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Rainfall Variability and Structural Shifts in South West Garo Hills, Meghalaya: Statistical Diagnostics and Agricultural Implications

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ABSTRACT

Background: The paper is an exploration of rainfall variability in the South West Garo Hills, one of the areas that is very sensitive to monsoonal variations of Meghalaya within India.

Methods: The monthly rainfall from October 2014 to August 2024 were undertaken to analyses and capture short term variability and localized structural changes. Though this data set duration does not represent long term climatic variability but provides valuable insights into stochastic rainfall behavior and agricultural implications at the district scale. The Shapiro-Wilk, Bartels and Wald-Wolfowitz tests were performed to test the normality, randomness and stationarity of the mean respectively. To detect trends, the Mann-Kendall test and its variants, along with Sen's slope estimator were utilized. Pettitt test, Buishand tests and CUSUM-PELT were used to find the Change-point detection. The visualization of localized changes and residual behavior was made using segment-wise linear regression technique and additive seasonal decomposition.

Result: The test provided rainfall series was non-normal, non-random and non-stationary. The Mann-Kendall and its variants revealed insignificant monotonic trends with $Z \approx -0.50$, $p > 0.6$, Sen's slope ≈ -0.012 mm/month. However, the Pettitt's test and segmented regression detected a short-term structural change between June 2019 and July 2020 along with $p = 0.045$, $R^2 = 0.317$. Moreover, Seasonal decomposition indicated weak seasonality with stochastic residuals. The rainfall variability showed stochastic nature with localized structural shifts but no persistent long-term trends during the study periods. Only univariate statistical methods are insufficient to capture rainfall anomalies in the study area. Future studies should incorporate machine-learning approaches to improve rainfall prediction and early warning systems in Northeast India, particularly in Meghalaya. The novelty of this research is the combination of multiple statistical methods and visualization techniques.

Key words: Change-point detection, Modified Mann-Kendall test, Rainfall variability, Seasonal decomposition, Sen's slope.

INTRODUCTION

The rainfall is an important factor in the maintenance of water cycle on Earth. It sustains important elements to achieve the ecological balance, enhances the agricultural output and manages the water resources. Rural lives of the northeastern state and, in particular, Meghalaya, depend on the monsoon rains. The South West Garo Hills is an agrarian district mainly. It also greatly reacts to changes in rain that impacts on crop growth, water diversity and general livelihood in the local communities.

It is essential to consider a change in rainfall over space and time in order to plan, develop sustainably and respond to climate changes. Further, the air movements and landforms and the interactions between oceans and land complicate rain patterns. The analyses based on meteorological data, allow assessment of short term variability, localized structural changes and seasonal patterns. This 10 year dataset is not sufficient to infer long term climatic trends but definitely is adequate for identifying stochastic fluctuations relevant to agricultural planning. It was also found in a study that the amount of rainfall events is potentially decreasing and the intensity of extreme rainfall events is increasing in most regions (Goswami *et al.*, 2006; Krishnamurthy *et al.*, 2009), thus showing the multifaceted nature of the rainfall variations and the necessity of the analytical frameworks. Agriculture in India primarily relies upon monsoon precipitation and this inconsistency has major serious food security and water

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resource management effects (Milly *et al.*, 2008). Climatological data should be carefully analyzed to make informed decisions that would apply to agricultural practices (Yue and Wang, 2004).

The nonparametric tests that have been already applied to examine the rainfall trends include Mann-Kendall test, Sen slope estimator and Pettitt test (Hirsch *et al.*, 1982; Pettitt, 1979). The modified form of Mann-Kendall test has also been used to explain the serial correlation, non-normality, which improves the dependability of the trend-detection information (Yue and Wang, 2004). The study area rainfall is a stochastic one although it has the impact that it has to agricultural farming, primarily. A strong multi-method statistical framework is then of great significance in the analysis of the abnormalities of the rainfall. The novelty of research lies in combining multiple statistical diagnostics with visualization techniques to detect localized structural shifts. Unlike previous single variable approaches, this framework incorporates trends detection, change point analysis and seasonal decomposition to show the short term anomalies in rainfall variability that are critical for agricultural decision making.

These methods provide more information about frequency components and nonlinearity that might be missed by traditional methodologies, as illustrated in Fig 3, where ten change points (2015-2024) reveal localized shifts and residual variance increases from 45.2 to 112.8 across segments A number of studies have focused on variability of rainfall that is susceptible to monsoon variation in Meghalaya and other North East states. Chakraborty *et al.* (2023) demonstrated that climate change has affected the distribution patterns of rainfall in Northeast India where it has inevitably caused water shortage and agricultural problems. According to Singh and Kumar (2024), extreme rainfall events reduced statistically significantly on the basis of IMD gridded datasets but the patterns of convective indices like CAPE and CIN showed mixed trends. Extreme variability of rainfall in Assam and Tripura compared with non-stationary frequency models and genetic algorithms indicated that actual variability could not be modeled using the traditional stationary models (Agarwal *et al.*, 2022). Ali *et al.* (2025) contended that the traditional univariate strategies lack the capability to determine the localized changes in the rainfall data because various diagnostic procedures revealed. The study by Mahanta *et al.* (2021) revealed high levels of intra-seasonal variations in the rainfall pattern amongst Central and Northeast India. Similarly, Borah *et al.* (2022) also recorded the intra-annual variability of rainfall in Assam through non-parametric. Recently, Ali *et al.* (2025); Jain *et al.* (2023); Sangma *et al.* (2020) affirmed that the variability in rainfall patterns across Northeast India has direct effect on the agricultural productivity as well as water resource planning.

This paper will discuss the purpose of understanding the patterns of rainfall of the study periods. These methods provide more information about frequency components and nonlinearity that might be missed by traditional methodologies, as illustrated in Fig 3, where ten changepoints (2015-2024) reveal localized shifts and residual variance increases from 45.2 to 112.8 across segments. The results of this research will contribute to sustainable management of water resources and climate-resistant agricultural planning of the research area. The following goals can be obtained by the current study:

1. To detect structural shifts and localized rainfall anomalies, moving beyond the conventional emphasis on long-run scale trends.
2. To use the Mann-Kendall test and its variants to identify seasonal variations in rainfall pattern.
3. To use change-point techniques for identifying structural shifts in the rainfall time series data.
4. To use segment-wise linear regression models for detecting monotonic trends and the model fitness.
5. To examine the stochastic residual and seasonality by using additive decomposition of the rainfall time series.

MATERIALS AND METHODS

The present study was carried out at the Department of Mathematics and IT under Faculty of Management Studies at The ICFAI University Meghalaya, in collaboration with the Department of Statistics, MIU, Imphal and the Department of Statistics, Assam Down Town University, Guwahati. Rainfall data for the period 2014-2024 were obtained from the BDO, Ampati. Various Statistical tests were analyzed with visualizations using R software with some packages. Descriptive statistics were computed to characterize rainfall variability.

Study area and data collection

The South west Garo Hills quarter of Ampati, Meghalaya, India was the location where the study was done as indicated in Fig 1 in blue color. Ampati is the executive center of the district with a latitude of 25°27.505°N and longitude of 89°56.456°E. The block development office (BDO), Ampati, which is South west Garo hills of Meghalaya, obtained monthly rainfalls data since September 2014-April

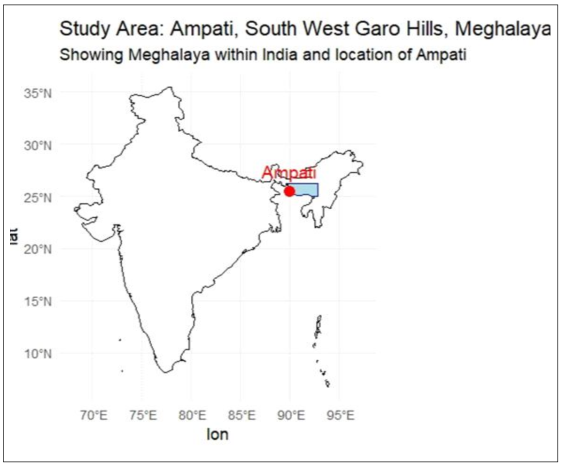

Fig 1: Site of the study in Ampati, South West Garo Hills district in Meghalaya, India.

2024 that were used to conduct statistical research. The town of Ampati is approximately 52 kilometers away on a straight-line distance, instead of 148 kilometers, as found between the district headquarters of West Garo Hills and the town of Tura. The geographical boundaries of this district share with South Salmara Mankachar district of Assam and Kurigram district of Bangladesh respectively to the north and south. It has a transnational boundary of approximately 35 kilometers on the southern and western borders which borders Bangladesh. About 1/3 of the South West Garo Hills villages of the state are set as border townlets by the Border Area Development Department and stress the strategic and socio-profitable value of the area. A different demographic community is found in the region; the Garos is the most common indigenous community on the hilly terrain, the Muslims and the Hindus form a significant population segment, particularly concentrated in market towns and lowland settlements. This coexistence of tribal and non-tribal communities contributes to a diverse socio-cultural fabric, which in turn influences livelihood strategies, settlement patterns and local responses to rainfall variability.

Tools for data analysis

The data on monthly rain falls were analyzed using the RStudio IDE. The data were analyzed using the R-packages: Trend, trendchange, modifiedmk and ggplot2.

The following statistical techniques were applied:

Shapiro-Wilk test: To assess normality Shapiro-Wilk test was employed.

Bartels and Wald-Wolfowitz tests: To test randomness and stationarity.

Mann-Kendall test: A non-parametric test for monotonic trend detection. The original Mann-Kendall test determines whether or not a time series has a monotonic trend. The test did not require the data to normal or linear but should have no autocorrelation. The null hypothesis for this test was that there existed no trend and the alternative hypothesis was that there was a trend in two-sided test or there were an upward or downward trend in the one-sided test. Let, x_1, x_2.., x_n, be the time series, the Man-Kendall test used to the S statistic as given below.

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} \text{sign}(X_j - X_k) \qquad ...(1)$$

Where,

n = Denoted the data length, denoted the observations at j and k = times with:

$$\text{Sign}(\times) = \begin{cases} -1, \text{ if } x < 0 \\ \text{o if } x = \text{o} \\ 1 \text{ if }, x > \text{o} \end{cases} \qquad ...(2)$$

In this case, the mean and variance of the test statistic S respectively were given by

mean E(S)= 0 and Var (S) =

$$\sigma_2 = \{n(n-1)(2n+5) - \sum_{j=1}^{p} t_j (t_j - 1)(2t_j+5)\}/18 \qquad (3)$$

Here,

p= Denoted the number of tied groups.

t= Denoted the number of tied groups in the data.

The S test statistic follows approximately normal provided the following Z-transformation was employed.

$$Z = \begin{cases} (S - 1)/\sigma, \text{ if } S > 0 \\ 0 \text{ if } S = 0 \\ (S + 1)/\sigma \text{ if, } S > 0 \end{cases}$$

The Kendell's tau $\iota = \frac{S}{D}$ Where D was given as follows:

$$D=[1/2n(n-1)-1/2\sum_{j=1}^{p}(t_j - 1)]^{1/2} [1/2n(n-1)]^{1/2} \qquad (4)$$

If there was no monotonic trend as stated, the null hypothesis in the data then Z ~ N (0,1) for a time series with more than 10 elements.

Modified Mann-Kendall test: The original Mann-Kendall Test is modified for Adjusting the autocorrelation.

Wallis and Moore Phase-Frequency Test: This non-parametric test used to evaluate the randomness of fluctuations and detect hidden trends or cyclic patterns in the monthly rainfall time series data set.

Here the Null hypothesis H_0= The monthly time series rainfall data was completely random (white noise) and the alternative hypothesis. H_1= The monthly time series rainfall data was not completely random.

For a monthly rainfall time series data with n number of observations, the standard test statistic Z was calculated by utilizing H as the number of phases and under the null hypothesis.

$$Z = \frac{|H - E(H)|}{\sqrt{Var(H)}} \sim N(0, 1)$$

Where,

E(H) = 1/3(2n-7).

Var(H) = 1/90(16n-29).

Sen's slope estimator: This method is used to quantify the magnitude of detected trends.

Usually, the method of least-square estimate is employed for estimating the slope of a regression line that fits the set of paired data. This method cannot be used if the data elements approximately do not fit a straight line. This approach is also sensitive to outliers.

As an alternative, a more robust, nonparametric method to estimate slope (of course, the linear rate of change), known as Sen's slope. Sen's slope (Sen, 1968) estimator is also used to estimate the magnitude of change of slope θ. The slope θ an be obtained from N pairs of data as follows

$$\text{Sen's slope } \theta_1 = \text{Median } \frac{X_k - X_j}{k - j} \quad i=1, 2, 3,...., N, k>j \qquad (5)$$

Where,

x_k and x_j = Characterized the values of data at.

k, j times and θt = Were the median slope.

Respectively and the intercepts are computed for each timestep t was given by

$$a_t = x_j - \theta_i * t \quad (6)$$

To calculate a 1-α confidence interval for Sen's slope (lower, upper).

Where,

$$N = C(n, 2),\ k = se \bullet z_{crit}$$
$$lower = m_{(N-k)/2} \quad upper = m_{(N+k)/2+1}$$

Where,

N= Number of pairs of time series elements (x_i, y_i).

Where,

i<j and se=σ= The standard error for the Mann-Kendall test.

m_h= The h^{th} smallest in the set $\{(x_j–x_i)/(j–i): i<j\}$ and z_{crit} = The 1-α/2 critical value for the normal distribution.

Pettitt test: This was the test that was used to identify single change-points.

The model generally employed to find one change of direction in climate series or rainfall series or environmental series of continuous data of Pettitt. In this case, the null hypothesis states that the T variables are distributed using a one or more distributions are of the same location parameter (no change points) when the alternative hypothesis states that there is at least one change. The non-parametric statistic KT was provided to be.

$$K_T = \max|Ut, T|, \quad (7)$$

Where,

$$Ut, T = = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} \text{sign}(X_j - X_k) \quad (8)$$

The change-point of the data series was located at $K_{T,}$ provided that the statistic was significant.

The significant probability of non-parametric statistic K_T is approximated for p≤0.05 with:

$$p = 2\exp\left(\frac{-6K_t^2}{T^3+T^2}\right) \quad (9)$$

Seasonal Mann-Kendall and CSMK: These tests were used to assess seasonal trends.

The Mann-Kendall g^{th} season statistic was given by

$$S_g = \sum_{i=1}^{n} \sum_{j=i+1}^{n} \text{sgn}(X_j g - X_i g),\ g = 1,2,...,m \quad (10)$$

According to Hirsch *et al.* (1982), the seasonal Mann-Kendall statistic, $\hat{S}$ for the entire series was calculated according to:

$$\hat{S} = \sum_{g=1}^{m} S_g$$

The CSMK test was implemented in case the data were related to *e.g.* the previous months.

Time series decomposition and regression: Time series data were visualized through the linear regression and additive time series decomposition as the analysis of localised changes, seasonal changes, trend and residual changes.

RESULTS AND DISCUSSION

Rainfall descriptive statistics

The data of the monthly rainfall since September 2014 to April 2024 presented a large range of variations. The minimum was 0.00 mm and the maximum were 812.80 mm. The mean amount of rainfall was 132.58 mm per month with median of 53.80 mm. The standard deviation was 170.20 mm, indicating substantial variability in the dataset. Skewness of the rainfall data set was 1.67 mm, indicates positively skewed distribution, reflecting the influence of occasional extreme rainfall events that pulled the average upward. Kurtosis was 2.65, suggesting a moderately peaked distribution with heavier tails compared to a normal distribution. These results confirm that rainfall

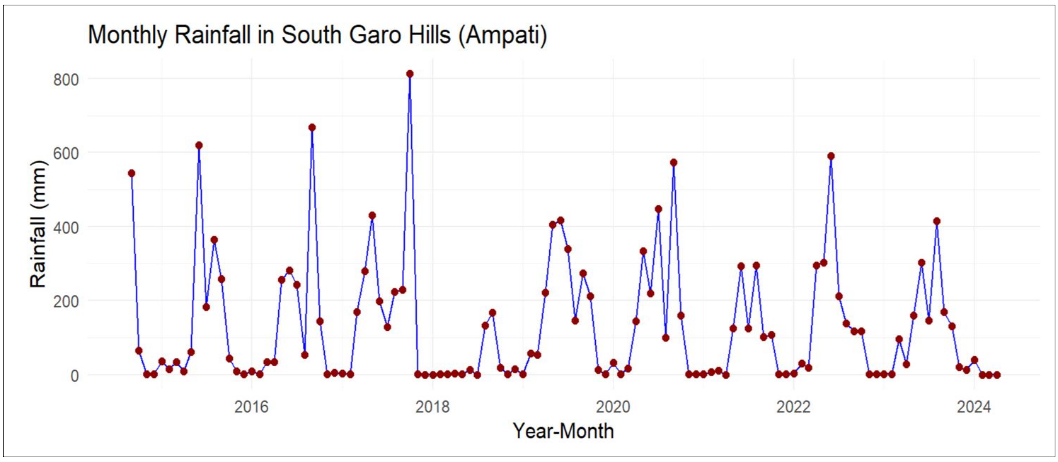

Fig 2: Monthly rainfall time series (September 2014 April 2024).

variability was high, with extreme values contributing disproportionately to the overall spread of the rainfall. However, the combination of a relatively low median and a high standard deviation highlights the stochastic nature of rainfall in the region, where most months experienced modest precipitation but occasional bursts of extreme rainfall created significant dispersion in the data.

The distribution of the rain patterns of this study area was inadequate and imbalanced as it was implied by the initial descriptive statistics above as depicted in Fig 2. Thus, parametric and classic non-parametric trend analysis tools, structural change detection tools, were also further investigated.

In analyzing this multidimensional nature of rainfall data, a comprehensive series of statistical tests to assess normality, randomness, independent, stationary, trends analysis and changing point were used to supplemented by visually presentable data including time series decomposition and regression analysis.

Normality, randomness and stationarity tests

The W of the Shapiro-Wilk test was 0.78331, p = 0.001 and normality was rejected. Bartels, Wald-Wolfowitz and Wallis-Moore tests also disapproved of random rainfall and were also in agreement that the rainfall series was non-normal, non-random and non-stationary as indicated in Table 1.

Therefore, the results of these successions of statistical tests proved that rainfall has strong deviations related to normality, randomness and stationarity that impelled the subsequent inquiry on the existence of underlying structural patterns or patterns as the following.

Trend analysis

The Mann-Kendall test value gave Z= -.5036, tau= -.0319, p=.6145, showing that there is no significant monotonic relationship. The slope of the Sen was = -0.012 mm/month, 95% intercept = (-0.2938, 0.1654). Variations of Mann-Kendall such as MMKY and PWMK and TFPWMK failed to find significant trends as they produced Z-values of (Z = 0.7372, p = 0.4609 and Z = 0.6913, p = 0.4894, respectively) of real significant monotonic trends even when conditioned on serial correlation.

Seasonal diagnostics

Tau and p values of Mann-Kendall were equal to -0.026, 0.724 and CSMK tests indicated the absence of significant seasonal trends. Other weak negative slopes with wide confidence intervals were also established by the Bootstrap-based seasonal Kendall tests which support stochastic behavior of the rainfall series.

Change-point detection

Pettitt's test and Buishand's tests highlighted to a possible structural shift around June 2019 (index 38), though p-values were not significant. CUSUM–PELT analysis detected multiple change points (indices 4, 16, 33, 41, 45, 57, 70, 94, 107, 113, 116) suggesting several localized shifts Buishand (1982).

Table 1: Results of normality, randomness and stationarity tests for monthly rainfall time series.

Test	Test statistic	p value	Decision
Shapiro-Wilk normality test	W = 0.78331	8.56×10^{-12}	Non-normal distribution (reject H_0)
Wallis and moore phase-frequency test	z = 2.6634	0.0077	Series is not random (reject H_0)
Bartels test	RVN = 0.81333	6.43×10^{-12}	Series is not random (reject H_0)
Wald-Wolfowitz runs test	z = 3.5063	0.00045	Series is not independent or stationary (reject H_0)

H0= Null hypothesis; significance tested at 5% level.

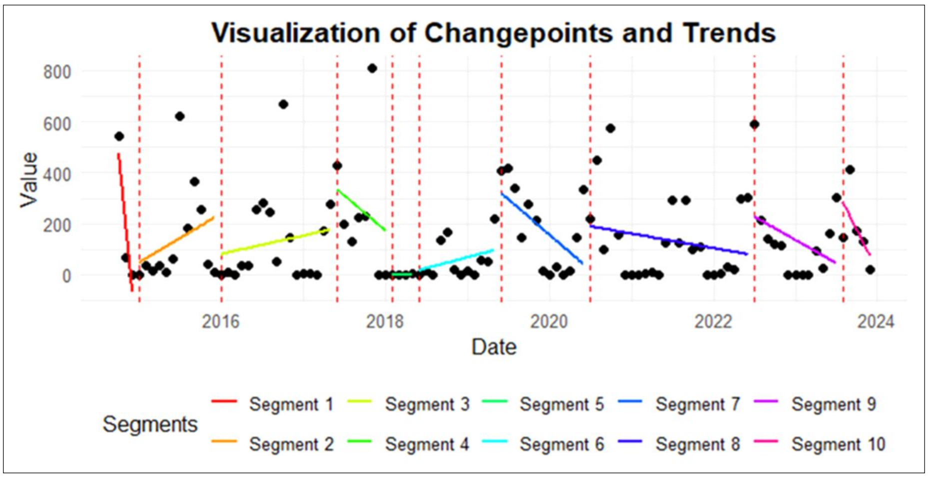

Fig 3: Segment-wise linear regression analysis showing structural change around June 2019.

Segment-wise regression with visualization

Segment 7 (June 2019-July 2020) showed a statistically significant decline yielded with slope = -0.76, p = 0.045, R^2 = 0.317 as shown in the Fig 3. However, other segments exhibited weak or insignificant trends, with low explanatory power.

Seasonal decomposition

Additive decomposition revealed weak seasonality and irregular residuals as shown in Fig 4. No clear long-term trend was observed, consistent with Mann-Kendall results. Residuals displayed stochastic fluctuations, validating the non-normal and random characteristics of rainfall.

The rainfall in South West Garo Hills was highly variable with mean= 132.58 mm, SD= 170.20 mm, with positive skewness= 1.67 and moderate kurtosis= 2.65, indicating the disproportionate influence of extreme rainfall events. Despite this variability, the Mann-Kendall diagnostic tests were utilized, fails to detect substantial monotonic changes, indicating the absence of long-term directional trends in rainfall. The findings are consistent with earlier studies in Northeast India that reported irregular rainfall variability without strong monotonic trends (Nongkynrih and Husain, 2011; Mahanta *et al.*, 2021; Borah *et al.*, 2022). A similar conclusion were drawn in MAUSAM (Singh and Kumar, 2022) and in recently published articles in the Indian Journal of Agricultural Research, highlighted the high rainfall variability but weak or inconsistent long-term trends in Meghalaya and adjoining hill regions (Chakraborty *et al.*, 2025; Gautam *et al.*, 2024). Thus, these results agree with the evidence of, reinforcing the conclusion that rainfall in this region is intermittent and highly variable, but not characterized by sustained monotonic shifts.The period of the short-term drop in Segment 7 (June 2019 to July 2020) is of particular interest as it is accompanied by the anomalies that were revealed in regional studies (Saji *et al.*, 1999; Chakraborty *et al.*, 2023; Singh and Kumar, 2024). In spite of no statistically significant findings of the homogeneity tests, the fact that a number of approaches converged to mid-2019 implies that a real structural change has occurred, which is consistent with the findings of Kumar and Jain (2015).

This pattern of seasonal decomposition demonstrated that seasonality was weak rather than being caused by internal seasonal processes, which suggested that a significant impact of large-scale climatic processes including ENSO phases and regional circulation anomalies but not internal seasonal processes on rainfall variability in Meghalaya (Sahu and Behera, 2023; Ghosh *et al.*, 2022). The non-uniform residuals also serve to point out the drawbacks of the univariate statistical methods, which (Ali *et al.*, 2025; Milly *et al.*, 2008) also note. (Cleveland *et al.*, 1990; Zhou and Wang, 2021). In brief, the paper revealed that variation in rainfall over the study area could not be exhaustively explained using conventional parametric or non-parametric tests. This outcome highlights a methodological recommendation such as more sophisticated approaches, particularly machine learning techniques, are necessary to detect non-linear and localized anomalies. These recommendations are consistent with recent advances in hydrological research (Cleveland *et al.*, 1990; Zhou and Wang, 2021), which focused on the potential of machine learning for rainfall anomaly detection rather than reporting it as a completed case study of successful rainfall analysis. The findings have direct application in Agriculture in Meghalaya where crop productivity, accomplishment of irrigation plans and rural livelihoods heavily depend on the variability of rainfall. The region should develop climate-resilient agricultural strategies by having reliable forecasting and early warning systems (Jyothi *et al.*, 2022; Singh *et al.*, 2009; Ashkra *et al.*, 2023).

Practical implications

The key findings that this research has are as follows and based on the findings listed the following implications can be made.

The values of rainfall in South West Garo Hills (2014-2024) varied widely.

- The statistical tests allowed concluding that the rainfall series was not-normal, non-random and non-stationary.

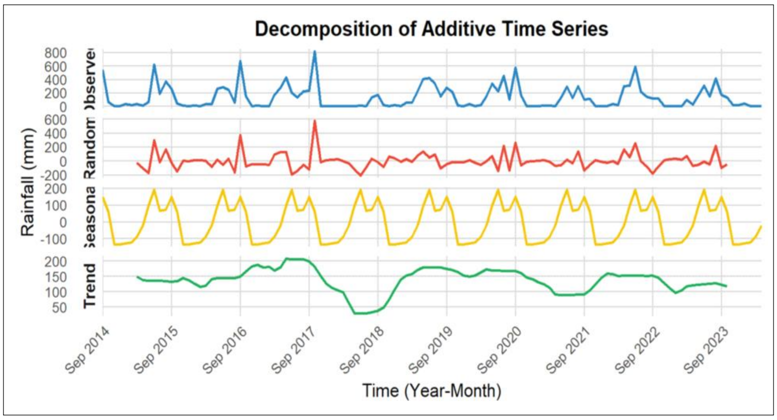

Fig 4: Additive time series decomposition of monthly rainfall (September 2014-April 2024) showing observed, trend, seasonal and residual components.

- The slope tests by Mann-Kendall and Sen showed that the long-term monotonic trend was not significant.
- It had been identified that a localized structural change existed in the data series between June 2019-July 2020, which showed a short-run decrease.
- Seasonal decomposition had weak seasonality and corrupt irregularity in residual values, which supported stochastic rainfall.

Policy makers can use the findings to formulate adaptive water management policies to solve rainfall variability, uncertainty and make sure there is a proper distribution of irrigation resources. Farmers of the study area even its adjacent sites may adjust crop planting schedules and adopt water-saving practices in response to irregular rainfall patterns. In consequence, these measures reduce the risks associated with rainfall variability and strengthen the sustainability of agriculture in the Garo Hills of Meghalaya (Jyothi *et al.*, 2022; Ashkra *et al.*, 2023).

CONCLUSION

South West Garo Hills rainfall is inconsistent, intermittent and characterized by localized changes as opposed to the global tendencies. This uncertainty has direct impact on agricultural planning, crop production and food security. The use of traditional statistical tools is not enough and a combination of machine learning and sophisticated prediction models would enhance rainfall prediction and early warning systems. This is essential to climate-resilient agriculture in Meghalaya and Northeast India.

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Disclaimers

The views and conclusions expressed in this article are solely those of the authors and do not necessarily represent the views of their affiliated institutions. The authors are responsible for the accuracy and completeness of the information provided, but do not accept any liability for any direct or indirect losses resulting from the use of this content.

Conflict of interest

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