Contribution to the diffuse radio background from extragalactic radio sources

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ABSTRACT
We examine the brightness of the cosmic radio background (CRB) by comparing the contribution from individual source counts to absolute measurements. We use a compilation of radio counts to estimate the contribution of detected sources to the CRB in several different frequency bands. Using a Monte Carlo Markov chain technique, we estimate the brightness values and uncertainties, paying attention to various sources of systematic error. At $\nu = 150$, 325, 408, 610, 1.4, 4.8 and 8.4 GHz, our calculated contributions to the background sky temperature are 18, 2.8, 1.6, 0.71, 0.11, 0.0032 and 0.0059 K, respectively. We then compare our results to absolute measurements from the Absolute Radiometer for Cosmology, Astrophysics and Diffuse Emission (ARCADE 2) experiment. If the ARCADE 2 measurements are correct and come from sources, then there must be an additional population of radio galaxies, fainter than where current data are probing. More specifically, the Euclidean-normalized counts at 1.4 GHz have to have an additional bump below about 10 $\mu$Jy.

Key words: galaxies: statistics – diffuse radiation – radio continuum: galaxies.

1 INTRODUCTION
Investigating what sources make up the diffuse extragalactic background over a wide range of wavelengths can help us to understand the different physical mechanisms which govern the generation and transport of energy over cosmic time (e.g. Longair & Sunyaev 1969; Ressell & Turner 1990). Much effort has gone into resolving the sources which comprise the background at $\gamma$-ray, X-ray, optical and infrared (IR) wavelengths (e.g. Madau & Pozzetti 2000; Hauser & Dwek 2001; Brandt & Hasinger 2005; Lagache, Puget & Dole 2005). However, the radio part of the spectrum has received far less attention. While there have been many radio surveys and compilations of source counts done over the years, there have been only a few attempts at using these to obtain estimates of the background temperature (Longair 1966; Pooley & Ryle 1968; Wall 1990; Feretti, Burigana & Enßlin 2004). With the advent of new absolute measurements of the radio background, coupled with radio source counts to ever-increasing depths, the topic has undergone something of a revival.

Recently a paper by Gervasi et al. (2008) attempted to obtain fits to the source count data across a range of frequencies from $\nu = 150$ to 8440 MHz. From their fits, which ranged from 1 $\mu$Jy to 100 Jy, they were able to integrate the source counts to obtain an estimate of the sky brightness temperature contribution at each of the frequencies. They determined a power-law sky brightness temperature dependency on frequency with a spectral index of $-2.7$, which is in agreement with the frequency dependence of the flux emitted by synchrotron-dominated steep-spectrum radio sources. These estimates were used to interpret absolute measurements of the radio sky brightness by the TRIS experiment (Zamoni et al. 2008).

More recently, the results of the 2006 ARCADE 2 balloon-borne experiment were released (Fixsen et al. 2009; Seiffert et al. 2009). This instrument provided absolute measurements of the sky temperature at 3, 8, 10, 30 and 90 GHz. These results showed a measured temperature of the radio background about five times greater than that currently determined from radio source counts, with the most notable excess of emission being detected at 3 GHz. Since most systematic effects explaining this emission were ruled out, we are left with the question of whether it could be caused by some previously unknown source of extragalactic emission.

It was suggested by Seiffert et al. in the ARCADE 2 results paper that this excess emission may be coming from the sub-$\mu$Jy range. One might imagine an unknown population of discrete sources existing below the flux limit of current surveys. This issue was further examined by Singal et al. (2010). Taking into account that a class of low-flux sources must extend to $\sim 10^{-2}$ $\mu$Jy (at 1.4 GHz), they concluded that this emission could primarily be coming from ordinary star-forming galaxies at $z > 1$ if the radio-to-far-IR observed flux ratio increases with redshift.

Before looking for radical causes of this emission, it is worth re-examining the observed radio source data to see if the ARCADE 2 result really does differ from what is expected. To do this we derive new estimates of the source-integrated cosmic radio background (CRB) at various frequencies and derive formal error estimates.

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for each. In Section 2 we describe the source count data used, together with our procedure and results for fitting the observed radio data. In Section 3 we present our estimates for the background sky temperature contributions and the analysis of the uncertainties associated with these estimates. In Section 4 we compare our results to those obtained by the ARCADE 2 and TRIS collaborations.

2 THE RADIO SOURCES AND THEIR COUNTS

2.1 The data set

Radio source counts at lower frequencies have been available since the 1960s. There are many compilations of radio source counts available, particularly in the last decade (e.g. Fomalont et al. 2002; Bondi et al. 2003; Hopkins et al. 2003; Prandoni et al. 2006). More recently, deep continuum surveys at higher frequencies have become available and, with the use of newer technologies, have dramatically increased the amount and quality of data. The data used in this paper are from continuum surveys carried out from 1979 to 2009 (see de Zotti et al. 2010; Sirothia et al. 2009). We used source count distributions from 150 to 8400 MHz, with the individual frequencies covered being \( \nu = 150, 325, 408, 610, 1.4, 4.8 \) and 8.4 GHz. References for all number counts used can be found in Table 1.

2.2 The number counts fit

For fitting the source count data, we opted to use a fifth-order polynomial. A third-order polynomial was used in source count fitting by Katgert, Oort & Windhorst (1988), and a sixth-order polynomial fit to the 1.4-GHz data was used by Hopkins et al. (2003), while Gervasi et al. (2008) used simple power-law fitting. Polynomial fits are simpler than some other choices of function, but still allow for fitting of different features in the data, such as the upturn at the-low flux end seen at some of the frequencies (where we note that an additional sub-mJy peak could make a substantial contribution to the background). We chose a fifth-order polynomial as it is a high enough order to account for the features seen in the 1.4-GHz data. Going to higher orders creates unnecessary extra parameters while not improving the \( \chi^2 \) by a significant amount. Our empirical fits are performed on the Euclidean-normalized counts, i.e.

\[
F(S) = S^{2.5} (dN/dS),
\]

with \( S \) being the flux density in Jy, using the polynomial with parameters

\[
F(S) = A_0 + A_1 S + A_2 S^2 + A_3 S^3 + A_4 S^4 + A_5 S^5.
\]

The fitting is initially performed using a \( \chi^2 \) minimization routine. The \( \chi^2 \) minima are then used as starting points in a Monte Carlo Markov chain (MCMC) approach (Lewis & Bridle 2002), which is used to refine the fits, and obtain estimates of uncertainty. More details on the MCMC method can be found in Section 3.2. The best-fitting values for all the parameters at each of the frequency bands can be found in Table 2 along with \( \chi^2 \) values for each fit. The data and the best-fitting lines are plotted in Fig. 1, which shows the Euclidean normalized data, as well as the \( S^2 \) normalized results. These \( S^2 (dN/dS) \) (surface brightness per logarithmic interval in flux density) plots are included to show where the peak contributions to the background arises. The right-hand panels in Fig. 1 show that the bulk of the background comes from relatively bright radio sources, with \( S \sim 1 \) Jy at the lowest frequencies to tens of mJy at the highest frequencies. However, there is a significant, and still poorly characterized, contribution from much fainter sources.

Table 2 shows that the \( \chi^2 \) values of the fits are generally good, with all but one of the reduced \( \chi^2 \) values being below 2. The exception is for the 1.4-GHz data set, with a \( \chi^2 \) of over 20 per degree of freedom. To obtain anything like a reasonable \( \chi^2 \), we would have to increase the errors by a factor of 4. It is worrisome that the 1.4-GHz compilation is the one containing most available data. As can be seen in the plot, there are many data points that are inconsistent with each other, even with the relatively large error bars.

There are clearly systematic differences between different surveys at 1.4 GHz, particularly at the faint end. In the \( \mu \)Jy range, it is

| Frequency | References |
|-----------|------------|
| 150 MHz   | Hales, Baldwin & Warner (1988); McGilchrist et al. (1990) |
| 325 MHz   | Owen & Morrison (2008); Oort, Steemers & Windhorst (1988); Sirothia et al. (2009) |
| 408 MHz   | Bennett et al. (1982); Grueff (1988); Robertson (1973) |
| 610 MHz   | Bondi et al. (2007); Garn et al. (2008); Ibar et al. (2009); Katgert (1979); Moss et al. (2007) |
| 1.4 GHz   | Bondi et al. (2008); Bridle et al. (1972); Ciliegi et al. (1999); Fomalont et al. (2006); Grupioni et al. (1999); Hopkins et al. (2003); Ibar et al. (2009); Miller et al. (2008); Mitchell & Condon (1985); Owen & Morrison (2008); Richards (2000); Seymour et al. (2008); White et al. (1997) |
| 4.8 GHz   | Altschuler (1986); Donnelly, Partridge & Windhorst (1987); Fomalont et al. (1984); Gregory et al. (1996); Kuehr et al. (1981); Pauliny-Toth, Steppe & Witzel (1980); Wrobel & Krause (1990) |
| 8.4 GHz   | Fomalont et al. (2002); Henkel & Partridge (2005); Windhorst et al. (1993) |

### Table 2. \( \chi^2 \) values for best fits at each of the frequencies.

| \( \nu \) (MHz) | \( \chi^2 \) | Degrees of freedom | \( A_0 \) | \( A_1 \) | \( A_2 \) | \( A_3 \) | \( A_4 \) | \( A_5 \) |
|---------------|-------------|--------------------|-------|-------|-------|-------|-------|-------|
| 150           | 68          | 45                 | 6.58  | 0.36  | -0.65 | -0.19 | 0.26  | 0.099 |
| 325           | 59          | 34                 | 5.17  | 0.029 | -0.11 | 0.36  | 0.17  | 0.20  |
| 408           | 66          | 44                 | 4.13  | 0.13  | -0.34 | -0.003| 0.035 | 0.01  |
| 610           | 75          | 59                 | 3.02  | 0.71  | 0.97  | 0.91  | 0.28  | 0.028 |
| 1400          | 4230        | 196                | 2.53  | -0.052| -0.020| 0.051 | 0.010 | -0.0013|
| 4800          | 32          | 47                 | 1.95  | -0.076| -0.15 | 0.020 | 0.0029| -0.00079|
| 8400          | 41          | 29                 | 0.79  | -0.10 | -0.23 | -0.051| -0.019| -0.0029|
difficult to obtain reliable counts, as this range is close to the natural confusion limit of most radio surveys (Condon & Mitchell 1984; Windhorst et al. 1985), and hence the level of incompleteness may be incorrectly estimated in some surveys. Moreover, at the bright end there are significant and systematic sources of error introduced when attempting to correct for source extension and surface brightness limitations (see discussion in Singal et al. 2010). In addition to these effects, sampling variance (enhanced by source clustering) can lead to differences in counts for small fields. All of these systematic effects make it difficult to assess robustly the uncertainties in the derived CRB, as we discuss in the next section.

3 CONTRIBUTION TO SKY BRIGHTNESS TEMPERATURE

3.1 Integration of radio counts

We integrate best-fitting polynomials to obtain the contribution from the sources to the sky brightness. To do this, we integrate the function \( S(dN/dS) \) for each data set only in the range where data are available. We make this conservative choice to avoid extrapolating at the very low and high flux density ends. Because of this, our estimates of the sky brightness should be seen as lower limits. Thus to estimate the intensity we integrate

\[
I(\nu) = \int_{S_{\text{min}}}^{S_{\text{max}}} \frac{dN}{dS}(\nu)SdS, \tag{2}
\]

where \( S_{\text{min}} \) and \( S_{\text{max}} \) are different for each frequency. Once the intensity is determined, we use the Rayleigh–Jeans approximation to convert it to a brightness temperature,

\[
T(\nu) = \frac{I(\nu) \lambda^2}{2k}, \tag{3}
\]

where \( k \) is the Boltzmann constant. The results from the integration at each of the seven frequencies are listed in Table 3.

After obtaining these conservative estimates, we next investigate the effect of reasonable extrapolations on the results, with the limits of integration broadened to \( 10^{-6} \) and \( 10^2 \) Jy for \( S_{\text{min}} \) and \( S_{\text{max}} \), respectively. The 1.4-GHz data set has the most extensive coverage across the flux density range. For this reason, we manually extrapolate the curve for the 1.4-GHz data set and integrate to get a new estimate for the background temperature. To extend the limits of integration for the 1.4-GHz data, the end behaviour of the polynomial is constrained with the assumption that the counts fall off beyond the low-intensity end of the data. Artificial points are added in this region and their positions varied until a reasonable fit to the data is achieved. This procedure is repeated with both a steep roll-off and a shallow roll-off to obtain high and low background estimates.
Table 3. Values of the integrated sky brightness and temperature contribution from radio source counts for different frequency bands. The uncertainties are 1σ limits determined from Markov chain polynomial fits to the data. The high and low extrapolations are discussed in the text.

| ν (MHz) | νIν (W m⁻² sr⁻¹) | T (mK) | δT High (mK) | Low (mK) | Extrapolated T High (mK) | Low (mK) |
|---------|-----------------|--------|---------------|---------|-------------------------|---------|
| 150     | 1.8 × 10⁻¹⁴     | 17 800 | 300           | 29 400  | 18 100                  |         |
| 325     | 2.1 × 10⁻¹⁴     | 2800   | 600           | 50 400  | 31 000                  |         |
| 408     | 2.9 × 10⁻¹⁴     | 1600   | 30            | 30 000  | 18 500                  |         |
| 610     | 4.2 × 10⁻¹⁴     | 710    | 90            | 12 000  | 7 400                   |         |
| 1400    | 7.5 × 10⁻¹⁴     | 110    | 20            | 18 000  | 11 000                  |         |
| 4800    | 8.0 × 10⁻¹⁴     | 3.2    | 0.2           | 10.8    | 6.7                     |         |
| 8400    | 9.6 × 10⁻¹⁴     | 0.59   | 0.05          | 3.0     | 1.9                     |         |

These slopes are chosen to be the most reasonable steep and shallow estimates, with the χ² values being a factor of 5 and 7 greater than the best fit to the data alone. The best fits for the extrapolations can be seen in Fig. 2. The higher estimate could have been allowed to have an even shallower slope, therefore allowing for an even higher background estimate; however, anything much shallower than the chosen fit would have χ² values several times larger again. This fact makes any shallower fits an unreasonable choice. The steep slope estimate for the 1.4-GHz data ends up giving nearly the same result for the background temperature as the unextrapolated estimate. This is because the unextrapolated estimate has a rising low-intensity tail (Fig. 1), while the extrapolated estimate (Fig. 2) has limits of integration extended with the roll-off procedure, whose end behaviour is controlled to produce a steep downturn beyond the available data.

From our conservative estimate of the 1.4-GHz background, a power law is fitted to the temperatures. This takes the form

$$T(ν) = A \left( \frac{ν}{1.4 \text{ GHz}} \right)^β,$$

where A is the power-law amplitude and β is the index. We set A to the 1.4-GHz value of 0.110 K, while MCMC (Section 3.2) were used to find the best value of β = −2.28 ± 0.1. The results of this power-law fit can be seen in Fig. 3. The fit is high for the two highest frequency points, primarily as a result of the 1.4-GHz data, which has the most flux density coverage and most available data. It should be noted that this is just a phenomenological fit; we see little merit in adopting a more complex model such as a broken power law just to satisfy two extreme data points, particularly when this power law is only used to obtain extrapolation estimates.

With the high and low extrapolation estimates from the 1.4-GHz data, we use equation (4) to obtain estimates for the other frequencies. The results of the extrapolated estimates are given in Table 3. As even these reasonable extrapolations can change the background estimates by about a factor of 2, it is clearly important to push counts at all frequencies to fainter levels.

3.2 Uncertainty – Monte Carlo Markov chains

To investigate the uncertainties thoroughly, we carry out our fits with MCMCs for each of the data sets, using CosmoMC (Lewis & Bridle 2002) as a generic MCMC sampler. The χ² function is sampled for each set using the polynomial in equation (1), which is then fed to the sampler to locate the χ² minimum. Each of the six parameters of the polynomials are varied for each step of the chain and the chains are run with 500 000 steps. CosmoMC generates statistics for the chains, including the minimum χ², the best-fitting values for each of the parameters and their uncertainties. As an example, Fig. 4 shows different polynomial fits tested by the MCMC and their relative probability for the 1.4-GHZ data set.
Histograms of the chain values for the background temperature are shown in Fig. 5. From the width of these histograms, we are able to measure the uncertainty in our estimates for the background temperature, taken here as the 68 per cent area values, fully accounting for the correlations among the parameters in the polynomial fits. The 1σ uncertainties are listed in Table 3.

Most of the histograms are fairly Gaussian, which is a reflection of the quality of the data. Frequencies with good data around the...
peak contribution (in the right-hand panels of Fig. 1) tend to have well-constrained background temperature values, e.g. at 408 MHz. However, there is a noticeable irregularity with the 325-MHz histogram. Because of the limited data available at 325 MHz, and with the peak area of contribution having little to no data, the histogram at this frequency does not have a well-defined shape; the uncertainty is far from Gaussian.

3.3 Comparison with previous estimates

Over the years, there have not been many estimates of the CRB made using source count data (Longair 1966; Pooley & Ryle 1968; Wall 1990; Feretti et al. 2004; Gervasi et al. 2008), and even within this small list, the frequencies covered were rather limited and uncertainties not always quoted. It is important to see how our estimates compare with these previous estimates. Longair (1966) gives a value for \( T_{178} = 23 \pm 5 \) K. Wall (1990) lists estimates of \( T_{\text{diff}} = 2.6 \) K, \( T_{1.4} = 0.09 \) K and \( T_{2.5} = 0.02 \) K. Our results are in agreement with these earlier estimates to within \( \pm 2\sigma \). The values for source contributions from Gervasi et al. (2008) tend to be a little higher than ours, the differences being traceable to choices made for the limits of integration and for the parametrized form for the fits.

The ARCADE 2 experiment reported an excess of emission beyond what we and others have estimated from source counts, with the excess largest at 3.4 GHz. We have also considered much lower frequencies in this paper than the 3.2-GHz detection limit of ARCADE 2. However, it is possible to calculate what temperatures would be expected using the best fit to the ARCADE 2 data:

\[
T(v) = T_0 + A \left( \frac{v}{1 \text{GHz}} \right)^\beta .
\]

(5)

Here \( T_0 \) is the cosmic microwave background (CMB) base temperature, and the best-fitting values for the parameters are \( \beta = -2.56 \) and \( A = 1.06 \) (Seiffert et al. 2009). Measurements from the TRIS experiment were performed at \( v = 0.6, 0.82 \) and 2.5 GHz, and compared with the Gervasi et al. source contribution calculations are within 3 per cent at 0.6 GHz and 50 per cent at 2.5 GHz.

The quantities detected by or extrapolated from ARCADE 2, those estimated from counts by Gervasi et al. (2008), the measurements from the TRIS experiment as well as our current estimates are shown in Fig. 6. Here it can be seen that the ARCADE 2 absolute measurements lie far above both source counts and TRIS measurements, particularly at lower frequencies. Clearly, the excess detected around 3 GHz would correspond to a large excess at lower frequencies if the power law continued.

3.4 Systematic errors

We have considered several possibilities for systematic errors in exploring whether our results might be compatible with those from the ARCADE 2 experiment. The first of these is possible bias from source clustering. This can be an issue when dealing with surveys covering small areas, where one might get more field-to-field variations than expected from Poisson errors. The two-point angular correlation function for NVSS and FIRST sources fits a power-law shape for separations up to at least 4° (Blake & Wall 2002; Overzier et al. 2003). From this angular correlation function, one can estimate the fractional variance of the counts (Seldner & Peebles 1980). This procedure was carried out by de Zotti et al. (2010) and has been taken into account in the errors provided and used in our estimations.

Another effect that could influence our results is the fact that in some of the surveys used in our compilation, the measurement frequency was slightly different from the nominal one, i.e. 5 GHz rather than 4.8 GHz. In such cases we scaled the original measurements to the nominal frequency using the assumed dependence of the source flux \( S(v) \sim v^{-0.7} \). This correction results in negligible change in the derived fits.

An additional effect that could account for the difference in the background temperatures is the possibility that some surveys have somehow missed extended high-frequency emission blobs which could integrate up to the required amounts. This seems an unlikely option, as such structures would have to be on degree scales or larger to escape detection, and because if these structures have features above a certain brightness temperature then they would have been seen.

Other possible effects to take into consideration for the uncertainties include the following:

1. calibration variations for different radio telescopes;
2. inaccurate determination of completeness corrections at the faint end;
3. contribution from diffuse emission from the intergalactic medium, intercluster medium and the warm-hot intergalactic medium;
4. missing low surface brightness emission from extended objects that are either large, or sources with extended components, or

![Figure 6. Integrated sky brightness temperature at each frequency from the estimates in this paper (open squares), Gervasi et al. (2008; stars), TRIS measurements (Zannoni et al. 2008; diamonds) and ARCADE 2 measurements (Seiffert et al. 2009; triangles). The dashed line at the bottom represents the CMB temperature at 2.726 K (Fixsen 2009).](https://academic.oup.com/mnras/article-abstract/415/4/3641/1749229/figures/6)
sources that are not detected if source surface brightness extends to low values.

Singal et al. (2010) provide a detailed discussion of items (3) and (4) as well as several other possibilities such as radio supernovae that could contribute to the CRB. We suspect that the most important effects are the first two items, particularly completeness at the faint end.

4 INVESTIGATION OF A FAINT ‘BUMP’ IN THE COUNTS

At 1.4 GHz, where we have the most data, our estimated background temperature plus a CMB baseline is 2.83 ± 0.02 K, while an extrapolation of the ARCADE 2 result gives 3.17 ± 0.01 K (error estimate from their measurement at 3.2 GHz). This corresponds to a difference that is nearly 17σ away from our estimate. It has been suggested that this could be explained through an extra population of faint radio galaxies, corresponding to a ‘bump’ in the Euclidean-normalized counts at flux densities near or below where the current data are petering out (see also Singal et al. 2010). We want to investigate how big this bump would need to be in order to explain the excess emission.

We carried out two separate approaches for modelling such a bump, the outcomes of which can be seen in Fig. 7. Our first approach is a simple extension of the current counts with an upward trend below 10 μJy, but one not quite as steep as the best-fitting line. To do this we simply added artificial data points past the lower flux density limit of the rest of the data in order to control the end behaviour of the fit line. We then investigated what was required to match the ARCADE 2 results. The solid line of Fig. 7 shows the results of this fitting. It is the best fit to the data, allowing for a moderate upward slope in the faint end. When integrated from 10^{-6} Jy, the result is enough to account for the temperature reported by ARCADE 2.

Our second method involved choosing a simple parabola with fixed width of a decade in log S and variable position for the peak, and running a Markov chain that fit the height parameter that would integrate to give the amount of excess emission needed to match the ARCADE 2 result. We found that the peak of the bump could be at flux densities as high as 8.0 μJy.

It is relatively easy to produce a bump big enough to account for the extra emission while still fitting the rest of the data reasonably well, with either method. However, we do know that any such bump is constrained by the observed IR background, through the IR–radio correlation (see e.g. Haarsma & Partridge 1998). This correlation will have to be taken into account in any modelling of this faint flux density bump so as not to overproduce the IR background. This essentially requires any faint radio population to be quite IR faint compared with known galaxy types.

5 CONCLUSIONS

We used source count data from ν = 150, 325, 408, 610, 1.4, 4.8 and 8.4 GHz to evaluate the contribution from sources to the diffuse CRB. Polynomials were fitted to the data and integrated to obtain lower bound estimates at each frequency for the sky brightness temperature. In addition, we also extrapolated our fits beyond the limits where data are available using reasonable assumptions for how the curves behave in those regions. We then used MCMCs to obtain estimates of the uncertainties of the temperature estimates at each frequency and also considered other possible sources of uncertainties that could affect the results.

Our estimates are considerably lower than the measurements of ARCADE 2, even when taking into account the uncertainties or extrapolations. We considered the possibility that the excess emission comes from a bump in the source counts in the μJy range at 1.4 GHz. We used modelling to see how large such a bump must be in order to obtain the necessary contribution to the background.

We saw that a bump could exist in this range, peaking at fluxes as bright as 8 μJy, and could integrate up to the excess emission of ±320 mK, with a height that is consistent with the data.

We still have no direct evidence that such a new population exists, and so further investigation into the faint end of the counts is needed. The IR and radio connection could be used to test this idea through use of signal stacking and by examining different possible luminosity functions to look at the evolution of such a population. The final answer may only be reached when source count data become available in the μJy range, perhaps in the era of the extended very large array (EVLA) and eventually the Square Kilometre Array.

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