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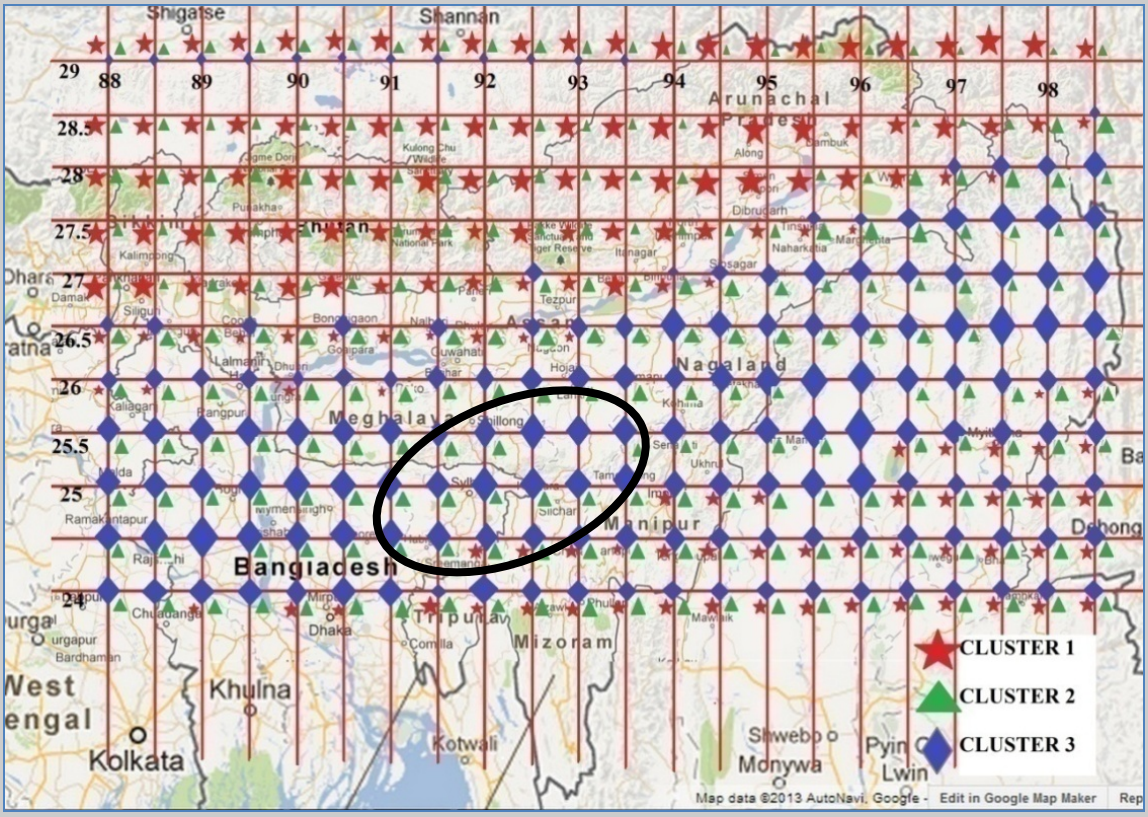
REPORT

IMPACT OF CLIMATE CHANGE ON PRECIPITATION OF BARAK BASIN



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IMPACT OF CLIMATE CHANGE ON PRECIPITATION OF BARAK BASIN

ABSTRACT

The North-eastern part of India, which receives heavier rainfall than other parts of the subcontinent, is of great concern now-a-days with regard to climate change. High intensity rainfall for short duration and longer dry spell, occurring due to impact of climate change, affects not only flood and draught situation, but river morphology too. Several studies have been done by IIT Guwahati on future prediction of rainfall at different locations of NE region of India using different GCMs and downscaling techniques. However, most of these studies were done on the impact of climate change on the precipitation and streamflow characteristic of Brahmaputra River or its tributaries. These studies show that results of statistical downscaling to different station-point shows different range of future changes, which indicates importance to determine hydrological homogeneity of the basin before concluding on a best-fit model. As the results of Brahmaputra and its tributary cannot be extended to predict changes in Barak Basin, therefore, a study is conducted first to delineate the north-eastern region of India into some homogeneous clusters. Suitable GCM parameters and data of 10 IMD (Indian Meteorological Department) stations, situated in various regions of the North-east, were used for making the clusters. The results of the Fuzzy C-Means (FCM) analysis show different clustering patterns for different conditions. Two clearly visible clusters can be determined from the study, one in the Brahmaputra valley region and the other in Barak valley region. Studies related to future prediction of rainfall pattern have been done on Silchar station, which is taken as a representative of the Barak basin. Calibration and validation as well as future prediction of rainfall pattern have been done for Silchar. From the analysis, it was seen that maximum monthly precipitation may increase by 16% to 19% in the next 60 years and may again become similar to that of the present situation by 2100. Shifting of peak monthly precipitation has been observed, i.e., there may be delay in peak monsoon. The average increase in total yearly precipitation was however found to be 2.1% from MLR analysis whereas from MLR analysis with residual r, it was found to be 1.97%.

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1. INTRODUCTION

In today's world, one of the most important issues related to various water resources planning is the impact of climate change on future water scenario. To have a fair idea on impact of climate change in a vast country like India, where climate conditions differ from place to place, is of major concern, because country's economic performance and social progress are dependent on rainfall. The north-eastern part of India receives heavier rainfall than other parts of the subcontinent. High intensity rainfall for short duration and longer dry spell are the major problems due to impact of climate change. Therefore planning and management of water resources related issues in the north-eastern part of India should definitely include the impacts of climate change.

Several studies have already been done on impact of climate change on water resources of various parts of the North-eastern region of India (Deka and Sarma 2010, Vinnarasi and Sarma 2011, Sarma and Kalita, 2012). Most of these studies were on the impact of climate change on the precipitation and streamflow characteristic of Brahmaputra River or its tributaries. To study the impacts of climate change on rainfall, future predictions of the rainfall patterns was done with the use of downscaling techniques. Three Global Climate Models (GCM), namely CGCM3, HadCM3, and MRCGCM2, were downscaled using statistical downscaling technique for predicting monthly weather data under A2 scenario. Depending on the location of interest downscaling was done to different points and interestingly the range of changes estimated at different points of the same river basin was found to vary significantly, though the trend of change was matching. The downscaling results, then, was used to predict the future rainfall intensity, number of dry days etc. These studies indicated that, in future, the maximum monthly precipitation may increase by as high as 20% and the rainfall intensity may increases by 14%. Such change in precipitation pattern is of major concern, as this may lead to several problems in the field of water and agricultural management. Severe flood during monsoon month and severe drought in lean period, morphological change in river causing bank erosion, reduction in ground water table etc. are some of the hydrological problems that are expected to increase because of climate change impact. To study the impacts of climate change on stream flow behaviour, two methods were used. The first one is rainfall-runoff modelling with an input of downscaled precipitation using Watershed Modelling System (WMS) Software. The second method is by direct downscaling of streamflow from HadCM3 model under A2 scenario using Artificial Neural Network (ANN) model. Direct downscaling of streamflow was found to be encouraging compared to rainfall-runoff modelling in climate change predictions because of paucity of landuse and other related data. From the results, it was found that maximum monthly streamflow is shifting towards late monsoon period. Result of these studies indicated that impact of climate change in the NE region is significant and its effect differs from point to pint. Therefore, to have clear idea about impact of Climate Change in Barak basin a detail study with delineation of hydrological homogeneous region is necessary.

This report contains a study of hydrological homogeneous region in the NE region of India and future precipitation prediction in the Barak basin due to impact of climate change.

2. FUZZY CLUSTERING AND ANALYSIS OF BARAK BASIN

Previous studies show that results of statistical downscaling to different station-point shows different range of future changes. Also, different GCMs perform differently in different station points. Hence, selection of appropriate model as well as downscaling technique is not very clear from any of those works. Therefore, it is important to determine hydrological homogeneity of the basin before concluding on a best-fit model. Moreover, because of the same reason, the result of Brahmaputra and its tributary cannot be extended to predict changes in Barak Basin even though Barak River is located in the same region and in fact can be considered as a tributary of Brahmaputra, which meets the river Brahmaputra beyond the territory of India, where Brahmaputra takes a different name. In addition, the hydrological setup of Barak Basin is different from that of the Brahmaputra basin, as low altitude hills without having snow cover surround this basin. Therefore, a study is conducted first to delineate the north-eastern region of India into some homogeneous clusters. The basic objective of clustering is to determine appropriate GCM and downscaling technique for a homogeneous region for water resources planning and management. The clustering analysis has been done based on the Fuzzy Clustering concept and the resulting clusters obtained by using conventional methods and non-conventional methods are being compared.

2.1 Methodology

Fuzzy clustering is the clustering technique which allows the objects to belong to several clusters simultaneously, with different degrees of membership. In many situations, fuzzy clustering is more natural than hard clustering, where an object is bound to belong to a single cluster. Objects on the boundaries between several classes are not forced to fully belong to one of the classes, but rather are assigned membership degrees between 0 and 1 indicating their partial membership.

Generalization of the hard partition to the fuzzy case follows directly by allowing μ_{ik} to attain real values in [0, 1]. Conditions for a fuzzy partition matrix are given by:

$$\mu_{ik} \in [0, 1],\ 1 \le i \le c,\ 1 \le k \le N,$$

$$\sum_{i=1}^{c} \mu_{ik} = 1, 1 \le k \le N,$$

$$0 < \sum_{k=1}^{N} \mu_{ik} < N, 1 \le i \le c.$$

The ith row of the fuzzy partition matrix **U** contains values of the ith membership function of the fuzzy subset A_i of **Z**. Second equation constrains the sum of each column to 1, and thus the total membership of each $\mathbf{z}_k$ in **Z** equals one.

2.1.1 Fuzzy C-Means (FCM) Clustering

Most analytical fuzzy clustering algorithms are based on optimization of the basic c-means objective function, or some modification of it. **The Fuzzy c-Means Functional**, which is to be minimised, is formulated as:

$$J(\mathbf{Z}; \mathbf{U}, \mathbf{V}) = \sum_{i=1}^{c} \sum_{k=1}^{N} (\mu_{ik})^m \|z_k - v_i\|^2 \ A$$

Where, $\mathbf{U} = [\mu_{ik}] \in M_{fc}$ is a fuzzy partition matrix of **Z.**

$\mathbf{V} = [\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_c]$, $\mathbf{v}_i \in R^n$ is a vector of cluster prototypes (centers), which have to be determined.

$d^2(z_k, v_i)A = D^2_{ikA} = \|z_k - v_i\|^2 A = (z_k - v_i)^T A (z_k - v_i)$ is a squared inner-product distance norm, and

$m = [1, \infty)$ is a parameter which determines the fuzziness of the resulting clusters.

2.1.2 Fuzzy C-Means (FCM) Algorithm to Delineate Homogeneous Precipitation Regions

Suppose there are N sites in a study area. The '*n*' attributes, influencing precipitation at each site, have to be identified. The attributes may include large scale atmospheric variables (LSAVs) or their principal components, location parameters (latitude, longitude and altitude), and seasonality measures. Subsequently, a feature vector is formed for each site using the identified attributes for the site.

The ith site is denoted in n-dimensional attribute space by the feature vector

$$\mathbf{y_i} = [y_{1i}, \ldots, y_{ji}, \ldots, y_{ni}]^T \in R^n,$$

Where, y_{ji} is the value of jth attribute in $\mathbf{y_i}$. The attributes of $\mathbf{y_i}$ are rescaled using:

$$x_{ji} = \frac{(y_{ji} - \bar{y}_j)}{\sigma_j}, \text{ for } 1 \le j \le n,\ 1 \le i \le n$$

Where, x_{ji} denotes the rescaled value of y_{ji},

σ_j represents the standard deviation of attribute j, and

$\bar{y}_j$ is the mean value of attribute j over all the N feature vectors.

Rescaling the attributes is necessary to nullify the differences in their variance, relative magnitude and importance. Otherwise, attributes having greater magnitude and variance influence the formation of clusters, which is undesirable. If certain attributes are known to be more important than others in influencing precipitation in the study area, the rescaling should be such that the variances of rescaled values of those attributes are greater than those of the less important attributes.

Let $\mathbf{X} = (\mathbf{x_1}, \ldots, \mathbf{x_i}, \ldots, \mathbf{x_N})$ denote matrix containing rescaled feature vectors, where $\mathbf{x_i}$ is rescaled feature vector for the ith site. Next task is to partition **X** into c soft clusters using Fuzzy c-means (FCM) algorithm, to arrive at optimum value of the following objective function:

$$\text{Minimize, } J(\mathbf{X}; \mathbf{U}, \mathbf{V}) = \sum_{k=1}^{c} \sum_{i=1}^{N} (\mu_{ki})^m \|\mathbf{x}_i - \mathbf{v}_k\|^2$$

or can be written as,

$$\text{Minimize, } J(\mathbf{X}; \mathbf{U}, \mathbf{V}) = \sum_{k=1}^{c} \sum_{i=1}^{N} (\mu_{ki})^m \; d^2(\mathbf{x}_i, \mathbf{v}_k)$$

Subject to the following constraints,

$$\sum_{k=1}^{c} \mu_{ki} - 1 \; \forall i \in \{1, \ldots, N\}$$

$$0 < \sum_{i=1}^{N} \mu_{ki} < N \; \forall k \in \{1, \ldots, c\}$$

Where $\mathbf{V} = (\mathbf{v_1}, \ldots, \mathbf{v_k}, \ldots \mathbf{v_c})$ represents a matrix containing cluster centroids. $\mathbf{v_k} = [v_{1k}, \ldots, v_{jk}, \ldots, v_{nk}] \in R^n$ denotes centroid of kth soft cluster,

$\mu_{ki} \in [0, 1]$ denotes the membership of x_i in the kth soft cluster;

U is the fuzzy partition matrix which contains the membership of each rescaled feature vector in each soft cluster;

the parameter $m \in [1, 1)$ refers to the weight exponent for each fuzzy membership, and is known as fuzzifier;

$d(\mathbf{x_i}, \mathbf{v_k})$ is the distance from $\mathbf{x_i}$ to $\mathbf{v_k}$.

The iterative procedure of **FCM algorithm** used to arrive at homogeneous precipitation regions is summarized below:

i. Initialize fuzzy partition matrix U using a random number generator.
ii. Adjust the initial memberships μ_{ki}^{init} of x_i belonging to cluster k using the following equation:

$$\mu_{ki} = \frac{\mu_{ki}^{init}}{\sum_{j=1}^{c} \mu_{ji}^{init}}, \text{ for } 1 \le k \le c, 1 \le i \le N$$

iii. Compute the fuzzy cluster centroid v_k as

$$\mathbf{v_k} = \frac{\sum_{i=1}^{N} (\mu_{ki})^m x_i}{\sum_{i=1}^{N} (\mu_{ki})^m}, \text{ for } 1 \le k \le c$$

iv. Update the fuzzy membership μ_{ki} as

$$\mu_{ki} = \frac{\left(\frac{1}{d^2(x_i, v_k)}\right)^{\frac{1}{m-1}}}{\sum_{k=1}^{c} \left(\frac{1}{d^2(x_i, v_k)}\right)^{\frac{1}{m-1}}}, \text{ for } 1 \le k \le c, 1 \le i \le N$$

v. Compute the value of objective function as

$$J(\mathbf{X}; \mathbf{U}, \mathbf{V}) = \sum_{k=1}^{c} \sum_{i=1}^{N} (\mu_{ki})^m \; d^2(\mathbf{x}_i, \mathbf{v}_k)$$

Repeat the steps (iii) to (v) until change in the value of objective function between two successive iterations becomes sufficiently small.

2.1.3 Parameters of the FCM Algorithm

Before using the FCM algorithm, the following parameters must be specified:

- the number of clusters, *c*,
- the 'fuzziness' exponent or fuzzifier, *m*,
- the termination tolerance (absolute diffenece between two successive iterations), and
- The fuzzy partition matrix, **U**.

The choices for these parameters are now described one by one.

- **Number of clusters:-** The number of clusters *c* is the most important parameter, in the sense that the remaining parameters have less influence on the resulting partition. When clustering real data without any a priori information about the structures in the data, one usually has to make assumptions about the number of underlying clusters. The chosen clustering algorithm then searches for *c* clusters, regardless of whether they are really present in the data or not.

- **Fuzziness Parameter:-** The weighting exponent m is an important parameter because it significantly influences the fuzziness of the resulting partition. As m approaches 1($m \rightarrow 1$), the partition becomes hard ($\mu_{ik} \in \{0, 1\}$). As $m \rightarrow \infty$, the partition becomes completely fuzzy ($\mu_{ik} = 1/c$). Usually, m = 2 is initially chosen.

- **Termination tolerance:-** The FCM algorithm stops iterating when the norm of the difference between **U** in two successive iterations is smaller than the termination tolerance. Usually 0.001 is taken, even though 0.01 works well in most cases, while drastically reducing the computing times.

- **Fuzzy partition matrix**, **U:-** The fuzzy partition matrix must be initialized at the beginning. However, taking random value for **U** is also acceptable as the algorithm is not affected by the initial value of **U.**

2.2 Application

In this study, for making the clusters, 10 IMD (Indian Meteorological Department) stations, situated in various regions of the North-east, have been selected (Table 1.1). On the Basis of IMD data available for those stations, homogeneous clustering has been done.

Table 1. 1 *Latitude-longitude-elevation of the IMD stations*

Index No.	Name of the stations	Region	Latitude	Longitude	Elevation
42220	Passighat (VEPG)	Arunachal	28˚6' 0" N (28.1˚)	95˚23' 0" E (95.3833˚)	157 m (515 ft)
42309	North-lakhimpur (VELR)	Assam	27˚14' 0" N (27.2333˚)	94˚7' 0" E (94.1167˚)	101 m (331 ft)
42314	Mohanbari (VEMN)	Assam	27˚29' 2" N	95˚1' 1" E	111 m

			(27.4839˚)	(95.0169˚)	(364 ft)
42404	Dhubri	Assam	26˚1' 0" N (26.0167˚)	89˚59' 0" E (89.9833˚)	35 m (115 ft)
42410	Guwahati (VEGT)	Assam	26˚6' 22" N (26.1061˚)	91˚35' 9" E (91.5859˚)	54 m (177 ft)
42415	Tezpur	Assam	26˚37' 0" N (26.6167˚)	92˚47' 0" E (92.7833˚)	91 m (299 ft)
42515	Cherrapunjee	Meghalaya	25˚15' 0" N (25.25˚)	91˚44' 0" E (91.7333˚)	1300 m (4265 ft)
42516	Shillong	Meghalaya	25˚34' 0" N (25.5667˚)	91˚53' 0" E (91.8833˚)	1600 m (5249 ft)
42619	Silchar	Assam	24˚45' 0" N (24.75˚)	92˚48' 0" E (92.8˚)	21 m (70 ft)
42623	Imphal (VEIM)	Manipur	24˚45' 36" N (24.7599˚)	93˚53' 48" E (93.8967˚)	774 m (2539 ft)

Three types of data have been used in this study, namely

1. Observed precipitation data of each station, collected from IMD
2. GCM (Global Climate models) data collected from IPCC
3. Daily gridded rainfall data of size 0.5 □ × 0.5 □, collected from IMD, Pune.

1. *Observed precipitation data*

Observed daily precipitation data have been collected from Indian Meteorological Department (IMD) under an MOU between IIT Guwahati and IMD. The time period of data collection is from 01-01-1969 to 31-01-2012. However, no data are available for any station from 2001 to 2005.

2. *GCM data*

The GCM data are downloaded from Intergovernmental Panel on Climate Change (IPCC) from Fourth Assessment Report (AR4). The time period of fourth assessment is from 2001 to 2100. In this study, GCM model, HadCM3, with A2 simulation run has been used. A2 scenario considers a very heterogeneous world with continuously increasing global population and regionally oriented economic growth. It considers the forcing effect of greenhouse gases and sulphate aerosol direct effect, which are based on IPCC SRES-A2 (Special Report on Emission Scenario A2).

3. *Daily gridded rainfall data*

Daily gridded rainfall data are collected from Indian Meteorological department, Pune. The time period of data collection is from 01-01-1971 to 31-12-2005. The data are available for whole Indian sub-continent with resolution as high as 0.5 □ × 0.5 □. Data of the North-eastern part, that is required for the analysis, are separated out from the whole data.

The clustering has been done for the following cases:

- Regionalization using GCM data of nearby grid points (both for annual data and monsoon data)

- Regionalization using observed precipitation data (both for annual data and monsoon data)
- Regionalization using interpolated GCM data (both for annual data and monsoon data)
- Regionalization using gridded rainfall data (both for annual data and monsoon data)

In cases where GCM data had been used, the first work is to find out the LSAVs, which influence the precipitation of a particular station. For doing this, a relation has to be established between the observed precipitation data and the LSAVs. In the present work, Pearson Correlation is considered to be an effective way to find out the relation. Hence, for each station, Pearson coefficients were calculated using the data available. It has been observed from the correlation results (not shown for brevity) that precipitation data of different stations have different correlation with different LSAVs. Hence those LSAVs, which have good relations with precipitation data of most of the stations, are selected as attributes.

To reduce the curse of high dimensionality, mean monthly values of each of the LSAVs were computed at each of the 10 stations. The mean monthly value of a variable denotes the average value of the variable computed for the month, overall years of the historical record. Thus, there are 12 mean monthly values for each LSAV at each IMD station. Since several of the atmospheric variables are correlated to each other, hence to avoid redundancy, Principal Component Analysis (PCA) has been done. In the present work, PCA has been done with the help of MATLAB program.

To proceed with the FCM algorithm, partition matrix $\boldsymbol{U}$ has to be initialized at first. The initial partition matrix $\boldsymbol{U_{init}}$ was determined with the help of geographical location of the stations and cross-correlation among the stations. Taking $\boldsymbol{U_{init}}$ and the data matrix as input the final partition has been calculated with the help of a MATLAB program made for the FCM algorithm.

From the results of the FCM analysis it came into notice that, different clustering has been found for different conditions. Different clustering patterns found from the FCM analyses are shown in the figures below:

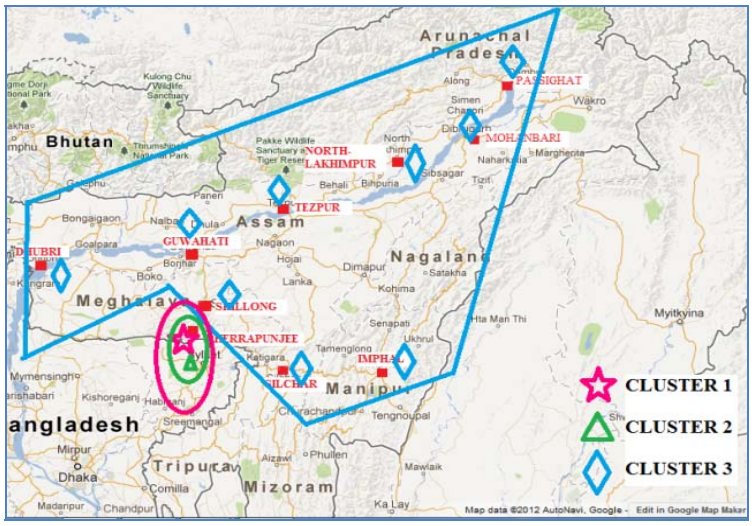

Figure 2. 1 *Clustering done using precipitation data (yearly data used)*

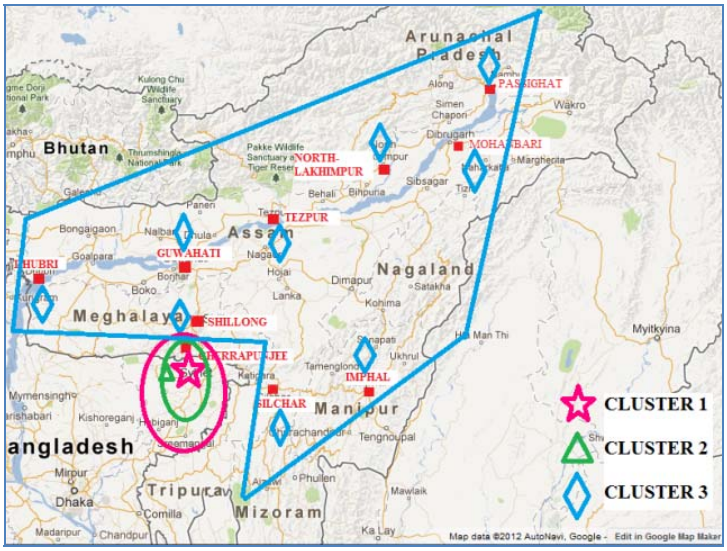

Figure 2. 2 *Clustering done using precipitation data (monsoon data used)*

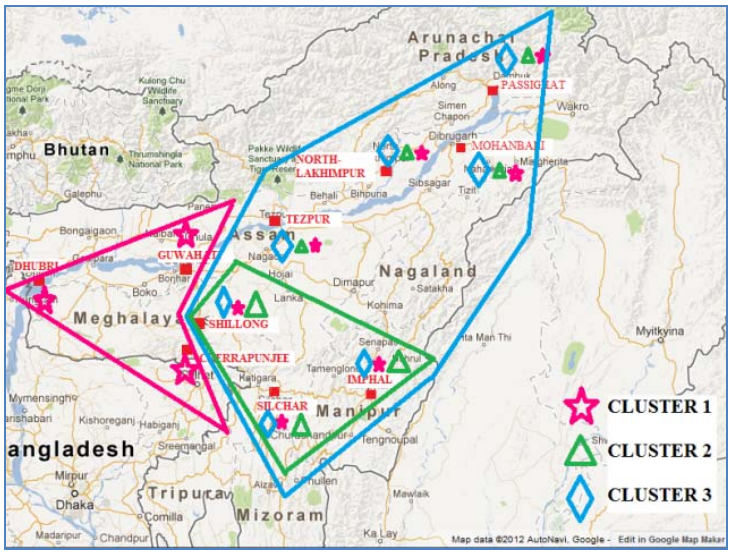

Figure 2. 3 *Clustering done using GCM data of nearby grid points (yearly data used)*

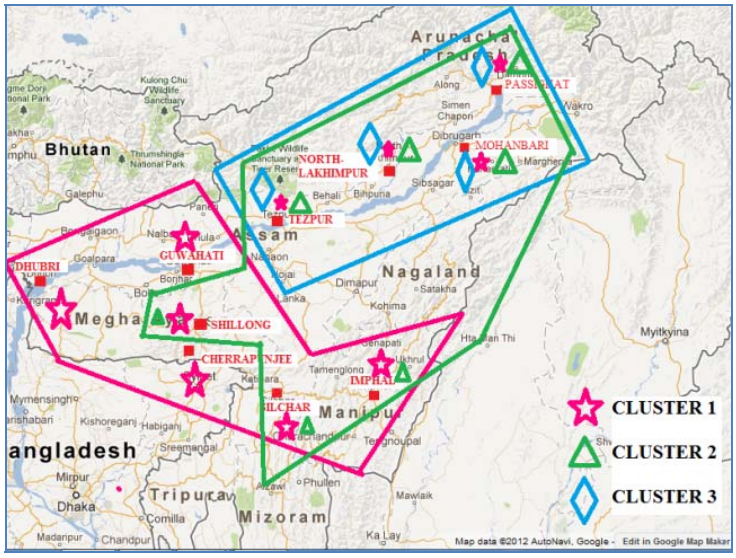

Figure 2. 4 *Clustering done using GCM data of nearby grid points (monsoon data used)*

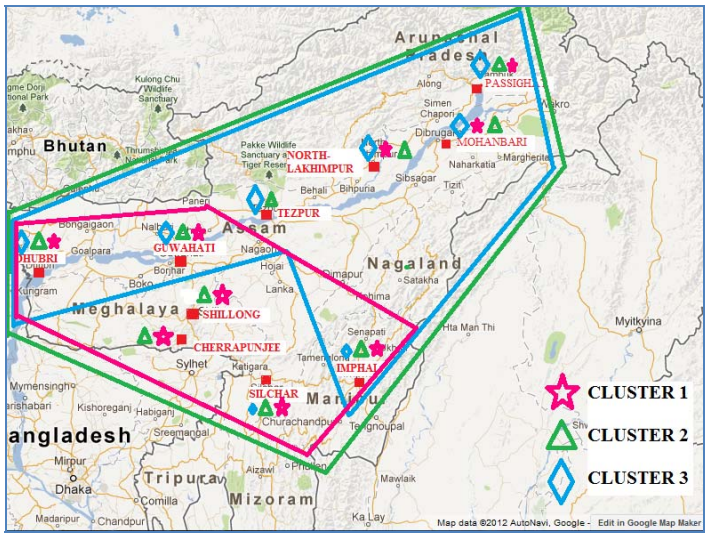

Figure 2. 5 *Clustering done using interpolated GCM data (yearly data used)*

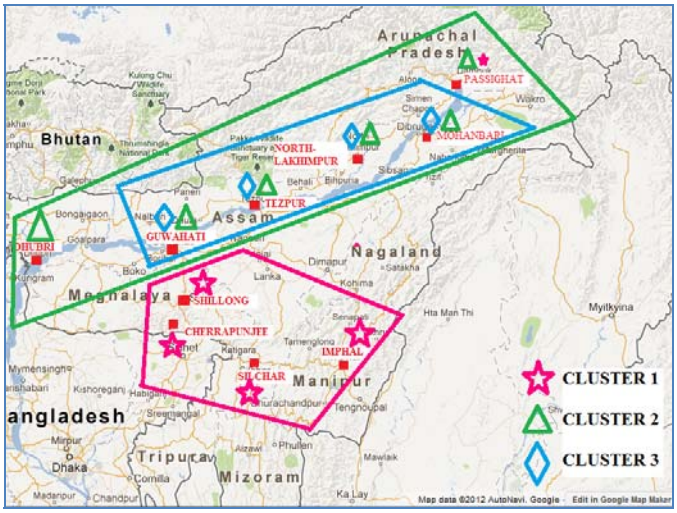

Figure 2. 6 *Clustering done using interpolated GCM data (monsoon data used)*

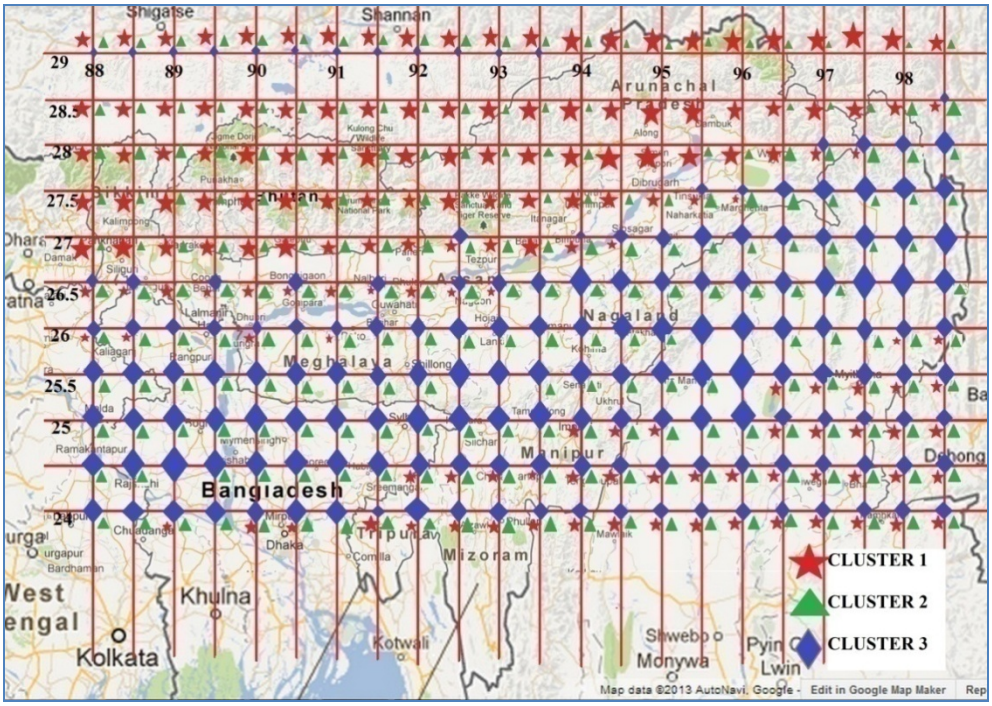

Figure 2. 7 *Clustering done for gridded rainfall data (both yearly data and monsoon data used)*

From the results of the FCM it is being noticed that Passighat, North-Lakhimpur, Mohanbari and Tezpur are always coming under the same cluster, which are situated in the Brahmaputra valley region. Hence it can be concluded that these four stations will always come under the same cluster. Similarly, Shillong, Silchar, Imphal and Cherrapunjee are also coming under the same cluster for most of the analyses. These four stations are situated in the Barak valley region. Guwahati is showing equal memebrship in both the clusters. Dhubri, is showing different results; hence clear statement cannot be given. Therefore, two clearly visible clusters can be determined from the study, one in the Brahmaputra valley region and the other in Barak valley region.

4. DOWNSCALING OF SILCHAR STATION SITUATED IN BARAK VALLEY REGION

As discussed in the previous part of this report, studies related to impacts of climate change on rainfall and stream flow pattern are being done on the Dhansiri river basin, which falls under the Brahmaputra valley region. The future scenario found for the basin represents a considerable part of the Brahmaputra basin. Presently studies are ongoing on prediction of future rainfall pattern of the Barak Valley region. Four stations have been selected viz. Shillong, Silchar, Imphal and Cherrapunjee for the analysis, which are found to be situated in or near the Barak Valley region and are coming under the same cluster from the FCM analyses. Calibration and validation of the GCM data (HadCM3 with A2 scenario) with relation to precipitation data is over. The future prediction part is ongoing for the stations.

Calibration and validation as well as future prediction of rainfall pattern have been done for Silchar. Calibration and validation have been done for different combination of GCM parameters (LSAV data) to find out the best combination of parameters. Furthermore, future data for the long run for some of the GCM parameters (e.g. for zg200, ua500 etc.) are not available with the IPCC site. Hence depending upon the availability of GCM data, some more calibrations and validations have been done for use in such cases. Seven LSAVs have been selected for Silchar station when the analysis had been done for full year viz. hur200, hur500, ta200, ta500, ua200, ua500 and zg200. When the analysis had been done for monsoon only, four LSAVs have been selected viz. ta500, ua200, ua500 and zg200. Figures are shown below:

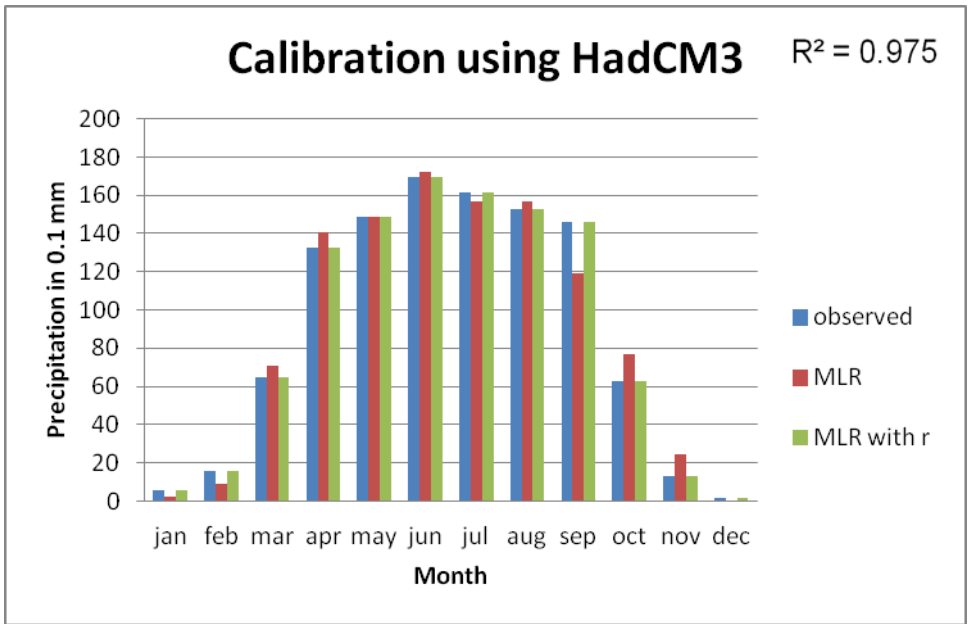

Figure 3. 1 *Calibration for Silchar station using HadCM3 model*

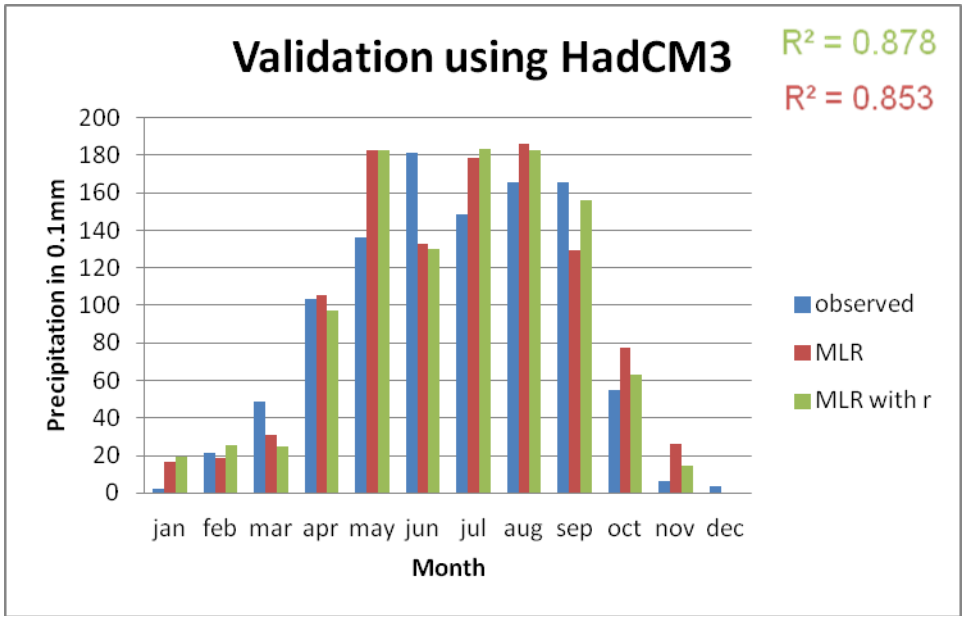

Figure 3. 2 *Validation for Silchar station using HadCM3 model*

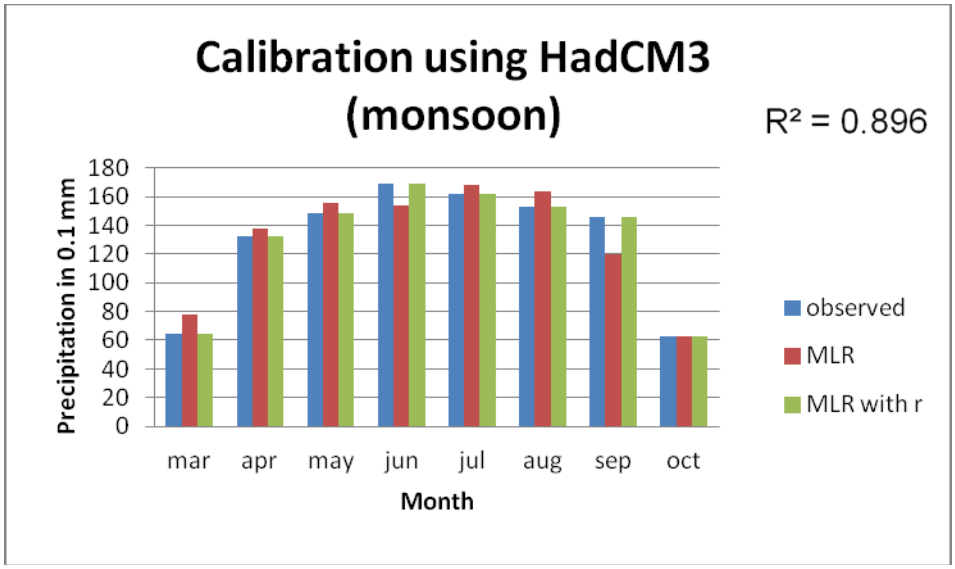

Figure 3. 3 *Calibration for Sichar using HadCM3 model for monsoon season*

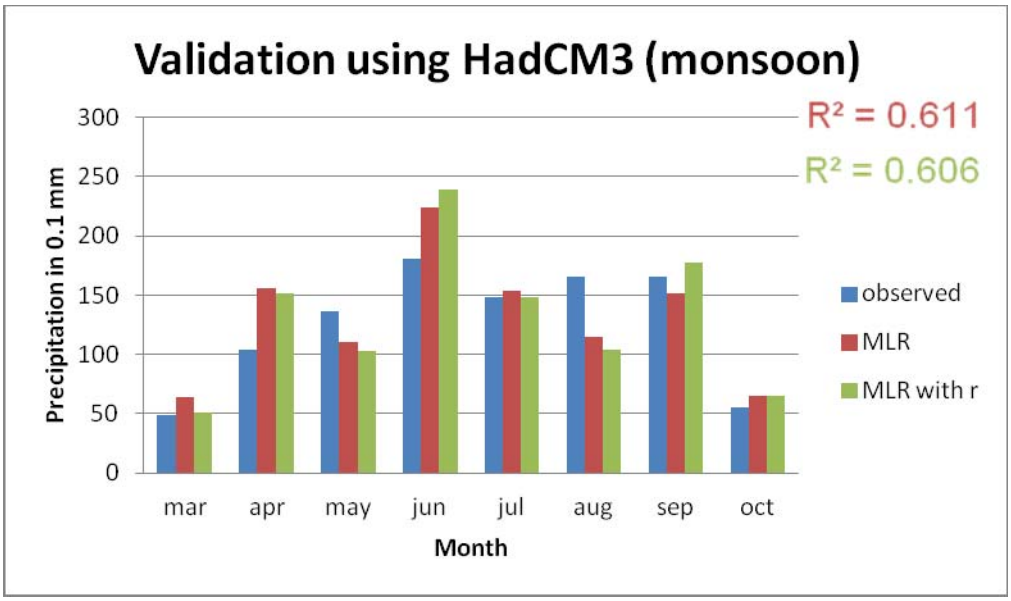

Figure 3. 4 *Validation for Sichar using HadCM3 model for monsoon season*

Calibration and validation done for other combinations of GCM data (LSAVs) are shown in the figures below:

- Analysis done for full years data:
    1. Calibration-validation done using 6 LSAVs (hur200, hur500, ta200, ta500, ua200 and ua500)

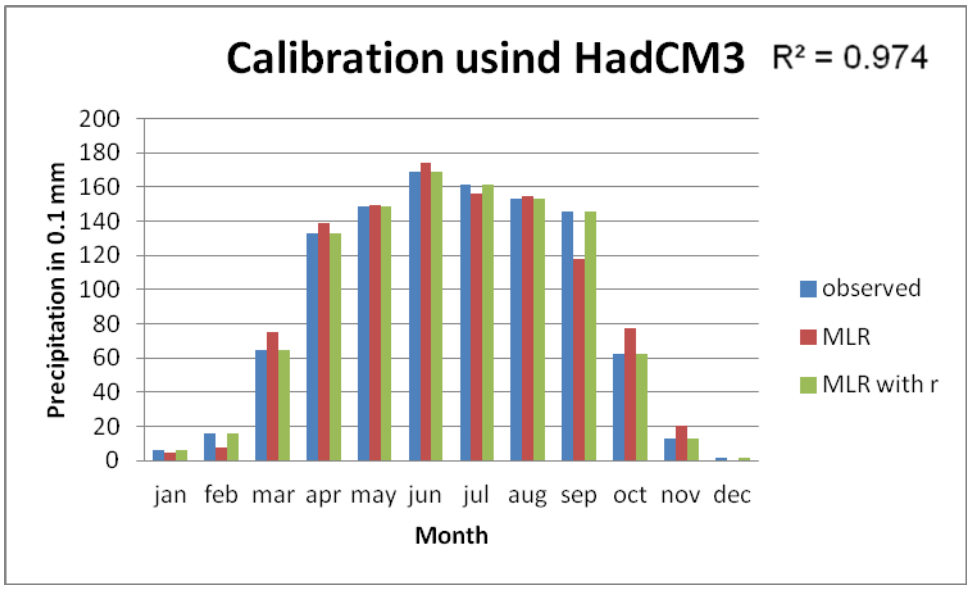

Figure 3. 5 *Calibration for Silchar using 6 LSAVs*

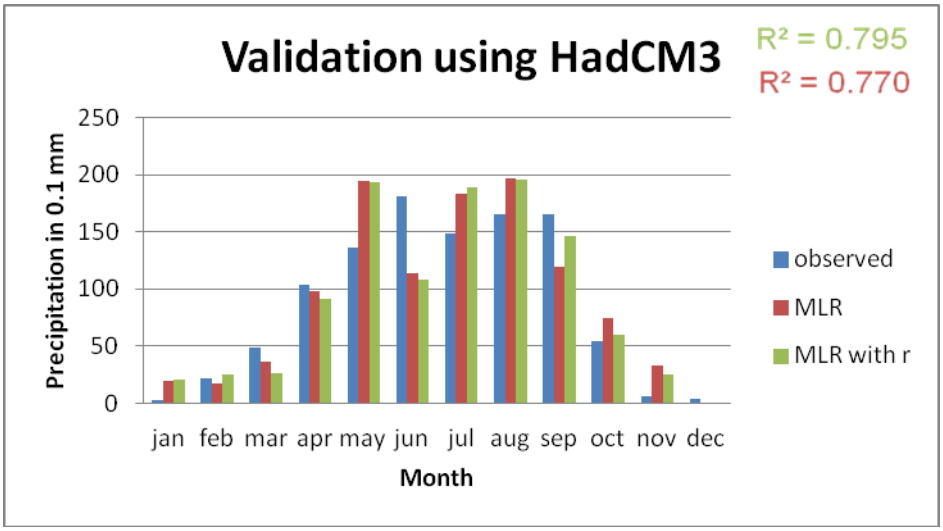

Figure 3. 6 *Validation for Silchar using 6 LSAVs*

2. Calibration-validation done using 4 LSAVs (hur200, hur500, ta200 and ta500)

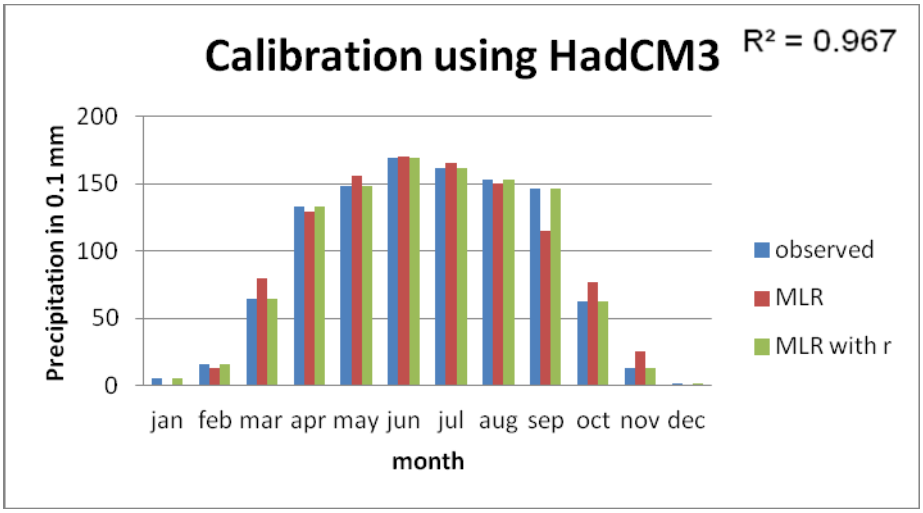

Figure 3. 7 *Calibration for Silchar using 4 LSAVs*

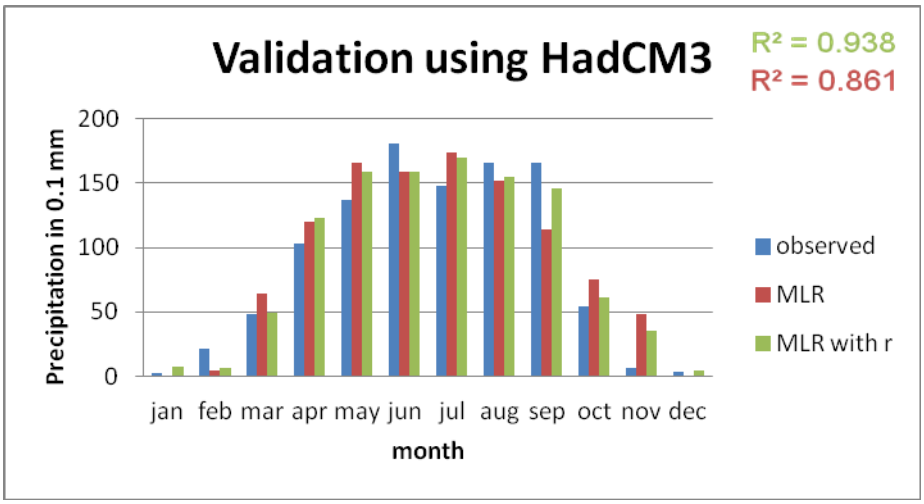

Figure 3. 8 *Validation for Silchar using 4 LSAVs*

- Analysis done for monsoon data:
    1. Calibration-validation done using 3 LSAVs (ta500, ua200 and ua500)

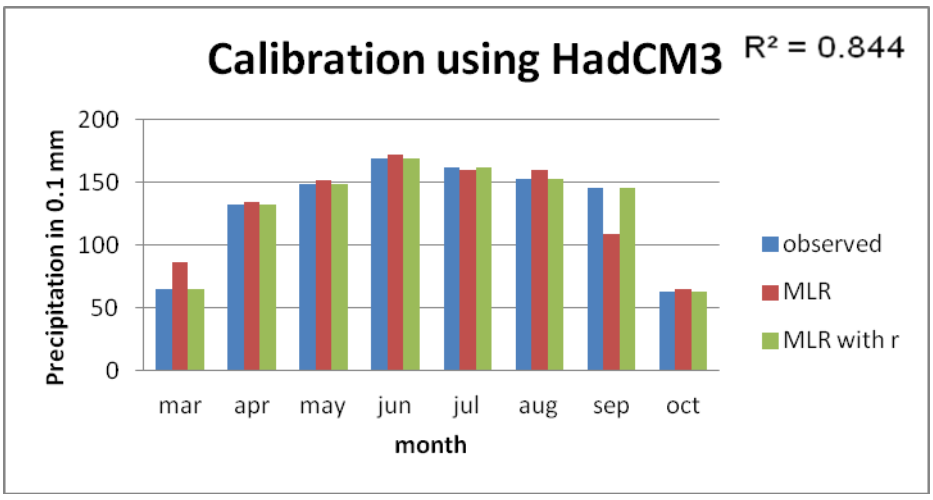

Figure 3. 9 *Calibration for Silchar using 3 LSAVs (for monsoon)*

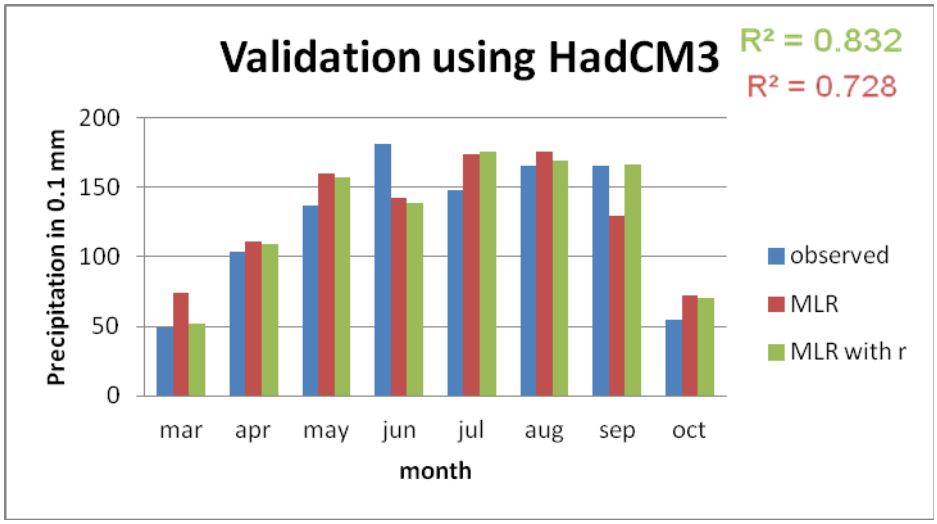

Figure 3. 10 *Validation for Silchar using 3 LSAVs (for monsoon)*

2. Calibration-validation done using 1 LSAVs (ta500)

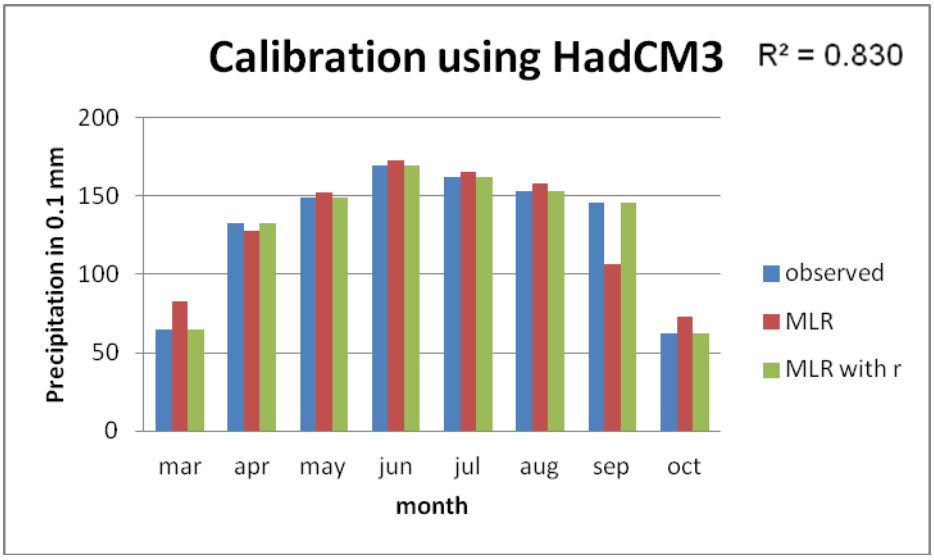

Figure 3. 11 *Calibration for Silchar using 1 LSAV (for monsoon)*

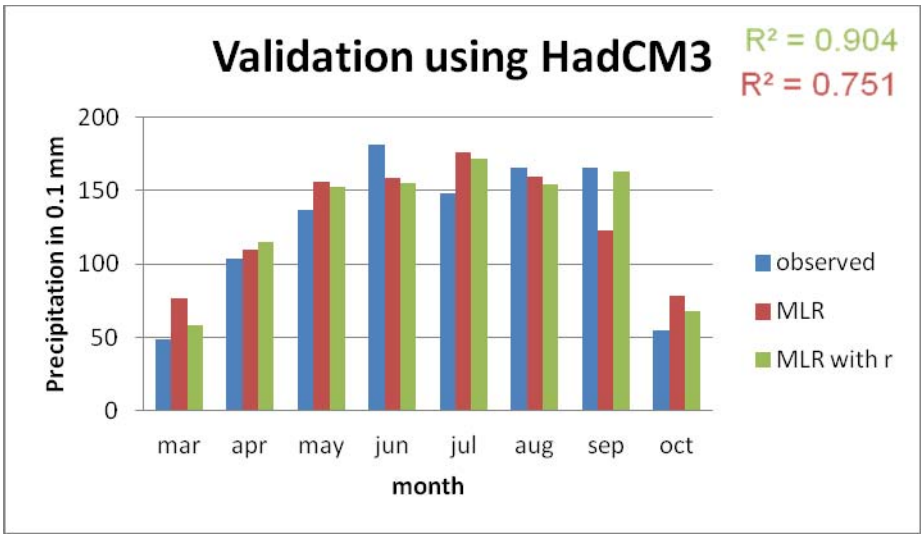

Figure 3. 12 *Validation for Silchar using 1 LSAV (for monsoon)*

Validation curves are shown below in one figure for better understanding.

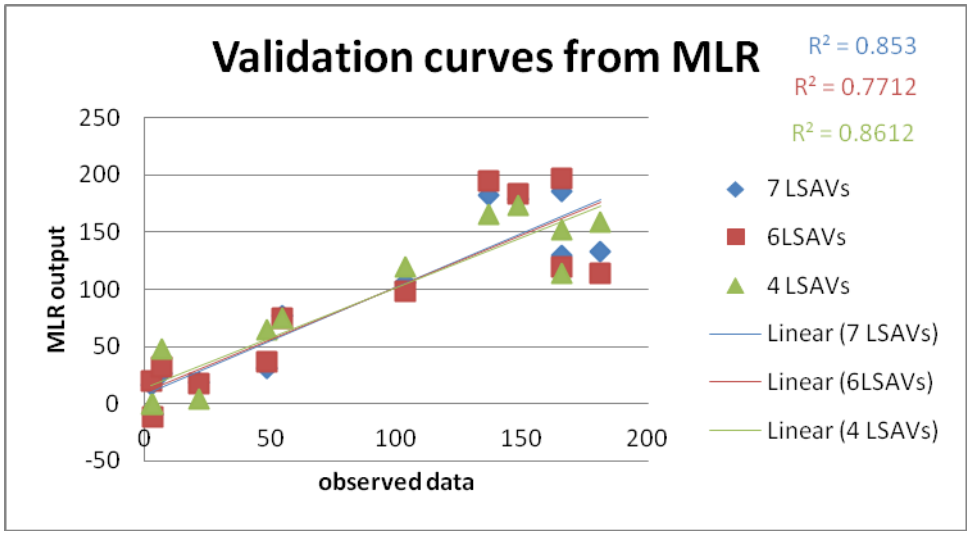

Figure 3. 13 *Validation curves obtained from MLR (for full years data)*

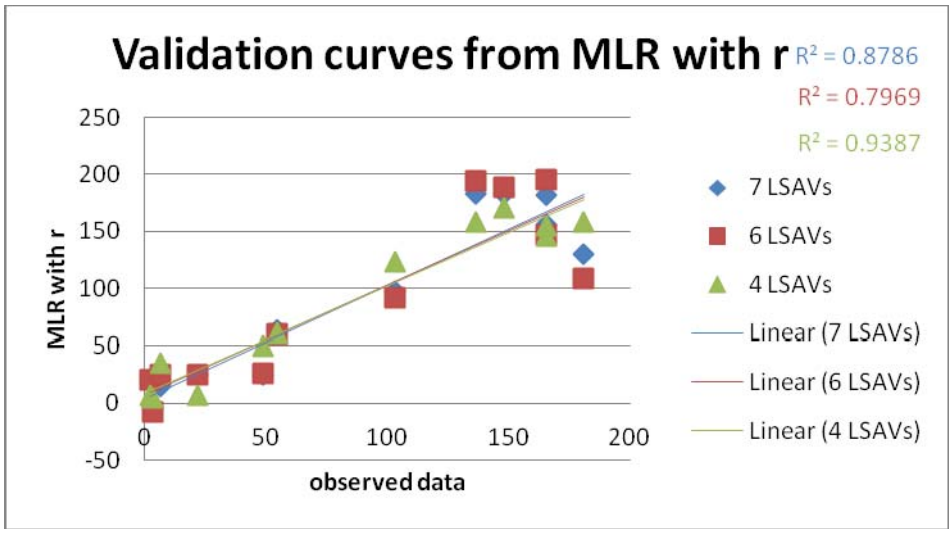

Figure 3. 14 *Validation curves obtained from MLR with r (for full years data)*

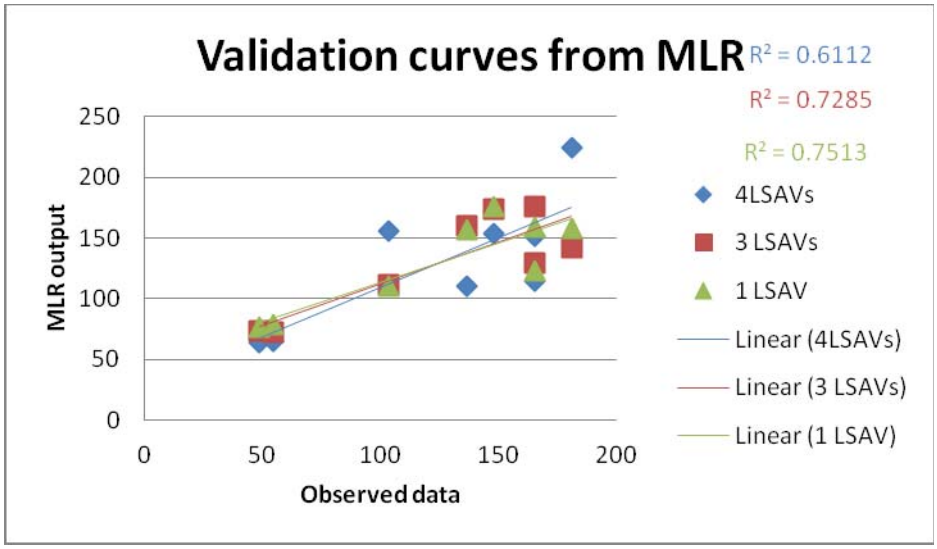

Figure 3. 15 *Validation curves obtained from MLR (for monsoon data)*

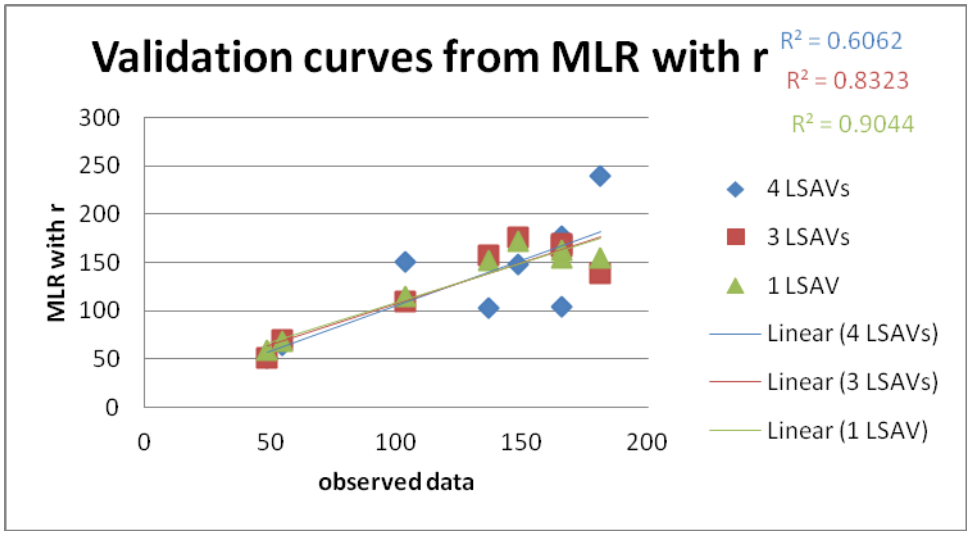

Figure 3. 16 *Validation curves obtained from MLR with r (for monsoon data)*

Based on the calibration-validation results future forecasting has been done for Silchar station. Total time period is divided into three time series i.e. 2012-2040, 2041-2070 and 2071-2099. Depending upon availability of LSAV data, suitable models, developed from calibration-validation, have been used for future forecasting. The output data are plotted in the graphs below:

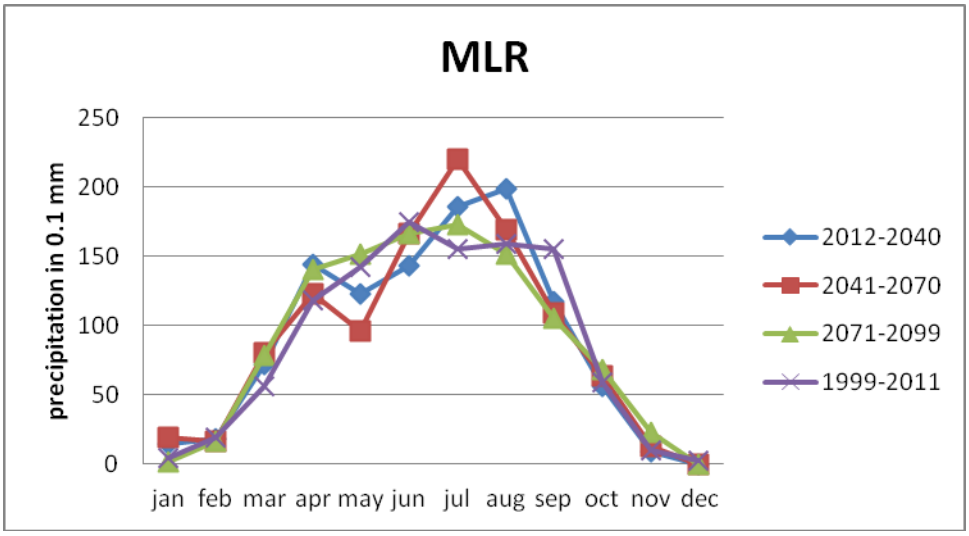

Figure 3. 17 *Precipitation for Silchar station*

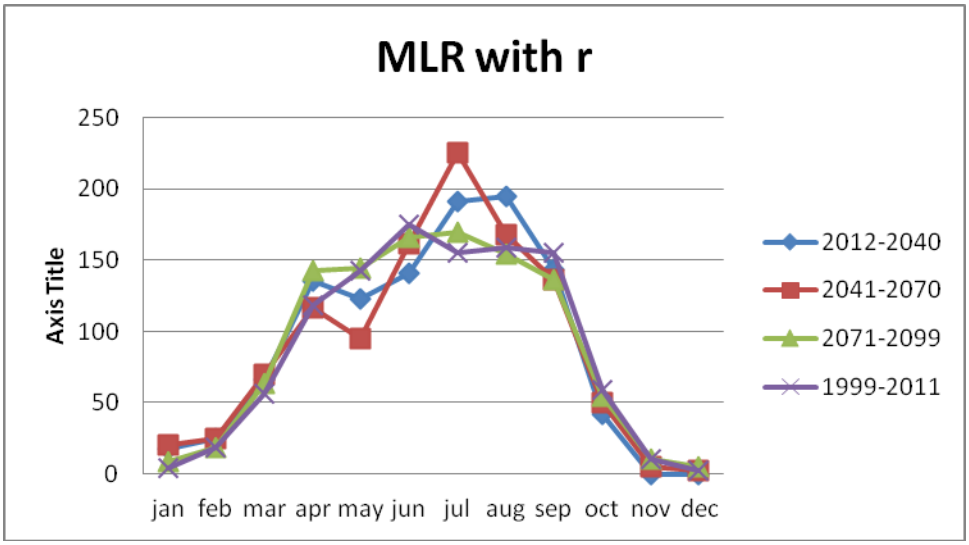

Figure 3. 18 *Precipitation for Silchar station*

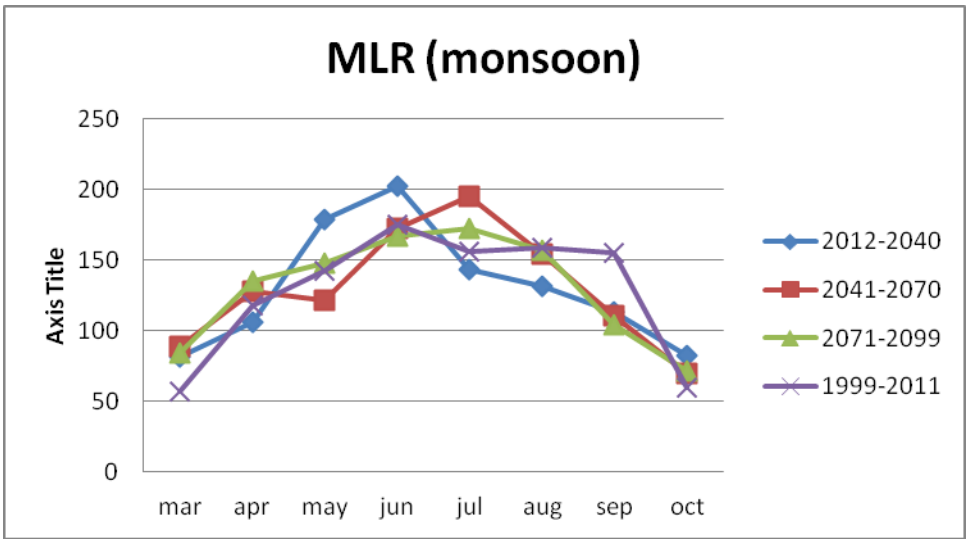

Figure 3. 19 *Precipitation for Silchar station in monsoon*

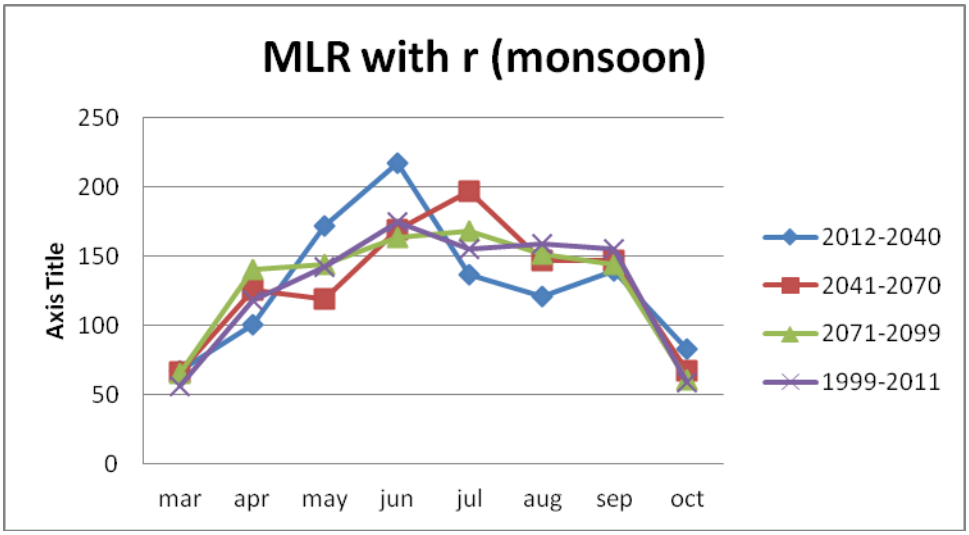

Figure 3. 20 *Precipitation for Silchar station in monsoon*

The peak value and total annual precipitation (as well as monsoon precipitation where monsoon data are used) for each time series are calculated and tabulated below:

Table 2. 1 Annual peak and total annual precipitation (from MLR)

		MLR			
		1999-2011	**2012-2040**	**2041-2070**	**2071-2099**
maximum value		174.7536938	198.7775606	220.0520334	173.2096936
%age increase			13.74727264	25.92124871	-0.883529355
total ppt		1056.149391	1082.246194	1077.047282	1075.569258
%age increase			2.47093863	1.978687013	1.838742392

Table 2. 2 Annual peak and total annual precipitation (from MLR with r)

		MLR with r			
		1999-2011	**2012-2040**	**2041-2070**	**2071-2099**
maximum value		174.753694	195.159485	225.478676	169.39138
%age increase			11.6768869	29.0265579	-3.06849808
total ppt		1056.14939	1079.86343	1075.45662	1075.45662
%age increase			2.24533005	1.82807743	1.82807743

Table 2. 3 Monsoonal peak and total monsoonal precipitation (from MLR)

		MLR (monsoon)			
		1999-2011	**2012-2040**	**2041-2070**	**2071-2099**
maximum value		174.7536938	202.1613652	194.9772947	172.5367131
%age increase			15.68360063	11.57263139	-1.268631685
total ppt		1020.534337	1038.674952	1038.674952	1038.674952
%age increase			1.777560493	1.777560493	1.777560493

Table 2. 4 Monsoonal peak and total monsoonal precipitation (from MLR with r)

		MLR with r (monsoon)			
		1999-2011	**2012-2040**	**2041-2070**	**2071-2099**
maximum value		174.753694	217.519013	196.648572	168.506864
%age increase			24.4717684	12.5289933	-3.57464799
total ppt		1020.53434	1038.67495	1038.67495	1038.67495
%age increase			1.77756049	1.77756049	1.77756049

From the above analysis, it is found that, peak value of the precipitation is increasing at the beginning i.e. during 2012-2040 and 2041-2070 and then it is showing more or less similar results to the observed precipitation during 2071-2099. When annual data series was considered, it is found that peak of the time series shifts from June to August during the time series 2012-2040 and then it shifts back to July during the time series 2041-2070 and 2071-2099. When monsoon data series was considered, peak remains in June during 2012-2040 and then it shifts to July during 2041-2070 and 2071-2099.

The average increase in total precipitation is found to be 2.1% from MLR analysis whereas from MLR analysis with residual r, it is found to be 1.97%. Average increase in monsoonal precipitation is found to be 1.78% from both the analyses.

Similarly, average value obtained from all the models for each of the time series are shown in the table below:

Table 2. 5 Average value obtained from all the models

			2012-2040	2041-2070	2071-2099
avg peak ppt increase (in %)			16.39488216	19.76235784	-2.198826777
avg total ppt increase (in %)			2.067847417	1.840471358	1.805485203

Computed results, based on the average value of all the model outputs, revealed that increase in monthly precipitation during monsoon period is in the order of 20%. However, maximum increase in the value of total yearly precipitation is in the order of 2%, which is not that much significant.

4. CONCLUSION

In the present study, an attempt is made to delineate the North-eastern region of India into some homogeneous clusters based on the Fuzzy Clustering concept and to compare the resulting clusters obtained by using conventional methods and non-conventional methods. For making the clusters, 10 IMD (Indian Meteorological Department) stations, situated in various regions of the North-east, have been selected. On the Basis of IMD data available for those stations, homogeneous clustering has been done. Since the GCM data are available only at the grid points, hence for a particular IMD station, firstly, data of the nearest grid point was taken for the analysis and thereafter interpolated GCM data were calculated for those stations and analyses were done. Clustering has been done considering gridded rainfall data (collected from IMD) also within which all the 10 IMD stations come.

From the results of the FCM it was being noticed that Passighat, North-Lakhimpur, Mohanbari and Tezpur are always coming under the same cluster. Hence it can be concluded that these four stations will always come under the same cluster. Similarly, Shillong, Silchar, Imphal and Cherrapunjee are also coming under the same cluster for most of the analyses. Guwahati is showing similarily with both the clusters. Dhubri, is showing different results; hence clear statement cannot be given. Therefore two clearly visible clusters can be determined from the study, one in the Brahmaputra valley region and the other in Barak valley region.

Presently studies are ongoing on prediction of future rainfall pattern of the Barak Valley region. Four stations have been selected viz. Shillong, Silchar, Imphal and Cherrapunjee for the analysis, which are found to be situated in or near the Barak Valley region and are coming under the same cluster from the FCM analyses. Calibration and validation of the GCM data (HadCM3 with A2 scenario) with relation to precipitation data is over. The future prediction part is ongoing for the stations. Calibration and validation as well as future prediction of rainfall pattern have been done for Silchar. Calibration and validation have been done for different combination of GCM parameters (LSAV data) to find out the best combination of parameters. Based on the calibration-validation results future forecasting has been done for Silchar station. Depending upon availability of LSAV data, suitable models, developed from calibration-validation, have been used for future forecasting.

From the above analysis, it is found that, peak value of the precipitation is increasing at the beginning i.e. during 2012-2040 and 2041-2070 and then it is showing more or less similar results to the observed precipitation during 2071-2099. When annual data series was considered, it is found that peak of the time series shifts from June to August during the time series 2012-2040 and then it shifts back to July during the time series 2041-2070 and 2071-2099. When monsoon data series was considered, peak remains in June during 2012-2040 and then it shifts to July during 2041-2070 and 2071-2099.

The average increase in total precipitation is found to be 2.1% from MLR analysis whereas from MLR analysis with residual r, it is found to be 1.97%. Average increase in monsoonal precipitation is found to be 1.78% from both the analyses.

Computed results, based on the average value of all the model outputs, revealed that increase in monthly precipitation during monsoon period is in the order of 20%. However, maximum increase in the value of total yearly precipitation is in the order of 2%, which is not that much significant.

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