Predictions of Sea Surface Temperature in Tropical Ocean Using Neural Networks

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ABSTRACT

A review of researches on the relationship between the tropical ocean sea surface temperatures (SST) and rainfall anomalies in Northeast Brazil was introduced. In this work, two neural network models are implemented to reconstruct and predict the time series of the SST in two regions: the tropical Atlantic ocean (Wright index, from 1854 to 1985) and the tropical Pacific ocean (regions Niño1-2: 0°N-10°S, 270°E-280°E and Niño4: 5°N-5°S, 160°E-150°E, from 1950 to 1995). The selected neural networks include Backpropagation Neural Network (BNN) and Time Delay Neural Network (TDNN). Both were implemented in the neural network stimulator SNNS. For the Wright index, the trained Backpropagation Neural Network successfully predicted the index of the following four months with the relative errors from 1.40 to 3.34%. For SST in Niño1-2 and Niño4 regions, the Time Delay Neural Network was used for reconstruction and prediction. Comparing with the next six month observations and predictions, all of them are located within the predicted error bars. These results show that neural network methods may be used, within certain limits, for prediction and evaluation of predictability of time series measured from phenomena influenced by complex climatic and geophysical processes, like SST.

Key words: neural networks, prediction, sea surface temperature, time series.

INTRODUCTION

Recently, many researchers have been convinced that, besides the tropical Pacific sea surface temperature (SST), the Atlantic sea surface temperature also represents an important index for climatic prediction of regions in Brazil (Hastenrath, Greischar, 1993; Studzinski, 1995), particularly of Northeast Brazil, a region of irregular and severe droughts. It also has been demonstrated that the memory effect of the upper part of tropical ocean in general, and particularly of the Pacific Ocean, is much greater than that of the atmosphere, reaching time scales of several months. This property has evident consequences on the predictability of the characteristic parameters of the state of the oceans, such as sea surface temperature (SST).

In the paper of Hastenrath and Greischar on the diagnostics and prediction of extreme climatic events in northeast Brazil, they have focused on the precipitation during March-June, deemed most relevant for practical application, and explored the potential of seasonal forecast with various lead times. In this process, they compared the usefulness of SST sets with different quality controls and experimented with various treatments, the prognostic information which is contained in the accu-

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mulated preseason precipitation and the Atlantic meridional wind component and SST fields. For these fields they have found effective to confine the information extraction by empirical orthogonal function (EOF) analysis to the more sensitive portion of the tropical Atlantic. They have shown that limited predictability of the March-June precipitation is apparent as early as December, from the accumulated rainfall, the Atlantic wind and SST fields.

To investigate rainfall in Southern Brazil and Sea Surface Temperature of the Tropical Atlantic Ocean, Studzinski (1995) used Canonical Correlation Analysis (CCA) which chooses among a numerous set of different variables, those which are the most important predictors of a unique (predicand) variable, as underlined by Barnett (1990).

For this study, Sea Surface Temperature (SST) monthly data of the Pacific and Atlantic Oceans, either together, either separately, were used as predictor field and rainfall monthly total of a Southern region of Brazil region of Brazil as predicand. Four distinct periods were selected for the analysis: December to February, March to May, June to August and September to November, corresponding to January 1946 to February, 1988. The influence of El Niño/Southern Oscillation (ENSO) was also studied in rainfall anomalies. Although evidence of relation between ENSO and Southern Brazil rainfall was found, an important part of the anomaly peaks was not related to this phenomenon.

About the analysis of the relation of the Atlantic Ocean with rainfall, it was shown that oceanic regions near the Brazilian Southern region coast, as well as other remote regions such as the Equatorial Atlantic (ITCZ region) and the Antilles Sea region, were related to the Southern region rainfall. According to the author, the influence of the Atlantic happens by the positioning of the cyclonic circulation anomaly (mainly from December to February). On the other hand, for periods from March to August, the influence of the Atlantic does not seem to be predominant. But from September, the Atlantic influence seems to be predominant in the anomaly localization.

Significant simultaneous correlation between temporal fluctuations in meteorological parameters at widely separated points on earth, commonly referred to as teleconnections in the descriptive literature, are of considerable interest because they provide evidence concerning the transient behavior of the planetary waves (Wallace & Gutzler, 1981). There is abundant evidence of the existence of such correlation, particularly in fluctuations with time scales of a week or longer. In a number of cases it has been possible to identify what appear to be standing wave structures with geographically fixed nodes and antinodes on the basis of multiple-correlation statistics derived from time series of a number of different stations or grid points (Wallace & Gutzler, 1981). However, the research on teleconnection between the tropical central and east Pacific SST on one side, and the climate of some South America regions on the other side, are more abundant and they seem more consistent. In that sense, the following works may be quoted: Kousky *et al.* (1984), Mo & White (1985), Aceituno (1988), Rao & Hada (1990), Philander (1990), among many others. These teleconnection effects may produce events of dramatic social consequences, when the important geophysical phenomenon named El Niño-Southern Oscillation (ENSO) occur, which is discussed by authors such as Wyrtki (1979), Cane (1983) and Philander (1990). El Niño event is characterized by a notable warming of the east and central parts of the equatorial part of the tropical Pacific Ocean, as it is the case of the Niño1-2 and Niño4 regions, object of this study. Such an event represents a complex phenomenon of interaction between ocean and atmosphere, which results in important modifications of the atmospheric circulation over Brazil, inducing drought occurrence in the Northeast region and heavy precipitation and flood in southern regions of the country (Rao *et al.*, 1986).

El Niño is not a periodical phenomenon, which obviously turns difficult its prevision by classical methods (harmonic analysis etc.). However, particularly favorable predictability conditions for the tropical Pacific ocean (Cane & Zebiak, 1985; Cane *et al.*, 1986; Sarachik, 1992; Woods, 1992; Penland & Sardeshmukh, 1995) gave incentive for researchers to look for and apply more efficient prediction methods for this phenomenon. This work follows this direction with the application of neural network techniques to tropical ocean temperature prediction (Hastenrath & Greischar, 1993; Derr & Slutz, 1995). Rao *et al.* (1993) have also examined the possible link existing between rainfall over the eastern northeast (ENE) Brazil and SST anomalies in the Atlantic. After them, the SST anomalies of the season January, February, March, April (JFMA) in the southeast Atlantic are positively correlated with the rainfall anomalies of ENE Brazil. The sea surface temperature (SST) anomaly pattern frequently becomes established by January/February over southeast Atlantic suggesting the predictive value of SST anomalies over southeast Atlantic for the rainfall over ENE Brazil.

Rao *et al.* (1993) have stressed that the physical mechanism that relates the SST over the South Atlantic Ocean to rainfall over ENE Brazil should await further studies. However, a preliminary explanation is that higher SST over the South Atlantic favors higher evaporation. Larger transport of water vapor to ENE Brazil can occur with a larger number of southern fronts.

There are many methods available for reconstruction and prediction of time series (Casdagli, 1989). Neural networks were found to be useful and competitive with the best recent approximation methods (Lapedes & Farber, 1987; Gallent & White, 1992; Gershenfeld & Weigend, 1993; Li *et al.*, 1996). A neural network is an interconnected network of simple processing elements. Communication between processing elements occurs along paths of variable connection weights. By changing the values of these connection strengths (weights) the network can collectively produce complex overall behavior (Welstead, 1994). To predict time series of sea surface temperature (SST) index in the tropical Atlantic ocean and the sea surface temperature (SST) in the tropical Pacific ocean, two neural network models are implemented: Backpropagation Neural Network (BNN) and the Time Delay Neural Network (TDNN). In the following sections, we first describe the data used and then introduce the neural network methods. In the section of results and discussions, we predict four monthly SST Wright index in the tropical Atlantic ocean. For the Niño1-2 and Niño4 regions of the tropical Pacific ocean, we predict the six months SST, all of these results are within the predicted error bars.

THE DATA

Two kinds of data were used in this work: the sea surface temperature (SST) index in the tropical Atlantic ocean and the sea surface temperature (SST) in the tropical Pacific ocean (Niño1-2 and Niño4). Concerning the influence of Atlantic SST on climate prediction in Brazil, some results were already obtained. Moura & Shukla (1981) proposed that a possible mechanism for the occurrence of severe droughts over northeast Brazil is the establishment of a thermally direct local circulation which has its ascending branch at about 10°N and its descending branch over the northeast Brazil and the adjoining oceanic region. The driving for this anomalies circulation is provided by warming due to enhanced moist convection associated with warmer sea surface temperature anomalies over the northern tropical Atlantic, and cooling associated with colder sea surface temperature anomalies in the southern tropical Atlantic.

Hasterah & Heller (1977) find a statistically significant negative linkage between northeast Brazil rainfall and SST along the Ecuador-Peru coast. Markham & McLain (1977) found a positive lag-correlation for as early as November between the SST at locations in the tropical Atlantic and the rainfall in Ceará during the following raining season. Hastenrath (1978) stressed that droughts are associated with anomalous high sea level pressure and cold SSTs in the southern equatorial, low sea level pressure and warm SSTs in a band across the northern equatorial Atlantic, and warm SSTs in the tropical eastern Pacific. Nevertheless, after Hastenrath (1990), the Atlantic SST field plays only a subordinate role as a predictor of northeast rainfall in the company of the preseason rainfall.

The monthly sea surface temperature (SST) index in the tropical Atlantic ocean for 1854-1985 (Wright, 1987) was used. This index of monthly anomalies was specially designed to characterize the variability of SST in regions where the tropical

Atlantic ocean is weakly related to ENSO. Data for 1854-1979 were obtained from COADS (Comprehensive Ocean-Atmosphere Data Set) which were converted to anomalies in 4° latitude by 10° longitude boxes using a procedure previously described (Wright, 1985). Data for 1980-1985 were obtained from a magnetic tape of gridded values supplied by Reynolds of the Climate Analysis Center (Wright, 1987). The missing values were interpolated by fitting polynomial curves of order 3 between successive data points.

The effect of sea surface temperature anomalies associated with the SO on the global circulation has been studied using general circulation models. Julian & Chervin (1978) performed experiment with warm surface temperature anomalies over the eastern Pacific starting from January initial condition. Sea level pressure anomalies given in their Fig. 8 show negative anomalies over Southern Brazil suggesting conditions favorable for higher amounts of rainfall (Rao & Hada, 1990).

The physical mechanisms which relate seasonal rainfall fluctuations with variations in the SO are not yet well known. Nevertheless, Bjerkness (1966) proposed that the anomalous warm waters in the equatorial Pacific noted during the negative phase of the SO cause the Hadley circulation to intensify. So, a stronger than normal Hadley circulation transports more absolute angular momentum and maintains a stronger than normal subtropical jet (Rao & Hada, 1990). Increased westerlies favor blocking action (Kousky *et al.*, 1984). This situation seems to maintain persistent frontal systems in Southern Brazil causing higher rainfall. Lack of penetration of frontal systems seems to reduce precipitation in the northeast (NE) Brazil (Rao & Hada, 1990). There is also some evidence that a link between the SO and the SST in all three tropical ocean (Wolter, 1987).

The Niño1-2 region (0°N-10°S, 270°E-280°E) and Niño4 5°N-5°S, 160°E-150°E) of the tropical Pacific ocean is among the places where El Niño phenomena happens with strong intensity. The sea surface temperature (SST) for this region is published every month by Climate Prediction Center (CPC, 1996), USA. The original data is from January 1950 to now.

NEURAL NETWORKS MODELS AND PREDICTION QUALITY ANALYSIS METHOD

In this research, the Backpropagation Neural Network (BNN) and Time Delay Neural Network (TDNN) were used and both of them were implemented in the Stuttgart Neural Network Simulator (SNNS). The SNNS is a simulator for neural networks developed at the Institute for Parallel and Distributed High Performance Systems (IPVR) at the University of Stuttgart. The goal of the project is to create an efficient and flexible simulation environment for research and application of neural networks (Zell *et al.*, 1995). Here, SNNS v.4.0 developed by IPVR since 1995 was used. To analyze the prediction quality, we used a simple method-independent technique (Gershenfeld & Weigend, 1993; Nordermann & Li, 1996). In the following we give a brief description about these neural network models and method-independent technique of prediction quality analysis.

BACKPROPAGATION NEURAL NETWORK (BNN)

The most popular neural network is the Backpropagation Neural Network (Rumelhart *et al.*, 1986). For a one hidden layer networks with a single output $x(t)$, the network structure is illustrated in Figure 1. 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, $j = 1,2,\ldots,q$. Each connection performs a

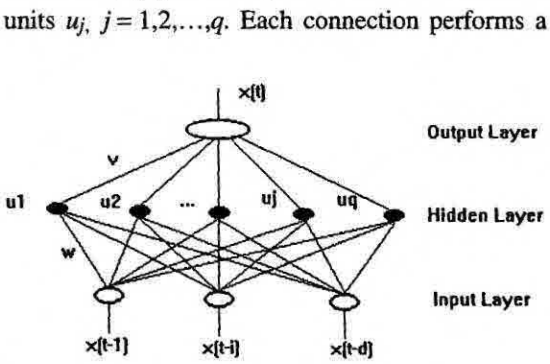

Fig. 1 — Architecture for a single hidden layer Backpropagation Neural Network.

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 the output:

$$u_j = \Psi\ (w_{0j} + \sum_{i=1}^{d} w_{ij}\ x(t-i)) \qquad (1)$$

The activation function Ψ is the same for all units, but each unit may have its own bias w_{0j}, representing an external input of the neuron's intrinsic activity level. Here, Ψ is a sigmoid function with limiting value 0 and 1 as $u_j \to -\infty$ and $u_j \to +\infty$, respectively:

$$\Psi(u_j) = \frac{1}{(1+e^{-u_j})} \qquad (2)$$

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

$$x(t) = v_0 + \sum_{j=1}^{q} v_j \cdot \Psi \cdot (w_{0j} + \sum_{i=1}^{d} w_{ji} \cdot x(t-i)) \qquad (3)$$

for d inputs and q units in the hidden layer.

Training a Neural Network involves the minimization of the mean-square error (MSE) of the outputs of the network:

$$MSE(w) = \frac{1}{N} \sum_{k=1}^{N} [\ \hat{x}_k(t) - x_k(t)\ ]^2 \qquad (4)$$

where the w is the weight set of w_{ij} of the network, N is the number of cases in the training set, and $\hat{x}_k(t)$ and $x_k(t)$ are the actual and the predicted values of a single output.

TIME DELAY NEURAL NETWORK (TDNN)

The Time Delay Neural Network is a layered network in which the outputs of a layer are buffered by several time lags and then fed fully connected to the next layer (Waibel *et al.*, 1989; Wan, 1993). Figure 2 shows the principal architecture for a single hidden layer Time Delay Neural Network. The activation of a unit is normally computed by passing the weighted sum of its inputs to an activation function, usually a threshold or sigmoid function. For TDNN, this behavior is modified through the introduction of delay (Zell *et al.*, 1995). In order to recognize time-invariant, older activation and connection values of the feature units have to be stored. This is performed by making a copy of the feature units with all their outgoing connections in each time step, before updating the original units. Training this kind of network is performed by a procedure similar to backpropagation, that takes the special semantics of coupled links into account. Training consists of fully buffering the states until the whole pattern of interest is captured and then used by backpropagation through multiple "time-shifted" versions of the network. To enable the network to achieve the desired behavior, a sequence of patterns has to be presented to the input layer with the feature of interest shifted within the patterns.

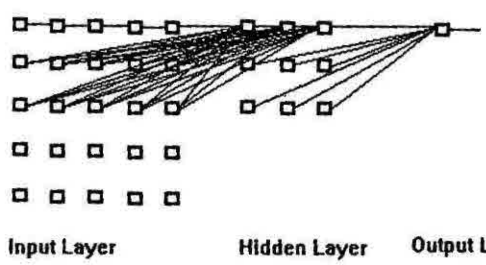

Fig. 2 — Architecture for a single hidden layer Time Delay Neural Network.

PREDICTION QUALITY ANALYSIS

A simple method-independent technique (Gershenfeld & Weigend, 1993) based on classical concepts (such as comparison of sums of squared differences, deviations of Gaussian distribution) is applied to determine how good is a prediction for test data subset, how good may be (or is) a prediction, how to improve the prediction and how to compare prediction methods.

It is necessary to perform an evaluation of the quality of a prediction to turn the prediction useful for practical purposes and applications. This is done by evaluating the quality of a prediction based on past observed values, when present values (the "future which already happened" or test data set) are available. Global indicators such as Normalized Mean Squared Error (*nmse*) and Negative Average Log Likelihood (*nall*) are very convenient (Gershenfeld & Weigend, 1993) and many easily be standardized for prediction method comparisons. The Normalized Mean Squared Error (*nmse*) is calculated from the sum of the squared difference between observed values are reconstructed values divided by the number of values concerned. The Negative Average Log Likelihood (*nall*) is related to the necessity of the knowing how confident on a prediction one may be, that is to say, what are the statistical differences between predicted values and values not already observed (the "future which did not already happened"). The detail procedure of the prediction quality analysis is described in the work of Nordemann & Li (1996).

RESULTS AND DISCUSSIONS

PREDICTION OF SST WRIGHT INDEX IN THE TROPICAL ATLANTIC OCEAN

Using the 1572 available monthly indexes (from January 1954 to December 1984), the trained Backpropagation Neural Network gives prediction results. As Table I shows, the relative errors of the predictions of the next four months are less than 5%. As Papoulis (1990) mentioned, for nonlinear prediction, mean-squared error is a reasonable criterion. For most neural networks, the mean-squared error is well defined. The advantage of mean-squared error is that it uniformly weights each training trial error in accordance with the square of magnitude of the error vector $[\hat{x}_k(t) - x_k(t,w)]$ in equation (4). In this case, the Root Mean Squared (RMS) error of trained neural network is 0.02. Figure 3 shows the reconstruction and predictions of the monthly sea surface temperature (SST) index in the Tropical Atlantic ocean.

TABLE I
Predictions of the monthly SST index (°C × 100): January to April 1985.

	January	February	March	April
Index	36	32	29	23
Predictions	25.68	40.31	34.1	18.88
Relative Errors*	3.34%	2.68%	1.67%	1.40%

*Relative Errors = (Index – Prediction) (273.15 + (Index + Prediction)/2) are expressed in terms of relative differences of temperatures (here Kelvin and not Celsius degrees are used: T(Kelvin) = T(Celsius) + 273.15).

PREDICTION OF SST IN THE TROPICAL PACIFIC OCEAN (NIÑO1-2 AND NIÑO4)

Figure 4 shows the reconstruction of Niño1-2 SST (from January 1987 to December 1995) and predictions (from January to June 1996) with Time Delay Neural Networks. 540 available data were used to train the network and 36 data were used to cross validate the training. In this case, the Normalized Mean Squared Error (*nmse*) of the reconstruction is 0.0525 and the Negative Average Log Likelihood (*nall*) is 0.5497 for prediction (from January to December 1996). Specially, we predicted the Niño1-2 SST from January to June 1996 and calculated the error bars of the prediction. Comparison with the observed SST values. All of these six month observations are within the error bars. This means that the prediction quality is acceptable. Table II gives the detail predictions values of the monthly Niño1-2 SST from January to June of 1996 and the relative errors of the prediction.

In some other situations, data records are not complete, or the amount of available data is not enough. So, a question may be asked: how many data are necessary for prediction using this Neural Network? This is an open problem in the neural network field. To begin investigating it, we used networks to test a group of data with 138 and 276 of Niño4 region. In order to have the same condi-

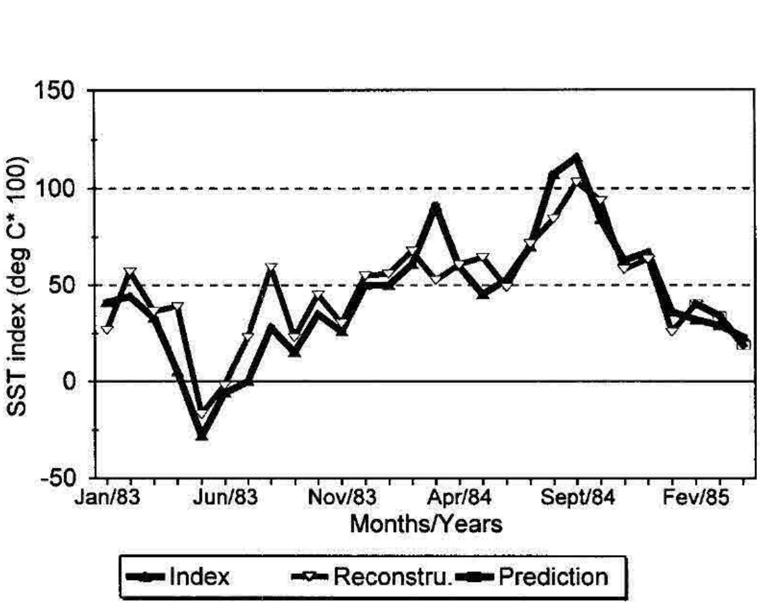

Fig. 3 — Reconstruction (January 1983 to December 1984) and Predictions (January to April 1985) of the monthly SST index.

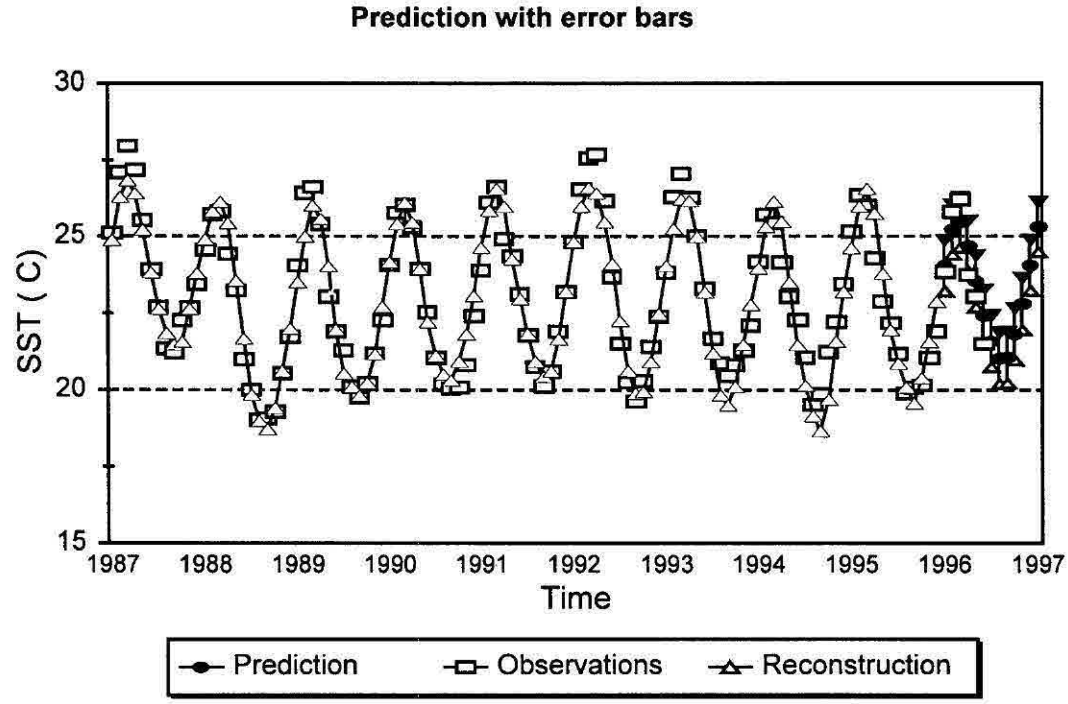

Fig. 4 — Reconstruction and prediction of SST in the region Niño1-2 using Time Delay Neural Networks.

TABLE II

Predictions of the monthly SST Niño1-2 (°C): from January to June 1996.

	January	February	March	April	May	June
Original	23.84	25.81	26.2	23.74	23.04	21.5
Prediction	24.04	25.22	25.46	24.68	23.53	22.43
Error bars	23.21- 24.87	24.39- 26.05	24.63- 26.28	23.85- 25.51	22.70- 24.37	21.50- 23.26
Rel. Error*	0.067%	0.2%	0.25%	0.31%	0.17%	0.31%

*Relative Errors = (Index – Prediction) (273.15 + (Index + Prediction)/2) are expressed in terms of relative differences of temperatures (here Kelvin and not Celsius degrees are used: T(Kelvin) = T(Celsius) + 273.15).

TABLE III

Predictions of the Niño4 monthly SST (°C): from January to June 1996.

	January	February	March	April	May	June
Original	27.88	27.56	27.68	28.04	28.4	28.54
Prediction (138 training data)	27.97	27.96	27.86	27.94	28.07	28.18
Relative Errors*	0.03%	0.13%	0.06%	0.03%	0.11%	0.12%
Prediction (276 training data)	27.94	27.88	27.88	27.96	28.12	28.27
Relative Error*	0.02%	0.11%	0.06%	0.03%	0.09%	0.09%

*Relative Errors = (Index – Prediction) (273.15 + (Index + Prediction)/2) are expressed in terms of relative differences of temperatures (here Kelvin and not Celsius degrees are used: T(Kelvin) = T(Celsius) + 273.15).

tions, all these sets were used to train the network for 20000 cycles. We tried to predict the data from January to June 1995. Table III shows the results. One can see that the subset of 276 data gave the best prediction results, but the difference is not very high.

DISCUSSIONS

The results which were presented above are qualitatively different. Reconstruction and prediction results for the Niño1-2 and Niño4 region SST raw series have shown better indexes of fit between observed and predicted values when comparing with the results of Hastenrath & Greischar (1993) and Derr & Slutz (1995). The same did not happen for Wright indexes of tropical Atlantic SST data. Two hypothesis should be suggested to explain this discrepancy:

a) the tropical Pacific SST predictability is greater than that of the Atlantic;

b) Neural Network is more capable to learn with raw data than with signal transformed to indexes.

Some justification of the hypothesis (a) is present in the literature. Authors such as Woods (1992), Sarachik (1992) and Penland, Sardeshmukh (1995) draw attention to the specially high tropical Pacific SST predictability degree, which has been recently demonstrated for models of upper tropical ocean coupled to the global atmosphere (Cane & Zebiak, 1985; Cane *et al.*, 1986; Chen *et al.*, 1995). Experiments with this kind of model have shown that 1) the memory of the coupled system is in the ocean and the initial state of the ocean yields the major part of the information on the future evolution of the system; 2) initial errors on the specification of the state of the ocean are slowly amplified in the tropical Pacific which makes prediction possible (Sarachik, 1992). For the tropical Pacific (Woods, 1992), this predictability comes from the fact that currents and planetary waves in the upper 100m of the tropical Pacific ocean present a high memory effect, which is several times greater than that of the atmosphere. Furthermore, this memory remains in spite of its interaction with the atmosphere, with some evidence of a positive feedback effect on the ocean-atmosphere coupling which may maintain the memory of the system in ENSO events.

As for the Atlantic ocean, although studies confirm its influence on the rainfall of the Southern region of Brazil, (Studzinski, 1995, among others) and of the Northeast Brazil (Hastenrath & Geischar, 1993), there are no proof that this ocean-atmosphere system should be specially as predictable as for the tropical Pacific.

The second hypothesis (b) is favored by the fact that the neural network learnt with much more facility how to reconstruct tropical Pacific Niño11 and Niño4 zone raw SST data than those which were "refined" by transformation into "indexes" (which represent the fluctuation around the climatologic monthly mean SST). One possible explication is that the index signal is more "complex" (Elsner & Tsonis, 1993) than the raw SST value, and former results of neural network application to climatological data reconstruction seem to confirm this suggestion (Li *et al.*, 1996). Another possible explication is that the index signal is "simpler" than the raw SST value, because of the filtering effect of the index determination, which cuts at least the one-year period region in the power spectrum. In this case, the lost information may carry away details and partially impairs the prediction capacity of the neural network.

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