Hydrological Sciences Journal

ISSN: 0262-6667 (Print) 2150-3435 (Online) Journal homepage: https://www.tandfonline.com/loi/thsj20

Optimization methodology for a river temperature monitoring network for the characterization of fish thermal habitat

Anik Daigle, Arnaud Caudron, Laure Vigier & Hervé Pella

To cite this article: Anik Daigle, Arnaud Caudron, Laure Vigier & Hervé Pella (2017) Optimization methodology for a river temperature monitoring network for the characterization of fish thermal habitat, Hydrological Sciences Journal, 62:3, 483-497, DOI: 10.1080/02626667.2016.1242869

To link to this article: https://doi.org/10.1080/02626667.2016.1242869

Published online: 24 Oct 2016.

HYDROLOGICAL SCIENCES JOURNAL – JOURNAL DES SCIENCES HYDROLOGIQUES, 2017
VOL. 62, NO. 3, 483–497
http://dx.doi.org/10.1080/02626667.2016.1242869

Optimization methodology for a river temperature monitoring network for the characterization of fish thermal habitat

Anik Daigle[a,b], Arnaud Caudron[c*], Laure Vigier[d] and Hervé Pella[e]

[a]Département de physique, Cégep Garneau, Québec, Canada; [b]Centre Eau Terre Environnement, Institut national de la recherche scientifique, Québec, Canada; [c]UMR CARRTEL, INRA - Un. Savoie Mont Blanc, Thonon-les-Bains, France; [d]Fédération de Haute-Savoie pour la pêche et la protection du milieu aquatique, St-Martin Bellevue, France; [e]Irstea, UR MALY, Villeurbanne, France

ABSTRACT
A methodology for planning an optimized river water temperature monitoring network is presented. The methodology is based on sampling of the physio-climatic variability of the region to be monitored. Physio-climatic metrics are selected to describe the study region, based on principal component analysis. The sites to be monitored are then identified based on a *k*-means clustering in the multidimensional space defined by the selected metrics. The methodology is validated on an existing dense water temperature network in Haute-Savoie, France. Different configurations of more or less dense network scenarios are evaluated by assessing their ability to estimate water temperature indices at ungauged locations. An optimized network containing 83 sites is found to provide satisfactory estimations for seven ecologically and biologically meaningful thermal indices defined to characterize brown trout thermal habitat.

ARTICLE HISTORY
Received 22 January 2016
Accepted 22 July 2016

EDITOR
M. C. Acreman

ASSOCIATE EDITOR
not assigned

KEYWORDS
Monitoring network; optimization; river water temperature; trout habitat

1 Introduction

Water temperature patterns in rivers and streams are crucial to define the quality of habitat, especially for ectothermic organisms such as fish (Pörtner and Farrell 2008, Elliott and Elliott 2010). Over the past decade, water temperature monitoring efforts have increased worldwide, motivated in part by the cost-effectiveness of modern temperature sensors and by the climate change issue (Isaak *et al*. 2012, Hannah and Garner 2015). A growing literature uses the water temperature data available in relation to thermal tolerances of fish to investigate the potential effects of increasing temperatures on suitable habitats (Eaton and Scheller 1996, Mohseni *et al*. 2003, Mantua *et al*. 2010, Souchon and Tissot 2012). In particular, many studies focus on the conservation of native salmonids and the reduction of their suitable thermal habitat, in association with the risk of invasion by non-native species. However, most studies use data from temperature monitoring networks that were not initially designed to study the thermal habitat of the targeted fish species and focus their analysis on simple thermal indices or single thermal limits (i.e. temperature thresholds for survival). While changes in water temperature continue to have an impact on fish, the fish responses are complex and difficult to predict (Graham and Harrod 2009). For a single species, temperature limits and requirements vary between life stages (Elliott and Elliott 2010) and thermal changes result in direct effects on numerous phenomena such as migration, spawning, embryonic development, hatching, emergence, growth and life-history traits (Jonsson and Jonsson 2009). Indirect impacts such as the development of temperature-dependent pathology are rarely investigated, whereas these can lead to important mortality in populations (Hari *et al*. 2006). Temperature data should thus provide accurate information on threatened species at relevant scales to help field biologists and resources managers to implement more effective conservation strategies at the population level. Elliott and Elliott (2010) showed the importance of accurately analysing long-term data on water temperature for different life stages of native salmonids in Europe in order to improve predictive models. Seasonality and variability in river thermal regimes need to be quantified using long-term water temperature records (Olden and Naiman 2010). Isaak *et al*. (2012) highlighted that water temperature data to describe biological responses at different life stages or across spatial distributions are rare. The strategic planning and/or adaptation of existing stream temperature monitoring networks could help improve water temperature modelling for aquatic

CONTACT Anik Daigle anik.daigle@ete.inrs.ca
*Present address: Science-management interface for biodiversity conservation, Thonon-les-Bains, France

conservation purposes and to better prioritize management interventions.

Implementing long-term water temperature monitoring in river networks with the aim of characterizing thermal regimes temporally and spatially represents a key challenge. Methods and tools regarding the optimization of river temperature monitoring networks are still lacking. Strategic planning of monitoring networks in rivers was often conducted in the context of water quality monitoring, for example for the systematic measurement of the concentration of various contaminants (e.g. Strobl *et al.* (2006), Khalil *et al.* (2011), and a review of the statistical approaches for water-quality monitoring network redesign and assessment by Khalil and Ouarda (2009)). In either case, the general idea is to design a network based on a low-density/high-information level trade-off.

Following this objective, our goal is to propose a design strategy that allows the optimization of a water temperature network based on the physio-climatic characteristics of the region to be monitored. The methodology presented can be used to optimize existing measurement networks, or to design a network for non-monitored regions.

The methodology presented here is based on the assumption that two rivers of similar size, sharing the same physiographic characteristics, and subjected to similar climatic conditions, will experience similar thermal regimes. "Prototype" monitoring sites should thus be selected such that they sample the whole physio-climatic variability of the river basins encountered in a study area. Such a network should provide water temperature-relevant information about any type of basin and thus allow one to estimate, or interpolate, water temperature at places where it is not measured, using the information gathered at the monitoring sites. The main steps in the application of the proposed methodology are as follows:

(1) identify the physio-climatic attributes that best represent all stream sub-basins in the study area; and
(2) proceed with an optimal sampling of these attributes.

This optimization method is tested on the existing Haute-Savoie (HS, Fig. 1) stream temperature monitoring network by evaluating different reduced-size network scenarios in their ability to estimate water temperature indices at ungauged locations. These indices are descriptive statistics that were defined to characterize brown trout (*Salmo trutta*) thermal habitat (Section 2.1, Table 2).

2 Material and methods

2.1 Description of the study area

The method was tested in the Haute-Savoie (HS) area, in the northern French Alps (Fig. 1). This area covers 4400 km^2 between 350 and 4810 m in elevation. It is drained by a hydrographic network of about 2800 km, consisting of rivers, mountain streams and small watercourses of 350–1800 m elevation, and bearing a diversified fish population. Most rivers have a typical nival (snow influenced) hydrological regime with secondary rain precipitation influence. High flows occur in spring until May–June due to snowmelt, and in autumn driven by precipitation, while low flows occur during summer and winter. Some streams show a glacial regime with high flows in summer and baseflows in winter. Landscapes and land uses are varied with regard to elevation, precipitation and topography.

The HS area represents an interesting test area for the methodology presented since it has a singular dataset of continuous stream temperature data from a dense monitoring network implemented over 7 years. Stream temperature measurements in the HS area were implemented by the Departmental Federation of Fishing and Protection of Aquatic Ecosystems (FDPPMA). The objective of the FDPPMA was to monitor accurate thermal conditions at hourly intervals in the different river systems inhabited by brown trout during a full-year period. In HS, brown trout occupies 97% of the fish-bearing streams (2700 stream km). Brown trout is a crucial species for recreational fishery and represents considerable socioeconomic value. This species is also of worldwide interest for conservation issues, as either native or invasive species. In its native range in Europe, five genetic lineages considered as evolutionary significant units (ESU) have been identified (Laikre 1999, Bernatchez 2001). In each ESU, remaining native populations are threatened by human activities and their effects (non-native introductions, habitat degradation and fragmentation, overharvest, climate change); hence, significant conservation efforts are underway. Brown trout is one of the most widely introduced fish species in the world and among the most successful freshwater fish invaders. Brown trout has been introduced outside its European native range since the mid-1800s because of its sport-fishery interest. It is listed as one of the "*100 worst invasive alien species*" (Lowe *et al.* 2000), and its impact on native fish communities is of increasing conservation concern in many regions of the world where it was not native. Finally, the thermal requirements at different stages of the brown trout lifecycle are well defined and

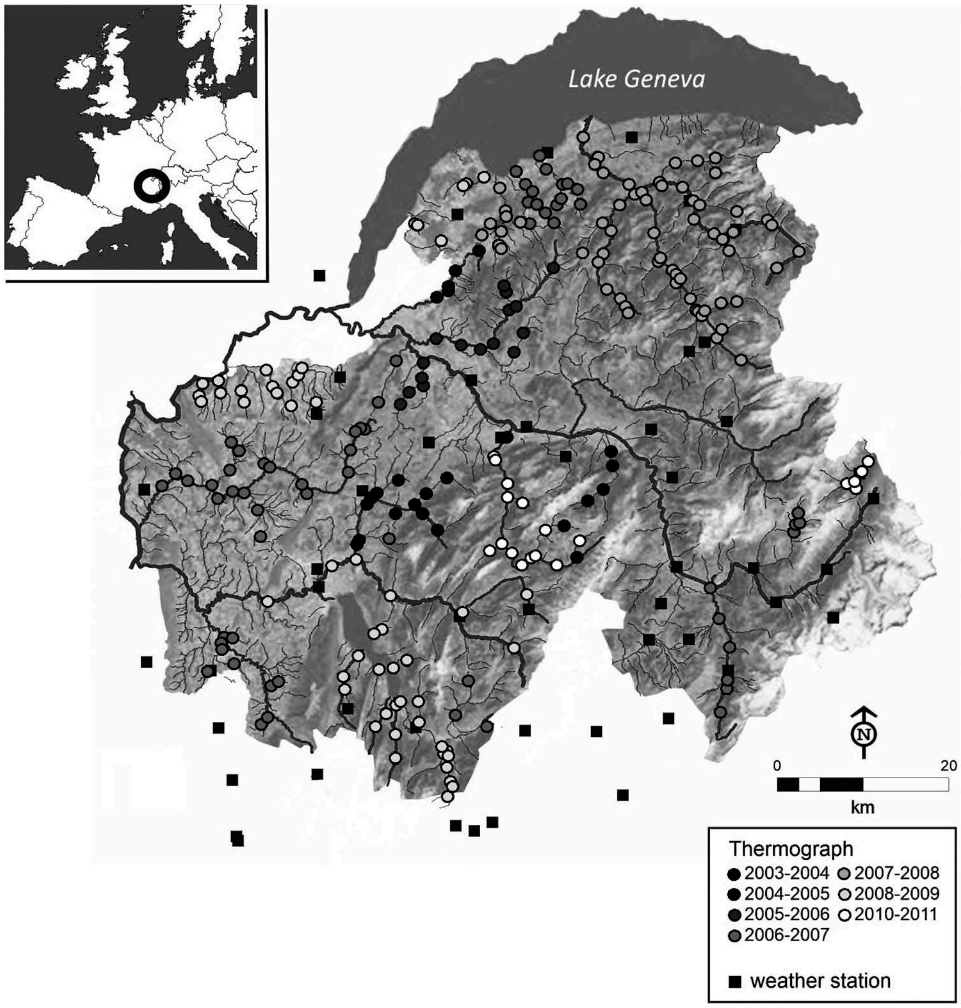

Figure 1. Hydrographic network of the Haute-Savoie area. Locations of the 238 water temperature measurement sites deployed between 2003 and 2011 are shown, as well as the locations of the 49 Météo France weather stations.

among the most documented (see Crisp 1996, and the review by Elliott and Elliott 2010).

A monitoring programme was thus established between 2003 and 2011 on different basins from year to year, according to the number of available thermographs (Fig. 1, Table 1). Stream temperatures were recorded using digital Onset Pendant Temperature loggers, with 0.10°C temperature resolution and ±0.47°C accuracy at 25°C. Two suitable periods were defined to deploy thermographs in streams: (a) from early June to early July and (b) between mid-September and mid-November. Thermographs were left in the water for at least one year. Water temperature time series were thus uninterrupted during crucial ecological and biological periods for the target species, such as the summer period showing the warmest values or the embryonic development phase from egg fertilization in winter to fry emergence in spring.

Table 1. Number of monitoring sites installed each year in the study area.

Year	No. of monitoring sites
2003/04	19
2004/05	5
2005/06	26
2006/07	53
2007/08	64
2008/09	52
2010/11	19
Total	238

After assessment of the data quality, the database used to test the optimization method included one complete year of hourly stream temperature at 238 sites (Fig. 1, Table 1). This measurement network covers the full range of elevations and is representative of the HS hydrographic network.

Hourly temperature data were used to calculate seven annual thermal indices with biological or ecological significance for different life stages of brown trout, based on its thermal requirements. All indices were computed at each site for the year surveyed. Calculations of the thermal indices were performed

Table 2. Thermal indices selected to describe the brown trout thermal habitat.

Index	Abbreviation	Rationale
Mean annual temperature	MAT	MAT and MDMT give indications about the overall thermal conditions and the thermal habitat suitability for brown trout.
Maximum daily mean temperature	MDMT	
Maximum 30-day mean temperature	M30DMT	Highest 30-day moving average of the daily mean temperatures. This index provides a good indicator of seasonal extreme conditions during the warmest period. It was initially used to support a fish stream typology (Verneaux 1973).
Time of suitable thermal condition for feeding	STCF	Total number of days showing a daily mean temperature between 4°C and 19°C. Globally, 4°C and 19°C could be considered respectively as the lower and upper temperature limits for brown trout feeding (Elliott and Elliott 2010).
Median hatching period time	H_{50}	H_{50} is the number of days taken for 50% of the eggs to hatch. We used the model proposed by Crisp (1988, 1992) to provide the estimates. The starting date for the calculations is the standardized median date of brown trout spawning (i.e. egg fertilization) in HS, fixed to 15 December (Champigneulle *et al.* 1988, 2003, A. Caudron (personal communication, 2014)).
Median emergence time	E_{50}	E_{50} is the number of days taken for 50% of the fry to emerge. The model of Elliott and Hurley (1998) was used to provide the estimates. The starting date was the same as for H_{50}.
Suitable thermal conditions for PKD infection	STCPKD	Proliferative kidney disease (PKD) is a parasitic infection of salmonids caused by *Tetracapsuloides bryosalmonae*. Development and pathology of PKD are strongly influenced by temperature (for details, see review from Okamura *et al.* 2011). This index takes the value 1 at sites showing at least 360 consecutive hours with a temperature equal to or greater than 15°C, and 0 if not. According to De Kinkelin *et al.* (2002), this threshold was selected as a thermal condition conducive to fish infection by parasites.

with the MACMA Salmo Excel macro (Dumoutier *et al.* (2010), in French, available free of charge upon request at info@pechehautesavoie.com). The seven indices are the mean annual temperature (MAT), the maximum daily mean temperature (MDMT), the maximum 30-day mean temperature (M30DMT), the time of suitable thermal condition for feeding (STCF), the median hatching period time (H_{50}), the median emergence time (E_{50}) and the suitable thermal conditions for PKD infection (STCPKD). Table 2 presents the seven thermal indices selected for the assessment of brown trout habitat, with their rationale.

2.2 Selection of the physio-climatic attributes

The proposed general strategy is to select sites with characteristics spanning the whole physio-climatic variability of the study region. The first step is to identify which physio-climatic attributes should be sampled. These should (a) be known to have an impact on water temperature, and (b) show an appreciable variability across the region.

Drivers of river water temperature are now well known and have been extensively reviewed (Caissie 2006, Webb *et al.* 2008). These include the atmospheric conditions, stream discharge, topography, land use and groundwater input. Forty-eight physio-climatic attributes were extracted for all measurement sites from the RHT digital hydrographical network (derived from the Alti® digital elevation model and the Carthage® hydrographical network of the French Geographic National Institute; see Pella *et al.* 2012), the Aurehly France climate database (Bénichou and Le Breton 1987) and the Corine Land Cover 2000 database (European Environment Agency 2004) (Table 3).

Table 3. Extracted physio-climatic attributes for each site sub-basin or reach. The attributes selected for the definition of the water temperature monitoring network are identified by an asterisk (*).

Physiography (12 attributes)	Source: RHT
Log of the drainage area*	
Basin minimum, maximum and mean* elevation (m)	
Site altitude (m)	
Basin minimum, maximum and mean slope (°)	
Slope at site (°)*	
River length (km)	
Headwater distance (km)	
Strahler order	
Land use (9 attributes)	Source: Corine Land Cover 2000
Hydrology (1 attribute)	Source: RHT
Climate (26 attributes)	Source: Aurelhy France
Urban (km^2)	
Industrial or commercial (km^2)	
Cropland (km^2)*	
Permanent cultures (km^2)	
Forested (km^2)	
Shrub and herbaceous vegetation (km^2)	
Open areas (km^2)	
Wetlands (km^2)	
Water (km^2)	
Inter-annual mean (m^3/s)	
Total annual precipitation (1961–1990 normal) (mm)	
Total summer precipitation (1961–1990 normal) (mm)	
Air T° monthly minima (1961–1990 normal) (°C)	
Air T° monthly maxima (1961–1990 normal) (°C)	

The sites to be included in the network should form a set of “prototype sites” that represent all the physio-climatic ranges encountered in the region. The selection should thus focus on the physio-climatic attributes that are the most contrasted in the area. Principal component analysis (PCA; Dunteman 1989) was used to compare the variance explanation capability of the physio-climatic attributes for the 238 sites in HS.

The original set of attributes consists of the 48 extracted physio-climatic variables (Table 3), extracted at all 238 water temperature recording sites. The first principal component, PC_1, defines the direction in the 48-dimensional space in which the 238 sites show the largest distribution. Since the PCs are orthogonal, they can be seen as the bases of a new coordinate system. Typically, the space defined by the first two or three PCs explains a high proportion of the dataset variance, and PCA can thus be used as an effective way to reduce the dimensionality of a dataset. Conversely, the relative contribution to the first PCs can be used as a criterion in selecting the attributes that are the most significant in describing the dataset variability. Since the correlation, or *loading*, of each original attribute to each PC is quantified, PCA can also help identify correlated attributes and thus reduce collinearity in a highly-dimensioned problem (Olden and Poff 2003, Daigle *et al.* 2011). The physio-climatic attributes used to define the optimized measurement network were thus selected based on two criteria:

(1) the selected attributes must present relatively high loading values on PC_1 or PC_2; and
(2) a group of attributes with similar PC_1 and PC_2 loading values is considered redundant and only one member of the group should be selected.

2.3 Sampling of the physio-climatic attributes

Once the physio-climatic attributes are selected, sites should be chosen so that the resulting network covers all possible attribute values in the area. Sites were thus selected using k-means clustering, an algorithm that groups data vectors of attributes into k clusters by minimizing the distance of each vector to its cluster's centre. Sites grouped into a given cluster thus have similar physio-climatic attributes. To select k sites, k clusters were first formed among all sites. To ensure that the sites with the most extreme physio-climatic characteristics were selected, the centres of the k clusters were multiplied by a constant proportional to the span of the considered attributes, resulting in a better coverage of the attribute extreme values. Sites closest to these k "inflated" centres made up the optimized measurement network.

2.4 Estimation of the thermal indices

The adequacy of the resulting network was evaluated by its ability to estimate water temperature indices at sites that were excluded from the network (or *left-out* sites), given the physio-climatic attributes of the sites.

The six continuous-value indices (MAT, MDMT, M30DMT, STCF, H_{50}, E_{50}) were estimated using stepwise regression. Stepwise regression is a systematic procedure that tests several models of multiple linear regressions including or excluding each of the explanatory variables, according to their explanatory power. If the hypothesis that the regression coefficient of a physio-climatic attribute is 0 cannot be rejected, this attribute is included in the regression model; otherwise, it is not used. The stepwise regression thus reduces the size of the model where relevant, allowing less complex and thus more stable models to be obtained.

Index STCPKD is related to threshold exceedences and thus takes values of either 0 or 1. This categorical index was modelled by a logistic regression (Pampel 2000), given a variable combining the most relevant physio-climatic attributes. Following Chokmani and Ouarda (2004) and Guillemette *et al.* (2011), this combined variable was defined using canonical correlation analysis (CCA; Thompson 1984). CCA is a statistical method similar to PCA in that it makes linear combinations of a set of attributes X to compute new linearly independent composite variables U. The new variables U, called *canonical variates*, are computed such that they have maximum correlation to another set of linearly independent composite variates V, which are linear combinations of a set of thermal indices Y. The first variate in U is thus made up of the physio-climatic information that is most correlated to the temperature information contained in V. Indices included in Y are chosen in relation to the thermal index to be modelled (here, indices MAT, MDMT and the number of consecutive hours with a temperature equal to or greater than 15°C).

The water temperature survey was conducted on a 7-year period; water temperature data available at the monitoring sites are thus not all concomitant (Fig. 1, Table 1). The inter-annual meteorological differences to which the watersheds were subjected were taken into account by including the annual daily mean air temperature as another physio-climatic attribute for the estimation of the thermal indices. The annual daily mean air temperature was computed from daily data measured at 49 Météo France stations (Fig. 1) and linearly interpolated at each water temperature measurement site, given its geographical coordinates and elevation.

The continuous-value thermal indices were estimated in networks of sizes ranging from 5% to 95% of the original network. The estimation errors on the sites that were not part of the network (left-out sites) were used to evaluate the interpolation performance of the network. The performance measure used for the continuous value indices was the root mean squared error (RMSE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2} \tag{1}$$

where y_i and $\hat{y}_i$ are the measured and estimated thermal index values at site i and N is the total number of estimations. Interpolation performance on the categorical index STCPKD was also evaluated in optimized networks of various sizes, using the percentages of false positives (FP) and of false negatives (FN):

$$\mathrm{FP} = \frac{\text{number of false positives}}{\text{number of true negatives}} \tag{2}$$

$$\mathrm{FN} = \frac{\text{number of false negatives}}{\text{number of true positives}} \tag{3}$$

The optimized networks with various densities were evaluated by a bootstrap cross-validation: 100 networks of a given density were sampled independently and the thermal index estimated at all L left-out cases, resulting in $N = 100 \times L$ estimated values. For the continuous-value indices, the performance measures were then computed given these $100 \times L$ estimations. For the categorical index, mean FP and FN values were computed given 1000 random samplings of 100 Category 0 and 100 Category 1 cases among the $100 \times L$ estimations.

A flowchart illustrating the steps for the design of the monitoring network and for the estimation of thermal indices at sites not included in the network is provided in Figure 2. Data processing and all analyses including PCA, CCA, k-mean clustering and the regressions were conducted using Matlab R2012a (The Mathworks, Inc., Natick, MA, USA).

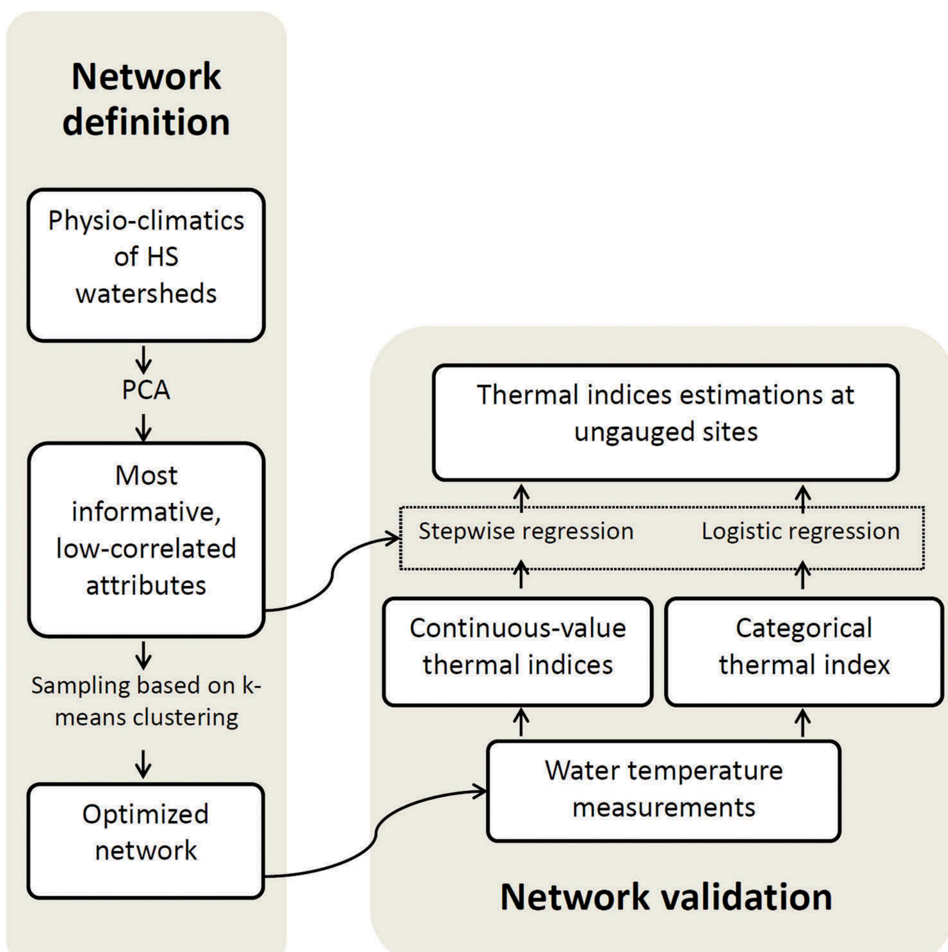

Figure 2. Steps for the design of the monitoring network and for the estimation of thermal indices at sites not included in the network.

3 Results

3.1 Selection of the physio-climatic attributes

Principal component analysis was performed given the values of the 48 attributes at all 238 monitoring sites. Most data variance is explained by the first two principal components, with PC_1 explaining 67% of the variance and PC_2, 11%. Figure 3 shows each of the 48 attributes loadings on the first two PCs. Loadings measure the correlation between the attributes and the (uncorrelated) PCs; attributes appearing at similar locations in Figure 3 are thus positively correlated (e.g. monthly minimum and maximum air temperatures), whereas attributes separated by a 180° angle with respect to $(0, 0)$ are negatively correlated (e.g. air temperatures and elevations. Important contributions to PC_1 include the attributes related to climate and topography, while attributes related to the size of the river (drainage area, headwater distance, river length, module, Strahler order) have important loadings on PC_2. Most significant land use attributes appear to be shrub/herbaceous vegetation, open and cropland areas, with ±0.14 loadings on PC_1. Four attributes were thus selected according to the two criteria defined earlier. The second criterion demands that the selected attributes should be at large angular distances from each other in the PC_1–PC_2 loadings graph. Selected attributes, shaded in Figure 3, are:

- basin mean elevation
- log value of the drainage area
- slope at station
- cropland area

3.2 Sampling of the physio-climatic attributes

The modified ("inflated") k-means clustering was performed in the four-dimensional space of the four selected attributes, with the number of clusters corresponding to the number of sites to be selected. This selection method was applied for sampling levels ranging from 5% to 95% of the original network. All 238 sites are plotted in the log(DA)-mean altitude space in Figure 4. The circled sites are an example of a 25%-level selection (60/238 sites) based on the modified k-means clustering. The same example (same 60-site selection) is shown in Figure 5, where it can be seen that the sampling method ensured a selection of sites in every range for each of the four individual attributes distributions.

3.3 Estimation of the thermal indices

The continuous-value thermal indices were estimated given networks of sizes ranging from 5% (12 sites) to 95% (226 sites) of the original network. Estimation

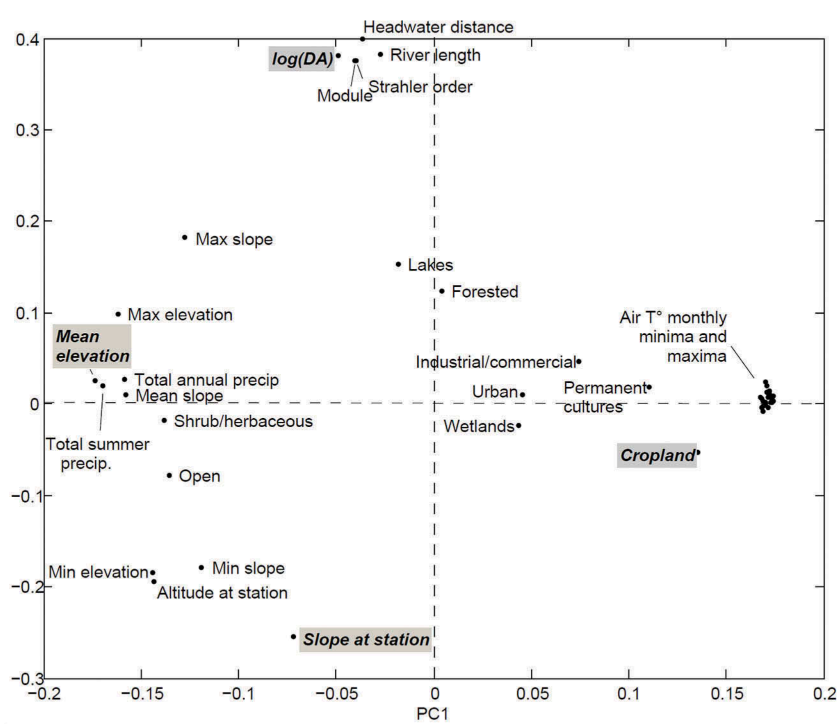

Figure 3. PC_1 and PC_2 loadings of the physio-climatic attributes. The attributes selected for the definition of the water temperature monitoring network are shaded.

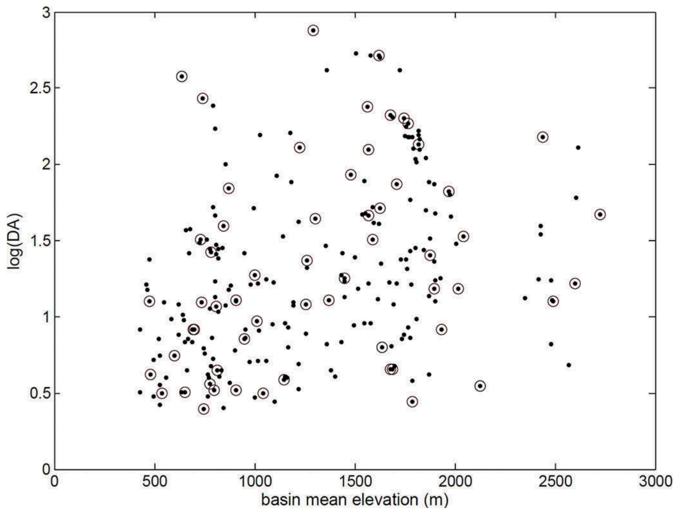

Figure 4. Distribution of the 238 sites in the log(DA)–mean altitude space. Circles represent 25% of the sites selected using a modified *k*-means clustering.

performances as a function of network density are plotted for the continuous-value thermal indices in Figures 6 and 7. Results obtained with a purely random site selection are also plotted for comparison.

The distribution of the categorical index STCPKD was found to be very much asymmetric, with STCPKD equal to 0 for 80% of all sites, while only 20% were categorized as 1. Such an unbalanced calibration dataset can lead the logistic regression to biased estimates. A post-sampling was thus made in the selected networks in order to rebalance the number of sites in each category for calibration of the logistic regression. Interpolation performance as a function of network density is plotted for the categorical thermal index in Figure 8. Plotted values are the mean FP and FN percentage values computed from 1000 random samplings of equal numbers (100) of Category 0 and 1 left-out cases for 100 different networks selected independently. Network sizes were limited such that at least 16 Category 1 sites were retained in the selected networks for the calibration of the logistic regression (~35% sampling of the original network), and a minimum of 8 Category 1 sites were left-out in order to compute FP values (~80% sampling of the original network).

The RMSE estimation values tend to increase when the number of stations is below ~50 sites for all continuous valued thermal indices, with lower increases for the networks selected based on the *k*-means classification as compared with a random selection. In the networks tested, STCPKD FP and FN values are stable to ~20% and ~17%, respectively, with large standard deviations (~4% for both FP and FN).

The ability of a single network to estimate all seven indices was assessed by applying the proposed methodology for the selection of 83 sites. This number of sites was chosen to ensure that satisfactory estimations could be obtained for all indices. More especially, and as mentioned above, the calibration of the logistic regression for the estimation of categorical index STCPKD requires about 32 sites, of which half (~16 sites) should be of Category 1. Considering the proportion of Category 1 sites in the whole dataset, the selection of 83 sites did allow 19 sites of Category 1 to be retained. Table 4 summarizes the estimations RMSEs, FP and FN obtained at the remaining sites for each index. It must be noted that, for a given network, FP and FN values depend on the Category 0 sites selected for the calibration of the logistic regression. Values in Table 4 are representative, but stand for one such selection. The physio-climatic attributes that were retained in the stepwise regression are listed for each thermal index in Table 5.

4 Discussion

Several methodologies for the optimization of existing monitoring networks have been proposed in the field of hydrology (e.g. Husain 1987, Li *et al.* 2012, Alfonso *et al.* 2013). These make use of historical data to assess the best monitoring locations to maintain in order to meet the minimum density/maximum information level criteria. In general, water temperature is much less monitored than flow, and dense networks such as the one existing in HS are rare. The methodology presented here can be used for planning a measurement network from the beginning, as it does not require historical data and is based rather on the physiographical and climatic characteristics of the region.

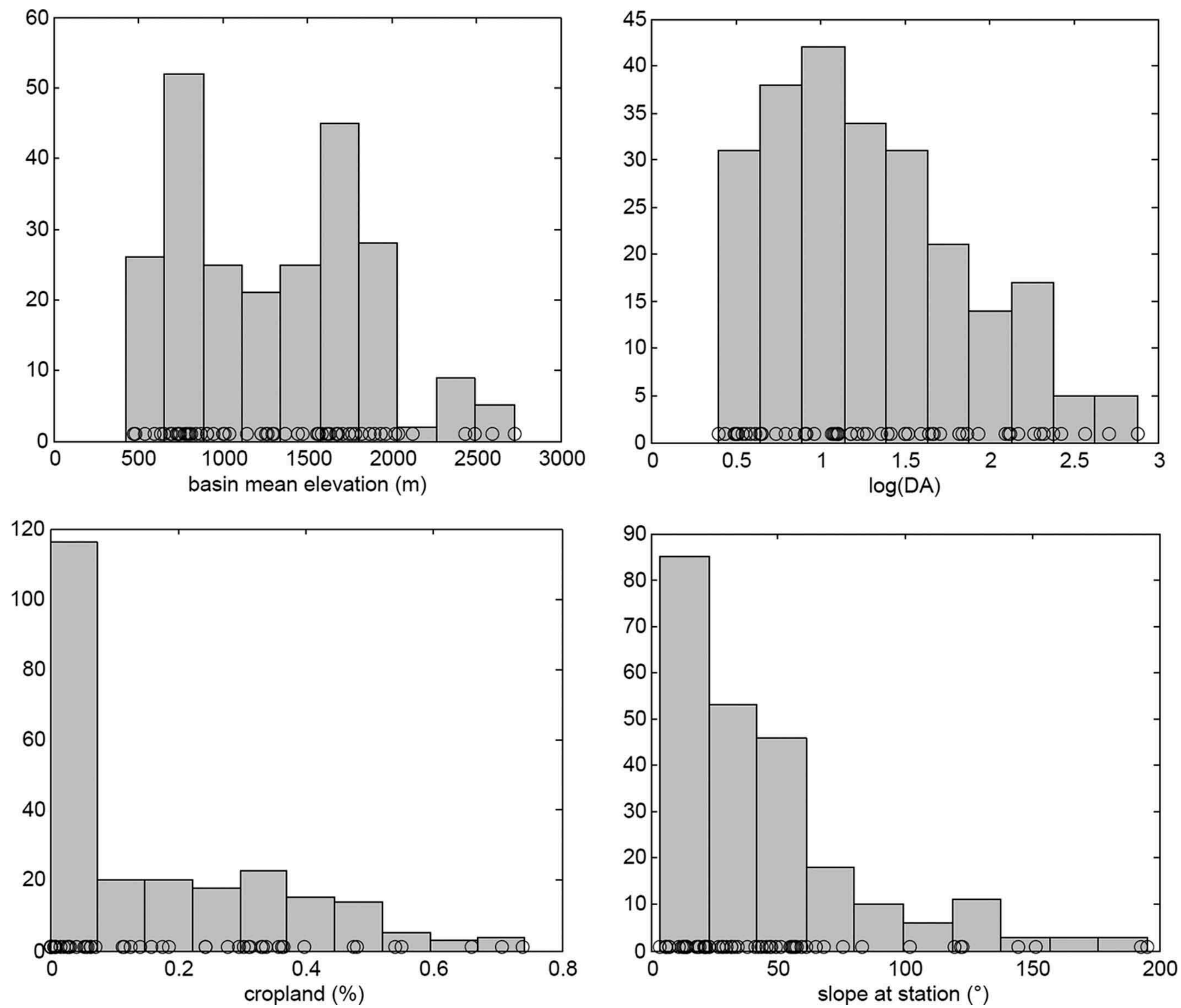

Figure 5. Distribution of the sites given the four selected attributes. Circles represent 25% of the sites selected using a modified *k*-means clustering.

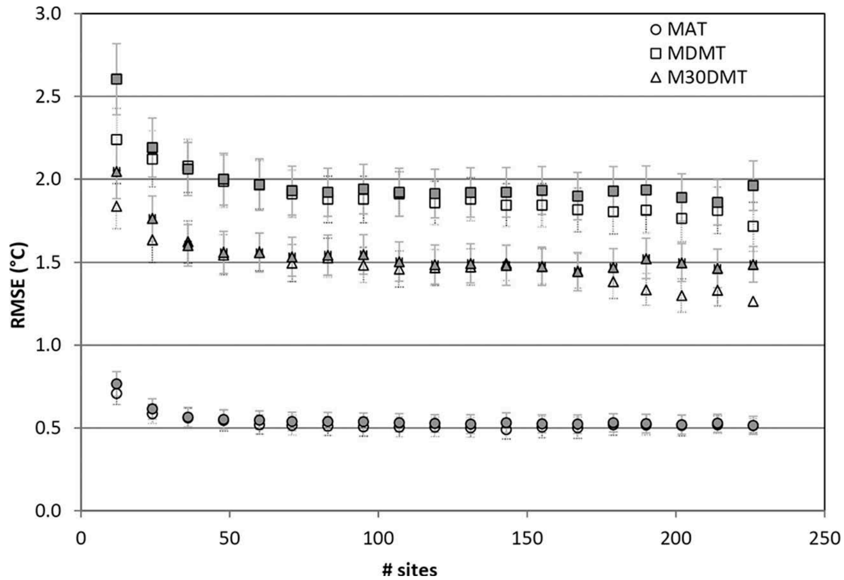

Figure 6. RMSE values computed from 100 different networks selected independently. Confidence intervals are the standard deviation of the RMSE values computed from 1000 resamplings of 100 test cases. Values represented by empty symbols were obtained using networks selected based on the proposed modified *k*-means clustering, while values represented by filled symbols were obtained using randomly selected networks.

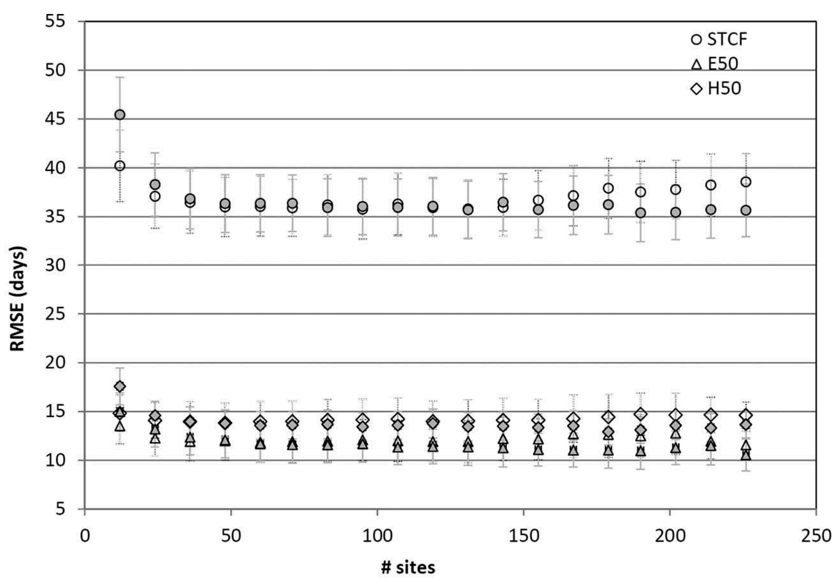

Figure 7. RMSE values computed from 100 different networks selected independently. Confidence intervals are the standard deviation of the RMSE values computed from 1000 resamplings of 100 test cases. Values represented by empty symbols were obtained using networks selected based on the proposed modified *k*-means clustering, while values represented by filled symbols were obtained using randomly selected networks.

Attributes other than the four selected could have been chosen to describe the study region: for example, monthly minimum and maximum air temperatures have high PC_1 loadings and either one could have been selected instead of the mean basin elevation. With the presence of important correlations in the set of considered attributes, the dependence on the dataset and presence of measurement errors, there is probably no real best set of attributes. The selection should be guided by the relevance of the attribute to explain the variable of interest and by the variance explanation proportion and low redundancy criteria mentioned earlier, but one must keep in mind that correlation is not a guarantee of a cause and effect relationship. The final selection should thus also be based, when possible, on expert knowledge and be physically and biologically

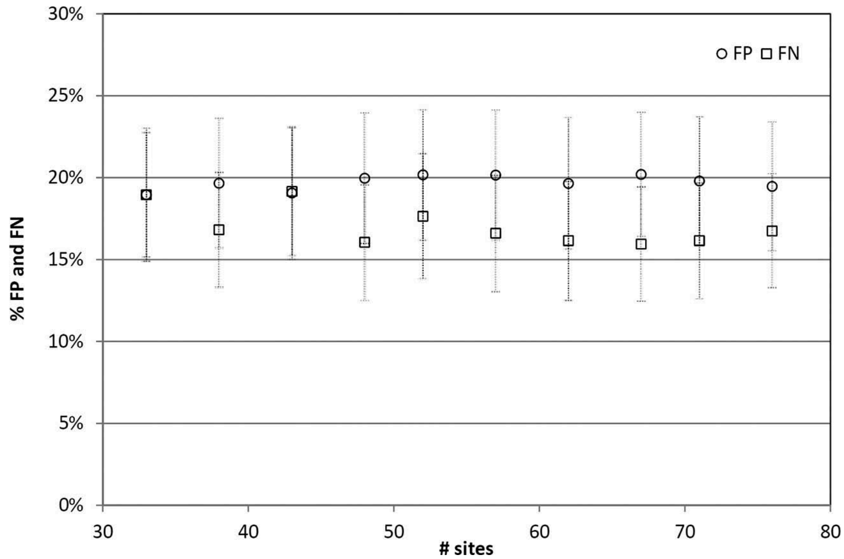

Figure 8. Mean FP and PN on STCPKD values computed from 1000 resamplings of 100 Category 0 and 100 Category 1 cases estimated given 100 different networks selected independently. The networks all included equal numbers of Categories 1 and 0 sites; values on the horizontal axis are thus the number of sites used to calibrate the logistic regression. Confidence intervals are the standard deviations of the FP and PN values computed from the 1000 resamplings.

Table 4. Estimation of RMSE, FP and FN obtained at the sites excluded from the optimized network. Indicated FP and FN values are representative, but highly dependent on the subset of Category 0 sites used to calibrate the logistic model.

	Stepwise regression	Logistic regression	
Index	RMSE	FP	FN
MAT (°C)	0.5	–	–
MDMT (°C)	1.9	–	–
M30DMT (°C)	1.6	–	–
STCF (d)	37.4	–	–
E_{50} (d)	14.8	–	–
H_{50} (d)	12.4	–	–
STCPKD	–	18%	17%

Table 5. The physio-climatic attributes that were retained (1) and excluded (0) in the stepwise regression.

Thermal index	Mean annual air T°	Basin mean elevation	Cropland area	Drainage area	Slope at station
MAT	1	1	0	0	1
MDMT	0	1	0	1	0
M30DMT	0	1	0	1	0
STCF	1	0	0	0	0
E_{50}	1	0	0	0	0
H_{50}	1	1	0	0	1

meaningful. Here, the mean basin altitude was selected as an easily accessible variable correlated to most air temperature statistics. In a region with highly contrasted orography such as HS, elevation can also be a measure of the proportion of groundwater flow. The drainage area is related to the river size and therefore to water volumes, as well as to water travel time, and thus to the exposure to atmospheric conditions. Slope at station is indicative of the time required for water to flow along a reach and can thus be a measure of exposure time to solar radiation. Stream slope also affects the rivers hydraulics and thus thermal advection. Land use can also affect river water temperature as it affects shading and soil humidity retention and overland flow temperature. Cropland area was selected as it is the most variable land use metric in HS region, while being the least correlated with the three other selected metrics. Other watershed/reach properties identified as being related to water temperature in other regions are the substrate type, which can be related to stream order and potential hyporheic flow (Johnson 2004), the proportion of the catchment that is covered by lakes or forest (Moore 2006, Chu *et al.* 2010, Daigle *et al.* 2010), hillslope shading and orientation of the basin (Brown and Hannah 2008, Hrachowitz *et al.* 2010).

Continuous value thermal indices were estimated with quite different accuracies given the selected networks, as shown by the fairly large standard deviations of the RMSE values. Best estimation accuracies were obtained for index MAT in networks down to ~50 sites, with mean RMSE of 0.5°C, corresponding to 6% of its range. Standard deviation on the RMSEs is about 0.06°C (Fig. 6). Worst estimation accuracies in continuous indices were obtained for index STCF, with best RMSE of 36 days in ~50-sites networks, corresponding to 15% of the index range (Fig. 7).

Stepwise regression also allowed identification of which physio-climatic attributes were useful in estimating each of the continuous-value thermal indices

(Table 5). The mean annual air temperature was retained in all models but one (index MDMT), while the percentage of cropland area was never used. This attribute was selected following the hypothesis that an as exhaustive as possible description of the physio-climatics of the HS watersheds would lead to a good description of their thermal regimes. The observation that this attribute did not help in estimating the selected thermal indices is interesting and leads to a number of remarks: (a) in cases where no river temperature data are available when defining the measurement network, it is not possible to predict with certainty what physio-climatic attributes will be useful in estimating selected thermal indices; (b) such *a posteriori* information about the un-usefulness of an attribute can allow managers to remove the attribute in the choice of future monitoring sites, reducing the number of constraints in the definition of the network; however, (c) other thermal and/or hydrological variables might benefit from this coverage of the region based on the percentage of cropland.

A stepwise regression establishes linear relationships between explanatory and explained variables, and is thus not suited to modelling a categorical index such as STCPKD. This index was thus estimated by a logistic regression defined by the first canonical variate combining physio-climatic information of the selected sites. The estimation performance of the model is quite variable, as illustrated by the high standard variation of both FP and FN values (Fig. 8). This high variability is due to three factors: firstly, each tested network leads to a different canonical space, in which the calibration and validation sites will have different coordinates. For a given set of sites, the canonical variates may lead to a decent separation of the 0 and 1 STCPKD values, while this separation may be less clear for another set, especially for low-density networks. Secondly, the number of Category 1 sites left for validation gets lower as the calibration set increases, and *vice versa*. Too few Category 1 sites in the calibration set leads to uncertain models, while a small number of Category 1 sites in the validation set will lead to more variable validation results. Thirdly, the estimation accuracy is also affected by the fact that only a subset of Category 0 sites is used to calibrate the logistic regression, in order to match the number of Category 1 sites. FP and FN values included in Table 4 are representative, but highly dependent on the specific Category 0 sites subset chosen to calibrate the logistic model.

Logistic regression outputs are continuous values ranging from 0 to 1 that can be interpreted as the probability of belonging to Category 1 (Fig. 9). Typically, as in the present study, the classification is performed by rounding outputs <0.5 to 0, and all others to 1. Such quantified probabilities could however allow one to adjust the classification, i.e. to make more or less conservative decisions. For example, a site for which the index STCPKD is estimated to be 0.4 could be considered at risk and classified 1. Otherwise, all sites estimated >0.8 could be prioritized in a management intervention. Figure 9 shows the logistic function model and validation (left-out) sites values for

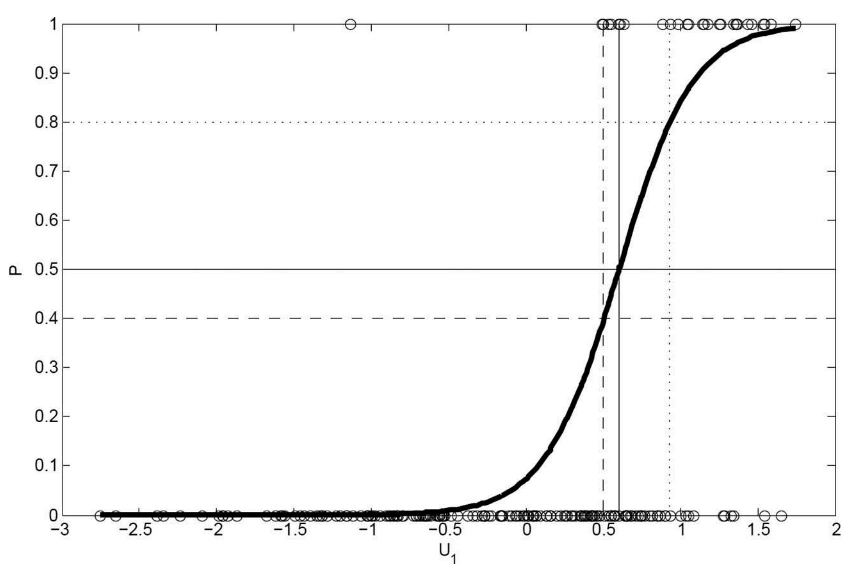

Figure 9. Logistic function outputs at validation (left-out) sites for thermal index STCPKD. Sites of Categories 0 and 1 are identified by circles. Thresholds of 0.4 (dashed line), 0.5 (solid line) and 0.8 (dotted line) are outlined. It can be observed that choosing a threshold of 0.4 would result in nine additional sites in Category 1. Otherwise, a high-value threshold can be used to detect the most at-risk sites (e.g. here, the 27 sites with $P > 0.8$).

thermal index STCPKD, as a function of the first canonical variate. It can be observed that choosing a threshold of 0.4 would result in 10 additional sites in Category 1. In contrast, 27 sites are located above the 0.8 threshold.

The methodology presented for the planning of optimized water temperature monitoring networks represents a useful tool for biological conservation purpose. Here, an example applied to the thermal habitat of brown trout in HS was presented, where a 15-year conservation programme of the remaining native populations is in progress (Caudron *et al.* 2012). An optimized network of 83 measurement sites is able to provide a performance estimation of the brown trout thermal habitat using seven relevant indices in the whole trout-bearing HS network. The primary interest of such optimal planning for resource managers is to define a "minimum" measurement network able to give a reliable spatial distribution of the thermal habitat. Such a network allows the estimation of several indices with biological significance for different life stages. The combination of these different indices provides valuable knowledge on the suitability of the thermal habitat in the area. For this purpose, the definition of the relevant thermal indices is a crucial step. These should be representative of the entire life-cycle, and include the most critical life stages and the most significant thermal requirements for the studied species. In the application presented here, the combination of the seven selected thermal indices gives a reliable overview of the thermal habitat suitability for brown trout in HS. They provide indications about the overall thermal conditions of streams, the extreme conditions during the summer season, the feeding and growth suitability, the pathological risk caused by a temperature-dependent infection, and the embryonic development, which is the life stage with the lowest thermal tolerance (Elliott and Elliott 2010). Other indices such as the number of days reaching the upper lethal limit (22–25°C) and the number of days lying in the maximum conversion efficiency range (i.e. growth efficiency in range 8–9°C) could also be of interest. However, these indices could not be estimated with satisfactory accuracy by the models used in the present study, probably due to nonlinear relationships among the selected physio-climatic attributes. More flexible interpolation methods, such as kriging or artificial neural networks, could help estimate such indices.

This approach could be used as a powerful management tool to detect current threats as well as potential future risks. It allows one to acquire accurate knowledge about thermal habitat suitability in a hydrographic network for the species monitored, and which life stage or biological function is primarily affected. This tool could also be used to test hypotheses about how thermal habitat may shift with water temperature increases. Conservation and resource managers could better identify areas that need interventions and then prioritize their restoration and conservation efforts to reduce thermal effects on vulnerable populations. In order to improve conservation planning efficiency, we suggest using optimized water temperature networks at regional or local scales, where ranges of native populations or species to be conserved are well known and where management actions can be implemented at relevant levels on populations and habitats.

Recently, several authors have highlighted the need to develop long-term monitoring of water temperatures with full-year data and to optimize measurement networks in order to better characterize the seasonality and the variability of thermal regimes (Olden and Naiman 2010). Such long-term monitoring is needed to improve predictive models on biological impacts of possible future temperature conditions (Elliott and Elliott 2010), to allow downscaling of the temperature increase effects to local habitats and populations (Isaak *et al.* 2010), and to understand the role of non-climate factors on thermal regimes at regional, landscape and stream scales, in order to prioritize conservation efforts (Isaak *et al.* 2012). The optimization methodology presented here for stream temperature monitoring networks represents a useful advance, with operational applications that match the needs of managers. In a broader perspective, this methodology could be also used to optimize other measurement networks, with conservation concerns for aquatic, terrestrial or aerial organisms.

5 Conclusions

The regional assessment of river thermal regimes requires the monitoring of water temperature at adequate spatial resolution. The strategic planning of a water temperature monitoring network requires choosing the number and locations of the monitoring sites. An optimal measurement network may be defined by minimizing its density while maximizing its information content. While several network optimization methodologies make use of historical data to assess the best monitoring locations to maintain in an existing network, the methodology presented here can be used for the planning of a measurement network from the onset, i.e. without *a priori* knowledge of the variable to be monitored, as it does not require historical data and is based rather on the sampling of the physiographical and climatic characteristics of the region. Its application in Haute-Savoie allowed the proposal of optimized networks defined using four physiographical metrics that have high variability in the region. Such optimized networks were able to provide satisfactory estimations for seven ecologically and biologically relevant thermal indices throughout the region for brown trout populations.

Acknowledgements

The authors would like to thank Météo France for providing air temperature and precipitation data, as well as H. Capra and A. St-Hilaire for helpful comments and advice.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was funded by Cégep international, the Fonds de recherche du Québec – Nature et technologies (Grant no. 177631) and the Fédération de Haute-Savoie pour la pêche et la protection du milieu aquatique.

References

Alfonso, L., *et al.*, 2013. Information theory applied to evaluate the discharge monitoring network of the Magdalena River. *Journal of Hydroinformatics*, 15, 211–228. doi:10.2166/hydro.2012.066

Bénichou, P. and Le Breton, O., 1987. *AURELHY: une méthode d'analyse utilisant le relief pour les besoins de l'hydrométéorologie*. Deuxièmes journées hydrologiques de l'ORSTOM, 1986/09/16-17 1987 Montpellier. 299–304.

Bernatchez, L., 2001. The evolutionary history of brown trout (Salmo trutta L.) inferred from phylogeographic, nested clade, and mismatch analyses of mitochondrial DNA variation. *Evolution*, 55, 351–379. doi:10.1111/evo.2001.55.issue-2

Brown, L.E. and Hannah, D.M., 2008. Spatial heterogeneity of water temperature across an alpine river basin. *Hydrological Processes*, 22, 954–967. doi:10.1002/(ISSN)1099-1085

Caissie, D., 2006. The thermal regime of rivers: a review. *Freshwater Biology*, 51, 1389–1406. doi:10.1111/fwb.2006.51.issue-8

Caudron, A., Vigier, L., and Champigneulle, A., 2012. Developing collaborative research to improve effectiveness in biodiversity conservation practice. *Journal of Applied Ecology*, 49, 753–757.

Champigneulle, A., Largiader, C.R., and Caudron, A., 2003. Reproduction de la truite (Salmo trutta L.) dans le torrent de chevenne, Haute-Savoie. Un fonctionnement original?. *Bulletin Français de Pêche et Pisciculture*, 369, 41–70. doi:10.1051/kmae:2003021

Champigneulle, A., *et al.*, 1988. Premières observations sur la truite (Salmo trutta L.) dans le Redon, un petit affluent frayère du Lac Léman. *Bulletin Français de la Pêche et de la Pisciculture*, 310, 59–76. doi:10.1051/kmae:1988006

Chokmani, K. and Ouarda, T.B.M.J., 2004. Physiographical space-based kriging for regional flood frequency estimation at ungauged sites. *Water Resources Research*, 40, W12514. doi:10.1029/2003WR002983

Chu, C., Jones, N.E., and Allin, L., 2010. Linking the thermal regimes of streams in the great lakes basin, Ontario, to landscape and climate variables. *River Research and Applications*, 26, 221–241.

Crisp, D.T., 1988. Prediction, from water temperature, of eyeing, hatching and "swim-up" times for salmonids embryos. *Freshwater Biology*, 19, 41–48. doi:10.1111/j.1365-2427.1988.tb00325.x

Crisp, D.T., 1992. *Measurement of stream water temperature and biologiacal applications to salmonid fishes, grayling and dace*. Ambleside: Freshwater Biological Association.

Crisp, D.T., 1996. Environmental requirements of common riverine European salmonid fish species in freshwater with particular reference to physical and chemical aspects. *Hydrobiologia*, 323, 201–221. doi:10.1007/BF00007847

Daigle, A., Ouarda, T.B.M.J., and Bilodeau, L., 2010. Comparison of parametric and non-parametric estimations of the annual date of positive water temperature onset. *Journal of Hydrology*, 390, 75–84. doi:10.1016/j.jhydrol.2010.06.032

Daigle, A., *et al.*, 2011. Multivariate analysis of the low-flow regimes in eastern Canadian rivers. *Hydrological Sciences Journal-Journal Des Sciences Hydrologiques*, 56, 51–67. doi:10.1080/02626667.2010.535002

De Kinkelin, P., Gay, M., and Forman, S., 2002. The persistence of infectivity of Tetracapsula bryosalmonae-infected water for rainbow trout, Oncorhynchus mykiss (Walbaum). *Journal of Fish Diseases*, 25, 477–482. doi:10.1046/j.1365-2761.2002.00382.x

Dumoutier, Q., Vigier, L., and Caudron, A., 2010. *Macro Excel d'Aide au Calcul de variables thermiques appliquées aux Milieux Aquatiques Salmonicoles, MACMASalmo1.0*. St-Martin Bellevue: Fédération de pêche de Haute Savoie.

Dunteman, G.H., 1989. *Principal components analysis*. Newbury Park, CA: Sage.

Eaton, J.G. and Scheller, R.M., 1996. Effects of climate warming on fish thermal habitat in streams of the United States. *Limnology and Oceanography*, 41, 1109–1115. doi:10.4319/lo.1996.41.5.1109

Elliott, J.M. and 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. *Journal of Fish Biology*, 77, 1793–1817. doi:10.1111/jfb.2010.77.issue-8

Elliott, J.M. and Hurley, M.A., 1998. An individual-based model for predicting the emergence period of sea-trout fry in a Lake District stream. *Journal of Fish Biology*, 53, 414–433. doi:10.1111/j.1095-8649.1998.tb00990.x

European Environment Agency, 2004. *Corine land cover 2000: mapping a decade of change*. EEA Brochure No. 4/2004.

Graham, C.T. and Harrod, C., 2009. Implications of climate change for the fishes of the British Isles. *Journal of Fish Biology*, 74, 1143–1205. doi:10.1111/jfb.2009.74.issue-6

Guillemette, N., *et al.*, 2011. Statistical tools for thermal regime characterization at segment river scale: case study of the Ste-Marguerite River. *River Research and Applications*, 27, 1058–1071. doi:10.1002/rra.v27.8

Hannah, D.M. and Garner, G., 2015. River water temperature in the United Kingdom: changes over the 20th century and possible changes over the 21st century. *Progress in Physical Geography*, 39, 68–92. doi:10.1177/0309133314550669

Hari, R.E., *et al.*, 2006. Consequences of climatic change for water temperature and brown trout populations in Alpine rivers and streams. *Global Change Biology*, 12, 10–26. doi:10.1111/gcb.2006.12.issue-1

Hrachowitz, M., *et al.*, 2010. Thermal regimes in a large upland salmon river: a simple model to identify the influence of landscape controls and climate change on maximum temperatures. *Hydrological Processes*, 24, 3374–3391. doi:10.1002/hyp.v24:23

Husain, T., 1987. Hydrologic network design formulation. *Canadian Water Resources Journal*, 12, 44–63. doi:10.4296/cwrj1201044

Isaak, D.J., *et al.*, 2010. Effects of climate change and wildfire on stream temperatures and salmonid thermal habitat in a mountain river network. *Ecological Applications*, 20, 1350–1371. doi:10.1890/09-0822.1

Isaak, D.J., *et al.*, 2012. Climate change effects on stream and river temperatures across the northwest U.S. from 1980–2009 and implications for salmonid fishes. *Climatic Change*, 113, 499–524. doi:10.1007/s10584-011-0326-z

Johnson, S.L., 2004. Factors influencing stream temperatures in small streams: substrate effects and a shading experiment. *Canadian Journal of Fisheries and Aquatic Sciences*, 61, 913–923. doi:10.1139/f04-040

Jonsson, B. and 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. *Journal of Fish Biology*, 75, 2381–2447. doi:10.1111/jfb.2009.75.issue-10

Khalil, B. and Ouarda, T.B.M.J., 2009. Statistical approaches used to assess and redesign surface water-quality-monitoring networks. *Journal of Environmental Monitoring: JEM*, 11, 1915–1929. doi:10.1039/b909521g

Khalil, B., Ouarda, T.B.M.J., and St-Hilaire, A., 2011. A statistical approach for the assessment and redesign of the Nile Delta drainage system water-quality-monitoring locations. *Journal of Environmental Monitoring: JEM*, 13, 2190–2205. doi:10.1039/c0em00727g

Laikre, L., 1999. *Conservation genetic management of brown trout (Salmo trutta) in Europe: [report by the concerted action on identification, management and exploitation of genetic resources in the brown trout (Salmo trutta), TROUTCONCERT; EU FAIR CT97-3882*]. Danmarks Fiskeriundersøgelser, Afd. for Ferskvandsfiskeri.

Li, C., Singh, V.P., and Mishra, A.K., 2012. Entropy theory-based criterion for hydrometric network evaluation and design: maximum information minimum redundancy. *Water Resources Research*, 48. doi:10.1029/2011WR011251

Lowe, S., *et al.*, 2000. 100 of the world's worst invasive alien species: a selection from the global invasive species database. *In*: *Aliens*. Auckland, New Zealand: The Invasive Species Specialist Group (ISSG).

Mantua, N., Tohver, I., and Hamlet, A., 2010. Climate change impacts on streamflow extremes and summertime stream temperature and their possible consequences for freshwater salmon habitat in Washington State. *Climatic Change*, 102, 187–223. doi:10.1007/s10584-010-9845-2

Mohseni, O., Stefan, H.G., and Eaton, J.G., 2003. Global warming and potential changes in fish habitat in U.S. streams. *Climatic Change*, 59, 389–409. doi:10.1023/A:1024847723344

Moore, R.D., 2006. Stream temperature patterns in British Columbia, Canada, based on routine spot measurements. *Canadian Water Resources Journal*, 31, 41–56. doi:10.4296/cwrj3101041

Okamura, B., *et al.*, 2011. Life cycle complexity, environmental change and the emerging status of salmonid proliferative kidney disease. *Freshwater Biology*, 56, 735–753. doi:10.1111/fwb.2011.56.issue-4

Olden, J.D. and Naiman, R.J., 2010. Incorporating thermal regimes into environmental flows assessments: modifying dam operations to restore freshwater ecosystem integrity. *Freshwater Biology*, 55, 86–107. doi:10.1111/fwb.2009.55.issue-1

Olden, J.D. and Poff, N.L., 2003. Redundancy and the choice of hydrologic indices for characterizing streamflow regimes. *River Research and Applications*, 19, 101–121. doi:10.1002/(ISSN)1535-1467

Pampel, F.C., 2000. *logistic regression*. *Sage University Papers*. Beverly Hills: Sage Publications.

Pella, H., *et al.*, 2012. Le réseau hydrographique théorique (RHT) français et ses attributs environnementaux. *Géomorphologie: Relief, Processus, Environnement*, 3, 317–336. doi:10.4000/geomorphologie.9933

Portner, H.O. and Farrell, A.P., 2008. ECOLOGY: physiology and climate change. *Science*, 322, 690–692. doi:10.1126/science.1163156

Souchon, Y. and Tissot, L., 2012. Synthesis of thermal tolerances of the common freshwater fish species in large Western Europe rivers. *Knowledge and Management of Aquatic Ecosystems*, 405, 3.

Strobl, R.O., *et al.*, 2006. A water quality monitoring network design methodology for the selection of critical sampling points: part I. *Environmental Monitoring and Assessment*, 112, 137–158. doi:10.1007/s10661-006-0774-5

Thompson, B., 1984. *Canonical correlation analysis: uses and interpretation*. Newbury Park, CA: Sage Publications.

Verneaux, J., 1973. *Cours d'eau de Franche-Comté (Massif du Jura). Recherches écologiques sur le réseau hydrographique du Doubs*. Besançon: Université de Franche-Comté.

Webb, B.W., *et al.*, 2008. Recent advances in stream and river temperature research. *Hydrological Processes*, 22, 902–918. doi:10.1002/(ISSN)1099-1085