Stream water temperature modeling under climate change scenarios B1 & A2

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List of acronyms and symbols

20C3M	Observed 20th century scenario
A2, B1	Climate scenarios
CCCma	Canadian Centre for Climate modeling and analysis
CGCM	Coupled General Climate Model
GMDH	Group Method of Data Handling
GP	Genetic Programming
IDW	Inverse Distance Weighting
IPCC	Intergovernmental Panel on Climate Change
LSWM	Little Southwest Miramichi
PNN	Polynomial Neural Network
RMSE	Root Mean Square Error
SM	Stochastic Model
SRES	Special Report on Emission Scenarios
WMO	World Meteorological Organization

A_1, A_2	Autocorrelation coefficients
b_1, b_2, b_3	Regression coefficients
$\overline{c}$	Vector of real constants
d	Day of year
K	Autocorrelation coefficient
Ra	Residual of air temperature
Rw	Residual of water temperature
T	Mean air temperature
$\bar{T}$	Mean air temperature
TA	Long-term annual component
T_{Δ}	Air temperature input for scenario simulation
T_{mx}	Maximum air temperature
T_{mn}	Minimum air temperature
T_{OBS}	Observed air temperature
T_W	Mean water temperature
T_W^{max}	Maximum water temperature
T_W^{min}	Minimum water temperature
Δ_T	Change in air temperature

ABSTRACT

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Stream water temperature is a very important parameter when assessing water quality and aquatic ecosystem dynamics. For instance, cold-water fishes such as Atlantic salmon can be adversely affected by maximum summer temperatures due to many anthropogenic activities (e.g., land-use activities, deforestation, urban development, etc.). The present study deals with the modeling of stream water temperatures under climate change scenarios. Two Stochastic Models (SM1 & SM2) and two intelligent algorithms, i.e. the genetic programming (GP) and polynomial neural networks (PNN), were used to relate air and water temperatures in Little Southwest Miramichi River, a tributary of the Miramichi River in New Brunswick. The results indicated that it was possible to predict daily mean and maximum stream temperatures using air temperatures and that the four models produced similar results in terms of model performances. The root mean square error (RMSE) varied between 1.51°C and 1.77°C on an annual basis from 1990 to 2010 for daily mean water temperatures. Future climate data were extracted from the Canadian Coupled General Climate Model (CGCM 3.1/T63) under the greenhouse emission scenarios B1 and A2 defined by the Intergovernmental Panel on Climate Change (IPCC). The air temperatures were downscaled using delta change approach. Using the PNN model the study predicts an increase in stream water temperature of between 2.1 ^{o}C to 3.7 ^{o}C, at the end of this century. The increase in water temperatures over the next century is slightly lower than the increase in air temperature (approximately 60-75% of the increase in air temperature).

RÉSUMÉ

Caissie, D. N. El-Jabi and N. Turkkan. 2014. Stream water temperature modeling under climate change scenarios B1 & A2. Can. Tech. Rep. Fish. Aquat. Sci. 3106: ix + 51p.

La température des cours d'eau est un paramètre fort important lors de l'évaluation de la dynamique des écosystèmes aquatiques. Par exemple, les poissons d'eau froide, tel que le saumon, peuvent être défavorablement affectés par les températures maximales estivales ou par celles amplifiées par les activités d'utilisation des sols, telle que la déforestation. La présente étude se concentre sur la modélisation des températures des cours d'eau sous changements climatiques. Quatre approches différentes sont utilisées afin d'associer les températures de l'air et de l'eau du cours d'eau Little SW Miramichi, situé au Nouveau-Brunswick. Ces approches sont les méthodes stochastiques, la programmation génétique (PG) et les réseaux de neurones polynomiaux (RNP). Les résultats ont indiqué qu'il est possible de prévoir les températures de l'eau quotidiennes pour des cours d'eau à l'aide des températures de l'air et que les quatre modèles ont produit des résultats similaires dans la prédiction des températures du cours d'eau. La racine du carré moyen des erreurs (RCME) variait entre 1,51°C et 1,77°C sur une base annuelle, de 1990 à 2010. Les données climatiques utilisées proviennent d'une simulation de la troisième génération du modèle couplé climatique global (MCCG3.1/T63) sous les familles de scénarios B1 et A2. La régionalisation des températures de l'air a été accomplie en utilisant la méthode des deltas. En utilisant les RNP les résultats montrent que vers la fin du siècle la température de l'eau subira une augmentation de 2.1 ºC à 3.7 ºC. L'augmentation de la température de l'eau au cours du prochain siècle est légèrement inférieure à l'augmentation de la température de l'air (soit environ 60 à 75% de l'augmentation de la température de l'air).

1. INTRODUCTION

Climate change impacts on river systems include changes in runoff, river flow, groundwater flow, and water temperatures among others. With respect to biogeochemical conditions and water quality in general, most climate change impacts can be attributed to changes in stream water temperature. When water temperature increases, dissolved oxygen decreases, and biological activities are enhanced. These changes have potential consequences on nutrients, organic matter and biomass in general. The impact of climate change on stream water temperature is highly dependent on the future evolution of air temperature as well as other meteorological and physical parameters. As water temperature is highly correlated to air temperature, water temperature is also expected to increase under climate change.

In recent years, research on regional and global climatic changes and their impacts on water resources have received considerable attention (e.g., Kaushal et al. 2010; Isaak and Rieman 2013). Higher water temperatures and greater variations in runoff resulting from climate change are likely to influence many physical, chemical and biological processes governing water quality (Dale 1997; Schindler 2001; Thorne and Fenner 2011). The predicted impact of climate change on the hydrological cycle and streamflow have been extensively analyzed in various parts of the world based on different emission scenarios and climate models (Muller-Wohlfeil *et al*. 2000; Christensen and Christensen 2003; Alcamo *et al*. 2007; El-Jabi *et al*. 2009, Turkkan *et al*. 2011). However, relatively little is known about the changes in water quality, which is largely dependent on stream water temperature.

Water temperature has both economic and ecological significance when considering issues such as drinking water quality and aquatic resources in rivers (Caissie 2006). These are mainly driven by the thermal regime of rivers which is influenced by many factors such as atmospheric conditions, topography, riparian vegetation, stream discharge, and heat fluxes (*e.g*. Poole and Berman 2001; Caissie 2006; Caissie *et al*. 2005; Caissie *et al*. 2007; Webb *et al*. 2008).

The knowledge and ability to predict stream water temperature are essential to address water resources problems, such as thermal discharges, water quality and conducting environmental impact studies. A better understanding of the natural thermal regime of river systems is also very important in the management fisheries resources (e.g., closures of angling fisheries). The first step in the overall understanding of the stream thermal regime is to be able to study and predict the natural variations in stream water temperature. As such, the present study will address the issue of modeling stream water temperature under current and future climate.

The objectives of the present study are:

- to study water-air temperatures relationships and to carry out a modeling of stream water temperatures using different statistical models.
- to use the modeled stream water temperatures with the Canadian Coupled General Climate Model CGCM 3.1/T63 in order to evaluate future river water temperatures under climate change.

The knowledge gained from the present study will enable water resources and fisheries managers to better understand the impact of future climate on the thermal regime of rivers and its impact on aquatic ecosystems.

2. LITERATURE REVIEW

2.1 River thermal regimes

The thermal regime of a river represents the natural variations in water temperatures for selected periods (seasonal, daily or diel) and watercourses. Many factors can influence the thermal regime and they can be classified using different factors. For example, Poole and Berman (2001) classified these factors in two categories: internal and external factors. The external factors consider the net energy and water inputs. Internal factors are related to the fluvial processes and river characteristics (riparian zone, surface-subsurface water interactions, etc.).

River temperatures are also influenced by factors such as atmospheric conditions, topography, stream discharge, and riverbed heat fluxes (Caissie 2006). Among these, atmospheric conditions are generally the most important forcing parameters. Atmospheric conditions are principally responsible for the heat exchange process at the water surface. Parameters of influence include solar radiation, air temperature, humidity, wind speed as well as the type and quantity of precipitation. Topography can also affect the thermal regime of rivers and it includes factors such as latitude/longitude, riparian vegetation, geology, river aspect (orientation) and landscape shading (e.g., prairie vs. mountain). Some factors can be influenced by human activities like timber harvesting, resulting in an increase solar radiation reaching the stream if the riparian vegetation is removed along river reaches. Stream discharge factors are mostly related to river hydraulic attributes (e.g. surface area, water volume, etc.). Some stream discharge factors are extremely important such as the volume of water whereas other can be neglected, *e.g*. slope. Streambed heat fluxes can also influence the thermal regime of rivers depending on the exchange processes and groundwater contribution.

The thermal regime of rivers has been widely studied for many years and in various parts of the world. For example, Macan (1958) was one of the early studies to look at the seasonal cycle in water temperature as well as showing the influence of solar radiation on water temperature variability. This study concluded that diel variations in water temperature were more significant during clear sky days than during overcast days. This study also showed that on a seasonal basis, the water temperature varied from low temperatures (close 0°C in northern latitude rivers) in winter and spring to maximum water temperatures in mid-summer. Such annual cycle was later described in more details using sinusoidal function by Caissie (2006). Daily water temperature fluctuations can be observed on a local scale or along a reach. For example, upstream reaches are generally colder due to groundwater contributions (Vannote and Sweeney 1980). In contrast, water temperature tends to be warmer in the downstream direction of a river due to a longer run and a longer heating exposition (Danehy *et al*. 2005). The diel variability is dependent on meteorological conditions and the physical characteristics of the river. For instance, the downstream reaches of rivers are deeper and the diel variability is generally less. All of these seasonal and daily variations of stream water temperatures are important for aquatic resources, as outlined in the 'River Continuum concept' (Vannote *et al*. 1980).

An important study on thermal regime of rivers was conducted by Ward (1985) who studied many watercourses within the southern hemisphere. Ward (1985) concluded that the difference in the thermal regime of southern and northern hemisphere rivers was mainly related to the size of rivers and not to thermal processes. A factor making the comparison difficult was the presence of important arid and semi-arid areas in the southern hemisphere (mainly in Australia).

Smith (1972) tried to categorize, without success, the thermal regime of rivers using latitude and altitude as the dominant factor. Other studies that looked at categorizing the thermal regime of rivers (e.g., Smith 1975; Smith and Lavis 1975) were also unsuccessful, mainly due to the complex nature of river thermal processes. Some studies have showed relations between different river parameters and their thermal regime. For instance, Webb and Walling (1986) established a relation between mean river temperature and the watershed elevation. However, it was difficult to generalize these results because small cold water streams are usually observed at higher altitude. Latitude and climate (e.g. air temperature) most certainly have a major influence on stream temperature as shown by Liu *et al*. (2005). Arscott *et al*. (2001) investigated daily and seasonal water temperatures and showed a relation between water temperature and stream order, groundwater contribution and cold-water tributaries. Some other studies showed that the temperature variability can be related to the dynamic and proximity of water sources and pathways (Brown *et al*. 2005; Cadbury *et al*. 2008).

Using multiple linear regressions, elevation and azimuth were found to be important variables explaining most of the average daily water temperature patterns (Brown and Hannah 2008). Water temperature can also vary at the micro-spatial scale (Clark *et al*. 1999) or be dependent on the type of rivers (Mosley 1983). Mosley (1983) showed that braided rivers are subjected to extreme high temperatures mainly due to their shallow water depths and higher exposition to meteorological conditions.

Regional differences in river thermal regimes can be explained by morphological conditions, hydrology, water use, elevation, slope, timber harvesting, as well as latitude (Mohseni *et al*. 2002). Other studies have shown basin-scale stream temperatures are strongly affected by water sources, as well as that basin characteristics (Brown and Hannah 2008). As such, a good description of the thermal regime of rivers at different spatial and temporal scales is important to understand the overall river temperature variability and predictability.

2.2 Climate change impacts on stream temperature

Climate change will most likely have a significant impact on river temperatures in Atlantic Canada, as air temperature is projected to increase significantly over the next 100 years. For instance, air temperature is expected to increase by 2°C to 6°C in the next 100 years in this region (Parks Canada 1999). The increase in air temperature and water temperature will likely affect fisheries resources and their distribution within river systems. Higher water temperatures and changes in extreme hydrological events are projected to affect water quality with possible negative impacts on ecosystems, human health, and water system reliability and operating costs (IPCC 2008). The awareness of climate change and concerns about its potential impacts are significantly influenced by the occurrence of extreme events as pointed out by Arnell and Delaney (2006). The impacts and adaption strategies will greatly depend on local hydrology, as well as on socioeconomic and political conditions (Kundzewicz *et al*. 2008). Different methods can be found in the literature to assess the impacts of climate change on hydrological responses (Rehana and Mujumdar 2011). Modeling is one such method and can include high-resolution regional climate models (Malmaeus *et al*. 2006), general circulation models (GCMs) processed through statistical downscaling techniques (Cruise *et al*. 1999; Burlando and Rosso 2002; Andersen *et al*. 2006) or hypothetical scenarios used as input into hydrologic models (Arnell *et al*. 1996; Nimikou *et al.* 2000; Chang 2004).

Studies have looked at the impact of climate change on river water temperatures and aquatic resources (Meisner 1990; Mohseni *et al*. 2003; Isaak et al. 2012). However, the impact of climate change on river temperature is difficult to assess due to a lack of long-term water temperature time series (Webb 1996). In fact, climate change studies require long-term river temperature data which are seldom available, although a few studies have been found in the literature. For example, Langan et al. (2001) studied 30 years of water temperature data in the Girnock catchment (Scotland) and found no increases in mean annual water temperatures; however, winter and spring maximum temperatures increased by approximately 2°C. Webb and Nobilis (1997) analysed over 90 years of water temperature data from north-central Austria and showed no specific trends in water temperatures. Foreman *et al*. (2001) studied long-term trends in water temperatures from simulated historical temperatures and they noted an increase of 0.12 °C per decade in British Columbia (1941-98). Another related study in British Columbia (Fraser River) showed that climate change could potentially alter the timing of peak flows as well as increase summer water temperatures by 2099 (Morrison *et al*. 2002). According to this study, summer water temperatures are projected to increase by 1.9°C by the end of the century (compared to the baseline period 1961-1990).

Results by Minns *et al*. (1995) showed that an increase in annual temperatures under climate change would have potential implications on Atlantic salmon populations. This study showed that juvenile Atlantic salmon habitat could be reduced in the order of 4% and that the smoltification age could decrease by 8–29% depending on the location and river. An increase in water temperatures combined with a potential reduction in precipitation could greatly affect water quality in streams, as pointed out by Nimikou *et al*. (2000). Morrill *et al*. (2005) predicted an increase of 2°C to 3°C in stream temperatures resulting from an increase of 3°C to 5°C in air temperatures. The River Dee in Scotland has experienced an increase in mean daily maximum stream temperatures in winter and spring since the 1960's (Langan *et al*. 2001). Over a 30-year period, they observed an increase in maximum water temperatures of 2°C.

Cooter and Cooter (1990) predicted that water temperature could increase to up to 7°C in the southern United States using three different Global Circulation Models (CGM). Mohseni *et al*. (1999) studied 803 streams across the United States and found that most streams (764 streams) are projected to increase in mean annual water temperature by 2°C to 5°C over the next century. This study showed that minimum and maximum weekly temperatures could potentially increase by 1°C to 3°C. According to this study, the most significant change in weekly temperatures would be in the spring (March – June). Similarly, Pilgrim et al. (1998) are projecting an average increase of 4.1°C in water temperature in Minnesota streams under a doubling of CO_2 scenario. Tung *et al*. (2006) predicted an increase of 0.5°C (short-term) to 2.9°C (long-term) in annual average stream temperatures in TaChia River (Taiwan). Leblanc et al. (1997) predicted an increase of water temperatures of almost 4°C on Morningside Creek (Ontario).

When studying forcing parameters, Mohseni and Stefan (1999) showed that water temperatures tends to level off at high temperatures due to evaporative cooling. This leveling off at high temperatures could have important implications under climate change. The upper bound stream temperature represents the highest temperature that a stream can physically attain without anthropogenic influences (Mohseni et al. 2003). The above climate change studies show the importance of modeling river temperature under different scenarios and meteorological conditions to better understand potential impacts on fisheries and aquatic resources.

3. MATERIALS AND METHODS

3.1 Study area

The study site of the present study is located within the Miramichi River system. This system has an annual precipitation ranging from 860 to 1365 mm, with a long-term average of 1142 mm (Caissie and El-Jabi 1995). On a monthly basis, average monthly precipitation is close to 100 mm per month, with values ranging between 72 mm (February) and 109 mm (November). January has the coldest mean monthly air temperature with a long-term mean of -11.8 °C. July is the warmest month with a mean monthly air temperature of 18.8 °C, although August at 17.7 °C is very close. Between these two extremes, mean monthly air temperature varies gradually, with seven months of the year experiencing temperatures above freezing. The mean annual runoff was estimated at 714 mm for the Miramichi region with values ranging from 631 mm to 763 mm (Caissie and El-Jabi 1995). The open-water period usually extends from mid-April to late November within the Miramichi River system and this period will be considered for modeling purposes.

The study site is located on the Little Southwest Miramichi (LSWM) River at approximately 25 km from the river mouth (Figure 1). Water temperature data have been collected at this site since 1992. The LSWM is approximately 80 m in width with an average water depth of 0.55 m. The drainage basin of the LSWM at the water temperature measurement site covers 1190 km^2. A water temperature sensor was installed at approximately 20 m upstream from the confluence of Catamaran Brook (at approximately 2 m from the True Right bank, near the bottom). The type of sensor used was a model 107B from Campbell Scientific Canada Corp. which incorporates the Fenwal Electronic thermistor probe. This probe was connected to a CR10 data logger. The error associated with this sensor is typically less than ±0.2 °C for the range of -30 °C to +40 °C. Water temperature measurements were carried out every 5 seconds during the last minute of every hour to calculate an hourly mean water temperature. Lateral variations in river water temperatures were investigated using measurements with a high precision mercury thermometer taken at approximately 0.5 m intervals (from bank to bank) and at different depths. No variations were observed, due to the well-mixed nature (high turbulence) of this river. The data used in the present study were daily mean, minimum and maximum water temperatures calculated from hourly data (24 observations). Although the riparian vegetation is mature along the banks of the LSWM, this river is nevertheless well exposed to meteorological conditions due to its relatively large width (~ 80 m). Therefore, it can be considered as a wide and shallow river for modeling purposes. The forest along the LSWM has a canopy closure of less than 20%.

A hydrometric station operated by Environment Canada (since 1951) is located on the LSWM (station 01BP001) approximately 16 km downstream from the water temperatures sampling point. The drainage area above this hydrometric station is 1340 km^2. The mean annual flow at the LSWM hydrometric station was calculated at 32.5 m^3/s (or 764 mm of runoff). The river discharge varied from a low of 1.70 m^3/s on January 14, 1959 to a record high value of 861 m^3/s on May 28, 1961.

Meteorological data to calibrate the water temperature model were obtained from the Catamaran Brook meteorological station, which is located less than 10 km from the water temperature study site (Figure 1). The station is located at the center of a 400 m x 400 m clear cut area to meet Environment Canada and the World Meteorological Organization (WMO) weather station specification (e.g., wind speed). Meteorological conditions measured at Catamaran Brook are reflective of conditions experienced by the LSWM due to climate homogeneity within the region (Caissie and El-Jabi 1995). Air temperature was required for the modeling of water temperature at the LSWM River. The air temperature was monitored at the Catamaran Brook meteorological station using a Vaisala Relative Humidity and Temperature sensor. It has an accuracy typically within ± 0.2 °C. The sensor was installed at approximately 1.8 m from the ground.

3.2 Global climate model

Once calibrated, the water temperature model was used to predict future water temperatures for the Little Southwest Miramichi River (LSWM) using data from climate models. The climate model used in the present study was the third generation coupled global climate model (CGCM3.1). The time-slice simulations follow the Intergovernmental Panel on Climate Change (IPCC) (Alcamo *et al*. 1995) "observed 20th century" 20C3M scenario for years 1970-2000 and the Special Report on Emissions Scenarios (SRES) B1 and A2 (Figure 2) for years 2010-2100 over the Gaussian 128x64 grid (Figure 3). The B1 storyline and scenario family describes a convergent world with low population growth and rapid changes in economic structures toward a service and information economy, with reductions in material intensity, and the introduction of clean and resource-efficient technologies. The emphasis of this scenario is on global solutions to economic, social, and environmental sustainability, including improved equity, but without additional climate initiatives. The A2 storyline and scenario family describes a very heterogeneous world. The underlying theme is self-reliance and preservation of local identities. Fertility patterns across regions converge very slowly, which results in high population growth. Economic development is primarily regionally oriented and per capita economic growth and technological changes are more fragmented and slower than in other storylines (CCCma - Canadian Centre for Climate Modelling and Analysis). Figure 2 shows the time evolution of the CO_2 concentrations and globally averaged sulphate aerosol loadings scaled to year 2000 for different scenarios including the 20C3M, SRES B1 and SRES A2 and the so-called "Committed" scenario in which the greenhouse gas concentrations and aerosol loadings were held fixed at the year 2000 level.

3.3 Simulated climate data

The water temperature models were calibrated with air and water temperature data described in section 3.1, i.e., using the Catamaran Brook meteorological station (Figure 1). The data used for the climate change study were daily minimum, mean and maximum air temperatures for the period 1970-2100 which were obtained from the Canadian Centre for Climate Modelling and Analysis (CCCma). The atmosphere model output is provided on a 128 x 64 Gaussian grid (Figure 3). Figure 4 shows the sub-region occupied by New Brunswick.

When using simulated data from the CCCma model, an inverse distance weighting (IDW) method was used to compute air temperatures at the Doaktown meteorological site (closest site to the Catamaran Brook meteorological station and Little Southwest Miramichi River with long-term data). Data at Catamaran Brook were used to calibrate the water temperature model; however, the long-term data at the Doaktown sites were used for the climate modeling. Future climate data at Doaktown were computed from the simulated values of the climate model at four grid points surrounding the site (Figure 4).

The interpolated data were then downscaled using the delta change approach. For temperature, the procedure is as follows:

$$T_{\Delta}(d,m) = T_{OBS}(d,m) + \Delta_T(m) \qquad (1)$$

where T_{Δ} is the temperature input for the scenario simulation, T_{OBS} is observed temperature in the historical period, (d,m) stand for day and month, and Δ_T is the change in temperature as simulated by the climate model. This value is calculated by:

$$\Delta_T(m) = \bar{T}_{scen}(m) - \bar{T}_{ctrl}(m) \quad ; \quad m = 1,2,\ldots,12 \qquad (2)$$

where $\bar{T}(m)$ is the mean daily temperature for month *m*, for all 30 years of reference period. The indices *scen* and *ctrl* stand for the scenario periods (2010-2039, 2040-69, 2070-2099) and control period (1970-1999), respectively.

3.4 Water temperature models

Stream water temperature and air temperature relationships were modeled by means of two Stochastic Models (SM1 & SM2) and two intelligent algorithms, i.e., genetic programming (GP) and polynomial neural networks (PNN) (El-Jabi *et al*. 2012).

Stochastic Models (SM1 & SM2)

The stochastic model consists of separating the water temperatures into two different components, namely the long-term seasonal component (or the annual cycle) and the short-term non-seasonal component. Stochastic models use both annual cycle and short-term component of water temperatures in the modeling. The short-term component represents the departure from the long-term annual cycle as a result of above or below normal daily air temperatures. Therefore, the water temperature, *Tw(t),* of any given river system can be represented by these two components, the long-term annual component, *TA(t),* and the short-term component, *Rw(t),* such that:

$$Tw(t) = TA(t) + Rw(t) \qquad (3)$$

where *t* represents the day of year (e.g. January 1 = 1 and July 1 = 182).

The annual component in water and air can be represented using a sine function (Caissie *et al*. 1998; Caissie *et al*. 2004) given by:

$$TA(t) = a + b\sin\left(\frac{2\pi}{365}(t - t_0)\right) \qquad (4)$$

where *a, b* and t_0 are estimated coefficients.

The short-term components in water temperature were obtained by the equations described below, in which air and water temperatures of the previous days are used. For the stochastic model 1 (SM1), a multiple regression equation was used (Caissie *et al*. 1998):

$$Rw(t) = b_1 Ra(t) + b_2 Ra(t-1) + b_3 Ra(t-2) \qquad (5)$$

For the stochastic model 2 (SM2), Markov process was used (Cluis 1972; Caissie *et al*. 1998; Caissie *et al*. 2004):

$$Rw(t) = A_1 Rw(t-1) + A_2 Rw(t-2) + K\ Ra(t) \qquad (6)$$

where *Rw(t)* and *Ra(t)* are non-seasonal components of water and air temperatures; b_1, b_2 and b_3 are regression coefficients; A_1 = $R_1(1-R_2)$ / $(1-R_1^2)$ and A_2 =$(R_2-R_1^2)$ / $(1-R_1^2)$. R_1 and R_2 represent the autocorrelation coefficients for a lag of one and two days respectively. Once A_1 and A_2 were obtained using the autocorrelation coefficient, *K* was estimated by minimizing the mean sum of squared errors between observed and predicted water temperatures during the calibration period.

Genetic programming (GP)

The genetic programming model consists of a set of functions involving various operators such as +, -, *, /, sin, cos, exp, <, >, =, IF; and a terminal set with variables and constants. An initial population is randomly created with a number of programs (equations) formed by nodes (operators plus variables, and constants) previously defined according to the problem domain. An objective function is also defined to evaluate the fitness of each program. Selection, crossover and mutation operators are then applied to the evolved programs and a new population is created. The whole process is repeated until the given generation number is reached; see Koza (1989) for more details.

In the present study, four arithmetic operators (+, -, ×, ÷), ten input variables; one output variable (e.g., T_w^{mean}) and a vector of real constants were selected (see equation 7). The same model structure was also used for T_w^{max}. Thus, the different variables used to predict stream water temperatures were:

$$\begin{Bmatrix} t, \bar{c}, \{+, -, \times, \div\} \\ T(t), T(t-1), T(T-2) \\ Tmx(t), Tmx(t-1), Tmx(t-2) \\ Tmn(t), Tmn(t-1), Tmn(t-2) \end{Bmatrix} \Rightarrow \begin{Bmatrix} Tw^{mean} \\ and \\ Tw^{max} \end{Bmatrix} \qquad (7)$$

where *Tw* is the stream temperature (mean and max), *t* is the day of year (100 … 320), e.g. July 1=182, $\bar{c}$ is a vector of real constants, and *T, Tmx* and *Tmn* are the mean, maximum and minimum air temperatures, respectively.

Polynomial Neural Networks (PNN)

PNN is a flexible neural networks architecture whose topology is not predetermined but developed through learning. The design is based on Group Method of Data Handling (GMDH) which was proposed by A. G. Ivankhnenko in the late 1960s (Ivankhnenko 1971) and later enhanced by others. He developed the GMDH as a means of identifying nonlinear relations between input and output variables. As described by Oh and Pedrycz (2002), the GMDH generates successive layers with complex links that are individual terms of a polynomial equation.

The individual terms generated in the layers are partial descriptions of data (PDs) being the quadratic regression polynomials with two inputs. The first layer is created by computing regressions of the input variables and choosing the best ones for survival. For example, if the first two variables, *x1* and x2, are taken and combined into a simple set of polynomial terms the terms would be (*1, x1, x2, x1.x2*). Thereafter, all possible models made from these terms are checked and the best one that satisfies an evaluation criterion (typically mean square error) is retained. The second layer is created by computing regressions of the values in the previous layer along with the input variables and retaining the best candidates. More layers are built until the network stops getting better based on termination criteria.

The following PNN model was used to predict mean, minimum and maximum stream temperature:

$$\begin{Bmatrix} t \\ T(t), T(t-1), T(T-2) \\ Tmx(t), Tmx(t-1), Tmx(t-2) \\ Tmn(t), Tmn(t-1), Tmn(t-2) \end{Bmatrix} \Rightarrow \begin{Bmatrix} Tw^{mean} \\ Tw^{min} \\ Tw^{max} \end{Bmatrix} \quad (8)$$

where *Tw* is the stream temperature (mean, min and max), *t* is the day of year (100 … 320, e.g., July 1=182), and *T, Tmx* and *Tmn* are the mean, maximum and minimum air temperatures, respectively.

Both algorithms, GP and PNN, will extract the most significant information from the data in order to find an optimal description of the output. Thus, some inputs may not be present in the solution.

3.5 Modeling performance criteria

To compare the relative performance among models, the root-mean-square error (RMSE) was used which is given by:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(O_i - P_i)^2}{N}} \quad (9)$$

with P_i and O_i being the predicted and observed water temperatures and *N* the number of observations.

The coefficient of determination was also used to compare the performances of the different models and the equation is given by:

$$R^2 = \left[\frac{N\sum_{i=1}^{N} O_i P_i - \left(\sum_{i=1}^{N} O_i\right)\left(\sum_{i=1}^{N} P_i\right)}{\sqrt{\left(N\sum_{i=1}^{N} O_i^2 - \left(\sum_{i=1}^{N} O_i\right)^2\right)\left(N\sum_{i=1}^{N} P_i^2 - \left(\sum_{i=1}^{N} P_i\right)^2\right)}} \right]^2 \tag{10}$$

4.0 RESULTS AND DISCUSSION

4.1 Water temperature characteristics and air temperature relationships

Prior to the modeling, important water temperature characteristics were studied for the Little Southwest Miramichi River, in particular the thermal regime (i.e., the annual cycle) as well as air to water temperature relationships. The first characterization analysis was carried out to study the linear relationship between mean (and maximum) daily air and water temperatures. Results of this regression model showed a significant scatter between air and water temperatures at the daily time step (Figure 5). This is mainly due to the fact that both air and water temperatures have some autocorrelation in the time series. In the case of the mean temperatures, 84% of the variability (R^2 = 0.838) was explained by air temperature, where only 72% (R^2 = 0.718) of the variability was explained for maximum temperatures. The slope of these equations can inform on the relationship. For instance, for mean temperature the slope was 0.94, which means that an increase in mean air temperature of 1°C will result in an increase in mean water temperature of only 0.94°C. This difference is also observed for maximum temperatures where the slope of the regression was 0.84. The linear regression model does not provide a very good water temperature model because of the significant scatter. However, it can already pointed out that under climate change, it would be expected that the water will increase with air temperature but at a slightly lower rate based on these observed relationships.

The next characterization analysis carried out was a study of monthly air to water relationships. At such time scale some of the variability is reduced and a better fit was obtained for both mean and maximum temperatures (Figure 6). Results showed that over 95% (R^2 = 0.95) of the variability in water temperature can be explained by air temperature on a monthly basis (Figure 6a). From this figure it can be observed that the months of August and July are those that experienced the highest temperatures. These months also showed the best fit (least scatter around the regression), although the months of June and September were close as well. The other months (April, May, October and November) showed a significant hysteresis where water temperatures were generally higher than the regression line for October and November (the opposite was observed for April and May). On a monthly basis, the slope of the regression was very close to unit (1.04), which implies that, at such scale, water temperature will most likely experience similar changes than air temperature. Similar results were observed for maximum monthly temperatures, although the explained variability was less (92%; R^2 = 0.922; Figure 6b). Similar to mean monthly temperatures, the slope of the regression line was very close to unity (1.01). For maximum monthly water temperatures, it was noticed that the hysteresis was more important than for mean temperatures, especially for low air temperatures in spring and autumn. The hysteresis has some impact on the regression line, particularly at high temperatures where the regression line underestimates water temperatures for most of the high temperature months (Figure 6b; July and August).

Following the linear regression analyses, a study of the annual cycle was carried out, as is required in both stochastic models (multiple regression SM1 and Markov process SM2). The annual cycle for both the mean and maximum water temperature is presented in Figure 7 and the fitted parameters of the annual component are provided in Table 1. This figure shows that the peak mean and maximum water temperatures are reached on day 210 (July 29) with temperatures of 20.4°C (mean) and 23.0 °C (maximum). The annual cycle was also calculated for air temperature (Table 1), as it is also required in the stochastic models.

4.2 Water temperature modeling

For the different models a combination of calibration, testing, training and validation were used and specific to each model. For example, the PNN model requires a training period whereas the stochastic model does not. For the PNN, the 1992-2005 data were used for training and validation (5-fold cross-validation) and the 2006-2010 data for testing (Table 2). In the case of

GP, training, validation and testing data were required. For this model, the first 8 years of available data (1992 to 1999) were used for model training. Data from 2000 to 2004 were used for validation, whereas a sequential data set (2005 and 2010) was used for testing the model. For both stochastic models (SM1 and SM2), data from 1992 to 2004 were used to calibrate the model whereas the data from 2005-2010 were used to validate the model. Model parameters are presented in Table 1 for the stochastic models. The calculated stream water temperatures using the four models, namely the GP, the PNN and the two stochastic models SM1 and SM2 are shown in Figure 8 (mean) and 9 (maximum) for two typical years during the testing period, e.g. 2005 and 2010.

The equations obtained for mean and maximum stream temperatures for the GP were as follows:

Mean stream temperature

$$\begin{aligned} T_w(t) = & -\frac{1}{t^4}0.19085\left(198.24 + 3.2635T(t-1) + 1.6318Tmn(t-1) + T(t)\right)^4 \\ & + 0.45515T(t) + 0.22839T(t-2) + 0.36733T(t-1) + 1.2353 \end{aligned} \quad (11)$$

Maximum stream temperature

$$\begin{aligned} T_w^{\max}(t) = & -\frac{0.0681}{t^4}\left\{84227 + 0.5031\left[-6.387 - 3Tmn(t-2) + 4Tmx(t-2)\right]^2 T(t-1)\right\}^2 \\ & + 0.2691Tmx(t) + 0.5134 + 0.2691T(t) + 0.2691T(t-1) + 0.2340Tmx(t-2) \end{aligned} \quad (12)$$

where each parameter is defined in equation 7.

In the case of PNN, the equations obtained for mean and maximum stream temperatures were as follows:

Mean stream temperature

$$
\begin{aligned}
T_w(t) &= 0.6480A + 0.4551B - 0.0200B^2 - 0.1361C + 0.0220C^2 \\
A &= -26.87 + 0.3372t - 0.0008t^2 + 0.2854T(t) + 0.0030T(t)^2 + 0.1345T(t-2) \\
&\quad + 0.0060T(t)T(t-2) + 0.0009T(t-2)^2 \\
B &= -33.96 + 0.4287t - 0.0010t^2 - 0.1391Tmn(t) + 0.0010t\,Tmn(i) + 0.4185T(t-1) \\
&\quad - 0.0008t\,T(t-1) + 0.0021Tmn(t)T(t-1) + 0.0070T(t-1)^2 \\
C &= -34.87 + 0.4442t - 0.0010t^2 - 0.0075Tmx(t-1) - 0.0001t\,Tmx(t-1) + 0.0037Tmx(t-1)^2 \\
&\quad + 0.1405T(t-1) + 0.0003t\,T(t-1) + 0.0060Tmx(t-1)T(t-1)
\end{aligned} \tag{13}
$$

Maximum stream temperature

$$
\begin{aligned}
T_w^{\max}(t) &= 0.9709A - 0.0735A^2 - 0.3653B + 0.1129AB - 0.0378B^2 + 0.3691C \\
A &= -33.33 + 0.4328t - 0.0010t^2 + 0.2095T(t) + 0.0162T(t)^2 + 0.1880T(t-1) \\
&\quad - 0.0191T(t)T(t-1) + 0.0128T(t-1)^2 \\
B &= -38.91 + 0.4986t - 0.0012t^2 + 0.0501Tmx(t) + 0.0115Tmx(t)^2 - 0.0097Tmx(t-1) \\
&\quad + 0.0002t\,Tmx(t-1) - 0.0118Tmx(t)Tmx(t-1) + 0.0119Tmx(t-1)^2 \\
C &= -33.39 + 0.4267t - 0.0010t^2 + 0.1771T(t-2) - 0.0002t\,T(t-2) + 0.0033T(t-2)^2 \\
&\quad + 0.0792Tmx(t) + 0.0002t\,Tmx(t) + 0.0029T(t-2)Tmx(t) + 0.0059Tmx(t)^2
\end{aligned} \tag{14}
$$

The performances of the water temperature models are presented in Tables 3 (mean) and 4 (maximum). These results show that, in general, the RMSEs for mean water temperature were slightly lower (1.28-1.77°C) than for the maximum water temperature (1.29-2.24°C). All models performed well; however, the stochastic SM1 and PNN models showed slightly better results. Figures 10 and 11 show, for the testing data set (2005-2010), a comparison between measured and calculated daily mean and maximum water temperatures for each model. These figures show a good correspondence between observed and predicted values; however, highest predicted temperatures were slightly lower than observed water temperatures. This was observed for both mean and maximum water temperatures.

For the testing data set, Tables 3 and 4 showed that the stochastic model SM1 (MultipleR) provided the best results for mean and maximum water temperatures with an RSME of 1.51 °C and 2.00 °C, respectively. This model also showed the highest R^2 (0.947 - mean and 0.933 - maximum). Although PNN algorithm showed slightly higher RMSE and lower R^2, it performed relatively well. A visual inspection of Figures 8 to 11 also confirms that all models showed a good correspondence between observed and predicted stream temperatures.

4.3 Water temperature modeling under climate change

The above calibration and testing of water temperature models showed that most models provided good and similar results in terms of modeling performances. As such, for the climate change study, only the PNN model was used to predict future water temperature conditions. For the climate change study, the PNN model was also used to predict the minimum water temperature as well as the mean and maximum water temperatures. Results of the climate change analysis are shown in Figures 12 (min), 13 (mean) and 14 (max). These figures show the changes in the annual cycle of stream water temperatures for the LSWM for the historical period (1970-99) and for the future periods (years 2010-39, 2040-69 and 2070-99), using emission scenarios B1 and A2. The averaged water and air temperature increases from the historical period are shown in Figure 15. The increase in air temperature was between 1.2°C and 5.0°C depending on the scenario and time period. The corresponding increase in water temperature was between 0.7°C and 3.7°C. The increase in air temperature within the Miramichi River area is very consistent with expected increase throughout the province of New Brunswick, as shown in Table 5 (Turkkan *et al*. 2011).

Over the next 30 years (2010-39), water temperatures are expected to increase by 0.7°C (B1) to 1.2°C (A2). The stream water temperatures show a more significant increase for the period 2070-99 compared to current climate conditions (1970-99), with an increase of 2.1 °C (B1) and

3.7 ^{o}C (A2). During all periods, the water temperature increases were in the range of 60%-75% of the increases projected for air temperature. This means that water temperature will increase in the future, but at a slower rate than air temperature. The evolution of mean summer water temperatures are plotted in Figure 16, for both climate scenarios.

Another aspect which is very important in stream water temperature is the analysis of extreme events, i.e., periods with temperature higher than certain thresholds. This is particularly important for the study of stress in aquatic resources and potential closures of angling fisheries during such events (Breau *et al*. 2013). These thresholds could also depend on the water quality parameter or fish species under investigation. Therefore, four different thresholds were investigated (20°C, 23°C 26°C and 29°C) for minimum, mean and maximum water temperatures. Figures 17, 18 and 19 illustrate the annual exceedance frequencies of minimum, mean and maximum stream water temperatures for LSWM, from an historical perspective and using emission scenarios B1 and A2. For example, during the historical period (1970-99) the minimum water temperature was exceeded 13 days per year on average (Figure 17). Under climate change the threshold temperature of 20°C could be exceeded between 32 (B1) and 51 (A2) days per year towards the end of the century (2070-99) depending on the scenario. Other threshold temperatures are presented in Figure 17 for minimum water temperature. In the case of mean water temperature, the threshold of 26°C is currently not reached (1970-99); however, in the future, this threshold will most likely be reached and exceeded (Figure 18).

The daily maximum river water temperature has a particular interest, as high temperatures could have a significant impact on both water quality and fishes (temperature could become lethal for some species). Figure 19 show that currently the maximum water temperature exceeds 29°C on average of 1 day per year. Such potential lethal events will most likely occur more frequently in the future. For example, during the period 2070-99, the 29 °C is projected to be exceeded on average 6 days per year (B1) and 15 day per year (A2). For lower thresholds, the impact will likely be significant as well. For instance, the 23°C is currently exceeded 37 days per year on average, while this number could be more than doubled in the future (60 days for scenario B2 to 75 days for scenario A1; for the period 2070-99).

5. CONCLUSION

Climate change impacts within river systems include changes in runoff, streamflow timing and groundwater storage among others. In addition to these quantitative aspects, some water quality parameters are also expected to change and they must be assessed to determine their physical and biogeochemical implications. With respect to biogeochemical water quality, most climate change impacts can be attributed to changes in stream water temperature. When river water temperature increases, dissolved oxygen decreases and biological activities are enhanced, with consequences on biomass and fish populations in general (Schindler 2001; Moore *et al*. 1997). As such, the impact of climate change on stream water temperature is highly dependent on the future evolution of meteorological and physical parameters, including air temperature. As air temperature is the parameter that is expected to change most significantly under climate change, therefore, water temperature is also expected to be an extremely important parameter.

To better understand stream water temperature under natural meteorological conditions, the present study used many different models, i.e., stochastic models (using both regression and the Markov process approach), genetic programming (GP) and the Polynomial Neural Networks (PNN), to predict stream water temperature variability under the historic and future climates. When dealing with the modeling of daily water temperatures, the stochastic, GP and PNN models showed a significant improvement over linear regression models. Regression models have shown to be effective only at the weekly and monthly time scales (Pilgrim *et al*. 1998; Mohseni *et al*. 1999). The present study showed that all models can be used to predict river water temperatures with RMSEs generally less than 2.0°C. This is due to the fact that these models take into consideration the autocorrelation in the water temperature time series whereas the linear regression model does not (e.g., Caissie *et al*. 1998; Caissie *et al*. 2004). It also showed that intelligent algorithms such as GP and PNN, as well as stochastic models, were able to closely follow the behaviour of stream water temperatures by providing equations which can be readily incorporated into any programming environment.

The water temperature models were calibrated using only air temperature as an exogenous input. This has the advantage of using simple models while also being adapted to climate change studies. The selected PNN water temperature model for the climate change has proven to be a useful tool in the modeling of water temperatures under different climate change scenarios. Results of the present study showed that water temperature will increase in the future but at a slower rate than air temperature. Results also showed that the increase in water temperature will be dependent on the scenario (B2 or A1) as well as the time period. The projected increase in water temperature was between 0.7°C and 3.7°C or between 60% and 75% of the projected increase in air temperature over the next 100 years. These results were consistent with those observed within the literature where reported increases were in the range of 2°C to 4°C (Leblanc *et al*. 1997; Pilgrim *et al*. 1998; Mohseni *et al*. 1999; Tung *et al*. 2006). The types of models used in the present study are also important to predict thermal habitat conditions within rivers as well as identifying reaches which may eventually become unsuitable for aquatic habitat due to high temperatures. Under such conditions, cold-water stream and thermal refugia (e.g. cold-water seeps, etc.) will become extremely important for the survival of some species (Breau *et al*. 2007).

Results of the present study showed that all studied models were effective in predicting river water temperature with RMSEs below 2°C. Better model performances were obtained for mean daily water temperature by all models compared to minimum and maximum water temperatures. These results were consistent with previous studies (Chenard and Caissie 2008). Data from the climate change model are showing an increase in air temperature that is very consistent throughout the province of New Brunswick (Table 6). As such, it is expected that future water temperatures at other sites within the province could be within the same orders of magnitude, based on projected air temperature increases at these sites.

An analysis of extreme events, by studying water temperature thresholds, showed that river water temperature threshold exceedances will experience significant increases under future climate. For instance, the number of days where summer water temperature will exceed 23°C will more than double towards the end of this century. The quantification of these extreme events has important implications on water quality parameters, such as dissolved oxygen, as well as on the stress level experienced by fishes. If such thresholds are used for the closing and subsequent reopening of angling fisheries (e.g., Atlantic salmon) then more occurrences of potentially longer duration are expected in the future. Water temperature models could provide managers with a better understanding of the future evolution of the thermal regimes in New Brunswick rivers. These models can also provide managers with better management tools to assess the potential impact on climate change on water quality and fisheries resources.

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Table 1 – Calculated parameters for the annual cycle and stochastic models during calibration (1992-2004)

		Annual cycle		
		a	*b*	t_0
Mean temperature	Air	4.8	14	114
	Water	4.5	15.9	119
Max temperature	Air	10.7	14.8	114
	Water	5.6	17.4	119
		Stochastic Model 1 (Multiple Regression)		
		b_1	b_2	b_3
Mean temperature	Water	0.137	0.215	0.328
Max temperature	Water	0.134	0.171	0.270
		Stochastic Model 2 (Markov Process)		
		A_1	A_2	K
Mean temperature	Water	1.12	-0.293	0.149
Max temperature	Water	0.838	0.663	0.149

Table 2. Periods of calibration, training, testing and validation for the different water temperature models

	Periods
PNN	Training and validation (1992 to 2005) Testing (2005 to 2010)
GP	Training (1992 to 1999) Validation (2000 to 2004) Testing (2005 to 2010)
SM1	Calibribration (1992 to 2004) Validlidation (2005 to 2010)
SM2	Calibribration (1992 to 2004) Validlidation (2005 to 2010)

Table 3. Model results and performances for the estimation of mean water temperatures

	Periods	RMSE	R^2
GP	Train (1992-99)	1.67	0.937
	Valid (2000-04)	1.55	0.953
	Test (2005-10)	1.77	0.926
PNN	Train (1992-04)	1.28	0.963
	Test (2005-10)	1.58	0.946
SM1	Calibr. (1992-04)	1.33	0.962
	Valid (2005-10)	1.51	0.947
SM2	Calibr. (1992-04)	1.53	0.946
	Valid (2005-10)	1.68	0.938

Note: In the case of PNN, the training data set was also used for cross-validation (5-fold)

Table 4. Model results and performances for the estimation of maximum water temperatures

	Periods	RMSE	R^2
GP	Train (1992-99)	1.29	0.960
	Valid (2000-04)	1.93	0.937
	Test (2005-10)	2.24	0.909
PNN	Train (1992-04)	1.76	0.944
	Test (2005-10)	2.02	0.926
SM1	Calibr. (1992-04)	1.73	0.942
	Valid (2005-10)	2.00	0.933
SM2	Calibr. (1992-04)	1.80	0.936
	Valid (2005-10)	2.00	0.932

Note: In the case of PNN, the training data set was also used for cross-validation (5-fold)

Table 5 – Mean air temperature increases (°C) at selected sites in New Brunswick

	Scenario B1			Scenario A2		
	2010-39	2040-69	2070-99	2010-39	2040-69	2070-99
Aroostook	1.2	2.2	2.9	1.5	3.3	5.3
Charlo	1.2	2.2	2.9	1.4	3.2	5.2
Chatham	1.2	2.2	2.9	1.4	3.2	5.2
Doaktown	1.2	2.2	2.9	1.2	2.9	5.0
Fredericton	1.2	2.2	2.9	1.5	3.2	5.3
Moncton	1.2	2.2	2.9	1.5	3.2	5.3
Saint John	1.2	2.3	3.0	1.5	3.2	5.3

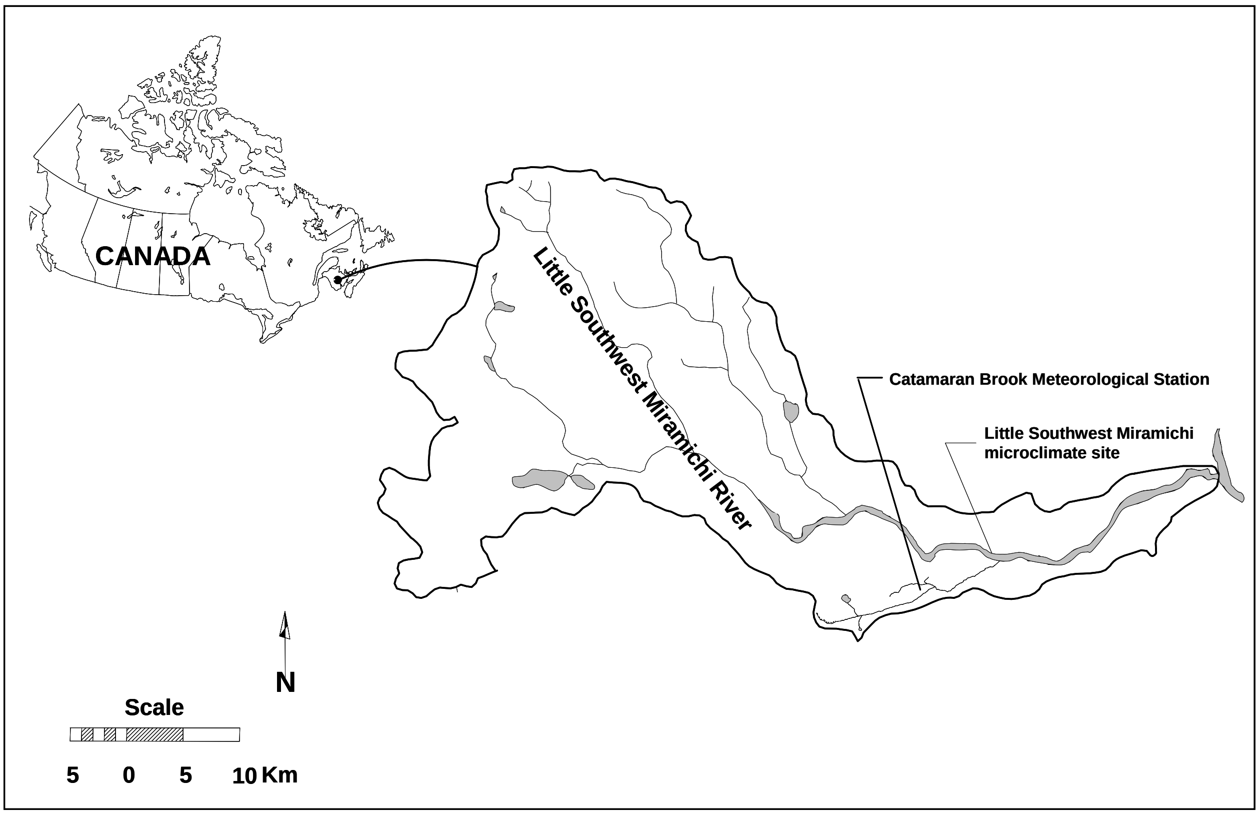


Figure 1. Map showing the location of the water temperature site on the Little Southwest Miramichi River and the meteorological station in Catamaran Brook.

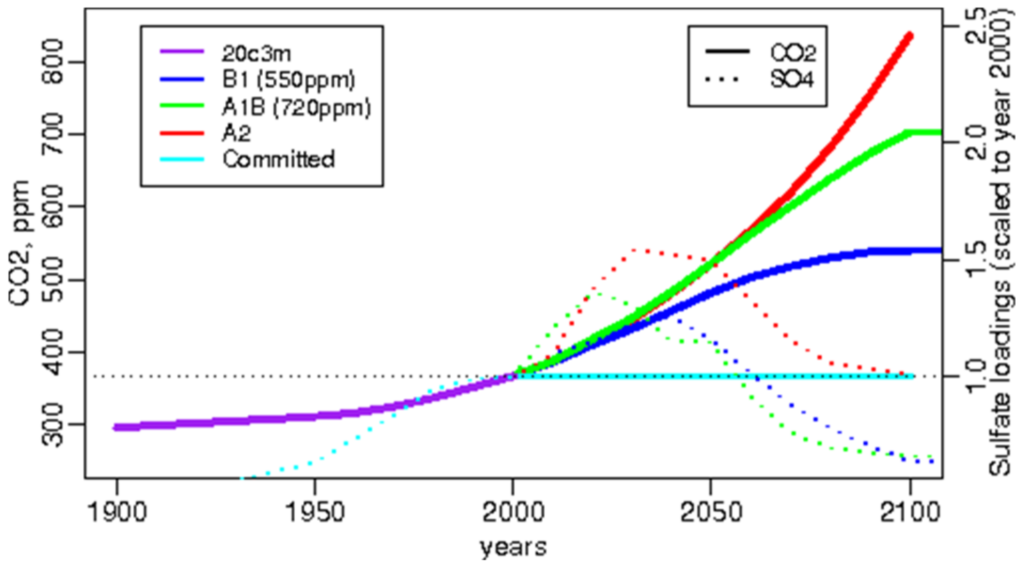


Figure 2 - Time evolution of the CO2 concentrations (solid line curves) and globally averaged sulphate aerosol loadings scaled to year 2000 (dotted line curves) as prescribed in the IPCC 20-th century 20C3M (purple), SRES B1 (blue) and A2 (red) experiments (source:www.ec.gc.ca/ccmac-cccma)

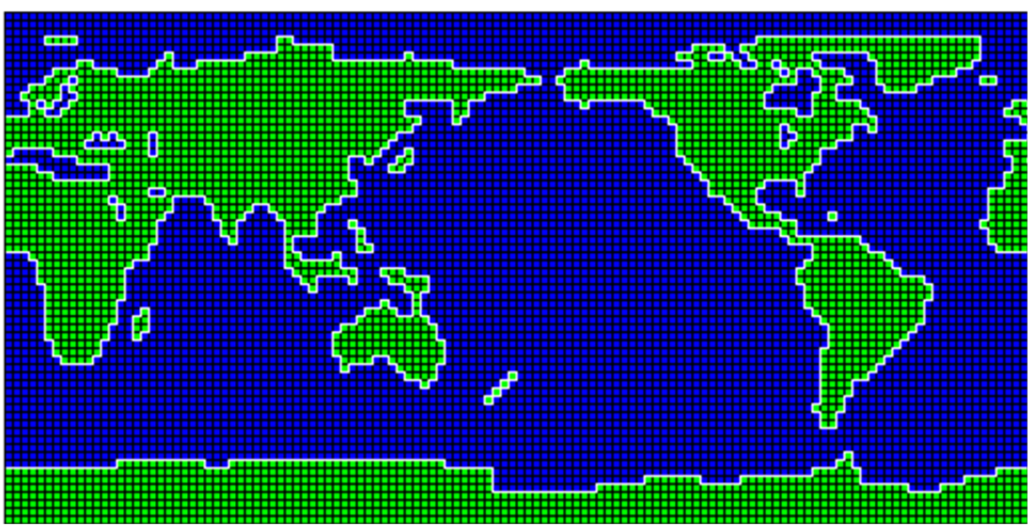


Figure 3 – CCCma 128 x 64 Gaussian grid (grid box size ~ 2.81^{o} lat x 2.81^{o} long; source:www.ec.gc.ca/ccmac-cccma)

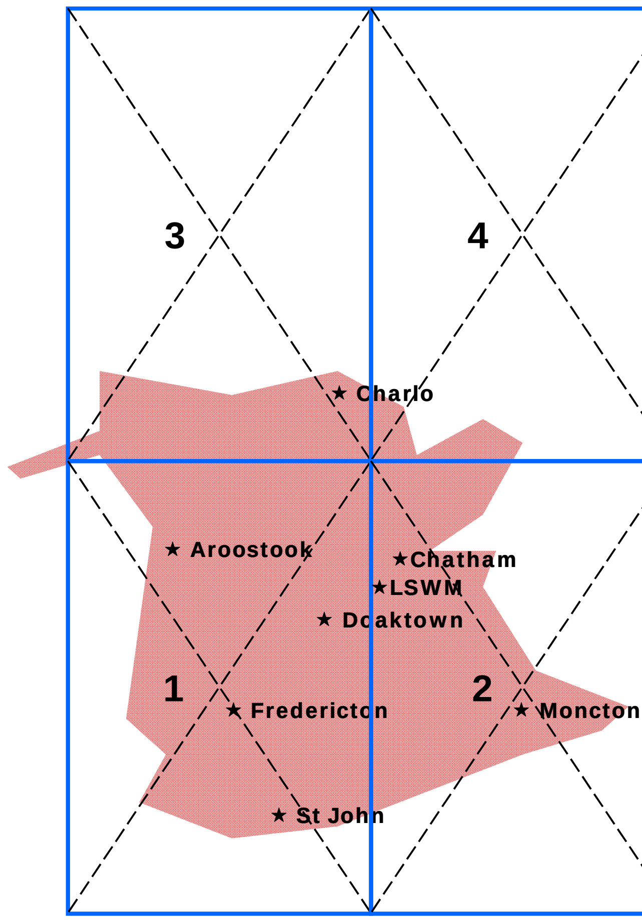
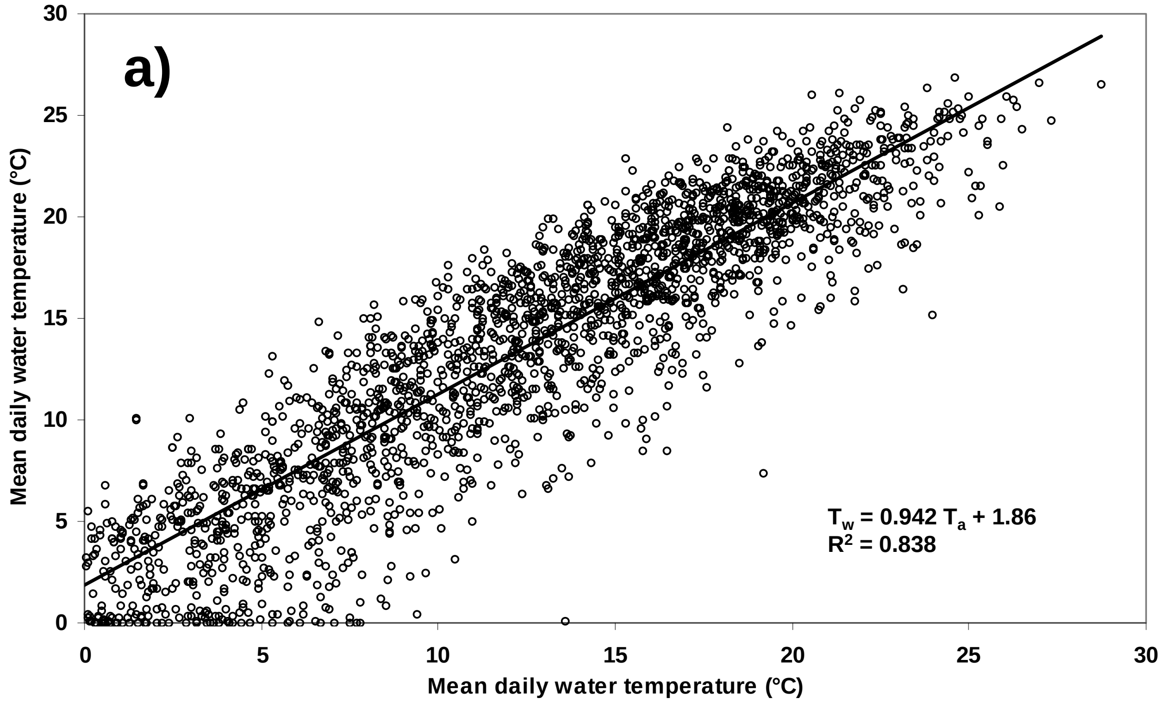


Figure 4 – CCCma subarea corresponding to New Brunswick : 4 grid boxes
(Box size ~200x300 km, ★meteorological station)
(1→67.5° W 46.04°N, 2→64.69°W 46.04°N, 3→67.5°W 48.84°N, 4→64.69°W 48.84°N)



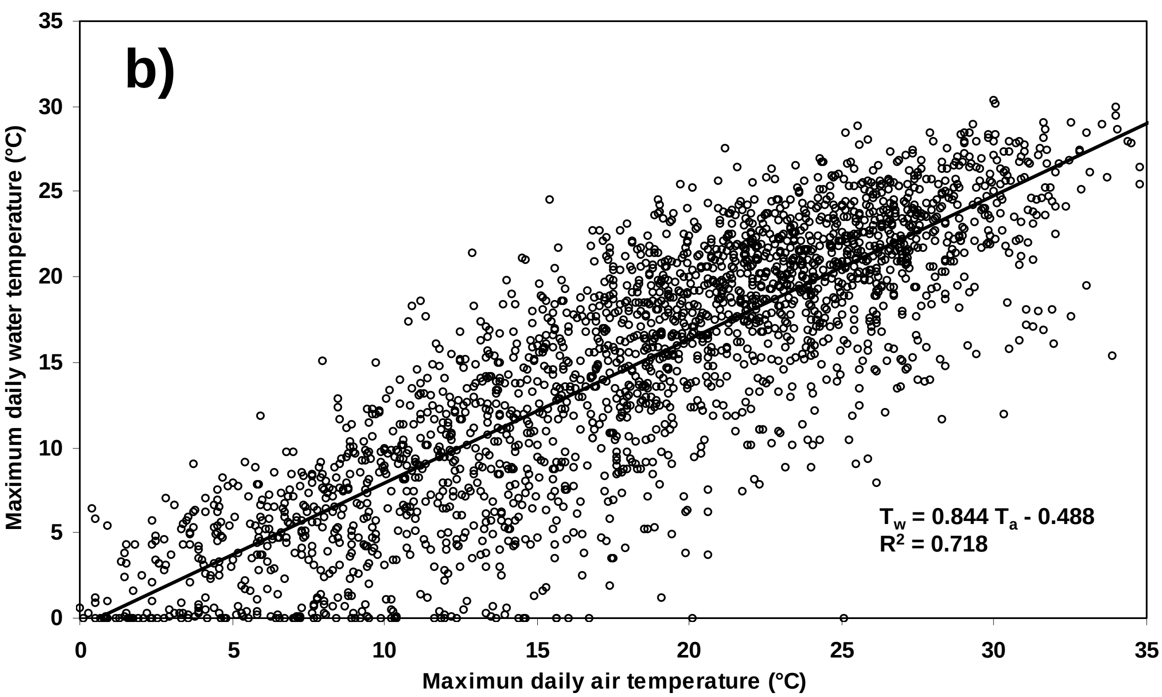


Figure 5. Relationship between a) mean daily air temperature and mean daily water temperature and b) maximum daily air temperature and maximum daily water temperature for the Little Southwest Miramichi River

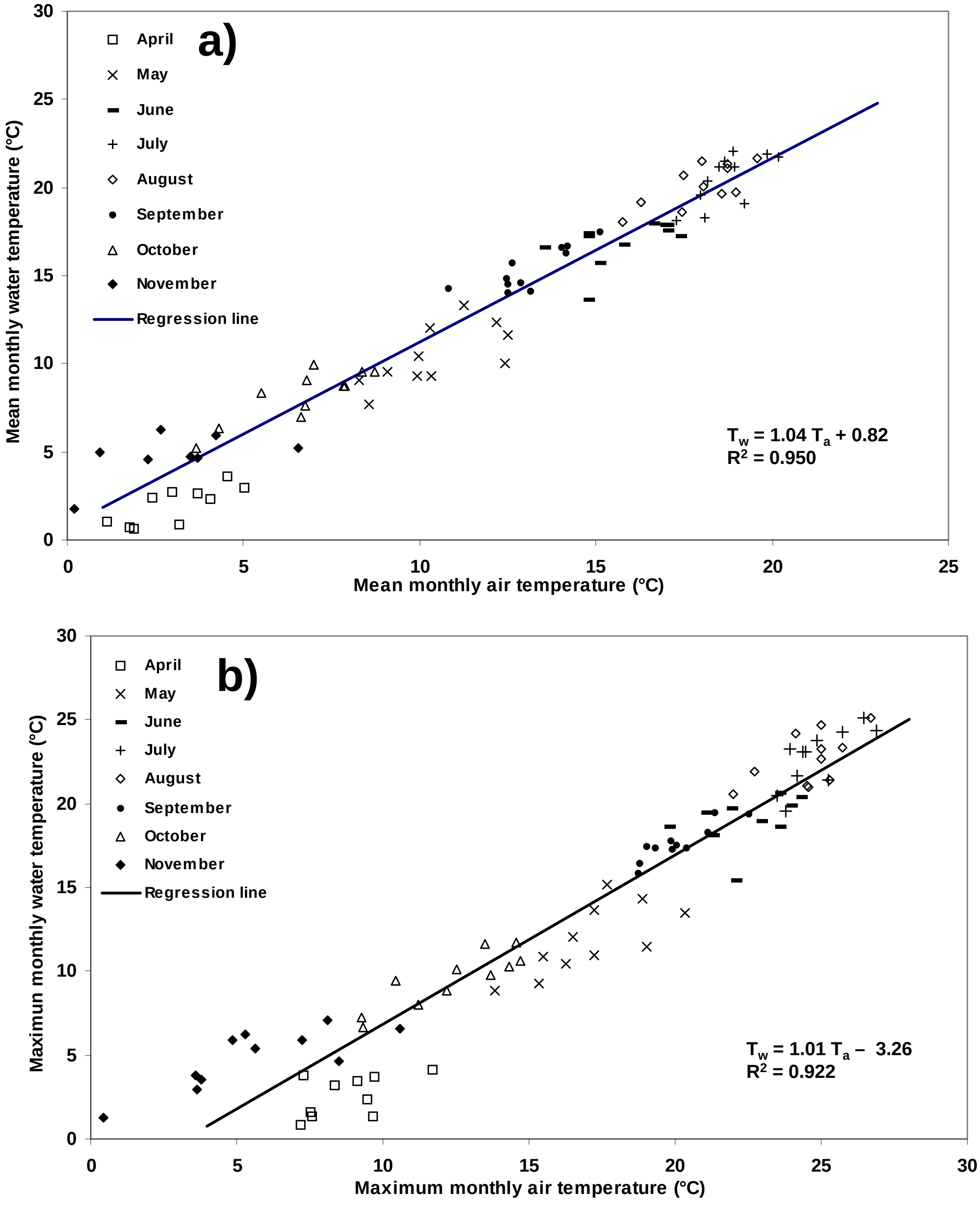


Figure 6. Relationship between a) mean monthly air temperature and mean monthly water temperature and b) maximum monthly air temperature and maximum monthly water temperature for the Little Southwest Miramichi River

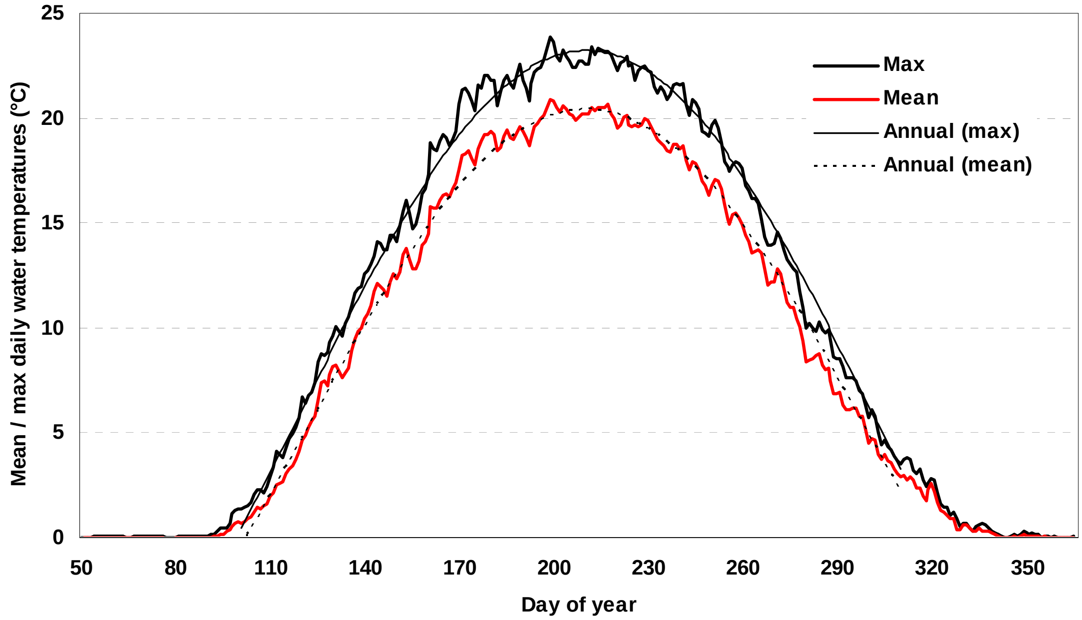
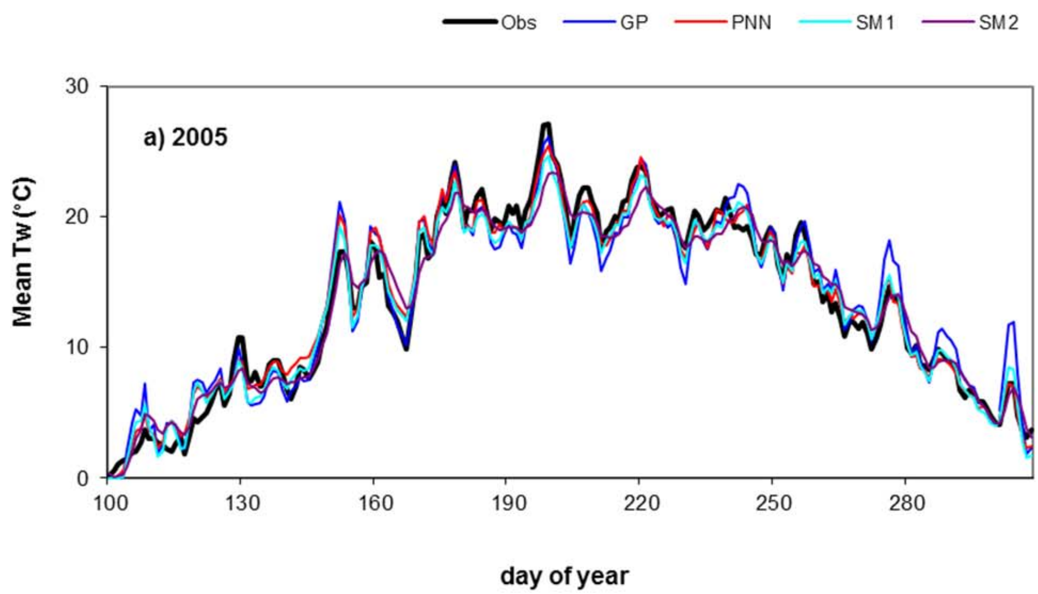


Figure 7. Annual cycle for both the mean water temperatures and maximum water temperatures for the Little Southwest Miramichi River



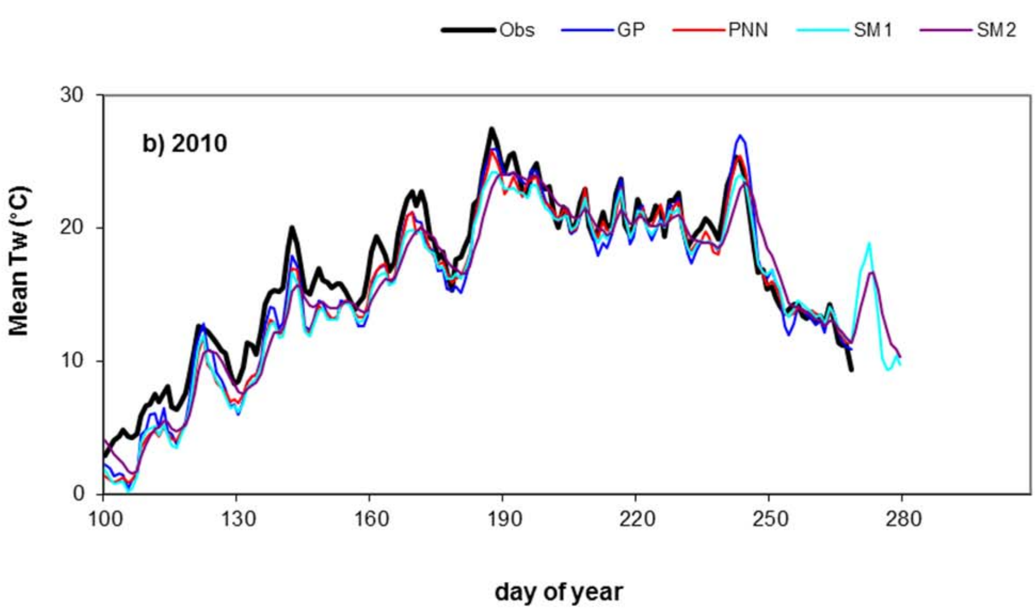


Figure 8 – Observed and modeled mean water temperature values for a) year 2005 b) year 2010

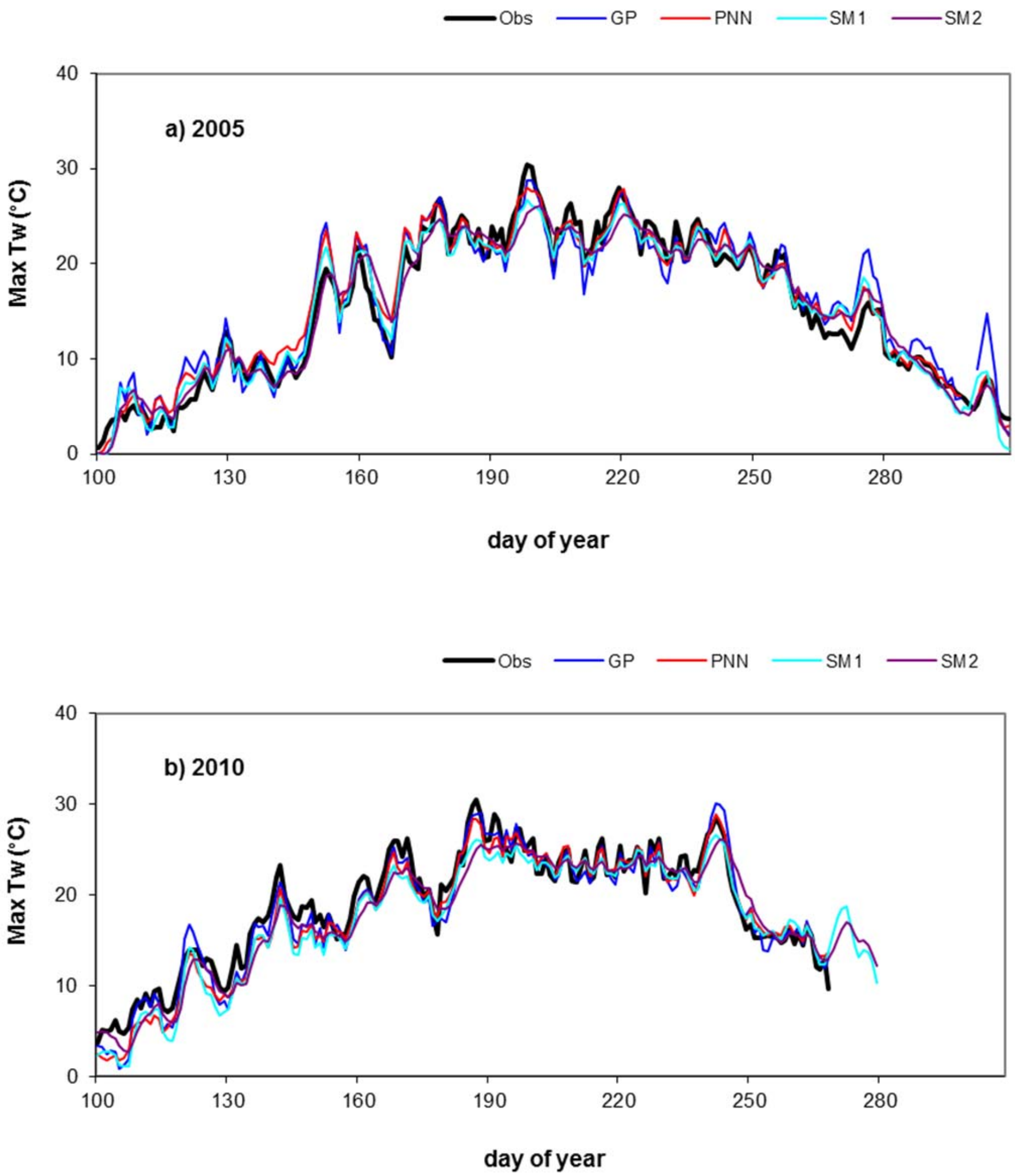


Figure 9 – Observed and modeled maximum water temperature values for a) year 2005 b) year 2010

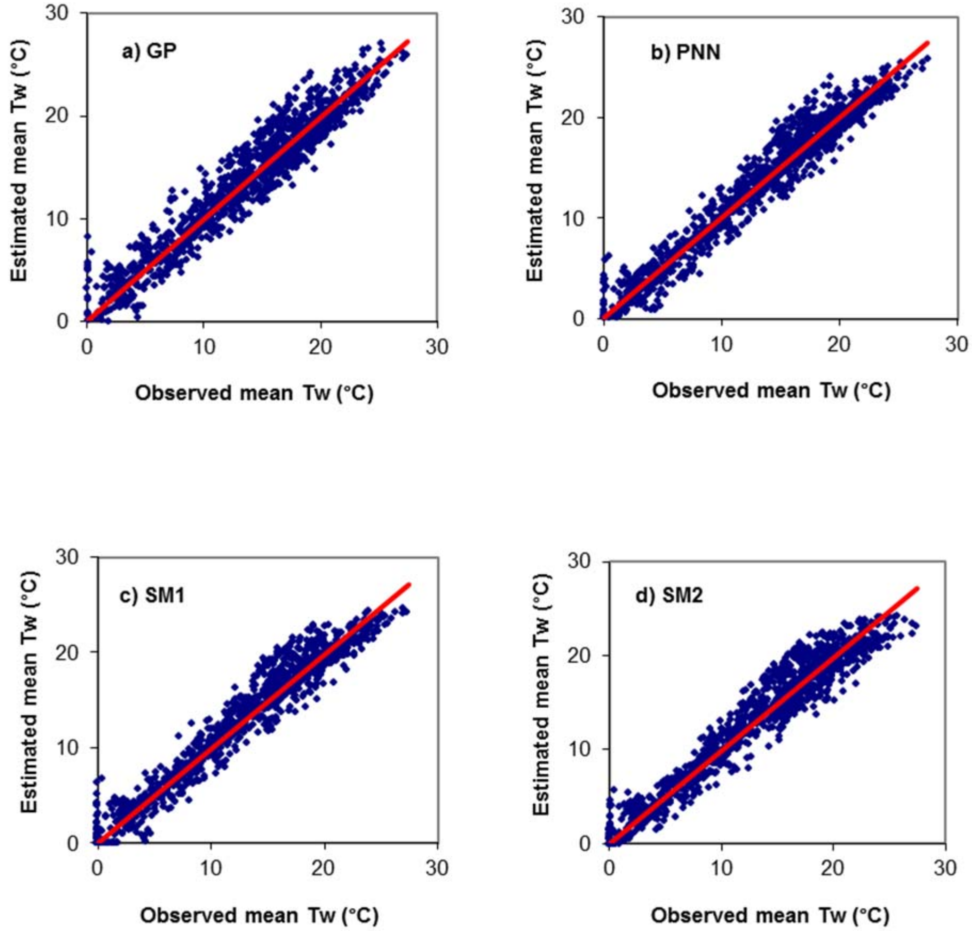


Figure 10 – Comparison between observed and estimated mean water temperature for the test set (2005-2010) using a) GP b) PNN c) SM1 (MutipleR) d) SM2 (Markov)

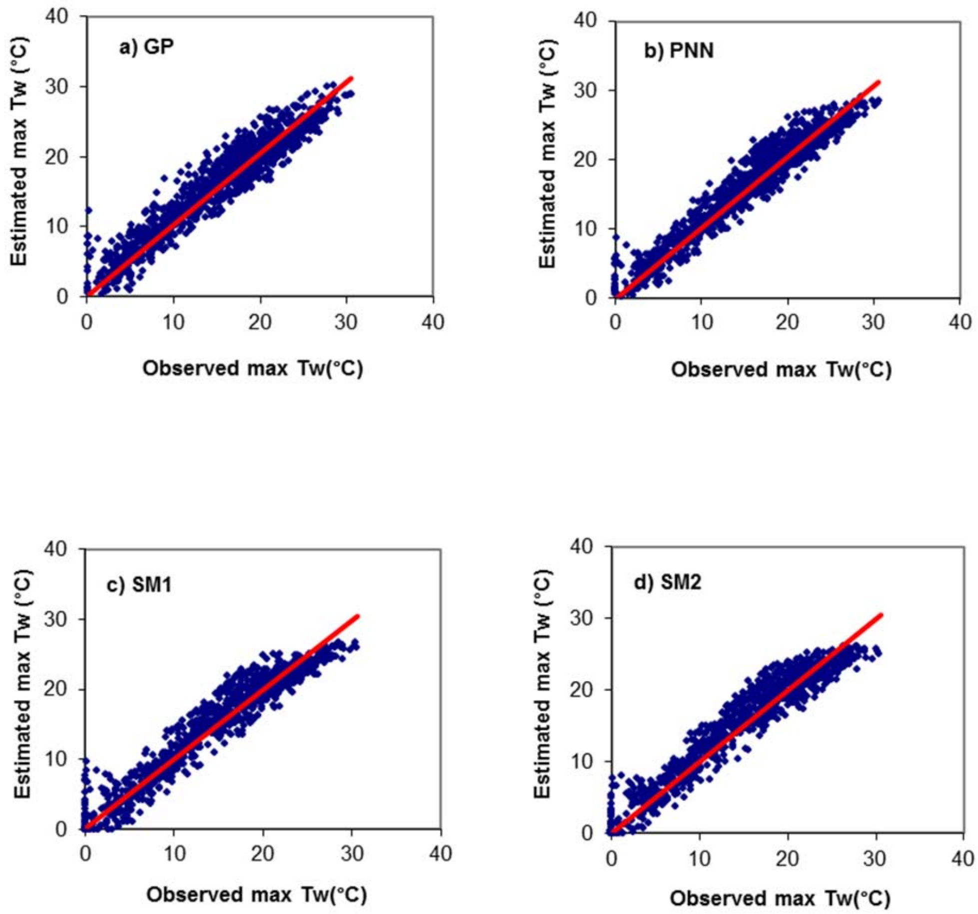


Figure 11 – Comparison between observed and estimated maximum water temperature for the test set (2005-2010) using a) GP b) PNN c) SM1 (MultipleR) d) SM2 (Markov)

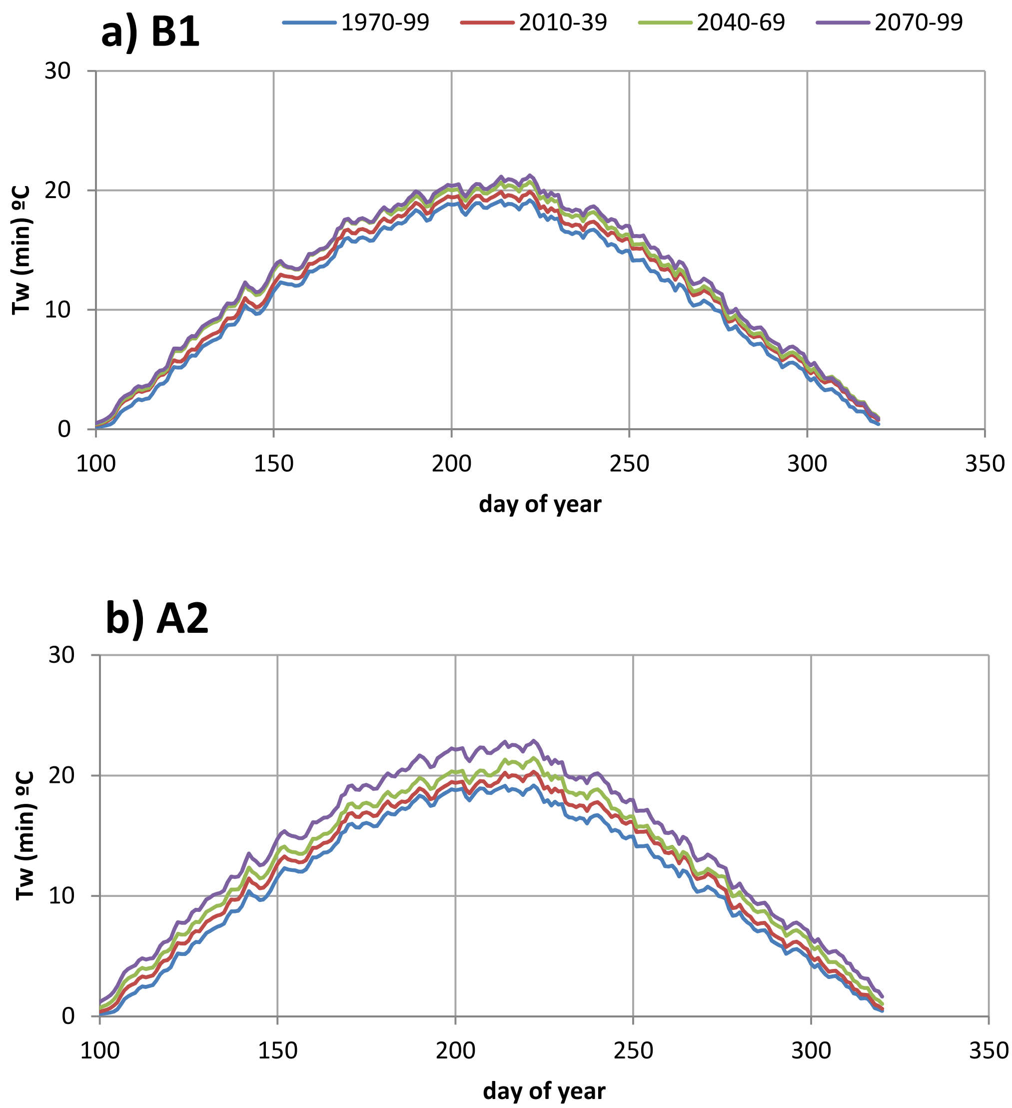


Figure 12. Historical (1970-99) and simulated (2010-39, 2040-69, 2070-99) minimum stream water temperatures for LSWM River a) using scenario B1 and b) scenario A2

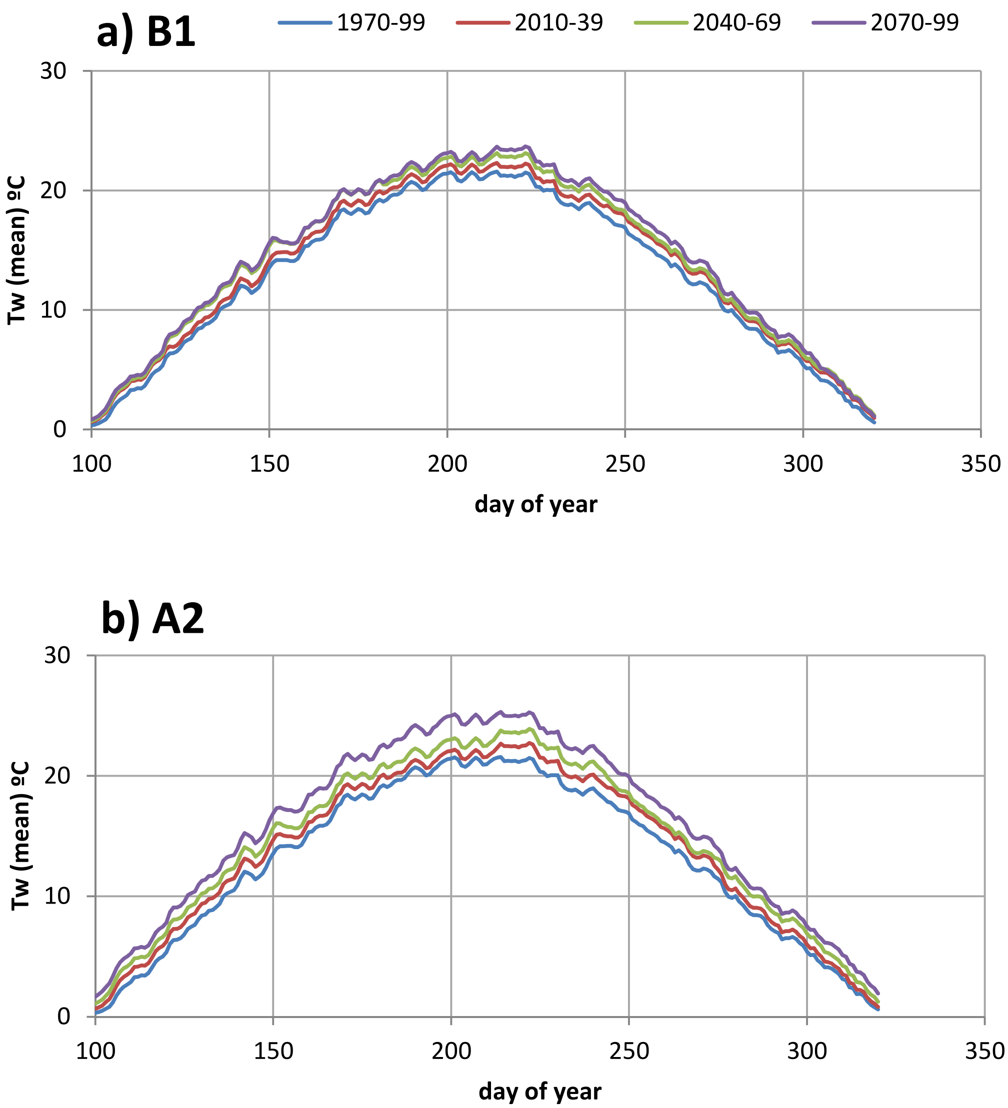


Figure 13. Historical (1970-99) and simulated (2010-39, 2040-69, 2070-99) mean stream water temperatures for LSWM River a) using scenario B1 and b) scenario A2

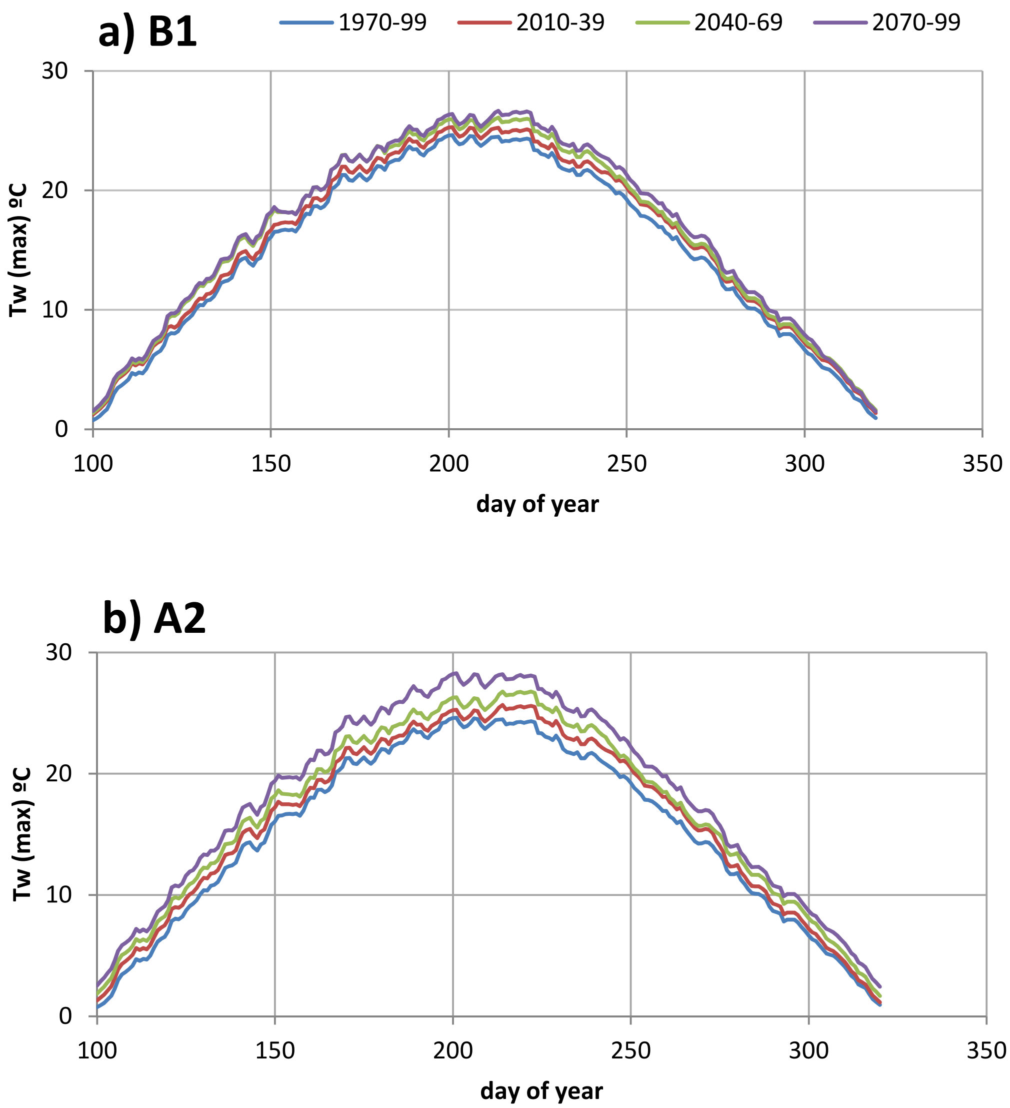
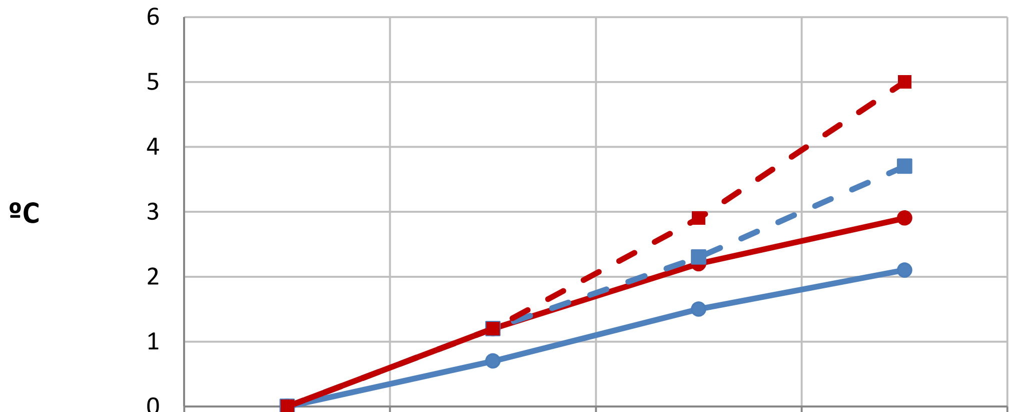
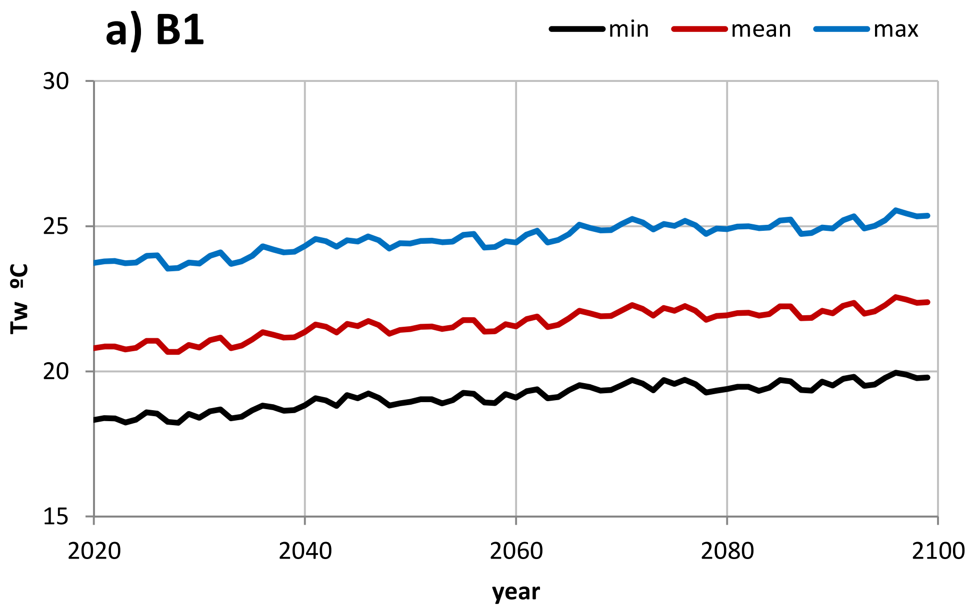


Figure 14. Histrocial (1970-99) and simulated (2010-39, 2040-69, 2070-99) maximum stream water temperatures for LSWM River a) using scenario B1 and b) scenario A2



	1970-99	2010-39	2040-69	2070-99
Tw (B1)	0	0.7	1.5	2.1
Ta (B1)	0	1.2	2.2	2.9
Tw (A2)	0	1.2	2.3	3.7
Ta (A2)	0	1.2	2.9	5.0

Figure 15. Averaged air temperature increases at Doaktown and averaged stream water temperature increases at LSWM River under B1 & A2 scenarios



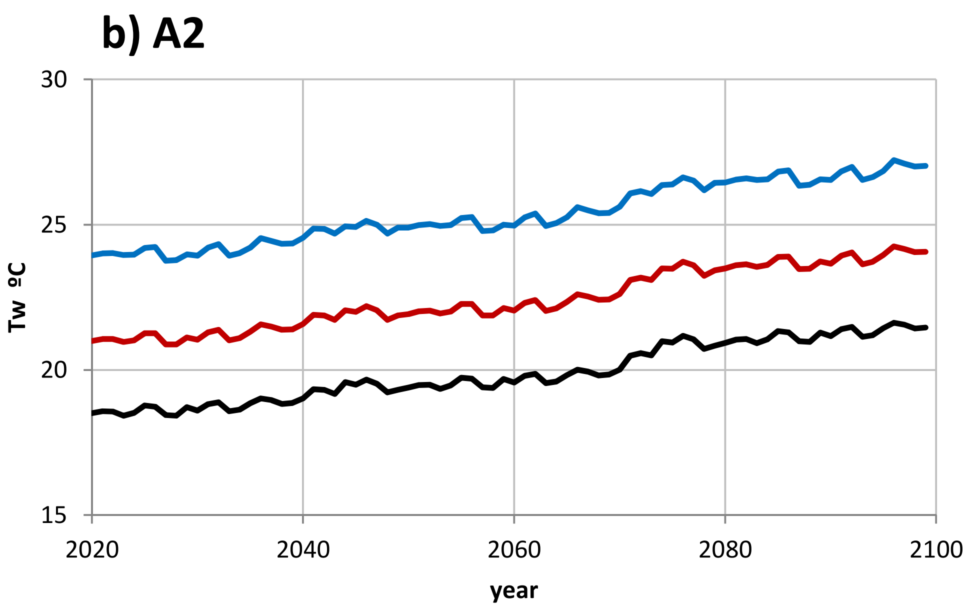
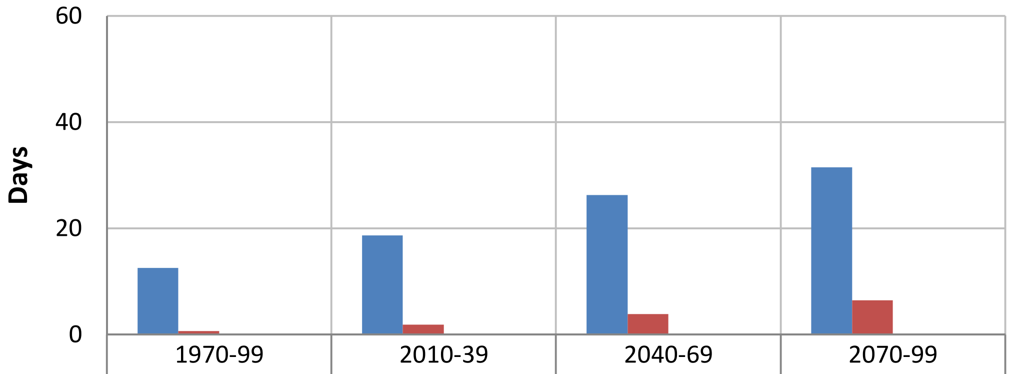


Figure 16. Trends in minimum, mean and maximum summer stream water temperatures for LSWM River a) using scenario B1 and b) scenario A2

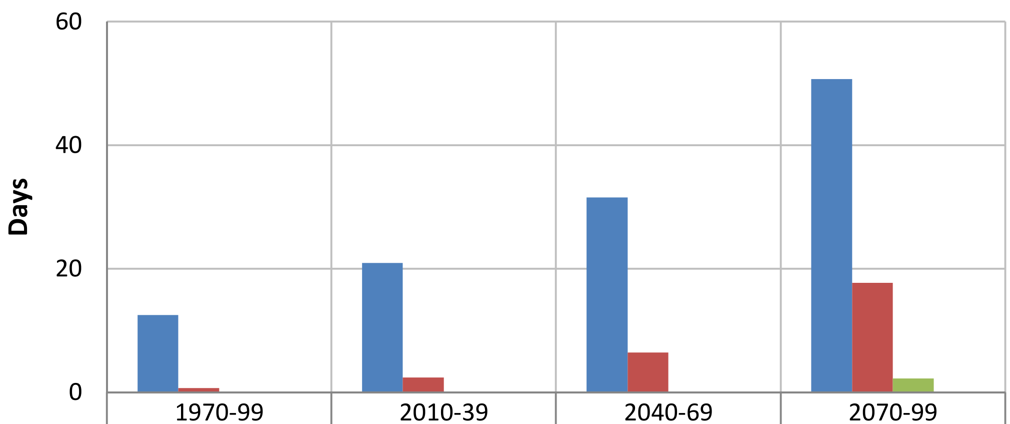
Tw (min) exceedance frequency

a) B1 scenario



	1970-99	2010-39	2040-69	2070-99
20 ºC	13	19	26	32
23 ºC	1	2	4	6
26 ºC	0	0	0	0
29 ºC	0	0	0	0

b) A2 scenario

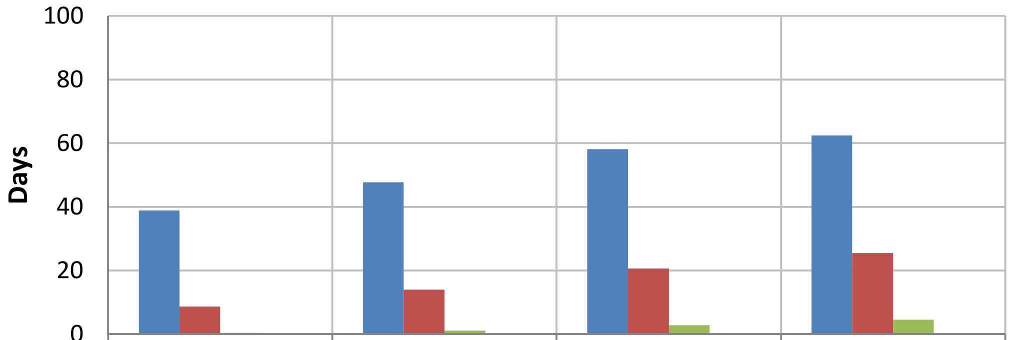


	1970-99	2010-39	2040-69	2070-99
20 ºC	13	21	32	51
23 ºC	1	2	6	18
26 ºC	0	0	0	2
29 ºC	0	0	0	0

Figure 17. Mean annual exceedance frequencies of minimum stream water temperatures for LSWM River a) using scenario B1 and b) scenario A2

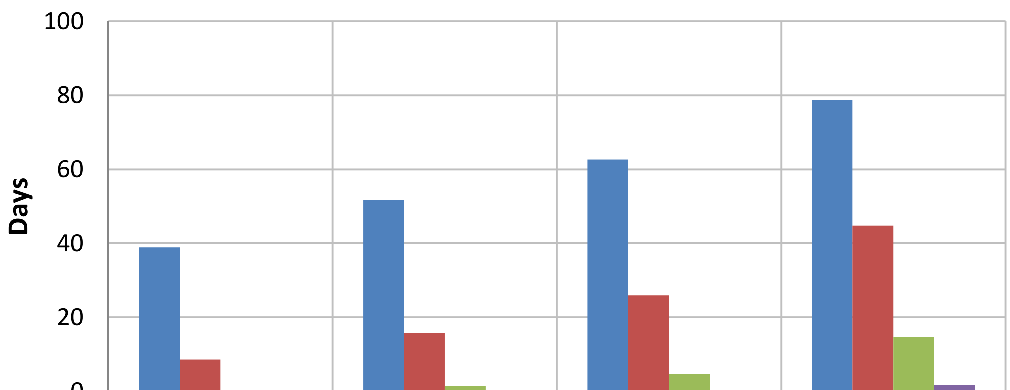
Tw (mean) exceedance frequency

a) B1 scenario



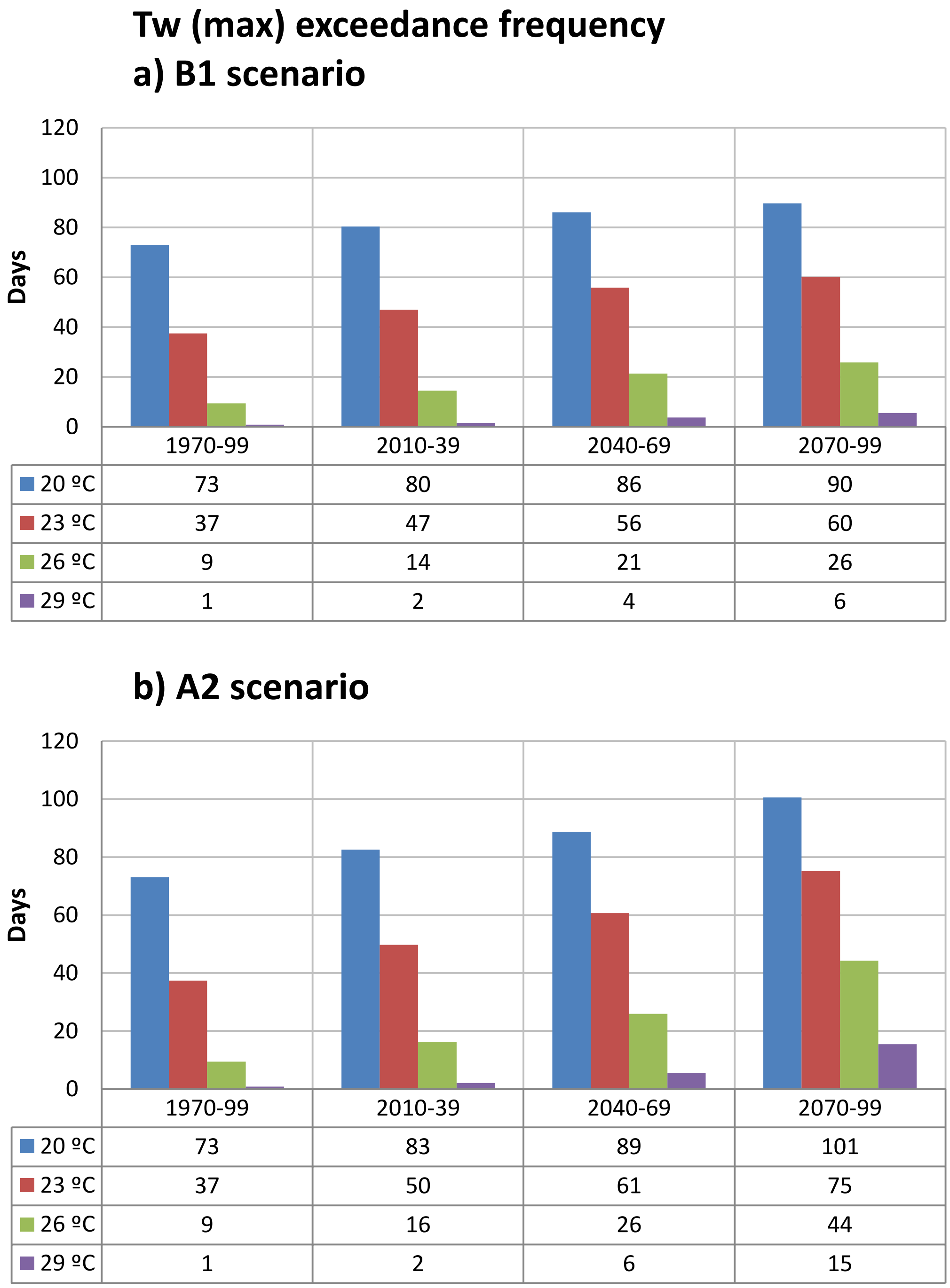
	1970-99	2010-39	2040-69	2070-99
20 ºC	39	48	58	62
23 ºC	9	14	21	26
26 ºC	0	1	3	5
29 ºC	0	0	0	0

b) A2 scenario



	1970-99	2010-39	2040-69	2070-99
20 ºC	39	52	63	79
23 ºC	9	16	26	45
26 ºC	0	2	5	15
29 ºC	0	0	0	2

Figure 18. Mean annual exceedance frequencies of mean stream water temperatures for LSWM River a) using scenario B1 and b) scenario A2



a) B1 scenario

	1970-99	2010-39	2040-69	2070-99
20 ºC	73	80	86	90
23 ºC	37	47	56	60
26 ºC	9	14	21	26
29 ºC	1	2	4	6

b) A2 scenario

	1970-99	2010-39	2040-69	2070-99
20 ºC	73	83	89	101
23 ºC	37	50	61	75
26 ºC	9	16	26	44
29 ºC	1	2	6	15

Figure 19. Mean annual exceedance frequencies of maximum stream water temperatures for LSWM River a) using scenario B1 and b) scenario A2