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Bias correction of ANN based statistically downscaled precipitation data for the Chaliyar river basin

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ABSTRACT

Any study to assess the impact of climate change on hydrology requires future climate scenarios at river basin scale. General Circulation Models (GCM) are the only reliable source for future climate scenarios, but they perform well only at coarse scale. Also, it may not be possible to straight away use the output from GCMs in hydrologic models applied at river basin scale. GCM simulations need to be downscaled to river basin scale. Uncorrected bias in the downscaled data, if any, should be corrected before the downscaled data is used in hydrologic applications. In this study, an advanced nonlinear bias correction method is applied to Artificial Neural Network (ANN) based downscaling models to obtain projections of monthly precipitation of station scale. The models were validated through application to downscale the monthly precipitation at two rain gauge stations, one in the Chaliyar river basin located in the humid tropics in Kerala, India, and other located close to it. The probable predictor variables are extracted from the National Centre for Environmental Prediction and National Centre for Atmospheric Research (NCEP/NCAR) reanalysis data and simulations from the third generation Canadian Coupled Global Climate Model (CGCM3) for the twentieth century experiment, 20C3M. The potential predictors were selected based on the values of the correlation coefficient between NCEP predictors and predictand precipitation and also between NCEP predictors and GCM predictors. Separate models were developed for each station and for each of the season and separate sets of potential predictors were used in each of the models. The models were validated using the data after year 2000; the performance of the models was reasonably good except for a few extremes.

KEYWORDS: statistical downscaling, precipitation, climate change, bias correction, ANN

NOMENCLATURE

$\bar{X}$	mean of the predictor
$\bar{Y}$	mean of the predictand
σ_X	standard deviation of the predictor
σ_Y	standard deviation of the predictand
$X_{c,i}$	i^{th} bias corrected value
$X_{o,i}$	i^{th} observed value
μ_p	mean simulated data in the projection period
μ_b	mean simulated data in the baseline period
$X_{p,i}$	predicted data in the validation period
a, b	parameters obtained from calibration
MB	mean bias
$x_{e,i}$	i^{th} predicted value

1. INTRODUCTION

It is widely believed and predicted that climate change will have a significant impact on water resources and hydrology. Any study related to this requires data at the river basin scale or even at station scale. General Circulation Models (GCMs) are the only reliable source for simulating future climate scenarios, but they perform well only at a coarse resolution like 2.5^0 and 3^0. Hence the GCM outputs cannot be used directly for climate change studies and they do not provide a direct estimation of the hydrological response to climate change [1]. Downscaling techniques are used to convert the coarse spatial resolution of the GCM output to a fine resolution, which may involve generation of point/station data of a specific area by using climatic output variables from GCMs [2-5]. Downscaling techniques can be broadly classified into two: (i) dynamic downscaling, and (ii) statistical downscaling. Typical application of dynamic downscaling is to derive a regional dynamic model at finer resolutions with the larger scale information from a General Circulation Model. But to date, they are extremely expensive to run and only a few simulations can be afforded. The alternate approach of empirical statistical downscaling (ESD) is computationally efficient and it is a two step process consisting of (i) development of a statistical relationship between local climate variables like surface air temperature and precipitation, and large scale predictors like pressure fields, wind speed, humidity etc. and (ii) application of such relationships to the output of the GCM experiments to simulate local climate characteristics in the future period. In this study, ANN is used to derive a statistical relationship between monthly precipitation, and the large scale predictors.

2. STUDY AREA AND DATA

The study area is the Chaliyar river basin in Kerala, India. The Chaliyar is the fourth longest river in Kerala with a length of 169km and is situated between 11^0 30'N and 11^0 10'N latitudes and 75^0 50'E and 76^0 30'E longitudes. The total area of the river basin is 2923 km^2 and the geographical area of the part of the total river basin in Kerala is 2530km^2.

The data used in this study are the observed monthly precipitation at the two raingauge stations - Kottaparamba observatory of the Centre for Water Resources Development and Management (CWRDM) (1980 to 2007) and the State Seed Farm, Puduppadi (1965 to 2011), NCEP/NCAR reanalysis data for 1965 to 2011and predictions from GCM simulations. Fig.1 is a map of the Chaliyar river basin in which the location of these stations is shown. The T63 version of CGCM3.1 for present-day (20C3M) at a monthly time scale for a period from January 1965 to December 2000, for four grid points whose latitude ranges from 9.77^o N to 12.56^o N and longitudes ranges from 75.94^o E to 78. 75^o E were downloaded from the website http://www.cccma.ec.gc.ca/data/cgcm3/cgcm3.shtml.

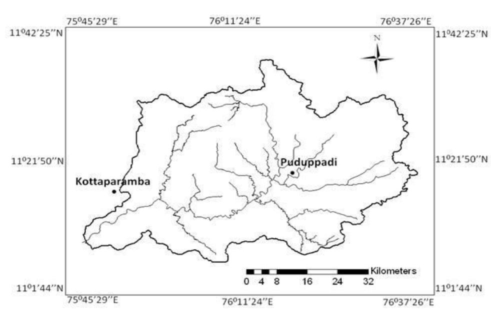

FIGURE 1. MAP OF THE CHALIYAR RIVER BASIN WITH THE RAINGAUGE STATIONS

3. METHODOLOGY

The possible bias in GCM output could be due to partial ignorance about the geophysical processes, assumptions made for numerical modeling, parameterization and the use of empirical relationships/ formulae [6]. Prior to statistical downscaling, standardization is performed to reduce systematic biases in the mean and variance of the GCM predictors relative to observations [7]. In this study, t his was done by subtracting the mean and dividing this quantity by the standard deviation of the predictor for a baseline period.

Seasonal stratification is also required to be done as the relationship between the predictor variables and the predictand varies seasonally because of seasonal variation in atmospheric circulation [8]. In the study area, the major part of precipitation occurs during the two monsoons - south west monsoon (June to September) and north east monsoon (October to November). 75% and 15% of the annual precipitation is received during the south west monsoon and the north east monsoon respectively. During April and May, about 10% of rainfall is received as pre-monsoon showers. January, February and March are dry months of the year.

3.1 Selection of Potential Predictors

Any variable can be used as a predictor as long as it is reasonable to expect that there exists a relationship between the predictor and the predictand [9]. In this study, the potential predictors were selected based on the correlation between the NCEP predictors viz. geopotential height, air temperature, eastward wind, northward wind, specific humidity etc. at various pressure levels and the predictand precipitation. The correlations were estimated based on the product moment correlation [10], which measures the linear relationship between the predictor and predictand and is given by

$$\mathrm{p} = \frac{\sum_{\mathrm{t}=1}^{\mathrm{N}}(\mathrm{X_t} - \overline{\mathrm{X}})(\mathrm{Y_t} - \overline{\mathrm{Y}})}{\mathrm{N}\sigma_{\mathrm{X}}\sigma_{\mathrm{Y}}} \qquad (1)$$

where X_t and Y_t represent the predictor and predictand for the month t; N refers to the number of data; X and Y represent means and σ and σ represent standard deviations of the predictor and the predictand respectively.

3.2 Development of ANN model

An ANN is a massively parallel-distributed information processing system having certain performance characteristics resembling biological neural networks of the human brain [11]. ANN based transfer functions have been used for downscaling large scale climatic variables [12-16]. These are complex nonlinear regression models structured between the predictors and the predictand. Its input layer consists of potential predictors, the second layer is a hidden layer to transform the inputs nonlinearly to output, and the output layer consists of the predictand precipitation. In this study, an ANN based transfer function was derived between the potential predictors and the predictand for the training period. The Levenberg-Marquardt feed forward back propagation algorithm was used for this purpose [17]. The normalized mean square error was used as an index for assessing the performance of the model. The trained network was further validated using observed data for the validation period.

3.3 Bias Correction after downscaling

The delta method [18-19] which is widely used for bias correction is given by:

$$X_{c,i} = X_{o,i} \times \frac{\mu_p}{\mu_b} \qquad (2)$$

where $X_{c,i}$ and $X_{o,i}$ denote the bias corrected data and observed data respectively; and μp and μb indicate the mean simulated data in the projection period and baseline period respectively. This method corrects only the mean of the precipitation. An advanced nonlinear bias correction method [20] that corrects both the mean and the coefficient of variation (CV) was used in this study. The bias corrected data ($X_{c,i}$) is obtained as:

$$X_{c,i} = a(X_{p,i})^b \qquad (3)$$

where $X_{p,i}$, is the predicted data in the validation period, and *a* and *b* are the parameters obtained from calibration and subsequently applied during the validation period. The performance of bias corrected models is assessed by determining the mean bias (*MB*) for each month using the equation:

$$MB = \frac{1}{N}\sum_{i=1}^{N}(x_{e,i} - x_{o,i}) \qquad (4)$$

where $x_{o,i}$ is the i^{th} observed value (monthly), $x_{e,i}$ is the i^{th} predicted value and *N* is the number of data.The validated network with bias correction can be used to predict future precipitation under various scenarios.

4. RESULTS AND DISCUSSION

Based on the values of the correlation coefficient between the observed precipitation at the two stations during various seasons and the NCEP predictors for various seasons and between the NCEP predictors and the GCM predictors, the potential predictors were identified from among the probable predictors for these stations during the three seasons. The potential predictors so selected for the two stations during the south west monsoon are presented in Table 1.

4.1 ANN based downscaling and bias correction

The data was split into two parts. The first part (from 1965 to 1999 for Puduppadi and from 1980 to 1999 for Kottaparamba) was used for training and the second part (from 2000 to 2011 for Puduppadi and 2000 to 2007 for Kottaparamba) was used for validation. The network was trained using the potential predictors and the predictand (monthly precipitation at both raingauge stations for the three seasons). ANN structures were constructed between the potential predictors and the predictand at each station and for each season. The number of hidden layers was fixed iteratively. The results of the validation, without bias correction and with bias correction for the Kottaparamba and Puduppadi raingauge stations during the SW monsoon are presented in Figs. 2 and 3 respectively. The monthly mean bias in the validation period for the Kottaparamba station (with and without bias correction) is presented in Fig. 4.

TABLE 1. POTENTIAL PREDICTORS FOR SOUTH WEST MONSOON

Kottaparamba	Puduppadi
1000mb geopotential height	925mb geopotential height
250mb air temperature	200mb air temperature
1000mb northward wind	200mb northward wind
850mb eastward wind	8850mb eastward wind
Surface pressure	925mb eastward wind
Surface sea level pressure	Surface pressure
925mb specific humidity	Surface sea level pressure
	850mb specific humidity
	925mb specific humidity

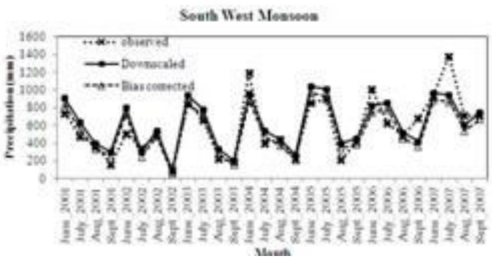

FIGURE 2. COMPARISON OF MONTHLY PRECIPITATION AT KOTTAPARAMBA STATION DURING SW MONSOON

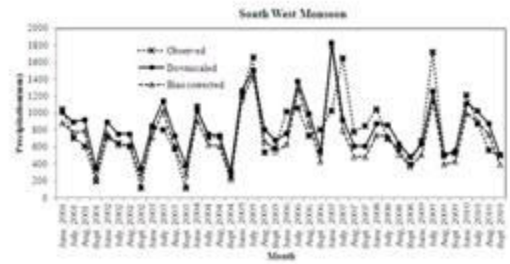

FIGURE 3. COMPARISON OF MONTHLY RECIPITATION AT PUDUPPADI STATION DURING THE SW MONSOON

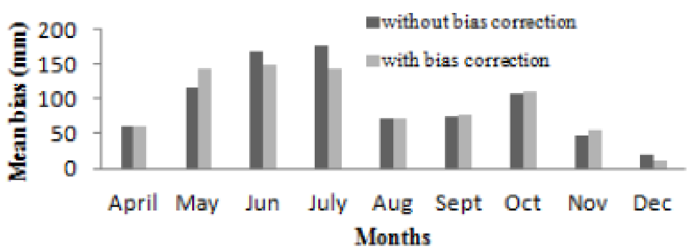

FIGURE 4. MEAN BIAS IN MONTHLY PRECIPITATION IN THE KOTTAPARAMBA STATION

5. SUMMARY AND CONCLUSIONS

A nonlinear bias correction method is applied to the statistically downscaled monthly precipitation data, which conserves the changes in mean precipitation and coefficient of variation between uncorrected and bias corrected data. ANN is used to derive relationships between the predictor and predictand in various seasons for the calibration period and the models are verified in the validation period. Bias correction is applied to the validated data for various seasons at two stations and the results showed that mean bias is reduced in most of the months by applying bias correction to the downscaled data.

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