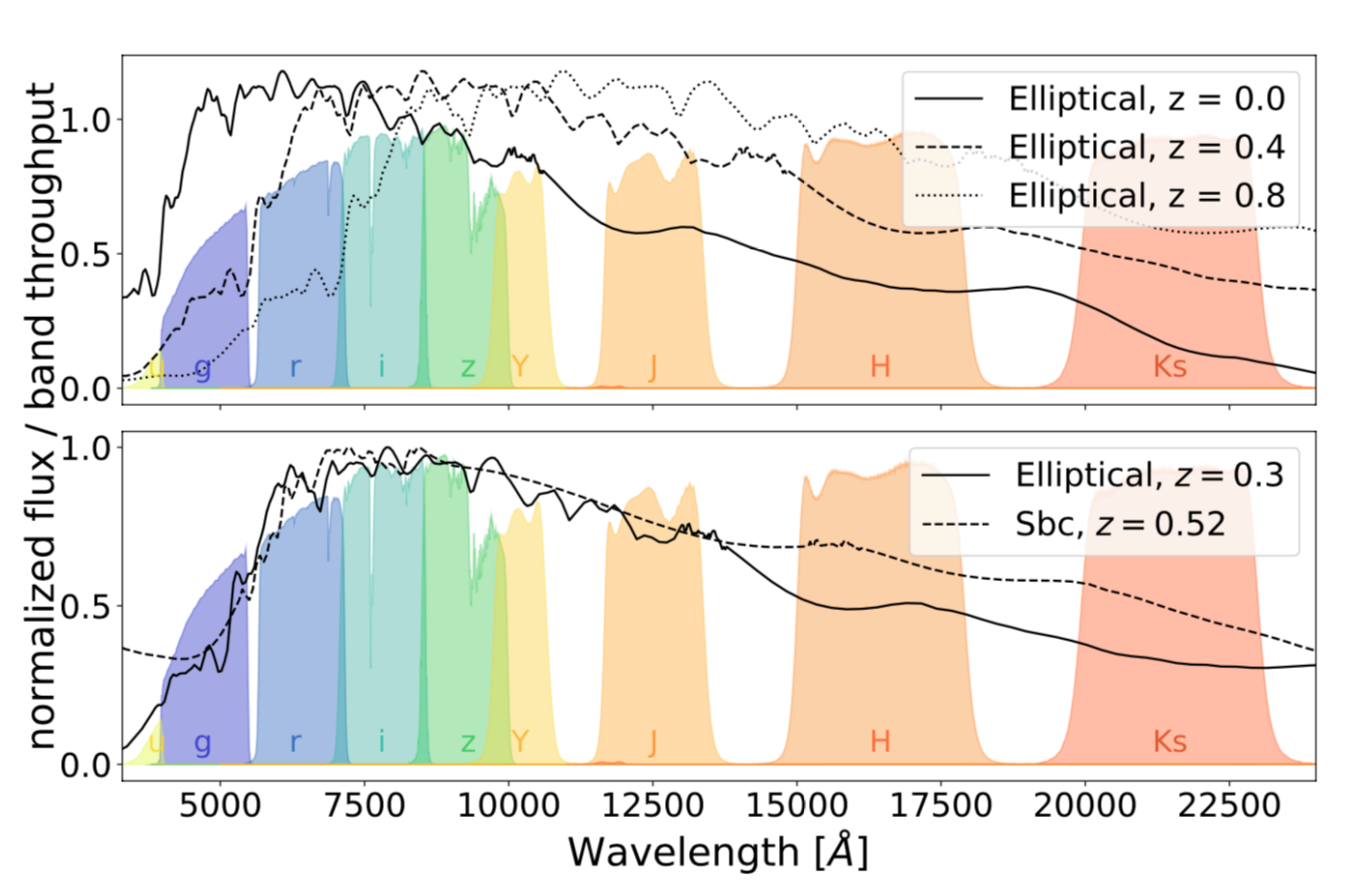
Clustering Redshifts in DES Y3 and the DES Y3 photo-z calibration strategy

Marco Gatti (UPenn)

Gatti, Giannini et al. :
https://arxiv.org/pdf/2012.08569.pdf

GCCL seminar
February, 12th 2021

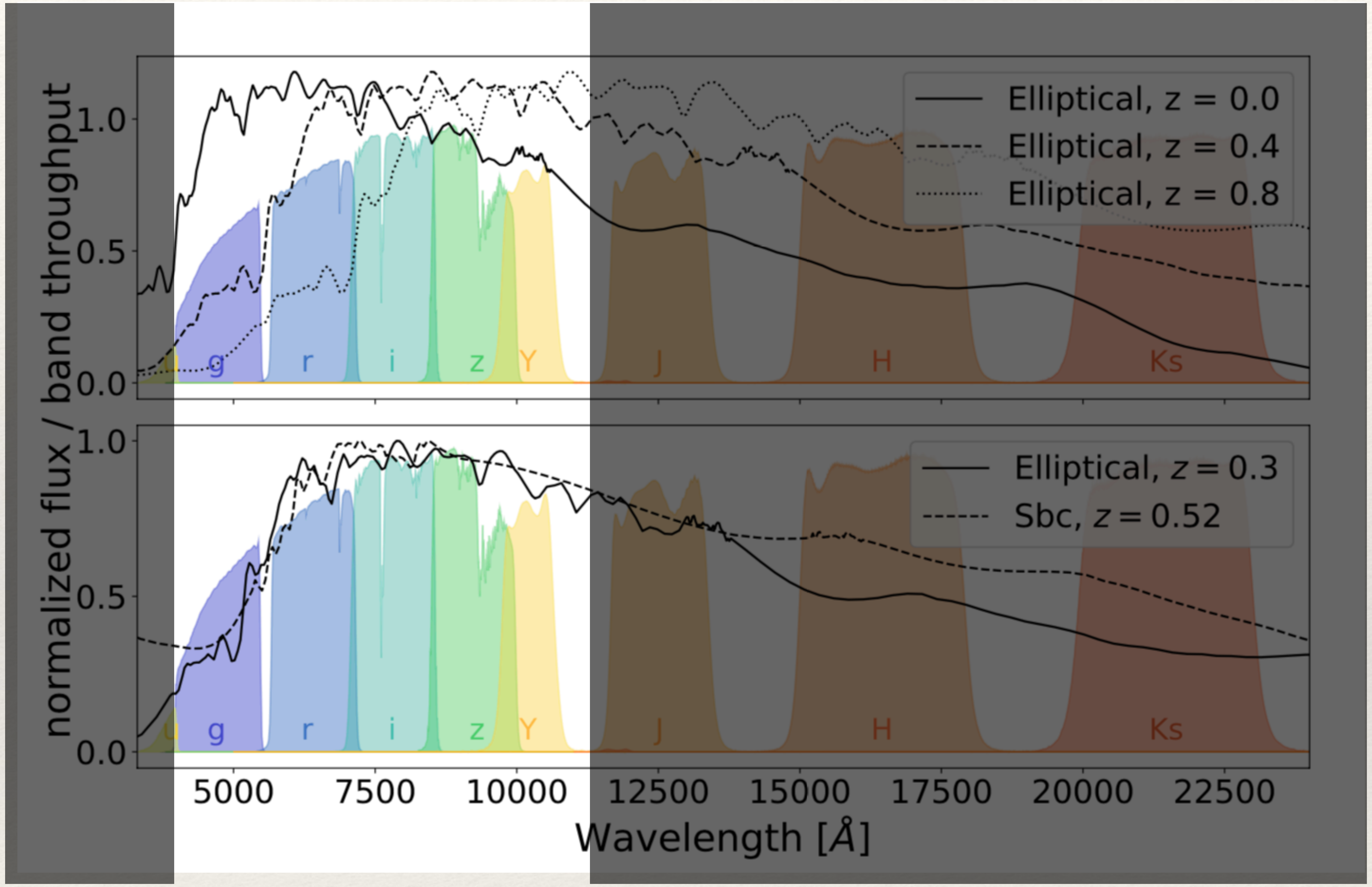
The redshift estimate challenge



Buchs+2019

Redshift distributions are key to cosmological inference

The redshift estimate challenge



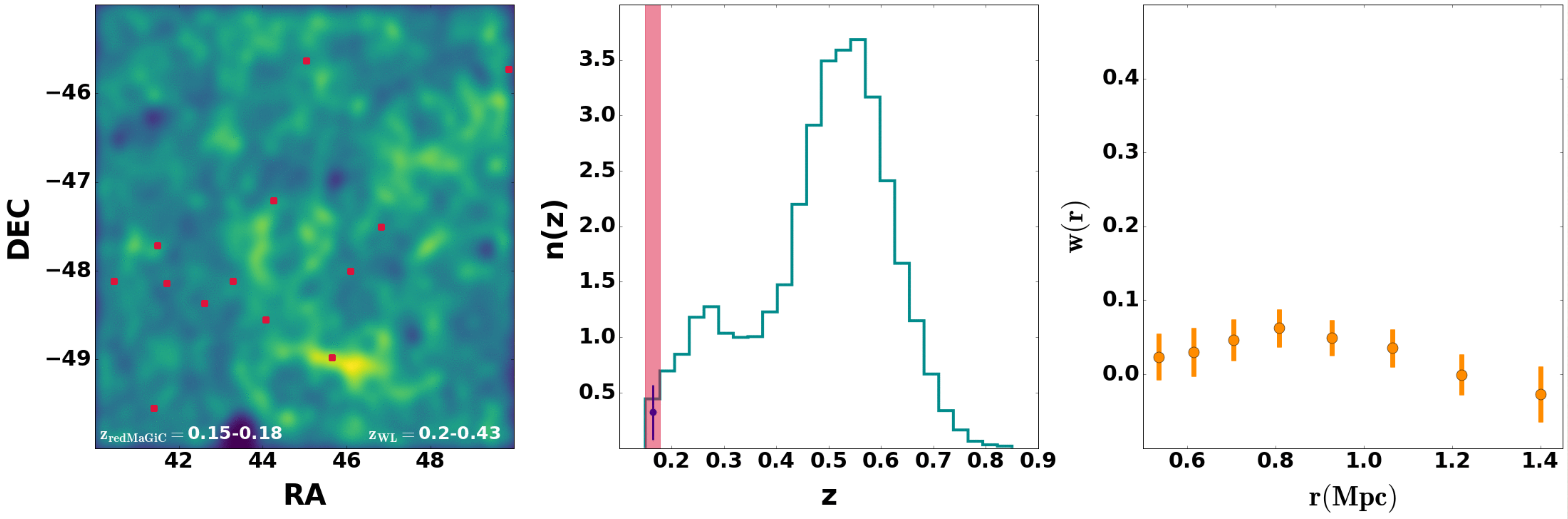
Buchs+2019

Redshift distributions are key to cosmological inference

Redshift estimation methods are prone to colour-redshift degeneracies when only a few broad bands are available

limited and incomplete spectroscopic samples available to calibrate the color-redshift relations

Alternative: clustering-based estimates

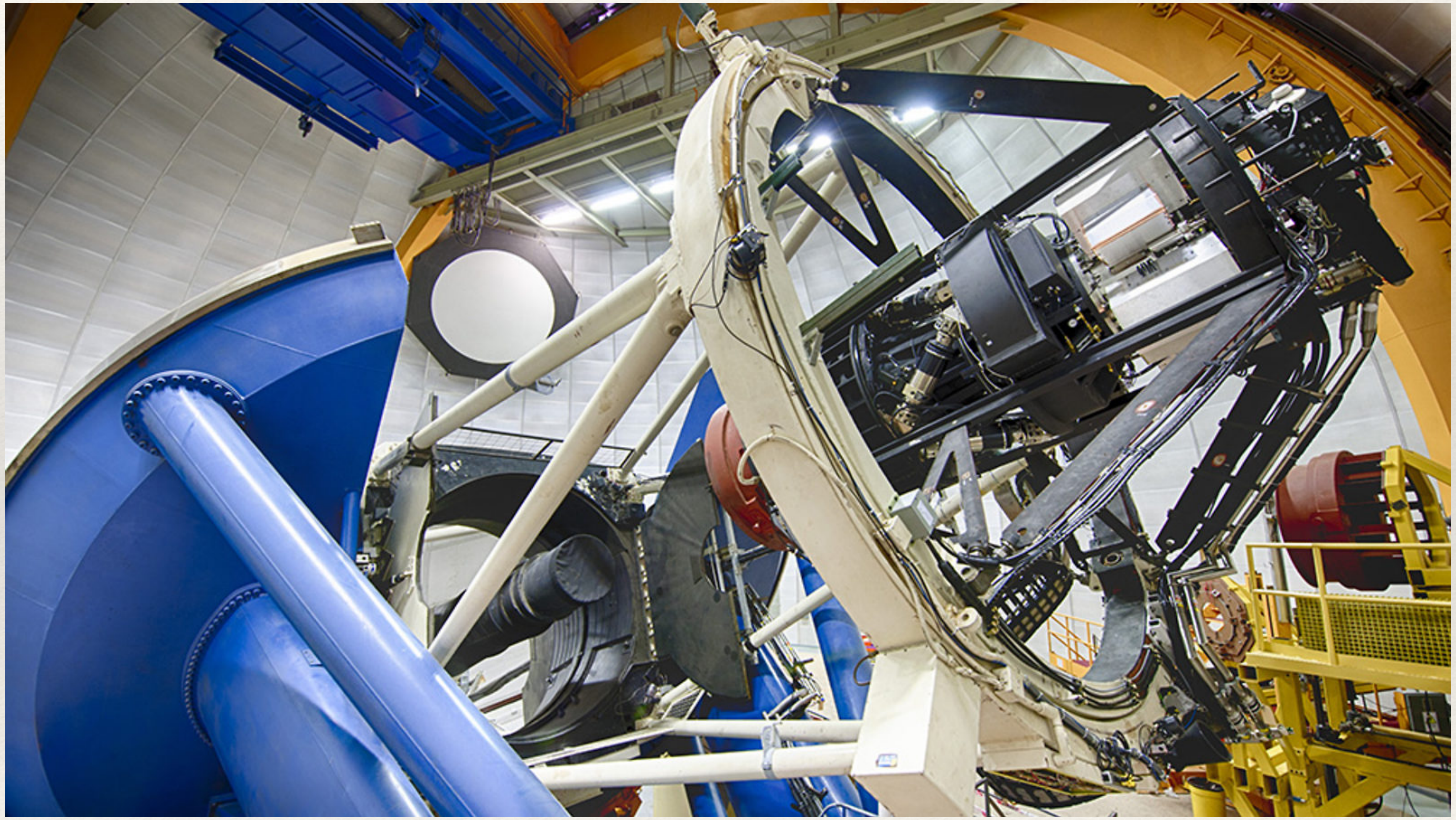


Credit: P. Vielzeuf

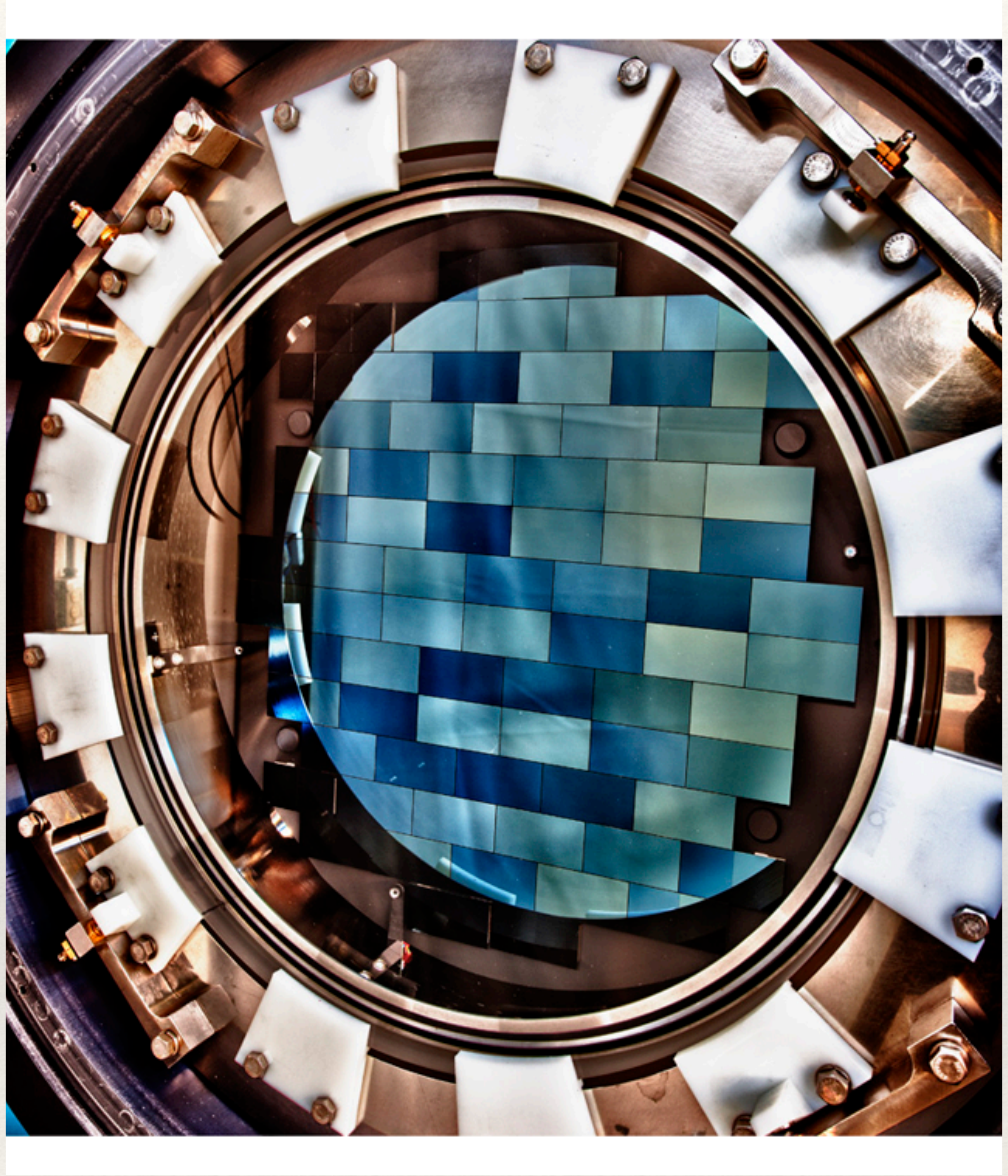
Clustering-z methods (WZ) allow to estimate the redshift distribution of a "unknown" sample by exploiting the cross-correlation signal with a "reference" sample with good redshifts.

WZ doesn't suffer from spectroscopic sample incompleteness / redshift ambiguities in few-band colors

The Dark Energy Survey

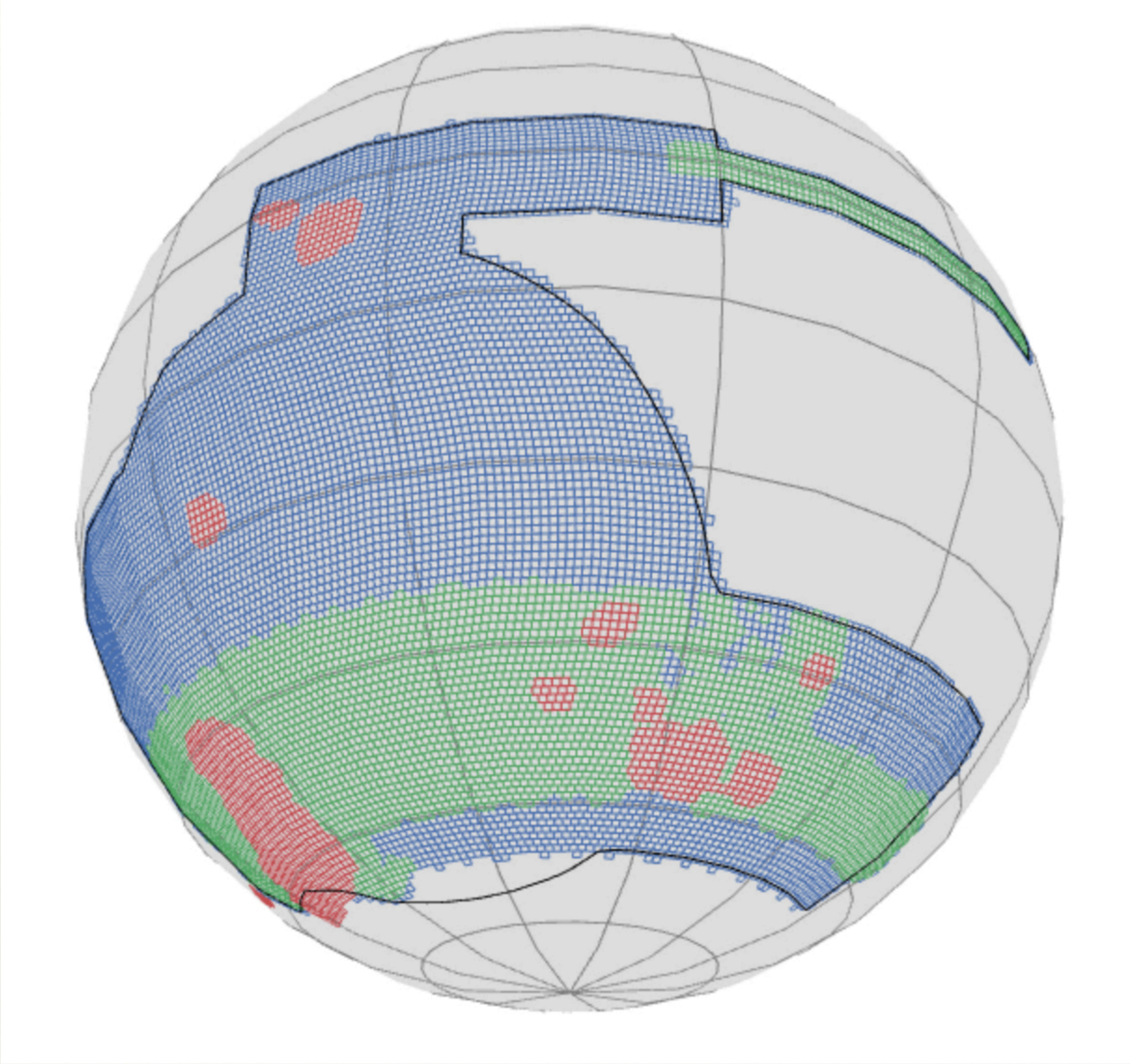


- Imaging galaxy survey.
- ~5000 sq. deg. after 6 years (2013-2019)
- Shapes, photometric redshifts and positions for 300 million galaxies.



The Dark Energy Survey

- 570-Megapixel digital camera, DECam, mounted on the Blanco 4-meter telescope at Cerro Tololo Inter-American Observatory (Chile).
- Five filters are used (grizY).

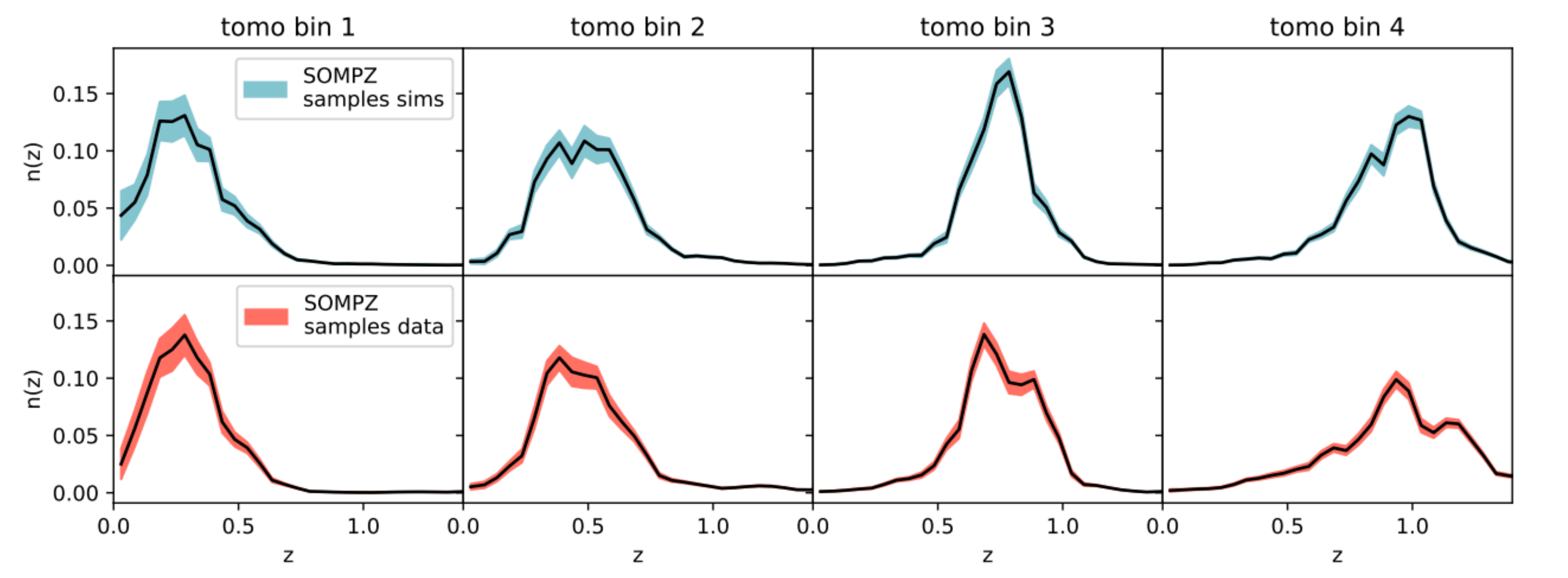


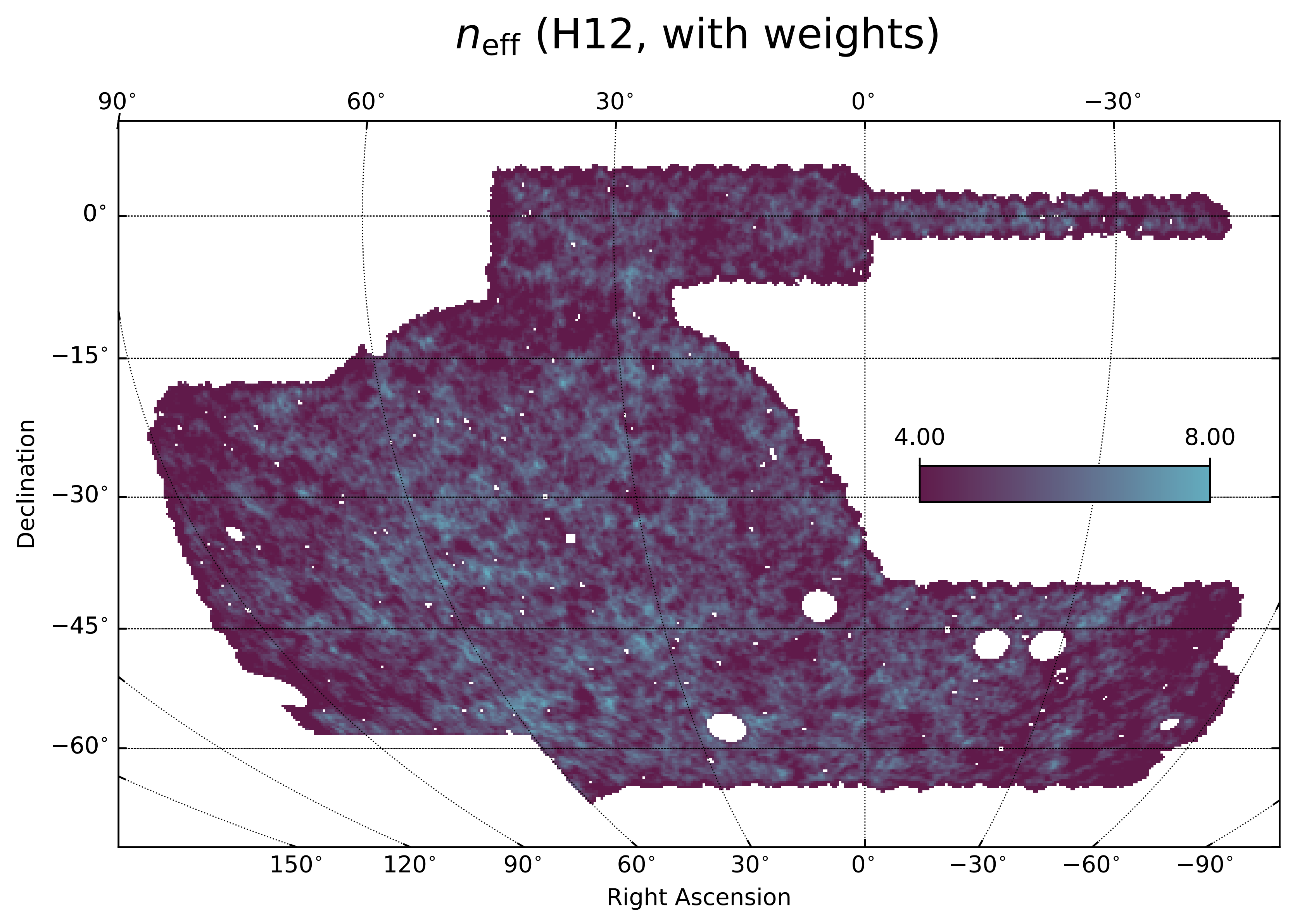
Red : Science verification data
Green: DES Y1
Blue: DES Y3

- Currently analysing the DES Y3 data

- Full footprint (4134 deg^2), limiting magnitude i=22.5, 100 million shapes

DES Y3 clustering estimates - WL sample



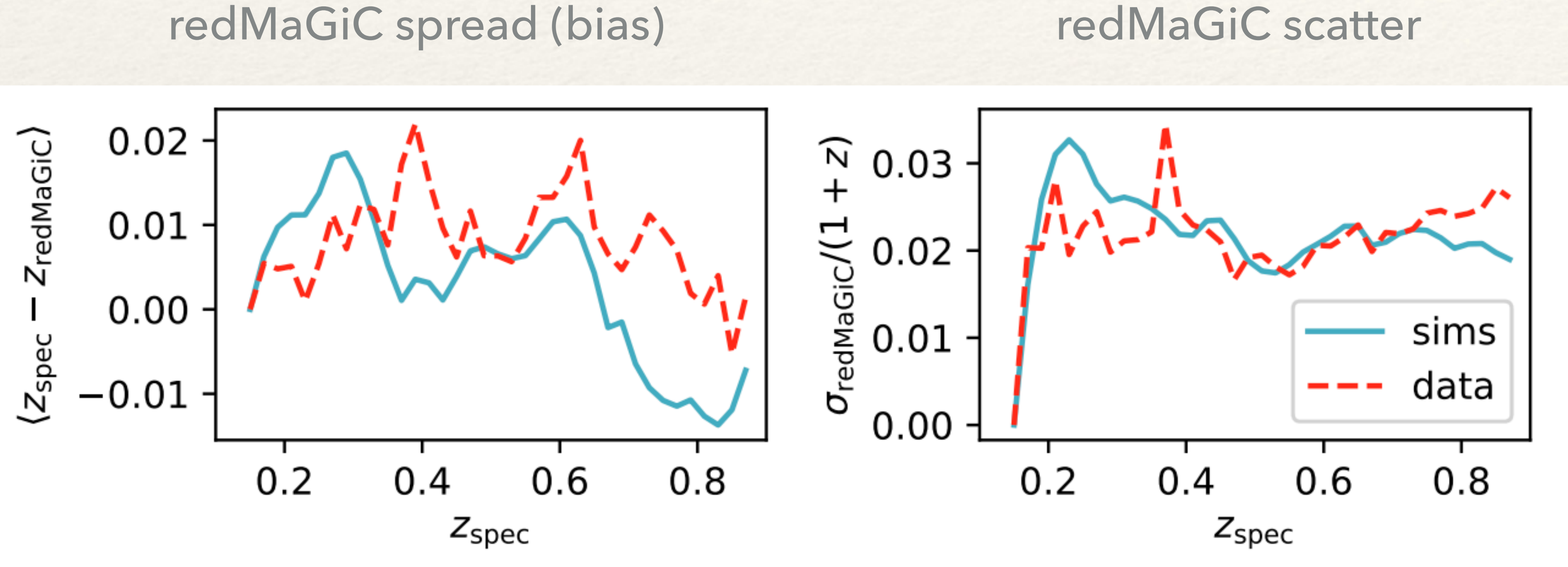


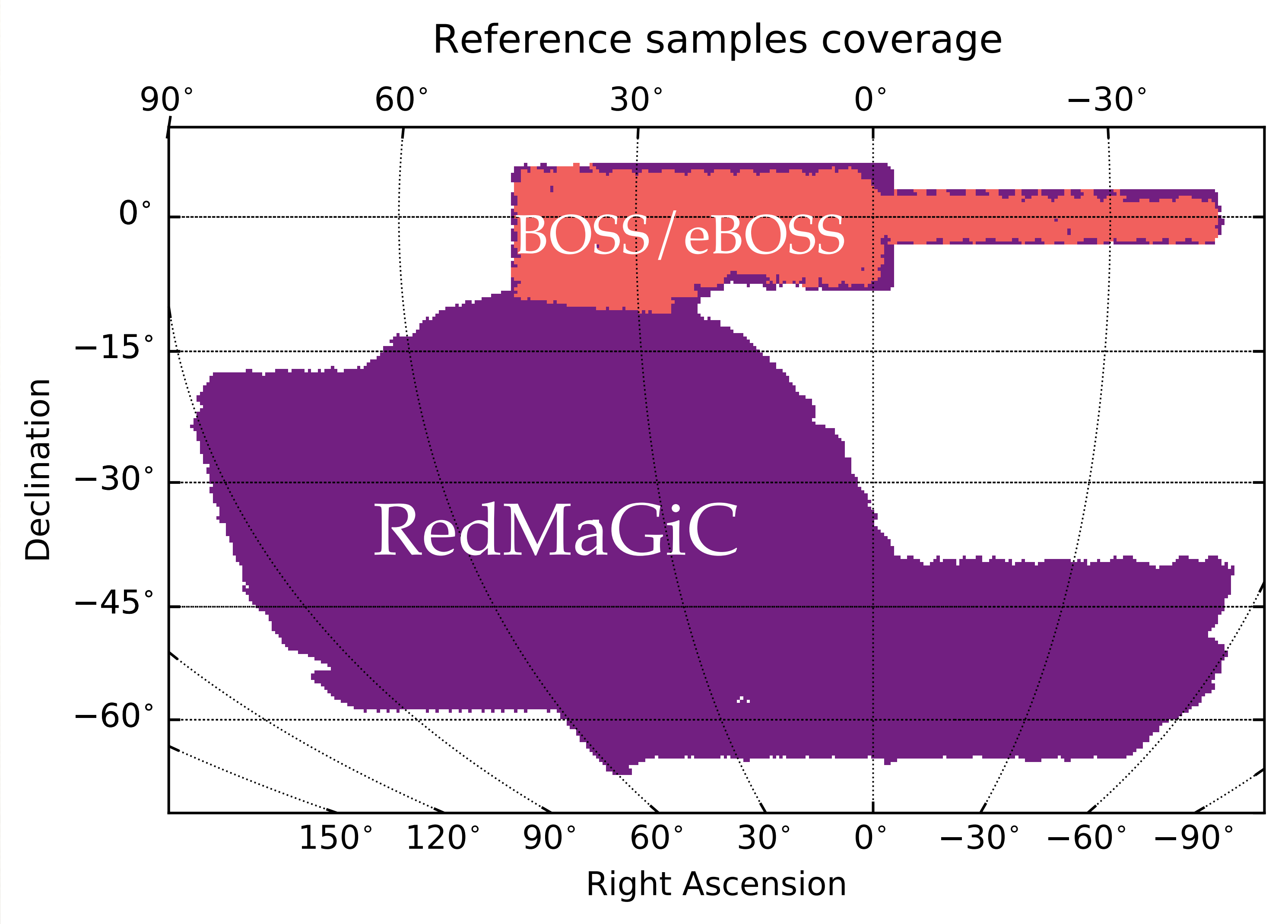
- Weak Lensing (WL) sample: ~100 milion galaxies (Gatti,Sheldon+ 2020),
- Divided into 4 tomographic bins [0.0, 0.358, 0.631, 0.872, 2.0] (Myles,Alarcon+2020)

DES Y3 clustering estimates - 2 reference samples

RedMaGiC galaxies

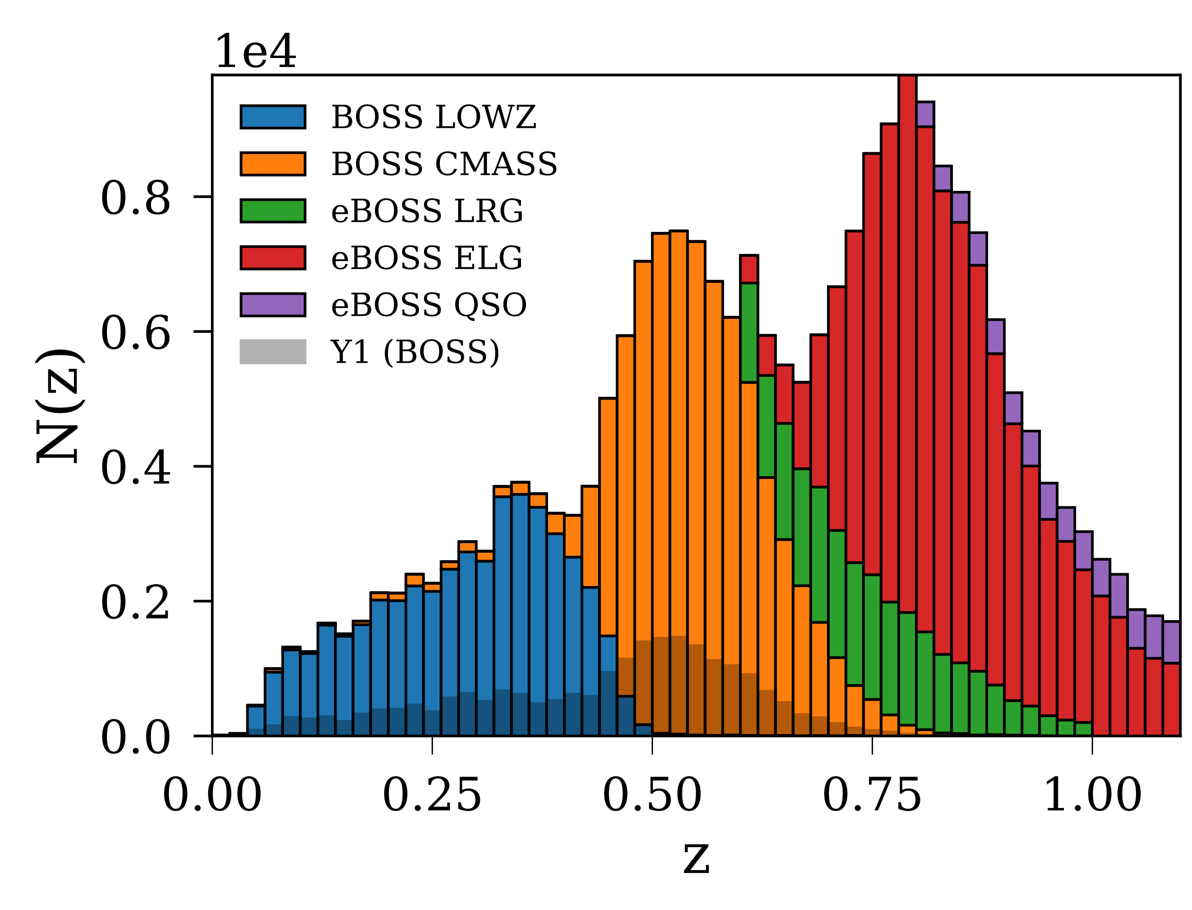
- Red luminous galaxies with high quality photometric redshift estimates (~3M)
- 0.15 < z < 0.95



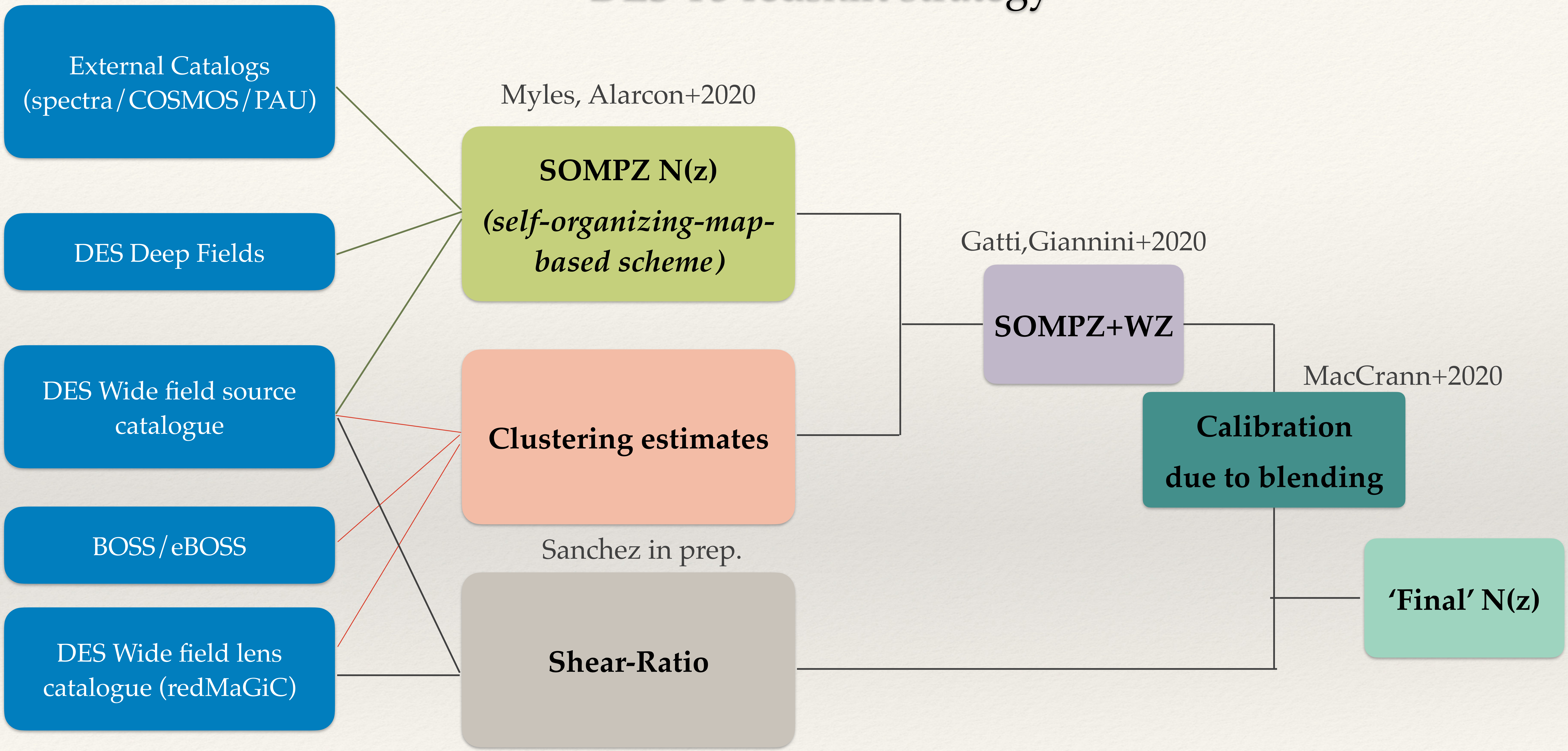


BOSS/eBOSS

- Spectroscopic redshifts from BOSS and eBOSS galaxies (250k)
- 0.1 < z < 1.1
- 17% DES footprint covered



DES Y3 redshift strategy



2 different methods to combine

SOMPZ N(z)

(self-organizing-map-based scheme)

+

Clustering estimates

Method 1: `mean-matching`

WZ N(z):

$$\tilde{n}_{\mathrm{u}}(z_i) \propto \frac{w_{\mathrm{ur}}(z_i)}{b_{\mathrm{r}}(z_i) w_{\mathrm{DM}}(z_i)},$$

Compare the windowed mean redshift of SOMPZ N(z) to the windowed mean of WZ N(z)

$$\langle z \rangle_{\mathrm{wz}} = \frac{\int_{z_{\min}}^{z_{\max}} dz\, z\, \tilde{n}_{\mathrm{u}}(z)}{\int_{z_{\min}}^{z_{\max}} dz\, \tilde{n}_{\mathrm{u}}(z)}$$

$$\langle z \rangle_{\mathrm{pz}} = \frac{\int_{z_{\min}}^{z_{\max}} dz\, z\, n_{\mathrm{pz}}(z)}{\int_{z_{\min}}^{z_{\max}} dz\, n_{\mathrm{pz}}(z)}$$

$$\mathcal{L}\left[\mathrm{WZ}|n_{\mathrm{u}}(z)\right] \equiv \mathcal{N}\left(\langle z \rangle_{\mathrm{pz}} - \langle z \rangle_{\mathrm{wz}}, \sigma_{\langle z \rangle}\right)$$

SOMPZ samples are assigned a weight through this likelihood

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Clustering signal

(integrated w(theta) between 1.5 and 5 Mpc)

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Galaxy-matter bias reference sample

(from autocorrelation of the reference sample)

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DM clustering (from theory)
(our results are insensitive to cosmology)

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Uncertainty of the method (syst+stat)

Systematic dominated, mostly galaxy-matter bias of the WL sample

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- Similar to DES Y1
- Magnification not included, and tails of the distributions are not calibrated
- It doesn't calibrate N(z) shape

Compare the windowed mean redshift of SOMPZ N(z) to the windowed mean of WZ N(z)

$$\langle z \rangle_{\mathrm{wz}} = \frac{\int_{z_{\mathrm{min}}}^{z_{\mathrm{max}}} dz\, z\, \tilde{n}_{\mathrm{u}}(z)}{\int_{z_{\mathrm{min}}}^{z_{\mathrm{max}}} dz\, \tilde{n}_{\mathrm{u}}(z)}$$

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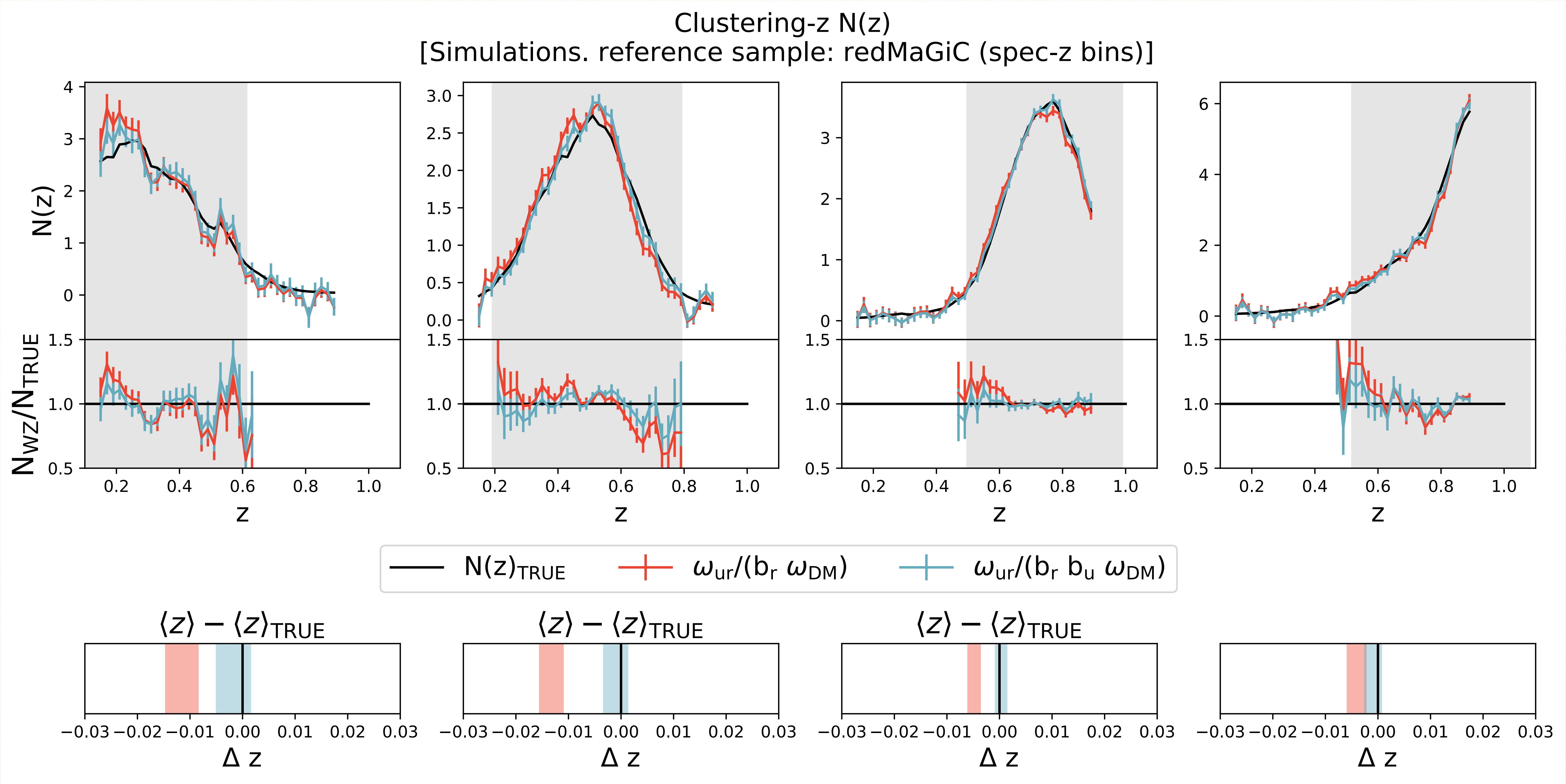
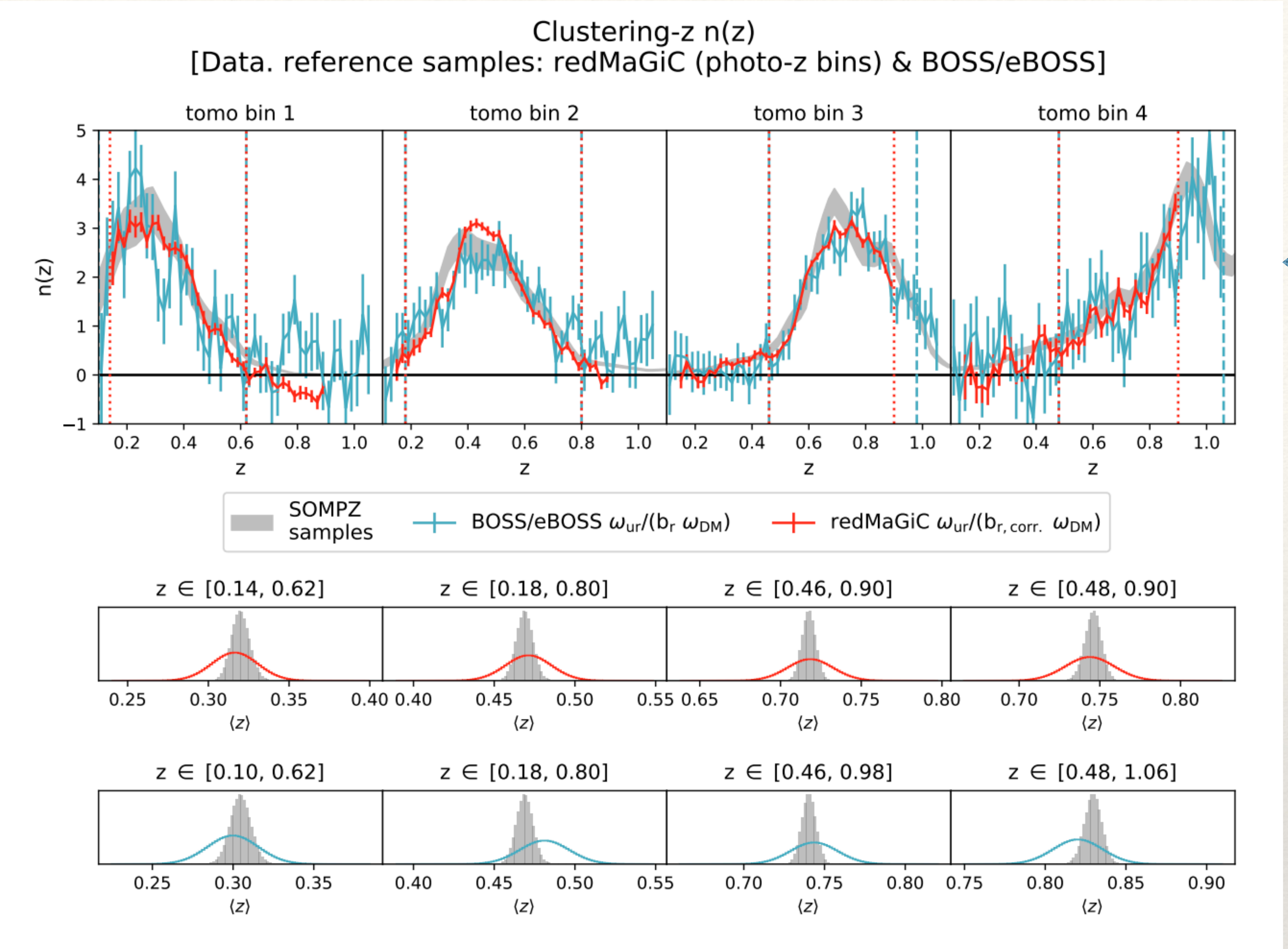
SOMPZ samples are assigned a weight through this likelihood

DES Y3 clustering estimates - systematic estimation in sims



Systematic	tomo bin 1	tomo bin 2	tomo bin 3	tomo bin 4
methodology:	0.002 ± 0.003	0.001 ± 0.002	0.000 ± 0.001	0.001 ± 0.002
magnification:	0.004	0.005	0.003	0.004
WL galaxy bias unc:	0.013	0.013	0.013	0.013
redMaGiC syst:	0.000 (0.014)	0.001 (0.007)	0.002 (0.000)	0.005 (0.003)
total systematic *redMaGiC*:	0.014	0.014	0.014	0.015
statistical *redMaGiC*:	0.003	0.002	0.001	0.002
total systematic BOSS/eBOSS:	0.014	0.014	0.014	0.014
statistical BOSS/eBOSS:	0.007	0.006	0.004	0.006

Dominant source of uncertainty:
Redshift evolution of the galaxy-matter bias of the WL sample

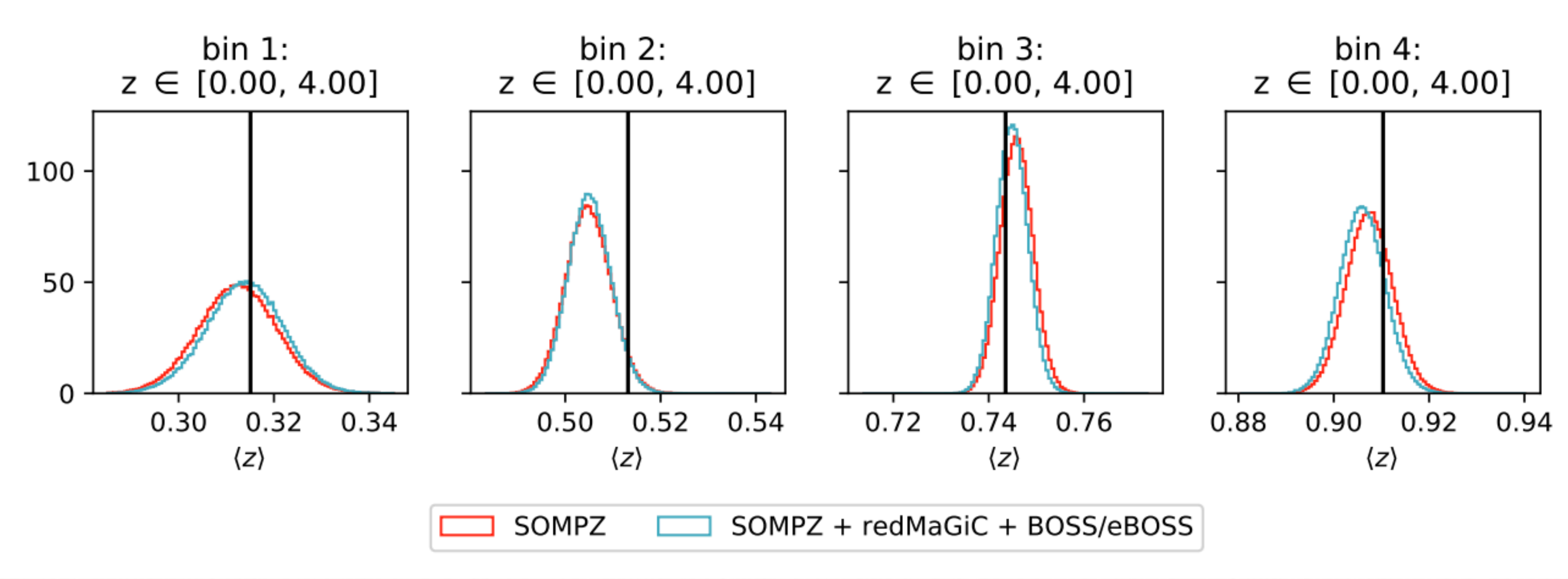


$$\tilde{n}_{\mathrm{u}}(z_i) \propto \frac{w_{\mathrm{ur}}(z_i)}{b_{\mathrm{r}}(z_i)\, w_{\mathrm{DM}}(z_i)},$$

left: WZ n(z) estimates compared to SOMPZ n(z) estimates

below: <z> from SOMPZ and SOMPZ+WZ

The mean matching approach only used as cross-check. It does not improve constraints on the <z> from SOMPZ



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Clustering estimates

Method 2: `shape-matching`

Forward model the clustering signal:

$$\hat{w}_{\mathrm{ur}}(z_i) = n_{\mathrm{u}}(z_i) b_{\mathrm{r}}(z_i) w_{\mathrm{DM}}(z_i) \times \mathrm{Sys}(z_i, \mathbf{s}) + b_{\mathrm{r}}(z_i) \alpha'_{\mathrm{u}}(z_i) \sum_{j>i} \left[D_{ij} n_{\mathrm{u}}(z_j) \right] + b'_{\mathrm{u}}(z_i) \alpha_{\mathrm{r}}(z_i) \sum_{j>i} \left[D_{ij} n_{\mathrm{u}}(z_j) \right] . \quad (19)$$

SOMPZ samples can be assigned a weight through this likelihood:

(In practice, joint WZ - SOMPZ likelihood sampled with a constrained HMC for efficiency reasons)

$$\mathcal{L}\left[\mathrm{WZ} | n_{\mathrm{u}}(z), b_{\mathrm{r}}(z), \alpha_{\mathrm{r}}(z), w_{\mathrm{DM}}(z)\right] \propto \int d\mathbf{s}\, d\mathbf{p} \exp\left[-\frac{1}{2} (w_{\mathrm{ur}} - \hat{w}_{\mathrm{ur}})^T \Sigma_w^{-1} (w_{\mathrm{ur}} - \hat{w}_{\mathrm{ur}}) \right] p(\mathbf{s}) p(\mathbf{p}). \quad (20)$$

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'predicted' clustering signal

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Galaxy-matter bias
reference sample
(from autocorrelation of the reference sample)

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Systematic function

(dominated by the galaxy-matter bias of the WL sample)

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WZ shape-matching systematic functions

Systematic function modelled as a sum of Legendre polynomials up to order 5.

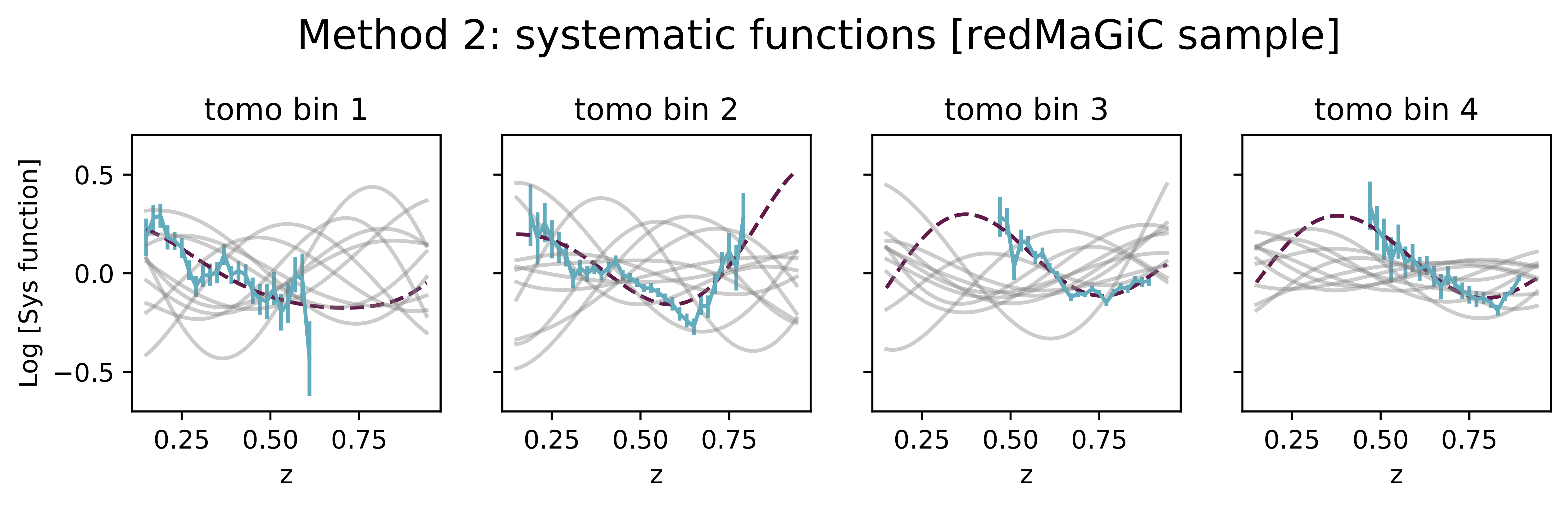
$$log[\mathrm{Sys}\,(\mathrm{z_i}, \{\mathrm{s_k}\})] = \sum_{k<M} s_k P_k(z_i),$$

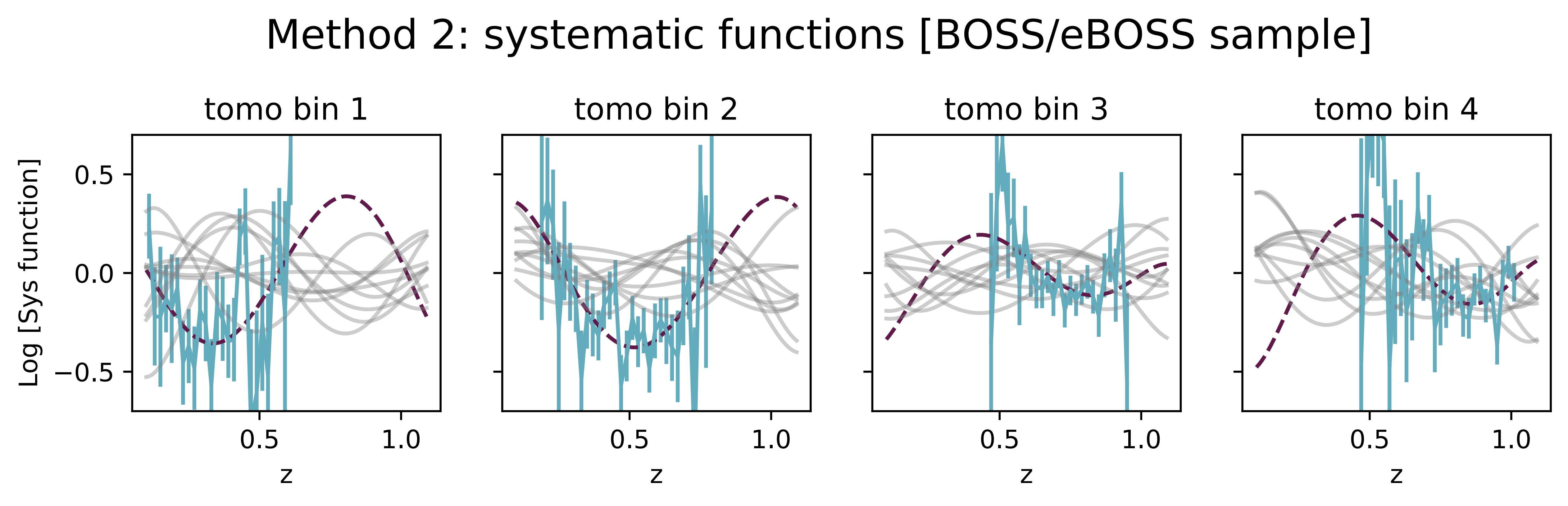
The RMS on s fixed to be the typical RMS measured in simulations

$$\mathrm{Sys}_{\mathrm{sim}}(z_i) = \frac{w_{\mathrm{ur}}(z_i) - M(z_i)}{\hat{w}_{\mathrm{ur}}(z_i) - M(z_i)},$$

measured cross-correlation signal

Model in simulation





Blue points: Sys_sim as measured in simulations
Purple line: best fit Sys(z,s) function
Grey lines: a few model draws for Sys(z,s)

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Magnification contribution

Magnification coefficients for the WL and reference samples:
alpha = C_sample-2

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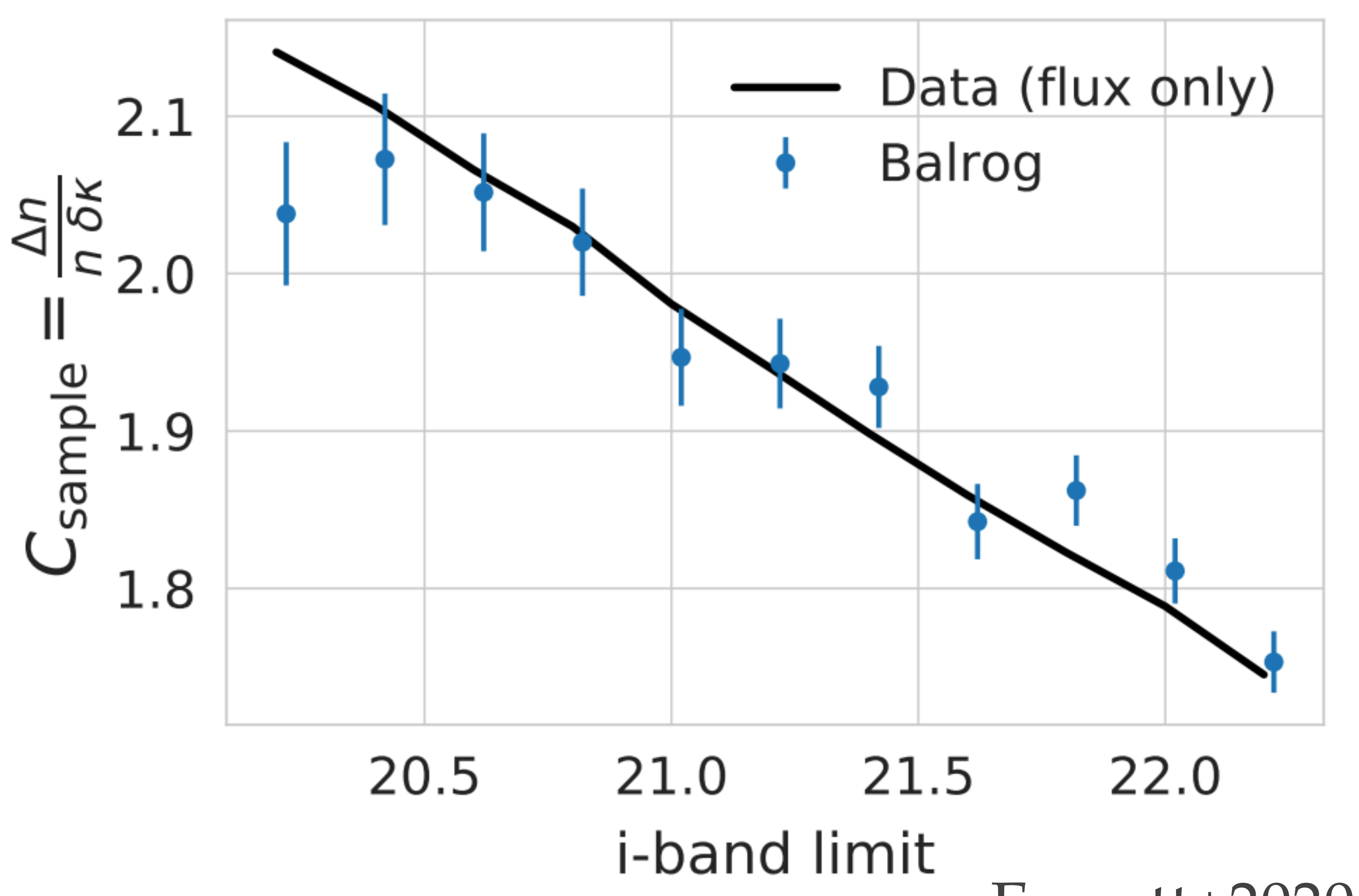
WZ shape-matching - estimate of the magnification parameters

The magnification coefficients are estimated using Balrog (Everett+2020). Balrog allows us to inject 'fake' galaxies into our real images. The procedure is as follows:

1) we inject galaxies into our images, and select a given sample (e.g., redMaGiC)
2) We inject the same galaxies but slightly magnified (2%), which increases flux and are of the objects; we then select a give sample (e.g., redMaGiC)



Everett+2020

$$C_{\rm sample}\delta_\kappa = \frac{n_{\rm int}(F, \kappa + \delta\kappa)}{n_{\rm int}(F)}$$

2 different methods to combine

SOMPZ N(z)
(self-organizing-map-based scheme)

+

Clustering estimates

Method 2: `shape-matching`

Forward model the clustering signal:

$$\hat{w}_{\mathrm{ur}}(z_i) = n_{\mathrm{u}}(z_i) b_{\mathrm{r}}(z_i) w_{\mathrm{DM}}(z_i) \times \mathrm{Sys}(z_i, \mathbf{s}) + b_{\mathrm{r}}(z_i)\alpha'_{\mathrm{u}}(z_i) \sum_{j>i} \left[D_{ij} n_{\mathrm{u}}(z_j)\right] + b'_{\mathrm{u}}(z_i)\alpha_{\mathrm{r}}(z_i) \sum_{j>i} \left[D_{ij} n_{\mathrm{u}}(z_j)\right]. \quad (19)$$

SOMPZ samples can be assigned a weight through this likelihood:

(In practice, joint WZ - SOMPZ likelihood sampled with a constrained HMC for efficiency reasons)

$$\mathcal{L}\left[\mathrm{WZ} | n_{\mathrm{u}}(z), b_{\mathrm{r}}(z), \alpha_{\mathrm{r}}(z), w_{\mathrm{DM}}(z)\right] \propto \int d\mathbf{s}\, d\mathbf{p} \exp\left[-\frac{1}{2}(w_{\mathrm{ur}} - \hat{w}_{\mathrm{ur}})^T \Sigma_w^{-1} (w_{\mathrm{ur}} - \hat{w}_{\mathrm{ur}})\right] p(\mathbf{s}) p(\mathbf{p}). \quad (20)$$

measured cross-correlation signal

Model

Measurement covariance (Jackknife)

Nuisance parameters

See Bernstein 2021 for the HMC implementation

2 different methods to combine

SOMPZ N(z)
(self-organizing-map-based scheme)

+

Clustering estimates

Method 2: `shape-matching`

Forward model the clustering signal:

$$\hat{w}_{\mathrm{ur}}(z_i) = n_{\mathrm{u}}(z_i) b_{\mathrm{r}}(z_i) w_{\mathrm{DM}}(z_i) \times \mathrm{Sys}(z_i, \mathbf{s}) + b_{\mathrm{r}}(z_i) \alpha'_{\mathrm{u}}(z_i) \sum_{j>i} \left[D_{ij} n_{\mathrm{u}}(z_j) \right] + b'_{\mathrm{u}}(z_i) \alpha_{\mathrm{r}}(z_i) \sum_{j>i} \left[D_{ij} n_{\mathrm{u}}(z_j) \right]. \quad (19)$$

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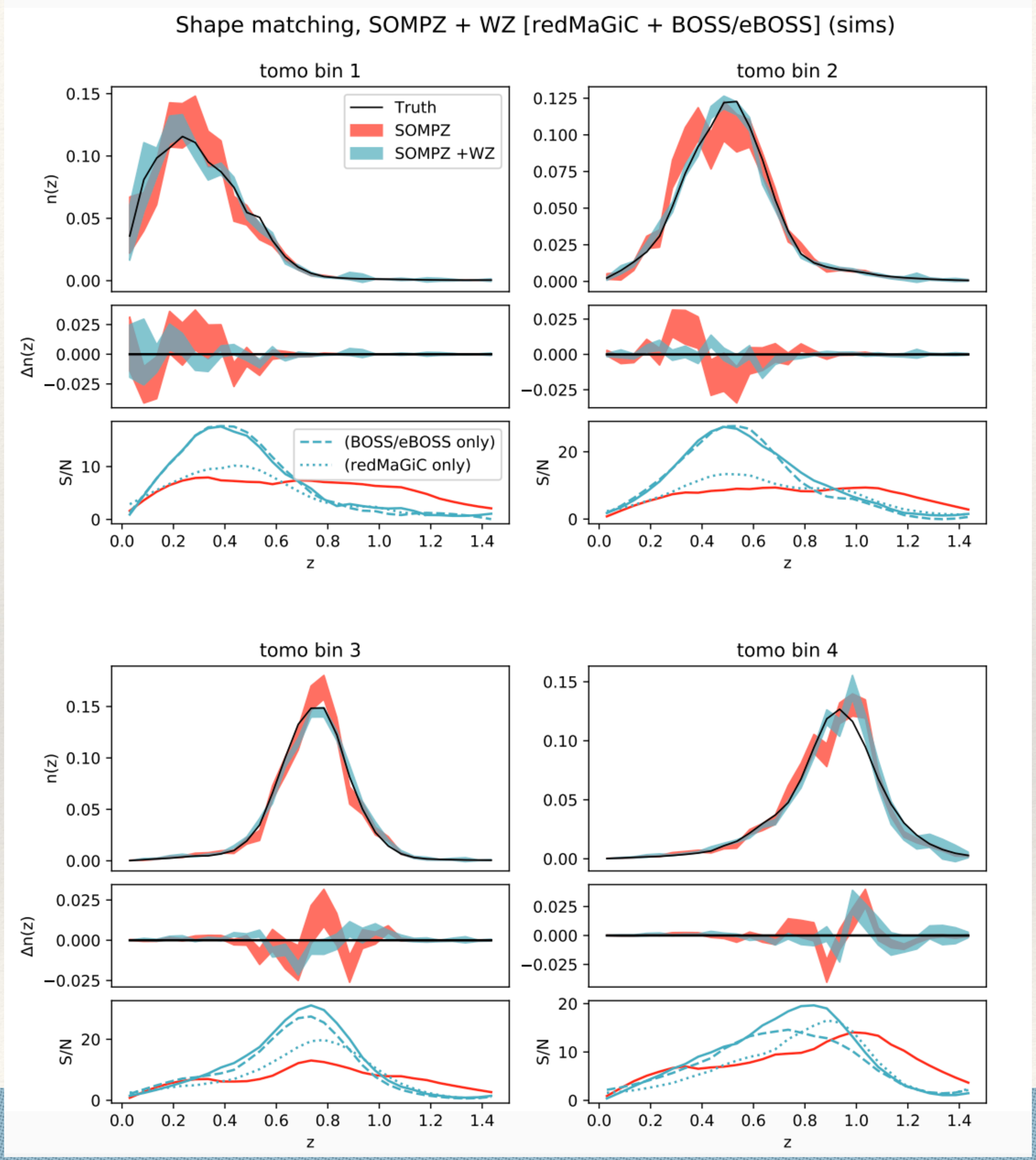
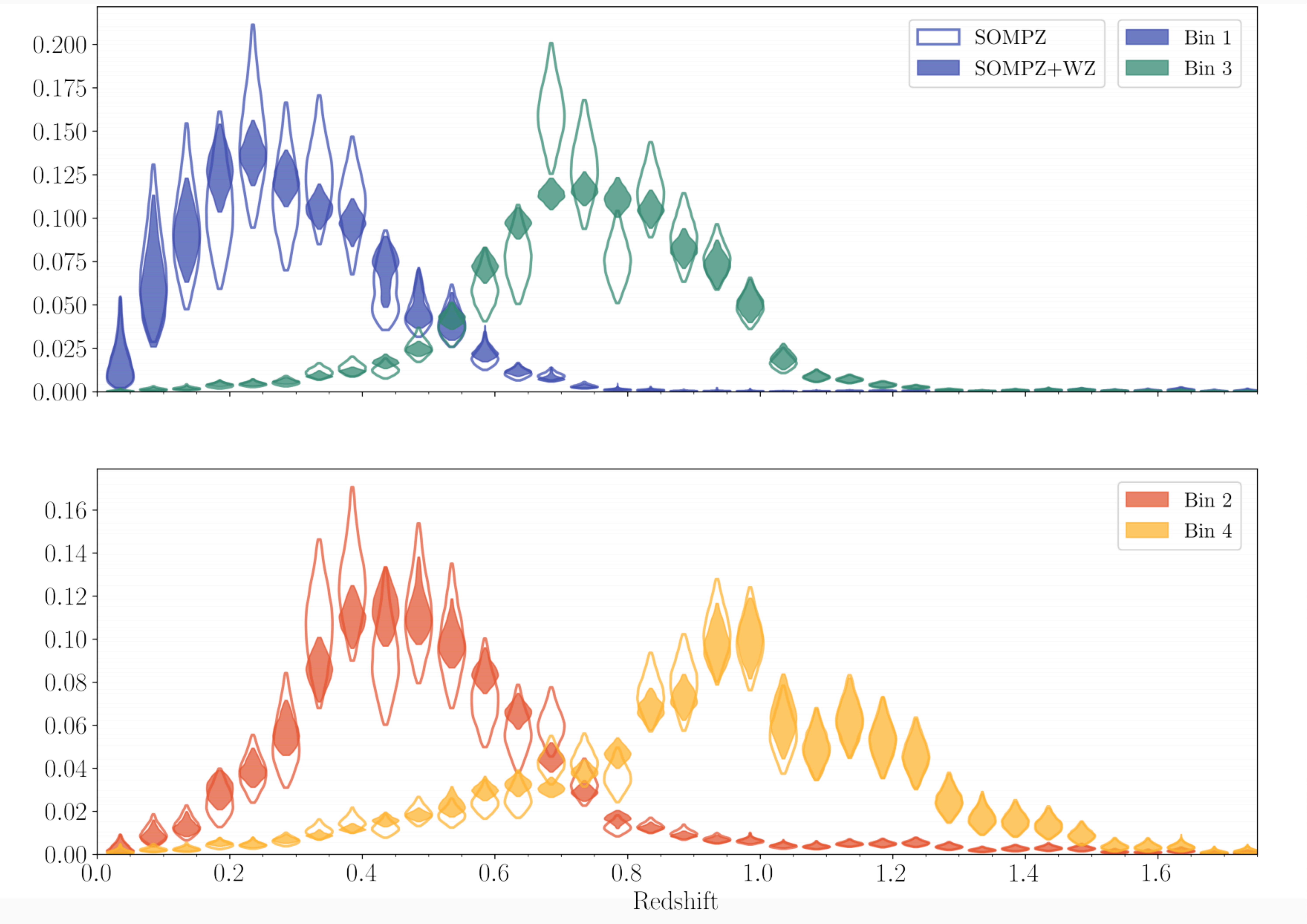
- It calibrates the full N(z) shape
- It properly accounts for magnification effects



Shape matching method

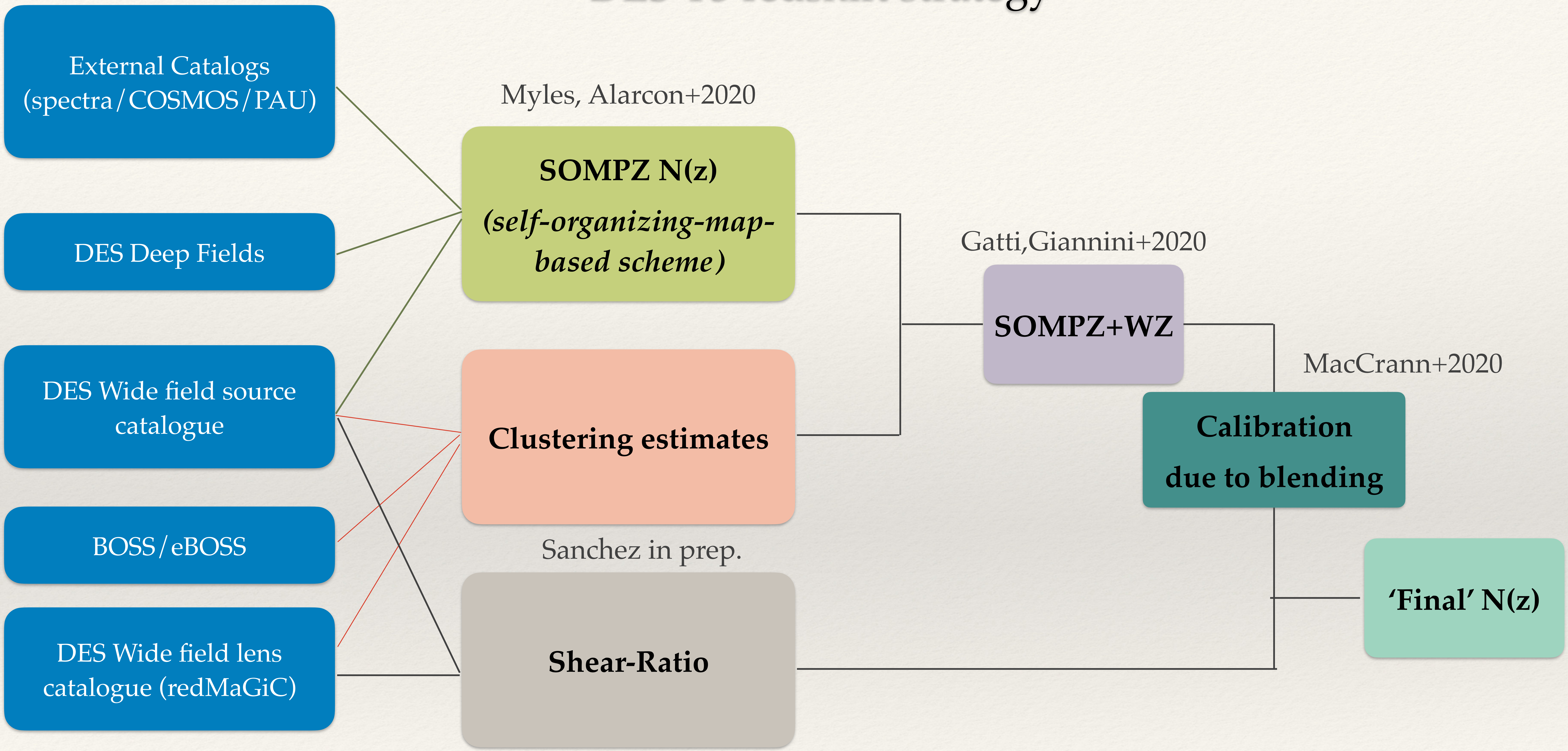
- WZ **does not tighten** the constraints on the **mean**
- WZ **does help tightening** the scatter in the SOMPZ **shape (S/N increased up to a factor 3)**
- BOSS/eBOSS mostly useful above z>0.8

Shape matching method - application to data



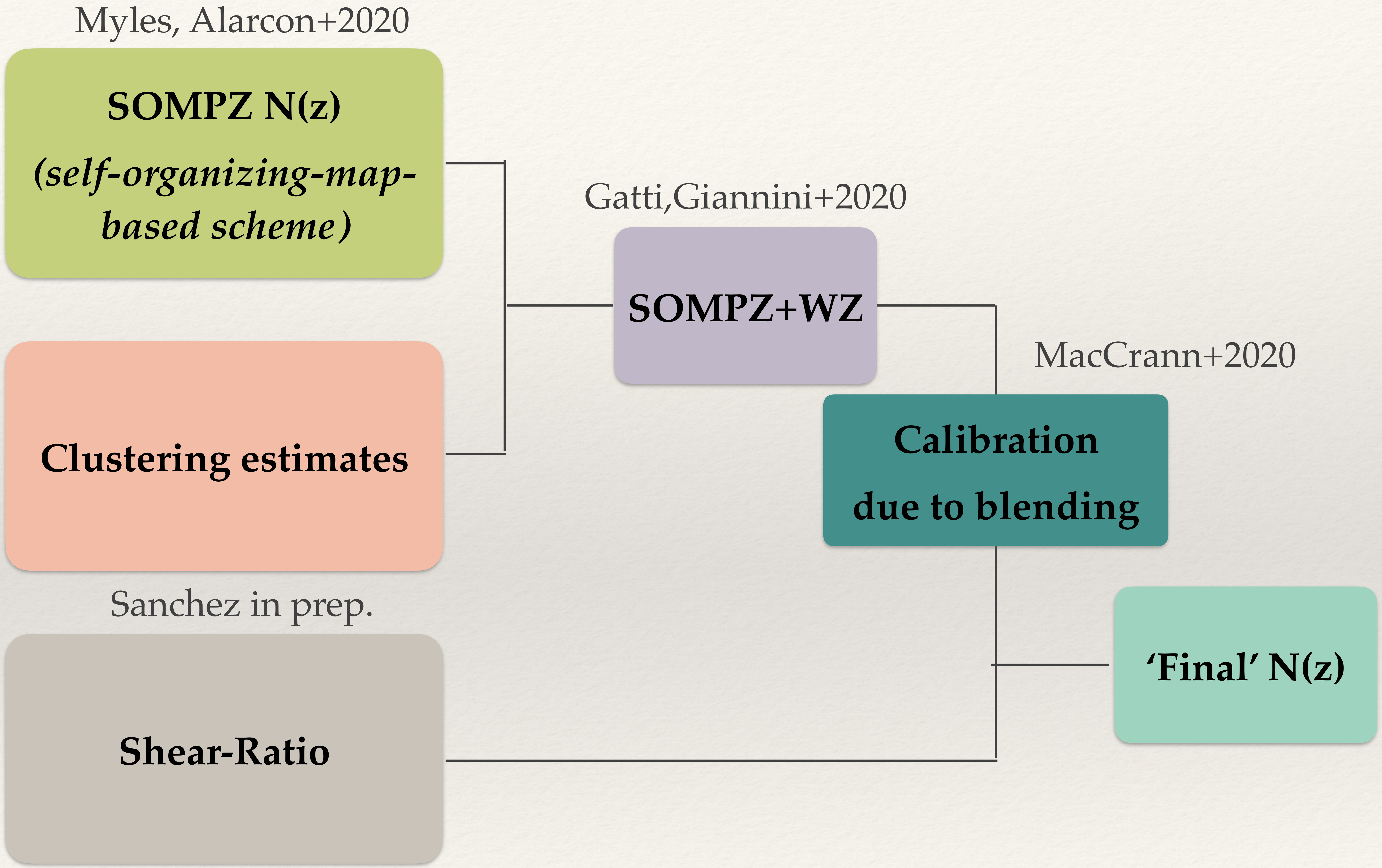
Myles,Alarcon+2020

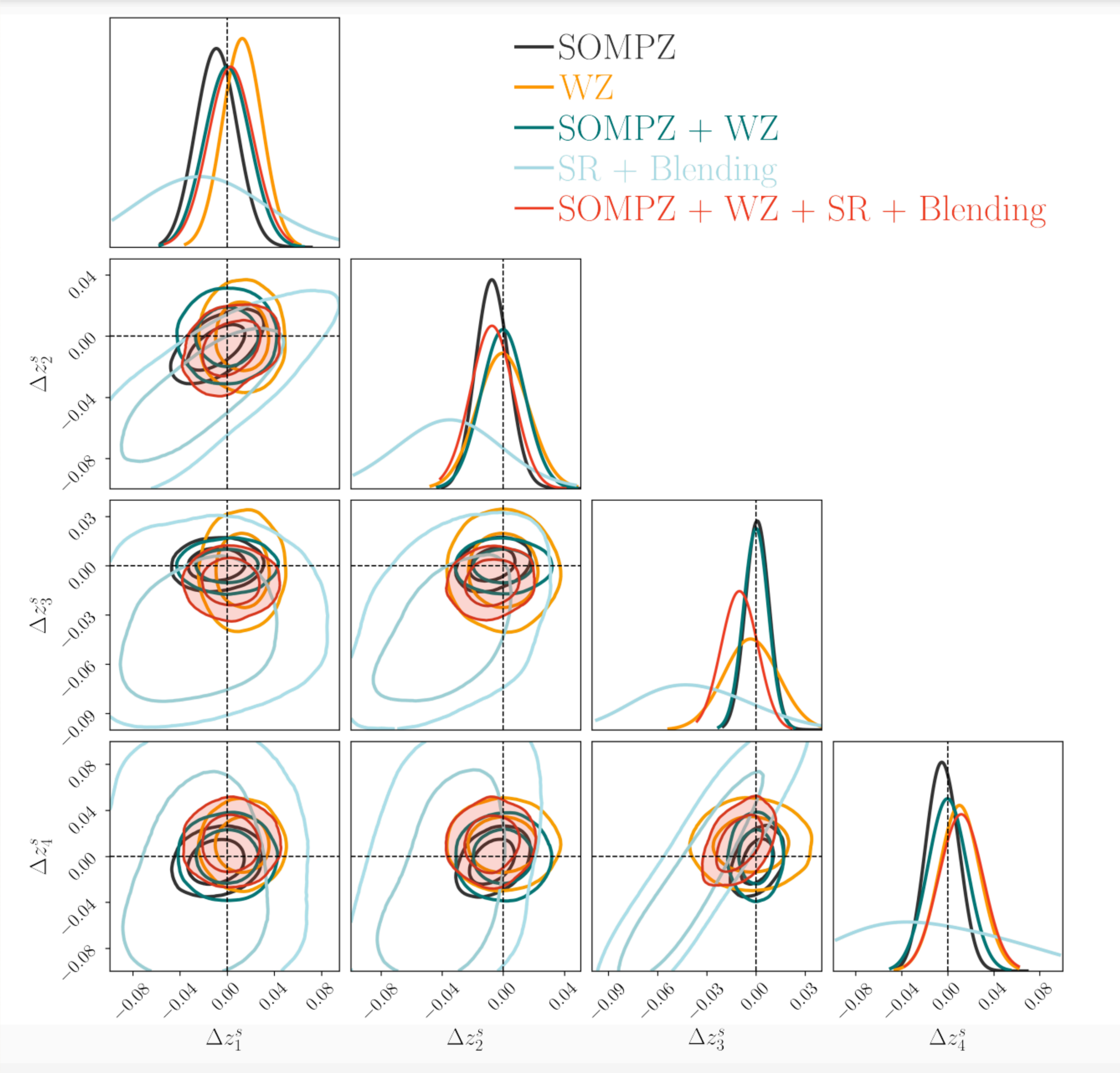
DES Y3 redshift strategy



DES Y3 redshift strategy

After the image simulation based recalibration, a set of smooth N(z) samples is available. The shear-ratio likelihood is included in the main cosmological MCMC analysis. The N(z) samples are sampled using hyper rank (Cordero+ in prep.)





Myles, Alarcon+2020

Summary

Gatti, Giannini et al. :
https://arxiv.org/pdf/2012.08569.pdf

Clustering-z methods (WZ) allow to estimate the redshift distribution of a “unknown” sample by exploiting the cross-correlation signal with a “reference” sample with good redshifts.

Two different WZ methods have been implemented to calibrate the DES Y3 WL n(z):

1. ‘mean matching’ : it provides independent constraints on the windowed mean of the WL sample n(z)
2. ‘shape matching’: it establishes a likelihood of the clustering as a function of n(z), and it can be used to generate samples of n(z) subject to clustering and photometric constraints.

With DES y3 data, the WZ information does not tighten constraints on the mean of the n(z) (i.e., SOMPZ is superior in this sense), but it improves the constraints on the shape of the n(z)