

# Local primordial non-Gaussianity from the large-scale clustering of photometric DESI luminous red galaxies

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## ABSTRACT

This paper uses the large-scale clustering of luminous red galaxies selected from the Dark Energy Spectroscopic Instrument Legacy Imaging Surveys Data Release 9 to constrain the local primordial non-Gaussianity (PNG) parameter  $f_{\text{NL}}$ . We thoroughly investigate the impact of various photometric systematic effects, such as those caused by Galactic extinction, local stellar density, varying survey depth, and astronomical seeing using spherical harmonics cross power spectrum and mean galaxy density statistics. Lognormal density fields are simulated with and without PNG to construct covariance matrices, evaluate the robustness of power spectrum modeling code, assess whether spurious fluctuations are properly mitigated, and calibrate imaging systematics cleaning methods. With harmonic modes from  $\ell = 2$  to 300, we find  $36.07(25.03) < f_{\text{NL}} < 61.44(75.64)$  with a conservative cleaning approach and  $13.09(-15.95) < f_{\text{NL}} < 69.14(91.84)$  with an extreme treatment of imaging systematics, both at 68%(95%) confidence. We find significant remaining systematic error raised by calibration issues in the South Galactic Cap and local stellar density in the North Galactic Cap, which induce noticeable biases in  $f_{\text{NL}}$  constraints. While our constraints are consistent with zero PNG at 95% confidence for the extreme approach, we show that the characterization of stellar contamination and calibration issues are crucial to derive unbiased constraints on  $f_{\text{NL}}$  in the era of DESI and LSST cosmology.

**Key words:** cosmology: inflation - large-scale structure of the Universe

## 1 INTRODUCTION

Current observations of the cosmic microwave background (CMB), large-scale structure (LSS), and supernovae (SN) Hubble diagrams are explained to great degrees by a cosmological model that consists of dark energy, dark matter, and ordinary luminous matter, which has gone through a phase of rapid expansion, known as *inflation*, at its early stages (see, e.g., Weinberg et al. 2013). The paradigm of inflation elegantly addresses fundamental issues, such as the isotropy, flatness, and homogeneity of the Universe as well

as the absence of magnetic monopole (see, e.g., Weinberg 2008). At the end of inflation, the Universe went through an unknown reheating process, and primordial fluctuations generated to seed the subsequent growth of structure (Kofman et al. 1994; Bassett et al. 2006; Lyth & Liddle 2009). Even though the reality of an inflationary era is almost certain from observations, characteristics of the field causing the inflationary expansion and its underlying mechanism are vastly unknown, and statistical properties of primordial fluctuations remain an interesting question in modern observational cosmology. Early analyses of cosmological datasets have suggested

that initial conditions of the Universe are consistent with Gaussian fluctuations (Guth & Kaiser 2005); however, alternative classes of inflationary models predict some levels of non-Gaussianities in the primordial gravitational field. In its simplest form, primordial non-Gaussianity (PNG) depends on the local value of the gravitational potential  $\phi$ , and it is parameterized by a nonlinear coupling constant  $f_{\text{NL}}$  (Komatsu & Spergel 2001),

$$\Phi = \phi + f_{\text{NL}}[\phi^2 - \langle \phi^2 \rangle]. \quad (1)$$

Standard slow-roll inflation predicts  $f_{\text{NL}}$  to be of order  $10^{-2}$  (see, e.g., Alvarez et al. 2014, for a review), while multi-field inflationary scenarios anticipate considerably higher  $f_{\text{NL}}$  values than unity (see, e.g., de Putter et al. 2017). Therefore, deriving robust constraints on  $f_{\text{NL}}$  are the first stepping stone toward better understanding the dynamic of the early Universe. PNG alters the local number density of galaxies by coupling the long and small wavelength modes of dark matter gravitational field, and as consequently, it induces a scale-dependent shift in halo bias (see, e.g., Dalal et al. 2008; Slosar et al. 2008),

$$\Delta b \sim f_{\text{NL}} \frac{(b - p)}{k^2}, \quad (2)$$

where  $p$  determines the response of the tracer to the halo gravitational field. If only mass determines how galaxies occupy a halo,  $p = 1$ , which is often referred to as the universality of halo occupation function. However, numerical simulations indicate that halo occupation distribution for different tracers, which are results of recent mergers, could depend on other properties besides mass, and thus  $p = 1.6$  (Slosar et al. 2008). Because of the dependence of  $\Delta b$  on  $k^{-2}$ , the signature of local primordial non-Gaussianity is more pronounced on small wavenumbers (or large scales) in the two-point clustering of galaxies and quasars.

The current tightest bound on  $f_{\text{NL}}$  comes from the three-point clustering analysis of the CMB temperature anisotropies by the Planck satellite,  $f_{\text{NL}} = 0.9 \pm 5.0$  (Akrami et al. 2019). Upcoming generations of CMB experiments will improve this constraint, but since CMB observation is limited by cosmic variance, it alone cannot enhance our understanding of  $f_{\text{NL}}$  further enough to break the degeneracy amongst various inflationary models (see, e.g., Ade et al. 2019). Nevertheless, combining CMB with LSS data could cancel cosmic variance, partially even if not completely, and improve these limits to a precision level required to differentiate between alternative inflationary scenarios (see, e.g., Schmittfull & Seljak 2018). Constraining  $f_{\text{NL}}$  with the three-point clustering of LSS is also hindered by the late-time nonlinear effects raised due to structure growth (Baldauf et al. 2011b,a), which is non-trivial to account for, and this limitation establishes the scale-dependent bias technique as the smoking gun for constraining local PNG with LSS. Although still not competitive with the current bounds from CMB and LSS, UV Luminosity Function is shown as a new approach for constraining  $f_{\text{NL}}$  by probing galaxy abundances and structure formation on small scales (e.g.,  $k \sim 2 \text{ Mpc}^{-1}$ ), which are otherwise impossible to explore with CMB and LSS clustering. With this technique, Sabti et al. (2021) uses the Hubble Space Telescope catalogs (Bouwens et al. 2015) to find a  $2\sigma$  bound of  $-166 < f_{\text{NL}} < 497$ , and predicts upcoming surveys such as the James Webb Space Telescope and the Nancy Grace Roman Space Telescope to yield up to four times improvements.

Measuring  $f_{\text{NL}}$  with the scale-dependent bias effect is nonetheless exceptionally challenging due to various systematic effects which prompt excess clustering signal on large scales sensitive to  $f_{\text{NL}}$ . These systematics are broadly classified into theoretical and

observational. Survey geometry is a major source of systematic error, which entangles clustering power on different angular modes (Beutler et al. 2014; Wilson et al. 2017). Relativistic effects also generate scale-dependent signatures on large scales, identical to PNG, which hinder measuring  $f_{\text{NL}}$  with the scale-dependent bias effect (Wang et al. 2020). Similarly, matter density fluctuations with wavelengths larger than survey volume, known as super-sample modes, modulate power spectrum of galaxies (Castorina & Moradinezhad Dizgah 2020). Integral constraint is another source for systematic error, which pushes clustering power on modes near survey size to zero (Peacock & Nicholson 1991; De Mattia & Ruhlmann-Kleider 2019). It is raised because the mean galaxy density for constructing the density contrast field is estimated from data directly rather than being known a priori. Neglecting any of these effects in modeling power spectrum leads to biased  $f_{\text{NL}}$  constraints (see, e.g., Riquelme et al. 2022).

On the other hand, observational systematics are driven predominantly by either varying imaging properties across the sky (Ross et al. 2011) or calibration issues that cause spurious fluctuations in the target density field (Huterer et al. 2013). This type of systematic error is much more challenging to model and mitigate, compared to integral constraint and survey geometry, and it has hampered previous studies of local PNG with the scale-dependent bias effect in the large-scale clustering of galaxies and quasars (see, e.g., Ho et al. 2015). For instance, Pullen & Hirata (2013) found that the level of systematic contamination in the quasar sample of Sloan Digital Sky Survey DR6 does not allow a robust  $f_{\text{NL}}$  measurement. These imaging systematic issues are expected to be severe for wide-area galaxy surveys that observe the night sky closer to the Galactic plane and attempt to relax the selection criteria cuts to accommodate fainter targets (see, e.g., Kitanidis et al. 2020).

The Dark Energy Spectroscopic Instrument (DESI) uses robots to collect 5000 spectra in parallel, and is designed to deliver unparalleled volume of spectroscopic data that will enable analyses to deepen our understanding of the energy contents of the Universe, specifically, the equation of state for Dark Energy (Aghamousa et al. 2016). Assuming imaging systematics are under control and with the volume probed, DESI along with other upcoming surveys, such as Rubin Observatory and SphereX, are expected to yield unprecedented constraints on  $f_{\text{NL}}$  (see, e.g., Heinrich & Doré 2022). DESI preselects its targets from its dedicated imaging surveys, known as the DESI Legacy Imaging Surveys, which are collected from observation conducted between 2014 and 2019 from three ground-based telescopes based in Chile and the US. The characterization of potential sources for systematic error in DESI imaging data is of paramount importance to DESI success, since these effects from imaging catalogs could potentially be inherited into spectroscopic catalogs and thus negatively influence the science goals with DESI data. DESI targets galaxies and quasars to construct a 3D map of LSS up to redshifts around 4.

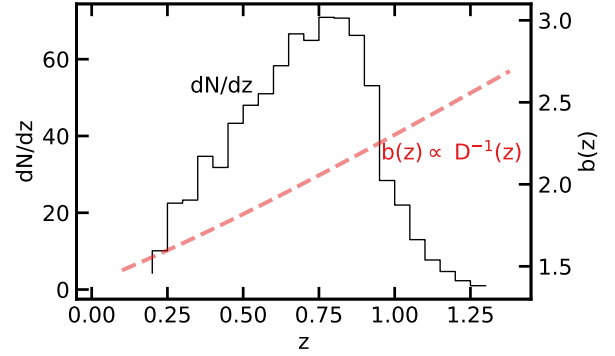
The effects of observational systematics in DESI targets have been studied in great detail (see, e.g., Kitanidis et al. 2020; Zhou et al. 2021; Chaussidon et al. 2022). Improving techniques to characterize systematic error in these tracers is crucial for the science beyond dark energy, such as constraining  $f_{\text{NL}}$  and other features in the primordial power spectrum (Beutler et al. 2019). Some of the current methods seek to mitigate systematic effects by either cross-correlating target density and imaging maps (mode deprojection) or solving a least-square optimization to estimate the contribution from each imaging property to target density field (template-based regression), ultimately to regress out the modes affected by imaging properties from the target density. Another class of methods aim to

cross correlate different tracers to improve constraints by canceling cosmic variance and by reducing the effect of systematic error, as each tracer might respond differently to a source of systematics. Giannantonio et al. (2014) presents improved  $f_{\text{NL}}$  constraints using the integrated Sachs-Wolfe effect. These methods have their limitations and strengths (see, e.g., Weaverdyck & Huterer 2021, for a review). For instance, mode deprojection yields an unbiased clustering but can be employed for angular clustering only, and its involved matrix algebra could turn out to be time-consuming for large survey sizes. Template-based regression is on the other hand computationally economic, but it returns biased clustering by removing some of clustering power, depending on the number of input templates and the flexibility of regression model. Specifically related to the template-based regression method, there is a little effort to calibrate and characterize the amount of clustering power removed during the cleaning process. For studies like BAO and RSD, these effects are demonstrated to be negligible (Merz et al. 2021); however, these effects introduce significant biases in  $f_{\text{NL}}$  constraints (Mueller et al. 2022) as they highly impact galaxy clustering on large scales (Rezaie et al. 2021).

This paper presents robust constraints on  $f_{\text{NL}}$  from DESI imaging with an exquisite characterization of imaging systematic error and mitigation biases. We measure the significance of residual systematic error in data using angular cross power spectrum (between galaxy density and imaging properties) and galaxy mean density contrast statistics. In this paper, the robustness of our results is validated against various sources of systematic error, including but not limited to photometric calibration and Milky Way extinction. For modeling angular power spectrum, we determine the redshift distribution of tracers by utilizing early spectroscopic data from the DESI Survey Validation. We cross-correlate the density field of galaxies with the templates of imaging properties to evaluate the effectiveness of different treatment methods and to characterize the significance of remaining systematic error. To quantify the sensitivity of  $f_{\text{NL}}$  signal to alternative cleaning methods, we apply various linear and nonlinear approaches with different combinations of imaging templates. This paper is structured as follows. Section 2 describes the DESI imaging galaxy sample and simulations with and without PNG and imaging systematic effects, and Section 3 outlines the theory framework for modeling angular power spectrum and analysis techniques to account for various observational and theoretical systematic error. Finally, we present  $f_{\text{NL}}$  constraints in Section 4, and conclude with a comparison to previous  $f_{\text{NL}}$  studies in Section 5.

## 2 DATA

Luminous red galaxies (LRGs) are massive galaxies that occupy massive halos, lack active star formation, and are one of the highly biased tracers of large-scale structure. LRGs are widely targeted in previous galaxy redshift surveys (see, e.g., Eisenstein et al. 2001; Prakash et al. 2016), and their clustering and redshift properties are well studied (see, e.g., Alam et al. 2021). Redshifts of LRGs are easily determined from a break around 4000 Å in their spectra. DESI is built to collect spectra of millions of LRGs covering the redshift range of  $0.4 < z < 1.0$  over the span of its five-year mission (Aghamousa et al. 2016). Targets for DESI spectroscopy are pre-selected from three dedicated ground-based imaging surveys that observed the night sky in the optical  $g$ ,  $r$ , and  $z$  bands between 2014 and 2019: the Mayall  $z$ -band Legacy Survey using the Mayall telescope at Kitt Peak (MzLS; Dey et al. 2018), the Beijing–Arizona



**Figure 1.** Redshift distribution (solid) and bias evolution (dashed) of DESI LRGs (Zhou et al. 2021, 2022). The LRG redshift distribution is deducted from early spectroscopy by DESI and the LRG bias model assumes a constant clustering amplitude.

Sky Survey using the Bok telescope at Kitt Peak (BASS; Zou et al. 2017), and the Dark Energy Camera Legacy Survey on the Blanco 4m telescope (DECaLS Flaugher et al. 2015). Additionally, the DECaLS program integrates observations conducted from the same instrument under the Dark Energy Survey (Abbott et al. 2016), which constitute about 1130 deg<sup>2</sup> of the South Galactic Cap (SGC) footprint. The BASS and MzLS surveys observed the same footprint in the North Galactic Cap (NGC) while the DECaLS observed both caps around the galactic plane; the BASS+MzLS footprint is distinguished from the DECaLS NGC by applying DEC > 32.375 degrees, although there is an overlap between the two regions for calibration purposes (Dey et al. 2018). The DESI imaging catalogs also incorporate the 3.4 (W1) and 4.6 μm (W2) infrared images from the Wide-Field Infrared Explorer (WISE; Wright et al. 2010).

### 2.1 DESI Imaging DR9 LRGs

We work with the photometric LRGs selected from the DESI Imaging Surveys Data Release 9 (DR9; Dey et al. 2018) using the selection and cuts designed for the DESI 1% survey (CITE), described as the SV3 selection in more detail in Zhou et al. (2022). The color-magnitude selection cuts are defined in the  $g$ ,  $r$ ,  $z$  bands in the optical and W1 band in the infrared frequencies, and summarized in Tab. 1. The selection cuts are designed differently for each imaging survey to attain almost uniform target surface density in spite of different survey efficiency and calibration between DECaLS and BASS+MzLS. The implementation of these selection cuts in the DESI data processing pipeline is explained in Myers et al. (2022). Fig. 1 shows the redshift distribution of the DR9 LRG sample (solid black), which is inferred from the spectroscopic DESI Survey Validation data (CITE), and the evolution of halo bias for the DR9 LRG sample (dashed red) adapted from Zhou et al. (2021), which is consistent with the assumption of a constant clustering amplitude.

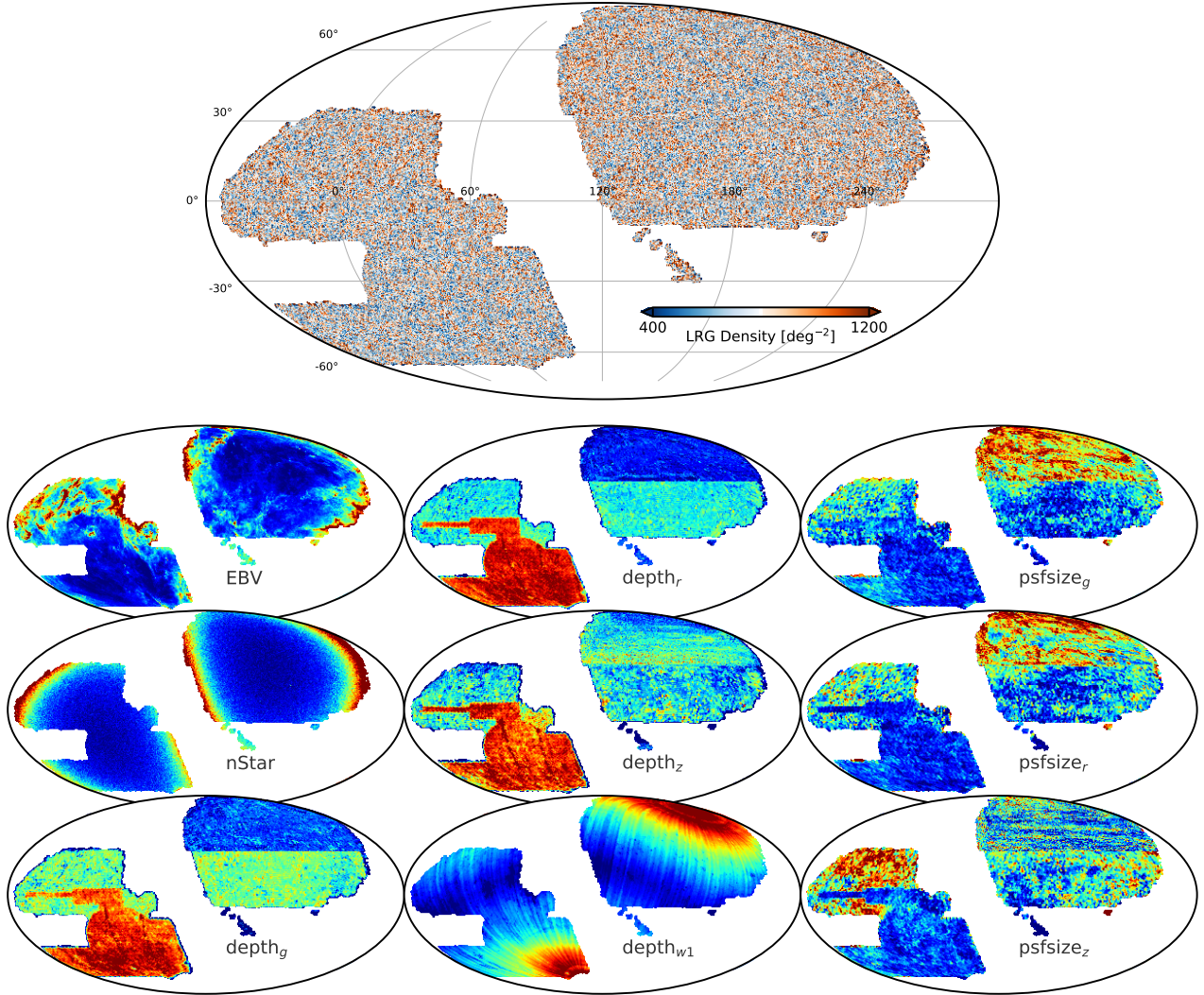
DESI-like LRGs are selected brighter than the imaging survey depth limits; therefore, the DR9 LRG density field is nearly homogenous unlike the other DESI tracers. To further reduce stellar contamination, the LRG sample is masked rigorously for foreground bright stars, galaxies, and clusters of galaxies<sup>1</sup>. Then, the sample

<sup>1</sup> See the maskbits at <https://www.legacysurvey.org/dr9/bitmasks/>



**Table 1.** Selection criteria for the DESI-like LRG targets (Zhou et al. 2022). Magnitudes are corrected for MW extinction.

Footprint	Criterion	Description
DECaLS	$z_{\text{fiber}} < 21.7$	Faint limit
	$z - W1 > 0.8 \times (r - z) - 0.6$	Stellar rejection
	$[(g - r > 1.3) \text{ AND } ((g - r) > -1.55 \times (r - W1) + 3.13)] \text{ OR } (r - W1 > 1.8)$	Remove low- $z$ galaxies
	$[(r - W1 > (W1 - 17.26) \times 1.8) \text{ AND } (r - W1 > W1 - 16.36)] \text{ OR } (r - W1 > 3.29)$	Luminosity cut
BASS+MzLS	$z_{\text{fiber}} < 21.71$	Faint limit
	$z - W1 > 0.8 \times (r - z) - 0.6$	Stellar rejection
	$[(g - r > 1.34) \text{ AND } ((g - r) > -1.55 \times (r - W1) + 3.23)] \text{ OR } (r - W1 > 1.8)$	Remove low- $z$ galaxies
	$[(r - W1 > (W1 - 17.24) \times 1.83) \text{ AND } (r - W1 > W1 - 16.33)] \text{ OR } (r - W1 > 3.39)$	Luminosity cut

**Figure 2.** DESI Legacy Imaging Survey Data Release 9 Luminous Red Galaxies and imaging properties (Dey et al. 2018). Top: Observed target density field in  $\text{deg}^{-2}$ . Spurious disconnected islands from the DECaLS North footprint at Declination below  $-11$  and parts of the DECaLS South with Declination below  $-30$  are dropped from the DR9 sample due to potential calibration issues. Bottom: Mollweide projections of the DR9 catalog imaging properties (depth and psfsize/seeing) and MW foregrounds (extinction and local stellar density) in celestial coordinates.

is binned into HEALPIX (Gorski et al. 2005) at  $n_{\text{SIDE}} = 256$  to construct the 2D density map with an average surface density of  $800 \text{ deg}^{-2}$  with sky coverage around 14000 square degrees. We correct for the pixel incompleteness and lost areas in the density field of LRGs using a catalog of random points, hereafter referred to as randoms, uniformly scattered over the footprint with the same cuts and masks applied. Fig. 2 (top) shows observed density field of the DR9

LRGs in  $\text{deg}^{-2}$  before applying any correction weights to account for imaging systematic effects.

The DR9 LRG density exhibits large-scale spurious fluctuations, which are likely to be of non-cosmological origin. Specifically, the SGC footprint indicates some systematic under-density while there are some systematic over-density near the boundaries in the NGC. We study the impact of imaging properties as poten-

tial sources of systematic error, mapped into HEALPIX at the same NSIDE. Similar to Zhou et al. (2022), the properties studied in this work are local stellar density constructed from point-like sources with a g-band magnitude in the range  $12 \leq g < 17$  from Gaia Data Release 2 (see, Gaia Collaboration et al. 2018; Myers et al. 2022); Galactic extinction E[B-V] from Schlegel et al. (1998); and other imaging properties include survey depth (galaxy depth in the g, r, and z bands and PSF depth in W1) and seeing in the g, r, and z bands. These maps are produced by making the histograms of randoms (painted with imaging properties) in HEALPIX and averaging over randoms in each pixel. Fig. 2 (bottom) illustrates the imaging templates investigated for potential sources of systematic error, each of which reflect their characteristic large-scale spurious fluctuations. For instance, the under-density with the SGC can be visually correlated with the depth maps, while the over-density in the NGC can be associated visually with the extinction map. There are some disconnected islands, hereafter referred to as *spurious islands*, in the DECaLS North region at Declination below  $-11$ , which are removed from the main analysis to minimize potential calibration issues. Additionally, some parts of the DECaLS South footprint with Declination below  $-30$  are removed from the sample, since similar calibration issues might tamper with our clustering measurement. We discuss how these data cuts influence our  $f_{\text{NL}}$  constraints in Section 4.

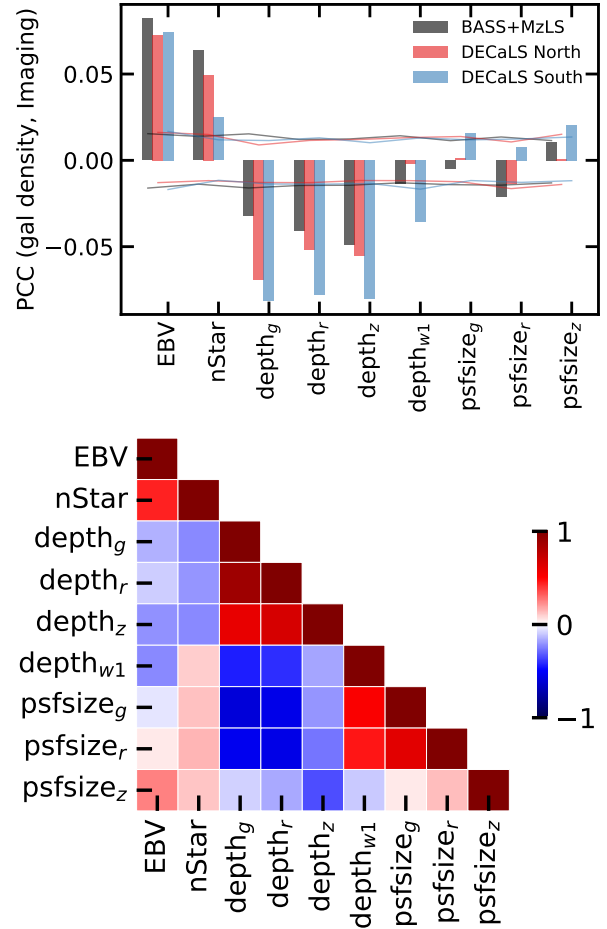
Fig. 3 shows the Pearson correlation coefficient between the DR9 LRG density and DESI imaging properties for the three imaging surveys (DECaLS North, DECaLS South, and BASS+MzLS) in the top panel. The horizontal curves are constructed from lognormal simulations (see, subsection 2.2) to quantify the significance of correlations. Fig. 3 (bottom) shows the correlation matrix among the imaging properties themselves for the full DESI survey. There is a strong correlation between the LRG density and depth maps, and then the second correlated property seems to be Galactic foregrounds. There is a little correlation between the LRG density and the W1 depth and psfsize properties. We observe a significant inner-correlation among the imaging properties themselves, especially between the local stellar density and Milky Way extinction; also, the r-band and g-band properties are more correlated with each other than with the z-band.

We follow a template-based approach to derive a set of weights to be multiplied by the LRG density in order to account for spurious fluctuations. Specifically, we regress out the DR9 density map against a set of imaging maps, referred to as templates or predictors. Because of the inner-correlation amongst the maps, a few subsets of maps are considered as well. These subsets are selected to minimize the correlations among the predictors while having maximum correlation with the observed LRG density map:

- Conservative I: Extinction,  $\text{depth}_z$
- Conservative II: Extinction,  $\text{depth}_z$ ,  $\text{psfsize}_r$
- All Maps: Extinction, depth in  $grz$  and W1, psfsize in  $grz$

We also investigate whether including external maps for neutral hydrogen column density (CITE) and photometric calibration (e.g., in the z band; CALIBZ) could provide more insights on remaining systematic effects. The results are discussed in Section 4.

Linear and nonlinear models (approximated using a neural network) are applied to assess the potential of nonlinear systematic error. Parameters of the models are fit by optimizing the negative Poisson log likelihood,  $= \sum \lambda - \rho \log(\lambda)$ , where the summation runs over pixels,  $\rho$  is the galaxy density, and  $\lambda$  is either a linear or nonlinear model for galaxy density given imaging properties  $\mathbf{x}$  as input,  $\lambda(\mathbf{x}) = \log(1 + e^{f(\mathbf{x})})$ . For finding the parameters of the



**Figure 3.** Top: Pearson correlation coefficient between galaxy density and imaging properties in the three imaging regions. Solid curves represent the 95% of correlation coefficients observed in 100 randomly selected lognormal mock density realizations. Bottom: Pearson correlation matrix from imaging properties for the full DESI footprint.

linear model, we perform a Monte Carlo Markov Chain (MCMC) search using the EMCEE package (CITE) and for the nonlinear model we use the implementation from Rezaie et al. (2021); specifically, the nonlinear model is an ensemble of 20 neural network models. Each neural network is constructed with three hidden layers and 20 rectifier units on each layer. Rectifier is identity function for positive input and zero for negative, and it introduces nonlinearities in the neural network. For the linear model we use all data for computing the log of posterior during MCMC while for the nonlinear approach we use 60% of data for training, 20% for validation, and 20% for testing; this is to minimize the chance of over-fitting by the nonlinear model. By changing the permutation of training-testing splits, we test the nonlinear model on entire data. The training is performed for up to 70 training epochs using ADAM optimizer, which is a variant of gradient descent, and the learning rate is tuned on the validation set to dynamically varying between 0.001 and 0.1, to enable learning robust against local minima. The best model is then selected with the lowest prediction error when applied to the validation set. Finally, we apply the ensemble of 20 best fit models to the test set and average over the predictions to construct the predicted galaxy density maps, which is used as imaging systematic weights to down-weight observed density map for removing imaging systematics.

Upon the inspection of the predicted density maps, we find that while most of the large-scale spurious fluctuations are explained by just the extinction map and depth in the  $z$  band, adding the  $\text{psfsize}$  in the  $r$  band results in finer structure in the predicted density map. Using all maps as input features for regression does not add much information. Comparing linear to nonlinear with the same input maps, we find that the nonlinear approach yields finer structure due to a higher flexibility. Overall, both models predict higher density near the boundaries where the surveys meet the high extinction regions of Milky Way. These regions are probably contaminated artifacts entering the selection either via the direct stellar contamination or the impact of extinction on colors.

## 2.2 Synthetic lognormal density fields

Lognormal distributions are shown to be appropriate for describing matter density fluctuations on large scales (Coles & Jones 1991). Unlike N-body simulations, the generation of lognormal density fields is rather quick and enables a computationally economic approach to generate a large ensemble of synthetic realizations of galaxy density fields which mimic the redshift and angular distribution of real data. Mocks will enable the validation of analysis software from an end-to-end perspective, and mocks can be used to construct covariance matrices for error estimation and perform statistical tests for characterizing remaining systematic effects. FLASK (Full-sky Lognormal Astro-fields Simulation Kit; Xavier et al. 2016) is used to generate series of lognormal galaxy density fields with  $f_{\text{NL}} = 0$  and 76.92 using a redshift dependent bias  $b(z) = 1.43/D(z)$ . 1000 realizations are generated for each  $f_{\text{NL}}$ . The fiducial cosmology to generate the mocks is based on a flat  $\Lambda$ CDM universe including one massive neutrino with  $m_\nu = 0.06$  eV, and the rest of cosmological parameters are chosen within 68% of the Planck 2018 results (Aghanim et al. 2020),

$$h = 0.67, \Omega_M = 0.31, \sigma_8 = 0.8, \text{ and } n_s = 0.97.$$

We use the same fiducial cosmology for the analysis of DR9 sample. Our robustness tests indicate that these parameters are not degenerate with  $f_{\text{NL}}$ , and thus fixing them would not induce biases in  $f_{\text{NL}}$  constraints.

## 3 ANALYSIS TECHNIQUES

This section describes the estimator for measuring the angular power spectrum and the methodology for modeling it in the presence of PNG. We also demonstrate how we correct for the effects of survey geometry and integral constraint in the modeling. The statistical tools for measuring the remaining systematic error are also presented.

### 3.1 Measuring Power Spectrum

The quantity that carries cosmological information is galaxy density contrast,  $\delta$ , which in pixel  $i$  is constructed as,

$$\hat{\delta}_i = \frac{\rho_i}{\hat{\rho}} - 1, \quad (3)$$

where  $\rho$  is the density of galaxies accounted for pixel area  $f_{\text{pix},i}$ , which is determined by uniformly distributed random galaxies over footprint, and  $\hat{\rho}$  is the mean galaxy density directly estimated from

the data,

$$\hat{\rho} = \frac{\sum_i \rho_i f_{\text{pix},i}}{\sum_i f_{\text{pix},i}}. \quad (4)$$

By definition, Eqs. 3 and 4 ensure that the integral of the observed quantity over the footprint vanishes:

$$\sum_i \hat{\delta}_i f_{\text{pix},i} = 0, \quad (5)$$

and this constraint causes an effect commonly referred to as *integral constraint*, which needs to be accounted for in the model. To estimate power spectrum, the galaxy density contrast is expanded in terms of Legendre polynomials,

$$\hat{\delta}_i = \sum_{\ell=0}^{\ell_{\text{max}}} \sum_{m=-\ell}^{\ell} a_{\ell m} Y_{\ell m}(\theta_i, \phi_i), \quad (6)$$

where  $\theta, \phi$  represent the polar and azimuthal angular coordinates of pixel  $i$  center, respectively. The cutoff at  $\ell = \ell_{\text{max}}$  assumes that modes with  $\ell > \ell_{\text{max}}$  do not contribute significantly to signal power. The coefficients  $a_{\ell m}$  are then obtained by integrating the density contrast field over the total number of non-empty pixels  $N_{\text{pix}}$  and using the orthogonality of Legendre polynomials:

$$\hat{a}_{\ell m} = \frac{4\pi}{N_{\text{pix}}} \sum_{i=1}^{N_{\text{pix}}} \hat{\delta}_i f_{\text{pix},i} Y_{\ell m}^*(\theta_i, \phi_i), \quad (7)$$

where  $*$  represents the complex conjugate. Then, the angular power spectrum estimator is defined as the variance of  $\hat{a}_{\ell m}$  coefficients:

$$\hat{C}_\ell = \frac{1}{2\ell+1} \sum_{m=-\ell}^{\ell} \hat{a}_{\ell m} \hat{a}_{\ell m}^*. \quad (8)$$

In order to extract  $\hat{a}_{\ell m}$  and compute the angular power spectrum,  $C_\ell$ , the function ANAFast is called from HEALPIX (Gorski et al. 2005) with the third order iteration of the quadrature to increase the accuracy<sup>2</sup>. Due to the survey geometry implicit in the summation over the non-empty pixels and explicit in  $f_{\text{pix},i}$ , our estimator does not return an unbiased estimate of power spectrum, as different harmonic modes are no longer independent. Therefore, we account for the same effect in the modeling of angular power spectrum. The survey geometry treatment is validated against synthetic datasets.

### 3.2 Modeling Power Spectrum

Angular power spectrum is a projection of 3D clustering along the line of sight over all possible wavenumbers  $k$ . With redshift space distortions included, the projected angular power spectrum of galaxies is related to the 3D linear power spectrum  $P(k)$  and shotnoise  $N_{\text{shot}}$  by (see, e.g., Padmanabhan et al. 2007),

$$C_\ell = \frac{2}{\pi} \int_0^\infty \frac{dk}{k} k^3 P(k) |\Delta_\ell(k)|^2 + N_{\text{shot}}, \quad (9)$$

where shotnoise is assumed to scale-independent, and kernel  $\Delta_\ell(k) = \Delta_\ell^{\text{g}}(k) + \Delta_\ell^{\text{RSD}}(k)$  determines how much each wavenumber  $k$  contributes to mode  $\ell$  by integrating over all comoving scales  $r$ ,

$$\Delta_\ell^{\text{g}}(k) = \int \frac{dr}{r} r b(r, k) D(r) \frac{dN}{dr} j_\ell(kr), \quad (10)$$

$$\Delta_\ell^{\text{RSD}}(k) = - \int \frac{dr}{r} r f(r) D(r) \frac{dN}{dr} j_\ell''(kr), \quad (11)$$

<sup>2</sup> We refer the reader to <https://healpix.sourceforge.io/pdf/subroutines.pdf>, p. 104-105.



where  $D(r)$  is the normalized growth factor such that  $D(0) = 1$ ,  $f(r)$  is the growth rate, and  $dN/dr$  is the normalized redshift distribution of galaxies<sup>3</sup> (see, Fig. 1). In the presence of local primordial non-Gaussianity,  $b(r)$  is the linear bias  $b$  (see, Fig. 1) plus the scale-dependent shift due to PNG (see, Eq. 2),

$$b(k, r) = b + \frac{2(b - p)f_{\text{NL}}\delta_c}{\alpha(k, r)}, \quad (12)$$

where  $\alpha(k, r) \propto k^2 D(r)$ ,  $\delta_c = 1.686$  is the critical density above which gravitational collapse occurs (Fillmore & Goldreich 1984), and the parameter  $p$  determines the response of the tracer to halo's gravitational field, e.g., 1 for luminous red galaxies following universality and 1.6 for tracers that are results of recent mergers like quasars. In order to overcome rapid oscillations in spherical Bessel functions, FFTLog<sup>4</sup> algorithm and its extension as implemented in Fang et al. (2020) are employed to evaluate the inner integrations over  $d \ln r$ .

For a galaxy survey that observes the sky partially, the measured power spectrum is convolved with the survey geometry. This means that the pseudo-power spectrum  $\hat{C}_\ell$  obtained by the direct Spherical Harmonic Transforms of a partial sky map, differs from the full-sky angular spectrum  $C_\ell$ . However, their ensemble average is related by a mixing matrix (Hivon et al. 2002),

$$\langle \hat{C}_\ell \rangle = \sum_{\ell'} M_{\ell\ell'} \langle C_{\ell'} \rangle, \quad (13)$$

where  $M_{\ell\ell'}$  represents the mode-mode coupling from the partial sky coverage. This is known as the Window Function effect and a proper assessment of this effect is crucial for a robust measurement of the large-scale clustering of galaxies. This window effect is a source of observational systematic error and impacts the measured galaxy clustering, especially on scales comparable to survey size.

We follow a similar approach to that of Chon et al. (2004) to model the window function effect on the theoretical power spectrum  $C_\ell$  rather than correcting the measured pseudo-power spectrum from data. First, we use HEALPIX to compute the pseudo-power spectrum of the window  $\hat{C}_\ell^{\text{window}}$ , which is defined by a mask file in ring ordering format with NSIDE= 256. Then, we transform it to correlation function by,

$$\omega^{\text{window}}(\theta) = \frac{1}{4\pi} \sum_{\ell} (2\ell + 1) \hat{C}_\ell^{\text{window}} P_\ell(\cos \theta). \quad (14)$$

Next, we normalize  $\omega^{\text{window}}$  such that it is normalized to one at  $\theta = 0$ . Finally, we multiply the theory correlation function by  $\omega^{\text{window}}$  and transform the result back to  $\ell$ -space,

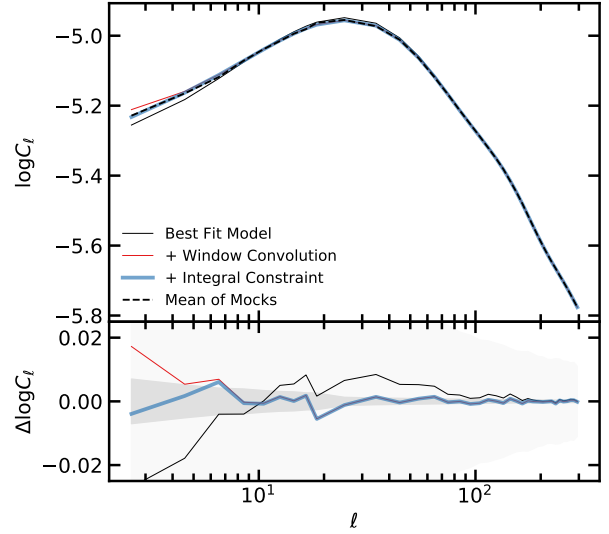
$$\hat{\omega}^{\text{model}} = \omega^{\text{model}} \omega^{\text{window}} \quad (15)$$

$$\hat{C}_\ell^{\text{model}} = 2\pi \int d\theta \hat{\omega}^{\text{model}}(\theta) P_\ell(\cos \theta). \quad (16)$$

The integral of the galaxy density contrast  $\delta$  on the footprint is bound to zero, which is often referred to as the *Integral Constraint*. We account for this effect in the modeling by,

$$\hat{C}_\ell^{\text{model, IC}} = \hat{C}_\ell^{\text{model}} - \hat{C}_{\ell=0}^{\text{model}} \left( \frac{\hat{C}_\ell^{\text{window}}}{\hat{C}_{\ell=0}^{\text{window}}} \right) \quad (17)$$

Fig. 4 shows the mean measured power spectrum of 1000 lognormal density fields (dashed) and best fit theory prediction.



**Figure 4.** Mean power spectrum of 1000 mocks with  $f_{\text{NL}} = 0$  and best fit theoretical prediction after accounting for various theoretical systematic effects, namely survey geometry effect and integral constraint. Dark and light shades represent  $1\sigma$  error on the mean and one realization, respectively. Bottom panel shows the residual relative to the mean of mocks. No imaging systematic effects are added to these mocks.

light and dark shades represent the 68% error on the mean and one single realization, respectively. DESI footprint mask is applied to the mocks, and even though DESI covers around 40% of the sky, but the window effect is affecting modes down to  $\ell = 200$ . On the other hand, integral constraint only alters the power in the first two bins.

### 3.3 Parameter estimation

Signature of local PNG is unique and cannot be reproduced with other cosmological parameters. We allow three parameters to vary;  $f_{\text{NL}}$ , shotnoise, and bias at  $z = 0$ . Throughout this manuscript, we bin each mode with  $\Delta\ell = 2$  between  $\ell = 2$  and 20 and  $\Delta\ell = 10$  from  $\ell = 20$  to 300, while weighting each mode by  $2\ell + 1$ . We also find that the distribution of power spectrum at the lowest bin,  $2 \leq \ell < 12$ , is not Gaussian and its standard deviation varies significantly from mocks with  $f_{\text{NL}} = 0$  to 76.9 (see, Fig. 5). Therefore, we attempt to fit  $\log C_\ell$  to make our constraints insensitive to the choice of covariance matrix. The parameter  $f_{\text{NL}}$  is constrained by maximizing a posterior defined as,

$$-2 \ln \mathcal{L} = (\log C(\Theta) - \log \hat{C})^\dagger \mathbb{C}^{-1} (\log C(\Theta) - \log \hat{C}) + \chi_{\text{priors}}^2, \quad (18)$$

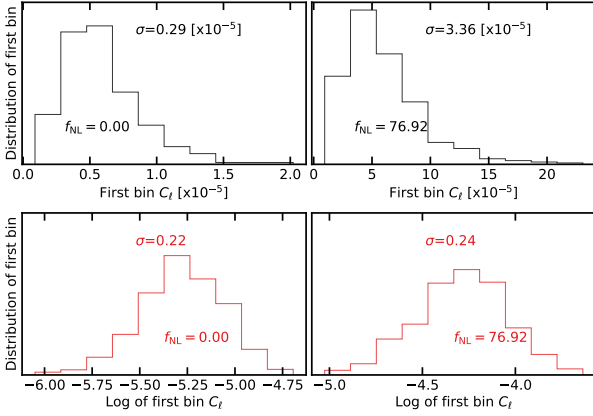
where  $\Theta$  represents the parameters,  $f_{\text{NL}}$ , bias at  $z = 0$ , and shotnoise, all of which are associated with a flat prior,  $\chi_{\text{priors}}^2$ ;  $C(\Theta)$  is the (binned) theoretical power spectrum including the effects for survey geometry and integral constraint;  $\hat{C}$  is the (binned) measured power spectrum; and  $\mathbb{C}$  is the covariance matrix constructed from simulations.

### 3.4 Characterization of residual systematic error

We use the diagnostic tests first applied to SDSS data in Rezaie et al. (2021) based on cross power spectrum between galaxy density field

<sup>3</sup>  $dN/dr = (dN/dz) * (dz/dr) \propto (dN/dz) * H(z)$

<sup>4</sup> [github.com/xfangcosmo/FFTLog-and-beyond](https://github.com/xfangcosmo/FFTLog-and-beyond)



**Figure 5.** Distribution of the first bin power spectrum constructed from  $f_{\text{NL}} = 0$  (left) and 76.92 (right) mocks. Differences in the standard deviations become less significant, and power spectrum measurements follow a more symmetric distribution after the log transformation.

and imaging maps and mean density contrast as a function of imaging properties to quantify the significance of imaging systematic effects.

### 3.4.1 Cross Spectrum

Taking  $C_\ell^{g,x}$  as the cross power spectrum between galaxy density contrast field and imaging map, one can normalize this quantity by auto power spectrum of imaging map itself:

$$\hat{C}_{x,\ell} = \frac{(\hat{C}_\ell^{g,x})^2}{\hat{C}_\ell^{x,x}}, \quad (19)$$

and then construct a vector from cross spectra against all other imaging maps:

$$\hat{C}_{X,\ell} = [\hat{C}_{x_1,\ell}, \hat{C}_{x_2,\ell}, \hat{C}_{x_3,\ell}, \dots, \hat{C}_{x_9,\ell}]. \quad (20)$$

Finally, cross power spectrum  $\chi^2$  can be defined as,

$$\chi^2 = C_{X,\ell}^T \mathbb{C}_X^{-1} C_{X,\ell}, \quad (21)$$

where covariance matrix  $\mathbb{C}_X = \langle C_{X,\ell} C_{X,\ell'} \rangle$  is constructed from mocks without systematic effects. This statistics is measured for every mock realization with the leave-one-out technique to construct a histogram, which is then compared to the  $\chi^2$  value observed from the DR9. Fig. 6 (top) shows the measured  $C_X$  the DR9 sample before and after applying various imaging weights, relative to that of the mocks with  $f_{\text{NL}} = 0$ . The dispersions of mocks with and without PNG are shown with the shade regions for comparison. We bin the  $C_X$  measurements from  $\ell = 2$  to 20 with  $\Delta\ell = 2$ . The mean and standard deviation of  $\hat{C}_{X,\ell}$  for 1000 mocks with and without  $f_{\text{NL}}$  are shown in Fig. 6. Extinction and stellar density have the highest cross power spectrum, and then depth in the z band. After applying the first version of weights with linear conservative I which includes extinction and depth-z, the cross power increases against psfsize in the r band. This indicates that only two maps are not sufficient to null out all of the cross correlations. With linear model there is residual power against extinction, depth-z, and psfsize-z; therefore, we apply weights based on a nonlinear model to account for more complex systematic effects.

Fig. 8 (top) shows the histogram of cross spectrum  $\chi^2$  from mocks with and without  $f_{\text{NL}}$ . Comparing with the data, the residual is 20014.8 before correction, and after applying the first set of

weights, it reduces to 375.1 with p-value XXX. Adding psfsize-z, the linear model reduces the error down to 195.9 (p-value = XXX). Although using all maps gives the lowest error i.e., 129.2, but it could potentially lead to over-fitting true clustering given how correlated the imaging maps are (see, Fig. 3). On the other hand, the nonlinear method with three maps yields a  $\chi^2$  value of 79.3 and p-value of XXX, and adding the stellar density map reduces the error to 70.9 (p-value=XXX). This test clearly shows that a nonlinear approach is desired to get a null test. We further test the stability of our results by extending the highest mode from  $\ell = 20$  to 100, or fluctuations over scales as small as 1.8 degrees (see, Fig. 9). The solid line shows how the median of 1000 mocks changes as the highest  $\ell$  increases from 20 to 100. The red circles show the  $\chi^2$  for the linear approach with three maps and the blue crosses show the  $\chi^2$  for the nonlinear approach with three maps.

### 3.4.2 Mean Density

In the absence of systematic error, the integral of mean density contrast over the footprint should be zero. As an alternative test, we calculate the histogram of the density contrast field relative to each imaging map.

$$\delta_x = (\hat{\rho})^{-1} \frac{\sum_i \rho_i f_{\text{pix},i}}{\sum_i f_{\text{pix},i}}, \quad (22)$$

where the summations are over pixels in each bin of imaging map  $x$ . Similarly, we construct the mean density contrast vector against all imaging maps,

$$\delta_X = [\delta_{x_1}, \delta_{x_2}, \delta_{x_3}, \dots, \delta_{x_9}], \quad (23)$$

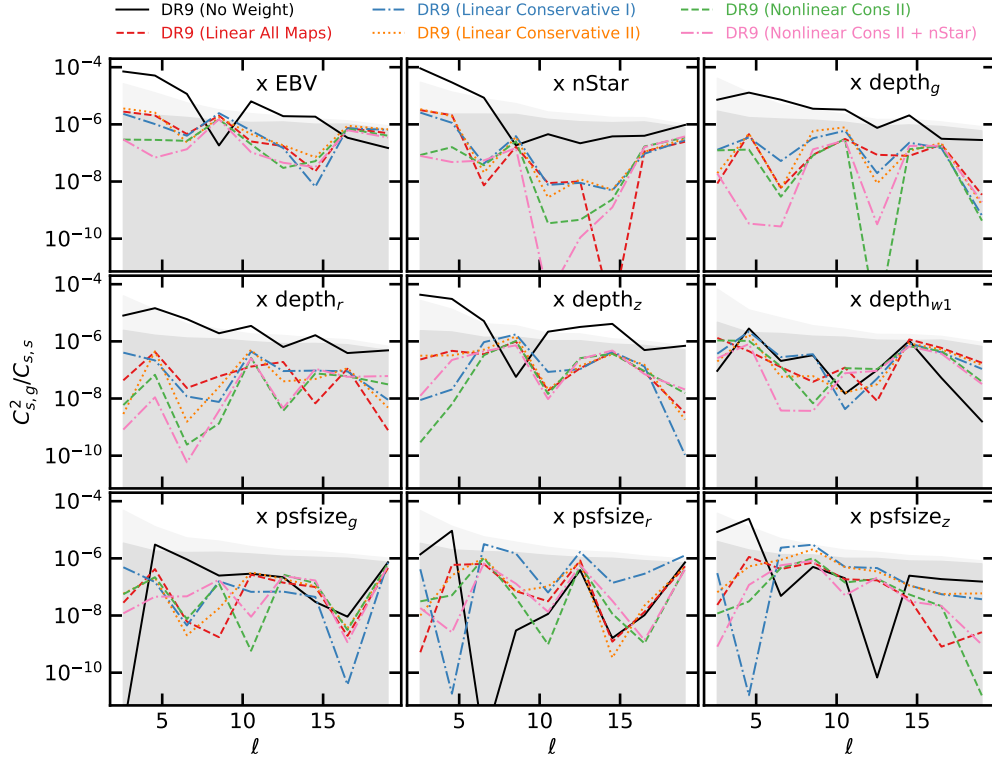
and the total residual error as,

$$\chi^2 = \delta_X^T \mathbb{C}_\delta^{-1} \delta_X, \quad (24)$$

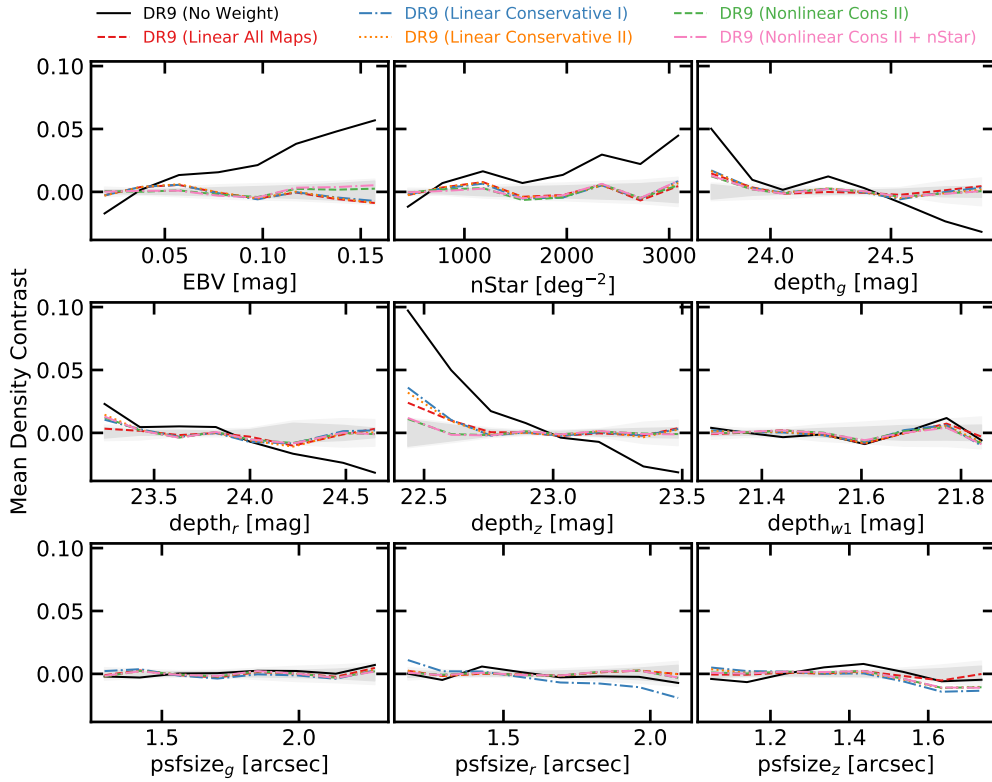
where the covariance matrix  $\mathbb{C}_\delta = \langle \delta_X \delta_X \rangle$  is constructed from mocks without systematic effects. Fig. 6 (bottom) shows the mean density contrast for the DR9 LRG sample. The shades represent the  $1\sigma$  level fluctuations observed in 1000 clean mocks with  $f_{\text{NL}} = 0$  and 76.92. Before treatment (solid) shows strong correlation around 10% against depth in the z band which is consistent with the cross power spectrum. Beside that, there are strong positive trends against extinction and stellar density at about 5 – 6%. The linear model is able to mitigate most of the systematic effects with only the extinction and depth-z maps as input, however a new trend appears against psfsize-r which is indicative of psfsize dependence in the sample. This finding is in agreement with the cross power spectrum. Even after applying the linear weights there is some residual against depth-z at around 2%, which indicates the systematic effects might be more complex than what can be removed using a linear model. Nonlinear model with three maps (or four maps including the stellar density) is capable of reducing the fluctuations below 2%.

Fig. 8 (bottom) shows the mean density  $\chi^2$  observed in the mocks vs DR9 sample before and after applying imaging weights. Linear weights with two maps reduce the chi-2 value from 679.8 (before) to 178.8. The p-value is indicative of remaining systematic effects. Adding psfsize-r does not help much with the p-value even though it reduces the chi-2 to 130. Using all maps with the linear model gives a more reasonable value however it leaves the analysis susceptible to over-fitting true clustering signal. With nonlinear approach two maps as input, the chi-2 is reasonable 74.3 with p-value XXX, and adding the stellar map does not change the p-value much, indicating the trend against stellar density can be explained with the extinction to a great extent.

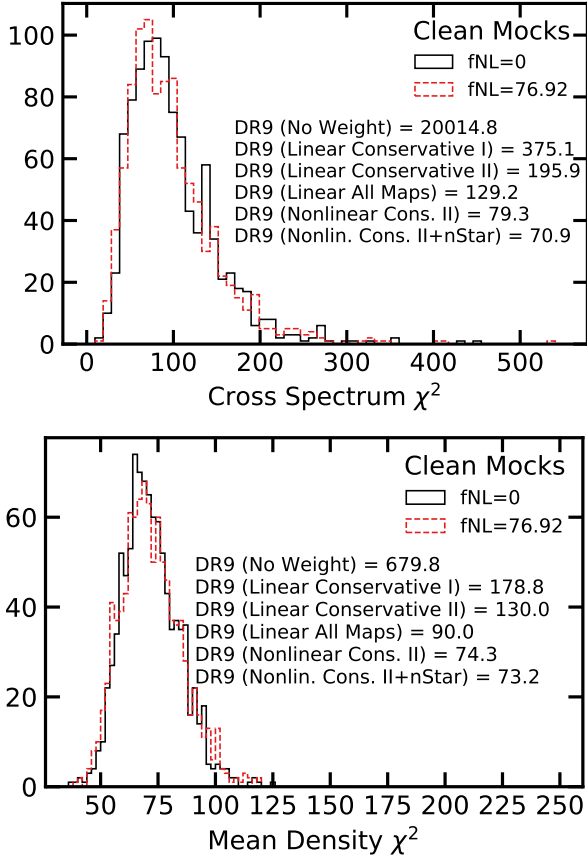




**Figure 6.** Cross power spectrum between the DR9 LRGs and imaging maps. Dark and light shades represent the 97.5 percentile of 1000 lognormal mocks without and with PNG, respectively.



**Figure 7.** Mean density contrast of the DR9 LRGs as a function of imaging maps. Dark and light shades represent the  $1\sigma$  dispersion of 1000 lognormal mocks without and with PNG, respectively.



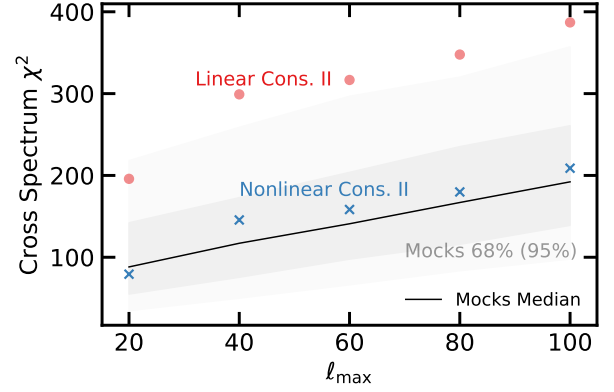
**Figure 8.** Top: Cross power spectrum  $\chi^2$  diagnostic. Bottom: Mean density contrast diagnostic. The values observed in DR9 before and after linear and nonlinear treatments are quoted and the histograms are constructed from 1000 realizations of clean mocks with  $f_{\text{NL}} = 0$  and 76.92.

## 4 RESULTS

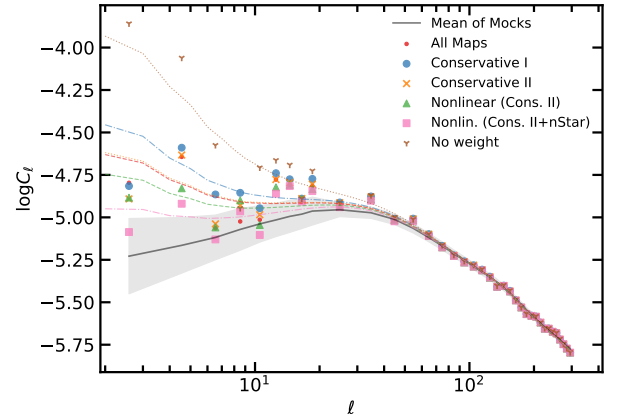
This section presents the constraint on  $f_{\text{NL}}$  from the DR9 LRG sample. The robustness of constraints are tested against various assumptions and details in survey mask, imaging weights, and calibration of data. The default analysis uses the covariance from  $f_{\text{NL}} = 0$  mocks. We also validate the modeling pipeline and characterize the amount of mitigation bias introduced in  $f_{\text{NL}}$  after cleaning for systematics.

### 4.1 DR9 LRGs

Fig. 10 shows the measured power spectrum of the DESI imaging DR9 LRG sample with different imaging weights applied, the best fit theory predictions, and the mean and  $1\sigma$  error on angular power spectrum measured from the  $f_{\text{NL}} = 0$  lognormal simulations. Power spectra are similar with differences less than 1% for small scales ( $\ell > 2$ ), and as we go to larger scales, the differences become more significant. There is a little difference between linear cons II and linear all maps. This proves that our feature selection procedure has worked to identify the important maps. Comparing linear cons I to linear cons II, modes with  $6 \leq \ell < 10$  are different, indicating scales where  $\text{psfsize-r}$  is affecting the signal. Comparing nonlinear cons II to linear cons II, modes at the second bin ( $4 \leq \ell < 6$ ) are very different, indicating the nonlinear approach is more flexible to reduce fluctuations on small scales as well large scales.



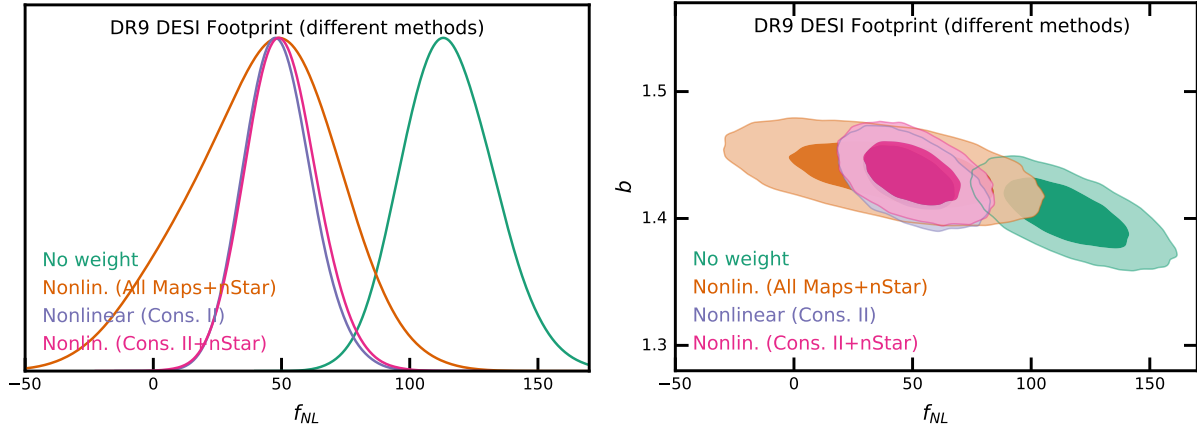
**Figure 9.** Cross Spectrum  $\chi^2$  for DR9 LRG density and imaging maps with linear and nonlinear cleaning (both with conservative II maps) as a function of the highest mode  $\ell_{\text{max}}$  while the lowest mode is fixed at  $\ell_{\text{min}} = 2$ . Solid curve and shade represent the median estimate and 68% confidence constructed from  $f_{\text{NL}} = 0$  mocks.



**Figure 10.** Measured power spectrum of the DR9 LRG sample before and after correcting for systematics with their corresponding best fit theory predictions. The shade represents  $1\sigma$  error constructed from the  $f_{\text{NL}} = 0$  mocks.

#### 4.1.1 Calibrated constraints

Tab. 2 summarizes the best fit and marginalized mean estimates of  $f_{\text{NL}}$  from fitting power spectrum of the DR9 LRG sample using the nonlinear approach with various combinations of imaging templates. All constraints are accounted for the mitigation bias using the lognormal mocks, which is further discussed in §4.2.2. With the corrections applied, we obtain  $36.07(25.03) < f_{\text{NL}} < 61.44(75.64)$  for nonlinear (conservative II),  $36.88(24.87) < f_{\text{NL}} < 63.31(77.78)$  for nonlinear (conservative II + nStar), and  $13.09(-15.95) < f_{\text{NL}} < 69.14(91.84)$  for nonlinear (all maps + nStar) at 68%(95%) confidence. Fig. 11 shows the 2D constraints with 68% and 95% confidence on  $f_{\text{NL}}$  and  $b$  for the DESI footprint from the DR9 sample before (no weight) and after applying different cleaning schemes. No weight constraint at 68% is  $98.14 < f_{\text{NL}} < 132.89$  with a best fit of 113.18 and marginalized mean of 115.49, and is more than  $2\sigma$  off from zero. Applying imaging weights shifts constraints to lower  $f_{\text{NL}}$  values, and  $b$  is slightly pulled upward since excess clustering due to systematics is removed. Using all maps with the linear model does not change the results, showing that three maps are sufficient at the linear level



**Figure 11.** Calibrated 1D and 2D  $f_{\text{NL}}$  constraints from the DR9 LRG sample before and after applying nonlinear cleaning methods. The dark and light 2D contours represent 68% and 95% confidence intervals, respectively.

**Table 2.** Calibrated best fit and marginalized mean estimates for  $f_{\text{NL}}$  from fitting power spectrum of the DESI DR9 LRG sample before and after correcting for systematics. Degree of freedom is 34 (37 data points - 3 parameters).

Footprint	Method	$f_{\text{NL}}$				$\chi^2$
		Best fit	Mean	68% CL	95% CL	
DESI	No Weight	113.18	115.49	$98.14 < f_{\text{NL}} < 132.89$	$83.51 < f_{\text{NL}} < 151.59$	44.4
DESI	Nonlinear (Cons. II)	47.38	48.81	$36.08 < f_{\text{NL}} < 61.44$	$25.03 < f_{\text{NL}} < 75.64$	34.6
DESI	Nonlin. (Cons. II+nStar)	48.92	50.10	$36.88 < f_{\text{NL}} < 63.31$	$24.87 < f_{\text{NL}} < 77.78$	35.2
DESI	Nonlin. (All Maps+nStar)	49.69	41.91	$13.10 < f_{\text{NL}} < 69.14$	$-15.96 < f_{\text{NL}} < 91.84$	39.5

to mitigate systematics. As an alternative, using a nonlinear model with three maps shows around  $1\sigma$  shift, with 68% confidence at  $18.91 < f_{\text{NL}} < 40.59$ , inconsistent with zero for more than  $2\sigma$ . Adding a template for the local stellar density shift constraints by  $1\sigma$ , making it consistent with zero. As the most rigorous approach, using all maps and stellar density included results in more than  $2\sigma$  shift. We emphasize that these shifts to lower  $f_{\text{NL}}$  are somewhat expected as more input maps results in regressing more modes from cosmological clustering signal. Therefore, we use lognormal mocks to calibrate the amount of signal that is removed in each case and attempt to undo the effect.

#### 4.1.2 Uncalibrated constraints: robustness tests

$f_{\text{NL}}$  constraints from DR9 LRG sample is summarized in Table 3. First, we focus on the DESI footprint and then compare constraints obtained from each sub-survey. We also evaluate the robustness of constraints against various cuts and configurations. First, we compare how constraints from whole DESI footprint compares to those from each survey individually, namely BASS+MzLS, DECaLS North, and DECaLS South. Fig. 12 shows 68% and 95% confidence on  $f_{\text{NL}}$  and  $b$  from each individual survey or all combined as DESI. Constraints from all surveys are consistent and agree with each other within 68%. Both BASS+MzLS and DECaLS South are consistent with zero PNG, but DECaLS North deviates from zero at more than  $2\sigma$ . Adding the stellar density template does not change constraints from BASS+MzLS much, but it shifts DECaLS North and DECaLS South by  $0.5\sigma$  and  $\sigma$ , respectively. This might indicate that there are some unresolved issues with stellar contamination in DECaLS North and DECaLS South. We note that differences are more significant when all maps and stellar density are used as input.

This is expected as more maps mean the model has more freedom to take out clustering modes.

- **Pixel completeness** We remove pixels with low completeness from the DESI footprint by applying  $f_{\text{pix}} > 0.5$ , and find that the impact is negligible. Specifically, the cut removes .6% survey area and causes best fit  $f_{\text{NL}}$  shifts only around 2%, from 28.58 to 28.07, see *comp cut* Table 3. When investigated this impact on each region separately, BASS+MzLS increases around 10%, DECaLS North decreases 1%, and DECaLS South decreases around 5%.
- **Imaging quality** We remove pixels with poor imaging from the DESI footprint by applying the following cuts on imaging properties;  $E[B - V] < 0.1$ ,  $n\text{Star} < 3000$ ,  $\text{depth}_g > 23.2$ ,  $\text{depth}_r > 22.6$ ,  $\text{depth}_z > 22.5$ ,  $\text{psfsize}_g < 2.5$ ,  $\text{psfsize}_r < 2.5$ , and  $\text{psfsize}_z < 2$ . Overall the constraints are consistent despite best fit and marginalized mean estimates shift. Quantitatively, we lose about 8.2% survey area, and the best fit  $f_{\text{NL}}$  estimate changes about 2% from 28.58 to 29.16. See *imag cut* in Table 3. For BASS+MzLS only, the imaging cut increases the best fit by 62% from 15.43 to 25.03. For DECaLS North and DECaLS South, the best fit increases by 5% and 15% respectively.
- **Covariance** We now use the mocks with  $f_{\text{NL}} = 76.92$  to construct a covariance matrix, and with the new covariance we observe a 12% increase in the  $f_{\text{NL}}$  constraint uncertainties and 11% increase in the best fit estimate of  $f_{\text{NL}}$ .
- **Lowest  $\ell$**  We decrease the largest mode (or increase the lowest  $\ell$ ) used in estimating the best fit and 68% confidence intervals. Fig. 13 illustrates the results for the DESI footprint and how they compared to BASS+MzLS, DECaLS North, or DECaLS South only results. Points represent marginalized mean estimates of  $f_{\text{NL}}$  and errorbars represent 68% confidence from MCMC results. Overall we find that the constraints are robust against the largest mode.
- **External maps** We also derive imaging weights using additional

**Table 3.** Uncalibrated best fit and marginalized mean estimates for  $f_{\text{NL}}$  from fitting power spectrum of DR9 LRGs before and after correcting for systematics. Degree of freedom is 34 (37 data points - 3 parameters).

Footprint	Method	$f_{\text{NL}}$				$\chi^2$
		Best fit	Mean	68% CL	95% CL	
DESI	No Weight	113.18	115.49	$98.14 < f_{\text{NL}} < 132.89$	$83.51 < f_{\text{NL}} < 151.59$	44.4
DESI	Linear (All Maps)	36.05	37.72	$26.13 < f_{\text{NL}} < 49.21$	$16.31 < f_{\text{NL}} < 62.31$	41.1
DESI	Linear (Conservative I)	49.58	51.30	$38.21 < f_{\text{NL}} < 64.33$	$27.41 < f_{\text{NL}} < 78.91$	38.8
DESI	Linear (Conservative II)	36.63	38.11	$26.32 < f_{\text{NL}} < 49.86$	$16.36 < f_{\text{NL}} < 63.12$	39.6
DESI	Nonlinear (Cons. II)	28.58	29.79	$18.91 < f_{\text{NL}} < 40.59$	$9.47 < f_{\text{NL}} < 52.73$	34.6
DESI	Nonlin. (Cons. II+nStar)	16.63	17.52	$7.51 < f_{\text{NL}} < 27.53$	$-1.59 < f_{\text{NL}} < 38.49$	35.2
DESI	Nonlin. (All Maps+nStar)	-5.87	-9.19	$-21.45 < f_{\text{NL}} < 2.40$	$-33.81 < f_{\text{NL}} < 12.06$	39.5
DESI (imag. cut)	Nonlin. (Cons. II)	29.16	30.57	$19.05 < f_{\text{NL}} < 42.18$	$9.01 < f_{\text{NL}} < 54.81$	35.8
DESI (comp. cut)	Nonlin. (Cons. II)	28.07	29.48	$18.38 < f_{\text{NL}} < 40.50$	$8.81 < f_{\text{NL}} < 53.10$	34.5
DESI	Nonlin. (Cons. II)+ $f_{\text{NL}} = 76.92$ Cov	31.62	33.11	$20.94 < f_{\text{NL}} < 45.24$	$10.56 < f_{\text{NL}} < 59.16$	33.5
BASS+MzLS	Nonlin. (Cons. II)	15.43	19.01	$-1.17 < f_{\text{NL}} < 39.43$	$-19.19 < f_{\text{NL}} < 63.56$	35.6
BASS+MzLS	Nonlin. (Cons. II+nStar)	13.12	15.39	$-4.59 < f_{\text{NL}} < 35.56$	$-24.88 < f_{\text{NL}} < 59.31$	34.7
BASS+MzLS	Nonlin. (All Maps+nStar)	-3.73	-6.34	$-27.11 < f_{\text{NL}} < 13.75$	$-47.44 < f_{\text{NL}} < 33.94$	36.8
BASS+MzLS (imag. cut)	Nonlin. (Cons. II)	25.03	29.12	$6.16 < f_{\text{NL}} < 52.44$	$-14.22 < f_{\text{NL}} < 80.54$	36.2
BASS+MzLS (comp. cut)	Nonlin. (Cons. II)	16.99	20.90	$0.26 < f_{\text{NL}} < 41.76$	$-18.30 < f_{\text{NL}} < 67.12$	35.8
DECaLS North	Nonlin. (Cons. II)	41.02	44.89	$23.33 < f_{\text{NL}} < 66.78$	$4.96 < f_{\text{NL}} < 93.02$	41.1
DECaLS North	Nonlin. (Cons. II+CALIBZ+HI)	55.46	60.44	$36.78 < f_{\text{NL}} < 84.05$	$17.86 < f_{\text{NL}} < 112.81$	38.4
DECaLS North	Nonlin. (Cons. II+nStar)	31.45	34.78	$14.14 < f_{\text{NL}} < 55.79$	$-5.81 < f_{\text{NL}} < 80.80$	41.2
DECaLS North	Nonlin. (All Maps+nStar)	0.81	-5.68	$-29.73 < f_{\text{NL}} < 16.71$	$-53.15 < f_{\text{NL}} < 36.19$	45.1
DECaLS North + islands	Nonlin. (Cons. II)	41.05	44.82	$23.58 < f_{\text{NL}} < 66.08$	$6.40 < f_{\text{NL}} < 91.42$	40.7
DECaLS North (imag. cut)	Nonlin. (Cons. II)	43.27	48.39	$24.60 < f_{\text{NL}} < 72.50$	$4.71 < f_{\text{NL}} < 101.42$	35.1
DECaLS North (comp. cut)	Nonlin. (Cons. II)	40.55	44.63	$22.41 < f_{\text{NL}} < 67.11$	$3.95 < f_{\text{NL}} < 94.06$	41.4
DECaLS South	Nonlin. (Cons. II)	31.24	33.21	$14.89 < f_{\text{NL}} < 52.40$	$-5.11 < f_{\text{NL}} < 74.35$	30.2
DECaLS South	Nonlin. (Cons. II+CALIBZ+HI)	33.79	37.50	$17.71 < f_{\text{NL}} < 57.42$	$-0.31 < f_{\text{NL}} < 80.94$	30.8
DECaLS South	Nonlin. (Cons. II+nStar)	14.34	6.28	$-21.19 < f_{\text{NL}} < 30.01$	$-53.63 < f_{\text{NL}} < 49.51$	31.9
DECaLS South	Nonlin. (All Maps+nStar)	-36.76	-32.01	$-49.38 < f_{\text{NL}} < -13.61$	$-65.26 < f_{\text{NL}} < 7.52$	31.5
DECaLS South + DEC < -30	Nonlin. (Cons. II)	43.79	46.79	$30.16 < f_{\text{NL}} < 63.41$	$16.38 < f_{\text{NL}} < 82.72$	23.8
DECaLS South (imag. cut)	Nonlin. (Cons. II)	26.47	23.36	$3.18 < f_{\text{NL}} < 47.84$	$-57.69 < f_{\text{NL}} < 71.39$	30.0
DECaLS South (comp. cut)	Nonlin. (Cons. II)	29.62	31.76	$13.00 < f_{\text{NL}} < 51.58$	$-9.78 < f_{\text{NL}} < 74.28$	29.7

external maps for the neutral hydrogen column density (HI) and magnitude calibration errors in the z band (CALIBZ). With the new weights, we find the best fit estimates increase from 41.02 to 55.46 for DECaLS North and from 31.24 to 33.79 for DECaLS South.

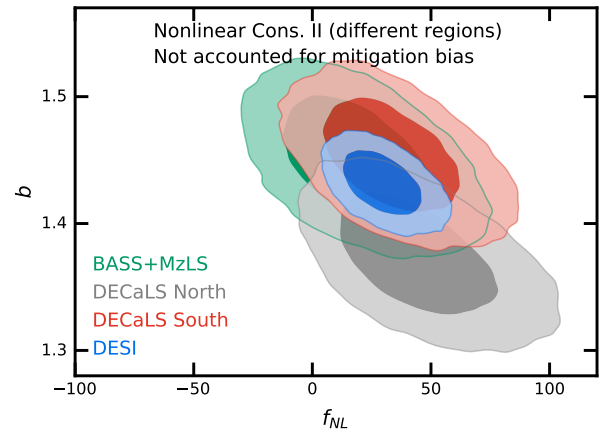
- **Declination cut** Our default analysis do not use the spurious islands in DECaLS North and DECaLS South below DEC = -30 to avoid potential calibration issues. **PANASTARS are used for calibration below DEC of -30.** Without these cuts, best fit  $f_{\text{NL}}$  estimates increase from 31.24 to 43.79 for DECaLS South and decrease from 41.02 to 41.05. This indicates that indeed there is an issue with DECaLS South below DEC of -30.

Overall we find that the declination cut is necessary for DECaLS South, while adding external templates for HI and CALIBZ, using a different covariance, or applying imaging and completeness cuts do not alter the constraints significantly.

## 4.2 Lognormal Mocks

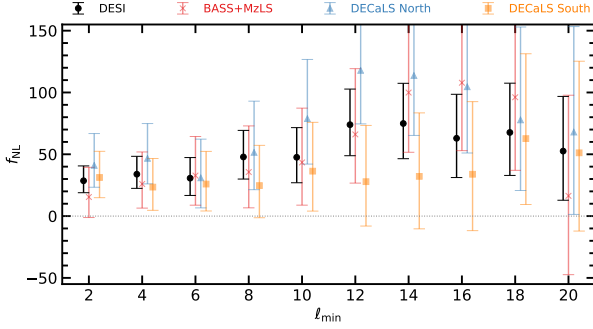
### 4.2.1 Clean mocks

Corner plots of the PNG parameter  $f_{\text{NL}}$  and bias coefficient are shown in Fig. ?? for fitting the mean power spectrum of mocks, with and without  $f_{\text{NL}}$ . Best fit estimates, marginalized mean,  $1\sigma$  and  $2\sigma$  confidence intervals are summarized in Tab. 4. Fig ?? (right) shows confidence contours for different combinations of target variable (e.g., either power spectrum or its log transform) and covariance matrix. First we attempt to understand the impact of covariance on confidence intervals. We fit the mean power spectrum of  $f_{\text{NL}} =$

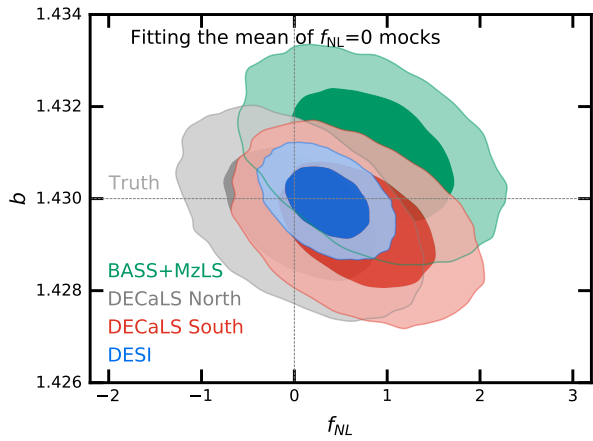
**Figure 12.** Uncalibrated 2D constraints from the DR9 LRG sample for each imaging survey compared with that for the whole DESI footprint. The dark and light shades represent the 68% and 95% confidence intervals, respectively.

76.9 mocks or its log transformation using covariance matrices constructed from the same set of mocks or from the  $f_{\text{NL}} = 0$  mocks. When covariance is consistent with mean, the difference between fitting power spectrum and log of it is only 2%. If a wrong covariance is used for the log power, the effect is only 7%. However, when mean power spectrum of the  $f_{\text{NL}} = 76.9$  mocks is fit using the covariance matrix estimated from the  $f_{\text{NL}} = 0$  mocks, the constraints improve





**Figure 13.** Robustness of the uncalibrated DR9 constraints w.r.t. the largest scale (lowest  $\ell$  mode) used in MCMC regression. Points represent marginalized mean estimates of  $f_{\text{NL}}$  and errorbars represent 68% confidence.



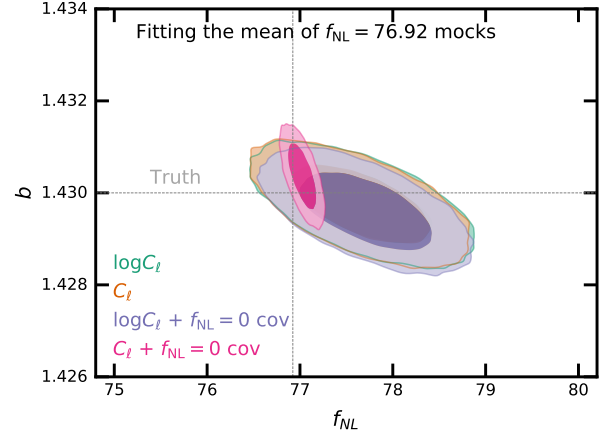
**Figure 14.** 68% and 95% confidence contours from the mean power spectrum of the  $f_{\text{NL}} = 0$  mocks for the DESI footprint and sub-imaging surveys. The truth values are represented by vertical and horizontal lines.

by a factor of 5, simply due to a false higher signal to noise ratio. Therefore, we argue that fitting logarithm of power spectrum would remove the need for having  $f_{\text{NL}}$ -dependent covariance matrices and make the constraints less sensitive to covariance construction. Fig. ?? (left) shows the confidence contours for  $f_{\text{NL}} = 0$  mocks when fit is done to the log of mean spectra of  $f_{\text{NL}} = 0$  mocks for the different regions. We find that the underlying true  $f_{\text{NL}}$  value is recovered within  $2\sigma$  confidence. **Add a paragraph for the constraining power vs fsky.**

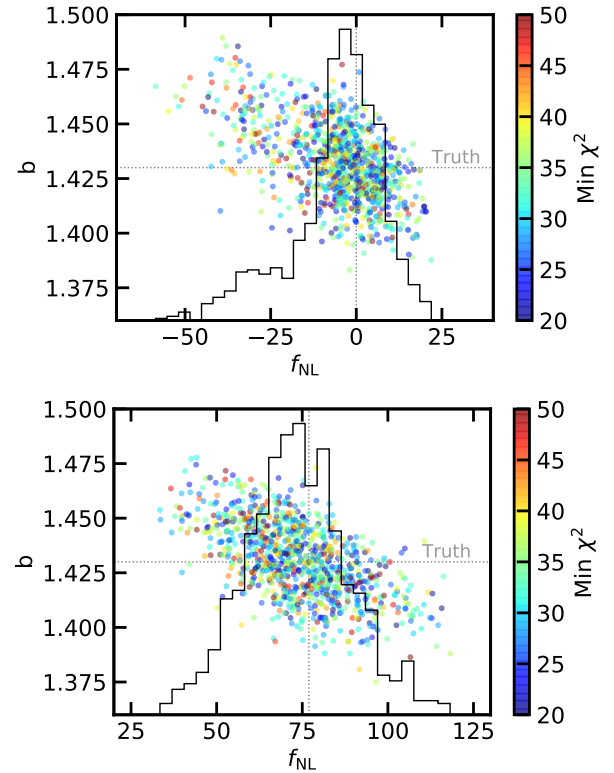
Fig 16 shows the best fit estimates for  $b$  vs  $f_{\text{NL}}$  for  $f_{\text{NL}} = 0$  and  $= 76.92$  mocks in the left and right, respectively. Truth values are represented via the dotted lines. The points are color-coded with the minimum  $\chi^2$  from fit for each realization. The histograms of best fit  $f_{\text{NL}}$  estimates are plotted in the background. We obtain  $f_{\text{NL}} = \text{MU} \pm \text{STD}$  and  $= \text{MU} \pm \text{STD}$  for the left and right panels, respectively.

#### 4.2.2 Contaminated mocks

With template based mitigation, the measured power spectrum is biased and the amount of bias depends on the number of input templates. We use a linear model with the set of conservative II maps to simulate imaging systematics in our lognormal density fields. Then, we apply the cleaning method based on nonlinear model with Conservative II, Conservative II + nStar, or All Maps



**Figure 15.** 68% and 95% confidence contours from the mean power spectrum of the  $f_{\text{NL}} = 76.92$  mocks for the DESI footprint. Using the  $\log C_\ell$  fitting yield constraints that are insensitive to the covariance used. The truth values are represented by vertical and horizontal lines.



**Figure 16.** Top: 68% and 95% confidence contours for  $f_{\text{NL}} = 0$  (left) and  $76.92$  (right) mocks. Using the  $\log C_\ell$  fitting yield constraints that are insensitive to the covariance used. Bottom: best fit estimates from fitting 1000 lognormal mocks with  $f_{\text{NL}} = 0$  (left) and  $76.92$  (right) in the DESI footprint. The truth values are represented by vertical and horizontal lines.

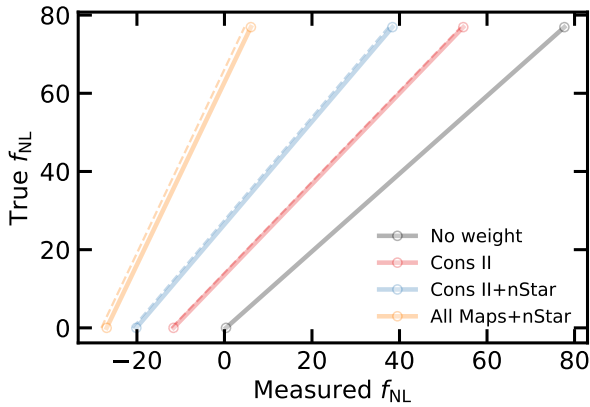
+ nStar sets of imaging maps to both set of mocks; with or without systematic effects (dashed or solid), and with and without  $f_{\text{NL}}$ . The marginalized mean, confidence intervals, and best fit estimates are presented in Tab 5. This test indicates that as more maps are input to the nonlinear model, more power is removed, and thus the constraints are systematically shifted to lower  $f_{\text{NL}}$  values. Fig 17 shows the true  $f_{\text{NL}}$  value and the measured  $f_{\text{NL}}$  value from fitting

**Table 4.** Best fit and marginalized mean estimates for  $f_{\text{NL}}$  from fitting the mean power spectrum of the mocks. Degree of freedom is 34 (37 data points - 3 parameters).

Mock / $f_{\text{NL}}$	Footprint	Observable	$f_{\text{NL}}$				$\chi^2$
			Best fit	Mean	68% CL	95% CL	
Clean 76.92	DESI	$\log C_\ell$	77.67	77.67	$77.17 < f_{\text{NL}} < 78.16$	$76.71 < f_{\text{NL}} < 78.64$	38.8
Clean 76.92	DESI	$C_\ell$	77.67	77.65	$77.17 < f_{\text{NL}} < 78.14$	$76.70 < f_{\text{NL}} < 78.60$	39.0
Clean 76.92	DESI	$\log C_\ell + f_{\text{NL}} = 0$ cov	77.70	77.71	$77.25 < f_{\text{NL}} < 78.17$	$76.81 < f_{\text{NL}} < 78.63$	39.9
Clean 76.92	DESI	$C_\ell + f_{\text{NL}} = 0$ cov	77.03	77.02	$76.93 < f_{\text{NL}} < 77.12$	$76.83 < f_{\text{NL}} < 77.22$	207.6
Clean 0	DESI	$\log C_\ell$	0.36	0.36	$0.06 < f_{\text{NL}} < 0.65$	$-0.23 < f_{\text{NL}} < 0.94$	35.7
Clean 0	DECaLS North	$\log C_\ell$	0.07	0.06	$-0.47 < f_{\text{NL}} < 0.60$	$-1.00 < f_{\text{NL}} < 1.12$	26.7
Clean 0	DECaLS South	$\log C_\ell$	0.67	0.67	$0.13 < f_{\text{NL}} < 1.22$	$-0.40 < f_{\text{NL}} < 1.75$	34.3
Clean 0	BASS+MzLS	$\log C_\ell$	0.83	0.82	$0.25 < f_{\text{NL}} < 1.40$	$-0.31 < f_{\text{NL}} < 1.96$	39.4

**Table 5.** Best fit and marginalized estimates for  $f_{\text{NL}}$  from fitting the mean power spectrum of the mocks before and after applying imaging weights.

Mock / $f_{\text{NL}}$	Method	$f_{\text{NL}}$				$\chi^2$
		Best fit	Mean	68% CL	95% CL	
Clean 0	No Weight	0.36	0.36	$0.06 < f_{\text{NL}} < 0.65$	$-0.23 < f_{\text{NL}} < 0.94$	35.7
Clean 0	ConsII	-11.64	-11.65	$-12.00 < f_{\text{NL}} < -11.30$	$-12.34 < f_{\text{NL}} < -10.97$	86.8
Clean 0	ConsII+nStar	-20.14	-20.13	$-20.44 < f_{\text{NL}} < -19.82$	$-20.74 < f_{\text{NL}} < -19.52$	472.8
Clean 0	All Maps+nStar	-26.91	-26.92	$-27.16 < f_{\text{NL}} < -26.68$	$-27.39 < f_{\text{NL}} < -26.46$	5481.0
Contaminated 0	ConsII	-12.12	-12.13	$-12.48 < f_{\text{NL}} < -11.78$	$-12.83 < f_{\text{NL}} < -11.44$	94.0
Contaminated 0	ConsII+nStar	-20.97	-20.98	$-21.28 < f_{\text{NL}} < -20.67$	$-21.58 < f_{\text{NL}} < -20.37$	556.3
Contaminated 0	All Maps+nStar	-28.13	-28.13	$-28.36 < f_{\text{NL}} < -27.90$	$-28.59 < f_{\text{NL}} < -27.67$	6760.5
Clean 76.92	No Weight	77.67	77.67	$77.17 < f_{\text{NL}} < 78.16$	$76.71 < f_{\text{NL}} < 78.64$	38.8
Clean 76.92	ConsII	54.57	54.57	$54.14 < f_{\text{NL}} < 55.01$	$53.72 < f_{\text{NL}} < 55.45$	603.5
Clean 76.92	ConsII+nStar	38.38	38.38	$37.99 < f_{\text{NL}} < 38.78$	$37.60 < f_{\text{NL}} < 39.16$	537.0
Clean 76.92	All Maps+nStar	6.04	6.04	$5.72 < f_{\text{NL}} < 6.36$	$5.41 < f_{\text{NL}} < 6.67$	694.0
Contaminated 76.92	ConsII	54.01	54.00	$53.57 < f_{\text{NL}} < 54.44$	$53.15 < f_{\text{NL}} < 54.86$	588.0
Contaminated 76.92	ConsII+nStar	37.48	37.49	$37.09 < f_{\text{NL}} < 37.88$	$36.70 < f_{\text{NL}} < 38.27$	510.7
Contaminated 76.92	All Maps+nStar	4.59	4.58	$4.26 < f_{\text{NL}} < 4.90$	$3.95 < f_{\text{NL}} < 5.22$	649.7

**Figure 17.** True  $f_{\text{NL}}$  vs measured  $f_{\text{NL}}$  from mocks with (dashed) and without systematics (solid).

the mean of mocks. The results for the contaminated mocks before cleaning (No weight) is not shown for clarity. From this graph, then a pair of linear coefficients are to be found for mapping measured  $f_{\text{NL}}$  to true  $f_{\text{NL}}$  values. At the first iteration, we think these coefficients should be applied to the values presented in Tab 3.

## 5 CONCLUSIONS

We have presented constraints on  $f_{\text{NL}}$  using the scale-dependent bias effect in the large-scale clustering of DESI imaging DR9 LRGs.

Methods from linear and nonlinear regressions are applied for data cleaning from foreground and imaging systematic effects. Same tools are tested on lognormal density fields to evaluate the sensitivity of signal to systematic error. As summarized in Table ??, we find that fitting  $\log C_\ell$  rather than  $C_\ell$  minimizes the dependence of constraints to the choice of covariance, and we are able to recover the truth  $f_{\text{NL}}$  at 95% confidence in both simulations with and without PNG. Table ??? summarizes the constraints from mocks undergone cleaning for systematics. We find that template-based regression removes clustering and thus biased constraints are obtained. We use the mock constraints to calibrate DR9 constraints. We obtain  $36.07(25.03) < f_{\text{NL}} < 61.44(75.64)$  when cleaning is performed with the nonlinear model using only three imaging maps. With more extreme cleaning using all maps and stellar density, we obtain  $13.09(-15.95) < f_{\text{NL}} < 69.14(91.84)$  at 68%(95%).

Various tests are performed to assess the robustness of constraints against analysis assumptions, and the results are summarized in Table ??. We find

- constraints from individual surveys are consistent with each other
- no significant shift observed in constraints after applying imaging cut, completeness cut
- no significant shift after including additional imaging templates for hydrogen column density or calibration in the z-band.
- region below dec of -30 indicates some issues probably due to unaccounted for calibration issues
- constraints are robust against the largest scales (lowest  $\ell$  mode) used in fitting for  $f_{\text{NL}}$ . **Some signs of systematics on  $10 < \ell < 18$ .**

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## DATA AVAILABILITY

DESI imaging DR9 catalogs are publicly available at <https://www.legacysurvey.org/dr9/>. Software for cleaning imaging data is available at <https://github.com/mehdirezaie/sysnetdev>. Mock catalogs can be made available upon reasonable request.

## REFERENCES

- Abbott T., et al., 2016, Monthly Notices of the Royal Astronomical Society, 460, 1270
- Ade P., et al., 2019, Journal of Cosmology and Astroparticle Physics, 2019, 056
- Aghamousa A., et al., 2016, arXiv preprint arXiv:1611.00036
- Aghanim N., et al., 2020, Astronomy & Astrophysics, 641, A6
- Akrami Y., et al., 2019, arXiv preprint arXiv:1905.05697
- Alam S., et al., 2021, Physical Review D, 103, 083533
- Alvarez M., et al., 2014, arXiv e-prints, [p. arXiv:1412.4671](#)
- Baldauf T., Seljak U., Senatore L., 2011a, Journal of Cosmology and Astroparticle Physics, 2011, 006
- Baldauf T., Seljak U., Senatore L., Zaldarriaga M., 2011b, Journal of Cosmology and Astroparticle Physics, 2011, 031
- Bassett B. A., Tsujikawa S., Wands D., 2006, Reviews of Modern Physics, 78, 537
- Beutler F., et al., 2014, Monthly Notices of the Royal Astronomical Society, 443, 1065
- Beutler F., Biagetti M., Green D., Slosar A., Wallisch B., 2019, Physical Review Research, 1, 033209
- Bouwens R. J., et al., 2015, [ApJ](#), 803, 34
- Castorina E., Moradinezhad Dizgah A., 2020, [J. Cosmology Astropart. Phys.](#), 2020, 007
- Center O. S., 1987, Ohio Supercomputer Center, <http://osc.edu/ark:/19495/f5s1ph73>
- Chaussidon E., et al., 2022, Monthly Notices of the Royal Astronomical Society, 509, 3904
- Chon G., Challinor A., Prunet S., Hivon E., Szapudi I., 2004, Monthly Notices of the Royal Astronomical Society, 350, 914
- Coles P., Jones B., 1991, [Monthly Notices of the Royal Astronomical Society](#), 248, 1
- Dalal N., Doré O., Huterer D., Shirokov A., 2008, Physical Review D, 77, 123514
- De Mattia A., Ruhlmann-Kleider V., 2019, Journal of Cosmology and Astroparticle Physics, 2019, 036
- Dey A., et al., 2018, arXiv preprint arXiv:1804.08657
- Eisenstein D. J., et al., 2001, The Astronomical Journal, 122, 2267
- Fang X., Krause E., Eifler T., MacCrann N., 2020, Journal of Cosmology and Astroparticle Physics, 2020, 010
- Fillmore J. A., Goldreich P., 1984, Astrophysical Journal, 281, 1
- Flaugher B., et al., 2015, The Astronomical Journal, 150, 150
- Gaia Collaboration et al., 2018, [A&A](#), 616, A1
- Giannantonio T., Ross A. J., Percival W. J., Crittenden R., Bacher D., Kilbinger M., Nichol R., Weller J., 2014, Physical Review D, 89, 023511
- Górski K. M., Hivon E., Banday A. J., Wandelt B. D., Hansen F. K., Reinecke M., Bartelmann M., 2005, The Astrophysical Journal, 622, 759
- Guth A. H., Kaiser D. I., 2005, Science, 307, 884
- Heinrich C., Doré O., 2022, in American Astronomical Society Meeting Abstracts. p. 202.03
- Hivon E., Górski K. M., Netterfield C. B., Crill B. P., Prunet S., Hansen F., 2002, The Astrophysical Journal, 567, 2
- Ho S., et al., 2015, [J. Cosmology Astropart. Phys.](#), 2015, 040
- Huterer D., Cunha C. E., Fang W., 2013, Monthly Notices of the Royal Astronomical Society, 432, 2945
- Kitanidis E., et al., 2020, Monthly Notices of the Royal Astronomical Society, 496, 2262
- Kofman L., Linde A., Starobinsky A. A., 1994, Physical Review Letters, 73, 3195
- Komatsu E., Spergel D. N., 2001, Physical Review D, 63, 063002
- Lyth D. H., Liddle A. R., 2009, The primordial density perturbation: Cosmology, inflation and the origin of structure. Cambridge University Press
- Merz G., et al., 2021, Monthly Notices of the Royal Astronomical Society, 506, 2503
- Mueller E.-M., et al., 2022, Monthly Notices of the Royal Astronomical Society
- Myers A. D., et al., 2022, arXiv e-prints, [p. arXiv:2208.08518](#)
- Padmanabhan N., et al., 2007, [MNRAS](#), 378, 852
- Peacock J., Nicholson D., 1991, Monthly Notices of the Royal Astronomical Society, 253, 307
- Prakash A., et al., 2016, The Astrophysical Journal Supplement Series, 224, 34
- Pullen A. R., Hirata C. M., 2013, Publications of the Astronomical Society of the Pacific, 125, 705
- Rezaie M., et al., 2021, Monthly Notices of the Royal Astronomical Society, 506, 3439
- Riquelme W., et al., 2022, arXiv preprint arXiv:2209.07187
- Ross A. J., et al., 2011, [Monthly Notices of the Royal Astronomical Society](#), 417, 1350
- Sabti N., Muñoz J. B., Blas D., 2021, [J. Cosmology Astropart. Phys.](#), 2021, 010
- Schlegel D. J., Finkbeiner D. P., Davis M., 1998, The Astrophysical Journal, 500, 525
- Schmittfull M., Seljak U., 2018, [Phys. Rev. D](#), 97, 123540
- Slosar A., Hirata C., Seljak U., Ho S., Padmanabhan N., 2008, Journal of Cosmology and Astroparticle Physics, 2008, 031
- Wang M. S., Beutler F., Bacon D., 2020, [MNRAS](#), 499, 2598
- Weaverdyck N., Huterer D., 2021, [MNRAS](#), 503, 5061
- Weinberg S., 2008, Cosmology. OUP Oxford
- Weinberg D. H., Mortonson M. J., Eisenstein D. J., Hirata C., Riess A. G., Rozo E., 2013, Physics reports, 530, 87
- Wilson M. J., Peacock J. A., Taylor A. N., de la Torre S., 2017, Monthly Notices of the Royal Astronomical Society, 464, 3121
- Wright E. L., et al., 2010, [AJ](#), 140, 1868
- Xavier H. S., Abdalla F. B., Joachimi B., 2016, [Monthly Notices of the Royal Astronomical Society](#), 459, 3693
- Zhou R., et al., 2021, Monthly Notices of the Royal Astronomical Society, 501, 3309
- Zhou R., et al., 2022, arXiv preprint arXiv:2208.08515
- Zou H., et al., 2017, Publications of the Astronomical Society of the Pacific, 129, 064101
- de Putter R., Gleyzes J., Doré O., 2017, Physical Review D, 95, 123507

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