Learning from small scales in weak lensing and CMB data

BCCP
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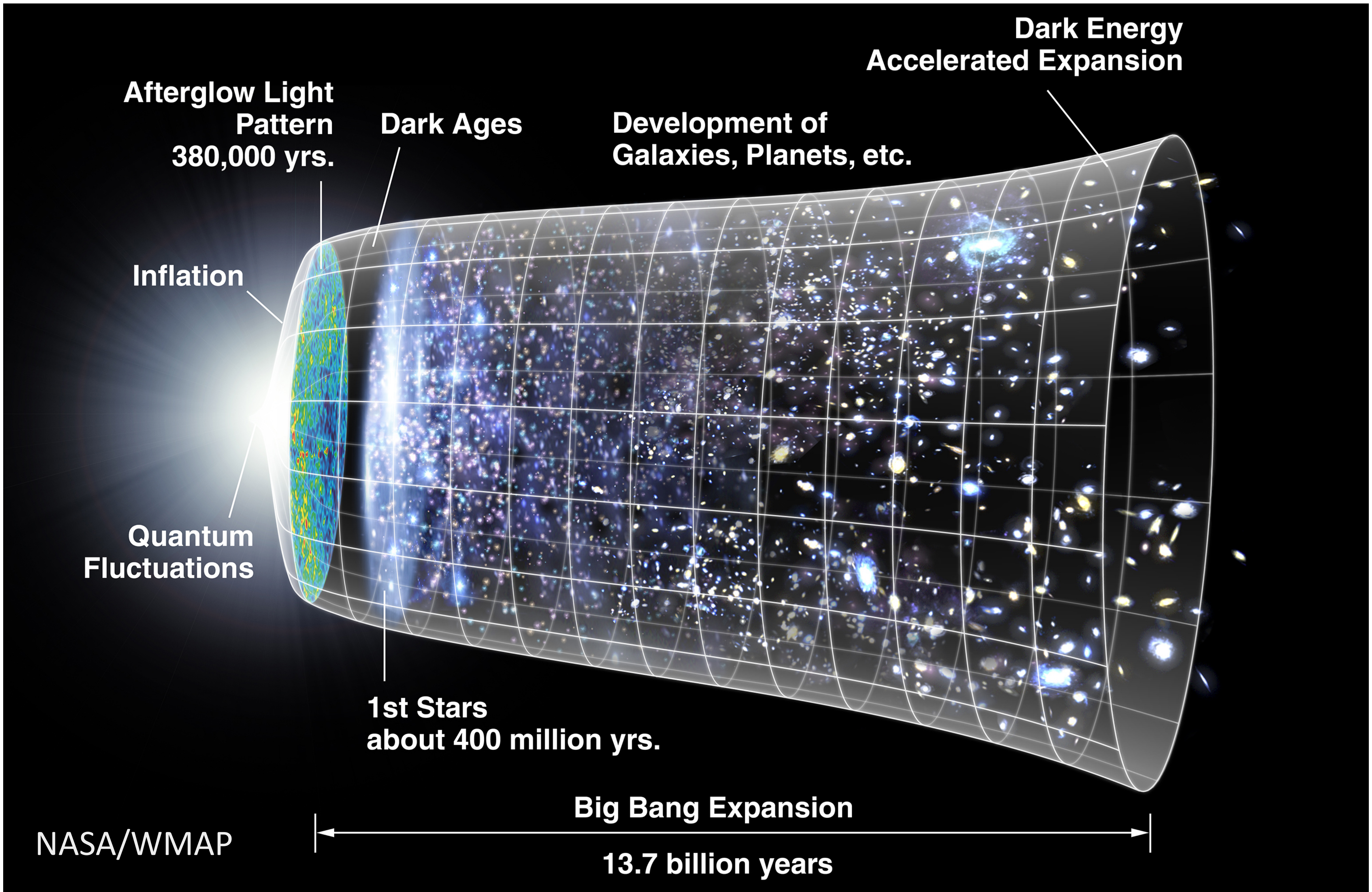
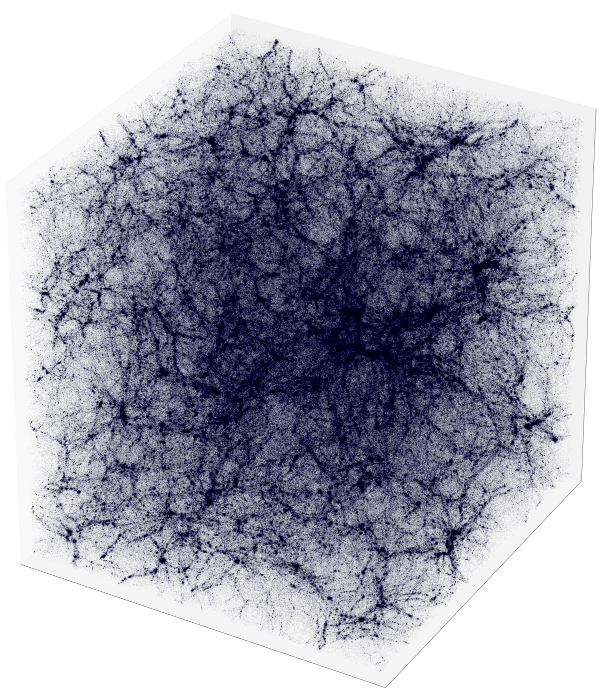
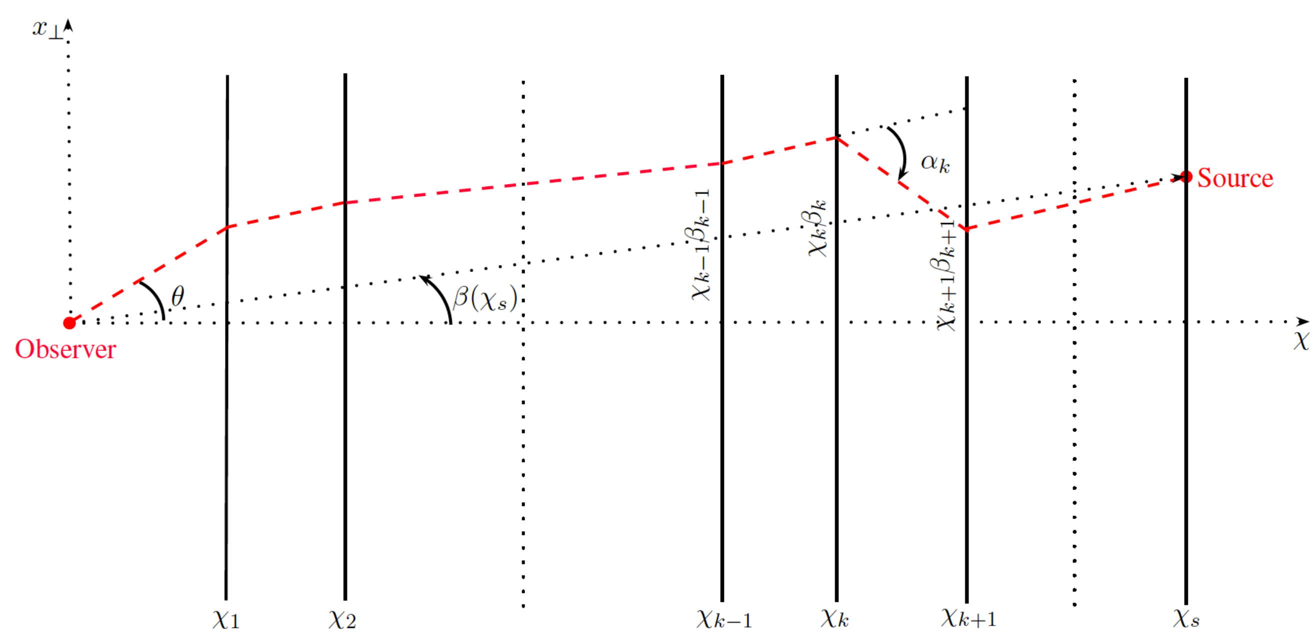
arXiv:1802.01212, arXiv:1902.03663, arXiv:1909.04690

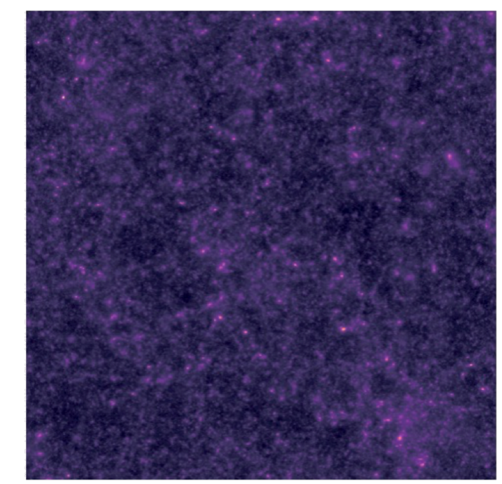
Standard cosmological model



Modeling small scales in WL





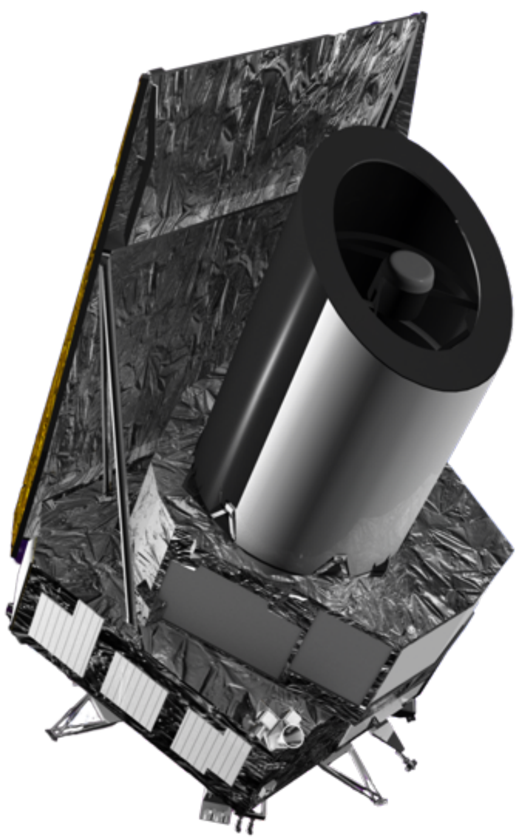


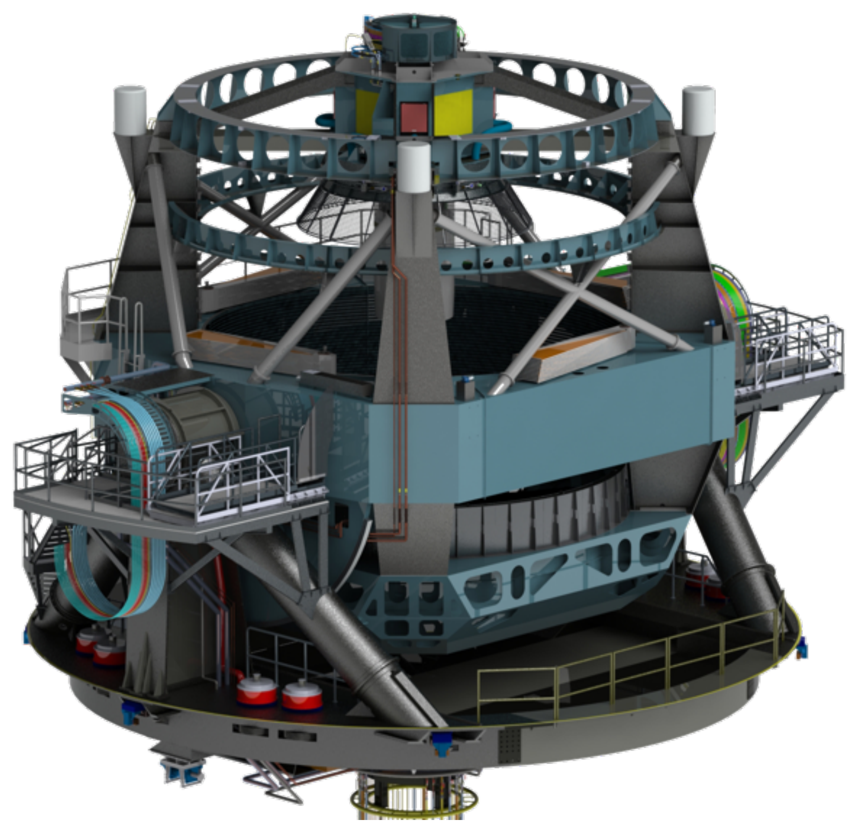
- DM-only N-body
- 240/h Mpc box
- 512^3 particles (mass resolution ~10^{10} Msun)
- No SSC

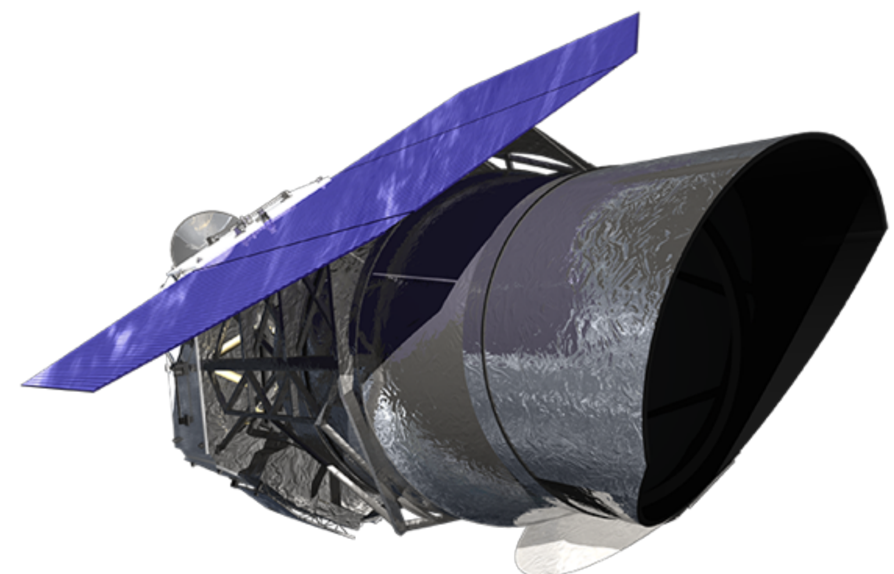
- Multi-plane algorithm
- Full ray-tracing (no Born)
- 80/h Mpc planes
- Flat-sky

- 3.5 x 3.5 deg2
- Past light-cone recycling
- Smoothing and noise added in post-processing

Upcoming WL surveys





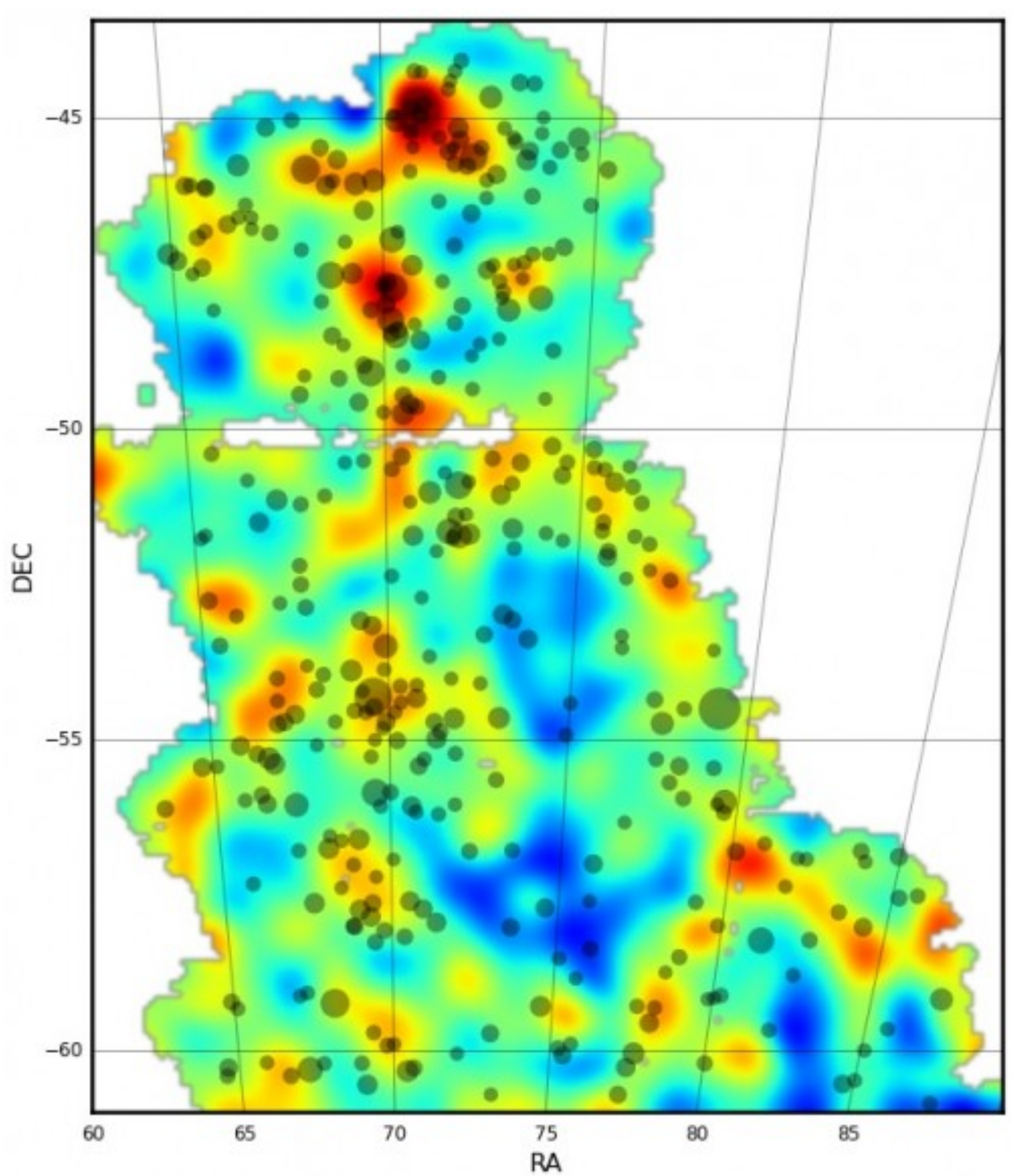


euclid

LSST
Large Synoptic Survey Telescope

Wide-Field Infrared Survey Telescope
WFIRST
Astrophysics • Dark Energy • Exoplanets

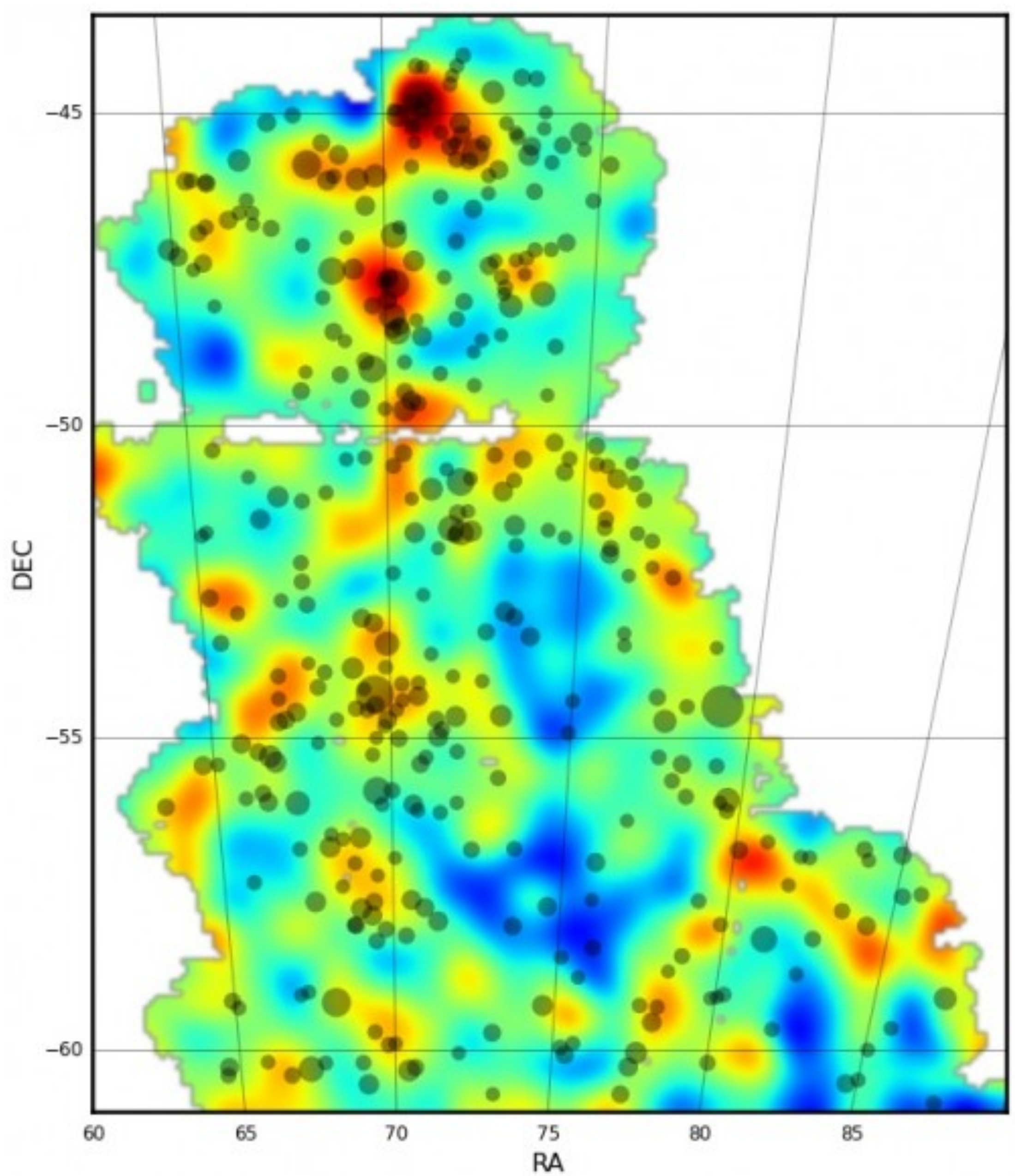
Extracting information from WL maps



DES Y1

$$\kappa(\vec{\theta}) = \frac{3\Omega_m H_0^2}{2c^2 D_S} \int_0^{D_S} dD_L \frac{D_{SL} D_L}{a(D_L)} \delta(D_L \vec{\theta}, D_L)$$

Extracting information from WL maps



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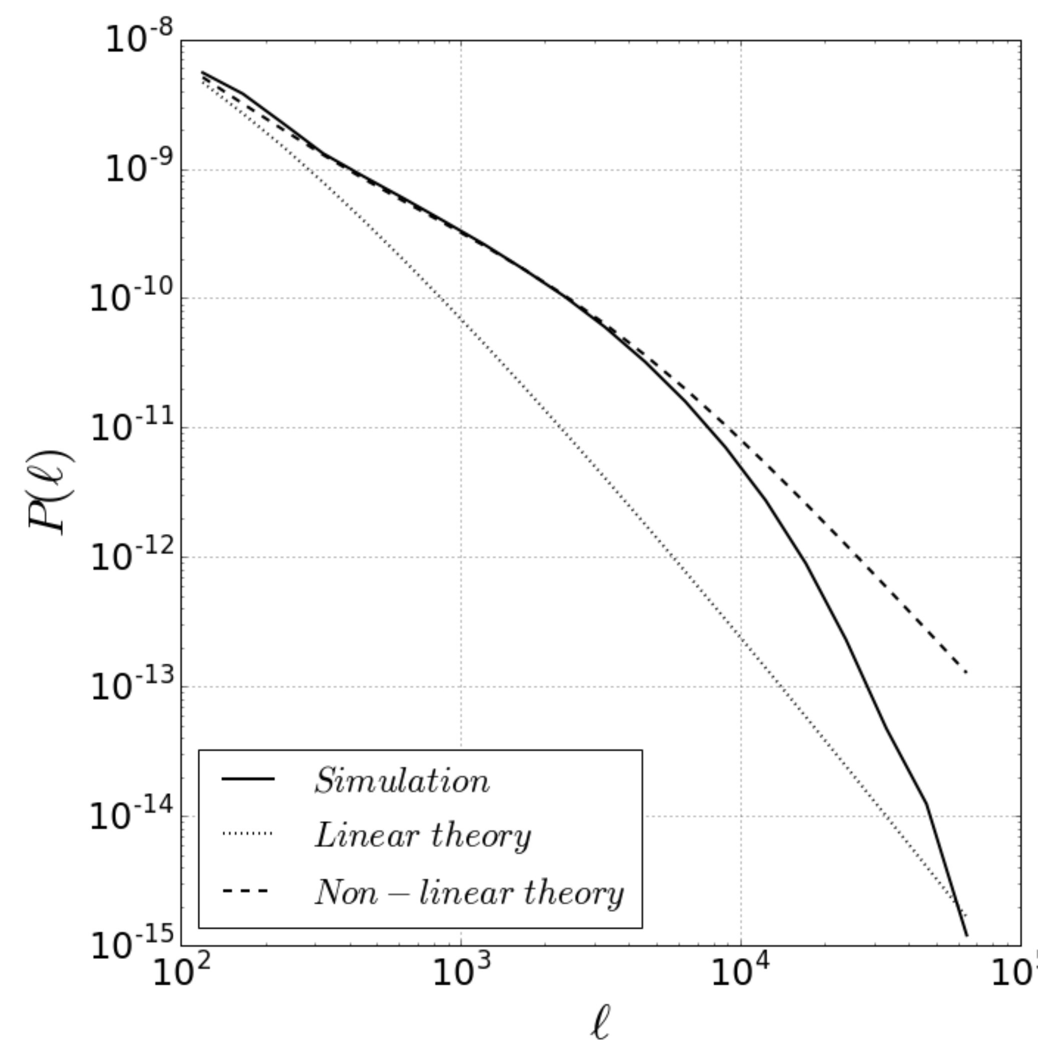
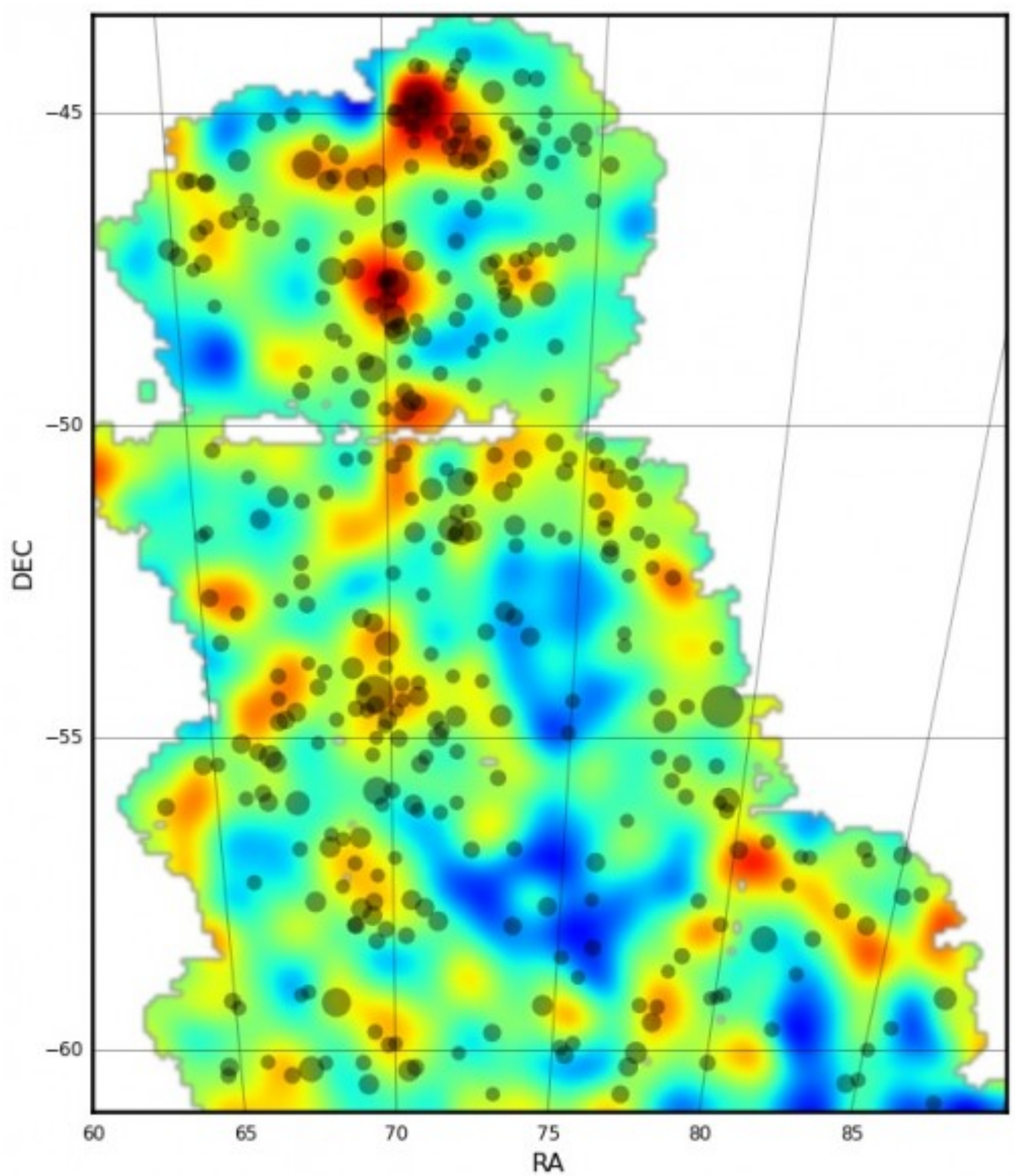


Extracting information from WL maps



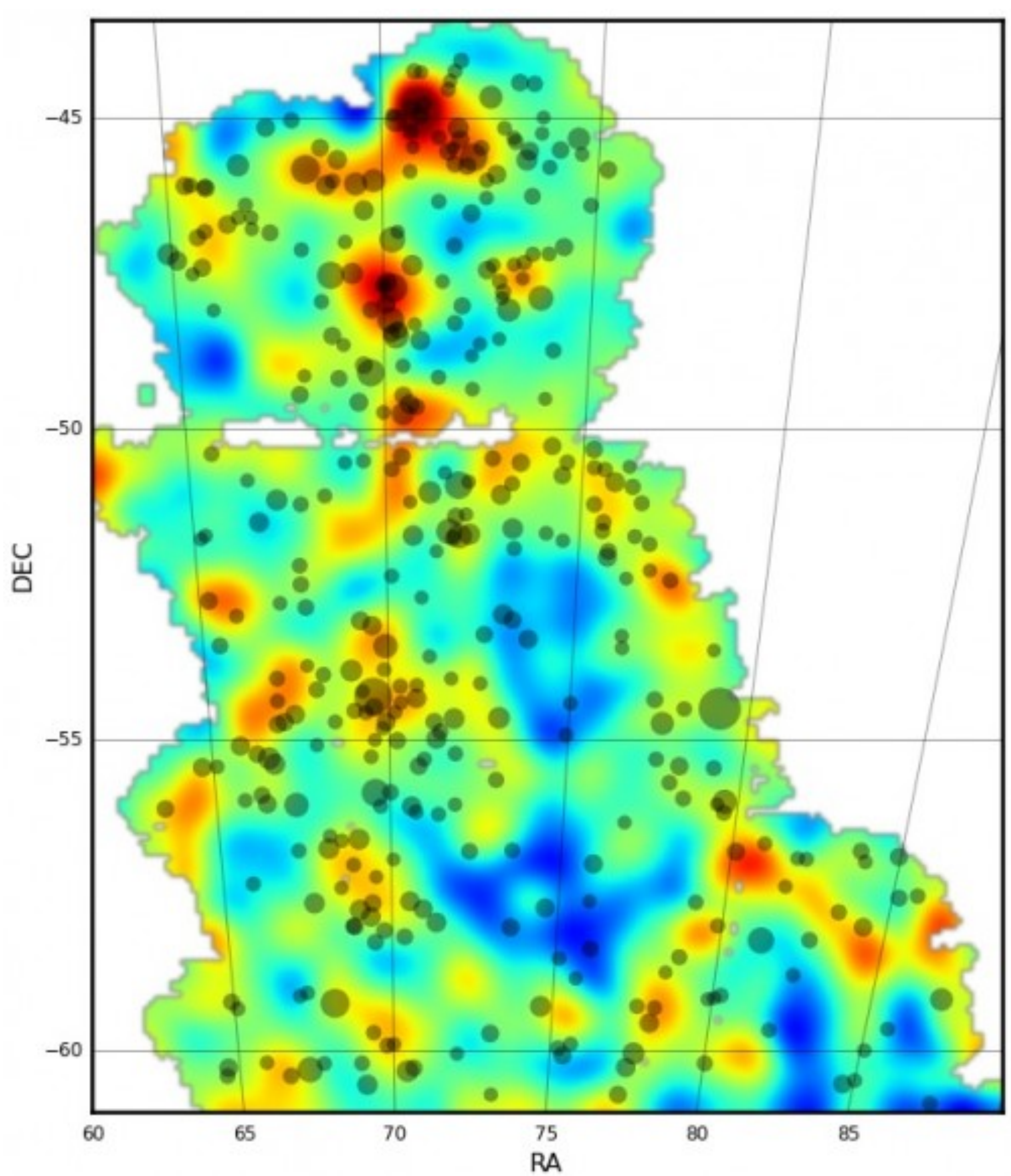
DES Y1

1

Transform the field to make it look more Gaussian, then use 2-point function / power spectrum

Neyrinck et al. 2009, Seo et al. 2011, Carron & Szapudi 2013,14, Shirasaki 2017

Extracting information from WL maps



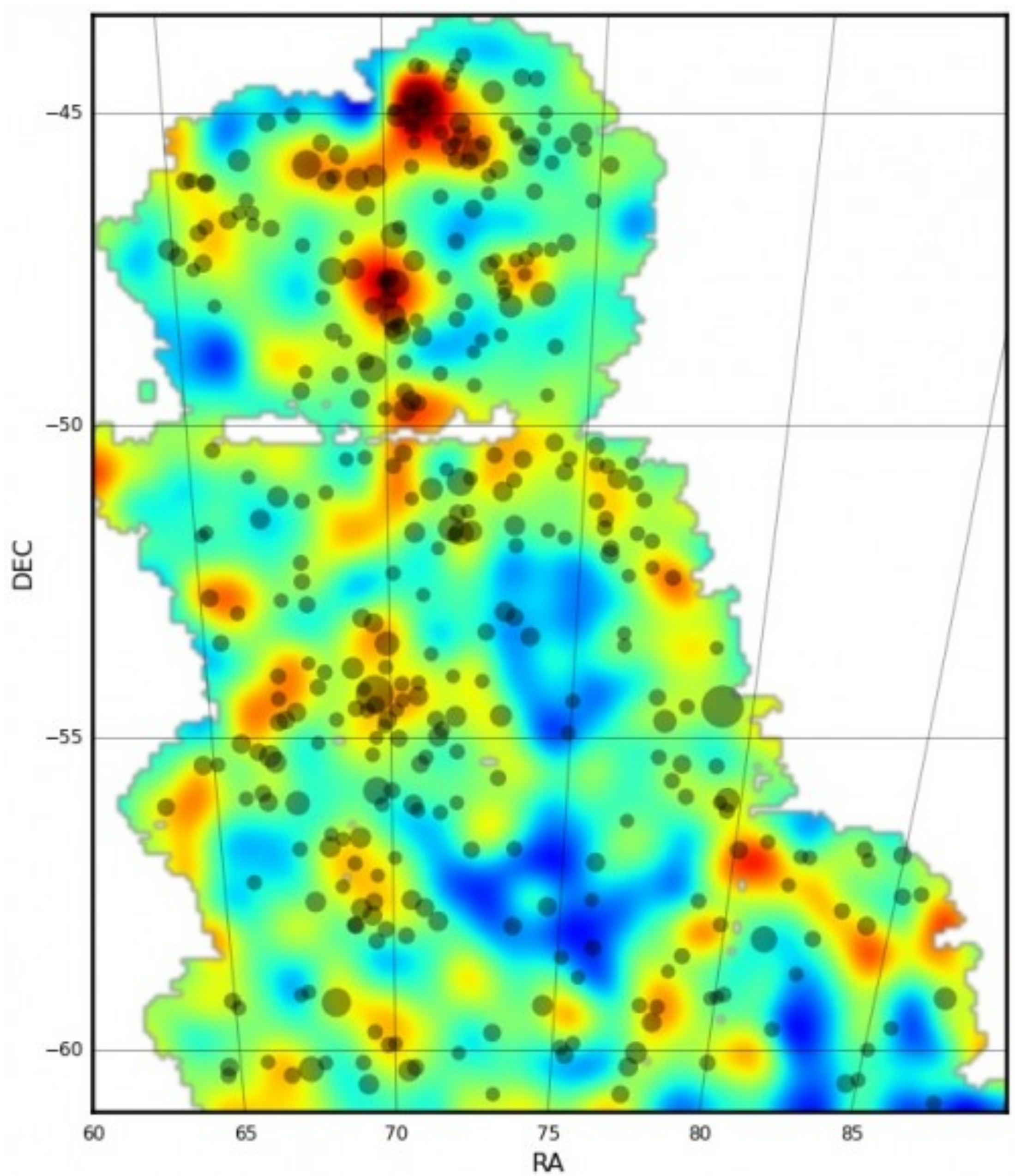
DES Y1

1 Transform the field to make it look more Gaussian, then use 2-point function / power spectrum

2 "Reconstruct" the field's initial conditions, when it was almost Gaussian, then use 2-point function/ power spectrum

Lagrangian reconstruction, sample ICs from with forward model, optimize ICs with forward model, ML…

Extracting information from WL maps



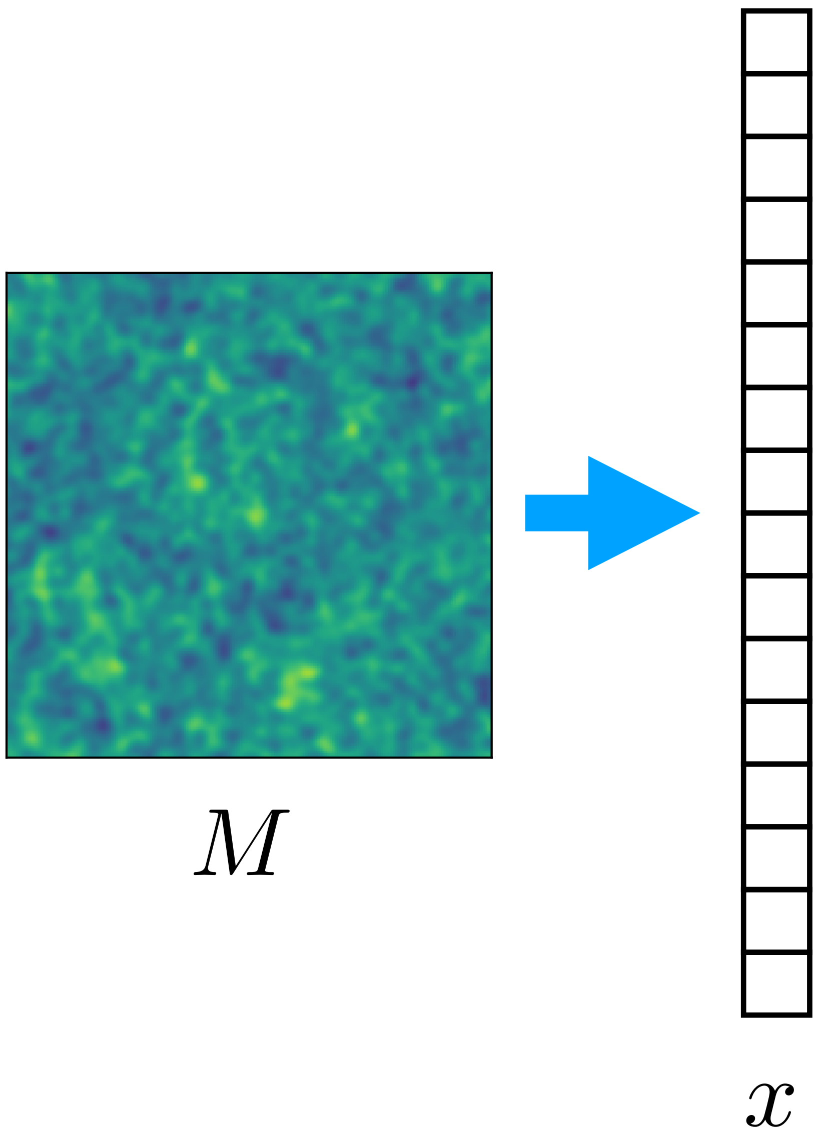
DES Y1

1. Transform the field to make it look more Gaussian, then use 2-point function / power spectrum

2. "Reconstruct" the field's initial conditions, when it was almost Gaussian, then use 2-point function/ power spectrum

3. Use higher-order statistics, either n-point functions or topological observables

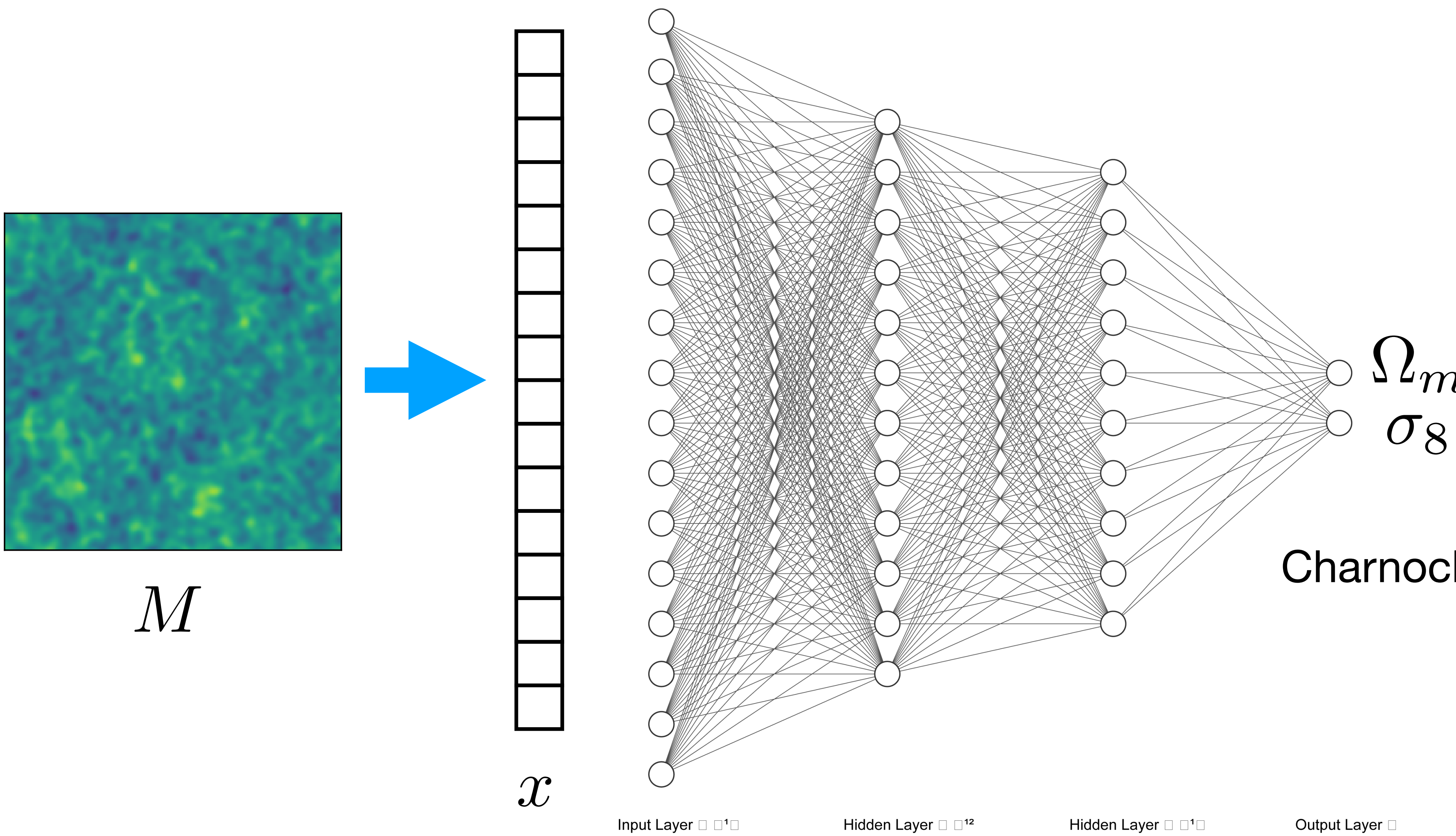
Extracting information from WL maps



Ω_m σ_8

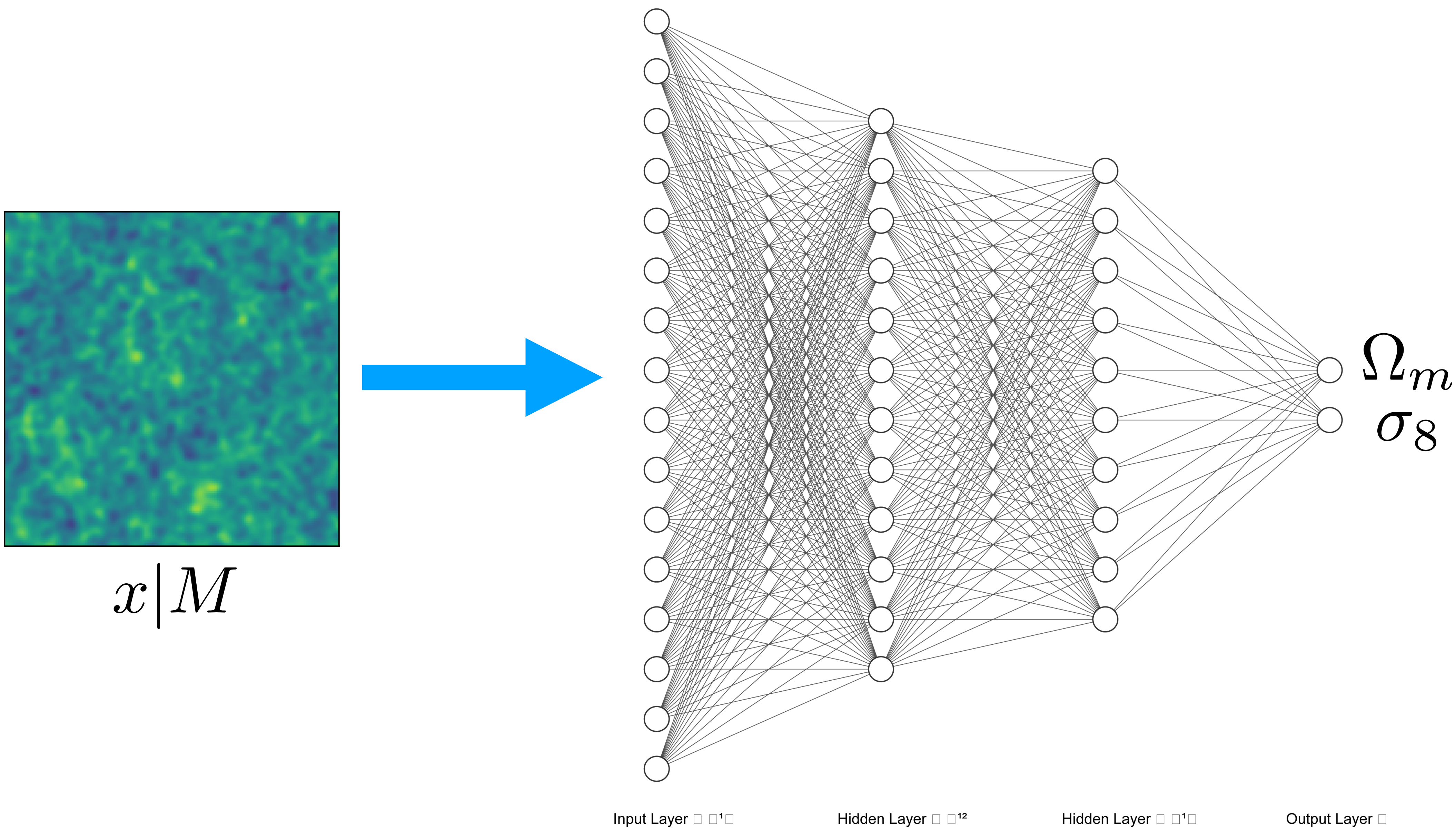
$$p(\theta|x, M) = \frac{p(x|\theta, M)p(\theta, M)}{p(x, M)}$$

Extracting information from WL maps

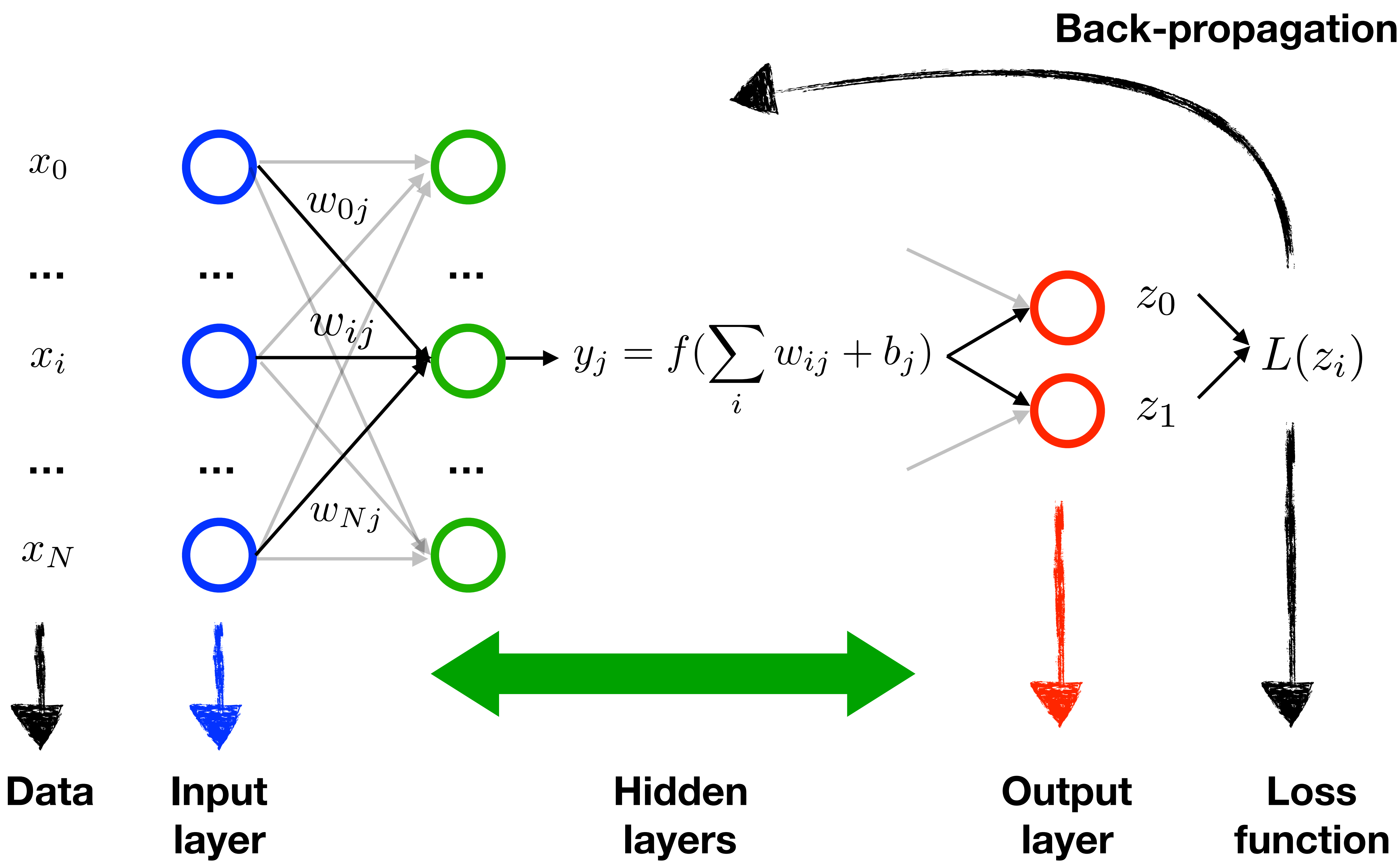


Charnock et al. 2018

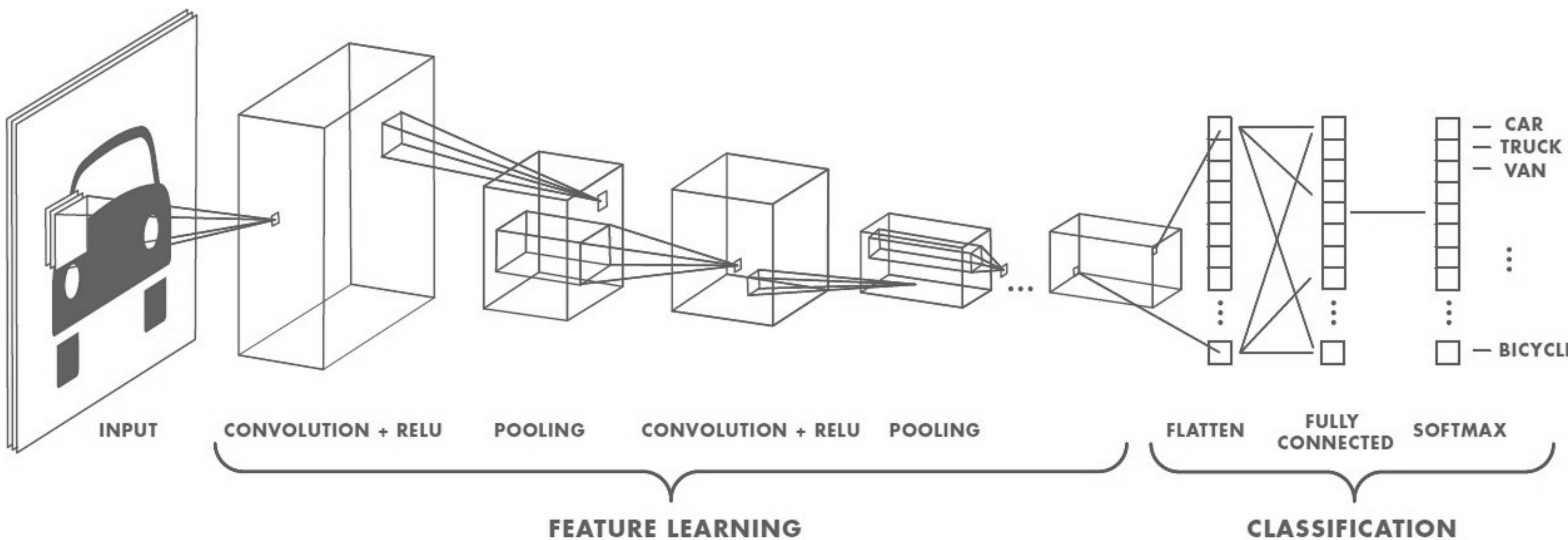
Extracting information from WL maps



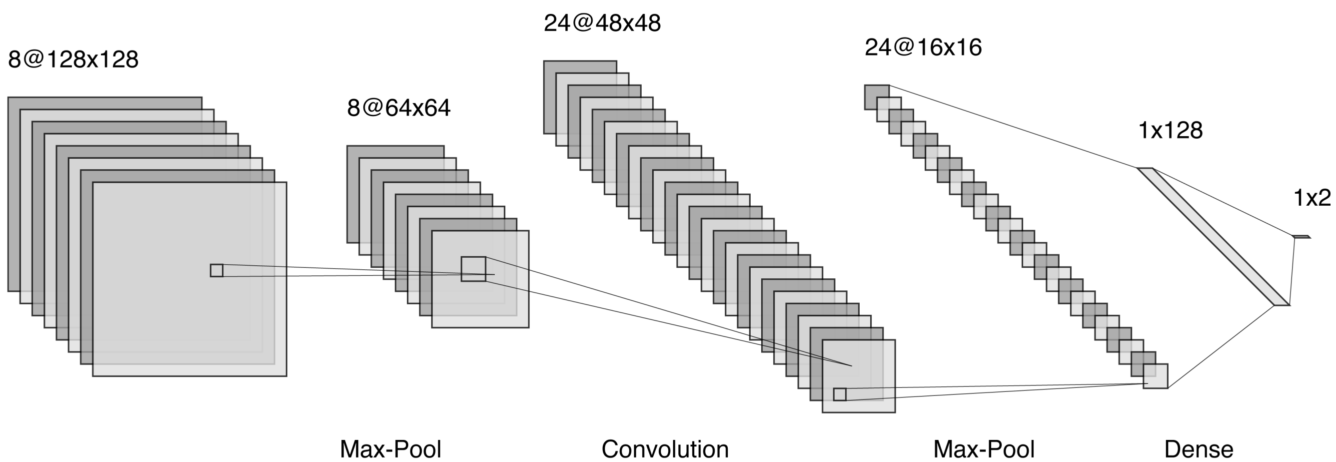
Neural networks



Convolutional neural networks

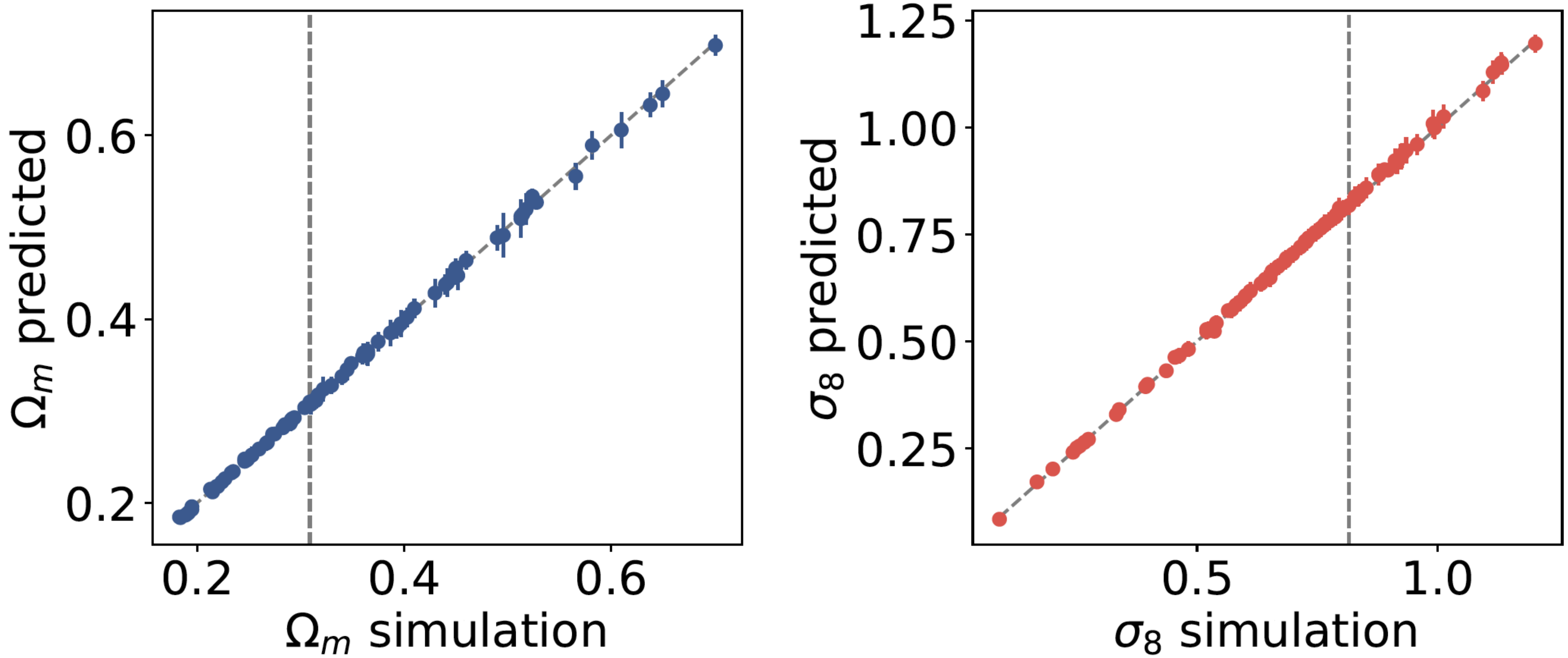


Architecture

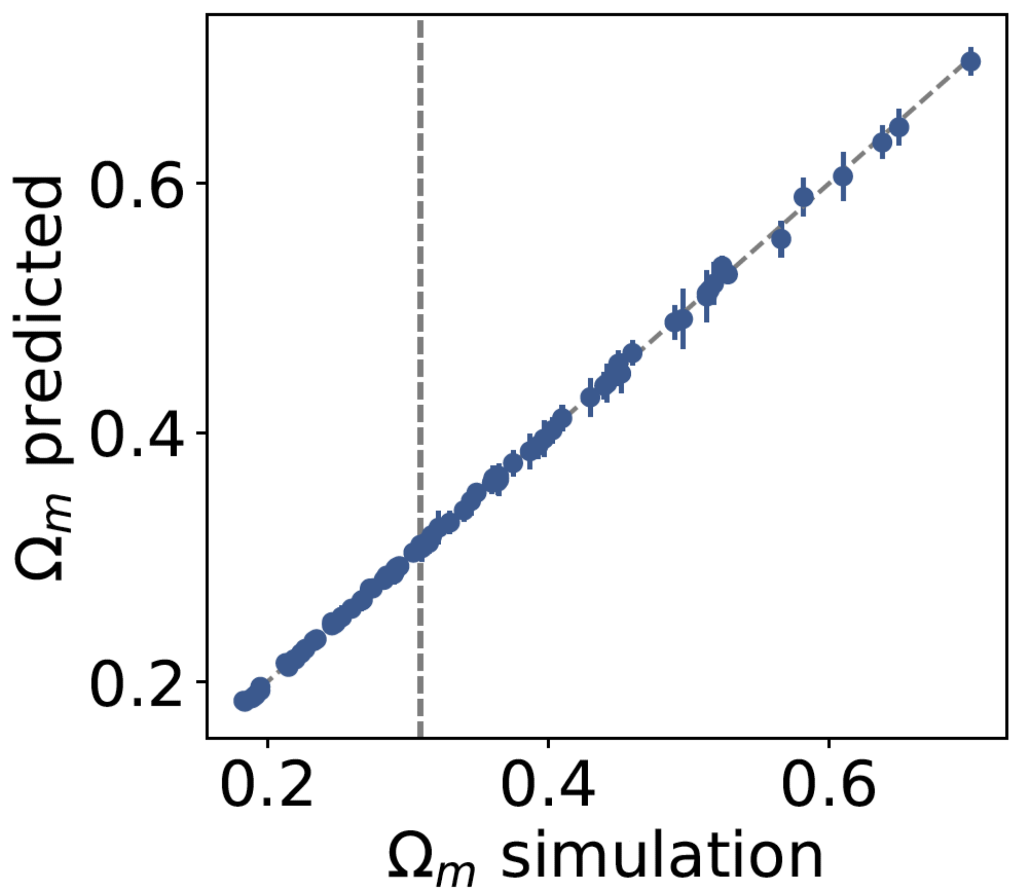


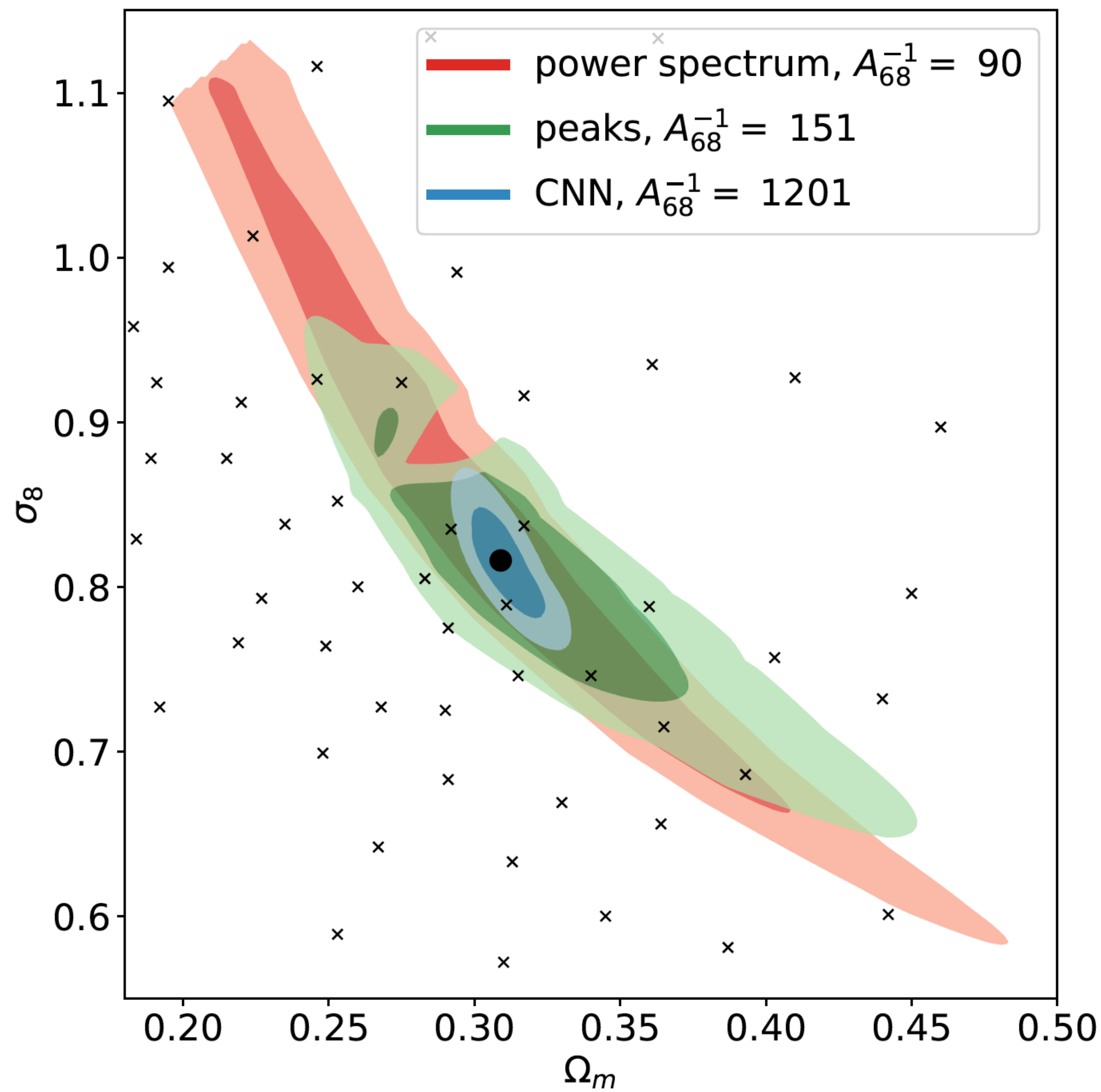
#	Layers	Output size
1	Convolution (3×3)	$510 \times 510 \times 32$
2	Convolution (3×3)	$508 \times 508 \times 32$
-	Average Pooling (2×2)	$254 \times 254 \times 32$
3	Convolution (3×3)	$252 \times 252 \times 64$
4	Convolution (3×3)	$250 \times 250 \times 64$
-	Average Pooling (2×2)	$125 \times 125 \times 64$
5	Convolution (3×3)	$123 \times 123 \times 128$
6	Convolution (1×1)	$123 \times 123 \times 64$
7	Convolution (3×3)	$121 \times 121 \times 128$
-	Average Pooling (2×2)	$60 \times 60 \times 128$
8	Convolution (3×3)	$58 \times 58 \times 256$
9	Convolution (1×1)	$58 \times 58 \times 128$
10	Convolution (3×3)	$56 \times 56 \times 256$
-	Average Pooling (2×2)	$28 \times 28 \times 256$
11	Convolution (3×3)	$26 \times 26 \times 512$
12	Convolution (1×1)	$26 \times 26 \times 256$
13	Convolution (3×3)	$24 \times 24 \times 512$
-	Average Pooling (2×2)	$12 \times 12 \times 512$
14	Convolution (3×3)	$10 \times 10 \times 512$
15	Convolution (1×1)	$10 \times 10 \times 256$
16	Convolution (3×3)	$8 \times 8 \times 512$
17	Convolution (1×1)	$8 \times 8 \times 256$
18	Convolution (3×3)	$6 \times 6 \times 512$
	Average Pooling $(\times)$	$1 \times 1 \times 512$
19	Dense	2

Performance on simulated, noiseless convergence maps

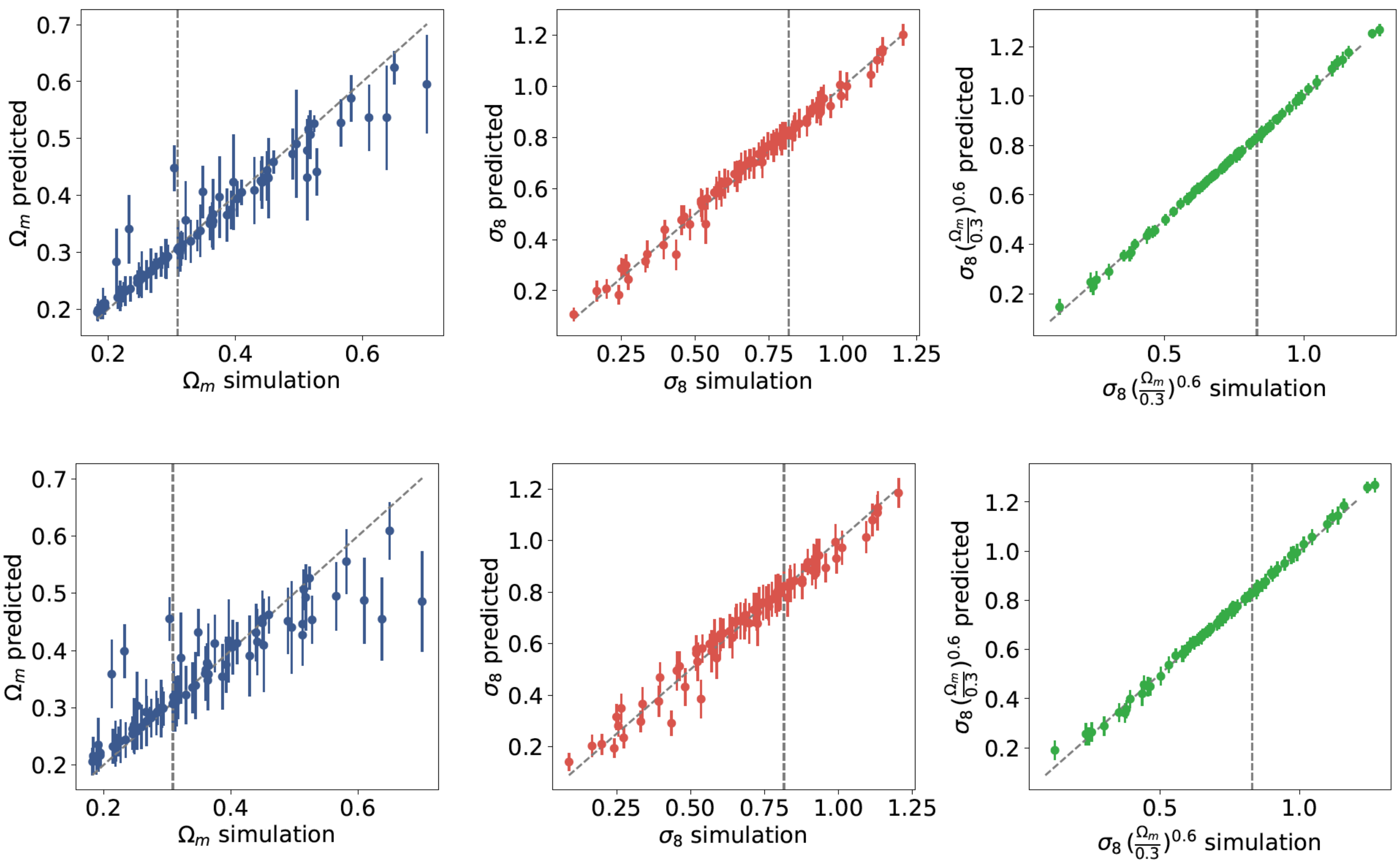


Performance on simulated, noiseless convergence maps

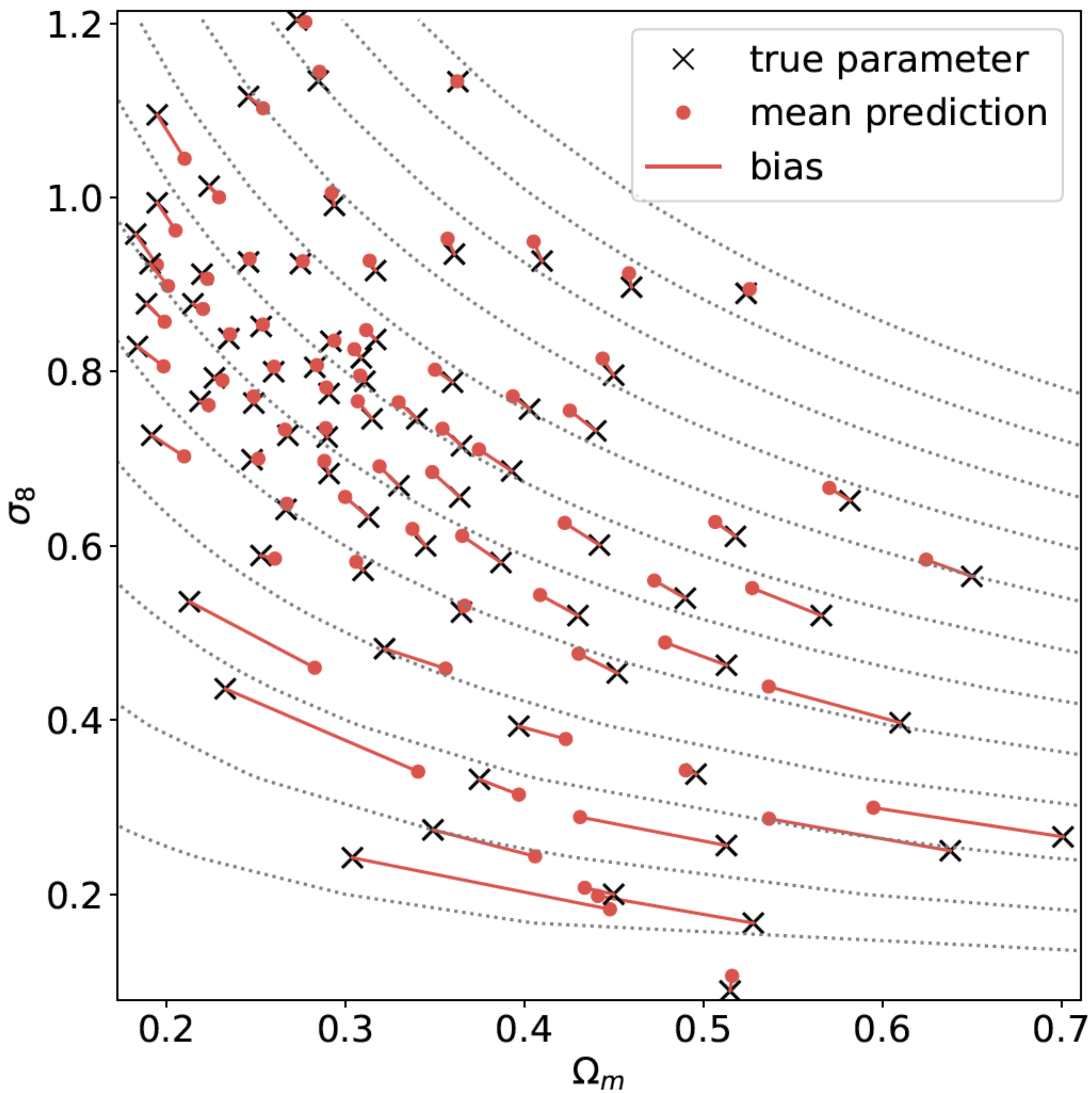




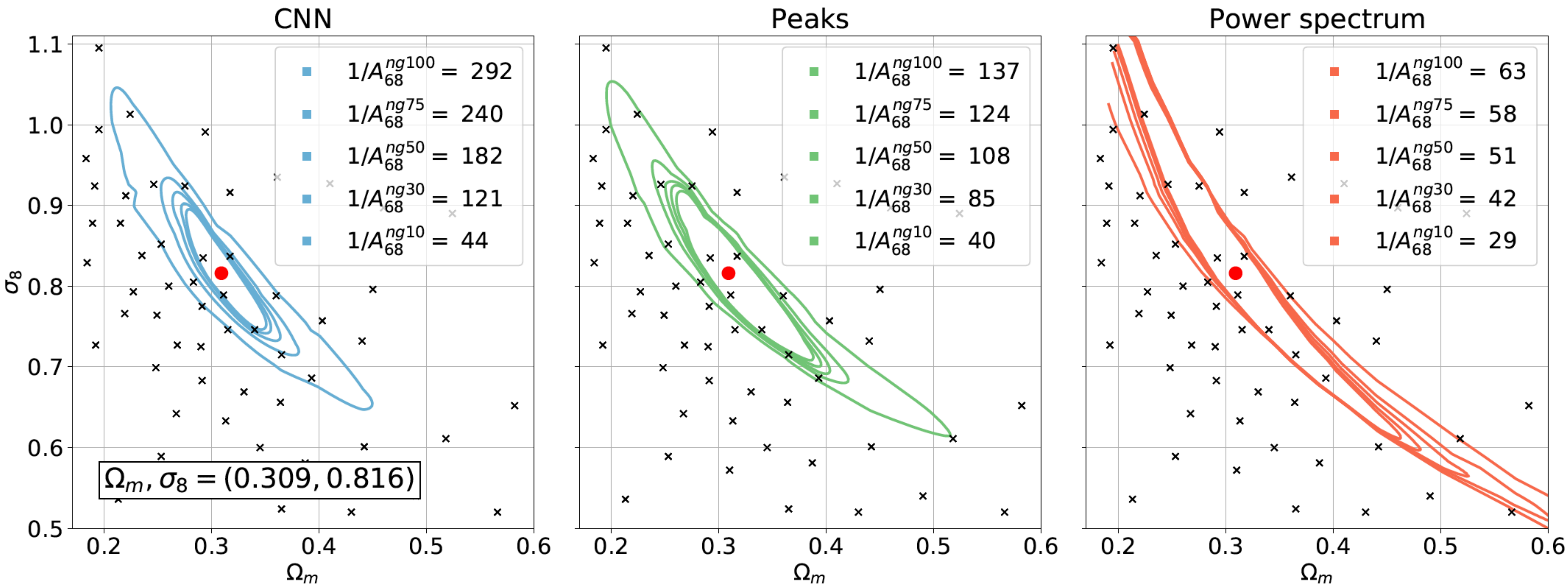
Predictions on noisy data



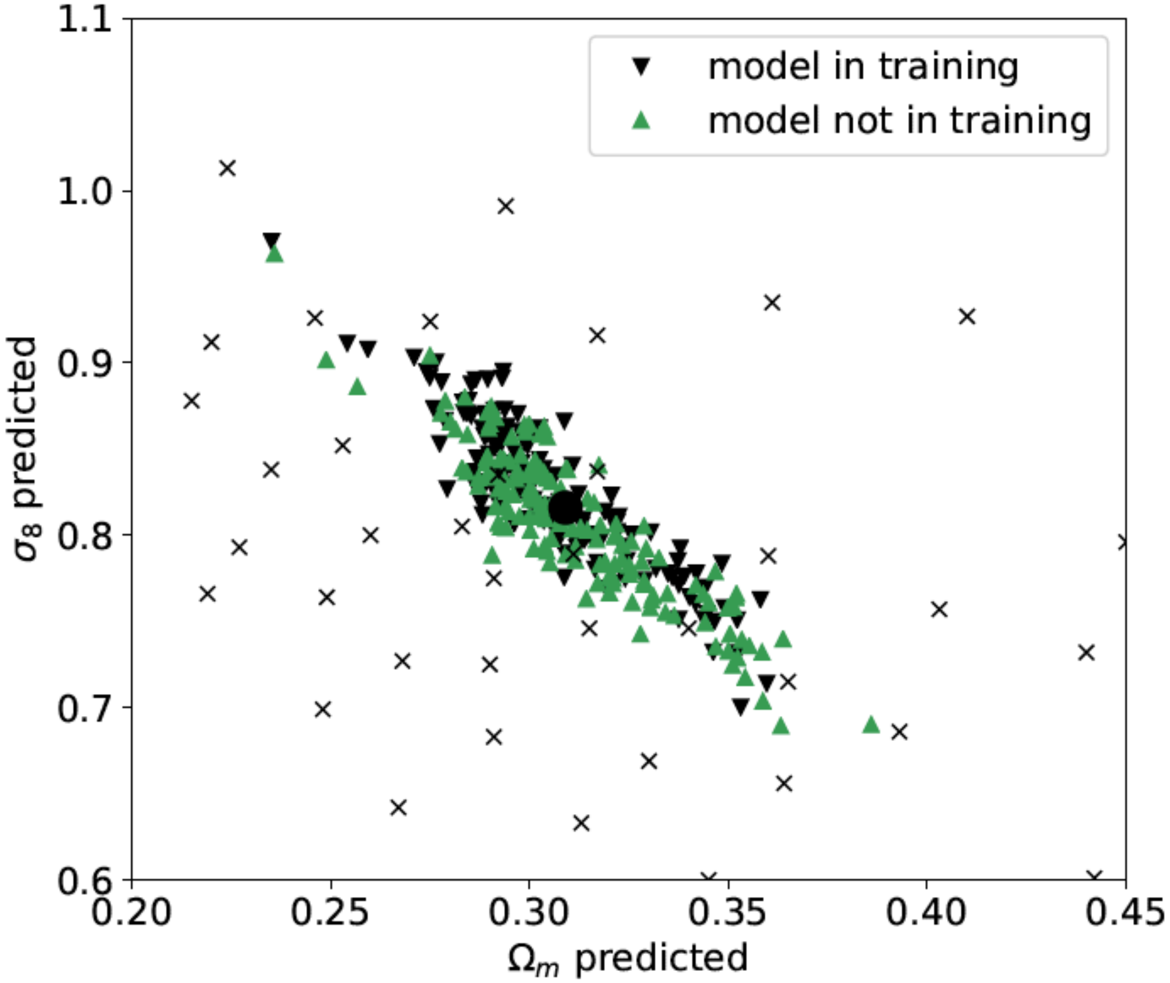
Predictions on noisy data

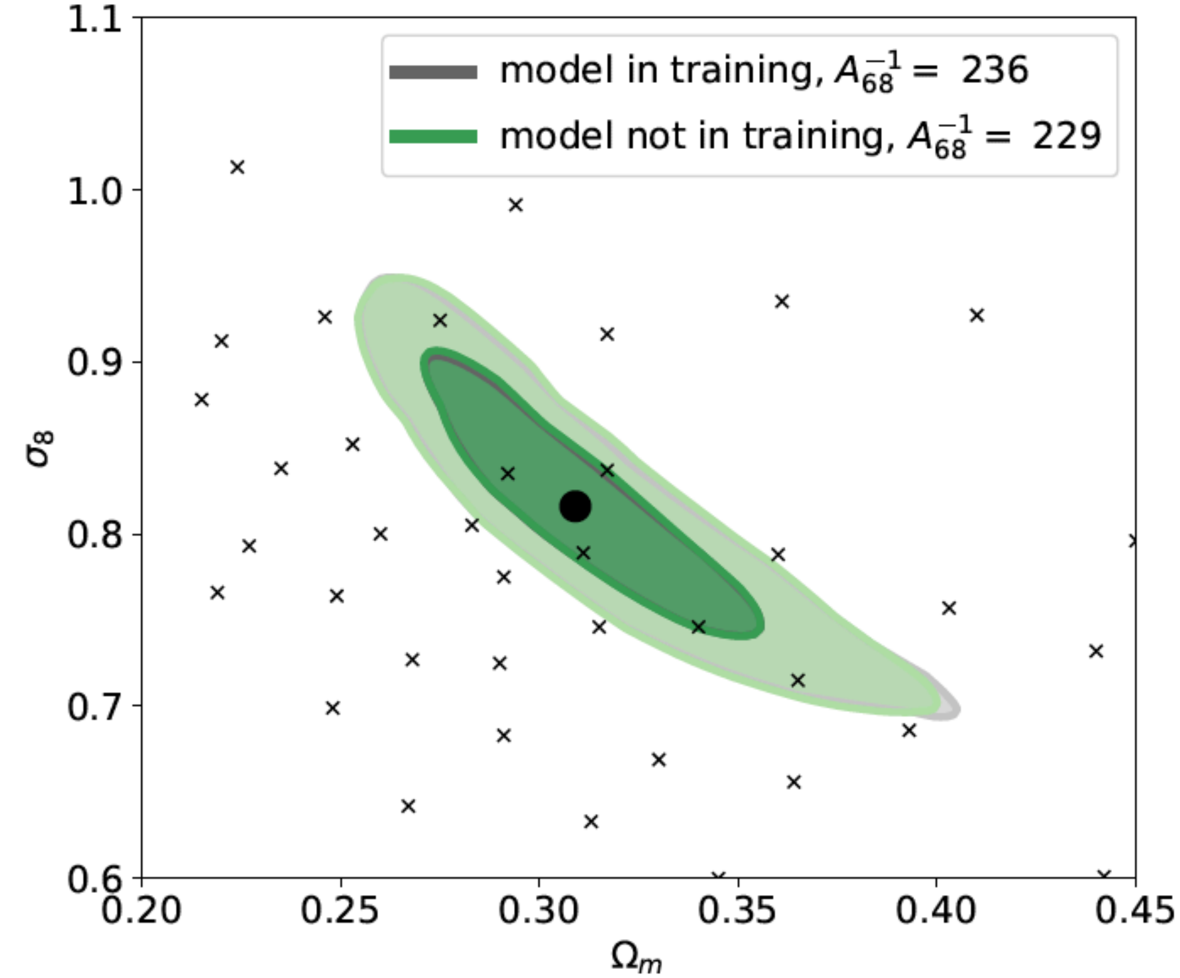


Constraints from noisy data

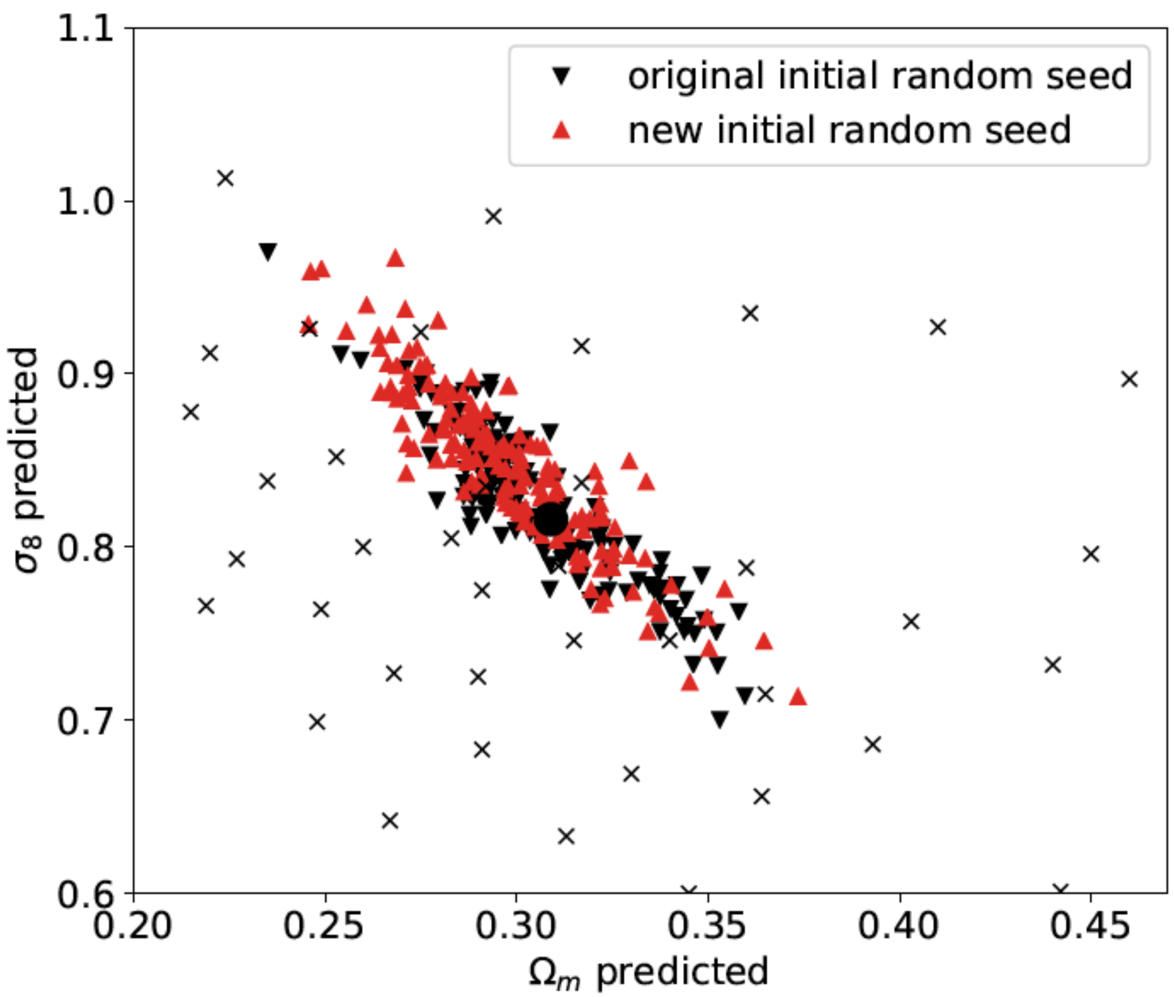


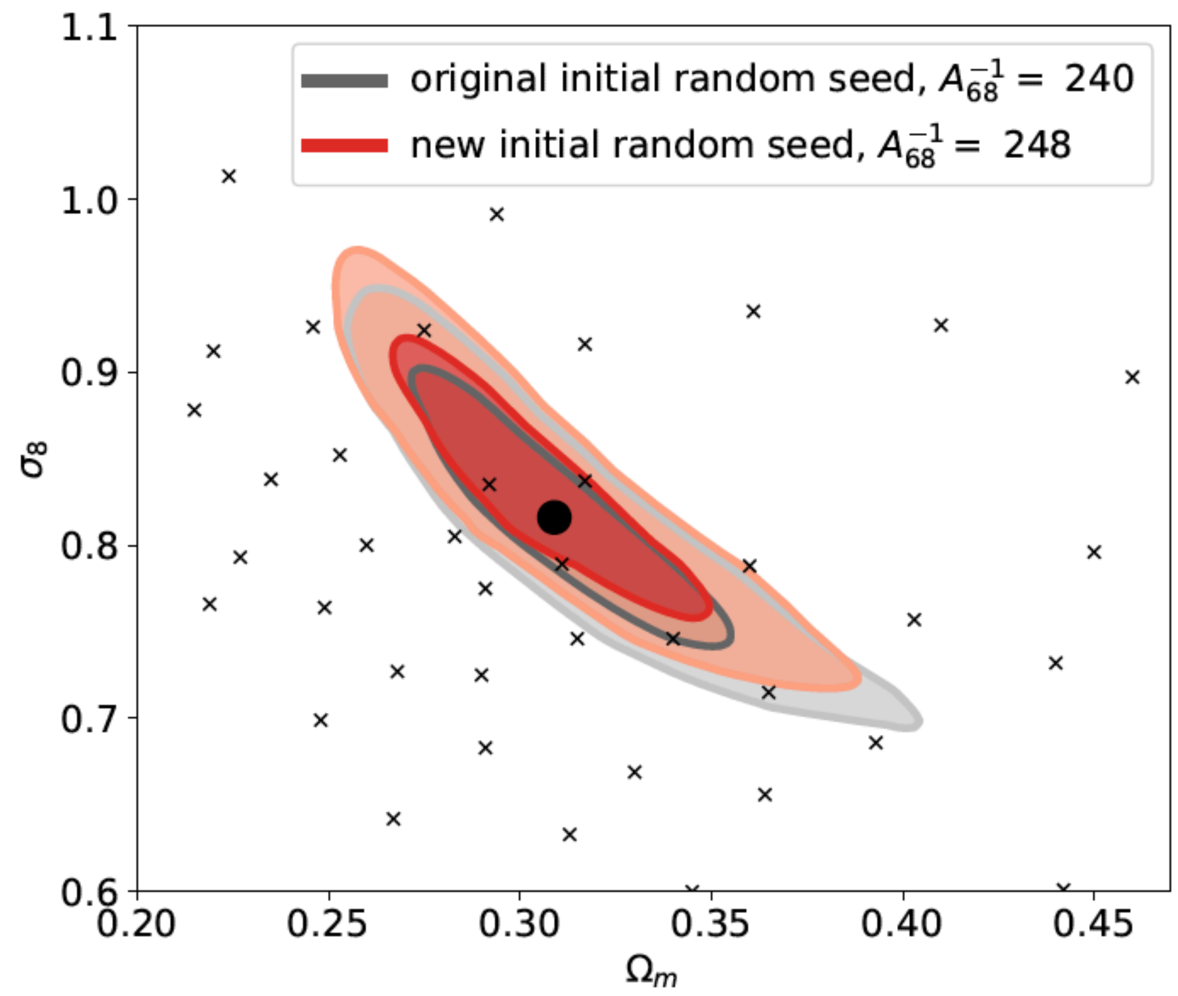
Robustness of the network: interpolation



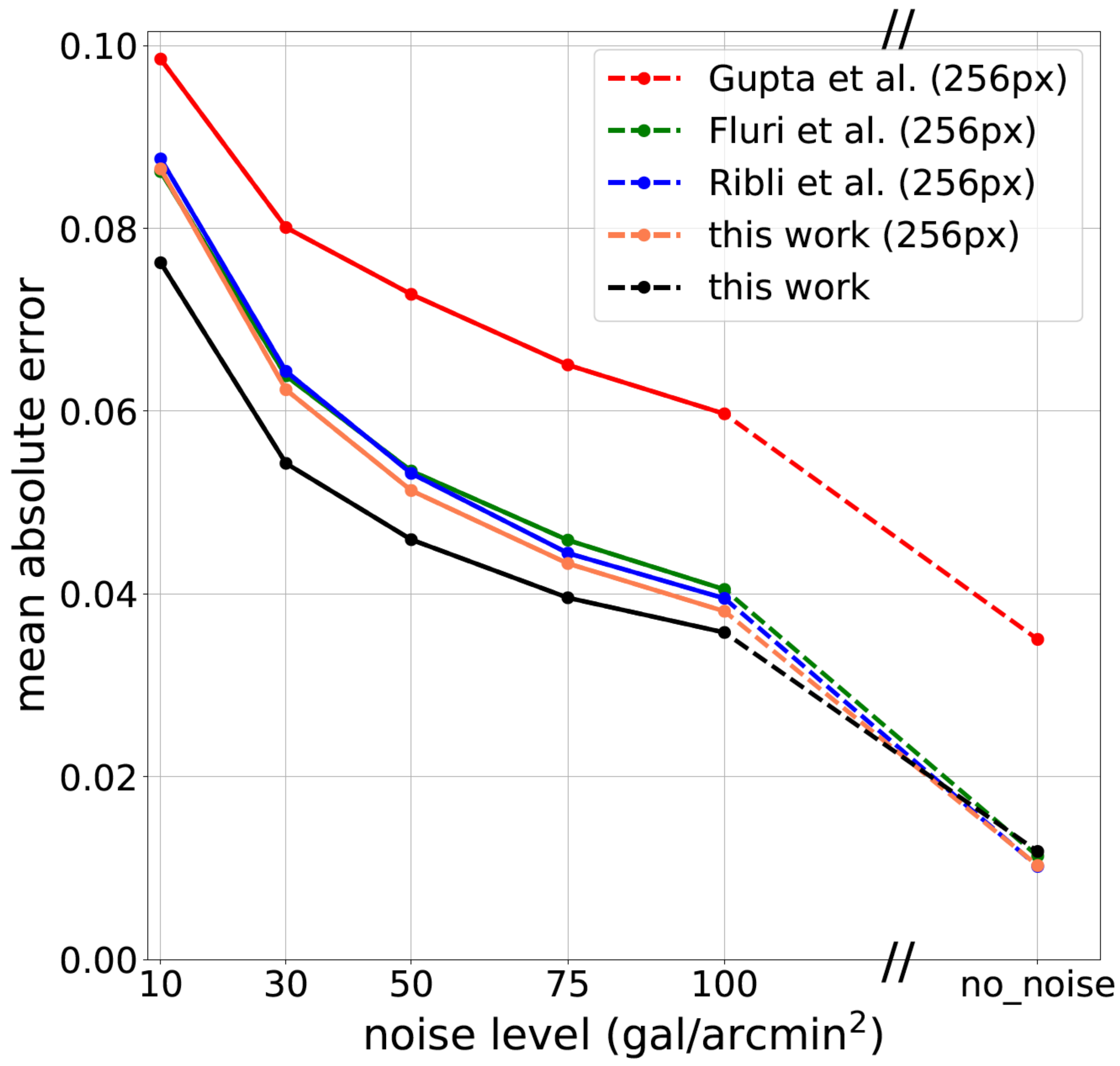


Robustness of the network: initial seed

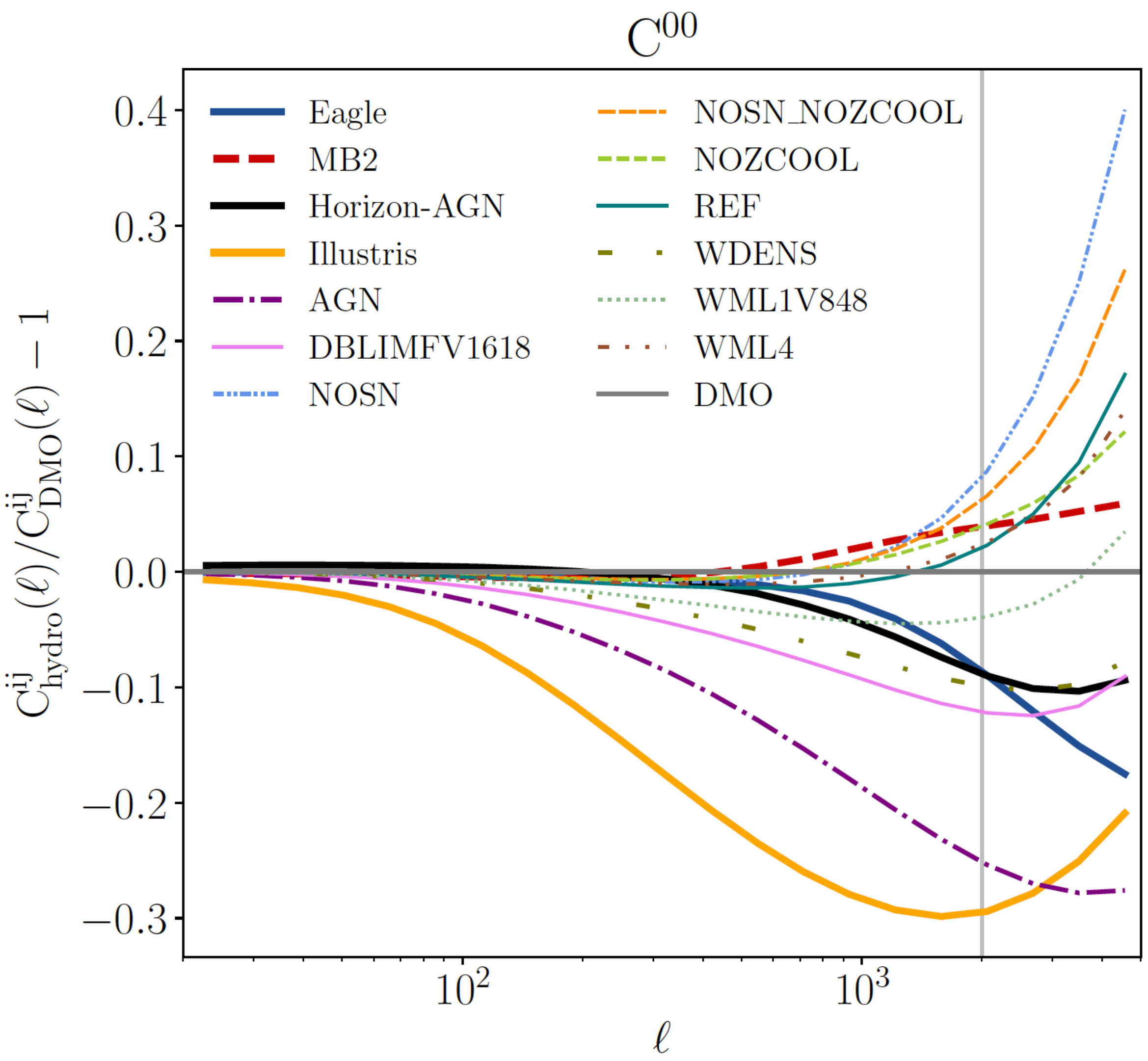


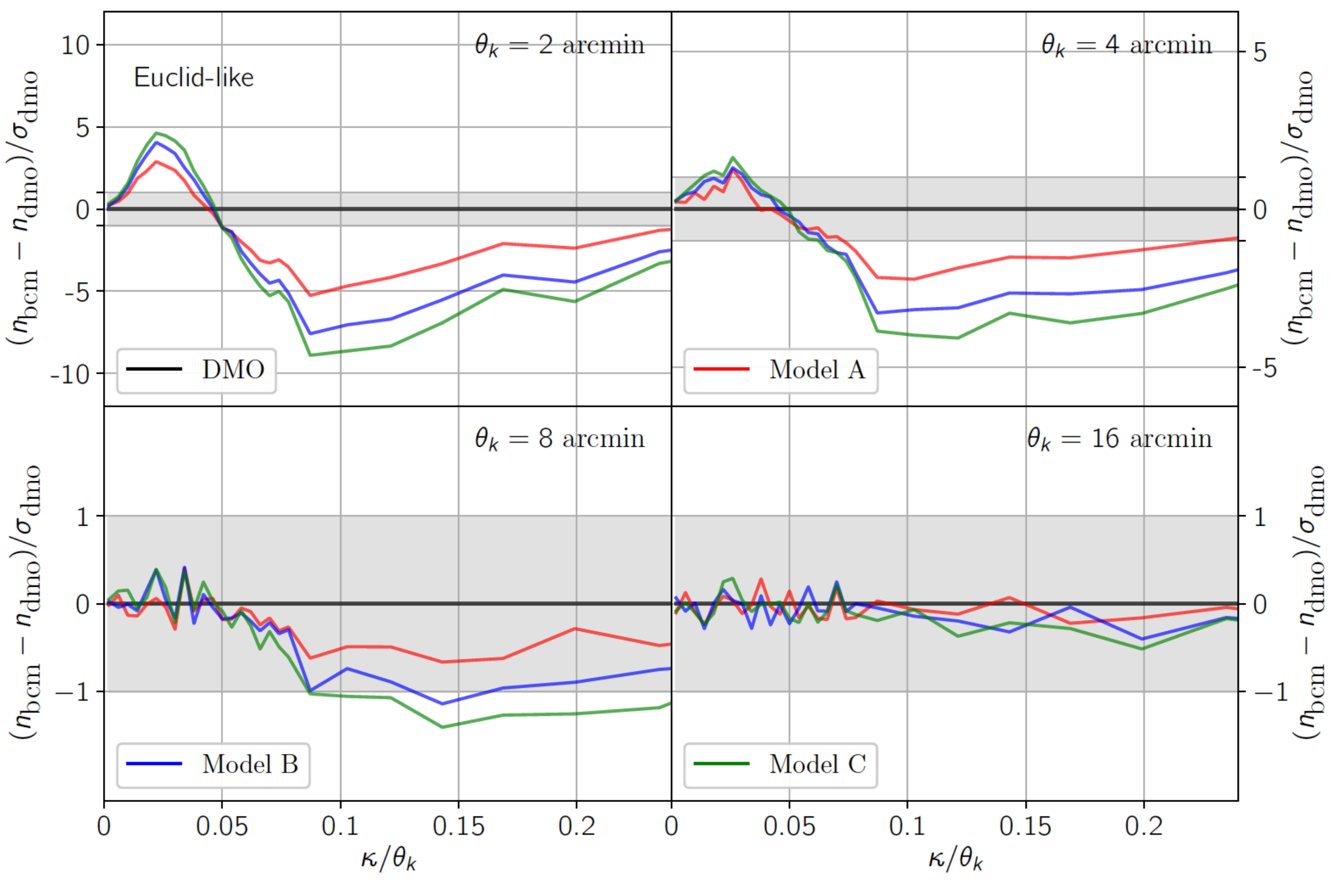


Interpreting the network



Limitation on small scales: baryonic effects

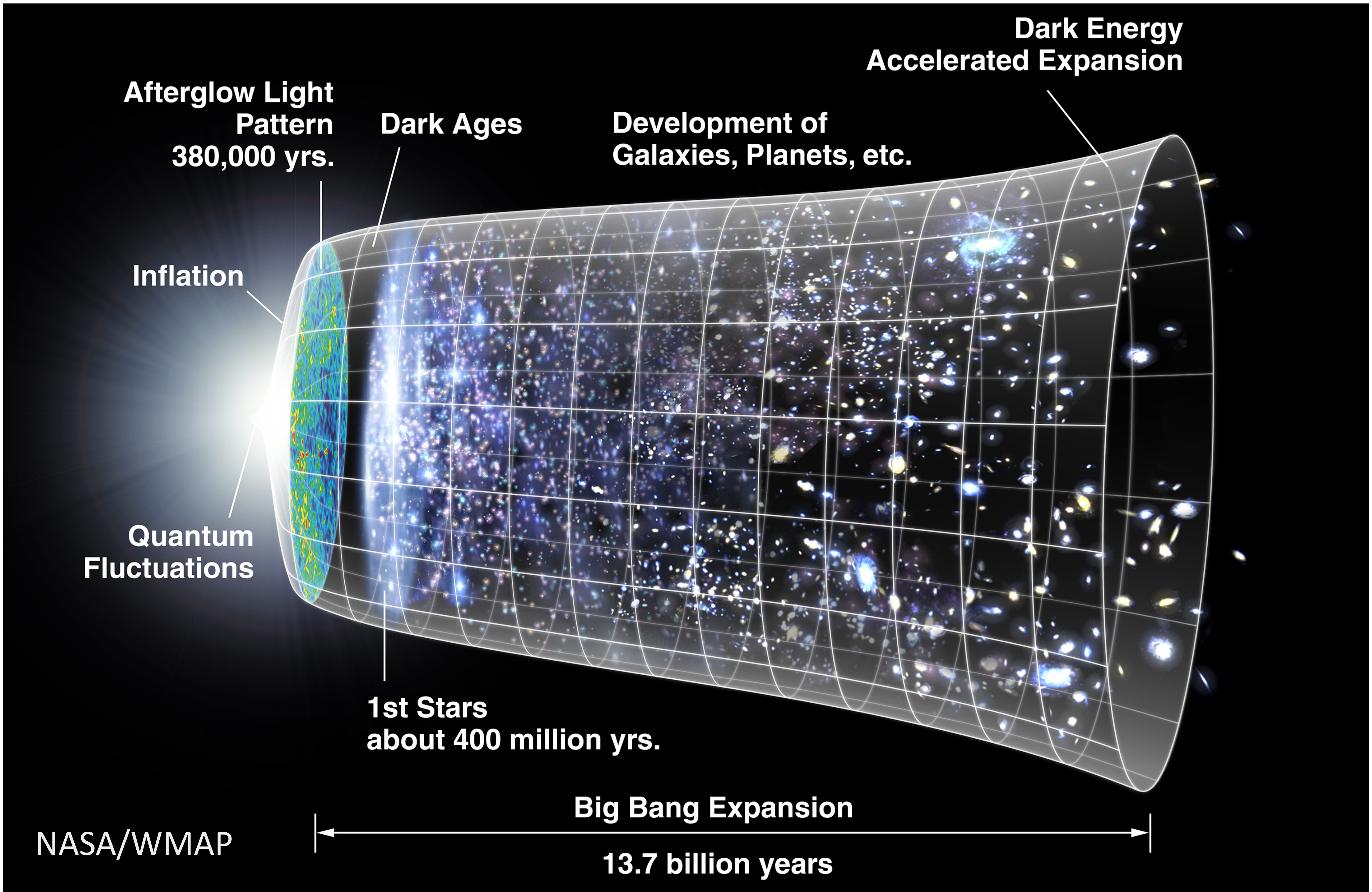




Huang et al. 2019

Weiss et al. 2019

Standard cosmological model



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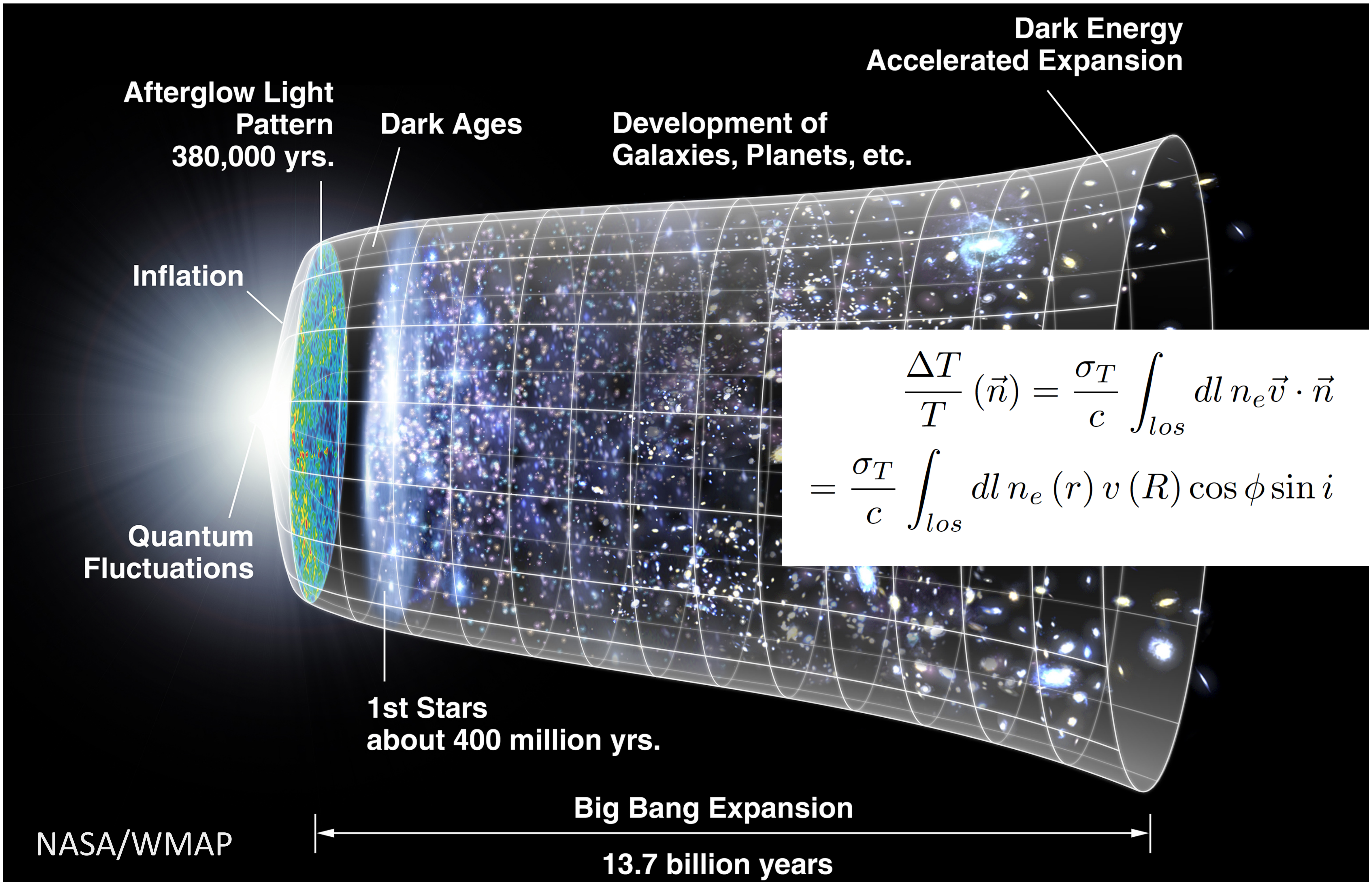
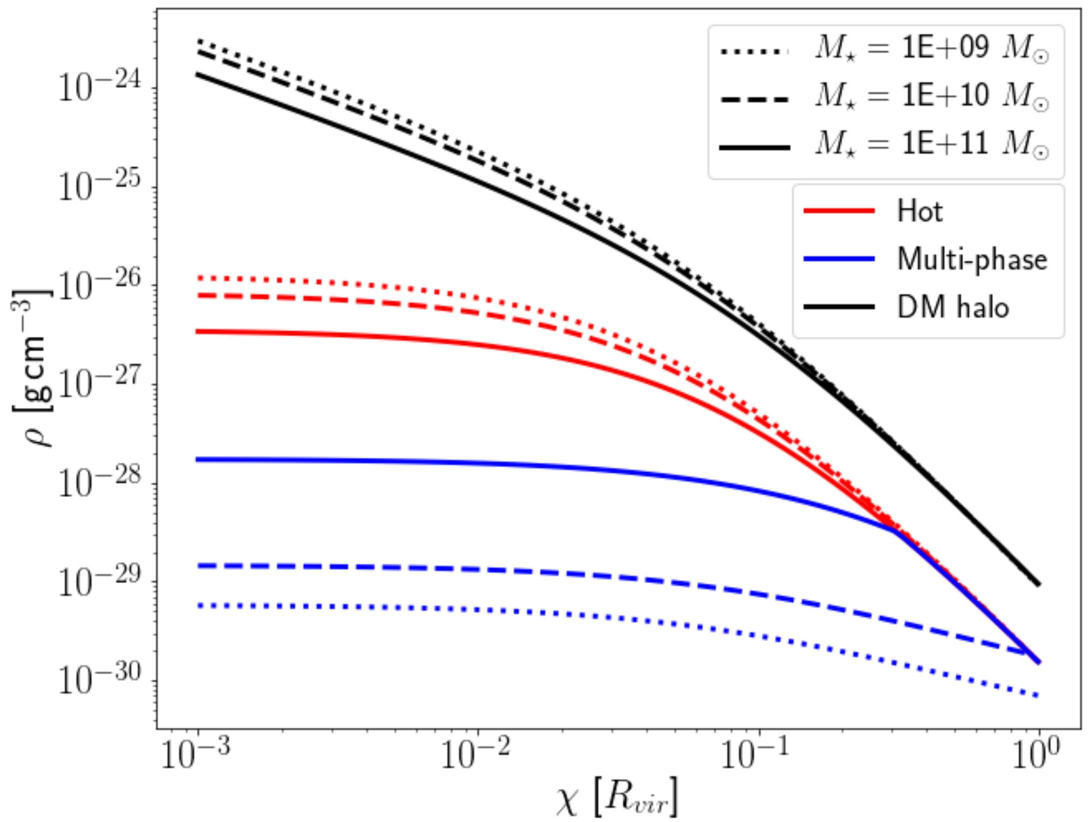


$$\frac{\Delta T}{T}(\vec{n}) = \frac{\sigma_T}{c}\int_{los} dl\, n_e \vec{v}\cdot\vec{n}$$

$$= \frac{\sigma_T}{c}\int_{los} dl\, n_e(r)\, v(R)\cos\phi\sin i$$

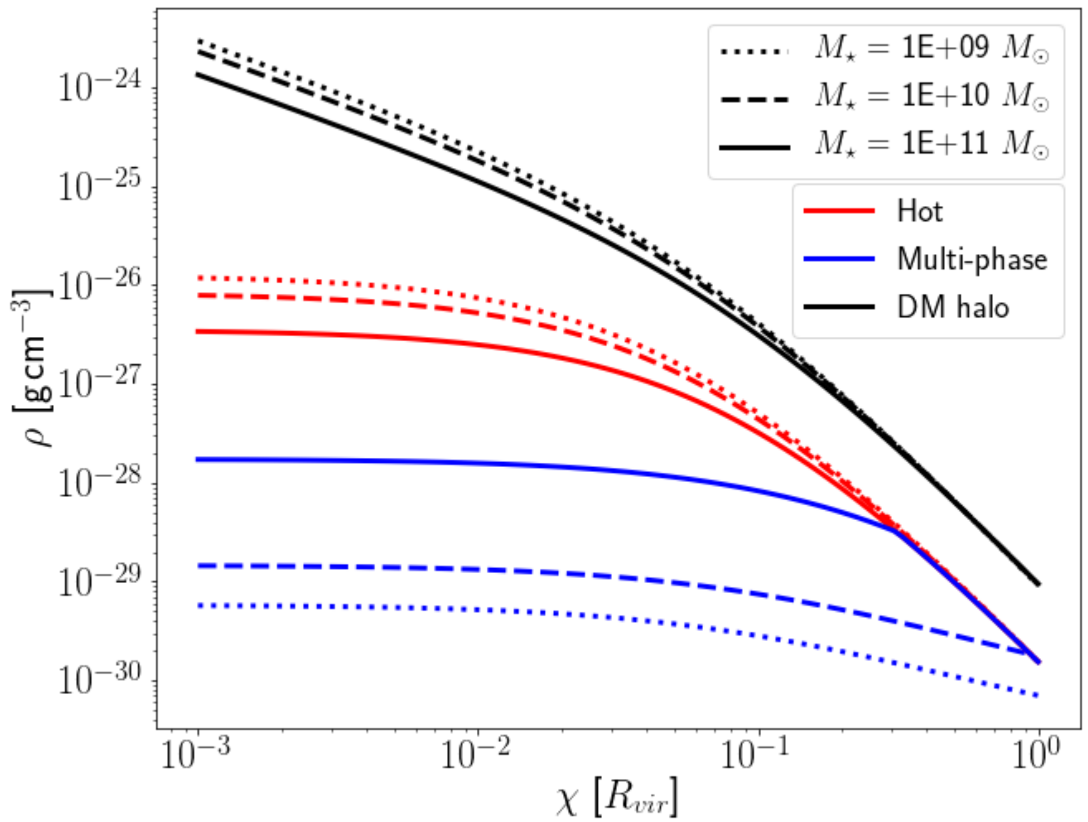
NASA/WMAP

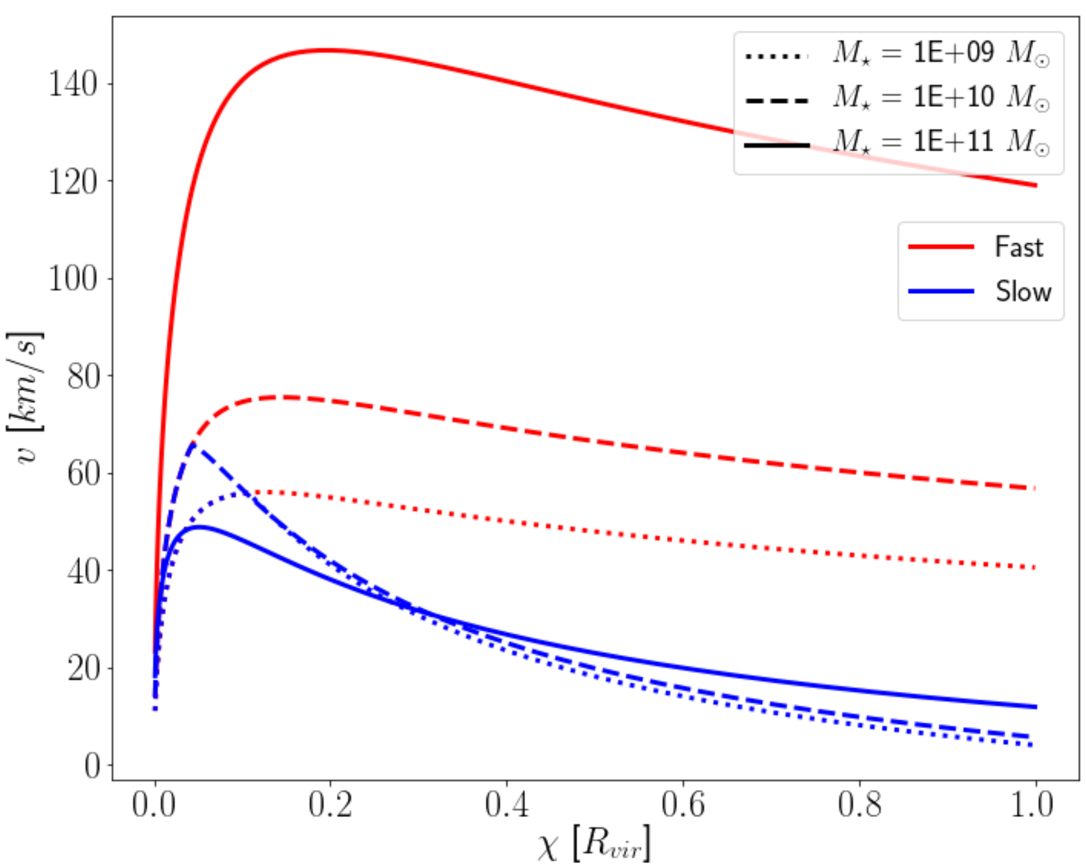
rkSZ model: signal



Following Maller & Bullock 2004

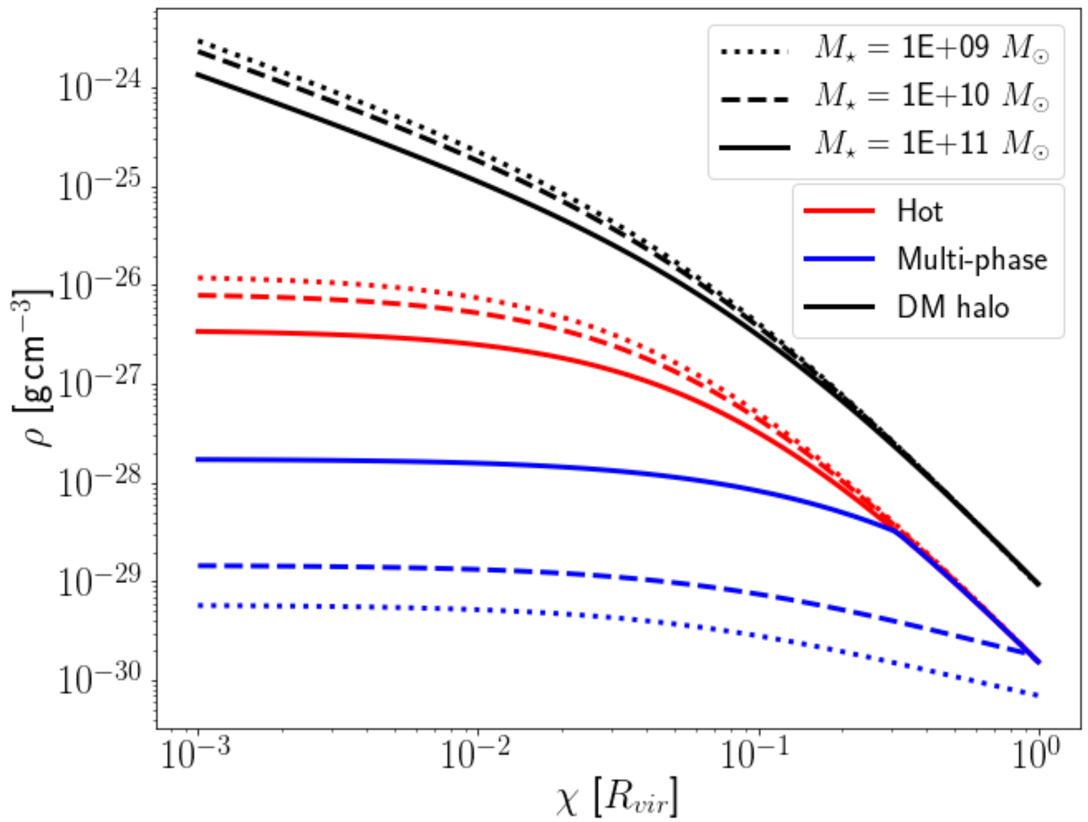
rkSZ model: signal

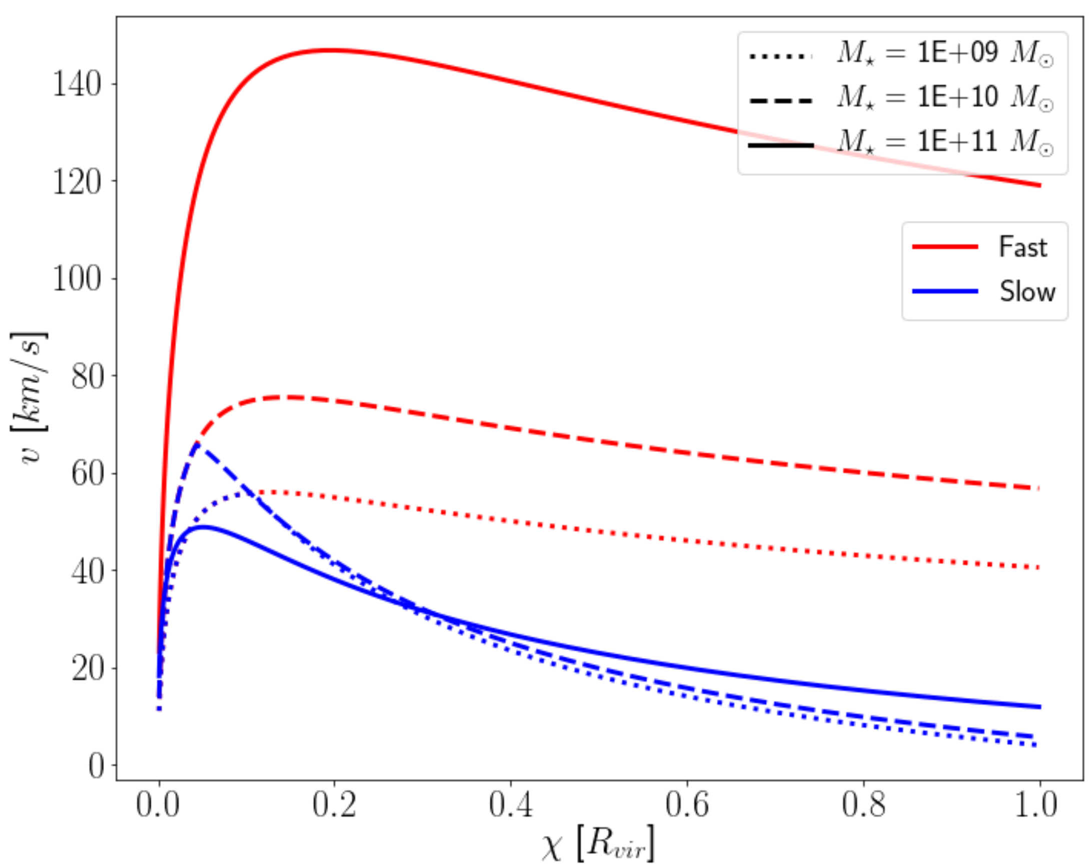


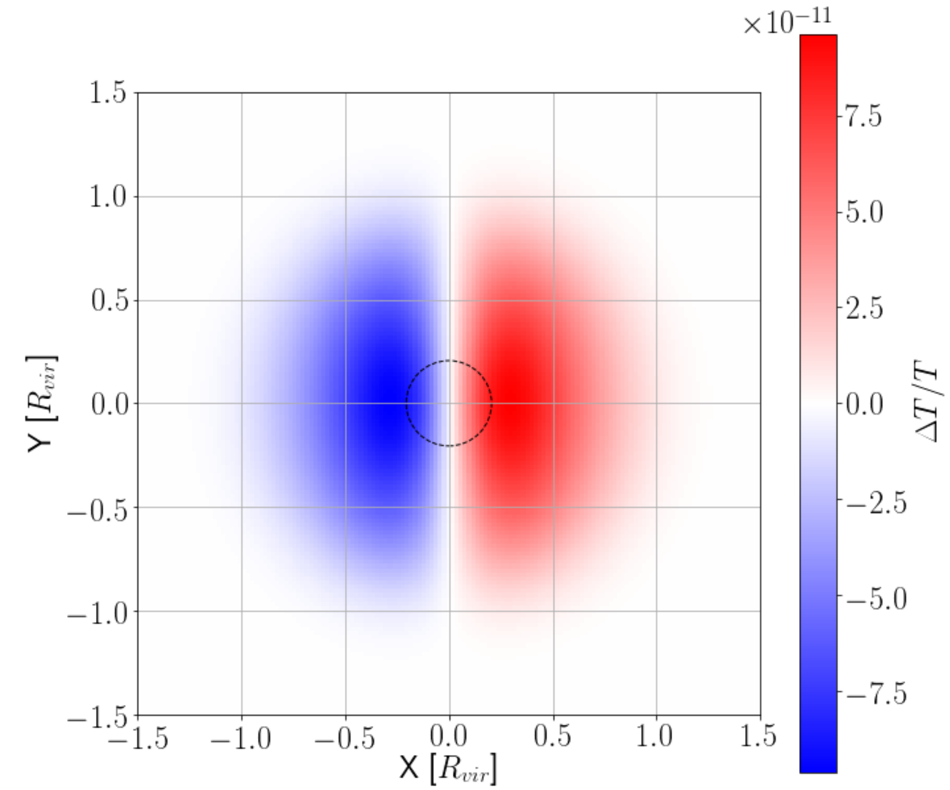


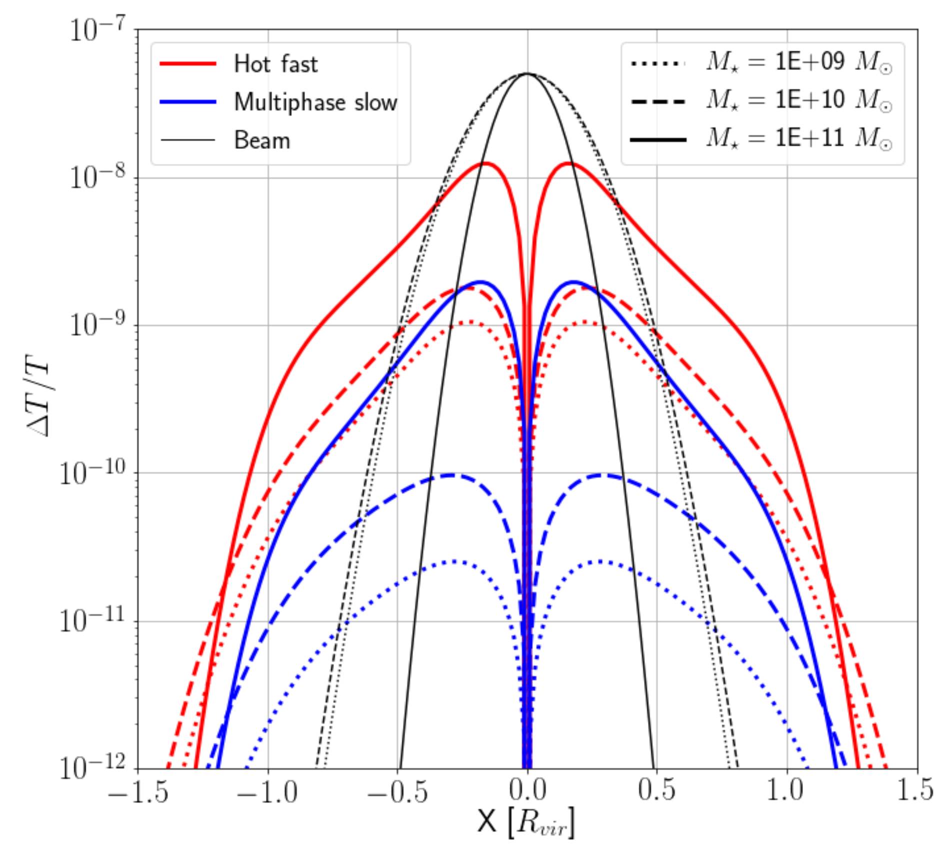
Based on Oppenheimer 2018

rkSZ model: signal



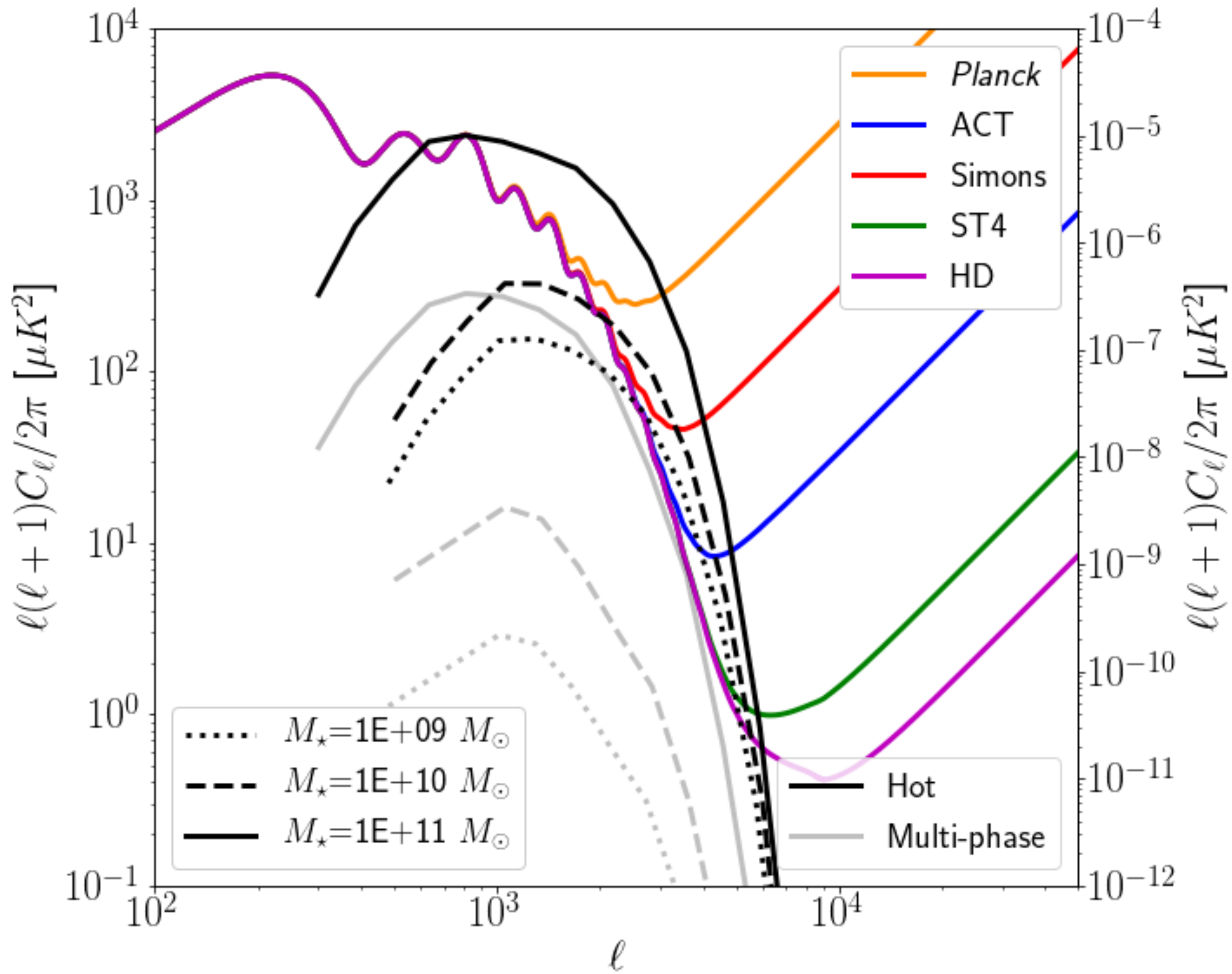






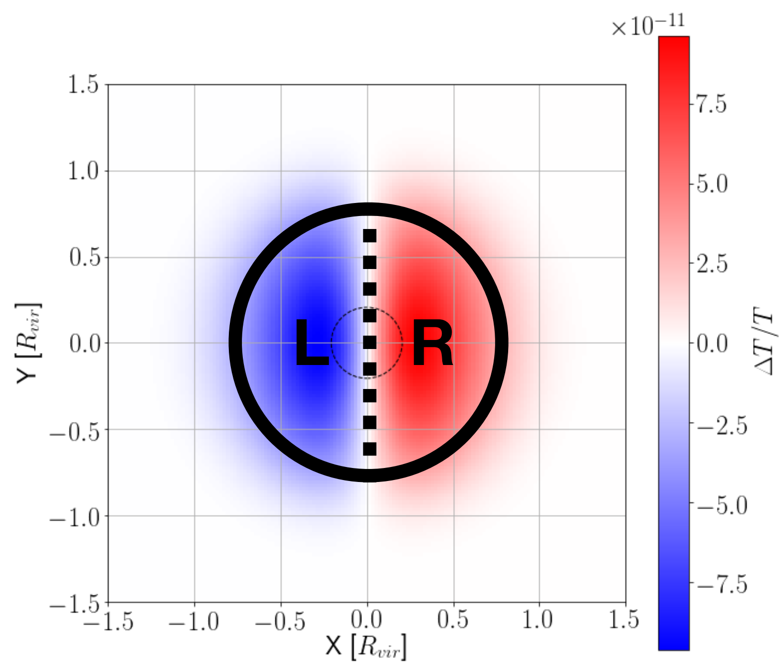
rkSZ model: noise

Experiment	FWHM [arcmin]	$\Delta T_{\rm noise}$ [μK arcmin]
Planck	5.00	45.6
ACT	1.40	15.0
Simons	1.40	6.0
CMB-S4	1.40	1.0
CMB-HD	0.25	0.5



rkSZ model: filtering

Aperture filter



$$s \equiv \overline{\Delta T}^R - \overline{\Delta T}^L$$

$$\left\langle \overline{\Delta T}^R \overline{\Delta T}^L \right\rangle = \int \frac{\mathrm{d}^2\boldsymbol{\ell}}{(2\pi)^2} b_\ell^2 C_\ell \widetilde{W}_L^*(\boldsymbol{\ell}) \widetilde{W}_R(\boldsymbol{\ell})$$

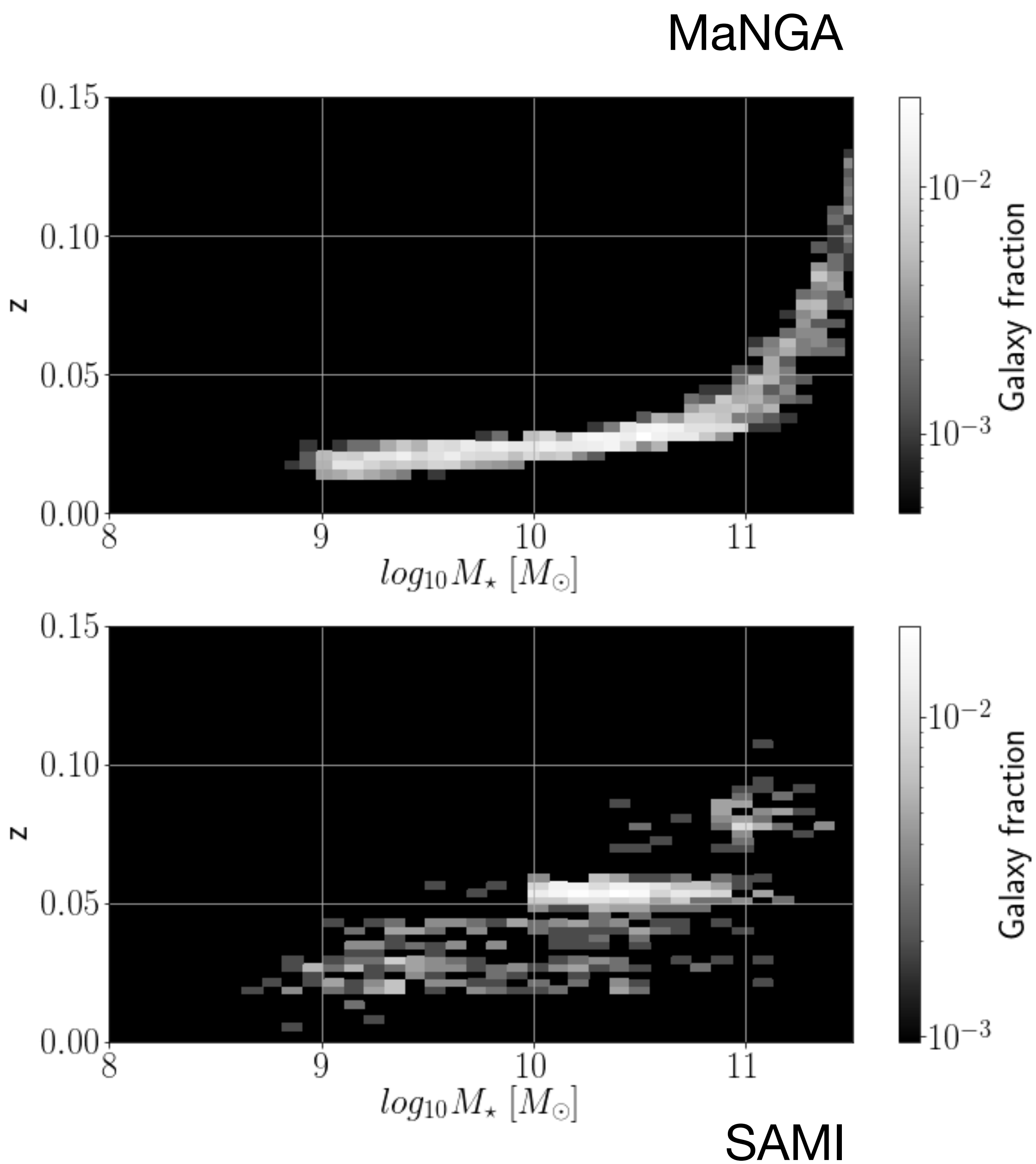
Ferraro & Hensley 2015

$$\widetilde{W}(\boldsymbol{\ell}) = \frac{8}{a\ell} J_1(a\ell) * \frac{\sin\left(\frac{a\ell_x}{2}\right)\sin(a\ell_y)}{\ell_x \ell_y} \exp\left[\mp \mathrm{i}\frac{a\ell_x}{2}\right]$$

Matched filter

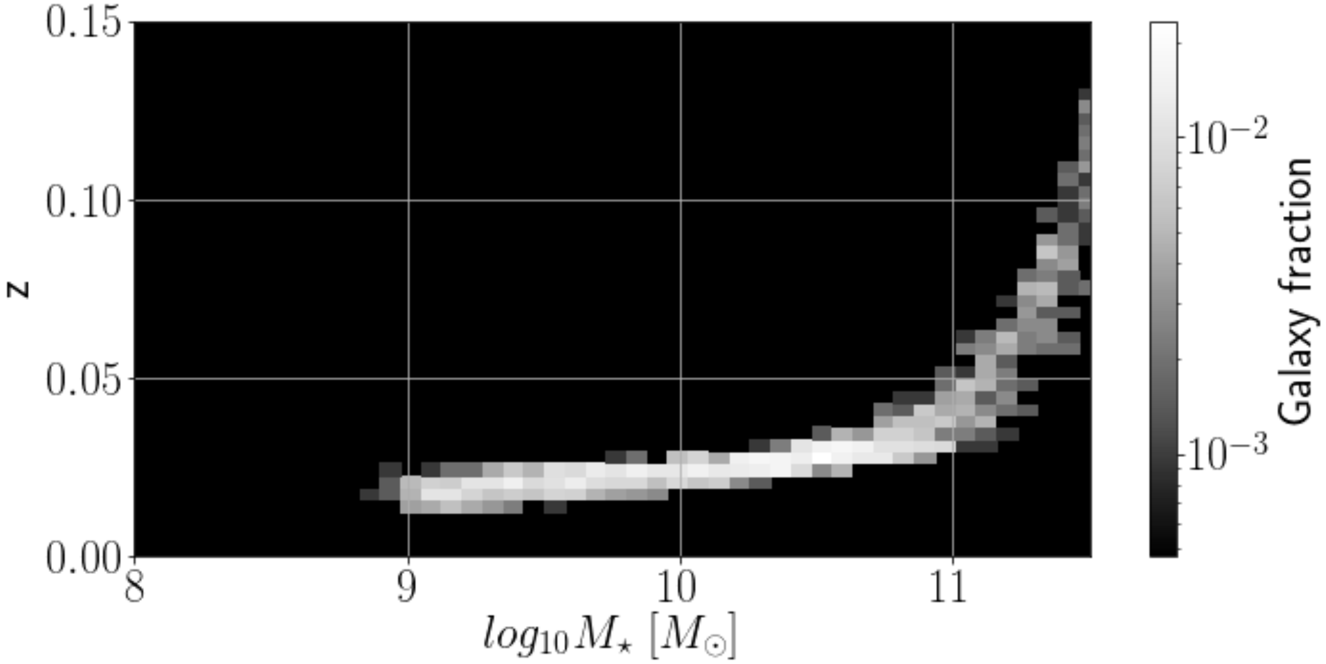
$$\widetilde{\mathrm{MF}}(\boldsymbol{\ell}) = \frac{1}{\int \mathrm{d}^2\boldsymbol{\ell} \frac{\left|\widetilde{\Delta T}_{kSZ}(\boldsymbol{\ell})\right|^2}{C_\ell}} \frac{\widetilde{\Delta T}^*_{kSZ}(\boldsymbol{\ell})}{C_\ell}$$

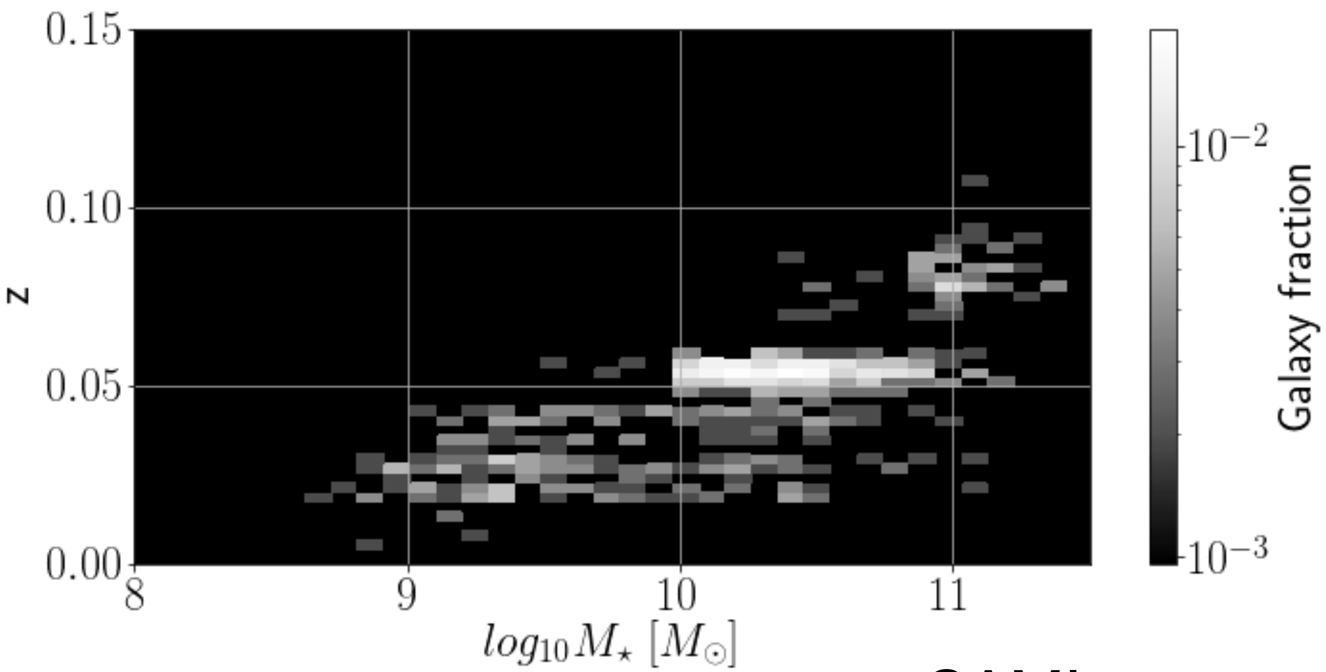
rkSZ model: detection requirements



rkSZ model: detection requirements

MaNGA



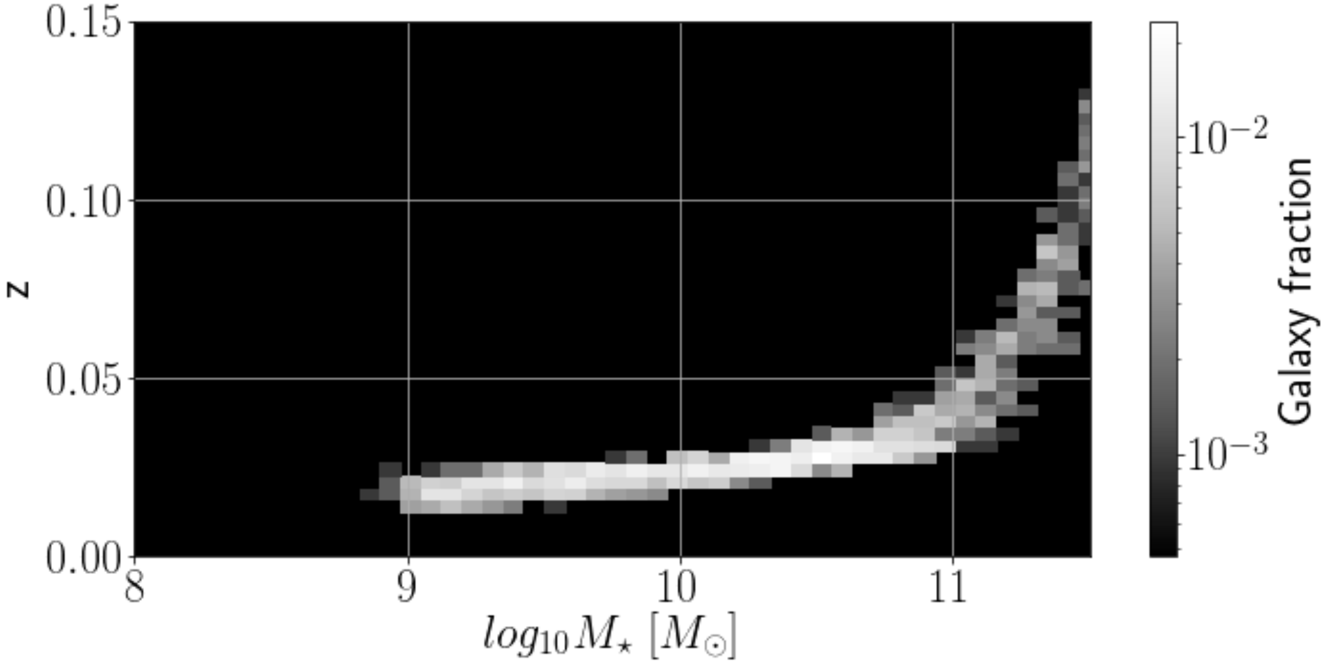


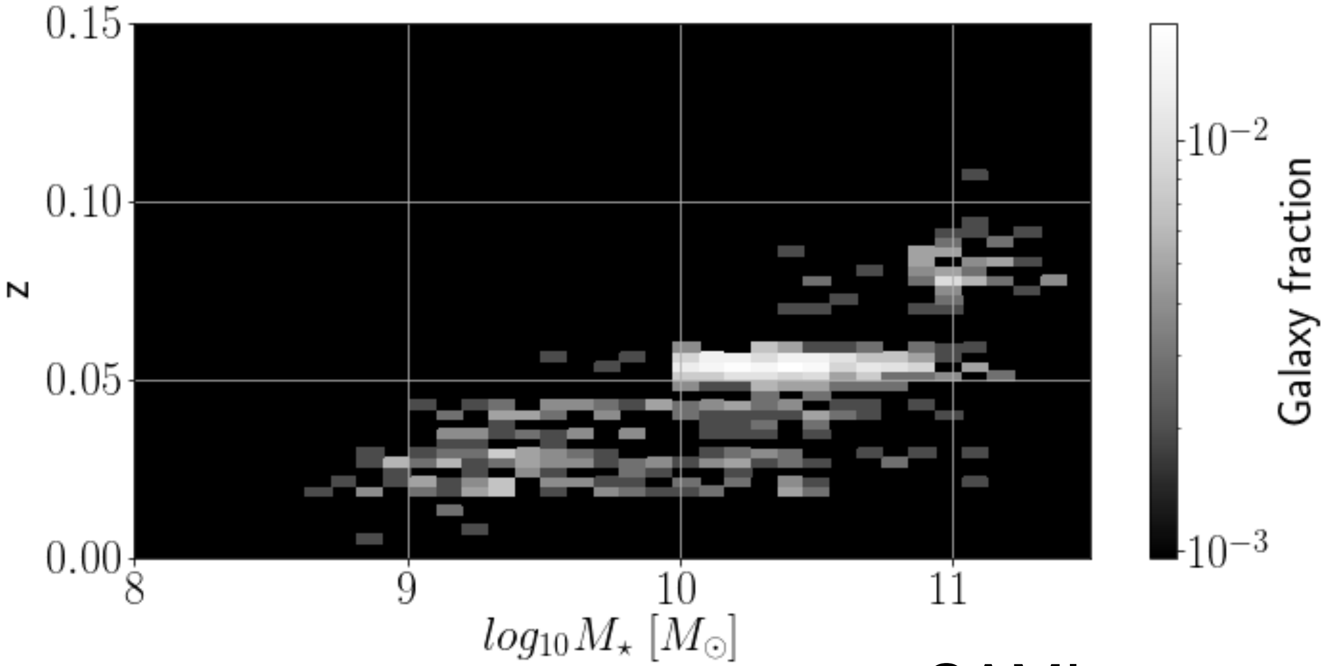
SAMI

	MaNGA-like	SAMI-like
	Hot, fast rotating corona	
Planck	**3.1e6** —**1.6e6**	1.2e7 — **6.1e6**
ACT	**2.6e5** — **9.2e4**	**7.1e5** — **3.0e5**
Simons	**2.2e5** — **2.3e4**	**5.5e5** — **7.2e4**
CMB-S4	**2.1e5** — **2.4e3**	**5.1e5** — **6.1e3**
CMB-HD	**9.5e4** — **7.5e2**	**9.9e4** — **1.4e3**
	multi-phase, slow rotating corona	
Planck	1.7e8 — 8.5e7	6.0e8 — 3.0e8
ACT	1.8e7 — 5.9e6	6.1e7 — 2.1e7
Simons	1.5e7 — **1.6e6**	4.8e7 — **5.7e6**
CMB-S4	1.4e7 — **1.9e5**	4.5e7 — **7.0e5**
CMB-HD	7.1e6 — **7.2e4**	1.8e7 — **2.6e5**

rkSZ model: detection requirements

MaNGA

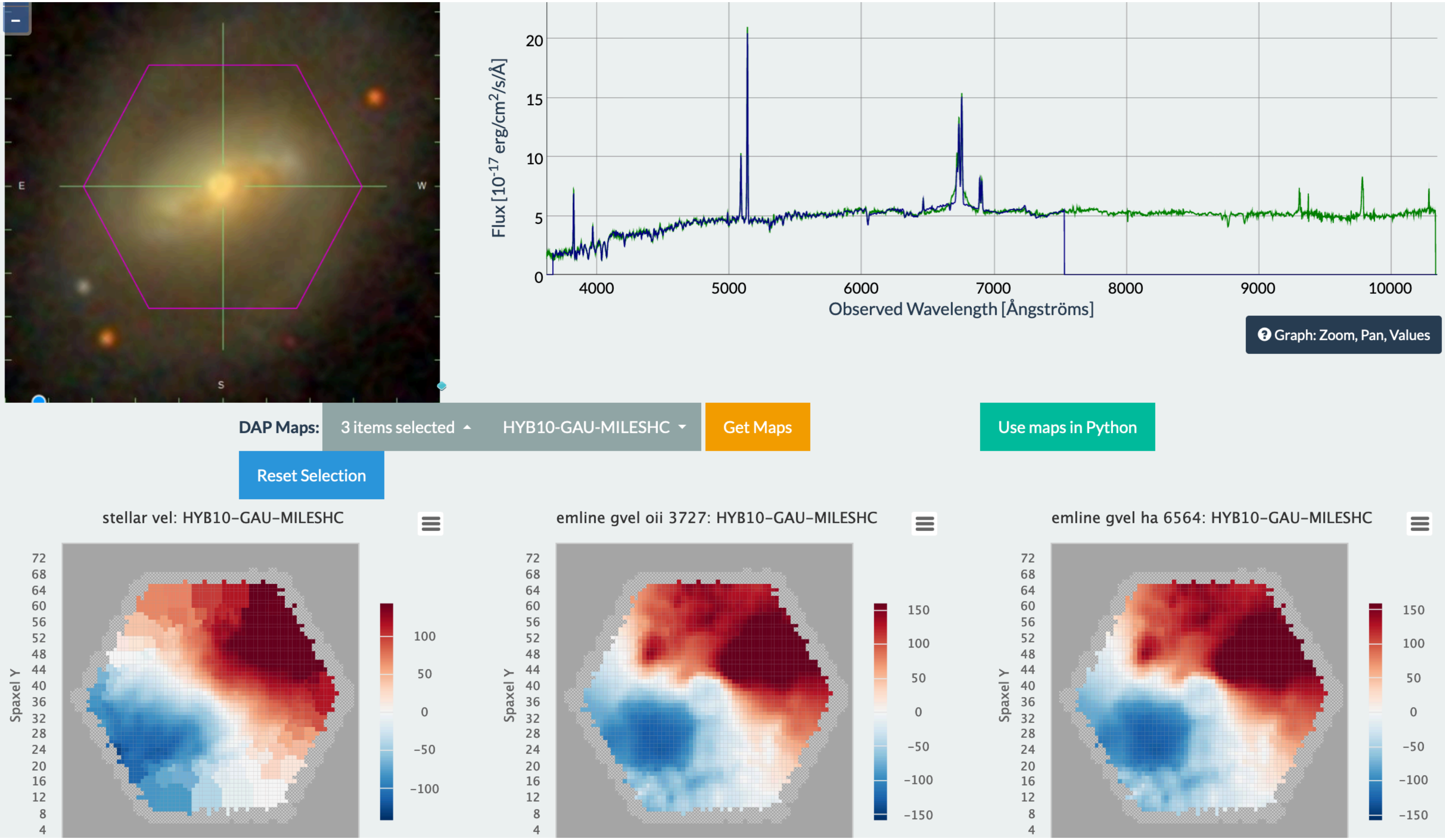




SAMI

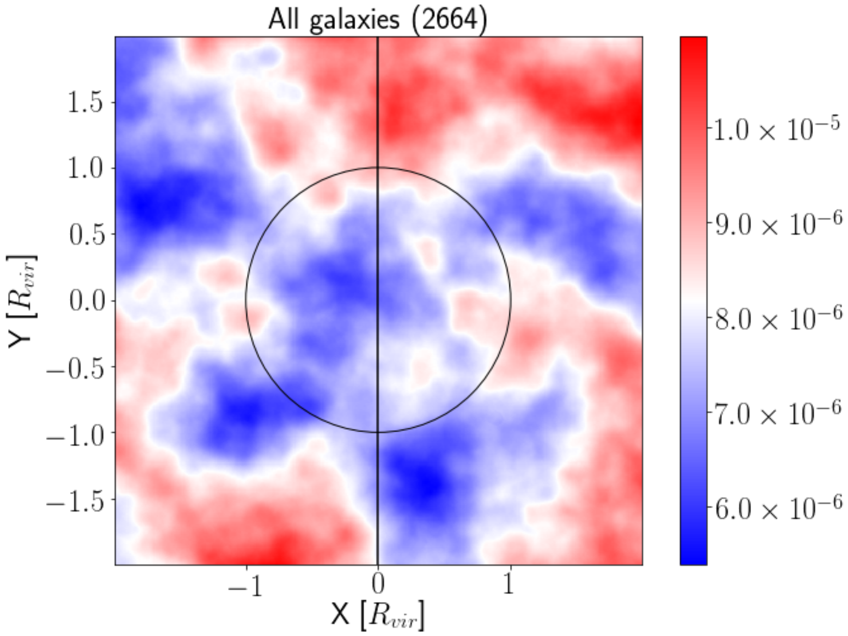
	MaNGA-like	SAMI-like
	Hot, fast-rotating corona	
Planck	21,945 — 11,588	X — 38,351
ACT	1,857 — 656	4,479 — 1,902
Simons	1,554 — 167	3,423 — 450
CMB-S4	1,456 — 17	3,216 — 38
CMB-HD	683 — 5	621 — 9
	multi-phase, slow-rotating corona	
Planck	X — X	X — X
ACT	X — X	X — X
Simons	X — 11,559	X — 35,896
CMB-S4	X — 1,386	X — 4,364
CMB-HD	X — 513	X — 1,611

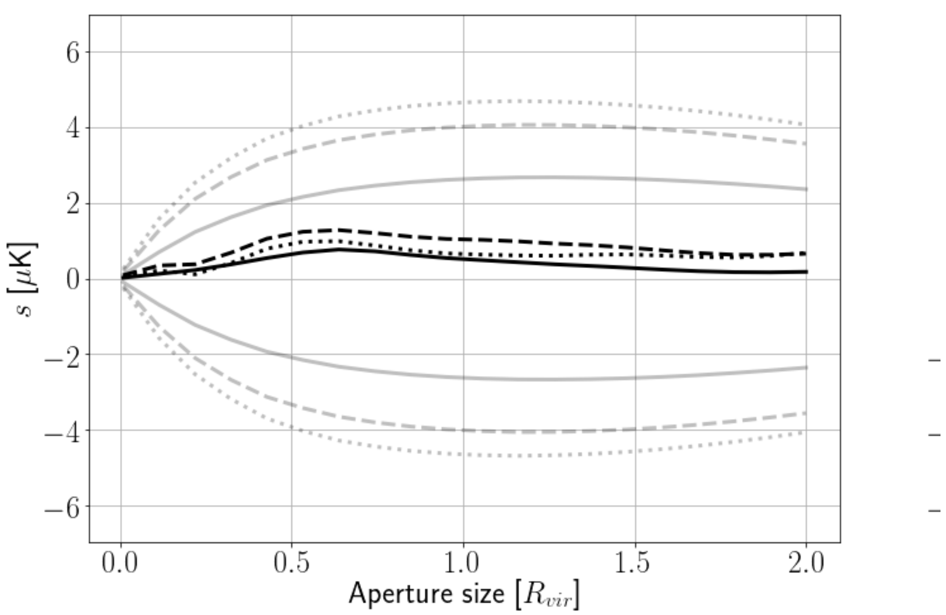
Stacking MaNGA galaxies



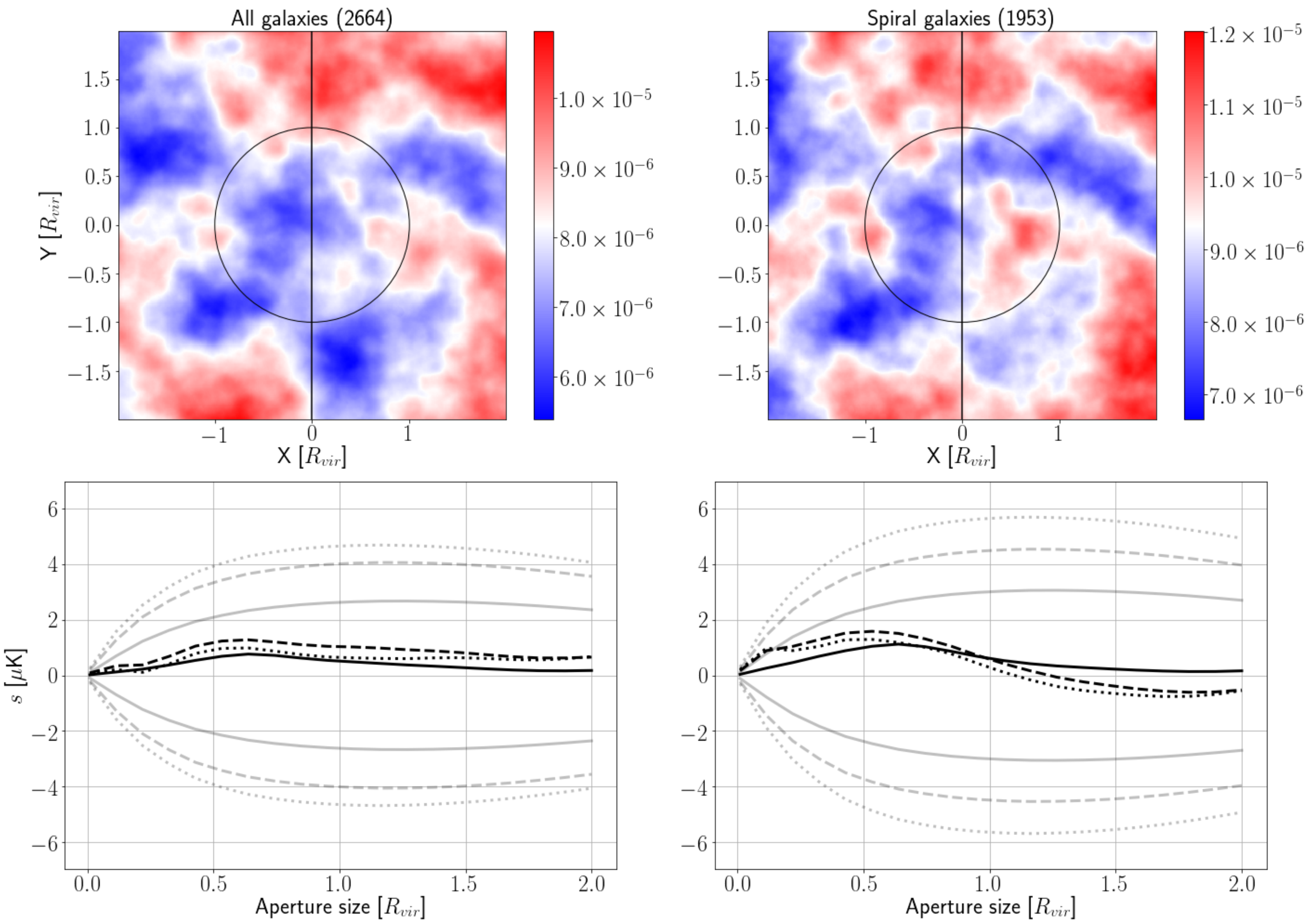
https://dr15.sdss.org/marvin

Stacking MaNGA galaxies

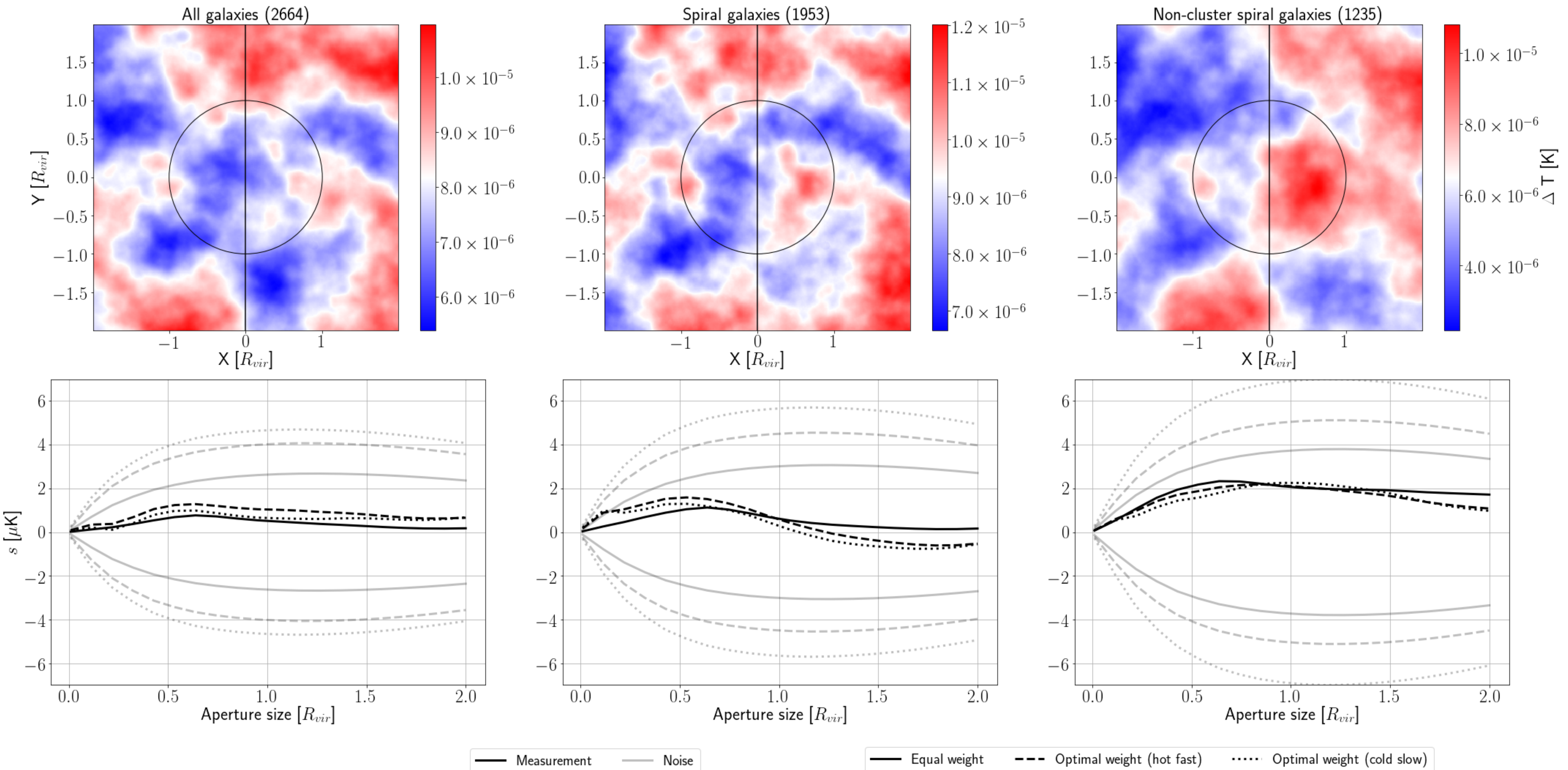




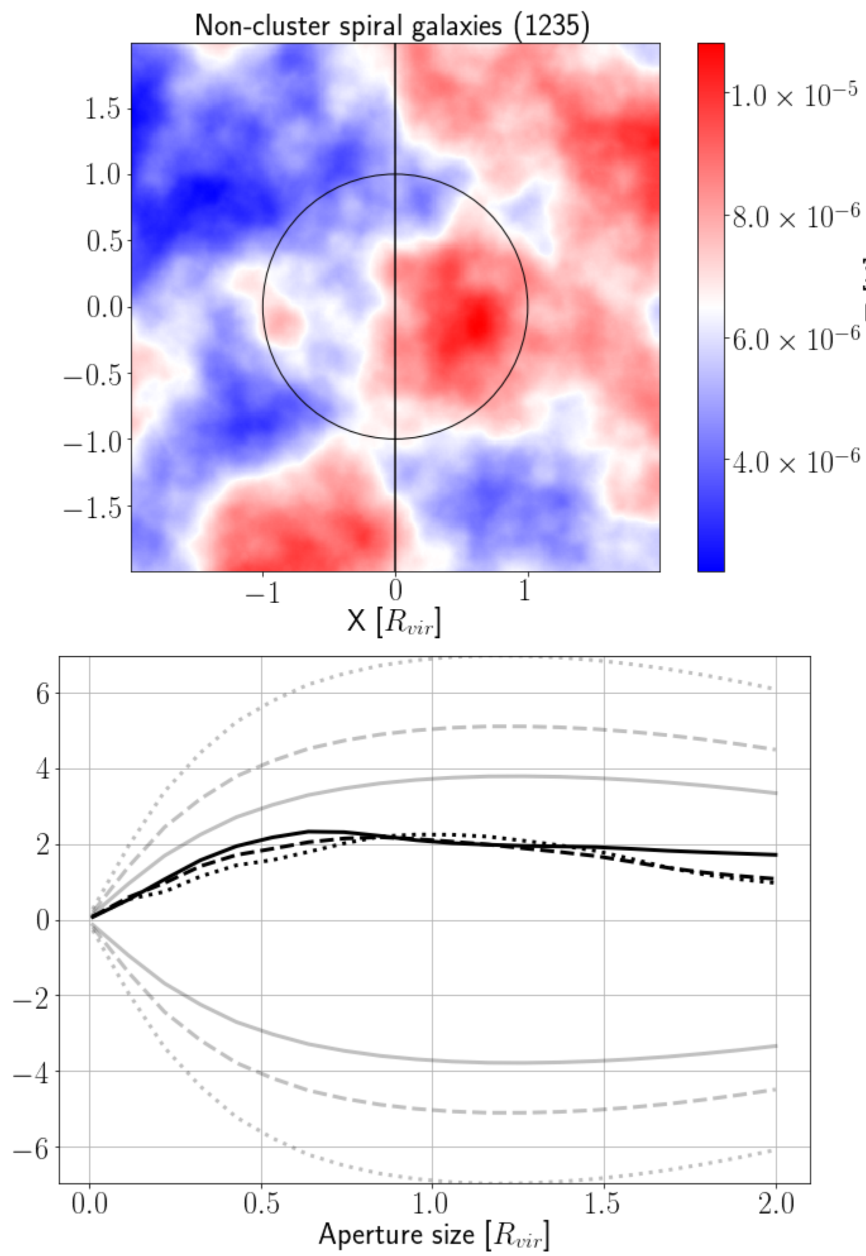
Stacking MaNGA galaxies

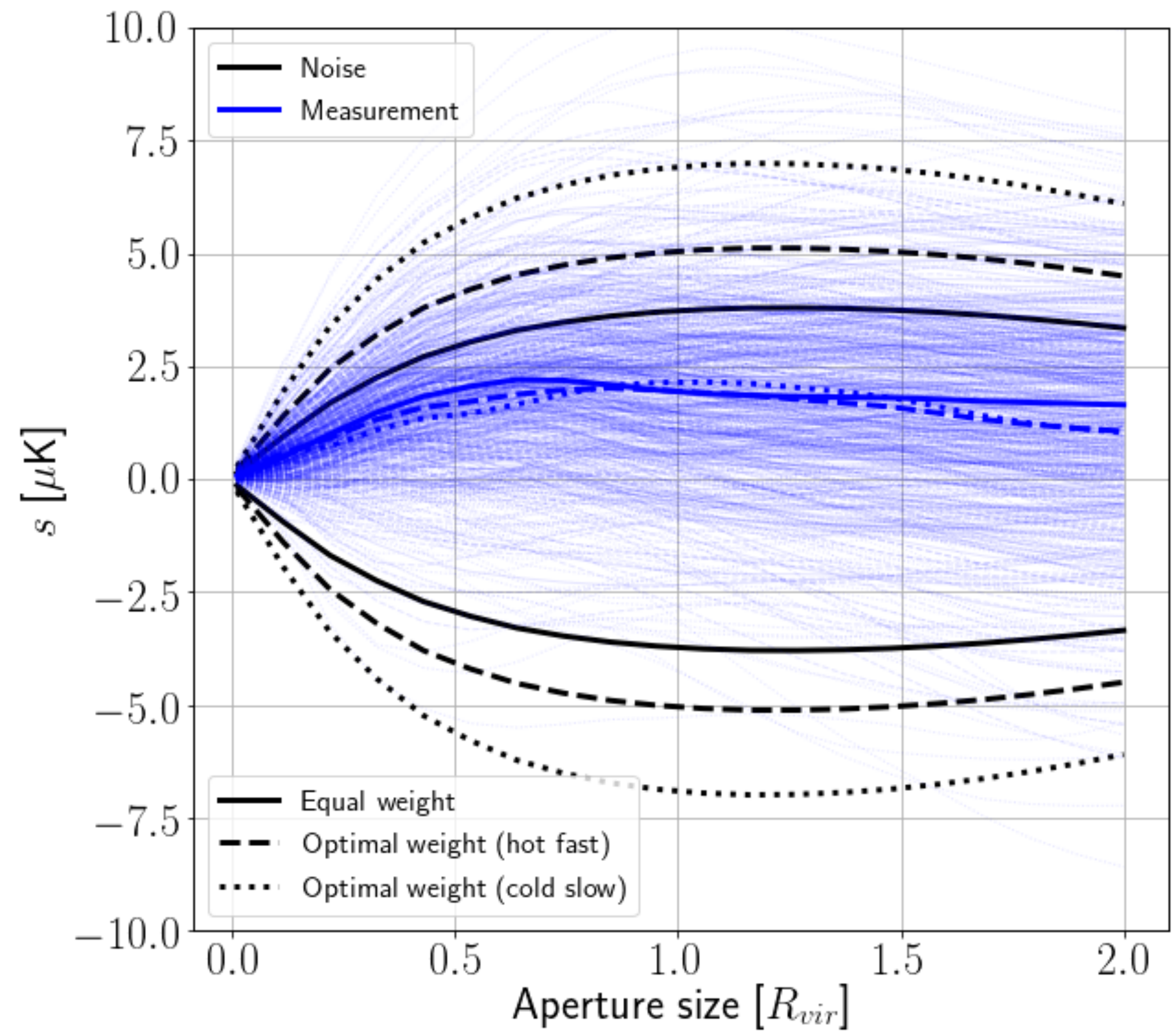


Stacking MaNGA galaxies



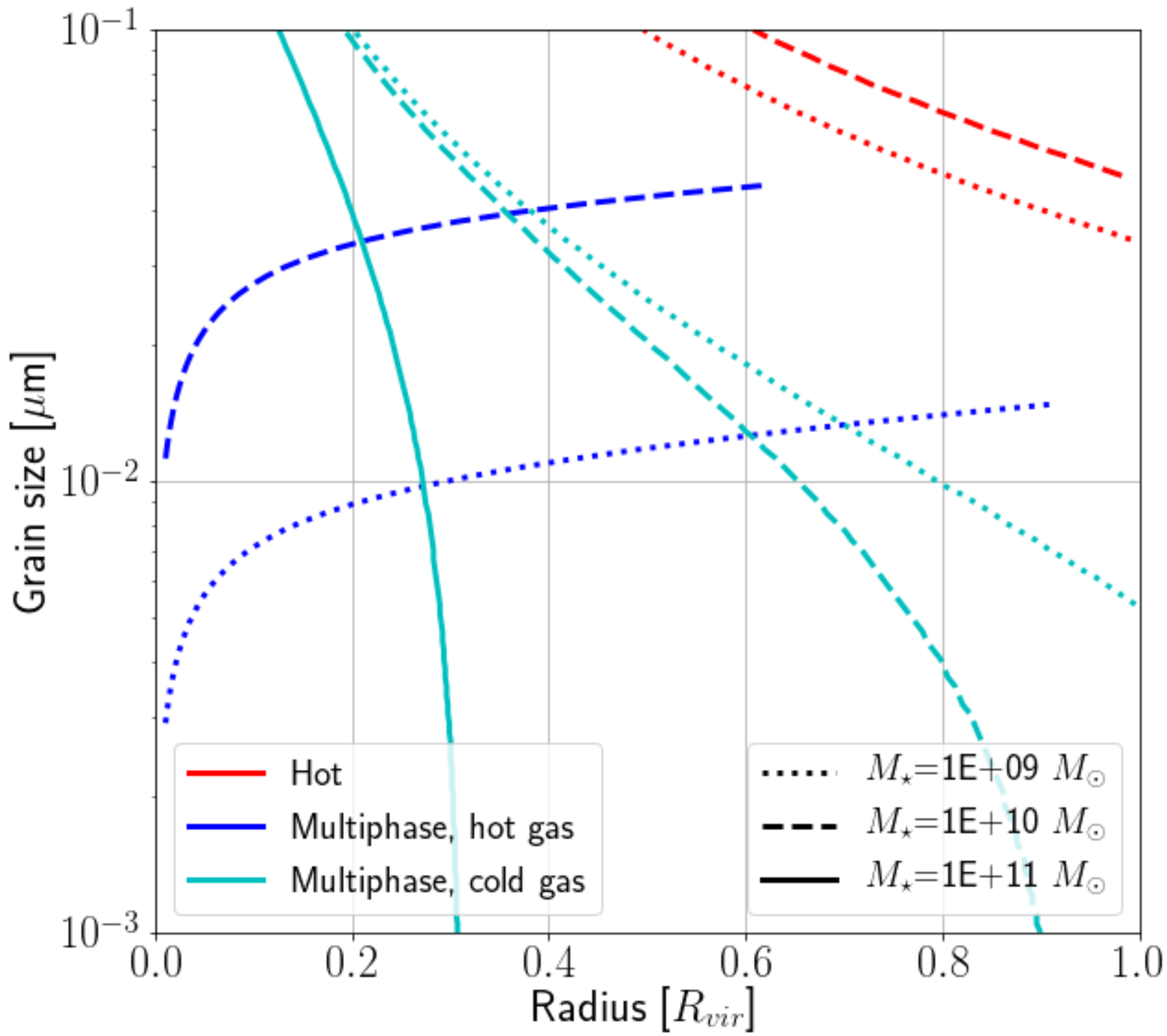
Stacking MaNGA galaxies





Dust as angular momentum tracer

$$t_s = \frac{\delta s}{\rho v_{th}} = 7.8 \times 10^{-3} \left(\frac{\delta}{3\,\mathrm{g\,cm^{-3}}}\right)\left(\frac{s}{0.1\mu\mathrm{m}}\right)\left(\frac{\rho}{10^{-26}\,\mathrm{g\,cm^{-3}}}\right)^{-1}\left(\frac{T}{10^6\mathrm{K}}\right)^{-\frac{1}{2}}\ \mathrm{Gyr}$$



Summary

- To fully realize the potential of upcoming WL experiments, we need to push the scales used for inference well into the non-linear regime.
- Extracting small-scale, non-linear information requires efficient statistics and accurate models.
  - Convolutional neural networks can be used as an efficient way to extract non-Gaussian information from WL datasets, and inspecting their inner workings may help us design new statistics to be used in a Bayesian framework.
  - Baryonic effects are a significant limitation to our ability to extract small -scale information, due to the lack of agreement between available hydro simulations.
    - We need more observations of baryonic properties to constrain current simulations, ideally properties the simulations were not designed upon. Angular momentum is such a property and could be used in combination with others.
    - In the future, the rkSZ effect can be used to probe angular momentum. Other tracers, such as dust may be easier to detect.