



Spatio-temporal analysis of rainfall dataset in the Mandakini Watershed, India using Mann-Kendall, Sen's slope, and ITA approach

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सार – हाल के दशकों में जलवायु परिवर्तन एक महत्वपूर्ण वैश्विक चिंता का विषय बन गया है और वर्षा में होने वाले परिवर्तन इसके प्रभावों को समझने में महत्वपूर्ण भूमिका निभाते हैं। वर्षा का स्थानिक-कालिक विश्लेषण वर्षा के प्रतिरूपों में होने वाली परिवर्तनशीलता की जानकारी प्रदान करता है। इस अध्ययन में 1983-2022 के बहु-कालिक वर्षा अभिलेखों का विश्लेषण किया गया है, जिसमें $0.25^\circ \times 0.25^\circ$ रिज़ॉल्यूशन वाले भारत मौसम विज्ञान विभाग (IMD) के ग्रिडित आँकड़ा-समुच्चय का उपयोग किया गया है। मंदाकिनी जलग्रहण क्षेत्र में 5% सार्थकता स्तर पर गुणांक विचरण (Coefficient of Variation–CV), मैन-केन्डल (Mann-Kendall–MK) परीक्षण, सेन का ढाल (Sen's Slope) तथा नवोन्मेषी प्रवृत्ति विश्लेषण (Innovative Trend Analysis–ITA) का उपयोग करके मौसम एवं वार्षिक वर्षा की परिवर्तनशीलता, परिमाण और प्रवृत्तियों का आकलन किया गया। अध्ययन में वर्षण में बढ़ती हुई उतार-चढ़ाव की प्रवृत्ति तथा मानसून और वार्षिक वर्षा में वृद्धि की प्रवृत्ति पाई गई। वार्षिक वर्षा उत्तरी और मध्य क्षेत्रों में विशेष रूप से अधिक रही तथा स्थानिक अंतर्वेशन मानचित्रण के अनुसार पिछले 40 वर्षों में रुद्रप्रयाग स्टेशन पर CV% के मानों (59.77-130.05) में उल्लेखनीय परिवर्तनशीलता देखी गई। मानसून-पूर्व और शीत ऋतु के दौरान कोई महत्वपूर्ण परिवर्तन नहीं पाया गया। अधिक वर्षा प्राप्त करने वाले ओखीमठ स्टेशन पर बाढ़, मृदा अपरदन और भूस्खलन का जोखिम अधिक पाया गया। मानसून-पूर्व तथा शीत ऋतु की वर्षा में लगातार कमी से जल की कमी उत्पन्न हो सकती है, जिससे कृषि और हिम संचयन पर प्रतिकूल प्रभाव पड़ सकता है, जबकि मानसूनी वर्षा में वृद्धि से बाढ़ एवं भूस्खलन का जोखिम बढ़ सकता है। मंदाकिनी जलग्रहण क्षेत्र में बदलती हुई इन परिस्थितियों से स्थानीय पारिस्थितिक तंत्र पर संभावित प्रभावों को कम करने के लिए अनुकूलनात्मक प्रबंधन रणनीतियों के महत्व पर बल मिलता है।

ABSTRACT. In recent decades, climate change has become a significant global concern, and variations in rainfall play a vital role in interpreting its impacts. The spatio-temporal analysis of rainfall provides insights into variability in rainfall patterns. This study investigates the multi-temporal rainfall records from 1983-2022, by utilizing Indian Meteorological Department (IMD) gridded dataset at a resolution of $0.25^\circ \times 0.25^\circ$. The seasonal and annual rainfall variability, magnitude, and trends were estimated using the Coefficient of Variation (CV), Mann-Kendall (MK) test, Sen's slope, and Innovative Trend Analysis (ITA) at a 5% significant level in the Mandakini watershed. This study reveals increased fluctuations in precipitation, with rising trends in monsoon and annual rainfall data. Annual rainfall is notably higher in the northern and central regions, and the Rudraprayag station has shown considerable variability in CV% (59.77-130.05) values over the past 40 years, as depicted through spatial interpolation mapping. There are no significant changes during the pre-monsoon and winter seasons. The Okhimath station, experiencing substantial rainfall, faces heightened risks of floods, soil erosion, and landslides. The consistent decline in pre-monsoon and winter rainfall may lead to water scarcity, negatively impacting agriculture and snow deposits, while increased monsoon precipitation raises the risk of flooding and landslides. This evolving situation in the Mandakini watershed underscores the importance of adaptive management strategies to mitigate potential impacts on local ecosystems.

Key words – Innovative trend analysis (ITA), Mandakini river watershed, Mann-kendall trend test, Rainfall variability, Sen's slope.

1. Introduction

The combined effects of climate change and human activities altered the atmospheric processes, leading to changes in weather patterns and contributing to variations in long-term climatic trends (Sen 2012). The increased greenhouse gas concentrations, significantly affect precipitation patterns on a global scale; from 1901 to 2012, the global mean surface temperature rose by 0.89 °C (IPCC 2013). According to Zhang *et al.* (2023), there has been a clear increase in minimum and maximum temperatures over land surfaces since 1950. However, the magnitude of these changes varies spatially and temporally across different regions. Alterations in rainfall concentration can significantly affect agricultural yields, soil structure, and the frequency of floods (Caloiero 2014). Understanding the spatial distribution of climate factors, such as rainfall and temperature, is essential for assessing the status of natural resources. Since the 1960s, human activities have considerably diminished snow cover on continental and regional scales, disrupting the global water cycle and contributing to increased climate extremes, particularly since the mid-20th century (Sonali & Nagesh, 2020; Banerjee *et al.* 2021). Recent shifts in climate patterns have adversely affected India's hydrological cycle, with multiple sources indicating a rise in global surface temperatures due to human interventions. In this context, Vani *et al.* (2023) emphasize that anthropogenic climate change is altering monsoon patterns, threatening food security and economic growth in agriculture, while Banerjee *et al.* (2023) explore the impact of climate variability and human activities on vegetation dynamics in northwest India. This comprehensive understanding of climate change and its multifaceted effects is crucial for developing adaptive management strategies to mitigate risks and enhance resilience in vulnerable regions. The examination of hydro-meteorological time series data aims to identify the pattern in trends, discerning whether they are upward, downward, or stable and the magnitude of the trend aiding in understanding their behavior (Meena *et al.* 2019; Mandal *et al.* 2021). In rainfall studies for regional planning, there is a focus on utilizing regional-scale data rather than relying on a global scale. This emphasis arises from the limitations of specificity, variability, and the restricted resolution of databases at the global level (Barsugli *et al.* 2009; Brekke *et al.* 2009; Das *et al.* 2021). Predicting future warming trends with precision at a regional level is more challenging compared to higher spatial scales.

The Indian Himalayan region (IHR), particularly Uttarakhand state, is vulnerable to climate-related disasters (NDMA 2009), with cloudbursts, flash floods, landslides, and soil loss increasingly observed over the last

few decades, where substantial rainfall plays a major role in accelerating these events. Studies indicate that daily precipitation exceeding 144 mm significantly increases landslide risk in the Himalayas (Khare *et al.* 2017). The occurrence of calamitous events is often linked to this heavy rainfall, with extreme rainfall events reported in various districts of Uttarakhand, such as the Malpa and Okhimath landslides (1998), the Munsiyari cloudburst (2009), the Okhimath-Rudraprayag landslides and cloudburst (2012), the Kedarnath floods (2013), the Pithoragarh cloudburst (2016), and the Chamoli flash flood (2021) (NDMA 2009; Banerjee *et al.* 2020; Bisht *et al.* 2022). The changes in both frequency and quantity of precipitation disrupted the natural stream flow pattern, imparting soil erosion (Srivastava *et al.* 2014; Malik *et al.* 2019). Several studies have been conducted on spatiotemporal trend and magnitude by using parametric and non-parametric tests (Yadav *et al.* 2014; Gajbhiye *et al.* 2015; Meshram *et al.* 2017; Meena *et al.* 2019; Das *et al.* 2021; Agarwal *et al.* 2021), these authors investigated the annual and seasonal rainfall trends over India.

The Mandakini River basin was chosen due to its vulnerability to flooding and landslides, (Joshi & Bohat. 2024) making it a critical area for studying environmental resilience. The basin is ecologically and culturally significant, supporting local agriculture, tourism, and traditional livelihoods. Insights gained here can inform strategies for similar Himalayan regions facing climate risks. Furthermore, limited investigations were reported on spatiotemporal mapping of rainfall on the watershed scale in the Rudraprayag district, and in this study, the detailed examination of rainfall variability on monthly and annual periods for the Mandakini River watershed has been analyzed so, this study aims to achieve the following objectives: (i) To examine the spatiotemporal trends of seasonal and annual rainfall in the Mandakini River watershed over 40 years (1983-2022) using the Mann-Kendall and Sen's slope tests. (ii) To detect temporal trends through the Innovative Trend Analysis (ITA) method. (iii) To analyze seasonal variability in the pre-monsoon, monsoon, post-monsoon, and winter seasons within the Mandakini River basin from 1983 to 2022.

2. Data and methodology

2.1. Geographical setting of the study area

The Mandakini River basin comprises a total area of ~1645 sq. km and it is located between 30°19'00"N to 30°49'00"N latitude and 78°49'00"E to 78°21'31"E longitude (Fig. 1). The tributaries of the Mandakini River are Vasuki Ganga, Madhyamaheshwar Ganga, Kali Ganga, Sina Gad, Kyar Gad, Mandani Ganga, Kakra Gad,

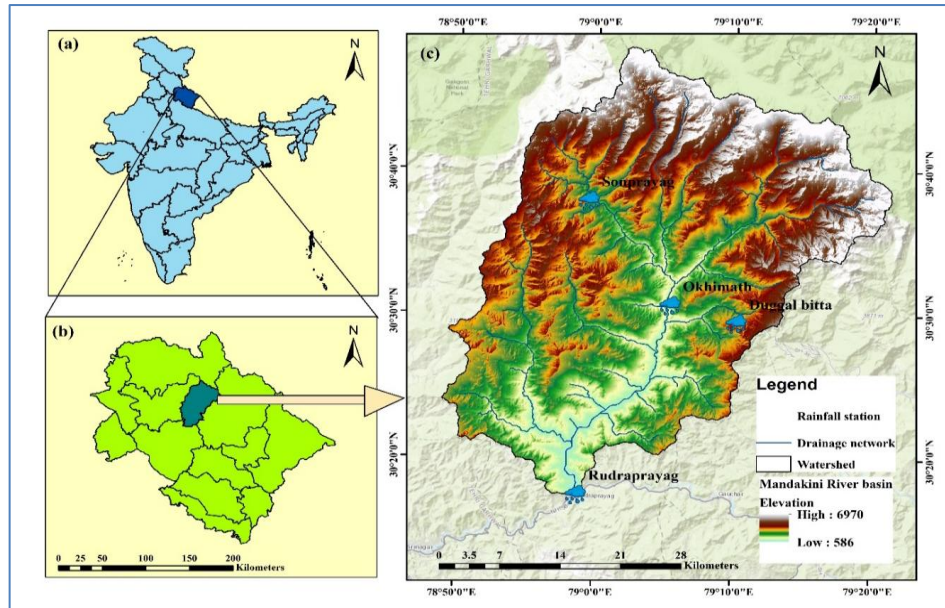


Fig. 1. Location map of the study area showing (a) India (b) Uttarakhand state (c) Mandakini River watershed

and Laster Gad. The Mandakini River basin lies majorly in the Rudraprayag district of Uttarakhand state and is partitioned into 4 tehsils, *i.e.*, Rudraprayag, Jakholi, Okhimath, and Basukedar. The elevation profile of the watershed ranges from 586 to 6970 m. The study region is characterized by gentle to moderate slopes (0° – 17°) and moderate to steep slopes (18° – 26°), with a large portion of the area falling under moderately steep terrain, while only a small segment in the northern part exhibits very steep slopes. (Bohat and Joshi, 2024). The study area falls within the zone (v) category of the earthquake and the northern part of the district experiences serious earthquakes (Bisht *et al.* 2022).

2.2. Climate

The average annual precipitation of the Rudraprayag district is 1867 mm. Fig. 2 shows the Box-Whisker plots for all stations, where all the stations exhibit inconsistent patterns in rainfall within the watershed throughout the year (Figs. 2a-d). An increasing trend in rainfall has been observed during the monsoon season (June to September), as shown by the Box-Whisker plots for four different seasons in Fig. 2e. The relative humidity is higher in the monsoon season. The coefficient of variation for the annual rainfall ranges from 1.44% to 39.34%. The maximum temperatures ranging from 30° to 35° °C and minimum temperatures ranging from 0° to 8° °C, the region experiences a significantly cooler climate. January is the coldest month while temperature ranges to maximum in June. In the upper basin, the western disturbances bring a lot of snow during the winter season.

TABLE 1

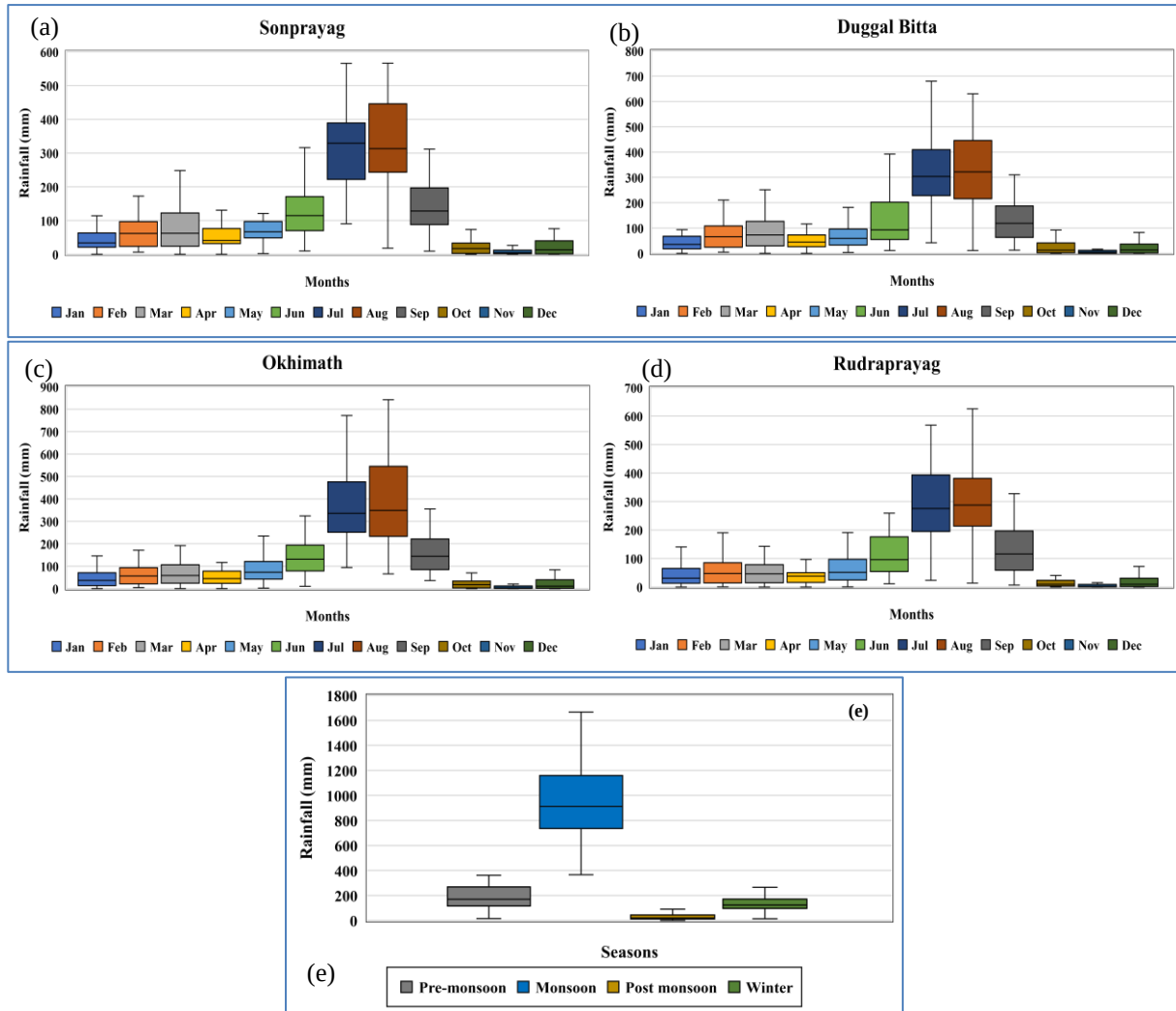
Location and data availability of rainfall

Name of station	Latitude	Longitude	Altitude	Rainfall data (year)
Sonprayag	30.63	79.99	1829	1983-2022
Duggal Bitta	30.49	79.17	2600	1983-2022
Okhimath	30.51	79.09	1311	1983-2022
Rudraprayag	30.29	78.98	895	1983-2022

2.3. Data collection

The gridded rainfall datasets with spatial resolution ($0.25^{\circ} * 0.25^{\circ}$) were extracted from the Indian Meteorological Department (IMD), Pune (Pai *et al.* 2014) (<https://www.imdpune.gov.in/cmpg/Griddata/Rainfall>). Initially, 10 locations were picked across the watershed. However, as the data values appeared similar across these points, the analysis was focused on four specific locations. This decision accounted for the coarse resolution of the gridded NetCDF (Network Common Data Form) data and the limited availability of observational data in mountainous regions. The four rainfall point locations were chosen to ensure a more reliable and representative analysis.

For this research, precipitation data of 40 years (1983–2022) was considered. Four rainfall locations named Sonprayag, Okhimath, Duggal Bitta, and Rudraprayag (Table 1) were selected to be analyzed



Figs. 2(a-e). Box-whisker plots of stations and seasonal-wise data (a) Sonprayag (b) Duggal Bitta (c) Okhimath (d) Rudraprayag (e) Seasonal

thoroughly (Fig. 3). The corresponding NetCDF data was processed and converted into a format suitable for further analysis in Excel. The gridded NetCDF format was chosen for its simplicity and effectiveness in analyzing self-descriptive geoscience data, making it widely used in geoscience workflows (Woolf *et al.* 2003; Vani *et al.* 2023).

The IMD, Pune's guidelines are adopted for this study, which takes into account all four seasons in a year. As a result, a four-season time series was adapted for the seasonal rainfall time series analysis: (i) pre-monsoon (March-May) (ii) monsoon (June-September) (iii) post-monsoon (October-November), and (iv) winter (December-February) (Mala and Kesarwani 2019; Malik *et al.* 2019; Banerjee *et al.* 2023). By adding the daily precipitation data over the corresponding periods, transformed into monthly, seasonal, and annual rainfall

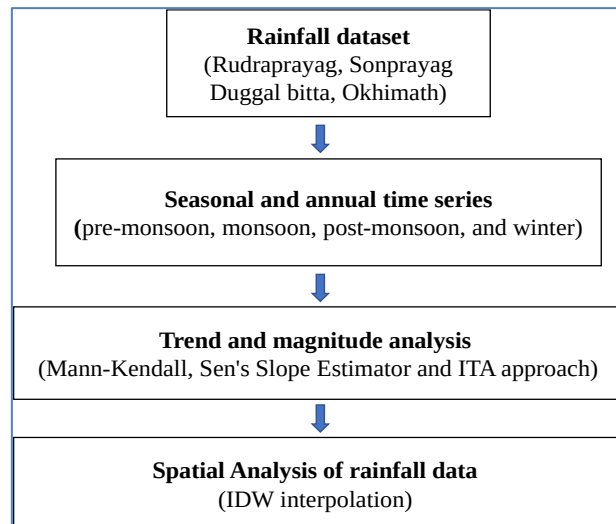
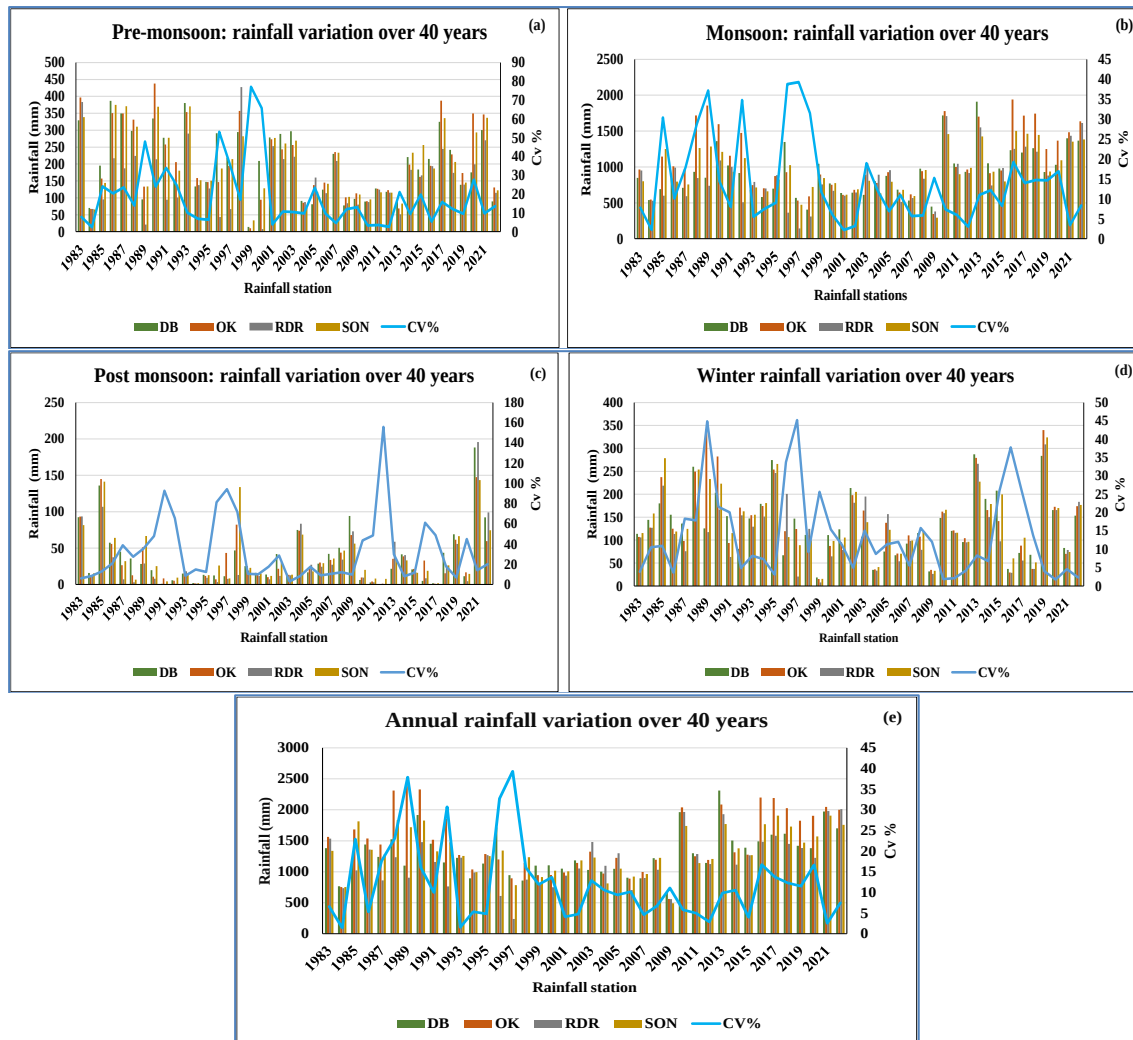


Fig. 3. Flow chart of the methodology



Figs. 4(a-e) Combo graph showing seasonal and annual rainfall trend over four stations including CV% (a) Pre-monsoon (b) Monsoon (c) Post-monsoon (d) Winter (e) Annual

time series using a pivot table in Excel. The spatial variability and trend maps for seasonal and annual rainfall were prepared by using the IDW interpolation method in the ArcGIS environment.

2.4. Statistical quantification of seasonal and annual rainfall

The key statistical attributes of the rainfall time series data were analyzed to identify trends and fluctuations (Table 3). Statistical parameters, including mean, minimum, maximum, standard deviation (SD), and coefficient of variation (CV%), were calculated for the four rainfall stations. Seasonal precipitation data (pre-monsoon, monsoon, post-monsoon, and winter) as well as annual precipitation data, along with CV%, were visualized using combination graphs to compare variations across years and

stations (Fig. 4). Additionally, the CV% and average precipitation data from all hydro-meteorological stations were spatially mapped using interpolation techniques to illustrate regional variability (Fig. 5).

2.5. Detection of trend and magnitude

2.5.1. Mann Kendall (MK) test

The Mann-Kendall (MK) test is used to identify monotonic patterns and trends in time series datasets (Mann 1945; Kendall 1975). The MK test examines the median of the dataset, in contrast to the average, and focuses only on median-related evaluations. The Mann-Kendall test statistic S is defined as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sign}(x_j - x_i) \quad (1)$$

TABLE 2

Descriptive statistics of seasonal and annual rainfall data (1983-2022)

Statistical parameters	Sonprayag	Duggal Bitta	Okhimath	Rudraprayag
Pre-monsoon				
Minimum	33.61	14.03	10.32	2.09
Maximum	374.63	386.88	437.70	427.18
Mean	204.78	201.34	207.91	154.84
SD	97.83	99.12	107.41	92.55
Kurtosis	-1.14	-1.17	-0.85	0.96
CV%	47.77	49.23	51.66	59.77
Skewness	0.25	0.13	0.42	0.76
Monsoon				
Minimum	293.46	406.19	344.55	143.51
Maximum	1503.28	1910.80	1940.19	1708.71
Mean	942.91	926.51	1083.30	859.50
SD	308.46	331.21	428.88	348.19
Kurtosis	-0.77	0.91	-0.92	0.23
CV%	32.71	35.75	39.59	40.51
Skewness	0.26	0.88	0.48	0.47
Post monsoon				
Minimum	1.72	0.00	1.04	0.00
Maximum	143.55	188.34	147.41	195.79
Mean	36.46	36.50	34.61	30.05
SD	36.71	39.57	35.06	39.58
Kurtosis	2.72	5.01	3.50	7.10
CV%	99.42	107.05	100.03	130.05
Skewness	1.70	1.97	1.75	2.33
Winter				
Minimum	15.52	18.65	15.19	7.61
Maximum	324.15	287.00	342.38	308.93
Mean	141.91	134.52	142.86	122.40
SD	70.99	68.55	80.44	70.29
Kurtosis	-0.02	-0.03	0.41	0.08
CV%	49.40	50.32	55.59	56.70
Skewness	0.54	0.55	0.78	0.52
Annual				
Minimum	492.69	669.29	560.76	238.62
Maximum	1906.10	2311.43	2383.33	2010.94
Mean	1326.05	1298.87	1468.68	1166.80
SD	362.68	359.06	496.88	402.07
Kurtosis	-0.71	0.48	-1.05	0.11
Skewness	-0.08	0.71	0.32	0.27

TABLE 3

Result of Mann-Kendall and Sen's slope method

	Tests	Sonprayag	Duggal Bitta	Okhimath	Rudraprayag
Pre-monsoon	Kendall's tau	-0.151	-0.174	-0.131	0.036
	Sen's slope	-1.799	-2.500	-1.714	0.644
	p-value	0.173	0.116	0.239	0.753
Monsoon	Kendall's tau	0.197	0.310	0.162	0.295
	Sen's slope	7.74	12.633	8.339	13.693
	p-value	0.075	0.005	0.145	0.008
Post monsoon	Kendall's tau	0.049	-0.003	0.038	0.136
	Sen's slope	0.124	-0.007	0.125	0.36
	p-value	0.666	0.991	0.735	0.221
Winter	Kendall's tau	-0.156	-0.110	-0.136	-0.049
	Sen's slope	-1.358	-1.182	-1.178	-0.577
	p-value	0.159	0.322	0.221	0.666
Annual	Kendall's tau	0.095	0.185	0.079	0.285
	Sen's slope	5.137	9.724	7.201	14.977
	p-value	0.395	0.096	0.477	0.010

where x_j and x_i represent the data values at time i and j ($j > i$), respectively, and n is the total number of observations. The sign function is given by:

$$\text{sign}(x_j - x_i) = \begin{cases} +1, & \text{if } (x_j - x_i) > 0 \\ 0, & \text{if } (x_j - x_i) = 0 \\ -1, & \text{if } (x_j - x_i) < 0 \end{cases} \quad (2)$$

For large sample size $n \geq 10$, The statistic 'S' follows an approximately normal distribution with mean $E(S)$ and $\text{Var}(S)$. The expected value of 'S' is:

$$E(S) = 0$$

The variance of 'S' for data without tied values is calculated as:

$$\text{Var}(S) = \frac{n(n-1)(2n+5)}{18} \quad (3)$$

In the presence of tied values (equal data points), the variance is adjusted as:

$$\text{Var}(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^P t_i(t_i-1)(2t_i+5)}{18} \quad (4)$$

where, P is the number of tied groups and t_i is the number of data points in the i^{th} tied group. The Z_{MK} esteem is utilized to figure out that the time series data is showing a significant pattern and utilizing the following equation:

$$Z_{\text{MK}} = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}}, & \text{if } S > 0 \\ 0, & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}}, & \text{if } S < 0 \end{cases} \quad (5)$$

The MK test utilizes two hypotheses for its analysis: Null hypothesis (H_0), which posits the absence of a trend, and alternate hypothesis (H_a), which signifies the rejection of H_0 , indicating the presence of an upward or downward trend in datasets at the 0.05 level of significance (Gajbhiye *et al.* 2015; Meshram *et al.* 2017; Malik *et al.* 2019; Jayanta *et al.* 2020; Agarwal *et al.* 2021).

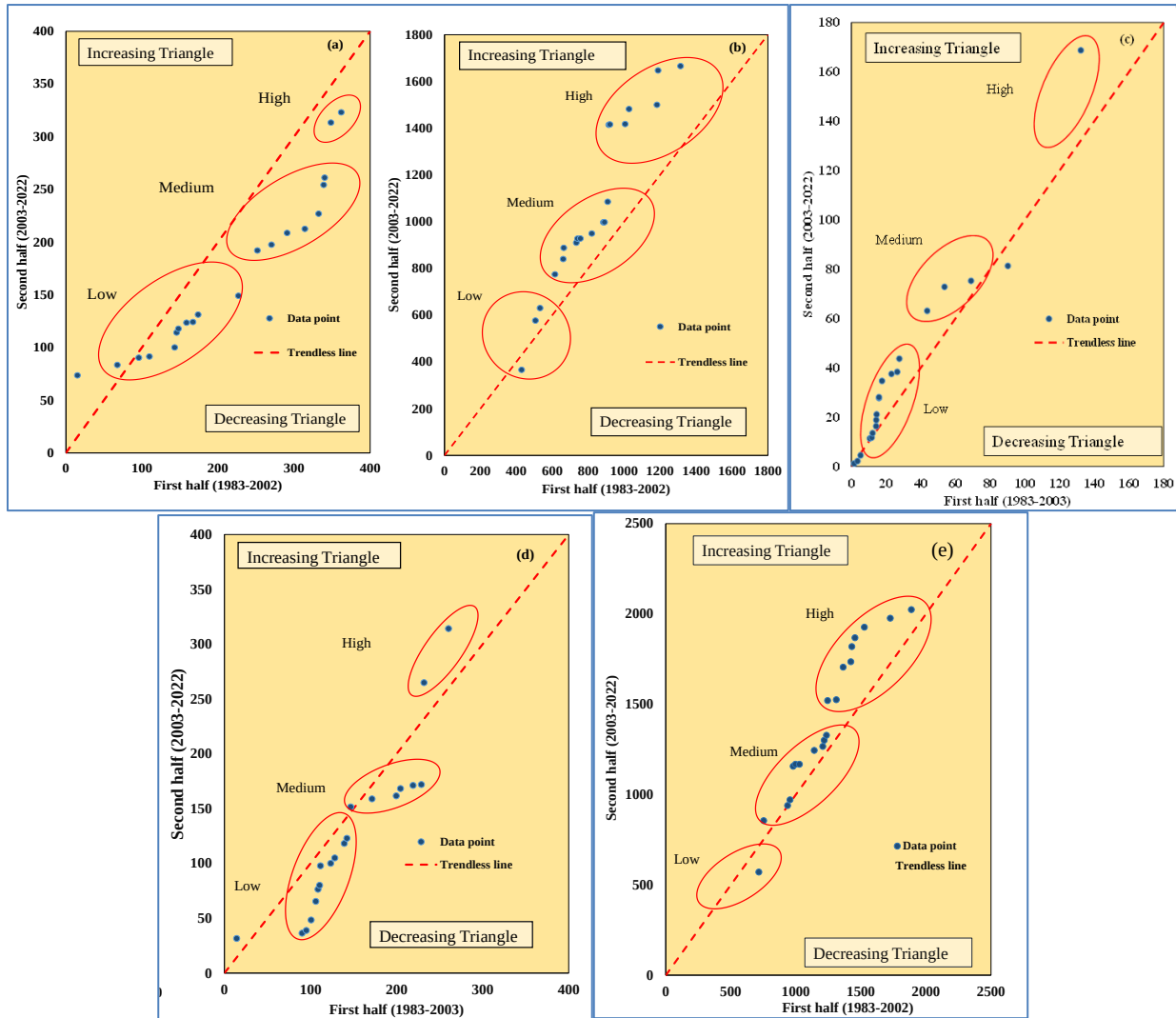
2.5.2. Magnitude estimation using Sen's slope

Sen (1968) pioneered a non-parametric method based on a linear model for estimating the actual slope of a trend. Sen's slope method is applied by calculating the median rate of change per time unit and these slopes for all ordinal time point pairs, the total slope has been estimated as follows:

$$Q_i = \frac{x_i - x_j}{i - j}, \text{ for } j > i \quad (6)$$

where Q is the slope between the data points, x_j and x_i are data values at time i and j . For a dataset with n observations, all possible slope estimates Q_i are calculated, and the overall Sen's slope Q is determined as the median of these values:

$$Q = \text{median}(Q_i) \quad (7)$$



Figs. 5(a-e). Graph showing ITA plots with high, medium, and low trend (a) Pre-monsoon (b) Monsoon (c) post-monsoon (d) Winter (e) Annual

A positive value of Q indicates an increasing trend, while a negative value indicates a decreasing trend over time.

2.5.3. Innovative Trend Analysis (ITA)

The MK test is ineffective, if the series exhibits serial correlation so, the Sen (2012), recently developed the ITA test to resolve the serial correlation issue. In this test, the time series datasets are divided into two halves, the first half (horizontal axis) of the whole time series is plotted against the second half part (vertical axis). When the plotted points fall exactly on a 1:1 (45°) straight line (trendless line), it demonstrates no pattern in the series. If the data points are located above the trendless line, it denotes the upward trend in the dataset and vice versa. The data series is classified into low, medium, and, high groups.

The ITA test is computed using following equation (Sen 2017):

$$s = \frac{2(\bar{y}_2 - \bar{y}_1)}{n} \quad (7)$$

where, $\bar{y}_1$ and $\bar{y}_2$ are arithmetic mean of first and second half of time series dataset, and 'n' is the total number of data in the series. The standard deviation of slope is calculated as follows:

$$\sigma_s = \frac{2\sqrt{2}}{n\sqrt{n}} \sigma \sqrt{1 - \rho_{\bar{y}_1\bar{y}_2}} \quad (8)$$

where, ' σ ' is the standard deviation of complete data series; ' $\rho_{\bar{y}_1\bar{y}_2}$ ' denotes the cross correlation between the ascending sorted two halves average of the series. The upper and lower confidence limit (CL) of the trend slope at α level of

significance are represented using the following expression:

$$CL_{1-\alpha} = 0 \pm s_{cri}\sigma_s \quad (9)$$

The alternative hypothesis of a significant trend is accepted at level of significance if the slope value of each station lies between the lower and upper CL values.

3. Results and discussion

The study encompassed the examination of temporal patterns in the rainfall time series data of seasonal (pre-monsoon, monsoon, post-monsoon, and winter) and annual precipitation. This assessment was executed by employing the MK and Sen's slope test with statistical significance set at a 5% level, across all the designated meteorological stations i.e., Sonprayag, Okhimath, Rudraprayag, Duggal Bitta. The spatial arrangement of trend values for both seasonal and annual data was represented through ArcGIS's Inverse Distance Weighted (IDW) interpolation method. The precipitation measurements of 4 stations utilizing long-term 40-year precipitation time series data for seasonal and annual are summed up in Table 2.

3.1. Temporal variability analysis of seasonal and annual rainfall data

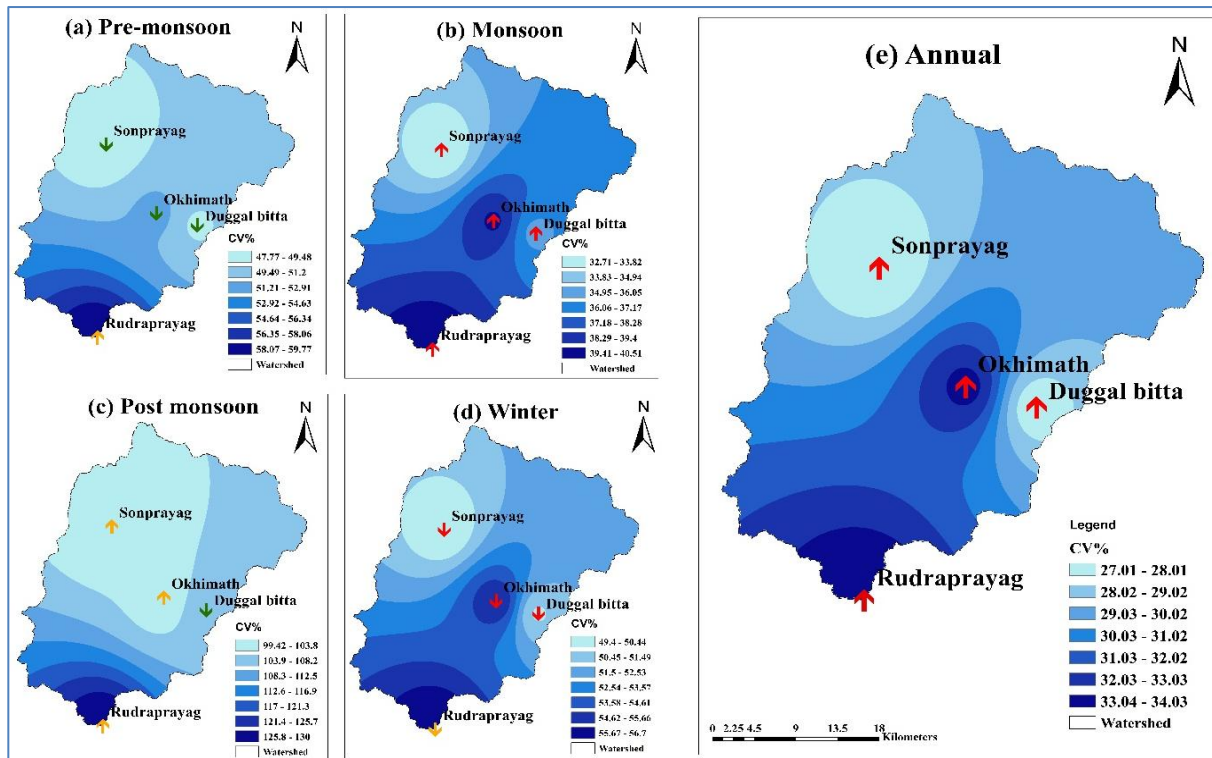
3.1.1. Trend, variability, and magnitude estimation of pre-monsoon season

The mean rainfall ranges of all the stations from 154.84 (mm) to 204.78 (mm), where the minimum precipitation observed in Rudraprayag and the maximum in Okhimath (Table 2). The mean of standard deviation (SD) of pre-monsoon (99.23) and platykurtic distribution of datasets indicates fewer extreme values. The Rudraprayag station has a higher CV % (59.77) followed by the Okhimath (51.66) station suggesting a significant amount of dispersion in data. The major variation in rainfall was observed in the year 1999, which is considered a drought year for the whole Uttarakhand state (Kumar *et al.* 2017) (Fig. 4 a). The skewness of the pre-monsoon season (0.13 – 0.76) shows the right skew distribution in the 1983-2022 rainfall data. The pre-monsoon season shows a negative trend in the MK test with no significant trend observed in all hydro-meteorological stations and a weak negative correlation depicted by Kendall's tau values (Table 3). The pre-monsoon season marks the beginning of the growing season, when demand for water in rainfed agriculture is high. Decreasing rainfall has led to the abandonment of agricultural lands. Variability and decline in rainfall can significantly influence ecosystem

processes, as reduced precipitation is closely associated with lower net primary productivity and overall vegetation health (Kumar *et al.*, 2025). A slightly positive Sen's slope value for Rudraprayag (0.64), followed by the downward trend in Sonprayag (-1.79), Duggal Bitta (-2.50), and Okhimath (-1.71) (Fig. 6). In the sub-temperate region of Uttarakhand, there was a significant decrease in pre-monsoon rainfall, showing a reduction of about 2.38 mm per year from 1980 to 2019 (Kumar *et al.*, 2021). This variability may be attributed to changes in pre-monsoon atmospheric dynamics, including weakened convective activity, variability in Western disturbances. The ITA graph illustrates the non-monotonic decreasing trend. (Fig. 5 a). These negative trends in pre-monsoon rainfall have considerable implications for the economy and local livelihoods (Singh & Mal. 2014).

3.1.2. Trend, variability, and magnitude estimation of monsoon season

The average precipitation value of the Mandakini River watershed for the monsoon season during 1983-2022 varied from Rudraprayag (859.50 mm) to Okhimath (1083.30 mm) (Table 2). About 72% of total rainfall was received in the monsoon season, which makes this region prone to flooding, landslides, and soil erosion. In the monsoon season, Okhimath station has a higher SD, and the mean SD of monsoon is 354.19, which is relatively high and suggests greater variability throughout all rainfall stations. The Okhimath station records the highest precipitation, linked to the occurrence of landslides, especially during extreme rainfall events of 1998, 2001, and 2012 (Martha & Vinod Kumar, 2013), which may be associated with localized atmospheric instability and topographic controls. This spatial contrast may be associated with the complex topography of the region, particularly the orographic lift influencing the Okhimath. The Kurtosis value of Sonprayag and Okhimath showed a platykurtic distribution, whereas Rudraprayag and Duggal Bitta depicted a mesokurtic distribution. The average value of CV% (37.14) shows variability in monsoon but lesser variation in data points as compared to pre-monsoon months. In a year, 1996-1998 greater variability in monsoon pattern leads to devastating landslides in Okhimath (Das 2015) (Fig 4 b). The maximum rainfall observed among the four stations was ~1960 mm at Sonprayag in 2013 year, which led to the Kedarnath flood and landslide events in the Mandakini River basin (Rautela. 2018). A slightly positive to strong positive skewed rainfall data observed in all stations suggests some years with above-average rainfall (Table 2). Notably, the monsoon season displays an upward trend, especially in the Okhimath block, suggesting evolving precipitation dynamics.



Figs. 6(a-e). Spatial distribution of CV % and mapping rainfall trend (1983-2022) in (a) Pre-monsoon (b) Monsoon (c) Post monsoon (d) Winter (e) Annual

The ITA graph illustrates the strongly increasing trend in high, medium, and low (Fig. 5b) and shows an increasing non-monotonic trend in the second half (2003-2022). The trend examined for the monsoon season using MK and Sen's slope test is calculated in Table 3. The MK test results show a significant positive trend at (Rudraprayag and Duggal Bitta) and a moderate positive trend (Sonprayag and Okhimath) at a 5% level of significance (Fig. 6 b).

3.1.3. Trend, variability, and magnitude estimation of post-monsoon season

The post-monsoon months receive < 3% total rainfall, whereas Rudraprayag received 21% rainfall which is lesser as compared to other rainfall stations. Rainfall during this period is often associated with residual monsoon activity and the increasing influence of western disturbances. The mean maximum rainfall among all stations was 195.79 mm, observed in the 2021 year, due to heavy non-seasonal rainfall responsible for increasing water level above the danger of Alaknanda River (Food list article 2021). Sonprayag (36.71) and Okhimath (35.06) show less variability and more consistency in rainfall as compared to Duggal Bitta (39.57) and Rudraprayag (39.58) (Table 2). The post-monsoon season suggests a leptokurtic (moderately skewed) distribution in all stations with

sharper peaks as compared to a normal distribution with positively skewed data. The substantial variability of rainfall was observed in the monsoon season. The analysis using the MK test reveals that Okhimath, Sonprayag, and Rudraprayag exhibit a weak positive trend in post-monsoon rainfall, and Duggal Bitta shows a weak negative trend (Fig. 6c). A declining or inconsistent trend during this season may reduce soil moisture recharge and affect crop preparation, thereby influencing agricultural sustainability in the region. In contrast, areas like Joshimath, Munsyari, and Tehri demonstrate either negative trends or no significant change, indicating a broader decline in post-monsoon rainfall across Uttarakhand (Singh & Mal, 2014), which supports the findings of this study. Variability in their frequency and intensity can lead to fluctuations in post-monsoon rainfall patterns.

3.1.4. Trend, variability, and magnitude estimation of the winter season

The statistics of the winter season for 40-year rainfall datasets are calculated, where maximum precipitation was observed at Okhimath station (342.48 mm) in the year 1989. Winter months receive ~10% of total rainfall and Okhimath station received moderately high rainfall among all the stations. The average rainfall in the winter season was 134.32 mm during the 1983-2022 time period. The

major variability of rainfall observed at Okhimath (80.44) station was followed by, Sonprayag (70.99) Rudraprayag (70.29), and Duggal Bitta (68.55) (Table 2). The overall trend in the Mandakini River watershed during the winter season indicates a decline in rainfall, which significantly affects snow deposits in the watershed (Myers *et al.* 2023; Banerjee *et al.* 2024). Changes in the frequency and severity of Western disturbances, which are the primary causes of precipitation in the Himalayan region, may be associated with the decrease in winter rainfall over the past few years. The MK and Sen's slope values exhibit a p-value higher than a significant level, showing a negative trend. The ITA graph also illustrates the decreasing trend in the first half (1983-2003) low and medium phases, where few rainfall datasets show an upward trend in the second half (2003-2022) due to few outliers in the rainfall dataset (Fig. 5d).

The results of the MK test and Sen's slope analysis reveal a p-value exceeding the threshold for significance, indicating a negative trend in winter rainfall. Specifically, a negative trend of winter rainfall was observed in Joshimath, located at higher elevations in the north-central part of Uttarakhand (Singh & Mal, 2014). Furthermore, the MK test also confirmed this negative trend in winter rainfall for Rudraprayag district (Malik *et al.*, 2019).

3.1.5. Trend, variability, and magnitude estimation of annual rainfall

The maximum annual rainfall was observed at Okhimath station (2383.32 mm) in the year 1989 followed by Duggal Bitta station (2311.43 mm) in the year 2013. The Sonprayag and Okhimath receive a major portion of rainfall from 1983-2022 in the annual data series. The mean annual rainfall of the Mandakini River watershed is ~1315 mm during 40 years over 4 stations. The SD values range from 496.88 (Okhimath) to 362.68 (Sonprayag) suggesting rainfall data points more spread out around the mean for 40 years. The Sonprayag and Okhimath have negative kurtosis values indicating a flatter distribution where, whereas Rudraprayag and Duggal Bitta have positive values depicting a slightly peaked distribution. The higher CV% values calculated for Rudraprayag and Okhimath station as compared to the rest of the hydro-meteorological stations with mean CV% of Mandakini watershed is 30.43% for the period of 1983-2022. The higher CV% experiences fluctuations in rainfall as compared to lower CV% values (Table 2).

The ITA graph depicts an overall increasing trend in the Mandakini River watershed with most of the rainfall points falling in an upward triangle (second half). The MK and Sen's slope test computed for annual precipitation are reported in Table 3. Which detected a positive upward trend

in rainfall among all stations at a 5% significance level. Rana *et al.* (2022) identified the maximum positive change in annual rainfall for Rudraprayag district among 13 districts from 2000 to 2017, while Dehradun district showed the highest percentage increase in annual rainy days, followed closely by Rudraprayag.

3.2. Spatial mapping of seasonal and annual rainfall data

The patterns distinguished by the MK test, Sen's slope test, and CV% for seasonal and yearly precipitation at the level are spatially mapped in Fig. 6. The pre-monsoon, three stations (Sonprayag, Okhimath, Duggal Bitta) show a strongly downward trend, and Rudraprayag station was showing weak upward trend at 5% level of significance (Fig. 6a). The greater variation in the dataset was observed in the south region (Rudraprayag) of the watershed. The monsoon season, a positive Sen's slope with an upward trend was detected in the middle and southern part of the Mandakini basin, showing Okhimath block receives higher precipitation in monsoon months as compared to the rest of the stations (Fig. 6b). The greater CV% in post monsoon phase was observed in the southern part of the watershed, with an increasing trend observed in Sonprayag, Okhimath, and Rudraprayag stations, where Duggal Bitta station showed a weak negative trend (Fig.6c). The winter months, the whole Mandakini basin shows a decreasing trend and the southern part of the Mandakini basin shows higher variation in rainfall (Fig.6d).

The spatially mapped annual CV% rainfall values illustrated the major variations in rainfall observed at the middle and southernmost part of the Mandakini River basin and the overall positive trend showcased (Fig. 6e). Annual rainfall variability is lesser in the high-altitude northernmost areas, but this region receives significantly more rainfall than the southern region due to its elevation and proximity to the Chorabari glacier, which contributes to increased precipitation through orographic lift (Khare *et al.* 2017). Whereas, maximum rainfall variability was observed in the southern part being lower in elevation, and experiencing less rainfall, than northern and middle regions of the watershed (Singh & Mal. 2014).

3.3. Challenge and prospects

This limitation of this study is particularly critical in high-elevation regions, where reliable station-observed datasets are often lacking and prone to inconsistencies in data availability, making the scarcity of observed rainfall records in high mountainous areas like the IHR a considerable challenge for the research community. Discrepancies in measurements and limited access to

comprehensive datasets may hinder the reliability of the findings. Additionally, the complex topography of the region poses difficulties in spatial interpolation, as elevation and geographic variations can significantly influence rainfall patterns. Another challenge lies in the inherent variability of climate systems, which can obscure long-term trends and make it difficult to establish clear causal relationships between rainfall changes and environmental impacts. This complexity necessitates the use of advanced analytical techniques and interdisciplinary approaches to fully understand the underlying dynamics.

Despite these challenges, the study presents significant prospects for enhancing water resource management and climate adaptation strategies in the region. By identifying rainfall trends and variability, this research can inform local stakeholders and policymakers about potential risks and vulnerabilities associated with changing precipitation patterns. Furthermore, the findings can contribute to developing sustainable agricultural practices, improving flood management, and enhancing ecosystem resilience. The insights gained from this analysis can also serve as a foundation for future studies, enabling more targeted research on the impacts of climate change in the Mandakini River watershed and beyond, ultimately fostering informed decision-making for sustainable development.

4. Conclusions

The study was conducted to examine the trend and variability of seasonal and annual (pre-monsoon, monsoon, post-monsoon, and winter) and annual rainfall datasets at four stations over 40 years at the watershed scale of the Mandakini River. The MK and Sen's slope test was performed at a 5% level of significance, which offers this research a more robust statistical framework for evaluating rainfall trends. The non-parametric tests showed a positive/negative trend for seasonally and annually and visualized using the IDW interpolation method. The great variability of rainfall datasets was observed in Rudraprayag station seasonally and annually. The post-monsoon season shows minimal rainfall contribution, showing a decreasing trend in precipitation, whereas Okhimath station received major rainfall in monsoon months.

The rainfall trend analysis has found this region experiencing increased seasonality in precipitation, with significant drying trends evident in both the pre-monsoon and winter seasons. The northern region receives higher rainfall due to its elevation and the orographic lift effect, while the southern region, at a lower elevation, experiences

significantly less precipitation and exhibits maximum rainfall variability. The ITA method outperformed the MK test in revealing rainfall trends, demonstrating its superior ability to capture intricate spatio-temporal dynamics in the Mandakini River Watershed. This emphasizes the need for utilizing diverse analytical techniques to achieve a more accurate understanding of rainfall variability. The ITA graph's increasing rainfall pattern in the second half of the study period (2003-2022) underscores the importance of spatio-temporal analyses in revealing regional differences in rainfall trends. Such variability can disrupt agricultural systems in the Rudraprayag district, making it essential to understand these patterns for informed decision-making. The continued elevated rainfall levels during both the monsoon and annual seasons may significantly increase the risks of flooding, soil erosion, and landslides within the Mandakini basin, adversely impacting agricultural productivity and local communities. Analyzing periodic patterns and variability in rainfall has the potential to diminish the frequency of such incidents. This study analyzes the rainfall patterns at the regional level in Rudraprayag district, an area not analyzed before, considering the primary focus of earlier studies at the district scale, and provides crucial insight into the trends in localized regions for rainfall that occurred during the past years. The shifting distribution of rainfall patterns presents a concerning situation for agriculture, water resources, and ecosystem health. The findings from this study thus provide a valuable contribution to the understanding of regional climate dynamics and support more effective strategies for managing water resources in the face of changing precipitation patterns. Analyzing trends in weather parameters is crucial for strategic planning related to agriculture, water storage, flood prevention, soil erosion, and other environmental factors.

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Data availability

All the data generated or analyzed during this study are included in this article.

Consent for publication

The authors express their consent for the publication of research work.

Competing interests

The authors declare no competing interests.

Authors' contributions

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References

- Agarwal, S., Suchithra, A. S., & Singh, S. P. 2021. Analysis and interpretation of rainfall trend using Mann-Kendall's and Sen's slope method. *Indian Journal of Ecology*, **48**, 2, 453-457. ISSN 0304-5250.
- Banerjee, A., Chen, R., E. Meadows, M., Singh, R. B., Mal, S., & Sengupta, D. 2020. An analysis of long-term rainfall trends and variability in the uttarakhand himalaya using google earth engine. *Remote Sensing*, **12**, 4, 709. <https://doi.org/10.3390/rs12040709>
- Banerjee, A., Chen, R., Meadows, M. E., Sengupta, D., Pathak, S., Xia, Z., & Mal, S. 2021. Tracking 21st century climate dynamics of the Third Pole: An analysis of topo-climate impacts on snow cover in the central Himalaya using Google Earth Engine. *International Journal of Applied Earth Observation and Geoinformation*, **103**, 102490. <https://doi.org/10.1016/j.jag.2021.102490>
- Banerjee, A., Kang, S., Meadows, M. E., Xia, Z., Sengupta, D., & Kumar, V. 2023. Quantifying climate variability and regional anthropogenic influence on vegetation dynamics in northwest India. *Environmental Research*, **234**, 116541. <https://doi.org/10.1016/j.envres.2023.116541>
- Banerjee, A., Kang, S., Moazzam, M. F. U., & Meadows, M. E. 2024. Climate dynamics and the effect of topography on snow cover variation in the Indus-Ganges-Brahmaputra River basins. *Atmospheric Research*, **309**, 107571. <https://doi.org/10.1016/j.atmosres.2024.107571>
- Barsugli J, Anderson C, Smith JB, Vogel JM, 2009, Options for improving climate modeling to assist water utility planning for climate change. White Paper, *Water Utility Climate Alliance*.
- Bisht, N. S., Sharma, M. R., & Pandey, M. T. D. 2022. Disaster Management in Mountain Regions: With Special Reference to Uttarakhand. *Journal of Acharya Narendra Dev Research Institute*. ISSN, 976, 3287.
- Bohat, N., & Joshi, V. 2024. Prioritization of sub-watershed using geospatial techniques and WSPM model in Mandakini River basin, Uttarakhand, India. *Proceedings of the Indian National Science Academy*, 1-11. <https://doi.org/10.1007/s43538-024-00292-z>
- Brekke LD, Kiang JE, Olsen JR, Pulwarty RS, Raff DA, Turnipseed DP, Webb RS, White KD, 2009, Climate change and water resources management: a Federal Perspective. *US Geological Survey Circular*, 1331, 65 pp. <https://pubs.usgs.gov/circ/1331/>
- Caloiero, T. Analysis of daily rainfall concentration in New Zealand. *Natural Hazards*, **72**, 389-404 (2014). <https://doi.org/10.1007/s11069-013-1015-1>
- Das PK, 2015, Global warming, glacial lakes, and cloud burst events in Uttarakhand-Kumaon Himalaya: a hypothetical analysis. *International Journal of Environmental Sciences* 5(4):697-708. <https://doi.org/10.6088/ijes.2014050100065>
- Das, J., Mandal, T., Rahman, A. S., & Saha, P. 2021. Spatio-temporal characterization of rainfall in Bangladesh: an innovative trend and discrete wavelet transformation approaches: *Theoretical and Applied Climatology*, **143**(3), 1557-1579. <https://doi.org/10.1007/s00704-020-03508>
- Gajbhiye, S., Chandrashekhar M., Rasoul M, and S. K. Sharma. Trend analysis of rainfall time series for Sindh river basin in India. *Theoretical and applied climatology* 125 2016: 593-608. <https://doi.org/10.1007/s00704-015-1529-4>
- IPCC (2013) Summary for policymakers. In: Stocker TF, Qin D, Plattner GK, Tignor M, Allen SK, Boschung J, Nauels A, Xia Y, Bex V, Midgley PM (eds) Climate change 2013: the physical science basis. Contribution of working group I to the fifth assessment report of the intergovernmental panel on climate change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA
- Jayanta, D., Tapash, M., Piu, S., & Kumar, B. S. 2020. Variability and trends of rainfall using non-parametric approaches: a case study of the semi-arid area. *Mausam*, **71**(1), 33-44. <https://doi.org/10.54302/mausam.v71i1.4>
- Joshi, V., & Bohat, N. 2024. Assessing soil erosion in Mandakini river watershed: a sub-watershed scale analysis using RUSLE model and geospatial tools. *Malaysian Journal of Geosciences*. 8(1): 10-16. <https://doi.org/10.26480/mjg.01.2024.10.16>
- Kendall MG, 1975, Rank correlation methods. 4th ed. Charles Griffin, London, p6
- Khare, D., Mondal, A., Kundu, S., & Mishra, P. K. 2017. Climate change impact on soil erosion in the Mandakini River Basin, North India. *Applied Water Science*, **7**, 2373-2383. <https://doi.org/10.1007/s13201-016-0419-y>
- Kumar, S., Kumar, R., Kumar, M., Pandey, A. K., Srivastava, P. K., Kumar, S., ... & Arya, V. S. 2025. Spatio-temporal variability analysis of evapotranspiration, water use efficiency and net primary productivity in the semi-arid region of Aravalli and Siwalik range, India. *Environment, Development and Sustainability*, **27**(3), 7897-7918. DOI: <https://doi.org/10.1007/s10668-023-04228-3>
- Kumar, U., Panday, S. C., Kumar, J., Meena, V. S., Parihar, M., Singh, S., ... & Kant, L. 2021. Comparison of recent rainfall trend in complex hilly terrain of sub-temperate region of Uttarakhand. *Mausam*, **72**(2), 349-358. <https://doi.org/10.54302/mausam.v72i2.622>
- Kumar, V., Shanu, & Jahangeer. 2017. Statistical distribution of rainfall in Uttarakhand, India. *Applied Water Science*, **7**, 4765-4776. <https://doi.org/10.1007/s13201-017-0586-5>
- Mala, A., & Kesarwani, K. 2019. Rainfall Trends (1998-2018) Over the Chorabari Glacier in Mandakini River Basin, Uttarakhand, India. *Himalayan Ecology*, **27**, pp. 111-116. ISSN: 2455-6815 (Online)

- Malik, A., Kumar, A., Guhathakurta, P., & Kisi, O., 2019. Spatial-temporal trend analysis of seasonal and annual rainfall (1966–2015) using innovative trend analysis method with significance test. *Arabian Journal of Geosciences*, 12, 1–23. <https://doi.org/10.1007/s12517-019-4454-5>
- Mandal, T., Das, J., Rahman, A.T.M.S., Saha, P. 2021. Rainfall Insight in Bangladesh and India: Climate Change and Environmental Perspective. In: Rukhsana, Haldar, A., Alam, A., Satpati, L. (eds) *Habitat, Ecology and Ektistics. Advances in Asian Human-Environmental Research*. Springer, Cham. https://doi.org/10.1007/978-3-030-49115-4_3
- Mann, H. B. 1945. Nonparametric tests against trend. *Econometrica: Journal of the Econometric Society*, 245–259.
- Martha, T. R., & Vinod Kumar, K. 2013. September, 2012 landslide events in Okhimath, India—an assessment of landslide consequences using very high-resolution satellite data. *Landslides*, 10, 469–479. <https://doi.org/10.1007/s10346-013-0420-6>
- Meena, H. M., Machiwal, D., Santra, P., Moharana, P. C., & Singh, D. V. 2019. Trends and homogeneity of monthly, seasonal, and annual rainfall over the arid region of Rajasthan, India. *Theoretical and Applied Climatology*, 136, 795–811. DOI: <https://doi.org/10.1007/s00704-018-2510-9>
- Meshram, S. G., Singh, V. P., & Meshram, C. 2017. Long-term trend and variability of precipitation in Chhattisgarh State, India. *Theoretical and Applied Climatology*, 129, 729–744. <https://doi.org/10.1007/s00704-016-1804-z>
- Myers, D. T., Ficklin, D. L., & Robeson, S. M. 2023. Hydrologic implications of projected changes in rain-on-snow melt for Great Lakes Basin watersheds. *Hydrology and Earth System Sciences*, 27(9), 1755–1770. <https://doi.org/10.5194/hess-27-1755-2023>
- NDMA, 2009. National Disaster Management Guidelines, Management of Landslides and snow avalanches. National Disaster Management Authority, New Delhi. 130–134. <https://nidm.gov.in/PDF/pubs/NDMA/7.pdf> [accessed Sep 11, 2023].
- Pai, D. S., Rajeevan, M., Sreejith, O. P., Mukhopadhyay, B., & Satbha, N. S. 2014. Development of a new high spatial resolution (0.25×0.25) long period (1901–2010) daily gridded rainfall data set over India and its comparison with existing data sets over the region. *Mausam*, 65(1), 1–18. <https://doi.org/10.54302/mausam.v65i1.851>
- Rana, S., Deoli, V., & Chavan, S. R. 2022. Detection of abrupt change in trends of rainfall and rainy-day pattern of Uttarakhand. *Arabian Journal of Geosciences*, 15(7), 618. <https://doi.org/10.1007/s12517-022-09883-w>
- Rautela, P. 2018. Lessons learnt from June 16/17, 2013 disaster of Uttarakhand, India. In *Science and Technology in Disaster Risk Reduction in Asia* (pp. 273–300). Academic Press. <https://doi.org/10.1016/B978-0-12-812711-7.00017-1>
- Sen PK 1968 Estimates of the regression coefficient based on Kendall's tau. *J Am Stat Assoc* 63(324):1379–1389
- Sen Z 2012 An innovative trend analysis methodology. *Journal of Hydrologic Engineering*. 17(9):1042–1046
- Sen Z 2017 Innovative trend significance test and applications. *Theoretical and Applied Climatology*. 127(3–4):939–947
- Singh, R. B., & Mal, S. 2014. Trends and variability of monsoon and other rainfall seasons in Western Himalaya, India. *Atmospheric Science Letters*, 15(3), 218–226. <https://doi.org/10.1002/asl2.494>
- Sonali, P., & Nagesh Kumar, D. 2020. Review of recent advances in climate change detection and attribution studies: a large-scale hydroclimatological perspective. *Journal of Water and Climate Change*, 11(1), 1–29. <https://doi.org/10.2166/wcc.2020.091>
- Srivastava, P. K., Han, D., Rico-Ramirez, M. A., & Islam, T. 2014. Sensitivity and uncertainty analysis of mesoscale model downscaled hydro-meteorological variables for discharge prediction. *Hydrological Processes*, 28(15), 4419–4432. <https://doi.org/10.1002/hyp.9946>
- Vani, P. C., Sahoo, B. C., Paul, J. C., Sahu, A. P., & Mohapatra, A. K. B. 2023. Trend Analysis in Gridded Rainfall Data Using Mann-Kendall and Spearman's Rho Tests in Kesinga Catchment of Mahanadi River Basin, India. *Pure and Applied Geophysics*, 180(12), 4339–4353. <https://doi.org/10.1007/s00024-023-03379-8>
- Woolf, A., Haines, K., & Liu, C. 2003. A web service model for climate data access on the grid. *Journal of High-Performance Computing Applications*, 17(3), 281–295. <https://doi.org/10.1177/1094342003173002>
- Yadav, R., Tripathi, S. K., Pranuthi, G., & Dubey, S. K. 2014. Trend analysis by Mann-Kendall test for precipitation and temperature for thirteen districts of Uttarakhand. *Journal of Agrometeorology*, 16(2), 164–171. <https://doi.org/10.54386/jam.v16i2.1507>
- Zhang, S., Ren, G., Zhan, Y., Zhang, C., & Ren, Y. 2023. Extreme precipitation changes over the Yangtze River Basin in 1901–2020. *Climate Research*, 90, 59–76. <https://doi.org/10.3354/cr01714>
- <http://floodlist.com/asia/india-floods-landslides-uttarakhand-october-2021>. [Accessed on Sep 18, 2023].
- <https://reliefweb.int/report/india/india-situation-report-uttarakhand-cloud-burst-2nd-july-2016>. [Accessed Sep 18, 2023]

