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Citizen science evidence from the past century shows that Scottish rivers are warming

Running head: **Evidence that Scottish rivers are warming**

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Abstract

Salmonid species are highly sensitive to river water temperature. Although long-term river temperature monitoring is essential for assessing drivers of change in ecological systems, these data are rarely available from statutory monitoring.

We utilized a 105-year citizen science data set of river water temperature from the River Spey, North-East Scotland, gathered during the fishing season (April - October) between

1912 and 2016. As there were gaps in the records we applied generalised additive models to reconstruct long-term daily river temperature in the fishing season from air temperature, cumulative air temperature, day length and runoff. For that, continuous hydrometeorological data have been obtained from statutory monitoring and process-based models.

Long-term warming trends of river temperature, namely an increase of 0.2 K per decade after 1961, have been mostly related to increasing air temperature of the same magnitude. Indirect impacts of rising air temperatures include less snow accumulation and snow melt as well as earlier snow melt. The snow free period starts around 2 days earlier per decade throughout the study period and 7 days earlier per decade after 1965. Consequently, the contribution of snow melt and its cooling properties to river temperature in spring are declining.

Citizen science delivered a data set that filled a vital knowledge gap in the long-term historical assessment of river temperatures. Such information provides a robust basis for future assessments of global change and can help inform decision-makers about the potential importance of enhancing the resilience of rivers and aquatic ecology to climate change.

Introduction

River water temperature influences many biochemical processes and aquatic ecology (Perkins et al., 2012; Verbrugge et al., 2012). The growth rate, habitat, life-cycle and reproduction of salmonid species are influenced by river temperature, either directly or indirectly through its influence on the oxygen content of water (Jonsson and Jonsson, 2009; Jonsson, 1991; O'Gorman et al., 2016). High river temperatures increase salmonid vulnerability to diseases (Carraro et al., 2017). Hence, increasing river temperature affects the suitable thermal habitat for salmonids (Isaak et al., 2015; Mohseni et al., 2003). In Switzerland, declining brown trout populations have been attributed to river temperature increases (Hari et al., 2006). In Scotland, decreasing trends of spring rod catches of Atlantic salmon have been reported

(Youngson et al., 2002) and earlier out-migration of smolts has been attributed to increasing spring river temperature (Langan et al., 2001).

Long-term river temperature monitoring forms a basis for robust estimations of warming rates (Isaak et al., 2018) and can provide information for catchment managers to support decision making aimed at increasing resilience to warming river temperatures. Yet, only few long-term datasets of river temperature from statutory or experimental monitoring exist (Arora et al., 2016). The longest record described in the scientific literature refers to daily records of the Danube at Linz, Austria, which began in 1901 (Webb and Nobilis, 1994). Only few other river temperature records dating back to the 1920s and 1930s are described in the scientific literature (Fofonova et al., 2016; Kaushal et al., 2010). With the exception of a study in the Girnock Burn, Scotland, with records dating back to 1968 (Langan et al., 2001), there is a lack of long-term monitoring of river temperature in the UK (Hannah and Garner, 2015; Jonkers and Sharkey, 2016).

Understanding long-term changes in river temperatures and their drivers of change is essential to reconstruct historic records and for future projections (Caldwell et al., 2015; Webb and Walling, 1992). River temperature is mainly controlled by thermal inputs into the catchment, hydrological conditions, landscape and channel characteristics (Dick et al., 2017; Jackson et al., 2017b). Observations of global radiation are rare, hence air temperature which is controlled by global radiation and routinely measured, is widely recognised as a surrogate variable (Johnson et al., 2014; Koch and Grünewald, 2010). Indirect influences on intra-annual variability of river temperature include precipitation, snowmelt and discharge (Arora et al., 2016; Merriam et al., 2017; Toffolon and Piccolroaz, 2015). High discharge from snow melt contributes to cooler river temperatures in spring and early summer (Toffolon and Piccolroaz, 2015). Low summer stream-flow results in small thermal capacity of the river and high sensitivity to air temperature (Arora et al., 2016). Due to the strong influence of landscape and channel characteristics on river temperature, its relationship with hydroclimatic variables are site-specific (Chen et al., 2016; Jackson et al., 2017b). Long-term trends in river temperature are influenced by land cover changes such as urbanisation and loss of riparian woodland (Isaak et al., 2010; Kaushal et al., 2010). Further influences on river temperature include thermal discharges, e.g. cooling water from power plants and distilleries (Baum et al., 2005; Hardenbicker et al., 2017; Koch et al., 2015; Müller et al., 2007).

We investigate a unique long-term record (1912-2016) of river temperatures collected through citizen science in the River Spey, a major salmonid river in North-East Scotland. The river is designated as a special area of conservation for Atlantic salmon (*Salmo salar*) and Freshwater pearl mussel (*Margaritifera margaritifera*) that depend on salmon, both of which are highly sensitive to changes in river temperature (Lopes-Lima et al., 2018). Specifically, we address two questions (1) Is there evidence for long-term changes in river temperature? (2) What are the key drivers?

Our analysis of long-term records of river temperature provides a) a robust baseline to assess future changes in river temperatures; b) relevant insights for ecosystem functioning; and c) evidence to inform stakeholders of the need for proactive mitigation to protect the biodiversity and rural economies that depend on healthy and sustainable fish populations.

Materials and Methods

Study area

River temperature data have been investigated at four fishing locations (beats) on the Tulchan Sporting Estate, River Spey in North-East Scotland (Fig. 1). The fishing beats are located approximately 20 km downstream of the gauging station Grantown-on-Spey. The model domain includes the entire catchment area draining to Boat o’ Brig (area approximately 2860 km^2). The land cover is characterized by montane habitats, heath, and bog (ca. 63 % in total), woodland (ca. 18 %), and grassland (ca. 16 %) and only small areas with arable and urban land use (CEH, 2012). The elevation ranges from 43 m to 1300 m above sea level. Characteristics of the River Spey catchment are representative of Scotland's upland and lowland systems in terms of land cover and management, population and industry. Sporting estates are an important part of Scotland's rural economy with revenue from game fishing on the River Spey exceeding £11 million per year (Butler et al., 2009).

The annual mean air temperature is 5.5°C (standard reference period 1961-1990) with pronounced seasonality (January mean: 0.2°C, July mean: 11.6 °C). Long-term average annual precipitation is approximately 1200 mm (standard reference period 1961-1990) with higher precipitation in winter (January: ca. 125 mm) than in summer (July: ca. 85 mm). Consequently, discharge is higher in winter than in summer, whereby snow plays a major role in the regional water balance (Helliwell et al., 1998).

The River Spey has been classed as 'good' with respect to its ecological status according to the European Water Framework Directive and relatively pristine and oligotrophic throughout (Joint Nature Conservation Committee, 2016). As there are few water quality, hydromorphological issues or barriers to fish migration in the catchment, the threat of increasing river temperatures is deemed a significant concern for the future.

Compilation of a data base of river temperature and explanatory variables River temperature and water level data were routinely collected by fishing attendants (ghillies) as part of a unique citizen science exercise. Every morning before fishing commenced, river temperature data were recorded using mercury thermometers to determine the type of fly required for fishing and water levels were measured from standard stage posts. It is understood from the

Estate manager of more than 40 years that the location and methods used for recording river temperature and level have remained unchanged for the record length. Data have been recorded in books from 1912 to 2016 and have been transcribed following strict quality control procedures at The James Hutton Institute. River temperature has been converted from degree Fahrenheit to degree Celsius, temperature differences have been converted to Kelvin, and water levels have been converted from feet and inches to metres. The availability of river temperature data is summarized in the supporting information 1 (Fig. S1.1). The data availability is highest within the fishing period, mostly between April (week 15) and October (week 40). Based on the data availability, two time windows covering spring (week 15-week 22) and the entire fishing season (week 15- week 40) in the ten year periods 1926-1935, 1956-1965, 1976-1985 and 2006-2015 have been selected for detailed analysis.

To explore the influences of hydroclimatic drivers on river temperature, we collated a data base of continuous daily values of meteorological and hydrological variables for the time period 1926-2015 as limited by data availability.

A data basis of continuous daily hydrometeorological data has been obtained from both conventional monitoring as well as simulation results. For the time period 1961-2015 daily air temperature and precipitation values were available for 25 km^2 grids derived from observational data by the Met Office (UKCP09 data, period 1961-2015). Values for subcatchments were derived using area-weighted averages for this period. For earlier years, air temperature records from the stations are transferred to the subcatchments using regression models of the form:

$$T_{a,subcatchment,d} = c + T_{a,station,d} + \varepsilon, \tag{S1.1}$$

where $T_{a,subcatchment,d}$ is the reconstructed daily mean air temperature of the subcatchment, $T_{a,station,d}$ is the daily air temperature at the station as calculated as the average of the observed minimum and maximum air temperature, c is a coefficient estimated as the intercept of a fitted linear model between the reconstructed and the observed air temperature with slope 1, and ε is the statistical error term.

Precipitation records from the surrounding stations are transferred to the subcatchments using regression models with zero intercept and slope as the ratio between precipitation of the subcatchment in the 1960s (obtained from the gridded product) and the station of the form:

$$P_{subcatchment,d} = P_{station,d} * \frac{P_{subcatchment,1960s}}{P_{station,1960s}} + \varepsilon, \qquad \text{(S1.2)}$$

where $P_{subcatchment,d}$ is the reconstructed daily precipitation of the subcatchment, $P_{station,d}$ is the daily observed precipitation at the meteorological station and $\frac{P_{subcatchment,1960s}}{P_{station,1960s}}$ is the ratio between precipitation for the subcatchment from the 25 km gridded product and the observation at the station between 1961 and 1969 for which data availability and quality at the stations is high. For each subcatchment, the station which corresponded well to the weighted gridded averages was selected (if data were available). Alternatively, another station was chosen. Details on the regression models used for reconstructing air temperature and precipitation are provided in Table S1.1.

A single layer degree-day snow model (Spencer, 2016) has been applied to simulate snow water equivalent, snow melt and effective precipitation. The model runs on a daily time step and uses air temperature and precipitation as input variables. The model had been parameterised by calibration and validation for Met Office snow records and data obtained through citizen science by the Snow Survey of Great Britain (Spencer et al., 2014). For the period 1961-2015 we applied the snow model to 5 km * 5 km grids for which meteorological variables were available and then averaged the results to subcatchments. For the years before 1961 the model was run for subcatchment averages of air temperature and precipitation.

Catchment runoff was simulated by the conceptual hydrological model TUWmodel (Parajka et al., 2007). To explicitly account for snow as simulated by the single layer degree-day snow model, the internal snow routine of TUWmodel was deactivated. The hydrological model was parameterised by calibrating observed daily discharge from the gauging station upstream of the fishing beats at Grantown-on-Spey using the Kling-Gupta Efficiency (Gupta et al., 2009) as objective function.

The parameter values of the calibrated snow and hydrological model are shown in the supplementary material (Tab. S1.2). The model performance with respect long-term annual runoff, root mean square error (RMSE), bias, mean absolute error (MAE), Nash-Sutcliffe Efficiency (NSE, Nash and Sutcliffe, 1970), Nash-Sutcliffe efficiency calculated for natural logarithms of observed and simulated discharge (NSEln), coefficient of determination (R^2), Volume Efficiency (VE, Criss and Winston, 2008) and Kling-Gupta Efficiency (KGE) is reported in Table 1. We applied this parameter set for the individual subcatchments of the fishing beats. The model was applied to simulate runoff using both reconstructed (years 1921-1960) and observed meteorological input variables (years 1961-2015). To minimize the influence of initial conditions on the model results we regarded the first four years of simulations as warm-up period and did not include these in further analysis.

Statistical analysis

Trends of observed data were only estimated for individual weeks with high data availability as gaps in the record would introduce a bias on trend estimation, e.g. annual average values would be underestimated in years with more observations in spring than in summer. To detect long-term changes in observed river temperatures, the weekly averages for periods with high availability of river temperature data were compared in terms of central tendency and variances using the Kruskal-Wallis test and the Levene test (implemented in the R-package car, Fox et al., 2018) respectively.

As a basis for long-term trend investigations, river temperature was reconstructed using generalised additive models (GAMs) which are widely applied to link river temperatures and hydrometeorological variables (Imholt et al., 2011; Jackson et al., 2018)We reconstructed continuous daily time series of river temperature in the fishing season (weeks 15-40) of the years 1925-2016.

As a prerequisite to model river temperature, regression relationships between river temperature and hydrometeorological variables were investigated. Based on factors influencing river temperature identified in the literature (Jackson et al., 2017a; Merriam et al., 2017; Mohseni et al., 1998; Toffolon and Piccolroaz, 2015) we considered the variables air temperature, runoff, precipitation, snow melt, the ratio of snow melt over total runoff and water levels. Additionally, we investigated the relationships between river temperature and cumulative air temperature from the beginning of the calendar year and day length. Antecedent conditions influencing river temperature (see e.g. Koch and Grünewald, 2010; Mohseni et al., 1998) were considered by analysing the relationship between river temperature and the moving average of each of these variables over the preceding days, including the day of river temperature measurements. We chose the number of preceding days for which the correlation between river temperature and air temperature was highest. In a next step, GAMs were fitted using the R-package mgcv (Wood, 2018) for data from Beat D, the fishing period in 1961-2015 was selected as the training period due the high availability and quality of river temperature records along with observed hydrometeorological variables for Beat D. At an early stage of the analysis, the model showed a number of residuals with absolute errors over 3 K. These values were visually checked and 144 implausible river temperature observations (e.g. in case of pronounced increases in river temperature despite declining air temperature) were removed. A model to predict river temperature for all fishing beats was selected based on the Akaike information criterion

(AIC), coefficient of determination (R^2), and root mean square error (RMSE) in the training period and the availability and influence of the predictor variables. To evaluate the model robustness over the entire study period and at all fishing beats the model was then evaluated for both the training and test period (1925-1960), using reconstructed meteorological variables) and at all fishing beats also for Kling-Gupta Efficiency (Gupta et al., 2009) and Nash-Sutcliffe Efficiency (Nash and Sutcliffe, 1970).

Trend analysis and change point analyses were conducted for both the hydrometeorological variables and modelled river temperatures using the Mann-Kendall trend test and the Pettitt test for change points of the central tendency in time series using the R-package trend (Pohlert, 2018). We fitted linear regressions for the entire record where hydrometeorological variables were available (1925-2015). To account for interannual variability and the influence of starting and ending year on trend detection, we performed trend and change point analysis for moving windows of forty year periodsand reported forty-year trends starting in five or more consecutive years. The modelled river temperatures for the decades 1926-1935, 1956-1965, 1976-1985 and 2006-2015 were compared to the observed values in these data-rich periods.

Results

Long-term changes in observed river temperature

The raw data at the fishing beats show tendencies of increasing river temperatures and an earlier warming in spring (Fig. 2). At Beat D, observed weekly river temperature tends to increase by around 0.02 K per year throughout the record length in weeks 15 and 22 for which data availability is relatively high. For periods with high data coverage (spring: weeks 15-22 and fishing season: weeks 15-40 in the decades 1926-1935, 1956-1965, 1976-1985 and 2006-2015), weekly river temperatures are shown in Table 2 (mean and maximum values for all fishing beats) and Figure 3 (weekly values exemplified for Beat D). Compared to 1926-1935, mean river temperatures in spring in 1976-1985 and 2006-2015 are between 0.2 K and 2.5 K higher. These changes are mostly statistically significant; the magnitude of change varies between the fishing beats (Tab. 2). The maximum weekly river temperature in spring increases for all beats by approximately 2 K between the decade 1926-1935 and later periods.

Mean and median river temperature in the typical fishing season (weeks 15-40) and 2006-2015 is significantly higher by up to 2 K than in 1926-1935 at Beats A, B and D. At Beats B and D significant increases also occur between 1926-1935 and 1976-1985. At Beats A and D, river temperature is significantly higher in 2006-2015 than in 1976-1985. The direction of change of maximum river temperature in the fishing season differs between the fishing beats. Also, there is no consistent spatial pattern in terms of mean values or variance of the fishing beats in different decades. River temperatures show high temporal variability within the fishing season with mean values around 5 to 7 °C in April and between 12 and 15 °C in July and August (Fig. 3c).

The correlation between river temperatures at the different fishing beats is highly positive (correlation coefficient > 0.85, Tab. S2.1) but differ slightly in magnitude (linear model intercept between Beat D and other fishing beats between 0.5 and 1.5, linear model slope > 0.90, percent bias < 5 %).

Modelling river temperature from relationships with hydrometeorological variables

River temperature is positively correlated with air temperature, cumulative air temperature from beginning of the year and day length, but negatively correlated with precipitation, snow melt, runoff, the ratio of snowmelt over total runoff and observed water level (Tab. 3). These relationships are mostly stronger when a moving average over the eight days preceding and including the day of river temperature observation is considered. For cumulative air temperature, a moving average of eight days preceding the temperature measurements does not improve the relationship. For water level the relationship could not be evaluated for eight day moving averages as continuous records of water level at the fishing beats were not available. Pronounced relationships exist between the different hydrometeorological variables, e.g. air temperature is positively correlated with cumulative air temperature and day length, but negatively correlated with precipitation, snow melt, runoff, snow melt ratio and water level (Tab. S2.2).

Air temperature is the most important predictor of river temperature, explaining more than 60 % of the variation of river temperature in GAMs (Tab. 4). The model performance improves when cumulative air temperature and day length are included. Together, air temperature, cumulative air temperature, and day length account for 78 % of the variation in river temperature in the training period. Minor improvements of the model performance (reduction of AIC and increasing coefficient of determination in the training period) are obtained when runoff, the ratio of snow melt over total runoff, and precipitation are included. Water level is a variable associated with a statistically significant coefficient in the GAM but only results in small improvements of the model performance (additional 1 % of the variation in river temperature explained in the training period). Julian day improves the model performance compared to using air temperature alone (explained variance: 81 % compared to 65 %) but does not improve the model performance when cumulative air temperature and day length are considered.

To be able to reconstruct daily river temperature from hydrometeorological variables in the fishing period, we decided to apply a GAM which includes air temperature, cumulative air temperature, day length, and log-transformed runoff (each averaged over the eight days preceding the water temperature measurements, model 8 in Tab. 4) for further analysis. The final model performs satisfactorily at all fishing beats with a coefficient of determination, Kling-Gupta Efficiency and Nash-Sutcliffe Efficiency mostly above 0.70 and percent bias below 10 % (Tab. 5). The model residuals are symmetric and approximately normally distributed, and do not show pronounced seasonality or differences between the years.

Long-term changes in hydrometeorological variables

Air temperature increased especially after 1958 and hence earlier snow melt and less snow melt during the fishing season are the most pronounced changes in hydrometeorological variables. Annual precipitation and thus modelled runoff increased, these changes occurred mostly in winter, while no significant changes occurred in the fishing season.

Mean annual air temperature increases by around 0.008 K $year^{-1}$ for the period 1926-2015 (Fig. 4a). All forty-year periods after 1958 show significant increases of mean annual air temperature increase by on average 0.023 K $year^{-1}$. Significant upward change points occur in 1931 and 1987 (depending on the forty-year periods for which change points have been analysed). In the fishing season, air temperature increases by around 0.006 K $year^{-1}$ for the period 1926-2015 (Fig. 4b) with a significant increase in all forty-year periods after 1958 (on average by 0.020 K $year^{-1}$). Upward change points of air temperature in the fishing season occur in 1932 and 1994 depending on the forty-year periods chosen for analysis; 1949 marks a downward change point. For the periods with high availability of water temperature observations at Beat D, significant increases in the mean air temperature in 2006-2015 compared to 1926-1935 occur both in the spring (weeks 15-22) and the entire fishing season (weeks 15-40, Tab. S.3.1). Furthermore, the cumulative air temperature from the beginning of the year is significantly higher in period 2006-2015 compared to the other periods investigated during the fishing season.

Annual precipitation slightly increases over the entire period 1926-2015 and especially in forty-year periods starting between 1959 and 1973 (around 5.8 mm year^{-1}, Fig. 4c). Precipitation in spring and the fishing season does not show pronounced long-term changes (Fig. 4d, Tab. S3.1).

Annual modelled runoff slightly increases with significant forty-year trends starting between 1945 and 1972 showing an average increase of 5.33 mm year^{-1} (Fig. 4e). Upward change points occur in the late 1970s and early 1980s. In the fishing season, runoff does not show pronounced changes (Fig. 4f, Tab. S3.1). The direction and magnitude of runoff change are consistent with observed records at Grantown-on-Spey and Boat o'Brig (Tab. S3.2, Fig. S3.1). In contrast, observed median water levels decrease, e.g. between 1926-1935 and 2006-2015 by 40 cm in spring (Tab. S3.3). Runoff and water levels show relatively high positive correlations in individual decades (Fig. S3.2 a-i). However, there is a clear tendency for a decreasing intercept in the relationships between runoff and water levels for individual decades (i.e. the same runoff resulting in lower water levels in later decades, Fig. S3.2 j).

Snow melt and thus the ratio of snow melt over total natural runoff tends to decline in spring, the fishing season and annually (Fig. 4g, Tab. S3.1). Averaged over the period 1925-2015 the snow melt ratio declines by around 0.1 % year^{-1} with most pronounced changes for forty-year periods starting between 1958 and 1975 (around 0.2 % year^{-1}). A downward change point occurs in 1984.

Between 1926 and 2015 the snow free period starts on average 0.18 days earlier per year. A faster shift (0.63 d year^{-1}) occurs after 1965, whereby 2001 marks a downward change point (Fig. 4h).

Long-term changes in modelled river temperature

Modelled river temperatures increase with strongest warming tendencies after 1960 (Fig.5, Tab. 6). The mean river temperature in spring and the entire fishing season increase by around 0.006 K year^{-1} and 0.004 K year^{-1} over the period 1926-2015, respectively (Fig. 5a,b). Significant increasing trends by around 0.024 K year^{-1} (spring) and 0.018 K year^{-1} (entire fishing season) occur for forty-year periods starting between 1962 and 1970 whereby 1988 marks an upward change point. Significant changes in the maximum river temperature in the entire fishing season occur for forty-year periods starting between 1958 and 1967 with an average warming of 0.044 K year^{-1} (Fig. 5d). Hereby, 1953 marks a downward and 1981 an upward change point. The comparison of seasonal patterns shows tendencies towards an earlier warming in spring in later decades (Fig. 5e). The comparison of mean and maximum values based on weekly averages over spring (weeks 15-22) and the entire fishing season (weeks 15-40), shows high variability between the decades but only few appreciable increases from one decade to the next (Tab. 6). The modelled mean and median river temperatures for both spring and the entire fishing season are around 1.5 K higher compared to the observations in 1925-1936, but are approximately 0.7 K lower than the values obtained from the observations in 1976-1985 and 2006-2015. The modelled maximum river temperature in the spring season is approximately 0.8 K lower than the observation with stronger differences for maximum values (compare Tab. 2).

The river temperature model captures the long-term dynamics of the river temperature observations at all fishing beats (Fig. 6, coefficient of determination > 0.7 in the fishing season when comparing averages of observations and modelled values for dates when observations are available). Annual values calculated from modelled daily continuous river temperatures show different dynamics with less pronounced warming tendencies compared to annual averages calculated from the records taken at irregular intervals.

Discussion

Influences on river temperature

Intra-annual variability of river temperature is dominated by thermal inputs to the catchment represented by air temperature, and day length (as additional surrogate for global radiation). Also heat storage in the catchment (represented by cumulative air temperature) and runoff influence intra-annual variations in river temperature.

We found air temperature to be the most important predictor of river temperature, which is consistent with the literature (Jackson et al., 2017a; Kelleher et al., 2012; Rabi et al., 2015). A higher correlation between river temperature and air temperature averaged over the preceding eight days, indicates the influence of thermal energy inputs and heat storage in the entire catchment, as noted by Koch & Grünewald (2010). The role of heat storage in the catchment is further reflected by the significant relationship of cumulative air temperature on river temperature also shown by the improved performance of the GAM. Day length shows positive correlation with river temperature and furthermore improves the GAM. Precipitation, snow melt, natural runoff as well as the ratio of snow melt over natural runoff reduce river temperature, which has been observed in various studies (Arora et al., 2016; Bolduc and Lamoureux, 2018). Lag times in the catchment are evident from hydrometeorological variables averaged over eight days preceding and including the day of river temperature measurements being stronger related to river temperatures than hydroclimatic variables at the day of river temperature measurement alone (Tab. 3, Tab. 4). The inclusion of water level did not improve the model performance as its influence is largely confounded with that of natural runoff. Due to gaps in the observed water level data and the inconsistency in the trend of water level with runoff, water level was not included in the final generalised additive model. Julian day, which is often used in statistical river temperature models (Jackson et al., 2017b), does not improve the model performance when cumulative air temperature and day length are considered. We argue that Julian day is a surrogate for both the influences of heat storage and global radiation which are captured by air temperature and day length. However, Julian day does not account for heat storage dynamics and is therefore not appropriate for long-term studies covering periods with trends in air temperature. Julian day was therefore excluded from further analysis.

The variation in river temperature in the training and test period was explained by a GAM which includes air temperature, cumulative air temperature, day length, and natural runoff as explanatory variables. The annual and seasonal variations of river temperature are captured by air temperature, cumulative air temperature and day length. Natural runoff accounts for short-term variations. As the fishing season includes relatively few days with snow melt, both snow melt and the ratio of snow melt over total runoff did not influence the model results substantially. The identification of the explanatory variables was consistent as shown by the satisfactory model performance at all fishing beats and for both the training and test period.

Long-term changes in river temperature and its drivers

Observed increases in river temperature can be attributed to increasing air temperatures. The long-term increase of river temperatures of 0.003 K per year averaged over the fishing season between 1926 and 2015 and around 0.020 K per year after 1961 is in the range of other studies around the world (e.g. around 0.009 - 0.08 K per year in the United States, Kaushal et al., 2010; around 0.007 K per year over a 122 year time series in France, Moatar and Gailhard, 2006). In our study, the changes are most pronounced in spring, which is consistent with findings from a 30-year record (1968-1997, Langan et al., 2001) from the Girnock Burn, North-Eastern Scotland. A direct comparison of observed trends, however, between the two catchments was not possible due to the gap in data from the River Spey between 1968 and 1997. However, a greater increase in spring water compared to the entire fishing season is also reflected in the modelled river temperature of our study. Increases of spring river temperature in our study (0.024 K per year after 1960) correspond well with a 0.03 K increase per year between 1981 and 2001 as simulated by Jonkers and Sharkey (2016).

Due to the close relationship between air temperature and river temperature, significant long-term increases in air temperature, especially since the 1960s, are found to drive the increase in river temperature. Air temperature increases relating to climate change found in the Spey catchment are consistent with general warming trends for Scotland and the entire United Kingdom related to global climate change (Kendon et al., 2018; Prior and Perry, 2014). An upward change point in air temperature in the late 1980s was also observed in other regions (Gädeke et al., 2017) and has been interpreted as a combination of air temperature cooling after the El Chichón (Mexico) volcanic eruption in 1982 and thereafter recovery in combination with anthropogenic warming (Reid et al., 2016). This change point in air temperature is reflected in a change point in modelled river temperature in our study (mean value in spring and the entire fishing season) and observed river temperature in Switzerland (Hari et al., 2006).

When comparing changes between the decades with high data availability, both air and river temperature in spring are lowest in the period 1926-1935 and comparably high in the periods 1956-1965 and 2006-2015. Consistent with other studies (e.g. Pekarova et al., 2011), over the entire study period 1926-2015, changes in modelled river temperature (ca. 0.003 K per year for the entire study period) are less pronounced than those of air temperature in the fishing season (ca. 0.001 K per year). After 1961, mean values of both air and modelled river temperature in the fishing season bothincrease by approximately 0.02 K per year.

Significant changes in snow melt timing and, to a lesser extent, snow melt amount as a consequence of air temperature increase may furthermore contribute to changes in river temperature in spring, which is consistent with findings for the Girnock Burn (Langan et al., 2001). Due to relatively few observations during snow melt and the relatively small influence of snow melt as well as the ratio of snow melt over total natural runoff we decided not to include snow melt in the final GAM. However, to some extent the earlier snow melt resulting from high air temperature in winter and spring also explains comparably high river temperature in spring of 1956-1965 and 2006-2015 compared to 1926-1935 and 1976-1985 (Fig. 3a, Fig. 4h).

Total annual precipitation and natural runoff show increases which mainly occur in the winter season, but not during the fishing season. Due to increases in air temperature and associated higher evaporation losses, annual natural runoff increases to a lesser extent than annual precipitation. The increases in modelled natural runoff are less pronounced in the observations at Grantown-on-Spey and Boat o’ Brig (Fig. 4e,Tab. S3.2, Fig. S3.1). The difference between long term changes in modelled and observed runoff can be explained by abstractions for irrigation, industry and potable use etc. As neither modelled nor observed runoff shows pronounced changes in the fishing season, changes in observed water levels at the fishing beats cannot be attributed. Hence, despite the significant influence of discharge on intra-annual variability of river temperatures, long-term changes in river temperature at the fishing beats were not influenced by changes in heat capacity related to long-term changes in discharge.

It has to be considered that river temperature has been obtained from citizen science monitoring and is limited to dates when fishing took place at the individual fishing beats, so records are not evenly distributed in time and this could affect assessments of historic changes (Gray et al., 2016). We tried to overcome this by focussing the analysis of observed river temperature on periods with high data coverage for four fishing beats and by trend analysis of explanatory variables and modelled river temperature for evenly-spaced data during the fishing season. Differences in the interpretation of long-term changes between the observed records which contain gaps and the continuous modelled river temperature in the fishing season can thus either be attributed to sampling bias or uncertainty with respect to the generalised additive model. The more pronounced differences in the maximum values compared to mean values indicate the influence of irregular sampling.

Uncertainties

Uncertainties are associated with (i) observations of river temperature data and hydrometeorological variables, (ii) reconstructing a continuous record of hydroclimatic variables, (iii) river temperature modelling and (iv) the interpretation of long-term changes.

To minimize the influence of observational uncertainties, the river temperature data were manually investigated and implausible values resulting from inaccurate recording or transcribing of data were excluded. Water levels are subject to observational uncertainties as visible from the disagreement of their long-term tendencies with those of modelled and observed runoff (Tab. S3.2, S3.3, Fig. S3.1, S3.2). The intercept in the relationship of water levels with runoff consistently declines over time and thus we assume local changes in river bed morphology or adjustments of the stage post (accumulation of sediments at the base of the post) as possible reasons for declining observed water levels. These reasons remain unsubstantiated, as anecdotal evidence from river managers indicate that the height of the stage posts have remained unchanged.

The reconstruction of daily values of air temperature can be considered credible, whereas the reconstruction of daily precipitation is subject to larger uncertainties (visible from the performance of the regression models in Tab. S.1.1). As both air temperature and precipitation do not show significant change points around 1960 (Fig. 4), we can assume that reconstructing these variables from nearby stations does not influence their long-term dynamics. As precipitation is not identified as a significant explanatory variable for river temperature, the relatively weak performance of the regression model in capturing short term precipitation dynamics does not directly influence river temperature modelling. However, uncertainties related to the reconstruction of precipitation and air temperature influence the results of the snow model and the hydrological model.

The inherent uncertainties related to structure and parameterisation of the snow and the hydrological model can be considered relatively small. The performance of the hydrological model can be considered acceptable as the evaluation criteria (Grantown-on-Spey: NSE, NSE_{ln}, R^2, VE, KGE greater than 0.70; Boat o' Brig: NSE, NSE_{ln}, greater than 0.65 and R^2, VE and KGE greater than 0.7) lie within the range reported for lumped hydrological models in other catchments (e.g. Gädeke et al., 2014; Parajka et al., 2007). Furthermore, the long-term tendencies of modelled runoff are in reasonable agreement with the observations at Grantown-on-Spey and Boat o' Brig (Tab. S 3.2, Fig. S 3.1).

Modelling river temperature from hydrometeorological data using GAM models is subject to uncertainties with respect to interpreting causation from correlation. To address this uncertainty, explanatory variables with physical relevance for river temperature have been chosen mostly in consent with other studies. The uncertainty relating to river temperature modelling can be considered low as the GAM model performs reasonably well in both a training and a test period (Tab. 5) and captures the long-term dynamics of observed river temperature when values of the same dates are compared (Fig. 6). As eight-day averages of the hydrometeorological variables are considered, the uncertainties in their short-term dynamics are not affecting modelled river temperature.

The interpretation of long-term changes based on observed river temperatures alone is subject to uncertainties introduced by irregular sampling as visible for example from the disagreement of the changes at the different fishing beats (Tab. 2). Hence, a trend interpretation based on observed values alone can only be recommended for individual weeks with high data availability (Fig. 2). The bias introduced by irregular sampling with higher warming tendencies interpreted based on the observations alone rather than the continuous river temperature in the fishing season is illustrated in Figure 6.

Despite the uncertainties in the data sets and analysis, the overall approach of investigating long-term changes in river temperature by combining citizen science records and GAM modelling can be considered robust.

Ecological relevance

Ecological responses to changes in river temperature can vary according to species resilience and resistance but also, in severe cases, can affect migration, embryonic development, hatching, emergence, growth, life-history traits, changes in behaviour and physiology and even local extinction (Jonsson and Jonsson, 2009; Parmesan, 2006). Salmonids can withstand short-term exposure to river temperatures higher than those needed for longer-term growth or survival without significant negative effects, however, brown trout *(Salmo trutta)* are more sensitive to temperature and acute increases in river temperature than Atlantic Salmon (*Salmo salar)*(Webb and Walsh, 2004). Furthermore, freshwater pearl mussels are vulnerable to temperature changes directly and to temperature effects on salmonid hosts (Lopes-Lima et al., 2017).

Both observed and modelled river temperatures in the River Spey rarely exceed 19°C which is the upper feeding threshold for *Salmo trutta* and below the upper threshold required for *Salmo salar* to feed (Elliott and Elliott, 2010). A daily maximum temperature of greater than 24°C was found to be stressful for trout (Jonsson and Jonsson, 2009) and increasing river temperatures adversely impact spawning and embryo development of trout (Webb and Walsh (2004).

When these statistics are related to the results in the current study, in general, river temperature at the fishing beats on the main stem of the River Spey is not, at present, critical for salmonid species. Yet, higher temperatures might occur both for downstream reaches with slow flow velocities and salmon spawning areas in the upstream reaches (Jackson et al., 2018, 2017a).

In line with this study, where increasing river temperatures were recorded in spring, Gregory et al. (2017) found a positive link between *Salmo salar* parr length and the effect of higher spring temperatures that are known to influence the metabolic rate of *Salmo salar*.

Implications for future change and climate change adaptation measures

Our analysis of long-term records of river temperature can provide a robust basis for future assessments and relevant insights for the ecosystem and rural economy, in terms of sport fishing and fish farms.

Climate change projections for Scotland assume increasing air temperature and precipitation shifts from summer to winter (Murphy et al., 2010). Further increases in atmospheric energy will contribute to warmer river temperatures directly as shown by van Vliet et al. (2016) in a global study. Indirect influences of changes in air temperature together with changing precipitation patterns on warmer river temperatures are expected, due to less snow, earlier snowmelt, and decreasing summer runoff (van Vliet et al., 2013).

Compared to the previous century, stronger air temperature trends are expected for the future whereby mostly lower river temperature compared to air temperature trends are expected (Caldwell et al., 2015; Hardenbicker et al., 2017). Albeit, Gunawardhana & Kazama (2012) expect differences between trends in air and river temperatures to cease due to increasing groundwater temperature and thus less cooling influence of groundwater contributions during summer months. In our study, this is indicated by comparable increases in river temperature and air temperature from the 1960s onwards.

As river temperature influences salmonid habitat and life cycle, potential global warming impacts on salmonid populations are highly relevant (Hari et al., 2006; Isaak et al., 2018; Jonsson and Jonsson, 2009; Young et al., 2017). If current trends continue in the River Spey, the aquatic life of the entire river network could be affected by rising river temperatures. For example, under a high emission scenario, Webb and Walsh (2004) modelled a temperature increase of 2 K by 2080 in the River Dee (a neighbouring catchment to the Spey) that was sufficient to induce a stressful thermal habitat for brown trout. Nonetheless, emerging evidence shows that cold water fish are adapting and becoming more resilient to climatic changes by changing behaviour and seeking cooler refuges in river systems (Isaak et al., 2016; Magoulick and Kobza, 2003). Local implications of these changes on river temperatures of the River Spey can be estimated for example by scenario assessments using the model cascade presented in our study to estimate river temperature under projections of air temperature and precipitation, similar to the approach by Merriam et al. (2017). Increasing abstraction for agriculture, industry and population should be included in future assessments.

Due to the strong influence of global radiation on river temperature, river managers can explore a variety of mitigation measures such as tree planting along the riparian corridor, controlling extraction, and releasing cold water from upstream impoundments (e.g. Dugdale et al., 2017; Imholt et al., 2013). Planning of measures require deeper understanding of the local conditions and should be designed (location, spatial extent, type of vegetation) to maximise effectiveness (Arora et al., 2018; Garner et al., 2017). For example Jackson et al. (2017a), found the warmest river temperatures in Scotland were predicted to occur where air temperatures and elevation were high and where the channels had a north-south orientation. In these circumstances, woodland planting in the riparian zone was most effective where channel widths were narrow, the gradient low and where the aspect and orientation of the river maximises shading by woodland. Measures to mitigate rising river temperature need to consider effects on fish habitats (Fullerton et al., 2017). Hence, our modelling cascade could be extended by process-based modelling approaches, such as the model presented by Fabris et al. (2018), to investigate the potential effects of mitigation measures.

Conclusion and Outlook

To understand long-term changes in river temperature, we investigated a 105-year record (1912-2016) of river temperature gathered by fishing attendants (ghillies) on the River Spey. The records indicate warming tendencies, however, due to data gaps it was not possible to quantitatively assess long-term changes based on the observations alone. Therefore, continuous daily river temperatures in the fishing season were reconstructed from explanatory variables (air temperature, cumulative air temperature from beginning of the year, day length, runoff) using GAMs. Long-term records of air temperature have been available from weather station records; runoff has been simulated using process-based models.

Long-term changes of reconstructed water temperatures were found in terms of significant increases by 0.2 K per decade after 1961 throughout the fishing season and slightly greater increases in spring. These changes can mostly be attributed to increasing air temperature which is most pronounced after 1958. Indirect impacts of rising air temperatures include less snow accumulation and snow melt as well as an earlier snow melt. The results of the study can provide a robust basis for future assessments of global change and can help inform decision-makers about the desirability of enhancing the resilience of rivers and aquatic ecology to warming. The methods applied can be used to understand long-term changes in river temperature in other catchments. For example, the catchment-specific drivers behind increasing river temperature trends in several Scottish catchments over the last thirty years (Lacout-Bonnamy, 2018) can be investigated using GAMs.

The GAMs produced in this study that explain river temperature from air temperature, cumulative air temperature, daylength and runoff are suitable for assessments of future climatic changes and can be combined with process-based modelling approaches, such as to spatially target mitigation measures.

Our research underlines the value of citizen science for supporting environmental research which has long been recognised in ecology (e.g. Isaak et al., 2015) and is becoming a more frequently used approach to increase temporal and spatial coverage of hydrological and water quality variables (Kampf et al., 2018; Loiselle et al., 2017; Weyhenmeyer et al., 2017).

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References

Arora, R., Tockner, K., Venohr, M., 2016. Changing river temperatures in northern Germany: trends and drivers of change. Hydrol. Process. 30, 3084–3096. https://doi.org/10.1002/hyp.10849

Arora, R., Toffolon, M., Tockner, K., Venohr, M., 2018. Thermal discontinuities along a lowland river : the importance of urban areas and lakes. J. Hydrol. https://doi.org/10.1016/j.jhydrol.2018.05.066

Baum, D., Laughton, R., Armstrong, J.D., Metcalfe, N.B., 2005. The effect of temperature on growth and early maturation in a wild population of Atlantic salmon parr. J. Fish Biol. 67, 1370–1380. https://doi.org/10.1111/j.1095-8649.2005.00832.x

Bolduc, C., Lamoureux, S.F., 2018. Multi-year variations in High Arctic river temperatures in response to climate variability. Arct. Sci. https://doi.org/10.1139/AS-2017-0053

Butler, J.R.A., Radford, A., Riddington, G., Laughton, R., 2009. Evaluating an ecosystem service provided by Atlantic salmon, sea trout and other fish species in the River Spey, Scotland: The economic impact of recreational rod fisheries. Fish. Res. 96, 259–266.

https://doi.org/10.1016/j.fishres.2008.12.006

Caldwell, P., Segura, C., Laird, S.G., Sun, G., McNulty, S.G., Sandercock, M., Boggs, J., Vose, J.M., 2015. Short-term stream water temperature observations permit rapid assessment of potential climate change impacts. Hydrol. Process. 29, 2196–2211. https://doi.org/10.1002/hyp.10358

Carraro, L., Bertuzzo, E., Mari, L., Fontes, I., Hartikainen, H., Strepparava, N., Schmidt-Posthaus, H., Wahli, T., Jokela, J., Gatto, M., Rinaldo, A., 2017. Integrated field, laboratory, and theoretical study of PKD spread in a Swiss prealpine river. Proc. Natl. Acad. Sci. 1–6. https://doi.org/10.1073/pnas.1713691114

CEH, 2012. National River Flow Archive [WWW Document]. URL http://nrfa.ceh.ac.uk (accessed 5.29.18).

Chen, D., Hu, M., Guo, Y., Dahlgren, R.A., 2016. Changes in river water temperature between 1980 and 2012 in Yongan watershed , eastern China : Magnitude , drivers and models. J. Hydrol. 533, 191–199. https://doi.org/10.1016/j.jhydrol.2015.12.005

Criss, R.E., Winston, W.E., 2008. Do Nash values have value? Discussion and alternate proposals. Hydrol. Process. 22, 2723–2725. https://doi.org/10.1002/hyp

Dick, J., Tetzlaff, D., Soulsby, C., 2017. Role of riparian wetlands and hydrological connectivity in the dynamics of stream thermal regimes in the dynamics of stream thermal regimes. Hydrol. Res. https://doi.org/10.2166/nh.2017.066

Dugdale, S.J., Malcolm, I., Hannah, D.M., 2017. Stream temperature under contrasting riparian forest cover : Understanding thermal dynamics and heat exchange processes. Sci. Total Environ. 610–611, 1375–1389. https://doi.org/10.1016/j.scitotenv.2017.08.198

Elliott, J.M., Elliott, J.A., 2010. Temperature requirements of Atlantic salmon Salmo salar, brown trout Salmo trutta and Arctic charr Salvelinus alpinus: Predicting the effects of climate change. J. Fish Biol. 77, 1793–1817. https://doi.org/10.1111/j.1095-8649.2010.02762.x

Fabris, L., Malcolm, I.A., Buddendorf, W.B., Soulsby, C., 2018. Integrating process-based flow and temperature models to assess riparian forests and temperature amelioration in salmon streams. Hydrol. Process. 32, 776–791. https://doi.org/10.1002/hyp.11454

Fofonova, V., Zhilyaev, I., Krayneva, M., Yakshina, D., Tananaev, N., Volkova, N., Wiltshire, K.H., 2016. The water temperature characteristics of the Lena River at basin outlet in the summer period. Hydrol. Earth Syst. Sci. Discuss. 1–32. https://doi.org/10.5194/hess-2016-254

Fox, J., Weisberg, S., Price, B., 2018. car. Companion to Applied Regression. R-Package.

Fullerton, A.H., Burke, B.J., Lawler, J.J., Torgerson, C.E., Ebersole, J.L., Leibowitz, S.G., 2017. Simulated juvenile salmon growth and phenology respond to altered thermal regimes and stream network shape. Ecosphere 8, 1–6. https://doi.org/10.1002/ecs2.2052

Gädeke, A., Hölzel, H., Koch, H., Pohle, I., Grünewald, U., 2014. Analysis of uncertainties in the hydrological response of a model-based climate change impact assessment in a subcatchment of the Spree River, Germany. Hydrol. Process. 28, 3978–3998. https://doi.org/10.1002/hyp.9933

Gädeke, A., Pohle, I., Koch, H., Grünewald, U., 2017. Trend analysis for integrated regional climate change impact assessments in the Lusatian river catchments (north-eastern Germany). Reg. Environ. Chang. 17, 1751–1762. https://doi.org/10.1007/s10113-017-1138-0

Garner, G., Malcolm, I.A., Sadler, J.P., Hannah, D.M., 2017. The role of riparian vegetation density, channel orientation and water velocity in determining river temperature dynamics. J. Hydrol. 553, 471–485. https://doi.org/10.1016/j.jhydrol.2017.03.024

Gray, B.R., Lyubchich, V., Gel, Y.R., Rogala, J.T., Robertson, D.M., Wei, X., 2016. Estimation of river and stream temperature trends under haphazard sampling. Stat. Methods Appt. 25, 89–105. https://doi.org/10.1007/s10260-015-0334-7

Gregory, S.D., Nevoux, M., Riley, W.D., Beaumont, W.R.C., Jeannot, N., Lauridsen, R.B., Marchand, F., Scott, L.J., Roussel, J.M., 2017. Patterns on a parr: Drivers of long-term salmon parr length in U.K. and French rivers depend on geographical scale. Freshw. Biol. 62, 1117–1129. https://doi.org/10.1111/fwb.12929

Gunawardhana, L.N., Kazama, S., 2012. Statistical and numerical analyses of the influence of climate variability on aquifer water levels and groundwater temperatures: The impacts of climate change on aquifer thermal regimes. Glob. Planet. Change 86–87, 66–78. https://doi.org/10.1016/j.gloplacha.2012.02.006

Gupta, H. V, Kling, H., Yilmaz, K.K., Martinez, G.F., 2009. Decomposition of the mean squared error and NSE performance criteria : Implications for improving hydrological modelling. J. Hydrol. 377, 80–91. https://doi.org/10.1016/j.jhydrol.2009.08.003

Hannah, D.M., Garner, G., 2015. River water temperature in the United Kingdom : Changes over the 20th century and possible changes over the 21st century. Prog. Phys. Geogr. 39, 68–92. https://doi.org/10.1177/0309133314550669

Hardenbicker, P., Viergutz, C., Becker, A., Kirchesch, V., Nilson, E., Fischer, H., 2017. Water temperature increases in the river Rhine in response to climate change. Reg. Environ. Chang. 17, 299–308. https://doi.org/10.1007/s10113-016-1006-3

Hari, R.E., Livingstone, D.M., Siber, R., Burkhardt-Holm, P., Guttinger, H., 2006. Consequences of climatic change for water temperature and brown trout populations in Alpine rivers and streams. Glob. Chang. Biol. 12, 10–26. https://doi.org/10.1111/j.1365-2486.2005.01051.x

Helliwell, R.C., Soulsby, C., Ferrier, R.C., Jenkins, A., Harriman, R., 1998. Influence of snow on the hydrology and hydrochemistry of the Allt a' Mharcaidh, Cairngorm mountains, Scotland. Sci. Total Environ. 217, 59–70. https://doi.org/10.1016/S0048-9697(98)00165-X

Imholt, C., Soulsby, C., Malcolm, I.A., Gibbins, C.N., 2013. Influence of contrasting riparian forest cover on stream temperature dynamics in salmonid spawning and nursery streams. Ecohydrology 6, 380–392. https://doi.org/10.1002/eco.1291

Imholt, C., Soulsby, C., Malcolm, I.A., Hrachowitz, M., Gibbins, C.N., Langan, S., Tetzlaff, D., 2011. Influence of scale on thermal characteristics in a large montane river basin. Limnetica 30, 307–328. https://doi.org/10.1002/rra

Isaak, D.J., Luce, C.H., Horan, D.L., Chandler, G.L., Wollrab, S.P., Nagel, D.E., 2018. Global Warming of Salmon and Trout Rivers in the Northwestern U.S.: Road to Ruin or Path Through Purgatory? Trans. Am. Fish. Soc. https://doi.org/10.1002/tafs.10059

Isaak, D.J., Luce, C.H., Rieman, B.E., Nagel, D.E., Peterson, E.E., Horan, D.L., Parkes, S., Chandler, G.L., 2010. Effects of climate change and wildfire on stream temperatures and salmonid thermal habitat in a mountain river network. Ecol. Appl. 20, 1350–1371. https://doi.org/10.1890/09-0822.1

Isaak, D.J., Young, M.K., Luce, C.H., Hostetler, S.W., Wenger, S.J., Peterson, E.E., Ver Hoef, J.M., Groce, M.C., Horan, D.L., Nagel, D.E., 2016. Slow climate velocities of mountain streams portend their role as refugia for cold-water biodiversity. Proc. Natl. Acad. Sci. 1–6. https://doi.org/10.1073/pnas.1522429113

Isaak, D.J., Young, M.K., Nagel, D.E., Horan, D.L., Groce, M., 2015. The cold-water climate shield : delineating refugia for preserving salmonid fishes through the 21st century. Glob. Chang. Biol. 21, 2540–2553. https://doi.org/10.1111/gcb.12879

Jackson, F.L., Fryer, R.J., Hannah, D.M., Millar, C.P., Malcolm, I.A., 2018. A spatio-temporal statistical model of maximum daily river temperatures to inform the management of Scotland's Atlantic salmon rivers under climate change. Sci. Total Environ. 612, 1543–1558. https://doi.org/10.1016/j.scitotenv.2017.09.010

Jackson, F.L., Hannah, D.M., Fryer, R.J., Millar, C.P., Malcolm, I.A., 2017a. Development of spatial regression models for predicting summer river temperatures from landscape characteristics: Implications for land and fisheries management. Hydrol. Process. 31, 1225–1238. https://doi.org/10.1002/hyp.11087

Jackson, F.L., Malcolm, I., Jackson, F.L., Fryer, R.J., Hannah, D.M., Malcolm, I.A., 2017b. Can spatial statistical river temperature models be transferred between catchments? Hydrol. Earth Syst. Sci. https://doi.org/10.5194/hess-21-4727-2017

Johnson, M.F., Wilby, R.L., Toone, J.A., 2014. Inferring air – water temperature relationships from river and catchment properties. Hydrol. Process. 28, 2912–2928. https://doi.org/10.1002/hyp.9842

Joint Nature Conservation Committee, 2016. NATURA 2000 - STANDARD DATA FORM For Special Protection Areas (SPA), Proposed Sites for Community Importance (pSCI), Sites of Community Importance (SCI) and for Special Areas of Conservation (SAC) SITE UK0019811 SITENAME River Spey.

Jonkers, A.R.T., Sharkey, K.J., 2016. The differential warming response of Britain's rivers (1982-2011). PLoS One 11, 1–23. https://doi.org/10.1371/journal.pone.0166247

Jonsson, B., Jonsson, N., 2009. A review of the likely effects of climate change on anadromous Atlantic salmon Salmo salar and brown trout Salmo trutta , with particular reference to water temperature and flow. J. Fish Biol. 75, 2381–2447. https://doi.org/10.1111/j.1095-8649.2009.02380.x

Jonsson, N., 1991. Influence of water flow, water temperature and light on fish migration in rivers. Nord. J. Freshw. Resour. 66, 20–35.

Kampf, S., Strobl, B., Hammond, J., Anenberg, A., Etter, S., Martin, C., Puntenney-Desmond, K., Seibert, J., Van Meerfeld, I., 2018. Testing the waters: Mobile apps for crowdsourced streamflow data. Eos, Trans. Am. Geophys. Union 99. https://doi.org/10.1029/2018EO096355

Kaushal, S.S., Likens, G.E., Jaworski, N.A., Pace, M.L., Sides, A.M., Seekell, D., Belt, K.T., Secor, D.H., Wingate, R.L., 2010. Rising stream and river temperatures in the United States. Front. Ecol. Environ. 8, 461–466. https://doi.org/10.1890/090037

Kelleher, C., Wagener, T., Gooseff, M., Mcglynn, B., Mcguire, K., Marshall, L., 2012. Investigating controls on the thermal sensitivity of Pennsylvania streams. Hydrol. Process. 26, 771–785. https://doi.org/10.1002/hyp.8186

Kendon, M., McCarthy, M., Jevrejeva, S., Matthews, A., Legg, T., 2018. State of the UK climate 2017. Int. J. Climatol. 38, 1–35. https://doi.org/10.1002/joc.5798

Koch, H., Grünewald, U., 2010. Regression models for daily stream temperature simulation: Case studies for the river Elbe, Germany. Hydrol. Process. 24, 3826–3836. https://doi.org/10.1002/hyp.7814

Koch, H., Vögele, S., Hattermann, F.F., Huang, S., 2015. The impact of climate change and variability on the generation of electrical power. Meteorol. Zeitschrift 24, 173–188. https://doi.org/10.1127/metz/2015/0530

Lacout-Bonnamy, T., 2018. Water quality seasonal and long-term trend analysis using STL decomposition in Scottish catchments. Internship Report. Supervisors: Pohle, I., Troldborg, M. (James Hutton Institute), Aliaume, C. (Polytech Montpellier).

Langan, S.J., Johnston, L., Donaghy, M.J., Youngson, A.F., Hay, D.W., 2001. Variation in river water temperatures in an upland stream over a 30-year period. Sci. Total Environ. 265, 195–207.

Loiselle, S.A., Frost, P.C., Turak, E., Thornhill, I., 2017. Citizen scientists supporting environmental research priorities. Sci. Total Environ. 598, 937. https://doi.org/10.1016/j.scitotenv.2017.03.142

Lopes-Lima, M., Burlakova, L.E., Karatayev, A.Y., Mehler, K., Seddon, M., Sousa, R., 2018. Conservation of freshwater bivalves at the global scale: diversity, threats and research needs. Hydrobiologia 810, 1–14. https://doi.org/10.1007/s10750-017-3486-7

Lopes-Lima, M., Sousa, R., Geist, J., Aldridge, D.C., Araujo, R., Bergengren, J., Bespalaya, Y., Bódis, E., Burlakova, L., Van Damme, D., Douda, K., Froufe, E., Georgiev, D., Gumpinger, C., Karatayev, A., Kebapçi, Ü., Killeen, I., Lajtner, J., Larsen, B.M., Lauceri, R., Legakis, A., Lois, S., Lundberg, S., Moorkens, E., Motte, G., Nagel, K.O., Ondina, P., Outeiro, A., Paunovic, M., Prié, V., von Proschwitz, T., Riccardi, N., Rudzīte, M., Rudzītis, M., Scheder, C., Seddon, M., Şereflişan, H., Simić, V., Sokolova, S., Stoeckl, K., Taskinen, J., Teixeira, A., Thielen, F., Trichkova, T., Varandas, S., Vicentini, H., Zajac, K., Zajac, T., Zogaris, S., 2017. Conservation status of freshwater mussels in Europe: state of the art and future challenges. Biol. Rev. 92, 572–607. https://doi.org/10.1111/brv.12244

Magoulick, D.D., Kobza, R.M., 2003. The role of refugia for fishes during drought: A review and synthesis. Freshw. Biol. 48, 1186–1198. https://doi.org/10.1046/j.1365-2427.2003.01089.x

Merriam, E.R., Fernandez, R., Petty, J.T., Zegre, N., 2017. Can brook trout survive climate change in large rivers ? If it rains. Sci. Total Environ. 607–608, 1225–1236. https://doi.org/10.1016/j.scitotenv.2017.07.049

Moatar, F., Gailhard, J., 2006. Water temperature behaviour in the River Loire since 1976 and 1881. Comptes Rendus Geosci. 338, 319–328. https://doi.org/10.1016/j.crte.2006.02.011

Mohseni, O., Stefan, H.G., Eaton, J.G., 2003. Global Warming and Potential Changes in Fish Habitat in U.S. Streams. Clim. Change 59, 389–409.

Mohseni, O., Stefan, H.G., Erickson, T.R., 1998. A nonlinear regression model for weekly stream temperatures. Water Resour. Res. 34, 2685–2692. https://doi.org/10.1029/98WR01877

Müller, U., Greis, S., Rothstein, B., 2007. Impacts on Water Temperatures of Selected German Rivers and on Electricity Production of Thermal Power Plants due to Climate Change, in: Disaster Reduction in Climate Change. Karlsruhe, pp. 8–11.

Murphy, J., Sexton, D., Jenkins, G., Boorman, P., Booth, B., Brown, K., Clark, R., Collins, M., Harros, G., Kendon, L., 2010. UK Climate Projections science report: Climate change projections.

Nash, J.E., Sutcliffe, J. V., 1970. River flow forecasting through conceptual models part I - A discussion of principles. J. Hydrol. 10, 282–290. https://doi.org/10.1016/0022-1694(70)90255-6

O'Gorman, E.J., Ólafsson, Ó.P., Demars, B.O.L., Friberg, N., Guðbergsson, G., Hannesdóttir, E.R., Jackson, M.C., Johansson, L.S., McLaughlin, Ó.B., Ólafsson, J.S., Woodward, G., Gíslason, G.M., 2016. Temperature effects on fish production across a natural thermal gradient. Glob. Chang. Biol. 22, 3206–3220. https://doi.org/10.1111/gcb.13233

Parajka, J., Merz, R., Blöschl, G., 2007. Uncertainty and multiple objective calibration in regional water balance modelling: case study in 320 Austrian catchments. Hydrol. Process. 21, 435–446. https://doi.org/10.1002/hyp

Parmesan, C., 2006. Ecological and Evolutionary Responses to Recent Climate Change. Annu. Rev. Ecol. Evol. Syst. 37, 637–669. https://doi.org/10.1146/annurev.ecolsys.37.091305.110100

Pekarova, P., Miklanek, M., Halmova, D., Onderka, M., Pekar, J., Kucarova, K., Liova, S., Skoda, P., 2011. Long-term trend and multi-annual variability of water temperature in the pristine Bela River basin (Slovakia). J. Hydrol. 400, 333–340. https://doi.org/10.1016/j.jhydrol.2011.01.048

Perkins, D.M., Yvon-Durocher, G., Demars, B.O.L., Reiss, J., Pichler, D.E., Friberg, N., Trimmer, M., Woodward, G., 2012. Consistent temperature dependence of respiration across ecosystems contrasting in thermal history. Glob. Chang. Biol. 18, 1300–1311. https://doi.org/10.1111/j.1365-2486.2011.02597.x

Pohlert, T., 2018. trend. Non-Parametric Trend Tests and Change-Point Detection. R-package. R Packag. https://doi.org/10.13140/RG.2.1.2633.4243

Prior, M.J., Perry, M.C., 2014. Analyses of trends in air temperature in the United Kingdom using gridded data series from 1910 to 2011. Int. J. Climatol. 34, 3766–3779. https://doi.org/10.1002/joc.3944

Rabi, A., Hadzima-Nyarko, M., Šperac, M., 2015. Modelling river temperature from air temperature : case of the River Drava (Croatia). Hydrol. Sci. J. 60, 1490–1507. https://doi.org/10.1080/02626667.2014.914215

Reid, P.C., Hari, R.E., Beaugrand, G., Livingstone, D.M., Marty, C., Straile, D., Barichivich, J., Goberville, E., Adrian, R., Aono, Y., Brown, R., Foster, J., Groisman, P., Hélaouët, P., Hsu, H.H., Kirby, R., Knight, J., Kraberg, A., Li, J., Lo, T.T., Myneni, R.B., North, R.P., Pounds, J.A., Sparks, T., Stübi, R., Tian, Y., Wiltshire, K.H., Xiao, D., Zhu, Z., 2016. Global impacts of the 1980s regime shift. Glob. Chang. Biol. 22, 682–703. https://doi.org/10.1111/gcb.13106

Spencer, M., 2016. Reanalysis of Scottish Mountain Snow Conditions. The University of Edinburgh.

Spencer, M., Essery, R., Chambers, L., Hogg, S., 2014. The Historical Snow Survey of Great Britain : Digitised Data for Scotland. Scottish Geogr. J. 130, 252–265. https://doi.org/10.1080/14702541.2014.900184

Toffolon, M., Piccolroaz, S., 2015. A hybrid model for river water temperature as a function of air temperature and discharge. Environ. Res. Lett. 10, 1–22. https://doi.org/10.1088/1748-9326/10/11/114011

van Vliet, M.T.H., Franssen, W.H.P., Yearsley, J.R., Ludwig, F., Haddeland, I., Lettenmaier, D.P., Kabat, P., 2013. Global river discharge and water temperature under climate change. Glob. Environ. Chang. 23, 450–464.

https://doi.org/10.1016/j.gloenvcha.2012.11.002

van Vliet, M.T.H., van Beek, L.P.H., Eisner, S., Flörke, M., Wada, Y., Bierkens, M.F.P., 2016. Multi-model assessment of global hydropower and cooling water discharge potential under climate change. Glob. Environ. Chang. 40, 156–170. https://doi.org/http://dx.doi.org/10.1016/j.gloenvcha.2016.07.007

Verbrugge, L.N.H., Schipper, A.M., Huijbregts, M.A.J., Van der Velde, G., Leuven, R.S.E.W., 2012. Sensitivity of native and non-native mollusc species to changing river water temperature and salinity. Biol. Invasions 14, 1187–1199. https://doi.org/10.1007/s10530-011-0148-y

Webb, B.W., Nobilis, F., 1994. Water temperature behaviour in the River Danube during the twentieth century. Hydrobiologia 291, 105–113.

Webb, B.W., Walling, D.E., 1992. Long term water temperature behaviour and trends in a Devon , UK , river system. Hydrol. Sci. J. 37, 567–580. https://doi.org/10.1080/02626669209492624

Webb, B.W., Walsh, A.J., 2004. Changing UK river temperatures and their impact on fish populations. Hydrol. Sci. Pract. 21st Century. Vol. II. II, 177–191.

Weyhenmeyer, G.A., Mackay, M., Stockwell, J.D., Thiery, W., Grossart, H.-P., Augusto-Silva, P.B., Baulch, H.M., de Eyto, E., Hejzlar, J., Kangur, K., Kirillin, G., Pierson, D.C., Rusak, J.A., Sadro, S., Woolway, R.I., 2017. Citizen science shows systematic changes in the temperature difference between air and inland waters with global warming. Sci. Rep. 7, 1–9. https://doi.org/10.1038/srep43890

Wood, S., 2018. mgcv. Mixed GAM computation vehicle with automated smoothness estimation. R-Package.

Young, M.K., Isaak, D.J., McKelvey, K.S., Wilcox, T.M., Campbell, M.R., Horan, D.L., Schwartz, M.K., 2017. Ecological segregation moderates a climactic conclusion to trout hybridization. Glob. Chang. Biol. 0, 1–3. https://doi.org/10.1111/gcb.13828

Youngson, A.F., Maclean, J.C., Fryer, R.J., 2002. Rod catch trends for early-running MSW salmon in Scottish rivers (1952 – 1997): divergence among stock components. ICES J. Mar. Sci. 59, 836–849. https://doi.org/10.1006/jmsc.2002.1195

Table 1. Performance of the hydrological model at the gauging stations Grantown-on-Spey and Boat o' Brig. Long term mean annual runoff R and evaluation criteria: root-mean-square-error (RMSE), bias, mean absolute error (MAE), Nash-Sutcliffe Efficiency (NSE), Nash-Sutcliffe Efficiency calculated for natural logarithms of observed and simulated discharge (NSEln), coefficient of determination (R^2), Volume Efficiency (VE) and Kling-Gupta Efficiency (KGE).

Criterion	Optimum value	Grantown-on-Spey		Boat o' Brig	
		Calibration (1963-1982)	Validation (1983-2012)	Calibration (1963-1982)	Validation (1983-2012)
R observed [mm/a]	-	648	713	690	745
R modelled [mm/a]	-	657	794	578	680
RMSE [mm/d]	0	0.70	0.88	0.85	0.84
BIAS [mm/d]	0	0.03	0.21	-0.31	-0.20
MAE [mm/d]	0	0.45	0.56	0.49	0.51
NSE	1	0.73	0.74	0.67	0.72
NSEln	1	0.71	0.71	0.66	0.71
R^2	1	0.76	0.79	0.72	0.74
VE	1	0.75	0.71	0.74	0.75
KGE	1	0.87	0.84	0.77	0.83

Table 2. Statistics of weekly observed river temperatures [°C]. Mean, maximum and variance of weekly averages in spring (weeks 15-22) and the fishing season (weeks 15-40) for periods with high data availability. Symbols for mean and variance denote statistically significant differences compared to 1926-1935 (* $p \leq 0.05$) and to the respective preceding periods (+ $p \leq 0.05$) based on the Kruskal-Wallis-Test for central tendency and the Levene Test for equality of variances.

Beat	Statistic	Weeks	1926-1935	1956-1965	1976-1985	2006-2015
A	Mean	15-22	7.8		8.2	10.0*,+

	Mean	15-40	10.5		11.3	12.5*,+
	Maximum	15-22	12.6		15.8	16.5
	Maximum	15-40	17.5		22.2	21.1
	Variance	15-22	5.2		6.2	4.6
	Variance	15-40	9.7		12.6	7.1*,+
B	Mean	15-22	7.8		9.2*	8.6
	Mean	15-40	10.6		12.0*	12.5*
	Maximum	15-22	12.8		15.9	14.4
	Maximum	15-40	17.8		22.2	19.7
	Variance	15-22	4.9		9.0+	6.4
	Variance	15-40	9.0		12.3	8.8*
C	Mean	15-22	7.9	9.8*	8.1+	8.6
	Mean	15-40	10.7		10.8	12.3
	Maximum	15-22	13.1	17.2	14.7	14.8
	Maximum	15-40	23.3		17.8	20.2
	Variance	15-22	5.1	4.1	5.8	6.1
	Variance	15-40	9.6		8.2	9.7
D	Mean	15-22	7.8	9.6*	8.9*	9.7*
	Mean	15-40	10.9		12.2*	12.5*
	Maximum	15-22	13.1	16.4	14.7	15.1
	Maximum	15-40	23.9		23.3	19.3
	Variance	15-22	5.1	4.41	6.6+	6.1
	Variance	15-40	9.9		12.7	7.8*,+

Table 3. Statistically significant relationships between observed river temperature and the covariates air temperature (T_a), cumulative air temperature since beginning of the year ($T_{a,cum}$), precipitation (P), day length (DL), snow melt (SM), natural runoff (R), snow melt ratio (SM/R), water level (W) at fishing beat D for the time period 1961-2015 (considering Bonferroni correction for eight covariates $p < 0.05/8$ (0.00625)). Intercept, slope, coefficient of determination (R^2), F statistic and degree of freedom (DF) of linear models between river temperature and covariates of the same day or averaged over a period of 8 days before the temperature measurement.

Variable	Moving average [days]	Linear model				
		Intercept	Slope	R^2	F Statistic	DF
T_a	1	5.24	0.73	0.61	5022	3160
	8	3.82	0.89	0.74	8909	3160
$T_{a,cum}$	1	9.29	0.003	0.25	1081	3160
	8	9.43	0.003	0.24	1008	3160
P	8	12.54	-0.23	0.02	62.8	3160
DL	1	-1.08	0.83	0.20	776.5	3160
	8	-3.71	1.00	0.28	1201	3160
SM	1	11.93	-1.00	0.04	149	3160
	8	12.04	-1.70	0.10	357	3160
R	1	14.69	-2.27	0.24	992.9	3160
	8	14.81	-2.23	0.26	1120	3160
SM/R	1	11.94	-3.23	0.05	180.7	3160
	8	12.15	-7.75	0.15	563.5	3160

W	1	13.11	-7.58	0.24	987.2	3119

Table 4. General additive models for predicting river temperatures from covariates air temperature (T_a), cumulative air temperature since beginning of the year (T_a,cum), day length (DL), modelled runoff (R), snow melt (SM), snow melt ratio (SM/R), precipitation (P), water level (W), day of year (DOY). Evaluation criteria: Akaike information criterion (AIC), coefficient of determination (R^2), percent bias (PBIAS), root-mean-square-error (RMSE) for the training period and in brackets for the test period. Note that 144 river temperature observations have been removed as they appeared as outliers. Asterisks denote significant coefficients (considering Bonferroni correction for nine covariates $p < 0.05/9$ (0.0056)) of covariates. The final model chosen (model 8) is highlighted in bold and italics.

ID	Covariates and length of smoothing window (days)									Performance Training Period (Performance Test Period)			
	T_a	$T_{a,cum}$	DL	R (log)	SM	SM/R	P	W	DOY	AIC	R^2	PBIAS	RMSE
1	1*									12551	0.65 (0.70)	0 (10.5)	1.93 (2.06)
2	8*									12513	0.66 (0.69)	0 (10.2)	1.91 (2.05)
3	8*	1*								11323	0.77 (0.74)	0 (6.1)	1.58 (1.77)
4	8*	8*								11263	0.78 (0.74)	0 (6.0)	1.56 (1.77)
5	8*	8*	1*							10485	0.83 (0.82)	0 (6.3)	1.37 (1.51)
6	8*	8*	8*							10453	0.83 (0.82)	0 (6.5)	1.36 (1.53)
7	8	8	8	1						1023	0.84	0	1.31

	*	*	*	*						8	(0.83)	(6.4)	(1.50)
8	***8****	***8****	***8****	***8****						***10231***	***0.84 (0.83)***	***0 (6.7)***	***1.31 (1.50)***
9	8*	8*	8*	8*	1					10230	0.84 (0.83)	0 (6.7)	1.31 (1.50)
10	8*	8*	8*	8*	8					10228	0.84 (0.83)	0 (6.7)	1.31 (1.50)
11	8*	8*	8*	8*		1				10228	0.84 (0.83)	0 (6.7)	1.31 (1.50)
12	8*	8*	8*	8*		8				10228	0.84 (0.83)	0 (6.7)	1.31 (1.50)
13	8*	8*	8*	8*		8	1			10227	0.84 (0.83)	0 (7.4)	1.31 (1.53)
14	8*	8*	8*	8*		8	8*			10222	0.84 (0.83)	0 (7.0)	1.31 (1.51)
15	8*	8*	8*	8**			8*			10226	0.84 (0.83)	0 (6.9)	1.31 (1.50)
16	8*	8*	8*	8*			8	1*		10074	0.84 (0.84)	0 (5.7)	1.30 (1.43)
17	8*	8*	8*	8*			8*	1*	1*	10008	0.85 (0.84)	0 (5.2)	1.29 (1.42)
18	8*	8*	8*	8*		8	8*		1*	10194	0.84 (0.83)	0 (7.2)	1.30 (1.52)
19	8*								1 *	10741	0.81 (0.80)	0 (9.5)	1.43 (1.72)
20	8*	8*	8*						1*	10381	0.83 (0.81)	0 (7.5)	1.34 (1.60)

Table 5. Performance of the chosen GAM (model 8 in Table 4) for river temperature of all fishing beats. Evaluation criteria: coefficient of determination R^2, PBIAS percent bias, RMSE root-mean-square-error, KGE Kling-Gupta Efficiency, NSE Nash-Sutcliffe Efficiency, n number of data pairs.

Beat	Period 1961-2015						Period 1925-1960					
	R^2	PBIAS	RMSE	KGE	NSE	n	R^2	PBIAS	RMSE	KGE	NSE	N
A	0.78	0.8	1.76	0.82	0.78	2394	0.88	9.0	1.46	0.84	0.82	790
B	0.75	3.7	1.78	0.83	0.74	2060	0.89	9.8	1.44	0.86	0.83	980
C	0.73	6.1	1.78	0.81	0.68	2964	0.78	4.9	1.47	0.81	0.75	933
D	0.84	0	1.31	0.88	0.84	3018	0.83	6.7	1.50	0.83	0.79	2006

Table 6. Modelled river temperature [°C] at Beat D based on weekly averages for the spring (weeks 15-22) and the entire fishing season (weeks 15-40) in 10-year periods.

Weeks	Statistics	1926-35	1936-45	1946-55	1956-65	1966-75	1976-85	1986-95	1995-06	2006-15
15-22	Mean	8.7	9.4	9.2	9.1	8.8	8.8	9.1	9.5	9.5
	Maximum	12.4	13.4	12.9	13.6	12.5	14.4	13.8	14.2	14.3
	Variance	3.6	3.7	4.2	4.2	4.1	4.8	4.5	4.2	4.3
15-40	Mean	11.7	12.3	12.0	11.7	11.9	11.8	12.0	12.3	12.2
	Maximum	18.1	17.5	16.9	16.4	18.5	18.4	17.8	18.9	18.2
	Variance	7.5	6.7	6.9	6.0	7.2	7.8	7.7	7.1	6.9

Figure

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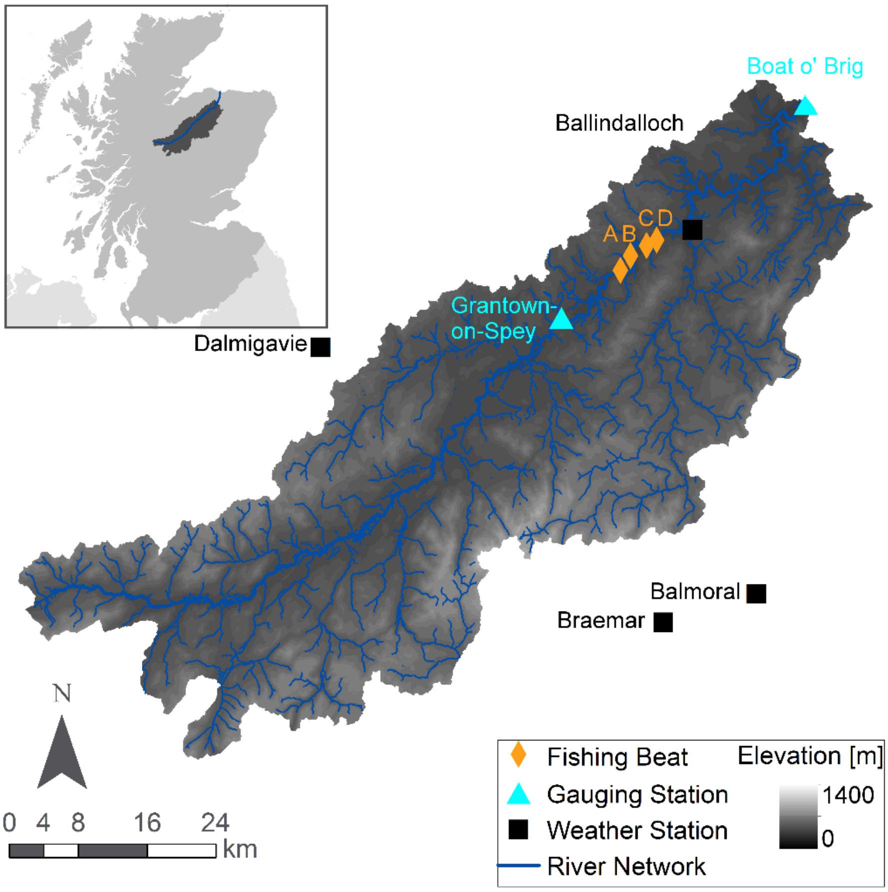

Figure 1. Overview of the study region including the monitoring stations: fishing beats (river temperature, water level), gauging stations (discharge), weather stations (precipitation and air temperature). This figure is available in colour online.

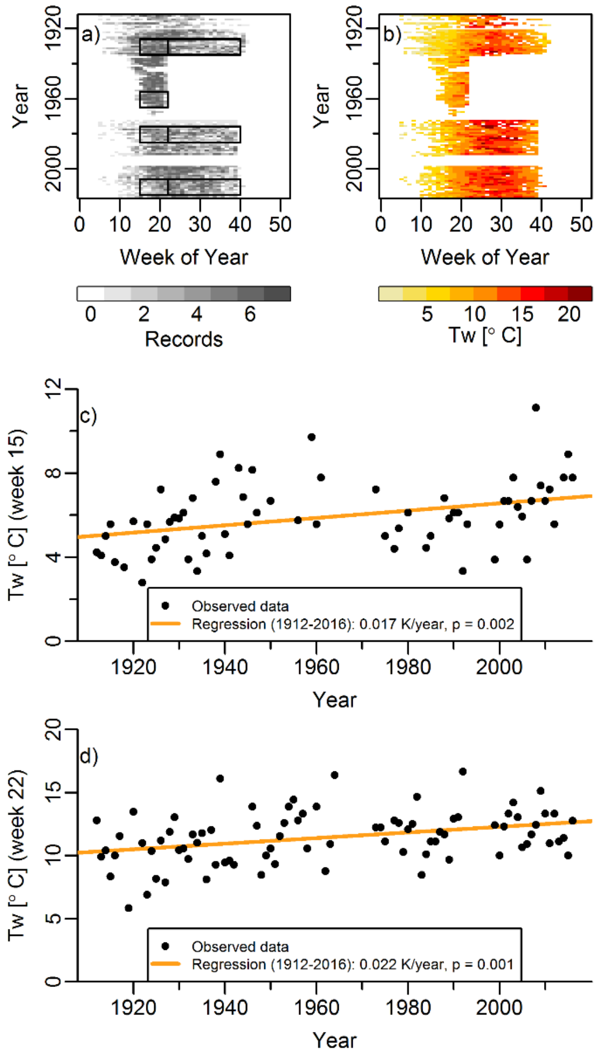

Figure 2. Raw data of observed river water temperature (T_w) [°C] at fishing Beat D. a) Number of weekly records, b) Weekly mean temperature, c) Water temperature in week 15 over the record length, d) Water temperature in week 22 over the record length. This figure is available in colour online.

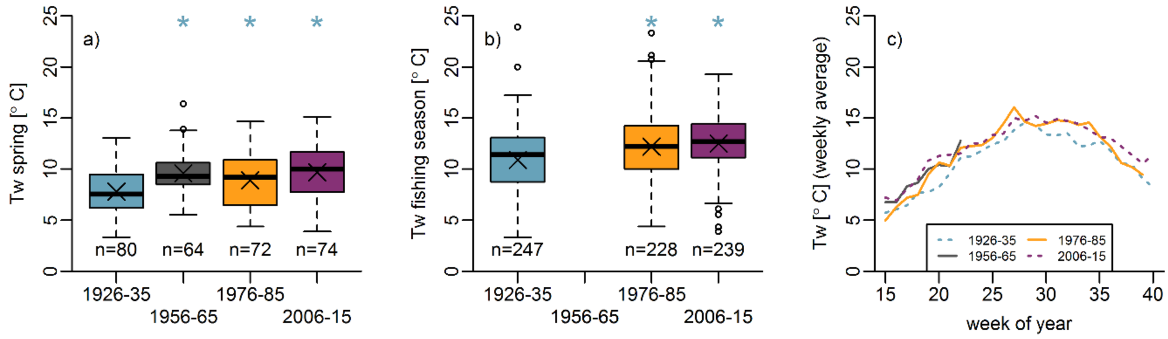

Figure 3. Observed river temperature T_w [°C] as weekly averages at fishing Beat D for periods with high data availability: a) spring (weeks 15-22), b) entire fishing season (weeks 15-40), c) weekly averages for decades. Boxes show 25th, 50th (middle line) and 75th percentile, whiskers show the lowest and highest datum within the 1.5 interquartile range of the lower and upper quartile, respectively, and individual points symbolize outliers. Cross symbols show mean value. Asterisks indicate significant difference from central tendency of water temperature in period 1926-1935 according to the Kruskal-Wallis test (* $p \leq 0.05$). This figure is available in colour online.

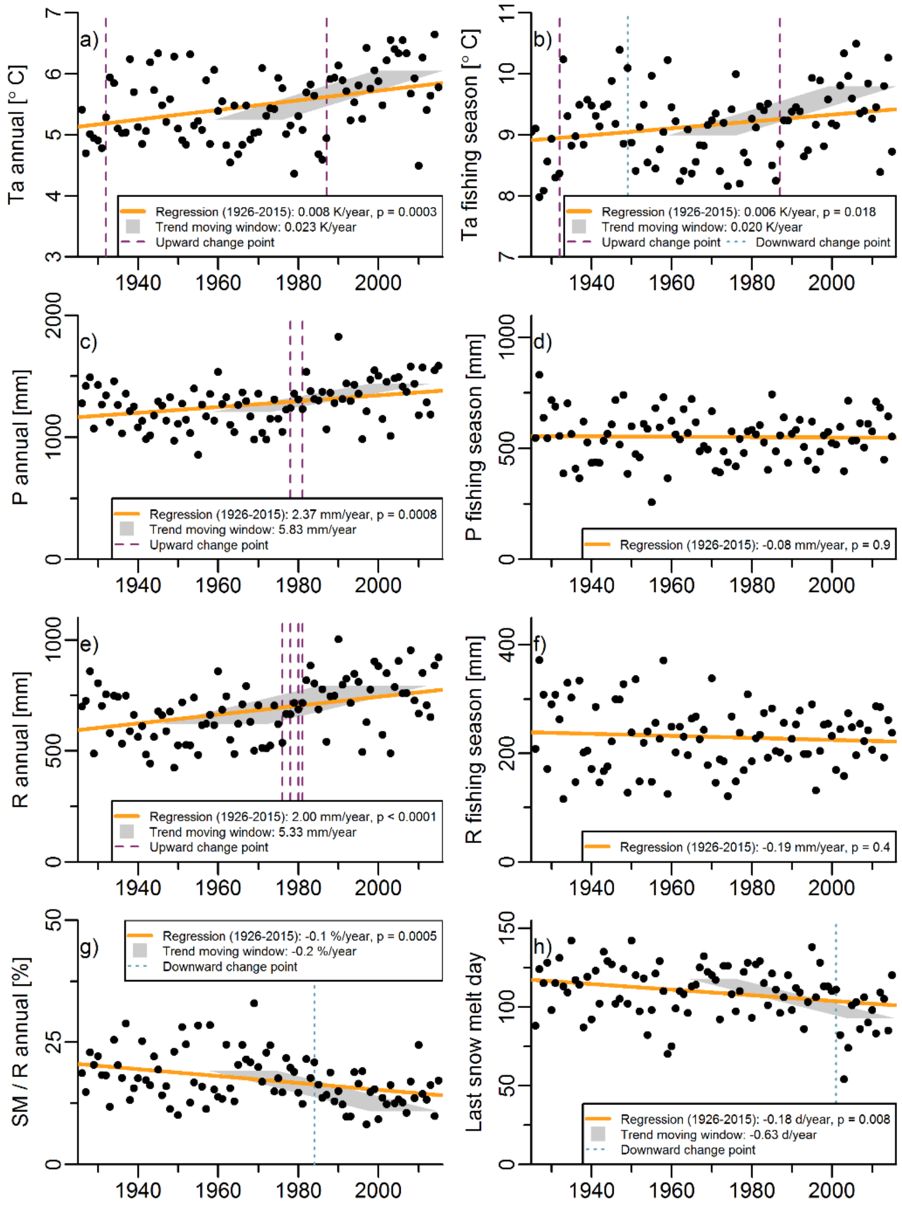

Figure 4. Long term changes in hydrometeorological variables: Top row: air temperature T_a [°C]: a) annual mean values, b) mean value in the fishing season (week 15-40), second row: precipitation P [mm]: c) annual sum, d) sum in the fishing season, third row: natural runoff R [mm]: e) annual sum, f) sum in the fishing season, bottom row: snow melt: g) ratio of snow melt over total natural runoff (SM / R) on an annual basis, h) last snow melt day in spring. Trend interpretation: linear regression over the time period 1926-2015 (orange line indicates intercept and slope), windows longer than 5 years with trend over a 40-year record (grey polygons indicate average intercept and slope for the windows), upward (purple line) and downward (blue line) change point according to the Pettitt test for different 40 year moving windows. This figure is available in colour online.

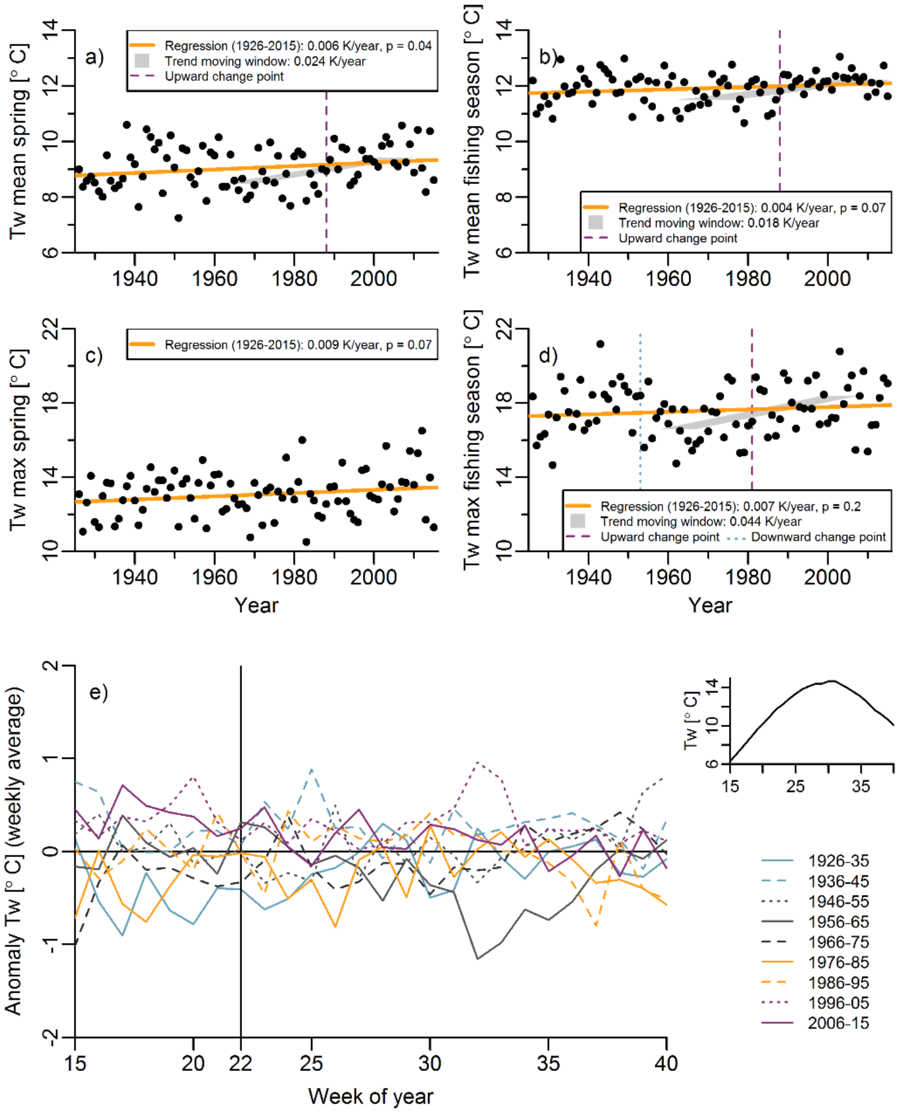

Figure 5. Modelled river temperatureT_w: a) mean values in spring (weeks 15-22), b) mean values in the fishing season (weeks 15-40), c) maximum values in spring, d) maximum values in the fishing season, e) anomalies of weekly averages for decades (weekly average in the respective decade minus weekly average over the period 1926-2015). The vertical line marks the end of the spring period (weeks 15-22), the inset figure shows weekly averages over the period 1926-2015.

Trend interpretation: linear regression over the time period 1926-2015 (orange line indicates intercept and slope), windows longer than 5 years with trend over a 40-year record (grey polygons indicate average intercept and slope for the windows), upward (purple line) and downward (blue line) change point according to the Pettitt test for different 40 year windows. This figure is available in colour online.

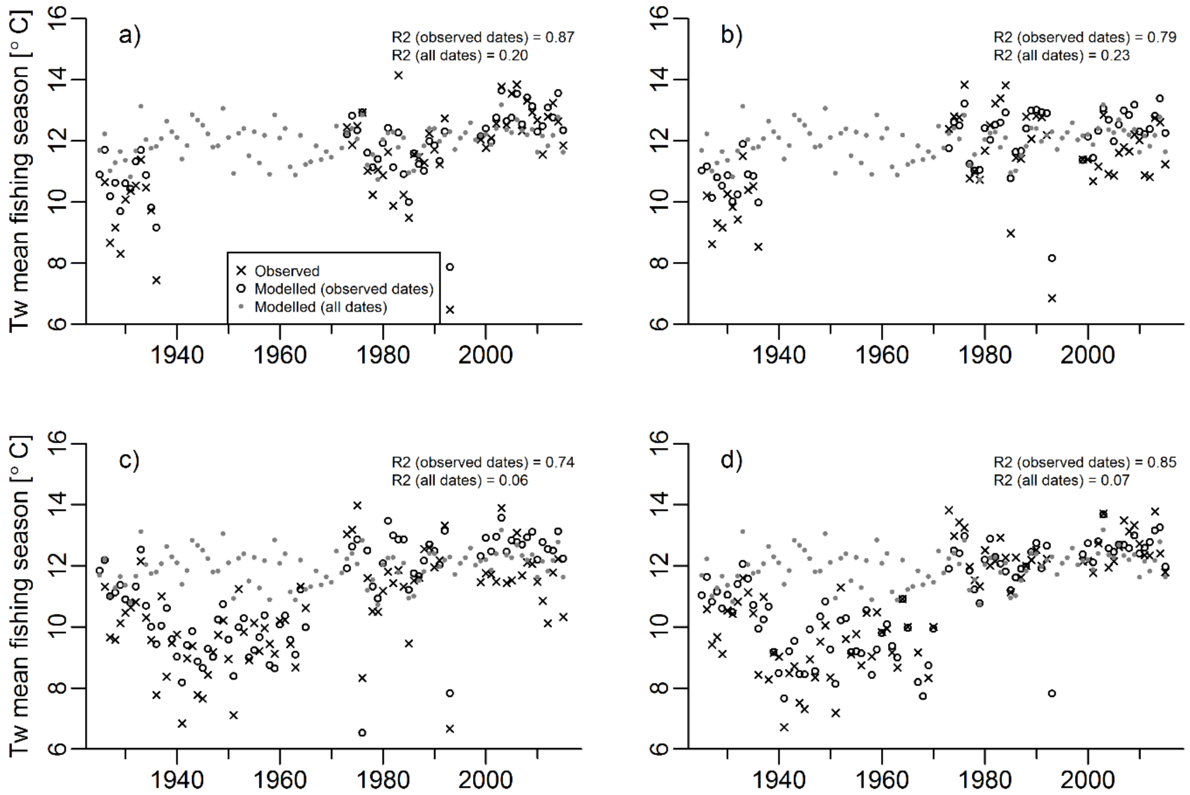

Figure 6. Observed and modelled river temperature aggregated for the fishing season of individual years: a) Beat A, b) Beat B, c) Beat C, d) Beat D. The modelled river temperature has been aggregated to averages in the fishing season considering only modelled values for which observations were available (observed dates) and for all values in the respective period (all dates). The coefficient of determination (R^2) refers to the aggregated values of the fishing season in individual years.