PREDICTION OF THE PARAGUAI RIVER LEVEL'S TIME SERIES USING NEURAL NETWORKS

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ABSTRACT

Feed-forward neural networks are implemented for predicting the level of Paraguai River, Ladario. By using the trained network , the reconstruction of the monthly data fit well with the observations. And the initial results show success predictions within two to three months.

Keywords: Neural networks, Prediction, Paraguai River.

I. INTRODUCTION

Predicting the level of Paraguai River with useful antecedence (and so estimating the area to be flooded) is a relevant scientific goal. Paraguai River levels are influenced by several different factors from micro to macro scales. Simple correlation between its levels and indexes of El Niño or SST in the Atlantic Ocean don't seem significant, probably because interactions among vegetation, soil and topographic characteristics result in important factors, too important to be neglected in this area and those teleconnections are masked. From the standpoint of global change the Pantanal deserves study because, due to its dimensions, it could, probably, both drive and respond to changes in climate. Neural networks can treat all these factors simultaneously, which was an incentive to apply this method to these complex time series of river levels. In this paper, about 1145 monthly data are used to train the neural network, which then give the monthly predictions.

II. FEED-FORWARD NEURAL NETWORKS

Prediction of time series is an exciting recent application of neural networks. There are a number of prediction methods available for this kind of problem (Casdagli, 1989). Neural networks were found to be useful and competitive with the best recent approximation methods (Lapdes and Farber, 1987, Gallent and White, 1992, Li , et al. 1995). To predict the time series of the level of Paraguai River, one type of network, feed-forward single hidden layer networks (Rumelhart et al., 1986), with Backpropagation learning laws will be used. The input values of time series $x(t-1)$, $x(t-2)$,...$x(t-d)$ are received through d input units, which simply pass the input forwards to the hidden units u_j, $j = 1,2,....q$. Each connection performs a linear transformation determined by the connection strength w_{ij}, so the total input for hidden unit u_j is $\sum_{i=1}^{d} w_{ij}\, x(t-i)$. Each unit performs a nonlinear transformation on its total input, producing output:

$$o_j = \Phi(w_{0j} + \sum^{d}_{i=1} w_{ij}\, x(t-i).) \qquad (1)$$

The activation function Φ is the same for all units. Here, Φ is a sigmoid function with limiting value 0 and 1 as $o_j \rightarrow -\infty$ and $o_j \rightarrow +\infty$ respectively:

$$\Phi(o_j) = 1/(1+\exp(-o_j)) \qquad (2)$$

The hidden layer outputs o_j are passed along to the single output unit with connection strength β_j, which performs an affine transformation on its total input. Then, the network's output x(t) can be represented as:

$$x(t) = \beta_0 + \sum^{q}_{j=1} \beta_j\, \Phi(w_{0j} + \sum^{d}_{i=1} w_{ij}\, x(t-i)) \qquad (3)$$

for d inputs and q units in the hidden layer.

One way to make predictions at various next step t, t-1, t-2,...t-$k\Delta t$ is to place previously predicted values on the input lines to bootstrap to higher i values (Lapedes and Farber, 1987). After training a network to predict at t, the predicted values can be fed back to the inputs to predict at t+1, t+2,... etc.

III. THE RESULTS

Using the 1142 monthly observations, the trained network give prediction results. As Table 3.1 shows, the relative errors of the predictions of the next four months are less than 17%. Figure 3.1 shows the reconstructions and predictions of the monthly observations of the levels of Paraguai River.

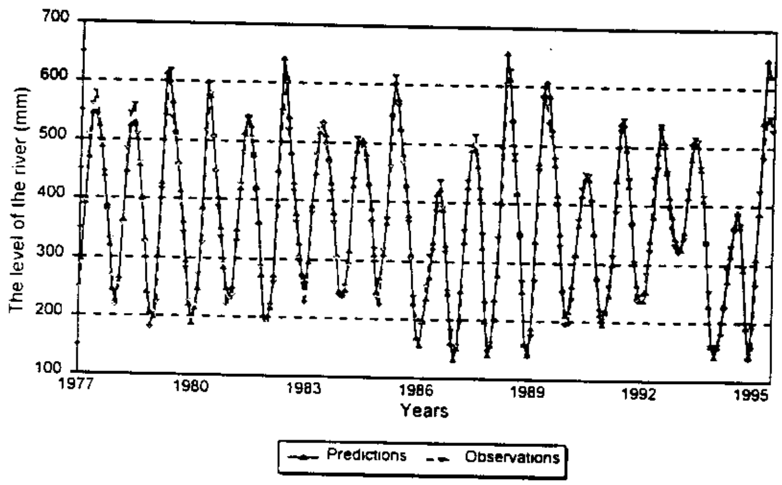

Figure 3.1 Reconstructions (01/77-02/95) & Predictions (03-06/95) of the monthly level of Paraguai River

Table 3.1 Predictions of the monthly level of Paraguai River: 03-06/95

	Mar	Apr	May	Jun
Observations	542.90	649.87	622.16	588.00**
Predictions	480.70	544.04	551.05	528.28
Relative Errors	11.45%	16.23%	11.43%	10.00%
RMSE*	0.019	0.019	0.019	0.019

*: RMSE: Root mean squared error of the trained neural network.

**: Mean of the first 8 daily observations of June.

V. CONCLUSIONS

Feed-forward neural networks were robust for predicting the level of the Paraguai River. The predictors give acceptable results which show that the neural network method seems efficient to process time series influenced by complex processes, not still understood, as it appear very often in the geophysical sciences. Although these are preliminary results, they are promising. In the future, To improve more the prediction with the help of predictors criteriously chosen and to understand the theoretical aspects of the predictability of this physical phenomena will be the further research.

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