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SPATIAL AND TEMPORAL VARIATIONS OF CLIMATE VARIABLES OVER A RIVER BASIN

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ABSTRACT

Variation in the climate acts as an important factor in managing the natural resources in order to meet the needs of human life for present and future generations. Future projections of the climate data obtained from the climate models help in developing the policies for the sustainable use of natural resources. In the present study, changes in the climate variables were assessed both spatially and temporally using Regional Climate Models (RCM) database under Coordinated Regional Downscaling Experiment (CORDEX) from Centre for Climate Change Research (CCCR), Pune, for Krishna river basin, India. Uncertainties in the climate variables were reduced by using Reliable Ensemble Averaging (REA) method. The results suggest that the ability of REA data performs well throughout the basin except in the upper region of the Krishna basin. First future period shows around 20 per cent decrease when compared to the historic period where the other two future periods show a less change in the precipitation.

Keywords: Climate Data, Regional Climate Models (RCM), Reliability Ensemble Averaging (REA), River Basin.

Introduction

The local and global pressures on natural resources are increasing because of the external forces like high living standards, anthropogenic changes, land use and water management policies etc. In addition, climate change is also contributing pressure on natural resources externally. Generally, the long-term change in the properties of climate system due to natural and forced variability and the effects of anthropogenic activities is known as climate change. The variations in climate system help in

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altering water availability regionally, selection of the crop and vegetation based on the evapotranspirative water demands, salt-water intrusion in coastal regions, floods and drought extremes, groundwater recharge, water quality and other related processes. The additional stress developed by this climate change on the natural resources like water provides a clarity to the water managers and policymakers for efficient water supply for future periods (Mondal and Mujumdar, 2015). The future water demands will be more uncertain in addition to the uncertainty developed due to changes in demography and climate (Yang et al., 2008).

Global Climate Models (GCMs) are the coarse resolution climate models projected under increased global temperatures for large spatial scales, whereas finer spatial scales climate models for the better management of the resources at the basin level. Many studies have proved that the use of regional climate data for impact assessment is more reliable compared to the global climate model data (Chien et al., 2013; Deshpande, 2014; Demaria et al., 2016). The climate models possess the biases and uncertainty from one model to another. The increase in skill and reliability of multi-model ensembles compared to the single climate model projections have demonstrated through various studies (Giorgi and Mearns, 2003; Tebaldi and Knutti, 2007). The Reliability Ensemble Averaging (REA) is the method used to address the uncertainty developed using different RCMs (Giorgi and Mearns, 2003; Chandra et al., 2015). The biases in the REA precipitation data are corrected statistically by Quantile- Quantile (Q-Q) mapping which improves the ability to project the future climate models data for the impact and vulnerable studies (Piani et al., 2010).

In India, Krishna river is categorised as the economical water-scarce and food-deficit basin (Amarasinghe et al., 2004; Gosain et al., 2006). The main feature of the basin being high crop production, the seasonal or regular water predictions are likely to experience stressed conditions. It is also evident that the annual average renewable water availability per person is less than 500m3/cap/yr (Gosain et al., 2011) which emphasise the importance of water supply and demand in the basin. The main objective of the study is to assess the changes in the climate variables like precipitation, maximum and minimum temperatures both spatially and temporally. The climate model data obtained from five RCMs of Representative Concentration Pathways 4.5 (RCP) scenario used in developing REA of the models. In addition to the REA, the precipitation is bias corrected by QQ mapping for projecting the future climate change. The REA precipitation, maximum and minimum temperatures are used in simulating the availability of the water in the river basin using any hydrological model. The climate variables thus obtained help water managers and policymakers in developing the adaptation strategies for the substantial use of the water resource.

Study Area and Data Description

Krishna river is the fourth biggest river in India with a total area of 258948 sq. km. It spreads across four States viz. Karnataka (43.8%), Andhra Pradesh and Telangana (29.81%) and Maharashtra (26.36%), India as shown in Figure 1. The basin lies between 3°10′ to 19°22′ North latitudes and 73°17′ to 81°9′ East longitudes.

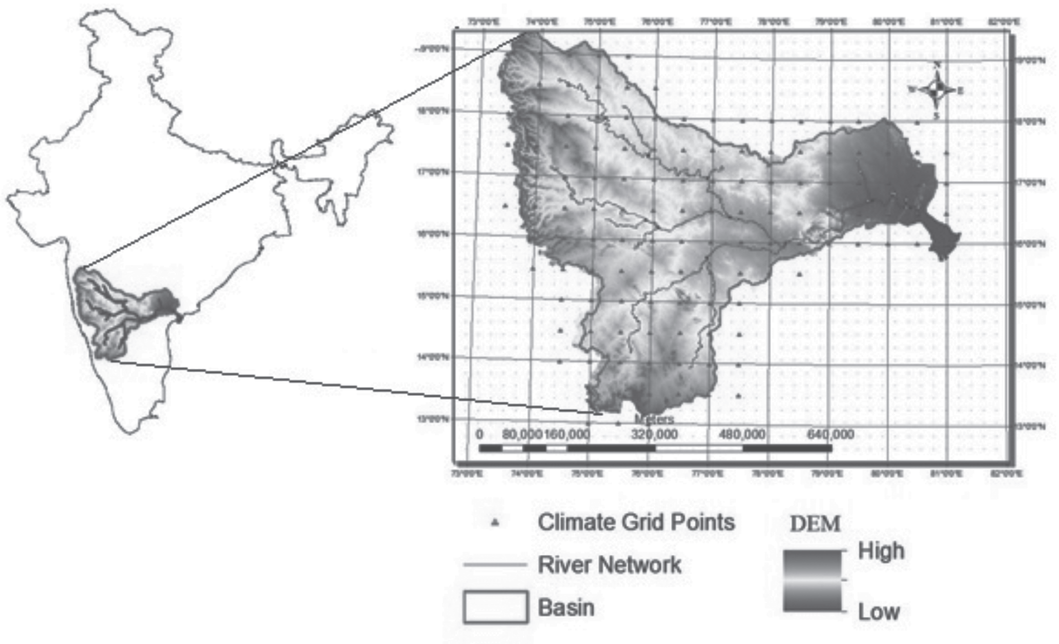


Figure 1: Location of the Krishna River Basin

The climate of the basin is tropical, with the average annual precipitation of 960 mm and the minimum and maximum temperature of the basin are 20.73°C and 32.2°C. Various datasets with their resolution are given in Table 1.

Table 1: Description and Source of the Data

Data Type	Resolution	Source
Digital Elevation Model	30m	Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER)
Observed Climate data	0.5° grid	Indian Meteorological Department, Pune
Climate Model data	0.5° grid	Centre for Climate Change Research (CCCR), Indian Institute of Meteorology (IITM) Pune. ftp://cccr.tropmet.res.in/iRODS_DATA/CORDEX-Data

The DEM projects the minimum, maximum and mean elevation of the basin as 18m, 1903m, and 518m. Approximately, 50.47 per cent of the total area falls under 500m to 750m elevation zone. The climate data include maximum temperature (Tmax), minimum temperature (Tmin) and precipitation with the spatial resolution of 0.5°x0.5° for 132 grid points.

The ensemble of high- resolution past and future climate projections from regional scales with a mid-range concentration path (RCP) 4.5 greenhouse gas (GHG) emissions scenario from CCCR, Indian Institute of Tropical Meteorology, Pune, India were obtained. The following are five RCMs (Table 2) data used for the study:

Table 2: Details of RCM Models

Acronym	Full Name
ACCESS	Australian Community Climate and Earth System Simulator
CCSM4	Community Climate System Model
CNRM_CM5	Centre National de Recherché Meteorologiques
NorESM 1	Norwegian Earth System Model 1
MPI-ESM-LR	Max Plank Institute Earth System Model

Among the different RCMS, it is difficult to choose the most reliable RCM using same anthropogenic forcing scenarios of GCMs as they project the inter-model uncertainty. The uncertainties in the climate model projections are quantified using REA method.

Reliability Ensemble Averaging (REA) Method

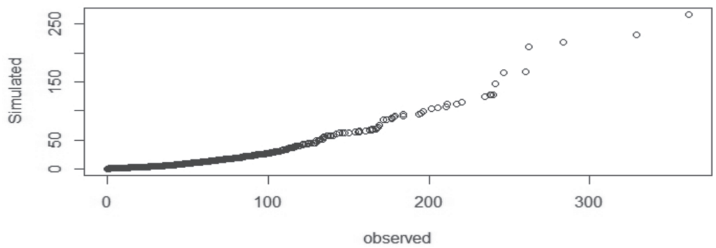
The REA method proposed by Giorgi and Mearns, 2003, provides the calculation of best estimate, range of uncertainty and the reliability of regional climate model data based on the ensemble of different climate change projections. This method comprises two criteria as model performance and convergence used in measuring the uncertainty and reliability of regional climate change. Chandra et al., 2015 proposed an algorithm for generating the REA climate variables like Precipitation, Minimum and Maximum Temperatures of the RCMs. Initially, model performance criteria carried by computing the Root Mean Square Error (RMSE) using the Cumulative Distribution Functions (CDF) deviations between the observed and simulated variables by dividing the total data into 10 equal intervals for the reference period 1975-2005. Inverse values of the RMSE considered as the initial weights of the RCMs proportionately with the sum of all weights equals to one. The model convergence criterion has been calculated by considering the CDF deviations between individual RCMs for future time slices of Future period 1(2010-2040), Future period 2 (2041-2070) and Future period 3 (2071-2100) and weighted mean CDF derived from model performance criterion. Further, biases present in REA variables were corrected using the non-parametric quantile method. The maximum and minimum temperatures of REA are more similar to the IMD data with less bias where the REA precipitation data possess the bias.

Quantile Mapping Method of Bias Correction

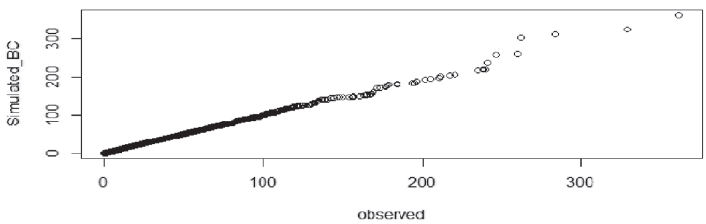
Ensemble mean obtained using the REA method compared with observed data results in underestimated precipitation, whereas minimum and maximum temperatures show better agreement. Quantile mapping was widely used statistical bias correction proposed by Gudmundsson et al., 2012 due to its computational efficiency and ability to handle higher order moments. It performs bias correction based on non-parametric transformation and the empirical quantile of the simulated and observed series. In addition, the major strength of the technique is that it removes the bias from data through entire range of distribution without any rior distribution of dataset. Therefore, in the present study, the authors applied the quantile mapping to correct the weighted precipitation series for all the grid points. The statistical transformation used will derive a function h, such that new distribution in mapping the modeled variable P_m is equal to the distribution with the observed variable P_o. The statistical transformation obtained from the Gudmundsson et al., (2012) is as follows:

$$P_o = h(P_m) \quad (1)$$

The statistical transformation is modeled using the non-parametric regression with the monotonic tricubic spline interpolation. The smoothing spline fits the fraction of the CDF-corresponding to observed wet days by assigning zero to the non-zero of the CDF-corresponding to observed wet days by assigning zero to the non-zero values of the modeled data. Figure 2 represents the REA precipitation data with observed data before and after the transformation for a grid.



a) Precipitation data without bias correction



b) Precipitation data with bias correction

Figure 2: QQ Map of Observed Vs Modelled REA Precipitation Data

Results and Discussion

REA method either carries out to improve the climate model simulations, which poorly perform in representing the present day climate over a region or contributes outlier simulations in the ensemble of the other models. Hence, it helps in extracting the most reliable information from each model for better agreement with the observed data. Figure 3 represents the comparison of mean monthly precipitation data of observed and REA data for the four time periods. It suggests lower average values of monthly precipitation in REA data throughout the year in the historic and future periods for the Upper Bhima, Upper Krishna and Upper Tungabhadhra compared to the observed values. The other sub- basins precipitation data propose ensemble model data and observed data follow the pattern with an annual change varying from 10 to 20 per cent. The patterns of the precipitation data in all the sub basins show a decreasing trend in comparison with the observed data for all the future periods.

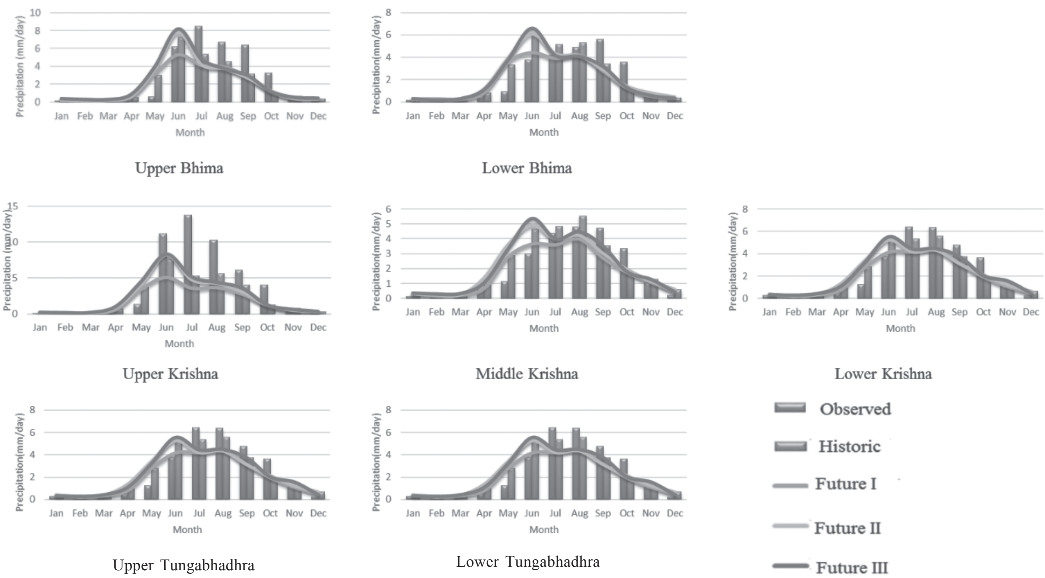


Figure 3: Sub-basin wise variations in the mean monthly precipitation of the REA climate data of the Krishna river basin for the Historic period (1970-2005), Future I (2010 – 2040), Future II (2041 – 2070) and Future III (2071 – 2099) with respect to Observed climate data (1970 – 2005).

The historic period temperature data obtained from the REA method projects has less variation when compared to the observed data where the precipitation data exhibits more variation as shown in Figure 3 for seven sub-basins of the Krishna River. Hence, the REA precipitation data with more variations are bias corrected using quantile mapping technique. The maximum and minimum temperatures obtained by the REA method were able to simulate well as it shows fewer changes when compared with observed data. Maximum and minimum temperatures of the observed data compared to the ensemble model data recommend increased trend in the patterns for the future periods as shown in Figures 4 & 5.

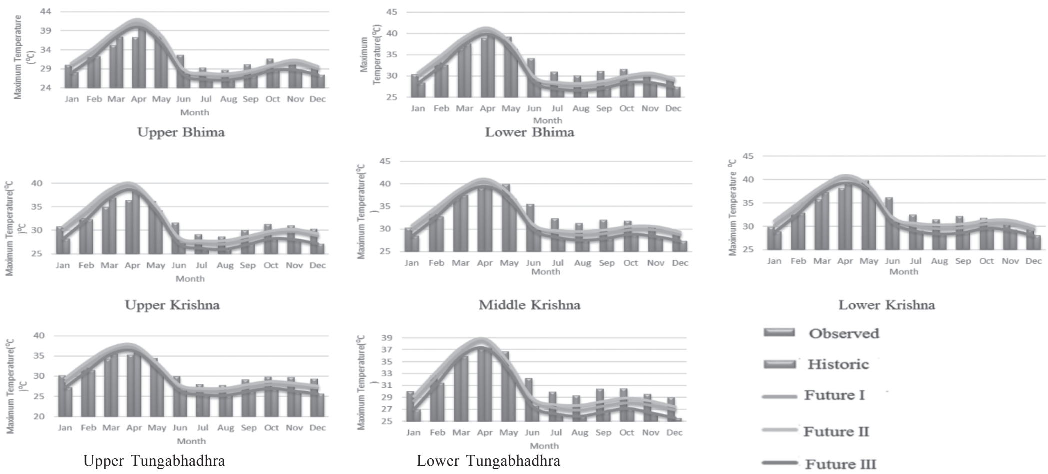


Figure 4: Subbasin-wise variations in the mean monthly maximum temperature of the REA climate data of the Krishna river basin for the historic period (1970-2005), Future I (2010 – 2040), Future II (2041 – 2070) and Future III (2071 – 2099) with respect to observed climate data (1970 – 2005)

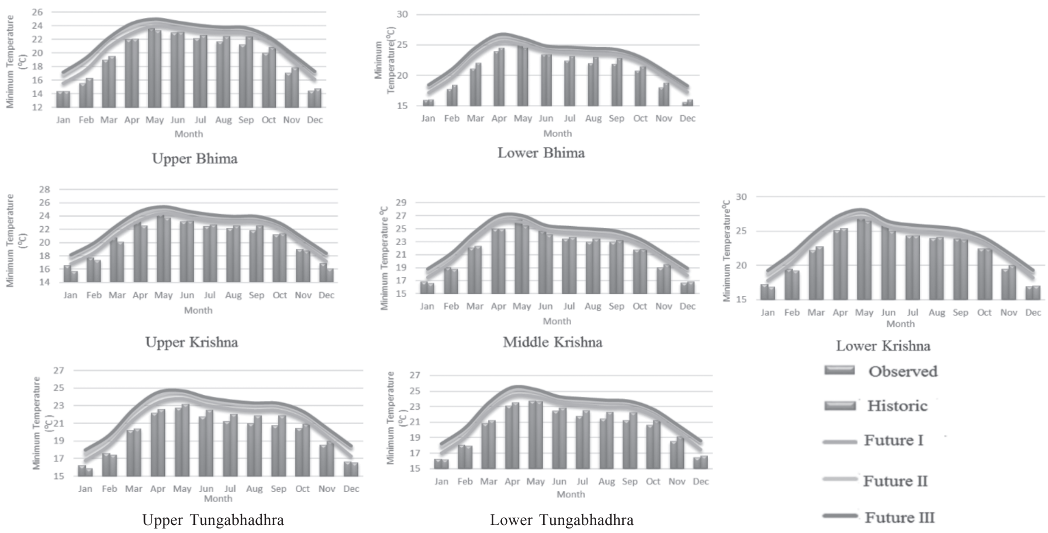


Figure 5: Subbasin-wise variations in the mean monthly minimum temperature of the REA climate data of the Krishna river basin for the historic period (1970-2005), Future I (2010 – 2040), Future II (2041 – 2070) and Future III (2071 – 2099) with respect to observed climate data (1970 – 2005)

The mean monthly maximum temperature for the future period 2 (2040-2070) projects highest values when compared to other three periods. Table 3 represents the maximum and minimum values of the REA data in comparison with the observed data projecting a decrease in the precipitation and increase in the temperature data.

Table 3: Subbasin-wise maximum and minimum values of the climate model data for Historic and Future periods in comparison with the observed data

Climate year		Observed (1970 - 2005)		Historic (1970 - 2005)		Future I (2006 - 2040)		Future II (2041 - 2070)		Future III (2071- 2099)	
		Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
Upper Bhima	Precipitation	0.06	8.48	0.12	7.27	0.14	5.29	0.20	7.80	0.24	8.19
	Maximum Temperature	28.61	37.41	26.13	39.99	27.24	40.97	27.72	42.01	26.13	39.99
	Minimum Temperature	14.35	23.59	14.39	23.25	15.57	23.93	16.78	24.70	17.20	25.01
Lower Bhima	Precipitation	0.09	5.59	0.16	6.05	0.21	4.39	0.25	6.09	0.19	6.60
	Maximum Temperature	29.45	39.23	26.62	39.85	27.65	40.90	28.28	41.34	26.62	39.85
	Minimum Temperature	15.56	25.08	16.00	24.56	17.15	25.51	18.16	26.37	18.31	26.70
Upper Krishna	Precipitation	0.05	13.75	0.12	7.64	0.09	5.07	0.18	8.25	0.19	8.32
	Maximum Temperature	28.62	36.35	25.98	38.56	27.12	39.50	27.78	39.95	25.98	38.56
	Minimum Temperature	16.52	24.24	15.71	23.68	16.81	24.43	17.85	25.14	18.14	25.41
Middle Krishna	Precipitation	0.15	4.81	0.20	5.53	0.16	3.96	0.24	4.91	0.28	5.35
	Maximum Temperature	29.38	39.88	27.30	39.46	28.58	40.60	29.28	41.08	27.30	39.46
	Minimum Temperature	16.67	26.33	16.61	25.48	17.51	26.01	18.43	26.86	18.78	27.02

(Contd........)

Table 3 (Contd.....)

Climate year		Observed (1970 - 2005)		Historic (1970 - 2005)		Future I (2006 - 2040)		Future II (2041 - 2070)		Future III (2071- 2099)	
	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	
Lower Krishna	Precipitation	0.24	6.41	0.27	5.58	0.20	4.43	0.28	5.24	0.28	5.54
	Maximum Temperature	29.25	39.77	28.04	39.31	29.29	40.45	29.99	40.95	28.04	39.31
	Minimum Temperature	16.91	26.95	16.88	26.44	17.81	27.03	18.77	27.94	19.22	28.11
Upper Tungabhadhra	Precipitation	0.03	13.93	0.15	6.71	0.09	5.01	0.21	6.42	0.15	6.75
	Maximum Temperature	27.69	35.25	25.24	36.17	26.34	37.14	27.03	37.64	25.24	36.17
	Minimum Temperature	16.20	22.74	15.87	23.17	16.79	23.82	17.59	24.49	17.97	24.71
Lower Tungabhadhra	Precipitation	0.07	5.62	0.16	5.50	0.12	4.21	0.23	5.62	0.22	5.71
	Maximum Temperature	28.96	37.11	25.54	37.29	26.92	38.36	27.49	38.80	25.54	37.29
	Minimum Temperature	16.23	23.71	16.18	23.63	17.03	24.36	17.87	25.13	18.21	25.46

Quantile Mapping

The climate models ability in predicting the precipitation data of the sub-basins like Upper Bhima, Upper Krishna and Upper Tungabhadra fails in projecting at the Western Ghats regions as it shows the maximum variations. Therefore, the bias in the REA climate model data is reduced by applying the statistical bias correction to the REA precipitation data. Spatial variations of the observed data and bias corrected ensemble precipitation data for the months of June, July, August and September for the historic and future periods are shown in Figures 6 to 10.

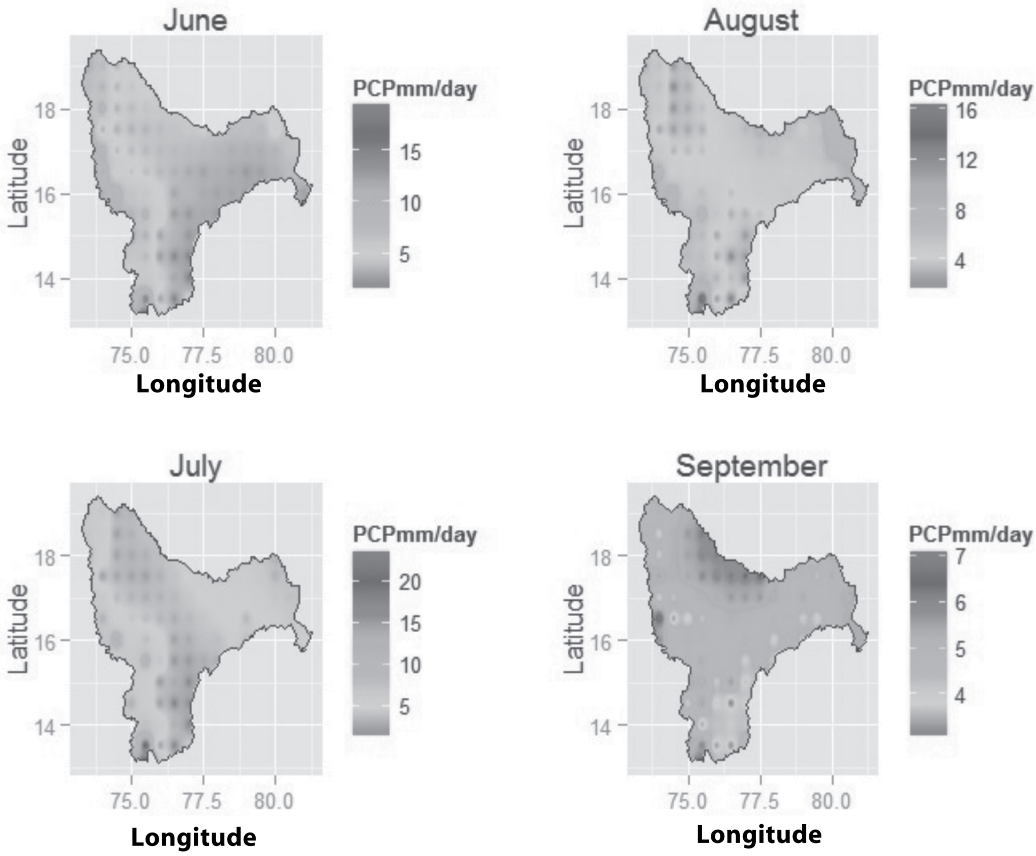


Figure 6: Observed mean monthly precipitation of June, July, August, and September during 1975 -2005

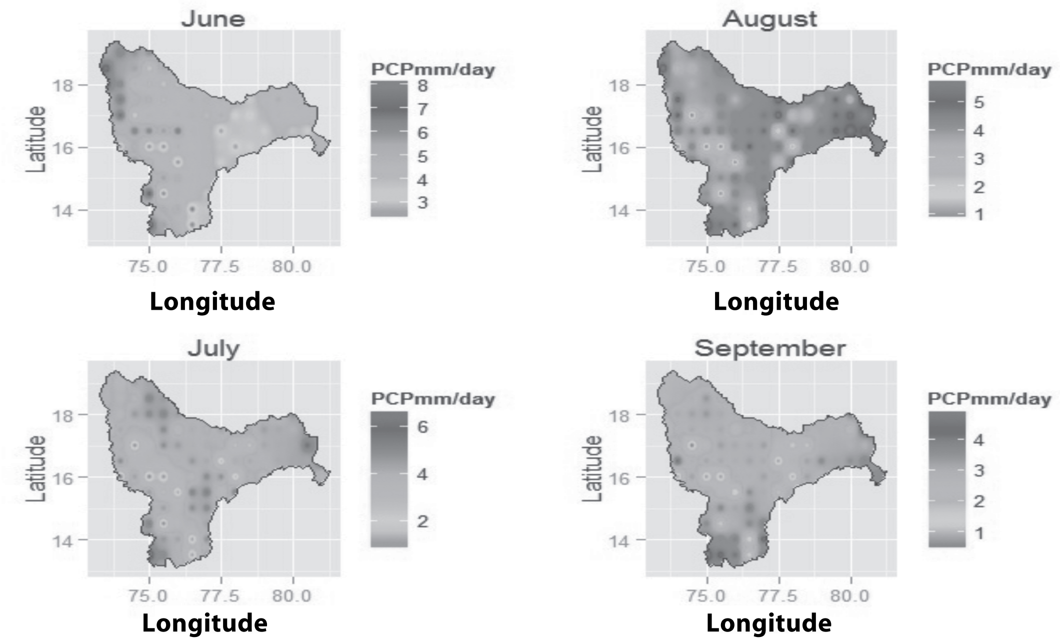


Figure 7: REA based mean monthly precipitation of June, July, August and September for Historic period (1975 -2005)

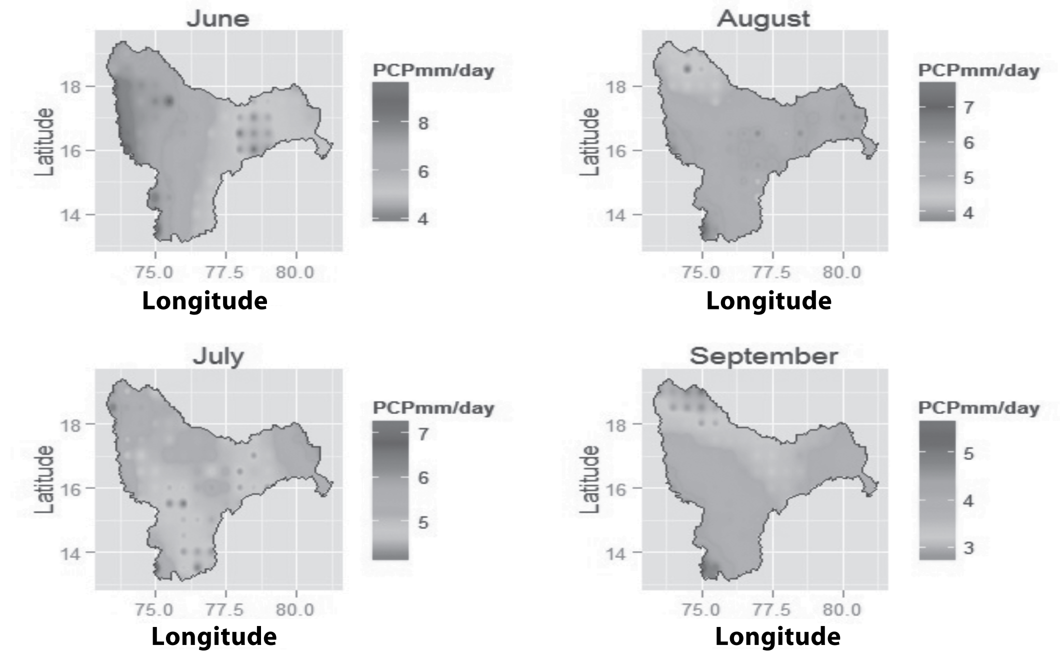


Figure 8: REA based mean monthly precipitation of June, July, August, and September for Future-I period (2006-2040)

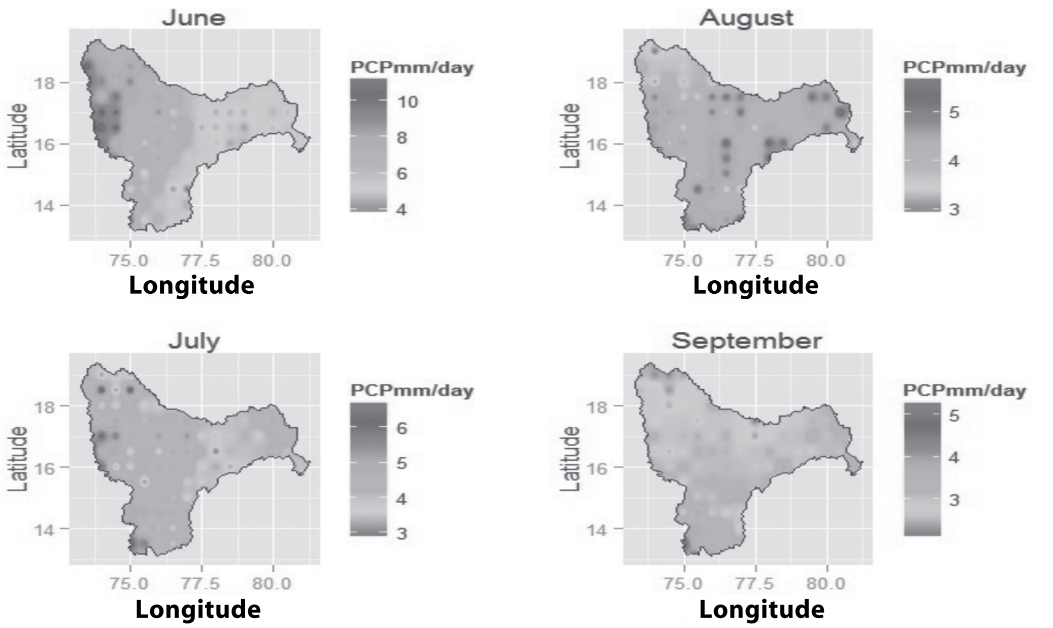


Figure 9: REA based mean monthly precipitation of June, July, August, and September for Future-I period (2041-2070)

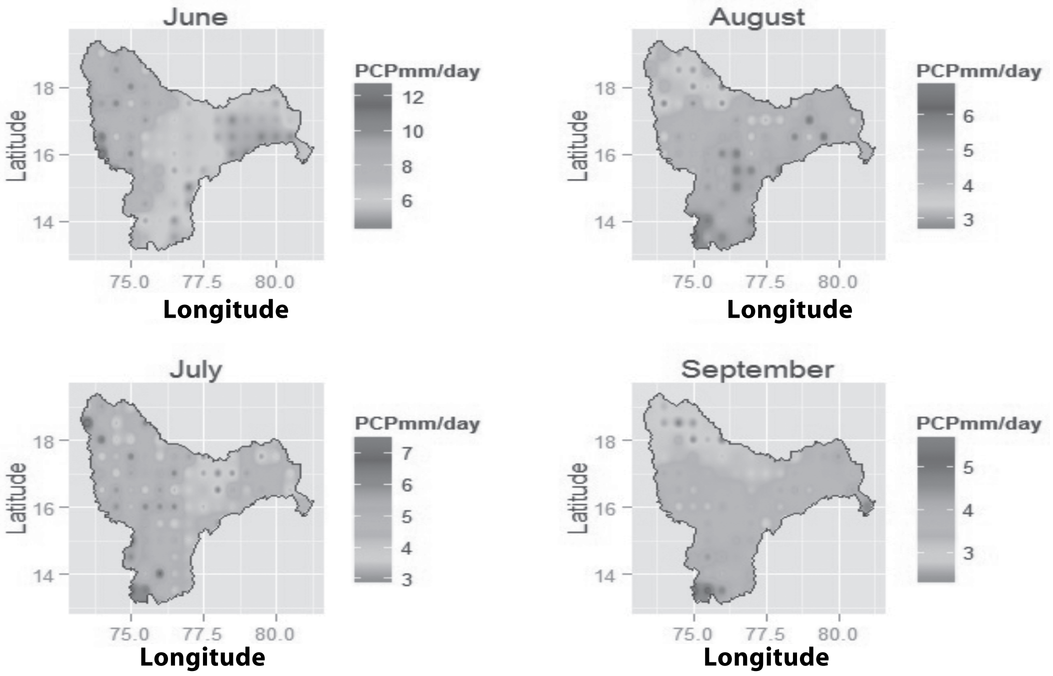


Figure 10: REA based mean monthly precipitation of June, July, August, and September for the Future3 period (2071 - 2099)

Observations were carried out by dividing the Krishna river basin into four regions such as the South East (SE), South West (SW), North East (NE) and North West (NW). Comparison of the precipitation data in the Figures 9&10 suggest highest observed value in the SW region of the basin than in the historic period, which projects the reliability of the models in projecting the outliers of the precipitation data. The other regions project similar variations of the historic precipitation data when compared to the observed data. For the future periods the mean monthly precipitation changes varying between 1mm/day to 8mm/day (Figure 7), 3mm/day to 10mm/day (Figure 9) and 3mm/day to 12mm/day (Figure 10).

Conclusion

In this paper, Reliability Ensemble Average (REA) method is used in assessing the impact of climate change on the Krishna river basin. The REA data obtained from the five climate models are in good correlation with the observed climate data obtained from IMD for the middle and lower regions of the Krishna river basin. The mean monthly precipitation data for the historic period obtained from the REA shows fewer variations in the Middle Krishna, Lower Krishna, and Lower Tungabhadra. Around 20 per cent decrease in the precipitation data in the Future 1 period is observed when compared to the Historic period. Therefore, hydrology of the river basin simulated using the climate data obtained from REA for the Future periods help water managers and policymakers in developing the adaptation strategies for proper utilisation of resources.

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