

# 1 Data Compression and Covariance Matrix Inspection: Cosmic Shear

2 Covariance matrices are among the most difficult pieces of end-to-end cosmological analyses. In  
3 principle, for two-point functions, each component involves a four-point function, and the resulting  
4 covariance often has hundreds of thousands of elements. We investigate various compression  
5 mechanisms capable of vastly reducing the size of the covariance matrix in the context of cosmic  
6 shear statistics. This helps identify which of its parts are most crucial to parameter estimation.  
7 We start with simple compression methods, by isolating and “removing” 200 modes associated with  
8 the lowest eigenvalues, then those with the lowest signal-to-noise ratio, before moving on to more  
9 sophisticated schemes like compression at the tomographic level and, finally, with the Massively  
10 Optimized Parameter Estimation and Data compression (MOPED). We find that, while most of  
11 these approaches prove useful for a few parameters of interest, like  $\Omega_m$ , the simplest yield a loss of  
12 constraining power on the intrinsic alignment (IA) parameters as well as  $S_8$ . For the case considered  
13 — cosmic shear from the first year of data from the Dark Energy Survey — only MOPED was able  
14 to replicate the original constraints in the 16-parameter space. Finally, we apply a tolerance test to  
15 the elements of the compressed covariance matrix obtained with MOPED and confirm that the IA  
16 parameter  $A_{\text{IA}}$  is the most susceptible to inaccuracies in the covariance matrix.

## 17 I. INTRODUCTION

18 Cosmic shear is a weak lensing effect caused by the  
19 large-scale structure of the universe and is an important  
20 tool for constraining cosmology. The most common way  
21 of obtaining information from cosmic shear is to use two-  
22 point functions and, as is often the case, this analysis  
23 assumes that the summary statistics have a gaussian dis-  
24 tribution, thus requiring a covariance matrix. For a two-  
25 point data vector of length  $N$ , the covariance matrix is  
26 a symmetric  $N \times N$  matrix with  $N \times (N + 1)/2$  individ-  
27 ual elements that capture the auto and cross-correlation  
28 of the data vector. As the length of the data vector in-  
29 creases, the number of elements in the covariance ma-  
30 trix grows quadratically and becomes harder to evaluate.  
31 Compression schemes resolve this by significantly reduc-  
32 ing the dimension of the matrix while still retaining rel-  
33 evant information about the parameters of interest, and  
34 also potentially speeding up computations. One way of  
35 accomplishing this is to use the Massively Optimized Pa-  
36 rameter Estimation and Data compression (MOPED), in  
37 which, if the noise in the data does not depend on the  
38 model parameters, then the Fisher matrix for both the  
39 full and compressed covariance matrices coincides and  
40 the compression is said to be lossless [8, 22]. MOPED  
41 has been widely used in literature for a variety of appli-  
42 cations, for example, CMB data [26], the redshift-space  
43 galaxy power spectrum and bispectrum [7], parameter-  
44 dependent covariance matrices [9], compression of the  
45 Planck 2015 temperature likelihood [18], weak lensing  
46 and galaxy clustering [19], and has been paired with a  
47 Gaussian Process emulator to analyze weak lensing data  
48 [17].

49 We will focus on cosmic shear measurements from the  
50 Dark Energy Survey Year 1 (DESY1) release [1, 23]  
51 (DES)-[23]-Year 1-release<sup>TF</sup>; the data vector has 227  
52 elements, varying with angular separation and different  
53 pairs of tomographic redshift bins. Since our parameter  
54 space consists of 16 free parameters, we can use MOPED  
55 to reduce the 25,878 independent elements of the covari-  
56 ance matrix, to only 136.

57 Apart from MOPED, we will be analyzing the covari-  
58 ance matrix with three other compression techniques:  
59 the first involves performing an eigenmode decomposi-  
60 tion then discarding the modes associated with the low-  
61 est eigenvalues; the second approach removes those with  
62 the lowest signal-to-noise ratio. In order to obtain a com-  
63 pression competitive with MOPED in terms of shrinkage,  
64 i.e. about 10% of the original size, we remove, in both  
65 cases, 200 such modes.

66 Finally, the third method consists of a map-level com-  
67 pression [2], where linear combinations of the tomo-  
68 graphic maps are used to retain as much information as  
69 possible. Compression of the tomographic bin pairs then  
70 considerably reduces the size of the data vector of the  
71 two-point functions. For example, we will see that most  
72 of the information in the four tomographic bins used by  
73 DESY1 can be compressed into a single linear combina-  
74 tion of those bins, or one Karhunen-Loéve (KL) mode.  
75 Therefore, instead of  $(4 \times 5)/2$  two-point functions for  
76 each angular bin, we need include only one or two. For  
77 this purpose, the data vector for each tomographic bin  
78 will have the same length, and so the angular cuts to  
79 the dataset and covariance matrix will be different from  
80 the ones used in the aforementioned DESY1 paper. The  
81 chosen covariance matrix has a dimension of  $190 \times 190$ .  
82 With one KL mode, we can compress the shear data vec-  
83 tor down to 10% of its original size, yielding 190 inde-  
84 pendent elements for the covariance matrix of the new  
85 data vector.

86 There are a number of codes that compute covariance  
87 matrices analytically, here we test two, which, despite  
88 being different produce compatible constraints. It must  
89 follow that the parts most relevant to parameter estima-  
90 tion be similar to each other. Establishing which regions  
91 of the covariance matrix are most informative is the first  
92 step towards building a tool for comparing these mat-  
93 rices without the need for a full cosmological analysis. In  
94 this work, we use compression schemes to look for an  
95 indication of which elements should be considered for co-  
96 variance matrix comparison.<sup>TF</sup>

97 In §II, we start by describing the dataset and the co-

variance matrices used. We then proceed to review each compression scheme and apply them to a DESY1 cosmic shear, demonstrating how well they reproduce the constraints obtained with the full covariance matrix. We follow this by showing that compression can be a [helpful](#) [useful](#)<sup>TF</sup> tool to compare two different covariance matrices, in §III. Our tolerance test is described in §IV, where we investigate the change in parameter constraints resulting from the addition of noise separately to elements and eigenvalues of the covariance matrix. Finally, our conclusions are summarized in §V.

## II. METHODS

### A. DES Cosmic Shear: Data and Analysis

In this section, we introduce the data and covariance matrices that are used in this work. Our tests are carried out using cosmic shear statistics  $\xi_{\pm}(\theta)$ , focusing on the results from DESY1. The data is divided into four tomographic redshift bins spanning the interval  $0.20 < z < 1.30$ , which yields 10 bin-pair combinations, each one containing 20 angular bins between 2.5 and 250 arcmin. We thus begin with 200 data points for statistic, giving 400 in total. We then apply the angular cuts described in [1], which removes the scales most sensitive to baryonic effects; this leaves 167 points for  $\xi_+(\theta)$  and 60 for  $\xi_-(\theta)$ , resulting in 227 data points corresponding to the aforementioned  $227 \times 227$  covariance matrix.

Table I shows the 16-parameters varied and the priors placed on them. Since cosmic shear is not sensitive to most of these, their constraints are largest dominated by the priors used. As such, throughout, we will only be showing constraints on three of those: the matter density parameter,  $\Omega_m$ , the amplitude of matter fluctuations,  $S_8 \equiv \sigma_8(\Omega_m/0.3)^{0.5}$ , and the amplitude of the intrinsic alignment,  $A_{\text{IA}}$ .

To perform cosmological parameter inference we use the `CosmoSIS` [3, 5, 10, 12, 13, 20, 21, 27] pipeline, while employing the `MultiNest` [6] sampler to explore the parameter space, with 1000 livepoints, efficiency set to 0.05, tolerance to 0.1 and constant efficiency set to True.

The covariance matrices are the following:

- the Full Covariance Matrix (FCM) used in the DESY1 analysis, which includes non-gaussian effects and super-sample variance; generated by `Cosmolike` [15];
- one containing only the gaussian part, which we will refer to as the Gaussian Covariance Matrix (GCM); generated by the same code used to analyze the KiDS-450 survey [11, 14].

Thus, throughout, the covariance labels FCM and GCM differ for several reasons: first, they are two independent codes and, second, although the code for the KiDS-450

Parameter	Prior
Cosmological	
$\Omega_m$	$\mathcal{U}(0.1, 0.9)$
$\log A_s$	$\mathcal{U}(3.0, 3.1)$
$H_0$ ( $\text{km s}^{-1}\text{Mpc}^{-1}$ )	$\mathcal{U}(55, 91)$
$\Omega_b$	$\mathcal{U}(0.03, 0.07)$
$\Omega_\nu h^2$	$\mathcal{U}(0.0005, 0.01)$
$n_s$	$\mathcal{U}(0.87, 1.07)$
Astrophysical	
$A_{\text{IA}}$	$\mathcal{U}(-5, 5)$
$\eta_{\text{IA}}$	$\mathcal{U}(-5, 5)$
Systematic	
$m^i$	$\mathcal{G}(0.012, 0.023)$
$\Delta z^1$	$\mathcal{G}(-0.001, 0.016)$
$\Delta z^2$	$\mathcal{G}(-0.019, 0.013)$
$\Delta z^3$	$\mathcal{G}(0.009, 0.011)$
$\Delta z^4$	$\mathcal{G}(-0.018, 0.022)$

TABLE I. List of the priors used in the analysis for parameter constraints ( $\mathcal{U}$  denotes flat in the given range and  $\mathcal{G}$  is gaussian with mean equal to its first argument and dispersion equal to its second). For the cosmological parameters, we fix  $w = -1.0$ ,  $\Omega_k = 0.0$  and  $\tau = 0.08$ . The astrophysical parameters are associated with the intrinsic alignment, they follow the relation  $A_{\text{IA}}(z) = A_{\text{IA}}[(1+z)/1.62]^{\eta}$ . Lastly, for systematics we have  $m^i$  corresponding to the shear calibration and  $\Delta z^i$  for the source photo-z shift, with  $i = [1, 4]$  in both cases.

survey does contain all the functionality in `Cosmolike`, we ran the GCM with the simplest settings in order to accentuate the differences. The ensuing discrepancies help us assess various validation techniques. Where not otherwise stated, the analysis and constraints will be performed on the FCM.

Figure 1 shows the projected cosmological constraints for the FCM and the GCM, using the same data vector and cuts. The 68% CL constraints are as follows: for the FCM:  $\Omega_m = 0.306^{+0.018}_{-0.023}$ ,  $S_8 = 0.784^{+0.054}_{-0.06}$  and  $A_{\text{IA}} = 0.852^{+0.359}_{-0.233}$ ; and for the GCM:  $\Omega_m = 0.309^{+0.017}_{-0.023}$ ,  $S_8 = 0.787^{+0.051}_{-0.058}$  and  $A_{\text{IA}} = 0.948^{+0.329}_{-0.22}$ . This shows that the variations we introduced to the calculation of the two matrices are measurable in the parameter constraints.

### B. Eigenvalues

Let us start with the easy task of analyzing the eigenvalues of the covariance matrix. Each eigenvalue is associated with a linear combination of the data vector, or a mode.

The idea is to remove the contribution of the lowest eigenvalues, since these are usually attributed to numerical noise and, as such, contain the least amount of in-

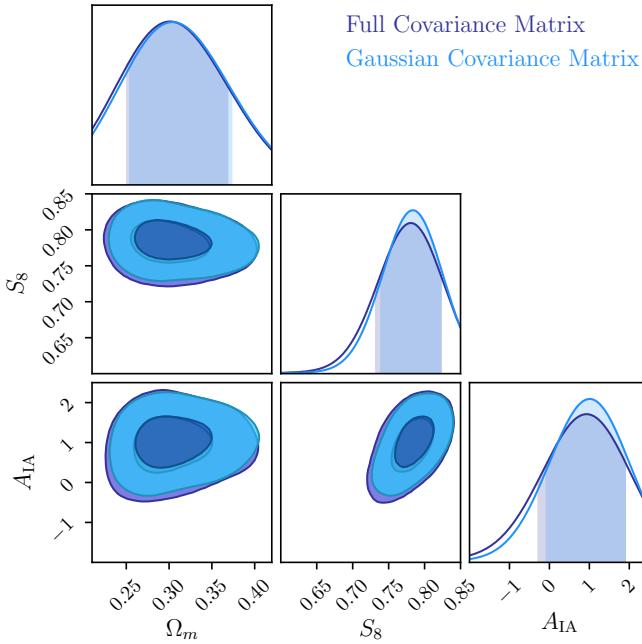


FIG. 1. Constraints on cosmological parameters  $\Omega_m$  and  $S_8$  and intrinsic alignment parameter  $A_{IA}$  for two covariance matrices produced for cosmic shear. The purple curve is for the FCM while the blue is for the GCM. In the 16-dimensional parameter space, the volume of the posterior is about 22% larger for the former.

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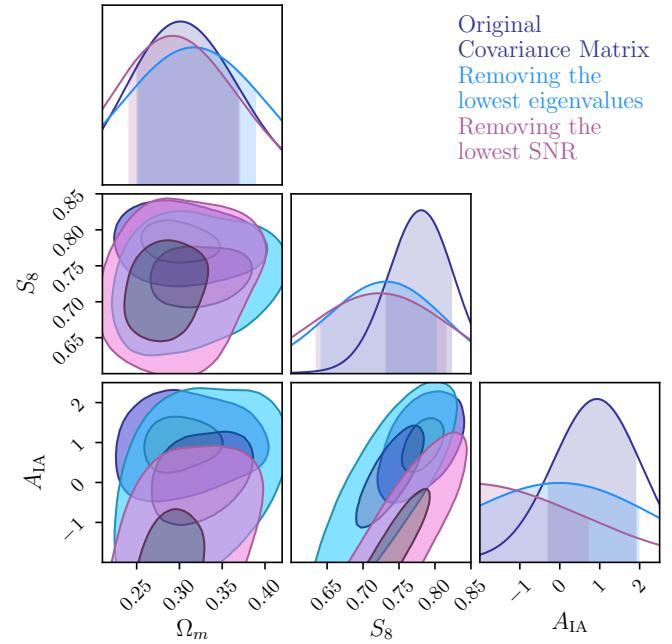


FIG. 2. Constraints on cosmological parameters  $\Omega_m$ ,  $S_8$  and the intrinsic alignment parameter  $A_{IA}$  for the original covariance matrix (in purple) and for the two new covariance matrices obtained in §II B (in blue) and §II C (in magenta).

### C. Signal-to-noise ratio

Instead of looking only at the “noise” – or the eigenvalues of the covariance matrix – a better way to assess the importance of modes is to consider the signal as well. We can define the expected signal-to-noise ratio (SNR) as

$$\left(\frac{S}{N}\right)^2 = T_i C_{ij}^{-1} T_j , \quad (1)$$

where  $T_i$  is the predicted theoretical signal for the  $i^{th}$  data point, given a fiducial cosmology, and  $C$  is the covariance matrix. Repeated indices are summed in all cases, throughout this work. If  $C$  were diagonal, then the eigenvectors would simply be the  $T_i$ s themselves, and not a linear combination of them, and we could estimate the SNR squared expected in each mode by just computing  $T_i^2/C_{ii}$ , with  $ii$  denoting the diagonal element  $i$ . Then we could throw out the modes with the lowest SNR. Since this is not the case here, we have to first diagonalize  $C$  and then order the values. We write the expected SNR squared as

$$\left(\frac{S}{N}\right)^2 = \frac{v_i^2}{\lambda_i} , \quad (2)$$

where  $\lambda_i$  are the eigenvalues of the covariance matrix, which is diagonalized with the unitary matrix  $U$ , and the eigenvectors are

$$v_i \equiv U_{ij}^T T_j , \quad (3)$$

formation. The highest eigenvalues, on the other hand,  
172 are said to be the most informative [24]. The procedure  
173 is simple, we first diagonalize the covariance matrix in  
174 order to calculate its eigenvalues then sort them into in-  
175 creasing order. Setting the lowest eigenvalues to zero  
176 would result in a non-positive definite (NPD) matrix, so  
177 we replace them instead with lower values (nine orders  
178 of magnitude lower), thus removing their effective con-  
179 tribution; we then transform back to the original basis and  
180 perform a cosmological analysis with the new covariance  
181 matrix.  
207

For the purpose of reducing the covariance matrix to  
182 about 10% of its original size, we follow the procedure  
183 above to discard the 200 eigenmodes with the lowest  
184 eigenvalues. The results reported in Figure 2 show a  
185 loss of constraining power on two of the three parame-  
186 ters shown. This is consistent with the fact that we are  
187 removing about 90% of the information contained in the  
188 covariance matrices. However, it is inconsistent with the  
189 conjecture that the modes with lowest eigenvalues are  
190 irrelevant, in fact, constraints on  $S_8$  for the FCM are  
191  $0.779^{+0.044}_{-0.46}$ , whereas, for the new covariance matrix,  
192 we obtain  $0.725^{+0.076}_{-0.083}$ , showing an increase in the errors of  
193 almost 77%. It is then clear that this method is incom-  
194 patible with a 10% reduction, and so we must look for a  
195 different way of ordering the modes.  
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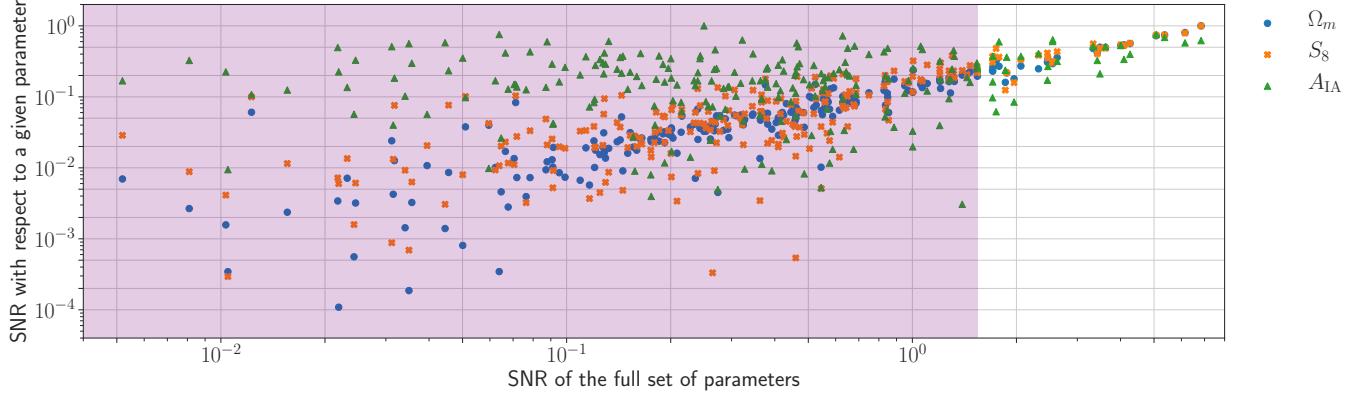


FIG. 3. Scatter plot for the relation between the signal to noise (SNR) for each parameter (y-axis) against that for the full set of parameters (x-axis). The derivatives are shown with respect to  $\Omega_m$  (blue circle), for  $S_8$  (orange x) and for the intrinsic alignment parameter  $A_{IA}$  (green triangle). The purple rectangle spreads until the two hundred lowest values of SNR, which corresponds to the values that are modified for parameter constraints.

with the superscript  $T$  denoting the transpose. From a naive point of view, this makes it clear which modes should be kept and which should be dropped; modes  $v_i$  for which  $(v^2/\lambda)_i$  is small can be discarded. As we will later see, however, it is not as simple as that.

After obtaining the SNR for the covariance matrix, we reduce the 200 lowest values to seven orders of magnitude lower, which is equivalent to increasing the noise (or decreasing the signal) of these modes. We then obtain a new covariance matrix with the corresponding modified SNR values. The parameter constraints for this method are shown in Figure 2, where we note that only  $\Omega_m$  is well constrained (in agreement with those obtained with the original covariance matrix to within a  $2\sigma$  interval). The constraining power on  $A_{IA}$  and  $S_8$ , on the other hand, is weakened, which suggests that the modes removed do indeed carry relevant information for these parameters.

We can investigate this loss by tweaking our understanding of which modes carry information. The “signal” that these modes are ordered by is the amplitude of the data points. The parameters, however, are sensitive to the shape as well as the amplitude. To address this, we can identify the SNR for each parameter individually by taking

$$\left( \frac{\partial S / \partial p_\alpha}{N} \right)^2 = \frac{(\partial v_i / \partial p_\alpha)^2}{\lambda_i}, \quad (4)$$

where  $\partial / \partial p_\alpha$  is the derivative with respect to each parameter. The importance of this procedure is illustrated in Figure 3, which shows the normalized SNR for a given mode on the  $x$ -axis against the SNR for  $\Omega_m$ ,  $S_8$  and  $A_{IA}$ . The shaded region shows the 200 modes excluded in the previous analysis, where we see the presence of low SNR modes that contain information about the parameters. This is particularly true for the intrinsic alignment parameter  $A_{IA}$ , which seems to explain the poor constraints shown in Figure 2. As a result, simply cutting on raw

SNR loses constraining power.

On the other hand, as [16] argues, removing the modes with the highest SNR is recommended in order to obtain a bias-free inference (another way would be to use a non-Gaussian likelihood). In light of that, we followed the same procedure used for removing the modes with the lowest SNR, but instead set the 200 highest modes to values several orders of magnitude lower. This yielded weaker constraints for not only for  $S_8$  and  $A_{IA}$ , but also for  $\Omega_m$ . We believe that this divergence was due to the large quantity of modes removed for our analysis and does not, in any way, invalidate the findings of the aforementioned work.

#### D. Tomographic Compression

The tomographic compression method of this section is based on a Karhunen-Loéve (KL) decomposition for the shear power spectrum suggested by [2] and later applied to real space two-point function in [4] for the CFHTLens survey. Its implementation consists of finding the eigenmode — in this case, a linear combination of the convergence in different tomographic bins — with most of the signal-to-noise ratio contribution to the power spectrum, and then transforming the two-point function of this eigenmode into real space. This is not the most general compression method for the two-point function in real space, since the weight is dependent on the multipole  $\ell$ . However, as found in [4], it is effective on the real space data, nonetheless.

Before diving into the derivation, it is worth summarizing the results. With CosmoSIS, we calculate the shear angular power spectrum  $\mathcal{C}_\ell$  of the convergence  $\kappa^i$ , where  $i = [1, 4]$  for the 4 tomographic bins probed by DES Year 1 with a fiducial cosmology at the best-fit parameters. We thus have  $4 \times 5/2 = 10$  pairs of bins for which we

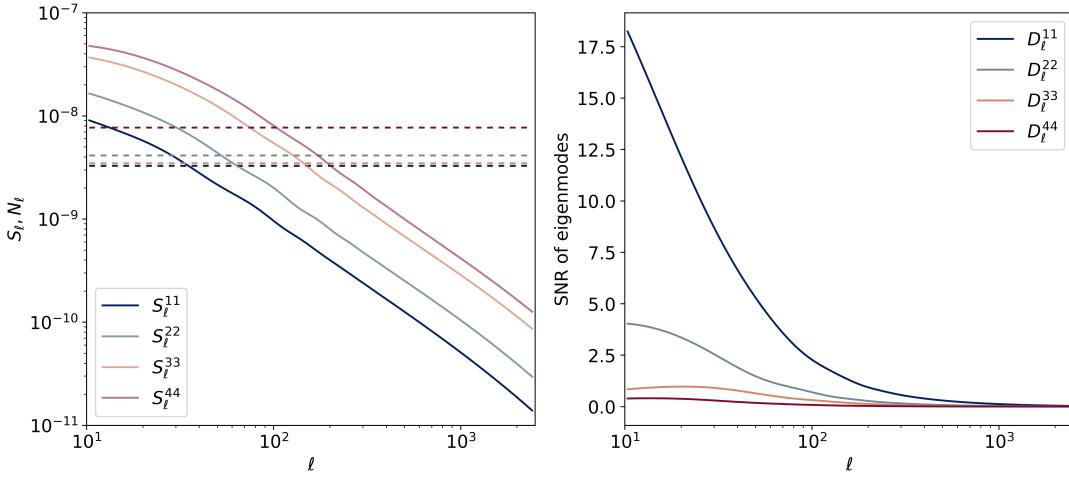


FIG. 4. **Left:** Shear power spectrum of the FCM. Solid lines are diagonal elements of the signal matrix  $S_\ell$ , and dashed lines are the diagonal elements of noise matrix  $N_\ell$ . **Right:** Signal-to-noise ratio matrix  $D_\ell$  of the first to fourth KL-modes of the power spectrum on the left.

can compute spectra. The left plot in Figure 4 shows<sup>316</sup> the diagonal elements of the signal part,  $S_\ell$ , and of the<sup>317</sup> noise part,  $N_\ell$ , of the spectrum. The right-hand panel<sup>318</sup> shows the signal to noise ratio for the KL-transformed<sup>319</sup> eigenmodes, which we call  $D_\ell$ , ranging from  $\ell = 10$  to<sup>320</sup>  $\ell = 2500$ . That is, we identify a mode as  $b_{\ell m} = r_i \kappa_{\ell m}^i$ ,<sup>321</sup> where  $r_i$  is the weight factor on the  $i^{\text{th}}$  tomographic bins.<sup>322</sup> We can see that the first KL mode contains most of the<sup>323</sup> SNR contribution to the power spectrum. However, if<sup>324</sup> we want to recover more information, we also should include the second and the cross mode between the first<sup>325</sup> and second KL-mode.

With the total power spectrum  $\mathcal{C}_\ell = S_\ell + N_\ell$ , we calculate the Karhunen-Loéve (KL) modes for each  $\ell$  (so we drop the  $\ell$  subscript) via a general eigenvalue problem<sup>326</sup>

$$\mathcal{C}^{ij} e_p = \lambda_p N^{ij} e_p . \quad (5)$$

The index  $p$  in  $e_p$  corresponds to the  $p^{\text{th}}$  KL-mode of  $\mathcal{C}$ .<sup>327</sup> Using Cholesky decomposition,  $N = LL^T$ , we express the<sup>328</sup> new observable as  $b_p = e_p L^{-1} \kappa$ . And we find that  $E_\ell = [e_1, e_2, \dots]^T$  is a basis transformation of basis so that the<sup>329</sup> shear signal is diagonalized. We can now calculate the<sup>330</sup> power spectrum  $D_\ell$  for the new uncorrelated observable<sup>331</sup>  $b_{\ell m}$ ,

$$D_\ell = \langle b_{\ell m} b_{\ell m}^T \rangle = E_\ell L^{-1} \mathcal{C}_\ell L^{-1} E_\ell^T = \Lambda_\ell , \quad (6)$$

where  $\Lambda_\ell = \text{diag}[\lambda_1, \lambda_2, \dots]$ . If we denote  $E_\ell N^{-1}$  as  $R_\ell$  and further write  $U_\ell^{ij} = R_\ell^i R_\ell^j$ , where  $i$  and  $j$  are the indices for the tomographic bin-pairs, we have the compression in terms of one simple linear combination,<sup>332</sup>

$$D_\ell = R_\ell^i \mathcal{C}_\ell^{ij} R_\ell^j = U_\ell^{ij} \mathcal{C}_\ell^{ij} , \quad (7)$$

with  $U_\ell^{ij}$  being the weight we will use to compress the two-point functions. We note that these KL-modes  $b_{\ell m}^p$ <sup>333</sup> are uncorrelated, so that their power spectrum  $D_\ell^{pp'}$  is<sup>334</sup>

a diagonal matrix whose entries are  $1+\text{SNR}$  of the corresponding eigenmodes. This allows us to compress ten tomographic bin-pairs to one, or two, by taking only the modes with the highest SNR.

We want, however, to eventually compress the two-point function data vector of DESY1, which is measured in the real space tomographic bin pair  $i, j$  and related to the angular power spectrum  $\mathcal{C}_\ell$  via

$$\begin{aligned} \xi_+^{ij}(\theta) &= \int \frac{\ell d\ell}{2\pi} J_0(\ell\theta) \mathcal{C}^{ij}(\ell) , \\ \xi_-^{ij}(\theta) &= \int \frac{\ell d\ell}{2\pi} J_4(\ell\theta) \mathcal{C}^{ij}(\ell) . \end{aligned} \quad (8)$$

In order to use linear combinations of all the tomographic bins, we need to ensure that the combination is  $\ell$ -independent, that is to say, the transformed two-point correlation function,  $\tilde{\xi}_\pm(\theta)$ , can be directly calculated from other two-point functions. In fact, Figure 5 shows that the  $U_\ell^{ij}(\ell)$  are generally  $\ell$ -independent, except for low  $\ell$ s, due to the existence of cosmic variance. Therefore, we have,

$$\begin{aligned} \tilde{\xi}_\pm(\theta) &= \int \frac{\ell d\ell}{2\pi} J_{0/4}(\ell\theta) D(\ell) \\ &= \int \frac{\ell d\ell}{2\pi} J_{0/4}(\ell\theta) U_\ell^{ij} \mathcal{C}^{ij}(\ell) \\ &= \bar{U}^{ij} \xi_\pm^{ij}(\theta) , \end{aligned} \quad (9)$$

where  $\bar{U}^{ij}$  is the average  $U_\ell^{ij}$  given by,

$$\bar{U}^{ij} = \frac{\int_{\ell_{\min}}^{\ell_{\max}} d\ell (2\ell + 1) U_\ell^{ij}}{\int_{\ell_{\min}}^{\ell_{\max}} d\ell (2\ell + 1)} . \quad (10)$$

We make a more conservative angular cut than the one discussed in [23], making sure that both  $\xi_\pm(\theta)$  are uni-

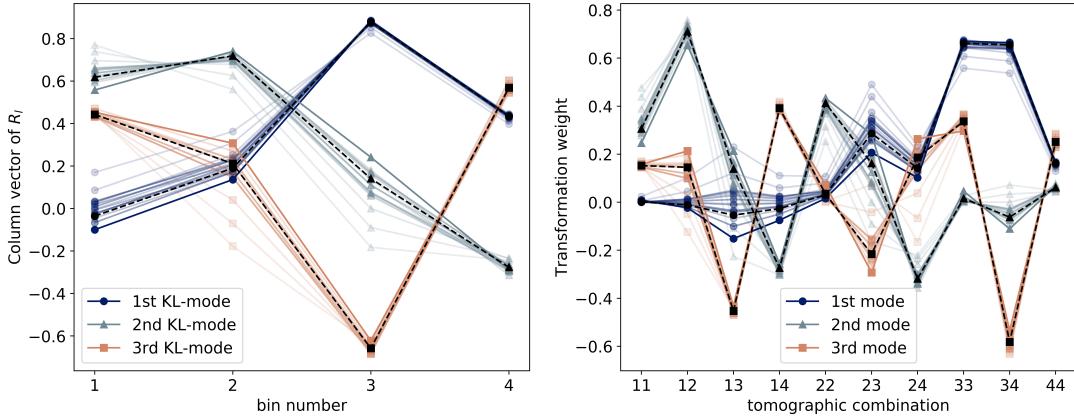


FIG. 5. **Left:** Column vectors of the matrix  $R_\ell$ , or  $e_\ell^p N^{-\frac{1}{2}}$ , for compressing the shear power spectrum  $C_\ell$ . **Right:** Transformation on tomographic bin combination  $U_{ij}$  constructed from the KL-eigenmodes. For both plots, the dashed black lines are the weighted average of each mode. The lightest shade represents  $\ell = 10$  and the increment is  $\Delta\ell = 10$  for each darker shade.

form in regard to tomographic combinations. We consider an angular scale for  $\xi_+$  from  $7.195'$  to  $250.0'$ , and for  $\xi_-$  from  $90.579'$  to  $250.0'$ . Therefore, for the purpose of exploring the KL-transform, the raw data vector has a length of 190. By shrinking 10 tomographic combinations for each angle into 1 KL-mode, the data vector is reduced to length 19, and so the number of elements in the covariance matrices has a compression of 99%.

In Figure 5, we plot the normalized KL-eigenmode  $e_\ell^p N^{-\frac{1}{2}}$  and its corresponding weight,  $U_\ell^{ij} = R_\ell^i R_\ell^j$ . Modes with increasing  $\ell$  are plotted in increasing opacity of the color. While the KL-modes do vary by a slight amount for different  $\ell$ , their sensitivity to it is not very significant since they converge for higher  $\ell$  to their weighted average, which we represent with the dashed black lines. For the first KL-mode, the tomographic bins with higher redshift are weighted more than those with low redshift. This is also shown in the right panel by the weight on tomographic combination that the combination of bin 3 and bin 4 carries most of the weight in the signal-to-noise ratio. This agrees with the fact that low-redshift galaxies are less affected by lensing than high-redshift galaxies, as indicated in the left panel of Figure 4.

We ran the likelihood analysis as detailed in §II A with the first KL-mode and the first two KL-modes with their cross correlation mode, which correspond to a 10-to-1 and 10-to-3 compression, respectively, and show the parameter constraints on the  $\Omega_m - S_8 - A_{IA}$  plane in Figure 6. We do not include the third and fourth KL mode because they contain considerably less signal to noise. We can see that the first KL-mode is generally not sufficient to recover the information in the data vector. Since the first two modes contain most of the SNR contribution at a map level, we were able to recover the  $\Omega_m$  constraints. However, information about the  $S_8 - A_{IA}$  combination is clearly lost. This could be due to the fact that the SNR-prioritized modes are not the sensitive direction for these

parameters, as was also the case in Figure 3. Indeed, the  $S_8 - A_{IA}$  plane shows a strong correlation between these two parameters. This likely explains why the constraints for  $S_8$  widened: the KL-modes fail to break the degeneracy on  $A_{IA}$ , which is mostly present in the modes that are insensitive to cosmic shear and are discarded in the compression process.

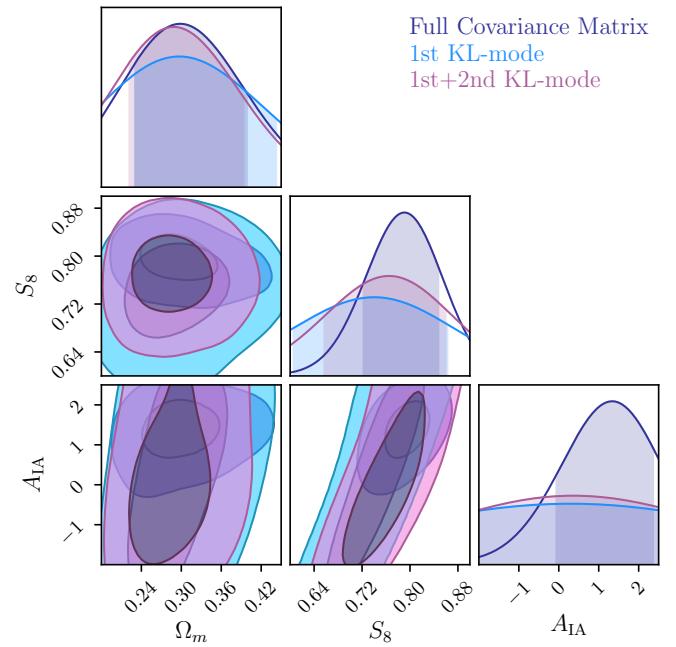


FIG. 6. Cosmological constraints marginalized over all 16 parameters for the  $190 \times 190$  FCM and that compressed using the first KL-mode and the first two KL-modes.

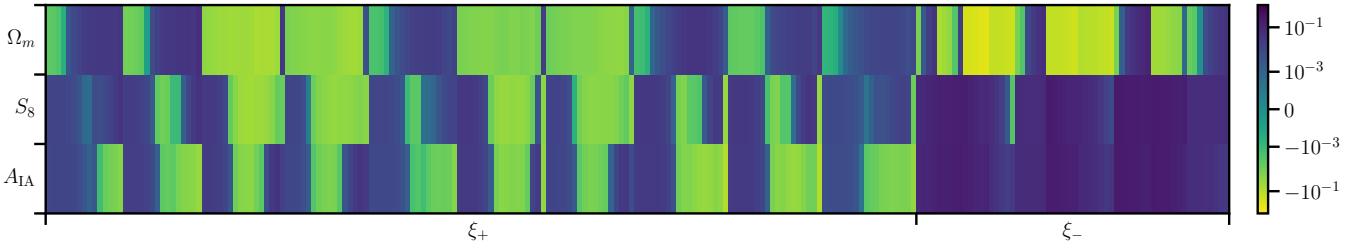


FIG. 7. An illustration of the 227 values of the weights corresponding to  $\Omega_m$ ,  $S_8$  and  $A_{IA}$  used for compressing the covariance matrices. Note the similarity of the weighting vectors for  $S_8$  and  $A_{IA}$ , and that the largest values correspond to the last 60 elements, i.e. those that we will use to compress the part of the covariance matrix that holds information for  $\xi_-$ .

### 380 E. Applying MOPED

381 The MOPED compression scheme takes place at the 416  
 382 two-point level, with the compressed data vector contain 417  
 383 ing linear combinations of the many two-point functions. 418  
 384 In principle, this requires only  $N_p$  linear combinations of 419  
 385 the two-point functions, where  $N_p$  is the number of free 420  
 386 parameters, and each mode, or linear combination, con- 421  
 387 tains all the information necessary about the parameter 422  
 388 of interest. 423

389 For each parameter  $p_\alpha$  that is varied one captures 424  
 390 single linear mode 425

$$y_\alpha = U_{\alpha i} D_i, \quad (11)_{427}$$

391 where  $D_i$  are the data points and the coefficients are 426  
 392 defined as

$$U_{\alpha i} \equiv \frac{\partial T_j}{\partial p_\alpha} C^{-1}_{ji}, \quad (12)$$

393 with  $T_j$  being the theoretical prediction for the data point 427  
 394  $D_j$  for a fiducial cosmology. An illustration of the matrix 428  
 395  $U_{\alpha i}$  is shown in Figure 7, showing the weighting vector 429  
 396 for parameters  $\Omega_m$ ,  $S_8$  and  $A_{IA}$ . 430

397 The now much smaller data set  $\{y_\alpha\}$ , which contains 431  
 398  $N_p$  data points, carries its own covariance matrix, from 432  
 399 which  $\chi^2$  can be computed for each point in parameter 433  
 400 space. Propagating through shows that this covariance 434  
 401 matrix is related to the original  $C_{ij}$  via 435

$$C_{\alpha\beta} = U_{\alpha i} C_{ij} U_{j\beta}, \quad (13)$$

402 which also happens to be identical to the Fisher matrix 436  
 403 of our likelihood. This compression was first suggested 437  
 404 by Tegmark et al. (1997) for a single parameter only. 438  
 405 The non-trivial extension to multiple parameters, where 439  
 406 the full Fisher matrix is reproduced with the compressed 440  
 407 data, is the MOPED algorithm [8]. One difference here 441  
 408 is that our weighing vector given by Eq. (12) does not 442  
 409 carry the normalizing factor of Eq. (11) in [8]. In our 443  
 410 case, the covariance matrix is  $227 \times 227$ , while the number 444  
 411 of parameters needed to specify the model is only 16, so 445  
 412  $C_{\alpha\beta}$  is a  $16 \times 16$  matrix. We have apparently captured 446  
 413 from the initial set of  $(227 \times 228)/2 = 25,878$  independent 447

elements of the covariance matrix a small subset (only 414  
 507 136) of linear combinations of these 26k elements that 415  
 508 really matter. If two covariance matrices give the same 416  
 509 set of  $C_{\alpha\beta}$ , it should not matter whether any of the other 417  
 510 thousands of elements differ from one another.

511 Ultimately, what matters is how well the likelihood 418  
 512 does at extracting parameter constraints. Since most 419  
 513 analyses assume a Gaussian likelihood, this boils down 420  
 514 to how well the contours in parameter space agree when 421  
 515 computing  $\chi^2$  using two different covariance matrices. 422

516 Figure 8 compares the constraints obtained for the 423  
 517 compressed covariance matrix and data set with results 424  
 518 from the full one. The two curves agree extremely well 425  
 519 for the parameters shown:  $\Omega_m$ ,  $S_8$  and  $A_{IA}$ . This is also 426

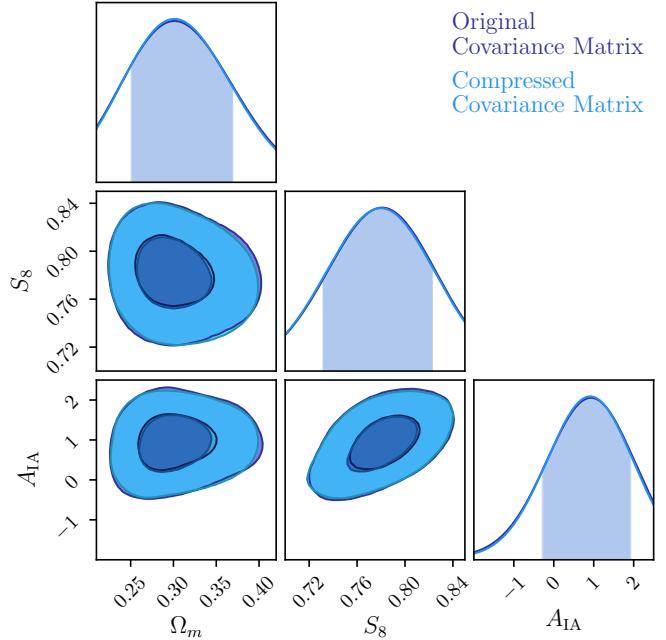


FIG. 8. Constraints on cosmological parameters  $\Omega_m$  and  $S_8$  and for the intrinsic alignment parameter  $A_{IA}$  for the original covariance matrix, FCM, (in purple) and for the compressed one (in blue).

428 true for all the other cosmological and intrinsic alignment  
 429 parameters, where their mean values agree at the  $1\sigma$  con-  
 430 fidence level. While the volume of the whole constrained  
 431 parameter space does increase by about 13%, the con-  
 432 straints for most parameters are less than 4% broader,  
 433 which shows that the information loss is negligible.

### 434 III. COMPARISON OF COVARIANCE 435 MATRICES

436 Armed with this information about compression, we  
 437 now set out to compare the two covariance matrices, the  
 438 GCM and the FCM, described in §II A.

#### 439 A. Element-by-element comparison

440 We begin by performing an element-by-element com-  
 441 parison between the two covariance matrices. If there  
 442 were only a single data point, then the covariance ma-  
 443 trix would be one number and comparing two covariance  
 444 matrices to try to understand why they give different  
 445 constraints would be as simple as comparing these two  
 446 numbers. The simplest generalization is then to do an  
 447 element-by-element comparison. We make a scatter plot  
 448 of the elements of the two matrices in the bottom panel of  
 449 Figure 9, where we can see that the elements of the FCM  
 450 are, in general, larger than the GCM's, with many of the  
 451 off-diagonal elements differing by 2 orders of magnitude  
 452 or more. In some ways, this is useful and reassuring, as it  
 453 aligns with what we see in the parameter constraints, in  
 454 Figure 1: larger elements in the covariance matrix trans-  
 455 lates to less constraining power.

456 The limitation of this method is that it remains unclear  
 457 which of the differences are driving the final discrepancies  
 458 in parameter constraints. This difficulty is an outgrowth  
 459 of the increasing size of the data sets and hence the grow-  
 460 ing number of elements of the covariance matrix that any  
 461 two codes are likely to disagree on. This element-by-  
 462 element comparison, however, would prove much more  
 463 practical useful<sup>TF</sup> if we fewer elements to compare. To-  
 464 wards that end, we turn to compressed covariance matri-  
 465 ces.

#### 466 B. Compressed Matrices Comparison

467 Since we have shown that, out of all the compression  
 468 schemes shown here, the only one capable of reproduc-  
 469 ing the original parameter constraints was MOPED, that is  
 470 what we will be using in this section.

471 We compress both covariance matrices using the same  
 472  $U_{\alpha,i}$  (we also tried using different  $U$ 's for each and ob-  
 473 tained similar results).

474 Figure 10 show a one-to-one scatter plot of the com-  
 475 pressed elements, which, as expected, exhibits a similar  
 476 behavior to that observed in Figure 9, with the elements

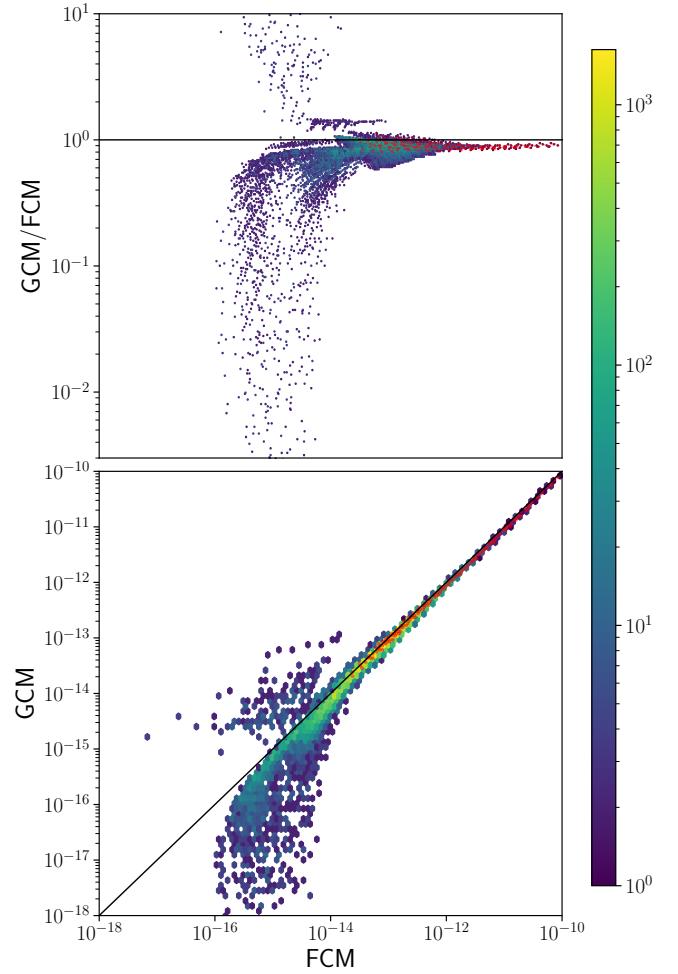


FIG. 9. In both plots, the red points refer to the diagonal elements, and the color bar varies according to the number of elements in one hexagonal bin, where the darkest blue color corresponds to only one element, and the brightest yellow shade to 2000. **Top:** Scatter plot of the ratio of the elements of the GCM and the FCM vs the FCM value. For illustrative purposes, we draw a black, horizontal line at  $GCM/FCM = 1$ . **Bottom:** Density of the scatter plot of the positive elements of the GCM and the FCM, with the black line showing  $FCM = GCM$ .

of the FCM being larger than those of the GCM. Here, however, the ratio of the diagonal elements is closer to 1, with a percentual difference of up to 17%, as compared to 26% with the original matrices. and the ratio of the diagonal elements goes up to only  $\approx 2.3$ .<sup>TF</sup> Perhaps even more importantly, there are much fewer points on this plot, since MOPED reduces the number of elements that need to be compared. These figures provide a greater insight into the relevant elements for parameter estimation: the dispersion is largely damped, and most of the elements are within 25% of each other, which explains what we see in the parameter constraints. Figure 11 shows the correlation matrix for the GCM and the FCM, and

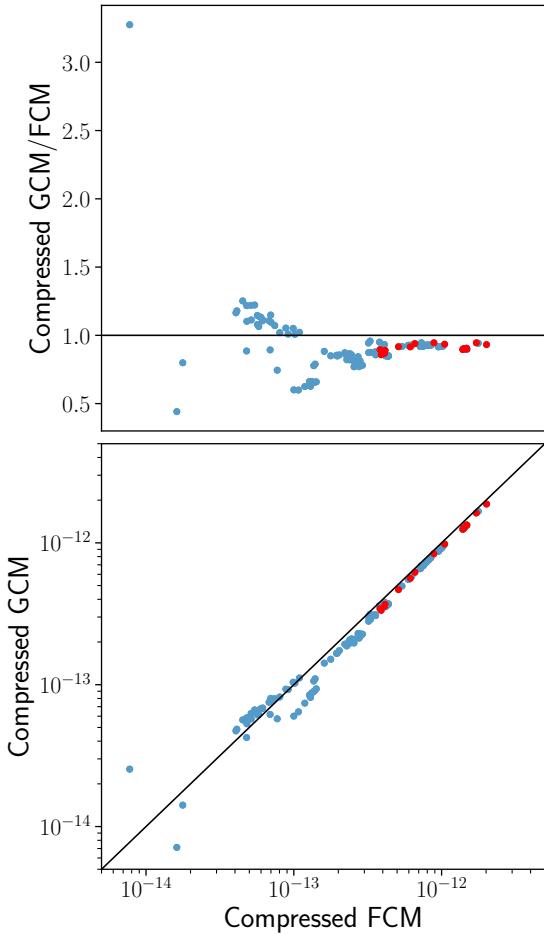


FIG. 10. Results for the covariance matrices compressed following the procedure described in §II E, with the red points corresponding to the diagonal elements. **Top:** One-to-one scatter of the ratio of the elements of the GCM and the FCM, over elements of the FCM. The black horizontal line is drawn at  $GCM/FCM = 1$ . **Bottom:** One-to-one scatter of the elements of the compressed matrices, with the black line describing  $FCM = GCM$ .

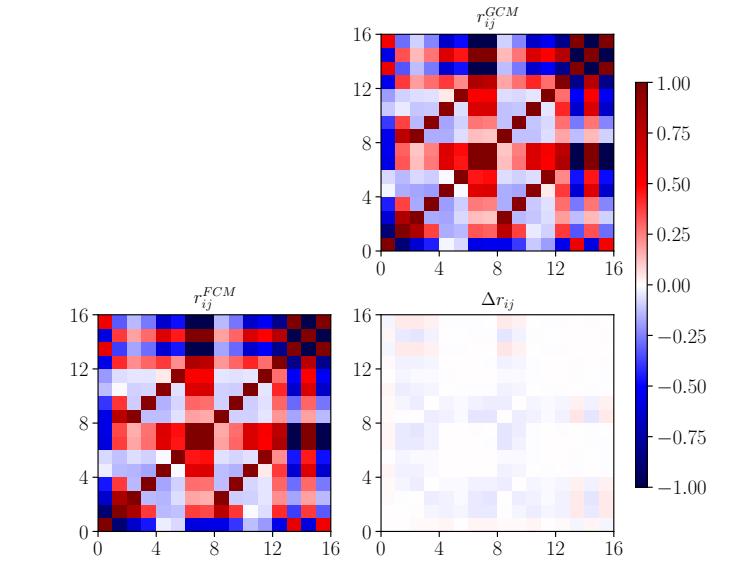


FIG. 11. The upper right and lower left plots display the correlation matrix for the GCM and the FCM respectively, and the difference between them,  $\Delta r_{ij}$ , is shown on the lower right.

504 In the next two sections we test two different ways  
 505 of perturbing the covariance matrix: first we consider an  
 506 error to the elements themselves, then we follow a similar  
 507 procedure to study the effects of introducing an error to  
 508 the eigenvalues of the compressed covariance matrix. In  
 509 both cases the perturbation is drawn in the following  
 510 manner: consider that we want to test the impact of an  
 511 error  $x\%$ ; this can either be an increase or a decrease in  
 512 the original element, or eigenvalue, as what we care about  
 513 most is not whether the parameter constraints will be  
 514 larger, but rather how different they are. For this error  
 515 to be random, but centered at our desired percentage,  
 516 we draw a  $\delta$ , for each new element/eigenvalue, from a  
 517 Gaussian distribution,  $\mathcal{G}(0, \frac{x}{100})$  and calculate the new  
 518 value to be

$$C_{\alpha\beta}^{\text{new}} = (1 + \delta) C_{\alpha\beta}^{\text{old}}, \quad (14)$$

where, for the eigenvalue, we replace  $C_{\alpha\beta}$  with  $\lambda_i$ . This analysis is done only for the FCM, with errors ranging from 5 – 45%, and for 50 realizations of the perturbed matrices.

523 One of the concerns that arises when modifying the  
 524 covariance matrix is that the resulting one has to be pos-  
 525 itive definite (PD). **For this reason, as such,**<sup>TF</sup> in each  
 526 section we also describe the steps taken to ensure this.  
 527 Another intelligent way of guaranteeing PD would be to  
 528 perturb the log of the covariance matrix. The issue, how-  
 529 ever, is how to introduce an error to the log matrix that  
 530 would be similar to what we expect to see in the original  
 531 covariance matrix. **For example, in**

$$C_{\alpha\beta}^{\text{new}} = e^{(1+\delta)(\log C_{\alpha\beta}^{\text{old}})}, \quad (15)$$

490 the difference between the normalized off-diagonal ele-  
 491 ments. The small differences suggest that the root of the  
 492 slightly looser constraints obtained with the GCM is the  
 493 larger diagonal elements of the MOPED-reduced covari-  
 494 ance matrix. That is, a problem that initially required  
 495 inspecting hundreds of thousands of elements is reduced  
 496 to one involving only 16.

#### 497 IV. TOLERANCE OF THE COMPRESSED 498 MATRICES

499 Now that we have shown that we are indeed able to  
 500 compress the covariance matrix into a much simpler and  
 501 considerably smaller one, our next step is to analyze the  
 502 amount of error the elements can tolerate while repro-  
 503 ducing compatible parameter constraints.

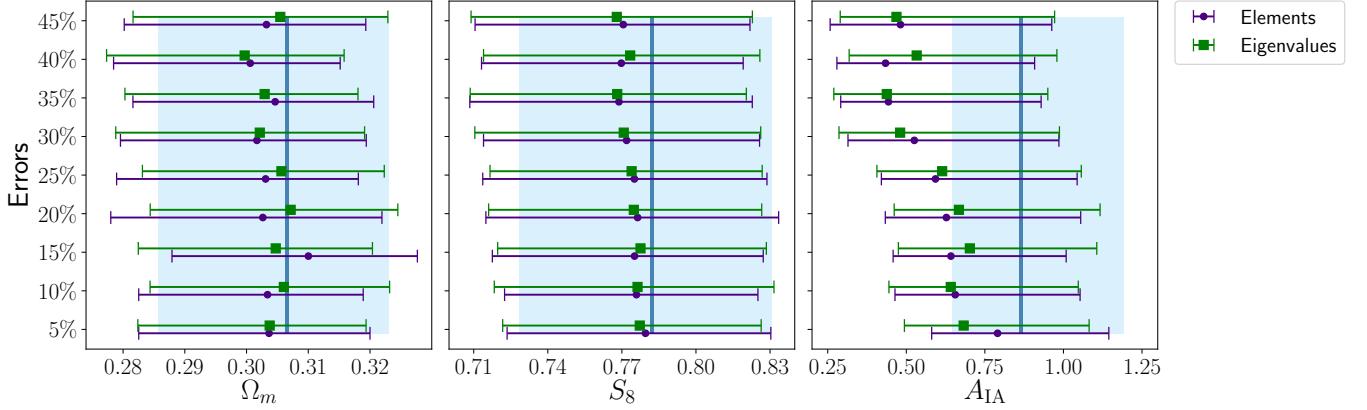


FIG. 12. An error plot showing the changes to the constraints for  $\Omega_m$ ,  $S_8$  and  $A_{IA}$  for errors added at 5%, 10%, 15%, 25%, 30%, 35%, 40% and 45% of the original elements (in purple) and eigenvalues (in green) of the compressed covariance matrix. The blue rectangle covers the 68% CL interval obtained for the FCM, and the darker blue vertical line shows the mean value for the respective parameter.

the value of  $C_{\alpha\beta}^{\text{new}}$  is not necessarily within  $\delta\%$  of  $C_{\alpha\beta}^{\text{old}}$ .  
 532 Introducing a 10% error, for example, in such a matrix,  
 533 results in a perturbed covariance matrix with some of  
 534 its elements differing by several orders of magnitude  
 535 from higher than the original one. A safer procedure  
 536 would then be to perturb the log of its eigenvalues, but,  
 537 since we have a section dedicated to perturbations to the  
 538 eigenvalues themselves, we deemed this would be repeti-  
 539 tive.  
 540

### A. Modifying the elements

Once we generate new values for each independent element, following Eq. (14), we check for positive definiteness. Since the resulting matrix is, more often than not, not PD, we correct this by identifying the smallest negative eigenvalue and adding it to the diagonal [25]. We check that, although doing this largely increases the values of the diagonal elements, less than 40% have a standard deviation of more than twice the original perturbation.

The constraints for  $\Omega_m$ ,  $S_8$  and  $A_{IA}$  are shown in Figure 12, in purple, where the blue rectangle spans over the constraints for the unchanged compressed covariance matrix. The relative change in size for the 68% CL interval is mostly  $> 10\%$  for the cosmological parameters; on the other hand, for the intrinsic alignment parameter  $A_{IA}$ , the mean values are more than  $1\sigma$  away from the original one and the loss in constraining power goes up to  $\sim 30\%$ .

### B. Modifying the eigenvalues

Another way of introducing error to the covariance matrix is to perturb its eigenvalues. For a symmetric matrix,

we have

$$C = Q\Lambda Q^{-1}, \quad (16)$$

where  $\Lambda = \lambda I$ , with  $\lambda$  being the eigenvalues and  $I$  the identity matrix; and  $Q$  is a square matrix whose columns are composed of the eigenvectors of  $C_{\alpha\beta}$ . The eigenvalues are then perturbed as described in Eq. (14), and the error,  $\delta$  is drawn from  $\mathcal{G}(0, \frac{x}{100})$ , with the requirement that  $|\delta| < 1$ . We then have  $\lambda^{\text{new}} > 0$ , and thus the perturbed covariance matrix associated with these new eigenvalues is PD.

The results for this method are also plotted in Figure 12, in green. Despite the results following the same tendency as those of the last section, we find that about 80% of the elements of the perturbed covariance matrices are within 10% of their original value.

## V. CONCLUSION

In this work, we set out to explore different ways of compressing, comparing and analyzing covariance matrices, giving particular emphasis to the MOPED compression scheme. We started by looking at the parameter constraints of two  $227 \times 227$  covariance matrices, the FCM and the GCM, generated for DESY1 cosmic shear measurements, and saw that, although some of their elements differed by several orders of magnitude, they generated similar constraints. It was clear, then, that not all elements contribute equally to the parameter constraints, and we needed to employ increasingly complicated methods to try and locate the most relevant parts of the covariance matrix.

The first step was then to analyze the eigenvalues. We began with the hypothesis that modes associated with the highest eigenvalues carry most information, as such,

those with the lowest eigenvalues would contribute less to parameter estimation. Using this notion to compress the covariance matrix we “removed” the lowest 200 eigenvalues, by setting them to several orders of magnitude lower. While the loss in constraining power for  $\Omega_m$  was only around 20%, we saw a loss of about 77% in the size of the constraints for  $S_8$ , and more than 100% for  $A_{IA}$ . Next, we moved on to the signal-to-noise ratio, and, using a similar procedure adopted for the eigenvalues, we “removed” the modes with the lowest SNR. The results were similar to those obtained with the eigenvalue cuts and showed us that these modes did not contribute significantly to constraining some cosmological parameters, like  $\Omega_m$ , however constraints on the intrinsic alignment parameters, and even  $S_8$  were more affected. This is consistent with the fact that the IA parameters are more sensitive to low SNR scales in cosmic shear, and it shows us that we need to look at the SNR per parameter before making any cuts, so that we do not lose important information for the parameters that we want to constrain.

The next step was to shrink the covariance matrix by applying a tomographic compression, where we decompose the shear angular power spectrum into KL modes, then we look for modes with the highest SNR and compress shear data vector by the modes. We thus go from ten tomographic bin combinations to only one or two. The resulting covariance matrix, for one mode, is then reduced from  $190 \times 190$  to  $19 \times 19$  or  $59 \times 59$ , showing a reduction of about 99% or 91%, respectively. We show, however, that one mode is not sufficient for constraining the parameters of our model, with the results being similar to our previous tests involving SNR: the constraints for  $\Omega_m$ , for example, are reproduced with the first and second KL-mode, but this is not the case for the IA parameters. Since essential information of IA parameters is contained in low SNR KL-mode, the high KL-modes failed to break the degeneracy of  $A_{IA} - S_8$  correlation, resulting in wider  $S_8$  constraints.

Finally, we applied MOPED, which uses linear combinations of the data vector. By transforming the data vector and covariance matrix with a weighting vector that is parameter dependent, we were able to reduce the  $227 \times 227$  matrix to a  $16 \times 16$  matrix. We show that the cosmological analysis using this compressed matrix reproduced similar constraints to the DESY1 analysis, for an uncompressed covariance matrix. We also showed a comparison of the elements of the compressed covariance matrix for the FCM and the GCM and found that the new elements show reasonable agreement, with their correlation matrices being very similar, and the diagonal elements showing a percentage difference of less than 15%.

Given these results, we successfully show that MOPED is the only compression scheme, out of the ones considered in this work, capable of capturing all the relevant information required to reproduce reliable parameter constraints for the 16 parameters of interest. It is worth noting here that compression does not automatically speed-

up the computation for parameter inference, since it has to be redone for every point in the parameter space. Recent work has been done by [17] to address this problem by using Gaussian Processes to generate the compressed theory.

When looking at the one-to-one element comparison of the FCM and the GCM, in Figure 9, the region of large variance suggests that there could be considerable differences in the parameter constraints. We see, however, in Figure 1, that this is not the case. This becomes clearer when comparing the elements of the compressed covariance matrices, where, while they do follow the same tendency as the full comparison, only a smaller portion of the elements display a greater dispersion. **In this sense, one of our most important results is in the ability of using MOPED to compare different matrices.**

One last step was taken to analyze the error tolerance of the compressed FCM. We adopted two ways of doing this, by introducing error taken from a Gaussian distribution for 5 – 45% of the original 1) element and, 2) eigenvalue of the compressed covariance matrix. For the latter, we checked that only about 20% of elements of the resulting, perturbed, covariance matrix showed errors within the expected value, while the vast majority had only about a 10% error. In both cases, however, the results were similar: for the cosmological parameters  $\Omega_m$  and  $S_8$ , the  $2\sigma$  constraints changed by about 7%, on average, while for the intrinsic alignment parameter  $A_{IA}$ , the constraints were up to 30% larger. Finally, we highlight the increasing shift, in the mean values of  $A_{IA}$ , to about 32% smaller than those obtained with the uncompressed FCM; while for the cosmological parameters this was only about 5%, in general.

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