

Euclid preparation

XC. Calibrated intrinsic galaxy alignments in the *Euclid* Flagship simulation

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ABSTRACT

The intrinsic alignments of galaxies are a potentially major contaminant among cosmological analyses of weak gravitational lensing. In this work, we constructed a semi-analytic model of galaxy ellipticities and alignments in the *Euclid* Flagship simulation to predict this contamination in *Euclid*'s weak lensing observations. Galaxy shapes and orientations were determined by the corresponding properties of the host haloes in the underlying *N*-body simulation, as well as the relative positions of galaxies within their halo. Alignment strengths were moderated via stochastic misalignments, separately for central and satellite galaxies, and were dependent on the galaxy's redshift, luminosity, and rest-frame colour. The resulting model was calibrated against galaxy ellipticity statistics from the COSMOS Survey, selected alignment measurements based on Sloan Digital Sky Survey samples, and galaxy orientations extracted from the Horizon-AGN hydrodynamic simulation at redshift $z = 1$. The best-fit model has a total of 12 alignment parameters and generally reproduces the calibration data sets well within the 1σ statistical uncertainties of the observations and the Flagship simulation, with notable exceptions for the most luminous subsamples on small physical scales. The statistical power of the calibration data and the volume of the single Flagship realisation are still too small to provide informative prior ranges for intrinsic alignment amplitudes in relevant galaxy samples. Given these uncertainties, we predict that *Euclid* end-of-mission tomographic weak gravitational lensing two-point statistics will end up modified due to intrinsic alignments, by up to 10%.

Key words. galaxies: statistics, large-scale structure of Universe

1. Introduction

The intrinsic alignments (IAs) of galaxy ellipticities constitute a potentially limiting factor in the cosmological interpretation of weak gravitational lensing (WL) by the large-scale structure (Kirk et al. 2015; Krause et al. 2016; Troxel & Ishak 2015). Alongside baryonic feedback on the dark matter distribution (van Daalen et al. 2011; Semboloni et al. 2011), IAs are determined by astrophysical processes in and around galaxies that need to be understood to enable inferences to be made on the cosmological parameters from WL surveys. As opposed to baryonic feedback, however, IA cannot be readily isolated from the cosmological signal by selection on the dataset (e.g. through small-scale cuts).

A model-independent removal of IA is possible by marginalising over the IA model parameters due to its distinctive scaling with the redshifts of the source galaxy samples (e.g. Wright et al. 2025). However, this comes at a significant cost to the cosmological constraining power; for example, reducing the figure of merit of dynamic dark energy constraints by an order of magnitude (Joachimi & Schneider 2009). Self-calibration algorithms, which rely on symmetries of the signal in redshift space, are being explored as an alternative path to IA removal, but are challenging to apply on photometric redshift samples as those used in *Euclid* (e.g. Yao et al. 2020; Chisari 2025).

Therefore, current surveys rely on physically motivated models to account for IA contamination (Asgari et al. 2021; Secco et al. 2022; Dalal et al. 2023). The vast majority of models rely on the assumption that galaxy ellipticities and their orientations are determined by the local tidal field of the surrounding dark matter distribution (Catelan et al. 2001; Hirata & Seljak 2004; Blazek et al. 2019; Vlah et al. 2020; Bakx et al. 2023; see Joachimi et al. 2015 for a review and discussion of alternative mechanisms and Lamman et al. 2024 for a practical introduction). Simple tidal field-based mod-

els have shown some success at explaining the scale and mass dependences of IA signals for certain types of galaxies (Joachimi et al. 2011; Piras et al. 2018; Johnston et al. 2019; Fortuna et al. 2021; Samuroff et al. 2019), but observational constraints remain scarce for the typical galaxy types, masses, and redshift ranges targeted by modern galaxy imaging surveys. Depending on the properties and statistical power of each survey, a careful balance has to be struck between conservative modelling of IA which minimises residual bias on cosmology and including robust prior knowledge on IA to preserve a maximum of cosmological information.

This work is the first of a series in which we explore this balance in the context of the European Space Agency's *Euclid* mission, which features WL as one of its primary cosmological probes (Euclid Collaboration: Mellier et al. 2025)¹. We introduce a semi-analytic model for galaxy ellipticities and alignments for the *Euclid* Flagship Simulation (Euclid Collaboration: Castander et al. 2025, Flagship hereafter). Unlike simple tidal field-based models, this semi-analytic approach utilises the high-resolution matter field as well as detailed galaxy photometry provided in Flagship to attribute IA characteristics to each galaxy in the simulation. It thereby matches multiple IA constraints simultaneously, enabling more physically grounded predictions for *Euclid*-like samples. Using this model, we have been able to build mock datasets for use in companion papers to analyse the range of validity and the performance of analytic IA models. The results of such studies will help inform analysis choices particularly for *Euclid*'s first data release, based on one year of observations.

Our semi-analytic model follows a similar approach to previous work on different simulations (Joachimi et al. 2013a,b; Hoffmann et al. 2022b, H22 hereafter), while advancing beyond

¹www.esa.int/Science_Exploration/Space_Science/Euclid

these in three aspects, as follows. First, we implemented a flexible model for controlling the colour, luminosity, and redshift dependences of the IA signal. Second, the model was calibrated against a selection of multiple constraints from observations, as well as from a hydrodynamic simulation when observational data are not available. Finally, the resulting mock catalogue is unprecedented in its volume and depth, covering one octant of the sky up to a redshift of $z = 3$, and containing 3.4 billion galaxies with magnitudes down to $H_E = 26$. These data ultimately enable the construction of realistic *Euclid*-like galaxy samples.

This paper is organised as follows. In Sect. 2 we introduce the Flagship simulation and relevant data products for IA calibration, followed by details on the galaxy samples used for calibrating the IA model in Sect. 3. Section 4 provides an overview of the summary statistics employed in the calibration process. In Sects. 5 and 6, the modelling of the mock galaxy shapes and orientations are described, respectively. The calibration of the orientations are described in Sect. 7. In Sect. 8 we investigate the statistical uncertainty of the semi-analytic model before computing the expected IA and WL signals for a *Euclid*-like survey in Sect. 9. We summarise our findings and conclusions in Sect. 10.

2. Flagship simulation

2.1. Dark matter simulation

The Flagship simulation is one of the largest cosmological N -body simulations of the Universe produced so far, with $(16\,000)^3$ particles over a simulation box of $3600\,h^{-1}\text{Mpc}$, leading to a mass resolution of $10^9\,h^{-1}M_\odot$. The simulation was run using PKDGRAV3 (Potter et al. 2017) with cosmological parameters similar to those of the *Planck* 2015 cosmology (Planck Collaboration XIII 2016). These are the density parameters of cold dark matter, $\Omega_{\text{CDM}} = 0.270$, of baryons, $\Omega_b = 0.049$, and of dark energy, $\Omega_\Lambda = 0.681 - \Omega_r - \Omega_\nu$, where Ω_r and Ω_ν are the density parameters of radiation and massive neutrinos, respectively (where the neutrino normal mass hierarchy is assumed). The other cosmological parameters are the equation of state parameter of dark energy, $w = -1$, the reduced Hubble constant, $h = 0.67$, the (linear) matter density fluctuation amplitude on scales of $8\,h^{-1}\text{Mpc}$, $\sigma_8 = 0.83$, and the slope of the primordial power spectrum of scalar density fluctuations, $n_s = 0.96$. A light-cone up to $z = 3$ was produced on the fly during the simulation, covering one octant of the sky, around 5157deg^2 , and centred at approximately the North Galactic Pole.

Weak lensing maps All-sky lensing convergence maps were constructed by decomposing and rotating the dark matter light-cone into a set of all-sky concentric spherical shells around the observer. Lensing observables were then derived from the 2D dark matter density maps of the different shells, using the Born approximation (Fosalba et al. 2008, 2015). The shells have a width of $\Delta_r \approx 95.22\text{Myr}$ in lookback time and an angular resolution of $\Delta_\theta \approx 0.43$. Further details on the construction of the lensing maps are given in (Fosalba et al. 2015).

By combining the dark-matter ‘onion shells’ that make up the light-cone, we can easily derive the lensing observables, as explained in Fosalba et al. (2008). This approach, based on approximating the observables by a discrete sum of 2D dark-matter density maps multiplied by the appropriate lensing weights, agrees with the much more complex and CPU time-consuming ray-tracing technique in the Born approximation limit; namely, in the limit where lensing deflections are calculated using unperturbed light paths (see e.g. Hilbert et al.

2020). Following this technique, we can produce all-sky maps of the convergence field (which is simply related to the lensing potential in harmonic space), as well as maps for other lensing fields obtained from covariant derivatives of the lensing potential, such as the deflection angle, shear, flexion, and so on. In particular, using the spherical transform of the lensing potential all-sky map one can obtain the corresponding maps for other lensing observables through simple relations (see Hu 2000). These WL maps allow us to predict the relative contribution of IA to the observed shear statistics.

2.2. Halo detection and halo shape measurement

Dark matter halos and sub-halos were identified in the particle distribution in phase space using ROCKSTAR (Behroozi et al. 2013), which provides positions, velocities, as well as 3D shapes and orientations for each object. The shapes and orientations are defined via the eigenvectors and eigenvalues of the moment of inertia,

$$I_{i,j} = \sum_n^{N_p} \frac{r_{n,i}r_{n,j}}{R_n^2}, \quad (1)$$

where N_p is the number of halo particles and $r_{n,i}$ are the components of the 3D position vector of the n th particle with respect to the halo centre (e.g. Dubinski & Carlberg 1991; Allgood et al. 2006). Then, R_n is a normalisation factor, which is set to $R_n = 1$ in the standard definition of the moment of inertia and to $R_n = (r_{n,1}^2 + r_{n,2}^2 + r_{n,3}^2)^{1/2}$ for the so-called reduced moment of inertia. The lengths of the halo’s principal axes are given by the square root of the eigenvalues λ of $I_{i,j}$ and $(A_{3D}, B_{3D}, C_{3D}) = (\sqrt{\lambda_A}, \sqrt{\lambda_B}, \sqrt{\lambda_C})$, while satisfying $A_{3D} \geq B_{3D} \geq C_{3D}$. The halo shapes are characterised by two of the three axis ratios,

$$q_{3D} \equiv \frac{B_{3D}}{A_{3D}}, \quad r_{3D} \equiv \frac{C_{3D}}{B_{3D}}, \quad s_{3D} \equiv \frac{C_{3D}}{A_{3D}}, \quad (2)$$

while the halo orientations are given by the normalised eigenvectors $\hat{\mathbf{A}}_{3D}$, $\hat{\mathbf{B}}_{3D}$, and $\hat{\mathbf{C}}_{3D}$. In this study, we used halo orientations that were measured via the reduced moment of inertia, as it assigns more weight to the mass distribution in the halo’s centre, where the central galaxies (whose orientations we aim to model) are located. Measurements of galaxy orientations from the stellar particle distribution in the hydrodynamic simulation (described in Sect. 3.4), on the other hand, are based on the standard moment of inertia, as it provides a higher signal-to-noise ratio (Chisari et al. 2015).

Orientations measured from discrete particle distributions are subject to sampling noise, which increases for decreasing numbers of particles. In the galaxy and halo samples used in this work, the average number of particles per object ranges from about 1000 to 18 000, for which we would expect only a moderate randomisation of below 5 degrees (Herle et al. 2025). However, the minimum number of particles per object can be as low as 10, in which case a strong randomisation of the orientation is expected. H22 demonstrated that randomly down-sampling halos to 10 particles reduces the alignment signal by roughly 30 percent, while increasing the particle limit to 100 lowers the impact of noise on the alignment signal to the percent level. For this reason, we did not expect for any noise in the measured orientations to have a dominant effect on the predicted IA statistics.

Table 1. Properties of the mock galaxy samples.

Sample		N_{gal}	$\langle z \rangle$	$\langle M_r \rangle$	$\langle u - r \rangle$	f_{sat}
SDSS	main	495502	0.10	-20.50	1.59	0.35
	blue	198674	0.09	-19.96	1.16	0.25
	red	296828	0.11	-20.87	1.87	0.43
BOSS	main	155290	0.28	-22.06	2.17	0.25
LOWZ	L1	31058	0.29	-22.60	2.08	0.22
	L2	31058	0.28	-22.25	2.11	0.23
	L3	31058	0.28	-22.05	2.15	0.24
	L4	62116	0.26	-21.69	2.26	0.28
HAGN	main	757638	1.00	-20.41	1.76	0.35
	H1	33311	1.00	-22.49	2.41	0.20
	H2	183915	1.00	-21.35	2.08	0.31
	H3	540412	1.00	-19.96	1.62	0.38

Notes. Columns list the number of galaxies N_{gal} , mean redshift $\langle z \rangle$, mean absolute r -band magnitude $\langle M_r \rangle$, mean rest-frame colour $\langle u - r \rangle$, and satellite fraction f_{sat} .

2.3. Galaxy modelling

Based on the dark matter halos, a galaxy catalogue was built using the SciPIC Scientific pipeline at Port d’Informació Científica (Carretero et al. 2017). SciPIC combines the halo occupation distribution technique with halo abundance matching (Carretero et al. 2015; Euclid Collaboration: Castander et al. 2025) to distribute central and satellite galaxy positions in the halos and then assign velocities as well as initial magnitudes and colours. The parameters of the model were calibrated such that the simulation reproduces Sloan Digital Sky Survey (SDSS; York et al. 2000) observations of the luminosity function, the colour-magnitude distribution, and the clustering in redshift space as a function of colour and luminosity (Blanton et al. 2003; Zehavi et al. 2011). In a subsequent step, the spectral energy distributions were derived for each galaxy based on its initial magnitude and colour. From these spectral energy distributions, additional magnitudes can then be derived for any filter, which enables the construction of mock galaxy catalogues of any desired galaxy survey.

3. Mock galaxy catalogues

We constructed mock galaxy catalogues to calibrate the IA simulation against measurements from reference samples. Specifically, we used a mock catalogue of the Cosmic Evolution Survey (COSMOS, Scoville et al. 2007) to adjust the definition of red and blue galaxies, used in the shape component of our IA model and to validate the shape distribution predicted by that model. In addition, we use mock catalogues of the SDSS main sample and the LOWZ sample of the Baryon Oscillation Spectroscopic Survey (BOSS, Reid et al. 2016) for calibrating the galaxy orientation model component at low redshifts. These low-redshift samples are complemented by a mock catalogue of the Horizon-AGN (HAGN) simulation (Dubois et al. 2014; Kaviraj et al. 2017), which we used for the calibration of the orientations at $z = 1$. In Fig. 1 we compare the colour-magnitude-redshift distribution of these different mock catalogues, while the main characteristics of each mock sample used in this work are summarised in Table 1. In the following, we give an overview of how the reference samples are selected and detail the construction of the corresponding mocks.

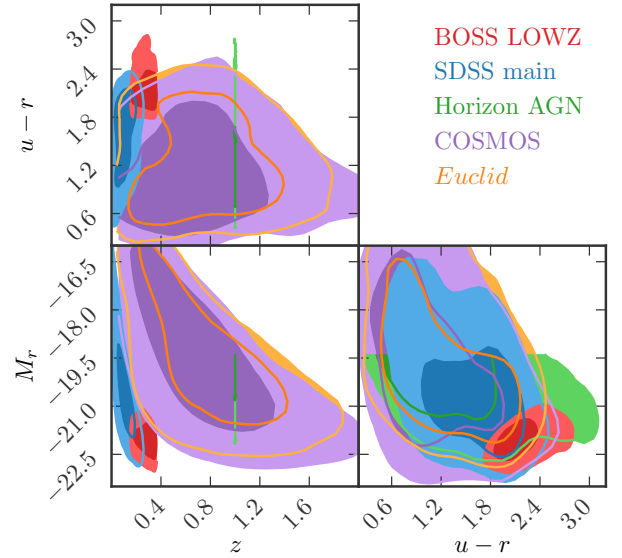


Fig. 1. Redshift, magnitude, and colour distributions of mock samples, used for calibrating the IA model parameters for galaxy misalignment. Contours enclose 68% and 95% of the distributions.

3.1. COSMOS

The COSMOS survey provides space-based imaging from the *Hubble* Space Telescope (HST) together with ground-based photometry in various bands, which allows for highly accurate measurements of galaxy shapes and redshifts. Primarily due to its relatively small area of roughly one square degree, two-point IA statistics have not been measured in COSMOS to date. However, it is large enough to provide constraints on galaxy shape distributions over a wide range of galaxy magnitudes, colours, and redshifts (e.g. Joachimi et al. 2013a). The reference sample of the COSMOS survey used in this work has been composed from the COSMOS2015 catalogue² (Laigle et al. 2016) and the Advanced Camera for Surveys General Catalog (ACS-GC³; Griffith et al. 2012). The COSMOS2015 catalogue provides photometry in 30 bands together with photometric redshift estimates. The ACS-GC catalogue provides measurements of galaxy shapes from imaging in the HST ACS F814W i band, corrected for the effects of the HST point spread function. For our analysis, we selected objects with apparent magnitudes brighter than $i = 24$ to ensure that the redshifts and shape measurements are reliable (Griffith et al. 2012; Laigle et al. 2016). The corresponding mock sample is constructed from Flagship by applying the same cut. Based on this mock, we would expect this matched COSMOS catalogue to overlap almost entirely with the *Euclid* sample in the colour-magnitude-redshift space, as we show in Fig. 1. A more detailed summary of the COSMOS2015 and the ACS-GC catalogues, as well as the procedure for matching these catalogues, can be found in Hoffmann et al. (2022a).

To introduce a colour dependence of galaxy shapes in our model, we assigned a colour type to each object, classifying it as either red or blue. Following H22, we define this colour type by a cut in the $u - r := M_u - M_r$ colour, where M_u and M_r are absolute rest-frame magnitudes in the u -band of the MegaCam instrument on the Canada-France-Hawaii Telescope and the r -band of the Suprime-Cam instrument on the Subaru Telescope, respectively.

²<https://www.eso.org/qi>

³vizier.u-strasbg.fr/viz-bin/VizieR-3?-source=J/ApJS/200/9/acs-gc

We compared the colour distribution in Flagship and COSMOS catalogues in the top panel of Fig. 2, for *Euclid*-like samples of galaxies with $i < 24$ and $z < 2.0$ and found a good agreement between both datasets.

For a more detailed validation of Flagship, we display the joint distribution of the $u - r$ colour and the r -band magnitude in three redshift bins in the central and bottom panels of Fig. 2. We find an overall good agreement between both datasets, with both showing similar trends of increasing brightness and blueness with redshift as well as comparable shapes of the distributions. However, our comparison also reveals a shift of the distribution in Flagship towards fainter magnitudes at all redshifts compared to COSMOS, while the colours in Flagship are slightly bluer in the lowest redshift bin ($0.1 < z < 0.3$) and significantly redder in the highest redshift bin ($1.9 < z < 2.1$).

For the colour type definition in COSMOS, we adopted the cut from H22 at $u - r = 1.2$, which leads to a global fraction of blue galaxies of $f_{\text{blue}} = 0.72$ for galaxies with $i < 24$. We adjusted this cut in Flagship to $u - r = 1.32$, such that f_{blue} has the same value as in COSMOS. In Fig. 2 we show that these simple cuts provide a reasonable separation between the red and blue sequences in colour-magnitude space in COSMOS as well as in Flagship within the redshift range probed by *Euclid*. A more quantitative validation of the colour cut is shown in Fig. 3, where we compare f_{blue} in Flagship and COSMOS in different redshift bins, showing that Flagship replicates the f_{blue} from COSMOS typically to within 10 percent or less.

3.2. SDSS main sample

The SDSS main sample⁴ consists of galaxies with an apparent SDSS r -band magnitude brighter than $r_{\text{lim}} = 17.77$. Spectroscopic redshifts from this sample as well as estimates of the absolute rest-frame magnitudes are publicly available in the New York University Value-Added Galaxy Catalog of the SDSS Data Release 7 (NYU-VAGC; Blanton et al. 2005)⁵, which we use in this work as an observational reference when constructing the mock sample. This catalogue consists of 741 874 galaxies and covers 7966 square degree, which results in a galaxy number density of 93 deg^{-2} .

When constructing the mock SDSS main sample from Flagship, we adjust the limiting magnitude by adding the constant $\Delta r = -0.15$ (i.e. $r_{\text{lim}} + \Delta r$), which is chosen such that the mock catalogue has the same number density as the reference sample for objects with redshifts above $z = 0.15$. Lower redshifts have been excluded for this adjustment to reduce the impact of sampling variance when comparing the number densities.

In the top-right panel of Fig. 4 we compare the differential redshift distributions of the galaxy number density in NYU-VAGC to the Flagship mock sample. We find a reasonable agreement between both datasets for $z > 0.15$ with absolute deviations around 15%. At lower redshifts both distributions appear to be similar but are strongly affected by fluctuations, which we attribute to sampling variance. The top-left panel of Fig. 4 shows a comparison between the differential galaxy number densities in the NYU-VAGC and Flagship as a function of the apparent r -band magnitude for objects above $z = 0.15$. We find the differential number density to be higher in the Flagship than in NYU-VAGC, which explains the necessity of reducing the limiting magnitude to obtain the observed cumulative number density.

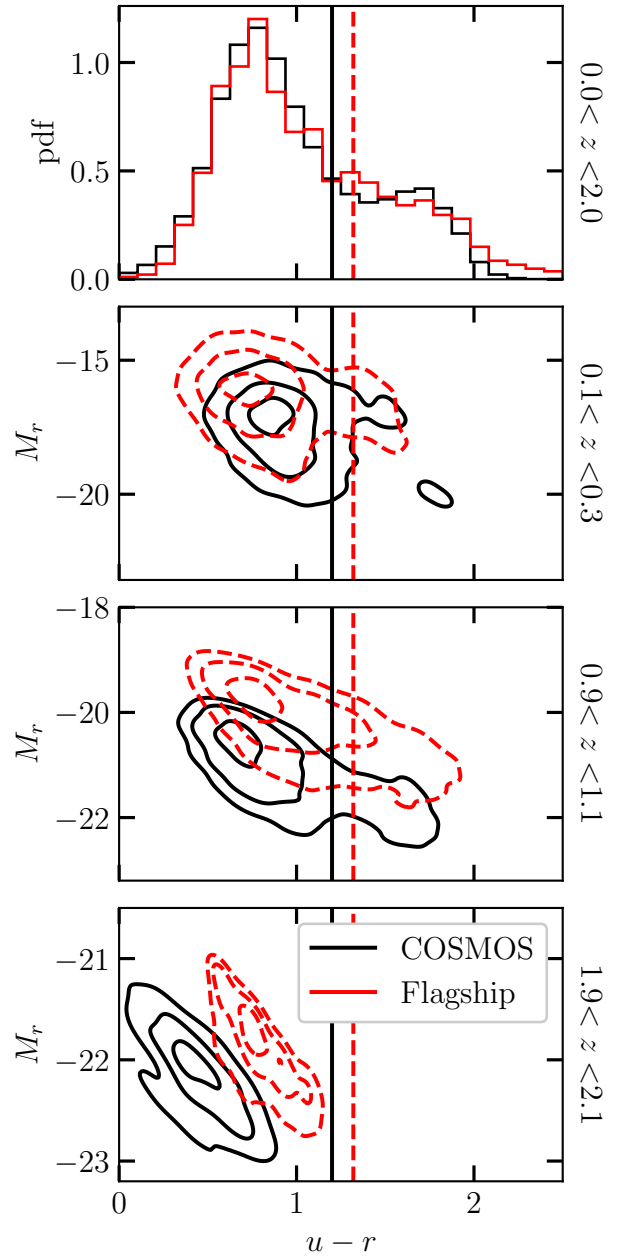


Fig. 2. Top: Distribution of the rest-frame colour $u - r \equiv M_u - M_r$ for galaxies in a *Euclid*-like sample, selected by $i < 24$ from COSMOS (black) and Flagship (red) across the full redshift range covered by *Euclid*. Centre to bottom: Joint distribution of the rest-frame colour and the absolute rest-frame magnitude in the Subaru r band in three redshift bins. Contours enclose the central 10, 40, and 70 percent of the distributions, while solid black and dashed red lines represent results for COSMOS and Flagship, respectively. Vertical lines at $u - r = 1.2$ and $u - r = 1.32$ indicate the colour cuts used to define red and blue subsamples in COSMOS and Flagship, respectively. The cut for Flagship is shifted such that the global fraction of blue galaxies matches that of COSMOS.

To calibrate our IA model against the IA statistics measured in the red and blue subsamples of the SDSS main sample used by Johnston et al. (2019, hereafter J19), we adopted the authors' methodology by splitting our mock SDSS main sample with a cut on the $g - r := M_g - M_r$ rest-frame colour. While J19 applied a cut at $g - r = 0.66$, we again adjust our cut in Flagship to $g - r =$

⁴<https://classic.sdss.org>

⁵<http://sdss.physics.nyu.edu/vagc>

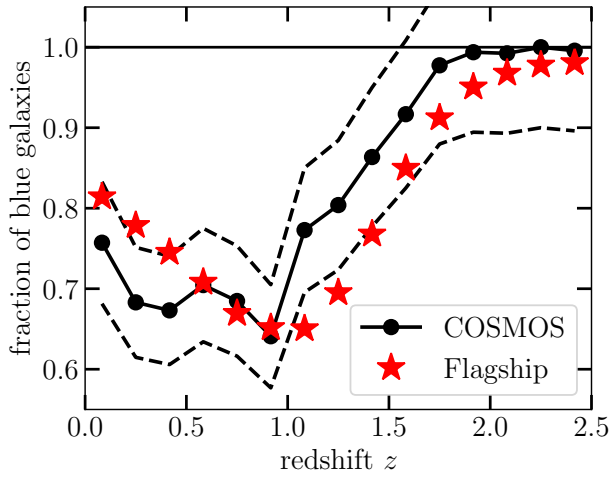


Fig. 3. Fraction of blue galaxies in Flagship and COSMOS, selected by the colour cuts shown in Fig. 2. The dashed lines mark $\pm 10\%$ deviations from the COSMOS data.

0.61 to obtain the same fraction of blue objects of $f_{\text{blue}} = 0.4$ as J19. In Fig. 5 we compare the distribution of the colours in the NYU-VAGC with the Flagship mock, showing that both datasets agree well with each other.

As an additional validation of the Flagship mock selection, we compared the two-point galaxy clustering statistics w_{gg} (described in Sect. 4) with the observational measurements of the red and blue subsamples from J19, as shown in Fig. 7. We find a good agreement between the two datasets, indicating that our mock selection is suitable for calibrating our IA model. We refer to Sect. 4.2 for a detailed discussion of the clustering comparison.

3.3. BOSS LOWZ sample

While the SDSS main sample provides IA constraints over a wide range of absolute magnitudes and colours, it is limited to relatively low redshifts. Therefore, we used direct IA measurements based on the LOWZ sample of the BOSS survey from Singh & Mandelbaum (2016, hereafter SM16), which provide constraints at higher redshifts when calibrating the IA model (see Figs. 1 and 4). The LOWZ sample consists of luminous red galaxies that were selected by multiple cuts in the apparent colour-magnitude space,

$$r < 13.5 + \frac{c_{\parallel}}{0.3} + \Delta r; \quad (3)$$

$$16.0 < r < 19.6 + \Delta r;$$

$$|c_{\perp}| < 0.2,$$

with

$$c_{\parallel} = 0.7(g - r) + 1.2[(r - i) - 0.18]; \quad (4)$$

$$c_{\perp} = (r - i) - (g - r)/4.0 - 0.18.$$

In addition to these cuts, we selected galaxies within the redshift range $0.16 < z < 0.36$ where SM16 performed their analysis. As for the SDSS selection, we introduced a parameter Δr , which is zero in the selection of observed data and is adjusted in the simulation to match the observed galaxy number density. For that adjustment, we used as our reference the LOWZ sample from the BOSS Data Release 12, which covers an area of

8337 deg² (here, we use the effective area from Reid et al. 2016, Table 2). It contains 249 938 galaxies within the SM16 redshift range, which leads to a galaxy number density of 29.98 deg⁻². To achieve the same density in Flagship we set $\Delta r = -0.17$, which led us to the 155 179 galaxies in the mock catalogue in the 5157 deg² octant of the Flagship simulation. In the bottom-right panel of Fig. 4, we compare the differential redshift distributions of the galaxy number density in the LOWZ sample from BOSS and the corresponding Flagship mock sample. We find both data sets to agree reasonably well with absolute deviations around 15% within the SM16 redshift range, given the complexity of the selection cuts and the fact that the galaxy colours and magnitudes in Flagship have not been calibrated against the LOWZ sample.

The bottom-left panel of Fig. 4 shows a comparison between the differential galaxy number densities in BOSS and Flagship as a function of the apparent r -band magnitude for objects within the redshift range analysed by SM16. For apparent magnitudes brighter than $m_r < 18$ we find the differential galaxy number density in Flagship to be slightly below the observational data, while it is significantly higher at dimmer magnitudes. This figure illustrates how reducing the limiting magnitude by Δr allows us to match the observed cumulative number density.

Following SM16, we split the LOWZ samples into four luminosity subsamples that are labelled from bright to faint L1 to L4. The samples were selected by performing cuts in the absolute SDSS r -band magnitude, which are chosen so that each of the L1 to L3 samples contains 20% of all galaxies, while L4 contains the faintest 40%. The distribution of absolute magnitudes is shown for the four subsamples from the Flagship mock in Fig. 6, while the main characteristics of these subsamples are given in Table 1.

To further validate the Flagship mock selection, we compared the two-point galaxy clustering statistics w_{gg} (see Sect. 4) with observational measurements of the luminosity subsamples from SM16, as shown in Fig. 7. We find overall good agreement, although significant deviations appear at small scales for the brightest samples (L1 and L2), which are taken into account when calibrating our IA model. Further details on this clustering comparison are provided in Sect. 4.2.

3.4. Horizon-AGN

The observational samples described in the previous subsections provide IA constraints up to redshifts of $z = 0.36$, which is well below the bulk of redshifts probed by *Euclid* (see Fig. 1). Since observations currently do not provide tight constraints at higher redshifts, we used data from the HAGN (Dubois et al. 2014; Kaviraj et al. 2017) simulation at $z = 1.0$ instead.

HAGN is a hydrodynamic simulation of cosmic structure formation within a $100 h^{-1}$ Mpc cube. It takes into account key processes in the formation of galaxies: cooling, heating, and the chemical enrichment of gas, the formation and evolution of stars and black holes, and feedback from stellar winds, supernovae, and active galactic nuclei as described in Dubois et al. (2014). Galaxies were identified in the simulation as groups of gravitationally bound stellar particles using the AdaptaHOP finder (Aubert et al. 2004).

The HAGN simulation has been used for extensive studies on the IA (Chisari et al. 2015; Codis et al. 2015; Chisari et al. 2016, 2017; Codis et al. 2018; Soussana et al. 2020; Bate et al. 2020). Galaxy shapes and orientations were derived from the standard moment of inertia of the galaxies' stellar particle distribution, analogously to the measurements of halo shapes and orientations

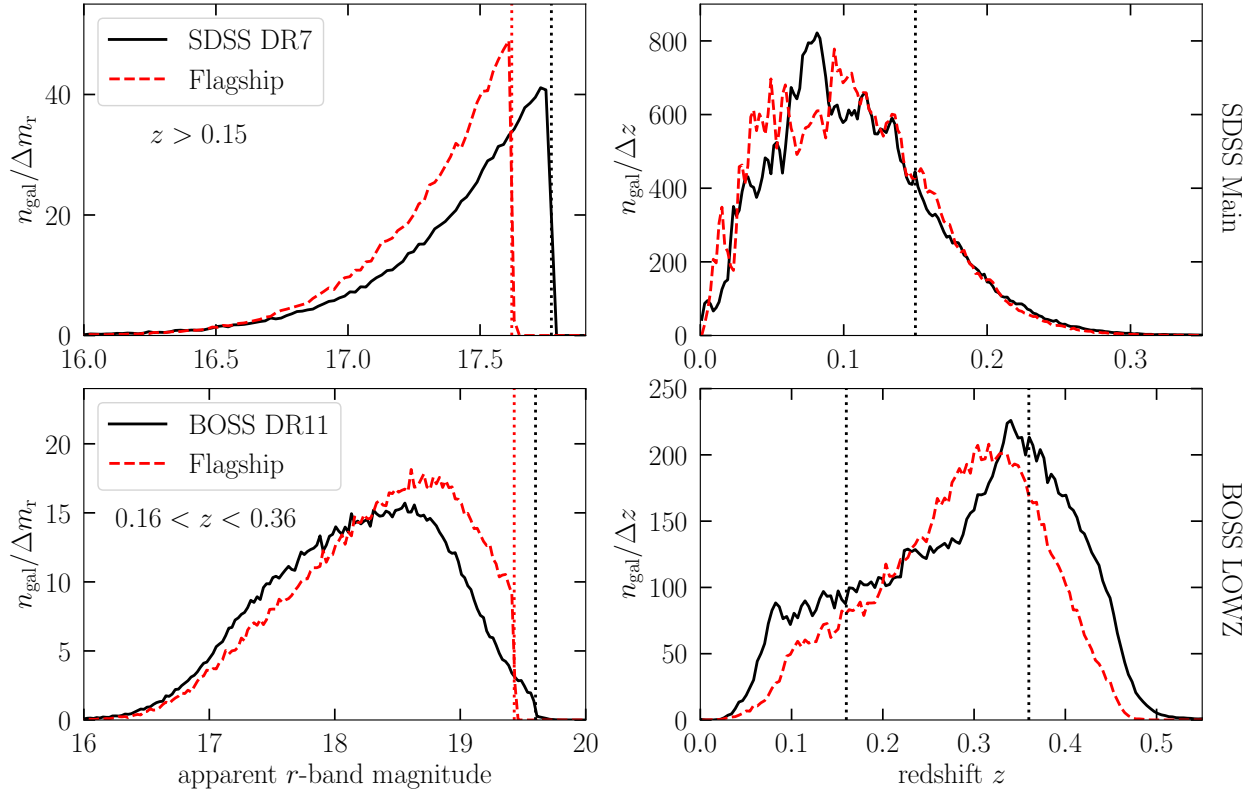


Fig. 4. Distribution of galaxy counts per square degree (n_{gal}) as a function of apparent r -band magnitude (m_r ; left) and redshift (z ; right). Results are normalised by the bin widths Δm_r and Δz to enable comparisons independent of bin size. Top: Results for the SDSS main sample. Bottom: Same but for the BOSS LOWZ sample. Solid black and dashed red lines represent observational data and the Flagship mock samples, respectively. Vertical dotted lines indicate the selection cuts in magnitude (left) and redshift (right) applied in our sample selection. The redshift cuts in Flagship coincide with those used for the observed samples.

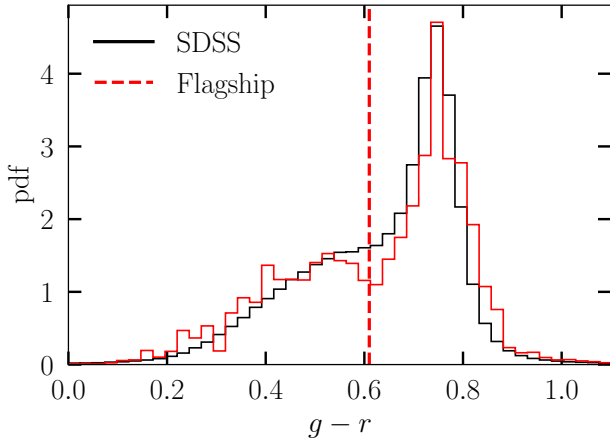


Fig. 5. Distribution of the rest-frame colour $g-r := M_g - M_r$ rest-frame colour in the SDSS main sample and the corresponding Flagship mock catalogue. The vertical red line shows the cut at $u-r = 0.61$ where we split the mock SDSS catalogue into a red and blue subsample. This cut is chosen such that we reproduce the fraction of blue galaxies from J19 of $f_{\text{blue}} = 0.4$.

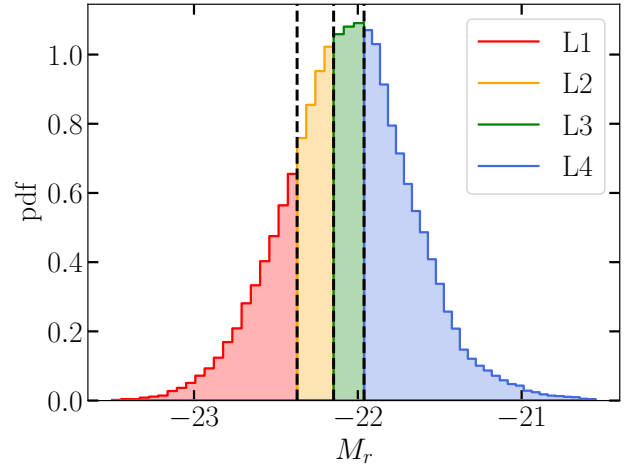


Fig. 6. Distribution of absolute SDSS r -band magnitude of the mock BOSS LOWZ sample constructed from Flagship. Vertical lines indicate the limits of the four luminosity subsamples L1 to L4.

in Flagship from the reduced moment of inertia, as detailed in Sect. 2.

For the calibration of the Flagship IA model against the predictions from HAGN, we select a main reference sample of galaxies from HAGN that consists of objects at $z = 1.0$ with

absolute SDSS r -band magnitudes brighter than $M_r = -20$. We further require stellar particle groups to be reliably detected at the AdaptaHOP tree level equal to 1. This selection leads to a minimum of 621 stellar particles per galaxy. We note that the HAGN simulation output is available at multiple redshifts, which could have been incorporated into the calibration for a more comprehensive coverage of the *Euclid* light-cone. However, due

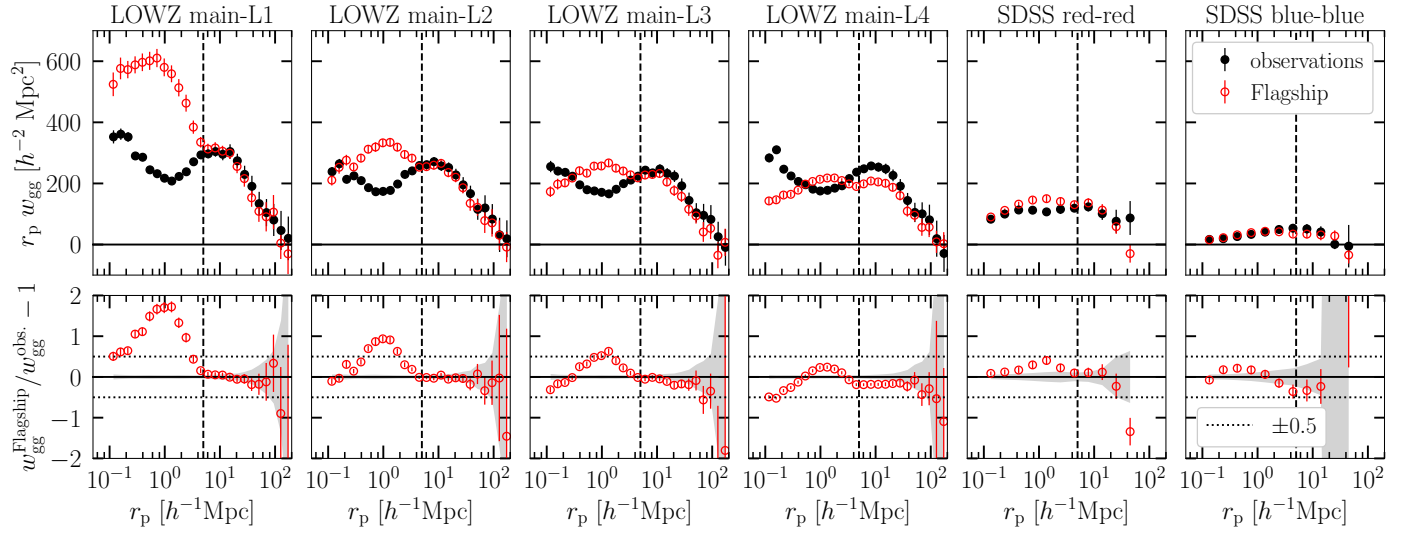


Fig. 7. Top: Projected galaxy-galaxy cross-correlations between different density and shape samples against the projected scale for different observations and corresponding mock samples from the calibrated Flagship simulation (black and red symbols, respectively). Four left panels: Results for the BOSS LOWZ sample. The density sample is the LOWZ main sample, while the shape samples are the magnitude-selected subsamples L1 to L4 (from bright to faint). The two right panels show results for SDSS, where both, density and shape samples are red and blue subsamples. Error bars indicate jackknife estimates of the standard deviation. Bottom: Relative deviations of the Flagship results from the observations. Grey areas show the standard deviation of the observational data. Dotted lines mark 50% deviations. The vertical dashed lines in the top and bottom panels at $5 h^{-1}$ Mpc indicate the approximate scale below (above) which we expect the alignment signal to be dominated by the alignment of satellites (centrals).

to the limited resources available for this work, we focus on the output at $z = 1.0$, as it is the redshift closest to the mean redshift of our mock *Euclid* sample when selecting objects at redshifts higher than those probed by the observational reference samples ($z > 0.36$).

We constructed a mock HAGN sample from Flagship by first selecting galaxies in a thin shell of the light cone around $z = 1.0$ with the width of $\Delta z = 0.02$. The comoving volume of this shell is 33 times larger than the volume covered by HAGN, leading to significantly smaller errors on the IA statistics measured in Flagship compared to HAGN. Galaxies in the Flagship redshift shell are required to be brighter than the absolute SDSS r -band magnitude $M_r = -20 + \Delta M_r$. Here, we have introduced the constant $\Delta M_r = 0.7$ which we adjust to match the comoving galaxy number density of the HAGN main reference sample of $0.023 h^3 \text{ Mpc}^{-3}$, analogously to the adjustment of the sample selections of the mock observational samples.

In Fig. 8 we compare the luminosity functions of HAGN and Flagship at $z = 1$ to each other as functions of M_r . At magnitudes brighter than $M_r = -22$, we find a similar decrease of the luminosity functions with magnitude for both simulations. At fainter magnitudes the luminosity function in HAGN is significantly higher than in Flagship, which explains why the limiting magnitude had to be set fainter in Flagship to reproduce the cumulative number density of HAGN. Please note here that Flagship as well as HAGN have been calibrated against luminosity functions at low redshifts, while the high-redshift luminosity functions are predictions which may differ due to the fundamental differences in the methods used in these simulations.

To probe the luminosity dependence of the IA signal in HAGN, we split the main sample into three luminosity subsamples at $M_r = -21$ and -22 , as illustrated in Fig. 8. The resulting samples, labelled H1 (bright) through H3 (faint) contain 4.4%, 24.3%, and 71.3% of the galaxies, respectively. The corresponding selection cuts in Flagship are adjusted to $M_r = -20.8$ and

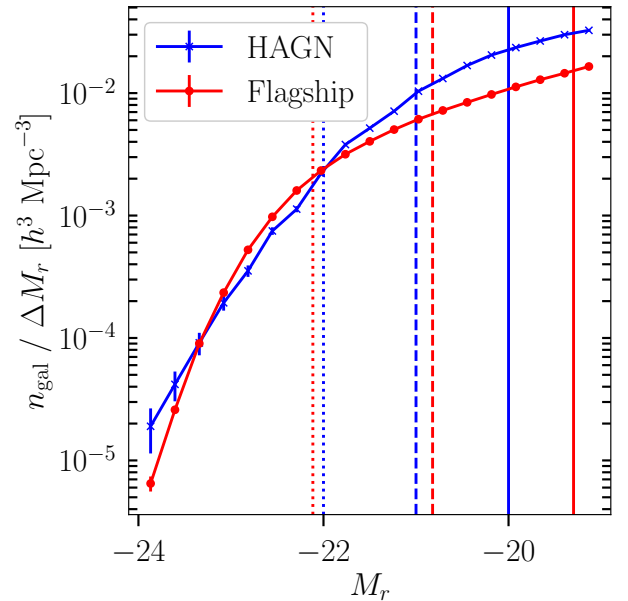


Fig. 8. Comoving galaxy number density, n_{gal} , as a function of absolute r -band magnitude (M_r). Values are normalised by the bin width ΔM_r to remove bin-size dependence. Results are shown at redshift $z = 1.0$ for Flagship and HAGN (red and blue lines, respectively). Error bars enclose the central 68% of a Poisson distribution. Blue vertical lines at $M_r = [-20, -21, -22]$ denote the lower limits of HAGN subsamples H1 to H3, used as high-redshift references for IA model calibration. The corresponding limits in Flagship (red vertical lines) are adjusted to $M_r \in [-19.3, -20.8, -22.1]$ to match the number densities in HAGN.

-22.1 to obtain the same fractions of galaxies per subsample. The main characteristics of the mock HAGN samples are summarised in Table 1.

4. Clustering and IA statistics

For the calibration of the Flagship IA model, we quantify the IA signal using two types of two-point statistics. First, we use the projected two-point correlation function w_{g+} to compare the IA signal predicted by the Flagship mock with direct measurements from observational data. For the calibration based on the HAGN simulation, we compute the two-point correlation of 3D galaxy orientations, η , and compare these directly to the corresponding measurements in HAGN.

4.1. Projected correlation functions w_{gg} and w_{g+}

We measure the projected galaxy-ellipticity correlation to calibrate the IA model against observational constraints derived from the BOSS LOWZ sample by SM16 and the SDSS main sample by J19. In addition, we measure projected galaxy-galaxy correlations to validate the galaxy clustering in the mock samples constructed from Flagship that are used for the calibration. When measuring these correlations we follow SM16 and J19 by studying the cross-correlation between a shape sample S, consisting of the galaxies whose IA signal we want to measure and a density sample D, which is used as a tracer for the underlying matter distribution.

The galaxy-galaxy cross-correlation function between two samples is defined as $\xi_{gg}(r_p, \Pi) := \langle \delta_g^S \delta_g^D \rangle(r_p, \Pi)$, where δ_g^S and δ_g^D are the galaxy density contrasts of the shape and density samples, respectively, and $\langle \dots \rangle$ indicates an ensemble average. Measurements are done in bins centred on a transverse comoving separation, r_p , and a line-of-sight comoving separation, Π . We measure this correlation from the data using the estimator from [Landy & Szalay \(1993\)](#),

$$\hat{\xi}_{gg}(r_p, \Pi) = \frac{SD - DR_S - R_D S + R_D R_S}{R_S R_D}. \quad (5)$$

Each term in the numerator and denominator on the right-hand side of this equation stands for the counts of galaxy pairs in bins separated by r_p and Π . The symbols R_S and R_D denote samples of randomly distributed points that are constructed to follow the redshift distributions and sky footprints of the S and D samples, respectively.

Analogously to the galaxy-galaxy correlation one can define the galaxy-ellipticity correlation function as $\xi_{g+,x}(r_p, \Pi) = \langle \delta_g^D \epsilon_{+,x} \rangle(r_p, \Pi)$. The ellipticity is defined for each position-ellipticity galaxy pair in the average $\langle \dots \rangle$ such that the orientation is the angle between the galaxies' major axis and the separation vector on the sky. An estimator for this correlation function can be defined as ([Mandelbaum et al. 2006](#))

$$\hat{\xi}_{g+,x}(r_p, \Pi) = \frac{S_{+,x}D - S_{+,x}R_D}{R_S R_D}, \quad (6)$$

with

$$S_{+,x}X = \sum_{i,j} \epsilon_{+,x}(i|j), \quad (7)$$

where $\epsilon_{+,x}(i|j) = \Re [\epsilon \exp(-2i\phi_{ij})]$ is the (+)-component of the ellipticity of a galaxy i in sample S, defined with respect to the separation vector pointing to position j in sample X. ϕ_{ij} is the position angle of this separation vector at the position i and X refers to either D or R_D . The (x)-component is defined analogously using the imaginary part of the expression above. Since ξ_{gx} changes sign under parity transformation, it does not contain

a physical signal, and we therefore do not consider it further in this study.

For the measurements in the mock BOSS LOWZ samples we follow SM16 by using 25 logarithmic bins in the interval $0.1 < |r_p|/(h^{-1} \text{ Mpc}) < 200$ and 20 linear bins in the range $|\Pi| < \Pi_{\max}$. Similarly, for the measurements in the mock SDSS main samples we follow J19 by using 11 logarithmic bins in the interval $0.1 < |r_p|/(h^{-1} \text{ Mpc}) < 60$ and 30 linear bins within $|\Pi| < \Pi_{\max}$. In both cases $\Pi_{\max} = 60 h^{-1} \text{ Mpc}$ was chosen. The projected correlation is then given by

$$w_{gx}(r_p) = \int_{-\Pi_{\max}}^{\Pi_{\max}} \xi_{gx}(r_p, \Pi) d\Pi, \quad (8)$$

where w_{gx} stands for w_{gg} or w_{g+} . In the measurement the integral above is approximated by a Riemann sum over the line-of-sight bins.

Errors on the measurements of w_{gg} and w_{g+} are estimated using jackknife resampling. The Flagship octant is therefore split into $N_{JK} = 88$ Healpix regions. The covariance is then estimated as

$$C_{ij}^{JK} = (N_{JK} - 1) \langle \Delta_i \Delta_j \rangle, \quad (9)$$

with $\Delta_i = w_i^{JK} - w_i$, where w_i is the projected correlation measured in the r_p bin i on the full sky area, w_i^{JK} is the same measurement, but dropping one jackknife sub-region at a time and $\langle \dots \rangle$ is the average over the N_{JK} measurements of Δ_j . Further details on the jackknife sampling, the construction of random catalogues and the code for performing the measurements are given in H22.

4.2. Galaxy clustering: Flagship versus observations

In Fig. 7 we compare the measurements of w_{gg} in the SDSS main and BOSS LOWZ samples, derived from observed data by J19 and SM16, respectively, to the corresponding measurements from Flagship as an additional validation of the mock samples described in Sect. 3. In the case of LOWZ, w_{gg} refers to the cross-correlations between the full LOWZ sample and the four luminosity subsamples, while for SDSS w_{gg} is the auto-correlation of the red and blue subsamples, respectively.

We find the deviations between Flagship and observations at scales above $5 h^{-1} \text{ Mpc}$ to be consistent with the 1σ jackknife errors. However, at smaller scales we find significant deviations, which are highest at roughly $1 h^{-1} \text{ Mpc}$ and increase with the brightness of the sample, reaching almost 200% for the LOWZ-L1 sample. It is interesting to note here that H22 did a similar comparison between w_{gg} in the LOWZ subsample and measurements from the MICE simulation ([Fosalba et al. 2015](#)), which is based on a similar combined HOD and abundance matching model as Flagship. This comparison revealed smaller deviations below 60%, indicating that the stronger deviations which we find in Flagship result from the choice of model parameters for the galaxy population, rather than from the simulation method itself. It is important to note here that the HOD–abundance matching model in Flagship was calibrated against the SDSS main sample, but not the LOWZ sample.

4.3. 3D correlation function of orientation vectors, η

When comparing the IA signal in Flagship with the HAGN simulation, we can take advantage of the fact that we have access to the 3D galaxy positions and orientations in both simulations. This allows us to measure the 3D alignment without losing

information due to projections, as in the analysis of observational samples. In addition, we can define the statistics to depend solely on galaxy orientations but not on the shapes. We expect the shapes of galaxies in HAGN to be, on average, rounder than those found in observations, due to an absence of thin disks, which results from resolution effects in the simulation (see Hoffmann et al. 2022a and references therein). This deficiency of disks may bias correlations of intrinsic ellipticity components, such as w_{g+} , when considering samples that include galaxies of all morphological types, as is the case in the present work. We measure the IA signal in HAGN independently of galaxy shapes as the two-point alignment statistics of galaxy orientation with their surrounding large-scale structure in three dimensions, as

$$\eta_X(r) = \langle |\hat{\mathbf{X}}_1 \cdot \hat{\mathbf{r}}_{12}| \rangle(r) - 1/2, \quad (10)$$

where $\hat{\mathbf{X}}_1$ refers to the normalised 3D major or minor axis vectors ($\hat{\mathbf{A}}_{3D}$ or $\hat{\mathbf{C}}_{3D}$, respectively, as defined in Sect. 2) of a galaxy at position 1, $\hat{\mathbf{r}}_{12}$ is the normalised distance vector that points to a galaxy at position 2, and $\langle \dots \rangle$ is the average over all galaxy pairs that are separated by the distance $r = |\mathbf{r}_{12}|$. The subtraction of 1/2 leads to $\eta_X(r) = 0$ if the alignment between $\hat{\mathbf{X}}_1$ and $\mathbf{r}_{12}$ is random⁶. Errors are estimated by jackknife resampling, using 88 Healpix regions for measurements in the Flagship light-cone and 64 cubical regions in HAGN. In the process the jackknife regions are used to organise the galaxy catalogue in a simple tree structure, which allowed for a significant acceleration of the search for galaxy pairs. As in the computation of w_{g+} we increase the signal-to-noise by computing the cross-correlation between the positions of galaxies in a density sample and the orientations of galaxies in magnitude-limited subsamples. The construction of these samples is described in Sect. 3.4. The code used for the measurements in the Flagship light-cone and the HAGN simulation box (including error estimation) is publicly available⁷. A potential concern for IA constraints from adaptive mesh refinement simulations such as HAGN is a systematic effect arising from the alignment between galaxy shapes and the axes of the Cartesian simulation grid, commonly referred to as grid locking. We do not expect the η_X statistic to be affected by this effect, based on the results of Chisari et al. (2015), who showed that grid locking has no significant impact on position–orientation correlations in HAGN.

5. Modelling galaxy shapes

Modelling the intrinsic 3D galaxy shapes is the first out of the two main steps in our IA model. Together with the intrinsic 3D galaxy orientations, which are discussed in Sect. 6, the 3D shapes allowed us to derive the 2D intrinsic galaxy shear components by projecting along the observer’s line of sight.

We modelled the 3D shapes following the methodology from H22, which takes into account observed dependences of galaxy shapes on redshift, magnitude, and colour. In that model, galaxies are approximated as 3D ellipsoids, whose shape is fully characterised by the axis ratios q_{3D} and r_{3D} , which we have defined in Eq. (2). At a fixed point in redshift-magnitude-colour space,

⁶In the literature, the 3D alignment statistic is commonly quantified as $\langle (\hat{\mathbf{X}}_1 \cdot \hat{\mathbf{r}}_{12})^2 \rangle(r) - 1/3$. Here, we instead adopt Eq. (10), as we find it more intuitive: for a random distribution, $|\hat{\mathbf{X}}_1 \cdot \hat{\mathbf{r}}_{12}|$ is uniformly distributed between 0 and 1 with an average value of 1/2. Both definitions are valid measures of 3D alignment and convey essentially the same information.

⁷<https://github.com/kaidhoffmann/covo>

the 3D axis ratio distribution is described by a Gaussian model,

$$\tilde{P}(q_{3D}, r_{3D}) = \exp \left\{ -\frac{1}{2} \left[\left(\frac{q_{3D} - q_0}{\sigma_{qr}} \right)^2 + \left(\frac{r_{3D} - r_0}{\sigma_{qr}} \right)^2 \right] \right\}, \quad (11)$$

where q_0 , r_0 , and σ_{qr} are free model parameters. The distribution is truncated as

$$P = \begin{cases} \tilde{P}_{3D}/N & \text{if } q_{3D}, r_{3D} \in (0, 1]; \\ 0 & \text{else,} \end{cases} \quad (12)$$

with

$$N = \int_0^1 \int_0^1 \tilde{P}_{3D}(q_{3D}, r_{3D}) \, dr_{3D} \, dq_{3D} \quad (13)$$

to ensure $A_{3D} \geq B_{3D} \geq C_{3D}$. This model is motivated by results from Hoffmann et al. (2022a), who showed that the distribution of q_{3D} and r_{3D} of disk galaxies in HAGN and IllustrisTNG (Pillepich et al. 2018) can be well approximated by a truncated diagonal Gaussian distribution⁸. H22 simplified this Gaussian model by assuming identical dispersion parameters σ_{qr} for q_{3D} and r_{3D} . This simplification was motivated by their finding that such an approach allows for more robust parameter estimations to me made from small, noisy samples, thereby facilitating the model calibration described below. Furthermore, H22 demonstrated that this model is sufficiently accurate for reproducing the observed 2D axis ratio distributions from COSMOS which included galaxies of all types.

The 3D shape of a given galaxy in the simulation can now be obtained from Eq. (12) by randomly drawing the axis ratios q_{3D} and r_{3D} from P . To introduce a dependence of galaxy shapes on galaxy properties, an additional modelling step is necessary. For that purpose, we modify the axis ratio distribution parameters based on each galaxy’s redshift, magnitude, and colour. This parameter dependence has been calibrated at distinct points in redshift-colour-magnitude space, such that the distribution of projected 2D axis ratios for an ensemble of randomly oriented ellipsoids matches the observed distribution from the COSMOS catalogue, described in Sect. 3.1. The parameters for a specific galaxy in the simulation are then obtained by interpolation between the points where the model was calibrated. Further details on the method, the motivation and the calibration of the galaxy shape model are given in H22.

The simulated galaxy shapes are publicly available as part of the Euclid Flagship Catalogue on CosmoHub⁹ (Tallada et al. 2020). The code used to generate these simulations is available on GitHub¹⁰.

In Fig. 9 we compare shape distributions of the projected 2D axis ratios in Flagship with the COSMOS reference data for a set of ten volume-limited samples of the red and blue galaxies, covering absolute magnitudes in the range of $-19.5 < M_r < -23.0$ and redshifts in the range of $0.2 < z < 1.5$ as detailed in Sect. 3.1. We find an overall good agreement between Flagship and COSMOS in all samples, demonstrating that the simulated 2D galaxy shape distribution follows the observed colour-magnitude-redshift dependence.

⁸Note: a diagonal Gaussian distribution may not be a suitable approximation for other combinations of shape parameters. For instance, the joint distribution of q_{3D} and s_{3D} must satisfy the constraint $s_{3D} \lesssim q_{3D}$, which is not captured by a diagonal Gaussian distribution.

⁹<https://cosmohub.pic.es>

¹⁰<https://github.com/kaidhoffmann/genIAL>

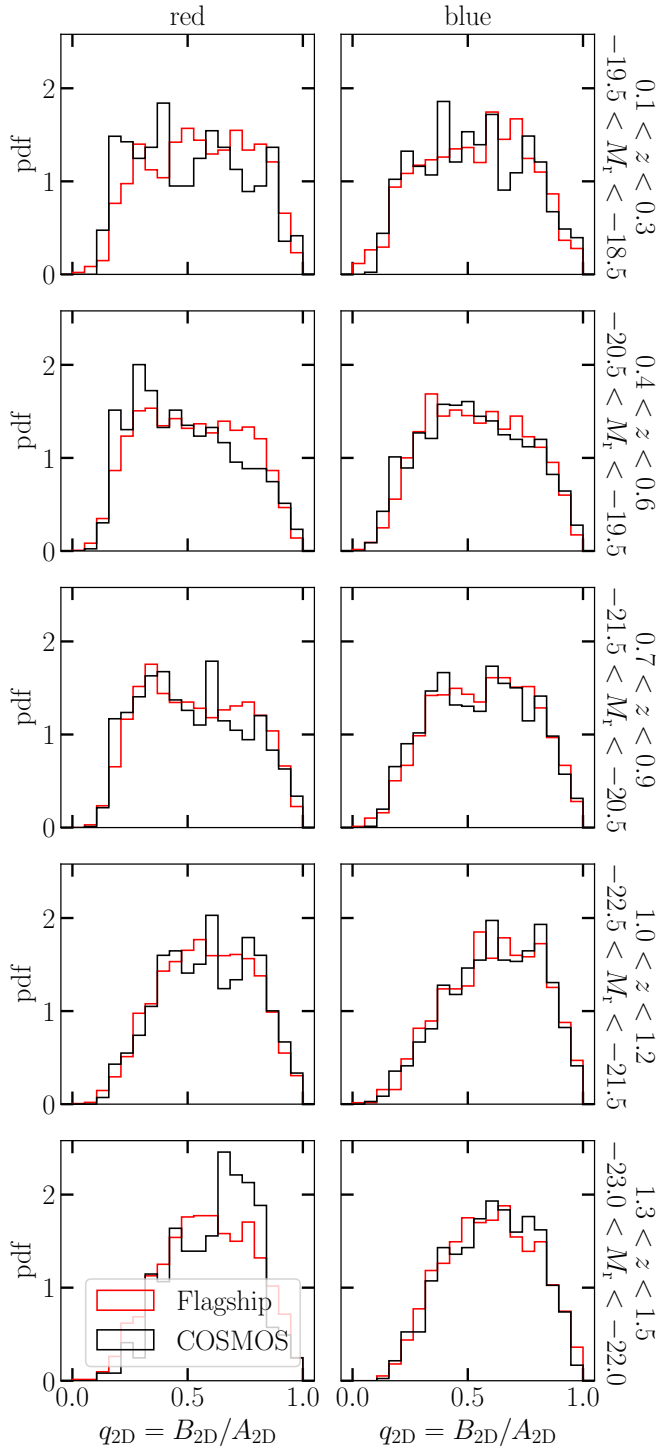


Fig. 9. 2D galaxy axis ratios measured for red and blue galaxies in different volume-limited samples. The redshift and absolute Subaru r -band limits of each sample are indicated on the right. Red and black histograms show results from the Flagship simulation and COSMOS observations, respectively.

6. Modelling galaxy orientations

We modelled the galaxy 3D orientations in two steps. In the first step, we set the initial orientations, which were then randomised in a second step, where the IA statistics in the simulations matched the reference measurements.

6.1. Initial orientations

The initial orientations were set separately for the central and satellite galaxies. We used two distinct methods for each type.

Centrals: All central galaxies are initially oriented by aligning their principle axes with those of their host dark matter halos, namely, $(\hat{\mathbf{A}}, \hat{\mathbf{B}}, \hat{\mathbf{C}})_{\text{gal}} = (\hat{\mathbf{A}}, \hat{\mathbf{B}}, \hat{\mathbf{C}})_{\text{halo}}$. This part of the modelling deviates from previous semi-analytic alignment models (e.g. J13, H22). In these models, only red central galaxies were aligned with the principle axes of their host halos, while blue centrals were assumed to be disks, whose minor axis is initially aligned with their host halo's angular momentum vector. We simplified this mixed modelling for red and blue galaxies for three reasons:

(1) A colour-dependent modelling of the orientations relies on a colour-based classification of galaxies into disks and ellipticals. Such a classification is known to be inaccurate, in particular when using a simple colour cut. For instance, disks can be red when being oriented edge-on to the observer due to dust extinction or when having a large central bulge (see e.g. the discussion in Xiao et al. 2012; Lackner & Gunn 2012; Hoffmann et al. 2022a; Uzeirbegovic et al. 2022). The mixed modelling further neglects the significant fraction of galaxies with irregular morphologies (e.g. Conselice et al. 2005; Huertas-Company et al. 2016). For these reasons, it is not obvious that the mixed model is more accurate than the simpler modelling procedure used in this work, which is described below.

(2) The minor axis direction of a dark matter halo correlates with the direction of its angular momentum (Bailin & Steinmetz 2005; Bett et al. 2007). In our model, this alignment will be weaker compared to the mixed alignment models, where it is set explicitly. However, since we randomised the galaxy orientations in the second step of our modelling, taking galaxy colour into account, we would expect the final alignment signal for blue galaxies to be similar to that obtained with the mixed modelling approach.

(3) A consistent description of all galaxies reduces the total number of parameters needed for introducing a redshift, magnitude, and colour dependence of the galaxy-halo misalignment.

Satellites: All satellite galaxies are initially oriented by pointing their major axis towards their host halo's centre, which is motivated by findings in hydrodynamic simulations (Pereira et al. 2008; Pereira & Bryan 2010; Welker et al. 2017) and observations (Johnston et al. 2019; Georgiou et al. 2019), as well as the success of this modelling approach in reproducing the observed alignment statistics at small scales (Fortuna et al. 2021, H22).

We note that this model component could be advanced by aligning satellites with their sub-halos or by introducing a radial dependence to the alignment model (Georgiou et al. 2019). However, in a comparison of these advanced models with the simpler radial alignment model used in this work, Van Alfen et al. (2024) found that the latter is sufficient for reproducing second-order IA statistics as measured in IllustrisTNG.

6.2. Random misalignment

It has been shown in the literature that semi-analytic IA models, which assume perfect alignment between galaxies and their host halos, predict IA statistics that are significantly higher than those

observed in the data (Heymans et al. 2004). This discrepancy can be removed by introducing a random misalignment between galaxies and their host dark matter halos (e.g. Heymans et al. 2006; Okumura et al. 2009), which is also predicted by hydrodynamic simulations (e.g. van den Bosch et al. 2002).

To randomise the 3D major and minor axes ($\hat{\mathbf{A}}_{3D}$ and $\hat{\mathbf{C}}_{3D}$, respectively), we followed the approach of H22 by first drawing two misalignment angles θ_A and θ_C from the von Mises–Fisher distribution (Fisher et al. 1993),

$$P(\cos \theta) = \frac{1}{2\sigma_{MF}^2 \sinh(\sigma_{MF}^{-2})} \exp\left(\frac{\cos \theta}{\sigma_{MF}^2}\right), \quad (14)$$

for each galaxy. The randomised principle axis vectors $\hat{\mathbf{A}}_{3D}^r$ and $\hat{\mathbf{C}}_{3D}^{r'}$ are then constructed such that $\hat{\mathbf{A}}_{3D} \cdot \hat{\mathbf{A}}_{3D}^r = \cos(\theta_A)$ and $\hat{\mathbf{C}}_{3D} \cdot \hat{\mathbf{C}}_{3D}^{r'} = \cos(\theta_C)$. Here $\hat{\mathbf{C}}_{3D}^{r'}$ is a temporary vector which is in general not perpendicular to $\hat{\mathbf{A}}_{3D}^r$ since θ_A and θ_C are drawn independently from each other. The final randomised minor axis orientation is therefore obtained as $\mathbf{C}_{3D}^r = (\hat{\mathbf{A}}_{3D}^r \times \hat{\mathbf{C}}_{3D}^{r'}) \times \hat{\mathbf{A}}_{3D}^r$ and is then normalised to $\hat{\mathbf{C}}_{3D}^r = \mathbf{C}_{3D}^r / |\mathbf{C}_{3D}^r|$.

We adopted the von Mises–Fisher distribution, since it was successfully employed by H22 to reproduce the observed IA signal from BOSS LOWZ data using a semi-analytical IA model similar to the one adopted in this work. Bett (2012) showed that this distribution provides a good fit to the misalignment angles between halo and galaxy angular momentum vectors in simulated haloes including baryons and galaxy formation physics. However, a direct validation of the von Mises–Fisher distribution against misalignment angles between the principal axes of central galaxies and haloes, as well as between the major axes of satellites and the halo-centre direction, remains to be done. Velliscig et al. (2015) analysed such distributions in the EAGLE and cosmo-OWLS simulations and proposed an alternative fitting model. While its functional form is similar to the von Mises–Fisher distribution, it requires four free parameters, which would make the parameter calibration in our work substantially more challenging. A further single-parameter alternative to the von Mises–Fisher distribution is the Dimroth–Watson distribution. Van Alfen et al. (2024) demonstrated that a semi-analytical IA model based on this distribution successfully reproduced IA statistics of galaxies in the IllustrisTNG hydrodynamic simulation.

The width of the distribution σ_{MF} is a free parameter that provides control over the alignment amplitude. Increasing (decreasing) σ_{MF} leads to a higher (lower) randomisation of the initial orientations and hence to a lower (higher) IA signal in the simulation. We can hence control the dependence of the predicted IA signal on galaxy properties by introducing a dependence of σ_{MF} on galaxy redshift z , absolute rest-frame magnitude M_r and rest-frame colour index $u - r$ (defined in Sect. 3),

$$\sigma_{MF} = p_0 \underbrace{\left(\frac{z}{z_0} + 1\right)^{p_1}}_{\sigma_z(p_1)} \underbrace{\left(\frac{M_r}{M_0} + p_2\right)^{p_3}}_{\sigma_{\text{mag}}(p_2, p_3)} \underbrace{\left(\frac{u-r}{(u-r)_0} + p_4\right)^{p_5}}_{\sigma_{\text{col}}(p_4, p_5)}. \quad (15)$$

The constants $M_0 = -22$, $(u-r)_0 = 1$ and $z_0 = 1$ are chosen to avoid large values of the bases of the σ_z , σ_{mag} and, σ_{col} terms¹¹. We chose the functional form of these terms to allow for a large range of dependences of the alignment signal on galaxy

properties, while avoiding negative values for σ_{MF} , as can arise for instance when extrapolating linear relations. In addition to the dependence on galaxy properties, we added a dependence on galaxy type (which could be either a central or satellite) by using a separate set of the parameters p_i for each type.

As a result, we obtained two von Mises–Fisher distributions in our model, $\sigma_{MF}^{\text{cent}}$ and σ_{MF}^{sat} , with a total number of 12 free parameters. By introducing a type dependence to the model, we gained control over the scale dependence of the final IA signal in the simulation (see Sect. 6.3). Another motivation for using two separate sets of misalignment parameters for centrals and satellites is that the initial orientations were set with different methods. Using a type-independent misalignment would therefore be an inconsistency in the model. The final form of Eq. (15) is a result of a development process, in which we gradually added complexity to the model until we were able to match the different constraints simultaneously with the simulation. This matching is achieved by calibrating the parameters p_i as described in Sect. 7.

6.3. Response of IA statistics to galaxy misalignment

In preparation for the calibration of the σ_{MF} parameters from Eq. (15), we studied our IA model in a simplified setting, fixing $\sigma_{MF}^{\text{cent}}$ and σ_{MF}^{sat} to constant values that are independent of galaxy redshift, magnitude, and colour.

In Fig. 10 we show w_{g+} versus the scale r_p for the LOWZ and SDSS subsamples, comparing the measurements in the observed reference samples with those from the Flagship mock samples for three cases of fixed $\sigma_{MF}^{\text{cent}}$ and σ_{MF}^{sat} values.

In the first case, we applied a minimal misalignment to both, centrals and satellites by setting $\sigma_{MF}^{\text{cent}} = \sigma_{MF}^{\text{sat}} = 0.05$ (red lines in Fig. 10). The resulting amplitudes are roughly between 2 and 20 times higher than those of the reference samples, depending on the sample and the scale. Besides these strong differences, we also find a similarity between the simulation and the reference samples in that the amplitudes increase the brighter and the redder the samples are. This finding might result from the similar magnitude and colour dependence of the galaxy clustering in the observations and the simulation (see Fig. 7).

In the second case of our simplified model, we kept the low misalignment for centrals in Flagship, while increasing the misalignment for satellites by setting $\sigma_{MF}^{\text{cent}} = 0.05$, $\sigma_{MF}^{\text{sat}} = 0.75$ (green lines in Fig. 10). We find that the amplitudes strongly decrease at small scales ($r_p \lesssim 5 h^{-1}$ Mpc), while we see no significant change at large scales in the LOWZ subsamples and a relatively weak decrease for the SDSS subsamples.

In the third case, we kept the low misalignment for satellites, while increasing the misalignment for centrals, setting $\sigma_{MF}^{\text{cent}} = 0.75$, $\sigma_{MF}^{\text{sat}} = 0.05$ (blue lines in Fig. 10). We now find a strong decrease of the amplitudes at large scales ($r_p \gtrsim 5 h^{-1}$ Mpc) compared to the first case and only mild or no significant changes at small scales compared to the first case, depending on the sample. These trends persist across a range of satellite fractions in the galaxy samples (see Table 1).

We extend this investigation in Fig. 11, where we compare the 3D alignment statistics η_A and η_C , measured in the three magnitude-limited samples H1 to H3 from HAGN (from bright to faint, as defined in Sect. 3) with the corresponding measurements derived from the mock HAGN samples from Flagship. The Flagship results are shown for the same three $\sigma_{MF}^{\text{cent}}$, σ_{MF}^{sat} combinations discussed above.

For the measurements in HAGN we find the behaviour expected from results in the literature (Chisari et al. 2015). In particular, η_A (η_C) have positive (negative) amplitudes, indicat-

¹¹The M_0 value in particular was motivated by the literature (Joachimi et al. 2011; Singh et al. 2015).

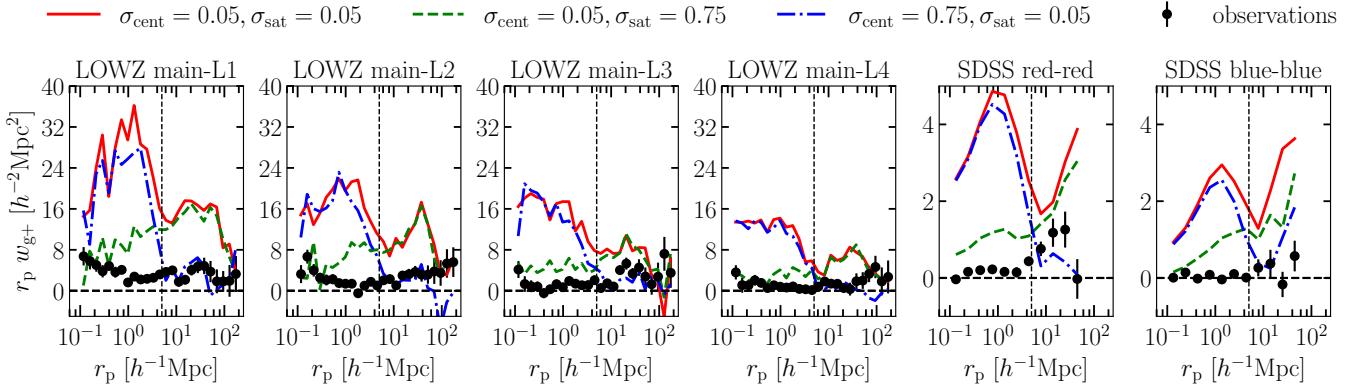


Fig. 10. Projected galaxy-ellipticity cross-correlation between a density sample and various shape samples. Four left panels: Results based on shapes from the luminosity subsamples, with the full LOWZ sample as the density sample. Two right panels: Results for SDSS, using the main sample as the density sample and colour subsamples as shape samples. Black dots represent observational data, while coloured lines represent Flagship simulations for three simplified IA models, each using different fixed values for $\sigma_{\text{MF}}^{\text{cent}}$ and $\sigma_{\text{MF}}^{\text{sat}}$.

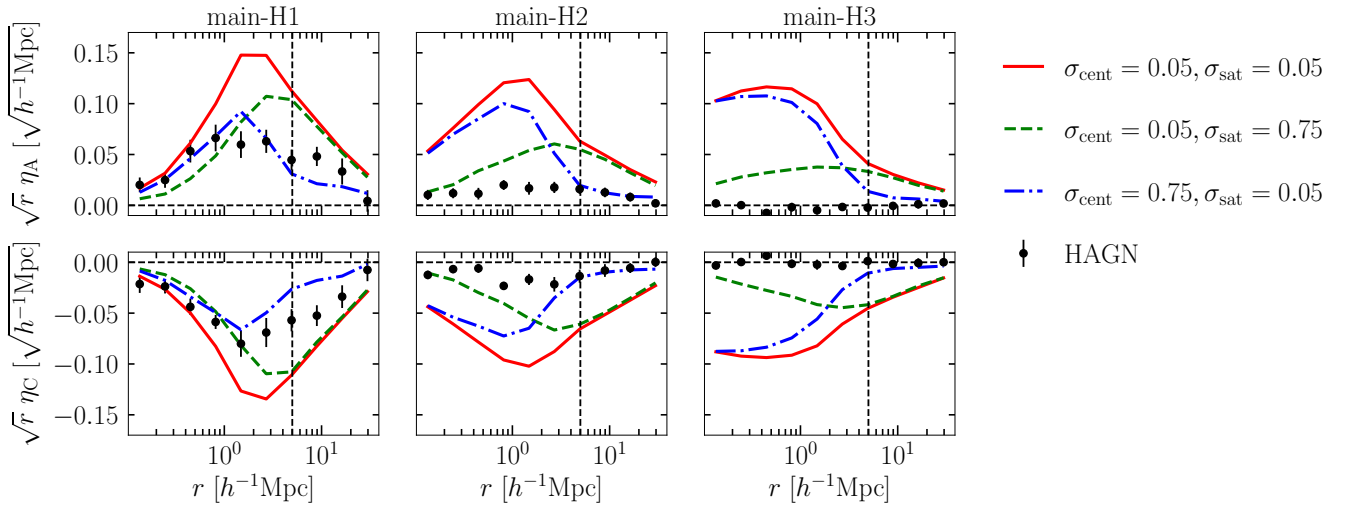


Fig. 11. 3D IA cross-correlations (η , as defined in Eq. (10)) between a main density sample and the orientations of galaxies in three luminosity-limited subsamples. Orientations are given by the 3D major and minor axes A and C. Black dots show measurements from the HAGN simulation at $z = 1.0$ with errors indicating the standard deviation. Coloured lines show the results from mock HAGN samples from Flagship for three simplified IA models with different combinations of fixed values for $\sigma_{\text{MF}}^{\text{cent}}$ and $\sigma_{\text{MF}}^{\text{sat}}$, analogously to Fig. 10. Errors for Flagship measurements are similar to those displayed in Fig. 16, but are not shown for concision.

ing a preference for the galaxies' 3D major (minor) axis to be oriented parallel (perpendicular) to the vector pointing to its neighbours.

The dependence of the total amplitudes in HAGN on scale and magnitude further follows our expectations, as it decreases with scale and increases with the samples brightness. The same dependences on scale and magnitude can be seen in Flagship at large scales ($r_{12} > 5 h^{-1} \text{Mpc}$) for the three cases of our simplified IA model. However, at small scales the magnitude dependence in Flagship is inverted, as the amplitude decreases with the brightness of the sample. This finding is interesting, as we have not seen such an inverted small-scale magnitude dependence in the Flagship mocks of the observed samples, where we found w_{g+} amplitudes to be lower for the SDSS samples than for the brighter LOWZ samples.

This behaviour poses a challenge for the calibration of the magnitude dependence of the IA model, as we need to randomise the orientations of faint satellites more than those of bright satellites to obtain an increase of the signal with brightness in the

mock HAGN samples. Besides this magnitude dependence, it is interesting to note in Fig. 11, that increasing the randomisation of orientations only for satellites decreases the signal only at scales below $r_{12} = 5 h^{-1} \text{Mpc}$ (compare the red and green lines). Increasing the randomisation for centrals on the other hand decreases the signal at large and at small scales simultaneously (compare the red and blue lines). Overall we conclude from this preliminary investigation that our IA model provides a high flexibility, as it allows for a significant variation of the IA amplitude in the simulation. The next goal is then to calibrate the dependence of $\sigma_{\text{MF}}^{\text{cent}}$ and $\sigma_{\text{MF}}^{\text{sat}}$ on galaxy properties, so that the signal ends up matching all reference measurements at all scales simultaneously.

6.4. Variations across random realisations

The IA model parameters in Eqs. (11) and (15) determine the probability distributions from which we draw random shapes and orientations for each galaxy, respectively. For a fixed set of

IA model parameters the shapes and orientations of individual galaxies will therefore vary across different random realisations. This variation translates into a variation of the resulting IA signal that is measured in the simulation.

We illustrate this effect in Fig. 12, where we show w_{g+} , measured in five random realisations of the IA model for the mock BOSS LOWZ L1 sample. The IA parameters used for generating these realisations are those used for the production of the final Flagship IA catalogue. We find a substantial variation across random realisations, which can reach the same order of magnitude as the signal itself. This variation poses a problem when calibrating the model, as it introduces noise in the cost function that we aim to minimise. To mitigate the impact of that noise on our calibration, we run the IA model up to five times at each point in the parameter space during the calibration. We obtain the final IA statistics that enter the cost function by averaging over measurements from the N_i random realisations, i.e. $X_{\text{model}} = \sum_i X_{\text{model}}^i / N_i$, where i indicates a single random realisation. These averaged statistics are shown as red symbols in Fig. 12.

7. Misalignment parameter space exploration

We explored the parameter space of the galaxy misalignment model component following two objectives. Firstly, we aimed to calibrate the model parameters by minimising the deviations between the IA statistics from the simulation and those from the reference samples. Our second objective was to trace the probability distribution of the IA model parameters, which enabled us to estimate the uncertainties on the IA contamination in *Euclid*-like sample predicted by the simulation.

7.1. Cost functions

We calibrated the parameters p_i in the σ_{MF} model from Eq. (15) by minimising the total deviation between the IA statistics measured in the different mock IA catalogues from Flagship and those obtained from the corresponding reference measurements. For a given sample, s , we define this deviation as

$$\chi_s^2 = \sum_i^{N_{\text{bin}}} \frac{(X_{\text{model}} - X_{\text{ref}})_i^2}{(\sigma_{\text{model}}^2 + \sigma_{\text{ref}}^2)_i}, \quad (16)$$

where X is either the projected statistics (w_{g+} in the case of the observational samples from SDSS and LOWZ) or the 3D statistic (η_A in the case of the HAGN samples), as defined in Sect. 4. The predictions of the model measured in Flagship and the measurements of the reference samples are denoted by X_{model} and X_{ref} , respectively. The corresponding standard deviations are denoted as σ_{model} and σ_{ref} , while N_{bin} is the number of scale bins in which the statistic X is measured.

When calibrating the misalignment parameters, our aim is to minimise the overall deviation between Flagship and the reference samples, which we define as the cost function

$$C = \sum_s^{N_s} w_s \chi_{s,r}^2, \quad (17)$$

where $N_s = 9$ is the number of galaxy subsamples summarised in Table 1, $\chi_{s,r}^2 = \chi_s^2 / N_{\text{bin}}$ is the reduced χ^2 of sample s , and w_s is a weight that we assign to each subsample. When calibrating the model parameters for central galaxies, we computed C from measurements of X at small and large scales, respectively,

as explained in Sect. 7.2, using slightly different weights in both cases.

For large scales ($>5 h^{-1}$ Mpc), we assigned weights of 0.1 to each of the four BOSS LOWZ subsamples, resulting in a combined weight of 0.4. Similarly, we assigned weights of 0.2 to each of the two SDSS samples, which led to a combined weight of 0.4 for SDSS and a total observational weight of 0.8. For the three HAGN subsamples, we set weights of 0.2/3 each, which leads to a total weight of 1.0 for all samples combined. This weighting strategy reduces the overall contribution of the HAGN samples, accounting for the higher confidence we place in the observational constraints and aiming to mitigate potential biases introduced by inaccuracies in the IA signal predicted by HAGN. When computing C at small scales ($<5 h^{-1}$ Mpc), we neglect the LOWZ samples L1 and L2 by setting their weights to zero. This is motivated by the strong deviations of the clustering in Flagship from the reference observations (see Fig. 7). Since these deviations in clustering also affect the w_{g+} predictions from the Flagship IA model, including L1 and L2 may bias the calibration results for satellite parameters. To maintain the same overall LOWZ contribution to C of 0.4 as on large scales, we increase the weights for the fainter subsamples, L3 and L4, to 0.2 each.

While the cost, C , is a valid measure for the deviations between the Flagship and the reference samples, it is not suitable for the error propagation technique, which we present in Sect. 8, since it is not directly related to the likelihood, $\mathcal{L}$, that σ_{model} and σ_{ref} are randomly sampled from the same underlying probability distribution. To establish this relation, we computed, in addition to C , the total deviation as

$$\chi_{\text{tot}}^2 = \sum_s^{N_s} w_s \chi_s^2. \quad (18)$$

Assuming a normal distribution of the likelihood for measuring X at a given point, $\mathbf{p}$, in the parameter space of the model, we can obtain the likelihood as $\mathcal{L} \propto \exp\{-\frac{1}{2}\chi_{\text{tot}}^2\}$. The weights w_s are the same as those we apply when computing C in Eq. (17).

In addition to weighting, our χ_{tot}^2 definition differs from the common statistics χ^2 in two aspects. (1) X_{model} is not an analytic prediction but a measurement with non-negligible errors that need to be taken into account when quantifying the significance of the difference between model and reference measurements. (2) We do not take into account the covariance between different scale bins. This simplification is valid if the signals are small and the errors are dominated by shot noise, but future calibration exercises should take into account the full covariance.

7.2. Parameter sampling method

A challenging aspect in the calibration is to efficiently sample the high-dimensional space spanned by the 2×6 parameters in Eq. (15) that describe the redshift, luminosity, and colour dependence of the misalignment parameters $\sigma_{\text{MF}}^{\text{cent}}$ and $\sigma_{\text{MF}}^{\text{sat}}$ in our IA model. This challenge is due to the numerical cost, which arises in part from generating the simulation, but mainly from the measurements of the various IA statistics at each sampling point.

To reduce the sampling volume in the parameter space and thereby lower the computational costs of the calibration, we leveraged a finding from our preliminary study, described in Sect. 6.3. There, we found that on large scales ($>5 h^{-1}$ Mpc), the alignment statistics w_{g+} and η_A are most sensitive to the parameters controlling the alignment of centrals (p_i^{cent}), while the impact of the parameters controlling satellite alignment (p_i^{sat})

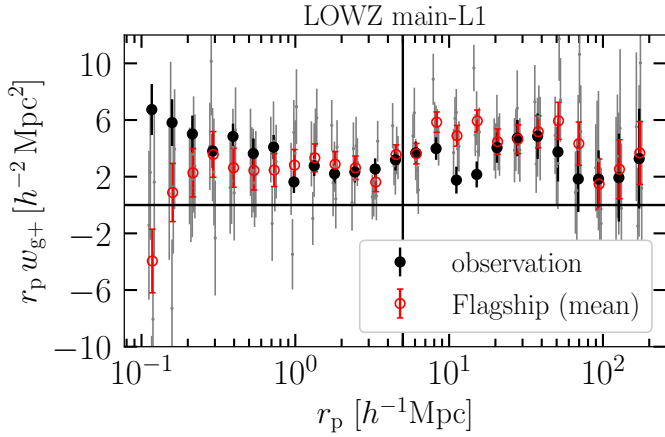


Fig. 12. Projected galaxy-ellipticity cross-correlation for the BOSS LOWZ sample L1. Grey dots represent results from five random model realisations using parameters from the final Flagship model. Red dots indicate the average across these random realisations with re-scaled errors, while black dots show observational results.

is relatively weak. This result allows us to first explore only the 6D space spanned by p_i^{cent} , by comparing the IA statistics from Flagship to those of the reference samples only at large scales between 5 and $40 h^{-1} \text{ Mpc}$ ¹². Once we have found a set of best-fit parameters for centrals, we fix these parameters and calibrate the parameters p_i^{sat} by comparing to the IA reference statistics at small scales, between 0.1 and $5 h^{-1} \text{ Mpc}$.

In both cases, we generated an initial set of sampling points by uniformly sampling the parameter space within the limits $0 < p_0 < 10$, $-10 < p_1 < 10$, $-0.5 < p_2 < 10$, $-10 < p_3 < 10$, $0.5 < p_4 < 10$, and $-10 < p_5 < 0$. The lower limits for p_2 and p_4 were chosen to ensure a positive basis of the σ_{mag} and σ_{col} terms in Eq. (15) for $M_r < -11$ and $u - r > -0.5$, respectively. Thus, we were able to avoid imaginary values for σ_{MF} within the magnitude and colour range covered by the mock *Euclid* sample (see Fig. 1). The constraint $p_5 < 0$ was imposed to ensure that σ_{MF} decreases with the $u - r$ colour index, leading to higher misalignment for bluer galaxies compared to red galaxies, and consequently a lower IA signal.

To further reduce the computational cost of the calibration, we discard sampling points from the initial distribution for which $\sigma_{\text{MF}} > 2$ within the volume of the redshift-magnitude-colour space covered by Flagship, i.e. $0.0 < z < 2.0$, $-23.0 < M_r < -16.0$, $0.5 < u - r < 3.0$ (see Fig. 1). Our reasoning behind this choice is that values of $\sigma_{\text{MF}} > 2$ lead to a distribution of random galaxy orientations that is close to a uniform distribution. It is therefore not necessary for our σ_{MF} model to predict higher values to include a zero alignment signal for any object in our *Euclid*-like sample as a possible calibration outcome. This pre-selection allows us to reduce the uniform initial random distribution by over 98% percent. We note that we applied this selection only on the initial sampling points, but not on those probed during the subsequent calibration. Starting from an initial set of 1000 points, we continued sampling the parameter space with an iterative procedure, consisting of the following steps:

¹²Note: the HAGN results may be affected by the limited box size of $100 h^{-1} \text{ Mpc}$. However, we do not expect this effect to significantly impact our calibration results, as the contributions of measurements to the cost function χ^2_{c} are down-weighted by their errors, which substantially increase with scale. In addition, we have reduced the weight of the HAGN constraints to the total cost C , as detailed in Sect. 7.1.

Table 2. Best-fitting parameters of the galaxy-halo misalignment model (Eq. (15)) implemented in Flagship.

Parameter	Centrals	Satellites	Component
p_0	$1.02^{+2.52}_{-1.02}$	4.74 ± 1.72	amplitude
p_1	-0.41 ± 0.24	0.43 ± 0.34	σ_z
p_2	3.46 ± 1.85	5.72 ± 2.33	σ_{mag}
p_3	2.71 ± 0.92	2.26 ± 1.12	
p_4	4.28 ± 1.27	4.27 ± 2.34	σ_{col}
p_5	-2.43 ± 0.59	-3.07 ± 0.88	
$\chi^2_{\text{tot}}/\text{d.o.f.}$	0.95	1.32	

Notes. Quoted errors denote 1σ uncertainties obtained from the sampling point distributions. The final row gives the total χ^2 (Eq. (18)), divided by the number of degrees of freedom.

1. Run the IA model on the mock galaxy samples at each sampling point in the parameter space, measure the IA statistics and compute the corresponding deviation from the reference samples, quantified by the cost function C from Eq. (17);
2. Select the fraction f_{low} of points with the lowest cost and compute their covariance matrix;
3. Draw N_r random points from the Gaussian distribution that is described by the covariance matrix from step 2.

For centrals, we repeated these steps 12 times, while gradually decreasing f_{low} from 5% to 0.5% from the first to the final iteration. For satellites, we performed only four iterations, decreasing f_{low} from 5% to 1%, as we find a faster convergence of the results. In each step of the iteration, we generated 250 new sampling points, which led to a total of 4000 and 2000 points for centrals and satellites, respectively, including the initial guess distribution.

As detailed in Sect. 6.4, we averaged the IA statistics over N random realisations to mitigate the impact of noise on the model predictions. We thereby set $N = 3$ for an initial ‘burn-in’ phase, which lasted over the first seven iterations for centrals and is restricted to the initial sampling step for satellites. Once we found the region with the lowest cost C to be visually well covered by new sampling points, we ended the ‘burn-in’ phase and increased the number of iterations to 5, gaining precision in the model predictions at the price of higher computational costs.

7.3. Calibration results

The set of galaxy-halo misalignment parameters for which we found the cost, C , to be minimal (hereafter referred to as best-fit parameters) is given in Table 2. These are the parameters we used to compute the alignment on the full light-cone output of Flagship.

To obtain a physical understanding of this result, we show in Fig. 13 the redshift, magnitude, and colour components of our σ_{MF} model for the parameter combinations probed during the calibration. The results are shown for central and satellite galaxies on the top and bottom panels, respectively. They are normalised to the model values at $z_0 = 1.0$, $M_0 = -22$, $(u-r)_0 = 1.0$ for a better visual comparison of the scaling with galaxy properties. The thick black line in this figure shows the model components for our best-fit parameters. The thin lines show the results for all parameter combinations that were sampled during the calibration process. Their colours indicate the corresponding χ^2_{tot} deviations between the IA statistics in Flagship and the reference samples, defined by Eq. (18).

Focussing on sampling points with the lowest χ^2_{tot} deviations from the reference samples ($\chi^2_{\text{tot}} < 1.5$), we find for both centrals and satellites that the dependence of the misalignment on redshift and magnitude, quantified by σ_z and σ_{mag} , is weak compared to the colour dependence, which is quantified by σ_{col} . Results are distributed around unity, which is consistent with a galaxy misalignment that is independent on redshift and magnitude. This weak dependence may allow for a reduction in the free parameters in a future version of the IA model, by assuming a constant relationship of σ_{MF} with redshift and magnitude. We note that such a constant relationship does not imply that the alignment signal is independent of these properties. This can be seen in Figs. 10 and 11, where we found a strong variation of the IA signal across different galaxy samples for fixed misalignment parameters. For centrals, a dependence on magnitude and redshift can be introduced solely through the mass and redshift dependence of the host halo alignment, where the former may be affected mass resolution effects, introducing mass dependent noise in the measured halo orientations (see discussion in Sect. 2.2 and H22). For satellites, such dependences may instead be introduced via the mass- and redshift-dependence of host-halo concentrations (Dutton & Macciò 2014). Therefore, a more detailed physical interpretation of the results may be misleading.

In contrast to σ_z and σ_{mag} , we find that σ_{col} deviates significantly from a constant relation, as the values decrease with larger $u-r$ colour. From our preliminary studies (Figs. 10 and 11), we would expect this decrease of misalignment to translate into an increase of the alignment signal with galaxy redness. The trends we find for the parameter sampling points with the lowest χ^2_{tot} values are also present for our best-fit model that is defined by the parameters for which the cost, C , is minimal. However, the latter shows a stronger dependence on redshift and colour. We attribute this offset to differences in the definitions of C and χ^2_{tot} , as well as the noise affecting both quantities (see Sect. 6.4), which may cause a displacement between the sampling point with the lowest C value and the minimum of the underlying distribution.

The impact of this noise on our constraints becomes more apparent in Fig. 14, which shows the distribution for the sampling points in the parameter space for centrals and satellites in the left and right panels, respectively. There are several interesting aspects to note in Fig. 14. Firstly, the χ^2_{tot} values are significantly higher for satellites than for centrals, which could result from the strong deviations between the 3D IA statistics of Flagship and HAGN at small scales that we see in Fig. 11.

Second, the shape of the parameter regions with good fits (with $\chi^2_{\text{tot}} < 2$) for centrals and satellites is similar, despite the fact that the misalignment described by these parameters is defined for very different initial orientations in both cases, as we have discussed in Sect. 6.1. One possible explanation for this finding could be that the constraints are too weak to reveal significant deviations. Another potential reason could be a bias introduced by using the same initial guess distribution for centrals and satellites. However, the fact that the best-fit volumes are significantly smaller than the volume spanned by the initial distributions (and are well enclosed by them) argues against a bias imposed by the initial guess.

A third aspect to note is the large uncertainty in the parameter p_0 , which controls the overall amplitude of the misalignment and therefore directly the amplitude of the alignment signals. This is because χ^2_{tot} is affected by the errors of the IA statistics in the reference samples as well as those from the measurements in the Flagship simulation (Eq. (18)). Correlations with the param-

eters p_1 and p_5 for centrals and p_4 for satellites further contribute to the uncertainty on p_0 . Finally, we observe a strong correlation between the parameters p_3 and p_5 , which are the exponents of the magnitude and colour terms of our misalignment model, and hence describe how strongly the galaxy misalignment scales with these galaxy properties. A possible explanation for the correlation of these parameters is the correlation between galaxy colours and magnitudes in Flagship, which can be seen in projection over redshift in Fig. 1.

However, we chose to refrain from a detailed physical interpretation of the calibration results, as these are likely influenced by two systematic effects. First, the mass dependence of noise in the measured halo orientations (Sect. 2.2) can impact the inferred dependence of galaxy-halo misalignment on galaxy properties. In addition, differences in clustering between Flagship and the observations (Sect. 4.2) are expected to further affect the calibration parameters. Since the clustering also affects the w_{g+} measurements, an overly high clustering will be compensated by an overly low alignment amplitude, and vice versa. We mitigate this effect by excluding data for which we find the most significant deviations in w_{gg} from the calibration (i.e. the measurements from the BOSS LOWZ samples L1 and L2 at scales below $5 h^{-1}$ Mpc; see Sect. 7.2). However, smaller deviations are still present in the remaining data and their strength depends not only on scale but also on the luminosity, colour and redshift of the samples. The deviations in the clustering may therefore affect the dependence of the IA signal on redshift and galaxy properties, as described by our calibration parameters. Since the statistical uncertainty of w_{g+} is generally much larger than that of w_{gg} , significant deviations in the clustering amplitude do not generally translate into significant bias in IA statistics. Nevertheless, the IA parameters controlling the galaxy-halo misalignment should be regarded as effective parameters that are specific to Flagship.

7.4. Validation

For our validation, we compared the predictions from our best-fit Flagship IA model, averaged over five realisations, against the reference samples used for calibration. In Fig. 15 we show the projected cross-correlation w_{g+} for the four luminosity subsamples of the BOSS LOWZ sample and the colour subsamples of the SDSS main sample (analogous to Fig. 10).

For the LOWZ subsamples, we find an overall good agreement between results from Flagship and the observational reference, as the discrepancies are within the standard deviations of the measurements. However, for the brightest samples L1 and L2 and at scales of less than $1 h^{-1}$ Mpc, we find the Flagship results to be consistently below the observational results. We note that for these samples, we also found the strongest deviations from the reference samples in clustering and have therefore set their weight in the cost function to zero when calibrating the misalignment parameters for satellites (Sect. 7). The simulation is hence not calibrated to match the LOWZ observations in this regime.

For the red SDSS subsample, we find the deviations between the Flagship results and the observations to be consistent overall within the errors, although we note that at scales above $5 h^{-1}$ Mpc the Flagship results are consistently below the observations. The Flagship results for the blue SDSS sample are consistent with zero at all scales and therefore below the observational reference. However, also here the deviations between Flagship and observations are consistent within the errors.

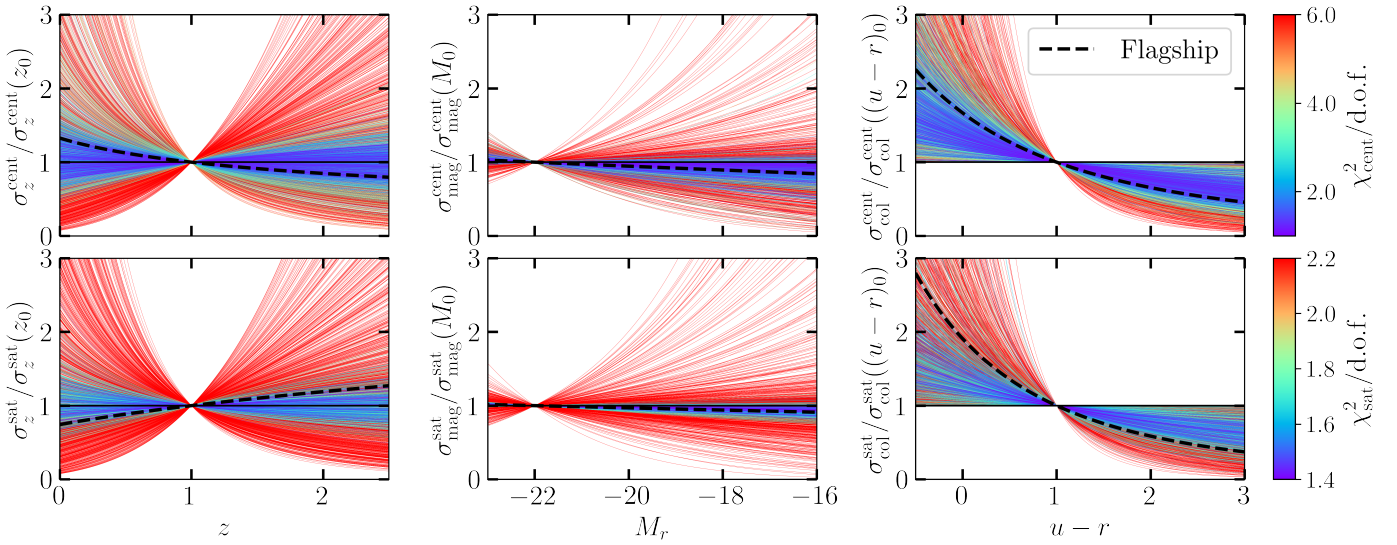


Fig. 13. Components of the model for the galaxy misalignment parameter σ_{MF} from Eq. (15) for the parameters sampled during the model calibration. Line colours indicate the χ^2_{tot} deviation between simulations and reference data (as defined in Eq. (18)) per degree of freedom (d.o.f.). The dashed black line corresponds to the model used in the production of the Flagship simulation. Top: Results for the calibration of central misalignment. Bottom: Same but for the satellite misalignment. All results are shown with respect to the values at $z_0 = 1.0$, $M_0 = -22$, $(u-r)_0 = 1.0$ to facilitate the comparison of the dependence of the misalignment amplitude on the different galaxy properties.

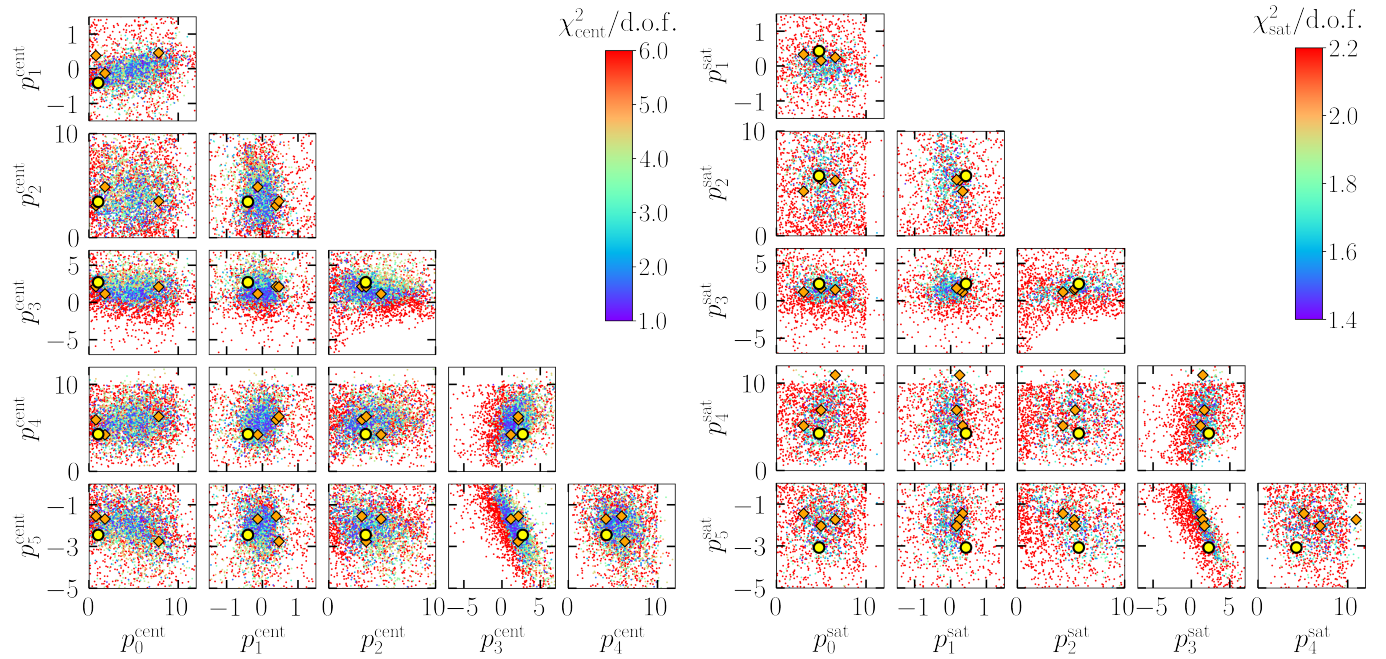


Fig. 14. Parameter combinations of the galaxy misalignment model (Eq. (15)) at which the simulation was evaluated in the calibration process, described in Sect. 6. Colours indicate the χ^2_{tot} deviations per degree of freedom (d.o.f.) of different IA statistics measured in the simulation from the reference measurements (see Eq. (18)). Left panels: Parameter combinations for centrals for which the χ^2_{tot} values are derived from IA statistics at scales larger than $5 h^{-1} \text{ Mpc}$. Right panels: Corresponding results for parameters of satellites, where χ^2_{tot} is derived at scales below $5 h^{-1} \text{ Mpc}$. The parameters used for the IA model in Flagship (see Table 2) are marked as yellow dots. Orange diamonds show the three sampling points with the lowest χ^2_{tot} values.

In Fig. 16 we compare the 3D IA statistics η , defined in Eq. (10), from Flagship with the reference measurements from HAGN for the three magnitude-limited samples H1 to H3. The top panels display η_A , which measures the average alignment between the major axis of a galaxy in a magnitude subsample with the direction of a neighbouring galaxy from the main sample. Similarly, the central panels show η_C , which quantifies the

same alignment but for the galaxy's minor axis (analogously to Fig. 11). The bottom panels show the relative deviations between Flagship and HAGN.

We find that Flagship matches the overall trends predicted by HAGN, showing a decrease in amplitude for fainter samples and at both small and large scales. However, our comparison also reveals several discrepancies: At scales above $5 h^{-1} \text{ Mpc}$ we find

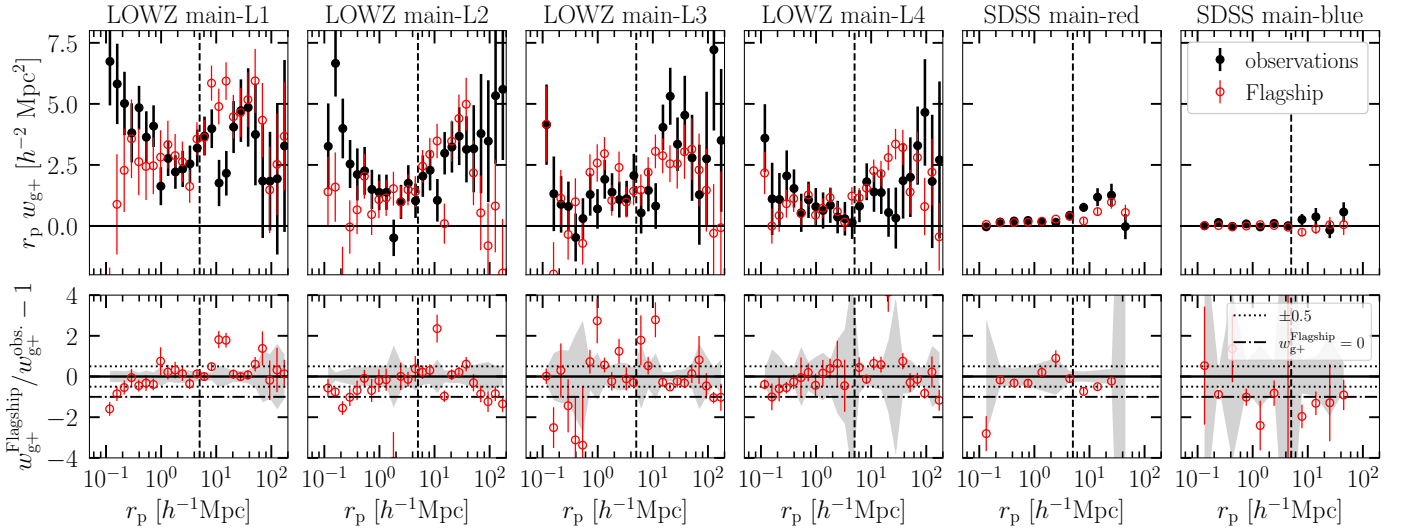


Fig. 15. Top: Projected galaxy-ellipticity cross-correlation function w_{g+} as a function of transverse separation for the observational reference samples (black points) and the corresponding calibrated Flagship mock samples (red points), analogous to Fig. 7. Bottom: Relative deviation of the Flagship signals from the observations. The dashed-dotted horizontal lines at -1 indicate the relative deviation expected for a null detection of the IA signal in Flagship; dotted horizontal lines indicate a relative deviation of ± 0.5 . The dashed vertical lines separate the regimes where central and satellite misalignment parameters were fitted in the simulation. The grey areas indicate the standard deviations of the observations.

the η_A measurements from Flagship to deviate from HAGN by up to 50% for the bright samples H1 and H2. While deviations in the largest-scale bin are greater, they are consistent with the increased measurement errors at that scale. For the faint sample, H3, we observe similar absolute deviations as for the brighter samples. However, due to the low amplitude of the signal, these absolute deviations result in large relative deviations of up to a factor of five. At scales below $5 h^{-1}$ Mpc, we find the Flagship results to be up to a factor 2 below those from HAGN, as the signal in Flagship decreases towards zero. This discrepancy is most notable for the brighter samples, H1 and H2, where the HAGN measurements exhibit a high signal-to-noise ratio.

Interestingly, we achieved better agreement between Flagship and HAGN for the brightest sample, H1, at small scales when fixing the misalignment parameters to $\sigma_{\text{MF}}^{\text{cent}} = 0.75$ and $\sigma_{\text{MF}}^{\text{cent}} = 0.05$ in our preliminary analysis (see Fig. 11). This demonstrates that the IA model can replicate the scale dependence of the HAGN signal within a specific luminosity and redshift range. However, obtaining highly accurate matches between the constraining datasets and Flagship across all luminosity, colour, redshift, and scale ranges simultaneously, while using misalignment parameters that vary based on galaxy properties, remains a challenge for our model.

This difficulty may stem from three primary factors. First, it is possible that the IA signal in HAGN is inconsistent with the observational constraints, making it difficult to match both HAGN and observational data, even with a realistic IA model. Second, there may be limitations in our modelling approach, including: (a) insufficient flexibility in the model to capture the full redshift, magnitude, and colour dependence of galaxy misalignment, (b) shortcomings in the model calibration process, or (c) the relatively low weighting of the HAGN sample in the cost function used for calibration. Third, inaccuracies of the Flagship properties, such as the clustering, colour, or luminosity distributions may reduce the accuracy of the IA model predictions, even if the latter is sufficiently realistic. These issues, either individually or in combination, may contribute to the discrepancies we observe for the HAGN H1 sample at small scales. However,

given the overall good agreement between Flagship and HAGN when considering all samples and all scales, we conclude that our IA model is sufficiently realistic to serve as a test-bed for analytical IA models.

The simulated galaxy orientations and the simulation code are publicly available^{9,10}.

8. Uncertainty propagation

To derive informative priors on IA model parameters, we need to propagate the uncertainty in the Flagship IA model inherited from the statistical uncertainty in the calibration observations (and simulations), as well as from the finite volume of Flagship. Both of these sources of uncertainty are included in the χ^2 of the calibration fits; see Eq. (16). Propagated into the IA signals measured from the Flagship mock, these uncertainties can then be translated into the permitted range of the parameters of analytic IA models fitted to the mock datasets, which can serve as informative priors for cosmological inference. Full error propagation (e.g. via Monte Carlo sampling) is computationally expensive because at each step the semi-analytic model needs to be optimised, and IA summary statistics re-measured. In this work we limit ourselves to order-of-magnitude estimates via an approximate scheme.

As shown in Fig. 10, to good approximation, we can control the small-scale (large-scale) IA amplitude via the satellite (central) model parameters of the semi-analytic model, with the transition at around $5 h^{-1}$ Mpc. We derive the covariance $\text{Cov}(\mathbf{p})$ of the fit parameters $p_{0.5}$ for both centrals and satellites from the distributions of χ^2_{tot} shown in Fig. 14. We linearly propagate the uncertainty on $p_{0.5}$ into the parameter controlling the misalignment distribution,

$$\text{Var}(\sigma_{\text{MF}}) = \sum_{i,j=0}^5 \frac{\partial \sigma_{\text{MF}}}{\partial p_i} \text{Cov}(\mathbf{p})_{ij} \frac{\partial \sigma_{\text{MF}}}{\partial p_j}, \quad (19)$$

where the derivatives are determined analytically from Eq. (15).

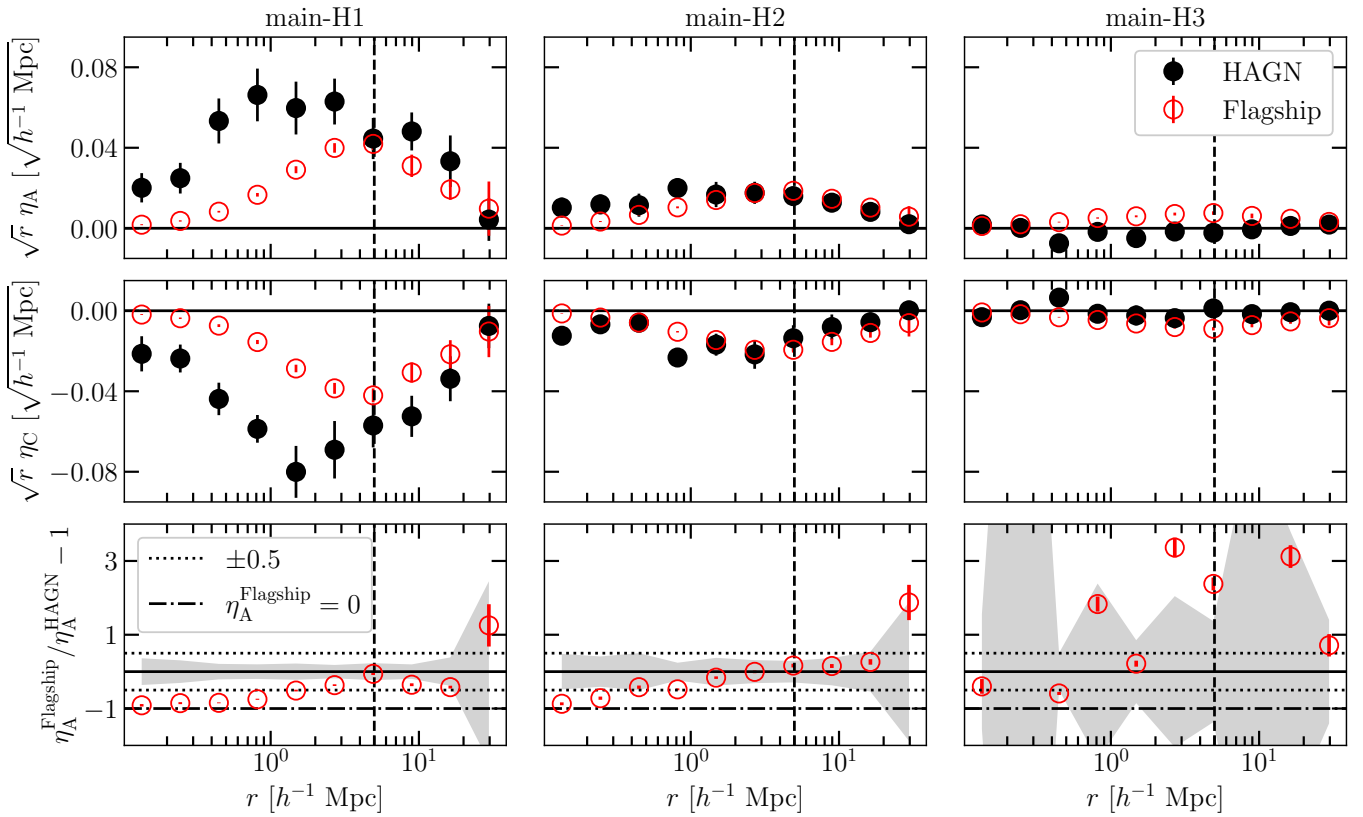


Fig. 16. Top: 3D correlations between galaxy major axis **A** and the vector **r** pointing to the position of a neighbouring galaxy (as defined in Eq. (10)). Black and red symbols show measurements from the comoving output of HAGN at $z = 1.0$ and Flagship light-cone at the same redshift respectively. Results are shown for the magnitude limited samples H1 to H3 (from bright to dim), as defined in Table 1. Error bars indicate the Jack-knife estimates of the standard deviation. Centre: Analogous to the top panel for the correlation of the galaxy minor axis **C**. Bottom: Relative deviations of the Flagship measurements from HAGN. Grey areas indicate the standard deviations of the HAGN measurements. Dashed lines mark 100% deviations.

Table 3. Best-fitting parameters of Eq. (20).

Sample	Type	a	b	c
LOWZ L1	cen	0.01	1.10	-2.40
	sat	8.75	68.26	-2.33
LOWZ L2	cen	0.01	0.77	-2.42
	sat	-0.33	52.86	-2.38
LOWZ L3	cen	0.01	0.56	-2.16
	sat	2.40	54.57	-2.49
LOWZ L4	cen	0.01	0.47	-2.19
	sat	-0.62	44.53	-2.26
SDSS red	cen	0.00	0.15	-2.18
	sat	0.29	12.96	-2.29
SDSS blue	cen	0.00	0.15	-2.04
	sat	0.33	5.65	-2.32

Notes. Results are shown for the observational galaxy samples (both centrals and satellites) used to calibrate the galaxy misalignment model.

We generated mock realisations of the SDSS samples used for calibration, systematically varying σ_{MF} separately for central and satellites (while holding the other fixed) and measuring the amplitude of the resulting IA signal on scales above and below $5 h^{-1} \text{ Mpc}$, which roughly separates the regimes where centrals and satellites drive the IA amplitude. The resulting relations are

well fit by the empirical model,

$$A_{\text{IA}} = a + b \exp(c\sigma_{\text{MF}}), \quad (20)$$

with the best-fit coefficients for the free parameters a, b, c per galaxy sample listed in Table 3. The offset a is generally small for all samples, while c shows only little variation with an average value around $c = -2.3$ because this scaling is a feature of the von Mises–Fisher distribution rather than a sample-dependent property. The parameter b scales with the luminosity of the sample, weakly for centrals, and approximately exponentially for satellites. Some residual luminosity trends are to be expected because the IA amplitude is not solely determined by either satellites or centrals, e.g. due to cross-correlations between centrals and satellites (see Fig. 10). Equations (19) and (20) can now be combined to propagate errors from the Flagship IA model to the amplitude of an IA correlation function, separately on small and large transverse scales. Through Eq. (15) this propagation depends on the galaxy sample’s typical redshift, luminosity, and colour.

Applying this scheme using typical values for the galaxy samples used for calibration, we find standard deviations on A_{IA} that exceed the parameter value, even for bright samples with strong signals and on both large and small transverse scales. This is caused by the additional uncertainty due to the finite volume of the Flagship in Eq. (16). The two sources of statistical error in the denominator have roughly the same order of magnitude:

while the real SDSS observations typically cover a larger volume, the Flagship measurements have been averaged over five shape noise realisations.

This means that to obtain informative priors on IA parameters in the future, we not only need to compile as many informative direct IA observations (and hydrodynamic simulation measurements) as possible over a wide range of galaxy sample properties, but also implement the IA models into simulations that exceed the constraining power of the observations by at least an order of magnitude to suppress additional statistical uncertainty beyond those of the observations to less than 10% (e.g. by using multiple light-cone realisations). While the HOD parameters in Flagship are held fixed here, their scatter against observational calibrators is likely to constitute another significant source of uncertainty in the overall IA model, especially on small scales. In conclusion, we are currently unable to derive meaningful, informative prior constraints on the amplitude of IA signals in *Euclid*'s WL samples directly from Flagship.

9. IA contamination in *Euclid*-like samples

As a first application of our semi-analytic IA model, we predicted the expected contribution of IA signals to the observed cosmic shear signals in a *Euclid*-like survey. We selected all galaxies brighter than $I_E = 24.5$ and with valid photometric redshift estimates in the full octant of Flagship. The latter were obtained with a template-based method (see Paltani et al., in prep.) applied to the mock photometry of the near-infrared *Euclid* bands and LSST *ugriz* fluxes to a depth expected by the time of *Euclid*'s final data release. The resulting galaxy sample has a number density of 26 arcmin^{-2} on the sky, close to, but slightly higher than, *Euclid*'s nominal wide survey expectation.

We divide the sample into 13 equi-populated tomographic bins via the first mode of the photometric redshift probability density function. This choice ensures good redshift resolution and a fairly even distribution of statistical errors across the signals we extract. For every combination of tomographic bins we measure angular pseudo-power spectra of galaxy ellipticity correlations up to a maximum multipole of $\ell = 3000$. Details of the methodology are described in [Euclid Collaboration: Tessore et al. \(2025\)](#); briefly, the power spectra are calculated from Healpix (Górski et al. 2005) maps at a resolution of $N_{\text{side}} = 2048$, shape noise-subtracted, and not corrected for the effect of the limited footprint of the mock. Since data is available over a full octant, the mixing between multipoles, and between E and B modes, is limited to large scales and has minor impact, particularly in the power spectrum ratios that we consider.

We separate the contributions to the ellipticity correlations by the cosmological signal (i.e. the gravitational shear correlations, denoted by GG) and the combined signal from intrinsic ellipticity correlations (II) and shear-intrinsic cross-correlations (GI). Figure 17 shows the relative contribution of the combined II and GI signal to the total ellipticity correlation in each tomographic bin combination.

As expected, the B -mode contribution is consistent with zero throughout as our model is based on tidal, as well as radial satellite, alignments, which only generate B modes at higher order (Hirata & Seljak 2004; Schneider & Bridle 2010). In the E mode, the IA contamination is fairly strong overall, reaching the 10% level and beyond over a broad range of redshifts and angular scales. This result should be interpreted with caution, not only because of the expected uncertainties in the IA model parameters discussed in Sect. 8, but also owing to potential inaccuracies

in the HOD model, for which we found indications when comparing the colour–magnitude distribution in Flagship with COSMOS observations (Sect. 3.1). Nevertheless, it is worth noting that our model predictions are of the same magnitude as the analytic forecasts made by Fortuna et al. (2021) who also considered a calibrated IA model for both central and satellite galaxies. Depending on modelling choices, they found a systematic shift in the parameter S_8 by up to 5%, which roughly corresponds to an average bias of 10% in power spectrum amplitude.

The figure shows that IA makes a positive contribution in tomographic auto-correlations due to the II term, and a negative contribution to tomographic cross-correlations where the GI term dominates. The GI term tends to be most significant when the tomographic bins are far apart in redshift so that the lensing efficiency of the foreground structures that align nearby galaxies is large. It is noteworthy that the opposing trends of the II and GI contributions are capable of breaking any degeneracy with shifts in the mean of the redshift distributions in the tomographic bins, which would move all signals coherently to larger or smaller amplitudes. This degeneracy breaking is not observed when binning more coarsely into fewer tomographic bins, as is done in current surveys mostly due to the lower overall galaxy number densities (see e.g. the discussion in [Dark Energy Survey and Kilo-Degree Survey Collaboration 2023](#)). Nevertheless, cross-talk between residual uncertainty in the modelling of IA and of tomographic redshift distributions will remain a major issue for *Euclid* and other Stage-IV surveys (Fischbacher et al. 2023; Leonard et al. 2024).

10. Summary and conclusions

This work describes the addition of realistic IAs of galaxies to *Euclid*'s Flagship simulation and mock galaxy catalogue ([Euclid Collaboration: Castander et al. 2025](#)), providing a test bed for the analysis choices and methods applied to forthcoming WL analyses of *Euclid*.

Our semi-analytic IA model consists of two main components. First, we randomly sampled galaxy ellipticities conditional on the redshift, luminosity, and colour in the simulation to ensure they matched the corresponding distributions observed in the COSMOS Survey (Scoville et al. 2007). Second, to determine alignment, we set central galaxies to follow the orientation of their host halo, while satellites were aligned radially towards the halo centre. Unlike previous works (e.g. Heymans et al. 2006; Joachimi et al. 2013b; Hoffmann et al. 2022b), we applied the same model to both early- and late-type galaxies, instead of aligning the minor axis of blue central galaxies with the halos' angular momentum vector, assuming they are rotationally supported discs. The strength of the alignment is controlled separately for centrals and satellites via random misalignments, which depend via power laws on galaxy redshift, luminosity, and colour. To calibrate these dependences, we employ constraints from multiple IA observations from the SDSS (Singh & Mandelbaum 2016; Johnston et al. 2019), providing constraints up to a redshift of $z = 0.36$. Since *Euclid* WL samples will reach $z \simeq 2$ and beyond, we want to compensate for the current dearth of observational IA constraints at high redshifts by using measurements in three luminosity subsamples from the HAGN hydrodynamic simulation (Dubois et al. 2014) at $z = 1$. However, the latter samples are down-weighted in the model optimisation, as there is still considerable uncertainty in IA predictions from simulations.

Optimising a total of 12 alignment parameters, we found an overall good agreement between Flagship and the different

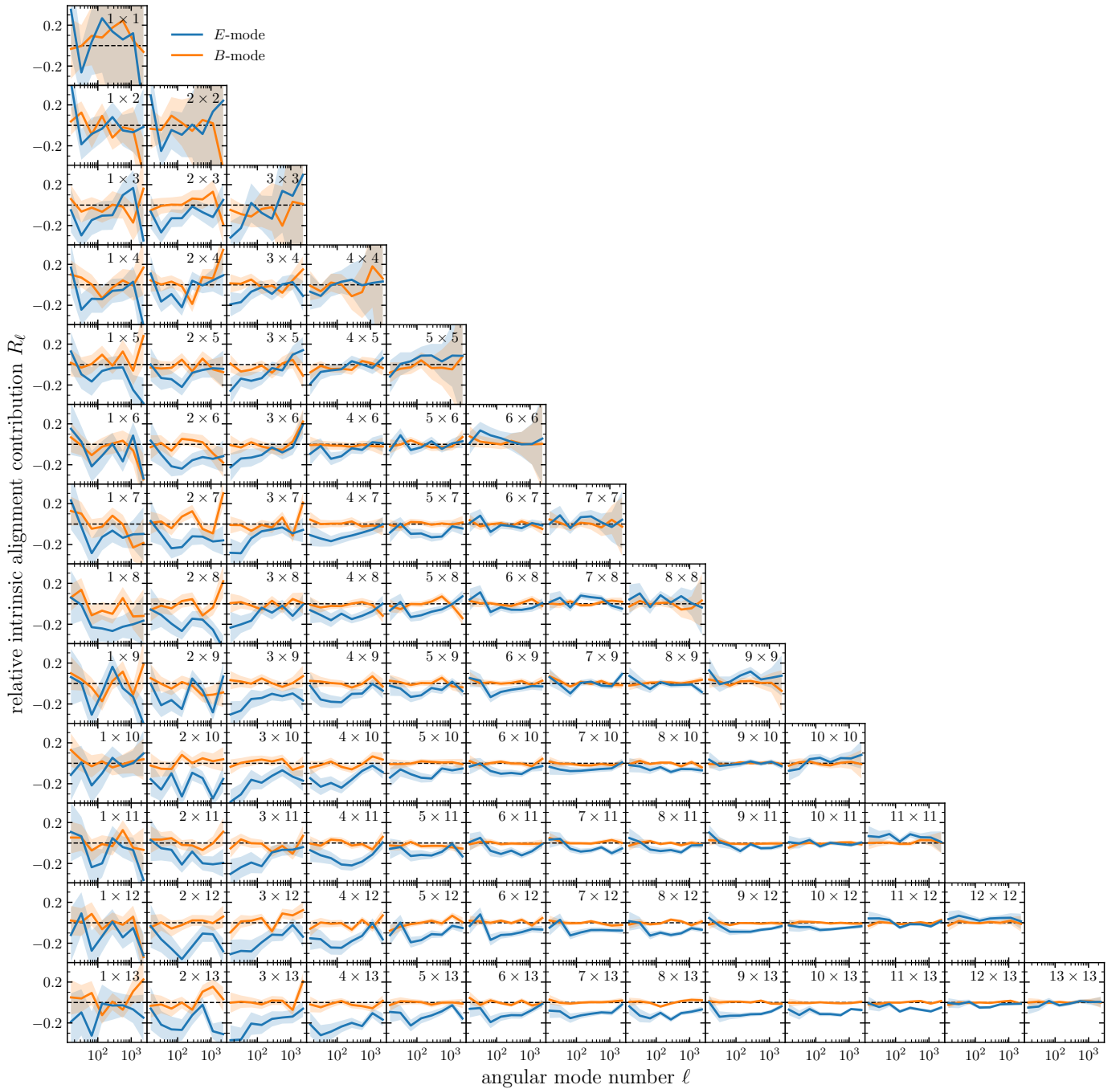


Fig. 17. Relative IA contribution $R_e^{ij} = C_{IA}^{ij} / (C_{IA}^{ij} + C_{GG}^{ij})$ to a tomographic cosmic shear analysis in a *Euclid*-like galaxy sample divided into 13 photometric redshift bins. Panels correspond to the different tomographic bin combinations, with auto-correlations along the diagonal and higher-redshift bins towards the bottom and right. Blue (orange) lines show the relative change to due IAs to the *E*-(*B*)-mode angular shear power spectra. Bands around the signals indicate the standard deviations as determined from a Jackknife covariance.

reference data sets, with close matches in the distributions of axis ratios to all COSMOS samples and agreement in the alignment statistics mostly within 1σ errors. However, significant discrepancies arose when comparing Flagship against the brightest HAGN subsample on small scales. These deviations might have resulted from the low weight that we assigned to HAGN in the optimisation or they could indicate that the IA observations and HAGN simulations are difficult to reconcile with a simple model, despite the long redshift baseline. A future, more detailed comparison of semi-analytic IA models against a range

of hydrodynamic simulations will be required to shed light on these model limitations. Significant discrepancies also occur in the small-scale clustering of the brightest SDSS-LOWZ subsample. Since we excluded these scales from the IA parameter optimisation, low-level differences are also apparent in the corresponding alignment signals. Improvements in this regard would require a revision of the hybrid halo occupation and abundance-matching approach for the Flagship galaxy mock.

For both centrals and satellites, the model optimally matches the constraints for parameters that set a strong dependence of

the galaxy misalignment on colour and a relatively weak dependence on magnitude and redshift, in agreement with the results from Hoffmann et al. (2022b), who employed a similar model. This result suggests that our IA model could potentially be simplified by eliminating the direct dependence on magnitude and redshift in the galaxy misalignment. Such a simplification would reduce the dimension of the model parameter space and remove parameter degeneracies. A simpler model is desirable to increase the predictiveness of the IA model given the limited number and constraining power of the calibration data sets.

Propagating the statistical uncertainty due to the calibration data and the limited precision of the Flagship mock measurements, we found the combined uncertainties on the IA amplitude are currently still too large to provide informative bounds on IA parameter ranges. Nevertheless, we conclude that the best-fit calibrated IA model presented in this work is a useful tool for creating realistic mock IA data sets for a wide range of observed one- and two-point statistics of galaxy ellipticities. As a first application, we predicted the IA contamination to a tomographic WL measurement akin to what can be expected for the final *Euclid* data release and found it to be significant, with $\sim 10\%$ IA contribution in some tomographic bin combinations, in line with earlier predictions. However, we generally expect to see a high uncertainty on this prediction, based on the aforementioned propagation of statistical uncertainties.

A companion paper (Euclid Collaboration: Paviot et al. 2026) investigates how well common analytic IA models can fit the combined clustering and IA measurements from Flagship, informing some of the modelling choices for WL inference from *Euclid*'s first data release, as well as comparing the simulation predictions with observational samples not used in the calibration procedure. In line with forthcoming updates of the Flagship galaxy models, we will also improve the IA generation procedure. This will include an expanded observational calibration data set, hydrodynamic simulation measurements from several projects (e.g. Nelson et al. 2019; Pakmor et al. 2023; Schaye et al. 2023) over a wider redshift range, multiple light-cone realisations, and tests of current modelling assumptions, such as the independence of galaxy shapes and orientations and the spatial isotropy of misalignments.

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