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Spatiotemporal Rainfall Variability and Trends in Tripura, India: Implications for Water Resource Management

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ABSTRACT: This study analyzes rainfall variability at 22 rainfall stations in Tripura, India, using 2000–2024 monthly rainfall data. The pre-processing data yields 17 stations used for the analysis. Monotonic changes are identified using the Modified Mann–Kendall test, and the rate is estimated by Sen's slope estimator. The spatial cohesion was determined by using the k-means method, and the number of clusters is determined by the elbow method. The result shows most stations experienced non-significant trends, but three stations, namely Bishalgarh, Gandacherra, and Chawmanu, experienced statistically significant decreases in rainfall. The rainfall variability is categorized by the cluster analysis into three sets, namely mild decreases, strong decreases, and mild increases. The study observes an asymmetric nature of rainfall change; the hilly center parts experience sudden decreases, while the peripheries shows consistency.

Key Words: Modified Mann-Kendall test, Sen's slope, Elbow method, K-means clustering, Tripura.

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1. Introduction

Spatiotemporal rainfall variability is central to maintaining agriculture, ecosystems, and freshwater in monsoon-driven regions of the world. The hilly Northeast Indian state of Tripura is dependent almost entirely on rainfall as the driving element for agriculture productivity and water security. Recent decades, however, have seen marked climatic uncertainties, i.e.,temperature increases, deforestation, intense urbanization, and alterations in the use of lands that have increased the complexity of behavior of rainfall. It is, therefore, critical that spatiotemporal rainfall variability, i.e., the behavior of rainfall in space and

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in time, be comprehended for sustainability in water resource management, planning for agriculture, as well as for hazard preparedness.

Classical statistical procedures such as the Mann–Kendall (Mann, 1945; Kendall, 1975) and Sen's estimator of the slope (Sen, 1968) remain the standard for discerning rainfall trends. Corrective effects from extensions for autocorrelation (Hamed and Rao, 1998; Yue and Wang, 2004) have strengthened them in terms of robustness. Current techniques rely on unsupervised learning such as k-means clustering in order to demarcate homogeneous zones of rainfall and provide hydrological models (Ghosh and Mujumdar, 2008). Other than those procedures, recent developments (2021–2025) engage in the integration of analyses of rainfall with wider climatic change, uncertainty, and decision-making reference frames. Singh et al. (2021) attributed Northeast India's rainfall anomalies to ENSO and Indian Ocean Dipole events, Prakash et al. (2022) intertwined gauge as well as satellite-rainfall data for local-scale analyses, and Kumar and Yadav (2023) noticed the representation of climatic change in replenishing rainfall extremes. Das and Mandal (2023) indicated the effect of urbanization within the rainfall distribution in east India. More recently, Ahmed et al. (2022) as well as Kundu et al. (2024) applied clustering as well as machine learning for the identification of the variability of Indian states' rainfall, demonstrating the significance of hybrid methodologies.

Some studies in Northeast India observed rainfall trends with inconsistent results. Increasing pre-monsoon rainfall in Agartala was suggested by Phukan and Saha (2022) while stable or increasing rainfall in Shillong and Agartala was suggested by Sangma et al. (2020). Strong seasonality was indicated by Vivekanandan et al. (2022) in Agartala Sadar, in terms of considerations for irrigation. Likelihoods of rainfall have been studied by Ganchaudhuri et al. (2022) for Tripura's districts for crop planning, and geospatial techniques have been used by Das et al. (2022) in rainfall erosivity assessment.

Additionally, uncertainty-based modeling (Shil et al., 2024; Pramanik et al., 2023; Das et al., 2024b; Das et al., 2025a, 2025b) demonstrates how environmental data imprecision is handled by fuzzy and neutrosophic decision models. These are particularly relevant for rainfall variability, whose behavior is dictated by both natural climatic variations as well as human-induced perturbations. Despite these efforts, Tripura hasfewer studies than other states within Northeast India. The majority of them are local in nature or are based on trend identification alone, while neglecting uncertainty management and the application of clustering algorithms. The study at hand aims to fill in these lacunae by applying Modified Mann–Kendall test, Sen's slope estimator, and k-means clustering for reaching a holistic representation of rainfall variations over Tripura.

1.1. Research Gap

Although there is increasing literature dealing with rainfall variability over Northeast India, both significant gaps exist when viewed in the context of Tripura. Initially, most studies employ regionally narrow scopes, frequently focusing on a single or two stations instead of characterizing the variability of climatic sub-regions over the entire state. This locally narrow scope limits our comprehension of the manner rainfall acts over diverse topographic regions and agro-climatic zones within the state. Secondly, there exist methodological shortcomings since many previous studies largely employ trend detection-based methods like the use of the Mann–Kendall test, yet ignore the opportunity to employ clustering approaches that would divide the stations into homogenous classes and bring into focus the spatial differences and similarity in rainfall regimes. Both these limitations highlight the importance of adopting a broader approach that combines solid trend analysis with clustering to offer an inclusive overview on rainfall variability within Tripura.

1.2. Motivation

This study is motivated by the compelling need to develop a richer and better-integrated understanding of rainfall behaviour in Tripura. As the State is heavily reliant on monsoon rainfall for agriculture, water provisioning, and ecosystem maintenance, there is a need to transcend isolated or station-level analysis and develop a rich spatiotemporal profile. This requires not just discerning rainfall trends over the long term but exploring spatial configurations that shed light on the ways in which diverse regions within Tripura experience variability. Further locating these findings within the context of rising climatic uncertainty lies the potential to provide rich information towards building resilience as well as towards guiding policy intervention across agriculture, water management, and hazard preparation.

2. Data Source

Month-wise rainfall data (2000-2024) of 22 weather stations were collected from the Department of Agriculture and Farmers Welfare, Government of Tripura.

3. Methodology

3.1. Data Preprocessing:

Let,

$$R_{ijt} = \text{Rainfall at station } i, \text{ in month } j, \text{ year } t,$$

Where,

$$\begin{aligned} i &= 1, 2, \ldots, 22 && \text{(Number of stations)},\\ j &= 1, 2, \ldots, 12 && \text{(Months)},\\ t &= 1, 2, \ldots, T_i && \text{(Number of years for station } i\text{)}. \end{aligned}$$

The missing values and "NR" entries were converted to `NA` and replaced using monthly station-wise median imputation. Thus, the cleaned rainfall data is defined as:

$$\hat{R}_{ijt} = \begin{cases} R_{ijt}, & \text{if } R_{ijt} \text{ is available},\\[2ex] \operatorname{median}\bigl(\{R_{ijt}^{\text{available}}\}\bigr), & \text{if } R_{ijt} \text{ is missing}, \end{cases}$$

Where,

$$\begin{aligned} \hat{R}_{ijt} &= \text{Final cleaned rainfall value for station } i, \text{ month } j, \text{ year } t,\\ T_i &= \text{Total number of years in the dataset for station } i. \end{aligned}$$

3.2. Annual Rainfall Computation

The annual rainfall of station i for year t was calculated as

$$A_{it} = \begin{cases} \sum_{j=1}^{12} \hat{R}_{ijt}, & \text{if } T_i > 10,\\ \text{not computed}, & \text{otherwise}. \end{cases}$$

3.3. Trend Detection:

For analyzing the trend, we have used two robust non-parametric methods:

1. Modified Mann-Kendall Test
2. Sen's Slope Estimator

3.3.1. ***Modified Mann-Kendall (MMK) Test:*** We have analyzed the presence of monotonic trends using the Modified Mann-Kendall (MMK) test (Mann, 1945; Kendall, 1975).

The test statistic is given by

$$S = \sum_{t=1}^{T_i - 1} \sum_{k=t+1}^{T_i} \operatorname{sgn}(A_{ik} - A_{it})$$

Where,

$$\operatorname{sgn}(A_{ik} - A_{it}) = \begin{cases} +1, & \text{if } A_{ik} - A_{it} > 0,\\[1ex] 0, & \text{if } A_{ik} - A_{it} = 0,\\[1ex] -1, & \text{if } A_{ik} - A_{it} < 0. \end{cases}$$

To account for serial autocorrelation in the rainfall data, we applied the MMK test proposed by Hamed and Rao (1998), which adjusts the variance using the effective sample size (ESS).

The standardized test statistic is computed as

$$Z = \begin{cases} \dfrac{S-1}{\sqrt{\mathrm{var}^*(S)}}, & \text{if } S > 0, \\ 0, & \text{if } S = 0, \\ \dfrac{S+1}{\sqrt{\mathrm{var}^*(S)}}, & \text{if } S < 0, \end{cases}$$

Where, $\mathrm{var}^*(S)$ denotes the adjusted variance and significance was tested at the $\alpha = 0.05$ level. The corresponding Kendall's Tau coefficient, which quantifies the strength and direction of the trend, is defined as

$$\tau = \frac{S}{\binom{n}{2}},$$

Where n is the number of years with data for that station. A positive τ implies an increasing trend, while a negative τ implies a decreasing trend.

3.3.2. ***Sen's Slope Estimator:*** The Sen's Slope Estimator (Sen, 1968) estimates the rate of change per year as

$$\beta = \text{median}\left(\frac{A_{ik} - A_{it}}{k - t}\right), \quad \forall\, k > t$$

This estimator is robust to outliers and does not assume any underlying distribution.

3.4. Cluster Analysis:

For identifying the stations based on their rainfall trend behavior, k-means clustering was applied using the following features:

$$\begin{aligned} \beta &= \text{Sen's Slope (Trend magnitude)}, \\ \tau &= \text{Kendall's Tau (Trend strength)}, \\ Z &= \text{MMK statistic (Trend significance)}, \\ p &= p\text{-value for the Mann-Kendall test.} \end{aligned}$$

Each feature was standardised as

$$z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j}$$

Where,

$$\begin{aligned} x_{ij} &= \text{the } j^{\text{th}} \text{ feature for the } i^{\text{th}} \text{ station}, \\ \mu_j &= \text{mean of feature } j, \\ \sigma_j &= \text{standard deviation of feature } j. \end{aligned}$$

The optimal number of clusters, k, was determined using the Elbow method. Subsequently, k-means clustering was performed to group the stations based on these standardised trend characteristics.

3.5. Visualization

1. To display Sen's slope values, we used bar plots.
2. Time series plots with fitted trend lines are used to highlight rainfall variability over time.
3. Cluster plots illustrate the spatial grouping based on rainfall trends.

4. Results and Discussion

4.1. Rainfall Trend Analysis: Station-wise Assessment

The results of the MMK trend test and Sen's slope estimator across the 17 stations with sufficient data (≥ 20 years) are presented in **Table: 1**. Among them, three stations—Bishalgarh (West Tripura), Chawmanu (Dhalai), and Gandacherra (Dhalai)—have shown statistically significant decreasing trends ($p < 0.05$). These stations also had large negative Sen's slope values: Bishalgarh, $-47.1\ \mathrm{mm\,yr^{-1}}$; Chawmanu, $-25.0\ \mathrm{mm\,yr^{-1}}$; and Gandacherra, $-30.4\ \mathrm{mm\,yr^{-1}}$, indicative of long-term rainfall decline. These areas are particularly at risk given their dependence on agriculture and the fragile nature of the local topography.

In that which did see, Kamalpur (Dhalai) reported a Sen's Slope of $+24.9\ \mathrm{mm\,yr^{-1}}$ and Teliamura (Khowai) that of $+8.2\ \mathrm{mm\,yr^{-1}}$, which they put forward as a mild increase which although present is not stats significant. Also, Amarpur (Gomati) and Sadar (West Tripura) saw a small positive slope of $+6.49\ \mathrm{mm\,yr^{-1}}$ and $+1\ \mathrm{mm\,yr^{-1}}$ respectively. While these are increases we must note that the statistical significance is lacking, which in turn may be a result of natural variation or data issues.

The remaining stations, including Belonia, Bogafa, Dharmanagar, Jirania, Kailashahar, Kanchanpur, Khowai, Sabroom, Sonamura, and Udaipur, predominantly reflected negative slopes but without statistical significance, suggesting a tendency toward declining rainfall without robust trend confirmation.
The remaining stations, including Belonia, Bogafa, Dharmanagar, Jirania, Kailashahar, Kanchanpur, Khowai, Sabroom, Sonamura, and Udaipur, predominantly reflected negative slopes but without statistical significance, suggesting a tendency toward declining rainfall without robust trend confirmation.

Table 1: Results of Rainfall Trend Analysis using Modified Mann–Kendall Test and Sen's Slope

Station	Years	Z corrected	p corrected	Tau	SenSlope	Significant	TrendType
Amarpur	25	0.7240	0.4691	0.1067	6.4854	FALSE	Non-significant
Belonia	25	-0.9812	0.3265	-0.1436	-15.5433	FALSE	Non-significant
Bishalgarh	23	-3.5390	0.0004	-0.5336	-47.0929	TRUE	Decreasing
Bogafa	24	-0.5920	0.5538	-0.0725	-4.9809	FALSE	Non-significant
Chawmanu	24	-3.2107	0.0013	-0.3478	-25.0121	TRUE	Decreasing
Dharmanagar	25	-1.4729	0.1408	-0.1400	-12.5185	FALSE	Non-significant
Gandacherra	24	-3.2665	0.0011	-0.3551	-30.4238	TRUE	Decreasing
Jirania	23	-1.6903	0.0910	-0.2569	-24.7235	FALSE	Non-significant
Kailashahar	25	-1.8918	0.0585	-0.2733	-25.8533	FALSE	Non-significant
Kamalpur	25	1.1444	0.2525	0.1667	24.9438	FALSE	Non-significant
Kanchanpur	24	-0.9178	0.3587	-0.1377	-12.6924	FALSE	Non-significant
Khowai	25	-1.7983	0.0721	-0.2600	-17.2344	FALSE	Non-significant
Sabroom	25	-0.7707	0.4409	-0.1133	-8.7222	FALSE	Non-significant
Sadar (AD Nagar)	25	0.0701	0.9441	0.0133	1.0131	FALSE	Non-significant
Sonamura	24	-0.5209	0.6024	-0.0797	-5.6887	FALSE	Non-significant
Teliamura	24	0.8682	0.3853	0.1304	8.2294	FALSE	Non-significant
Udaipur	25	-0.7751	0.4383	-0.1400	-12.6558	FALSE	Non-significant

4.2. Visual Patterns of Rainfall Change

To provide a visual understanding, **Figure:1** presents a bar graph of Sen's slope estimates at all 17 stations, grouped by trend significance. The figure clearly distinguishes significant declines in stations such as Bishalgarh, Chawmanu, and Gandacherra, which appear in red. Other stations are marked sky blue, indicating nonsignificant trends. The horizontal dashed line at zero serves as a baseline for neutral change.

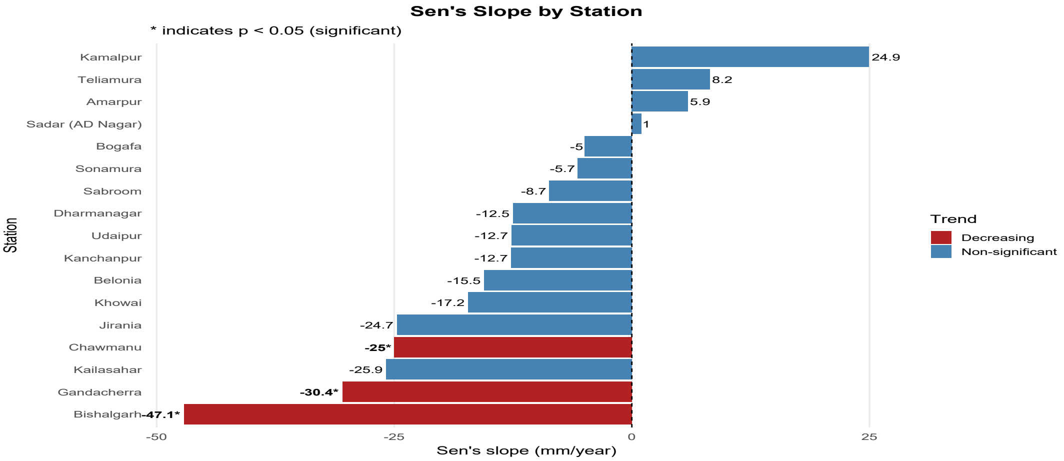

Figure 1: Bar Plot of Sen's Slope Estimates for Annual Rainfall Trends

More information is obtained from Figure:2, showing annual rainfall time series at each station considered during the analysis period with linear trend lines superimposed. A seemingly uneven behaviour heterogeneity across the state is discernible from the figure. Significant downward trends exist at sites such as Bishalgarh, Gandacherra, and Chawmanu, manifested by abrupt and consistent annual total decreases, although many other alternative stations exhibit weak non-significant slopes. Jirania, Khowai, Belonia, and Kailasahar, e.g., show slow downward decreases but which are overridden by strong interannual variability. Such locations as Khowai, Dharmanagar, and Sabroom remain especially prominent due to their strong oscillations, years of precipitous decrease often being balanced off by strong increases, highlighting the complexity of rainfall dynamics within regions subject to climatic variability. By sharp contrast, few locations—most significantly Kamalpur, Teliamura, and Amarpur—are indicative of gentle rising trends, although these continue to be statistically insignificant and most likely indicative of localised variability rather than strong long-term increases. Generally speaking, the figure highlights the fact that even though year-to-year variability is extreme, the larger-scale overall trend within most of Tripura is toward slow drying, the midregion bands suffer the steepest and most ominous decreases.

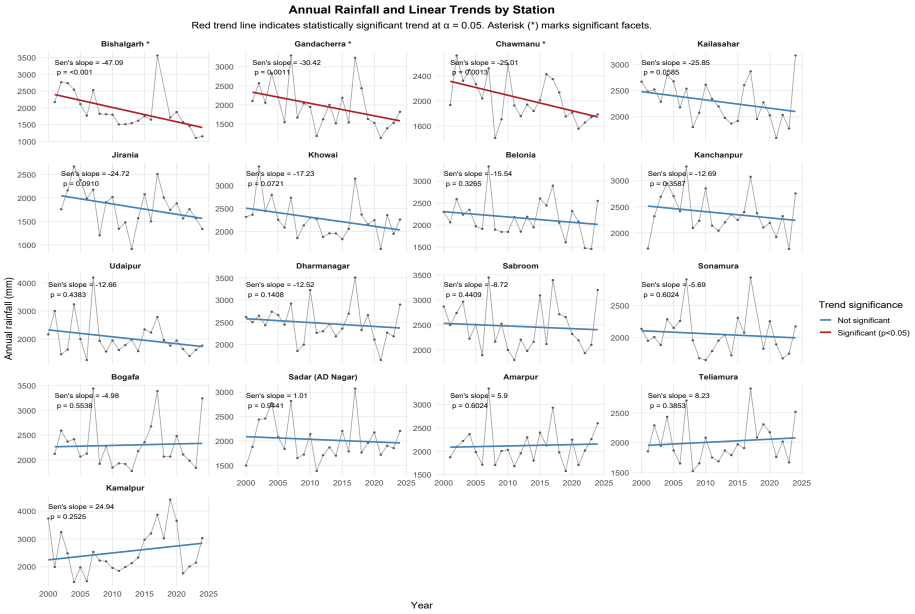

Figure 2: Time Series Plot with Linear Trends for Annual Rainfall.

4.3. Regional Clustering of Rainfall Trends

To understand spatial patterns in rainfall variability, k-means clustering was applied based on Sen's Slope, MMK Z scores, and corrected p-values. The elbow method **(Figure:3)** suggested that three groups best capture the heterogeneity of the data set.

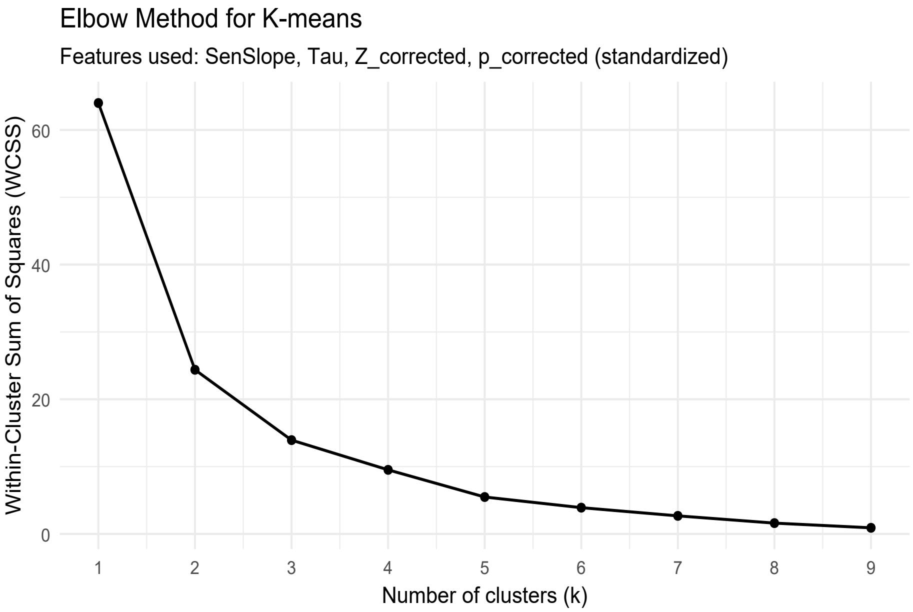

Figure 3: Elbow Plot for Optimal Cluster Selection.

The stations are grouped into the following clusters (summarised in **Table:2** and visualised in **Figure:4**):

i. Cluster 1 (Mild Decreasing Trend, Non-significant): Comprises stations like Belonia, Bogafa, Dharmanagar, Kanchanpur, Sabroom, Sonamura, and Udaipur. They show relatively gentle decreases or unchanged rainfall conditions, with no long-term statistically significant decline. Their clustering indicates an area of relative hydroclimatic stability, geographically covering mostly the southern and western parts of the state.

ii. Cluster 2 (Strong Decreasing Trend): Comprises the stations Bishalgarh, Chawmanu, Gandacherra, Kailasahar, Jirania, and Khowai. This group is comprised mostly of stations having strongly negative rainfall trends, three of which—Bishalgarh, Gandacherra, and Chawmanu—have statistically significant reductions. This grouping geographically relates to the northeastern hilly belt and the geographical center of Tripura, implying this region is most susceptible to continuous rainfall loss.

iii. Cluster 3 (Mild Increasing Trend): Includes Amarpur, Kamalpur, Teliamura, and Sadar (A.D. Nagar), predominantly located in central and southeastern Tripura. These stations show upward trends, though not statistically significant.

Table 2: Cluster-wise summary of rainfall trend analysis results.

Station	SenSlope	Tau	Z corrected	p corrected	Significant	TrendType	Cluster
Belonia	-15.5433	-0.1436	-0.9812	0.3265	FALSE	Non-significant	1
Bogafa	-4.9809	-0.0725	-0.5920	0.5538	FALSE	Non-significant	1
Dharmanagar	-12.5185	-0.1400	-1.4729	0.1408	FALSE	Non-significant	1
Kanchanpur	-12.6924	-0.1377	-0.9178	0.3587	FALSE	Non-significant	1
Sabroom	-8.7222	-0.1133	-0.7707	0.4409	FALSE	Non-significant	1
Sonamura	-5.6887	-0.0797	-0.5209	0.6024	FALSE	Non-significant	1
Udaipur	-12.6558	-0.1400	-0.7751	0.4383	FALSE	Non-significant	1
Bishalgarh	-47.0929	-0.5336	-3.5390	0.0004	TRUE	Decreasing	2
Chawmanu	-25.0121	-0.3478	-3.2107	0.0013	TRUE	Decreasing	2
Gandacherra	-30.4238	-0.3551	-3.2665	0.0011	TRUE	Decreasing	2
Jirania	-24.7235	-0.2569	-1.6903	0.0910	FALSE	Non-significant	2
Kailasahar	-25.8533	-0.2733	-1.8918	0.0585	FALSE	Non-significant	2
Khowai	-17.2344	-0.2600	-1.7983	0.0721	FALSE	Non-significant	2
Amarpur	6.4854	0.1067	0.7240	0.4691	FALSE	Non-significant	3
Kamalpur	24.9438	0.1667	1.1444	0.2525	FALSE	Non-significant	3
Sadar (AD Nagar)	1.0131	0.0133	0.0701	0.9441	FALSE	Non-significant	3
Teliamura	8.2294	0.1304	0.8682	0.3853	FALSE	Non-significant	3

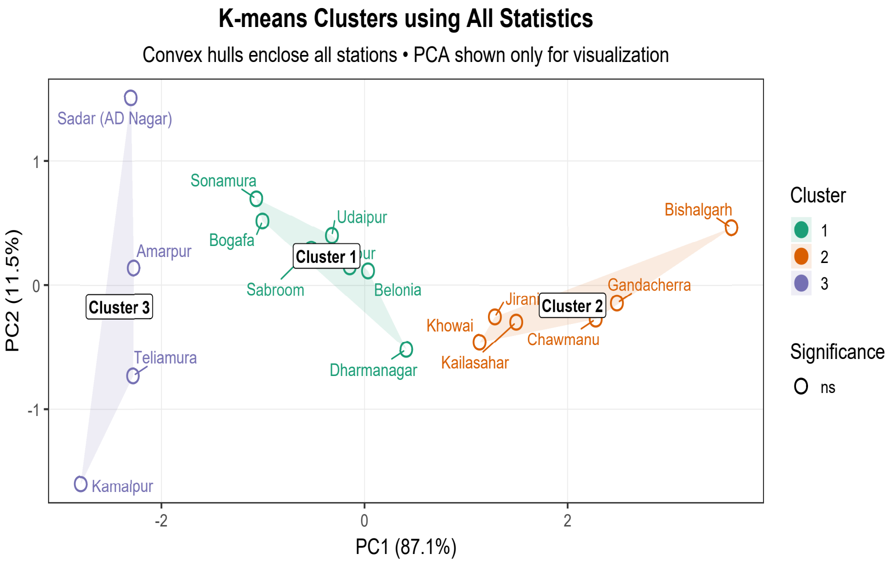

Figure 4: K-means Clustering of Stations Based on Rainfall Trend Indicators.

This clustering approach allows for a regional understanding of rainfall change, potentially linked to geography, elevation, and land-use differences. For instance, Cluster 2's strong declining trend includes stations from hilly areas like Dhalai and West Tripura, which are more sensitive to deforestation and soil degradation.

5. Conclusion

This study has offered an in-depth assessment of rainfall variability in Tripura over the past two decades. Using the Modified Mann-Kendall test, Sen's slope estimator, and k-means clustering, the analysis has uncovered significant spatial diversity in rainfall trends. Three stations—Bishalgarh, Chawmanu, and Gandacherra—have shown marked and statistically significant declines, suggesting growing vulnerability to water scarcity and ecological stress. In contrast, stations such as Kamalpur, Teliamura, and Amarpur have shown mild, non-significant increases, highlighting localised variability that warrants continued monitoring. The clustering analysis also highlights regional variations, classifying stations into three rainfall patterns with different properties. The results highlight region-based water management approaches: water resilience measures within decline trend areas and enhanced rainwater storage, as well as floods control measures within rising trend areas. More broadly speaking, we demonstrate that Tripura's precipitation is affected as much by internal climatic variations as by bigger uncertainties due to environmental and human-induced changes. There is thus a clear argument for adaptive and forward-focused policy which synthesises scientific evidence with practical planning.

5.1. Future Research

Although the current study establishes a solid foundation, several promising directions remain open for further exploration:

i. Integration of Remote Sensing Data: The incorporation of satellite-based rainfall products such as TRMM (Tropical Rainfall Measuring Mission) and GPM (Global Precipitation Measurement) can enhance spatial coverage and complement ground-based observations, offering a more detailed representation of rainfall patterns.

ii. Coupling with Climate Models: Linking observed rainfall variability with outputs from regional climate models (RCMs) could provide insight into projected future changes under different climate change scenarios, aiding in long-term planning and vulnerability assessments.

iii. Multivariate Hydro-Climatic Analysis: A broader understanding of water availability could be achieved by incorporating additional variables such as temperature, soil moisture, and evapotranspiration. This multivariate approach would provide a more holistic perspective on hydro-climatic dynamics.

iv. Human-Environment Interactions: Further studies can investigate the influence of anthropogenic factors—such as deforestation, urbanisation, and land use change—on rainfall behaviour, potentially revealing important feedbacks between human activity and climatic systems.

v. Uncertainty-Based Approaches: The application of fuzzy logic, neutrosophic sets, and other soft computing methods can be valuable in dealing with the inherent uncertainty and imprecision in climatic datasets, thereby improving robustness in decision-making processes.

vi. Risk and Policy Applications: Bridging rainfall variability analyses with hydrometeorological risk indicators—such as drought and flood indices—can support the development of early warning systems and inform adaptive policy interventions for climate resilience.

Pursuing these directions can significantly enrich our understanding of rainfall variability and support the development of sustainable water resource strategies in Tripura and other regions facing similar climatic uncertainties.

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Data availability: The processed dataset and analysis scripts can be obtained from the corresponding author upon reasonable request.

Author's Contribution: All the authors have equal contributions for the preparation of this article.

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