# Imaging Surveys and ML

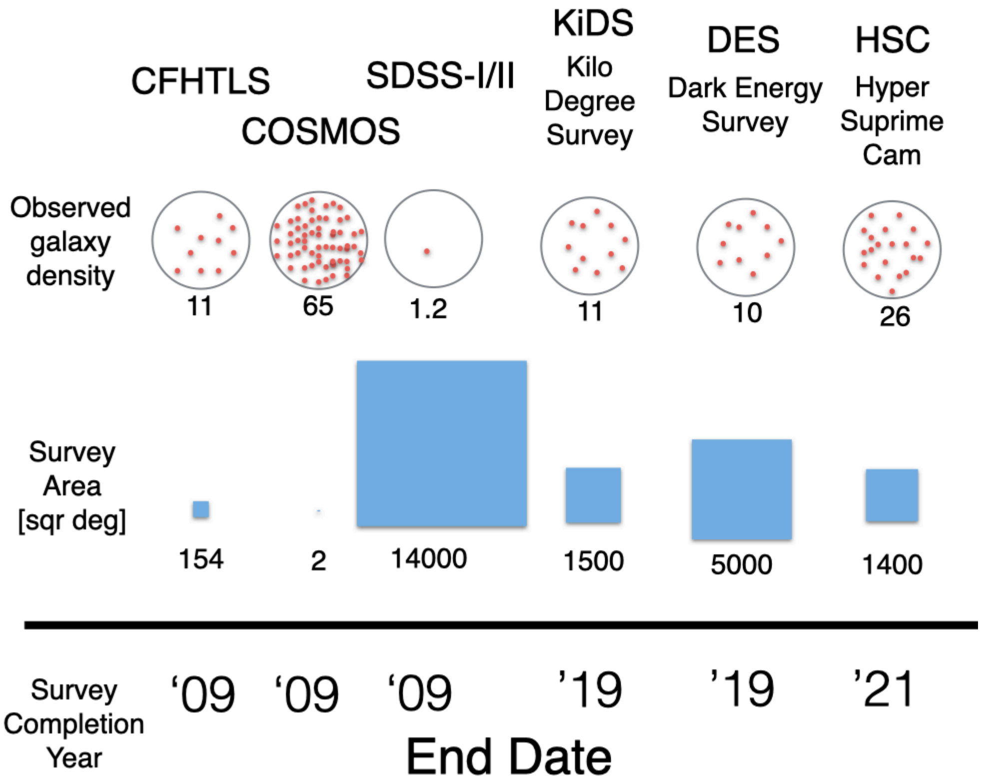
*Elisabeth Krause (UArizona)*

*A biased perspective from the Dark Energy Survey*

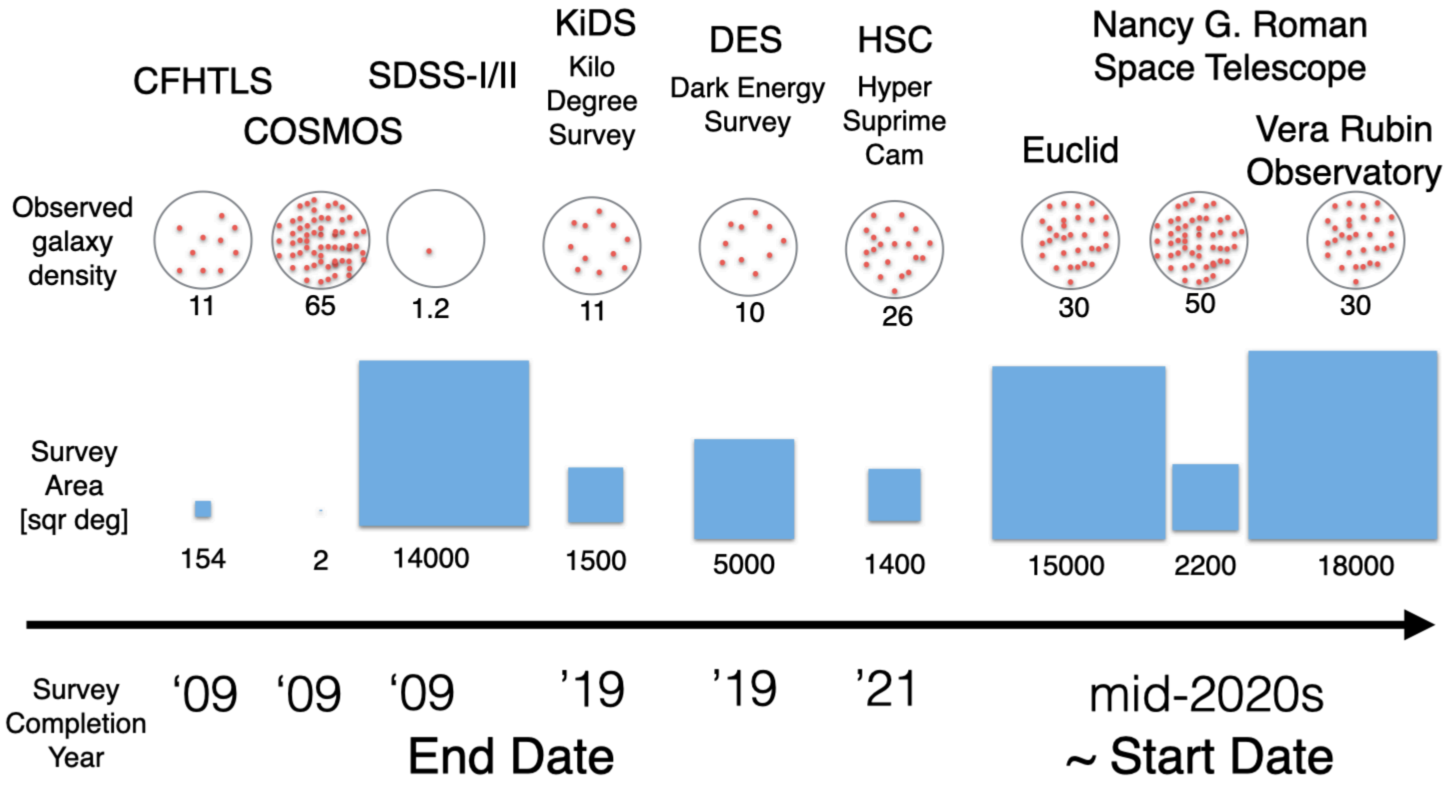
# Outline

- From Imaging Surveys to Parameter Constraints
- Pixel-domain Classification
  - Milky Way Science
  - Galaxy Evolution
  - Galaxy Clusters, Strong Lensing
- Time-domain Classification
  - Solar System
  - Supernovae
- Systematics Calibration for 3x2pt cosmology
  - Photometric Redshift Distributions
  - Blending
  - Galaxy Clustering Systematics

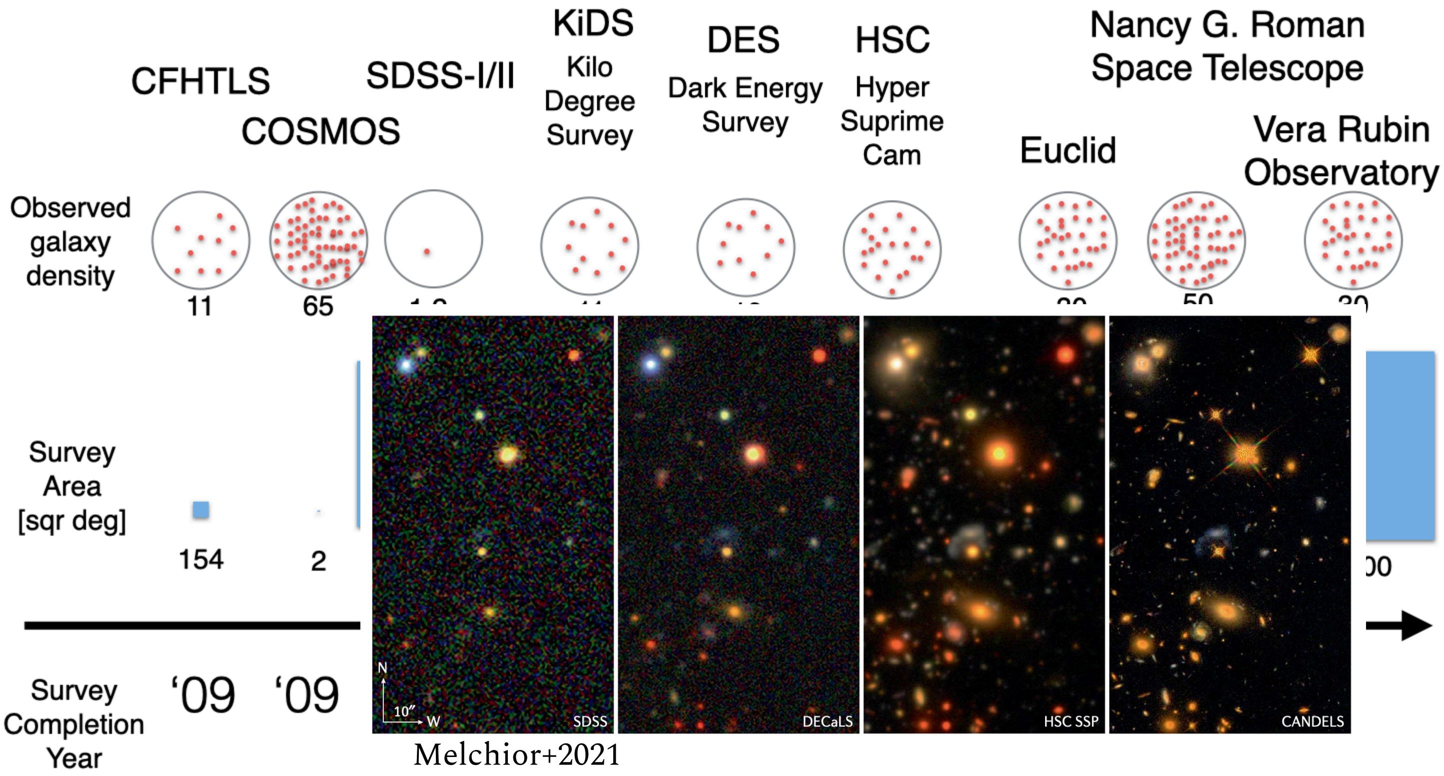
# Large-Scale Structure Imaging Surveys



# Large-Scale Structure Imaging Surveys



# Large-Scale Structure Imaging Surveys




Melchior+2021
Credit: Legacy Surveys/D. Lang, NAOJ/HSC

# From Images to (Astro)Physics Constraints

- Source catalog & photometry
- Object classification/detection
- Sample selection - characterize selection probability (distribution & biases)
- Measurement of sample properties/summary statistics
- Modeling & inference

# From Images to (Astro)Physics Constraints

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- Modeling & inference    Ben's & Paco's reviews

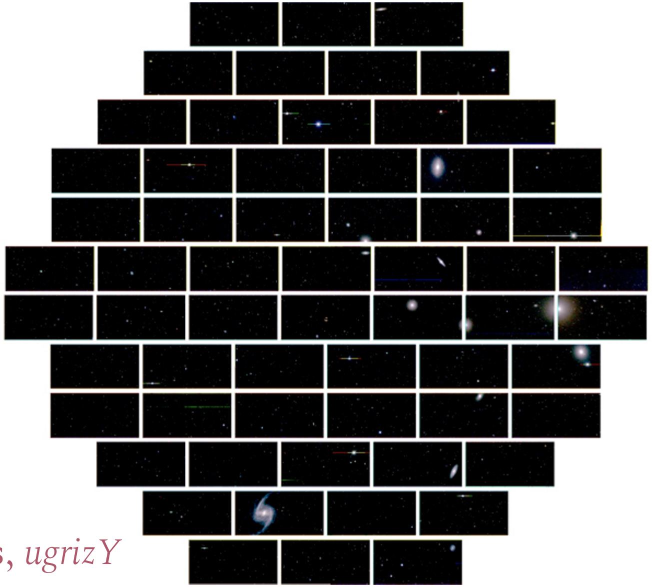
This talk will highlight some examples on the importance of selection functions and (systematic) uncertainty quantification.

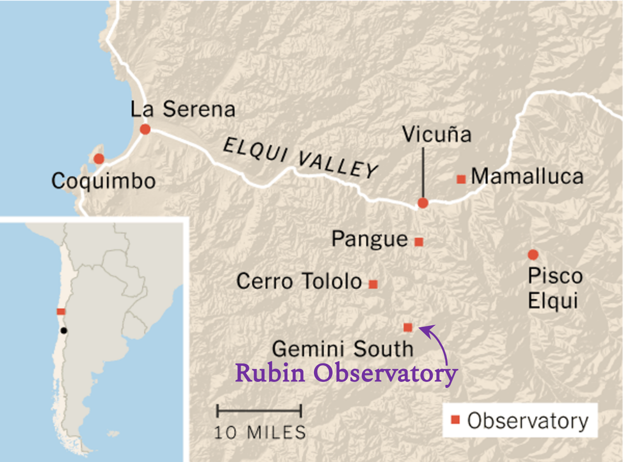
My selection bias for this talk: examples from the Dark Energy Survey.

# DES Basics

- Blanco 4-meter telescope at Cerro Tololo (CTIO) in Chile Dark Energy Camera (DECam)
- 3.0 sq. deg. field-of-view, 70 4kx2k CCD chips, 570 Mpixels, *grizY* filters

c.f. Rubin LSST Camera 9.6 sq. deg, 189 4kx4k CCD chips, 3.2 Gpixels, *ugrizY*

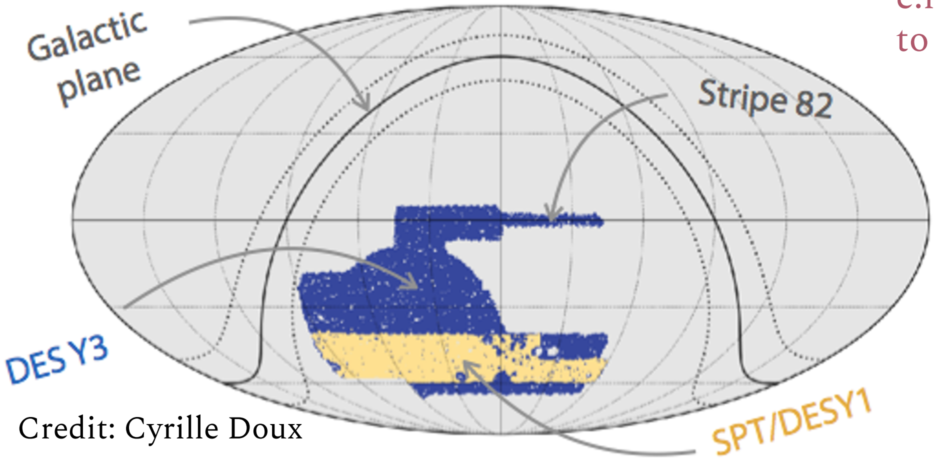





# The Survey

- 5000 sq. deg. footprint, observed 2013-2019, wide field + supernova fields
- Overlap with SPT, ACT, Stripe 82
- DR2 (6 years) of 543M galaxies + 145M stars to $r$~23.5
- Data released to the public: [https://des.ncsa.illinois.edu/home](https://des.ncsa.illinois.edu/home)

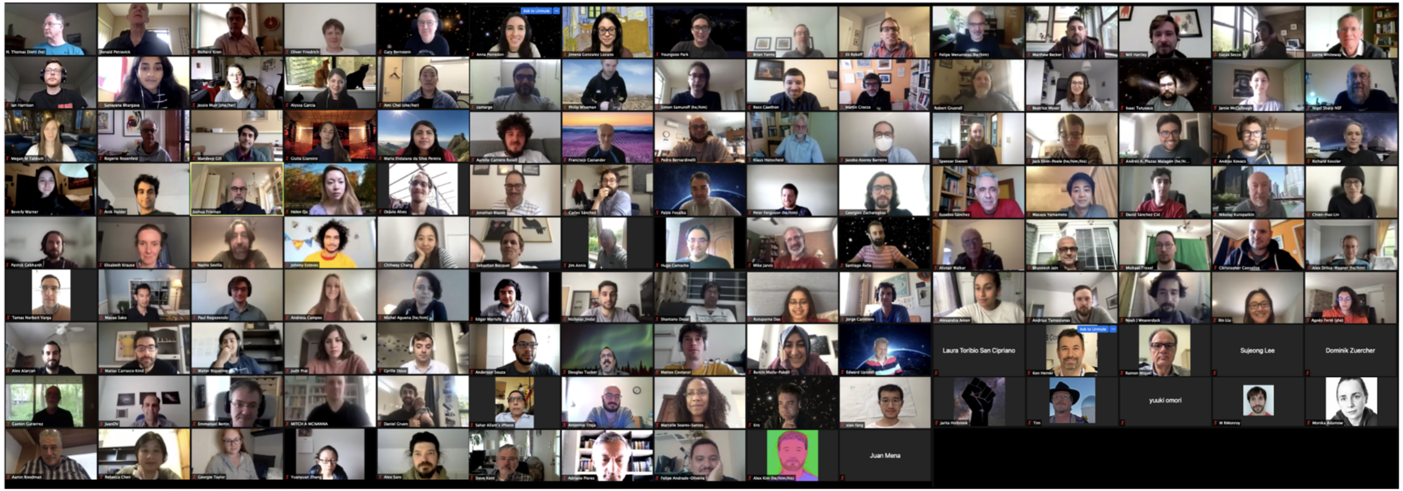
c.f. LSST 18,000 sq. deg., 20B galaxies + 17B stars to $r$~27.8, also much higher cadence time domain




Credit: Cyrille Doux

# The People

- DES is a collection of ~400 scientists from 25 institutions in 7 countries (USA, UK, Spain, Brazil, Switzerland, Germany, Australia)
- Lots of Early Career Scientists leadership
- Checkout Scientists of the Week, Darchive, #ThisIsDES, #Darkbite




May 2021 Virtual Collaboration Meeting

# DES Science Spans a Wide Range

- Transients and Moving Objects
- Milky Way
- Galaxy Evolution and QSOs
- Supernova
- Strong Lensing
- Galaxy Clusters
- Large-scale Structure
- Weak Lensing

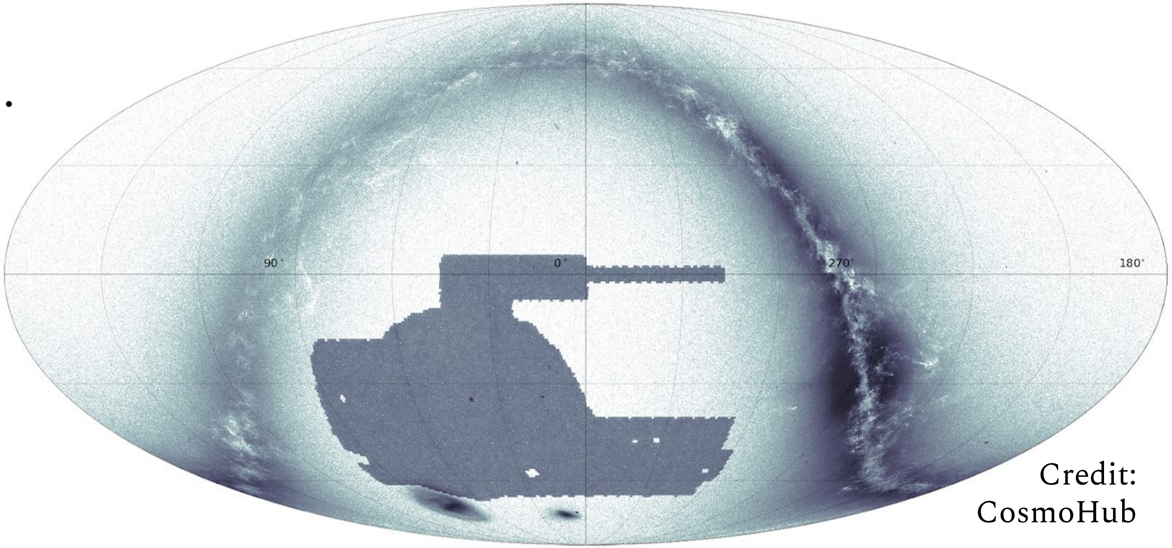
Astrophysics
Cosmology
Particle physics

DES Collaboration 2016
*The Dark Energy Survey: more than dark energy – an overview.*

# A very incomplete list of science highlights...

380+ papers have been posted from DES to date, check out the full list here:
https://dbweb8.fnal.gov:8443/DESPub/app/PB/pub/pbpublished

Lots of methodology advance accompanying science results.



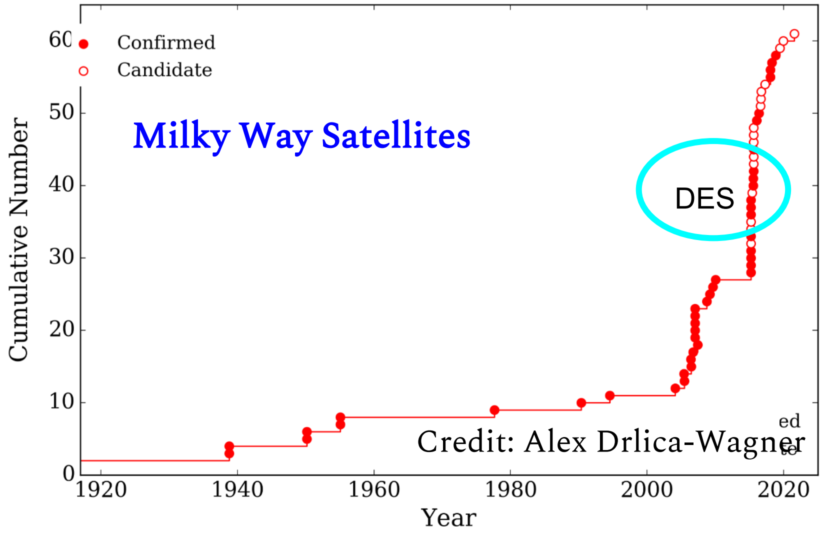

Credit: CosmoHub

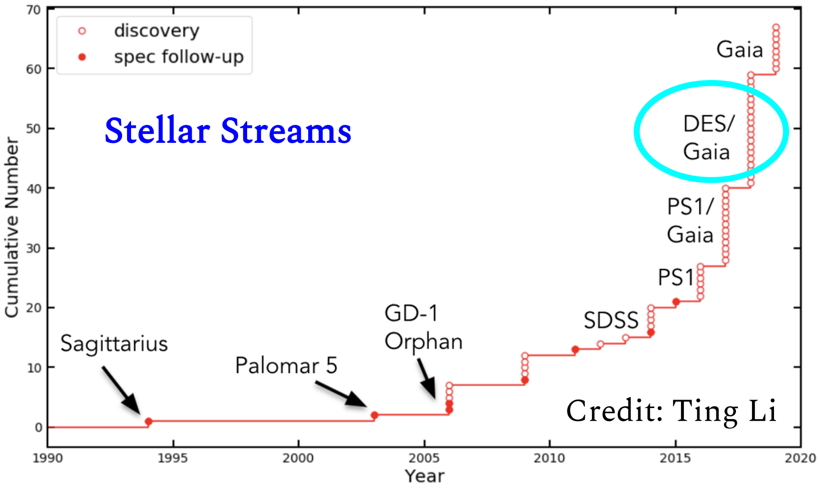
# Milky Way

Massive discovery space:

- Dwarf Galaxies
- Stellar Streams
- Globular Clusters
- Proper Motion
- Brown dwarfs and ultra-cool objects
- MW stellar distribution

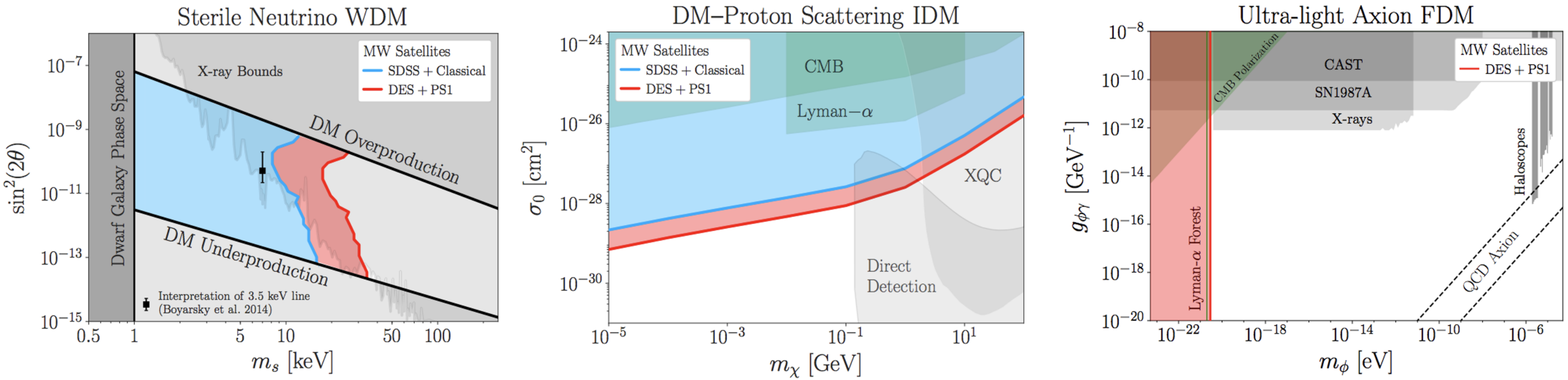
MW Satellites identified using matched filter (Koposov+’15) and likelihood-based search(`ugali`, Bechtol+’15, Drlica-Wagner+’15), selection function characterized through artificial injections (Drlica-Wagner+’20) .



# Milky Way Satellites

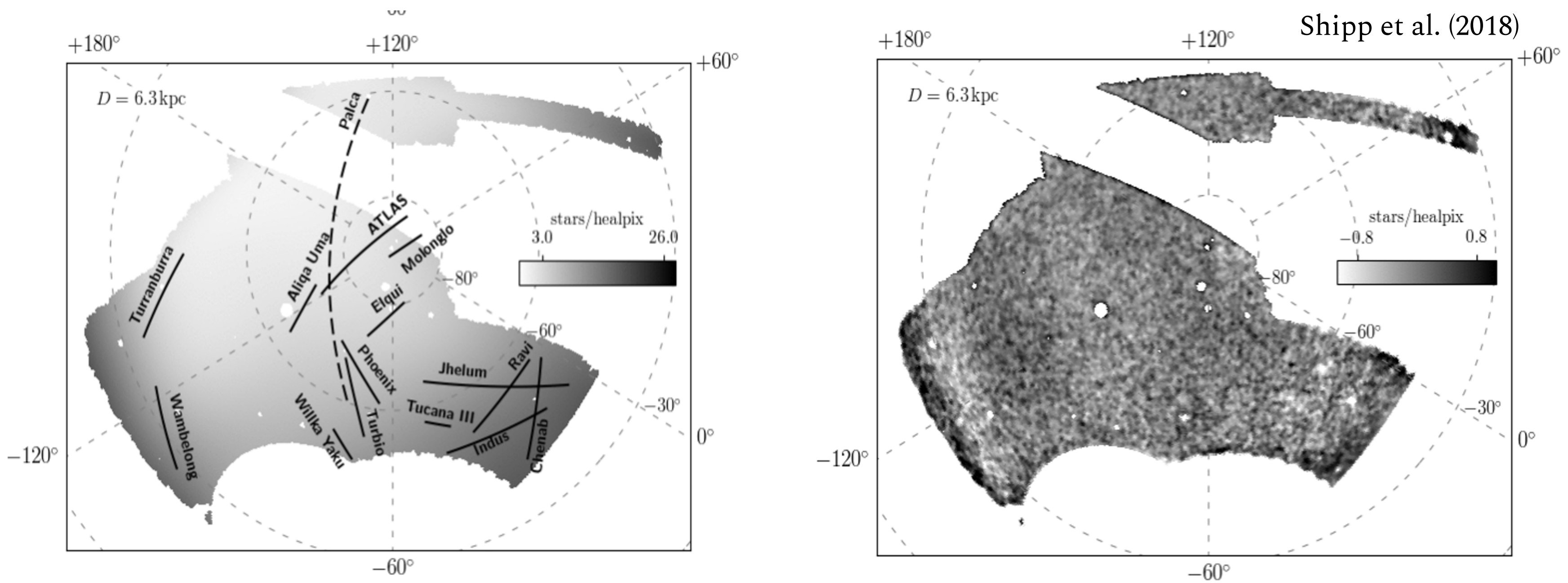
The position-dependent Milky Way satellite luminosity function provides information to constrain different dark matter properties. Need to account for both satellite detectability and uncertainties in the galaxy-halo connection.




Nadler et al. (2021)

# Milky Way Stellar Streams

Shipp et al. (2018)




Isochrone-fitting + matched-filter technique to search for streams that composes of stars formed at the same time and located at approximately the same distances.

See Helena Dominguez Sanchez’s talk for DL stream detection in HSC-SSP.

Tanoglidis+2021ab

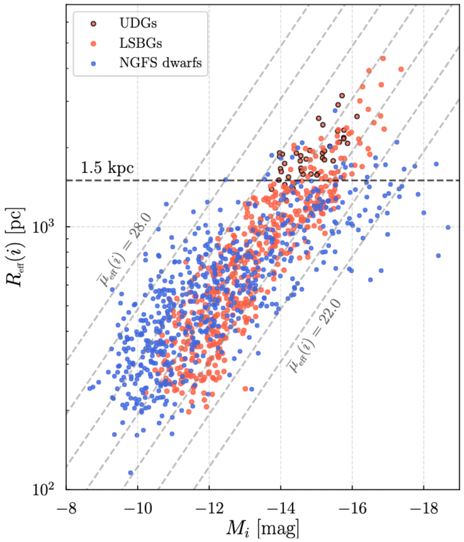
# Low Surface Brightness Galaxies (LSBG)

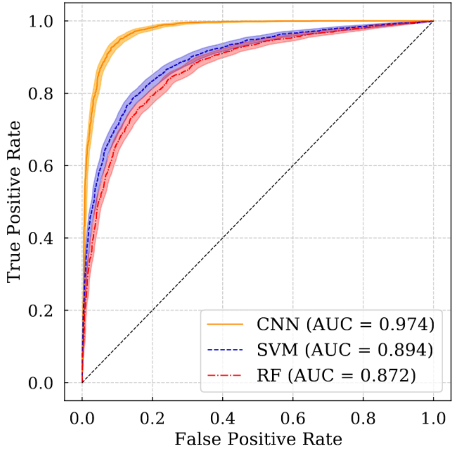
LSBGs probe halo-galaxy connection at extreme end. Individual systems with extremely high dark matter content (van Dokkum+'18,'19) may challenge LCDM galaxy formation - requires wide-field census + completeness.

23,790 LSBGs from DES (Tanoglidis+2021ab)

- Detection plagued by galactic cirrus, diffuse light from bright objects, star formation knots
- CNN trained on visually confirmed LSBGs and artefacts outperforms feature-based ML due to better artefact rejection
- Good transfer learning to deeper HSC data with small retraining sample

See also SMUDGes Survey (DECaLS re-reduction on S82, Zaritski+21) for related automated classification and artefact rejection. Complete match with DES sample to 25 mag/arcsec$^2$.



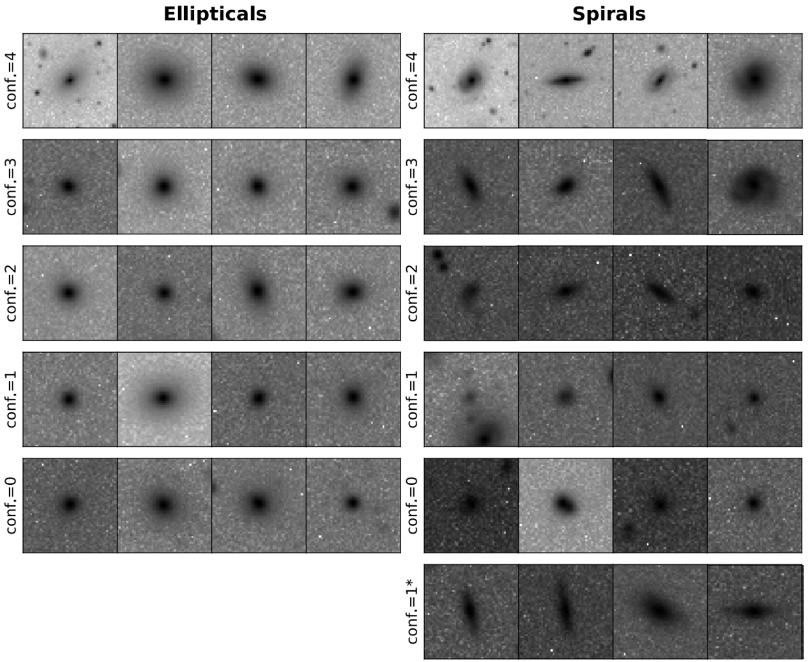
# Galaxy Evolution

Galaxy morphology classification of 27M DES-DR1 galaxies using CNN (Vega-Ferrero+'21)

Enables galaxy evolution studies with v.large sample

Comparison of ML and DL morphology classifiers, trained on Galaxy Zoo, using DES galaxies (Chen+'20)

Comparison of both catalogs forthcoming




Related talks:
J. Vega-Ferrero: Pushing automated morphological classifications to their limits with DES
A. Gosh: Morphology & Quenching of Galaxies […] using Interpretable Bayesian CNNs
Y.-T. Chen: Beyond the Hubble Sequence - Exploring galaxy morphology with unsupervised machine learning

# DES-Y1 Cluster Cosmology

Galaxy clusters are the largest virialized objects in the Universe, sensitive probe of structure growth - requires "mass-observable" relation between observed mass proxy and halo mass.

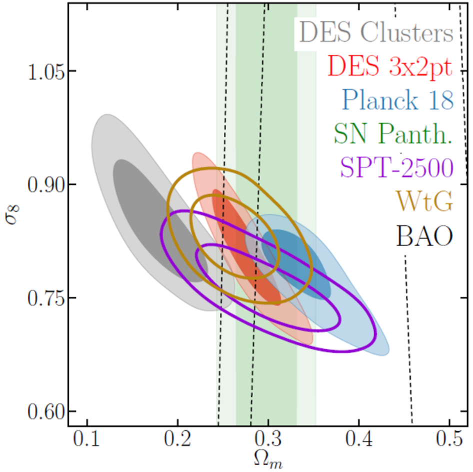
DES uses redMaPPer algorithm to find clusters.

Count clusters in bins of optical richness (+redshift), model selection function using simulations and test on SDSS (Costanzi+'18).

DES et al. 2020: combine number counts with mass calibration using weak lensing on small and large scales (McClintock,Varga+'18).

DES Clusters are contained in the volume probed by **DES 3x2pt** (galaxy clustering + weak lensing), should be highly correlated!

DES et al. '20



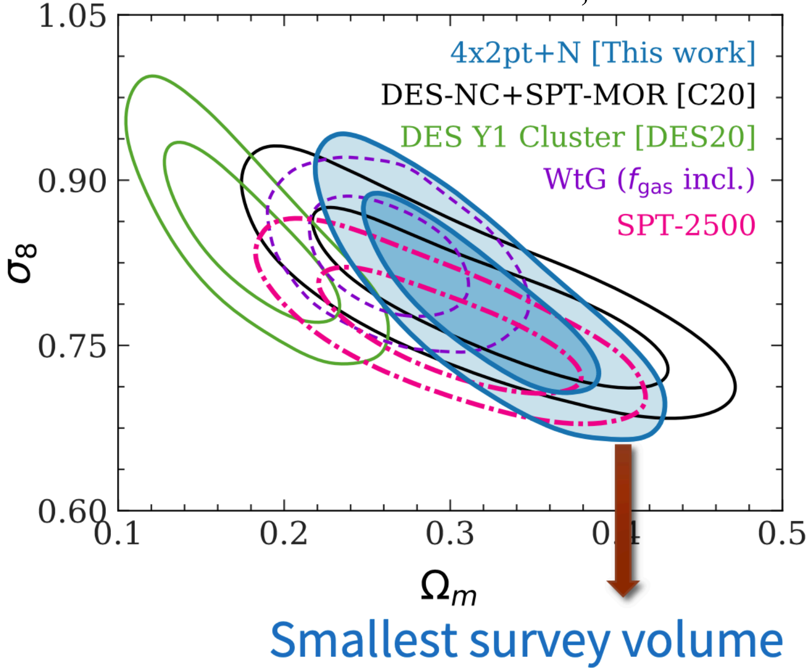
# DES-Y1 Cluster Cosmology

Contrast **DES-Y1 cluster lensing cosmology result** (weak lensing mass calibration) with different cluster selections and mass calibrations:

**4x2pt+N**: same sample, mass calibration from large-scale clustering – marginalized over wide range of selection bias

**DES-NC+SPT+MOR**: high-mass Y1 clusters, mass calibration from SPT+weak lensing (Costanzi+'20)

To,Krause+'21




**Y1 cluster lensing** ↔ **DES-NC+SPT+MOR**: issue with low-mass clusters

**Y1 cluster lensing** ↔ **4x2pt+N** : issue with small-scale lensing

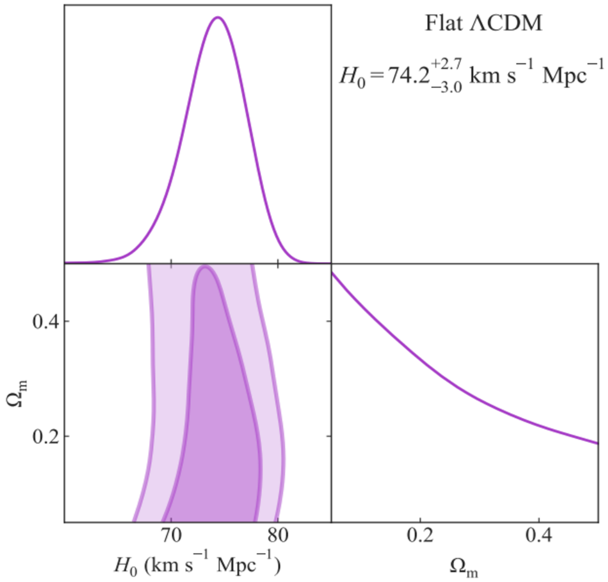
# Strong Lensing with DES

Lens System DES J0408-5354 discovered through visual search (Diehl+'14), two sets of multiple images at different redshifts.

Time-delay cosmographic analysis using external

- High-resolution imaging (Shajib+'19)
- Redshifts for lens components (Lin+'17)
- Time delays (Courbin+'18)
- Velocity dispersion for main lens (Buckley-Geer+'20)

Strong lens classification using CNNs (Jacobs+'19) trained on 250,000 simulated lenses: identified 7301 candiates, 84 'probably' or `definitely' lenses after visual inspection.




Shajib+'20

Future-looking Strong Lensing Searches:
F. Courbin: Search for galaxy-scale strong lenses in DES and CFIS
R. Canameras: Identifying strong gravitational lenses in current and future large-scale imaging surveys

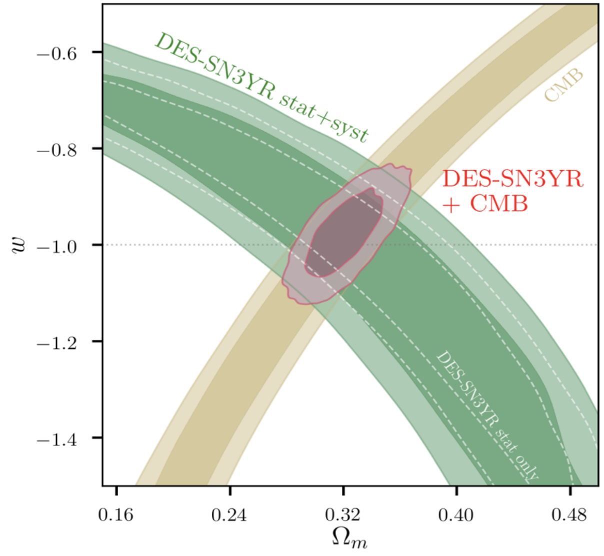
# Time-Domain Science: Supernovae

DES-SN fields imaged with ~1 week cadence.
SN candidates for spectroscopic follow-up from difference imaging pipeline (Kessler+'15) and RF `autoScan` classifier (trained on early DES data, Goldstein+'15).

Final DES-Y5 SN Ia cosmology results will use 1800 photometrically-typed SNIa (Vincenci+'21) whose host galaxies have spectroscopic redshifts.

Stage-IV: Orders of magnitude more transients + variable objects, requires more robust classifiers and follow-up criteria - PLAsTiCC Photometric LSST Astronomical Time-Series Classification Challenge (Kessler+'19,Hlozek+'20)

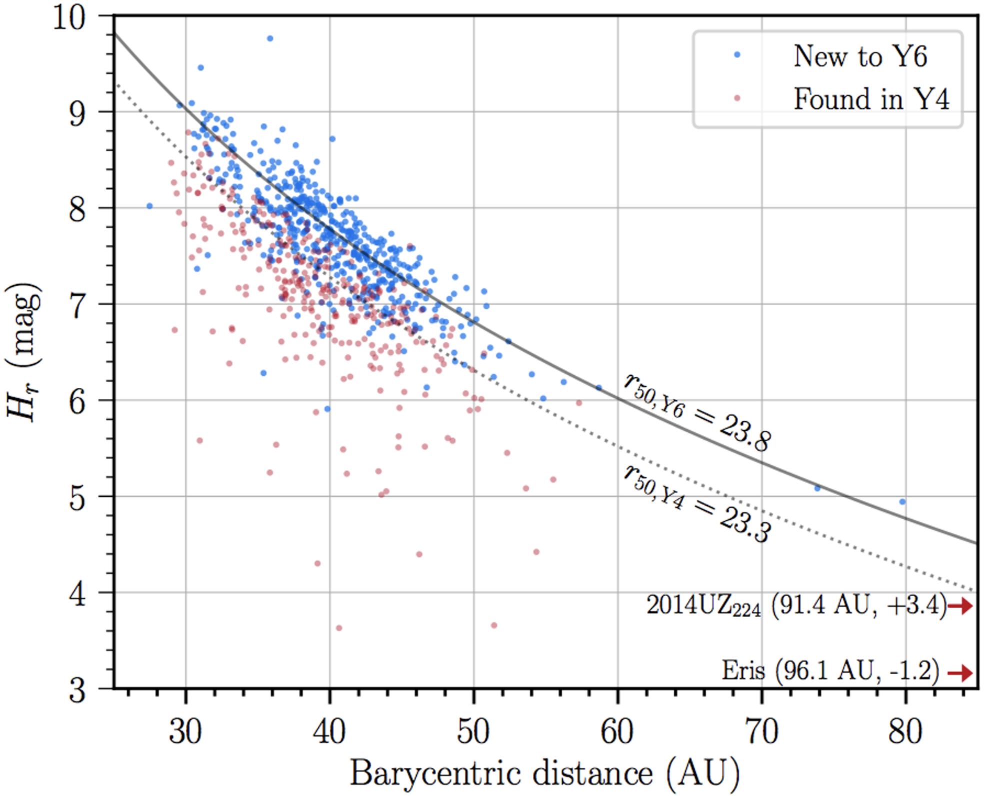
DES et al. (2019)



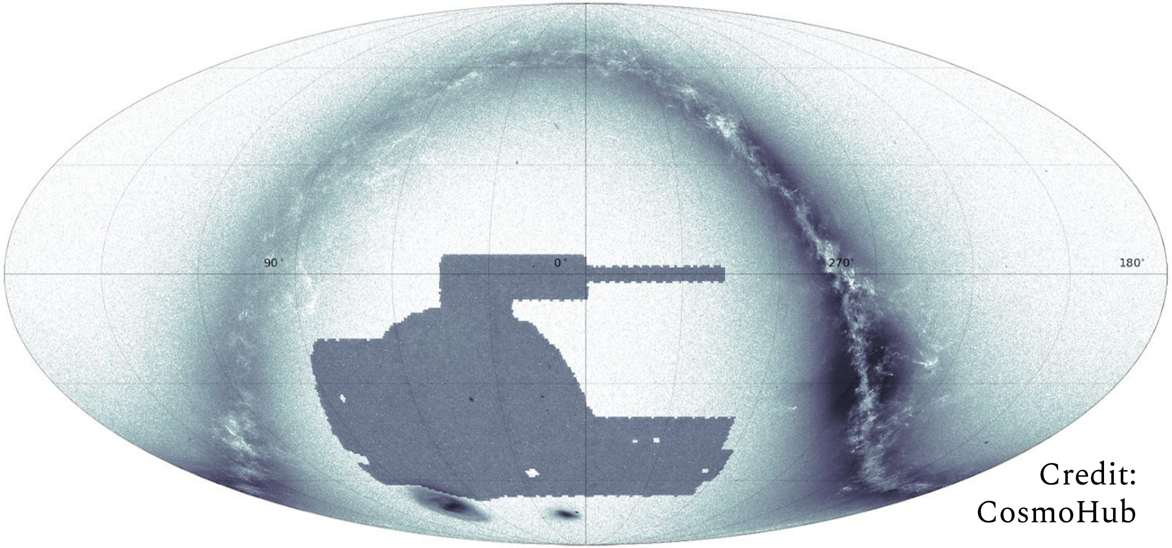
# Time-Domain Science: Solar System

- Method:
  - Look for moving objects by comparing multiple exposures at the same sky
  - Orbit linking and S/N selection
- Catalog of 815 TNOs
- Comet C/2014 UN271 (Bernardinelli-Bernstein)
  - Largest well-studied comet to date
  - Most distant comet to be discovered on its incoming path, will make its closest approach to Earth in 2031
  - Informs early migration scenarios for large objects in the Oort Cloud and their connection with the Solar System

Bernardinelli, Bernstein et al. (2021)

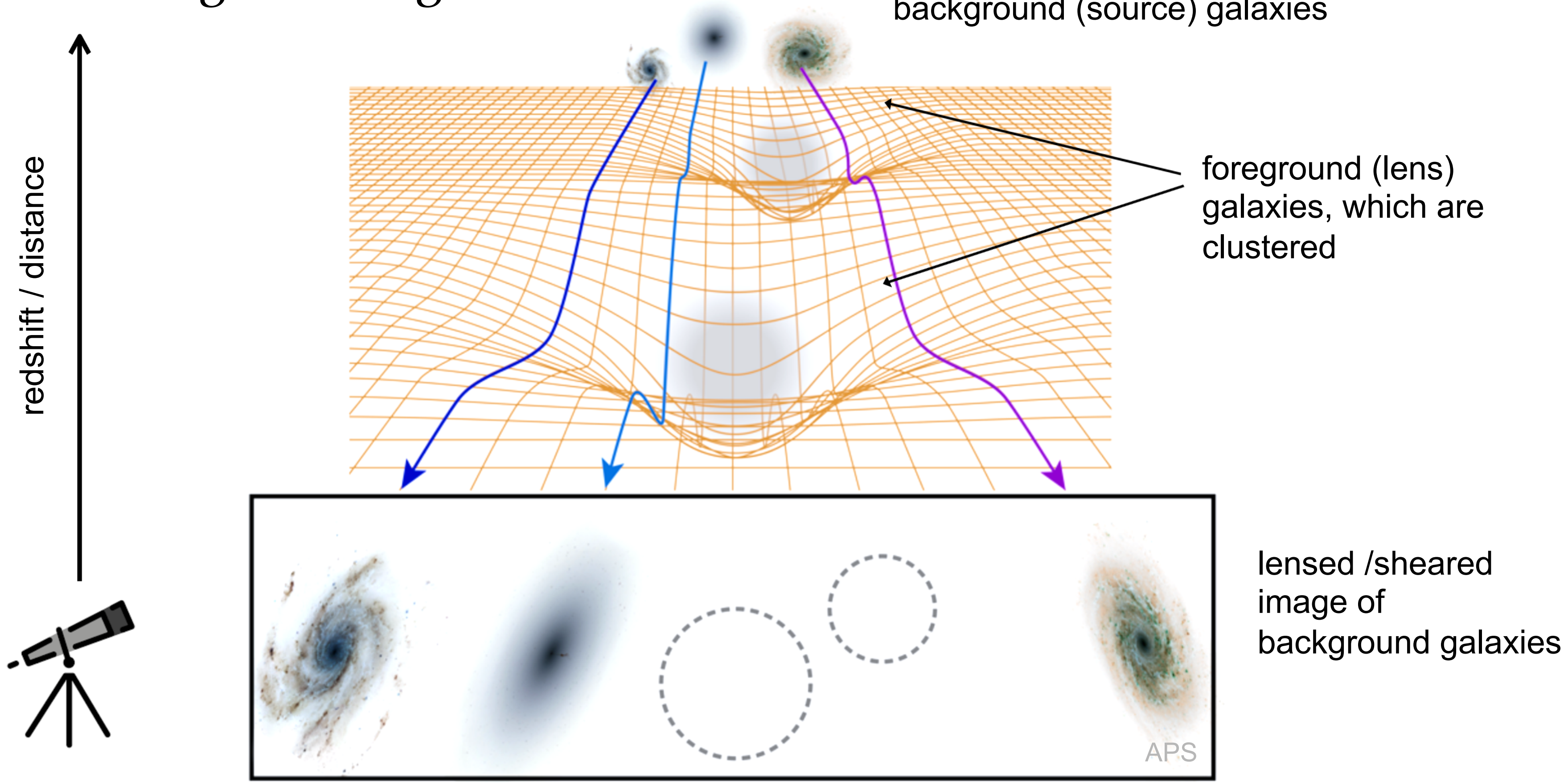


# Systematics Calibration for 3x2pt Cosmology




Credit:
CosmoHub

# Observing the large scale structure

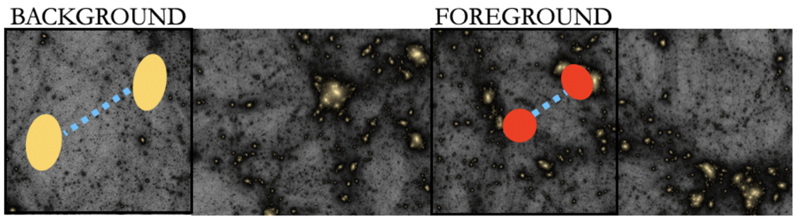


# *3x2pt* cosmology

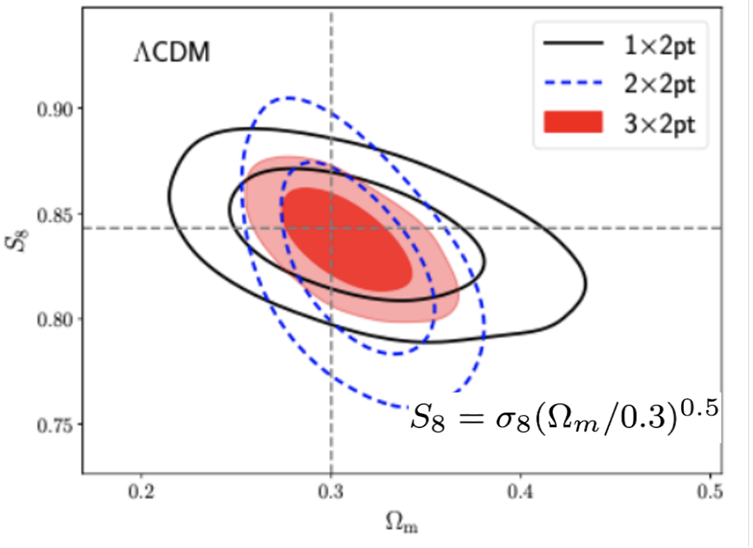
Cosmic Shear : shape-shape

*2x2pt*

- Galaxy Clustering : position-position
- Galaxy-Galaxy Lensing : position-shape

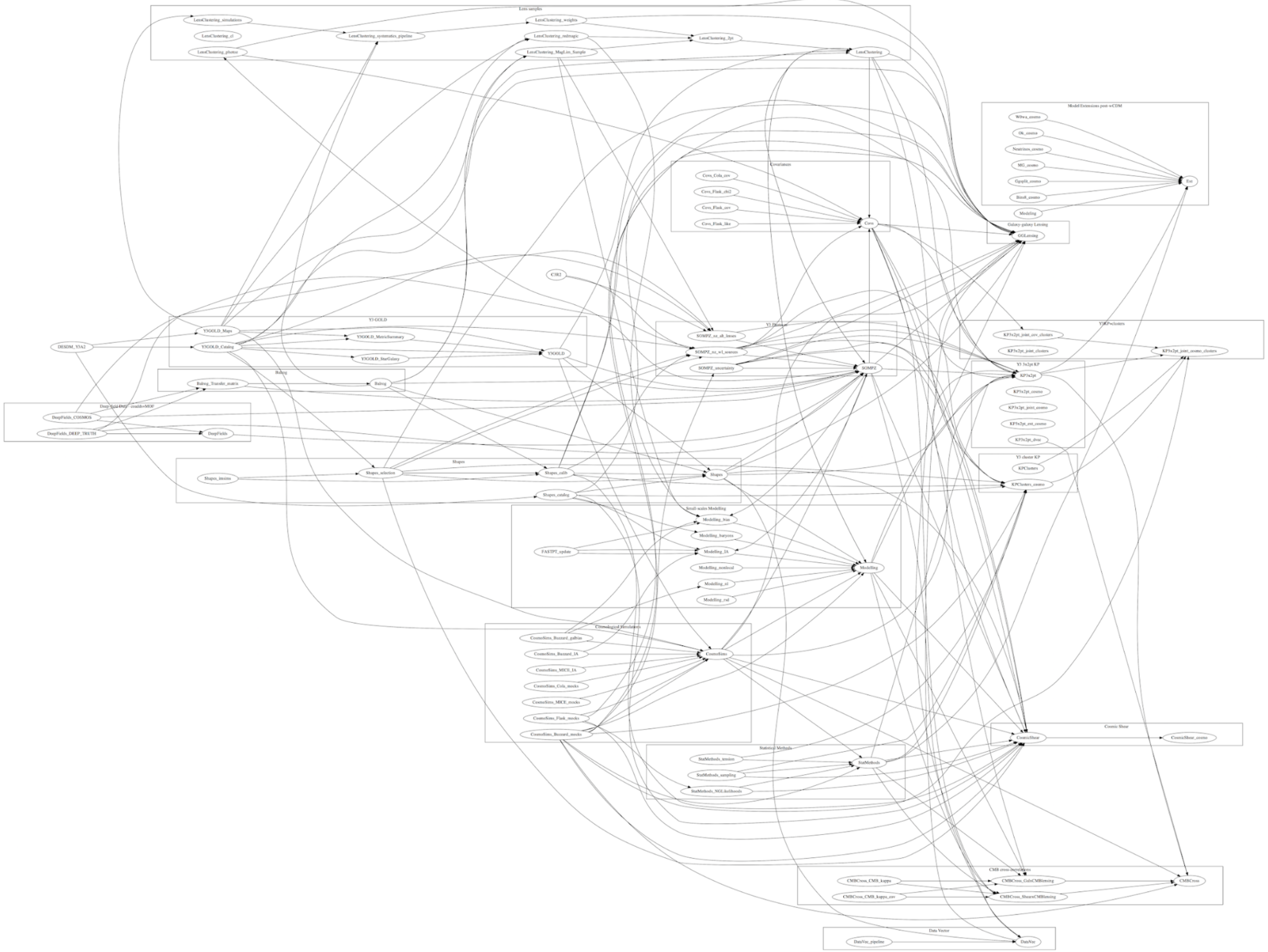



redshift




A joint analysis maximises the cosmological information and robustly constrains astrophysical & observational systematic priors in the analysis!

# **Dark Energy Survey Year 3 Analysis.** How it started...



# **Dark Energy Survey Year 3 Analysis.** How it started...

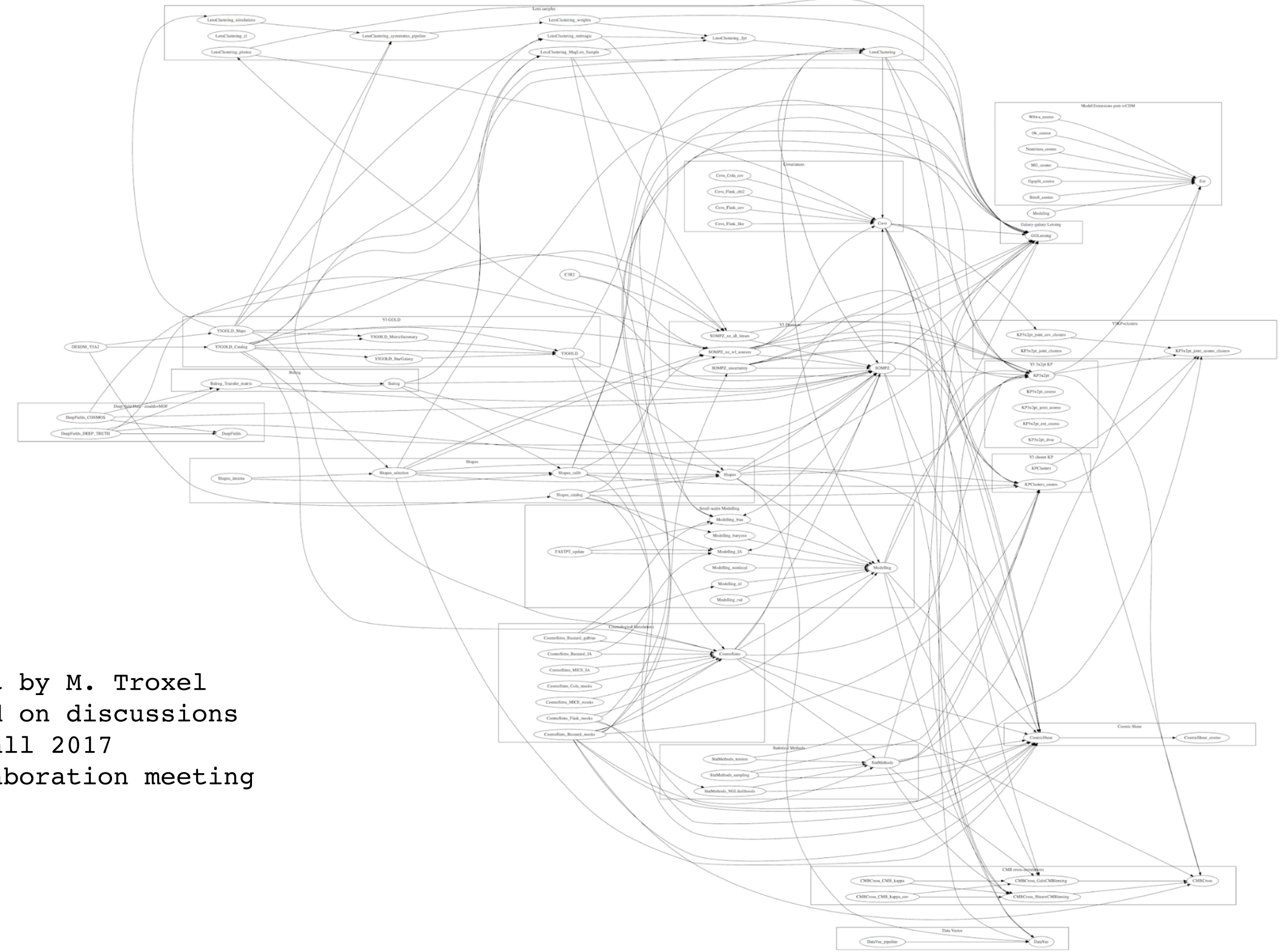
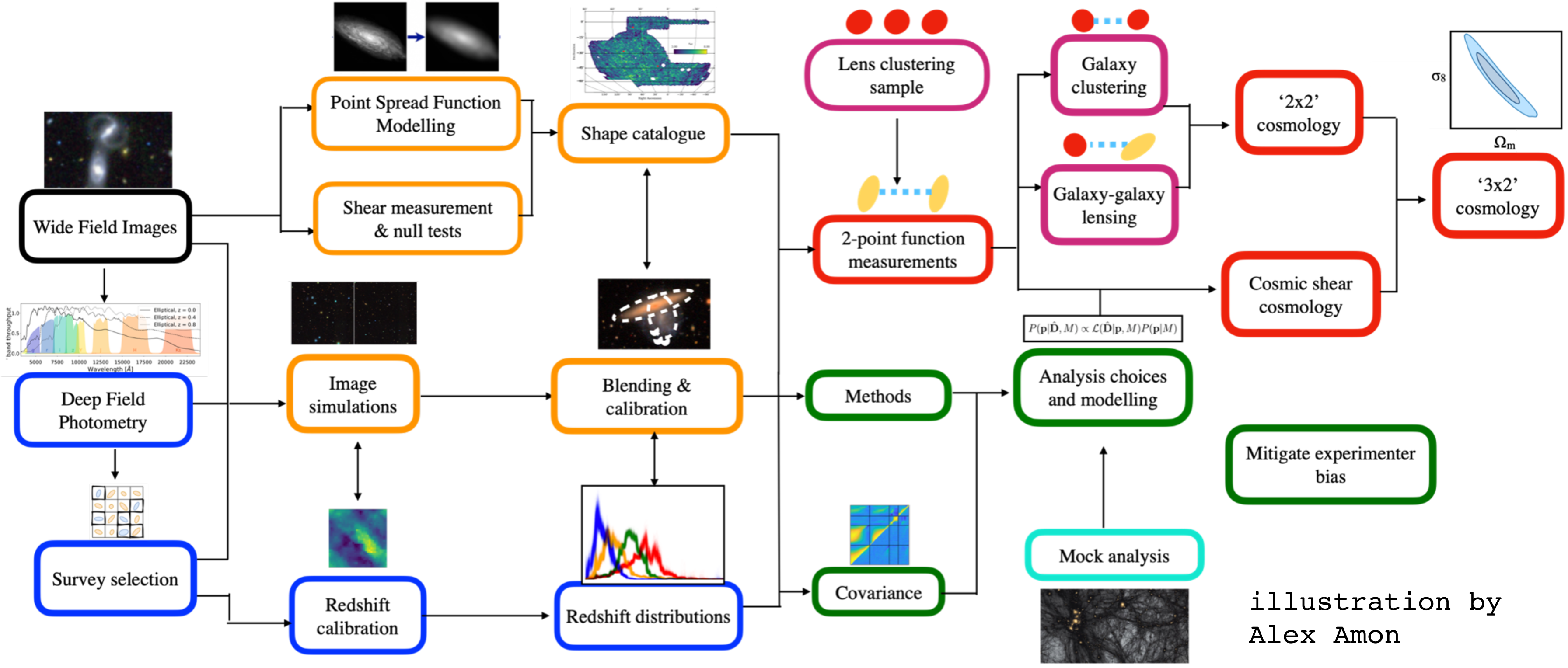


chart by M. Troxel
based on discussions
at fall 2017
collaboration meeting

# DES Year 3: pixels to cosmology




Redshifts —— Shapes —— Clustering —— Simulations —— Theory —— Results

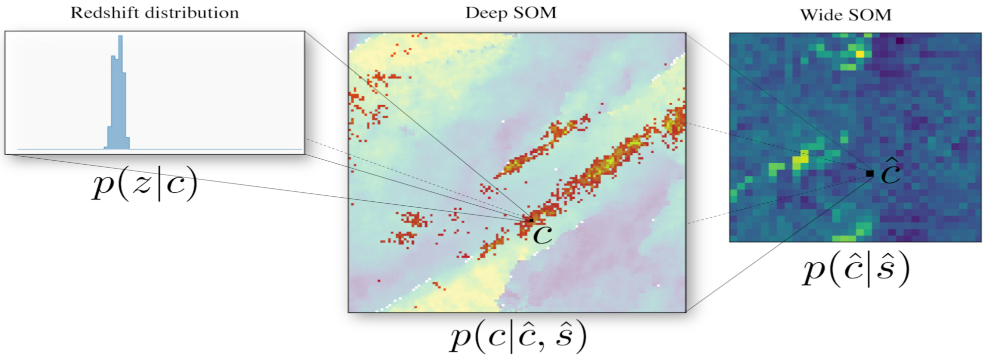
# **Dark Energy Survey Year 3 results.** List of key and supporting papers

1. "Blinding Multi-probe Cosmological Experiments" J. Muir, G. M. Bernstein, D. Huterer et al., arXiv: 1911.05929, MNRAS 494 (2020) 4454
2. "Photometric Data Set for Cosmology", I. Sevilla-Noarbe, K. Bechtol, M. Carrasco Kind et al., arXiv:2011.03407, ApJS 254 (2021) 24
3. "Weak Lensing Shape Catalogue", M. Gatti, E. Sheldon, A. Amon et al., arXiv:2011.03408, MNRAS 504 (2021) 4312
4. "Point Spread Function Modelling", M. Jarvis, G. M. Bernstein, A. Amon et al., arXiv:2011.03409, MNRAS 501 (2021) 1282
5. "Measuring the Survey Transfer Function with Balrog", S. Everett, B. Yanny, N. Kuropatkin et al., arXiv:2012.12825
6. "Deep Field Optical + Near-Infrared Images and Catalogue", W. Hartley, A. Choi, A. Amon et al., arXiv:2012.12824
7. "Blending Shear and Redshift Biases in Image Simulations", N. MacCrann, M. R. Becker, J. McCullough et al., arXiv:2012.08567
8. "Redshift Calibration of the Weak Lensing Source Galaxies", J. Myles, A. Alarcon, A. Amon et al., arXiv:2012.08566
9. "Redshift Calibration of the MagLim Lens Sample using Self-Organizing Maps and Clustering Redshifts", G. Giannini et al., in prep.
10. "Clustering Redshifts – Calibration of the Weak Lensing Source Redshift Distributions with redMaGiC and BOSS/eBOSS", M. Gatti, G. Giannini, et al., arXiv:2012.08569
11. "Calibration of Lens Sample Redshift Distributions using Clustering Redshifts with BOSS/eBOSS", R. Cawthon et al. arXiv:2012.12826
12. "Phenotypic Redshifts with SOMs: a Novel Method to Characterize Redshift Distributions of Source Galaxies for Weak Lensing Analysis" R. Buchs, C.Davis, D. Gruen et al. arXiv:1901.05005, MNRAS 489 (2019) 820
13. "Marginalising over Redshift Distribution Uncertainty in Weak Lensing Experiments", J. Cordero, I. Harrison et al., in prep.
14. "Exploiting Small-Scale Information using Lensing Ratios", C. Sánchez, J. Prat et al., rXiv:2105.13542
15. "Cosmology from Combined Galaxy Clustering and Lensing - Validation on Cosmological Simulations", J. de Rose et al., arXiv:2105.13547
16. "Unbiased fast sampling of cosmological posterior distributions", P. Lemos et al., in prep.
17. "Assessing Tension Metrics with DES and Planck Data", P. Lemos, M. Raveri, A. Campos et al., arXiv:2012.09554
18. "Dark Energy Survey Internal Consistency Tests of the Joint Cosmological Probe Analysis with Posterior Predictive Distributions", C. Doux, E. Baxter, P. Lemos et al. arXiv:2011.03410, MNRAS 503 (2021) 2688
19. "Covariance Modelling and its Impact on Parameter Estimation and Quality of Fit", O. Friedrich, F. Andrade-Oliveira, H. Camacho et al., arXiv:2012.08568
20. "Multi-Probe Modeling Strategy and Validation", E. Krause et al., arXiv:2105.13548
21. "Curved-Sky Weak Lensing Map Reconstruction", N. Jeffrey, M. Gatti, C. Chang et al., arXiv:2105.135439
22. "Galaxy Clustering and Systematics Treatment for Lens Galaxy Samples", M.Rodríguez-Monroy, N. Weaverdyck, J. Elvin-Poole, M. Crocce et al., arXiv:2105.13540
23. "Optimizing the Lens Sample in Combined Galaxy Clustering and Galaxy-Galaxy Lensing Analysis", A. Porredon, M. Crocce et al., arXiv:2011.03411 PhRvD 103 (2021) 043503
24. "High-Precision Measurement and Modeling of Galaxy-Galaxy Lensing", J. Prat, J. Blazek, C. Sánchez et al., arXiv:2105.13541
25. "Constraints on Cosmological Parameters and Galaxy Bias Models from Galaxy Clustering and Galaxy-Galaxy Lensing using the redMaGiC Sample", S. Pandey et al., arXiv:2105.13545
26. "Cosmological Constraints from Galaxy Clustering and Galaxy-Galaxy Lensing using the Maglim Lens Sample" A. Porredon et al., arXiv:2105.13546
27. "Cosmology from Cosmic Shear and Robustness to Data Calibration", A. Amon, D. Gruen, M. A. Troxel et al., rXiv:2105.13543
28. "Cosmology from Cosmic Shear and Robustness to Modeling Assumptions", L. Secco, S. Samuroff et al., rXiv:2105.13544
29. "Magnification modeling and impact on cosmological constraints from galaxy clustering and galaxy-galaxy lensing", J. Elvin-Poole, N. MacCrann et al., in prep.
30. "Cosmological Constraints from Galaxy Clustering and Weak Lensing" The DES Collaboration arXiv:2105.13549

# Photometric redshift characterization

Imaging surveys need an accurate characterization of their redshift distributions, for both lens and source galaxies, in order to yield unbiased cosmological constraints.

Self-organizing maps (SOM, Kohonen'82): unsupervised learning technique, increasingly used for photometric redshift characterization (Masters+'15,'17,'19; Buchs, Davis+'19, Myles, Alarcon+'21; Wright+'20).




Buchs,Davis+'21

# DES Year 3 redshift characterization

For the redshift characterization of lensing sources, we use three independent sources of information:

**Photometry (colors): SOMPZ**
Myles, Alarcon+ 2021

**Clustering (positions): WZ**
Gatti, Giannini+ 2021

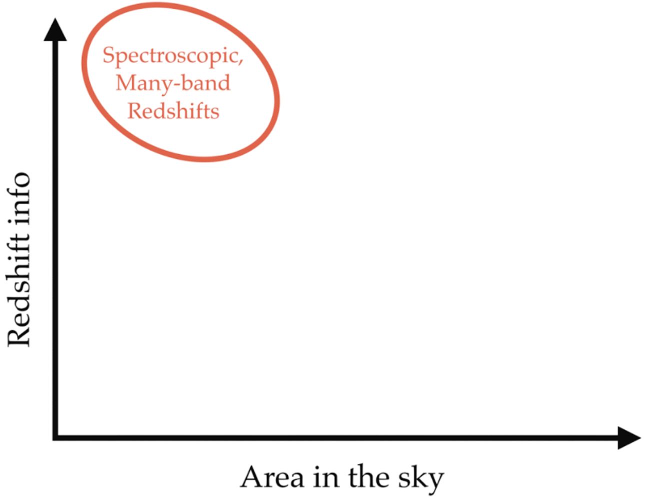
**Lensing (shapes): Shear Ratio (SR)**
Sánchez, Prat+ 2021

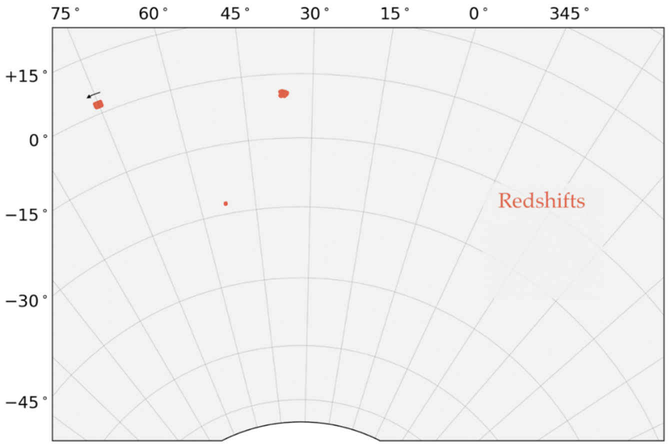
DF: **Hartley, Choi,** et al. (2021)
Balrog: **Everett** et al. (2021)
SOMPZ: **Myles, Alarcon,** et al. (2021)

# SOMPZ: Redshift distributions from galaxy colors

SOMPZ is a Bayesian redshift scheme to use the DES deep fields as an intermediate step between small redshift samples and the wide-field DES sample.

We use artificial galaxy injections (Balrog) to characterize how deep-field galaxies would look like in the noisier wide-field conditions.



DF: **Hartley, Choi,** et al. (2021)
Balrog: **Everett** et al. (2021)
SOMPZ: **Myles, Alarcon,** et al. (2021)

# SOMPZ: Redshift distributions from galaxy colors

To characterize the deep and wide photometric spaces, we create two different SOMs. The Bayesian formalism allows us to connect the two, and to separate different pieces.

Likelihood of deep and wide-field color

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

$$c = \begin{cases} \text{Deep SOM cell index:} \\ (u,g,r,i,z,J,H,K) \end{cases}$$

$$\hat{c} = \begin{cases} \text{Wide SOM cell index:} \\ (r,i,z) \end{cases}$$

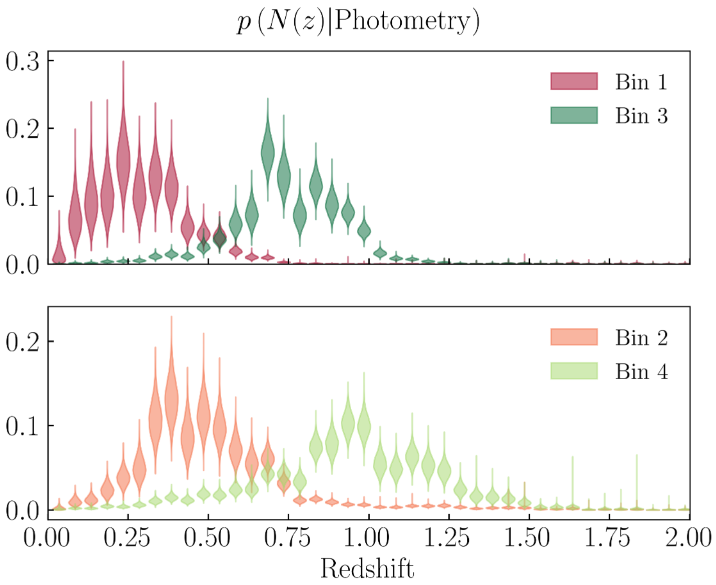
$\hat{s}$ = weak lensing sample selection

$\hat{b}$ = tomographic bin selection

$z$ = redshift bin index

Redshift at a given deep photometric color

Probabilistic mapping between deep and wide photometric colors



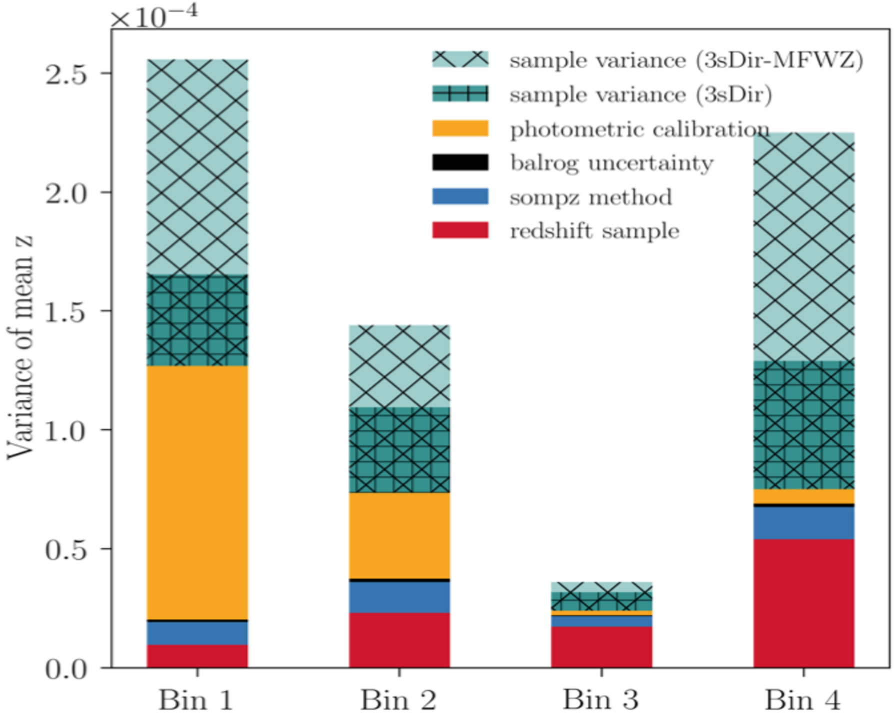
Hyperrank: **Cordero, Harrison** et al. (2021)
SOMPZ: **Myles, Alarcon,** et al. (2021)

# SOMPZ: Redshift distributions from galaxy colors

We separate source galaxies into four redshift bins, and produce realizations of their redshift distributions.

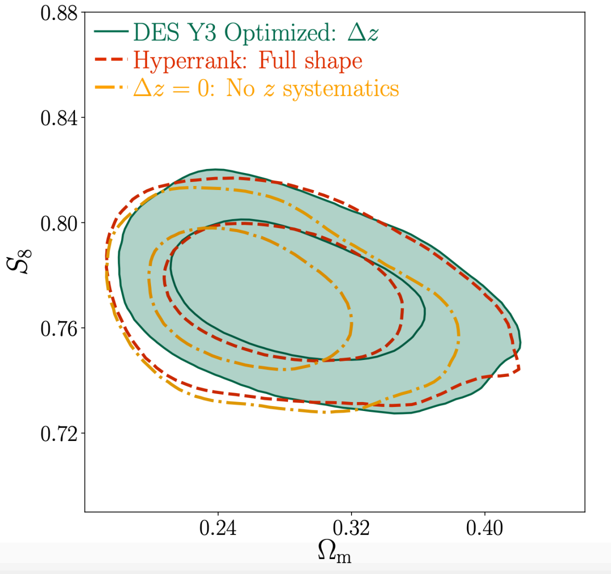
Such realizations include several sources of uncertainty coming from:

- Redshift samples.
- Shot noise and sample variance.
- Photometric calibrations.
- Transfer function.
- Assumptions in the method.

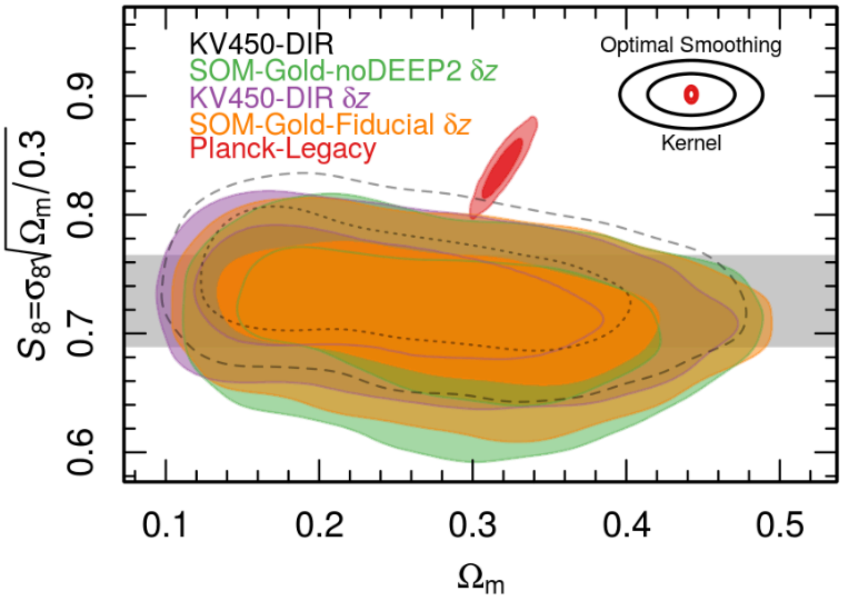


# Impact of Photometric Redshift Modeling on Cosmology

**DES-Y3** `Amon+'21`



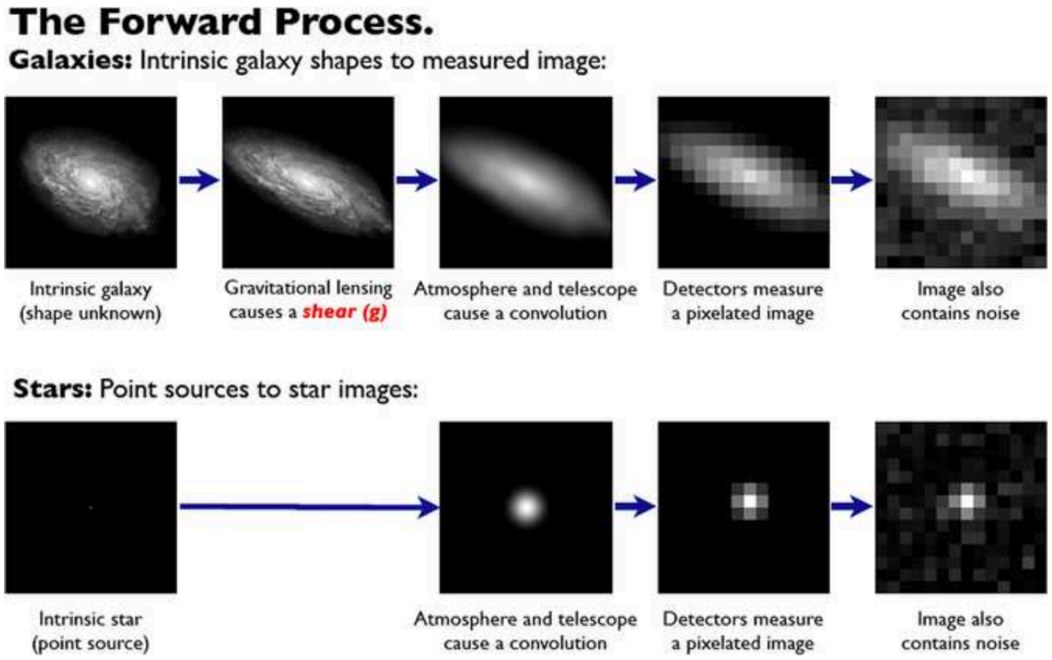

**KiDS-Viking 450** `Wright+'20`




A. Wright: Machine Learning Calibration of Cosmic Shear Redshift Distributions

A. Malz: Machine learning for experimental design: stress-testing redshift uncertainty quantification and propagation with Redshift Assessment Infrastructure Layers (RAIL)

# Galaxy shapes encode the Universe and more...




Bridle+2008

To model the point-spread function (PSF) on stars, DES Y3 uses Piff: PSFs In the Full Field-of-view (based on GP interpolation)

Jarvis+2021
https://github.com/rmjarvis/Piff

# Galaxy shapes measured using *Metacalibration*

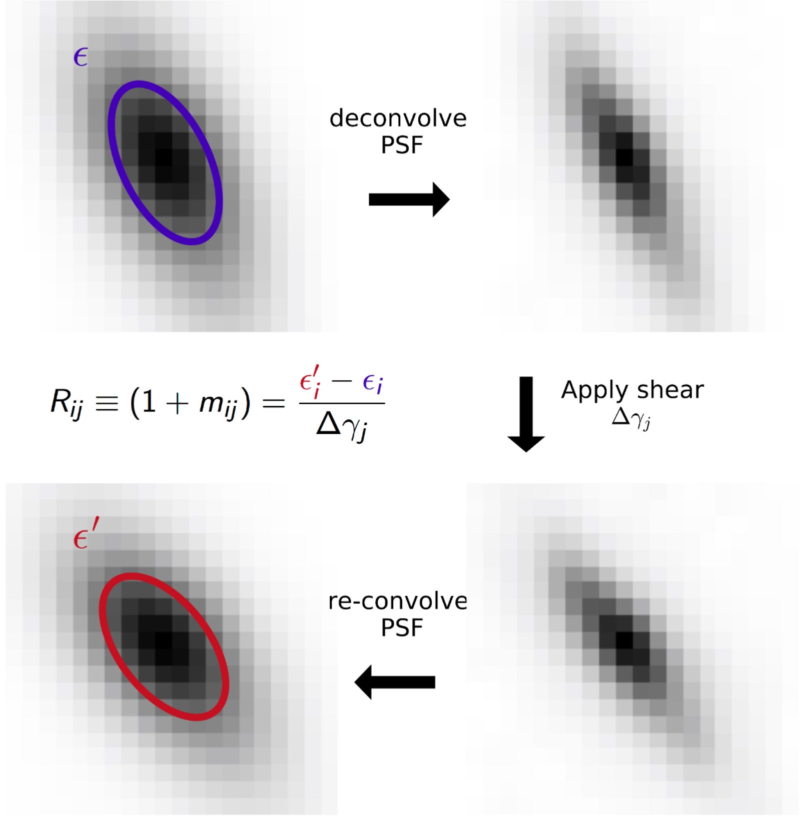



Image credit: **Niall MacCrann**

**Measure response on ellipticity estimator to artificially-applied shear**
(Huff & Mandelbaum 2017, Sheldon & Huff 2017)

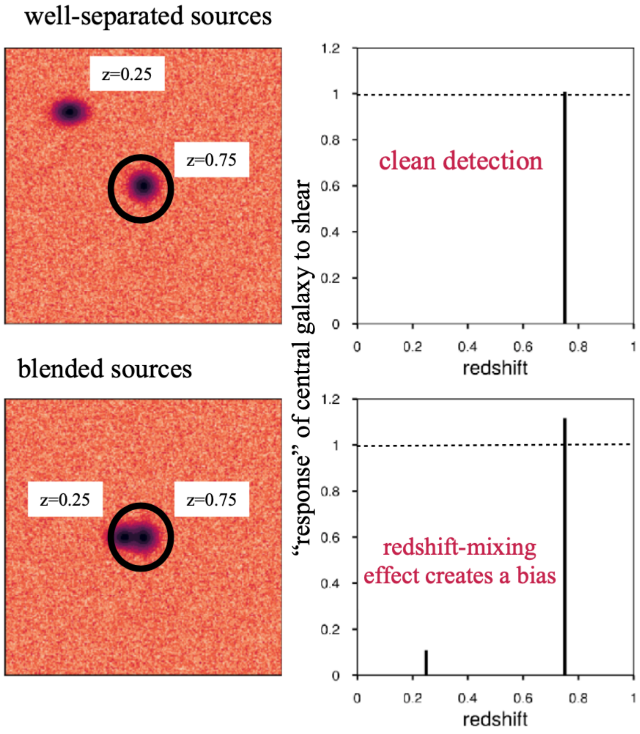
Unbiased in limit of:

- weak shear
- isolated galaxy images
- perfect knowledge of PSF

Use **simulations to calibrate bias** from, e.g., **blending** of galaxy images

# Image Simulations for Blending Calibration

- `GalSim` (Rowe+'15) image simulations that are matched to DES-Y3 data
- Detected that measured shapes "respond" to the shear of galaxies at other redshifts.
- Modelled and accounted for the impact of blending as a redshift-mixing effect




**MacCrann**+2021

# Calibrate shear biases with image simulations

*lensing shear*

$$\bar{\epsilon}^{\mathrm{obs}} = (1+m)\,\bar{\gamma} + c$$

*observed ellipticity* *multiplicative error* *additive error*

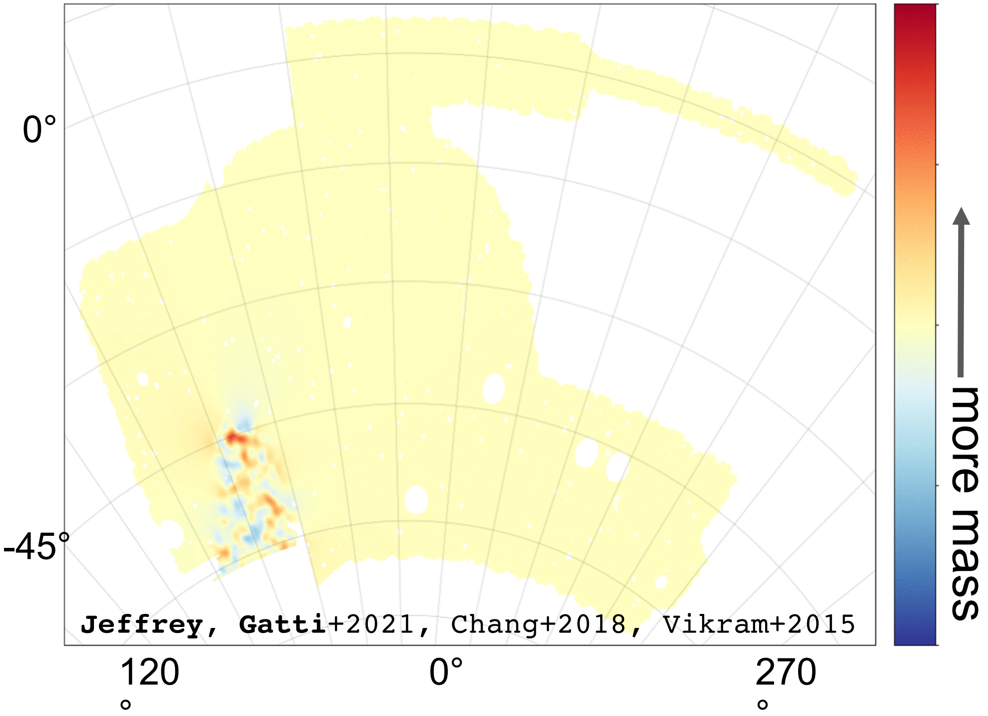
- Few percent multiplicative biases **due to blending** (-1.5 to -4% depending on redshift bin)
- Joint impact of blending on shear and photo-z characterized by **effective redshift distribution**

$$\bar{\epsilon}^{\mathrm{obs}} = \int \mathrm{d}z\, n_{\gamma}(z)\gamma^{\mathrm{true}}(z) + c$$

MacCrann+2021

# 100.2 million galaxy shapes for DES Y3

cf. DES SV: 2-3 million shapes
DES Y1: 34.8 million




Key improvements over DES Y1:

- More accurate **PSF modeling** (Jarvis+2021)
- Improved astrometry
- Expanded suite of **null tests** (**Gatti**, Sheldon+2021)
- Calibration using realistic image simulations that characterize the impact of **blending** on both shear and redshifts (**MacCrann**+2021)

| # galaxies | $n_{eff}$ | $\sigma_e$ |
|---|---|---|
| 100 204 026 | 5.590 | 0.268 |

# Galaxy Clustering

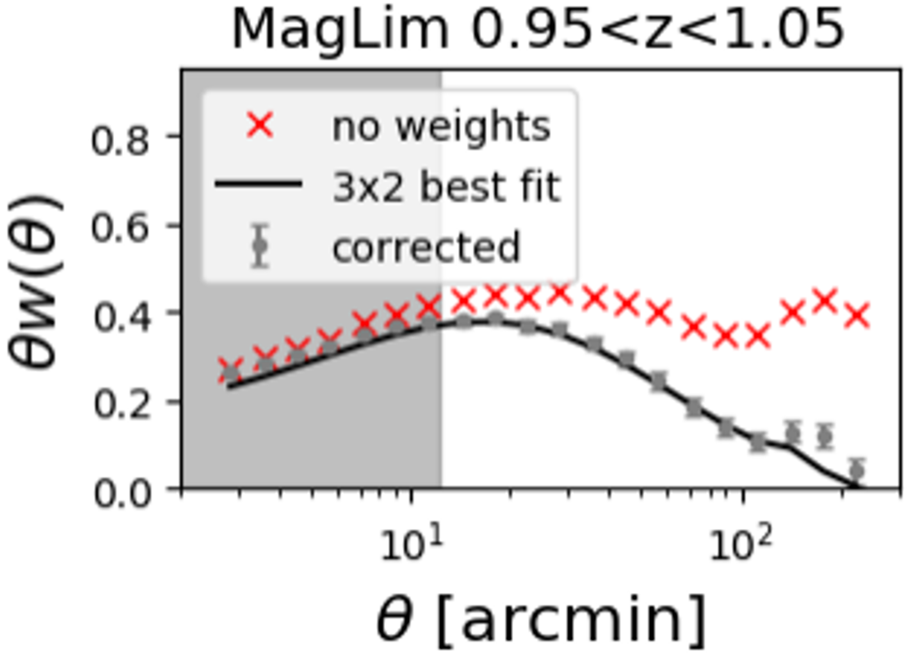
**Rodriguez-Monroy** et al. (2021)

Correlation of observed galaxy density with survey properties and astrophysical maps are removed by re-weighting galaxy sample by relation calibrated from data.

Position-Position auto-correlations analyzed on large scales

Combination with galaxy-galaxy lensing calibrates linear galaxy bias

position-position




clustering: **Rodriguez-Monroy** et al. (2021)
g-g lensing: **Prat** et al. (2021)

# LSS systematics

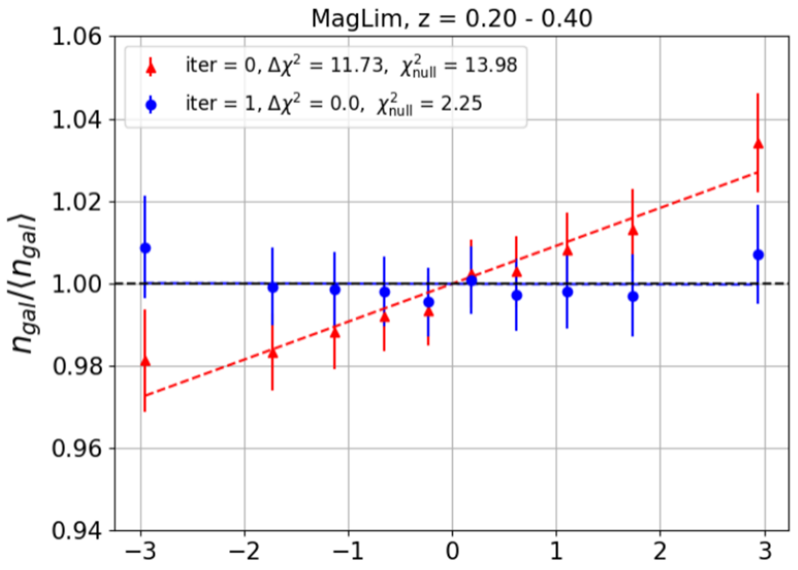
Correlation with systematics maps are removed by re-weighting galaxy sample by fitted relation

Accounts for correlation with:
**airmass, seeing, exposure time, depth, stellar density, dust, sky brightness, calibration residuals**

**Example (right):** correlation with a PCA of the above survey property maps

Correct with two template based methods:

- **Iterative systematics decontamination (ISD)** (**Elvin-Poole** et al 2017 **Rodriguez-Monroy** et al 2021)
- **Elastic Net (ENET)** (**Weaverdyck** et al 2020)




**Linear combination of survey maps**

**Rodriguez-Monroy** et al. (2021)

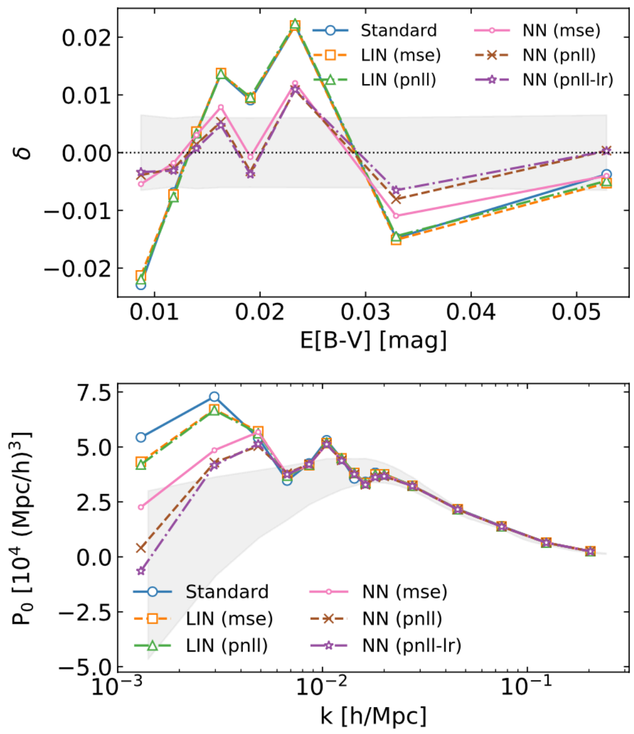
# Beyond Linear Systematics Mitigation (eBOSS)

So far, considered only linear effect of foreground/observing systematics on galaxy density.

Rezaie+'20,'21 validated FCNN for non-linear weights of imaging systematics affecting eBOSS ELGs/quasars. Randomly split footprint into 60/20/20 training/validation/testing.

Check mean density as a function of Galactic extinction against expected variance from **`EZmocks`** (Zhao+'21) without systematics.

Notable effect on low-k power spectrum monopole.




**Rezaie** et al. (2021)

# DES LSS systematics validation

## Systematic mitigation method was validated on simulations

Clustering residuals from:

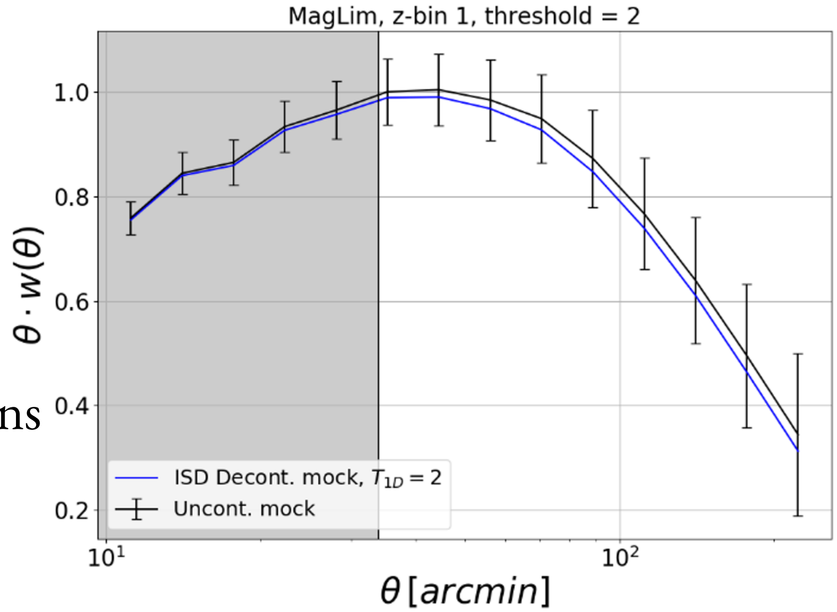
- Over-correction
- Method choices, incl. NN
- Template choices

all very small on log-normal mocks

+ Analytically marginalize over overcorrection bias, difference in methods and bias from simulations

Balrog Image simulations (**Everett** et al 2020)

- <10% of signal , consistent with zero




**Rodriguez-Monroy** et al. (2021)

# From 3x2pt Measurements to Cosmology Constraints

Infer parameter posterior $P(\mathbf{p}|\hat{\mathbf{D}}, M)$ within model M using Bayes' theorem

$$P(\mathbf{p}|\hat{\mathbf{D}}, M) \propto \mathcal{L}(\hat{\mathbf{D}}|\mathbf{p}, M) P(\mathbf{p}|M)$$

**Required Ingredients**

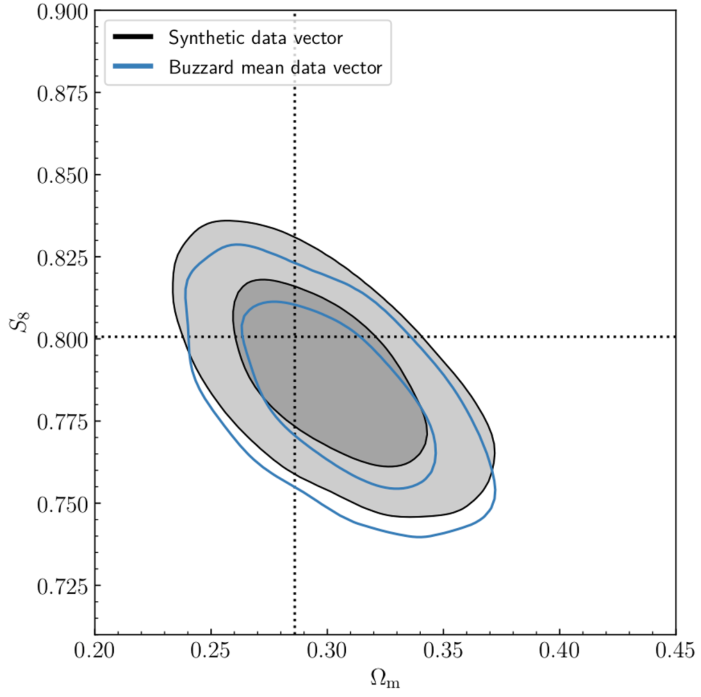
- Data likelihood $\mathcal{L}(\hat{\mathbf{D}}|\mathbf{p}, M)$ with data covariance **C**
    - **Friedrich**+2020: Gaussian data likelihood ✓, halo model covariance ✓
- Krause+ 2021: Model M with parameters **p**, and prior
- **Doux**+2021, **Lemos**, **Raveri**+2021: Criteria which measurements to combine
- Blinding scheme to minimize observer bias

# Catalog-to-Cosmology Pipeline Validation

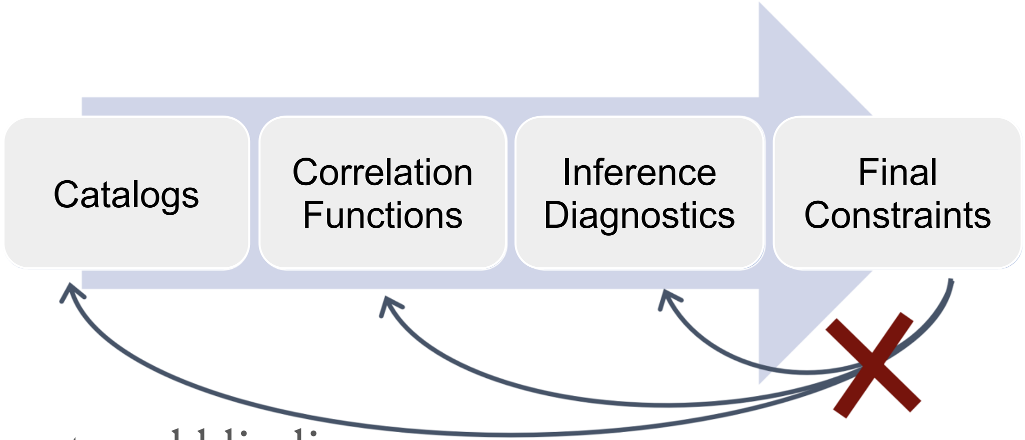
**DeRose+** 2021

Measurements on the full suite of simulations enabled us to demonstrate that our analysis was robust to a range of systematics in a complex simulated setting.

End-to-end tests, starting from redshift calibration and correlation function estimation, all the way to cosmological parameter posteriors show that our 3x2-point methodologies are unbiased at <0.3 sigma.



# Blind Analysis Protocol




Minimize observer bias through three-staged blinding

1. Catalog: rescaling of galaxy ellipticities by unknown factor
2. Correlation functions: transformation of summary statistics corresponding to unknown change in wCDM parameters **Muir+2020**
3. Parameters: shift of parameter values, axes of posterior plots by unknown offset

Unblinded parameter constraints after data vectors and modeling were frozen.
Finalized List of model tests and combinations with external data before unblinding.

# Internal consistency

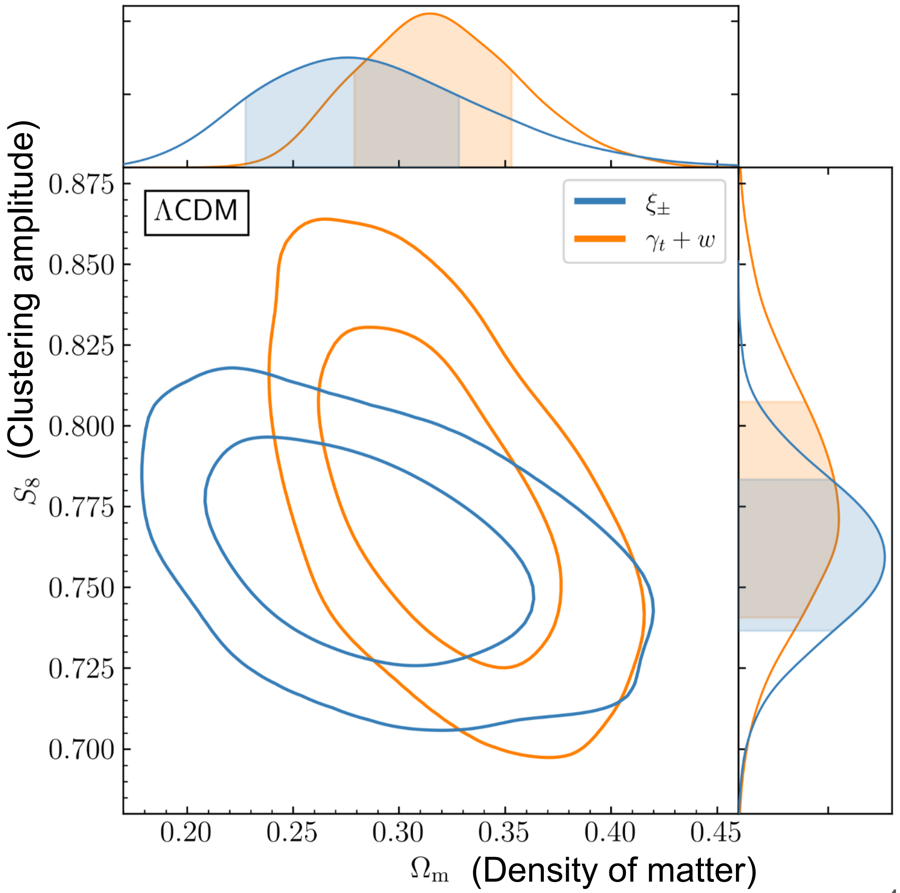
Two correlated cosmological probes:

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:

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

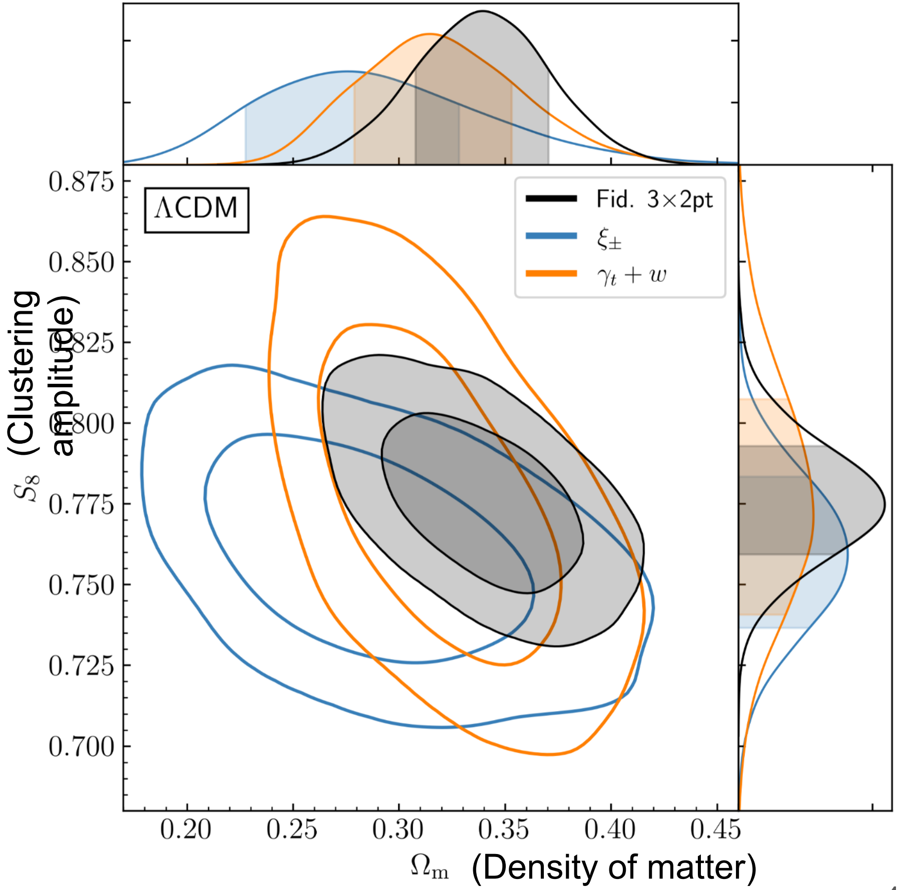
$$\Omega_m = 0.339^{+0.032}_{-0.031} \quad (0.372)$$

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

In *w*CDM:

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

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



# Conclusions – Imaging Surveys and ML

Very broad range of science enabled by imaging surveys!

Data is often more complicated than anticipated at the start of the analysis.

Accurate selection functions are crucial for correct interpretation, but rarely straightforward.

ML excels at certain classification tasks. However, training data already requires realistic selection function.

ML promises transformative speed-up for some cosmology problems that are intractable today. However, posing those problems well will often require considerable ingenuity, especially for Stage-IV accuracy requirements.