Interferometric HI intensity mapping: perturbation theory predictions and foreground removal effects

Alkistis Pourtsidou$^{1,2,3}$

$^1$ Institute for Astronomy, The University of Edinburgh, Royal Observatory, Edinburgh EH9 3HJ, UK
$^2$ Higgs Centre for Theoretical Physics, School of Physics and Astronomy, The University of Edinburgh, Edinburgh EH9 3FD, UK
$^3$ Department of Physics & Astronomy, University of the Western Cape, Cape Town 7535, South Africa

ABSTRACT

We provide perturbation theory predictions for the HI intensity mapping power spectrum multipoles using the Effective Field Theory of Large Scale Structure (EFTofLSS), which should allow us to exploit mildly nonlinear scales. Assuming survey specifications typical of proposed interferometric HI intensity mapping experiments like CHORD and PUMA, and realistic ranges of validity for the perturbation theory modelling, we run mock full shape MCMC analyses at $z = 0.5$, and compare with Stage-IV optical galaxy surveys. We include the impact of 21cm foreground removal using simulations-based prescriptions, and quantify the effects on the precision and accuracy of the parameter estimation. We vary 11 parameters in total: 3 cosmological parameters, 7 bias and counterterms parameters, and the HI brightness temperature. Amongst them, the 4 parameters of interest are: the cold dark matter density, $\omega_c$, the Hubble parameter, $h$, the primordial amplitude of the power spectrum, $A_s$, and the linear HI bias, $b_1$. For the best case scenario, we obtain unbiased constraints on all parameters with $< 3\%$ errors at $68\%$ confidence level. When we include the foreground removal effects, the parameter estimation becomes strongly biased for $\omega_c$, $h$, and $b_1$, while $A_s$ is less biased ($< 2\%$). We find that scale cuts $k_{\text{min}} \geq 0.03 h$/Mpc are required to return accurate estimates for $\omega_c$ and $h$, at the price of a decrease in the precision, while $b_1$ remains strongly biased. We comment on the implications of these results for real data analyses.

Key words: cosmology: theory – cosmology: observations – large-scale structure of the Universe – methods: statistical

1 INTRODUCTION

Over the next few years, observations of the redshifted 21cm line emission from neutral hydrogen gas (HI) with a new generation of radio telescopes can push the boundaries of our understanding of cosmology and galaxy evolution. Remarkably, HI surveys can trace the matter distribution from the present time ($z = 0$) to the Epoch of Reionization ($z \sim 10$) and beyond, mapping a large part of the observable volume of the Universe.

In the meantime, spectroscopic optical galaxy surveys have already proven extremely successful at mapping the low redshift Universe, and providing exquisite constraints on dark energy and gravity (see, for example, Mueller et al. 2018; Alam et al. 2021). These surveys operate by detecting galaxies in 3D, i.e., by measuring the redshift and angular position of each galaxy very precisely. In the radio wavelengths, due to the weakness of the HI signal, being competitive with optical galaxy surveys using the traditional approach of detecting individual galaxies is extremely challenging. This challenge gave rise to an alternative observational technique, dubbed HI intensity mapping, which maps the entire HI flux coming from many galaxies together in 3D voxels. (Battye et al. 2004; Chang et al. 2008; Peterson et al. 2009; Seo et al. 2010; Ansari et al. 2012). Provided several observational challenges and systematic effects are mitigated or controlled, the HI intensity mapping method has the potential to provide detailed maps of the Universe back to ~1 billion years after the Big Bang (Ahmed et al. 2019; Kovetz et al. 2020; Moresco et al. 2022).

A number of HI intensity mapping experiments are expected to come online over the coming years, with some of them already taking data with pilot surveys. Examples are the proposed MeerKAT survey using the South African MeerKAT array (Santos et al. 2017), FAST (Hu et al. 2020), CHIME (Bandura et al. 2014), HIRAX (Newburgh et al. 2016; Crichton et al. 2022), Tianlai (Li et al. 2020; Wu et al. 2021), PUMA (Slosar et al. 2019), and CHORD (Vanderlinde et al. 2019). Pathfinder surveys with the Green Bank Telescope (GBT), Parkes, CHIME, and MeerKAT, have achieved detections of the cosmological 21 cm emission, but have relied on cross-correlation analyses with optical galaxy surveys (Chang et al. 2010; Masui et al. 2013; Anderson et al. 2018; Wolz et al. 2022; Amiri et al. 2022a; Cunnington et al. 2022).

A major challenge for the HI intensity mapping method is the presence of strong astrophysical emission: 21cm foregrounds such as galactic synchrotron (Zheng et al. 2017), point sources, and free-free emission, contaminate the maps and can be orders of magnitude stronger than the cosmological HI signal (Oh & Mack 2003). Hence, they have to be removed. We can differentiate these dominant foregrounds from the signal taking advantage of their spectral smoothness (Liu & Tegmark 2011; Chapman et al. 2012; Wolz et al. 2014; Shaw et al. 2016). Providing foreground removal effects are properly estimated, the future of HI intensity mapping as a tool for cosmology is promising. In this paper we study the impact of 21cm foreground removal on the estimation of cosmological parameters using a combination of data from pilot surveys and simulations.
et al. 2015; Alonso et al. 2015; Cunnington et al. 2020). As an example, 21cm foreground removal studies using low redshift Hı intensity mapping simulations and real data employ blind foreground removal techniques like Principal Component Analysis (PCA) (Switzer et al. 2013, 2015; Alonso et al. 2015) or Independent Component Analysis (Hyvärinen et al. 1999; Wolz et al. 2017). The procedure of foreground removal results in Hı signal loss, removing power from modes along the parallel and perpendicular to the line-of-sight (LoS) directions, with the parallel to the LoS effect being more severe than the perpendicular one (Witzemann et al. 2019; Cunnington et al. 2020).

The aim of this work is to investigate the systematic biases from 21cm foreground removal assuming state-of-the-art interferometric perpendicular and parallel to the line-of-sight (LoS) directions, with the parallel to the LoS and perpendicular to the line-of-sight (LoS) directions, 21cm foreground removal effects. We will also benchmark our predictions against a “Stage-IV” spectroscopic optical galaxy survey like DESI (Aghamousa et al. 2016) or Euclid (Laureijs et al. 2011; Blanchard et al. 2018). The noise power spectrum for a typical interferometer (linear) Hı brightness temperature. The antennae distribution function

\begin{equation}
\mathcal{P}_{\text{HI}}(k,\mu) = \left(\mathcal{T}_{\text{HI}}b_1 + \mathcal{T}_{\text{HI}}f \mu^2\right)^2 P_{\text{HI}}(k) + P_{\text{SN}} + P_N \tag{1}
\end{equation}

Here, \( P_{\text{HI}}(k) \) is the underlying matter power spectrum, \( b_1 \) is the (linear) Hı bias, and \( \mathcal{T}_{\text{HI}} \) is the mean Hı brightness temperature. \( P_N \) is the thermal noise of the telescope and \( P_{\text{SN}} \) is the shot noise, \( P_{\text{SN}} = \mathcal{T}_{\text{HI}}^2/(1/\pi) \), where \( \pi \) is the number density of objects. The \( P_{\text{SN}} \) contribution is expected to be subdominant (smaller than the thermal noise of the telescope) and is usually neglected (Villaescusa-Navarro et al. 2018). The noise power spectrum for a typical interferometer is given by (Zaldarriaga et al. 2004; Bull et al. 2015): \( P_N = \mathcal{T}_{\text{sys}}^2 r y_\nu \left(\frac{A_{\nu}}{A_L^2}\right)^2 \frac{1}{2\pi(\nu-k_r/2\pi)} \left(\frac{S_{\text{area}}}{\text{FOV}}\right) \tag{2} \)

Here, \( A_L \) is the effective beam area, \( \text{FOV} \approx A/(D_{\text{dish}})^2 \), \( r \) is the comoving distance to the observation redshift \( z \), and \( y_\nu = c(1+z)^2/(\nu_0 H(z)) \) with \( \nu_0 = 1420 \text{ MHz} \). \( T_{\text{sys}} \) is the system temperature, \( S_{\text{area}} \) is the survey area, and \( f_{\text{total}} \) is the total observing time.

The antennae distribution function \( n(a) \) can be calculated using a fitting formula (Ansari et al. 2018). For a square array with \( N_s^2 \) receivers, the number of baselines as a function of physical distance of antennas is given by

\begin{equation}
n_b^\text{phys}(l) = n_0 \frac{a + b(l/L)}{1 + c(l/L)} e^{-(l/L)r}, \tag{3}
\end{equation}

where \( n_0 = (N_s/D_{\text{dish}})^2 \), \( L = N_s D_{\text{dish}} \), and the \( uv \)-plane density is

\begin{equation}
n(u) = l^2 n_b^\text{phys}(l = u_l). \tag{4}
\end{equation}

The Hı abundance and clustering properties have been studied using simulations and semi-analytical modeling (see, e.g., Padmanabhan et al. 2017; Villaescusa-Navarro et al. 2018; Spinelli et al. 2020). The clustering of Hı should be accurately described by perturbative methods at mildly nonlinear scales (Sarkar et al. 2016; McQuinn & D’Aloisio 2018; Sarkar & Bharadwaj 2019; Castorina & White 2019; Sailer et al. 2021; Karagiannis et al. 2022; Qin et al. 2022). Modelling nonlinear scales is necessary in order to get precise and accurate cosmological constraints with instruments like HIRAX, CHIME, CHORD, and PUMA, and it also helps break degeneracies, for example between \( b_1 \) and the primordial power spectrum amplitude, \( A_s \). Similar degeneracies exist for \( \Omega_\text{HI} \), which is proportional to the Hı mean density, \( \Omega_\text{HI} \). Accurate (< 5%) measurements of \( \Omega_\text{HI}(z) \) are available at low redshifts (Crighton et al. 2015), and it can also be constrained by joint analyses of different probes (Obuljen et al. 2018; Chen et al. 2019) or by exploiting very small scales that can be described using bespoke Hı halo models (Chen et al. 2021).

In this work we will use the “EFTofLSS” formalism that has been developed to model the power spectrum multipoles of biased tracers in redshift space. The main difference between this model and the standard 1-loop Standard Perturbation Theory (SPT) formalism (Bernardeau et al. 2002) is that the EFTofLSS approach accounts for the impact of nonlinearities on mildly nonlinear scales by introducing effective stresses in the equations of motion. This results in the addition of counterterms to the 1-loop power spectrum, which represent the effects of short distance physics at long distances.

The EFTofLSS model we will employ is described in various papers (see e.g. Perko et al. (2016) and references therein), and we refer to D’Amico et al. (2020) for its application to the DR12 BOSS data. Main assumptions are that we live in a spatially expanding, homogeneous and isotropic background spacetime, and that we work on sub-horizon scales with \( \delta, \theta \ll 1 \) (where \( \delta \) and \( \theta \) are the density and velocity perturbations, respectively).

The 1-loop redshift space galaxy power spectrum then reads (Perko et al. 2016; D’Amico et al. 2020):

\begin{equation}
P_g(k,\mu) = Z_1(\mu) Z_2(\mu) P_{11}(k) + 2 \int \frac{d^3 q}{(2\pi)^3} Z_2(q, k-q, \mu) P_{11}(\mu) P_{11}(q) + 6 Z_1(\mu) P_{11}(k) \int \frac{d^3 q}{(2\pi)^3} Z_3(q, k, \mu) P_{11}(q) + 2 Z_1(\mu) P_{11}(k) \left( c_{\text{cl}} \frac{k^2}{k_M^2} + c_{r,1} \frac{Z_1^2}{k_M^2} + c_{r,2} \frac{Z_2^2}{k_M^2} + c_{r,3} \frac{Z_3^2}{k_M^2} \right) + \frac{1}{n_g} \left( c_{\text{cl}} + c_{r,2} \frac{k_2^2}{k_M^2} + c_{r,3} \frac{k_3^2}{k_M^2} \right), \tag{5}
\end{equation}

where \( k_M = 0.7 h/\text{Mpc} \) and \( n_g \) is the mean galaxy density. The various terms are summarised nicely in Nishimichi et al. (2020), and we follow this description here: the \( c_{\text{cl}} \) term represents a combination
of a higher derivative bias and the speed of sound of dark matter; the \( c_{i,j} \) terms represent the redshift-space counterterms, while the \( c_{e,i} \) terms represent the stochastic counterterms. The kernels \( Z_1, Z_2, \) and \( Z_3 \) are the redshift-space galaxy density kernels appearing in the 1-loop power spectra. They are expressed in terms of the galaxy density and velocity kernels and 4 bias parameters: \( \{b_1,b_2,b_3,b_4\} \).

For flat CDM, which we will assume in this work, the logarithmic growth rate \( f \) is calculated by solving for the linear growth factor \( D \) (with \( a \) the scale factor), and yields: \( f(a) = \frac{(5a-3D(a))\Omega_m}{D\Omega_m^2 + a(1-\Omega_m)} \).

The model of Equation 5 has recently been implemented in a publicly available Python code, PyBird (D’Amico et al. 2021). In principle, the model can describe any biased tracer of matter, so we can straightforwardly apply it to H\( \iota \). Following the literature we perform the following changes of variables: \( b_2 = \frac{1}{\sqrt{6}}(c_2 + c_4), b_4 = \frac{1}{\sqrt{2}}(c_2 - c_4), c_{e,\text{mono}} = c_{e,1} + \frac{1}{2}c_{e,2}, c_{e,\text{quad}} = \frac{3}{2}c_{e,2}, \) and also fix \( c_4 = c_{r,2} = c_{e,\text{mono}} = 0 \) so that our final set of nuisance parameters is: \( \{b_1,c_2,c_3,c_{e,1},c_{e,1},c_{e,2}\} \).

We will comment on these choices when we construct our mock data in section 3.

The cosmological parameters that the code takes as input are: the cold dark matter density \( \Omega_c = \Omega h^2 \), the baryonic matter density \( \omega_b = \Omega h^2 \), the Hubble parameter \( h \), the amplitude of the primordial power spectrum, \( A_s \), and the scalar spectral index, \( n_s \).

We describe the code and other software we used to speed-up the parameter inference in more detail in section 4.

### 3 MOCK DATA

For our analysis we produce synthetic H\( \iota \) monopole and quadrupole data running PyBird for a central redshift \( z = 0.5 \). We will not use the hexadecapole as it is not expected to add significant cosmological information, and it is more affected by nonlinear uncertainties. In addition, as shown in Cunnington et al. (2020); Soares et al. (2021), the H\( \iota \) intensity mapping hexadecapole (as well as higher order multipoles) can be used for identifying the effects of foreground removal and other systematics. Not using the hexadecapole allows us to set \( c_{r,2} = 0 \). The choice \( c_4 = c_{e,\text{mono}} = 0 \) is motivated by the assumption that the functions multiplying \( c_4 \) and \( c_{e,\text{mono}} \) are too small to affect the results. These assumptions follow the BOSS data analyses choices (D’Amico et al. 2020), but they will need to be reaffirmed with bespoke H\( \iota \) simulations and real data. The fiducial cosmological parameters are (Aghanim et al. 2020):

\[
\{\Omega_c, h, A_s, \omega_b, n_s\} = \{0.1193, 0.677, 3.047, 0.0224, 0.967\}.
\]

For setting the fiducial values of the nuisance parameters, we perform fits to H\( \iota \) intensity mapping simulations. These are described in section A, and we find:

\[
\{b_1,b_2,b_3,c_{e,1},c_{e,1},c_{e,\text{quad}}\} = \{1.1, 0.6, 0.1, 0.1, -10.0, 0.0, -0.8\}.
\]

We remark that the value of the linear H\( \iota \) bias \( b_1 \) is in very good agreement with values found at similar redshifts in other works (Sarkar et al. 2016; Villaescusa-Navarro et al. 2018). We also note that in all our MCMC forecasts we will marginalise over the nuisance parameters.

The model in Equation 5 has to be rescaled by the square of the H\( \iota \) brightness temperature, \( T_{\text{HI}}(z) \), which in turn depends on the H\( \iota \) abundance, \( \Omega_{\text{HI}}(z) \). Using the fitting function from SKA Cosmology SWG et al. (2020) we set \( T_{\text{HI}}(z = 0.5) = 0.168 \) mK as our fiducial value for this parameter.

We also need a data covariance. To calculate this we will assume an ambitious CHORD-like intensity mapping survey (Vanderlinde et al. 2019). CHORD (Canadian Hydrogen Observatory and Radio transient Detector) is a successor to CHIME (Amiri et al. 2022b), aiming to perform a very large sky H\( \iota \) intensity mapping survey. Its core array consists of 512 dishes, each 6m in diameter. The bandwidth is large, covering the 300-1500 MHz band, or redshifts up to \( z = 6 \). We will assume \( T_{\text{sys}} = 50 \) K in our forecasts. Another very ambitious proposal is PUMA, a close-packed interferometer array with 32,000 dishes, covering the frequency range 200-1100 MHz, or redshifts 0.3 < \( z \) < 6 (Slosar et al. 2019). We expect both of these instruments to be able to achieve similar signal-to-noise ratios \( (S/N) \), and we will focus on CHORD from now on.

Aiming to establish how CHORD can complement and compete with state-of-the-art optical galaxy surveys, we choose a low redshift bin centred at \( z = 0.5 \) with width \( \Delta z = 0.3 \). Our fiducial CHORD-like survey covers 20,000 deg\(^2\) on the sky, resulting in a survey bin volume \( V_{\text{sur}} = 4246^3 \) (Mpc/\( h \))^3. We assume a 20,000 hrs survey and calculate the noise power spectrum using Equation 2, with the fitting parameters needed in Equation 4 being \( a = 0.4847, b = -0.3300, c = 1.3157, d = 1.5974, e = 6.8390 \) (Ansari et al. 2018). The corresponding baseline density \( n(u) \) for our CHORD-like array is shown in Figure 1 (see Appendix A of Karagiannis et al. 2022) for the case of a HI-RAX-like array.

We can now calculate \( P_N \) for our CHORD-like survey using Equation 2. Dividing by \( T_{\text{HI}}^2 \) and inverting, we can define an effective mean number density \( \bar{n}_{\text{HI}} \). For a Stage-IV spectroscopic galaxy survey like DESI (Aghamousa et al. 2016) or Euclid (Laureijs et al. 2011;Blanchard et al. 2020), the shot noise is the inverse of the number density of galaxies, \( \bar{n}_g \). In Figure 2 we plot the signal-to-noise-ratio (squared) for the power spherically averaged power spectrum (the monopole, \( P_0 \)) for different surveys. Stage-IV corresponds to a spectroscopic optical galaxy survey with \( \bar{n}_g = 0.0005 \) h\(^3\)/Mpc\(^3\). “CHORD-optimal” corresponds to an idealised case for an interferometric H\( \iota \) intensity mapping survey without any systematic effects, while “CHORD-with-sys” illustrates the case where sensitivity is lost at small \( k \) (see also Fig. 15 in (Ansari et al. 2018)). This can be due to foreground removal effects which mainly affect the small \( k \) and/or inability to probe the small \( k \) due to baseline restrictions. For the case of the CHORD-like survey at \( z = 0.5 \), this can result to loss of sensitivity in a range \( \sim 0.001 \leq k \leq 0.06 \) h/Mpc, and we will consider different \( k_{\text{min}} \) scale cuts in our forecasts to take this into account. In all cases, Figure 2 demonstrates that a CHORD-like experiment can achieve a higher signal-to-noise-ratio in the nonlinear regime, compared to a Stage-IV optical galaxy survey.

We can now proceed to calculate the multipole covariances analyt-
Figure 2. Signal-to-noise-ratio (squared) for the spherically averaged power spectrum, $P_0$, for different surveys. “Optical Stage-IV” represents a spectroscopic galaxy survey with $n_g = 0.0005 \, h^3 \, \text{Mpc}^{-3}$. “CHORD-optimal” corresponds to an idealised Hi intensity mapping survey, while “CHORD-with-sys” illustrates the case where sensitivity is lost at small $k$.

Figure 3. Our fiducial monopole ($\ell = 0$) and quadrupole ($\ell = 2$) data, assuming the CHORD-optimal Hi intensity mapping survey. The vertical dashed grey line denotes the maximum wavenumber (smallest scale used in the MCMC) $k_{\text{max}} = 0.2h/\text{Mpc}$ at our chosen central redshift $z = 0.5$.

4 MCMC ANALYSES

To calculate posterior distributions on the parameters we have run MCMCs using the ensemble slice sampling codes emcee (Foreman-Mackey et al. 2013) and zeus (Karamanis et al. 2021). The latter has been recently used to run mock full shape MCMC analyses assuming galaxy surveys specifications using the Matryoshka suite of neural network based emulators (Donald-McCann et al. 2021, 2022). Due to the impressive increase in computational speed for the inference ($\sim 3$ orders of magnitude improvement with respect to the PyBLoR runs), we opted for this setup to run and present our final MCMC forecasts$^1$. We vary three cosmological parameters, $[\omega_c, h, \ln(10^{10} A_s)]$, seven bias and counterterms parameters, $[b_1, c_2, b_3, c_4, c_5, c_e, c_{e,\text{quad}}]$, and, in the case of IM, we also vary $T_{\text{HI}}$. The scalar spectral index $n_s$ is fixed to its true value, and so is the baryon fraction $\Omega_b = \Omega_m + \omega_c$.

For the 3 cosmological parameters and $b_1$, we assume the uniform flat priors shown in Table 1. We do not employ Planck priors on $A_s$, $\omega_c$, $h$ because we wish to assess the precision vs accuracy performance of interferometric Hi intensity mapping independently of CMB experiments. For $T_{\text{HI}}$ we take a flat prior $[0, 1]$. For the rest of the bias and counterterms parameters, we follow D’Amico et al. (2020) and set:

$$c_2 \sim \mathcal{U}(-4, 4), \quad b_3 \sim \mathcal{N}(0, 2),$$
$$c_{ct} \sim \mathcal{N}(0, 2), \quad c_{e,1} \sim \mathcal{N}(0, 8), \quad c_{e,\text{quad}} \sim \mathcal{N}(0, 2).$$

Finally, we assume a Gaussian likelihood given by:

$$\ln L(p^d | \theta) = -\frac{1}{2} (p^d - p^m)^T C^{-1} (p^d - p^m),$$

with $p^d$ being the mock data (the power spectrum monopole, $P_0$, and quadrupole, $P_2$), $p^m$ being the EFTofLSS model predictions for a given set of parameters, $\theta$, and $C$ being the covariance matrix.

4.1 The systematics-free, Stage-IV survey scenario

We start by comparing the performance of a Stage-IV spectroscopic galaxy survey and an analogous intensity mapping survey, assuming both of them are free of systematic effects. The volumes of the surveys are taken to be exactly the same$^2$, but the effective mean number densities (i.e., the noise components) are different as we have described in detail in section 3 (see e.g. Figure 2). Following up on the discussion in the previous section, we emphasise again that in the case of Hi intensity mapping there is an additional overall amplitude parameter, $P_m^2 \propto \Omega_{\text{HI}}^2$, which we vary. This means that a total of 10 (11) parameters are varied in the MCMC for the optical (IM) surveys under consideration.

The MCMC contours for the idealised case are shown in Figure 4. We are able to recover the true values in an unbiased manner, which also confirms the accuracy of the Matryoshka emulator (see Donald-McCann et al. (2022) for a suite of validation tests). The Stage-IV spectroscopic optical galaxy survey and the CHORD-like Hi intensity mapping survey have similar constraining power when the same survey volume is assumed. An exception is the primordial amplitude $A_s$. In the CHORD-like IM case, additional degeneracies due to $^1$ An alternative approach to speed-up the inference is to use a fast and accurate linear matter power spectrum emulator such as bacco (Arićo et al. 2021) or CosmoPower (Spurio Mancini et al. 2022) as input in a perturbation theory code, instead of running a Boltzmann solver like CAMB (Lewis et al. 2000) or CLASS (Lesgourgues 2011; Blas et al. 2011).

$^2$ Hi intensity mapping surveys can cover a much wider redshift range compared to spectroscopic optical galaxy surveys, but our goal here is to compare their performance on a given redshift bin.
varying $\bar{T}_{\text{H}}$ increase the uncertainty in $A_s$ compared to the optical case.

From Table 1 we see that, in the absence of systematics, the CHORD-like $\text{Hi}$ intensity mapping survey determines $\omega_c$ with < 3% error, $h$ with 1% error, $\ln(10^{10}A_s)$ with < 3% error, and $b_1$ (the linear $\text{Hi}$ bias) with < 2% error. The survey can also constrain $\bar{T}_{\text{H}} = 0.171^{+0.005}_{-0.006}$, demonstrating how exploiting mildly nonlinear scales can break degeneracies.

### 4.2 Contaminating the data vector with 21cm foreground removal effects

In order to contaminate our synthetic data vector (i.e., the $\text{Hi}$ power spectrum multipoles $P_0$ and $P_2$ in Figure 3) with 21cm foreground removal effects, we will use the simulations-based prescription by Soares et al. (2021). This prescription can fit $\text{Hi}$ intensity mapping simulations with foreground removal effects, assuming that PCA or FastICA with $N_{\text{IC}} = 4$ independent components was used for the foreground cleaning. The choice $N_{\text{IC}} = 4$ corresponds to an excellent calibration scenario (which will hopefully be the case by the time CHORD and PUMA come online) and no polarization leakage (Wolz et al. 2014; Alonso et al. 2015; Liu & Shaw 2020; Cunnington et al. 2021). For existing $\text{Hi}$ intensity mapping surveys, we know that much more aggressive foreground removal (much higher $N_{\text{IC}} \sim 20 - 30$) is employed to deal with more complicated foregrounds, noise, and unknown systematics (see e.g. Switzer et al. (2013); Masui et al. (2013); Wolz et al. (2022); Cunnington et al. (2022)).

We present the result of contaminating our data vector with 21cm foreground removal effects in Figure 5. This is our mock data vector for the remainder of the paper. As we can see, foreground cleaning results in the damping of power across a wide range of scales in the spherically averaged power spectrum (the monopole, $P_0$). This is a well known effect, which has also been identified in the context of high redshift 21cm surveys of the Epoch of Reionization (Petrovic & Oh 2011). Higher order multipoles were first studied extensively in Blake (2019); Cunnington et al. (2020); Soares et al. (2021), focusing on post-reionization $\text{Hi}$. In the case of the quadrupole ($P_2$), where $P(k, \mu)$ is weighted as a function of $\mu$, we see an enhancement of power on large scales. It is also important to note that, both for $P_0$ and $P_2$, while the largest effect is clearly on small $k$, there is still an effect along larger $k$. Given that the error bars of our chosen surveys
Figure 5. *Top:* Fiducial monopole ($ℓ = 0$) and quadrupole ($ℓ = 2$) data, with and without foreground removal effects, assuming a CHORD-like intensity mapping survey. *Bottom:* The ratios of the power spectrum multipoles illustrate the amplitude and scale dependence of the foreground removal effects.

Figure 6. The effect of ~ 10% variations of the 4 parameters of interest on the EFTofLSS model predictions. For comparison, we also plot the simulations-based effect of 21cm foreground removal.

4.3 Imposing $k_{\text{min}}$ cuts: precision vs accuracy

In this section we perform an MCMC analysis for the CHORD-like survey under consideration, using the contaminated Hi intensity mapping data vector with different $k_{\text{min}}$ limits. Our results for the 4 parameters of interest are summarised in Table 1 and Figure 7. The different scale cuts we consider are the following:

- **Case I:** We start by imposing a scale cut $k_{\text{min}} = 0.01 \ h/{\text{Mpc}}$ in order to exclude the largest scales where foreground subtraction has the most impact. This is not enough: the parameter estimation becomes strongly biased for $\omega_c$, $h$, and $b_1$. The primordial amplitude is unbiased within $\sim 2\sigma$ because of the marginalisation of $\bar{T}_H$ (i.e., if $\bar{T}_H$ was kept fixed, $A_s$ would also be strongly biased). For the HI brightness temperature we get: $\bar{T}_H = 0.174_{-0.004}^{+0.004}$.
- **Case II:** Imposing a stricter scale cut $k_{\text{min}} = 0.03 \ h/{\text{Mpc}}$. In this case the $\omega_c$, $h$, and $A_s$ parameters are unbiased within $2\sigma$, while $b_1$ remains biased. For the HI brightness temperature we get: $\bar{T}_H = 0.174_{-0.005}^{+0.005}$.
- **Case III:** Imposing a scale cut $k_{\text{min}} = 0.05 \ h/{\text{Mpc}}$. In this case the $\omega_c$, $h$, and $A_s$ parameters are unbiased within $1\sigma$, while...
Reionization surveys. The main conclusions we draw from this work are:

- In the idealised case without any systematic biases in the data, interferometric HI intensity mapping surveys with instruments like CHORD and PUMA are competitive with Stage-IV optical galaxy surveys. Our results, summarised in Table 1, assume a single redshift bin centred at $z = 0.5$. In the case of redshift-independent parameters like $\omega_c$, $A_s$, and $h$, we naively expect the parameter estimation uncertainties to be reduced by roughly $1/\sqrt{N}$, where $N$ is the number of redshift bins. This is an advantage for HI intensity mapping surveys with respect to optical surveys, since the former are not shot-noise limited and can rapidly cover very large redshift ranges. However, the thermal noise of an interferometer can increase rapidly with redshift. Nevertheless, forecasts for experiments similar to what we consider here have shown that interferometric HI intensity mapping should be advantageous at high redshift $2 < z < 6$. The cosmological volume spanned at this range is three times higher than the typical optical galaxy surveys range, $0 < z < 2$, with an increased $k_{\text{max}}$, i.e., an increased number of (easier to model) linear and mildly nonlinear modes. Forecasts for a dedicated “Stage-II” HI intensity mapping experiment showed that $S/N > 1$ is achievable for all modes with $k \leq 0.4h$/Mpc at $z \leq 6$ (Ansari et al. 2018).

- Including 21cm foreground removal effects based on simulations-based prescriptions, the parameter estimation becomes strongly biased for $\omega_c$, $h$, and $b_1$, while $A_s$ is less biased ($< 2\sigma$).

- Adopting the scale cuts approach to try and mitigate the biases, we find that scale cuts $k_{\text{min}} \geq 0.03 h$/Mpc are required to return accurate estimates for $\omega_c$ and $h$, at the price of a decrease in the precision, while $b_1$ remains biased.

In future work it would be interesting to investigate the possible HI and cosmology dependence of the foreground transfer function. This is a method to correct for signal loss from foreground removal, which has been used in all the HI-galaxy cross-correlation detections so far. Due to the low $S/N$ of current experiments, the cosmology is kept fixed to the Planck best-fit values and the only parameter we can constrain is $\Omega_{\text{HI}} b_1 r$, with $r$ the HI-galaxy cross-correlation coefficient (Masui et al. 2013; Anderson et al. 2018; Wolz et al. 2022; Cunningham et al. 2022). The foreground transfer function is constructed using mock simulations with fixed HI and cosmological parameters. In light of our results, we believe it is important to study how robust the transfer function construction (and the resulting HI signal loss correction) is with respect to varying the parameters in the mock simulations.

5 CONCLUSIONS

We have provided perturbation theory predictions for HI intensity mapping, and performed full shape MCMC analyses including the impact of 21cm foreground removal. Albeit our framework was developed in the context of low-redshift, interferometric HI intensity mapping surveys like CHIME, HIRAX, CHORD, and PUMA, our results are also relevant for single-dish surveys as well as Epoch of

![Figure 7](https://example.com/figure7.png)

Figure 7: Violin plots showing the marginalised 1D posteriors on the 4 parameters of interest for the different $k_{\text{min}}$ limits we have considered for the CHORD-like IM survey contaminated by foreground removal effects. The dashed blue lines show the true (fiducial) values. The white points show the median values. The thick solid (thin dotted) blue lines show the 1σ (2σ) regions. The shaded cyan regions show the density of the marginalised posteriors. We remind the reader that a total of 11 parameters are included in the MCMC.

$h_1$ remains biased. For the HI brightness temperature we get: $\bar{T}_{\text{HI}} = 0.175 \pm 0.004$.

In Figure 8 we compare the idealised case (noFG) and the cases with $k_{\text{min}} \geq 0.03 h$/Mpc limits that lead to unbiased (within 2σ) constraints on $\omega_c$, $h$, and $A_s$. Looking back at Figure 6, we deduce that for $k_{\text{min}} \geq 0.03 h$/Mpc the scale-dependent features of varying $\omega_c$ and $h$ are sufficient to constrain them accurately, in contrast to $b_1$, which gets significantly biased due to the amplitude change from the 21cm foreground removal. The primordial amplitude $A_s$ is less affected because of the marginalisation of $\bar{T}_{\text{HI}}$ (we have checked that when $\bar{T}_{\text{HI}}$ is kept fixed, $A_s$ becomes strongly biased).

From Table 1, Figure 7 and Figure 8 we also see that the price to pay for the unbiased estimates of $\omega_c$ and $h$ parameters is a decrease in the precision with respect to the idealised case, as expected.
| Parameters of interest | $\omega_c$ | $h$ | $\ln\left(10^{10}A_s\right)$ | $b_1$ |
|-----------------------|----------|-----|---------------------------|------|
| Fiducial values       | 0.1193   | 0.677| 3.047                     | 1.1  |
| Priors                | [0.101,0.140] | [0.575,0.748] | [2.78,3.32] | [0,4] |

| Case                  | $k$-range [h/Mpc] | $\omega_c$ | $h$ | $\ln\left(10^{10}A_s\right)$ | $b_1$ |
|-----------------------|-------------------|----------|-----|---------------------------|------|
| Optical galaxy survey (Figure 4) | $0.01 < k < 0.2$ | $0.119^{+0.003}_{-0.003}$ | $0.676^{+0.008}_{-0.008}$ | $3.05^{+0.04}_{-0.04}$ | $1.1^{+0.03}_{-0.02}$ |
| IM-noFG (Figure 4)    | $0.01 < k < 0.2$ | $0.119^{+0.003}_{-0.003}$ | $0.676^{+0.007}_{-0.007}$ | $3.00^{+0.08}_{-0.08}$ | $1.1^{+0.02}_{-0.02}$ |
| IM-subFG, $k_{\text{min}} = 0.01 h$/Mpc (Figure 7)  | $0.01 < k < 0.2$ | $0.128^{+0.011}_{-0.009}$ | $0.697^{+0.003}_{-0.002}$ | $3.12^{+0.06}_{-0.05}$ | $0.95^{+0.02}_{-0.02}$ |
| IM-subFG, $k_{\text{min}} = 0.03 h$/Mpc (Figure 7 and Figure 8) | $0.03 < k < 0.2$ | $0.125^{+0.004}_{-0.003}$ | $0.689^{+0.010}_{-0.005}$ | $3.12^{+0.07}_{-0.07}$ | $0.96^{+0.02}_{-0.02}$ |
| IM-subFG, $k_{\text{min}} = 0.05 h$/Mpc (Figure 7 and Figure 8) | $0.05 < k < 0.2$ | $0.121^{+0.007}_{-0.004}$ | $0.679^{+0.015}_{-0.010}$ | $3.09^{+0.09}_{-0.07}$ | $0.98^{+0.03}_{-0.03}$ |

Table 1. Fiducial values, prior ranges, and marginalised constraints for the 4 parameters of interest (68% confidence level). We vary 10 parameters in total for optical galaxy surveys, and 11 for intensity mapping (IM) (adding the $T_{\text{HI}}$ parameter). For the IM surveys, we consider different $k_{\text{min}}$ limits to mitigate 21cm foreground removal effects.

Figure 8. Marginalised 1D and 2D posterior distributions, and 1$\sigma$ and 2$\sigma$ contours for a CHORD-like H\textsc{i} intensity mapping survey. We compare the idealised case and the cases with $k_{\text{min}} \geq 0.03 h$/Mpc limits that lead to unbiased (within 2$\sigma$) constraints on $\omega_c$, $h$, and $A_s$. The black dashed line shows the fiducial (true) parameters. We show the 4 parameters of interest and $T_{\text{HI}}$, but we remind the reader that a total of 11 parameters are included in the MCMC (see section B, Figure B1).
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DATA AVAILABILITY

The data products will be shared on reasonable request to the corresponding author.

REFERENCES

Abadi M., et al., 2015, TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems, https://www.tensorflow.org/
Ade P. A. R., et al., 2016, Astron. Astrophys., 594, A13
Aghanousa A., et al., 2016, The DESI Experiment Part I: Science,Targeting, and Survey Design (arXiv:1611.00936)
Aghanim N., et al., 2020, Astron. Astrophys., 641, A6
Ahmed Z., et al., 2019, arXiv e-prints, p. arXiv:1907.13090
Alam S., et al., 2021, Phys. Rev. D, 103, 083533
Aloni D., Bull P., Ferreira P. G., Santos M. G., 2015, Mon. Not. Roy. Astron. Soc., 447, 400
Amiri M., et al., 2022a, Detection of Cosmological 21 cm Emission with the Canadian Hydrogen Intensity Mapping Experiment (arXiv:2201.07869)
Amiri M., et al., 2022b, An Overview of CHIME, the Canadian Hydrogen Intensity Mapping Experiment (arXiv:2202.01242)
Anderson C., et al., 2018, MNRAS, 476, 3382
Ansari R., et al., 2012, Astron. Astrophys., 540, A129
Ansari R., et al., 2018, Inflation and Early Dark Energy with a Stage II Hydrogen Intensity Mapping experiment (arXiv:1810.09572)
Aricò G., Angulo R. E., Zennaro M., 2021, Accelerating Large-Scale-Structure data analyses by emulating Boltzmann solvers and Lagrangian Perturbation Theory (arXiv:2104.14568)
Astropy Collaboration et al., 2018, AJ, 156, 123
Bandura K., et al., 2014, Proc. SPIE Int. Soc. Opt. Eng., 9145, 22
Battye R. A., Davies R. D., Weller J., 2004, Mon. Not. Roy. Astron. Soc., 355, 1339
Bernardeau F., Colombi S., Gaztanaga E., Scoccimarro R., 2002, Phys. Rept., 367, 1
Blake C., 2019, Mon. Not. Roy. Astron. Soc., 489, 153
Blanchard A., et al., 2020, Astron. Astrophys., 642, A191
Blas D., Lesgourgues J., Tram T., 2011, JCAP, 07, 034
Bull P., Ferreira P. G., Patel P., Santos M. G., 2015, Astrophys. J., 803, 21
Castorina E., White M., 2019, JCAP, 06, 025
Chapman E., et al., 2012, Mon. Not. Roy. Astron. Soc., 423, 2518
Chapton D., et al., 2022, J. Astron. Telesc. Instrum. Syst., 8, 011019
Crichton D. J., et al., 2016, Astrophys. J. Suppl., 222, 22
Crichton N. H., et al., 2015, Mon. Not. Roy. Astron. Soc., 452, 217
Cunmo S., et al., 2022, HI intensity mapping: perturbation theory predictions

Cunnington S., Poursiadou A., Soares P. S., Blake C., Bacon D., 2020, Mon. Not. Roy. Astron. Soc., 496, 415
Cunnington S., Irfan M. O., Carucci I. P., Poursiadou A., Bobin J., 2021, Mon. Not. Roy. Astron. Soc., 504, 208
Cunnington S., et al., 2022, HI intensity mapping with MeerKAT: power spectrum detection in cross-correlation with WiggleZ galaxies (arXiv:2206.01579)
D’Amico G., Gleyzes J., Kokron N., Markovic K., Senatore L., Zhang P., Beutler F., Gil-Marín H., 2020, JCAP, 05, 005
D’Amico G., Senatore L., Zhang P., 2021, JCAP, 01, 006
Donald-McCann J., Butler F., Koyama K., Karamanis M., 2021, matrystema: Halo Model Simulator for the Galaxy Power Spectrum (arXiv:2109.15236), doi:10.1093/mnras/stac239
Donald-McCann J., Koyama K., Butler F., 2022, matrystema II: Accelerating Effective Field Theory Analyses of the Galaxy Power Spectrum (arXiv:2202.07557)
Foreman-Mackey D., 2016, The Journal of Open Source Software, 1, 24
Foreman-Mackey D., Hogg D. W., Lang D., Goodman J., 2013, Publ. Astron. Soc. Pac., 125, 306
Huang J. H., Xiao Y., Zhang P., Chen X., 2020, Mon. Not. Roy. Astron. Soc., 493, 5854
Hunter J. D., 2007, Computing In Science & Engineering, 9, 90
Hyvärinen A., 1999, IEEE transactions on neural networks, 10, 3, 626
Kaiser N., 1987, Mon. Not. Roy. Astron. Soc., 227, 1
Karamanis M., 2022, Matrystema II: Accelrating Effective Field Theory Analyses of the Galaxy Power Spectrum (arXiv:2205.06270)
Klypin A.,Yepes,Gottlöber,S.,Prada,F.,Hess,S.,2016,Mon. Not. Roy. Astron. Soc., 457, 4340
Knebe A., et al., 2018, Mon. Not. Roy. Astron. Soc., 474, 5206
Kovetz E. D., et al., 2020, Bull. Am. Astron. Soc., 51, 101
Laureijs R., et al., 2011, Euclid definition study report (arXiv:1104.2932)
Lesgourgues J., 2011, The Cosmic Linear Anisotropy Solving System (CCLASS) I: Overview (arXiv:1104.2932)
Lewis A., 2019, GetDist: A Python package for analysing Monte Carlo samples (arXiv:1910.13970)
Lewis A., Challinor A., Lasenby A., 2000, Astrophys. J., 538, 473
Li J., et al., 2020, Sci. China Phys. Mech. Astron., 63, 129862
Liu A., Shaw J. R., 2020, Publ. Astron. Soc. Pac., 132, 062001
Liu A., Degmark M., 2011, Phys. Rev. D, 83, 103006
Masui K. W., et al., 2013, Astrophys. J., 763, L20
McQuinn M., D’Aloisio A., 2018, JCAP, 10, 016
Moresco M., et al., 2022, Unveiling the Universe with Emerging Cosmological Probes (arXiv:2201.07241)
Mueller E.-M., Percival W., Linder E., Alam S., Zhao G.-B., Sánchez A. G., Butler F., Brinkmann J., 2018, Mon. Not. Roy. Astron. Soc., 475, 2122
Newburgh L., et al., 2016, Proc. SPIE Int. Soc. Opt. Eng., 9906, 99065X
Nishimichi T., D’Amico G., Ivanov M. M., Senatore L., Simonovic M., Takada M., Zaldarriaga M., Zhang P., 2020, Phys. Rev. D, 102, 123541
Obuljen A., Castorina E., Villaescusa-Navarro F., Viel M., 2018, JCAP, 05, 004
Oh S. P., Mack K. J., 2003, Mon. Not. Roy. Astron. Soc., 346, 871
Pudmananabhan H., Refregier A., Amara A., 2017, Mon. Not. Roy. Astron. Soc., 469, 2323
Perko A., Senatore L., Jennings E., Wechsler R. H., 2016, Biased Tracers in Redshift Space in the EFT of Large-Scale Structure (arXiv:1610.09321)
Peterson J. B., et al., 2009, in astro2010: The Astronomy and Astrophysics Decadal Survey. p. 234 (arXiv:1610.09321)
Petkov N., 2012, Monthly Notices of the Royal Astronomical Society, 431, 2103
Qin W., Schutz K., Smith A., Garaldi E., Kannan R., Slatyer T. R., Vogelsberger M., 2022, An Effective Bias Expansion for 21 cm Cosmology in Redshift Space (arXiv:2205.06270)
SKA Cosmology SWG et al., 2020, Publ. Astron. Soc. Aust., 37, e007
Sailer N., Castorina E., Ferraro S., White M., 2021, JCAP, 12, 049
Santos M. G., et al., 2017, in MeerKAT Science: On the Pathway to the SKA (arXiv:1709.06999)
Here we fit the EFTofLSS model of Equation 5 to $H_0$ simulations in order to determine fiducial values for our bias and counter terms parameters. The simulations we use have been described in detail in Soares et al. (2022), but we summarise them here for completeness. They are based on the MULTIDARK-PLANCK dark matter N-body simulation (Klypin et al. 2016), which follows $3840^3$ particles evolving in a box of side $1\ Gpc/h$. The cosmology is consistent with PLANCK15 (Ade et al. 2016). From this, the MULTIDARK-SAGE catalogue was produced by applying the semi-analytical model SAGE (Knebe et al. 2018; Croton et al. 2016). These simulated data products are publicly available in the Skies & Universe web page, and we use the $z = 0.39$ snapshot. The method used for generating $H_0$ intensity mapping simulations is as follows: Each galaxy in the MULTIDARK-SAGE catalogue has an associated cold gas mass, which is used to calculate an $H_0$ mass. The $H_0$ mass of each galaxy belonging to each voxel is binned together, and then converted into an $H_0$ brightness temperature for that voxel. A crucial limitation comes from the fact that low mass halos (lower than $\leq 10^{10} h^{-1} M_\odot$) are not included in the simulation.

To account for these missing halos, which would contribute to the total $H_0$ brightness of each voxel, we need to rescale the mean $H_0$ temperature of the simulation to a more realistic value. In the power spectrum measurements, this is an overall amplitude $T_0^2$ which we have divided out for the purposes of this fit.

We then proceed to find the maximum a posteriori (MAP) estimate to the power spectrum measurements from these simulations. We plot the result in Figure A1. The MAP values of the bias and counter terms parameters are:

$$\{b_1, c_2, b_3, c_{\Delta t}, c_{r_1}, c_{\epsilon_1}, c_{\epsilon_{\quad \text{quad}}}\} = \{1.1, 0.6, 0.1, 0.1, -10.0, -0.8\}.$$ 

**APPENDIX B: FULL POSTERIORS**
Figure B1. Marginalised 1D and 2D posterior distributions, and 1σ and 2σ contours, for a CHORD-like H\textsubscript{i} intensity mapping survey, including all 11 parameters varied in the MCMC. We show the idealised case (noFG) and a case with 21cm foreground removal effects and a scale cut $k_{\text{min}} = 0.03 \, h/\text{Mpc} \, (\text{subFG})$.

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