Letter to the Editor

Starlet higher order statistics for galaxy clustering and weak lensing

Virginia Ajani1,2, Joachim Harnois-Déraps3, Valeria Pettorino1, and Jean-Luc Starck1

1 Université Paris-Saclay, Université Paris Cité, CEA, CNRS, AIM, 91191 Gif-sur-Yvette, France
2 Institute for Particle Physics and Astrophysics, Department of Physics, ETH Zürich, Wolfgang Pauli Strasse 27, 8093 Zürich, Switzerland
3 School of Mathematics, Statistics and Physics, Newcastle University, Herschel Building, NE1 7RU Newcastle-upon-Tyne, UK

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Abstract

We present a first application to photometric galaxy clustering and weak lensing of wavelet-based multi-scale (beyond two points) summary statistics: starlet peak counts and starlet ℓ1-norm. Peak counts are the local maxima in the map, and ℓ1-norm is computed via the sum of the absolute values of the starlet (wavelet) decomposition coefficients of a map, providing a fast multi-scale calculation of the pixel distribution, encoding the information of all pixels in the map. We employ the cosmo-SLICS simulations sources and lens catalogues, and we compute wavelet-based non-Gaussian statistics in the context of combined probes and their potential when applied to the weak-lensing convergence maps and galaxy maps. We obtain forecasts on the matter density parameter Ωm, the reduced Hubble constant h, the matter fluctuation amplitude σ8, and the dark energy equation of state parameter w0. In our setting for this first application, we consider the two probes to be independent. We find that the starlet peaks and the ℓ1-norm represent interesting summary statistics that can improve the constraints with respect to the power spectrum, even in the case of photometric galaxy clustering and when the two probes are combined.

Key words. large-scale structure of Universe – methods: statistical – cosmological parameters

1. Introduction

Past, present, and future cosmological surveys, such as the Canada-France-Hawaii Telescope Lensing Survey (CFHTLenS) (Heymans et al. 2012), the Kilo-Degree Survey (KiDS) (Heymans et al. 2021), the Dark Energy Survey (DES) (Abbott et al. 2019; To et al. 2021), Hyper SuprimeCam (HSC) Mandelbaum & Hyper Suprime-Cam (HSC) Collaboration 2017, Euclid (Laureijs et al. 2011), and the Rubin Observatory (Abell 2009), use weak gravitational lensing by large-scale structure and galaxy clustering as the main physical probes to explore the unknown properties of dark energy and dark matter. The correlation between the positions of foreground galaxies with the shapes of the source galaxies, also known as 3 × 2pt analysis, is very sensitive to the amplitude of matter clustering in the low-redshift universe and represents a powerful test of consistency between the growth of structure and the expansion history of the Universe (Porredon et al. 2021; Abbott et al. 2022). Since they bring complementary cosmological information, the combination of cosmic shear, galaxy clustering, and galaxy-galaxy lensing has proved to be very powerful to test cosmological models and modified gravity models and in enhancing the constraining power (Zhang et al. 2007; Eriksen & Gaztañaga 2018; Heymans et al. 2021; Euclid Collaboration 2020; Tutusaus et al. 2020 and references therein) and for dealing with systematic effects (Mandelbaum et al. 2013; Camera et al. 2016; Haronois-Déraps et al. 2018; Joachimi et al. 2021; Krause et al. 2021) as they are typically distinct and uncorrelated in different probes. Furthermore, the increasing precision reached with next-generation surveys will enable us to access the non-Gaussian part of cosmological signals, induced by the non-linear evolution of structure on small scales and low redshifts, which is not captured with second-order summary statistics alone. Specifically for weak lensing, a rich literature proposing several non-Gaussian statistics (Euclid Collaboration 2023), such as Minkowski functionals (e.g., Kratochvil et al. 2012 and Parroni et al. 2020), higher order moments (e.g., Petri et al. 2016 and Gatti et al. 2020), bispectrum (Takada & Jain 2004; Coulton et al. 2019), peak counts (Kruse & Schneider 1999; Dietrich & Hartlap 2010; Liu et al. 2015; Lin & Kilbinger 2015; Peel et al. 2017; Martinet et al. 2017; Li et al. 2019; Ajani et al. 2020; Zücher et al. 2022b; Ayçoberry et al. 2023), Betti numbers (Parroni et al. 2021), the scattering transform (Cheng et al. 2020), wavelet phase harmonic statistics (Allys et al. 2020), and machine learning-based methods (e.g., Fluri et al. 2018 and Shirasaki et al. 2021), is catching the attention of the community. The ℓ1-norm of wavelet coefficients of weak-lensing convergence maps has been proposed (Ajani et al. 2021) as a new summary statistics for weak lensing as it provides a unified framework to perform a multi-scale analysis that takes into account the information encoded in all pixels of the map. Moreover, Grewal et al. (2022) have explored the addition of DES-like and LSST-like mock clustering maps to an analysis of Minkowski functionals; they find a significant improvement with respect to a weak lensing-only analysis. Kacprzak & Fluri (2022) show that a deep learning analysis of combined weak...
lensing and galaxy clustering at the map level can help break the degeneracy between cosmological and astrophysical parameters. As the wavelet-based statistics presented in Ajani et al. (2020, 2021), and Zücher et al. (2022a) were limited to weak lensing, we propose in this work a first application of such statistics in the context of joint weak lensing and galaxy clustering with the final goal of showing the potential of wavelet-based non-Gaussian statistics in the framework of probe combination.

The scope of this study is to extend the application of starlet peaks and ℓ₁-norm to photometric galaxy clustering and its combination with weak lensing. Specifically, we employ lensing and clustering data from the cosmo-SLICS simulations to build convergence and density maps from which we obtain various weak lensing and clustering predictions. We perform a likelihood analysis using the power spectrum, the starlet peaks, and ℓ₁-norm, and constrain the matter density parameter Ω_m, the reduced Hubble constant h, the matter fluctuation amplitude σ_8, and the dark energy equation of state parameter w. The Letter is structured as follows. In Sect. 2 we provide some background definitions for weak lensing and photometric galaxy clustering. In Sect. 3 we present the mock data, the catalogues, and our map-making procedure. We describe our analysis in Sect. 4. In Sect. 5 we present and discuss the results, limitations, and perspectives of this work. We conclude in Sect. 6.

2. Background

2.1. Weak lensing

The distortions caused by gravitational lensing in the original source image can be summarised in the distortion matrix:

\[
\mathcal{A} = \begin{pmatrix}
1 - \kappa - \gamma_1 & -\gamma_2 \\
-\gamma_2 & 1 - \kappa + \gamma_1
\end{pmatrix}
= (1 - \kappa) \begin{pmatrix}
1 - g_1 & -g_2 \\
-g_2 & 1 + g_1
\end{pmatrix}.
\]

Here \( \gamma = (\gamma_1, \gamma_2) \) is the shear, also defined in terms of the lensing potential \( \psi \) as \( \gamma_1 = \frac{1}{2}(\partial_1 \psi - \partial_2 \psi) \) and \( \gamma_2 = \partial_1 \psi - \partial_2 \psi \), which describes the anisotropic distortion of the image; \( \kappa \) is the convergence field, also defined as \( \kappa = \frac{1}{2} \nabla^2 \psi \), which describes the isotropic dilation of the source; and \( g \) is the reduced shear. The observed ellipticity \( \epsilon_{\text{obs}} \) is related with the intrinsic ellipticity of the galaxy \( \epsilon^* \) and the reduced shear through the relation (Seitz & Schneider 1997)

\[
\epsilon_{\text{obs}} = \frac{\epsilon^* + g}{1 + g^* \epsilon^*},
\]

where \( g^* \) is the complex conjugate of \( g \). In the weak-lensing regime, where \( |\gamma|, k \ll 1 \), this relation can be approximated as \( \epsilon_{\text{obs}} \approx \epsilon^* + \gamma \). Moreover, if the intrinsic ellipticity of galaxies has no preferred orientation, its expectation value vanishes, \( \langle \epsilon^* \rangle = 0 \), and the observed ellipticity can be employed as an unbiased estimator of the reduced shear, as \( \langle \epsilon_{\text{obs}} \rangle \approx \gamma \) (Kilbinger 2015). In this study, we work under these assumptions; including the effect of the intrinsic alignments goes beyond the purposes of this work. The shear field can be related to the underlying matter density field using the relations connecting \( \gamma \) and \( \kappa \) to the lensing potential along with the fact that \( \kappa \) is a line-of-sight integral of the matter density field. Working in Fourier space, we obtain an estimator of the convergence field starting from the shear field through the Kaiser-Squires inversion (KS) (Kaiser & Squires 1993) as

\[
\hat{k} = \frac{k_1^2 - k_2^2}{k_1} \hat{1} + \frac{2k_1 k_2}{k_1} \hat{2},
\]

where \( k^2 = k_1^2 + k_2^2 \).

2.2. Photometric galaxy clustering

As second-order statistics for photometric galaxy clustering, we employed the angular power spectra in harmonic space, \( C_{\ell}^{GG}(\ell) \), measured on the galaxy maps. Given the redshift distribution of the galaxies \( n_g(z) \) in each tomographic bin \( i \) of a photometric survey, the average galaxy density in this redshift bin is given by (Euclid Collaboration 2020)

\[
\overline{n}_g^G(z) = \int_{z_{\min}}^{z_{\max}} dz n_g^G(z).
\]

Then the radial weight function for a given tomographic bin \( i \) for galaxy clustering can be defined as

\[
W_{gi}(z) = \frac{n_g^G(z)}{\overline{n}_g^G(z)} H(z).
\]

The observable spectrum is theoretically given by the expression

\[
C_{Gij}(\ell) = \int dz \frac{W_{gi}(z) W_{jj}(z) P_{gg}^{\text{photo}}}{H(z)^2(z)} P_{gG}^{\text{photo}} \left[ \ell + 1/2, r(z) \right],
\]

where \( P_{gG}^{\text{photo}}(\ell, z) \) is the galaxy–galaxy power spectrum, which, under the assumption of a linear galaxy bias, is linked to the matter power spectrum \( P_{\text{mol}}(\ell, z) \) through the bias \( b_g \):

\[
P_{gG}^{\text{photo}}(\ell, z) = [b_g^{\text{photo}}(z)]^2 P_{\text{mol}}(\ell, z).
\]

In this first application we consider only the auto-spectra (\( i = j \)) for our power spectrum measurements, and that the galaxy bias \( b_g \) is fixed in the simulations.

3. Mock data

We modelled our non-Gaussian statistics with mock data constructed from the cosmo-SLICS (Harnois-Déraps et al. 2019), a suite of high-resolution N-body simulations consisting of 25 different cosmologies organised in a Latin hypercube obtained by varying the matter density parameter \( \Omega_m \) in the range \([0.10, 0.55] \), the reduced Hubble constant \( h \) in the range \([0.60, 0.82] \), the combination between \( \Omega_m \) and the matter fluctuation amplitude \( \sigma_8 \), \( S_8 = \sigma_8 \sqrt{\Omega_m/0.3} \) in the range \([0.60, 0.90] \), and the dark energy equation of state parameter \( w_0 \) between \([-2.0, -0.5] \). Each gravity-only calculation evolves 1536^3 particles in a box of comoving side of 505 h^{-1} Mpc with the Poisson solver CUBEP^3M (Harnois-Déraps et al. 2013). These were then ray-traced under the Born approximation to construct the sources and lenses catalogues of 100 deg^2. To reduce the impact of cosmic variance, two simulations were provided for each cosmology with different initial conditions, each re-sampled to create 25 pseudo-independent light cones.

3.1. Source catalogue

For the weak lensing analysis we used the KiDS-1000-like sources catalogue described in Harnois-Déraps et al. (2021), which mimics the survey properties of the KiDS-1000 data described in Giblin et al. (2018) and Hildebrandt et al. (2021). These catalogues are available for five different tomographic redshift bins, with a corresponding galaxy number density of \( n_{\text{gal}} = [0.62, 1.18, 1.85, 1.26, 1.31] \). For each source galaxy, the catalogue contains the positions \((x, y)\) in arcmin and in redshift \( z \), the values for the components of the true shear \((\gamma_1, \gamma_2)\) and the values for the components of the observed ellipticities \((\epsilon_{1\text{obs}}, \epsilon_{2\text{obs}})\).
3.2. Building convergence maps

To get the convergence map, we used the KS inversion: we projected the shear onto a 600\textsuperscript{2} Cartesian grid (resolution of 1 arcmin per pixel), which we then smoothed with a Gaussian filter of width 0.7 arcmin following Giblin et al. (2018) to reduce the impact of potential empty pixels. This was implemented using the Python package lenspack\textsuperscript{1}. We provide an example of our validation against the theoretical prediction in Appendix C.

3.3. Lens catalogues

To perform the galaxy clustering analysis, we employed the KiDS-1000-like lens catalogues of luminous red galaxies (LRGs) provided by the cosmo-SLICS simulations. This simulated foreground LRG sample reproduces the characteristics described in Vakili et al. (2020) and is split into four tomographic bins (see Burger et al. 2022, for a recent study employing the same catalogues). Each catalogue contains the position and redshift of each galaxy. The LRGs trace the underlying projected mass sheets, hence their redshift distribution is heavily discretised in bins of $\Delta z = 257.5$ Mpc h$^{-1}$. The catalogues are generated assuming linear galaxy bias, whose values and uncertainties are from Vakili et al. (2020) and summarised in Table B.1.

3.4. Building galaxy maps

Starting from the lens catalogue described in Sect. 3.3, we built galaxy maps for each light cone by assigning the galaxies onto a 600\textsuperscript{2} grid. We validated our maps by comparing our measured power spectra against the theoretical prediction obtained with the Python library pyccl\textsuperscript{2}. The shot noise of the galaxy maps was approximated as Gaussian noise with a variance equal to the mean of each galaxy map.

As the map is intrinsically noisy (due to the presence of shot noise), while the theoretical prediction is obtained for a noiseless case, we computed the power spectrum of the noise map and then subtracted it from the power spectrum of the map. Since we did not have a model including non-linear bias, we started with a conservative analysis and included scales up to $\ell_{\text{max}} = 780$. An example of the comparison between our measurement on the simulated galaxy map and the corresponding theoretical prediction can be found in Fig. C.1.

4. Analysis

4.1. Summary statistics

We compute our summary statistics on convergence maps for weak lensing and galaxy maps for galaxy clustering. When computing the power spectra, we smooth the noisy convergence and galaxy maps with a Gaussian kernel of size $\theta_{\text{ker}} = 1$ arcmin. For weak lensing we use 33 bins in the range $\ell = [180, 2040]$, which lies within the region where we are confident that the power spectra are in agreement with the theoretical predictions. For galaxy clustering, we use 14 bins in the range $\ell = [120, 780]$, following the pessimistic setting of Euclid Collaboration (2020). These regions in $\ell$ are shown in Appendix C. For the non-Gaussian statistics, we filter the noisy maps with a starlet filter (Starck & Murtagh 1998). On the same maps, we also compute the starlet $\ell$-norm, which is the absolute value of the sum of all wavelet coefficients for each scale of the decomposition within a chosen range of amplitude (Ajani et al. 2021). For both starlet peaks and $\ell$-norm we use for inference four scales corresponding to [2\textsuperscript{\text{rd}}, 4\textsuperscript{th}, 8\textsuperscript{th}, 16\textsuperscript{th}, coarse], with 29 linearly spaced bins for each scale between the minimum and maximum values of each S/N map.

4.2. Likelihood

To perform Bayesian inference and obtain the probability distributions of the cosmological parameters we want to constrain, we use a Gaussian likelihood for a cosmology-independent covariance:

$$
\log L(\theta) = -\frac{1}{2} \sum_\alpha (d - \mu(\theta))_\alpha^T C_\alpha^{-1} (d - \mu(\theta))_\alpha.
$$

Here $d$ is the data array given by the average of the summary statistics over the different realisations at fiducial model, $C$ is the covariance matrix of the observable defined in the next section, $\mu$ is the model prediction as a function of the cosmological parameters $\theta$, and $\alpha$ denotes the physical probe (i.e., weak lensing and galaxy clustering). At second order, the cross-correlation between the galaxy clustering and weak-lensing mock catalogues from two different surveys can be neglected if the overlap between the two surveys is sufficiently small (Heymans et al. 2021). We are aware that in our case the galaxy density and convergence maps can in reality be correlated, as shown in Fig. 1, where the structures of the galaxy map are traced by the lensing convergence map. For this first application, we ignore these correlations that could actually bring additional information. For map level studies it has been shown that cross-probes can help in breaking degeneracies and in increasing the constraining power (Kacprzak & Fluri 2022; Grewal et al. 2022). We leave for a future study the inclusion of their cross-correlation. The cosmological parameters are the ones that vary in the simulations, namely $\theta = [\Omega_m, \sigma_8, h, w_0]$. To model the summary statistics at arbitrary cosmologies, we employ an interpolation with Gaussian processes regression (Rasmussen & Williams 2005), using the scikit-learn\textsuperscript{3} Python package. For more details, the emulator

\textsuperscript{1} https://github.com/ComSoStat/lenspack
\textsuperscript{2} https://pypi.org/project/pyccl/
\textsuperscript{3} https://scikit-learn.org/
used in this Letter is the same as the one employed in Li et al. (2019) and in Ayçoberry et al. (2023).

4.3. Covariance matrix

To compute the covariance matrix we employ the SLICS simulations (Harnois-Déraps et al. 2018). These are obtained as described in Sect. 3 but are specifically designed for the estimation of covariance matrices: they consist of 800 fully independent ΛCDM runs in which the cosmological parameters are fixed to the cosmology $[\Omega_m, \sigma_8, h, n_s, \Omega_b] = [0.2905, 0.826, 0.6898, 0.969, 0.0473]$ and the random seeds in the initial conditions are varied. The covariance matrix elements are computed as

$$C_{ij} = \frac{1}{N-1} \sum_{r=1}^{N} (x_i^r - \mu_i)(x_j^r - \mu_j),$$  \hspace{1cm} (9)

where $N = 800$ is the number of observations, $x_i^r$ is the value of the $i$th data element for a given realisation $r$, and $\mu_i$ is the mean over all realisations. We take into account the loss of information due to the finite number of bins and realisations by adopting the estimator introduced by Hartlap et al. (2007) for the inverse of the covariance matrix $C^{-1} = \frac{N-n_{\text{bins}}}{N-1} C^{-1}$, where $n_{\text{bins}}$ is the number of bins and $C$, the covariance matrix computed for the power spectrum, the peak counts, and the $\ell_1$-norm, whose elements are given by Eq. (9). We area-rescale the covariance matrix to model the statistical accuracy of the KiDS-1000 survey, with $\Delta \text{KiDS-1000} = 1000 \text{deg}^2$.

4.4. MCMC simulations and posterior distributions

We explore and constrain the parameter space with the emcee package, the affine invariant ensemble sampler for Markov chain Monte Carlo (MCMC) introduced by Foreman-Mackey et al. (2013). We assume a flat prior for all parameters over the range modelled by the cosmo-SLICS, with the Gaussian likelihood defined in Eq. (8). We use 120 walkers initialised in a tiny Gaussian ball of radius $10^{-3}$ around the fiducial cosmology $[\Omega_m, \sigma_8, h, w_0] = [0.2905, 0.8364, 0.6898, -1]$.

5. Results

We first derive constraints with the power spectrum for both weak lensing and galaxy clustering, shown in Fig. 2. We see how, in our setting, the galaxy clustering alone outperforms the weak lensing contours, breaking the degeneracies especially in the $(\Omega_m, \sigma_8)$ plane. At the same time, combining them brings additional information, improving the constraining power and the degeneracy break even more, underlying the complementarity of cosmological information encoded in the two probes.

In Fig. 3 we show the comparison among the constraints obtained using the galaxy clustering power spectrum, the starlet peak counts measured on galaxy density maps, and the galaxy clustering $\ell_1$-norm to explore this statistics in the context of galaxy clustering. We see how, as for weak lensing, the starlet peaks improve the constraining power with respect to the power spectrum and the $\ell_1$-norm outperforms the other two. We are aware that the massive improvement in constraining power for galaxy clustering is very likely overestimated due to the fact that the galaxy bias in these simulations is kept fixed and assumed to be perfectly linear. In Appendix B we perform an analysis using the power spectrum with four different values of the galaxy bias parameters sampled from the measured uncertainty on these, as
In this Letter we proposed using for the first time starlet-based non-Gaussian statistics on weak-lensing convergence maps and galaxy clustering. We performed a single probe and a combined non-Gaussian analysis that accounts for the inclusion of systematic effects and help during the first phase of development of the project. VA wishes to thank François Lanusse, for useful discussions and help during the first phase of development of the project. VA wishes to thank Tomasz Kacprzak and Alexandre Refregier for useful discussions. VA acknowledges support by the Centre National d’Etudes Spatiales and the project Initiative d’Excellence (IdEx) of Université de Paris (ANR-18-IDEX-0001) at the start and during the preparation of this work. VA acknowledges support by the grant Cosmological Weak Lensing and Neutral Hydrogen, 200021_192243 of Prof. Alexandre Refregier. JHD acknowledges support from an STFC Ernest Rutherford Foundation Fellowship (project reference ST/S004858/1). The N-body simulations were enabled by the Digital Research Alliance of Canada (https://alliancecan.ca/).
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Appendix A: Starlet transform

We provide here a brief introduction to the starlet filter that we employed in this study to filter our input noisy maps. The starlet is a wavelet transform, namely a function that decomposes a signal into a family of scaled and translated functions. More specifically, wavelets are highly localised functions with vanishing mean since they satisfy the admissibility condition $\psi (t_0) (|t_0|^2 + \int_{-\infty}^{\infty} |\psi(t)|^2 dt < +\infty)$, which implies that $\int \psi(t) dt = 0$ (i.e. they integrate to zero over their domain). We can define the starlet $\phi$ in relation to its scaling function, which is a B-spline function $\phi$ of order 3,

$$\psi(t_1, t_2) = 4\phi(2t_1, 2t_2) - \phi(t_1, t_2),$$

with

$$\phi(t) = \frac{1}{12} (1-t)^3 - 4(1-t)^2 + 6(1-t) + 3t + 2t^2)$$

and $\phi(t, t') = \phi(t)\phi(t')$ (for a complete description and derivation of the starlet transform algorithm, see Stark et al. 2007). We show its 1D and 2D profiles in Fig. A.1. When applying this transform in practice, an original $N \times N$ map $I$ is decomposed into a coarse version of $c_j$ plus several images of the same size at different resolution scales $j$:

$$I(x, y) = c_j(x, y) + \sum_{j=1}^{j_{max}} w_j(x, y).$$

Here the images $w_j$ represent the details of the original image at dyadic (powers of two) scales, corresponding to a spatial size of $2^j$ pixels and $J = j_{max} + 1$. Its shape emphasises round features, making it very efficient when dealing with peaks.

Appendix B: Uncertainty on the bias

As the mock catalogues used in the galaxy clustering analysis are produced with a fixed galaxy bias, we provide here an estimate of the impact of the uncertainty of the galaxy bias on the parameter contours through MCMC forecasts. Specifically, we consider the best values and corresponding ±1σ and ±2σ found by Vakili et al. (2020) for the sample of luminous red sequence galaxies for the fourth data release of the Kilo-Degree Survey. We provide in Table B.1 the values corresponding to Table 5 of Vakili et al. (2020).

In order to do so, we consider the bias "unknown" using as mock data the power spectrum computed on simulations with respectively ±2σ, ±1σ, −2σ, and −1σ uncertainty on its value and for inference what was found as best fit (see ‘best’ in Table B.1) for the KiDS-1000 LRG set. We compare the results for these four settings with the case in which the galaxy bias is instead fixed (orange contours in Fig. B.1), namely the same in both mock data and simulations used for inference. We see how the ±1σ uncertainties in galaxy bias already induce a 2σ offset in the inferred $\sigma_8$, highlighting the importance of taking into account this uncertainty for real data application. In the future, we plan to perform a deeper investigation of how the uncertainty on the bias impacts the results, for example by emulating and marginalising over the effect.

Table B.1. Model constraints and uncertainties on the galaxy bias for the luminous red galaxies from Vakili et al. (2020) derived from the median and the 68% confidence intervals of the marginalised posterior distributions.

| bin      | −2σ  | −1σ  | best | +1σ  | +2σ  |
|----------|------|------|------|------|------|
| 1        | 1.36 | 1.53 | 1.70 | 1.88 | 2.06 |
| 2        | 1.46 | 1.59 | 1.72 | 1.86 | 2.00 |
| 3        | 1.62 | 1.68 | 1.74 | 1.80 | 1.86 |
| 4        | 1.85 | 1.93 | 2.01 | 2.09 | 2.17 |

Fig. B.1. Forecast contours at confidence levels of 68% and 95% using the power spectrum for four different uncertainties on the galaxy bias (dashed contours) compared to when the galaxy bias is fixed (continuous contours). The light blue dashed contours are obtained using the columns ‘+1σ’ and ‘+2σ’ in Table B.1; the light pink dashed contours using the columns ‘−1σ’ and ‘−2σ’; and the orange continuous contours refer to the column ‘best’.

Fig. A.1. One-dimensional profile of the starlet function.
Appendix C: Map validation

We validate the convergence and galaxy maps for the two probes that we built from the simulations by comparing our measured two-point statistics with the theoretical prediction. In order to do so we measure the power spectrum respectively on the convergence maps from the source catalogue and the galaxy density map from the lens catalogues built as described in Sect. 3. We show this in the top panel of Fig. C.1 for weak lensing and the bottom panel for galaxy clustering, where the black dots represent the angular power spectrum we measure from the galaxy map we built from the simulations averaged here across the 50 light cones, and the dashed line is the theoretical prediction using pyccl (Chisari et al. 2019). The grey areas indicate the scales excluded in the analysis. Concerning galaxy clustering, as the map is intrinsically noisy (due to the presence of Poisson noise), while the theoretical prediction is obtained for a noiseless case, we compute the power spectrum of the noise and then subtract it from the power spectrum of the map. At high $\ell$ a noisy behaviour can be seen. The scales where this happens are excluded from the analysis, as we include multipoles up to $\ell_{\text{max}} = 780$.

Fig. C.1. Comparison between the power spectrum measured from maps built from the simulations and the corresponding theoretical prediction. \textbf{Top panel}: Weak-lensing power spectrum measured from convergence maps built from the simulations and the corresponding theoretical prediction obtained using pyccl. An example of this comparison is shown for the fiducial cosmology of the cosmo-SLICS simulations of the third tomographic bin. \textbf{Bottom panel}: Same, but for the galaxy density map used for clustering.