Theor Appl Climatol (2010) 100:413–421
DOI 10.1007/s00704-009-0193-y

ORIGINAL PAPER

Temporal downscaling: a comparison between artificial neural network and autocorrelation techniques over the Amazon Basin in present and future climate change scenarios

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Received: 13 October 2008 / Accepted: 25 July 2009 / Published online: 23 August 2009

Abstract Several studies have been devoted to dynamic and statistical downscaling for both climate variability and climate change. This paper introduces an application of temporal neural networks for downscaling global climate model output and autocorrelation functions. This method is proposed for downscaling daily precipitation time series for a region in the Amazon Basin. The downscaling models were developed and validated using IPCC AR4 model output and observed daily precipitation. In this paper, five AOGCMs for the twentieth century (20C3M; 1970–1999) and three SRES scenarios (A2, A1B, and B1) were used. The performance in downscaling of the temporal neural network was compared to that of an autocorrelation statistical downscaling model with emphasis on its ability to reproduce the observed climate variability and tendency for the period 1970–1999. The model test results indicate that the neural network model significantly outperforms the statistical models for the downscaling of daily precipitation variability.

1 Introduction

Numerical models (general circulation models or GCMs) representing physical processes in the atmosphere, ocean, cryosphere, and land surface are the most advanced numerical tools currently available for weather and climate forecasts and for simulating the response of the global climate system to increasing greenhouse gas concentrations. A complete review of GCMs used in climate variability and change can be found in Meehl et al. (2007).

GCM simulations of local climate at individual grid points are often poor, especially in areas near mountains or coastlines. The notion that the increase of anthropogenic greenhouse gases will lead to significant global climate change over the next century is the accepted consensus of the scientific community. Human activities have been pointed out to have a significant contribution to the observed warming in the last 50 years and in the projections of climate until the end of the twenty-first century (Meehl et al. 2007). Human-related activities, as compared to natural climate variability (Zhang et al. 2007), are pointed out as the main cause of the observed warming in the twentieth century and the projected warming possible in the twenty-first century. In this context, an assessment of possible future changes of precipitation and temperature over the continents is highly relevant, considering the possible impacts of those changes and the issues of vulnerability that lead to consideration of adaptation measures.

For applications to impact studies such as hydrological impacts of climate change, impact models are usually required to simulate sub-grid scale phenomenon and therefore require input data (such as precipitation and temperature) on a similar sub-grid scale. The methods used to convert GCM outputs into regional high-resolution meteorological fields required for reliable hydrological modeling are usually referred to as "downscaling" techniques (e.g., Hewitson and Crane 1992). In recent years, a number of papers within the climatological community have adopted artificial neural networks as a tool for downscaling, principally in spatial resolution, from the large-scale atmospheric circulation to local or regional climate variables (Cavazos 1999).

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There are various downscaling techniques available to convert GCM outputs into daily meteorological variables appropriate for studies of hydrological impact and climate change variability (e.g., Dibike and Coulibaly 2006). Widmann et al. (2003) developed a method to downscale precipitation, referred to as "local rescaling".

There are several different methods that can be used to derive the relationship between local and large-scale climates. There is statistical downscaling used for spatial downscaling; but, mostly multiple linear regression, principle component analysis, and artificial neural networks are used. However, the procedure selected mainly depends on the objective of the study and its applications (Solman and Nuñez 1999). Dynamical downscaling generates regional-scale information by developing and using regional climate models (RCMs) with the coarse GCM data used as boundary conditions. The RCMs represent an effective method of adding fine-scale detail to simulated patterns of climate variability and change, as they resolve better the local land-surface properties such as orography, coasts and vegetation, and the internal regional climate variability through their better resolution of atmospheric dynamics and processes (Giorgi et al. 2004; Marengo et al., in revision).

Artificial neural networks (ANNs) denote a set of connectionist models inspired by the behavior of the human brain. In particular, the multilayer perceptron is the most popular ANN architecture, where neurons are grouped in layers and only forward connections exist. This provides a powerful base learner, with advantages such as nonlinear mapping and noise tolerance, increasingly used in the data mining and machine learning fields due to its good behavior in terms of predictive knowledge (e.g., Rumelhart et al. 1995). The simplest form of ANN (e.g., multilayer perceptron) is reported to give results similar to those from multiple regression downscaling methods.

The objective of this study is to identify temporal empirical functions, using ANNs and autocorrelation functions (ACs) that can capture the complex relationship between selected large-scale predictors and locally observed meteorological variables for a given temporal scale (predictands).

The ANN method uses feed-forward, which has temporal processing capability without resorting to complex and costly training methods. The emphasis of the feed-forward method is to evaluate and compare the optimal method with the most commonly used regression-based downscaling method and some of the IPCC AR4 models to which the downscaling technique is applied. The AOGCMs used in this paper derive from the IPCC project (CGCM3, CSIRO-MK3.5, ECHAM5-MPI, GFDL-CM2.1, and MIROC3.2-MEDRES) simulation for the twentieth century (present day—20C3M) and SRES scenarios (A2, B1, and A1B). All five models represent the state-of-the-art AOGCMs (e.g., Boulanger et al. 2006, 2007).

2 An overview of downscaling methods

Spatial downscaling is a technique by which finer-resolution climate information is derived from coarser-resolution GCM output. The basic assumption of spatial downscaling is that it is possible to derive significant relationships between local and large-scale climates. Since the spatial resolution of current GCMs varies between 250 and 600 km while the forcing that affects regional climate occurs generally at a much finer spatial scale, downscaling may lead to a significantly different regional climate.

Spatial downscaling techniques can be divided mainly into empirical/statistical methods and statistical/dynamical methods (Salathe 2003; Weichert and Burger 1998). The dynamic downscaling approach is a method of extracting local-scale information by developing RCMs (with the coarse GCM data used as boundary conditions). Statistical downscaling methods, on the other hand, involve developing quantitative relationships between large-scale atmospheric variables—the predictors—and local surface variables the predictands (e.g., Giorgi 1990; Kidson and Thompson 1998).

These techniques refer to a method in which sub-grid scale changes in climate are calculated as a function of large-scale climate. Statistical relationships are calculated between large area and site-specific surface climate or between large-scale upper air data and local surface climate. Stochastic weather generators may also be conditioned on the large-scale state in order to derive site-specific weather.

Dynamic downscaling is being used in Europe and North America to quantify regional climate change and provide regional climate scenarios for assessing climate change impacts and vulnerability. Projects include the UK Climate Impacts Programme (Hulme et al. 2002), the PRUDENCE (European Projects; Christensen et al. 2007; Gao et al. 2006; Giorgi et al. 2004), and the North American Project NARCCAP (Mearns 2004). These have all followed a standard experimental design that of using one or more GCMs to drive various existing regional models from meteorological services and research institutions in the regions in order to provide dynamically downscaled regional climate projections. A similar initiative has been recently implemented in South America, CREAS (*Regional Climate Change Scenarios for South America*—Marengo and Ambrizzi 2006; Marengo et al., in revision).

Thus, ANN represents a statistical procedure employed to estimate possible changes in local climate parameters as a function of the large-scale climatic changes simulated by a given GCM (spatial downscaling). Large amounts of observed data may be required to establish statistical relationships for the current climate.

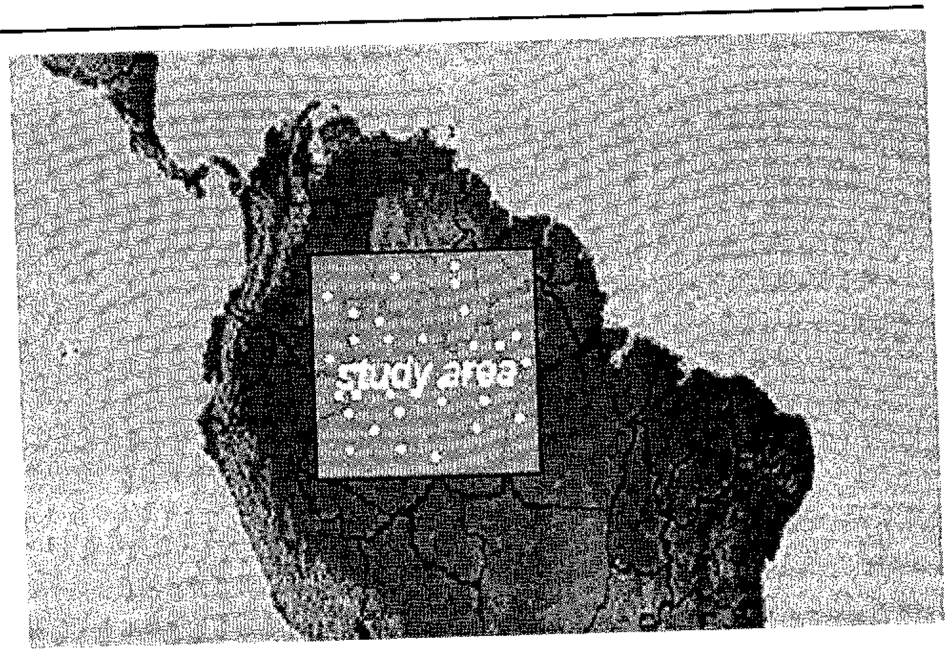

Fig. 1 Study area, with stations used

3 Datasets, method, and predictor choice

3.1 Observed and model datasets

a. The data used in these studies were from rain gauges located within the Brazilian Amazon Basin (Fig. 1), which are part of the Brazilian national hydrometeorological network. They were provided by the National Water and Electric Energy Agency of Brazil (ANEEL), whose sources include the ANEEL network. Precipitation (P) is computed from rainfall observations in the Amazon Basin and is derived for the entire basin, using the records of 33 rainfall stations.
b. The AOGCM outputs are interpolated over the 2.5°× 2.5° grid defined for the observation. The period used for present conditions (20C3M run scenario) is 1970–1999, and the future is 2070–2099 as derived from five IPCC AR4 models. The five models (Table 1) represent state-of-the-art AOGCMs. In this paper, we use the 20C3M run and SRES scenarios for futures A2, B1, and A1B described in Nakicenovic et al. (2000). It is important to note, however, that the 20C3M simulation is intended to represent the same historical total-forcing scenarios, including both natural variability and the effect of human emissions on climate (e.g., Marengo et al., in revision.

3.2 Method

3.2.1 Artificial neural network

An ANN is a system based on the operation of a biological neural network; in other words, it is an emulation of biological neural system.

Advantages of the artificial neural network:

1. An ANN can perform tasks that a linear program cannot.

Table 1 Climate models with daily data for precipitation available from PCMDI

Acronym	Model	Resolutions	Source
CGCM3	cccma_cgcm3_1_t63	T63L31	Canadian Centre for Climate Modeling and Analysis
CSIRO	csiro_mk3_0	T63L18	Australian Commonwealth Scientific Industrial and Research Organization
ECHAM	mpi_echam5	T42L19	Max-Planck-Institut für Meteorologie
GFDL2.1	gfdl_cm2_1	M45L24	Geophysical Fluid Dynamics Laboratory
MIROC-m	miroc3_2_medres	T42L20	Centre for Climate System Research, University of Tokyo; National Institute for Environmental Studies; Frontier Research Centre for Global Change

Column 1 is the acronym used in the text, column 2 is the name of the model used in the PCMDI archive, columns 3 is the model resolution, and column 4 is the source of the model

2. When an element of the ANN fails, it can continue without any problem due to its parallel nature.
3. An ANN learns and does not have to be reprogrammed.
4. It can be implemented in any application.

Disadvantage of an ANN:

1. Large amounts of observational data may be required to establish statistical relationships for the current climate.
2. Specialized knowledge is required to apply the techniques correctly.
3. Relationships are only valid within the range of the data used for calibration; projection for some variables may lie outside this range.
4. It might not be possible to derive significant relationships for some variables.

ANN is among the newest signal-processing technologies in the engineer's toolbox. The field is highly interdisciplinary, but our approach will be restricted to the engineering perspective. Definitions and style of computation in an ANN are of an adaptive nature and often nonlinear systems learn to perform a function from data (input/output).

An input is presented to the ANN along with a corresponding desired, or target, response set for the output (when this is the case, the training is called supervised). An error field is constructed from the difference between the desired response and the system output. The error information is used as feedback to the system and adjusts the system parameters in a systematic fashion. The process is repeated until the performance is acceptable. It is clear from this description that the performance hinges heavily on the data.

The network diagram shown (Fig. 2) is a full-connected two-layer, feed-forward, perceptron ANN. Full-connected means that the output from each input and hidden neuron is distributed to all of the neurons in the following layer. Feed-forward means that the values only move from the input layer to hidden layers and, then to the output layer, with no values fed back to earlier layers.

The goal of the training process is to find the set of weight values that will cause the output from the ANN to match the actual target values as closely as possible. There are several issues involved in designing and training a multilayer perceptron network:

1. Selecting how many hidden layer to use in the network
2. Deciding how many neurons to use on each hidden layer
3. Finding a globally optimal solution that avoids local minima
4. Converging to on optimal solution in a reasonable period of time
5. Validating the neural network to test for overfitting

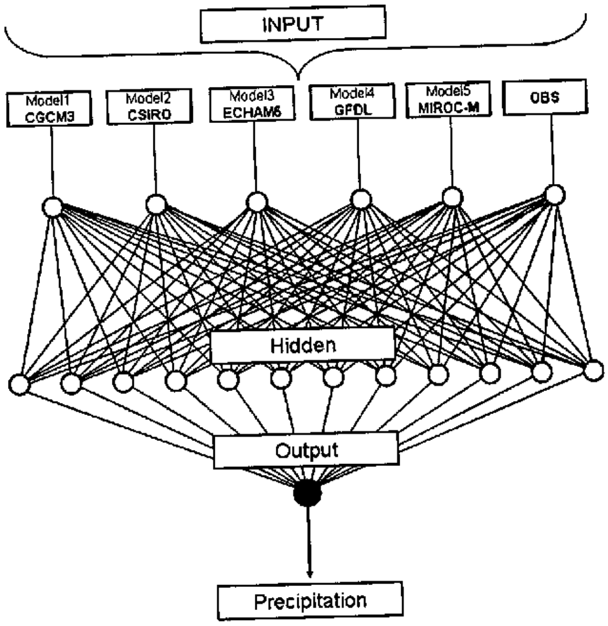

Fig. 2 Structure of the artificial neural network

3.2.2 *The statistical modeling (autocorrelation)*

Autocorrelation is the expected value of the product of a random variable or signal realization with a time-shifted version of itself obtained from a simple calculation and analysis of the autocorrelation function. We can discover a few important characteristics about our random process. These include:

1. How quickly our random signal or processes changes with respect to the time function
2. Whether our process has a periodic component and what the expected frequency might be

Since the autocorrelation functions are simply the expected value of a product, let us assume that we have a pair of random variables from the same process,

$X_1 = x(t_1)$ and $X_2 = x(t_2)$,

then the autocorrelation is often written as

$$R_{XXX}(t_1, t_2) = E[X_1, X_2] = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x_1 x_2 f(x_1, x_2)\, dx_2\, dx_1 \quad (1)$$

The above equation is valid for stationary and non-stationary random processes. For stationary process, we can generalize this expression a little further. Given a wide-sense stationary process, it can be proven that the expected values from our random process will be independent of the origin of our time function. Therefore, we can say that our autocorrelation function will depend on the time difference and not some absolute time. For this discussion, we will $\tau = t_2 - t_1$, and thus, we generalize our autocorrelation expression as

$$R_{XX}(t, t+\tau) = R_{XX}(\tau) \qquad (2)$$
$$= [X(t), X(t+\tau)]$$

for the continuous-time case.

Below, we will look at several properties of the autocorrelation function that hold for a stationary random process.

Autocorrelation is an even function for τ;

$$R_{XX}(\tau) = R_{XX}(-\tau)$$

The mean-square value can be found by evaluating the autocorrelation where $\tau = 0$, which gives us

$$R_{XX}(0) = \overline{X_2}$$

The autocorrelation function will have its largest value when $\tau = 0$. This value can appear again—for example, in a periodic function at the values of the equivalent periodic points —but will never be exceeded:

$$R_{XX}(0) \geq |R_{XX}(\tau)|$$

If we take the autocorrelation of a periodic function, then $R_{XX}(\tau)$ will also be periodic with the same frequency.

4 Procedure for training the network

Training of the ANN is accomplished by providing inputs to the model, computing the output, and adjusting the interconnection weight until the desired output is reached. The error back-propagation algorithm is used to train the network, using the mean-square error over the training samples as the objective function. One part is used for training, the second is used for cross-validation, and the third part is used for testing.

The architecture of the ANN in the present study consisted of an input layer, a hidden layer, and an output layer. The number of intermediate units was obtained through a trial-and-error procedure. The error between the value predicted by the ANN and the value actually observed was then measured and propagated backward along the feed-forward connection. The final error, after a given number of training cycles, was noted. The number of intermediate units that gave the minimum system error was accepted. During training, the performance of the ANN was also evaluated on the validation set.

The ANN and statistical procedures presented above were applied to modeling the daily precipitation data from five models (Table 1) derived from IPCC AR4, representing the current climate (i.e., 1970–1999), as well as daily observed precipitation measured during the concurrent period. The different parameters of each model are adjusted during calibration to get the best statistical agreement between observed and simulated meteorological variables.

The downscaling experiment was conducted with the one statistical method (autocorrelation) and the ANN methods (back-propagation) presented in Section 3. The ANN training needs six predictors (five output models plus observation data) as input to the network, and the best-performing network is selected. A hyperbolic tangent activation function is used at both the hidden and output layers of the ANN, and the networks are trained using a variation of feed-forward back-propagation algorithms.

A sensitivity analysis is done to determine the most relevant predictors, which need to be selected for further retraining. Sensitivity analysis provides a measure of the relative importance among the predictors (input of the ANN) by calculating how the model output varies in response to variation of an input.

5 Downscaling

5.1 Validation results

The ANN was developed using various hidden nodes and layers. The final error after a given number of training cycles was observed. The number of intermediate nodes varied from three to eight, and the number of iterations varied from 500 to 1 for converging to a desired mean-square error and cross-evaluation on the validation set (Fig. 3).

The synthesis of precipitation was carried out using statistical procedures for the purpose of comparison to the ANN results. The autocorrelation function for precipitation for the Amazon Basin is shown in Fig. 5.

The time series plots in Fig. 4 shows observed precipitation by day of season (JFM and JJA) and results of simulations using ANN from the AOGCMs. The use of ANN compared with autocorrelation results in a satisfactory performance, principally in daily variation (Fig. 5).

The autocorrelation and partial autocorrelation analysis suggest the modeling of precipitation using multivariate autoregressive model (AR). An AR model was applied to generate the series and an inverse path of model fitting used to obtain the original variables. The residual series were tested for independence and normality. The test for normality indicated that the residual series followed a normal distribution.

Comparison of results obtained using the ANN compared with those obtained using an alternative statistical

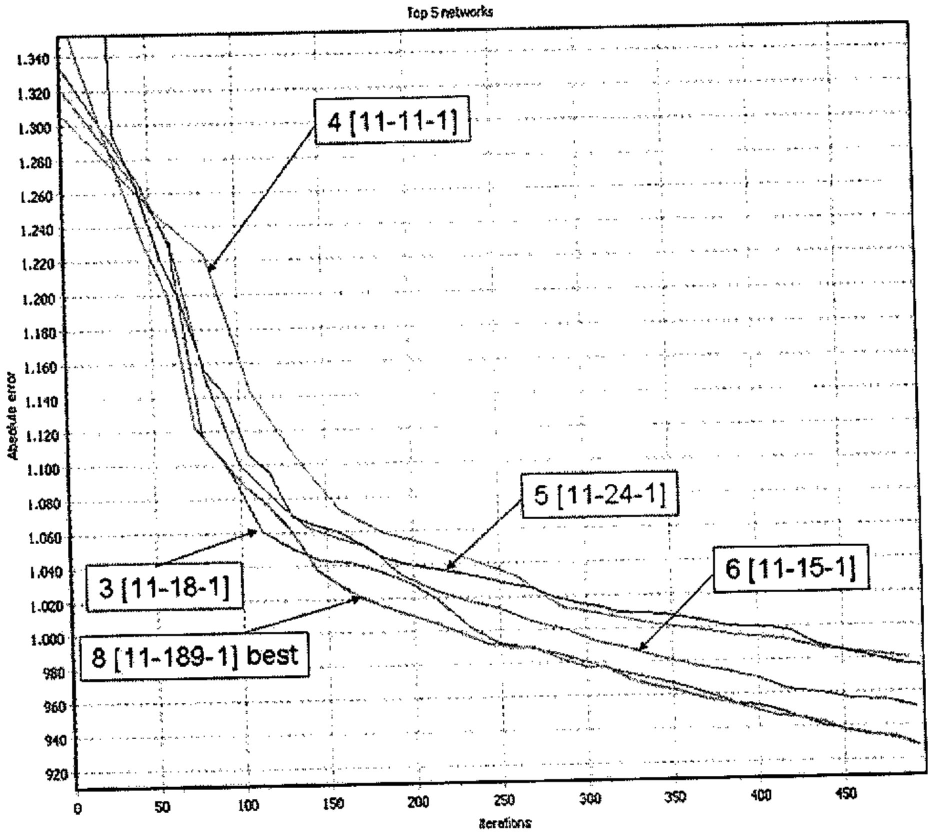

Fig. 3 The absolute error as a function of the number of iterations for various numbers of intermediate nodes (*colors*)

model indicates that the network is a potential competitive alternative tool for the analysis of multivariate time series.

Table 2 shows the comparison of monthly means and standard deviation of the series generated using both the ANN and statistical model from the Amazon Basin. Table 3 gives the comparison of the monthly skewness of the generated series using the ANN and AR for the Amazon Basin.

The ANN preserved the mean skewness (skewness is a measure of the asymmetry of the probability distribution of a real-valued random variable) of the generated series about as well as the statistical models did. Table 3 gives the comparison of the monthly values of skewness of the series generated by the use of the ANN and AR for the Amazon Basin. To conclude, each of these measures of performance

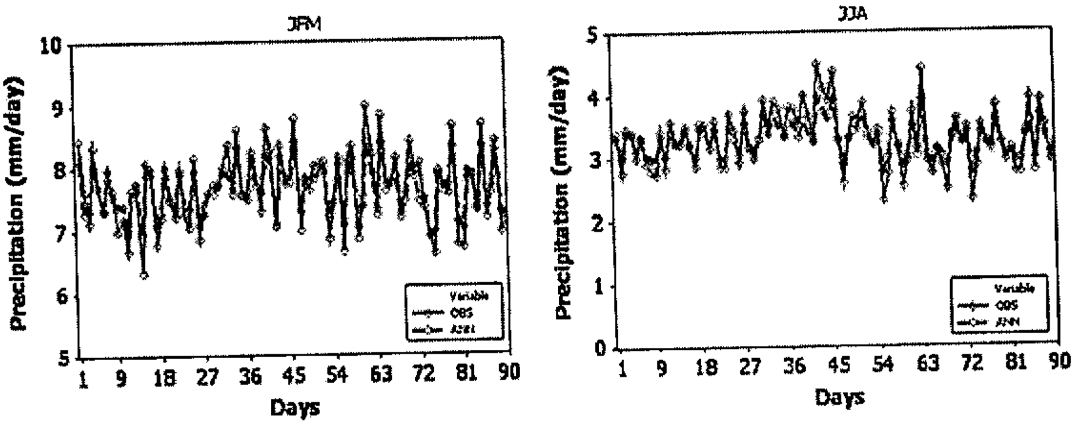

Fig. 4 Observed historical precipitation (*black*) by day of season (*JFM* and *JJA*) and results of simulations (*red*) using artificial neural network from AOGCMs, for Amazon Basin

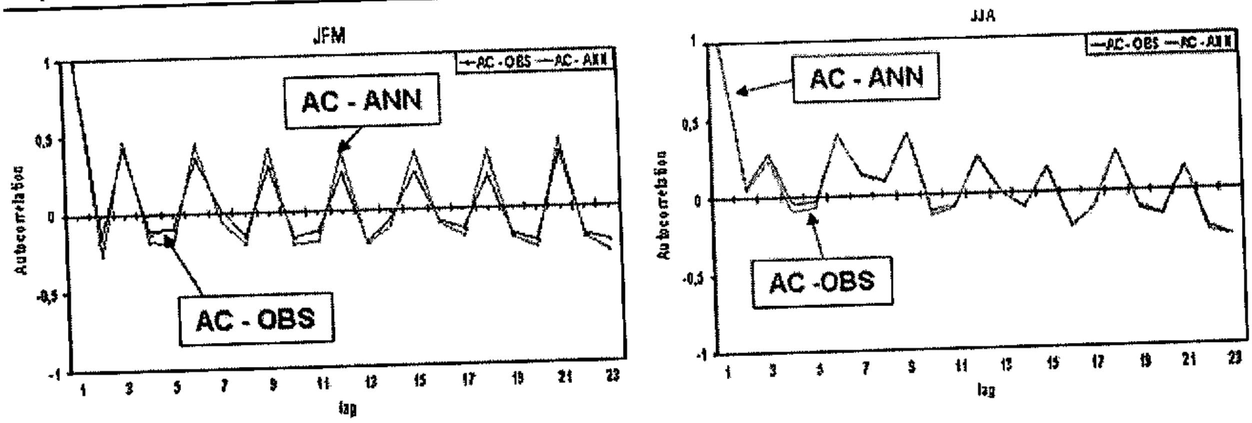

Fig. 5 Autocorrelation of historic precipitation in the Amazon Basin from observed data and ANN downscaling for 1970–1999

in the Amazon Basin showed the overall high skill of the models (Section 3) in representing precipitation patterns and variability.

5.2 Downscaling scenarios

These data cover one period (2070–2099) and three scenarios (A2, A1B, and B1). The ANN downscaling results in Fig. 5 indicate a decrease of one third both in the mean daily precipitation, with low difference between scenarios, principally between May and September and an increase between January and March (Fig. 5; Table 4).

Table 4 summarizes the downscaling results by presenting the simulated increase or decrease in monthly values of the difference 1970–1999 (present from 20C3M and observation data) and the future 2070–2099 from the five models, in mm day^{-1} and percentage (%), for each of the downscaling methods.

In the A2 scenario, ANN and autocorrelation method results predicted a small increase (+1.60 and 2.90% for ANN and AC, respectively). In the A1B scenario, ANN showed no increase/decrease, and AC gave a decrease of −2.50%. For the B1 scenario, ANN gave a decrease (−0.90%) and AC an increase (+0.68%).

In summary, the result suggests a slight increase in the mean annual precipitation values in the study area about 1.78% for the future years. Generally, there is good regional agreement between the signs of the precipitation changes in the AOGCM and the downscaled result in seasons (Table 4). The downscaling results from climate change scenarios (A2, A1B, and B1) presenting the increase or decrease in seasonal values of precipitation between the current (1970–1999) and future (2070–2099) time period for each of the downscaling methods are as follows:

1. JFM (January–February–March) increase
2. JJA (June–July–August) decrease

Table 2 Comparison of mean and standard deviation of observed and generated precipitation series for Amazon Basin for1970–1999 (present conditions)

	Mean			Standard DEVIATION		
	Observed	ANN	AR	Observed	ANN	AR
January	6.13	6.00	6.25	0.85	0.93	0.94
February	6.40	6.55	6.49	0.93	0.94	0.95
March	6.15	6.29	6.35	1.25	1.05	1.15
April	5.65	5.60	5.90	1.30	1.25	1.23
May	4.21	4.25	4.20	0.98	0.96	0.93
June	2.99	3.05	2.99	0.85	0.71	0.99
July	2.22	2.55	2.51	0.83	0.93	0.93
August	2.16	2.19	2.25	0.93	0.83	0.95
September	2.90	3.00	2.95	0.90	0.99	1.01
October	3.86	3.99	4.00	0.99	1.03	0.93
November	4.78	5.05	5.31	1.05	1.02	1.03
December	5.44	5.30	5.25	1.03	1.00	1.05

Table 3 Comparison of skewness of observed and generated precipitation series for Amazon Basin from 1970 to 1999 (present day)

	MEAN		
	Observed	ANN	AR
January	0.05	0.03	0.03
February	0.01	0.01	0.02
March	0.03	0.05	0.06
April	0.01	0.04	0.03
May	0.05	0.09	0.05
June	0.06	0.03	0.04
July	0.03	0.05	0.03
August	0.01	0.03	0.07
September	0.02	0.02	0.08
October	0.04	0.09	0.05
November	0.01	0.04	0.03
December	0.04	0.03	0.04

6 Conclusions

This paper investigates the applicability of a temporal neural network as a downscaling method using an artificial neural network and an autocorrelation model for the generation of daily precipitation over the Amazon Basin (for the current years—20C3M—and future scenarios). The ANN as well as the autocorrelation model both provided a very good fit to the data. This indicates that an ANN offers a viable alternative for multivariate modeling of precipitation time series.

The results obtained using the ANN model compared with those obtained using an alternative statistical model indicate that the network is a potentially competitive alternative tool for the analyses of multivariate time series. Comparison of the monthly values of skewness generated by the use of ANN with those generated by autocorrelation showed little difference between the two methods.

In relation to the three scenarios (A2, A1B, and B1), the ANN indicates a decrease by about a third both in the mean daily precipitation and very low difference between scenarios (May to September) and an increase between January and April (Fig. 5). Performance of the ANN, principally for present-day conditions (1970–1999) for most seasons, was better than that of the autocorrelation method.

However, one should also remember that all the downscaling in this study uses outputs from only one of various general circulation models. Previous studies showed that data taken from different GCMs could produce significantly different downscaling outputs.

In considering the method and results, it is important to note that our method is actually based on a hypothesis. The hypothesis is that the weight given to each of the various models when computing their differing estimates of twenty-first century climate conditions should depend on the skill of each in representing present-climate conditions.

A major difficulty in using ANN for climate change lies in determining the network's capability to extrapolate. A comparison between ANN and a linear projection based on statistical downscaling allowed us to determine that the ANN penalizes climate change projections. The ratio between ANN and autocorrelation is sensitive to two

Table 4 Changes of monthly precipitation for the Amazon Basin in terms of increase or decrease (mm day^{-1}) in comparison to the period 2070–2099 for different scenarios

	Increase/decrease					
	A2		A1B		B1	
	ANN */+	AR */+	ANN */+	AR */+	ANN */+	AR */+
JAN	0.86/14.0	0.76/12.40	0.68/11.1	0.87/9.4	0.26/4.2	−0.03/−0.5
FEB	1.69/26.4	1.72/26.90	0.99/15.5	0.72/11.3	1.21/18.9	1.12/17.5
MAR	2.46/40.0	2.40/39.00	2.30/37.4	2.18/35.4	2.0/32.5	2.4/39.0
APR	0.78/13.8	1.24/21.90	0.64/11.3	0.91/16.1	0.55/9.7	0.60/10.6
MAY	−1.31/−31.1	−1.36/−32.3	−1.19/−28.3	−1.09/−25.9	−1.01/−24.0	−0.65/−15.4
JUN	−1.70/−56.9	−1.43/−47.8	−1.70/−56.9	−1.44/−−48.2	−1.76/−58.9	−1.78/−59.5
JUL	−1.22/−55.0	−1.20/−54.1	−1.23/−55.4	−0.97/−43.7	−1.37/−61.7	−1.22/−55.0
AUG	−1.13/−52.3	−1.17/−54.2	−1.21/−56.0	−1.05/−48.6	−1.26/−58.3	−1.17/−54.2
SEP	−1.15/−39.7	−1.11/−38.3	−1.07/−36.9	−1.15/−39.7	−0.9/−31.0	−1.01/−34.8
OCT	−0.07/−1.80	0.03/0.80	−0.04/−1.0	−0.04/−1.0	0.09/2.3	0.13/3.4
NOV	0.52/10.9	0.67/14.0	0.81/16.9	−1.06/−22.2	0.77/16.1	1.22/25.5
DEC	1.09/20.0	1.0/18.40	1.05/19.3	0.88/16.2	0.95/17.5	0.81/14.9

Difference between 2070–2099 and 1971–1999 indicated by * and percentage difference (increase or decrease) indicated by +

factors: the bias and the divergence criteria. They represent, respectively, the error between the linear combination and present-day climate conditions and the variance between the models.

In conclusion, when applied to precipitation, the ANN approach makes it possible to compute the optimal set of weights for autocorrelation of the models (used in this paper), and a penalty function or probability that such a change occurred, based on the present-climate model biases and their projected dispersion.

The main advantages of this downscaling method (ANN) are its temporal processing ability and its ability to incorporate not only the concurrent, but also several preceding predictor values as input without any additional effort.

Acknowledgments The present work was supported by the FAPESP grant 07/50145-4, and Jose A. Marengo was funded by the Brazilian Conselho Nacional de Desenvolvimento Cientifico e Tecnologico—CNPq. We are also grateful for the helpful comments made by anonymous reviewers.

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