Comparison of a deterministic and statistical approach for the prediction of thermal indices in regulated and unregulated river reaches: case study of the Fourchue River (Québec, Canada).

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Abstract

Water temperature is an important factor modifying fish distribution patterns and community abundance in streams and this is especially true for salmonids. Knowing that dams often modify the thermal regime of rivers, understanding these changes is of crucial importance for fish habitat management. This study aims to improve knowledge about the impact of dams on the thermal regime of rivers during the summer season and to assess the relative efficiency of two modelling tools used to predict water temperatures downstream of dams. A deterministic model (SNTEMP) and a statistical model based on a canonical correlation analysis were calibrated on the Fourchue River (St-Alexandre-de-Kamouraska, Québec, Canada) upstream and downstream of a reservoir. SNTEMP was used to simulate mean water temperatures time series using meteorological inputs and discharge. The statistical model was used to directly estimate thermal indices (descriptive statistics of the thermal regime). The two models were compared based on their efficiency to estimate thermal indices such as mean and maximum monthly water temperatures and other parameters of importance in the understanding of the distribution and growth of ichthyofauna. Water temperature was monitored at 18 locations in the Fourchue River during the summers of 2011 and 12 locations in 2012 to describe the thermal regime and calibrate the models. The statistical model achieved better results than SNTEMP in estimating most of the thermal indices, especially the mean and maximum daily ranges with RMSEs of 4.1 °C and 4.9 °C respectively for SNTEMP as compared to 0.5 °C and 1.1 °C for the leave-one-out validation and 0.6 °C and 1.4 °C for the split-sample mode for the statistical model. The better performance of the statistical model for metrics related to thermally stressful events for fish make it more appealing as a management tool for water resources and fisheries managers. However, SNTEMP should be considered when the objective is to investigate the impact of climate change, reservoir operations or other anthropogenic impacts.

KEYWORDS: modeling, temperature, river, SNTEMP, multivariate, geostatistics

Introduction

The thermal regime of rivers is of interest for fisheries management because most of the physical, chemical and biological properties of fish habitat are temperature-dependent (Magnuson et al., 1979; Cassie, 2006). Because fish are ectotherms, they are highly dependent on water temperature to maintain important physiological and life history processes (Becker and Genoway, 1979; Wood and McDonald, 1997; Beitinger *et al*., 2000). Their suitable thermal habitats are constrained by both maximum and minimum thermal tolerances (Mohseni *et al*., 2003). Laboratory studies have been conducted for decades to define optimum temperatures for maximum fish growth (e.g. Jobling, 1981). For instance, the optimal growth temperature of brook trout (*Salvelinus fontinalis*) is 14.2 °C and the mortality rates increase when temperature exceeds 24.9°C, which is the upper limit of their thermal tolerance (Hasnain *et al*., 2010). This was further ascertained by Hasnain et al. (2013) who reviewed thermal metrics for numerous fish species, including salmonids, in North America.

Anthropogenic regulation of rivers also alters thermal conditions. The effects of dams on the thermal regime of rivers have been widely investigated and include changes in the temperature mean and variance at several temporal scales (Petts 1984; Preece and Jones 2002; Steel and Lange 2007; Olden and Naiman, 2010, Maheu et al., 2016). Thermal regimes downstream of impoundments depend on the dam operating mode and the depth of water intake. A significant number of large dams release cold hypolimnetic water establishing highly desirable habitats for trout and salmon. On the other hand, smaller dams and diversions can increase water temperature by releasing warm water directly from the reservoir surface (Maheu et al., 2016). These dam-induced modifications to the thermal conditions can have both direct and indirect consequences on fish by altering the quality of their habitat or their prey's habitat (Ward, 1985; Angilletta *et al*., 2008; Olden and Naiman, 2010).

On regulated rivers, adequate fisheries management can be achieved by mitigating the thermal stressful events via cold water releases below dams. One way to assess the impact of stream regulation on a river is to compute thermal indices at an impacted site and to compare them with those calculated from similar unregulated control rivers or river reaches. These indices are descriptive statistics of hourly or daily mean temperatures that characterize the thermal regime in terms of amplitude (mean and extremes), variability, duration and timing of events (cold or warm spells). Examples of amplitude indices include the monthly means of the maximum daily temperature (Arismendi *et al*., 2013). Some jurisdictions use thermal indices to manage fisheries. For instance, on the Miramichi River (Canada) angling for Atlantic salmon (*Salmo salar*) is not allowed when maximum daily summer temperature exceeds 23 °C and minimum temperature is greater than 20 °C (Caissie, Thistle, and Benyahya 2017). In western Canada and north-western U.S., the highest average of maximum daily temperatures over any 7-day period (maximum weekly maximum temperature, MWMT) and the highest average of mean daily temperatures over any 7-day period (maximum weekly average temperature MWAT) are used as thermal metrics for fisheries management (Welsh et al. 2001).

Unfortunately, temperature gauging stations that could be used to calculate these thermal indices are relatively scarce in Canada. To overcome the lack of data, many different simulation tools are used to characterize the thermal conditions in rivers. These tools can be classified in two main categories: deterministic models (Theurer *et al*., 1984; St-Hilaire *et al*., 2003; Cassie *et al*., 2007 Ouellet *et al*., 2013) and empirical or statistical models (Bélanger *et al*., 2005; Benyahya *et al*., 2007; Chenard and Caissie, 2008; Guillemette *et al*., 2009). Deterministic models typically calculate a heat budget at one or many points in the river using meteorological inputs and information on stream geomorphology and hydraulics. However, these variables are not always readily available and the gathering of these data can be a long and expensive process. Statistical approaches can be an interesting alternative because they generally require fewer input variables. These latter models are based on statistical relationships between water temperature and correlated independent variables such as air temperature (Benyahya *et al*., 2007). While most statistical models use only meteorological inputs (mostly air temperature), some approaches allow for the inclusion of physiographic information. One such model was adapted to water temperature modelling by Guillemette *et al*. (2009). It combines multivariate methods and geostatistics. The main perceived advantage, compared to traditional deterministic models, is that the simulation of temperature time series can be bypassed and thermal indices can be modelled directly. This can be an attractive alternative for managers who may prefer a more direct, less cumbersome approach than deterministic modelling. However, the performance of this alternative needs to be equivalent to that of the more classic models. In the context of impounded rivers, the performance of the two models can be compared both upstream and downstream of dams, as reservoirs are often an important impediment to thermal connectivity.

There are very few studies that compare statistical and deterministic river temperature models using the same data sets. Massé and Armengol (2008) used a deterministic model and compared it to a hybrid approach (deterministic hydrological model combined with a linear regression between air and water temperature) on Mediterranean streams. They concluded that including empirical or hybrid formulations that use air temperature as a predictor is not optimal (compared to a deterministic model) when local meteorological data are available and should only be preferred when meteorological stations are far from the river reaches under study. Our study may be the first Canadian comparison between the two types of models on an impounded river.

The present study therefore aims to evaluate the efficiency of the multivariate geostatistical model used by Guillemette *et al*. (2009) by comparing it to a well-established deterministic model called Stream Network Temperature (SNTEMP) (Theurer *et al.*, 1984). The comparison is performed on two river reaches, upstream and downstream of a dam reservoir.

The statistical model is based on the identification of appropriate physiographical variables as predictors of water temperature indices at the stream segment scale. Thermal indices are obtained by interpolation in an orthogonal space constructed using a multivariate approach called canonical correlation analysis (Chokmani and Ouarda, 2004). The interpolation is made by using a multiple linear regressions in canonical space.

SNTEMP is a mechanistic, one dimensional heat transport model used to simulate daily mean and maximum water temperatures. SNTEMP was selected in this study because of its extensive use for regulated and unregulated rivers (Horne *et al*., 2004; Norton and Bradford, 2009; Voss *et al*., 2008; Shepard *et al*., 2009).

The general objective of this study is to compare the two different modeling approaches in order to determine which one is the most suitable for water resources managers in estimating selected thermal indices.

Methodology

Study site and data collection

The Fourchue River is a regulated river with a drainage basin of 261 km^2 and a tributary of the Du Loup River, located in eastern Quebec, Canada (Figure 1). The Morin dam was built to regulate flows in the Du Loup River. The reservoir occupies an area of 6.8 km^2 at top water level and has a storage capacity of 38 880 000 m^3. The water level into the reservoir is kept between 188 m and 195 m above sea level during summer. In order to maintain these levels, the flows evacuated are usually kept between 0.06 m^3/s and 4 m^3/s. Details on the dam, spillway and draw-offs, together with a description of the operation mode, are provided by the Centre d’Expertise Hydrique du Québec (CEHQ, 2008).

Water temperature time series were obtained for summer 2011 (July to September) and 2012 (June to September) with Hobo Pro V2 thermographs (± 0.2 °C) recording water temperature at 15 minutes intervals at approximately 15 cm from the stream bed. The loggers were deployed into two reaches of the Fourchue River considered relatively similar in topography, land use and climate. One reach is located directly downstream of the Morin dam and the other, which served as a control reach, is located10 km upstream of the reservoir, in the unregulated portion of the river. A total of 18 loggers were deployed in 2011, seven upstream of the reservoir in a 9 km reach and eleven downstream in a 5 km reach. For 2012, the downstream reach was extended to include the only major tributary of the Fourchue River, the Carrier stream, for a total of 12 loggers deployed over 8 km. Low water levels in the upstream reach in 2012 resulted in many thermographs being exposed to air and thus the 2012 upstream data could not be used. Hydrological and stream geometry data were also obtained from field measurements as well as the meteorological conditions for the study area.

Meteorological inputs

To calculate the energy budget equations, SNTEMP requires the following meteorological inputs: air temperature, relative humidity, wind speed, solar radiation and cloud cover. Daily air temperature (± 0.1°C) and relative humidity (±0.8%) were measured with a Rotronic HygroClip2 relative humidity and temperature probe (HC2-S3-L). Wind speed was measured with a RM Young wind monitor (05103-10, ±0.3 m/s) and solar radiation data were measured with a Kipp and Zonen pyranometer (SP-LITE-L, ± 10 µV W^{-1} m^2). The meteorological data were averaged hourly at a station located 100m north-east of the reservoir.

The solar radiation was used to estimate the percent possible sun (a surrogate for cloud cover) using a cloud cover correction algorithm from Reifsnyder and Lull (1965):

$$\frac{E_c}{E_m} - 10^{-0.99C_{okt}} \qquad (2)$$

Where:

E_c= Irradiance under cloudy condition

E_m= Irradiance under clear sky condition

C_{okt}= Cloud oktas

Hydrology

Rating curves were developed for the two reaches and the tributary to establish the relationship between discharge and water level. The daily water levels were obtained with Hobo U20 water level data loggers. Several spot measurements of discharges were taken between 1.2 and 3.8 $m^3 s^{-1}$ in the downstream reach, 0.1 and 2.5 $m^3 s^{-1}$ in the upstream reach and between 0 and 0.5 $m^3 s^{-1}$ in the tributary. The discharge data were collected using the velocity-area method with a Marsh McBirney Flo-Mate 2000 flow velocimeter.

Stream geometry

The sites elevations were obtained with a Novalynx barometer altimeter (230-M202) with 3 m accuracy. It was calibrated using the elevation of the CEHQ hydrometric station located 100 m downstream of the dam.

A pebble count was performed to characterize the composition of the streambed. In every stream segment, 100 particles were measured in the normal low flow channel. The cumulative frequency curve generated from pebble counts led to the estimation of the median particle diameter (D_{50}). Manning's roughness coefficient, *n,* was calculated from the following equation (Robert, 2003):

$$n = 0.048\ \mathrm{D}_{50}{}^{1/6} \tag{3}$$

In order to account for the riparian shade, an SNTEMP component estimates an attenuation factor using information on the streamside vegetation and the topography, on the average tree height, the crown diameter, and the distance from the water's edge. These variables were estimated from field observations. The topographic horizon angles on both sides of the river were measured with a clinometer. These angles are used by the model to calculate the local times of sunrise and sunset. Stream widths as a function of flow were also obtained from field measurements.

Thermal indices

Thermal indices are used to describe the magnitude, variability, frequency and duration of thermal events across space and time (Arismendi *et al*., 2013). The thermal indices calculated from the water temperature time series are monthly means and maxima of daily temperatures, the mean and maximum daily ranges, cumulative degree-days, the monthly standard deviation and the number of days over 24.9 °C, which is the upper incipient lethal temperature (UILT) for brook trout, one of the fish species found throughout the study area (Hasnain *et al.*, 2010). Mean temperatures were first selected as one of the amplitude metrics that represent the thermal "climate" of a river. Daily ranges and standard deviation are important because it has been shown that adequate range and variability that include low temperature at nights can allow fish to recuperate from (high) stressful temperature events (e.g. Brodeur et al., 2015). Temperature maxima exhibited by streams during summer can affect fish species limited by low survival threshold temperatures. The UILT is defined as the upper boundary to the "zone of thermal tolerance" within which there is no mortality from temperature (Fry *et al*., 1946). A metric like the UILT can be used to identify affected species. The indices were first used to compare and contrast the thermal regimes in the unregulated and regulated reaches. The models were also compared on their ability to predict these thermal indices.

Deterministic approach

The Stream Network Temperature Model (SNTEMP) was created by Theurer *et al.* (1984). SNTEMP is a steady state, one-dimensional heat-transport model used to predict daily mean and maximum water temperatures. The model is composed of six components, starting with the heat flux model that predicts the energy balance between the water and its environment. It is defined as the arithmetic sum of the solar, atmospheric and vegetative radiations, evaporation loss, heat conduction and convection, conduction and water back radiation. To predict the average mean daily and diurnal water temperatures as a function of stream distance, the heat transport component uses a dynamic temperature, steady flow equation. The solar component predicts the amount of solar radiation penetrating the stream water as a function of the time of year by calculating the radiation amount reaching the earth. The latitude is used to determine the day length and the meteorological conditions are used to estimate the attenuation of the radiation due to its travel through the atmosphere. Because the solar radiation reaching the stream can be reduced by the local environment and the riparian vegetation, the shade component estimates the attenuation using information on the streamside vegetation and the topography. Finally, to consider the adiabatic process, the meteorological component corrects for variations in elevation within the watershed that cause changes in atmospheric pressure, air temperature and relative humidity.

The first step of the SNTEMP modeling process is to represent the river as homogeneous segments with similar attributes like flows, width and streamside vegetation. The study area was partitioned into segments based on field observations, for a total of seven segments upstream and nine downstream in 2011 and twelve downstream in 2012. These homogeneous segments are called nodes. There are 14 different nodes available in the model to represent the network (presence of a tributary, structure, etc.). The use of these nodes will depend on the size of the study reach, the complexity of the system and the data availability. In the case of the Fourchue River, six nodes were required to represent the study area (figure 2). The description of the node types are presented in Table 1.

Table 1: Description of the node types used for the composition of the network of Fourchue River in SNTEMP

Node type	Abbreviation	Description
Source	H	The upstream boundary usually located at a gage or a zero flow headwater.
Structure	S	A point (reservoir) that may have discontinuity in discharge and will have a released temperature defined by the user.
Change	C	The upstream end of a reach with new stream shading or hydraulic properties
Validation	V	Node where the temperature is known and can be compared to predicted temperature
Point load	P	Node where a point load discharges into the river at a known temperature
End	E	The network end point (most downstream point)

Model calibration and validation

The deterministic model was calibrated in the downstream reach using a split-sample approach. The first two weeks of June and August 2012 were used as calibration periods in order to include the whole water temperature range in the calibration set. The calibration consists in adjusting the model parameters for a better representation of the river's environment (Table 2). For instance, the air temperature above the stream is usually lower than the temperature measured at the meteorological station. A correction factor of -0.5 °C was applied. Similarly, the relative humidity values were corrected and increased by 10 % over recorded values to account for humidity above the river. Finally, because wind speed was measured in an open area while wind above the water surface is impacted by canopy, the wind speed was reduced by 15% to represent the wind speed conditions in the sheltered river channel (Nieto et al., 2019). This percentage was determined by trial and error.

Table 2: SNTEMP's global calibration factors and the corrections applied for a better representation of the Fourchue River conditions.

SNTEMP global calibration factors	Corrections applied
Air temperature calibration constant	↓0.5 ºC
Air temperature calibration coefficient	-
Wind speed calibration constant	-
Wind speed calibration coefficient	↓15%
Humidity calibration constant	-
Humidity calibration coefficient	↑10%
Sunshine calibration constant	-
Sunshine calibration coefficient	-
Solar calibration constant	-
Solar calibration coefficient	-

The model temperature estimations were compared to the continuous temperature measurements into two segments, referred to as verification nodes, in the upstream reach, and to three segments in the downstream reach. The model was validated in the downstream reach over July 2012. Finally, the thermal indices were calculated using the mean and maximum daily water temperatures simulated by SNTEMP. The performance of the model was assessed by considering two specific performance evaluation criteria: the BIAS and the root mean square error (RMSE) (See Laanaya et al. 2017 for detailed equations). Given that thermographs precision is of the order of 0.5 °C, a RMSE value of the order of 1 °C can be considered as a low error for a water temperature model. Bias should, of course, also be minimized, especially as it relates to high temperatures.

SNTEMP does not have the ability to model temperatures within impoundments so the sections upstream and downstream of the reservoir were modelled separately for August 2011.

Statistical approach

The statistical model is based on an interpolation technique that estimates the thermal indices in a mathematical multivariate space rather than a geographical space, as proposed by

Guillemette *et al*. (2009). The approach relies on the construction of an orthogonal space defined by the canonical correlation analysis (CCA) of the physiographical and water temperature characteristics of the stream segments. CCA is a multivariate approach that produces linear combinations of two sets of observations in order to maximize the associations (measured by the correlations) between the two data sets, while ensuring orthogonality of the canonical variates within the same group. Here, those two data sets are the matrix X of the thermal indices and the matrix Y of the predictors, which are the physiographic variables representing the environment of the river. In this case, only four metrics, strongly correlated with water temperature, were necessary to characterize the stream segment; these were the distance from the dam (positive downstream and negative upstream), the elevation, the Stralher order and the vegetation density. CCA produces the orthogonal linear combinations U of variables in matrix X, known as canonical variates that maximally correlate with the linear combinations V of variables in matrix Y. The coefficient vectors a and b are respectively associated with the thermal indices (X) and the physiographical variables (Y):

$$a)\quad U = aX$$

$$\text{b)}\quad V = bY \tag{4}$$

Pairs of vectors (Ui, Vi) are identified as the he ith canonical variate pair. There are p possible canonical covariate pairs, where p is the smallest vector length of X or Y. The vectors are found by a joint covariance analysis of the variables (Härdle and Simar, 2003). This allows to maximize the canonical correlation between (Ui, Vi), calculated as:

$$\rho_i = \frac{cov\ (U\text{i},V\text{i}),}{var\ (Ui)var\ (Vi)} \tag{5}$$

A multiple linear regression (MLR) was performed in the orthogonal plane composed of the first two dimensions of the canonical variates V, which constitute the axes of the physiographic space. For a given water temperature index, values at monitoring stations were projected in the V space and interpolation at ungauged sites was achieved by fitting a linear equation that best approximate all individual data points in the least square sense. It was also possible to find the V coordinates of an ungauged site by using equation 6(b). Figure 3 summarizes the main steps of the statistical model.

In order to assess the performance of the statistical approach, two validation techniques were used: a cross validation using a leave-one-out resampling (jackknife) and a split-sample validation. In the jackknife, the value of a station is temporarily removed from the data set and this value is estimated using the remaining stations. This operation is repeated for the whole station set. The estimated values are then compared with the observed data. For the split-sample validation, almost all stations were removed from the observed sample to serve as a validation group except for the stations at the most upstream and downstream points of the two stream reaches. These remaining four stations in 2011 and three stations in 2012 were used as calibration group. The BIAS (equation 4) and the RMSE (equation 5) were calculated for the two validation techniques (Chokmani and Ouarda, 2004). The performance of SNTEMP and the statistical model were compared on the basis of the two aforementioned evaluation criteria (BIAS and RMSE).

Results and discussion

The total rain amount in the region exceeded the normal in August 2011 (106.6 mm as compared to the monthly mean of 89.1 mm), resulting in a water level 2.4 m over the monthly mean recorded at the CEHQ hydrometric station. On the opposite, rainfall was below normal in August 2012, with only 53.2 mm of total precipitations. The mean air temperature was 2.1°C above the normal conditions. This resulted in low water levels and warmer water temperatures as compared to 2011. Because it captures a fair range of the possible summer hydroclimatic conditions, the results of the modeling approaches will be presented for these two months.

The canonical space was defined for every thermal index. Figure 4 shows an example of a canonical space for August 2011 mean temperature. There is a clear separation between the upstream and downstream sections and the two stations located downstream of the tributary. The interpolation was performed within that space.

Thermal indices based on mean temperature for August 2011 and 2012.

Both models showed very similar good performance for the estimation of the thermal indices based on monthly mean water temperature (Figure 5). The performance measures indicate that SNTEMP is slightly more accurate for the prediction of the mean monthly (August) water temperature, with a RMSE of 0.2 ºC compared to 0.4 ºC and 0.3 ºC for the leave-one-out and split-sample validation of the statistical model, respectively. BIAS was much smaller that sensor precision (< 0.01 °C) for these thermal indices. No estimation was performed with SNTEMP for stations 17 and 18 due to the lack of flow data from the tributary of the Fourchue River, the Carrier River, located in that reach, just upstream of these two stations. To evaluate thermal mixing below tributaries, SNTEMP requires daily discharge and temperature from the tributary, which were not available for 2011. The statistical model does not use discharge as a metric so it was possible to estimate temperature at these stations. The accurate estimations of these downstream stations are explained by the fact that the longitudinal variability of the monthly means is well represented by the Strahler order, which is a component of canonical variate V1.

The same observations can be made for the cumulative degree-days, an important metric for the evaluation of the growth rate for fish (Neuheimer and Taggart, 2007). The obtained RMSE are 5.0 ºC-days, 11.5 ºC-days and 9.4 ºC-days for SNTEMP, the leave-one-out and the split-sample validations of the statistical model, respectively. The RMSEs are considered relatively low for the two approaches because the observed cumulative degree-days vary between 540 and 625 ºC-days. There was no significant BIAS in the estimation of this thermal index with either of the two approaches. Hence, SNTEMP outperformed the statistical model for this metric.

The monthly standard deviation was estimated with more accuracy by the statistical model with a RMSE of 0.2 ºC and no BIAS for both leave-one-out and split-sample, as compared to a RMSE of 1.0 ºC and a BIAS of 0.5 °C for SNTEMP.

In August 2012, the main tributary of the Fourchue River, located 3 km downstream of the dam, was included in SNTEMP with the point source model configuration. This means that the water temperature was not simulated in the tributary but the discharge and water temperature of the tributary was included in the modeling of the main river. Both models predicted mean daily water temperature with a RMSE of 0.1 ºC and no significant BIAS (Figure 6). In contrast with 2011, the cumulative degree-day was simulated with more accuracy with the statistical model than SNTEMP in 2012 (RMSE of 0.6 ºC-days (jackknife validation) and 2.9 ºC-days, respectively). However, the statistical model could not produce good estimations given only three calibration stations: RMSE associated with the split-sample validation using three calibration stations is 22.8 ºC-days. RMSE could be lowered to 0.7 ºC-days with eight out of thirteen calibration stations uniformly distributed over the downstream reach.

Thermal indices based on maximum temperature for August 2011 and 2012

The statistical model surpassed SNTEMP in the estimation of the thermal indices based on maximum temperature (figures 7 and 8).

In 2011, the Fourchue River has not experienced temperatures exceeding the zone of thermal tolerance of the brook trout, which was well predicted by the statistical model. SNTEMP predicted 3 days over 24.9 ºC, leading to a RMSE of 1.2 days. With the warmer conditions experienced in 2012, one to eleven days over the UILT was recorded in the river. The jackknife and split-sample RMSEs were less than 1 day and BIASes under 0.4 day, while SNTEMP gave 8.7 days RMSE and a BIAS of 4.8 days. The UILT can hardly be used adequately by river managers using this deterministic model as it would always over estimate the number of days where fish experiment temperature over their zone of thermal tolerance.

The calculations of the daily maxima in SNTEMP are based on an empirical model. Theurer *et al.* (1984) elaborated a method to estimate average afternoon air temperature, the main component for the estimation of maximum daily water temperature. Regression coefficients were determined for normal meteorological conditions, based on the arithmetic mean of historical data at 16 selected weather stations around the United States, which is not representative for the current study site. SNTEMP does not explicitly model minimum temperatures, which are estimated using the daily mean and maximum temperatures.

SNTEMP overestimated maximum daily water temperatures, especially downstream of the dam. This is due to the fact that the model extends the current reach stream geometry indefinitely upstream in order to simulate the conditions through which the water must travel from solar noon (considered as the mean daily water temperature) to solar sunset (considered as the maximum daily water temperature) and thus, does not include the reservoir in its simulation. The water released in the downstream reach from the shallow reservoir is warmer compared to the upstream reach. Information about the reservoir is not considered in SNTEMP when it calculates maxima based on the extension of the current reach stream geometry. In 2011, SNTEMP resulted in a RMSE of 2.5 ºC and a BIAS of 0.1 °C. However, if it is calculated separately, the RMSE for the upstream reach (1.4 °C) is lower than the RMSE for the downstream reach (3.1 °C). Information about the location of the dam is included in the statistical model in the metric “distance from the dam”, allowing the model to estimate maximum water temperature with more accuracy (leave-one-out and split-sample RMSEs of 0.7 ºC and 0.8 ºC, respectively) and no BIAS.

The lack of information on the dam reservoir prevented accurate estimations of the conditions through which water travels from solar noon to solar sunset, which explains the differences between the models for the estimations of the thermal indices based on maximum temperatures.

Water temperatures show diurnal variations depending on the heat energy gained and lost by a stream and the volume and source of runoff contributing to discharge (Ward, 1985; Webb, 1996). The presence of the dam reduces the range between temperature extremes at the stations located downstream (Ward and Stanford, 1979). This reduction in daily variability is represented by the metric “distance from the dam” in the statistical model, which resulted in a better estimation of the mean and maximum daily ranges. The overestimation of maximum temperature by SNTEMP led to an overestimation of the mean and maximum daily ranges in 2011 (RMSEs of 4.1 ºC and 4.9 ºC and BIAS of 4.7 °C and 2.4 °C for the mean maximum ranges, respectively). The statistical model estimated the mean and maximum daily ranges with RMSEs equal to 0.5 ºC and 1.1 ºC in leave-one-out mode and of 0.6 ºC and 1.4 ºC for the split-sample mode. The BIAS of the statistical validation methods was of -0.2 °C for both indices for the leave-one-out and 0.2 °C for the split-sample. Similar observations were made with the simulation of the mean and maximum daily ranges in 2012.

3.7 Discussion and Conclusion

The objective of this study was to compare the relative efficiency of a deterministic and a statistical model in the estimation of selected thermal indices, in order to determine which one is the most suitable for the river managers. SNTEMP showed good results for the estimation of monthly mean temperatures and cumulative degree-days but overall, the statistical model was more efficient for the estimation of most selected thermal indices.

SNTEMP is limited by the fact that it does not model temperatures within impoundments, nor does it explicitly model minimum temperature. These limitations impacted the performance of the deterministic model in the estimation of the selected thermal indices, leading to inaccurate estimations of three out of seven thermal indices. The multivariate geostatistical model showed good results for the seven thermal indices for both regulated and unregulated reaches. This model however requires water temperatures time series for each stream segment, while SNTEMP requires mean daily temperature only at the verification nodes and for the upstream and downstream headwater segments. This represents six gauging stations in 2011 and four in 2012. The split-sample validation technique aimed to reduce the number of gauging stations required for the statistical model with minimum accuracy loss. It turned out that four water temperature measurement stations in 2011 and three in 2012 were sufficient to simulate the selected thermal indices adequately.

Although many studies have compared different statistical models (e.g. Laanaya et al., 2017), very few have compared statistical vs deterministic approaches. Marceau et al., (1986) compared a Box-Jenkins statistical approach to the CEQUEAU deterministic model. They concluded that both had similar performances. SNTEMP, which has been used extensively in other studies, has seldom been compared to other models, with the exception of Norton and Bradford (2009). They compared SNTEMP to CE-QUAL-W2 and concluded that both had similar performances, but that the latter showed more consistent performance across space and time. Our results corroborate past studies indicating some equivalence in performances of both methods for simulating the mean temperature regime. However, our results also indicate a superior performance of the statistical approach for temperature extremes. Of course, model selection is always dependent on river management needs. For the management of brook trout, thermal indices related to high temperature and daily variability are the most important. Those metrics are better estimated by the statistical approach. The lower input requirements for the statistical approach and its relative good performance for indices that may be indicative of thermal stress for fish (e.g. number of days above a high temperature threshold) make this approach very attractive for manager. However, since the statistical model does not use explicit hydraulic or climatic inputs, it is not possible to evaluate different scenarios related to climate change and dam operations with this model in its current form. These kinds of scenarios could however be simulated with SNTEMP. The input data requirements are lower for the statistical model, resulting in lower implementation cost and less field work.

It can thus be seen that both models offer different advantages and should perhaps be used in conjunction in future studies. Therefore, if the management objective is to forecast temperature extremes in a drainage basin with little anthropogenic perturbations, the CCA-MLR model is adequate. However, if anthropogenic impacts are present or anticipated, SNTEMP should be the preferred choice for water resource managers.

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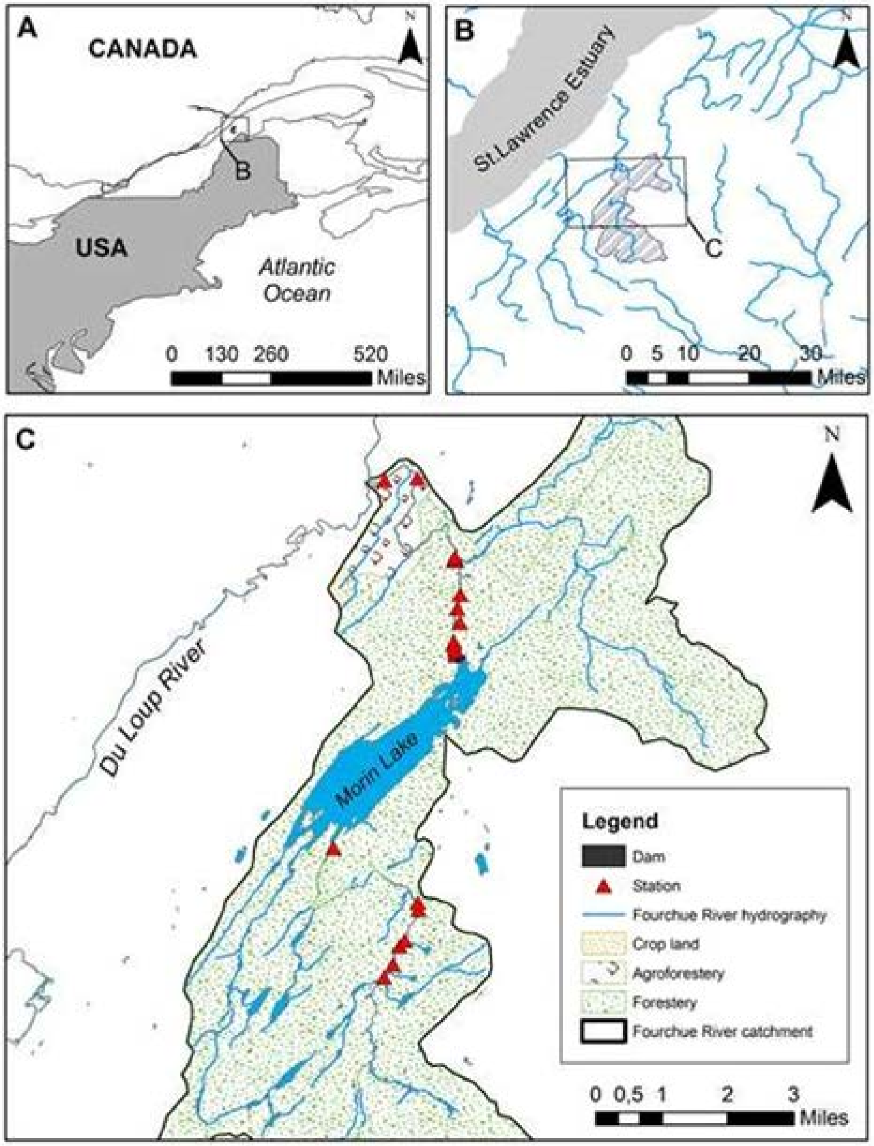

Figure 1. Location of the Fourchue River watershed and the water temperature monitoring stations.

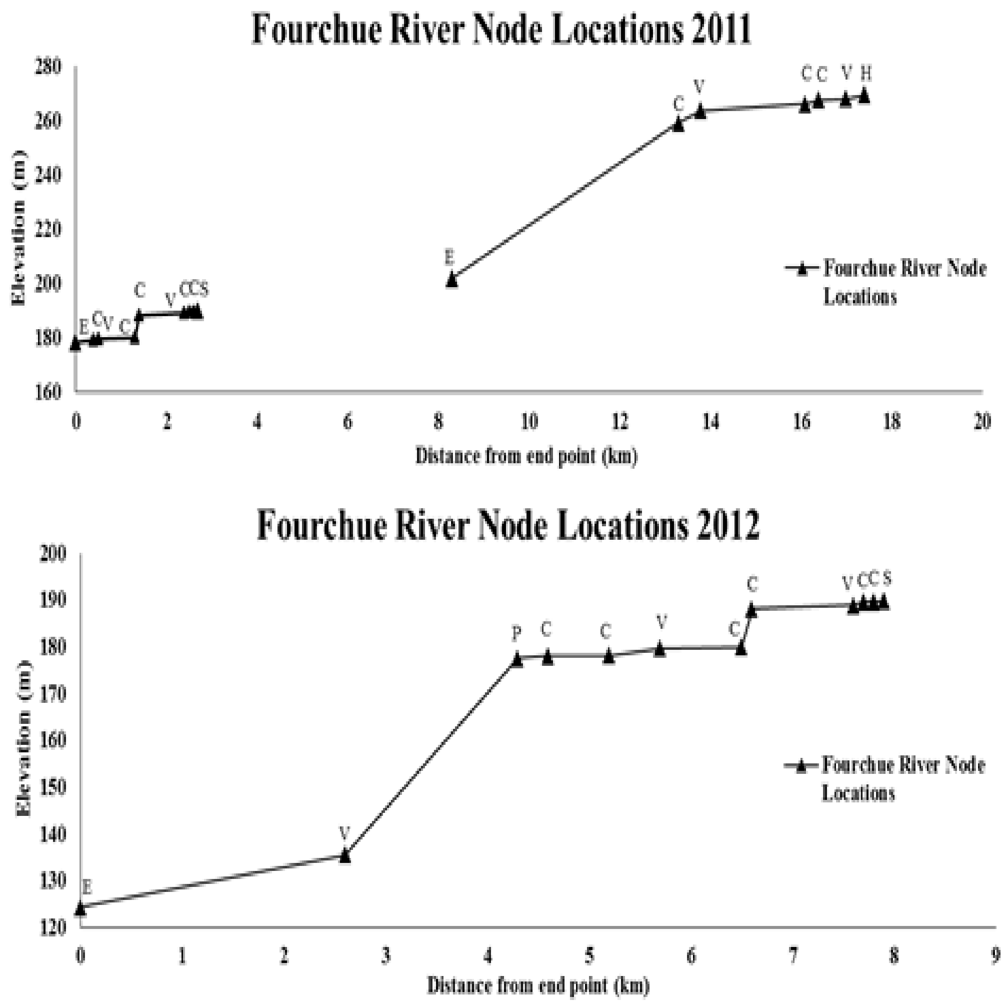

Figure 2. Longitudinal profile of the Fourchue River Illustrating the composite node network along the relative river gradient. Points along the diagram depict the node types including headwater (H), change (C), validation (V), structure (S), point load (P) and end (E).

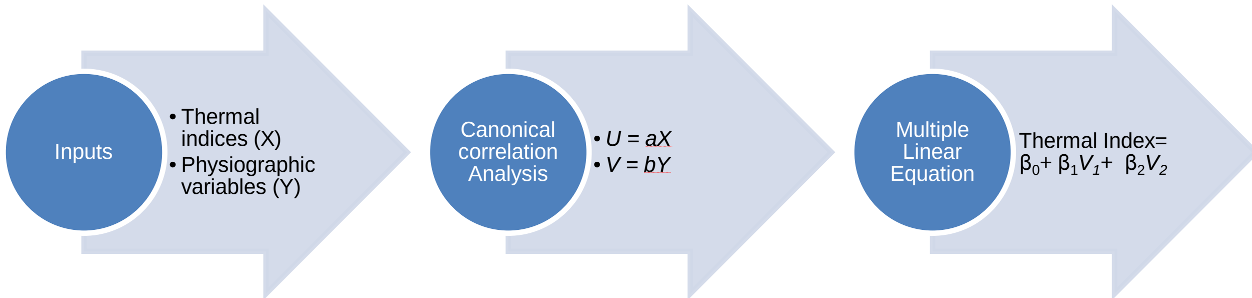

Figure 3. Main methodological steps of the statistical model.

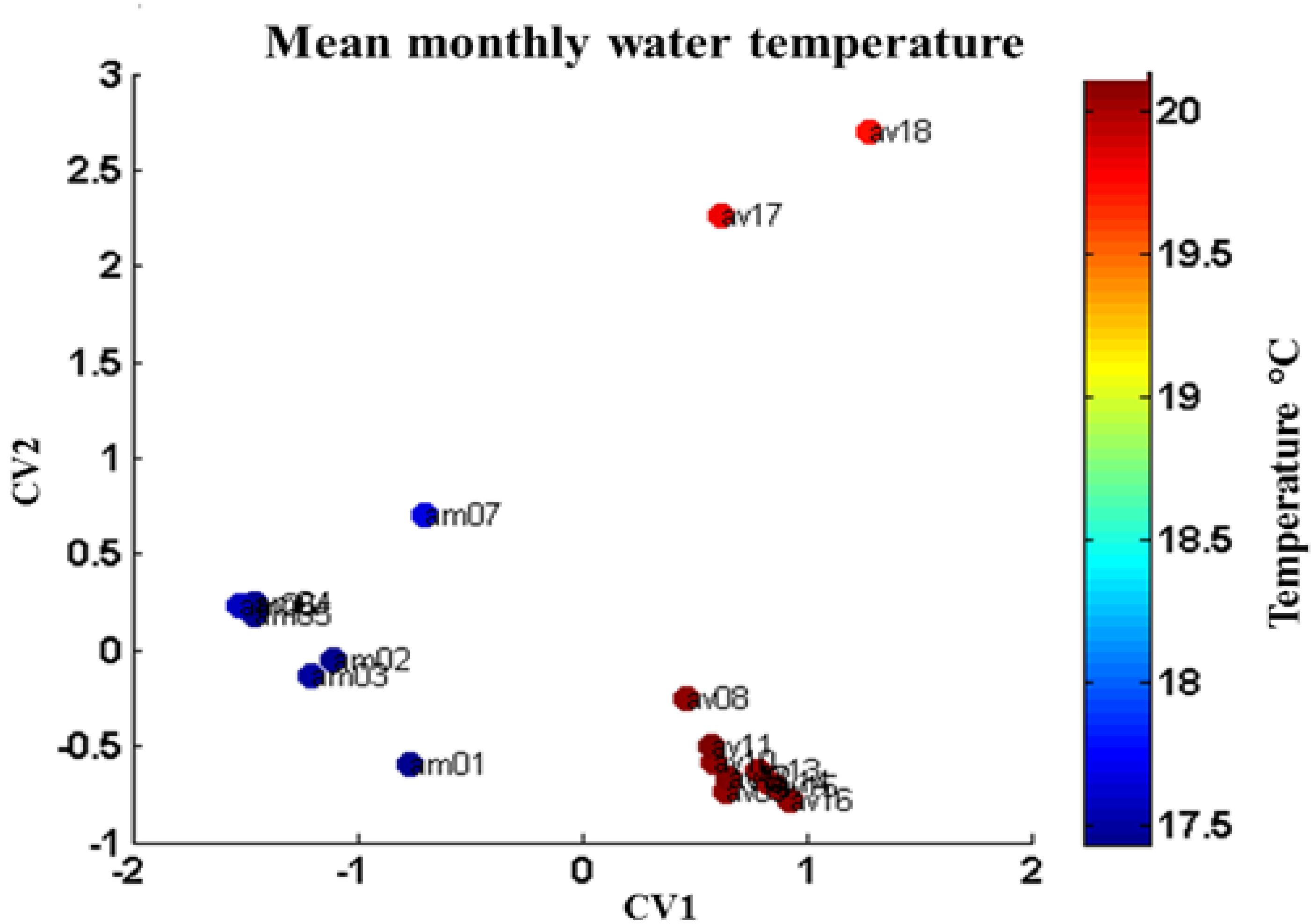

Figure 4. Canonical space for August 2011 mean temperatures. The upstream stations are referred as am01 to am07 and the downstream stations are referred as av08 to av18.

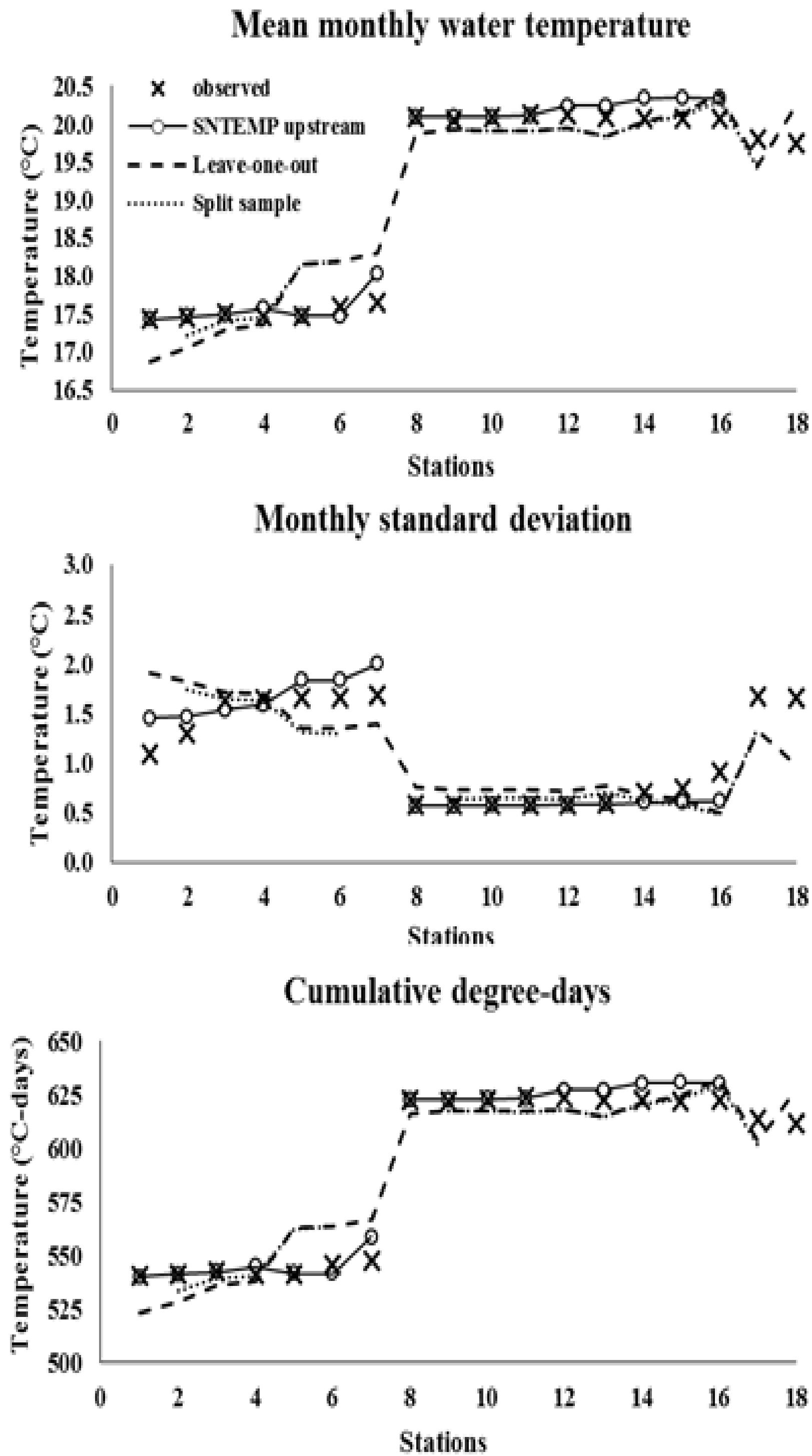

Figure 5. Observed and simulated mean monthly water temperatures, standard deviation and cumulative degree-days for August 2011, using SNTEMP and the statistical model in leave-one-out and split sample modes. Stations 1 to 18 are from upstream to downstream.

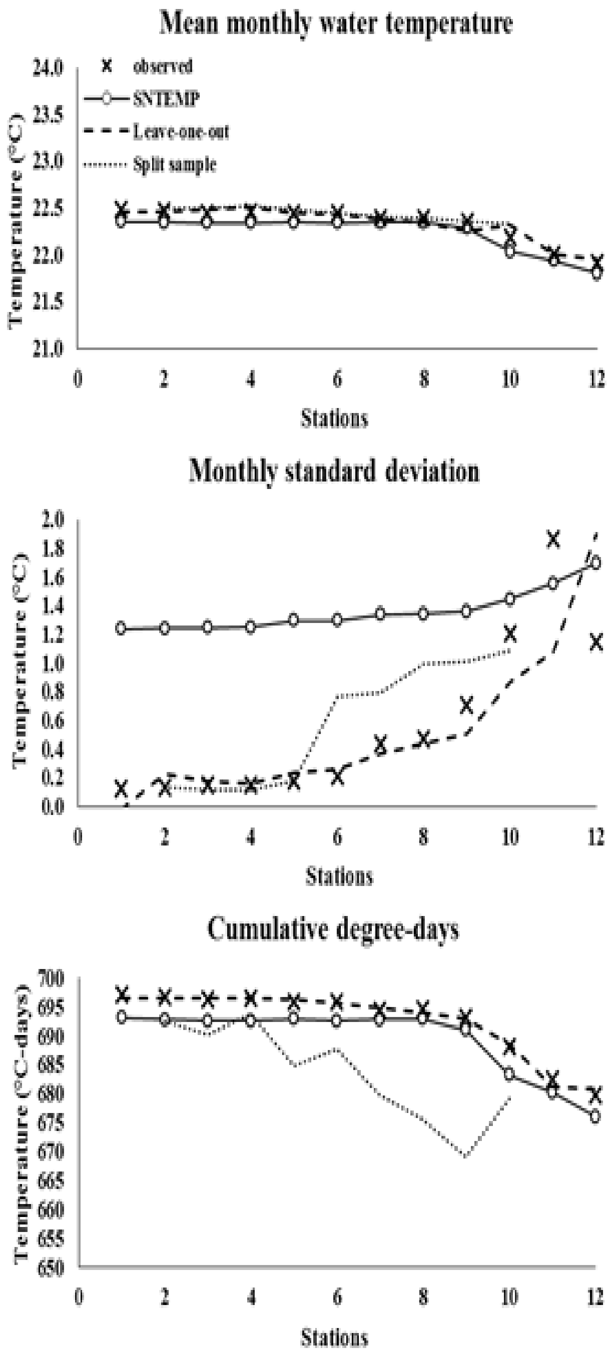

Figure 6. Observed and simulated mean monthly water temperatures, standard deviation and cumulative degree-days for August 2012, using SNTEMP and the statistical model in leave-one-out and split sample modes. Stations 1 to 12 are from upstream to downstream.

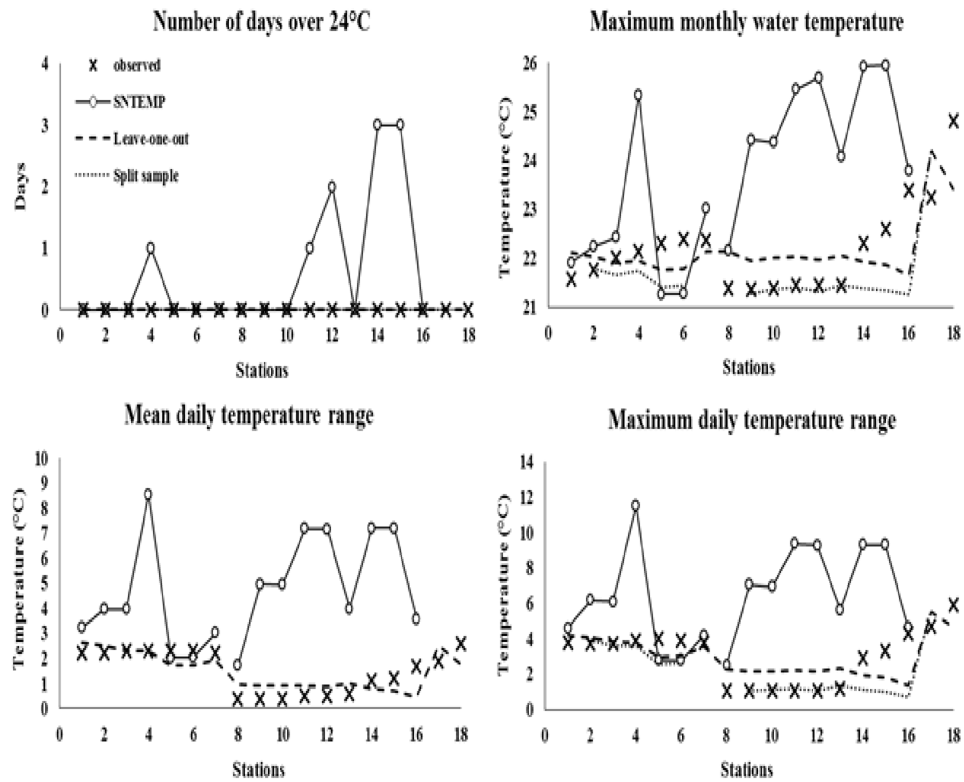

Figure 7. Observed and simulated mean monthly maximum temperatures, mean and maximum daily temperature ranges and the number of days over 24.9 °C for August 2011, using SNTEMP and the statistical model in leave-one-out and split-sample modes. Stations 1 to 18 are from upstream to downstream.

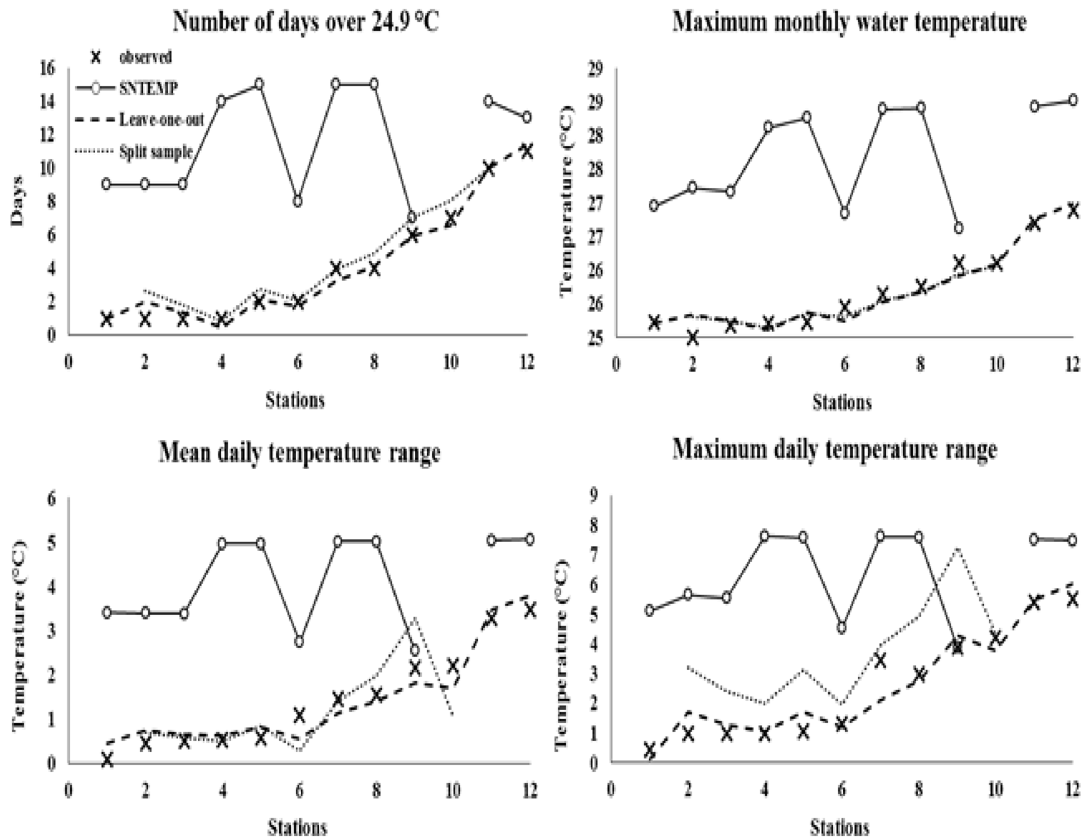

Figure 8. Observed and simulated mean monthly maximum temperatures, mean and maximum daily temperature ranges and the number of days over 24.9 °C for August 2012, using SNTEMP and the statistical model in leave-one-out and split-sample modes. Stations 1 to 12 are from upstream to downstream.