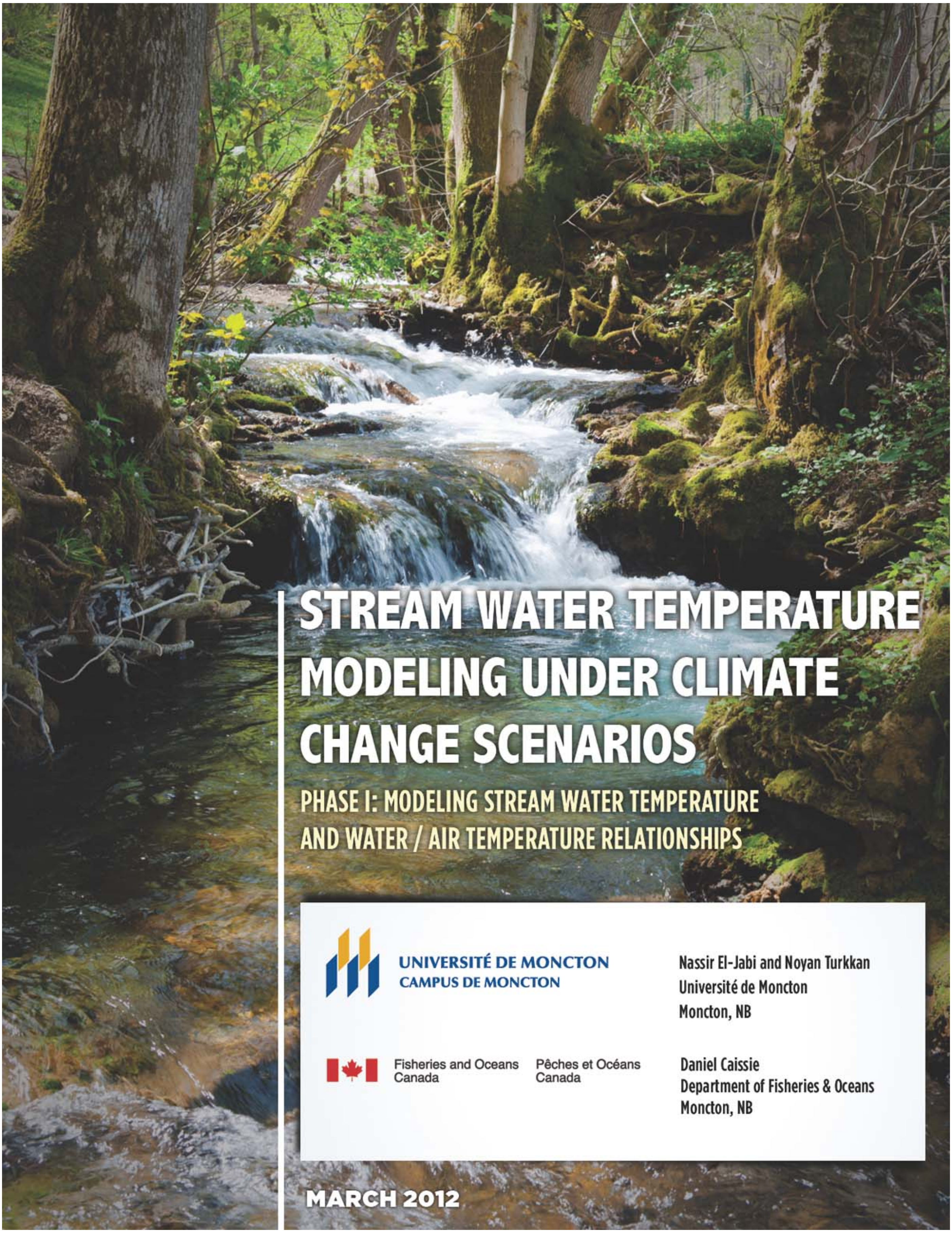

STREAM WATER TEMPERATURE MODELING UNDER CLIMATE CHANGE SCENARIOS

PHASE I: MODELING STREAM WATER TEMPERATURE AND WATER / AIR TEMPERATURE RELATIONSHIPS

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GP	Genetic Programming
LSWM	Little SW Miramichi
PNN	Polynomial Neural Network
RMSE	Root Mean Square Error
SM	Stochastic Model
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
TA	long-term annual component
Tmn	minimum air temperature
Tmx	maximum air temperature
T_w	mean water temperature
T_w^{max}	maximum water temperature

ABSTRACT / RÉSUMÉ

Abstract: Stream water temperature is a very important parameter when assessing aquatic ecosystem dynamics. For instance, cold-water fishes such as salmon can be adversely affected by maximum summer temperatures or by those exaggerated by land-use activities such as deforestation. The present study deals with the modelling of stream water temperatures by means of two Stochastic Models (SM1 & SM2) and two intelligent algorithms such as genetic programming (GP) and polynomial neural networks (PNN) to relate air and water temperatures in Little SW Miramichi, a 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 predicting these temperatures. The root mean square error (RSME) varied between 1.51°C and 1.77°C on an annual basis from 1990 to 2010. Of the four models, the SM1 using multiple regression and PNN were preferred based on performance and simplicity in development.

Résumé : 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 en utilisant quatre approches différentes afin d'associer les températures de l'eau et de l'air du cours d'eau Little SW Miramichi, situé au Nouveau-Brunswick. Ces approches sont : les méthodes stochastiques, la programmation génétique et les réseaux de neurones polynomiaux. 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. Le carré moyen des erreurs (CME) variait entre 1,51°C et 1,77°C sur une base annuelle, de 1990 à 2010. Des quatre modèles, le modèle stochastique utilisant multiple régression et les réseaux polynomiaux furent les plus performants et simples à développer.

1. Introduction

Water temperature has both economic and ecological significance when considering issues such as water quality and biotic conditions in rivers (Caissie, 2006). The thermal regime of rivers is influenced by many factors such as atmospheric conditions, topography, riparian vegetation, stream discharge, and streambed thermal fluxes (Poole and Berman, 2001; Caissie, 2006; Webb et al., 2008).

Knowledge and the ability to predict stream water temperature are essential to address thermal discharge problems, water quality and in conducting environmental impact studies. A better understanding of the natural thermal regime of a river system is also very important in the management of water supply. The first step in the overall understanding of the stream thermal regime is to be able to study and predict natural variation in stream water temperatures.

Stream water temperatures have been studied for many years (Macan, 1958; Raphael, 1962; Brown, 1969). Water temperature controls the rate of decomposition of organic matter, dissolved oxygen content and chemical reactions in general. Stream temperatures have also been monitored in order to evaluate the impact of human activities due to urbanisation (Kinouchi et al., 2007; Nelson and Palmer, 2007), thermal pollution (Bradley et al., 1998) as well as land-use activities (Nagasaka et al., 1999). Flow reduction and flow alteration have also been observed to have an impact on the thermal regime of rivers (Morin et al., 1994; Sinokrot and Gulliver, 2000). It is therefore important to consider the thermal regime of rivers during water withdrawal projects and when conducting instream flow studies.

Water temperature models can be classified into two groups: deterministic or statistical. The statistical approach predicts water temperatures by linking water temperatures to relevant meteorological parameters, usually air temperature (Sinokrot and Stefan, 1993; Caissie et al., 2001; Ahmadi-Nedushan et al., 2007). It is often determined by classical regression analysis, autoregressive processes, or by using time series analysis such as the Box-Jenkins modeling approach (Box and Jenkins 1976).

The objectives of the present study are to study Water/Air temperatures relationships and to carry out a modeling of Stream Water Temperatures.

2. Materials and methods

2.1 Study area

The study site 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, precipitation was close to 100 mm per month, with values ranging between 72 mm in February and 109 mm in 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.

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 Little Southwest Miramichi River is approximately 80 m in width with an average water depth of 0.55 m. The drainage basin of Little Southwest Miramichi River at the water temperature measurement site covers 1190 km^2. A water temperature sensor was installed on this river 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 are 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 water temperatures calculated from hourly data (mean of 24 observations). Although the riparian vegetation is mature along the banks of the Little Southwest Miramichi River, this river is nevertheless well exposed to meteorological conditions due to its relatively large width. 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 Little Southwest Miramichi (station 01BP001) approximately 16 km downstream from the water temperatures sampling point. The drainage area above this hydrometric station measures 1340 km^2. The mean annual flow at the Little Southwest Miramichi River hydrometric station was 32.5 m^3/s or

764 mm of runoff. The river discharge varies 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 were obtained from the Catamaran Brook meteorological station, which is located less than 10 km from the water temperature study sites (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, solar radiation). Meteorological conditions measured at Catamaran Brook are reflective of conditions experienced by the Little Southwest Miramichi River due to climate homogeneity within the region (Caissie and El-Jabi 1995). Therefore, this data base will be used for the water temperature modeling of the Little Southwest Miramichi River. Air temperature was required for the modeling. The air temperature was monitored 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.

2.2 Water temperature modeling

Stream water temperature and air temperature relationships were modeled by means of a Regression Model (RM) and Stochastic Model (SM) and two intelligent algorithms: genetic programming (GP) and polynomial neural networks (PNN).

Stochastic Models (SM1 & SM2)

Stochastic models use the short-term component and water temperatures of previous days in the predictions of daily water temperatures. The stochastic model consists of separating the water temperatures into two different components, namely the long-term seasonal component (or the annual component) and the short-term non-seasonal component. The short-term component represents the departure from the long-term annual component during each day, as a result of above or below normal 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:

$$Tw(t) = TA(t) + Rw(t) \tag{1}$$

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 and 2004) given by:

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

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

The short-term components in water temperature were obtained by the following equations:

For the stochastic model 1 (SM1) using multiple regression (Caissie et al., 1998):

$$Rw(t) = b_1 Ra(t) + b_2 Ra(t-1) + b_3 Ra(t-2) \qquad (3)$$

For the stochastic model 2 (SM2) using Markov process (Caissie et al., 2004):

$$Rw(t) = A_1 Rw(t-1) + A_2 Rw(t-2) + K\,Ra(t) \qquad (4)$$

where *Rw(t)* and *Ra(t)* are non-seasonal component 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)

A genetic programming 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 (Koza, 1989).

In the present study, four arithmetic operators (+, -, *, /), ten input variables; one output variable and a vector of real constants were selected. Thus, the terminal set to predict the stream water temperature was:

$$\left\{\begin{matrix} t, \bar{c} \\ T(t), T(t-1), T(t-2) \\ Tmx(t), Tmx(t-1), Tmx(t-2) \\ Tmn(t), Tmn(t-1), Tmn(t-2) \end{matrix}\right\} \Rightarrow \left\{\begin{matrix} Tw^{mean} \\ or \\ Tw^{\max} \end{matrix}\right\} \qquad (5)$$

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

Polynomial Neural Networks (PNN)

PNN is a flexible neural architecture whose topology is not predetermined but developed through learning. The design is based on Group Method of Data Handling (GMDH) which was invented by Prof. 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 and maximum stream temperature:

$$\left\{ \begin{array}{l} t \\ T(t), T(t-1), T(t-2) \\ Tmx(t), Tmx(t-1), Tmx(t-2) \\ Tmn(t), Tmn(t-1), Tmn(t-2) \end{array} \right\} \Rightarrow \left\{ \begin{array}{c} Tw^{mean} \\ or \\ Tw^{\max} \end{array} \right\} \tag{6}$$

where *Tw* is the stream temperature (mean or max), *t* is the day of year (100 … 320, july 1=182), *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 the solution.

To compare the relative performance among models, the root-mean-square error

(RMSE) was used which is given by:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (O_i - P_i)^2}{N}} \tag{7}$$

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

3. Results and discussion

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 component) as well as the diel variability. The first characterization analysis was carried out to study the 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 2). This is mainly due to the fact that both air and water temperatures have some level of memory (or 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) 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 10°C will result in an increase in mean water temperature of only 9.4°C. This difference is also observed for maximum temperatures where the slope of the regression was 0.844. Therefore, an increase of 10°C in maximum air temperature will results in an increase in maximum water temperature of only 8.4°C. The linear regression model does not provide a very good water temperature model because of the significant scatter. However, we can already point out that under climate change, it would be expected that the water will increase with air temperature but at a slightly low rate based on these observed relationships.

The next characterisation 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 both mean and maximum temperatures (Figure 3). 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 3a). From this figure it can be observed that the month 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 month 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 also observed for April and May). On a monthly basis the slope of the recession was very close to unit (1.04), which implies that, at such scale, water temperature will most like experience similar changes than air temperature during climate change. Similar results were observed for maximum monthly temperatures, although the explained variability was less (92%; R^2 = 0.922; Figure 3b). Similar to mean monthly temperatures, the slope of the regression line was very close unity (1.01) therefore any changes in air temperature will be equally transferred to water temperatures. For maximum monthly water temperatures, it was noticed that the hysteresis was more important than for mean temperatures, especially for low air temperature in spring and autumn. This 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 (July and August).

Following the linear regression analyses, a study of the annual component was carried out, as it is required in both stochastic models (based on multiple regression and Markov process). The annual component for both the mean and maximum water temperature is presented in Figure 4 and the fitted parameters of the annual component are provided in Table 1. This figure shows that the peak mean and maximum water temperatures is reached on day 210 (July 29) with temperatures of 20.4°C (mean) and 23.0 (maximum). The annual component was also calculated for air temperature (Table 1). Thereafter, the short-term components were calculated for both mean and maximum air and water temperatures to carry out the stochastic modeling SM1 and SM2.

The computed stream water temperatures using the four models, namely the GP, the PNN and the two stochastic models SM1 and SM2 are shown in Figure 5 (mean) and 6 (maximum) for the years 2005 and 2010 (see also Appendix). In the case of GP, 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 equations obtained for mean and maximum stream temperatures were as follows:

Mean stream temperature

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

Maximum stream temperature

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

In the case of PNN, the 1992-2005 data were used for training and validation (5-fold cross-validation) and the 2006-2010 data for testing. The equations obtained for mean and maximum stream temperatures were as follows:

Mean stream temperature

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

Maximum stream temperature

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

The stochastic models were calibrated using data from 1992 to 1999 and tested with data from 2000 to 2010. The parameters calculated during the calibration period for each model are presented in Table 1. The annual components for both the mean water temperature and maximum water temperature were discussed previously and are shown in Figure 4.

The performances of the water temperature models are presented in Tables 2 and 3. These results showed that in general the RMSEs for mean water temperature were slightly lower than for the maximum water temperature. All models performed well; however, the stochastic SM1 (MutipleR) and PNN models showed slightly better results. Figures 7 and 8 show, for the testing data set (2005-2010), a comparison between measured and calculated daily average and maximum water temperatures for each model.

For the testing data set, Tables 2 and 3 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 5 and 6 also confirms that all models showed a good correspondence between observed and modeled stream temperatures.

4. Conclusion

Climate Change impacts within river systems include changes in runoff, river flow and groundwater storage. To these quantitative aspects, some water quality parameters are also expected to change and must be assessed to determine their physical and biogeochemical implications. With respect to this biogeochemical water quality, most climate change impacts can be attributed to changes in stream water temperature. When river water temperature increases, dissolved oxygen decrease, and biological activities is enhanced, with consequences on nutrients, organic matter and biomass. The impact of climate change on stream water temperature is highly dependent on the future evolution of air temperature and other meteorological and physical parameters. 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 modeling approaches, i.e., linear regression, stochastic models, GP and PNN, to predict in stream water temperature variations. When dealing with the modeling of daily water temperatures, the stochastic, GP and PNN models showed a significant improvement over a linear regression model. However, monthly water temperatures can be modeled effectively using linear regression. The present study showed that all modeling approaches can be used to model river water temperatures with RMSEs generally less than 2.0°C. This is most likely 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). It also showed that intelligent algorithms such as GP and PNN were able to closely follow the behaviour of stream water temperatures by providing simple equations which can be readily incorporated into any programming environment.

Based on these findings, these water temperature models, using only air temperature as an exogenous input, can be useful tools in the modeling of water temperatures under different climate change scenarios. Such analyses could focus on future spatial and temporal distribution of important thermal habitats in river as well as the identification of reaches, which will eventually become unsuitable for aquatic habitat.

The objective of this study was to link changes in air temperature and water temperature, as at high temperature the relationship will not be linear (due to evaporative cooling). Future studies will also concentrate on using most reliable climate change scenarios available (CGCM 3.1/T63, SRES 20C3M, A1B, B1, A2) to predict future water temperatures. Such studies are required to improve our current understanding of the impact of various climate change scenarios on Stream Water Temperature, a subject which has not been adequately addressed within the stream temperature modeling literature. Such a study, will illustrate the usefulness of the Stream Water Temperature models, coupled with Climate Change Scenarios to explain the evolutions of future water temperature regimes and associated biogeochemical water quality impacts. The knowledge gained from this study will enable engineers and water resources managers to better understand the thermal regime of rivers and its impact on water quality related to climate change impact.

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References

Ahmadi-Nedushan, B., A. St-Hilaire, T.B.M.L. Ouarda, L. Bilodeau, E. Robichaud, N. Thiémonge, B. Bobée B. 2007. Predicting river water temperature using stochastic models: case study of the Moisie River (Québec, Canada). Hydrological Processes 21(1): 21–34.

Box, G.E.P., and G.M. Jenkins. 1976. Time series analysis, forecasting and control. Enders Robinson, Holden-Day Inc., San Francisco, Calif.

Bradley, A.A., R.J. Jr. Holly, W.K. Walker and S.A. Wright. 1998. Estimation of water temperature exceedance probabilities using thermo-hydrodynamic modeling. Journal of the American Water Resources Association 34 (3): 467-480.

Brown, G.W. 1969. Predicting temperatures of small streams. Water Resources Research 5 (1): 68-75.

Caissie, D. and N. El-Jabi, 1995. Hydrology of the Miramichi River drainage basin, p.83-93. In E.M.P. Chadwick [ed.] Water, science, and the public: the Miramichi ecosystem. Can. Spec. Publ. Fish. Aquat. Sci. 123

Caissie, D., N. El-Jabi and A. St-Hilaire, 1998. Stochastic modelling of water temperature in a small stream using air to water relations, Canadian Journal of Civil Engineering, 25: 250-260.

Caissie, D., N. El-Jabi and M.G. Satish. 2001. Modelling of maximum daily water temperatures in a small stream using air temperatures. Journal of Hydrology 251: 14-28.

Caissie, D., St-Hilaire, A. and El-Jabi, N., 2004. Prediction of water temperatures using regression and stochastic models. 57th CWRA, Montreal, Canada.

Caissie, D. 2006. The thermal regime of rivers: A review. Freshwater Biology 51: 1389-1406.

Ivakhnenko, A.G., 1971. Polynomial theory of complex systems. IEEE transactions on systems, man and cybernetics, 1(4): p. 364-378.

Kinouchi, T., H. Yagi, M. Miyamoto. 2007. Increase in stream temperature related to anthropogenic heat input from urban wastewater. Journal of Hydrology 335: 78–88.

Koza, J. R., 1989. Hierarchical genetic algorithms operating on populations of computer programs. In: Proceeding of the 11th International Joint Conference on Artificial Intelligence. Morgan Kaufmann, 1: 768-774.

Macan, T.T. 1958. The temperature of a small stony stream. Hydrobiologia 12: 89-106.

Morin, G., T.-J. Nzakimuena and W. Sochanski. 1994. Prévision des températures de l'eau en rivières à l'aide d'un modèle conceptuel: le cas de la rivière Moisie, Canadian Journal of Civil Engineering 21 (1):63-75.

Nagasaka, A., F. Nakamura. 1999. The influence of land-use changes on hydrology and riparian environment in a northern Japanese landscape. Landscape Ecology 14: 543–556.

Nelson, K.C., M.A. Palmer. 2007. Stream temperature surges under urbanization and climate change: data, models, and responses. Journal of the American Water Resources Association 34(2): 440–452.

Oh, Sung-Kwun and Pedrycz, W., 2002. The design of self-organizing Polynomial Neural Networks. Information Sciences, 141: p. 237-258.

Poole, G.C., and C.H. Berman. 2001. An ecological perspective on in-stream temperature: natural heat dynamics and mechanisms of human-caused thermal degradation. Environmental Management 27 (6): 787-802.

Raphael, J.M. 1962. Prediction of Temperature in Rivers and Reservoirs. ASCE, Journal of the Power Division 88 (PO2): 157 181.

Sinokrot, B.A., and J.S. Gulliver. 2000. In-stream flow impact on river water temperatures. Journal of Hydraulic Research 38 (5): 339-349.

Sinokrot, B.A., and H.G. Stefan. 1993. Stream temperature dynamics: Measurements and modeling. Water Resources Research 29 (7): 2299-2312.

Webb, B.W., D.M. Hannah, R.D. Moore, L.E. Brown, F. Nobilis. 2008. Recent advances in stream and river temperature research. Hydrological Processes 22(7): 902–918.

Table 1 – Calculated parameters for the annual components and stochastic models during calibration (1992-1999)

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

Table 2. Model results for the estimation of mean water temperatures

	Periods	RMSE	R^2
GP	Train (1992-96)	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
	Test (2005-10)	1.51	0.947
SM2	Calibr. (1992-04)	1.53	0.946
	Test (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 3. Model results for the estimation of maximum water temperatures

	Periods	RMSE	R^2
GP	Train (1992-96)	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
	Test (2005-10)	2.00	0.933
SM2	Calibr. (1992-04)	1.80	0.936
	Test (2005-10)	2.00	0.932

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

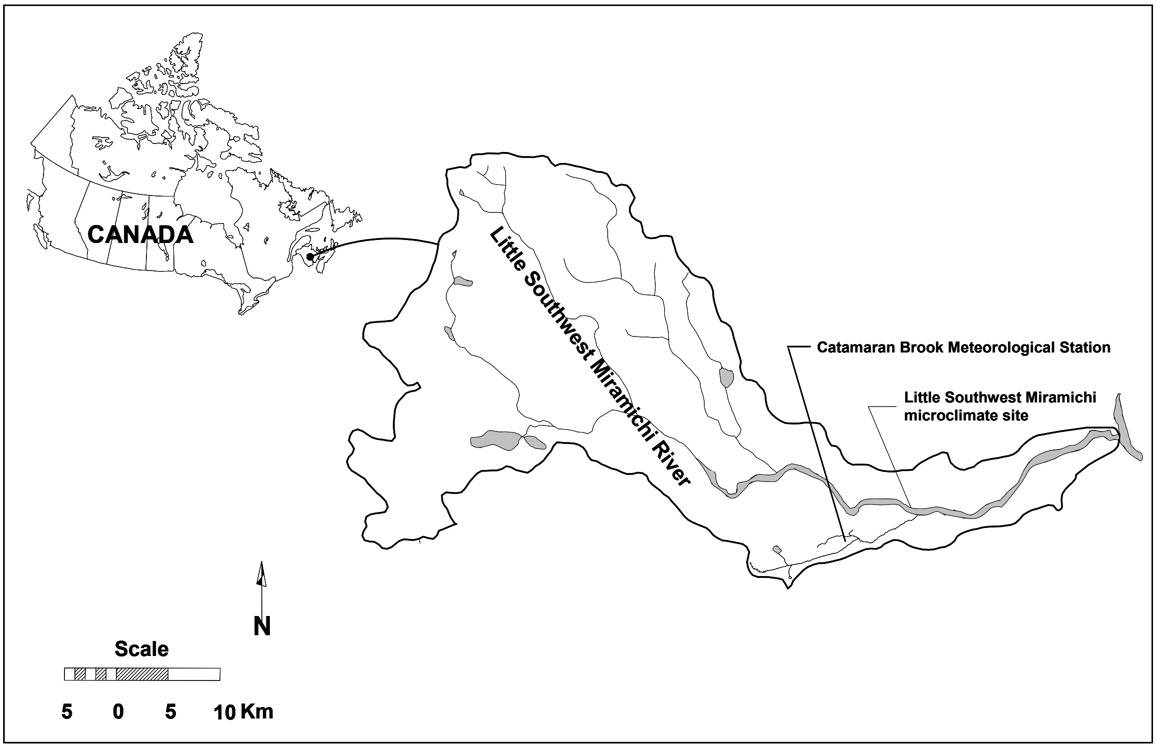


Figure 1. Map showing the location of the water temperature site and the meteorological station

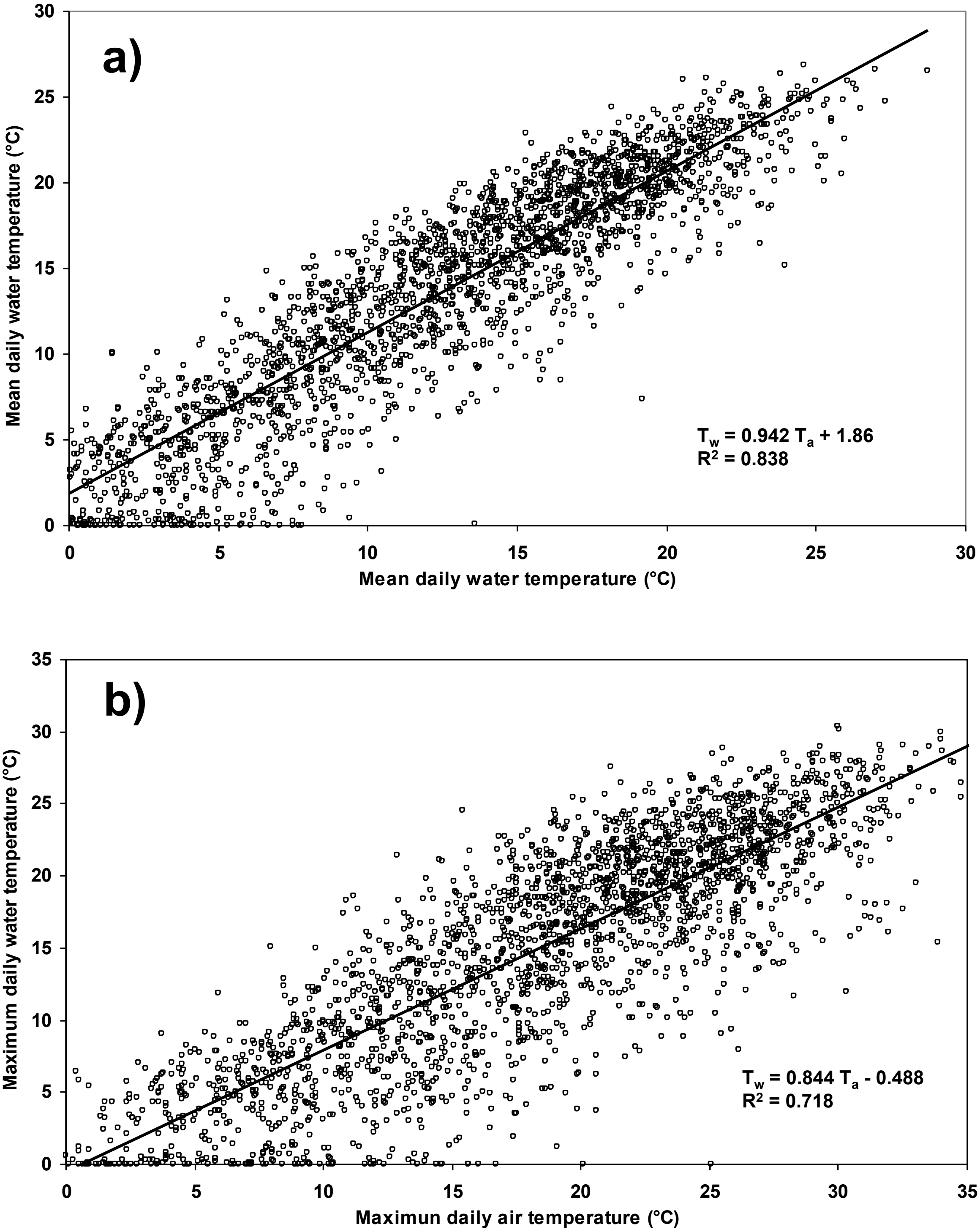
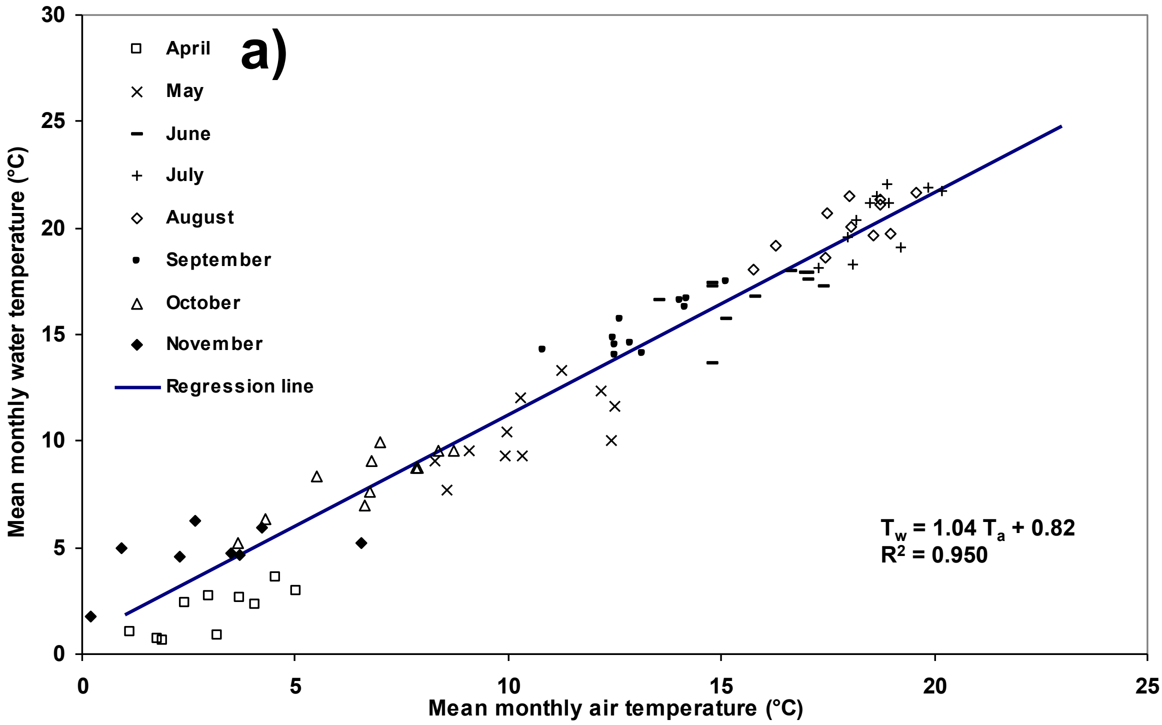


Figure 2. Relationship between a) mean daily air temperature and mean daily water temperature and b) maximum daily air temperature and maximum daily water temperature for Little Southwest Miramichi River.



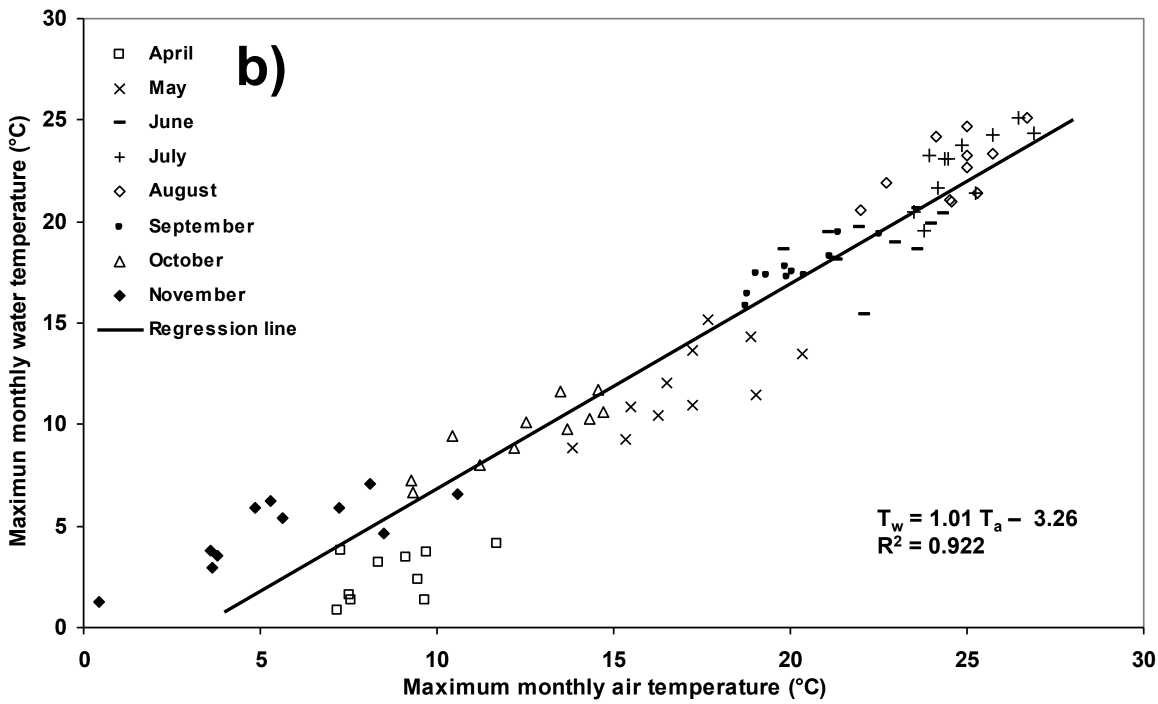


Figure 3. Relationship between a) mean monthly air temperature and mean monthly water temperature and b) maximum monthly air temperature and maximum monthly water temperature for Little Southwest Miramichi River.

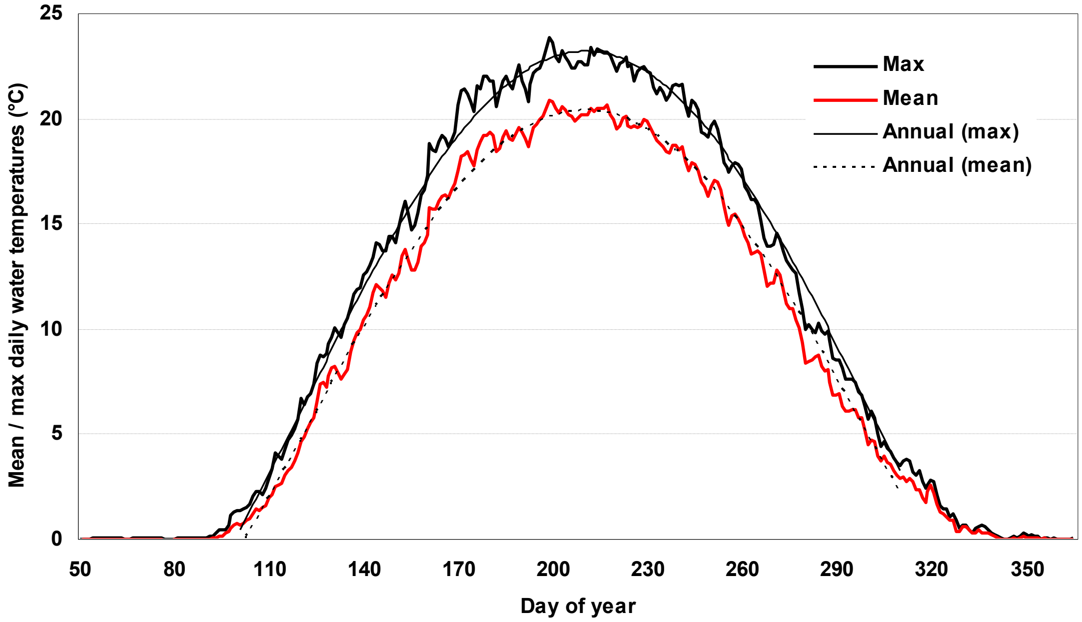
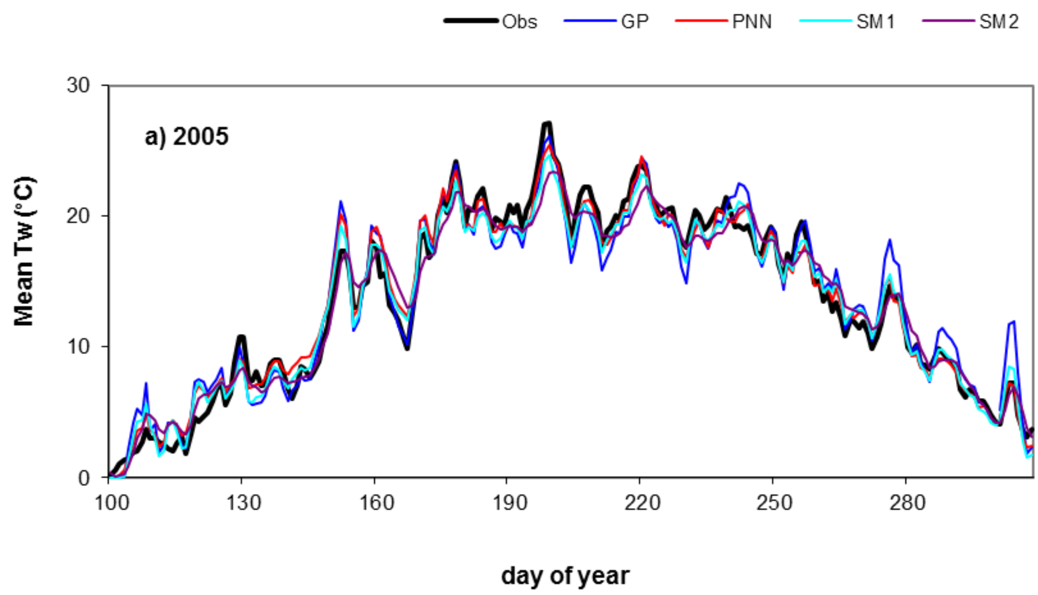


Figure 4. Annual component for both the mean water temperature and maximum water temperatures for Little Southwest Miramichi River.



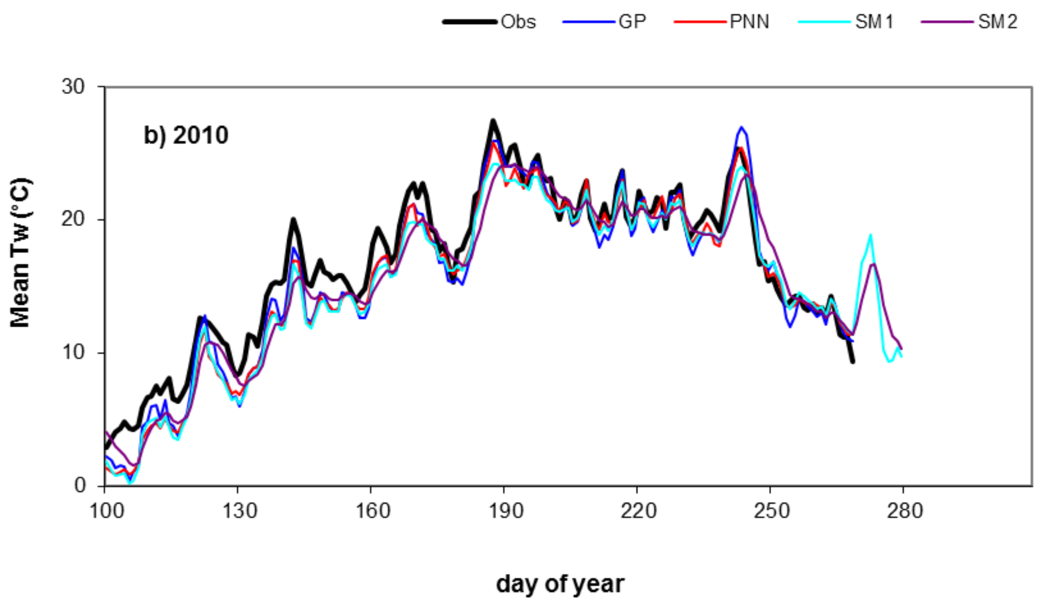
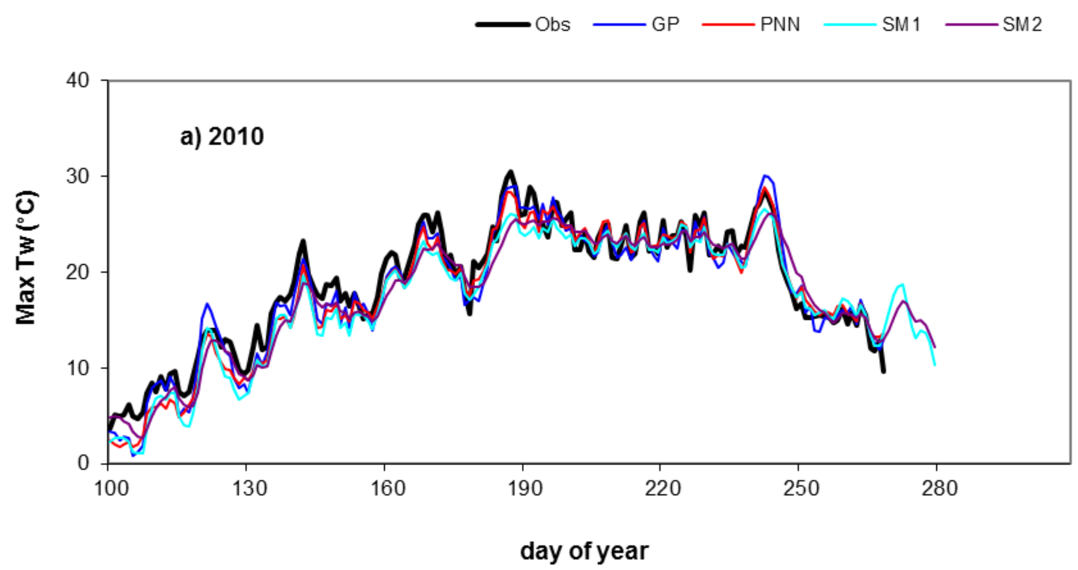


Figure 5 – Observed and modeled mean water temperature values for

a) year 2005 b) year 2010



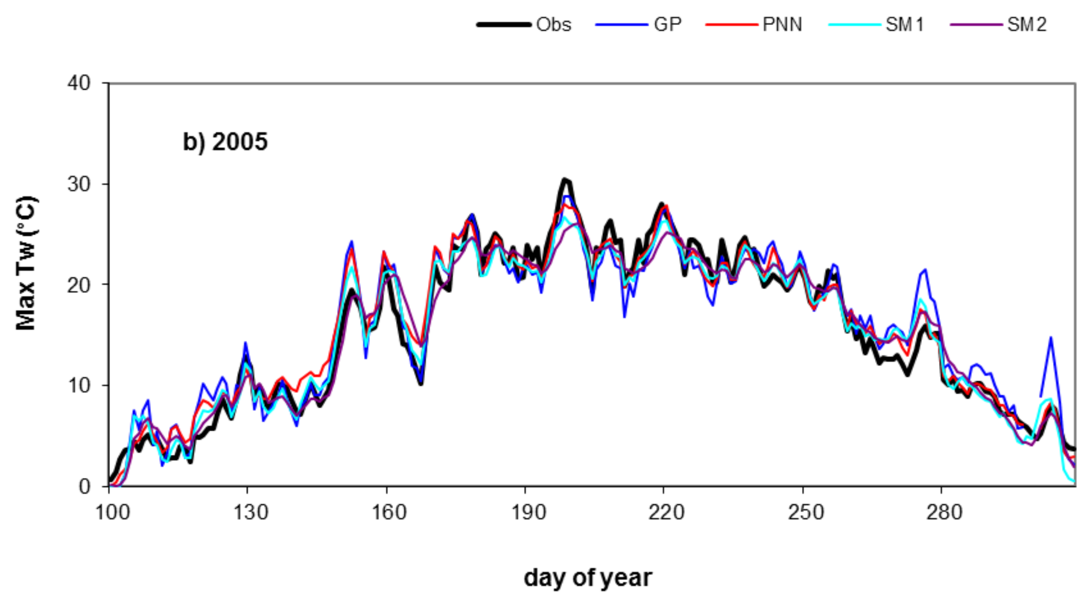


Figure 6 – Observed and modeled maximum water temperature values for

a) year 2005 b) year 2010

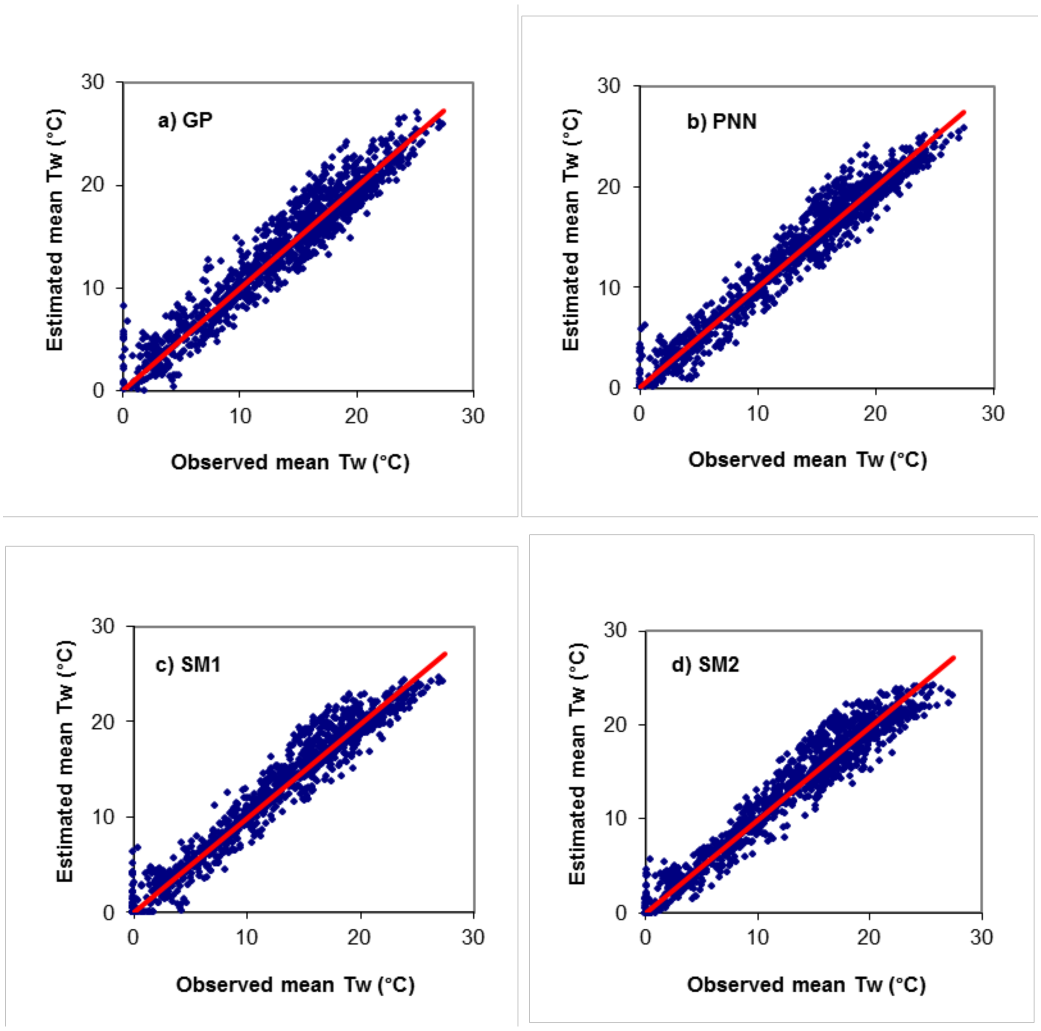


Figure 7 – Comparison between observed and estimated mean water temperature for the test set (2005-2010) using a) GP b) PNN c) SM1 (MutipleR) d) SM2 (Markov)

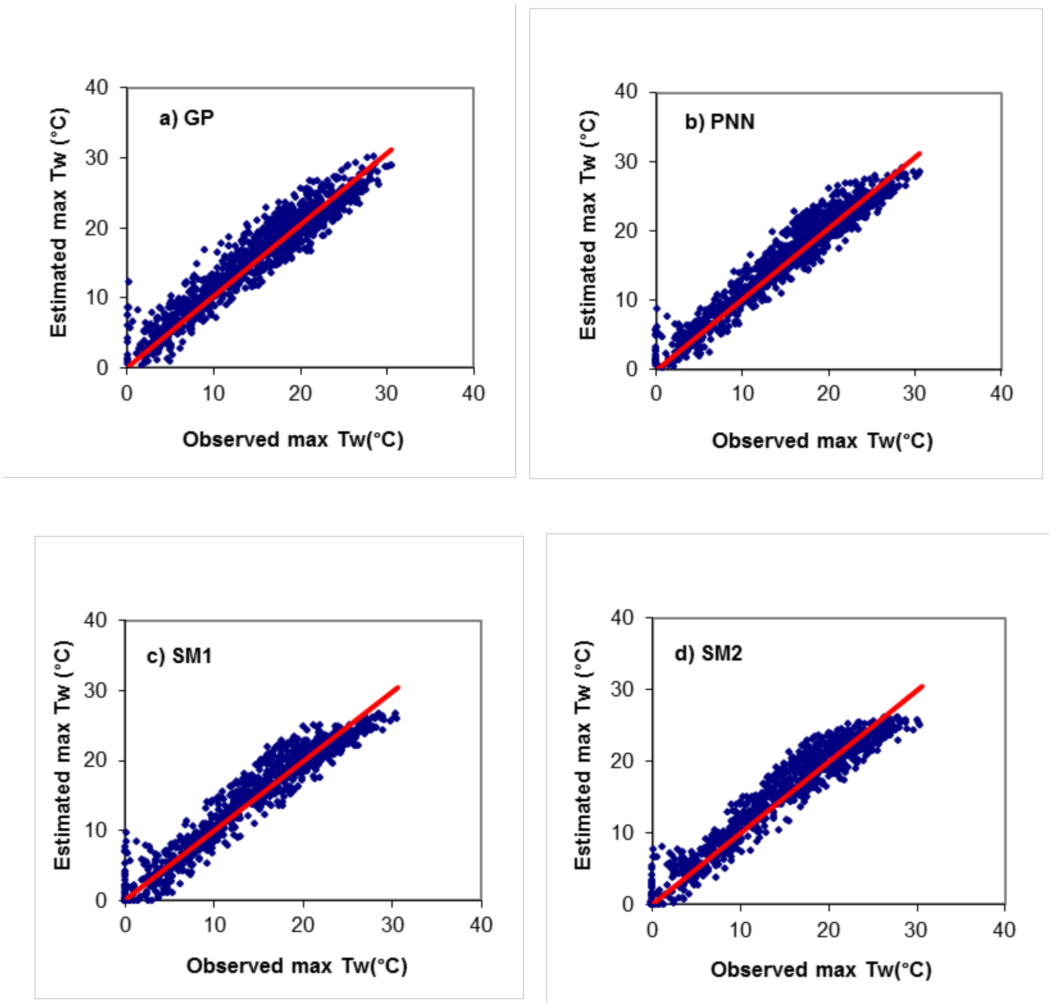
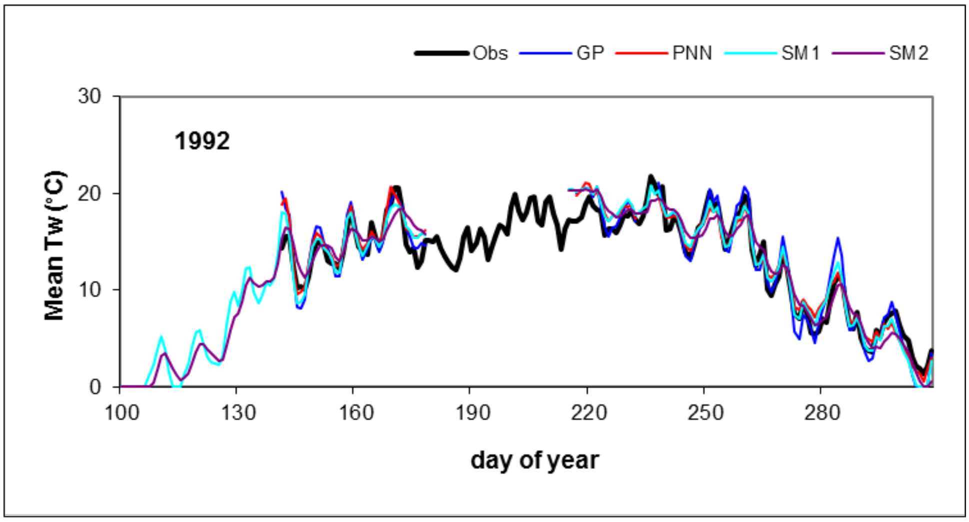
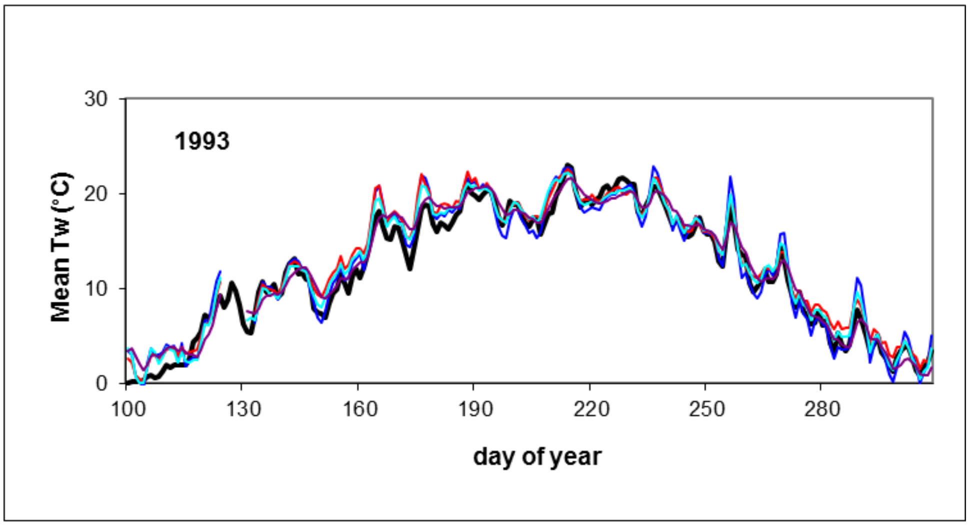


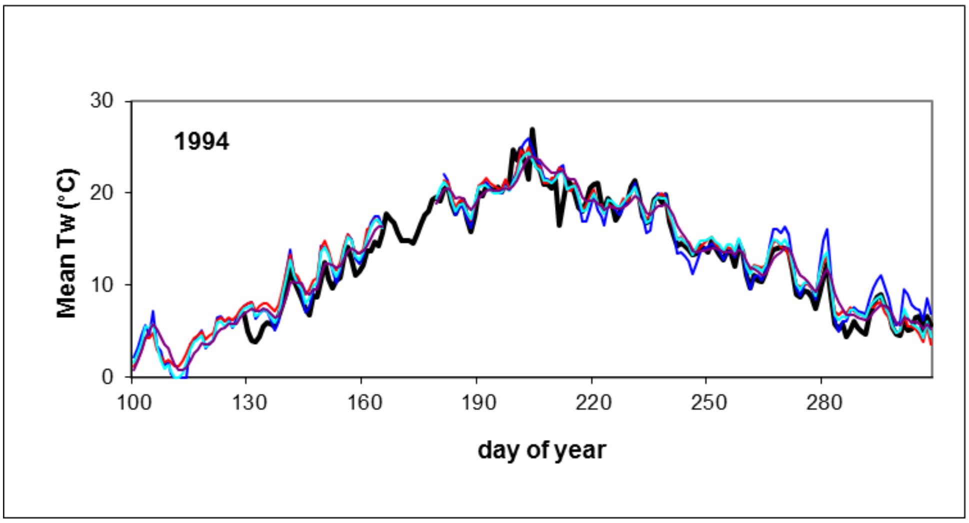
Figure 8 – Comparison between observed and estimated maximum water temperature for the test set (2005-2010) using a) GP b) PNN c) SM1 (MultipleR) d) SM2 (Markov)

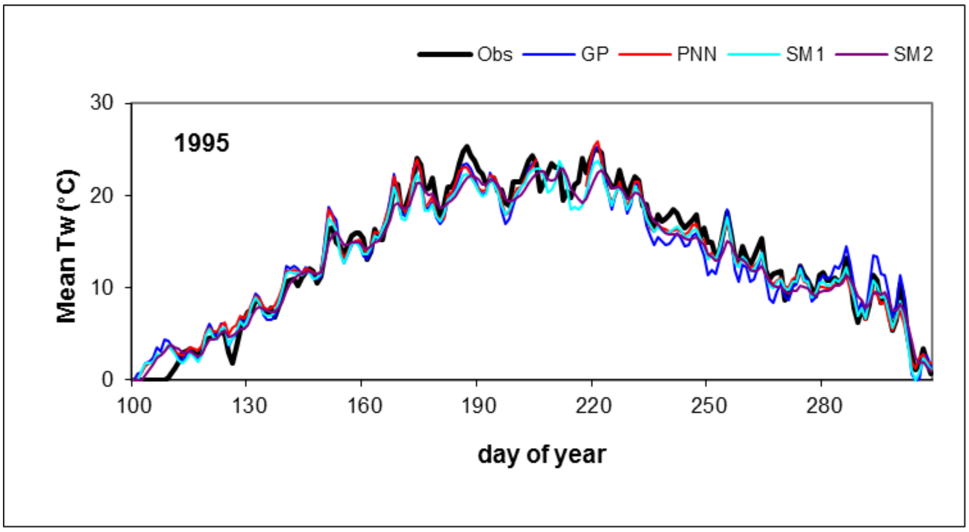
APPENDIX

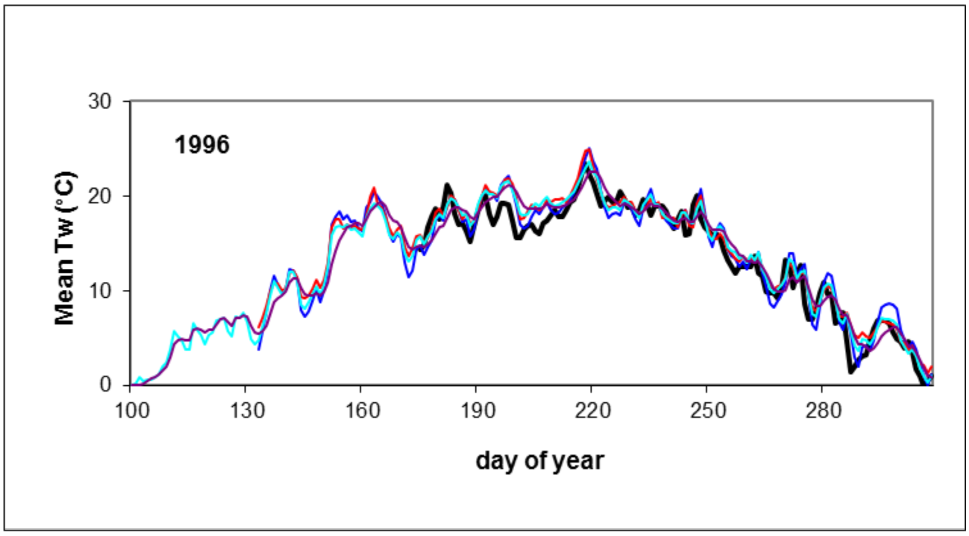
Mean and maximum water temperatures (1992-2010)

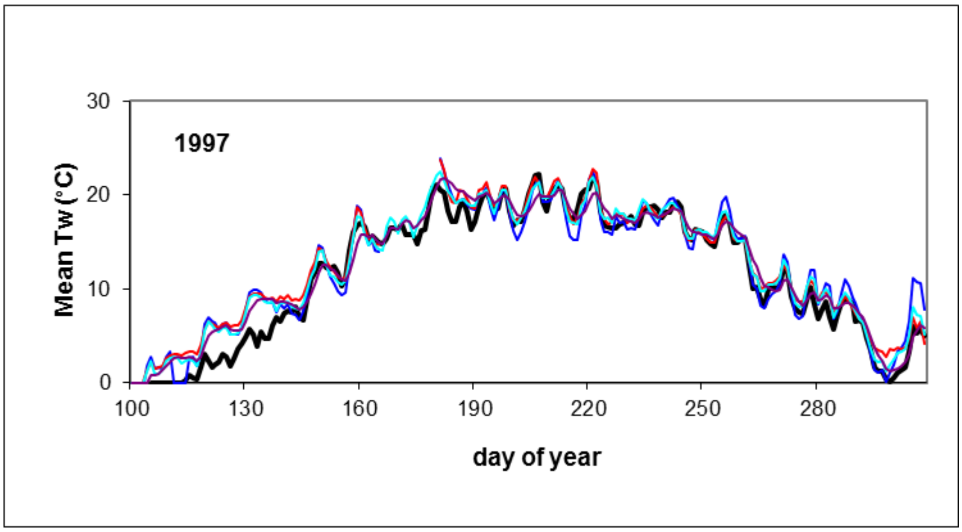

Obs
GP
PNN
SM1
SM2
1992
Mean Tw (°C)
30
20
10
0
100
130
160
190
220
250
280
day of year

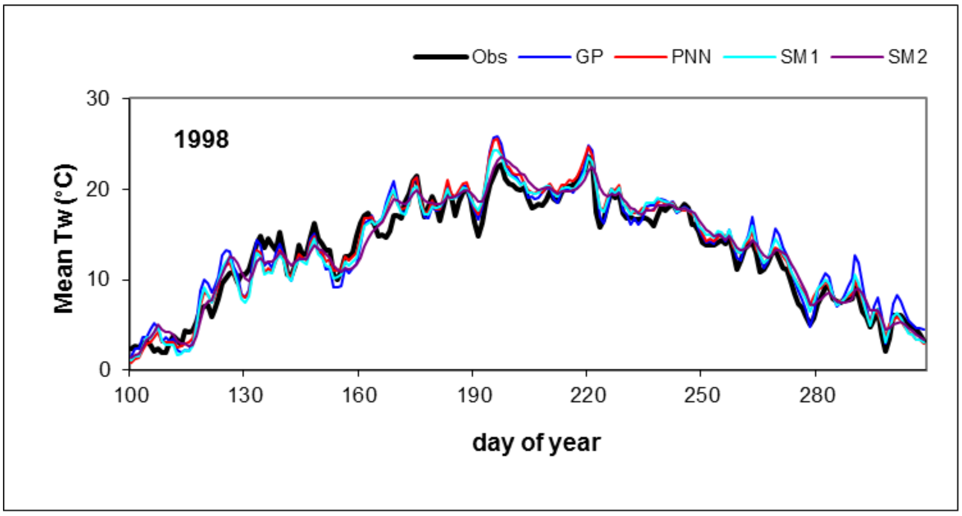

1993
Mean Tw (°C)
30
20
10
0
100
130
160
190
220
250
280
day of year

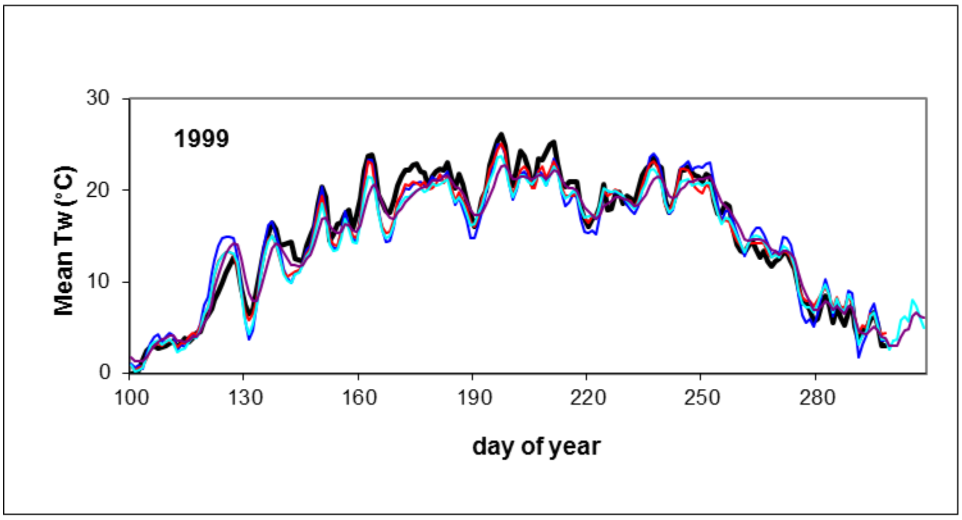

1994
Mean Tw (°C)
30
20
10
0
100
130
160
190
220
250
280
day of year

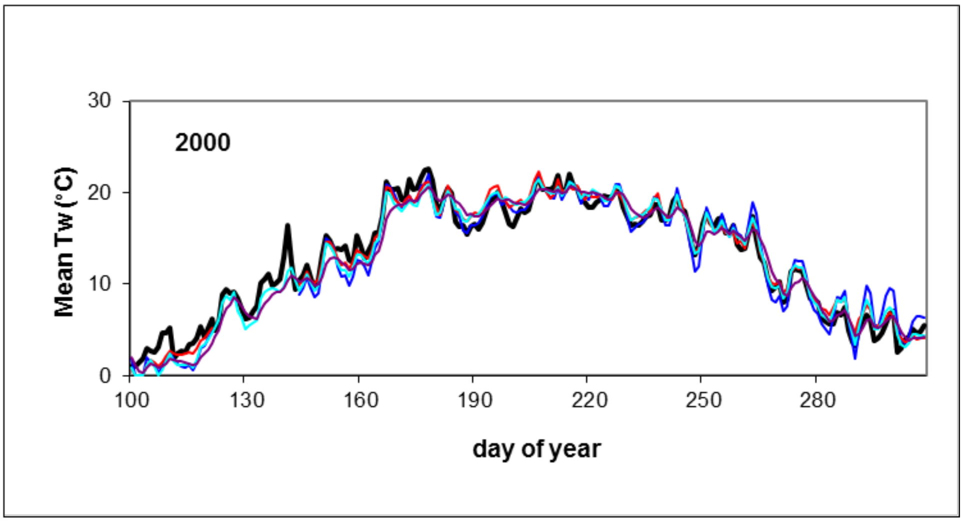

Obs
GP
PNN
SM1
SM2
1995
Mean Tw (°C)
day of year

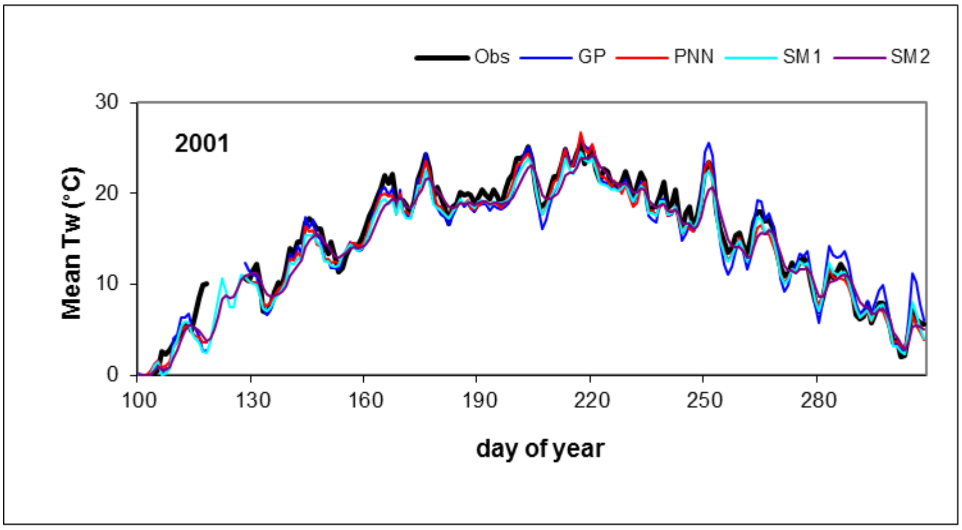

1996
Mean Tw (°C)
day of year


1997
Mean Tw (°C)
day of year

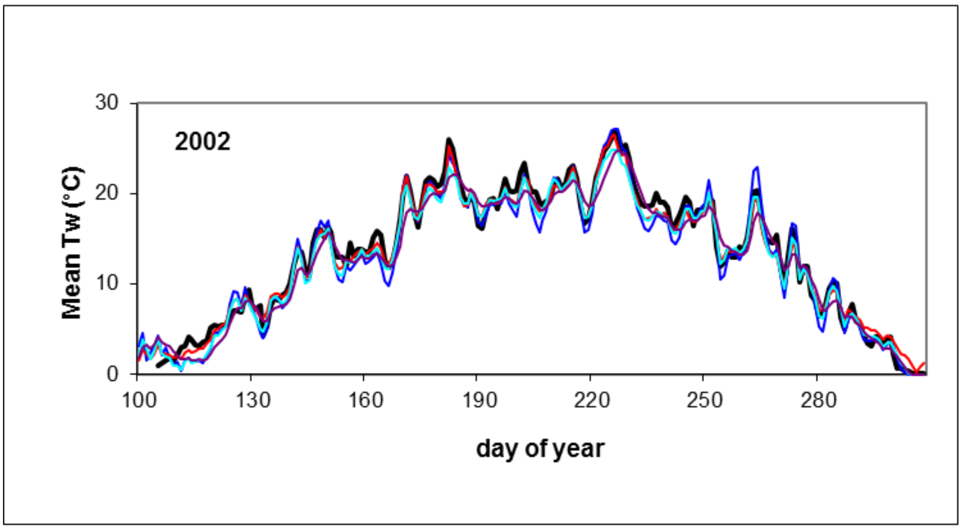

Obs
GP
PNN
SM1
SM2
1998
Mean Tw (°C)
day of year


1999
Mean Tw (°C)
day of year

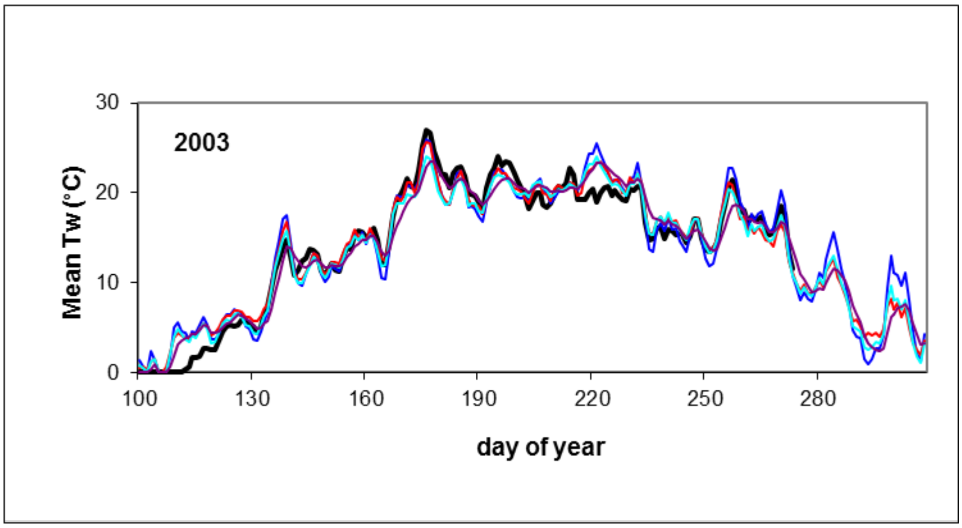

2000
Mean Tw (°C)
day of year



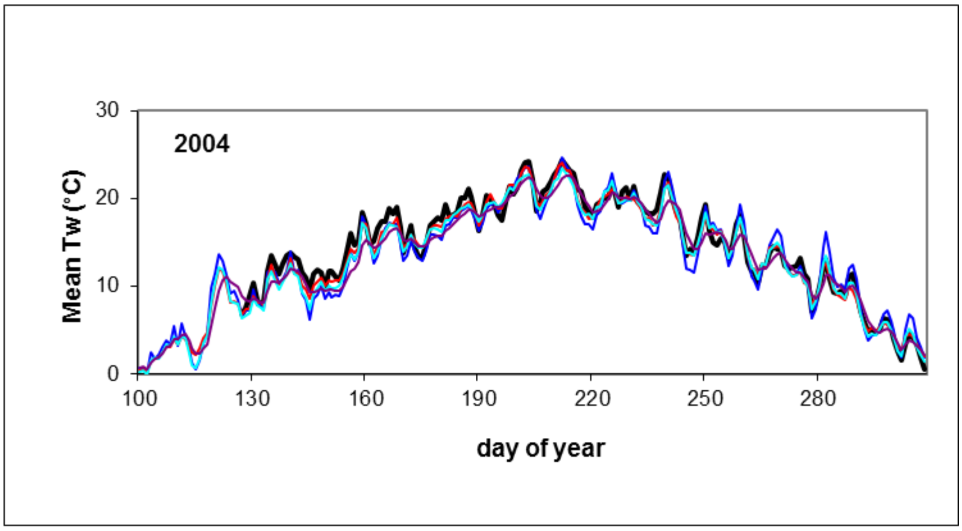
Obs
GP
PNN
SM1
SM2
2001
Mean Tw (°C)
day of year



2002
Mean Tw (°C)
day of year



2003
Mean Tw (°C)
day of year


30
20
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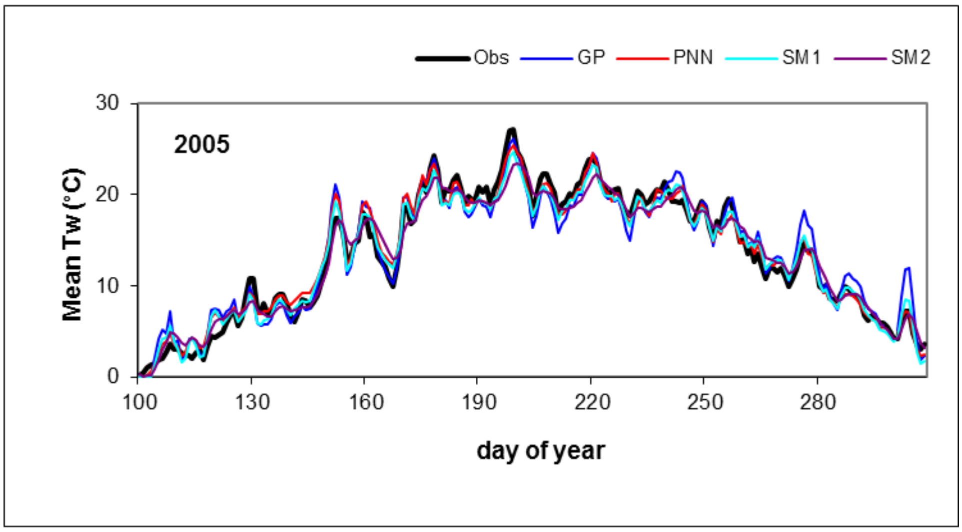
2004
Mean Tw (°C)
100
130
160
190
220
250
280
day of year


Obs
GP
PNN
SM1
SM2
30
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0
2005
Mean Tw (°C)
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190
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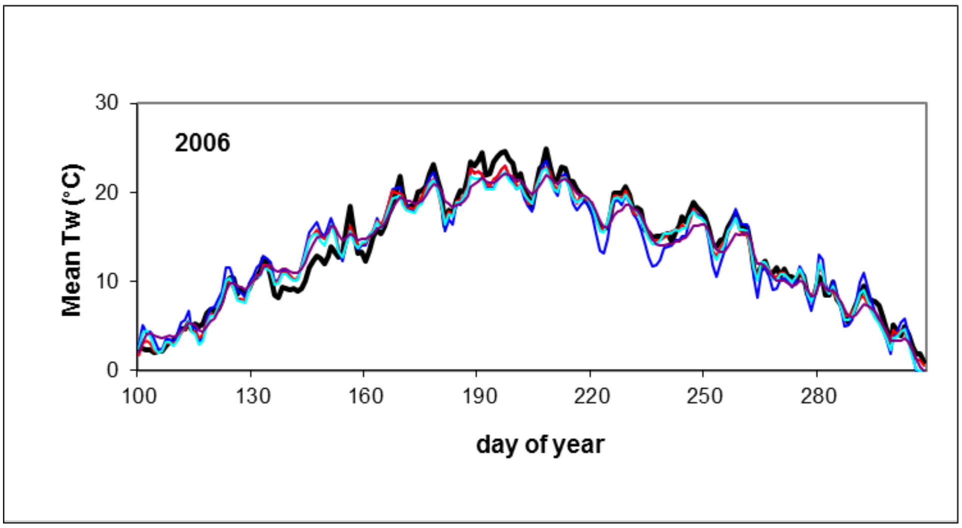
250
280
day of year


30
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2006
Mean Tw (°C)
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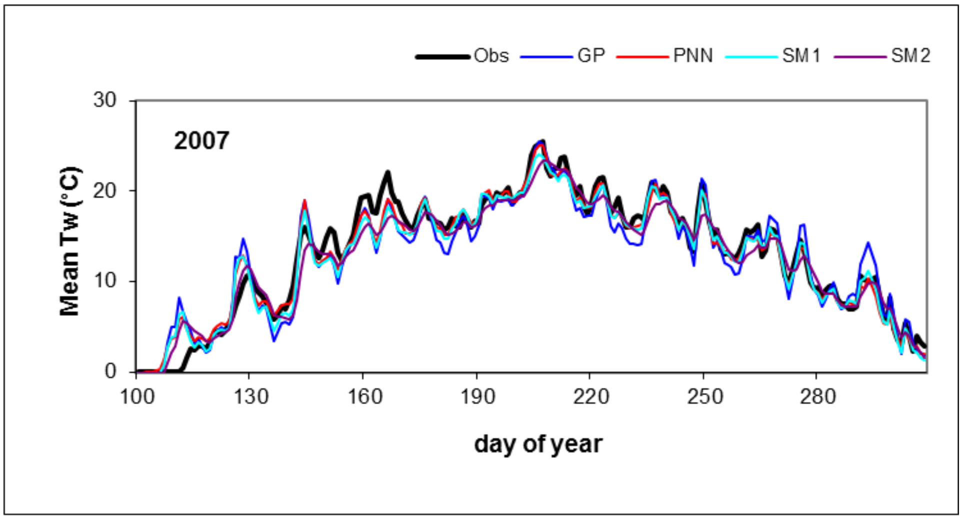
160
190
220
250
280
day of year


Obs
GP
PNN
SM1
SM2
2007
Mean Tw (°C)
30
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10
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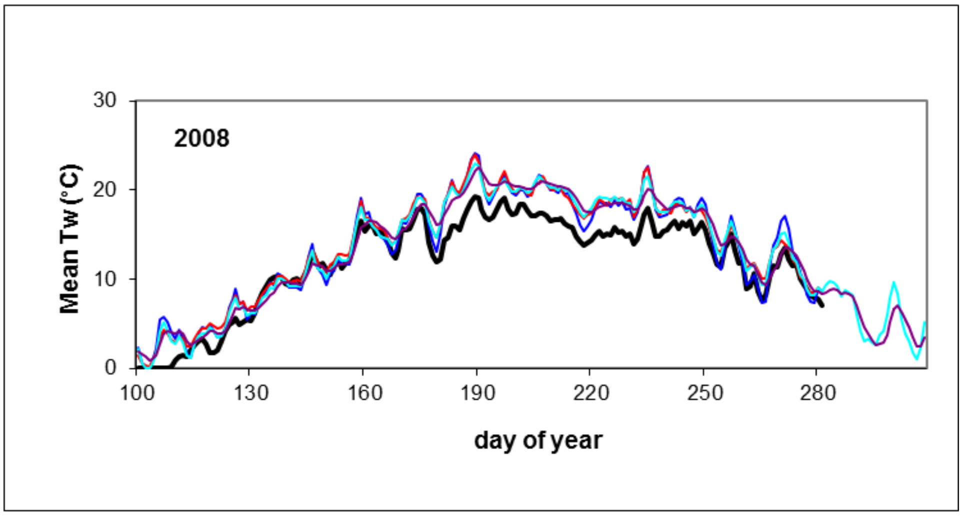
100
130
160
190
220
250
280
day of year


2008
Mean Tw (°C)
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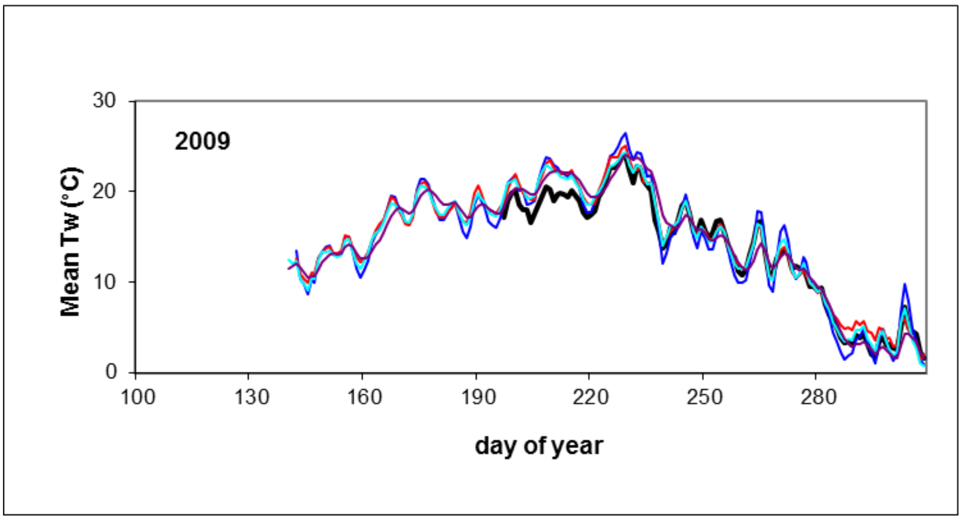
250
280
day of year


2009
Mean Tw (°C)
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190
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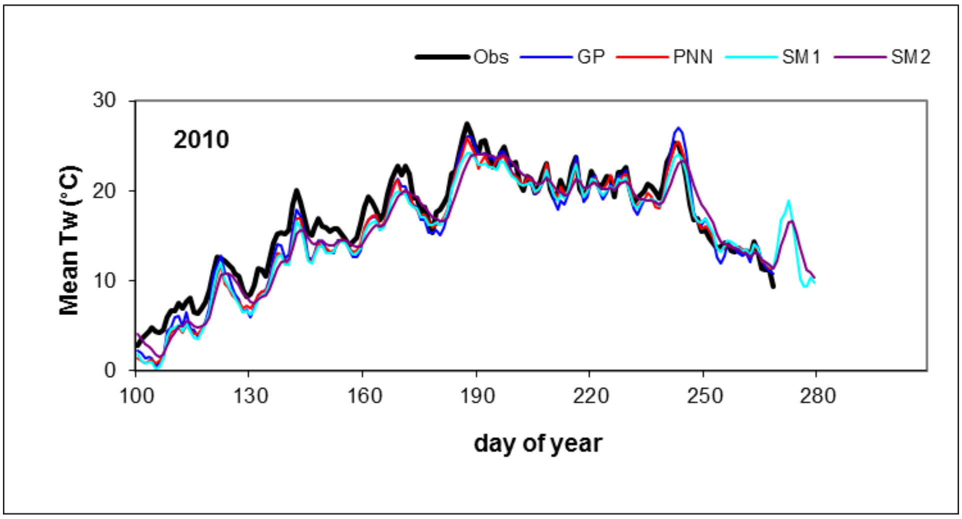
250
280
day of year


Obs
GP
PNN
SM1
SM2
2010
Mean Tw (°C)
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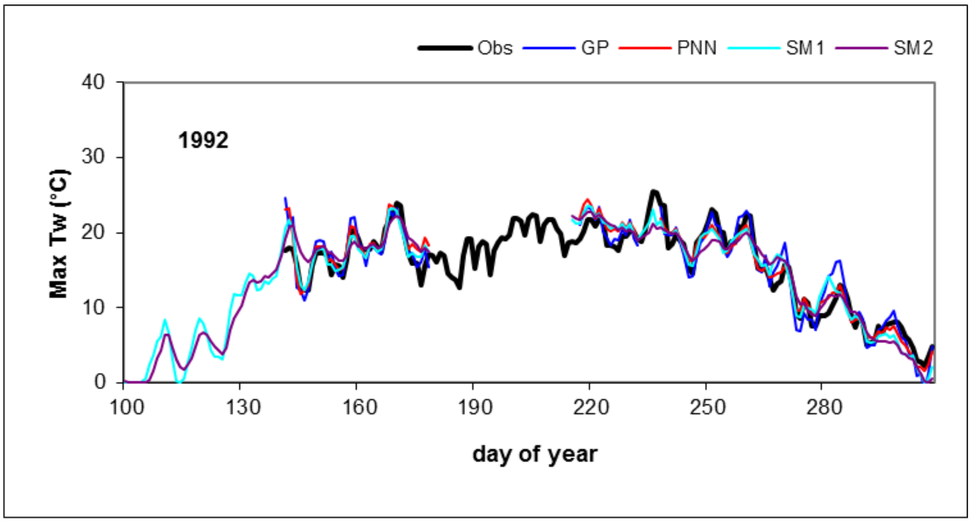
day of year


Obs
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SM1
SM2
1992
Max Tw (°C)
day of year
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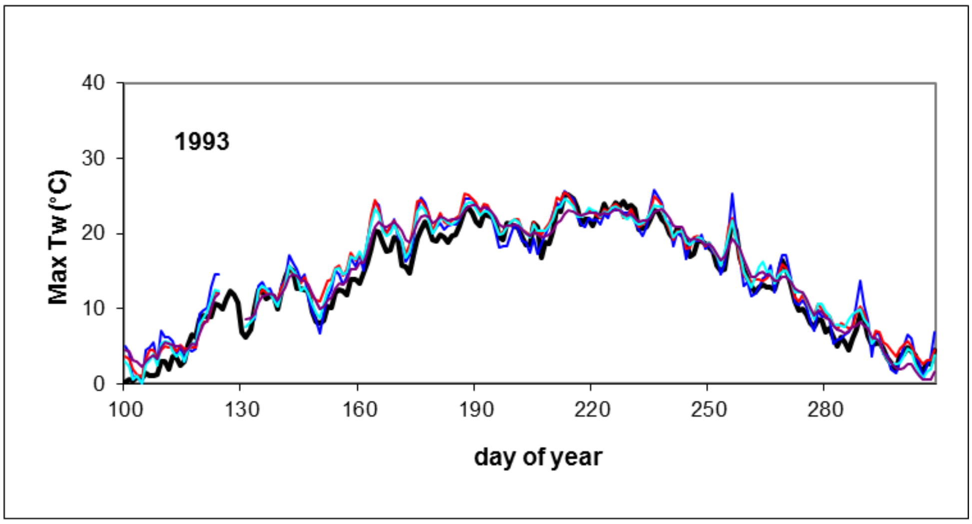
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Max Tw (°C)
day of year
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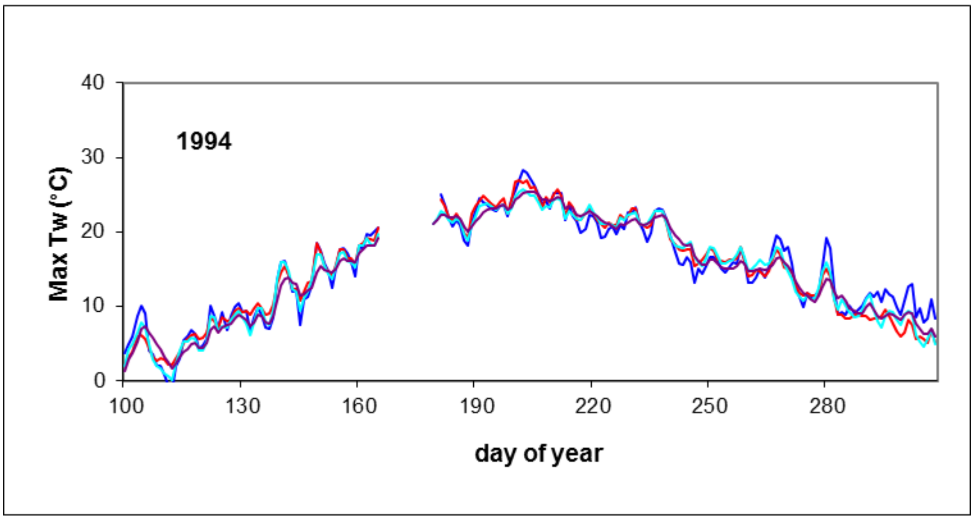
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Max Tw (°C)
day of year
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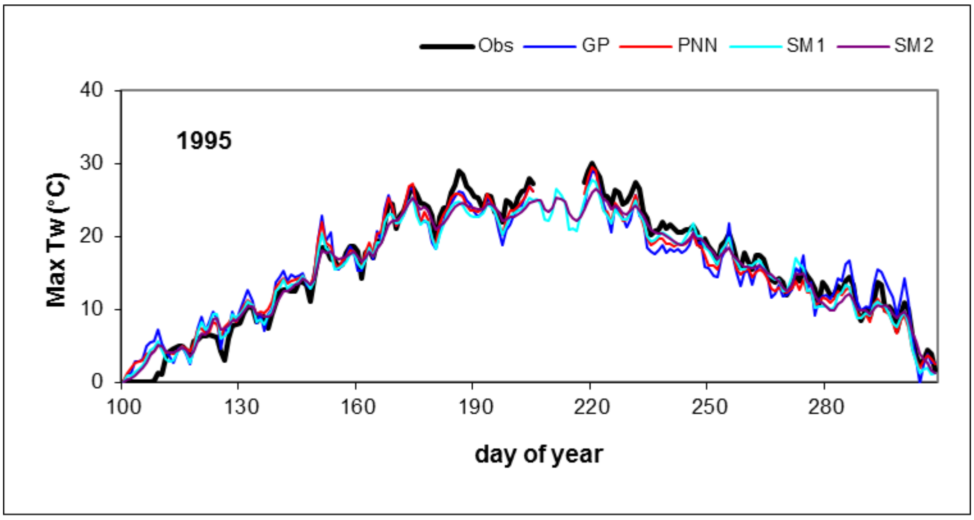
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SM2
1995
Max Tw (°C)
day of year
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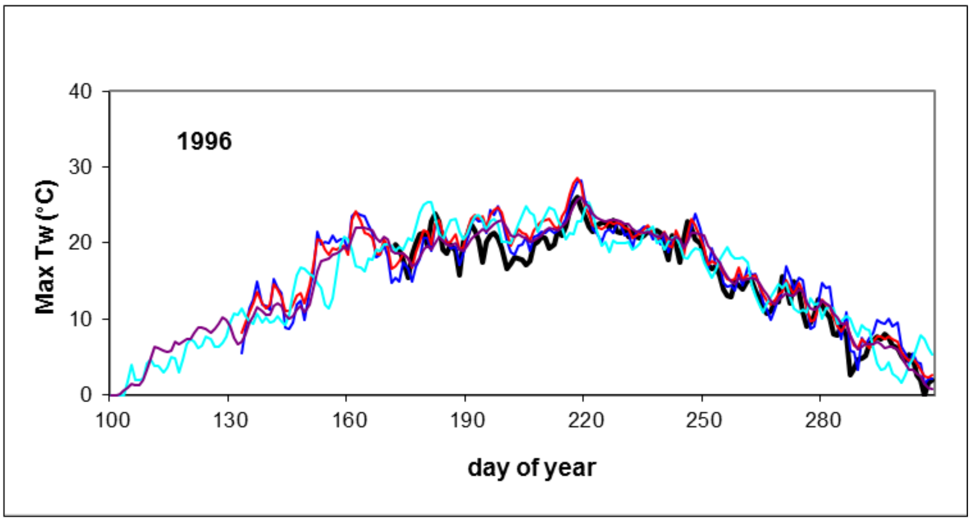
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Max Tw (°C)
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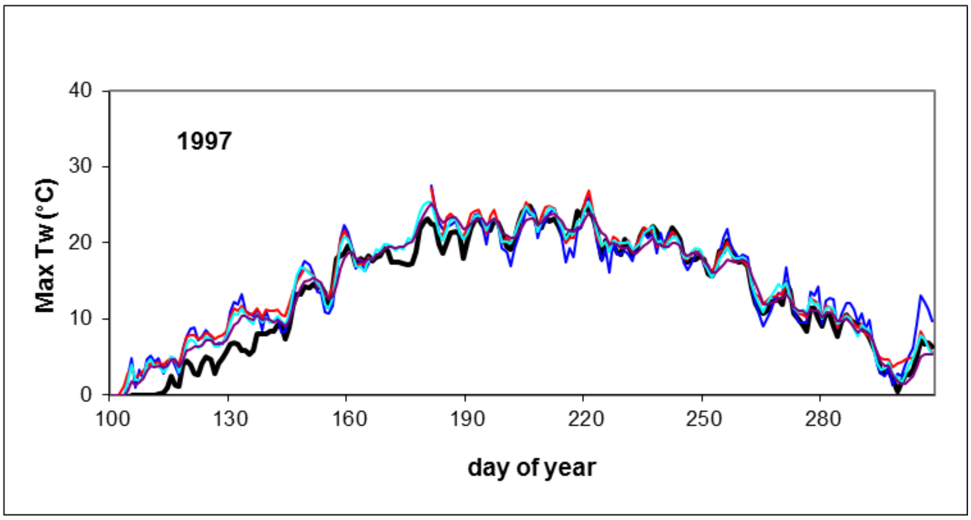
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Max Tw (°C)
day of year
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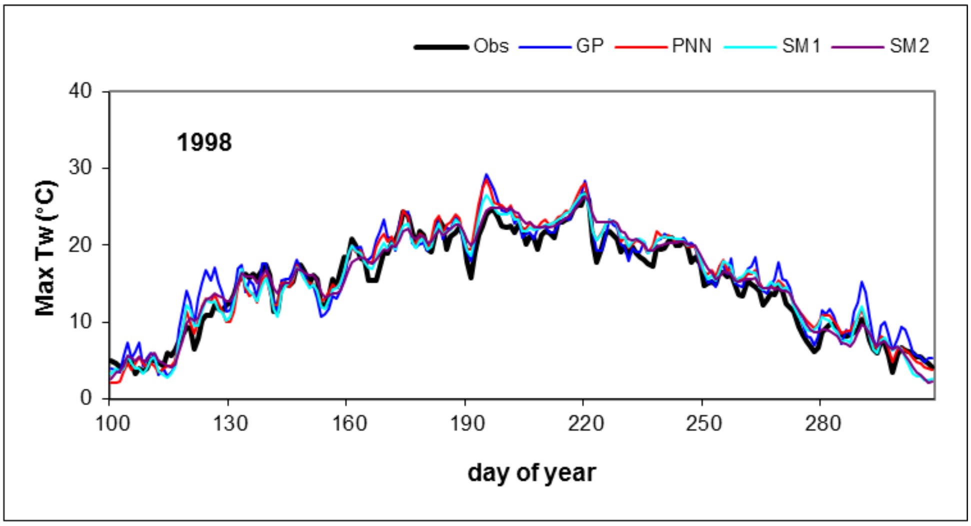
Obs
GP
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SM1
SM2
1998
Max Tw (°C)
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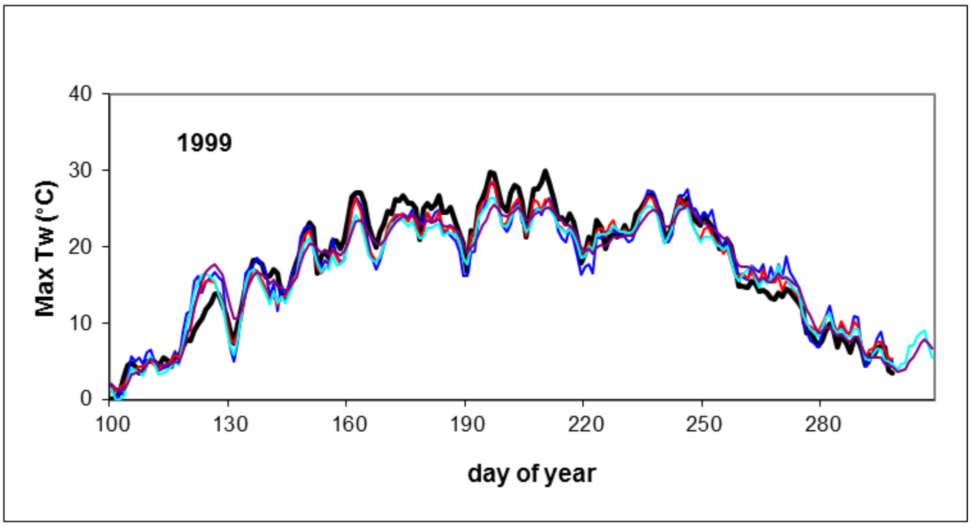
day of year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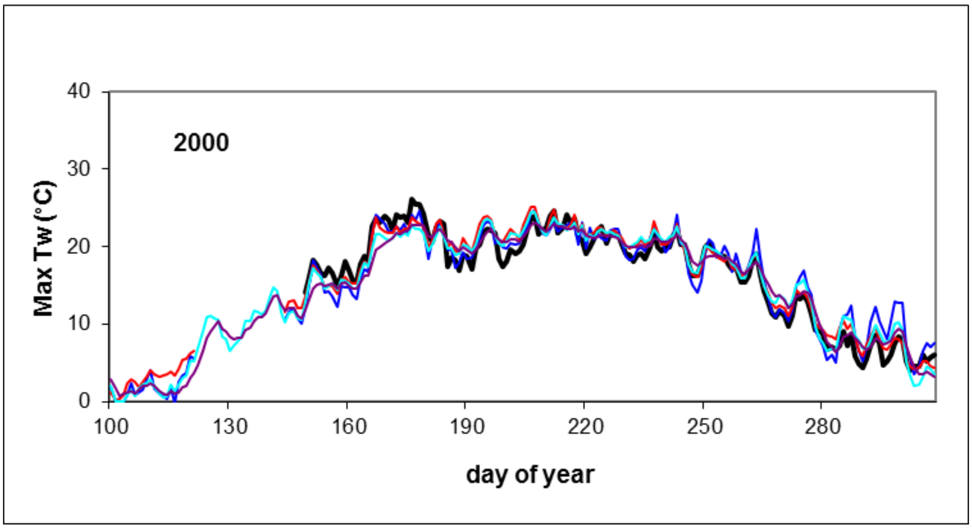
day of year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Max Tw (°C)
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190
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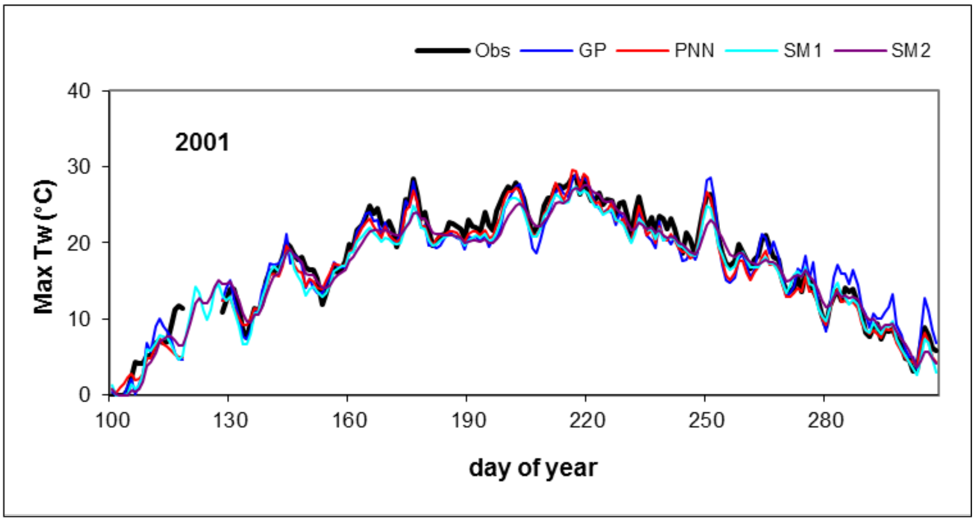
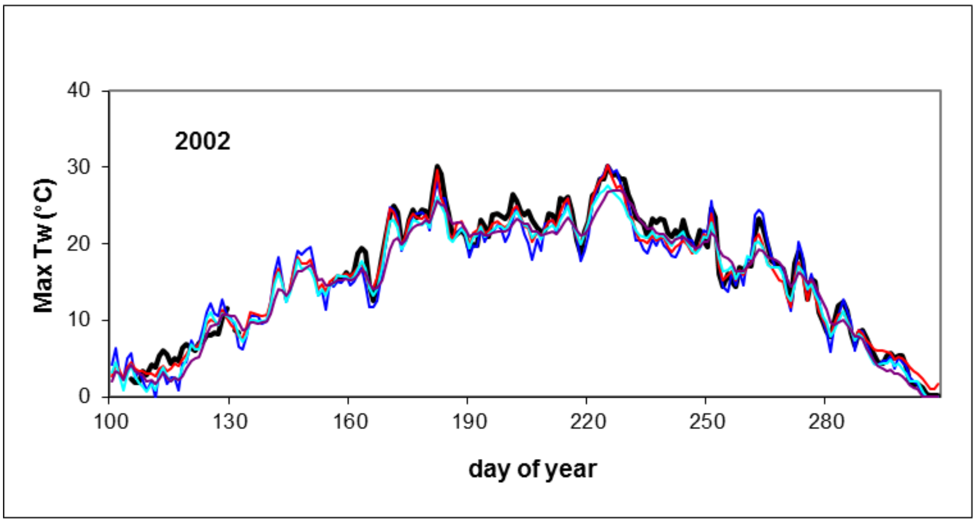
250
280
day of year


Obs
GP
PNN
SM1
SM2
2001
Max Tw (°C)
day of year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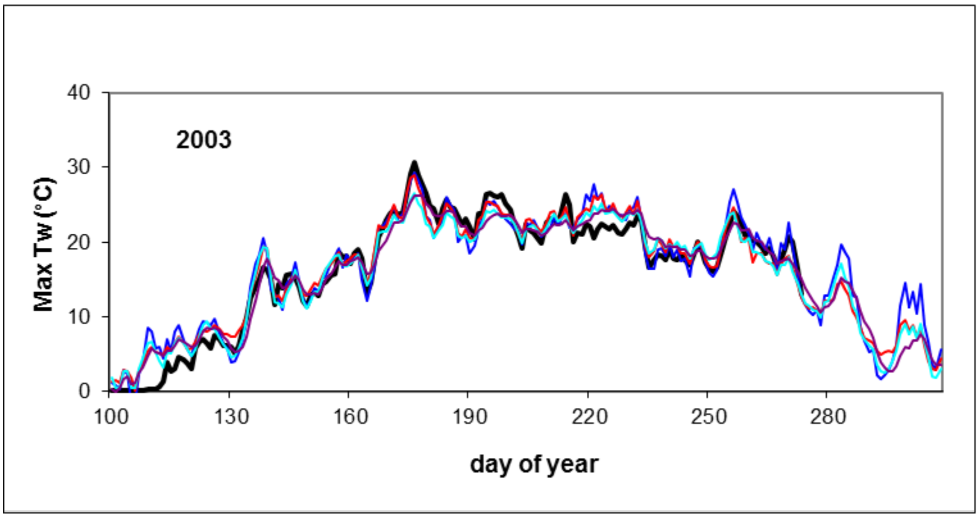
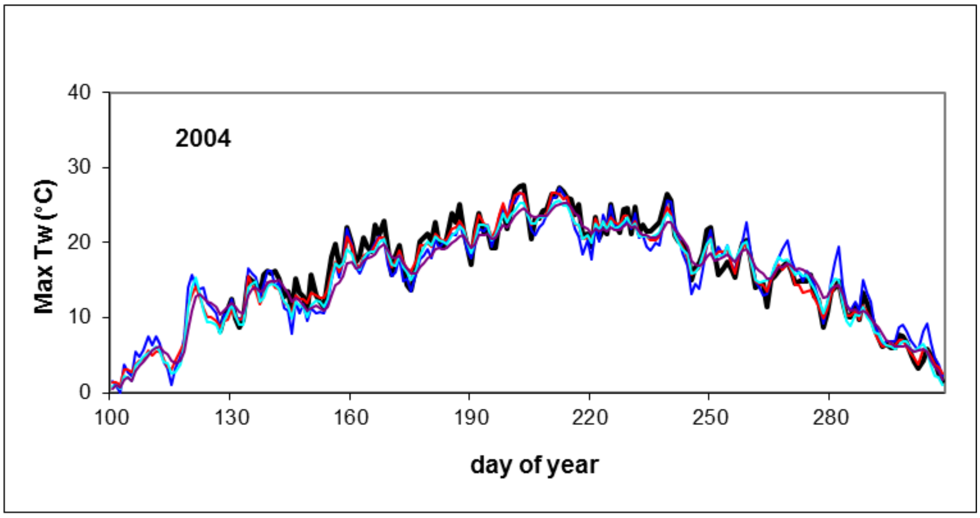
Max Tw (°C)
day of year


2003
Max Tw (°C)
day of year


40
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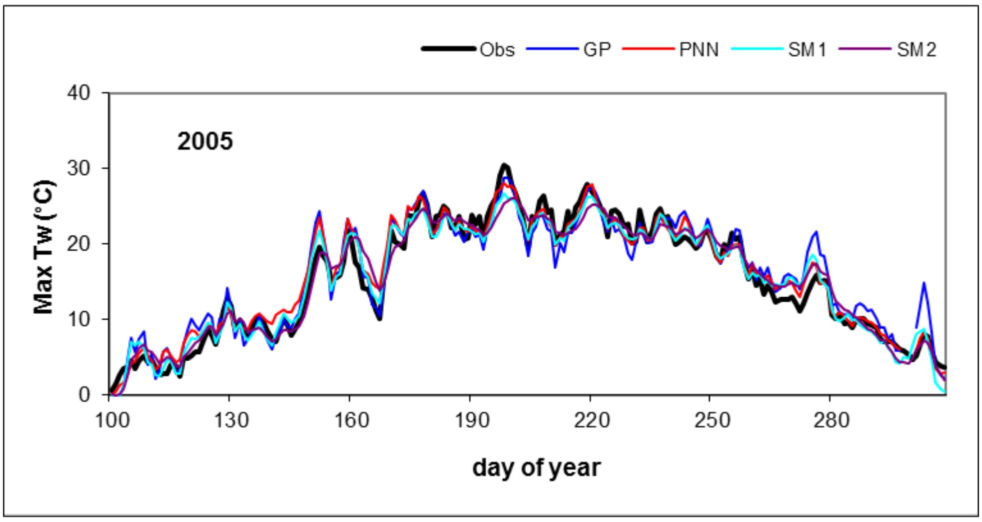
0
2004
Max Tw (°C)
100
130
160
190
220
250
280
day of year


Obs
GP
PNN
SM1
SM2
40
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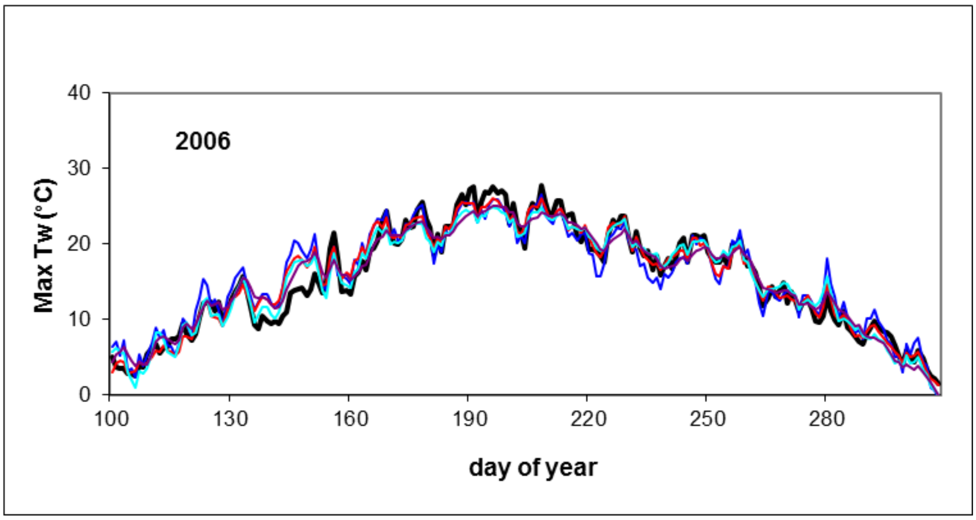
2005
Max Tw (°C)
100
130
160
190
220
250
280
day of year


40
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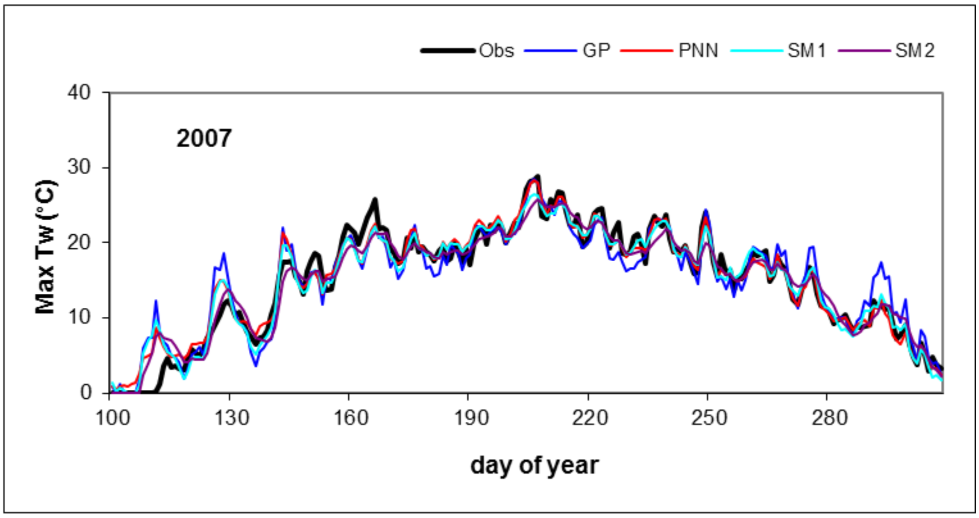
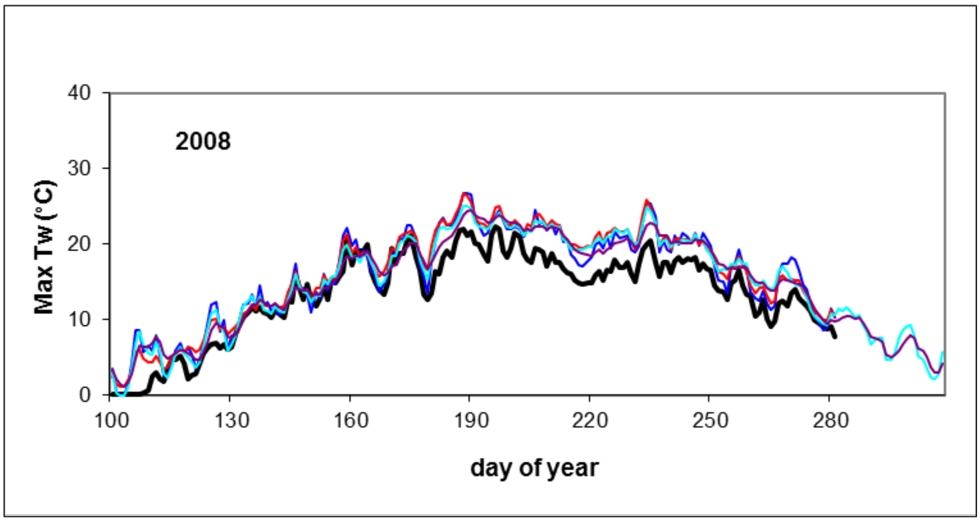
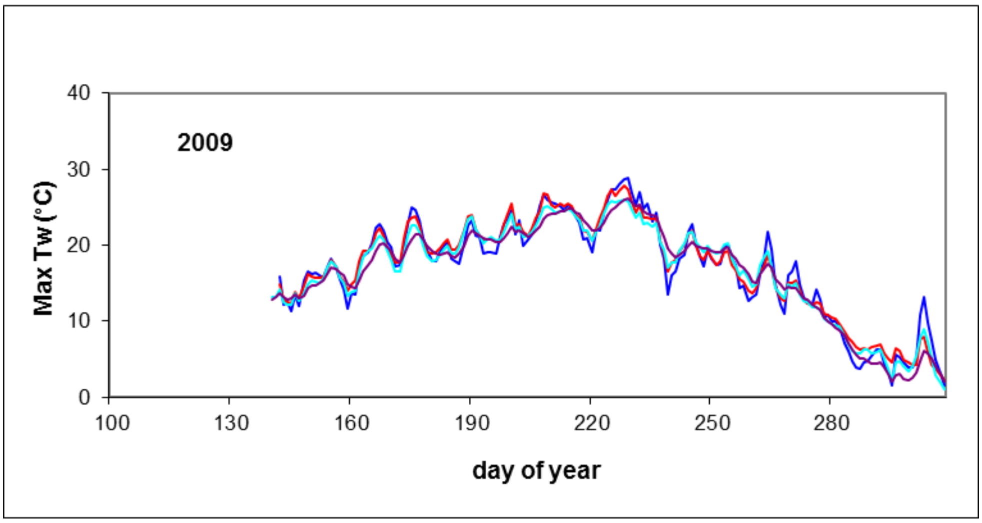
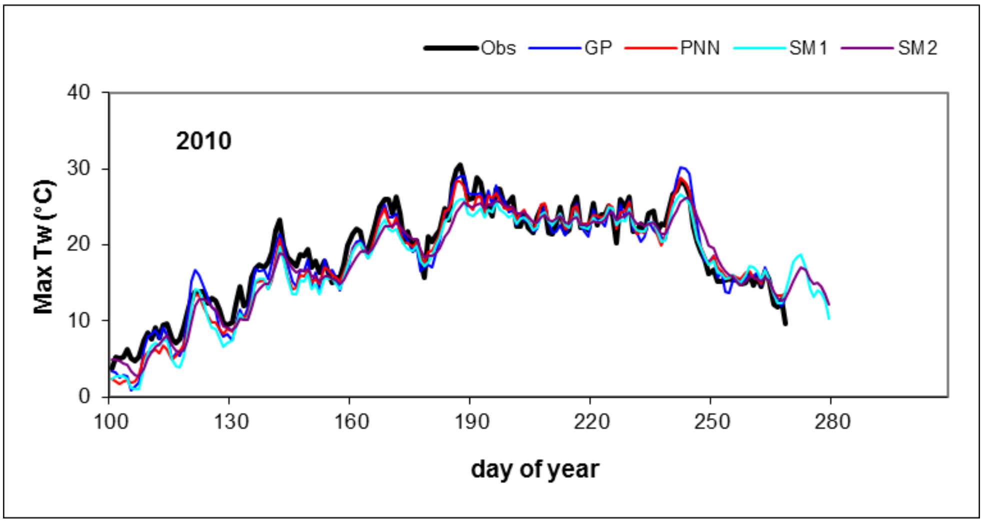
2006
Max Tw (°C)
100
130
160
190
220
250
280
day of year


Obs
GP
PNN
SM1
SM2
2007
Max Tw (°C)
40
30
20
10
0
100
130
160
190
220
250
280
day of year


2008
Max Tw (°C)
40
30
20
10
0
100
130
160
190
220
250
280
day of year


2009
Max Tw (°C)
40
30
20
10
0
100
130
160
190
220
250
280
day of year


Obs
GP
PNN
SM1
SM2
2010
Max Tw (°C)
40
30
20
10
0
100
130
160
190
220
250
280
day of year