METEOROLOGICAL DOWNSCALING METHODS WITH ARTIFICIAL NEURAL NETWORK MODELS: ADVANTAGES AND DISADVANTAGES

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The mathematical models used to simulate the present climate and project future climate with forcing by greenhouse gases and aerosols are generally referred to as General Circulation Models or Global Climate Models (GCMs). While they demonstrated significant skill at the continental and hemispherical scales and incorporate a large proportion of the complexity of the global system, they are inherently unable to present local subgrid scale features and dynamics (Wigley el al., 1990).

However, the spatial resolution of GCMs remains quite coarse, in the order of 300 x 300 km, and at scale, the regional and local details of the climate which are influenced by spatial heterogeneities in the regional physiography are lost. Therefore, there is the need to convert the GCM outputs into a reliable data set with higher spatial resolution, with daily rainfall and temperature time series at the scale of the watershed or a region to which the climate impact is going to be investigated. The methods used to convert GCM outputs into local meteorological variables required for reliable climate modeling are usually referred to as *downscaling* techniques.

There are various downscaling techniques available to convert GCM outputs in to meteorological variables appropriate for climate impact studies. Spatial downscaling means to relating the large-scale atmospheric predictor variables simulated by GCMs to local or station-scale using numerical methods. There are a variety of downscaling techniques in the literature, but two major approaches can be identified at the moment, namely, dynamic downscaling and empirical (statistical) downscaling. Dynamic downscaling approach is a method of extracting local-scale information by developing regional climate models (RCMs) with the coarse GCM data used as boundary conditions. Empirical downscaling, on the other hand, starts with the premise that the regional climate is the result of interplay of the overall atmospheric and oceanic circulation as well as of regional topography, land-sea distribution and land use (e.g. von Storch et al., 2000). The most widely used empirical downscaling methods are the multiple linear regression and stochastic weather generation. However, the interest in nonlinear regression methods, namely, artificial neural network (ANN), is nowadays increasing because of their high potential for complex, nonlinear and time-varying input-output mapping. Although the weight of an ANN are similar to nonlinear regression coefficient, the unique structure of the network and the nonlinear transfer function associated with each hidden and output nodes allows ANNs to approximate highly nonlinear relationships.

The simplest form of ANN (i.e. multilayer perceptron) is reported to give similar results compared to multiple regression downscaling methods (Schoof and Pryor, 2001). Furthermore, ANN model was found to account for some heavy rainfall events, while they were not identified by the linear regression downscaling technique (Weichert and Burger, 1998). More recently, Cannon and Whitfeld (2002) found that an ensemble ANN downscaling model was capable of predicting changes in stream flows using only large-scale atmospheric conditions as model input.

There are, however, other categories of neural network that have feedback connections and are thus inherently dynamic in nature. Dynamic neural network are topologies designed to include time relationships explicitly in the input-output mappings and the application of feedback enables the networks to acquire state representations, which make them more suitable for complex nonlinear system modeling (Gautan and Holz, 2000).

The neural network approach should to determining which model contributes most to the output and to extrapolation the optimal combination of models to twenty first conditions.

1) The importance of an input to a trained variable is actually measured by the magnitude of the weights fanning out from the input. If the weights are small, the input contributes little, if the weights are large, the input contributes more.
2) The neural network parameters, also called weights, are optimized, based on a training dataset. If the distribution of the datasets changes dramatically, the method usually does not project, i.e., usually considered to have good skills when the input data belong to a distribution similar or close to the distribution of the training dataset.

The advantage of the neural network for downscaling is:

a) Much less computationally demanding than physical downscaling using numerical models;

b) Ensembles of high resolution climate scenarios may be produced relatively easily.

and disadvantages is:

a) Large amounts of observational data may be required establish statistical relationships for the current climate;
b) Specialist knowledge required to apply the techniques correctly;
c) Relationships only valid within the range of the data used for calibration projections for some variables may lie outside this range;
d) May not be possible to derive significant relationships for some variables;
e) A predictor which may not appear as the most significant when developing the transfer functions under present climate may be critical for determining climate change.

The Climate Change Group from INPE-Brazil is working on a project using statistical downscaling technique based on the use of Artificial Networks for climate change. The models will be constructed using observed data (South America sector) and then applied to AOCGM output from IPCC AR4 in order to evaluate their ability to produce higher resolution climate change scenarios and improved short-term weather forecast over South America.

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