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Comparisons of Different Cluster Analysis Methods with Application to Mizoram Rainfall Data

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Abstract: Analysing rainfall patterns in Mizoram from 1998 to 2017 reveals diverse trends. The highest average rainfall occurred in 2004, reaching 292.8 mm, while 2014 marked the lowest at 151.77 mm. Siaha District experienced the highest average rainfall (3020.2 mm), while Champhai District had the lowest (1663 mm). In 2017, the Kendall method showed correlations between temperature and relative humidity, rainfall and relative humidity, but not between rainfall and temperature. Cluster analysis, a technique partitioning datasets into cohesive groups, was applied to Mizoram's district-wise rainfall data using single, complete, and average linkage methods. The Single Linkage Method formed one large cluster with under 26% similarity and the shortest distances between data points. The complete linkage method divided districts into two clusters with under 26% similarity and maximal inter-cluster distance. The Average Linkage Method merged all districts into one cluster with under 26% similarity and minimised inter-cluster distances. Comparing the techniques, Single and Complete Linkage Methods proved most effective for Mizoram's district-wise rainfall data. With only eight districts, forming additional clusters remained limited. This analysis highlights the significance of rainfall patterns in agricultural ecosystems and the utility of statistical methodologies like cluster analysis in understanding long-term trends.

Key words: Mizoram, rainfall, dendrogram, cluster analysis.

Introduction

Mizoram, influenced by the southwest monsoon, experiences a substantial amount of rainfall, with the rainy season spanning from April to late October (Lallianthanga, n.d.). Rainfall peaks from May to September, dwindling in October, while November to February sees dry weather. In 2017, Mizoram received 2712.3 mm of rainfall, the highest being 534.2 mm in June (Meteorological Data of Mizoram 2017 P R E F A C E, n.d.). January had no precipitation. Rainfall patterns in Mizoram are vital for agriculture and environmental stability. Adequate rainfall supports crop growth and water resources, while irregular or excessive rainfall can lead to floods, landslides, and soil erosion, affecting both farming and ecological balance. These patterns directly influence agricultural sustainability. This pattern highlights the region's reliance on monsoons for water supply and seasonal variations experienced by residents.

Mizoram, located in northeast India near Burma and Bangladesh, receives abundant rainfall annually, with the monsoon season spanning from April to October

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(Lallianthanga, n.d.). Its rich forest cover contributes to heavy rainfall. Rainfall is crucial for agriculture, climate, and daily life, necessitating the study of rainfall patterns. However, Mizoram faces climate challenges, with increasing temperatures. Afforestation efforts can mitigate this by affecting rainfall and climate, leading to a better Mizoram. In this research, we analyse Mizoram's rainfall pattern using Cluster Analysis methods like Single Linkage, Average Linkage, and Complete Linkage. Many scientists use cluster analysis to categorise rainfall data. Yashwant and Sananse applied cluster analysis to categorise 40 years of monthly rainfall data from 36 stations in Marathwada, finding single and centroid linkage methods most effective for rainfall pattern identification (Yashwant and Sananse, 2007). Machiwal et al. employed HCA and PCA to analyse 55 years of rainfall data in India (Machiwal et al., 2019). Lin et al. studied rainfall forecasting in Taiwan's Tamsui River Basin using cluster analysis and pattern recognition techniques (Lin et al., 2017). Teodoro et al. applied cluster analysis in Mato Grosso do Sul, Brazil, revealing diverse rainfall patterns influenced by meteorological systems like SASA and UTCV (Teodoro et al., 2016). Santos et al. used cluster analysis in Paraiba state's precipitation to reveal spatiotemporal variations influenced by climate systems. Santos et al. found that coastal and high-altitude areas exhibit the highest precipitation, reflecting diverse climatic influences across mesoregions (Santos et al., 2019). Siva et al. applied hierarchical cluster analysis to explore rainfall patterns in Visakhapatnam district, Andhra Pradesh, over 25 years (Machiwal et al., 2019). Alam and Paul employed clustering algorithms on Bangladesh's precipitation data, highlighting optimal clusters for various periods, with fuzzy c-means showing superior homogeneity (Alam and Paul, 2020). Pansera et al. used diverse clustering methods to optimise rainfall station groupings for hydrological planning in Parana, Brazil, demonstrating the efficacy of a hybrid approach over 31 years of data (Pansera and Gomes, 2005). Nasseria and Zahraie introduced a method for space-time estimation of cumulative mean monthly rainfall in watersheds with limited rain gauges, integrating time-varying variogram with Kriging and K-means clustering (Nasseri and Zahraie, 2011). Muñozmu˜muñoz-Díaz and Rodrigo applied cluster and principal component analysis to delineate Spain into climatically homogeneous zones based on seasonal rainfall (Muñozmu˜muñoz-Díaz and Rodrigo, 2004).

Objectives

This study primarily focusses on analysing annual rainfall patterns in Mizoram from 1998 to 2017, categorised by district and year. It includes a comparative assessment of cluster analysis techniques using rainfall data and examines the mean annual rainfall, temperature, and relative humidity in Aizawl City from 1998 to 2017. Additionally, correlations between temperature, relative humidity, and rainfall in Aizawl City during 2017 will be investigated. Analysing Mizoram's rainfall data about broader climate trends, such as El Niño, La Niña, and global warming, is essential for understanding long-term impacts. This comparison aids in predicting rainfall patterns and improving agricultural planning, water management, and disaster preparedness.

Data Source

To fulfill the objectives of this project, the data considered is secondary in nature. It has been collected from the report entitled "Meteorological Data of Mizoram 2017" (Meteorological Data of Mizoram 2017 P R E F A C E, N.d.) published on 21st March 2018 by the Directorate of Economics and Statistics, Planning, and Programme Implementation Department, Government of Mizoram. Website www.des.mizoram.gov.in

Methodology

This research focusses on Mizoram's eight districts: Aizawl, Mamit, Champhai, Lawngtlai, Lunglei, Saiha, Kolasib, and Serchhip. We analysed monthly and annual rainfall data spanning the last 20 years. The secondary data was obtained from the "Meteorological Data of Mizoram 2017" report published by the Directorate of Economics and Statistics, Planning, and Programme Implementation Department, Government of Mizoram (Meteorological Data of Mizoram 2017 P R E F A C E, N.d).

Descriptive Statistics

Descriptive statistics, including Maximum, Minimum, Mean, Standard Deviation, Coefficient of Variation, and Skewness (Gupta and Kapoor, 2002), were calculated decade-wise to analyse rainfall fluctuations across Mizoram's districts. Yearly statistics for each district were also examined to identify trends, following established formulae.

Cluster Analysis

Cluster analysis, a statistical technique grouping entities based on similarities (Yashwant and Sananse, 2007), utilises two methods: hierarchical and non-hierarchical. With 20 years of seasonal rainfall data (1998-2017) from Mizoram's eight districts, three techniques—Single Linkage, Average Linkage, and Complete Linkage—were applied. It unveils homogenous clusters for pattern recognition, structured as an (*n x p*) matrix with *n* entities and *p* attributes (Gadgil and Narayana Iyengar, 1980; Yashwant and Sananse, 2007).

Hierarchical Clustering Method

Hierarchical clustering methods, notably agglomerative clustering, form tree-like structures during analysis. Objects start as standalone clusters and gradually merge based on similarity, creating clusters at various hierarchy levels (Yashwant and Sananse, 2007). In this study, the hierarchical cluster technique, following Kaufman and Rousseum (1990), categorises synoptic rainfall stations into spatial groups effectively. Various techniques like Ward's, Complete Linkage, Single Linkage, Average Linkage, Centroid Linkage, Median Linkage, and McQuitty Linkage are utilised to create a dendrogram, visually representing cluster relationships (Yashwant and Sananse, 2007).

Dendogram

A dendrogram is a graphical technique used to categorise clusters based on minimal distance and maximal similarity levels in hierarchical clustering (Yashwant and Sananse, 2007). It provides a two-dimensional diagram that portrays the amalgamations or subdivisions during the cluster analysis process (Gadgil and Iyengar, 1980). In this study, three hierarchical clustering methods are employed, selected based on insights from dendrogram analysis. These three methods encompass the following:

Single Linkage Method

The single linkage method is prominent in hierarchical clustering (Yashwant and Sananse, 2007). It determines cluster proximity by identifying the minimum distance between points in different clusters or the maximum similarity level between points. This method prioritises the closest pairs of points, ensuring clusters are anchored to their most similar constituents. In the single linkage method, D (r , s) is computed as

$D\ (r\ ,s)$ = Min $\{d\ (i, j)$: Where object i is in cluster r and object j is cluster $s\}$

Complete Linkage Method

Complete Linkage, a hierarchical clustering method (Yashwant and Sananse, 2007), merges clusters progressively until forming a single cluster. It measures cluster distance based on the farthest-separated elements. In the complete linkage method, D (r, s) is computed as

$D\ (r;\ s)$ = Max {d $(I\ ,j)$: Where object i is in cluster r and object j is cluster $s\}$

Average Linkage Method

In Average Linkage clustering, a variant of single or complete linkage (Yashwant and Sananse, 2007), the distance is the mean of all point-pair distances.

In the average linkage method, $D\ (r, s)$ is computed as

$$D\ (r;\ s) = T_{rs}/(N_r * N_s)$$

Where T_{rs} is the sum of all pairwise distances between cluster r and cluster s. N_r and N_s are the sizes of the clusters r and s, respectively**.**

Kendall Tau-b Correlation Coefficient

Kendall Tau-b calculates the correlation between monthly rainfall and temperature, especially useful when data violates Pearson's correlation assumptions (Michaelides et al., 2001). The formula for calculation of the Kendall coefficient is given by

let C = the number of concordant pairs and D = the number of discordant pairs. Then define tau as

$$\pi = \frac{C - D}{C(n-2)}$$

Data Analysis and Discussion

Descriptive Statistics

Discussion

Descriptive Statistics of Mizoram's Last 20 Years

Table 1 presents annual rainfall data for Mizoram from 1998 to 2017, showing significant fluctuations. The highest rainfall was recorded in 2004 (850.8 mm), while some years, including 0 mm, had minimal levels. The average annual rainfall peaked at 292.2 mm in 2004 and dropped to 151.8 mm in 2014. Rainfall variability, measured by the coefficient of variation, decreased over time. Table 2 highlights district-wise rainfall trends, with Saiha recording the highest average rainfall and Lawngtlai showing the most variability. Lunglei exhibited the most consistent rainfall patterns.

Table 1: Year-wise descriptive statistics of Mizoram for the last 20 years

Descriptive statistics last 20 years							
Annual rainfall (in mm)							
Years	*Min*	*Max*	*Range*	*Mean*	*S.D*	*C.V(%)*	*Skewness*
2017	0	534.2	534.2	226	184.1	81.46018	0.1
2016	0	407.6	407.6	190.1	156.9	82.53551	0.2
2015	1.5	481.9	480.4	181.6	176.5	97.19163	0.5
2014	0	381.7	381.7	151.8	156.7	103.2279	0.3
2013	0	519.9	519.9	201.9	216.4	107.1818	0.4
2012	0	456.7	456.7	190.6	167	87.61805	0.2
2011	0.1	547.9	547.8	210.5	205.3	97.52969	0.4
2010	0	524.7	524.7	219.5	209.9	95.62642	0.4
2009	0	468.2	468.2	154.8	164.3	106.137	0.7
2008	0	411.5	411.5	157.7	150.6	95.49778	0.6
2007	0	603.2	603.2	246.9	212	85.86472	0.3
2006	0	558	558	173.5	206	118.732	0.9
2005	2.8	409.4	406.6	174.5	146.9	84.18338	0.2
2004	0	850.8	850.8	292.2	305.4	104.5175	0.6
2003	0	740	740	212.1	219.1	103.3003	1.3
2002	1	566.8	565.8	220.7	212.3	96.19393	0.7
2001	0	531.2	531.2	213.1	185.8	87.18911	0.3
2000	0	616.9	616.9	240.4	207.9	86.48087	0.5
1999	0	488	488	216.8	213	98.24723	0.1
1998	0	513	513	206.8	192.9	93.27853	0.5

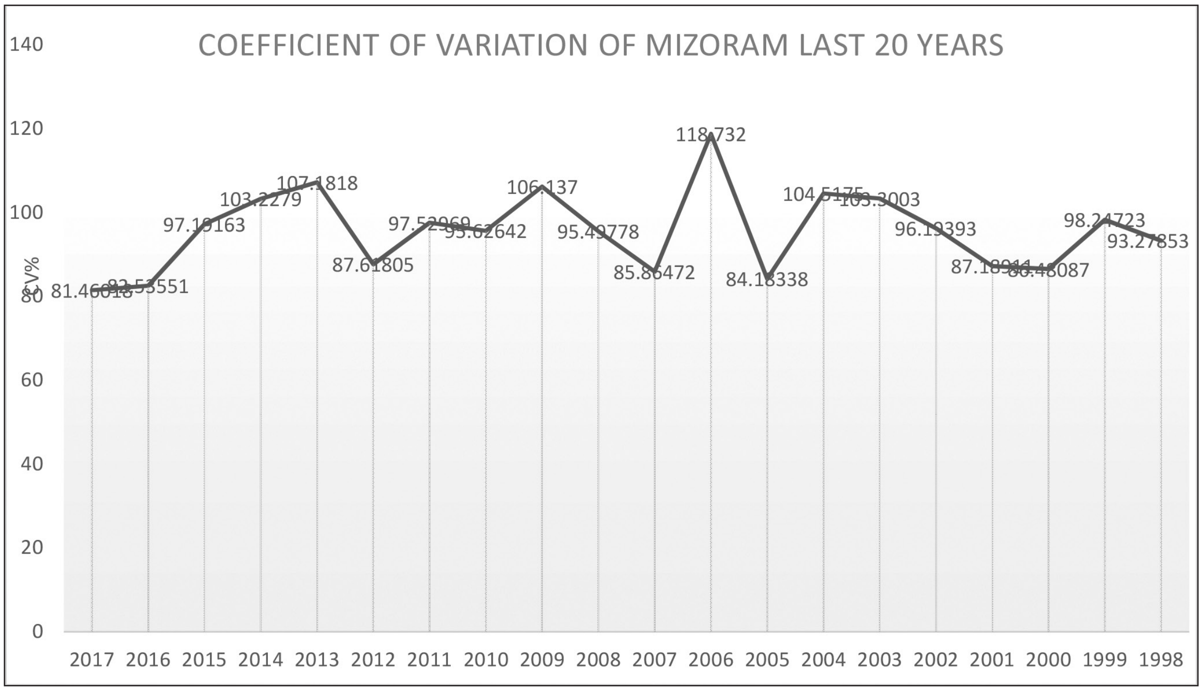

Figure 1: Coefficient of variation (%) in annual rainfall of Mizoram last 20 years.

Comparison of Different Methods of Cluster Analysis with Application to the Rainfall Data

The single Linkage method was applied to 20 years of rainfall data in 8 districts. The results show that the district is classified with one big cluster on the basis of a dendogram. Figure 3 represents a dendrogram of two clusters of a single linkage method**.**

Drawing insight from the Dendogram generated via the Single Linkage method, a conclusive classification emerged wherein a singular extensive cluster was formed, predicated upon the highest degree of similarity.

Cluster 1: Champhai, Serchhip, Lawngtlai, Mamit, Kolasib, Aizawl, Lunglei, Saiha.

In Table 3, the result shows that cluster have 25 % similarity with a minimum distance level of 8396.9.

Table 3: Amalgamation result of single linkage method

No. of cluster	*Similarity level*	*Distance level*
1	25	8396.9

The distance is calculated by

Let P1 = Mamit, P2= Kolasib, P3=Aizawl, P4= Champhai, P5= Serchhip, P6= Lunglei, P7= Lawngtlai, P8= Saiha.

Min[distn{P(5,4),P1}] = Min[P(5,1),P(4,1)]=8844.0000 and so on.

Table 2: District-wise descriptive statistics of Mizoram's last 20 years district-wise

District-wise descriptive statistics last 20 years							
			Annual rainfall (In Mm)				
District	*Min*	*Max*	*Range*	*Mean*	*S.D*	*C.V(%)*	*Skewness*
Mamit	0	3493.1	3493.1	2153.4	986.5	45.81128	-1.6
Kolasib	0	3477.2	3477.2	2229.5	1055.1	47.32451	-1.4
Aizawl	1604.1	3251.8	1647.7	2425.8	493.93	20.36153	-0.2
Champhai	0	2874.9	2874.9	1668.9	779.9	46.73138	-1.4
Serchhip	0	2942.6	2942.6	1711.2	827.9	48.38125	-1.2
Lunglei	1863.5	3435.5	1572	2600.3	444.4	17.09034	0.2
Lawngtlai	0	3203	3203	1826.4	940.3	51.48379	-0.9
Saiha	20.41.9	4722.9	2681	3020.2	716.7	23.73022	1

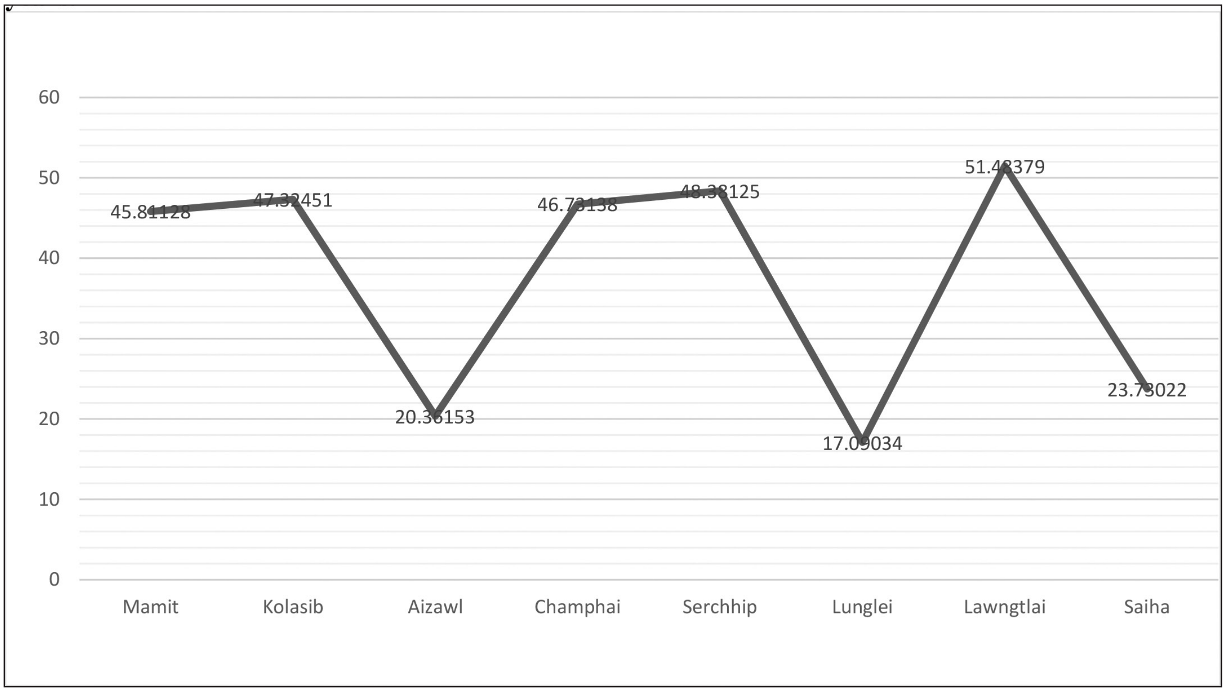

Figure 2: Coefficient of variation (%) in annual rainfall of Mizoram district-wise last 20 years.

Distance calculation: The Euclidean Matrix is given:

Case	*Euclidean Distance*							
	Mamit	*Kolasib*	*Aizawl*	*Champhai*	*Serchhip*	*Lunglei*	*Lawngtlai*	*Saiha*
Mamit	0	1522.7	5448.2	9688.3	8844.2	8938.6	6540.7	17336
Kolasib	1522.7	0	3925.5	11211	10367	7415.9	8063.4	15813
Aizawl	5448.2	3925.5	0	15137	14292	3490.4	11989	11887
Champhai	9688.3	11211	15137	0	844.1	18627	3147.6	27024
Serchhip	8844.2	10367	14292	844.1	0	17783	2303.5	26180
Lunglei	8938.6	7415.9	3490.4	18627	17783	0	15479	8396.9
Lawngtlai	6540.7	8063.4	11989	3147.6	2303.5	15479	0	23876
Saiha	17336	15813	11887	27024	26180	8396.9	23876	0

This is a dissimilarity matrix

The complete linkage method was employed for 20 years of rainfall data in 8 districts. The result reveals that the district is classified into two (2) clusters on the basis of dendogram. Figure 4 represents the dendrogram of two clusters of the Complete linkage method.

Upon careful analysis of the dendogram produced by employing the complete linkage method, a definitive classification emerged. This entailed the partitioning of the data into two distinct clusters, delineated by their highest level of similarity.

Cluster 1: Champhai, Serchhip, Lawngtlai.

Cluster 2: Mamit, Kolasib, Aizawl, Lunglei, Saiha**.**

Table 4: Amalgamation result of complete linkage method

No. of cluster	*Similarity level*	*Distance level*
1	25	3147.6
2	16	17335.5

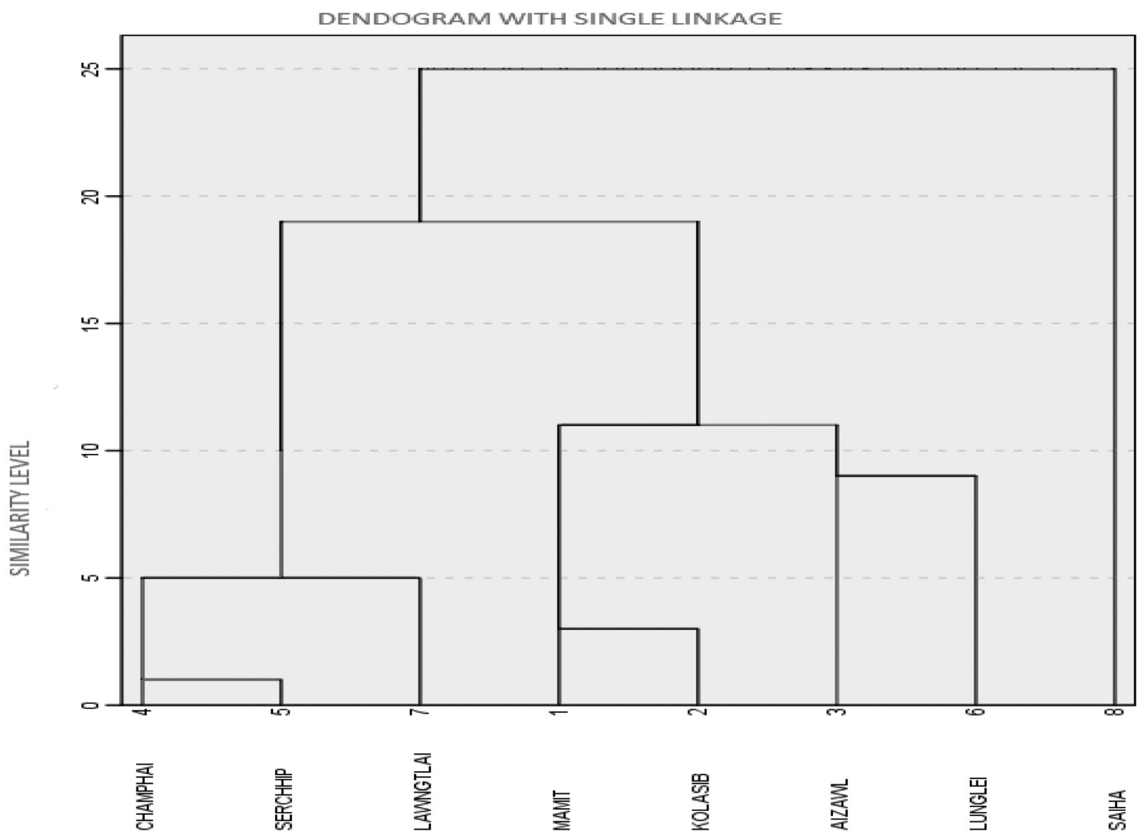

Figure 3: Dendrogram of single linkage for selected 8 districts.

Distance calculation

The Table 4 result shows that clusters no 1&2 have a similarity of 25% and 16% with minimum distance levels of 3147.6 and 17335.5 respectively. The cluster 1 and 2 similarity level is approximately 26%. In this method all clusters greater than 15% of similarity level.

The Euclidean Matrix is given:

Case	*Euclidean Distance*							
	Mamit	*Kolasib*	*Aizawl*	*Champhai*	*Serchhip*	*Lunglei*	*Lawngtlai*	*Saiha*
Mamit	0	1522.7	5448.2	9688.3	8844.2	8938.6	6540.7	17336
Kolasib	1522.7	0	3925.5	11211	10367	7415.9	8063.4	15813
Aizawl	5448.2	3925.5	0	15137	14292	3490.4	11989	11887
Champhai	9688.3	11211	15137	0	844.1	18627	3147.6	27024
Serchhip	8844.2	10367	14292	844.1	0	17783	2303.5	26180
Lunglei	8938.6	7415.9	3490.4	18627	17783	0	15479	8396.9
Lawngtlai	6540.7	8063.4	11989	3147.6	2303.5	15479	0	23876
Saiha	17336	15813	11887	27024	26180	8396.9	23876	0

This is a dissimilarity matrix

The distance is calculated by

Let P1 = Mamit, P2 = Kolasib, P3 = Aizawl, P4 = Champhai, P5 = Serchhip, P6 = Lunglei, P7 = Lawngtlai, P8 = Saiha.

Max[distn{P(5,4), P1}] = Max[P(5,1),P(4,1)] = 9688.000 and so on.

The Average Linkage method was applied to 20 years of rainfall data in 8 districts. The results show that the district is classified with one big cluster on the basis of Dendogram. Figure 5 represent the dendrogram of two clusters of the Average linkage method.

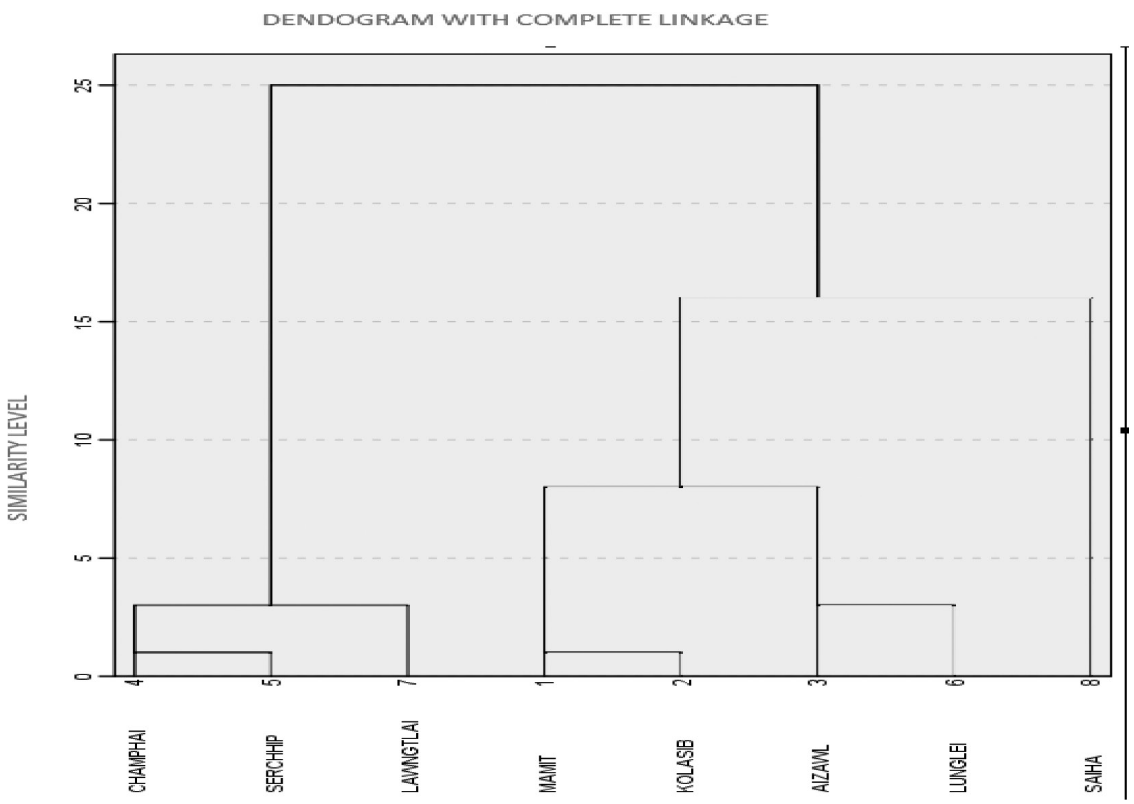

Figure 4: Dendrogram of complete linkage for selected 8 districts.

Extracting insights from the Dendogram resulting from the application of the Average Linkage method, a conclusive classification was attained. This culminated in the identification of a solitary extensive cluster, formed on the foundation of the highest level of similarity.

Cluster 1: Champhai, Serchhip, Lawngtlai, Mamit, Kolasib, Aizawl, Lunglei, Saiha

The distance is calculated by

Let P1=Mamit, P2= Kolasib, P3=Aizawl, P4= Champhai, P5= Serchhip, P6= Lunglei, P7= Lawngtlai, P8= Saiha.

Average [distn {P (5,4), P1}] =Average [distn {P (5,1) + P (4,1)}] = (1/2) [P (5,1) + P (4,1)] = 9266.25and so on.

Discussion

The study aimed to analyse rainfall data from Mizoram's districts (1998-2017) using three cluster analysis techniques. Results showed Single Linkage Method grouped districts into one cluster (<26% similarity), while the Complete Linkage Method formed two clusters (<26% similarity) with maximum inter-cluster distances. Similarly, the Average Linkage Method unified all districts into one cluster (<26% similarity). Single and complete linkage methods were deemed effective in categorizing Mizoram's rainfall data due to their ability to capture complex patterns.

Table 5: Amalgamation result of average linkage method

No. of cluster	*Similarity level*	*Distance level*
1	25	15428.73

Distance calculation:

In Table 5, the result shows that cluster have 25 % similarity with a minimum distance level of 15428.73.

Comparison Between Average Rainfall, Average Temperature and Average Relative humidity (RH) in Aizawl City Over the Last 20 Years

The relationship between average rainfall, average temperature and average relative humidity is represented in the following graphical representation as follows:

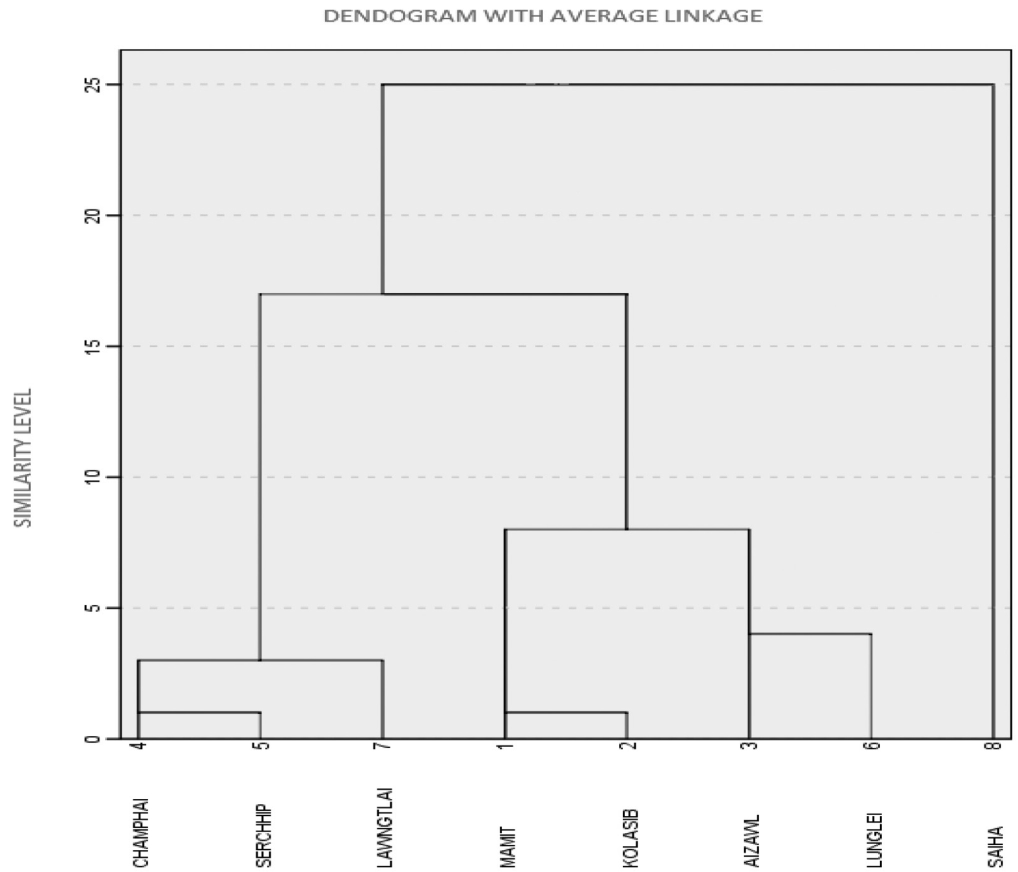

Figure 5: Dendrogram of average linkage for selected 8 districts.

The Euclidean Matrix is given:

Case	*Euclidean Distance*							
	Mamit	*Kolasib*	*Aizawl*	*Champhai*	*Serchhip*	*Lunglei*	*Lawngtlai*	*Saiha*
Mamit	0	1522.7	5448.2	9688.3	8844.2	8938.6	6540.7	17336
Kolasib	1522.7	0	3925.5	11211	10367	7415.9	8063.4	15813
Aizawl	5448.2	3925.5	0	15137	14292	3490.4	11989	11887
Champhai	9688.3	11211	15137	0	844.1	18627	3147.6	27024
Serchhip	8844.2	10367	14292	844.1	0	17783	2303.5	26180
Lunglei	8938.6	7415.9	3490.4	18627	17783	0	15479	8396.9
Lawngtlai	6540.7	8063.4	11989	3147.6	2303.5	15479	0	23876
Saiha	17336	15813	11887	27024	26180	8396.9	23876	0

This is a dissimilarity matrix.

In 2014, despite high rainfall, relative humidity and temperatures remained stable. A consistent trend shows rising temperatures accompany increased humidity, indicating a positive correlation. Conversely, higher rainfall and humidity coincide with lower temperatures, indicating a negative correlation.

Correlation Between the Temperature, Relative Humidity, and Rainfall of Aizawl City in 2017 by Kendall Correlation Coefficient Method

Kendall tau enables the assessment of similarity or correlation between rainfall data from various regions or periods. This analysis aids in identifying trends or relationships in rainfall patterns across different regions or over time.

Table 6: By Kendall Correlation Coefficient Method, the correlation between temperature and rainfall in Aizawl City 2017 is given by

Here, the null hypothesis is

Ho: There is no association between temperature and rainfall.

H1: There is an association between temperature and rainfall

Kendall correlation coefficient	0.29
P-value	0.192

Table 7: By Kendall Correlation Coefficient Method, the correlation between relative humidity and rainfall in Aizawl City 2017 is given by

Here the null hypothesis is

Ho: There is no association between relative humidity and rainfall.

H1: There is an association between relative humidity and rainfall.

Kendall correlation coefficient	0.545
P-value	0.014

Table 8: By Kendall Correlation Coefficient method, the correlation between relative humidity and temperature in Aizawl City 2017 is given by

Here the null hypothesis is

Ho: There is no association between relative humidity and temperature.

H1: There is an association between relative humidity and temperature.

Kendall correlation coefficient	0.565
P-value	0.011

Discussion

Rainfall and Temperature

Utilizing the Kendall Correlation Coefficient method and referencing data from Table 6, an evident positive correlation of 0.92 emerged between rainfall and temperature. Notably, the associated p-value of 0.192, as indicated in Table 6, permits us to uphold the null hypothesis Ho at a 5% level of significance. Consequently, the deduction drawn is that no substantial association exists between rainfall and temperature.

Rainfall and Relative Humidity

Applying the Kendall Correlation Coefficient method and from Table 7, a discernible positive correlation of 0.545 between rainfall and relative humidity. This observation is underpinned by the p-value of 0.014, also presented in Table 7, which leads us to reject the

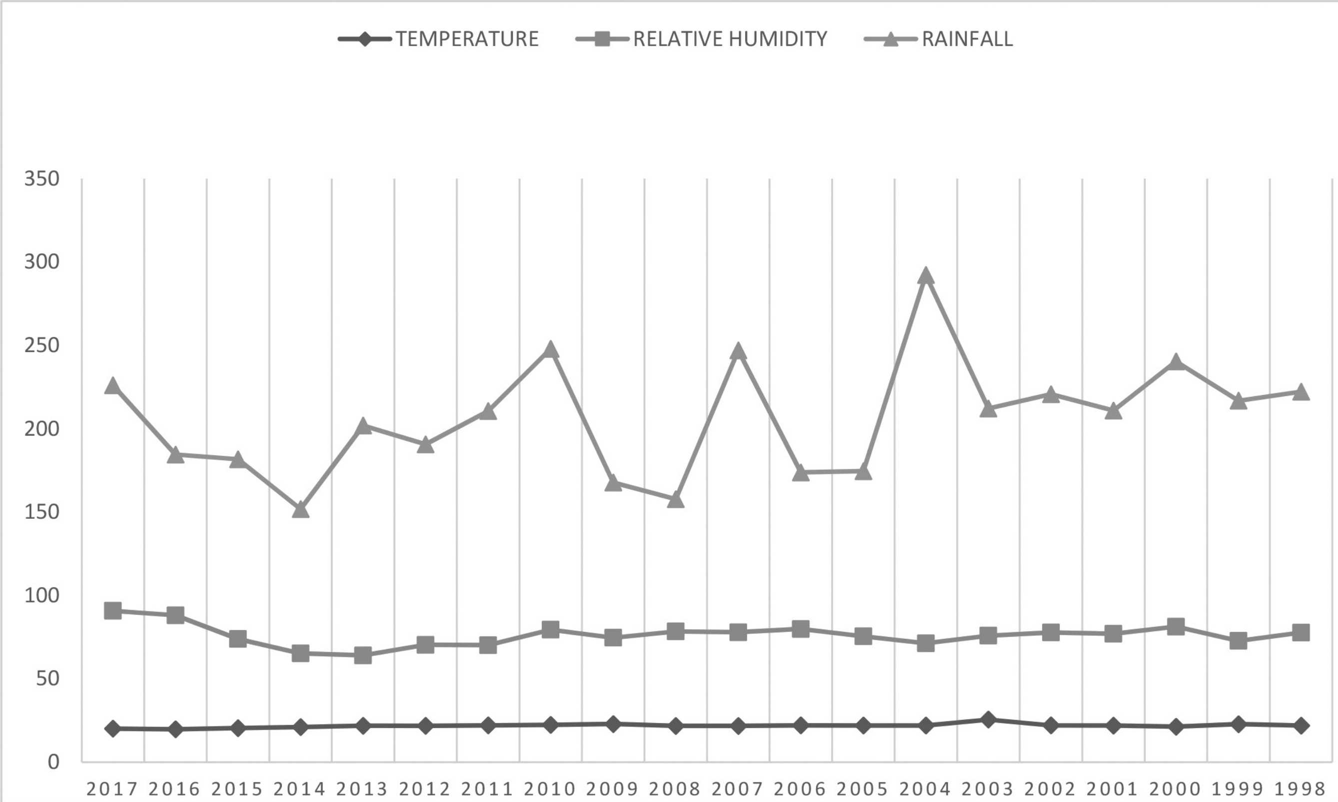

Figure 6: Average rainfall, temperature, and relative humidity in Aizawl city last 20 years.

null hypothesis Ho at a 5% level of significance. So, we ascertain that a meaningful association exists between rainfall and relative humidity.

Temperature and Relative Humidity

Through the utilisation of the Kendall Correlation Coefficient method and a thorough examination of the data presented in Table 8, a notable positive correlation of 0.565 was established between rainfall and relative humidity. This finding is substantiated by the p-value of 0.011, as outlined in Table 8, prompting the rejection of the null hypothesis Ho at the 5% level of significance. Hence, we deduce that a significant association exists between temperature and relative humidity.

Conclusion

Errors and biases in Mizoram's rainfall data may arise due to equipment issues and insufficient manpower, affecting its accuracy. However, the data still provides a general understanding of rainfall patterns. The findings highlight rainfall's importance and the need to address future water challenges. From 1998 to 2017, Mizoram experienced varied annual rainfall, with the highest recorded in 2014 at 850.8 mm. Conversely, several years saw minimal or zero rainfall. Saiha District observed the highest annual rainfall (2600.3 mm), while others encountered exceptionally low levels, even as low as 0 mm. The coefficient of variation ranged from 118.732% in 2006 to 81.46018 mm in 2017, with a decreasing trend noted from 2008 onwards. Lawngtlai District showed the highest coefficient of variation (51.48379%), while Lunglei District had the lowest (17.09034%). Cluster analysis techniques revealed Single and Average Linkage Methods as effective. A temperature-relative humidity inverse relationship was observed, with higher temperatures associated with decreased relative humidity. In 2014, despite high rainfall, relative humidity wasn't significantly impacted, possibly due to moderate temperatures. Kendall's analysis in Aizawl City (2017) highlighted positive correlations between rainfall, temperature, and relative humidity, emphasizing complex climate dynamics.

References

Alam, M.S. and S. Paul (2020). A comparative analysis of clustering algorithms to identify the homogeneous rainfall gauge stations of Bangladesh. *J Appl Stat*, **47:** 1460-1481. https://doi.org/10.1080/02664763.2019.1675606

Gadgil, S. and R. Narayana Iyengar (1980). Cluster analysis of rainfall stations of the Indian peninsula. *Quarterly Journal of the Royal Meteorological Society*, **106:** 873-886. https://doi.org/10.1002/qj.49710645016

Gupta, S.C. and V.K. Kapoor (2002). Fundamentals of mathematical statistics : A modern approach. Sultan Chand.

Lallianthanga, R.K., n.d. Climate Profile of Mizoram.

Lin, F.R., Wu, N.J. and T.K. Tsay (2017). Applications of cluster analysis and pattern recognition for typhoon hourly rainfall forecast. *Advances in Meteorology*, **2017(2):** 1-17. https://doi.org/10.1155/2017/5019646

Machiwal, D., Kumar, S., Meena, H.M., Santra, P., Singh, R.K. and D.V. Singh (2019). Clustering of rainfall stations and distinguishing influential factors using PCA and HCA techniques over the western dry region of India. Meteorological Applications **26:** 300-311. https://doi.org/10.1002/met.1763

Meteorological Data of Mizoram 2017. P R E F A C E, n.d. Directorate of Economics & Statistics, Planning & Programme Implementation. Department Government of Mizoram

Michaelides, S.C., Pattichis, C.S. and G. Kleovoulou (2001). Classification of rainfall variability by using artificial neural networks. *International Journal of Climatology*, **21:** 1401-1414. https://doi.org/10.1002/joc.702

Muñozmu˜muñoz-Díaz, D. and F.S. Rodrigo (2004). Spatio-temporal patterns of seasonal rainfall in Spain (1912-2000) using cluster and principal component analysis: Comparison. *Annales Geophysicae*, **22(5):** 1435-1448.

Nasseri, M. and B. Zahraie (2011). Application of simple clustering on space-time mapping of mean monthly rainfall pattern. *International Journal of Climatology*, **31:** 732-741. https://doi.org/10.1002/joc.2109

Pansera, W. and B.M. Gomes (2005). Clustering rainfall stations aiming regional frequency analysis. *Journal of Food Agriculture and Environment*, **11(2):** 877-885.

Santos, C.A.G., Neto, R.M.B., da Silva, R.M. and S.G.F. Costa (2019). Cluster analysis applied to spatiotemporal variability of monthly precipitation over Paraíba state using tropical rainfall measuring mission (TRMM) data. *Remote Sens (Basel)*, **11(6):** 637. https://doi.org/10.3390/rs11060637

Teodoro, P.E., de Oliveira-Júnior, J.F., da Cunha, E.R., Correa, C.C.G., Torres, F.E., Bacani, V.M., Gois, G. and L.P. Ribeiro (2016). Cluster analysis applied to the spatial and temporal variability of monthly rainfall in Mato Grosso do Sul State, Brazil. Meteorology and Atmospheric Physics, **128:** 197–209. https://doi.org/10.1007/s00703-015-0408-y

Yashwant, S. and S.L. Sananse (2007). Comparisons of different methods of cluster analysis with application to rainfall data. *International Journal of Innovative Research in Science, Engineering and Technology*. **4(11):** 10861-10872. https://doi.org/10.15680/IJIRSET.2015.0411087

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