

Robust Cosmology with the Dark Energy Survey

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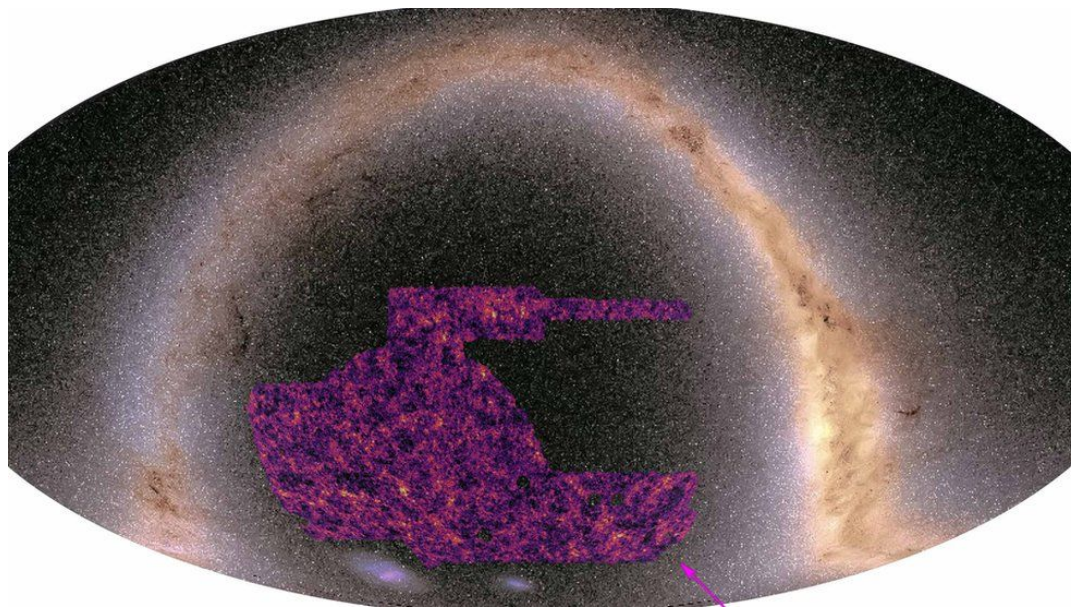
Sept 7, 2023 - CIEMAT

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Outline

- Background: Cosmology
- Large-scale structure surveys and the Dark Energy Survey
- Treating spatial systematics
- Pushing beyond the standard model with FastISMoRE
- Conclusions



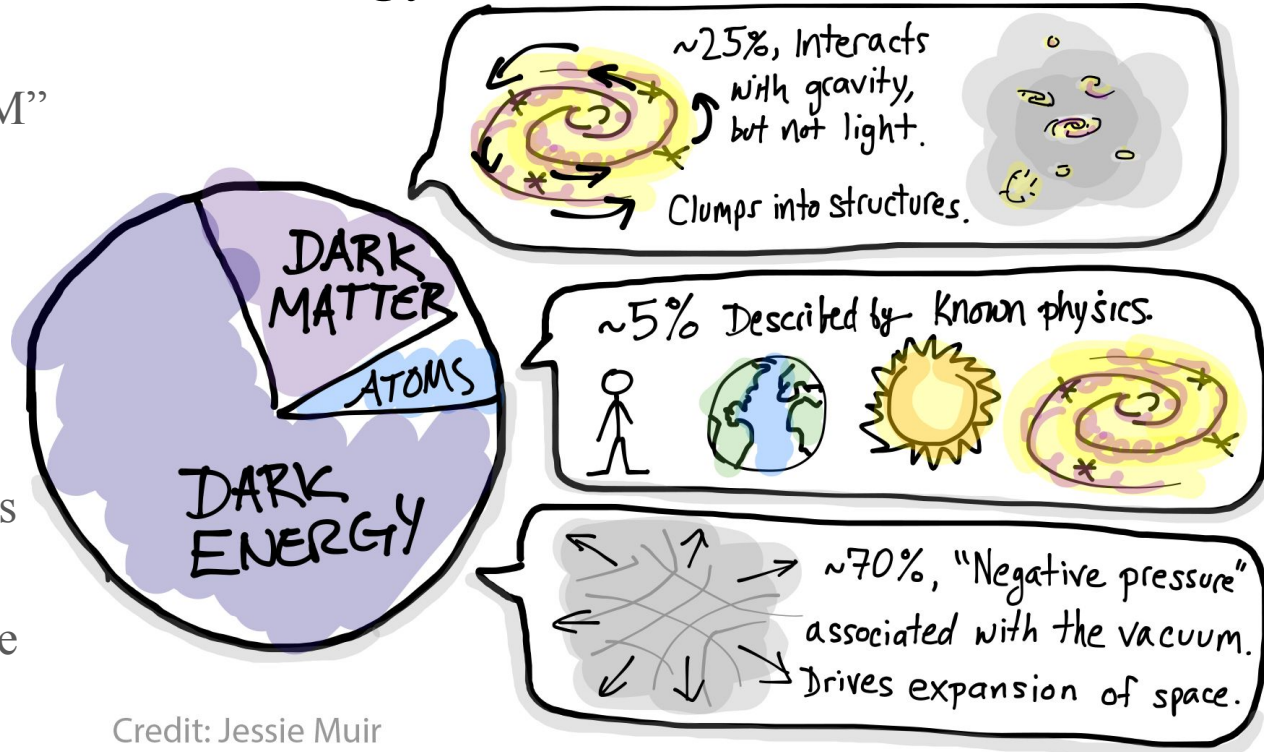
Credit: N. Jeffrey, DES Collab

Cosmology (The Big Picture)

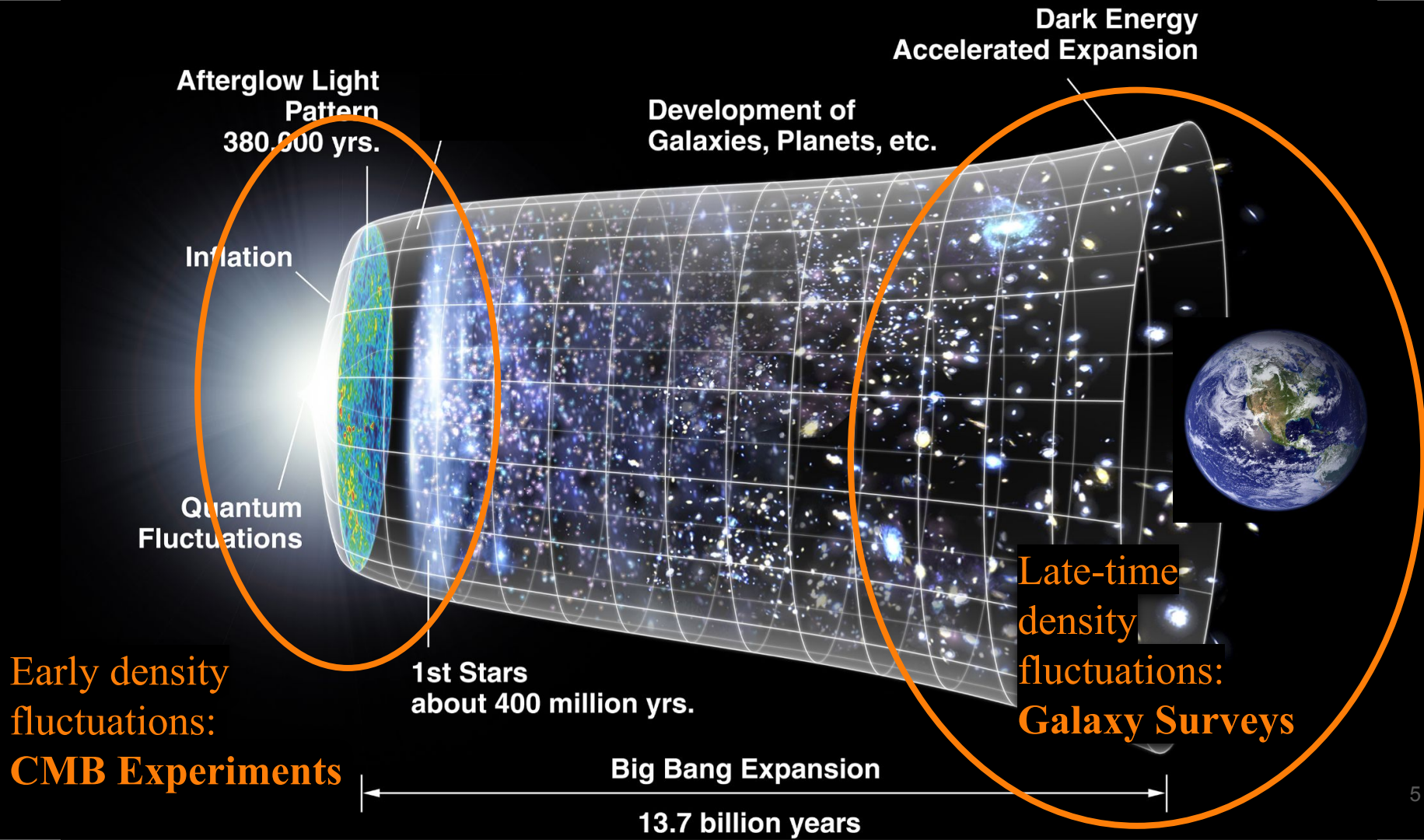
- Dynamics and evolution of the universe at largest scales
($\sim 10+$ Mpc; 30+ million light-years)
- General Relativity:
Relate space-time \leftrightarrow matter/energy content
- Basic idea:
Measure *history of expansion* and *history of structure growth*
→ constrain key cosmological parameters

“Standard Model” of cosmology

- 7 parameter “ $(\nu)\Lambda$ CDM”
- Composition (right)
+ amplitude,
spectral index,
local expansion rate
sum of neutrino masses
- Focus: “measure” these
parameters

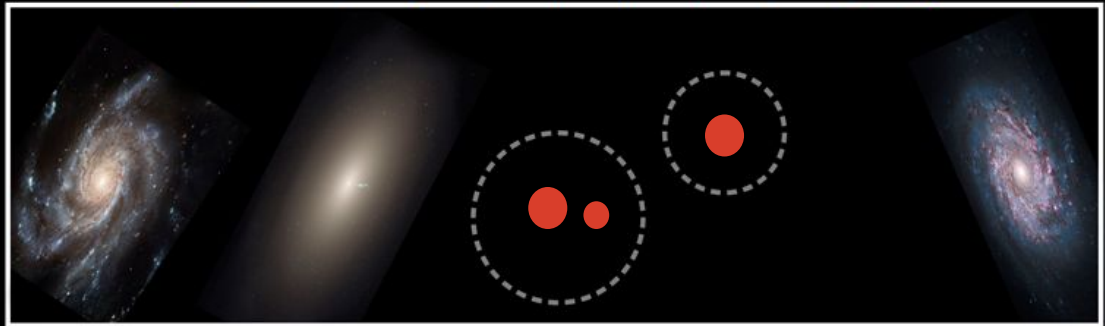
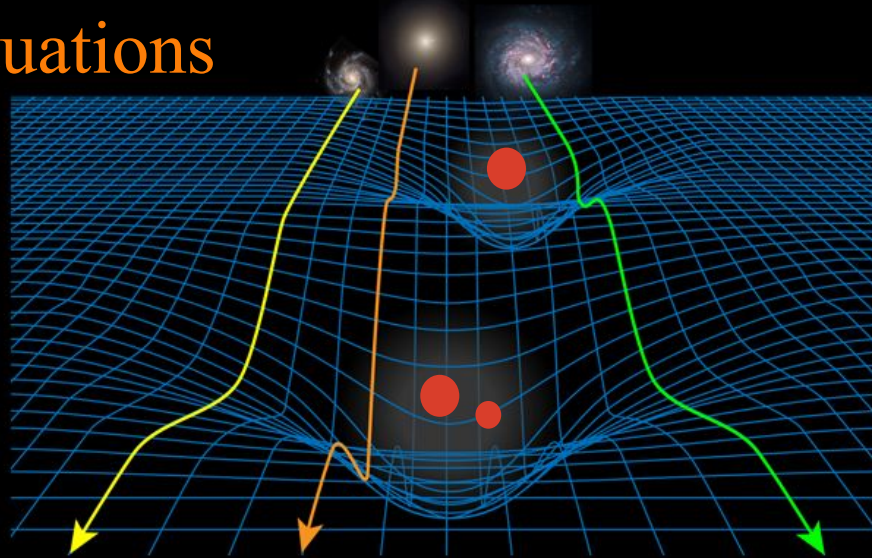


Credit: Jessie Muir

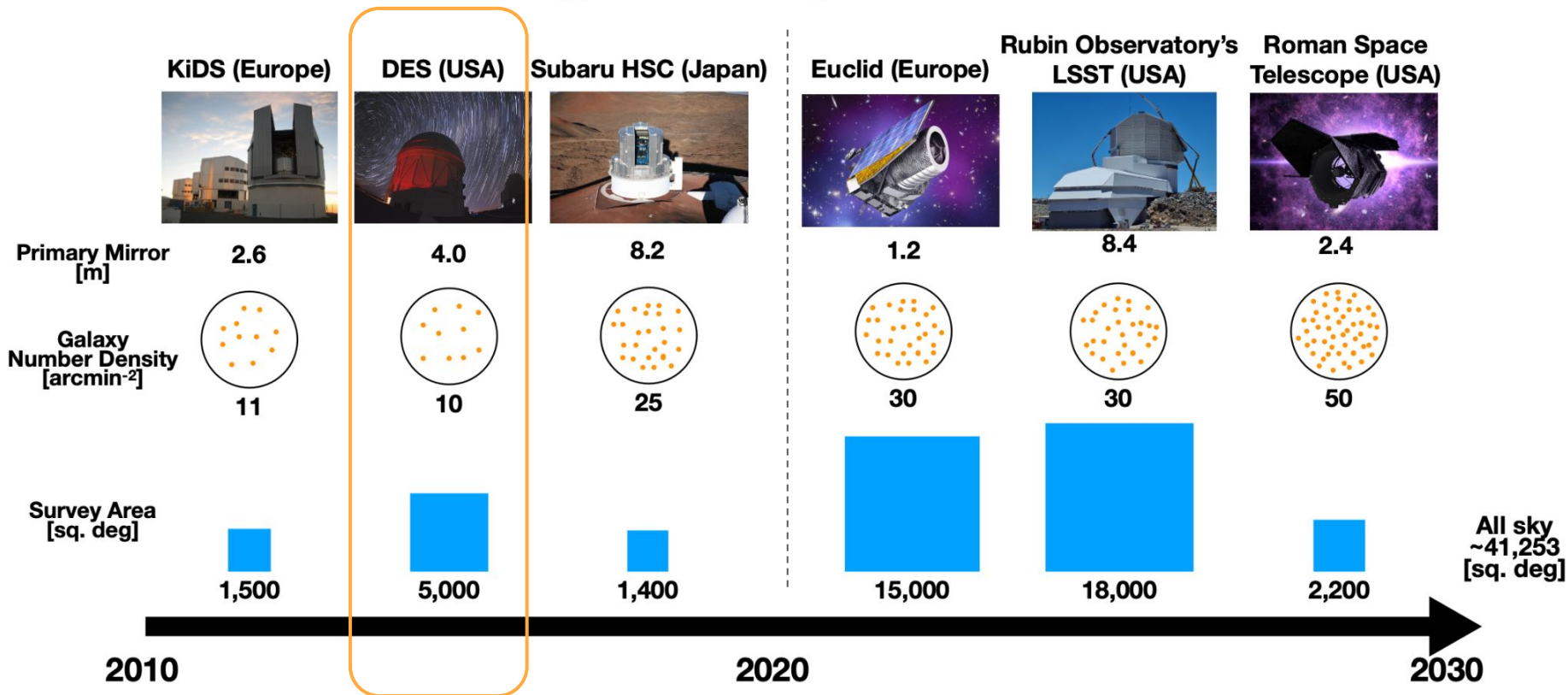


Measuring density fluctuations

- *Galaxy positions:*
trace dark matter
(DM) halos
("Galaxy clustering")
- *Galaxy shapes:*
Images warped by
intervening DM
("Weak lensing",
"Cosmic shear")

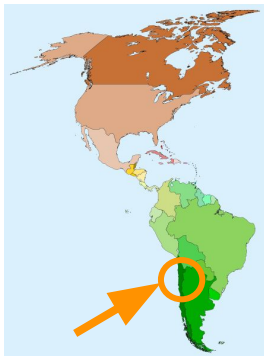


Weak Lensing Surveys: Now and Future

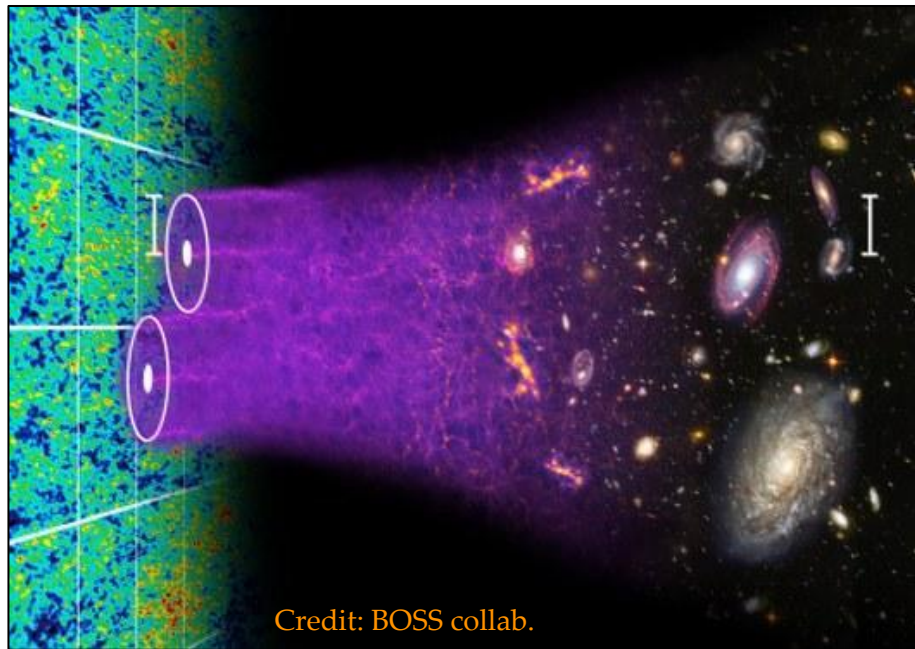


Dark Energy Survey (DES)

- 4-meter optical telescope in Chile
- 1/8 of sky between 2013 - 2019
- >300 million galaxies
- ~400 scientists
~30 institutions
7 countries



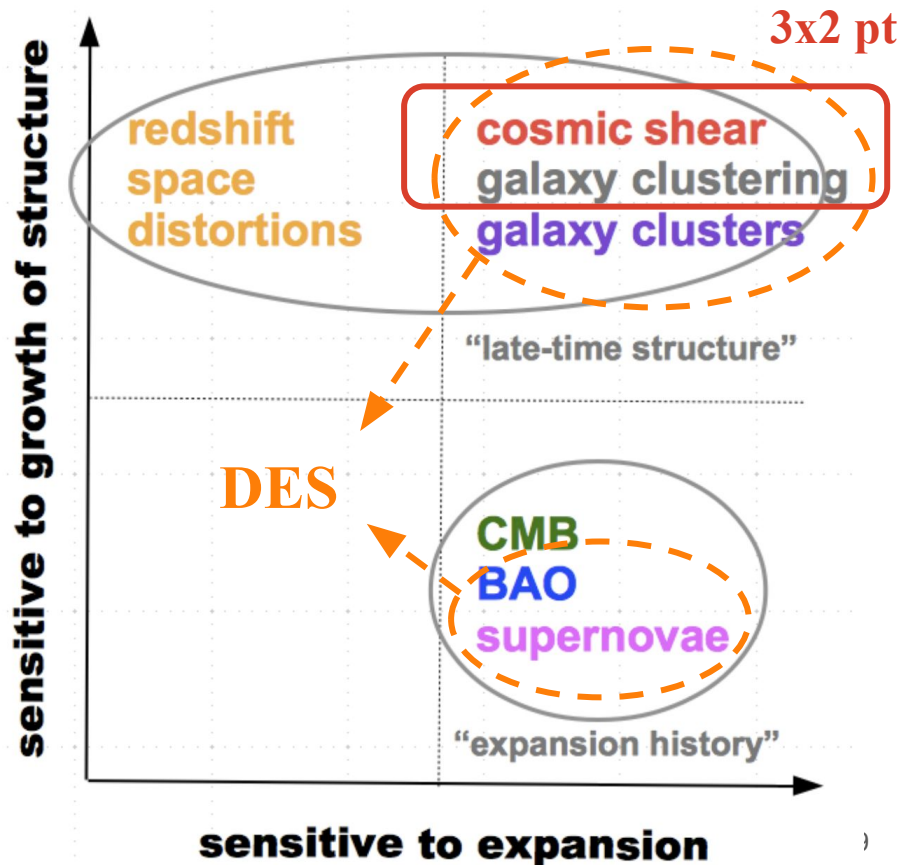
Probes of Structure Growth and Cosmic Evolution



CMB

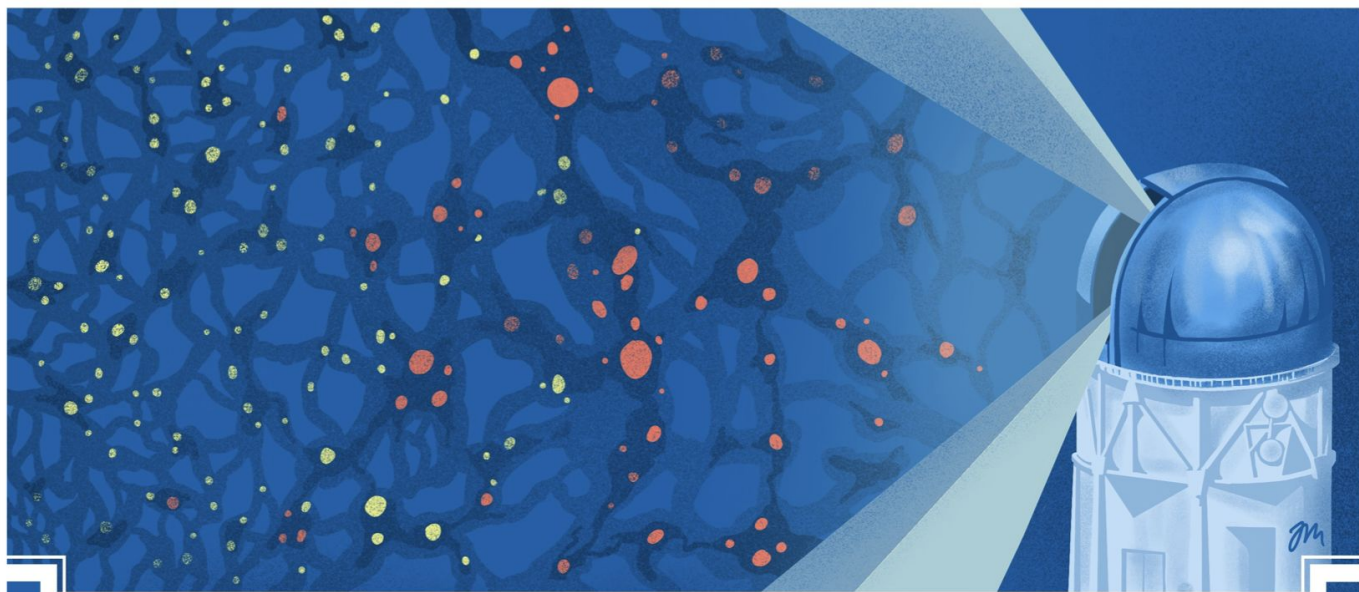
LSS

14 Gyr



“3x2pt”

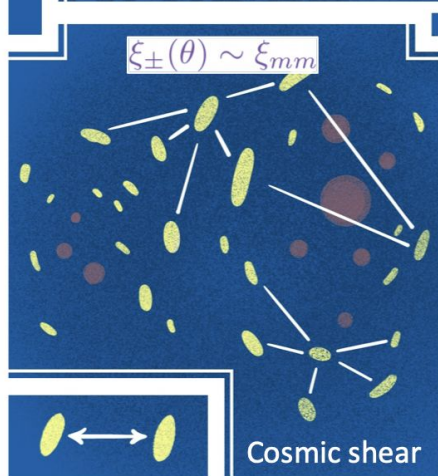
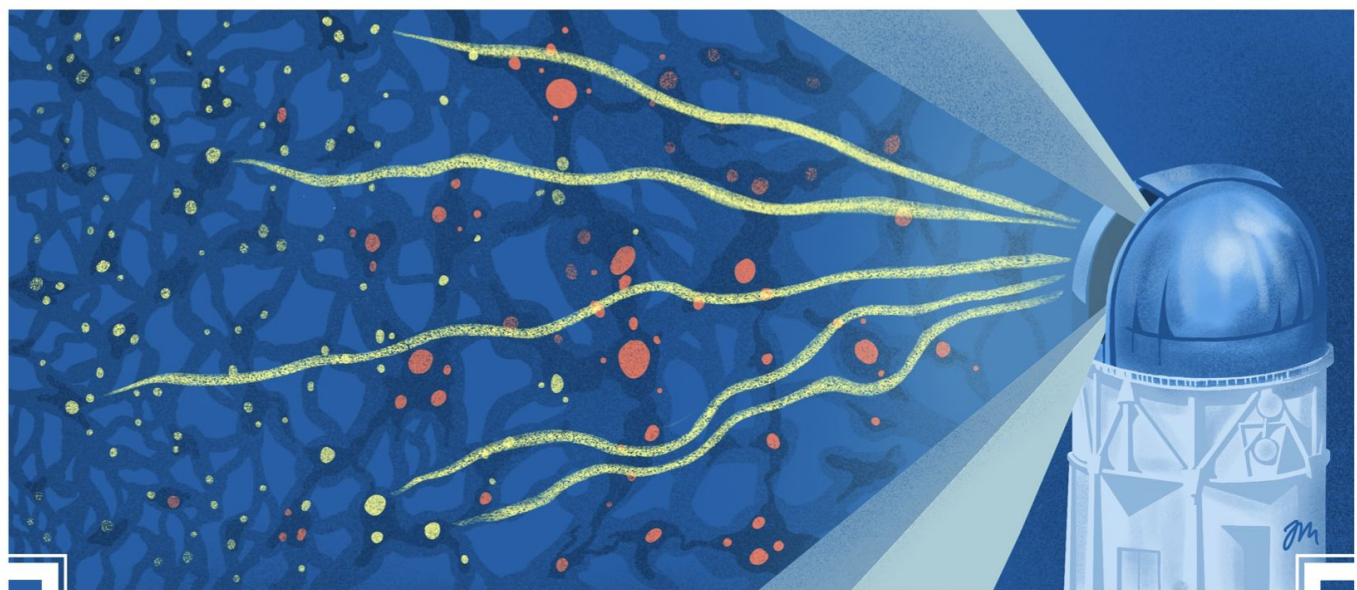
Uses 2-pt correlation functions



“3x2pt”

Uses 2-pt correlation functions

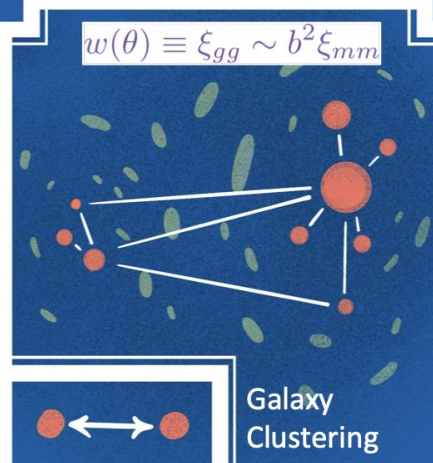
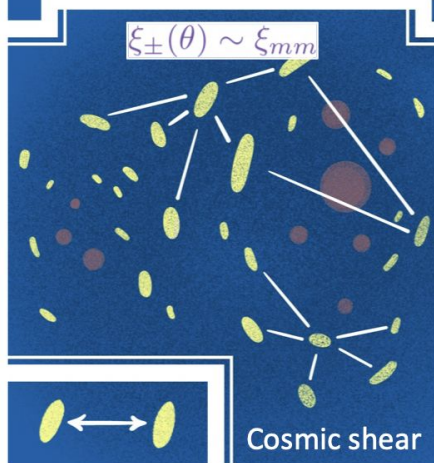
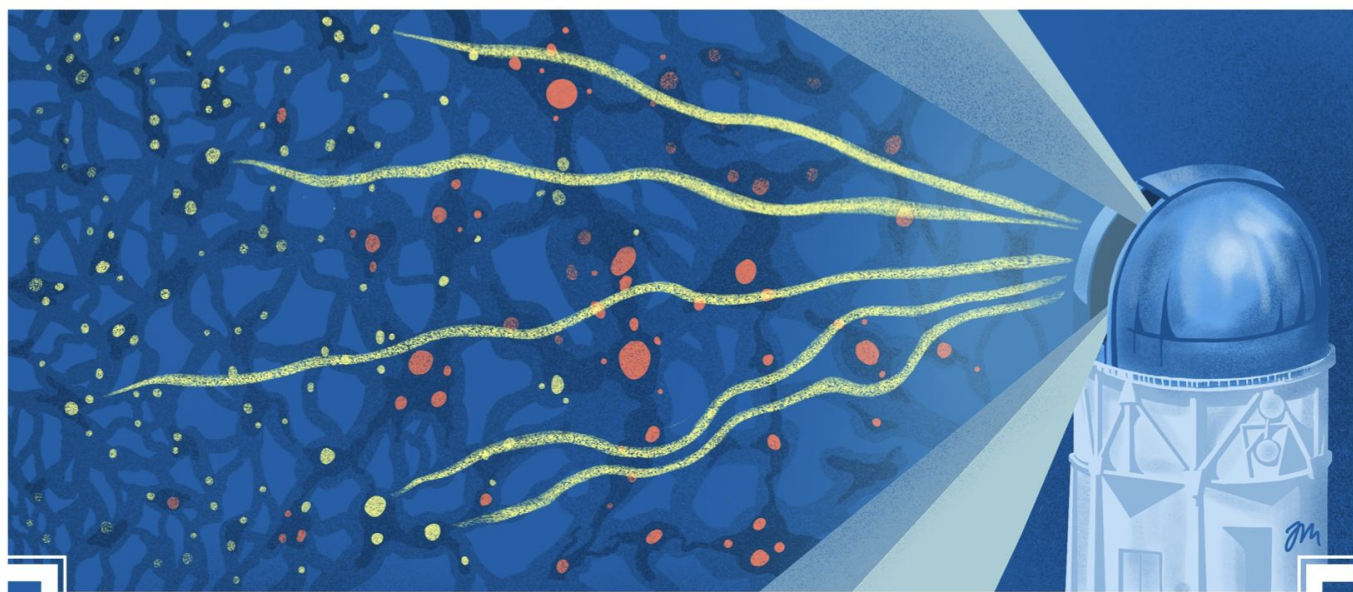
- Cosmic Shear



“3x2pt”

Uses 2-pt correlation functions

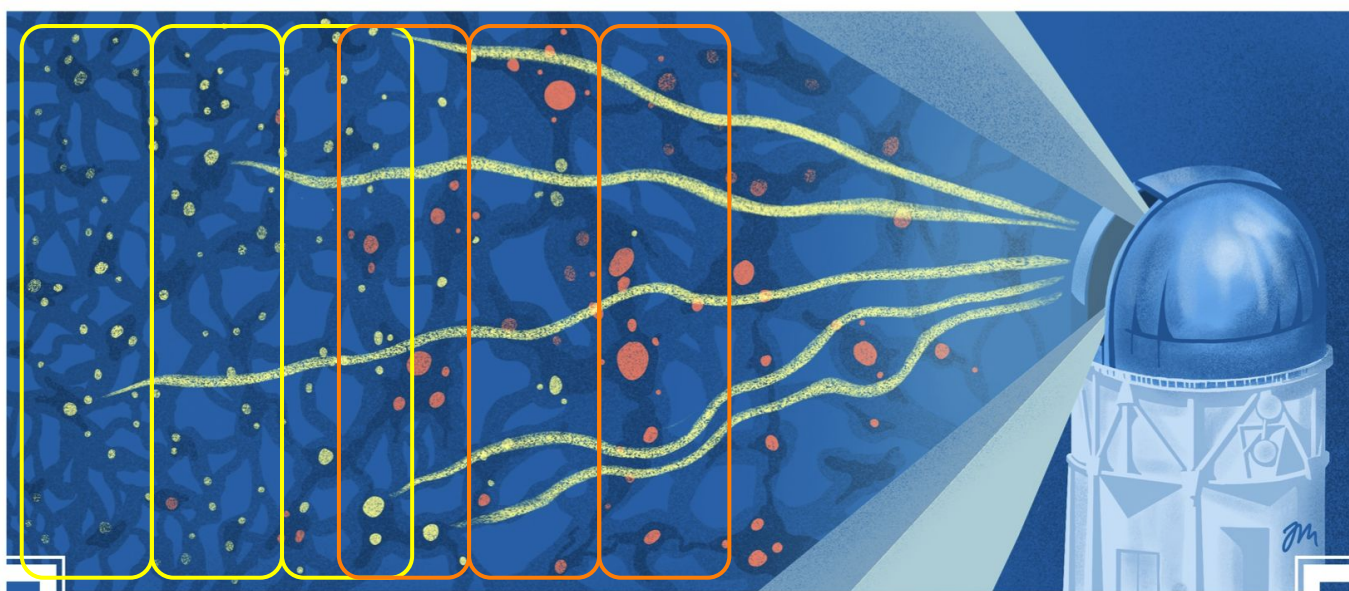
- Cosmic Shear
- Galaxy Clustering



“3x2pt”

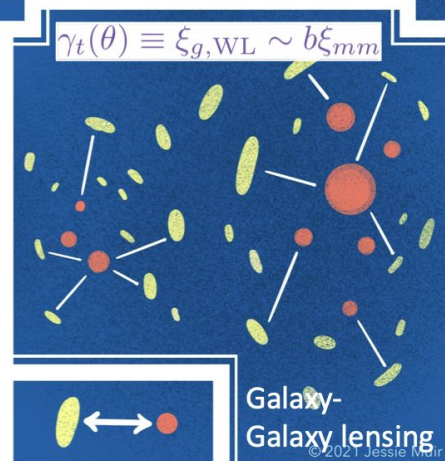
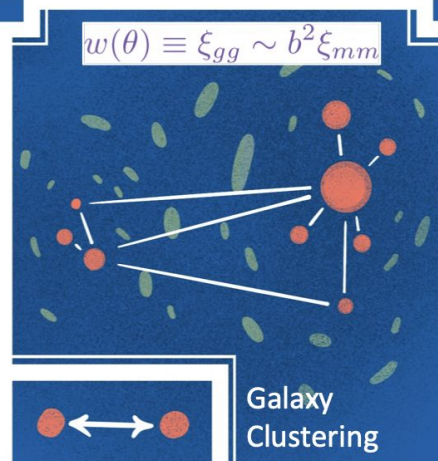
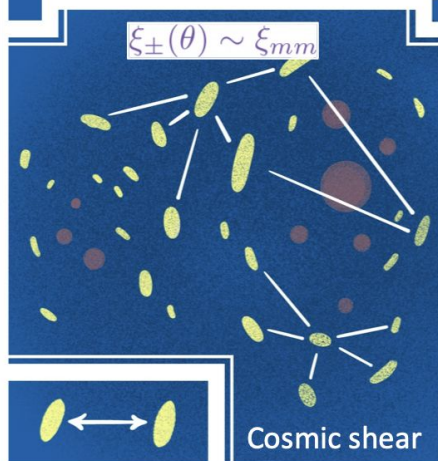
Uses 2-pt correlation functions

- Cosmic Shear
- Galaxy Clustering
- Galaxy-Galaxy Lensing



Gain further information
by binning in redshift

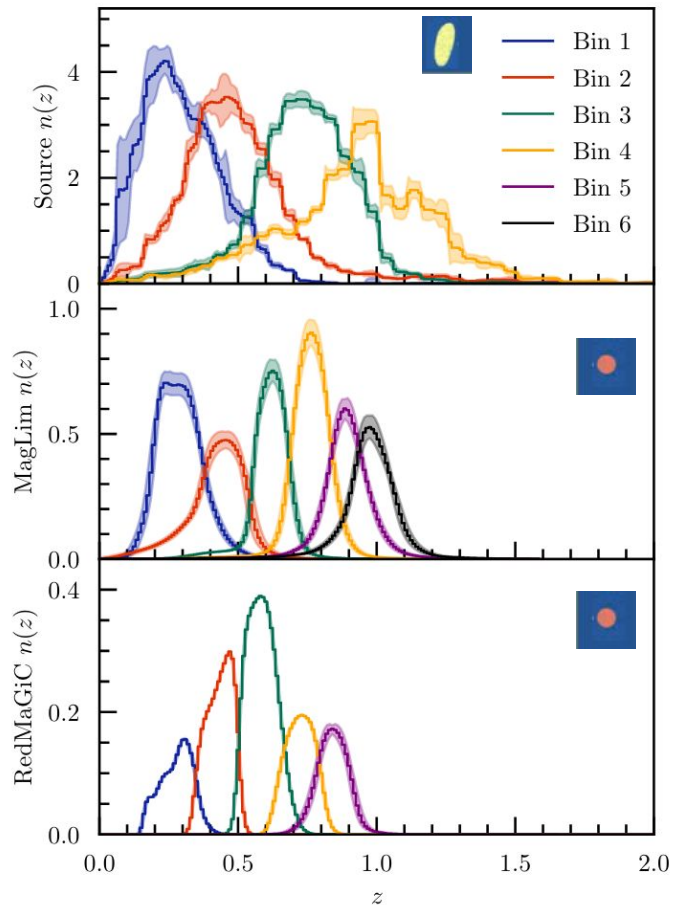
(“DNF” algorithm:
J. De Vicente, E. Sánchez &
I. Sevilla-Noarbe, 2016)



Galaxy Catalogs

- Galaxies drawn from “Gold” sample with photometric processing and corrections (I. Sevilla-Noarbe et al. 2020)
- $\sim 10\text{M}$ “lens” galaxies:
 - MagLim (Porredon et al. 2021)
 - RedMagic (Rozo, Rykoff et al., 2016)
- $\sim 100\text{M}$ shapes from “source” galaxies (Gatti & Sheldon, et al. 2021)

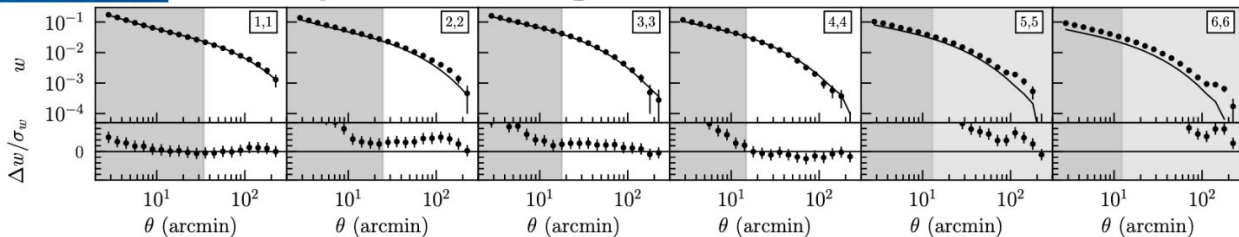
Distribution of galaxies in redshift bins





Galaxy clustering

Rodríguez-Monroy, Weaverdyck, et al., arXiv:2105.13540



Data in practice

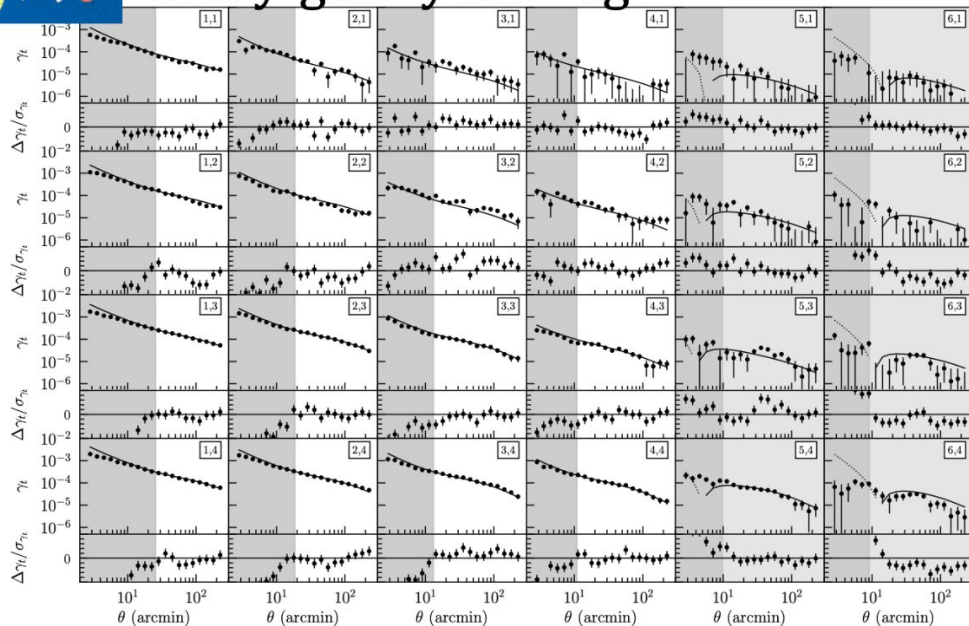
Gray: remove data where theory not good enough



Galaxy-galaxy lensing

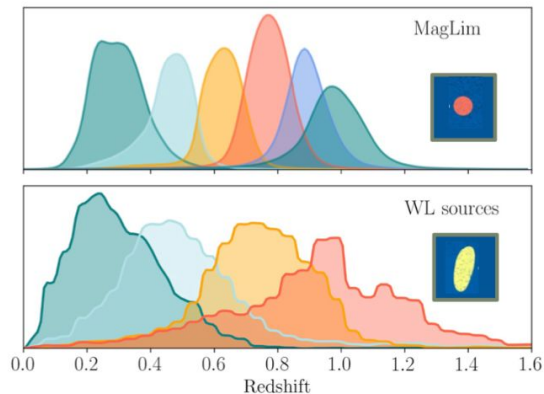
Prat et al. [DES], arXiv:2105.13541

WL bins



Galaxy Clustering bins

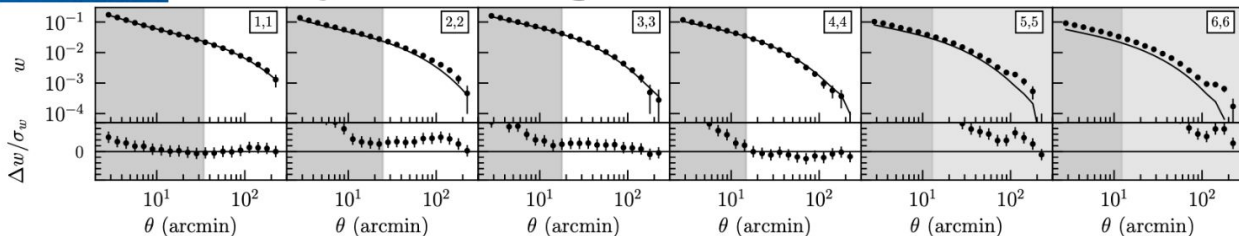
Distribution of galaxies in redshift bins





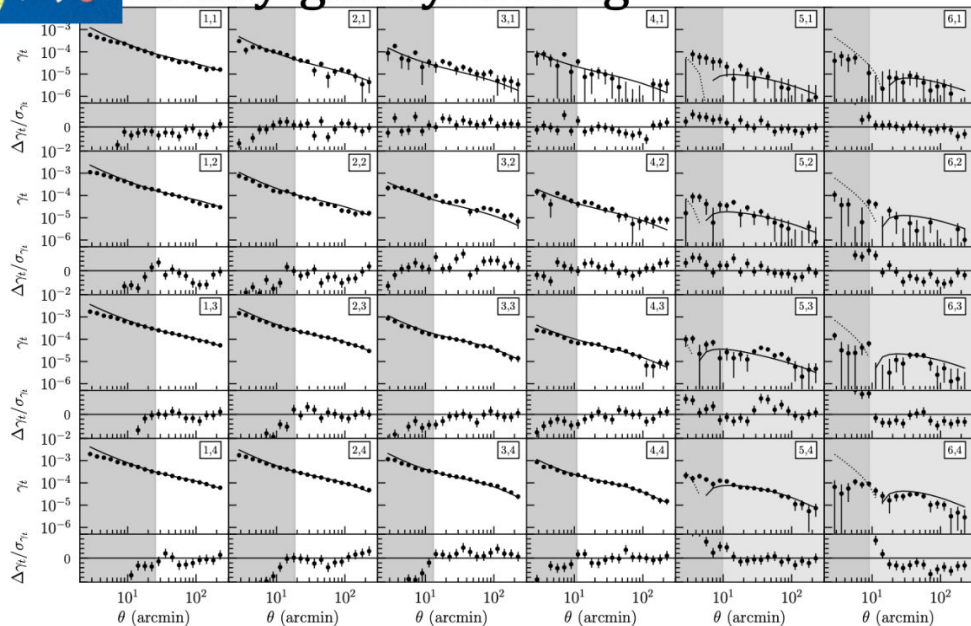
Galaxy clustering

Rodríguez-Monroy, Weaverdyck, et al., arXiv:2105.13540



Galaxy-galaxy lensing

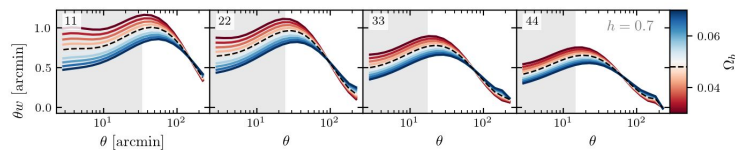
Prat et al. [DES], arXiv:2105.13541



WL bins

Galaxy Clustering bins

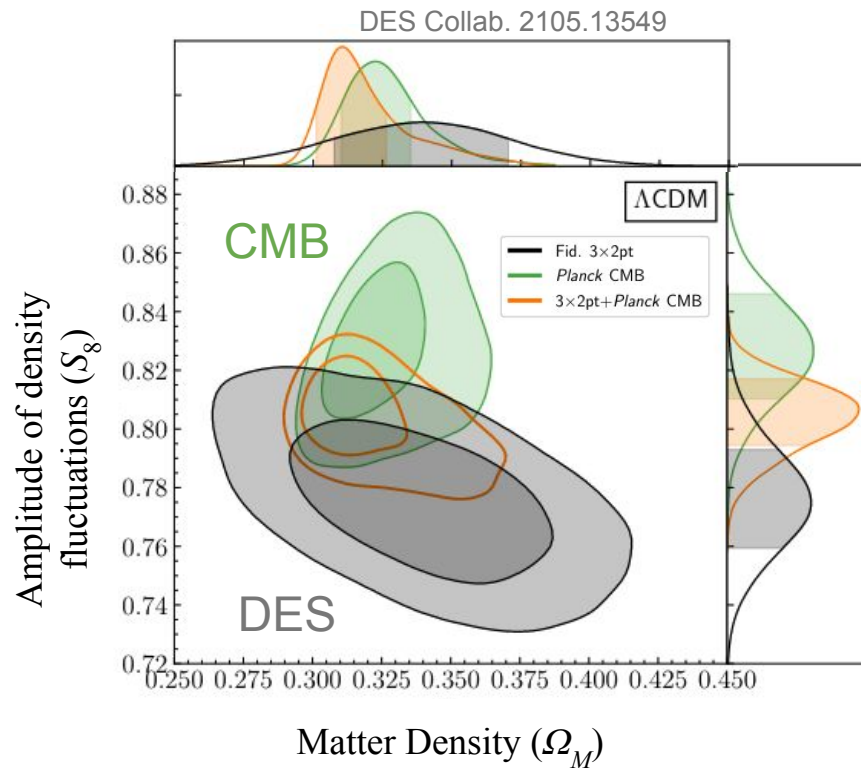
Compare to theory,
constrain parameters



Colors: vary baryon density

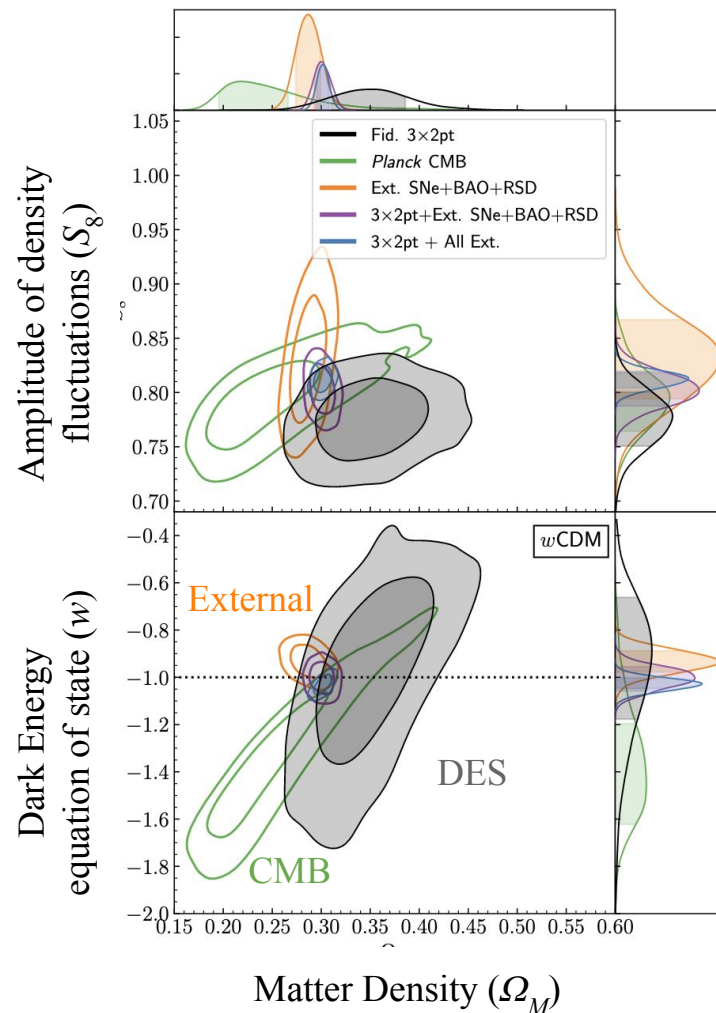
Results: Λ CDM

- Most powerful 3x2pt constraints from a single galaxy survey
- 2x improvement in S/N over Year 1
- LSS competitive with CMB constraints
→ but tension in S_8 ?



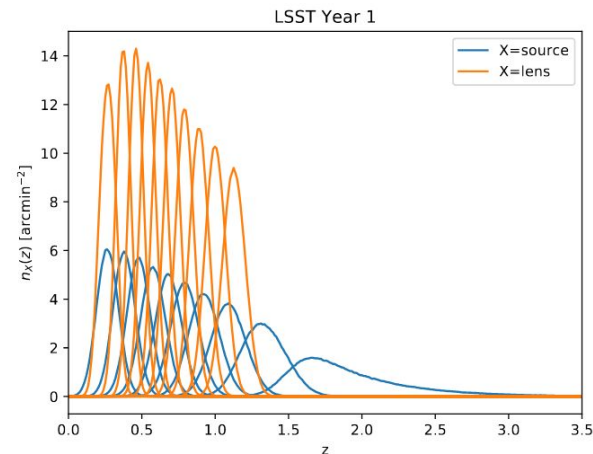
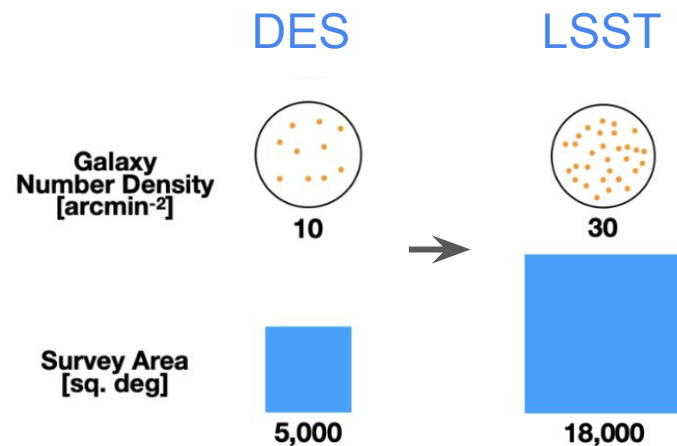
Dark Energy Results (w CDM)

- No evidence for $w \neq -1$
(Λ CDM, cosmological constant)
- Highly complementary to other probes!
- Tension remains (pushed into Ω_M)



LSST: Order of magnitude larger

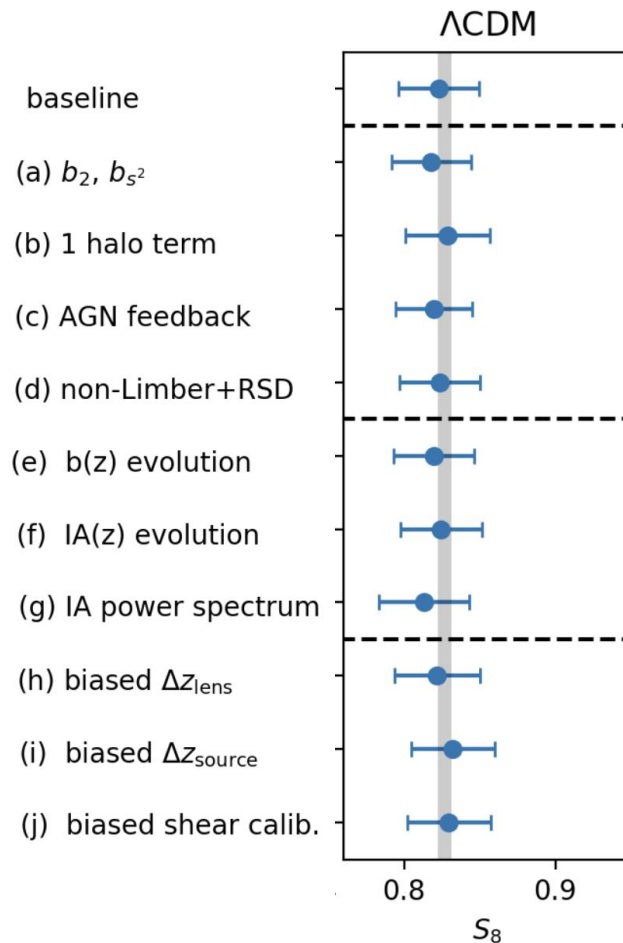
- LSST, DESI, Roman, SPHEREx...
Large areas, number densities
→ **small** statistical error
- Existing tensions → definitive detections
- **Need exquisite control of systematics to claim new physics**



(some) LSS systematics

- Galaxy bias
- Small-scales (baryons, non-linearities...)
- Intrinsic alignment of galaxies
- Photometric redshift estimation errors
- **Angular systematics**
 - Modify *map*, leverage spatial info

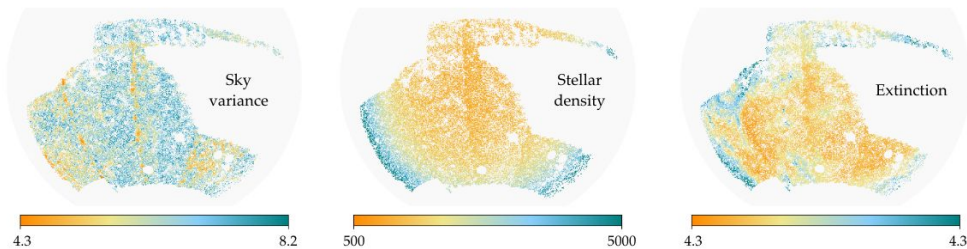
*Add
Nuisance
parameters*



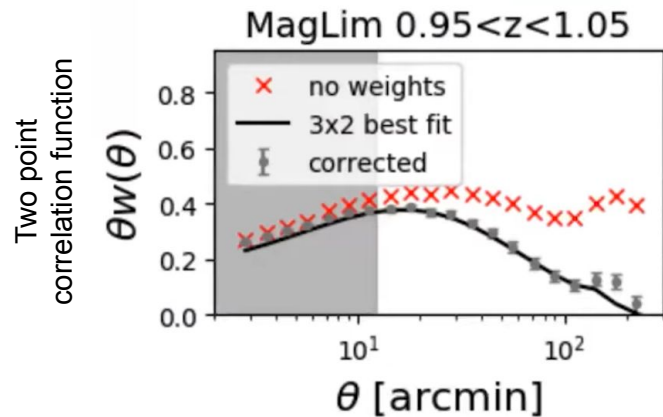
Spatial systematics

Observed galaxy field \neq truth

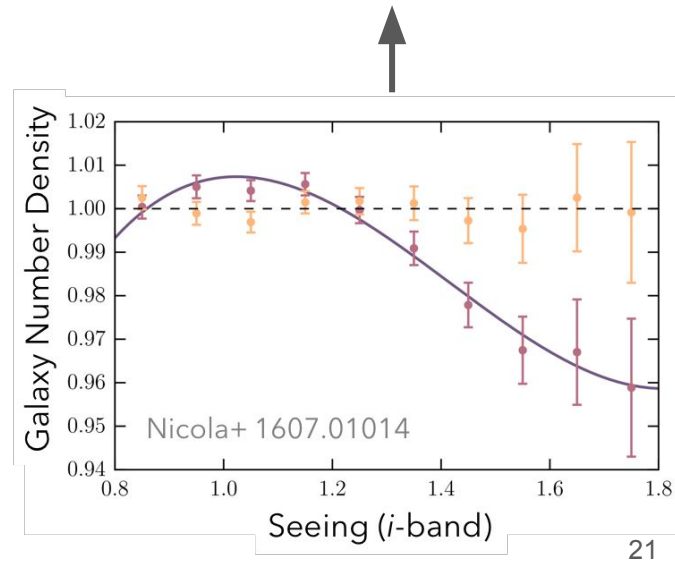
- *Astrophysical* (stellar contamination, dust, ...)
- *Observing conditions* (seeing, sky brightness, ...)
- *Instrumental* (flux calibration, source detection, ...)
- **Result:** density maps biased (and 2-pt functions, 3-pt, ...)



Sánchez et al. 2211.16593



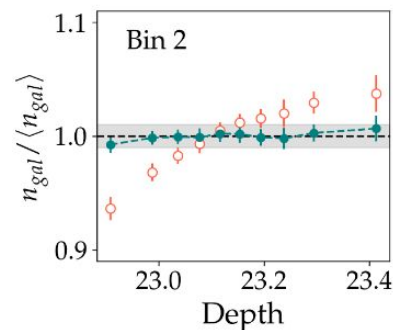
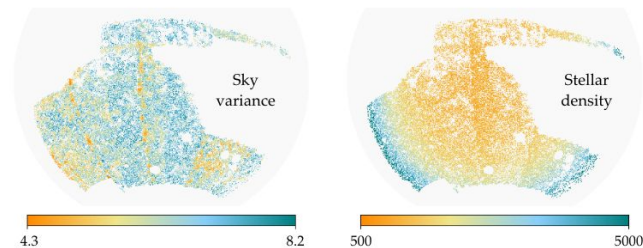
Rodriguez-Monroy, NW,
et al. 2105.13540



How to mitigate spatial systematics?

- Use *systematic templates* that trace potential contamination
 - Mask extremes
 - Estimate and correct for contamination via *weights*
 - Also *simulation-based* approaches
e.g. Balrog (Everett+ 2021), Obiwan (Kong+ 2021)
- Many estimators
 - Can formulate methods as regression (Weaverdyck & Huterer 2007.14499)
 - Identify different implicit assumptions
 - Regression well-studied:
enables refinements, improvements

Sánchez et al. 2211.16593



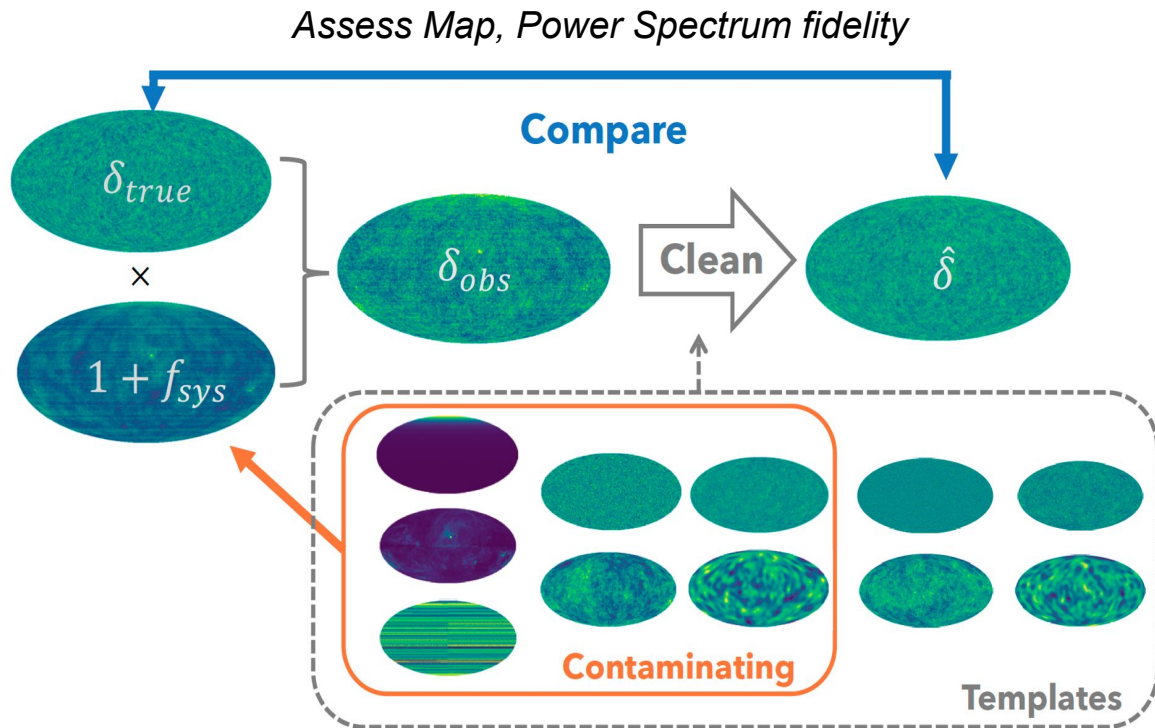
$$\delta_{\text{obs}} \approx \delta_{\text{true}} + f_{\text{sys}}(t)$$

Template map

Compare Methods on Simulations

Methods used:

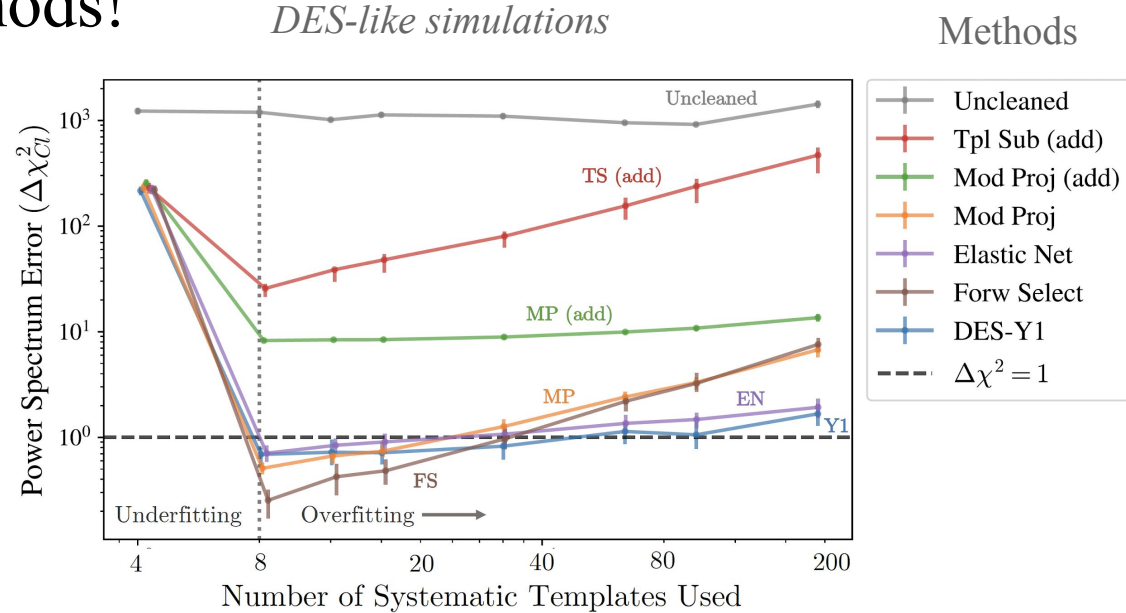
- Mode (De)Projection
(e.g. HSC, SDSS QSOs)
 - Template Subtraction
(e.g. BOSS LRGs)
 - Multiple Linear Regression
(e.g. KiDS LRGs, CFHTLenS)
 - Iterative Systematics
Decontamination (DES lenses)
 - “E.Net”
 - “Forward Selection”
- } **New**



Weaverdyck & Huterer 2007.14499)

Clear differences in methods!

- **DES-Y1 method** (or “ISD”) and **ENet** methods perform best
→ Most robust to removing true LSS fluctuations
- Different assumptions (i.e. theory systematics)



Galaxy Clustering Power Spectrum Error

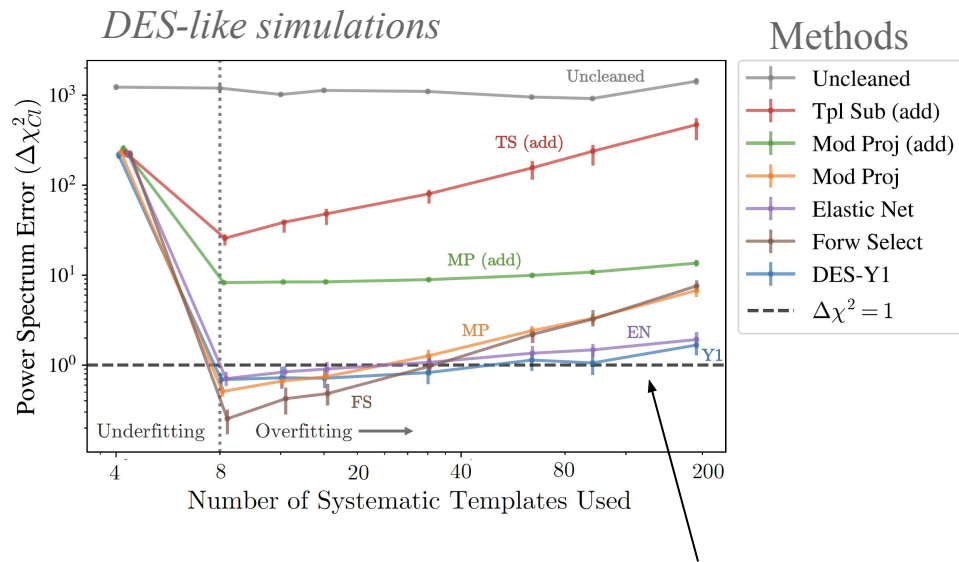
$$\Delta\chi^2_{C_\ell} = \sum_{z \text{ bins}} \sum_{\ell=\ell_{\min}}^{350} \frac{(\tilde{C}_\ell^{\text{est}}(z) - \tilde{C}_\ell^{\text{ss}}(z))^2}{\sigma_{C_\ell^{\text{ss}}(z)}^2}$$

(power spectrum \approx correlation function)

Performance of Different Methods

- EN shows comparable performance with ISD method across metrics
1 day \rightarrow 5 sec
- Different “theory systematics”
- So who cares?

Weaverdyck & Huterer 2007.14499

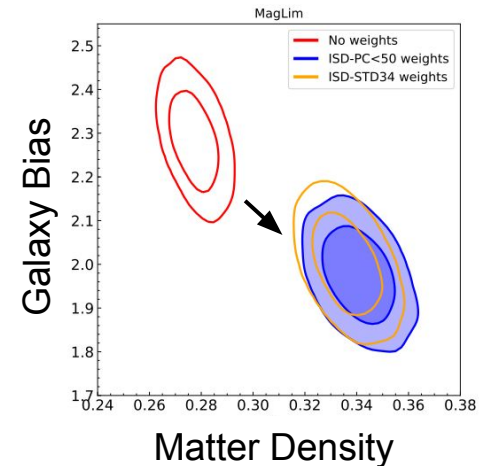
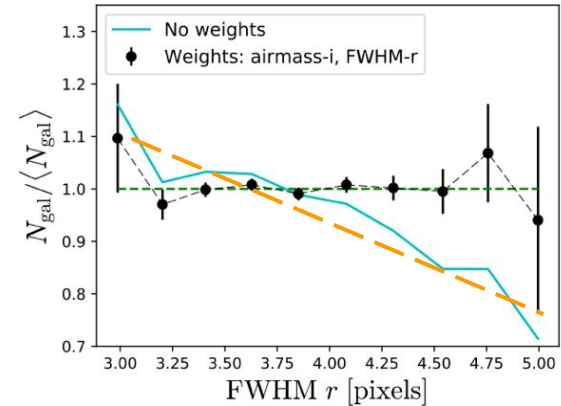


$$\Delta\chi^2_{C_\ell} = \sum_{z \text{ bins}} \sum_{\ell=\ell_{\min}}^{350} \frac{(\tilde{C}_\ell^{\text{rest}}(z) - \tilde{C}_\ell^{\text{ss}}(z))^2}{\sigma_{C_\ell^{\text{ss}}}^2(z)}$$

As good as fiducial DES method, but 10,000x faster

ISD (DES Y1 and Y3)

- “Iterative Systematics Decontamination”
- Series of 1D, binned regressions on each template, iteratively reweight galaxies
- Pros vs other methods:
 - **Covariance** from mocks
 - **Significance** threshold to control overfitting
- Cons vs OLS methods:
 - Only detect marginal relationships
 - CPU and time intensive (~1 day)



Elastic Net Weighting

- Regression extension: form of regularization (Zou & Hastie 2005)
- Incorporate template selection,
- Operate in full-D space (weak sensitivity to template basis)

$$\hat{\alpha} = \underset{\alpha}{\operatorname{argmin}} \left(\underbrace{\|\delta_{\text{obs}} - T\alpha\|^2}_{\text{OLS penalty}} + \underbrace{\lambda_1 \|\alpha\|_1}_{\text{Sparsity prior (LASSO)}} + \underbrace{\lambda_2 \|\alpha\|_2^2}_{\text{Regularization (Ridge)}} \right)$$

Contamination amplitudes

In terms of Maximum Posterior Estimate, equivalent to:

<i>Gaussian Likelihood</i>	<i>Laplace prior on coefficients</i>	<i>Gaussian prior on coefficients</i>
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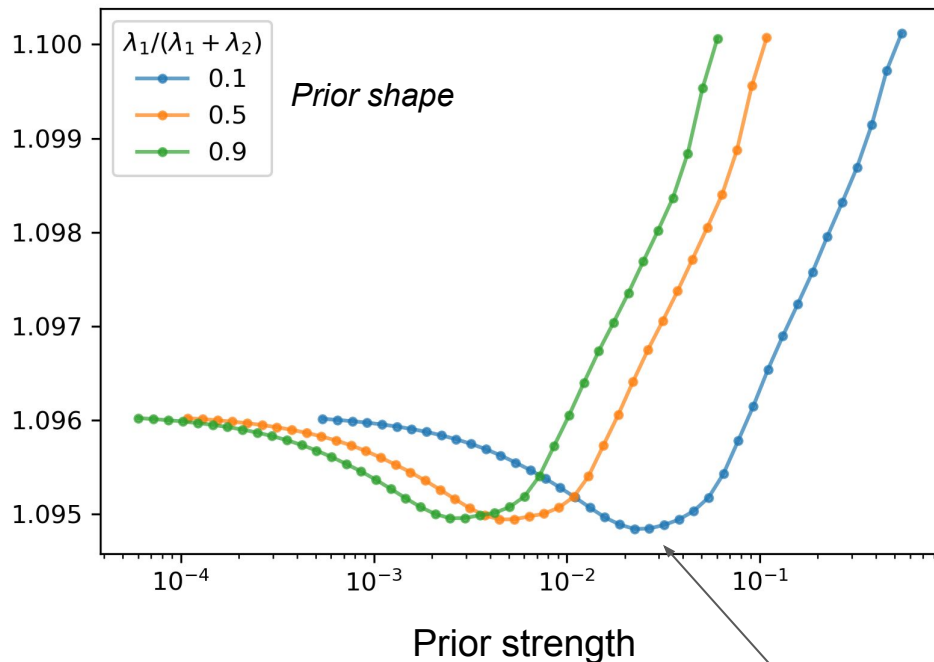
In practice, select $\{\lambda_1, \lambda_2\}$ through cross-validation
(trained on subsets of the data)

Elastic Net Weighting

Use all templates
(OLS)

High variance

Average
mean
squared
error on test



$N_{tpl} = 0$
(no cleaning)

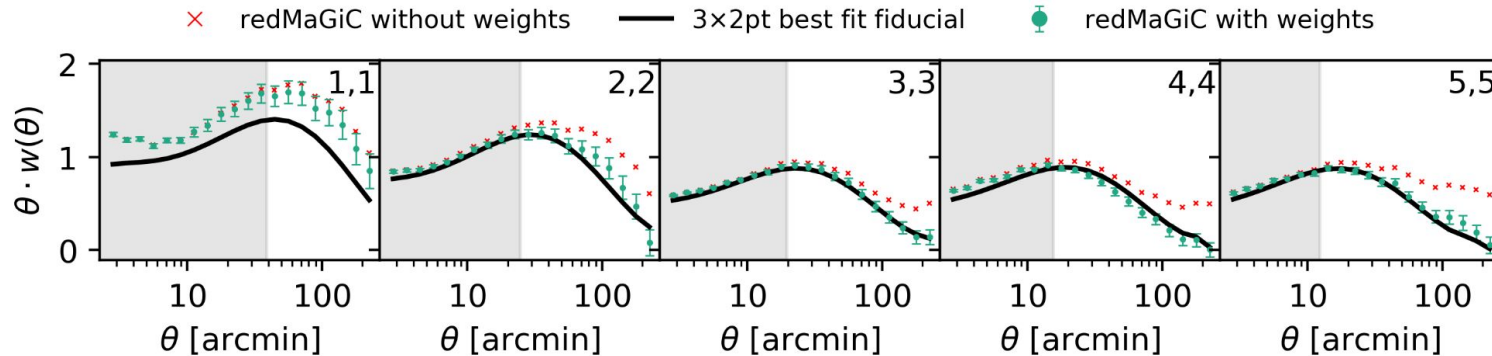
High bias

Let data
determine
effective number
of templates

Optimal hyperparameters

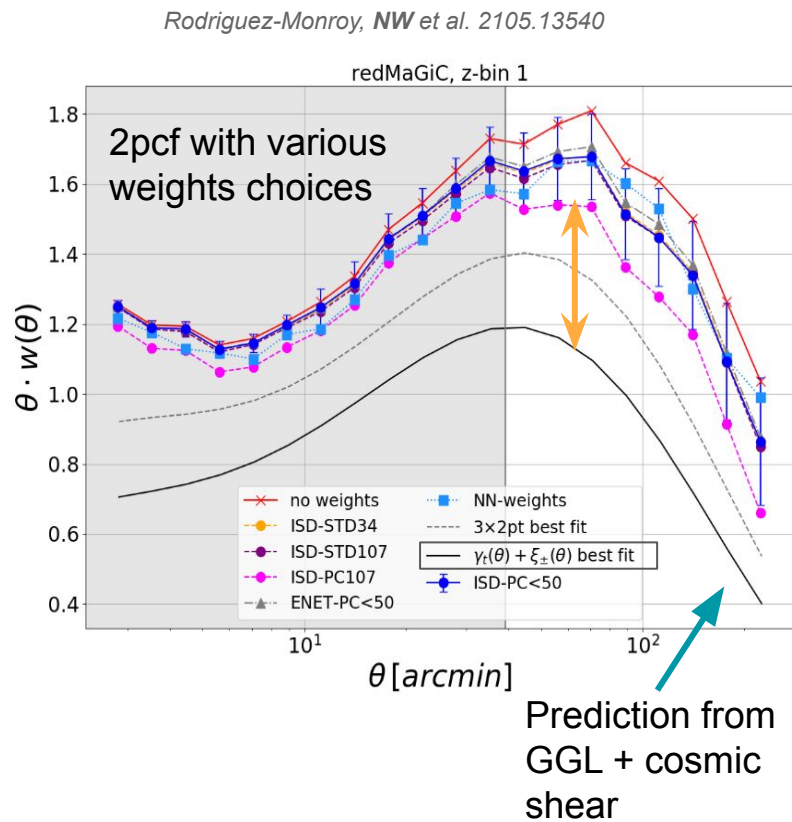
Problems in DES Y3 Key Project Analysis

- Original fiducial lens sample (“Redmagic”):
3x2pt inconsistent under LCDM
- Many post-unblinding tests
- Prime suspect: unfixed galaxy clustering systematic
- **Problem:** $\sim O(1 \text{ day})$ for new weights



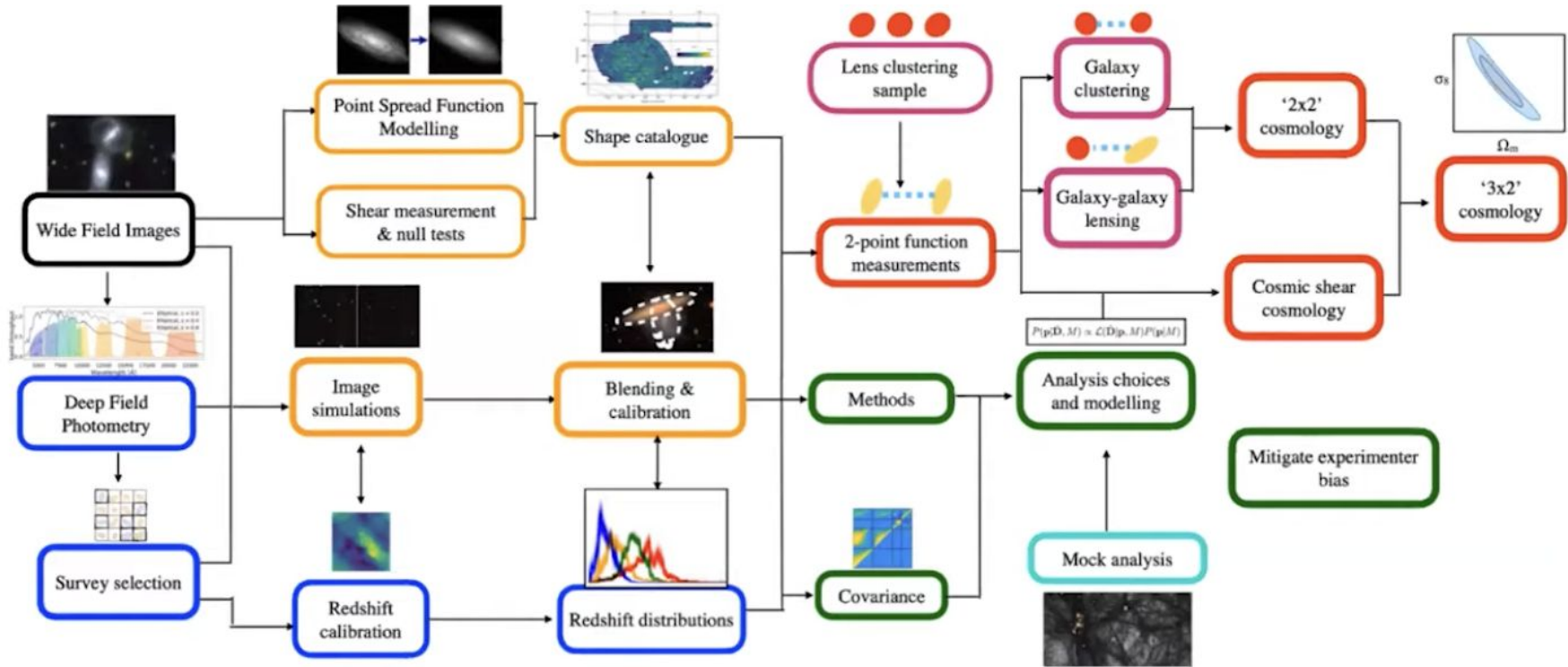
Rapid, complementary weights estimation

- Able to assess impact of mask, templates, contamination models
→ Demonstrate robustness of weights
- Critical for identifying problematic cut in selection
→ Motivate change in lens sample
- Marginalize over differences in decontamination models



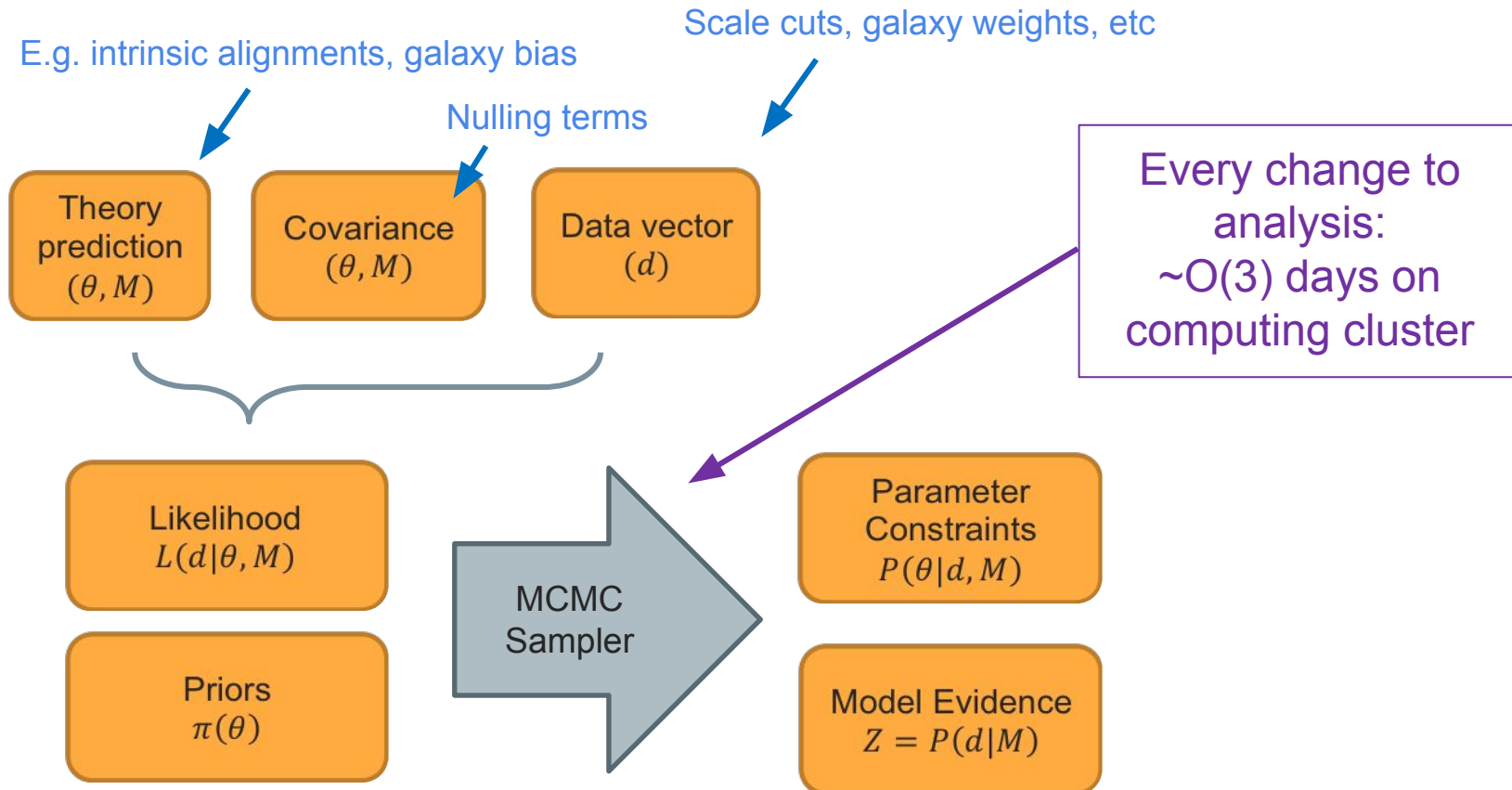
DES: Pixels to Cosmology (3x2pt)

Fig: Alex Amon



LCDM — WL+LSS — Redshifts — Shapes — Clustering — Simulations — Theory — Results

Simplified picture



Approach: FastISMORE

Fast Importance Sampling for Model Robustness Evaluation

- *Directly* probe response of posterior to change in likelihood (DV or model)

$$\mathcal{P}(\theta|d_{\text{cont}}) \propto \mathcal{P}(\theta|d_{\text{base}}) \frac{\mathcal{L}(d_{\text{cont}}|\theta)}{\mathcal{L}(d_{\text{base}}|\theta)}$$

From fiducial chain

From d_{cont} , d_{thry} & data covariance

- 1000x speedup → vastly expand range of testable systematics
- Eliminates sampler variance
- Used to validate: DES Y3 Covariance, and LCDM 3x2pt, and extended analysis choices to systematics

Input shift

FastISMORE

Ω_m

Baseline

0.1 σ

0.2 σ

0.3 σ

0.4 σ

0.5 σ

0.6 σ

0.7 σ

0.8 σ

0.9 σ

1.0 σ

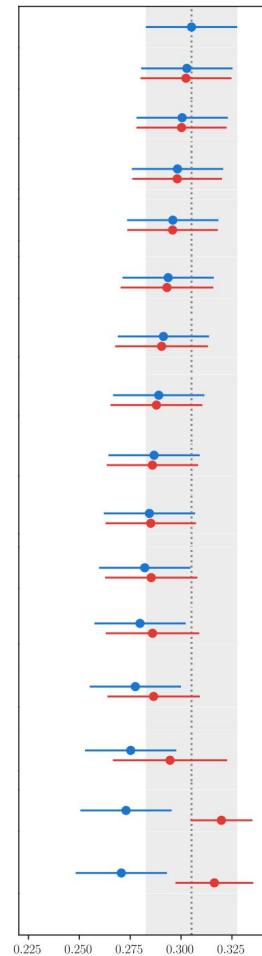
1.1 σ

1.2 σ

1.3 σ

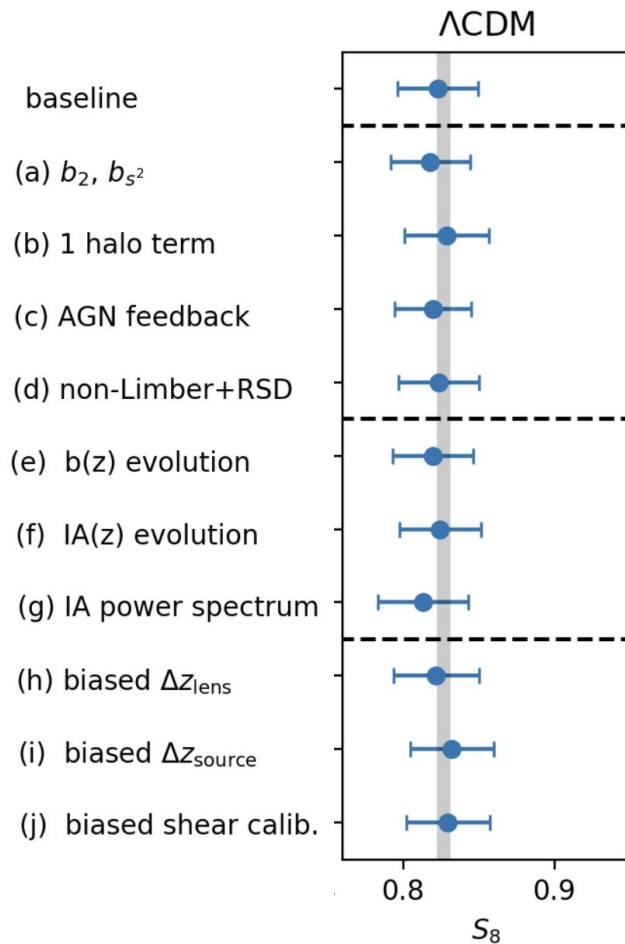
1.4 σ

1.5 σ



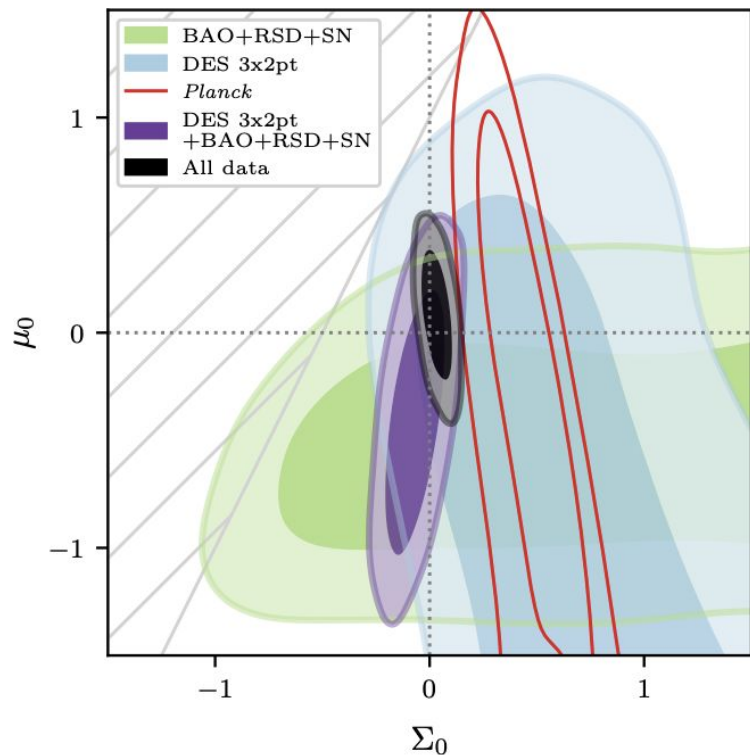
DES Y3: Testing Extended Models

- Validate inference architecture:
 - Simulate contaminated data vectors,
 - Verify inference **unbiased**
- Testing models beyond Λ CDM
 - w_0w_a , Ω_k , modified gravity, sterile neutrinos, etc.
 - **700+ chains!**
 - (Cosmo model) x (astro model) x (data combo)..

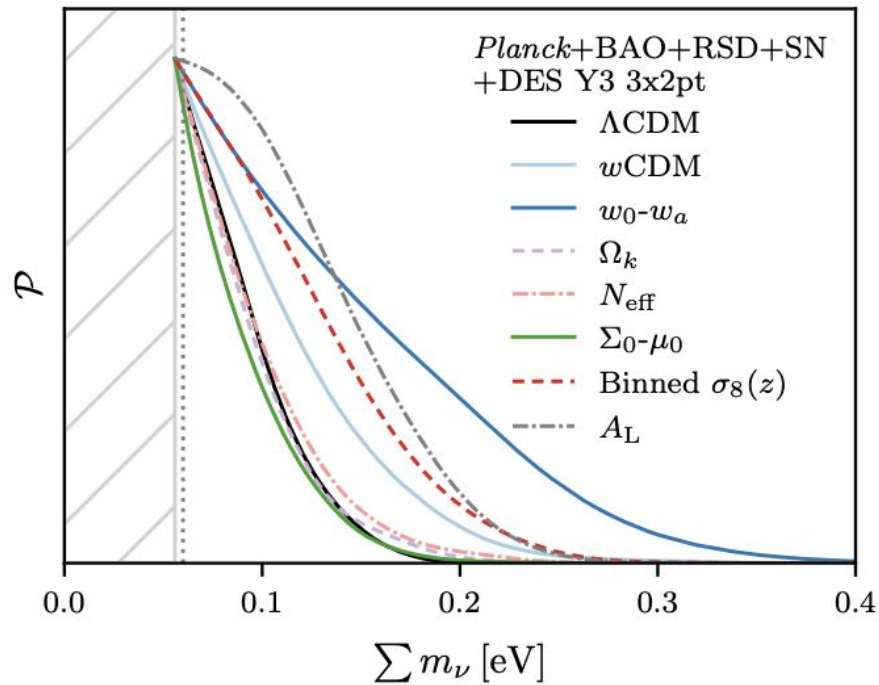


DES Y3: Testing Extended Models

Phenomenological Modified Gravity parameters



Sum of neutrino masses under extended models



DES Y3 papers on galaxy clustering and weak lensing

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., arXiv:2109.09636
14. "Exploiting Small-Scale Information using Lensing Ratios", C. Sánchez, J. Prat et al., arXiv:2105.13542
15. "Cosmology from Combined Galaxy Clustering and Lensing - Validation on Cosmological Simulations", J. de Rose et al., arXiv:2105.13547.
16. "Robust sampling of cosmological posterior distributions", P. Lemos, N. Weaverdyck, R. Rollins, J. Muir, A. Ferté, A. Liddle 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:2105.13539
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, M. Crocce et al., arXiv:2105.1354
27. "Cosmology from Cosmic Shear and Robustness to Data Calibration", A. Amon, D. Gruen, M. A. Troxel et al., arXiv:2105.13543
28. "Cosmology from Cosmic Shear and Robustness to Modeling Assumptions", L. Secco, S. Samuroff et al., arXiv: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

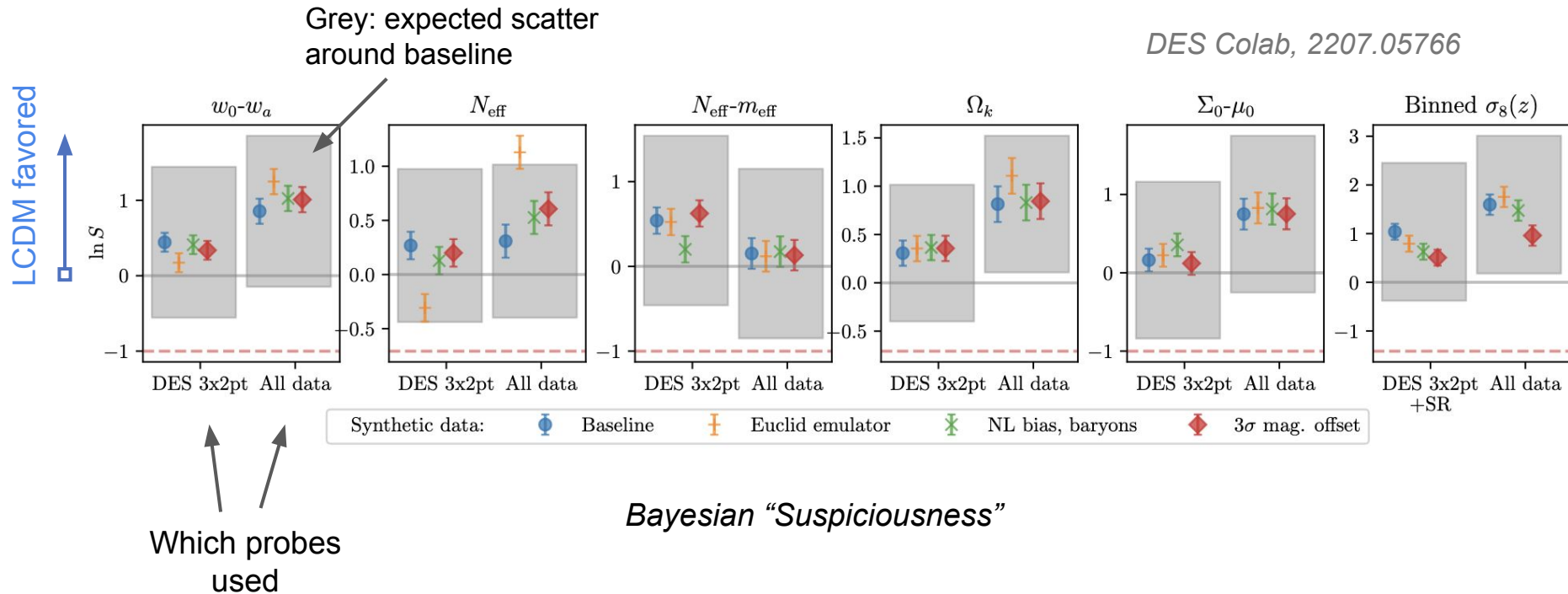
Conclusions

- “Golden era” of Observational Cosmology
 - Increasingly *systematics limited*
- DES is state-of-the-art survey with leading constraints on cosmological parameters
 - Novel systematics treatments crucial
 - Y6 Legacy Science analysis even better!
→ Talk to D. Sanchez Cid, J. Mena, S. Avila, ...
- Spatial systematics remain key systematic
- Systematics or new physics?
Accelerated, integrated systematics testing crucial for harnessing precision of Stage IV surveys



Bonus Slides

Can assess robustness of Model Comparison stats

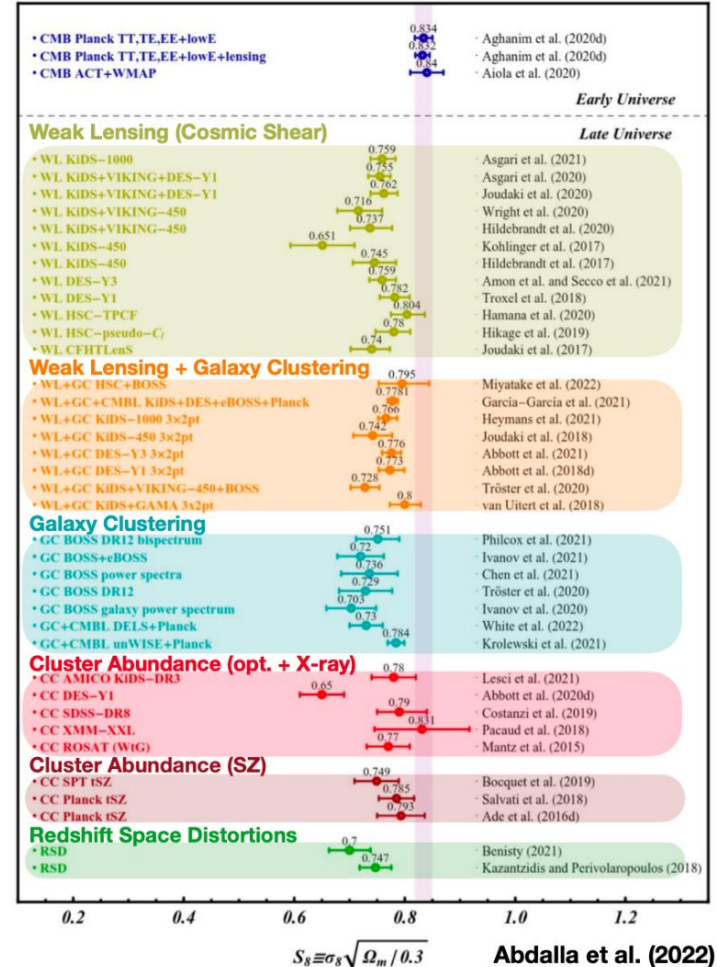


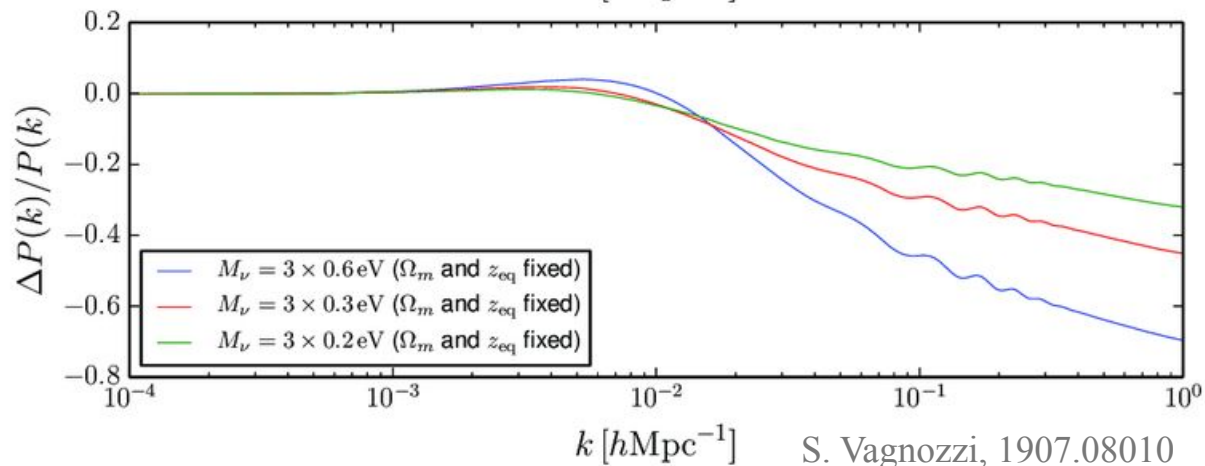
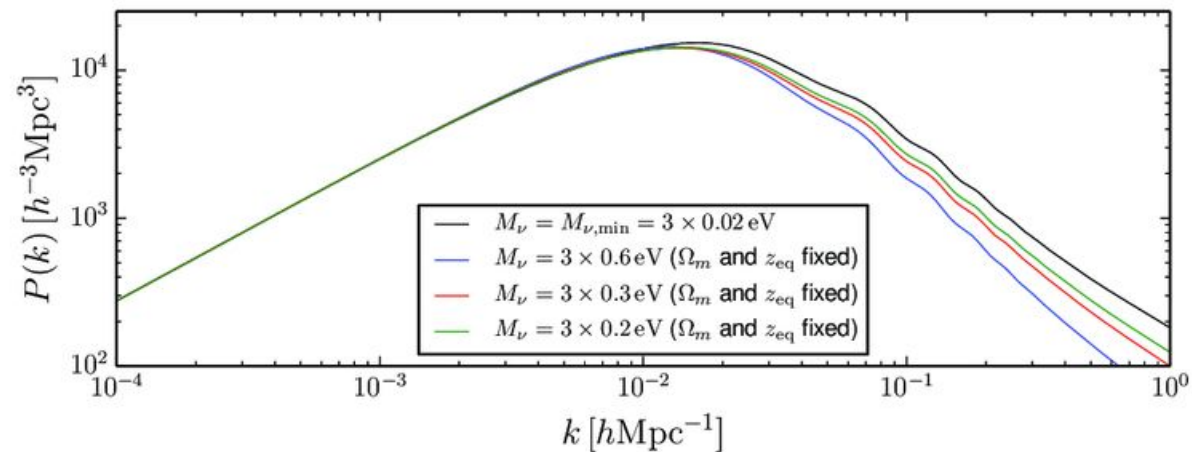
S_8 Tension

$$S_8 \equiv \sigma_8 \sqrt{\Omega_m / 0.3}$$

- σ_8 : Amplitude of linear power spectrum on the scale of 8 Mpc/h
- Ω_m : Energy dense of matter (incl. dark matter)

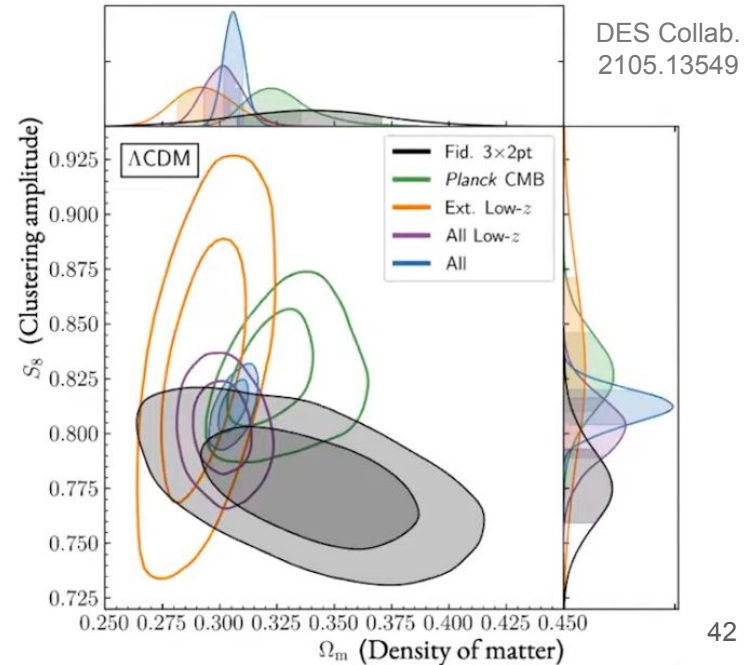
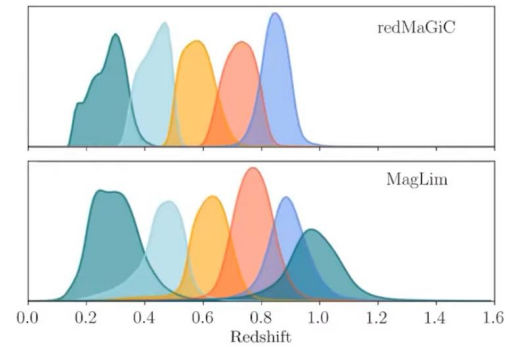
Most **large scale structure** probes prefer smaller S_8 compared to **CMB**, if we assume Λ CDM.





DES Y3

- Two lens samples:
redMaGiC and MagLim
- Apply both ISD and ENET weight methods
 - Good agreement
- Analytically marginalize over:
 - Difference in method predictions
 - Over-correction bias
- Rapid assessment of mask, template, method choices
(~2 min vs 1 day)

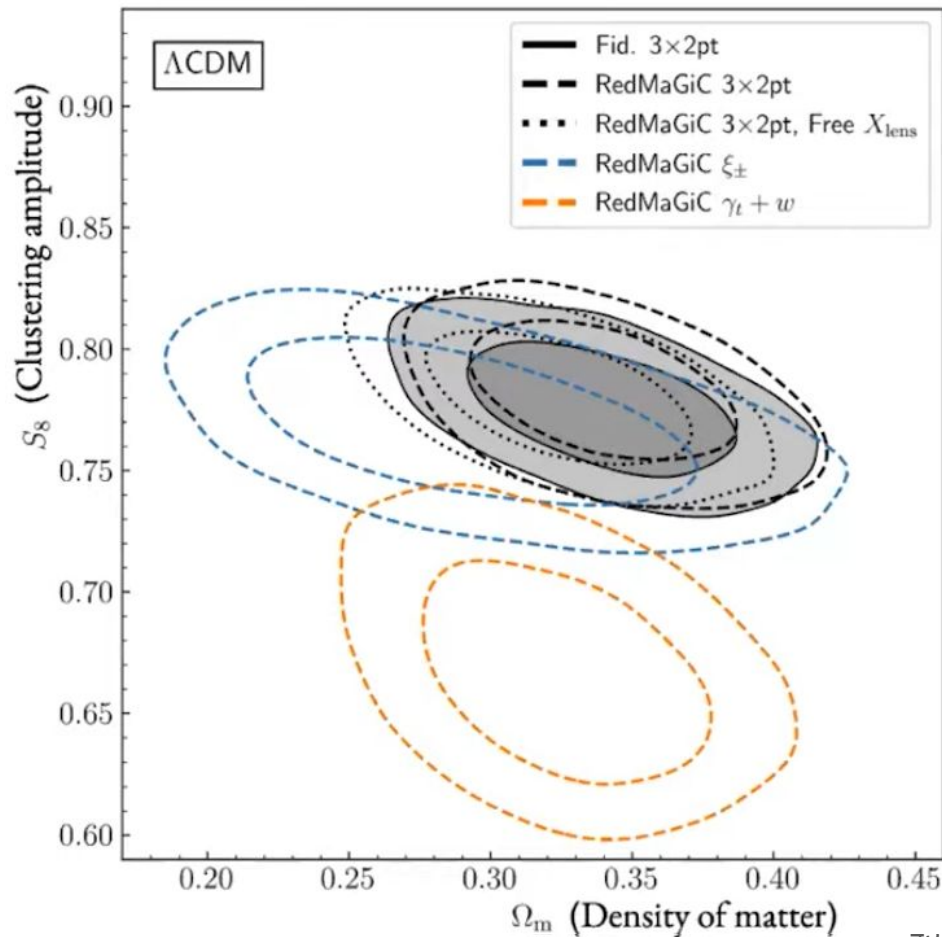


DES Y3

- Two lens samples: RedMaGiC, Maglim
Strong excess clustering in RedMaGiC
- Fiducial sample changed to MagLim,
(though cosmology results consistent
for 3x2pt)
- Parameterize via X_{lens}

$$X_{\text{lens}}^i = b_{\gamma_t(\theta)}^i / b_{w(\theta)}^i$$

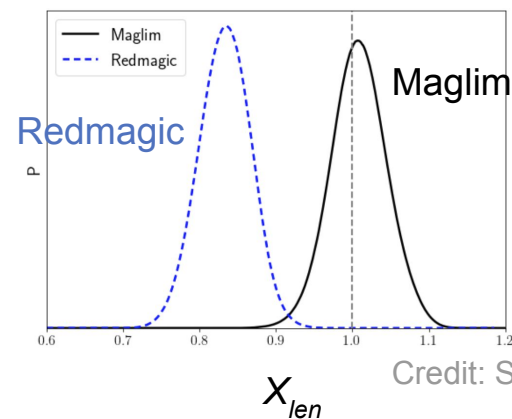
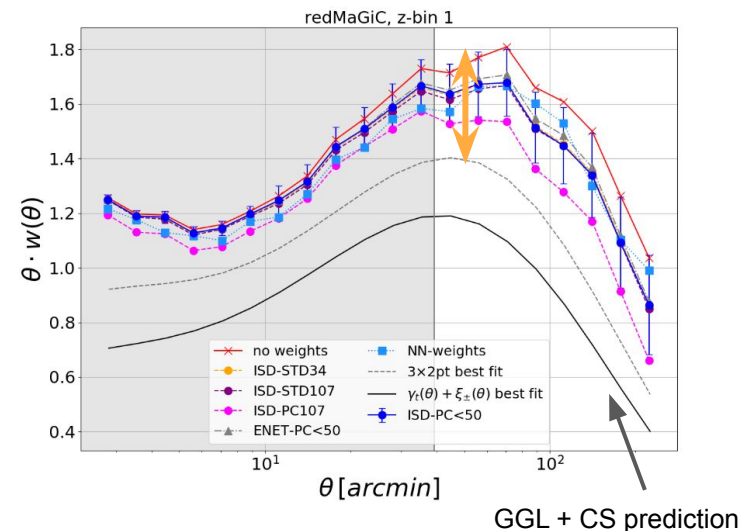
- Consistent with, without X_{lens}
but much better goodness-of-fit
- Orthogonal to Λ CDM cosmo
parameters (but not w CDM)



DES Y3

- Data inconsistency robust to wide variation of weights methodology, systematic templates
- Later: can mitigate by loosening RedMaGiC χ^2 selection criterion (Pandey+ 2105.13545)
 - Likely problem with *sky background estimation*

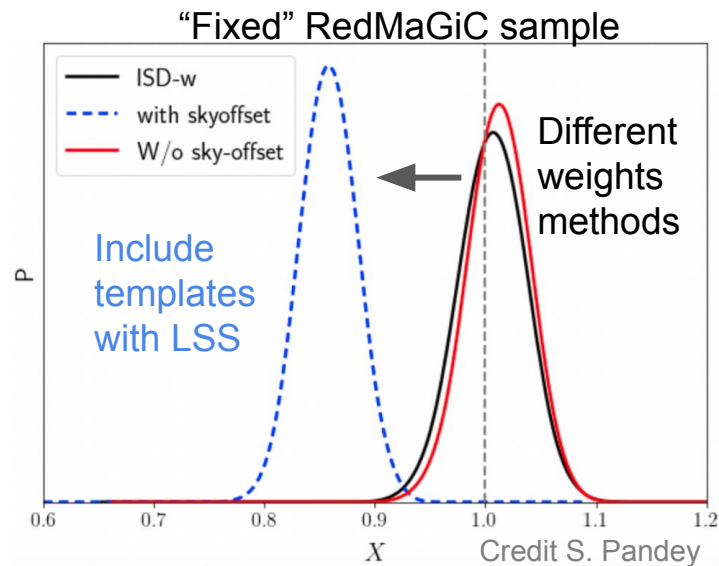
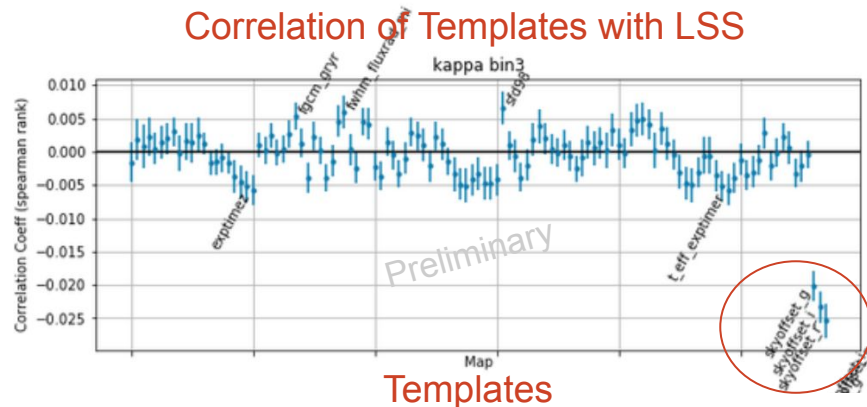
Rodriquez-Monroy, NW et al. 2105.13540



Credit: S. Pandey

Useful Things to Know

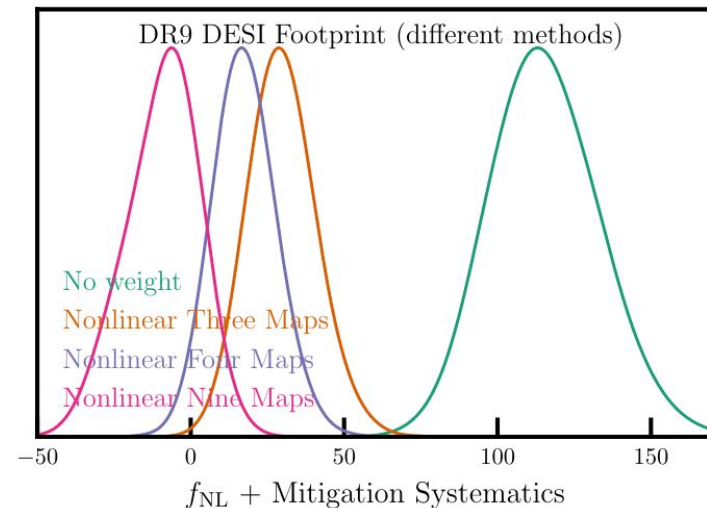
- Identified strong *basis*-dependence of fiducial weights method
 - Also for BOSS weights, which used similar approach
- Can induce $X_{lens} < 1$ if $f_{sys}(t)$ (i.e. weights) correlates with LSS (NW+, in prep)



Going Forward

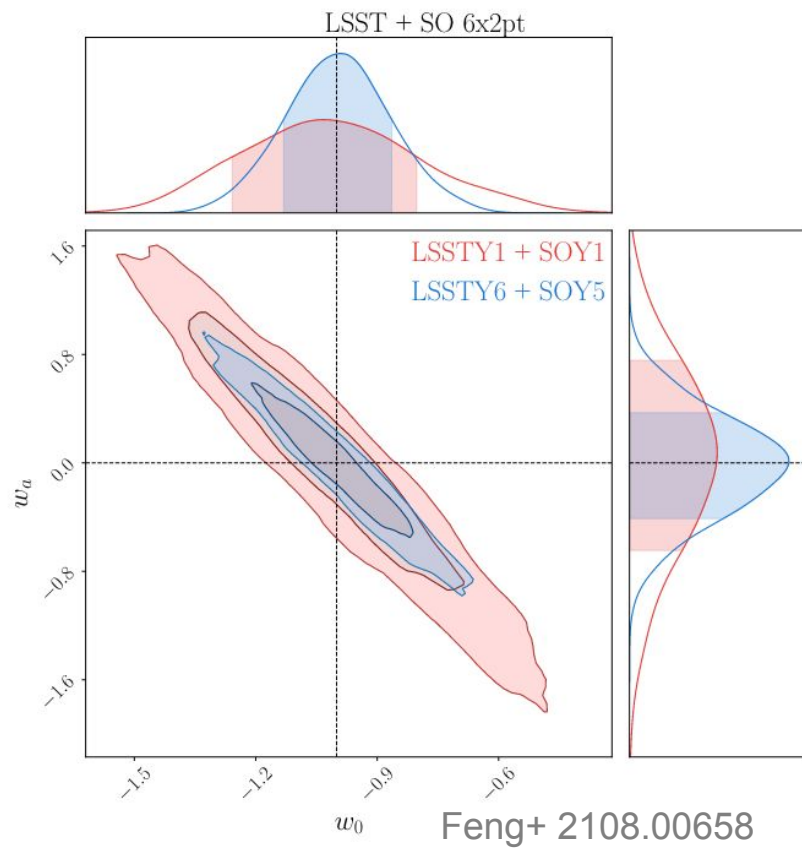
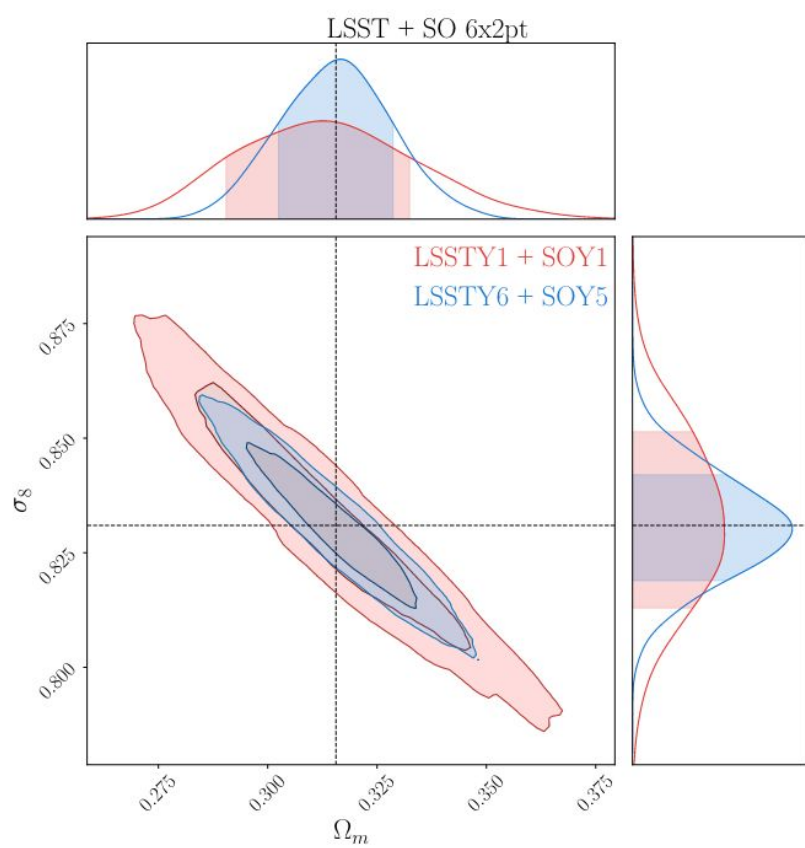
- Multiple ways to get $X_{lens} \neq 1$
clustering high, GGL low, or both
- Motivate and test mask, templates, contamination model (rapid weights estimator useful)
- Test for LSS in weights
 - Avoid highly-correlated data-derived templates
- Quantify and report 2pt *overcorrection*
- Report measure of *uncertainty* on weights (e.g. alternative reasonable sets)
 - Particularly important for beyond-2pt stats

Rezaie+ 2307.01753



Especially critical for f_{nl} analyses!

LSST + SO



LSST + SO

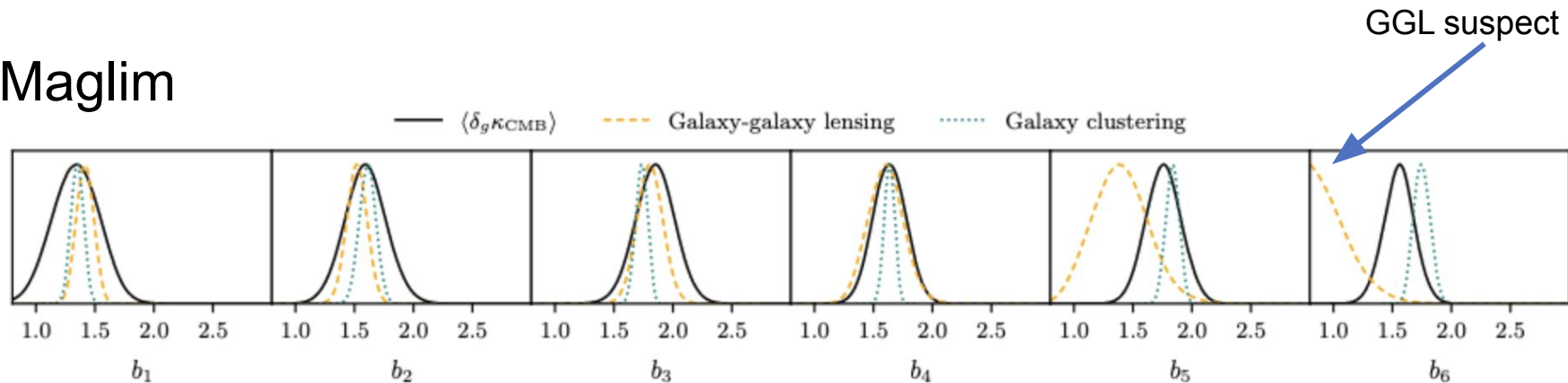
Posterior 1D σ of cosmological parameters

LSST Y1 + SO Y1	σ_{p_i} for Fiducial $w_0 - w_a$ CDM									σ_{p_i} for MG		
	Ω_m	σ_8	n_s	w_0	w_a	Ω_b	h	s_8^*	w_p^*	μ_0	Σ_0	$\mu_0 + 4\Sigma_0$
6×2pt	0.019	0.018	0.036	0.21	0.65	0.0040	0.054	0.0059	0.069	0.40	0.080	0.23
LSST-only 3×2pt	0.020	0.020	0.039	0.22	0.76	0.0040	0.059	0.0076	0.098	0.43	0.079	0.41
6×2pt “lens=source”	0.019	0.017	0.035	0.19	0.61	0.0038	0.054	0.0054	0.056	-	-	-
LSST Y6 + SO Y5	Ω_m	σ_8	n_s	w_0	w_a	Ω_b	h	s_8	w_p	μ_0	Σ_0	$\mu_0 + 4\Sigma_0$
6×2pt	0.014	0.012	0.029	0.14	0.40	0.0037	0.043	0.0040	0.036	0.32	0.064	0.16
LSST-only 3×2pt	0.015	0.014	0.033	0.15	0.50	0.0038	0.050	0.0044	0.062	0.35	0.070	0.31
6×2pt “lens=source”	0.013	0.011	0.024	0.12	0.36	0.0037	0.039	0.0036	0.031	-	-	-

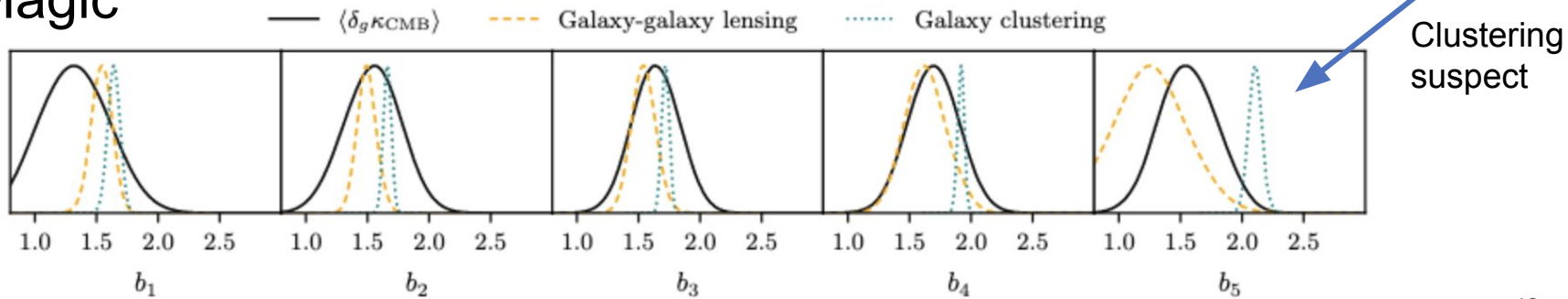
*Define $s_8 = \sigma_8(\Omega_m/0.3)^{0.35}$, $w_p = w(1/(1+z_p))$ at $z_p = 0.5$.

Galaxy Bias inferred via DES x CMB

Maglim

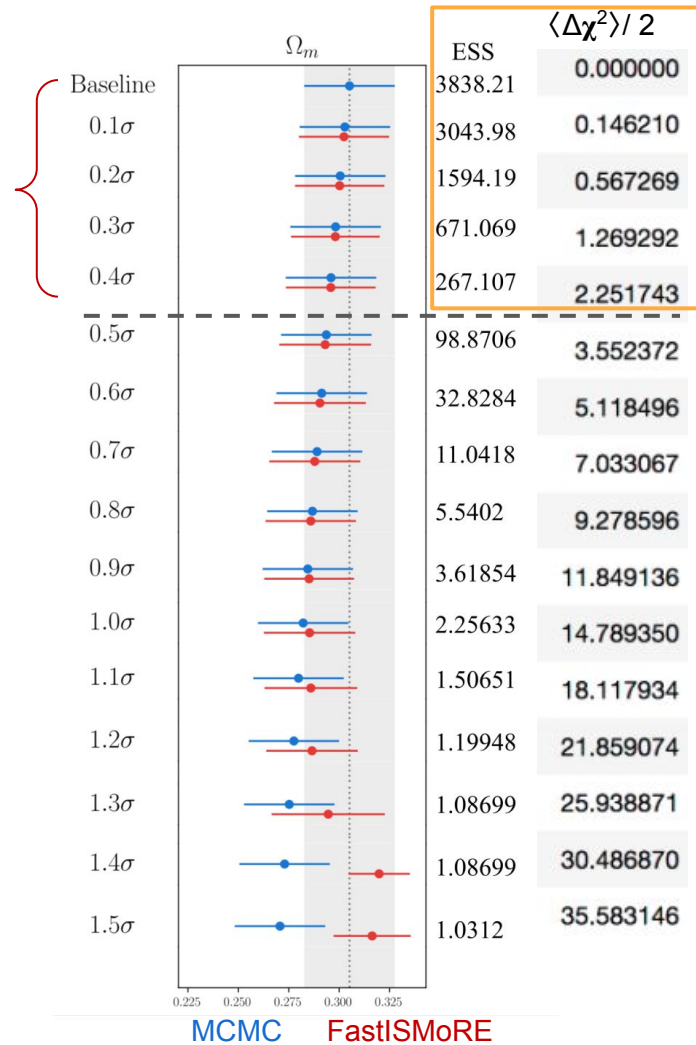
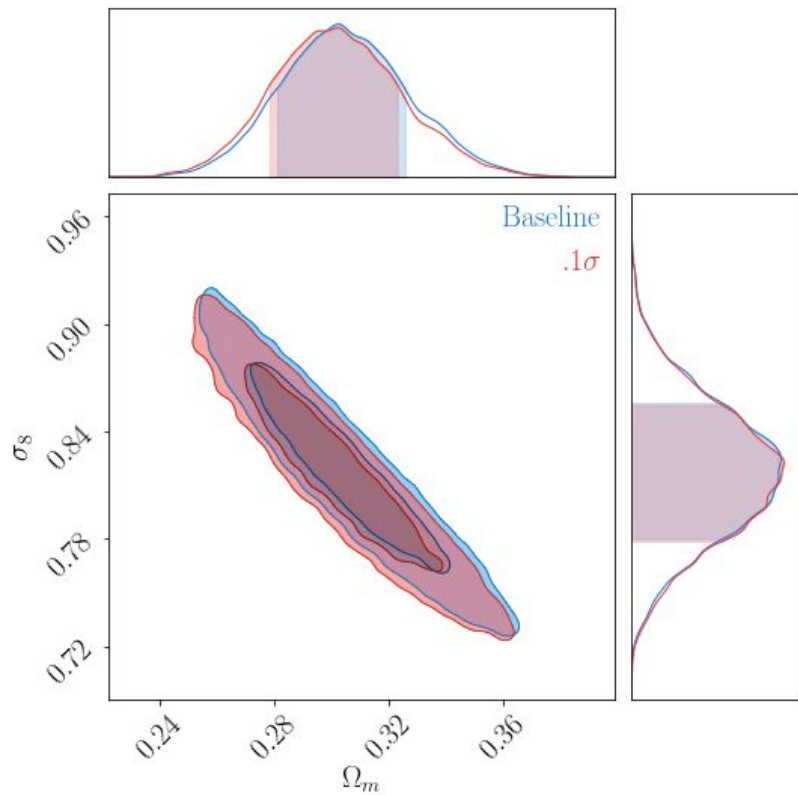


RedMagic



Approach: FastISMoRE

$$\sigma_{\Delta\theta} < 0.1 \sigma_{\theta}$$



Quality stats indicate when IS fails

Ensure negligible impact ($<0.3\sigma$ shift) of:

Unmodeled systematics (synthetic **data vectors**):

- **Nonlinear bias + baryons** (OWLS, high AGN feedback)
- **Nonlinear $P(k)$ prescription**: Halofit \rightarrow Euclid Emulator
- **3σ Magnification** offset

**For each extended model,
For each combination of
probes...
>700 chains!**

Alternative inference **models** (tested on synthetic and blinded real data):

- Intrinsic alignment: NLA (2 params) \rightarrow TATT (5 params)
- Vary X_{lens} parameter ($X_{\text{lens}}^i = b_{\gamma_i(\theta)}^i / b_{w(\theta)}^i$)
- Change $n(z)$ nuisance parameterization
(shift/stretch \rightarrow Hyperrank [Cordero et al., 2109.09636])

Model Comparison

- Bayes factor $R = \frac{Z_0}{Z_X} = \frac{P(d|M_0)}{P(d|M_X)}$

- Suspiciousness (Handley and Lemos 1902.04029)
removes much of prior dependence, can compute p -value

$$\ln S = \ln R - \ln I$$

$$\ln I \equiv \mathcal{D}_X - \mathcal{D}_0$$

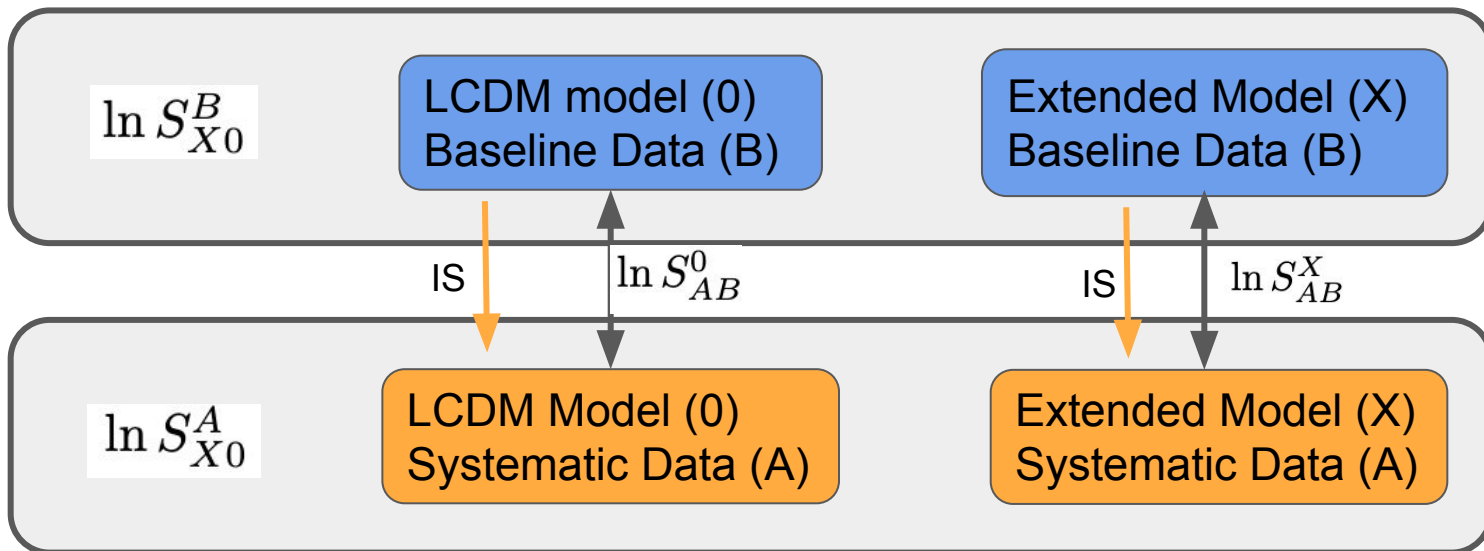
← Contains prior information

- Also $\Delta\chi^2$, DIC, AIC

Do systematics map to a preference for extended models?

Systematic Impact on Model Comparison Statistics

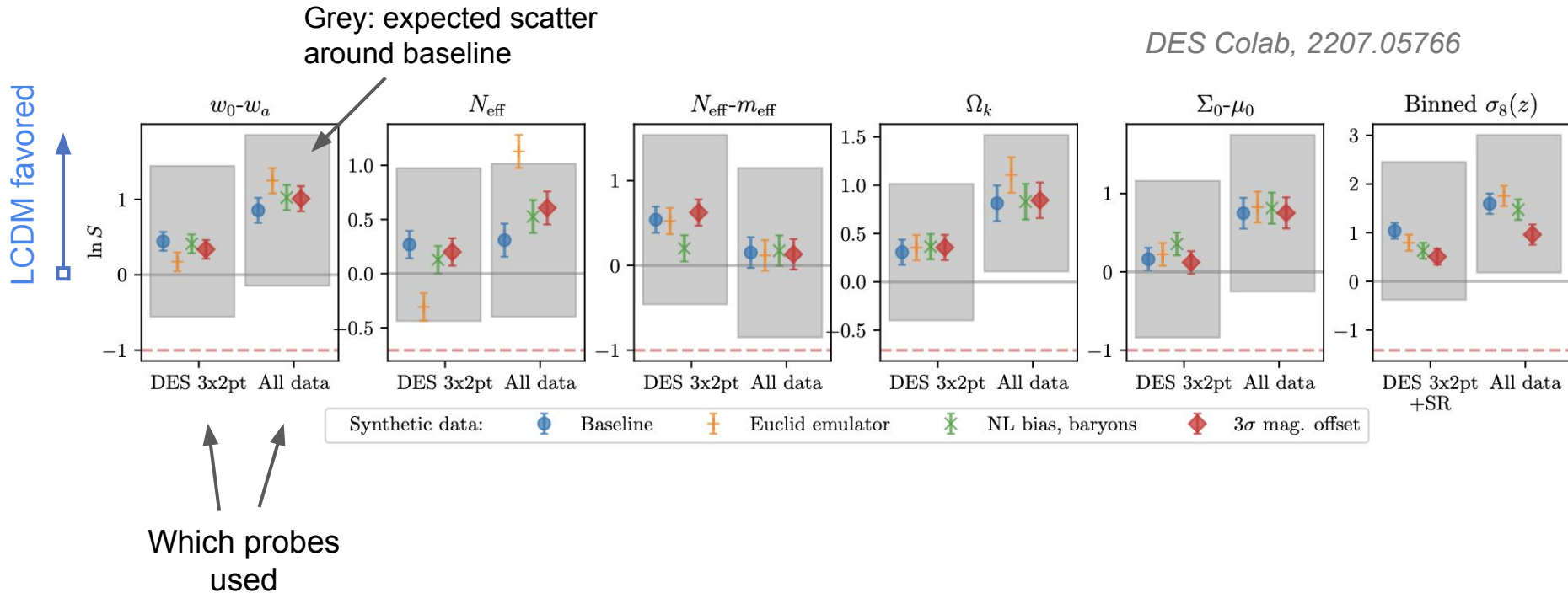
We assume this.



Change in Suspiciousness model comparison stat if systematic in data:

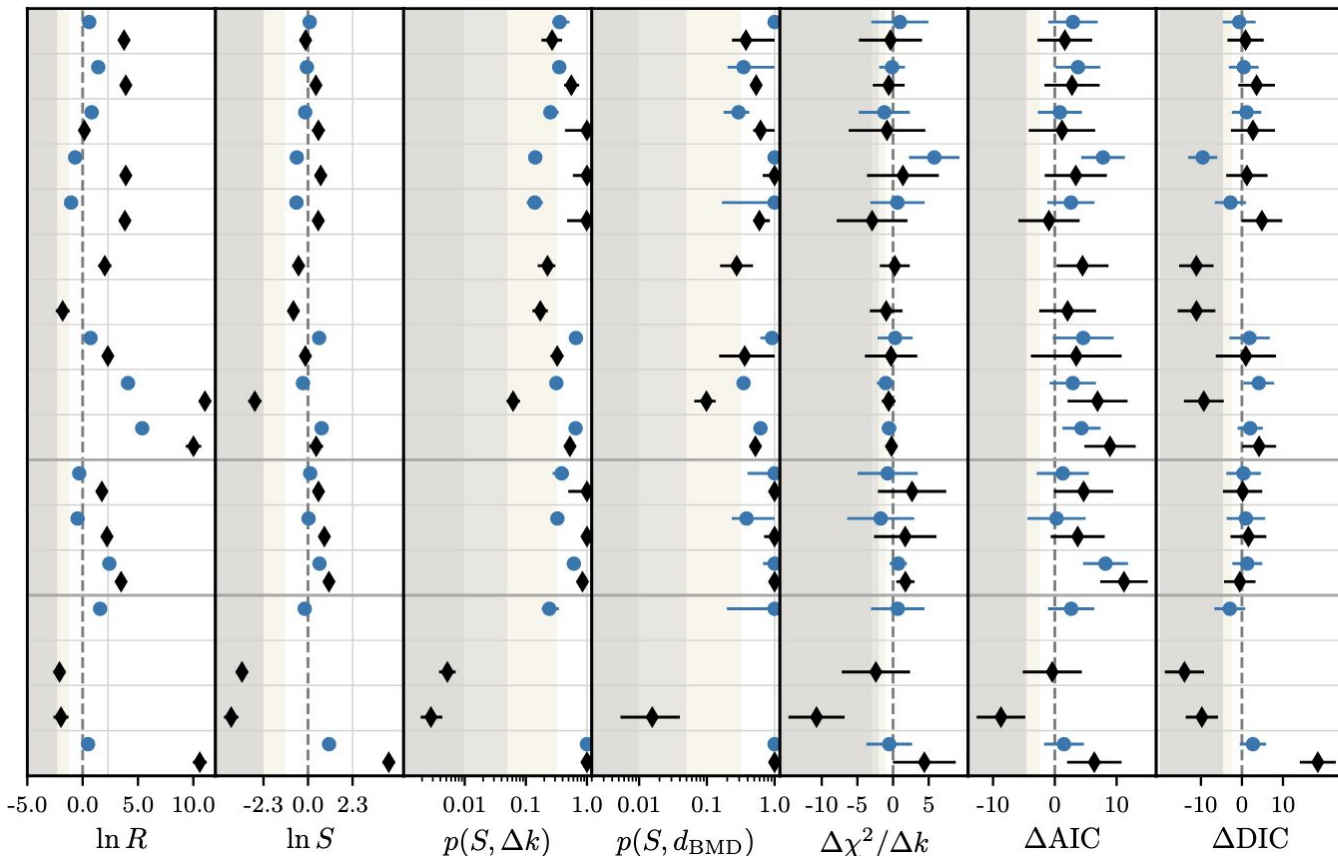
$$\begin{aligned} \Delta \ln S_{X0} &= \ln S_{X0}^A - \ln S_{X0}^B \\ &= \ln S_{AB}^X - \ln S_{AB}^0 \end{aligned}$$

Suspiciousness: Robust to Systematics



● DES 3x2pt
 ◆ 3x2pt+BAO+RSD+SN+Planck

Model Comparisons

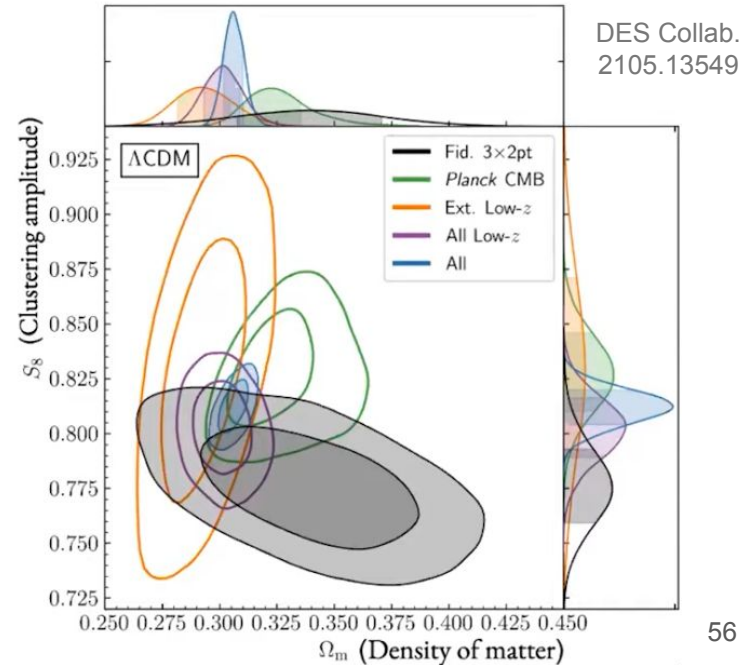
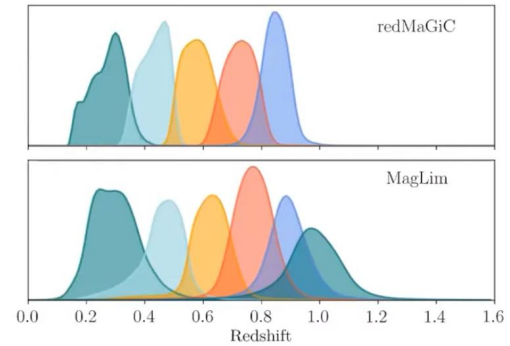


- [w CDM] vs. [Λ CDM]
- [w_0-w_a] vs. [Λ CDM]
- [w_0-w_a] vs. [w CDM]
- [Ω_k] vs. [Λ CDM]
- [N_{eff}] vs. [Λ CDM]
- [$N_{\text{eff}}-m_{\text{eff}}, \Delta N_{\text{eff}} > 0.047$] vs. [Λ CDM, fix m_ν]
- [$N_{\text{eff}}-m_{\text{eff}}, m_{\text{th}} < 10$ eV] vs. [Λ CDM, fix m_ν]
- [$\Sigma_0-\mu_0$] vs. [Λ CDM]
- [Binned $\sigma_8(z)$] vs. [Λ CDM]
- [Binned $\sigma_8(z)$, hyp] vs. [Λ CDM, hyp]
- [Λ CDM] vs. [Λ CDM, fix m_ν]
- [Λ CDM, lin. $P(k)$ +cuts] vs. [Λ CDM, fix m_ν]
- [TATT IA model] vs. [Λ CDM]
- [X_{Lens}] vs. [Λ CDM]
- [A_L] vs. [Λ CDM]
- [A_L , fix m_ν] vs. [Λ CDM, fix m_ν]
- [A_L] vs. [A_L , fix m_ν]

Model Comparison Statistics

DES Y3

- Two lens samples:
redMaGiC and MagLim
- Apply both ISD and ENET weight methods
 - Good agreement
- Analytically marginalize over:
 - Difference in method predictions
 - Over-correction bias
- Rapid assessment of mask, template, method choices
(~2 min vs 1 day)



Simulation Pipeline

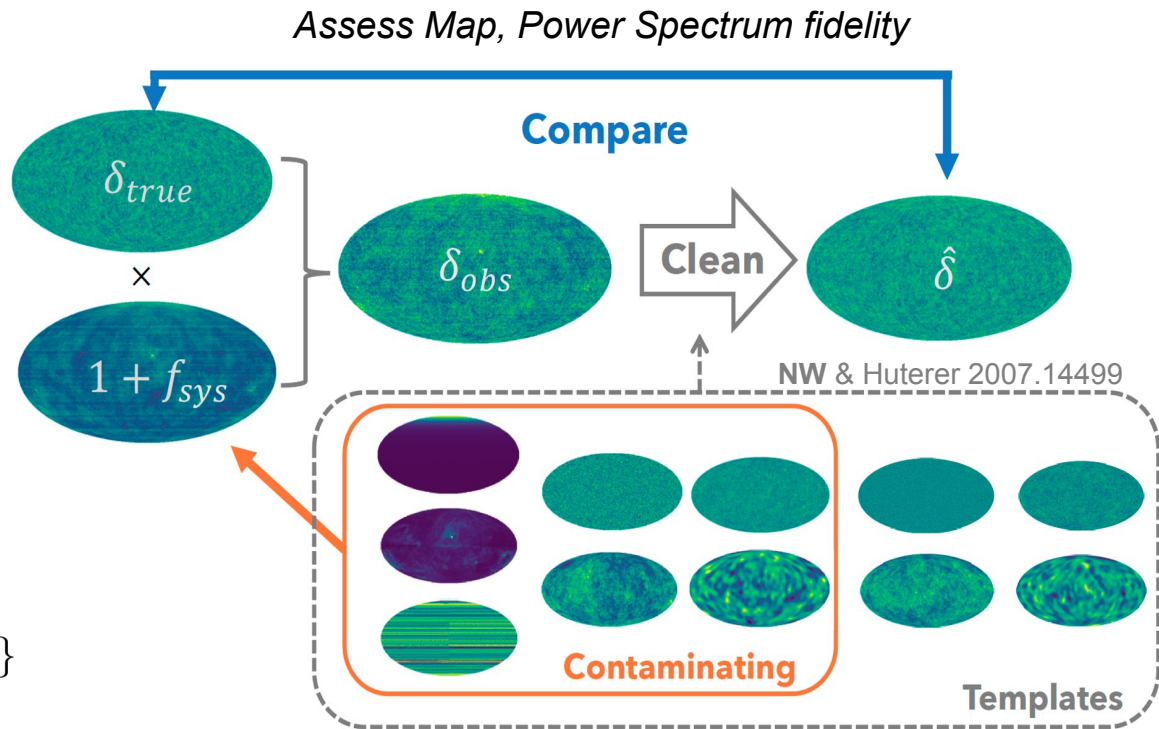
- DES-Y6 like
- 5 z-bins
- Results not strongly sensitive to survey specs

Templates:

- Gaussian realizations

$$C_\ell \propto (\ell + 1)^{-p} \quad p \in \{0, 1, 2\}$$

- Static (Dust, scanning strategy, etc)



Note: Methods applicable to any contaminated signal with templates. Here galaxy clustering, with signal = galaxy overdensity.

Generically: $\delta_{true} \rightarrow s$, $\delta_{obs} \rightarrow d_{obs}$

Mode (De)Projection

MP for Pseudo-CI

$$\begin{aligned}\hat{\delta} &= \mathbf{F} \delta_{\text{obs}} \\ &= \left[\lim_{\beta \rightarrow \infty} (I + \beta t t^\dagger)^{-1} \right] \delta_{\text{obs}} \\ &= \left[I - \underbrace{t(t^\dagger t)^{-1} t^\dagger} \right] \delta_{\text{obs}}\end{aligned}$$

Map estimate

$$\hat{\delta} = \delta_{\text{obs}} - t \hat{\alpha}$$

MP estimate of contamination coefficient α
Is MLE, assuming:

$$\delta \sim \mathcal{N}(0, \sigma^2 I)$$

i.e. $\hat{\alpha} = \text{argmin}_{\alpha} \|\delta_{\text{obs}} - T\alpha\|^2$

Template map

$$\delta_{\text{obs}} \approx \delta_{\text{true}} + \alpha t$$

Multiple systematic templates:

$$t \rightarrow T \quad (N_{\text{pix}} \times N_{\text{tpl}})$$

$$\left. \begin{aligned}y &= X\beta + \epsilon \\ \hat{\beta} &= (X^\dagger X)^{-1} X^\dagger y\end{aligned} \right\} \text{OLS to predict } y \text{ from } X$$

$$\begin{aligned}y &= X(X^\dagger X)^{-1} X^\dagger y + \hat{\epsilon} \\ \delta_{\text{obs}} &= \underbrace{T[T^\dagger T]^{-1} T^\dagger}_{\hat{\alpha}} \delta_{\text{obs}} + \hat{\delta}\end{aligned}$$

Actually care about residuals and their clustering

Multiplicative Correction

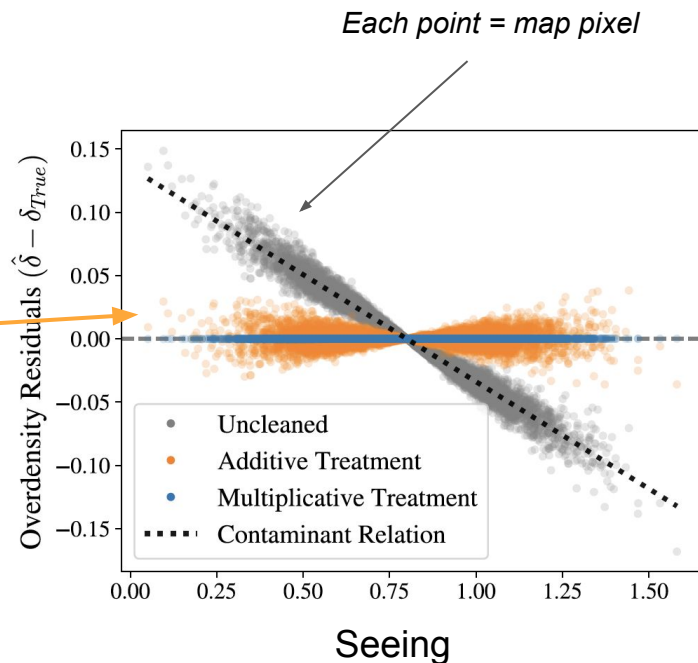
$$1 + \delta_{\text{obs}} = (1 + \delta_{\text{true}})(1 + f_{\text{sys}})\gamma$$

$$\delta_{\text{obs}} \approx \delta_{\text{true}} + \underbrace{f_{\text{sys}}}_{\text{Additive}} + \underbrace{\delta_{\text{true}} f_{\text{sys}}}_{\text{Multiplicative}}$$

- **Additive** estimates (MP, EN, OLS...) leave residual scatter in map
 - Contaminant to small-scale power
- Fix via **multiplicative correction**

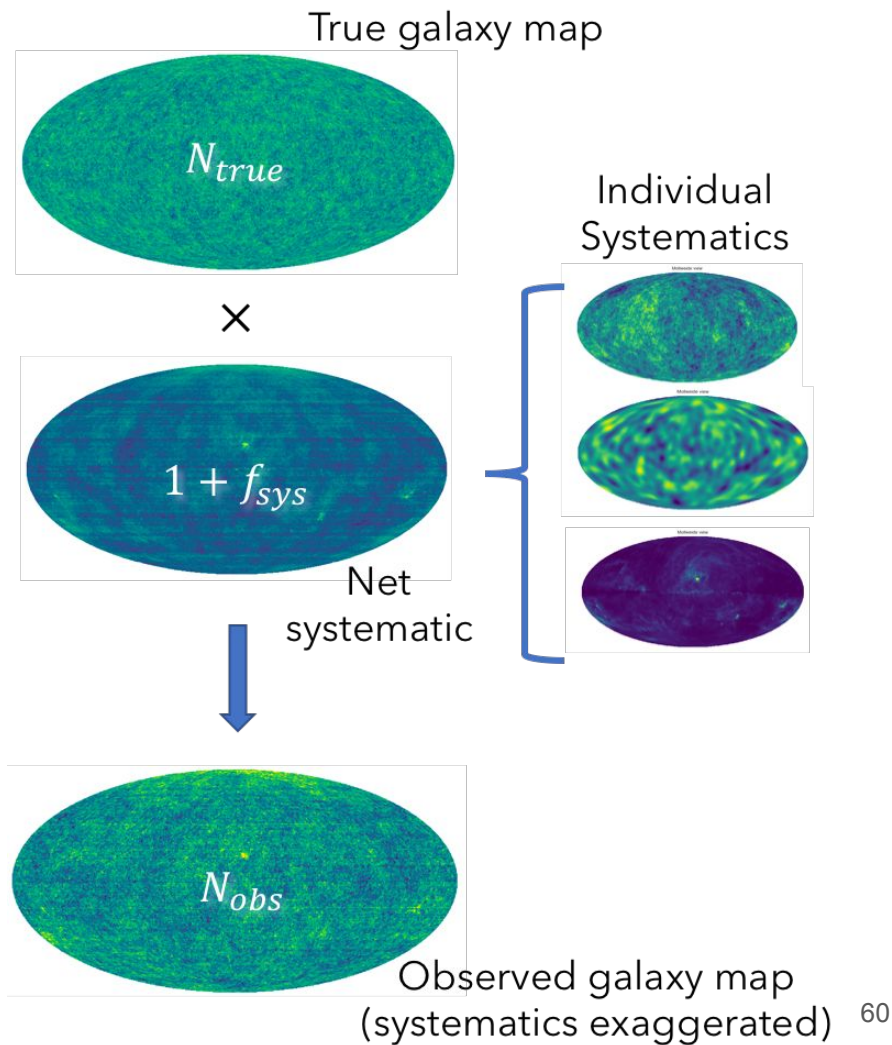
$$\hat{\delta} = \frac{\delta_{\text{obs}} - \hat{f}_{\text{sys}}}{1 + \hat{f}_{\text{sys}}}$$

Next → compare methods on simulation



Model spatial systematics

- Spatially dependent screen (f_{sys}) modulates galaxy density
- Result: density maps biased! (and 2-pt functions, 3-pt, ...)



“Theory” uncertainty in weights methodology

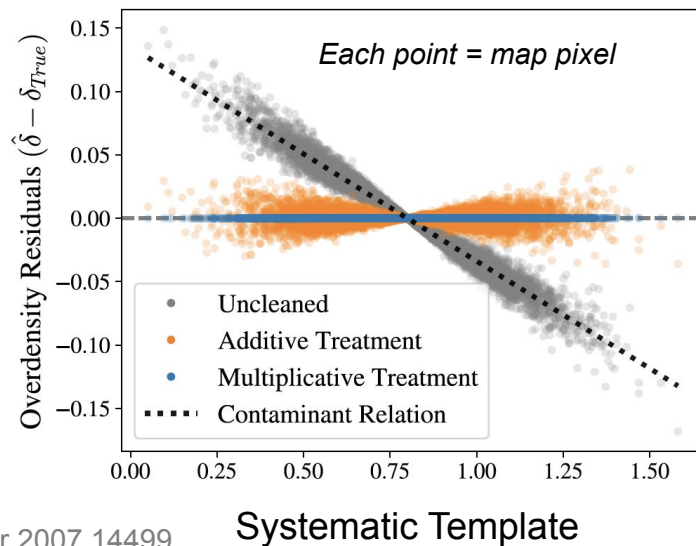
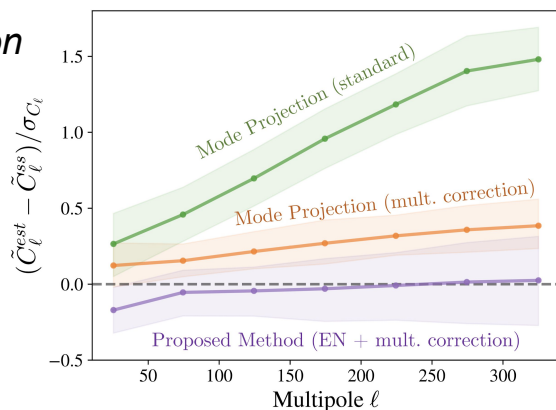
- Additive vs multiplicative treatment
 - Most systematics *multiplicative* (exception: stellar contamination)
 - **Additive** correction methods neglect *multiplicative* term (e.g. Mode Deprojection)
 - BUT! Multiplicative correction “for free”

$$1 + \delta_{\text{obs}} = (1 + \delta_{\text{true}})(1 + f_{\text{sys}})\gamma$$

$$\delta_{\text{obs}} \approx \delta_{\text{true}} + f_{\text{sys}} + \delta_{\text{true}}f_{\text{sys}}$$

Compare methods on mocks

Power Spectrum Error ($N\sigma$)

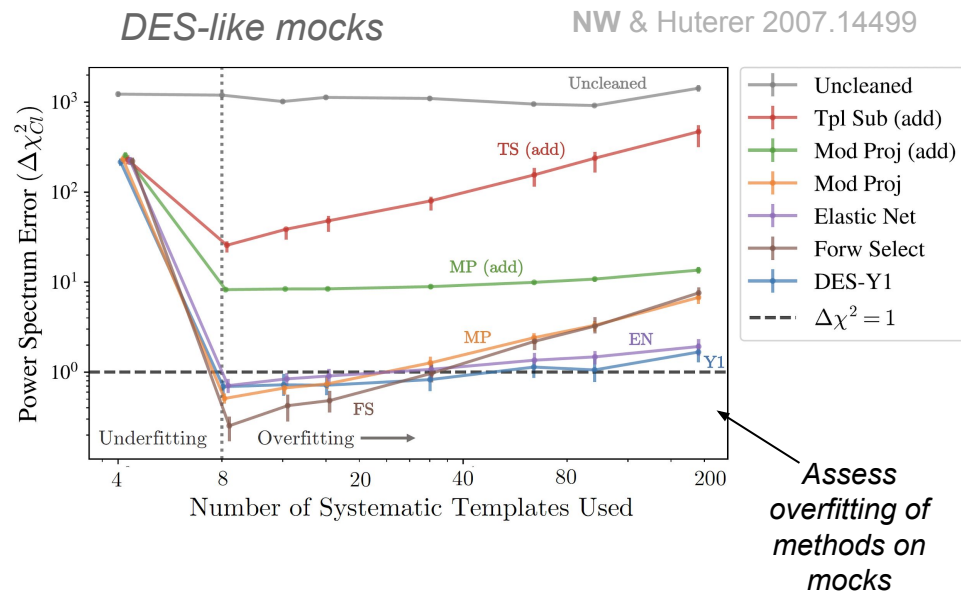


“Theory” uncertainty in weights methodology

- What model for f_{sys} ?

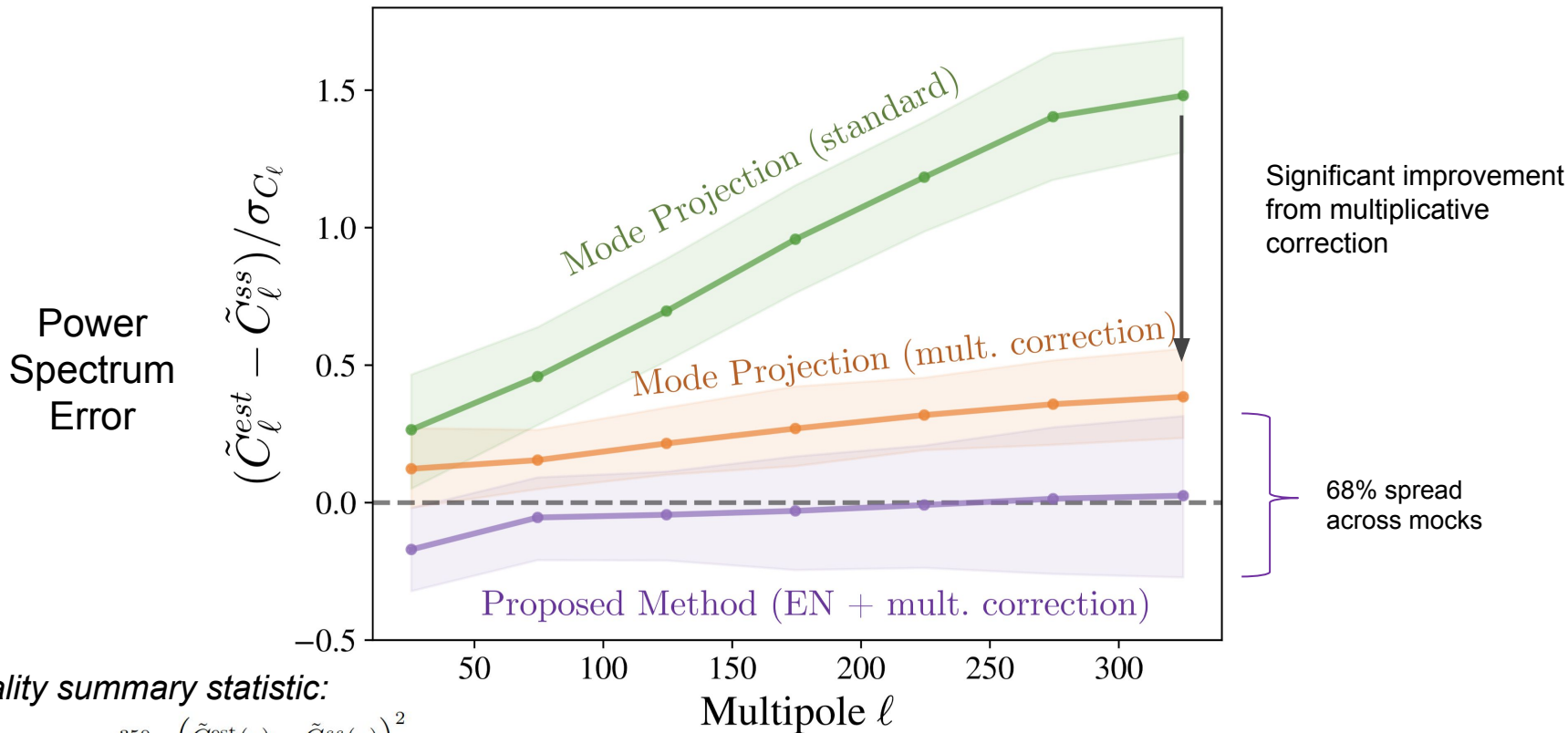
Which systematics templates?

- Defines *contamination degrees of freedom*
E.g. linear, quadratic, or ML-built models (NNs, RFs etc)
- E.g. with BOSS data,
Use ~10 (Ross+ 2012) or
~2000? (Leistedt & Peiris 2015)
- More templates → more *statistical nulling of LSS modes* → *galaxy power suppressed*
 - Can “harden” methods to overcorrection,
different scaling with N_{tpl}



$$\Delta\chi^2_{C\ell} = \sum_{z \text{ bins}} \sum_{\ell=\ell_{\min}}^{350} \frac{(\tilde{C}_{\ell}^{\text{est}}(z) - \tilde{C}_{\ell}^{\text{ss}}(z))^2}{\sigma_{C_{\ell}^{\text{ss}}(z)}^2}$$

Importance of Multiplicative Correction



Quality summary statistic:

$$\Delta\chi_{C_\ell}^2 = \sum_{z\text{bins}} \sum_{\ell=\ell_{\min}}^{350} \frac{(\tilde{C}_\ell^{\text{est}}(z) - \tilde{C}_\ell^{\text{ss}}(z))^2}{\sigma_{C_\ell^{\text{ss}}(z)}^2},$$

MP Assumptions on Noise

- True clustering signal = regression “noise”

Only optimal if clustering signal

- 1) Gaussian
- 2) Diagonal
- 3) Flat

Can estimate α in pixel space or harmonic space $\hat{\alpha} = [T^\dagger T]^{-1} T^\dagger \delta_{\text{obs}}$

Diagonalize and optimally weight in harmonic space

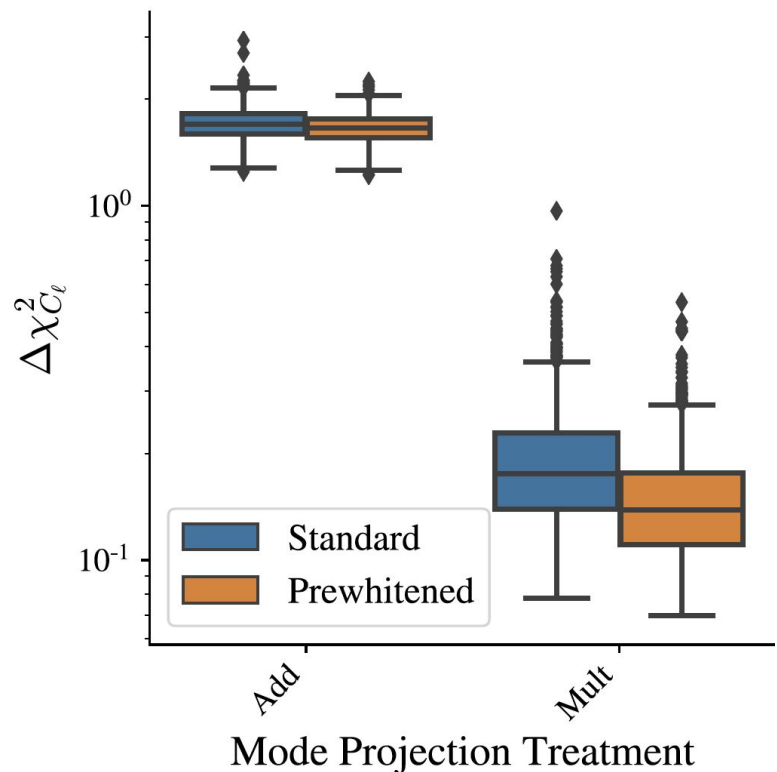
$$\hat{\alpha} = \frac{\sum_{\ell=0}^{\ell_{\max}} (2\ell + 1) \tilde{C}_\ell^{td} / C_\ell^{ss}}{\sum_{\ell=0}^{\ell_{\max}} (2\ell + 1) \tilde{C}_\ell^{tt} / C_\ell^{ss}}.$$

	Pixel Space	Harmonic Space
Data	$\delta_{\text{obs}}(\hat{n}_i)$	$[\delta_{\text{obs}}]_{\ell m}$
Dims of T	$N_{\text{pix}} \times N_{\text{tpl}}$ (real)	$N_{\ell m} \times N_{\text{tpl}}$ (complex)
Regression Noise (additive)	$\delta(\hat{n}_i)$	$\delta_{\ell m}$
Gaussian	Approx. (~lognormal)	Yes
Diagonal	No	Yes
Flat	Yes	No

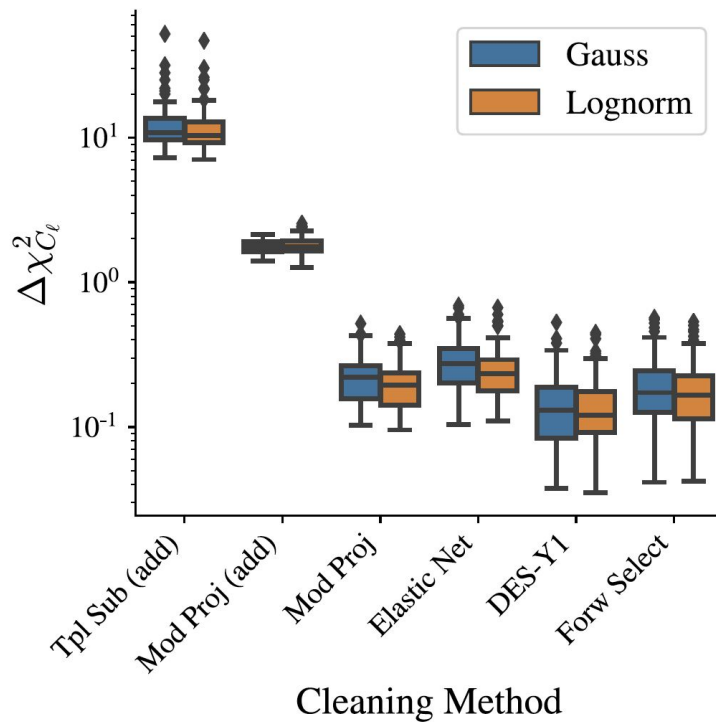
$$(d_{\text{obs}})'_{\ell m} = (d_{\text{obs}})_{\ell m} / \sqrt{C_\ell^{ss}}.$$

$$(t_i)'_{\ell m} = (t_i)_{\ell m} / \sqrt{C_\ell^{ss}},$$

Impact of pixel covariance
Minor compared to methodological differences.

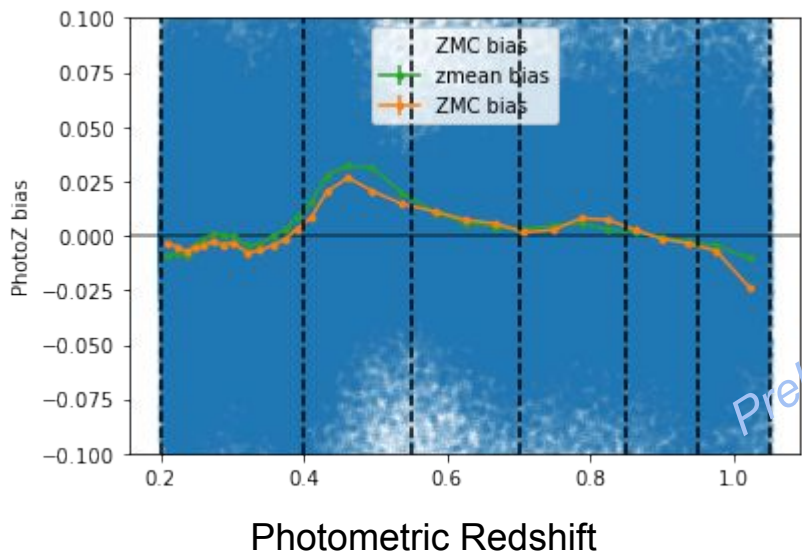


No method particularly susceptible to Gaussian assumption

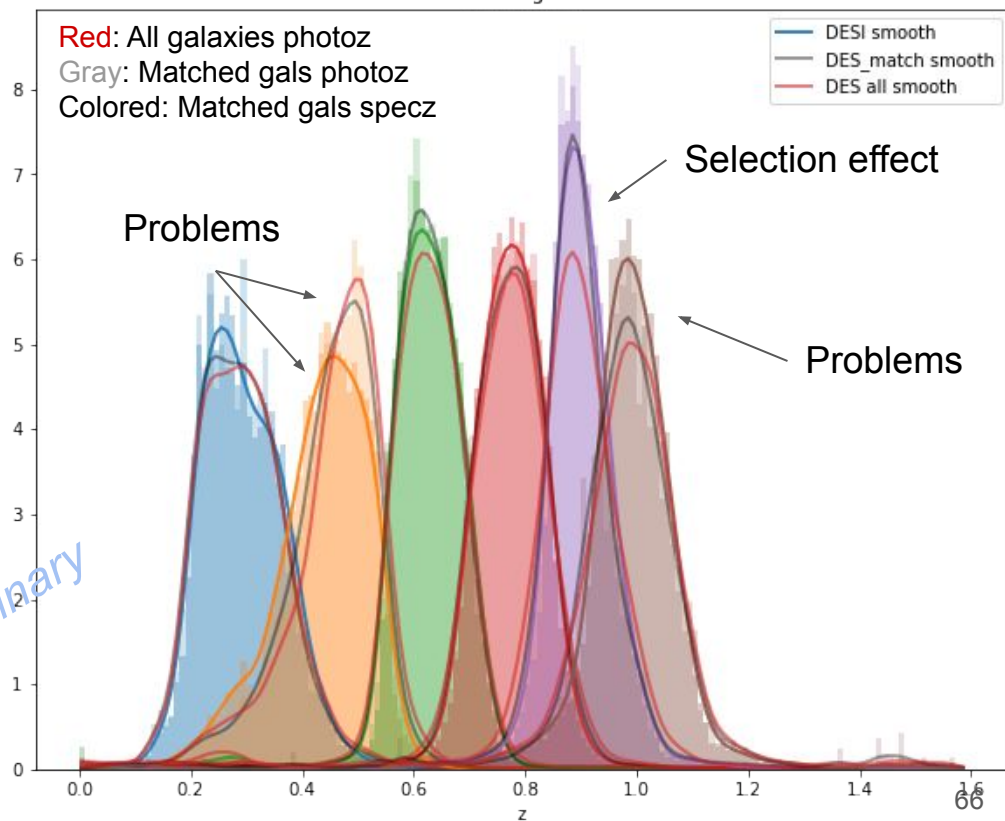
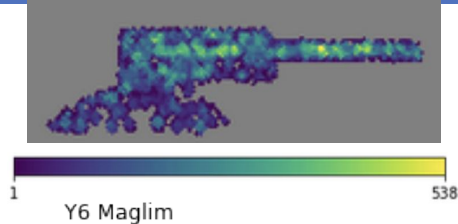


Let's leverage DESI

- Look at 400k lenses with DESI spectra
- (But selection effects)

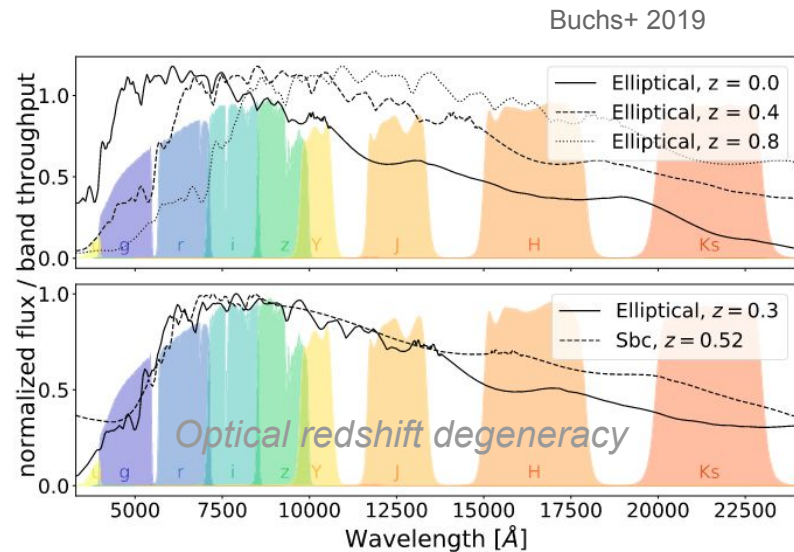


N spectra



Photometric Redshifts

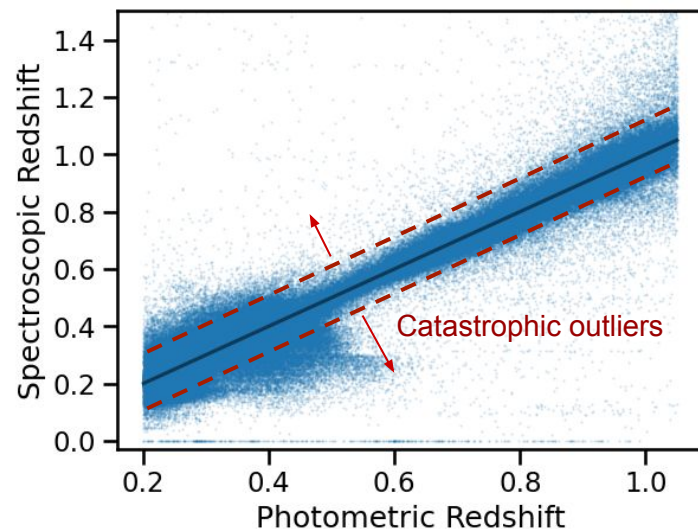
- Photo-z's: major systematic of weak lensing surveys
- LSST is big, limited by control of systematics
- Spectra from DESI and DESI-II foundational for LSST science
- Photo-z estimation: learn $z \sim f(\text{photometry})$ from existing spectroscopy
 - Two types: $p(z)$ per *galaxy*, and $N(z)$ for full *sample*
 - $N(z)$ main target for 3x2pt, though $p(z)$ important for narrow redshift bins



Problem of Representativity

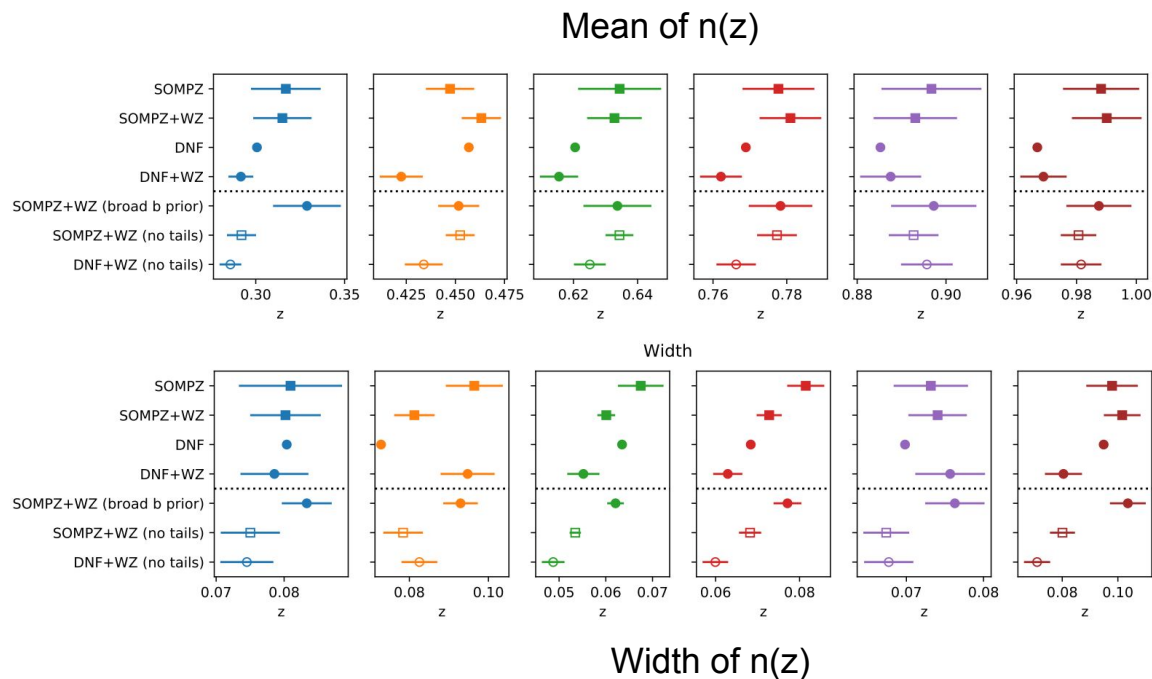
Key challenge: spec samples not representative of target photometric samples!

- Different selections, spec failure rates, sample variance etc (e.g. Hartley+ 2021, Newman & Gruen 2022)
- Hard to quantify
- Myriad photo-z codes with different approaches, all with own secret sauce

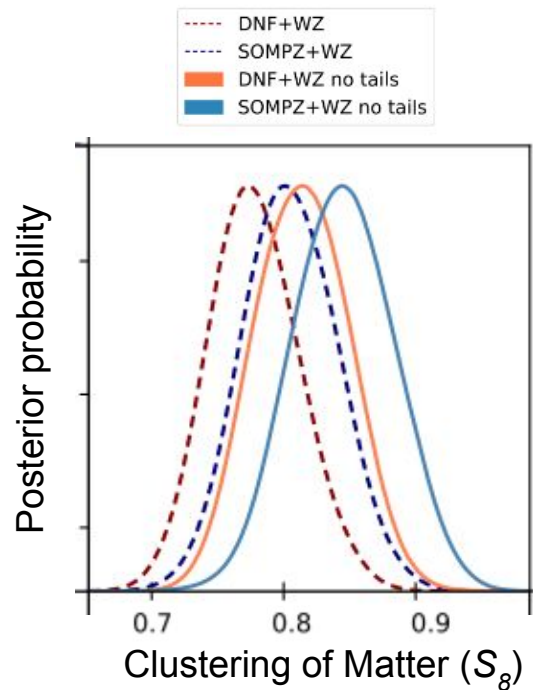


Choices important!

- E.g. impact of different choices when combining/comparing different methods



Systematic impact of
different photo- z choices
DES Y3, 2x2pt



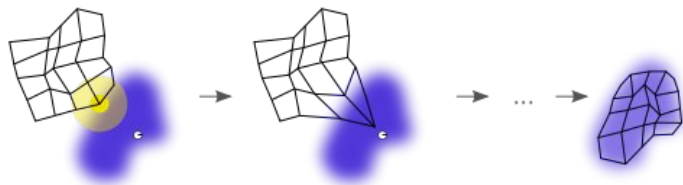
Implications for DESI/DESI-II

1. *Direct calibration* of $N(z)$ via targeted follow-up: circumvent most photo-z systematics
 - a. Can we identify regions in color-mag space where reasonable?
 - i. Don't need to calibrate all possible galaxy samples
 - ii. Inform LSST color selections
 - b. Opportunity: hybrid selection — sample cleaning for free!
2. Training: important to get spectra for full range of color-mag space relevant for WL studies.
 - a. Is this possible? (See also Biprateep and Jeff's talk)

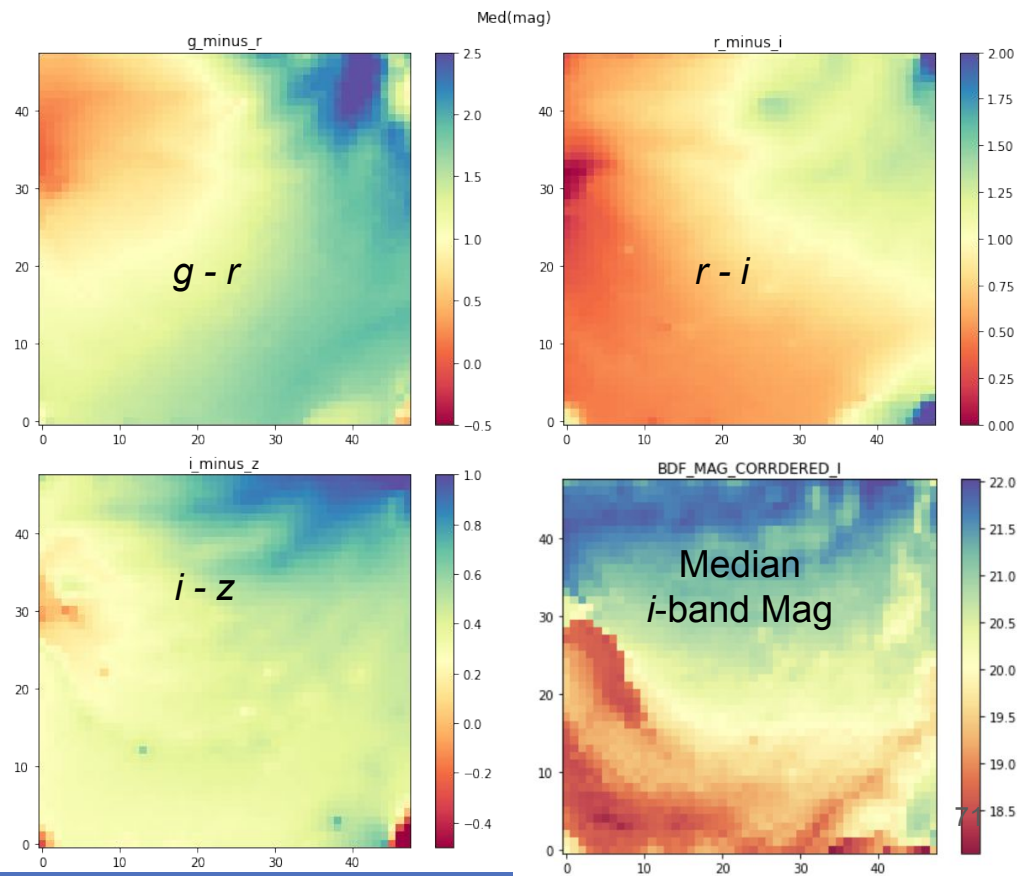
Characterize galaxies in mag-color space using SOM

10M lens galaxies from DES

- Self-Organizing Map (SOM): 2D non-linear projection of full color-mag space
 - Learned from data
- Galaxies grouped into cells, neighboring cells similar
- Axes arbitrary (but fixed)

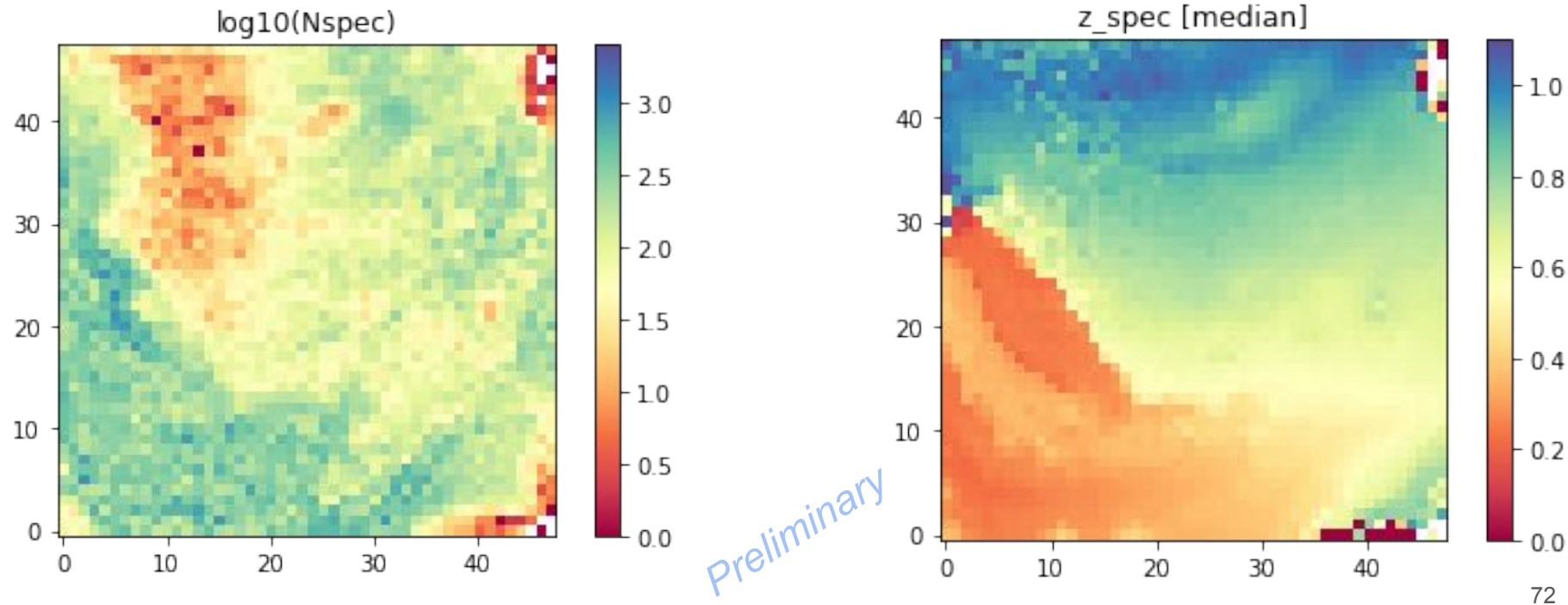


https://en.wikipedia.org/wiki/Self-organizing_map



Match to DESI objects, populate with spec info (N=400k)

- Summarize *spectroscopic* characteristics for each cell



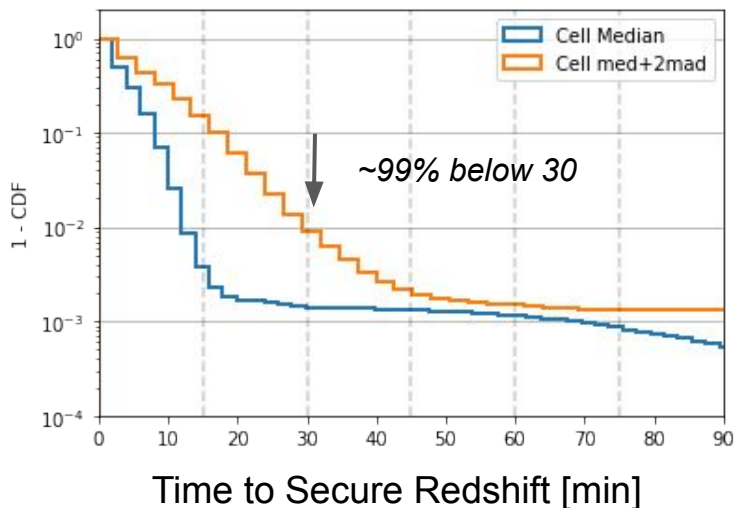
Estimate time to obtain good redshift with DESI

- Compute **estimated observing time** for each spec gal

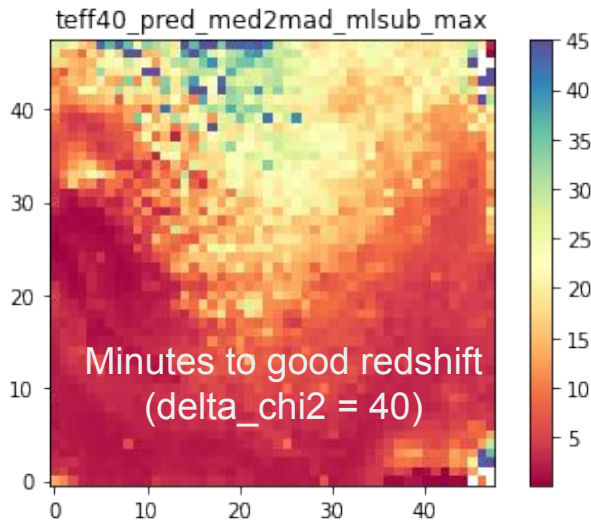
Characteristic observing time for standardized delta chi²:

$$\tau(\Delta\chi^2_{\text{char}}, i_{\text{char}}) = \text{TSNR2_LRG} \times \left(\frac{12.15}{60}\right) \left(\frac{\Delta\chi^2_{\text{char}}}{\Delta\chi^2}\right)$$

Cumulative fraction of galaxies requiring more time

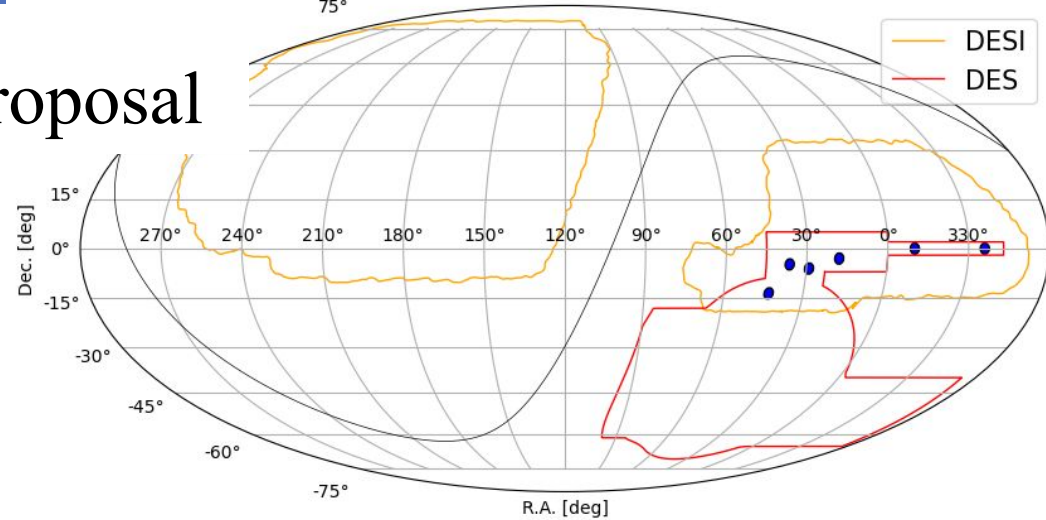


Summarize cell via (Median + 2*(1.48*MAD))

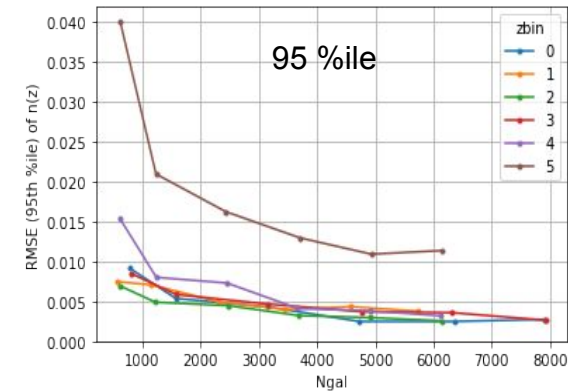
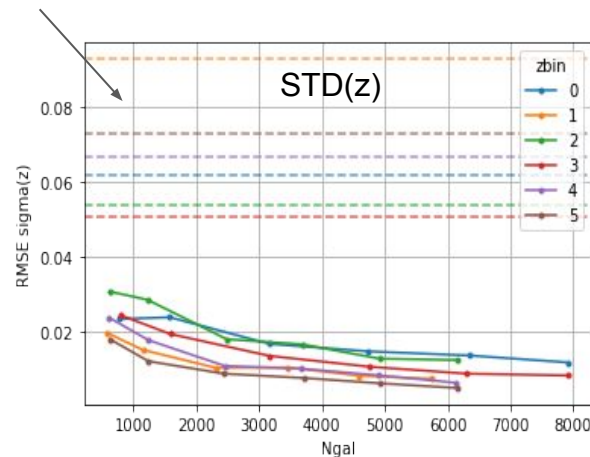
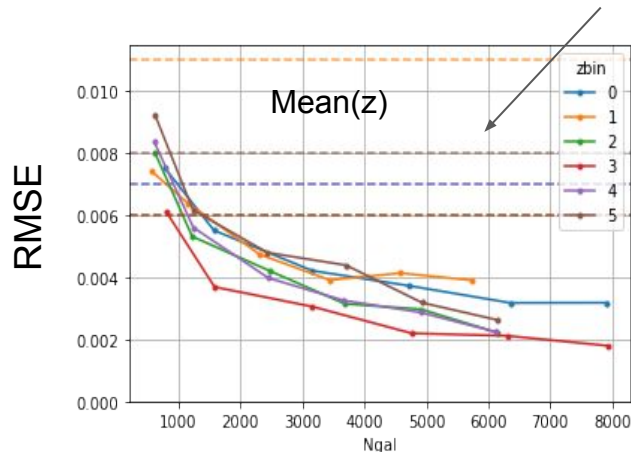


DirCal proof of concept proposal

- Initially proposed for ongoing DES Y6 legacy analysis
- 6 pointings, spread across overlap
- No dark time, but single pointing in XMM for 12 mins bright time



Clustering redshift constraints

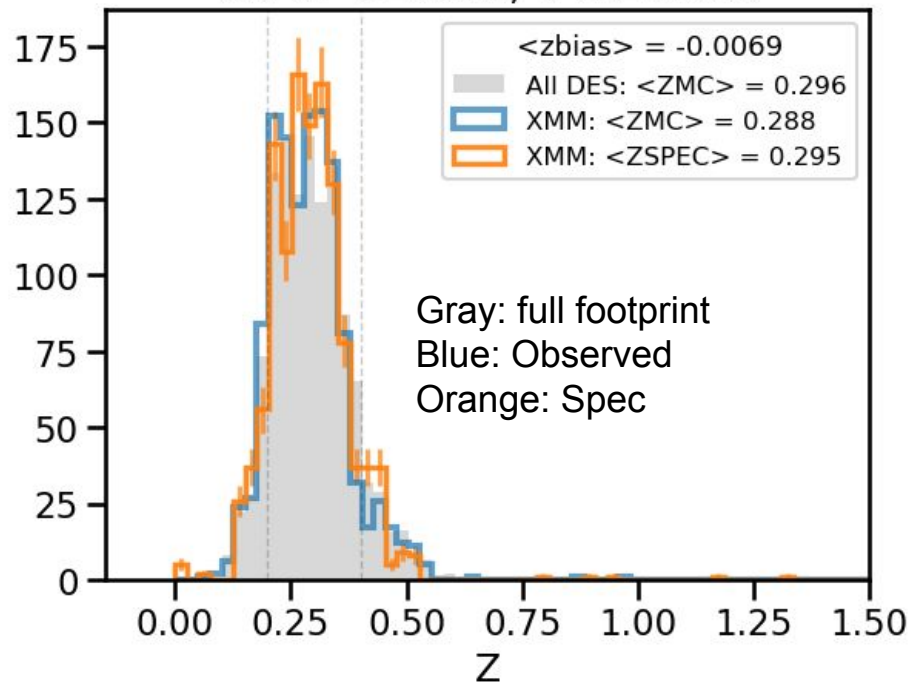


Number of spectra per redshift bin

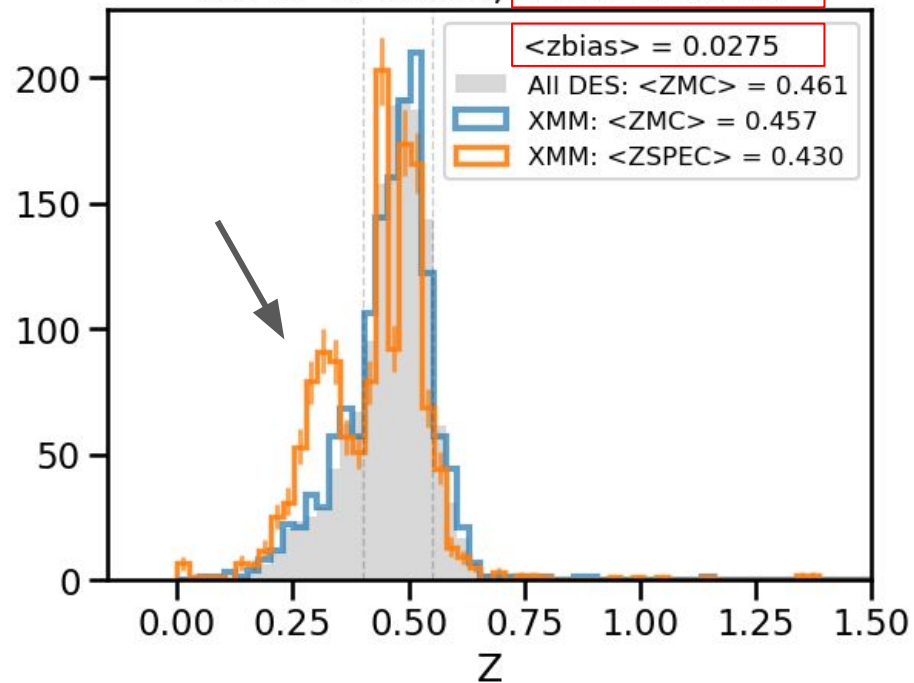
Results Promising!

Single pointing, $\sim 99\%$ success, reveals features missed by photo-z's

Bin 0. $N=1211$, $PTE=0.084$

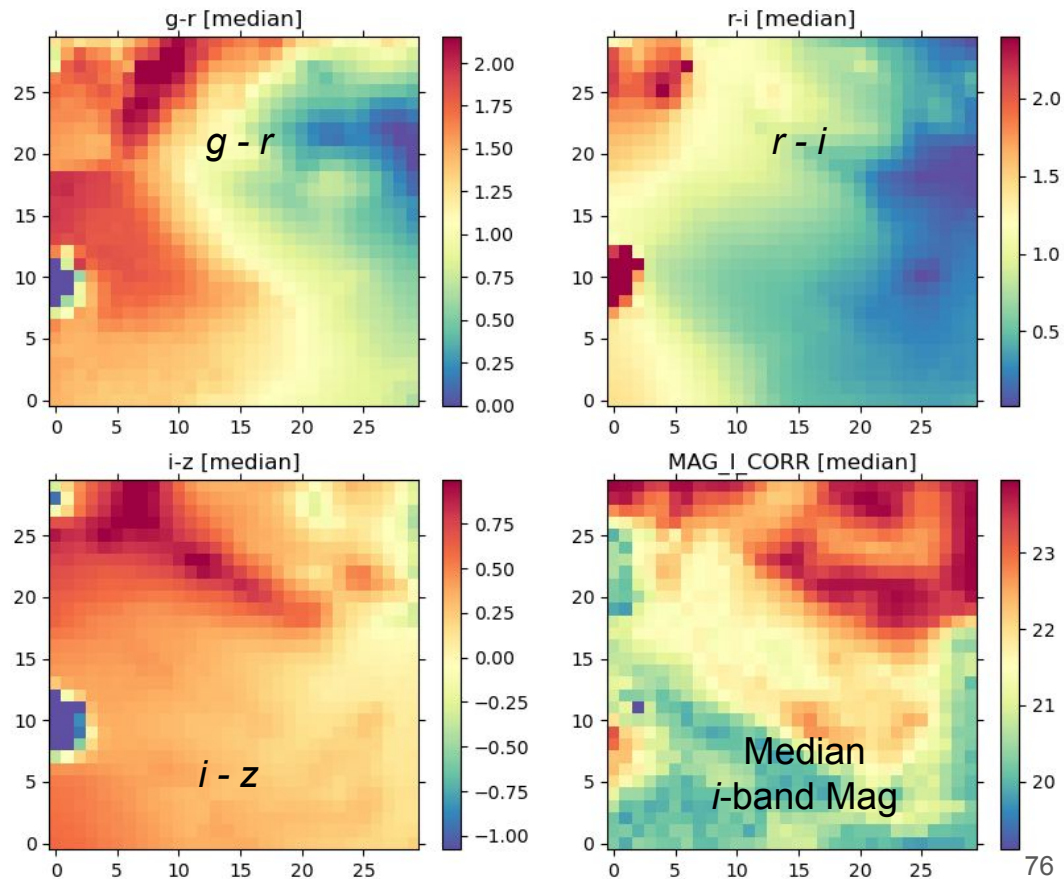
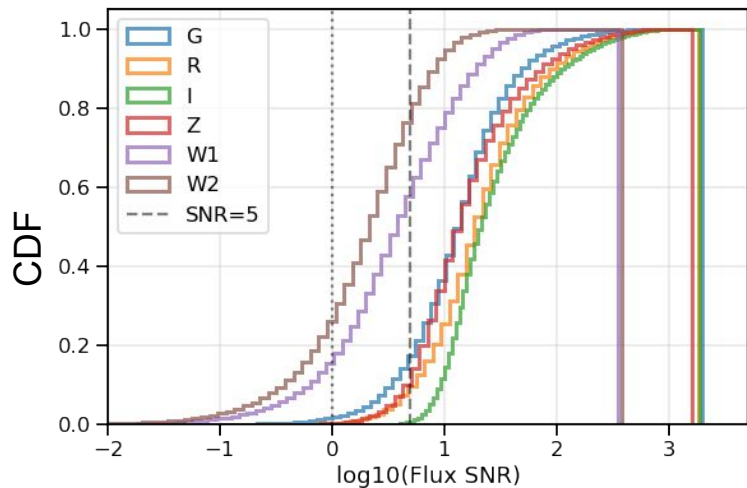


Bin 1. $N=1388$, $PTE=4.4e-18$



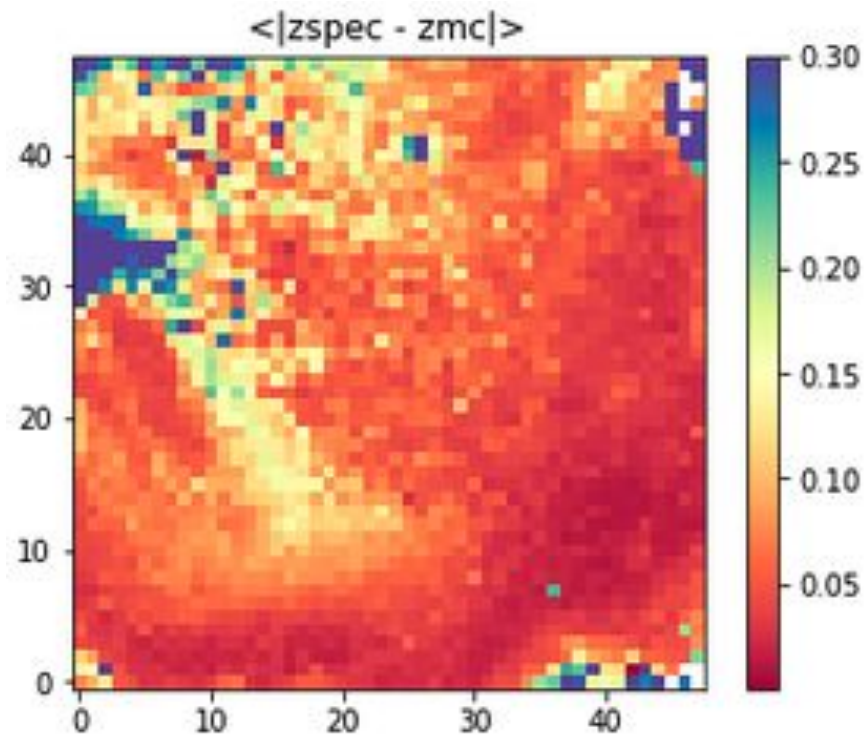
Looking toward LSST

- Sample with LSST Y1 depth
- All DR10 objects in COSMOS with $19 < i < 24.1$ (N~610k)
- GRIZ



Can use DESI to identify problematic galaxy types in lens sample

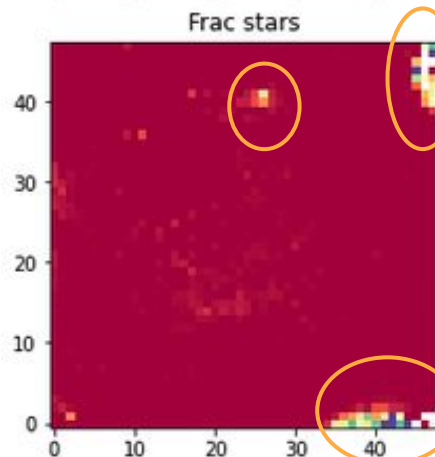
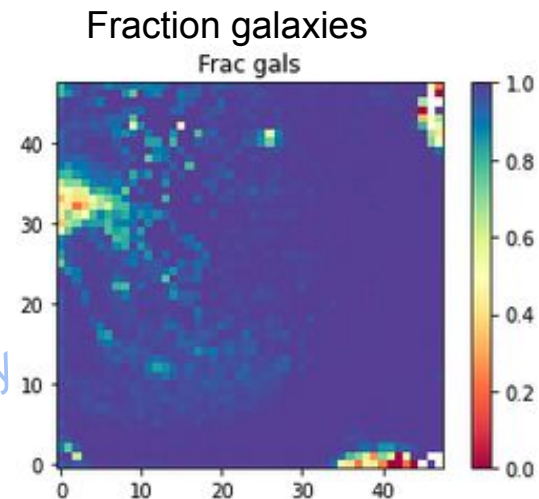
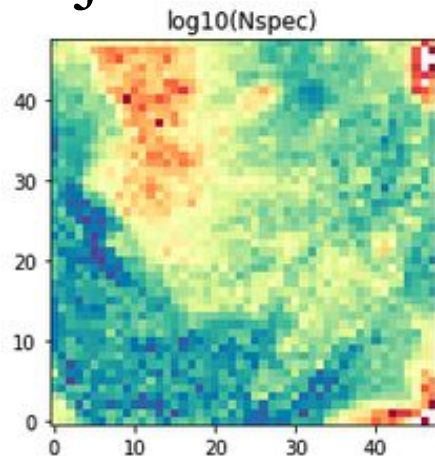
- Assess photo-z bias per cell



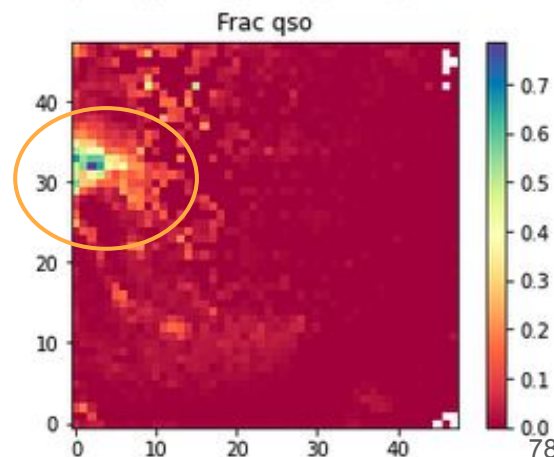
Preliminary

What are these bad objects?

Contamination in the lenses!



Fraction stars



Fraction quasars

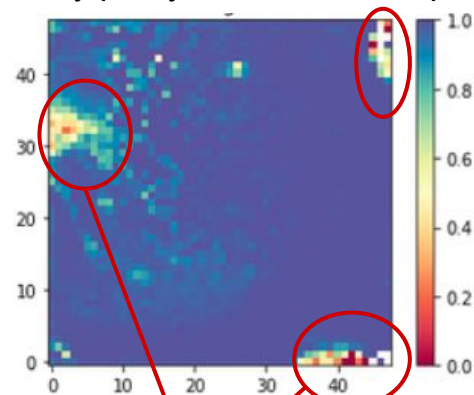
preliminary

Current Work

- Co-leading DES Y6 LSS systematics mitigation with improved methods
- Characterizing impacts of photo-z errors on WL surveys
- Synergies between spectroscopic surveys (e.g. DESI) and imaging surveys (e.g. LSST)
 - Direct $n(z)$ calibration
 - Sample cleaning and optimization
- How to do cosmology in the era of climate change

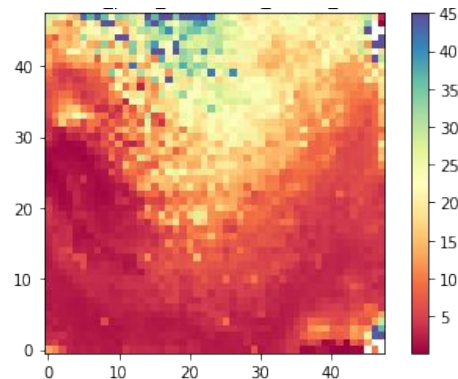
2D projection of
4D photometric
color space

Galaxy purity in WL lens sample



Regions in color space
with large contamination
fraction

Time to secure spectroscopic
redshift [min]

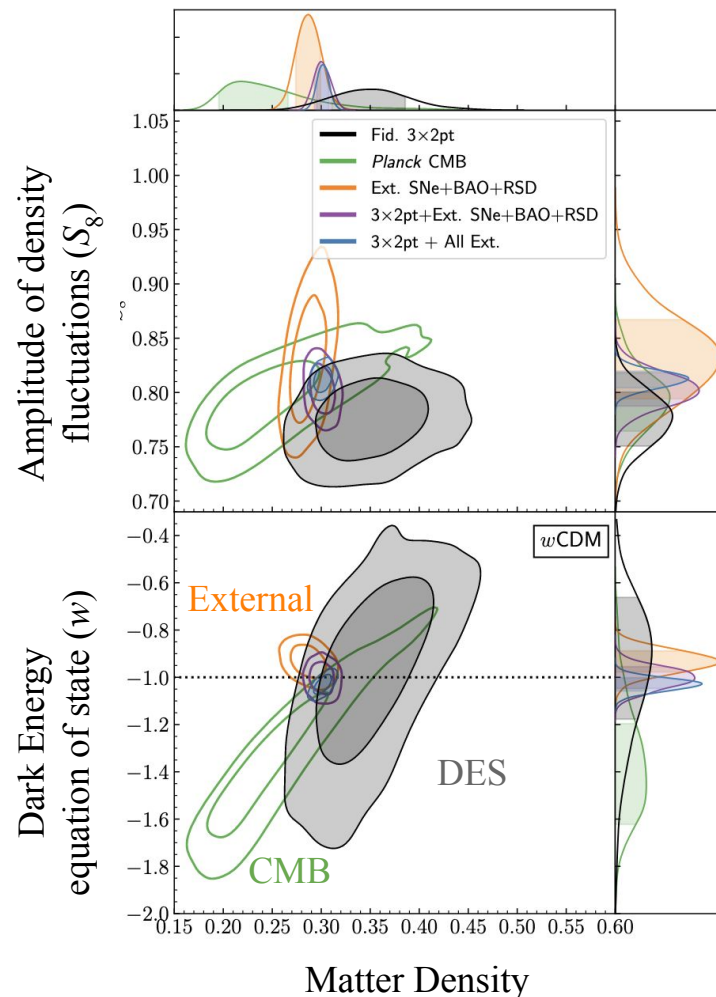


Feel free to reach out!
NWeaverdyck@lbl.gov



Dark Energy Results

- Most powerful 3x2pt constraints from a single galaxy survey
- 2x improvement in S/N over Year 1
- Highly complementary to other probes!
- No evidence for deviation from $w = -1$ (Λ CDM, cosmological constant)



In Λ CDM

- LSS competitive with CMB constraints
→ but S_8 tension!
- LSST, DESI, Roman, SPHEREx...
Large areas, number densities
→ **small** statistical error
- **Need exquisite control of systematics to claim new physics**

