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A comparative study for water temperature modelling in a small basin, the Fourchue River, Quebec, Canada

Jaewon Kwak[1], Andre, St-Hilaire[2] and Fetah Chebana[2]

[1]Nakdong River Flood Control Office, Busan, South Korea,
[2]INRS-ETE, INRS, Quebec, Canada,
Corresponding author : A. St-Hilaire: email: Andre.St-Hilarie@ete.inrs.ca

Abstract

Analysis and forecasting of water temperature are important for water-ecological management. The objective of this study is to compare models for water temperature during the summer season for an impounded river. In a case study, we consider hydro-climatic and water temperature data of the Fourchue River (St-Alexandre-de-Kamouraska, Quebec, Canada) ~~from~~ between 2011 ~~to~~ and 2014. Three different models were applied, which are broadly characterized as deterministic (CEQUEAU), stochastic (Auto-regressive Moving Average with eXogenous variables or ARMAX) and nonlinear (Nonlinear Autoregressive with eXogenous variables or NARX). The efficiency of each model was analyzed and compared. The r~~R~~esults show that the ARMAX is the best performing water temperature model for the Fourchue River and the CEQUEAU model also simulated water temperature adequately without the overfitting issues that seem to plague the autoregressive models.

Keywords water temperature; CEQUEAU; ARMAX; NARX

1. INTRODUCTION

Water temperature affects physical and biological processes in the river system and is one of the most important physical characteristics for aquatic organisms (Beschta *et al.*~~,~~ 1987~~,~~; Hammitt and Cole~~,~~ 1998~~,~~; Coutant~~,~~ 1999~~,~~; Nunn *et al.*~~,~~ 2003). Among them, fish species are sensitive to water temperature for growth rate and spawning (Ojanguren *et al.*, 2001; Selong *et al.*, 2001; Lessard and

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Hayes, 2003; Handeland *et al*., 2008). Furthermore, it is also an important factor for water quality (Singh *et al*., 2004; Morrill *et al*., 2005; Chang, 2008). There are many models and studies which contribute to more accurate water temperature simulations and forecasts. Caissie (2006) suggested that most models can be classified into three categories: regression-based, deterministic and stochastic. Following the early work of Johnson (1971) and Kothandaraman (1972), parametric statistical models such as regressions have been applied in many studies (Benyahya *et al*., 2007a). Simple linear regressions have been used with air temperature as a predictor (Crisp and Howson, 1982; Mackey and Berrie, 1991; Stefan and Preud'Homme. 1993). Also, multiple regression (Jeppesen and Iversen, 1987; Jourdonnais *et al*., 1992), logistic regression (Mohseni *et al*., 1998; Mohseni and Stefan, 1999), ridge regression (Ahmadi-Nedushan *et al*, 2007) and Gaussian-process regression (Grbi• *et al*, 2013) have been used in water temperature models.

Deterministic models are based on the governing laws of heat exchanges and they consider the different energy fluxes and (in some cases) mixing process in the rivers with various degrees of complexity (Morse, 1970; Caissie, 2006, 2007). Due to this, they are widely used in applications with complex thermal in/outflows (Sinokrot and Stefan, 1993; Kim and Chapra, 1997; Younus *et al*., 2000; Danner *et al*., 2012). However, these models typically require more data than statistical models (Benyahya *et al*., 2007b). In contrast, stochastic models often require one or few predictors that are correlated with water temperature (Caissie, 1998; Webb *et al*., 2008). This category of models is very efficient when air temperatures are the only available data (Caissie, 2006). Hence, they have been widely applied to estimate weekly/monthly water temperature (Mohseni *et al*., 1998; Benyahya *et al*., 2007b, 2008), daily water temperature (Caissie *et al*., 1998, 2001; Pal'shin and Efremova, 2005; Ahmadi-Nedushan *et al*, 2007; Larnier *et al*., 2010) and hourly temperature (Mestekemper *et al*., 2010; Pike *et al*., 2013; Jeong *et al*., 2013). Furthermore, Artificial neural networks (ANN), which belong to the non-parametric category **(**Chenard and Caissie, 2008; Sahoo *et al*., 2009; DeWeber and Wagner, 2013; Hadzima-Nyarko *et al*., 2014), k-nearest neighbors algorithm (k-NN), which is a nonlinear dynamic model (Benyahya *et al*., 2008; Nowak *et al*., 2010; St-Hilaire *et al*., 2012; Caldwell *et al*., 2013) and dynamic chaotic models (Sahoo *et al*., 2009) have been applied to estimate water temperature. While the literature on water temperature modelling is growing rapidly, relatively few

comparative modelling studies have been completed on rivers with dams, especially in Canada.

The objective of this study is therefore to investigate the simulation efficiency of a number of water temperature models using hydro-climatic variables in the context of regulated flows. The models were compared on the Fourchue River basin, a forested catchment on which there is a managed reservoir. The Fourchue River has been previously studied by Beaupré (2014). She compared a deterministic model (SNTEMP; Bartholow, 1995) and a geostatistical model (Guillemette et al., 2009) both upstream and downstream of the dam. Beaupré (2014) showed that the geostatistical model outperformed SNTEMP for directly predicting temperature metrics that are relevant for salmonids, especially when these metrics are calculated using simulated maximum temperatures. For this follow-up study, hydro-climatic data were collected from 2011 to 2014 and models that represent three categories: deterministic, stochastic and nonlinear were used.

2. STUDY AREA AND DATA

The Fourchue River, with a drainage basin of 261 km^2, is a tributary of the Du-Loup River, located in the eastern Quebec region, Canada. The Fourchue River is regulated by the Morin Dam, with flows of between 0.06 ~~to~~ and 4.0 $m^3/$, which discharge~~d~~ from the epilimnion zone of the reservoir (184 ~~E.L.m~~ to 188 E.L.m).

Fig. 1 Study area and measuring station.

Many factors influence water temperature variability, which can be classified into four groups; atmospheric, topographic, hydrologic and streambed conditions. Selected predictors included atmospheric variables because atmospheric conditions are mainly responsible for the heat exchange processes. In addition, stream discharge was selected because it influences the heating capacity by determining the volume of water in the river reach (Caissie, 2006), but also because all models compared in this study need to be able to account for the impact of impoundment and the associated regulated flows.

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Atmospheric variables used as potential predictors include air temperature, solar radiation, relative humidity and wind speed, which are known to be related to water temperature. Water temperature were obtained during the summer seasons (June to September) from 2011 to 2014 with Hobo Pro V2 thermographs (±~~–~~0.2° ~~–°C~~C) sampling at 15~~–~~min~~utes~~ interval~~s,~~ and hourly solar radiation data were measured with a Kipp and Zonen pyranometer (SP-LITE, ± 10uV/W/m2), connected to a Campbell Scientific CR1000 datalogger, powered by a solar panel and a 12~~-~~-V battery. The water temperature loggers were deployed over a 8~~-~~-km river reach, from directly downstream of the Morin D~~d~~am to its confluence with the Du-Loup River. Air temperature and relative humidity were obtained from the Fourchue River meteorological station (Environment Canada; http://climate.weather.gc.ca). Also, hydro-physiographic properties of the Fourchue River basin, required to run the deterministic model, were extracted from a 3 km ~~*~~× 3 km grid DEM and l~~L~~and-use map (http://srtm.csi.cgiar.org/) (Fig~~ure~~ 2).

Fig. 2 Hydro-physiographical characteristics of the study area~~.~~, showing ~~Map shows~~ land use, whole squares (elementary hydrological units) and arrows indicat~~e~~ing water routing used for the deterministic (CEQUEAU) model.

3. METHODOLOGY

3.1 Test statistics for selection of model and predictors ~~selection~~

Given the plethora of potential models, five test statistics were used to identify the main characteristics of collected temperature data and potential predictors in order to select reasonable candidate models to simulate water temperatures of the Fourchue River. The considered tests are: the Spearman rank correlation coefficient for randomness (Myers and Well, 2003), the Ljung-Box Q test for autocorrelation (Ljung, 1978), Levene's test for heteroscedasticity (Levene, 1960), the Lyapunov exponent test (Bask and Gençay, 1998) and the BDS statistics test for chaotic characteristic (Brock et

al. 1987) of data time series.

Mutual Information (I) was also used to select appropriate predictors among the collected data set~~.~~, where I(X;Y) is a measure of the amount of information that one continuous random variable X contains about another continuous random variable Y (Cover and Thomas, 2006):

$$\mathrm{I(X:Y)} = \int_Y \int_X p(x,y)\, \log\left(\frac{p(x,y)}{p(x)\,p(y)}\right) dx\, dy \qquad (1)$$

where, $p(x)$ and $p(y)$ are the marginal probability density functions of X and Y and $p(x,y)$ is the joint probability density function. The mutual information will be larger for variables which have a stronger relation and vice versa. So, predictors selection based on value of I(X:Y) of each input variable with the output variable can be used to identify the most important predictors (Battiti, 1994).

3.2 Water t~~T~~emperature m~~M~~odels

Given the large number of available water temperature models in use, the aforementioned criteria were used to find the most suitable ones for the Fourchue River. Three types of candidate model~~s~~ were considered: (a~~i~~) ~~one~~ a deterministic model called CEQUEAU (Morin *et al*., 1998); (b~~ii~~) the ARMAX (A~~a~~utoR~~r~~egressive-M~~m~~oving A~~a~~verage with eX~~x~~ogenous terms) model, which is in the stochastic category; and (c~~iii~~) the NARX (Nonlinear AutoRegressive model with eXogeneous input) for the nonlinear approach.

The CEQUEAU model is a hydrological model that is combined with a heat budget model and has shown applicability in Canada (Morin and Slivitzky, 1992; St-Hilaire *et al*., 2000, 2003; Seiller and Anctil, 2014) and in other countries (Dibike and Coulibaly, 2005; Ba *et al*., 2009; Sauquet *et al*., 2009; Eleuch *et al*., 2010). The ARMAX model is useful when the data are noisy, so it has the potential to show good results and provide flexibility in describing the properties of the noise associated with water temperature time series (Breaker and Brewster, 2009) and NARX models also show good performance for several types of chaotic time series (Diaconescu, 2008).

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3.2.1 CEQUEAU model: deterministic approach

The CEQUEAU model is a semi-distributed hydrologic model which takes into account the hydro-physiographic characteristics of the basin (Morin *et al*., 1981). It is based on a water balance calculations and subsequent runoff generation through a set of elementary hydrological units called "whole squares", which are further divided in "partial squares" according to the water divide (Morin *et al*., 1998). The CEQUEAU model comprises two functions to describe the runoff mechanism and upstream-downstream routing: (a) the production function represents vertical water routing from rainfall, snowmelt, infiltration and evapotranspiration used in water-balance calculations; and (b) the routing function is used to estimate the amount of water transiting to the downstream partial squares and ultimately to the outlet of the basin in the drainage network (Figure 3).

Fig. 3 Schematic description of CEQUEAU model:: *(a) production function (b) routing function (Morin, 2007).*

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Prior to modelling water temperature, the hydrological model component of CEQEAU needs to be calibrated against observed flows and/or water levels. Model parameters were adjusted by hand using water level and runoff data of the Morin Dam between June 2011 and September 2014 (Figure 4). Subsequently, the water temperature module of the CEQEAU model was used (Morin *et al*, 1998). This component computes a heat budget on each elementary hydrological unit (whole squares) based on the volume of water modelled by the hydrological module of CEQUEAU. Heat budget terms include incoming short wave solar radiation, net longwave radiation, latent heat, sensible heat, heat advected from upstream, heat loss downstream and local contributions from groundwater and interflow. Each heat budget term can be adjusted using a weighing coefficient. Average water temperatures are thus estimated at a daily time step.

Fig. 4 Observed and simulated flows with CEQUEAU hydrological model for both

calibration and validation periods (June~~,~~ 2011 to September~~,~~ 2014).

3.2.2 ARMAX: stochastic approach

The ARMAX model is useful when the input data have noise, has more flexibility than other stochastic model, such as ARMA or ARX, and is defined as:

$$\mathrm{A}(z)y(t) = B(z)u(t-k) + C(z)e(t) \quad (2)$$

w~~W~~here $y(t)$ is the output, $u(t)$ is the input, $e(t)$ is the system error and k is the time delay of the system. The terms $A(z)$, $B(z)$, and $C(z)$ are polynomial with respect to the backward shift operator z^{-1} and defined as:

$$\mathrm{A}(z) = 1 + a_1 z^{-1} + \cdots + a_{t_a} z^{-t_a}$$
$$\mathrm{B}(z) = b_0 + b_1 z^{-1} + \cdots + b_{t_b} z^{-(t_b-1)}$$
$$C(z) = 1 + c_1 z^{-1} + \cdots + c_{t_c} z^{-t_c} \quad (3)$$

In this study, the ARMAX model has second order AR and MA processes and one day time lag (k), which were optimized by trial and error method (ARMAX(2,2,1)).

3.2.3 NARX~~:~~ nonlinear approach

Non-linear AutoRegressive model with eXogeneous input (NARX), is a special form of recurrent neural network with the outputs fed back to the input by delay line (Haykin, 1999). It has been demonstrated that they are well suited for modeling nonlinear and chaotic time series (Lin *et al*, 1996; Gao and Joo, 2005) and also solve vanishing gradient problem, which occur in the prediction of nonlinear data (Haykin, 1999). A NARX model can be expressed as ~~(Eq(4) and~~ Figure 5):

$$y_t(t+1) = \begin{Bmatrix} \emptyset(u(t), y_i(t), & i = 1 \\ y_i(t), & i = 2,3,\ldots,k \end{Bmatrix} \quad (4)$$

wWhere the output $y_t(t+1)$ and $y_i(t)$, $i = 1, 2, \ldots, k$, are state variables of a recurrent neural network that contains feed-back connection for water temperature of the previous time step. t denotes the time series index set and $\emptyset$ denotes the neural network system. The Levenberg-Marquardt-QNBP algorithm was used to train the network and to optimize the parameters. It is known to show good results for non-linear problems such as related meteorological and hydrological data (Battiti, 1989). NARX model of this study has 12 hidden layers that include one feed-back layer with one day time lag (k) for water temperature.

Fig. 5 NARX network schematization (Jose *et al.*, 2008), where. $u(t)$ *is the input set,* $y_i(t)$ *is the exogeneous input, k is the input delay and each circle represents an artificial neuron.*

To compare the results of each model, Root Mean Square Error (RMSE (Root Mean Square Error; Hyndman and Koehler, 2006; Eq. 5), Bias (Eq. 6) and Nash–Sutcliffe model efficiency coefficient of model efficiency (*E*; Nash and Sutcliffe, 1970; Eq. 7) were applied:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(O_{obs}-O_{sim})^2}{n}} \quad (5)$$

$$\text{Bias} = \frac{\sum_{i=1}^{n}(O_{obs}-O_{sim})}{n} \quad (6)$$

$$\text{Nash E} = 1 - \frac{\sum_{i=1}^{n}(O_{obs}-O_{sim})^2}{\sum_{i=1}^{n}(O_{obs}-\overline{O_{obs}})^2} \quad (7)$$

where O_{obs} and O_{sim} are the observed and simulated values at the same time step, $\overline{O_{obs}}$ denotes mean value of O_{obs}, n denotes the number of observations. The RMSE describes an average measure of the error in prediction but it doesn't provide any information on phase differences. The bias represents the mean of all the individual errors and shows whether the model over or under estimates. The Nash–Sutcliffe model efficiency coefficient, *E*, has been widely used to assess the

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predictive power of hydrological models (Moriasi *et al*., 2007).

4. MODEL AND PREDICTOR SELECTION

We applied five test statistics (Spearman rank correlation coefficient, Ljung-Box Q, Levene, Lyapunov exponent and BDS test) to determine the characteristics of the collected data (water and air temperature, runoff, solar radiation, relative humidity and wind speed). Through the Spearman Rank Correlation and Ljung-Box Q tests, all time series except solar radiation, which is a truly random series (calculated 0.154 *versus* critical value 1.96 in the Spearman Rank Corr. Coeff. test, and *p*-value 0.997 in Ljung Box-Q test), were identified as stochastic time series. Other test results are shown in Table 1.

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~~**Table 1** Test statistics for each dependent and independent variables.~~

As the result of test statistics indicate, solar radiation data are categorized as a random series, runoff is a chaotic time series which has heteroskedasticity, relative humidity is also a chaotic time series and other data time series (water temperature, air temperature and wind speed) are categorized as nonlinear stochastic time series. Water temperature (target variable) can be classified as a nonlinear stochastic time series and most of the input predictors are chaotic, nonlinear and stochastic time series. Therefore, models such as multiple regression or zero-mean AR(1) models that cannot account for such characteristics are not eligible to simulate water temperatures in the Fourchue River. From the conclusions drawn from Table 1, the NARX and ARMAX models were selected because they are adapted to model time series such as water temperature and they show good results with chaotic and nonlinear data (Diaconescu, 2008; Diversi *et al*., 2011). These models will be compared to the deterministic model (CEQUEAU).

Also, selection of the appropriate inputs is one of the main challenges. For the stochastic models, this selection can be done by trial and error models with different number of input variables (Grbi• *et al*., 2013). However, that trial and error method can be time-consuming and lead to poor

performance for neural networks (Haykin, 1999; Maier and Dandy, 2000). So, mutual information theory was employed to select the most important predictor variables for the NARX models. As the result of the computation of mutual information, air temperature (1.28), runoff (0.82) and relative humidity (1.09) are shown to have more meaningful mutual information value with water temperature than solar radiation (0.30) and wind speed (0.09). The positive high value of the mutual information is indicative that the potential predictor has a stronger relation with the dependent variable, i.e. water temperature (May *et al*., 2008; Sahoo *et al*., 2009). So, air temperature, runoff and relative humidity were selected as the appropriate predictors.

To corroborate the results of the Mutual Information analysis, a trial and error jackknife method was used. One of the hydro-climatic variable was removed from the input data set, which consist of air temperature, runoff, relative humidity, solar radiation and wind speed. Then the NARX and ARMAX models were simulated 200 times with each removed data set. Figure 6 shows boxplots of the evaluation result of simulation with each removed set.

Fig. 6 Performance statistics from jackknife simulations to select predictor~~:~~; (a) RMSE of NARX, (b) *E~~Nash~~* of NARX, (c) Bias of NARX, (d) RMSE of ARMAX, (e) *~~Nash~~ E* of ARMAX, and (f) Bias of ARMAX.

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As the mutual information results and boxplots show and as expected, air temperature is the most suitable predictor for water temperature simulation. Runoff and relative humidity are also revealed as suitable independent predictors. The fact that runoff was included in the list of predictors is of the utmost importance, given that the river is regulated and that the models must be able to account for flow management. On the contrary, the inclusion of solar radiation and wind speed showed no improvement and in some cases, slightly better results were obtained if they were removed from the input data set.

Also, as shown in F~~f~~ig.~~ure~~ 4, the summer season (June~~. to~~ – September~~.~~) of 2011 has a high runoff event (peaking at over 30 m^3/s), while the other periods do not include such extreme events (i.e.

flows remain below 10 m^3/s). In spite of the inclusion of flow as a predictor, model performances are not as good during high runoff period as for the rest of the time. Longer time series will be required to improve model calibration on the Fourchue River.

5. RESULTS AND DISCUSSION

To partially overcome the challenges associated with the relatively small time series that can be used form model calibration, we divided the data set in two cases and perform calibration and validation in both cases.

Case 1: 2011, 2012, 2013 as calibration period and 2014 as validation period.

Case 2: 2012, 2013, 2014 as calibration period and 2011 as validation period.

The calibration results with selected models and predictors, which consist of air temperature, runoff and relative humidity, are shown in Ffigures 7 and 8.

Fig. 7 Calibration results for Case 1:: (a) CEQUEAU model, (b) ARMAX, (c) NARX.

Fig. 8 Calibration results for Case 2:: (a) CEQUEAU model, (b) ARMAX, (c) NARX.

The ARMAX model shows the best results among all the selected models, with an RMSE, Bias and Nash values of 0.56 °C, 0.03 °C and 0.96, respectively, during the calibration period. It is closely followed by the other model with an autoregressive component, i.e. the NARX model (see Table 2). The CEQUEAU model simulation is characterized by a larger bias than the statistical models in cases 1 and 2, mostly caused by an underestimation of the warm period in 2012. Validation results are shown in Figures 9 and 10 and performance metrics are provided in Table 2. As it is often the case, all models show higher RMSE and lower Nash coefficient values for the validation than the calibration phase, except for the CEQUEAU model, which shows similar results for both calibration

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and validation phases albeit with a higher bias (Table 2). Overall, the ARMAX model has the best performance, in spite of a slightly higher RMSE and lower NASH value than the deterministic model during one validation phase (in Case 2, Table 2).

Fig. 9 Validation results for Case 1; (a) CEQUEAU model, (b) ARMAX, (c) NARX.

Fig. 10 Validation results for Case 2; (a) CEQUEAU model, (b) ARMAX, (c) NARX.

Table 2 Calibration and validation performance statistics for each Case.

The CEQUEAU model showed some modeling potential, in spite of a systematic negative bias (-0.41°C for calibration and -1.06°C for validation phase). It seems that the proximity of the monitoring station to the dam, may be one cause of the bias. The thermal regime in the Fourchue River is very strongly influenced by the presence of the reservoir. The travelling time is very short between the dam and the monitoring station (<0.5 day) and thus, the reservoir thermal regime, which affects the thermal regulation in the lower reach of the Fourchue River, may come into play. For instance, there may be some occasional stratification and mixing of the water column in the reservoir that may modulate the temperature of the discharged water. Such an affect is not accounted for by CEQUEAU. In order to account for stratification, CEQUEAU would need to be coupled to a lake or reservoir temperature model. If stratification were present, it would also affect the ARMAX and NARX models. However, in spite of the fact that water was drawn from the reservoir epilimnion, stratification and mixing may have been an occasional source of error.

Also, in the validation result of Case 2 (Figure 10), all of the selected models, except CEQUEAU show highly over and under estimated water temperatures between August 27 August, 2011 to and September 8, September 2011 (Figure 10(b) and 10(c)). The high rainfall-runoff events in 2011 seem to be one of the causes of this discrepancy (Figure 4).

Given their autoregressive structure, the ratio of the training sample size to the number of

weights is 29 (Wang et al., 2005) and overfitting may have occurred for ARMAX and NARX during the calibration phase in Case 2. If this is the case, these models may lack the required robustness to be operationally implemented. Longer time series would be required to fully investigate this. This phenomenon shows the potential disadvantage of the statistic and stochastic models. The CEQUEAU model shows worse results than ARMAX and NARX model, but its performance is more constant throughout the calibration and validation periods, with 0.8°C in RMSE and 0.9 in Nash coefficient (Table 2). Otherwise, the deterministic model (CEQUEAU) will be good alternative when the hydro-climatic data has extreme events which are expected as the cause of overfitting issue.

CONCLUSIONS

This study performed a comparative analysis of three models used to simulate water temperatures in the Fourchue River, Quebec, Canada. The main conclusions are:

1. As shown by the result of test statistics, water temperature data and most input variables of the Fourchue River were proven to be chaotic, nonlinear and stochastic time series. Simple statistic models such as linear regression may prove to be inadequate. For this reason, more sophisticated time series models (ARMAX and NARX) were tested.
2. The CEQUEAU showed weaker performances than ARMAX and NARX, with systematic bias. But its performance is constant throughout with 0.8°C in RMSE and 0.9 in Nash coefficient and there is no indication of overfitting.
3. The fact that the ARMAX model proved to have the best performance is not surprising, given the non-linear autoregressive nature of the model. Water temperatures in any river have strong autocorrelation. This phenomenon is exacerbated in the Fourchue River, because of the presence of the reservoir, which has a strong dampening effect.
4. Two models except CEQUEAU show potential overfitting, as shown by their weaker performance in the validation phase in Case 2. Therefore, the CEQUEAU model (deterministic approach) will expect the stable performance for the Fourchue River.

Acknowledgements

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[**Table 1.** Test statistics for each dependent and independent variables.; W(m): indicated embedding dimension; 95% C.I.: indicated 95% confidential inbound for test; and rejected data are marked as in bold character].

Test Stat.	Value	Dependent and independent variables						
		Water Temp. of Upstream	Water Temp. of Downstream (Target)	Air Temp.	Runoff from Fourchue Ddam	Solar Radiation	Relative humidity	Average Wind Speed
Levene's test	*p*-value	**0.448**	**0.877**	**0.548**	0.000	**0.239**	**0.992**	**0.657**
Lyapunov exponent Lamda test	calculated	1.82 x 10^{-6}	1.62 x 10^{-6}	0.000	**1.000**	0.0003	**0.274**	0.000
	95% C.I.	-0.0653	-0.1486	-0.3825	0.1245	-0.1868	-0.2372	-0.6811
BDS test	W(2)	**79.02**	**62.15**	**20.96**	**16.49**	**2.82**	**19.58**	**2.53**
	W(3)	**85.80**	**67.11**	**20.30**	**15.17**	0.81	**18.29**	**2.42**
	W(4)	**94.52**	**73.32**	**19.81**	**13.79**	0.46	**17.12**	**2.05**
	W(5)	**106.87**	**82.27**	**19.86**	**12.74**	0.54	**16.62**	**1.74**
	95% C.I	[-1.96, +1.96]						
Result		Nonlinear stochastic time series	Nonlinear stochastic time series	Nonlinear stochastic time series	Chaotic time series with hetero-skedasticity	Random series	Chaotic time series	Nonlinear stochastic time series

Comment [F14]: Please edit tables:
-remove [ ] from the caption and remove bold and italics (I have done Table 1 caption)
-remove shading/colour and all lines except horizontal line above and below the table and below the header row
remove upper case initials except for the first word in each heading unless proper noun, e.g. Dam

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-remove upper case initials except for the first word in each heading unless proper noun, e.g. Dam

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[Table 2. Calibration and validation performance statistics for each Case]

CASE	Model	Calibration phase			Validation phase		
		RMSE(°C)	NASH	BIAS(°C)	RMSE(°C)	NASH	BIAS(°C)
CASE 1	CEQUEAU	0.80	0.91	-0.36	0.77	0.91	-1.14
	ARMAX	0.57	0.96	0.04	0.68	0.94	0.82
	NARX	0.67	0.94	0.11	0.80	0.91	0.75
CASE 2	CEQUEAU	0.78	0.92	-0.45	0.83	0.88	-0.97
	ARMAX	0.55	0.96	0.01	1.14	0.83	1.60
	NARX	0.65	0.94	-0.18	1.46	0.77	4.20
Overall Result	CEQUEAU	0.79	0.92	-0.41	**0.80**	**0.90**	**-1.06**
	ARMAX	**0.56**	**0.96**	**0.03**	0.91	**0.89**	**1.21**
	NARX	0.66	0.94	-0.18	1.13	0.84	2.48

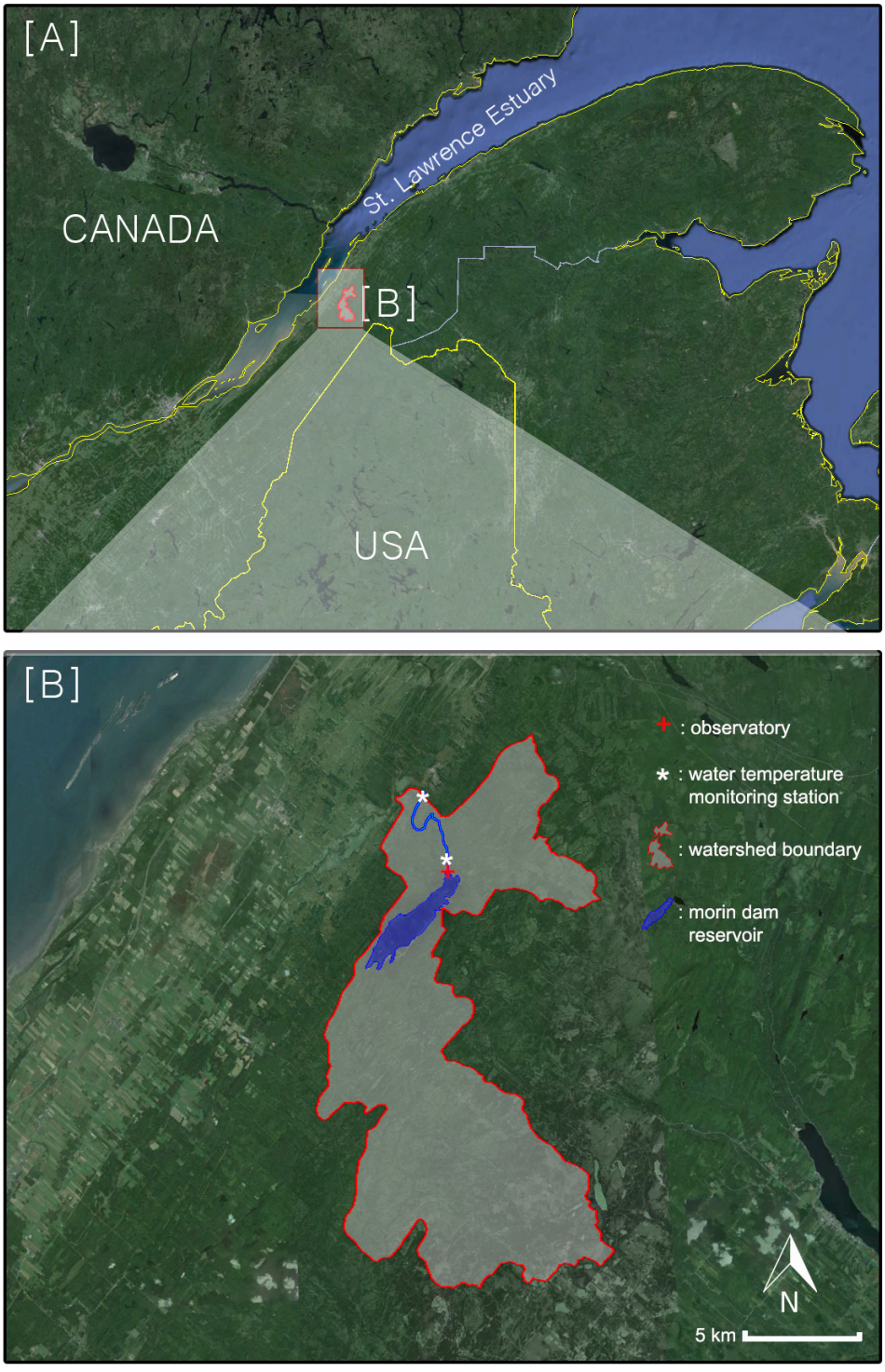

Fig. 1 Study area and measuring station.

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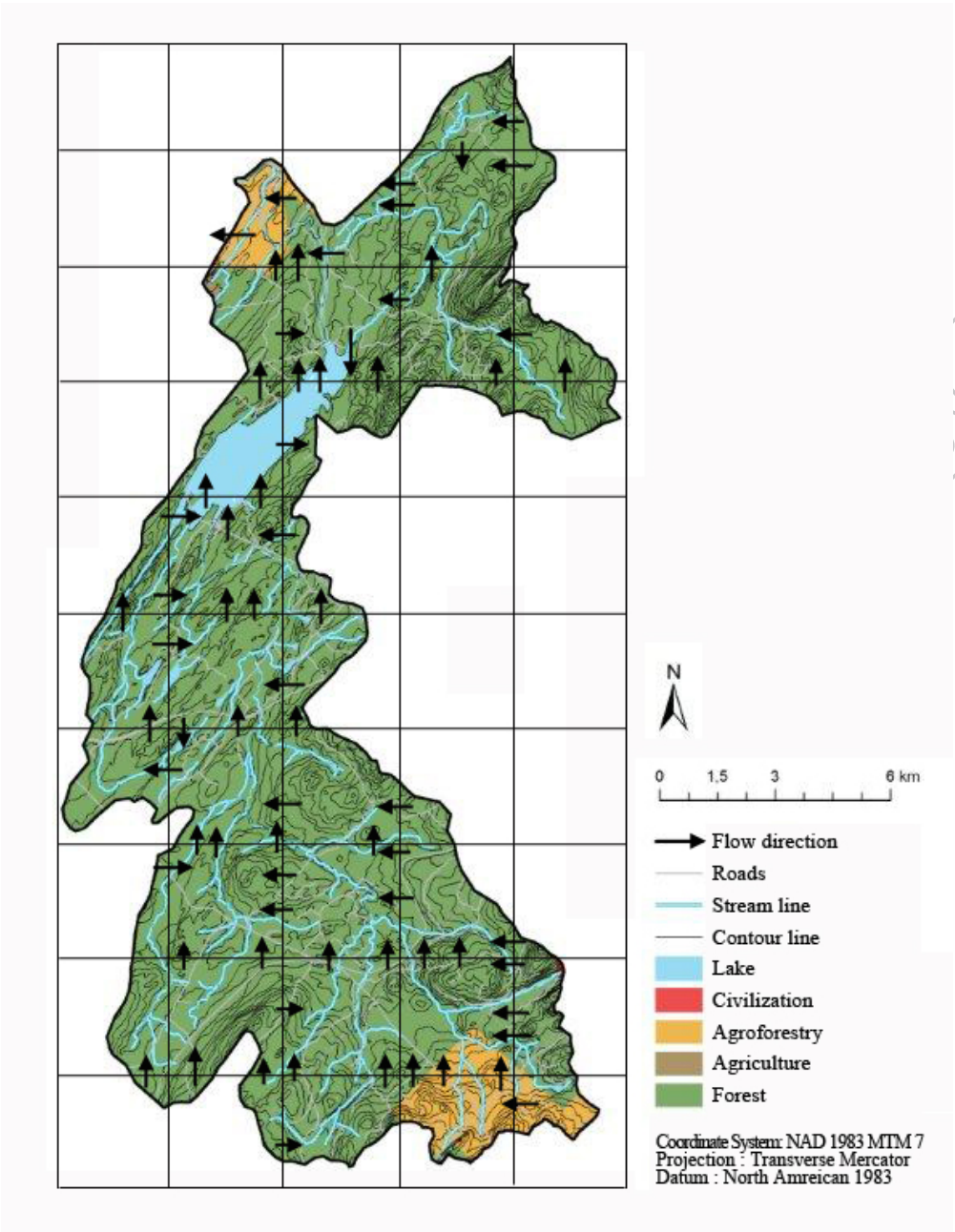

Fig. 2 Hydro-physiographical characteristics of study area. Map shows land use, whole squares (elementary hydrological units) and arrows indicate water routing used for the deterministic (CEQUEAU) model.

Comment [F17]: in fig. 2, after Datum: North, you have spelled American incorrectly (Amreican)

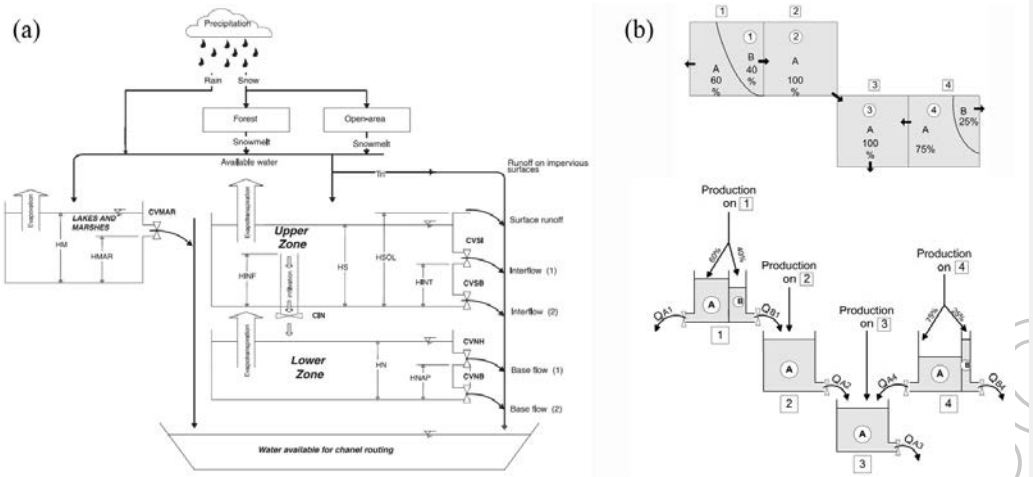

Fig. 3 Schematic description of CEQUEAU model; (a) production function (b) routing function (Morin, 2007).

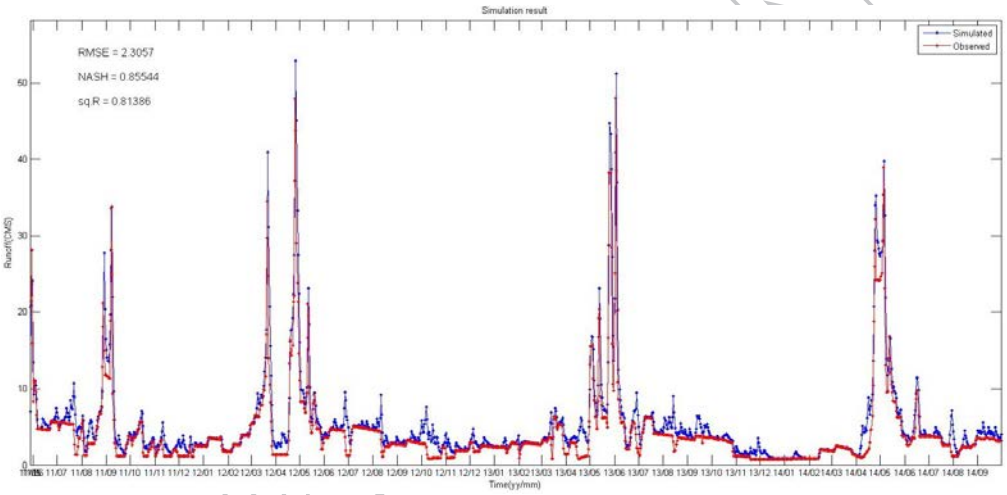

Fig. 4 Observed and simulated flows with CEQUEAU hydrological model for both calibration and validation periods (June, 2011 to September, 2014).

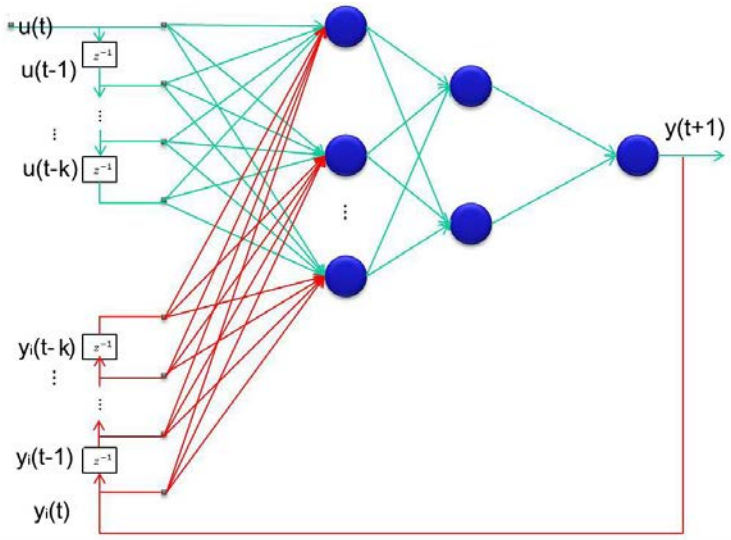

Fig. 5 NARX network schematization (Jose *et al*., 2008). $u(t)$ *is the input set,* $y_i(t)$ *is the exogeneous input, k is the input delay and each circle represents an artificial neuron.*

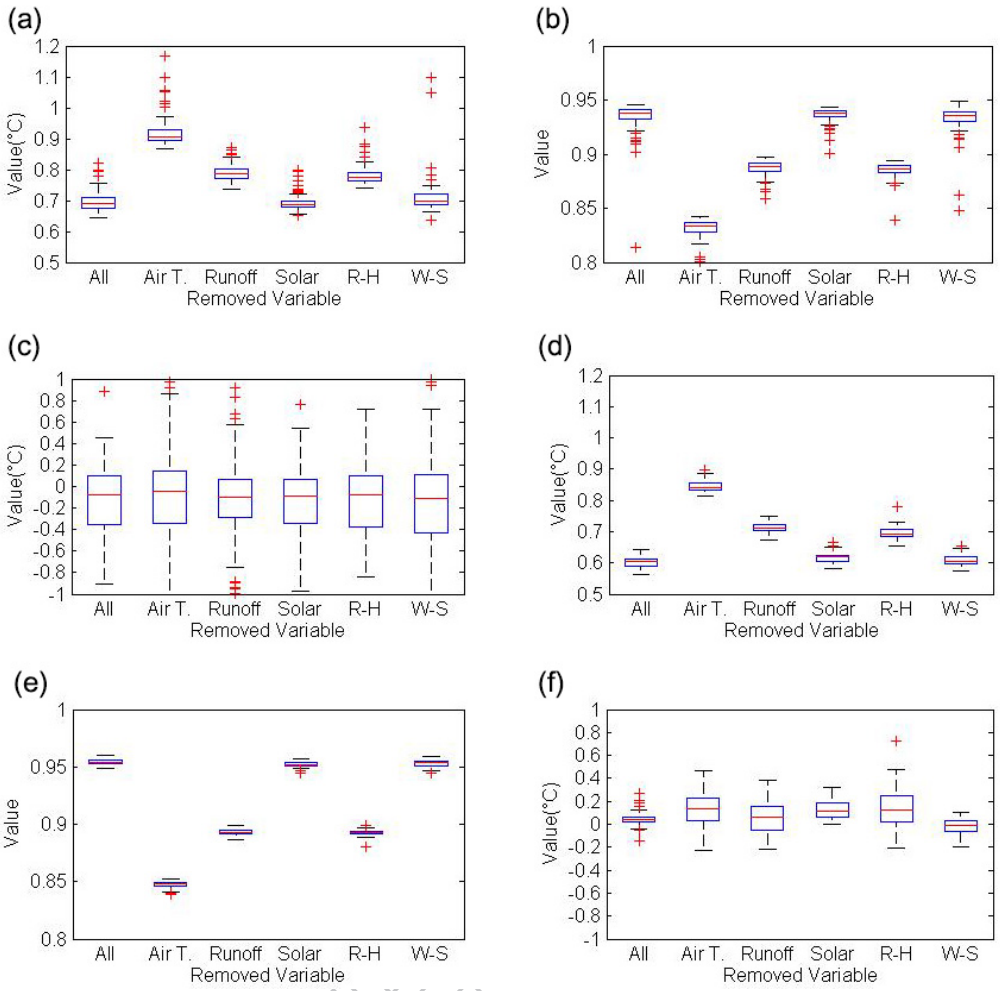

Fig. 6 Performance statistics from jackknife simulations to select predictor; (a) RMSE of NARX, (b) Nash of NARX, (c) Bias of NARX, (d) RMSE of ARMAX, (e) Nash of ARMAX, (f) Bias of ARMAX.

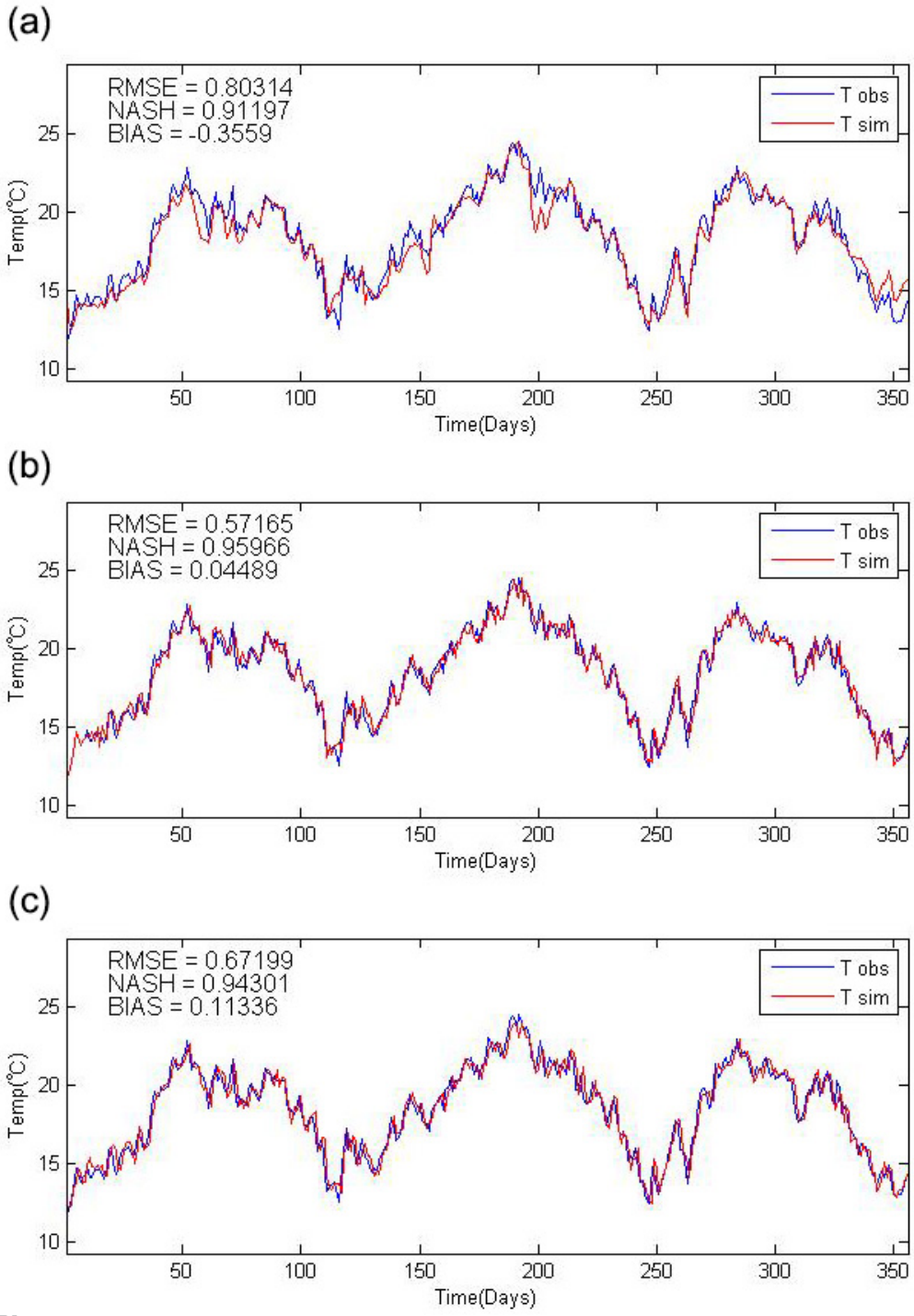

Fig. 7 Calibration results for Case 1; (a) CEQUEAU model, (b) ARMAX, (c) NARX.

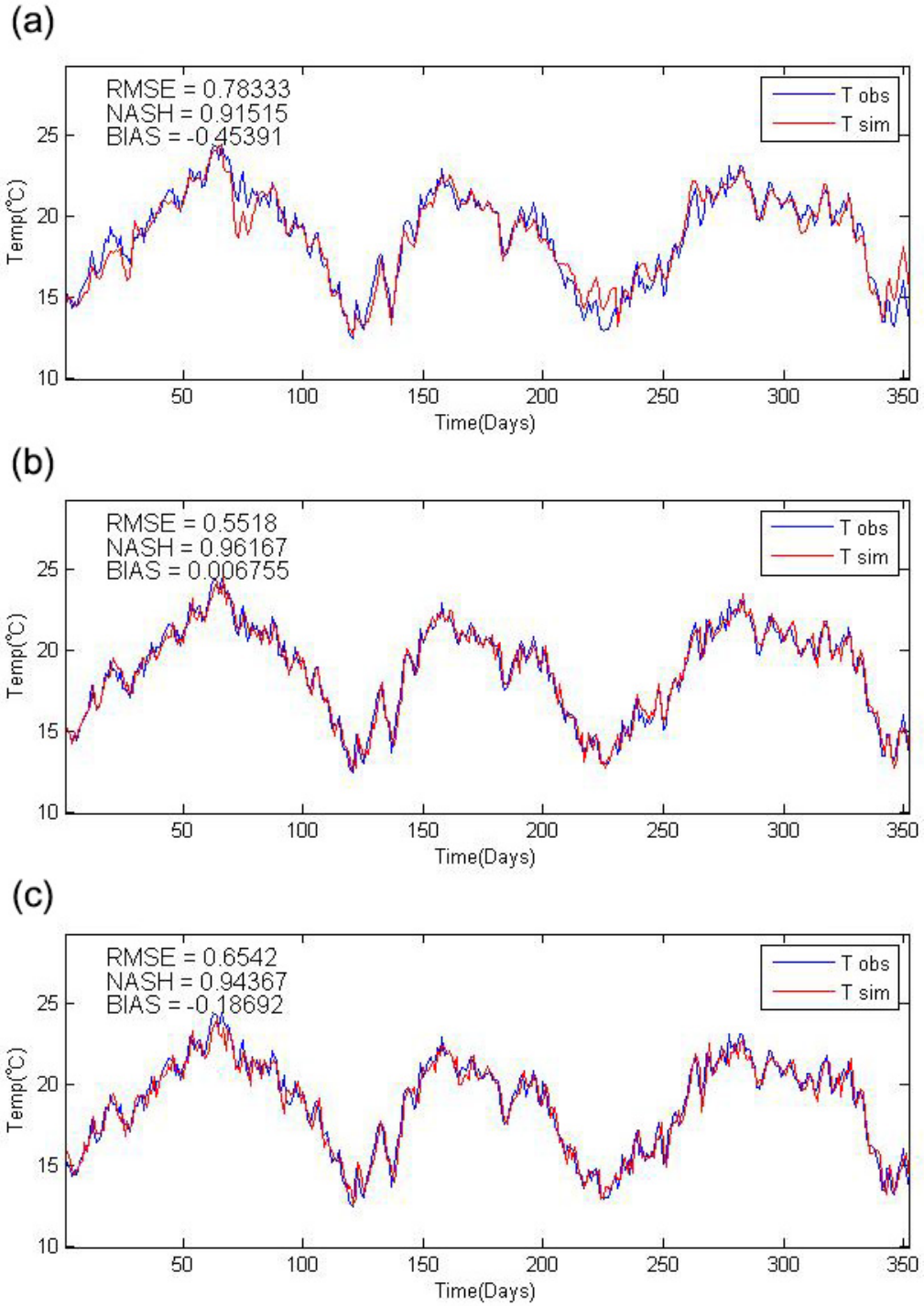

Fig. 8 Calibration results for Case 2; (a) CEQUEAU model, (b) ARMAX, (c) NARX.

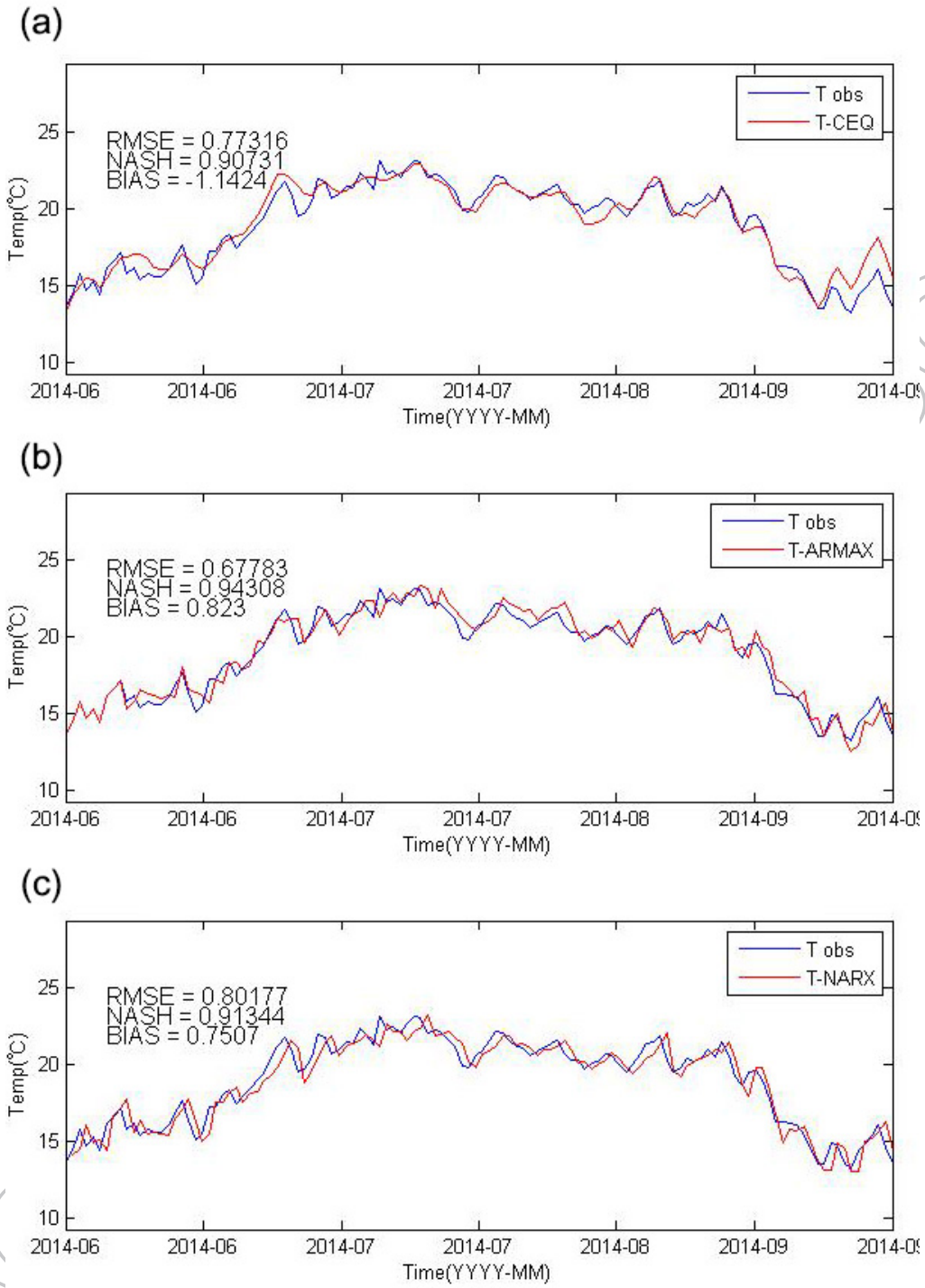

Fig. 9 Validation results for Case 1; (a) CEQUEAU model, (b) ARMAX, (c) NARX.

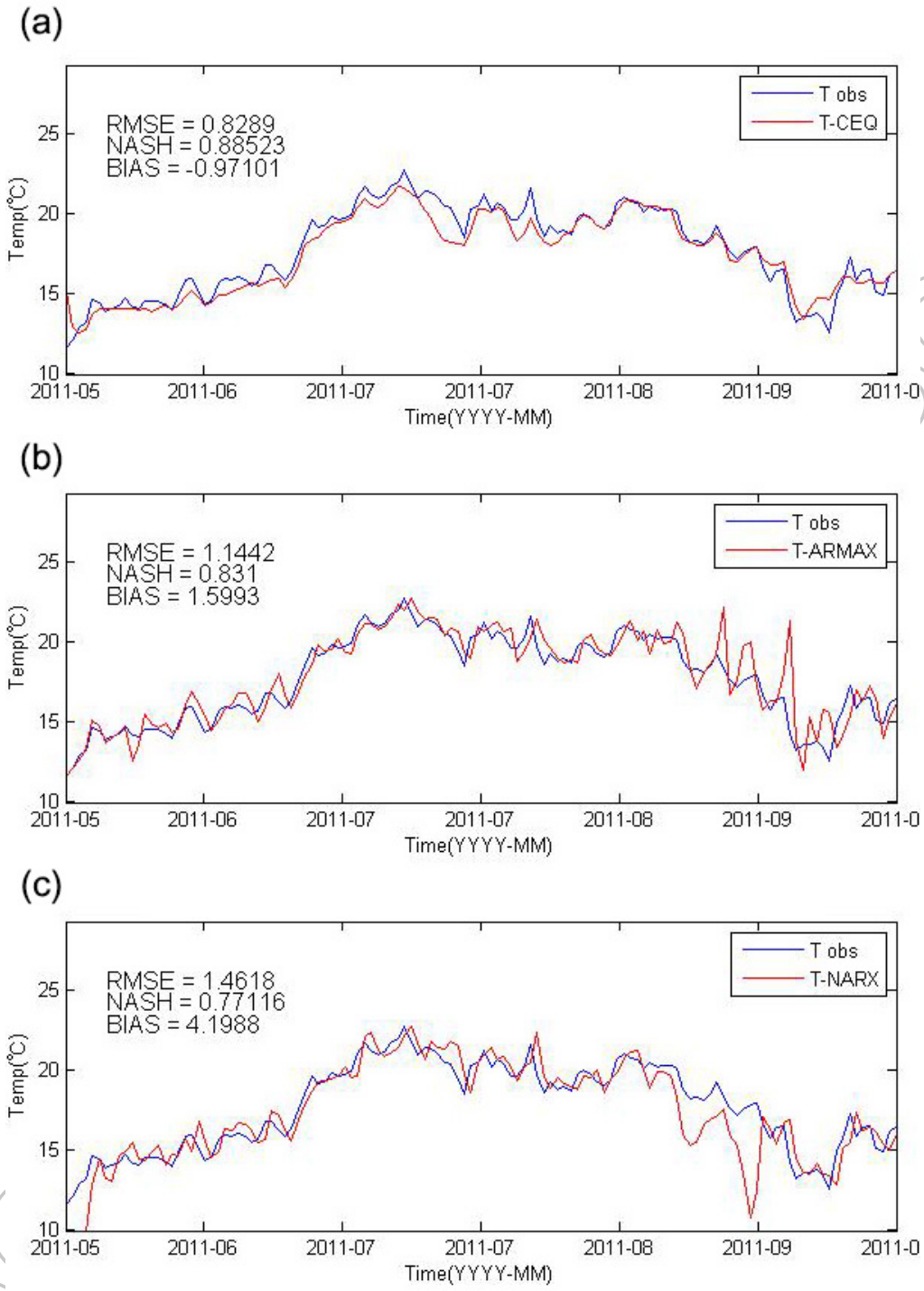

Fig. 10 Validation results for Case 2; (a) CEQUEAU model, (b) ARMAX, (c) NARX.