Neural Networks for Downscaling Climate Change Scenarios

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ABSTRACT

Global climate models (GCMs) are inherently unable to present local subgrid-scale features and dynamics and consequently, outputs from these models cannot be directly applied on impact studies. Several studies have been devoted on dynamics and statistical downscaling for both climate variability and change in the recent years. This paper introduces a methodology of downscaling applied to GCMs model output using an Artificial Neural Network (ANN) approach and linear regression. The method is proposed for downscaling daily precipitation series for a Amazon Region over the South America Continent. The performance of the temporal neural network downscaling model is compared to a regression-based statistical downscaling model with emphasis on their ability in reproducing the observed climate variability and tendency for the period 1970-2000. Furthermore, the different model test results indicate that the Neural Network Model significantly outperforms the statistical models for the downscaling of daily precipitation variability.

Keywords: Downscaling, Neural network, models, and IPCC.

1. INTRODUCTION

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

GCM simulations of local climate at individual grid points are often poor especially in areas nearby mountains or coastal lines. The notion that the increase of anthropogenic greenhouse gases will lead to significant global climate changes over the next century is the accepted consensus of the scientific community and 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 unto the end of the Century XXI (IPCC AR4-2007). In this context, an assessment of possible future changes of precipitation and temperature over the continents is highly relevant, considering the possible impacts on those changes and the vulnerability issue that led to adaptation measures..

However, in most climate change 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) at similar sub-grid scale. The methods used to convert GCM outputs into local meteorological variables required for reliable hydrological modeling are usually referred to as “downscaling” techniques. In recent years, a number of paper within the climatological community have adopted artificial neural networks as a tool to downscaling from the large-scale atmospheric circulation to local or regional climate variables (Cavazos, 1997).

There are various downscaling techniques available to convert GCM outputs into daily meteorological variables. Widmann et al., (2003) developed method to downscale precipitation, referred to as the “local scaling”. The method used three statistical downscaling methods are investigated; local rescaling of the simulated precipitation; downscaling using singular value decomposition (SVD) with simulated precipitation as the predictor, and local rescaling with a dynamical correction.

There are several different methods, which can be used to derive the relationship between local and large-scale climates. There is no standard method used for spatial downscaling, though mostly multiple linear regression, principle component analysis, and artificial neural networks are used, however the selection procedure mainly depends on the paper objective. Dynamical downscaling generates regional-scale information by developing and using Regional Climate Models (RCMs) with the coarse GCMs 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.

Artificial Neural Networks (ANNs) denote a set of connectionist models inspired in the behavior of the human brain. In particular, the Multilayer Perceptron (MLP) 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 (DM) and Machine Learning (ML) 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 similar results compared to multiple regression downscaling methods.

The objective of this study is to identify temporal neural networks that can capture the complex relationship between selected large-scale predictors and locally observed meteorological variables (predictands).

The specifically focus of this paper on the time lagged feed-forward neural networks (NEURAL NETWORK) which have temporal processing capability without resorting to complex and costly training methods. In addition, emphasis is given to evaluating and comparing the optimal (NEURAL NETWORK) method with the most commonly used regression based downscaling method and the best models are applied to downscale the outputs of model (CGCM3.1, CSIRO-MK3.5, ECHAM5-MPI, GFDL-CM2.1, and MIROC3.2-MEDRES) Intergovernmental Panel on Climate Change (IPCC) AR4.

2. AN OVERVIEW OF DOWNSCALING METHODS

Two major downscaling approaches, namely, dynamical downscaling and statistical downscaling, are commonly used for climate scenario development at higher resolution. Dynamic downscaling generates regional scale using RCMs with coarse GCMs data. Statistical downscaling (SD) methods, on the other hand, involve developing methods; on the other hand, involve developing quantitative relationships between large-scale atmospheric variables, the predictors, and local surface variables, the predictands.

Therefore a statistical procedure is employed to estimate possible shifts in local climate parameters as a function of the large-scale climatic changes simulated by a given GCM simulation (Spatial downscaling).

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 is between 250 and 600 km and as the forcing that affects regional climate occurs generally at a very finer spatial scale when compared to GCMs, it may lead to a significantly different regional climate conditions compared to larger spatial scales. Spatial downscaling techniques can be divided mainly into empirical/statistical methods and statistical/dynamical methods (Salathe, 2003) (Weichert and Burger, 1998).

These techniques refer to a method in which sub-rid 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.

The fundamental assumption behind all these methods is that the statistical relationships, which are calculated using observed data, will remain valid under future climate conditions.

There are several different methods, which can be used to derive the relationship between local and large-scale climates. There is no standard method used for spatial downscaling , thou h mostly multiple linear regression, principle component analysis, and artificial neural networks are used.

Spatial downscaling techniques provide more realistic scenarios of climate change at individual sites than the straight application of GCM-derived scenarios to an observed climate data set. These techniques are much computationally demanding than the physical downscaling using numerical models (von Storch et al., 2000).

Large amounts of observed data may be required to establish statistical relationships for the current climate. Specialist knowledge may be required to apply the techniques correctly. It may not be possible to derive significant relationships for some variables.

The used of downscaling in Europe and North America, quantify better regional climate change and provide regional climate scenarios for assessing climate change impacts and vulnerability. This projects include the UK Climate Impacts Programme (Hulme et al., 2002), the PRUDENCE (European Projects) (Christensen et al., 2007b; Gao et al., 2006; Giorgi et al., 2004), and the North American Project NARCCAP (Mearns, 2004). These have all followed a standard experimental design of using one or more GCMs to drive various regional models from meteorological services and research institutions in the regions 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., 2007).

3. DATA AND STUDY AREA

The study area considered in this paper is the Amazon Basin Region (Fig. 1). Forty years of daily total precipitation as well as daily precipitation records representing the current climate (1970-2000) were prepared for the downscaling experiments.

At the same time, observed daily data of large-scale predictor variables representing the current climate condition of the region is derived from the observation station over Amazon Basin (33 stations) The data used in this study were from rain gauges located within the Brazilian Amazon basin, 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.

Climate variables corresponding to the climate change scenario for the study area are extracted from the IPCC models (CGCM3.1, CSIRO-MK3.5, ECHAM5-MPI, GFDL-

CM2.1, and MIROC3.2-MEDRES). As planning for the IPCC Fourth Assessment Report (AR4) commenced in 2003, the climate modeling community, as represented at the international level by Working Group on Coupled Model (WGCM), recognized that this process had to be better organized and carefully coordinated. The modeling group proceeded to complete as many of the experiments as they could manage during 2004. By early 2005, a total of 16 modeling groups from 11 countries participated with 23 models (Meehl et al., 2007).

4. NEURAL NETWORK METHOD

The most widely used neural classifier today is Multilayer Perceptron (MLP) network which has also been extensively analyzed and for which many learning algorithms have been developed. The MLP belongs to the class of supervised neural networks.

MLP networks are general-purpose, flexible, nonlinear models consisting of a number of units organized into multiple layers. The complexity of the MLP network can be changed by varying the number of layers and the number of units in each layer. Given enough hidden units and enough data, it has been shown that MLPs can approximate virtually any function to any desired accuracy. In other words, MLPs are universal approximates. MLPs are valuable tools in problems when one has little or no knowledge about the form of the relationship between input vectors and their corresponding outputs (Smith, 1993).

The multi-layer feed-forward neural network is trained by supervised learning using the iterative back-propagation algorithm. In the learning phase a set of input patterns, called the training set, are presented at the input layer as feature vectors, together with their corresponding desired output pattern which usually represents the classification for the input pattern (e.g. Rumelhart et al., 1995).

Network Design: Downscaling Experiment

The neural network models in this study are developed using the Neuro-Solutions software. First Neural Network with different lag time (time delay) is trained with all (the twenty two) predictor variables as input to the networks and the best performing network is selected. Then, the most relevant input variables (predictors) are identified by performing sensitivity analysis on the selected Neural Network. Sensitivity analysis provides a measure of the relative importance among the predictors (inputs of the neural network) by calculating how the model output varies in response to variation of an input.

The results provide a measure of the relative importance of each input (predictor) in the particular input-output transformation. Several training experiments are conducted with different combinations of time lags and number of neurons in the hidden layer till the optimum network is identified. For the case of downscaling of precipitation with Neural Network, a time lag of five (days) and 15 neurons in the hidden layer gave the best performing network.

5. DOWNSCALING RESULTS

From the forty years of observed data representing the current climate, the first 21 years (1970-1990) are considered for calibrating the downscaling models while the remaining ten years of data (1991-2000) are used to validate those models. The different parameters of each model are adjusted during calibration to get the best statistical agreement between observed and simulated meteorological variables.

The accuracy of the downscaling models, the downscaling model validation statistics are presented in Table 2 in terms of seasonal model biases.

These validation results indicate different bias between models, principally in June, July and August (JJA). In January, February, and Mach (JFM) the models super-estimate precipitation over Amazon Basin, the accepting GFDL-CM2.1. In JJA, the patterns are relatively symmetric respective to JFM, excepting CSIRO-MK3.5.

Once the downscaling models have been calibrated and validated, the next step is to use these models to downscale the control scenario simulated by the GCM. In this case, instead of the precipitation data observation used as input to each of the downscaling models earlier, the large-scale predictor variables are taken from IPCC models simulation output covering the four distinct periods corresponding to “business” as usual scenario explained earlier.

The Figure 3, show normal histogram for JFM, showed that on the Amazon region model GFDL presents a large dispersion that others models. This result is similar to the verified in table 2, where the GFDL is what it show positive bias.

In relation Figure 4 (JJA), show different conditions in relation Figure 3, principally in relation between CSIRO model, neural network simulation and observation data. The CSIRO model show large frequency concentration between 4 and 6 mm day^{-1}, differentiating the others models and neural network simulation.

The table 3 summarizes the downscaling results by presenting the simulated increase or decrease in seasonal values of average precipitation between the current (1970-1990) and the 1990s (1991-2000) time periods for each of the downscaling methods. The results show that both Neural Network and Linear Regression predicted a relative increase in precipitation. However, while neural network predicted a seasonal variation in precipitation increase (with around 1.00 mm day^{-1} for CGCM3, ECHAM5, CSIRO and MIROC increase in JFM, excepted GFDL with increase around 3.0 mm day^{-1}). In JJA, the precipitation increase around 0.75 mm day^{-1} for CGCM3, ECHAM5, GFDL, and MIROC. CSIRO increase around of 2.20 mm day^{-1}.

The linear regression resulted in a smaller difference in relation neural network predicted, principally in relation of the extreme, GFDL in JFM and CSIRO in JJA.

6. CONCLUSION

This paper investigates the applicability of temporal neural network a downscaling method using Artificial Neural Network for the generation of daily precipitation over the Amazon Basin (Fig. 1). The study results show that the time lagged feed-forward network (Neural Network) can be an effective method for downscaling daily precipitation data as compared to the commonly used method (linear regression).

The main advantage of this downscaling method is its ability to incorporate not only the concurrent, but also several antecedent predictor values as input and its temporal processing ability without any additional effort.

The results show different values from models in relation of neural network, linear regression and observation data. The models show super-estimate precipitation in comparison with observation data. In JFM the GFDL model, increase precipitation around 3.10 mm day^{-1}, for JJA the CSIRO model increase precipitation around 2.20 mm day^{-1}, this results so much for neural network as linear regression.

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

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TABLE 1 - ALL CLIMATE MODELS WITH DAILY DATA FOR *P* AVAILABLE FROM PCMDI. COLUMN 1 IS THE ACRONYM USED IN THE TEXT. COLUMN 2 IS THE NAME OF THE MODEL USED IN THE PCMDI ARCHIVE, COLUMNS 3 DENOTE HOW MANY REALIZATIONS FROM EACH MODEL COULD BE USED, AND COLUMN 4 IS THE SOURCE OF THE MODEL.

Acronym	**Model**	**prp**	**Source**
CGCM3	cccma_cgcm3_1_t63	0	Canadian Centre for Climate Modeling and Analysis
CSIRO	csiro_mk3_0	3	Australian Commonwealth Scientific Industrial and Research Organization
ECHAM	mpi_echam5	1	Max-Planck-Institut für Meteorologie
GFDL2.1	gfdl_cm2_1	1	Geophysical Fluid Dynamics Laboratory
MIROC-m	miroc3_2_medres	3	Centre for Climate System Research, University of Tokyo; National Institute for Environmental Studies; Frontier Research Centre for Global Change

TABLE 2 – BIAS FOR THE SEASONS AND MODELS.

	Biases	
Models	**JFM**	**JJA**
CGCM3.1	-1.875	0.520
CSIRO-MK3.5	-2.125	-0.031
ECHAM5-MPI	-0.833	2.930
GFDL-CM2.1	1.010	2.590
MIROC3.2-MEDRES	-0.666	1.583

TABLE 3 - AVERAGE INCREASE / DECREASE IN SEASONAL VALUES OF METEOROLOGICAL VARIABLES BETWEEN THE CURRENT (1970-1990) AND THE 1990S (1991-2000) SIMULATION PERIODS (mm day^{-1}).

	Neural		**Linear Regr.**	
Models	**JFM**	**JJA**	**JFM**	**JJA**
CGCM3.1	1.06	1.00	1.12	0.98
CSIRO-MK3.5	0.69	0.67	0.87	0.55
ECHAM5-MPI	0.85	2.24	0.95	1.11
GFDL-CM2.1	3.13	0.37	2.65	2.01
MIROC3.2-MEDRES	1.25	0.99	1.21	1.12

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Figure 1 - Location of study area

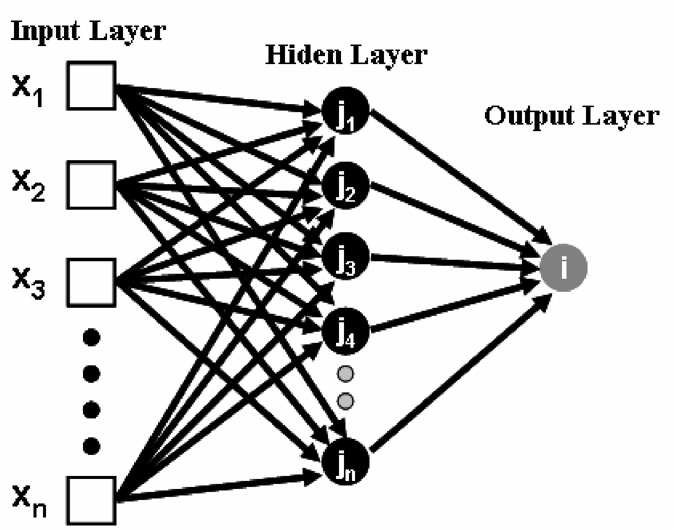

Figure 2 - Architecture of multi-layer perceptron.

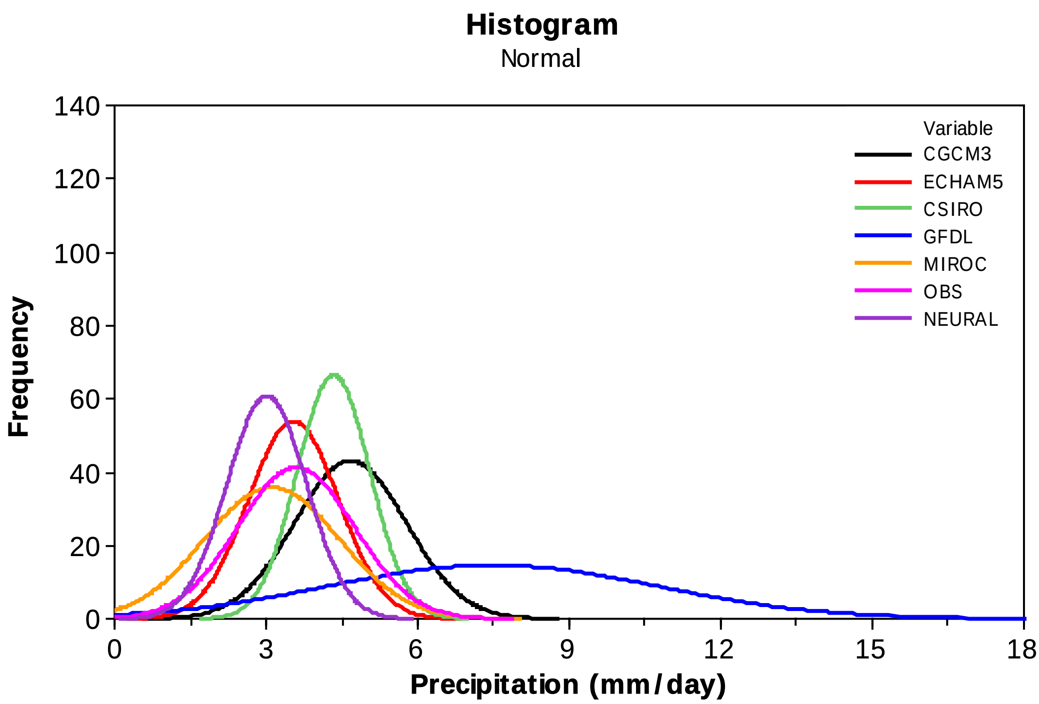

Figure 3 – Normal histogram for the models, observation data and neural network precipitation in JFM

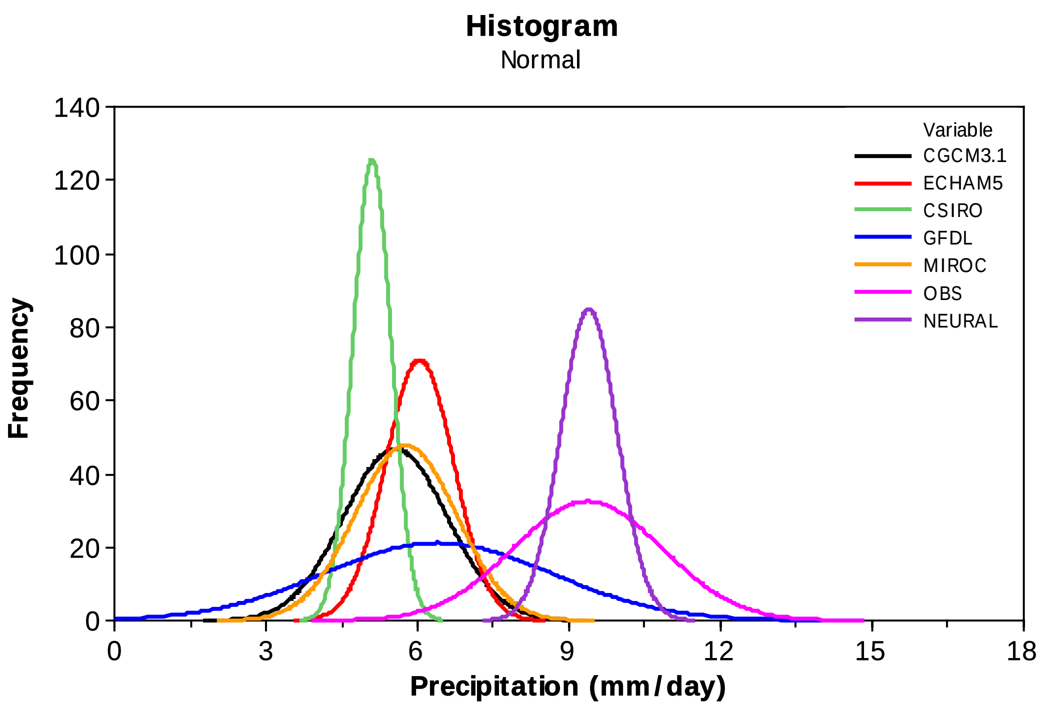

Figure 4 – Same as Fig. 3 but for the JJA season.