$\kappa$TNG: Effect of Baryonic Processes on Weak Lensing with IllustrisTNG Simulations

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ABSTRACT
We study the effect of baryonic processes on weak lensing (WL) observables with a suite of mock WL maps, the $\kappa$TNG, based on the cosmological hydrodynamic simulations IllustrisTNG. We quantify the baryonic effects on the WL angular power spectrum, one-point probability distribution function (PDF), and number counts of peaks and minima. We also show the redshift evolution of the effects, which is a key to distinguish the effect of baryons from fundamental physics such as dark energy, dark matter, and massive neutrinos. We find that baryonic processes reduce the small-scale power, suppress the tails of the PDF, peak and minimum counts, and change the total number of peaks and minima. We compare our results to existing semi-analytic models and hydrodynamic simulations, and discuss the source of discrepancies. The $\kappa$TNG suite includes 10,000 realisations of $5 \times 5$ deg$^2$ maps for 40 source redshifts up to $z_s = 2.6$, well covering the range of interest for existing and upcoming weak lensing surveys. We also produce the $\kappa$TNG-Dark suite of maps, generated based on the corresponding dark matter only IllustrisTNG simulations. Our mock maps are suitable for developing analytic models that incorporate the effect of baryons, but also particularly useful for studies that rely on mass maps, such as non-Gaussian statistics and machine learning with convolutional neural networks. The suite of mock maps is publicly available at Columbia Lensing (http://columbialensing.org).

Key words: large-scale structure of Universe – gravitational lensing: weak – methods: numerical

1 INTRODUCTION

Weak gravitational lensing (WL; for reviews, see Bartelmann & Schneider 2001; Hoekstra & Jain 2008; Kilbinger 2015; Mandelbaum 2018) is a promising cosmological probe of fundamental physics such as the nature of dark energy and dark matter, theory of gravity, and the mass sum of neutrinos. By measuring the distortion in shapes of background galaxies caused by the foreground matter, we can infer the intervening large-scale structure. Ongoing Stage-III WL surveys, such as the Subaru Hyper Suprime-Cam (HSC; Aihara et al. 2018; Mandelbaum et al. 2018; Hikage et al. 2019), Dark Energy Survey (DES; Dark Energy Survey Collaboration 2016; Abbott et al. 2018), and Kilo Degree Survey (KiDS; de Jong et al. 2015; Hildebrandt et al. 2017; Heymans et al. 2020), have already achieved competitive cosmological constraints. Stage-IV cosmological surveys, such as the Vera C. Rubin Observatory Legacy Survey of Space and Time (LSST; LSST Science Collaboration et al. 2009), and large-area surveys by Euclid (Amendola et al. 2018), and the Nancy Grace Roman Space Telescope,1 are expected to revolutionise our understanding of the cosmos as well as fundamental physics, enabled by their large sky coverage and deep photometry.

In order to realise the full potential of ongoing and upcoming WL surveys, we urgently need to improve our understanding of baryonic physics (see a recent review by Chisari et al. 2019). Baryonic processes during galaxy formation, such as radiative cooling, feedback from black hole accretion, star formation, and supernova feedback, redistribute the gas inside a halo and reshape its gravitational potential. Signals from these astrophysical processes can mimic those expected from varying cosmological parameters, causing biases in our parameter inference if left untreated (Rudd et al. 2008; Semboloni et al. 2011; Zentner et al. 2013; Mohammed et al. 2014; Osato et al. 2015; Harnois-Déraps et al. 2015; Huang et al. 2019). At low redshift relevant to most WL surveys, the effects of baryons are predominately due to black hole activities, manifested as a $\geq 10\%$ level suppression in clustering around Mpc scale, though the exact level and its redshift- and scale-dependence remains ill-constrained. As a result, current WL surveys often need to apply aggressive scale cuts to mitigate contamination from baryonic effects. For example, DES applied lower limits as large as a few $10\$ arcmin in some redshift bins in analysing their Y1 data, discarding well-measured smaller-scale data (Abbott et al. 2018). This strategy will not be sustainable for Stage-IV surveys, which will provide high-precision measurements on sub-arcmin scales. Recently, Huang et al. (2020) have extended their analysis to smaller scales with the same DES Y1 data, by modelling and marginalising over baryonic feedback using a principal component analysis (PCA) method based on 11 hydrodynamic simulations. With a 2.5 arcmin scale cut, they already found a 20\% improvement on the $S_8 = \sigma_8 (\Omega_m/0.3)^{0.5}$ constraint.

Existing works in modelling the baryonic effects mainly focus on

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1 https://roman.gsfc.nasa.gov

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their impact on the two-point statistics — the correlation function, or its Fourier transform, the power spectrum — of the 3D matter distribution and of the 2D WL shear or convergence. These approaches incorporate the baryonic effects as free parameters that either alter the halo mass-concentration relation based on the halo model (Cooray & Sheth 2002; Yang et al. 2013; Mead et al. 2015), modify the gas, stellar, and dark matter density components separately (Schneider et al. 2019, 2020; Aricò et al. 2020), quantify the changes on the full power spectrum as PCAs (Eifler et al. 2015; Huang et al. 2019), or displace the matter following a pressure-like potential (Dai et al. 2018). All these methods are calibrated against observations and/or hydrodynamic simulations.

Recently, it has been recognised that non-Gaussian WL statistics contain rich information beyond the traditional two-point statistics and that they will be a powerful tool in constraining cosmological parameters. This has been partly demonstrated on Stage-II and Stage-III surveys (Liu et al. 2015a; Kacprzak et al. 2016; Shan et al. 2018; Martínez et al. 2018). However, the study of baryonic effects on non-Gaussian statistics have been limited mainly due to the lack of analytic theories. Therefore, these studies typically rely on simulated WL maps (Yang et al. 2013; Osato et al. 2015; Weiss et al. 2019; Coulton et al. 2020).

Hydrodynamic simulations are currently the state-of-the-art tool to study baryonic physics. In these simulations, baryonic processes are modelled with subgrid prescriptions, enabling us to capture the nonlinear astrophysics over a wide dynamic range (for reviews, see Somerville & Davé 2015; Vogelsberger et al. 2020). Mock WL maps generated from hydrodynamic simulations are a critical component in studying the effect of baryons on WL observables.

In this paper, we introduce kTNG, a suite of mock WL maps generated from the IllustrisTNG simulations. We quantify the baryonic effects on WL statistics including the angular power spectrum, peak counts, counts of minima, and the probability distribution function (PDF). We compare them to those measured from the corresponding dark matter only (DMO) simulations, TNG-Dark, which adopts the same initial condition but without baryonic physics. In addition, we compare our results to existing analytic models as well as other hydrodynamic simulations.

This paper is organised as follows. In § 2, we describe our numerical methods to generate mock WL maps from the existing IllustrisTNG simulations. We present in § 3 our results of the baryonic effects on WL statistics by comparing the kTNG and kTNG-Dark pairs. We show their redshift dependence as well as comparisons to existing models and other hydrodynamic simulations. We summarise our main conclusions in § 4.

2 NUMERICAL SIMULATIONS

In this section, we briefly describe the underlying IllustrisTNG hydrodynamic simulations and the ray-tracing methodology we follow to generate the kTNG mock WL maps. Throughout this paper, we adopt a flat Λ-cold dark matter Universe at the Planck 2015 cosmology (Planck Collaboration 2016), as used in the IllustrisTNG simulations, with Hubble constant $H_0 = 67.74 \text{ km} \text{s}^{-1} \text{ Mpc}^{-1}$, baryon density $\Omega_b = 0.0486$, matter density $\Omega_m = 0.3089$, spectral index of scalar perturbations $n_s = 0.9667$, and amplitude of matter fluctuations at 8 $h^{-1}$ Mpc $\sigma_8 = 0.8159$. We assume massless neutrinos, with an effective number of neutrino species $N_{\text{eff}} = 3.046$.

2.1 IllustrisTNG Hydrodynamic Simulations

Because galaxy formation involves a wide dynamic range — from structures internal to stars to beyond the virial radii of the largest haloes — it is impossible to resolve all the relevant physical processes simultaneously in a cosmological simulation. Therefore, baryonic processes are typically approximated by subgrid prescriptions, in which empirical recipes are implemented to inject or remove energy and momentum from regions of the simulation box when certain conditions are met. Recent cosmological hydrodynamical simulations, such as the Horizon-AGN (Dubois et al. 2014), EAGLE (Schaye et al. 2015), BAHAMAS (McCarthy et al. 2017, 2018), Illustris (Vogelsberger et al. 2014), and its successor IllustrisTNG simulations (Nelson et al. 2019; Pillepich et al. 2018; Nelson et al. 2018; Springel et al. 2018; Naiman et al. 2018; Marinacci et al. 2018) have already provided invaluable insights into the impact of baryons on cosmological observables.

In this work, we use the IllustrisTNG simulations as our base. They are a set of cosmological, large-scale gravity and magneto-hydrodynamical simulations generated with the moving mesh code AREPO (Springel 2010). Subgrid prescriptions are incorporated to model stellar evolution, chemical enrichment, gas cooling, and black hole feedback (Pillepich et al. 2018). The full simulation set includes three box sizes, each with simulations of different resolutions. Here, we employ the highest-resolution simulation for the largest box, TNG300-1 (hereafter TNG), which covers a comoving volume of $(205 h^{-1} \text{ Mpc})^3$. It has a mass resolution of $7.44 \times 10^9 h^{-1} \text{ M}_\odot$ and $3.98 \times 10^7 h^{-1} \text{ M}_\odot$ for initial gas and dark matter particles, respectively. To discriminate baryonic effects, we make use of the corresponding DMO simulations TNG300-1-Dark (hereafter TNG-Dark), which has a mass resolution of $4.73 \times 10^7 h^{-1} \text{ M}_\odot$ for DM particles. TNG and TNG-Dark have the same initial conditions and only differ in the inclusion of baryonic physics. These simulations accurately resolve the small-scale, nonlinear gravitational evolution of the matter density field that is accessible by Stage-IV cosmological surveys.

To study the WL observables, we need to generate mock maps with a reasonable area (at least a few deg$^2$) and redshift coverage (up to $z \approx 2$). In addition, a large number of realisations is important to suppress cosmic variance. The TNG simulation snapshots are outputted at 99 redshifts between $z = 0$–20, allowing one to build light cones that are necessary to construct mock WL maps. However, since IllustrisTNG was not tailored to build mock WL maps, we must overcome some difficulties to achieve our goal. First, these snapshots are not output at regular intervals of comoving distance, as would have been required for standard WL ray-tracing schemes (Dietrich & Hartlap 2010; Liu et al. 2018; Harnois-Dérap et al. 2018, 2019). Second, the box size, despite being very large for hydrodynamic simulations, is relatively small compared to the usual DMO cosmological simulations; and hence it can only cover a small patch of the sky at high redshifts. Finally, due to the high computational cost, only one simulation was generated at the box size and resolution we need. We adapt our ray-tracing method to accommodate these pre-existing settings, which we describe in detail next.

2.2 kTNG: Ray-Traced Weak Lensing Mock Maps

To build a light cone, we stack the TNG snapshots along the line-of-sight in a fixed interval of $205 h^{-1} \text{ Mpc}$ (= TNG box size). The comoving distance between $z = 0$ and $z \approx 2.5$ is approximately $4000 h^{-1} \text{ Mpc}$, which requires 20 boxes in total to cover. We select the TNG snapshots that are the closest to the centres of the 20 light
Table 1. Summary of our light cone. Columns: (1) snapshot number; (2) comoving distance and (3) redshift at the snapshot centre; (4) corresponding TNG snapshot redshift and (5) TNG file number.

| Snapshot | \(\chi\) (h^{-1} \text{Mpc}) | \(z\) | \(z_{\text{TNG}}\) | TNG File |
|----------|-----------------|-----|-----------------|-----------|
| 1        | 102.5           | 0.034 | 0.03 | 96         |
| 2        | 307.5           | 0.105 | 0.11 | 90         |
| 3        | 512.5           | 0.179 | 0.18 | 85         |
| 4        | 717.5           | 0.255 | 0.26 | 80         |
| 5        | 922.5           | 0.335 | 0.33 | 76         |
| 6        | 1127.5          | 0.418 | 0.42 | 71         |
| 7        | 1332.5          | 0.506 | 0.50 | 67         |
| 8        | 1537.5          | 0.599 | 0.60 | 63         |
| 9        | 1742.5          | 0.698 | 0.70 | 59         |
| 10       | 1947.5          | 0.803 | 0.79 | 56         |
| 11       | 2152.5          | 0.914 | 0.92 | 52         |
| 12       | 2357.5          | 1.034 | 1.04 | 49         |
| 13       | 2562.5          | 1.163 | 1.15 | 46         |
| 14       | 2767.5          | 1.302 | 1.30 | 43         |
| 15       | 2972.5          | 1.452 | 1.41 | 41         |
| 16       | 3177.5          | 1.615 | 1.60 | 38         |
| 17       | 3382.5          | 1.794 | 1.82 | 35         |
| 18       | 3587.5          | 1.989 | 2.00 | 33         |
| 19       | 3792.5          | 2.203 | 2.21 | 31         |
| 20       | 3997.5          | 2.440 | 2.44 | 29         |

cone intervals, if they were equally spaced in comoving distance.\(^2\) We summarise our light cone configuration in Table 1, including the comoving distance \(\chi\) and redshift for each snapshot, as well as the corresponding TNG file. We illustrate our light cone configuration in Figure 1. The opening angle of the light cone is 5 x 5 deg\(^2\). The last 10 snapshots are replicated 4 times in the transverse direction, so that we can cover the desired map size (5 x 5 deg\(^2\)) at the highest-redshift maps. Our light cone extends up to redshift \(z = 2.57\). We construct mock WL maps at 40 source redshifts using this light cone.

To model the propagation of light rays in our light cone, we employ a multiple lens plane approximation (Blazek et al. 1994; Jain et al. 2000; Vale & White 2003; Hilbert et al. 2009), where the smooth matter distribution is approximated as discrete density planes of thickness \(\Delta \chi\). Light rays originating from the observer at \(z = 0\) are deflected only at the planes and travel in straight lines between the planes. At the angular position \(\beta^k\) at the \(k\)th plane, the deflection angle \(\alpha\) is the gradient of the 2D lensing potential \(\psi\):

\[
\alpha^k (\beta^k) = \nabla_{\beta^k} \psi^k (\beta^k). \tag{1}
\]

The lensing potential can be computed from the Poisson equation,

\[
\nabla^2 \psi^k (\beta^k) = 2 \alpha^k (\beta^k), \tag{2}
\]

where the dimensionless surface density \(\sigma^k\) is the projected matter distribution of the \(k\)th lens plane,

\[
\sigma^k (\beta^k) = \frac{3H_0^2 \Omega_m \chi^k}{2c^2} \frac{1}{a^k} \int_{\chi^k-\Delta \chi/2}^{\chi^k+\Delta \chi/2} \delta (\beta^k, \chi') d\chi', \tag{3}
\]

where \(c\) is the speed of light, \(a\) is the scale factor, and \(\delta = (\rho - \bar{\rho})/\bar{\rho}\) is the three-dimensional matter overdensity. The lensed position \(\beta^k\) is the sum of previous deflection angles,

\[
\beta^k (\theta) = \theta - \sum_{i=1}^{k-1} \chi^k - \chi^i \alpha^i (\beta^i), \quad (k = 2, 3, \ldots) \tag{4}
\]

where we impose \(\beta^0 = \theta^1 = \theta\) for initial rays. By differentiating \(\beta^k\) with respect to \(\theta\), we can obtain the distortion matrix that maps the initial position to the lensed position \(\theta \rightarrow \beta^k\),

\[
A_{ij} (\theta, \chi) = \frac{\partial \beta_i (\theta, \chi)}{\partial \theta_j} = \left( \begin{array} {cc} 1 - k - \gamma_1 & -\gamma_2 + \omega \\ -\gamma_2 - \omega & 1 - k - \gamma_1 \end{array} \right), \tag{5}
\]

where, for legibility, we suppressed the dependence on \((\theta, \chi)\) for the convergence \(k\), the shear components \(\gamma_1, \gamma_2, \omega\) and the rotation \(\omega\). To obtain \(\beta^k\) and \(A_{ij}\), we employ a memory-efficient ray-tracing scheme developed in Hilbert et al. (2009), where the computation for the \(k\)th plane depends only on the quantities at \((k - 1)\)th and \((k - 2)\)th planes.

The configuration of our source planes and lens planes are illustrated in Figure 1. We also summarise the corresponding comoving distances and redshifts in Table 2. We divide each snapshot into 2 density slices of thickness \(\Delta \chi = 102.5 h^{-1} \text{Mpc}\). We then project each slice onto a regular grid of 4096\(^2\) pixels. The dark matter, gas, and star particles (in the case of TNG-Dark, only dark matter particles) are assigned to the grid with a triangular-shaped cloud scheme. Next, we apply a fast Fourier transform (FFT) to Eq. (2) to obtain the derivatives of the lensing potential. We evaluate the deflection angle and the distortion matrix at the angular position \(\beta^k\) and generate \((k, \gamma_1, \gamma_2, \omega)\) maps at each source plane. Each map is on a regular grid with 1024\(^2\) pixels, corresponding to a pixel size of 0.29 arcmin. In total, we generate 40 source planes. Note that \(i\)th lens plane contains the contribution from the range \((\chi^i - \Delta \chi/2, \chi^i + \Delta \chi/2)\), but observables (e.g., \(\beta^i\)) are defined at \(\chi^i\). Thus, the \(i\)-th source plane, where the observables are output, is placed at \(\chi^i + \Delta \chi/2\).

To suppress sample variance, we need a large number of map realisations. To accomplish this goal with only one simulation of TNG, we exploit the periodic boundary condition and the fact that the light cone does not cover the whole simulation box. We construct pseudo-independent map realisations by randomly translating and rotating the snapshots. First, for each snapshot, we (1) translate all particles by a random number along each of the 3 axes, (2) rotate the snapshot by 0, 90, 180, or 270 degrees around each of the three axes, and (3) apply a random flip along any of the 3 axes. We repeat this process 100 times and generate lensing potential planes from these randomised snapshots. Next, for each lens plane set, we further translate and rotate the planes randomly, for 100 times. Finally, we obtain 10,000 pseudo-independent realisations. Such procedure has been studied thoroughly in the past by Petri et al. (2016), who found that even with only one simulation, the snapshots can be repeatedly recycled to produce up to a few \(\times 10^4\) WL map realisations whose power spectra and high-significance peak counts can be treated as statistically independent. Such a large number of realisations would also allow the application of machine learning to study the mapping from the DMO to hydrodynamic WL maps.

3 RESULTS

In Figure 2, we show an example of \(\kappa\)TNG map at \(z_f = 1.034\) (S23), as well as the difference between the pair of hydrodynamic
Figure 1. The construction of our light cone. Each red box corresponds to one snapshot. The last 10 snapshots are replicated 4 times (twice in each transverse direction) to increase the solid area to cover $5 \times 5$ degrees. Each box is divided into 2 lens planes of $\Delta z = 102.5 h^{-1}$ Mpc thickness. We list the redshifts at the central positions of source (blue dashed lines) and lens (orange dash-dotted lines) planes. The black lines correspond to our opening angle of 5 deg. We generate lensing mocks at 40 source redshifts.

and DMO maps. The amplitude of the difference appears to be correlated with the $\kappa$ values of the pixels, but in a somewhat complex fashion. For example, some dipole patterns are clearly seen in the overdense regions. Such anisotropy is not captured in most baryonic simulation models. It may be caused by collimated active galactic nuclei (AGN) jets or changes in halo positions and ellipticities. We leave a thorough investigation to future work. Next, we quantify these effects with the power spectrum, PDF, and peak and minimum counts. Together, they capture both Gaussian and non-Gaussian information and are complementary probes for cosmology.

3.1 Power Spectrum

We measure the angular power spectra of the convergence map $C_\kappa$ using a binned estimator,

$$C_\kappa(\ell) = \frac{1}{N_\ell} \sum_{\ell \in [\ell_{\text{min}}, \ell_{\text{max}}]} |\tilde{\kappa}(\ell)|^2,$$

where $\ell_i$ is the mean of multipoles in the $i$th bin with bounds $[\ell_{\text{min}}, \ell_{\text{max}}]$, $N_\ell$ is the number of modes, and $\tilde{\kappa}(\ell)$ is the Fourier transform of the convergence field, computed on a $102^2$ regular grid with FFT. We assign 10 log-equally spaced bins in the range of $[10^2, 10^7]$ and 20 log-equally spaced bins in the range of $[10^3, 10^4]$ — in total 30 multipole bins.

We first validate our ray-tracing code by comparing the $\kappa$TNG-Dark power spectra with the theoretical prediction from halo fit (Smith et al. 2003; Takahashi et al. 2012). We show the comparison for all 40 source redshifts in Figure 3. On large scales ($\ell \approx 100$), our measured power spectra are lower than the theoretical prediction by $\approx 5\%$. The reduced power reflects the missing large-scale modes due to the limited TNG box size. However, since both the $\kappa$TNG and $\kappa$TNG-Dark maps are impacted by this effect on the same footing, it is expected to be canceled out when we consider the differences between the simulation pairs. On small scales ($\ell > 1000$), the differences for $z_s > 0.4$ curves are within the known halo fit modelling uncertainty of $\approx 10\%$. For low redshifts $z_s < 0.4$, the discrepancies become larger, because the same $\ell$ value corresponds to smaller structures, some of which are below the simulation resolution. To investigate the effect of map resolution, we generate 50 additional high-resolution test maps with number of grids doubled at a side. The fiducial power spectra are consistent with these high-resolution maps within 1% for $100 < \ell < 5000$, but are suppressed by $\approx 5\%$ at $\ell = 10000$.

Finally, we note that the halo fit model was calibrated against simulations with lower resolution than the TNG and is known to over-predict the WL power on small scales, so it should only be considered as a rough estimate in this regime.

We investigate the effect of baryons on the WL power spectrum next. In Figure 4, we present the redshift evolution of the $\kappa$TNG power spectrum in the upper panel, as well as the fractional differences between the $\kappa$TNG and $\kappa$TNG-Dark maps in the lower panel. Both the power spectra and ratios are averaged over $N_p = 10000$ realisations.

In general, a spoon-like feature is seen. At large scales, the ratio is close to unity, i.e., no significant baryonic effects. On small scales, a suppression up to 20% is seen. This is mainly because feedback processes such as feedback from black hole accretion and supernova explosions, which can remove gas from the halo centre, reduce the matter clustering on relevant scales. The location of the dip moves

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3. The suppression in the power spectrum due to resolution can be corrected by introducing a damping factor (Takahashi et al. 2017).
4. We take the mean of ratio, instead of the ratio of the mean power spectra, to reduce the cosmic variance.
from small angular scales at high redshift to larger angular scales ($\ell \approx 1000$) at lower redshift, mainly because the same physical scales extend larger angles at lower redshift. In addition, at low redshift, baryonic feedback is also more powerful, reaching further in physical scales. Finally, the upturn seen at much smaller scales is the result of radiative cooling, which enhances the matter clustering.

In Appendix A, we present a fitting formula for the suppression due to baryons on the angular power spectrum.

The characteristic shape of the baryonic effects on the WL power spectrum mimics the effect of changing cosmological parameters, in particular the mass sum of neutrinos, which also shows a spoon-like feature (Lesgourgues & Pastor 2006; Hannestad et al. 2020). The key to distinguish them is their different redshift- and scale-dependence.

In addition, they may also manifest differently in other statistics beyond the power spectrum, such as the ones we study next.
Table 2. The comoving distance $\chi$ and redshifts ($z_s, z_l$) for our source and lens planes. The light cone configuration is illustrated in Figure 1.

| Source Plane | $\chi$ ($h^{-1}$ Mpc) | $z_s$ | Lens Plane | $\chi$ ($h^{-1}$ Mpc) | $z_l$ |
|--------------|------------------------|-------|-------------|------------------------|-------|
| S1           | 102.5                  | 0.034 | L1          | 51.25                  | 0.017 |
| S2           | 205.0                  | 0.070 | L2          | 153.75                 | 0.052 |
| S3           | 307.5                  | 0.105 | L3          | 256.25                 | 0.087 |
| S4           | 410.0                  | 0.142 | L4          | 358.75                 | 0.123 |
| S5           | 512.5                  | 0.179 | L5          | 461.25                 | 0.160 |
| S6           | 615.0                  | 0.216 | L6          | 563.75                 | 0.197 |
| S7           | 717.5                  | 0.255 | L7          | 666.25                 | 0.236 |
| S8           | 820.0                  | 0.294 | L8          | 768.75                 | 0.275 |
| S9           | 922.5                  | 0.335 | L9          | 871.25                 | 0.314 |
| S10          | 1025.0                 | 0.376 | L10         | 973.75                 | 0.355 |
| S11          | 1127.5                 | 0.418 | L11         | 1076.25                | 0.397 |
| S12          | 1230.0                 | 0.462 | L12         | 1178.75                | 0.440 |
| S13          | 1332.5                 | 0.506 | L13         | 1281.25                | 0.484 |
| S14          | 1435.0                 | 0.552 | L14         | 1383.75                | 0.529 |
| S15          | 1537.5                 | 0.599 | L15         | 1486.25                | 0.576 |
| S16          | 1640.0                 | 0.648 | L16         | 1588.75                | 0.623 |
| S17          | 1742.5                 | 0.698 | L17         | 1691.25                | 0.673 |
| S18          | 1845.0                 | 0.749 | L18         | 1793.75                | 0.723 |
| S19          | 1947.5                 | 0.803 | L19         | 1896.25                | 0.766 |
| S20          | 2050.0                 | 0.858 | L20         | 1998.75                | 0.830 |
| S21          | 2152.5                 | 0.914 | L21         | 2101.25                | 0.886 |
| S22          | 2255.0                 | 0.973 | L22         | 2203.75                | 0.944 |
| S23          | 2357.5                 | 1.034 | L23         | 2306.25                | 1.003 |
| S24          | 2460.0                 | 1.097 | L24         | 2408.75                | 1.065 |
| S25          | 2562.5                 | 1.163 | L25         | 2511.25                | 1.130 |
| S26          | 2665.0                 | 1.231 | L26         | 2613.75                | 1.197 |
| S27          | 2767.5                 | 1.302 | L27         | 2716.25                | 1.266 |
| S28          | 2870.0                 | 1.375 | L28         | 2818.75                | 1.338 |
| S29          | 2972.5                 | 1.452 | L29         | 2921.25                | 1.413 |
| S30          | 3075.0                 | 1.532 | L30         | 3023.75                | 1.492 |
| S31          | 3177.5                 | 1.615 | L31         | 3126.25                | 1.573 |
| S32          | 3280.0                 | 1.703 | L32         | 3228.75                | 1.659 |
| S33          | 3382.5                 | 1.794 | L33         | 3331.25                | 1.748 |
| S34          | 3485.0                 | 1.889 | L34         | 3433.75                | 1.841 |
| S35          | 3587.5                 | 1.989 | L35         | 3536.25                | 1.938 |
| S36          | 3690.0                 | 2.084 | L36         | 3638.75                | 2.041 |
| S37          | 3792.5                 | 2.203 | L37         | 3741.25                | 2.148 |
| S38          | 3895.0                 | 2.319 | L38         | 3843.75                | 2.260 |
| S39          | 3997.5                 | 2.440 | L39         | 3946.25                | 2.379 |
| S40          | 4100.0                 | 2.568 | L40         | 4048.75                | 2.503 |

3.2 Probability Distribution Function (PDF)

Here, we present the effect of baryons on the WL one-point PDF. Past studies of the WL PDF have shown that it has the potential to significantly tighten the cosmological constraints, compared to using the power spectrum alone (Wang et al. 2009; Liu et al. 2016; Patton et al. 2017; Liu & Madhavacheril 2019). Recently, Theile et al. (2020) developed an analytic model for the WL one-point PDF and its auto-covariance, based on a halo-model formalism. While baryonic effects have not been included in these studies, future extensions could incorporate baryonic effects.

We first smooth the maps with a $\theta_G = 2$ arcmin Gaussian window to suppress small scale noise. The window function is given as

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

We exclude pixels within $2\theta_G$ from the edge due to incomplete smoothing. To measure the PDF, we then measure the histogram

![Figure 5. Upper panel: The PDFs for all source redshifts from our $k$TNG maps (red to blue: low to high redshifts). Lower panel: Fractional differences between the $k$TNG and $k$TNG-Dark maps for all 40 source redshifts, where $\Delta P/P = \frac{P_{kTNG} - P_{kTNG-Dark}}{P_{kTNG-Dark}} - 1$. The maps are smoothed with a 2 arcmin Gaussian filter. The PDFs and ratios are means over 10,000 map realisations.](image)

3.3 Peaks and Minima

The number count of WL peaks — pixels with a higher value than their surrounding 8 pixels — is the most well-studied non-Gaussian statistic (e.g. Kratochvil et al. 2010; Dietrich & Hartlap 2010). It has been applied to observational data from the CFHTLenS (Liu et al. 2015a), CS82 (Liu et al. 2015b), DES (Kacprzak et al. 2016), and KiDS surveys (Shan et al. 2018; Martinet et al. 2018) and returned comparable or better constraints to those from the two-point statistics. The convergence peaks originate from single massive haloes or superpositions of multiple intermediate mass haloes (Yang et al. 2011; Liu & Haiman 2016). They are sensitive to both the growth of the pixels, binned by their $k$ value with the bin width $\Delta k = 0.025^5$.

In Figure 5, we present the redshift evolution of the $k$TNG PDF in the upper panel, as well as the fractional differences between the $k$TNG and $k$TNG-Dark maps in the lower panel. The PDF is skewed with a high $k$ tail for all redshifts considered in our work, indicating the non-Gaussian information that is not captured by the power spectrum.

The primary effect of baryonic processes is the suppression of the intermediate positive and negative $k$ regions, as well as an enhancement at the very high $k$ tail. In the intermediate positive convergence regime, feedback processes tend to expel the gas from overdense regions, resulting in a suppression of the most clustered, nonlinear structures. Consequently, even the void regions can acquire some mass, resulting in the observed decrease in number of highly-negative pixels. The redistribution of matter by baryonic effects smoothes the overall density fluctuation, resulting in more pixels with small convergence ($k \approx 0$) signals. The enhancement at the very high $k$ tail is due to radiative cooling.

Note: To account for the slight (de)magnification of the ray bundles during ray-tracing, we weight the pixels by the inverse magnification in computing the PDF. Since smoothing smears the small-scale structures, the PDFs from high-resolution and fiducial maps are consistent within 1%. We expect this to have negligible effect on our results. The smoothing further reduces its effect. See more discussion in Takahashi et al. (2011).
of structure and the expansion history of the universe. In contrast, WL minima – pixels with a lower value than their surrounding 8 pixels – also contain information complementary to peaks (Maturi et al. 2010; Coulton et al. 2020). WL peaks and minima are easily measurable in WL mass maps, without the need to identify physical structures such as clusters or voids. Past works studying the baryonic effects on WL peaks and minima have found that they are affected differently than the power spectrum (Yang et al. 2013; Osato et al. 2015; Weiss et al. 2019; Coulton et al. 2020), in terms of biases in cosmological parameters. Therefore, they can also serve as a tool to calibrate potential systematics. Compared to the simulations used in previous studies, the \( \kappa \)TNG mock WL maps cover a wide range of redshifts and take advantage of the state-of-the-art subgrid models developed by the TNG team.

In Figure 6, we show the number of peaks and minima in the upper panels, as well as the fractional differences between the \( \kappa \)TNG and \( \kappa \)TNG-Dark maps in the lower panels. To measure the number of counts of peaks and minima, we again smooth the convergence maps with a \( \theta_G = 2 \) arcmin Gaussian window. The peaks and minima are counted in equally spaced bins with width \( \Delta \kappa = 0.025 \). Similarly to PDFs, pixels within 2\( \theta_G \) from the edge are discarded, and the results with high-resolution and fiducial maps are consistent within 1\%. The overall baryonic effects in peaks and minimum counts are somewhat similar to that in PDF: both the positive and negative tails are suppressed. However, we also see an additional effect of reduced number of peaks or minima in contrast to the PDF, which is always normalised to unity. These findings are consistent with previous studies (Osato et al. 2015; Coulton et al. 2020), though the amplitude of the change depends on the strength of the baryonic feedback implemented in the underlying hydrodynamic simulations. We compare our results to previous works, including both (semi-)analytic models and other hydrodynamic simulations, in the next subsection.

3.4 Comparison with Previous Studies

We compare our results to previous works, including analytic models for the power spectrum from the HMcode (Mead et al. 2015) and cosmological hydrodynamic simulations, BAHAMAS (McCarthy et al. 2017, 2018) and Horizon-AGN (Dubois et al. 2014; Gouin et al. 2019). We show the comparison for the power spectrum, PDF, peaks, and minima in Figure 7. All maps are smoothed with a 2 arcmin Gaussian window for the PDF, peaks, and minima. All our comparisons are done for \( z_s = 1 \), which is close to the expected mean redshift of source galaxies expected from Stage-IV surveys (Laureijs et al. 2011; LSST Science Collaboration et al. 2009).

We compare our results to the halo/fit-based HMcode model using several sets of parameters, all calibrated against different runs of the OWLS simulations (Schaye et al. 2010; van Daalen et al. 2011), including (1) DMONLY, in which only gravity from dark matter is implemented and no baryonic physics is included, (2) REF, in which radiative cooling and heating, star formation and evolution, chemical enrichment, and supernovae feedback are included, (3) DBLIM, which adopts a top-heavy initial mass function and stronger supernovae feedback in addition to the REF model, and (4) AGN, which includes feedback due to active galactic nuclei to the REF model. In addition, we compare our results to two other hydrodynamic simulations. For BAHAMAS, there are 10,000 maps at source redshift \( z_s = 1 \), each covers 5 \( \times \) 5 deg\(^2\) sky and has a resolution of 0.17 arcmin per pixel. In addition to the fiducial model, there are two additional runs, where AGN feedback is tuned to be more ("high AGN") or less ("low AGN") effective. These simulations are useful to address the impact of AGN feedback. For Horizon-AGN, there is only one map at \( z_s = 1 \) and only power spectrum information is available. Because the simulations adopt different cosmological parameters, it is infeasible to directly compare the statistics. Therefore we focus only on the ratio of statistics between the hydrodynamic and corresponding DMO simulations.

For the power spectrum, the suppression seen in \( \kappa \)TNG is comparable to that from Horizon-AGN, BAHAMAS "low AGN", and HMcode REF. This is in general agreement with past results of matter power spectrum (Chisari et al. 2019) and baryon fractions in massive halos (van Daalen et al. 2020). For the PDF, the overall trends are similar between TNG and BAHAMAS. The slightly different zero-crossing is likely due to their different cosmologies and hence the overall skewness and width of the PDFs. For peaks and minima, it is interesting to see that the overall baryonic effects are quite similar between the TNG and BAHAMAS, despite the very different subgrid models implemented in them. In particular, the TNG results are comparable to the "low AGN" run. In addition, Yang...
et al. (2013) studied the baryonic effects on peak counts by manually boosting the halo concentration by 50%. They found that low peaks are less affected, as these peaks are typically associated with several small haloes along the line-of-sight direction and sensitive to only the outer regions of these haloes, while high peaks are sensitive to the inner regions of single massive haloes. In contrast, we find that low peaks are equally impacted by baryons, an evidence that baryons are impacting small haloes beyond their virial radii.

Within the current observational limit, we are not able to distinguish the best model among these curves. However, future data from optical, X-ray, and thermal and kinetic Sunyaev–Zel’dovich observations are expected to put significantly tighter constraints on the level of baryonic feedback (Battaglia et al. 2012; Hill et al. 2016; Amodeo et al. 2020), and these constraints can then be compared with the WL data.

4 CONCLUSIONS

The uncertainty in modelling baryons is already limiting the cosmological analysis with current generation weak lensing surveys (Abbott et al. 2018). If left unaccounted for, the effects of baryons will significantly bias our constraints on dark energy, dark matter, and neutrino mass from upcoming surveys. In this work, we generate a suite of mock WL maps, the \( \kappa \)TNG, by ray-tracing through the IllustrisTNG hydrodynamic simulations. We produced 10,000 pseudo-independent maps at a wide source redshift range 0.034 \( \leq z_s \leq 2.568 \), well covering the range probed by existing and upcoming WL surveys. Furthermore, we also generate the \( \kappa \)TNG-Dark maps from the corresponding DMO simulations. We release our mock convergence maps at our website (http://columbialensing.org). By comparing the pair of maps with and without baryonic physics, one can isolate the baryonic effects on the WL statistics.

We find that baryonic processes suppress the WL angular power spectrum by up to 20%. Towards low redshift, the level of suppression is larger, potentially due to stronger stellar and AGN feedback; in addition, the onset of the suppression occurs at larger scales, as the same physical object extends over a larger angular scale. We also observe an enhancement on smaller scales due to radiative cooling. The overall suppression from \( \kappa \)TNG is moderate compared to results from other analytic models and simulations, consistent with previous works comparing their matter power spectra (Springel et al. 2018).

We also show the effects of baryons on higher-order weak lensing statistics: the PDF, peak counts, and counts of minima. These statistics contain rich non-Gaussian information beyond the power spectrum and have the potential to place a tighter constraint on cosmological parameters with upcoming surveys. Our work is the first to show detailed redshift-evolution for these statistics. In general, baryonic processes suppress both the positive and negative tails of all three statistics. The change is asymmetric on the two tails and hence is not captured by the power spectrum. In addition, we also find changes in the total number of peaks and minima. Compared to past works on baryonic effects with weak lensing non-Gaussian statistics, mainly from the BAHAMAS simulations, the overall trends are surprisingly similar, despite the very different subgrid models implemented in these simulations. The only exception is at the positive tail of the
PDF, where an enhancement is seen in BAHAMAS. This is likely due to the stronger gas cooling implemented in their simulations. While contributing to a large body of semi-analytic tools and hydrodynamic simulations that have already paved the road to study the effect of baryons on weak lensing observables, our newly developed κTNG suite of mock WL maps provide a venue to extend the studies to those requiring mass maps, such as non-Gaussian weak lensing statistics and machine learning with convolutional neural networks (Schmelzele et al. 2017; Gupta et al. 2018; Ribli et al. 2019a; Merten et al. 2019; Ribli et al. 2019b; Fluri et al. 2019). Our maps will also be useful for testing pioneering works on analytic models for higher-order statistics (Fan et al. 2010; Thielemann et al. 2020), which, in the future, could be extended to incorporate baryonic effects. With the κTNG and κTNG-Dark map pairs, one can also learn the DMO-to-hydrodynamic mapping using the generative adversarial network or variational auto-encoder (see, e.g., Tröster et al. 2019) and augment existing DMO simulations. It is also possible to explore physically motivated mapping methods, similar if the gradient-descent method adopted by Dai et al. (2018) for the three-dimensional density field.

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DATA AVAILABILITY

The data underlying this article will be partially available at Columbia Lensing (http://columbialensing.org), with 100 realisations for three source redshifts (\(z_s = 0.5, 1.0, 1.5\)). The remaining data will be shared on reasonable request to the corresponding author.

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APPENDIX A: FITTING FORMULA FOR THE POWER SPECTRUM RATIO

We provide a fitting formula that allows a quick exploration of baryonic effects on the angular power spectrum:

$$ C_{\ell}^{\text{baryon}}(\ell)/C_{\ell}^{\text{DMO}}(\ell) = \frac{1 + (\ell/\ell_1)^{\alpha_1}}{1 + (\ell/\ell_2)^{\alpha_2}}, \quad (A1) $$

where $\ell_1$, $\ell_2$, $\alpha_1$, and $\alpha_2$ are redshift-dependent free parameters. Their values are tabulated in Table A1. In optimising the fitting formula, we excluded measurements of $\ell = 3771.0-9465.6$ for the first source redshift $z_s = 0.034$ (S1) because of strong artefacts due to resolution. We show an example for $z_s = 1.034$ (S23) in the upper-left panel of Figure 7.

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