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Rainfall Variability Analysis In The Nira River Basin Using Multi-Model GCM Ensemble

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RAINFALL VARIABILITY ANALYSIS IN THE NIRA RIVER BASIN USING MULTI-MODEL GCM ENSEMBLE

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Observed daily rainfall data during baseline period i.e. 1961-1990 of four rain gauge stations namely; Akluj, Baramati, Bhor and Malsiras located in the Nira River basin in Central India were analyzed to study the impact of climate change on rainfall. LARS-WG incorporating 15 GCM's from the CMIP3 predictions for A1B, A2 and B1 emission scenarios was used to statistically downscale the daily rainfall data during three time spans centred at 2020's, 2055's and 2090's. Uncertainty in GCMs rainfall predictions was analyzed on monthly, seasonal and annual scales. Kolmogorov-Smirnov test, t-test, and Fisher test have shown average to good performance during synthetic rainfall data generation for all the stations. The analysis of the data shows that the uncertainty in the prediction increases with the timescale. Also, the variability in the predictions is smaller in annual values followed by seasonal and monthly values. Maximum uncertainty is observed in A2 scenario, followed by A1B, and B1 Scenarios. Monsoon months show minimum uncertainty in all the scenarios. The rainfall of December, March, April and May months are expected to increase in first two spans while expected to decrease in the last time span 2080 -2099 under all the scenarios. The monsoon month's rainfall is expected to increase slightly in the future for all the scenarios. Baramati shows maximum increase in annual rainfall for all scenarios while rainfall at Malsiras is expected to decrease only during third time span for all three scenarios.

KEYWORD: Downscaling, Climate Change, Uncertainty, Ensemble, GCM, CMIP3

INTRODUCTION

Global Climate Models (GCMs) are the primary tools for understanding how the global climate may change in the future. The hydrological processes typically occur on finer scales [1]. In particular, GCMs cannot resolve circulation patterns leading to hydrological extreme events [2]. Hence, to reliably assess hydrological impacts of climate change, higher resolution scenarios are required for the most relevant meteorological variables. Downscaling technique attempts to resolve scale discrepancy between higher resolution climate change scenarios and the resolution required for impact assessment. It is based on the assumption that large scale weather exhibits a strong influence on local scale weather; but, in general, disregards any reverse effects from local scales upon global scales. Two approaches of downscaling are: dynamical downscaling, and statistical downscaling. Dynamical downscaling nests a regional climate model (RCM) into the GCM to represent the atmospheric physics with a higher grid box resolution within a limited area of interest. Statistical downscaling establishes statistical links between larger scale weather and observed local scale weather.

Stochastic weather generator is one of the statistical downscaling tools, widely used by many researchers world-wide [3][4][5][6]. Some stochastic weather generators may be site-specific, i.e., they generate weather time-series for a single site; while others may be spatially distributed, i.e., they generate weather for a number of locations simultaneously, and reflect the spatial correlation of the different climate variables [7][8]. LARS-WG (Long Ashton Research Station Weather Generator) model, a stochastic weather generator, has been tested in diverse climates and demonstrated a good performance in reproduction of various weather statistics including extreme weather events [9][10].

The latest report of the Intergovernmental Panel on Climate Change (IPCC) has presented long-term projections of climate change into the next century. Atmospheric evolution of that prediction is chaotic, i.e. sensitive to initial-condition uncertainty. A standard approach to reduce climate noise in model predictions is used by averaging the ensemble of forecasts initiated from different initial conditions [11]. The performance of multi-model climate predictions produced by three GCMs and found that the multi-model approach offers a systematic improvement when using the ensemble to produce probabilistic forecasts [12]. The multi-model ensemble improves skill only marginally when verifying the ensemble mean, however. On the other hand, found an apparent systematic improvement in mean square error for a multi-model forecast over that of the individual model forecasts [13].

The aim of this study was to assess the impact of climate change on rainfall at local scale by predicting future ensemble rainfall using 15 GCMS in three different scenarios with the help of LARS-WG statistical downscaling tool. Furthermore, the manuscript/paper presents an analysis of monthly, seasonal and annual changes in rainfall pattern in the Nira River Basin, Maharashtra (India).

MATERIAL AND METHODS

Study Area and Data

The Nira catchment is a sub-basin of the Bhima watershed in the state of Maharashtra (India), and covers an area of 6900 km^2. The river flows to the southeast, over the plains of the Deccan Plateau, a fertile agricultural area with densely populated riverbanks [14]. The Nira catchment and locations of four rain gauge stations are shown in Figure 1. Daily rainfall data (1961-1990) of four stations were obtained from the India Meteorological Department (IMD), Pune.

Methodology

The process of generating synthetic weather data by using LARS-WG can be divided into three distinct steps:

1. Model Calibration - **SITE ANALYSIS** - observed weather data are analyzed to determine their statistical characteristics. This information is stored in two parameter files.
2. Model Validation - **QTEST** - the statistical characteristics of the observed and synthetic weather data are analyzed to determine if there are any statistically-significant differences.
3. Generation of Synthetic Weather Data - **GENERATOR** - the parameter files derived from observed weather data during the model calibration process are used to generate

synthetic weather data having the same statistical characteristics as the original observed data, but differing on a day-to-day basis. Synthetic data corresponding to a particular climate change scenario may also be generated by applying global climate model-derived changes in precipitation, temperature and solar radiation to the LARS-WG parameter files.

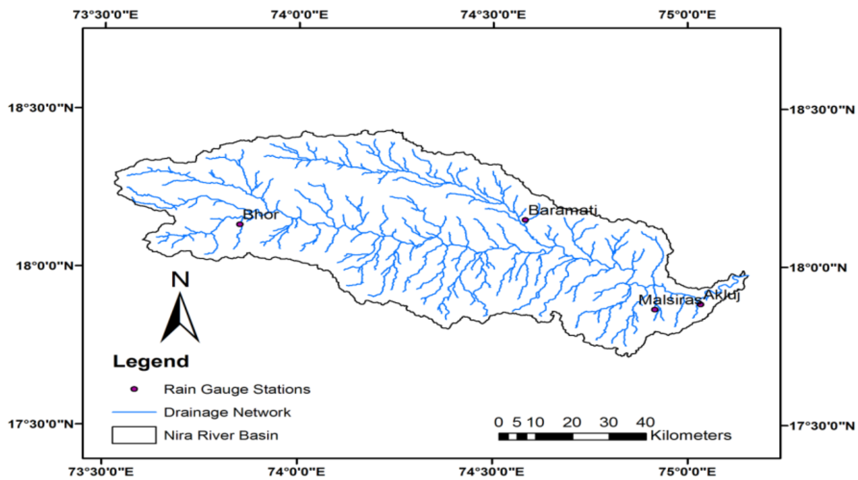


Figure. 1 Nira Catchment and locations of four rainfall station

LARS enlists the 15 GCMs (Coupled Atmosphere-Ocean models) incorporated in LARS-WG [15] with varying resolution from 1.1^0 x1.1^0 to 4^0 x 5^0. The weather generator was used to forecast rainfall data of four stations (Akluj, Baramati, Bhor and Malsiras) for three emission scenarios namely; A1B, A2, and B1 using these GCMs at each stations. The outputs from these GCMs involved baseline period corresponding to 1960-1990 and three future time spans i.e. 2011-2030, 2045-206, and 2080-2099 [15]. Each year was divided into quarters that represented four seasons, viz. DJF (December 1st of previous year through February 28th), MAM (March 1st through May 31st), JJA (June 1st through August 31st) and SON (September 1st through November 30th). The Kolmogorov-Smirnov (K-S), goodness-of-fit test was used to compare the probability distributions of lengths of wet series (rainfall > 0 mm) and dry series (no rainfall), respectively for each season as well as distributions of daily rainfall for monthly data. The monthly mean of the observed series with that of the synthetic series were compared using t-test. The Fisher F-test usually measures the inter-annual variability of observed and generated monthly rainfall means. The p-value associated with the t-test indicates the probability that monthly mean rainfalls are derived from the same population. In this study p-values less than 0.05 were considered as indicators of the likelihood of a substantial difference between the 'true' and simulated climate for that particular variable.

To evaluate the change in daily rainfall due to climate change, we compared the annual mean rainfall, seasonal mean rainfall and monthly mean rainfall of both observed and downscaled rainfall data. The relative changes in these variables were calculated using equation 1.

$$\text{Change} = ((\text{Future} - \text{Current})/\text{Current})*100 \qquad (1)$$

Calibration and Validation

First, the daily rainfall data (nearly 30 years) were imported into the weather generating model for analysis and computation of the statistical properties, viz. distribution types for the lengths of wet and dry series, daily rainfall distributions for each month, and monthly means and standard deviations. Secondly, the weather generating models were calibrated using the computed properties. After calibration, random seed values were selected at each station, and each model was subjected to different numbers of runs over a length of 300 years for the generation of synthetic rainfall data that exhibits the same statistical properties as the observed data.

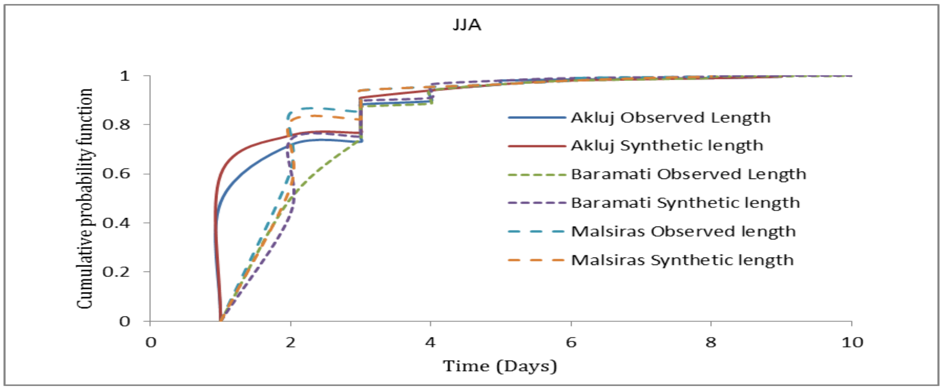


Figure 2 (a) Cumulative probability functions for the distributions of wet series for observed data and synthetic data generated by LARS-WG in monsoon (JJA) at each rainfall station

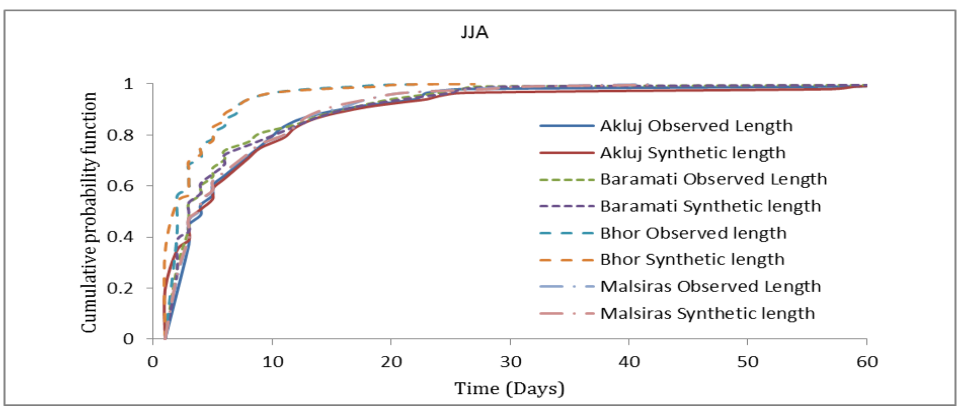


Figure 2 (b) Cumulative probability functions for the distributions of dry series for observed data and synthetic data generated by LARS-WG in monsoon (JJA) at each rainfall station

The graphs comparing the shapes of cumulative probability functions for the distributions of the length of wet and dry series in monsoon (JJA) season are shown in Figures 2(a) and 2(b), respectively. In general, the model did not reproduce correctly the distribution for the length of wet days less than 5 days. The results based on t-test were good for the majority on the months indicating the equal means of observed and synthetic data, respectively. All WGs have a problem in reproducing inter-annual variability [9]. The results have shown that the LARS-WG had faced problems to reproduce this inter-annual variability at each station. In general, a model was considered validated for the generation of synthetic data, if it showed good performance indices for the periods of monsoon and post-monsoon seasons, respectively. This approach was adopted since more than 95% rainfall occurs during these two seasons.

RESULTS

Generation of Future Scenarios

The generator option was used to generate the synthetic rainfall data corresponding to climate change scenarios (A1B, A2 and B1) for 15 GCMs in three time spans namely; 2011-2030, centered at 2020; 2046-2055, centred at 2055; and 2080-2099, centred at 2090. These data were analyzed further to study the changes on annual, seasonal and monthly scales. A box-plot (Figure 3) illustrates the range of uncertainty in predicting the impact associated with the uncertainty in rainfall predictions on monthly, seasonal on annual basis at Akluj station for 2011-2030 time spans in A1B emission scenarios.

Predicted uncertainty was conditioned on the ensembles of climate models used for simulation. Ensemble mean was computed using the GCMs available for a particular emission scenario in a particular time span. All GCMs were given equal weightage while computing the ensemble mean. The lengths of the box plots show the uncertainties associated with different GCMs in three emission scenarios used for downscaling of rainfall data. It was also found that the variability in the predictions was the least in annual values followed by seasonal and monthly values, respectively. Maximum uncertainty was observed in A2 scenario followed by A1B and B1 scenarios, respectively. Monsoon months (JJA; June, July and August) showed minimum uncertainty in all scenarios. After analyzing the standard deviations of the ensemble model, the highest monthly uncertainty was observed in February-March for all periods and the lowest was observed in August-September months. At seasonal time scale, the Pre-monsoon (MAM; March, April and May) season was associated with the highest uncertainty, followed by Monsoon (JJA) and Post-Monsoon (SON; September, October and November) seasons, respectively. Overall, it could be concluded that the model was able to downscale rainfall in wet season and tends to diverge and increase the uncertainty in dry season.

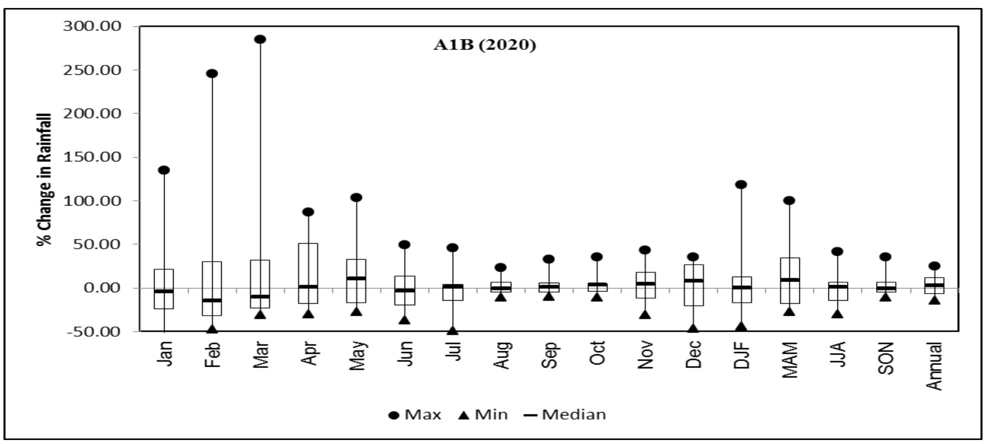


Figure 3. Changes in monthly, Seasonal and annual mean rainfall as predicted by 15 global climate models for the A1B emissions scenario for 2011–2030 compared with the baseline scenario (1961–1990) at Akluj. Box boundaries indicate the 25th and 75th percentiles, the line within the box marks the median and outliers show minimum and maximum values.

Impact of Climate Change on Rainfall

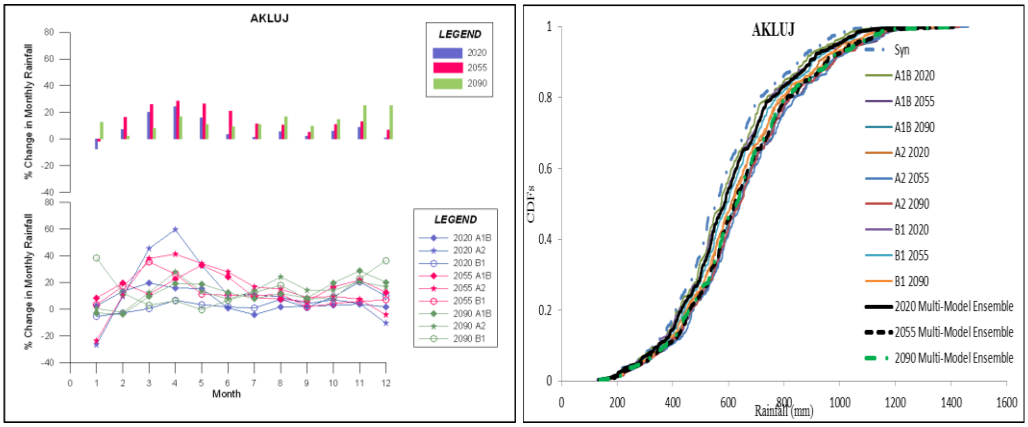
The ensemble average of percentage changes in monthly, seasonal and annual mean rainfall at each station are shown in Table 1. In general, the change in monthly mean rainfall at all the stations was positive for all the months (with some exceptions, discussed below), indicating that the monthly rainfall amounts are expected to increase in the future (Figure 4a (at Akluj only)). The magnitudes of average percent changes in monthly mean rainfall for the months of June through November are expected to be smaller as compared to those for the months of March through May and December. The negative values of percent change for the month of January indicated decrease in mean monthly rainfall for the first time span (i.e. 2020's) at all stations. Greater variability was observed in percent change in monthly mean rainfall for the months of March, April, May, and December, at all stations. In the time span centered at 2055, monthly mean rainfall is expected to increase in greater amounts as compared to the other two time spans (i.e. 2020's and 2090's) at all stations for all three scenarios.

Changes in Seasonal rainfall ensemble by the 15 GCMs are also shown in Table 1 for the three scenarios and all time spans at all stations. The A2 scenario showed greater percent change in seasonal rainfall for all seasons followed by A1B and B1, respectively. Pre-monsoon (MAM) rainfall is expected to increase in greater amounts as compared to the monsoon (JJA) season in all scenarios at all stations. Winter (DJF) rainfall is expected to decrease in first two span of time for A2 scenario at all stations.

Table 1. Ensemble average of Percent Change in monthly, seasonal and annual mean rainfall at each station for three time spans

Stations	**Akluj**			**Baramati**			**Bhor**			**Malsiras**		
Months/ Seasons	**2020**	**2055**	**2090**	**2020**	**2055**	**2090**	**2020**	**2055**	**2090**	**2020**	**2055**	**2090**
Jan	-7.42	-1.53	12.63	-5.60	3.25	10.37	0.00	0.00	0.00	-3.41	-1.71	16.60
Feb	7.28	16.48	2.31	-3.32	10.08	-6.77	0.00	0.00	0.00	12.13	22.30	6.70
Mar	20.27	25.88	7.93	26.77	34.96	5.74	15.14	26.78	9.34	27.53	34.50	12.95
Apr	24.19	28.60	16.71	8.14	9.21	-1.73	19.50	24.48	11.67	27.76	29.32	17.10
May	16.16	26.53	10.90	14.87	24.26	6.75	19.53	28.16	11.83	12.50	22.33	7.50
Jun	3.58	20.89	9.34	5.82	22.74	11.52	3.27	17.64	7.00	6.05	23.18	11.79
Jul	1.42	11.20	10.95	1.70	11.28	14.80	1.03	8.25	9.48	3.59	13.31	13.79
Aug	5.45	10.70	16.84	2.91	6.70	13.51	-0.26	4.97	9.85	1.65	6.43	11.65
Sep	2.31	5.23	9.48	1.28	4.23	9.47	6.13	10.40	15.79	2.48	5.40	9.82
Oct	6.00	11.00	14.47	8.65	13.20	17.50	9.07	13.23	15.01	6.78	11.63	16.02
Nov	9.13	13.21	24.92	9.03	11.03	20.08	11.87	11.16	21.90	11.96	15.34	27.33
Dec	1.16	6.64	24.96	7.97	12.76	34.53	4.90	6.52	29.72	1.24	6.19	29.23
DJF	3.25	10.28	15.08	2.57	9.61	23.55	4.9	6.52	29.72	2.63	8.22	25.86
MAM	17.02	26.69	11.3	14.28	22.58	5.35	19.42	26.99	17.72	16.68	24.65	9.82
JJA	3.26	15.08	11.66	3.52	13.31	13.23	0.98	8.76	9.17	3.61	13.74	12.31
SON	4.52	8.13	13.76	4.33	7.65	13.03	7.61	11.43	16.04	4.89	8.49	13.7
Annual	5.46	12.98	12.72	4.73	10.83	12.72	3.53	10.26	11.18	5.06	11.88	13.09

The change in mean annual rainfall are shown in Table 1 at all stations. The Cumulative Distribution Functions (CDFs) obtained with synthetic and predicted rainfall data (using Weibull's plotting position formula) are displayed in Figure 4b at Akluj stations for annual rainfall change analysis. The graph is exhibiting positive change in annual mean rainfall at all stations. An A2 scenario shows greater percent change in annual rainfall amount followed by B1 and A1B, respectively.



(a) (b)

Figure 4. Changes in (a) monthly mean (Bar charts indicate the ensemled mean whereas line for individual emission scenarios) and (b) annual mean rainfall as ensembled by 15 GCMs for the A1B, A2 and B1 emissions scenarios in three time spans at Akluj

Overall, the ensemble of 15 GCM models, helped improve the reliability of predictions by for all the scenarios at all the stations. Thus, a single GCM model may not be appropriate for downscaling purpose. The results of this study highlight the importance of using a multi-model approach because in order to minimize the uncertainties associated with the individual models.

CONCLUSIONS

The study investigated the ability of the weather generator model (LARS-WG) to downscale the daily rainfall by using 15 GCM's predictions for A1B, A2 and B1 emission scenarios for impact assessments of climate change on rainfall in Nira Basin (Maharashtra, India).

The Kolmogorov-Smirnov (K-S), Student (t-test), and Fisher (f-test) tests showed an average to good performance for generation of synthetic rainfall data at all stations. The analysis of the data shows that greater uncertainty is associated with using individual GCMs for downscaling purpose as compared to using an ensemble of GCMs. It was also found that the variability in the predictions was less for annual values followed by that for seasonal and monthly values, respectively. Maximum uncertainty was observed for predictions under A2 scenario followed by A1B and B1 scenarios, respectively. Monsoon months showed minimum uncertainty in all scenarios. The rainfall of December, March, April and May months was expected to increase in first two time spans and decrease during 2080 -2099 in all three scenarios. Other reaming months showed lesser variation in change in rainfall for all three scenarios in all time spans. The monsoon months' rainfall is expected to slightly increase in the future as compared to the pre-monsoon rainfall for all scenarios. Akluj showed maximum increase in annual rainfall for all scenarios. The results of this study suggest that, overreliance of a single GCM model may not be correct for downscaling purposes. Therefore it is important to use ensemble mean of multi-model GCMs. Finally, the downscaled rainfall data can be used for future planning, design and operation of different existing as well as future water resources systems and structures in the region.

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