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Investigation of rainfall variability of the southern part of Uttarakhand using entropy theory

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ABSTRACT

Rainfall is a natural phenomenon with high probability of randomness. The extent of rainfall variability may be an indicator of wet season or dry season. The information on rainfall variability can be used to understand the dynamics of seasonal or annual weather pattern, which can further be adopted to study the extent of climatic variability of a region. The rainfall variability in the present study has been studied using entropy theory. Entropy theory gives transitory information about the uncertainty in rainfall patterns on behalf of the stochastic approach. In this study, three rain gauge stations, situated in southern part of Uttarakhand, were selected. The rain gauge stations were situated at Almora, Nainital and Pauri. The temporal data of rainfall from 1901 to 2016 has been taken from India Meteorological Department (IMD). Disorder index (DI), estimated using entropy equations, has been derived for winter, pre–monsoon, monsoon, and post–monsoon seasons for the study period. The study suggested that DI and mean marginal disorder index (MMDI) were observed high (*i.e.* 0.351) for the post–monsoon season at Nainital station, followed by Pauri, and Almora stations. In terms of total seasonal variation in rainy days at the selected stations, Almora station has relatively high degree of DI and MMDI. The highest and lowest MMDIs value were 0.235 and 0.122 observed for pre–monsoon and post–monsoon season respectively. It indicated that rainy day's variation was high in post–monsoon and low in pre–monsoon season for the study period. This variation in the distribution of rainfall over the area may lead to inconsistency in the rainfall pattern.

1. INTRODUCTION

India lies in the Central region of South Asia and is well recognized for its unique geography and topography, which influences the climatic condition. It experiences a heterogeneous climate because of its geographical area. The distribution of rainfall patterns is primarily influenced by its relief features on earth. Also, among all the meteorological parameters, rainfall is regarded as a major parameter that directly influences the socio–economic wealth of the country and the people, who depend on agriculture (rainfed agriculture) (Koutsoyiannis, 2005; Sahoo *et al.,* 2019). A large degree of variation in rainfall distribution pattern with respect to time and space is termed as "rainfall variability" (Xu *et al*., 2015). Rainfall has a direct impact on agriculture since Indian agriculture mostly depends on rain. Good distribution of rainfall during the crop growing period results in higher crop production whereas, variation in the pattern of rainfall leads to a crop failure in rainfed areas (Kumar, 2009; Alam *et al.,* 2016). A comprehensive information of rainfall pattern plays significant role in planning and designing of different water conservation structures (Sharma and Dubey, 2013; Kar *et al.,* 2017; Singh *et al.,* 2019). Therefore, it is very essential to study about the behavior of rainfall patterns. To analyze the behavior of rainfall patterns, entropy theory gives brief information about the stochastic component, which is responsible for the uncertainty or randomness in a system domain (Da Silva *et al*., 2016; Tongal and Sivakumar, 2017; Roushangar and Alizadeh, 2018). The concept of entropy theory and temporal variability analysis is used to examine the daily precipitation data by many researchers (Maruyama *et al.,* 2005; Cheng *et al.,* 2017; Wang *et al.,* 2018). The theory of entropy is also used to investigate the rainfall variability on a monthly, seasonal and annual basis. For different climatic zones, time–period and variations in distances would affect the analysis of rainfall distribution, therefore entropy theory is applied to encounter (Mishra *et al.,* 2009; Hao and Singh, 2013) these kinds of problems and also entropy approach gives an alternative idea to assess the rainfall pattern. The low values of entropy show that there is less uncertainty in rainfall pattern (variation or randomness) and *vice−versa* (Chou, 2014; Wrzesinski, 2016; Zhang *et al.,* 2016). In this study, a statistical and entropy approach was used for evaluating the rainfall variability in the southern part of Uttarakhand. The present study is aimed to analyze monthly, seasonal, and annual rainfall variability using entropy theory for three selected stations located in the southern part of Uttarakhand state.

2. MATERIALS AND METHODS

Uttarakhand is a hilly state of India consisting of 13 districts with a geographical area of 53483 km^2. It consists of two sub−divisions *i.e.* Kumaun and Garhwal region. The latitude and longitude of Uttarakhand state are 30.066^{o}N and 79.019^{o}E, respectively with an elevation ranging from 210 m to 7817 m. It is enclosed by Tibet to the north and Nepal to the east. For analyzing the variability of rainfall, stations located in the southern part of Uttarakhand namely Almora, Nainital, Pauri stations were selected (Fig.1).

Data Acquisition

Monthly rainfall and rainy days' data of three stations under the study from 1901 to 2016 was obtained from IMD. A day is said to be a rainy day, if the depth of rainfall is more than or equal to 2.5 mm in a day (IMD). In this study, the seasons were taken as listed in Table 1 (IMD). All the analysis of entropy theory and statistical parameters study have been carried out in MS Excel tool.

Statistical Parameters

In this study, to express the data in statistical form, mean, standard deviation (SD), and coefficient of variation (CV) have been used. Formulae of a statistical parameter were used in this study are presented in Table 2.

Entropy Theory

The entropy theory was introduced by Shannon in 1948. The entropy gives us a brief knowledge of the variability or uncertainty of the system domain. The entropy can be defined as; it is a measure of variability or randomness in the dataset. For selecting a numerical model and for quantifying the disorderliness, entropy theory plays a vital

Table: 1
Seasons as per to IMD

Seasons	Months
Winter	January – February
Pre–monsoon	March – May
Monsoon	June – September
Post–monsoon	October – December

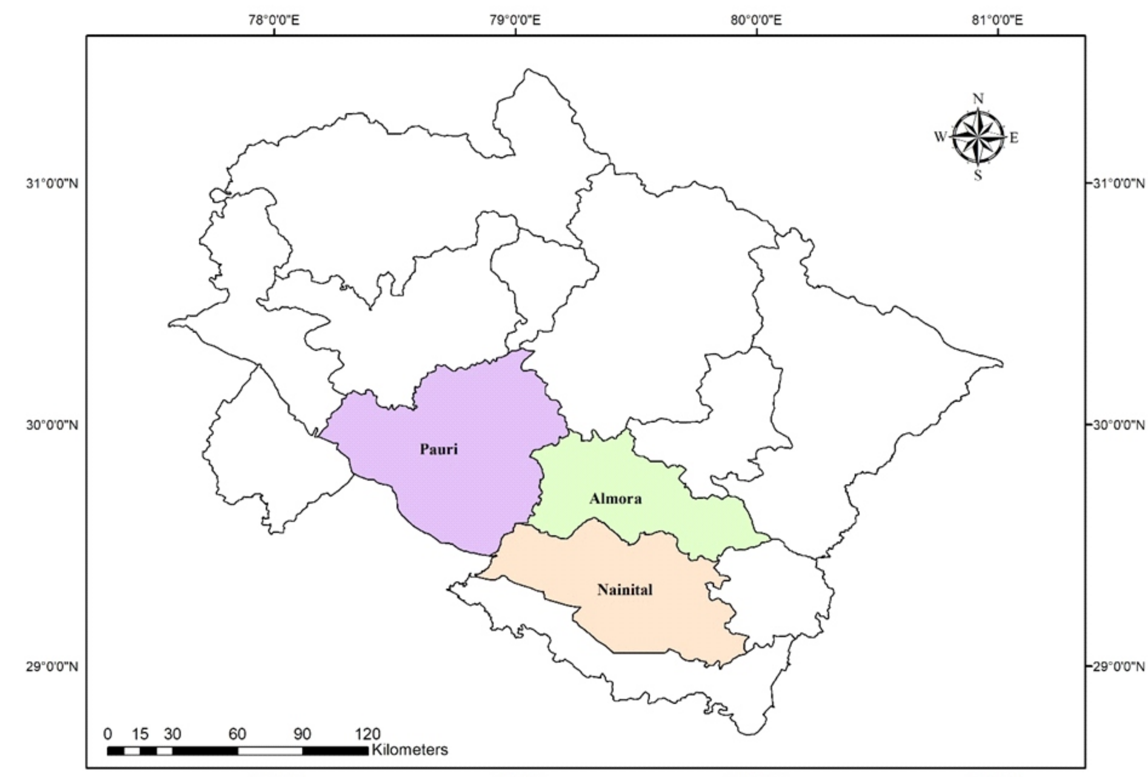

Fig. 1. Map showing study area in Uttarakhand

Table: 2
Statistical parameters and its formula used for the study

Statistical parameter	Formula	
Mean	$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$	... (i)
Standard deviation (SD)	$SD = \sqrt{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2\right)}$	... (ii)
Coefficient of variation (CV)	$CV(\%) = \frac{SD}{\bar{x}} \times 100$	... (iii)

Where, $\bar{x}$ is mean of observation and n is the total length of data; x_i is the values in the observation

role (Singh *et al.,* 2019). In recent years, entropy theory is used to analyze the uncertainty of an event of a random variable. The continuous form of entropy having the probability density function of a random variable x is given in eq. 1.

$$H_s(X) = -k\int f(x)\log\left(\frac{f(x)}{m(x)}\right)dx \quad ...(1)$$

The modified form of entropy can be described by eq. 2.

$$H_s(X) = -\int f(x)\log f(x)dx \quad ...(2)$$

Where, k is the constant and it depends upon the base algorithm; $f(x)$ is the probability density function; $m(x)$ is the measure of entropy and it depends upon the choice of a co−ordinate system. Furthermore, the discrete form of entropy is expressed in eq. 3.

$$H(x) = -\sum_{k=1}^{K} p(x_k)\log_2 p(x_k) \quad ...(3)$$

Where, k is the time interval of K 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 (ME). If the probability of the random variables is the same then the value of H would be maximum and $H = 0$; it means the probability of that event is 1 and for all other events, it will be zero. Hence the value of H lies between zero to 2logK (Mishra *et al.,* 2009; Cheng *et al.,* 2017; Wang *et al.,* 2018) and if the number of constraints is increasing it means values of entropy would be decreased (Martino *et al.,* 2013).

Apportionment Entropy (AE)

It is defined as, if m_j is the monthly rainfall in a j^{th} month *i.e.* $j = 1, 2, 3, 4…, 12$ and R is the total rainfall in that year then AE is expressed in eq. 4.

$$AE = -\sum_{j=1}^{n}(m_j / R)\log_2(m_j / R) \quad ...(4)$$

Where, R is the summation of all months in a year *i.e.* 12 months; p_j is the rainfall probability *i.e.* m_j / R and n is the total length of the dataset. The temporal variability of monthly rainfall in a year is obtained by AE.

Decadal Apportionment Entropy (DAE)

In decadal analysis, randomness or disorderliness of rainfall data is determined by DAE (Chou, 2011). If annual rainfall data for a station is denoted by a_j where j varies from 1 to 10 and total rainfall in a decade, is given by DR then DAE expressed in eq. 5 (Pechlivanidis, 2016).

$$DAE = -\sum_{j=1}^{10} d_j \log_2 d_j = -\sum_{j=1}^{10}(a_j / DR)\log_2(a_j / DR) \quad ...(5)$$

Where, d_j is the ratio between the annual rainfall for the j^{th} year and total rainfall in a decade and DR is the Decadal Rainfall, it is described in eq. 6.

$$\text{Decadal Rainfall } (DR) = \sum_{j=1}^{10} a_j \quad ...(6)$$

Intensity Entropy (IE)

It is defined as the ratio between the total numbers of rainy days of a year and the number of rainy days of a month for that year and it is called relative frequency (Xavier *et al.,* 2019) and it is expressed by n_j / N or p_j. If the number of rainy days in a j^{th} month for a year *i.e.* j ranges from '1 to 12' and the total sum of rainy days is denoted by N, then the IE is expressed in eq. 7.

$$IE = -\sum_{j=1}^{r}(p_j)\log_2(p_j) = -\sum_{j=1}^{r}(n_j / N)\log_2(n_j / N) \quad ...(7)$$

Where, N is the total sum of rainy days for a year; r is the number of class length; n_j is the number of rainy days for j^{th} month where $j = 1, 2, 3…12$; p_j is the probability of rainy days for every month *i.e.* n_j / N (relative frequency).

Disorder Index (DI)

The DI can be explained as the change between 'maximum possible entropy' and 'actual entropy' in the time series (Mishra *et al.,* 2009). The variability is directly associated with the DI *i.e.* when the value of the DI is found to be high which means, variability is also high in that state or system (Sun, 2019). When DI is determined by IE it is recognized as intensity disorder index similarly, if DI is evaluated by AE and ME, called as apportionment disorder index (ADI) and marginal disorder index (MDI), respectively (Roushangar *et al.,* 2018). In a decadal analysis, decadal apportionment disorder index (DADI) is also obtained by DAE (Guntu *et al.,* 2020).

Mean Marginal Disorder Index (MMDI)

The comparison of temporal and spatial variability can be done on the MMDI basis. In this study, temporal variability was obtained based on MMDI (Kalimeris *et al.,* 2012) and is described in eq. 8.

$$MMDI = \frac{1}{n}\sum_{i=1}^{n} MDI \quad ...(8)$$

Where, *n* is the total number of the length in a time–series; MDI stands for marginal disorder index. Similarly, the mean intensity disorder index (MIDI) was measured by taking the average of the intensity disorder index (Kawachi *et al.,* 2001).

3. RESULTS AND DISCUSSION

In this section, results on rainfall variability of three rain gauge stations of Uttarakhand, *i.e.* Almora, Nainital and Pauri, has been discussed. The variability of rainfall for the aforesaid gauge stations has been studied using DI and MMDI. The annual data at a gauge station has been divided into winter, pre–monsoon, monsoon, and post–monsoon seasons for the study period.

Statistical Analysis of Seasonal Rainfall

The seasonal rainfall statistics of Almora, Nainital and Pauri has been shown in Table 3. The lowest and highest mean seasonal rainfall was found to be 60.4 mm and 746.8 mm during post–monsoon and monsoon seasons, respectively at Almora. The CV ranged between 25% to 120%, whereas SD varied from 57.1 mm to 683.1 mm in all the stations. At Nainital station, the lowest mean seasonal rainfall (100.2 mm) for post–monsoon and highest mean seasonal rainfall (2176.9 mm) for monsoon seasons were recorded during the study period. Further, at Pauri, the highest mean seasonal rainfall of 911.2 mm was recorded during monsoon, while the post–monsoon season recorded the lowest seasonal rainfall (61.6 mm). Among all the stations, it was noticed that the highest mean seasonal rainfall (2176.9 mm) was observed during monsoon for the Nainital station followed by Pauri and Almora stations, while the lowest mean seasonal rainfall (60.6 mm) during post–monsoon was observed for the Almora station followed by Pauri and Nainital stations.

Rainfall Variability Using Entropy Theory

Seasonal rainfall variability over selected stations

The MMDI of gauge stations studied are presented in Fig. 2. It observed that the rainfall variability was highest for post–monsoon season for all the three station under study. The high variability of MMDI in monsoon season can be an indicator of local climate change. At Almora, the MMDI was 0.213 for winter season, but it decreased in pre– monsoon and then increased again in monsoon as well as for post–monsoon season. The estimated MMDI values were 0.213, 0.186, 0.198, and 0.304 during the winter, pre–monsoon, monsoon, and post–monsoon seasons, respectively. At Nainital station, the estimated MMDI values were 0.230, 0.258, 0.268, and 0.351 during the winter, pre–monsoon, monsoon, and post–monsoon seasons, respectively. The estimated MMDI were 0.198, 0.204, 0.219, and 0.326 for the winter, pre–monsoon, monsoon, and post–monsoon season, respectively, at Pauri.

Monthly rainfall variability over selected stations

The monthly variability in MMDI for selected stations has been shown in Fig. 3. The MMDI for Almora station was

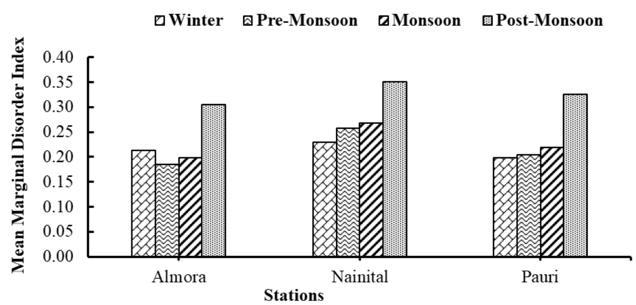

Fig. 2. Seasonal rainfall variability over selected stations in terms of MMDI

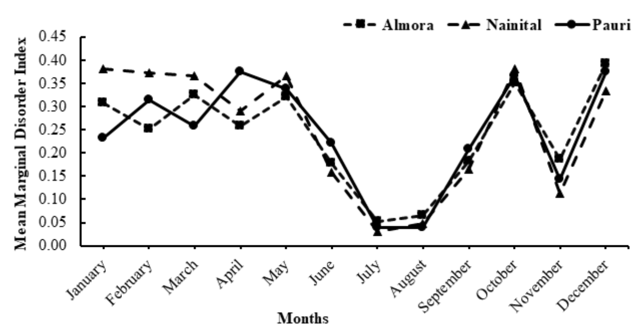

Fig. 3. Monthly rainfall variability over selected stations in terms of MMDI

Table: 3
Descriptive statistics of seasonal rainfall (mm) for different station(s)

Station(s)	Statistical parameter	Winter	Pre–monsoon	Monsoon	Post–monsoon
	Mean (mm)	91.1	112.4	746.8	60.4
Almora	SD (mm)	57.1	59.3	185.6	65.6
	CV (%)	63	53	25	109
	Mean (mm)	135.5	188.1	2176.9	100.2
Nainital	SD (mm)	111.9	155.9	683.1	137.6
	CV (%)	83	83	31	137
	Mean (mm)	109.9	132.2	911.2	61.6
Pauri	SD (mm)	73.1	103.8	279.3	74.2
	CV (%)	67	79	31	120

0.308 in the month of January. The highest MMDI for Almora was observed in the month of December and lowest MMDI in July. There was not a definite pattern in MMDI from January to December for all the three stations. At the Nainital station, MMDI values were found to be decreasing from January to April month. The MMDI value for Nainital was seen lowest during the month of July which indicated that the variation of rainfall was low.

At Pauri station, the MMDI was 0.231 and 0.314 in January and February month, respectively. This increment in MMDI value from January to February showed a relatively high variability in rainfall in February as compared to January. There was a sharp decline in the MMDI value from April to July for Pauri station. The MMDI for October and December was almost similar.

Seasonal Variation in Rainy Days

The variability of rainy days has also been studied using entropy theory and expressed in terms of MIDI. The results of rainy days' variability are shown in Fig. 4. At Almora station, the highest MIDI (0.235) was observed during the post–monsoon season, while the lowest MIDI (0.122) was recorded during the pre–monsoon season. The lowest and highest MIDIs indicated that variations in rainy days were lowest and highest respectively in terms total number of days on which rainfall occurred annually for a gauge station. At Nainital, the highest MIDI was for monsoon season followed by winter season. At Pauri station, the MIDI was 0.175 during the winter season, after that, its value decreased for monsoon and pre–monsoon season. The highest MIDI value for rainy days was observed for post–monsoon season (Fig. 4).

Decadal annual rainfall variation

The bar graph (Fig. 5), represents the variability in the annual rainfall (averaged for each 10 years) for eleven decades in terms of DADI. Almora, among all the stations studied, the highest DADI (1.863) was found for Almora during 1971–1980. Similarly, the lowest DADI (0.246) was observed for Almora station during the decade 1941–1950. At Nainital station, the highest value of DADI (1.608) was

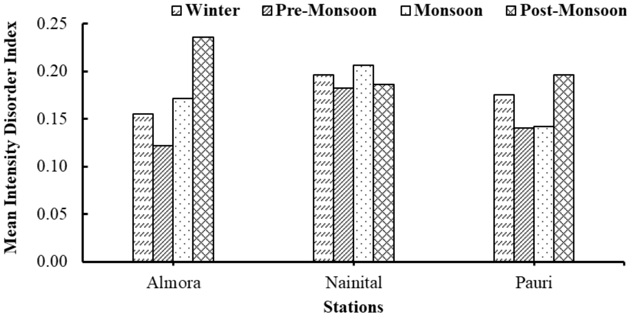

Fig. 4. Seasonal variation in rainy days in terms of mean intensity disorder index

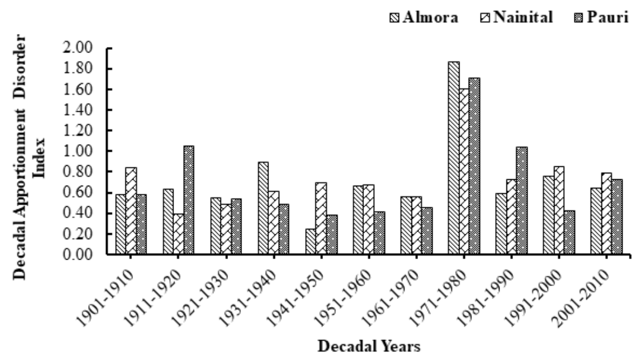

Fig. 5. Decadal annual rainfall variation over three station in terms of DADI

also found during 1971–1980, while the lowest value of DADI (0.391) was during 1911–1920 decade. At Pauri station, the highest value of DADI (1.712) was estimated during 1971–1980 decade and the lowest value (0.380) was estimated during 1941–1950 decade.

This study was carried to discover the variation in rainfall patterns with the help of different indices such as MMDI, DADI and MIDI. The values of MMDI according to month within the seasons, helped to discover the responsible months in seasonal inconsistency or unevenness of rainfall events. The highest and lowest value of MMDI for different months and seasons can also be used as an indicator of local climate change. Moreover, the lowest and highest value of MIDI indicated that variations in rainy days were less and more respectively, in terms of total number of days on which rainfall occurred. The highest value of DADI revealed the higher variation in rainfall data whereas the lowest variation shows a lesser variation in rainfall data for the respective decades. The results of this study can be further used for the suggestion of rainfall model, agriculture measures of the area, implementation of soil water conservation structure.

4. CONCLUSIONS

Entropy theory was used to study variability in rainfall for the three gauged station of southern Uttarakhand namely Almora, Nainital, and Pauri. The variability of rainfall was assessed using statistical technique and Entropy theory. The analysis was done on the basis of monthly, annual and seasonal rainfall data. The highest mean seasonal rainfall was found during the monsoon season of the Nainital station (2176.9 mm), followed by Pauri and Almora stations during the study period. The results indicated that the highest MMDI was noticed during the post–monsoon season of Nainital station followed by Pauri and Almora station. On the basis of monthly MMDI analysis, the lowest DI was found for the month of July, which means variation or uncertainty in the rainfall pattern was less, whereas high variability was recorded during December for Almora station. The variation in rainy days (in terms of MIDI) was found to be highest in post–monsoon, whereas it was lowest during the pre–monsoon season of Almora station. As per decadal analysis, highest variability in annual rainfall was found during the 1971–1980 decade followed by Almora, Pauri and Nainital stations. The fluctuations at the stations could be seen due to the change in climatic conditions of the study area. The high range in the DI signified the presence of inconsistency in rainfall pattern or the unevenness in the occurrence of rainfall, this may lead to a higher degree of risk in the ensuing years. Thus, it may be concluded that entropy theory provides a significant judgement to discover the inconsistency in rainfall patterns on the behalf of stochastic flair.

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