Importance of Regional Rainfall Data in Homogeneous Clustering of Data Sparse Areas: A Study in the Upper Brahmaputra Valley Region

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1 Importance of Regional Rainfall Data in Homogeneous Clustering of Data

2 Sparse Areas: A Study in the Upper Brahmaputra Valley Region

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10 Abstract

11 Delineation of homogeneous regions has found its way into many hydrological applications as
12 it helps in addressing the challenges in understanding the behavior of rainfall distribution and
13 its variability at a local scale. In the present study, rainfall data recorded by 83 tea gardens in
14 the upper Brahmaputra valley region of Assam have been used to identify homogeneous
15 rainfall regions by using fuzzy clustering analysis. Further, seven different cluster validity
16 indices (CVs) were utilized to find out the optimum clustering in the fuzzy c-means (FCM)
17 algorithm. The clusters thus formed were assessed for statistical homogeneity by performing
18 homogeneity tests based on L-moment. Three different combinations of feature vectors were
19 employed in FCM algorithm and the outputs were compared for attaining best solutions to
20 regionalization. The results were further compared with previous regionalization studies. The
21 analysis and comparison conclude that if regionalization needs to be done at a local scale,
22 further sub-clustering of a larger clustered region to smaller regions may be required. Local
23 rainfall data can be used for the purpose provided a good dataset with large number of station
24 points are available within the region. Along with rainfall data, geographical location

25 parameters (latitude, longitude and elevation) need to be taken into account for getting a
26 definite conclusion.

27

28 **Keywords:**

29 Regionalization, L-moments, Fuzzy clustering, Homogeneity test

30

1. Introduction

Rainfall is one of the most important hydrological parameters that requires to be studied scrupulously, both in spatial and temporal scale. However, challenge comes in understanding the behavior of rainfall distribution pattern when applied on a regional scale. Pattern of rainfall, its frequency and magnitude may drastically vary depending upon the orography (Venkatesh and Jose 2007), large-scale synoptic and convective precipitation types (Karaca et al. 2000, Unal et al. 2012; Baltacı et al. 2015; Efe et al. 2019) of the region. Scarcity of sufficient data at many sites of interest, may further complicate the investigation. To address this issue, the region may be classified into few homogeneous rainfall regions of similar rainfall distribution, also termed as regionalization. The Brahmaputra valley region is situated in the northeastern part of India, that has its own peculiar topography. The variations in the orographic arrangements and altitude differences in the region give rise to irregular and complex rainfall patterns at a local scale, which eventually amplifies the need of regionalization.

Regionalization has found its way into many applications in water resources planning, agricultural planning, drainage design, and estimating magnitude and frequency of extreme events like flood and drought. Literatures indicate that, in the past, political and geographical boundaries are used as a basis of forming homogeneous regions (Thomas and Benson 1970; NERC 1975; Beable and McKercher 1982; Chew et al. 1987). However, use of political and geographical boundaries is found to be not very convincing while forming hydrologically homogeneous regions (Bonell and Sumner 1992; Burn 1997; Rao and Srinivas 2006b; Satyanarayana and Srinivas 2011; Dikbas et al. 2012). A considerable amount of researches have been carried out in the recent years to identify homogeneous rainfall regions with various methods other than geographical divisions (Bedi and Bindra 1980; Barring 1987; Sumner and Bonell 1988; Kulkarni et al. 1992; Gadgil et al. 1993; Burn 1997; Adelekan 1998). Regionalization with the use of principal component analysis (PCA) was found to be of use

(Singh and Singh 1996; Wotling et al. 2000). When subjectivity involved with PCA came into notice, the concept of cluster analysis started getting attention (Bonell and Sumner 1992; Guttman 1993; Venkatesh and Jose 2007; Machiwal et al. 2019). Cluster analysis refers to a varied group of statistical procedures used to classify a multivariate dataset into some clusters or groups (Rao and Srinivas 2006a, b; Srinivas et al. 2008; Dikbas et al. 2012). Studies have also been done where PCA was further associated with various cluster analysis techniques for homogeneous clustering (Dinpashoh et al. 2004; Satyanarayana and Srinivas 2011; Darand and Daneshvar 2014; Machiwal et al. 2019). Ward's hierarchical cluster analysis is one of the widely used methods, that is found to be suitable for homogeneous regionalization (Unal et al. 2003; Baltacı et al. 2017). Another vastly applied method is the k-means clustering (Rao and Srinivas 2006a; Pelczer et al. 2007; Agarwal et al. 2016). K-means clustering splits a region into hard clusters, i.e. with a degree of membership 1 or 0. This means that a site can at most belong to only one cluster. However, this may not be valid in real world cases. To address this matter, the concept of fuzzy clustering was introduced to regionalization, which allows a site to fit into several clusters concurrently with a certain membership value. The fuzzy membership value of a site signifies the extent to which it fits into a particular group of sites (Rao and Srinivas 2006b). A lot of studies have successfully applied fuzzy clustering technique for clustering of hydrologically homogeneous regions in the recent years (Hall and Minns 1999; Owen et al. 2006; Plain et al. 2007; Sadri and Burn 2011; Satyanarayana and Srinivas 2011; Chen et al. 2011; Dikbas et al. 2012; Mok et al. 2012; Chavoshi et al. 2013; Asong et al. 2015; Bharath and Srinivas 2015; Goyal and Sharma 2016; Irwin et al. 2017; Wang et al. 2017). On the basis of critical reviews of earlier studies on regionalization, the aim of the current study is defined as to identify homogeneous rainfall regions in upper Brahmaputra Valley region of northeast India by using fuzzy clustering analysis. To achieve the best possible partition from the fuzzy c-means (FCM) algorithm, seven different cluster validity indices (CVs) were used.

Three different combinations of feature vectors were employed in FCM algorithm and the outputs were compared for attaining best solutions to regionalization. The homogeneous rainfall regions (fuzzy clusters) thus formed by the use of FCM algorithm and validated with CVs were then assessed for statistical homogeneity by performing homogeneity tests using L-moment approach (Hosking and Wallis 1997). The results were further compared with some previous regionalization studies and finally concluding remarks were presented.

2. Methodology

In the subsections below, the fuzzy c-means (FCM) algorithm for delineation of homogeneous clusters is described at first, which is followed by a brief description of the CVs, homogeneity test methods and process of adjustment of heterogeneous clusters. The methodology used is shown in Fig. 1, by means of a flow chart.

2.1 Fuzzy C-Means clustering (FCM)

The FCM approach is basically optimization of fuzzy c-means objective function. It was initially developed by Dunn (1973) and afterwards modified by Bezdek et al. (1984). The fuzzy c-means function to be minimized, is expressed as:

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

$\mathbf{U} = [\mu_{ik}] \in M_{fc}$ is the fuzzy partition matrix of $\mathbf{Z}$; $\mathbf{V} = [\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_c]$, $\mathbf{v}_i \in R^n$ is vector of cluster centers to be determined; $d^2(\mathbf{z}_k, \mathbf{v}_i)A = D_{ikA}^2 = \|\mathbf{z}_k - \mathbf{v}_i\|^2 A = (\mathbf{z}_k - \mathbf{v}_i)^T A (\mathbf{z}_k - \mathbf{v}_i)$ is a squared distance norm; and m is the fuzziness parameter or fuzzifier, where $m = [1, \infty)$. Usually, its value falls between 1 and 2.5 (Pal and Bezdek 1995).

2.1.1 FCM algorithm for delineation of homogeneous rainfall regions

(i) The initial fuzzy partition matrix $\mathbf{U}$ is set.

(ii) Then, initial membership values μ_{ki}^{init} of x_i that belongs to cluster k , is adjusted by using equation:

$$\mu_{ki} = \frac{\mu_{ki}^{init}}{\sum_{j=1}^c \mu_{ji}^{init}}, \text{ for } 1 \leq k \leq c, 1 \leq i \leq N \quad (2)$$

(iii) Fuzzy cluster centroid $\mathbf{v}_k$ is then calculated as

$$\mathbf{v}_k = \frac{\sum_{i=1}^N (\mu_{ki})^m \mathbf{x}_i}{\sum_{i=1}^N (\mu_{ki})^m}, \text{ for } 1 \leq k \leq c \quad (3)$$

(iv) Fuzzy membership value μ_{ki} is updated as

$$\mu_{ki} = \frac{\left(\frac{1}{d^2(\mathbf{x}_i, \mathbf{v}_k)}\right)^{\frac{1}{m-1}}}{\sum_{k=1}^c \left(\frac{1}{d^2(\mathbf{x}_i, \mathbf{v}_k)}\right)^{\frac{1}{m-1}}}, \text{ for } 1 \leq k \leq c, 1 \leq i \leq N \quad (4)$$

(v) The objective function is then calculated as

$$J(\mathbf{X}; \mathbf{U}, \mathbf{V}) = \sum_{k=1}^c \sum_{i=1}^N (\mu_{ki})^m d^2(\mathbf{x}_i, \mathbf{v}_k) \quad (5)$$

The above steps from (iii) to (v) are repeated till the difference in the objective function for two consecutive iterations becomes adequately small.

2.2 Cluster validity indices (CVs)

FCM algorithm divides the data into well separated and compact clusters, provided the optimal values of c and m . Hence deciding the optimal values of these parameters is very crucial.

Bezdek (1981) addressed this matter by stating the concept of validity indices. These indices

essentially measure the goodness of the partitioned clusters. In hydrological studies several indices are used (Hall and Minns 1999; Srinivas et al. 2008). In case of FCM algorithm, the following CVs are found to perform well:

1. Fuzzy partition coefficient (V_{PC})

$$V_{PC}(U) = \frac{1}{N} \sum_{k=1}^c \sum_{i=1}^N (\mu_{ki})^2 \quad (6)$$

2. Fuzzy partition entropy (V_{PE})

$$V_{PE}(U) = -\frac{1}{N} [\sum_{k=1}^c \sum_{i=1}^N \mu_{ki} \log(\mu_{ki})] \quad (7)$$

3. Fuzziness performance index (V_{FPI})

$$V_{FPI}(U) = 1 - \frac{c \times V_{PC}(U) - 1}{c - 1} \quad (8)$$

4. Normalized classification entropy (V_{NCE})

$$V_{NCE}(U) = \frac{V_{PE}(U)}{\log(c)} \quad (9)$$

Bezdek (1974a, b) formulated V_{PC} and V_{PE} , whereas V_{FPI} and V_{NCE} were proposed by Roubens (1982). The range for V_{PC} is $[1/c, 1]$; $V_{PC} = 1/c$ indicates equal sharing of clusters i.e. equal membership values of a data in all clusters (i.e. $\mu_{ki} = 1/c \forall i, k$) and $V_{PC} = 1$ indicates no sharing of membership among the clusters. Similarly, the range of V_{PE} is $[0, \log(c)]$. $V_{PE} = 0$ implies no sharing of membership among clusters and $V_{PE} = \log(c)$ implies equal sharing of clusters (i.e. $\mu_{ki} = 1/c \forall i, k$). On the contrary, this range is $[0, 1]$ for V_{FPI} and V_{NCE} ; 0 implies no membership sharing between clusters and 1 implies equal sharing of clusters (i.e. $\mu_{ki} = 1/c \forall i, k$). As such, a maximum value for V_{PC} indicates optimum partition (i.e. minimum value for V_{PE} , V_{FPI} and V_{NCE}), that means least overlap among clusters.

Earlier studies have stated that these four CVs tend to display monotonous increasing or decreasing trend (Rao and Srinivas 2006b, Srinivas et al., 2008). Hence, they are not very effective in obtaining optimum partition to delineate rainfall regions. Xie and Beni (1991) found no direct correlation of V_{PC} and V_{PE} with any property of the data. Furthermore, they are

found to be very sensitive to the fuzzifier value, m (Halkidi et al. 2001). Here, these indices are used mainly to validate their performances in detecting optimum cluster number. To eliminate this drawback the other validity indices are introduced, as explained below:

5. Extended Xie and beni index (V_{XB})

$$V_{XB,m}(U, V: X) = \frac{\sum_{k=1}^c \sum_{i=1}^N (\mu_{ki})^m \|x_i - v_k\|^2}{N \min_{l, l \neq k} \|v_l - v_k\|^2} \quad (10)$$

Xie and Beni (1991) proposed the cluster validity index $V_{XB,m}$. It quantifies the ratio of compactness within a fuzzy cluster to separation of clusters. Optimal partition of clusters should exhibit minimum value of $V_{XB,m}$.

6. Fukuyama and Sugeno index (V_{FS})

$$V_{FS}(U, V: X) = \sum_{i=1}^N \sum_{k=1}^c (\mu_{ki})^m \|x_i - v_k\|^2 A - \sum_{i=1}^N \sum_{k=1}^c (\mu_{ki})^m \|v_i - \bar{v}\|^2 A \quad (11)$$

Proposed by Fukuyama and Sugeno (1989), optimum partition is indicated by a minimum value of V_{FS} .

7. Kwon index (V_K)

$$V_K(U, V: X) = \frac{\sum_{k=1}^c \sum_{i=1}^N (\mu_{ki})^m \|x_i - v_k\|^2 + \frac{1}{c} \sum_{k=1}^c \|v_i - \bar{v}\|^2}{\min_{i \neq k} \|x_i - v_k\|^2} \quad (12)$$

The Extended Xie and beni index (V_{XB}) exhibits monotonous decreasing tendency as $c \rightarrow N$. To address this problem Kwon (1998) proposed another index V_K that has an ad-hoc punishing function in numerator.

To determine the optimal values of c and m , a range of values for the two parameters are selected and subsequent partitioning results show different sets of clusters, along with their validity indices. To decide the optimal set of values for c and m among those sets, first the optimum selection criteria of each of the validity indices are examined. Then, the sites having greater membership value in the clusters are identified, based on a threshold value of fuzzy membership (T_i). Thus, a fuzzy cluster is made by allocating those sites to the cluster, whose membership values are found to be higher than or equal to the threshold fuzzy membership

value (T_i). The selection of this threshold value is subjective (Satyanarayana and Srinivas 2011). The most reasonable explanation would be to allocate the site to that group where its membership value is the highest. Yet, uncertainty arises when a site has low membership value in all the clusters or has equal memberships. To address this issue homogeneity test is done which is followed by adjustment of heterogeneous clusters. The methodologies for both of these are explained in the following subsection.

2.3 Homogeneity test and adjustment of heterogeneous clusters

The fuzzy clusters thus formed by using FCM algorithm and validated with CVs are then required to be assessed for statistical homogeneity by performing homogeneity tests. Heterogeneity measure (L-moment based) proposed by Hosking and Wallis performs better when skewness is low (average L-skew < 0.23) for a sample set of data, whilst for higher skewness bootstrap Anderson-Darling test is recommended (Viglione et al. 2007). Previous studies have shown that Hosking and Wallis's homogeneity test is appropriate for delineation of homogeneous rainfall regions (Satyanarayana and Srinivas 2011), hence is considered in this study.

2.3.1 L-moment of data samples

L-moment is a method of explaining the probability distribution shape and evaluating the distribution parameters, especially for small sample sizes of environmental data, since it is unbiased and has a nearly normal distribution (Hosking 1990). Like usual moments, L-moments too determines the location, dispersion, peakedness, skewness and any other feature of shape of probability distribution. However, L-moments are derived from linear combination of data (Hosking 1990). These statistics are established by modifying "probability weighted moments" (Greenwood et al. 1979), which explains L-moments by means of linear combinations. Sample probability weighted moments as explained by Greenwood et al. (1979) is given below:

$$b_0 = n^{-1} \sum_{j=1}^n x_j \quad (13)$$

$$b_r = n^{-1} \sum_{j=r+1}^n \frac{(j-1)(j-2)\dots(j-r)}{(n-1)(n-2)\dots(n-r)} x_j \quad (14)$$

The first few L-moments and L-moment ratios are defined as:

$$\text{Location, mean } (l_1): l_1 = b_0 \quad (15)$$

$$\text{Scale, L-Cv } (t_2): t_2 = \frac{l_2}{l_1}, \text{ where } l_2 = 2b_1 - b_0 \quad (16)$$

$$\text{L-Skewness } (t_3): t_3 = \frac{l_3}{l_2}, \text{ where } l_3 = 6b_2 - 6b_1 + b_0 \quad (17)$$

$$\text{L-Kurtosis } (t_4): t_4 = \frac{l_4}{l_2}, \text{ where } l_4 = 20b_3 - 30b_2 + 12b_1 - b_0 \quad (18)$$

2.3.2 Discordancy measures, heterogeneity measures and adjustment of heterogeneous clusters

1. Discordancy measures

Discordancy measure (D_i) detects those sites which are unacceptably discordant with the designated cluster (Hosking and Wallis 1993). This discordancy value for i^{th} site (Hosking and Wallis 1995) is given as,

$$D_i = \frac{N}{3(N-1)} (u_i - \bar{u})^T S^{-1} (u_i - \bar{u}) \quad (19)$$

Here, S is the sample covariance matrix expressed as:

$$S = (N - 1)^{-1} \sum_{i=1}^N (u_i - \bar{u})(u_i - \bar{u})^T \quad (20)$$

where $u_i = [t^{(i)} t_3^{(i)} t_4^{(i)}]^T$ means a vector comprising of the values of t , t_3 and t_4 for i^{th} site.

$$\text{Hence, } \bar{u} = N^{-1} \sum_{i=1}^N u_i \quad (21)$$

Large values of D_i indicate probable errors in the site data. Hosking and Wallis (1993) explained that a particular site is not considered to be homogeneous with the region if D_i is more than a certain critical value, than that. $D_i \geq 3$ is suggested as the criterion for affirming a site to be discordant, for regions with 15 or more sites. However, Hosking and Wallis (1993,

1995) have advised to scrutinize the dataset for the largest D_i values, irrespective of their magnitude.

2. Heterogeneity measures

Heterogeneity measures give the degree of heterogeneity existing within the region. It is estimated based on the extent of actual variability in L-moment ratios in relation to the expected variability in a homogeneous region. The heterogeneity measures to be estimated are H_1 , H_2 and H_3 . These measures are defined based on L-Cv, L-Skewness and L-Kurtosis. These three heterogeneity measures are given below.

i. Heterogeneity measures based on L-Cv

$$H_1 = \frac{V - \mu_V}{\sigma_V} \quad (22)$$

ii. Heterogeneity measures based on L-Cv and L-Skewness

$$H_2 = \frac{V_2 - \mu_{V_2}}{\sigma_{V_2}} \quad (23)$$

iii. Heterogeneity measures based on L-Cv and L-Kurtosis

$$H_3 = \frac{V_3 - \mu_{V_3}}{\sigma_{V_3}} \quad (24)$$

Here V is the weighted standard deviation or dispersion of the sample coefficients of L-variation (L-Cv); V_2 and V_3 denote weighted average distance from the site to group weighted mean in a 2-D space of L-Cv/L-Skewness and L-Skewness/L-Kurtosis, respectively; μ_V , μ_{V_2} and μ_{V_3} are the mean of V , V_2 and V_3 values, respectively, calculated from a large number of simulations (N_{sim}); σ_V , σ_{V_2} and σ_{V_3} are standard deviations of V , V_2 and V_3 , respectively, calculated from a number of simulations. In this study N_{sim} is taken as 1000, simulated from kappa distribution and fitted using regional average L-moment ratios.

$$V = \left\{ \frac{\sum_{i=1}^N n_i (t^{(i)} - t^{(R)})^2}{\sum_{i=1}^N n_i} \right\}^{1/2} \quad (25)$$

$$V_2 = \frac{\sum_{i=1}^N n_i \{ (t^{(i)} - t^{(R)})^2 + (t_3^{(i)} - t_3^{(R)})^2 \}}{\sum_{i=1}^N n_i}^{1/2} \quad (26)$$

$$V_3 = \frac{\sum_{i=1}^N n_i \{ (t_3^{(i)} - t_3^{(R)})^2 + (t_4^{(i)} - t_4^{(R)})^2 \}^{1/2}}{\sum_{i=1}^N n_i} \quad (27)$$

Here N indicates number of sites/stations in the clustered region; n_i indicates record length of site i ; $t^{(i)}$, $t_3^{(i)}$ and $t_4^{(i)}$ indicate sample L-moment ratios of site i ; $t^{(R)}$, $t_3^{(R)}$ and $t_4^{(R)}$ indicate regional average L-moment ratios (L-Cv, L-Skewness and L-Kurtosis respectively). If $H < 1$ for a region, it is described as ‘acceptably homogeneous’, $1 \leq H < 2$ implies ‘possibly heterogeneous’, and $H \geq 2$ implies ‘definitely heterogeneous’. For further details on heterogeneity measures, Hosking and Wallis (1997) can be referred.

3. Adjustment of heterogeneous clusters

Clusters formed by the use of clustering algorithms does not always exhibit statistical homogeneity. Even after performing homogeneity test, there is a need to adjust the possibly or definitely heterogeneous clusters to come to a definite conclusion. Furthermore, it is assumed that there is not any cross-correlation among the data. Nevertheless, in actual scenarios there is gradual variation of rainfall across space, which implies that there exists cross-correlation among geographically contiguous sites (Satyanarayana and Srinivas 2011). So further adjustments are essential to form homogeneous regions. Studies suggest that, to decrease heterogeneity measures values, the discordant sites of one region can be either removed or shifted to some other region, after confirming that the site has not exhibited high fuzzy membership value in that cluster and discordancy of that site is not because of sampling variability (Rao and Srinivas 2006b; Satyanarayana and Srinivas 2011). The heterogeneous regions can also be broken into two or more regions, and if required two or more small regions can be merged together.

3. Results and discussion

3.1 Geographic and climate properties of the study area

Fig. 2 shows the study area, that is situated in the upstream part of Brahmaputra River in the state of Assam, covering the central Brahmaputra valley and the eastern Brahmaputra valley

region. It covers most of the upper and middle Assam districts. This region of the valley is surrounded by Eastern Himalayas towards the north, the Patkai Bum in the east, the Naga Hills in the southern side and Meghalaya plateau in the far south. The Brahmaputra valley has a great geographical as well as political significance. It is surrounded by Bhutan in the north, Arunachal Pradesh in the north and east, Nagaland and Karbi-Anglong hills in the south. The study area lies between 25.921° N and 27.619° N latitudes and 91.896° E and 95.768° E longitudes. Mean annual precipitation varies from 859 mm to 3412 mm and the elevation varies from 67 m to 427 m. Seasonal precipitation is found to be the highest in June-July-August (JJA) (406 mm – 1880 mm) and the lowest in December-January-February (DJF) (9 mm – 222 mm). The Brahmaputra valley has a subtropical climate which is influenced by northeast and southwest monsoon. The Meghalaya plateau, the Himalayas and the surrounding hills of Arunachal Pradesh, Manipur, Nagaland and Mizoram influences the climate. The monsoon winds coming from Bay of Bengal move towards the northeast and hits these mountains causing heavy precipitation on the valley.

3.2 Data used

A total of 83 raingauge stations with observed periods of varying number of years (from 5 years daily data to as long as 84 years and up to year 2016) were selected from various tea gardens of Assam. The location (longitude and latitude), seasonal precipitation (in mm), mean annual precipitation (in mm) and elevation (in m) of the raingauge stations are shown in the Table 1. Elevation of each station was determined from Shuttle Radar Topography Mission's digital elevation model data (DEM) version 2.1 (SRTM-1) of 30m resolution. The DEM files come in tiles, that come as zipped SRTMHGT files at 1-arcsecond resolution (3601x3601 pixels) in a latitude/longitude projection (EPSG:4326).

3.3 Cluster analysis with Fuzzy C-Means (FCM) algorithm

295 Previous studies suggest that, the attributes to be considered in clustering of homogeneous
296 rainfall regions may include large scale atmospheric variables (LSAVs) of Global Climate
297 Models (GCMs) or else principal components (PCs) of GCMs, location parameters (latitude,
298 longitude, elevation etc.), and seasonality measures (maximum, minimum, standard deviation
299 of rainfall etc.). In the present study, total annual rainfall, total monthly rainfall, standard
300 deviation of total annual rainfall and total monthly rainfall and all three location parameters i.e.
301 latitude, longitude and elevation of all the 83 raingauge stations were included as attributes.
302 Here three different combinations of feature vectors were used to form, consequently, three
303 different sets of input data matrices (for FCM algorithm). This was done in order to observe
304 the effect of a particular attribute in the cluster formation. The three combinations were as
305 follows:

306 Case 1: Input data matrix with total monthly rainfall as attributes,

307 Case 2: Input data matrix with standard deviation of total monthly rainfall as attributes,

308 Case 3: Input data matrix with latitude, longitude, elevation, total annual rainfall and standard
309 deviation of total annual rainfall as attributes.

310 To acquire reliable results from clustering, most crucial point is to assume the cluster number
311 (c), since the number of regions is unknown beforehand. The best way to do that is to choose
312 a range of values for c , and then to find out the most appropriate one. To achieve that, the
313 cluster number c is changed from 2 to k , k being a quantity lesser than total number of sites, N .
314 The lower bound of c is taken as 2, because the dataset is apparently clustered into more than
315 one group. The interesting point here is to define the upper bound of c , i.e. the parameter k .
316 Varying the k value impacts the reliability of cluster number. From research, it was noticed that
317 increasing the k value generates more consistent cluster number division (Mok et al 2012).
318 Many works can be found in literature on identification of optimal cluster numbers. In most of
319 the cases, $k \leq N^{1/2}$ is suggested as the upper bound (Xie and Beni 1991; Pal and Bezdek 1995;

320 Mok et al 2012). In a similar way, optimum value of fuzzifier (m) also needs to be found out.
 321 Pal and Bezdek (1995) presented that FCM algorithm works well when m varies from 1–2.5.
 322 It is hence suggested (Satyanarayana and Srinivas 2011) to attain a number of sets of clustered
 323 regions by selecting a range of values for c and m , and then identify the final clustered regions
 324 based on the optimal values of c and m and by means of CVs.
 325 In this study, FCM algorithm was executed for each case with cluster number varying from
 326 $c_{min} = 2$ to c_{max} or $(k) = (83)^{1/2} \approx 10$, with increment 1. The fuzzifier value (m) is increased from
 327 1.1 to 3.0, with increment 0.1. Change in the values of objective functions with respect to that
 328 of fuzzifier m were plotted for cluster number varying from 2 to 10, for all the three cases and
 329 are shown in Fig. 3a, 3b and 3c. It is observed that, as the fuzzifier value increases the optimum
 330 value of objective function declines, for a given cluster number. In a similar way, the optimum
 331 value decreases with rise in cluster number, for a given value of fuzzifier. The FCM algorithm
 332 was found to perform better for m in the range of 1.5–2.5.
 333 Further, the CVs described in section 2.2, were calculated to achieve the optimal value of c and
 334 m , for each case. The values of V_{PC} , V_{PE} , V_{FPI} , V_{NCE} , V_{XB} , V_{FS} , and V_K are tabulated in
 335 supplementary material. Since the FCM algorithm performed better for m in the range of 1.5–
 336 2.5, the CVs for higher value of m are not considered and hence are not shown in the tables. In
 337 all the three cases, it is observed that, V_{PC} decreases monotonously whereas V_{PE} , V_{FPI} and V_{NCE}
 338 show increase monotonously with increase in the fuzzifier value, m , for a given value of cluster
 339 number c . Moreover, they show overall monotonous decreasing (V_{PC}) and increasing (V_{PE} , V_{FPI}
 340 and V_{NCE}) tendency with increase in the cluster number c , hence giving always low value of c
 341 and m as the optimum set of values for homogeneous clustering. This indicates their
 342 ineffectiveness in determining optimum number of homogeneous rainfall regions.
 343 Extended Xie and beni index (V_{XB}) as well as the Kwon index (V_K) were found to be relatively
 344 effective in these cases. They didn't show any monotonous increasing or decreasing tendency

with change in the values of c and m , and were in line with each other. In case of Fukuyama and Sugeno index (V_{FS}), although it didn't have any monotonic tendency, the values were found to be in a conflict to the values of V_{XB} , and V_K in some cases. Taking into account of the similar studies on homogeneous rainfall region identification, found in literature (Rao and Srinivas 2006b; Satyanarayana and Srinivas 2011; Farsadnia et al. 2014; etc.), V_{XB} and V_K were opted for clustering of rainfall regions. Henceforth, the clusters found from these two indices were considered for further analysis. The optimal value of clusters $c=3$ was identified for all the three cases, using these CVs with the corresponding value of $m=1.5$ for all three cases.

3.4 Homogeneity test and adjustment of heterogeneous clusters

The H values of homogeneity test for all the three cases are given in Table 2. Initially, out of the nine clusters (three clusters for each case), four clusters were acceptably homogeneous, four clusters were possibly heterogeneous and one cluster was definitely heterogeneous. Hence, adjustments were done to make the possibly and definitely heterogeneous clusters as homogeneous, by either shifting discordant sites from one cluster to another or by removing those sites if necessary. For case 1, stations Chubwa and Dilli were found to discordant with all the clusters; hence they are removed during adjustment which lead to three acceptably homogeneous clusters with the rest 81 stations. Similarly, station Chubwa was found to be discordant for case 2; hence removed from the clusters and adjustments were done for 82 stations. However, in case 3, no stations were removed. The reason that the two stations did not show any discordancy in case 3 is because the geographic locations of the stations were considered during cluster analysis for case 3. The H values of homogeneity test after adjustment and number of sites in each cluster are shown in Table 2. Final clusters formed after adjustment are shown in Fig. 4a, 4b and 4c.

3.5 Comparison with similar studies done previously

369 Although this is the first and foremost study to divide the Brahmaputra valley region of India
370 into hydrologically homogeneous regions with the use of rainfall data record by the tea gardens
371 by applying fuzzy clustering technique and seven cluster validity indices (CVs), few previous
372 studies can be found on use of various clustering techniques for Indian subcontinent. Hence,
373 comparisons have been made with those closely related studies to validate the performance of
374 the present study. The homogeneous regions developed by Indian Meteorological Department
375 (IMD) displays five large provinces, which are although delineated based on rainfall
376 characteristics but are influenced by contiguity of area and administrative state boundaries.
377 Iyengar and Basak (1994) used principal component analysis (PCA) for regionalization of
378 Indian monsoon rainfall and recommended the PCA approach for further subdivision of the
379 region. Ten homogeneous sequential regions were formed in India from their analysis, in which
380 the stations of upper Brahmaputra valley regions were seemed to form similar kind of clusters
381 as found in the present study, although few stations remained un-clustered. Singh and Singh
382 (1996) have done regionalization of monthly as well as seasonal rainfall for sub-Himalayan
383 areas and Gangetic plains, by using principal component analysis (PCA). They used rainfall
384 data for a period of 114 years (1871-1984) from 90 well distributed stations which resulted into
385 four distinct homogeneous rainfall areas for both monthly and seasonal scales. Srinivasa and
386 Kumar (2007) utilized fuzzy cluster analysis (FCA) to classify 159 meteorological stations in
387 India and concluded that FCA method performs well than the Kohonen Artificial Neural
388 Networks (KANN) method in finding meteorologically homogeneous groups. They utilized
389 location parameters (latitude, longitude and elevation) along with other meteorological
390 parameters for clustering and the results exhibited 14 clusters over Indian region, the North-
391 eastern region being in one cluster. Satyanarayana and Srinivas (2008) have done regional
392 frequency analysis using LSAVs that affects the precipitation in a region instead of observed
393 precipitation data and have used K-means clustering with adjustments and L-statistics for

394 regionalization. 17 homogeneous regions were formed after the analysis, two regions covering
395 the northeastern states. The upper Brahmaputra valley region came under the same
396 homogeneous cluster, hence producing similar results to those of the present study.
397 Satyanarayana and Srinivas (2011) have done regionalization of rainfall data, based on fuzzy
398 clustering method by utilizing GCM data, location parameters and seasonal precipitation data.
399 The stations of upper Brahmaputra valley regions were seemed to form similar kind of clusters
400 as found in the present study. Stations in middle Assam were found to form one cluster while
401 other stations on the upper Assam formed a different cluster. Saikranthi et al. (2013) used
402 correlation analysis for regionalization based on seasonal and annual rainfall data. They used
403 51 years (1951–2001) daily rainfall data collected for more than 1000 rain gauges across India
404 for the analysis, which produced 26 homogeneous rainfall zones. However, because of data
405 scarcity northeastern states were not included in the analysis. Bharath and Srinivas (2015) used
406 wavelet-based global FCM analysis, instead of PCA for determining homogeneous
407 hydrometeorological regions in India. The new approach proposed by them clustered the Indian
408 territory into 29 regions, northeastern region having 7 clusters. The clusters formed in the upper
409 Brahmaputra valley region were similar to the present study. Kulkarni (2017) has used
410 probability density function to divide the Indian subcontinent into homogeneous clusters, using
411 daily summer monsoon rainfall at 357 square grids of size 10000 sqkm. The study produced
412 five clusters, out of which one cluster covered adjoining regions and all other clusters were
413 scattered indicating irregular behaviour of daily rainfall pattern in India. The study was done
414 by using two time periods 1901–1975 and 1976–2010, and the resulting clusters were found to
415 be extremely different in the two time periods. The clusters formed in the northeastern region
416 is also different for the two periods which are not entirely in line with the present study.
417 However, they used gridded rainfall data instead of station data, thus the difference. Mannan
418 et al. (2018) have used climatic variables and self-organizing maps to regionalize India.

Artificial neural network is used along with four CVs for clustering and applied on gridded rainfall dataset ($0.25^\circ \times 0.25^\circ$) from IMD for 34 years (1980–2013) as well as climatic variables such as air temperature, surface pressure, geo-potential height, specific humidity, etc. 10 homogeneous regions were formed when only rainfall data was used, whereas incorporation of climatic variables divided the region into 15 regions. The region 2 in their study covered the northeast India with rainfall of 7.2 mm/day.

4. Conclusion

In this paper, fuzzy clustering approach has been used to classify regions with homogeneous rainfall in upper Brahmaputra Valley region of northeast India. Three different combinations of feature vectors were employed in FCM algorithm to attain the best solutions to regionalization. Seven different CVs were used to determine the optimal partition in the fuzzy c-means (FCM) algorithm, out of which Extended Xie and beni index (V_{XB}) and Kwon index (V_K) were opted for clustering of rainfall regions owing to their satisfactory performance. The optimal value of cluster number for all three cases was identified as $c=3$, with corresponding value of $m=1.5$. The clustered regions were then assessed for statistical homogeneity by performing homogeneity tests using L-moment approach. Four clusters were found to be acceptably homogeneous. Other possibly heterogeneous and definitely heterogeneous clusters were made homogenous by adjusting the discordant sites. It was found from the results that the clustering pattern was improved in case 3, where geographical location parameters (latitude, longitude and elevation) were included along with local rainfall data of tea gardens. It indicates that if regionalization needs to be done at a local scale such as an average sized watershed, further sub-clustering of a clustered region may be required. Local rainfall data, along with geographical location parameter details, can be used for the purpose since GCM data will not be of much use in this aspect because of their coarse resolution. However, a good rainfall dataset with large number of station points is required to be available within the region.

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Author's Contribution

Conceptualization: Jayshree Hazarika, Arup Kumar Sarma; methodology: Jayshree Hazarika, Arup Kumar Sarma; formal analysis and investigation: Jayshree Hazarika; writing - original draft preparation: Jayshree Hazarika; writing - review and editing: Arup Kumar Sarma; resources: Arup Kumar Sarma; supervision: Arup Kumar Sarma.

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Availability of data and material

All relevant data are provided in both main manuscript and supplementary material.

Code availability

Not applicable

Declaration

Ethics approval All procedures performed in this study were in accordance with the ethical standards of the institution or any comparable ethical standards.

Consent to participate We (authors) are agreed that Jayshree Hazarika planned, performed the analysis, and wrote the paper, while Arup Kumar Sarma provided the resources and added his expertise in the analysed results.

Consent for publication We give consent for our paper to be published in your *Theoretical and Applied Climatology* journal.

Conflict of interest The authors have no conflicts of interest to declare that are relevant to the content of this article.

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660

661 LIST OF TABLES

662 **Table 1** Location details of raingauge stations located in various tea gardens of the upper

663 Brahmaputra valley region with mean annual and seasonal precipitation

664 **Table 2** Results of homogeneity test

665

666

Table 1 Location details of raingauge stations located in various tea gardens of the upper

667

Brahmaputra valley region with mean annual and seasonal precipitation

Sl. No.	Name of the station	Longitude (°E)	Latitude (°N)	Seasonal rainfall in mm				Total annual rainfall in mm	Elevation in m
				DJF	MAM	JJA	SON		
1	Abhoijan	93.8986111	26.4225	70	610	1127	510	2317	121
2	Achabam	95.2644444	27.24	82	579	1249	401	2312	123
3	Amsoi	92.4102778	26.1433333	31	326	843	346	1546	67
4	Anand	94.2300797	27.4619764	101	525	1880	719	3225	112
5	Arin	93.9752778	26.4877778	49	478	831	321	1679	100
6	Arun	92.4402778	26.6669444	32	451	823	257	1563	80
7	Athabari	94.0347222	26.4138889	9	301	525	162	996	104
8	Azizbagh	95.1302778	27.2063889	111	698	1354	479	2642	113
9	Bahani	94.2025	26.7555556	79	552	905	449	1985	93
10	Basmatia	95.0671167	27.3605556	81	637	1126	409	2253	113
11	Bateli	92.2537422	26.7759589	35	430	907	340	1712	112
12	Bhelaguri	94.3846566	26.7048311	57	489	830	279	1654	116
13	Bokajan	93.7751667	26.022	22	260	548	254	1084	136
14	Bokakhat	93.6438889	26.6377778	58	553	975	382	1968	87
15	Borahi	94.9902778	27.0433333	59	684	1291	454	2488	104
16	Borchapori	93.6899	26.6381972	75	550	1143	406	2174	92
17	Borhat	95.2888889	27.1388889	29	238	406	187	859	122
18	Borjan	94.0577778	26.5619444	39	393	745	271	1448	104
19	Borpathar	93.8488889	26.2722222	44	404	708	274	1430	127
20	Chubwa	95.1730556	27.4661111	99	835	1447	601	2981	118
21	Cinnatolliah	94.0857124	27.342037	110	653	1709	589	3061	123
22	Dalowjan	93.9747222	26.4338889	54	425	729	347	1555	105
23	Deamoolie	95.5388889	27.5905556	91	670	1275	442	2478	134
24	Dejoo	94.0031433	27.2807217	106	661	1690	544	3002	123
25	Dekorai	92.9636778	26.81	56	608	1238	445	2347	83
26	Deohall	95.2890372	27.4223095	103	710	1152	379	2344	125
27	Dhekiajuli	92.4615703	26.6904332	57	572	1090	391	2110	77
28	Dholaguri	93.84161	26.5128231	49	479	822	272	1622	99

29	Digulturrung	95.4119444	27.6104528	58	631	905	309	1903	126
30	Dilli	95.3672222	27.1638889	118	732	1507	519	2877	132
31	Diphloo	93.5685556	26.6394444	31	578	910	303	1822	84
32	Doorria	93.9191667	26.6316667	46	460	927	242	1675	97
33	Duklingia	94.2852151	26.6861544	74	685	1329	428	2515	112
34	Durrung	92.7297222	26.7227778	50	445	768	271	1534	76
35	Furkating	94.0137903	26.4617283	55	395	768	318	1535	106
36	Halem	93.4523611	26.8696667	44	449	1022	341	1856	90
37	Halmira	93.9466667	26.5241667	47	468	832	340	1688	101
38	Harchurah	92.7537139	26.7775488	61	561	1226	435	2282	94
39	Hatigarh	94.0433333	26.3888889	44	452	785	309	1590	102
40	Hatikhuli	93.370899	26.5848439	51	540	906	373	1870	87
41	Kakojan	94.3886111	26.735	46	440	786	247	1518	107
42	Kellyden	92.948746	26.483845	41	440	927	292	1700	86
43	Keyhung	95.3279024	27.4345426	101	658	1238	461	2457	127
44	Khowang	94.8938766	27.2431657	80	627	1052	337	2096	103
45	Koomsong	95.6537533	27.6188283	109	925	1182	476	2693	144
46	Kopati	92.25073	26.59	45	504	839	297	1685	75
47	Lakwa	94.8722222	27.0244444	93	607	1286	429	2416	100
48	Lamabari	92.277784	26.842633	35	504	1218	408	2166	134
49	Ledo	95.7683333	27.3020278	77	392	577	288	1333	153
50	Lengeree	93.7166667	25.9211111	41	299	711	302	1354	154
51	Lepetkata	94.8635316	27.3783221	222	649	1113	417	2402	104
52	Madhuting	95.3667005	27.3581907	27	262	451	157	897	129
53	Mahalakshmi	93.0608333	26.8555556	28	432	733	280	1473	88
54	Maijan	94.9783246	27.5079422	118	623	1359	529	2629	111
55	Mancotta	94.9175806	27.4385028	130	865	1764	653	3412	108
56	Mazbat	92.2515106	26.7810162	37	559	1185	379	2160	113
57	Moran	94.8846352	27.1563477	72	609	1060	405	2146	103
58	Murphuloni	93.9247879	26.457985	36	495	868	295	1694	106
59	Nahorjan	93.6065063	26.6075556	62	553	895	302	1812	98
60	Namburnodi	93.83188	26.29877	50	399	731	326	1506	134
61	Namdang	95.7220833	27.2655556	111	730	1555	534	2930	427

62	Namrup	95.3286111	27.1947222	50	429	731	256	1465	125
63	Nitinnagar	94.052032	26.345432	35	294	561	223	1113	107
64	Nonoi	92.9216667	26.4041667	35	487	1090	383	1994	79
65	Ouphulia	95.0147222	27.2177778	92	704	1350	493	2639	109
66	Paneery	91.8962681	26.7463385	64	680	1057	453	2254	122
67	Panitola	95.2573121	27.4941394	95	470	1087	463	2114	124
68	Pavojan	93.9055538	26.2978396	44	371	654	275	1344	116
69	Powai	95.6482333	27.3478431	77	613	1262	377	2329	158
70	Rungamatty	93.8986111	26.6702778	53	543	894	335	1825	90
71	Rupai	95.4952778	27.6123056	111	726	1313	458	2608	132
72	Rupajuli	92.7217448	26.7260395	53	584	1225	440	2301	78
73	Sagmootea	93.004862	26.544426	49	480	1013	309	1851	92
74	Santi	95.4125	27.3038889	102	965	1368	447	2882	127
75	Sepoi	92.4102034	26.7837818	17	704	1077	327	2125	110
76	Sepon	94.845947	27.1150673	77	584	1141	394	2195	103
77	Sockeiting	94.087428	26.546912	57	422	900	314	1693	98
78	Sonabheel	92.7849483	26.7369584	48	465	1045	364	1921	76
79	Sundarpur	95.1924133	27.1453118	53	725	1612	656	3046	113
80	Teloijan	94.9437618	27.2513485	55	355	798	329	1537	103
81	Tezpore & gogra	92.7395976	26.7232366	61	570	1030	359	2020	79
82	Thanai	95.0936111	27.5357694	73	576	1071	396	2116	116
83	Uday jyoti	93.9638889	26.5	19	383	678	264	1344	99

668 Note: DJF = December, January, February

669 MAM = March, April, May

670 JJA = June, July, August

671 SON = September, October, November

672

Table 2 Results of homogeneity test

Case	Cluster no.	H test			Homogeneity result	After adjustment			Homogeneity result	Final no of sites
		H1	H2	H3		H1	H2	H3		
1	C1	-0.08	-1.25	-0.99	Acceptably homogeneous	0.68	-0.97	-1.06	Acceptably homogeneous	31
	C2	1.08	-0.69	1.1	Possibly heterogeneous	0.49	-1.04	0.9	Acceptably homogeneous	34
	C3	2.96	1.11	0.46	Definitely heterogeneous	-0.84	0.56	-0.05	Acceptably homogeneous	16
2	C1	-0.98	-0.73	0.04	Acceptably homogeneous	-0.91	-0.62	0.1	Acceptably homogeneous	31
	C2	0.54	-1.25	0.09	Acceptably homogeneous	0.41	-0.71	0.39	Acceptably homogeneous	44
	C3	1.52	0.86	0.69	Possibly heterogeneous	0.41	-1.23	-1.28	Acceptably homogeneous	7
3	C1	1.86	0.91	0.15	Possibly heterogeneous	0.71	0.85	-0.11	Acceptably homogeneous	13
	C2	-0.88	-2.24	-0.25	Acceptably homogeneous	0.73	-1.95	0.16	Acceptably homogeneous	49
	C3	1.62	-0.05	-0.16	Possibly heterogeneous	0.69	-0.86	-0.93	Acceptably homogeneous	21

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679 **Fig. 3** Variation in the optimum value of objective function of FCM algorithm with variation of
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681 with standard deviation of total monthly rainfall as attributes; and (c) Case 3: with latitude, longitude,
682 elevation, total annual rainfall and standard deviation of total annual rainfall as attributes

683 **Fig. 4** Clusters formed by the FCM algorithm after adjustment for (a) Case 1: with total monthly
684 rainfall as attributes; (b) Case 2: with standard deviation of total monthly rainfall as attributes; and (c)
685 Case 3: with latitude, longitude, elevation, total annual rainfall and standard deviation of total annual
686 rainfall as attributes

687

Fig. 1 Methodology used to identify homogeneous rainfall regions

Fig. 2 Raingauge stations located in various tea gardens of the upper Brahmaputra valley region

(a) Case 1

(b) Case 2

(c) Case 3

Fig. 3 Variation in the optimum value of objective function of FCM algorithm with variation of fuzzifier m and cluster number c , for (a) Case 1: with total monthly rainfall as attributes; (b) Case 2: with standard deviation of total monthly rainfall as attributes; and (c) Case 3: with latitude, longitude, elevation, total annual rainfall and standard deviation of total annual rainfall as attributes

(a) Case 1

(b) Case 2

(c) Case 3

Fig. 4 Clusters formed by the FCM algorithm after adjustment for (a) Case 1: with total monthly rainfall as attributes; (b) Case 2: with standard deviation of total monthly rainfall as attributes; and (c) Case 3: with latitude, longitude, elevation, total annual rainfall and standard deviation of total annual rainfall as attributes

Figures

Figure 1

Methodology used to identify homogeneous rainfall regions

Figure 2

Raingauge stations located in various tea gardens of the upper Brahmaputra valley region. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

(a) Case 1

(b) Case 2

(c) Case 3

Figure 3

Variation in the optimum value of objective function of FCM algorithm with variation of fuzzifier m and cluster number c , for (a) Case 1: with total monthly rainfall as attributes; (b) Case 2: with standard deviation of total monthly rainfall as attributes; and (c) Case 3: with latitude, longitude, elevation, total annual rainfall and standard deviation of total annual rainfall as attributes

(a) Case 1

(b) Case 2

(c) Case 3

Figure 4

Clusters formed by the FCM algorithm after adjustment for (a) Case 1: with total monthly rainfall as attributes; (b) Case 2: with standard deviation of total monthly rainfall as attributes; and (c) Case 3: with latitude, longitude, elevation, total annual rainfall and standard deviation of total annual rainfall as attributes. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal

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