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Downscaling of Precipitation using Multiple Linear Regression over Rajasthan State

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Abstract

Statistical downscaling method is mainly practiced to relate atmospheric circulation to surface variables for forecast and prediction of the regional climate. As we know in Rajasthan drought is foremost problem due to scanty of rainfall. The core objective of present study stands to prognosis rainfall variation also assess the recital of Multiple Linear Regression (MLR) to access the variation in rainfall. The data were analyzed using higher resolution atmospheric data which includes daily National Centers for Environmental Prediction (NCEP)/ National Center for Atmospheric Research (NCAR) reanalysis data and daily mean climate model result intended for A2 and B2 scenarios of the Hadley Centre Climate Model (HadCM3) model. The period from 1961-1990 used as base line due to availability of adequate period which are required to established a reliable climatology. Results of the study shows increasing trend of future precipitation intended for both A2 and B2 scenarios. From the study it has been found that MLR model is more superior to downscale precipitation in most districts under study area.

Article History

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Keywords

Downscaling;
Precipitation;
Scenarios;
Temperature.

Introduction

The natural as well as socioeconomic variability of state Rajasthan which includes water resource management, agriculture, forestry, tourism etc. are highly influenced by key component of hydrological cycle i.e. precipitation. Therefore, it is necessitated for predicting future precipitation change since it is an input for climate impact model to assess the consequences of global change in climate. GCMs under climate input model often found inadequate due to limited depiction of mesoscale atmospheric processes, topography and sea distribution. Besides,

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with respect to precipitation, GCMs show higher spatial scale (grid point area) compare to require in climate impact model and ultimately it will lead to in frequency statistics like exceedance of heavy precipitation.

As response from state control board, though several studies, Rajasthan is more likely to face the problem of increased water scarcity because of overall decrease in rainfall and augmented evapotranspiration as a result of global warming. During the year, 1988, 1998, 1999, 2000 and 2001, Rajasthan has faced drought like situation. In addition to this state also has maximum susceptibility and lowest adaptive capacity fluctuating climate. Drought is frequent in state like Rajasthan and intensity of droughts will determine the condition of state, in terms of its natural and socioeconomic studies. Evapotranspiration can be increase by even one percent increased the temperature from base data. Therefore, the quality and quantity of surface and ground water resources of Rajasthan are drastically deteriorated in last twenty years.

Material and Method

Study Area

In terms of area, Rajasthan is largest state in country occupying 3,42,000 square kilometers area. It has 33 districts and situated between 69°30' to 78°17'E longitude and 23°30'to 30°12' N latitude. Climate of Rajasthan in northwestern India is usually arid to semi-arid with hot temperatures over the year with extreme temperatures in both summer and winter. The state has two different epoch of rainfall, one is due to the South-West Monsoon after summer and another rainfall due to Western Disturbances.

Multiple Linear Regressions

MLR model are used to build the linear relationship between dependent variable (predictand) and one or more than one independent variables (predictor). This method allows the prediction of a single predictand variable from a set of predictors variables. The equation of MLR represents as:

$$Y^{MLR} = \propto + \sum_{i=1}^{n} \beta_p X_p + \varepsilon \qquad ...(i)$$

Where, Y^{MLR}= Estimated predict and (rainfall); α = Intercept; β = Regression coefficients; X = Predictors (26 predictors) which varies up to suitable n^{th} terms and ε = error term.

Multiple linear regression attendant or observed a best fit plane. It was evaluated with R^2. As response to correlation coefficient (R) expresses the degree to which two or more predictors are related to the predictand.

Using the proposed methodology and The Pearson correlation coefficients amongst possible predictors as well as the recorded monthly precipitation were

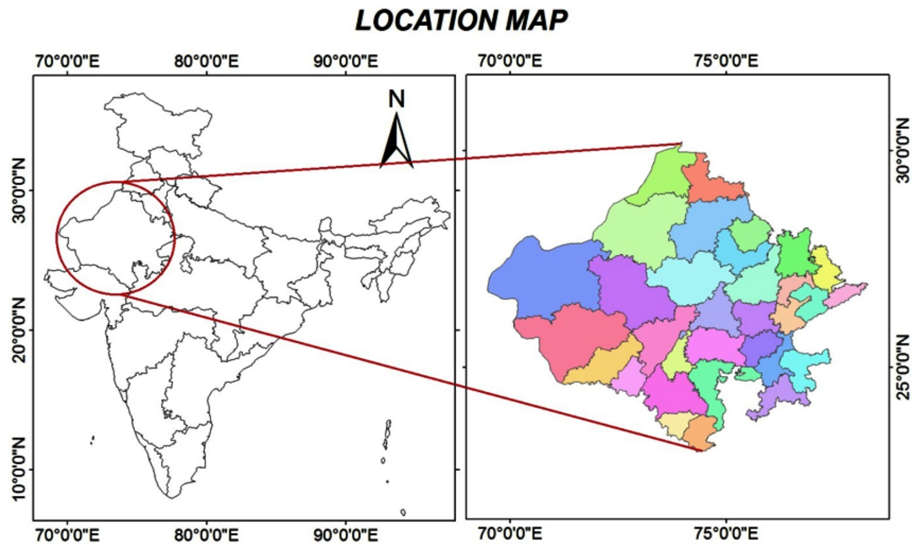

Figure 1

premeditated each time part and the entire period, at all grid points in the atmospheric province.

In study 26 NCEP variables gives in table 1, that are used by means of substitution of recent opinion of GCM variables, and then were composed from the website of the Canadian Climate Change Scenarios Network (CCCSN) and it used in place of predictors in downscaling model. There are no general rules for selection of predictors but few researchers, suggested that the way to choose an appropriate NCEP predictor. Selection of predictors differ from single province to other and mostly be contingent on the physiognomies of large-scale atmospheric circulation, seasonality, regional topography, and the predictand to be downscaled. The aerial scope of the climatic province is used the assortment of predictors is frequently selected which depend on the mechanism of rainfall in an extent.

Estimation of Performance Downscaling Model

Downscaling model performance was evaluated on the basis of comparison between mean, variance and quartiles (25th, 50th and 75th) of observed and downscaled values of precipitation during both calibration and validation of model. Various statistical parameters like RMSE, R^2, NSE were utilized to show the efficiency of downscale model. The most widely used statistical parameter were selected for assessing the efficiency of downscaled model.

Generally, higher value of NS and CC indicates well correctness of model prediction whereas lesser value of NS shows a poor model prediction. Nash-

Table 1: NCEP variables used by the select predictors for downscaling rainfall

S. No.	Atmospheric pressure level	NCEP Variables Descriptions	Code	Unit
A	1013.25 hPa (1)	Mean sea level pressure	ncepmslpas	Pa
B	1000 hPa (6)	Surface airflow strength	ncepp__fas	m/s
		Surface zonal velocity	ncepp__uas	m/s
		Surface meridional velocity	ncepp__vas	m/s
		Surface vorticity	ncepp__zas	s^{-1}
		Surface wind direction	ncepp_thas	degree
		Surface divergence	ncepp_zhas	s^{-1}
C	850 hPa (8)	850 hPa airflow strength	ncepp8_fas	m/s
		850 hPa zonal velocity	ncepp8_uas	m/s
		850 hPa meridional velocity	ncepp8_vas	m/s
		850 hPa vorticity	ncepp8_zas	s^{-1}
		850 hPa wind direction	ncepp8thas	degree
		850 hPa divergence	ncepp8zhas	s^{-1}
		850 hPa geopotential height	ncepp850as	m
		Relative humidity at 850 hPa	ncepr850as	%
D	500 hPa (8)	500 hPa airflow strength	ncepp5_fas	m/s
		500 hPa zonal velocity	ncepp5_uas	m/s
		500 hPa meridional velocity	ncepp5_vas	m/s
		500 hPa vorticity	ncepp5_zas	s^{-1}
		500 hPa wind direction	ncepp5thas	
		500 hPa divergence	ncepp5zhas	s^{-1}
		500 hPa geopotential height	ncepp500as	m
		Relative humidity at 500 hPa	ncepr500as	%
E	Near surface (3)	Surface specific humidity	ncepshumas	g/kg
		Mean temperature at 2m	nceptempas	^{o}C
		Near surface relative humidity	nceprhumas	%

Table 2: Results for accuracy assessment during the calibration and validation for monthly rainfall time series in different location of Rajasthan

Name of station	NCEP	Cali/Vali.	RMSE	NMSE	NASH	CC
Ajmer	1961-1990	Calibration	38.58	0.24	0.75	0.86
	1991-2001	Validation	46.81	0.3	0.5	0.83
Baran	1961-1990	Calibration	39.18	0.13	0.86	0.93
	1991-2001	Validation	50.55	0.2	0.72	0.89
Bhilwara	1961-1990	Calibration	39.78	0.21	0.78	0.88
	1991-2001	Validation	53.5	0.31	0.51	0.82
Bharatpur	1961-1990	Calibration	43.54	0.18	0.81	0.9
	1991-2001	Validation	40.57	0.17	0.79	0.9
Barmer	1961-1990	Calibration	22.02	0.25	0.74	0.86
	1991-2001	Validation	35.93	0.28	0.71	0.71
Bundi	1961-1990	Calibration	36.46	0.14	0.85	0.92
	1991-2001	Validation	53.31	0.25	0.64	0.86
Chittaurgarh	1961-1990	Calibration	42.52	0.16	0.83	0.91
	1991-2001	Validation	59.09	0.27	0.61	0.85
Churu	1961-1990	Calibration	31.23	0.34	0.65	0.81
	1991-2001	Validation	27.58	0.36	0.55	0.8
Dausa	1961-1990	Calibration	39.7	0.17	0.82	0.91
	1991-2001	Validation	41.38	0.18	0.75	0.9
Dhaulpur	1961 - 1990	Calibration	49.56	0.18	0.81	0.9
	1991 - 2001	Validation	45.55	0.18	0.78	0.9
Dungarpur	1961 - 1990	Calibration	52.19	0.18	0.81	0.9
	1991 - 2001	Validation	64.3	0.26	0.62	0.9
Ganganagar	1961 – 2001	Calibration	19.85	0.35	0.64	0.8
	1991 - 2001	Validation	17.89	0.41	0.58	0.77
Hanumangarh	1961-1990	Calibration	25.59	0.34	0.65	0.81
	1991-2001	Validation	21.95	0.35	0.64	0.8
Jaipur	1961-1990	Calibration	38.88	0.21	0.78	0.88
	1991-2001	Validation	41.43	0.22	0.76	0.87
Jaisalmer	1961-1990	Calibration	17.59	0.37	0.62	0.79
	1991-2001	Validation	22.91	0.42	0.53	0.68
Jalor	1961-1990	Calibration	32.5	0.24	0.75	0.86
	1991-2001	Validation	44.66	0.37	0.62	0.79
Jhalawar	1961-1990	Calibration	47.67	0.16	0.83	0.91
	1991-2001	Validation	58.03	0.23	0.76	0.87
Jhunjhunu	1961-1990	Calibration	33.42	0.23	0.76	0.87
	1991-2001	Validation	29.96	0.23	0.76	0.87
Jodhpur	1961-1990	Calibration	25.58	0.29	0.69	0.83
	1991-2001	Validation	31.09	0.38	0.61	0.78
Karauli	1961-1990	Calibration	43.53	0.16	0.83	0.91
	1991-2001	Validation	43.84	0.16	0.83	0.91
Kota	1961-1990	Calibration	37.83	0.13	0.86	0.93
	1991-2001	Validation	3.88	0.22	0.77	0.87
Pali	1961-1990	Calibration	40.93	0.28	0.71	0.84
	1991-2001	Validation	48.72	0.34	0.65	0.81
Nagaur	1961-1990	Calibration	34.86	0.31	0.68	0.83

	1991-2001	Validation	37.32	0.33	0.66	0.81
Rajsamand	1961-1990	Calibration	41.1	0.23	0.76	0.82
	1991-2001	Validation	50.5	0.31	0.68	0.87
Sikar	1961-1990	Calibration	35.08	0.24	0.75	0.87
	1991-2001	Validation	34.97	0.25	0.74	0.86
Sirohi	1961-1990	Calibration	45.81	0.27	0.72	0.85
	1991-2001	Validation	55.21	0.33	0.66	0.81
Swaimadhopur	1961-1990	Calibration	1.05	0.02	0.97	0.98
	1991-2001	Validation	0.92	0.01	0.98	0.99
Tonk	1961-1990	Calibration	34.5	0.15	0.84	0.92
	1991-2001	Validation	43.98	0.21	0.78	0.88
Udaipur	1961-1990	Calibration	44.56	0.17	0.81	0.91
	1991-2001	Validation	59.22	0.28	0.71	0.84
Alwar	1961-1990	Calibration	37.14	0.17	0.82	0.91
	1991-2001	Validation	37.11	0.18	0.81	0.9
Bikaner	1961-1990	Calibration	23.57	0.39	0.6	0.78
	1991-2001	Validation	21.5	0.42	0.57	0.76

Sutcliffe ranges from $-\infty$ to 1. The value of NS = 1 shows a faultless match among the model and annotations, Whereas efficiency of 0 shows that the model forecasts are as precise as the mean of the detected data. if value of efficiency is less than zero ($-\infty < E < 0$) then detected mean is a superior predictor than the model.

Lesser valves of RMSE and NMSE during model calibration and validation, gives smaller discrepancy among observed and predicted time series, therefore provide high accuracy in prediction. The correlation coefficient value can ranges from -1.00 to +1.00 where negative range shows the negative correlation while positive ranges shows the positive correlation. The correlation coefficient value “1” shows the perfect correlation while “0” shows there is no correlation.

Results and Discussion

Development of Downscaled MLR model for prediction of rainfall

Model’s Calibration and Validation

The NCEP predictors used for MLR model calibration for epoch 1961-1990 and validated for period 1991-2001 in contradiction of the experiential rainfall. Data of 30 years (1961-1990) used as base line due to availability of adequate period which are required to established a reliable climatology, to include resilient global change signal. Calibration and validation were done separately for all the districts under study.

Predictors Selection

In this research, selection of predictors has been considered using cross correlation technique. About ten parameters i.e., Mean sea level pressure, Surface wind direction, Surface divergence, 500 hPa airflow strength, 500 hPa zonal velocity, 500 hPa vorticity, 500 hPa wind direction, 850 hPa geopotential height, Relative humidity at 500 hPa and Surface specific humidity were commonly used for all the 32 districts. However, out of these the ten predictors about 4-6 parameters showed strong correlation among the predictand and predictors for each district. Both positive as well as negative correlation has also been considered for estimation of downscaled rainfall.

Standardization and Validation of Downscaling Model

As per the assortment of predictors and predictands, The MLR was applied for every district to downscale rainfall. MLR model was based on regression coefficients, intercepts and error term, which depends upon relationship between selected predictors and predictand. The performance of downscaled model was judged on basis of comparison between various statistical parameters like RMSE, NMSE, NASH and CC of detected and modeled precipitation during standardization and validation of model. The observed result during the study was shown in table 2.

The calibration, results of correlation coefficients for all the districts were found to be more than 0.8, which indicate good correlation between observed and modeled rainfall. The validation of correlation coefficient gave good result and it more than 0.68 for all the districts showing good correlation between observed and modeled rainfall. The NMSE in the case of calibration and validation of MLR downscaling models range from 0.02 to 0.39 and 0.01 to 0.41 respectively, which is indicate less discrepancy between observed and predicted time series. Further, NASH efficiency for both calibration and validation period is about 0.60-0.97 and 0.50-0.98 respectively. The overall model results indicate good performance during calibration as well as validation using NCEP variables.

Table 3: Mean and coefficient of variation for observed and modeled precipitation during model calibration and validation

Station	Calibration Period (1961-1990)				Validation Period (1991-2001)			
	Mean		Coefficient of Variation		Mean		Coefficient of Variation	
	Obs	Mod	Obs	Mod	Obs	Mod	Obs	Mod
Ajmer	46.05	47.89	1.68	1.31	48.43	46.14	1.73	1.44
Baran	68.46	71.79	1.57	1.35	67.67	69.19	1.65	1.41
Bhilwara	53.07	56.51	1.61	1.30	55.20	53.51	1.71	1.43
Bharatpur	60.41	64.39	1.69	1.37	60.53	62.23	1.60	1.43
Barmer	24.05	26.42	1.81	1.35	26.40	25.14	1.92	1.43
Bundi	61.14	64.29	1.57	1.35	63.42	64.04	1.67	1.39
Chittorgarh	66.70	71.45	1.57	1.29	68.22	66.69	1.65	1.41
Churu	31.61	32.13	1.67	1.23	29.89	31.96	1.54	1.29
Dausa	57.29	61.74	1.65	1.35	60.06	59.10	1.60	1.43
Dhaulpur	66.44	69.88	1.72	1.40	64.36	69.19	1.66	1.42
Dungarpur	71.81	76.80	1.68	1.37	72.54	72.77	1.70	1.44
Ganganagar	21.17	21.57	1.56	1.13	18.74	20.76	1.48	1.13
Hanumangarh	27.79	28.46	1.57	1.17	25.25	25.87	1.46	1.27
Jaipur	50.70	54.86	1.65	1.31	53.07	51.15	1.63	1.42
Jaisalmer	15.28	16.63	1.88	1.30	16.73	15.41	1.88	1.42
Jalor	36.41	40.19	1.79	1.37	40.11	37.78	1.83	1.44
Jhalawar	75.19	75.83	1.54	1.31	74.59	77.23	1.60	1.35
Jhunjhunu	41.35	43.94	1.66	1.28	40.19	41.77	1.54	1.32
Jodhpur	27.05	29.14	1.72	1.29	28.23	26.92	1.77	1.42
Karauli	64.43	67.72	1.67	1.39	65.28	68.56	1.63	1.41
Kota	66.67	70.41	1.56	1.35	68.37	67.51	1.65	1.42
Pali	43.78	46.88	1.76	1.34	46.07	46.61	1.80	1.40
Nagaur	36.24	39.05	1.72	1.27	37.31	36.05	1.72	1.41
Rajsamand	50.71	54.25	1.66	1.30	52.16	51.64	1.72	1.40
Sikar	42.37	45.43	1.66	1.26	42.84	43.72	1.60	1.35
Sirohi	48.24	52.55	1.79	1.35	52.60	51.12	1.80	1.44
Swai-madhopur	19.55	19.56	0.34	0.34	19.80	19.78	0.34	0.33
Tonk	53.89	58.23	1.62	1.34	56.30	55.84	1.67	1.41
Udaipur	62.96	67.17	1.65	1.35	64.80	64.85	1.71	1.45
Alwar	54.1	57.8	1.64	1.37	55.2	54.7	1.56	1.39
Bikaner	22.17	22.73	1.69	1.20	20.58	22.47	1.60	1.22

The calculation of downscaling model performance was done because of comparison between mean and variance values of both experiential and modeled precipitation throughout standardization and validation of model, outcomes are shown in Table 3. The coefficient of variation between detected and modeled rainfall of downscaled model for all districts were ranged from 0.34 to 1.89, 0.34 to 1.35 for model calibration respectively, which clearly indicate that the downscaling model indicates that the downscaled model has predicted the observed precipitation with high accuracy during calibration of model. Similarly results during model validation also, the coefficient of variation in the observed and modelled precipitation of downscaling model of all the districts range from 0.34 to 1.92 and 0.33 to 1.45 indicating good match between the observed and modelled precipitation. However,it has been found that precipitation is minute over or under-predicted in approximately districts during model validation. For specimen, at Chittorgarh district, the detected precipitation was 68.22 mm whereas model produces 66.69 mm.

The observed precipitation variance was much higher than the simulated precipitation variance. Therefore, downscaled models were failed to capture full spectrum of precipitation variance. The outcome of this study also revealed that the performance of downscaled models was not much efficient in arresting mean precipitation. But, the model was quiet compatible to arrest variance in most of the districts. E.g. least variance of 0.34 and 0.33 was obtained in the observed and downscaled precipitation respectively at Swaimadhopur district and in other districts differences were not large throughout model calibration and validation (appendix-I).

Time Series Analysis of Detected and Downscaled Rainfall

Based on comparison between monthly time series of detected and downscaled precipitation, efficacy of downscaled model during calibration and validation was estimated. This comparison was done for all districts under study individually. The result was shown in table 2 for all districts. Results describes that the monthly precipitation follows the analogous pattern like the detected precipitation. In limited districts, some months consume extreme precipitation standards, which remained under-predicted by the model. The extreme measures occurrences are common phenomenon in hydrology, which frequently cannot be estimated with NCEP predictors. Testified that the downscaling model flops near arrest the extreme precipitation. However, it can successfully arrest the mean. The model used in this study was observed to capture the mean and low precipitation more accurately.

Projection of Monthly Rainfall using HadCM3 (A2 & B2 Scenario)

Projection of future scenarios has been carried out using the HadCM3 A2 & B2 emission scenarios with selected predictors. However, MLR downscaling techniques has been utilized for future projection of predictand. Further, whole time series of monthly predictand has been divided into decadal form (10 year time scale) for better representation of results. Box plot of decadal time steps are used for the determination of pattern in predictand. The projected rainfall of all district for decadal periods of 2001-2010, 2011-2020, 2021-2030, 2031-2040, 2041-2050, 2051-2060, 2061-2070, 2071-2080, 2081-2090 and 2091-2099 are Appendix II. The box middle line showed median valves whereas upper and lower edges gives the 75 per and 25 per of datasets respectively. The difference between 75 per and 25 per called inter quartile range (IQR). The box plot of rainfall shows the increase in future rainfall in both cases of A2 and B2 scenarios for whole Rajasthan.

Conclusion

The native hydrological regimes of the arid and semi-arid regions are highly prejudiced by the changes in climatic variables. Therefore, it remains very much imperative to comprehend and model the influence of climate change over arid and semi-arid region under current and future scenario. A Multiple Linear Regression (MLR) model was used in the study to downscale the precipitation in data scarce arid and semi-arid regions of Rajasthan state of India, which considered as most susceptible areas to climate change. The dataset of NCEP reanalysis from twenty grid points which surrounds the study range were used to select the predictors based on principal component analysis (PCA). The data of monthly rainfall from 1961-1990 time periods were used for calibration as well as from 1991-2001 time period for authentication of MLR model.

Performance of MLR model to downscale monthly rainfall of Rajasthan was assessed to evaluate the climate change impact. The study showed that MLR model is more superior to downscale precipitation in most districts under study area. Statistical downscaling of rainfall is quite difficult as a result of erratic pattern of rainfall, poor relation local rainfall and ocean atmospheric circulation parameters of arid regions. The outcome of the present study indicates that MLR could be used for downscaling of monthly rainfall of regions under arid and semi-arid. The result observed that the downscaling of rainfall showed increase in future rainfall for both A2 and B2 scenario.

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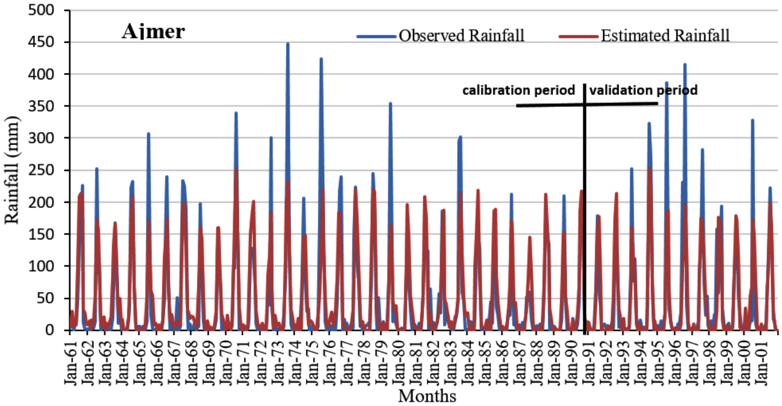
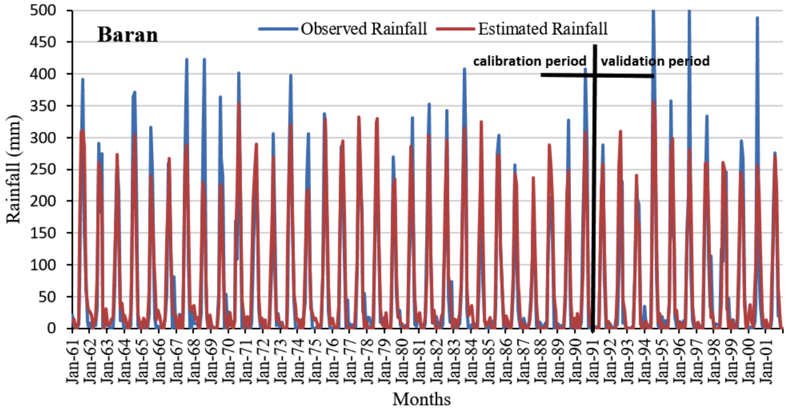
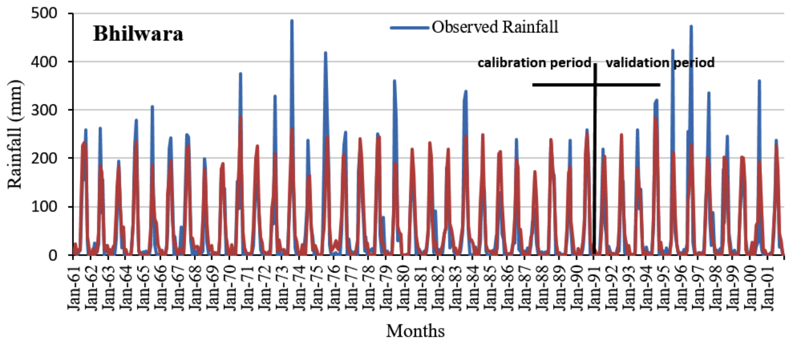
Appendix-I



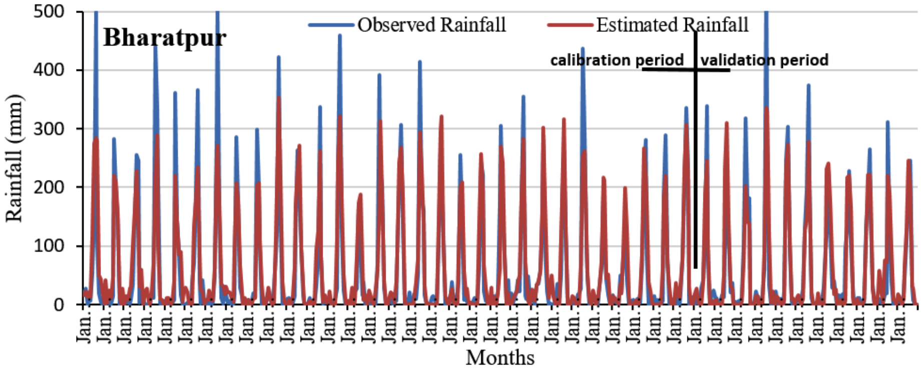
1: The monthly time series of observed and downscaled rainfall of Ajmer district



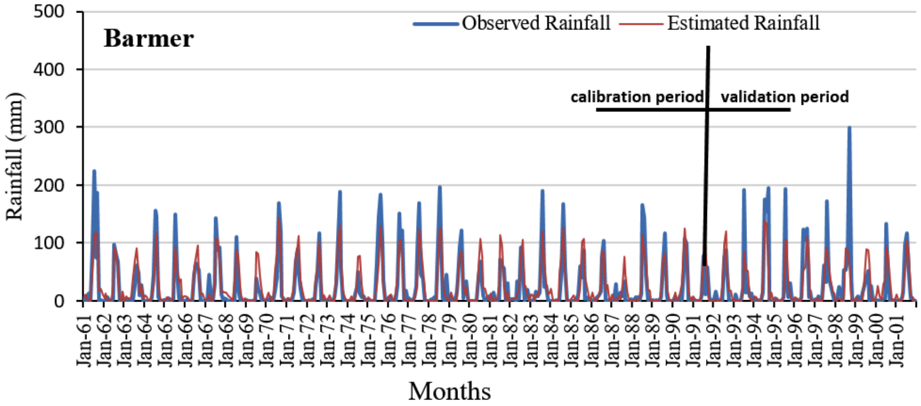
2: The monthly time series of observed and downscaled rainfall of Baran district



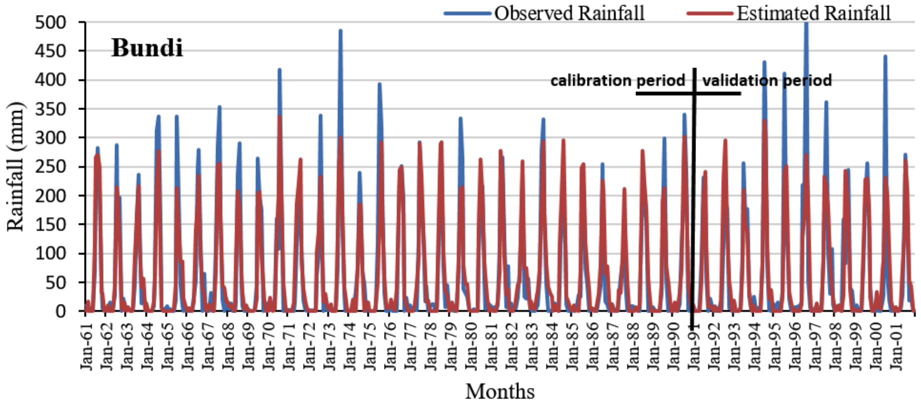
3: The monthly time series of observed and downscaled rainfall of Bhilwara district



4: The monthly time series of observed and downscaled rainfall of Bharatpur district



5: The monthly time series of observed and downscaled rainfall of Barmer district



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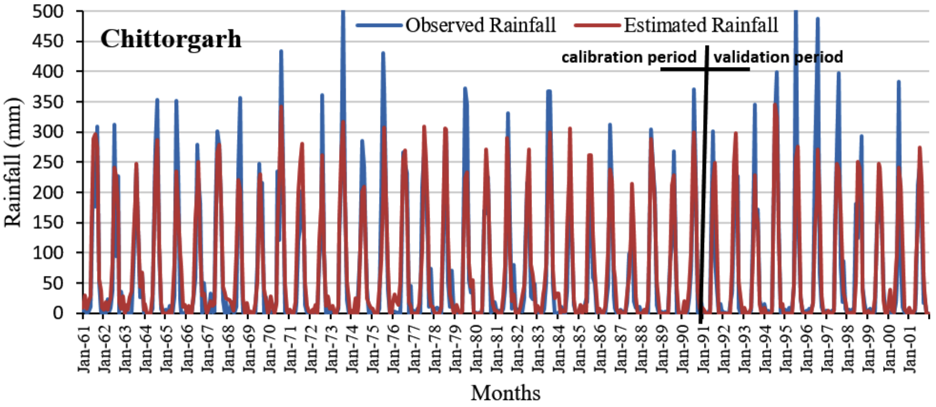

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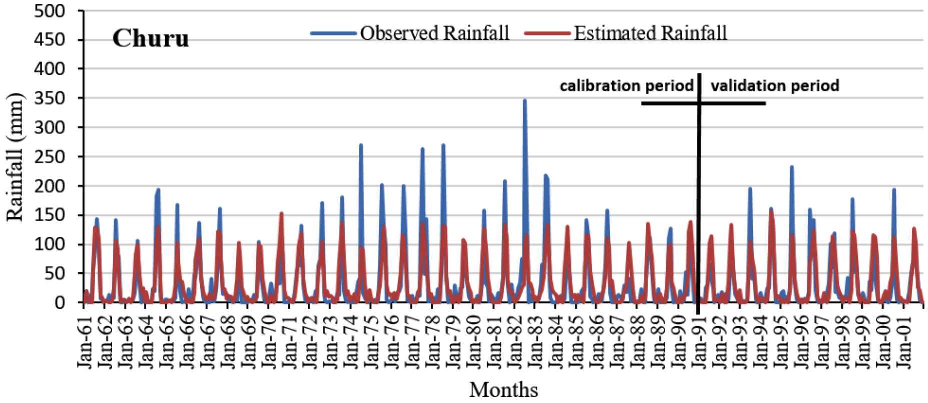

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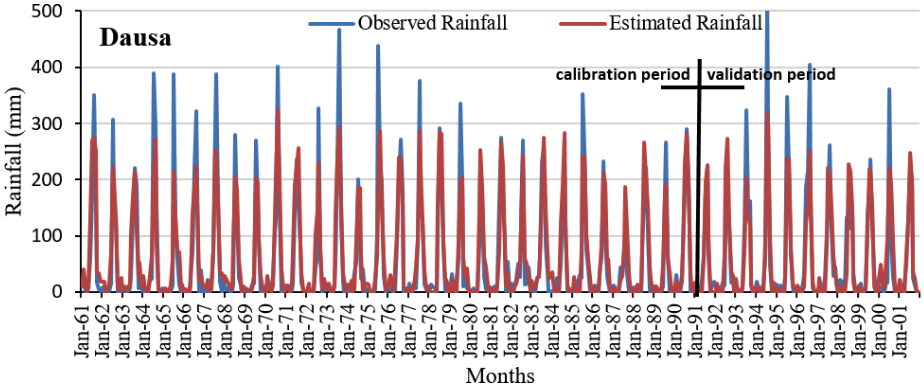

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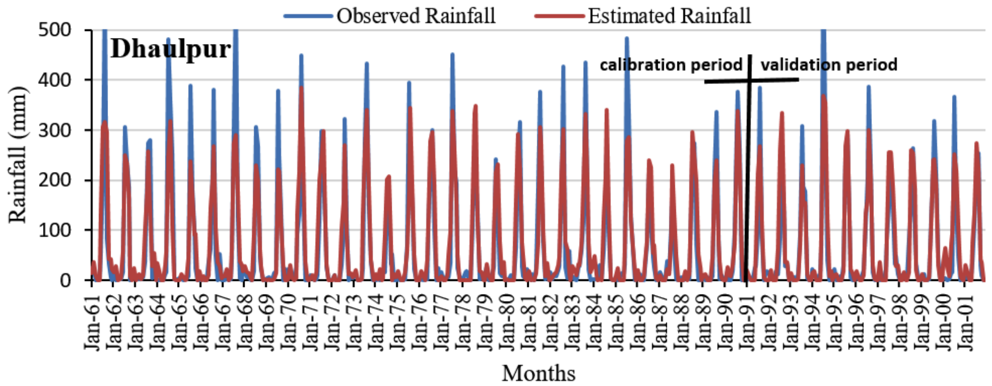

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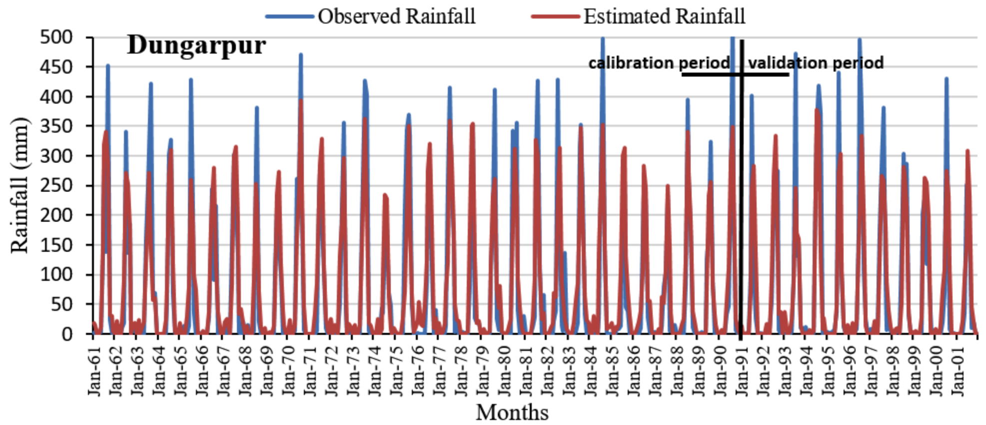

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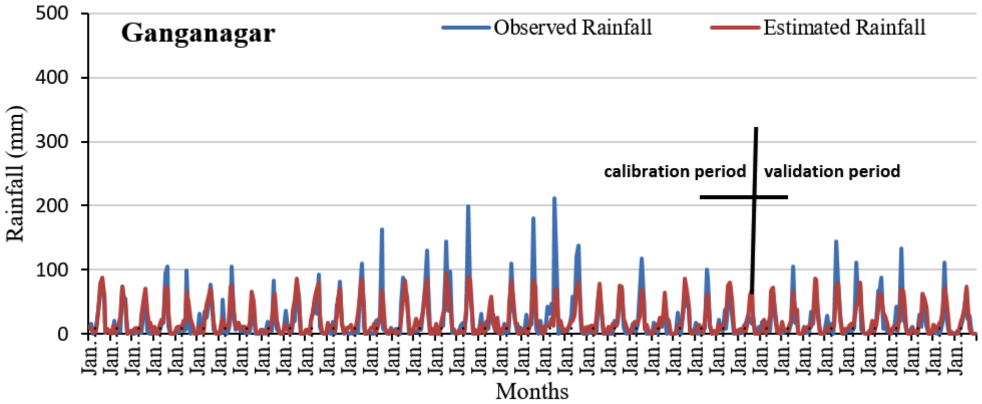

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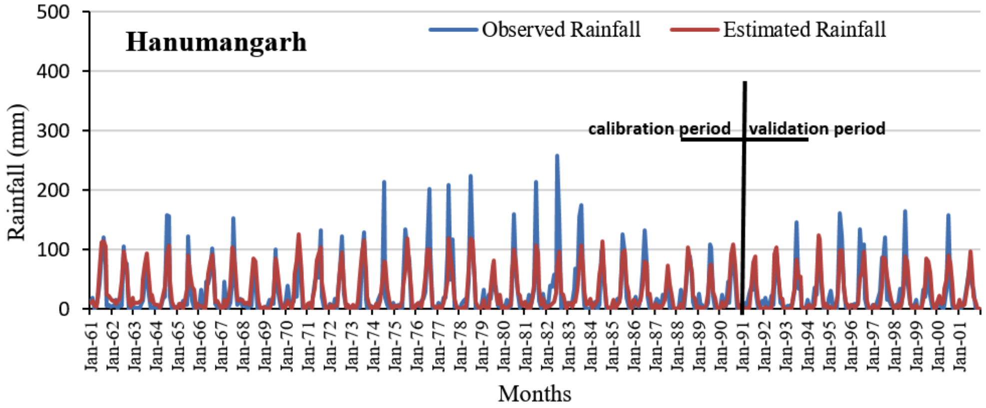

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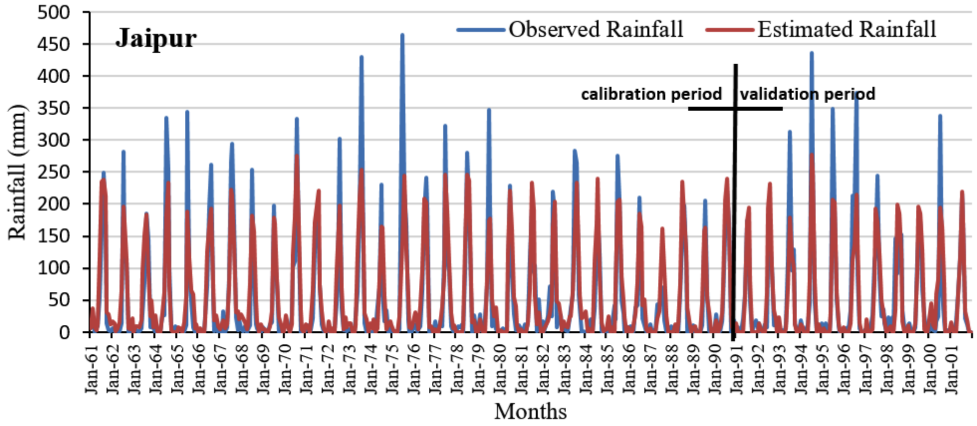

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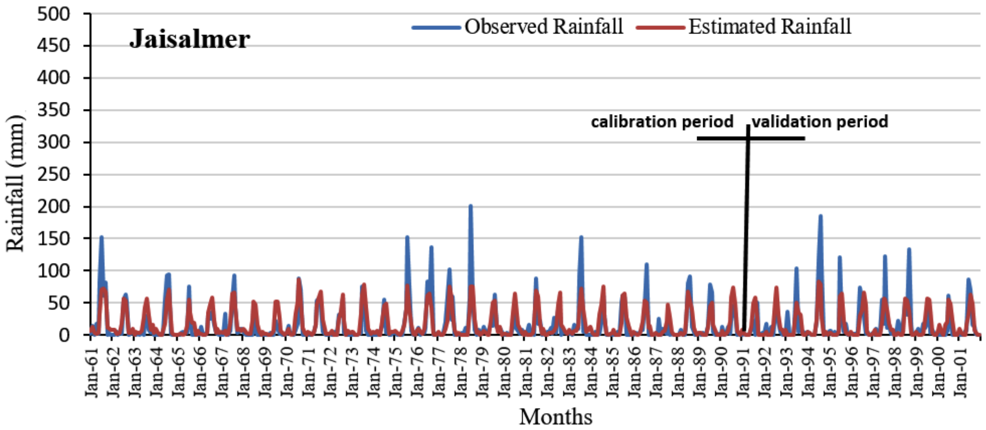

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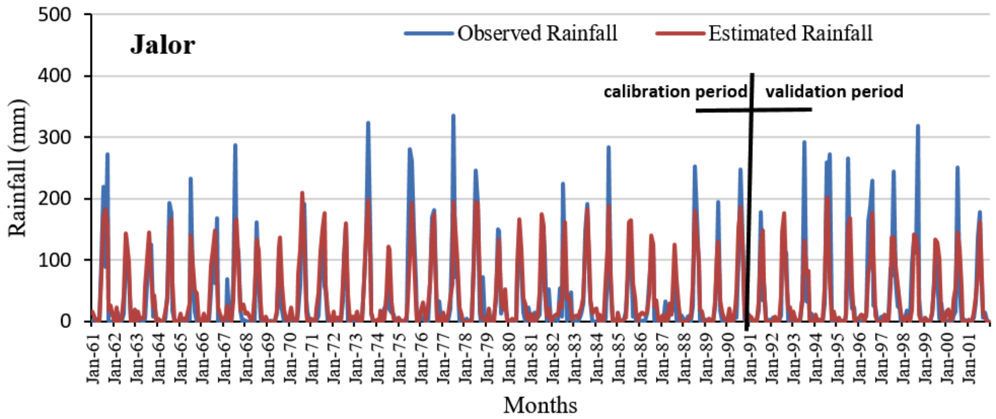

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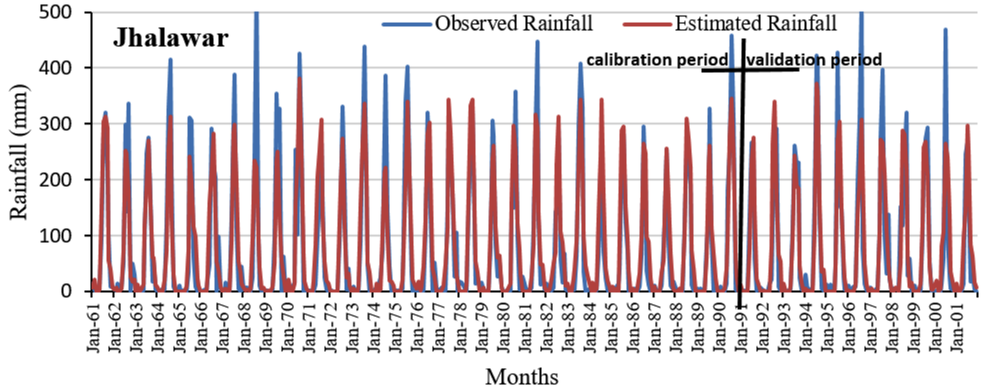

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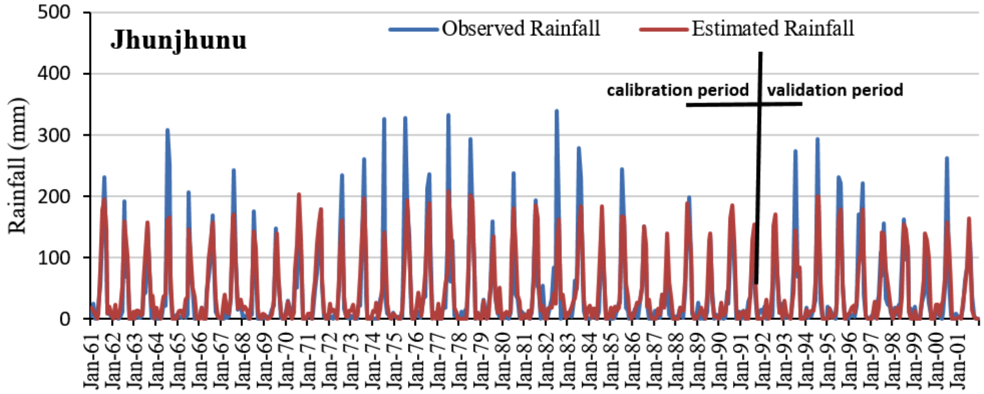
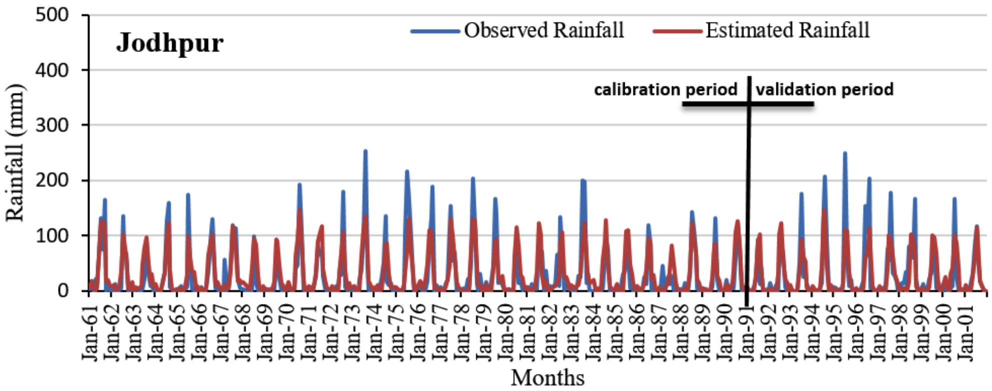
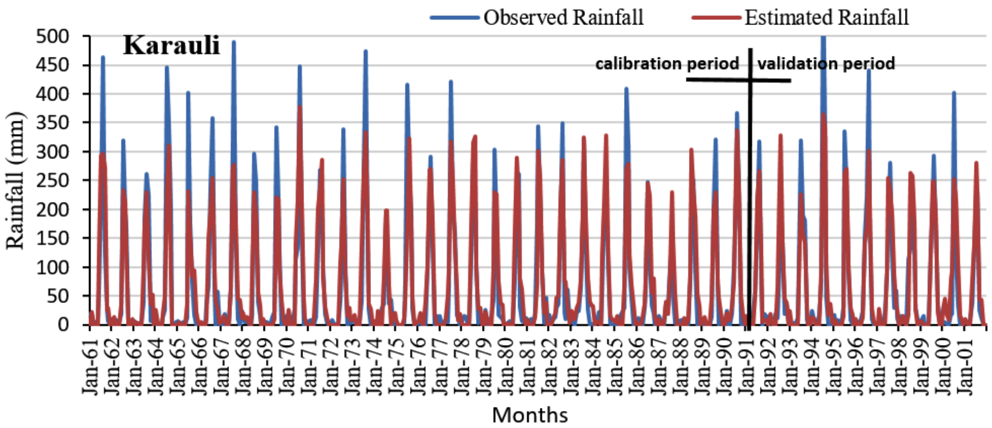


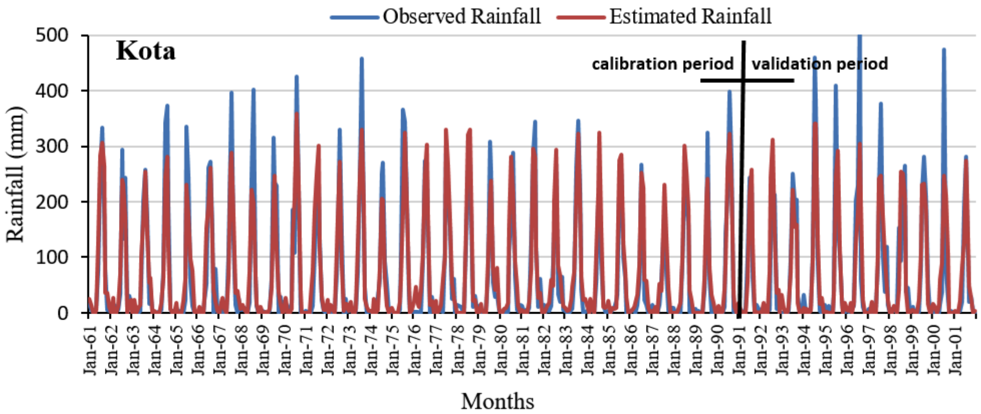
18: The monthly time series of observed and downscaled rainfall of Jhunjhunu district



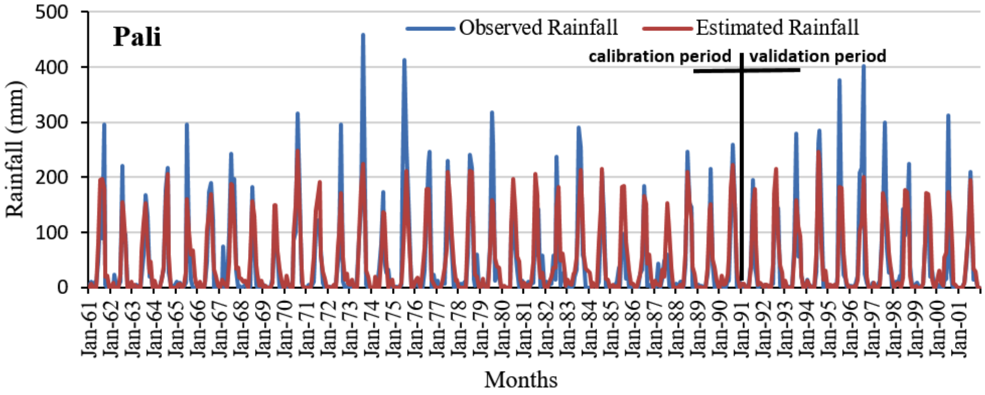
19: The monthly time series of observed and downscaled rainfall of Jodhpur district



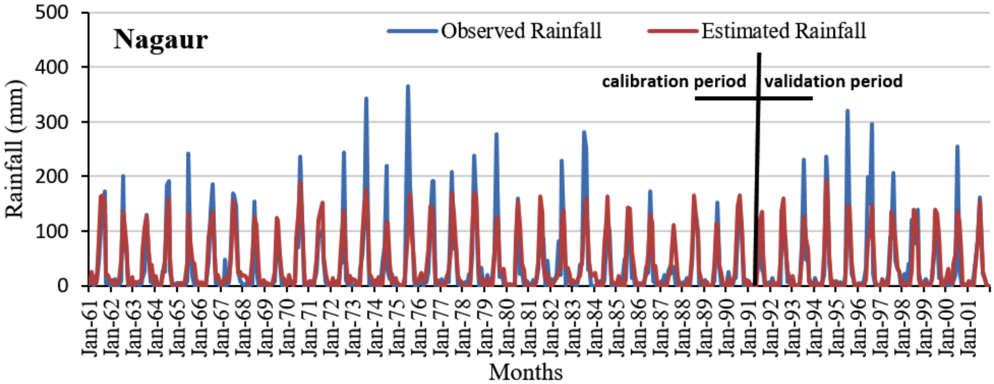
20: The monthly time series of observed and downscaled rainfall of Karauli district



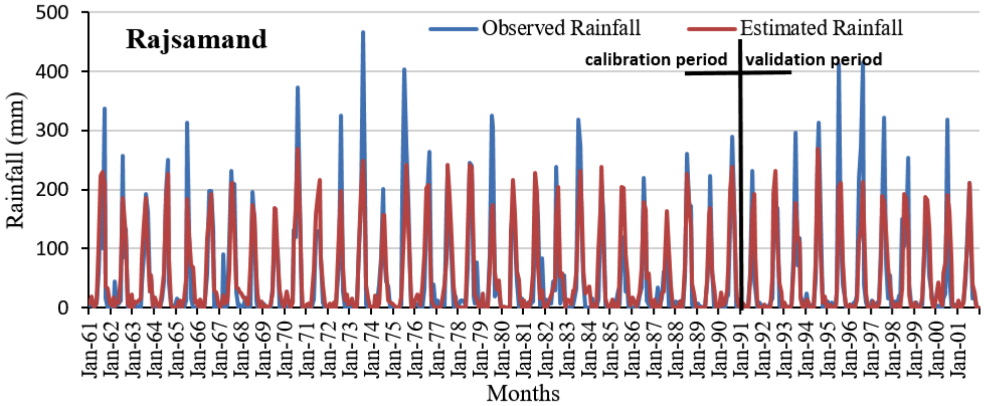
21: The monthly time series of observed and downscaled rainfall of Kota district



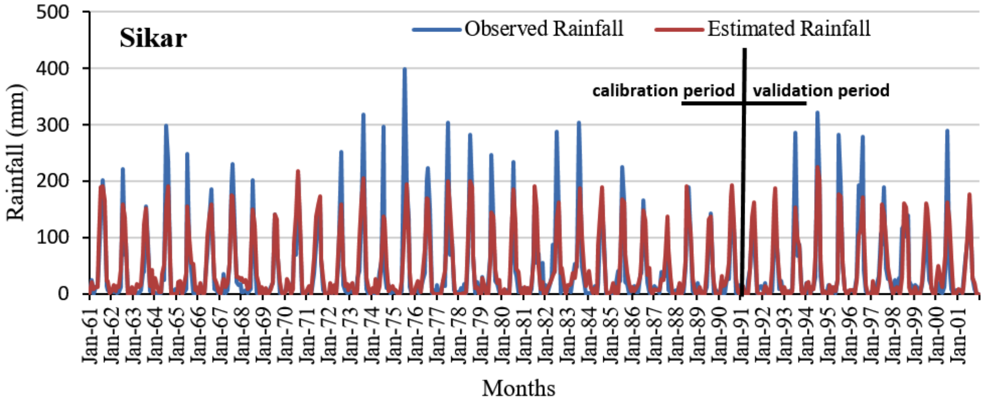
22: The monthly time series of observed and downscaled rainfall of Pali district



23: The monthly time series of observed and downscaled rainfall of Nagaur district



24: The monthly time series of observed and downscaled rainfall of Rajsamand district



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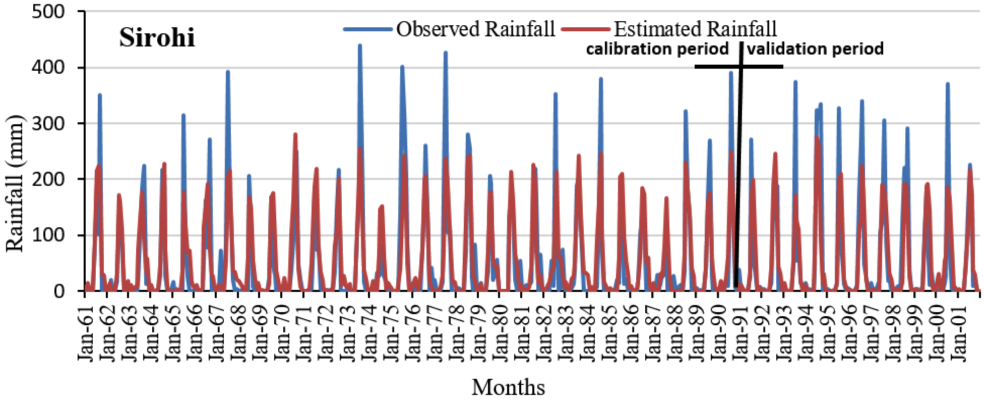

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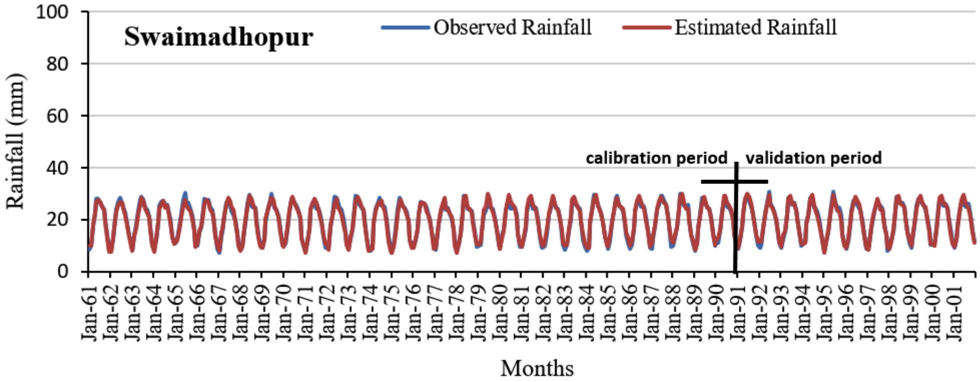
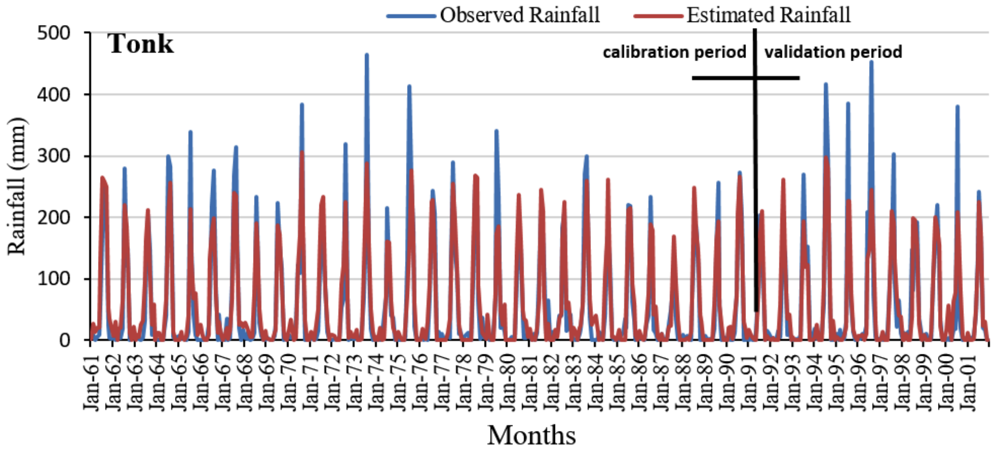


27: The monthly time series of observed and downscaled rainfall of Swaimadhopur district



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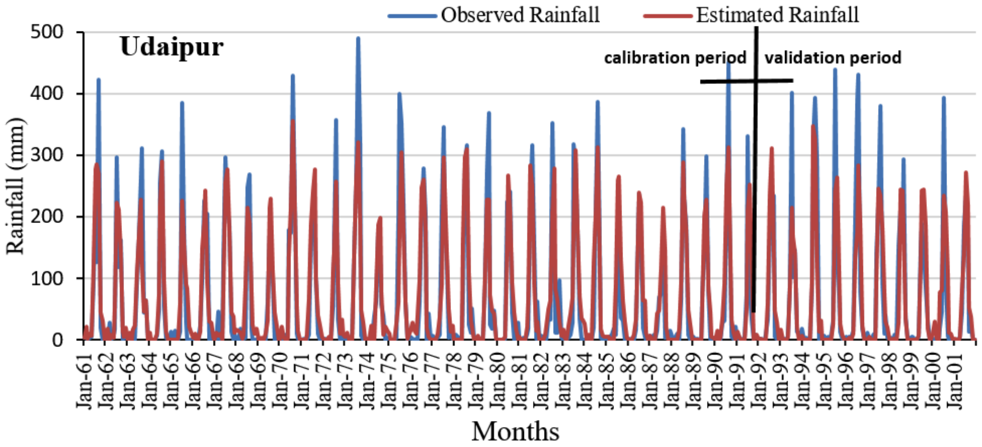

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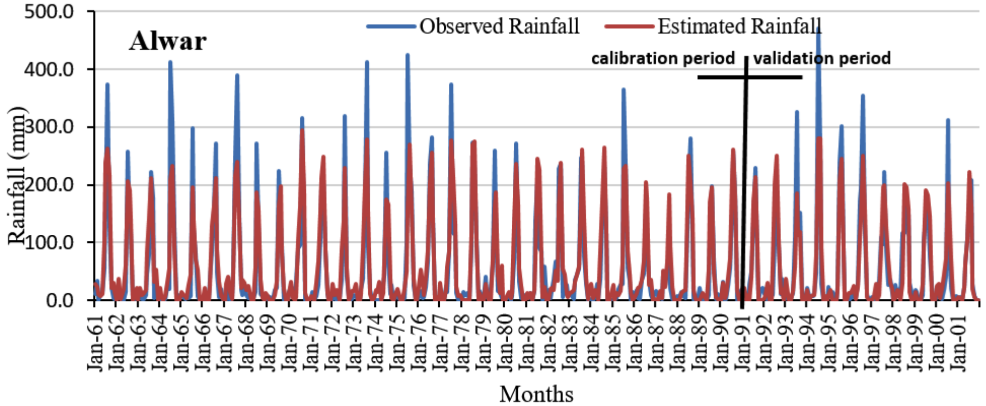

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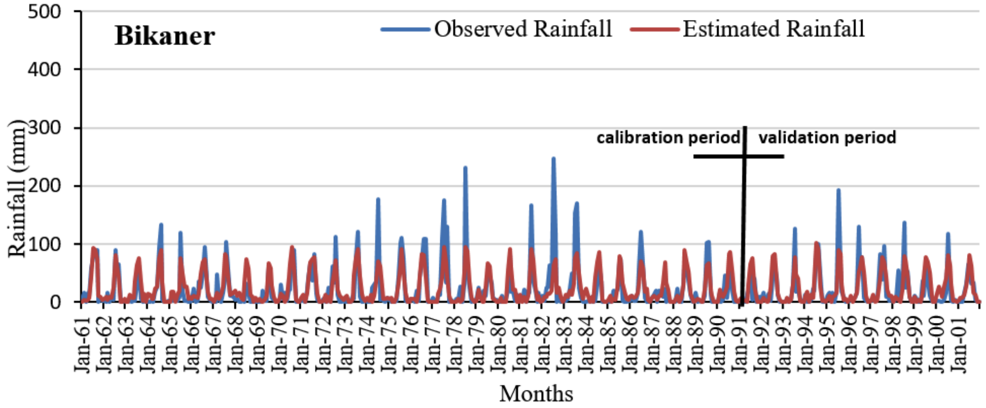
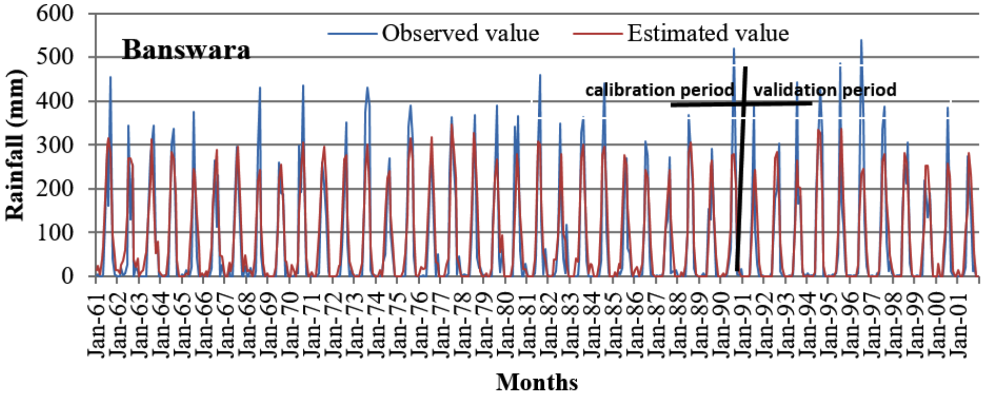


31: The monthly time series of observed and downscaled rainfall of Bikaner district

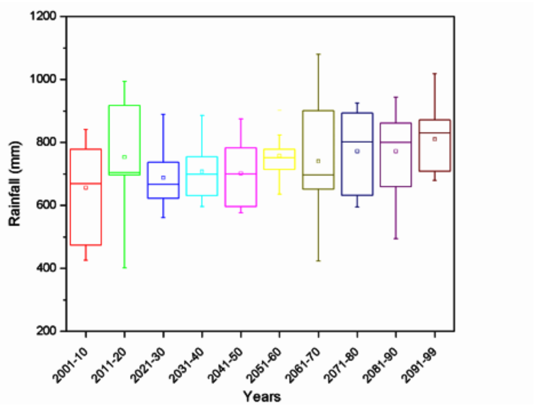


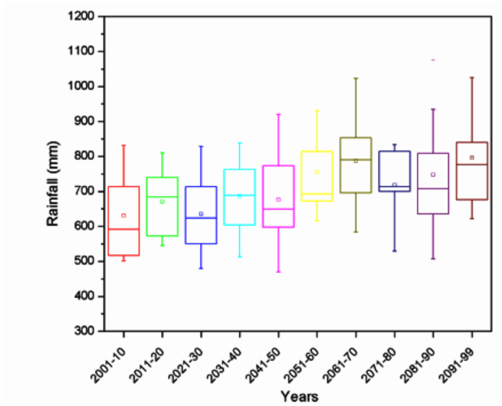
32: The monthly time series of observed and downscaled rainfall of Banswara district

Appendix II

Box plot of all the districts of Rajasthan showing projected rainfall in MLR-A2 and B2 scenario.

MLR-A2 scenario	MLR-B2 scenario





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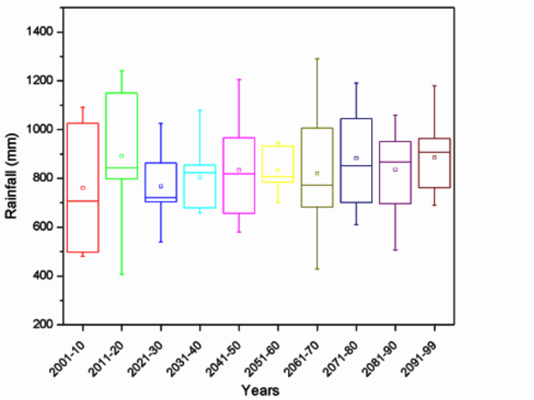
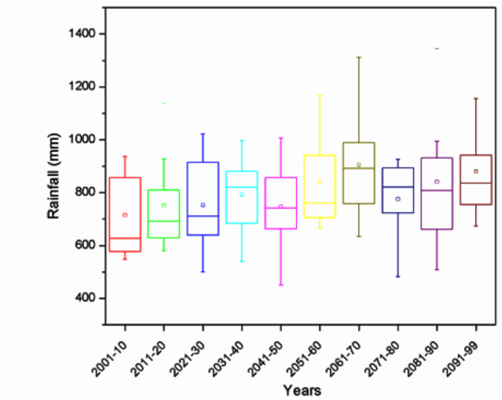
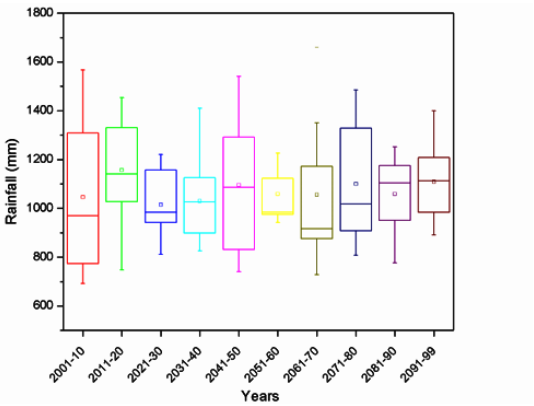
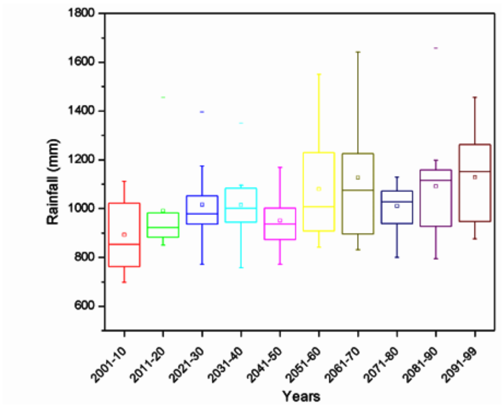


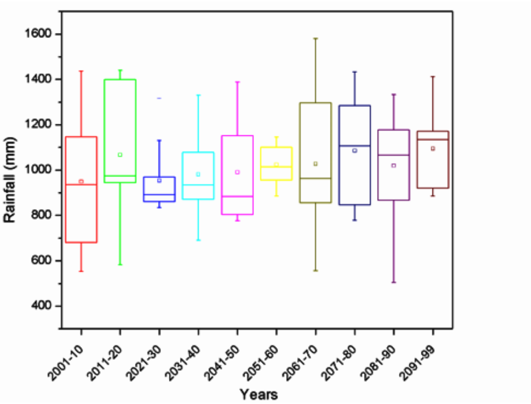


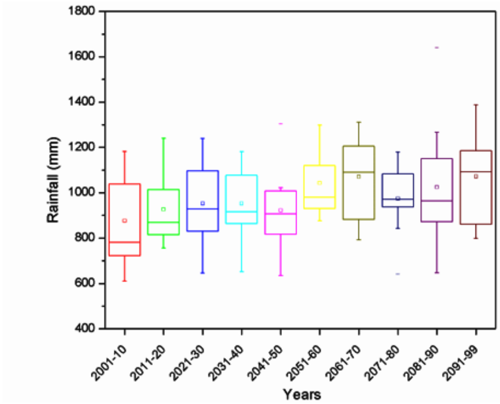
Alwar



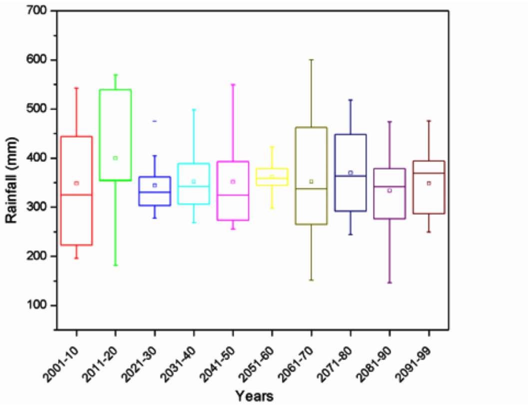


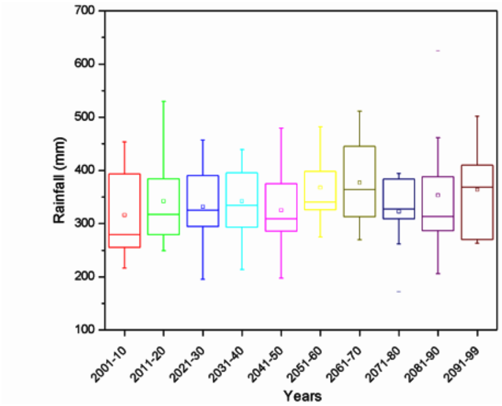
Banswara



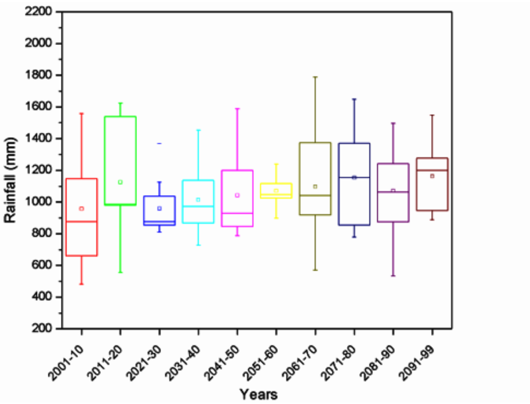


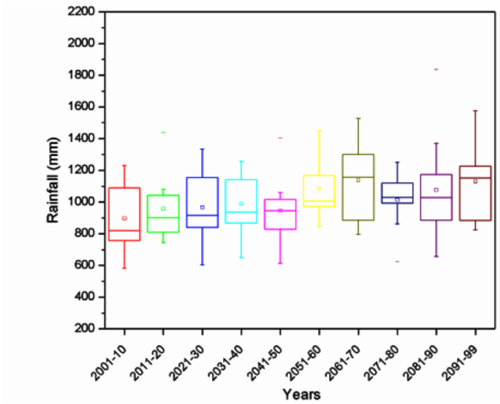
Baran





Barmer





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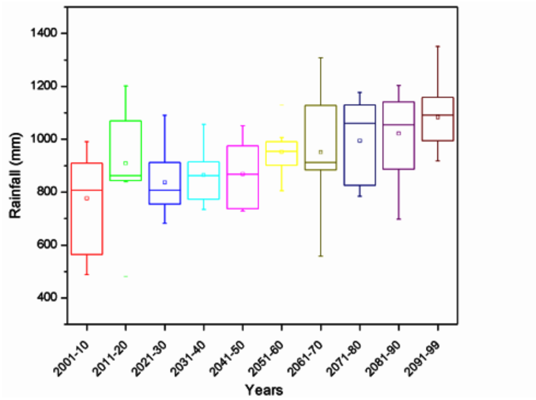

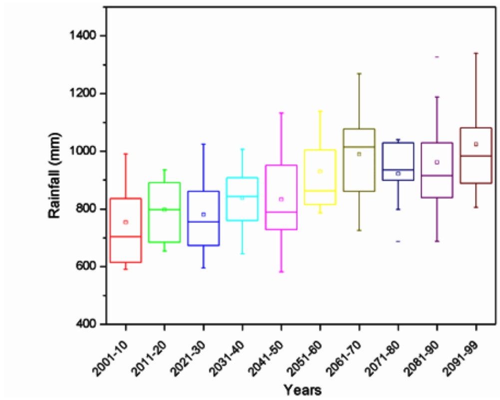

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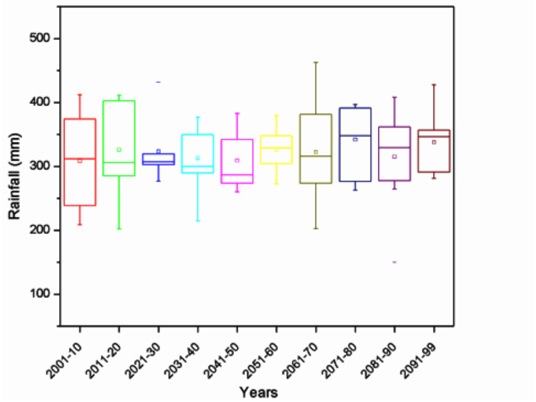

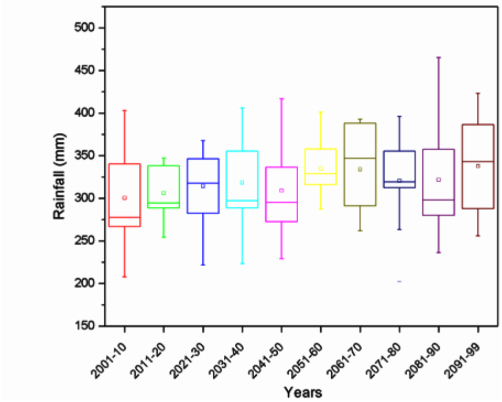

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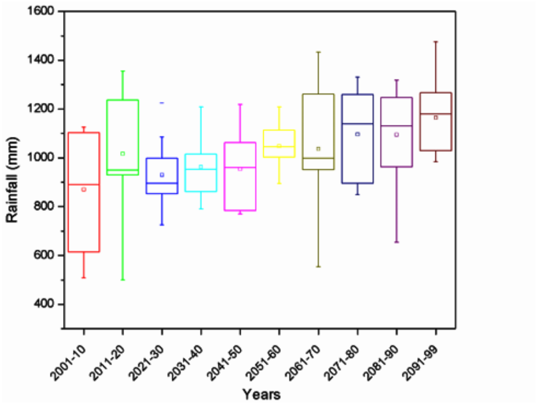

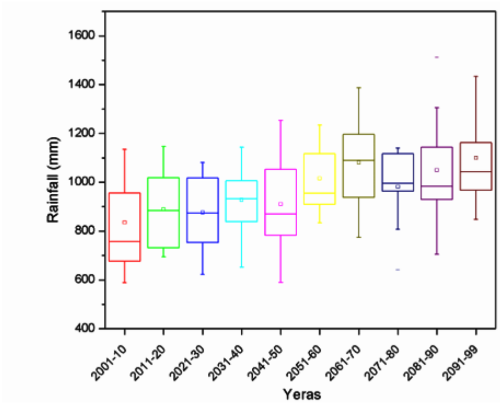

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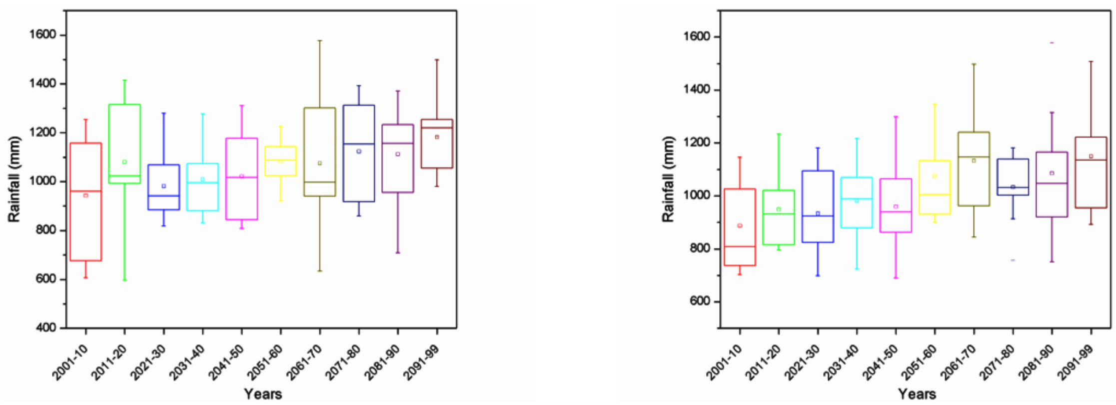

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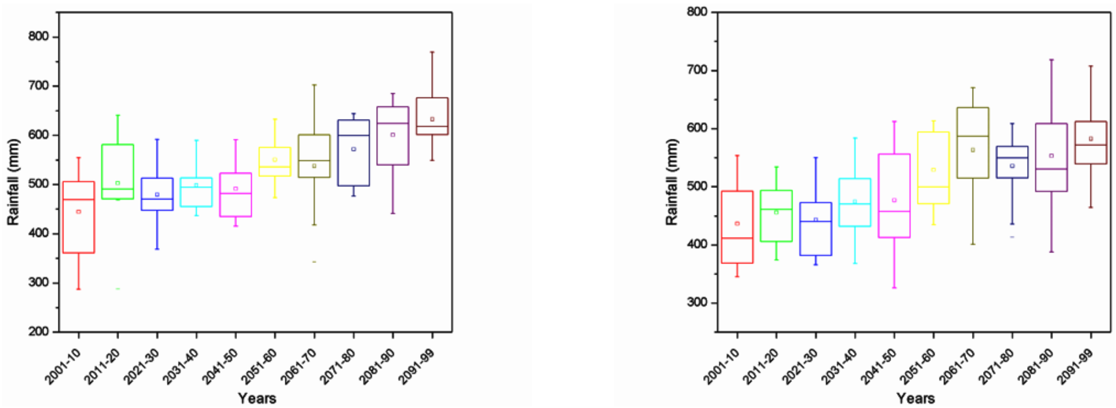

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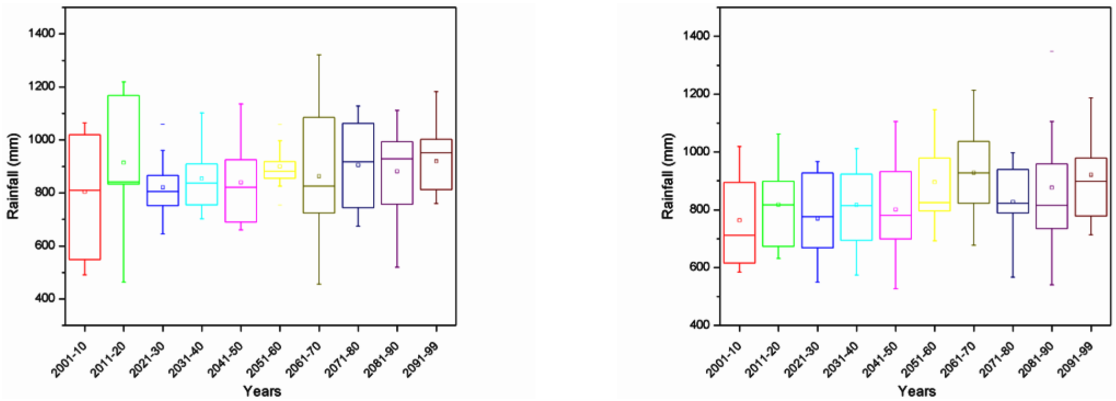

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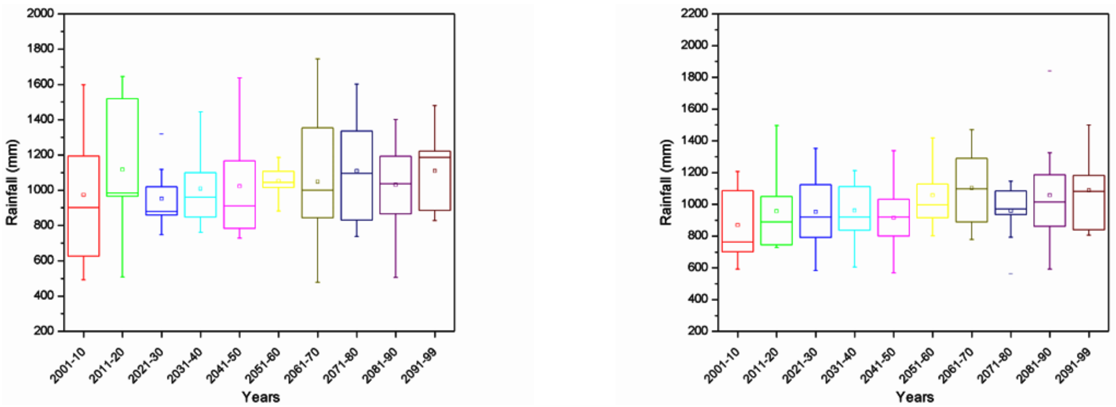

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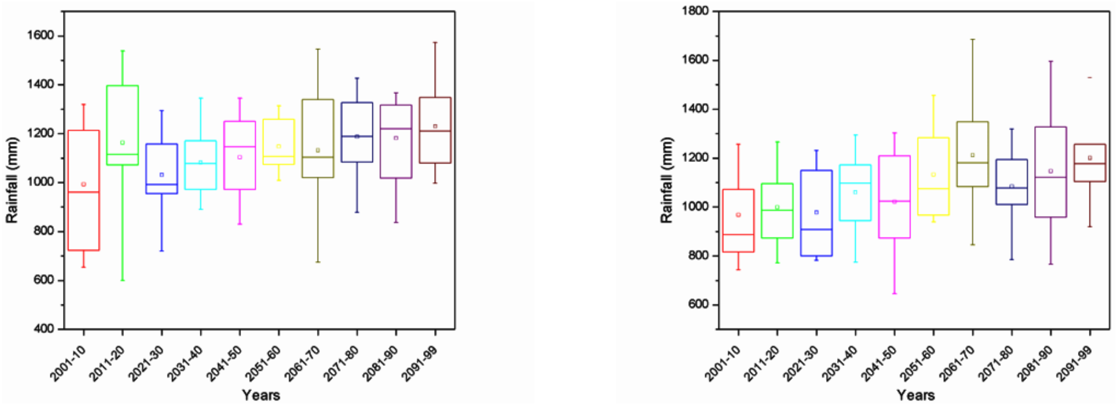

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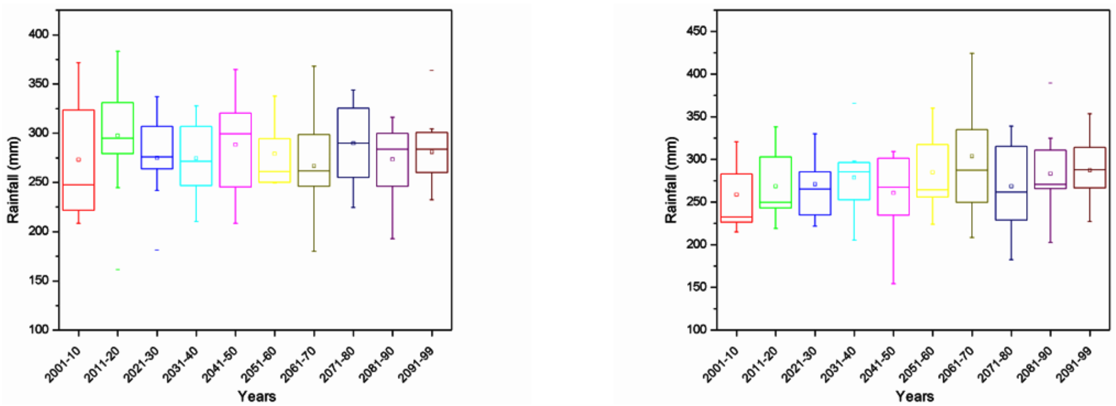

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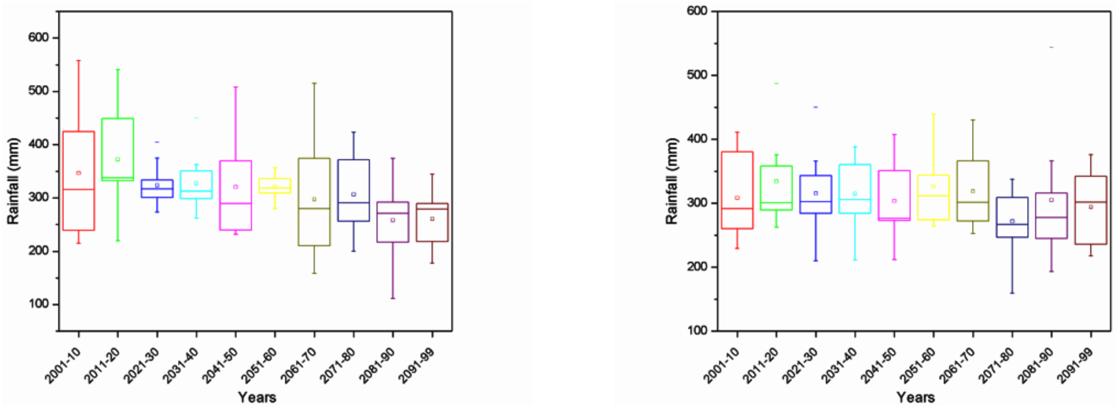

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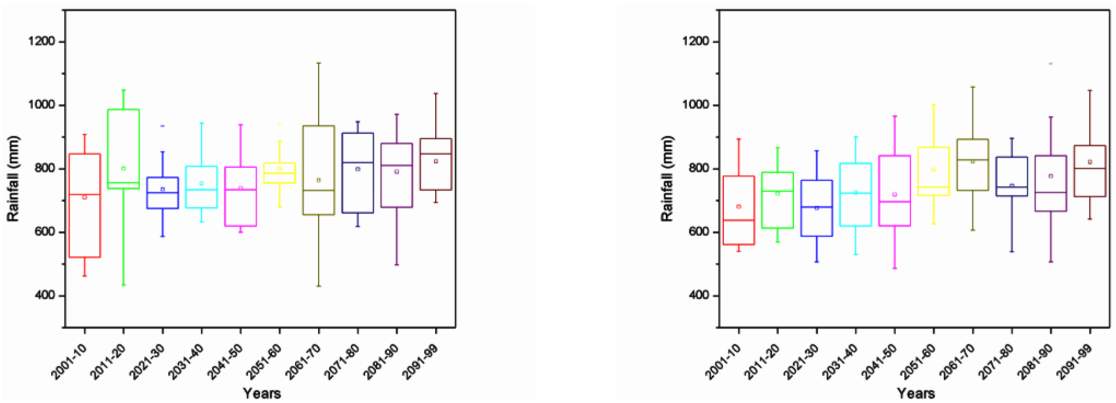

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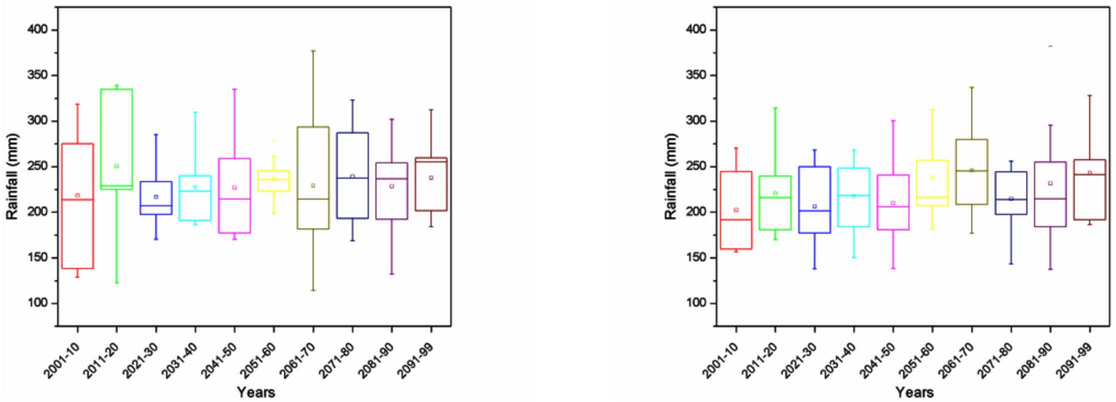

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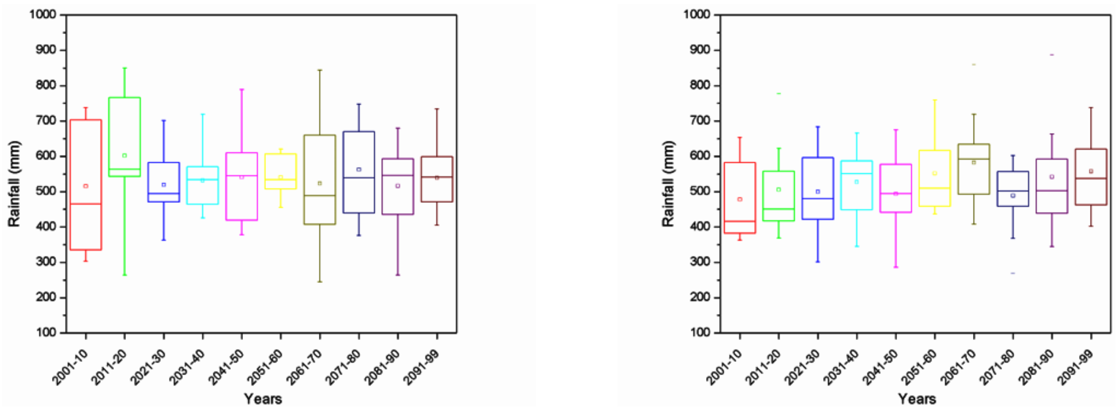

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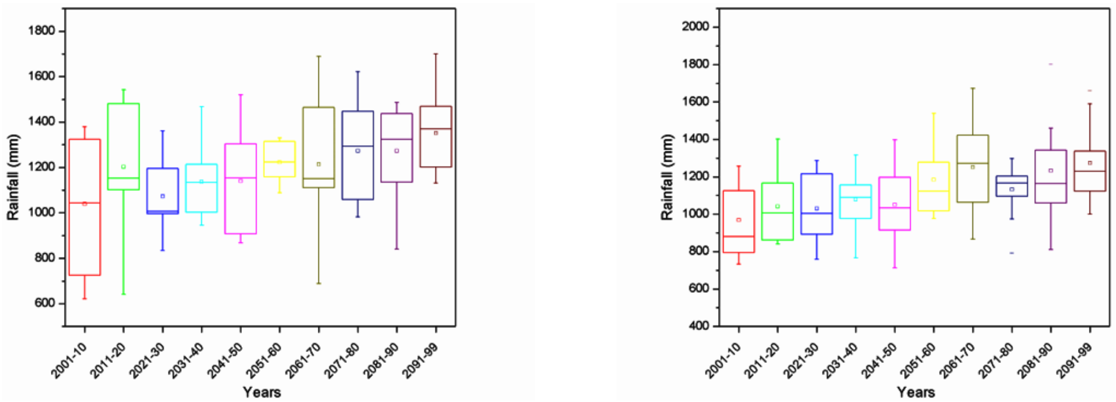

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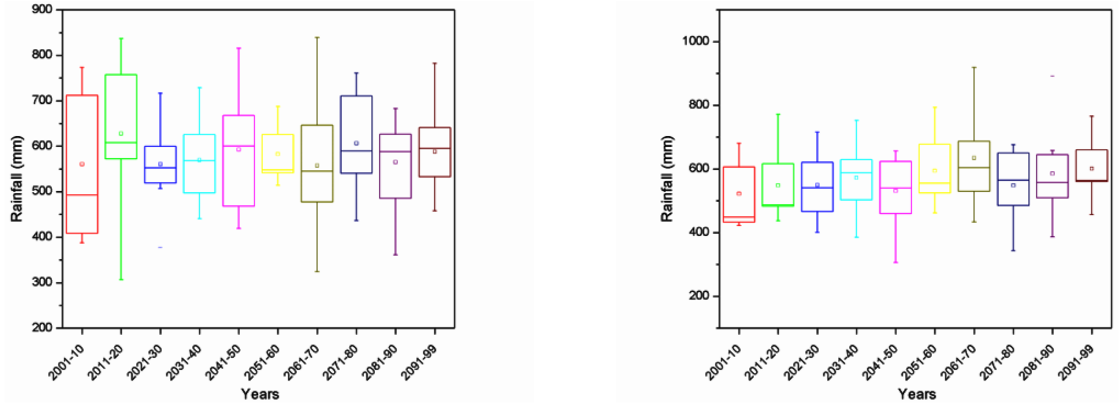

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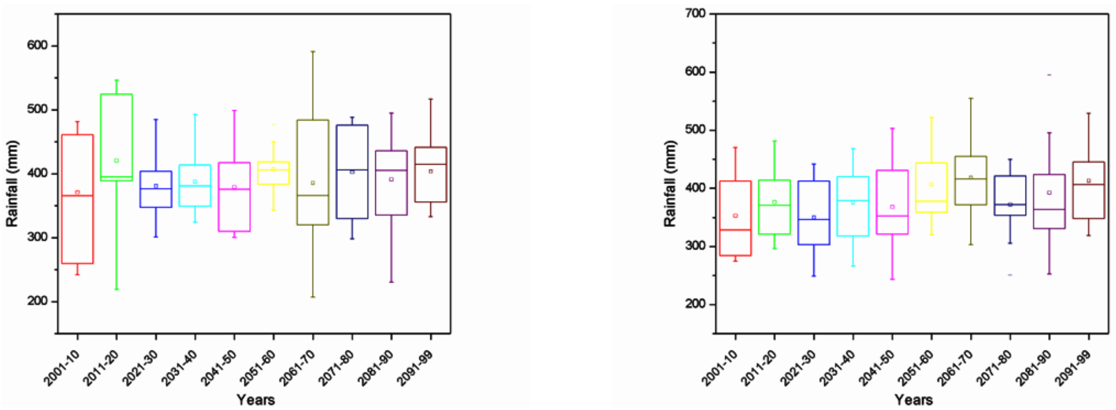

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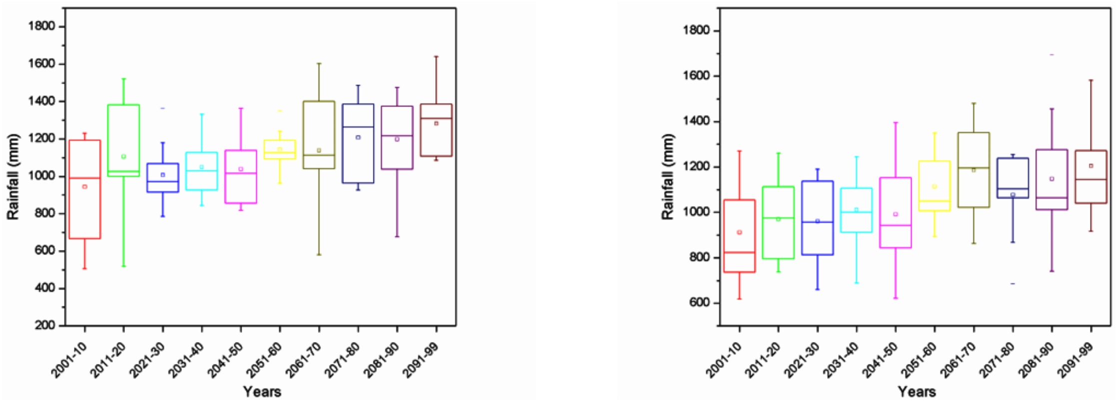

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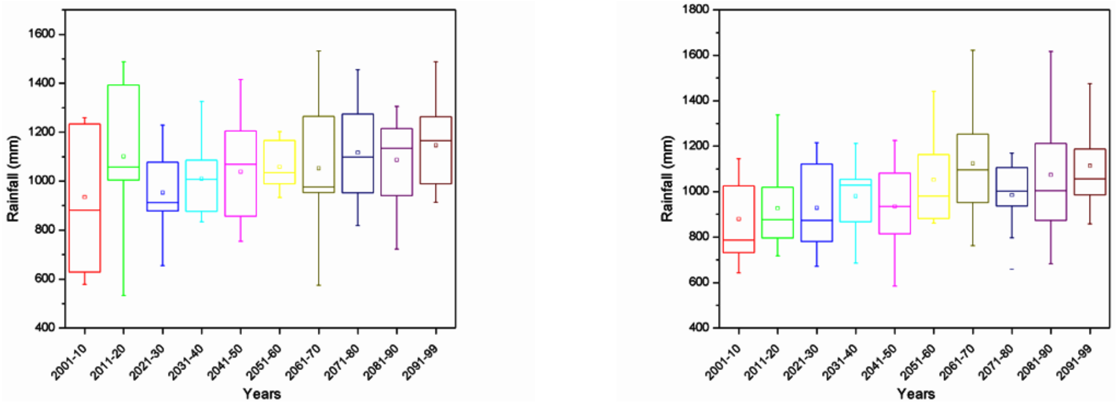

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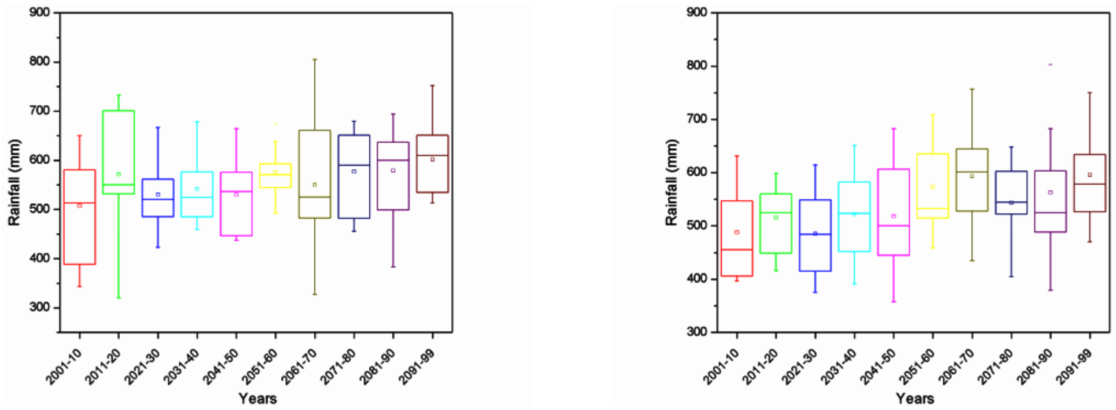

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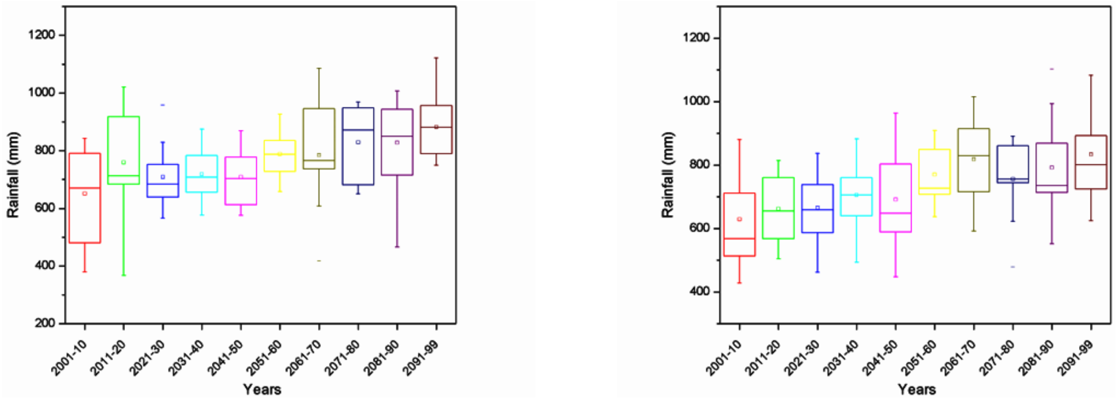

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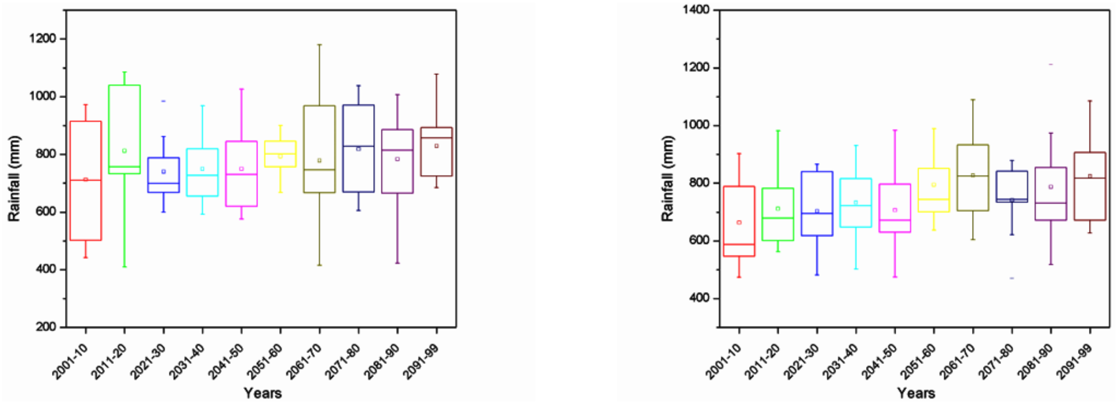
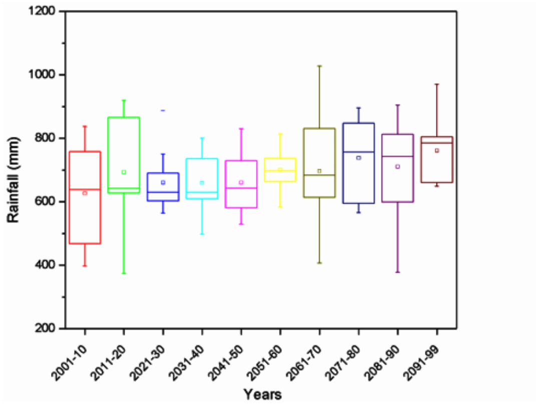
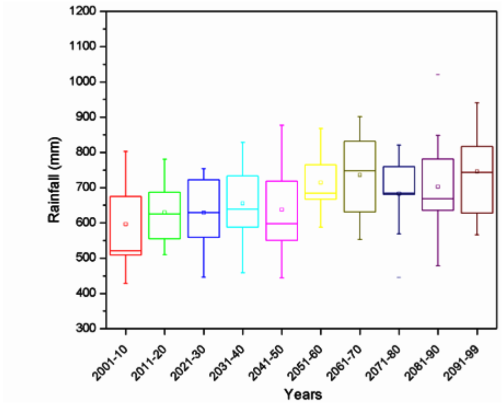


Rajasmand





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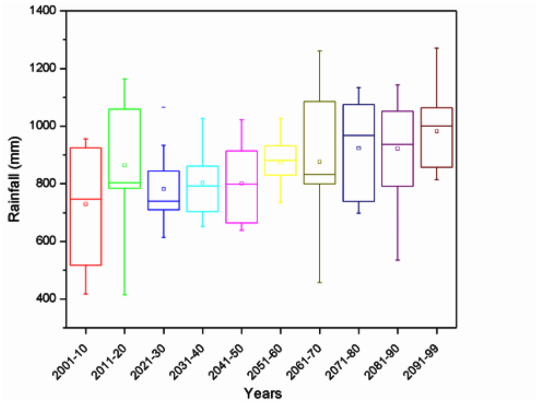

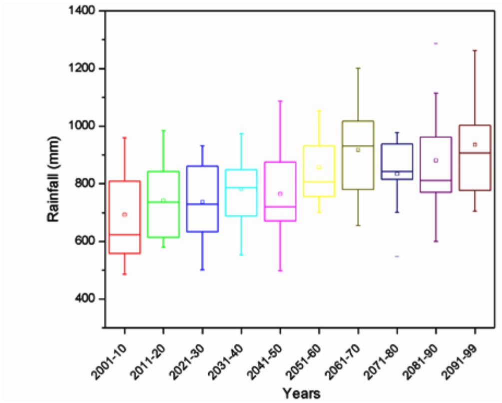

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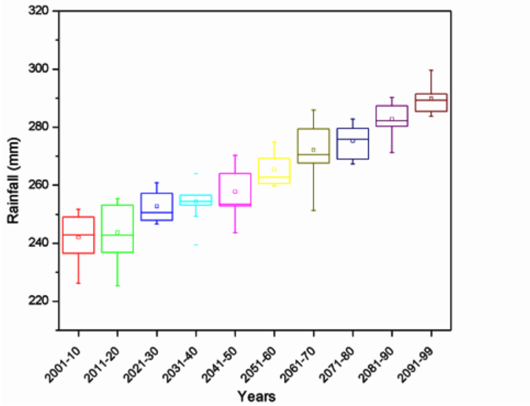

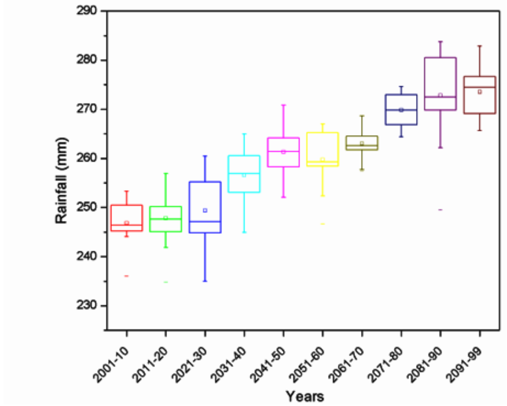

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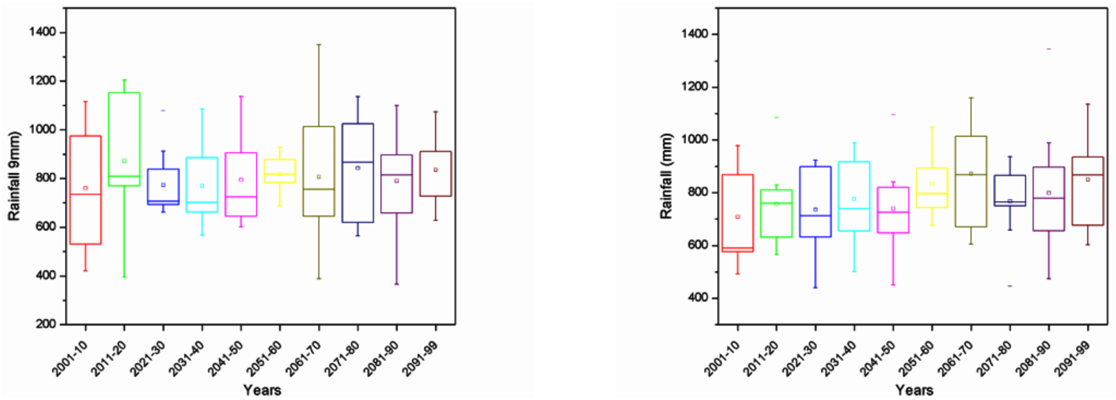

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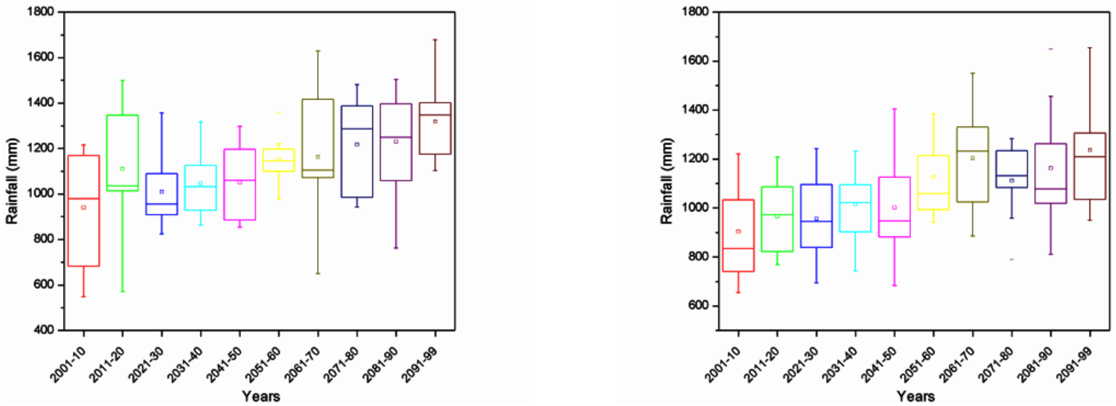

Udaipur