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River water temperature demonstrates resistance to long-term air temperature change

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Abstract

Ecosystem health and water quality of rivers are dependent on their temperature. With ongoing human-induced climate change causing increases in air temperature across the globe, it is anticipated the stream temperatures will rise too—in turn increasing the rates of biogeochemical stream processes and potentially threatening the viability and health of aquatic organisms. To understand the relationship between climate change and stream temperature response, the longer the records that can be analysed, the more the robust the analysis for detecting change. In this study, we analyse records from 263 catchments from across the United Kingdom for 45 years from 1974 to 2019 to assess the link between air temperature and stream temperature change. To give the most precise analysis of these long records, Bayesian hierarchical modelling was used and showed that: (i) The Bayesian hierarchical approach was 59% more precise, that is, reduced uncertainty on long-term trends, than using simple linear regression. (ii) The increase in annual average air temperature over 45 years across the United Kingdom showed no significant differences between 22 weather stations and gave a 45-year change of 1.35 ± 0.9°C. (iii) Trends in annual mean stream temperature change varied from −2.3 °C to 2.0 °C over 45 years, with the mean over 263 sites being 0.5 °C over 45 years. (iv) 1% of rivers showed a stream temperature trend significantly greater than the air temperature trend but 3% of sites showed a stream temperature trend significantly lower than zero. (v) 74% of all river sites showed no significant monotonic trend, either positive or negative, in water temperature even after 45 years. The observed declines in stream temperature could be ascribed to the closures of thermoelectric power stations but it is unclear why the stream temperature at some sites has risen faster than air temperature. The study shows that mean river temperature was well buffered against changes in air temperature—a 1°C rise in air temperature giving 0.37°C in mean stream temperature.

KEYWORDS
Bayesian hierarchical analysis, resilience, streamwater temperature

1 | INTRODUCTION

Water temperature is a fundamental property of river water (Webb et al., 2008; Ouellet et al., 2020) and, given human-induced climate change, there is a concern that in a warming climate river water temperature will increase (Garner et al., 2017; Jackson et al., 2020). Warming of the river water could be exacerbated or alleviated by climate-induced changes in the amounts and pathways contributing to the stream flow (van Vliet et al., 2013; Wanders et al., 2019; Watts et al., 2015). Warmer river water will have multiple impacts, for example, influence the growth and performance of a range of aquatic organisms (Ouellet et al., 2020; Strayer et al., 2004); and increase reaction rates in biogeochemical process (e.g., carbon cycling - Comer-Warner et al., 2018). Warming of river water can lead to both acute and chronic impacts on fish, for example, Brown trout (*Salmo trutta*) are at mortality risk at stream temperatures >24.7°C (Jonsson & Jonsson, 2009) and >33°C is lethal for juvenile Atlantic salmon (Elliott & Elliott, 1995). Warmer river water has economic and social impacts (Hannah et al., 2008; PACEC, 2017). Tourism related to game fishing of cold water species (trout, salmon and charr) will be impacted as warmer water reduces the habitat of the important species (Elliott & Elliott, 2010). Heberling et al. (2015) have shown a 1.5% increase in water treatment cost for every 1°C rise in river temperature exceeding 23°C.

Multiple studies have drawn the link between climate change, and specifically air temperature, and changing stream water temperature. Linking air temperature to stream water temperature has long been a research goal (e.g., Macan, 1958) as such a link provides an easy way to predict stream temperature as air temperature is often readily available in comparison to values of parameters required in more physically-based models. However, link between air temperature and stream temperature will always be moderated by catchment properties, land use and hydrology (Garner et al., 2014). Studies of long-term patterns in river temperature have been limited to individual sites or a few basins (e.g., Langan et al., 2003; Webb et al., 2003) - as reviewed in the next paragraph. Arismendi et al. (2012) concluded that our perspective of climate impacts on stream temperatures had been clouded by a lack of long-term data.

Webb and Nobilis (1997) considered time series of stream water temperature (1901–1990) for a catchment in Austria; and they were able to develop good relationships between monthly air and water temperatures, but did not find a significant trend in either air or water temperature over the 90 years. Basarin et al. (2016) considered a 60-year record of water temperature from three sites on the River Danube with an increase in water temperature of up to 0.5°C/year; but this was not compared to the long-term trend in air temperature at the sites. Jonkers and Sharkey (2016) considered stream temperature records from 1982 to 2011 from British catchments and found a median water temperature increase of 0.02°C/year with the highest median water temperature increase of 0.06°C/year; but this result is not based on actual trend analysis of water temperature records, but multivariate modelling based on stream reach properties. Orr et al. (2015) analysed stream temperature records across England and Wales and found that 8% of the records showed a significant increase over the time period 1990–2006 with a median increase equivalent to 0.03°C/year. They state that this river temperature change is comparable to the air temperature change over the same period, but their study gave no formal comparison. Graf and Wrzesinski (2020) analysed 35 years of daily water temperature records from 53 rivers recorded at 94 gauging stations and air temperature at 43 meteorological stations. All air temperature records showed significant increases over the period compared to 85% of water temperature records. The global modelling by Wanders et al. (2019) suggested a global increase in average river water temperature of 0.016°C/year (quoted as 0.16°C per decade) between 1960 and 2014, although water temperature decreases downstream of melting glaciers associated with high mountain ranges (e.g., Himalayas). Johnson et al. (2009) predicted that summer temperatures in some UK river systems would rise by up to 4°C by 2080 based on a 1: 1 linear relationship with air temperature change. For the United States, Kaushal et al. (2010) analysed stream temperature for 40 major rivers and showed significant, long-term warming trends for 20 rivers that were significantly correlated with air temperature. Isaak et al. (2017) studied stream temperature data from 22 700 sites from 2011 from across the Western United States to predict impact of climate change and specifically air temperature increases. Hare et al. (2021) considered 1729 sites across the United States with 184 having stream temperature time series of up to 30 years showed sites with deep groundwater influence showed no stream temperature increase. In Japan, Ye and Kameyama (2021) found that between 1981 and 2016, 42% of 153 sites were warming faster than air temperature.

Anthropogenic activity and interventions can influence stream temperature. Relatively warm water can come from a number of anthropogenic sources, including: thermal power stations (Worthington et al., 2015); land use and land use change (Laizé et al., 2017); urban paved area (Croghan et al., 2019; Herb et al., 2008); urban wastewater (Kinouchi et al., 2007); or dam impoundment or management (Casado et al., 2013). Therefore, continuing human development within any catchment (e.g., urbanization) may alter the influence of increasing air temperature, leading to river water temperatures being more or less sensitive to ongoing climate change. So, the aim of this study was to consider how stream water temperature had changed over periods of decades in relation to air temperature (sometimes referred to as thermal sensitivity – Kelleher et al., 2012) change across catchments with diverse land use (a) to understand the space–time patterns of change; and (b) to infer underlying factors controlling river temperature response.

2 | METHODS

To understand the link between stream temperature change and local air temperature change, the stream temperature records are compared to air temperature records of the same length, and over the same time period, from sites across Great Britain. Air temperature records were chosen from across Great Britain so that stream temperature records could be compared to local air temperature change. Daraio et al. (2017) used a Bayesian hierarchical regression to quantify variation in stream temperature (T_w) and its relationship with air temperature (T_a) at 11 sites across 1.3 km reach of an urban stream. Sohrabi et al. (2017) used a Bayesian regression approach to estimate daily stream water temperature from air temperature and stream water discharge in 34 sites across the United States. Letcher et al. (2016) used a Bayesian hierarchical approach to improve models of stream temperature in a single catchment in United States. Similarly, we use Bayesian hierarchical general linear modelling to estimate the annual trend in stream temperature and the Bayesian hierarchical general linear modelling approach offers several benefits. First, the Bayesian approach means that all data has value so that in such a large dataset the precision of the analysis at individual sites will be increased, that is, the uncertainty on any estimated trend will be smaller, therefore increasing the sensitivity of the analysis to detecting significant trends. Second, this approach is robust against the irregular sampling common in national monitoring; this is because factorial information (e.g., month of sampling) can be included in the analysis. By including factorial information such as the month of sampling, this can account for uneven sampling across a year and so provide more accurate and precise expected values for sampling sites. However, to demonstrate the advantage of the Bayesian hierarchical approach simple linear regression was also applied to the dataset.

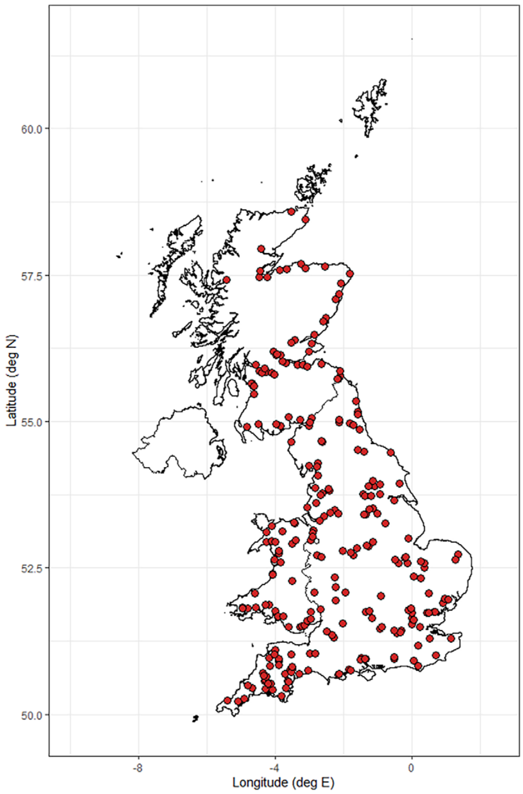


FIGURE 1 The location of monitoring sites that were used in this study.

2.1 | River temperature data

This study uses data from the Harmonized Monitoring Scheme sites (HMS - Bellamy & Wilkinson, 2001). There are 56 sites in Scotland and 214 sites in England and Wales but only 263 sites were ever monitored for stream temperature (Figure 1 and Table 1), that is, for seven sites in the HMS no stream temperature data was ever recorded. The river temperature was measured in the field on spot samples taken approximately monthly. Monitoring sites were included in the original HMS monitoring programme if they were at the tidal limit of rivers with an average annual discharge greater than 2 $m^3\ s^{-1}$, or any tributaries that also had a mean annual discharge above 2 $m^3\ s^{-1}$ (Bellamy & Wilkinson, 2001). The catchment areas vary between 40 and 9885 km^2 (Table 1) These discharge criteria means that there may be several HMS monitoring sites in a single, large catchment. These criteria provided good spatial coverage of the coast of England and Wales, but in Scotland many of the west-coast rivers are too small for inclusion in the HMS. No HMS data were available from Northern Ireland. The separate HMS monitoring programme ceased at the end of 2014, but the same monitoring sites were maintained by the national agencies in England, Scotland and Wales. Therefore, stream temperature data could be considered from 263 sites between 1974 and 2018 (45 years).

2.2 | Air temperature data

To compare the trends estimated for stream records to local air temperature change, we used the UK Met Office long-term, onshore weather station dataset (Figure 2). To be included in this analysis, the records for the weather had to exist for the period 1974–2019 and only sites at lower altitudes were used (<200 m above sea level). Lower-altitude sites were used because the majority of HMS sites were below this altitude and lapse rates across terrain may alter with ongoing climate change. These data from UK Met Office long-term,

TABLE 1 Range of properties of the catchments considered in this study.

Catchment property	Range	Catchment property	Range (%)
Area (km^2)	40–9885	Mineral soil cover	0–100
(mm)	426–588	Organo-mineral soil cover	0–100
Annual rainfall (mm)	561–2606	Organic soil cover	0–100
Baseflow index	0.3–0.9	Arable land cover	0–70
		Urban land cover	0–78
		Grass land cover	0–36

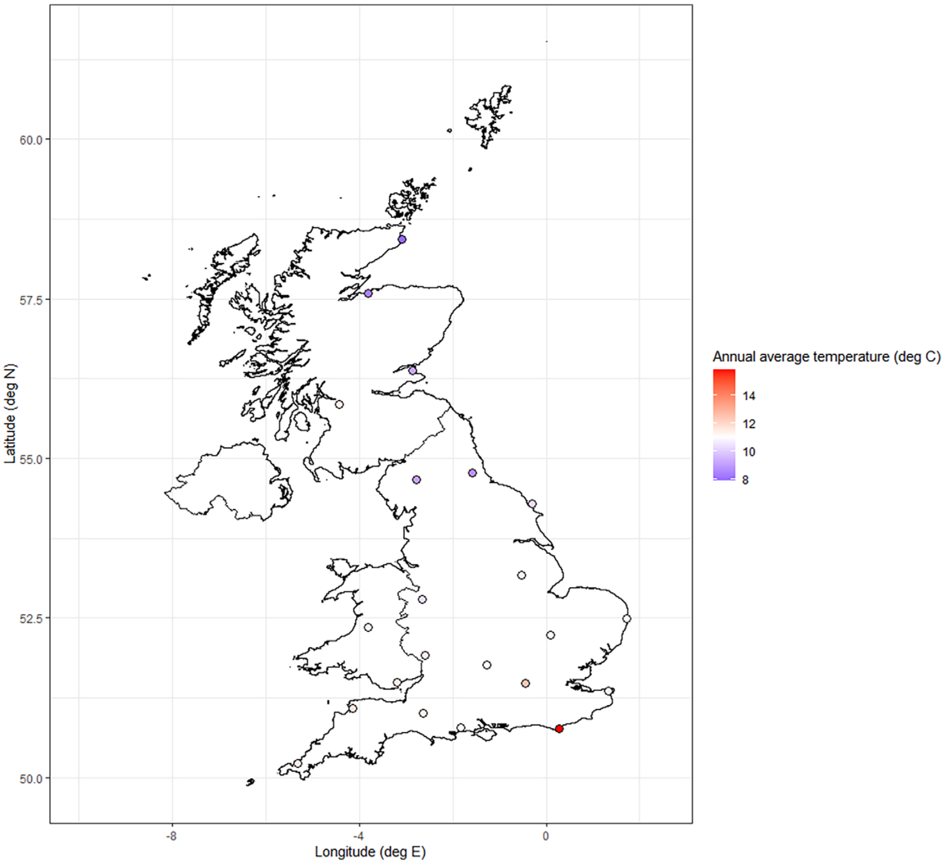


FIGURE 2 The onshore weather stations used in the study and their annual average temperature (1974–2019).

onshore weather station dataset are reported as mean monthly maximum ($\overline{T}_{max}$) and mean monthly minimum temperature ($\overline{T}_{min}$) and so monthly average temperature was considered where monthly average temperature was $\frac{(\overline{T}_{max}-\overline{T}_{min})}{2}$. The long-term station dataset were analysed in exactly the same way as the stream temperature data, that is, using a Bayesian hierarchical approach as described below.

2.3 | Bayesian hierarchical generalized linear modelling

The same approach was used for air temperature as for river temperature. The approach was based upon Bayesian hierarchical general linear modelling. The preferred model was fitted to these data:

$$E(T)_{xt} = N\left(\mu_{xt}, \frac{1}{\sigma^2}\right) \quad (1)$$

$$\mu_{xt} = (\alpha_{xt} + \beta_{xt}(\text{Site, Month})\Delta[\text{Year}]_{xt}) \quad (2)$$

$$\Delta[\text{Year}]_{xt} = [\text{Year}]_{xt} - \overline{[\text{Year}]} \quad (3)$$

where, $E(T)_{xt}$, is the expected value of the stream, or air, temperature for site x at time t (°C); Site, a factor representing the different monitoring sites for which data were available and so had 263 levels one for each site within the dataset; Month is a factor representing the calendar months of sampling and hence there are 12 levels in this factor; Year is the year of the sampling, but taken as a covariate and not as a factor. In this way, β_{xt} were calculated for each monitoring site, for each month, across the record and represents the trend in the stream temperature across the period for a particular site and month. Note that year was given as the difference from the mean of all the data and in this way α_{xt} is not the y-intercept, that is, the value of T (be that stream or air temperature) at year 0, rather α_{xt} is the expected value of T at site x in 1996, that is, the middle year of the record. The approach of expressing year as the difference from the global mean value is to make estimation of α more precise as α now sits in the middle of the observations rather than at one extreme (year = 0) as would be the case if α was the y-intercept. The model in Equations (1)–(3) is henceforward referred to as the preferred model as it included both Site and Month factors. Other models using only one or other of these two factors were fitted as a means of testing model fit.

Markov Chain Monte Carlo (MCMC) simulation was used for the Bayesian estimation using Jags code called from R using the R2Jags library (R and JAGS code and example code are included in supplementary material, S1). An MCMC chain of length 10 000 iterations after a 2000 burn was used with samples saved every 10 cycles and with 3 chains.

For all models fitted in this study for both river and air temperature and for any combination of available factors, the prior distribution for values of β were set as normal distributions with a mean of zero so that both positive and negative trends over time were equally favoured at the outset. The prior distributions for the values of α were also set as a normal distribution but with the mean set to be the mean of all the dataset and a standard deviation chosen to make negative values unlikely. The choice of such a distribution is justified because if values of β are small then α is the prediction of a particular monitoring site's expected value and thus should approximate the expected value of the distribution of the data as a whole. A half-t distribution was used for the prior distributions of the standard deviations for all terms as half-t distributions mean that a negative value of the standard deviation cannot occur. The size of the dataset means that the assumptions about the magnitude of the prior will become important.

A number of approaches were used to test the fit of the models, including the preferred model - Equations (1)–(3). First, adequacy of the MCMC process was assessed using $\widehat{R}$, the convergence statistic, and values $1 < -\widehat{R} < 1.1$ were considered acceptable. If$\widehat{R} > 1.1$ then the burn in process and number of iterations were increased to 20 000 although this did not prove necessary in this case. Second, that for any factor, the 95% credible interval does not include zero, going forward this is referred to as being a 95% probability of being significantly different from zero. Third, that when a factor, interaction, or covariate is included, this caused total model deviance to decrease – deviance is a goodness of fit measure and is a generalization of the idea of using the sum of squares of residuals in ordinary least squares. This third criteria was tested by fitting the preferred model (Equations 1–3) with the three possible combinations of the two factors included, that is, month only, Site only and Site and Month. Fourth, when an additional factor, interaction or covariate is included, there is a resulting decrease in the deviance information criterion (DIC). Because inclusion of additional factors, covariates or interactions will increase the degrees of freedom of any fitted model; such inclusion would lead to a decrease in the total deviance of any particular model, and hence the need for another measure rather than simply total deviance. The DIC accounts for the trade-off between the inclusion of more parameters against the additional fit of the model and penalizes for additional parameters relative to the fit of a particular model – DIC is the general case of Aikake Information Criterion. As for the third criteria, this fourth criteria was assessed by fitting models with the separate factors (site and month) in comparison to the model including both the Site and Month factors. Fifthly, the effective number of parameters (pD) was monitored: it would be expected that as a factor or covariate was added to a model, then the number of effective parameters would likewise increase. If pD did not increase with inclusion of a factor or covariate, then that parameter is having no effect on a model and can be removed. Furthermore, pD should be close to the ideal case if all parameters are contributing, and so the calculated pD can be expressed as a percentage of that maximum possible—this value can never be greater than 100%. Finally, the fit of any model was judged using a posterior prediction check, that is, the output of the preferred model was plotted against the observed values and the fitted line between these two examined—it would be expected that a good fit model would give a 1:1 line between observed and posterior predicted values. In addition, the underlying assumption of the nature of the likelihood function was tested. The approach of this study assumes that the residuals of the models will be independent in time and so the residuals from the preferred model were tested for their normality and homoscedasticity. Normality was tested using the Anderson-Darling test (Anderson & Darling, 1952); the presence of homoscedasticity or heteroscedasticity was tested by plotting the residuals against the fitted values and by use of the Breusch-Pagan test (Breusch & Pagan, 1979); and tested for autocorrelation within the residuals using the Durbin-Watson statistics (Durbin & Watson, 1950).

To quantify the benefit of using a Bayesian hierarchical approach two other approaches to the estimation of trend at the river monitoring sites were used. First, a non-Bayesian hierarchical model was fitted to the data using a linear mixed effects model. The linear mixed effects model was fitted to the data using a maximum likelihood method and the lme4 library in R and considering the Site and Month as fixed factors and Year as the random factor. In this way, Equation (2) is being fitted to the whole dataset, just as in the Bayesian approach, but without the advantage of prior knowledge. Second, a linear regression was fitted, separately, to each monitored site. Linear regression, applied individually and separately at each site is the most commonly used approach for estimating river temperature trends (e.g., Kaushal et al., 2010) and so a linear regression was applied separately to each site. The model fitted to each site was where the stream temperature for year is:

$$T_{xt} = (\alpha_x + \beta_x \Delta \text{Year}) \tag{4}$$

Terms are as described above and for comparison with the Bayesian approach ΔYear was used. When simple linear regression was used then least squares fitting was used with the fit of the model being assessed by the significance of the β_x. Note that in Equation (4) there is no allowance for the seasonal cycle, that is, month has not included as a fixed factor nor transformed to be included as a continuous variable. The results from the Bayesian, linear mixed effects and simple linear regression were compared by considering the slope estimates (i.e., the estimated in stream temperature between the two methods) and the 95% confidence interval on the slope estimates for each site.

2.4 | Comparative data and analysis

To give context to the UK stream temperature data, the Environment Agency databases were examined to give the distribution of temperature for groundwater, lake water and sewage treatment discharge for all the sites the Environment Agency monitored across England. There was only one measurement of rainwater temperature within the Environment Agency database and so it was not included.

To understand the reason for changes in the trend between the study catchments, the slope estimates (β) were compared to the properties of the catchments (Table 1). The land use for each 1 km^2 of Great Britain (i.e., the UK minus Northern Ireland) was classified into:

arable, grass and urban from the June Agricultural Census for 2004 (DEFRA, 2005). The dominant soil-type of each 1 km^2 grid square in Great Britain was classified by this study into mineral, organo-mineral and organic soils based upon the classification system of Hodgson (1997), and used nationally-available data (Lilly et al., 2009; Smith et al., 2007). Note that, by this definition, peat soils are a subset of organic soils. The catchment area to each monitoring point was calculated from the CEH Wallingford digital terrain model which has a 50 m grid interval and a 0.1 m altitude interval (Morris & Flavin, 1994). The soil and land-use characteristics for each 1 km^2 were summed across each catchment to the monitoring points with available stream temperature information. For each of the catchments, for which the study could calculate a stream temperature trend, the following hydrological characteristics were used: the base flow index, the average actual evaporation, the average annual total river discharge and the average annual rainfall. The hydrological characteristics for each catchment were available from the National River Flow Archive (www.ceh.ac.uk/data/nrfa/).

The measure of the stream temperature trend was compared to the catchment properties in two ways. First, multiple linear regression was performed with both explanatory variables and the response variable untransformed and then log-transformed. Normality of transformed and untransformed variables was tested using the Anderson-Darling test (Anderson & Darling, 1952). Variables were only included in the model if they were statistically significant (probability of difference from zero at $p < 0.05$). The second approach was to use logistic regression. Logistic regression is an ideal technique for understanding the difference between binary outcomes. The slope estimated (β_{Bayes}) for each of the study site was classified into binary groups for: (i) β_{Bayes} greater or less than zero; (ii) β_{Bayes} greater or less than the air temperature change; and (iii) β_{Bayes} significantly greater or less than zero. Logistic regression was then used for predicting a binary outcome (e.g., slope greater or less than zero) from continuous explanatory variables (e.g., proportion of organic soil in a catchment)—the prediction is the probability of being in one of the two groups. This regression method does not use a least squares fitting method as used by multiple linear regression, but rather uses maximum likelihood estimation. Logistic regression allows the significance of parameters included in the model to be assessed, thus aiding the mechanistic interpretation of the model. The goodness of fit of any logistic regression model was tested as being the proportion of correct classification based upon a 50% probability of a slope greater than zero.

3 | RESULTS

Between 1974 and 2019, there were 175 834 spot measurements of river temperature from 263 sites. The arithmetic annual mean was 11.0°C with a 95th percentile range of 2.5–20.3°C. The least sampled site was the River Teign at Clifford (13 measurements) and the most sampled was the River Wensum at Sweet Brier Road Bridge (1714 measurements). The warmest site was the River Lee (Carpenters Road) at an arithmetic mean of 13.8°C and the coldest was River Findhorn (A96 road bridge) with an arithmetic mean of 8.1°C. The coldest year was 1986 with an average 10.1°C and the warmest year was 2014 with an average of 11.8°C. The most sampled year was 1977 (6451 samples) and the least sampled year was 2013 (1007 samples).

The comparative data for freshwater compartments and air temperature are given in Table 2. The visual inspection of the comparative data show that, without being able to make direct comparisons for influences on individual rivers or at individual sites, it would appear that river water temperatures are increased by presence of lakes, sewage and wastewater discharges, trade effluents and power station discharges. It should be noted that this is a study about trend and not a study of the absolute value of stream temperature at the study sites. Thus it is not so much the actual temperature of sources that is critical in this study so much as the changes in the temperature of these water sources that may be key to driving changes in stream temperature.

3.1 | Air temperature trends

The model fitted had a deviance = 135 895, DIC = 135 952 and a pD = 43.5 giving an efficiency of 99%; a model at 100% efficiency would mean that all terms in the model were contributing, in this case it would be that the intercept and slope for each onshore station is contributing.

TABLE 2 Summary of the temperature for comparative freshwater compartments.

Type	Expected value	95% interval	*N*	Source
Groundwater	11.2	6.3–17.6	11 945	Environment Agency
Riverwater	11.0	2.5–20.3	175 834	This study
Lakewater	12.3	3.0–22.5	11 808	Environment Agency
Air	9.9	2.2–18.1	12 074	UK Met Office
Final sewage effluent	13.3	5.9–20.6	317 694	Environment Agency
Trade effluent	14.4	4.5–29.4	46 224	Environment Agency
Thermoelectric power station discharge[a]	16.0	5.7–23.2	97	Environment Agency

[a]These data are only for coal-fired power stations which discharge to rivers. Data for power stations of other types or discharging beyond the tidal limit were not included. The data are from four power stations in four different rivers.

The slopes for the weather stations were not significantly different from each other (Figure S1) with a mean 45-year slope of 1.35 ± 0.9°C (0.03 ± 0.01°C year), the greatest increase was for Whitby (1.37°C over 45 years) and the smallest was for Chivenor (1.33°C over the 45 years). This result only refers to the trend in the average monthly air temperature at the chosen weather stations; the actual average monthly air temperatures at these weather stations do differ significantly and the coolest average temperatures are in northern Britain and warmest are in southern Britain (Figure 2).

When separate linear regressions were considered for each of the weather stations, a mean 45-year slope was 1.30 ± 2.8°C (0.03 ± 0.03°C/year), that is, implying the same results as for the Bayesian analysis, but the uncertainty was approximately three times greater for the linear analysis. From the linear regression analysis, as for the Bayesian hierarchical modelling, there was no significant differences between onshore stations. However, for 12 out of the 22 stations considered, the trend from the linear regression analysis was not significantly different from zero, that is, the Bayesian hierarchical method provided more precise results. Both the Bayesian and the linear regression analysis shows that, with respect to air temperature trends, we did not need to compare trends in stream records with a local air temperature trend and need only compare the stream temperature records' mean 45-year slope of 1.35 ± 0.9°C (0.03 ± 0.01°C/year). If we were compare weekly or daily values than more local comparison might be needed.

3.2 | Stream temperature trends

The comparison of the fitted models is given in Table 3. A model using only the Site factor was the most efficient showing that 91% of sites were significantly different and contributed to the model fit. The model with only the Month factor showed that most months made a significant contribution to the model outcome and was better a fitting the data than using only the Site factor. The preferred model with both factors had a deviance = 106 893, DIC = 107 684 and a pD = 805 giving an efficiency 11% efficiency which would mean that many of the sites are not showing significant trends with time or there are months at sites which make no significant difference to the prediction of the result The Anderson-Darling test showed that the residuals of the site + month model were not significantly different from normally distributed ($P < 0.00$). The Breusch-Pagan test showed that residuals of the Site + Month model were homoscedastic at $P < 0.00$, and the Durbin-Watson statistic was used for autocorrelation in the residuals. Therefore, the Site + Month model was sufficient to meet the assumptions of the likelihood function and the Bayesian hierarchical model has removed sufficient temporal structure in the dataset.

The fit of Equations (1)–(3) generated 12 estimates of β for each site, a slope estimate for each month at each site, these estimates were summarized to give a single value of β for each site. The estimated 45-year trends varied from −2.3 ± 1.1°C to 2.0 ± 1.4°C, with the mean of the 263 sites being 0.5 ± 1.1°C and the distribution of the trends at all 263 sites is shown in Figure 3. Only two sites, out of all 263, had slopes greater than the 95% confidence interval of the UK air temperature change, that is, greater than 2.25°C (1.35 + 0.9°C). A total of 22 sites had a 45-year change greater than the mean air temperature change, that is, greater than 1.35°C over 45 years. Of the 263 sites in the study, a total of 62 sites had a positive increase in stream over the 45 years which was significantly greater than zero at a 95% confidence limit. For a further 171 sites the 45-year stream temperature change was not significantly greater than zero even the mean estimate of the 45 year stream temperature change was greater than zero. In total, 233 sites have a 45-year stream temperature increase greater than zero. The remaining 30 sites had a 45-year stream temperature change that was less than zero, that is, have a long-term decrease in temperature. Of these 30 sites with a stream temperature decrease, six sites had a change significantly lower than zero. Or to state the results another way, out of 263 sites considered, 203 showed no significant increase in annual average stream temperature over a 45 year period while six sites showed a significant decrease in annual average stream temperature over a 45 year period.

In comparison, the linear mixed effect model, a significant trend was found at 75 of the 263 sites with the 45-year stream temperature

TABLE 3 Fitting properties of the model combinations applied. The pD is expressed as both its absolute value and the % of that which could expected if all new parameters included in the model were effective.

Factors	pD (% expected)	DIC	Deviance
Site	479 (91)	1 053 900	1 053 421
Month	25.2 (70)	816 659	816 664
Site + Month	805 (11)	107 684	106 893

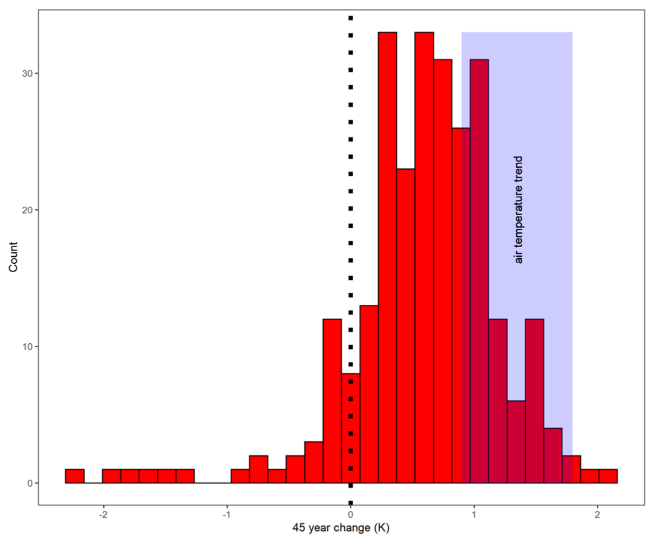


FIGURE 3 Distribution of the mean slope estimates for each of the HMS sites. The comparison to both no change ($\beta_{Bayes} = 0$) and to the change in UK air temperature (95% confidence interval).

changes varying from −0.42 to 0.47. Of the 263 sites in this study, 75 showed significant slope at 95% probability, with the significant slopes varying 0.10–0.47°C.

For the linear regression approach slope estimates varied from a 45-year stream temperature change of 7.9 to −18.9°C (0.18 to −0.42°C/year), that is, a physical impossible range, and only 153 out of 263 sites showed a significant slope at the 95% probability, with the significant slopes varying 0.03–2.2°C over 45 years (0.0007–0.05°C/year).

Comparing the slope estimates between the Bayesian and linear regression methods shows that there was a significant relationship between the slope estimates based upon the two estimates (Figure 4).

$$\beta_{\mathrm{Bayes}} = \underset{(0.02)}{0.47}\beta_{\mathrm{LR}} + \underset{(0.02)}{0.25}\quad n = 263, r^2 = 0.82 \tag{5}$$

where, β_{Bayes} = 45-year slope estimate based upon the Bayesian hierarchical approach; and β_{LR} = 45-year slope estimate based upon linear regression. Values in brackets below the equation are the standard errors of the coefficient and the constant term. Equation (5) shows that slope estimates from the Bayesian are on average 48% lower than estimates from linear regression. For a value β_{LR} >0.47 the value of $\beta_{\mathrm{Bayes}} < \beta_{\mathrm{LR}}$, that is, the Bayesian hierarchical method produces lower values for the larger slope values predicted by the linear regression approach. Conversely, for a value β_{LR} <0.47 the value of $\beta_{\mathrm{Bayes}} > \beta_{\mathrm{LR}}$ and so the Bayesian hierarchical approach produced negative values of slope.

Comparing the error on slope estimates between the Bayesian and linear regression methods shows that there was a significant relationship between the slope estimates based upon the two estimates (Figure 5).

$$e_{\mathrm{Bayes}} = \underset{(0.02)}{0.41}e_{LR} + \underset{(0.02)}{0.43}\quad n = 263, r^2 = 0.45 \tag{6}$$

where, e_{Bayes} = 95th confidence interval based upon the Bayesian hierarchical approach; and e_{LR} = 95th confidence interval based upon linear regression.

On average, the confidence interval was 59% smaller for the Bayesian estimate than the linear regression approach. For five sites, the confidence interval of the linear regression was smaller than that for the same sites under the Bayesian hierarchical approach and in Figure 4 that these are relatively close to the 1:1 line which represents an upper bound to the plot with the majority of the sites plotting below this line. Simple linear regression would be more precise than non-parametric approaches such as the Sen slope estimator (Sen, 1968).

The spatial distribution of the trends across Great Britain shows that, although it was difficult to visually discern a pattern amongst sites with positive trends, the six sites with negative trends are clustered in two locations (Figure 6a,b). In the eastern cluster, it is possible to associate the sites that have shown significant declines with thermoelectric power stations. The largest decline was observed for the River Aire at Beal weir (British National Grid SE534255); this monitoring point is 6 km downstream of the Ferrybridge power station that by 1981 was producing 1600 GWh of electricity from burning coal. Similarly, there is also a significant decline in stream temperature at the other monitoring site on the River Aire (Fleet weir - SE381285) and is again within 6 km of the former Skelton Grange thermal power station that in 1981 was producing 1790 GWh of electricity but was decommissioned by 1994. The second largest decline in stream temperature was observed for the River Calder (Methley, SE409258) which is downstream of the Wakefield power station that in 1981

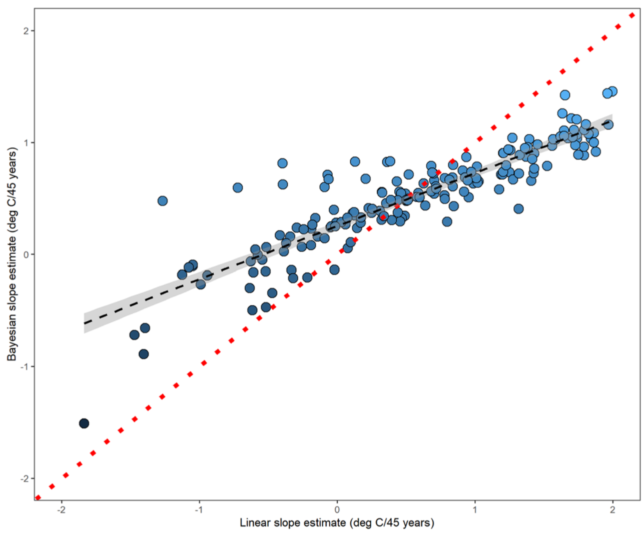


FIGURE 4 Comparison of slope estimates between the Bayesian hierarchical and linear regression methods. The two methods are compared to the 1:1 line and the best-fit linear regression.

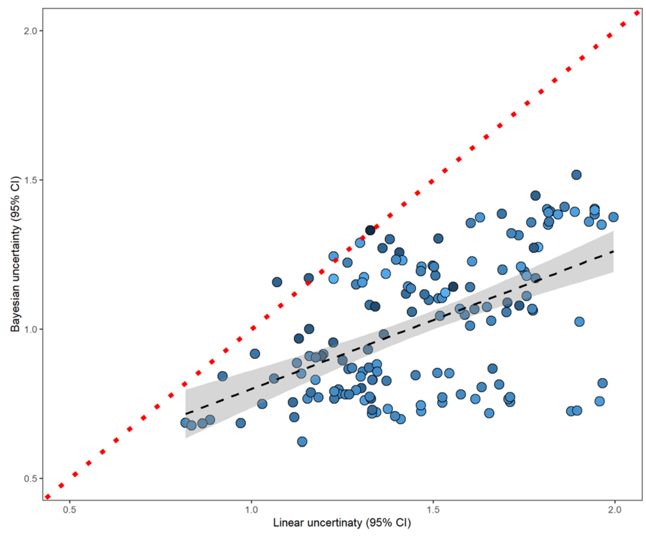
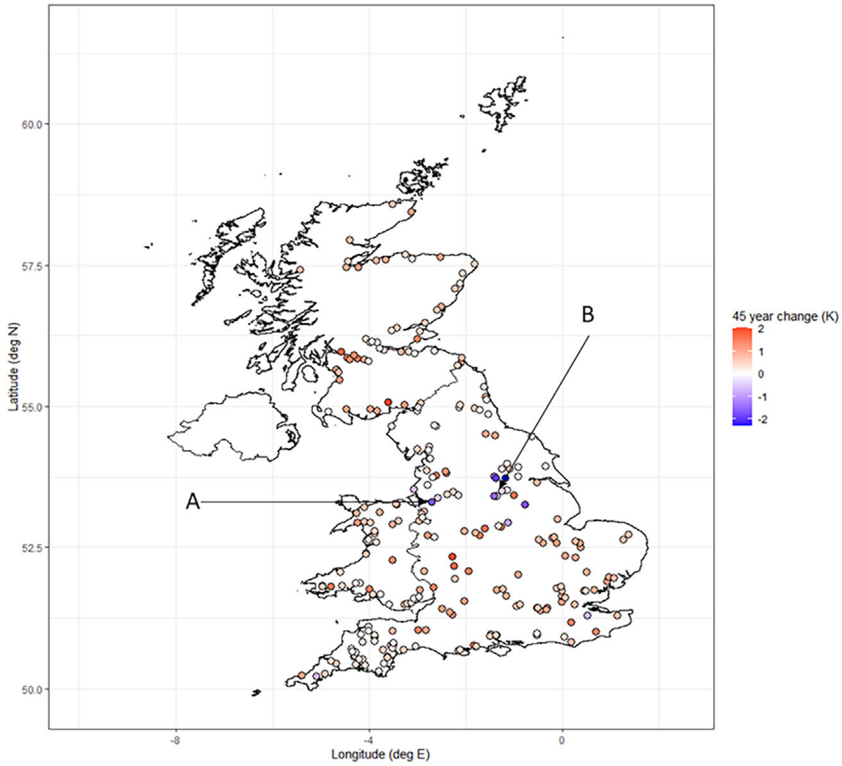


FIGURE 5 The comparison of the confidence interval on the slope estimation between the two methods. The two methods are compared to the 1:1 line and the best-fit linear regression.

FIGURE 6 The distribution of the slopes (β_{Bayes}) across all the study sites.



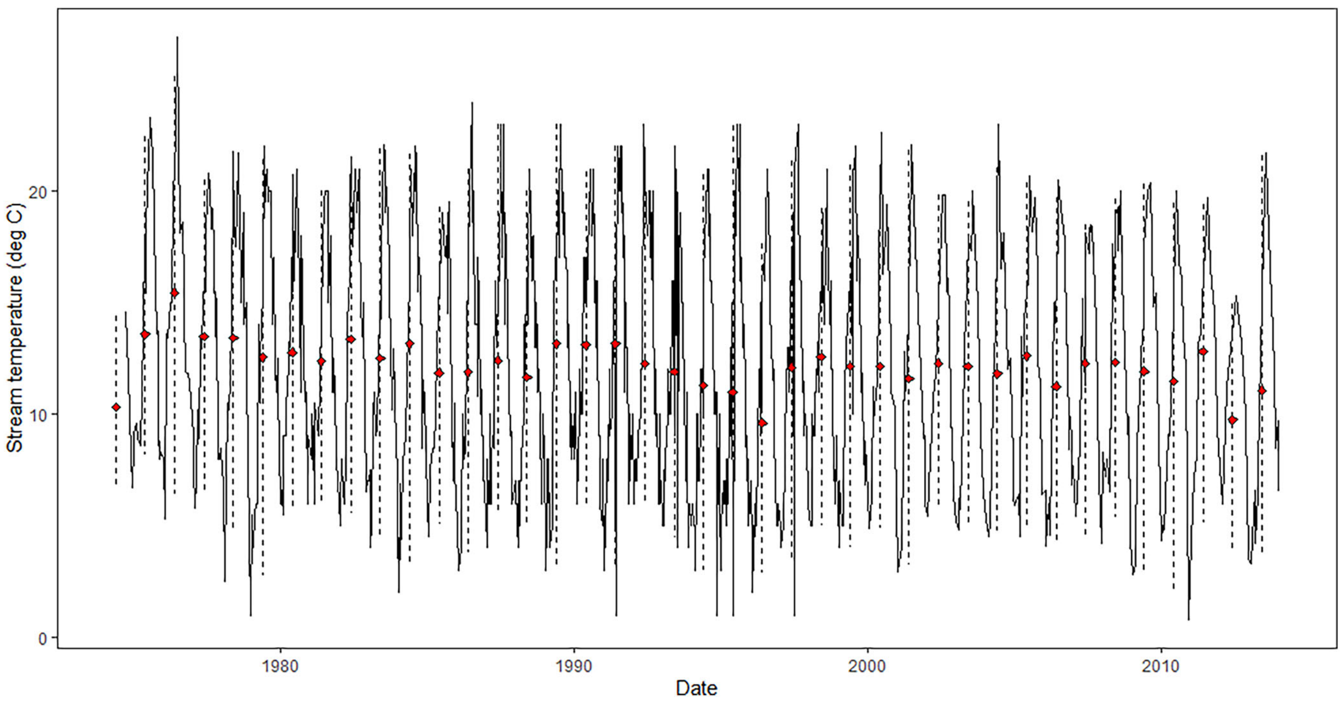


FIGURE 7 The Trent at Dunham, one of the sites with a significant decline. (_) is the observed data; (---) is the fitted data; and (◆) is the annual average river temperature.

was a 640 GWh power station but was decommissioned in 1993. Former thermal power stations can be associated with the two other monitoring sites where significant declines in stream temperature were observed on the River Trent and Don – although in none of these cases was a step change in the river temperature record visible (an example is given in Figure 7). The exception is the third largest decline which for the River Weaver at Frodsham (SJ530785) where there is no thermal power station upstream of it and other drivers of change are not known. For the River Trent, there is contrasting behaviour with a significant decline at the most downstream site, although the decline is not significantly different from zero. However, the most upstream site on the River Trent shows an increase in stream temperature which, although significantly greater than zero, was less than the increase in air temperature. Although, in this study we were able to examine trends versus catchment properties, there is not the level of detailed land use change records available to test trends against changing properties of the study catchments.

Two sites showed a positive trend that was significantly greater than the change in the air temperature, but it is not clear what could have been the cause. The two sites are in quite distinct parts of the United Kingdom with one in a predominantly rural catchment of south west Scotland (River Nith - NX973765) and the other in a suburban catchment (River Stour - SO814709), example is shown in Figure 8.

Comparing the estimated trends with catchment properties using multiple regression showed the best-fit line to be:

$$\underset{(0.7)}{\beta_{\text{bayes}} = 2.2} + \underset{(0.00006)}{0.00026\text{Area}} - \underset{(0.001)}{0.003E_{\text{Act}}} - \underset{(0.0002)}{0.0003\text{Org}} - \underset{(0.0005)}{0.0022\text{Urban}} \quad r^2 - 0.13,\ n = 235 \tag{7}$$

where: Area = catchment area (km^2); E_{Act} = annual actual evaporation (mm); Org = area of organic soils in the catchment (km^2); Urban = urban area of the catchment (km^2). The values in the brackets below the equation represent the standard errors in the constant and coefficient terms. Equation (7) suggests a weak relationship implying that increases in stream temperature were more likely in larger catchments but lower in catchments with a higher proportion of organic soils and urban land use. Kelleher et al. (2012) has shown that controls on stream temperature do change significant with scale.

Of the three classifications used only one, classification based on β_{Bayes} >0, gave a significant model:

$$\ln\left(\frac{\theta}{1-\theta}\right) = \underset{(0.2)}{2.13} + \underset{(0.002)}{0.003\text{Arable}} - \underset{(0.002)}{0.007\text{Urban}} \tag{8}$$

where terms are as defined above and values in brackets below the equation are the standard errors in the constants and coefficients. Equation (8) confirms the association between cooling trends and urbanized catchments where thermoelectric power stations have closed, but there is also a weak, but significant association with warming trends being in arable catchments. The data available to this study could not be used to consider land use change and urbanization, as opposed to just urban area – urbanization has been linked to increasing stream temperature (e.g., Ye & Kameyama, 2021).

4 | DISCUSSION

This study has found that the UK rivers are not warming faster than the local air temperature. Of the 263 sites considered, only 2 had a trend significantly greater than air temperature change. Alternatively, 60 further sites had a positive stream temperature trend, although increasing, was lower than the air temperature change and 195 sites

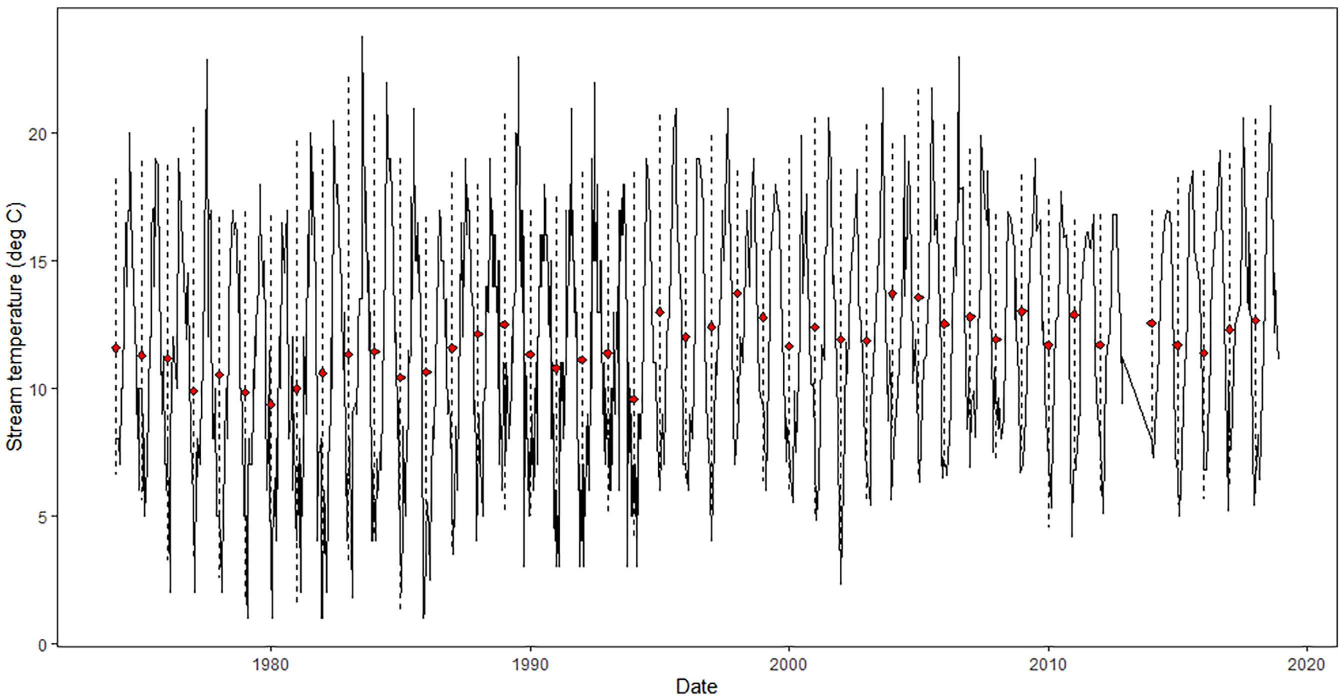


FIGURE 8 The Stour at Stourport, one of the sites with an increase significantly greater than air temperature. (_) is the observed data; (---) is the fitted data; and (◆) is the annual average river temperature.

had a stream temperature trend not significantly different from zero. The question is then: why have UK stream temperatures not risen as fast as air temperature? First, there were identifiable events that caused significant declines in stream temperature. There were six sites that became significantly cooler over the 45-year study period and these could be identified with the closure of thermoelectric power stations. Given the decline of the manufacturing sector in the United Kingdom and the switching away from coal as a source for power generation, then there will have been other power stations, or industrial sources of warm water that have closed over the period of the study. However, what is noticeable is that the closure of the power stations, or other industrial sources of warm water, are one-off events but even over a 45-year history, the closure of a power station was of sufficient impact that even ongoing rising air temperature was not sufficient to mask the impact of that plant closure. However, each plant can only close once and so the impact with the closure of the thermoelectric power plants would be expected to have diminishing effect with ongoing climate change. Furthermore, such one of closures of hot water sources would be expected to lead to step changes in the stream temperature, but this was not observed in this study. Second, these are large enough catchments that change is distributed in time and space so that a change in water temperature in one part of the catchment may be offset a lack of change in other part of the catchment. Garner et al. (2014) has suggested that larger catchments are better buffered against change than smaller catchments unless the latter are groundwater dominated. Such an explanation could suggest that smaller values of β_{Bayes} would be in the larger catchments; no such relationship was found. Third, as noted by van Vliet et al. (2013), changes in climate might lead to changes in flow paths and sources of water to the streams. If, for example, changes in rainfall or evaporation lead to a decreased proportion of groundwater in river flow, then the annual average stream temperature might decline (Watts et al., 2015). Fourth, this study has only considered the annual average stream temperature and not other components of the stream temperature time series (i.e., not the regime or different temperature metrics). The annual average may mask changes that might have been apparent in some other component of the time series, for example, assessing changes in the maximum stream temperature. However, in this study the annual stream temperature trend at river monitoring sites was compared to annual air temperature trend at a range of locations across the UK, and not to some other component of the air temperature time series and catchment properties—future work could target the detail of change over the annual cycle.

Changing river discharge and thus altered in-stream residence time could lead to changing thermal regime and potentially the buffering being exhausted. Huntington (2006) has proposed that climate change would bring about an intensification of the water cycle that would lead to increased average river flows and reduced in-stream residence times. Marsh and Dixon (2012) showed that outflows increased from the United Kingdom for the period 1961–2011, although it was only statistically significant in Scotland. Hannaford and Marsh (2006) for two study periods (1963–2002 and 1973–2002) found there were increases in western and northern Britain (especially Scotland), in contrast to southern and eastern England where no trend was apparent. Increases in annual runoff reported by Marsh and Dixon (2012) were as high as 22.2% in Scotland but only 1.7% in England. If stream temperature was being buffered by river discharge, then that effect would have been chiefly found in Scotland – that spatial pattern was not observed here.

The comparative freshwater temperature data given in Table 2 shows that for both the lake and final sewage waters sampled in England have, in general, higher temperatures than river water. Could the muted response observed in river temperatures observed in this study be due to change in these sources of warmer water? Lakes are not widespread in the United Kingdom and are present in only a minority of the study catchments. However, wastewater treatment works (sewage works) are widespread and multiple works would be found in the majority of the study catchments. During the period covered by this study, the Urban Waste Water Treatment Directive came in to force in the United Kingdom (UWWTD - European Commission, 1991). The UWWTD required secondary treatment (meaning at least biological treatment of waste water, e.g., activated sludge process) for treatment works greater than 15 000 population equivalent (p.e.) by the 31 December 2000, for works greater than 2000 p.e. by 2005 and by then the United Kingdom was 99% compliant. Implementation of the UWWTD can include interventions to remove nutrients but can also include measures to lower the organic matter, and indeed the impact of the UWWTD on water quality has already been demonstrated for phosphorus (Civan et al., 2018), nitrogen (Worrall et al., 2016), particulates (Worrall et al., 2014); and DOC (Worrall et al., 2018), this it would be expected, a priori, that the UWWTD would have altered the supply of hot water to surface waters. Despite the demonstrated warming effect of sewage effluent (Kinouchi et al., 2007), we do not know whether changes implemented to improve water quality would change the volume or temperature of the final sewage effluent. In 1974, the population of the United Kingdom was 56 million and in 2020 it was 67 million and so an increase in the volume of final sewage effluent entering UK rivers over the study period would have been expected.

Since the majority (92%) of the 263 sites in this study showed a 45-year trend in stream temperature that was less than change in air temperature, and 176 sites (65%) showed no significant increase, implying that streams are not vulnerable to climate change. Walker et al. (2004) have defined an ecological resilience as "the capacity of a system to absorb disturbance and reorganize while undergoing change so as to still retain essentially the same function, structure, identity and feedbacks". In the case of UK stream temperatures, this study has shown that for change in energy equivalent to 1.35°C, the average change was 0.5°C, which gives a strain (change in output compared to change in the input), or stream thermal sensitivity, of 0.35, and modulus (the change in input required for a unit change in output) of 3.6°C. Walker et al. (2004) go further and describe four critical aspects of resilience – latitude, resistance, precariousness, and panarchy. First, latitude represents the maximum amount a system can be changed before losing its ability to recover. This is an elastic limit and there is no evidence that UK rivers have not reached a point of regime change. Second, resistance is the ease or difficulty of changing the system, that is, how difficult it is to change. With respect to the rivers in this study, we can interpret this as the reciprocal of the strain. Thermal resistance is 2.7; this assumes that a linear change in air temperature represents a linear change in energy input in to the rivers. Third, precariousness (or precarity) is how close the current state of the system is to a limit or threshold. Carpenter et al. (2011) have demonstrated methods by which precarity could be assessed for the status of lakes given the removal of warm water sources. Walker et al. (2004) define a fourth term, panarchy, which represents the degree to which a certain hierarchical level of an ecosystem is influenced by other levels: it is unclear whether rivers have different thermal states that would interact with each other.

The approach used in this study is demonstrably more sensitive than simple linear regression; the advantage of the Bayesian approach is then clear. The Bayesian approach means all information has some value. First, this means that information from monitoring sites not in a catchment of interest help inform the distribution of data within the catchment of interest. Second, information is drawn from all the data means that missing values in a particular catchment are less important because an estimate can be made for any catchment in the dataset as long as it is sampled sometime within the larger dataset and that other catchments are sampled during the period with the missing values. Assessing low-frequency monitoring data within a Bayesian framework with its improved sensitivity (e.g., Figures 4 and 5) maximizes the information available and makes most efficient use of publicly-funded data.

This study considers more rivers over more time than any previous study, although other studies have considered more sites (Isaak et al., 2017; Hare et al., 2021) these studies consider shorter time periods, or there are studies consider fewer longer records (e.g., Webb & Nobilis, 1997), and the purpose of these studies was different from the current one. However, it is still restricted to the UK. However, the scale of UK rivers, their mix of land uses, and the nature of industrial and land use change within the United Kingdom make them very similar to much of the developed world. Therefore, we would propose that the resistance and buffering observed in these 263 river temperature records would be a more general result.

The study implies that UK rivers are somewhat disconnected from atmospheric heat source and respond more to changes in hydrological pathway resulting from land use. Similarly, Arismendi et al. (2012) found some disconnect between climate and stream temperature trends in the catchment of US Pacific North West. Such work illustrates the importance of considering river temperature as a "hydrological phenomenon" that takes into account climate drivers but also how they are modified by catchment properties and hydrological processes of water storage and release.

The disconnect observed in the United Kingdom could be due to the average river water being governed by the groundwater sources. Groundwater is typically warmer than air temperature (e.g., Table 2) and its controlled by the geotherm. The average geotherm in the United Kingdom is 28°C/km (Busby et al., 2011) and no groundwater in the study of Busby et al. was taken from below 400 m depth below surface (UKTAG, 2011). Geothermal heat is independent air temperature and climate change and so this heat source can buffer stream temperature until the point that average air temperature (9.9°C, Table 2) goes above average groundwater temperature (11.2°C, Table 2). Kurylyk et al. (2014) have considered the impact of climate change scenarios on the impact of groundwater on temperature of rivers and showed that shallow groundwater begin to warm in line with air temperature change which then impacted the streams of the catchment. The study of Kurylyk et al. (2014) shows that potential for groundwater buffering may breakdown with ongoing climate change.

5 | CONCLUSION

This study considered long term records of stream temperature across a diverse set of catchments. Over a 45-year period, for the majority (92%) of 263 UK rivers, stream temperature changed less than the local air temperature change. Only for 1% of the 263 rivers did the stream temperature rise significantly faster than the air temperature, while for 3% the stream temperature significantly declined over the 45 years of the record. The study used a Bayesian hierarchical approach which proved to be 59% more precise than linear regression, but even so 74% of 263 river sites showed no significant trend in stream temperature over 45 years of air temperature increase. The study shows that average river temperature is well buffered and resistant to changes in air temperature although some of this resistance can be attributed to one-off events such as closures of thermal power stations. Our work makes it clear that we must consider river temperature as a "hydrological phenomenon" and take into account the interactions between climate-catchment properties-hydrology to understand past trends and to underpin robust projections of future river temperatures under climate change and with increasing interference of people in the water cycle.

DATA AVAILABILITY STATEMENT

The water temperature used was from https://environment.data.gov.uk/water-quality/view/landing. The air temperature data used was from https://www.metoffice.gov.uk/research/climate/maps-and-data/historic-station-data. The other data used are listed in the references.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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