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Intrinsic galaxy alignments in the KiDS-1000 bright sample: Dependence on colour, luminosity, morphology, and galaxy scale

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ABSTRACT

The intrinsic alignment of galaxies is a major astrophysical contaminant to weak gravitational lensing measurements, and the study of its dependence on galaxy properties helps provide meaningful physical priors that aid cosmological analyses. This work studied for the first time the dependence of intrinsic alignments on galaxy structural parameters. We measured the intrinsic alignments of bright galaxies, selected on apparent r -band magnitude $r < 20$, in the Kilo-Degree Survey (KiDS). Machine-learning-based photometric redshift estimates are available for this galaxy sample that helped us obtain a clean measurement of its intrinsic alignment signal. We supplemented this sample with a catalogue of structural parameters from Sérsic profile fits to the surface-brightness profiles of the galaxies. We split the sample on galaxy intrinsic colour, luminosity, and Sérsic index, and we fitted the non-linear linear alignment model to galaxy position–shape projected correlation function measurements on large scales. We observe a power-law luminosity dependence of the large-scale intrinsic alignment amplitude, A_{IA} , for both the red and high-Sérsic-index ($n_s > 2.5$) samples, and find no significant difference between the two. We measure an $\sim 1.5\sigma$ lower A_{IA} for red galaxies that also have a Sérsic index of $n_s < 4$ compared to the expected amplitude predicted using the sample's luminosity. We also probe the intrinsic alignment of red galaxies as a function of galaxy scale by varying the radial weight employed in the shape measurement. On large scales (above 6 Mpc/h), we do not detect a significant difference in the alignment. On smaller scales, we observe that alignments increase with galaxy scale, with outer galaxy regions showing stronger alignments than inner regions. Finally, for intrinsically blue galaxies, we find $A_{IA} = -0.67 \pm 1.00$, which is consistent with previous works, and we find alignments to be consistent with zero for the low-Sérsic-index ($n_s < 2.5$) sample.

Key words. gravitational lensing: weak – galaxies: general

1. Introduction

The orientation of galaxies in the Universe, usually probed statistically with wide astronomical imaging surveys, has gathered significant attention in the last few decades (see Joachimi et al. 2015 for a historical review). It is understood that galaxy shapes are not randomly oriented in the Universe, instead, they have an imprint of the tidal gravitational field that can be studied through correlations involving galaxy shapes (e.g. Troxel & Ishak 2015; Lamman et al. 2024). This intrinsic alignment (IA) of galaxies establishes galaxy shapes as a tracer that can reveal cosmological information, such as the imprint of baryon acoustic oscillations (see e.g. van Dompsele et al. 2023), primordial gravitational waves (Schmidt et al. 2014; Chisari et al. 2014), primordial non-Gaussianity (Schmidt et al. 2015), parity-breaking (Biagetti & Orlando 2020), and the growth of the structure (Taruya & Okumura 2020; Okumura & Taruya 2022, 2023), among other applications.

Besides the cosmological information available in galaxy intrinsic-shape statistics, another important reason to study the phenomenon is its implications for measurements of weak gravitational lensing. The apparent distortion of light bundles from the intervening matter distribution produces correlations of observed galaxy shapes that encode cosmological information (Bartelmann & Schneider 2001). Consequently, cosmic shear – the weak gravitational lensing caused by the large-scale structure of the Universe – is one of the main science drivers of prominent astronomical survey missions. Examples include ongoing or recently completed Stage-III surveys such as the Kilo-Degree Survey (KiDS, de Jong et al. 2013), the Dark Energy Survey (DES, The Dark Energy Survey Collaboration 2005), the Hyper Suprime-Cam Subaru Strategic Program (HSC, Aihara et al. 2018), as well as starting or upcoming Stage-IV missions such as Euclid (Laureijs et al. 2011), the Vera C. Rubin Observatory LSST (Ivezic et al. 2019), or the Roman Space Telescope (Spergel et al. 2015). Since galaxy shapes are not intrinsically random, the IA signal needs to be carefully considered when measuring weak gravitational lensing in order to arrive at accurate, unbiased cosmological results (see e.g. Kirk et al. 2015).

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The need for mitigation of the IA signal’s contamination of weak gravitational lensing measurements has driven much of the development in the field. Advancements in the theoretical modelling now go beyond the linear alignment (LA) model of Catelan et al. (2001) and Hirata & Seljak (2004) and the phenomenological non-linear linear alignment model (NLA, Bridle & King 2007) – which substitutes the linear matter power spectrum for the non-linear counterpart in the LA model. State-of-the-art models consider the full expansion of biased tracers in the matter density field with standard perturbation theory (Blazek et al. 2019; Chen & Kokron 2024) or effective field theory (Vlah et al. 2020, 2021). These more complex models have been shown to adequately describe the quasi-linear regime of IA correlations in simulated data (Bakx et al. 2023) and are necessary to reach the stringent accuracy requirements of future cosmic shear surveys on the scales of interest (Paopiamsap et al. 2024). Hybrid Lagrangian extensions also serve to reduce the number of free parameters of these models and extend their validity regime (Maion et al. 2024). On even smaller scales, comparable to the sizes of dark-matter haloes, the only theoretical description available comes from halo models of intrinsic alignments (Schneider & Bridle 2010; Fortuna et al. 2021a; see Asgari et al. 2023 for a review).

At the same time, the IA signal has been extensively studied in observational data, enabled by the wide-field imaging surveys of this century. Galaxy samples have been typically split in two populations: intrinsically red galaxies (which are generally elliptical and pressure supported) and blue galaxies (which are generally spiral and rotationally supported), since the IA signal is believed to depend strongly on the galaxy support mechanism. Intrinsic alignments have been detected for samples of intrinsically red galaxies (Hirata et al. 2007; Joachimi et al. 2011; Singh et al. 2015; Johnston et al. 2019; Fortuna et al. 2021b; Samuroff et al. 2023; Hervas Peters et al. 2024) with high significance, confirming the validity of the linear alignment model on large scales. On quasi-linear scales, the accuracy of IA measurements have not yet revealed any deviations from the effective description of the NLA model. For blue or emission-line galaxies the picture is more complicated; no detection has been made with the statistics that are useful for quantifying IA contamination to weak lensing (Mandelbaum et al. 2011; Tonegawa et al. 2018, 2025; Johnston et al. 2019, 2021; Samuroff et al. 2023), but such galaxies have been shown to align in some numerical simulations, albeit to different degrees of significance (Chisari et al. 2015; Tenneti et al. 2016; Kraljic et al. 2020; Samuroff et al. 2021; Delgado et al. 2023). Intriguingly, some simulations propose that their rotational axis aligns parallel to the separation vector, which would mean their shape alignment signal has the same sign as the cosmic shear signal (see e.g. Chisari et al. 2015; Kraljic et al. 2020). Consequently, the impact of blue galaxy alignments on cosmic shear measurements remains an open question.

The importance of IA in cosmology from weak gravitational lensing necessitates the development and testing of our models for IA through observations. This is especially important since the samples of galaxies that are used in cosmic shear studies differ significantly from those where intrinsic alignments can be studied directly and robustly. Therefore, understanding the general dependence of the IA signal on galaxy properties is crucial.

It is understood that the large-scale alignment amplitude of red galaxies scales with their luminosity (Joachimi et al. 2011; Singh et al. 2015; Fortuna et al. 2021b). Recently, the universality of this scaling has been called into question, with red galaxies occupying different regions of the intrinsic colour – absolute

magnitude diagram shown to follow inconsistent scaling relations (Samuroff et al. 2023). On theoretical grounds, the intrinsic colour of a galaxy does not directly determine its alignment mechanism; rather, it is the mechanism of internal dynamical support with galaxies split into pressure-supported and rotationally supported types (Catelan et al. 2001; Kiessling et al. 2015; Ghosh et al. 2024). This distinction in galaxy populations might manifest more clearly with measurements of the galaxy’s morphology rather than its intrinsic colour alone.

In this work, we aim to test the universality of the large-scale IA amplitude scaling with galaxy luminosity using data from KiDS. We used a bright sub-sample of the full survey, ensuring the high quality of the estimated photometric redshifts (photo-*z*s), together with a catalogue of Sérsic surface-brightness profile fits, providing morphological information of the galaxies. We also studied the alignment of blue galaxies and obtain upper bounds on their signal. Lastly, we utilised the flexibility of our shape measurement method to study the degree to which the IA signal depends on the scale of the galaxy being probed, a dependence that has been shown in Singh & Mandelbaum (2016) and Georgiou et al. (2019a). Such a dependence can influence the choice of intrinsic alignment priors, and it might also have further applications with regard to IA mitigation (Leonard et al. 2018) and cosmology (Chisari et al. 2016).

In Sect. 2, we introduce the data sets used in this work, the shape measurement procedure, and the morphological classification strategy. Section 3 describes our methodology for measuring and modelling the relevant correlations and their covariance matrix. Section 4 presents our results, and conclusions are given in Sect. 5. Throughout this work, we adopted a flat Λ -Cold-Dark-Matter (Λ CDM) cosmology with the best-fit cosmological parameters from the *Planck* 2018 analysis (Planck Collaboration VI 2020), from the Plik likelihood, and we use $\Omega_m = 0.315$, $\Omega_b = 0.0493$, $h = 0.673$, $\sigma_8 = 0.811$ and $n_s = 0.965^1$.

2. Data

Direct measurements of the intrinsic alignment of galaxies require a galaxy catalogue containing shape and redshift information from which physically associated galaxies can be identified, typically in pairs. The galaxies for which shapes have been successfully measured constitute the shape sample. The highest IA signal is measured when this shape sample is correlated with positions of galaxies, which is called the density sample. These two samples do not need to contain the same galaxies, but they have to overlap in real space. When measuring real-space correlation functions, as we did in this work, a sample of random points that follow the angular and radial (in redshift) selection function of the two galaxy samples is also required. In this section, we detail the characteristics of the shape, density, and random samples employed in this work.

2.1. Kilo-Degree Survey

We studied the intrinsic alignment of galaxies using data from the Kilo-Degree Survey (KiDS, de Jong et al. 2013). KiDS is a wide-field imaging survey carried out using the European Southern Observatory (ESO) VLT Survey Telescope. The survey covers four optical broad bands, *ugri*, and survey operations are now completed, with a total coverage of 1347 deg² (Wright et al.

¹ In the rest of the manuscript, n_s is used to describe the Sérsic index and not the spectral index of the primordial power spectrum.

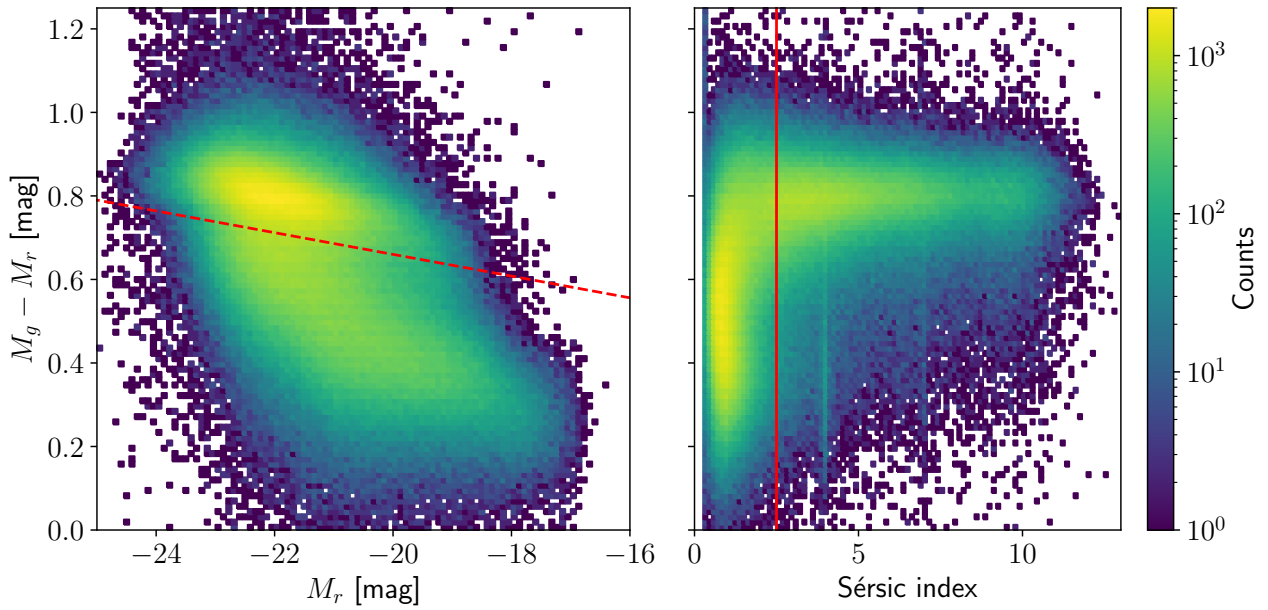


Fig. 1. Two-dimensional histograms of properties of galaxies in final sample of KiDS bright catalogue. *Left:* Distribution of rest-frame $g-r$ colour (y -axis) against absolute magnitude in the r band (x -axis). The dashed red line shows our criteria for splitting the sample in intrinsically red and blue galaxies. *Right:* Same as before, but with the Sérsic index, n_s , in the x -axis (see Sect. 2.3 for details). The solid red line indicates our $n_s = 2.5$ selection for high- and low-Sérsic-index galaxies.

2024). The recent data releases also combine the optical data with photometry from the VISTA Kilo-degree INfrared Galaxy (VIKING) survey (Edge et al. 2013), resulting in nine-band $ugriZYJHK_s$ photometry. KiDS was designed with weak gravitational lensing as its main scientific goal, with r -band observations restricted to the best dark-time night-sky conditions. As a result, the r -band images exhibit very high quality, with a limiting magnitude depth of 24.8 (at 5σ) and a median seeing of $0.7''$. This makes it an excellent choice for measuring galaxy shapes and extracting their intrinsic alignment signal.

In this work, we used the KiDS ‘bright’ galaxy sample² (Bilicki et al. 2021). This sample is a high-quality subset of the full KiDS data, which contains galaxies with an apparent r -band magnitude of $r \leq 20$ and was produced using the fourth KiDS data release (DR4, Kuijken et al. 2019). The sample selection was chosen to mimic, as closely as possible, galaxies from the equatorial fields of the Galaxy And Mass Assembly (GAMA) survey (Driver et al. 2011), a highly complete spectroscopic survey. The third data release of the GAMA survey (labelled GAMA II) achieves 98.5% completeness in these fields – which cover 180 deg^2 and fully overlap with the KiDS footprint – down to a limiting magnitude of Petrosian r -band $r_{\text{petro}} \leq 19.8$ (Liske et al. 2015) based on the Sloan Digital Sky Survey (SDSS) DR7 photometry (Abazajian et al. 2009). This makes it a well-suited calibration sample for acquiring photo- z estimates for the KiDS bright galaxies. These photo- z s are obtained using the neural-network-based redshift estimation software ANNz2 (Sadeh et al. 2016) with GAMA galaxies serving as the training sample, resulting in a high-quality photo- z sample with a mean bias of $\sim 5 \times 10^{-4}$ and a photo- z scatter of $\sim 0.018(1+z)$ quantified as scaled median absolute deviation (SMAD). We restricted the sample to galaxies outside masked regions and also with photo- z in the range of $0.05 \leq z_{\text{phot}} \leq 0.5$, as recommended in Bilicki et al. (2021), where the photo- z performance is optimal.

Accompanying the released KiDS bright sample is a catalogue of galaxy stellar masses and rest-frame absolute magnitudes produced using the spectral-energy-distribution (SED) template-fitting software LEPHARE (Ilbert et al. 2006). We made use of this catalogue to acquire rest-frame colour and luminosity information for our galaxy sample, allowing us to divide galaxies into intrinsically red and blue populations. The distribution of galaxy rest-frame colour (computed using the absolute magnitudes, M_g and M_r , in filters g and r) compared to r -band absolute magnitude and the red and blue galaxy selection criteria can be seen in the left panel of Fig. 1; it is given by

$$M_g - M_r = 0.14 - 0.026M_r. \quad (1)$$

The absolute magnitudes in the g and r bands in the above equation have also been corrected for the finite apertures used as input for LEPHARE and the different value of the dimensionless Hubble parameter, h , assumed in this work (see Appendix C in Bilicki et al. 2021). We also removed galaxies with inferred stellar masses outside the range of $7 < \log_{10}(M/M_{\odot}) < 12$ to avoid galaxies that might have problematic template fits, though this only affects 2511 galaxies. In total, all our cuts remove 20.8% of the sample, which consists of 980 837 galaxies.

2.2. DEIMOS galaxy shapes

Galaxy shapes for the majority of the bright galaxy sample are not obtained with the standard KiDS pipelines due to limitations in the implementation of the shape-measurement pipeline, which prioritises faint galaxies. Here, we describe the galaxy shape catalogue that we produce for the KiDS bright sample using DEIMOS (Melchior et al. 2011), a galaxy surface-brightness moment-based shape-measurement method. The methodology here is identical to the one presented in Georgiou et al. (2019b), and we refer the reader to that work for additional details of the DEIMOS implementation.

² <https://kids.strw.leidenuniv.nl/DR4/brightsample.php>

Table 1. Multiplicative bias corrections for our shape measurements at different weight function sizes.

$r_{\text{wf}}/r_{\text{iso}}$	m
0.5	0.021
1.0	-0.004
1.5	-0.011

The ellipticity of galaxies is obtained via a combination of the second-order galaxy moments, which is given by

$$\epsilon_1 + i\epsilon_2 = \frac{Q_{20} - Q_{02} + i2Q_{11}}{Q_{20} + Q_{02} + 2\sqrt{Q_{20}Q_{02} - Q_{11}^2}}, \quad (2)$$

where $\epsilon \equiv \epsilon_1 + i\epsilon_2$ is the galaxy ellipticity and Q_{ij} are the (unweighted) moments of the galaxy surface brightness, $G(\mathbf{x})$, with the coordinate vector $\mathbf{x} = (x_1, x_2)$ given as

$$Q_{ij} = \int d\mathbf{x} G(\mathbf{x}) x_1^i x_2^j. \quad (3)$$

Astronomical observations are sensitive to distortions due to optics and, for Earth-based observations, the atmosphere. These distortions are characterised by the point-spread function (PSF), which needs to be deconvolved from the observed moments to obtain the true galaxy moments. At the centre of the DEIMOS method is this deconvolution, which can be done analytically if the PSF moments are also known, up to the same order as the galaxy moments.

Additionally, the presence of noise in astronomical images prevents the measurement of unweighted galaxy moments, making it necessary to employ a weighting scheme. A common choice, which we adopted here, is to use a multivariate Gaussian weighting function (Bernstein & Jarvis 2002) whose ellipticity and centroid is matched per galaxy. The size of this weight function, r_{wf} , was fixed per galaxy and is related to the galaxy's isophotal radius, r_{iso} , measured at 3σ above the noise background. Our fiducial sample was generated with $r_{\text{wf}} = r_{\text{iso}}$, but we also explore other choices in Sect. 4.3. The de-weighted moments are then recovered via a Taylor expansion, implemented to the fourth order in our case.

The PSF was modelled using a shapelets expansion described in Appendix A.1 of Kuijken et al. (2015), and the second-order moments of the PSF were computed from this model at the position of each galaxy for the deconvolution. For the galaxy sample where shapes are necessary, we only used those that pass several quality control flags, ensuring the correct behaviour and convergence of the measured ellipticity. Lastly, we corrected the output ellipticity measurements for multiplicative bias, m , according to $\epsilon_{\text{true}} = (1 + m)\epsilon_{\text{observed}}$, with values derived from Georgiou et al. (2019a) and summarised in Table 1. Note that additive bias is consistent with zero.

2.3. Galaxy morphology

In order to study the dependence of galaxy intrinsic alignments on their morphology, we used an updated catalogue of galaxy structural parameters, which was first described in Roy et al. (2018) but are now applied to KiDS-DR4. This catalogue was generated by fitting a PSF-convolved 2D Sérsic galaxy surface-brightness profile in the r -band KiDS DR4 images. The galaxy sample for this morphology catalogue was

selected from the KiDS photometry catalogue by setting the star/galaxy separation flag CLASS_STAR=1. In addition, the sample is restricted to galaxies with a high signal-to-noise ratio by requiring $1/\text{MAGAUTO_ERR} > 40$ in order to ensure accurate determination of the structural parameters. This corresponds to a completeness limit of $r < 20.5$, which is deeper than that of the KiDS bright catalogue.

The estimation of galaxy structural parameters was done using the 2DPHOT algorithm (La Barbera et al. 2008). This algorithm performs PSF-convolved 2D Sérsic profile fits to the galaxy surface brightness. The PSF correction is crucial for obtaining accurate structural parameters, and in 2DPHOT this was done by selecting two or three (depending on distance) high-confidence stars that are close to the modelled galaxy and modelling the PSF 2D profile by fitting two Moffat profiles to those star images. The resulting structural parameters are the effective semi-major axis, R_m , central surface brightness, I_0 , and Sérsic index, n_s , of the best-fit Sérsic profile, together with the axis ratio, q , position angle, photometric centre, and local background of each galaxy. From these parameters, we also obtain the circularised effective radius, $R_e = \sqrt{q}R_m$, and the apparent total modelled magnitude, m_T (see Roy et al. 2018 for further details on this procedure).

The resulting galaxy morphology catalogue was further cleaned by requiring a sensible reduced chi-square value of the 2D profile fit, with $\chi_{\text{red}}^2 < 10$. We also rejected galaxies that exhibit a very large effective radius, requiring $R_e < 10$ arcsec, as the structural parameters of these galaxies are usually affected by large uncertainties. Lastly, we expect the modelled apparent magnitudes to be fairly close to the measured ones, and we required $|m_T - m_r| < 1$. With this selection, we were left with ~ 4 million galaxies. After spatial matching of the structural parameter catalogue with the KiDS bright sample, the resulting catalogue had 779 780 galaxies. We used this reduced sample only when selecting from the Sérsic index and kept the larger, original, bright sample otherwise.

The parameter we are most interested in for this analysis is the Sérsic index, n_s , the value of which describes the steepness of the central surface-brightness profile. A low value of n_s describes a smooth galaxy-brightness profile that extends further out, while a high value describes a profile more concentrated in the centre. Because of this, spiral galaxies are roughly described by a Sérsic profile with $n_s = 1$ (exponential profile), while elliptical galaxies are described with $n_s = 4$ (de Vaucouleurs profile). Hence, the Sérsic index might serve as a proxy to study the alignment of rotationally supported and pressure-supported galaxies, which is one of the goals of this work.

In the right panel of Fig. 1 we show the 2D histogram of the rest-frame colour and Sérsic index of galaxies from the structural parameter catalogue matched with the KiDS bright catalogue. We notice that galaxies can be divided into two distinct populations. On the top of the figure's right panel, we find galaxies that are intrinsically redder ($g - r > 0.7$) and have a wide range of n_s values with most of the galaxies having a value close to $n_s = 4$. On the left side of the panel, we see a clump of galaxies that are intrinsically bluer and have a much lower value of n_s , with most of them being close to $n_s = 1$. This relation between galaxy colour and Sérsic index is well established from previous surveys, for example Blanton et al. (2003). In Roy et al. (2018) it was shown that a split at $n_s = 2.5$ best divides the galaxy population into spheroids and disks, and we adopted this value to split the sample into high- and low-Sérsic-index galaxies.

2.4. Galaxy And Mass Assembly

So far, we have detailed our sample of galaxies for which shapes have successfully been measured. In this section, we describe the galaxy sample acting as a density tracer. The first consideration would be to use the full KiDS bright sample as the density tracer, especially since we are not interested in measuring and interpreting the galaxy bias (i.e. the relation between the galaxy and the matter overdensity), but instead we treat it as a nuisance (see Sect. 3). However, the galaxy clustering measurement used to infer the linear galaxy bias is very sensitive to the accuracy of the catalogue of random points used to normalise the measurement (Yang & Li 2023). This sensitivity is not as severe in the projected galaxy position–shape correlation, which we measured to infer the intrinsic alignment signal, since it is less dependent on the position of galaxies and also has a much lower signal-to-noise ratio (S/N). Generating a random sample for a photometrically selected flux-limited sample presents additional challenges (Johnston et al. 2021).

Given the challenge of producing a random catalogue accurate enough for the clustering measurements, we chose to follow a different approach. We aimed to create a sample that matches GAMA II galaxies more closely than the full KiDS bright sample – which contains some galaxies that are fainter than the GAMA Petrosian r -band limit (Bilicki et al. 2021). To do this, we took advantage of the latest GAMA data release, GAMA III (Driver et al. 2022), which assimilates data from the KiDS and VIKING surveys to provide more complete and homogeneous photometry of the GAMA galaxy sample (Bellstedt et al. 2020). Consequently, a more precise magnitude limit can be constructed that matches both GAMA III and the KiDS bright galaxies, since the samples use the same photometry.

We selected GAMA III galaxies using the `gkvScienceCat` data management unit (DMU) version 02 (Bellstedt et al. 2020) and selected all objects with sample class $SC \geq 6$ corresponding to a sample with 90% completeness down to an r -band magnitude of 19.77. This sample excludes objects identified as ambiguous, stars, or masked. We were not interested in having a highly complete density sample and chose this SC cut with lower completeness but higher number density to increase the statistical power of our measurements. We supplemented this catalogue with local flow corrections (to account for flows in the nearby Universe) to the galaxy redshifts from the `DistancesFrames` DMU version 14 (Baldry et al. 2012), and we used the `Z_TONRY` column for our galaxy redshifts.

We used the resulting galaxy catalogue, restricted to the equatorial regions, to measure the clustering and infer the linear galaxy bias of the sample. The advantage of doing this is that we were able to use the randoms DMU specifically built for GAMA galaxies from Farrow et al. (2015)³. We then restricted the KiDS bright sample to $r \leq 19.77$ and used it as our density sample in our projected galaxy position–shape correlations, and we assume the linear galaxy bias is the same as that for the GAMA III clustering measurement. We confirmed the selection produces a KiDS bright density sample that is similar to the GAMA III sample by examining the redshift and observed colour distribution, which is shown in Fig. 2. We see that the KiDS bright sample limited to an r -band magnitude of $r \leq 19.77$ matches the observed $g - r$ colour and redshift distribution of the GAMA III sample better than that considering the full KiDS

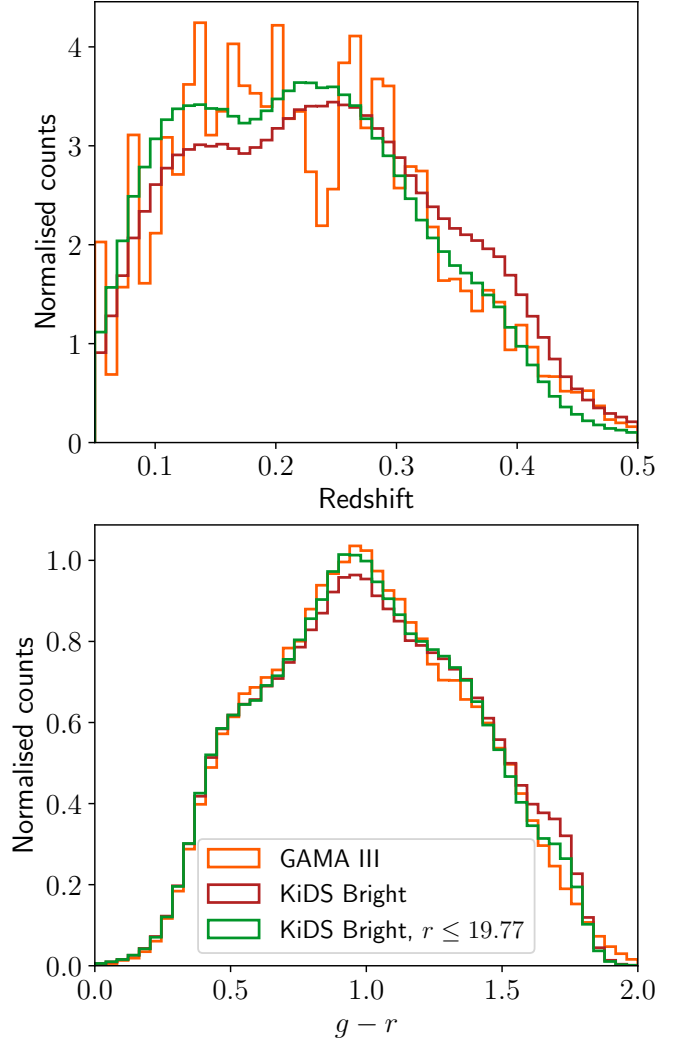


Fig. 2. Redshift (top) and observed colour distribution (bottom) of the GAMA III (orange) and KiDS bright (red) samples. Limiting the KiDS bright sample to $r \leq 19.77$ yields a clustering sample (green) that better matches the properties of the GAMA III sample.

bright sample. These findings are consistent with what is seen in Jalan et al. (2024), and the brighter cut implemented here is also expected to improve the quality of the photometric redshifts.

2.5. Galaxy sub-samples

To examine the dependence of intrinsic alignments on colour, morphology, and both traits combined, we split the sample into several sub-samples, as detailed in Table 2. Following the cuts presented in Fig. 1, we defined the red and blue samples in terms of their intrinsic rest-frame colour. The red sample was further split into five equipopulated luminosity bins using L/L_0 , where L_0 is the luminosity of a galaxy corresponding to an absolute magnitude of $M_r = -22$. The luminosity bins contain approximately 80 000 galaxies each. Note that these bins do not contain exactly the same number of galaxies due to galaxies being rejected from shape-measurement flags. We checked that these flags do not alter the sample characteristics seen in Table 2 by more than 1% (and in most cases it is less than that). The mean redshift of the various sub-samples ranges from 0.15–0.36.

Alternatively, we selected galaxies based on the Sérsic index, placing a cut at $n_s > 2.5$ to select elliptical galaxies as discussed

³ Note that these randoms were built for GAMA II, but they should be representative of the selection function of the GAMA III sample as well since the target selection was not changed, particularly in the equatorial regions.

Table 2. Different KiDS bright galaxy sub-samples considered in this work.

Selection	$\log(L/L_0)$	N_{gal}	$\langle z \rangle$	$\log(\langle L \rangle/L_0)$
Red	$(-\infty, -0.55]$	79584	0.16	-0.74
Red	$(-0.55, -0.33]$	81220	0.21	-0.43
Red	$(-0.33, -0.16]$	82043	0.26	-0.24
Red	$(-0.16, 0.00]$	82498	0.31	-0.08
Red	$(0.00, +\infty)$	85354	0.36	0.16
$n_s > 2.5$	$(-\infty, -0.55]$	50464	0.15	-0.77
$n_s > 2.5$	$(-0.55, -0.33]$	52470	0.21	-0.43
$n_s > 2.5$	$(-0.33, -0.16]$	56212	0.26	-0.24
$n_s > 2.5$	$(-0.16, 0.00]$	59040	0.31	0.08
$n_s > 2.5$	$(0.00, +\infty)$	65429	0.36	0.16
Red, $n_s > 4$	–	145297	0.28	-0.09
Red, $n_s < 4$	–	203526	0.25	-0.24
Blue	–	385142	0.22	-0.45
$n_s < 2.5$	–	400786	0.22	-0.42
Density	–	675724	0.22	-0.42

Notes. Samples are split by colour, morphology, or both. We indicate the selection in luminosity ($\log(L/L_0)$), the number of galaxies in each bin (N_{gal}), the mean redshift of the sub-sample ($\langle z \rangle$), and the logarithmic mean luminosity of the galaxies in the bin ($\log(\langle L \rangle/L_0)$).

in Sect. 2.3. We subdivided these galaxies further into the same five luminosity bins as for the red sample. Finally, we considered a joint colour and morphology cut by separating red galaxies into those that have $n_s < 4$ and those that have $n_s > 4$, which gives roughly equal sample sizes. This was done to further isolate dependence on morphology within our red sample. Distributions of galaxy properties for our different samples are presented in Appendix B.

In this analysis, we do not consider any evolution of the intrinsic alignment signal with redshift. Several studies have looked at this evolution and there does not seem to be a significant trend for the redshift baseline considered in this work (e.g. Johnston et al. 2019; Samuroff et al. 2023).

3. Methodology

We quantified the intrinsic alignment of galaxies by measuring the projected two-point correlation function between a galaxy-shape sample and a galaxy-position sample, the latter acting as a tracer of the density field. The projected correlation function between two fields, a and b , is given by

$$w_{ab}(r_p) = \int dz \mathcal{W}_{ab}(z) \int_{-\Pi_{\text{max}}}^{\Pi_{\text{max}}} d\Pi \xi_{ab}(r_p, \Pi, z), \quad (4)$$

where r_p and Π are the projected and radial separations between tracers of fields a and b , and ξ_{ab} is the correlation function at redshift z . The correlation function ξ_{ab} is projected by integrating along the line-of-sight direction up to a maximum separation of Π_{max} . The kernel function, $\mathcal{W}_{ab}(z)$, depends on the comoving radial distance, $\chi(z)$, and the redshift distribution of the tracers, $n_{a,b}(z)$, and is given by Mandelbaum et al. (2011)

$$\mathcal{W}_{ab}(z) = \frac{n_a(z)n_b(z)}{\chi^2(z)d\chi/dz} \left(\int dz \frac{n_a(z)n_b(z)}{\chi^2(z)d\chi/dz} \right)^{-1}. \quad (5)$$

The main observable of intrinsic alignment for this work is the correlation of galaxy shapes with galaxy positions. For any

galaxy pair with a separation vector forming an angle, θ , with an arbitrary coordinate-system axis, the ellipticity of a galaxy, $\epsilon = \epsilon_1 + i\epsilon_2$, can be decomposed in the tangential and cross-component with respect to the separation vector as

$$\begin{aligned} \epsilon_+ &= \epsilon_1 \cos(2\theta) + \epsilon_2 \sin(2\theta) \\ \epsilon_\times &= \epsilon_1 \sin(2\theta) - \epsilon_2 \cos(2\theta), \end{aligned} \quad (6)$$

respectively. Here, we followed the convention that when the semi-major axis of the ellipse is parallel to the separation vector (indicating radial alignment), ϵ_+ is positive. We computed the correlation function of galaxy positions and the tangential ellipticity component between galaxy pairs, denoted as ξ_{g+} . Note that if assuming parity is not violated in the Universe, the $\xi_{g\times}$ correlation is expected to be zero. This serves as a null test for any systematic effects that are not accounted for in the shape-measurement method, such as imprecise PSF modelling.

In the presence of uncertain redshift information, as is the case for our sample of galaxies with photometrically obtained redshifts, we need to take into account the probability distribution function of a galaxy's true redshift given the estimated redshift when modelling the correlation function. To do this, we first write the correlation function of galaxy shapes and positions following Joachimi et al. (2011):

$$\xi_{g+}^{\text{phot}}(r_p, \Pi, z_m) = \int_0^\infty \frac{d\ell}{2\pi} J_2(\ell\theta(r_p, z_m)) C_{g1}(\ell|z_m, \Pi), \quad (7)$$

where $J_n(x)$ is the Bessel function of the first kind. The mean redshift, z_m , at which the correlation function is estimated and the line-of-sight separations Π are related to the redshifts of a galaxy pair, z_1, z_2 , through

$$\begin{aligned} z_m &= \frac{1}{2}(z_1 + z_2), \\ \Pi &= \frac{c}{H(z_m)}(z_2 - z_1), \end{aligned} \quad (8)$$

where c and H are the speed of light and Hubble parameter, respectively, while the angle is given by $\theta = r_p \chi^{-1}(z_m)$. Equation (7) relates the correlation function to the angular power spectrum, C_{g1} , which is given by

$$\begin{aligned} C_{g1}(\ell|z_1, z_2) &= \int_0^{\chi_{\text{hor}}} d\chi' \frac{p_g(\chi'|\chi(z_1)) p_\epsilon(\chi'|\chi(z_2))}{\chi'^2} \\ &\times P_{g1}\left(k = \frac{\ell + 0.5}{\chi'}, z_m\right). \end{aligned} \quad (9)$$

Here, $p_{g,\epsilon}$ is the probability density function of a galaxy's true redshift given the observed one (z_1 or z_2), but expressed in terms of the comoving radial distance. Subscripts indicate the galaxy-position sample (g) or the galaxy-shape sample (ϵ), and the integral is carried out to the comoving radial horizon distance. We also used the Limber (1953) approximation.

The power spectrum of galaxy position and galaxy intrinsic shape, P_{g1} , contains the statistical information of galaxy intrinsic alignments and is the relevant quantity we needed to model. We restricted our analysis to large enough scales where we were able to treat the tracer fields as related linearly to the matter density field, δ . Consequently, we assumed linear galaxy bias, b_g , with the galaxy density given by $\delta_g = b_g \delta$, and we employed the linear alignment model (Catelan et al. 2001; Hirata & Seljak 2004), resulting in

$$P_{g1}(k, z) = -b_g A_{\text{IA}} \frac{\rho_{\text{crit}} \Omega_m \bar{C}_1}{D(z)} P_\delta(k, z). \quad (10)$$

The intrinsic alignment amplitude, A_{IA} , is the quantity that describes the intrinsic alignment of galaxies on large scales, for a given set of cosmological parameters and modulated by the linear galaxy bias. A positive value of A_{IA} indicates galaxies orient their semi-major axis in the direction of the position of other galaxies, with higher values indicating a stronger statistical alignment. The amplitude, \bar{C}_1 , is a normalisation factor, and a common choice is the value given in [Bridle & King \(2007\)](#), with $\bar{C}_1 = 5 \times 10^{-14} (h^2 M_\odot / \text{Mpc}^{-3})^{-2}$. Lastly, ρ_{crit} is the critical matter density, $D(z)$ is the growth factor normalised to 1 at $z = 0$, and P_δ is the matter power spectrum. The linear expansion described in [Hirata & Seljak \(2004\)](#) requires the linear matter power spectrum be used in Eq. (10). We followed [Bridle & King \(2007\)](#) and used the non-linear matter power spectrum.

To obtain the probability density function of a galaxy's true redshift given its observed one, we computed the distribution of redshift error, $\delta z = (z - z_{\text{phot}})/(1 + z)$, and fitted a generalised Lorentzian distribution to it:

$$p_{g,\epsilon}(z, z_{\text{phot}}) \propto \left(1 + \frac{\delta z}{2\alpha s^2}\right)^{-a}. \quad (11)$$

This distribution is shown to describe the photometric redshift errors of the sample very well, particularly in the long tails of the distribution ([Bilicki et al. 2021](#)). We obtained the galaxy true redshift by spatially matching our galaxy sample to GAMA III galaxies (finding matches within 2 image pixels chosen to strike a balance between failing to find true matches and finding false ones), and then we determined the values of α and s for each of our galaxy sub-samples (see Sect. 2.5).

When measuring correlations between galaxy shapes and positions, if galaxy pairs are separated by a large enough distance, the signal from the weak gravitational lensing of the background galaxy caused by the foreground galaxy can be non-negligible. This is especially common when galaxy distances are based on photometric redshifts, and galaxies need to be correlated to high Π_{max} in order to recover the intrinsic alignment signal that gets redistributed out to large values of Π by the photo- z uncertainty. The weak gravitational lensing contribution to the correlation function, ξ_{gG} , has the same form as Eq. (7), but with the angular power spectrum substituted for

$$C_{gG}(\ell|z_1, z_2) = \int_0^{\chi_{\text{hor}}} d\chi' \frac{p_g(\chi'|\chi(z_1)) q_\epsilon(\chi'|\chi(z_2))}{\chi'^2} \times P_\delta\left(k = \frac{\ell + 0.5}{\chi'}, z_m\right), \quad (12)$$

where the lensing kernel for the galaxy shape sample is given by

$$q_\epsilon(\chi, \chi_1) = \frac{3H_0^2 \Omega_m}{2c^2} \frac{\chi}{a(\chi)} \int_\chi^{\chi_{\text{hor}}} d\chi' p_\epsilon(\chi'|\chi_1) \frac{\chi' - \chi}{\chi'}, \quad (13)$$

and $a(\chi)$ is the scale factor. In Fig. 3, we show the ratio between the lensing contamination and the full signal, $w_{gG}/(w_{gG} + w_{g+})$. The weak lensing contamination is stronger for samples with larger errors in their redshift distributions and for samples at higher redshift, with both effects playing an important role. In principle, lensing magnification will also impact our measured signal, but its effect is expected to be very small by comparison ([Samuroff et al. 2023](#)), especially over the relatively low redshift baseline of our galaxy sample. For this reason, we neglect its impact here.

The last ingredient in our modelling is the linear galaxy bias, b_g , which we treated as a nuisance parameter. The most common

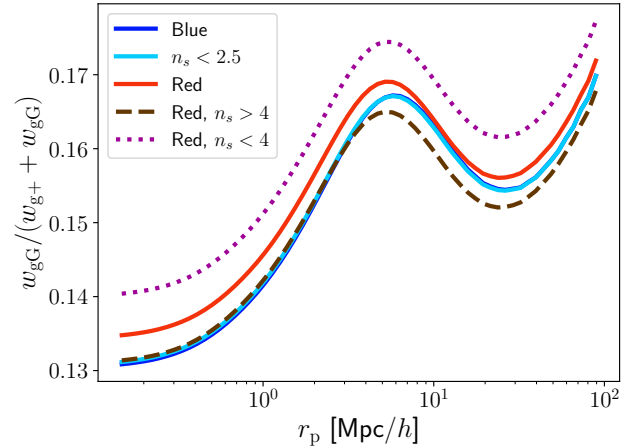


Fig. 3. Contamination of weak gravitational lensing measurements in the intrinsic alignment measurements, expressed as a ratio of the lensing signal over the total signal.

way to constrain it is to measure the projected auto-correlation function of galaxy positions, the galaxy clustering. However, as mentioned in Sect. 2.4, this measurement is highly dependent on the accuracy of the random points used in the Landy-Szalay estimator, which are even more challenging to construct for a flux-limited, photometric galaxy sample with photo- z uncertainty ([Johnston et al. 2021](#)). Instead, we chose to select a sub-sample of the full KiDS bright sample to act as the density sample that better matches galaxies in the GAMA III sample. We then made the assumption that these two samples have the same linear galaxy bias and used the GAMA III sample to measure the galaxy clustering signal and determine b_g . For a sample with precise redshift information, the projected galaxy clustering is equal to

$$w_{gG}^{\text{spec}}(r_p) = b_g^2 \int dz \mathcal{W}_{ab}(z) \int \int \frac{dk_\perp dk_\parallel}{\pi^2} \frac{k_\perp}{k_\parallel} \sin(\Pi_{\text{max}} k_\parallel) \times J_0(k_\perp r_p) P_\delta\left(\sqrt{k_\parallel^2 + k_\perp^2}, z\right), \quad (14)$$

with k_\parallel and k_\perp being the components of the Fourier wave-number vector that are parallel and perpendicular to the line of sight, respectively.

A similar equation can be written for the position–shape correlation of a galaxy sample with accurate redshift information, as in the case of spectroscopic redshifts, where

$$w_{g+}^{\text{spec}}(r_p) = \int dz \mathcal{W}_{ab}(z) \int \int \frac{dk_\perp dk_\parallel}{\pi^2} \frac{k_\perp^3}{(k_\parallel^2 + k_\perp^2) k_\parallel} \sin(\Pi_{\text{max}} k_\parallel) \times J_2(k_\perp r_p) P_{gI}\left(\sqrt{k_\parallel^2 + k_\perp^2}, z\right). \quad (15)$$

We used this to validate our code that computes the photometric w_{g+} by ensuring the two predictions match when we use an extremely narrow distribution for $p_{g,\epsilon}(z, z_{\text{phot}})$ in Eq. (9).

3.1. Estimators

In this section, we describe how to connect the theoretical models of galaxy statistics, outlined in Sect. 3, to estimators obtained

from observational data. We used the Landy-Szalay estimator (Landy & Szalay 1993) to measure the auto-correlation of galaxy positions, which is given by

$$\hat{\xi}_{gg} = \frac{DD - DR - RD + RR}{RR}. \quad (16)$$

The terms in the above equation denote measurements of galaxy-pair counts within a specific bin of galaxy-pair projected and line-of-sight separation, r_p and Π . The variable D is for a sample of galaxy positions taken from the density sample, and R is for galaxy positions obtained from a sample of random data points that mimic the angular and radial selection function of sample D . We connected the measured correlation function to our observed, projected correlation function via

$$\hat{w}_{ab}(r_p) = \int_{-\Pi_{\max}}^{\Pi_{\max}} d\Pi \hat{\xi}_{ab}(r_p, \Pi), \quad (17)$$

where the integral is reduced to a Riemann sum over the Π bins. For the galaxy clustering signal, measured from the GAMA III spectroscopic galaxies, we used $\Pi_{\max} = 60 \text{ Mpc}/h$ and binned Π linearly in 30 bins. We used TreeCorr⁴ (Jarvis et al. 2004) to measure the correlation functions. We measured all correlations in 11 bins of r_p logarithmically spaced from 0.1 to 60 Mpc/h.

For the measurement of the galaxy position–shape correlation, we followed Mandelbaum et al. (2006) and computed the estimator

$$\hat{\xi}_{g+} = \frac{S_+ D - S_+ R}{RR}. \quad (18)$$

Here, the terms on the nominator are the sum of the tangential ellipticity component of galaxy pairs that lie within a bin of r_p and Π . This is given by

$$S_+ A = \sum_{i \neq j} \epsilon_+(i|j)/\mathcal{R}, \quad (19)$$

where the galaxy i belongs to the shape sample and the galaxy j to the density or random sample, for $A = D$ and R , respectively. To connect the inferred intrinsic alignment amplitudes with their impact on measurements of weak gravitational lensing, we need to correct the ellipticity measurements for the responsivity⁵ of the ellipticity estimate to the shear: $\mathcal{R} = \partial\epsilon/\partial\gamma \approx 1 - \epsilon_{\text{rms}}^2$ (Mandelbaum et al. 2006). To speed up the computation of the correlations, we chose to use the pair counts DR instead of RR in the denominator of Eq. (18), which has a negligible effect on the measurement (Johnston et al. 2019).

3.2. Covariance estimation

We used jackknife resampling to estimate the covariance of our measurements directly from the data. This method provides a way to estimate the covariance of a sample without the need to simulate the observations or develop an analytical description. It can be a noisy estimate of the covariance, but for large enough samples (large in area and number density in the case of astronomical observations) this noise does not significantly impact the estimation (Hartlap et al. 2007). However, it does not include contributions to the covariance from modes beyond the survey’s window (super-sample covariance, Takada & Hu 2013)

⁴ <http://rmjarvis.github.io/TreeCorr> (version 4.3.3).

⁵ Note that the responsivity here differs from what was used in Mandelbaum et al. (2006), because the ellipticity measure we used is the third flattening.

for which an analytic description is not available in the case of intrinsic alignment measurements, and we chose to ignore it here given the relatively low S/N .

We split our sample by area into jackknife regions using a kmeans clustering algorithm in the sphere, KMEANS-RADEC⁶. This ensures the different jackknife regions contain an approximately equal area and number density, avoiding the need to correct for that later on. By removing a jackknife patch labelled a from the full sample and measuring the correlation function in this ‘delete-one’ jackknife sample we obtain a jackknife measurement w^J of the projected correlation function (for w_{gg} or w_{g+}). We then estimated the full sample’s covariance matrix from N jackknife sub-samples via

$$C = \frac{N-1}{N} \sum_{a=1}^N (w^J - \bar{w})(w^J - \bar{w})^T, \quad (20)$$

where \bar{w} is the average of all the delete-one jackknife measurements. The covariance estimated in this way is biased, and we applied a correction multiplying the covariance matrix by $(N-D-2)/(N-1)$ to correct this bias (Hartlap et al. 2007). Here, N is the number of jackknife realisations and D is the number of data points in our data vector. Lastly, we made sure to include the responsivity factor in the covariance from Eq. (19).

The number of jackknife patches plays an important role in the validity of the estimated covariance. We need jackknife patches that are large enough in area to sample the largest physical scales of interest, but we also need a large number of patches to avoid a very noisy covariance estimate. This is particularly challenging for low-redshift samples, where the area of a patch on the sky does not correspond to a particularly large physical separation between objects in that area (compared to high-redshift samples).

We chose to use 40 jackknife regions that roughly correspond to patch sizes of 25 deg^2 or angular separations of 5.64 deg (if assumed circular). This is a good balance between the number of patches and scales we can analyse. The patch size corresponds to $60 \text{ Mpc}/h$ physical separation (our largest r_p bin edge) at redshift of 0.28, which means galaxies at lower redshift inside the patch will be separated by less than $60 \text{ Mpc}/h$. A large fraction of galaxies fall below this redshift for all galaxy samples except the two most luminous ones, and for this reason we chose to ignore the highest r_p bin in our analysis. For the second largest r_p bin at $33.5 \text{ Mpc}/h$, this redshift is much lower: 0.14. The two lowest luminosity samples have approximately 40% of their galaxies below this redshift, while for all other samples this fraction is much lower. Hence, we trust that the covariance for this bin is accurate.

4. Results

In this section, we present the results from measurements of the intrinsic alignment signal of galaxies in the sub-samples defined in Sect. 2.5. We measured the position–shape two-point projected correlation function and the jackknife covariance. We also measured the position–position projected correlation of the GAMA III sample. We then jointly fitted the w_{gg} and w_{g+} measurements for each sub-sample to determine the linear galaxy bias and the intrinsic alignment amplitude, A_{IA} . Since we used linear models for the galaxy bias and intrinsic alignments, we restricted our fits to scales of $r_p > 6 \text{ Mpc}/h$. The best-fit linear galaxy bias – which is the same in all our

⁶ <https://github.com/esheldon/kmeans-radec> (version 0.9.1).

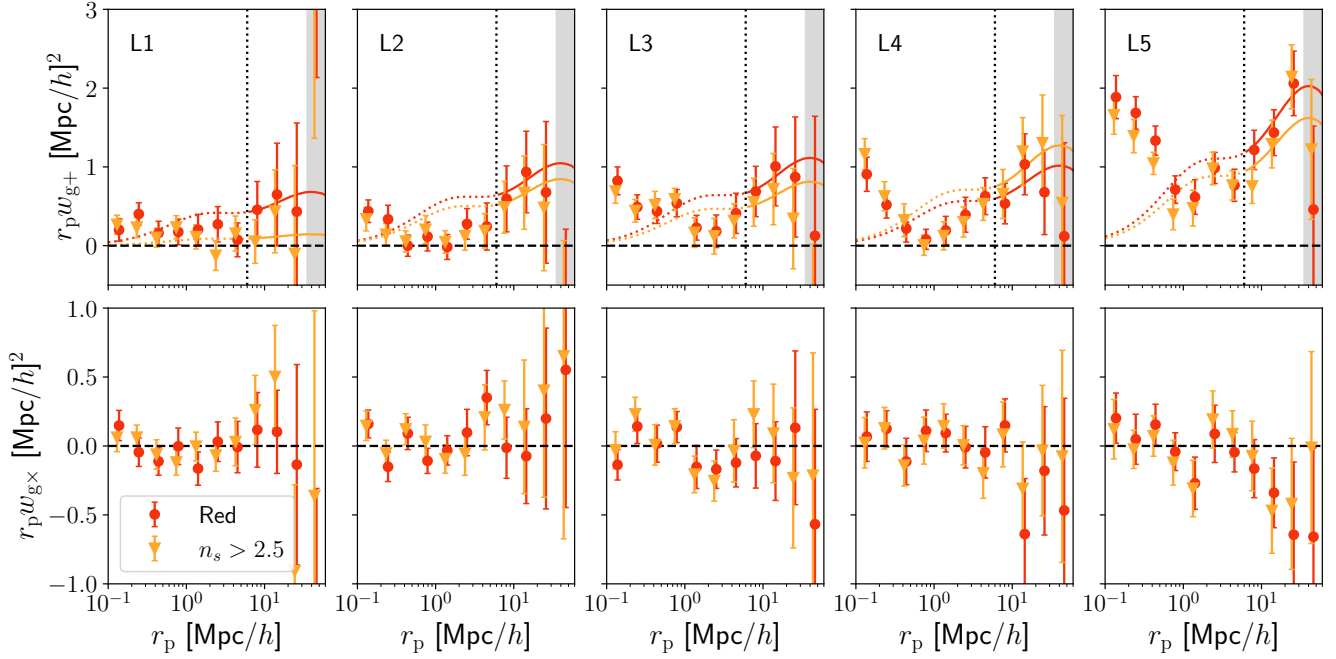


Fig. 4. *Top:* Projected position–shape correlation function measurements as a function of galaxy pair separation for the red (red circles) and high n_s (orange triangles) galaxy sub-samples. The different luminosity sub-samples are indicated in the top left of each panel, with luminosity increasing from left to right. The best-fit NLA model is shown as solid lines of corresponding colour – with dotted lines where the model is no longer valid, at $r_p < 6 \text{ Mpc}/h$, which is also indicated with a vertical dotted black line. The grey area indicates the region where the covariance estimation is no longer accurate. Points are slightly offset for visual clarity. *Bottom:* Projected correlation measurements between galaxy positions and the cross ellipticity component.

measurements since the sample for galaxy positions remains the same – was determined to be $b_g = 1.23 \pm 0.09$. Model power spectra were computed using the CORE COSMOLOGY LIBRARY⁷ (CCL Chisari et al. 2019) version 3.1.2, and the fitting was done using the SCIPY python library (Virtanen et al. 2020). The non-linear matter power spectrum was obtained using HALOFIT (Takahashi et al. 2012).

4.1. Luminosity dependence of IA

We first focus on the well-studied dependence of the intrinsic alignment signal on the average luminosity of the galaxy sample. We measured A_{IA} for our intrinsically red sample split into five different luminosity bins (labelled L1 through L5 with increasing luminosity) and we repeated this for samples selected according to Sérsic index, with $n_s > 2.5$. We present the measurements together with the best-fit NLA model in Fig. 4.

Firstly, we see that the position–cross ellipticity correlation (bottom panels) is consistent with 0 across all samples, which serves as a good null test for systematics in the shape-measurement method. Looking at the w_{g+} measurements, we see that galaxies of higher luminosity show a stronger alignment overall, a result consistent with several other studies in the literature. We do not see a significant difference in the measured correlations between the samples selected on colour (red) or morphology (n_s), given the measured uncertainty.

The resulting best-fit NLA model is also seen in the figure, with the values of A_{IA} shown in Table 3 and plotted more clearly in Fig. 5 for the different samples. While for most of our measurements the A_{IA} of high- n_s -selected galaxies is lower than for red galaxies, this difference is small compared to the uncertainty in the derived A_{IA} . We fitted the dependence of alignment ampli-

Table 3. Best-fit NLA amplitude and luminosity-scaling parameters.

Selection	A_{IA}	A_0	β
Red (L1)	2.44 ± 1.41	5.95 ± 0.49	0.68 ± 0.18
Red (L2)	3.82 ± 1.59		
Red (L3)	4.14 ± 1.23		
Red (L4)	3.96 ± 1.18		
Red (L5)	8.07 ± 1.04		
$n_s > 2.5$ (L1)	0.51 ± 1.20	5.11 ± 0.43	0.79 ± 0.16
$n_s > 2.5$ (L2)	3.04 ± 1.30		
$n_s > 2.5$ (L3)	3.03 ± 1.25		
$n_s > 2.5$ (L4)	4.98 ± 1.61		
$n_s > 2.5$ (L5)	6.54 ± 1.45		
Red, $n_s > 4$	5.24 ± 0.85	-0.67 ± 1.00	
Red, $n_s < 4$	1.12 ± 1.18		
Blue	-0.67 ± 1.00		
$n_s < 2.5$	0.64 ± 0.88		

tude on luminosity with a single power law,

$$A_{IA}(L) = A_0 \left(\frac{\langle L \rangle}{L_0} \right)^\beta, \quad (21)$$

and we fitted for A_0 and a slope β . The best-fit values for these parameters are shown in Table 3, and the parameters are approximately within $2\text{-}\sigma$ of each other’s interval (however, they are not independent).

4.2. Morphological dependence of red galaxies

In the previous section we validated that the dependence of alignment amplitude on the galaxy sample’s average luminos-

⁷ <https://github.com/LSSTDESC/CCL>

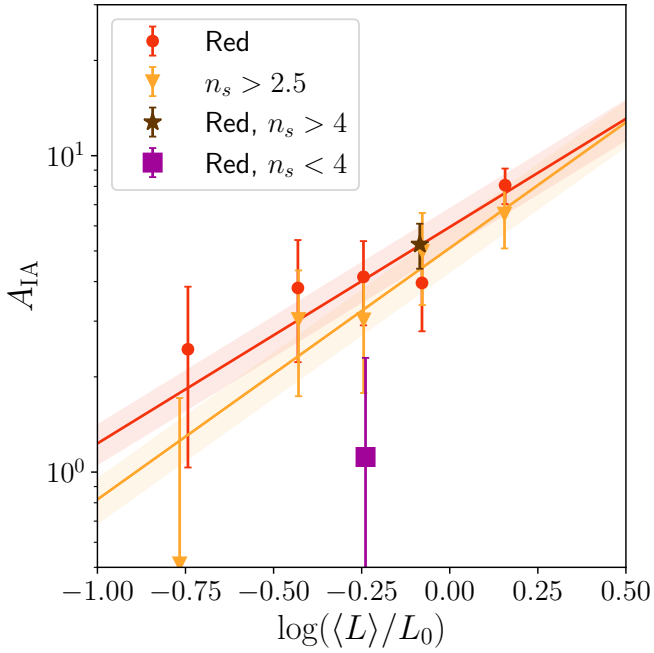


Fig. 5. Best-fit intrinsic alignment amplitude of NLA fits to w_{g+} measurements from the different galaxy sub-samples, plotted against their average luminosity logarithm. The red or $n_s > 2.5$ galaxy samples (red circles and orange triangles, respectively) are split into five luminosity bins, while the galaxy samples selected on both colour and n_s (brown star or square) are not split in luminosity. A power-law luminosity-dependent A_{IA} is fitted to the intrinsically red and $n_s > 2.5$ samples, plotted as red and orange solid lines, respectively, with the colour band indicating $1-\sigma$ intervals of the best-fit parameters.

ity is consistent if the samples are selected according to colour or morphology. This dependence has been observed so far for intrinsically red galaxy samples, but it is not yet clear if this dependence is universal. In Samuroff et al. (2023), it was hinted that the colour–magnitude distribution of the galaxy sample might play a role in at least the amplitude of the luminosity dependence, A_0 . Here, we aim to probe this question by selecting the intrinsically red galaxies in our sample and then splitting by morphology, to answer whether the structure of galaxies might affect this relation more strongly.

We measured w_{g+} and fitted for A_{IA} for red galaxies with $n_s > 4$ and $n_s < 4$, and the results are shown in Table 3. We see a large difference in the amplitude of the alignment signal, with the low Sérsic index sample having a much lower amplitude than the high- n_s sample. We then compare the measured value of A_{IA} to the expected one given the average luminosity of the samples. Those values are over-plotted in Fig. 5. We see that A_{IA} for the high- n_s red sample is consistent with the amplitude we expect from luminosity dependence alone. However, the low- n_s red sample exhibits a value of A_{IA} that is lower than this expectation by more than $1-\sigma$.

This finding suggests that the luminosity dependence observed for red galaxies is not universal, but it seems to be affected by the structure of galaxies. Red galaxies that are more disk-like and less concentrated in the centre seem to have a lower large-scale alignment amplitude than red galaxies that are more centrally concentrated. We note, however, that this difference is below 2σ . In addition, while we plot the logarithm of the average luminosity for each sample in Fig. 5, the red samples that are further sub-divided by Sérsic index are not split by luminosity since we are limited by statistics. As such, these galaxy sam-

ples are not very localised in their luminosity, meaning very low luminosity galaxies could potentially be pulling the measured A_{IA} low for the red, low- n_s sample. A larger sample of galaxies with higher statistical power is needed to be able to split them according to their colour, Sérsic index, and luminosity, and further confirm this result.

4.3. IA for different radial weighting

When measuring galaxy shapes with a moment-based method, where a radial weight function needs to be applied to the galaxy images, it is possible to vary the size of the weight function to effectively probe the shape of different galaxy regions (see Sect. 2.2). A larger weight function will up-weight the outer regions of a galaxy compared to a smaller one. We used this to study galaxy alignments as a function of the scale at which the galaxy shape is measured. The size in our case is tied to the isophotal radius of the galaxy, and we measure it in ratios of r_{wf}/r_{iso} .

To study the alignment signal as a function of galaxy scale, we first ensured we selected the exact same galaxies in all of the different shape-measurement catalogues by requiring that galaxies pass all flags for all shape measurements on top of any other galaxy sub-sample selection. This minimises any variation due to sub-sample selection between the different shape measurements. We then measured the w_{g+} correlation as before, and we present our results in Fig. 6.

As previously, we report that the $w_{g\times}$ component is consistent with zero. The alignment measurements show a strong, non-zero signal for all methods across all scales. On large scales, the w_{g+} measured using the different shape methods do not differ significantly, but the values obtained using the largest weight function are higher than values using the smaller ones. Since the measurements are highly correlated, we quantified the significance of this difference by computing the quantity $w_{g+}(r_p; r_{wf}/r_{iso} = 1.5) - w_{g+}(r_p; r_{wf}/r_{iso} = 1.0)$ and its jack-knife covariance. We chose this combination of values for the weight functions because it gives the highest S/N⁸. We find this is consistent with zero at 1σ , and we fitted an NLA model to this w_{g+} difference between the two weight functions. Since the same galaxies were used here, the measurement is proportional to $b_g \Delta A_{IA}$ with $\Delta A_{IA} = A_{IA}^{r_{wf}/r_{iso}=1.5} - A_{IA}^{r_{wf}/r_{iso}=1.0}$, and we constrained the difference in large-scale alignment amplitude between the two shape measurement methods. We find $\Delta A_{IA} = 0.38 \pm 0.71$. Note that when fitting only to $w_{g+}(r_p; r_{wf}/r_{iso} = 1.0)$, we find $A_{IA}^{r_{wf}/r_{iso}=1.0} = 3.28 \pm 0.61$. We repeated this process for our highest S/N sample, which in Table 3 is our highest luminosity intrinsically red galaxy sub-sample. We find similar results, with a $\Delta A_{IA} = 1.74 \pm 1.01$. This is a more significant result, which hints to the fact that this trend with increasing weight function size on large scales might be physical.

Interestingly, the picture is much more clear when looking at smaller scales, below 1 Mpc/h. The measurements show a clear trend, with the smallest and largest weight-function samples resulting in the lowest and highest measured alignment signals, respectively. While at small galaxy pair separations the effect of galaxy blending and stray light becomes important and

⁸ Even though we measured shapes with a smaller weight function and we expect the signal to be stronger when using the largest weight function difference possible, the correlation we measure is noisier when using $r_{wf}/r_{iso} = 0.5$. This can be due to the weight function being too small and susceptible to modelling bias. See Georgiou et al. (2019b) for more details.

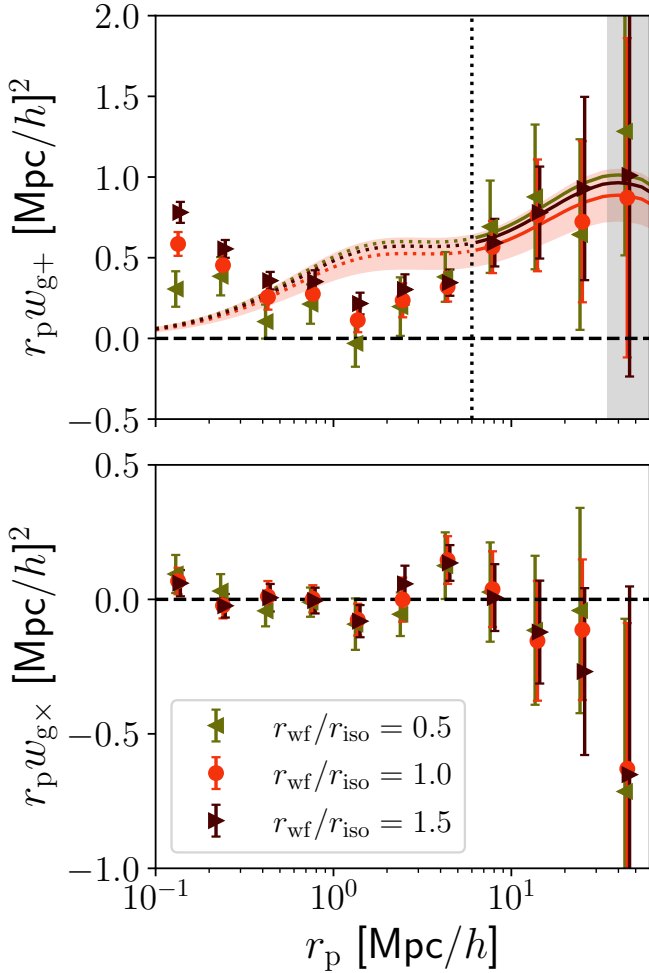


Fig. 6. Similar to Fig. 4, but showing measurements of intrinsically red galaxies with shapes measured using different sizes for the radial weight function (compared the isophotal radius of galaxies), as indicated in the legend. Over-plotted in the top panel are the best-fit NLA models for each sub-sample, with a red band indicating the $1\text{-}\sigma$ region around the best-fit model for the fiducial sample, with $r_{wf}/r_{iso} = 1$.

can induce an artificial alignment signal, this effect is expected to be small, especially on scales of $\sim 1 \text{ Mpc}/h$ (see e.g. Fig. 2 in Georgiou et al. 2019a). Hence, it is more likely that this difference in alignment is caused by isophotal twisting, making outer regions of satellite galaxies more strongly aligned than inner ones. We discuss the interpretation of these results further in Sect. 5.

4.4. IA of blue and disk-like galaxies

Having looked at intrinsically red and/or elliptical galaxies, we turn our attention to blue and disk-like ($n_s < 2.5$) galaxies in this section. For these two sub-samples, we performed the projected position–shape correlation function measurement similarly to in the previous sections and present the results in Fig. 7. Again, we note that the position–cross ellipticity measurements are consistent with zero. We see that the w_{g+} measurements are also very close to zero, meaning we do not detect a signal of either blue or low- n_s galaxy alignment. We fitted the NLA model to these data points to determine bounds on the effective large-scale intrinsic alignment amplitude for these galaxies, and our best-fit values are presented in Table 3. These A_{IA} values are simply an effective

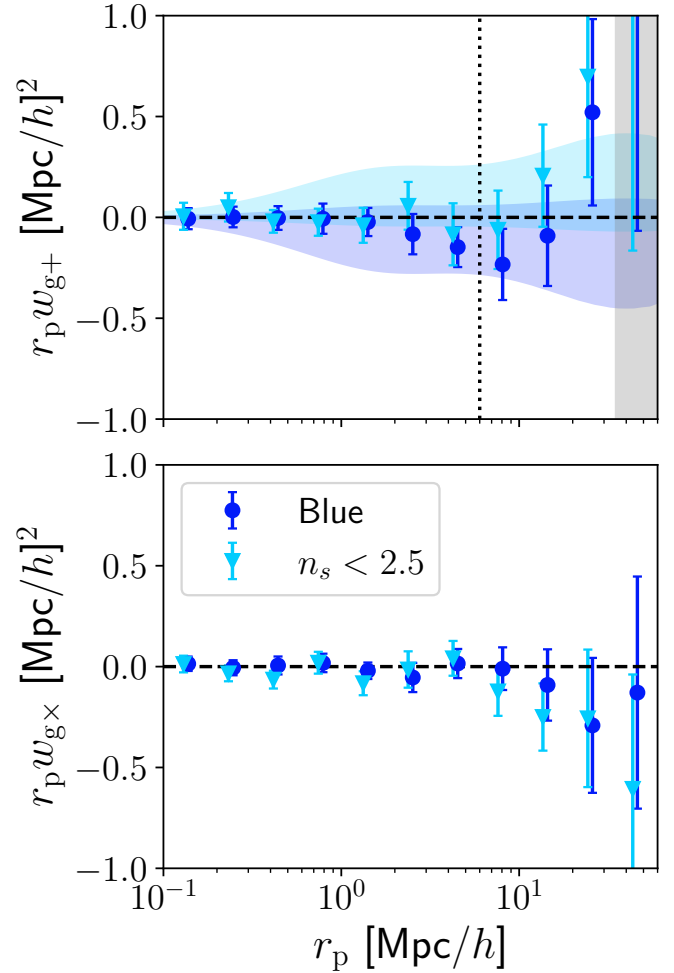


Fig. 7. Similar to Fig. 4, but for the intrinsically blue and low-Sérsic-index sub-samples with dark blue circles and light blue triangles, respectively. We also plot the $1\text{-}\sigma$ region around the best-fit NLA models for both samples.

description, since we do not expect the linear alignment model to accurately describe the alignment of rotationally supported galaxies, but its determination can be useful when mitigating the IA impact of these galaxies on weak lensing measurements.

5. Conclusions

The aim of this work was to study the intrinsic alignment of galaxies and its relationship to several galaxy properties, such as intrinsic colour, luminosity, and structural parameters. We used the KiDS bright sample catalogue and matched with the structural parameter catalogue, which were derived using Sérsic surface-brightness profile fits following Roy et al. (2018) and made available to the KiDS collaboration for internal use. We find that selecting intrinsically red galaxies or galaxies with a high Sérsic index ($n_s > 2.5$) does not significantly alter the power-law luminosity scaling of the large-scale intrinsic alignment amplitude.

This luminosity dependence of intrinsic alignments is well-established in the literature (e.g. Joachimi et al. 2011; Singh et al. 2015; Fortuna et al. 2021b). Joachimi et al. (2011) used a full sample to constrain $A_0 = 5.76^{+0.6}_{-0.62}$ and $\beta = 1.13^{+0.25}_{-0.2}$, while the constraints of Singh et al. (2015) were $A_0 = 4.9 \pm 0.6$ and $\beta = 1.30 \pm 0.27$, both of which are in statistical agreement

with our measurements. Fortuna et al. (2021b) used a luminous red galaxy sample also based on KiDS data, and they measured $A_0 = 5.98 \pm 0.27$ and $\beta = 0.93 \pm 0.11$, which is consistent with our results. That study also looked at using a double power law to describe the $A_{\text{IA}}(L)$ function, which provided a better fit to the data and is likely a reflection of the ‘knee’ in the stellar-to-halo mass relation (Fortuna et al. 2025). The S/N in our measurements is not high enough to be able to distinguish this feature, and for that reason we only constrained a single power-law luminosity dependence.

When selecting red galaxies and then further sub-dividing them into high and low Sérsic index (with a boundary at $n_s = 4$), we see a hint that red, low- n_s galaxies have a weaker alignment than expected from their average luminosity, though not at a high significance level. This galaxy sample is likely to have a large fraction of red spiral galaxies (Cui et al. 2024) that are rotationally supported and therefore expected to have a lower alignment signal, which would explain the trend seen in this work. If this behaviour is confirmed with better data in the future, it would change our basic understanding of how the alignment of intrinsically red galaxies depends on the galaxy’s luminosity and mass.

This may also have implications for the mitigation of intrinsic alignments in weak-lensing measurements. The galaxy Sérsic index has been shown to evolve with redshift for very massive galaxies and is also a strong function of galaxy stellar mass (e.g. Lang et al. 2014; Martorano et al. 2025). In addition, the galaxy samples used across different redshift bins in weak-lensing analyses span a wide range of redshift and stellar mass. Consequently, using the same luminosity dependence on intrinsic alignment bias (e.g. keeping A_0 and β the same) for galaxies in different redshift bins runs the risk of mismodelling intrinsic alignments, since galaxies in these bins can have a very different Sérsic index distribution. It also means that if priors are determined for these parameters at low-redshift samples, they might not be accurate for the deep samples employed in weak-lensing measurements. Furthermore, our results can have implications for methods where cosmological inference is carried out using the connection between IA and the luminosity function (see e.g. Šarčević et al. 2025). This motivates further exploration of the dependence of intrinsic alignment on the structural parameters of galaxies.

We also explored the dependence of the intrinsic alignment signal on the effective galaxy scale at which the shapes are measured. By varying the size of the weight function used in the shape measurement process, we are able to up-weight or down-weight outer regions of galaxies and measure their shape on different galaxy scales. At large galaxy pair separations, we do not see a statistically significant difference in the alignment signal, although our data are consistent with outer regions of a galaxy having an $\sim 15\text{--}20\%$ stronger alignment signal (at $1\text{-}\sigma$). At small separations, we see a clear galaxy-scale dependence, with outer regions of galaxies being much more strongly aligned than inner ones.

Similar measurements have been made in the literature. In Singh & Mandelbaum (2016), the NLA model is fitted to w_{g+} measurements from three different shape-measurement methods that each approaches galaxy-shape estimation in a different way. They find a difference of $\sim 35\%$ in the largest and smallest estimated A_{IA} , which is consistent with our findings. It is worth noting that these results are based on very different shape measurement methods that make it more complicated to compare them, since they depend on systematic effects in different ways, and it is less clear how the different regions of galaxies are weighted. In Georgiou et al. (2019a), the alignment of satel-

ite galaxies in GAMA galaxy groups was studied as a function of galaxy scale with the same shape-measurement method used in this work, and it was shown that outer regions of satellites align more strongly with their group’s centre than inner ones. The alignment of satellite galaxies is expected to dominate the w_{g+} signal on small scales (Johnston et al. 2019), and we indeed see a stronger alignment on those scales for larger weight functions in Fig. 6; this is in agreement with the measurements from Georgiou et al. (2019a).

Lastly, we also looked at intrinsically blue galaxies as well as galaxies with a low Sérsic index ($n_s < 2.5$). As these types of galaxies compose a large fraction of the samples used in weak-lensing measurements, it is interesting to explore their alignment signal. For both of these samples, we measure intrinsic alignments consistent with zero at the $1\text{-}\sigma$ level, with bounds presented in Table 3. While constraints of emission-line galaxies exist in the literature, the flux-limited sample used here more closely resembles the galaxy samples used in weak-lensing measurements (though at much lower redshift) and can be used to better understand the level of contamination that can be expected in such weak-lensing measurements (extrapolating in redshift).

This is the first study that aims to measure the dependence of intrinsic alignment on galaxy structural parameters, which might reveal a more nuanced effect of tidal fields on galaxies than a simple intrinsic colour split. It motivates the creation of more surface-brightness profile measurements of galaxies that are typically used in direct intrinsic alignment studies. Such measurements can help gain a deeper understanding of the physical mechanisms with which galaxies align and improve our theoretical models and mitigation strategies.

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Appendix A: Comparison of luminosity scaling with previous measurements

Here we compare our measurements of the large-scale intrinsic alignment amplitude, A_{IA} , as a function of luminosity to previous measurements in the literature for red galaxy samples. The results are summarised in Fig. A.1. Note that the galaxy samples used in each of the referenced measurements differ in selection, so exact agreement across datasets is not necessarily expected.

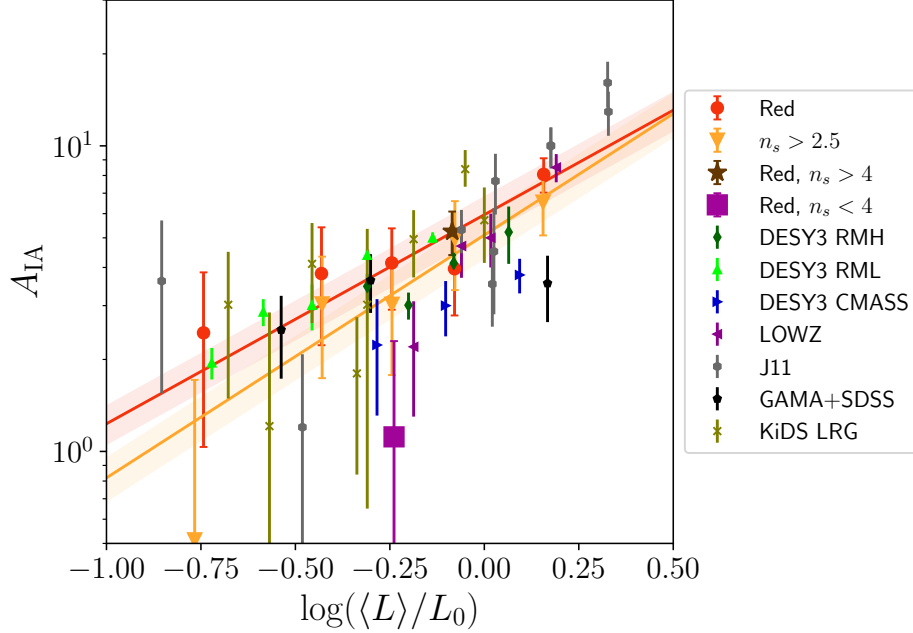


Fig. A.1. Same as Fig. 5 but including measurements of A_{IA} from other studies: samples DESY3 RMH (dark green diamonds), DESY3 RML (light green upper triangles), and CMASS (blue right-facing triangles) are from Samuroff et al. (2023), LOWZ (purple left-facing triangles) from Singh et al. (2015), J11 (gray hexagons) from Joachimi et al. (2011), GAMA+SDSS (black pentagons) from Johnston et al. (2019) and KiDS LRG (olive x-markers) from Fortuna et al. (2021a). The last two samples are not entirely independent of our measurements in this work.

Appendix B: Galaxy sample distributions

In this section we show distributions of several properties of our galaxy sample, which are summarised in Fig. B. The top panel of the figure shows the distribution of galaxy luminosity for red galaxies, as well as red galaxies split in Sérsic index. The middle panel of the figure shows the distribution of Sérsic index for the full galaxy sample, the intrinsically red, and blue galaxies. We note that blue galaxies have n_s very localised around the value of 1 while red galaxies have a wider range of n_s values. Lastly, the bottom panel of the figure shows the distribution of rest-frame $g - r$ colour for the full sample and for a split in Sérsic index to distinguish between spheroidal ($n_s < 2.5$) and elliptical ($n_s > 2.5$) galaxies. Interestingly, we see that there is a population of spheroidal galaxies that exhibit red intrinsic colour.

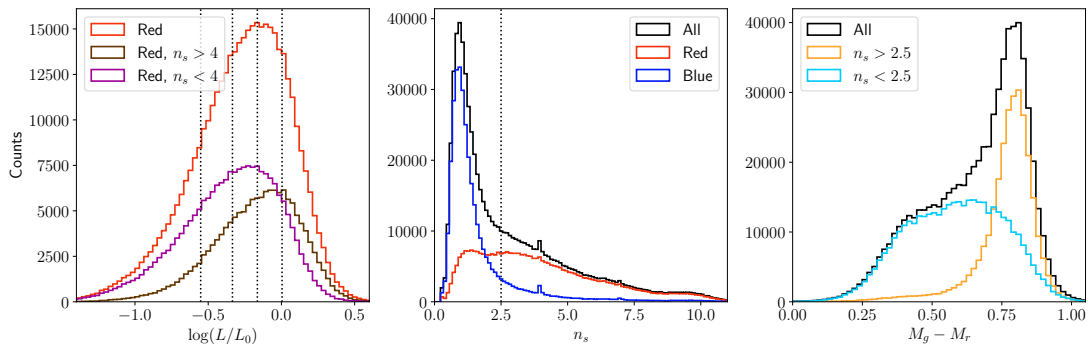


Fig. B.1. Distributions of galaxy properties of our sample. *Top:* Distributions of galaxy luminosity for our red sample (red line), red sample with high n_s (brown), and red sample with low n_s (purple). *Middle:* Distributions of Sérsic index, n_s , for the full sample, red, and blue galaxy samples (in black, red and blue line, respectively). *Bottom:* Distributions of restframe $g - r$ colour for our full sample (black), spheroidal ($n_s < 2.5$, light blue), and elliptical ($n_s > 2.5$, orange) galaxy samples.