Pathway to measuring robust large-scale structure statistics for primordial non-Gaussianity and beyond

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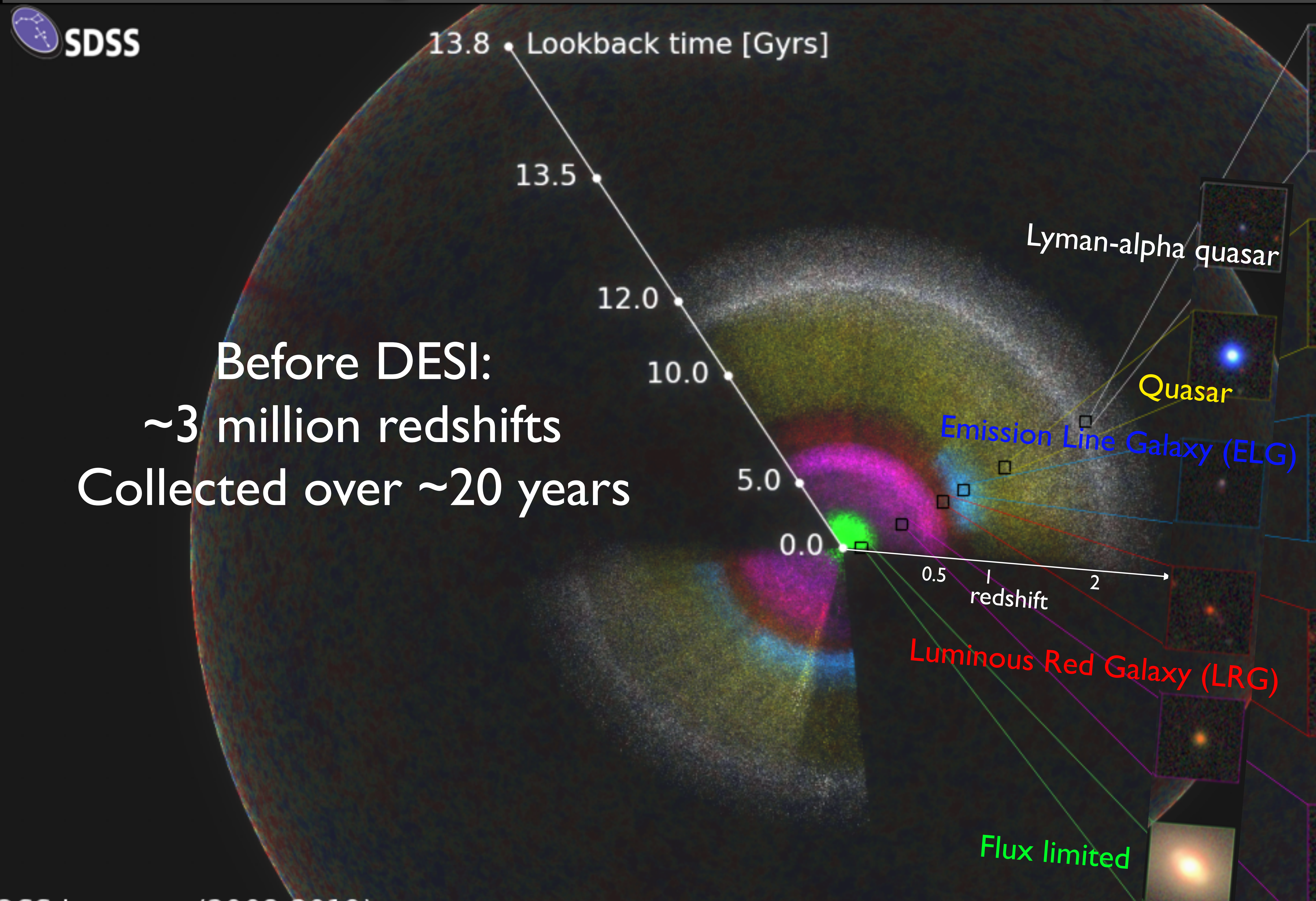
CCAPP

Some Motivation

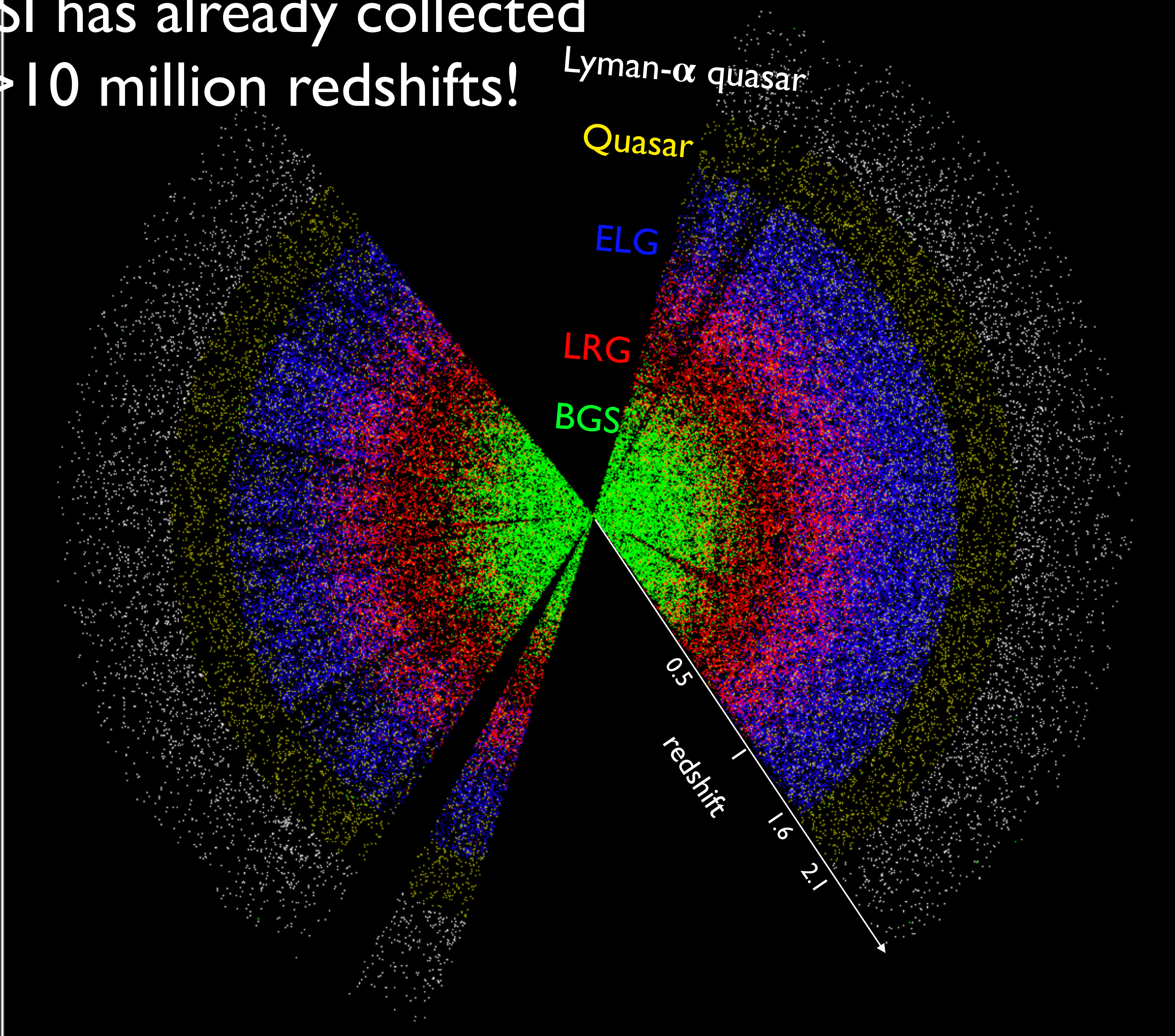
3D Large-scale Structure Maps



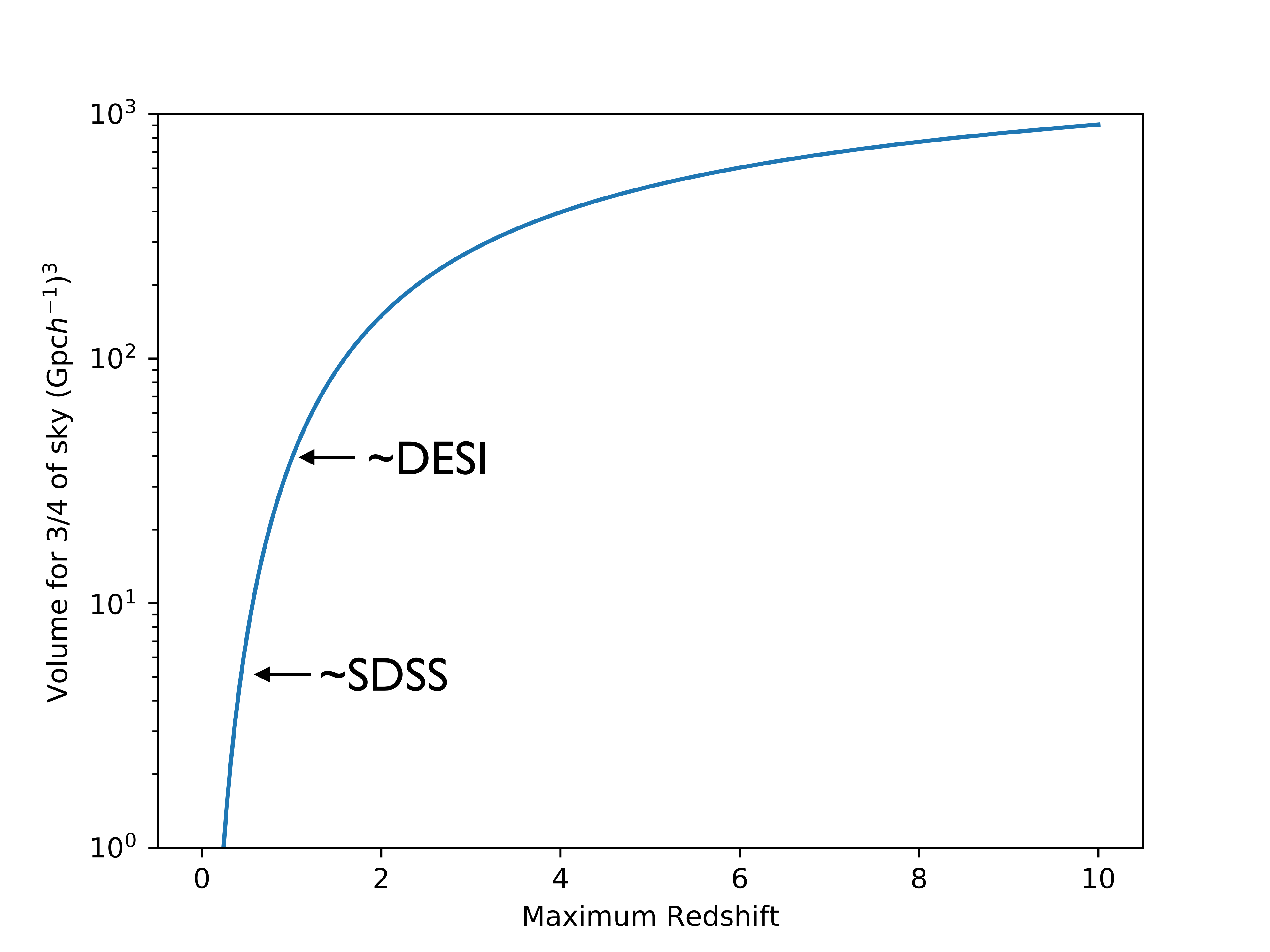
Before DESI:
~3 million redshifts
Collected over ~20 years

DESI

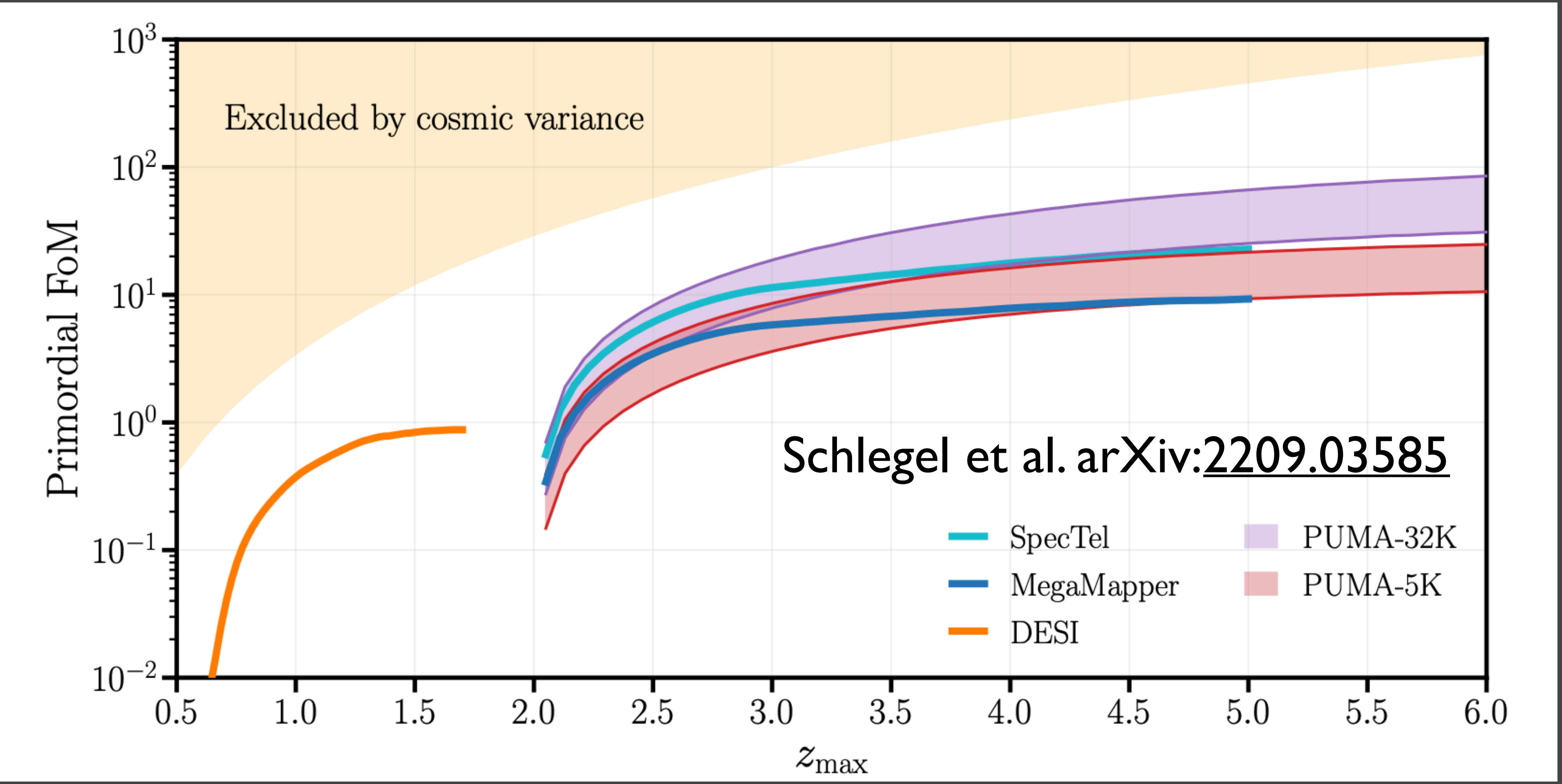
DESI has already collected >10 million redshifts!



Available Volume



Available Volume (more sophisticated)



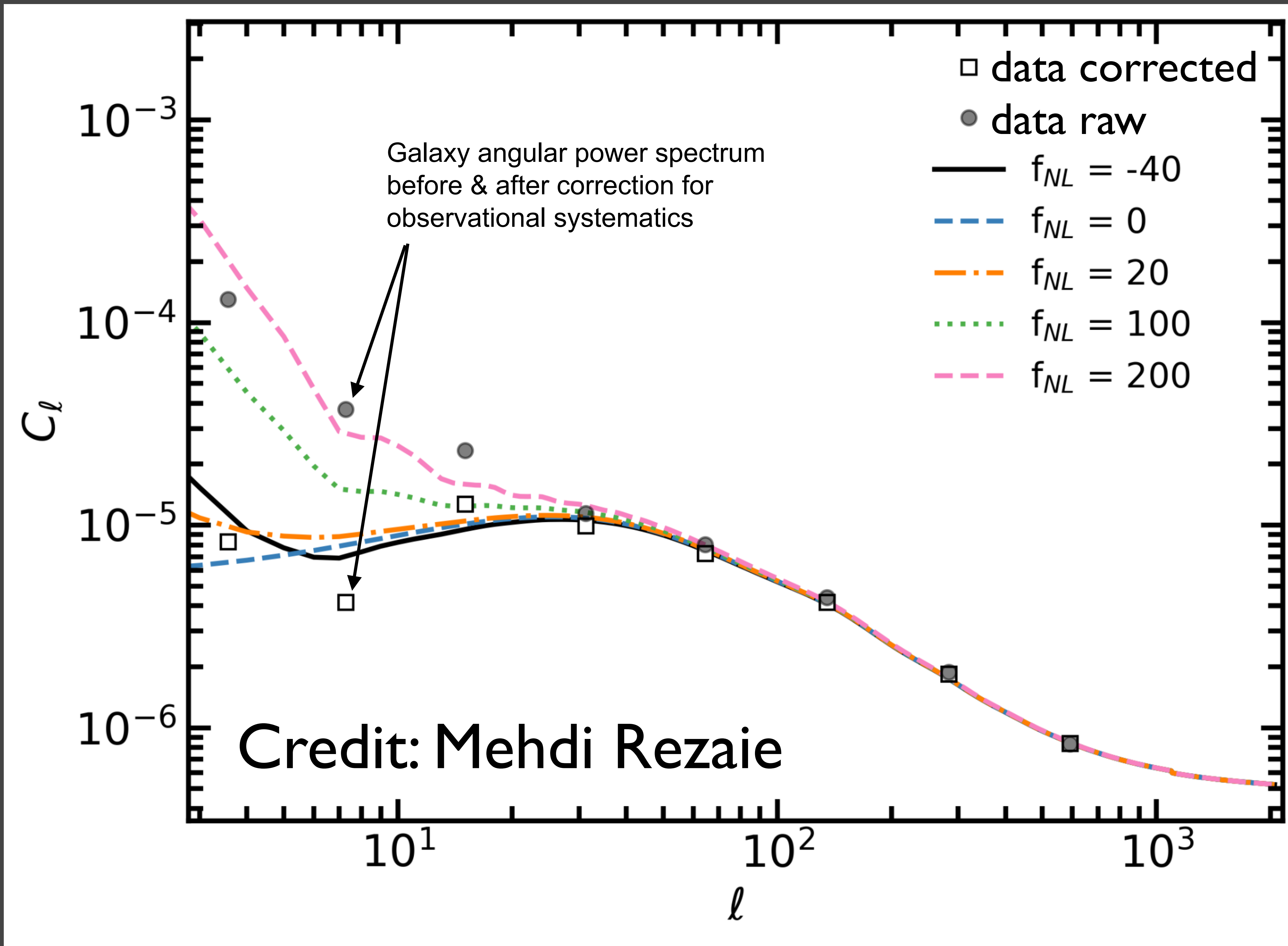
Available Volume

- We will probe this volume; when?
- We need this volume to effectively probe inflation
- We need to do a good job with ~current data in order to probe this volume soon

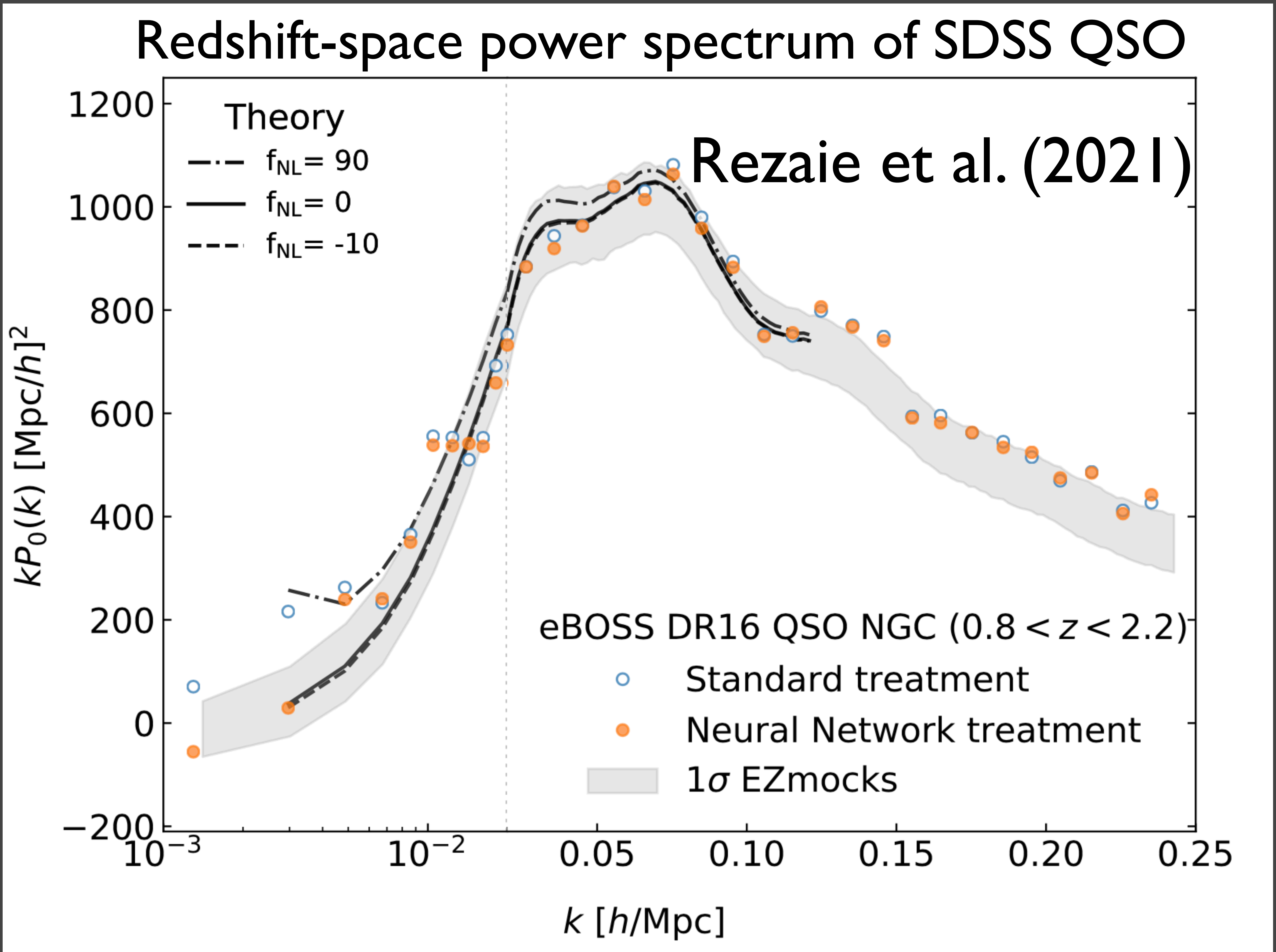
Outline

- Large-scale clustering measurement systematics and PNG
  - Focus on local f_{NL} *only because this what has actually been studied, w.r.t. obs sys in galaxy clustering*
- Causes of systematic variation
- Mitigation methods
- Path forward

Observational Systematics and local f_{NL}



Observational Systematics and local f_{NL}



"Observational Systematics"

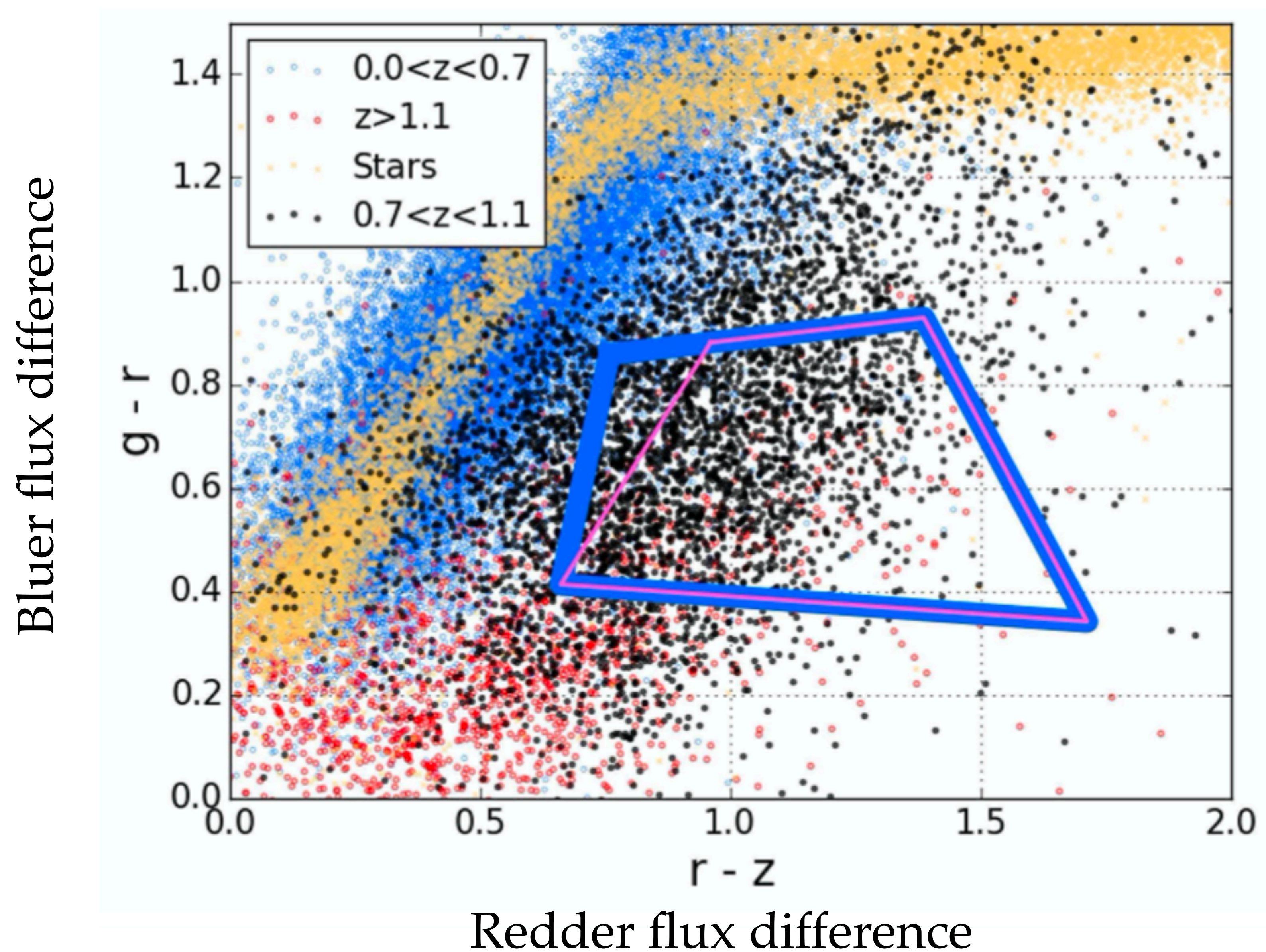
- Essentially, properties of the observed data that are changing the expected number density

$$\delta(\overrightarrow{x}) = n(\overrightarrow{x})/\langle n \rangle - 1$$

  - I.e., $\langle n \rangle$varies with properties of observations
- Variations natural due to photometric cuts we apply to select samples
- e.g., if S/N the imaging data varies, statistical scatter across cuts will vary
  - Resulting $\langle n \rangle$depends on truth Ngal(flux) distribution

Example of selecting galaxies

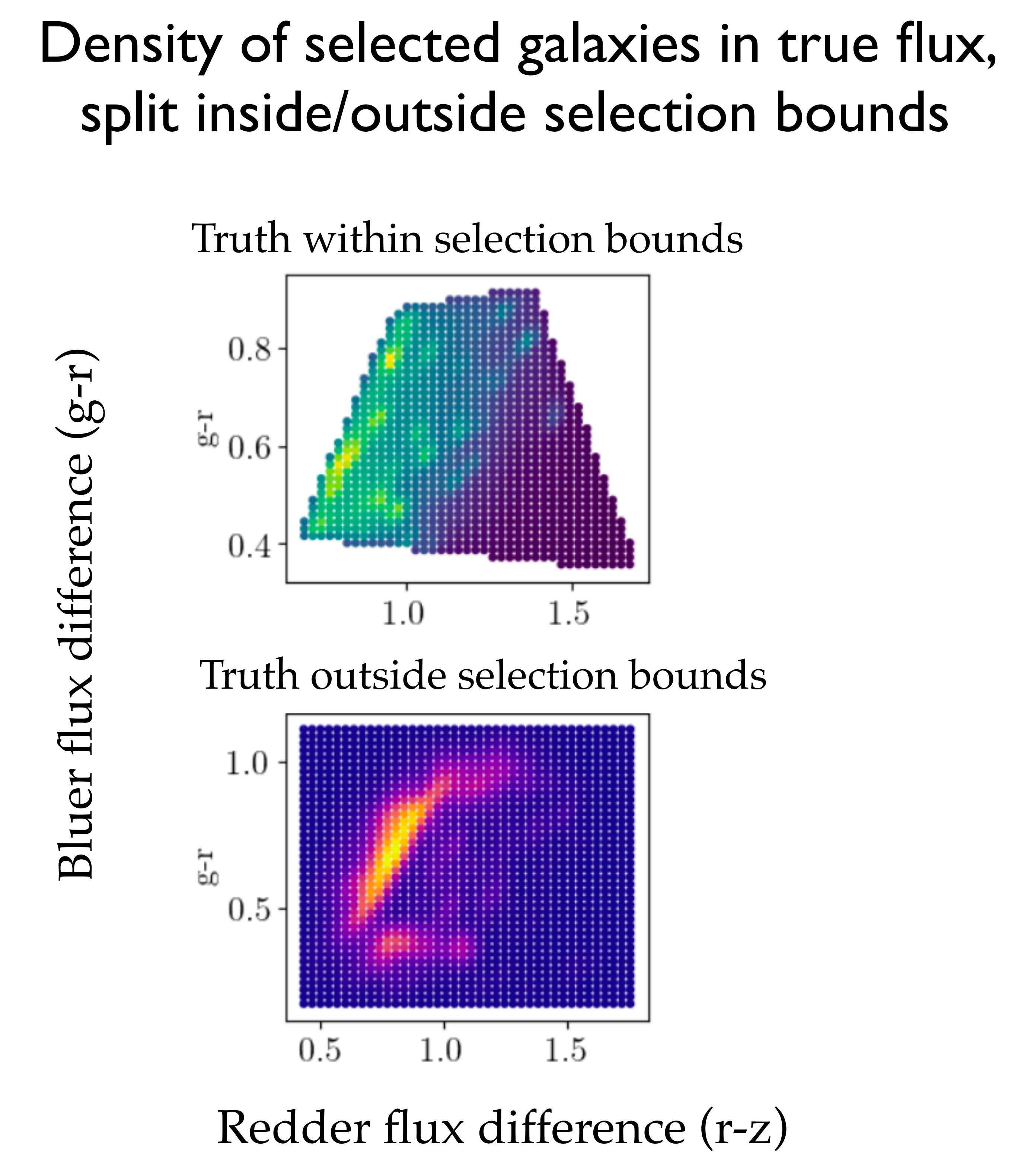
- eBOSS emission line galaxies (ELGs)



Raichoor et al. (2017)

Example of selecting galaxies

- Effect of scatter across selection bounds demonstrated by Kong et al. (2020) image simulations
- (eBOSS emission line galaxies)



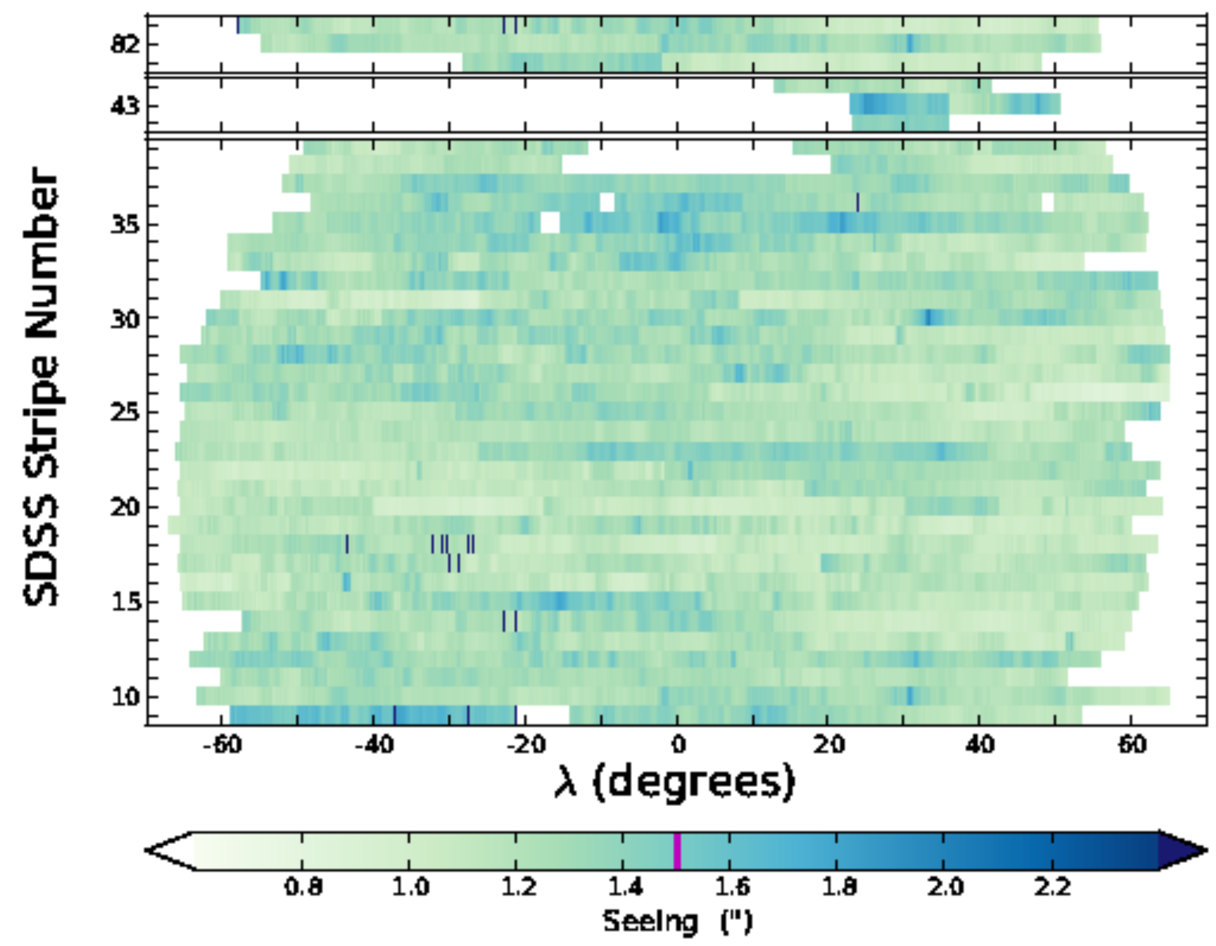
Observational Systematics

- 3 classes drive fluctuations:
  - Data quality variations
  - Foregrounds
  - Calibration uncertainties

Data Quality Variations

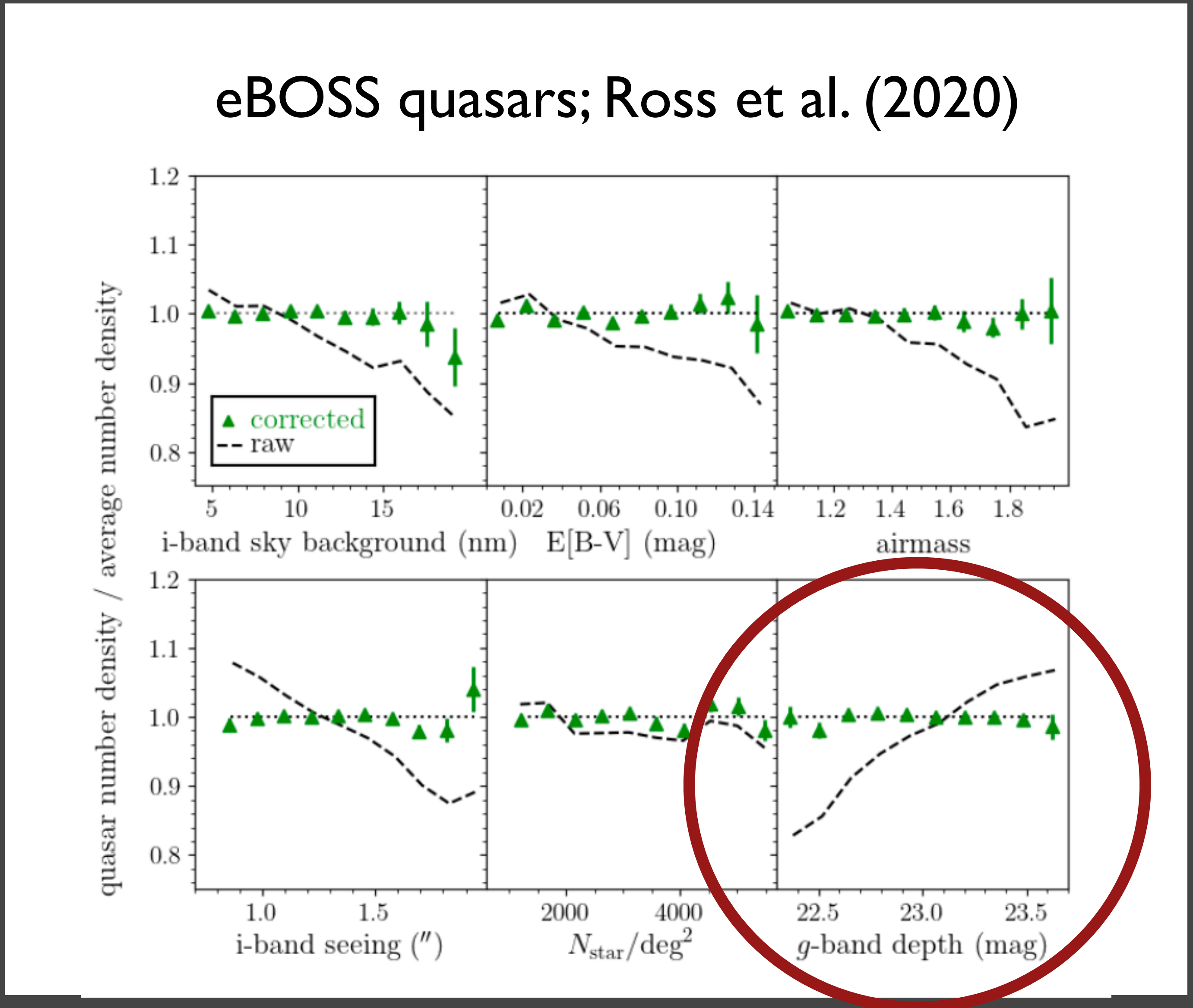
- Expected S/N for given galaxy changes w.r.t. its true light distribution
- e.g., exposure time, PSF size, sky brightness,… contribute
- Quantities are recorded and mapped

SDSS DR7; Wang et al. (2013)



Data Quality Variations

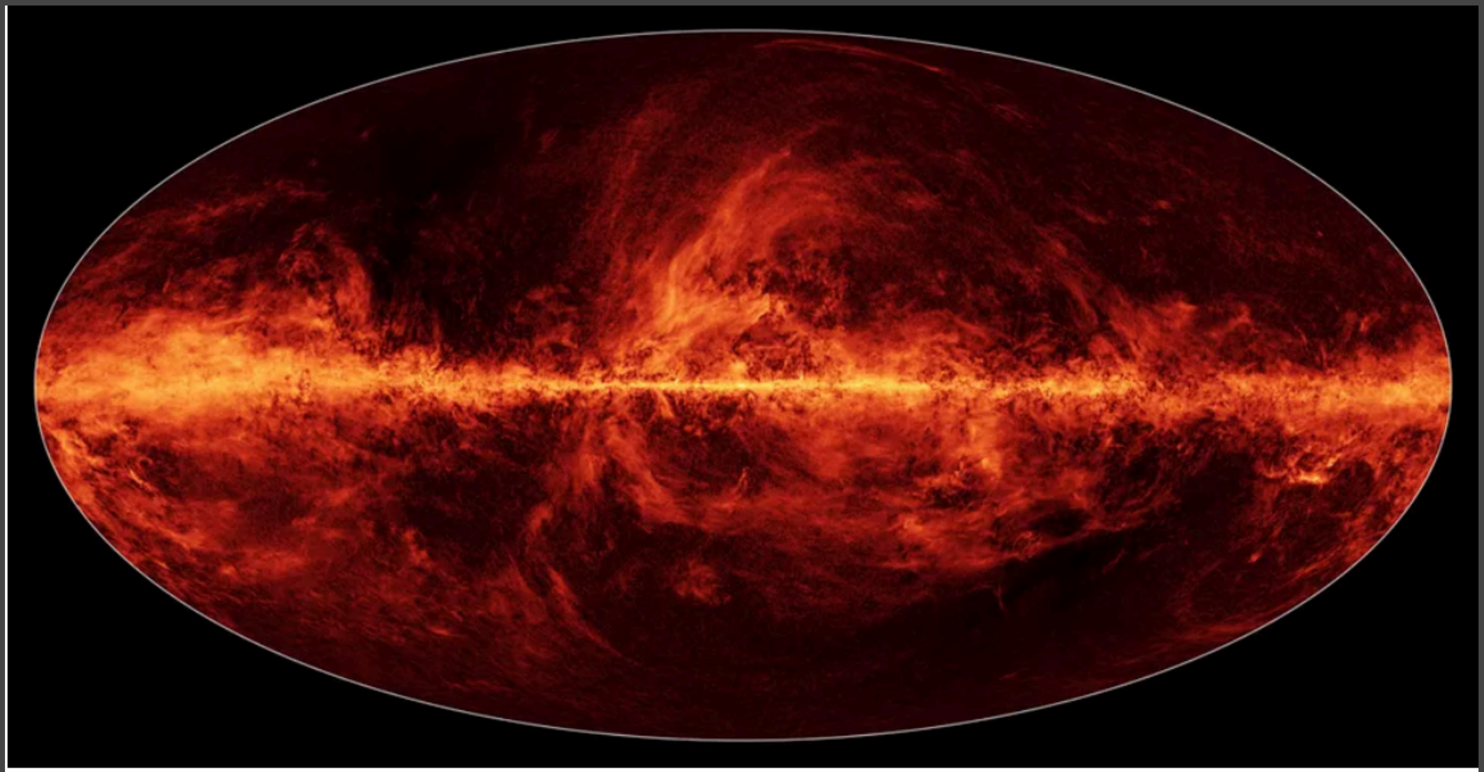
- SDSS eBOSS quasars selected to be those most likely to be quasars
- More were selected where imaging depth (aka expected S/N) is higher



Foregrounds

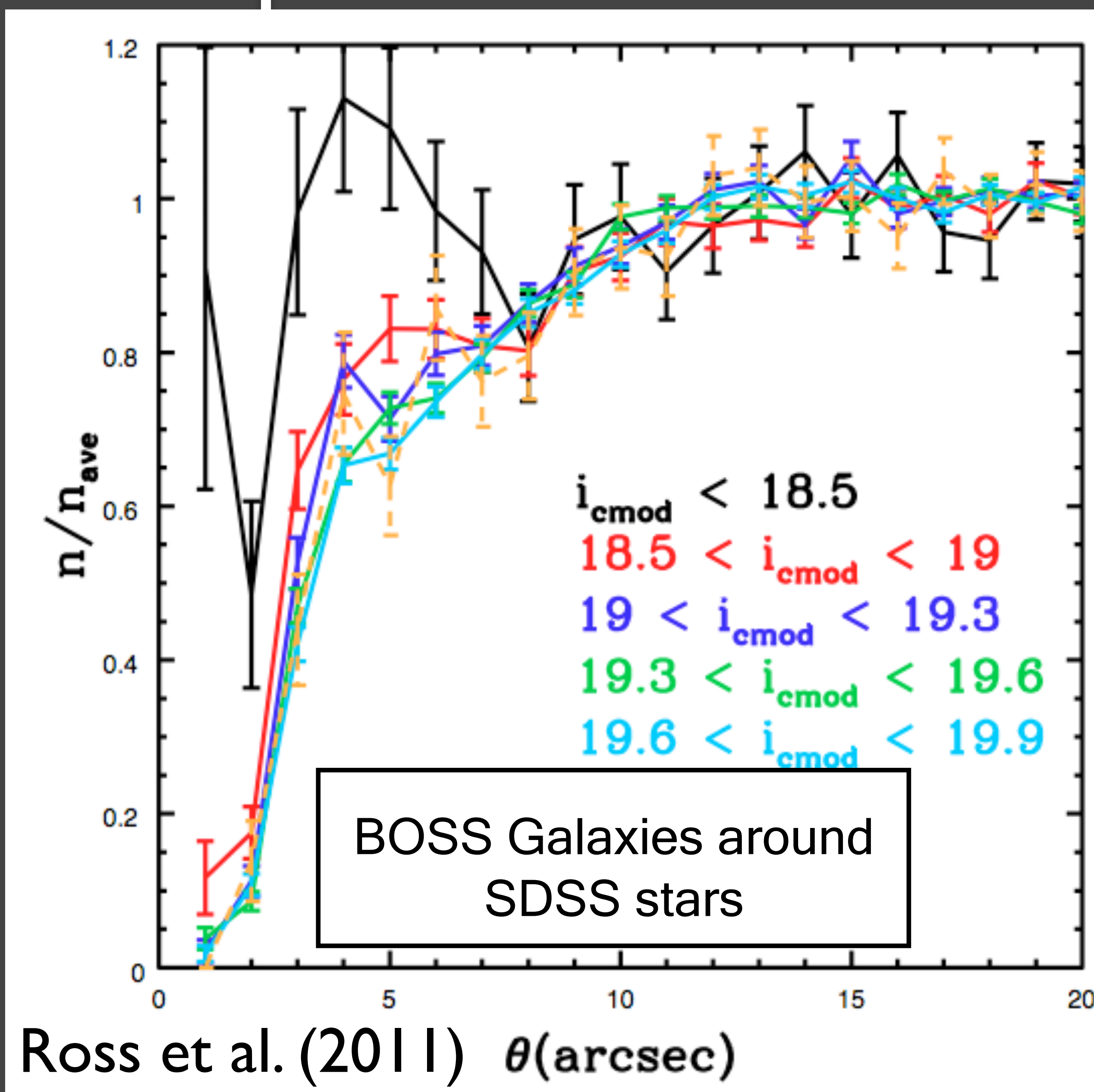
- i.e., the Milky Way
  - Static (within measurement uncertainties)
  - E.g., dust maps, stellar density maps
  - Can be taken from one instrument and used for another

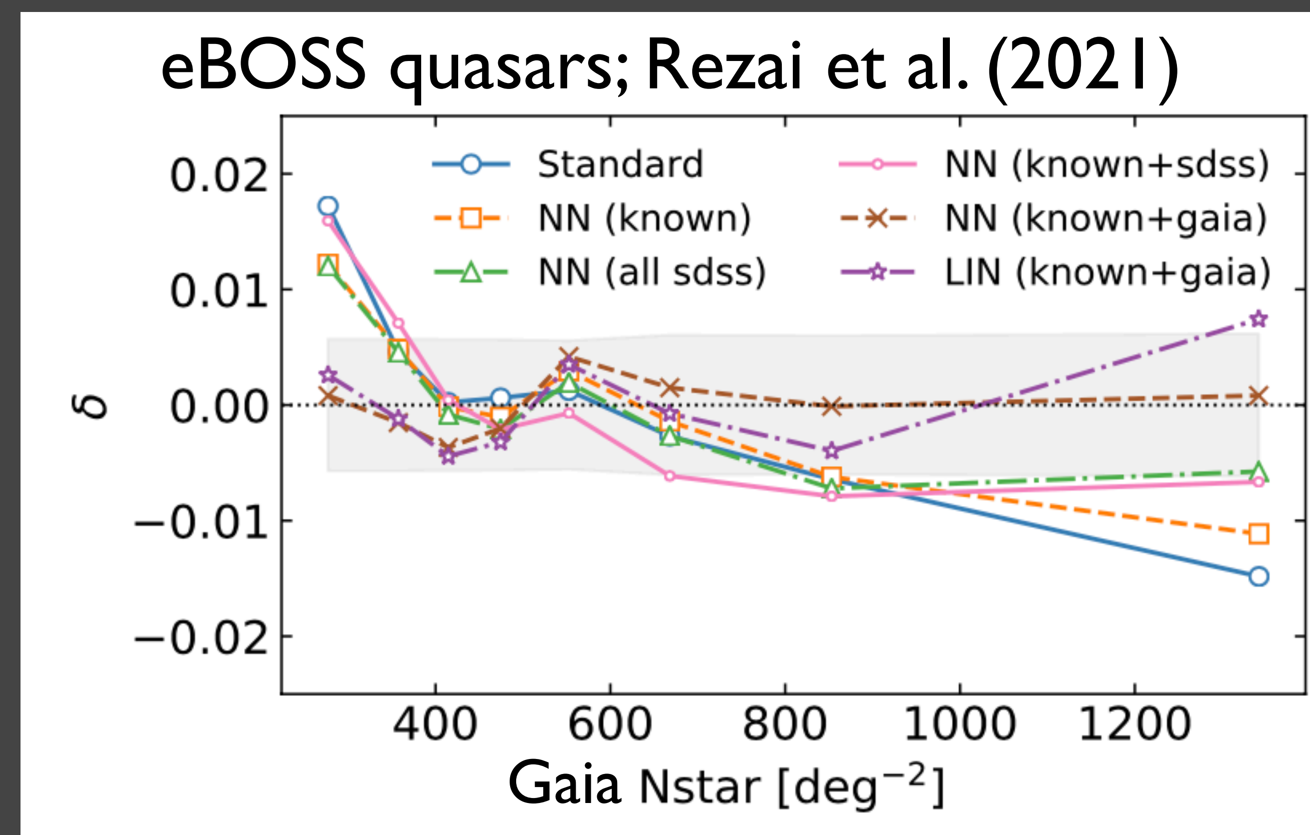
Planck at 353GHz



Stellar Density

- Example of how construction of foreground map matters





Calibration uncertainties

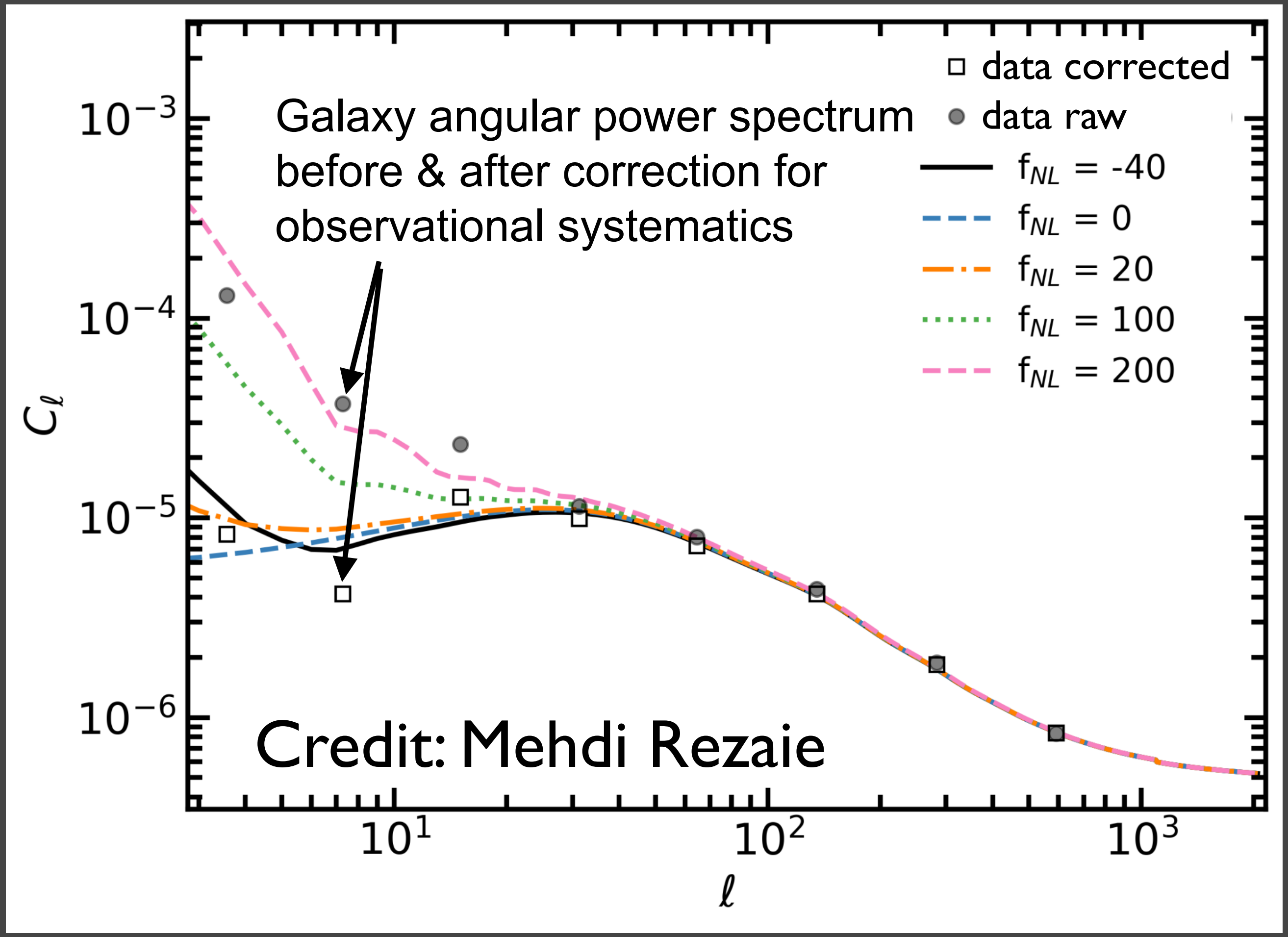
- Relative/absolute photometric calibration between two observations
- Sky background variation over image
  - Requires separation of sources/background
- PSF size
  - Estimated from measurements of stars and knowledge of optics
- Amount of Galactic dust -> extinction at given wavelength

Galactic extinction is a calibration issue

- Flux measurements are corrected based on how much we believe Galactic dust has extincted the light
- Map of dust content generated via infrared maps of whole sky
  - Cosmic Infrared Background contamination
- Extrapolation from amount of dust to extinction as function wavelength
  - Coefficients somewhat regularly re-calibrated

Correcting Observational Systematics

- Generally, need to predict $\langle n\rangle(\overrightarrow{x})$ everywhere and use $\delta(\overrightarrow{x}) = n(\overrightarrow{x})/\langle n\rangle(\overrightarrow{x}) - 1$
- Calibrate effect of method to predict $\langle n\rangle(\overrightarrow{x})$
- Marginalize over any remaining uncertainties

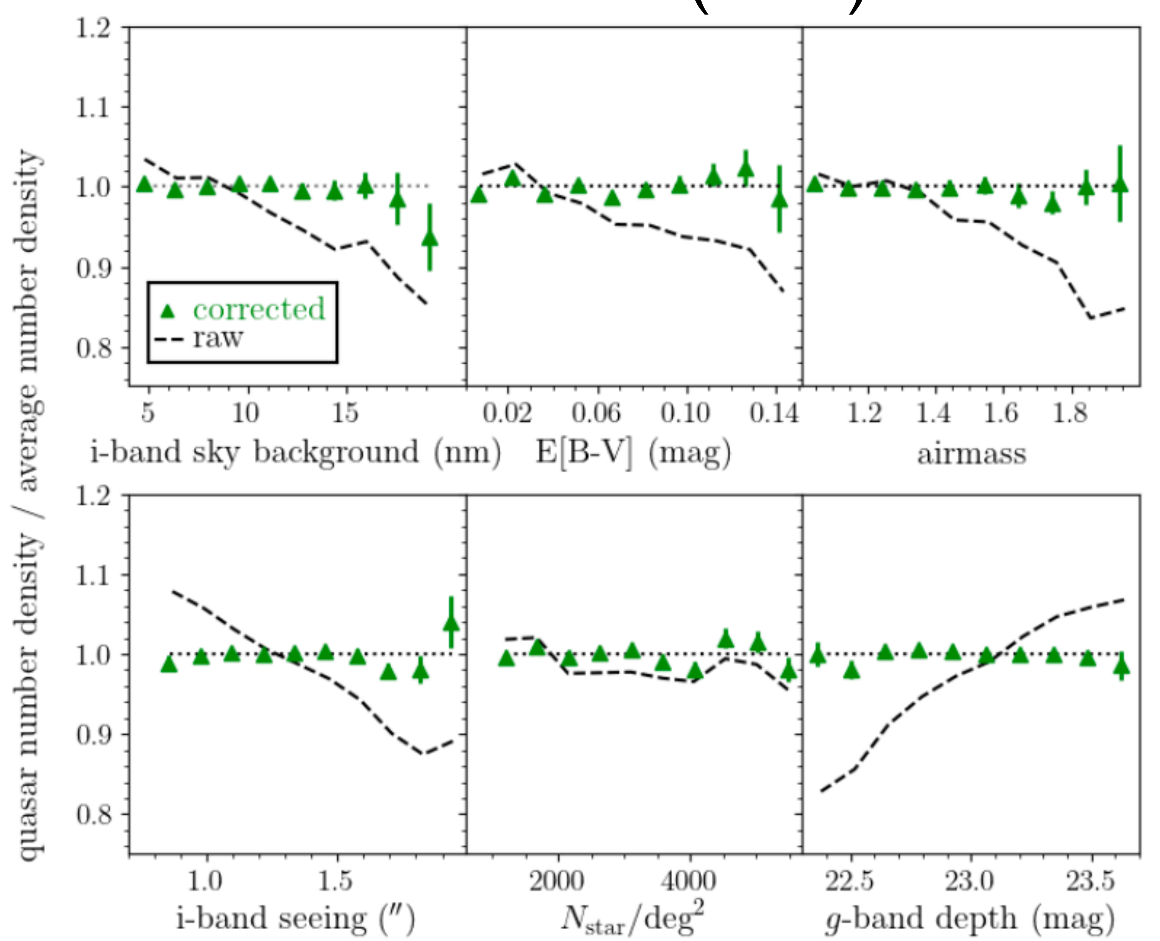


Map Based Approaches

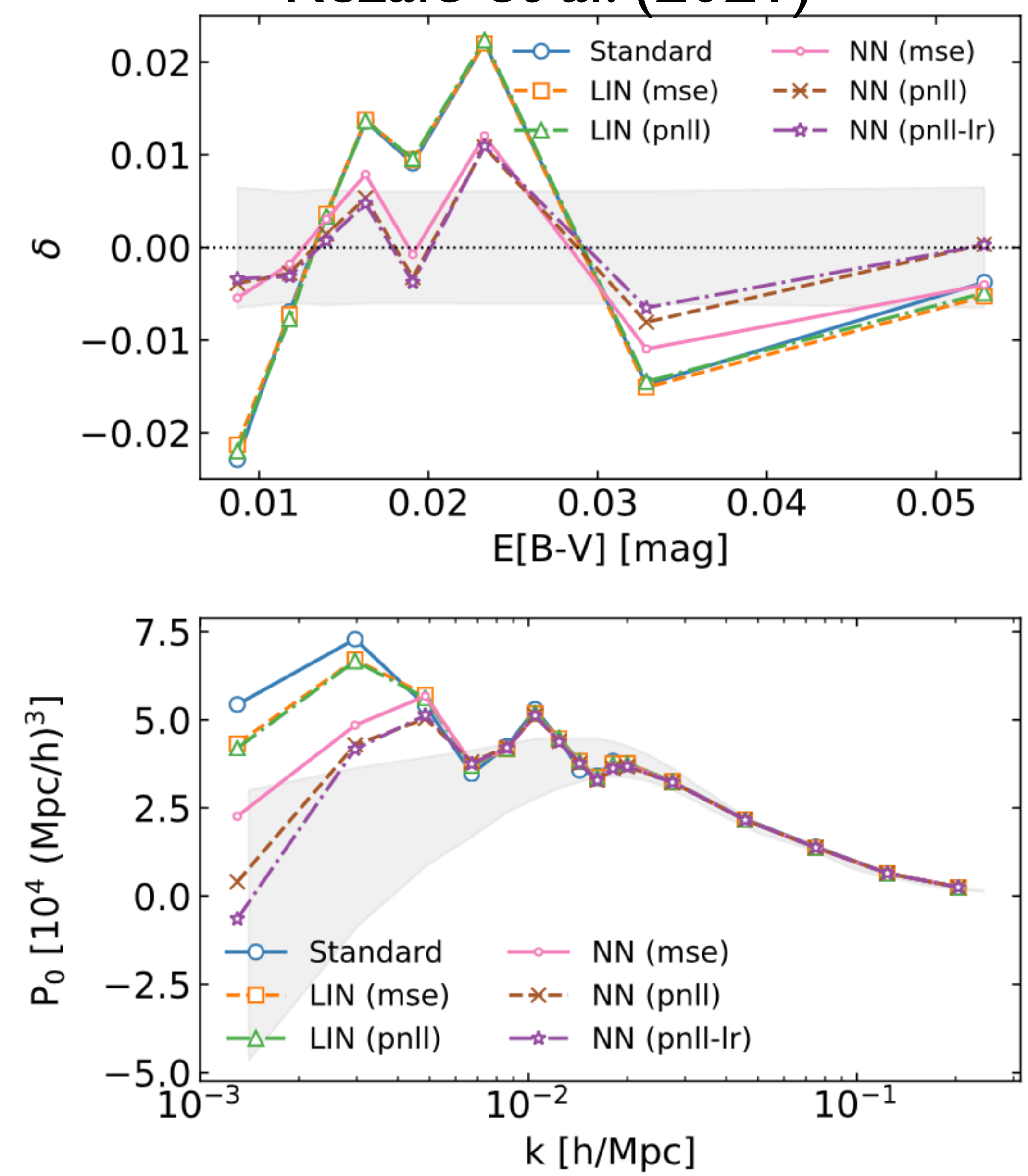
- N maps give N dimensional observing property vector $\vec{P}$
- Essentially have a regression problem; given observed $n(\vec{P})$, solve for a function $\langle n \rangle(\vec{P})$
  - Weaverdyck & Huterer (2020) shows mode projection (e.g., Leistedt et al 2014, Kalus et al. 2018) equiv. linear regression
- Regression problems naturally suited to machine learning and non-linear modeling of $\langle n \rangle(\vec{P})$
  - e.g., Rezai et al. (2019,2021; NN), Chaussidon et al. (2021; RF), Weaverdyck & Huterer (2020; EN)

Non-linear regressions

eBOSS quasars, linear regression
Ross et al. (2020)



Adding NN
Rezaie et al. (2021)



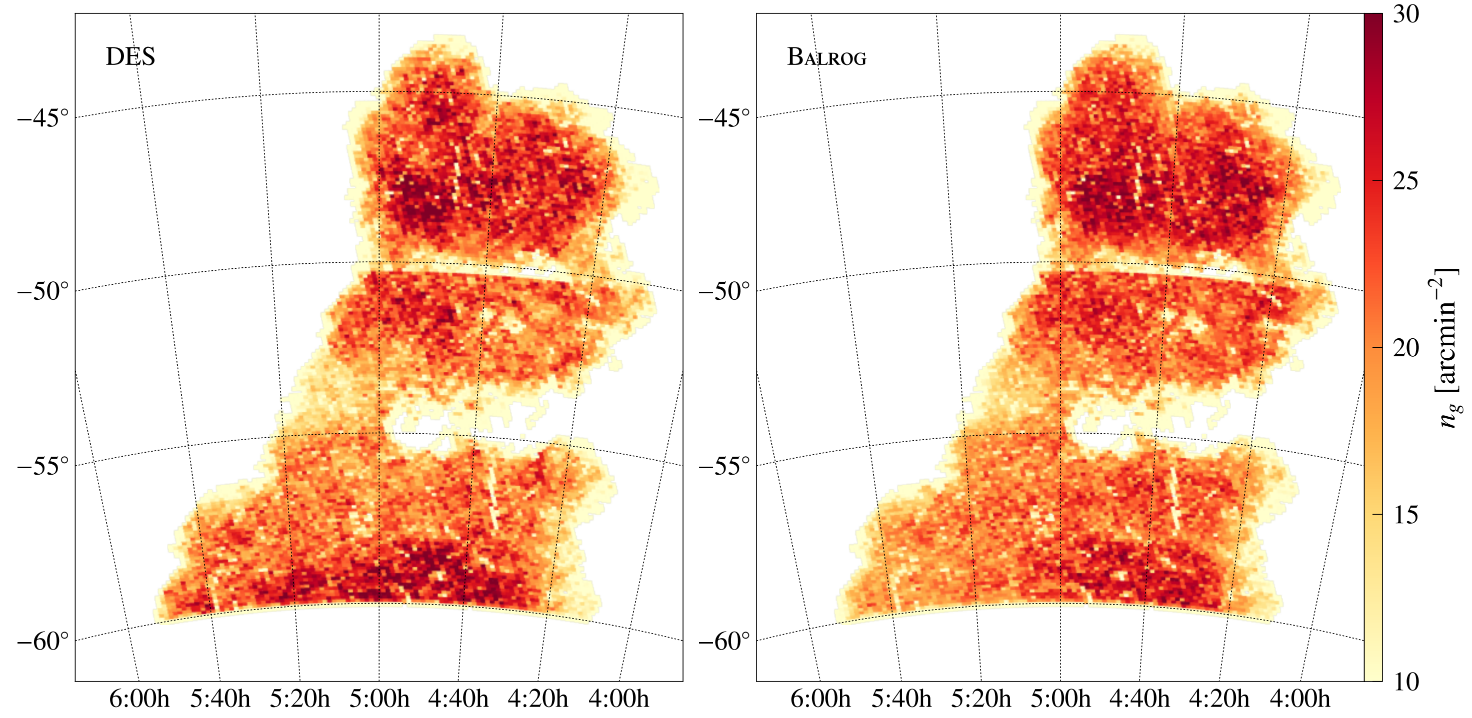
Map Based Limitations

- Are maps complete?
- Are maps contaminated?
  - E(B-V) CIB is correlated with real LSS
  - DES Y3 found high numbered PCA maps to be correlated with lensing maps
- All methods remove some true clustering modes
  - Signal lost even if resulting P(k) is unbiased
  - Validation/adjustment base on mocks generally necessary, especially for any non-linear regressions
- Effect of calibration uncertainties only included if they are (somewhat luckily) traced by maps

Forward Model Approach

- Inject galaxies into images, perform selection
- Should predict all variations due to data quality
- Requires representative input sample
- DES, "Balrog", Suchyta et al. (2016); DESI, "Obiwan", Kong et al. (2020)
- Inclusion of calibration uncertainties could fit naturally

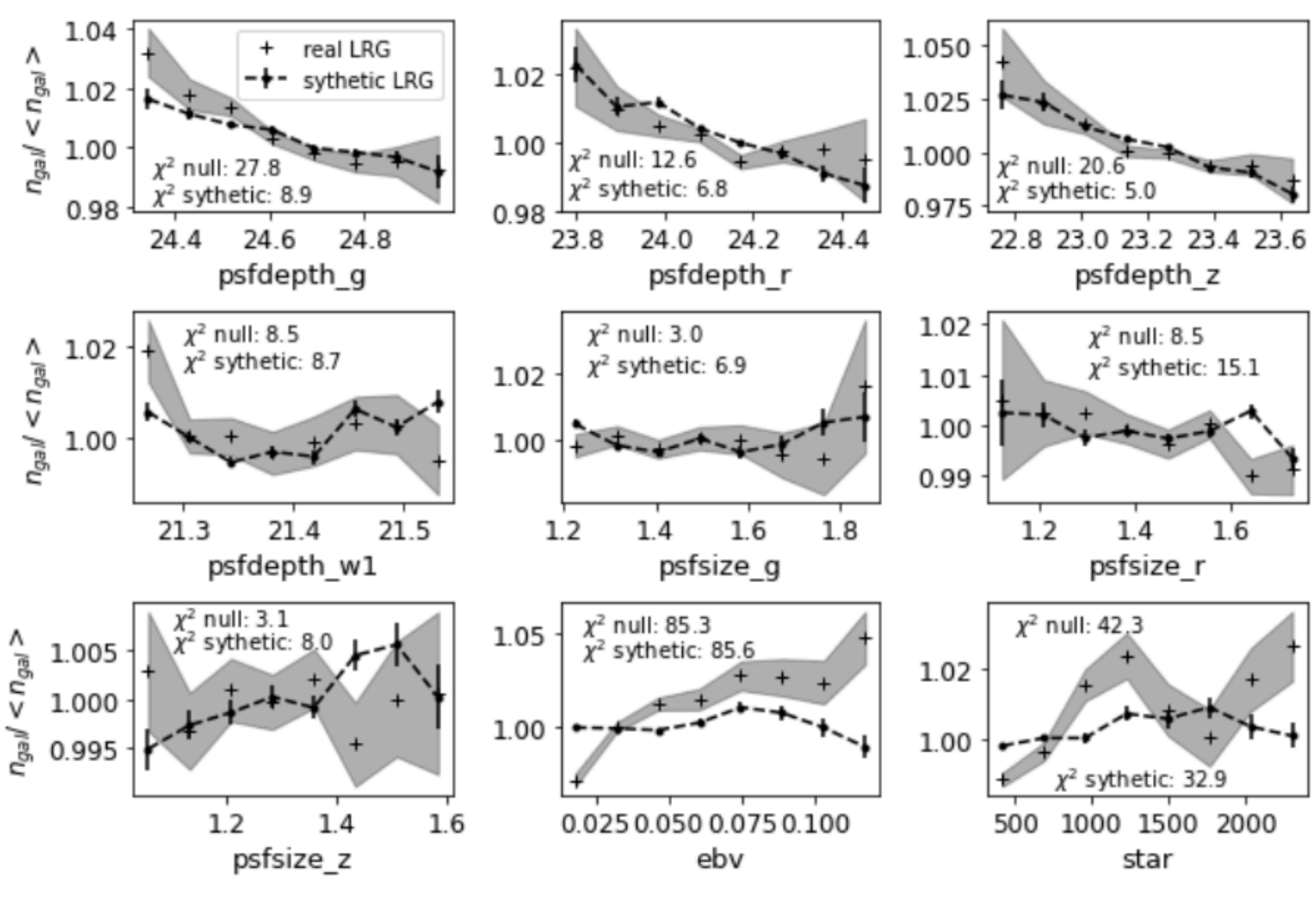
Suchyta et al. (2016)
Balrog input is constant
Output gives selection function



Forward Model + Map Approach

- Forward model not efficient enough (yet) to use on own
- Simulating any calibration steps usually skipped for efficiency reasons
- One path forward: regress on image simulation outputs to predict $\langle n \rangle(\overrightarrow{P})$, simpler regression can fit data residuals

Kong et al. (in prep.), using "Obiwan" DESI image simulations



Approach ~now

- (i.e., realistic for DESI Y1 collaboration analysis)
- Forward model + maps for $\langle n \rangle(\overrightarrow{P})$
- Testing on mocks w./w.o. f_{NL} and systematic variation
- Estimate remaining systematic uncertainty from remaining calibration uncertainty
  - E.g., should be able to quantify effect of assuming different dust maps are truth
- Robustness test: Null transverse modes
  - Simple at catalog level: e.g., shuffle data ra, dec and redshifts to construct randoms
  - Paviot et al. (2022) arXiv:2110.10184

Going further: Higher order

- Use, e.g., bispectrum
- Effect of systematics likely there but different
- Effect of systematics needs to be characterized
- Recent work (thank you!) means this is goal for DESI Y3 collaboration analysis

Going further: Multi-tracer

- From same survey, requires an additional selection
- Can possibly engineer cuts where systematic trends are complementary
- Full benefit requires two over-lapping cosmic variance limited samples

Going further: Space

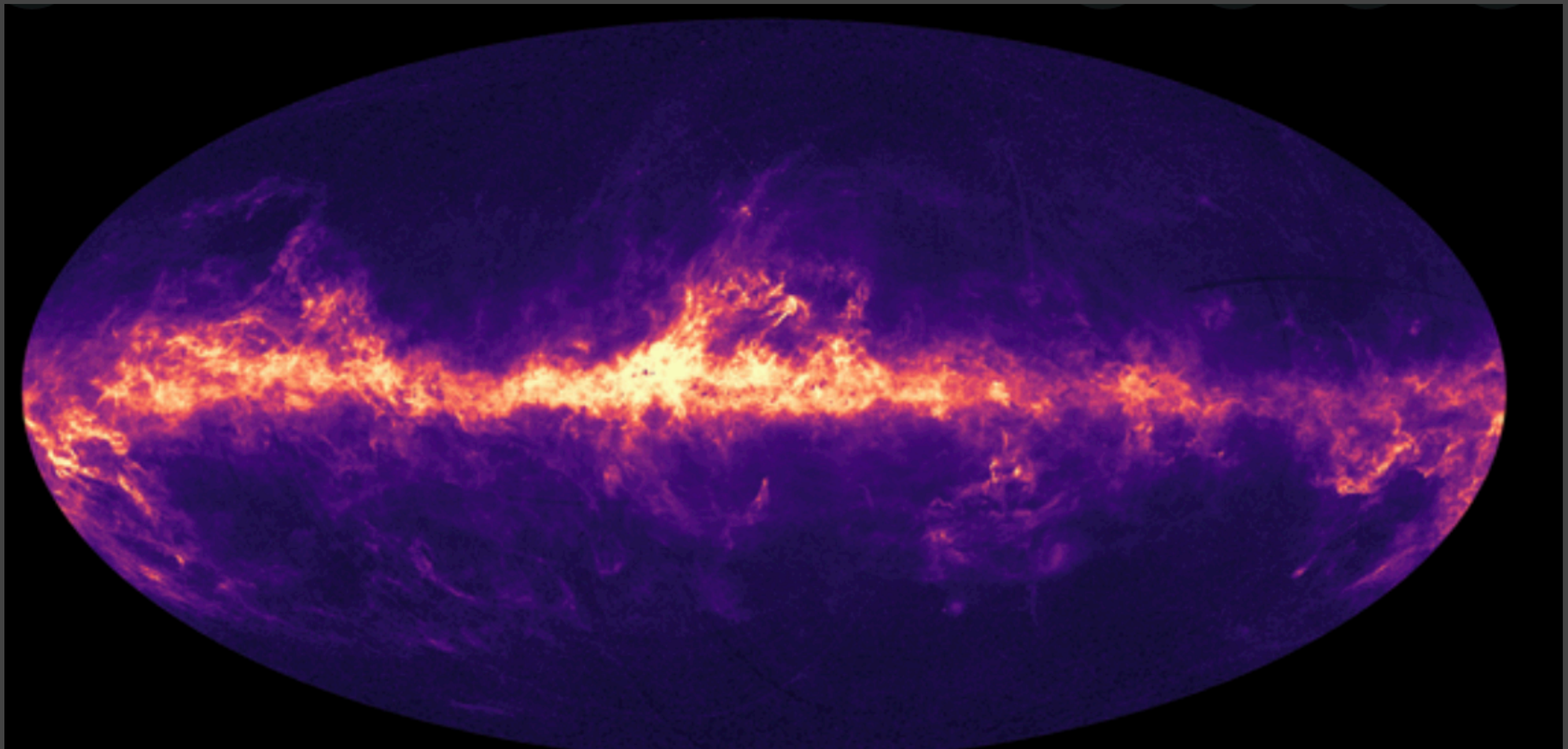
- EUCLID, SPHEREx, and Roman are coming
- Variations in data quality are much less of an issue at L2
  - Mostly background from zodiacal light
- Also mean relative calibration uncertainty should be much smaller (?)
- Milky Way dust still an issue
- Redshift systematics are much worse of an issue with a grism
  - But this might essentially just be added noise for PNG
  - Given strong effect on RSD, strong motivation for all of collaboration to address it

Going further: Cross-correlations

- Survey-specific calibration residuals should go from bias in signal to noise
  - *still important to estimate noise*
- Milky Way dust still an issue
- I’m skeptical of any galaxy clustering analysis using photozs beyond what we have large representative spec samples for

Milky Way Dust

- Issue in all analyses
- Program across all experiments (incl. CMB) to deal with this coherently?



Dust map from ESA Gaia

Conclusion

- Considerable work to be done before any fNL detection from LSS would be believed
- Program of work fairly clear, with some details to fill in
- Status reminds me a little of lensing surveys
  - Much work required to create/calibrate catalogs and simulate effect of baryons (b_ϕ)
- Dust, dust, dust

Conclusion

- Considerable work to be done before any fNL detection from LSS would be believed
- Program of work fairly clear, with some details to fill in
- Status reminds me a little of lensing surveys
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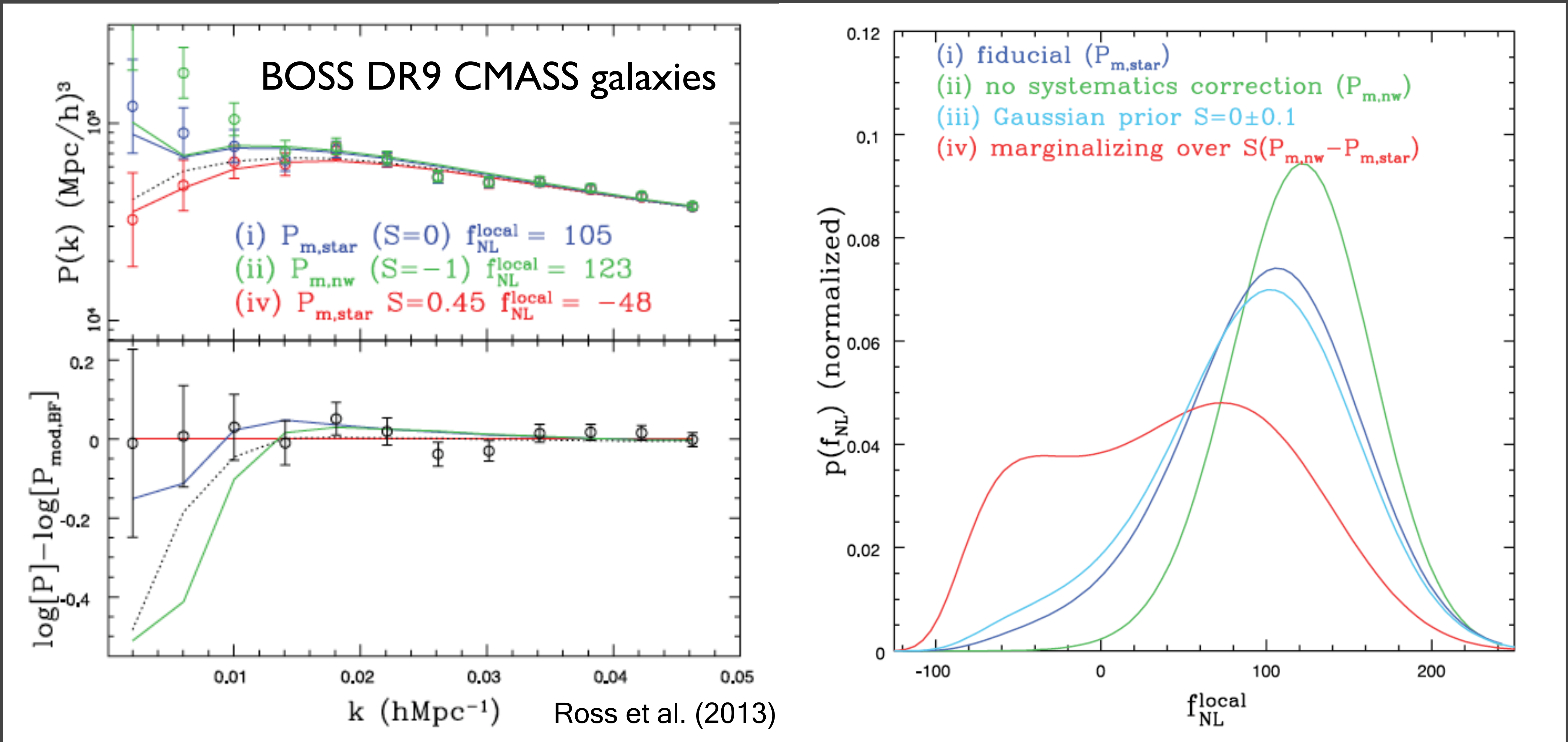
- Dust, dust, dust

We exist, dust exists, structure exists: why?

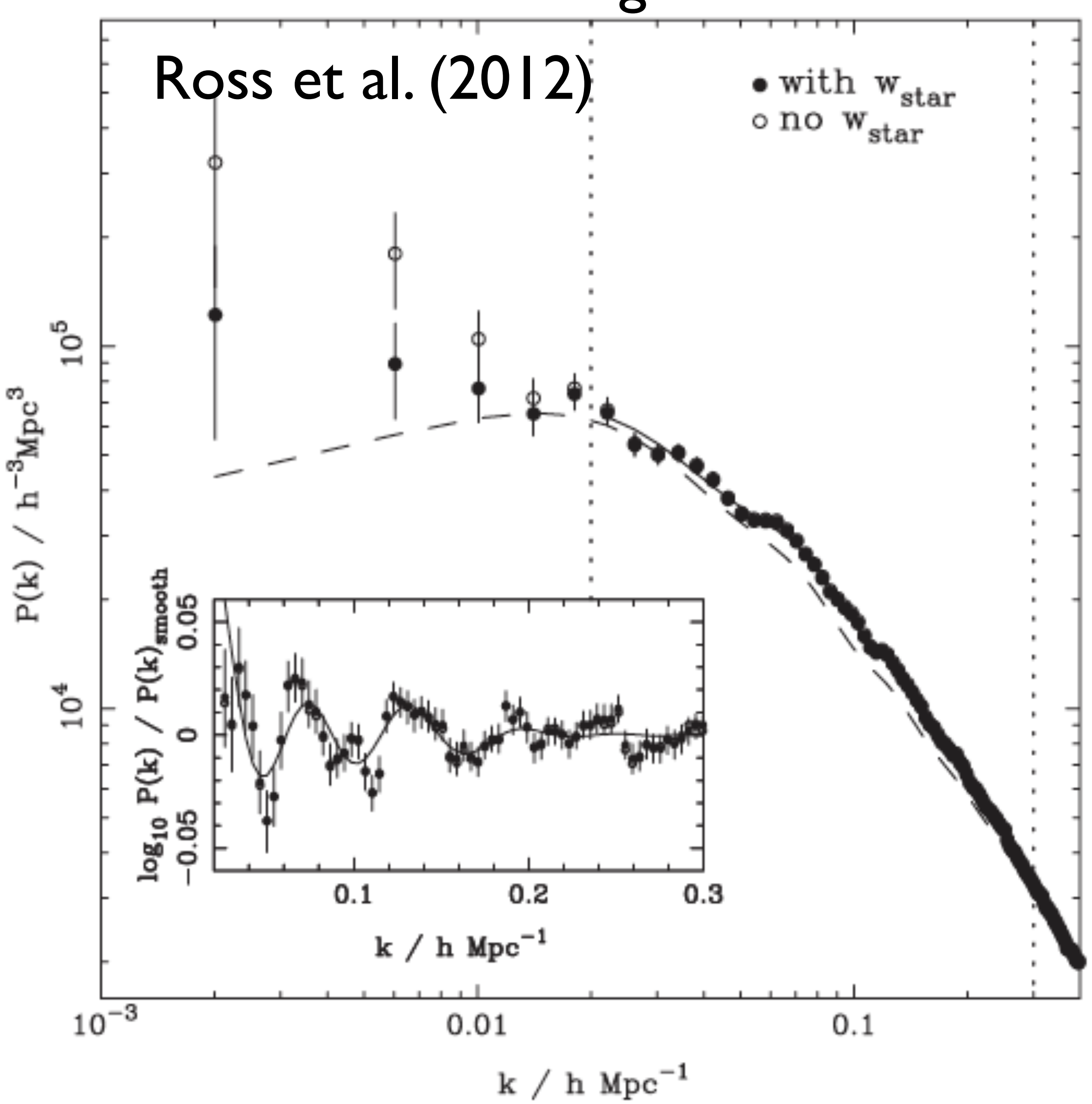
Observational Systematics: f_{NL}



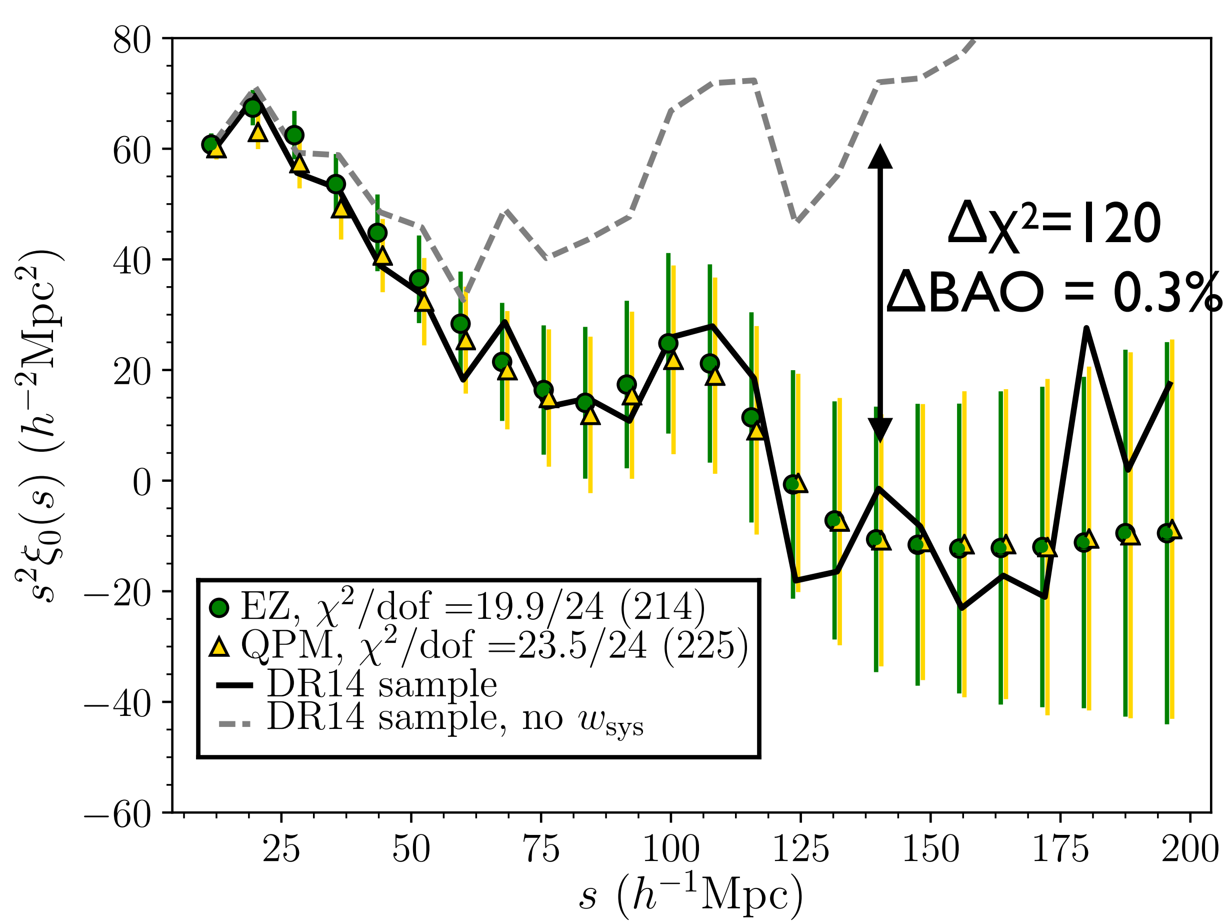
BAO Don't Budge

- BOSS galaxies (Ross et al. 2017), Ly-α forest (Bautista et al. 2017), quasars, DES photozs…

BOSS DR9 CMASS galaxies



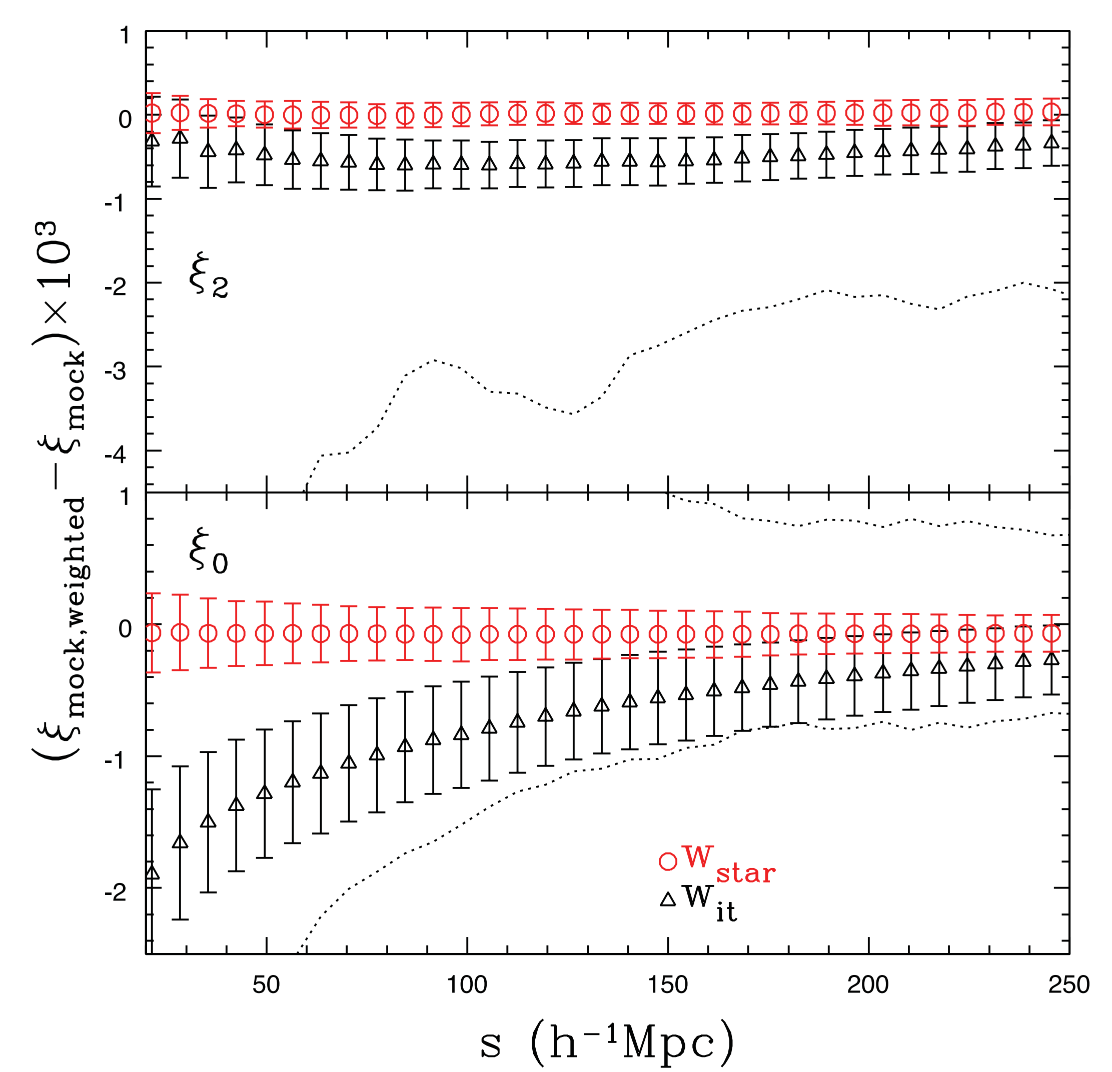
eBOSS DR14 quasars
Ata et al. (2017)



Details Matter

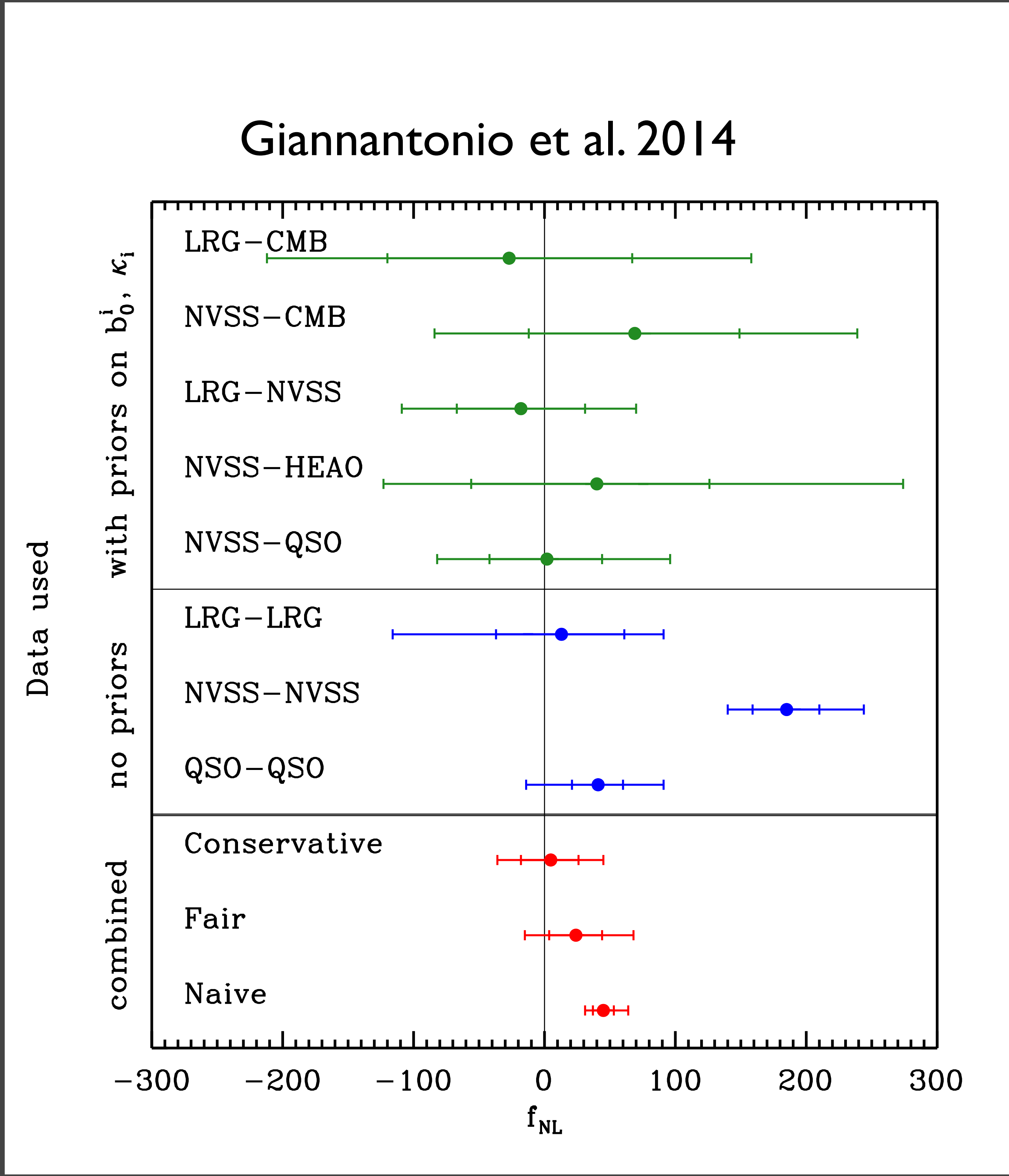
- Clustering modes are removed by these methods
- Need to be careful, show that method is unbiased for *model* it is testing
- Elsner et al. (2016), Kalus et al. (2016)

BOSS DR9 Ross et al. (2012)



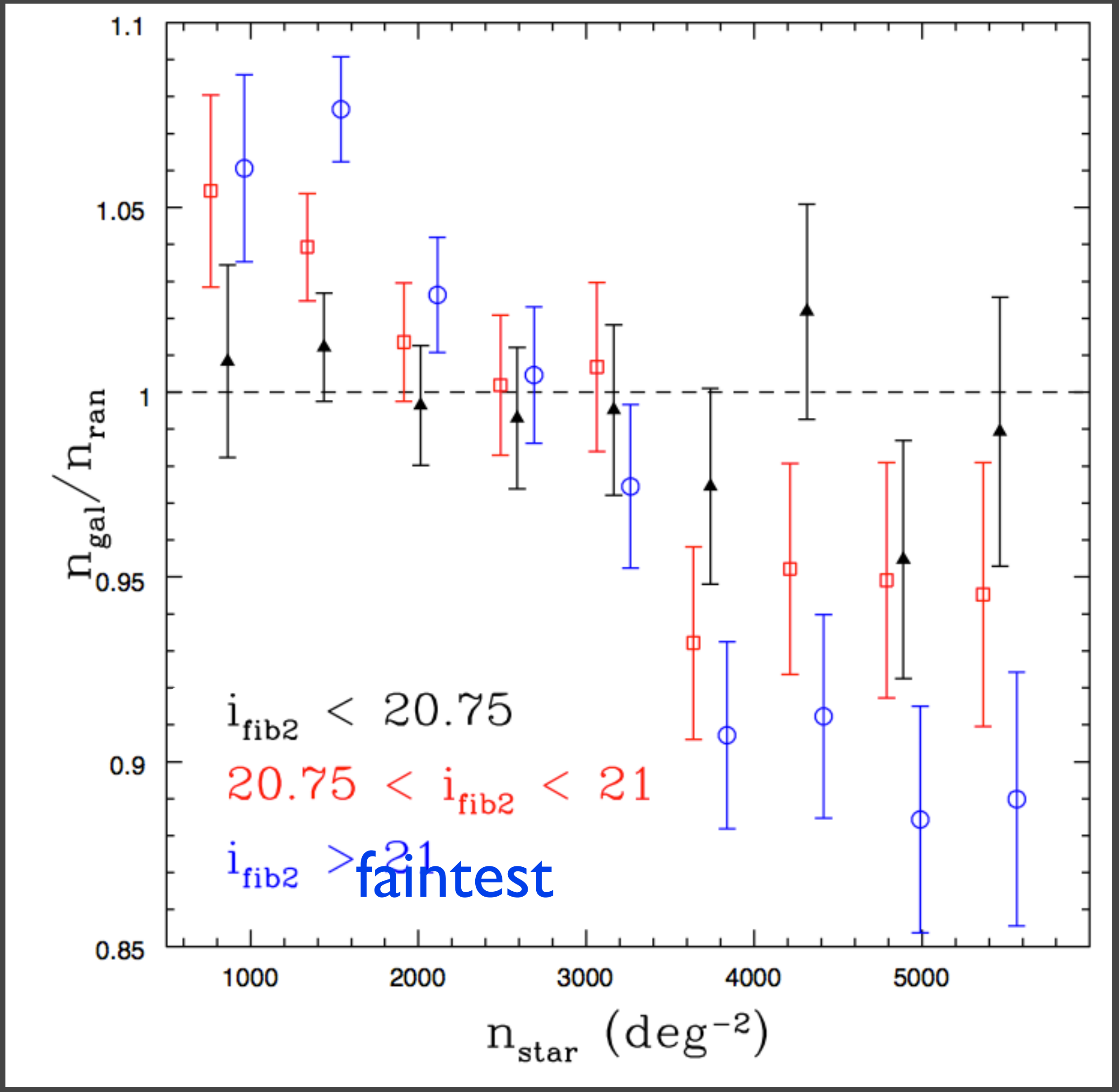
Cross-correlations

- calibration and data quality concerns (mostly) drop out

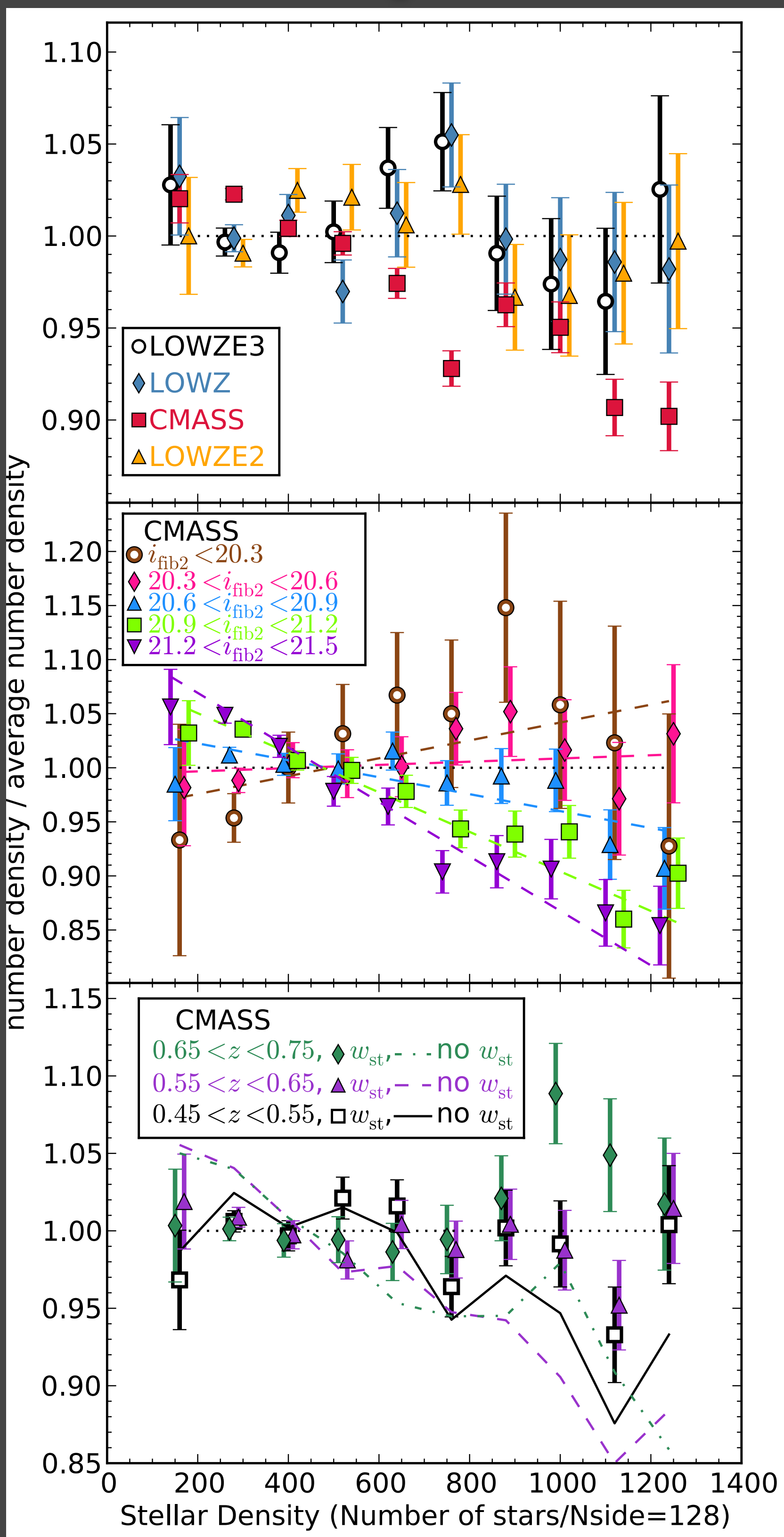


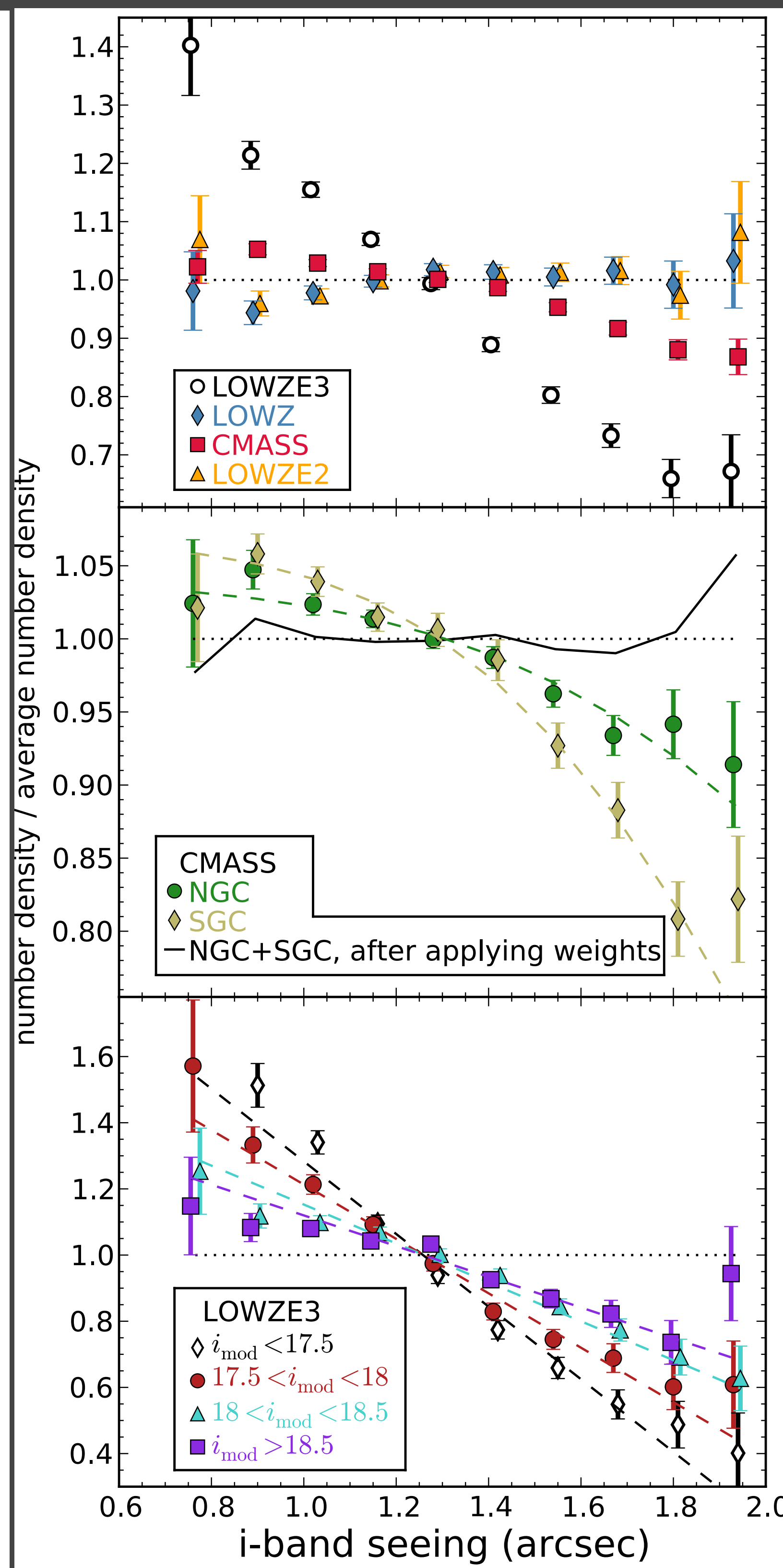
Stars and BOSS Surface Brightness

- Spectroscopic results confirm galaxy vs. stellar density relationship
- Depends on surface brightness
- Corrected with weights based on linear fits



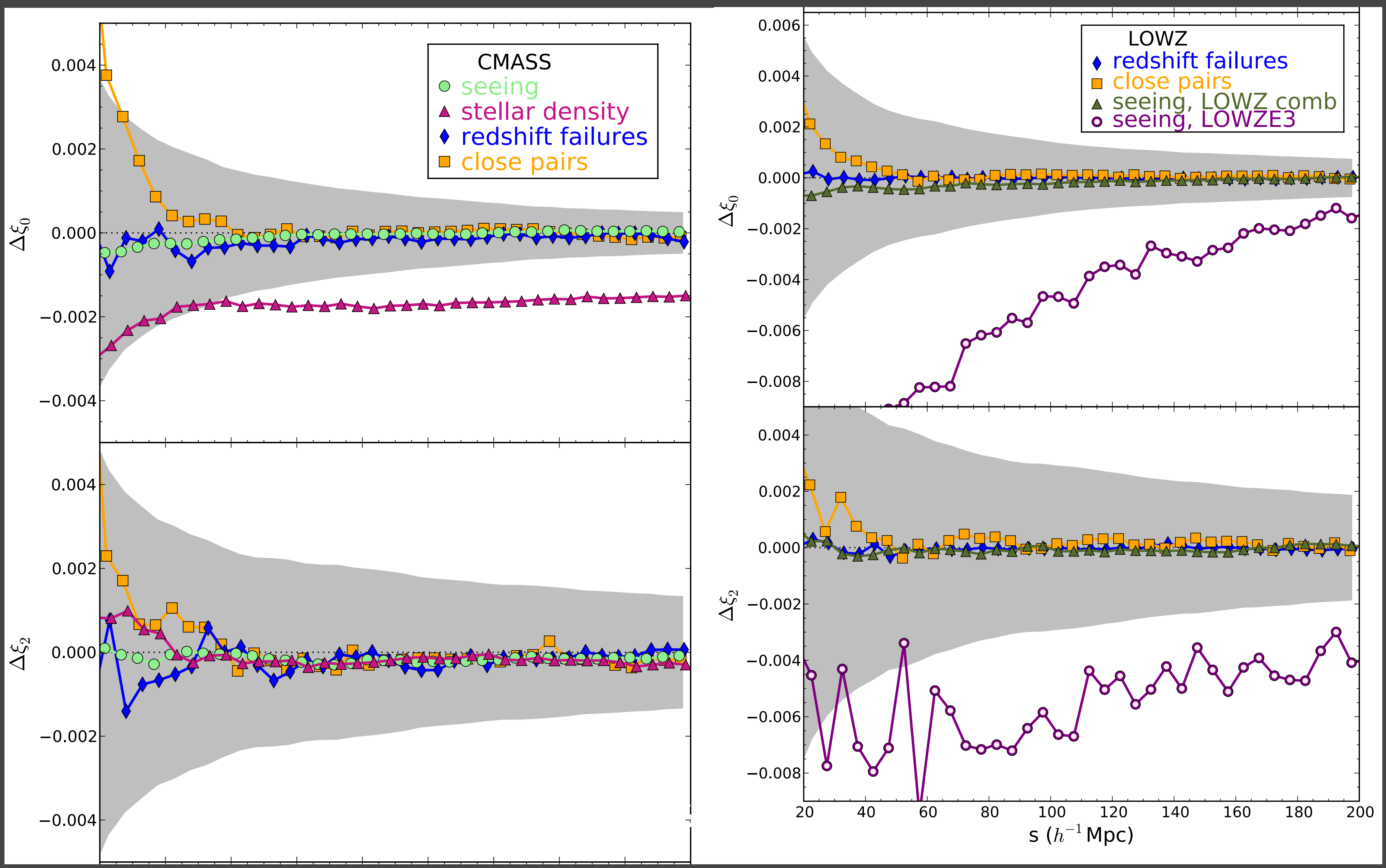
Systematics in final data set





- Stellar density effect remains strong
- Significant effect with seeing due to morphological star/ galaxy separation cuts

Systematics in final data set



- Only stellar density has strong effect over full footprint
- (LOWZE3 result is over full footprint, but it is only 660 deg^2 in combined)
- Simulating effects yield no bias in BAO, negligible effect on statistical uncertainty