Understanding Cosmological Observations: Angular Systematics in LSS Surveys and Lessons from DES Y3

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(with Dragan Huterer and lots of DES folks)

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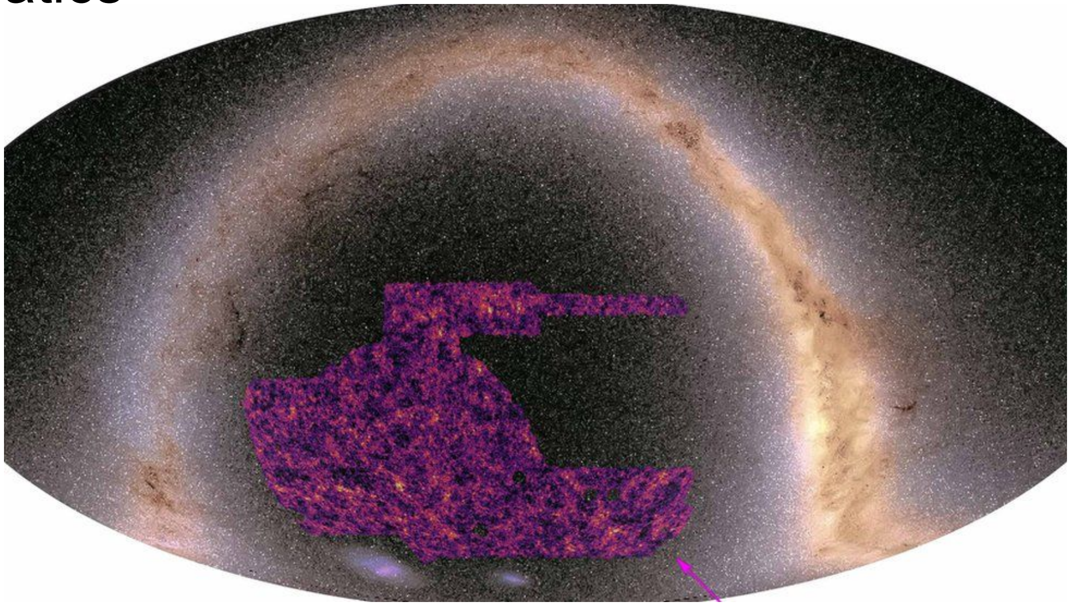
Outline

- Background: LSS Systematics
- Mitigation methods
- DES Y3
  and Lessons Learned

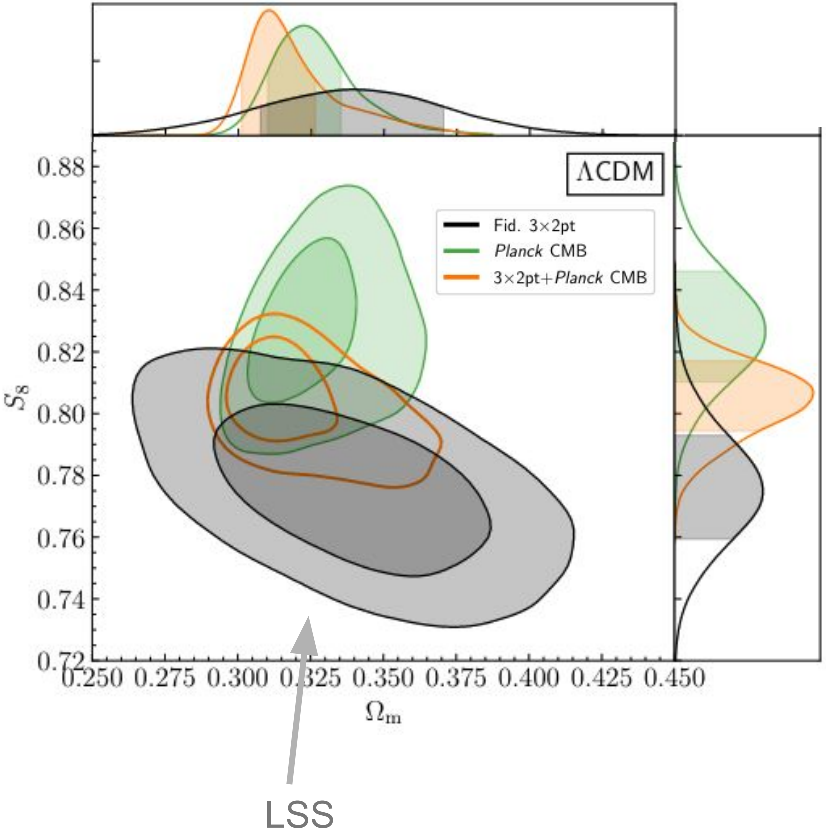


Credit: N. Jeffrey, DES Collab

LSS surveys

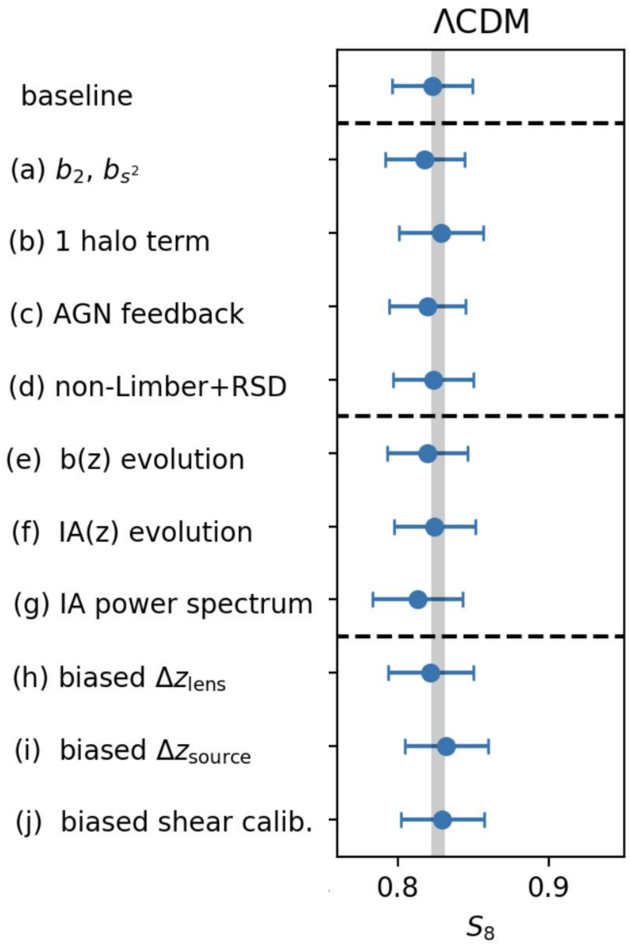
- Key observables: 2pt functions
  - Auto/cross-power of galaxy density and shapes (3x2pt)
  - But also higher order stats
- Becoming competitive with CMB constraints → tension?
- LSST, DESI, Roman, SPHEREx... **Large** number densities → **small** statistical error
  - Need exquisite control of systematics to claim new physics

DES Collab. 2105.13549



(some) LSS systematics

- Galaxy bias
- Small-scales (baryons, non-linear P_k…)
- Intrinsic alignments
- Photo-z errors
- ***Angular systematics***
    - Modify selection function at *map*-level, leverage spatial info to address



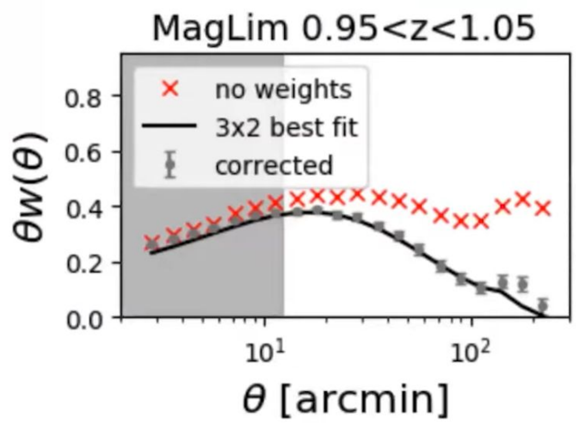
Krause et al. (DES) 1706.09359

Spatial systematics

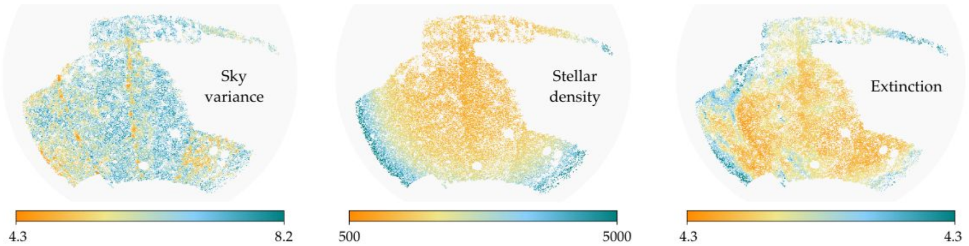
Observed galaxy field ≠ truth

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

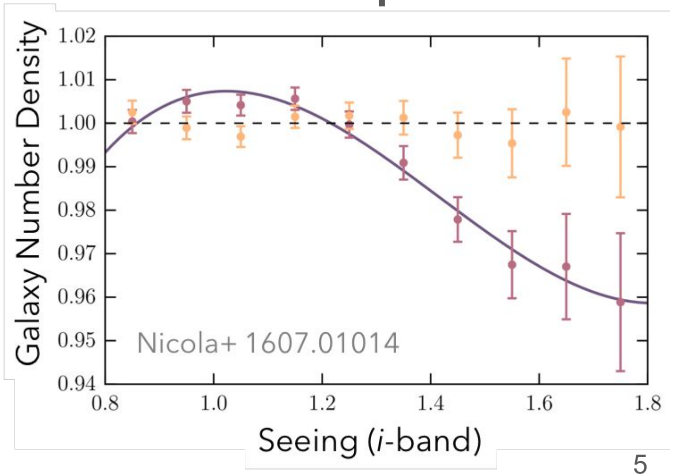
Two point correlation function



Rodriguez-Monroy, **NW**, et al. 2105.13540



Sánchez et al. 2211.16593

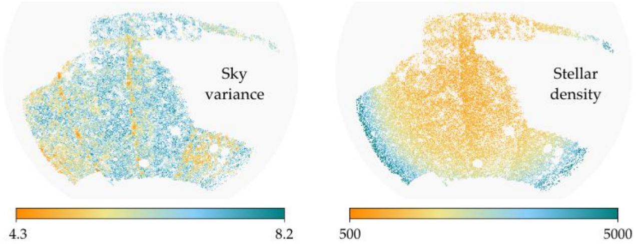


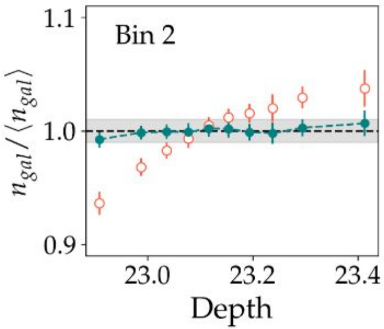
How to mitigate spatial systematics?

Sánchez et al. 2211.16593

- Use *systematic templates* that trace potential contamination
  - Mask extremes
  - Estimate and correct for contamination
  - Also *simulation-based* approaches
    e.g. Balrog (Everett+ 2021), Obiwan (Kong+ 2021)

- Many estimators
  - All essentially regression with different (often implicit) assumptions (**NW** & Huterer '21)
  - Fit for $f_{\text{sys}}(t)$
    → Regression uncertainty comes from δ_{true}
  - Theory systematics when computing weights?





Basic additive model for 1 template:

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

Template map

"Theory" uncertainty in weights methodology

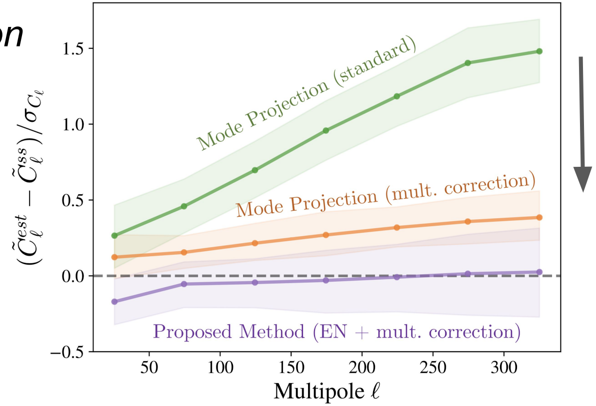
- Additive vs multiplicative treatment
  - Most systematics *multiplicative* (exception: stellar contamination)
  - Additive correction methods neglect *multiplicative* term (e.g. Mode Deprojection)
  - BUT! Multiplicative correction "for free"

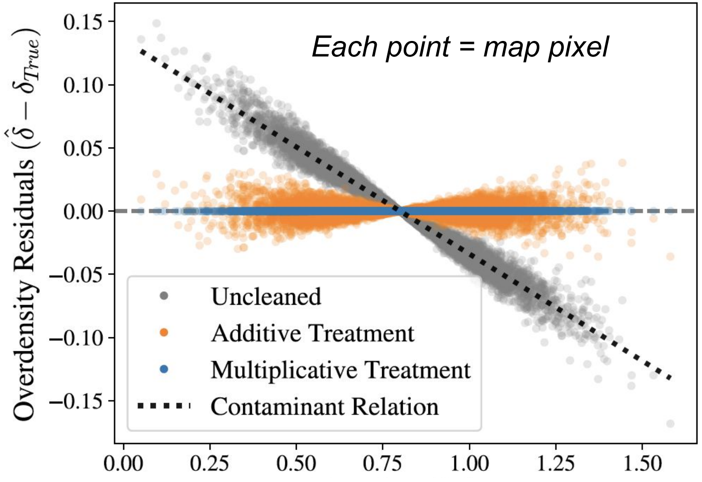
$$1 + \delta_{\rm obs} = (1 + \delta_{\rm true})(1 + f_{\rm sys})\gamma$$

$$\delta_{\rm obs} \approx \underline{\delta_{\rm true} + f_{\rm sys}} + \underline{\delta_{\rm true} f_{\rm sys}}$$

Compare methods on mocks

Power Spectrum Error (Nσ)





Systematic Template

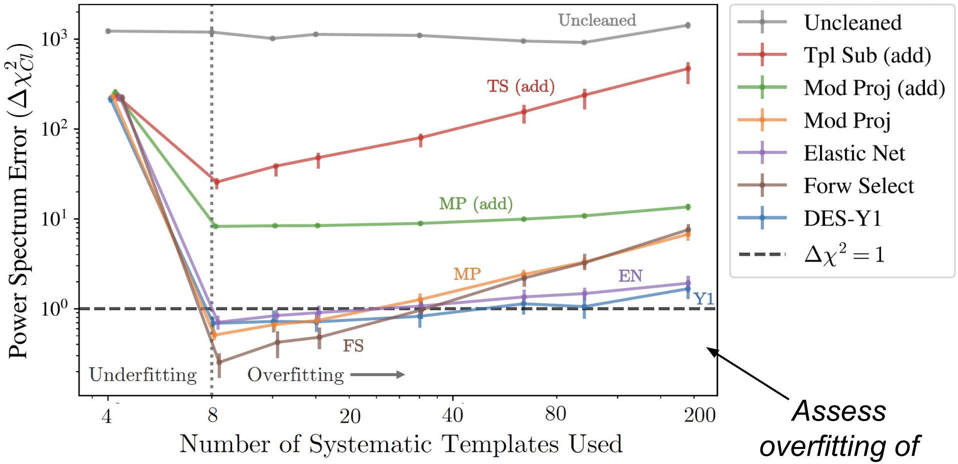
NW & Huterer 2007.14499

“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}

DES-like mocks

NW & Huterer 2007.14499



Assess overfitting of methods on mocks

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

DES Collab, 2105.13549

DES Y3

- Two lens samples: RedMaGiC, Maglim
  Strong excess clustering in RedMaGiC

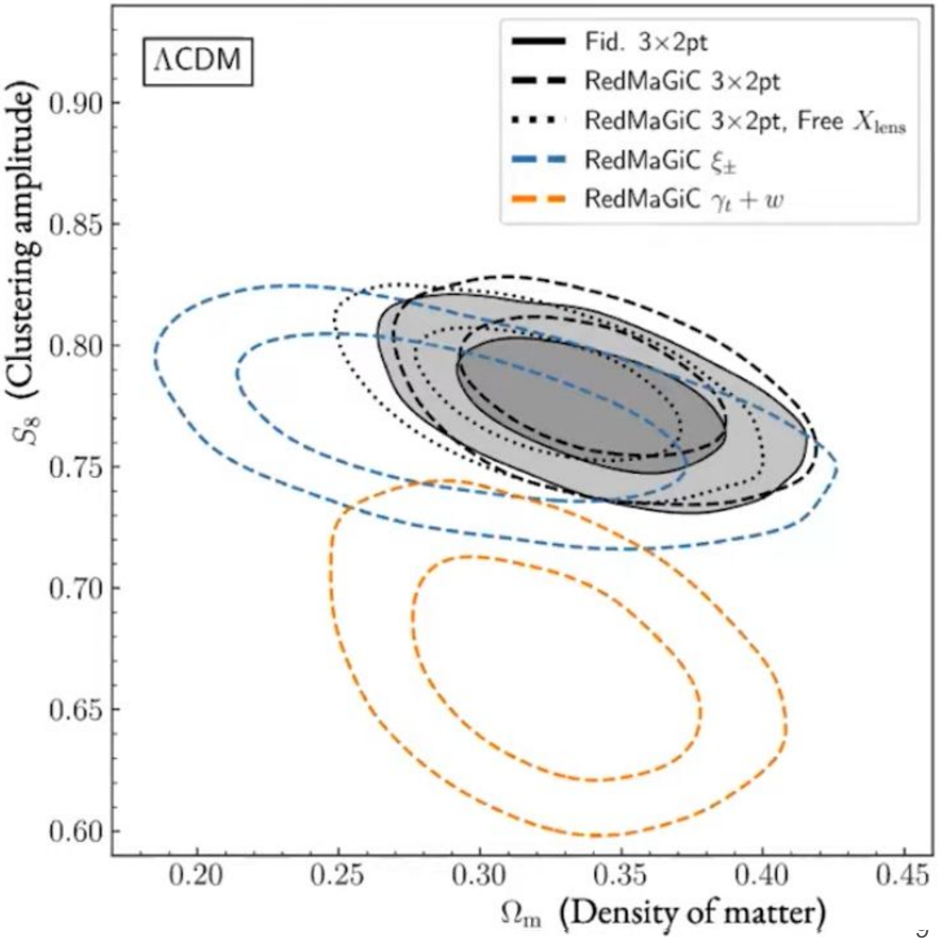
- Fiducial sample changed to MagLim, (though cosmology results consistent for 3x2pt)

- Parameterize via *Xlens*

$$X^i_{\rm lens} = b^i_{\gamma_t(\theta)} / b^i_{w(\theta)}$$

- Consistent with, without *Xlens*
  but much better goodness-of-fit

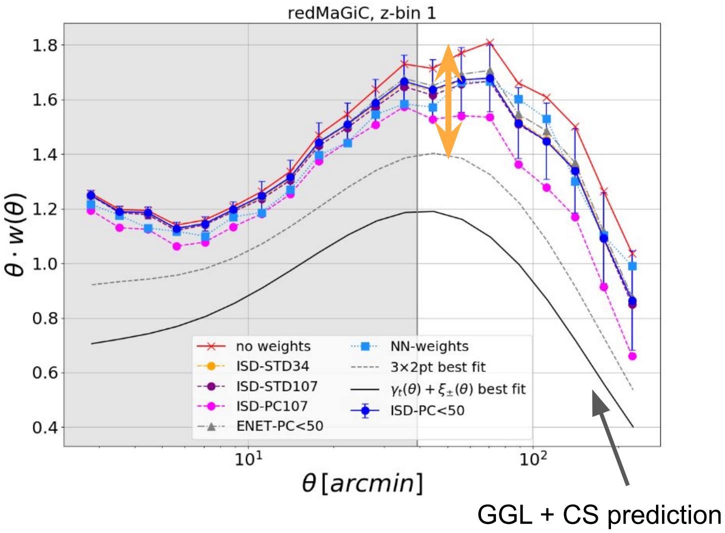
- Orthogonal to LCDM cosmo parameters (but not *w*CDM)

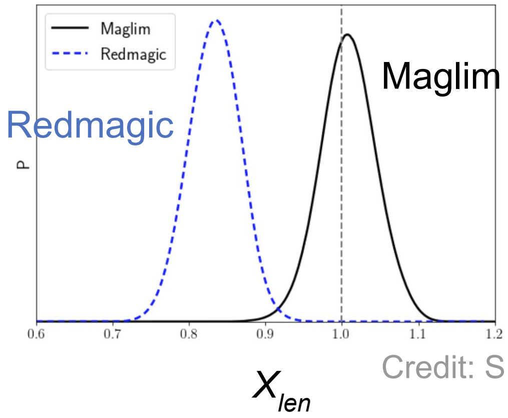


DES Y3

- 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



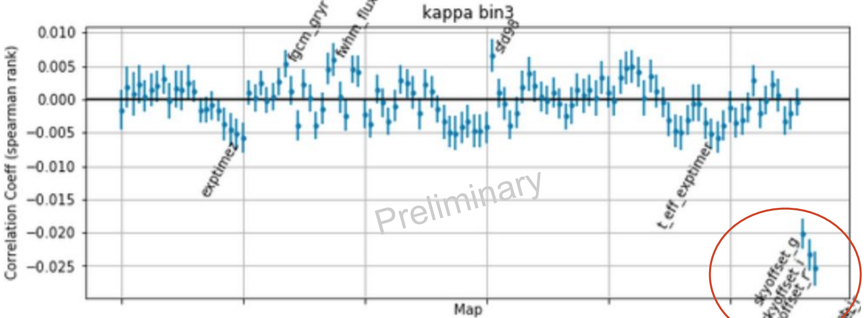


Credit: S. Pandey

Useful Things to Know

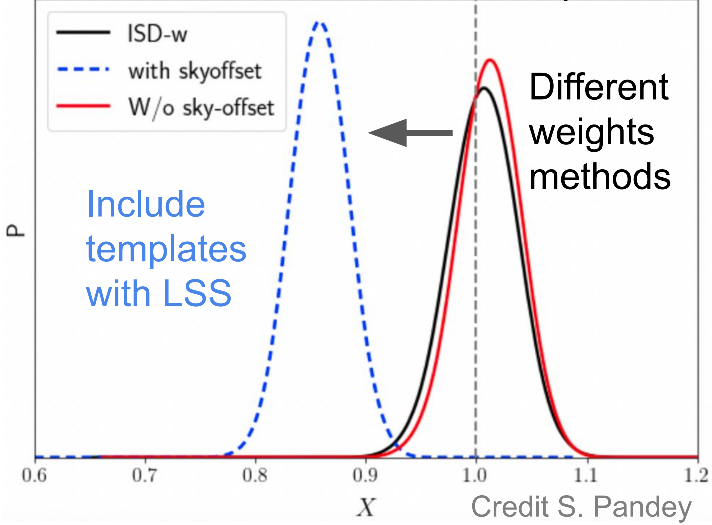
- Identified strong *basis*-dependence of fiducial weights method
  - Also for BOSS weights, which used similar approach
- Can *induce* $X_{lens} < 1$ if $f_{sys}(t)$ (i.e. weights) correlates with LSS (**NW**+, in prep)

Correlation of Templates with LSS



Templates

“Fixed” RedMaGiC sample

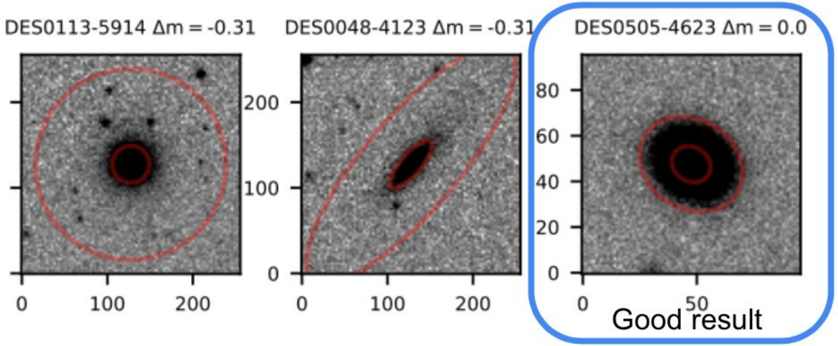


Credit S. Pandey

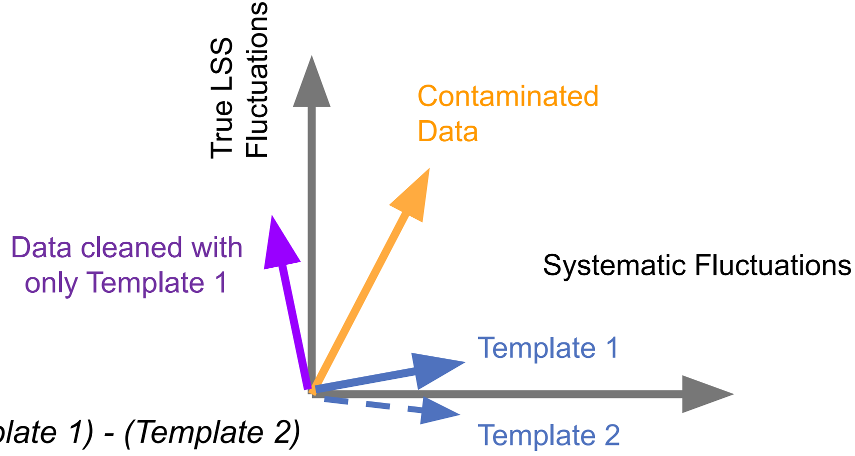
Useful Things to Know

- Similar templates can unexpectedly fit LSS
  - Two PSF estimators with different LSS response
  - Mean vs. Median of coadds if LSS in tails
  - Two dust maps with different LSS contamination

Everett+ '21



`fwhm_fluxradr` overestimated in *crowded environments* (i.e. LSS)



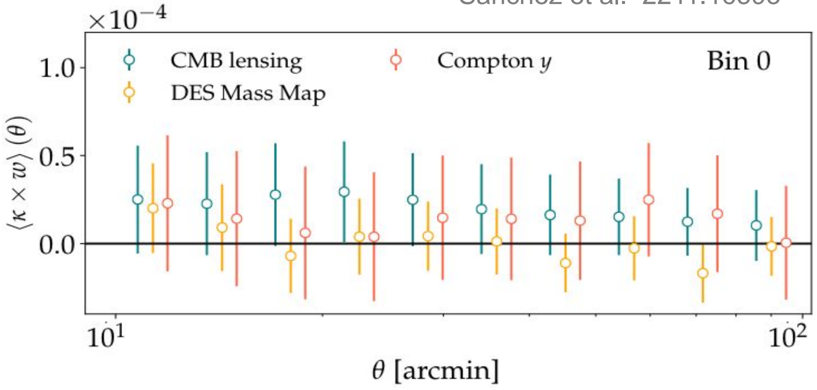
LSS ≈ (Template 1) - (Template 2)

Useful Things to Know

- Similar templates can unexpectedly fit LSS
  - Two PSF estimators with different LSS response
  - Mean vs. Median of coadds if LSS in tails
  - Two dust maps with different LSS contamination

- Check null tests of weights against external LSS tracers

Sánchez et al. 2211.16593



	Bin0	Bin1	Bin2
Planck CMB lensing	9.6/9	6.4/10	6.8/10
DES Mass Map	8.2/9	9.9/10	16.1/10
Planck Compton y	7.3/9	5.9/10	2.7/10

Going Forward

- Multiple ways to get Xlens ≠ 1
  clustering high, GGL low, or both

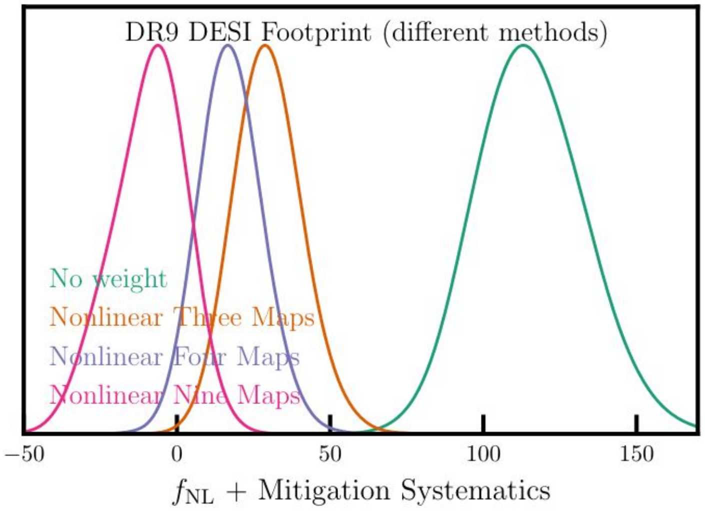
- Motivate and test mask, templates, contamination model (rapid weights estimator useful)

- 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

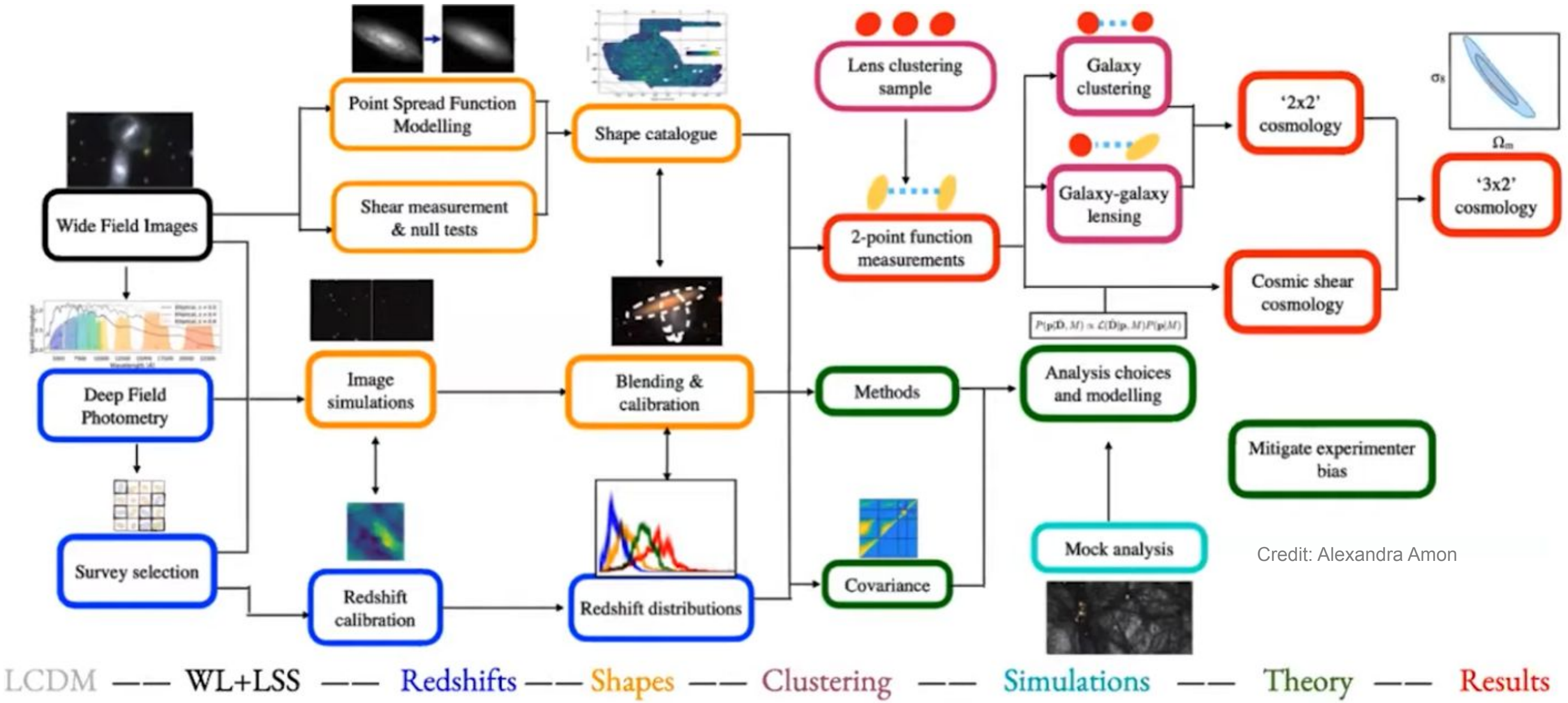
Rezaie+ 2307.01753



Especially critical for f_{nl} analyses!

Bonus Slides

Pixels to Cosmology for DES Y3:

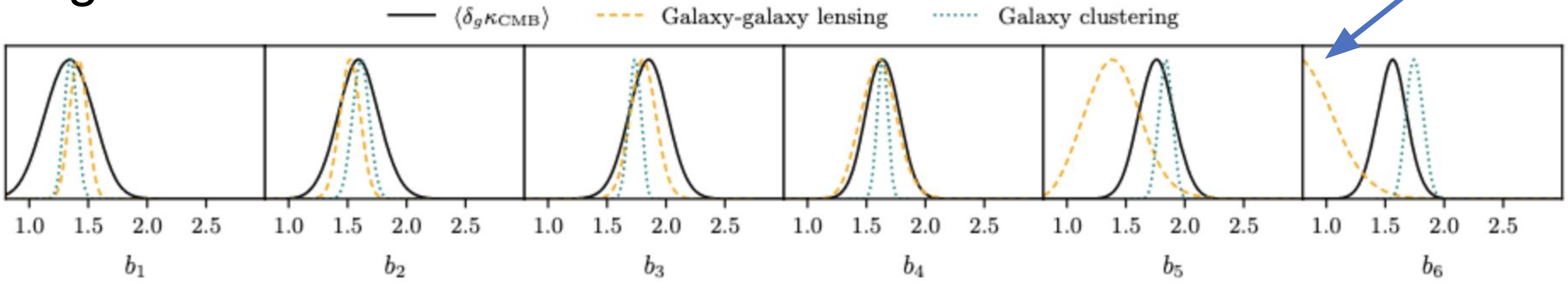


Credit: Alexandra Amon

Galaxy Bias inferred via DES x CMB

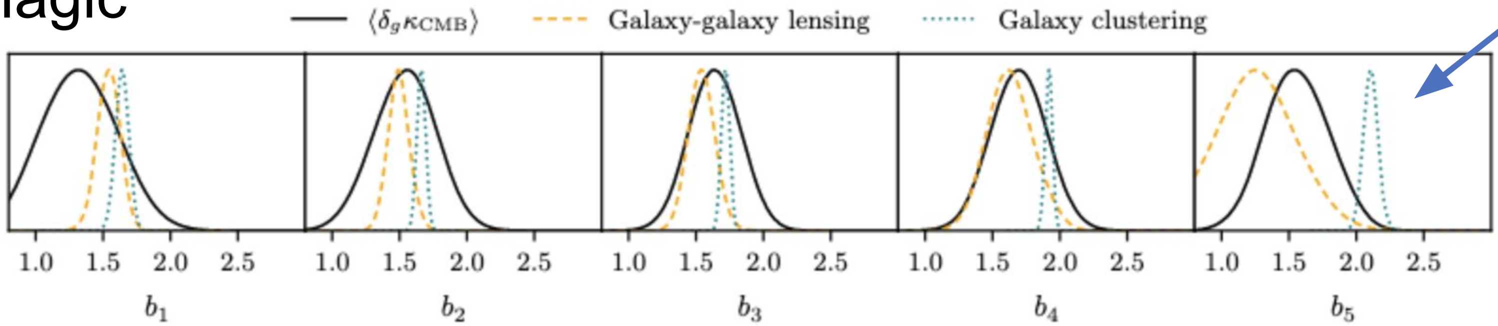
GGL suspect

Maglim



RedMagic

Clustering suspect



Chang et al. 2203.12440

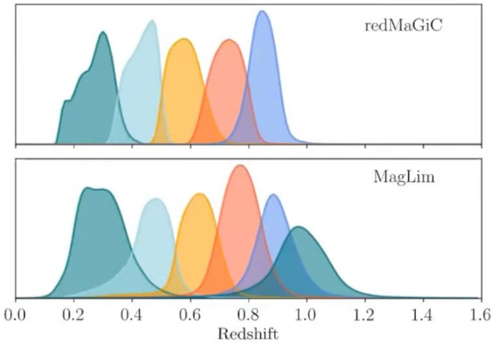
DES Y3

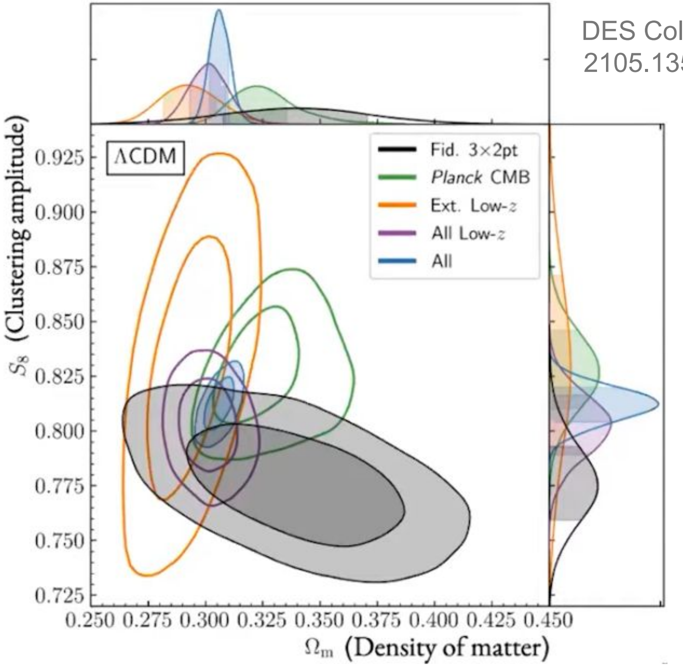
- Two lens samples:
  redMaGiC and MagLim

- 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)



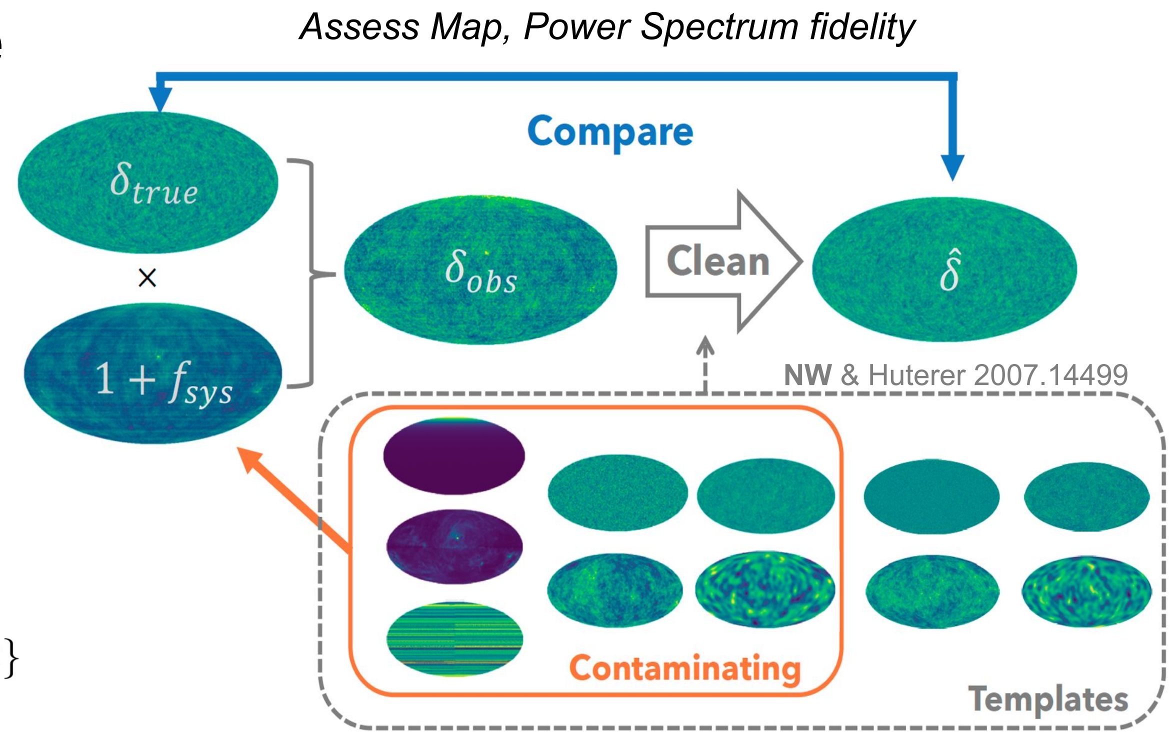


DES Collab. 2105.13549

*Rodriquez-Monroy, **NW**+. 2105.13540*

Simulation Pipeline

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



Templates:

- Gaussian realizations

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

- 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

Template map

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

Multiple systematic templates:

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

MP for Pseudo-Cl

$$\hat{\delta} = \boldsymbol{F}\delta_{\rm obs}$$

$$= \left[\lim_{\beta\rightarrow\infty} \left(I + \beta t t^{\dagger}\right)^{-1}\right]\delta_{\rm obs}$$

$$= \left[I - t(t^{\dagger}t)^{-1}t^{\dagger}\right]\delta_{\rm obs}$$

Map estimate

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

$$y = X\beta + \epsilon$$

$$\hat{\beta} = (X^{\dagger}X)^{-1}X^{\dagger}y$$

OLS to predict y from X

$$y = X(X^{\dagger}X)^{-1}X^{\dagger}y + \hat{\epsilon}$$

$$\delta_{\rm obs} = T[T^{\dagger}T]^{-1}T^{\dagger}\delta_{\rm obs} + \hat{\delta}$$

$\hat{\alpha}$

Actually care about residuals and their clustering

MP estimate of contamination coefficient α
Is MLE, *assuming*:

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

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

Elastic Net Weighting

- Regression extension: form of regularization (Zou & Hastie 2005)
- Incorporate template selection, operate in full-D space

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

In terms of Maximum Posterior Estimate, equivalent to:	Gaussian Likelihood	Laplace prior on coefficients	Gaussian prior on coefficients

In practice, select $\{\lambda_1, \lambda_2\}$ through cross-validation (trained on subsets of the data)

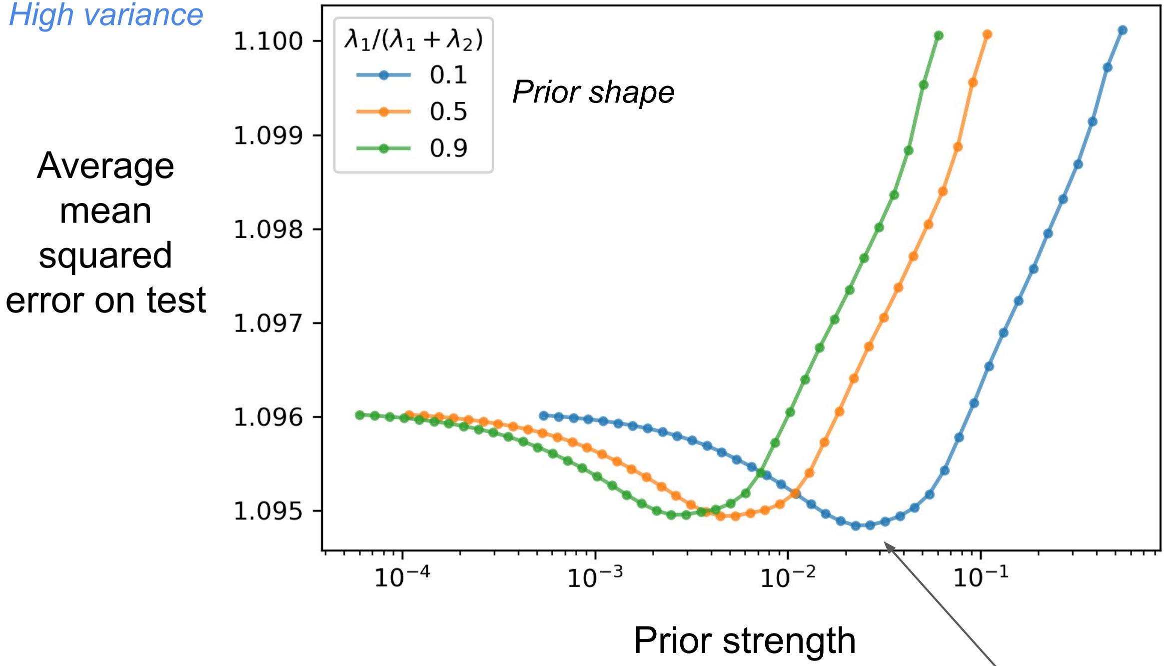
Elastic Net Weighting

Use all templates (OLS)

High variance

N_{tpl} = 0 (no cleaning)

High bias



Let data determine effective number of templates

Also apply multiplicative correction

Optimal hyperparameters