

# The clustering of active galactic nuclei and star-forming galaxies in the LoTSS Deep Fields

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## ABSTRACT

Using deep observations across three of the LOFAR Two-metre Sky Survey Deep Fields, this work measures the angular clustering of star-forming galaxies (SFGs) and low-excitation radio galaxies (LERGs) to  $z \lesssim 1.5$  for faint sources,  $S_{144\text{ MHz}} \geq 200\text{ }\mu\text{Jy}$ . We measure the angular auto-correlation of LOFAR sources in redshift bins and their cross-correlation with multiwavelength sources to measure the evolving galaxy bias for SFGs and LERGs. Our work shows the bias of the radio-selected SFGs increases from  $b = 0.90^{+0.11}_{-0.10}$  at  $z \sim 0.2$  to  $b = 2.94^{+0.36}_{-0.36}$  at  $z \sim 1.2$ ; faster than the assumed  $b(z) \propto 1/D(z)$  models adopted in previous LOFAR cosmology studies (at sensitivities where active galactic nuclei dominate), but in broad agreement with previous work. We further study the luminosity dependence of bias for SFGs and find little evidence for any luminosity dependence at fixed redshift, although uncertainties remain large for the sample sizes available. The LERG population instead shows a weaker redshift evolution with  $b = 2.33^{+0.28}_{-0.27}$  at  $z \sim 0.7$  to  $b = 2.65^{+0.57}_{-0.55}$  at  $z \sim 1.2$ , though it is also consistent with the assumed bias evolution model ( $b(z) \propto 1/D(z)$ ) within the measured uncertainties. For those LERGs that reside in quiescent galaxies, there is weak evidence that they are more biased than the general LERG population and evolve from  $b = 2.62^{+0.33}_{-0.33}$  at  $z \sim 0.7$  to  $b = 3.08^{+0.85}_{-0.84}$  at  $z \sim 1.2$ . This suggests the halo environment of radio sources may be related to their properties. These measurements can help constrain models for the bias evolution of these source populations, and can help inform multi-tracer analyses.

**Key words:** large-scale structure of Universe – cosmology: observations – radio continuum: galaxies.

## 1 INTRODUCTION

Large-area spectroscopic surveys have been instrumental in allowing us to observe how galaxies are distributed and to build up knowledge of the cosmic web. These surveys demonstrate that galaxies are not uniformly distributed and that there is large-scale structure within the Universe. Surveys such as the 2dF Galaxy Redshift Survey (2dFGRS; M. Colless et al. 2001), 6dF Galaxy Survey (6dFGS; D. H. Jones et al. 2004), Sloan Digital Sky Survey (SDSS; D. G. York et al. 2000), and Galaxy And Mass Assembly (GAMA; S. P. Driver et al. 2011) survey have all been crucial in making detailed maps of the distribution of galaxies in the Universe, though many of these were limited to more local structures  $z < 1$ . These observations show clusters filled with galaxies, filaments connecting the clusters, and regions with a clear deficit of galaxies, known as voids.

By studying how different galaxies are distributed within this cosmic web, we are able to gain greater understanding of the impact of the underlying environments on galaxies and their properties. This distribution of galaxies in the large-scale structure can be studied through the spatial two-point correlation function (TPCF),  $\xi(r)$  (see e.g. P. J. E. Peebles 1980).  $\xi(r)$  quantifies the excess probability to find galaxy pairs at a comoving spatial scale ( $r$ ), compared to if galaxies are randomly distributed in the Universe. More formally,  $\xi(r)$  is defined by

$$dP(r) = \bar{n} [1 + \xi(r)] d^3r, \quad (1)$$

where  $\bar{n}$  is the mean density of sources and  $dP$  the probability to observe galaxies in a volume,  $d^3r$ , at a given spatial separation,  $r$ . The spatial clustering of the aforementioned spectroscopic surveys has been studied in great detail and allows the properties of galaxies to be related to their underlying dark matter environments (in numerous works including D. S. Madgwick et al. 2003; I. Zehavi et al. 2011; H. Guo et al. 2015).

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However, for the majority of surveys both at radio wavelengths and across the electromagnetic spectrum, we are unable to obtain spectroscopic completeness for large area, deep surveys of galaxies. This is especially true for the radio surveys that are being carried out with state-of-the-art radio facilities such as LOFAR (M. P. Haarlem et al. 2013), ASKAP (A. W. Hotan et al. 2021), and MeerKAT (J. L. Jonas 2009; J. Jonas & MeerKAT Team 2016). Continuum surveys from such facilities instead image galaxies at specific frequencies, and cannot directly provide redshift information. Instead, radio surveys rely on counterpart sources from other wavebands across the electromagnetic spectrum to determine redshifts. Where spectroscopic redshifts are unavailable, photometric redshifts are relied upon. These photometric redshifts combine the available multiwavelength data and use template fitting (e.g. G. B. Brammer, P. G. van Dokkum & P. Coppi 2008; S. Arnouts & O. Ilbert 2011) or machine learning methods (see e.g. I. A. Almosallam et al. 2016a; I. A. Almosallam, M. J. Jarvis & S. J. Roberts 2016b; S. Cuvuoti et al. 2017) to assign redshifts ( $z$ ). Such redshifts can have broad probability density functions (PDFs), arising from uncertainties in modelling photometric redshifts using the data available, and the distributions can often have multiple peaks. The spatial distribution of samples where photometric redshifts dominate are therefore much more uncertain. However, we are still able to gain an understanding of the distribution of galaxies using their projected clustering by measuring the angular TPCF,  $\omega(\theta)$ , defined by

$$dP(\theta) = \sigma [1 + \omega(\theta)] d\Omega. \quad (2)$$

This is similar to equation (1), where now  $dP$  is the probability to observe galaxies within angular separations ( $\theta$ ),  $\sigma$  is the average surface density of sources, and  $d\Omega$  is the solid angle element being considered.

In practice,  $\omega(\theta)$  is calculated from galaxy surveys using estimators (such as from A. J. S. Hamilton 1993; S. D. Landy & A. S. Szalay 1993) through comparing counts of galaxies within angular separations compared to randomly distributed galaxies. This does not rely upon any redshift information. However, using the overall redshift distribution of the sources, and assuming a model for  $\xi(r)$ , the spatial clustering can be inferred (see e.g. Limber inversion and its use in a number of radio studies; D. N. Limber 1953, 1954; P. J. E. Peebles 1980; R. A. Overzier et al. 2003; S. N. Lindsay, M. J. Jarvis & K. McAlpine 2014; C. L. Hale et al. 2018). Knowledge of the clustering and the redshift distribution of sources can be further used to relate their clustering to that of the spatial clustering of the underlying matter,  $\xi_m$ . This allows quantification for a parameter known as bias,  $b$  (see e.g. discussions in P. J. E. Peebles 1980; J. A. Peacock & R. E. Smith 2000; V. Desjacques, D. Jeong & F. Schmidt 2018), defined by

$$\xi(z, r) = b^2(z, r) \xi_m(z, r). \quad (3)$$

Through tracing how bias evolves for a population of sources, the relationship between galaxies, their properties, and the underlying matter environment can be studied to better quantify the evolving galaxy–halo connection.

The angular TPCF has been relied upon for a number of studies into the clustering of radio sources. These cover both wide area surveys (e.g. C. Blake & J. Wall 2002; R. A. Overzier et al. 2003; C. Blake, T. Mauch & E. M. Sadler 2004) and smaller regions over which there is deep ancillary data (e.g. S. N. Lindsay et al. 2014; M. Magliocchetti et al. 2017; C. L. Hale et al. 2018; A. Chakraborty et al. 2020). Recent studies with LOFAR have also been used to probe the clustering of radio-detected sources and study the relationship of such galaxies to their dark matter environment; however, they

have typically focussed on bright populations ( $S_{144 \text{ MHz}} \gtrsim 2 \text{ mJy}$ ; T. M. Siewert et al. 2020; D. Alonso et al. 2021; N. Bhardwaj et al. 2024; C. L. Hale et al. 2024; S. J. Nakoneczny et al. 2024). While radio clustering studies often rely on the angular clustering due to the dominance of photometric redshifts, this will be improved upon with future spectroscopic surveys, which specifically target the host galaxies of radio-detected sources (see e.g. D. J. B. Smith et al. 2016; K. Duncan et al. 2023; S. Jin et al. 2023).

With the radio observations of recent deeper surveys with telescopes such as LOFAR (W. L. Williams et al. 2016; C. L. Hale et al. 2019; J. Sabater et al. 2021; C. Tasse et al. 2021), MeerKAT (e.g. T. Mauch et al. 2020; I. Heywood et al. 2021; C. L. Hale et al. 2025), ASKAP (R. P. Norris et al. 2021; G. Gürkan et al. 2022), u-GMRT (e.g. A. Mazumder et al. 2020; E. F. Ocran et al. 2020), and the VLA (e.g. V. Smolčić et al. 2017a; D. der Vlugt et al. 2021), we are in the regime where star-forming galaxies (SFGs) contribute a significant fraction to, and can even dominate, the total source population (see e.g. V. Smolčić et al. 2017b; H. S. B. Algera et al. 2020; P. N. Best et al. 2023). Using such surveys that combine area, sensitivity, and have a wealth of ancillary data it is possible to identify host galaxies for these radio sources and classify these sources into different sub-classes (e.g. active galactic nuclei, AGN, and SFGs, see e.g. V. Smolčić et al. 2017b; H. S. B. Algera et al. 2020; I. H. Whittam et al. 2022; P. N. Best et al. 2023; S. Das et al. 2024). This classification allows for in-depth studies of the statistical properties of different source populations and their connection to their host properties, environments, and redshifts.

Furthermore, AGN can be further categorized based on their properties. Historically, AGN have both been split based on morphological properties (B. L. Fanaroff & J. M. Riley 1974) and into radio ‘loud’ and ‘quiet’ populations, which distinguish the significance of the radio emission from the jets (see e.g. A. S. Wilson & E. J. M. Colbert 1995). For radio-loud AGN (RLAGN), these are often further split based on their accretion on to the central AGN, which may occur in two fundamental modes based on their radiative efficiency (see e.g. T. M. Heckman & P. N. Best 2014 and M. J. Hardcastle & J. H. Croston 2020, which provide reviews on this topic). Those radio sources that accrete from radiatively efficient discs are known as high-excitation radio galaxies (HERGs) and are believed to be geometrically thin optically thick accretion discs (N. I. Shakura & R. A. Sunyaev 1973). Conversely, low-excitation radio galaxies (LERGs) are believed to accrete from a radiatively inefficient disc, which are thought to be fuelled by advection-dominated flows (R. Narayan & I. Yi 1994, 1995). However, recent studies such as those from I. H. Whittam et al. (2018, 2022) have indicated a greater overlap in the accretion efficiency of these two populations.

Previous clustering studies in the radio have shown that different source populations cluster differently, with AGN found to be, in general, more highly clustered than their star-formation dominated counterparts (see e.g. M. Magliocchetti et al. 2017; C. L. Hale et al. 2018; A. Chakraborty et al. 2020; A. Mazumder, A. Chakraborty & A. Datta 2022). Owing to this, it is important for radio clustering studies to study the evolution of different source populations independently. It is also important to understand the clustering of different source populations so that their bias can be applied to multi-tracer techniques to help overcome cosmic variance at large scales (see e.g. A. Raccanelli et al. 2012; L. D. Ferramacho et al. 2014; Z. Gomes et al. 2020). Recent work has also indicated that there may be a connection between the accretion mode of radio-loud AGN and their clustering, through the study of high-redshift analogues of high-/low-excitation radio galaxies (H/LERGs; see C. L. Hale et al. 2018). A recent summary of a number of radio-based clustering studies can

be found in M. Magliocchetti (2022). Moreover, other studies that probe the environments of H/LERGs through other measurements have also suggested differences in their local environments may be important (see e.g. C. Tasse et al. 2008; M. A. Gendre et al. 2013; M. J. Hardcastle & J. H. Croston 2020).

In this work we make use of some of the deepest LOFAR observations to date and complementary multiwavelength data to study the clustering of SFGs and LERGs in three of the LOFAR Two-metre Sky Survey (LoTSS) Deep Fields. SFGs and LERGs represent the two most populous source types identified in the LoTSS deep fields (P. N. Best et al. 2023). This paper is presented as follows. In Section 2 we present the data used in this work both from LOFAR and the associated multiwavelength catalogues. In Section 3 we outline the methods used to measure the angular clustering of the SFGs and LERGs and we present the results of such analysis in Section 4. We then discuss the galaxy bias and present its evolution in Section 5. Furthermore, owing to the larger radio samples available from the LOFAR Deep Fields, we further investigate the evolving bias as a function of luminosity for LOFAR detected SFGs. We present the conclusions of our analysis in Section 6. Unless otherwise stated, our work assumes a constant spectral index for radio sources,  $\alpha = 0.7$ , where  $S_\nu \propto \nu^{-\alpha}$  and we adopt the cosmology used in R. Kondapally et al. (2021) and P. N. Best et al. (2023), namely,  $H_0 = 70 \text{ km s}^{-1} \text{ Mpc}^{-1}$ ,  $\Omega_m = 0.3$ ,  $\Omega_\Lambda = 1 - \Omega_m$  and also adopt  $n_s = 0.965$  and  $\sigma_8 = 0.8$ .

## 2 DATA

The data used in this work come from LOFAR observations across the LoTSS Deep Fields and their associated value added catalogues. We summarize the data here but comprehensive details can be found in J. Sabater et al. (2021) and C. Tasse et al. (2021) for the radio continuum images and catalogues and K. J. Duncan et al. (2021), R. Kondapally et al. (2021), and P. N. Best et al. (2023) for the host galaxy identification, redshift estimation, and source classification, respectively.

### 2.1 Radio Data: LoTSS Deep Fields

The LoTSS Deep Fields consist of four well-studied multiwavelength fields: Boötes, Lockman Hole, the European Large-Area ISO Survey Northern Field 1 (ELAIS-N1), and the North Ecliptic Pole (NEP) field. These fields are all located in the northern sky, at optimal locations for LOFAR (which is not a physically steerable telescope) to observe. Using the high band antenna (HBA) of LOFAR, the first observations at 144 MHz of three of these deep fields were published in a combination of papers for ELAIS-N1 (J. Sabater et al. 2021) and the Boötes and Lockman Hole (C. Tasse et al. 2021) fields. J. Sabater et al. (2021) and C. Tasse et al. (2021) presented images and catalogues for observations totalling 164, 80, and 112 h on target for the ELAIS-N1, Boötes, and Lockman Hole fields, respectively, covering approximately  $25 \text{ deg}^2$  in each field<sup>1</sup>.

Processing of the data used a combination of flagging and averaging of the raw data set, then calibrating the data. This calibration consisted of both direction-independent and direction-dependent calibration, making use of the packages kMS (C. Tasse 2014; O. M. Smirnov & C. Tasse 2015; C. Tasse 2023) and DDFacet (C.

Tasse et al. 2018, 2023). Direction-dependent calibration is crucial for observations at such low frequencies to account for the effects of the ionosphere, which can cause the apparent movements of sources across the sky, but also is necessary to account for primary beam effects over long-duration observations. These direction-dependent corrections allow for images with an angular resolution of 6 arcsec to be produced, compared to 25 arcsec with direction-independent calibration alone (see T. W. Shimwell et al. 2017).

Source catalogues were extracted in each of the fields using the Python Blob Detection Source Finder (PyBDSF; N. Mohan & D. Rafferty 2015), using a  $5\sigma$  peak signal-to-noise thresholding criterion. Owing to its longer observations, ELAIS-N1 is the deepest field with an average rms of  $\sim 30 \mu\text{Jy beam}^{-1}$  across the image. This compares to  $\sim 60 \mu\text{Jy beam}^{-1}$  in Boötes and  $\sim 40 \mu\text{Jy beam}^{-1}$  in the Lockman Hole field. This results in the detection of a total of  $\sim 157\,000$  sources across the  $\sim 25 \text{ deg}^2$  of radio area in each of the three fields, with  $\sim 70\,000$ ,  $\sim 37\,000$ ,  $\sim 50\,000$  sources in the ELAIS-N1, Boötes, and Lockman Hole fields, respectively. In this paper we will adopt a subset of these catalogues for the analysis; we describe such cuts to the data in the following sections.

### 2.2 Multiwavelength data

Alongside the radio data, we make use of the multiwavelength catalogues of sources detected in the three fields. These were not only used to provide counterparts to the radio sources (see Section 2.3) but are also used here to measure the angular cross-correlation of these multiwavelength galaxies with the radio sources. These catalogues combine data from the UV to the far-IR and are described in detail in R. Kondapally et al. (2021); their overlapping regions cover a reduced area compared to the radio data alone (see fig. 1 of R. Kondapally et al. 2021, where we make use of their shaded regions for this work).

For the Boötes field, the multiwavelength catalogue originates from 4.5  $\mu\text{m}$  and  $I$ -band point spread function (PSF) matched catalogues from M. J. I. Brown et al. (2007, 2008), which combine data from the NOAO Deep Wide Field Survey (NDWFS; B. T. Jannuzi & A. Dey 1999) as well as optical imaging from F. Bian et al. (2013) and near-IR data from A. H. Gonzalez et al. (2010). For ELAIS-N1 and the Lockman Hole field, R. Kondapally et al. (2021) created their own combined matched-aperture catalogues. This includes data from the UV to IR: the *Galaxy Evolution Explorer* (GALEX) space telescope (D. C. Martin et al. 2005; P. Morrissey et al. 2007); Hyper-Suprime-Cam Subaru Strategic Program (HSC-SSP) survey (H. Aihara et al. 2018); the Canada–France–Hawaii Telescope MegaCam instrument (H. Hildebrandt et al. 2016); Panoramic Survey Telescope and Rapid Response System (Pan-STARRS-1; K. C. Chambers et al. 2016); the Herschel Space Observatory (M. J. Griffin et al. 2010; A. Poglitsch et al. 2010); and from the *Spitzer Space Telescope* (from C. J. Lonsdale et al. 2003; J. C. Mauduit et al. 2012). R. Kondapally et al. (2021) generated 0.2 arcsec pixel scale images and detected sources using SEXTRACTOR (E. Bertin & S. Arnouts 1996) to create the multiwavelength catalogues that we use in this work. Aperture corrections are additionally applied to account for varying PSF sizes between the images.

These combined multiwavelength catalogues contain over 2 million sources in each of the three fields used in this work:  $\sim 2.1$  million in ELAIS-N1,  $\sim 3.0$  million in Lockman Hole and  $\sim 2.2$  million in Boötes. This is reduced in numbers when only the areas which have overlap between all the best multiwavelength surveys are considered and masking is applied (see fig. 1 of R. Kondapally et al. 2021). This overlapping area covers  $\sim 26 \text{ deg}^2$  in total across the three fields and reduces the number of multiwavelength sources to  $\sim 1.4$  million sources in ELAIS-N1 ( $6.74 \text{ deg}^2$ ),  $\sim 1.9$  million

<sup>1</sup>Where the  $\sim 25 \text{ deg}^2$  corresponds to the area of the images released in C. Tasse et al. (2021) and J. Sabater et al. (2021), which are truncated at the 30 per cent power point of the primary beam. PyBDSF was run for each image over this full  $\sim 25 \text{ deg}^2$ .

**Table 1.** Table outlining the number of sources (across all redshift ranges) from the initial catalogues and after applying the subsequent cuts that are used in this analysis. Each row is cumulative and includes the cuts applied to all previous rows. These numbers are indicated for the radio and multiwavelength catalogues separately, for each of the three fields (Boötes, ELAIS-N1, and Lockman Hole) and are not split by source type (i.e. SFG versus LERG). The numbers indicated in bold show the final numbers of either radio or multiwavelength sources used across all redshifts. Those used for each redshift sample considered in this work can be found in Table 3. We note that in this table, the starting criteria ‘Original Catalogue’ for the radio populations refers to the source catalogue over the  $\sim 25$  deg<sup>2</sup> of each field within the primary beam cut, as described in J. Sabater et al. (2021) and C. Tasse et al. (2021). For the multiwavelength data the full catalogue relates to the ‘Science Ready’ catalogues released with K. J. Duncan et al. (2021).

Description	Radio catalogue			Multiwavelength catalogue		
	Boötes	ELAIS-N1	Lockman	Boötes	ELAIS-N1	Lockman
Original source catalogue	36 767	70 544	50 112	2 214 329	2 105 993	3 041 793
In FLAG_OVERLAP and FLAG_CLEAN regions (+ (for radio) in cross-matched catalogue of R. Kondapally et al. 2021)	18 553	30 768	30 347	1 911 265	1 446 319	1 837 134
Band Used for magnitude and $5\sigma$ Cut	–	–	–	4.5 $\mu$ m	<i>K</i>	4.5 $\mu$ m
Magnitude Cut Applied	–	–	–	$\leq 21.33$	$\leq 21.78$	$\leq 21.18$
Applying $5\sigma$ Cut and Magnitude Cuts	–	–	–	317 022	282 871	302 530
With redshifts from K. J. Duncan et al. (2021)	18 238	30 470	30 161	216 708	272 315	297 071
With source classification from P. N. Best et al. (2023)	17 707	30 182	29 595	–	–	–
Additional spatial masking applied (additional star masks for all fields + masking of Table 2 for Boötes)	15 905	28 772	27 977	210 714	260 949	284 576
Radio flux density ( $\geq 200 \mu$ Jy) & SNR ( $\geq 5\sigma$ ) cuts	<b>14 925</b>	<b>17 289</b>	<b>22 797</b>	–	–	–
Mass cut applied ( $M_* \geq 10^{10.5} M_\odot$ )	–	–	–	<b>68 257</b>	<b>59 636</b>	<b>87 525</b>

sources in the Lockman Hole field (10.28 deg<sup>2</sup>), and  $\sim 1.8$  million sources in Boötes (8.63 deg<sup>2</sup>). For full details of the sources used after cuts to the catalogues are applied see Table 1. The sources in the areas adopted are identified using a combination of the ‘FLAG\_OVERLAP’ (==1 for Boötes, ==3 for Lockman Hole and ==7 for ELAIS-N1) and ‘FLAG\_CLEAN’ (! = 3) identifiers in the source catalogue. This restricts the data to the best multiwavelength regions, avoiding objects such as stars that may be impacting the multiwavelength photometry. Further details of the flag can be found in R. Kondapally et al. (2021)<sup>2</sup>, where FLAG\_OVERLAP is indicative of the availability of multiwavelength coverage in different bands and FLAG\_CLEAN relates to the masking around bright stars. In Boötes an additional flag to mask ultra deep regions is also applied: ‘FLAG\_DEEP’ (= 1).

Finally, we also apply a stellar mass cut of  $M_* \geq 10^{10.5} M_\odot$  to the multiwavelength data, which, as can be seen in fig. 11 of K. J. Duncan et al. (2021), is predominately larger than the 90 per cent magnitude completeness limits already applied in this work. Applying a constant high mass cut is generally more restrictive than using the magnitude cuts of K. J. Duncan et al. (2021) alone to impose completeness. As discussed in K. J. Duncan et al. (2021), the stellar masses in their catalogue are believed to be robust up to a redshift of  $z = 1.5$  and so we restrict ourselves to such a redshift range over which to probe the clustering. The result of such a high mass cut is a robust sample of massive galaxies for cross-correlating to the radio data. The high stellar mass cut also restricts the samples to the most massive galaxies, which is beneficial when considering the angular cross-correlation, due to the larger bias (see e.g. P. W. Hatfield et al. 2016). Finally, it also ensures that a similar reference sample of galaxies is considered across the redshift samples used in this work as well as between the three fields, to ensure we cross-correlate to a similar population. Such cuts reduced the number of multiwavelength

sources across the three fields. For more details on the effect of source numbers on the cuts applied see Table 1.

### 2.3 Radio data: host identification and redshifts

In order to obtain redshift information and source classifications for the radio-detected galaxies, a catalogue of multiwavelength counterparts with redshifts is essential. The cross-matching process for the LoTSS Deep Fields is described in R. Kondapally et al. (2021), where a combination of likelihood ratio (LR) analysis (see e.g. W. Sutherland & W. Saunders 1992; K. McAlpine et al. 2012; W. L. Williams et al. 2019; I. H. Whittam et al. 2024) as well as visual classification was used to identify the host for the radio sources as in W. L. Williams et al. (2019)<sup>3</sup>. Due to the availability of multiwavelength data, a restricted region of the three fields was used for the host identification process, as discussed in Section 2.2 and presented in Table 1. Over these smaller multiwavelength areas, which are closer to the primary beam centre, the sensitivity improves, now measuring a typical rms of  $\sim 20 \mu$ Jy beam<sup>−1</sup> in ELAIS-N1,  $\sim 30 \mu$ Jy beam<sup>−1</sup> in Lockman Hole, and  $\sim 40 \mu$ Jy beam<sup>−1</sup> in Boötes.

R. Kondapally et al. (2021) used a number of decision trees in order to identify which sources had a reliable identification of a host galaxy from the LR analysis, and which sources instead needed visual identification to obtain a host galaxy match. Sources with compact sizes or secure radio positions were determined to be most suitable for LR cross-matching; sources with a large size or in a crowded region of the field were instead sent to visual analysis. For visual identification, R. Kondapally et al. (2021) used the Zooniverse<sup>4</sup>

<sup>2</sup>and in the read me files available at <https://lofar-surveys.org/index.html>

<sup>3</sup>For clarity, prior to source association a radio source refers to the source as defined by the source finder, PyBDSF. After source associations and classifications a source refers to the object within the catalogue of R. Kondapally et al. (2021). This is assumed to be from an individual galaxy, which may include multiple of the original PyBDSF radio sources.

<sup>4</sup><https://www.zooniverse.org>



**Table 2.** Additional regions within the Boötes field that are masked within the field, see Section 3.2.2.

Region	RA range (°)	Dec. range (°)
1	218.90–219.00	33.45–33.70
2	216.10–219.00	33.45–33.53
3	218.20–218.30	32.85–33.70
4	216.10–218.30	32.85–32.96
5	217.50–217.60	32.32–33.68
6	216.78–216.90	32.32–33.68

platform (see e.g. C. Lintott et al. 2012; J. K. Banfield et al. 2015; W. L. Williams et al. 2019) where LOFAR surveys team members used the interface to help visually cross-match sources to a host galaxy. Each source required at least five independent classifications and a host galaxy was assigned if at least 60 per cent of users who analysed a source agreed on a match. Sources without a clear match or that were flagged as requiring further detailed inspection were sent to experts for assessment. Approximately 97 per cent of the LOFAR-detected sources within the multiwavelength region have host galaxies identified.

Alongside the work of R. Kondapally et al. (2021), K. J. Duncan et al. (2021) used the wealth of multiwavelength data across the three LoTSS Deep Fields to obtain redshift estimates for the host galaxies. These redshifts are a combination of photometric redshifts and spectroscopic redshifts, where available. Photometric redshifts were generated through a hybrid method which combines redshifts from spectral energy distribution (SED) fitting techniques and machine learning methods (GPz; I. A. Almosallam et al. 2016a; I. A. Almosallam et al. 2016b). This method produced redshifts for as many sources as possible in the full multiwavelength catalogue (described in Section 2.2), which in turn can provide redshifts for a number of LOFAR-detected sources. In total, 21 per cent of cross-matched sources in the Boötes field have spectroscopic redshifts, reducing to 5 per cent in the other two fields at the time of release. Further details of these catalogues can be found in K. J. Duncan et al. (2021). We note that additional spectra have subsequently been obtained with the Dark Energy Spectroscopic Instrument (DESI; DESI Collaboration 2024, 2025); however, these were not available when host identification was conducted and when the redshifts were used to help in the classification of sources in P. N. Best et al. (2023). We therefore rely on the redshift information from K. J. Duncan et al. (2021).

### 2.3.1 Additional spatial masking

We apply additional spatial cuts to remove some remaining non-uniformity. First, we apply additional spatial masking in the Boötes field, detailed in Table 2. This avoids areas in the Boötes field that appeared deeper than the surrounding image and this was depth was not removed by use of FLAG-DEEP in the catalogue. Secondly, we expand the stellar masks of R. Kondapally et al. (2021) to provide more conservative masking around the brightest stars in the Gaia catalogue (Gaia Collaboration 2016, 2018). This is to ensure uniformity in the optical catalogues close to bright stars. We create a mask around sources with magnitudes in the G band  $\leq 10$  of 2 and 4 arcmin for those source with G band magnitudes  $\leq 7.5$ . This masks 42, 61, and 64 stars across the Boötes, ELAIS-N1, and Lockman Hole fields, respectively, and removes an additional 1–2 per cent of sources in the original cross-matched catalogue of R. Kondapally et al. (2021) compared to the flagged regions discussed

earlier of R. Kondapally et al. (2021). Such spatial cuts were applied to both the radio and multiwavelength data as well as the random catalogues.

## 2.4 Source classifications

For the cross-matched sources, classifications were determined using the abundance of multiwavelength data and were released in P. N. Best et al. (2023). In their work, P. N. Best et al. (2023) used a combination of SED fitting codes to assign classifications for the sources. This included the SED fitting codes AGNFITTER (G. Calistro Rivera et al. 2016), BAGPIPES (A. C. Carnall et al. 2018), CIGALE (M. Boquien et al. 2019), and MAGPHYS (E. da Cunha, S. Charlot & D. Elbaz 2008; E. da Cunha & S. Charlot 2011) to provide source properties for the host galaxies. For sources with an identified host, these were classified as either an SFG or an AGN. For those classified as an AGN, these were sub-classified as either radio loud (RL) or radio quiet (RQ) and for those RLAGNs, these were classed as either HERGs or LERGs. P. N. Best et al. (2023) present a consensus classification for the majority of the LOFAR cross-matched sources, while  $\sim 1500$  sources per field remain unclassified (see table 2 of P. N. Best et al. 2023). This is a small fraction of the total sources within the multiwavelength region,  $\sim 5$  per cent, and this number includes those sources without an assigned host galaxy and redshift. Further details of the classification methods used are provided in P. N. Best et al. (2023). For the classified population, approximately 68 per cent of sources within the multiwavelength region were identified as SFGs, with LERGs being the next biggest fraction of sources at  $\sim 16$  per cent.

Owing to SFGs and LERGs being the two largest populations in the LoTSS Deep Fields, we investigate the clustering of these two populations in this work. We also study the clustering for a subset of the LERG population, namely, quiescent LERG (or QLERGs). These are discussed in R. Kondapally et al. (2022) and are useful to this work as they provide a more representative comparison to the LERG population used in the clustering work of C. L. Hale et al. (2018), who measure the clustering from a sample of QLERGs from the catalogues from V. Smolčić et al. (2017b). We use the same criterion as in R. Kondapally et al. (2022) to classify sources as QLERGs, namely, making cuts based on the specific star formation rate (SFR) of the sources. We note, though, that alternative classifications for the ELAIS-N1 field were subsequently presented in S. Das et al. (2024) using the SED fitting code, PROSPECTOR (J. Leja et al. 2017; B. D. Johnson et al. 2021). Comparison of the ELAIS-N1 field classifications are presented in fig. 8 of S. Das et al. (2024). For SFGs,  $\sim 90$  per cent of sources determined to be SFGs in P. N. Best et al. (2023) are also described as SFGs in the work of S. Das et al. (2024); however, this is closer to  $\sim 70$  per cent for the LERGs of P. N. Best et al. (2023). As such, we acknowledge that differences in the classification process will affect some of the samples of sources used in this work. We also note that recent works using physical processes to split sources by AGN and star formation physical processes using high-resolution LOFAR data may indicate some underestimation of AGN activity in some sources (see L. K. Morabito et al. 2025).

In this work, we continue with the catalogues of P. N. Best et al. (2023). This is because they are the source classifications that were used to study the luminosity functions of LOFAR-detected sources (R. Kondapally et al. 2022; R. K. Cochrane et al. 2023). The luminosity functions from these studies will be important to generate random catalogues, which are necessary to measure the clustering of sources in this work, as described in Section 3.2.

### 3 DATA AND RANDOM CATALOGUES FOR $\omega(\theta)$

#### 3.1 Calculating $\omega(\theta)$ from auto-correlation and cross-correlations

As discussed in Section 1, the two-point correlation is one commonly used method to study the large-scale structure of galaxies within a survey. As the LoTSS sources are dominated by those with photometric redshifts we rely on the angular TPCF,  $\omega(\theta)$ , to quantify the clustering within the fields. We measure  $\omega(\theta)$  using the Landy–Szalay estimator S. D. Landy & A. S. Szalay (1993):

$$\omega(\theta) = \frac{DD(\theta) - 2DR(\theta) + RR(\theta)}{RR(\theta)}. \quad (4)$$

This uses normalized pairs of galaxies within the data catalogue,  $DD(\theta)$ , pairs in a random catalogue,  $RR(\theta)$ , and between the two catalogues,  $DR(\theta)$ . The normalization ensures that across all  $\theta$  bins, the sum of the normalized pairs sums to one, e.g.  $\sum DD(\theta) = 1$ . The random catalogues should be a random distribution of galaxies, but that account for observational systematics in the data and so mimic detection across the field of view. Such systematics can be complex to account for (see e.g. discussions in C. L. Hale et al. 2024) and so we describe the creation of our random catalogues in detail in Section 3.2.

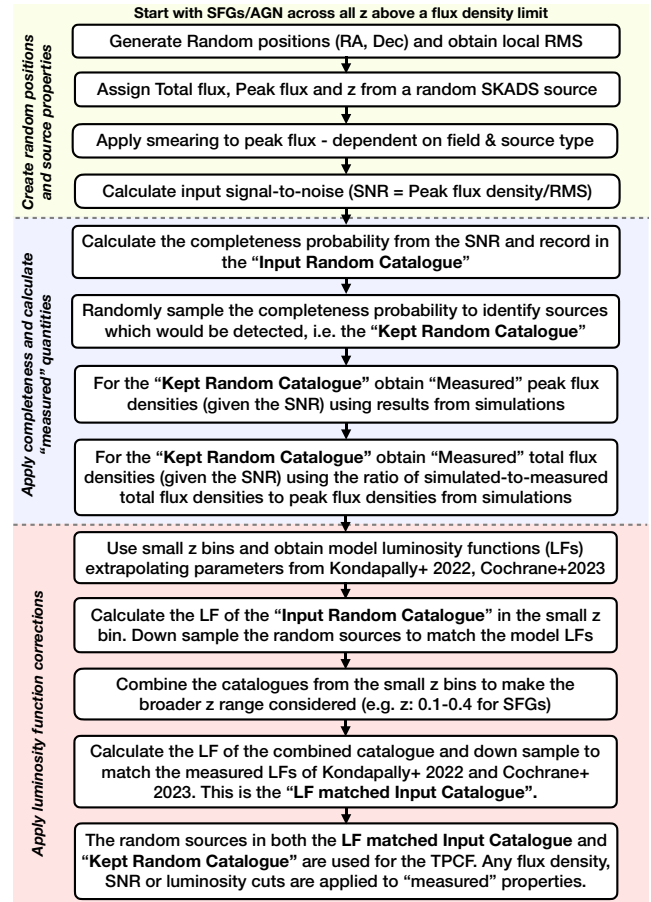
Whilst we can rely on the auto-correlation to measure source clustering, in this work we also use the multiwavelength data from R. Kondapally et al. (2021) and K. J. Duncan et al. (2021) to study the angular cross-correlation function between the radio and multiwavelength data. These multiwavelength catalogues have a higher source density than the radio sources over the same area. Cross-correlating between two catalogues can reduce the impact of any remaining systematics and help improve constraints on the biases of the radio sources by reducing the statistical uncertainties. Combined, this can help improve constraints on the physical properties derived from modelling the angular clustering. The angular cross-correlation function is given by

$$\omega_{CC}(\theta) = \frac{D_1 D_2(\theta) - D_1 R_2(\theta) - D_2 R_1(\theta) + R_1 R_2(\theta)}{R_1 R_2(\theta)}. \quad (5)$$

Here ‘1’ and ‘2’ relate to the radio and the multiwavelength catalogues respectively. Such a formalism has been used in a number of studies (see e.g. W. G. Hartley et al. 2013; S. N. Lindsay et al. 2014; R. M. Bielby et al. 2016; C. Krishnan et al. 2020).

#### 3.2 Random catalogues

As discussed, a catalogue of randomly distributed sources is necessary to measure  $\omega(\theta)$  using both the auto-correlation and cross-correlations. These random catalogues must have no underlying large-scale structure, but must mimic the detection of sources across the fields, accounting for observational effects and spatial masks. This means that the distribution of the random catalogue will be non-uniform. Observational effects, such as sensitivity variations, are more challenging to account for and require understanding of the systematic effects which affect source detection. Therefore, either conservative flux density limits should be applied or these observational effects need to be accounted for within the random catalogues. The latter approach allows more sources across the field to be used to measure the clustering for the population and so has been adopted in a number of studies, such as C. L. Hale et al. (2018); A. Mazumder et al. (2022); C. L. Hale et al. (2024). In this work, we account for the observational systematics for our random catalogues



**Figure 1.** Flowchart outlining the steps to make the catalogue of random sources associated with the radio data that are used to measure the clustering, divided into three stages. The first (yellow) relates to the creation of the general simulated source properties, as in Section 3.2.1. The second (in blue) describes the method of applying completeness effects and measurement errors, as in Section 3.2.1(i). The final stage is the effect of applying corrections for the intrinsic luminosity distribution (pink), as in Section 3.2.1(ii).

and outline this process in the next sections. Fig. 1 provides a schematic representation of the steps involved.

##### 3.2.1 Radio random catalogues

To generate our radio random catalogues we first generate positions across the LoTSS Deep Fields over the regions that the radio data has been restricted to (as outlined above, namely the best ancillary regions of R. Kondapally et al. 2021). Each position is assigned the source properties (flux density, redshift, shape) from a simulated source of the SKA Design Studies (SKADS; R. J. Wilman et al. 2008, 2010), using the modified SKADS catalogue (with double the number of SFGs) as used in C. L. Hale et al. (2024)<sup>5</sup>. A peak flux density for the source is calculated by convolving the source model with the LOFAR 6 arcsec beam. We restrict the SKADS catalogue to integrated flux densities  $S_{144\text{MHz}} \geq 0.05$  mJy<sup>6</sup>. Whilst updated radio simulations are available from T-RECS (A. Bonaldi et al. 2019, 2023), we found (similarly to J. Asorey & D. Parkinson 2021) that the

<sup>5</sup>This accounts for known differences between SKADS and faint source counts (see e.g. S. Mandal et al. 2021; C. L. Hale et al. 2023).

<sup>6</sup>scaled from the 1.4 GHz flux densities in SKADS are used.

T-RECS source model for bright AGN generated larger sources than anticipated, affecting source completeness<sup>7</sup>. Though AGN are not the dominant source population in this work (see P. N. Best et al. 2023), it is important to consider such effects and, as such, we used SKADS.

(i) *Accounting for incompleteness and measurement errors:*

To generate the random catalogue, we broadly followed the method of C. L. Hale et al. (2024), who used the results from completeness simulations in the LOFAR Two-metre Sky Survey (LoTSS-DR2; T. W. Shimwell et al. 2022) to quantify (i) completeness of source detection as a function of input signal-to-noise (SNR); (ii) the measured-to-simulated peak flux density as a function of input SNR; and (iii) the ratio of the measured-to-simulated peak flux density compared to the measured-to-simulated integrated flux density as a function of SNR. These factors were combined with a distribution of sources from the modified SKADS catalogue described above to determine which sources would be considered detected within the data. C. L. Hale et al. (2024) also accounted for a positional dependent smearing of sources across the field of view. Combined, C. L. Hale et al. (2024) created a catalogue of random sources which accounted for the detection across the field of view and had associated ‘measured’ peak and integrated flux densities.

In this work, we produce our own completeness simulations to be analogous to those of T. W. Shimwell et al. (2022), using the methodology described in C. L. Hale et al. (2023). This uses an input source counts model (the modified SKADS catalogue, as above) at 144 MHz to generate simulated sources which are injected into the radio image. We then use the PyBDSF parameters of J. Sabater et al. (2021) and C. Tasse et al. (2021) to generate catalogues of sources which would be detected by PyBDSF. For each field 1000 simulations are run each with 2000 sources per simulation randomly injected into the image. These sources have a random flux density assigned from SKADS, with a source model that is convolved with the 6 arcsec LOFAR beam. For those sources that are detected by PyBDSF, they are matched to an input source using a 3.5 arcsec match radius. This is smaller than the angular resolution to ensure these are true matches. This output matched catalogue allows the calculation of the necessary measurements outlined above, such as the completeness and measured source properties as a function of SNR.

Using the catalogue of simulated random sources, we calculate their SNR based on their peak flux density and the rms at the source location. Using the results of the completeness simulations and the methodology from C. L. Hale et al. (2024) to measure completeness as a function of SNR, we obtain the probability that each source in the catalogue of random sources is detected and then use a process of random sampling to determine the random sources which will be used to measure the clustering. Unlike in C. L. Hale et al. (2024), we do not apply position-dependent smearing as we are unable to independently measure it and, in any case, smearing effects should be reduced given that only a smaller sky area closer to the pointing centre is used. Instead, we apply a constant smearing factor to the simulated peak flux density of the random sources in each field. This factor is allowed to be different for each sub-population in a field, as in addition to accounting for physical smearing effects, it can also empirically correct for differences between the simulated and true source size distributions. These values are chosen to ensure that the peak of the ratio of the measured integrated-to-peak flux density

distribution for the simulated random sources matches that of the data within each field. These factors varied in the range of  $\sim 1$ – $1.15$  across the fields.

For those random sources which are considered detected, a ‘measured’ peak and integrated flux density is then obtained based on the input SNR as in C. L. Hale et al. (2024), using the measured output-to-input flux density distributions as a function of SNR found from the completeness simulations above. These ‘measured’ values are more similar to the flux densities in the PyBDSF data catalogues. Such flux densities have differences to the intrinsic flux densities due to both the noise in the image and measurement differences introduced by the source finder.

At this stage, two catalogues of random sources are retained. The first contains the input catalogue of random sources and their position, local rms, simulated integrated and peak flux densities and the completeness probability for the source. It also contains a flag for whether the source is considered to be ‘detected’ (or not) from the completeness probability and random sampling. We call this the *input random catalogue*. The second catalogue contains the subset of these sources which were considered ‘detected’ and for which a ‘measured’ peak and integrated flux density are also recorded. We refer to this catalogue as the ‘*kept*’ catalogue of random sources. The ‘kept’ catalogue is the basis for the catalogue we use for the radio random terms in equations (4) and (5) and will apply all SNR, spatial masks and flux cuts that are applied to the data to this catalogue of random sources (see Sections 2.3.1 and 3.3). We ensure each catalogue of random sources is more numerous compared to the number of data sources to ensure that the errors will be dominated by uncertainties in the data. The ratio of randoms to data is given in Table 3.

(ii) *Ensuring an accurate intrinsic luminosity distribution for each population over the  $z$  range:*

Though the source counts distributions of the modified SKADS catalogue agrees well with deep radio surveys (e.g. S. Mandal et al. 2021; A. M. Matthews et al. 2021; D. der Vlught et al. 2021; C. L. Hale et al. 2023), we need to ensure that this remains true when we split sources as a function of redshift, source type and flux density. To do this, we use modelled luminosity functions,  $\Phi(L_{144\text{MHz}})$ <sup>8</sup>, of SFGs (R. K. Cochrane et al. 2023) and the LERGs (and QLERGs; R. Kondapally et al. 2022) in the LoTSS Deep Fields. We use these models to down-sample the catalogue of random sources so their input luminosity functions match the models for each redshift bin/source type, as outlined below.

First, we use the  $1/V_{\text{max}}$  method (M. Schmidt 1968) to measure  $\Phi(L)$  for the *input catalogue of random sources*. This method is regularly used for radio luminosity functions (see e.g. T. Mauch & E. M. Sadler 2007; M. Novak et al. 2017; R. Kondapally et al. 2022). Following this method  $\Phi(L)$  is defined as:

$$\Phi(L) = \frac{1}{\Delta \log_{10}(L)} \frac{1}{A_{\text{corr}}} \sum_i \frac{1}{V_{\text{max},i}}, \quad (6)$$

where:  $\Delta \log_{10}(L)$  is the width of the log luminosity bins used to calculate  $\Phi(L)$ ;  $A_{\text{corr}}$  is a correction for the finite area of the observations; and  $V_{\text{max},i}$  is the maximum comoving volume within which the  $i^{\text{th}}$  source between  $\log_{10}(L)$  and  $\log_{10}(L) + \Delta \log_{10}(L)$  can be observed within, given the sensitivity of the data, and the redshift

<sup>7</sup>Though we note that a similar analysis with T-RECS led to radio bias values broadly similar to those derived using SKADS.

<sup>8</sup>We will now drop the 144 MHz subscript when referring to luminosities such that  $L$  refers to a spectral luminosity at 144 MHz, unless otherwise stated.



range being studied<sup>9</sup>. This work will study the evolving clustering of radio sources, using the redshift binning of R. K. Cochrane et al. (2023) for SFGs and R. Kondapally et al. (2022) for LERGs to  $z \lesssim 1.5$  (where stellar masses are estimated to in K. J. Duncan et al. 2021). In the work of R. K. Cochrane et al. (2023), the lowest redshift bin considered begins at  $z = 0.1$ . Below such redshifts the size of sources may affect estimates of the host galaxy properties, using aperture based fluxes.

Next, for an accurate input catalogue of random sources, we must ensure that both the input luminosity distribution and the redshift distribution mimic that of the data. This is to ensure an accurate flux density distribution (or source counts) within the redshift bin for the source type considered. Therefore, we use fine redshift bins ( $\Delta z = 0.025$ ) to match the input luminosity function of the catalogue of random sources to the model luminosity functions. In each redshift bin, we use a quadratic (linear) fit extrapolation of the best-fitting parameters of the models from R. K. Cochrane et al. (2023) (or R. Kondapally et al. 2022) to estimate the luminosity function parameters (and therefore, models) within the  $\Delta z = 0.025$  bins. We compare  $\Phi(L)$  for the input catalogue of simulated random sources assuming no incompleteness within the field and using a minimum flux density limit (see Section 3.3) term<sup>10</sup> in equation (6)<sup>11</sup>. Using the ratio of the observed  $\Phi(L)$  for the input catalogue of random sources to the model  $\Phi_{\text{mod}}(L)$ , we find the smallest value of this ratio across each  $\Delta z$  and luminosity bin<sup>12</sup>. We then normalize all luminosity functions of the input catalogue of random sources by this minimum ratio and downsample the random sources to match the luminosity function model in each  $\Delta z$  bin. Combining the random sources from each of the  $\Delta z$  bins in this way provides an input random catalogue with a luminosity function that reflects the intrinsic models and redshift distributions of radio sources in the Universe.

However, we note that the parametrized models of the luminosity functions for the SFGs and LERGs from R. K. Cochrane et al. (2023) and R. Kondapally et al. (2022) are smoothed models for  $\Phi(L)$ . In practice there may be larger deviations between the model and the data than at some luminosities. This is more prevalent for LERGs (see  $0.5 < z \leq 1.0$  in fig 6. of R. Kondapally et al. 2022). To avoid large differences in the luminosity distributions of the catalogue of random sources to the data  $\Phi(L)$ , we downsample the input catalogues of random sources across the full redshift bin range to match the measured luminosity functions of R. Kondapally et al. (2022) and R. K. Cochrane et al. (2023). The random catalogues which are then used to measure  $\omega(\theta)$  are the subset of this new input random catalogue that were determined to be ‘detected’ in Section 3.2.1(i). The sources in the ‘detected’ catalogue should then have luminosities,  $z$  and flux density distributions which are similar

to those of the observed data and which also suffer from similar incompleteness effects across the fields.

### 3.2.2 Multiwavelength random catalogues

As discussed in Section 3.1, we also make use of the cross-correlation between the LoTSS Deep Fields data and the multiwavelength catalogues within the field to trace the bias evolution of LOFAR sources. This requires an additional catalogue of random sources for the multiwavelength catalogue ( $R_2$  in equation 5). For this we use a uniform distribution of sources across the fields. This assumes that the mass and magnitude limits applied to the multiwavelength data in Section 2.2 provide high completeness and uniformity across each of the three fields.

### 3.3 Additional SNR and flux density cuts

As discussed in C. L. Hale et al. (2024), the wavelet fitting mode which can be used with the source finding of PyBDSF can introduce the detection of a large number of sources below the nominal  $5\sigma$  detection limit across the rms maps. Therefore, we apply a  $5\sigma$  peak SNR cut to the radio catalogues for both the data and catalogue of randoms. Moreover, we apply a constant flux density cut to normalize the different flux limits in the three fields. Since, Boötes is the shallowest field with a typical rms  $\sim 44 \mu\text{Jy beam}^{-1}$  over the multiwavelength region (see tables in R. Kondapally et al. 2021; S. Mandal et al. 2021), we therefore impose a  $200 \mu\text{Jy}$  integrated flux density limit such that our data is at  $\text{SNR} \gtrsim 5$  in the shallowest field.

The catalogues of random sources generated per field are also reduced in numbers to ensure a constant ratio of the number of data to randoms in each field and for each of the radio sources subsamples (e.g. split by redshift). This avoids spuriously large  $\omega(\theta)$  (at higher  $\theta$ ) when a constant ratio was not applied. For each sub-sample we ensure that the ratio of data to randoms is constant in each field and that this ratio is in the range of  $\sim 10$ – $15$ , see Table 3.

At this stage we now have the catalogues necessary to measure  $\omega(\theta)$  across the combined three fields using both the auto-correlation (equation 4) and cross-correlation (equation 5).

### 3.4 Resampling of the data to probe $p(z)$

To determine the clustering as a function of redshift, and accurate uncertainties on the measured clustering, it is necessary to take account of the uncertainties in the redshifts of the sources, encoded in the redshift posterior probability distribution,  $p(z)$ , for each source. To do this, we construct 100 new redshift values for each source from sampling from the  $p(z)$  derived in the analysis of K. J. Duncan et al. (2021). For those sources with a spectroscopic redshift we use a constant value for  $z$  in each resample. Combining the redshift resamples for all the sources provides 100 possible data samples for which we apply the necessary masking and flux density/SNR cuts and then compute the angular clustering for sources with a resampled redshift in the  $z$  range being considered.

### 3.5 Comparison of data and random catalogues

Comparisons of the data to the randoms are presented in Fig. 2 for the SFGs and in Fig. 3 for the LERGs and QLERGs. Shown are comparisons of the flux density, redshift, luminosity and SNR distributions for the randoms and data both when split into redshift bins using the Z\_BEST redshift column (from the catalogue of K.

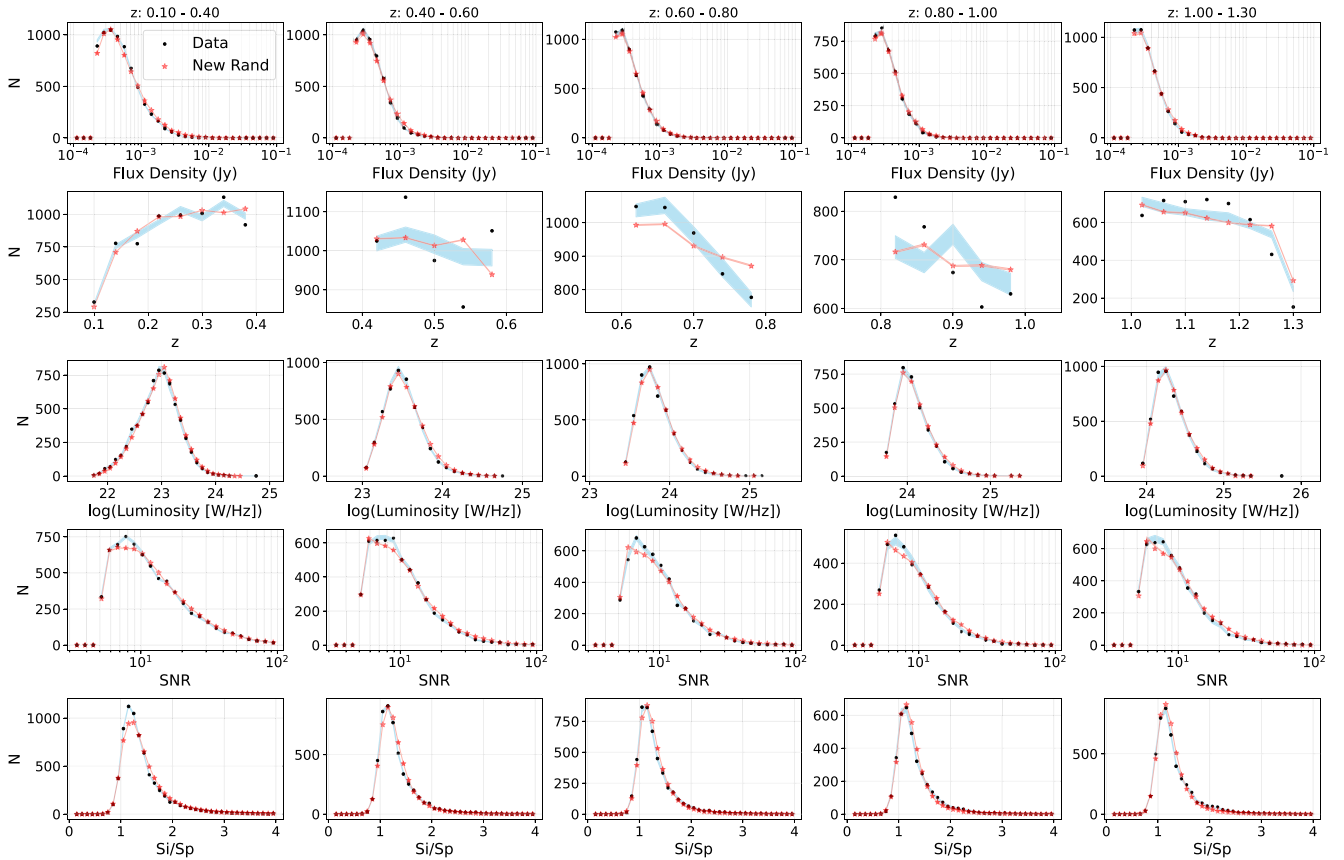
<sup>9</sup>Though it can also be used, as in M. Novak et al. (2017), to account for incompleteness effects within the data.

<sup>10</sup>The input catalogue of random sources should have no incompleteness effects and be representative of the true underlying population. The effects of incompleteness will be accounted for when a  $\Phi(L)$  model matched sample of the catalogue of random sources is made and the sources that were considered ‘detected’ in the catalogue generation earlier are used.

<sup>11</sup>In reality,  $V_{\text{max}}$  should also account for limitations in the multiwavelength catalogues. However, owing to the deep nature of the optical and IR data and the high fraction of host galaxy association (97 per cent), we neglect this compared to the  $V_{\text{max}}$  of the radio emission.

<sup>12</sup>As the ratio in the first and last luminosity bin may not be fully probed by the data or randoms, we do not use these values to find the minimum ratio. The minimum ratio itself will be  $\gg 1$  due to the much higher number density of randoms.





**Figure 2.** Comparison plots of the flux density distributions (first row); redshift distributions (second row); luminosity distribution (third row); signal-to-noise (SNR, fourth row); and integrated-to-peak flux density ratio ( $S_I/S_P$ ; fifth row) for SFGs in the different redshift bins considered in this work, increasing in redshift from left to right. In each panel, the data catalogue with redshift cuts applied on the Z.BEST column is shown as black dots, while each blue shaded region represents the output distribution from the data samples given in the range of the 16th–84th percentiles of the values from the  $p(z)$  resamples. The randoms for the full sample are shown as red stars. These have associated red shaded regions with the range of randoms from those associated with each of the data  $p(z)$  resample (to ensure a constant ratio of random sources to data), though these are small as they are drawn from the same random sample and only have small differences reflecting the number of data per  $p(z)$  sample.

J. Duncan et al. 2021) and also using the resampled  $z$  values from the  $p(z)$ . These allow us to demonstrate the accuracy of the random catalogues in accounting for the observational effects within the data.

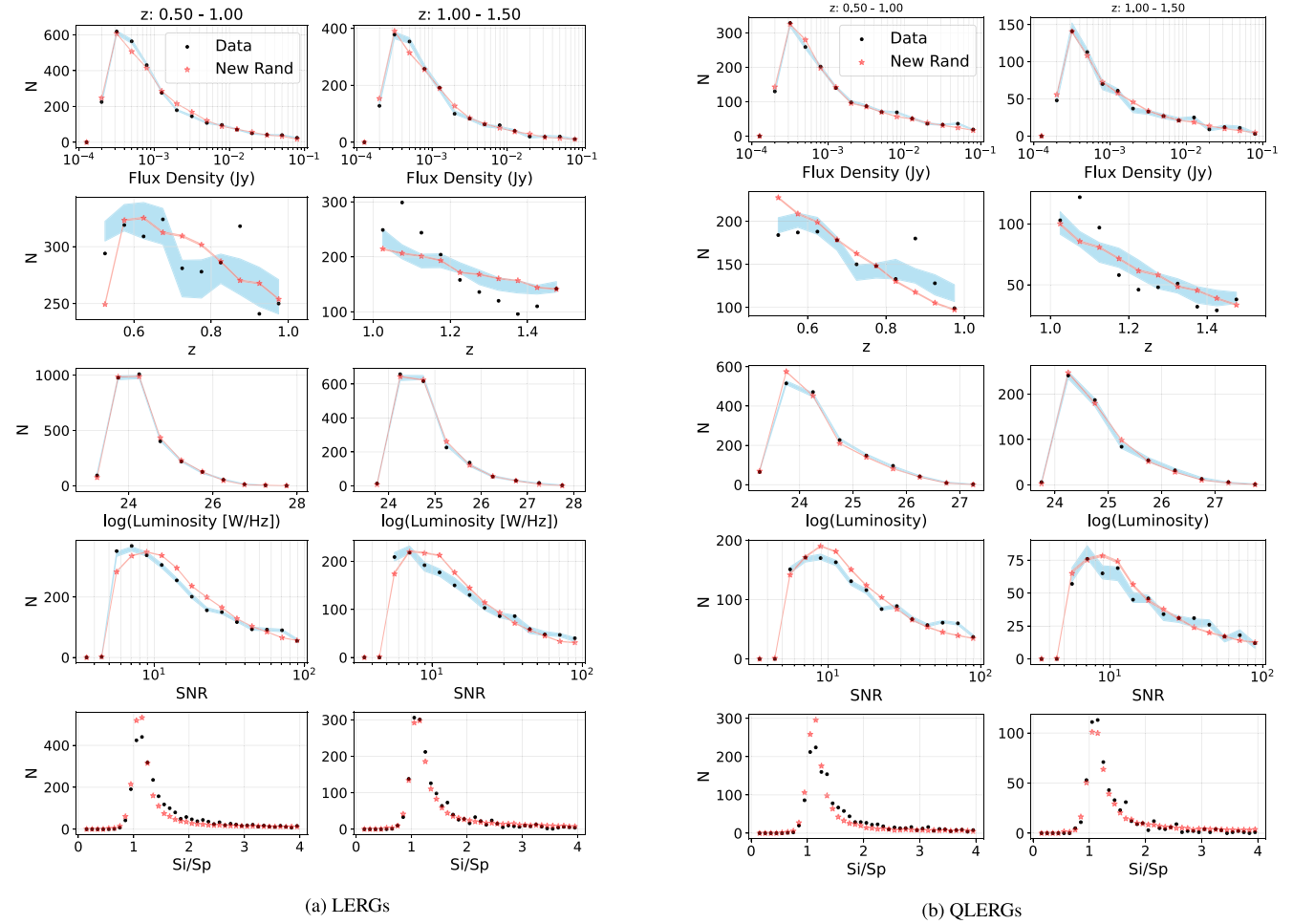
As can be seen from Figs 2 and 3, the randoms broadly provide a good representation of the data, especially when the data from the resampled  $p(z)$  are compared to. This suggests the random catalogues should provide a good simulated catalogue to measure  $\omega(\theta)$ . As discussed in R. Kondapally et al. (2021) and R. K. Cochrane et al. (2023), at some redshifts, there can be large uncertainties on the photometric redshifts with some aliasing of the ‘Z.BEST’ value, whereas the  $p(z)$  better captures this effect. The redshift distributions do present some larger discrepancies within some of the sub-samples. However, we note that the flux density comparisons and SNR comparisons are the most important, as incompleteness relates to the observed properties of the source and knows nothing of their  $z$  or luminosity. Provided these flux distributions appear appropriate, differences in the  $z$  distribution are of less concern. Examples of such differences in the  $z$  distribution can be seen for the  $0.6 \leq z < 0.8$  redshift bin of SFGs, however the flux density and SNR distribution appear to be in good agreement with the data. For LERGs and QLERGs (see Fig. 3), these distributions show broad agreement to those of the data resamples, though the differences in SNR distributions are greater than seen for SFGs. This is, in part, related to the source models used for such sources. As SKADS does

not have L/HERG classification, we use a mixture of AGN (Fanaroff & Riley Type I and II sources B. L. Fanaroff & J. M. Riley 1974, and radio-quiet quasars). However this may provide a mixture of source models not wholly representative of the demographics of LERGs.

For SFGs we also intend to study the luminosity dependence of the clustering of SFGs and so present similar plots to that as in Fig. 2 for each of the luminosity ranges considered within each redshift bin investigated. These are presented in the appendix in Figs A1–A5 and again broadly show good agreement with the relevant data.

#### 4 $\omega(\theta)$ – MEASUREMENTS, RESULTS, AND DISCUSSION

To measure  $\omega(\theta)$  we use TREECORR (M. Jarvis 2015) to calculate the pairs of galaxies within different angular separation bins from our data and random catalogues and then use these alongside equations (4) and (5) to measure the auto-correlation and cross-angular correlation functions. Aside from differences in the angular bins used, we adopt the same parameters for TREECORR as in C. L. Hale et al. (2024) and subsequently use these pairs to calculate  $\omega(\theta)$  as in equations (4) and (5), ensuring to correctly normalize for the number of possible pairs across full angular range. In order to determine the impact of the redshift (and its uncertainties) on our



**Figure 3.** As for Fig. 2 but for LERGs (left two panels) and QLERGs (right two panels). Owing to differences in the source models between the data (where sources are assumed to be Gaussians) and the randoms (which are ellipses convolved with the beam) and that LERGs are likely to have more extended morphologies than for SFGs, we expect larger differences in  $S_I/S_P$  for the LERGs than for SFGs compared to the randoms.

clustering measurements, we calculate  $\omega(\theta)$  for both those sources split by Z.BEST and those split into the redshift bins using the 100 resampled redshifts for each source. The  $\omega(\theta)$  presented for the  $p(z)$  resampled data is the mean  $\omega(\theta)$  from the resamples in each angular bin.

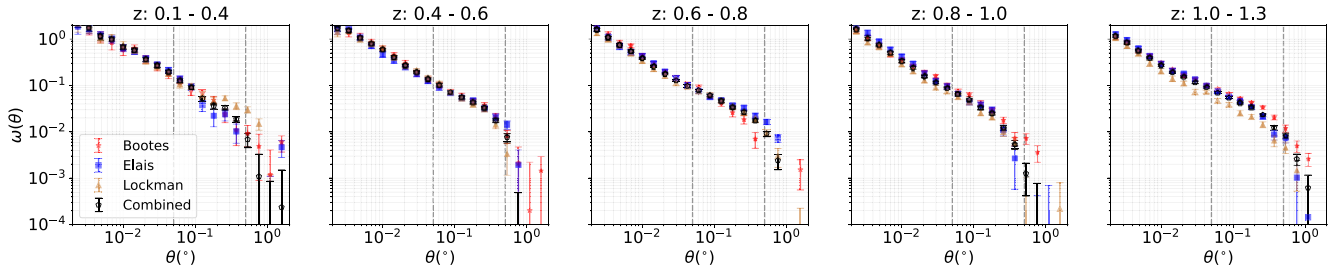
We estimate the uncertainties on  $\omega(\theta)$  using a process of bootstrapping (see e.g. E. N. Ling, C. S. Frenk & J. D. Barrow 1986) where we resample the data to generate new samples of the data which have the same size as the original data sample but containing randomly selected sources and then using these to calculate  $\omega(\theta)$ <sup>13</sup>. As such, a given source may be repeated in a sample or may be missing from a given bootstrap resample. We repeat this process 100 times. Furthermore, when we consider the effect of the  $p(z)$  resampling, we estimate the error by repeating the bootstrapping process for each

of the resampled  $p(z)$  data sets. The errors are calculated from the combination of all of the bootstrap resamples in each of the redshift resamples and determining the uncertainties as would be measured for a set of bootstrap resamples (as described in P. Norberg et al. 2009).

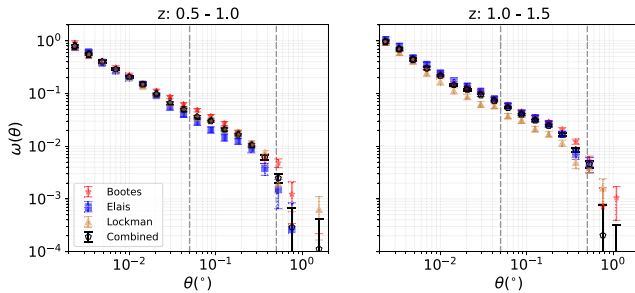
We only resample redshifts for the radio catalogue, not for that of the optical catalogue. Whilst there are also uncertainties in the redshift distributions of the multiwavelength catalogues, these galaxies are used as a reference sample in the cross-correlation. As the properties of the galaxies such as their mass (which are used in the completeness cuts) are calculated assuming the measured ‘best’ redshift of the sources, re-calculating such mass parameters for a different redshift is an intensive process and so it would be challenging to implement such a resampling of redshifts for the multiwavelength galaxies. We therefore make redshift cuts for the multiwavelength galaxies on the ‘best’ redshift for the source. The auto-correlation functions for the multiwavelength data are shown in Figs 4 and 5 for the  $z$  binning of the SFGs and (Q)LERGs respectively.

We present a comparison of both the auto-correlation and cross-correlation functions for SFGs, LERGs and QLERGs in Figs 6, 7, and 8, respectively. This is shown for both the redshift binning based on the separation using the Z.BEST column the catalogues of R. Kondapally et al. (2022) and K. J. Duncan et al. (2021) and also from

<sup>13</sup>We note that other methods to generate errors are possible such as Jackknife errors and using bootstrapping with sub-regions as opposed to individual sources. We choose to remove individual sources, which more closely mimics how we resample galaxies based on their  $p(z)$ . While this can be found to underestimate uncertainties in some conditions (see e.g. P. Norberg et al. 2009), bootstrap resampling using sub-volumes can also be found to overestimate errors. We take this individual source approach for more consistency with previous work of (C. L. Hale et al. 2018) and note that we will discuss these errors in Section 5.2.



**Figure 4.** Auto-correlation of the multiwavelength sample of galaxies in each of the redshifts bins used to measure  $\omega(\theta)$  for SFGs. The black open pentagons indicate the combined TPCF across the three fields, with their individual  $\omega(\theta)$  shown for Boötes (red stars), ELAIS-N1 (blue squares), and Lockman Hole (gold triangles). The dashed vertical lines highlight the region used to fit the correlation function over in order to measure the bias.



**Figure 5.** Similar to Fig. 4, shown are the auto-correlation for the multiwavelength sample within the redshift bins used for the LERG (and QLERG) studies.

the resamples which probe the full  $p(z)$ . These figures demonstrate that the measured clustering within the fields can exhibit differences when the full  $p(z)$  is not used to associate a redshift, which in turn will affect measurement of bias, though we note that most differences are within the uncertainties of the measurements. More broadly, it can be seen that these measurements of  $\omega(\theta)$  from both the auto-correlation and cross-correlations exhibit close to expected power law behaviour on the majority of angular scales, up to  $\sim 0.5^\circ$ . At larger angular scales, the clustering signal declines more sharply, this is in part as a result of the finite field size limiting the number of observable pairs of galaxies at the largest angular scales. When fitting our model we will account for this using an integral constraint (see e.g. N. Roche & S. A. Eales 1999) evaluated across the size of individual fields.

At the smallest angular scales there is continued increased clustering to the smallest scales considered. In shallower radio surveys with comparatively more AGN, such clustering at small angular scales often has a significant contribution from the clustering between multiple components associated with a single galaxy which have not been combined together into a single source (see e.g. C. Blake & J. Wall 2002; R. A. Overzier et al. 2003). However, as radio components have already been cross-matched in the work of R. Kondapally et al. (2021), we are likely observing genuine departures from the large-scale power-law like clustering due to the ‘1- and 2-halo’ clustering, i.e. the clustering of sources within the same dark matter halo (see e.g. A. V. Kravtsov et al. 2004; I. Zehavi et al. 2004).

Fitting the 1- and 2-halo clustering is possible within a halo occupation distribution (HOD) framework. Such a method allows the properties of the haloes that can host both central and satellite galaxies to be measured, under the assumption of an HOD parametrization (see e.g. A. A. Berlind & D. H. Weinberg 2002; Z. Zheng et al. 2005; Z. Zheng, A. L. Coil & I. Zehavi 2007; P. W. Hatfield et al.

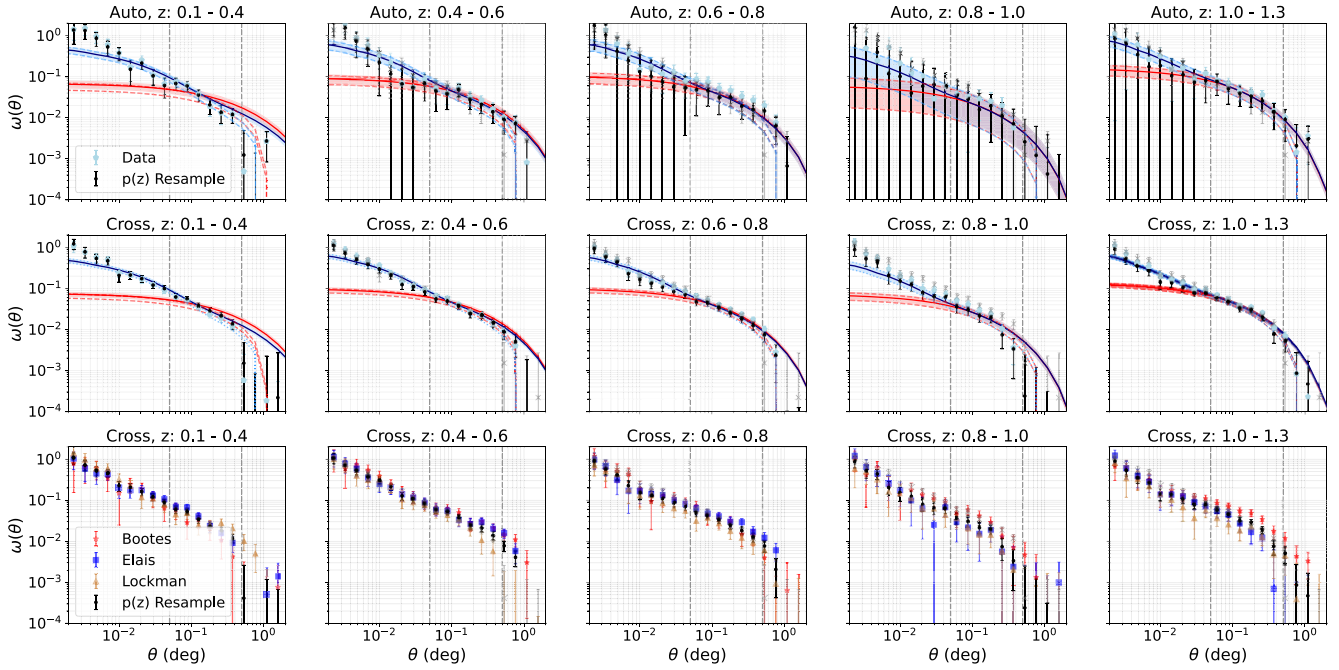
2016). Such modelling of the full HOD parametrization is beyond the scope of this work, but will be considered in future work, with deep surveys from telescopes such as LOFAR and MeerKAT (e.g. C. L. Hale et al. 2025). We instead focus on the larger scale, 1- and 2-halo clustering, in order to measure the galaxy bias and how this evolves with redshift for different source populations. However, we will present our results of fitting  $\omega(\theta)$  with models from the cosmology code the Core Cosmology Library (CCL, N. E. Chisari et al. 2019) which take into account both the (i) 1- and 2-halo clustering only (the ‘linear’ model) and (ii) a model which combines the 1- and 2-halo clustering (the ‘HaloFit’ model, see e.g. R. E. Smith et al. 2003; R. Takahashi et al. 2012) in Section 5.2. This is under default HOD used in CCL for the model, which may not be appropriate for the radio sources, especially on the smallest angular scales. Both models are fit to the data to demonstrate that irrespective of the model assumed, we measure comparable values for the large-scale bias.

As can be seen from Figs 6–8, at low redshifts the difference in both the auto-correlation and cross-correlations between the values of  $\omega(\theta)$  when using the Z.BEST values and the  $p(z)$  resamples are small, likely owing to the fact that spectroscopic redshifts will likely dominate at low redshifts and sources are more likely detected across a wealth of multiwavelength bands. Therefore, the differences between the  $p(z)$  samples and the Z.BEST selected sample is reduced, compared to higher redshifts. Figs 6–8 also demonstrate the large uncertainties found in the auto-correlation, especially for SFGs and LERGs at high redshifts, are reduced when the cross-correlation is instead measured. This is especially true for the LERGs, where the reduced number of sources compared to the SFGs presents challenges in measuring the bias from the auto-correlation function alone. We will therefore present the comparison of the bias measurements from the auto-correlation for the SFGs in Section 5.2 and then proceed with the cross-correlation functions to measure the bias evolution of SFGs and LERGs in the LoTSS Deep Fields to draw conclusions.

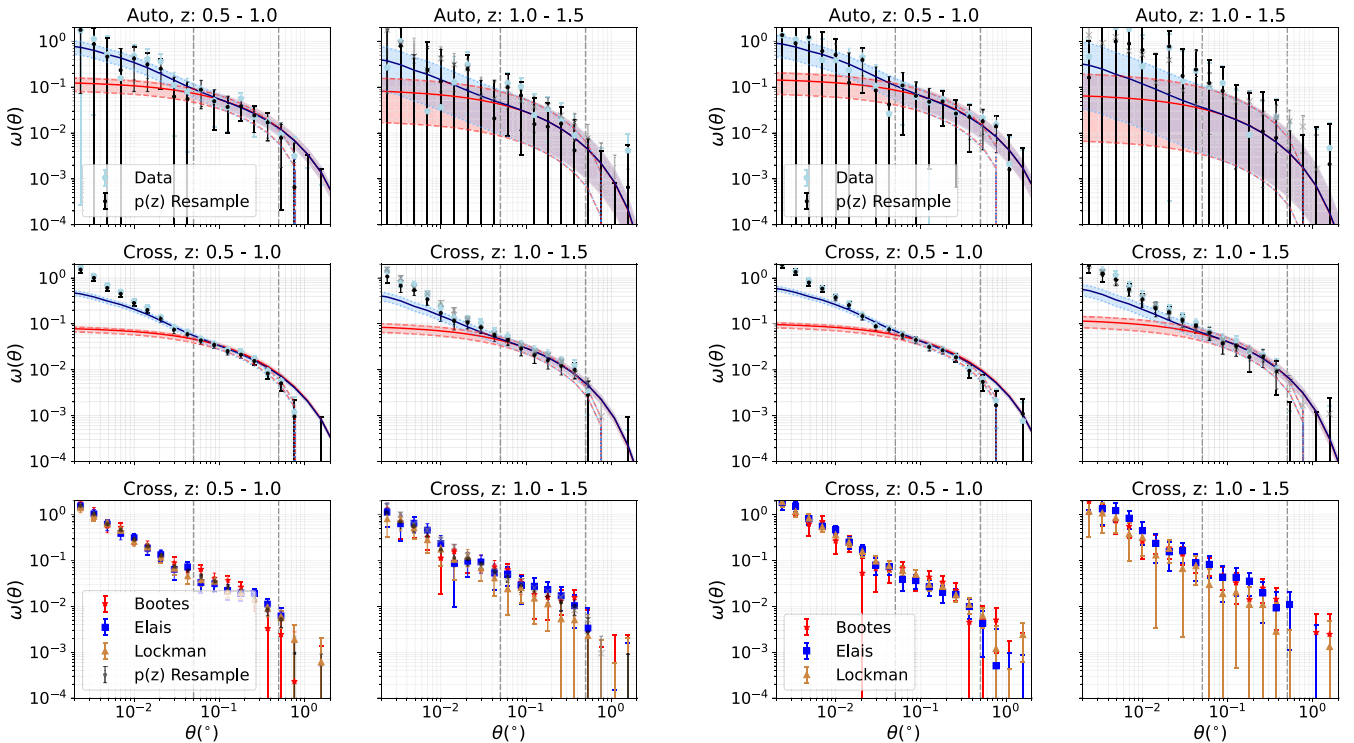
## 5 GALAXY BIAS RESULTS AND DISCUSSIONS

### 5.1 Measurement of Galaxy bias, $b$

To measure the bias from  $\omega(\theta)$ , we follow the methodology in C. L. Hale et al. (2024) and use CCL, which uses cosmology packages such as CAMB (A. Lewis, A. Challinor & A. Lasenby 2000) and CLASS (J. Lesgourgues 2011) to generate models of the power spectrum and infer the angular clustering, through assuming cosmological parameters, bias models and redshift distributions. As in D. Alonso et al. (2021) and C. L. Hale et al. (2024) we use an evolving galaxy bias model ( $b(z) = \frac{b_0}{D(z)}$ , where  $D(z)$  is the growth factor, see e.g. A.



**Figure 6.** Comparison of  $\omega(\theta)$  for SFGs in different  $z$  bins (left to right), using  $z$  cuts based on (i) the data's best redshift value in the source catalogue (light blue) and (ii) from the  $p(z)$  resampled value of  $z$  (black). This is shown in increasing redshift bins (left to right) and for the auto-correlation (upper panel), cross-correlation (middle panel), and for the cross-correlation compared to each of the three individual fields (lower panel) for Boötes (red stars), ELAIS-N1 (blue squares), and Lockman (gold triangles). In the top and middle panels the red line and shaded region represents the best-fitting 'Linear' model, while the blue line represents the best-fitting 'HaloFit' model to the black data points. Also shown is the model minus the integral constraint indicated by the red dashed line (for the 'Linear' model) and the blue dotted line (for the 'HaloFit' model). The dashed vertical lines indicate the  $\theta$  ranges, which we fit the data over. The grey crosses indicate the value of the  $p(z)$  resampled  $\omega(\theta)$  for the combined fields in the lowest redshift bin, purely to guide the eye.



**Figure 7.** As for Fig. 6 for the LERG samples.

**Figure 8.** As for Fig. 6 for the QLERG samples.



J. S. Hamilton 2001) to quantify the evolution of the bias for a given population of sources within the redshift bin. A constant bias model was also used in D. Alonso et al. (2021), C. L. Hale et al. (2024) and S. J. Nakoneczny et al. (2024), but we note that due to the narrow redshift ranges considered in this work, the bias measured assuming a constant bias model ( $b(z) = b$ ) showed little differences compared to when the evolving galaxy bias model was assumed when evaluated at the average redshift in the bin being considered.

In order to measure galaxy bias, a redshift distribution is also required for the radio and optical sources. For the radio sources we use a different redshift distribution for each of the  $p(z)$  resamples. This is taken the combined histogram of the resampled redshifts for each source in the resample, normalized to form a  $p(z)$ . Using the resampled  $z$  values avoids unphysical spikes in the combined redshift distribution for all sources in the sample, which would be produced from spectroscopic redshifts. For the multiwavelength sources we take a similar approach to create a combined redshift distribution for sources with a Z\_BEST value within the redshift range. These redshift distributions are therefore peaked within the redshift bin, but with wings in the  $p(z)$  to redshifts beyond the bin value, due to uncertainties in the redshift values. We discuss this further in Section 5.4.

The redshift distribution is provided to CCL and  $b_0$  is determined for the auto correlation through first calculating the CCL model assuming  $b_0 = 1$  and then scaling by  $b^2$ . This allows the  $\chi^2$  distribution to be calculated as a function of bias, using the full covariance as given by

$$\chi^2 = (\vec{\omega} - \vec{\omega}_M)^T \text{Cov}^{-1} (\vec{\omega} - \vec{\omega}_M), \quad (7)$$

where  $\vec{\omega}$  is the angular TPCF which is measured for the data sources,  $\vec{\omega}_M$  is the modelled  $\omega(\theta)$  which includes the subtraction of an integral constraint (see e.g. N. Roche & S. A. Eales 1999, to account for the limited field sizes) and Cov is the covariance matrix calculated from the bootstrap resampling methods across the  $p(z)$  samples considered. The covariance takes into account the correlations between  $\theta$  bins which may impact the inferred bias values, compared to when the diagonal elements alone (i.e. the errorbars in Figs 4–8) are used.

In the work of C. L. Hale et al. (2024) both the linear and HaloFit models (R. E. Smith et al. 2003; R. Takahashi et al. 2012) within CCL were used to model the angular clustering. C. L. Hale et al. (2024) determined that the linear model was more appropriate for the LoTSS-DR2 data across the angular ranges considered, where data at  $\theta \leq 0.03^\circ$  could also not be used to fit the bias in C. L. Hale et al. (2024) due to the excess clustering at small angular scales being partly attributable to multicomponent sources. Due to differences in the ‘linear’ and ‘HaloFit’ models, these were in the best agreement when fitting above  $\sim 0.3^\circ$ . Due to the smaller maximum angular separations which can be probed in this work, we must use different  $\theta$  ranges to fit the data, where we use  $0.05^\circ \leq \theta < 0.5^\circ$ .

We fit for both the ‘HaloFit’ and ‘linear’ models and fit for  $b_0$  through minimizing  $\chi^2$ . We determine the uncertainties on  $b_0$  through modelling the probability distribution from the  $\chi^2$  distribution of  $b_0$  (assuming  $P \propto e^{-\chi^2/2}$ ). We randomly sample from this distribution and use this to determine the associated median, 16th and 84th percentiles for  $b_0$ . To account for uncertainties introduced due to the  $p(z)$  distribution of sources we fit the galaxy bias for each  $\omega(\theta)$  measured for the  $p(z)$  subsamples. Combining together the randomly sampled bias values from fitting each of these  $\omega(\theta)$  then gives a larger sample of bias values which we use to then quote the associated median and errors from the 16th and 84th percentiles.

To determine  $b_0$  from the cross-correlation,  $\omega_{CC}(\theta)$ , we follow a similar method to that for the auto-correlation, but using two tracers. This makes use of the relationship:

$$b_{CC}^2 = b_{AC,1} b_{AC,2}, \quad (8)$$

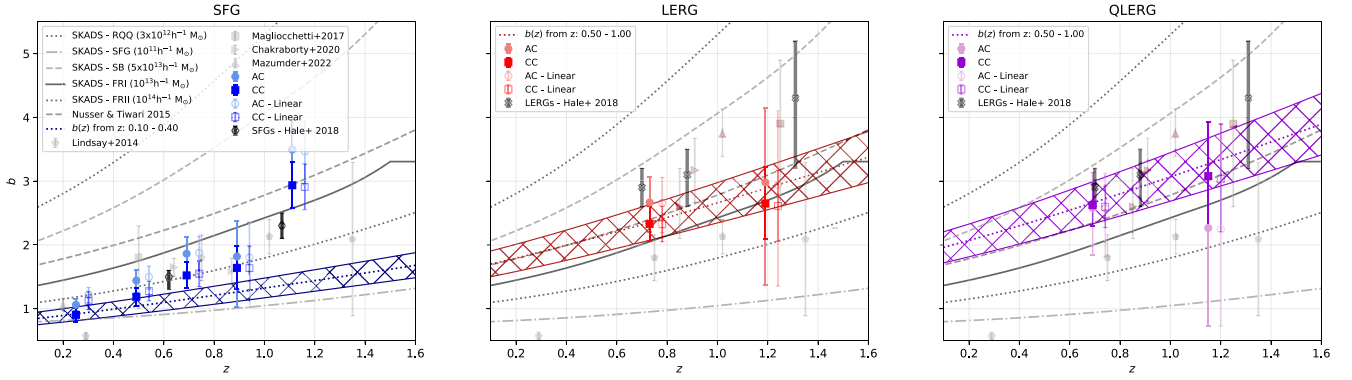
where  $b_{AC,1}$  is the bias of the first sample (radio) and  $b_{AC,2}$  is the bias for the second sample (multiwavelength), as also used in works such as S. N. Lindsay et al. (2014)<sup>14</sup>.  $b_{AC,2}$  is determined from the auto-correlation of the multiwavelength data alone, with the redshift distribution of the multiwavelengths sources taken as the combined  $p(z)$  of sources with Z\_BEST values within the given redshift range. To determine the bias of the radio sample from the cross-correlation we calculate  $\omega_{CC}(\theta)$  assuming the radio bias,  $b_{0,\text{radio}} = 1$ . We then follow a similar method to the auto-correlation and, in every redshift bin for the population being considered, scale this correlation function using the radio bias (having assumed an optical bias, discussed below). However, in contrast to the auto-correlation, we now scale by the radio bias,  $b$ , as opposed to  $b^2$ . In this way, by varying  $b$  and scaling the cross-correlation function by this, we are able to again measure the probability distribution of bias and quantify the best fit of  $b$  for each radio source population in the given redshift bin.

Uncertainties on the radio bias from the cross-correlation need to account for both uncertainties in the measured values of  $\omega_{CC}(\theta)$  (which include the uncertainties in the  $p(z)$  of the radio sample) and the uncertainties in the bias of the multiwavelength sources. We therefore, calculate the radio bias,  $b$ , through drawing 100 random samples of the bias from auto-correlation of the optical sample. For each optical bias value we combine this with the  $\omega_{CC}(\theta)$  from the  $p(z)$  resampling and use this to calculate the radio bias through evaluating the  $\chi^2$  and solving similarly to the auto-correlation. After combining the radio bias samples derived for each of the resamples we have a bias distribution for the radio sample which is derived from the cross-correlation and accounts for the redshift uncertainties in the radio sources and uncertainties in the multiwavelength bias. The bias values reported are then taken as the median bias values and associated errors are calculated from the 16th and 84th percentiles. We will present a comparison of the bias results for the Linear and HaloFit models respectively in Section 5.2, to demonstrate the effect it has on our measurements of  $b$ . The properties of the data in the redshift bins considered and the bias fitting parameters (assuming the HaloFit model) are presented in Table 3.

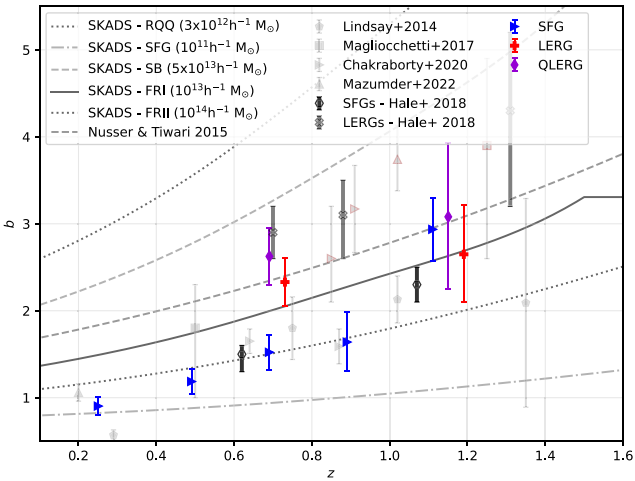
## 5.2 $b(z)$ Results for SFGs versus LERGs

We present our measurements of bias for SFGs and LERGs in Table 3 and in Figs 9 and 10 alongside the comparison to previous models adopted in R. J. Wilman et al. (2008, 2010) and for the previous measurements of A. Nusser & P. Tiwari (2015) and S. N. Lindsay et al. (2014) which are flux-limited samples (dominated by AGN), and for the classified samples (AGN versus SFGs) of M. Magliocchetti et al. (2017); C. L. Hale et al. (2018); A. Chakraborty et al. (2020) and A. Mazumder et al. (2022). As discussed, C. L. Hale et al. (2018), use the VLA 3 GHz COSMOS Survey (V. Smolčić et al. 2017a, b) to study the clustering of SFGs and AGN, as well as high-redshift analogues for HERG and LERG populations.

<sup>14</sup>While S. N. Lindsay et al. (2014) include a growth factor term in their work, as we fold in the evolving bias and redshift distribution of the two populations in the modelling in CCL and do not evaluate at a single average redshift, this is not believed to be necessary for this work.



**Figure 9.** Comparisons of  $b(z)$  for SFGs (left), LERGs (centre), and QLERGs (right). The filled light colours indicate results from the auto-correlation function (circles) and dark colours (for red, blue, and purple) indicate the results from the cross-correlation function (squares), when using the ‘HaloFit’ function. Additionally, artificially offset by  $\delta z = 0.05$  and semitransparent are the results from using the ‘linear’ model. We also show previous results of A. Nusser & P. Tiwari (2015, dark grey dashed lines; this is for an AGN-dominated population), S. N. Lindsay et al. (2014, grey pentagons; for sources not categorized by source type), M. Magliocchetti et al. (2017, grey squares), A. Chakraborty et al. (2020, grey right pointing triangles), A. Mazumder et al. (2022, grey upwards pointing triangles), and C. L. Hale et al. (2018, black diamonds for SFGs and black crosses for LERGs). For M. Magliocchetti et al. (2017), A. Chakraborty et al. (2020), and A. Mazumder et al. (2022), who measure the bias of AGN and SFGs separately, the points outlined in red represent the bias measurements for AGN and we only plot the source type relevant measurements in each given panel. The hatched regions indicate the evolutionary bias model that would be observed using the  $b(z) \propto 1/D(z)$  model, using the bias in the lowest redshift bin for that source type. Additionally, the models used in R. J. Wilman et al. (2008, 2010) are also shown as grey lines for RQQs (light grey dotted), SFGs (light grey dot-dashed), starburst galaxies (SB, dark grey dashed), FRI galaxies (dark grey solid, see B. L. Fanaroff & J. M. Riley 1974, for descriptions of FRI sources) and FRII galaxies (dark grey dotted).



**Figure 10.** As for Fig. 9, now showing the comparisons of bias between the different source populations (SFGs, LERGs and QLERGs), using the bias derived from the cross-correlation function and using the ‘HaloFit’ fitting model. The previous models (A. Nusser & P. Tiwari 2015) and data (S. N. Lindsay et al. 2014; M. Magliocchetti et al. 2017; C. L. Hale et al. 2018; A. Chakraborty et al. 2020; A. Mazumder et al. 2022) shown use the same plotting style as in Fig. 9. Additionally, the models used in R. J. Wilman et al. (2008, 2010) are also shown as grey lines for RQQs (light grey dotted), (light grey dot-dashed), starburst galaxies (SB, dark grey dashed), FRI galaxies (dark grey solid, see B. L. Fanaroff & J. M. Riley 1974, for descriptions of FRI and FRII sources), and FRII galaxies (dark grey dotted). The halo masses assumed for these populations are also shown in the legend.

This provides the closest comparison to the studies presented in this work. However, the classification adopted for the clustering of LERGs in C. L. Hale et al. (2018) is more similar to the QLERG population discussed in R. Kondapally et al. (2021) and adopted in this work. In the SKADS models, fixed halo masses were assumed for each population using the formalism of H. J. Mo & S. D. M. White (1996) and we highlight these halo masses on Fig. 10. We

note, though, that the masses assumed by R. J. Wilman et al. (2008) will not be a directly transferable to the full population of sources considered as this make assumptions about the source populations being dominated by central (not satellite) galaxies, see e.g. the works of J. Aird & A. L. Coil (2021) and so we use them indicative only for comparisons.

Fig. 9 presents the bias measured from the auto-correlation and cross-correlation, for both the ‘linear’ and ‘HaloFit’ derived models. We find good agreement, in general, between the auto-correlation and cross-correlation methods, which are consistent within  $1\sigma$ , as well as good agreement when the ‘linear’ and ‘HaloFit’ models are compared. This provides confidence that the measured bias values are not being affected by the choice of model. We note, though, that constraints on the auto-correlations can be very uncertain, which is evident to be the case considering the auto-correlation in Figs 6–8. We also note that when considering the fitting of  $\omega(\theta)$ , the minimum reduced  $\chi^2$  (hereafter  $R\text{-}\chi^2$ ) values found can be  $\ll 1$  (where a value of 1 would be expected for a good fit of the data), suggesting that our estimation of the uncertainties in  $\omega(\theta)$  may be larger than they should be. We note though that the  $R\text{-}\chi^2$  of all resamples which are generated (from which the bias is obtained from the 16th, 50th and 84th percentiles) will have larger average  $R\text{-}\chi^2$ , as these values in the table represent the minimum possible  $R\text{-}\chi^2$  found. As discussed, we have aimed to combine uncertainties on the TPCF (through bootstrap resampling), cosmic variance (through combining the three deep fields) and uncertainties in the redshift distributions of our radio sources (through the  $p(z)$  resamples). The  $R\text{-}\chi^2$  found in the fitting of  $b$  could therefore be indicative that we have provided too conservative values for the uncertainties in  $\omega(\theta)$ , which have folded through to the fitting of  $b$ . This therefore could suggest that either (i) the variance between fields is larger than is expected, (ii) that the uncertainties associated with the  $p(z)$  for the sources may be too broad for a subset of sources or this is related to the uncertainty method used, or (iii) that the spread between the fields is a result of remaining systematics or classification issues per field. Uncertainties in the redshift distribution will be greatly reduced with the upcoming WEAVE-LOFAR (D. J. B. Smith et al. 2016) survey, which will provide spectroscopic follow-up

**Table 3.** Summary table for fitting the bias from the auto-correlation and cross-correlation for SFGs, LERGs and QLERGs within the redshift bins considered in this work. Included is the number of radio ( $N_{\text{Radio}}$ ) and multiwavelength sources ( $N_{\text{Multi}}$ ) within the redshift bin, the median radio redshift in the bin ( $z_{\text{med}}$ ), the median mass of radio sources in the bin from the consensus mass of P. N. Best et al. (2023) and the ratio of randoms to data in the sample ( $N_{\text{R}}/N_{\text{D}}$ ). Finally the bias from the auto-correlation ( $b_{\text{AC}}$ ) and cross correlation ( $b_{\text{CC}}$ ) at the average redshift of the bin alongside the minimum reduced- $\chi^2$  when fitting for  $b$  is included. The bias results assume the Halofit model is used.

Source type	$z$ range	$z_{\text{med}}$	$N_{\text{Radio}}$	$N_{\text{Multi}}$	$\log_{10}(M_* [\text{M}_{\odot}])$	$N_{\text{R}}/N_{\text{D}}$	$b_{\text{AC}}(z_{\text{mid}})$	$R\text{-}\chi^2_{\text{min, AC}}$	$b_{\text{CC}}(z_{\text{mid}})$	$R\text{-}\chi^2_{\text{min, CC}}$
SFG	0.10–0.40	0.25	6 923	15 117	10.4	15.0	$1.06^{+0.09}_{-0.10}$	0.1	$0.90^{+0.11}_{-0.10}$	0.2
SFG	0.40–0.60	0.49	5 044	29 199	10.7	15.0	$1.44^{+0.17}_{-0.19}$	0.1	$1.19^{+0.14}_{-0.14}$	0.3
SFG	0.60–0.80	0.69	4 686	44 396	10.8	10.5	$1.86^{+0.26}_{-0.30}$	0.03	$1.52^{+0.20}_{-0.20}$	0.1
SFG	0.80–1.00	0.89	3 504	47 295	10.9	12.8	$1.82^{+0.56}_{-0.79}$	0.02	$1.64^{+0.34}_{-0.34}$	0.2
SFG	1.00–1.30	1.11	4 683	59 949	11.0	9.8	$3.49^{+0.47}_{-0.53}$	0.02	$2.94^{+0.36}_{-0.36}$	0.3
LERG	0.50–1.00	0.73	2 900	108 633	11.1	11.5	$2.67^{+0.40}_{-0.47}$	0.03	$2.33^{+0.28}_{-0.27}$	0.02
LERG	1.00–1.50	1.19	1 758	79 211	11.1	15.0	$2.98^{+1.17}_{-1.60}$	0.1	$2.65^{+0.57}_{-0.55}$	0.2
QLERG	0.50–1.00	0.69	1 575	108 633	11.2	13.8	$2.58^{+0.55}_{-0.74}$	0.01	$2.62^{+0.33}_{-0.33}$	0.1
QLERG	1.00–1.50	1.15	624	79 211	11.2	15.0	$2.27^{+1.66}_{-1.53}$	0.1	$3.08^{+0.85}_{-0.84}$	0.1

of LOFAR-detected sources, thus accurately constraining redshifts for a significant population of sources, and allowing for direct spatial clustering measurements as well as aiding in the source classification process.

In general, the constraints on  $\omega(\theta)$  from the cross-correlation are less uncertain than from the auto-correlation alone. The comparisons in Fig. 10 between the three populations also shows, in agreement with C. L. Hale et al. (2018), that over medium redshifts ( $z \sim 0.5\text{--}1.0$ ) LERGs and QLERGs appear to be more biased tracers of dark matter compared to those radio sources classified as SFGs. Comparing to those models assumed in SKADS, this supports the idea from other radio clustering studies that AGN are typically found in more massive haloes than star formation dominated radio sources (see e.g. M. Magliocchetti et al. 2017; C. L. Hale et al. 2018; A. Mazumder et al. 2022). This is also in line with numerous studies at other wavelengths and in simulations where redder galaxies are typically more clustered than blue galaxies (see e.g. R. S. Somerville et al. 2001; I. Zehavi et al. 2005; A. L. Coil et al. 2008; J. G. Cresswell & W. J. Percival 2009) and may reflect the LERGs residing in galaxies that typically have larger stellar masses than SFGs (which can be demonstrated from the average consensus masses of P. N. Best et al. 2023, for which the median value is given in Table 3). We note though that at the highest redshift bin for the SFG population, the average mass is similar to that for the LERGs. These in turn may be hosted by more massive haloes, given correlations between galaxy clustering and stellar mass (see e.g. D. J. Farrow et al. 2015; R. K. Cochrane et al. 2017; A. Durkalec et al. 2018).

For the SFGs, our work shows remarkable agreement across the redshift bins studied here to that of the studies of C. L. Hale et al. (2018), A. Chakraborty et al. (2020) and A. Mazumder et al. (2022). We measure a smooth evolution in the bias of SFGs, increasing from a bias,  $b = 0.90^{+0.11}_{-0.10}$  ( $1.06^{+0.09}_{-0.10}$ ) for the cross-correlation (auto-correlation) at the lowest redshift ( $z \sim 0.2$ ) to  $b = 2.94^{+0.36}_{-0.36}$  ( $3.49^{+0.47}_{-0.53}$ ) at the highest redshifts considered ( $z \sim 1.2$ ). An evolution in the bias for SFGs is in part expected, as there is evidence (e.g. P. S. Behroozi, R. H. Wechsler & C. Conroy 2013), that halo masses of  $\sim 10^{12} \text{ M}_{\odot}$  are the most efficient dark matter haloes for forming stars across a vast range of redshifts. As radio luminosity is known to be correlated to SFR (see recent studies in e.g. L. J. M. Davies et al. 2017; G. Gürkan et al. 2018; D. J. B. Smith et al. 2021), we are likely observing highly efficient SFGs. In order to reside in such a similar halo mass over cosmic time, this will require an evolution in the bias.

In other LOFAR clustering studies that average across all redshifts (e.g. D. Alonso et al. 2021; C. L. Hale et al. 2024; S. J. Nakoneczny et al. 2024), we have assumed the bias evolves inversely proportional to the growth factor,  $b(z) = b_0/D(z)$ . However, in this work we split into smaller redshift ranges than these previous studies and do not force  $b_0$  to be the same in each redshift bin. Therefore, we are able to test whether this functional form is suitable to found in this work using smaller redshift bins. To do this we use the value of  $b_0$  found in the lowest redshift bin considered for the source population (SFG/LERG/QLERG) and trace its evolution under such a model. This is given by the hatched regions on Fig. 9. This comparison demonstrates that the bias values for SFGs are evolving at a more rapid rate than this previously assumed model, with the evolutionary models used in R. J. Wilman et al. (2008), suggesting that while the bias does increase with redshift (as for the models of R. J. Wilman et al. 2008), the SFGs here are evolving at a quicker rate and with larger bias than for the ‘normal’ SFG population of R. J. Wilman et al. (2008). Assuming the models of R. J. Wilman et al. (2008), our SFGs also suggest there may be some potential evolution above that for a constant halo mass. We note that R. J. Wilman et al. (2008) split the SFGs into a starburst population, and a population of ‘normal’ SFGs galaxy population, whilst we do not distinguish the radio-detected SFGs into sub-classes. However, our findings contribute to the growing evidence (from e.g. studies of C. L. Hale et al. 2018; A. Mazumder et al. 2022) that for a typical radio population at current sensitivities, using the bias models adopted in R. J. Wilman et al. (2008) to make predictions (such as for cosmological predictions A. Raccanelli et al. 2012; L. D. Ferramacho et al. 2014; Square Kilometre Array Cosmology Science Working Group et al. 2020) may not be appropriate (though see Section 5.4). Therefore, works such as Z. Gomes et al. (2020) which adopt more recent bias measurement based models are key. Rapid evolution in bias has also been previously found for multi-wavelength studies of SFGs (M. Magliocchetti et al. 2014) between  $z \sim 1 - 2$ .

This rapid evolution may relate to an intrinsic evolution for the star forming population, but may also relate to differences in the populations, where the higher redshift sources will typically be more luminous sources. Therefore, a dependence of the bias on the radio luminosity of the source could drive an apparent evolution with redshift. This is investigated in Section 5.3. However, such results may also be indicative of sources with increased AGN activity at higher redshift. Given the typically larger bias of our LERG

population compared to the SFGs (and more generally for AGN in the works of e.g. C. L. Hale et al. 2018; A. Mazumder et al. 2022), greater AGN contamination at the highest redshifts could increase the observed bias of SFGs. Indeed, there are different approaches taken to classify radio galaxies both on their multiwavelength information such as through ultra-high-resolution imaging (see e.g. L. K. Morabito et al. 2025) as well as using different SED fitting codes (see e.g. S. Das et al. 2024). Both these approaches have been used to classify LOFAR data in these deep fields and while the majority of classifications agree between the different methods, some differences are found in their proposed classifications to that of P. N. Best et al. (2023) which is used in this work. This includes at the higher redshifts for SFGs considered in this work. This could be an alternative explanation for the agreement between the SFGs and LERGs in the highest redshift bins considered. However we do note that the bias measured for SFGs in the highest redshift bin is consistent with the evolution seen when the results of C. L. Hale et al. (2018) is combined in this work.

For the LERG population, we measure a lower bias compared to the LERG analogues of C. L. Hale et al. (2018). However, as noted in Section 2.4, the QLERG population is believed to be a more direct comparison to the LERG population used in C. L. Hale et al. (2018). In the current work, QLERGs show better agreement with the lower redshift work of C. L. Hale et al. (2018), though the LERGs are consistent within  $\sim 0.5\sigma$  to the QLERGs of this study and  $\sim 1\sigma$  to the work of C. L. Hale et al. (2018). Therefore we have weak evidence to suggest that QLERGs reside in more biased haloes than the general LERG population. This could suggest that similar to the wider population of galaxies, those with more significant star formation in the host galaxy appear to reside in less massive haloes. This would imply that the underlying dark matter halo of a radio source may be influential in the properties of the radio source itself, or it appears at least related. The bias of the QLERG and LERG populations are more uncertain though and so could also be consistent with little-to-no evolution.

Previous works studying the bias evolution in the LOFAR surveys have typically been limited to higher flux density limits than considered in this work (see e.g. D. Alonso et al. 2021; C. L. Hale et al. 2024; S. J. Nakoneczny et al. 2024; G. C. Petter et al. 2024) by approximately a factor of  $\sim 10$  and will be more dominated by AGN populations (see P. N. Best et al. 2023). As such, for those brighter populations the  $b(z) \propto 1/D(z)$  may have been an appropriate model for the bias. We note that in C. L. Hale et al. (2018), it was noted that for the full AGN population the bias appeared to flatten at the highest redshifts considered ( $z \sim 1.2-1.8$ ), which could be indicative of the downsizing of haloes required to host equivalent sources at higher redshifts. Supporting the results of C. L. Hale et al. (2018), we also conclude that the bias models of R. J. Wilman et al. (2008) for SFGs more closely reflect that assumed for their radio-quiet quasar (RQQ) population in this sample. R. J. Wilman et al. (2008) split the SFG populations into normal and starburst galaxies, therefore if such bias models are adopted for cosmological analysis (e.g. A. Raccanelli et al. 2012; L. D. Ferramacho et al. 2014) then a bias more representative for a realistic radio SFG population should be adopted. The halo mass estimates from R. J. Wilman et al. (2008) suggest such differences in the halo masses assumed for SFGs could be an order of magnitude and should be accounted for in order to place constraints on non-Gaussianity (as updated in Z. Gomes et al. 2020). Studies similar to this work using deeper observations from precursor and pathfinder telescopes prior to the Square Kilometre Array Observatory (SKAO) are crucial to help understand the bias models to adopt in such studies. Our

results for LERGs suggest that AGN sources, of this type are more biased than star formation dominated galaxies up to intermediate redshifts ( $z \lesssim 1$ ), but that the populations become more similar in their bias at higher redshifts. This may be related to findings that the LERG populations appear to become dominated by star-forming hosts for  $z \gtrsim 1$  in the luminosity functions of R. Kondapally et al. (2022).

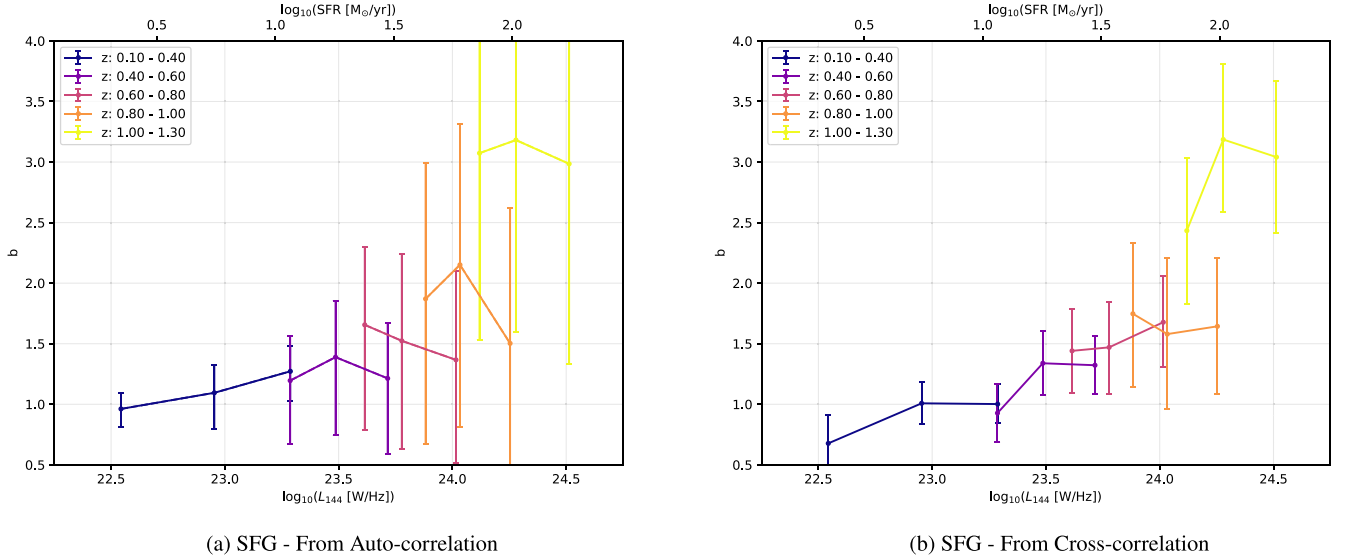
### 5.3 Luminosity dependence of bias for SFGs

As discussed in Section 5.2, the bias of the SFGs appears to grow at a much faster rate than for the evolving model assumed in previous LOFAR studies (D. Alonso et al. 2021; C. L. Hale et al. 2024; S. J. Nakoneczny et al. 2024, where  $b(z) \propto 1/D(z)$  is assumed). In this section we consider if this is driven by more luminous populations at higher redshifts, which are intrinsically more biased. This reflects work especially at other wavelengths such as that of I. Zehavi et al. (2011); R. K. Cochrane et al. (2017) and C. Clontz, D. Wake & Z. Zheng (2022). For the work of I. Zehavi et al. (2011), their study of the clustering length,  $r_0$ , of blue galaxies compared to red galaxies shows an increase in  $r_0$  with luminosity, while R. K. Cochrane et al. (2017) used  $H\alpha$  detected SFGs at  $z \sim 0.8$  and found these populations to be more biased when more  $H\alpha$  luminous populations were considered. We note, though, that R. K. Cochrane et al. (2023) appeared to observe a flattening in bias at larger  $H\alpha$  luminosities for  $z \sim 1.5$  sources. However, the clustering of radio-detected SFGs as a function of luminosity over a wide range of redshifts has not been studied in detail and can be limited by the redshift regimes probed by high- and low-luminosity samples (see e.g. C. L. Hale et al. 2018). This is because large samples of SFGs from deep radio imaging are required, in regions where redshifts are available, such as from the LoTSS Deep Fields. As discussed in Section 5.2, at radio wavelengths, the SFR and radio luminosities are known to be well correlated for SFGs (see e.g. T. Garn et al. 2009; L. J. M. Davies et al. 2017; G. Gürkan et al. 2018; D. J. B. Smith et al. 2021). If the bias of radio SFGs is correlated with the radio luminosity, this could in part explain the bias evolution as an effect of tracing different populations and more luminous SFGs at the highest redshifts.

The LoTSS Deep Fields data set is sufficiently large to allow us to investigate whether we are able to constrain how the bias of SFGs varies with both redshift and radio luminosity simultaneously. To do this we take the same approach as in the previous sections (where a given redshift range is selected) but additionally split into luminosity bins for each of the redshift bins that is considered. Specifically we use three luminosity bins for each of the redshift ranges considered, defined by taking the luminosities for sources with Z\_BEST values within the redshift range being considered and take the 33rd and 67th percentiles of the luminosities. For the  $p(z)$  resampled data sets these will not be exactly even percentiles as the sources being considered in each redshift bin (and their luminosity) will vary, though should be approximately evenly distributed between luminosity bins. We apply the same luminosity cuts on the randoms using a combination of the redshift and the ‘measured’ integrated flux density to obtain their luminosities. As for the SFG sample where no luminosity cuts are applied, we compare the flux density, redshift and luminosity distributions of the data compared to the randoms, for which there is broad agreement, especially when the  $p(z)$  resampled data are considered. These distributions are shown in Figs A1–A5.

The bias as a function of luminosity is presented in Fig. 11 and the measured values are given in Table 4. This is given for both the auto-correlation and cross-correlation derived values. Such bias measurements are plotted at the median luminosity for sources





**Figure 11.** Bias as a function of luminosity for the auto-correlation (left) and cross-correlations (right) of SFGs across the redshift bins considered in this work. Each colour represents a different redshift bin ranging from  $z$ : 0.10–0.40 (purple) to  $z$ : 1.00–1.30 (yellow). The equivalent SFR is also given on the top  $x$ -axis using the mass-independent conversion between luminosity and SFR of D. J. B. Smith et al. (2021).

**Table 4.** Bias from the auto-correlation ( $b_{AC}$ ) and cross-correlation ( $b_{CC}$ )  $\omega(\theta)$  for SFGs for different luminosity bins within the redshift bins considered in this work, evaluated at the mid point of the redshift bin. All luminosities are 144 MHz luminosities. We note that  $N$  is the number of sources in the luminosity bin based on Z.BEST and is only indicative of the number of sources, as we use the resampled  $z$  values from the  $p(z)$  to make samples to make measurements of  $\omega(\theta)$ .

$z$ range	$\log_{10}(L \text{ [W/Hz]})$ range	Median $\log_{10}(L \text{ [W/Hz]})$	$N$	$b_{AC}(z_{mid})$	$R\text{-}\chi^2_{min}$	$b_{CC}(z_{mid})$	$R\text{-}\chi^2_{min}$
0.10–0.40	21.74–22.79	22.54	2324	$0.96^{+0.13}_{-0.15}$	0.05	$0.68^{+0.23}_{-0.23}$	0.06
0.10–0.40	22.79–23.10	22.95	2307	$1.09^{+0.23}_{-0.30}$	0.04	$1.01^{+0.17}_{-0.17}$	0.06
0.10–0.40	23.10–24.79	23.29	2291	$1.27^{+0.21}_{-0.25}$	0.22	$1.00^{+0.16}_{-0.16}$	0.06
0.40–0.60	23.01–23.40	23.29	1705	$1.20^{+0.37}_{-0.52}$	0.04	$0.93^{+0.24}_{-0.24}$	0.21
0.40–0.60	23.40–23.58	23.49	1621	$1.39^{+0.47}_{-0.64}$	0.05	$1.34^{+0.26}_{-0.26}$	0.21
0.40–0.60	23.58–24.72	23.72	1717	$1.21^{+0.46}_{-0.63}$	0.02	$1.32^{+0.24}_{-0.24}$	0.21
0.60–0.80	23.42–23.70	23.61	1567	$1.66^{+0.64}_{-0.87}$	0.06	$1.44^{+0.35}_{-0.35}$	0.05
0.60–0.80	23.70–23.88	23.78	1562	$1.52^{+0.72}_{-0.89}$	0.05	$1.47^{+0.38}_{-0.38}$	0.05
0.60–0.80	23.88–25.16	24.02	1555	$1.37^{+0.73}_{-0.85}$	0.06	$1.68^{+0.38}_{-0.37}$	0.05
0.80–1.00	23.71–23.96	23.88	1174	$1.87^{+1.12}_{-1.20}$	0.05	$1.75^{+0.59}_{-0.60}$	0.15
0.80–1.00	23.96–24.12	24.03	1164	$2.15^{+1.16}_{-1.34}$	0.03	$1.58^{+0.63}_{-0.62}$	0.15
0.80–1.00	24.12–25.33	24.25	1165	$1.50^{+1.11}_{-1.01}$	0.07	$1.64^{+0.56}_{-0.56}$	0.15
1.00–1.30	23.93–24.20	24.12	1579	$3.07^{+1.07}_{-1.54}$	0.03	$2.43^{+0.60}_{-0.60}$	0.11
1.00–1.30	24.20–24.38	24.28	1581	$3.18^{+1.12}_{-1.59}$	0.02	$3.19^{+0.63}_{-0.60}$	0.11
1.00–1.30	24.38–25.79	24.51	1551	$2.99^{+1.20}_{-1.65}$	0.03	$3.04^{+0.63}_{-0.62}$	0.11

with a Z.BEST value in the redshift and luminosity (from Z.BEST) within the appropriate bin. The results show broadly good agreement between the auto-derived and cross-derived bias values, though due to the smaller sample sizes being considered, the errors are larger for the auto-correlation and so challenging to draw any conclusions from. Therefore, our conclusions need to be drawn from the cross-correlation derived values. The cross-correlation results in Fig. 11 show that any dependence of the median bias on luminosity is weak. To quantify this, we fit a simple linear model and using `scipy`'s (P. Virtanen et al. 2020) `curve_fit` module. We find slopes in the linear fit which are consistent with no evolution within  $\sim 1\sigma$ . Therefore, we cannot comprehensively determine whether the

differences in the luminosity are driving the evolution for SFGs seen in Fig. 9 or if the redshift evolution of bias is the only factor at play. Larger source populations will be crucial for such studies which will be provided through deep surveys such as the second data release of the LOFAR deep fields (T. W. Shimwell et al. 2025) and the MIGHTEE survey (C. L. Hale et al. 2025).

#### 5.4 Limitations of this analysis

Whilst this work presented has placed constraint on the evolving bias of SFGs and LERGs within the LoTSS Deep Fields, there are limitations to the analysis, which we outline here for completeness.

First, systematics may remain that are unaccounted (or not fully accounted) for when obtaining the random catalogues of sources. This may impact the measurements of  $\omega(\theta)$  and  $b(z)$ . However, there has been considerable effort to account for the observational systematics (see Section 3.2.1), so we believe remaining effects are less significant.

Moreover, there are significant uncertainties of the redshift distributions for both the radio and multiwavelength sources. Uncertainty/variation in the  $p(z)$  will affect measurements of bias (through the conversion of  $\omega(\theta)$  to  $b$ ). For example, broader  $p(z)$  models was found to raise the bias, compared to if the Z\_BEST values were assumed to be correct. This is because sources over a much larger redshift range require a larger bias is needed to recreate the observed clustering compared to if they were accurately constrained within the redshift range in the bin. Whilst we adopt the redshift uncertainties of K. J. Duncan et al. (2021), if these are overestimated the bias measurements could be reduced. Redshift uncertainty will be reduced with higher spectroscopic coverage for radio sources using surveys such as WEAVE-LOFAR (D. J. B. Smith et al. 2016).

We also note that whilst there are redshifts uncertainties for the data sources, the random catalogues are idealized and so do not have the same uncertainties in their redshifts. However, what is important for the random sources is that they reflect the observational detection across the fields. We therefore considered the impact of redshift uncertainties for the random catalogues by measuring  $\omega(\theta)$  from using the random source catalogues in the neighbouring redshift bins (where available). This saw little change in the measured values of  $\omega(\theta)$ . Therefore, we believe our results are robust against the lack of uncertainties in the redshifts for the random catalogues.

Such redshift uncertainties further affect the multiwavelength catalogues which we cross-correlate to. In our analysis, we choose to cut the optical galaxies based on their Z\_BEST redshift, with a mass limit applied (where the mass is determined assuming the best redshift). This allows for a consistent population for the radio galaxies to be correlated to. However, the large uncertainties in the redshift leads to a  $p(z)$  with more dominance in broad wings, compared to some previous works (such as P. W. Hatfield et al. 2016; M. Shuntov et al. 2022). This results in bias values for the optical sample with significant deviations to that of previous work. In order to test such effects, we considered the effect on the bias of the radio SFGs using the method adopted in this work, but also assuming the multiwavelength redshift distribution is (i) the obtained from the redshift distribution of the Z\_BEST values and (ii) resampling the optical redshifts. In case (i), bias values for the multiwavelength catalogue were reduced, and are more comparable to P. W. Hatfield et al. (2016), and yet we observe the same trend in the evolving bias for the radio-selected SFGs. We note that in case (ii) it is computationally expensive to recalculate the stellar mass based on the new redshift and so we do not recalculate the mass of the sample. We again find the same trend in the bias evolution of the SFGs is recovered. For both cases the radio biases are within  $\sim 1\sigma$  of the results presented in this work.

Finally, this analysis will be improved in the future through full HOD analysis (as in e.g. Z. Zheng et al. 2005; Z. Zheng et al. 2007; P. W. Hatfield et al. 2016). The approach used in this work invokes a simpler approach of only fitting the large-scale clustering with a simple scaling for a functional form of  $\omega(\theta)$ . Whilst this is different to the approaches of e.g. C. L. Hale et al. (2018); A. Chakraborty et al. (2020); A. Mazumder et al. (2022) who fit a power-law distribution, there are similarities in the approach that full HOD fitting is not used. Therefore, the approach in this work allows for a more similar comparison to these previous works, without restricting

ourselves to a power-law model, which will not be appropriate across the range of angles considered. Our approach, though, may have differences to the effective bias found from HOD modelling which accounts for satellite galaxies within the samples to obtain halo mass estimates, halo properties and constrain bias values. Such relationships between halo mass and bias need to account for the full HOD in order to accurately probe halo masses, see discussion in J. Aird & A. L. Coil (2021). The combination of large radio samples and accurate redshifts such as WEAVE-LOFAR will, in future, allow more accurate constraints of the clustering evolution (and halo property evolution) for the dark matter environments hosting radio sources.

## 6 CONCLUSIONS

In this work we present a comparison of the clustering of SFGs and LERGs across the three LoTSS Deep Fields to trace both their evolution with redshift and the relationship between radio source populations and their underlying dark matter environments. We measure both the auto-correlation of the angular clustering of radio sources and the cross-correlation with a catalogue of multiwavelength sources across the fields, which total  $\sim 26 \text{ deg}^2$  of combined area with deep multiwavelength observations. By combining measurements of the angular TPCF with knowledge of the redshift distribution within the fields assuming the full redshift distribution,  $p(z)$ , we obtain measurements of the galaxy bias (an indicator of how clustered galaxies are to dark matter) and traces its evolution to  $z \lesssim 1.5$  in a number of redshift bins. This evolution is measured both for sources separated as a function of source type, and for the SFG population also as a function of radio luminosity (a proxy for SFR).

Our work suggests an evolution in the bias for SFGs from  $b = 0.90^{+0.11}_{-0.10}$  at  $z \sim 0.2$  to  $b = 2.94^{+0.36}_{-0.36}$  at  $z \sim 1.2$ . This is at a quicker evolutionary rate than evolving bias model used for previous LOFAR studies of brighter populations (with a more significant AGN population in e.g. D. Alonso et al. 2021 and C. L. Hale et al. 2024), where  $b(z) = b_0/D(z)$  and that this bias model may need to be modified for future work where broad redshift bins are considered. This may reflect a need for increasing mass haloes to host SFGs over cosmic time; however, such rapid evolution at the highest redshift bin could also be indicative of either mis-classification of sources in the highest redshift bin (where AGN activity may actually be dominating the emission), or a luminosity dependence of the bias could be contributing to the rapid evolution seen in the bias at the highest redshifts studied, where in flux-limited surveys sources are naturally more luminous. However the LERGs exhibit no such rapid evolution ( $b = 2.33^{+0.28}_{-0.27}$  at  $z \sim 0.7$  to  $b = 2.65^{+0.57}_{-0.55}$  at  $z \sim 1.2$ ), though are a factor of  $\sim 1.5\times$  more biased compared to SFGs at lower redshift ( $z \lesssim 0.8$ ). This suggests that the dark matter haloes in which radio sources reside have a clear correlation to the radio populations they host and that the haloes supporting SFGs may be less massive (by potentially an order of magnitude). We further consider the clustering of a subset of the LERG population known as QLERGs, which do not have significant star formation contributions to their overall emission. These QLERGs have evidence that their bias may evolve ( $b = 2.62^{+0.33}_{-0.33}$  at  $z \sim 0.7$  to  $b = 3.08^{+0.85}_{-0.84}$  at  $z \sim 1.2$ ), and weak evidence that they are more clustered than the full LERG population at  $z < 1$ . This bias evolution for LERGs and QLERGs is consistent the bias evolving inversely proportional to the growth function; however, the uncertainties associated with such measurements means this could also be weaker and consistent with potentially no evolution.

Such differences in the bias evolution of different source populations will likely be important for future cosmology studies, such as with the SKAO, to exploit the differences in bias of the populations for cosmological studies (e.g. L. D. Ferramacho et al. 2014; Z. Gomes et al. 2020). However, such studies need accurate models of the bias dependence of radio sources and so require studies with deep radio imaging where source classifications are either through multiwavelength source classifications (e.g. I. H. Whittam et al. 2022; P. N. Best et al. 2023) or through morphological classifications through high-resolution studies (e.g. L. K. Morabito et al. 2025). Such studies would help disentangle the evolving bias evolution for different source populations and could also help understand more comprehensive dependencies of the radio populations on parameters intrinsic to the sources, such as their redshift, AGN activity, SFR, and luminosity. To this end, we consider the relationship of bias for SFGs on both the redshift and radio luminosity (a proxy for SFR) of the population being considered. This was in order to establish whether the rapidly evolving bias evolution for SFGs is as a direct result of observing typically more luminous populations when higher redshifts are considered. We find that any luminosity-dependence of the bias is inconclusive, as whilst there is weak evidence at some redshifts for the best-fitting bias to increase with luminosity, these results are not statistically significant. Therefore, it could instead be that the redshifts of the population are driving the evolution in bias.

In the future, spectroscopic surveys such as WEAVE-LOFAR will help further address the question of the evolving relationships between radio sources and the underlying large-scale structure, allowing more accurate measurements of the redshift of sources and reducing the uncertainties introduced by the potentially broad  $p(z)$ . Moreover, the combination of spectra alongside high-resolution imaging will help to more comprehensively categorize sources and reduce potential classification errors. This combined with deeper radio data from the full LOFAR Deep Fields observations will improve our understanding of the galaxy–halo connection for radio sources.

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LOFAR is the Low Frequency Array designed and constructed by ASTRON. It has observing, data processing, and data storage facilities in several countries, which are owned by various parties (each with their own funding sources), and which are collectively operated by the ILT foundation under a joint scientific policy. The ILT resources have benefited from the following recent major

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This research made use of a number of tools and python packages: *ASTROPY*, community developed core Python package for astronomy (Astropy Collaboration 2013, 2018) hosted at <http://www.astropy.org/>; *TOPCAT* (M. B. Taylor 2005; M. Taylor 2011); *MATPLOTLIB* (J. D. Hunter 2007); *NUMPY* (S. der Walt, S. C. Colbert & G. Varoquaux 2011; C. R. Harris et al. 2020); *SCIPY* (P. Virtanen et al. 2020); *TREECORR* (M. Jarvis 2015); and *TQDM* (C. da Costa-Luis et al. 2021).

## DATA AVAILABILITY

Data of the LoTSS Deep Fields are available through the LOFAR Surveys website <https://lofar-surveys.org> and further information of the data products can be found in K. J. Duncan et al. (2021), R. Kondapally et al. (2021), J. Sabater et al. (2021), C. Tasse et al. (2021), and P. N. Best et al. (2023). Results presented in this work can be obtained through a reasonable request to the author.

## REFERENCES

- Aihara H. et al., 2018, *PASJ*, 70, S8
- Aird J., Coil A. L., 2021, *MNRAS*, 502, 5962
- Algera H. S. B. et al., 2020, *ApJ*, 903, 139
- Almosallam I. A., Lindsay S. N., Jarvis M. J., Roberts S. J., 2016a, *MNRAS*, 455, 2387
- Almosallam I. A., Jarvis M. J., Roberts S. J., 2016b, *MNRAS*, 462, 726
- Alonso D., Bellini E., Hale C., Jarvis M. J., Schwarz D. J., 2021, *MNRAS*, 502, 876
- Arnouts S., Ilbert O., 2011, *Astrophysics Source Code Library*, record ascl:1108.009
- Asorey J., Parkinson D., 2021, *MNRAS*, 506, 4121
- Astropy Collaboration, 2013, *A&A*, 558, A33
- Astropy Collaboration, 2018, *AJ*, 156, 123
- Banfield J. K. et al., 2015, *MNRAS*, 453, 2326
- Behroozi P. S., Wechsler R. H., Conroy C., 2013, *ApJ*, 770, 57
- Berlind A. A., Weinberg D. H., 2002, *ApJ*, 575, 587
- Bertin E., Arnouts S., 1996, *A&AS*, 117, 393
- Best P. N. et al., 2023, *MNRAS*, 523, 1729
- Bhardwaj N. et al., 2024, *A&A*, 692, A2
- Bian F. et al., 2013, *ApJ*, 774, 28
- Bielby R. M. et al., 2016, *MNRAS*, 456, 4061
- Blake C., Mauch T., Sadler E. M., 2004, *MNRAS*, 347, 787
- Blake C., Wall J., 2002, *MNRAS*, 337, 993

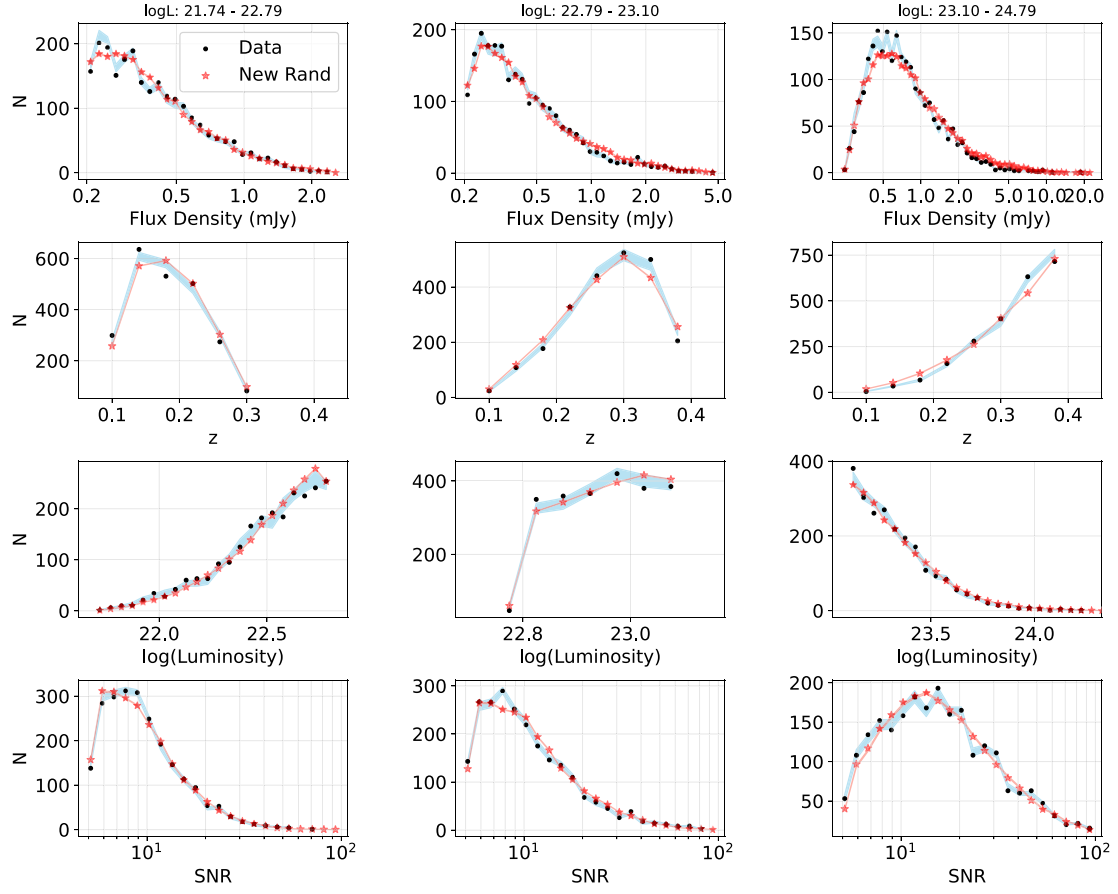
- Bonaldi A., Bonato M., Galluzzi V., Harrison I., Massardi M., Kay S., De Zotti G., Brown M. L., 2019, *MNRAS*, 482, 2
- Bonaldi A., Hartley P., Ronconi T., De Zotti G., Bonato M., 2023, *MNRAS*, 524, 993
- Boquien M., Burgarella D., Roehlly Y., Buat V., Ciesla L., Corre D., Inoue A. K., Salas H., 2019, *A&A*, 622, A103
- Brammer G. B., van Dokkum P. G., Coppi P., 2008, *ApJ*, 686, 1503
- Brown M. J. I. et al., 2008, *ApJ*, 682, 937
- Brown M. J. I., Dey A., Jannuzi B. T., Brand K., Benson A. J., Brodwin M., Croton D. J., Eisenhardt P. R., 2007, *ApJ*, 654, 858
- Calistro Rivera G., Lusso E., Hennawi J. F., Hogg D. W., 2016, *ApJ*, 833, 98
- Carnall A. C., McLure R. J., Dunlop J. S., Davé R., 2018, *MNRAS*, 480, 4379
- Cavuoti S., Amaro V., Brescia M., Vellucci C., Tortora C., Longo G., 2017, *MNRAS*, 465, 1959
- Chakraborty A., Dutta P., Datta A., Roy N., 2020, *MNRAS*, 494, 3392
- Chambers K. C. et al., 2016, preprint ([arXiv:1612.05560](https://arxiv.org/abs/1612.05560))
- Chisari N. E. et al., 2019, *ApJS*, 242, 2
- Clontz C., Wake D., Zheng Z., 2022, *MNRAS*, 515, 2224
- Cochrane R. K. et al., 2023, *MNRAS*, 523, 6082
- Cochrane R. K., Best P. N., Sobral D., Smail I., Wake D. A., Stott J. P., Geach J. E., 2017, *MNRAS*, 469, 2913
- Coil A. L. et al., 2008, *ApJ*, 672, 153
- Colless M. et al., 2001, *MNRAS*, 328, 1039
- Cresswell J. G., Percival W. J., 2009, *MNRAS*, 392, 682
- da Costa-Luis C. et al., 2021, tqdm: A fast, Extensible Progress Bar for Python and CLI, Zenodo. Available at: <https://doi.org/10.5281/zenodo.5109730>
- da Cunha E., Charlot S., 2011, Astrophysics Source Code Library, record ascl:1106.010
- da Cunha E., Charlot S., Elbaz D., 2008, *MNRAS*, 388, 1595
- Das S. et al., 2024, *MNRAS*, 531, 977
- Davies L. J. M. et al., 2017, *MNRAS*, 466, 2312
- DESI Collaboration, 2024, *AJ*, 168, 58
- DESI Collaboration, 2025, preprint ([arXiv:2503.14745](https://arxiv.org/abs/2503.14745))
- Desjacques V., Jeong D., Schmidt F., 2018, *Phys. Rep.*, 733, 1
- Driver S. P. et al., 2011, *MNRAS*, 413, 971
- Duncan K. et al., 2023, *The Messenger*, 190, 25
- Duncan K. J. et al., 2021, *A&A*, 648, A4
- Durkalec A. et al., 2018, *A&A*, 612, A42
- Fanaroff B. L., Riley J. M., 1974, *MNRAS*, 167, 31P
- Farrow D. J. et al., 2015, *MNRAS*, 454, 2120
- Ferramacho L. D., Santos M. G., Jarvis M. J., Camera S., 2014, *MNRAS*, 442, 2511
- Gaia Collaboration, 2016, *A&A*, 595, A1
- Gaia Collaboration, 2018, *A&A*, 616, A1
- Garn T., Green D. A., Riley J. M., Alexander P., 2009, *MNRAS*, 397, 1101
- Gendre M. A., Best P. N., Wall J. V., Ker L. M., 2013, *MNRAS*, 430, 3086
- Gomes Z., Camera S., Jarvis M. J., Hale C., Fonseca J., 2020, *MNRAS*, 492, 1513
- Gonzalez A. H. et al., 2010, American Astronomical Society Meeting Abstracts #216, p. 415.13
- Griffin M. J. et al., 2010, *A&A*, 518, L3
- Guo H. et al., 2015, *MNRAS*, 453, 4368
- Gürkan G. et al., 2018, *MNRAS*, 475, 3010
- Gürkan G. et al., 2022, *MNRAS*, 512, 6104
- Hale C. L. et al., 2019, *A&A*, 622, A4
- Hale C. L. et al., 2023, *MNRAS*, 520, 2668
- Hale C. L. et al., 2024, *MNRAS*, 527, 6540
- Hale C. L. et al., 2025, *MNRAS*, 536, 2187
- Hale C. L., Jarvis M. J., Delvecchio I., Hatfield P. W., Novak M., Smolčić V., Zamorani G., 2018, *MNRAS*, 474, 4133
- Hamilton A. J. S., 1993, *ApJ*, 417, 19
- Hamilton A. J. S., 2001, *MNRAS*, 322, 419
- Hardcastle M. J., Croston J. H., 2020, *New Astron. Rev.*, 88, 101539
- Harris C. R. et al., 2020, *Nature*, 585, 357
- Hartley W. G. et al., 2013, *MNRAS*, 431, 3045
- Hatfield P. W., Lindsay S. N., Jarvis M. J., Häußler B., Vaccari M., Verma A., 2016, *MNRAS*, 459, 2618
- Heckman T. M., Best P. N., 2014, *ARA&A*, 52, 589
- Heywood I. et al., 2021, *MNRAS*, 509, 2150
- Hildebrandt H. et al., 2016, *MNRAS*, 463, 635
- Hotan A. W. et al., 2021, *PASA*, 38, e009
- Hunter J. D., 2007, *Comput. Sci. Eng.*, 9, 90
- Jannuzi B. T., Dey A., 1999, in Weymann R., Storrie-Lombardi L., Sawicki M., Brunner R. eds, ASP Conf. Ser. Vol. 191, Photometric Redshifts and the Detection of High Redshift Galaxies. Astron. Soc. Pac., San Francisco, p. 111
- Jarvis M., 2015, Astrophysics Source Code Library, record ascl:1508.007
- Jin S. et al., 2023, *MNRAS*, 530, 2688
- Johnson B. D., Leja J., Conroy C., Speagle J. S., 2021, *ApJS*, 254, 22
- Jonas J. L., 2009, *IEEE Proc.*, 97, 1522
- Jonas J., MeerKAT Team, 2016, *Proc. MeerKAT Science: On the Pathway to the SKA. Vol. 277*, p. 1
- Jones D. H. et al., 2004, *MNRAS*, 355, 747
- Kondapally R. et al., 2021, *A&A*, 648, A3
- Kondapally R. et al., 2022, *MNRAS*, 513, 3742
- Kravtsov A. V., Berlind A. A., Wechsler R. H., Klypin A. A., Gottlöber S., Allgood B., Primack J. R., 2004, *ApJ*, 609, 35
- Krishnan C. et al., 2020, *MNRAS*, 494, 1693
- Landy S. D., Szalay A. S., 1993, *ApJ*, 412, 64
- Leja J., Johnson B. D., Conroy C., van Dokkum P. G., Byler N., 2017, *ApJ*, 837, 170
- Lesgourgues J., 2011, preprint ([arXiv:1104.2932](https://arxiv.org/abs/1104.2932))
- Lewis A., Challinor A., Lasenby A., 2000, *ApJ*, 538, 473
- Limber D. N., 1953, *ApJ*, 117, 134
- Limber D. N., 1954, *ApJ*, 119, 655
- Lindsay S. N., Jarvis M. J., McAlpine K., 2014, *MNRAS*, 440, 2322
- Ling E. N., Frenk C. S., Barrow J. D., 1986, *MNRAS*, 223, 21
- Lintott C. et al., 2012, American Astronomical Society Meeting Abstracts #219, p. 125.07
- Lonsdale C. J. et al., 2003, *PASP*, 115, 897
- Madgwick D. S. et al., 2003, *MNRAS*, 344, 847
- Magliocchetti M., 2022, *A&AR*, 30, 6
- Magliocchetti M., Lapi A., Negrello M., De Zotti G., Danese L., 2014, *MNRAS*, 437, 2263
- Magliocchetti M., Popesso P., Brusa M., Salvato M., Laigle C., McCracken H. J., Ilbert O., 2017, *MNRAS*, 464, 3271
- Mandal S. et al., 2021, *A&A*, 648, A5
- Martin D. C. et al., 2005, *ApJ*, 619, L1
- Matthews A. M., Condon J. J., Cotton W. D., Mauch T., 2021, *ApJ*, 909, 193
- Mauch T. et al., 2020, *ApJ*, 888, 61
- Mauch T., Sadler E. M., 2007, *MNRAS*, 375, 931
- Mauduit J. C. et al., 2012, *PASP*, 124, 714
- Mazumder A., Chakraborty A., Datta A., 2022, *MNRAS*, 517, 3407
- Mazumder A., Chakraborty A., Datta A., Choudhuri S., Roy N., Wadadekar Y., Ishwara-Chandra C. H., 2020, *MNRAS*, 495, 4071
- McAlpine K., Smith D. J. B., Jarvis M. J., Bonfield D. G., Fleuren S., 2012, *MNRAS*, 423, 132
- Mo H. J., White S. D. M., 1996, *MNRAS*, 282, 347
- Mohan N., Rafferty D., 2015, Astrophysics Source Code Library, record ascl:1502.007
- Morabito L. K. et al., 2025, *MNRAS*, 536, L32
- Morrissey P. et al., 2007, *ApJS*, 173, 682
- Nakoneczny S. J. et al., 2024, *A&A*, 681, A105
- Narayan R., Yi I., 1994, *ApJ*, 428, L13
- Narayan R., Yi I., 1995, *ApJ*, 452, 710
- Norberg P., Baugh C. M., Gaztañaga E., Croton D. J., 2009, *MNRAS*, 396, 19
- Norris R. P. et al., 2021, *PASA*, 38, e046
- Novak M. et al., 2017, *A&A*, 602, A5
- Nusser A., Tiwari P., 2015, *ApJ*, 812, 85
- Ocran E. F., Taylor A. R., Vaccari M., Ishwara-Chandra C. H., Prandoni I., 2020, *MNRAS*, 491, 1127
- Overzier R. A., Röttgering H. J. A., Rengelink R. B., Wilman R. J., 2003, *A&A*, 405, 53
- Peacock J. A., Smith R. E., 2000, *MNRAS*, 318, 1144



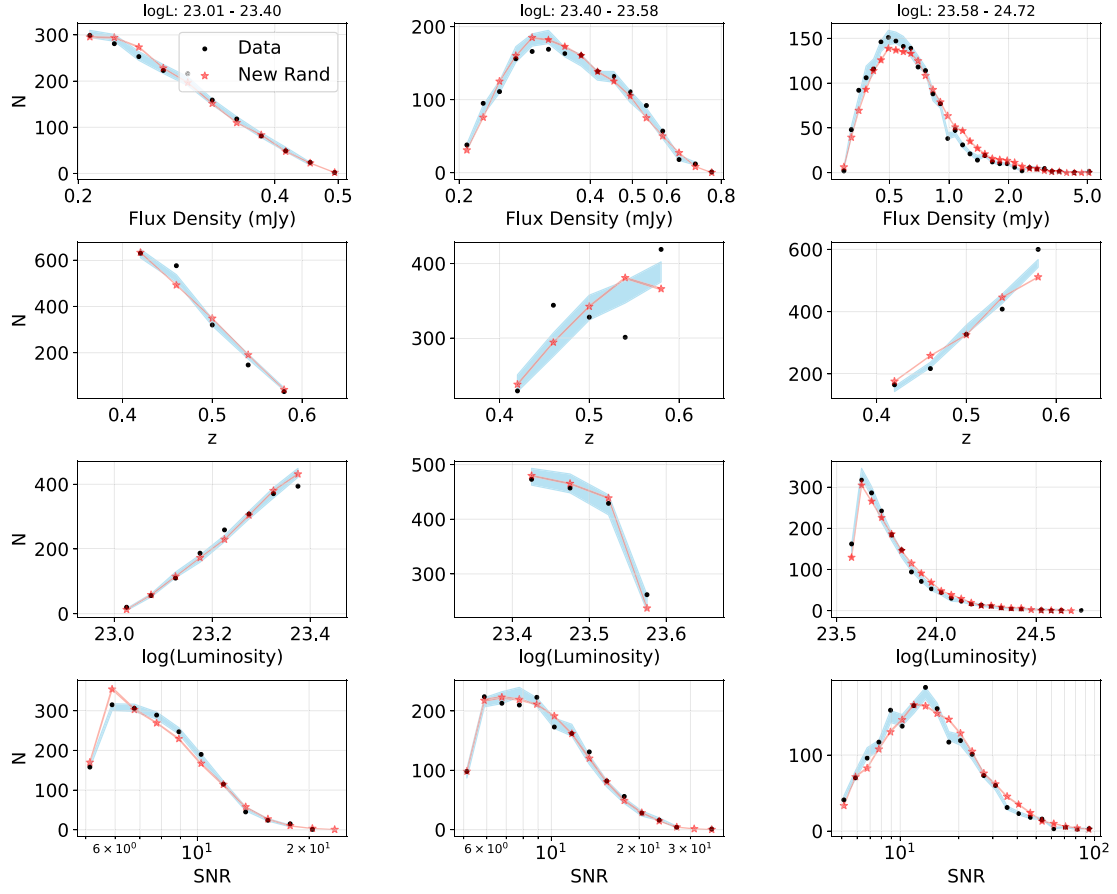
- Peebles P. J. E., 1980, *The Large-Scale Structure of the Universe*, Princeton Univ. Press, Princeton, NJ
- Petter G. C., Hickox R. C., Morabito L. K., Alexander D. M., 2024, *ApJ*, 972, 184
- Poglitich A. et al., 2010, *A&A*, 518, L2
- Raccanelli A. et al., 2012, *MNRAS*, 424, 801
- Roche N., Eales S. A., 1999, *MNRAS*, 307, 703
- Sabater J. et al., 2021, *A&A*, 648, A2
- Schmidt M., 1968, *ApJ*, 151, 393
- Shakura N. I., Sunyaev R. A., 1973, *A&A*, 24, 337
- Shimwell T. W. et al., 2017, *A&A*, 598, A104
- Shimwell T. W. et al., 2022, *A&A*, 659, A1
- Shimwell T. W. et al., 2025, *A&A*, 695, A80
- Shuntov M. et al., 2022, *A&A*, 664, A61
- Siewert T. M. et al., 2020, *A&A*, 643, A100
- Smirnov O. M., Tasse C., 2015, *MNRAS*, 449, 2668
- Smith D. J. B. et al., 2016, in Reylé C., Richard J., Cambrésy L., Deleuil M., Pécontal E., Tresse L., Vauglin I. eds, *SF2A-2016: Proceedings of the Annual meeting of the French Society of Astronomy and Astrophysics*. p. 271
- Smith D. J. B. et al., 2021, *A&A*, 648, A6
- Smith R. E. et al., 2003, *MNRAS*, 341, 1311
- Smolčić V. et al., 2017a, *A&A*, 602, A1
- Smolčić V. et al., 2017b, *A&A*, 602, A2
- Somerville R. S., Lemson G., Sigad Y., Dekel A., Kauffmann G., White S. D. M., 2001, *MNRAS*, 320, 289
- Square Kilometre Array Cosmology Science Working Group, 2020, *PASA*, 37, e007
- Sutherland W., Saunders W., 1992, *MNRAS*, 259, 413
- Takahashi R., Sato M., Nishimichi T., Taruya A., Oguri M., 2012, *ApJ*, 761, 152
- Tasse C. et al., 2018, *A&A*, 611, A87
- Tasse C. et al., 2021, *A&A*, 648, A1
- Tasse C. et al., 2023, *Astrophysics Source Code Library*, record ascl:2305.008
- Tasse C., 2014, preprint ([arXiv:1410.8706](https://arxiv.org/abs/1410.8706))
- Tasse C., 2023, *Astrophysics Source Code Library*, record ascl:2305.005
- Tasse C., Best P. N., Röttgering H., Le Borgne D., 2008, *A&A*, 490, 893
- Taylor M. B., 2005, in Shopbell P., Britton M., Ebert R. eds, *ASP Conf. Ser. Vol. 347, Astronomical Data Analysis Software and Systems XIV*. Astron. Soc. Pac., San Francisco, p. 29
- Taylor M., 2011, *Astrophysics Source Code Library*, record ascl:1101.010
- van der Vlugt D. et al., 2021, *ApJ*, 907, 5
- van der Walt S., Colbert S. C., Varoquaux G., 2011, *Comput. Sci. Eng.*, 13, 22
- van Haarlem M. P. et al., 2013, *A&A*, 556, A2
- Virtanen P. et al., 2020, *Nat. Methods*, 17, 261
- Whittam I. H. et al., 2022, *MNRAS*, 516, 245
- Whittam I. H. et al., 2024, *MNRAS*, 527, 3231
- Whittam I. H., Prescott M., McAlpine K., Jarvis M. J., Heywood I., 2018, *MNRAS*, 480, 358
- Williams W. L. et al., 2016, *MNRAS*, 460, 2385
- Williams W. L. et al., 2019, *A&A*, 622, A2
- Wilman R. J. et al., 2008, *MNRAS*, 388, 1335
- Wilman R. J., Jarvis M. J., Mauch T., Rawlings S., Hickey S., 2010, *MNRAS*, 405, 447
- Wilson A. S., Colbert E. J. M., 1995, *ApJ*, 438, 62
- York D. G. et al., 2000, *AJ*, 120, 1579
- Zehavi I. et al., 2004, *ApJ*, 608, 16
- Zehavi I. et al., 2005, *ApJ*, 630, 1
- Zehavi I. et al., 2011, *ApJ*, 736, 59
- Zheng Z. et al., 2005, *ApJ*, 633, 791
- Zheng Z., Coil A. L., Zehavi I., 2007, *ApJ*, 667, 760

## APPENDIX A: FURTHER VALIDATION PLOTS FOR SOURCES SPLIT BY BOTH RADIO LUMINOSITY AND REDSHIFT

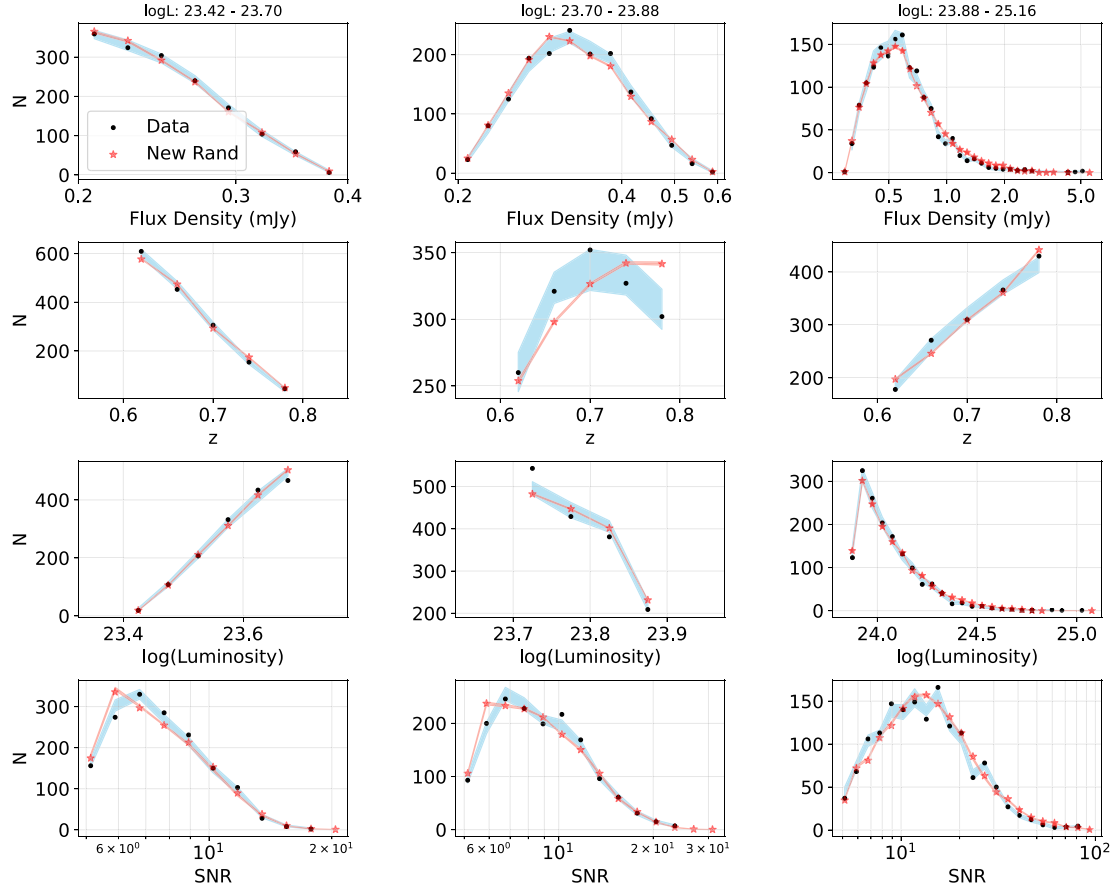
In Figs A1–A5 we present the validation plots for SFGs split into luminosity bins within a given redshift range. The rows are the same as used in Fig. 2, but now left to right indicates different luminosity ranges investigated.



**Figure A1.** As for Fig. 2 but for SFGs in the  $z: 0.1-0.4$  redshift bin and then split into luminosity bins, increasing in luminosity from left to right.

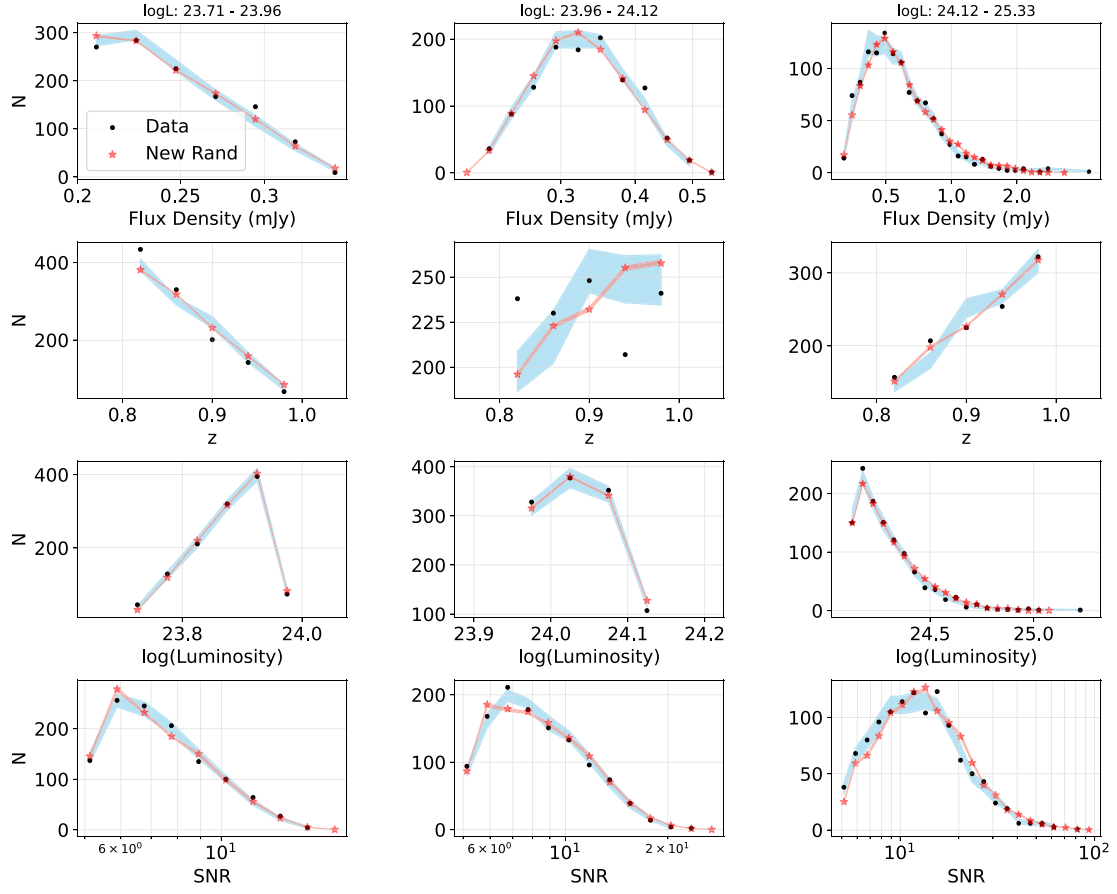


**Figure A2.** As for Fig. 2 but for SFGs in the  $z: 0.4\text{--}0.6$  redshift bin and then split into luminosity bins, increasing in luminosity from left to right.

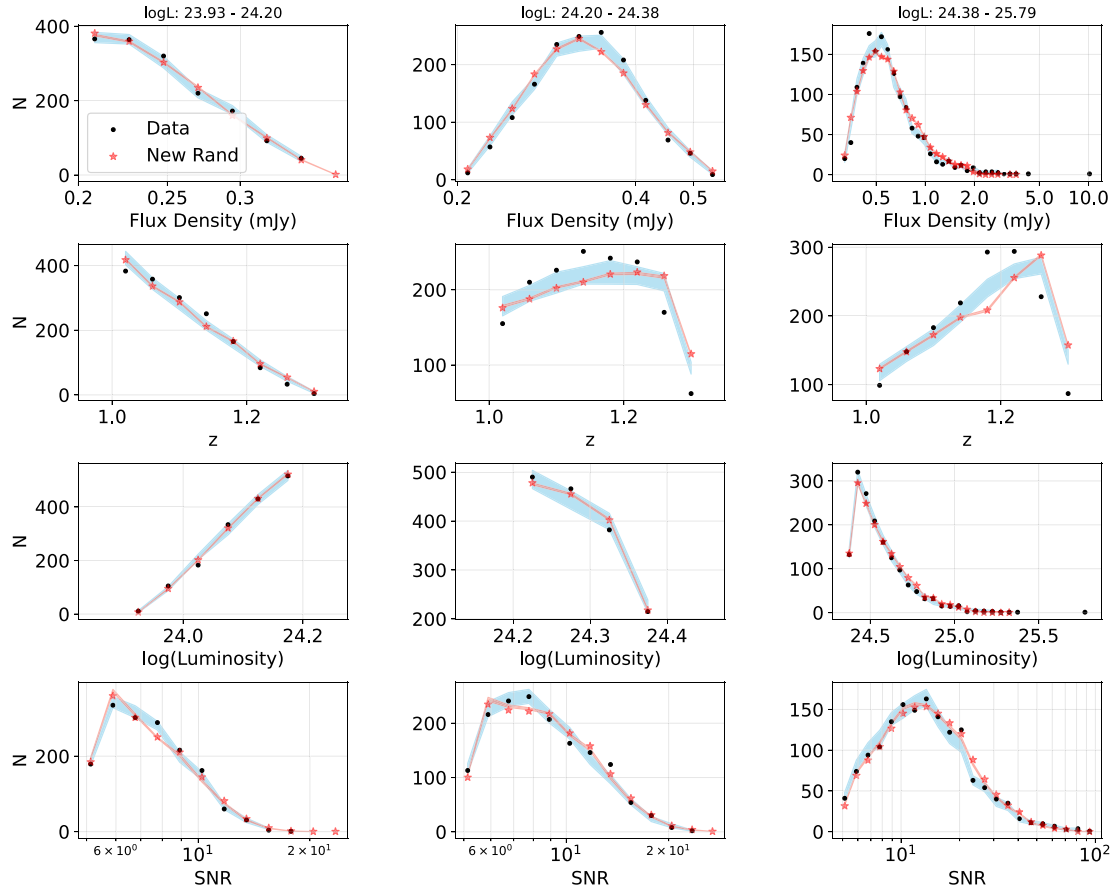


**Figure A3.** As for Fig. 2 but for SFGs in the  $z: 0.6-0.8$  redshift bin and then split into luminosity bins, increasing in luminosity from left to right.





**Figure A4.** As for Fig. 2 but for SFGs in the  $z$ : 0.8–1.0 redshift bin and then split into luminosity bins, increasing in luminosity from left to right.



**Figure A5.** As for Fig. 2 but for SFGs in the  $z$ : 1.0–1.3 redshift bin and then split into luminosity bins, increasing in luminosity from left to right.

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