

A CLASSIFICATION OF STREAM WATER TEMPERATURE REGIMES IN THE CONTERMINOUS USA

A. MAHEU^{a*}, N. L. POFF^b AND A. ST-HILAIRE^{a,c}^a *Centre Eau-Terre-Environnement, Institut National de la Recherche Scientifique, Québec, Canada*^b *Department of Biology and Graduate Degree Program in Ecology, Colorado State University, Fort Collins, Colorado, USA*^c *Canadian Rivers Institute, University of New Brunswick, Fredericton, Canada*

ABSTRACT

Temporal variability in water temperature plays an important role in aquatic ecosystems, yet the thermal regime of streams has mainly been described in terms of mean or extreme conditions. In this study, annual and diel variability in stream water temperature was described at 135 unregulated, gauged streams across the USA. Based on magnitude, amplitude and timing characteristics of daily water temperature records ranging from 5 to 33 years, we classified thermal regimes into six distinct types. This classification underlined the importance of including characteristics of variability (amplitude and timing) in addition to aspects of magnitude to discriminate thermal regimes at the continental scale. We used a classification tree to predict thermal regime membership of the six classes and found that the annual mean and range in the long-term air temperature average along with spring flows were important variables defining the thermal regime types at the continental scale. This research provides a framework for a comprehensive characterization of the thermal regimes of streams that could provide a basis for future assessment of changes in water temperature caused by anthropogenic activities such as dams, land use changes and climate change. Copyright © 2015 John Wiley & Sons, Ltd.

KEY WORDS: water temperature; thermal regime; stream; Fourier series; variability; classification

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INTRODUCTION

Managing for natural variability has been proposed as the new paradigm for the management of freshwater ecosystems (Poff, 2009). This holistic approach has been well embraced for flow management and only recently has this approach gained momentum in the context of managing stream water temperature. The thermal regime of streams has predominantly been described in terms of magnitude (mean or extreme conditions). However, in addition to magnitude, temporal variation in water temperature plays an important ecological role. For example, the life history of freshwater organisms is generally tightly coupled with the seasonal signal of water temperature (Ward and Stanford, 1982; McCullough, 1999). Cumulative degree days, a measure of magnitude and timing, has also been considered in biological models given water temperature limitations associated with growth (Vannote and Sweeney, 1980; Neuheimer and Taggart, 2007). Variability at shorter timescales can also play an important ecological role. For example, diel variability has been shown to influence the distribution and the timing of life history processes of aquatic organisms (Ward and Stanford, 1982; Wehrly *et al.*, 2003; Steel *et al.*, 2012).

Recent characterization efforts have in fact embraced the importance of variability in the management of stream water temperatures. Borrowing from the natural flow regime concept (Poff *et al.*, 1997) and calculation of metrics associated with the time series of hydrologic records (Olden and Poff, 2003), the thermal regime of streams has been described through a series of metrics describing magnitude, frequency, duration, timing and rate of change in water temperatures (Chu *et al.*, 2010; Olden and Naiman, 2010; Arismendi *et al.*, 2013; Rivers-Moore *et al.*, 2013). This approach provides a comprehensive characterization of thermal regimes, although it requires numerous metrics to capture the multivariate properties of water temperature variability and faces the inherent difficulty of selecting the most appropriate and informative ones. Recent efforts in the classification of flow regimes have shown the value of using scale-independent methods based on fundamental characteristics of the flow signal as opposed to winnowing down a large set of correlated metrics (Archfield *et al.*, 2013).

Environmental drivers at multiple spatial scales interact to bring about a given thermal regime. Thus, an important challenge in managing water temperatures lies in the difficulty of reconciling variability arising from processes occurring at the reach, catchment and regional scales. Classification can help address this challenge by providing an organizational framework and offering guidance on when and where streams

*Correspondence to: A. Maheu, Centre Eau-Terre-Environnement, Institut National de la Recherche Scientifique, Québec, Canada.
E-mail: audrey.maheu@ete.inrs.ca

are comparable. In the context of water temperature management, classification offers an appropriate way of considering water temperature variability in the definition of desirable conditions as well as in the assessment of anthropogenic impacts. For example, Rivers-Moore *et al.* (2013) used classification to identify river reaches sharing similar thermal regimes and defined reference conditions against which the thermal regime of a stream below a reservoir could be compared. At the landscape scale, existing spatial classifications such as ecoregions have been found inadequate to capture spatial variability in stream water temperature (Makarowski, 2009; Chu and Jones, 2010). Therefore, the question of how to classify streams according to their thermal regime at large spatial scales is particularly relevant.

The objectives of this research were to (1) characterize the thermal regime of streams, with an emphasis on water temperature variability; (2) describe patterns of variability in water temperature and propose a classification of thermal regimes; and (3) identify key drivers that influence the thermal regime of streams at the continental scale.

METHODS

Site selection

The aim of this study was to characterize the thermal regime of minimally impacted streams, and as such, we selected 76 reference sites for which daily water temperature data were available from the Geospatial Attributes of Gages for Evaluating Streamflow, version II (GAGES-II) database developed by Falcone *et al.* (2010). To expand spatial coverage, we also selected 59 sites with a hydrological disturbance index below the median in each of the 18 two-digit hydrologic unit code regions. The hydrological disturbance index provides a qualitative assessment of hydrologic alteration based on the presence of dams and canals, change in reservoir storage from 1950 to 2009, road density, proximity to major pollutant discharge site, water withdrawals and landscape fragmentation (Falcone *et al.*, 2010). We also used site description in United States Geological Survey (USGS) annual data reports to avoid the selection of sites with a strong influence from regulation and diversion. We selected sites where the annual mean water temperature was stationary in time, which was assessed with a Mann–Kendall test ($\alpha=5\%$). At eight sites in the GAGES-II reference set, the annual mean water temperature was not stationary, but we included these ‘reference’ sites in the selection to ensure broader spatial coverage. In total, 135 sites were selected to characterize the thermal regime of streams in the conterminous USA. The record period spanned from 1952 to 2012, although 91 sites had a median year greater than 1990. The selection included a wide range of catchment sizes, and drainage area varied from 4 to 33 198 km². We

performed the selection of sites to be representative of the main landscape and climatic regions in the study area. Still, the selection of minimally impacted sites implied a certain bias. For example, small mountain basins in remote areas were generally better represented than large river basins. In addition, regions such as the Great Plains are underrepresented given ubiquitous alteration (i.e. agriculture).

Daily minimum, mean and maximum water temperature data were extracted from the USGS National Water Information System (NWIS) database (<http://waterdata.usgs.gov/nwis>). Each site was required to have at least 5 years of data, and each year had to have no more than 30 days of missing data to be included in the analysis. The data record was not required to be continuous, and non-consecutive years were used as needed to compute the average daily mean and daily range water temperature at each site. The number of years of data varied between 5 and 33 years for selected sites. For 56 sites, mean daily water temperature was not available and was estimated as the average of daily minimum and maximum water temperatures. (A separate analysis of 30 randomly selected data pairs of daily maximum and minimum temperatures showed this procedure to return estimated mean values with a mean error of 0.2 °C compared with observed values.)

Environmental attributes

For each selected site, environmental attributes related to topography (elevation, slope and aspect), climate (long-term air temperature and precipitation, and proportion of precipitation as snow), geology, soil properties (bulk density, permeability and clay/silt/sand content) and land cover (developed/forested/cultivated land cover and density of lakes) were extracted from the GAGES-II database. In this database, long-term air temperature and precipitation information were compiled from the PRISM dataset at each site (PRISM Climate Group, Oregon State University, Corvallis, OR, USA: www.prismclimate.org). Given that diel variability was also examined in this study, we compiled metrics describing sub-daily variations (i.e. daily range) in air temperature at each site using the PRISM surface air temperature climatology dataset. In addition, 118 hydrological indices selected by Olden and Poff (2003) were calculated to describe the magnitude, duration, frequency, timing and rate of change in flow conditions at each site. Hydrological indices were calculated using flow time series that were concomitant with water temperature data.

Characterization of the temporal variability in water temperature

The thermal regime of streams was characterized by describing two timescales of variability: annual and diel.

Annual variability. Annual variability was characterized using a Fourier series. This method has the advantage of summarizing a large proportion of the variance using a small number of coefficients rather than calculating a large set of correlated metrics. The Fourier series decomposes the time series into a sum of sinusoidal components and quantifies the periodic variation in water temperature. A Fourier series was fit to the average mean daily water temperature for the open-water period:

$$T_w(t) = a_0 + \sum_{i=1}^n a_i \cos\left(2\pi \frac{t}{c_i}\right) + b_i \sin\left(2\pi \frac{t}{c_i}\right) \quad (1)$$

where T_w is the mean daily water temperature, t is the Julian date (1 to 365), a_0 is the mean annual water temperature ($^{\circ}\text{C}$), a_i and b_i are coefficients fit through non-linear least square regression and c_i are the periods of variation or harmonics (e.g. 365 and 182 days). One to four harmonics are generally sufficient to model annual variation in water temperature (Kothandaraman, 1971; Caissie *et al.*, 1998). In this study, the first harmonic ($c_1=365$ days) explained between 80% and 99% of the variance in mean daily water temperature. Only for 12 sites (9%) did the first harmonic explain less than 90% of variance, and for 75% of sites, the first harmonic explained at least 94% of variance in mean daily water temperature. As such, only the first harmonic was used to characterize annual variability. This choice allowed a good balance between the number of parameters needed to describe annual variability and variance explained.

We fit the Fourier series for the open-water period, which was defined according to the method described by Daigle *et al.* (2010). For streams with an ice cover, less than 365 days of data were available to fit the Fourier series, and frequencies of variation failed to be orthogonal given only a fraction of the periods of variation was observed (Bloomfield, 2000). As a result, small differences can occur between the observed mean annual water temperature and the a_0 coefficient. These differences were generally small (mean difference = 0.1°C), and a difference larger than 1°C was observed only at three sites.

Three parameters were used to describe annual variability in stream water temperatures: mean annual temperature (a_0) as well as the amplitude and phase of the first harmonic (Figure 1). The amplitude of the first harmonic was calculated as by Anderson (1971):

$$A_1 = \sqrt{a_1^2 + b_1^2} \quad (2)$$

The phase of the first harmonic was calculated as by Anderson (1971):

$$\phi_1 = \tan^{-1}(b_1/a_1) \quad (3)$$

where A_1 is the annual amplitude ($^{\circ}\text{C}$), ϕ_1 is the phase in radians (between 0 and 2π) and a_1 and b_1 are coefficients

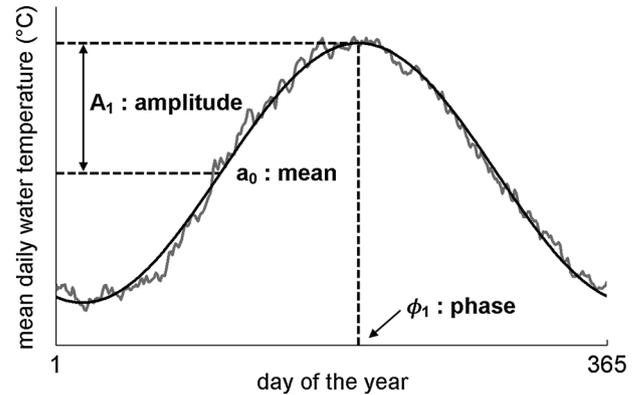


Figure 1. The three parameters describing the annual thermal regime of streams

derived for the first harmonic ($c_1=365$) of the Fourier series (Equation 1). The phase provides information on the timing of the annual water temperature cycle. For example, the occurrence of the maximum annual water temperature can be expressed as

$$JD_{\max} = \frac{365}{2\pi} \phi_1 \quad (4)$$

where JD_{\max} is the Julian date (between 1 and 365) of the occurrence of maximum annual water temperature as predicted by the Fourier series.

In order to propose a typology of annual thermal regimes, we characterized similarity among streams using hierarchical clustering with the Euclidean distance as a measure of dissimilarity and Ward's method as an agglomerative algorithm. We used standardized scores of the three parameters (a_0 , A_1 and ϕ_1) to perform the clustering analysis. The number of clusters was determined by examining the dendrogram and the Calinski and Harabasz's ratio of between-cluster to within-cluster sum of square differences (Milligan and Cooper, 1985). We also assessed the stability of clusters through a bootstrap approach with the R package *fpc* (Hennig, 2007). First, hierarchical clustering was performed on a resample of selected sites (with replacement to keep size constant). Second, the similarity between each new cluster set and the original clusters was assessed with the Jaccard index, which is the ratio between the number of elements that share the same membership and the total number of distinct elements in both datasets. We performed the comparison between the original and resampled partition 1000 times, and we computed the mean Jaccard coefficient for each cluster. The Jaccard coefficient ranges from 0 to 1. A stable cluster is generally characterized by a Jaccard coefficient larger than 0.75, while a value of 0.5 indicates that a cluster could be broken down into a simpler partition (Hennig, 2007). Given that water temperature time series could span different periods at each site, we evaluated if the lack of temporal overlap between sites could have

affected the classification. For each cluster, we selected the site with the longest record (≥ 16 years), and we divided the time series into periods of 5 years. We calculated Fourier coefficients for each 5-year period and assessed uncertainty through the coefficient of variation of the parameters. We also compared the interquartile range of 5-year period coefficients with the interquartile range of clusters to evaluate if uncertainty related to temporal coverage could have influenced cluster assignment.

Diel variability. In contrast to annual variability, diel variability was not described with Fourier series given the diel cycle is not stationary throughout the year in temperate streams. For example, diel variability tends to be of lower magnitude in the winter compared with the summer when diel range generally reaches a maximum. Furthermore, diel variability also varies through time because of the considerable influence of cloud cover. We characterized diel variability by quantifying the mean summer daily range, that is the months of July and August, which are the hottest months with the greatest expected contrast in diel variability.

Identify drivers of thermal variability

The thermal regime of a stream is influenced by climate, hydrology, geology and other environmental characteristics. To gain a better understanding of their relative influence at the continental scale, two complementary approaches were used: a classification tree and a random forest (RF) model.

A classification tree was used to attempt to predict membership to thermal regime classes using environmental attributes and a subset of the 118 hydrologic indices calculated. The subset of hydrological indices was selected with the RF model. Classification trees are well adapted for high-dimensionality datasets with various data types (continuous and categorical) with non-linear relationships (Breiman *et al.*, 1984). The classification tree partitioned data through binary splits in a recursive way in order to obtain homogenous classes with respect to predefined groups. The R package *rpart* was used to produce the classification tree. To avoid overfitting, the tree was pruned to the node within one standard deviation of the minimum standard error over all nodes (Breiman *et al.*, 1984).

An RF model was used both to evaluate the robustness of the classification tree and to identify important explanatory variables for the prediction of thermal variability. RF combined a large number of classification trees computed with a bootstrap sample of 70% of observations and a random selection of predictors at each node (Breiman, 2001). Using the left-out observations, the relative importance of a predictor was measured by randomly permuting a predictor and computing the difference in prediction accuracy (number of correctly classified observations) before and after the

permutation. The permutation of an important predictor should result in a large decrease in prediction accuracy. The number of trees ($n=2000$) to grow was determined by comparing models with different random seeds, and a model was considered stable when the relative variable importance remained relatively constant. The RF model was computed with the R package *party* using the conditional permutation importance measure to evaluate variable importance. This unbiased tree algorithm was chosen to avoid the overestimation of variable importance for correlated predictors as it has been discussed by Strbol *et al.* (2008). Because of the large number of predictors, a two-step approach was used to compute the classification tree and RF model. First, an RF model was fit using the complete list of 118 hydrological indices. Five hydrological indices were selected by evaluating variable importance as calculated by the RF model. Second, the classification tree and RF model were fit using environmental attributes and the five selected hydrologic indices.

RESULTS

Annual thermal regimes

Mean annual water temperature (a_0) of selected sites ranged from 2.6 to 21.6 °C, and the amplitude of the first harmonic ranged from 1.7 to 16.1 °C. The phase of the first harmonic (ϕ_1) ranged from 3.34 to 4.05 rad, which corresponded to maximum water temperature occurring on July 13 (Julian date 194) and August 23 (Julian date 235), respectively.

Classification that combined both diel and annual variability was generally unstable. As a result, a classification based only on annual variability was constructed. Annual thermal regimes were divided into six groups: highly variable cool, variable cold, variable cool, variable warm, stable cool and stable cold (Figure 2). We named the regimes by considering the magnitude (cold, cool and warm) and amplitude (variable and stable) characteristics of regimes. To describe magnitude, we followed the naming convention of fish thermal guilds based on temperature tolerance: the annual maximum water temperature was generally below 20 °C for cold regimes, between 20 and 28 °C for cool regimes and greater than 28 °C for warm regimes (Rahel and Olden, 2008). While the Calinski and Harabasz index had minimum values for a solution with seven and eight clusters, inspection of the dendrogram favoured a solution with six clusters, which also exhibited a small Calinski and Harabasz index compared with other partitions. The variable warm, stable cool and stable cold regimes were generally stable clusters and had a mean Jaccard coefficient larger than 0.7. The variable cold and variable cool regimes were less stable as clusters and had Jaccard coefficients of 0.61 and 0.63, respectively. The highly variable cool regime was the least stable with a

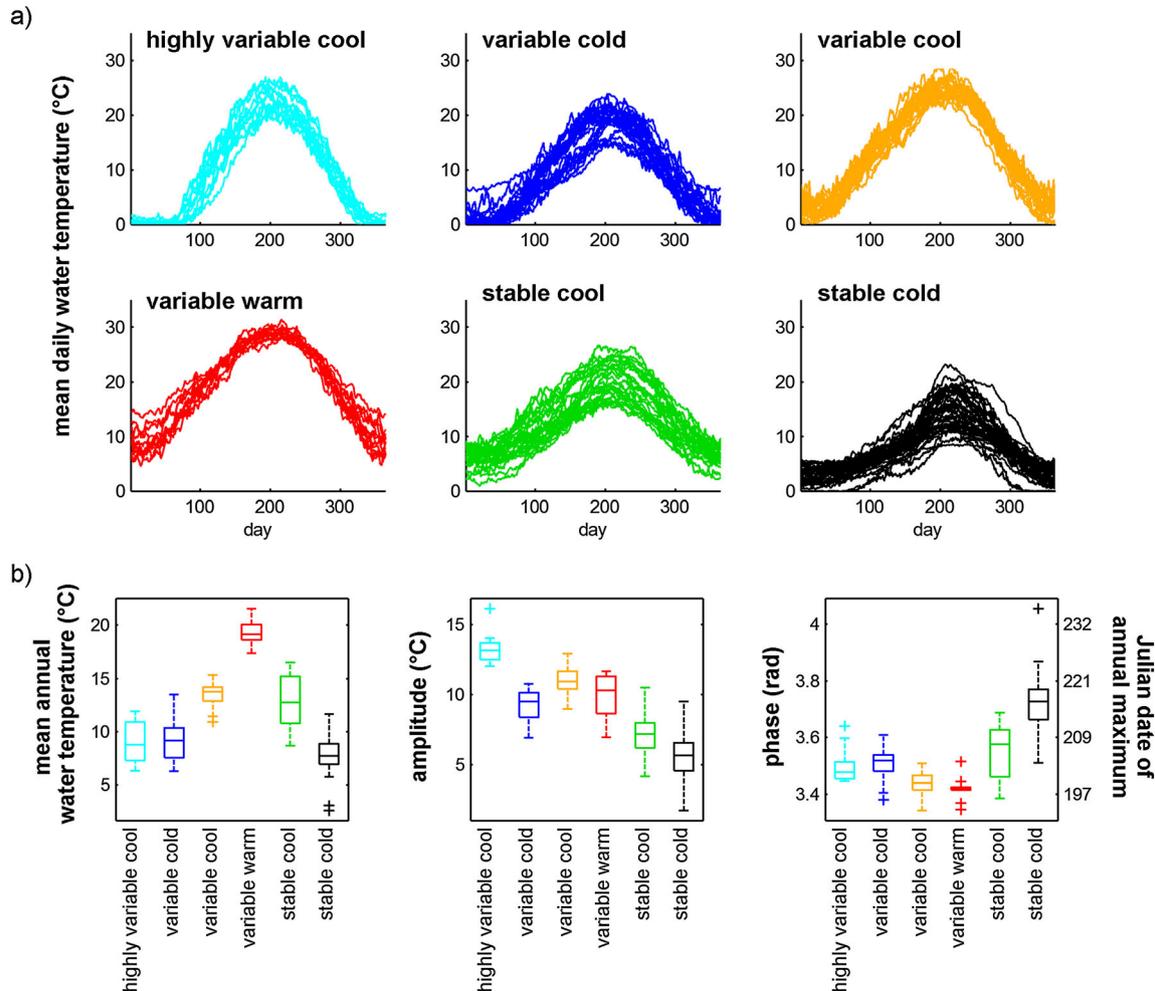


Figure 2. (a) Mean daily observed water temperatures for each annual thermal regime and (b) modelled characteristics of annual thermal regimes. The central mark is the median, edges of the box represent interquartile range, whiskers represent extreme values that are not considered outliers and crosses represent outliers. This figure is available in colour online at wileyonlinelibrary.com/journal/rra

mean Jaccard coefficient of 0.52, which indicated that further partitioning should be considered. However, this cluster was relatively small ($n=12$ sites), and a strong physical basis (i.e. presence of ice cover) supported the presence of this cluster.

Uncertainty in Fourier coefficients associated with varying temporal coverage was relatively small. The coefficient of variation in Fourier parameters calculated for each 5-year period of the longest record at each cluster ranged between 0.3% and 5.1%. The interquartile range of coefficients for every 5-year period was generally 2 to 16 times larger than the interquartile range of the cluster. These results suggest that temporal coverage did not likely exert a strong influence on cluster assignment. Only for the phase of the variable warm regime was the interquartile range of every 5-year period relatively similar to the interquartile range of the cluster (ratio=30%). However, the interquartile range of this cluster was particularly small (Figure 2b).

Figure 2a shows the observed mean daily water temperature at each site according to the six annual regimes. Figure 2b illustrates the magnitude, amplitude and timing parameters for the six annual regimes. For the discriminating parameters, the means were overall significantly different between annual thermal regimes (Kruskal–Wallis test, $\alpha=0.05$), and we performed a post hoc multiple-comparison test to further examine differences between regimes (Tukey–Kramer test, $\alpha=0.05$).

The highly variable cool, variable cold and stable cold regimes all had a mean annual water temperature below 10°C but differed significantly in terms of their amplitude. The highly variable cool regime was characterized by a large amplitude (mean= 13.3°C), and these streams were subject to the largest within-year fluctuations in water temperature compared with the other regimes. As such, these streams exhibited rapid warming in the spring, and the observed annual maximum water temperature ranged

between 20.3 and 27.0 °C. Highly variable cool streams also distinguished themselves from other streams in the northeastern USA by formation of an ice cover during winter. As such, water temperature was generally stable at 0 °C during the winter, and the ice cover typically appeared to extend until early March in these streams. On the other hand, an ice cover also likely formed on variable cold streams, but only sporadically from year to year.

Amplitude was the main discriminating parameter between the highly variable cool and variable cold regimes given the magnitude and timing parameters were not significantly different between those two regimes. The variable cold regime had a mean amplitude of 9.2 °C, and the observed annual maximum water temperature ranged between 15.0 and 23.9 °C. The variable cold regime had a widespread geographical distribution, and we identified variable cold streams across an important longitude gradient, from the west to the east coast (Figure 3).

The stable cold regime was characterized by the lowest amplitude (mean = 5.7 °C) compared with other regimes, and the annual maximum water temperature remained below 23 °C in these streams. Maximum water temperatures also occurred late in these streams, on average in early August (mean phase = 3.72, Julian date 216).

The variable warm regime was characterized by a large magnitude, and the mean annual water temperature ranged between 17.4 and 21.6 °C. The observed annual maximum water temperature exceeded 28 °C in these streams. The amplitude of variable warm streams (9.9 °C) was generally similar to variable cold (mean = 9.2 °C) and variable cool streams (mean = 11.0 °C). The variable warm regime exhibited strong geographical affiliation, and this regime was mainly found in the southeastern USA (Figure 3).

The variable cool and stable cool regimes were comparable in terms of magnitude with annual mean temperature averaging 13.5 and 12.8 °C, respectively. However, the stable cool regime was characterized by a smaller amplitude (mean = 6.9 °C) compared with the variable cool regime (mean = 11.0 °C). The stable cool regime had a particularly widespread geographical distribution, ranging from the west coast to the southeastern plains (Figure 3).

Drivers of annual variability

In addition to the physiography and climate variables, five hydrologic indices were selected to compute the classification tree: the mean flow in May and June, the mean minimum flow in May and June and the coefficient of variation in the mean flow in May (MA16, MA17, ML5, ML6 and MA28 in Olden and Poff, 2003). These indices were identified as important explanatory variables with the RF model. Indices describing the mean and minimum flow in May and June were strongly correlated to one another ($R > 0.8$) but only weakly correlated with the coefficient of variation in the mean flow in May ($|r| < 0.4$). Figure 4 shows the classification tree for annual thermal regimes. The classification tree performed generally well. The misclassification error of the training dataset was 19%, and the 10-fold cross-validation error was 30%, which provides a more honest prediction error estimate. We also validated the classification tree using the RF model. Three of the four environmental attributes used in the classification tree ranked in the top 20 important variables as identified with the RF model. Only the annual air temperature range was not identified as an important variable with the RF model.

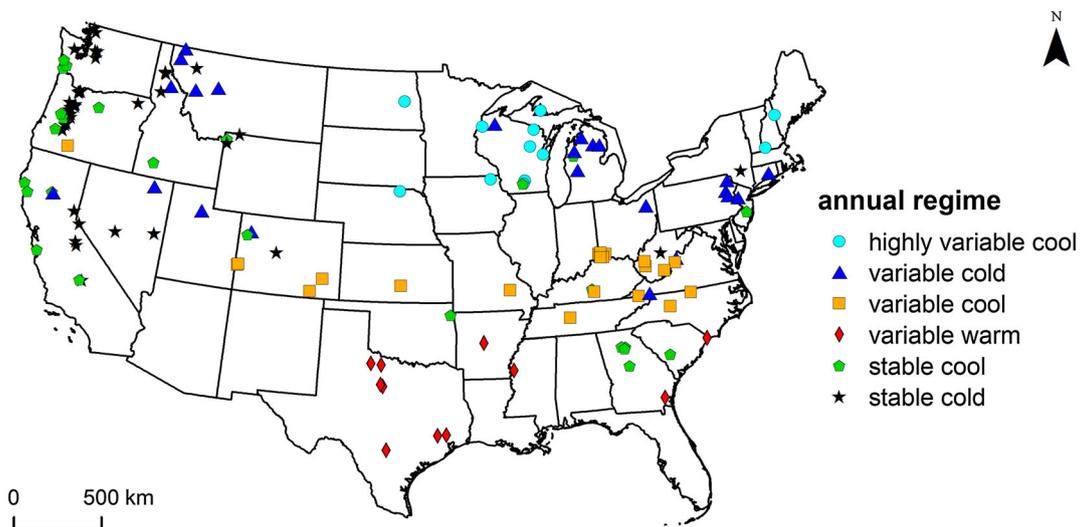


Figure 3. Spatial distribution of annual water temperature regimes. This figure is available in colour online at wileyonlinelibrary.com/journal/rra

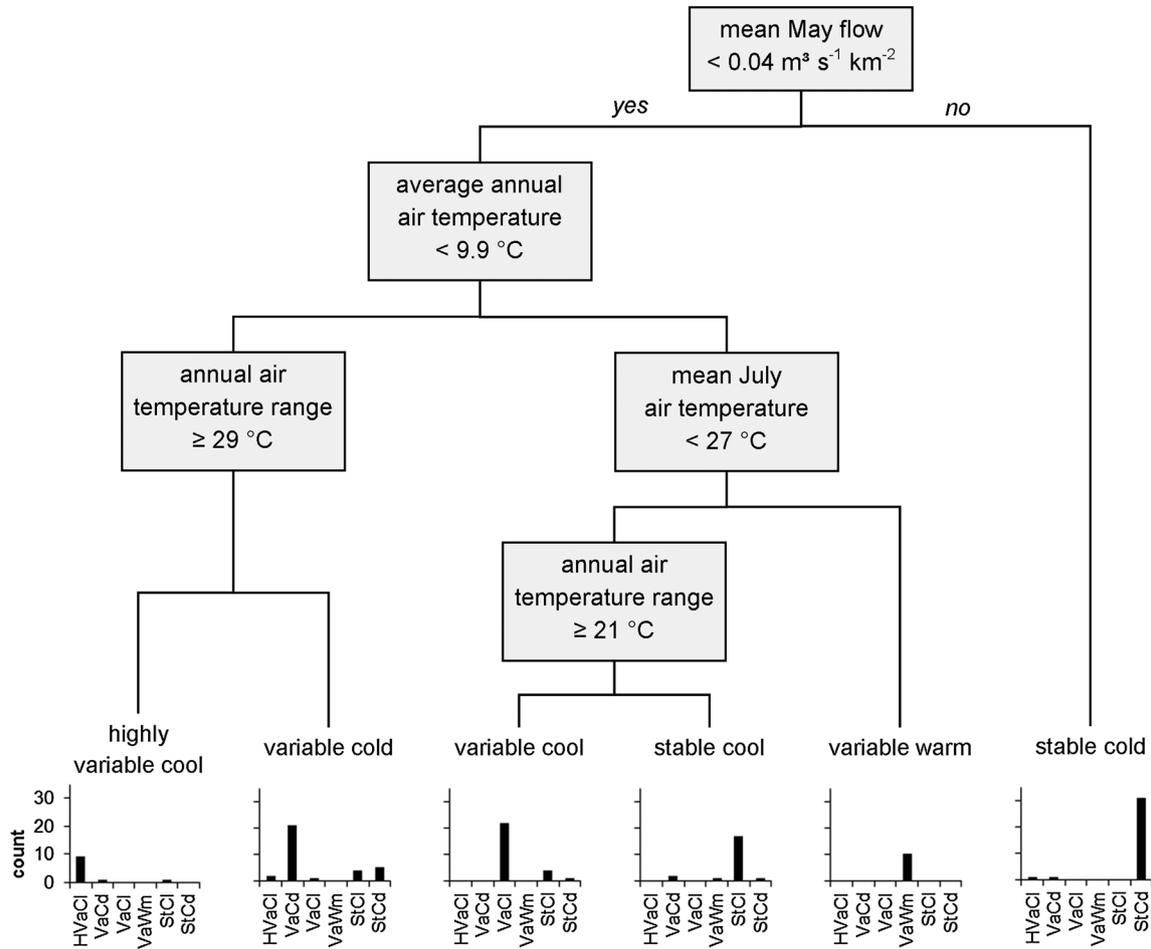


Figure 4. Classification tree for annual thermal regimes. Histograms under each regime indicate the misclassification error (HVaCl, highly variable cool; VaCd, variable cold; VaCl, variable cool; VaWm, variable warm; StCl, stable cool; StCd, stable cold)

With the exception of the stable cold regime, annual thermal regimes were mainly discriminated on the basis of climate (e.g. long-term air temperature average), as opposed to more static physiographic basin properties. Streams at lower latitudes where a warmer climate prevails were characterized with a variable warm water temperature regime. Mean July air temperatures exceeded 27 °C at these sites, which led to the higher magnitude of the water temperature regime compared with other regimes (Figure 2b). The highly variable cool and variable cold regimes were both characterized by a cool climate, and the annual mean air temperature was below 9.9 °C. Based on the within-partition heterogeneity criterion of the algorithm used to build the classification tree, these two regimes should be differentiated by their precipitation regime: the mean January precipitation was below 3 cm for the highly variable cool streams and above 3 cm for variable cold streams. However, this criterion led to the misclassification of the two northeastern streams and was potentially an artifact of the underrepresentation of this region in the site selection

compared with ice-covered streams in the dry north-central region. To test this idea, we produced a classification tree between these two regimes only, and the annual air temperature range came up as the best discriminating variable. As such, we used the annual air temperature range in the classification tree of water temperature regimes (Figure 4).

The main discriminating characteristic between the variable cool and stable cool regimes was the amplitude of the annual air temperature cycle. A large proportion of the stable cool sites were located on the west coast characterized by mild temperatures with an annual air temperature range between 11 and 17 °C. Similarly, stable cool sites in Georgia and South Carolina were also characterized by a relatively small annual air temperature range (between 19 and 20 °C). The importance of the annual air temperature range in discriminating water temperature regimes emphasized the need to consider not only the magnitude of the air temperature regime but also its annual variability when using air temperature as a predictor of stream water temperature regimes.

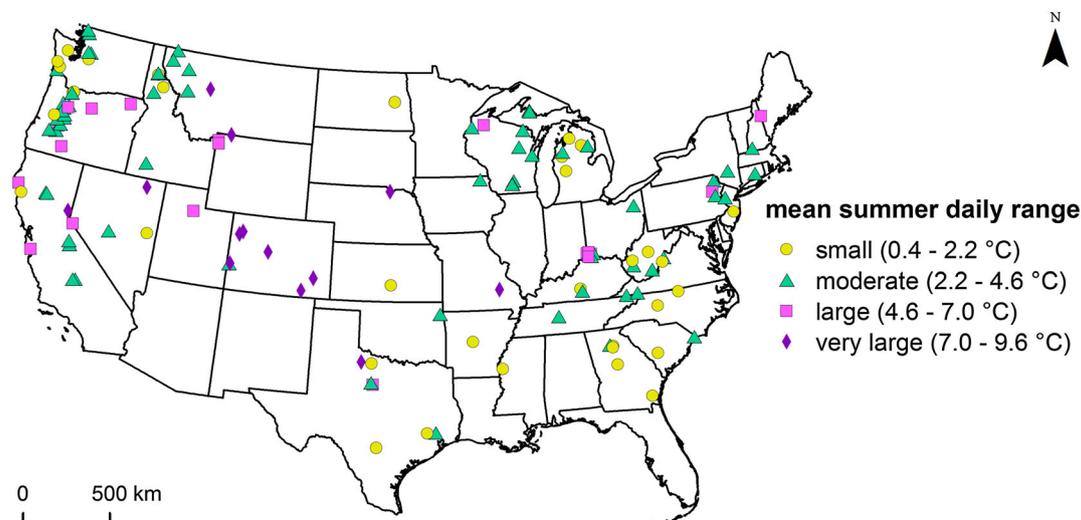


Figure 5. Spatial distribution of diel water temperature regimes. This figure is available in colour online at wileyonlinelibrary.com/journal/rra

The stable cold regime was the only regime differentiated by a variable not related to air temperatures. Sites classified with a stable cold regime were characterized by a large spring run-off compared with streams with other water temperature regimes. Streams identified as stable cold were primarily small mountain basins with a large catchment slope (mean = 32%) and large base flow index (ratio between base flow and total flow; mean = 32%). The stable cold regime mainly comprised streams with a consolidated period of high run-off in the spring (stable high-run-off and snowmelt regimes in McManamay *et al.*, 2013). Maximum flows tended to occur late for stable cold streams (mean Julian date of annual maximum flow = 252), and snowmelt likely sustained these cold streams until midsummer. Accordingly, stable cold streams had a large phase indicating a late warming of the stream. As a result of cool air temperatures associated with high elevation and a large groundwater contribution, the amplitude of stable cold streams was generally small compared with streams with a similar mean annual water temperature (highly variable cool and variable cold).

Diel thermal regimes

The mean summer daily range varied between 0.4 and 9.6 °C with a mean value of 3.7 °C. Figure 5 shows how the mean summer daily range varied across the study area. The distribution of the mean summer daily range was right skewed, and diel thermal regimes were divided into four groups according to the 25th (2.2 °C), 75th (4.6 °C) and 90th percentiles (7.0 °C). At the continental scale, our ability to predict diel variability from environmental attributes was limited. Correlation between the mean summer daily range and environmental attributes was generally weak ($|r| < 0.4$). When attempting to distinguish sites in terms of diel

variation, the difficulty lay in finding environmental attributes that would discriminate between streams with a relatively small (< 2.2 °C) and moderate (between 2.2 and 4.6 °C) mean daily range at the continental scale. Interestingly, we found that diel variability in air temperature explained certain broad patterns in diel variability in water temperature at the continental scale. Sites with a very large daily range in water temperature (mean summer daily range > 7 °C) were generally located in the central USA (Figure 5), and these sites were characterized by relatively large diel variability in air temperature as well. For example, sites with very large diel variability (mean daily range > 7.0 °C) had a mean summer daily range in air temperature of 17.1 °C, whereas sites with small or moderate diel variability (mean daily range < 4.6 °C) had a mean summer daily range in air temperature of 13.9 °C.

Figure 6 shows the relationship between diel and annual variability. The mean summer daily range was not significantly different between the annual regimes (Kruskal–Wallis test, $p = 0.13$), and the mean summer daily range could vary by as much as 8 °C for streams sharing a similar annual regime. Correlation between the two timescales of variability was generally weak. For example, the absolute correlation coefficient between the mean daily range and parameters describing annual variability (magnitude, amplitude and phase) ranged between 0.1 and 0.2.

DISCUSSION

Fourier series: a parsimonious framework to characterize annual variability

From a methodological perspective, Fourier series are well suited to model annual variability in water temperature

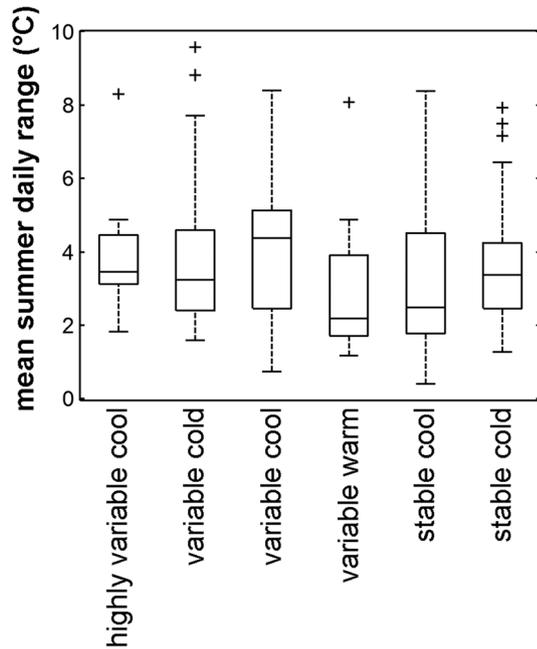


Figure 6. Diel variability in water temperature within each annual thermal regime. The central mark is the median, edges of the box represent interquartile range, whiskers represent extreme values that are not considered outliers and crosses represent outliers

(Kothandaraman, 1971; Caissie *et al.*, 1998). Fourier series provide a mathematical description of the seasonal water temperature signal using only three parameters (magnitude, amplitude and timing). These parameters are mathematically grounded but also describe ecologically relevant dimensions of water temperature variation. Fourier series offer a net advantage over data-driven methods (Chu *et al.*, 2010; Rivers-Moore *et al.*, 2013) where a large number of metrics are required to describe annual variability. These metrics generally exhibit a high degree of redundancy, and the selection of representative metrics can be partially subjective as a result of characteristics of the study area and its scale. For example, metrics of magnitude and rate of change were identified as good discriminants of thermal regimes in the Great Lakes region, Canada (Chu *et al.*, 2010), while metrics of magnitude and annual variability were identified as good discriminant variables in the southern Cape region of South Africa (Rivers-Moore *et al.*, 2013). In contrast, Fourier series consistently summarize annual variability using the same three parameters, and as such, this approach offered an effective and parsimonious framework to compare and classify annual thermal regimes across different regions and spatial scales.

However, the use of additional and specific descriptors is still relevant and can help provide a better understanding of the interaction between water temperature and ecosystem

processes. For example, specific descriptors of the thermal regime can help map out the ecological response associated with certain types of thermal alteration induced by dams (Olden and Naiman, 2010). Furthermore, a better consideration of water temperature variability should not be made to the detriment of acute temperature effects, and both aspects should be integrated in management goals.

A classification of annual thermal regimes

Classification provides an organizing framework for river research and management by identifying similarities across space regarding how a given abiotic factor varies in time (Olden *et al.*, 2012). For example, classifications of flow regimes have been proposed to better understand patterns of flow variation in streams of the conterminous USA (Poff and Ward, 1989; McManamay *et al.*, 2013). Likewise, a continental classification of thermal regimes provides insight as how to make cross-system comparisons by improving our understanding of how environmental drivers at different spatial scales interact. Results of this research underlined the importance of amplitude and timing parameters to discriminate thermal regimes at the continental scale. For example, we observed that streams with similar mean annual temperatures could vary significantly regarding seasonality (e.g. highly variable cool, variable cold and stable cold regimes; Figure 2). Variability at annual (Chu *et al.*, 2010; Rivers-Moore *et al.*, 2013) and seasonal (Wehrly *et al.*, 2003) scales have also been identified as important discriminants when classifying thermal regimes at the regional scale, further emphasizing the importance of considering aspects of variability in addition to mean conditions in thermal assessments.

At the continental scale, spatial variation in water temperature regimes was largely explained by climate. The long-term air temperature average, a proxy for climate, was identified as the strongest discriminating variable between annual water temperature regimes. This finding is consistent with Hill *et al.* (2013), who also identified air temperature to be a strong predictor of mean annual, summer and winter water temperature across the USA. The relation between air and water temperature has also been well exploited in statistical models (Benyhaya *et al.*, 2007). While mean air temperature conditions were strongly correlated with the magnitude of water temperature regimes, this research underlined the importance of considering climate seasonality as a predictor of spatiotemporal patterns in stream thermal regimes. As such, we identified the annual air temperature range as a strong discriminating variable between the highly variable cool and variable cold regimes as well as between the variable cool and stable cool regimes (Figure 4).

In addition to air temperature, results also suggest the importance of the flow regime in explaining some of the

spatial variation in water temperature regimes. The magnitude and timing of peak flows explained some of the spatial variation in stream thermal regimes across the USA. For example, we identified the mean May flow as an important variable to differentiate the stable cold regime from regimes that shared similar air temperature characteristics (highly variable cool and variable cold; Figure 4). This relationship stems from the important role snowmelt plays in water temperature variability (Smith, 1975). For example, MacDonald *et al.* (2014) found that water temperatures were strongly linked to the onset of the spring freshet in headwater streams in western Alberta. As such, changing patterns in the magnitude and timing of snowmelt in certain regions (Barnett *et al.*, 2005; Stewart, 2009) highlights the potential sensitivity of snowmelt-driven water temperature regimes to climate change.

The strong influence of climate on annual variability in water temperature can explain the general spatial coherence of most regimes (Figure 3). However, the lack of geographic affiliation for certain regimes (variable cold, stable cool and stable cold), as well as the presence of a few geographical outliers, could be due to the contribution of local-scale factors that were not considered in this continental scale analysis. For example, Chu *et al.* (2010) noted how local and macroscale factors, such as riparian vegetation, groundwater contribution and air temperature, interact to produce a given thermal regime. While results from this research suggest that climate and peak flows are good predictors of stream thermal regimes at the continental scale, a better understanding of the relative influence of local factors across different regions is needed to make statistical prediction of local thermal regime more precise.

Diel variability at the continental scale

This study generally had a limited ability to describe diel regimes given only minimum and maximum daily values were available at study sites. Data at a finer temporal scale (e.g. hourly) would have allowed the consideration of other aspects of diel variability (e.g. timing and rate of change), which could have facilitated the classification of diel regimes. Still, results suggest that climate influenced patterns of diel variability in water temperature at the continental scale, although to a lesser extent than what was observed for annual regimes. Streams with large diel variability in water temperature were generally associated with large diel variability in air temperature. Our ability to discriminate between small and moderate diel variability was particularly limited at the continental scale. Local, unmeasured factors likely had a predominant influence on the mean summer daily range. For example, riparian vegetation may not have been captured with sufficient precision in this continental assessment, and information on important local factors (e.g. width-to-depth or entrenchment ratios) was not available. Although an important aspect of water temperature

regimes, only few studies have attempted to model diel variability (Link *et al.*, 2013). Still, the weak correlation between annual and diel regimes emphasizes the importance of characterizing both diel and annual variability in thermal assessments. The classification scheme constructed in this study mainly focused on annual variability; however, further research should examine how other timescales of variability (e.g. diel and interannual) can be incorporated in classification schemes.

CONCLUSION

In this research, we proposed a framework for a comprehensive characterization of stream thermal regimes across the conterminous USA. Such framework can facilitate cross-system comparison as well as provide a basis for the definition of reference conditions. For example, this framework can help managers set expectations in terms of the natural range of variation in water temperature in a given region. Moreover, expectations regarding water temperature can be set for the entire open-water period rather than focusing only on the summer. Such information is particularly important given the life cycle of many species is timed with certain conditions in water temperature. Thermal alteration in a given stream could be assessed by evaluating if magnitude, amplitude and timing parameters fall outside the natural range of variation from reference conditions. Accordingly, this approach provides an efficient framework to assess and describe the alteration of water temperature by dams, land use changes as well as climate change. Furthermore, this framework could also be used to gain a better understanding of the sensitivity of different regimes to different sources of change.

Thermal classification is an important first step towards a better understanding of what factors influence stream thermal regimes at different geographic scales and for predicting the ecological response to changes in water temperature. At the continental scale, the modification of stream thermal regimes is expected to affect species distribution as well as the dispersal of invasive species (Rahel and Olden, 2008). The proposed classification can help develop regime-specific generalization about the role of water temperature in shaping aquatic ecosystems and as such guide management decisions in the context of a changing environment.

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