Chapter 44
Analysis of Precipitation Variability using Memory Based Artificial Neural Networks

Shyama Debbarma
Regent Education and Research Foundation Group of Institutions, India

Parthasarathi Choudhury
NIT Silchar, India

Parthajit Roy
NIT Silchar, India

Ram Kumar
Katihar Engineering College, Katihar, India

ABSTRACT

This article analyzes the variability in precipitation of the Barak river basin using memory-based ANN models called Gamma Memory Neural Network(GMNN) and genetically optimized GMNN called GMNN-GA for precipitation downscaling precipitation. GMNN having adaptive memory depth is capable techniques in modeling time varying inputs with unknown input characteristics, while an integration of the model with GA can further improve its performances. NCEP reanalysis and HadCM3A2 (a) scenario data are used for downscaling and forecasting precipitation series for Barak river basin. Model performances are analyzed by using statistical criteria, RMSE and mean error and are compared with the standard SDSM model. Results obtained by using 24 years of daily data sets show that GMNN-GA is efficient in downscaling daily precipitation series with maximum daily annual mean error of 6.78%. The outcomes of the study demonstrate that execution of the GMNN-GA model is superior to the GMNN and similar with that of the standard SDSM.

DOI: 10.4018/978-1-6684-2408-7.ch044

1. INTRODUCTION

Recently, climate change has attracted the attention of scientific community of multidisciplinary area due to its effects on human society and natural resources. Anthropologic activities have provoked the climate system causing significant changes in hydrologic cycle, ecosystem etc. Changes in hydrologic cycle have direct impact on human society due to changes in rainfall distribution, water availability, flood and drought (Gleick, 1987; Burn, 1994; Simonovic, 2001; Sivakumar, 2011). Water resource of a region is often affected due to changes in the precipitation pattern. Precipitation being a critical element speaking to atmosphere of a locale is viewed as the most vital variable for examining the effects of atmospheric changes, particularly on the water assets of an area. To study the climate change effects on water resources because of changes in precipitation, its changeability in the spatial and temporal domain is required to be assessed (Langousis and Kaleris, 2014). Global climate models (GCMs) are an important tool available for estimating the anticipated impacts of changing climate. GCMs are the numerical models that are normally used to simulate the response of the changing climate both in present and future climate based on the forcing by greenhouse gases and aerosols. GCM outputs are coarse in spatial resolution and often required to convert the outputs of GCMs into local climatological variables necessary for analysis of changes in the climate. A technique known as 'downscaling techniques' is used to convert the coarse GCM output into finer resolution.

Two major approaches of downscaling techniques are dynamical downscaling and statistical or empirical downscaling technique. Dynamic downscaling derives local-scale information through Regional Climate Model (RCM) while empirical downscaling is based on the principle that regional and local climates are the results of the interaction of the atmospheric and oceanic circulation as well as regional topography, land-sea distribution and land use, etc. (von Storch et al., 2000). Thus, empirical downscaling derives local climatic information from the larger scale through inference using stochastic or deterministic functions. Statistical downscaling models usually implement linear methods such as multiple linear regression, local scaling, canonical correlation analysis, or singular value decomposition (Salathe, 2003; Schubert and Henderson-Sellers, 1997; Conway et al., 1996). Statistical downscaling model (SDSM) is a well-recognized statistical downscaling tools to implements a regression based method (Wilby et al., 2002). Linear methods generally do not provide reliable information on various projected meteorological variables which includes rainfall and temperature (Xu, 1999; Schoof and Pryor, 2001). To overcome the situation, attempts were made to investigate the applicability of nonlinear methods such as artificial neural network (ANN) and analogue methods (Bishop, 1995; Zorita et al., 1995; Singh and Borah, 2013; Shao and Li, 2013). ANNs is recognized as one of the effective method in solving nonlinear and time-varying problems (Aziz et al., 2014; Jeong et al., 2012; Bhattacharjee et al., 2016). ANNs can approximate highly nonlinear relationships of input-output data series better than other nonlinear regression techniques due to their typical network structure and the nonlinear (Acharya and Nitha, 2017; Sharma and Virmani, 2017; Chatterjee et al., 2016). The performance of standard ANN models like Multilayer perceptron are comparable to that of the multiple regression downscaling methods (Weichert and Bürger, 1998; Cannon and Whitfield, 2002; Coulibaly, 2001). All things considered, a few studies have additionally demonstrated that the standard ANNs that are often utilized for hydrologic modeling are not appropriate to time varying problems, and often fail to yield optimal solution (Aksoy and Dahamsheh, 2009; Coulibaly et al., 2001; Lang, 1990).