Influence of landscape and hydrological factors on stream–air temperature relationships at regional scale
Beaufort, Aurélien; Moatar, Florentina; Sauquet, Eric; Loicq, Pierre; Hannah, David M.

DOI: 10.1002/hyp.13608
License: Creative Commons: Attribution (CC BY)

Document Version
Publisher's PDF, also known as Version of record

Citation for published version (Harvard):
Beaufort, A, Moatar, F, Sauquet, E, Loicq, P & Hannah, DM 2020, 'Influence of landscape and hydrological factors on stream–air temperature relationships at regional scale', Hydrological Processes, vol. 34, no. 3, pp. 583-597. https://doi.org/10.1002/hyp.13608

Link to publication on Research at Birmingham portal

General rights
Unless a licence is specified above, all rights (including copyright and moral rights) in this document are retained by the authors and/or the copyright holders. The express permission of the copyright holder must be obtained for any use of this material other than for purposes permitted by law.

• Users may freely distribute the URL that is used to identify this publication.
• Users may download and/or print one copy of the publication from the University of Birmingham research portal for the purpose of private study or non-commercial research.
• Users may use extracts from the document in line with the concept of ‘fair dealing’ under the Copyright, Designs and Patents Act 1988 (?)
• Users may not further distribute the material nor use it for the purposes of commercial gain.

Where a licence is displayed above, please note the terms and conditions of the licence govern your use of this document.

When citing, please reference the published version.

Take down policy
While the University of Birmingham exercises care and attention in making items available there are rare occasions when an item has been uploaded in error or has been deemed to be commercially or otherwise sensitive.

If you believe that this is the case for this document, please contact UBIRA@lists.bham.ac.uk providing details and we will remove access to the work immediately and investigate.

Download date: 07. Nov. 2020
Influence of landscape and hydrological factors on stream–air temperature relationships at regional scale

Aurélien Beaufort1,2 | Florentina Moatar2 | Eric Sauquet2 | Pierre Loicq1 | David M. Hannah3

1EA 6293 GéHCO Géo-Hydrosystèmes Continentaux, Université François-Rabelais de Tours, Parc de Grandmont, Tours, 37200, France
2UR RiverLy, Irstea, centre de Lyon-Villeurbanne, 5 rue de la Doua CS 20244, Villeurbanne, 69625, France
3School of Geography, Earth and Environmental Sciences, University of Birmingham Edgbaston, Birmingham, B15 2TT, United Kingdom

Correspondence
Aurélien Beaufort, UR RiverLy, Irstea, centre de Lyon-Villeurbanne, 5 rue de la Doua CS 20244, Villeurbanne 69625, France.
Email: aurelien.beaufort@irstea.fr

Funding information
French Agency for Biodiversity

Abstract
Identifying the main controlling factors of the stream temperature (Tw) variability is important to target streams sensitive to climate and other drivers of change. The thermal sensitivity (TS), based on relationship between air temperature (Ta) and Tw, of a given stream can be used for quantifying the streams sensitivity to future climate change. This study aims to compare TS for a wide range of temperate streams located within a large French catchment (110,000 km²) using 4 years of hourly data (2008–2012) and to cluster stations sharing similar thermal variabilities and thereby identify environmental key drivers that modify TS at the regional scale. Two successive classifications were carried out: (a) first based on Ta–Tw relationship metrics including TS and (b) second to establish a link between a selection of environmental variables and clusters of stations. Based on weekly Ta–Tw relationships, the first classification identified four thermal regimes with differing annual Tw in terms of magnitude and amplitudes in comparison with Ta. The second classification, based on classification and regression tree method, succeeded to link each thermal regime to different environmental controlling factors. Streams influenced by both groundwater inflows and shading are the most moderated with the lowest TS and an annual amplitude of Tw around half of the annual amplitude of Ta. Inversely, stations located on large streams with a high distance from source and not (or slightly) influenced by groundwater inflows nor shading showed the highest TS, and so, they are very climate sensitive. These findings have implications for guiding river basin managers and other stakeholders in implementing thermal moderation measures in the context of a warming climate and global change.

KEYWORDS
CART method, classification, regional scale, stream temperature, thermal sensitivity

1 | INTRODUCTION

Water temperature (Tw) is a fundamental water quality parameter that controls aquatic community structure and affects ecological processes in rivers and streams (Caissie, 2006; Comte, Buisson, Daufresne, & Grenouillet, 2013; Jonsson & Jonsson, 2009; Webb, Hannah, Moore, Brown, & Nobilis, 2008). The impacts of global change on hydro-systems are potentially numerous and result from changes in extreme precipitation frequency and increased air temperature (Ta), evaporation, and dry periods (e.g., Garner, Hannah, & Watts, 2017; Watts...
et al., 2015). The rise of $Ta$ is expected resulting in warmer stream $Tw$ (Garner, Hannah, Sadler, & Orr, 2014; Hannah & Garner, 2015; Mohseni & Stefan, 1999; van Vliet et al., 2013), which could be exacerbated by the reducing of summer stream flows especially in temperate climate (Isaak et al., 2010; van Vliet et al., 2013). In France, several studies have already highlighted an increase in $Tw$ across various rivers (Bustillo, Moatar, Ducharme, Thiéry, & Poirel, 2014; Jackson, Fryer, Hannah, & Malcolm, 2017; Jackson, Fryer, Hannah, Millar, & Malcolm, 2018; Jackson, Hannah, Fryer, Millar, & Malcolm, 2017; Moatar & Gailhard, 2006). There is therefore a growing interest in understanding the spatio-temporal variability of river thermal regime given the likely effects of climate change (increase of both the $Ta$ and the evapotranspiration, shift in river flow regimes and of groundwater inflows, etc.; Webb et al., 2008; Moatar et al., 2010). The goal is to develop opportunities for mitigation and adaptive management of river systems (Boisneau, Moatar, Bodin, & Boisneau, 2008; Hrachowitz, Soulsby, Imholt, Malcolm, & Tetzlaff, 2010; Jackson, Malcolm, & Hannah, 2015; Kurylyk, MacQuarrie, Linnansaari, Cunjak, & Curry, 2015).

The $Tw$ variability, described by metrics of flow magnitude, frequency, duration, timing, and rate of change, on various timescales (Jones & Schmidt, 2018), is influenced by complex processes related to atmospheric, hydrogeological, geomorphic, and landscape characteristics and anthropogenic pressures, which could interact at multiple spatial scales (Caissie, 2006; Hannah & Garner, 2015). Numerous studies have highlighted the importance of riparian forest and groundwater inflows in moderating $Tw$ variability (Dugdale, Malcolm, Kantola, & Hannah, 2018; Garner, Malcolm, Sadler, & Hannah, 2017; Kelleher et al., 2012; Lalot et al., 2015; Loïc, Moatar, Jullian, Dugdale, & Hannah, 2018). Identifying the main controlling factors of $Tw$ variability remains an important task to target streams sensitive to climate change and to develop mitigation action to preserve aquatic ecosystems (Jackson et al., 2018).

Classification and regression tree (CART) of hydrological and landscape-dependent variables are informative and revealing methods to answer explore patterns without introducing an a priori structure of the link between explanatory variables and metrics describing $Tw$ variability (Arismendi, Johnson, Dunham, & Haggerty, 2013; Casado, Hannah, Peiry, & Campo, 2013; Chu, Jones, & Allin, 2009).

Some studies, in various parts of the world, considered explicitly and empirically the role of a limited number of basin properties on $Tw$ (e.g., Garner et al., 2014; Hrachowitz et al., 2010; Jackson et al., 2015; Faye L. Jackson, Fryer, et al., 2017; Faye L. Jackson et al., 2018; Jackson, Hannah, et al., 2017 in the UK; Isaak & Hubert, 2001; Isaak et al., 2010; Nelitz, Maclsaac, & Peterman, 2007, in North America). Analyses in most of these studies are carried out on a site-by-site basis, which limits the extent to which broad patterns can be inferred (Laizé, Bruna Meredith, Dunbar, & Hannah, 2017). Some regional-scale studies have used spatial thermal regime classification based on a large set of catchment properties (Chu et al., 2009; Laizé et al., 2017; Maheu, Poff, & St-Hilaire, 2016; Rivers-Moore, Dallas, & Morris, 2013; Tague, Farrell, Grant, Lewis, & Rey, 2007). These studies succeeded in identifying key drivers that influence the thermal regime of streams at the regional scale. Most of these studies use on metrics summarizing the warmest aspects of the $Tw$ regime to examine the threats to cold-water species under climate change.

Several researchers analyse the relationship between $Tw$ and $Ta$, with $Ta$ taken as a surrogate of the main climatic drivers (Ducharme, 2008; Garner et al., 2014). $Ta$ is a common variable, easily measured on the field, and it is strongly correlated to solar radiation (Bustillo et al., 2014). Kelleher et al. (2012) studied the thermal sensitivity ($TS$) of streams to represent the relative sensitivity of $Tw$ of a given stream to environmental change. $TS$ is defined as the slope of the regression line between $Ta$ and $Tw$, which can be linear (or logistic) and can be fitted on data averaged at different timescales (Mohseni & Stefan, 1999; O’Driscoll & DeWalle, 2006; Stefan & Preudhomme, 1993). $TS$ summarizes the cumulative buffering effects of local landscape characteristics on stream temperatures. Although $TS$ may evolve into the future due to the changing drivers considered above, $TS$ computed for a specific period of record gives insight of which streams have the greatest sensitivity to climate based on contemporary conditions, which can be used as a baseline for responsiveness (Kelleher et al., 2012). However, this integrated variable cannot distinguish the cause and effect of groundwater and riparian vegetation shading on $Tw$ variability (Chang & Psaris, 2013; Chu et al., 2009; O’Driscoll & DeWalle, 2006). Understanding the importance of these driving factors is essential to develop appropriate strategies to mitigate and adapt to stream heating under anticipated climate warming.

The aim of our study is (a) to provide a comparison of thermal sensitivity ($TS$) across a wide range of French temperate streams, based on 4 years of hourly data (2008–2012), and (b) to identify groups of streams with similar sensitivity and so infer the environmental key factors that control $TS$ at the regional scale. For that purpose, two successive classifications of 127 stations located in the Loire catchment (Beaufort et al., 2016) were carried out: (a) first based on $Ta$–$Tw$ relationship metrics including $TS$ and (b) second to establish a link between a selection of environmental variables and thermal regimes of stations. Finally, the relative importance of environmental variables on the $TS$ of streams is investigated, and the implication for river management and river restoration is discussed.

## 2 MATERIAL AND METHODS

### 2.1 Sites and temperature data

#### 2.1.1 Basin description

The Loire basin (Figure 1) comprises a hydrographical network of 88,000 km and drains a catchment area of 117,000 km². It is characterized by varying climates between the upstream and the downstream (annual rainfall between 550 and 2,100 mm/year and annual air temperature between 6°C and 12.5°C), landform (10% of the basin area >800 m; mean altitude = 300 m), and lithology (metamorphic, magmatic, and sedimentary rocks). The percentage of riparian vegetation, defined on a buffer zone of 10 m on both sides of the streams, is globally greater in the southern basin where the altitude is the highest (mean ratio of the riparian
vegetation = 75%; dark green; Figure 1c). Streams located in the central part of the basin, mainly composed of sedimentary rocks, benefit more from groundwater contributions (Figure 1d). The main aquifers are found in the sedimentary rocks in the centre of the basin. The Beauce formations (12,700 km²) are composed of many semipermeable aquifers (Mohseni & Stefan, 1999) with numerous groundwater inflows located at the north of the Loire basin. Some streams are very directly connected to this aquifer, and their flow depends on the level of the Beauce water table (Baratelli, Flipo, & Moatar, 2016).

### 2.1.2 Field monitoring

Tw was monitored, hourly, at 127 stations managed by the French Agency for Biodiversity (http://www.naiades.eaufrance.fr), between July 2008 and December 2012, distributed across the Loire basin (Figure 1b). The monitoring stations are mainly located on streams with a Strahler order between 3 and 5 (78% of stations). All monitoring stations are located on streams with low direct human influence on the flow regime, and all time series of Tw have been scrutinized to discard streams influenced by dam operations. The mean annual water temperatures of these stations range from 7.5°C to 15.7°C. The highest mean annual temperatures were observed on large rivers such as the Loire (Strahler Order 8) and its main tributaries, where mean annual Tw ranged between 14°C and 15.7°C between 2008 and 2012 (Figure 1a; Beaufort et al., 2016). Colder temperatures (<9°C) were observed in the upstream reaches of the Loire River where the altitude is above 1,000 m. The annual Tw at stations located on small streams (51 stations <30 km from upstream sources) did not exceed 13°C (Figure 1b). Moreover, gaps in Tw time series between 2008 and 2012 exist, and the proportion of missing values is about 35% on average for the 127 stations (80 stations with more than 20% of missing values).
values in time series). To limit biases in the calculation of indicators for each station, hydrological years with more than 15% of missing daily values (threshold based on previous studies (Beaufort et al., 2016; Aurélien Beaufort, Lamouroux, Pella, Datry, & Sauquet, 2018)) or with missing values during August or January are excluded from the analysis. The length of available records for the 127 stations time series varies between 1 (56 stations), 2 (29 stations), 3 (27 stations), and 4 years (15 stations).

The hourly $T_a$ was taken from the SAFRAN (Système d’analyse fournissant des renseignements atmosphériques à la neige) reanalysis data (grid 8 km) at hourly time step between 2008 to 2012 (Quintana-Seguí et al., 2008; Vidal, Martin, Franchistéguy, Baillon, & Soubeyroux, 2010). $T_a$ is extracted from the SAFRAN mesh (64 km$^2$) overlapping the station. The mean annual $T_a$ of these stations ranges from 6.4°C to 12.5°C. The coldest temperatures are observed in the mountainous part of the basin (mean annual $T_a < 10°C$), whereas the warmest temperatures are observed in the west and in the sedimentary plain (mean annual $T_a > 11°C$).

Both hourly $T_a$ and $T_w$ have been averaged over the day and over the week in the next section.

### 2.2 Metrics of air–water temperature relationship

We used four metrics to characterize the relation between air and water temperature. (a) Two of these metrics, the thermal sensitivity (TS) and intercept ($b$), provide information on the link between weekly $T_w$ and $T_a$ over the year. Weekly linear regressions were selected on the basis of the best mean $R^2$ fitted for the 127 stations in comparison with daily or logistic regressions.

For each station, a linear regression is fitted between the weekly $T_w$ ($T_{w7D}$) and the weekly $T_a$ ($T_{a7D}$) and the distribution of slopes, hereafter called thermal sensitivity (TS), and intercept ($b$) were analysed (Equation 1; Kelleher et al., 2012; O’Driscoll & DeWalle, 2006).

$$T_{w7D} = T_{a7D} \times TS + b. \tag{1}$$

(b) Two others metrics, $\Delta T_{Jan}$ and $\Delta T_{Aug}$, are based on the seasonal difference between monthly $T_w$ and $T_a$. For all stations, the monthly $T_w$ ($MT_w$) is the coldest in January and the warmest in August. To account for the relative sensitivity of $T_w$ during extreme months, we introduced two metrics, which are the differences between the monthly $T_w$ ($MT_w$) and $T_a$ in January ($\Delta T_{Jan}$) and in August ($\Delta T_{Aug}$) averaged between 2012 and 2016:

$$\Delta T_{Jan} = \frac{\sum_{i=1}^{Ny} (MT_{aJan}(i) - MT_{wJan}(i))}{Ny}, \tag{2}$$

$$\Delta T_{Aug} = \frac{\sum_{i=1}^{Ny} (MT_{aAug}(i) - MT_{wAug}(i))}{Ny}. \tag{3}$$

where $\Delta T$ is the mean difference between monthly $T_a$ ($MT_a$) and $T_w$ ($MT_w$) calculated in January or August, $MT_{aJan}(i)$ and $MT_{wJan}(i)$ are respectively the monthly $T_a$ in January and August of the year $i$, $MT_{aAug}(i)$ and $MT_{wAug}(i)$ are respectively the monthly $T_w$ in January and August of the year $i$, and $Ny$ is the number of year where monthly $T_a$ and $T_w$ are both available (1 ≤ $Ny$ ≤ 4, see Section 2.1).

### 2.3 Explanatory variables

A set of eight explanatory variables was selected to explain the observed spatial pattern in TS and identify main drivers of thermal streams moderation. The variable selection was based on the most pertinent variables identified in literature and on the results of a principal component analysis (not presented here) to minimize dependency between variables.

The distance from the source ($D$ in km) and the elevation ($E$ in m) are determined at the location of each monitoring station. The slope of the river reach ($S$ in m m$^{-1}$) where the station is located is determined with BD ALTI® 25-m resolution DTM dataset (IGN Paris, France). A higher $S$ increases the flow velocity, and $E$ influences $T_w$ through the association with the adiabatic lapse rates of $T_a$ and also through snow and glacier meltwater inflow, which should cool $T_w$ at higher elevations. Streams with a high $D$ have more time to equilibrate their $T_w$ with $T_a$.

Two hydrological indicators were also introduced. (a) The baseflow index ($BFi$) was estimated with the method of the Institute of Hydrology (1980) between 2008 and 2012. The $BFi$ is a measure of the proportion of the low-flow component to the total river flow with values between 0 and 1. Details on calculation can be found in Gustard, Bullock, and Dixon (1992). Low values are related to catchments with no storage capacity and also to catchments exposed to very high climate variability resulting in severe low-flow and quick run-off in response to rainfall events. High values are observed where artificial reservoirs, large aquifers, and storage in snow packs moderate the variability of daily flow. In our study, $BFi$ is considered as a proxy of groundwater influence. The discharge $Q$ was not monitored at $T_w$ station, and each $T_w$ station was coupled to the nearest gauging station (distance between both stations ranges from 10 m to 15 km). The matching is based on two criteria: (a) The gauging stations has to be located in the same or nearby streams and (b) the difference of catchment area between the location where $T_w$ was measured and the location where $Q$ was measured was kept to a maximum of ±20%. The daily discharge was extracted from the French river flow monitoring network (HYDRO database, http://www.hydro.eaufrance.fr/).

(b) The average specific discharge in August ($Q_{Aug}$) is calculated at each station between 2008 and 2012. The goal is to measure the capacity of the catchment to produce a flow in summer, when precipitation is low. The specific discharge is the ratio between the discharge and the corresponding catchment area (in L s$^{-1}$ km$^{-2}$) and is used to standardize discharge for basin area.

Two climatic variables were determined from the Safran reanalysis data: (a) the mean summer cumulated precipitation ($P$ in mm) and (b) the mean summer potential evapotranspiration ($PET$ in mm) both
calculated between June 1 and September 30 of each year between 2008 and 2012 for the entire upstream area of each monitoring station. Streams with wetter basin (high P and low PET) are expected to have higher water yields and more groundwater contributions that should cool streams (Isaak et al., 2017).

One variable was determined to characterize the riparian vegetation. A shading factor (SF), corresponding to a coefficient of reduction of the overall incident radiation, was estimated by Valette et al. (2012). SF gives the averaged vegetation cover (%) derived from a buffer of 10 m of vegetation polygons on both sides of reaches from the BD TOPO® database, provided by Institut national de l’information géographique et forestière (IGN). SF has been calculated between 7 a.m. and 9 p.m. over the summer period between June 1 and September 30 over the period 2008–2012, when the effect of shading is at its annual seasonal maximum for the North Hemisphere. The model of Li, Jackson, and Kraseski (2012) was implemented in its simplest version, that is, considering rectangular trees, located at the edge of the bank, without overhang.

\[ SF = \frac{H \times \cot \Psi \times \sin \delta}{W} \times \text{vc}, \]  

where \( H \) is the tree height (assumed to be 20 m everywhere), \( W \) is the stream width, estimated using the ESTIMKART empirical model (Lamouroux et al., 2010), \( \Psi \) is the solar elevation angle, \( \delta \) is the angle between solar azimuth and the mean azimuth (0–180°) of the river reach, and \( \text{vc} \) is the vegetation cover (%).

2.4 | Statistical classification and explanatory variables

2.4.1 | Thermal regimes clustering

To identify natural thermal regimes of stations sharing similar \( Ta-Tw \) relationship, an agglomerative hierarchical clustering (AHC) has been used. The AHC is based on the four metrics described above (\( TS, b, \Delta T_{\text{av}}, \text{ and } \Delta T_{\text{max}} \)). The Euclidean distance is used to measure the dissimilarity, and clusters are found with the Ward’s minimum variance method. The stability of clusters is assessed through a bootstrap approach with the \texttt{R} package “fpc” (Hennig, 2019), and the similarity between each new cluster set and initial cluster was assessed with the Jaccard index (Hennig, 2007; Maheu et al., 2016). The Jaccard coefficient ranges from 0 to 1, and a cluster with a coefficient larger than 0.75 can be considered as stable (Maheu et al., 2016). Each thermal regime identified is described in terms of magnitude (mean \( Tw \) over a month) and amplitude (differences between the maximum and minimum values of \( MTw \)) and compared with \( MTa \).

2.4.2 | Identification of environmental drivers in thermal sensitivity

A CART is used to examine the relationship between \( TS \) and the set of explanatory variables described above. CART analysis (Breiman, Friedman, Stone, & Olshen, 1984) is nonparametric and non-linear and does not introduce an a priori structure of the link between explanatory variables and the variable to be explained contrary to generalized linear models implicit assumption (Breiman et al., 1984; Ripley, 1996). CART recursively partitions observations in a matched data set, consisting of \( TS \) (response) and the eight explanatory variables, into progressively smaller groups (De’ath & Fabricius, 2000). Each partition is a binary split. During each recursion, splits for each explanatory variable are examined, and the split that leads to the most homogeneous subgroups with respect to the dependent variable is chosen. The interpretation of results summarized in a tree with series of logical if-then conditions (tree nodes) is very simple. We used the \texttt{R} package “rpart” (Version 4.1, Therneau & Atkinson, 2018) for implementing the CART model. The random forest (RF) model was used to assess the importance of explanatory variables for the prediction of \( TS \) and to evaluate the robustness of the classification. RF combines decision trees obtained by resampling the calibration set (Breiman, 2001), which is constituted by selecting randomly 80% of the observations (80% of 127 stations \( \times \) eight explanatory variables \( \times \) TS), and the test set consists of the remaining 20%. We used the implementation in the \texttt{R} package “randomForest” (Liaw & Wiener, 2002). The explanatory variable importance is given directly by the “randomForest” algorithm, which determines how much the mean square errors in prediction increases when that covariate is randomly permuted within the tree. The random selection is performed 100 times, and the explanatory variables importance for each test set was then averaged.

3 | RESULTS

3.1 | Distribution of thermal sensitivity and link with catchment size

The \( R^2 \) values for weekly \( Ta \) and \( Tw \) ranged from 0.83 to 0.98, with values greater than 0.9 at 123 of the 127 sites. \( TS \) ranges from 0.42 (Figure 2b) to 1.2 (Figure 2a), and \( b \) ranges from 0.5°C to 7.5°C. Regression lines plotted for the 127 stations showed a higher range of values of Tw when \( Ta \) is high at the regional scale (\( Tw \) ranges between 15°C and 30°C when \( Ta \) is 25°C) than when \( Ta \) is low (\( Tw \) ranges between 0°C and 7.5°C when \( Ta \) is 0°C; Figure 2c).

The relationship between \( TS \) and \( b \) shows a moderate negative correlation with \( R^2 \approx 0.7 \). Stations with the lowest \( TS \) (<0.6) and the highest \( b \) have the highest residual and seemed to follow a different pattern than other stations (Figure 3a; all the points are located above the regression line). Stations having a moderate \( TS \) between 0.6 and 0.9 are most often observed across the Loire River basin, and their associated \( b \) ranges from 1°C to 5°C. Stations with a high \( TS \) (>0.9) and a small \( b \) (<3) follow the same trend and have small residuals of the slope intercept regression. The analysis of weekly \( Ta-Tw \) relationship indicates that \( TS \) generally increases with stream size and the distance from source (Figure 3b). Streams with a distance from source higher than 100 km\(^2\) obtain a \( TS \) higher than 0.7. For small and medium rivers (\( D < 100 \text{ km} \)), the range of \( TS \) is large and between 0.42 and 1.
The analysis of the spatial distribution of $T_S$ in the Loire basin shows that the stations obtaining the smallest $T_S$ ($T_S < 0.5$) are located in the sedimentary plain where the main aquifer formations are located (Figure 4). The stations with the highest $T_S$ ($T_S > 0.9$) are located along large rivers in the sedimentary plain and in the western side of the basin where the altitudes are the lowest and $T_a$ the highest. Finally, stations located in the regions with the highest altitude obtain a moderate $T_S$ lower than 0.7.

### 3.2 Cluster classification analysis

The AHC yielded four clusters of station corresponding to four thermal regimes:

- **WarmHighVar**—warm and high variability (47 sites—37%): stations characterized by low $b$ (<3°C) and high $T_S$ (>0.8). At these stations, $MT_w$ is higher than $MT_a$ in January and August with a median difference of 1.5°C (Table 1). These stations are those with the highest annual amplitude of $MT_w$ reaching 18°C with similar annual $MT_a$ amplitude (red area; Figure 5a,b). Their $MT_w$s are the warmest during summer and exceed 21°C on average.
- **WarmLowVar**—warm and low variability (23 sites—18%): These stations are characterized by a smaller $T_S$ and a higher $b$ (median $b = 3.5°C$) than stations from WarmHighVar. $MT_a$ is less than $MT_w$ in winter with a median deviation of 3°C. In August, the $MT_w$ is very close to $MT_a$, and $\Delta T_{Aug}$ does not exceed 1°C. They have annual $MT_w$ amplitude of 14°C and $MT_w$ smaller than 4°C in...
summer in comparison with the MTw of stations from WarmHighVar (yellow area; Figure 5a,b).

- ColdHighVar—cold and high variability (44 sites—35%): Stations have MTw higher than MTa in January by 2°C (Table 1). Inversely, in August, MTw is less than MTa by 2°C. The TS and b of stations have rather average values with medians of 0.7 and 2.9, respectively. They have annual MTw amplitude of 14°C and MTw less than 5°C in summer in comparison with the MTw of stations from WarmHighVar (green area; Figure 5a,b).

- ColdLowVar—cold and low variability (13 sites—10%): Stations demonstrate the lowest TS of each class (TS < 0.7) and the highest b (greater than 4.9°C). The differences between MTw and MTa are high, in comparison with other thermal regimes, whether in August (MTa > MTw by 3.5°C) or in January (MTa < MTw by 4°C). These stations are those with the lowest annual MTw amplitude of 9°C, which is one half less than the amplitude of stations from WarmHighVar (blue area; Figure 5a). The MTw of stations from ColdLowVar is the lowest during summer (MTw = 15°C) and the warmest during winter in comparison with others thermal regimes (Figure 5c).

The thermal regimes named “WarmHighVar” and “ColdLowVar” were stable clusters and had a Jaccard coefficient larger than 0.7. The thermal regimes called “WarmLowVar” and “ColdHighVar” were less stable clusters and had Jaccard coefficients of 0.55 and 0.61, respectively. The analysis of the deviation from the mean annual Tw (MTw) and of MTw averaged over the four clusters identified by AHC led to distinguish significantly different thermal regime in terms of magnitude and amplitudes (Figure 5a,c) in comparison with MTa (Figure 5b,d).

The MTa patterns of each cluster demonstrate a very similar amplitude and magnitude (Figure 5b,d) with annual amplitude close to 18°C following the same amplitude of thermal regime WarmHighVar. The different response of each thermal regime to same climate conditions suggests other controlling factors than climate determine the annual amplitude and magnitude of Tw.

### 3.3 Drivers of thermal sensitivity (TS)

The CART model output leads to develop dichotomic tree plots to better visualize the effects of main drivers (Figure 7). The three most important explanatory variables used by the model to cluster stations as a function of their TS are SF, D (distance from source), and BFI (Figure 6). This is consistent with the RF model output where D, SF, and BFI are identified as the main environmental variables to explain the TS of streams (variable importance >15%; Figure 6). The variables QAug and S are also used to differentiate clusters in the CART model and obtained a moderate importance close to 8% with RF. Elevation (E) is identified as the fourth relevant variable with RF model (variable importance = 11%; Figure 6) but is not used by the CART model for

### TABLE 1 Metrics averaged for each thermal regime determined with the agglomerative hierarchical clustering

| Cluster                        | TS    | b     | ΔTJan | ΔTAug |
|-------------------------------|-------|-------|-------|-------|
| WarmHighVar—warm and high variability | Max   | 1.2   | −0.4  | 1.1   |
| 47 sites—37%                  | Med   | 0.9   | −1.4  | −1.6  |
|                               | Min   | 0.8   | −2.7  | −4.2  |
| WarmLowVar—warm and low variability | Max   | 0.8   | −1.7  | 1.0   |
| 23 sites—18%                  | Med   | 0.8   | −3.1  | −0.3  |
|                               | Min   | 0.7   | −4.0  | −1.1  |
| ColdHighVar—cold and high variability | Max   | 0.8   | −0.8  | 5.8   |
| 44 sites—35%                  | Med   | 0.7   | −1.8  | 1.9   |
|                               | Min   | 0.6   | −4.1  | 0.7   |
| ColdLowVar—cold and low variability | Max   | 0.7   | −2.9  | 4.7   |
| 13 sites—10%                  | Med   | 0.5   | −4.0  | 3.5   |
|                               | Min   | 0.4   | −5.7  | 1.1   |
stations clustering. Others variables have a lower influence on TS and are not used in the dichotomic tree plot from the CART model.

- **C1**—low TS with high SF and high BFI: The combined effect of a high SF (SF > 30%) and a high BFI (BFI > 0.8) led to strongly reduce TS of streams (mean TS of 0.5; Figure 7). The 11 stations having these characteristics belong to the thermal regime ColdLowVar (Table 2).

- **C2** and **C3**—low and moderate TS with high SF: Streams with an SF higher than 30% and a BFI less than 0.8 belong mostly to the thermal regime ColdHighVar from AHC results (Figure 7). \( Q_{\text{Aug}} \) has also an important influence, and we can see contrasts in terms of TS within this class. The TS was lower for the 17 stations located on streams with a \( Q_{\text{Aug}} \) value higher than 5 \( \text{L s}^{-1} \text{km}^{-2} \) (mean TS = 0.67; C2) than for the 29 remaining stations in C3 with a \( Q_{\text{Aug}} \) value less than 5 \( \text{L s}^{-1} \text{km}^{-2} \) (mean TS = 0.76).

- **C4**—moderate TS with low SF, low D, and high BFI: The six stations with SF less than 30%, a D less than 120 km, and a BFI greater than 0.8 have a moderate TS (mean TS of 0.71, C4) and belong to the two thermal regimes WarmLowVar and ColdLowVar (Table 2).

- **C5** and **C6**—moderate and high TS with low SF, low D, and low BFI: Stations located on small and medium streams (S < 120 km) with a BFI lower than 0.8 obtained moderate and high TS. The TS of the 13 stations located on streams with a higher slope (S > 2.5 m km\(^{-1}\))

**FIGURE 5** Representation of (a) the deviation from the mean annual \( T_w \), (b) the deviation from the mean annual \( T_a \), (c) the monthly \( T_w \), and (d) the monthly \( T_a \) averaged over the four thermal regimes identified by agglomerative hierarchical clustering. The colour area bars represent ± standard deviation of each series.

**FIGURE 6** Variable importance to explain TS for all stations ranking from the highest to the lowest obtained from random forest.
have a lower sensitivity (mean TS of 0.81; C5) in comparison with the 28 remaining stations from C6 (mean TS of 0.88; C6). The 13 stations in C5 mostly belong to the thermal regime WarmLowVar, whereas the 28 stations in C6 mostly belong to the thermal regime WarmHighVar (Table 2).

- C7—high TS with low SF, low D, and high BFI: Stations located on streams with low SF (SF < 30%) and a high D (D > 120 km) have the highest TS (mean TS of 1; C7; Figure 7). The 23 stations having these characteristics belong to the thermal regime WarmHighVar (Table 2).

4 | DISCUSSION

4.1 | Regression robustness and comparison with other studies

In our case study, best correlations between Ta and Tw were obtained with linear regression models and at the weekly time step, with a mean R² of 0.96 (standard deviation [SD] = 0.02) determined for the 127 stations. Weekly Ta–Tw linear regressions slightly outperform daily Ta–Tw linear regressions (mean R² = 0.88; SD = 0.03) as well as
daily (mean $R^2 = 0.86; SD = 0.05$) and weekly (mean $R^2 = 0.93; SD = 0.03$) logistic regressions. The weekly time step is more accurate because this time step filters out the lag time between $T_a$ and $T_w$ peaks, which can be of several days. In contrast to other studies (e.g., Kelleher et al., 2012), taking into account a non-linear relationship between $T_a$ and $T_w$ did not improve the performance of the regressions. This is probably explained by the fact that the Loire basin is not subject to $T_a$ (min weekly $T_a$ across the Loire basin between 2008 and 2012 = $-8^\circ\text{C}$) as low as in cold, continental regions studied in the contiguous United States (min $T_a = -20^\circ\text{C}$; Omid Mohseni, Stefan, & Erickson, 1998; Kelleher et al., 2012), which makes $T_a$–$T_w$ relationship more non-linear for low values. In comparison with the studies using weekly $T_a$–$T_w$ linear regressions, the $R^2$ values calculated on the 127 stations are on average higher (mean $R^2 = 0.96$) and comparable with the results of Webb (1992) and O’Driscoll and DeWalle (2006). The negative correlation between $TS$ and $b$ is also consistent with previous studies. Streams controlled by groundwater inflows are characterized by intercepts closer to the regional groundwater temperature and low slopes. Inversely, streams more sensitive to climate conditions have steeper slopes and lower intercepts closest to $Ta$.

Our $TS$ and $b$ range were consistent with other studies results for linear regression models using a weekly time scale (Table 3). These $TS$ and $b$ values were close to those found by Webb (1992), Stefan and Preud’homme (1993), and Morrill et al. (2005) except that we observe no negative $b$ and the range of our $TS$ and $b$ is slightly higher (Figure 8). This can be explained by a higher number of streams used in our study and by the larger size of the watershed compared with other studies (Table 3). O’Driscoll and DeWalle (2006), Kelleher et al. (2012), and Krider et al. (2013) obtained lower values of $TS$ and higher $b$ values for their studied streams located in karst basins.

### 4.2 Groundwater influence on $TS$  

In theory, groundwater influence is more visible on smaller streams because the volume of water is small and the travel time of the water from the source is short and not sufficient to equilibrate $T_w$ with the atmosphere (Beaufort et al., 2016; Mohseni & Stefan, 1999). Groundwater inflow is a heat source during winter and a heat sink during summer resulting in little seasonal variation in $T_a$ and a low $TS$ (Hannah, Malcolm, Soulsby, & Youngson, 2004; Kelleher et al., 2012). Stations with a thermal regime ColdLowVar have low $TS$ and a high intercept (median $b = 5.7^\circ\text{C}$). In other studies, low $TS$ could be due to the upstream influence of reservoirs or impoundments (Erickson & Stefan, 2000; Morrill et al., 2005) or to high groundwater contribution (Kelleher et al., 2012). The 13 stations from the thermal regime ColdLowVar have a reduced annual variation of $T_w$ (blue area; Figure 5a), and their low $TS$ could be reasonably related to the groundwater inflows that decrease $T_w$ response to changes in $T_a$ and increase the thermal inertia of streams (O’Driscoll & DeWalle, 2004). This statement is reinforced by their location on small streams above the main aquifer formations (Figure 4).

CART model results showed that all stations of the thermal regime ColdLowVar have $BFI$ greater than 0.8, which seems to confirm

---

**Table 3**: $TS$, $b$, and $R^2$ values found in reviewed publications for linear regression models of weekly $T_a$–$T_w$ relationship

| Study | Location | $TS$-slope | $b$-intercept | $R^2$ | Length of record | Kopp-Geiger climate designation |
|-------|----------|------------|--------------|-------|------------------|---------------------------------|
| Webb (1992) | 36 streams in the United Kingdom | 0.67 to 1.16 (1.00) | -0.4 to 1.1 (1.0) | 0.86 to 0.97 (0.99) | 1 to 8 years | Cfb |
| Stefan and Preud’homme (1993) | 11 rivers located in the Mississippi River (USA), 150,000 km² | 0.67 to 1.02 (0.86) | 0.4 to 5.2 (2.9) | 0.75 to 0.97 (0.89) | 1 to 8 years | Cfa/Dfa |
| Pilgrim, Feng, and Stefan (1998) | 39 streams in Minnesota (USA), 50,000 km² | 0.71 to 1.15 (0.99) | -0.15 to 4.8 (1.7) | 0.67 to 0.96 (0.89) | 1 to 32 years | Dfb/Dw/DNh/D Nh |
| Morrill, Naeser, and Concordt (2005) | 40 U.S. and international streams, 175,000 km² | 0.5 to 1.19 (-) | 0.15 to 5.86 (-) | 0.62 to 0.83 (-) | 1 to 12 years | Dfb/Dw/DNh/D Nh |
| O’Driscoll and DeWalle (2006) | 39 streams in Pennsylvania (USA), 15,000 km² | 0.3 to 1.06 (0.47) | 0.3 to 9.1 (6.1) | 0.83 to 0.97 (0.96) | 1 to 8 years | Cfa |
| Kelleher et al. (2012) | 12 streams in Pennsylvania (USA), 450 km² | 0.01 to 1.05 (-) | 0.09 to 0.98 (-) | 0.09 to 0.98 (-) | 2 years or greater | Dfa/Dfb/Cla |
| Chang and Psaris (2013) | 74 streams in the Columbia River basin (USA), 450 km² | 0.10 to 0.81 (-) | 0.10 to 0.81 (-) | 0.1 to 0.72 (0.3) | 2 years or greater | Dfa/Dfb/Cla |
| Krider, Magner, Perry, Vanderack, and Ferrington (2013) | 177 streams in the Loire basin, 110,000 km² | 0.10 to 1.19 (-) | 0.10 to 1.19 (-) | 0.1 to 1.19 (-) | 2 years or greater | Cfa |

Note. The value in brackets corresponds to the average value.
groundwater influences (C1 and C4; Figure 7). The decrease of TS is accentuated when a high BFI is combined with an SF higher than 30% as on the 11 stations in C1 (mean TS = 0.5). The shading of riparian vegetation leads to increase the thermal moderation of surface water in summer by shading from solar radiation. The BFI appears as a very influential variable in TS (Figure 6). However, in the Loire basin, TS remains greater than 0.4 even when the BFI is higher than 0.8 and when b is higher than 6°C. In other studies, TS values are close to 0 when the BFI is close to 1 (Kelleher et al., 2012). It could be suspected that the temperature of groundwater inflows feeding streams follows a seasonal trend correlated with $T_a$ and more marked than those observed in the literature (Kelleher et al., 2012; Krider et al., 2013; O’Driscoll & DeWalle, 2006). This could also explain the high residuals of slope intercept regression for stations having a TS lower than 0.6 (Figure 3a).

The variable $Q_{Aug}$ is the mean specific discharge during the warmest month and represents the sustainability of low flows. It is a moderately influential variable in TS (Figure 6). It can be assumed that a stream with a high $Q_{Aug}$ in the case of natural flowing, benefits from groundwater inflows and/or of important contribution of its tributaries allowing it to maintain a sufficient depth to moderate $T_w$ in summer. CART analysis results showed that streams with a $Q_{Aug}$ value higher than 5 L s$^{-1}$ km$^{-2}$, associated to an SF less than 30% and a BFI less than 0.8, have a lower TS than others stations (C2 vs. C3; Figure 7), which seems to confirm our assumption. However, the importance of $Q_{Aug}$ remains applies to a subset of stations and the BFI remains the main variable representing the influence of groundwater inflows in our dataset.

4.3 | Riparian shading influence on TS

Shortwave (solar) radiation is one of the most influential factors that influence stream temperature and is related directly to the amount of shading provided by riparian vegetation (O’Driscoll & DeWalle, 2006; Sinokrot & Stefan, 1993). The riparian vegetation captures solar radiation and leads to reduced $T_w$ resulting in a decrease of TS. This effect is particularly visible in summer when the solar radiation is the strongest and represents the main source of energy inputs (e.g., Hannah, Malcolm, Soulsby, & Youngson, 2008). In addition, the riparian vegetation of the Loire basin is mainly composed of deciduous trees, which considerably limit the effect of shading in winter. The influence of the riparian vegetation shading on TS was highlighted by several studies (Chang & Psaris, 2013; Dugdale et al., 2018; Garner, Malcolm, et al., 2017; Hrachowitz et al., 2010; F.L. Jackson et al., 2017; Loicq et al., 2018). However, it is still complex to characterize the own effect of riparian shading, and shading effect is regularly lumped to other drivers of TS moderation (Kelleher et al., 2012; O’Driscoll & DeWalle, 2006).

In our study, we tried to differentiate the effects of shading and of groundwater inflows. The only study of TS and b does not allow to clearly make this distinction because the effect of riparian vegetation shading could be mixed with the effect of groundwater inflows. The $\Delta T_{Jan}$ and $\Delta T_{Aug}$ were introduced in the AHC model to help make this distinction. Stations in thermal regime WarmHighVar have a high TS (TS > 0.8) combined to a small intercept ($b < 3.5^\circ C$) and are supposed the most influenced by climate and $T_a$. Their amplitude and magnitude of $M_{Ta}$ and $M_{Tw}$ are very similar and follow the same trend (amplitude of 18°C; Figure 5a) and do not seem to be moderated by any drivers. Stations in thermal regime ColdHighVar have a lower TS (TS < 0.8) and slightly higher intercept (median $b = 2.9^\circ C$) than in thermal regime WarmHighVar (Table 1). Between thermal regimes ColdHighVar and WarmHighVar, their $\Delta T_{Jan}$ is similar ($\Delta T_{Jan} = -1.6^\circ C$), but $T_w$ is clearly lower than $T_a$ during August for stations in thermal regime ColdHighVar (median $\Delta T_{Aug} = 1.9$). The influence of the riparian vegetation shading is suspected. CART model results seems to confirm this assumption because all stations in ColdHighVar were identified with an SF higher than 30% (C2 and C4; Figure 7). The effects of shading could be accentuated when the specific discharge in August is higher than 5 L s$^{-1}$ km$^{-2}$ (C2; TS ≈ 0.67) because the thermal inertia of the streams is increased.

4.4 | Landscape factors influence

The distance from the source ($D$) is a key driver of TS (Figure 6). CART model results showed that stations with a $D$ higher than 120 km obtained the highest TS ($TS = 1$; C7; Figure 7). $D$ is highly positively correlated with the drainage area, and several studies identified this driver as playing an important role in the TS of rivers (Chang & Psaris, 2013; Garner et al., 2014; Hrachowitz et al., 2010; Imholt et al., 2013). Some others studies have also identified the Strahler order, which is correlated to $D$ ($R^2 = 0.6$), as a strong influence factor of TS (Chang & Psaris, 2013; Ducharme, 2008; Kelleher et al., 2012; Wehrly, Wiley, & Seelbach, 1998). Streams with a high $D$ and a large drainage area are weakly dependent on upstream conditions, and the travel time of the water body between upstream and downstream allows $T_w$ to equilibrate with $T_a$ (Mohseni & Stefan, 1999), leading to increase TS. Also, a longer $D$ and a larger

---

**FIGURE 8** Representation of the range of TS and b found in reviewed publications for linear regression models of weekly $T_a$-Tw relationship

$\Delta T_{Jan}$ and $\Delta T_{Aug}$ were used in the AHC model to help make this distinction. Stations in thermal regime WarmHighVar have a high TS (TS > 0.8) combined to a small intercept ($b < 3.5^\circ C$) and are supposed the most influenced by climate and $T_a$. Their amplitude and magnitude of $M_{Ta}$ and $M_{Tw}$ are very similar and follow the same trend (amplitude of 18°C; Figure 5a) and do not seem to be moderated by any drivers. Stations in thermal regime ColdHighVar have a lower TS (TS < 0.8) and slightly higher intercept (median $b = 2.9^\circ C$) than in thermal regime WarmHighVar (Table 1). Between thermal regimes ColdHighVar and WarmHighVar, their $\Delta T_{Jan}$ is similar ($\Delta T_{Jan} = -1.6^\circ C$), but $T_w$ is clearly lower than $T_a$ during August for stations in thermal regime ColdHighVar (median $\Delta T_{Aug} = 1.9$). The influence of the riparian vegetation shading is suspected. CART model results seems to confirm this assumption because all stations in ColdHighVar were identified with an SF higher than 30% (C2 and C4; Figure 7). The effects of shading could be accentuated when the specific discharge in August is higher than 5 L s$^{-1}$ km$^{-2}$ (C2; TS ≈ 0.67) because the thermal inertia of the streams is increased.

4.4 | Landscape factors influence

The distance from the source ($D$) is a key driver of TS (Figure 6). CART model results showed that stations with a $D$ higher than 120 km obtained the highest TS ($TS = 1$; C7; Figure 7). $D$ is highly positively correlated with the drainage area, and several studies identified this driver as playing an important role in the TS of rivers (Chang & Psaris, 2013; Garner et al., 2014; Hrachowitz et al., 2010; Imholt et al., 2013). Some others studies have also identified the Strahler order, which is correlated to $D$ ($R^2 = 0.6$), as a strong influence factor of TS (Chang & Psaris, 2013; Ducharme, 2008; Kelleher et al., 2012; Wehrly, Wiley, & Seelbach, 1998). Streams with a high $D$ and a large drainage area are weakly dependent on upstream conditions, and the travel time of the water body between upstream and downstream allows $T_w$ to equilibrate with $T_a$ (Mohseni & Stefan, 1999), leading to increase TS. Also, a longer $D$ and a larger
catchment area corresponds to lower topographical slopes, slower flow velocities, and greater regional residence time, which allow more time for $Tw$ to adjust to local $Ta$ (Mayer, 2012).

Stations located on small and medium streams, not influenced by shading and groundwater inflows ($SF < 30\%$; $BFI < 0.8$; and $D < 120$ km) belonging to cluster C5 and C6 (Figure 7), obtained a $TS$ less than those of large rivers in C7. There is an influence of $S$ because stations located on streams with a high slope ($S < 2.5$ m km$^{-1}$) had a mean $TS$ of 0.8 (C5; Figure 7), whereas others had a mean $TS$ of 0.88 (Cluster C6; Figure 7). The stream slope is mostly linked to elevation ($R^2 = 0.65$). A higher slope increases the flow velocity, and the elevation influences $Tw$ over the adiabatic lapse rates of $Ta$ (Hrachowitz et al., 2010) and also through snow and glacier meltwater inflow (Arora, Toffolon, Tockner, & Venohr, 2018; Morrill et al., 2005), which may contribute to decrease $TS$. $P$ and $PET$ are not relevant in CART model, which may be explained by the relative climatic homogeneity of the study area (Cfb = temperate oceanic climate, Table 3).

4.5 | Implication for river management and river restoration

The study of streams $TS$ makes it possible to identify the most sensitive streams to environmental change (high $TS$) and potentially the most sensitive to the effects of climate change. The stationarity of all processes influencing $Tw$ is difficult to estimate because it implies the use of physically based models directly integrating energy fluxes because the only study of $TS$ tends to underestimate the warming of climate change (Leach & Moore, 2019). However, streams studied here have a natural thermal regime and are not influenced by anthropogenic activities. These natural streams sensitive to environmental changes in the present time (high $TS$) will always be sensitive to environmental changes in the future without human actions. The goal of our approach is to identify the most climate-sensitive streams, linking them to environmental or hydrological features, to guide stakeholders to pay particular attention to them.

Our analysis identified $D$, $BFI$, and $SF$ as the main factors influencing $TS$ in the Loire basin. The major streams of the Loire catchment ($D > 120$ km) show the highest $TS$ value (mean $TS = 1$) and appear highly sensitive to the effects of global warming. For these streams having a large wet width ($>50$ m), the effects of shading from riparian vegetation are very small, and actions to reduce $TS$ are limited. Thermal anomalies could be detected by aerial infrared survey (Wawrzyniak, Pliégay, & Poirel, 2011) and be preserved by limiting advective thermal mixing (Kurylyk et al., 2015) or activated by geomorphological restoration of streams (Eschbach et al., 2017; Loheide & Gorelick, 2006). On small and medium streams, it is necessary to preserve and/or favour the presence of riparian vegetation to moderate $TS$ (Fabris, Malcolm, Buddendorf, & Soulsby, 2018). The effects will be most pronounced, in comparison with large streams, because of their smaller width, but investments have to be made strategically (Isaak et al., 2017; Johnson & Wilby, 2015). From a watershed management perspective, stream shading would be less effective in streams where $Tw$ is already strongly moderated by groundwater inflows but more effective along losing reaches or stream reaches distant from groundwater inflows (O’Driscoll & DeWalle, 2006).

Streams with a low $TS$ have a limited surface water heating during summer and may provide thermal refuges for thermo-sensitive aquatic species (macroinvertebrates, stream-dwelling amphibians, and fish species; Isaak et al., 2017). In order to limit these warmings and preserve ecosystems, it seems important to identify streams constituting cold-water thermal refuges (with low $TS$) and to restore and preserve thermal diversity in the hydrographical network (Torgersen, Ebersole, & Keenan, 2012). However, the main factors limiting $TS$ ($BFI$ and $SF$) could change in the future, and several streams could become much more sensitive to environmental change (Leach & Moore, 2019). For example, the loss in groundwater inflows would result in greater meteorological controls increasing the annual amplitude of $Tw$ (O’Driscoll & DeWalle, 2006). Limiting water abstraction during low-flow periods may avoid a disconnection of groundwater/surface water exchanges and ensure environmental flows during the summer (Elmore, Null, & Mouzon, 2016). Some cooling strategies proposed to reconnect streams to floodplains and to facilitate greater lateral and hyporheic flow exchanges (Beechie et al., 2012; Daniel Caissie & Luce, 2017; Kurylyk et al., 2015) but need to be tested at a regional scale. To apply efficient and effective actions, river managers have to focus on small and medium streams and can use the environmental variables identified in our classification results as indicators to assess the climate sensitivity of unmonitored streams.

5 | CONCLUSION

In this study, we proposed a framework to compare thermal sensitivity ($TS$) for 127 stations located on temperate streams between 2008 and 2012 and to cluster stations sharing similar natural thermal regimes, not influence by anthropogenic effects. On the basis of weekly $Ta$–$Tw$ relationships, four thermal regimes were identified with differing annual $Tw$ in terms of magnitude and amplitudes in comparison with $Ta$. We linked each cluster to different environmental controlling factors as inferred by $TS$. This highlighted that shading from riparian vegetation, groundwater inflows, and the distance from the source of streams were the main drivers of the moderation of streams located in the Loire catchment. Streams influenced by both groundwater inflows and shading are the most moderated with the lowest $TS$ and an annual amplitude of $Tw$ around half the annual amplitude of $Ta$. Inversely, stations located on large streams or on streams slightly or not influenced by groundwater inflows and/or shading showed the highest $TS$ and are very climate sensitive. Their $Tw$ amplitude and magnitude were very close to those of $Ta$; consequently, these rivers are deemed the most sensitive to the effects of future climate change.

The $Tw$ metrics and the environmental variables remain simple to determine and can easily be applied in others catchments at a regional scale. One of the perspectives to this work would be to explore if main controlling factors of the $Tw$ variability identified here are the same in different climate and physiographical regions elsewhere. We observe that almost invariability streams studied in reviewed publications for
linear regression models of weekly \(Ta-Tw\) relationship (Table 3) correspond to temperate and continental climatic regions. It would be interesting to study streams from different climatic contexts to understand how controls of TS may vary. Furthermore, it would be insightful to explore how TS may be modified by anthropogenic effects (dams, weirs, and other flow augmentation/abstractions, etc.). Management agencies can use our findings on thermal sensitivity for prioritizing restoration areas to moderate stream temperature and undertake mitigation and adaptation actions to protect sensitive aquatic species in the context of a changing environment.

**DATA AVAILABILITY STATEMENT**

Temperature used in this study are available from the French Biodiversity Agency (AFB; www.afbiodiversite.fr). Restrictions apply to the availability of these data, which were used under license herein. Data are available at http://www.naiades.eaufrance.fr with the permission of the French Biodiversity Agency (www.naiades.eaufrance.fr/formulaire/contact). Discharge data are available from the French river flow monitoring network (HYDRO database, http://www.hydro.eaufrance.fr/). Restrictions apply to the availability of meteorological data, which were used under license herein with the permission of Météo France (www.meteo.fr).

**ACKNOWLEDGMENTS**

The authors wish to thank the two reviewers for their valuable comments, suggestions, and positive feedback on the manuscript. The research project was funded by the French Agency for Biodiversity (AFB). Thanks are due to the AFB, the DREAL Auvergne, the DREAL Pays de Loire and the DREAL Centre for the temperature data.

**ORCID**

Aurélien Beaufort https://orcid.org/0000-0002-6523-8269
Florentina Moatar https://orcid.org/0000-0002-9251-6420
Eric Sauquet https://orcid.org/0000-0001-9539-7730
David M. Hannah https://orcid.org/0000-0003-1714-1240

**REFERENCES**

Arismendi, I., Johnson, S. L., Dunham, J. B., & Haggerty, R. (2013). Descriptors of natural thermal regimes in streams and their responsiveness to change in the Pacific Northwest of North America. *Freshwater Biology*, 58(5), 880–894. https://doi.org/10.1111/fwb.12094

Arora, R., Toffolon, M., Tockner, K., & Venohr, M. (2018). Thermal discontinuities along a lowland river: The importance of urban areas and lakes. *Journal of Hydrology*, 564, 811–823. https://doi.org/10.1016/j.jhydrol.2018.05.066

Baratelli, F., Flipo, N., & Moatar, F. (2016). Estimation of stream–aquifer exchanges at regional scale using a distributed model: Sensitivity to in-stream water level fluctuations, riverbed elevation and roughness. *Journal of Hydrology*, 542, 686–703. https://doi.org/10.1016/j.jhydrol.2016.09.041

Beaufort, A., Lamouroux, N., Pella, H., Darty, T., & Sauquet, E. (2018). Extrapolating regional probability of drying of headwater streams using discrete observations and gauging networks. *Hydrology and Earth System Sciences*, 22(5), 3033–3051. https://doi.org/10.5194/hess-22-3033-2018

Beaufort, A., Moatar, F., Curié, F., Ducharme, A., Bustillo, V., & Thiéry, D. (2016). River temperature modelling by Strahler order at the regional scale in the Loire River basin, France. *River Research and Applications*, 32(4), 597–609. https://doi.org/10.1002/rra.2888

Beechie, T., Imaki, H., Greene, J., Wade, A., Wu, H., Pess, G., ... Mantua, N. (2012). Restoring salmon habitat for a changing climate: Restoring salmon habitat for a changing climate. *River Research and Applications*, 939–960. https://doi.org/10.1002/rra.2590

Boisneau, C., Moatar, F., Bodin, M., & Boisneau, P. (2008). Does global warming impact on migration patterns and recruitment of Allis shad (*Alosa alosa*) young of the year in the Loire River, France? *Hydrobiologia*, 602, 179–186. https://doi.org/10.1007/s10750-008-9291-6

Breiman, L. (2001). Random forests. *Machine learning*, 45(1), 5–32. https://doi.org/10.1023/A:1010933404324

Breiman, L., Friedman, J., Stone, C. J., & Olshen, R. A. (1984). Classification and regression trees (Wadsworth International Group).

Bustillo, V., Moatar, F., Ducharme, A., Thiéry, D., & Poirel, A. (2014). A multimodel comparison for assessing water temperatures under changing climate conditions via the equilibrium temperature concept: Case study of the Middle Loire River, France. *Hydrological Processes*, 28(3), 1507–1524. https://doi.org/10.1002/hyp.9683

Caisse, D. (2006). The thermal regime of rivers: A review. *Freshwater Biology*, 51(8), 1389–1406. https://doi.org/10.1111/j.1365-2427.2006.01597.x

Caisse, D., & Luce, C. H. (2017). Quantifying streambed advection and conduction heat fluxes. *Water Resources Research*, 53(2), 1595–1624. https://doi.org/10.1002/2016WR019813

Casado, A., Hannah, D. M., Peiry, J.-L., & Campo, A. M. (2013). Influence of dam-induced hydrological regulation on summer water temperature: Sauce Grande River, Argentina. *Ecohydrology*, 6(4), 523–535. https://doi.org/10.1002/eco.1375

Chang, H., & Psaris, M. (2013). Local landscape predictors of maximum stream temperature and thermal sensitivity in the Columbia River Basin, USA. *Science of The Total Environment*, 461-462, 587–600. https://doi.org/10.1016/j.scitotenv.2013.05.033

Chu, C., Jones, N. E., & Allin, L. (2009). Linking the thermal regimes of streams in the Great Lakes Basin, Ontario, to landscape and climate variables. *River Research and Applications*, n/a-n/a. https://doi.org/10.1002/rra.1259

Comte, L., Buisson, L., Daufresne, M., & Grenouillet, G. (2013). Climate-induced changes in the distribution of freshwater fish: Observed and predicted trends. *Freshwater Biology*, 58(4), 625–639. https://doi.org/10.1111/fwb.12081

De’ath, G., & Fabricius, K. E. (2000). Classification and regression trees: A powerful yet simple technique for ecological data analysis. *Ecology*, 81(11), 3178–3192. https://doi.org/10.1890/0012-9658(2000)081[3178:CARTAP]2.0.CO;2

Ducharme, A. (2008). Importance of stream temperature to climate change impact on water quality. *Hydro. Earth Syst. Sci.*, 14.

Dugdale, S. J., Malcolm, I. A., Kantola, K., & Hannah, D. M. (2018). Stream temperature under contrasting riparian forest cover: Understanding thermal dynamics and heat exchange processes. *Science of The Total Environment*, 610-611, 1375–1389. https://doi.org/10.1016/j.scitotenv.2017.08.198

Elmore, L. R., Null, S. E., & Mouzon, N. R. (2016). Effects of environmental water transfers on stream temperatures: Effects of environmental water transfers. *River Research and Applications*, 32(7), 1415–1427. https://doi.org/10.1002/rra.2994
Li, G., Jackson, C. R., & Kruseski, K. A. (2012). Modeled riparian stream shading: Agreement with field measurements and sensitivity to riparian conditions. Journal of Hydrology, 428–429, 142–151. https://doi.org/10.1016/j.jhydrol.2012.01.032

Liaw, A., & Wiener, M. (2002). Classification and Regression by randomForest. 2, 5.

Loheide, S. P., & Gorelick, S. M. (2006). Quantifying stream–aquaer interactions through the analysis of remotely sensed thermographic profiles and in situ temperature histories. Environmental Science & Technology, 40(10), 3336–3341. https://doi.org/10.1021/es0522074

Loicq, P., Moatar, F., Jullian, Y., Dugdale, S. J., & Hannah, D. M. (2018). Improving representation of riparian vegetation shading in a regional stream temperature model using LIDAR data. Science of The Total Environment, 624, 480–490. https://doi.org/10.1016/j.scitotenv.2017.12.129

Mahieu, A., Poff, N. L., & St-Hilaire, A. (2016). A classification of stream water temperature regimes in the conterminous USA: Classification of stream temperature regimes. River Research and Applications, 32(5), 896–906. https://doi.org/10.1002/rra.2906

Mayer, T. D. (2012). Controls of summer stream temperature in the Pacific Northwest. Journal of Hydrology, 475, 323–335. https://doi.org/10.1016/j.jhydrol.2012.10.012

Moatar, F., Ducharme, A., Thiéry, D., Bustillo, V., Sauquet, E., & Vidal, J. P. (2010). La Loire à l’épreuve du changement climatique. Géosciences, 12, 78–87. http://www.brgm.fr/doc/newsFile?id=13006

Moatar, F., & Gailhard, J. (2006). Water temperature behaviour in the River Loire since 1976 and 1881. Comptes Rendus Geoscience, 338(5), 319–328. https://doi.org/10.1016/j.crte.2006.02.011

Mohseni, O., & Stefan, H. G. (1999). Stream temperature/air temperature relationship: A physical interpretation. Journal of hydrology, 218(3), 128–141.

Mohseni, O., Stefan, H. G., & Erickson, T. R. (1998). A nonlinear regression model for weekly stream temperatures. Water Resources Research, 34(10), 2685–2692. https://doi.org/10.1029/98WR01877

Morrill, J. C., Bales, R. C., & Conklin, M. H. (2005). Estimating stream temperature from air temperature: Implications for future water quality. Journal of Environmental Engineering, 131(1), 139–146. https://doi.org/10.1061/(ASCE)0733-9372(2005)131:1(139)

Nelitz, M. A., Maclsaac, E. A., & Peterman, R. M. (2007). A science-based model for weekly stream temperatures. Water Resources Research, 43(1), 428–429. https://doi.org/10.1029/2006WR005406

O’Driscoll, M. A., & DeWalle, D. R. (2004). Stream–air temperature relationships as indicators of groundwater inputs. 2(6), 5.

O’Driscoll, M. A., & DeWalle, D. R. (2006). Stream–air temperature relations to classify stream–ground water interactions in a karst setting, central Pennsylvania, USA. Journal of Hydrology, 329(1-2), 140–153. https://doi.org/10.1016/j.jhydrol.2006.02.010

Pilgrim, J. M., Fang, X., & Stefan, H. G. (1998). Stream temperature correlations with air temperatures in Minnesota: Implications for climate warming. Journal of the American Water Resources Association, 34(5), 1109–1121. https://doi.org/10.1111/j.1752-1688.1998.tb04158.x

Quintana-Segui, P., Le Moigne, P., Durand, Y., Martin, E., Habets, F., Baillon, M., ... Morel, S. (2008). Analysis of near-surface atmospheric variables: Validation of the SAFRAN analysis over France. Journal of Applied Meteorology and Climatology, 47(1), 92–107. https://doi.org/10.1175/2007JAMC1636.1

Ripley, B. D. (1996). Pattern recognition and neural networks. Cambridge: Cambridge University Press.

Rivers-Moore, N. A., Dallas, H. F., & Morris, C. (2013). Towards setting environmental water temperature guidelines: A South African example. Journal of Environmental Management, 128, 380–392. https://doi.org/10.1016/j.jenvman.2013.04.059

Sinokrot, B. A., & Stefan, H. G. (1993). Stream temperature dynamics: Measurements and modeling. Water Resources Research, 29(7), 2299–2312. https://doi.org/10.1029/93WR00540

Stefan, H. G., & Preud’homme, E. B. (1993). Stream temperature estimation from air temperature. Journal of the American Water Resources Association, 29(1), 27–45. https://doi.org/10.1111/j.1752-1688.1993.tb01502.x

Tague, C., Farrell, M., Grant, G., Lewis, S., & Rey, S. (2007). Hydrogeologic controls on summer stream temperatures in the McKenzie River basin, Oregon. Hydrological Processes, 21(24), 3288–3300. https://doi.org/10.1002/hyp.6538

Therneau, T., & Atkinson, B. (2018). rpart: Recursive partitioning and regression trees. R package version. 4, 1–13. https://CRAN.R-project.org/package=rpart

Torgersen, C. E., Ebersole, J. L., & Keenan, D. M. (2012). Primer for identifying cold-water refuges to protect and restore thermal diversity in riverine landscapes. U.S. Environmental Protection Agency, EPA 910-C-12-001, 91.

Valette, L., Pillfady, J., Chandesris, A., & Souchon, Y. (2012). SYRAH-CE: description des données et modélisation du risque d’altération de l’hydromorphologie des cours d’eau pour l’Etat des lieux DCE. Rapport final, Pôle Hydroécologie des cours d’eau Onema-Irstea Lyon. MALY-LHQ, Lyon.

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. Global Environmental Change, 23(2), 450–464. https://doi.org/10.1016/j.gloenvcha.2012.11.002

Vidal, J.-P., Martin, E., Franchistéguy, L., Baillon, M., & Soubeyroux, J.-M. (2010). A 50-year high-resolution atmospheric reanalysis over France with the Safran system. International Journal of Climatology, 30(11), 1627–1644. https://doi.org/10.1002/joc.2003

Watts, G., Battarbee, R. W., Bloomfield, J. P., Crossman, J., Daccache, A., Durance, I., ... Wilby, R. L. (2015). Climate change and water in the UK—Past changes and future prospects. Progress in Physical Geography: Earth and Environment, 39(1), 6–28. https://doi.org/10.1177/030913331452957

Wawrzyniak, V., Piégay, H., & Poirel, A. (2012). Longitudinal and temporal thermal patterns of the French Rhône River using Landsat ETM+ thermal infrared images. Aquatic Sciences, 74(3), 405–414. https://doi.org/10.1007/s00227-011-0235-2

Watts, G. D., Battarbee, R., Bloomfield, J. P., Crossman, J., Daccache, A., Durance, I., ... Wilby, R. L. (2015). Climate change and water in the UK—Past changes and future prospects. Progress in Physical Geography: Earth and Environment, 39(1), 6–28. https://doi.org/10.1177/030913331452957

Webh, B. W., Hannah, D. M., Moore, R. D., Brown, L. E., & Nobilis, F. (2008). Recent advances in stream and river temperature research. Hydrological Processes, 22(7), 902–918. https://doi.org/10.1002/hyp.6994

Wellry, K. E., Wiley, M. J., & Seelbach, P. W. (1998). Landscape-based models that predict July thermal characteristics of lower Michigan rivers. Michigan Department of Natural Resources, 2037, 24.

How to cite this article: Beaufort A, Moatar F, Sauquet E, Loicq P, Hannah D. Influence of landscape and hydrological factors on stream–air temperature relationships at regional scale. Hydrological Processes. 2020;34:583–597. https://doi.org/10.1002/hyp.13608