Effects of Galaxy Intrinsic Alignment on Weak Lensing Peak Statistics

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Abstract

The galaxy intrinsic alignment (IA) is a dominant source of systematics in weak lensing (WL) studies. In this paper, by employing large simulations with semianalytical galaxy formation, we investigate the IA effects on WL peak statistics. Different simulated source galaxy samples of different redshift distributions are constructed, where both WL shear and IA signals are included. Convergence reconstruction and peak statistics are then performed for these samples. Our results show that the IA effects on peak abundances mainly consist of two aspects. One is the additional contribution from IA to the shape noise. The other is from the satellite IA that can affect the peak signals from their host clusters significantly. The latter depends on the level of inclusion in a shear sample of the satellite galaxies of the clusters that contribute to WL peaks and thus is sensitive to the redshift distribution of source galaxies. We pay particular attention to satellite IA and adjust it artificially in the simulations to analyze the dependence of the satellite IA impacts on its strength. This information can potentially be incorporated into the modeling of WL peak abundances, especially for high peaks physically originated from massive clusters of galaxies, and thus mitigate the IA systematics on the cosmological constraints derived from WL peaks.

Unified Astronomy Thesaurus concepts: Weak gravitational lensing (1797)

1. Introduction

Weak gravitational lensing (WL) effects by large-scale structures induce shear and magnification signals on background sources and are playing increasingly important roles in cosmological studies (Bartelmann & Schneider 2001; Hoekstra & Jain 2008; Fu & Fan 2014; Kilbinger 2015). By accurately measuring the shapes and photometric redshifts of distant galaxies, WL observations have been developing at a fast pace, from the early detections of cosmic shears (e.g., Van Waerbeke et al. 2000), to the demonstration of the feasibility of the WL probe in observations (Fu et al. 2008; Heymans et al. 2012; Kilbinger et al. 2013), and now to the near completion of the Stage III surveys covering a few thousand square degrees with \( \sim 10^7 \) galaxies in the samples (Kuijken et al. 2019; Abbott et al. 2021; Aihara et al. 2022). Consequently, the delivered cosmological constraints are being improved significantly, revealing the potential \( S_8 \) discrepancy between the results from WL analyses and that extrapolated from the Planck cosmic microwave background observations (Hikage et al. 2019; Hildebrandt et al. 2020; Planck Collaboration et al. 2020; Heymans et al. 2021). Here \( S_8 = \sigma_8 (\Omega_m / 0.3)^{0.5} \), and \( \Omega_m \) and \( \sigma_8 \) are the present dimensionless cosmic matter density and the amplitude of the extrapolated linear density fluctuations over \( 8 h^{-1} \) Mpc, with \( h \) the dimensionless Hubble constant in units of \( 100 \) km s\(^{-1}\) Mpc\(^{-1}\). On the other hand, from the current surveys, the statistical significance of the \( S_8 \) discrepancy is still low, and different survey analyses give rise to somewhat different confidence levels. Thus, whether this is a true problem for the \( \Lambda \)CDM model is still under debate (e.g., Abbott et al. 2022).

The upcoming Stage IV surveys will increase the data volume to about \( 10^8 \) galaxies for WL analyses, leading to dramatic reductions of the statistical uncertainties in comparison with the current survey results. The representative projects include the ground-based Vera Rubin Observatory Legacy Survey of Space and Time (Ivezić et al. 2019) and the space-based Euclid (Laureijs et al. 2011), Roman Space Telescope (Spergel et al. 2015), and China Space Station Telescope (Gong et al. 2019). For them, systematics will become the dominant concerns in obtaining cosmological constraints with high accuracy.

The WL studies rely on the extraction of coherent shape distortions from galaxy samples; thus, their intrinsic alignments (IAs) lead to apparent contamination to WL signals (Joachimi et al. 2015; Kiessling et al. 2015; Kirk et al. 2015; Trexel & Ishak 2015). For cosmic shear two-point correlation (2PCF) or power spectrum analyses, IA effects have been extensively investigated and included in deriving cosmological constraints from observations (e.g., Hikage et al. 2019; Hildebrandt et al. 2020; Yao et al. 2020; Heymans et al. 2021; Abbott et al. 2022).

To fully explore the physical information embedded in WL data, different statistics beyond 2PCFs are necessary because of the non-Gaussian nature of large-scale structures (e.g., Fu et al. 2014; Petri et al. 2015). For that, peak statistics are important means to probe nonlinear structures (e.g., Waerbeke 2000; Hamana et al. 2004; Dietrich & Hartlap 2010; Fan et al. 2010; Maturi et al. 2010; Yang et al. 2011; Hamana et al. 2012; Lin & Kilbinger 2015; Yuan et al. 2018, 2019; Martinet et al. 2021) and have been applied to different WL surveys to obtain cosmological information (Shan et al. 2012, 2014; Liu et al. 2015a; Liu et al. 2015b; Kapczak et al. 2016; Liu et al. 2016; Martinet et al. 2018; Shan et al. 2018; Hamana et al. 2020; Oguri et al. 2021; Zurcher et al. 2022). Aiming at utilizing their power in precision cosmological studies, it is important to understand the impacts of different systematics. For IA effects
on peak statistics, the investigations are not yet as detailed as that for cosmic shear 2PCF but are getting more and more attention.

In Fan (2007), the IA contribution to the shape noise variance is analyzed, and its effects on the number of noise peaks are explored. In performing shear peak studies using Dark Energy Survey Science Verification data, Kacprzak et al. (2016) evaluated the potential impact of IA by assuming radial alignment of satellite galaxies in cluster halos with a scaling parameter $\gamma_{\text{scale}} = 0.21$ accounting for some misalignment angles (Schneider & Bridle 2010). They concluded that the IA-induced bias in cosmological constraints is not significant for their analyses limited to peaks with a signal-to-noise ratio $(S/N) < 4$. For higher peaks, however, their heights can be considerably negatively biased.

Recently, Harinos-Deraps et al. (2022) carried out investigations of the impact of IA on WL statistics from aperture mass maps, including peaks, minima, and the full distribution of pixel values. In their studies, an IA infusion method is taken to generate IA signals of galaxies. Specifically, from N-body simulations, they constructed light cones for WL ray-tracing calculations. Meanwhile, they converted the mass sheets into tidal tensors and coupled them to the intrinsic ellipticity of galaxies under the nonlinear tidal alignment (NLA) model (Bridle & King 2007) controlled by the coupling parameter $A_{\text{IA}}$. To better address the IA effects from galaxy positions rather than random positions, they generated mock galaxy positions by tracing the projected density distribution of each redshift slice assuming a linear bias parameter. Thus, the galaxy clustering is included in the IA modeling, which is referred to as $\delta$-NLA (Harinos-Deraps et al. 2022). For peaks, their studies show that IA affects high-S/N ones the most, with relative number deviation caused by IA reaching about $-30\%$ and $-10\%$ for Euclid- and KiDS-like surveys, respectively, for $A_{\text{IA}} = 1.5$.

In this paper, we study the IA effects on WL peaks based on large simulations with semianalytic galaxy formation (Wei et al. 2018). Thus, galaxies and their clustering, particularly satellite galaxies in clusters, are self-consistently included. From the simulated galaxies, we construct different catalogs with different redshift distributions. Furthermore, for satellite galaxies, we build different alignment samples to systematically study the dependence of the IA impacts on satellite alignment angles.

The paper is structured as follows. In Section 2, we summarize the basic theory of WL. Section 3 describes the simulations and the construction of mock galaxy catalogs. In Section 4, we present the results. An empirical fitting model is given in Section 5. A summary and discussions are presented in Section 6.

## 2. Theory

In this section, we briefly summarize the theoretical background of WL and the convergence field reconstruction used in our peak analyses.

### 2.1. WL Basics

The WL-induced distortions on background sources are characterized by the following Jacobian matrix (Bartelmann & Schneider 2001; Fu & Fan 2014):

$$A = \begin{pmatrix} 1 - \kappa - \gamma_1 - \gamma_2 \\ -\gamma_2 \\ 1 - \kappa + \gamma_1 \end{pmatrix},$$  

(1)

where the convergence $\kappa$ and shear $\gamma_1$ are calculated from the lensing potential $\psi$ with $2\kappa = \nabla^2 \psi$, $2\gamma_1 = \partial^2 \psi/\partial \theta_1 - \partial^2 \psi/\partial \theta_2$, and $\gamma_2 = \partial^2 \psi/\partial \theta_1 \partial \theta_2$.

Under the first-order Born approximation, $\kappa$ is given by

$$\kappa(\theta) = \frac{3H_0^2 \Omega_m}{2c^2} \int_0^{\chi} d\chi' \int_0^{\chi} d\chi \left[ p_s(\chi) \frac{r(\chi - \chi')r(\chi')}{r(\chi) a(\chi')} \right] \delta[J(\chi') \cdot \theta, \chi'],$$  

(2)

where $\chi$, $r$, and $a$ are the comoving radial distance, comoving angular diameter distance, and cosmic scale factor, respectively. The function $p_s$ is the source galaxy distribution function, and $\delta$ is the 3D density perturbation.

Observationally, WL signals are extracted from the measurements of galaxy ellipticities. They are directly related to the reduced shear $\epsilon = \gamma/(1 - \kappa)$ given by Seitz & Schneider (1997):

$$\epsilon = \begin{cases} \frac{\epsilon_s + g}{1 + g \epsilon_s}, & |g| \leq 1 \\ \frac{1 + g \epsilon_s}{\epsilon_s^* + g^*}, & |g| > 1 \end{cases}.$$  

(3)

Here the bold symbols represent the quantities written in the complex form, e.g., $\gamma = \gamma_1 + i\gamma_2$, and $\epsilon$ and $\epsilon_s$ are, respectively, the observed and intrinsic ellipticities of a galaxy.

If the orientations of galaxies are intrinsically random, the expectation value of $\epsilon$, averaged over an infinite number of galaxies should vanish, i.e., $\langle \epsilon_s \rangle = 0$; thus, the observed ellipticity is an unbiased estimator of the reduced shear with

$$\langle \epsilon \rangle = g.$$  

(4)

In practice, the average can only be done over a finite number of galaxies; therefore, a residual shape noise from the intrinsic ellipticities is inevitable. Moreover, the existence of the IA of the galaxy leads to a bias in Equation (4), as well as a contribution to the variance of the shape noise.

### 2.2. Convergence Reconstruction

While WL shears are extractable quantities from observed ellipticities of galaxies, the convergence fields or their variants are more intuitively related to the projected mass distributions and thus are normally used in WL peak analyses.

Because both $\gamma$ and $\kappa$ are determined by the lensing potential, they are mutually dependent with the following relation in the Fourier space:

$$\tilde{\gamma}(k) = \frac{1}{\pi} \tilde{D}(k) \hat{\kappa}(k),$$  

(5)

with

$$\tilde{D}(k) = \frac{\pi k_t^2 - k_i^2 + 2 i k_t k_2}{k_t^2 + k_i^2}.$$  

(6)

As described later, in our analyses, we first select a galaxy sample from the simulations with the semianalytic galaxy
formation and calculate their mock ellipticities following Equation (3) to generate a shear sample. We then use the above relation to reconstruct the convergence fields from the shear fields by employing the nonlinear iterative Kaiser–Squires reconstruction method (Kaiser & Squires 1993; Seitz & Schneider 1995; Squires & Kaiser 1996; Liu et al. 2015). For that, we first calculate the smoothed fields $\langle \epsilon \rangle$ on grid positions $\theta$ by

$$\langle \epsilon \rangle = \frac{\sum_j W_{\theta j}(\theta_j - \theta) \epsilon(\theta_j)}{\sum_j W_{\theta j}(\theta_j - \theta)}.$$

where $\theta_j$ is the position of a galaxy in the shear sample, and $W$ is the smoothing function taken to be Gaussian as follows:

$$W_{\theta j}(\theta) = \frac{1}{\pi \theta_G^2} \exp\left(-\frac{|\theta|^2}{\theta_G^2}\right).$$

We adopt the smoothing scale $\theta_G = 1.5$ as the fiducial value in our studies.

From $\langle \epsilon \rangle$, we obtain the smoothed convergence fields $K_N$ from the reconstructions, which can be written as the sum of the WL convergence term $K$ and the shape noise term $N$, i.e., (e.g., Waebeke 2000)

$$K_N(\theta) = K(\theta) + N(\theta).$$

In view of IA, it can affect both $K$ and $N$.

3. Simulation Catalogs

In this section, we describe the simulations used in our analyses and the construction of different galaxy catalogs with different redshift distributions and satellite IA.

3.1. Simulations of Wei et al. (2018)

The simulation data used in this study are from Wei et al. (2018). They started from a set of $N$-body simulations within the ELUCID project (Wang et al. 2014, 2016). The simulation box size is $L_{\text{box}} = 500 h^{-1} \text{Mpc}$, and the total number of particles is $3072^3$. The cosmological parameters are from WMAP9 with $\Omega_m = 0.282$, $\Omega_{\Lambda} = 0.718$, $\sigma_8 = 0.82$, and $h = 0.697$, where $\Omega_{\Lambda}$ is the present dimensionless density of dark energy in the form of a cosmological constant (Hinshaw et al. 2013).

From the $N$-body simulation, they built a full-sky light cone up to $z_{\text{max}} = 2$ by chopping the simulation box into smaller ones with a size of $\sim 100 h^{-1} \text{Mpc}$ and carefully piling them up. Spherical ray-tracing calculations are then performed on a set of spherical mass shells with a width of $50 h^{-1} \text{Mpc}$ to obtain full-sky WL shear and convergence maps with a resolution of $\sim 0.43$. For details, please see Wei et al. (2018).

The great advantage of this set of simulations is the inclusion of the semianalytical galaxy formation based on the model of Luo et al. (2016), which is the modified version of Fu et al. (2013) and Guo et al. (2013), to improve the prescription for low-mass galaxies by considering the physics of gas stripping and the modeling of orphan galaxies. This improvement is important for properly modeling satellite galaxies.

This semianalytical model predicts the ratio of the bulge to the total mass $B/T$ for a galaxy. This is used to divide galaxies into two classes, with $B/T > 0.6$ as the early type and $B/T < 0.6$ as the late type. For early-type central galaxies, their ellipticities and orientations are assumed to be the same as their host halos calculated from the inertia tensor using dark matter particle distributions and then projected along the line of sight. For late-type centrals, their shapes are assigned according the angular momentum vector of the host halos. The 2D axial ratio and thus the ellipticities of late-type galaxies are calculated through the projection based on the ratio of the line-of-sight angular momentum component to the total angular momentum. There the ratio of the galactic disk thickness to the diameter is set to be $0.25$ (Wei et al. 2018).

For satellite galaxies, Wei et al. (2018) generated two sets of data with different alignments. One is to follow Joachimi et al. (2013) to set the 3D major axis of an early-type satellite radially toward the center of its host cluster. For late-type satellites, their spin directions are assumed to be perpendicular to the line connecting the satellites and their centrals. In this setup, satellite galaxies are essentially radially aligned toward the cluster centrals. We refer to this as highIA. The other is to assume a random distribution of satellite orientations without alignments. We refer to this case as lowIA.

Figure 1 presents the fractions of the total number of central galaxies (blue), centrals with satellites (red), and centrals with more than 10 satellites (yellow) to the total number of all simulated galaxies at different redshifts. We can see that over the whole redshift range, centrahs account for about 50%-60% of the total simulated galaxies, and the rest are satellites. Among the centrals, about 20% of them have satellites, and about 2% have more than 10 satellites. With the increase of the redshift, the yellow line decreases in accord with less massive clusters. It is noted that for WL high peaks, most of them arise from the lensing effects of massive clusters, which contain a relatively large number of satellites. From our analyses shown later, if the satellites are in a shear sample and have strong IA signals, the WL high peaks will be significantly affected. This effect depends sensitively on the redshift distribution of a shear sample.

3.2. Shear Catalog Construction

As described in the previous section, in the simulation of Wei et al. (2018), the formation and evolution of galaxies are modeled semianalytically, and their intrinsic ellipticities and orientations are also assigned. From the spherical ray-tracing
different narrow redshift bins are constructed from Martinet et al.\(^\text{\footnotesize{2018}}}\) calculations, shear and convergence maps are generated up to \(z \sim 2\). Based on these, we construct different shear catalogs for analyses.

In total, we build five samples with different redshift distributions. One is the KiDS-like sample with the redshift distribution from Martinet et al.\(^\text{\footnotesize{2018}}}\) and the number density \(n_\varphi = 8\ \text{arcmin}^{-2}\). Another is the Euclid-like sample following the redshift distribution used in Harnois-Deraps et al.\(^\text{\footnotesize{2022}}}\) and \(n_\varphi = 30\ \text{arcmin}^{-2}\). In addition, three samples at three different narrow redshift bins are constructed with \(z = [0.9, 1.14], [1.45, 1.60],\) and \([1.94, 2.09]\) and \(n_\varphi \approx 26, 23.5,\) and \(23.8\ \text{arcmin}^{-2}\), respectively. In Figure 2, we show the normalized redshift distributions of our selected samples with the yellow, red, and gray shaded bins for KiDS-like, Euclid-like, and narrow bins, respectively. We also show the redshift distribution of the original galaxy sample in blue for comparison.

For each catalog, we have two satellite IA settings, highIA and lowIA, from Wei et al.\(^\text{\footnotesize{2018}}}\). To understand in detail the dependence of the IA effects on the behavior of satellite alignments within clusters, we further artificially adjust their orientations to generate different satellite IA for each shear sample.

To do this, we first identify satellite galaxies in a shear sample and their corresponding central galaxies using the IDs from Wei et al.\(^\text{\footnotesize{2018}}}\). We then set the 3D orientation of a satellite galaxy based on a local spherical coordinate system \((\theta_{3D}, \phi)\) in which \(\theta_{3D}\) is the zenith angle between the satellite orientation direction and the line connecting it to its central galaxy. Thus, \(\theta_{3D} = 0\) means that the satellite is radially aligned; i.e., for an early-type satellite, its long axis points toward its central, and for a late-type one, its spin is perpendicular to the radial direction. This is the highIA case. For the case of lowIA, the satellite orientations are completely random. To construct more IA cases, we artificially set \(\theta_{3D}\) to different fixed values. Specifically, \(\theta_{3D} = 5^\circ, 10^\circ, 15^\circ,\ldots,\) and \(45^\circ\) are considered. Furthermore, we also construct cases with \(\theta_{3D} = 60^\circ\) and \(75^\circ\). For these two, satellite galaxies, on average, have different levels of 3D tangential alignments, which might be unphysical but useful for our systematic investigations of IA effects.

Besides fixed \(\theta_{3D}\), we also generate satellite alignments considering a dispersion of \(\theta_{3D}\). Specifically, we adopt the following probability distribution for \(\theta_{3D}\) and \(\phi\):

\[
f(\theta_{3D})d\theta_{3D} d\phi = A \exp \left[ -\frac{1}{2} \frac{(\theta_{3D} - \theta_0)^2}{\sigma_\theta^2} \right] d\theta_{3D} \sin(\theta_{3D}) d\phi,
\]

where \(A\) is the normalization parameter, \(\theta_0\) is the average of \(\theta_{3D}\), and \(\sigma_\theta\) is its dispersion. When \(\sigma_\theta\) goes to infinity, this distribution is back to the 3D uniform distribution, i.e., \(\sin(\theta_{3D})d\theta_{3D} d\phi\). We take \(\theta_0 = 0^\circ\) and consider different dispersions with \(\sigma_\theta = 10^\circ, 20^\circ, 30^\circ, 45^\circ, 60^\circ,\) and \(75^\circ\). They are labeled in a format of \(0\sigma_\theta\). For example, \(030\) stands for \(\sigma_\theta = 30^\circ\). This set of samples corresponds to the averagely radially aligned satellites with different levels of misalignment. The above settings are for the adjustment of satellite alignments. For the central galaxies, their alignments are assigned as in Wei et al.\(^\text{\footnotesize{2018}}}\). To build a reference for comparison, we further generate a noIA sample by randomly rotating both central and satellite galaxies.

For a sample with a specific 3D alignment setting, we then perform 2D projections following the same approach as Joachimi et al.\(^\text{\footnotesize{2013}}}\) and Wei et al.\(^\text{\footnotesize{2018}}}\). For late-type galaxies, we take the disk thickness-to-diameter ratio \(r_{edge-on} = 0.25\) in accord with Wei et al.\(^\text{\footnotesize{2018}}}\). With the 2D projected intrinsic ellipticity \(e_i\) of a galaxy, we build its observed \(e\) by using Equation (3). This completes the construction of a shear catalog with an assigned alignment model.

The upper panel of Figure 3 shows the distribution of the angle \(\theta_{2D}\) between the intrinsic 2D projected orientation of a satellite galaxy and the radial direction to its central galaxy, where different lines correspond to satellite alignments with different settings as labeled in the legend. For example, the green solid line labeled “30” is for the alignment model with \(\theta_{3D} = 30^\circ\), and the line labeled “30” is for \(\theta_0 = 0^\circ\) and \(\sigma_\theta = 30^\circ\). It is seen that for the lowIA case with randomly oriented satellite galaxies, their 2D orientations are also random, with the distribution being a flat line. For other cases, the distributions of \(\theta_{2D}\) show peaks at \(\theta_{3D} \approx \theta_{3D}\). Adding a dispersion \(\sigma_\theta\), the peaks are getting smoothed as expected.

The lower panel presents the median (blue) and average (red) of \(|\theta_{2D}|\) for different \(\theta_{3D}\). It is noted that for \(\theta_{3D} < 40^\circ\), the median value of \(\theta_{2D}\) is less than \(45^\circ\), showing that the 2D orientations of satellite galaxies possess a level of radial alignment. For \(\theta_{3D} > 40^\circ, \theta_{2D}\) (median) \(> 45^\circ\), indicating a trend of tangential alignment in 2D. The change of the 2D orientation trend from radial to tangential at \(\theta_{3D} \approx 40^\circ\) rather than \(\theta_{3D} = 45^\circ\) is due to the projection. As will be seen in the next section, our analysis results of the IA effects on WL peak statistics show consistent behaviors, as expected from the trend change shown here.

### 4. Results

To do peak analyses, we randomly select 156 patches from the full-sky map of Wei et al.\(^\text{\footnotesize{2018}}}\), and each patch is \(3 \times 3\ \text{deg}^2\). For each considered galaxy sample with a particular satellite IA model, we perform convergence reconstruction for each patch on \(1024 \times 1024\) grids from galaxy ellipticities \(e\) as described in Section 2.2. We exclude \(5 \times \theta_G \sim 43\) pixels from
the edges of each convergence map in peak counting to suppress the boundary effect (e.g., Bartelmann 1995). The final effective sky coverage is then about 1178 deg². For each sample, we identify and bin peaks in terms of \( S/N_\nu = K/\sigma_0 \) with the shape noise \( \sigma_0 \) calculated from the corresponding noIA sample without lensing signals. This is in accord with real observations where the noise can only be estimated by randomly rotating galaxies.

It is noted that in our setting, for different IA samples with the same redshift distribution and \( n_g \), their galaxies have exactly the same positions and lensing signals. Thus, the differences of their peak statistics solely arise from the different IA modeling. We can therefore cleanly reveal the impacts of IA on peak statistics.

4.1. Dependence on the Satellite IA Angle

To see the dependence of IA impacts on the satellite alignment angle, we focus on the samples with the Euclid-like redshift distribution and \( n_g = 30 \text{ arcmin}^{-2} \).

We first present the results of highIA and lowIA in Figure 4, where the vertical axis is the relative difference of the peak numbers with respect to those of the corresponding noIA case, and the error bars are Poisson errors calculated from the peak numbers in \( \sim 1178 \text{ deg}^2 \). It is seen that the two lines are very different. For lowIA, the difference from the noIA case is due to the IA of central galaxies, and we have \(|n_{\text{lowIA}}/n_{\text{noIA}} - 1| < 10\%\) over the whole considered range of peaks. For highIA, the relative difference is much larger, showing the dominant effects of satellite IA on peak statistics. For high peaks, the satellite radial IA leads to significant decreases of the peak numbers, and \((n_{\text{highIA}}/n_{\text{noIA}} - 1) \sim -40\%\) and \(\sim -70\%\) for \( \nu \approx 5 \) and 6, respectively.

To further see the IA effects, we cross-match the peaks in the two IA models with that of the corresponding noIA case. The matching radius is 17 and 5 pixels for the highIA and lowIA case, respectively. In the highIA case, the peaks are affected more for both heights and positions than that of the lowIA case, and we therefore choose a larger matching radius. In Figure 5, we show the direct peak height comparison of the matched peaks with the upper and lower panels for highIA and lowIA, respectively. The gray points are the scatter plots of the matched peaks, and the blue lines are the median peak values of \( \nu_{\text{highIA}}/\nu_{\text{noIA}} \) of different bins based on \( \nu_{\text{noIA}} \), with the error bars showing the 1σ dispersions. The red dashed lines show the 1:1 relation. We can see that in the highIA case, the high peaks are significantly lower than their noIA counterparts, while the differences are much smaller in the lowIA case. These are in accord with the peak statistics shown in Figure 4.

As discussed in Wei et al. (2018), the comparison with the cosmic shear 2PCF analyses from KiDS indicates that the highIA model leads to too-high 2PCF signals at small scales, and the lowIA model is more consistent with the observational results. For peak statistics, its dependence on IA can be different from that of 2PCF. For the systematic trend, we show

**Figure 3.** Upper panel: 2D satellite orientation angle \( \theta_{2D} \) distribution of different samples as measured from \( \theta_{1D} \) without adding lensing signals. Lower panel: median (blue) and mean (red) values of \( |\theta_{2D}| \) with the change of \( \theta_{1D} \). The gray horizontal dashed line indicates \( |\theta_{2D}| = 45° \), and the red and blue vertical dashed lines mark the corresponding values of \( \theta_{3D} \) inferred from the intersections of the gray dashed line with the red and blue solid lines, respectively.

**Figure 4.** Relative changes of peak counts for lowIA (blue) and highIA (red) samples in comparison with the noIA case for the Euclid-like sample.
the peak results with different satellite IA angles in Figure 6, where different lines are for different 3D satellite alignment angles $\theta_{3D}$, as explained in the legend. Being consistent with the 2D alignment angles $|\theta_{2D}|$ shown in the lower panel of Figure 3, when $\theta_{3D} \lesssim 40^\circ$, $|\theta_{2D}| \lesssim 45^\circ$, leading to a radial alignment tendency and resulting in a number decrease of high peaks. For $\theta_{3D} \gtrsim 40^\circ$, the number of high peaks is significantly boosted due to the tangential trend of the 2D alignments of satellite galaxies. We also note that the IA effects on peak statistics depend sensitively on the median value of $|\theta_{2D}|$. For $\theta_{3D} < 20^\circ$, the median of $|\theta_{2D}| \sim 20^\circ$ and changes slowly with the increase of $\theta_{3D}$. As a result, the IA effects on peak statistics from these IA models are very similar, with the corresponding lines in Figure 6 being very close to each other. For $\theta_{3D} > 20^\circ$, the slope of $|\theta_{2D}|$ in the right panel of Figure 3 increases; thus, the differences in peak statistics between different IA models are more apparent. For $\theta_{3D} = 30^\circ$, $(n_{IA}/n_{noIA} - 1) \sim -5\%, -10\%$, and $-25\%$ for $\nu \sim 4$, 5, and 6, respectively.

It is known that WL high peaks are typically associated with massive clusters (Hamana et al. 2004; Fan et al. 2010; Yang et al. 2011; Martinet et al. 2018; Shan et al. 2018; Yuan et al. 2018; Oguri et al. 2021). Thus, the IA effects on their peak heights mainly arise from the inclusion of their satellite members in a shear catalog. If these member galaxies have IA signals, they can affect the peaks significantly. To illustrate this clearly, in Figure 7, we show zoom-in convergence maps for a high peak in different satellite IA cases. For this peak, we can find a clear association with a massive cluster. We then identify its satellite galaxies in the shear sample and show their orientation maps with different IA settings in the right panels. It can be seen clearly that when the satellites have perfectly radial alignments with $\theta_{3D} = 0^\circ$, the peak from the cluster is considerably suppressed. With $\theta_{3D} = 30^\circ$, the suppression is less. For $\theta_{3D} = 60^\circ$, the IA signals have tangential trends in line with the tangential WL signals from the cluster, leading to a significant increase of the peak height.

### 4.2. Dependence on the Satellite IA Angle Dispersion

In the previous subsection, we present the impacts of satellite IA assuming they have a same alignment angle $\theta_{3D}$ toward their host central galaxies. A more physical modeling about the satellite IA should additionally include a certain misalignment dispersion. For that, we generate satellite IA samples using the distribution of Equation (10). In line with other studies (e.g., Knebe et al. 2008; Schneider & Bridle 2010; Kacprzak et al. 2016), we consider the case of average radial alignment by taking $\theta_{0} = 0$ with different dispersions $\sigma_{\theta}$.

The corresponding peak analysis results for the Euclid-like sample are shown in Figure 8. The upper panel is $(n_{IA}/n_{noIA} - 1)$ versus peak height $\nu$, with different lines for different $\sigma_{\theta}$ from 0° to 75°. For comparison, the result of lowIA is also shown. As expected, the IA impact decreases with the increase of the dispersion $\sigma_{\theta}$. It is noted that the results shown here have some degeneracies with the ones shown in Figure 6. For example, the result with $\theta_{0} = 0^\circ$ and $\sigma_{\theta} = 60^\circ$ is very similar to that of the case with a fixed $\theta_{3D} = 30^\circ$.

In the lower panel of Figure 8, we present the dependence of $(n_{IA}/n_{noIA} - 1)$ on $\sigma_{\theta}$, where different lines are for different peak heights. For clarity, only the central values are shown without adding the error bars. In the Euclid-like case here, $(n_{IA}/n_{noIA} - 1) < 10\%$ for peaks with $-1 \leq \nu \leq 4$ for all of the $\sigma_{\theta}$ values considered. For $\nu < 0$, the IA effect leads to negative changes of the peak numbers. For $0 < \nu < 4$, the peak numbers increase with respect to the case of noIA. For peaks with $\nu > 4$, the numbers are suppressed due to the satellite IA, and the suppression gets larger for higher $\nu$. To link the dispersion $\sigma_{\theta}$ to the scaling factor $\gamma_{\text{scale}}$ in terms of the intrinsic alignment contribution to the cosmic shear 2PCFs (Schneider & Bridle 2010), in Appendix A, we calculate the correlation between galaxy intrinsic ellipticities (Intrinsic-Intrinsic, II). Using correlation data on small scales where satellite IA contributes dominantly, we compute $\gamma_{\text{scale}}$ by assuming $\Pi(\sigma_{\theta}) = \gamma_{\text{scale}}^{2} \times \Pi(\sigma_{\theta} = 0)$ to obtain the relation between $\gamma_{\text{scale}}$ and $\sigma_{\theta}$.
By analyzing the subhalo alignments from simulations, Knebe et al. (2008) proposed a distribution function about the misalignment angle of subhalos, which gives rise to \( \gamma_{\text{scale}} \approx 0.21 \) (Schneider & Bridle 2010). This value was used in Kacprzak et al. (2016) to evaluate the IA impacts on shear peak statistics with DES data. From Appendix A, we can see that when \( \sigma_{\theta} \approx 70^\circ \), \( \gamma_{\text{scale}} \approx 0.21 \). This is indicated by the vertical dashed line in the lower panel of Figure 8. At this \( \sigma_{\theta} \), \( (n_{\text{IA}}/n_{\text{noIA}} - 1) \approx 5\% \) and 25\% for \( \nu = 4.75 \) and 7.75, respectively.

The information presented in Figure 8 can be utilized in peak analyses to take into account the satellite IA impacts. In particular, the dependence of \( (n_{\text{IA}}/n_{\text{noIA}} - 1) \) on \( \sigma_{\theta} \) can potentially allow us to constrain \( \sigma_{\theta} \) together with cosmological parameters. On the other hand, as presented in the next subsection, the IA effects on peak statistics are redshift-dependent. Thus, for a specific survey, its redshift distribution is needed to generate plots similar to Figure 8.

### 4.3. The Redshift Dependence of the IA Effects

In the above discussions, we show that satellite IAs affect peak statistics, especially high peaks, because of the inclusion of them in a shear sample. Shear samples with different redshift distributions can contain different fractions of satellites, and we
therefore expect a redshift dependence of the IA impacts on peak statistics.

In Figure 9, we show the results from the KiDS-like sample in comparison with those of the Euclid-like sample. The highIA and lowIA cases are presented. For the KiDS-like sample, $n_g = 8 \text{ arcmin}^{-2}$. Thus, the shape noise is larger and the number of high peaks is smaller than that of the Euclid-like case, leading to larger error bars. Within the statistical uncertainties, $(n_{\text{highIA}}/n_{\text{noIA}} - 1)$ have similar behaviors in the lowIA case for the two samples. For the highIA case, the suppression of the high peak counts is stronger in the KiDS-like sample with $(n_{\text{highIA}}/n_{\text{noIA}} - 1) \sim -60\%$ and $-90\%$ for $\nu \sim 5$ and $6$, in comparison with $\sim -40\%$ and $-70\%$ in the Euclid-like case. We note that the higher shape noise in the KiDS-like sample leads to a lower $\nu$ for the same peak. While we do see the red line shifting to the left compared to the gray line (highIA case) at the high-peak region partly due to the lower $\nu$, additional suppression in the KiDS-like case can be seen. This arises because in the KiDS-like sample, we have a larger fraction of galaxies in the redshift range of $\sim 0.2$–$0.6$ than that of the Euclid-like case. As clusters in this redshift range are abundant and contribute to WL high peaks, the higher fraction of satellite galaxies in the KiDS-like sample leads to stronger IA effects on high-peak statistics.

To see the redshift dependence further, we present the simulation results in the upper panels of Figure 10 for the three narrow redshift bin samples with the satellite IA being highIA (left) and for the sample of $z \sim 1$ with different IA angle $\theta_{3D}$. It is seen that the lines have markedly different trends compared to the results of Euclid- or KiDS-like cases. For high peak counts, there are no suppressions; instead, they increase with $(n_{\text{IA}}/n_{\text{noIA}} - 1) > 0$. The behaviors shown in Figure 10 can be explained qualitatively as follows. For sources in narrow redshift bins, the foreground clusters that contribute to WL high peaks have a negligible number of satellites in the source sample; thus, these satellite IAs do not affect the corresponding peaks. We therefore see no suppressions for high peak counts. On the other hand, the existence of IA induces shape noise correlations and thus changes the noise properties. This, in turn, can affect peak statistics (Fan 2007).

As shown in Equation (3), the observed ellipticities of galaxies include both their intrinsic ellipticities $\epsilon_i$ and the lensing signals $g$. Thus, the reconstructed convergence maps contain noises arising from $\epsilon_i$. The noise field $N$ can be approximated as a Gaussian random field because of the central limit theorem (Waerbeke 2000; Fan et al. 2010). We therefore use the Gaussian random field theory to illustrate the IA effects on noise and further on peak statistics.

In Appendix B, we describe the 2D Gaussian peak theory and present the changes of the noise parameters for different $\theta_{3D}$. From this, we do Gaussian model calculations to illustrate the IA effects on peak counts arising from their contributions to noise.

The model results are shown in the lower panels of Figure 10 for the cases corresponding to the upper panels. It is seen that they show qualitatively similar behaviors as the simulation results. For the three samples, the IA contributions $\sigma_{\text{corr}}$ decrease with the increase of redshift due to the decrease of the number of clusters at high redshift (see the yellow line in Figure 1). Thus, the relative differences of $(n_{\text{IA}}/n_{\text{noIA}} - 1)$ also decrease. The dependence on $\theta_{3D}$ is also qualitatively alike between the results of simulations and the Gaussian model calculations. These demonstrate that the IA contributions to noise do affect peak statistics.

We need to emphasize that the Gaussian model calculations here are only for qualitative illustrations of the noise effects. For quantitative modeling, we must consider the non-Gaussian nature of the foreground structures, especially for high peaks.

In our previous studies (Fan et al. 2010; Yuan et al. 2018), we develop a halo-based theoretical model for high peak counts in which massive halos contribute dominantly to high peaks, and the shape noise and the LSS effect other than the massive halos are modeled as Gaussian random fields. In our future studies, we aim to further develop the model by including the IA effects both from the noise perspective and from the inclusion of cluster satellites in shear samples.

4.4. Dependence on the Smoothing Scale

For the results shown above, our fiducial smoothing scale is taken to be $\theta_G = 1.5$. To see the smoothing scale dependence, we further analyze how the IA effects change with different $\theta_G$.

Figure 11 presents the results for the Euclid-like sample in the highIA and lowIA cases. Three values of $\theta_G$ are considered. We can see a clear dependence on $\theta_G$ in the highIA case, with the IA effects less significant for larger $\theta_G$. This can be understood as follows. Consider a massive cluster giving rise to a WL peak as the one shown in Figure 7. Its satellite galaxies in the shear sample lead to strong IA effects on the peak. With the increase of $\theta_G$, more galaxies outside the cluster region enter the convergence reconstruction and dilute the satellite IA effects on the peak. Statistically, we therefore have smaller $(n_{\text{highIA}}/n_{\text{noIA}} - 1)$ for larger $\theta_G$, especially for high peaks. For $\nu \sim 5$, $(n_{\text{highIA}}/n_{\text{noIA}} - 1) \sim -60\%$, $-40\%$, and $-15\%$ for $\theta_G = 1$, $1.5$, and $3 \text{ arcmin}$, respectively. The corresponding values are $\sim -80\%$, $-70\%$, and $-35\%$ for $\nu \sim 6$.

5. An Empirical Fitting Model

Our results show that WL peak counts are sensitive to IA effects. With proper modeling, it is possible to extract IA signals, particularly satellite IA, from observed peak statistics simultaneously with the cosmological information.
Here, based on our simulation analyses, we present an empirical fitting model that allows us to build the peak counts with IA from those of noIA simulations. The model relies on the following information: the matching fractions of peaks between the cases with IA and noIA, and the average peak height shifts $\Delta \kappa$ and their scatters $\sigma_{\Delta \kappa}$ for the matched peaks.

Figure 12 shows the matching results of peaks for the Euclid-like sample with the IA being highIA (red), $\theta_{3D} = 30^\circ$ (green), and lowIA (blue). The corresponding matching radius is 17, 9, and 5 pixels for the three IA cases. The dotted lines are the fractions of matched peaks. The solid and dashed lines are the fractions of newly born and disappeared peaks in the maps with IA compared to those of noIA. Note that $n_{\text{all}}$ here is the total number of peaks in a certain bin in the case of noIA.

It is seen that in general, the fractions of matched peaks increase with the peak height as expected. For the case of highIA, because of the relatively large matching radius, there are significant fractions of matched low peaks. We need to note, however, that low peaks largely arise from random fields including LSS and the shape noise. Thus, those matched low peaks are likely just by chance to be close to each other in the cases of IA and noIA but not physically linked. Therefore, our empirical fitting model is more meaningful for high peaks, although we present the relevant results extending to low peaks. The shaded regions are excluded in the model fitting analyses because of the small numbers of peaks and thus large statistical fluctuations there.

In Figure 13, we show $\Delta \kappa$ and $\sigma_{\Delta \kappa}$ for the matched peaks, where the points are from simulations, and the lines are the corresponding fits. We adopt a functional form of $\Delta \kappa = A + B\kappa_{\text{noIA}} + C\kappa_{\text{noIA}}^2 + D\kappa_{\text{noIA}}^3$ and a form of $\sigma_{\Delta \kappa} = a + b\kappa_{\text{noIA}}$.
for the fits. For the three considered IA cases, we obtain the fitting parameters as listed in Table 1.

With the information above, we proceed to generate peak counts in the IA cases from the ones of noIA. Specifically, for each bin of \( \kappa_{noIA} \) we select a number of peaks based on the fraction of matched peaks shown in Figure 12. For each of these peaks, we then assign it a peak height \( \kappa_{IA} \) using a Gaussian probability distribution given as

\[
p(\kappa_{IA}) \propto \exp \left[ -\frac{(\kappa_{IA} - \kappa_{noIA} - \Delta \kappa)^2}{2 \sigma_{\Delta \kappa}^2} \right].
\]

For the nonmatched peaks, we keep the peak heights as those in noIA.

The results are shown in the upper panel of Figure 14, where the solid and dashed lines are from simulations and the empirical fitting model, respectively. It is seen that within the statistical uncertainties, the fitting model can recover well the simulation results with IA for \( \nu > \sim 3 \). This provides a possible way to generate templates of peak counts with IA effects from simulations without IA. Following the same procedures, we also obtain fitting models for the samples with \( \theta_0 = 0^\circ \) and \( \sigma_\theta = 10^\circ \) and \( 60^\circ \), and the results are presented in the lower panel of Figure 14. For these cases, the fitting models also perform well.

6. Summary and Discussion

In this study, we systematically investigate the impacts of galaxy IA on WL peak statistics using simulations with semianalytical galaxy formation. The main conclusions are as follows.

1. The satellite IAs affect WL peak statistics significantly if they are included in a shear sample. When the 3D alignment angle of satellite galaxies with respect to the radial direction toward their centrals \( \theta_{3D} \approx 40^\circ \), their projected 2D orientations have a radial tendency, on average, and can suppress high peak counts significantly.

2. For average radially aligned satellite samples with \( \theta_0 = 0^\circ \) and different misalignments represented by the dispersion \( \sigma_\theta \), we systematically investigate the dependence on \( \sigma_\theta \) of the IA impacts on peak statistics. By analyzing the II correlations, we derive a relation between \( \gamma_{scale} \) and \( \sigma_\theta \) and find that \( \gamma_{scale} \approx 0.21 \) corresponds to \( \sigma_\theta \approx 70^\circ \). At this \( \sigma_\theta \), \( (n_{IA}/n_{noIA} - 1) \sim 5\% \) and 25\% for \( \nu = 5 \) and 8, respectively, for the Euclid-like sample.

3. The IA effects on WL peak counts depend on the redshift distribution of a shear sample. A sample including more satellite galaxies suffers more from the IA impacts.

4. For narrow redshift bin samples with minimal satellites from foreground clusters, the IA effects mainly arise due to their contributions to the shape noise. On the one hand, this changes the noise parameters. On the other hand, it also leads to a scaling factor \( \sigma_{0,IA}/\sigma_{0,IA} \) in the peak S/N binning in model calculations when comparing with observed peak counts. This is because in real observations, we normally estimate the noise r.m.s. by randomly rotating galaxies in a shear sample; thus, only \( \sigma_{0,IA} \) can be obtained and used in defining peak S/N. As a result, high peak counts are enhanced instead of suppressed in such cases.

5. The IA impacts also depend on the smoothing scale used in WL peak analyses. A larger smoothing scale tends to smooth out the satellite IA effects because more galaxies outside a cluster contribute to the reconstruction of the cluster convergence from the shears.

6. We build an empirical fitting model to calculate peak counts with IA effects from the ones in noIA. This can be useful in generating templates of peak counts with IA from noIA simulations so that the IA effects can be included in deriving cosmological constraints from observed peak counts.

Kacprzak et al. (2016) pointed out the importance of satellite IA on peak statistics and evaluated their effects by considering radially aligned satellites with a particular scaling factor \( \gamma_{scale} = 0.21 \). In comparison, here we construct samples with different satellite IA directly from simulations and perform systematic studies of the IA impacts. Because of the differences in the specific analyses, it is not straightforward to quantitatively compare our results with theirs. Qualitatively, similar behaviors are seen in the two studies, with the IA effects stronger for higher peaks. Our systematic analyses are able to reveal the dependence of the IA impacts on the satellite alignment angles.

For shear samples in narrow redshift bins, the strong suppression for high peak counts does not occur, which is also mentioned in Kacprzak et al. (2016). Our studies provide quantitative results of the IA effects on peak statistics for samples with different redshift distributions and demonstrate the impacts from the IA contributions to the shape noise in the cases with source galaxies in narrow redshift bins.

In comparison with the analyses of Hamois-Deraps et al. (2022) using the infusion method to generate IA signals of galaxies based on the tidal field calculations, our settings to adjust the satellite IA to different \( \theta_{3D} \) are, to a certain extent, effectively similar to adjusting the overall IA amplitude parameter \( A_{IA} \) used in their studies. The advantage of our simulations with semianalytical galaxy formation is that we have galaxies of different types, particularly centrals and satellites, and their clustering is naturally included. We therefore are able to treat centrals and satellites separately and single out the effects of satellite IA, instead of adjusting the overall \( A_{IA} \) without distinguishing different types of galaxies.
For the IA impacts, Harnois-Deraps et al. (2022) showed that for tomographic peak analyses, the IA effects for the cases of source galaxies in auto and cross bins show different behaviors, with the strong high-peak suppression occurring in cross-bin samples. This is qualitatively consistent with our results because cross bins contain a low-redshift bin and a high-redshift bin. Clusters in the low-redshift bin contribute to shear signals to galaxies in the high-redshift bin, leading to high peaks in the case of cross bins. Meanwhile, the satellites of these clusters are in the cross-bin sample, and their IA affects the high peaks significantly. On the other hand, the cases of their auto bins are close to our narrow redshift bin cases, where the IA effects come from the IA contributions to noise.

We note that the inclusion of cluster satellites in a shear sample can affect WL peak signals even without IA. This arises because these satellites do not carry the WL signals of their host clusters. When they are included in generating convergence or aperture mass maps, they tend to dilute the WL signals of clusters. In addition, the clustering of the satellites boosts the local density of galaxies around a cluster, leading to a smaller noise compared to the average, which also affects the peak counts (Kacprzak et al. 2016; Martinet et al. 2018; Shan et al. 2018; Zurcher et al. 2022). If satellites have IA, they lead to additional effects on peak heights and thus peak statistics. In our analyses shown here, the positions of satellite galaxies are exactly the same in the noIA and IA cases; thus, the differences ($n_{IA}/n_{noIA} - 1$) arise solely from their IA signals.

In real observational analyses, the dilution and the IA effects are correlated and need to be considered simultaneously. Kacprzak et al. (2016) considered the two statistically by adjusting the S/N of the peaks. In Shan et al. (2018), we included the satellite dilution and noise change due to the

![Figure 13](image1.png)

**Figure 13.** Average peak height shifts $\Delta \kappa$ (upper panel) and scatters $\sigma_{\Delta \kappa}$ (lower panel) in $\kappa_{noIA}$ bins for the three considered cases: highIA (red), $30^\circ$ (green), and lowIA (blue). Dots are the results measured from the data, and the solid lines are the fitting results using the parameters listed in Table 1 as described in the text.

![Figure 14](image2.png)

**Figure 14.** Results from the empirical fitting model (dashed lines) in comparison with those from simulations (solid lines). The upper panel is for the highIA (red), $30^\circ$ (green), and lowIA (blue) cases, and the lower panel is for $\theta_0 = 0^\circ$ and $\sigma_\theta = 10^\circ$ (red) and $60^\circ$ (orange), respectively.

| Table 1 | Fitting Parameters of $\Delta \kappa$ and $\sigma_{\Delta \kappa}$ |
|---------|---------------------------------------------------------------|
|         | highIA | 30 | 010 | 060 | lowIA |
| A       | 0.0088 | 0.0073 | 0.0074 | 0.0086 | 0.0071 |
| B       | $-0.6981$ | $-0.6637$ | $-0.5947$ | $-0.7088$ | $-0.6563$ |
| C       | 3.1884 | 8.0604 | 8.5450 | 4.1635 | 8.6635 |
| D       | $-3.2230$ | $-29.7478$ | $-35.6911$ | $-10.4547$ | $-36.7084$ |
| a       | 0.0088 | 0.0091 | 0.0092 | 0.0090 | 0.0094 |
| b       | 0.0704 | 0.0340 | 0.0343 | 0.0591 | 0.0189 |
boosted number density around clusters in our theoretical high-
peak model in deriving cosmological constraints from the
observed peak counts using KiDS data. In our future studies,
we will further develop the model to include the IA effects. For
that, we need to carefully analyze the IA effects on WL peak
signals at the level of individual clusters with different masses
and at different redshifts. We note that the satellite IA effects
can be regarded as strong gravitational-intrinsic correlation
(GI) between gravitational lensing signal from background
galaxy and intrinsic alignment of foreground galaxy effects. In
addition, galaxies in a shear sample other than these satellites
can also have GI signals. Together with the II term, they
change the noise properties, which should also be included in
the modeling. The success of such a model and its application
to WL observations can not only mitigate the systematic biases
on cosmological parameters due to the IA effects but also allow
us to extract the satellite IA information simultaneously from
observed WL high peaks.

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Appendix A

The $\sigma_\theta$ Dependence of $\gamma_{\text{scale}}$

In Schneider & Bridle (2010), they propose to model small-
scale IA by placing satellites in dark matter halos. By
introducing a scaling factor $\gamma_{\text{scale}}$ with respect to the II
correlations from perfectly radially aligned satellites, the
misalignment of satellites can be accounted for. Adding the
NLA modeling for large scales (Hirata & Seljak 2004; Bridle &
King 2007) gives rise to the IA contributions to the cosmic shear 2PCF.

In our study here, we consider satellite IA with the average
$\theta_0 = 0^\circ$ and different dispersions $\sigma_\theta$. This is well in line with
the model of Schneider & Bridle (2010). To derive the relation
between $\gamma_{\text{scale}}$ and $\sigma_\theta$, we calculate the II correlations from our
IA samples without adding shear signals. The results are shown
in Figure 15. Different data points with error bars are for
different $\sigma_\theta$.

It is seen that at an angular separation larger than about 5’,
the II correlations are about the same for different $\sigma_\theta$ because at
these scales, the central–central galaxy II correlations play
dominant roles, which are the same for all of the samples
considered here. They can be well described by the NLA model
given by Hirata & Seljak (2004) and Bridle & King (2007):

$$P_{\text{II}}(z) = F^2(z)P_{\text{m}}^{\text{NL}}(k, z).$$

(A1)

Here $P_{\text{m}}^{\text{NL}}(k, z)$ is the nonlinear matter power spectrum, and

$$F(z) = -A_{\text{IA}}C_1\rho_{\text{crit}}\frac{\Omega_m}{D_+(z)}\left(\frac{1 + z}{1 + z_0}\right)^{\eta_{\text{eff}}}.\quad (A2)$$

where $A_{\text{IA}}$ is the amplitude parameter, $\rho_{\text{crit}}$ is the current critical
density, and $D_+(z)$ is the linear growth factor.

By setting $C_1 = 5 \times 10^{-14}h^{-2}M_\odot^{-1}\text{Mpc}^3$ and $\eta_{\text{eff}} = 0$ (Wei et al. 2018) and taking into account the Euclid-like redshift
distribution, we fit the NLA model to the II correlation data
points at $\theta \geq 5$ arcmin to obtain $A_{\text{IA}}$. The black line in
Figure 15 is the theoretical result with $A_{\text{IA}} = 0.98$. The derived relation
between $\gamma_{\text{scale}}$ and $\sigma_\theta$ is shown in Figure 16. The

![Figure 15](image_url)

**Figure 15.** The II correlations measured from our IA samples with $\theta_0 = 0^\circ$ and
different $\sigma_\theta$ without adding shear signals. Colored lines with error bars are the
results of different $\sigma_\theta$ as indicated in the legend, where, e.g., 0 for $\sigma_\theta = 0^\circ$ and
30 for $\sigma_\theta = 30^\circ$. The black line is the theoretical NLA prediction with
$A_{\text{IA}} = 0.98$.

![Figure 16](image_url)

**Figure 16.** Dependence of $\gamma_{\text{scale}}$ on $\sigma_\theta$. The horizontal dashed line indicates
$\gamma_{\text{scale}} = 0.21$, and the red point marks its intersection with the blue line.
horizontal black dashed line indicates $\gamma_{\text{scale}} = 0.21$ from Knabe et al. (2008), and the red point shows its intersection with the blue solid line, which is at $\sigma_{\theta} \approx 70^\circ$. We mark this $\sigma_{\theta}$ in the lower panel of Figure 8.

**Appendix B**

**The 2D Gaussian Peak Model**

For a 2D Gaussian random field, the peak density distribution function is given by Bond & Efstathiou (1987), Waerbeke (2000), and Fan (2007),

$$N(\nu)d\nu = \frac{1}{2\pi\theta_\nu^2} \exp(-\nu^2/2) \frac{d\nu}{(2\pi)^{1/2}} G(\gamma_G, \gamma_G\nu), \quad (B1)$$

where $\nu = \kappa/\sigma_\nu$ is the $S/N$, $\theta_\nu = \sqrt{2} \sigma_1/\sigma_2$, and $\gamma_G = \sigma_1^2/(\sigma_1\sigma_2)$. The function $G$ is

$$G(\gamma_G, x) = \frac{1}{2} \left( x^2 + b^2 - 1 \right) \text{erfc} \left( -\frac{x}{b} \right) + \frac{1}{\sqrt{1+b^2}} \text{erfc} \left( -\frac{x}{\sqrt{1+b^2}} \right). \quad (B2)$$

with $b = [2(1 - \gamma_G^2)]^{1/2}$. The moment $\sigma_i$ of the field $N$ is given by

$$\sigma_i^2 = \int dk k^i \langle |N(k)|^2 \rangle, \quad (B3)$$

where $|N(k)|^2$ is the power spectrum of $N$.

In the case of noIA, we have $\sigma_{0,\text{noIA}} = \sigma_i \sqrt{4\pi \theta_\nu^2 H_k}$ under the Gaussian smoothing, and $\sigma_{0,\text{noIA}}$, $\sigma_{1,\text{noIA}}$, $\sigma_{2,\text{noIA}} = 1/\sqrt{2}/\theta_G; 2/\sqrt{2}/\theta_G$. This leads to $\gamma_{G,\text{noIA}} = \sqrt{2}/2$ and $\theta_{G,\text{noIA}} = \theta_G/\sqrt{2}$. The existence of IA gives rise to additional contributions to $\sigma_i$ with $\sigma_{i,\text{IA}} = (\sigma_{i,\text{noIA}} + \sigma_{i,\text{corr}})^{1/2}$, where $\sigma_{i,\text{corr}}$ is from IA. For illustration here, for the three narrow redshift bin samples, we estimate $\sigma_{i,\text{IA}}$ directly from the galaxy ellipticities including IA but without adding lensing signals. Thus, the II correlation term is accounted for, but the GI part is missed. For the considered samples in narrow redshift bins, we expect minimal GI signals. In general, for a sample with a redshift distribution, the GI contributions to noise should be included.

Besides the shape noise, to some extent, the WL effects from large-scale structures can also be described as a random field. In Yuan et al. (2018), in modeling high peak counts, we consider the massive halos as the dominant sources for high peaks. The additional WL contributions from large-scale structures other than those massive halos (LSS) are modeled as a Gaussian random field. Although this Gaussian assumption is an approximation, it can model well the LSS contributions to high-peak statistics (Yuan et al. 2018). Here, for the purpose of qualitative illustration, we also include LSS as a Gaussian random field. Thus, the total $\sigma_{\text{total}}^2$ becomes $(\sigma_{\text{noIA}}^2 + \sigma_{\text{LSS}}^2)^{1/2}$ and $\sigma_{\text{IA}}^2 = (\sigma_{\text{LSS}}^2 + \sigma_{\text{corr}}^2)^{1/2}$, where $\sigma_{\text{LSS}}^2$ are calculated following the approach described in Yuan et al. (2018).

In Figure 17, we show the dependence of the noise parameters on $\theta_{\text{3D}}$ for the three narrow redshift bin samples with red, orange, and blue lines for $z \sim 1, \sim 1.5,$ and $\sim 2$, respectively. The left, middle, and right panels are for $\sigma_0^2$, $\gamma_G^2$, and $\theta_{G,\text{IA}}^2$, respectively. The dotted lines in the left panel are the $\sigma_{0,\text{noIA}}$ of the three samples, and the vertical shifts of the solid lines from their corresponding dotted lines are due to $\sigma_{0,\text{LSS}}$, which is redshift-dependent but independent of IA.

Besides the changes of the noise parameters, in accord with real observations, we use $\sigma_{0,\text{noIA}}$ to define $\nu$ in our simulation analyses for all cases. To be consistent, we need to scale $\nu$ to $(\sigma_{0,\text{noIA}}/\sigma_{0,\text{noIA}}^2)^{1/2}$ and $(\sigma_{0,\text{noIA}}/\sigma_{0,\text{IA}}^2)^{1/2}$ in noIA and IA cases, respectively, in calculating the peak distributions using Equation (B1). This also affects peak statistics.

With the above information, we calculate the peak distributions for the narrow redshift bin samples, and the results are shown in the lower panels of Figure 10.

![Figure 17](image-url)
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