Modeling of hourly river water temperatures using artificial neural networks
Cindie Hebert, Daniel Caissie, Mysore G. Satish and Nassir El-Jabi

ABSTRACT
Water temperature is an important component for water quality and biotic conditions in rivers. A good knowledge of river thermal regime is critical for the management of aquatic resources and environmental impact studies. The objective of the present study was to develop a water temperature model as a function of air temperatures, water temperatures and water level data using artificial neural network (ANN) techniques for two thermally different streams. This model was applied on an hourly basis. The results showed that ANN models are an effective modeling tool with overall root-mean-square-error of 0.94 and 1.23 °C, coefficient of determination ($R^2$) of 0.967 and 0.962 and bias of −0.13 and 0.02 °C, for Catamaran Brook and the Little Southwest Miramichi River, respectively. The ANN model performed best in summer and autumn and showed a poorer performance in spring. Results of the present study showed similar or better results to those of deterministic and stochastic models. The present study shows that the predicted hourly water temperatures can also be used to estimate the mean and maximum daily water temperatures. The many advantages of ANN models are their simplicity, low data requirements, their capability of modeling long-term time series as well as having an overall good performance.

Key words | artificial neural network, modeling, river/streams, temperature

LIST OF SYMBOLS

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN</td>
<td>artificial neural network</td>
</tr>
<tr>
<td>$b_j$</td>
<td>bias weight of the $j$th hidden node</td>
</tr>
<tr>
<td>$b_k$</td>
<td>bias weight of the $k$th hidden node</td>
</tr>
<tr>
<td>CatBk</td>
<td>Catamaran Brook</td>
</tr>
<tr>
<td>$f(n_j)$</td>
<td>activation function of $n_j$ (hyperbolic tangent function)</td>
</tr>
<tr>
<td>$I$</td>
<td>total number of input nodes</td>
</tr>
<tr>
<td>$J$</td>
<td>total number of hidden nodes</td>
</tr>
<tr>
<td>$K$</td>
<td>total number of output nodes</td>
</tr>
<tr>
<td>LSWM</td>
<td>Little Southwest Miramichi River</td>
</tr>
<tr>
<td>$N$</td>
<td>total number of observations (hourly water temperatures)</td>
</tr>
<tr>
<td>$n_j$</td>
<td>sum of input and bias of the $j$th hidden node</td>
</tr>
<tr>
<td>$O_i$</td>
<td>observed value (hourly water temperatures)</td>
</tr>
<tr>
<td>$P_i$</td>
<td>predicted value (hourly water temperatures)</td>
</tr>
<tr>
<td>RMSE</td>
<td>root-mean-square-error</td>
</tr>
<tr>
<td>$R^2$</td>
<td>coefficient of determination</td>
</tr>
<tr>
<td>$T_w(O)$</td>
<td>observed water temperatures</td>
</tr>
<tr>
<td>$T_w(O)_{\text{max}}$</td>
<td>observed daily maximum water temperatures</td>
</tr>
<tr>
<td>$T_w(O)_{\text{mean}}$</td>
<td>observed daily mean water temperatures</td>
</tr>
<tr>
<td>$T_w(P)$</td>
<td>predicted water temperatures</td>
</tr>
<tr>
<td>$T_w(P)_{\text{max}}$</td>
<td>predicted daily maximum water temperatures</td>
</tr>
<tr>
<td>$T_w(P)_{\text{mean}}$</td>
<td>predicted daily mean water temperatures</td>
</tr>
<tr>
<td>$w_{ij}$</td>
<td>connection weight between the $i$th input node and $j$th hidden node</td>
</tr>
<tr>
<td>$w_{jk}$</td>
<td>connection weight between the $j$th hidden node and the $k$th output node</td>
</tr>
<tr>
<td>$x_i$</td>
<td>$i$th input node</td>
</tr>
<tr>
<td>$y_k$</td>
<td>$k$th hidden node</td>
</tr>
</tbody>
</table>
INTRODUCTION

Water temperature is an important component for water quality and biotic condition in rivers. In fact, most water quality parameters are dependent on water temperature (e.g., physical, chemical, and biochemical conditions) (Nemerow 1985). Among others, water temperature controls the rate of decomposition of organic matter, the dissolved oxygen content, and chemical reactions in general. Stream water temperature can also affect recreational activities such as swimming and fishing. The thermal regime of a river influences many aspects of fish habitat, life condition, and the distribution of aquatic species. For example, river water temperatures (Webb & Walling 1993; Johnston 1997) influence the growth rate of aquatic organisms (Edwards et al. 1979; Coutant 1999; Swansburg et al. 2002) as well as the period of egg incubations. High water temperatures can be detrimental to fish habitat and sustained high temperatures can result in fish mortalities or physiological stress (Huntsman 1942; Garside 1973; Lee & Rinne 1980; Lund et al. 2002). Most species of fish have a preferred range of water temperatures (Coutant 1977; Wichert & Lin 1996) and at the upper lethal temperatures, fish often seek thermal refugia to avoid adverse stress conditions (Torger- sen et al. 1999; Ebersole et al. 2001). Studies have also monitored water temperatures to evaluate the impact of human activities due to urbanization (Krause et al. 2004; Nelson & Palmer 2007), thermal pollution (Bradley et al. 1998), as well as land-use activities (Hester & Doyle 2010). Therefore, both a good knowledge of river thermal regimes and the ability to predict water temperatures are critical for the management of aquatic resources and environmental impact studies.

The most influential factors on water temperature are atmospheric conditions, although other factors (e.g., water depth, groundwater contribution, etc.) play an important role as well (Caisisie 2006). All these factors can be input parameters in many water temperature models (especially deterministic models); however, the development of such models is often dependent on data availability.

Water temperature models can generally be classified into two groups: deterministic or statistical. The statistical approach predicts water temperatures by relating water temperatures to relevant meteorological parameters, usually air temperature (Harvey et al. 2011). Deterministic models consider the cause and effect relations between meteorological parameters and the river environment (Raphael 1962; Morin & Couillard 1990; Morin et al. 1994). Deterministic models take into account the energy exchange (energy budget) to predict variation in water temperatures. This modeling approach estimates the energy flux at the water surface and at the stream bottom to estimate the total energy exchanged. The major disadvantage of this approach is the large number of input parameters required to run the model and these input parameters are generally only available at the nearest weather stations. Some of the most commonly used parameters are the net short-wave radiation, net long-wave radiation, convection, evaporation/condensation, precipitation, streambed (sediment/geothermal), and groundwater contribution (Caisisie 2004). Among these, the two most important parameters were found to be air temperature and solar radiation (Sinokrot & Stefan 1994).

Since the 1990s, artificial neural networks (ANNs) have been widely used in the field of hydrology, namely in modeling of precipitation and runoff, water demand predictions, groundwater, and water quality modeling (Govindaraju 2000). ANNs have become an interesting modeling tool for many reasons. One of the main reasons for this is the fact that ANNs have the capacity to recognize relations between input and output variables without necessarily requiring any physical explanations. This approach can be very useful in hydrology because most relationships are non-linear, very complex, and sometimes unknown. ANNs also work well when the data sets contain noise, due to their generalizing capabilities (Govindaraju 2000), and once calibrated, ANN models are simple to use.

Hourly water temperature models are not as common as mean daily temperature models, but they have the advantage of predicting the diel variability in water temperature. This variability can, in many cases, be more important for aquatic resources than average values. For instance, during periods of high water temperatures, it is important to estimate both maximum and minimum temperatures in order to assess the stress and subsequent recovery periods of
aquatic resources (e.g., salmonids; Breau et al. 2007). Previous studies have shown that ANN models are good models for the prediction of mean daily river water temperatures (Bélanger et al. 2005; Chenard & Caissie 2008). However, few studies have used ANN models for predicting hourly river water temperatures (e.g., Risley et al. 2003).

Therefore, the objective of the present study was to develop a water temperature model to predict hourly river water temperatures using minimal and accessible input data for a long-term data series. The specific objectives were (1) to develop an ANN model to predict hourly water temperatures, (2) to apply the water temperature model to two thermally different streams, (3) to examine the performance of the ANN model under different meteorological and hydrological conditions, and (4) to calculate the daily mean and maximum water temperatures from the predicted hourly water temperatures.

**METHODOLOGY**

**Study area**

The two study sites were located on the Miramichi River system (New Brunswick, Canada), which is world renowned for its population of Atlantic salmon (Figure 1). This system has an annual precipitation ranging from 860 to 1,365 mm, with a long-term average of 1,142 mm (Caissie & El-Jabi 1998). Mean monthly air temperature varies between −11.8°C (January) and 18.8°C (July). The mean annual runoff was estimated at 714 mm, ranging from 631 to 763 mm. The vegetation consisted mainly of second-growth, mature forest species estimated at 65% coniferous and 35% deciduous (Cunjak et al. 1990).

The first study site was located on Catamaran Brook (CatBk) approximately 8 km upstream of the mouth. CatBk is also 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). CatBk has a drainage area of 27 km² at the study site, an average stream width of 9 m and a depth of 0.21 m. CatBk is well mixed due to high turbulence and the brook is sheltered by streamside vegetation and upland slopes. The canopy closure for Catamaran was estimated at 55–65% with a forest composition of 60% hardwood and 40% softwood.

The second study site was located on the Little Southwest Miramichi River (LSWM) approximately 25 km from the river mouth (Figure 1). The drainage area of this basin is 1,190 km² (Johnston 1997). The LSWM has a river width of approximately 80 m, with a depth of 0.55 m on average during mean flow conditions. No lateral variations of water temperatures were observed due to the well-mixed nature of the river (Caissie et al. 2007). The forest along the LSWM is mainly composed of 70% hardwood, with presence of 30% softwood. The canopy closure is less than 20%.

Air temperatures for both study streams were collected at the meteorological station located at mid-basin on the CatBk (Figure 1). Sensors at the meteorological station were installed approximately 2 m above the ground. ‘Water temperatures were recorded using a 107B Water Temperature Probe (Campbell Scientific Corps) at both stream temperature sites’. Sensors of air and water temperatures were scanned every 5 seconds by a CR10 (Campbell Scientific Corp.) data logger and hourly averages were then calculated. Hourly air temperatures varied between –14.6 and 35.7 °C. Hourly water temperatures varied between 0 and 26.4 °C at CatBk and between 0 and 30.2 °C at LSWM. Daily mean discharges were obtained from Environment Canada’s hydrometric station (01BP001 and 01BP002) on both river systems. CatBk had mean water depth of 0.16 m over the study period, but LSWM was deeper with a 0.52 m daily water level. Mean water depth was obtained from discharge and a power function as described in Caissie (2004).

Artificial neural network

The development of ANNs started 50 years ago, aiming to understand the human brain and to imitate its functions. In the last 10 years, this technique has grown in popularity due to the development of more sophisticated algorithms and due to the availability of powerful data processing tools.

The basic elements used in a neural network are called ‘nodes’ or ‘neurons’, which are non-linear algebraic functions, parameterized and with bound values (Dreyfus et al. 2002). The signal goes through each node associated with a weight and is modified by a transfer function. A neural network consists of a finite number of layers as presented in Figure 2 where each layer is composed of a number of nodes. The entrance of the neural network is called the input layer, and the values of the function are called the output layer. The intermediary layers are called the hidden layers. At each node, the information is processed and passed on to the following layer with connection strength (weight). The output is the function of a summation and a transformation of different nodes.

The learning process consists of updating the network architecture and the weight connections. There are three main learning paradigms: supervised, unsupervised and hybrid (Jain et al. 1996). The supervised learning uses pairs of data to have a correct answer (output) for every input. The weights adjust to produce an output as close as possible to the known answer (target). The unsupervised learning consists of using correlations between patterns in the data. Hybrid learning uses a combination of both supervised and unsupervised learning. For the application within the present study, the supervised learning process was used.

The most popular algorithm is the error backpropagation algorithm based on the error-correction learning rule. It is a commonly used learning algorithm mainly due to its simple conception, effective computation, and efficiency (Smith 1993). The backpropagation algorithm was also used and consisted of distributing the error (predicted output – observed output) to have the lowest or minimal errors. With this algorithm, the information goes through the network and the network predicts an output. The predicted output is then compared to the observed output (real or measured data) and the error (difference between observed and predicted) is calculated. The weights are readjusted. This iterative process is done many times until the error is inferior to a desired level.

First, each input \( x_i \) sends a copy of its value to all the hidden nodes of the network. Each hidden node calculates
the weighted sum of inputs and bias as in:

\[ n_j = b_j + \sum_{i=1}^{I} w_{ij} x_i \]  

(1)

where \( I \) is the total number of input nodes, \( j \) is the \( j \)th hidden node, \( w_{ij} \) is the connection weight between the \( i \)th input and \( j \)th hidden node, \( b_j \) is the bias weight of each hidden nodes and \( x_i \) is the \( i \)th input node.

Then, each hidden node computes a function of its sum through an activation function \( f(n_j) \). The activation function can be sigmoidal, linear, threshold-type Gaussian or hyperbolic tangent depending on the type of network and training algorithm employed (Dawson & Wilby 2001). The most commonly used activation function found in hydrology is the hyperbolic tangent function (Govindaraju 2000; Shamseldin et al. 2002; Shrestha et al. 2005; Yonaba et al. 2010). The hyperbolic tangent function selected in this study is given by:

\[ f(n_j) = \frac{2}{1 + e^{-2n_j}} - 1 \]  

(2)

Then, each hidden node sends its result to all the output nodes \( (y_k) \). Each output node value is calculated with the following formula:

\[ y_k = b_k + \sum_{j=1}^{J} f(n_j) w_{jk} \]  

(3)

where \( k \) is the \( k \)th the output node, \( b_k \) is the bias weight of the \( k \)th output node, \( w_{jk} \) is the connection weight between the \( j \)th hidden node and the \( k \)th output node, \( y_k \) is the \( k \)th output node and \( f(n_j) \) is the activation function.
Many factors can influence the sample size used with a neural network, like the choice of the modeling technique, the target function and the noise in the data. In fact, the sample size increases with the complexity of the function and the noise to maintain accuracy and prevent overfitting. The largest sample available should be used as long as it fits in the memory or storage. Smith (1993) recommends dividing the sample into three subsamples: training, validation, and testing. The validation and testing subsample are commonly grouped together to measure the performance of the network.

**Water temperature model**

Water temperature data for the ANN were collected for the period of April 15 (day 105) to October 31 (day 304) and for years between 1998 and 2007 at both CatBk and LSWM. This period corresponded approximately to the period of the year without ice cover, i.e., open water condition. Some years had missing data for a few days and these days were not included in the ANN model. Data were separated into two subsamples: training data (1998–2002) and validation data (2003–2007).

The prediction of water temperatures in this study used two ANN models. The first ANN model was developed to predict daily mean water temperatures to be used as input in a second ANN model in order to predict hourly water temperatures. The first ANN model used four input data: air temperature of the present and previous day (°C), water level (m), and time of year (day). The selection of air temperature, as input data, was based on the availability of data and their strong correlation to water temperatures (Cluis 1972; Song & Chen 1977; Stefan & Preud’homme 1993; Mohseni & Stefan 1999; Bélanger et al. 2005; Chenard & Caissie 2008). The air temperature of the previous day was used as input because air and water temperature are strongly correlated (Kothandaraman 1971; Cluis 1972). These simulated daily mean water temperatures of the first ANN model were used as input data into the second ANN model.

The second ANN model was developed to predict hourly water temperatures at both streams. The hourly ANN model used six input nodes: air temperature of the present and previous hour (°C), time of day (hour), time of year (day), daily mean water temperature (simulated from the first ANN) (°C), and the mean daily water level (m). During the training, the observed daily mean water temperatures were used; however during the validation the simulated daily mean water temperatures were used. The output of the developed ANN model was hourly water temperature at both CatBk and LSWM.

The complexity of a function estimated by an ANN increases with the training. During the training, the network will come to a certain number of epochs that will give the best generalization and after this critical point, it will start overfitting. The performance should be measured during the training and validation phase with different numbers of hidden nodes. When the performance during the validation phase starts to decrease for a certain number of hidden nodes, the network should stop the training and use the corresponding hidden nodes. The limitation procedure of the number of hidden nodes can also be applied to the number of epochs. Smith (1993) suggested limiting the number of hidden nodes within a network and then limiting the training (based on validation sample error) to prevent overfitting. The ANN model was adjusted until the difference between predicted and observed water temperatures was minimized. The feed-forward backpropagation ANN models were created using Matlab (MATLAB student version 7.1). The ANN model had six input nodes (I = 6), five hidden nodes (J = 5) in one hidden layer and only one output node (K = 1).

Four different time periods of 7 days were selected to examine in more detail the performance of the ANN model under different meteorological and hydrological conditions. The selection was made to include two training periods and two validation periods over the three seasons: spring, summer and autumn (Table 1). The two training periods comprised of days (1) in summer 1998 (days 221–227) where a significant change in temperature was observed and (2) in spring 1999 (days 132–138) where water temperatures increased rapidly. The two validation periods included a period in autumn 2006 (days 292–298) to reflect the autumn conditions and days of summer 2007, to look at the warmest temperature conditions (days 203–209).

This study also examined if the prediction of hourly water temperatures of the ANN model could be used to...
predict the daily mean and daily maximum water temperatures. The daily mean water temperatures were estimated as an average of the predicted hourly water temperatures over 24 hours. Daily maximum water temperatures were estimated as the maximum of the predicted hourly water temperature of each day.

Modeling performance criteria

To compare modeling performances for different years and study periods (training/validation) three criteria were used: the root-mean-square error (RMSE), the coefficient of determination ($R^2$), and the bias. They were selected because they are often used in modeling studies and results from these performance criteria were also available for other water temperature models at CatBk and LSWM. The RMSE represents the mean errors associated with the model. It was calculated using the following equation:

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

(4)

where $N$ is the number of hourly water temperature observations, $O_i$ is the observed hourly water temperature and $P_i$ is the predicted hourly water temperature.

The coefficient of determination ($R^2$) represents the percentage of variability that can be explained by the model. It was calculated with the following formula:

$$R^2 = \frac{\sum_{i=1}^{N} (P_i - \bar{O})^2}{\sum_{i=1}^{N} (O_i - \bar{O})^2} \times 100$$

(5)

The bias is an indication of the overestimation or underestimation of the water temperature model and represents the mean of errors calculated with the following equation:

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

(6)

RESULTS

In this study, an ANN model was developed to predict hourly water temperatures for two different watercourses: Catamaran Brook (CatBk) and Little Southwest Miramichi (LSWM). Results of the ANN models (RMSE, $R^2$, and bias) are represented in Table 2. The ANN model generally provided the best results at CatBk with a RMSE of 0.63 °C for the training and 1.19 °C for the validation period. At CatBk, the coefficient of determination ($R^2$) was 0.986 (training) and 0.948 (validation). The bias was 0.00 °C for the training period and −0.28 °C for the validation period. For LSWM, the ANN model performed comparably well, especially during the training (RMSE = 0.69 °C and $R^2$ = 0.989). However, during the validation period, the RMSE was higher at 1.62 °C and a correspondingly lower $R^2$ at 0.930. The bias for LSWM was 0.00 °C (training) and 0.05 °C (validation). Overall (all years), the ANN model performed well for both watercourses with RMSE of 0.94 °C (CatBk) and 1.23 °C (LSWM) and with $R^2$ of 0.967 (CatBk) and 0.962 (LSWM). Water temperatures were slightly underestimated at CatBk with a bias of −0.13 °C and the overall bias for LSWM was very low (0.02 °C).

A comparison by year showed consistent results during the training period with RMSE between 0.53 and 0.91 °C and $R^2$ between 0.980 and 0.991 (Table 2). The bias was

<table>
<thead>
<tr>
<th>Sample</th>
<th>Season</th>
<th>Year</th>
<th>Day of year</th>
<th>Dates</th>
<th>Hydrological conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>Summer</td>
<td>1998</td>
<td>221–227</td>
<td>August 9–August 15</td>
<td>Sudden decrease of air and water temperatures</td>
</tr>
<tr>
<td>Training</td>
<td>Spring</td>
<td>1999</td>
<td>132–138</td>
<td>May 12–May 18</td>
<td>Gradual increase of air and water temperatures</td>
</tr>
<tr>
<td>Validation</td>
<td>Autumn</td>
<td>2006</td>
<td>292–298</td>
<td>October 19–October 25</td>
<td>Autumn conditions</td>
</tr>
<tr>
<td>Validation</td>
<td>Summer</td>
<td>2007</td>
<td>203–209</td>
<td>July 22–July 29</td>
<td>Warmest temperature conditions</td>
</tr>
</tbody>
</table>
also consistent among years and generally low (less than ±0.06 °C). The validation RMSEs were two to three times higher than for those of the training years. CatBk showed RMSEs between 1.02 and 1.40 °C and LSWM showed RMSEs between 1.33 and 1.91 °C during the validation period. Coefficients of determination ($R^2$) were similar throughout the validation years at CatBk (0.948 to 0.959) and more variable at LSWM (between 0.868 and 0.971).

The bias was highest at CatBk in 2005 (−0.66 °C) and 2006 (−0.69 °C) with correspondingly lower values for LSWM (±0.40 °C).

Table 2 also shows the performance of the model on a seasonal basis. Spring was between April 15 and June 21 (day 105–171), summer between June 22 and September 20 (day 172–263) and autumn between September 21 and October 31 (day 264–305). For the training period, autumn

![Table with data](https://iwaponline.com/wqrj/article-pdf/49/2/144/379510/144.pdf)
showed the best performance with a RMSE of 0.47 °C (CatBk) and 0.52 °C (LSWM). Spring (training period) showed a poorer performance with RMSE of 0.70 °C (CatBk) and 0.85 °C (LSWM). RMSEs during the summer were similar at CatBk and LSWM with values of 0.64 and 0.67 °C. Coefficients of determination ($R^2$) were similar in autumn and spring with values over 0.979; however, lower values were observed in summer (0.942–0.961). The biases were generally small for both watercourses for the training period with seasonal values less than ±0.02 °C.

Seasonal results were similar during the validation period, although RMSEs and biases were generally higher with lower $R^2$. Highest RMSEs were observed during the spring (1.38 °C CatBk and 1.76 °C LSWM) and best performances were in summer in CatBk (1.02 °C) and autumn in LSWM (1.59 °C). Summer had the lowest $R^2$ (0.776), whereas spring had the highest $R^2$ (0.922). Spring showed a general overestimation of predicted water temperature in LSWM with a bias of 0.78 °C. In general (all years), the ANN model showed similar seasonal performances in CatBk and a better performance in summer and autumn for LSWM.

Figure 3 shows observed water temperatures ($T_w(O)$) and predicted water temperatures ($T_w(P)$) at CatBk. The training period (Figures 3(a)–3(e)) showed good agreement between observed ($T_w(O)$) and predicted water temperatures ($T_w(P)$). However, the validation period (Figures 3(f)–3(j)) showed more discrepancies between the observed and predicted water temperatures, mainly in early spring (days 105–120) and late autumn (days 290–305). Figures 4(a)–4(e) show good prediction of water temperatures ($T_w(P)$) by the ANN model compared to the observed water temperatures ($T_w(O)$) for LSWM. Similar to CatBk, the validation years at LSWM (Figures 4(f)–4(j)) showed more difference between observed ($T_w(O)$) and predicted water temperatures ($T_w(P)$) in early spring and late autumn.

The performance of the ANN model was examined under different meteorological and hydrological conditions. The results of the four detailed time periods at CatBk and LSWM are shown in Figure 5. Figures 5(a) and 5(b) show days 221 to 227 of summer 1998 (August 9 to August 15). This period showed a sudden decrease in air ($T_a$) and observed water temperature ($T_w(O)$) at CatBk and LSWM, caused by rain and heavy fog on day 223. The predicted water temperature ($T_w(P)$) was slightly overestimated during the first two days, where air temperature was higher, and during the decrease of air temperature ($T_a$), where water levels increased from 0.088 to 0.313 m at CatBk and from 0.374 to 0.970 m at LSWM. During the following days, the predicted water temperature ($T_w(P)$) closely followed the observed water temperature ($T_w(O)$).

The second period included days 132–138 (May 12 to May 18) in the spring of 1999 (Figures 5(c) and 5(d)). The first days (132–133) experienced a few showers, followed by days of mainly clear sky. Water level decreased throughout the period at both CatBk and LSWM. At CatBk (Figure 5(c)), the ANN model showed some difficulties in estimating water temperatures; more so than in LSWM. Water temperatures at night were generally underestimated, whereas day time temperatures were overestimated. At LSWM, predicted water temperatures closely followed observed water temperatures throughout the period.

In 2006, during the validation period, days 292 to 298 (October 19 to October 25) were analyzed (Figures 5(e) and 5(f)). This period reflected autumn conditions, with low air temperature and an increase in water level due to precipitation (day 294). Predicted water temperatures were clearly underestimating compared to observed water temperatures at both watercourses.

Figures 5(g) and 5(h) include days 203 to 209 (July 22 to July 29), a period of warm air temperatures ($T_a$) and water temperatures ($T_w(O)$) in summer 2007. Predicted water temperatures ($T_w(P)$) closely followed the observed water temperatures ($T_w(O)$) during a gradual increase in air temperatures ($T_a$) at both CatBk and LSWM. During most of the days, water temperatures were slightly underestimated and delayed, except at LSWM where a slight overestimation occurred at night.

The predicted hourly water temperatures from the ANN model were used to estimate the daily mean and daily maximum water temperatures (Table 3). The RMSEs for the daily mean water temperatures were slightly better than the ones calculated with hourly water temperatures (ANN model) for all years: the RMSEs were 0.74 °C at CatBk and 0.82 °C at LSWM. The predicted hourly water temperatures from the ANN
Observed water temperatures ($T_w(O)$) and predicted water temperatures ($T_w(P)$) obtained from the ANN model at Catamaran Brook. (continued)
Figure 3 | continued.
model were also used to estimate the maximum daily water temperatures (Table 3). The RMSEs over the entire study period (all years) were 1.04 and 1.09 °C for the predicted maximum daily water temperatures, at CatBk and LSWM, respectively.

DISCUSSION

The objective of the present study was to develop an ANN model to estimate hourly river water temperatures from readily accessible hydrological and meteorological data.
The developed ANN model used hourly air temperature of the present and previous day (°C), daily water level (m), mean daily water temperature (°C) (predicted from a previous ANN model), time of year (day), and time of day (hour). This study showed that ANN models are good for the prediction of hourly river water temperatures, with overall RMSEs of 0.94 °C (CatBk) and 1.23 °C (LSWM) and $R^2$ of 0.967 (CatBk) and 0.962 (LSWM; Table 2). The ANN model generally underestimated the water temperatures at CatBk with a bias of −0.13 °C and a very small bias at
Figure 5 | Observed water temperatures ($T_w(O)$), predicted water temperatures ($T_w(P)$) and air temperatures ($T_a$) for the four detailed time periods at Catamaran Brook and Little Southwest Miramichi.
LSWM (0.02 °C). The training period showed better results than the validation period, which is consistent in modeling.

Most ANN models have estimated daily mean water temperatures. The modeling of hourly stream water temperature in this study was found to be as good as the modeling of daily mean stream water temperatures. For example, Chenard & Caissie (2008), who modeled daily mean stream temperatures in Catamaran Brook using an ANN, achieved similar results with overall RMSE of 0.96 °C and \( R^2 \) of 0.971. Their ANN model performed best using eight input parameters: minimum, maximum, and mean air temperature of current and previous day, day of year and water level. Bélanger et al. (2005) calculated an overall RMSE of 1.06 °C when applying an ANN model at Catamaran Brook (daily mean temperatures). The study by Bélanger et al. (2005) used only air temperature and water level as input parameters. Risley et al. (2005) have modeled hourly water temperatures using a complex ANN model for 148 sites (western Oregon) on a short-term period (June 21 to September 20, 1999). Three different ANN models were developed to estimate hourly water temperatures along first, second, and third order streams using meteorological data (air temperature, dew-point temperature, short-wave solar radiation, air pressure, and precipitation), riparian habitat characteristics (stream bearing, gradients, depth, substrate, wetted widths, and canopy cover), and basins landscape characteristics (topographic and vegetative), acquired by using a geographic information system. Their results showed RMSEs ranging between 0.05 and 0.59 °C and with \( R^2 \) ranging from 0.88 to 0.99. The present study differs from Risley et al. (2005), since it achieved acceptable results using less input parameters with data easily accessible, and was applied for a long-term data series (April 15 to October 31; 1998–2007).

The results of the present ANN model were comparable to and/or better than those of deterministic and stochastic models modeling water temperatures. At CatBk, a stochastic model for daily mean stream temperatures (Caissie et al. 1998) showed a higher RMSE of 1.26 °C. The equilibrium temperature model (Caissie et al. 2005) developed for both CatBk and LSWM also showed slightly poorer performance than the ANN model developed for this study. They showed RMSEs of 1.21 and 1.52 °C for CatBk and LSWM, respectively. Caissie et al. (2007) modeled daily river water temperatures of CatBk and LSWM using a deterministic model. RMSEs were higher than the present study with values of 1.58 and 1.53 °C.

Comparison of seasonal performance showed that the ANN model performed best in summer or autumn, which is consistent with other temperature models (Caissie et al. 1998, 2005; Chenard & Caissie 2008). It could suggest the potential role of discharge in the modeling performance, as low water levels are usually observed in autumn and mid-summer, resulting in more effective thermal exchange and giving better performances. The poorer but still good performance in spring could be explained by the higher discharge caused by snowmelt, resulting in a poorer air to water temperature relationship (Caissie et al. 1998). The performance of the model was closely linked to water levels, meaning that the performance was better when water levels were low. At LSWM, the ANN model performed best in autumn for all the years, whereas at CatBk, some years had their best performance during summer. These
results suggest that the thermal exchange is more efficient for a less sheltered river under low flow (autumn at LSWM). CatBk is more sheltered and could potentially be influenced by other factors (e.g., groundwater) reducing the efficiency of the thermal exchange. For example, Hébert et al. (2011) showed that the impact of groundwater on hourly water temperatures was more significant on smaller streams, like CatBk.

High water levels seemed to have had important influence in the modeling of water temperatures by the ANN model, mostly when water levels experienced an important increase following a storm event or during the spring high flows. For example, the ANN model at CatBk clearly overestimated water temperature in early spring 2003 (days 110 to 120) (Figure 3(f)). This also corresponds to a period of high water levels and low air temperatures (up to −14 °C on day 107 and 108). For instance, on day 143 in 2005 at CatBk, Figure 3(h) shows a clear underestimation of approximately 5 °C of water temperature by the ANN. During this period, water levels showed a sudden increase from 0.390 m in day 142 and increased to 0.647 m. Another peak of underestimation was also observed on day 162 (2006). This day also experienced an increase in water level from 0.344 m (day 161) to 0.570 m (day 162).

**Figure 6** | Predicted ($T_w(P|_{\text{mean}})$) versus observed daily mean water temperatures ($T_w(O|_{\text{mean}})$) and predicted ($T_w(P|_{\text{max}})$) versus observed daily maximum water temperatures ($T_w(O|_{\text{max}})$) at Catamaran Brook and Little Southwest Miramichi.
Early spring and late autumn at LSWM also showed high water levels (Figure 4). However, they were not as marked as in CatBk, since LSWM was less affected by storm events. As in CatBk, spring water temperatures in 2003 (days 105–135) were clearly overestimated by the ANN model (Figure 4(f)). This period also included days with high water levels. The water level was over 1.0 m from day 113 to 135, whereas the mean spring water level at LSWM for the study period (1998–2007) was calculated at 0.740 m.

Daily water levels used in the modeling were estimated using power functions (Caissie 2004). Using hourly water levels instead of daily water levels could potentially improve the modeling, especially during days when discharge varied significantly. However, hourly water levels were not available for the present study.

A comparison of observed versus predicted daily mean and maximum water temperatures was carried out for both CatBk and LSWM (Figure 6). It showed good agreement for the daily maximum with $R^2$ of 0.964 (CatBk) and 0.975 (LSWM) and higher agreement for the daily mean water temperatures with $R^2$ of 0.979 (CatBk) and 0.982 (LSWM). These results showed that hourly water temperatures developed with the ANN model could be used for the prediction of daily mean and maximum water temperatures.

ANN models cannot give any physical explanation of the relationship between the input and output data. These models should therefore be used with caution, especially when using input data that are outside the range of the training period (Risley et al. 2003). Results of ANN models are not easily transferable and they are sometimes dependent on the type of software used for the development of the model. Another disadvantage of the ANN model is that the contribution of input variables is unknown.

Nevertheless, ANN models have major advantages over more commonly used water temperature models, as they do not need many input data. In this case, only air temperature, water temperature and water level time series were used to achieve good predictions. For instance, deterministic models need many hydrological and meteorological parameters that are not always readily available (e.g., solar radiation). Another major advantage of ANNs is that they are easy to use and very simple in their application.

**CONCLUSIONS**

This study showed that an ANN could be an effective tool for the prediction of hourly stream temperatures. ANN models achieved comparable performances to other water temperature models reported in the literature. The ANN model performed best in summer and autumn and showed poorer performance in spring, suggesting the potential role of discharge in the modeling performances. They showed their good generalization capability by modeling long-term water temperature time series. They also have proved to be effective when applied to two thermally different streams providing similar results and performances. As such, ANN models can be considered as an effective modeling tool in water resources and fisheries management.

**ACKNOWLEDGEMENTS**

We would like to acknowledge the Natural Sciences and Engineering Research Council of Canada for funding the present research.

**REFERENCES**


First received 21 January 2013; accepted in revised form 6 January 2014. Available online 4 February 2014