Predicting Sediment Concentrations Using a Nonlinear Autoregressive Exogenous Neural Network

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Abstract. An application of a Nonlinear Autoregressive Exogenous Neural Network (NARX) to predict total suspended sediment concentrations (SST) for a water body located in central Chile (Francia Creek, Valparaiso) is presented. Input data consisting of precipitation and stream flow time-series were fed to the developed NARX, for prediction of daily SST concentrations for a whole year. Sensitivity analysis was used for achieving the best NARX configuration that provided the best fit of simulated vs. measured data for year 2014. Parameters varied during sensitivity analysis were: number of nodes, number of iterations, feedback and forward delays, years of daily data used as training dataset. The resulting NARX is an open-loop net, consisting of a 12-node hidden layer, 100-iterations, using the Bayesian regularization backpropagation algorithm. SST concentrations predicted by the NARX net agreed successfully with measured SST concentrations ($r = 0.73$, $r^2 = 0.53$, NSE = 0.18, PBIAS = −13.6%, Index of Agreement = 0.87).

Keywords: NARX · Neural network · Sediment concentrations · Prediction

1 Introduction

Response variables in hydrology (streamflow, sediment and pollutant concentrations, etc.) strongly depend in antecedent and current conditions of processes that determine the status of the response variable under study. The magnitude and duration of state variables in previous days will determine the magnitude and duration of the response variable, during an individual event. Seasonality is also a factor: most hydrological variables vary drastically during the year with trends particular to dry or wet seasons. Hydrological and water quality models capture that dependence using mechanistic and empirical algorithms that represent the physical processes. In particular, response variables such as stream flow and contaminant concentrations in rivers are studied not only for scientific purposes but also for water quality management and restoration.

Total suspended sediment concentrations (SST) in water bodies are indicators of several hydrological processes taking place within a watershed. The presence of SST depends on intensity and duration of rainfall events, soil matrix and surface characteristics, hillslopes conditions, land cover, stream flow. Antecedent conditions of most

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of those hydrological variables are also determinant of the current SST status. Estimating or predicting SST in rivers, lakes or estuaries it is usually performed through hydrological and water quality modeling. The resulting hydrological and water quality models have been proven to be very useful for water quality management purposes. However, the models are user-specific because of their complexity and, hence, require skilled operator expertise. Options more amenable for use by non-experts requiring water quality predictions are badly needed.

Event-based models use simple formulations for rainfall-runoff generation [1] but are usually developed for short-term purposes such as flood/flow forecasting and/or infrastructure designing. Other approaches that do not require to know any information regarding the physical process (such as non-parametric algorithms) constitute an alternate method. Continuous non-parametric hydrological models were shown to be very useful for long-term water resources management (e.g., estimation of design flows, land-use change impacts, effects of climate change, etc.). Non-parametric models such as antecedent precipitation indices, regression, artificial neural networks, fuzzy logic, and frequency analysis were used extensively [1]. From those available options, artificial neural networks seem to provide opportunities for implementing a tool that do not require extensive input information regarding the physical process, is user-friendly, and provides reliable predictions.

The Artificial Neural Network (ANN) approach to time-series prediction is a non-parametric method. For simple non-linear functions of one or several independent variables ANN are universal interpolators, but simple ANN configurations have limitations modeling seasonal patterns. Special configurations of ANN have been used with success to predict flows and sediment concentrations for rivers around the world. For example, [2–5] report good predictions of streamflow under flood and drought conditions. Similarly, ANN was used extensively for estimating sediment concentrations (e.g., [6–9]). However, in most of those applications of ANN, the validation period of the model output corresponded to within-year events or seasons because the input data was partitioned following the seasonality dependence of the input time-series. Also, some of those researches scaled the input data for improving predictions. There are not ANN models' validations for a whole year where all seasonality dependence is captured that use raw (not scaled) input data.

In this research, an application of a Nonlinear Autoregressive Exogenous Neural Network (NARX) to predict total suspended sediment concentrations (SST) for a water body located in central Chile (Francia Creek, Valparaiso). The NARX application is used to predict daily SST concentrations for year 2014 without scaling the input data, neither partition the input data per season.

2 Methods

2.1 Data Used for the Development of the Neural Network

Francia Creek watershed is a 324-hectares catchment located in the city of Valparaiso, Chile (Fig. 1). Precipitation, stream flow, and sediment concentrations (SST) from 2006 through 2014 for the exit of the catchment are reported in [10].

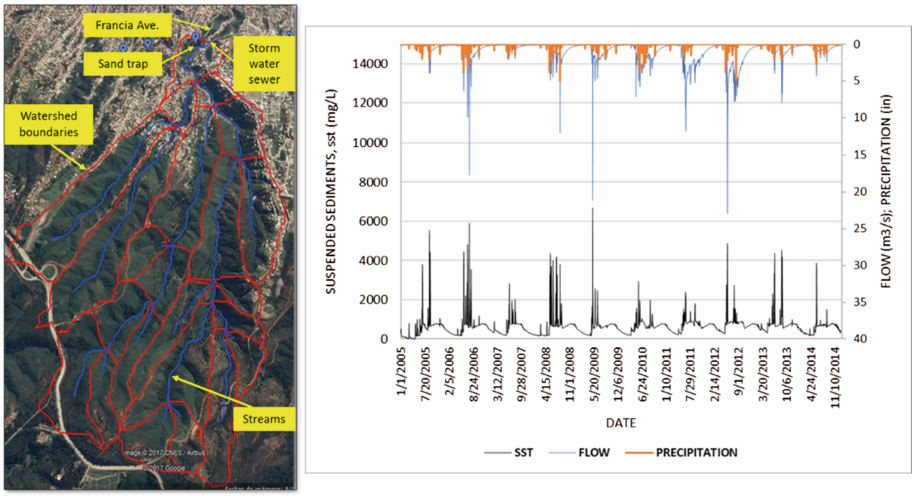

Fig. 1. Study area and data used for building the NARX net. The left-hand side of the figure shows Francia Creek watershed. The catchments exit is located at a sand trap at the outskirts of Valparaiso city. Time series of SST, precipitation and stream flow are shown at the right-hand side of the figure. Daily data beginning 1/1/2005 through 12/31/2014 are shown.

As shown in Fig. 1, three time-series were used for the development of the neural network. Daily total suspended solids concentrations *SST(t)*, precipitation *p(t)*, and stream flow *q(t)*, where time (*t*) spans from 2005 through 2014 at daily time step.

2.2 NARX Neural Network

An artificial neural network is composed by several processing elements (neurons) that interact between each other through weights and activation functions that are adjusted until a desired output is achieved. NARX neural networks are recurrent dynamic networks, provided with feedback connections which enclose at least two layers of the network, and can use past values of predicted or true (measured) time-series [11]. NARX nets are particularly applicable for prediction of time-series. There are two types of NARX architectures: the closed-loop NARX architecture in which prediction of total suspended solids, $SST(N + 1 \ldots N + K)$, is done from the present and past measured values of precipitation, $p(1, 2 \ldots N)$, and stream flow, $q(1, 2 \ldots N)$, and the past predicted values of total suspended solids $SST(N - 1)$, $SST(N - 2) \ldots SST(N - J)$.

In the open-loop architecture, the future value of total suspended solids, $SST(t + 1)$, is predicted from the measured present and past values of precipitation, $p(t)$, stream flow, $q(t)$, and the measured past values of total suspended solids, $SST(t)$. In this research, an open-loop NARX net was used. Figure 2 presents a conceptual description of the NARX net used in this research.

All computations were performed using MATLAB. The Bayesian regularization backpropagation algorithm was used.

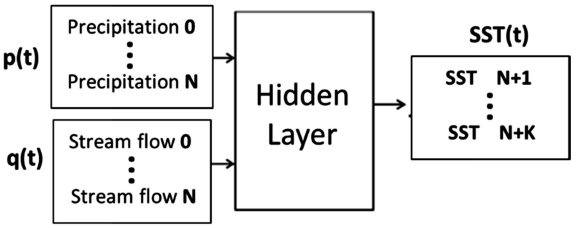

Fig. 2. Conceptual description of the open-loop NARX net used in this research. Input data consist of measured precipitation and stream flow time-series: *p(0, 1, 2..., N)* and *q(0, 1, 2..., N)*, correspondingly. Training is performed using measured total suspended solids, *SST(0, 1, 2..., N)*. The NARX net predicts total suspended solids *SST(N + 1, N + 2, N + 3 ... N + K)*.

2.3 Sensitivity Analysis

Training Data Size. In order to explore the effect of training data size to achieve a successful prediction of SST, the number of years for training and prediction was varied. Table 1 details the process.

Table 1. Training data size

Model run	Number of years used for training			Number of years used for Prediction		
	Precipitation *p(t)*	Flow *q(t)*	*SST*	Precipitation *p(t)*	Flow *q(t)*	*SST*
1	9	9	9	10	10	Predicted
2	3	3	3	4	4	Predicted
3	2	2	2	3	3	Predicted

Initially, all data (9 years) previous to 2014 were used for training. For the prediction phase, precipitation (p) and flow data (q) from years 2005 through 2014 were used to predict total suspended solids, *SST*, for year 2014. Similarly, p and q data from years 2011–2013 were used for training and subsequently predictions for *SST* for year 2014 was done using p and q data from 2011–2014. Finally, training was performed with data from 2 years previous to 2014, and predictions of *SST* were done with q and p data from years 2012–2014.

Number of Neurons in Hidden Layer. In conjunction with the variation of other NARX net characteristics, the number of hidden layer nodes ranged from 5 to 50.

Number of Iterations. The variation of the number of iterations ranged from 50 to 1000. Its effects on SST predictions for year 2014 were explored.

3 Results

3.1 Effects of Number of Iterations

The effects on the prediction of daily SST concentrations for year 2014, when the number of iterations is varied during training of the NARX net, is shown in Fig. 3.

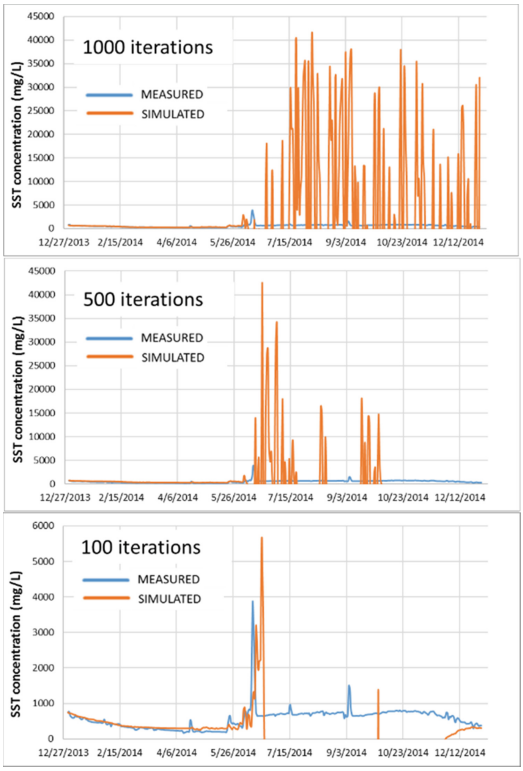

Fig. 3. Number of iterations effect on prediction of sediment concentrations, SST, for 2014. For simplicity only positive SST values are shown in the comparison charts.

Figure 3 shows that overtraining of the NARX net produce unstable results. For 1000 and 500 extreme (positive and negative) sediment concentrations SST values are estimated. For simplicity all charts show only positive value. Very high negative SST values were estimated. For 100 iterations, the NARX net produces SST values within the range of measured SST concentrations for the first half of year 2014. For the second half of the year extreme positive and negative SST are incorrectly estimated.

3.2 Input Data-Size Effects

Figure 4 clearly shows that there is a non-linear effect of the number of years used for NARX net training on estimation of SST values for year 2014. While using 9 years (2005–2013) of daily precipitation, flow and SST data for training the net produces SST estimations for 2014 within the range of measured SST values (although skewed to the right), using 3 and 2 years of training data produce good SST predictions for the firsts half of year 2014 and negative and inconsistent SST values for the second half of the year.

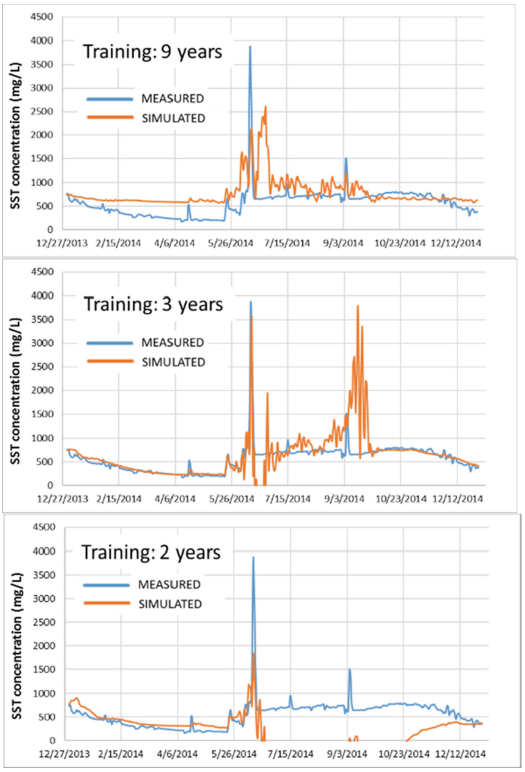

Fig. 4. Input data-size effect on prediction of sediment concentrations (SST) for 2014. For simplicity, only positive SST values are shown in the comparison charts.

3.3 Effects of Number of Hidden Layer Nodes

The previous sections showed that fewer number of iterations (100), and input-data size (3 and 2 years of training data), predicted SST values within the range of measured SST concentrations for year 2014. In both explorations 19 nodes in the hidden layer were implemented. In this section, the number of nodes were varied to test if better SST predictions were achieved. Figure 5 summarizes the effects of different number of

nodes on SST predictions when an input-data size of 3 years of daily precipitation, flow and SST are used for the NARX net training.

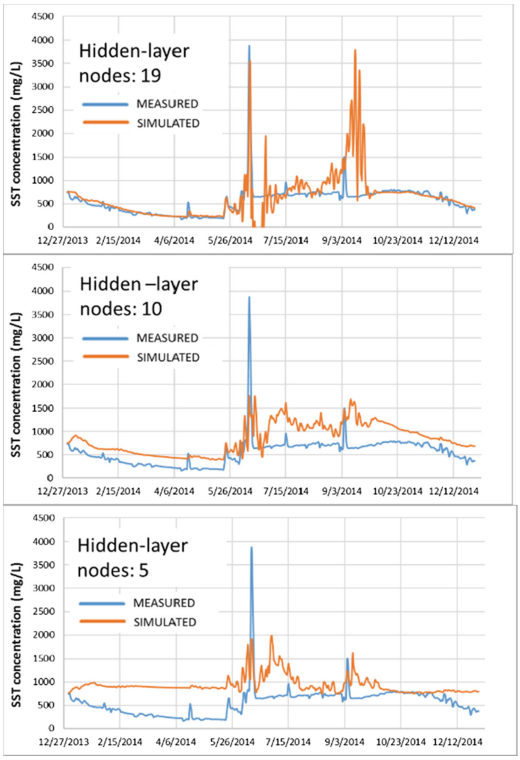

Fig. 5. Number of hidden-layer nodes effect on prediction of sediment concentrations (SST) for 2014. For simplicity, only positive SST values are shown in the comparison charts.

Figure 5 shows that keeping the number of iterations constant (100) and input-data size limited to 3 years while varying the number of nodes, better predicted values for SST concentrations are achieved. While using 19 nodes in the hidden layer still produces instability at mid-year (negative SST values), using 10 and 5 nodes produce SST predictions within the range of measured SST values and with similar temporal trends.

3.4 Fine-Tuning the NARX Net

The exploration of previous sections shows that using around 10 nodes in the hidden-layer, while using 100 iterations and three years of daily data for training the NARX net, SST predictions fit better with measured SST values. In this section, fine-tuning of the NARX net is performed further reducing the input-data size to 2 years, varying the number of nodes, and varying other NARX net parameters such as input and feedback delays, and train- value- and test- ratios. Figure 6 shows the results of the process.

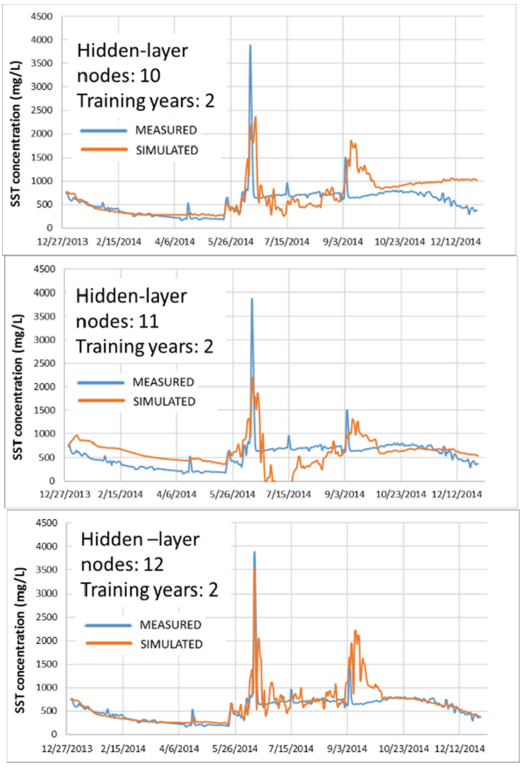

Fig. 6. Fine-tuning the NARX net. For simplicity, only positive SST values are shown in the comparison charts.

Other NARX net parameters were varied in the fine-tuning process. Input delays were varied from 1/15 to 1/60, feedback delays from 1/2 to 1/6, train ratios from 60 to 95, value ratios from 5 to 40, and test ratios from 1 to 10.

3.5 Goodness of Fit

Figure 6 shows that the best fit between simulated and measured SST values for year 2014 is achieved with a NARX net with a 12-node hidden layer, using 2 years of daily precipitation, flow and SST data for NARX net training, and 100 iterations. Figure 7 and Table 2 present goodness of fit indicators and their quality level.

Figure 7 shows that standard indicators of fit for predicted vs. measured SST concentrations for year 2014 are good. The Pearson correlation coefficient (R = 0.73) shows that measured and predicted SST values follow a linear trend. The R^2 value (0.53) shows that the fit of measured vs predicted SST is moderate, however, F-value and P-values show that the correlation is significant. Most important, P-values show that the regression line has an approximate slope of 1 (slope = 0.93), meaning that predicted and measured SST concentration values are not only linearly correlated but their magnitudes are similar.

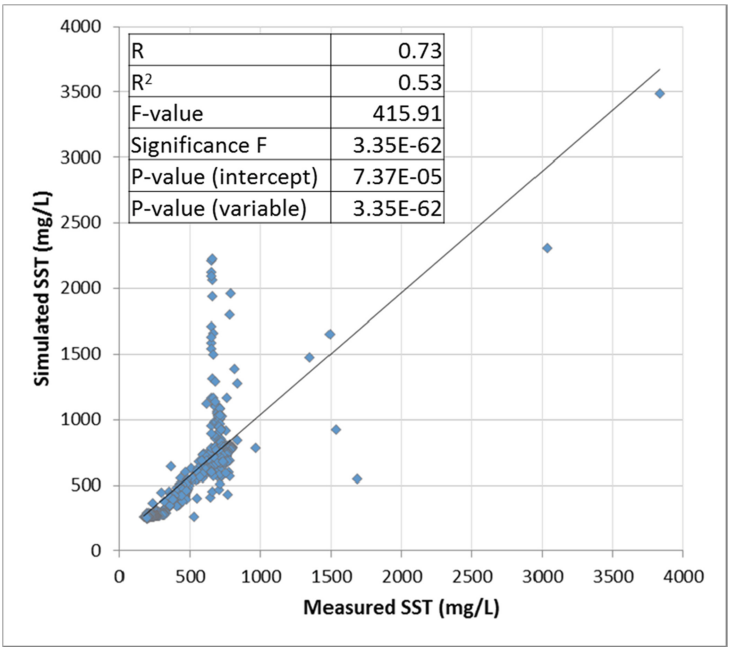

Fig. 7. Comparison of predicted vs. measured SST concentrations for year 2014. Statistical indicators of fit are shown to be good in the context of SST concentration prediction.

Table 2. Indicators of fit for the comparison of predicted SST vs. measured SST

Indicator	Value	Recommended range	Goodness of fit	Source
NSE*	0.18	0–1	Acceptable	[12]
PBIAS**	−13.6%	±15%	Very good	[12]
Index of agreement	0.82	>0.7	Very good	[13]

(*) NSE: Nash–Sutcliffe efficiency coefficient. (**) Percent bias.

Table 2 shows values of indicators of fit for the comparison of predicted SST vs. measured SST. All indicators rank the fit between acceptable (NSE = 0.18) to very good (PBIAS = −13.6%, Index of Agreement = 0.82).

4 Conclusions

This computational exploration shows that a NARX net can be used for predicting total suspended sediment concentrations for a complete calendar year (at daily time step) for the Francia Creek watershed (Valparaiso, Chile). Sensitivity analysis showed that the NARX parameters that are most influential on the generation of results consistent with measured data are: number of nodes in the hidden layer, number of iterations, and number years of daily precipitation, flow and sediment data (during network training).

The resulting NARX net configuration consisted of an open-loop network, with a 12-node hidden layer, using Bayesian regularization backpropagation algorithm. The number of iterations for achieving a trained network was 100, with 2-years of daily data (precipitation, flow, SST). Indicators of fit were calculated to compare how the predicted SST concentrations resemble measured data (for year 2014). SST concentrations predicted by the NARX net agreed successfully with measured SST concentrations ($r = 0.73$, $r^2 = 0.53$, NSE = 0.18, PBIAS = −13.6%, Index of Agreement = 0.87).

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