility.
- We must test the sensitivity of the machine learning algorithms to systematics and details of theory prediction.
- Different types of tests can be employed:
  - convergence tests
  - modified mock observation tests



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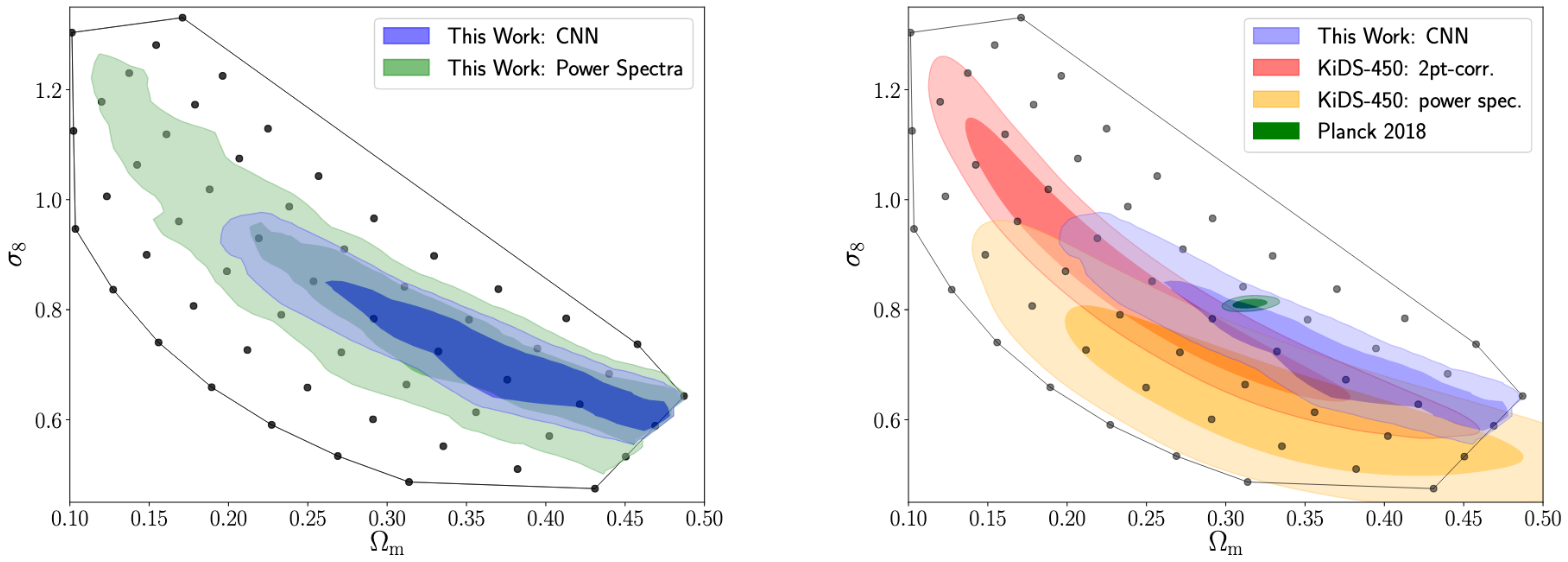


$S_8 = \sigma_8(\Omega_m/0.3)^{0.5} = 0.777$ +/- 0.037

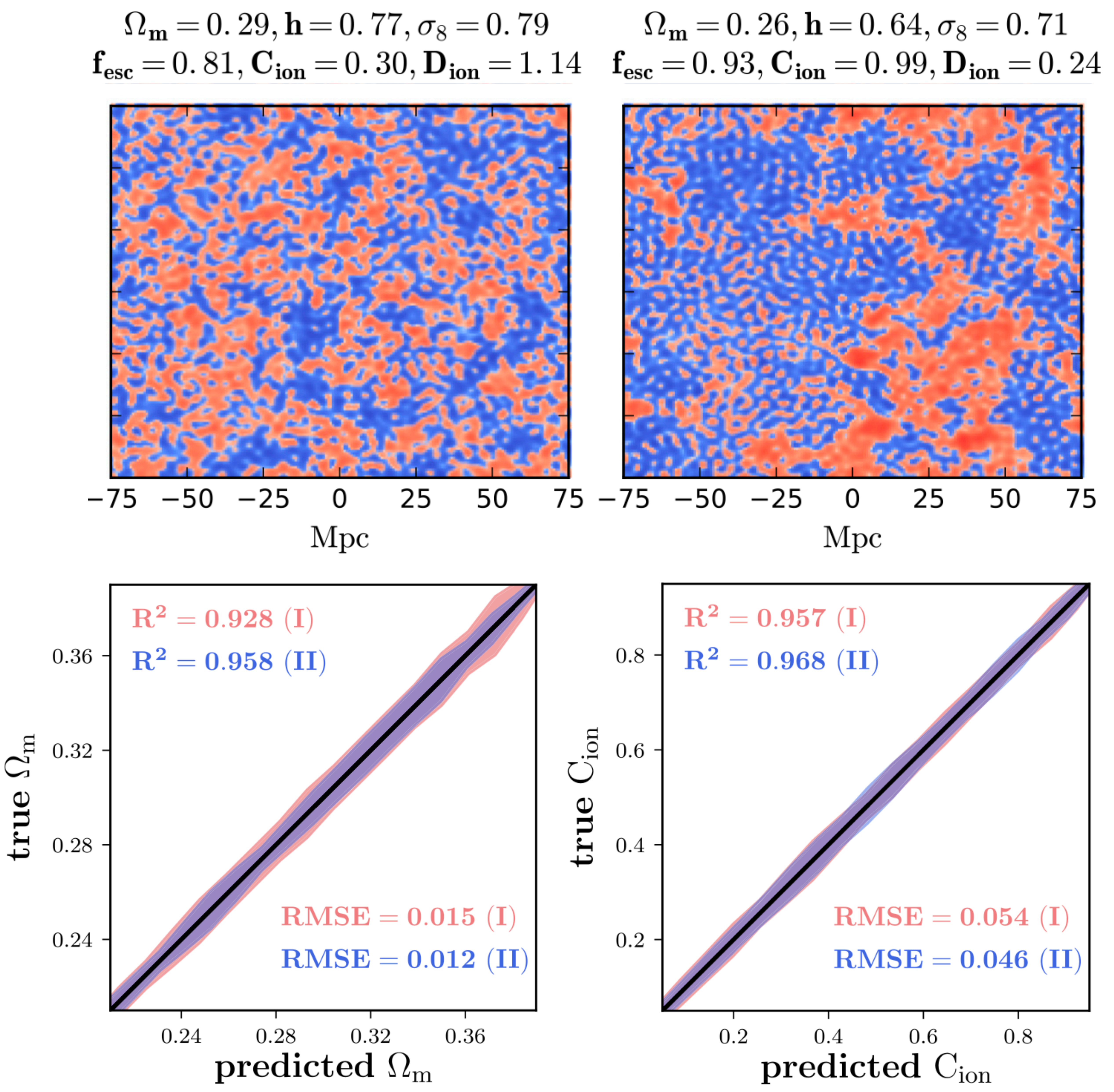
first results using machine learning inference in LSS cosmology

blinded analysis

Fluri, TK, et al. 1906.03156

AI cosmology with 21cm maps from SKA

- Use the SKA 21-cm instrument model, including noise, angular resolution, foreground cleaning
- Using the SIMFAST21 simulation code
- Using CNN architectures: VGGNet, ResNet
- Simultaneously Ω_m, σ_8, h and astrophysics:
  - Photon escape fraction f_{esc}
  - ionizing emissivity power dependence on halo mass C_{ion}
  - ionizing emissivity redshift evolution index D_{ion}
- Very good accuracy!



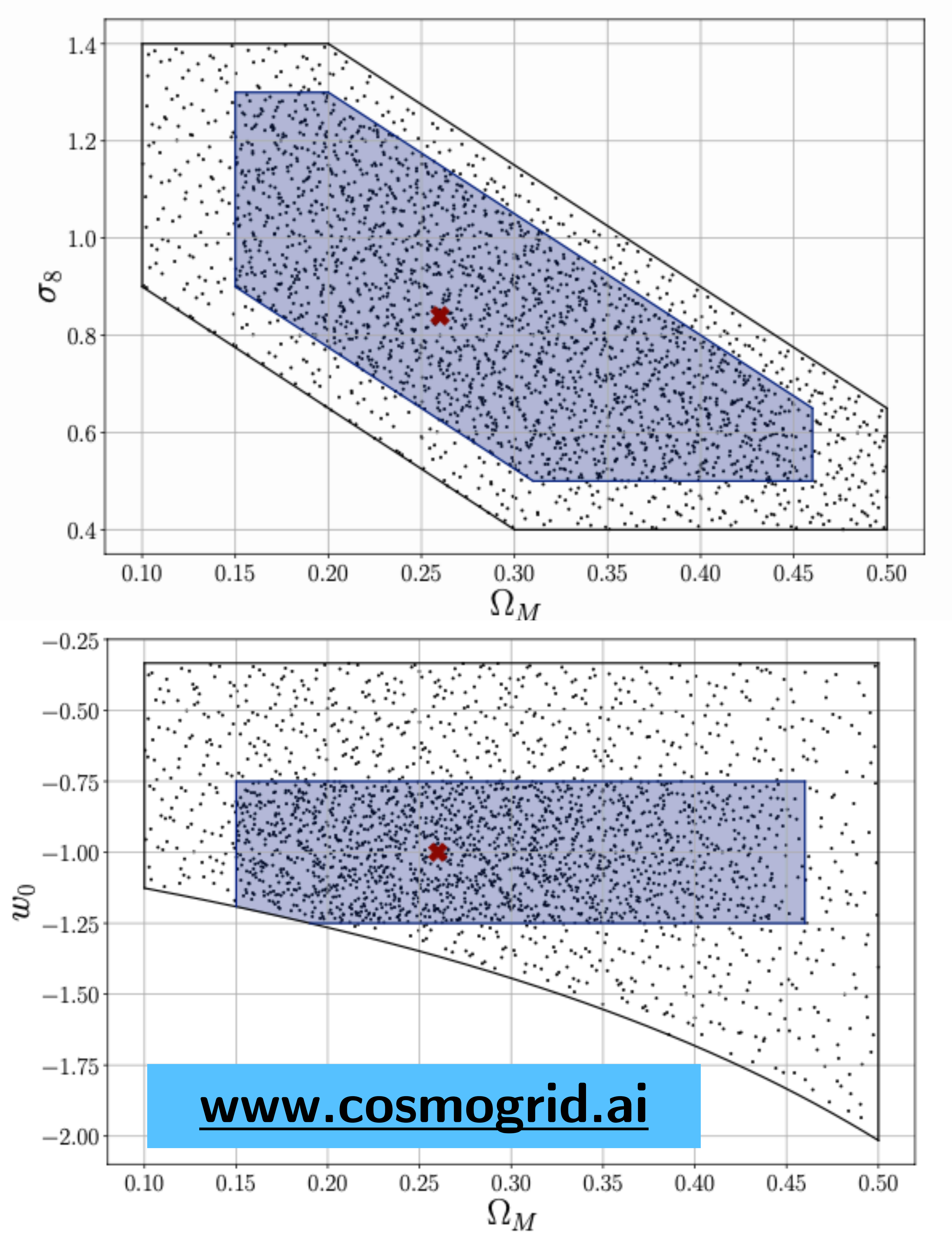
Hassan Andrianomena Doughty 2019 1907.07787

CSCS production project: “Measuring Dark Energy with Deep Learning”

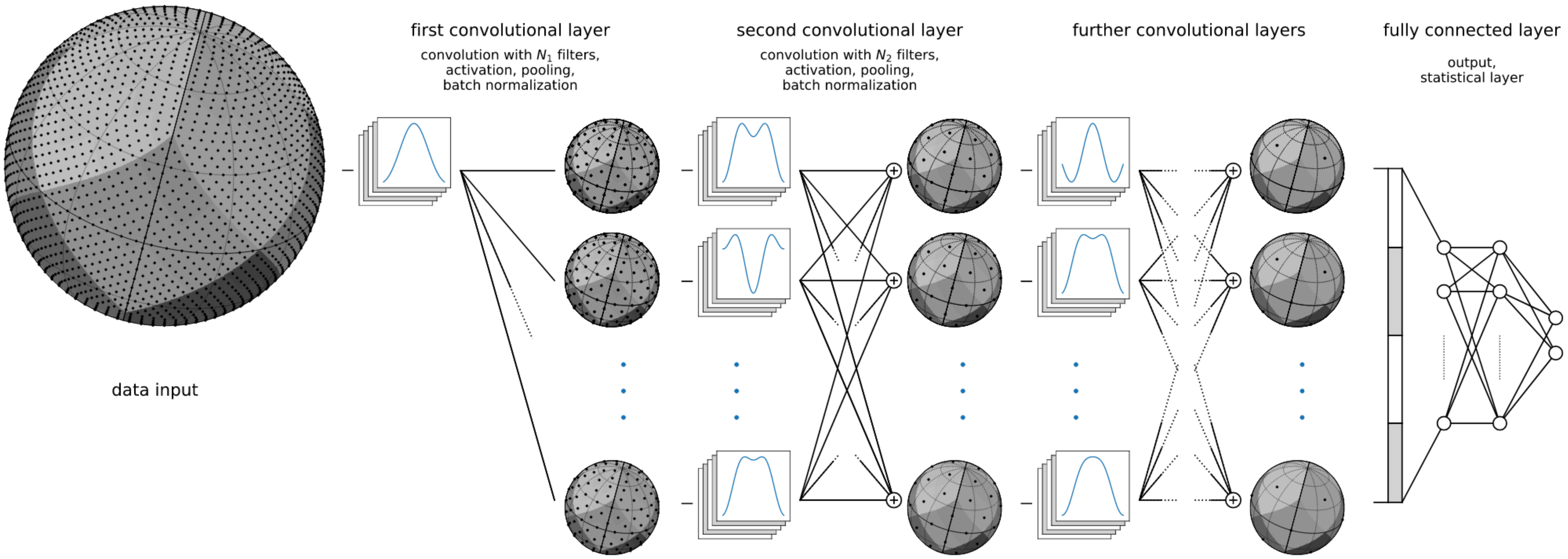
TK, Janis Fluri, Joachim Stadel, Aurel Schneider, Alex Refregier (The CosmoGrid collaboration)

CosmoGridV1:

- 2500 full sky simulations at full wCDM, wide and zoom-in grids, +200 simulations at the fiducial cosmology
- derivatives at fiducial cosmology
- 5 cosmological parameters, fixed neutrinos
- around Healpix 80 maps per sim at redshifts from z=3.5
- max resolution: Healpix nside 2048
- weak lensing and NLA intrinsic alignment maps
- baryonic feedback+intrinsic alignment
- (large) halo catalogs
- extendible Sobol sequence grid → possible to add new parameters easily
- ran at Piz Daint in Switzerland, large production project, 750m GPU node hours
- 120 TB compressed light cone output
- The CosmoGrid Collaboration: University of Zurich and ETH Zurich
- Used for KiDS-1000 deep learning constraints paper by Janis Fluri, et al. 2201.07771
- Paper in preparation



Deep learning on the sphere: a tool for large area sky maps



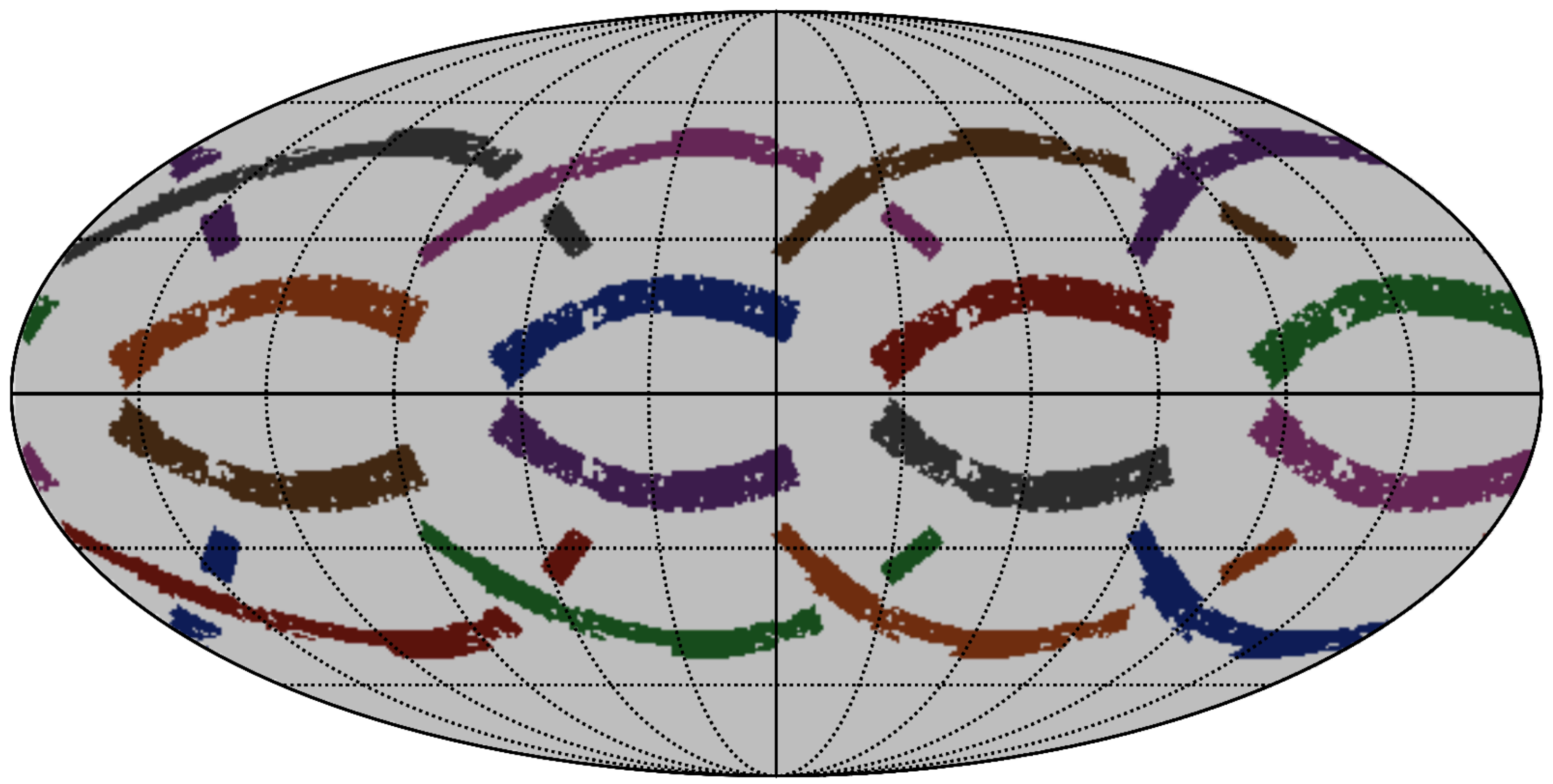
- Various CNN architectures on the sphere with Healpix sampling
- Using graph representation, useful for analysis of data on part of the sphere
- One of the fastest sphere convolutions available (but slightly approximate)
- Used by other domains: weather, geo-sciences
- Tensorflow and PyTorch interfaces

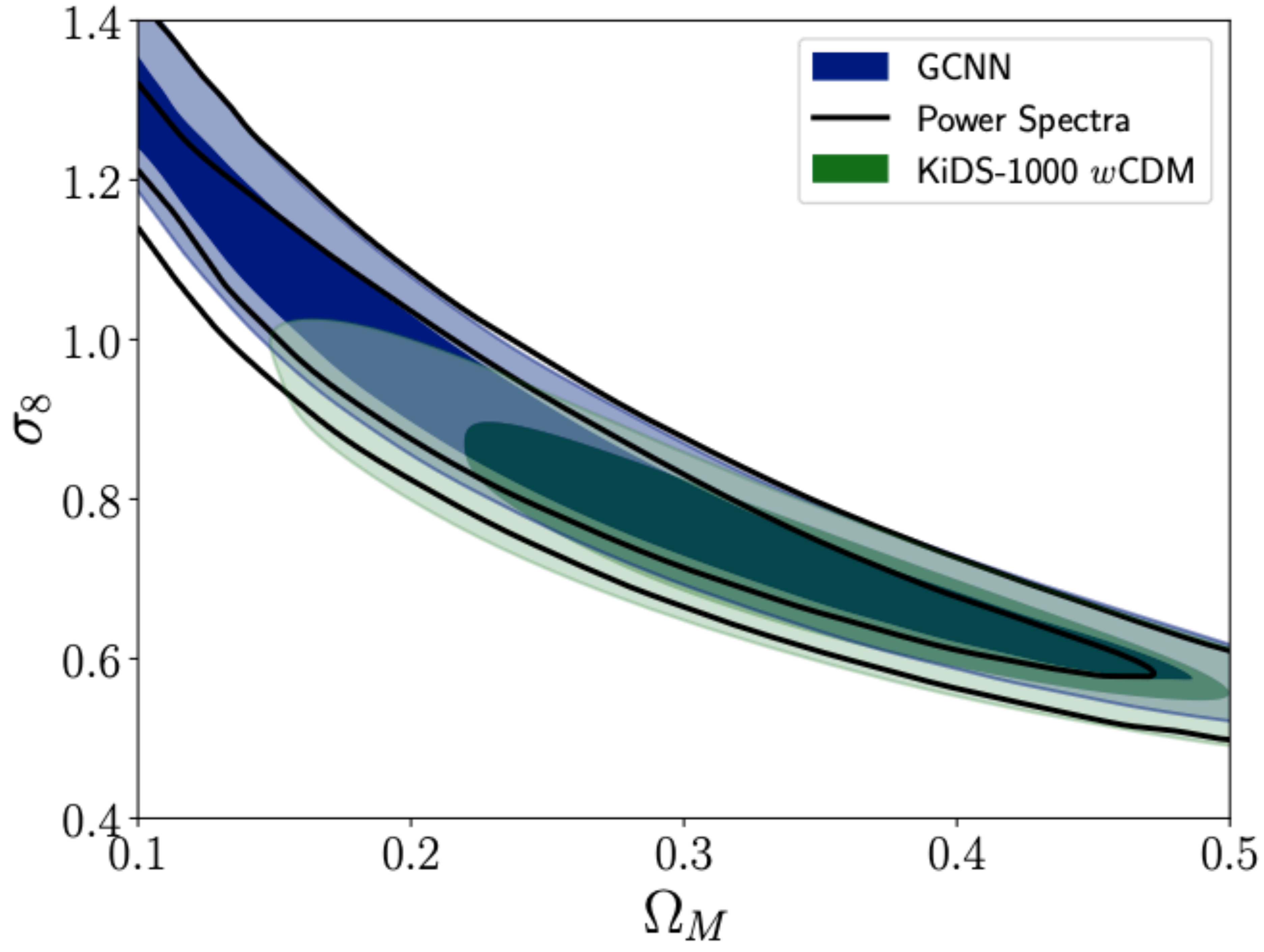
github.com/deepsphere

Perraudin, TK, et al. 1810.12186

KiDS-1000 constraints and CosmoGrid

- Demonstration of the scalability of the deep learning approach
- Full KiDS-1000 survey analysis of the 1000 deg^2 survey
- Using full CosmoGrid simulation volume
- Using low-resolution maps due to processing power limitations
- Intrinsic alignments and baryonic feedback included in the model
- Improved results compared to power spectra
- Blinded analysis with results consistent with main KiDS results

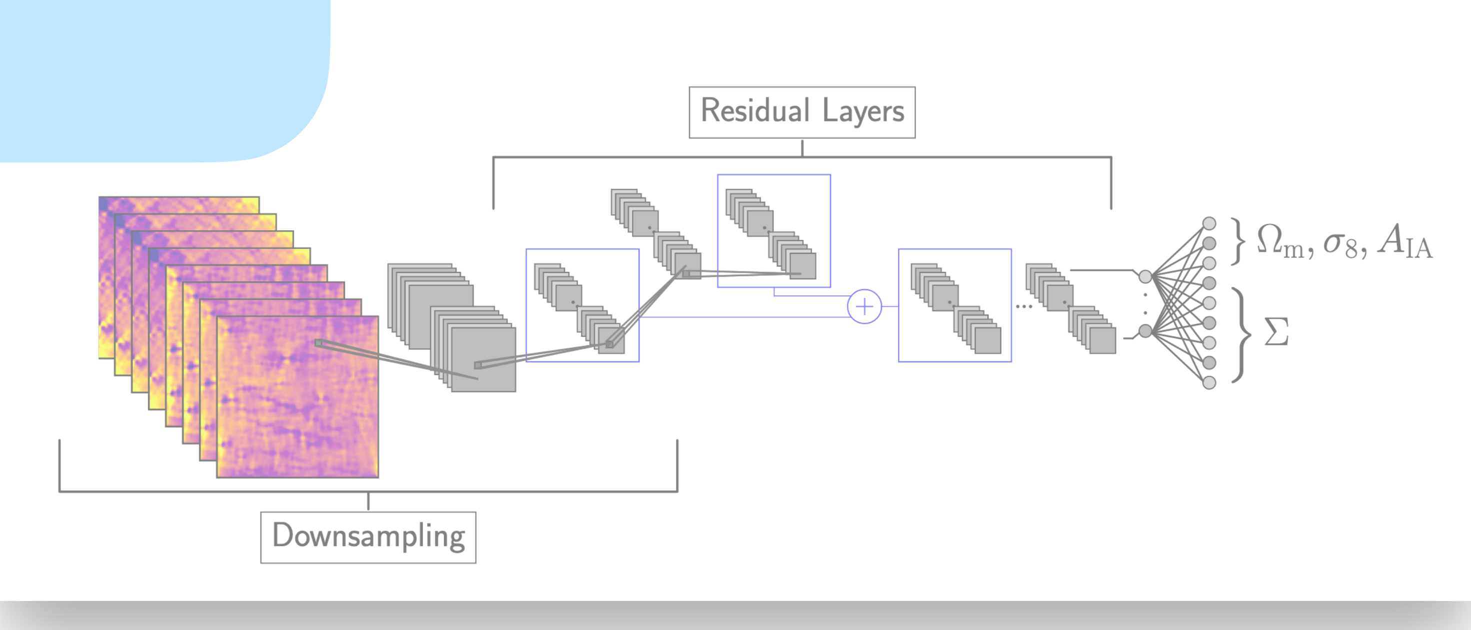




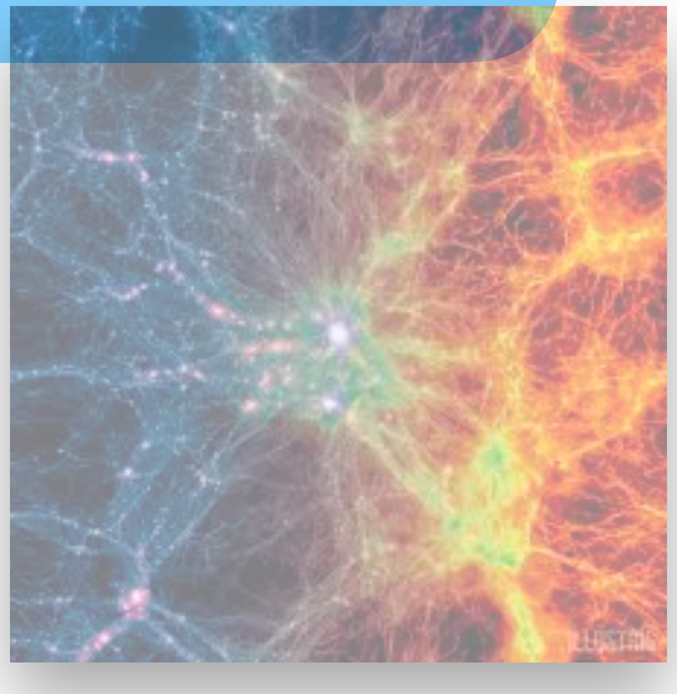
Fluri, TK, et al. 2022, arXiv:2201.07771

How can AI open new possibilities in cosmological analysis?

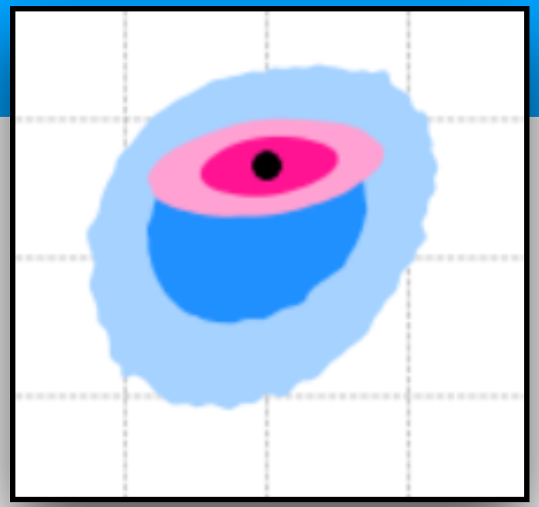
Reaching the information floor of the data



Accelearating simulations



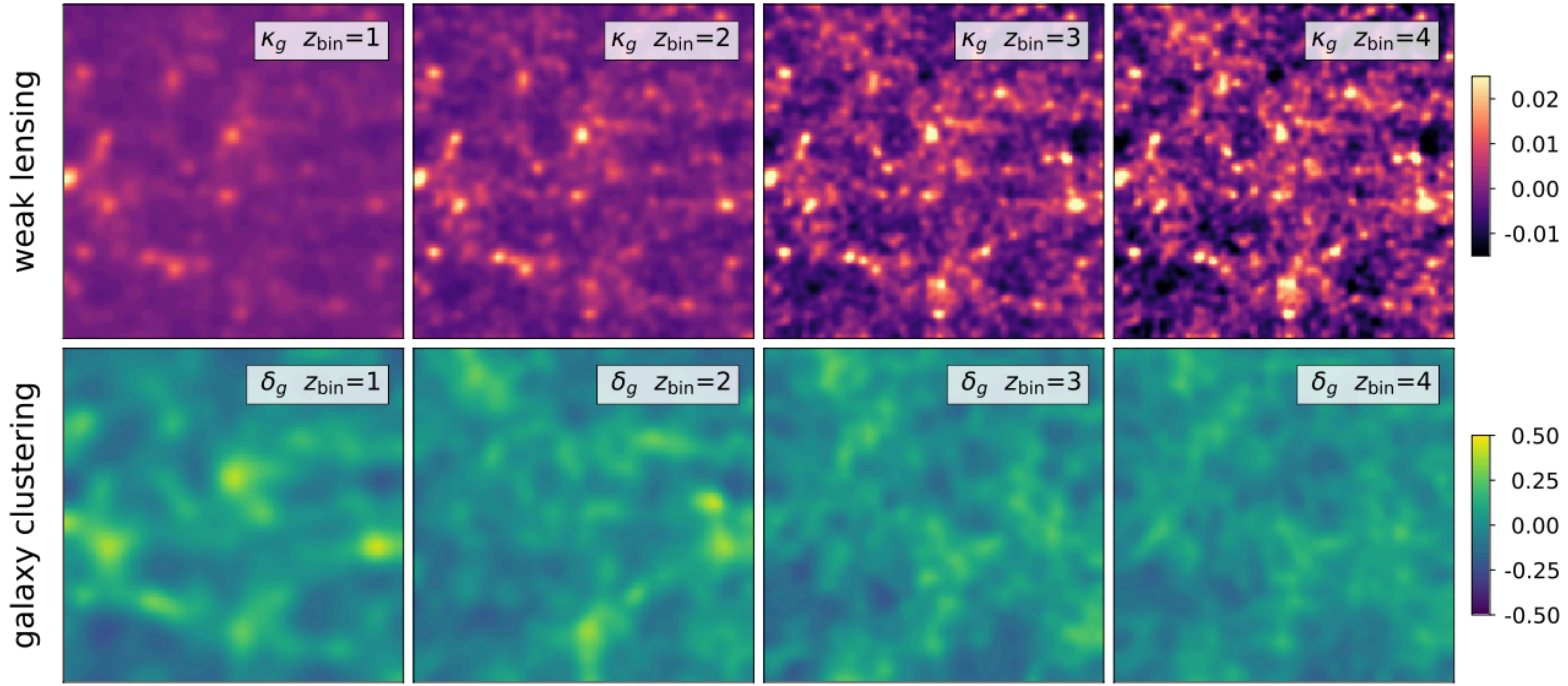
Breaking degeneracies between cosmology and systematics



DeepLSS: combined probes with deep learning

Breaking parameter degeneracies in large scale structure with deep learning analysis of combined probes

Kacprzak and Fluri 2022, arXiv:2203.09616, accepted to PRX



Open source code: github.com/tomaszkacprzak/DeepLSS

DeepLSS: combined probes with deep learning

- Combining:

  ✓Weak gravitational lensing (galaxy shapes)

  ✓Galaxy clustering (galaxy positions)

  ✓… more in the future!

- Weak gravitational lensing is very powerful but degenerate with intrinsic galaxy alignments

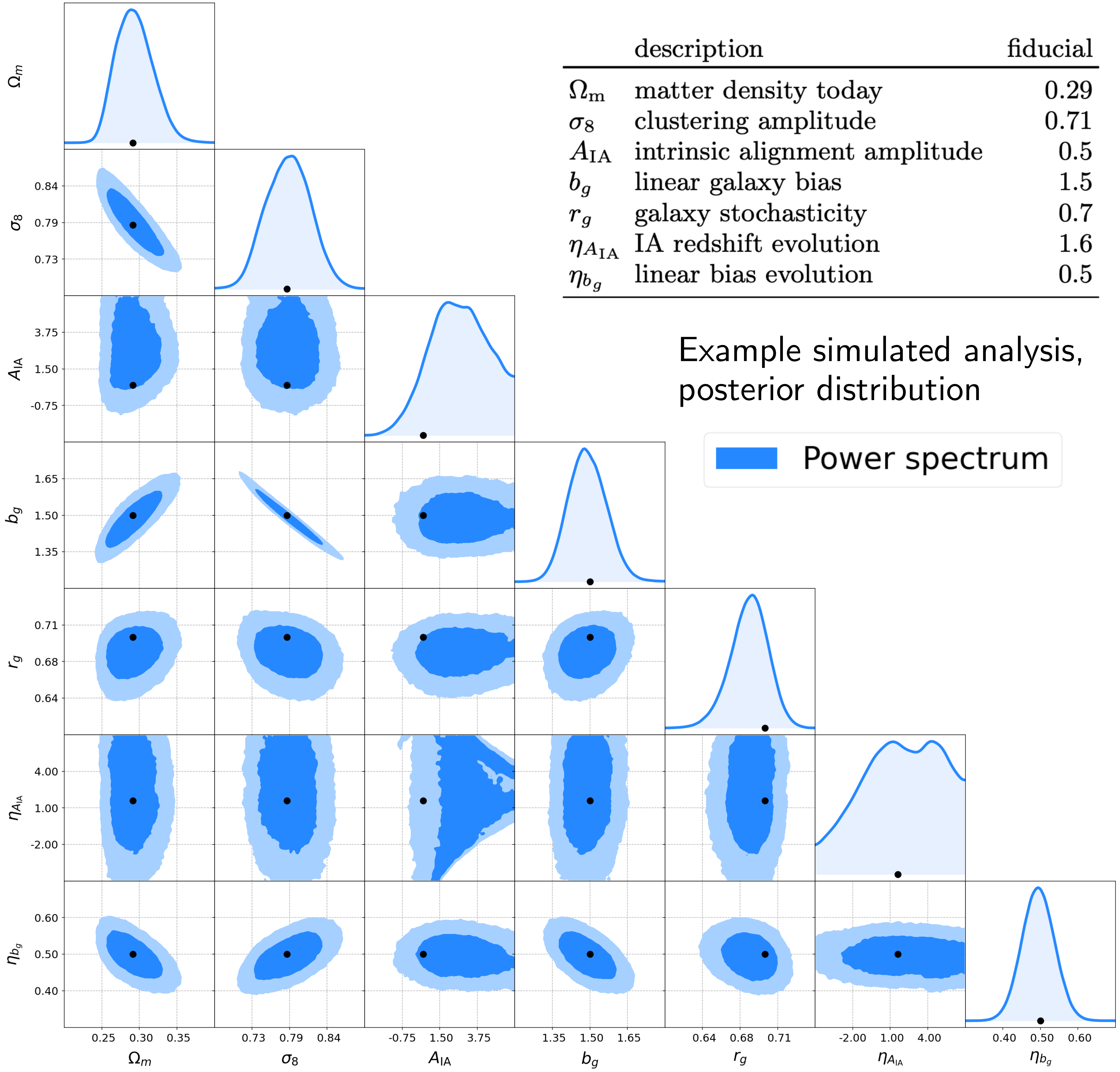
- Intrinsic galaxy alignment (IA) is the correlation between the shape of a galaxy and the shape of the dark matter halo it occupies

- Probe combination is a powerful way to disentangle gravitational lensing and intrinsic alignments

- However, many degeneracies between the parameters of the model remain in the joint analysis

	description	fiducial
Ω_m	matter density today	0.29
σ_8	clustering amplitude	0.71
A_IA	intrinsic alignment amplitude	0.5
b_g	linear galaxy bias	1.5
r_g	galaxy stochasticity	0.7
η_{A_IA}	IA redshift evolution	1.6
η_{b_g}	linear bias evolution	0.5

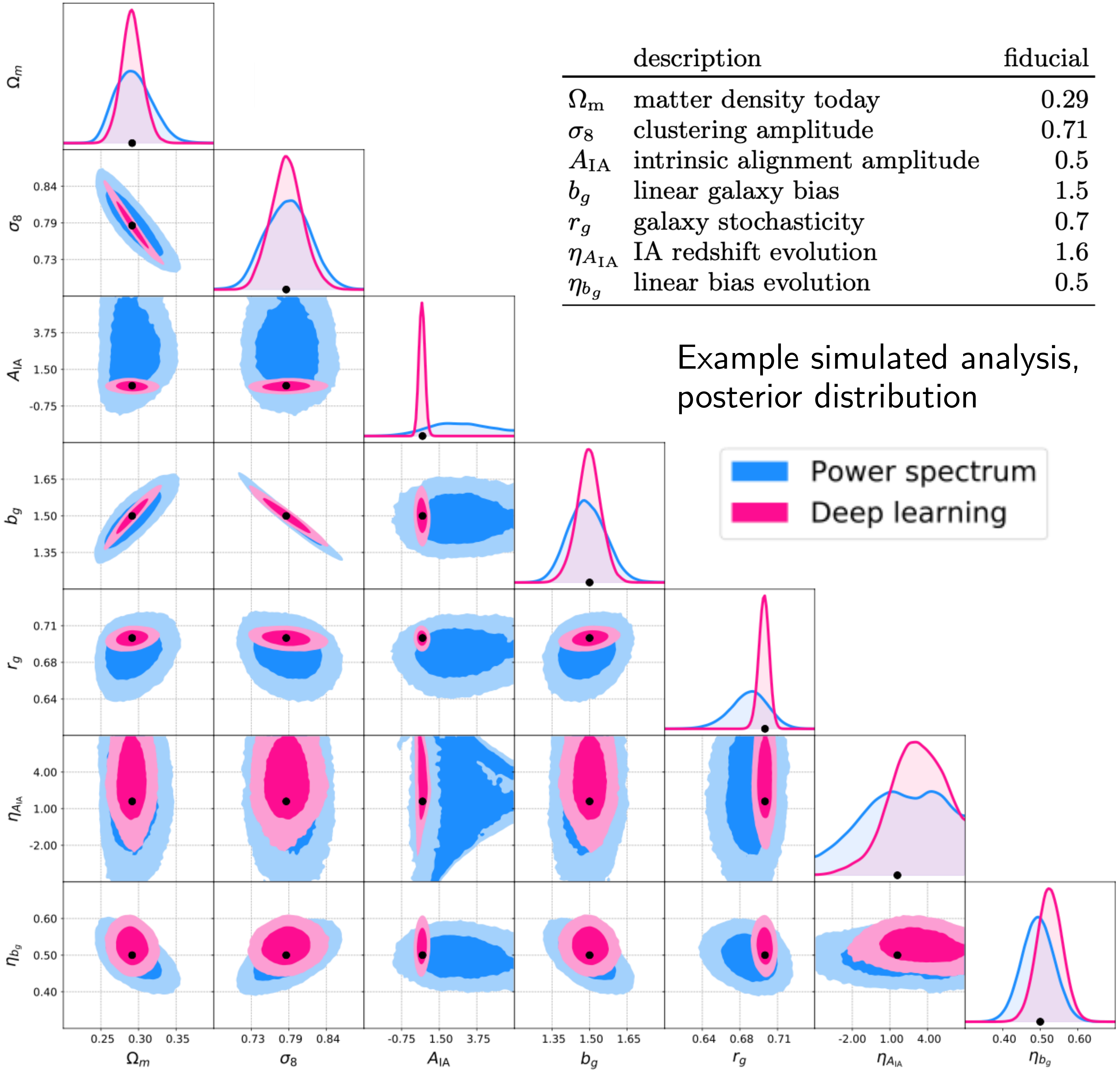
Example simulated analysis, posterior distribution



Kacprzak and Fluri 2022, arXiv:2203.09616

DeepLSS: combined probes with deep learning

- Deep learning analysis breaks several key degeneracies
- Intrinsic alignment measurement is greatly de-correlated from cosmology
- Galaxy biasing evolution is also de-correlated from cosmology
- Cosmology constraints greatly improved due to degeneracy breaking



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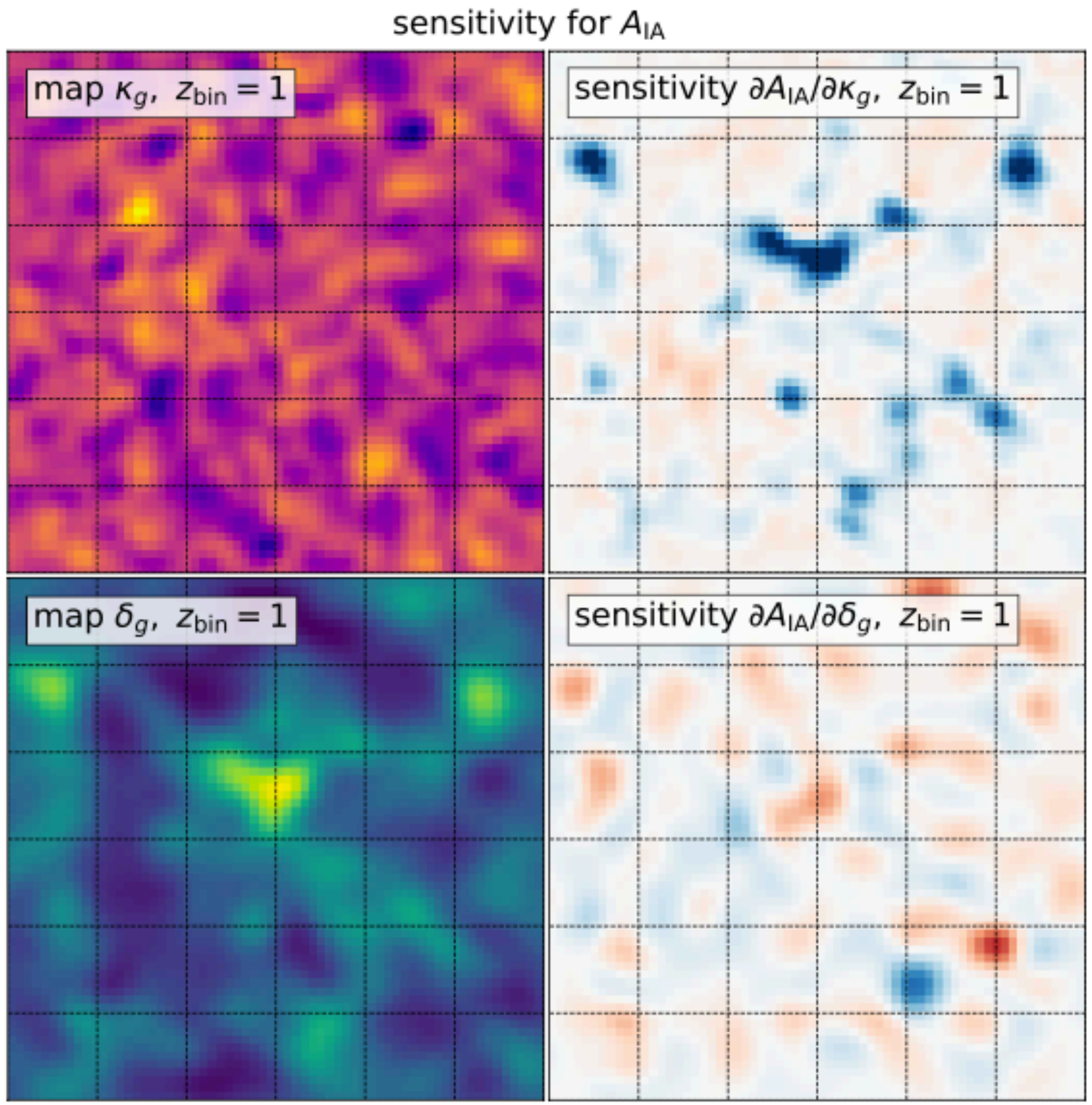
Kacprzak and Fluri 2022, arXiv:2203.09616

Where is the additional information coming from?

- Sensitivity maps show which pixels have the most impact on the final prediction of the network
- The networks focuses on very specific regions in the galaxy positions and lensing maps
- Power spectra average over the entire map, even with empty regions
- Thus power spectra dilute the signal with empty parts of the map, which contains only noise
- Deep learning weights the data in a way that maximises information gain



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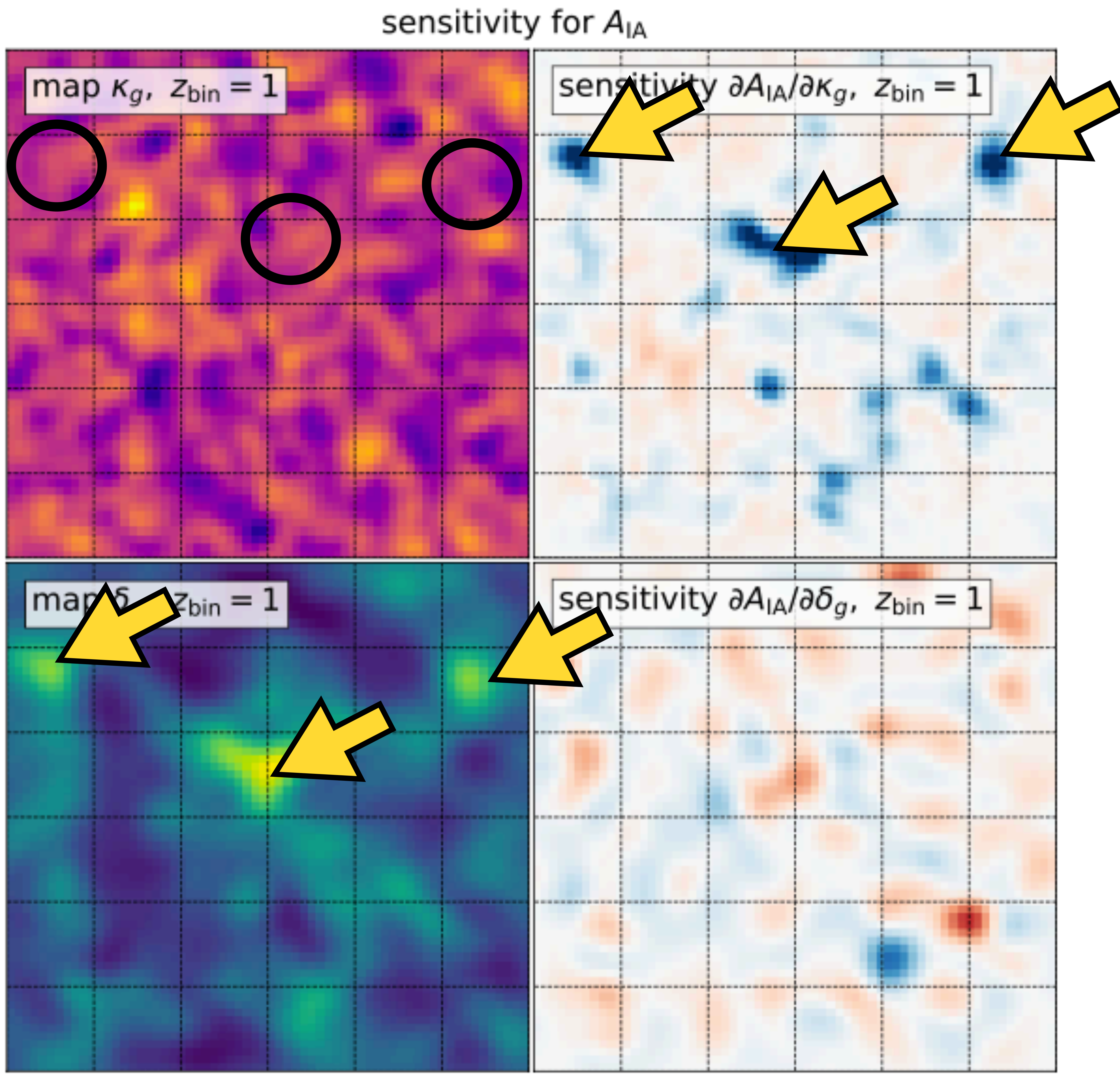

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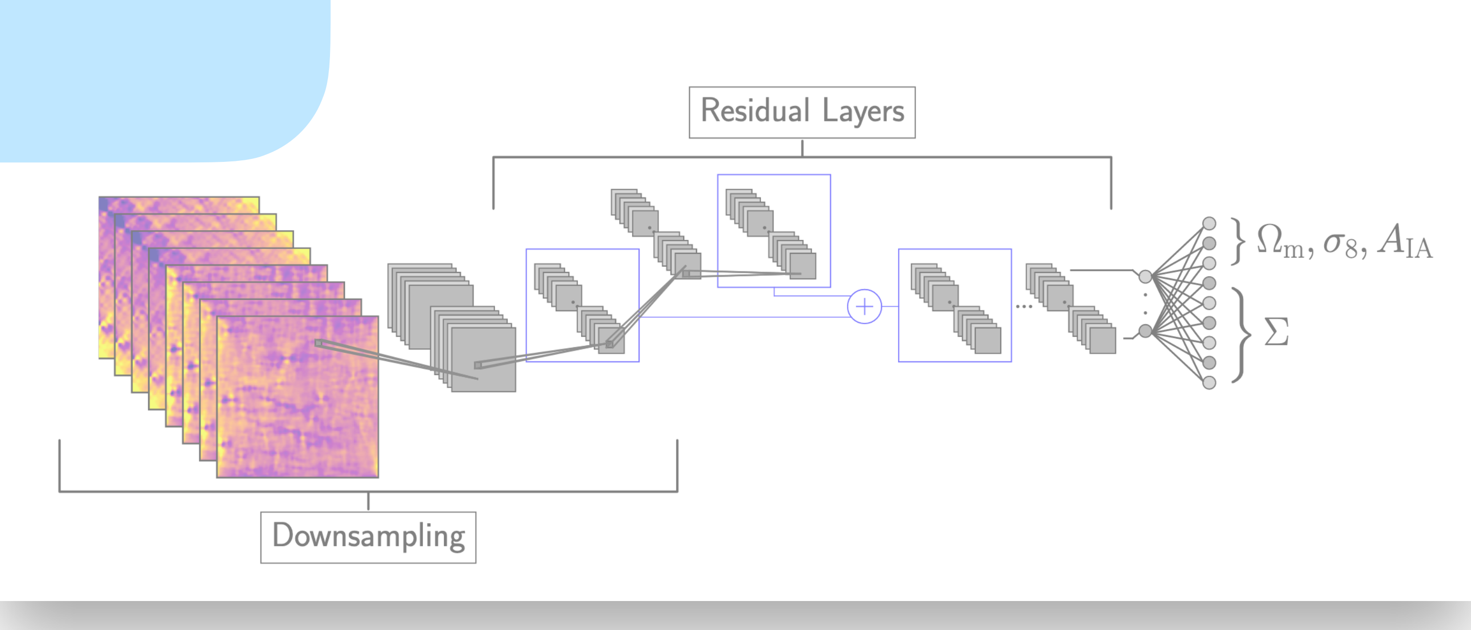

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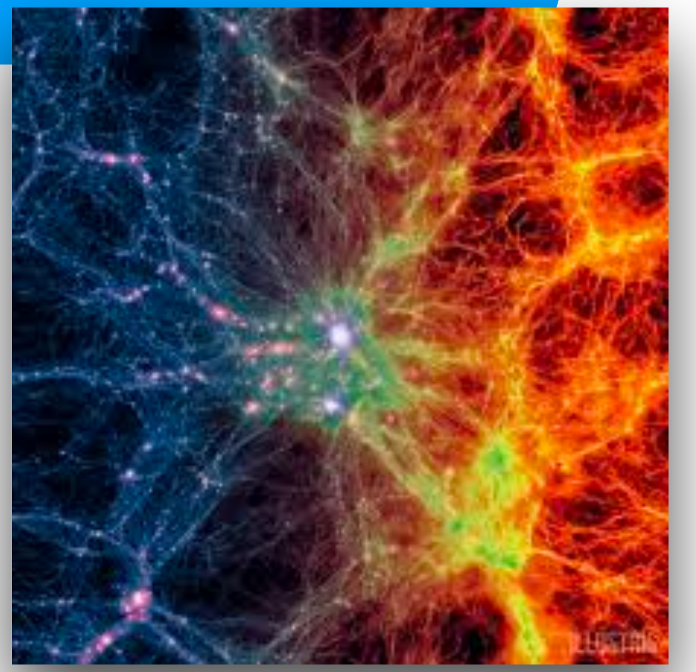
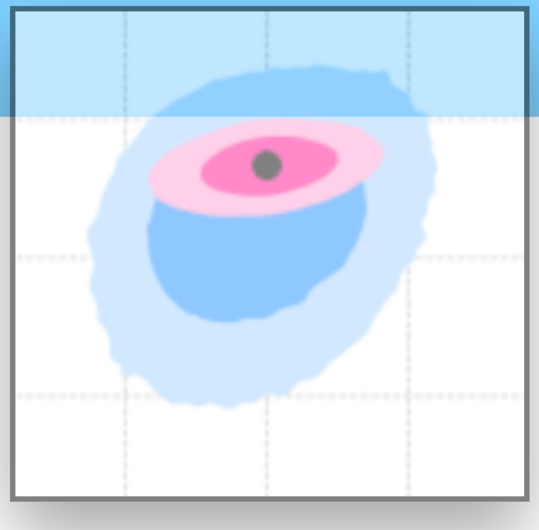


Breaking degeneracies between cosmology and systematics



AI for cosmological simulations

Several key applications of deep learning and generative models can significantly aid generation of simulations, whether for traditional or machine learning inference:

1. Enable precise simulations on small scales: simulation **super-resolution**
2. Fast **emulators** of projected survey maps
3. Use dark matter as a skeleton, **painting** consistent fields, for example baryons

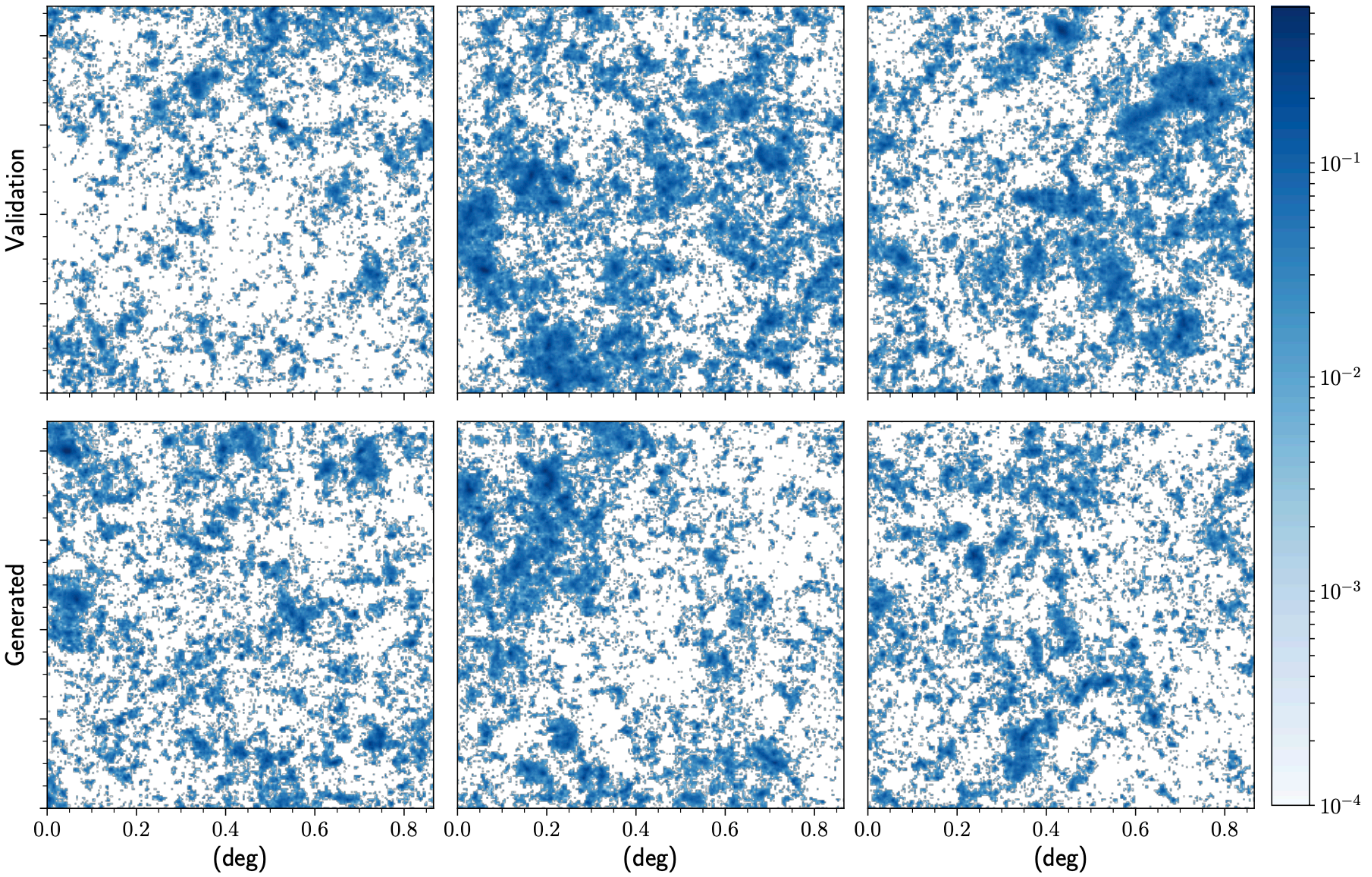
First Generative Model for cosmological mass maps

- First generative model trained on simulations applied to cosmological fields

- N-body vs GAN visually indistinguishable

- Excellent agreement on (non-Gaussian) summary statistics

- Very simple networks, worked out-of-the-box

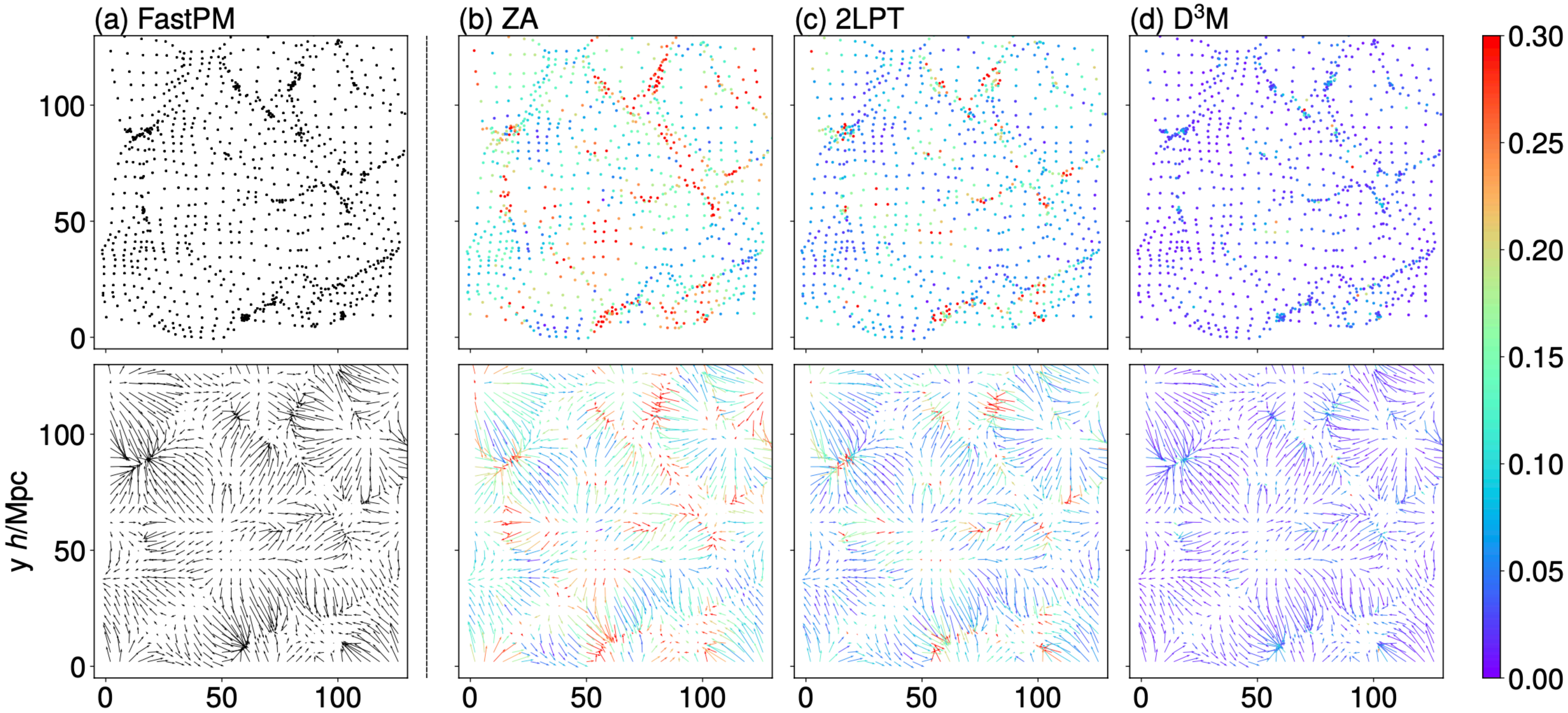


Mustafa et al. 2017 1706.02390

Learning to Predict the Cosmological Structure Formation

He at al. 2018 1811.06533

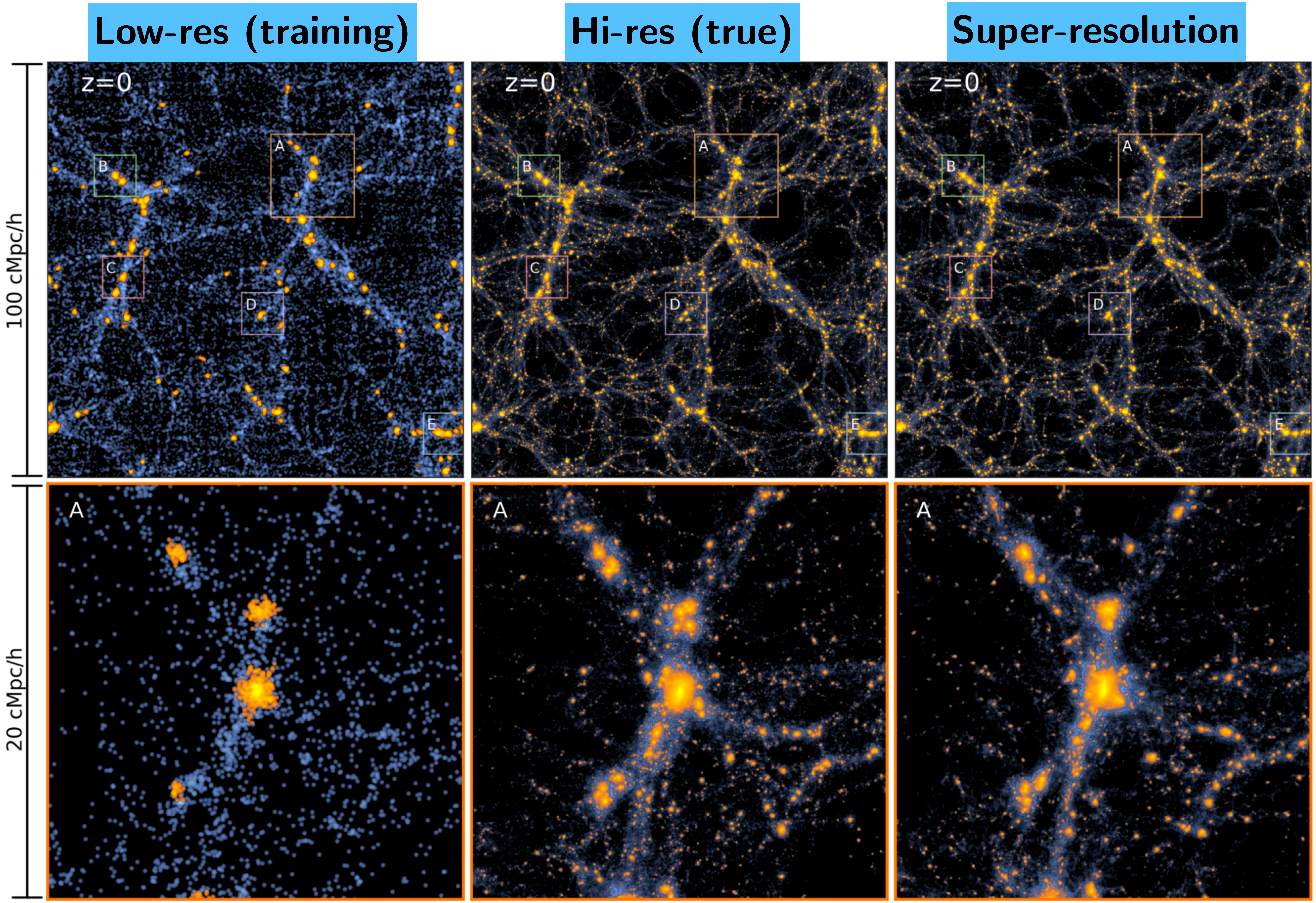
- Use a U-net trained on pairs of N-body and corresponding Zel'dovich Approximation (ZA) input
- The Deep Density Displacement Model (D³M) successfully displaces particles to match N-body
- ZA + D³M is extremely fast compared to full N-body
- Hints that a training on single cosmology generalises to other cosmologies!



AI super-resolution of N-body simulations

Li et al. 2021 2010.06608

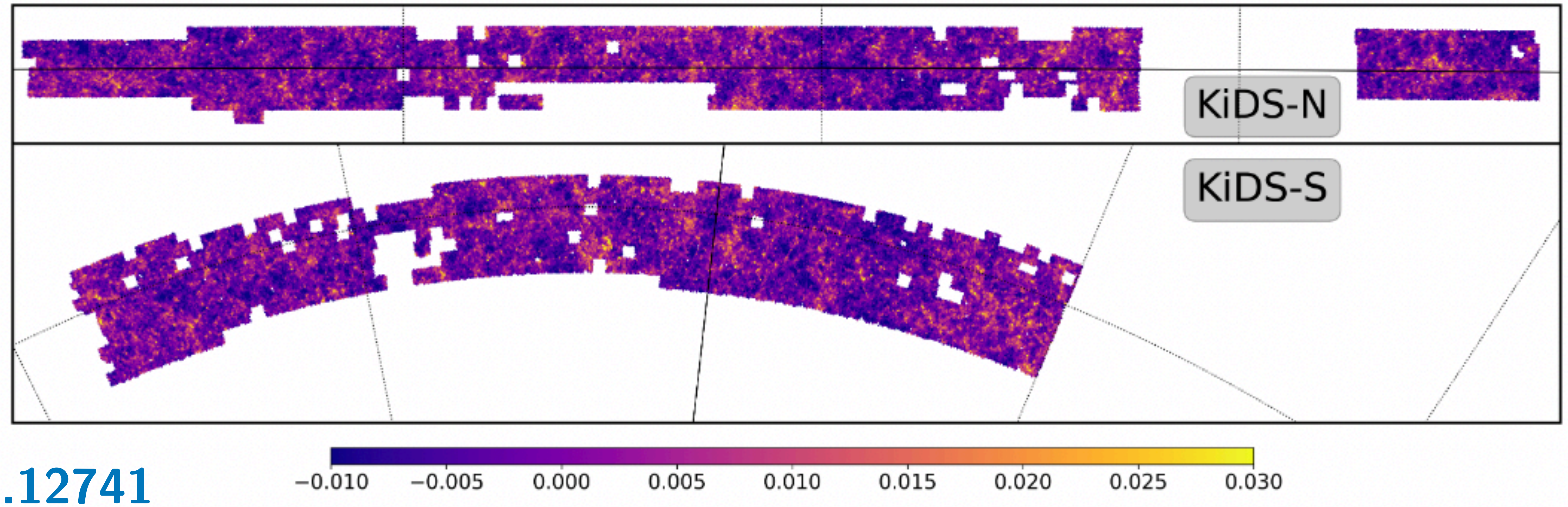
- Learn the mapping from the low to high resolution simulations
- Works on 3D volumes!
- Using Wasserstein GANs with gradient penalty on 3D volumes
- Increase of resolution by a factor of 8
- Super-resolution is extremely fast
- Reproduces well the halo mass function (10^{11}-10^{14} $M_\odot$) and power spectra (k between 0.1 - 10)
- Works for a single cosmology, separate GAN for each redshift



KiDS-1000 conditional mass map emulator

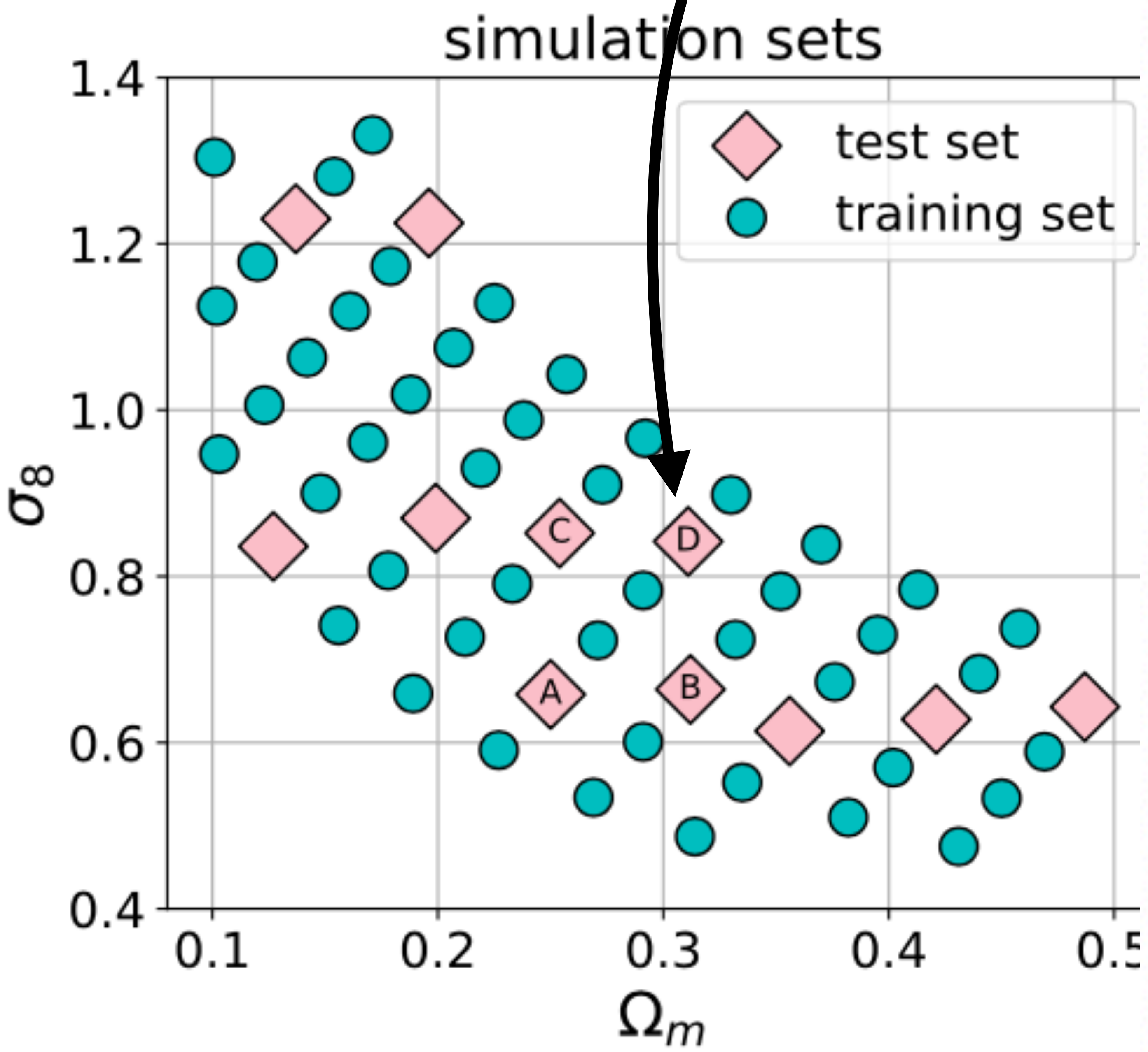
- Emulators of the non-linear Pk are becoming more commonly used in cosmology
- EuclidEmulator and BACCO are state of the art P(k) emulators
- Separate simulations are used to calculate the covariance matrices
- Idea: create an emulator of mass maps directly on pixel level
  - Independent of summary statistic of choice, suitable for non-Gaussian and ML analyses
  - Accurate mean and variation in the signal, no splitting between them
  - Very fast to generate on-the-fly for a given cosmology
  - Maps are differentiable with respect to the input cosmological parameters
  - Interpolation to unseen cosmologies on the map level

simulated mass maps at KiDS-1000 footprint:

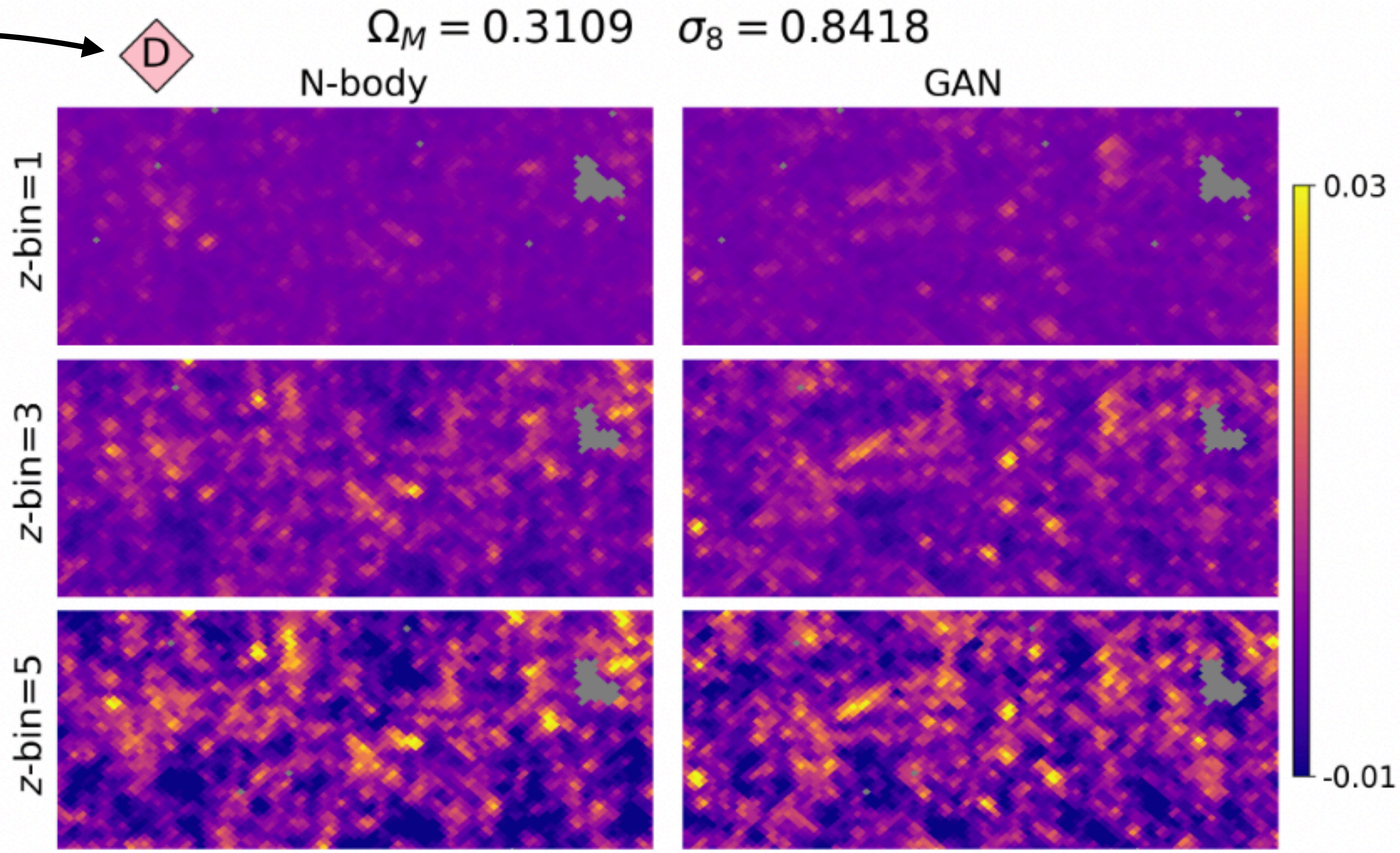


Timothy Wing Hei Yiu, Janis Fluri, TK 2112.12741

KiDS-1000 mass map emulator



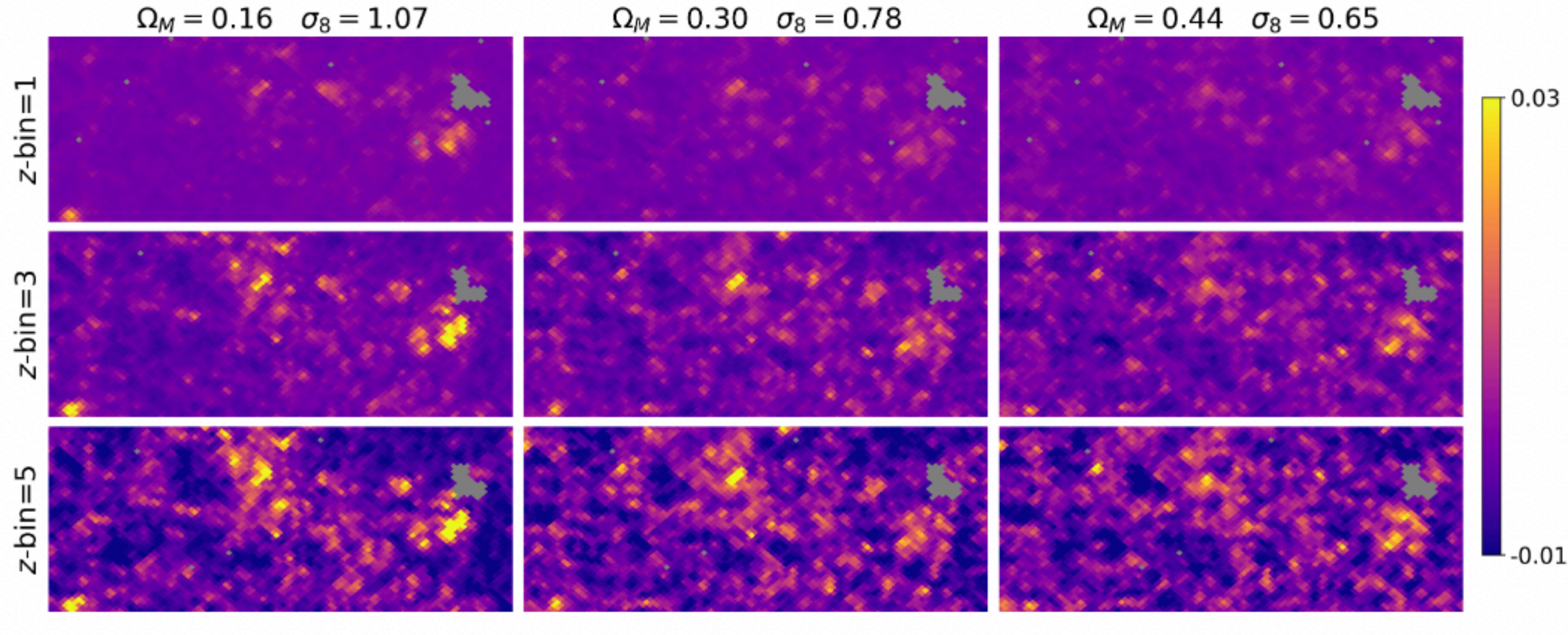
Grid of simulations as train/test set



Visual comparison between original N-body and GAN maps

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

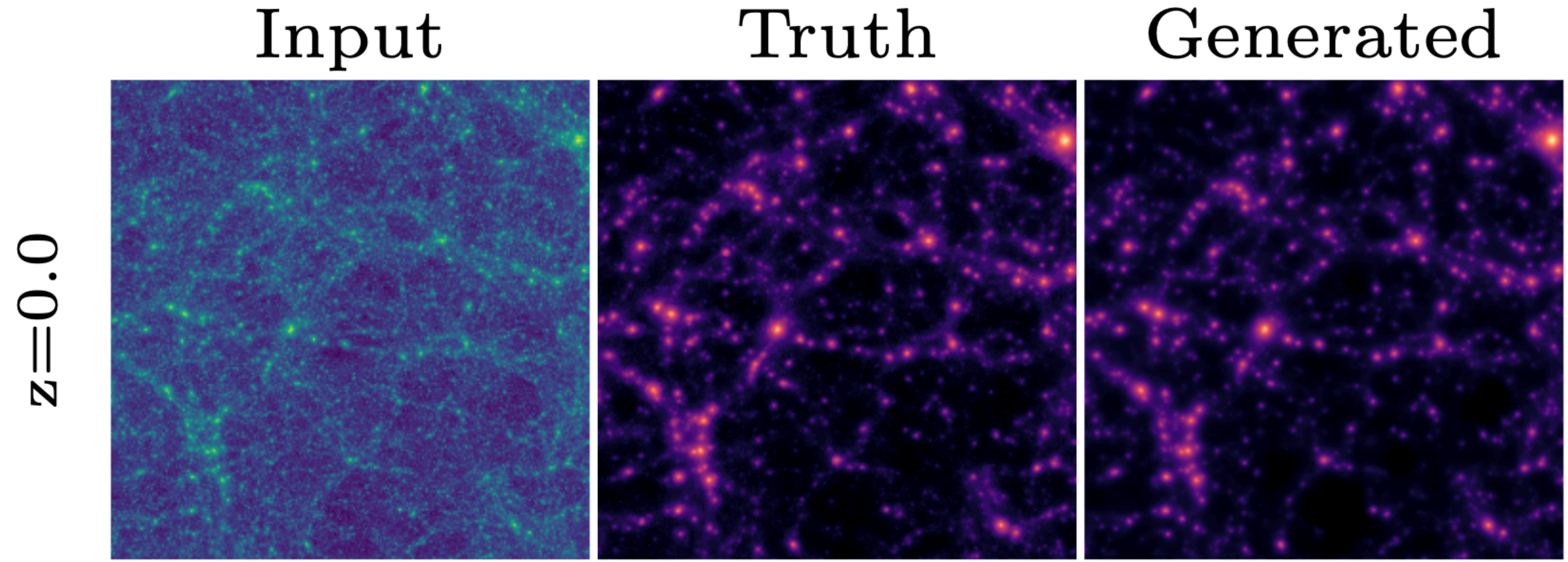
KiDS-1000 mass map emulator



The generated maps are differentiable with respect to the input cosmological parameters

Very good agreement on power spectra and non-Gaussian summary statistics

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



Dark matter map

Gas pressure map

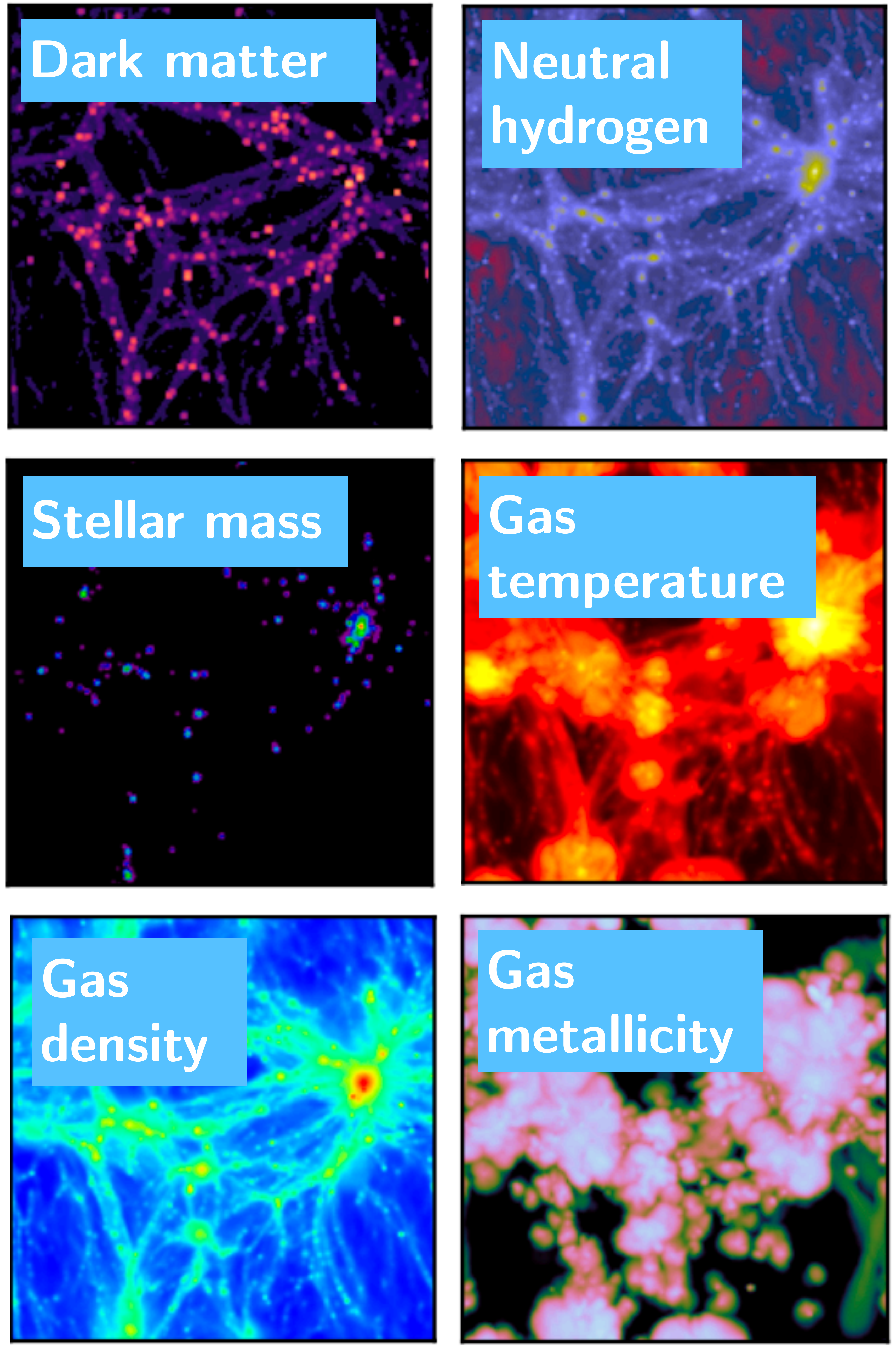
- Using BAHAMAS simulations to create gas pressure maps for the corresponding dark matter maps
- Using Generative Adversarial Nets and Variational Autoencoders to create the gas pressure maps based on the dark matter map only

Troester et al. 2019, 1903.12173

CAMELS: Cosmology and Astrophysics with MachinE Learning Simulations

General, precise simulations including all of the important effects

- Magneto-hydrodynamic simulations using AREPO and GIZMO, employing baryonic subgrid physics as IllustrisTNG and SIMBA
- Dataset used to demonstrate the possibilities of machine learning to understand astrophysics and cosmology jointly
- 4233 small boxes $(25\ h^{-1}\ \mathrm{Mpc})^3$ spanning the wCDM cosmological model and different AGN feedback models
- New CAMELS-SAM suite: 1000 dark-matter only simulations of $(100\ h^{-1}\ \mathrm{Mpc})^3$ with semi-analytic galaxy catalogs Perez et al. 2022 2204.02408
- 16 methods papers for various problems in the last 2 years
- Data publicly available at https://camels.readthedocs.io



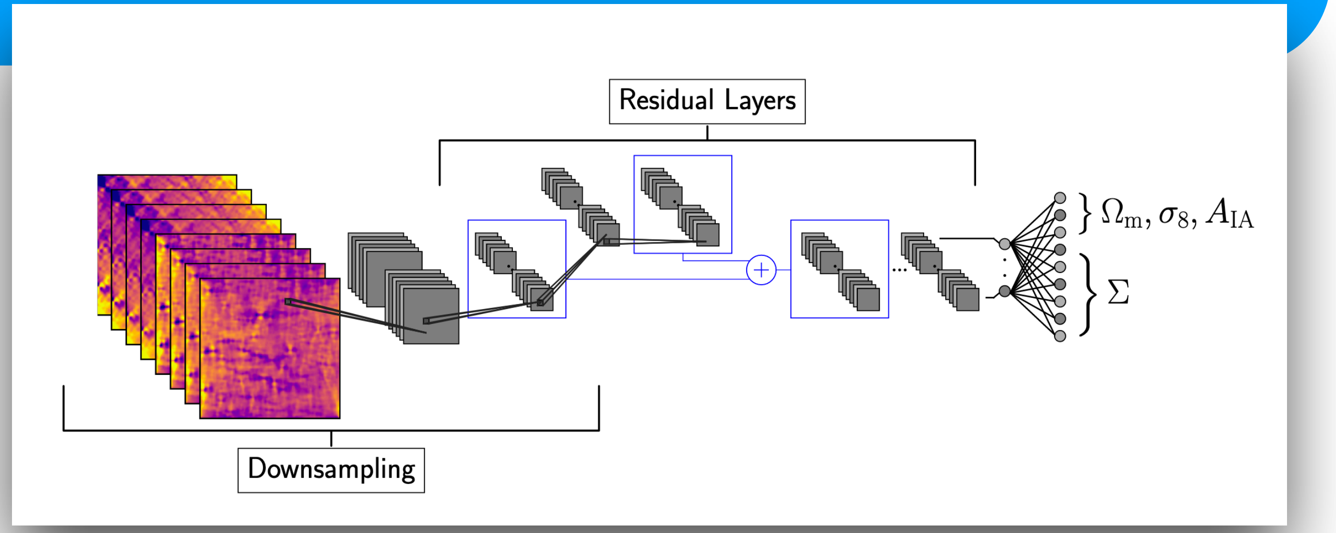
Villaescusa-Navarro et al. 2022 2201.01300

Changing the cosmology game with AI

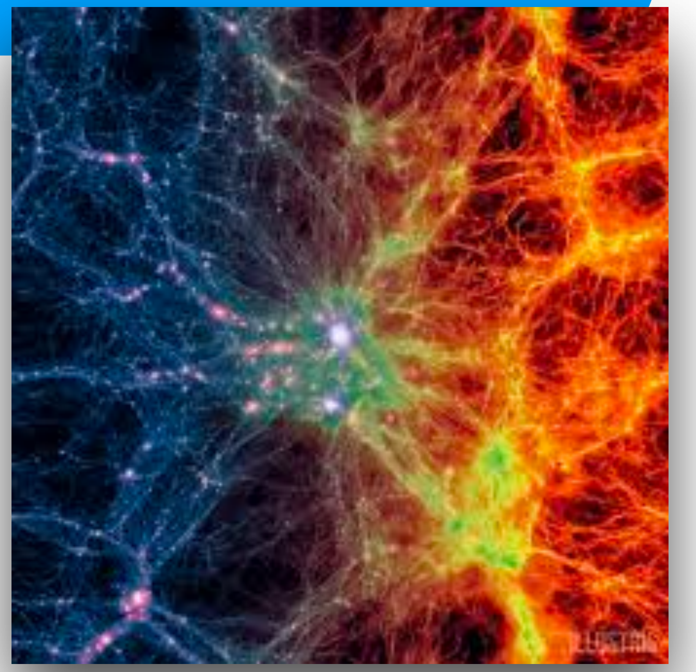
The ways that AI is opening new possibilities in cosmology:

1. Improved inference using beyond-Gaussian information with automatic feature selection
2. Efficient, map-level probe combination
3. Creating handy map-level emulators of survey data
4. Improving resolution of simulations on small scales
5. Creating consistent multi-field simulations for combined probes inference

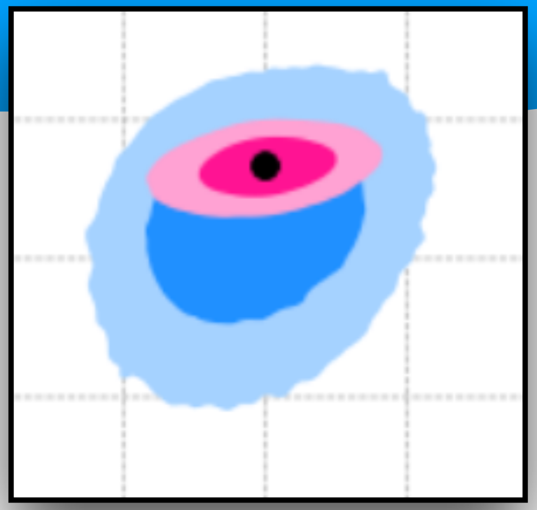
Reaching the information floor of the data



Accelearating simulations



Breaking degeneracies between cosmology and systematics



The way forward →

→ Moving towards **Computational Cosmology**

→ Reaching the **information floor** of cosmological datasets with AI- based parameter inference

→ Cosmological constraints using **large-scale simulation grids**

→ Building large simulations in a **collaborative way**, publishing data sets to the community

→ Using AI to build multi-field, high resolution simulations - creating a **simulations ladder**

→ Capitalising on **latest advances in AI** in practical cosmological measurements

Extra slides

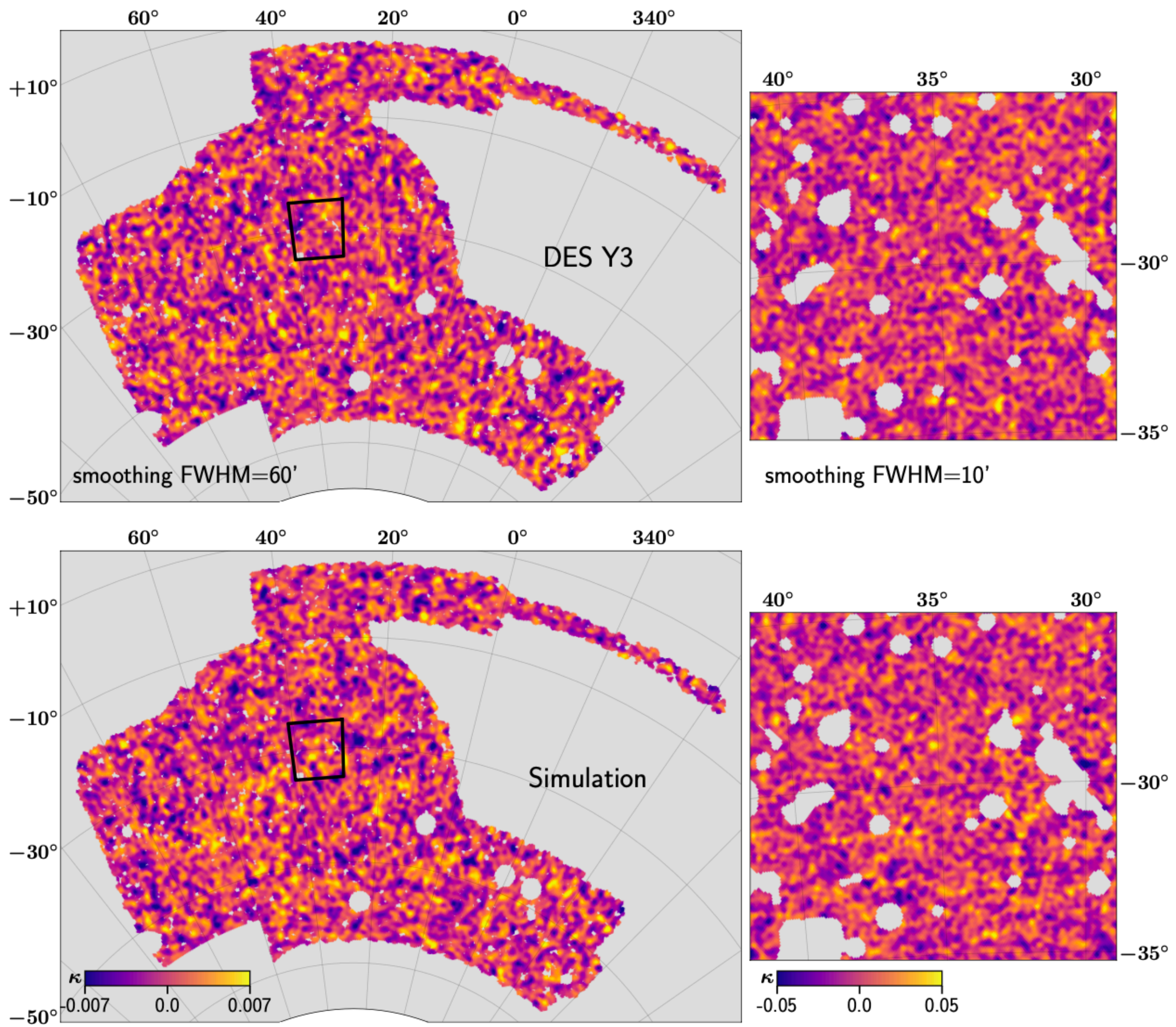
Non-Gaussian statistics

Automatically designed features	Deep neural networks
Human intuition features	Three-point functions Higher-order moments of the map Full map histogram Minkowski functionals Counting peaks and voids

Human vs machine: peaks statistics for DES Y3

Image credit: Samantha Bond (SKIM Group)

Human intuition statistics: peaks for DES-Y3



DES Y3 data

- 5000 deg^2
- Up to redshift z=1.5
- ≈6 galaxies/arcmin^2

Simulations

Constrain:

- σ_8 : clustering strength
- Ω_m : matter density
- A_{IA} : intrinsic galaxy alignment amplitude

Marginalize:

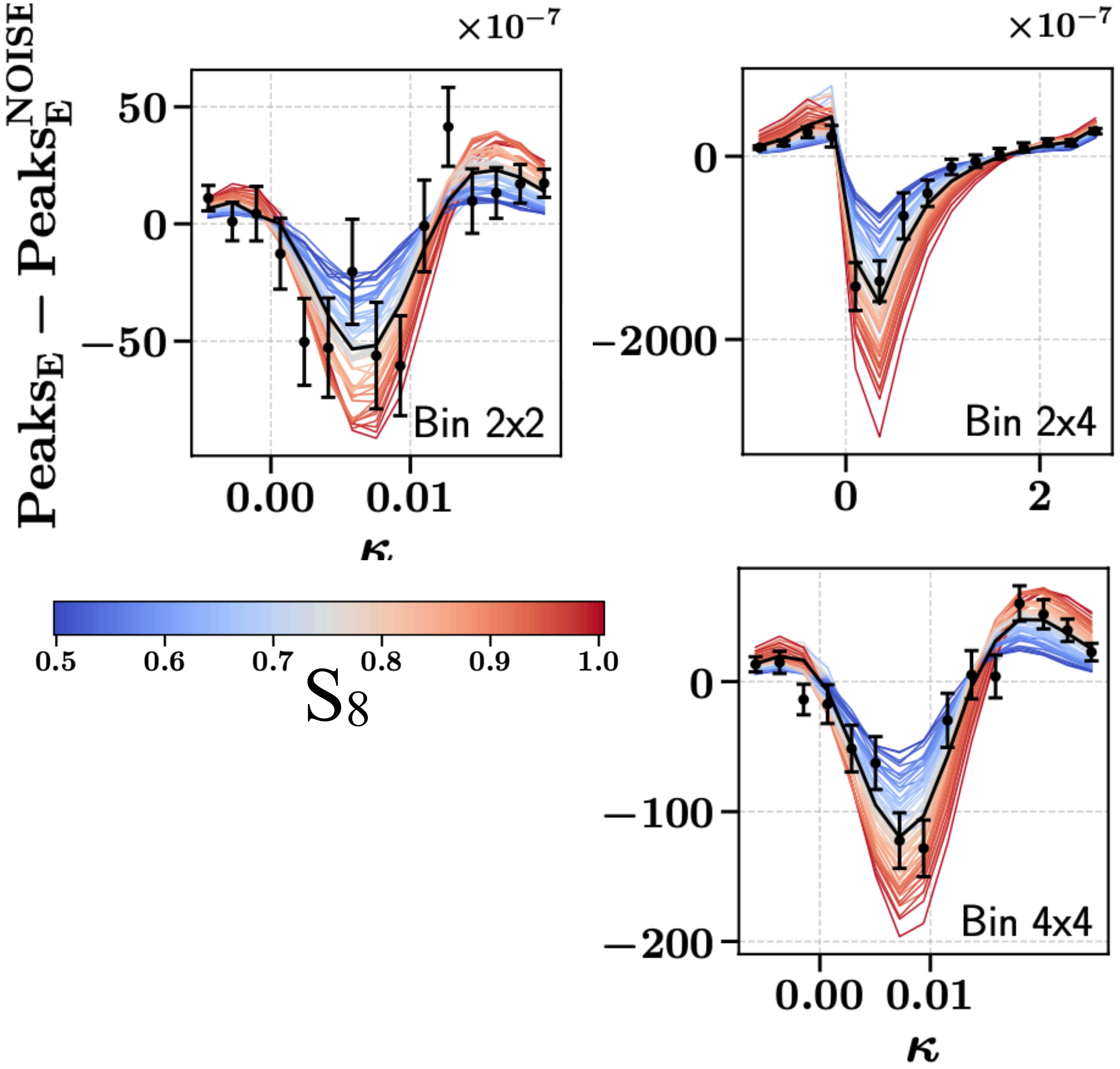
➡ n_s, Ω_m,h

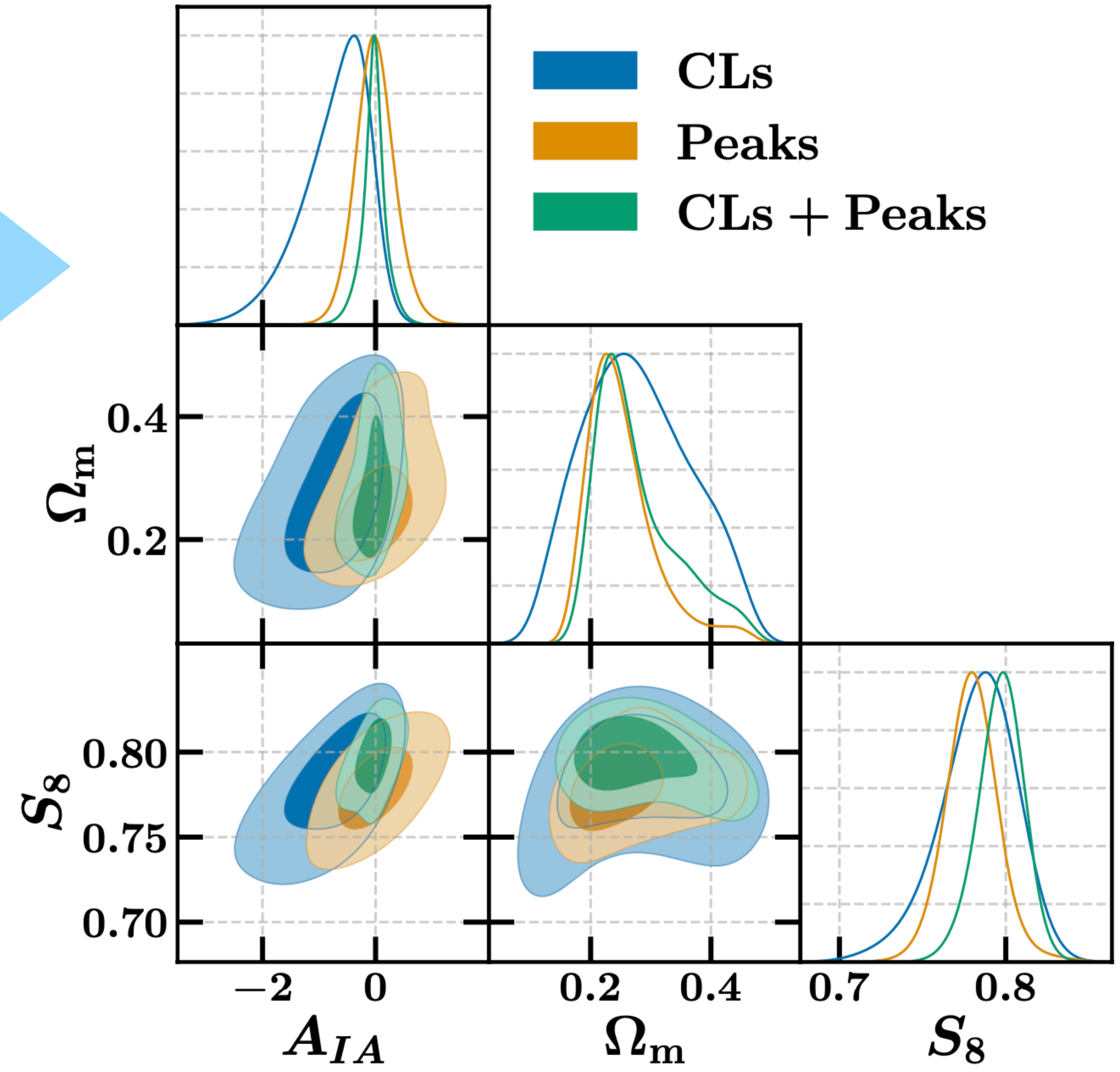
➡ n(z) error

➡ Shear calibr. error

Zuercher, +TK, +DES Collaboration 2110.10135

Human intuition statistics: peaks for DES-Y3





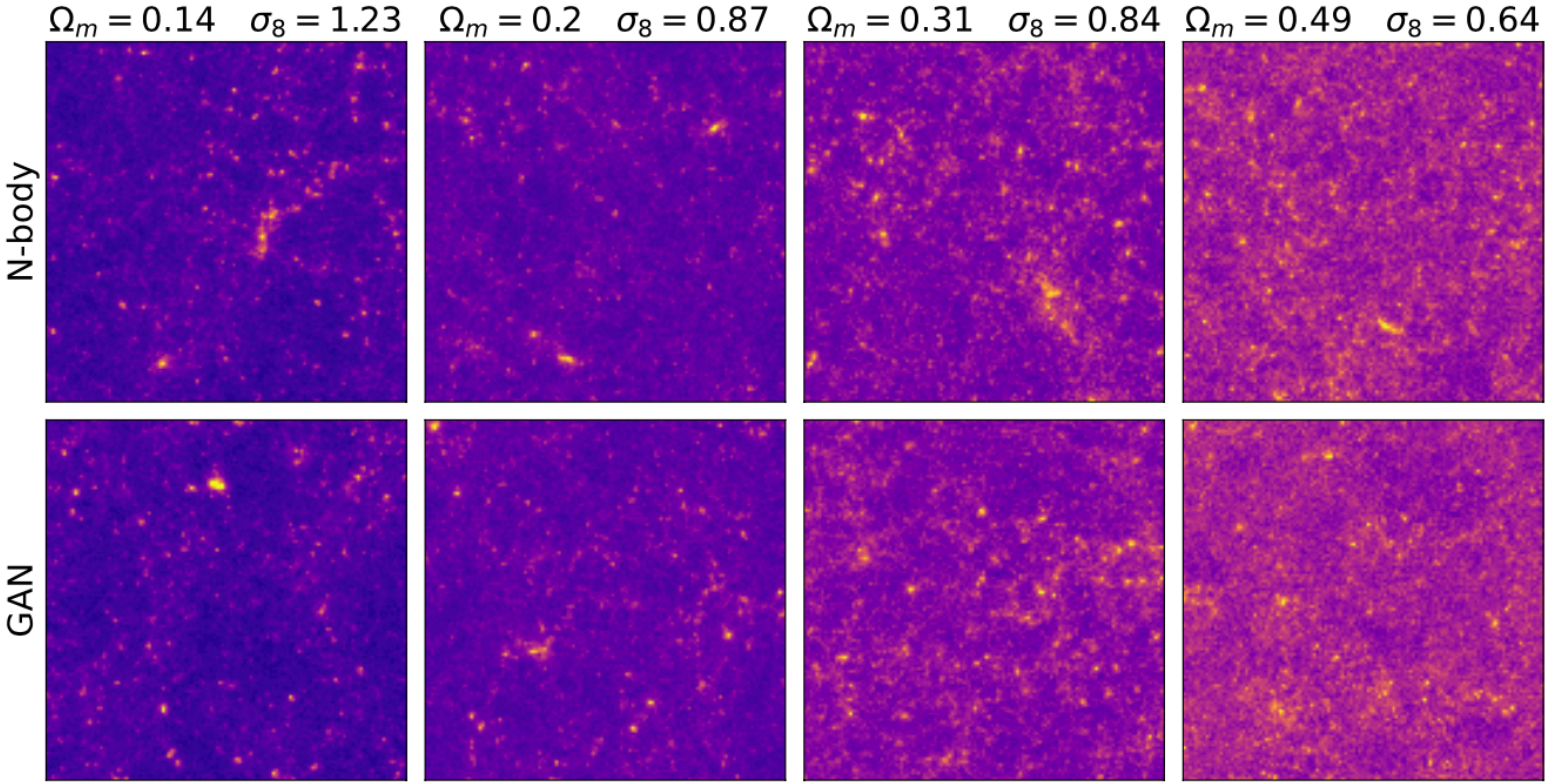
- Tomographic peaks measurement
- Conservative scales
- Using a Peaks + Cl emulator
- 40% improvement for combined analysis

$$S_8 = 0.797^{+0.015}_{-0.013}$$

$$A_{IA} = -0.03 \pm 0.23$$

Zuercher, +TK, +DES Collaboration 2110.10135

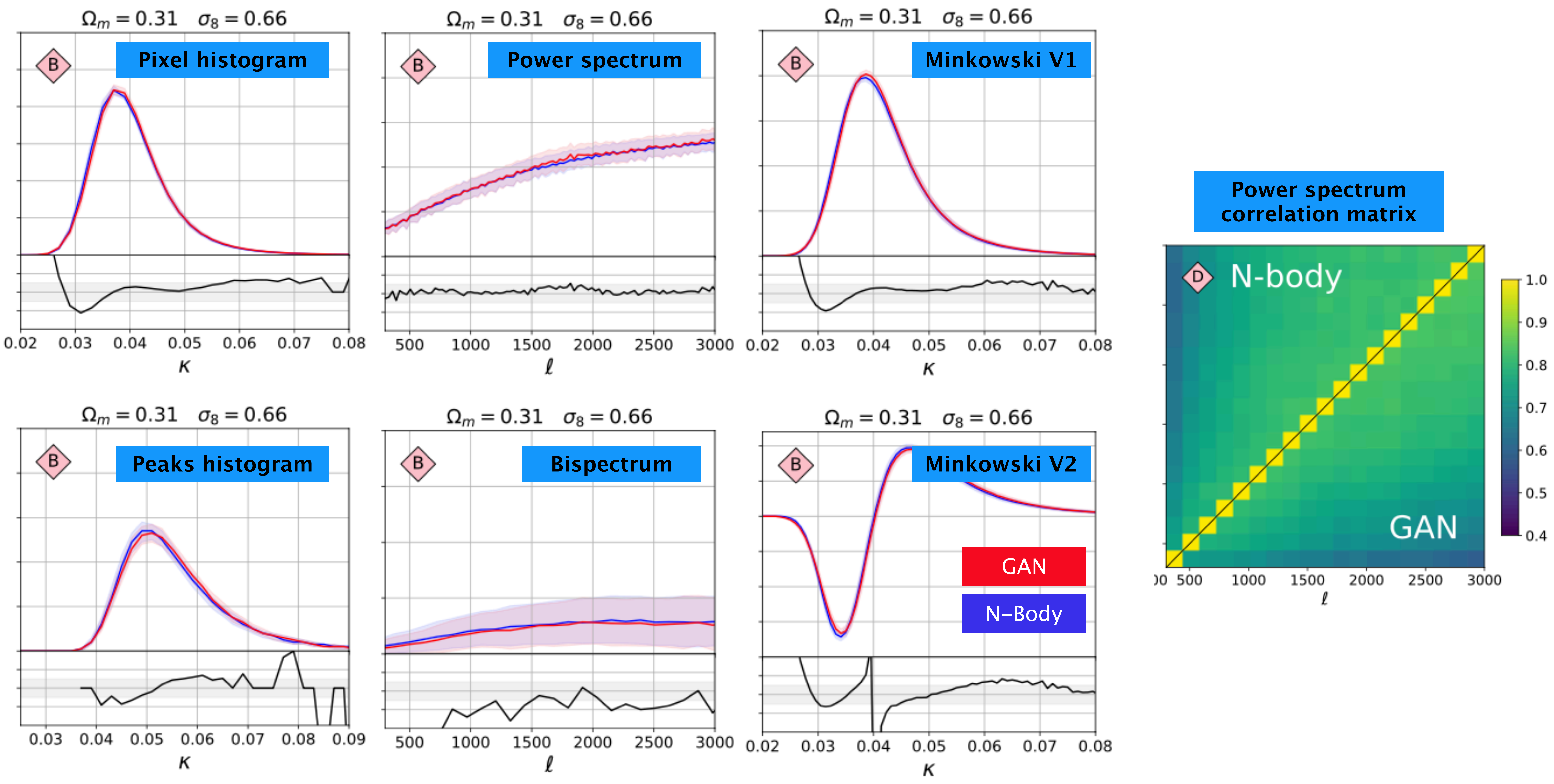
Emulation of cosmological mass maps with conditional GANs



Comparison between the N-body and GAN-generated mass maps for varying cosmological parameters

Perraudin, TK, et al. 2020, 2004.08139

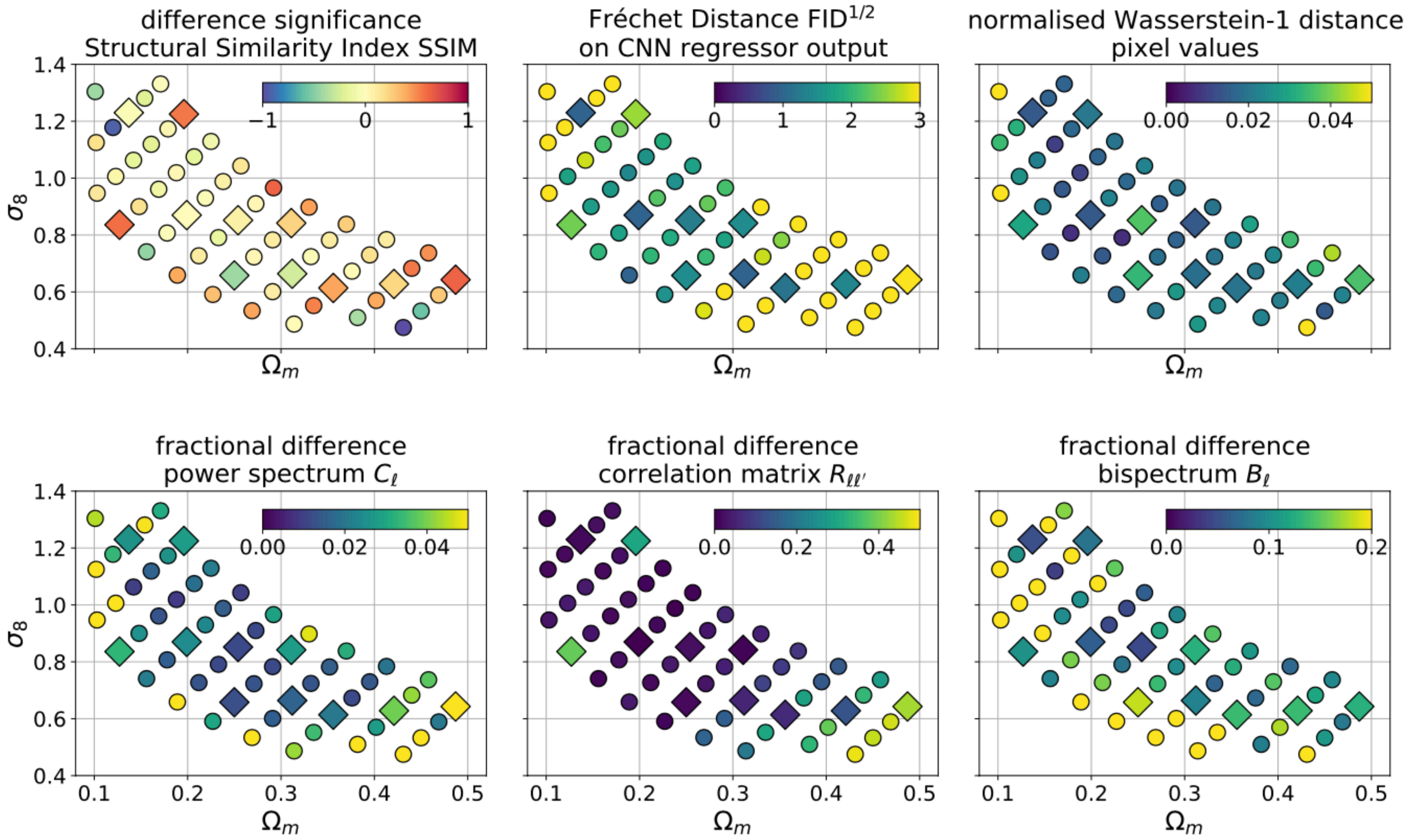
Emulation of cosmological mass maps with conditional GANs



Quantitative comparison: a very good match of summary statistics

Perraudin, TK, et al. 2020, 2004.08139

Emulation of cosmological mass maps with conditional GANs

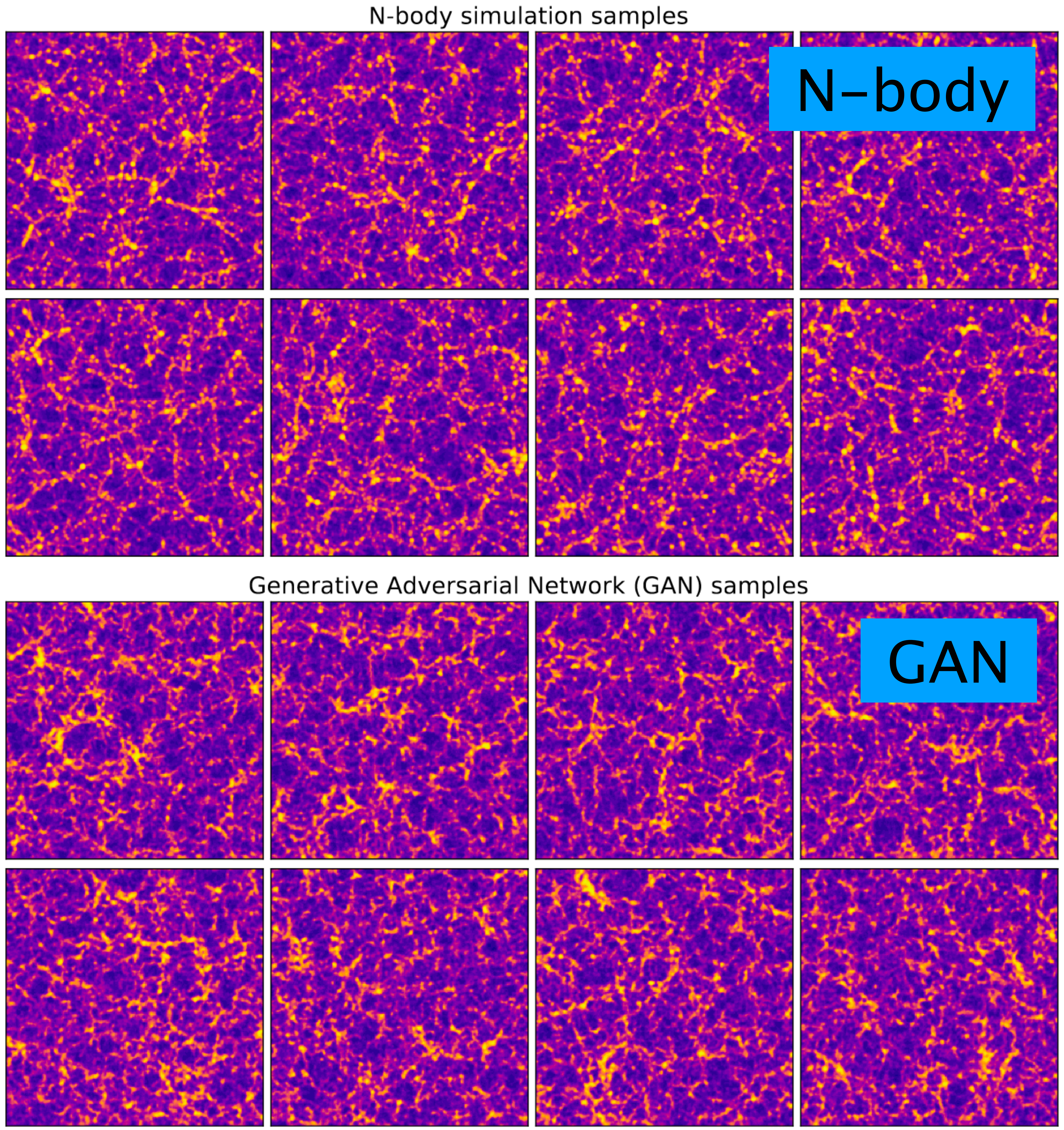


Quantitative comparison as a function of cosmology: very good match, with a some room for improvement

Perraudin, TK, et al. 2020, 2004.08139

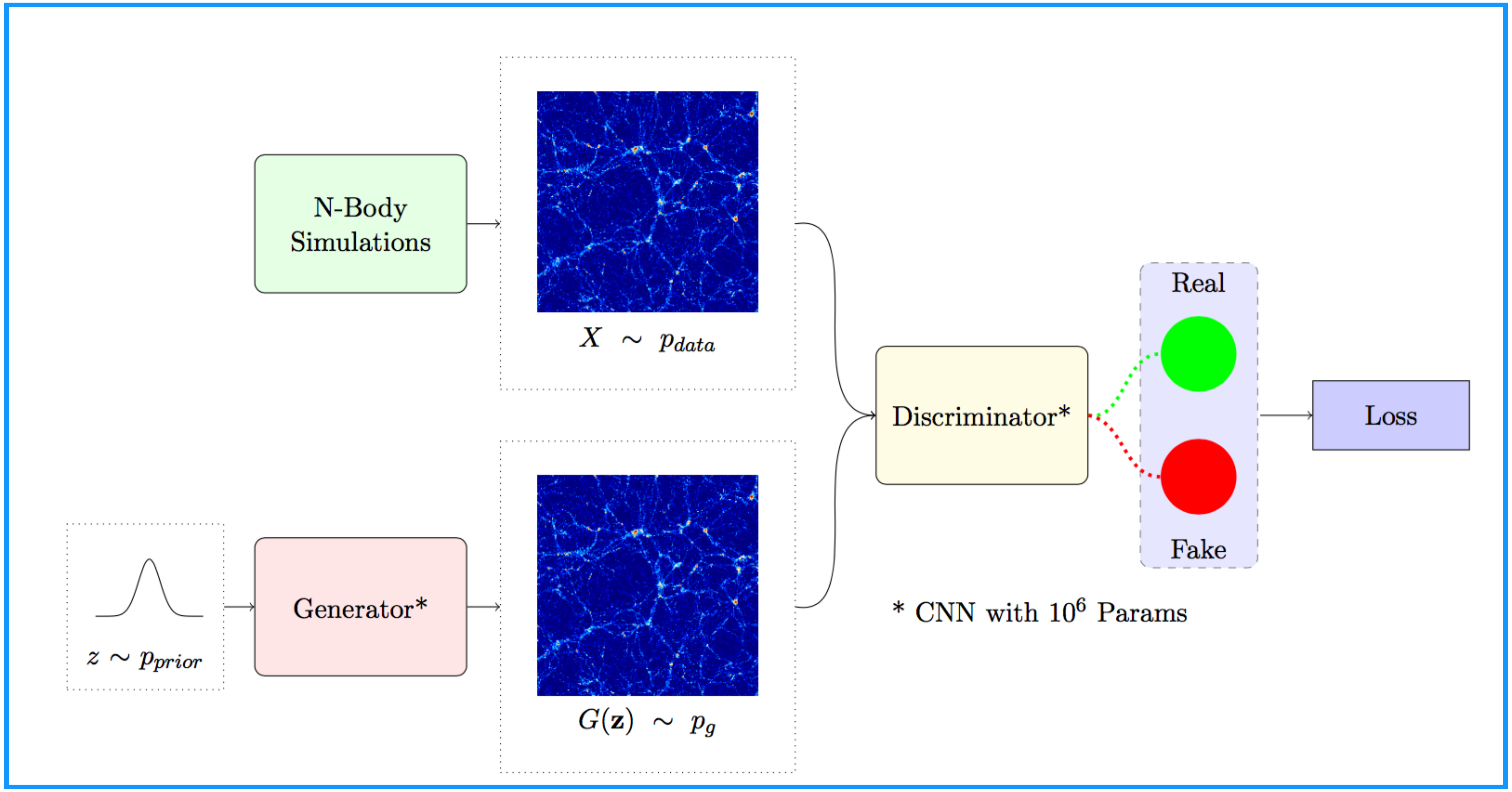
Simulations with generative models

- Training on 2D images of N-body simulations of cosmic web
- Generative model samples new realisations
- New realisations are statistically consistent with training set
- Good agreement on summary statistics



Rodriguez, TK, et al. 2018, 1801.09070

AI for cosmological simulations

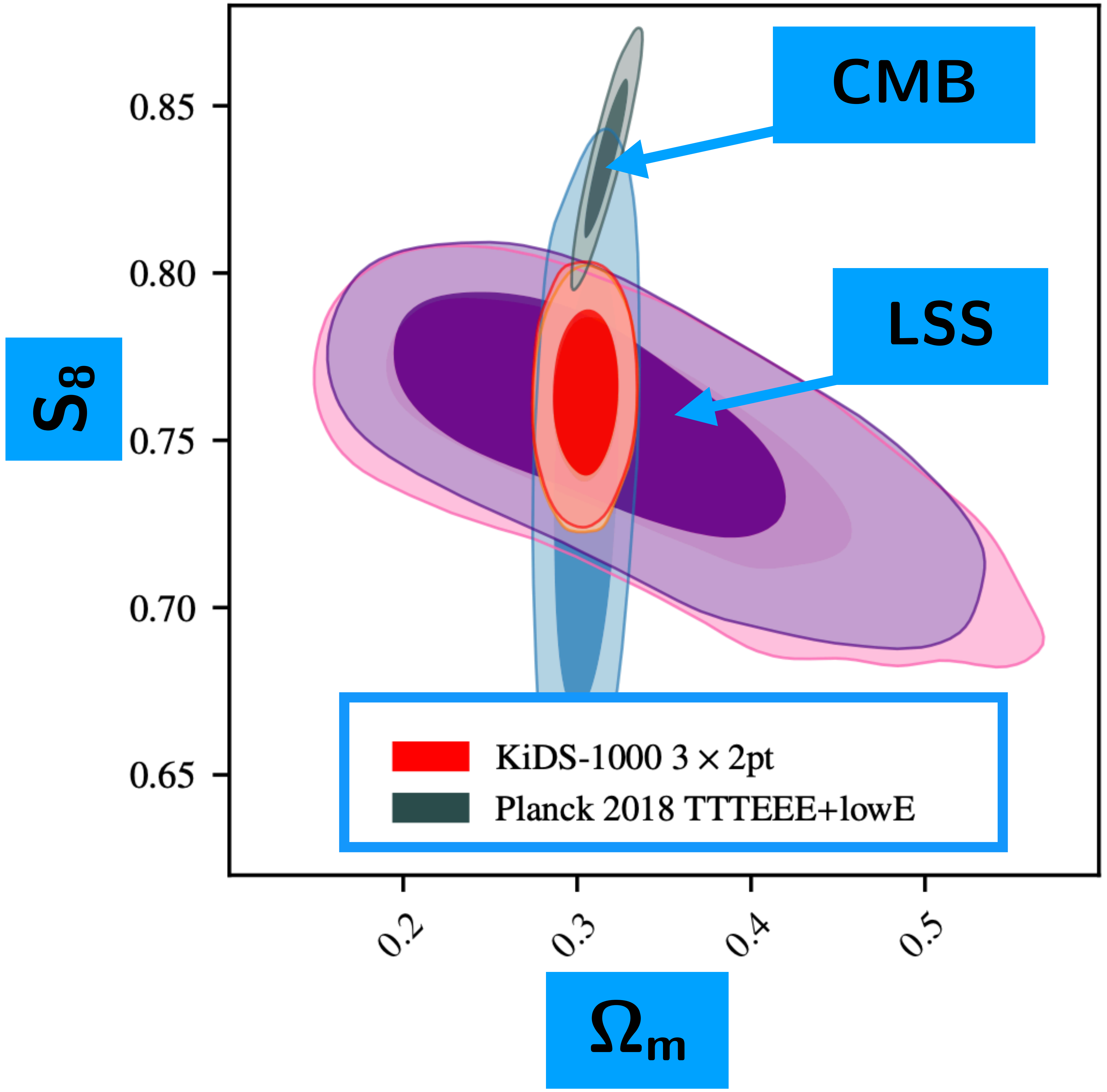


- Learn a mapping from a random vector to a cosmic web map
- Train on existing simulations
- Generate new cosmic web in a fraction of a second on a laptop

image by Aurelien Lucchi and Andres Rodrigues

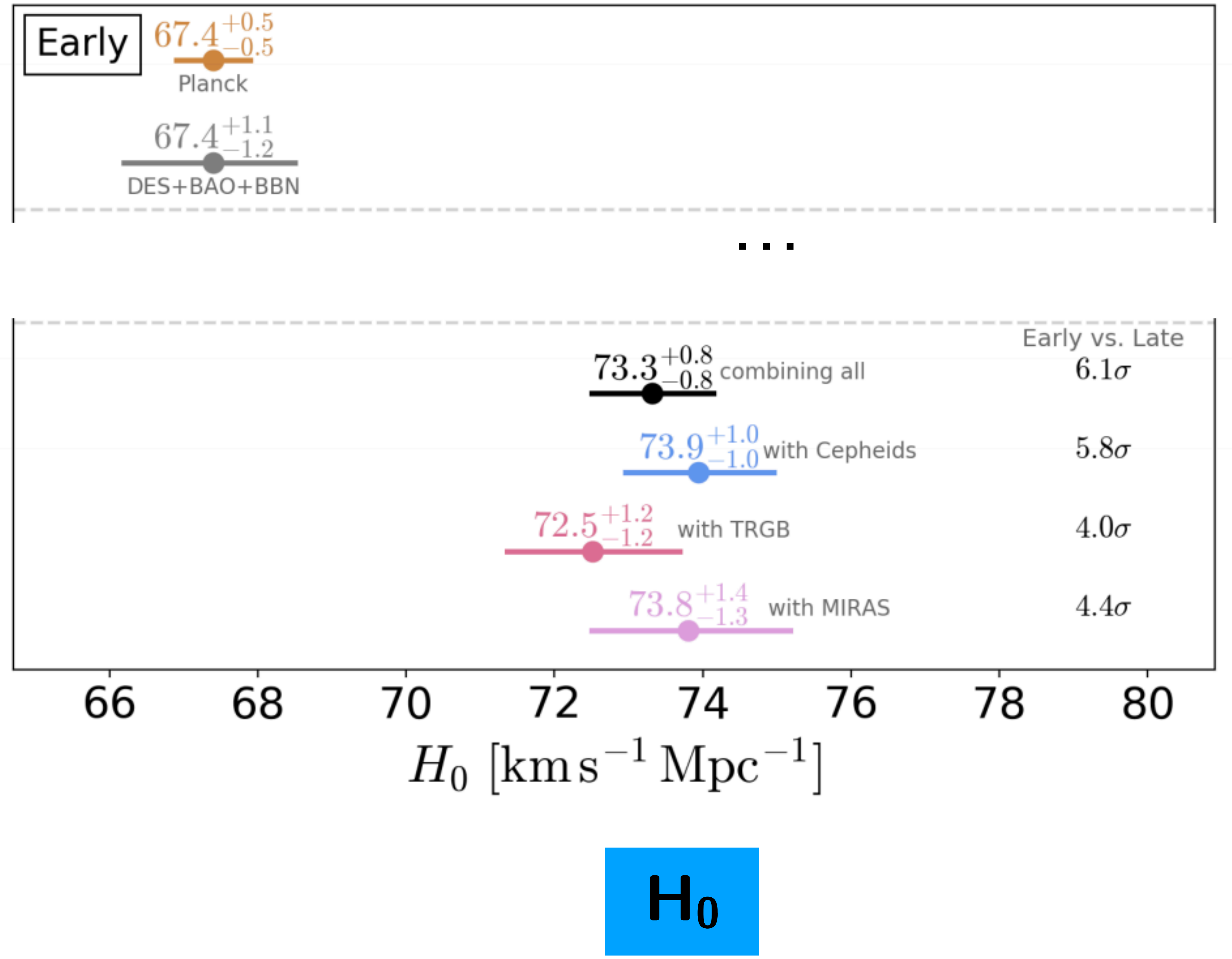
Tensions between early and late universe

3σ tension on S_8



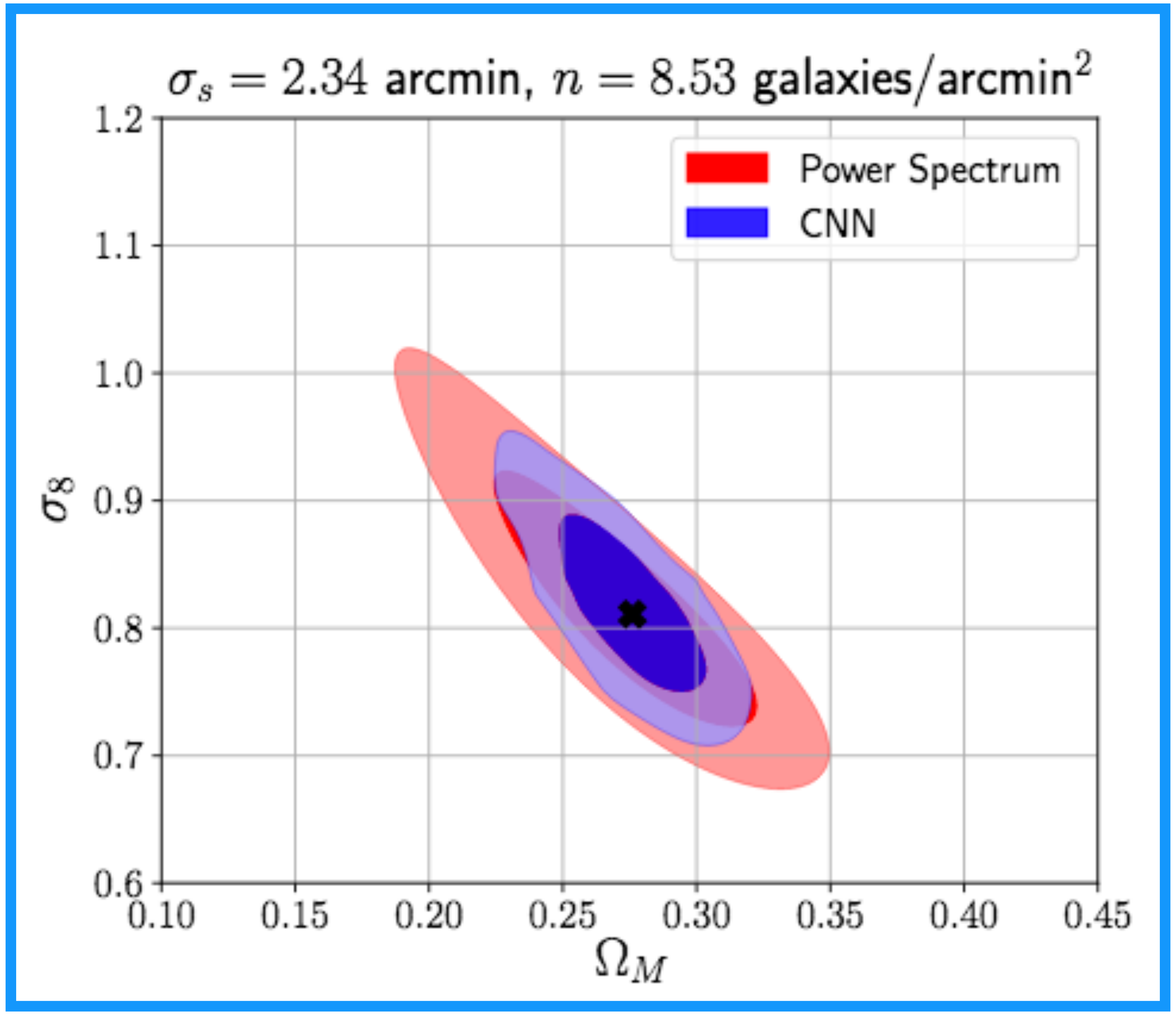
Heymans et al. 2020, 2007.15632

4-5σ tension on H_0



Verde et al. 2019, 1907.10625

Deep learning captures more information



40% increase in constraining power
equivalent to collecting 2x more data

Fluri, TK, et al. 1807.08732

Next steps for the deep learning analysis

- Bring the machine learning analysis on the same level of maturity as the traditional 2-pt analysis for weak lensing maps
  - expand the simulation set to cover the entire standard cosmological model: include Ω_b, n_s, H_0, as well as the dark energy equation of state w 👍✅
  - add baryonic feedback models 🥵☑️
- Adjust the analysis to large data sets from Stage III and IV LSS surveys
  - create deep learning algorithms on the sphere 👍✅
  - overcome difficulties in simulations processing and ML training 😰☑️
- Create the deep learning analysis of combined probes
  - combination of galaxy shapes and positions: equivalent of 3 x 2-pt 🥳✅
  - combination with CMB SZ and X-rays data 🏃‍♀️
  - create a consistent set of simulations for all these probes 🏆