Entropy-based assessment of climate dynamics with varying elevations for hilly areas of Uttarakhand, India

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Abstract

Water is important to the planet's long-term sustainability since it affects where and how inhabitants may survive. Rainfall is the main element of the hydrological cycle and directly impacts agriculture sectors; a regular pattern of rainfall results in healthy crop production, extreme events such as floods and drought, and industrial and domestic sectors, among others. The present study tried to explore the variability in rainfall patterns and the effect of altitudinal differences on rainfall patterns using different measures of entropy indices based on a monthly, seasonal, and annual scale. The study was carried out for the southern part of Uttarakhand, namely Almora, Kashipur, Lansdowne, and Mukteshwar stations, using 116 years of rainfall data from 1901 to 2016. Considering seasonal analysis, the post-monsoon season had a high MMDI (0.345) for Lansdowne station, followed by Mukteshwar (0.309) and Almora (0.304). However, the highest MMDI (0.340) was recorded for Kashipur during the pre-monsoon season. Pre-monsoon season had the lowest MMDI for Mukteshwar station, followed by Almora and Lansdowne stations. However, the lowest MMDI was recorded during the winter season at Kashipur station. The results revealed that Kashipur and Lansdowne's stations had a high variation. In contrast, Almora and Mukteshwar stations had less variation in rainfall amounts. In adition, altitudinal assessment based on the entropy approach, a unique aspect of the study, can demonstrate an inverse relationship between elevation, rainfall patterns, and rainy days, suggesting that rainy days and rainfall patterns vary less frequently at higher elevations. The results of this study can also be used to make recommendations for future development in rainfall models, local agricultural policies, and management of extreme events such as droughts and floods, among others.

Keywords Rainfall pattern · Entropy theory · Uttarakhand · Elevation · MMDI

Introduction

Water is a critical constituent of the Earth's long-term sustainability, determining where and how animals and plants can thrive on the planet. It contributes significantly to a country's prosperity and progress (Zezza and Tasciotti 2010). Water is needed for human consumption, food production, and industrial purposes, as well as for its aesthetic value, recreational opportunities, and other living organisms that rely on it to survive (UNDP 2006; WHO/UNICEF 2015). Water is essential for native flora in grasslands and forests, wheat and corn crops in agricultural fields, wetlands insects, amphibians, birds, fish in streams and lakes, wild mammals and reptiles, and domesticated pets and cattle (Sharma et al. 2013).

Uttarakhand is known for its natural beauty and has a total geographical area of 53,485 Km². About 83% of the landmass comes under the hills, and the rest live in the Tarai plains' belt. This state greatly experiences disasters related to the climatological factor in recent years. The mean annual precipitation of Uttarakhand state is 1896 mm, and the average annual temperature is around 21.8 ℃. A variation of about 200 m is found in relief in the southern part of the

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state. There is a large variation in the pattern because of the melting of glaciers and topography. Understanding rainfall distribution pattern is important for rainfall frequency analysis, trend analysis, and stochastic modeling. Analysis based on the rainfall data of the state is highly recommended for managing resources and meeting sufficient water demand for irrigation and drinking purposes, which is one of the challenging tasks. Most systems are composed of stochastic or deterministic components, and numerous empirical methodologies have been proposed by various scholars (Renschler et al. 1999; Mishra et al. 2009; Vallebona et al. 2015; Cui et al. 2017; Delgado-Bonal and Marshak 2019).

The primary component of the hydrological cycle is rainfall, which mainly deals with the transfer of mass and energy from the earth's surface to the atmosphere and vice versa (Sivakumar et al. 2014). A regular pattern of rainfall results in healthy crop production; however, fluctuation in the pattern of rainfall results in a disastrous scenario in crop production (Hao et al. 2008; Trenberth and Shea 2005). Flood disasters threaten 13.78 percent of India's geographical region, according to the Indian Planning Commission, because of excessive rainfall caused by climate change and anthropogenic activity (Planning Commission 2011).

Rainfall directly impacts Indian agriculture, which feeds 17.2 percent of the world's population and accounts for more than 56 percent of the country's agricultural land (Mishra et al. 2009; Prajapati et al. 2021; Singh et al. 2021). Due to this fact, monitoring the variation in rainfall patterns is urgent. Moreover, the rainfall distribution pattern varies greatly from place to place and concerning time. This shift in rainfall patterns is referred to as "rainfall variability," and analyzing the hydrologic time series of rainfall patterns is highly difficult in both temporal and geographical domains (Wu and Qian 2017; Guntu et al. 2020). Entropy is a measure of the disorder or uncertainty in a system (Cheng et al. 2017; Zhang et al. 2016). In the context of time and prediction, entropy is often used to describe the amount of information or randomness in a sequence of events or data (Singh 2013). The concept of entropy can help us understand the predictability or predictiveness of a system. In general, as time progresses and a system evolves, its entropy tends to increase. This means that the system becomes more unpredictable or uncertain over time (Shannon 1948). The Entropy theory gives a succinct description of the system domain for coping with the stochastic component (which is responsible for uncertainty or unpredictability), as well as temporal analysis of time-series data (Singh 1997; Li et al. 2020; Gao et al. 2022). Since the study of rainfall variability using continuous data based on the Entropy approach has received less attention in the state of Uttarakhand, this region has been preferred for the examination. Furthermore, understanding rainfall's temporal variability is precarious for water resource planning and management and in the prevention of extreme events like floods, droughts as well as the control of soil erosion (Karmakar et al. 2017; Pendergrass et al. 2017; Jin and Wang 2017; Kurths et al. 2019; Yaduvanshi et al. 2019). Despite the limited attention given to the impact of elevation on rainfall patterns in previous studies, this research distinguishes itself by embracing a novel approach involving entropy. Furthermore, by exploring the intricate interplay between elevation and precipitation through the lens of entropy, this study not only pushes the boundaries of knowledge but also uncovers new perspectives, expanding our understanding of this complex relationship. In addition, the author intends to explore the temporal variability of rainfall using different time scales of the Entropy technique.

Material and methods

Study area and dataset

Uttarakhand is a hilly Indian state with 13 districts and a land area of 53,483 km^2. It is split into two regions: Kumaun and Garhwal. It lies between latitudes of 30.066°N and longitudes of 79.019°E, with elevations ranging from 210 to 7817 m. The current study was conducted for the southern part of Uttarakhand state, specifically Almora, Kashipur, Lansdowne, and Mukteshwar, to cover some hilly and plain terrain. In-situ monthly rainfall data from 1901 to 2016 was obtained from India Meteorological Department (IMD), Pune. The detailed map of the Uttarakhand state is depicted in Fig. 1.

Methodology

In the present study, entropy theory is tried to implement to investigate the variability of rainfall patterns based on three different time scales. Marginal Entropy (ME), Apportionment Entropy (AE), and Intensity Entropy (IE). For finding the variability in rainfall patterns, different Indices, i.e., Marginal Disorder Index (MDI), Apportionment Disorder Index (ADI), and Intensity Disorder Index (IDI), were used. Furthermore, an altitudinal study is carried out to see the competency of the entropy technique to detect rainfall variability as elevation changes.

Shannon entropy

In communication engineering, Shannon (1948) developed information entropy, commonly known as Shannon entropy, to quantify information concerning an idea termed "surprise." According to Shannon, it measures the randomness, dispersion, or uncertainty in the Dataset. Singh (1997) reviewed its application, advantages, and disadvantages and proposed that it might be used as a supervisory tool in
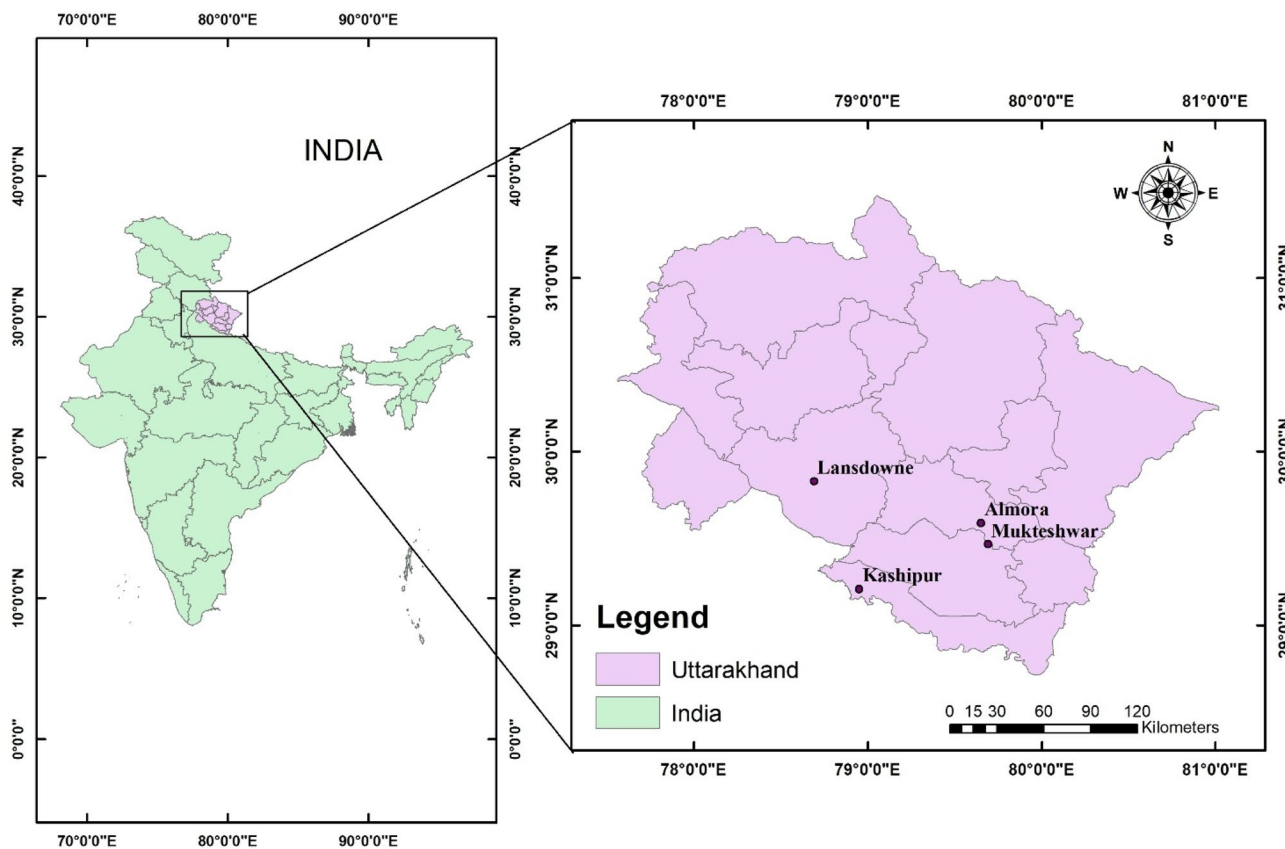
Fig. 1 Detailed map of the study area

hydrology and water resources. The governing equations for entropy theory are given below.

$$H(x) = -\sum_{k=1}^{N} p(x_k) \log_2 p(x_k) \tag{1}$$

where; k is the time interval of Nth events; x_k is an event corresponding to the interval k; $p(x_k)$ is the probability of x_k, $H(x)$ is the value of entropy and it is also known as marginal entropy.

Suppose the probabilities of the random variables are the same. In that case, the value of H will be maximal, and $H = 0$, indicating that the likelihood of that event is one and zero for all other events. As a result, the value of H varies from zero to N, and entropy values rise as the number of constraints increases.

Marginal entropy (ME)

For assessing the uncertainty, it is the average information about the random variable X with the probability distribution $P(x)$ (Mishra et al. 2009). When we have monthly time series data, it tells us about the unpredictability of the entire dataset.

ME was used monthly and seasonally in the current investigation to detect intra-variability among the stations. The expression for calculating ME is described below.

$$\text{ME} = -\sum_{k=1}^{N} \left(\frac{r_k}{R}\right) \log_2 \left(\frac{r_k}{R}\right) \tag{2}$$

where; r_k is the rainfall for the kth year, and R is the total rainfall of the entire dataset length. N is the number of class intervals.

Apportionment entropy (AE)

AE is used to measure the intra-variability of rainfall amount. It may be defined as if m_j is the monthly rainfall in a jth month, i.e., $j = 1, 2, 3, 4…0.12$, and M is the total rainfall amount each year. (Guntu et al. 2020). Apportionment entropy is described by Eq. (3).

$$\text{AE} = -\sum_{j=1}^{N} \left(\frac{m_j}{M}\right) \log_2 \left(\frac{m_j}{M}\right) \tag{3}$$

where R is the summation of all months in a year, i.e., 12 months, and N is the number of class intervals.

Decadal apportionment entropy (DAE)

The beauty of DAE is that it may be applied to any hydro-meteorological time series data. The current study is employed to determine rainfall variability over ten years. If annual rainfall data for a station is designated a_j by where j varies from 1 to 10 and total rainfall in a decade is given by DR (Mishra et al. 2009), DAE is expressed by Eq. (4).

$$\text{DAE} = -\sum_{j=1}^{10} d_j \log_2 d_j = -\sum_{j=1}^{10} \left(a_j/\text{DR}\right) \log_2 \left(a_j/\text{DR}\right) \quad (4)$$

where DR is the Decadal Rainfall and calculated by using Eq. (5).

$$(\text{DR}) = \sum_{j=1}^{10} a_j \quad (5)$$

Intensity entropy (IE)

It measured the variability of rainy days and was proposed by (Maruyama et al. 2005). It is the ratio of the variability of rainy days in a month to the total number of rainy days in a particular year. It is also called relative frequency. Its mathematical expression is shown below.

$$\text{IE} = -\sum_{k=1}^{N} \left(\frac{p_k}{P}\right) \log_2 \left(\frac{p_k}{P}\right) \quad (6)$$

where, p_k is the number of rainy days for k^{th} month, P is the sum of total rainy days in a year, and N is the number of class intervals, and it depends upon the types of time-scale; for example, $N = 4$ for seasonal time-scale, $N = 12$ for monthly time-scale and $N = 365$ for daily time-scale.

Mean marginal disorder index (MMDI)

The marginal disorder index (MDI) compares temporal and geographical variability. The Mean Marginal Disorder Index (MMDI) was used in this study to calculate temporal variability. Its mathematical expression is given below.

$$\text{MMDI} = \left(1 - \frac{H}{H_{\text{max}}}\right) \quad (7)$$

where: H is the average value obtained from time series data; H_{max} is the maximum possible value of time-scale.

Disorder index (DI)

DI may be defined as the difference between the maximum possible and actual entropy from an individual time series (Mishra et al. 2009). When the disorder index (DI) is calculated using intensity entropy, it is known as the Intensity Disorder Index. Likewise, when DI is calculated using allocation entropy (AE) and marginal entropy (ME), it is known as the Apportionment Disorder-Index (ADI) and the Marginal Disorder Index (MDI), respectively. Decadal Apportionment Disorder-Index (DADI) is also obtained in a decadal study using Decadal Apportionment Entropy. The variation in rainfall amount, rainy days, and corresponding months and seasons are all intimately related to the word "DI." Higher DI values will result in periods of greater period variability.

Results and discussion

Seasonal rainfall variability at different stations

The Mean Marginal Disorder Index (MMDI) at Lansdowne was high (0.345) during the post-monsoon season, followed by winter, pre-monsoon, and monsoon. Furthermore, the MMDI value for the Almora during the post-monsoon season is high (0.304). However, the lowest MMDI was recorded for the monsoon season. The Mukteshwar station showed a similar pattern to that of Almora station, as shown in Fig. 2. At Kashipur station, the highest variability (0.340) was seen during the pre-monsoon period followed by post-monsoon, monsoon, and winter periods.

In the post-monsoon season, the MMDI values for Lansdowne, Almora, Mukteshwar, and Kashipur, respectively, were 0.345, 0.304, 0.309, and 0.326, and variation was particularly significant for Lansdowne station. Similarly, in the pre-monsoon season, the value of MMDI was less for the Mukteshwar station. The calculated MMDIs values were 0.244, 0.186, 0.173, and 0.340 for the Lansdowne, Almora, Mukteshwar, and Kashipur stations, respectively, whereas, for monsoon season, calculated MMDIs were 0.216, 0.198, 0.179 and 0.290 for Lansdowne, Almora, Mukteshwar, and Kashipur respectively. Moreover, for the winter season, the MMDIs at Lansdowne, Almora, Mukteshwar, and Kashipur were 0.287, 0.213, 0.231, and 0.260, respectively, these ranges of entropy indices have received additional support and validation from previous studies in the field (Mishra et al. 2009), and comparatively slight change was seen in the MMDI values at Almora and Mukteshwar station. However, there was significant variation at Lansdowne when compared to other stations.

Fig. 2 Seasonal variation in rainfall amounts over selected stations
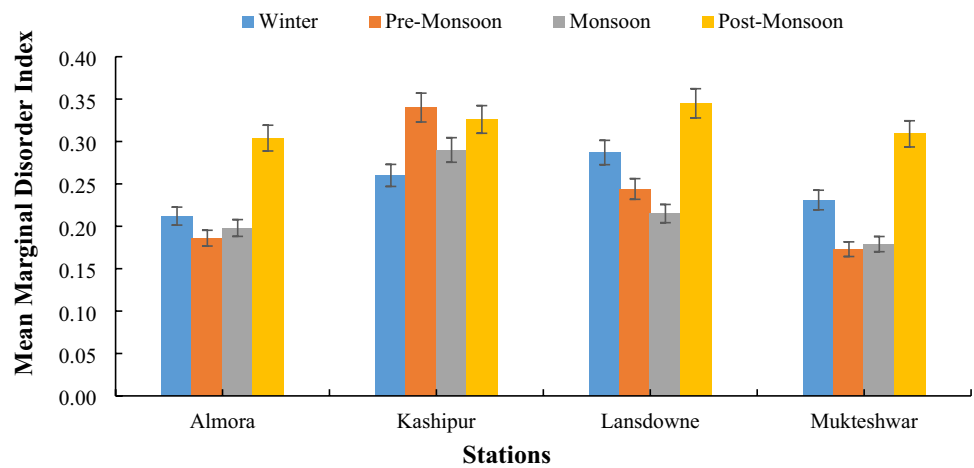
Monthly rainfall variability at different stations
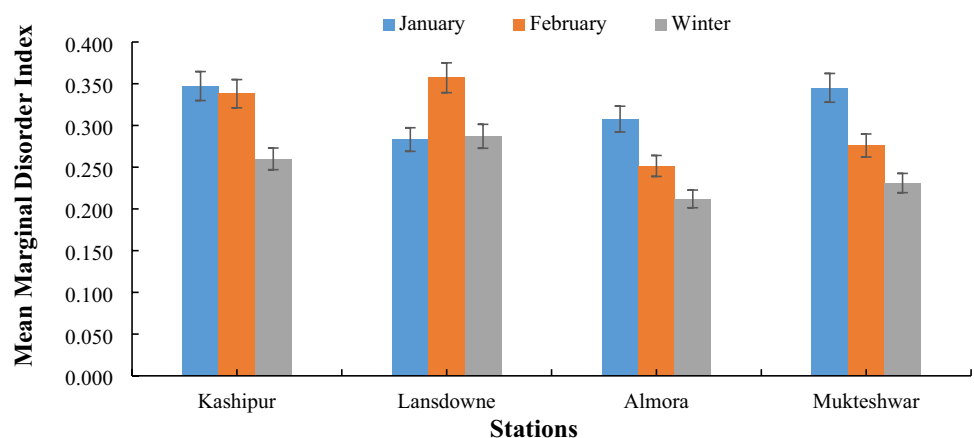
Monthly rainfall variability of the winter season

In Fig. 3, the bar graph displays the monthly variation of rainfall amount in the southern region of Uttarakhand state. In February, the highest MMDI (0.357) was recorded, indicating more variation in rainfall. A major contributing variability in the winter season (Sahany et al. 2018; Shukla et al. 2019; Guntu et al. 2020) is the variation in the February month for the Lansdowne station. However, for the Kashipur station, January (0.347) and February (0.338) contributed to variations in rainfall amounts. Furthermore, for the Mukteshwar (0.345) and Almora (0.308) stations, January contributes a major portion for rainfall variation, a high MMDI value. The lowest MMDI (0.251) was recorded during February for the Almora station, which means contributing variation in the rainfall amount is quite less.

### Monthly rainfall variability of pre-monsoon season

May had the highest MMDI, or 0.398, of any month during the pre-monsoon season at the Kashipur station, showing that May has a significant role in the pre-monsoon season's variability. This variation may be due to the change in climatic conditions or altitudinal differences in the study area (Shukla et al. 2019). The lowest MMDI, i.e., 0.22, is determined during April for the Lansdowne station, which means responsible months that are contributing variability are March and May months or in other words, April month causes less variability in the rainfall amounts during the pre-monsoon season; shown in Fig. 4. According to the findings, Kashipur station had a higher MMDI score, indicating a significant amount of rainfall variability.

For March, April, and May at Lansdowne station, the MMDI values were 0.255, 0.220, and 0.332, respectively; variability was comparatively high in May. Similar results were found in Almora station, where MMDI values for March, April, and May were 0.325, 0.257, and 0.320, respectively. It also noted that no appreciable variance was evident between March and May. However, when compared

Fig. 3 Monthly rainfall variability of the winter season

Fig. 4 Monthly rainfall variability of Pre-monsoon season
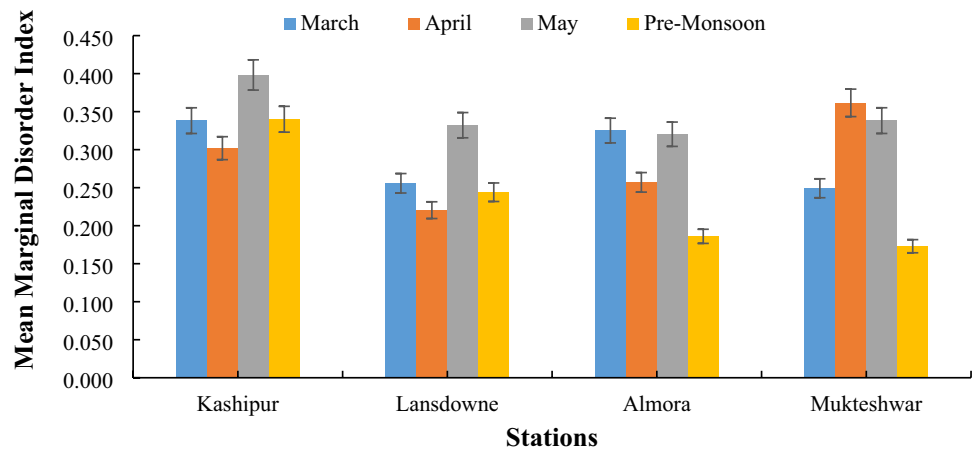
to April month, they had significant variation. The MMDI fluctuation was significant at Mukteshwar station between April and May, while it was considerably smaller in March, with computed MMDI values of 0.249, 0.360, and 0.338 for March, April, and May, respectively. The MMDIs measured at Kashipur station in March, April, and May were 0.338, 0.320, and 0.398. It has been noticed that there was a high variation in May compared to March and April.

Monthly rainfall variability of post-monsoon season

At Almora station, the computed MMDIs for October, November, and December were 0.352, 0.185, and 0.393. The MMDIs value for November was much lower than that of the other months, such as October and December. For October, November, and December of the post-monsoon season, the MMDI values at Mukteshwar station were 0.373, 0.171, and 0.202. It was discovered that October had the greatest MMDI value compared to the other months at Mukteshwar station, as shown in Fig. 5. The computed MMDIs for October, November, and December for Kashipur station were 0.330, 0.141, and 0.239, respectively. In contrast to previous months at Kashipur station, the computed MMDI value

indicated that October had a significant level of variability. Additionally, according to Fig. 5, the months of December (at the Almora station) and November (at the Kashipur station) had the greatest MMDI values of 0.393 and the lowest, 0.141, respectively; this indicates that a greater and less variation in rainfall amounts is present in December and November, respectively, of the post-monsoon season.

Monthly rainfall variability of monsoon season

At Lansdowne station, the measured values of MMDIs were 0.222, 0.036, 0.032, and 0.179 during the June, July, August, and September monsoon seasons, respectively. These numbers demonstrated the irregularity of the monthly rainfall. The MMDI value was quite high in June and September, but it was found to be much lower in July and August compared to the other months. Like this, the MMDI recorded at the Almora station was low for July and August compared to other months, ranging from 0.053 to 0.181 during monsoon seasons, as shown in Fig. 6. The MMDI values at Mukteshwar station ranged from 0.065 to 0.198. Higher values were seen in June and September than in other monsoon months. Furthermore, in June, July, August, and September,

Fig. 5 Monthly rainfall variation in the post-monsoon season
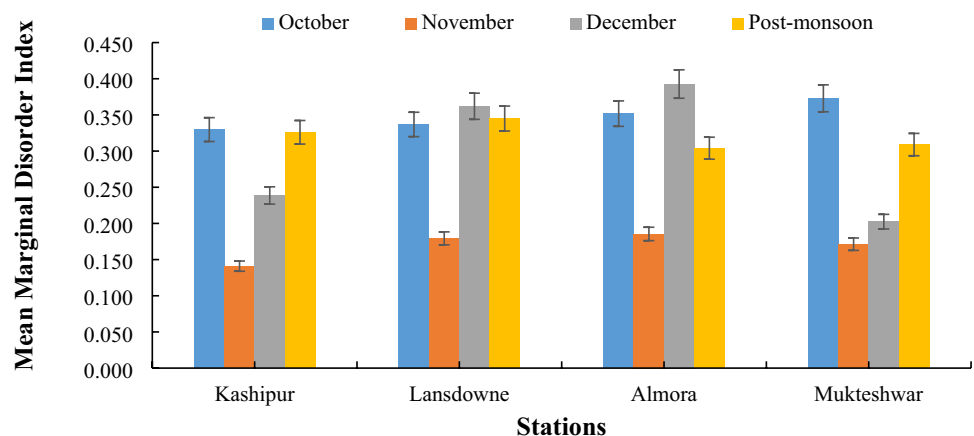
Fig. 6 Monthly rainfall variation in rainfall amounts
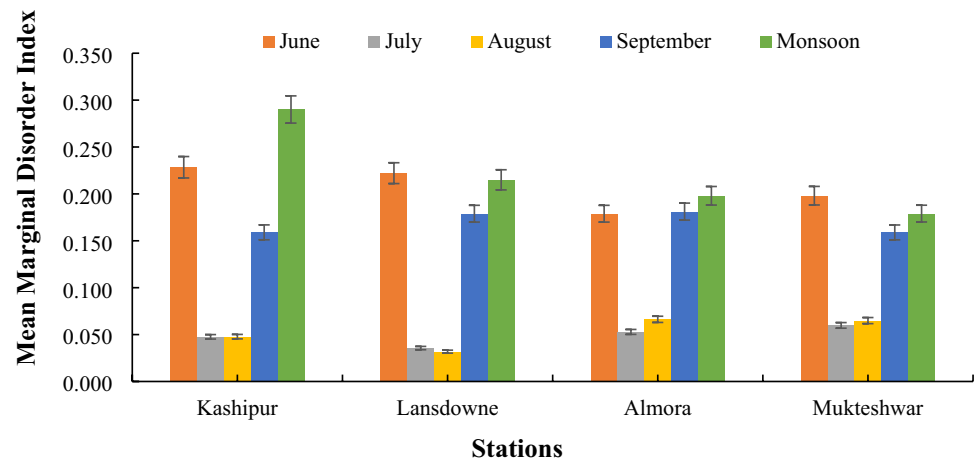
the computed MMDI values for Kashipur station were 0.228, 0.048, 0.048, and 0.159.

The lowest and highest variation in rainfall amounts was noticed during August (Lansdowne) and June (Kashipur), respectively, based on MMDI values. From the findings above, we may also infer that variations in the monsoon season are caused by the more variable months of June and September. However, this situation is not limited to the Kashipur station; it is also evident at the other stations. Additionally, the first and last months of the *monsoon season* encounter abrupt low and abrupt high rainfall, respectively; due to the low and high MMDI values, these rainfall patterns may result in catastrophic situations like a flood and drought (Singh et al. 2014; Cheng et al. 2017; Liu et al. 2019; Li et al. 2020).

Seasonal variation of rainy days

This section explains how the Mean Intensity Disorder Index (MIDI), for the selected stations, such as Lansdowne, Almora, Mukteshwar, and Kashipur, varies concerning the number of rainy days during the winter, pre-monsoon, post-monsoon, and monsoon seasons. At Lansdowne station, the highest MIDI value, i.e., 0.279, was observed for the post-monsoon season, the lowest MIDI value was 0.170 for the pre-monsoon season, and the calculated MIDIs were 0.180, 0.170, 0.279 and 0.178 for the winter, pre-monsoon, post-monsoon and monsoon seasons respectively. At Almora station, the highest MIDI value, 0.235, was recorded for the post-monsoon season, and the lowest MIDI value, 0.122, was recorded for the pre-monsoon season. The calculated MIDIs for the winter, pre-monsoon, post-monsoon, and monsoon seasons, respectively, were 0.155, 0.122, 0.235, and 0.171.

At the Mukteshwar station, the MIDI analysis revealed that the winter season exhibited the highest MIDI value (0.199), signifying a notable level of variability in the

occurrence of rainy days. This finding further implies that rainfall events were concentrated at specific intervals during that particular year (Zhang et al. 2016; Sahany et al. 2018). The pronounced fluctuations in rainy day patterns during the winter season suggest a distinct pattern of precipitation distribution, with periods of intense rainfall followed by relatively dry intervals. In contrast, the pre-monsoon season had the lowest (0.125). The computed MIDIs for the winter, pre-monsoon, post-monsoon, and monsoon seasons, respectively, were 0.199, 0.125, 0.178, and 0.134. Similarly, at Kashipur station, the post-monsoon season had the greatest MIDI value, which was 0.273, and the monsoon season had the lowest MIDI value, 0.178. The computed MIDIs for the winter, pre-monsoon, post-monsoon, and monsoon seasons, respectively, were 0.197, 0.207, 0.273, and 0.178. The observed reduction in the frequency of rainy days signifies a limited occurrence of rainfall within the specified period. Their research also noted a similar trend (Kumar and Jain 2011), reinforcing the notion that the occurrence of rainfall has become more sporadic and infrequent. This information contributes to our understanding of the temporal dynamics of rainfall in the region, aiding in the assessment of hydrological processes and their potential impact on various sectors reliant on consistent and evenly distributed rainfall.

Comparing intra-variability on rainy days for the selected station

The Lansdowne station had the highest variability (0.279) of rainy days during the post-monsoon season, followed by Kashipur, Almora, and Mukteshwar stations, while the Almora station had the lowest variability (0.122) of rainy days during the pre-monsoon season, followed by Mukteshwar, Lansdowne, and Kashipur stations. According to most of the results, Kashipur station received greater variations on rainy days. In contrast, Mukteshwar station experienced the lowest variations, as shown in Fig. 7. These findings can

also be cross-verified using another entropy theory index, i.e., the Mean Marginal Disorder Index (MMDI).

Annual decadal variation based on apportionment disorder index (ADI)

Decadal annual variation for four stations

The bar graph, as shown in Fig. 8, represents the variability in the annual rainfall for eleven decadal years concerning the Decadal Apportionment disorder index (DADI). Among all the decades, the Kashipur station's DADI variability was the highest from 1971 to 1980, followed by Lansdowne and Almora, which showed significant annual variations in rainfall amounts. However, the Mukteshwar station's highest and lowest DADI levels were recorded between 1991 and 2000. The Almora station, followed by Mukteshwar and Kashipur stations, had the lowest fluctuation in DADIs value during

the period 1941–1950, which further indicated that the period had less fluctuation in the pattern of annual rainfall.

Altitudinal analysis based on MMDI

Mukteshwar is the station with the highest elevation, at 2311 m above mean sea level, while Kashipur is the station with the lowest elevation, at 183 m above mean sea level. According to Table 1, the highest MMDIs were 0.287 (Lansdowne), 0.340 (Kashipur), 0.290 (Kashipur), and 0.345 (Lansdowne) recorded during winter, pre-monsoon, monsoon, and post-monsoon seasons respectively, after seasonal assessment. Moreover, the lowest MMDIs were 0.212 (Almora), 0.173 (Mukteshwar), 0.179 (Mukteshwar), and 0.304 (Almora) during winter, pre-monsoon, monsoon, and post-monsoon seasons determined, respectively as depicted in Table 1. The range of values of entropy obtained in Tables 1 and 2 is also supported by various published

Fig. 7 Seasonal variation in rainy days over selected stations
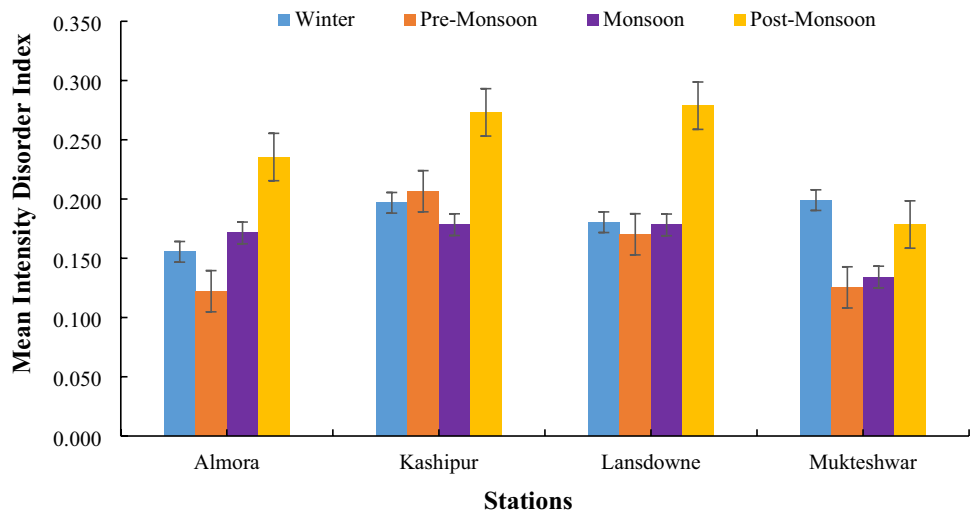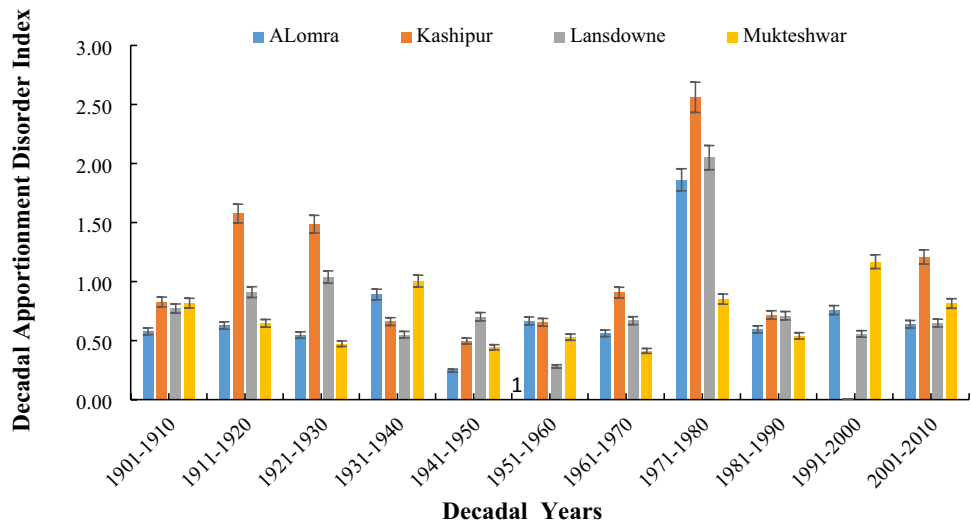
Fig. 8 Decadal analysis of annual rainfall data over selected stations

studies (Mishra et al. 2009; Guntu et al. 2020; Li et al. 2021; Sreeparvathy and Srinivas 2022).

As a result of their lower elevation but higher entropy index values than the other two stations, Kashipur and Lansdowne's stations had greater variation in their rainfall patterns. It is also obvious from Fig. 9 that there is an inverse relationship between elevation and rainfall amounts. Like this, Mukteshwar and Almora are higher in elevation than the other stations. However, they have lower entropy indices, indicating less rainfall variability than Kashipur and Lansdowne.

Altitudinal analysis based on MIDI

According to the seasonal analysis of rainy days based on MIDI value, Table 2, the highest MIDIs were 0.1991 (Mukteshwar), 0.207 (Kashipur), 0.1783 (Kashipur) and 0.2788 (Lansdowne) recorded during winter, pre-monsoon, monsoon, and post-monsoon seasons respectively. In

contrast, the lowest MIDIs were 0.1554 (Almora), 0.1222 (Almora), 0.1341 (Mukteshwar), and 0.1785 (Mukteshwar) observed during winter, pre-monsoon, monsoon, and post-monsoon seasons, as represented in Table 2. Kashipur station experienced more variation on rainy days. In contrast, Almora and Mukteshwar stations had a lower variation on rainy days. However, Mukteshwar station had a higher variation during the winter season. Overall, Almora (1676 m above mean sea level) and Kashipur (183 m above mean sea level) stations experienced less variation and more variation on rainy days, respectively, due to differences in elevation and belonging to different regions of the Himalayan plateau (Rajeevan et al. 2012; Shukla et al. 2019; Guntu et al. 2020; Li et al. 2021). Furthermore, it is evident from Fig. 10 that the relation between elevation and rainy days is inverse, i.e., rainy days vary less frequently at higher elevations.

Table 1 Effect of altitudinal differences on Rainfall based on MMDI

Stations	Altitude in meters (above M.S.L)	Winter	Pre-monsoon	Monsoon	Post-monsoon
Almora	1676	**0.212** (↓)	0.186	0.198	**0.304** (↓)
Kashipur	183	0.260	**0.340** (↑)	**0.290** (↑)	0.326
Lansdowne	1532	**0.287** (↑)	0.244	0.215	**0.345** (↑)
Mukteshwar	2311	0.231	**0.173** (↓)	**0.179** (↓)	0.309

Table 2 Effect of altitudinal differences on Rainy days based on MIDI

Stations	Altitude in meters (above M.S.L)	Winter	Pre-monsoon	Monsoon	Post-monsoon
Almora	1676	0.1554 (↓)	0.1222 (↓)	0.1714	0.2354
Kashipur	183	0.1968	**0.2070** (↑)	**0.1783** (↑)	0.2731
Lansdowne	1532	0.1804	0.1702	0.1782	**0.2788** (↑)
Mukteshwar	2311	**0.1991** (↑)	0.1254	0.1341 (↓)	0.1785(↓)

Fig. 9 Effect of Elevation on rainfall pattern
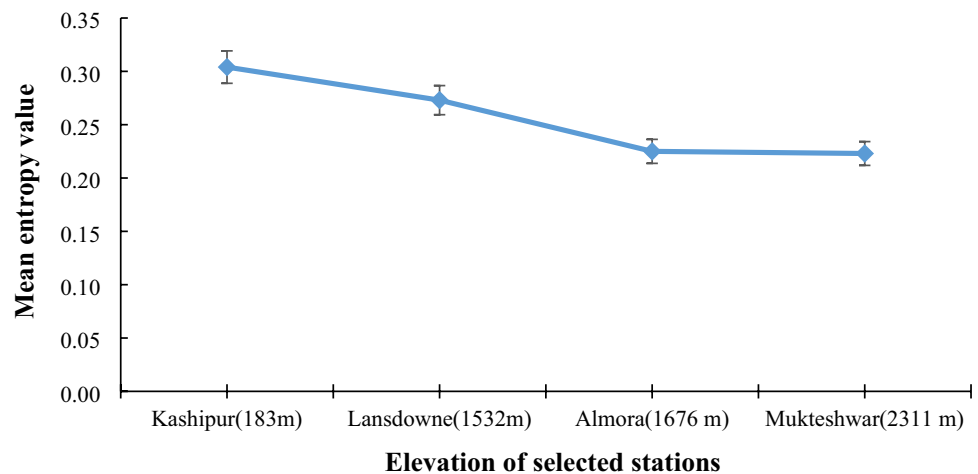
Fig. 10 Effect of Elevation on rainy days
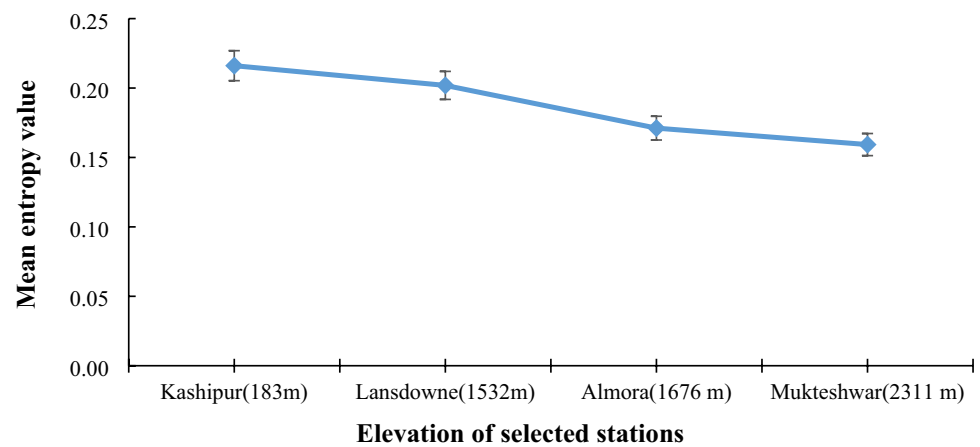
Scenario of recharge zones in the studied area

The study regions, specifically Almora, Lansdowne and Mukteshwar, being situated in a hilly area, rely on various water bodies such as rivers, springs, and gaderas to meet the basic needs of the local population. These water bodies serve as important sources of water for drinking, irrigation, and other domestic uses in the region. Springs have power relationship with rainfall which signifies that recharging is primarily governed by rainfalls (Agarwal et al. 2012; Panwar 2020). According to a study conducted by Dass et al. (2021), the spring flow in Shiv gadera, located in the Almora district, was found to be perennial, indicating a gradual depletion of the groundwater aquifer and exhibit better stability compared to other gaderas. This observation suggests that the recharging zones in the area are consistently available. Moreover, a study made by Malik et al. (2021), the possibility of normal drought conditions occurring in Mukteshwar (Nainital district) at around 69% and in Almora at approximately 68%. These statistics and outcomes obtained by entropy suggest that the water resources in the study region are still sufficiently accessible and not extensively depleted in the recharging zones.

Conclusions

In the present study, the multi-scale entropy method was used to suggest a novel way to detect variations in rainfall patterns and the influence on rainfall as elevation varies. This study primarily focuses on precipitation data that may be used to calculate various indices. It records variations in the rainfall pattern across various stations based on those indices. According to an altitudinal study, since the elevation of Kashipur station (183 m above M.S.L.) is lower than all other stations, the variations in rainfall amounts were found to be more as the high entropy indices during the pre-monsoon and monsoon seasons among all the stations.

Similar results were also recorded at the Lansdowne station (1532 m above M.S.L) during post-monsoon and winter seasons across the stations. Another intriguing finding from the study was that as elevation increased, fluctuations or inconsistency in rainfall patterns decreased significantly; in other words, for the station with the lower elevation, rainfall amounts were more frequently seen, as depicted in Fig. 9. The impact of elevation on rainy days is also investigated. The same pattern is observed for rainy days, indicating the entropy theory's reliability. If we talk about how rainy days and elevation are related, this study has effectively found a significant connection between the two, which are inversely proportionate to elevations, i.e., lower variations in rainy days are found at higher elevations.

The following conclusions can be drawn from this study:

- Kashipur station, which had the lowest height of all the stations, i.e., 183 m above mean sea level, had substantial variability according to the altitudinal analysis, demonstrating that variability was more noticeable at lower elevations.
- The Almora and Mukteshwar stations experienced less variability in rainfall and rainy days, which significantly contributes to reinforcing the understanding of the water resource dynamics in the region.
- Another measure of entropy, the Mean Intensity Disorder Index, can also be used to confirm these results.
- The results of this study also show that variations in rainfall patterns and the number of rainy days increase with decreasing altitude.
- The outcomes of this study revealed that the entropy approach could capture the variability in rainfall patterns based on several scales as well as the influence on rainfall when elevation varies.

These results or outputs can also be utilized to provide recommendations for changes to the rainfall model, local agricultural policies, the deployment of soil water

conservation measures, and solutions to problems related to water scarcity. In the current study, the estimation of rainfall pattern variability using entropy theory focuses on selected point locations. However, a promising avenue for future investigation lies in the utilization of remote sensing, which enables the analysis of continuous rainfall data. This opens up possibilities for predicting entropy as a function of elevation through the application of advanced machine learning techniques. This potential direction could be pursued by researchers aiming to expand upon the findings of this study and uncover further insights into the complex relationship between rainfall, elevation, and entropy.

Declarations

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