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Stream temperature modelling using artificial neural networks: application on Catamaran Brook, New Brunswick, Canada†

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Abstract:

Fish habitat and aquatic life in rivers are highly dependent on water temperature. Therefore, it is important to understand andto be able to predict river water temperatures using models. Such models can increase our knowledge of river thermal regimes as well as provide tools for environmental impact assessments. In this study, artificial neural networks (ANNs) will be used to develop models for predicting both the mean and maximum daily water temperature. The study was conducted within Catamaran Brook, a small drainage basin tributary to the Miramichi River (New Brunswick, Canada). In total, eight ANN models were investigated using a variety of input parameters. Of these models, four predicted mean daily water temperature and four predicted maximum daily water temperature. The best model for mean daily temperature had eight input parameters: minimum, maximum and mean air temperatures of the current day and those of the preceding day, the day of year and the water level. This model had an overall root-mean-square error (RMSE) of 0·96 °C, a bias of 0·26 °C and a coefficient of determination $R^2 = 0{\cdot}971$. The model that best predicted maximum daily water temperature was similar to the first model but excluded mean daily air temperature. Good results were obtained for maximum water temperatures with an overall RMSE of 1·18 °C, a bias of 0·15 °C and $R^2 = 0{\cdot}961$. The results of ANN models were similar to and/or better than those observed from the literature. The advantages of artificial neural networks models in modelling river water temperature lie in their simplicity of use, their low data requirement and their good performance, as well as their flexibility in allowing many input and output parameters. Copyright © 2008 Crown in the right of Canada and John Wiley & Sons, Ltd.

KEY WORDS artificial neural networks; stream; temperature; modelling

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INTRODUCTION

With ever-increasing environmental concern related to streams and rivers, water temperature has become an important parameter to understand and to model (Caissie, 2006). Physical, chemical and biological processes are all influenced by water temperature (Nemerow, 1985). For instance, many physical characteristics (such as viscosity, vapour pressure, density, and surface tension) are dependent on water temperature. Also, many chemical reactions, as well as the assimilation of organic matter and gas solubility (dissolved oxygen), are influenced by changes in water temperature.

River water temperature is a parameter that influences almost every aspect of aquatic life. Water temperature influences the development and the growth rate of aquatic organisms (Elliot and Hurley, 1997). At high water temperatures, the metabolic rate of salmonids increases and, as a result, their energy reserves decline rapidly, which increases the risk of death among fish (Langford, 1990). Furthermore, temperatures above a lethal threshold (e.g. 24 °C) may cause a thermal shock capable of killing fish after only a few hours of exposure (Bouke *et al.*, 1975). Therefore, a better understanding of the thermal regime of streams and rivers and the ability to predict water temperatures is a great advantage in the management of water and fisheries resources. It is also an essential component of environmental impact studies.

Water temperature variations in streams can be influenced by different factors, which are generally characterized as meteorological and geophysical parameters. The principal meteorological factors include solar radiation, wind speed and air temperature. The water depth, discharge, turbulence, and stream width are important geophysical parameters affecting water temperature variability. Human activity can affect both meteorological and geophysical parameters, which ultimately impacts on water temperature. For example, studies have shown that deforestation near rivers can cause a rise in water temperatures due to reduced shading (Chen *et al.* 1998a,b). Climate change, another consequence of anthropogenic impacts, is projected to impact future water temperature significantly (Mohseni *et al.*, 2003).

There are many approaches to modelling river water temperatures, and these can generally be classified into regression models, stochastic models and deterministic

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models. Regression and stochastic models use classic statistical techniques where water temperature is related to relevant input parameters, such as air temperature. In a deterministic water temperature model, the different energy components are calculated based on meteorological parameters. These energy components are then added up to reflect the total energy transferred to the river, and the total energy is also used to explain the water temperature variability.

Many studies have been conducted on the modelling of water temperatures in streams and rivers. Caissie *et al.* (2001) and Marceau *et al.* (1986) have used stochastic and deterministic models, whereas Mohseni *et al.* (1998) used non-linear regression to predict river water temperature. Deterministic models use a more conceptual modelling approach with cause-and-effect relations between site characteristics, meteorological parameters and river water temperatures (Raphael, 1962; Marcotte and Duong, 1973; Morin and Couillard, 1990). Deterministic models use parameters such as air temperature, relative humidity, solar radiation, and wind velocity in the calculation of energy fluxes. A major disadvantage of deterministic models is the extent of data required to run these models, data that are seldom available near study sites. Therefore, many researchers have relied on stochastic or other models that are based on statistical relationships between fewer input parameters and water temperature. Many of these models require only air temperature and a continuous time-series of water temperature for the model calibration. Artificial neural network (ANN) modelling applications have steadily increased over the years; however, very few applications have addressed the modelling of river water temperatures. ANNs have become an alternative and a complementary tool to conventional modelling. As such, ANN models will be developed and used in the present study to predict both mean and maximum temperatures of a small stream catchment.

ANNs have been used since the early 1990s as a hydrologic modelling tool, particularly in rainfall–runoff, water quantity and quality predictions, as well as in groundwater systems modelling and water resources management (Govindajaru, 2000). The advantage of ANNs is that the user does not need to know the relationship between the input and output parameters, *a priori*. ANNs are also useful in describing complex non-linear relationships even when data time-series have inherent noises or errors (Dreyfus *et al.*, 2002).

Although ANNs have been applied in hydrology during the past few decades, very few water temperature modelling studies are found within the literature where ANNs have been used (Bélanger *et al.* 2005). Also, many statistical water temperature models (e.g. stochastic and/or regression models) used only the mean air temperature to predict mean water temperature. Therefore, the objective of the present study was to develop ANN models using many input parameters (such as the minimum, maximum and mean daily air temperatures) to see whether added parameters could potentially improve the model's performance. The specific objectives are: (1) to develop ANN models to predict the mean daily water temperatures based on air and water temperature (mean, minimum and maximum) and (2) to develop ANN models to predict the maximum daily water temperatures using the same data set as for the mean temperature. In fact, both of these metrics are generally important from an ecological perspective and we could not find any instances where both mean and maximum water temperatures have been considered within the same modelling study. As a practical application, these models were developed, tested and validated using data from Catamaran Brook (New Brunswick, Canada) and using data from 1992 to 2002.

Previous water temperature modelling studies have been carried out in Catamaran Brook (Caissie *et al.*, 1998, 2001, 2005); however, none of these models was well adapted to consider many input parameters (e.g. mean, minimum, and maximum temperatures) within the same model. ANN models have this ability of considering many input parameters; therefore, the present study will extend current knowledge and understanding on how this added information can contribute to potentially better modelling performances.

DATA AND METHODS

Study area

This study was carried out within the Catamaran Brook in central New Brunswick, Canada, which is a tributary of the Little Southwest Miramichi River. Catamaran Brook is located at latitude 46°52·7′N and longitude 66°06·0′W (Figure 1). It is the site of a 15-year multidisciplinary hydrobiological research study aimed at quantifying stream ecosystem processes and the impact of timber harvesting (Cunjak *et al.*, 1990). Catamaran Brook is 20·5 km long, approximately 15 m wide, 0·3 m deep and has a total drainage basin area of approximately 52 km^2. It is one of the Miramichi River's most productive Atlantic salmon streams (Randall, 1981). It is well sheltered by upland slopes and streamside vegetation, mainly consisting of second-growth, mature forest species, estimated as 65% coniferous and 35% deciduous (Cunjak *et al.*, 1990).

A meteorological station situated at mid-basin collects air temperature data used in this study (Figure 1). Mean, minimum and maximum values were calculated from hourly data to carry out the analysis within the present study. July has the highest mean monthly air temperature at 18·8 °C and January has the lowest with a temperature of −11·8 °C (Caissie and El-Jabi, 1995). A hydrometric gauge situated at mid-basin monitors the streamflow in the brook. This station measures hourly water level, from which discharge is then calculated using a rating curve. The high flow period occurs from late April to early May. To date, the highest measured flow at the gauge was 13 $m^3 s^{-1}$ on 3 May 1991 and the lowest measured flow was 0·016 $m^3 s^{-1}$ on 3 September 1994. The mean annual flow was calculated at 0·62 $m^3 s^{-1}$.

A water temperature sensor was also installed at mid-basin and it collects hourly water temperature data

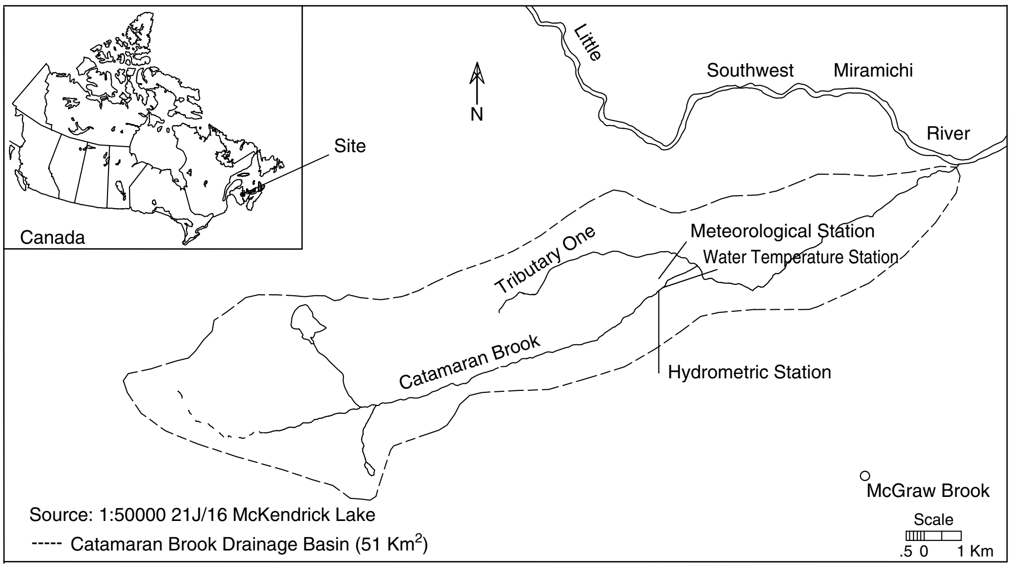

Figure 1. Map of Catamaran Brook showing the location of the water temperature site, hydrometric station and meteorological station

from which mean, minimum and maximum values were obtained. The study was carried out during the ice-free period, which extends from approximately day 100 (10 April) to day 320 (16 November). The maximum temperature recorded for the study period (1992–2002) was 24·3 °C on 17 July 1999. The mean annual water temperature was calculated at 9·8 °C, with July the warmest month at 15·5 °C. The daily summer temperatures follow an annual cycle (warming and cooling periods), which peaked on 30 July (Caissie *et al.*, 2005).

Artificial neural networks

The development of ANNs began in the 1950s with the objective of understanding the functioning of the human brain and emulating some of its functions. Since the early 1990s, the method has developed largely because of powerful new algorithms and computational tools (Govindajaru, 2000).

The basic element used in ANNs is called a neuron or a node. A neuron is a non-linear algebraic function, parameterized with boundary values (Dreyfus *et al.*, 2002). The signal passing through the neuron is modified by weights w and transfer functions f. Groups of neurons are called layers. A neural network generally consists of a finite number of these layers (Figure 2). The first layer, called the input layer, is where the information is fed into the network before it goes through a number of hidden layers and ends up in the output layer. Hidden layers are intermediate layers between input and output layers. Input parameters and output variables are often represented by p_i and y_i respectively. Signals passing through a neuron are modified and then passed to neurons in the adjacent layer (never in the same layer). This process is repeated until the output layer is reached (Govindajaru 2000).

This study used an ANN model called the multilayer perceptron, which is only one of many models (e.g. Hopfield, Hamming, Carpenter, one-layer perceptron, etc.). The multilayer perceptron uses the back propagation of

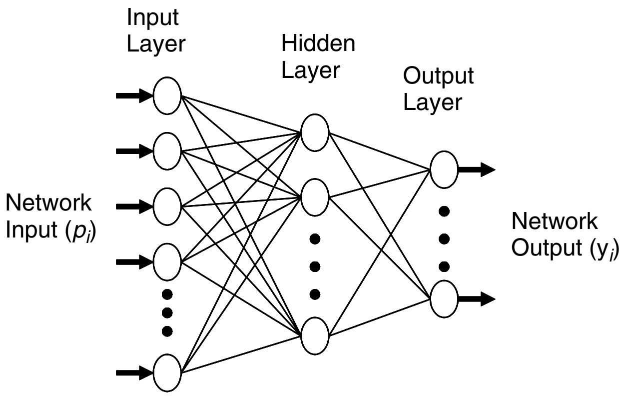

Figure 2. Illustration of ANN structure

the error gradient. This training algorithm is a technique that helps distribute the error in order to arrive at a best fit or minimum error, i.e. a network that best represents observed versus predicted outputs. After the information has gone through the network in a forward direction and the network has predicted an output, an error is associated with this output in relation to observed data. The back-propagation algorithm redistributes the errors back through the model, and weights are adjusted accordingly. Several iterations are carried out until the error is minimized.

Each neuron from a layer is linked to every neuron from the next layer. These links are given a synaptic weight that represents its connection strength (Govindajaru, 2000). A summation is then calculated following Equation (1) before going through another function f, called the activation function, to obtain the output:

$$n = w_{1,1}p_1 + w_{1,2}p_2 + \ldots + w_{1,i}p_i + b \qquad (1)$$

The activation function is a function that transforms the signal and is usually a sigmoid function represented

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by

$$f(n) = \frac{1}{1 + e^{-\beta n}} \tag{2}$$

The sigmoid function is often used in hydrology as it and its derivative are relatively simple and it accurately represents non-linear relations (Govindaraju, 2000).

In hydrologic studies, ANN models generally consist of generating an output given a specific input time-series. The learning phase, or training, is the process whereby the network estimates the synaptic weights (Dreyfus *et al.*, 2002). There are two types of training: supervised and unsupervised (Dreyfus *et al.*, 2002). The supervised training needs input and output parameters, unlike the non-supervised training which needs only input parameters to run. The present study used the supervised training method. The ANN model is established through the training process and while being trained the model's performance is tested with different and independent data (i.e. the testing data set). The testing data set consists of generally 10–20% of the data set, selected randomly or sequentially. Although data from the testing are independent of those from the training, the testing helps the training process of ANNs. As such, if the network performs well on the testing data, then the ANN model is expected to perform well on any other data. During the testing, the model is evaluated to make sure that the model is not overtraining. The testing is a validation that is done simultaneously with the training process. Once the network has been trained, another independent set of data is sent through the ANN model as a true validation phase. This is carried out to see how well the ANN model is able to predict the underlying phenomenon using an independent data set that was not part of the training process. If the ANN produces similar results in the training, testing and validation phases, i.e. similar coefficients of determination R^2, then it can be used as a modelling tool. The present study used the software NNMODEL 32 (version 1·2 2·0 Copyright 1994–1998 Neural Fusion Shareware) to develop an ANN model to predict water temperatures.

River water temperature models

In total, eight models were developed in this study: four models predicting the mean water temperature (MEAN1 to MEAN4) and four predicting the maximum water temperature (MAX1 to MAX4; Table I). Predictions were made at the daily time step for both mean and maximum water temperatures. The input parameters for these models are combinations of the following parameters: day of the year, the minimum, maximum and mean air temperatures of the present day, the minimum, maximum and mean air temperatures of the previous day, and the water level. The mean air temperature and the mean water temperature at Catamaran Brook were calculated based on data taken each hour over a 24 h period.

These specific parameters were selected because they were more readily available than complete weather station data (including solar radiation, wind speed, etc.) and because previous studies had shown their importance in non-deterministic water temperature models (Cluis, 1972; Song and Chen, 1977; Stefan and Preud'homme, 1993; Mohseni and Stefan, 1999; Bélanger *et al.*, 2005). The air temperature of the previous day was used in all models, because air and water temperature are strongly correlated and they both show some level of autocorrelation (Kothandaraman, 1971; Cluis, 1972).

Table I. Different ANN models developed to predict mean and maximum river water temperatures at Catamaran Brook

Model	Input parameters[a]
Mean daily water temperature	
MEAN1	1–8 (day, min., max., mean, level)
MEAN2	1, 4, 7, 8 (day, mean, level)
MEAN3	1, 3, 4, 6, 7, 8 (day, max., mean, level)
MEAN4	1, 2, 3, 5, 6, 8 (day, min., max., level)
Maximum daily water temperature	
MAX1	1–8 (day, min., max., mean, level)
MAX2	1, 3, 6, 8 (day, max., level)
MAX3	1, 3, 4, 6, 7, 8 (day, max., mean, level)
MAX4	1, 2, 3, 5, 6, 8 (day, min., max., level)

[a] (1) Day of year (e.g. 1 April = 91); (2) minimum air temperature of the present day (°C); (3) maximum air temperature of the present day; (4) mean air temperature of the present day; (5) minimum air temperature of the previous day; (6) maximum air temperature of the previous day; (7) mean air temperature of the previous day; (8) water level (m).

Data from days 100 to 320 (10 April to 16 November) were used for each year of the study. This corresponds approximately to the period of the year when there is no ice in the brook. Missing data were present in 1992 from day 100 to day 127 (10 April to 7 May) and day 218 to day 224 (6–12 August). Therefore, periods of missing data in 1992 were not modelled. The first 7 years of data (1992 to 1998) were used for model training and testing. Data from 1992 to 1996 were used for the training itself, whereas a sequential data set (1997 and 1998) was used for testing. The testing is considered a validation step while the ANN model is being trained. The remaining 4 years (1999 to 2002) were used for model validation.

For the training period, the parameters of the ANN (i.e. maximum number of iterations, maximum number of hidden neurons and learning rate) were selected to minimize the error between the predicted and observed water temperatures. This was carried out by selecting different parameters until the best results were obtained without overtraining the ANN model.

Modelling performance criteria

To determine the performance of each model, three criteria were used: the RMSE, the bias and the coefficient of determination R^2.

The RMSE represents the error associated with the model and can be calculated using

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(P_i - O_i)^2}{N}} \tag{3}$$

Table II. Results of ANN models for the prediction of mean water temperatures at Catamaran Brook

Model	Input parameters[a]	Period	Bias	RMSE[b]	R^2
MEAN1	1–8	Training (1992–1996)	0·47	0·96	0·974
		Testing (1997–1998)	0·69	1·17	0·965
		Validation (1999–2002)	−0·20	0·84	0·981
		All years (1992–2002)	0·26	0·96	0·971
MEAN2	1, 4, 7, 8	Training	0·51	1·01	0·972
		Testing	0·70	1·27	0·957
		Validation	−0·20	0·87	0·979
		All years	0·28	1·01	0·967
MEAN3	1, 3, 4, 6, 7, 8	Training	0·57	1·03	0·973
		Testing	0·80	1·27	0·961
		Validation	−0·11	0·82	0·981
		All years	0·36	1·01	0·970
MEAN4	1, 2, 3, 5, 6, 8	Training	0·60	1·05	0·972
		Testing	0·81	1·30	0·960
		Validation	−0·07	0·82	0·981
		All years	0·39	1·03	0·969

[a] (1) Day of year (e.g. 1 April = 91); (2) minimum air temperature of the present day (°C); (3) maximum air temperature of the present day; (4) mean air temperature of the present day; (5) minimum air temperature of the previous day; (6) maximum air temperature of the previous day; (7) mean air temperature of the previous day; (8) water level (m).
[b] RMSE: root-mean-square error.

where P_i represents the predicted water temperature, O_i represents the observed water temperature and N represents the number of daily water temperature observations within a given time period.

The bias represents the mean of all the individual errors and indicates whether the model overestimates or underestimates the water temperature within a particular time period. It is calculated using

$$\text{bias} = \frac{1}{N}\sum_{i=1}^{N}(P_i - O_i) \tag{4}$$

The coefficient of determination represents the percentage of variability that can be explained by the model. It is calculated using

$$R^2 = \left[\frac{N\sum_{i=1}^{N} O_iP_i - \left(\sum_{i=1}^{N} O_i\right)\left(\sum_{i=1}^{N} P_i\right)}{\sqrt{\left[N\sum_{i=1}^{N} O_i^2 - \left(\sum_{i=1}^{N} O_i\right)^2\right] \times \left[N\sum_{i=1}^{N} P_i^2 - \left(\sum_{i=1}^{N} P_i\right)^2\right]}}\right]^2 \tag{5}$$

where parameters have been defined above.

Table III. Results of ANN models for the prediction of maximum water temperatures at Catamaran Brook

Model	Input parameters[a]	Period	Bias	RMSE	R^2
MAX1	1–8	Training (1992–1996)	0·87	1·53	0·952
		Testing (1997–1998)	1·62	1·94	0·962
		Validation (1999–2002)	−0·05	1·28	0·967
		All years (1992–2002)	0·67	1·53	0·948
MAX2	1, 3, 6, 8	Training	−0·97	1·59	0·952
		Testing	−0·35	1·37	0·950
		Validation	−1·84	2·22	0·962
		All years	−1·18	1·82	0·946
MAX3	1, 3, 4, 6, 7, 8	Training	0·43	1·11	0·969
		Testing	1·05	1·59	0·956
		Validation	−0·27	1·06	0·974
		All years	0·29	1·19	0·962
MAX4	1, 2, 3, 5, 6, 8	Training	0·30	1·07	0·968
		Testing	0·91	1·52	0·955
		Validation	−0·41	1·12	0·973
		All years	0·15	1·18	0·961

[a] (1) Day of year (e.g. 1 April = 91); (2) minimum air temperature of the present day (°C); (3) maximum air temperature of the present day; (4) mean air temperature of the present day; (5) minimum air temperature of the previous day; (6) maximum air temperature of the previous day; (7) mean air temperature of the previous day; (8) water level (m).

RESULTS

Results for the eight ANN models developed for Catamaran Brook are shown in Table II (mean daily water temperature) and Table III (maximum daily water temperature). Table II shows that MEAN1 (i.e. when considering all input parameters) provided the best overall results for mean daily water temperature with an RMSE of 0·96 °C (1992–2002). This model also showed the lowest overall bias at 0·26 °C and the highest R^2 (0·971). Although other models showed slightly higher RMSE and biases, as well as lower R^2, it was noted that all ANNs developed for mean daily water temperature performed relatively well with RMSE below 1·03 °C (all years).

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Among these models, it should be noted that MEAN2 represents a more classic modelling application, where mean water temperatures are predicted using mean air temperatures.

A comparison by periods showed that the testing period generally had higher RMSEs (1·17–1·30 °C), higher biases (0·69–0·81 °C) and correspondingly lower coefficients of determination than the training period (Table II). In contrast, the validation period showed the lowest RMSEs (0·82–0·87 °C) with a generally negative bias (−0·07 to −0·20 °C) and the highest R^2.

When considering the modelling of maximum water temperature, the best overall model was MAX4 with an RMSE of 1·18 °C (1992–2002; Table III), although MAX3 provided very good results as well (RMSE = 1·19 °C). The best overall bias was also observed for MAX4 at 0·15 °C and the coefficient of determination was calculated at 0·961. Unlike ANNs for mean water temperatures, which all performed well, some ANN models for maximum water temperatures showed significantly higher RMSE, particularly MAX1 (RMSE = 1·53 °C) and MAX2 (RMSE = 1·82 °C), with correspondingly lower coefficients of determination (0·948 and 0·946; Table III).

A comparison of performances during different periods showed that RMSEs were generally higher during the testing (1·52–1·94 °C) than during the training, with the exception of MAX2 (Table III). Results during the validation period were variable among models. For instance, MAX1 showed the best performance during the validation (RMSE = 1·28 °C), whereas MAX2 showed the worst performance at 2·22 °C. MAX3 and MAX4 showed similar performances during the validation and training periods. For maximum water temperature, coefficients of determination were somewhat variable among periods and varied between 0·950 and 0·974 (Table III). The bias was generally positive during the training and testing periods (with the exception of MAX2), whereas negative values were observed during all validation periods.

Among all ANN models, two were chosen out of the eight to study intra- and inter-annual performances: one for the mean daily water temperature and one for the maximum daily water temperature. MEAN1 was chosen for the mean temperature and MAX4 was chosen for the maximum temperature based on the best overall performance of these models (RMSE, bias and R^2). MAX4 had the same input parameters as MEAN1, with the exception that mean values of air temperatures were not included.

When looking at interannual performance, MEAN1 performed best in years 1995, 1999 and 2000, with RMSEs of 0·72 °C, 0·79 °C and 0·77 °C respectively (Table IV). The years 1994 and 2002 were very similar, with RMSEs of 0·81 °C. The worst performance was observed in 1997, with an RMSE of 1·30 °C. The lowest biases for MEAN1 were observed in 1996 and 2002, with respective values of −0·02 °C and −0·07 °C, whereas the worst biases were observed in 1993 (1·03 °C) and 1997 (1·06 °C). The highest coefficients of determination were observed in 1993–1995, 1999 and 2002, with all values exceeding 0·98.

Table IV. Results of the ANN (MEAN1) in the modelling of mean water temperatures at Catamaran Brook

Year	Bias	RMSE	R^2
1992	0·62	1·08	0·959
1993	1·03	1·15	0·990
1994	0·31	0·81	0·984
1995	0·40	0·72	0·988
1996	−0·02	0·99	0·973
1997	1·06	1·30	0·979
1998	0·32	1·03	0·964
1999	−0·23	0·79	0·985
2000	−0·19	0·77	0·978
2001	−0·32	0·97	0·977
2002	−0·07	0·81	0·988
All years	0·26	0·96	0·971

Table V. Results of the ANN (MAX4) in the modelling of maximum water temperatures at Catamaran Brook

Year	Bias	RMSE	R^2
1992	0·35	1·06	0·955
1993	0·97	1·18	0·986
1994	0·03	0·88	0·981
1995	0·29	0·81	0·985
1996	−0·18	1·31	0·957
1997	1·35	1·64	0·973
1998	0·47	1·39	0·963
1999	−0·71	1·23	0·977
2000	−0·47	1·11	0·973
2001	−0·42	1·12	0·976
2002	−0·05	1·02	0·979
All years	0·15	1·18	0·961

With regard to MAX4 for the prediction of maximum water temperatures, the lowest RMSEs were attained in 1994 and 1995, with values of 0·88 °C and 0·81 °C respectively (Table V). Other years generally revealed values exceeding 1 °C; however, very good performances were observed in 1992 (1·06 °C) and 2002 (1·02 °C). The highest RMSEs for maximum water temperatures were observed in 1997 and 1998, with values of 1·64 °C and 1·39 °C respectively. The best performances in relation to biases for MAX4 were observed in 1994 and 2002, with values of 0·03 °C and −0·05 °C, although most years showed a bias lower than 1 °C (with the exception of 1997, which showed a bias of 1·35 °C). Coefficients of determination among years were consistent with other performance criteria, and values generally exceeded 0·97 for most years.

Figure 3 provides information on the intra-annual water temperature variability and the overall ANN modelling performance for mean daily temperatures at Catamaran Brook using MEAN1. This figure shows that MEAN1 captured the water temperature variability very well, particularly in 1994, 1995, 1999 and 2002, where

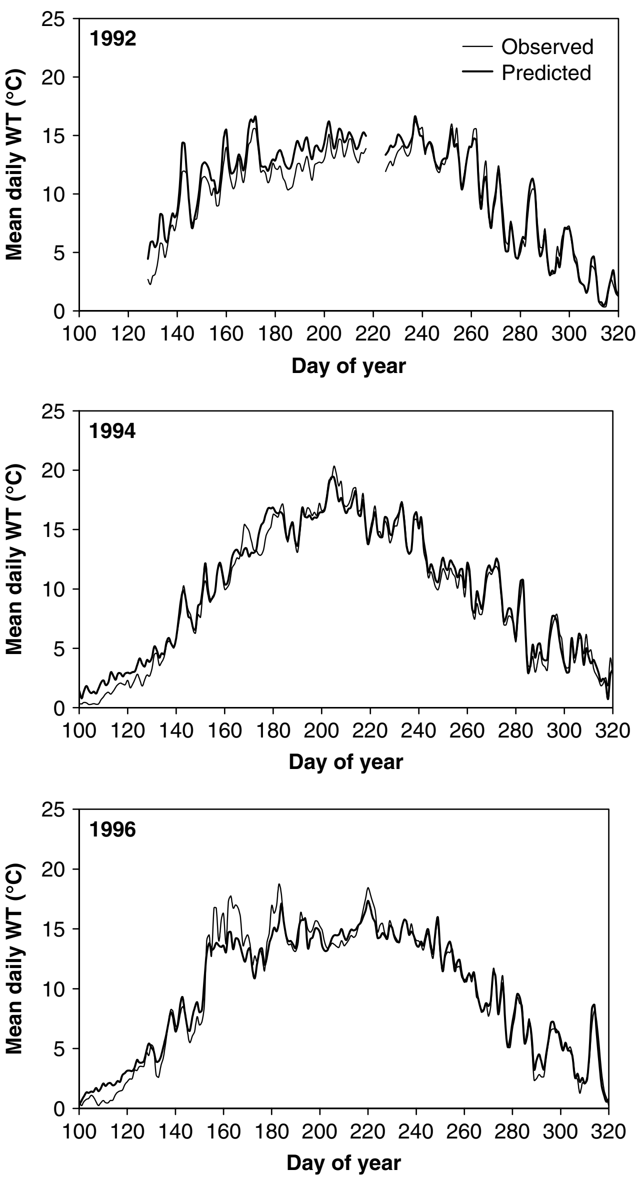

Figure 3. Mean daily water temperature modelling for Catamaran Brook (New Brunswick, Canada) using ANN MEAN1

both time-series (observed and predicted) were almost superimposed. A poorer modelling performance was observed in 1993, although an offset of approximately 1 °C seems evident. Moreover, the ANN model generally showed poorer predictions early in the spring of each year with an overestimation of water temperature. This overestimation was most noticeable in the years 1997 and 2001, although 1994 and 1996 showed some overestimation as well. In contrast, ANN models showed excellent predictions towards the end of each year. There are other short periods where the water temperatures were poorly predicted (e.g. 1996, days 158 to 169). Conversely, midsummer water temperatures (between day 180 and 240) were very well captured by the ANN model for mean water temperature, particularly in 1994, 1995, 1999 and 2001, where summer temperatures were slightly higher than in other years. In general, MEAN1 captured the water temperatures well and no systematic or consistent departures were noticeable.

Intra-annual results for MAX4 (maximum daily water temperature) are presented in Figure 4. As reflected by slightly higher RMSEs, this model did not predict the maximum water temperature as well as the mean daily water temperature (i.e. MEAN1). However, the overestimation observed in MEAN1 at the beginning of each year was not present in MAX4. As in MEAN1, the predictions were better in autumn than during other times of year. Very good results were observed in 1992, 1994, 1995 and 2001, where a very close fit was observed between predicted and observed autumn temperatures. The ANN model for maximum daily temperatures produced less satisfying results in 1993, 1997 and 1998, where it overestimated water temperatures throughout the summer. There is also a short period in 1996 (between days 156 and 183) where the model underestimates the highest temperatures, and this period was consistent with that of a lower performance for mean water temperatures (i.e. MEAN1).

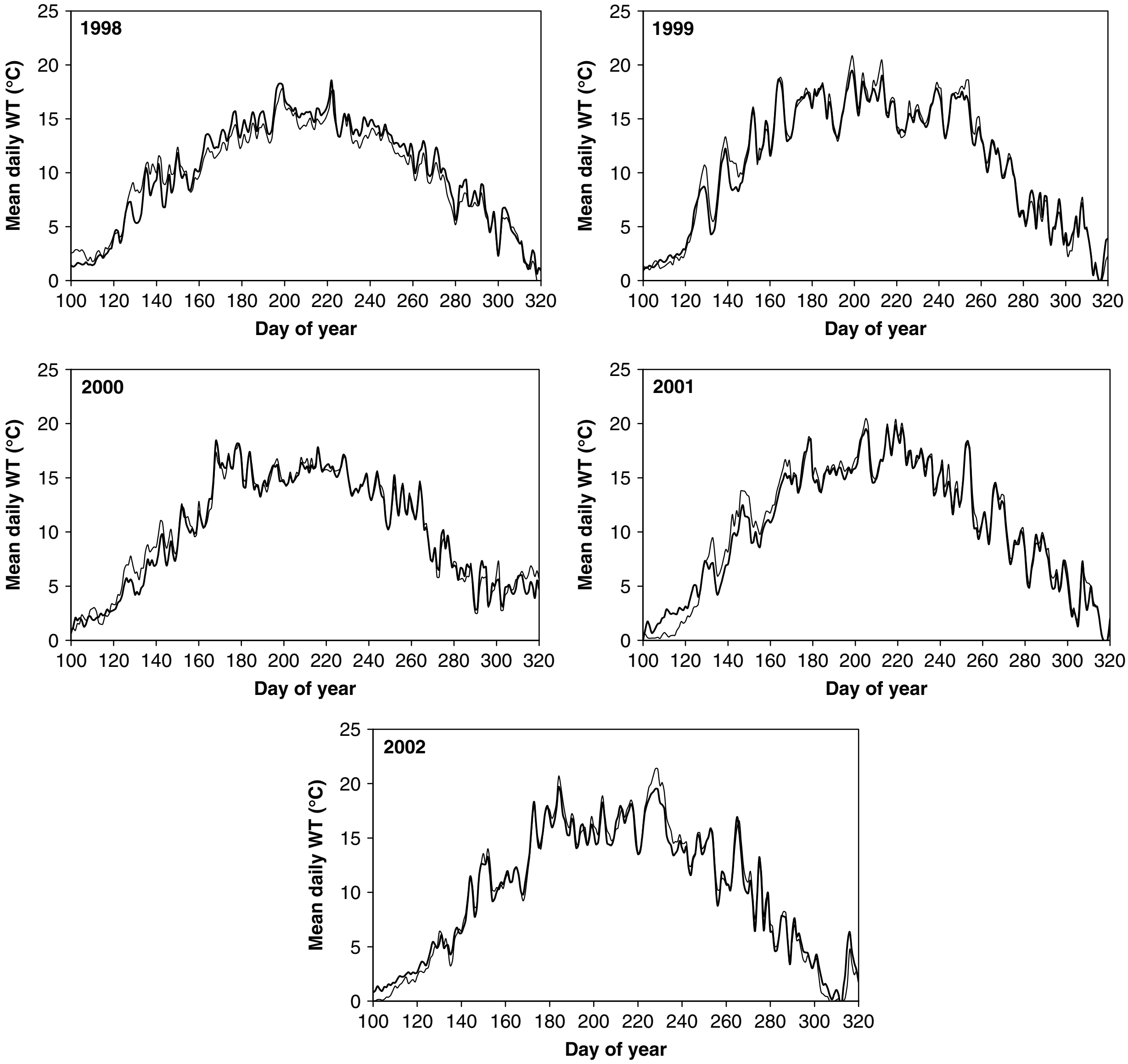

Figure 3. (*Continued*)

DISCUSSION

In general, it was observed that ANN models were very good for the prediction of river water temperatures, with RMSE close to 1 °C for mean daily water temperature and with a slightly higher RMSE for maximum water temperature (i.e. RMSE = 1·2 °C). ANN models with the best overall performances were then chosen for both mean and maximum temperatures (i.e. based on the R^2, RMSE and bias). The models that showed the best results using a variety of input parameters were MEAN1 for the mean water temperature and MAX4 for the maximum temperature.

MEAN1 showed the best results for the prediction of the mean daily water temperatures; however, MEAN2 is considered a more classic application where mean daily water temperature is predicted using mean daily air temperature (i.e. using the mean to predict the mean). Whereas MEAN1 gave the best overall results, the performances of MEAN2 and other models showed good results, comparable to MEAN1 (Table II). The biases and coefficients of determination among all ANN models predicting mean water temperatures showed very comparable results, with $R^2 > 0{\cdot}97$ and bias $<0{\cdot}39$ °C.

The ANN modelling results were compared with those of previous studies. For example, the results of MEAN1 were comparable to and/or better than those of Marceau *et al.* (1986), which used both deterministic and stochastic models. For instance, Marceau *et al.* (1986) showed RMSEs ranging from 1·10 to 2·52 °C with a mean overall RMSE of 1·86 °C (1968–1971) for their stochastic model, whereas their deterministic model showed a slightly higher mean RMSE (2·30 °C). The results of ANN models were also compared with other modelling results from Catamaran Brook, namely those obtained using a stochastic model (Caissie *et al.*, 1998) and using an equilibrium temperature concept model (Caissie *et al.*, 2005) (Table VI). At Catamaran Brook, a mean overall RMSE of 1·21 °C was calculated using the equilibrium temperature concept model (Caissie *et al.*,

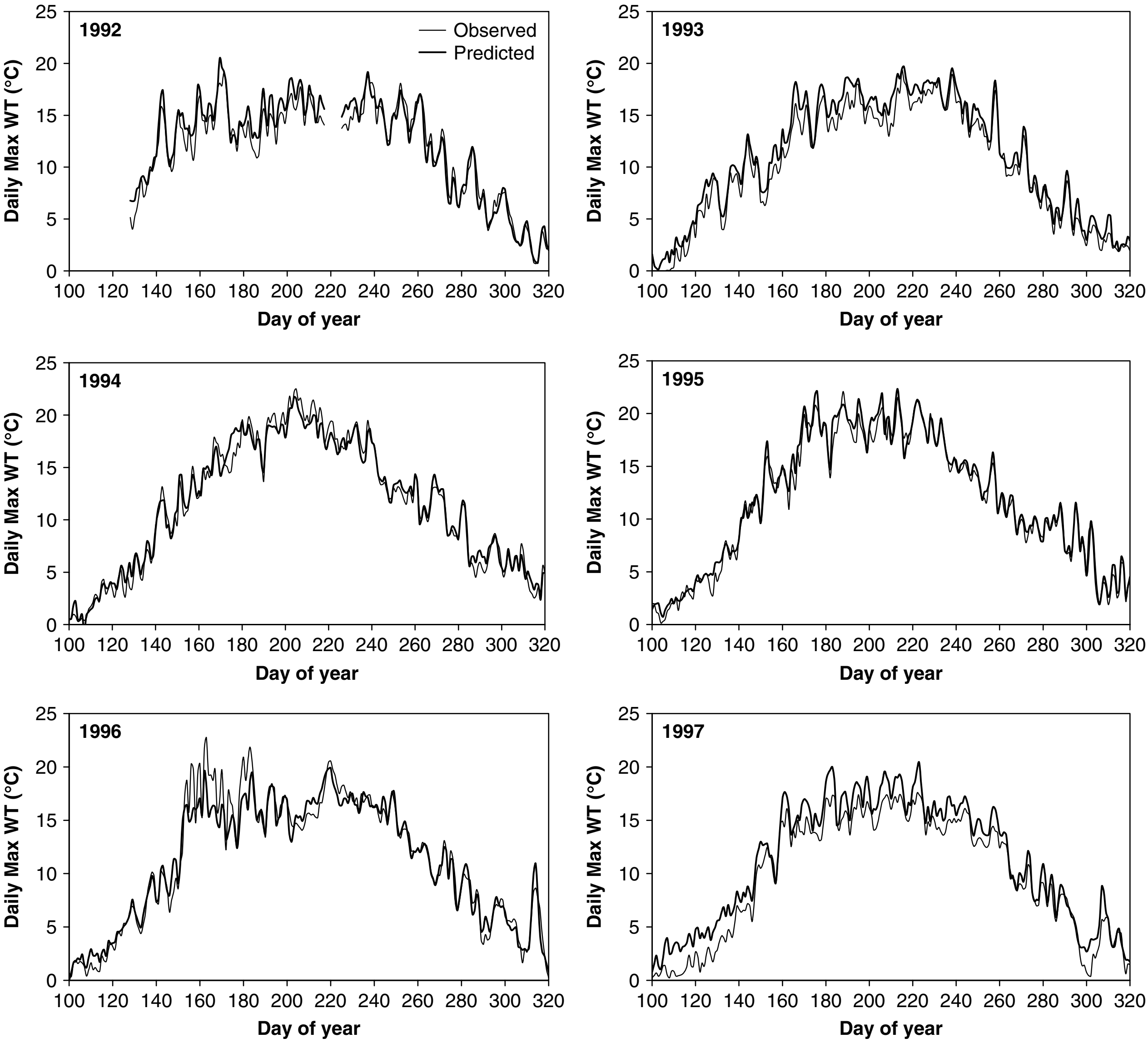

Figure 4. Maximum daily water temperature modelling for Catamaran Brook (New Brunswick, Canada) using ANN MAX4

2005), whereas RMSEs ranged between 1·0 and 1·3 °C when using stochastic models (Caissie *et al*., 1998). The results of this and previous studies show that the present ANN model (i.e. MEAN1) provides a slightly better modelling performance with an improvement exceeding 0·2 °C, which can be considered significant within these magnitudes of temperatures (∼1 °C).

For the prediction of the maximum water temperatures, MAX2 represents a more classic approach to modelling, where maximum air temperatures are used to predict maximum water temperatures. MAX2 performed somewhat poorly compared with MAX4, which showed the best overall results (using the minimum and maximum air temperature, day of year and water level as input parameters). In particular, MAX2 had an RMSE of 1·82 °C compared with 1·18 °C for MAX4, which represents an improvement of 0·64 °C over the period of 11 years. Unlike mean water temperature, where a significant improvement was not necessarily obtained by

Table VI. Modelling performances of previous studies at Catamaran Brook for both mean and maximum water temperatures

Year	Mean water temperature (°C)		Maximum water temperature (°C)
	Stochastic modelling[a]	Equilibrium temperature concept[b]	Stochastic modelling[c]
1992	1·28	0·95	1·48
1993	0·96	1·20	1·51
1994	1·57	1·13	1·62
1995	1·24	1·04	1·48
1996	—	1·33	1·48
1997	—	1·24	1·49
1998	—	1·29	—
1999	—	1·38	—
All years	1·26	1·21	1·51

[a] Caissie *et al.* 1998.
[b] Caissie *et al.* 2005.
[c] Caissie *et al.* 2001.

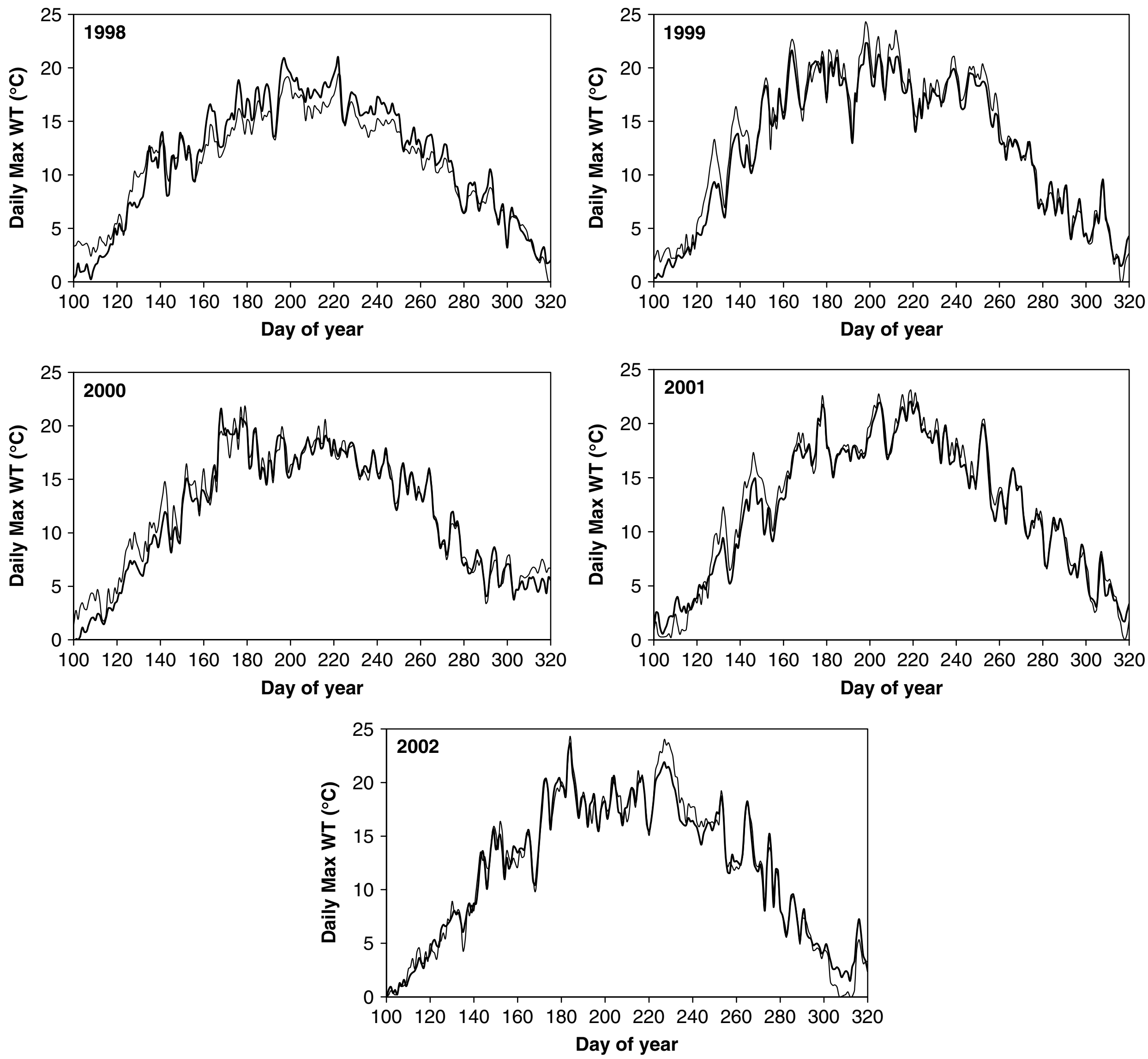

Figure 4. (*Continued*)

adding more input parameters, adding parameters significantly improved the ANN modelling of maximum water temperatures. In fact, the results showed that, when adding another input parameter, a significant improvement was realized in the modelling (e.g. MAX3 and MAX4; Table III). This represents one of the strengths of ANN models, whereby they can easily accommodate a variety of input parameters within the same study.

Very few studies are found within the literature where the maximum water temperatures are modelled on a daily basis, although this is a very important parameter from an aquatic habitat perspective. One such study was conducted at Catamaran Brook, where six years of data were analysed using a stochastic model (Caissie *et al*., 2001) and the RMSEs are also presented in Table VI. The results of MAX4 were compared with those results. In that study, Caissie *et al*. (2001) calculated an overall RMSE of 1·51 °C (1992–1997) using a stochastic water temperature model. MAX4 showed an RMSE of only 1·18 °C (1992–2002), which represents an improvement of 0·33 °C, although the study period was different. For the stochastic model, the worst performance year was in 1994, with an RMSE of 1·62 °C, which is comparable to the worst performance year for MAX4 (1997 at 1·64 °C; Table V). Conversely, the best performance year with the ANN model was significantly better than the stochastic model (0·81 °C for the ANN model compared with 1·48 °C for the stochastic model).

Intra-annual performances showed that ANN models (for both mean and maximum temperatures) performed best in late summer and autumn, although the midsummer temperatures were also well captured during most years. These results suggest that discharge potentially plays a role in the modelling performance, as the autumn period frequently experiences predominantly low water levels. This could potentially result in more effective thermal exchange during this time of year and, therefore, result in better modelling performances. MEAN1 showed a slight overestimation of water temperatures in early spring, which is consistent with results from other models predicting mean water temperatures (Caissie *et al*., 1998, 2005). In fact, stochastic and equilibrium temperature models both showed such an overestimation in early spring, a phenomenon that has been previously explained as a potential snowmelt influence. During the early spring, the atmospheric energy is most likely contributing to snowmelt and soil heating processes and, therefore, the water temperatures are not increasing as rapidly as air temperatures. ANN models within this study showed results consistent with those of previous studies. In contrast, ANN models for maximum temperature, particularly MAX4, did not show such an overestimation in early spring, and this model performed relatively better during that time of year. Overall, it was observed that both mean and maximum water temperature models showed consistent intra-annual performances. For example, when the mean water temperature model performed well, such as in 2001, the maximum water temperature ANN model performed equally well (Figures 3 and 4). The same is true for the period where the model did not perform as well. For instance, a slight overestimation was observed in 1997 and 1998 for mean temperatures, and such was also the case for the maximum temperature of the same years.

CONCLUSIONS

Studies have shown that river water temperatures can depend on complex factors, including climate (altitude, latitude), streamside vegetation, river geomorphology, basin topography and others (Ward, 1985; Caissie, 2006). Although water temperature is influenced by many hydrometeorological and geophysical factors, it can be predicted using a variety of models (from simple to complex models). These include regression models (Crisp and Howson 1982; Erickson and Stefan 2000), stochastic models (Marceau *et al*., 1986; Caissie *et al*., 1998) and full energy budget or deterministic models (Raphael, 1962; Morin and Couillard, 1990; Sinokrot and Stefan, 1993).

ANN hydrology modelling applications have steadily increased over the past decade; however, very few applications have addressed the modelling of river water temperatures. As such, the present study investigated ANN models using a variety of input parameters to predict both mean daily and maximum daily water temperature within the same study.

In conclusion, ANN models were very effective in the predicting of both mean and maximum daily water temperatures conducted within the present study. The ability to predict both of these temperature metrics within the same study can be very important in aquatic and ecosystem studies. We also concluded from the present study that the combination of input parameters does not seem to be as important for predicting daily water temperatures, as most models provided very similar results and performances. Such was not the case for predicting maximum water temperature, where different input parameters provided much more variable results. Nonetheless, in the case of maximum water temperatures, significant improvements in the modelling could be realized by adding more input parameters over the more classic approach (e.g. using maximum air temperature to predict maximum water temperature). ANN models are well adapted to these types of analysis, where different input parameters are tested to find out which parameters provide the best outcome. It was also concluded from the present study that ANN water temperature models are as good as other water temperature models, namely models based on the equilibrium temperature concept and stochastic models, with performances in the range of 1 °C (mean water temperature) to 1·2 °C (maximum temperature).

ANNs are first and foremost interpolation tools with good generalization capability. This was shown in the present study by modelling long-term water temperature time-series. However, ANN models should be applied with caution, especially in the extrapolation domain, as unexpected results could arise because the model may not be trained for those conditions. Nevertheless, the advantage of ANN models was shown within this study. This is based on their capability as a universal approximator, as well as on the simplicity of model development, application, and future model updating. Current study results showed that ANN models can effectively extract water temperature relationships between input and output time-series; as such, ANN models can be a very powerful modelling tool in water resources and fisheries management, which should not be neglected.

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