Measuring the EoR Power Spectrum without Measuring the EoR Power Spectrum

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Abstract

The large-scale structure of the universe should soon be measured at high redshift during the epoch of reionization (EoR) through line-intensity mapping. A number of ongoing and planned surveys are using the 21 cm line to trace neutral hydrogen fluctuations in the intergalactic medium during the EoR. These may be fruitfully combined with separate efforts to measure large-scale emission fluctuations from galactic lines such as [C II], CO, H-α, and Lyα during the same epoch. The large-scale power spectrum of each line encodes important information about reionization, with the 21 cm power spectrum providing a relatively direct tracer of the ionization history. Here we show that the large-scale 21 cm power spectrum can be extracted using only cross-power spectra between the 21 cm fluctuations and each of two separate line-intensity mapping data cubes. This technique is more robust to residual foregrounds than the usual 21 cm auto-power spectrum measurements and so can help in verifying auto-spectrum detections. We characterize the accuracy of this method using numerical simulations and find that the large-scale 21 cm power spectrum can be inferred to a simulated accuracy of within 5% for most of the EoR. Our estimate of the 21 cm power spectrum reaches 0.6% accuracy on a scale of $k \sim 0.1$ Mpc$^{-1}$ at $(\chi_i) = 0.36$ ($z = 8.34$ in our model). An extension from two to $N$ additional lines would provide $N(N-1)/2$ cross-checks on the large-scale 21 cm power spectrum. This work strongly motivates redundant line-intensity mapping surveys probing the same cosmological volumes.

Key words: cosmology: theory – dark ages, reionization, first stars – diffuse radiation – large-scale structure of universe

1. Introduction

Upcoming 21 cm surveys are poised to make a first detection of redshifted 21 cm fluctuations from the epoch of reionization (EoR) within the next several years (DeBoer et al. 2017). These measurements will provide a direct probe of the distribution of neutral hydrogen in the intergalactic medium (IGM), revealing the spatial structure of the reionization process, and its redshift evolution. Along with these measurements, several other “line-intensity” mapping surveys are planned to map out large-scale structure in the galaxy distribution using convenient emission lines with current targets including [C II], CO, Lyα, and H-α (see, e.g., Kovetz et al. 2017, and references therein). These surveys study the spatial fluctuations in the collective emission from many individually unresolved sources (e.g., Sugino et al. 1999; Rigbi et al. 2008; Visbal & Loeb 2010). These measurements should nicely complement 21 cm observations (e.g., Gong et al. 2011; Lidz et al. 2011); while the 21 cm fluctuations trace-out remaining neutral hydrogen residing mostly in the low-density IGM, the galactic emission lines track the galaxies themselves, which presumably lie within “bubbles” of mostly ionized hydrogen (Lidz et al. 2009).

In fact, recent work has led to detections in various lines at low redshift (Davis et al. 2001; Chang et al. 2010; Croft et al. 2016, 2018; Keating et al. 2016; Pullen et al. 2018), bolstering efforts to employ the line-intensity mapping technique at earlier times during the EoR. It is hence timely to explore the scientific benefits of combining 21 cm observations of the EoR with line-intensity mapping surveys in other emission lines.

Here we consider, for the first time, one potential advantage of combining 21 cm surveys of the EoR with line-intensity mapping surveys in two additional lines. Specifically, we show that the linear bias factor of the 21 cm field may be extracted solely from cross-power spectra between the 21 cm fluctuations and those in each of two separate lines. This can provide an important cross-check on inferences from the 21 cm auto-power spectrum because cross-power spectra should be less prone to bias from residual foregrounds (e.g., Furlanetto & Lidz 2007; Lidz et al. 2009); only shared foregrounds contribute to the average cross-spectrum signal. The possibility of extracting the fluctuations in one line intensity field from the combination of three has been considered before in the case of low redshift intensity mapping (Serra et al., 2016).

The foreground problem is especially daunting in the case of redshifted 21 cm surveys, where the expected foreground-to-signal strength is on the order of $10^7$ (e.g., Bernardi et al. 2009; Pober et al. 2013; Dillon et al. 2014). The basic strategy for extracting the signal is to exploit the fact that the foregrounds should be smooth functions of frequency, while the reionization signal has a great deal of spectral structure. In practice, this is challenging because the instrument, calibration errors, and other effects may imprint artificial spectral variations. Cross-spectrum measurements should be less sensitive to such systematic effects and can therefore help confirm early detections. For instance, Villaescusa-Navarro et al. (2015) show that cross-spectra can be robustly measured even in the presence of polarized synchrotron foregrounds; this is a troublesome case for auto-spectrum analyses because Faraday rotation leads to frequency structure.

The amplitude of the 21 cm power spectrum evolves with redshift in a distinctive way as reionization proceeds (e.g., Lidz et al. 2008), and recent work has demonstrated that linear biasing describes the large-scale 21 cm power spectrum rather well (Beane & Lidz 2018; Hoffmann et al. 2018; McQuinn & D’Aloisio 2018). Therefore, if our three-field method may be employed over a range of redshifts, it can be used to extract key
and robust information regarding the reionization history of the universe.

In recent related work we showed that the large-scale 21 cm bias factor may be recovered using suitable cross-bispectra between the 21 cm fluctuations and the [C II] emission field (Beane & Lidz 2018). While the cross-bispectra method requires only the 21 cm fluctuations and one additional tracer field, the technique we propose here should be vastly simpler to implement in practice (provided two additional tracers are available with common sky and redshift coverage). This is the case because our present method relies only on two-point statistics, and it therefore avoids practical difficulties in carrying out cross-bispectra analyses. For example, it is challenging to estimate the bispectrum covariance as this involves computing a six-point function. In addition, we will show that our present technique allows for a more faithful extraction of the 21 cm bias factor. Ultimately, both analyses may be carried out for additional cross-checks.

There are a broad range of possible lines that may be combined with the 21 cm surveys. Currently, there are projects—either ramping-up or in the planning stages—to perform EoR-era line-intensity surveys in [C II] 158 µm (Crites et al. 2014; Lagache et al. 2017; Vavagiakis et al. 2018), rotational transitions from CO molecules (Chung et al. 2017), Lyα (Doré et al. 2016), and H-α (Cooray et al. 2016). Additional fine-structure lines such as [O III] 88 µm (Moriwaki et al. 2018) and [N II] 122 µm (Serra et al. 2016) may also be suitable—in some cases, these lines will land in the proposed frequency bands of the planned [C II] surveys. The [O III] 88 µm line appears especially promising because targeted ALMA observations around z ~ 7–9 galaxies have found that this line is brighter at high redshift than expected based on local correlations between line-luminosity and star formation rate (e.g., Moriwaki et al. 2018, and references therein).

In principle, one could extract the 21 cm bias using the cross-spectrum with a traditional galaxy survey, in which case the galaxy bias may be measured robustly from the auto-power spectrum. In practice, this is extremely challenging because one needs spectroscopic redshifts for the galaxy survey over a huge sky area at z ~ 8. If only photometric redshifts are available, then one only accesses long-wavelength line-of-sight modes (with small or vanishing line-of-sight wavenumbers) in the galaxy survey but precisely these modes are lost to foreground cleaning/avoidance in the 21 cm surveys (e.g., Lidz et al. 2009). Fortunately, multi-line intensity mapping provides a promising way forward here and our approach avoids measuring bias factors from auto spectra.

In Section 2, we describe our three cross-spectra approach in detail. In Section 3 we briefly discuss the radiative transfer simulations of reionization (McQuinn et al. 2007b; Lidz et al. 2008) used in our analysis, the reionization model assumed, and our method for generating mock line-intensity mapping data cubes. We then quantify the accuracy of our technique in Section 4. The survey specifications required to extract bias factors with this method are discussed briefly in Section 5. We conclude in Section 6. We assume a ΛCDM cosmology, parameterized by (Ω_m, Ω_b, h, σ8, n_s) = (0.27, 0.73, 0.046, 0.7, 0.8, 1) as in the simulations used in this work (McQuinn et al. 2007a). While these parameters differ slightly from presently favored values (e.g., Planck Collaboration et al. 2018), this should not impact our conclusions.

2. Approach

Here we define terms and describe our three cross-spectra approach. Ignoring redshift space distortions and spin-temperature fluctuations, the 21 cm brightness temperature contrast between neutral hydrogen gas and the cosmic microwave background is:

\[ T_{21}(x) = T_0 X_{H_1}(x)[1 + \delta_p(x)]. \]  

where the $T_0$ indicates that the fields are either correlated (+) or anticorrelated (−) during the bulk of the EoR, the 21 cm and density fields are anticorrelated on large scales in most models (e.g., Lidz et al. 2009). Here $T_{21}(k)$ is the Fourier transform of the brightness temperature field (Equation (1)) and $\delta_{\text{lin}}(k)$ is the Fourier transform of the linear density contrast. The quantity $b_{21}$ is the dimensionless, and scale-independent, linear bias factor of the 21 cm fluctuation contrast, $\delta_{21}(x) = \langle T_{21}(x) \rangle / \langle T_{21}^2 \rangle$, while the $\langle T_{21} \rangle$ factor reverts to brightness temperature units (because the average brightness temperature is not itself observable from interferometric measurements). In this work we refer to the “bias” we mean $T_{21} b_{21}$ (and likewise for the intensity mapping surveys.)

Likewise, we can consider additional tracer lines, such as [C II]. On large scales, the Fourier transform of the specific intensity of each of these lines should be well-described by

\[ I_{\ell}(k) = \langle I_{\ell} \rangle b_\ell \delta_{\text{lin}}(k), \]

where $\langle I_{\ell} \rangle$ is the mean specific intensity of the emission line. For the case of emission lines sourced by gas within galaxies, the relevant bias factor is the luminosity-weighted bias of the line-emitting host halos (e.g., Lidz et al. 2011). To be completely general we should also include a ± here (as in Equation (2)), but for the galactic emission lines we generally expect brighter line emission in overdense regions.

On sufficiently large scales, the auto-power spectrum of the fluctuations in each tracer line (Equation (3)) will be

\[ P_{\text{lin}}(k, z) = \langle I_{\ell}(k, z) I_{\ell}^*(k, z) \rangle = \langle I_{\ell} \rangle^2 b_{\ell}^2 P_{\text{lin}}(k, z), \]

where $P_{\text{lin}}(k, z)$ is the linear matter power spectrum. Similarly, on large scales the 21 cm auto-power spectrum should follow

\[ P_{21,21}(k, z) = \langle T_{21}(k) T_{21}(k)^* \rangle P_{\text{lin}}(k, z). \]

In principle, one can infer the bias factors $\langle I_{\ell} \rangle b_\ell$ and $\langle T_{21} \rangle b_{21}$ from auto-power spectrum measurements (assuming a model for the linear
power spectrum). However, foreground cleaning/avoidance present significant challenges here (e.g., Liu & Tegmark 2012; Moore et al. 2013; Thayagaran et al. 2015; Pober et al. 2016; Ewall-Wice et al. 2017) and residual foregrounds may bias such inferences.

Another approach is to measure the cross-power spectrum between two lines $i$ and $j$. In this case, one measures

$$P_{ij} = r_{ij} \langle l_i \rangle b_i b_j P_{\text{lin}},$$  \hspace{1cm} (5)

where $r_{ij}$ is the cross-correlation coefficient, which ranges from $-1$ to $1$.\footnote{Note that here we adopt the convention that the bias factors are always positive and that the sign of the cross-spectrum is determined solely by that of the correlation coefficient. This convention differs from our previous work (Beane & Lidz 2018).} In the above equation and in what follows, we generally suppress redshift and wavenumber labels for brevity. In general, $r_{ij}$ is scale-dependent, but asymptotes to $-1$ (for anticorrelated fields) or $1$ (for correlated fields) on large scales.\footnote{Note that we neglect shot-noise contributions to the auto spectrum in Equation (4), as well as correlated shot-noise terms in the cross-power spectrum. This should be a very good approximation on the scales of interest unless the line-emitting sources are quite rare (e.g., Lidz & Taylor 2016). Even in the case of rare sources, the shot-noise term should be a white-noise contribution on scales much larger than the size of the host halos. In this case, one can perform a joint fit for the shot-noise along with the clustering terms.} If one of the lines is the 21 cm field, we replace $\langle l_i \rangle$ with $\langle T_2 \rangle$ in Equation (5).

However, in the presence of a third line $k$, and with $P_{jk}$ and $P_{kj}$ defined analogously as in Equation (5), we can simply write

$$P_{i} = \langle \langle l_i \rangle b_i \rangle^2 P_{\text{lin}} = \frac{r_{ijk} P_{jk} P_{ki}}{r_{ij} r_{kj} r_{ik}} \equiv R_{ij,k} P_{ij,k},$$  \hspace{1cm} (6)

where we have defined $R_{ijk} \equiv r_{ijk}/(r_{ij} r_{kj} r_{ik})$ and $P_{ijk} \equiv (P_{ij} P_{ik})/P_{jk}$. On sufficiently large scales, $R_{ijk} \to 1$, but on intermediate scales $R_{ijk} > 1$ for most reasonable cases when the various $r$’s are close in magnitude. Equation (6) shows that (on sufficiently large scales where linear biasing holds and $R_{ijk} \sim 1$) we can recover the linear bias factor of field $i$ from a suitable ratio of cross-spectra. Here we suppose that the underlying density power spectrum is well known.

Equation (6) is the main point of this paper; in the remainder of this work we consider an application to the EoR and quantify its accuracy. Specifically, we will test the range of validity—in spatial scale and redshift/ionization fraction—of the assumption that $R_{ij,k} = 1$, along with the linear biasing approximations of Equations (2) and (3). Note that testing the assumption that $R_{ij,k} = 1$ directly from upcoming data will require reliable auto spectra.

We turn now to the specific case of EoR surveys with the goal of extracting the 21 cm bias factor using only cross-power spectra. For further specificity we suppose that the two additional tracer lines are [C II] and [O III], although little of the analysis that follows depends on the choice of these two lines—any of the lines mentioned in Section 1 can be used instead of [C II] or [O III]. In this case, Equation (6) may be applied as

$$P_{21,21} = \frac{(\langle T_3 \rangle b_2)^2 P_{\text{lin}}}{P_{C,O,0 \text{ II}}},$$  \hspace{1cm} (7)

i.e., assuming $R_{21,C,O,II} = 1$.

We expect this approach to break down on small scales. First, the three fields will be well correlated (or anticorrelated) only on large scales, with the 21 cm field and the [C II], [O III] fields decorrelating on scales smaller than the size of the ionized regions (Lidz et al. 2011). Second, we assume linear biasing, which should break down on scales where second-order bias terms become significant (McQuinn & D’Aloisio 2018).

One caveat here is that we neglect redshift space distortions throughout. Including these effects will make the power spectra in Equation (7) angle-dependent. Although these effects are well studied in the case of the 21 cm auto spectrum (e.g., Mao et al. 2012), an extension of our three cross-spectra method may be needed to account for these distortions.

3. Simulations

In order to investigate the accuracy of Equation (7) we turn to (186 Mpc)$^3$ radiative transfer simulations of the EoR (McQuinn et al. 2007a, 2007b; Lidz et al. 2008). In these calculations, radiative transfer is post-processed onto a (1024)$^3$ dark matter only simulation run with GADGET-2 (Springel 2005). The dark matter simulation resolves halos only down to $10^{10}$ $M_\odot$; however, halos down to $10^8$ $M_\odot$ are added manually in post-processing with the correct statistical properties (McQuinn et al. 2007b). Halos resolved directly in the simulation (i.e., $>10^{10}$ $M_\odot$) are identified with a Friends-of-Friends algorithm with a linking length of 0.2.

In what follows, we adopt the abundant mini-halo sink scenario (McQuinn et al. 2007b; Lidz et al. 2008) as our baseline reionization model. Although the detailed model for photon sinks implemented in these simulations may not be fully realistic, the smaller ionized regions in “abundant sink” scenarios may, in fact, be more plausible than the other cases considered previous work (McQuinn & D’Aloisio 2018). In any case, the accuracy of our method does not depend strongly on the precise reionization model assumed.

In order to model the [C II] and [O III] emission fluctuations, we assume that the luminosity in each line is correlated with the host halo mass. Specifically, we adopt a power-law average relation between line luminosity and halo mass:

$$\langle L_i \rangle (M) = L_{i,0} \left( \frac{M}{M_0} \right)^{\beta_i},$$  \hspace{1cm} (8)

where $M$ is the mass of the halo, $\langle L_i \rangle$ is the average luminosity, and $L_{i,0}$ is the luminosity at characteristic mass $M_0$. In order to account for scatter in this relation, we add a random number so that each halo’s luminosity is $L_i = \langle L_i \rangle (1 + \epsilon)$ where $\epsilon$ is drawn from a zero-mean lognormal distribution of width 0.4 dex.

In what follows we assume that each host halo in the simulation hosts a [C II] and/or [O III] emitter. If only a random fraction $f$ of halos host active [C II] and/or [O III] emitters while $L_{i,0}$ is boosted to fix the average specific intensity in each line, this does not change the 21 cm-[C II] or 21 cm-[O III] cross-power spectra. This represents the case in which star...
formation activity has a short duty cycle, yet the total star formation rate density is fixed to the observed value. If the same random fraction emit in both [C II] and [O III] this can boost the cross-shot noise contribution to $P_{C_{II},O_{III}}$, but this is highly subdominant on the scales of interest ($k \lesssim 0.4 \text{ Mpc}^{-1}$) even for $f = 10^{-2}$.

In order to estimate the specific intensity of the two fields, we use nearest grid-point interpolation to estimate the emissivity on a $512^3$ Cartesian grid, matching the resolution of the density and 21 cm fields from Lidz et al. (2008). Note that we can test the accuracy of Equation (7) without specifying the numerical value of $L_{0,0}$ or $M_0$ because they cancel in the ratio. The value of $\alpha_i$ on the other hand, controls which host halos (and galactic star formation rates) produce most of the specific intensity in line $i$. If the value of $\alpha_i$ is the same for [C II] and [O III], then the two fields differ only by an overall multiplicative factor and Equation (7) reduces to a simple ratio between a single cross-spectrum and an auto spectrum.

We consider three different values for $\alpha_i$: $2/3$, $1$, and $4/3$. We refer to these as L, M, and H because they provide most weight to low-, medium-, and high-mass host halos respectively. We allow for the case that the two lines have different values of $\alpha_i$; i.e., we consider 21 cm-L-M, 21 cm-M-H, and 21 cm-H-L, with L, M, or H standing in for [C II] or [O III] in Equation (7). We then measure the various cross-spectra using a slightly modified version of the power spectrum calculator in 21cmFAST (Mesinger et al. 2011; Park et al. 2018).

4. Results

We first investigate how well our three cross-spectra approach for measuring the large-scale 21 cm bias agrees with the true bias. We measure the true bias as

$$\langle T_{21} \rangle_{b_{21}}(k) = \frac{P_{21,21}(k)}{P_{b,b}(k)},$$

and also estimate the bias as

$$\langle T_{21} \rangle_{b_{21}}(k) \approx \frac{P_{21,\alpha}(k)}{P_{b,b}(k)},$$

where $P_{b,b}(k)$ is the auto-power spectrum of the simulated density field and $P_{21,\alpha}(k)$ is the 21 cm density cross-power spectrum. Note that Equation (10) assumes that the correlation coefficient $|r_{21,\alpha}| = 1$ and so will depart from Equation (9) on small scales, but the two should converge on large scales (see Section 1). The absolute value in Equation (10) comes about from the convention adopted in Section 2. On large scales where the 21 cm, [C II], and [O III] fields are each well correlated or anticorrelated with the density field and linear theory applies, we expect all estimates of $\langle T_{21} \rangle_{b_{21}}$ to agree. When we estimate the bias factors using our three cross-spectra method (Equation (7)) we use the simulated density power-

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\textsuperscript{7} Note that we assume the minimum host halo mass of the [C II] and [O III] emitters is $10^7 M_\odot$, comparable to the atomic cooling mass. The true minimum host mass of the emitters may, in fact, be larger. However, note that the average specific intensity may be fixed by the total star formation rate density and the line-luminosity star formation rate correlation. Provided these quantities are fixed, then the main impact of boosting the minimum host halo mass will be to increase slightly the bias factors, $b_p$, and the signal strength. See, e.g., Lidz & Taylor (2016) for more details regarding line-intensity fluctuation models.

\textsuperscript{8} This assumes, as we do here, that the scatter in the luminosity–mass relation is perfectly correlated between [C II] and [O III] at fixed $\alpha_i$.

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Figure 1. Top: the simulated, dimensionless 21 cm auto-power spectrum (gray) compared to that inferred from our three cross-spectra approach assuming linear biasing at $\langle x_i \rangle = 0.36$, $z = 8.34$. The different colors correspond to various possible line luminosity–mass relations (L, M, H), as described in Section 3. The shaded area shows the 1σ expected errors for the 21 cm-L-M survey described in Section 5. Middle: the 21 cm bias factor extracted from our three cross-spectra approach in the different line-luminosity models. These are compared with that inferred from the 21 cm auto spectrum (solid gray) and the 21 cm density cross-spectrum (gray dashed). Bottom: the relative difference between the different bias-factor models. On large scales all inferences agree.

Figure 2. The absolute value in Equation (10) comes about from the convention adopted in Section 2. On large scales where the 21 cm, [C II], and [O III] fields are each well correlated or anticorrelated with the density field and linear theory applies, we expect all estimates of $\langle T_{21} \rangle_{b_{21}}$ to agree. When we estimate the bias factors using our three cross-spectra method (Equation (7)) we use the simulated density power-
L-L, 21 cm-M-M, or 21 cm-H-H models the agreement is slightly worse but still at the percent level. Note that another approach for estimating the 21 cm bias would use only the 21 cm-[C II] cross-spectrum and the [C II] auto spectrum. This requires measuring the [C II] auto spectrum, which is subject to contamination from interloping line emission, and so we pursue only the more robust three-field technique here.

The success results because the ionized regions are sufficiently smaller than this scale ($k = 0.1\,\text{Mpc}^{-1}$), ensuring that the 21 cm and line-intensity fields are highly anticorrelated and that second-order biasing contributions are small. For example, the cross-correlation coefficient between the 21 cm field and the density field is $r_{21,\delta} = -0.99$ at $k = 0.1\,\text{Mpc}^{-1}$ for $\langle x_i \rangle = 0.36$, $z = 8.34$.

On smaller scales, our approach breaks down. At $\langle x_i \rangle = 0.36$, the different bias-factor estimates begin diverging at the $\pm10\%$ level near $k \sim 0.4\,\text{Mpc}^{-1}$. This occurs because the fields start to decorrelate and second-order biasing terms become more important. As anticipated after Equation (6), the three cross-spectra approach underestimates the bias factor in this regime. This underestimation may allow one to place robust lower limits on $P_{21,21}$ that are only $\sim 50\%$ smaller than the true value down to $k \sim 2\,\text{Mpc}^{-1}$ at this stage of the EoR, although the model-dependence of such limits warrants further investigation.

At later times, the average ionization fraction and the bubble sizes increase and so the scale at which the linear biasing approximation breaks down moves to larger scales. For example, at $\langle x_i \rangle = 0.7$ ($z = 7.32$), the approach breaks down at the $\sim 10\%$ level at $k \sim 0.3\,\text{Mpc}^{-1}$, though an accuracy of only a few percent is achieved at the largest scales considered here. We suspect better agreement on even larger scales than probed by our relatively small simulation volume.

In Figure 2 we turn to consider the redshift evolution of the 21 cm bias factor at $k = 0.1\,\text{Mpc}^{-1}$. As emphasized earlier, the redshift evolution of the 21 cm bias factor encodes interesting information about how reionization proceeds. The three cross-spectra method generally recovers the overall evolution of the 21 cm bias factor with redshift and volume-averaged ionization fraction quite accurately. This suggests that our technique may help in reconstructing the reionization history of the universe, or in verifying the results from 21 cm auto-spectrum measurements.

The one exception is near $\langle x_i \rangle \sim 0.15$, where our technique is relatively inaccurate. This occurs because large-scale overdense regions are initially brighter in 21 cm than typical regions in our model and so the 21 cm fields are initially positively correlated with the density fluctuations. As reionization begins, the large-scale overdense regions ionize first, which causes the correlation coefficient between the 21 cm and density fields to reverse signs. Consequently, there is an intermediate period (near $\langle x_i \rangle \sim 0.15$ in this model) where the two fields are roughly uncorrelated on large scales (Lidz et al. 2008). This causes our method to break down; though, we caution that incorporating spin-temperature fluctuations into the modeling may modify this conclusion. Note also that it will be challenging to perform line-intensity mapping observations at very early times before, e.g., sufficient metal enrichment occurs.

While our baseline model assumes the abundant mini-halo sinks scenario we have also investigated the fiducial model used in Lidz et al. (2008). Although this latter model has a different ionization history and bias-factor evolution, the accuracy of our three cross-spectra method is broadly similar in this case. For example, near the midpoint of reionization in this model ($z = 7.32$, $\langle x_i \rangle = 0.54$), the 21 cm bias extraction also reaches subpercent accuracy.

5. Detectability

Encouraged by the success of our approach in simulations, we briefly describe the survey specifications required to infer 21 cm bias factors using this technique. Here we consider only rough estimates and defer an in-depth treatment of noise power spectra, variance from residual foregrounds, and a full probabilistic, multi-field framework to future work.

We first describe the relevant variance and covariance formulae (for derivations, see, e.g., Villaescusa-Navarro et al. 2015):

$$\text{Var}[P_{i,j}] = P_{i,j}^2 + P_{i,\text{tot}}P_{j,\text{tot}},$$
$$\text{Cov}[P_{i,j}, P_{i,k}] = P_{i,\text{tot}}P_{j,k} + P_{j,\text{tot}}P_{i,k},$$

(11)

where $P_{i,\text{tot}} = P_i + N_i$ and $N_i$ is the instrumental noise power spectrum of line $i$. For simplicity, we neglect the shot-noise contribution to each field. We note that Equation (11) is only
valid in the Gaussian approximation, but this is suitable for the large scales of interest in our approach.

We can now apply the standard propagation of errors formula to Equation (7) and substitute Equation (11), yielding:

\[
\text{Var}[P_{21}] = \left( \frac{P_{21,C}}{P_{21,O}} \right)^2 \left( P_{21,O} + P_{21,\text{tot}}P_{O,\text{tot}} \right) \\
+ \left( \frac{P_{21,O}}{P_{21,C}} \right)^2 \left( P_{21,C} + P_{21,\text{tot}}P_{C,\text{tot}} \right) \\
+ \left( \frac{P_{21,C}^2}{P_{21,O}^2} \right) \left( P_{21,O}^2 + P_{21,\text{tot}}P_{O,\text{tot}} \right) \\
+ \left( \frac{P_{21,C}^2}{P_{21,O}^2} \right) \left( P_{21,O}P_{21,C} + P_{21,\text{tot}}P_{C,\text{tot}} \right) \\
- \frac{P_{21,C}^2}{P_{21,O}^2} \left( P_{O,\text{tot}}P_{21,C} + P_{21,\text{tot}}P_{C,\text{tot}} \right) \\
- \frac{P_{21,C}^2}{P_{21,O}^2} \left( P_{C,\text{tot}}P_{21,O} + P_{21,\text{tot}}P_{C,\text{tot}} \right). \tag{12}
\]

The number of modes in a bin of width \( \delta k \) centered on \( k \) is,

\[
N_m = \frac{4\pi k^3 \delta k}{V_{\text{fund}}},
\]

where \( V_{\text{fund}} \) is the volume of a fundamental mode. We assume a square survey area and therefore compute,

\[
V_{\text{fund}} = \frac{(2\pi)^3 L_\perp^2 L_z^2}{L_\perp^3 L_z},
\]

where \( L_\perp \) is the side length of the survey area and \( L_z \) is the length of the redshift bin \( \Delta z \).

We assume a joint survey area of 100 deg\(^2\) and bin widths of \( \delta k = 0.03 \text{ Mpc}^{-1} \) and \( \Delta z = 0.25 \). In order to make a rough estimate, we assume that each experiment reaches sample-variance limited sensitivity at \( k = 0.1 \text{ Mpc}^{-1} \), with \( N_f = P_f \) at this wavenumber and adopt a pure, isotropic white-noise power spectrum. In the case of [C\ II], the required noise depends on the uncertain average specific intensity, which determines, in part, the signal strength, \( P_f \). A plausible value is \( \langle I_{C\ II} \rangle = 5 \times 10^{12} \text{ Jy/str} \) at \( z = 8.34 \) (Beane & Lidz 2018). In this case, \( N_{C,\text{II}} = 1.6 \times 10^5, 2.5 \times 10^5, 3.9 \times 10^5 (\text{ Jy/str})^2 \text{ Mpc}^3 \) for the L, M, and H models of the [C\ II] line, respectively, at \( z = 8.34 \). These noise requirements are comparable to the values forecasted for Stage-II [C\ II] line-intensity mapping forecasts in Silva et al. (2015) and Lidz & Taylor (2016). We expect broadly similar noise requirements for hypothetical future [O\ III] surveys but defer detailed forecasts to future work. As we discussed previously (Beane & Lidz 2018), the 21 cm sensitivity requirement assumed here seems plausible considering HERA-350 will image some large-scale modes (DeBoer et al. 2017)—although the white-noise approximation is rather crude and should be refined in future work.

We caution that the strength of the [C\ II] signal at the redshifts of interest is quite uncertain. A broad range of estimates appear in the current literature, depending on assumptions about the correlation between [C\ II] luminosity and SFR at high redshift, the total star formation rate density (estimates from UV luminosity functions are sensitive to whether and how one extrapolates to faint luminosities beyond current detection limits), and the host halo masses of [C\ II] emitters. For example, our model values for \( \langle I_{C\ II} \rangle \) are similar to a number of recent forecasts (Silva et al. 2015; Dumitru et al. 2019), but are more than an order of magnitude larger than some more pessimistic estimates in Silva et al. (2015) and Chung et al. (2018). In any case, at fixed luminosity-weighted bias, the required noise scales quadratically with the average specific intensity and so the reader can rescale our results according to their preferred specific intensity model. For instance, in the case of \( \langle I_{C\ II} \rangle = 20 \text{ Jy/str} \) (Chung et al. 2018), one would require that \( N_{C,\text{II}} = 2.6 \times 10^6, 4 \times 10^6, 6.2 \times 10^6(\text{ Jy/str})^2 \text{ Mpc}^3 \) for the L, M, and H models of the [C\ II] line, respectively at \( z = 8.34 \). On the other hand, a more moderate estimate of \( \langle I_{C\ II} \rangle = 100 \text{ Jy/str} \) (Silva et al. 2015; Dumitru et al. 2019), requires \( N_{C,\text{II}} = 6.4 \times 10^7, 1 \times 10^8, 1.6 \times 10^8(\text{ Jy/str})^2 \text{ Mpc}^3 \) for the L, M, and H models of the [C\ II] line, respectively, at \( z = 8.34 \).

With the assumed noise and survey requirements for our fiducial model, we show the resulting error bars in the top and middle panels of Figure 1 for our particular choice of binning. At least for the hypothetical surveys considered here, the 21 cm bias factor may be recovered with good statistical precision. In other words, if sample-variance limited sensitivity may be reached at \( k = 0.1 \text{ Mpc}^{-1} \) in each line over a common survey area of \( \sim 100 \text{ deg}^2 \), then a strong detection appears feasible. Of course we have neglected sample variance contributions from residual foregrounds among other complications, and so this should be interpreted as a best-case scenario. On the other hand, increasing the common survey area above 100 deg\(^2\), for example, could help shrink the error bars.

While our fiducial [C\ II] survey is somewhat futuristic, we can also consider the prospects with current, shortly upcoming surveys, specifically CCAT-prime\(^9\) (Stacey et al. 2018), CONCERTO\(^10\) (Lagache et al. 2017), and TIME\(^11\) (Crites et al. 2014). We use the pixel noise values, \( \sigma_{\text{pix}}^{-1/2} \), for each survey from Chung et al. (2018). We report the noise power spectrum at \( z = 7.4 \) (assuming a pure white-noise spectrum) in Table 1. We generically find that \( N \sim 2 \times 10^9 (\text{ Jy/str})^2 \text{ Mpc}^3 \). If we assume a model with \( \langle I_{C\ II} \rangle \sim 500 \text{ Jy/str} \), then even the first-generation surveys reach our requisite noise. However, deeper surveys will be needed in the case of the more pessimistic estimates of \( \langle I_{C\ II} \rangle \sim 100 \sim 20 \text{ Jy/str} \). That being said, our fiducial calculations also assume a larger survey area of 100 deg\(^2\). At \( z = 8.34 \) we find an S/N of 3, 2.7, and 2.9 for the L-M, M-H, and H-L models, respectively, at \( k = 0.1 \text{ Mpc}^{-1} \) and bin width of \( \Delta k = 0.03 \text{ Mpc}^{-1} \). Since

9. http://www.ccatastronomy.org
10. https://people.lam.fr/lagache_guillaume/CONCERTO.html
11. https://cosmology.caltech.edu/projects/TIME
the number of modes scale with the square root of the survey area, we estimate that CCAT-p might be able to recover an S/N of 0.5, 0.4, and 0.4 for the L-M, M-H, and H-L models, respectively, at \( k = 0.1 \text{ Mpc}^{-1}. \) Including some higher \( k \)-modes, even this first-generation survey might be capable of a marginal detection (if [O III] can be surveyed as well), but this is only for our optimistic signal strength model.

Since the strength of the [C II] signal is likely a strong function of redshift, the survey requirements should be less stringent at \( z \sim 7 \) than the \( z \sim 8 \) case considered above. The main effect here should be from redshift evolution in the average specific intensity; again, the noise requirements scale with the average intensity squared. The required noise can therefore be adjusted according to one’s preferred model for redshift evolution in the signal strength.

6. Conclusions

We have shown that the amplitude of large-scale 21 cm fluctuations may be inferred from measuring cross-power spectra between the 21 cm fluctuations and each of two separate line-intensity maps, such as [C II] or [O III]. Although it has long been recognized that the cross-power spectrum between two fields is more robust to foreground contamination than the auto-power spectrum of either field alone, the amplitude of a single cross-power spectrum provides only a product of two bias factors. We found that using a suitable combination of three cross-power spectra (Equations (6) and (7)) one can instead infer the 21 cm bias alone to high accuracy.

Quantitatively, in the reionization model we considered, the accuracy reaches percent level on large scales (\( k \sim 0.1-0.3 \text{ Mpc}^{-1} \)) during much of the EoR. The inferred bias-factor evolution can then be compared to that extracted from the 21 cm auto spectrum. In principle, checking whether the 21 cm auto-power spectrum follows linear biasing on large scales might itself be a good systematics check. However, linear biasing holds only over a limited span of wavenumbers and early measurements may probe a small dynamic range in spatial scale. Hence we believe that our three cross-spectra approach might play an important role in confirming initial detections. Since our method underestimates \( P_{21,21} \) on intermediate scales, it can place informative lower limits (i.e., \( \sim 50\% \) of the true value) down to \( k \sim 1 \text{ Mpc}^{-1} \), depending on the stage of reionization. More work is necessary, however, to see if there are some allowed reionization and line-intensity models where our technique actually overestimates bias factor in each line using the same basic technique outlined here.

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Software: colossus (Diemer 2018), matplotlib (Hunter 2007), numpy (Van Der Walt et al. 2011), and scipy (Jones et al. 2001).

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