WEAK LENSING TOMOGRAPHIC REDSHIFT DISTRIBUTION INFERENCE FOR HSC YEAR 3

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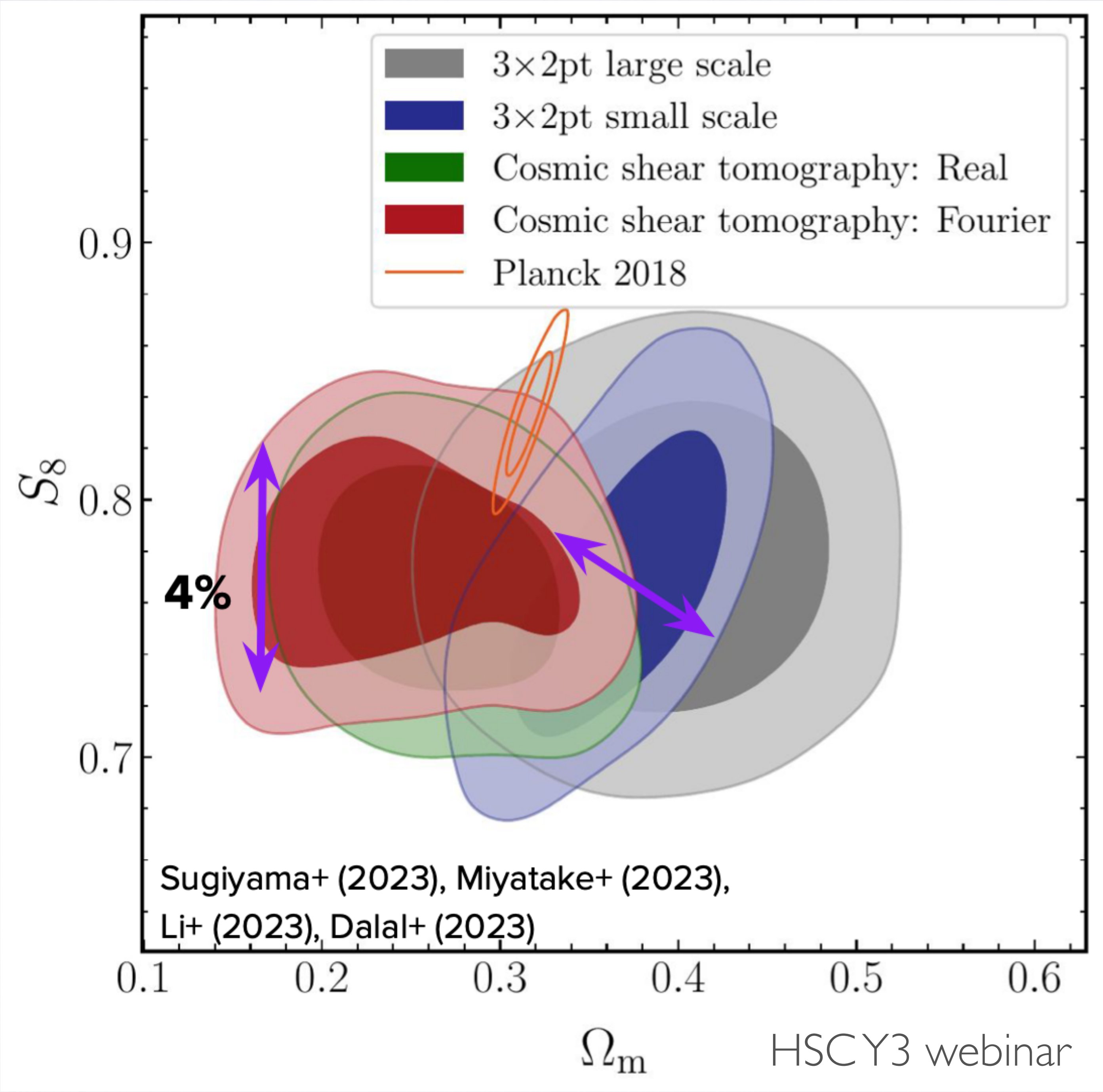
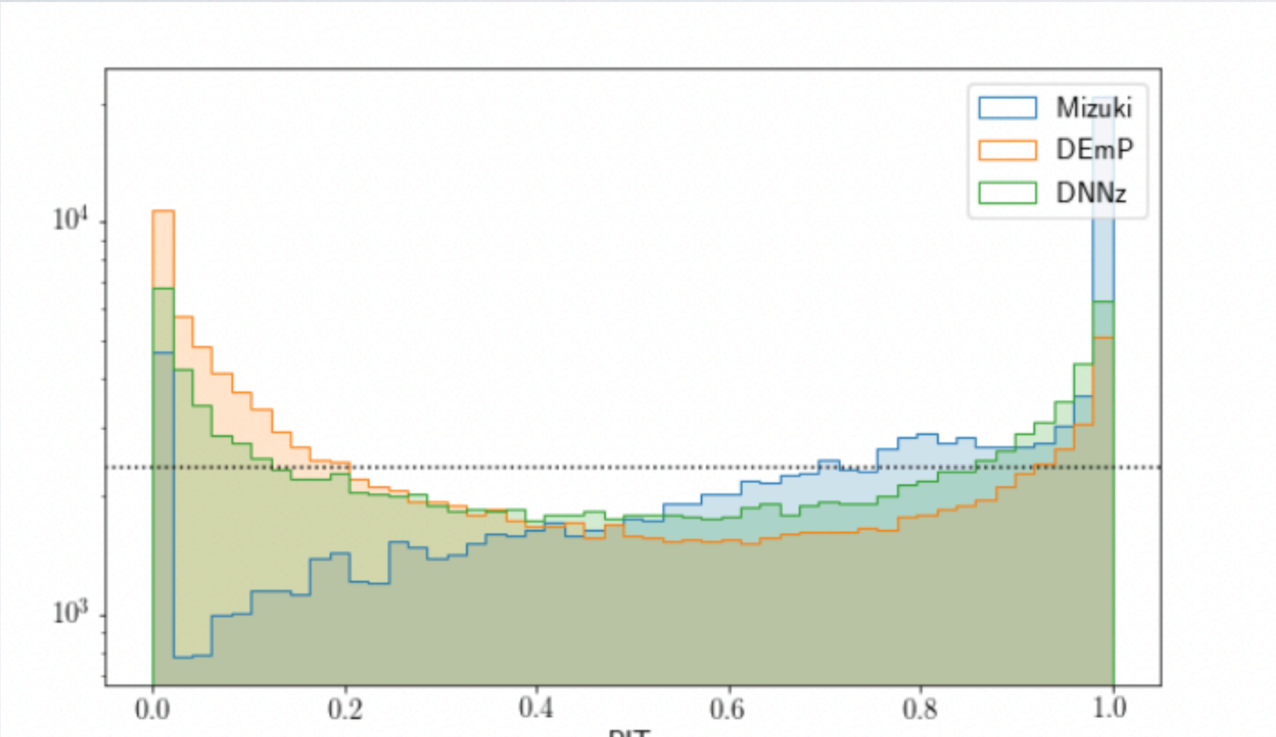
OVERVIEW

- HSC Y3 Tomographic Sample Redshift Distribution Inference
    - Tomographic Sample Redshift Inference Methodology
    - Choice of prior for weak lensing cosmological analysis
- Outlook towards LSST
    - Upcoming Challenges for Redshift Estimation
- Conclusions

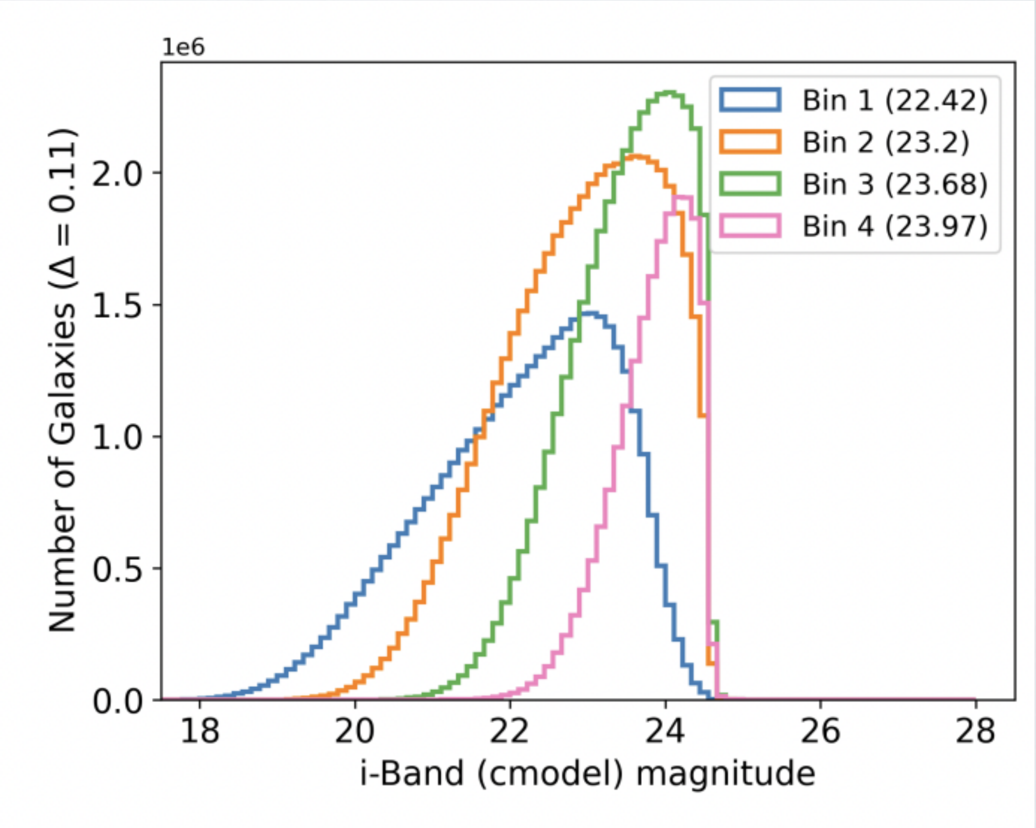
HSC YEAR 3 RESULTS



PZ FOR THE HSC Y3 SHAPE CATALOG

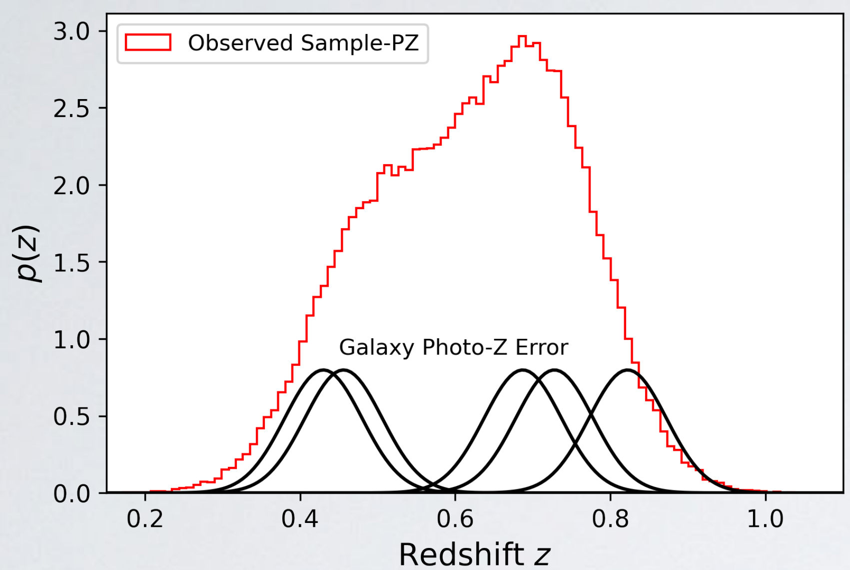


Nishizawa, et al. in prep.



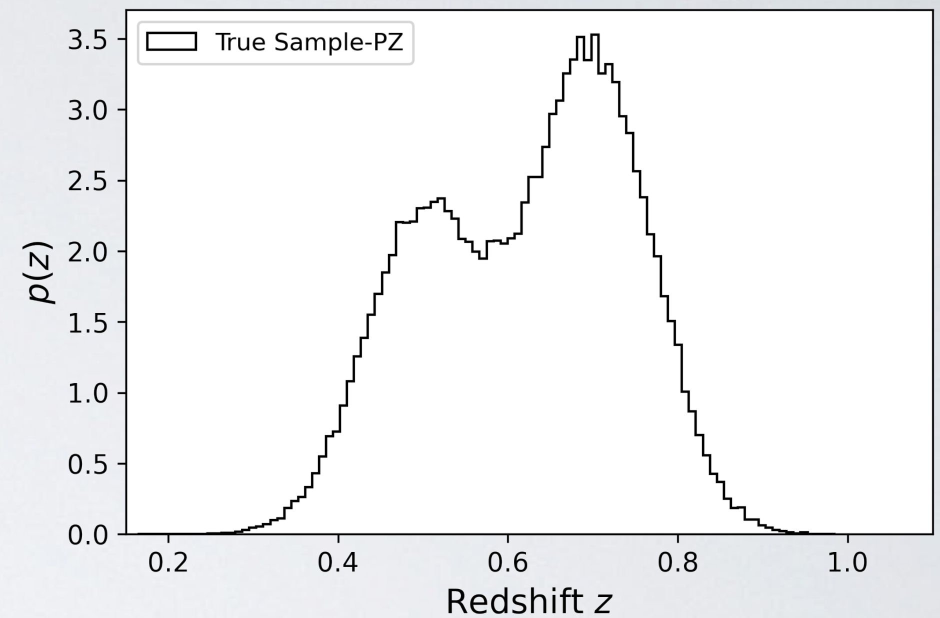
- HSC Y3 shape catalog: 417 sq. deg. Area
- 4 tomographic bins: raw (effective) galaxy number densities: 3.92 (3.77), 5.63 (5.07), 4.68 (4.00), 2.60 (2.12) arcmin−2
- 3 photometric redshift codes run on the data: DnnZ (ML), Dempz (ML) and Mizuki (SED fit)
- Scope: Perform Sample redshift inference based on the provided codes

THE PHOTOMETRIC REDSHIFT PROBLEM



Deconvolution

Recover Redshift distributions using:
Spatial Distribution
Photometry



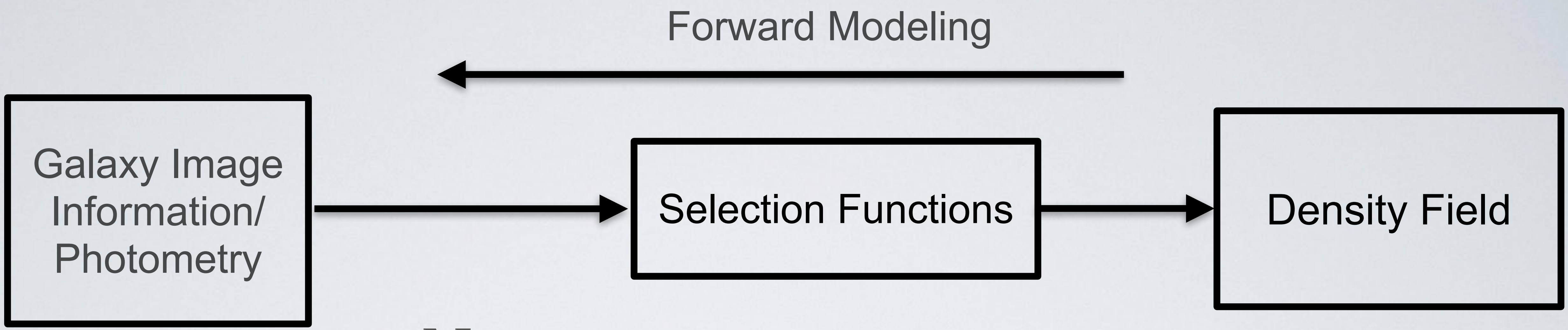
Map a high dimensional parameter space that describes galaxy populations to a low dimensional data vector

Challenges:

- Mapping can be ill-conditioned
- Multiple solutions reproduce similar photometry (outlier populations)
- Incomplete spectroscopic calibration for faint samples

HSC PZ analysis Strategy:

- Optimize sample selection to minimize the impact of multiple solutions
- Include using spatial cross-correlations with CAMIRA-LRG
- Perform Sample Redshift inference using multiple individual galaxy redshift pz. Construct a conservative error budget



$$p(\hat{\mathbf{F}}\,|\,\nu) = \prod_{i=1}^{N_{\rm gal}} \int dz_i\, \omega_i\, p(\mathbf{f}_i\,|\,z_i)\, p(z_i\,|\,\nu)$$

Image info Of Galaxies

Selection Weights

Likelihood for each Galaxy

Sample Redshift Distribution

Illustration $$p(z^{\rm noisy}) = \int p_{\rm Error}(z^{\rm noisy} - z)\, p(z)\, dz$$

$$\mathbf{p}^{\rm noisy} = \mathbf{K}_{\rm error} \cdot \mathbf{p}^{\rm true}$$

Condition number can be large —> Regularization is Key

Assumption: Photometry-Redshift mapping representative.

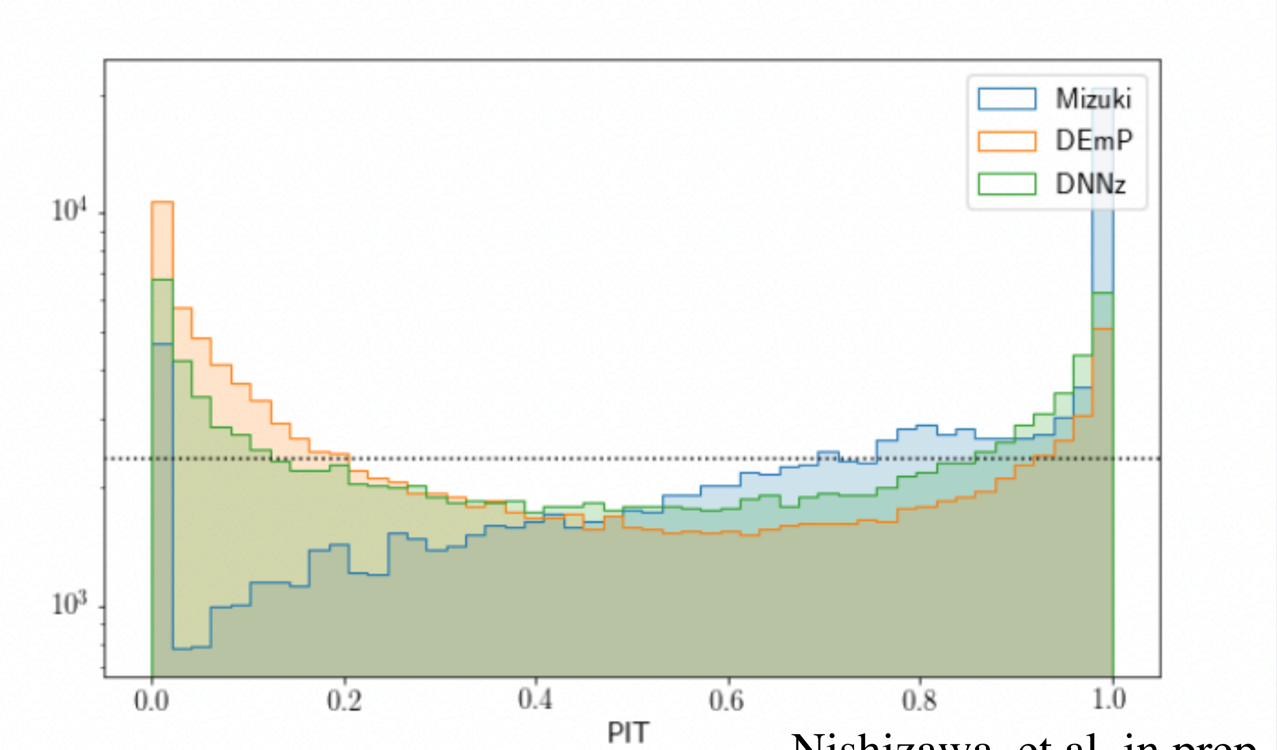
Regression Analysis

Population Distributions (Galaxy Type, Redshift, Stellar Mass, etc.) ← Selection Functions ← Observed Photometry

$$\boxed{p_{\rm samp}(z)} = \int \boxed{p(z\,|\,\mathbf{f})}\boxed{p(\mathbf{f})}\,d\mathbf{f}$$

Density Estimate: Sample Redshift Distribution (Kernel, KNN, …)	Conditional Density Estimate trained on a calibration dataset	Density Estimate of the observed photometry

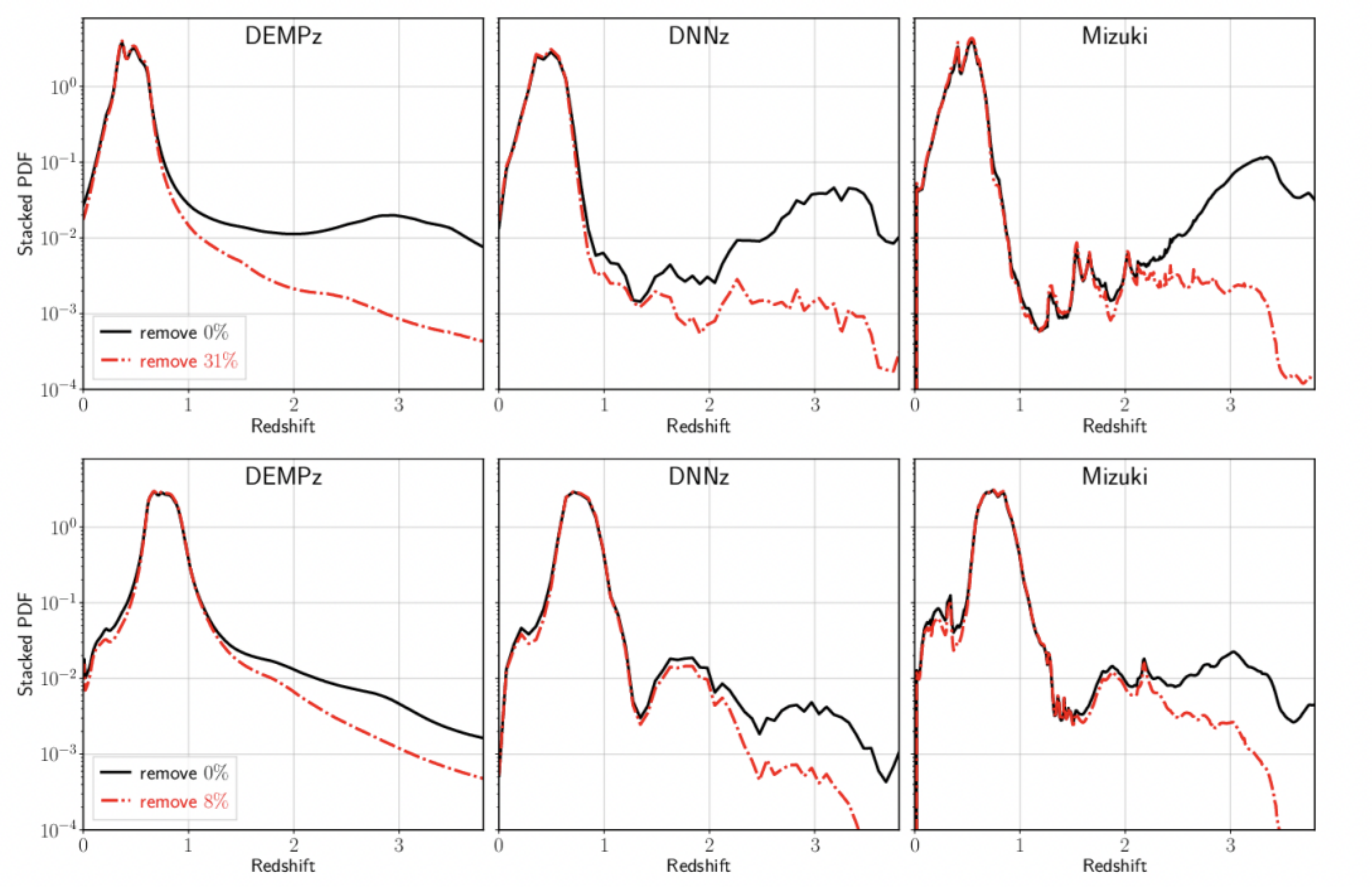
Based on the consistency with WX and the available calibration data, we selected the DNNz method from the available techniques provided by the HSC PZ working group.



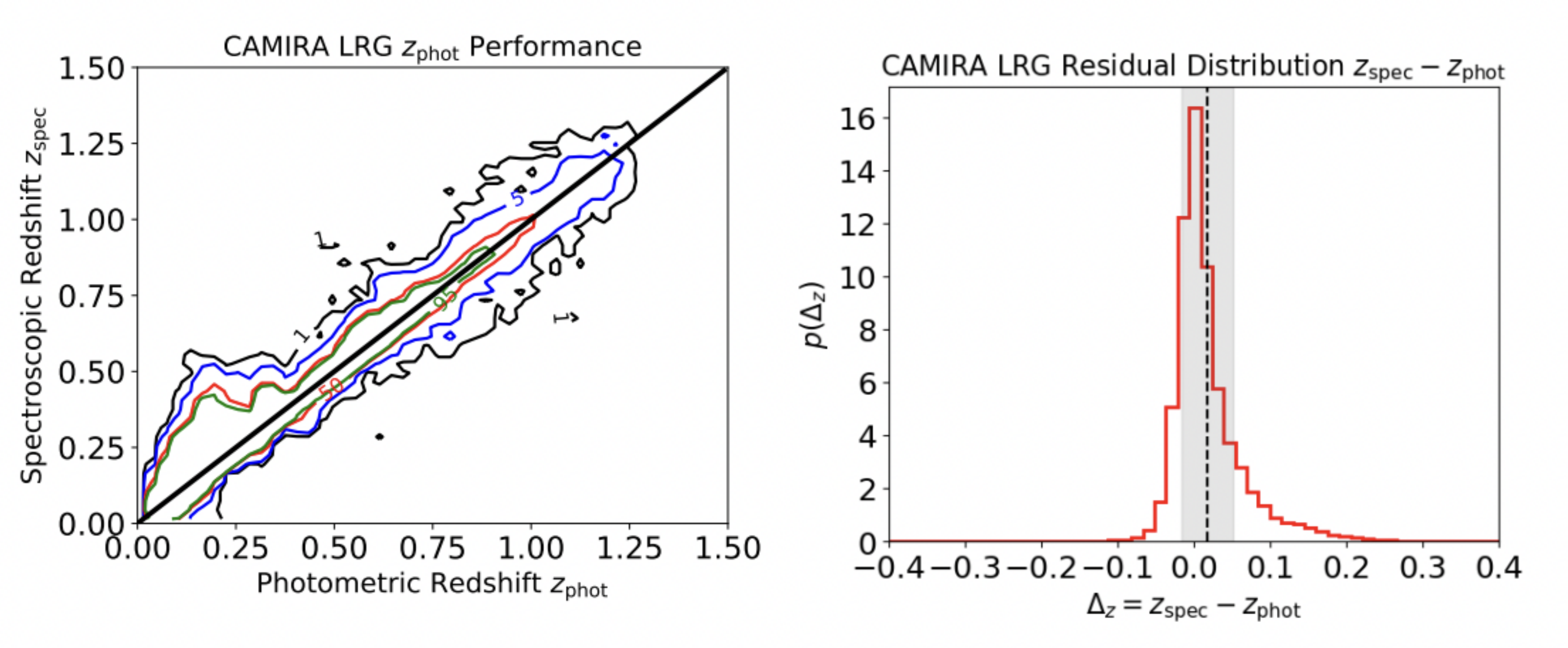
Nishizawa, et al. in prep.

Sample Selection

Criterium: $$\left(z_{0.975,i}^{\mathrm{Mizuki}} - z_{0.025,i}^{\mathrm{Mizuki}}\right) < 2.7 \quad \text{and} \quad \left(z_{0.975,i}^{\mathrm{DNNz}} - z_{0.025,i}^{\mathrm{DNNz}}\right) < 2.7\,,$$



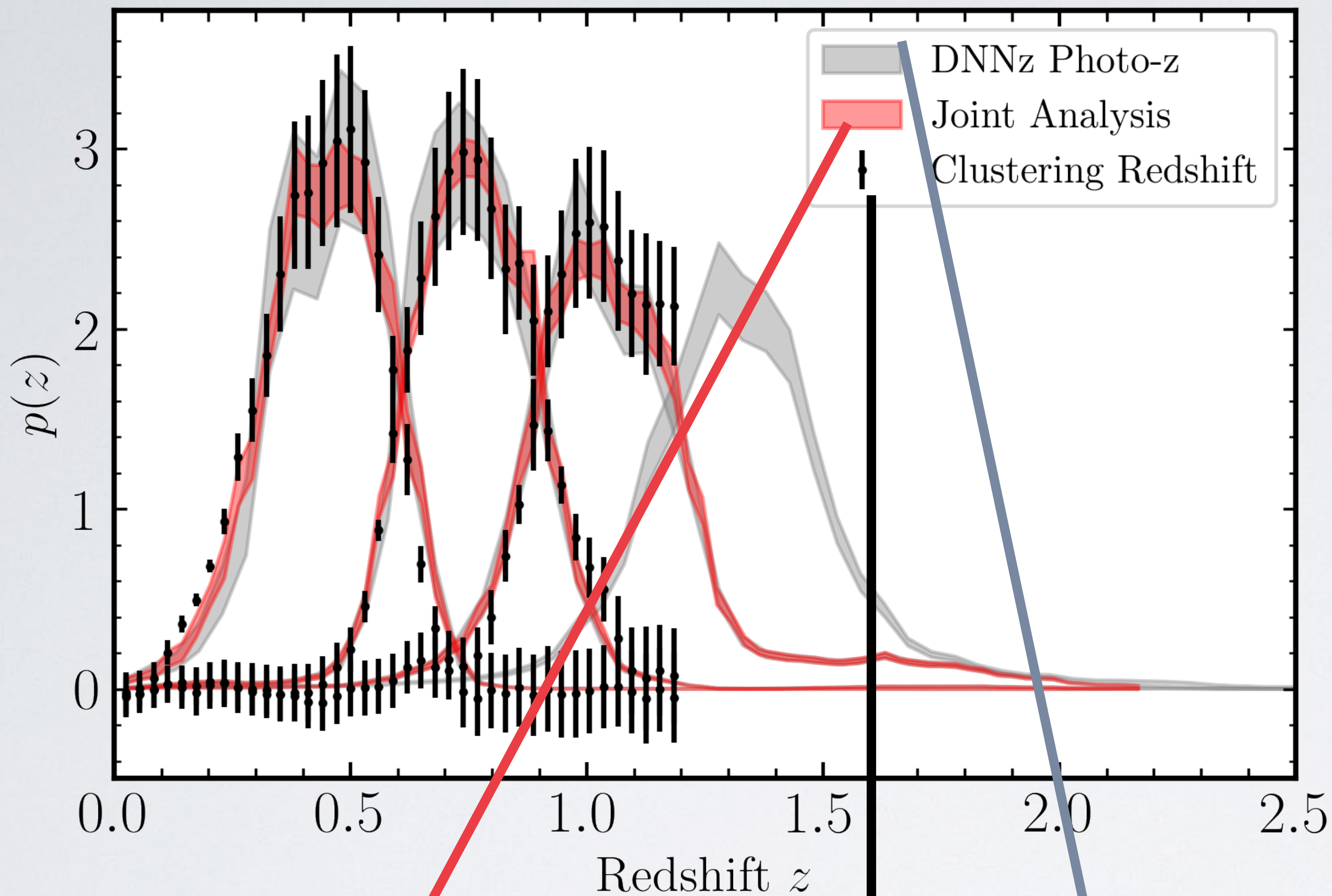
CAMIRA LRG PHOTOMETRIC REDSHIFT ERROR



Spatial Cross-Correlations with the CAMIRA Luminous Red Galaxy Sample

- Spatial Cross-Correlations are systematically affected by PZ systematics.
- Photometric redshift error in the CAMIRA LRG sample
- Marginalize over this redshift error in the analysis

Rau et al. 2023: HSC SSP Year 3 Results



$\mathbf{r}$: Pair Counts
$\mathbf{F}$: Set of photometry of galaxies
$\mathbf{f}_i$: Photometry of single galaxy
Ω: Additional Parameters
$p(z)$: Redshift probability density function
ν: Parameters of basis function model
$\phi_i(z)$: Basis Functions
N_{Basis}: Number of Basis Functions

Formulate a composite likelihood

$$p(\mathbf{r}, \mathbf{F} \,|\, \nu, \Omega) = p(\mathbf{r} \,|\, \nu, \Omega) p(\mathbf{F} \,|\, \nu) \qquad p(z) = \sum_{i=1}^{N_{\text{Basis}}} \nu_i \phi_i(z)$$

Impose a logistic Gaussian process prior to $p(z)$ or $\boldsymbol{\nu}$ spatial model to quantify spatial variations in density

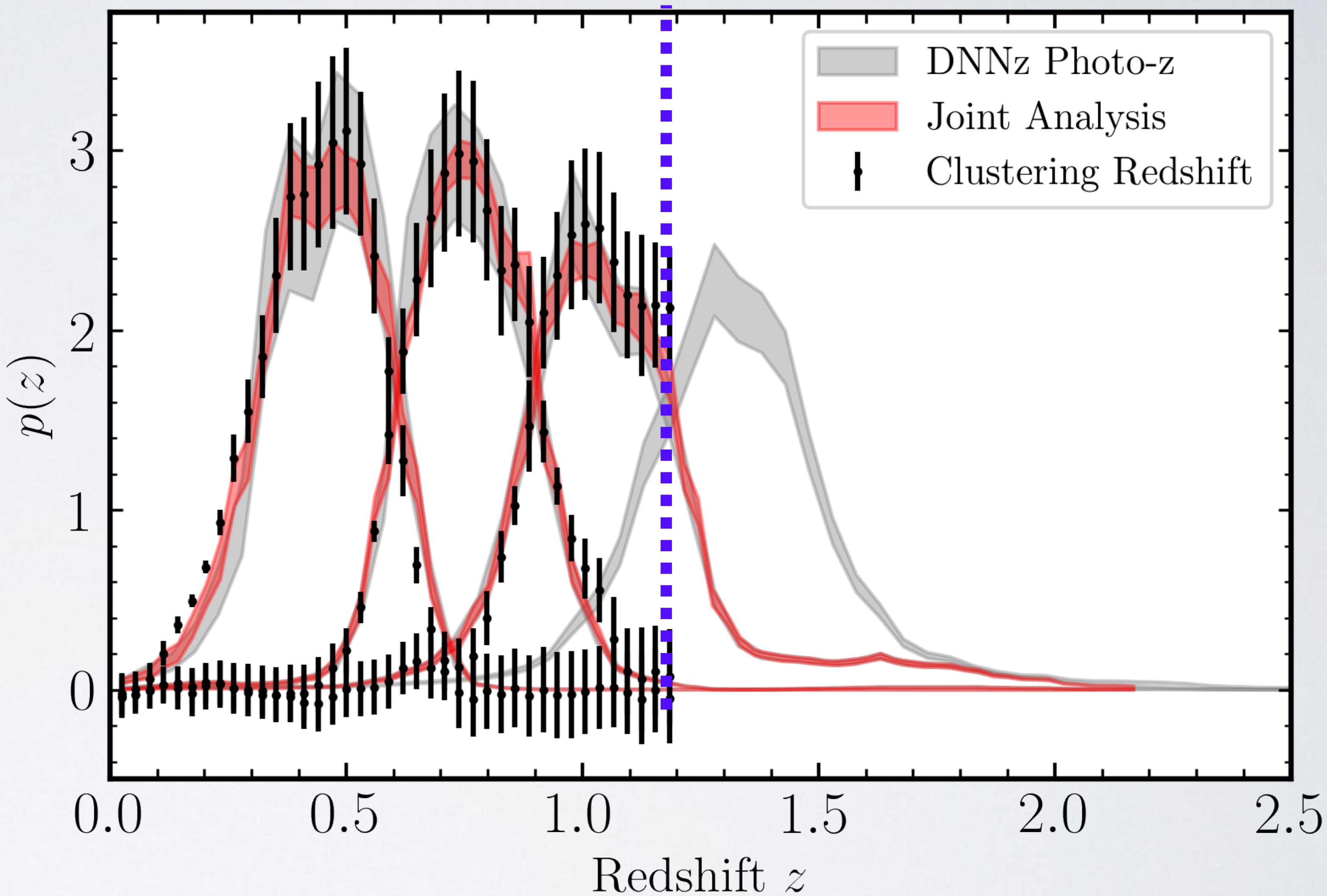
LIMITATIONS

- Treatment of selection functions of the specXphot calibration sample
- Improvements in the quantification of model error in ML (DEMPz, DNNz), selection functions in Template Fitting (Mizuki)
- Limitations in the treatment of cosmic variance induced by redshift calibration using the specXphot calibration sample: Conditioning on color and other quantities of interest
- Quantification of photometric redshift uncertainties and systematics of CAMIRA LRG galaxies
- Astrophysical effects in modeling the cross-correlation data vector: more complex galaxy-dm bias model, magnification bias, etc.
- Improve high redshift coverage with DESI in future analysis

Due to these limitations, the HSC Y3 analysis uses a flat prior on the posterior mean for the high redshift tomographic bins.

PRIOR CHOICE FOR THE COSMOLOGICAL ANALYSIS

$$\Delta z_1 = 0.452 \pm 0.024$$
$$\Delta z_2 = 0.766 \pm 0.022$$
$$\Delta z_3 = \mathcal{U}(-1,1)$$
$$\Delta z_4 = \mathcal{U}(-1,1)$$



We adopt informative priors based on the presented analysis for the low-redshift bins and a flat prior at high redshift where, our calibration is incomplete

Moving from Stage III (HSC) to Stage IV (LSST)

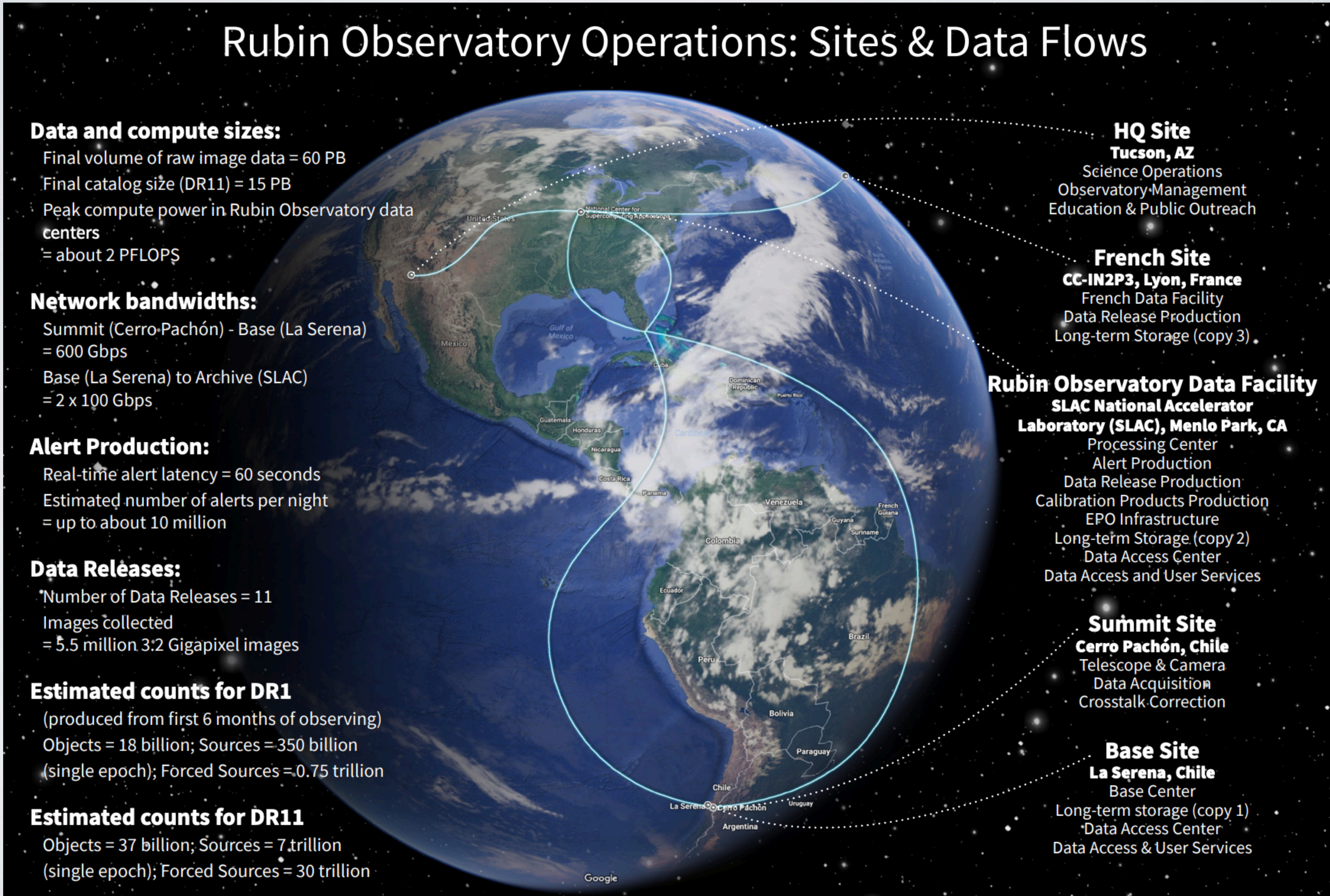
Credit: hsc.mtk.nao.ac.jp

HSC SSP in Year 3: a "small LSST"
Area $\sim 400\,\mathrm{deg}^2$

LSST:
Area $\sim 20000\,\mathrm{deg}^2$

The **Hyper Supreme-Cam Subaru Strategic Program** (HSC SSP), a great precursor survey to develop LSST relevant Data Science methodology

Big Data Survey Science



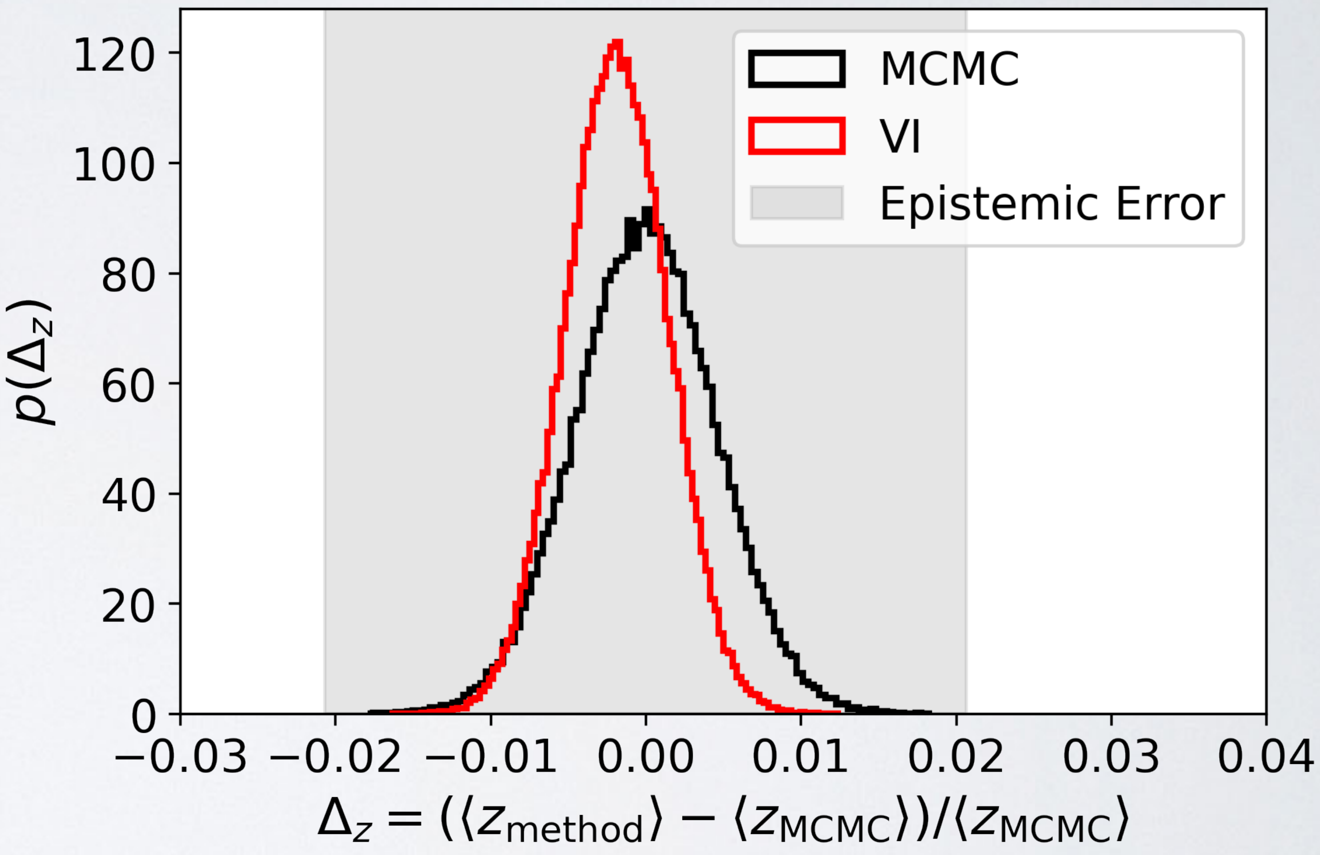
Credit: lsst.org

SCALABILITY

Large Epistemic error
in astrophysical modeling

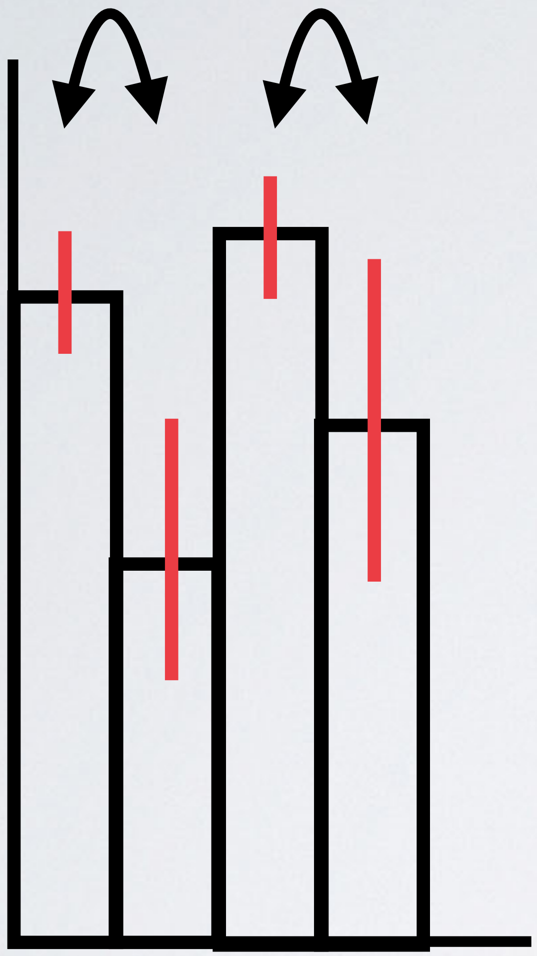
Approximate Inference schemes
In combination with appropriate
Regularization

—> Dramatic Speedup with
acceptable additional misestimation
Error budget

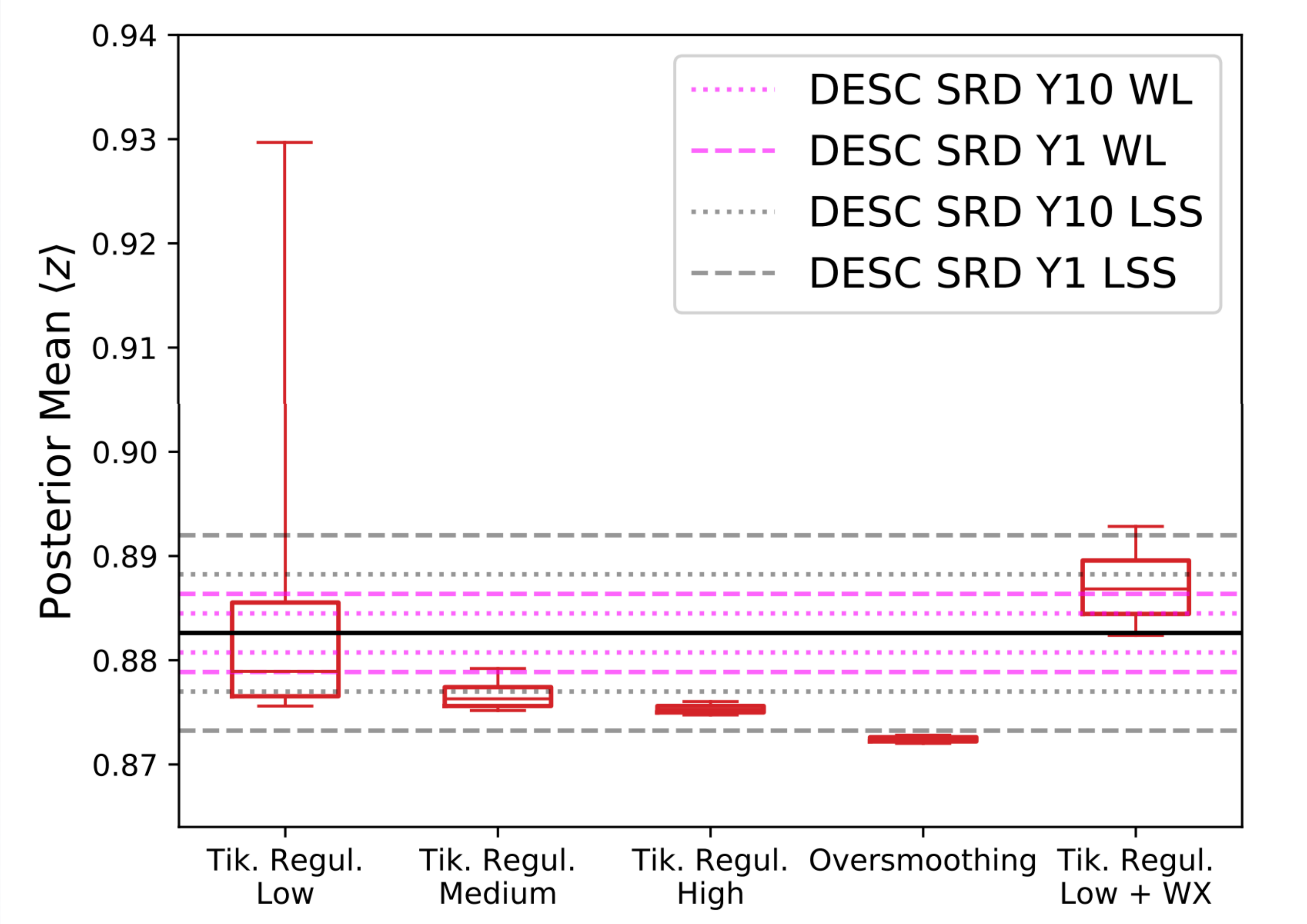


See Rau et al. 2023

REGULARIZATION



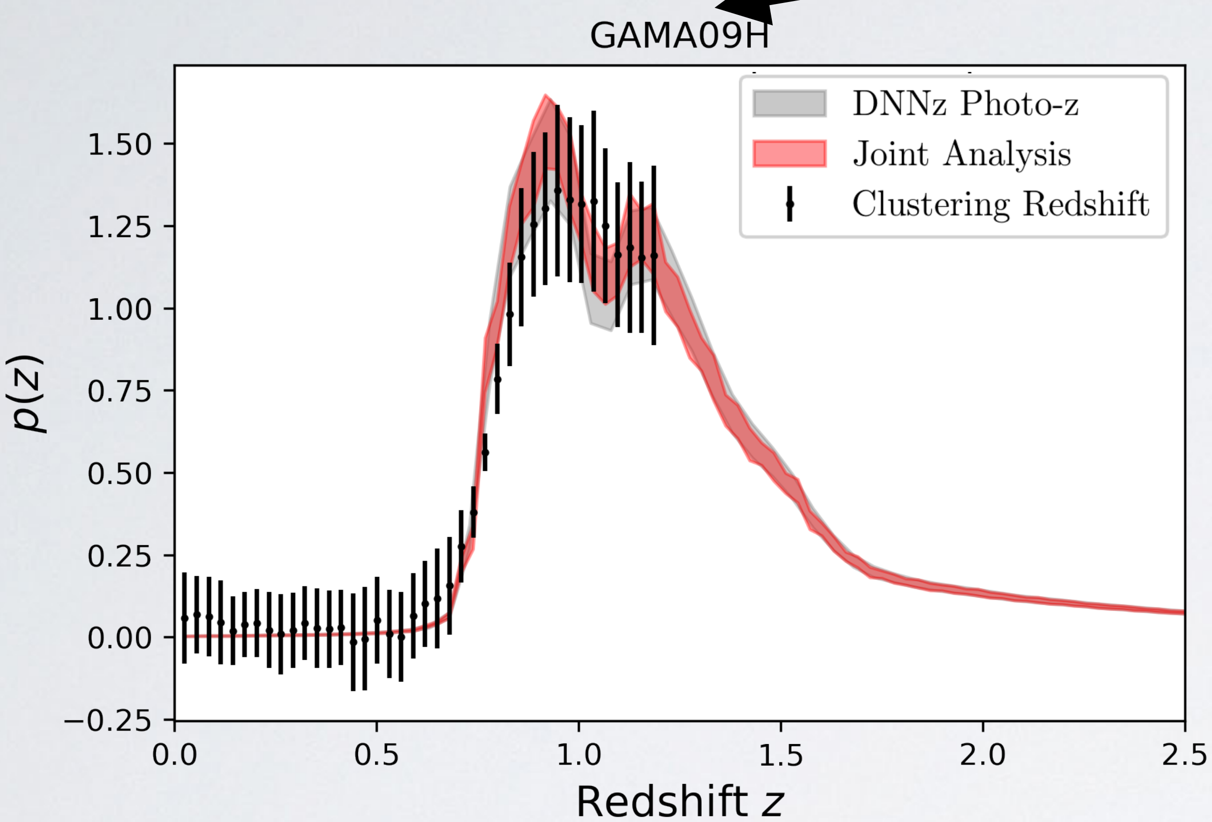
Bins are merged to reduce variance

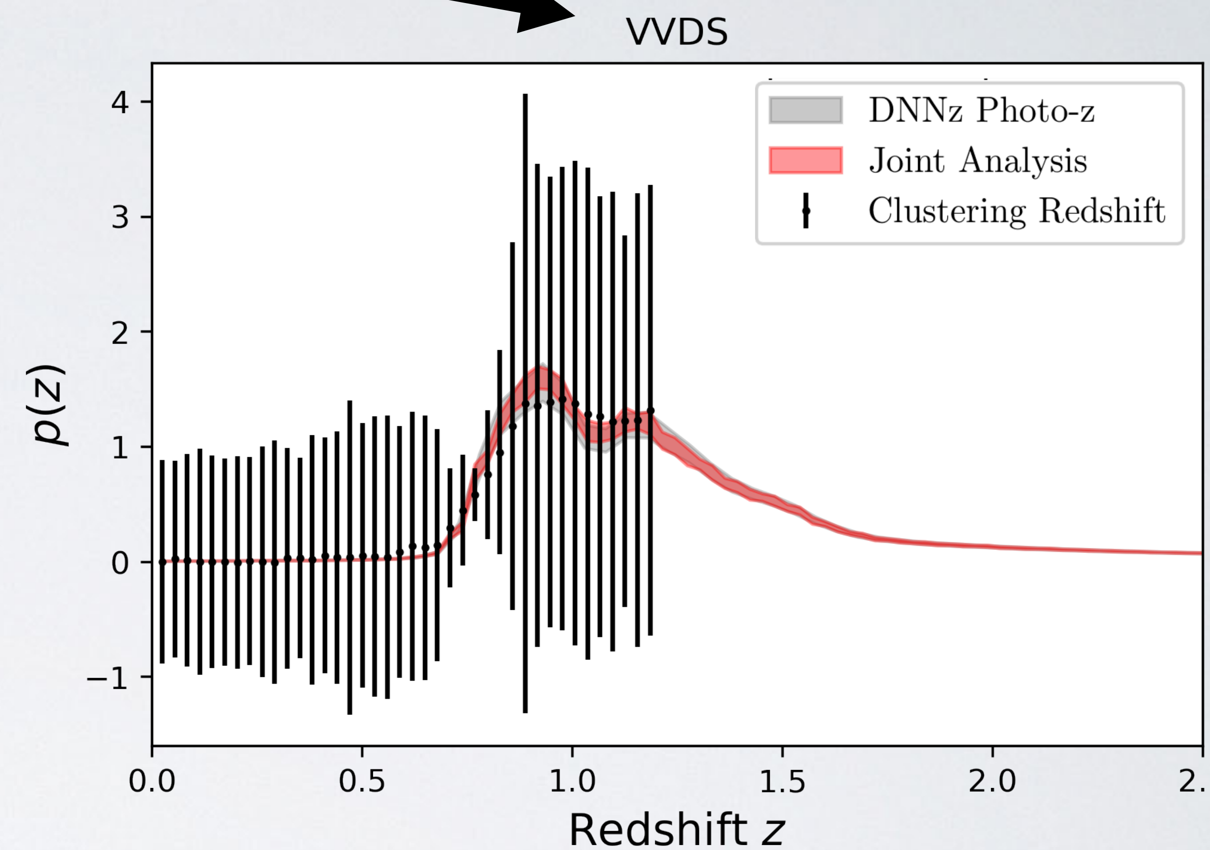


Rau et al. 2022

Oversmoothing and Tikhonov's regularization induce under-coverage.
Solution: inference in high resolution and merge bins to reduce variance
Adaptation of Burrus, Rust 1972, Kuusela 2016

Spatial variation in number density in different regions on the sky





Rau, et al. in prep.

The inference scheme developed by Rau et al. 2020, 2023 fits a log-gaussian cox process to the galaxy density and allows quantifying field-to-field variations in data. Applied here to the HSC Year 3 cluster-lensing analysis.

CONCLUSIONS

- Survey Science rapidly advances into the era of petascale cosmology and astronomy.
- At the same time the modeling of systematics becomes more complex
- Photometric Redshift estimation is challenging due to the lack of calibration sources that are robust against model misspecification
- Inclusion of complementary data vital to reach high fidelity of LSST
- The next 2-5 years will be a critical time window for Data Science development in this area