Photometric redshifts and observational systematics on DES Y3 analyses

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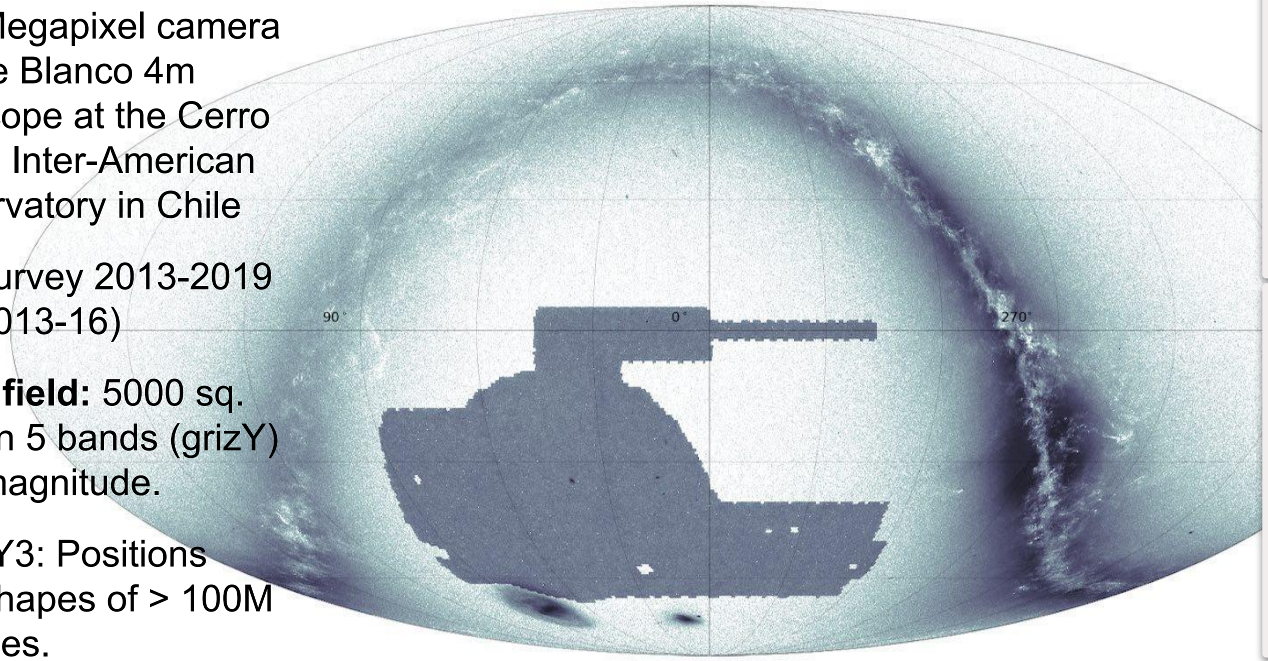
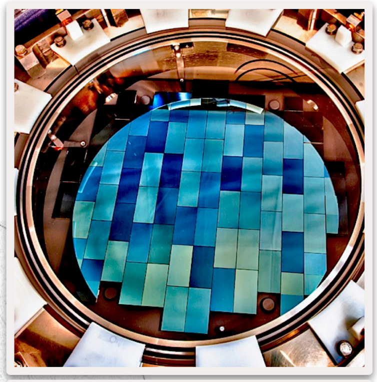
The Dark Energy Survey (DES)

- 570 Megapixel camera for the Blanco 4m telescope at the Cerro Tololo Inter-American Observatory in Chile
- Full survey 2013-2019 (**Y3** 2013-16)
- **Wide field:** 5000 sq. deg. in 5 bands (grizY) ~23 magnitude.
- DES Y3: Positions and shapes of > 100M galaxies.





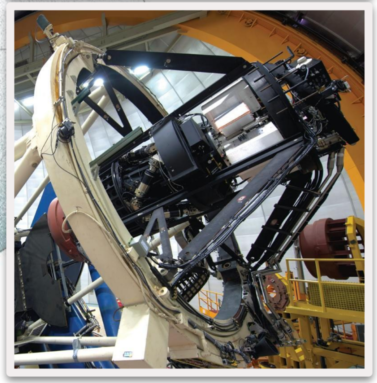


Image Credit: CosmoHub, Port d'Informació Científica (PIC)

Galaxy clustering and 3x2pt

Three different correlation functions to maximise cosmological information and constraint systematic effects:

- **Cosmic shear,** $\xi_{\pm}(\theta)$: correlation of **shapes** with **shapes** **1x2pt**
- **Galaxy clustering,** $w(\theta)$: correlation of **positions** with **positions**
- **Galaxy-galaxy lensing,** $\gamma_t(\theta)$: correlation of **positions** with **shapes**

2x2pt

3x2pt

We use two different samples of galaxies:

- **Source galaxies** $\longrightarrow$ **galaxy shapes**
- **Lens galaxies** $\longrightarrow$ **galaxy positions**

DES Y3 lens samples

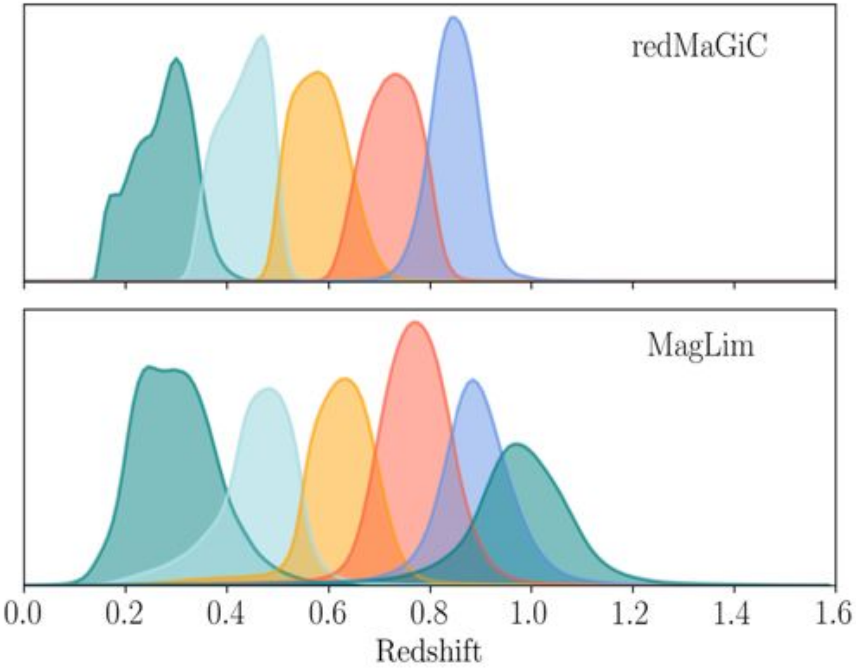
RedMaGiC

- Red luminous galaxies with high quality photometric redshift estimates
- 0.15 < z < 0.90
- 3 million galaxies

MagLim (fiducial Y3 sample)

larger N density (11 million galaxies)
lower S/N

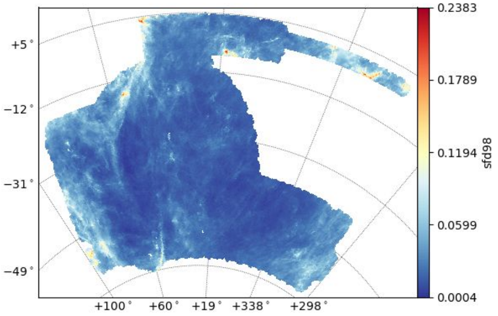
- Bright magnitude limits at each tomographic bin imposed to reduce photo-z error
  - Sample selection is function of redshifts from the photometric code DNF:
    - mag_i < 4 * z + 18
    - mag_i > 17.5



- 6 tomographic bins:
  - Bin edges optimised for the cosmological analysis

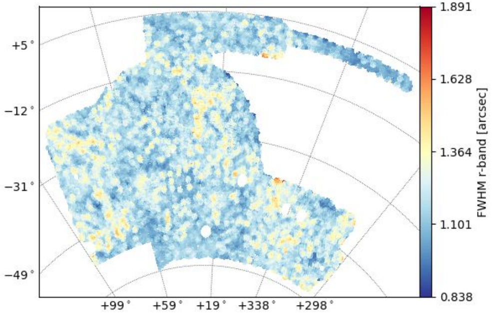
Main sources of systematic errors in galaxy clustering

Observing conditions and astrophysical sources



<u>Astrophysical sources:</u>

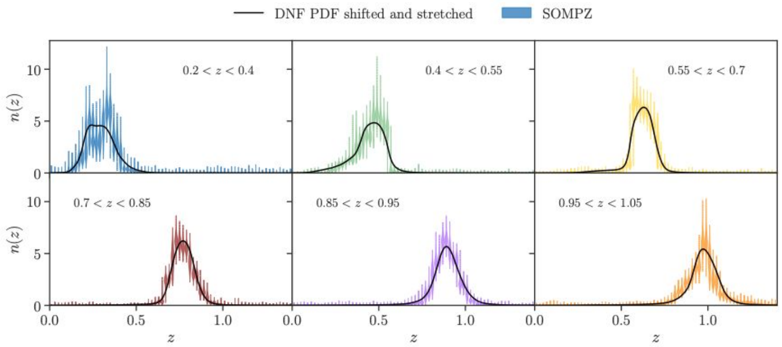
- Dust extinction
- Stellar density



<u>Observing conditions:</u>

- Seeing
- Exposure time
- Sky brightness
- Depth, …

Photometric redshift calibration



<u>Systematic affecting n(z) higher moments:</u>

- Sample variance
- Biases in the redshift of spec-z and high quality photo-z samples
- Redshift dependence of the galaxy-matter bias
- Small number of bands, ...

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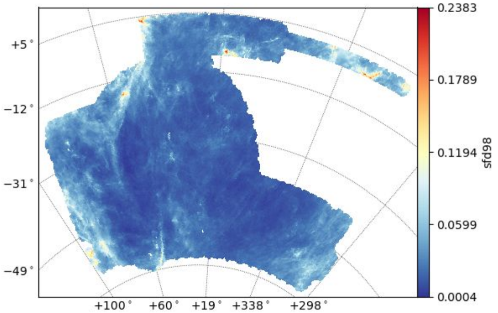

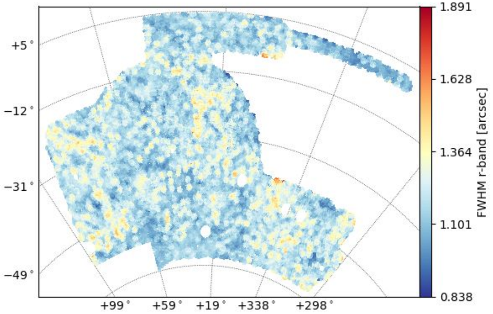

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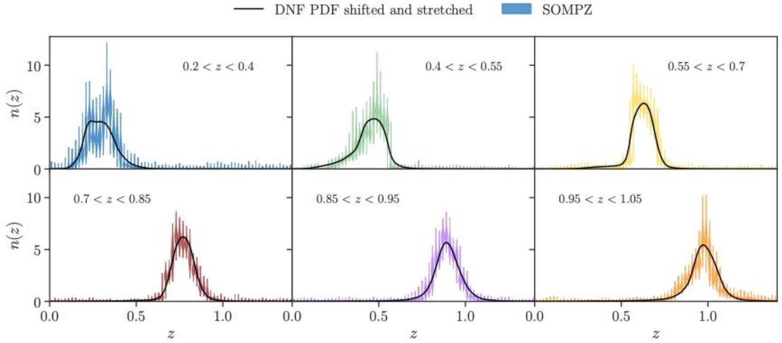

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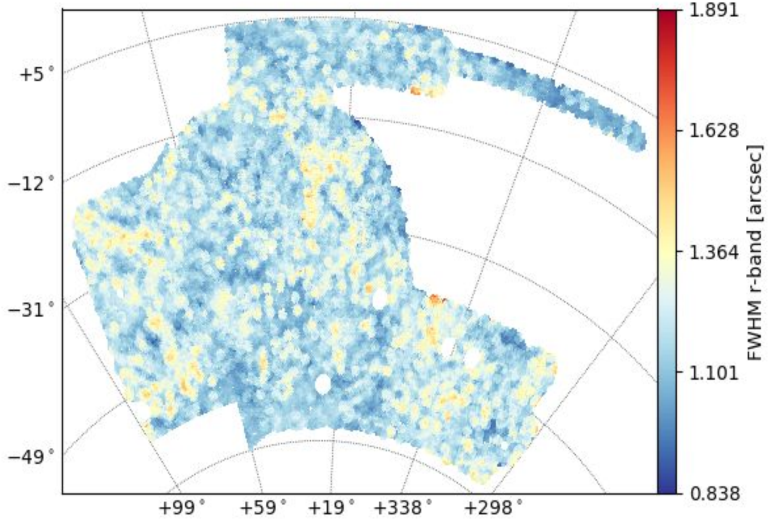
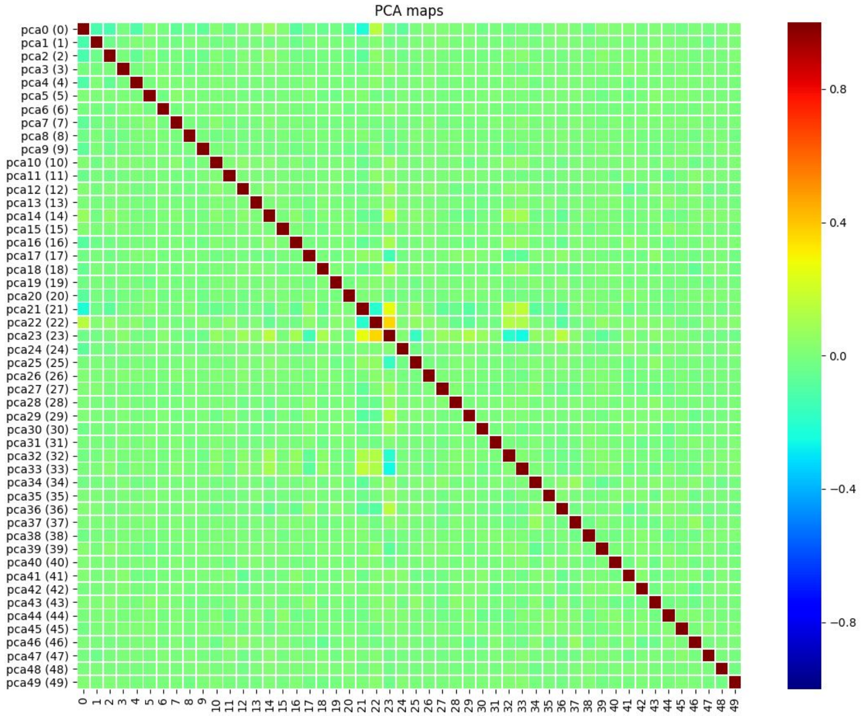
Survey property (SP) maps

- HEALPix maps that track the spatial variations of the survey properties
- We have 107 of them!
  - Too many maps can lead to overcorrection
  - Too few maps can lead to undercorrection



Survey property (SP) maps

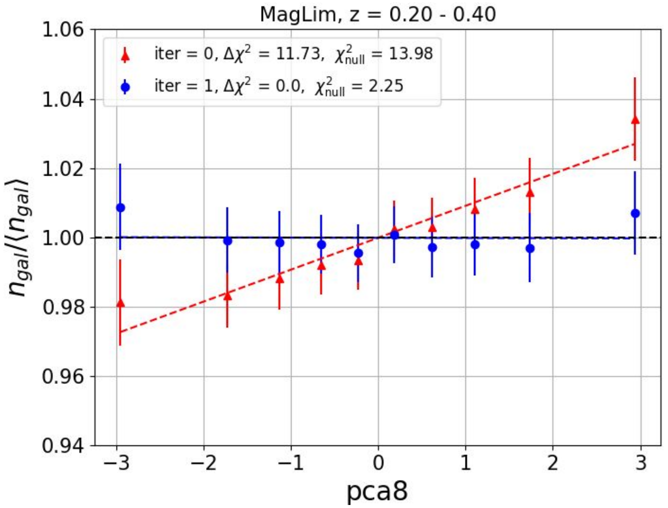
- HEALPix maps that track the spatial variations of the survey properties
- We have 107 of them!
  - Too many maps can lead to overcorrection
  - Too few maps can lead to undercorrection
- Dimensionality reduction:
  - Pearson’s correlation matrices
  - **Principal component analysis (PCA)**
- We select the **50 first PC maps:**
  - **Explain ~98% total variance**
  - Our decontamination methods perform a **data-driven selection** of the contaminant maps



Correction methods

We employ **two methods** to mitigate the impact from SP maps:

- ***Iterative Systematics Decontamination* (ISD):**
  - **Iterative** method that evaluates the significance of each SP map and correct for them stepwise
  - Computes the relation between galaxy number density and SP map value on the sky: **1D relation**



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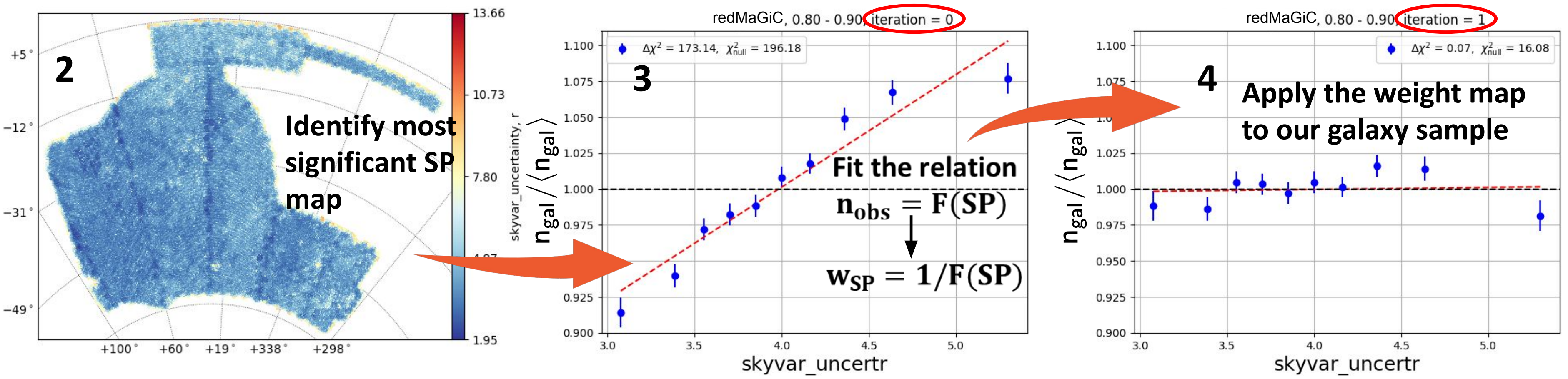
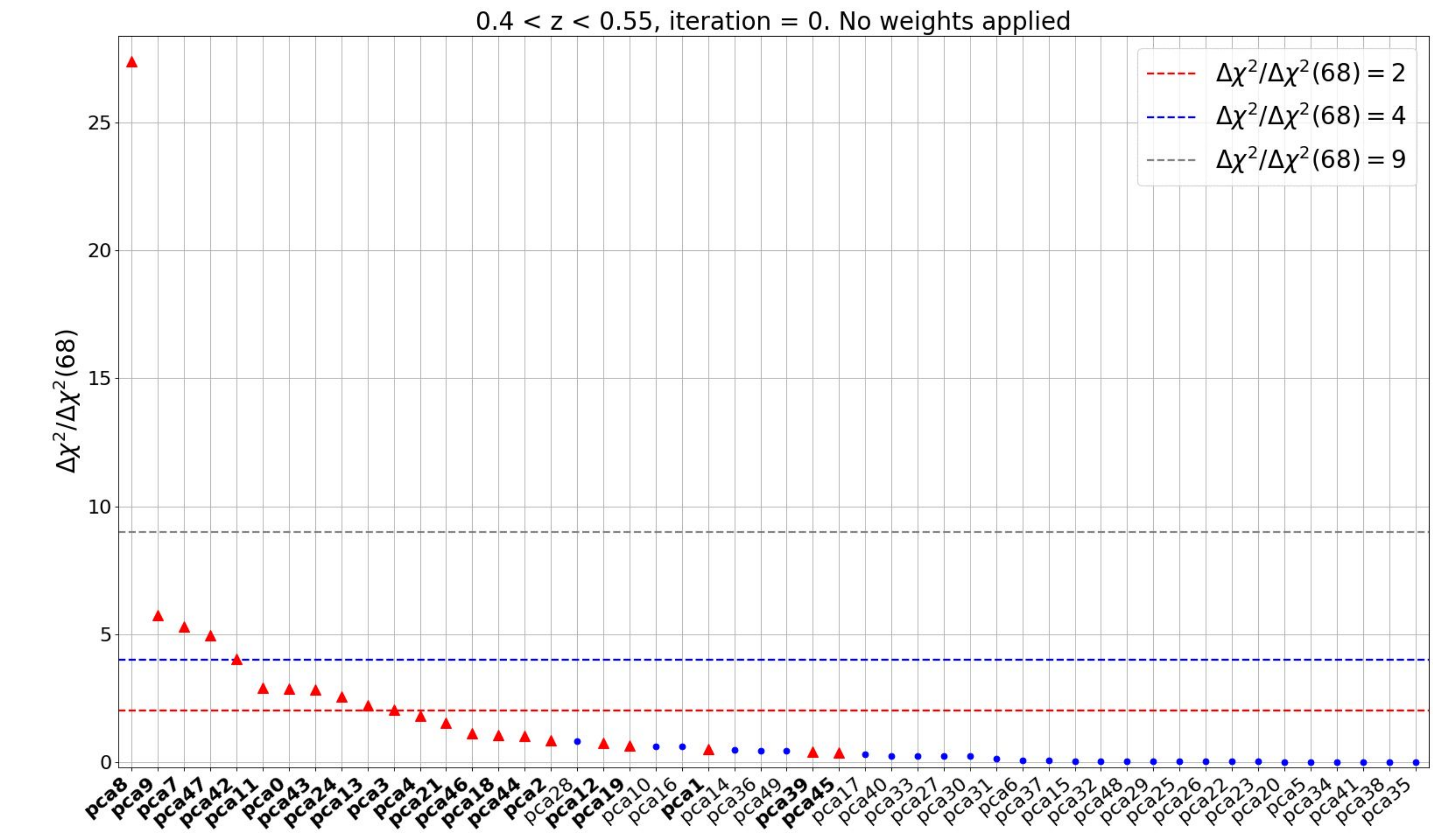
- ***Elastic Net* (ENet):**
  - **Multilinear fit** to all SP maps performing a elastic net regularisation = ridge + LASSO regularisation
- Both methods produce **weight maps** that are applied to the data
- ISD is our **fiducial method**
- We use ENet as
  - **robustness test** of ISD (validating on log-normal mocks)
  - an estimator of the **systematic contribution** to the covariance matrix

Iterative Systematics Decontamination (ISD)

- Iterative process:
  - Fix a **threshold** for 1D contamination
  - **1** Define 1D **significance** by evaluating against **log-normal mocks**



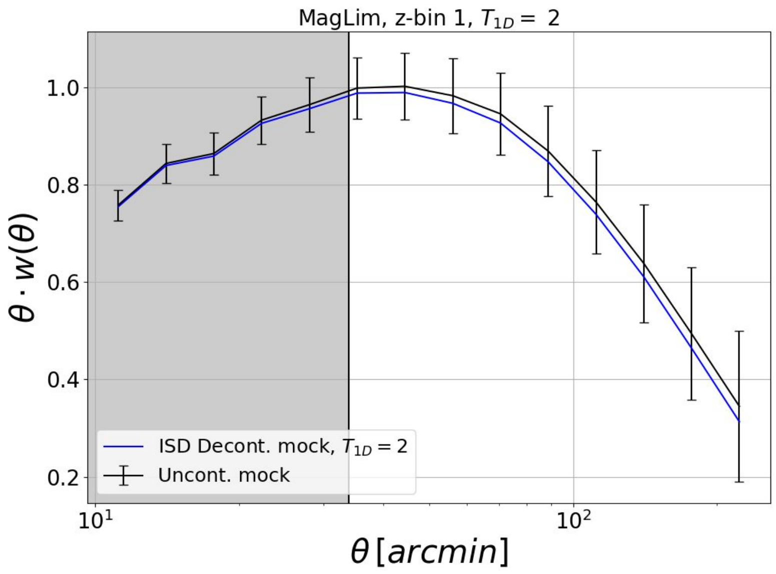
  - **5** **Re-evaluate** significance of SPs until process **converges**
  - This method has been applied to the DES Y3 lens galaxy samples, **MagLim and redMaGiC**, and to the **BAO sample**


0.4 < z < 0.55, iteration = 0. No weights applied
$\Delta\chi^2/\Delta\chi^2(68) = 2$
$\Delta\chi^2/\Delta\chi^2(68) = 4$
$\Delta\chi^2/\Delta\chi^2(68) = 9$
$\Delta\chi^2/\Delta\chi^2(68)$
0
5
10
15
20
25
pca8 pca9 pca7 pca47 pca42 pca11 pca0 pca43 pca24 pca13 pca3 pca4 pca21 pca46 pca18 pca44 pca2 pca28 pca12 pca19 pca10 pca16 pca1 pca14 pca36 pca49 pca39 pca45 pca17 pca40 pca33 pca27 pca30 pca31 pca6 pca37 pca15 pca32 pca48 pca29 pca25 pca26 pca22 pca23 pca20 pca5 pca34 pca41 pca38 pca35

Validation and robustness of the correction

We check the **potential biases** introduced by ISD and we account for them in the **covariance matrix:**

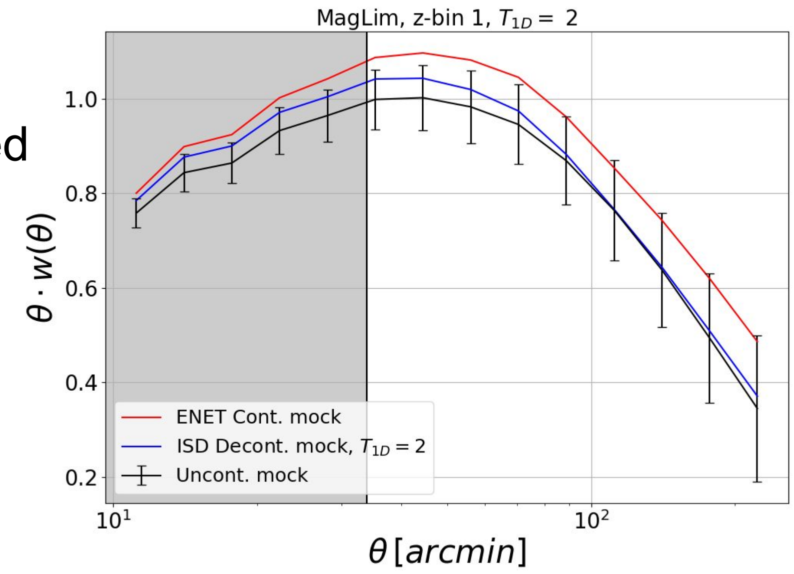
- False correction bias: **chance correlations.** Use uncontaminated **mocks**



Validation and robustness of the correction

We check the **potential biases** introduced by ISD and we account for them in the **covariance matrix:**

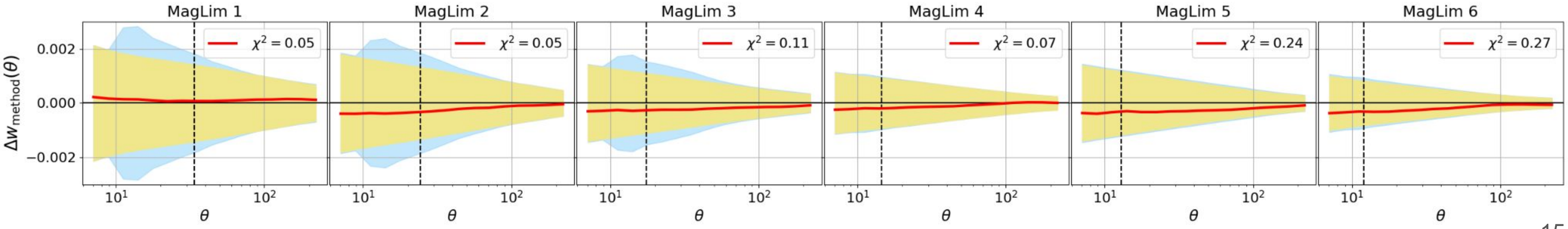
- False correction bias
- Residual systematic bias: **uncorrected contamination.** Use **ENet** contaminated mocks and decontaminate with **ISD**



Validation and robustness of the correction

We check the **potential biases** introduced by ISD and we account for them in the **covariance matrix:**

- False correction bias
- Residual systematic bias
- Modifications to the covariance matrix: **systematic uncertainty from:**
  - **choice** of method (subdominant)
  - **bias** from contaminated mocks



Validation and robustness of the correction

We check the **potential biases** introduced by ISD and we account for them in the **covariance matrix:**

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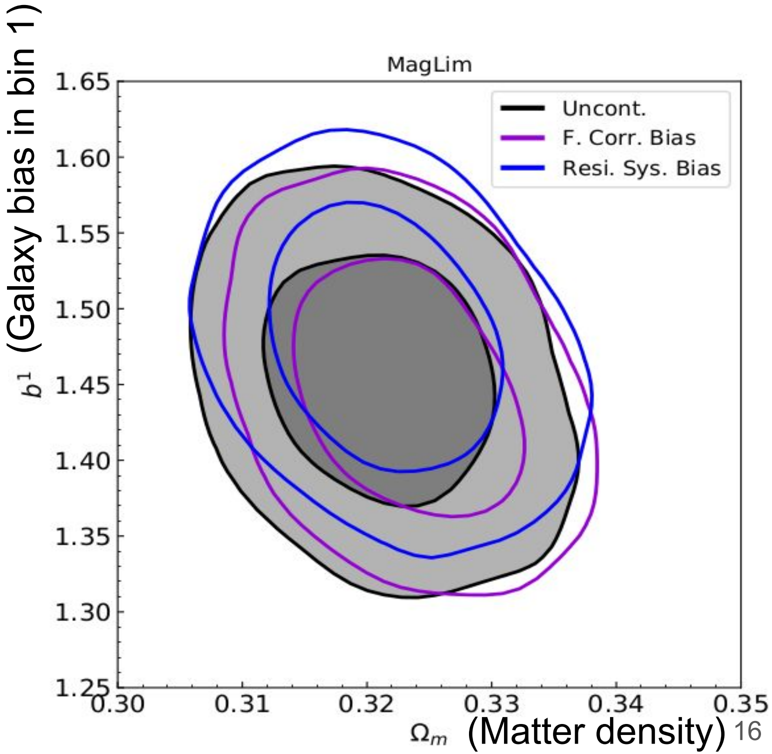
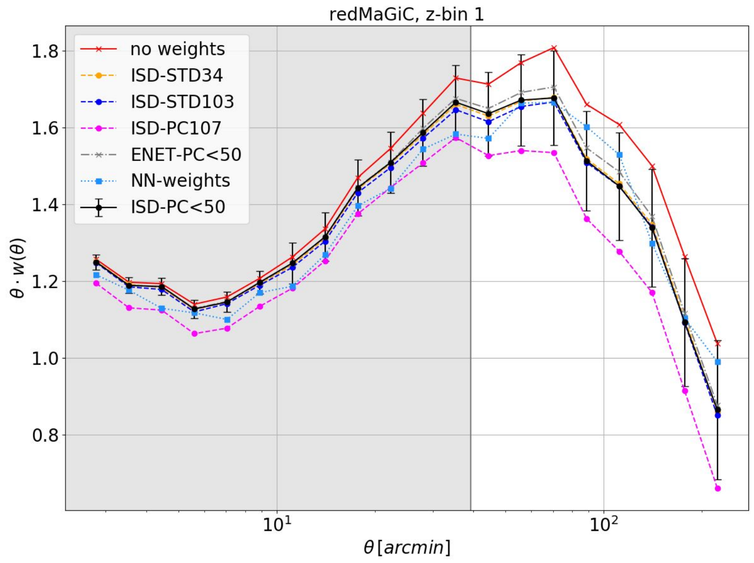
- Residual systematic bias
- Modifications to the covariance matrix
- Impact on parameter estimation: effect of the decontamination on the **estimated parameters**



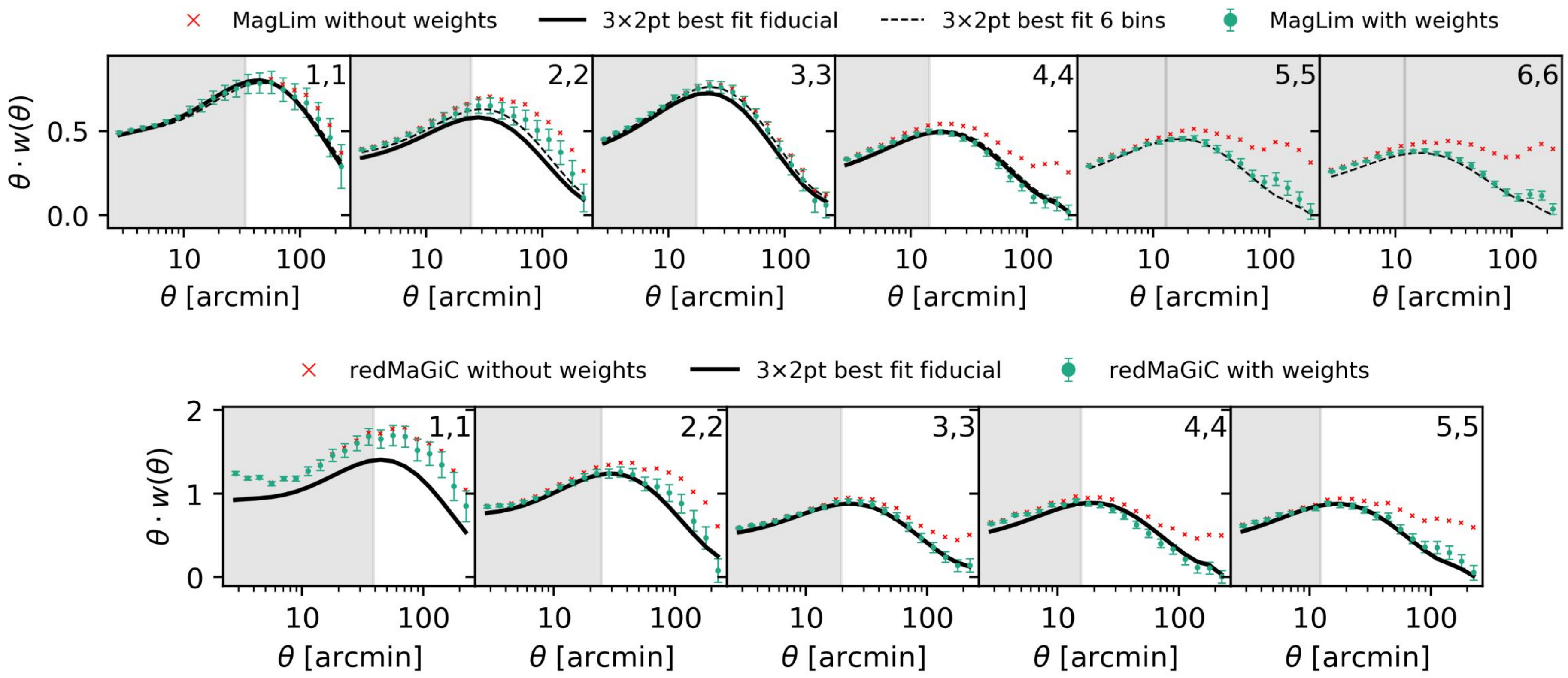
Validation and robustness of the correction

We check the **potential biases** introduced by ISD and we account for them in the **covariance matrix:**

- False correction bias
- Residual systematic bias
- Modifications to the covariance matrix
- Impact on parameter estimation
- Additional robustness tests: **alternative configurations** of ISD, ENet and **alternative methods**



Galaxy clustering results



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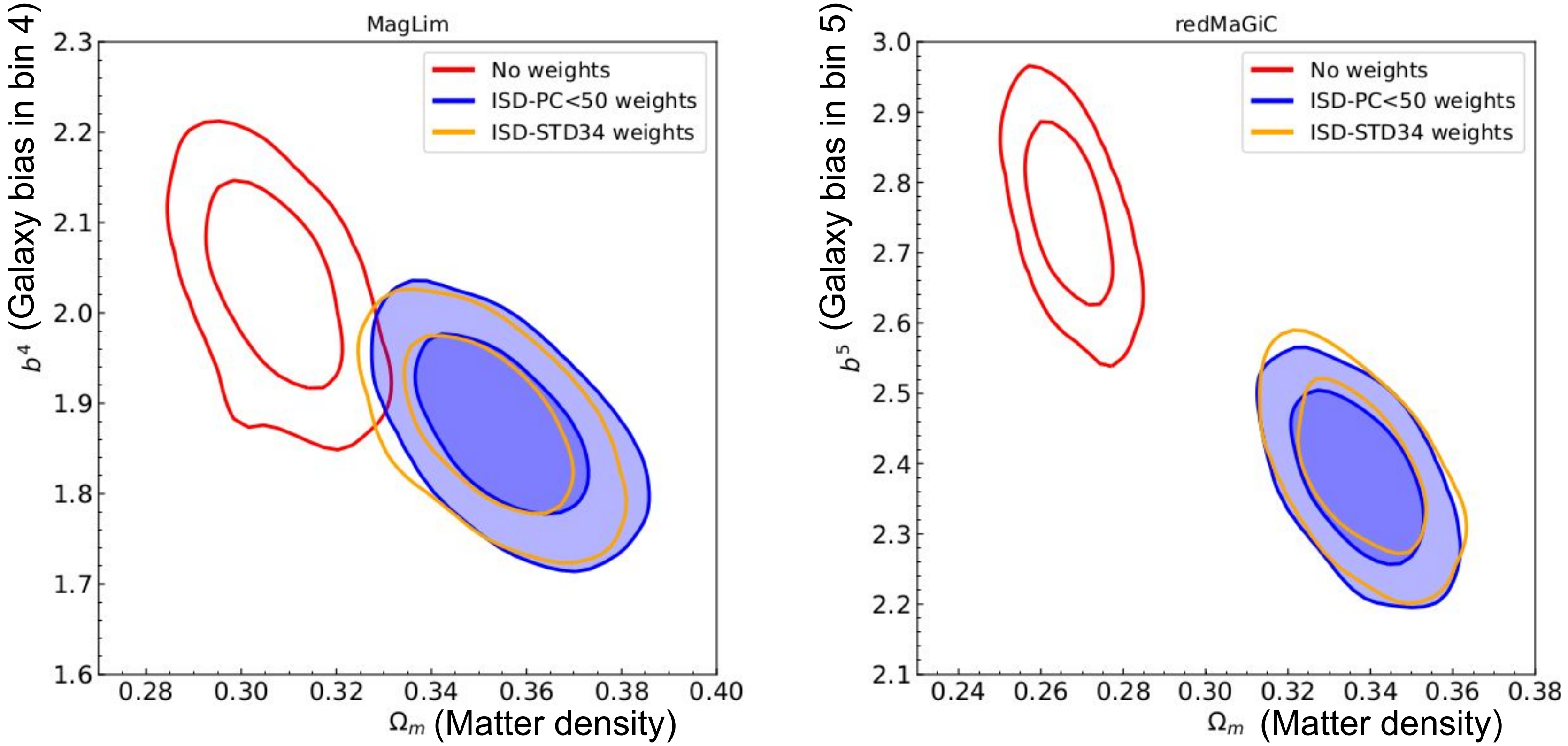


Internal consistency

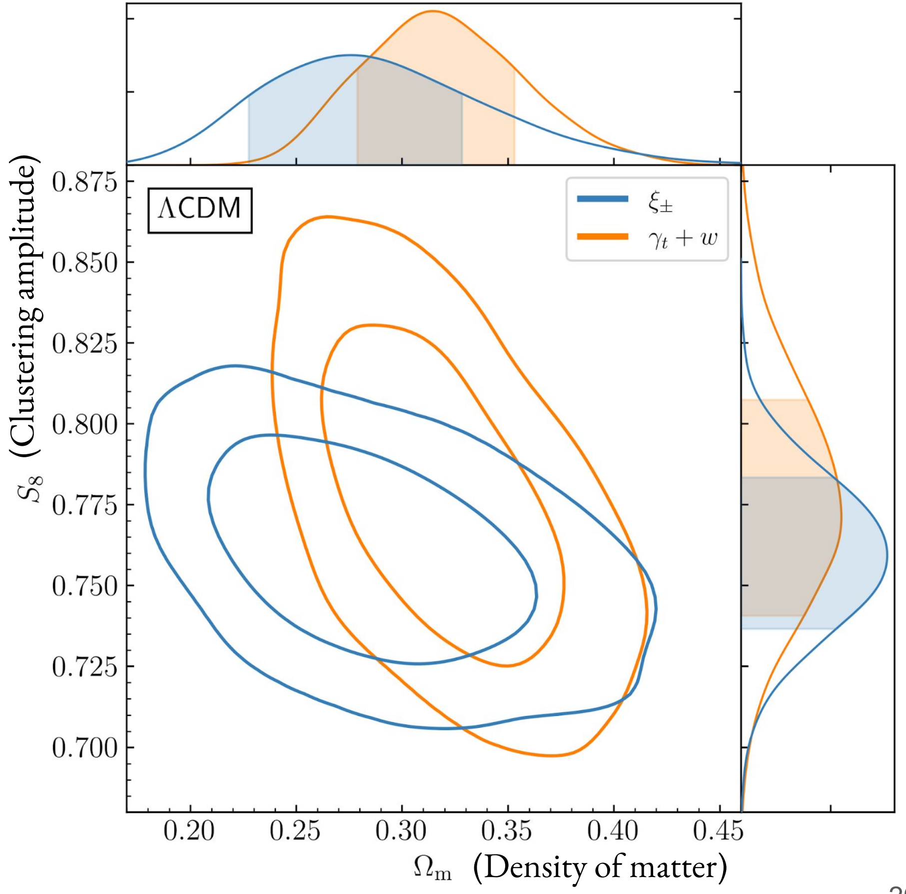
Two correlated cosmological probes:

1. **Cosmic shear** (blue)
2. **Galaxy clustering** and **tangential shear** (orange)

We find consistency between them.

Cosmic shear most sensitive to clustering amplitude.

Galaxy clustering and tangential shear more sensitive to total matter density.



3x2pt results

We combine these into the **3x2pt** probe of large-scale structure.

A factor of 2.1 improvement in signal-to-noise from DES Year 1.

In ΛCDM:

$$S_8 = 0.776^{+0.017}_{-0.017} \quad (0.776)$$

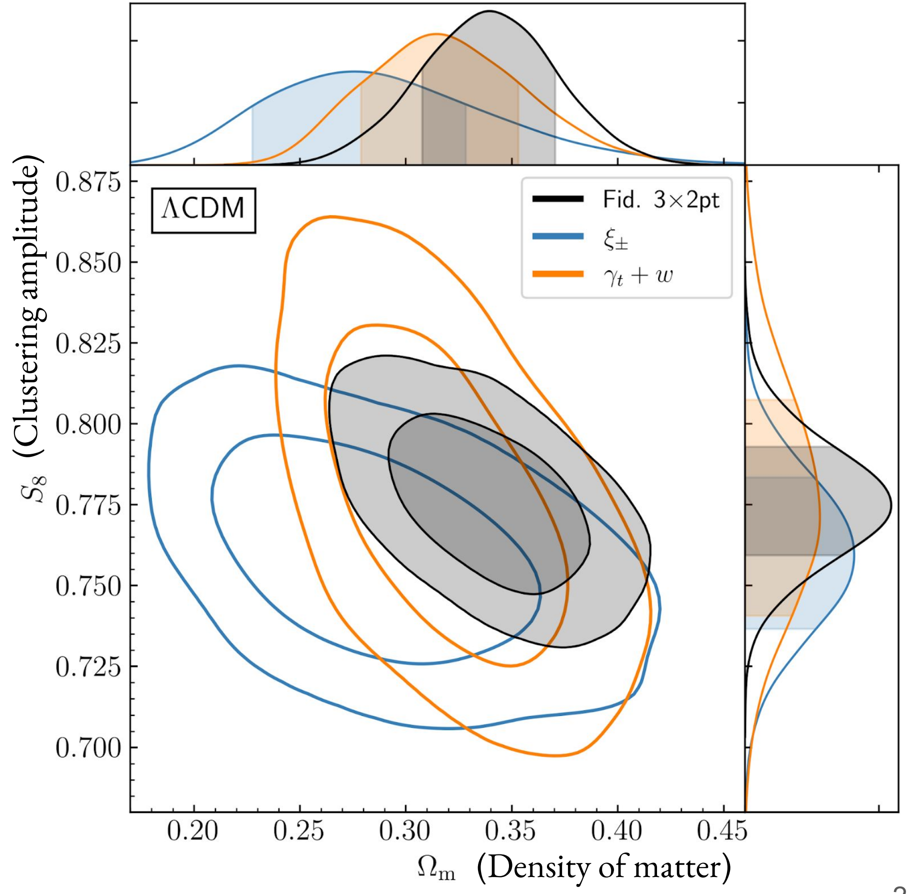
$$\Omega_\mathrm{m} = 0.339^{+0.032}_{-0.031} \quad (0.372)$$

$$\sigma_8 = 0.733^{+0.039}_{-0.049} \quad (0.696)$$

In *w*CDM:

$$\Omega_\mathrm{m} = 0.352^{+0.035}_{-0.041} \quad (0.339)$$

$$w = -0.98^{+0.32}_{-0.20} \quad (-1.03)$$



Main sources of systematic errors in galaxy clustering

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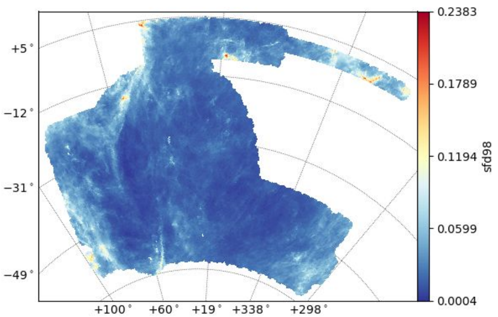
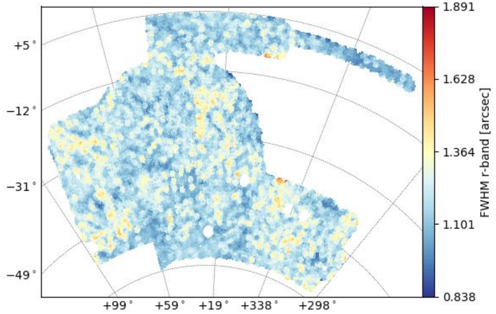
- Dust extinction
- Stellar density

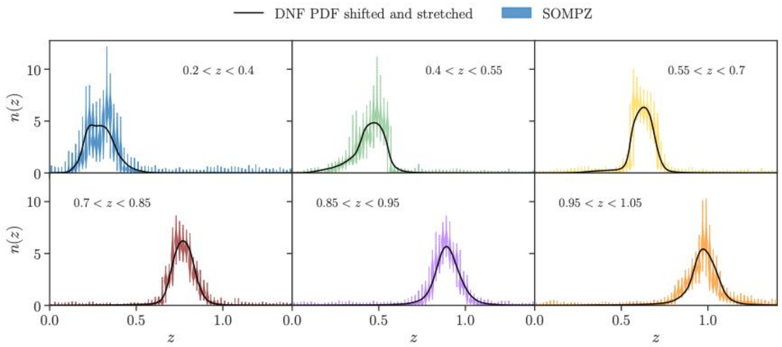




<u>Observing conditions:</u>

- Seeing
- Exposure time
- Sky brightness
- Depth, …

Photometric redshift calibration

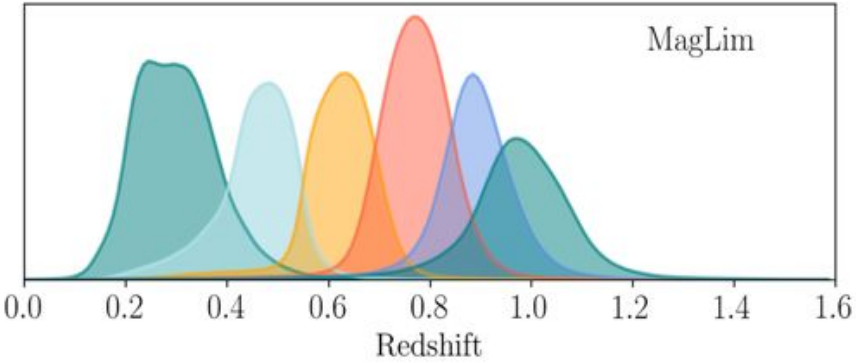


<u>Systematic affecting n(z) higher moments:</u>

- Sample variance
- Type-redshift degeneracy
- Redshift dependence of the galaxy-matter bias
- Small number of bands, ...

MagLim redshift distributions

While redMaGiC consists of red galaxies with high S/N, MagLim includes all galaxies brighter than a magnitude threshold, function of DNF redshifts

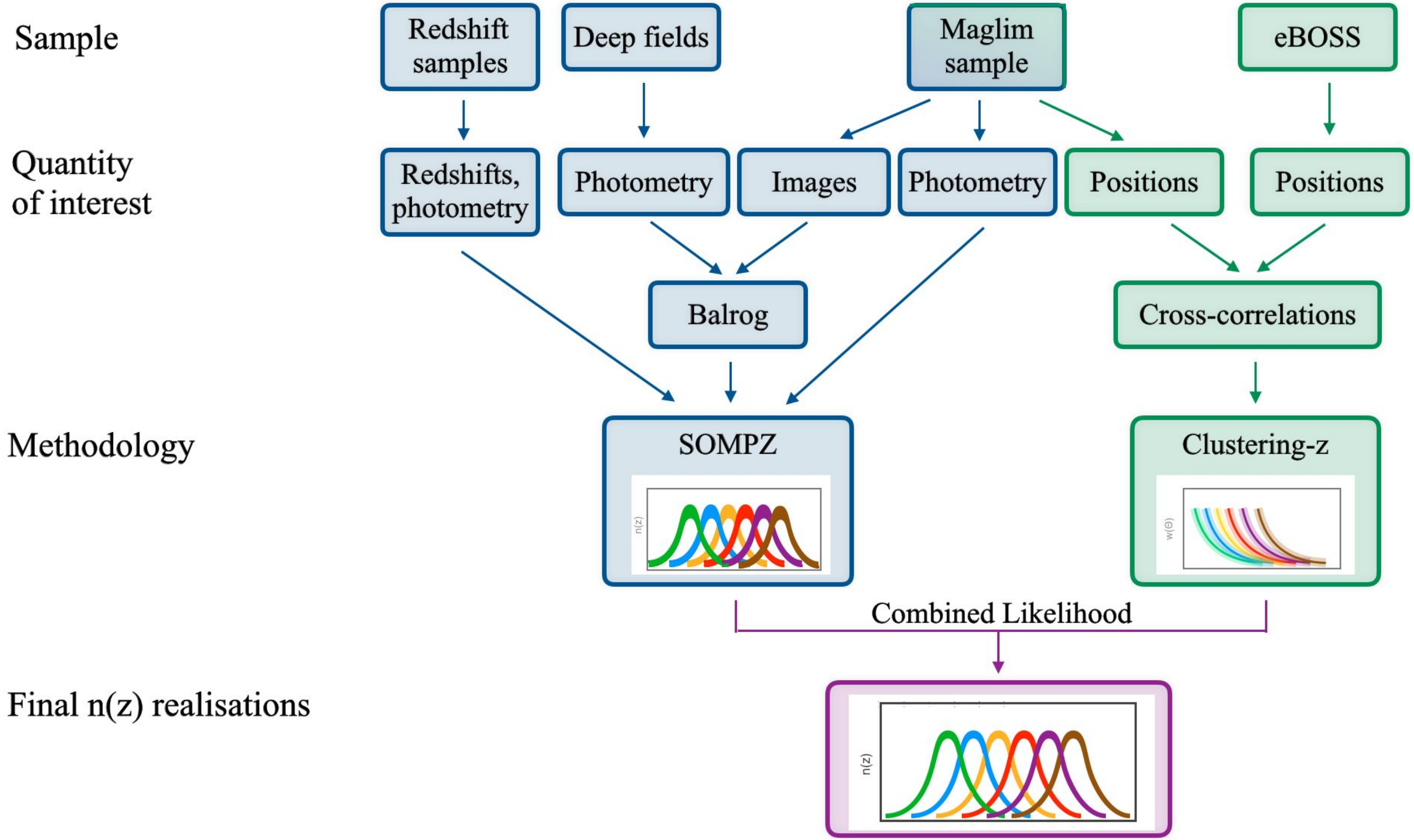


- larger N density
- noisier than redMaGiC

It is necessary to further calibrate its redshift distributions

- Fiducial DES Y3 results: DNF-estimated n(z), shifted and stretched to match cross-correlations measurements in a restricted redshift range, marginalising over the shift and stretch parameters only
- In this work, we apply a similar methodology as the one used for the DES Y3 source sample, which **combines cross-correlations and phenotypic calibration to allow a marginalisation over the n(z) full shape**, and we compare simulated chains results with the fiducial methodology.

Redshift calibration pipeline



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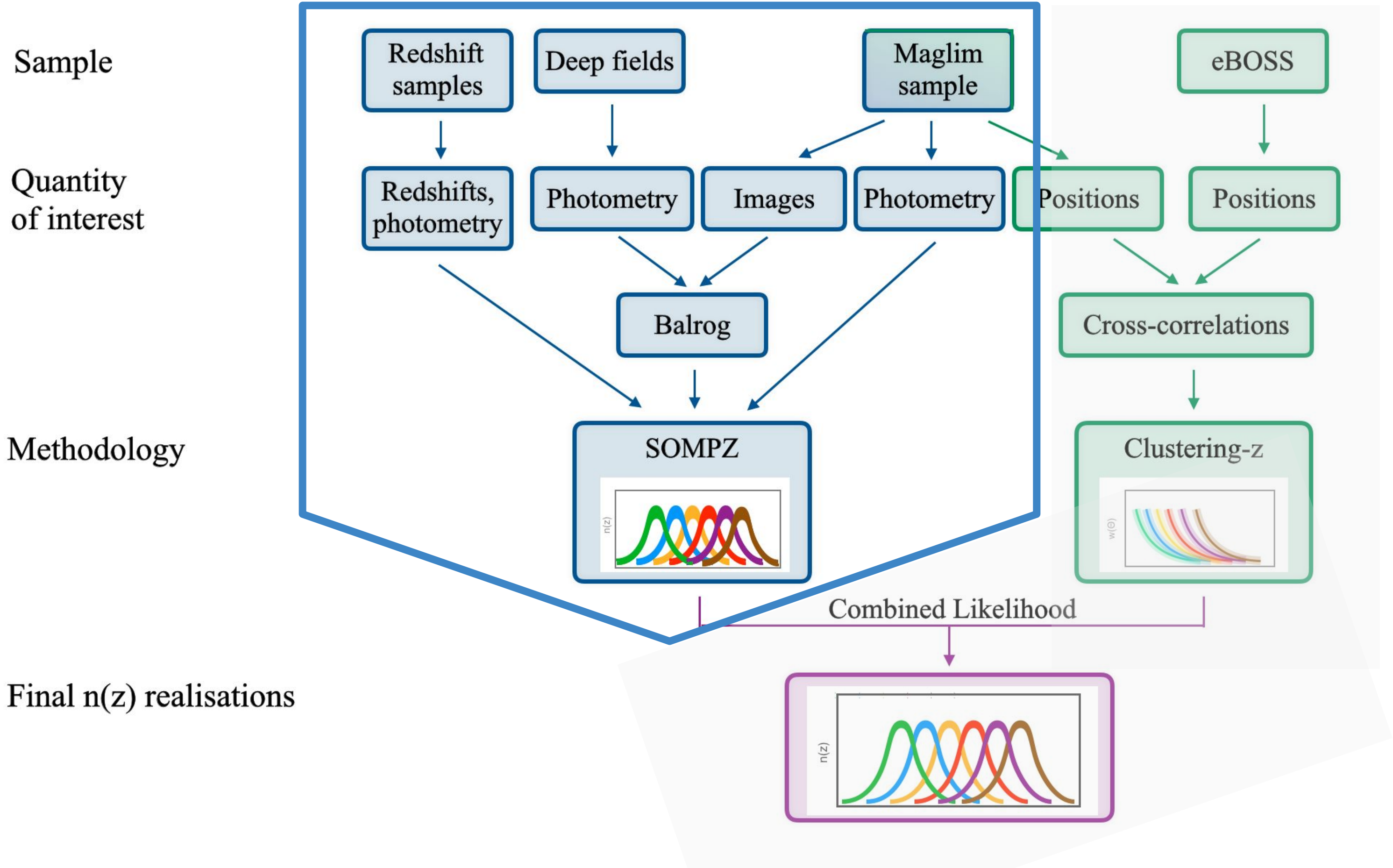
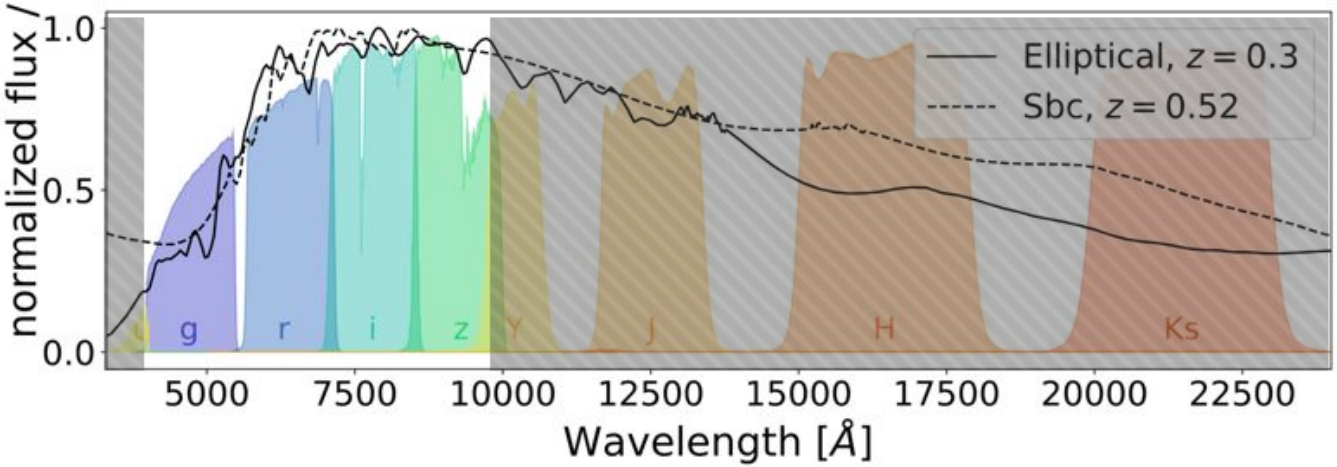


Redshift calibration pipeline

- In the griz bands used to target the whole wide field, redshifted SEDs of two types of galaxies are indistinguishable
  - Type-redshift degeneracy is the fundamental cause of uncertainty in redshift calibration



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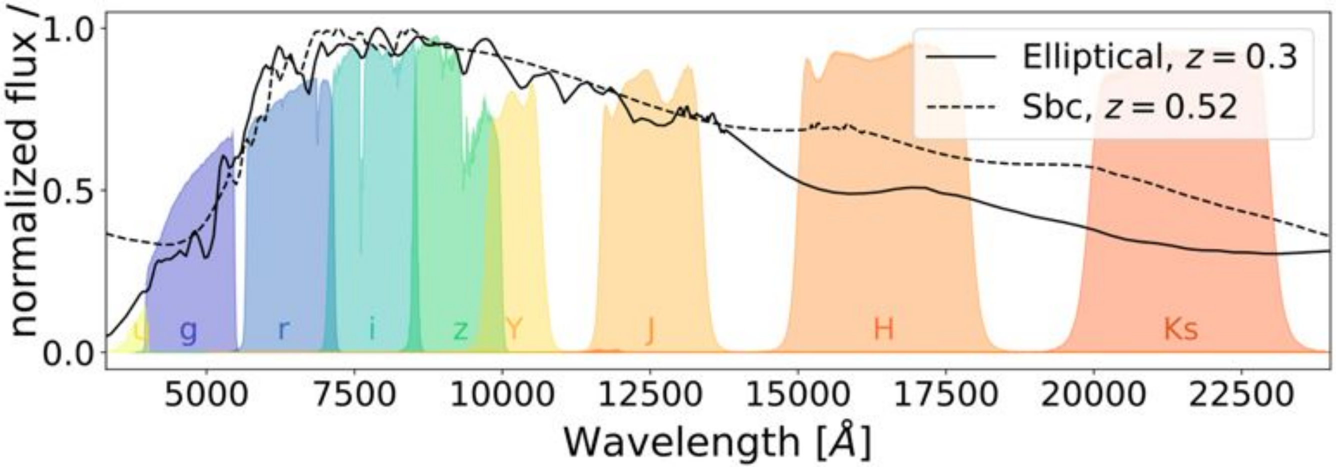
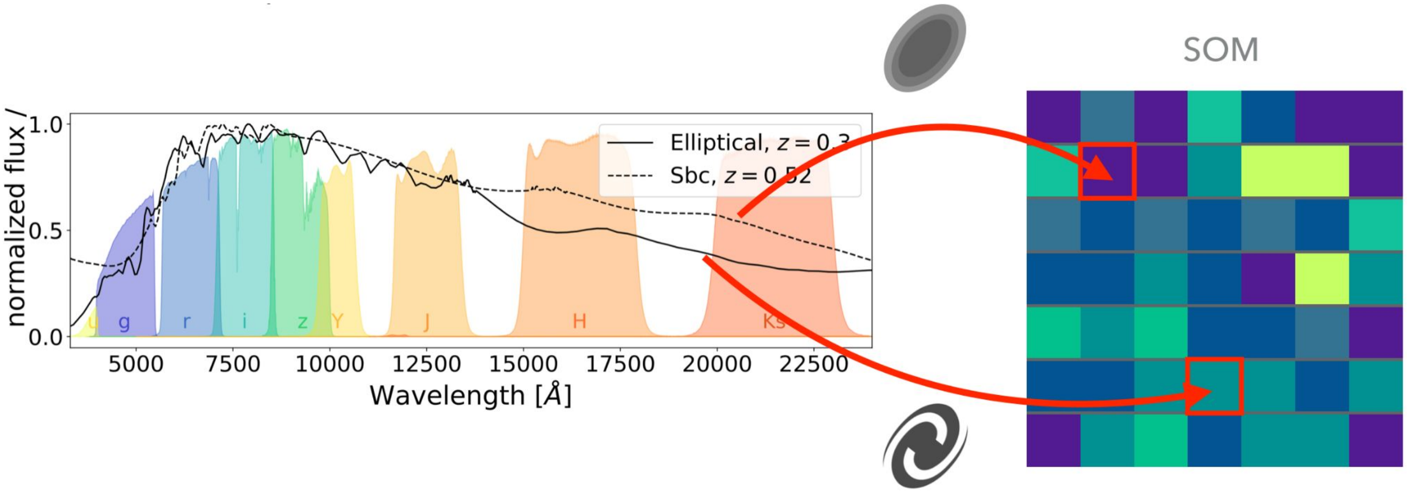


- Adding extra bands from DES or other survey's deep fields helps to break said degeneracy
- Extra bands are available only for a subset of the wide field galaxies

Self-Organizing Maps

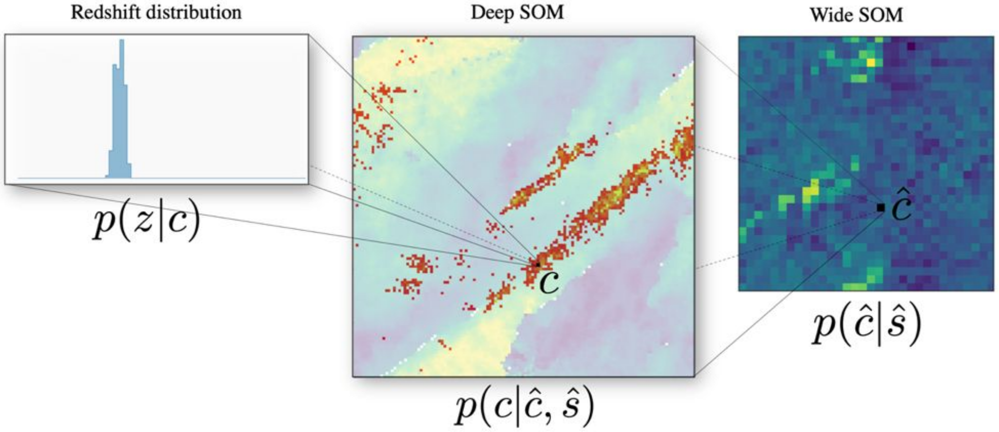
- Self Organising Map (SOM) is a unsupervised artificial neural network that produces a discretized and low-dimensional representation of the input space
- In the SOMPZ method SOMs are used to classify galaxies in phenotypes according to their properties
- Accurate phenotype classification is possible including the extra bands available in the deep fields

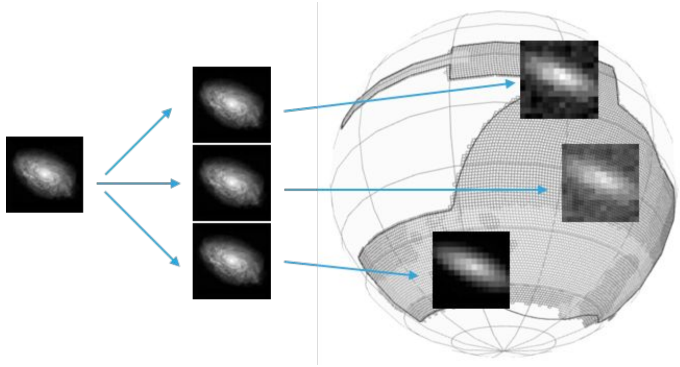


SOMPZ methodology

- Galaxies from wide and deep fields are grouped into phenotypes using SOMs
- Redshifts in the deep fields are validated through high precision redshift samples
- Redshifts are assigned back to the wide field by mapping the two SOMs through a **transfer function**

$$p(z|\hat{b}, \hat{s}) \approx \sum_{\hat{c} \in \hat{b}} \sum_{c} \underbrace{p(z|c)}_{\text{Redshift}} \underbrace{p(c)}_{\text{Deep}} \underbrace{\frac{p(c, \hat{c})}{p(c)p(\hat{c})}}_{\text{Balrog}} \underbrace{p(\hat{c})}_{\text{Wide}}$$

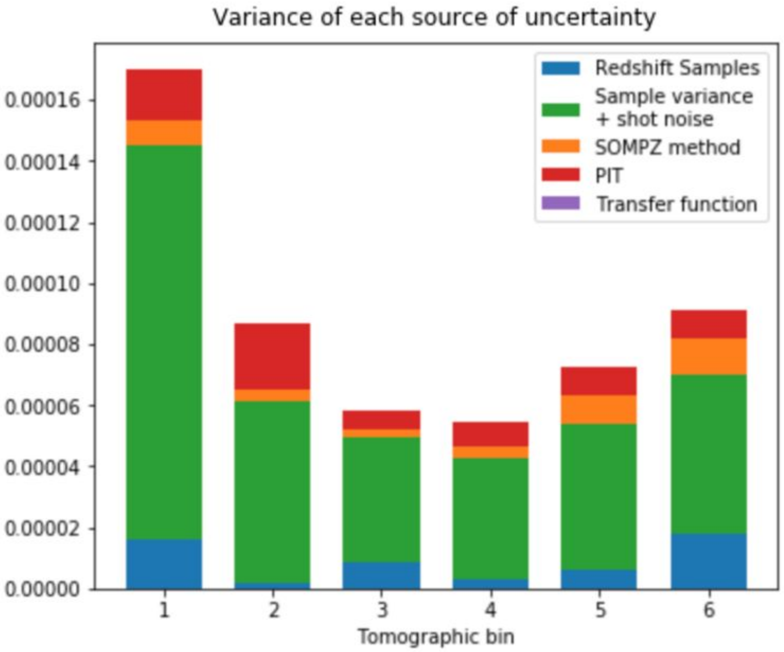




Balrog is a code creating noisy replicas of deep field galaxies by injecting them many times into real DES wide field images and processing them through the whole pipeline

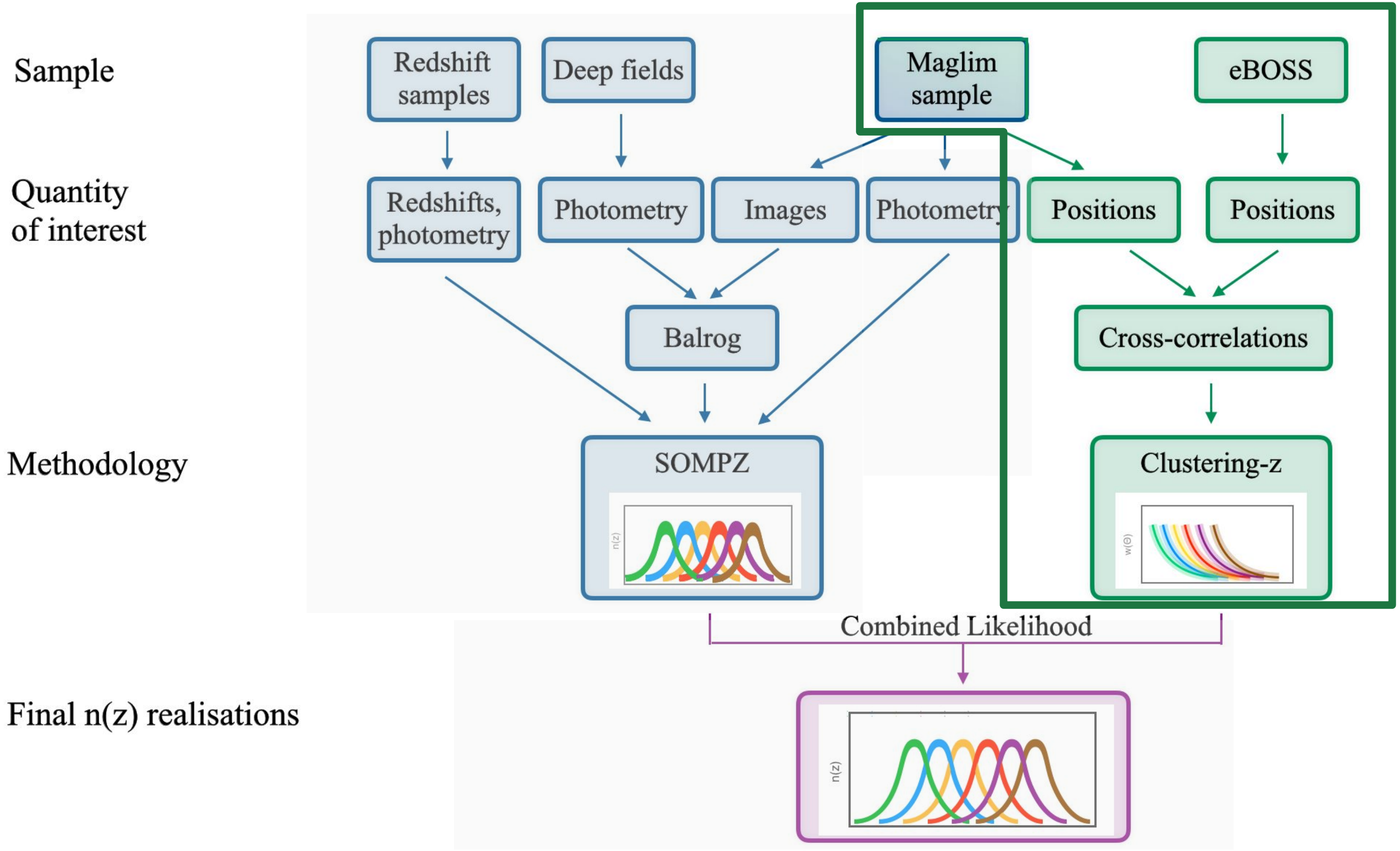
SOMPZ Uncertainties

- **Sample Variance in the Deep Fields**: main uncertainty, caused by the limited area of the deep fields;
- **Shot noise**: induced by the limited size of the deep fields sample;
- **Inherent SOMPZ Method uncertainty**: due to discretising a continuous color space;
- **Redshift Sample Biases**: introduced when using redshifts originating from different photometric or spectroscopic surveys;
- **Photometric Calibration**: the deep fields have different zeropoint uncertainties.



⇒ The product of this calibration is a **set of n(z) realisations** whose overall variance span all the uncertainties included in our SOMPZ methodology

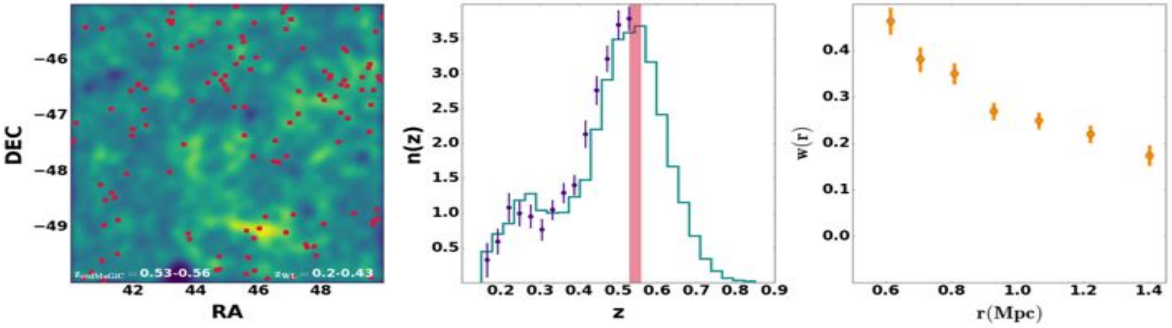
Redshift calibration pipeline



Clustering Redshifts (WZ)

Clustering redshifts method allows to estimate the redshift distribution of a target sample ("unknown") by exploiting the cross-correlation signal with a spatially overlapping "reference" sample with good redshifts

1. Divide reference sample with spec-z or high quality photo-z into small redshift bins
2. Measure the cross-correlation signal with the given science sample



$$\bar{w}_{\rm ur}(z_i) \approx n_{\rm u}(z_i) b_{\rm u}(z_i) b_{\rm r}(z_i) \bar{w}_{\rm DM}(z_i) + \bar{M}(z_i)$$

Redshift distribution *unknown* sample

Galaxy-matter bias of *unknown* sample

Galaxy-matter bias of reference sample

Dark matter clustering

Magnification effects

WZ systematic uncertainties

We forward **model the full clustering signal**, using as n(z) each SOMPZ realisation
The model is multiplied by Sys(z,**s**), a smooth function whose form has been chosen in a way to be flexible enough to fully describe the systematic uncertainties:

- **Unknown bias evolution systematic**: we ignore the true redshift evolution of the galaxy-matter bias of the MagLim sample $b_u(z)$
- **Methodology systematic**: failure in the linear-bias model at small scales

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

WZ likelihood

- We assign a likelihood to the measured cross-correlation signal wur (zi) in data given a proposal for the redshift distributions n(z), assuming the previously shown model
- The covariance matrix for the data (shot noise and sample variance) is computed from simulated data with jackknife

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

SOMPZ n(z)

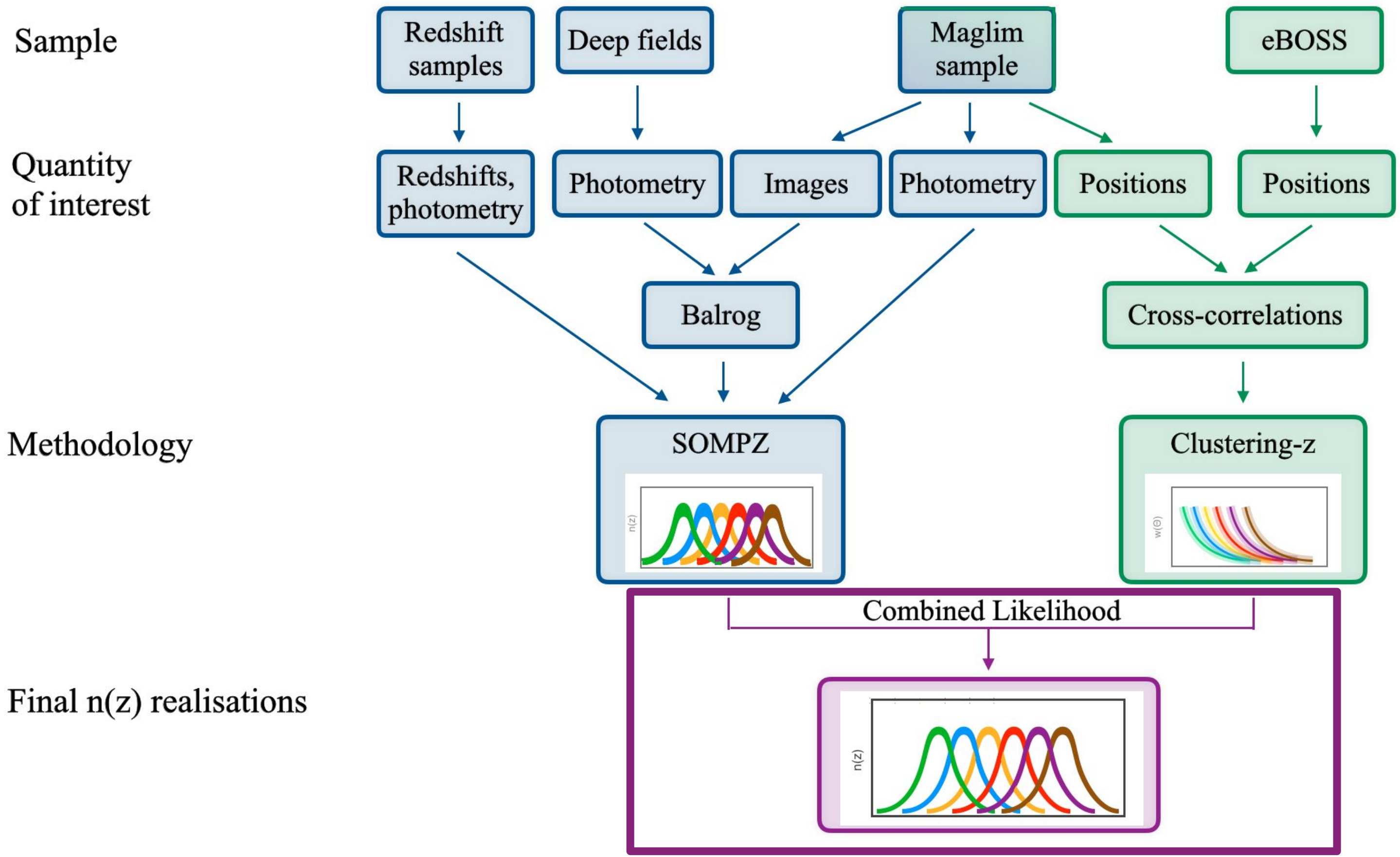
$\boxed{p(\mathbf{s})} p(\mathbf{p})$

Prior on the nuisance parameters s
of the Sys(z, s) systematic function

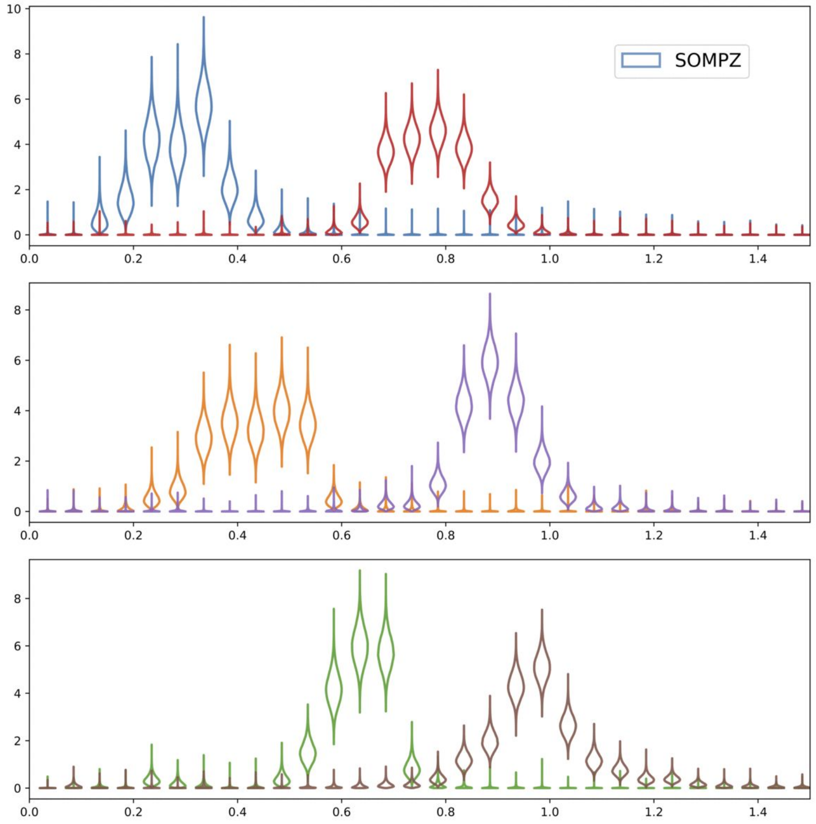
$p(\mathbf{s}) \boxed{p(\mathbf{p})}$

Prior on p = [b_u ,α_u] (the b_u appearing in the magnification term is not assumed equal to the b_u that multiplies w_{DM})

Redshift calibration pipeline



Combination

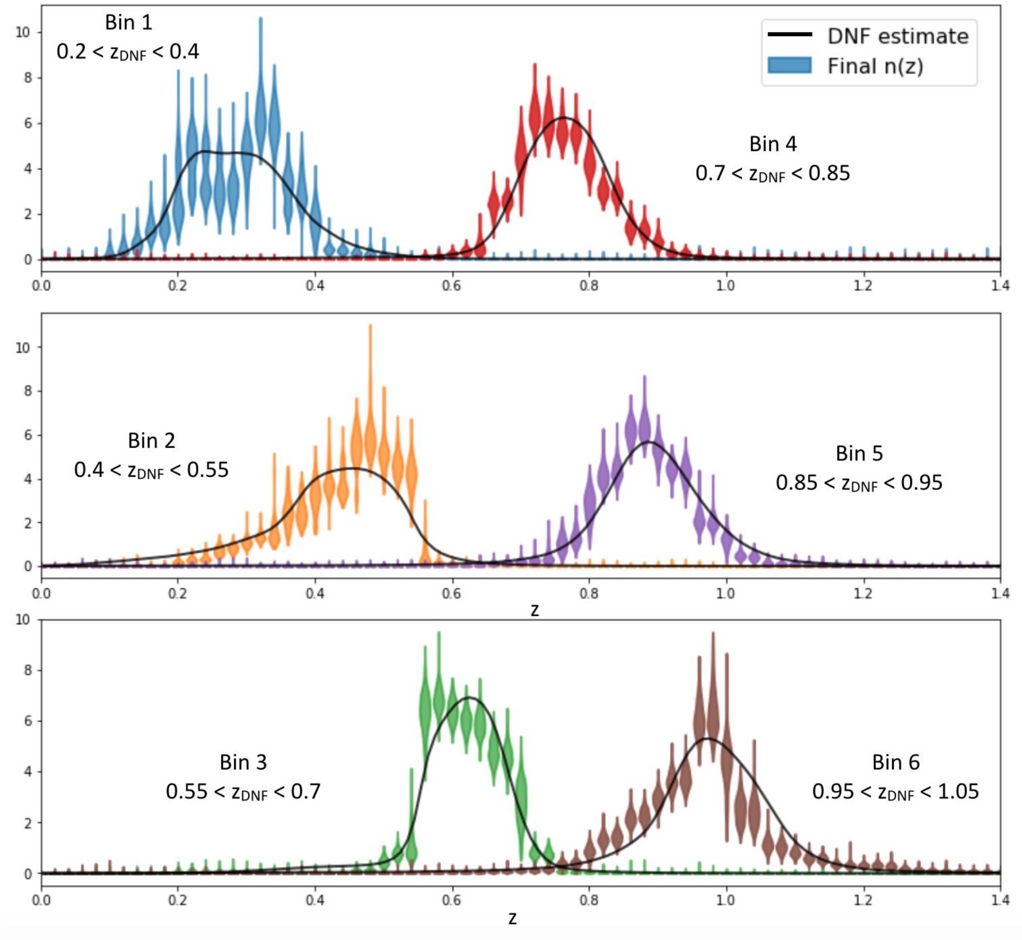


- We sample the final n(z) from a joint likelihood using an Hamiltonian Monte Carlo method
- WZ is able to improve constraints on the SOMPZ shape and to produce a smoother n(z) distribution
- This is particularly important for lenses since w(Θ) and γt are more sensitive to n(z) higher moments

Comparison with DNF

- Good compatibility with the fiducial redshift estimate for MagLim
- SOMPZ+WZ provides a more accurate estimate, especially on the tails

		BIN 1	BIN 2	BIN 3	BIN 4	BIN 5	BIN 6
MEAN	SOMPZ+WZ	0.309	0.451	0.617	0.762	0.883	0.967
	DNF	0.291	0.422	0.615	0.761	0.887	0.968
WIDTH	SOMPZ+WZ	0.077	0.080	0.057	0.066	0.067	0.089
	DNF	0.078	0.094	0.055	0.062	0.075	0.080



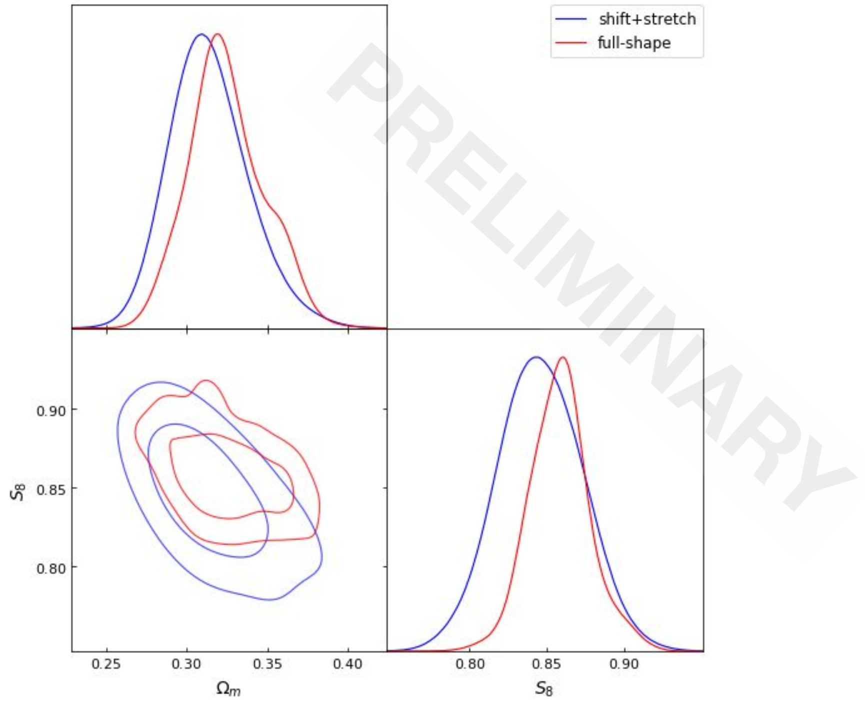
Simulated datavectors

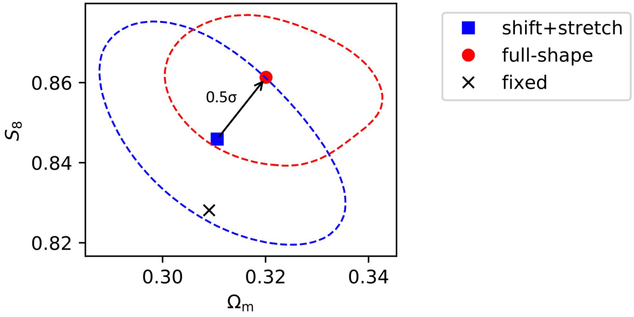
We simulated a potentially realistic scenario, where the 'true' n(z) differs slightly from the SOMPZ+WZ n(z).
We compare:

- marginalisation over a **shift** on the mean and a **stretch** on the width of the average SOMPZ+WZ realisation
- **full-shape marginalisation**: at each step one realisation is sampled out of the ensemble thanks to the Hyperrank code

We obtained some slight differences at the level of 0.5σ, and less correlated biases

This is driven by the uncertainties in the higher order moments of the n(z). We believe that for our modelling of the uncertainties hyperrank is the correct approach, as we know it recovers unbiased parameters on tests on simulations





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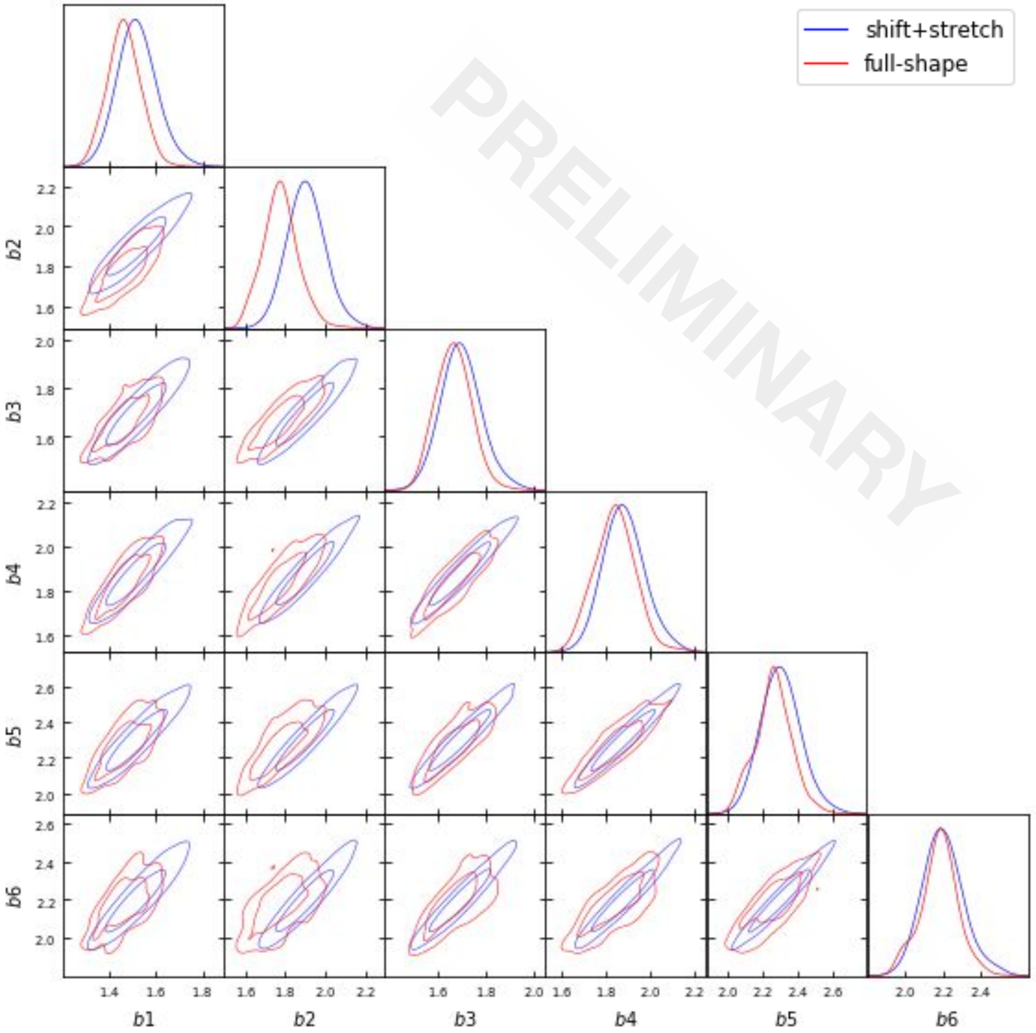

Conclusions

- As the area and depth increase, the statistical errors are dramatically reduced
- This means that the correct characterisation and mitigation of systematic effects is becoming an ever more critical task for photometric surveys
- In this talk we have presented newly developed techniques that improve our treatment of systematics tied with **photometric redshift** calibration and the correction of **observational effects**, two of the most challenging sources of error for current surveys as DES, and for the next generation ones, as LSST or Euclid