Assessment of Climate Change Impact on Precipitation Using Machine Learning Based Statistical Downscaling Method

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Abstract. Future predictions of precipitation are highly important for effective water resources management. The Global circulation models (GCMs) are commonly used to make such predictions. In this paper, the effect of climate change on precipitation was investigated for Damaturu station located in Yobe state, Nigeria from 2050-2080. For this purpose, the BNU-ESM GCMs under the emission scenario RCP 4.5 was used to downscale observed precipitation data via Artificial Neural Network (ANN). Various climatic predictors were considered and ranked according to their impact on precipitation using the mutual information (MI) method. A total of 5 ANN models were subsequently developed using different combinations of predictors as inputs to downscale the precipitation data. The Determination Coefficient (DC) and Root Mean Square Error (RMSE) performance indicators were then employed. M1 which used a combination of top 8 ranked predictors was found to have the best performance in both downscaling and projection phases. The final results from M1 showed that, over the specified period, the Damaturu region will generally experience a decrease in precipitation, which will be more prevalent in months that experience the most precipitation with the most decrease of 20% in monthly precipitation sum occurring during the wettest month of August, towards the end of the 21st century.

Keywords: Global Circulation Models, Climate Change, ANN, Nigeria

1 Introduction

The water resources assessment for catchments is significant as the changes in climate highly influenced the water resources temporal and spatial variability [1]. Hence, for climate change projections of hydroclimatic variables in global scale, General Circulation Models (GCMs) are regarded as the most advanced tools available [2]. GCMs are forced

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with likely future GHG emission scenarios in order to create scenarios of global climate likely to occur in the future. As GCMs operate in coarse spatial scale, they are not capable of resolving sub-grid scale processes including cloud physics and land surface processes. However, within the structure of GCMs, Earth topography is coarsely represented [3]. Consequently, in catchment scale applications including hydrologic modelling and water resources allocation modelling, projections of GCMs cannot be readily used.

In order to fill the disparity in the spatial scale between the hydroclimatic variables in the catchment scale and coarse scale GCM outputs, dynamic and statistical downscaling methods have been established [4]. In statistical downscaling, the conventional relationships are statistically developed between hydroclimatic variables in the catchment scale and GCM outputs [5]. In dynamic downscaling, equations derived from physics are used for bridging the gap between local or catchment scale variables and GCM outputs [6]. Due to simplicity and low computational cost, statistical downscaling approach has gained wide popularity [7], in comparison to dynamic downscaling.

In recent decades, Machine Learning (ML) models such as Artificial Neural Network (ANN) have been applied successfully for prediction of complex hydro-climatological parameters. For instance, [8] employed ANN and other approaches to predict daily global solar radiation for Iraq. [9] performed spatiotemporal prediction of reference evapotranspiration in Araban Region, Türkiye using ML based Gaussian Processing Regression model. Regarding statistical downscaling and future projection of climate variables, many ML based studies can be found in the literature. [10] employed ANN and several ML techniques to downscale precipitation across the Australian State of Victoria. [11] considered ANN, Adaptive Neuro-fuzzy Inference System (ANFIS) and Multiple Linear Regression (MLR) for statistical downscaling and future forecasts of precipitation and temperature across Nicosia, Kyrenia and Famagusta stations of Cyprus. [12] applied machine learning models and Statistical Downscaling Model (SDSM) to downscale temperature and precipitation extremes for the Prince Edward Island (PEI). Despite the global adaptation of ML models and their successful applications for downscaling climate variables, their application in Nigeria is very limited. Therefore, this study aimed at investigating the applicability of ANN model in downscaling and forecasting the future changes of precipitation for Damaturu station, Nigeria.

2 Materials and methods

2.1 Study area

Yobe state (capital Damaturu) is in northeastern Nigeria and is characterized as having tropical climate with distinct dry and wet seasons. Yobe state in the semi-arid corridor is described generally as a major wetland. Tamarind, acacia species, some edulious plants and scattered shrubs characterized the tropical vegetation of the area [13].

2.2 Study data

In this research, the mean monthly predictand data of precipitation was obtained for the years 1990-2020 from Nigeria Meteorological Agency, and a total of 15 large scale GCM predictors for a grid point located at Damaturu for the BNU-ESM GCM under Representative Concentration Pathway (RCP) 4.5 were downloaded from http://cera-www.dkrz.de for the same 30-year span as the predictand data. Figure 1 shows the study location and Table 1 shows the descriptive statistics of the precipitation data.

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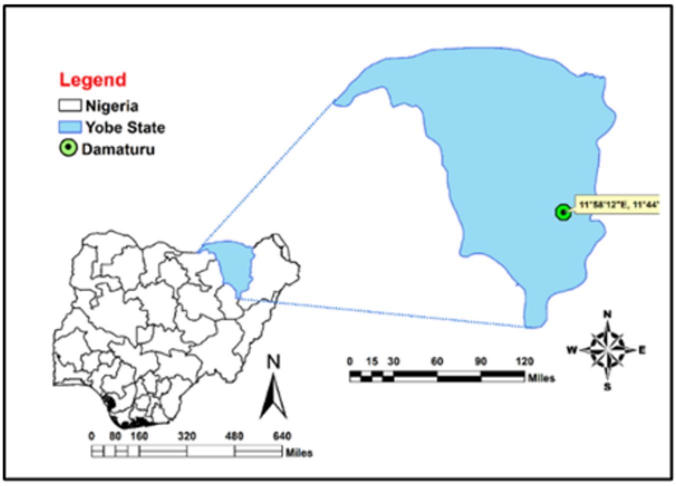

Fig. 1. Location map of the study area

Table 1. Descriptive statistics of the precipitation data

Station	Parameter	Unit	Min	Max.	Average	St. Deviation
Damaturu	Precipitation	mm	0	272.65	50.33	70.5

2.3 Proposed methodology

In this study, the downscaling modelling and future projection of precipitation was performed using ANN. The proposed methodology was therefore designed in three phases.

2.4 Model performance criteria

To analyze the performance of the model, the determination coefficient (DC) and root mean square error (RMSE) performance indicators were employed, given as:

$$DC = 1 - \frac{\sum_{i=1}^{N}(p_i - \hat{p}_\iota)^2}{\sum_{i=1}^{N}(p_i - \bar{\bar{p}}_\iota)^2} \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(p_i - \hat{p}_\iota)^2}{N}} \quad (2)$$

Where $p_n, \bar{\bar{p}}_\iota, \hat{p}_\iota, and\ N$are the ith value, mean of the observed values, predicted ith value, and number of observations respectively. The value of the DC ranges from negative infinity to 1, with increasing model efficiency as its value gets closer to 1. While the value of the RMSE ranges from 0 to infinity with increasing model efficiency as its value gets closer to 0 [14].

2.5 Artificial neural network (ANN)

Artificial neural network (ANN) is a ML model inspired by biological neurons of human structure [15]. Details on the application of ANN can be found from [15] study.

3 Results and discussions

As the study comprises of three phases including selection of the best predictor variables in phase 1, statistical downscaling in phase 2 and future projection of precipitation in phase 3, the results are presented accordingly.
Phase 1 results: Sensitivity analysis
The results of the sensitivity analysis are presented in Figure 2.

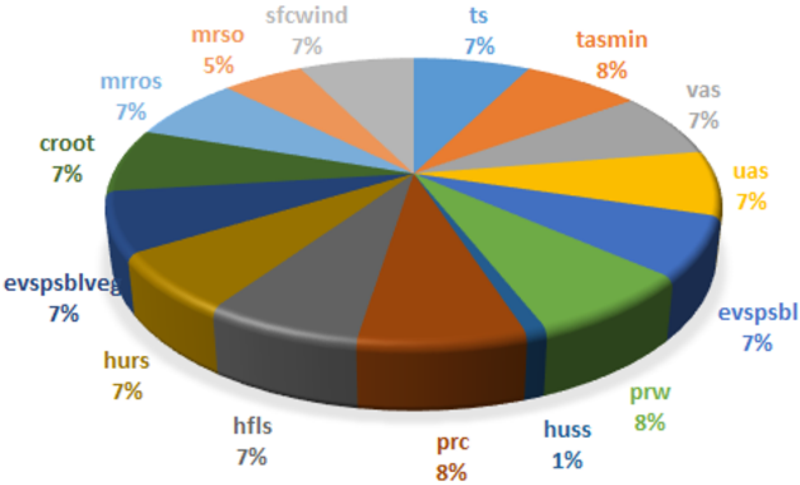

Fig. 2. Results of the applied input selection technique

From the results of the MI method shown below, higher percentage implies better performance of the variables.

Phase 2 results: Statistical downscaling results
Table 2 presents the results of the ANN based statistical downscaling applied

Table 2. Statistical downscaling results

Model	Inputs	Structure	Training		Validation	
			DC	RMSE	DC	RMSE
M1	Prw, tasmin, prc, vas, ts, uas,sfcwind, mrros	8-17-1	0.8310	0.1070	0.8266	0.1044
M2	Prw, tasmin, prc, vas, ts, uas	6-15-1	0.8274	0.1081	0.8240	0.1052
M3	Prw, tasmin, prc, vas, ts	5-10-1	0.8342	0.1060	0.8239	0.1052
M4	Prw, tasmin, prc, vas	4-8-1	0.8302	0.1072	0.7863	0.1159
M5	Prw, tasmin, prc	3-9-1	0.8162	0.1075	0.8050	0.1149

As shown in Table 2, the downscaling performance of each model is evaluated according to the DC and RMSE performance indicators. For each model configuration, DC indicates the “goodness of fit” of the predicted precipitation to the actual/observed precipitation, while RMSE indicates prediction errors. Based on the validation results, the ANN model M1—which used the top 8 ranked predictors as inputs was found to be the most efficient downscaling model in relation to both performance indicators. In general, it can be observed that a sequential increase in the number of ranked predictors included as inputs for the ANN model produced better downscaling efficiency of precipitation. Figure 3 shows the performance of the 5 developed models for the statistical downscaling of precipitation.

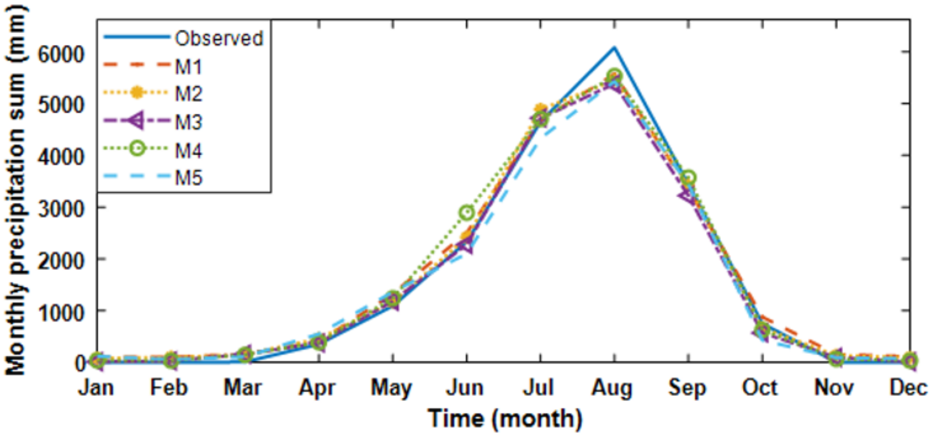

Fig. 3. Performance comparison of the developed models

From Figure 3, it can be seen that each model produced a downscaled monthly precipitation time series pattern similar to that of the observed monthly precipitation time series, however, the observed peak precipitation values that occurred over the span of the time series were generally underestimated by each model (i.e. the peak of each parabolic formation in the observed pattern was on average higher than those of the patterns made by the downscaling models). As shown in Figure 4 January and December are the months that experience the least amount of precipitation, while the months from June to September experience the most precipitation for the study station. Giving the closeness/fitness of the downscaled models to the observed precipitation in January and December, it can be deduced that the models are most reliable within periods of low precipitation. This is a reasonable train of thought, as an increase in precipitation would most likely increase the difficulty of monitoring and capturing the linear and nonlinear processes that define the phenomenon of precipitation, which will further result in more fluctuations and less efficiency in the downscaling of the precipitation.

Phase 3 results: Future precipitation projection

In this section, the future projection of precipitation over a 30-year span (2050-2080) is presented. Figures 4 and 5 present the future projected precipitation based on the applied models and percentage increase or decrease in the precipitation amount.

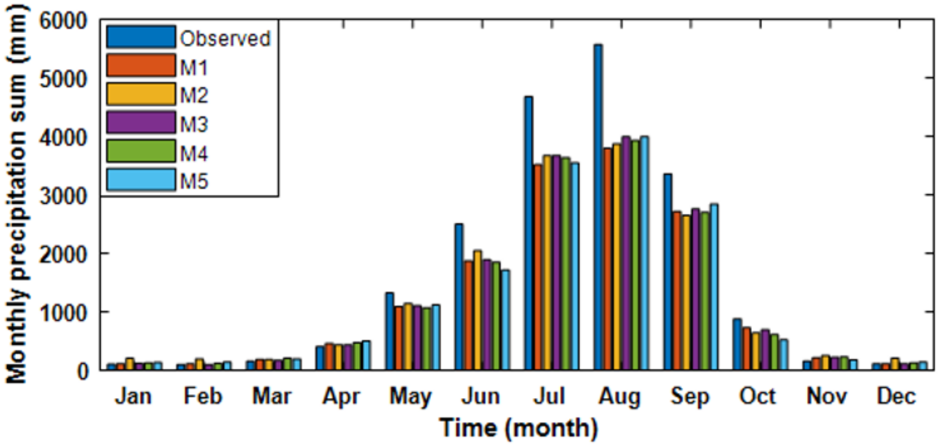

Fig. 4. Past and future projected precipitation

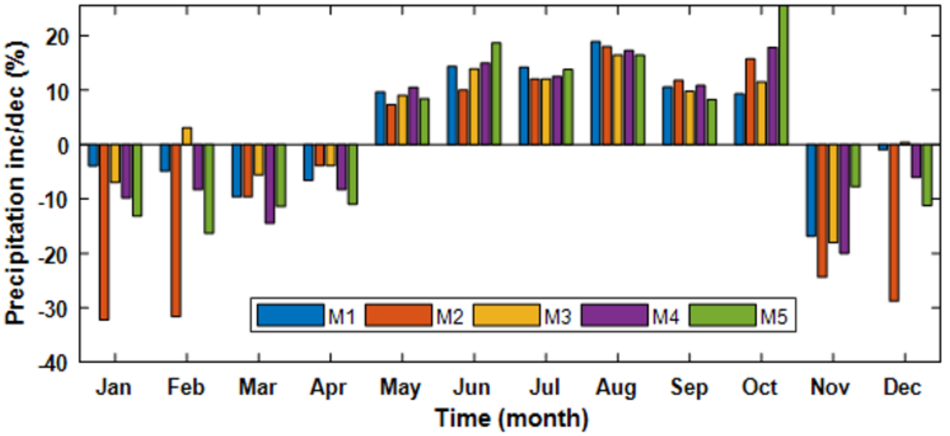

Fig. 5. Percentage increase or decrease of precipitation between 2050-2080

From Figure 4 and Figure 5, it can be seen that for every model there was a decrease in precipitation during the wetter months (i.e. May-October), while the drier months saw an increase in precipitation with the only exception to this pattern occurring in model M3 which saw a decrease in precipitation for the dry month of February.

4 Conclusion

In this paper the effect of climate change on the monthly precipitation values of the Damaturu station located in Yobe, Nigeria was investigated for the period 2050-2080.The final projections from M1 show that the Damaturu region will experience a decrease in its monthly precipitation sum during wetter months and an increase during drier months with the most decrease of 20% occurring during the month of August and the most increase of about 17% occurring during the month of November. The variation between the time series of precipitation generated by model M1 for the specified past and future time periods showed climatic change will generally result in a decrease in precipitation within the Damaturu region, which will be more prevalent in months that experience the most precipitation.

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