Tomographic detection of the kinematic Sunyaev-Zel’dovich effect using angular redshift fluctuations

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ABSTRACT

Determining the large-scale distribution of baryons in the late universe is a long-standing challenge in cosmology. To gain insight into this problem, we present a new approach for extracting the kinematic Sunyaev-Zel’dovich (kSZ) effect from observations, ARF-kSZ tomography. This technique involves the cross-correlation of maps of Angular Redshift Fluctuations (ARF), which contain precise information about the cosmic density and velocity fields, and cosmic microwave background (CMB) temperature maps high-pass filtered using aperture photometry. To produce the first and second, in this work we resort to galaxies and quasars from 6dF and SDSS and foreground-cleaned CMB maps from Planck, respectively. We detect statistically significant cross-correlation between ARF and filtered CMB maps for a wide range of redshifts and filter apertures, yielding a joint detection of the kSZ effect at the \(>10\sigma\) level. Using measurements of the kSZ optical depth extracted from these cross-correlations, we then set constraints on the properties of the gas responsible for the kSZ effect, finding that the kSZ gas resides mostly outside haloes and presents densities from 10 to 250 times the cosmic average, which is the density of baryons in filaments and sheets according to cosmological hydrodynamical simulations. Finally, we conduct a tomographic census of baryons from \(z \approx 0\) to 5, finding that ARF-kSZ tomography is sensitive to approximately half of all baryons in the Universe.

Key words: cosmic background radiation – cosmology: observations – large-scale structure of Universe – diffuse radiation – intergalactic medium

1 INTRODUCTION

Observations of primordial CMB anisotropies (e.g., Planck Collaboration et al. 2018a) and of the abundance of light elements formed through Big Bang nucleosynthesis (BBN, e.g., Cooke et al. 2018) set tight constraints on the number density and distribution of baryons in the early universe. Conversely, the rarefied character of the late universe hinders the detection of baryons outside high-density regions, leaving most cosmological volume practically invisible. As a result, low-redshift observations were only able to detect \(\sim 70\%\) of the expected abundance of baryons until recently (Fukugita & Peebles 2004; Nicastro et al. 2008; Shull et al. 2012).

Lately, some studies have successfully detected baryons outside haloes by resorting to kinematic Sunyaev-Zel’dovich (kSZ) effect observations (Hernández-Monteagudo et al. 2015; Hill et al. 2016), stacking thermal Sunyaev-Zel’dovich (tSZ) emission between galaxy pairs (de Graaff et al. 2017; Tanimura et al. 2019) or low-redshift Lyman-\(\alpha\) emission (Gallego et al. 2018), or conducting deep X-ray campaigns (Nicastro et al. 2018; Kovács et al. 2019). Despite this great accomplishment, these works only set constraints on the large-scale distribution of baryons at a few specific redshifts or across a reduced number of line-of-sights; consequently, a

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complete census of baryons is still missing in the late universe.

Of the approaches listed above, we pay special attention to kSZ studies. The kSZ effect is the Doppler boosting of CMB photons as they scatter off free electrons moving with respect to the CMB rest frame (Sunyaev & Zeldovich 1972, 1980); thereby, this effect is sensitive to the peculiar momentum of all free electrons independently of their density or temperature, becoming a perfect candidate to study the large-scale distribution of baryons in the late universe. Unfortunately, the detection of the kSZ effect is very challenging; temperature fluctuations induced by this effect and primordial CMB anisotropies present an indistinguishable spectral shape, and the amplitude of the first is approximately two orders of magnitude smaller relative to that of the later. Furthermore, to extract the kSZ effect, most methods require precise knowledge about the peculiar velocity field of the intervening matter, which is difficult to achieve.

Even though precise and large datasets facilitate the detection of the kSZ effect, the inference of peculiar velocities is still a well-known issue. There are some approaches that enable circumventing the estimation of these such as the kSZ-peculiar pairwise momentum (Ferreira et al. 1999; Hand et al. 2012) or the projected-kSZ method (Hill et al. 2016; Ferraro et al. 2016); however, these methods either demand to be calibrated using cosmological simulations since observables are intrinsically “placed” at the non-linear regime, or require the precise modelling and subtraction of other intervening effects. A distinct approach is to infer the peculiar velocity field from the observed density field (as suggested by Ho et al. 2009), and then cross-correlate this field and CMB observations (Planck Collaboration et al. 2016a; Schaan et al. 2016); nevertheless, this density-into-velocity inversion inevitably adds significant uncertainties.

In this scenario, the cross-correlation of angular redshift fluctuations (ARF; Hernández-Monteagudo et al. 2019, HM19, submitted), which encode precise information about the cosmic density and velocity fields, and CMB observations provides a novel and clean window towards a tomographic detection of the kSZ effect. This approach, which we refer to as ARF-kSZ tomography, requires redshift information from either spectroscopic or spectro-photometric surveys as well as theoretical predictions for the large-scale cross-correlation of ARF and kSZ anisotropies. Moreover, and in contrast with most previous kSZ estimators, ARF-kSZ tomography involves a new observable that cannot be reduced to the bispectrum of density fluctuations and temperature anisotropies (Smith et al. 2018).

To extract the kSZ effect from observations using ARF-kSZ tomography, we proceed as follow. First, we generate ARF maps using galaxies from the 6dF Galaxy Survey (6dF; Jones et al. 2004) and the Baryon Oscillation Spectroscopic Survey (BOSS; Eisenstein et al. 2011; Dawson et al. 2013) at low redshift and quasars from the extended Baryon Oscillation Spectroscopic survey (eBOSS; Myers et al. 2015) at high redshift. Then, we cross-correlate these maps with foreground-cleaned CMB temperature maps publicly released by the Planck collaboration (Planck Collaboration et al. 2018b), to which we apply aperture photometry filters of different apertures in the directions associated with galaxies and quasars. This technique results in a tomographic study of the kSZ effect from the local universe to redshift \( z = 5 \), from which we later extract constraints about the location, properties, and abundance of diffuse gas in the Universe.

The remainder of this paper is organised as follows. We start deriving the dependence of the power spectrum of both ARF and kSZ maps on cosmological parameters in §2, and then we use this information to establish the foundations of ARF-kSZ tomography in §3. In §4, we resort to cosmological simulations to gain further insight into this technique and assess the precision of our theoretical derivations. In §5, we apply ARF-kSZ tomography to observations, obtaining statistically significant measurements of the kSZ effect from the local universe to redshift \( z = 5 \), and in §6 we analyse these measurements to extract constraints about the location, properties, and abundance of the gas responsible for the kSZ effect. In §7, we address the robustness of our results, and in §8 we summarise our main findings and conclude.

Throughout this work we use Planck 2015 cosmological parameters (Planck Collaboration et al. 2014b): \( \Omega_m = 0.314, \Omega_l = 0.686, \Omega_b = 0.049, \sigma_8 = 0.83, h_0 = 0.67, \) and \( n_s = 0.96 \).

2 THEORETICAL PREAMBLES

This work aims to present ARF-kSZ tomography, a new technique for extracting the kSZ effect from observations. In this section, we derive the cosmological information encoded in the angular power spectrum of each of the two observables of interest in ARF-kSZ tomography: angular redshift fluctuations and the kinematic Sunyaev-Zel’dovich effect.

2.1 Angular redshift fluctuations

As recently shown by HM19, fluctuations in sky maps of galaxy redshifts contain precise information about the cosmic density and velocity fields; for brevity, we refer to these as angular redshift fluctuations. We proceed to study the dependence of the power spectrum of ARF maps on cosmological parameters.

We start our derivation by projecting the redshift of galaxies selected under a radial selection function \( \phi \) onto a sky map

\[
Z^{2D}(\vec{\Omega}) = \int dr r^2 \left[ z + (1 + z) \frac{v_g(r) \cdot \vec{\Omega}}{c} \right] \phi(s) n(r),
\]

where \( r \) denotes comoving coordinates, \( \vec{\Omega} \) stands for a unitary angular vector, \( v_g \cdot \vec{\Omega} \) refers to the radial component of the peculiar velocity of tracers, \( s = r + (1 + z) \frac{v_g(r) \cdot \vec{\Omega}}{c} \) indicates redshift-space coordinates, \( H(z) = H_0 \sqrt{\Omega_m (1 + z)^3 + \Omega_k} \) is the Hubble parameter in a flat universe dominated by matter and dark energy, and \( n \) denotes the number density of tracers.

In Eq. 1, the first and second terms enclosed in brackets account for the dependence of galaxy redshifts on the Hubble flow and peculiar velocities, respectively; we ignore relativistic effects in our derivations because these are much smaller than non-relativistic terms. We refer the reader to HM19 for further details.
To gain insight into the cosmological information encoded in $2D$, we decompose fluctuations in this map into a series of spherical harmonics $Y_{em}$ as follows

$$\delta r_m = \int d\Omega \int dr^2 \left[ z + (1 + z) \frac{\mathbf{v}_c(r) \cdot \mathbf{\hat{\Omega}}}{c} \right] \phi(s) \hat{n}(r) \delta_g(r) Y_{em}(\mathbf{\hat{\Omega}}),$$

where $\Omega_0 = \int dz z \phi(z) N(z)$ is the integral of the redshift of the tracers weighted by the value of the selection function, $N(z)$ refers to the number of tracers at redshift $z$, $\delta_g(r) = \frac{n(r) - \bar{n}(r)}{\bar{n}(r)}$ indicates the density contrast of these tracers, and $\bar{n}(r)$ denotes the average number density of tracers at a comoving distance $r$.

Before pursuing our derivation, we find useful to introduce a few simplifying assumptions:

- We restrict our analysis to first-order terms in perturbations; i.e., we disregard terms proportional to the bispectrum and trispectrum of both the cosmic density and velocity fields. We leave the derivation of higher-order terms to future studies.
- Motivated by the well-established result that the large-scale bias of galaxies is nearly scale-independent (e.g., Mo & White 1996), we assume that the Fourier transform of the scale bias of galaxies is nearly scale-independent (e.g., Mo & White 1996).
- Before expanding the selection function to first order, $\phi(s) \simeq \phi(r) + (1 + z) \frac{\mathbf{v}_c(r) \cdot \mathbf{\hat{\Omega}}}{c}$, and then considering the approximations outlined above; the main drawback of these simplifications is that the precision of our derivations degrades on small scales. As a result, we can now compute the power spectrum of angular redshift fluctuations by convolving the matter power spectrum with the following two redshift-dependent kernels

$$W^{(1)}_f(k) = \int dz z D(z) b(z) \phi(z) N(z) j_0(|k r(z)|),$$

and

$$W^{(2)}_f(k) = \int dz \frac{\mathbb{H}(z)}{c} D(z) f(z) D_v(k) \left( 1 + \frac{\Delta \ln \phi}{\Delta \ln z} \right) \phi(z) N(z) \bar{\delta}_g(z) |k r(z)|,$$

where the first and second kernels encode the dependence of angular redshift fluctuations on the density and velocity fields, respectively. In the previous expressions, $j_0$ is the spherical Bessel function of order 0, $\bar{\delta}_g$ indicates the derivative of $\delta_g$, and $D_v = \exp(-k^2 \sigma^2_v)$ accounts for the suppression of the power spectrum on small scales owing to small-scale velocities. We perform the convolution of the matter power spectrum and these two kernels as follows

$$C_{\alpha\beta} = \frac{2}{\pi} \int dk k^2 P(k, z = 0) W^{(1)}_f(k) W^{(2)}_f(k),$$

where $P(k, z = 0)$ indicates the matter power spectrum at present time, and $\alpha$ and $\beta$ run over the kernels $\delta_k$ and $v_c$.

Throughout this work, we use the publicly available Boltzmann solver CAMB (Lewis et al. 2000) to compute the matter power spectrum.

### 2.2 Kinematic Sunyaev-Zel’dovich effect

The kinematic Sunyaev-Zel’dovich effect is one of the most important sources of secondary anisotropies in the cosmic microwave background (Sunyaev & Zeldovich 1980). In the non-relativistic limit, temperature anisotropies induced by the kSZ effect can be written as

$$T_{\text{kSZ}}(\mathbf{\hat{\Omega}}) \equiv \frac{\delta T_{\text{kSZ}}(\mathbf{\hat{\Omega}})}{T_{\text{CMB}}} = -\sigma_T \int dl n_e \left( \mathbf{v} \cdot \mathbf{\hat{\Omega}} \right),$$

where $T_{\text{CMB}}$ is the average temperature of primordial CMB radiation, $\sigma_T$ stands for the Thomson scattering cross section, $n_e$ and $\mathbf{v}$ refer to the number density and peculiar velocity of free electrons, respectively, $c$ denotes the speed of light, and the integral is performed along the line-of-sight. As it is standard in the spherical coordinate system, we consider that gas moving away from (towards) the observer has a positive (negative) radial velocity.

Relativistic corrections to the kSZ effect are of the order of 10% for the most massive clusters of galaxies (Nozawa et al. 1998; Sazonov & Sunyaev 1998); conversely, the magnitude of these corrections decreases rapidly for lower mass systems. In §5, we attempt to detect the kSZ signal induced by gas surrounding $M_8 = 10^{11} - 10^{13} h^{-1} M_\odot$ haloes; therefore, it is well-motivated to neglect relativistic corrections in our derivations.

The detection of the kSZ effect is very challenging because the spectral distribution of temperature fluctuations induced by this effect is Planckian, unlike that of other secondary anisotropies such as the thermal Sunyaev-Zel’dovich effect (Sunyaev & Zeldovich 1970, 1972); consequently, it is impossible to disentangle the kSZ effect from primordial CMB anisotropies just resorting to CMB observations. Furthermore, the amplitude of these temperature fluctuations is much smaller than that of primordial CMB anisotropies. To extract the kSZ effect from observations, we follow a novel approach: we resort to the cross-correlation of ARF maps and high-pass filtered CMB maps containing noisy estimates of the kSZ effect. We proceed to derive the dependence of the power spectrum of maps containing just kSZ signal on cosmological parameters.

We start by projecting the kSZ signal resulting from gas surrounding a set of tracers onto a sky map

$$T_{\text{kSZ}}(\mathbf{\hat{\Omega}}) = \frac{n_{\text{in}}}{\Omega} \int d^2 r r^2 \hat{n}(r) \phi(s) \int d^2 r' g(r, r') \left[ \frac{\mathbf{v}(r') \cdot \mathbf{\hat{\Omega}}}{c} \right],$$

\( T_{\text{kSZ}}(\mathbf{\hat{\Omega}}) \equiv \frac{\delta T_{\text{kSZ}}(\mathbf{\hat{\Omega}})}{T_{\text{CMB}}} = -\sigma_T \int dl n_e \left( \mathbf{v} \cdot \mathbf{\hat{\Omega}} \right), \)

\( C_{\alpha\beta} = \frac{2}{\pi} \int dk k^2 P(k, z = 0) W^{(1)}_f(k) W^{(2)}_f(k), \)

\( T_{\text{kSZ}}(\mathbf{\hat{\Omega}}) \equiv \frac{\delta T_{\text{kSZ}}(\mathbf{\hat{\Omega}})}{T_{\text{CMB}}} = -\sigma_T \int dl n_e \left( \mathbf{v} \cdot \mathbf{\hat{\Omega}} \right), \)

\( \int d^2 r r^2 \hat{n}(r) \phi(s) \int d^2 r' g(r, r') \left[ \frac{\mathbf{v}(r') \cdot \mathbf{\hat{\Omega}}}{c} \right], \)
where \( n_0 = \int dr r^2 \phi(r) \tilde{n}(r) \) is the integral of the number density of tracers weighted by the selection function, \( g(r,r') = -\sigma_T n_e(r,r')(1+z)^{-1} \) refers to the strength of the kSZ effect generated by a distribution of gas \( n_e(r,r') = \tilde{n}_e \Delta_{\text{gas}}(r,r') \), \( \tilde{n}_e = \int \frac{d \nu}{d \nu} \Omega_b(1+z)^3 \) is the cosmic number density of electrons, \( \Delta_{\text{gas}}(r,r') \) denotes the overdensity of gas relative to the cosmic average at a distance \( r-r' \) from the tracers, \( \mu_e \) stands for the critical density at present time, and \( m_p \) is the proton mass. The number of electrons per unit of baryonic mass is given by

\[
f_e = \frac{1 - Y [1 - N_{\text{He}}(z)/4]}{\mu_e (1 - Y/2)},
\]

where \( N_{\text{He}} \) indicates the number of helium ionizations, \( Y = 0.248 \) denotes the primordial helium abundance, and \( \mu_e = 1.14 \) is the effective number of electrons per nucleon.

In what follows, we assume that the ionization of hydrogen gas relative to the cosmic average at a distance \( r \) is the proton mass. The number of electrons per unit of baryonic mass is given by

\[
f_e = \frac{1 - Y [1 - N_{\text{He}}(z)/4]}{\mu_e (1 - Y/2)},
\]

where \( N_{\text{He}} \) indicates the number of helium ionizations, \( Y = 0.248 \) denotes the primordial helium abundance, and \( \mu_e = 1.14 \) is the effective number of electrons per nucleon. In what follows, we assume that the ionization of hydrogen is completed before \( z \approx 5 \), and that the reionization of HeII occurs instantaneously at \( z = 3 \); consequently, the number of helium ionizations is two at \( z < 3 \) and one at \( z \geq 3 \).

We now proceed as in §2.1: we first decompose Eq. 7 into a series of spherical harmonics, we then expand the selection function to first order, and we finally consider the same simplifying assumptions. As a result, we find that the angular power spectrum of the kSZ effect can be assembled by introducing in Eq. 5 the kernel

\[
W_{\ell}^{\text{KSZ}}(k) = \frac{-\tau_{\text{eff}}}{n_0} \int dz (1+z)^{-2} \frac{H(z)}{c} D(z) f(z) D_r(k) \phi(z) N(z) \frac{\delta'[kr(z)]}{k},
\]

where \( \tau_{\text{eff}} = \sigma_T \tilde{n}_e \int dr \Delta_{\text{gas}}(r,0) \) provides the amplitude of the kSZ effect as a function of the overdensity of gas surrounding tracers. In what follows, we refer to \( \tau \) as the kSZ optical depth.

### 3 FOUNDATIONS OF ARF-KSZ TOMOGRAPHY

In §2, we derived the dependence of the angular power spectrum of both ARF and the kSZ effect on cosmological parameters. Using these results, we proceed to establish the theoretical basis of ARF-kSZ tomography, a new technique for extracting the kSZ effect from observations. In §3.1 and 3.2, we detail our procedure for generating maps of angular redshift fluctuations and for using aperture photometry to high-pass filter CMB maps, respectively. We then derive the dependence of the cross-correlation of ARF and filtered CMB maps on cosmological parameters in §3.3.

#### 3.1 Angular redshift fluctuations maps

To generate sky maps of angular redshift fluctuations, we project galaxy redshifts onto the pixelated surface of a sphere using the following expression

\[
M_{\text{ARF}}(\hat{\Omega}_i) = \log \left[ \frac{\sum_i \phi(z_i) \Delta_{\text{gas}}(r_i)}{\sum_i \phi(z_i) \frac{n_0}{\mu_e}} - \delta_{0i}^{\text{K}} \right],
\]

where \( i \) and \( j \) run over galaxies and pixels, respectively, and \( \delta_{0i}^{\text{K}} \) is the Kronecker delta function.

The value of the map in a certain pixel is the weighted-average redshift of all tracers falling in that pixel; consequently, this estimator\(^1\) is very robust against systematic uncertainties affecting the angular number density of tracers. This is because even though the precision estimating the weighted-average redshift improves with the number of tracers considered, random fluctuations in this number leave its value mostly unchanged. We explore the impact of this type of systematic uncertainties in §7.2.

### 3.2 Filtered cosmic microwave background maps

In this section, we first explain how to filter a CMB map using aperture photometry. Then, we model the impact of the AP filter on measurements of the kSZ effect. For the sake of definiteness, we will assume that CMB maps contain just primordial anisotropies and temperature fluctuations induced by the kSZ effect.

As noted in §2.2, the extraction of the kSZ effect very challenging. In a first attempt to isolate this signal from primordial CMB anisotropies, we resort to aperture photometry (Hernández-Monteagudo & Rubiño-Martín 2004). Albeit the performance of this technique is lower than the efficiency of others such as matched filtering, aperture photometry does not require to specify the spectral shape of the target signal, which is critical to our work (see §6).

To filter CMB maps using aperture photometry, we start by computing the average temperature of the CMB in both a circle of radius \( \theta_{\text{AP}} \) and an annulus of radii \( \theta_{\text{AP}} \) and \( \theta_{\text{AP}}/2 \) centred at each tracer. Then, we subtract the average temperature in the annulus from that in the circle, removing CMB fluctuations that are constant over the aperture. Therefore, aperture photometry provides a noisy estimate of the kSZ effect in the direction associated with each tracer. Finally, we combine all these measurements to create a filtered CMB map

\[
M_{\text{kSZ}}(\hat{\Omega}_i) = \frac{\sum_i T_{\text{AP},i} \phi(z_i) \delta_{\text{K}}^{\text{K}}}{\sum_i \phi(z_i) \delta_{\text{K}}^{\text{K}}},
\]

where \( i \) and \( j \) run over tracers and pixels, respectively, and \( T_{\text{AP},i} \) indicates the result of applying an AP filter to the tracer \( i \).

As we can see, the value of the map in each pixel is the weighted-average kSZ estimate of all tracers falling in that pixel; therefore, both ARF and filtered CMB maps are robust against systematic uncertainties in the angular number density of tracers.

It is important to note that an AP filter removes not only primordial anisotropies that are constant over its aperture, but also kSZ signal that so it is. Consequently, kSZ optical depth measured by an AP filter is always underes-
3.3 Cross-correlation of ARF and filtered CMB maps

Extracting the kSZ effect from the power spectrum of filtered CMB maps is quite challenging due to both primordial CMB signal not subtracted by aperture photometry and the large number of tracers required to beat the shot-noise level; to circumvent these issues, we follow a novel approach in which we cross-correlate ARF and filtered CMB maps to extract the kSZ effect; we refer to this technique as ARF-kSZ tomography. The main advantage of ARF-kSZ tomography is that systematic uncertainties affecting either ARF or filtered CMB maps are not correlated. Building upon the results presented in §2, we proceed to derive a theoretical estimate for the cross-correlation of ARF and filtered CMB maps.

To continue our derivations, it is useful to separate the cross-correlation of ARF and filtered CMB maps into the product of two terms: $C_{\ell}^{\text{ARF-kSZ}} = \tau_{\text{AP}}^{\text{th}} C_{\ell}^{\text{eff}_1} C_{\ell}^{\text{eff}_2}$; the first accounts for the kSZ optical depth (see Eq. 12), while the second captures the dependence of the cross-correlation of these maps on cosmological parameters. To assemble the second term, we introduce in Eq. 5 the redshift-dependent kernels corresponding to ADF, ARF, and the kSZ effect

$$
C_{\ell}^{\text{eff}_i} \equiv \tau_{\text{AP}}^{-1} \left( C_{\ell}^{\text{kSZ}_i - \delta_z} - C_{\ell}^{\text{th}_i - \delta_z} + C_{\ell}^{\text{ns}_i - \delta_z} - C_{\ell}^{\text{th}_i - \delta_z} \right),
$$

where the first (last) two terms in brackets encode information about the cross-correlation of the kSZ effect and density (velocity) terms. We already introduced the kernels $W^{\text{th}_i}$, $W^{\text{vn}_i}$, and $W^{\text{kSZ}_i}$ in Eqs. 3, 4, and 9, respectively; to derive $W^{\text{th}_i}$ and $W^{\text{vn}_i}$, we follow the same approach as in §2.1 but for angular density fluctuations, finding

$$
W^{\text{th}_i}(k) = n_{\Omega}^{-1} \int dz D(z) \delta(z) N(z) N(z) \delta_{\text{th}}(k \tau(z)),
$$

$$
W^{\text{vn}_i}(k) = n_{\Omega}^{-1} \int dz \frac{H(z)}{c} D(z) f(z) \delta_{\text{vn}}(k \tau(z)) \frac{d\phi}{dz} N(z) N(z) \delta_{\text{vn}}(k \tau(z)),
$$

where the first and second encode the dependence of ADF upon the cosmic density and velocity fields, respectively.

Finally, we resort to a simple $\chi^2$ minimisation to extract the kSZ optical depth from the cross-correlation of ARF and filtered CMB maps

$$
\tau_{\text{AP}}(\theta_{\text{AP}}) = \frac{\sum_{\ell} C_{\ell}^{\text{ARF-kSZ}}(\theta_{\text{AP}}) C_{\ell}^{\text{eff}_1}(\theta_{\text{AP}}) C_{\ell}^{\text{eff}_2}}{\sum_{\ell} C_{\ell}^{\text{eff}_1}(\theta_{\text{AP}}) C_{\ell}^{\text{eff}_2}},
$$

where $C_{\ell}^{\text{ARF-kSZ}}$ indicates the cross-correlation of ARF and filtered CMB maps generated using the same tracers and selection function, and $C_{\ell}^{\text{eff}_i}$ denotes the covariance matrix of this cross-correlation.

Thanks to the convenient separation of the cross-correlation of ARF and filtered CMB maps into two terms, we can now easily explore the range of angular scales from which the kSZ effect can be optimally extracted. In Fig. 1, we present theoretical predictions for the correlation of ARF and filtered CMB maps. Black, red, blue, and green lines indicate theoretical predictions for tracers selected under Gaussian shells with centre at $z_{\text{cen}} = 0.5$ and different comoving widths. As we can see, ARF and filtered CMB maps are strongly correlated just on large angular scales.

Figure 1. Correlation between ARF and filtered CMB maps. Coloured lines indicate theoretical predictions for tracers selected under Gaussian shells with centre at $z_{\text{cen}} = 0.5$ and different comoving widths. The main advantage of ARF-kSZ tomography is to circumvent these issues, we follow a novel approach in which the number of tracers required to beat the shot-noise level; to to...
4 INSIGHT INTO ARF-KSZ TOMOGRAPHY FROM SIMULATIONS

In §3, we established the theoretical foundations of ARF-kSZ tomography; in this section, we resort to cosmological simulations to gain further insight into this technique. First, we use cosmological gravity-only simulations to characterise the precision of our theoretical derivations in §4.1. In §4.2, we then take advantage of cosmological hydrodynamical simulations to improve our understanding of the large-scale distribution of gas surrounding galaxies.

4.1 Precision of theoretical derivations

In §2 and 3, we derived a set of theoretical expressions for ARF-kSZ tomography that are correct just to first order in perturbation theory. Ideally, we would resort to cosmological hydrodynamical simulations to evaluate the precision of these expressions; nonetheless, even the largest simulations of this kind cannot sample the scales of interest for ARF-kSZ tomography correctly (see §3.3). In contrast, cosmological gravity-only simulations can access to these scales accurately; in what follows we use these to assess the precision of our theoretical derivations.

Even though the amplitude of the cross-correlation of ARF and filtered CMB maps differs a factor of \(\sigma_{\text{AP}} / (1 + z)\) relative to that of ARF and peculiar velocity maps, both cross-correlations present the same dependence upon cosmological parameters to first order in perturbations. Motivated by this, we address the precision of the former using the latter. Given that the cosmic velocity field is independent of the subtleties of baryonic physics on the scales of interest for ARF-kSZ tomography, this approximation enables resorting to cosmological gravity-only simulations to do so. We proceed to detail the main characteristics of the simulations that we use.

We carry out an ensemble of 100 gravity-only \(N\)-body lightcone simulations using \textsc{l-picola} (Howlett et al. 2015), an efficient parallel implementation of the Comoving Lagrangian Acceleration method (COLA; Tassev et al. 2013). This technique presents a significant improvement in execution speed relative to full \(N\)-body simulations at the expense of loss of precision on small scales: \textsc{l-picola} recovers the power spectrum of the cosmic density and velocity fields as predicted by a full \(N\)-body simulation to within 2 and 3% up to \(k = 0.3\) and 0.15 \(h\) Mpc\(^{-1}\) (Howlett et al. 2015; Koda et al. 2016), respectively.

Each \textsc{cola} simulation evolves \(1024^3\) dark matter particles of mass \(1.7 \times 10^{10} h^{-1} M_{\odot}\) in a periodic cubic box of \(3 h^{-1}\) Gpc on a side from different initial conditions, delivering an on-the-flight all-sky lightcone from \(z = 0\) to 1. Even though the generation of a lightcone requires four replications of the simulation box, the impact of these replications on the angular power spectra of both the cosmic density and velocity fields is negligible (Klypin & Prada 2019). Further information about how we configure \textsc{l-picola} to carry out this set of simulations can be found in Chaves-Montero et al. (2018).

To generate sky maps, we first select dark matter particles from \textsc{cola} lightcones under Gaussian redshift shells; we use dark matter particles instead of haloes due to the reduced mass resolution of our simulations. Then, we project these particles onto the surface of a sphere using the publicly available package \textsc{healpix}\(^2\) (Górski et al. 2005; Zonca et al. 2019), which includes a set of routines for partitioning

\(^2\) \url{http://healpix.sourceforge.net}
the sphere into equal-area pixels. To ensure that the number of tracers falling in each pixel is large enough for statistical studies, we generate maps of resolution $N_{side} = 64$, which corresponds to dividing the sphere into $12 \times N_{side}^2$ equal-area pixels.

We proceed to evaluate the precision of our theoretical derivations using the auto- and cross-correlation of ARF, ADF, and radial peculiar velocity maps; we generate these maps using, respectively, Eq. (10), $M_{\text{ADF}}(\Omega_i) = \sum_i \phi(z_i) \delta K_{\Omega_i}$, and

\[ M_{\text{VEL}}(\Omega_i) = \frac{\sum_i v(z_i) \delta K_{\Omega_i}}{\sum_i \phi(z_i) \delta K_{\Omega_i}}, \tag{17} \]

where $i$ and $j$ run over tracers and pixels, respectively. The value of the map in each pixel is the weighted-average of the radial peculiar velocity of all sources falling in that pixel; consequently, peculiar velocity and CMB filtered maps are both robust against systematic uncertainties in the angular number density of tracers.

To compute the auto- and cross-correlation of these maps, we resort to the publicly available program POLSPICE (Szapudi et al. 2001; Chon et al. 2004). This code includes routines for analysing pixelated data on the surface of a sphere, allows accounting for the impact of the survey mask on the results, and can deal with inhomogeneous weights. Due to the dependence of statistical uncertainties affecting ARF and peculiar velocity maps on the number of sources falling in each pixel, we correct the cross-correlation of these maps using the $M_{\text{ADF}}$ map.

In the top panel of Fig. 2, we display the cross-correlation of ARF and radial peculiar velocity maps ($C_{\ell}^\text{ADF}$, in green), together with, for completeness, the power spectrum of ADF maps ($C_{\ell}^\text{ADF}$, in black), ARF maps ($C_{\ell}^\text{ADF}$, in red), and radial peculiar velocity maps ($C_{\ell}^\text{vel}$, in blue). Lines and symbols indicate theoretical predictions and average results from our set of simulations, respectively, while shaded areas denote mock-to-mock $1\sigma$ uncertainties. To generate these results, we consider a Gaussian selection function centred at $z_{\text{cen}} = 0.5$ with comoving width $\sigma_v = 100 \, h^{-1}\text{Mpc}$, and we account for the impact of small-scale velocities using $\sigma_v = 7 \, h^{-1}\text{Mpc}$; we estimate this value from simulations. For clarity, the amplitude of the power spectrum of ADF is divided by 100. Due to non-linearities not captured by our model, the power spectrum of radial velocity maps grows with $\ell$ on scales smaller than $\ell = 80$; the purple dotted line shows an experimental power-law fit to $C_{\ell}^\text{ADF}$ in this regime.

Overall, we find that the power spectra of both ADF and ARF maps look pretty much alike: the amplitude of these grow monotonically with $\ell$ across the range of scales shown, and their shapes present wiggles induced by baryonic acoustic oscillations. In contrast, the power spectra $C_{\ell}^\text{vel}$ and $C_{\ell}^\text{vel}$ present a different shape: both increase with $\ell$ on large scales, peak at $\ell = 10 \sim 30$, and decrease thereafter. As we can see, all these trends are qualitatively captured by our theoretical predictions. More quantitatively, we present the relative difference between theoretical predictions and results from simulations in the bottom panel of Fig. 2. As we can see, both agree to within $\pm 5\%$ across the whole range of multipole shown; accordingly, we expect our theoretical expression for the cross-correlation of ARF and filtered CMB maps to present a similar level of precision.

In §5, we estimated the range of scales from which the kSZ effect can be optimally extracted using ARF-kSZ tomography; we proceed to validate these predictions using simulations. In Fig. 3, we display the correlation between ARF and radial peculiar velocity maps. Distinct colours indicate the results for Gaussian selection functions centred at $z_{\text{cen}} = 0.5$ and with different widths. In broad strokes, the correlation between ARF and radial peculiar velocity maps grows with $\ell$ on large angular scales, reaches a maximum, and plummets thereafter. We also find that the range of scales across which these maps are strongly correlated decreases with the width of the selection function. All these trends are in agreement with our theoretical predictions for the cross-correlation of ARF and filtered CMB maps (see Fig. 1), supporting that we can only extract the kSZ effect from large angular scales using ARF-kSZ tomography.

### 4.2 Large-scale distribution of gas surrounding tracers

In ARF-kSZ tomography, extracting the kSZ effect from observations does not require to specify the overdensity profile of gas surrounding tracers; however, so it does interpreting kSZ measurements. In this section, we seek to identify a functional form able to capture the overdensity profile of gas surrounding haloes of different masses.

To get insight into the large-scale distribution of gas in the Universe, we resort to the cosmological hydrodynamical simulation Borg Cube (Emberson et al. 2018). This simulation evolved $2 \times 2304^3$ dark matter plus baryonic particles of masses $2.56$ and $0.52 \times 10^9 \, h^{-1}\text{M}_\odot$, respectively, in a periodic comoving box of $800 \, h^{-1}\text{Mpc}$ on a side while treating baryons in the non-radiative regime. We consider the Borg...
Cube simulation because its large volume enables accessing the distribution of gas surrounding haloes of a broad range of masses. Even though Borg Cube does not incorporate baryonic processes, we do not expect these to affect the large-scale distribution of gas strongly (Burns et al. 2010).

In Fig. 4, we display the overdensity profile of gas surrounding spherical overdensity haloes at $z = 0.24$. Symbols indicate results from the simulation, while lines denote the best-fitting solution to these using three distinct functional forms: a $\beta$-profile $\Delta_{\text{gas}}(r, r') = \Delta_b \left[1 + \frac{(r - r')^2}{r_{\Delta b}^2}\right]^{-3/2} + 1$, a double exponential profile $\log \Delta_{\text{gas}}^\text{dex}(r, r') = \Delta_r \exp \left[-(r - r')^3/r_{\Delta r}^3\right]$, and a Gaussian profile $\Delta_{\text{gas}}^\text{gauss}(r, r') = \Delta_g \exp \left[-0.5(r - r')^2/r_{\Delta g}^2\right] + 1$. These three forms are controlled by the free parameters $\Delta_b$ and $r_s$: the first and second regulate the amplitude and breadth of the profile, respectively. As we can see, the $\beta$- and double exponential profiles are flexible enough to capture the large-scale distribution of gas surrounding haloes of different masses in hydrodynamical simulations. In contrast, the Gaussian profile is not able to reproduce the distribution of gas in simulations. We check that these results can be extrapolated to $z = 0.5, 1, 2,$ and 4.

5 APPLYING ARF-KSZ TOMOGRAPHY TO OBSERVATIONS

Since the kSZ effect results from scattering of CMB photons off free electrons moving with respect to the CMB rest frame, the magnitude of this effect is redshift independent. It is thus just natural to carry out kSZ measurements across a broad redshift range; in this section, we use ARF-KSZ tomography to conduct a tomographic study of the kSZ effect from redshift range $z < 0.43$ and the CMASS sample, which contains slightly bluer galaxies at $0.43 < z < 0.7$. The average halo mass and large-scale bias of both LOWZ and CMASS galaxies are $M_h \approx 10^{12} h^{-1} M_\odot$ and $b = 2$ (Parejko et al. 2013; Saito et al. 2016; Rodriguez-Torres et al. 2016), respectively. The footprint of the BOSS survey spans $9.376$ deg$^2$ of the sky.

- 6dF-G sample. The final data release of the 6dF Galaxy Survey comprises $108\,030$ galaxies with reliable redshifts covering $\sim 17\,000$ deg$^{2}$ of the southern sky (Jones et al. 2009). These galaxies are located in $10^{11} - 10^{12} h^{-1} M_\odot$ haloes, exhibit a large-scale bias of $b = 1.48$, and present a median redshift of $z = 0.053$ (Beutler et al. 2012).

- SDSS-G sample. To access intermediate redshifts, we resort to the $1\,325\,856$ galaxies with secure redshifts from the final data release of the BOSS survey (Alam et al. 2015). These galaxies are divided into two main groups: the LOWZ sample, which includes the brightest and reddest galaxies at $z < 0.43$, and the CMASS sample, which contains slightly bluer galaxies at $0.43 < z < 0.7$. The average halo mass and large-scale bias of both LOWZ and CMASS galaxies are $M_h \approx 10^{12} h^{-1} M_\odot$ and $b = 2$ (Parejko et al. 2013; Saito et al. 2016; Rodriguez-Torres et al. 2016), respectively. The footprint of the BOSS survey spans $9.376$ deg$^2$ of the sky.

- SDSS-Q sample. We study the high redshift universe using quasars with secure redshifts from the 14th data release of the eBOSS quasar catalogue (Paris et al. 2018), which comprises $526\,356$ quasars observed during a time span of more than 16 years as part of any of the stages of SDSS (York et al. 2000; Eisenstein et al. 2011; Blanton et al. 2017). Distinct selection criteria were followed to target quasars during this time; as a result, the properties of SDSS quasars vary across the $9.376$ deg$^2$ of the survey footprint. On average, these quasars are located in $M_h = 10^{12} - 10^{13} h^{-1} M_\odot$ haloes and present a large-scale bias of $b = 0.278[1 + z]^{-2} - 6.565] + 2.393$ (Laurent et al. 2017; Ata et al. 2018).

5.1 Creation of ARF and filtered CMB maps

As discussed in §3, the creation ARF and filtered CMB maps demands specifying a sample of tracers, a selection function, precise CMB observations, and the resolution of these maps. In this section, we describe and motivate different selections for these ingredients; once these are specified, we generate sky maps following the procedure outlined in §4.1.

5.1.1 Tracers

Due to their abundance and luminosity, galaxies are the most natural tracer of the density and velocity fields at low redshift. However, galaxies are too faint to be optimally observed at high redshift, and thus it is typical to resort to much brighter sources, such as quasars, to get access to the early universe. Motivated by this, we use galaxies from the 6dF Galaxy Survey (6dF; Jones et al. 2004) and the Baryon Oscillation Spectroscopic Survey (BOSS; Eisenstein et al. 2011; Dawson et al. 2013) to sample low and intermediate redshifts, respectively, and we turn to quasars from the extended Baryon Oscillation Spectroscopic survey (eBOSS; Myers et al. 2015) to access higher redshifts. We proceed to detail the main properties of the galaxies and quasars that we consider.

- 6dF-G sample. The final data release of the 6dF Galaxy Survey comprises $108\,030$ galaxies with reliable redshifts covering $\sim 17\,000$ deg$^{2}$ of the southern sky (Jones et al. 2009). These galaxies are located in $10^{11} - 10^{12} h^{-1} M_\odot$ haloes, exhibit a large-scale bias of $b = 1.48$, and present a median redshift of $z = 0.053$ (Beutler et al. 2012).

- SDSS-G sample. To access intermediate redshifts, we resort to the $1\,325\,856$ galaxies with secure redshifts from the final data release of the BOSS survey (Alam et al. 2015). These galaxies are divided into two main groups: the LOWZ sample, which includes the brightest and reddest galaxies at $z < 0.43$, and the CMASS sample, which contains slightly bluer galaxies at $0.43 < z < 0.7$. The average halo mass and large-scale bias of both LOWZ and CMASS galaxies are $M_h \approx 10^{12} h^{-1} M_\odot$ and $b = 2$ (Parejko et al. 2013; Saito et al. 2016; Rodriguez-Torres et al. 2016), respectively. The footprint of the BOSS survey spans $9.376$ deg$^2$ of the sky.

- SDSS-Q sample. We study the high redshift universe using quasars with secure redshifts from the 14th data release of the eBOSS quasar catalogue (Paris et al. 2018), which comprises $526\,356$ quasars observed during a time span of more than 16 years as part of any of the stages of SDSS (York et al. 2000; Eisenstein et al. 2011; Blanton et al. 2017). Distinct selection criteria were followed to target quasars during this time; as a result, the properties of SDSS quasars vary across the $9.376$ deg$^2$ of the survey footprint. On average, these quasars are located in $M_h = 10^{12} - 10^{13} h^{-1} M_\odot$ haloes and present a large-scale bias of $b = 0.278[1 + z]^{-2} - 6.565] + 2.393$ (Laurent et al. 2017; Ata et al. 2018).

5.1.2 Selection function

For simplicity, we adopt a Gaussian in redshift space as selection function. The width of this function needs to be carefully chosen as a compromise between the range of scales across which ARF and filtered CMB maps are strongly correlated and the number of tracers selected under this function; the first (second) decreases (increases) with the function width. To ensure enough tracers at all redshifts, we select sources from the 6dF-G, SDSS-G, and SDSS-Q samples under Gaussian shells centred at $z_{cen} = 0.18, 0.27, 0.42, 0.59,$ and $0.78$; and $0.72, 0.92, 1.15, 1.41, 1.71, 2.07, 2.50, 3.01, 3.64, 4.43,$ and $5.42$, respectively; we leave an inter-shell separation of $\Delta z = 0.18 h^{-1}$Mpc. Due to the broad redshift range spanned by our galaxies and quasars, we generate ARF and filtered CMB maps at 16 different redshifts. To do so, we select sources from the 6dF-G, SDSS-G, and SDSS-Q samples under Gaussian shells centred at $z_{cen} = 0.18, 0.27, 0.42, 0.59,$ and $0.78$; and $0.72, 0.92, 1.15, 1.41, 1.71, 2.07, 2.50, 3.01, 3.64, 4.43,$ and $5.42$, respectively; we leave an inter-shell separation of $\Delta z = 0.18 h^{-1}$Mpc. To reduce correlations. For each sample, we check that the number of sources selected under shells centred at higher redshifts is not large enough for statistically significant studies.

To characterise the median redshift of tracers selected under Gaussian shells, we resort to the weighted average redshift of these tracers, $z_{med} = z_{cen}/n_{cen}$. We find that the effective redshift of 6dF-G, SDSS-G, and SDSS-Q sources...
selected under the redshift shells outlined above is $z_{\text{eff}} = 0.09; 0.29, 0.44, 0.56,$ and $0.65;$ and $0.73, 0.92, 1.14, 1.41, 1.70, 2.07, 2.43, 2.85, 3.35, 4.03,$ and $4.62;$ respectively.

### 5.1.3 CMB observations

To produce filtered CMB maps, we consider as input CMB temperature maps from the final data release of the Planck survey (Planck Collaboration et al. 2018c). Specifically, we resort to the four CMB maps generated applying the foreground-cleaning algorithms COMMANDER, NILC, SEVEM, and SMICA to single-frequency maps (Planck Collaboration et al. 2016b, 2018b), one map produced employing an improved version of SMICA that also attempts to reduce tSZ contamination, and three single-frequency maps cleaned of foregrounds using SEVEM. We refer to these eight maps as COMMANDER, NILC, SEVEM, SMICA, SMICA-NOSZ, SEVEM-100, SEVEM-143, and SEVEM-217.

For each selection function and foreground-cleaned map listed above, we produce 33 filtered CMB maps using AP filters of apertures $\theta_{\text{AP}} = 3, 4, ... 20, 22, ... 48,$ and $50$ arcmin. We do not consider apertures either smaller than $3$ arcmin or larger than $50$ arcmin because the first are dominated by the Planck beam, while the second are strongly contaminated by CMB signal not subtracted by the filter.

### 5.1.4 Map resolution

As explained in §5, we generate ARF and filtered CMB maps using HEALPix. The resolution of these maps has to be chosen as a comprise between the range of scales accessible from the cross-correlation of these maps and the average number of tracers falling in pixels; the first (second) increases (decreases) with map resolution. Given that we only need to compute the cross-correlation of ARF and filtered CMB maps on the large scales on which these are correlated, we set the resolution of sky maps to be $N_{\text{side}} = 64$, which corresponds to $0.84 \, \text{deg}^2$.

### 5.2 Extraction of the kSZ effect

To extract the kSZ optical depth from the cross-correlation of ARF and filtered CMB maps using Eq. 16, we can follow two distinct approaches: the first is to set joint constraints on the kSZ optical depth, cosmological parameters, and large-scale bias of the tracers; the second is to determine the kSZ optical depth while holding fixed cosmological parameters and large-scale bias. Due to the limited precision of our measurements, we assume the Planck 2015 cosmology and use the large-scale biases quoted in §5.1.

To apply Eq. 16, we need to compute the cross-correlation of ARF and filtered CMB maps and estimate the uncertainty associated with it; we proceed to do so. To compute the cross-correlation of these maps, we follow the procedure outlined in §4.1. Due to the limited footprint of 6dF and SDSS, we limit the analysis of the cross-correlation to multipoles larger than $\ell = 3$ and $13$, respectively; these two values are inversely proportional to the sky area spanned by these surveys. We also apply a binning of $\Delta \ell' = 2$ to $C_{\ell'}^{\text{ARF}-\text{kSZ}}$.

The two main sources of uncertainty in the cross-correlation of ARF and filtered CMB maps are CMB contamination not subtracted by aperture photometry and statistical errors at the pixel level; to estimate the impact of these, we resort to simulations. Using the HEALPix routine SYNFAST, we produce 1000 random realisations of a Gaussian field characterised by the Planck temperature power spectrum; for consistency with observations, we generate maps with analogous resolution to Planck maps and convolve these with a Gaussian beam of FWHM $5$ arcmin to mimic the Planck beam. Starting from these each simulated map, we then produce a distinct map for each foreground-cleaned Planck map. To do so, we introduce to simulated maps uncertainties associated with each foreground-cleaned map, which we estimate by taking the difference between publicly available foreground-cleaned half-mission maps. Moreover, we apply to these maps a mask corresponding to each foreground-cleaned map, which is also publicly available. Following this procedure, we end up with 1000 mock maps for each foreground-cleaned map.

After that, we use these simulated maps to produce a distinct filtered CMB map for each redshift, aperture, and foreground-cleaned map considered in §5.1; and once these are generated, we cross-correlate simulated filtered CMB maps with ARF maps from observations. Given that simulated maps only do not include kSZ signal, any departure of these cross-correlations from zero can only result from uncertainties. We estimate these as follows:

$$C_{\ell'\ell}^{\text{ARF}}(\theta_{\text{AP}}) = \frac{1}{M - 1} \sum_{m=1}^{M} \left[ S_{\ell',m}^{\text{ARF}-\text{kSZ}}(\theta_{\text{AP}}) - S_{\ell'}^{\text{ARF}-\text{kSZ}}(\theta_{\text{AP}}) \right] \left[ S_{\ell,m}^{\text{ARF}-\text{kSZ}}(\theta_{\text{AP}}) - S_{\ell}^{\text{ARF}-\text{kSZ}}(\theta_{\text{AP}}) \right],$$

where $S_{\ell',m}^{\text{ARF}-\text{kSZ}}$ refers to the cross-correlation of ARF and simulated filtered CMB maps, $M = 1000$ is the number of simulated maps, and bars indicate an average across simulations.

We find that covariance matrices estimated for distinct foreground-cleaned maps are very similar; this is not surprising owing to the very good consistency between these maps. We also find that the diagonal elements of these matrices decrease slowly with the filter aperture for $\theta_{\text{AP}} \leq 30$ arcmin and increase quickly for larger apertures. This trend is explained as follows. The precision of kSZ estimates increases a priori with the filter area; however, larger apertures result in more CMB contamination leaking in. The second effect starts to outweighing the first at apertures of approximately half a degree due to the shape of the CMB power spectrum. It is also worth noticing that our simulations do not include other sources of contamination such as residual foregrounds that would also impact more severely large apertures.

Extracting the kSZ optical depth from Eq. 16 also requires computing the inverse of $C_{\ell'\ell}$; to do so, we resort to an algorithm based on LU factorisation. Then, due to the limited number of mocks used to estimate covariance matrices, we correct inverse matrices using the factor $(M - N_{\ell} - 2)/(M - 1)$ (e.g., Hartlap et al. 2007), where $N_{\ell}$ is the number of $\ell$-bins.
5.3 Results from observations

In §5.1, we generated ARF and filtered CMB maps using distinct samples, selection functions, apertures, and foreground-cleaned maps. In §5.2, we then detailed how to extract the kSZ optical depth from the cross-correlation of these maps. In this section, we start by presenting the cross-correlation of ARF and filtered CMB maps from observations, and then estimate the correlation between measurements of the kSZ optical depth from different redshifts and apertures.

Due to the large number of ARF and filtered CMB maps produced in §5.1, we only show a few illustrative examples of their cross-correlations. In the top and bottom panels of Fig. 5, we display the cross-correlation of ARF and filtered CMB maps generated using SDSS-G galaxies and SDSS-Q quasars at \( z_{\text{eff}} = 0.56 \) and 4.03, respectively, and an AP filter of aperture \( \theta_{\text{AP}} = 17 \) arcmin. Symbols indicate the results for distinct foreground-cleaned maps, while dashed lines and error bars present the best-fitting model and \( 1\sigma \) uncertainties for COMMANDER data, respectively. As we can see, best-fitting models capture the angular dependence of the cross-correlation precisely.

![Figure 5. Cross-correlation of ARF and filtered CMB maps. The top and bottom panels display \( C_{\ell}^{\text{ARF-kSZ}}(\theta_{\text{AP}} = 17 \) arcmin) for SDSS-G galaxies and SDSS-Q quasars at \( z_{\text{eff}} = 0.56 \) and 4.03, respectively. Symbols indicate the results for four distinct foreground-cleaned maps, while dashed lines and error bars present the best-fitting model and \( 1\sigma \) uncertainties for COMMANDER data, respectively. As we can see, best-fitting models capture the angular dependence of the cross-correlation precisely.](image)

**Figure 5.** Cross-correlation of ARF and filtered CMB maps. The top and bottom panels display \( C_{\ell}^{\text{ARF-kSZ}}(\theta_{\text{AP}} = 17 \) arcmin) for SDSS-G galaxies and SDSS-Q quasars at \( z_{\text{eff}} = 0.56 \) and 4.03, respectively. Symbols indicate the results for four distinct foreground-cleaned maps, while dashed lines and error bars present the best-fitting model and \( 1\sigma \) uncertainties for COMMANDER data, respectively. As we can see, best-fitting models capture the angular dependence of the cross-correlation precisely.

**Figure 6.** Correlation between measurements of the kSZ optical depth from different redshifts and apertures for COMMANDER. On (off) diagonal squares show correlations between measurements at the same (different) redshift. As expected, measurements of the kSZ optical depth from similar apertures and redshifts are correlated.

In §5.3, we present the cross-correlation of ARF and filtered CMB maps from observations. In the top and bottom panels of Fig. 5, we display the cross-correlation of ARF and filtered CMB maps generated using SDSS-G galaxies and SDSS-Q quasars at \( z_{\text{eff}} = 0.56 \) and 4.03, respectively, and an AP filter of aperture \( \theta_{\text{AP}} = 17 \) arcmin. Symbols indicate the results for distinct foreground-cleaned maps, while dashed lines and error bars present the best-fitting model and \( 1\sigma \) uncertainties for COMMANDER data, respectively. As we can see, best-fitting models capture the angular dependence of the cross-correlation precisely.

**Figure 6.** Correlation between measurements of the kSZ optical depth from different redshifts and apertures for COMMANDER. On (off) diagonal squares show correlations between measurements at the same (different) redshift. As expected, measurements of the kSZ optical depth from similar apertures and redshifts are correlated.

The multipole at which the cross-correlation of ARF and filtered CMB maps departs from zero increases with redshift; this is because so it does both the range of scales across which these maps are strongly correlated and the physical scale corresponding to a multipole. Remarkably, best-fitting models capture precisely this trend. We can also see that the results for distinct foreground-cleaned maps show very good consistency, suggesting that the impact of residual foreground contamination on ARF-kSZ tomography is very weak (see also §7.1).

Measurements of the kSZ optical depth from similar apertures at the same redshift are sensitive to practically the same underlying gas distribution (see Eq. 12), and thus we expect these measurements to be correlated. To estimate these correlations, we resort to the simulated CMB maps produced in §5.2. First, we extract measurements of \( \tau_{\text{AP}} \) from the cross-correlation of ARF and each simulated filtered CMB maps using Eq. 16; as a result, we end up with 1000 mock measurements of \( \tau_{\text{AP}} \) for each redshift, aperture, and foreground-cleaned map. Given that simulated CMB maps do not include kSZ signal, any deviation of these measurements from zero can only arise from uncertainties. Interestingly, we find that measurements of the kSZ optical depth from mocks are compatible with zero to within statistical uncertainties for all apertures, redshifts, and foreground-cleaned maps considered. We thus conclude that ARF-kSZ tomography results in unbiased measurements of the kSZ effect.

Using mock measurements, we estimate a covariance matrix for each foreground-cleaned map as follows

\[
C_{\ell}(i, j) = \frac{1}{M-1} \sum_{m=1}^{M} \left[ T_{\text{sim}}^m(i) - \bar{T}_{\text{sim}}(i) \right] \left[ T_{\text{sim}}^m(j) - \bar{T}_{\text{sim}}(j) \right], \tag{19}
\]

**Figure 6.** Correlation between measurements of the kSZ optical depth from different redshifts and apertures for COMMANDER. On (off) diagonal squares show correlations between measurements at the same (different) redshift. As expected, measurements of the kSZ optical depth from similar apertures and redshifts are correlated.
ARF-kSZ tomography

kSZ measurements under consideration. Then, we compute the weighted average of this vector, \( \mathbf{T} = \sigma_\tau^2 (\mathbf{W}^T \mathbf{C}_\tau^{-1} \mathbf{T}) \), where \( \sigma_\tau^2 = (\mathbf{W}^T \mathbf{C}_\tau^{-1} \mathbf{W})^{-1} \) indicates the variance of the weighted average, \( \mathbf{C}_\tau \) is computed using Eq. 19, and \( \mathbf{W} \) denotes a vector of ones with the same number of elements as \( \mathbf{T} \). The standard score associated with these measurements is

\[
Z = \sqrt{2} \text{erf}^{-1} \left[ \frac{1}{2} - \frac{1}{2} \text{erf} \left( \frac{T}{\sigma_T \sqrt{2}} \right) \right],
\]

where erf and erf\(^{-1}\) refer to the error function and its inverse, respectively. Note that we set the value of \( Z \) to zero for measurements with \( T \leq 0 \).

To determine the power of ARF-kSZ tomography detecting the kSZ effect, we introduce kSZ measurements from all redshifts and apertures in Eq. 20. We treat distinct foreground-cleaned maps separately; this is because these are sensitive to the same underlying signal, and thus differences among these maps arise from systematics. We find that the average of the standard score for distinct foreground-cleaned maps is \( Z = 10.7 \pm 1.2 \), where the error indicates the standard deviation among maps; this the highest significance detection of the kSZ effect. Note that the standard deviation of \( Z \) is small, further confirming that ARF-kSZ tomography is very robust against residual foreground contamination.

In §6, we analyse measurements of the kSZ optical depth from distinct apertures at the same redshift to set constraints on the properties of the gas responsible for the kSZ effect. We thus need to assess which shells present statistically significant results. As discussed in §3 and 5.2, the value of (uncertainty on) \( \tau_{\alpha\beta} \) should increase (decrease) with the filter aperture, reach a maximum (minimum), and decrease (increase) thereafter. We expect uncertainties to increase on apertures larger than approximately half a degree; consequently, the joint significance of kSZ measurements on smaller apertures should be greater than zero. Motivated by this, we compute the standard score of kSZ measurements on apertures smaller or equal to \( 22 \) arcmin for each redshift shell, \( Z_{22} \).

In the top panel of Fig. 7, we display the value of \( Z_{22} \) for the 6dF-G, SDSS-G, and SDSS-Q samples using green, blue, and orange colours, respectively. Each symbol indicates
the distribution of standard scores for distinct foreground-cleaned maps at the same redshift, while bars denote the median of these distributions. As we can see, the number of redshift shells with a median standard score greater than $Z_{22} = 1, 2,$ and 3 is twelve, five, and two, respectively. In contrast, we find that the significance of four redshift shells is smaller than $1\sigma$; we highlight these using a grey colour. Most redshift shells present statistically significant results on apertures smaller or equal to 22 arcmin, supporting the intuitive model presented above.

Due to correlations between kSZ optical depths from close apertures (see §5.3), the standard score of a shell depends weakly on the maximum aperture considered. Indeed, we find that the same number of shells present a joint significance greater than 1, 2, and $3\sigma$ for $Z_{20}$, $Z_{22}$, or $Z_{24}$. On the other hand, our predictions suggest that the standard score of some shells should decrease for even larger apertures. We proceed to compute the standard score also considering apertures larger than 22 arcmin.

In the bottom panel of Fig. 7, we display the joint significance of kSZ measurements on apertures smaller or equal to $\theta_{\text{AP}} = 50, Z_{50}$. We find that the standard score of nine, eight, and four redshift shells is greater than $Z_{50} = 1, 2,$ and 3, respectively; conversely, seven shells present a joint significance lower than $1\sigma$. As expected, some shells present $Z_{22} > Z_{50}$; this is because the signal-to-noise of the kSZ optical depth for the largest apertures is very small. To avoid considering apertures dominated by uncertainties in §6.1, we will only analyse kSZ measurements on apertures smaller or equal to 22 arcmin ($50$ arcmin) for shells with $Z_{22} > Z_{50} > 1$ ($Z_{50} > Z_{22} > 1$).

### 6 Setting Constraints on the kSZ Gas

In §5, we extracted the kSZ optical depth from distinct redshifts, apertures, and foreground-cleaned maps using ARF-kSZ tomography. In this section, we start by setting constraints on the properties of the gas responsible for the kSZ effect in §6.1. We then use this information to determine the location and density of kSZ gas in §6.2, and we conduct a baryonic census from the local Universe to redshift $z \approx 5$ in §6.3.

#### 6.1 Inferring the properties of the kSZ gas

In this section, we resort to the theoretical model introduced in Eq. 12 to extract information about the gas responsible for measurements of the kSZ effect. This model requires assuming a functional form for the overdensity of gas surrounding tracers; we shall adopt a two-parameter $\beta$-profile due to the ability of this profile in capturing the distribution of gas surrounding haloes of different masses in hydrodynamical simulations (see §4.2). Using kSZ measurements from each shell with statistically significant results, we proceed to set constraints on the parameters controlling the overdensity profile.

The $\beta$-profile introduced in §4.2 has two free parameters, $\beta \equiv \{\Delta_b, r_s\}$, the first and second control the amplitude and shape of the profile, respectively. To set constraints on these parameters, we use measurements of $\tau_{\text{AP}}$ extracted from distinct apertures for the same redshift and foreground-cleaned map. We first create a vector $\mathbf{T}^{\text{th}}$ containing measurements from apertures smaller or equal to 22 arcmin ($50$ arcmin) for shells with $Z_{22} > Z_{50} > 1$ ($Z_{50} > Z_{22} > 1$) (see §5.4). Then, we resort to Latin Hypercube Sampling (LHS; McKay et al. 1979) to generate $10{,}000$ logarithmically spaced samples of $\pi$ within flat priors $\pi \in ([10^0, 10^1] : [10^{-2}, 10^4])$, and using each of these we create a vector $\mathbf{T}^{\text{th}}(\pi)$ containing theoretical predictions for the kSZ optical depth at each of the apertures considered. After that, we compute the distance between the vector $\mathbf{T}$ and each of the vectors $\mathbf{T}^{\text{th}}$ using $D^2_m(\pi) = |\mathbf{T} - \mathbf{T}^{\text{th}}(\pi)|_T^{-1} |\mathbf{T} - \mathbf{T}^{\text{th}}(\pi)|_T$ (Mahalanobis 1936). Finally, we determine the best-fitting model to $\mathbf{T}$ by computing the parameters that maximise the likelihood of the model, which we assume to be Gaussian and given by $\mathcal{L}(\mathbf{T} | \pi) = \exp[-0.5 D^2_m(\pi) + K]$, where $K$ encompasses normalisation terms not depending on $\pi$.

In each panel of Fig. 8, we display kSZ optical depth measurements extracted from a distinct shell with statistically significant results. For clarity, we only show results for COMMANDER. Symbols indicate measurements from observations, orange dashed lines present best-fitting models to these measurements, error bars denote $1\sigma$ uncertainties, and green dot-dashed lines show the overdensity profile that produces the best-fitting model. As we can readily see, the kSZ optical depth grows with $\theta_{\text{AP}}$ on small scales, reaches a maximum at a few Megaparsecs, and decreases thereafter. Remarkably, our theoretical model captures this trend precisely, thereby supporting the intuitive physical picture outlined in §2.2.

Interestingly, we find that the maximum value of the best-fitting model to kSZ optical depth measurements, $\max(\mathbf{T}^{\text{th}}(\pi^{\text{MLE}}))$, increases with redshift. It is natural to consider whether this trend is reflected by the redshift-evolution of the optical depth

$$\tau^{\text{max}}(z) = \sigma_T \int_{0}^{z} \frac{c \bar{n}_e(z') dz'}{(1 + z') H(z')},$$

(21)

where $\bar{n}_e$ is the physical cosmic number density of electrons (see §2.2). To assemble this expression, we assume that all baryons contribute to the optical depth, and thus $\tau^{\text{max}}$ provides an upper limit for its value.

In Fig. 9, we display the maximum kSZ optical depth extracted from each shell with statistically significant measurements. Each symbol indicates the distribution of kSZ optical depths from distinct foreground-cleaned maps at the same redshift, error bars denote $1\sigma$ confidence intervals for COMMANDER, and the dashed line shows the redshift evolution of $\tau^{\text{max}}$. Remarkably, we find that measurements and theoretical predictions exhibit a very good agreement.

To estimate these confidence intervals, we proceed as follows for each redshift shell. First, we select all samples produced via LHS to within $1\sigma$ from the best-fitting solution, $\log \mathcal{L}(\pi^{\text{MLE}}) - \log \mathcal{L}(\pi) < 0.5$ (Barlow 1989), where $\mathcal{L}(\pi^{\text{MLE}})$ indicates the value of the likelihood for the best-fitting parameters. Then, we compute the value of the vector $\mathbf{T}^{\text{th}}$ using each of the selected samples. After that, we take the maximum and minimum of each of these vectors. Finally, we choose the maximum and minimum of the resulting distribution of values; these provide the upper and lower ends of the error bar for $\max(\mathbf{T})$. We check that confidence intervals es-
Figure 8. kSZ optical depths extracted from redshift shells with $Z_{22} > 1$ for the map COMMANDER. Symbols indicate measurements from observations, orange lines show the best-fitting model to these, green lines present the gas profile corresponding to the best-fitting model, and error bars denote 1σ uncertainties. In broad strokes, the value of $\tau_{AP}$ grows with $\theta_{AP}$, reaches a maximum, and decreases thereafter. As we can see, our model captures this trend precisely.

estimated via LHS and Markov Chain Monte Carlo (MCMC) sampling are essentially the same; we resort to LHS for computational efficiency. We follow this procedure to estimate error bars throughout the remainder of this section.

6.2 Location and density of the kSZ gas

According to the location of baryons relative to galaxies, these are classified into three main phases: interstellar medium (ISM), involving gas filling the space between stars in a galaxy, circumgalactic medium (CGM), including gas outside galaxies but within the virial radius of dark matter haloes, and intergalactic medium (IGM), comprising gas outside haloes. In this section, we start by assessing the location of baryons detected via ARF-kSZ tomography; then, we compute the average density of these baryons.
in §6.1, we compute the fraction of baryons within haloes as follows

$$f_{\text{collapse}} = \frac{\int_{r_{\text{in}}}^{r_{\text{out}}} \Delta_{\text{gas}}(r) \, dr}{\int_{r_{\text{in}}}^{r_{\text{out}}} \Delta_{\text{gas}}(r) \, dr},$$

(22)

where $r_{\text{in}} = 2 \, h^{-1}\text{Mpc}$ indicates our choice for the extent of the CGM, while $r_{\text{out}} = 10 \, h^{-1}\text{Mpc}$ refers to the maximum aperture considered for most shells. The virial radius of the host haloes of 6dF galaxies, SDSS-G galaxies, and SDSS-Q quasars is much smaller than $2 \, h^{-1}\text{Mpc}$; we select this value for $r_{\text{in}}$ to ensure that we do not overestimate the fraction of kSZ gas in the IGM. On the other hand, note that the value of $f_{\text{collapse}}$ depends weakly on $r_{\text{out}}$; this is because according to the best-fitting overdensity profiles more than 75% of the kSZ gas resides to within $10 \, h^{-1}\text{Mpc}$ from the tracers.

In the top panel of Fig. 10, we display the value of $f_{\text{collapse}}$ for redshift shells with statistically significant measurements of the kSZ effect. We use the same coding as in Fig. 9. As we can see, more than 90% of the baryons detected via ARF-kSZ tomography reside in the IGM; interestingly, this is in line with the fraction of diffuse gas located in this phase according to state-of-the-art cosmological hydrodynamical simulations (Martizzi et al. 2019). Note that the value of $f_{\text{collapse}}$ is much higher for the shell centred at $z_{\text{eff}} = 0.09$ because the maximum aperture considered for this shell corresponds to $3.5 \, h^{-1}\text{Mpc}$, biasing the results towards gas close to haloes.

We now proceed to compute the average overdensity of kSZ gas in the IGM using

$$\Delta_h = \frac{3}{r_{\text{out}} - r_{\text{in}}} \int_{r_{\text{in}}}^{r_{\text{out}}} r^2 \Delta_{\text{gas}}(0, r) \, dr,$$

(23)

where the values chosen for $r_{\text{in}}$ and $r_{\text{out}}$ are the same as those considered above. In the bottom panel of Fig. 10, we show the average overdensity of kSZ gas in the IGM. We find that the average overdensity of IGM gas ranges from 10 to 250 times the cosmic density, in agreement with predictions from hydrodynamical simulations for the density of IGM gas in filaments and sheets (Martizzi et al. 2019). Taken together with the fraction of kSZ gas in the IGM, these results strongly suggest that ARF-kSZ tomography is mostly sensitive to IGM gas in filaments and sheets.

### 6.3 Abundance of the kSZ gas

Due to the sensitivity of the kSZ effect to all ionized gas moving with respect to the CMB rest frame, ARF-kSZ tomography is especially suited to conduct a baryonic census in the late universe. In closely related contexts, Hernández-Monteagudo et al. (2015) and Hill et al. (2016) resorted to kSZ measurements to set constraints on the amount of gas surrounding, respectively, galaxies at $z \sim 0.1$ from the seventh data release of the SDSS survey (Abazajian et al. 2009), and galaxies at $z \sim 0.3$ from the Wide-field Infrared Survey Explorer (WISE; Wright et al. 2010), finding that their measurements were compatible with detecting all baryons surrounding these sources. In this section, we start by exploring the ability of ARF-kSZ tomography to detect baryons as a function of the number density of tracers employed; then, we carry out a baryonic census from the local universe to $z \simeq 5$.

To determine the cosmic baryon fraction that we detect via ARF-kSZ tomography, we create HEALPIX maps onto which we project the distribution of gas surrounding tracers. We proceed as follows for each redshift shell. First, we select all pixels to within 22 arcmin from the sky coordinates of...
ARF-kSZ tomography

Figure 11. Cosmic baryon fraction detectable via ARF-kSZ tomography as a function of the number density of tracers considered. Lines indicate the results for redshift shells with comoving width $\sigma_r = 180 h^{-1} \text{Mpc}$ and centres at different redshifts. As we can see, the value of $f_b$ increases with the number density of tracers, asymptotically approaching a limiting value that depends on the parameters controlling the overdensity gas profile. 

one of the tracers selected under this shell, and we assign to these the integral of the overdensity gas profile over their area

$$M_{\text{gas}}(\Omega_j) = \int_{A_j} dA \int \Delta_{\text{gas}}(r_g, r) \phi(r_g) \, dl,$$  \hspace{1cm} (24)$$

where $A_j$ indicates the area of the pixel $j$, $dA \equiv \theta \, d\theta \, d\phi$ denotes the differential area element in cylindrical coordinates, $\theta$ and $l$ refer to the axial and vertical coordinates of an imaginary cylinder centred at this tracer, $r = \sqrt{\theta^2 + l^2}$ is the radial distance in spherical coordinates, and $r_g$ is the distance to this tracer. $M_{\text{gas}}$ has thus units of volume. We then iterate over all other tracers selected under this shell; if more than one of these lies to within 22 arcmin from the same pixel, we assign to this pixel the maximum value of $M_{\text{gas}}$ found for tracers satisfying this condition. The primary purpose of doing so is to avoid accounting for the same gas more than once.

Finally, we compute the cosmic baryon fraction that we detect in this shell using

$$f_b = \frac{\sum_j M_{\text{gas}}(\Omega_j)}{V_{\text{shell}}},$$  \hspace{1cm} (25)$$

where $V_{\text{shell}} = 4\pi f_{\text{sky}} \int dz' \int_{\theta_{\text{min}}}^{\theta_{\text{max}}} \int_{\ell_{\text{min}}}^{\ell_{\text{max}}} [r(z')]^2 \phi(z')$ is the volume subtended by the shell, and $f_{\text{sky}}$ stands for the sky fraction covered by the footprint of the selected sample. Note that to perform these calculations we resort to HEALPix maps of resolution $N_{\text{side}} = 1024$; we check that the value of $f_b$ remains unchanged for maps with higher resolution.

Qualitatively, we expect the cosmic baryon fraction to increase with the number of tracers considered, and asymptotically approach unity as the cosmic volume sampled by these approaches $V_{\text{shell}}$. For a more quantitative assessment, we generate mock samples of tracers both randomly distributed on the sphere and uniformly sampling the selection function, while holding fixed the parameters controlling the overdensity profile to $\Delta_b = 100$ and $r_s = 10 h^{-1} \text{Mpc}$. In Fig. 11, we display the value of $f_b$ for each of these mock samples. Lines indicate the results for shells with comoving width $\sigma_r = 180 h^{-1} \text{Mpc}$ and centres at different redshifts, while the $x$-axis denotes the number density of tracers weighted by the selection function, $n_\phi = V_{\text{shell}}^{-1} \sum_i \phi_i$.

As we can see, the detectable cosmic baryon fraction grows with the number of tracers and approaches a limiting value; thereby confirming our predictions. At a fixed number density, we also find that the cosmic baryon fraction is redshift-dependent; in contrast, its limiting value is reached for number densities greater $n_\phi^{\text{lim}} \simeq 10^{-1} h^3 \text{Mpc}^{-3}$ at all redshifts. In this basic exercise, the limiting value of $f_b$ is smaller than unity because the amplitude chosen for the overdensity profile is too low. Taken together, we conclude that ARF-kSZ tomography is sensitive to all diffuse baryons for number densities greater than $n_\phi^{\text{lim}}$.

Following the procedure described above, we conduct a baryonic census from $z \approx 0$ to 5. In Fig. 12, we display the cosmic baryon fraction that we detect in redshift shells with statistically significant results. We find that the value of $f_b$ is approximately one half for most redshifts; consequently, ARF-kSZ tomography is sensitive to $\approx 50\%$ of all baryons in the Universe. Interestingly, $\approx 80\%$ of the baryonic matter resides in the intergalactic medium according to a recent baryonic census (Nicastro et al. 2018); taken together in combination with the fact that ARF-kSZ tomography is mostly sensitive to IGM gas, our measurements are compatible with detecting nearly all baryons in the intergalactic medium.

As we can see, the value of $f_b$ is greater than unity for quasars at $z_{\text{eff}} = 0.73$ and 0.92. Given that these two
values are correlated and compatible with unity at the 2σ level, this is likely due to random fluctuations. In contrast, we find that the cosmic baryon fraction at $z_{\text{eff}} = 0.09, 4.02$, and 4.62 is well below unity. To gain further insight into why these shells present such a small $f_b$, we consider the influence of the number density of tracers on the results. In Fig. 12, triangles indicate the limiting value of $f_b$ for the best-fitting overdensity profile to COMMANDER data. We can see that the limiting value of $f_b$ is above unity for all shells, even for those at $z_{\text{eff}} = 0.09, 4.02$, and 4.62, thereby letting us conclude that the cosmic baryon fraction is very low for these shells due to the reduced number of tracers selected under these.

It is important noticing that the limiting value of $f_b$ does not translate into the cosmic baryon fraction that we would measure by considering more tracers; this is explained as follows. When computing the limiting value of $f_b$, we hold fixed the parameters controlling the best-fitting overdensity profile; nonetheless, the amplitude of the overdensity profile is inversely proportional to the linear-bias of the tracers (see §7.3), which decreases by increasing the number of sources considered. Even though the limiting value of $f_b$ thus provides an upper limit to the cosmic baryon fraction, it serves the purpose of indicating how $f_b$ evolves with the number density of tracers.

7 ROBUSTNESS OF THE RESULTS

In this section, we first address the robustness of ARF-kSZ tomography against residual foreground-contamination in §7.1 and observational systematics in §7.2. Then, we explore the impact of the linear bias of the tracers on measurements of the kSZ optical depth in §7.3, and in §7.4 we finish exploring whether the location, density, and abundance of kSZ gas are sensitive to the functional form assumed for the overdensity profile.

7.1 CMB foreground contamination

The most important sources of foreground contamination to the CMB are synchrotron, free-free, and dust emission from our Galaxy (e.g., Tegmark et al. 2000). Due to differences in the spectral shape of foregrounds and primordial CMB anisotropies, reducing the impact of these on CMB observations is straightforward when considering data from a few different frequency bands (e.g., Planck Collaboration et al. 2016b); to do so, the Planck collaboration resorts to four distinct foreground-cleaning algorithms (see §5.1). In this section, we first address the impact of residual foreground contamination not subtracted from these cleaning procedures on ARF-kSZ tomography. Then, we consider other effects that could affect our measurements.

In each panel of Fig. 13, we display measurements of the kSZ optical depth extracted from a distinct foreground-cleaning map for SDSS-G galaxies at $z_{\text{cen}} = 0.56$. As we can readily see, kSZ measurements from distinct maps are very similar, which is consistent with the fact that the cross-correlation of ARF and filtered CMB maps is weakly affected by foregrounds (see §5.3).

The tSZ effect, which results from CMB photons inverse Compton scattering off hot electrons in haloes and filaments, is another possible source of contamination. Nonetheless, temperature variations induced by the tSZ effect are not correlated with either angular redshift fluctuations nor the kSZ effect; this is because at a fixed frequency the former results in same sign anisotropies, while the latter induce positive and negative fluctuations. Furthermore, due to the steep decrease of the tSZ magnitude with halo mass, current CMB surveys can only detect clusters of $M_{\text{cen}} = 4 \times 10^{14} h^{-1} M_\odot$ masses via tSZ studies (e.g., Bleem et al. 2019). Given that the galaxies and quasars that we consider in this work reside in much lighter haloes (see §5.1), we expect very low tSZ emission from these. In Fig. 13, we can see that measurements extracted from SMICA-NOSZ, the only map attempting to reduce tSZ contamination, are indeed very close to those from other foreground-cleaning maps.

Taken together, these results strongly suggest that ARF-kSZ tomography is robust against residual contamination affecting CMB maps; this is further supported by the fact that the breadth of the symbols in Figs. 9, 10, and 12, which indicate the results for distinct maps, is smaller than error bars, which capture other sources of uncertainty.

7.2 Observational systematics

In §3, we argue that ARF and filtered CMB maps are both robust against systematic uncertainties affecting the angular number density of sources. Distinct effects may induce this type of systematics in galaxy surveys (e.g., Ross et al. 2017), including seeing, sky background, airmass, galactic extinction, and stellar density. In this section, we characterise the impact of angular systematics on the cross-correlation of ARF and filtered CMB maps.

To study the effect of angular systematics on ARF-kSZ tomography, we resort to the suite of COLA lightcone simulations described in §4.1. Specifically, we create sky maps of ADF, ARF, and radial peculiar velocities following the same procedure as in §4.1 after modulating the angular number density of dark matter particles in the lightcones according to a Planck map of Galactic extinction (Planck Collaboration et al. 2014a).

In Fig. 14, we present the impact of angular systematics on the power spectrum of ADF, ARF, and radial peculiar velocity maps, and the cross-correlation of ARF and radial peculiar velocity maps. As discussed in §4.1, the latter presents, at first order and modulo a sign, the same dependence on cosmological parameters as the cross-correlation of ARF and filtered CMB maps. Symbols indicate measurements from simulations after modulating the angular number density of sources according to the extinction map, while lines denote theoretical predictions. As expected, only the power spectrum of ADF maps is affected by these systematics. More quantitatively, in the bottom panel of Fig. 14 we display the relative difference between the power spectra of maps with and without angular modulation. As we can see, the impact of angular systematics on the cross-correlation of ARF and radial peculiar velocity maps is below the 1% level, letting us conclude that ARF-kSZ tomography is very robust against this type of systematics.

3. http://pla.esac.esa.int/pla/aio/product-action?MAP_MAP_ID=CDM_CompMap_Dust-DL07-AvMaps_2048_B2.00.fits

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7.3 Large-scale bias of tracers

To extract the kSZ optical depth from a set of tracers, we need to specify the large-scale bias of these (see §5). In this section, we explore how uncertainties in their bias translate into changes in the kSZ optical depth.

Even though we can propagate uncertainties in the large-scale bias through our methodology, these uncertainties are not usually provided in the literature. We thus restrict ourselves to the following sensitivity analysis. We extract the kSZ optical depth from each sample after assuming slightly different values for the large-scale bias, finding that an increment of 10% in its value translates into an equivalent decrement in the kSZ optical depth: this is because density terms dominate the amplitude of $C_y^T$ for all shells considered in §5. We check that this proportionality is maintained up to variations of the order of 50% in the large-scale bias. Given that the amplitude of the best-fitting overdensity profile to kSZ measurements increases with the amplitude of these, underestimating the large-scale bias of tracers results in overestimating the cosmic baryon fraction.

7.4 Functional form of the overdensity profile

Setting constraints on the properties of the gas responsible for kSZ measurements in §6 required adopting a specific functional form for the overdensity profile of this gas. We considered a $\beta$-profile because this profile is flexible enough to capture the distribution of gas surrounding haloes of different masses in cosmological hydrodynamical simulations (see §4.2). In this section, we address the impact of this election on the results.

In §4.2, we showed that not only a $\beta$-profile but also a double exponential profile are flexible enough to capture the distribution of gas surrounding haloes of different masses in hydrodynamical simulations. Conversely, we found that a Gaussian profile cannot do it. Following the same methodology as in §6.1 for a $\beta$-profile, we proceed to set constraints on the parameters controlling these two other functional forms. We find that the $\beta$-profile and the double exponential profile result in very similar constraints for the location, density, and abundance of baryons, while a Gaussian profile yield noticeably different results. Taken together, we conclude that any functional form able to capture physically motivated...
overdensity gas profiles leads to essentially the same constraints on the kSZ gas.

8 SUMMARY AND CONCLUSIONS

Detecting intergalactic gas in the late universe is very challenging due to intermediate temperatures of this gas and the rarefied character of the intergalactic medium; as a result, determining the large-scale distribution of baryons at late times is a long-standing problem in cosmology. In this work, we set constraints on the location, density, and abundance of intergalactic gas using ARF-kSZ tomography, a novel approach for extracting the kinematic Sunyaev-Zel’dovich effect from the cross-correlation of large-scale structure and CMB observations. We proceed to summarise our main findings.

• We start establishing the theoretical foundations of ARF-kSZ tomography in §2 and 3. This technique consists of extracting the kSZ effect from the cross-correlation of sky maps of angular redshift fluctuations, which encode precise information about the cosmic density and velocity fields, and CMB maps high-pass filtered using aperture photometry. Then, we resort to cosmological simulation to gain further insight into ARF-kSZ tomography in §4.

• In §5, we carry out a tomographic study of the kSZ effect from $z = 0$ to 5 using ARF-kSZ tomography. To do so, we cross-correlate foreground-cleaned CMB maps publicly released by the Planck collaboration and ARF maps generated using galaxies and quasars from the 6dF Galaxy Survey and the Sloan Digital Sky Survey. Remarkably, ARF-kSZ tomography results in a $>10\sigma$ detection of the kSZ effect across this redshift range.

• In §6, we resort to measurements of the kSZ optical depth to set constraints on the properties of gas responsible for the kSZ effect. In Fig. 10, we show that more than 90% of this gas resides outside haloes and that its average density ranges from 10 to 250 times the cosmic average, which is the density of baryons in filaments and sheets according to cosmological hydrodynamical simulations. Taken together, these results let us conclude that ARF-kSZ tomography is mostly sensitive to IGM gas.

• In §6.3, we conduct a baryonic census from $z \approx 0$ to 5 using results from ARF-kSZ tomography, finding that this technique is sensitive to approximately half of the baryons in the Universe.

Throughout this work, we do not let vary cosmological parameters when extracting the kSZ optical depth; this is because the precision of our measurements is not high enough for cosmological studies. On the other hand, future CMB experiments like CMB-S4 and galaxy surveys such as DESI, Euclid, J-PAS, SPHEREx, and WFIRST will deliver precise datasets with which we envision setting constraints on cosmological parameters using ARF-kSZ tomography. These constraints will be very reliable owing to the robustness of this technique against systematics and because the cosmological information encoded in ARF-kSZ tomography resides mostly on large and well-understood scales.

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Figure 14. Impact of angular systematics on the power spectrum of ADF, ARF, and radial peculiar velocity maps, and on the cross-correlation of the last two. Symbols indicate results from simulations after modulating the angular number density of tracers according to Galactic extinction, while lines present theoretical predictions. In the bottom panel, we display the relative difference between the power spectra of maps with and without angular systematics. As we can see, the impact of angular systematics on the power spectrum of ARF and radial velocity maps, as well as on their cross-correlation, is below 1%, letting us conclude that ARF-kSZ tomography is very robust against this type of systematics.
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