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Research Article

Prediction of water flows in Colorado River, Argentina

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ABSTRACT. The identification of suitable models for predicting daily water flow is important for planning and management of water storage in reservoirs of Argentina. Long-term prediction of water flow is crucial for regulating reservoirs and hydroelectric plants, for assessing environmental protection and sustainable development, for guaranteeing correct operation of public water supply in cities like Catriel, 25 de Mayo, Colorado River and potentially also Bahía Blanca. In this paper, we analyze in Buta Ranquil flow time series upstream reservoir and hydroelectric plant in order to model and predict daily fluctuations. We compare results obtained by using a three-layer artificial neural network (ANN), and an autoregressive (AR) model, using 18 years of data, of which the last 3 years are used for model validation by means of the root mean square error (RMSE), and measure of certainty (Skill). Our results point out to the better performance to predict daily water flow or refill them of the ANN model performance respect to the AR model.

Keywords: prediction, time series, neural networks, autoregressive models, flows, Colorado River, Argentina.

Predicción de caudales en río Colorado, Argentina

RESUMEN. La identificación de modelos adecuados para predecir caudales diarios es importante para la planificación y la gestión de almacenamiento de agua en los embalses de la Argentina. La predicción a largo plazo del caudal es crucial para la regulación de los embalses y centrales hidroeléctricas, evaluar la protección del medio ambiente y el desarrollo sostenible, garantizar el correcto funcionamiento del abastecimiento público de agua en ciudades como Catriel, 25 de Mayo, río Colorado y también, eventualmente, en Bahía Blanca. En este trabajo, se analizan series de tiempo de caudales de agua, arriba del embalse y de la planta hidroeléctrica en Buta Ranquil, para modelar y predecir las fluctuaciones diarias. Se comparan los resultados obtenidos mediante el uso de una red neuronal artificial (ANN) de tres capas y un modelo autoregresivo (AR), con 18 años de datos, cuyos últimos 3 años se utilizan para la validación del modelo por medio de la raíz del error cuadrado medio (RMSE) y medida de certeza (Skill). Para predecir o rellenar el caudal diario, los resultados indican que el mejor desempeño es del ANN con respecto al modelo AR.

Palabras clave: predicción, series temporales, redes neuronales artificiales, modelos autorregresivos, caudales, río Colorado, Argentina.

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INTRODUCTION

The identification of suitable models for forecasting daily inflows to hydropower reservoirs is an essential pre-requisite for the effective reservoir management and scheduling. The long-term forecasting, in particular, is useful in many water resource applications, like environmental protection, drought management, operation of water supply utilities, optimization of reservoir activities, involving irrigation and hydropower generation (Casa de Piedra in Colorado River basin). In this context, hydrologic time series forecasting has always been receiving particular interest in operational hydrology (Krzysztofowicz, 2001, 2002).

Water resource planning and management requires that magnitude of hydrological variables like precipitation, streamflow and groundwater level, are estimated or forecasted with good accuracy. Forecasting of hydrological variables, especially stream flow, is important for providing warnings on the occurrence of extreme events (like floods or heavy droughts), thus contributing to develop multipurpose reservoir operations (Coulibaly *et al.*, 2000, 2001a). It is necessary to forecast both short and long term water flows in order to optimize the reservoir or to plan future expansion or reduction (Dong *et al.*, 2006). Colorado River basin is a large reservoir and is characterized by a very sparse hydrographic data collection network, implying a considerable uncertainty in the hydrologic information.

Furthermore, the inherently non-linear relationship between inflow and outflow makes the forecasting of streamflow events very complex.

Many of the techniques currently used in modeling hydrological time series, and used for generating synthetic streamflow series, assume that the involved variables are linearly related. Such models are essentially: i) physically based conceptual models, and ii) time series models. The former are specifically designed to mathematically simulate the subprocesses and physical mechanisms that govern the hydrological cycle, usually incorporating simplified forms of physical laws and being generally nonlinear, time-invariant, and deterministic. These techniques, although they use representative parameters of watershed characteristics (Gupta *et al.*, 2000), they ignore the spatial distribution, the time-varying properties and the stochastic nature of the rainfall. Yang & Michel (2000) state that conceptual watershed models are reliable in forecasting the most important features of the hydrograph; but, the implementation and calibration of such a model can typically present some difficulty, because it requires sophisticated mathematical tools, significant amounts of calibration data and some degree of expertise and experience with the model (Zhang *et al.*, 1998; Sudheer *et al.*, 2007). The further problem that physically-based conceptual models present is that observational periodicities are not always evidenced, and can often be hidden by noise.

Time-series analysis models are based on fitting the stochastic model to the time-series, in order to forecast, generate synthetic series useful for simulation, and investigate and model the underlying characteristics of the system under study. Most of these time-series models are multivariate autoregressive moving average (ARMA or ARMAX) model type (Ochoa-Rivera *et al.*, 2002).

Artificial Neural Networks (ANNs), have been successfully applied in many fields, also in water resources. ANNs revealed to be a promising alternative for rainfall-runoff modeling (Ahmad & Simonovic, 2005; Rajukar *et al.*, 2004), streamflow prediction (Muttiah *et al.*, 1997; Maier & Dandy, 2000; Dolling & Varas, 2002; Sivakumar *et al.*, 2002; Kisi, 2004; Cigizoglu & Kisi, 2005; Cigizoglu, 2008) and reservoir inflow forecasting (Saad *et al.*, 1996; Jain *et al.*, 1999). Recently, Coulibaly *et al.* (2001b) and Kisi & Cigizoglu (2007) reviewed ANN-based models developed over the last years in hydrology, showing the extensive use of multi-layer feed-forward neural networks (FFNN), trained by standard back propagation (BP) algorithm (Magoulas *et al.*, 1999). BPNNs represent a supervised learning method, requiring a large set of complete records, including the target variables. As each observation from the training set is processed through the network, an output value is produced from output nodes. These values are then compared to the actual values of the target variables for this training set observation and the errors are calculated.

There are many parameters (evapo-transpiration, rainfall, ground water, moisture content of soil, etc.), that affect the next day runoff. Although it is possible to identify sophisticated models, taking into consideration the hydrological and hydro-meteorological variables such as precipitation, runoff, temperature and evaporation, it is cost-effective and technically easier to prefer a model that simulates the flow variations on the basis of only past discharge records, which are the only values available to the decision maker, whether administrator, local authority or technical operator. Therefore, only the past discharge records were used as inputs in the present study.

The main objectives of this study is to analyze and evaluate stochastic time series measured at Buta Ranquil, upstream the Colorado River reservoir and the hydroelectric dam, by means of the FFNN and AR models. To our knowledge, FFNN and AR models are applied for the first time to forecast daily river flow at Colorado River in Argentina (Fig. 1).

MATERIALS AND METHODS

Data

The daily flow data (1990-2008), of the river gauging station, operated by the Subsecretaría de Recursos Hídricos de la Nación Argentina, involves the separate measurement of river stage and river flow. A continuous record of flow is subsequently computed from stage record, using a rating curve method between the measured flows and their corresponding river stages (accuracy 0.01 m) (Fig. 2). Fig. 1 shows the location of the measurement station, which is at 850 m above sea level, on the Colorado River, near Buta Ranquil (37º06'S, 69º44'W), in Neuquen, Argentina. The drainage area at this site is 47,458.89 km^2. Data from April 1st 1990, to March 31st 2005, were used for calibration, while data from April 1st 2005 to April 1st 2008, were used for validation. Note that calibration and validation periods include the same season (April- March).

Artificial Neural Networks

ANNs have a highly interconnected structure and consist of large number of simple processing elements called neurons, which are arranged in different layers in the network: input layer, output layer and one or more hidden middle layers. One of the well known advantages of ANN is its ability to learn from the sample set, called training set. Once the architecture of network is defined, then weights through learning process are calculated in order to achieve the desired output. Neural networks are adaptive statistical devices; they can change iteratively the values of their parameters (*i.e.*, weights), as a function of their performance according to the learning rules of gradient descent method. Detailed description of the mathematical formulation of the back propagation algorithm can be found in Roiger & Geatz (2003), Negnevitsky (2005) and Larose (2005).

The multilayer feed-forward neural represents the most used method in hydrology (Govindaraju, 2000; Othman & Naseri, 2011). Each neuron in a layer is connected to all the neurons of the next layer, and the neurons in one layer are not connected among themselves. All the nodes within a layer act synchronously. The neurons of the input layer receive the input vector and transmit the values to the next layer of processing elements across connections. This process continues up to the output layer. In the feed-forward network data flows in one direction (forward) (Fig. 3). The data passing through the connections from one neuron to another are multiplied by weights that control the strength of a passing signal. When these weights are modified, the data transferred through the network changes; consequently, the network output also changes. The signal coming out from the output node(s) is the network's solution to the input problem. The sum of the products of every input with the neuron interconnection weight is passed through a transfer function to the next layer. This transfer function is usually a steadily increasing S-shaped curve, called sigmoid function. The sigmoid function is the most common activation function in ANN, because it combines nearly linear behavior, curvilinear behavior and nearly constant behavior, depending on the value of the input. The sigmoid function is sometimes called a squashing function, since it takes any real valued input and returns an output bounded between (0,1). The sigmoid function is continuous, differentiable everywhere, and monotonically increasing. Under this threshold function, the output y_j from the *jth* neuron in a layer is:

$$y_i = f\left(\sum w_{ji}\, x_i\right) = \frac{1}{1 + e^{-\left(\sum w_{ji}\, x_i\right)}} \tag{1}$$

where w_{ji} is the weight of the interconnection between the *jth* neuron and the *ith* neuron in the previous layer, x_i is the value of the *ith* neuron in the previous layer.

The performance of the ANN model is evaluated by separating the data into two sets: the training set and the testing or validation set. The parameters (*i.e.*, the value of weights) of the network are computed using the training set. At the beginning of training, the weights are initialized, either with a set of random values or based on some previous knowledge. Then, the weights are systematically changed by the learning algorithm such that, for a given input, the difference between the ANN output and actual output is small. Many learning examples are repeatedly presented to the network, and the process is terminated when this difference is less than a specified value. At this stage, the ANN is considered trained. The backpropagation algorithm based upon the generalized delta rule, proposed firstly by Rumelhart *et al.* (1986) and later by Al Bayati *et al.* (2009), was used to train the ANN in the present study. In the back-propagation algorithm, a set of inputs and outputs is selected from the training set and the network calculates the output based on the inputs. This output is subtracted from the actual output to find the output-layer error. The error is backpropagated through the network, and the weights are suitably adjusted. This process continues for the number of prescribed sweeps, or until a prespe-

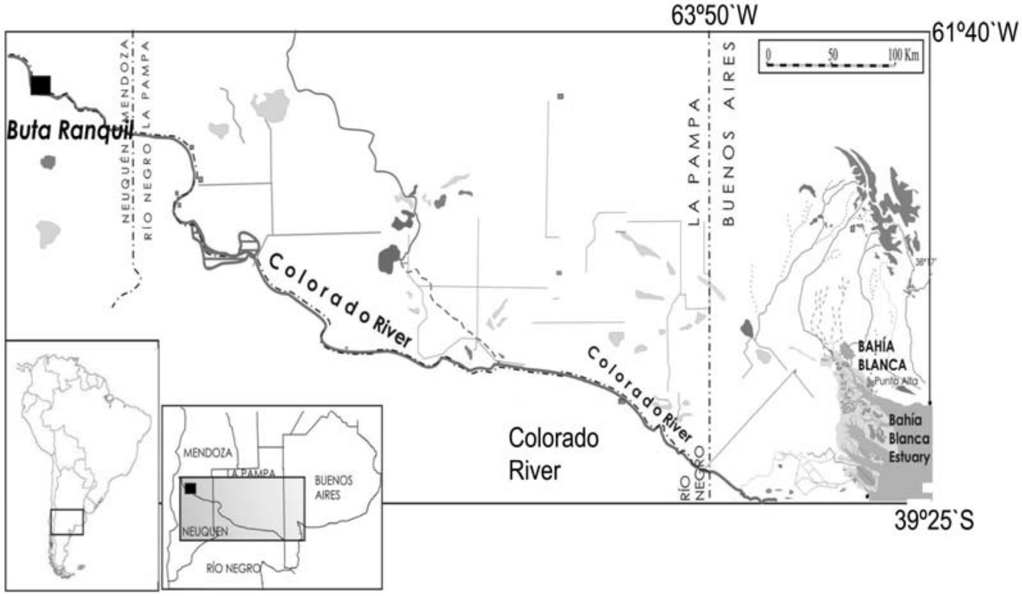

Figure 1. Location of Buta Ranquil gauging station in the Colorado River, Argentina.

Figura 1. Localización de la estación de aforo de Buta Ranquil en el río Colorado, Argentina.

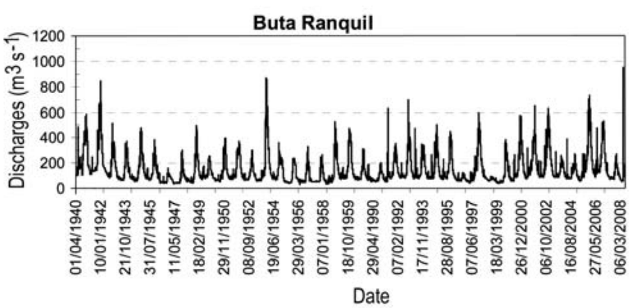

Figure 2. Stream flow data over the period of study (1990-2008) in Buta Ranquil.

Figura 2. Datos de caudales sobre el área de estudio en Buta Ranquil.

cified error tolerance is reached. The root mean square error over the training samples is the typical objective function to be minimized. After training is complete, the ANN performance is validated. Depending on the outcome, either the ANN has to be retrained or it can be implemented for its intended use. An ANN is better trained as more input data are used. The number of input, output, and hidden layer nodes depend upon the problem being studied. If the number of nodes in the hidden layer is small, the network may not have sufficient degrees of freedom to learn the process correctly. If the number is too high, the training will take a long time and the network may sometimes overfit the data (Karunanithi *et al.*, 1994; Zhang *et al.*, 1998). So, a good compromise needs to be taken.

AR models

Autoregressive (AR) models have been extensively applied to hydrology and water resource analysis, and are based on the dependence of the actual value of the variable on its values in the past. The AR models of order *p* (AR(*p*)) are defined as:

$$Q_t = \alpha_1 Q_{t-1} + \alpha_2 Q_{t-2} + \alpha_3 Q_{t-3} + ... + \alpha_p Q_{t-p} + E_t \quad (2)$$

where E_t is a purely random process and $E(E_t) = 0$. The parameters $\alpha_1 .... \alpha_p$ are the AR coefficients. The name "autoregressive" comes from the fact that Q_t is regressed on the past values of itself.

RESULTS

The three-layer FFNN (Fig. 3) used in this study contains only one intermediate (hidden) layer. Theoretical studies have shown that a single hidden layer is sufficient for ANNs to approximate any complex nonlinear function (Cybenko, 1989; Hornik *et al.*, 1989), and many experimental results seem to confirm that one hidden layer may be enough for most forecasting problems (Zhang *et al.*, 1998; Coulibaly *et al.*, 1999).

It's challenging the choice of parameters like the number of hidden nodes, the learning rate, and the initial weights. In the present study, the common trial and error method was used to select the number of hidden nodes. The logistic function (Eq. 1) is used as the hidden node and the output node activation function. Before applying the ANN, the input data were normalized in order to fall in the range [0.1-0.9] to distribute the data evenly and scale it into an acceptable range for the network and remove local variations or extreme skewness (Zadeh *et al.*, 2010).

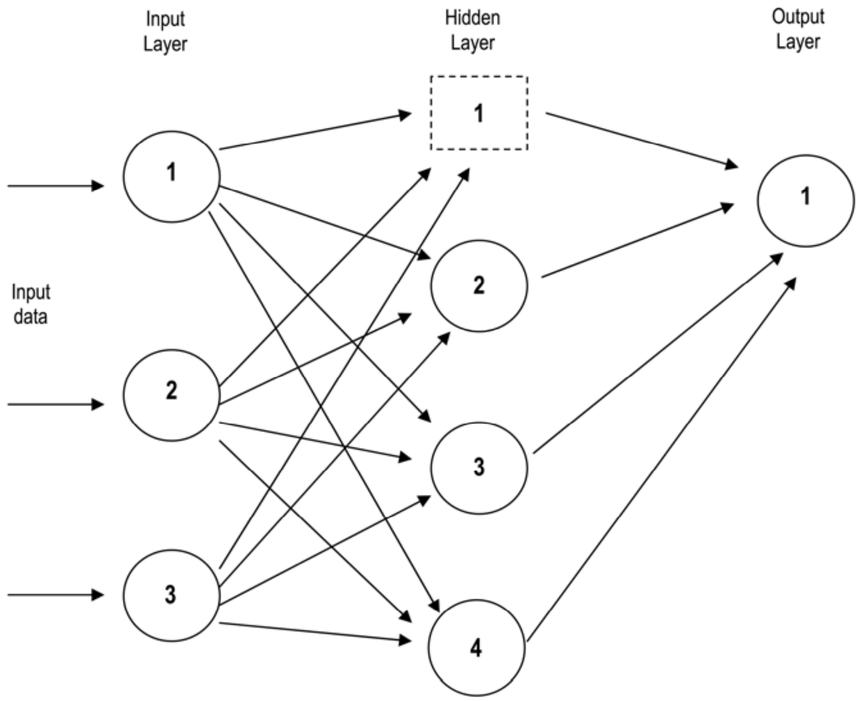

Figure 3. Schematic representation of three-layer feedforward neural network.
Figura 3. Representación esquemática de la red neuronal feedforward de tres capas.

The river flow Q was normalized by the following formula:

$$Q_n = \left[\frac{Q}{1.21 Q_{\max}} + 0.08 \right] \quad (3)$$

where Q_n is the normalized flow, Q is the observed flow, and Q_{max} is the maximum value of the flow. The following combinations of input data of flow were evaluated:

Colorado River stream flow ANN input data					
Case					
1	Q_{t-1}				
2	Q_{t-1}	Q_{t-2}			
3	Q_{t-1}	Q_{t-2}	Q_{t-3}		
4	Q_{t-1}	Q_{t-2}	Q_{t-3}	Q_{t-4}	
5	Q_{t-1}	Q_{t-2}	Q_{t-3}	Q_{t-4}	Q_{t-5}

The output layer had 1 neuron for current flow Q_t. In the trials, the number of neurons in the hidden layer varied between 1 and 5.

To compare between the observed and the predicted flow obtained through the ANN, or the AR model, we used the indicators suggested by Willmott (1982). The mean bias (MB), indicates the averaged difference between observed and predicted values. The root mean square error (RMSE), is the square root of the variance, which represents that 95% of the model predictions do not differ from the observations (in absolute value), by more than twice the RMSE. The skill index (or index of agreement), quantifies the "predictive skill" between model results and observations by using the following formula:

$$Skill = 1 - \frac{\sum_{i=1}^{N} \left(X_{Mod\_i} - X_{Obs\_i} \right)^2}{\sum_{i=1}^{N} \left(\left| X_{Mod\_i} - \overline{X}_{Obs} \right| + \left| X_{Obs\_i} - \overline{X}_{Obs} \right| \right)^2}, \quad 0 \le Skill \le 1$$

where X is the flow data in our case, X_{Mod_i} is the model result at the time i, X_{Obs_i} is the observation result at time i, and $\overline{X}_{Obs}$ is the mean of the observations, and N is the number of observations. The Skill index provides a measure of the model performance. If the skill index is 1, the model presents an optimal predictive skill. In our case, the skill index is approximately 1, indicating a large model performance (Table 1).

The correlation of the Colorado River flow is high (Table 2). The input to the ANN was 1 up to 5 previous flow values; similarly the AR models were fitted to the river flow data using for the regression 1 up to 5 past values. In both cases, the best model was selected on the base of maximum skill and minimum root mean square errors.

Table 3 reports the skill index and RMSE in each case. It can be seen that the RMSE for the ANNs is smaller than the skill index during the calibration period. The configuration giving the minimum RMSE and maximum skill was selected for each combination. From the results shown in Table 3, the ANN combination (4) and AR (4) are characterized by best performance. Figs. 4a and 4b show the observed and forecasted discharges (with AR (4) and ANN combination (4)) of the Colorado River using 2005-2008 as validation period. Although from eye inspection the two models do not reveal any apparent difference, closely examining them, we see that ANN estimates better than AR the time evolution of the water flow. In particular, the ANN predicts the flow peak occurred on December 14, 2005 (730.5 $m^3 s^{-1}$) with an overestimation of 8% (789.9 $m^3 s^{-1}$); while the AR (4) model predicts it with an overestimation of 10% (799.0 $m^3 s^{-1}$). Regarding the peak occurred on July 12, 2005 (476.6 $m^3 s^{-1}$), the ANN predicts the value of 481.3 $m^3 s^{-1}$ with an overestimation of 0.09%; while the AR (4) model predicts it with the value of 493.1 $m^3 s^{-1}$ with an overestimation of 1.03%. The peak occurred on December 12, 2005 (524.3 $m^3 s^{-1}$) was predicted by the ANN with an overestimation of 2.1% (535.4 $m^3 s^{-1}$), while by the AR (4) model with an underestimation of 15.1% (445.1 $m^3 s^{-1}$). For clarity reasons, Figs. 4a and 4b show only the results for 2005-2007. The ANN performs better than AR (4), although two peaks were overestimated. Figs. 5a and 5b show the scatter diagram of the measured versus predicted daily water flow by using ANN and AR models. The skill index of ANN model is slightly better than that of AR model. The relative RMSE difference between the ANN combination (4) and the AR (4) model in the calibration period for the Colorado River is 38%. In other words, results produced by the ANN model are almost concurrent with the Colorado River stream flow values, while the AR model results show some difference from the original river data.

Table 1. Representation of correlation, determination coefficient, mean bias, RMSE and Skill with ANN (Q_{t-1}), during calibration period.

Tabla 1. Representación de la correlación, coeficiente de determinación, sesgo medio, RMSE y Skill con la ANN(Q_{t-1}), durante el período de calibración.

Station	Buta Ranquil
Correlation (r)	0.95
Determination Coef. (r^2)	0.90
Mean Beas	34.1
RMSE	28.9
Skill	0.94

DISCUSSION

It is recognized that data preprocessing can have a significant effect on model performance (Maier & Dandy, 2000). It is commonly considered that because the outputs of some transfer functions are bounded, the outputs of an ANN must be in the interval [0,1] or depending on the transfer function used in the neurons. Some authors suggest using even smaller intervals for streamflow modeling, such as [0.1-0.9] (Hsu *et al.*, 1995). Time series forecasting has an important role for water resources planning and management. Conventionally, researchers have employed traditional methods such as AR, ARMA, ARIMA, etc, (Gupta & Sorooshian, 2000; Cigizoglu & Kisi, 2005; Cigizoglu, 2008). The daily discharge data, from actual field observed data in Ruta Ranquil (Colorado River), was employed first time to develop several models investigated in this study, explore the performance of the ANN approach for the estimation of river flow, and compare its result to those of the autoregression technique (AR). The greatest difficulty lays in determining the appropriate model inputs for such a problem. Although ANN's belongs to the class of data-driven approaches, it is important to determine the dominant model inputs, as this reduces the size of

Table 2. ANN Buta Ranquil (Colorado River) autocorrelation.
Tabla 2. Autocorrelación de la ANN en Buta Ranquil (Río Colorado).

Colorado River					
Period	Q_{t-1}	Q_{t-2}	Q_{t-3}	Q_{t-4}	Q_{t-5}
Calibration (1/4/90 – 31/3/05)	0.94	0.88	0.75	0.69	0.61
Validation (1/4/05 – 1/4/08)	0.94	0.88	0.72	0.64	0.55

Table 3. RMSE and skill during training and validation data of Buta Ranquil (Colorado River).

Tabla 3. RMSE y Skill durante el entrenamiento y validación de datos en Buta Ranquil (río Colorado).

Colorado River									
Case	Hidden layer	Calibration (1/4/90 – 31/3/05)				Validation (1/4/05 – 1/4/08)			
		ANN		AR		ANN		AR	
		RMSE $m^3 s^{-1}$	Skill	RMSE $m^3 s^{-1}$	Skill	RMSE $m^3 s^{-1}$	Skill	RMSE $m^3 s^{-1}$	Skill
1	1	29.5	0.94			28.9	0.95		
2	4	21.1	0.96			19.3	0.96		
3	3	17.8	0.96			17.6	0.97		
4	4	13.9	0.97			12.5	0.98		
5	3	18.3	0.96			17.0	0.97		
AR(1)				37.8	0.92			36.7	0.92
AR(2)				27.8	0.93			26.1	0.94
AR(3)				26.7	0.94			23.3	0.94
AR(4)				25.0	0.94			22.2	0.94
AR(5)				25.0	0.94			22.8	0.94

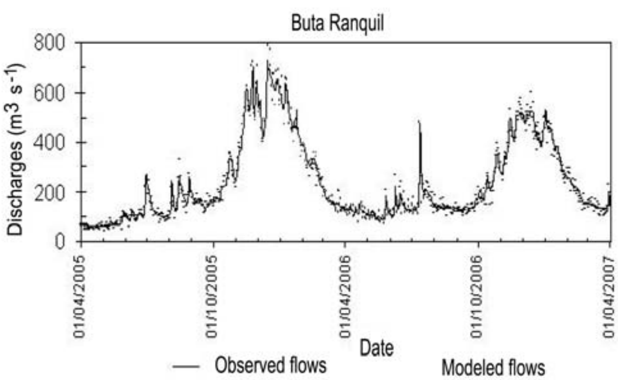

Figure 4a. ANN observed and predicted flows of Colorado River; the validation period from 1 April 2005 to 31 March 2008.

Figura 4a. Caudales observados y modelados con ANN, con período de validación de 1 de Abril 2005 al 31 de Marzo 2008.

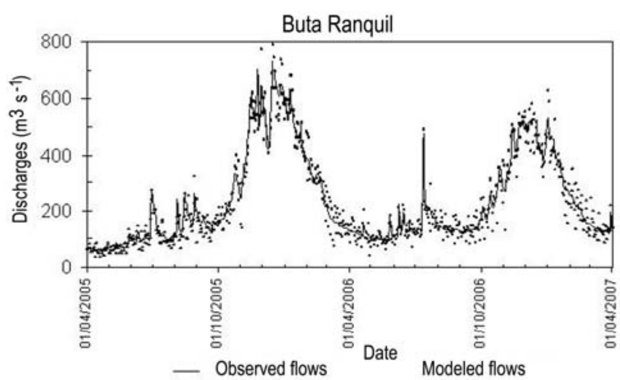

Figure 4b. AR observed and predicted flows of Colorado River; the validation period from April 1st 2005 to March 31st 2008.

Figura 4b. Caudales observados y modelados con AR, en río Colorado, con período de validación de 1 de Abril de 2005 al 31 de Marzo 2008.

the network and consequently reduces the training times and increases the generalization ability of the network for a given data set. Two standard statistical erformance evaluation measures (RMSE and Skill) are adopted to evaluate the performances of each model (Willmott, 1982). The results of the research illustrated that ANN (4) algorithm and AR (4) can be applied to a flow data set to make successful estimations over the Argentina basin. While the performance of the AR method is 22.2 $m^3 s^{-1}$ and 0.94 for RMSE and Skill, respectively, estimation of daily flow ANN method is fulfilled within 13 $m^3 s^{-1}$ accuracy and about 98% correlation value. The best result among all of the methods was obtained using the ANN (4) algorithm with a 12.5 $m^3 s^{-1}$ value for RMSE and a 0.98 value for Skill. The results show that the ANN model performs better in predicting discharge data, even if a certain deviation of the

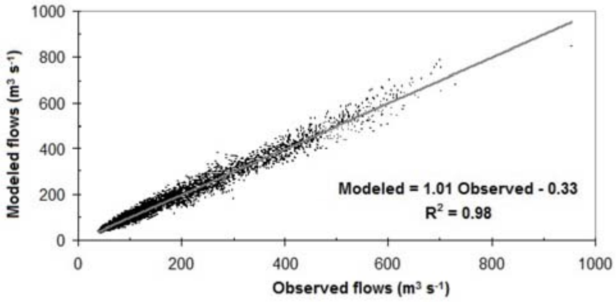

Figure 5a. ANN model: correlation between observed and predicted flows of Buta Ranquil.

Figura 5a. Modelo ANN: correlación entre caudales observados y modelados en Buta Ranquil.

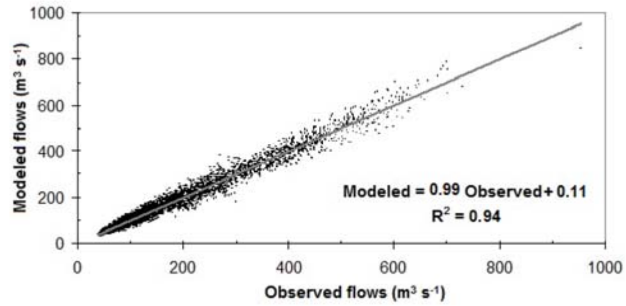

Figure 5b. AR model: correlation between observed and predicted flows of Buta Ranquil.

Figura 5b. Modelo AR: correlación entre caudales observados y modelados en Buta Ranquil.

predicted values from the observed ones can be seen during the validation period. The improvement in the RMSE provided by the ANN's for the testing period was 11%. The plots of AR models were more scattered (higher standard deviation) compared with those of the neural networks. From the graphs and statistics it is apparent that ANN's can provide a fit to the data better than the ARs reducing the number of outliers: in fact the AR estimates and forecasts for high flows were beyond standard deviation (SD) band, while those obtained by the ANN were generally within the one SD band. ANN's main advantage is its ability to model nonlinear processes of the system without any a priori assumptions about the nature of the generating processes. Therefore, the ANN provides more reliable forecasts, especially of discharge flows.

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