



# Exploring of the summer monsoon rainfall around the Himalayas in time domain through maximization of Shannon entropy

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## Abstract

The present study reports a thorough information theory–based investigation of the time series of rainfall in seasonal scale as well as yearly scale in the Himalayas during the summer monsoon (June–September). In this paper, the inbred uncertainty of rainfall series has been evaluated through Shannon entropy by fitting a probability distribution. The entropy has been measured for seasonal scales as well as yearly scales. A few parameters relating to the summer monsoon rainfall series over parts of North Mountainous India (NMI) from 1844 to 2005 are considered for computing entropy. Maximization of Shannon entropy is done to examine the parallel contributions of these parameters in this meteorological phenomenon. Finally, we have shown how entropy is affected by the fluctuation of mean rainfall in seasonal scale as well as yearly scale. We have also computed the decade-wise intrinsic uncertainty of rainfall series as rainfall is the most important parameter for climate risk. Besides, we also fitted the probability distribution curve generated by rainfall series.

## 1 Introduction

The average rate of stochastic source of data produced information is called entropy. In 1850, the modern ergodic theory has begun with the evolution of the concept of entropy of a stochastic variable by Rudolf Clausius, and in 1870 Ludwig Boltzmann showed it statistically. In that subsequent time period, the idea of entropy was developed by J. Willard Gibbs in thermodynamics and Von Neumann in quantum mechanics. Then, in 1948, it was reintroduced by Claude Shannon to find fundamental limits on signal processing and communication operations in a paper titled “A Mathematical Theory of Communication.” A developmental approach from information is the measurement in pursuance of information in stuff like events, random variables, and distributions. Quantification of the load of info signal is the procedure of probabilities. This relates information theory to probability. In his information theory, Claude Shannon defined “entropy” as a measure of uncertainty with respect to some event or variable. The higher value of Shannon entropy is the maximum quantitative recognition of uncertainty with respect to the

system. On the basis of maximum entropy, we can evaluate geophysical processes consistently. Then, it has also been asserted in the paper that the forecasts might be improved by the larger amount of information involved in a probabilistic forecast than in a deterministic forecast (Palmer 2000; Richardson 2000). Roulston and Smith (2002) entrenched a convenient analytical groundwork of information theory for foretelling realization and quantifying weather and climate. For further analysis on the Shannon entropy, we can refer to Gray (1990). For mutual information, the perception of entropy is

$$I(X, Y) = H(X) + H(Y) - H(X, Y)$$

where  $X$  and  $Y$  are respective random variables.

The consisted information in one process subtracting the consisted information in the other process when it is well-known is the mutual collective information. In spite of the presence of another perception of conditional entropy, the fore ( $I$ ) has been concentrated by the information logicians as it does not need any interpretation of what conditional entropy signifies and is more well-formed than the definition of conditional. Mathematicians and statisticians have elongated the principle of Shannon entropy in the models of information sources, coding structures, and performance measures. Xu (2007) conferred a precise study on the diversity of relative entropy and Shannon entropy in estimating contained information and dropping information and deduced that the difference of Shannon entropy computes only the part of variability and the relative entropy

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computes both the signal and variability parts of the contained information from observations. An important application of information theory to the study of rainfall has been reported in Brunzell (2010). In another study, Kawachi et al. (2001) demonstrated an application of Shannon entropy to rainfall over Japan. Liu et al. (2011) reviewed the application of Shannon entropy to meteorology and allied areas. Nebot et al. (2008) reported a Fuzzy-based methodology in combination with Shannon entropy in the study of uncertainty.

Uncertain time series (Radzuan et al. 2013; Kalamaras et al. 2017) treated to be an expanded group of actualizations of a respective accustomed random variable and recorded by a time appearing normally in environment, meteorology, economics, and other study areas. The uncertain chronological time series has been manifested in literatures: Lykoudis et al. (2010), Cloke and Pappenberger (2009), Efstathiou and Varotsos (2010), Varotsos et al. (2013, Varotsos et al. 2015), and Radzuan et al. (2013). The maximum entropy explains the distributional properties and endurance in the hydrological processes. Hydrological examples with respect to this include Koutsoyiannis (2005), Singh (1997, 2011), Kawachi et al. (2001), Mukhopadhyay and Khan (2015), da Silva et al. (2016), and Agarwal et al. (2016). In the paper of Chattopadhyay et al. (2018), there is the theory of Shannon entropy maximization in discussing the relative contribution of different surface parameters in the genesis of a severe weather system over a part of India. Plethora of literatures have explored the complexity associated with meteorological processes and related prediction. Examples include Bandyopadhyay et al. (2016); Chattopadhyay (2007); Chattopadhyay and Bandyopadhyay (2008); Chaudhuri (2006); Chaudhuri (2008); Chaudhuri and Chattopadhyay (2005); Dallachiesa et al. (2011); Dash et al. (2007); De et al. (2011a, b); Gardner and Dorling (1998); Gutierrez-Coreaa et al. (2016); Hontoria et al. (2005); Hsieh and Tang (1998), Varotsos et al. (2014) and Cracknell and Varotsos (2007)

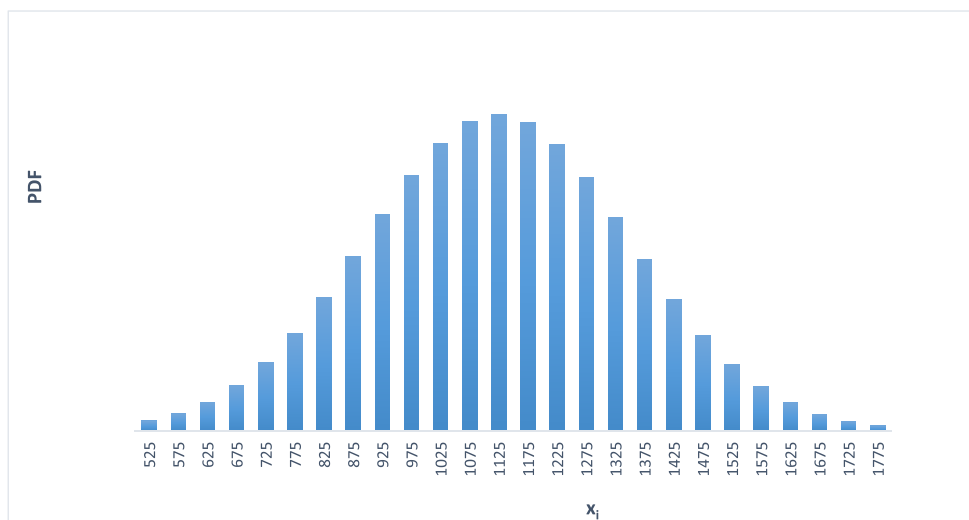
Meteorological conditions over India and the subcontinent as well are significantly influenced by the Himalayas that act an extraordinary climatic separation. The course of air as well as water of the said region depends heavily upon it toward the south and in the Central Asian good countries toward the north. As per prudence of the area and its marvelous tallness, the Higher Himalayas blocks the entry of chill mainland air from the northern part into India in wintertime and furthermore powers the storm toward South-West (downpour bearing) breeze to surrender a large portion of their dampness before entering the northern area. The outcome is overwhelming rain and day of downfall precipitation in the Indian side yet bone-dry environment in Tibet. The normal yearly precipitation on the south inclines fluctuates between 60 in. (1530 mm) at Shimla, Himachal Pradesh, and Mussoorie, Uttarakhand, in the western half of the Himalayas and 120 in. (3050 mm) at Darjeeling, West Bengal, in the eastern half of Himalayas. North of the Great Himalayas, at spots, for example, Skardu, Gilgit, and Leh in the Kashmir segment of the Indus river valley, just 3 to 6 in. (75 to 150 mm) of downfall happens.

The period of summer monsoon (June to September) contributes the maximum to the annual rainfall over entire India. Interactions of a number of complex meteorological processes at different scales lead to the Indian summer monsoon rainfall (ISMR). The amount of ISMR is characterized by huge degree of spatial variability ranging from 160 to 1800 mm/year (Kishore et al. 2016). It has been demonstrated in Kishore et al. (2016) that the highest amount of annual ISMR is received by the northeast, west coast, western Himalayas, and north central parts of India.

The Himalayan range, a highly elevated land area, has a major role to play in the climate and is regarded as one of the most important mountainous regions in the world. The significance of the Himalayan region and the adjacent Tibetan Plateau in the modulation of regional monsoon climate is well discussed in the literatures (Bhatt and Nakamura 2005). The processes of atmospheric circulation including monsoon depression and westerly disturbances are significantly influenced by the Himalayan range. During the period of summer monsoon, the said region is affected by abundant rainfall and episodes of flood. In particular, the slopes that are facing south and the Gangetic plains fall under this climatic condition. Landslides connote the most perennial feature of the Himalayas during the summer monsoon. On the other hand, it should also be noted that the rainfall has substantial importance in the agricultural practices over this region. Plethora of literature have emphasized upon the role of convection in the Tibetan Plateau and its adjacent region in the process of monsoon circulation through the release of latent heat. Studies on the summer monsoon over the Himalayas mostly include the techniques of ground of satellite-based investigations. In a recent study, Vellore et al. (2016) have demonstrated a rigorous study to understand the evolution of the monsoon-extratropical circulation features through reanalysis of circulation products pertaining to some extreme events of precipitation over the western Himalayas.

In the theory of time series analysis, there are two fundamental approaches, namely time domain and frequency domain. The two processes are distinct in implementation procedures and are complementary to each other. In the time domain approach, a data series is characterized in the same terms in which they have been observed. In the present work, we have implemented the entire methodology to the data in the form which they have been reported by the Indian Institute of Tropical Meteorology (IITM), Pune, because of the title which contains the term “time domain.” Here, we are going to explore the intrinsic complexity of the ISMR over the Himalayan region through probabilistic information theory. At this juncture, we explain the motivation behind the study. It is more difficult to study the pattern of the monsoon rainfall over the Himalayan region than that in the remaining parts of India. This difficulty is attributed to the complex topography of the Himalayas. The terrain induces waves such as the lee-wave and seeder-feeder mechanism and as a consequence severe modifications happen to the precipitation process. Furthermore, the nature of convection, altitudinal variation, and slope-wise variation contributes to the complexity of the pattern of monsoon rainfall over this zone (Shrestha et al. 2000). The details of the methodology to

**Fig. 1** The pictorial presentation of the probability densities corresponding to the classified rainfall data fitted with normal distribution with parameters  $\mu = 1123.765$  and  $\sigma = 227.164$



be adopted in the present study with the maximization of Shannon entropy is presented in the subsequent sections. The rest of the paper is organized as follows: in Section 2, we have fitted normal and log-normal distributions to the rainfall data. In a subsection of Section 2, we have presented the methodology of deriving the maximum entropy probability distribution. In Section 3, we have demonstrated the computation of Shannon entropy and maximum entropy probability distribution. We have the conclusion in Section 4.

## 2 Methodology

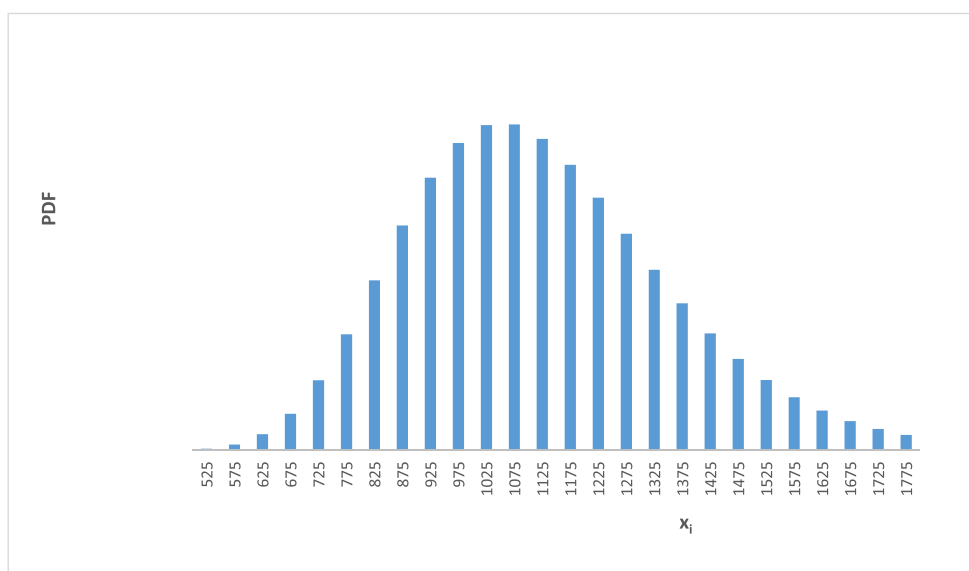
### 2.1 Data and source

In this present work, our adoptive methodology is entropy based. The observational data on rainfall over the Himalayan Mountain

Region for the period 1844 to 2005 were collected from the India Meteorological Department (IMD). At first, these discrete data have been classified into continuous distribution by the exclusive method of classification with a class interval of 50. The calculated mean was 1123.765, and standard deviation was 227.164. We have tested the data in various scales for normal and log-normal distributions. In this connection, it may be stated that a positive random variable  $X$  follows log-normal if the logarithm of  $X$  follows normal distribution, i.e.,  $\ln X \sim N(\mu, \sigma^2)$ . In order to check the data for these two distributions, we have considered the null hypothesis that the distribution is a good fit to the data. The alternative is the negation. After carrying out  $\chi^2$  test, it has been observed that the JJAS rainfall data over the study zone satisfies both the probability distributions. The outcomes have been pictorially presented in Figs. 1 and 2.

Therefore, most rainfall data are close to the mean 1123.765 (mm). Small differences between an individual rainfall data and the mean were obtained more frequently than substantial

**Fig. 2** The pictorial presentation of the probability densities corresponding to the classified rainfall data fitted with log-normal distribution with parameters  $\mu = 7.003$  and  $\sigma = 0.212$



deviations from the mean. The standard deviation is 227.164 (mm), which indicates the typical behavior that individual data tend to fall from the mean rainfall. The distribution is symmetric. The number of rainfall data lower than average equals the number of rainfall data greater than average. In both tails of the distribution, extremely low rainfall data occur as infrequently as extremely high rainfall data.

In Fig. 2, we fitted log-normal distribution to seasonal summer monsoon rainfall data by converting it into continuous exclusive method of classification from 1844 to 2005 over the Himalayan Mountain Region. Here, the larger values tend to be farther away from the mean than the smaller values; therefore, it has skew distribution to the right, which is positive skewness.

## 2.2 Determining ignorance

It has already been demonstrated in the preceding sections that we intend to quantify the intrinsic uncertainty associated with the JJAS rainfall over the Himalayan mountainous region. This section demonstrates a brief overview of the entropy function required for the said purpose. Details of this methodology are available in Klir and Folger (2009) and references therein. In the process of entropy maximization, out of all probability distributions that hold on to the evidence, the chosen distribution has to have maximum uncertainty. So, the primary focus is to determine a probability distribution that maximizes the entropy:

$$H_P(f) = - \sum_{a \in A} P(f = a) \ln P(f = a) \quad (1)$$

Here,  $f$  is a discrete random variable which is defined on the probability space  $(\Omega, B, P)$ , where  $\Omega$  denotes the sample space,  $B$  denotes the set of events, and  $P$  is a function from events to probabilities. The entropy can be safely regarded not as a function of the particular outputs of  $f$  but as a function of the partition that  $f$  induces on  $X$ . That means,  $Q$  is made up of disjoint sets that group the points in  $\Omega$  as per what output the measurement  $f$  produces. Therefore, the entropy function can be written as

$$H_P(Q) = - \sum_{i=1}^{|A|} P(Q_i) \ln P(Q_i) \quad (2)$$

## 2.3 Entropy maximization

Here, we are about to present the methodology based on the old principle of probability theory alternatively known as the principle of insufficient reason. This principle calls for our methodology to eliminate all probability distributions that is not in line with the evidence in hand. Out of all the remaining probability distributions, those are selected that fully validates our ignorance. They ultimately provide for the maximum entropy (Lesne 2014). Considering a probability distribution function (PDF), defined by the vector  $\mathbf{f}$  consisting of  $n$  components (the  $i$ th component defining the happening of  $i$ th outcome), then we can rewrite Eq. (2) as (Roulston and Smith

2002)

$$H(\mathbf{p}) = - \sum_{i=1}^n p_i \ln p_i \quad (3)$$

We try to maximize  $H(\mathbf{p})$  as in Eq. (3) under the constrains

$$p_i \geq 0 \forall i \quad (4)$$

$$\sum_{i=1}^n p_i = 1 \quad (5)$$

$$E(x) = \sum_{i=1}^n p_i x_i \quad (6)$$

Now, the following formed Lagrangian is

$$L = - \sum_{i=1}^n p_i \ln p_i - \alpha (\sum_{i=1}^n p_i - 1) - \beta (\sum_{i=1}^n p_i x_i - E(x)) \quad (7)$$

Here,  $\alpha$  and  $\beta$  are Lagrange multipliers. The following partial differential equations are derived from Eq. (7):

$$\frac{\delta L}{\delta \alpha} = 1 - \sum_{i=1}^n p_i \quad (8)$$

$$\frac{\delta L}{\delta \beta} = E(x) - \sum_{i=1}^n p_i x_i \quad (9)$$

$$\frac{\delta L}{\delta p_i} = - \ln p_i - 1 - \alpha - \beta x_i \quad (10)$$

For optimization, we set  $\frac{\delta L}{\delta \alpha} = 0$ ,  $\frac{\delta L}{\delta \beta} = 0$ ,  $\frac{\delta L}{\delta p_i} = 0$ . Equation (10) gives

$$p_i = \exp(-1 - \alpha - \beta x_i) \quad (11)$$

From Eqs. (11) and (9), we arrive at

$$p_i = \exp(-1 - \alpha - \beta x_i) \quad (12)$$

From Eq. (11),

$$p_i = \frac{\exp(\beta x_i)}{\exp(1 + \alpha)} \quad (13)$$

Using Eqs. (5) and (13), we get

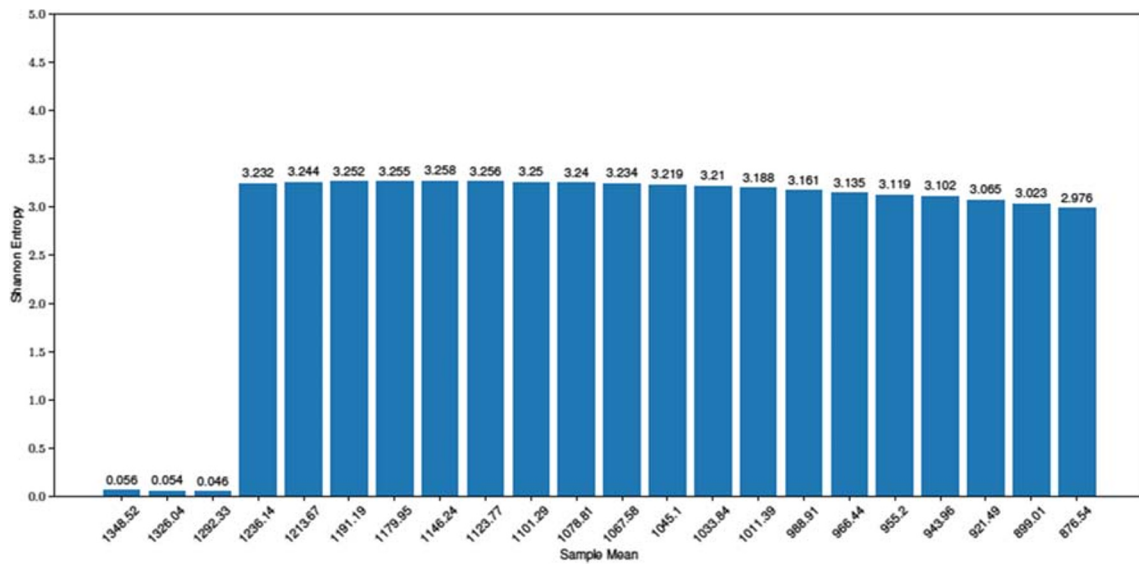
$$p_i = \frac{\exp(-\beta x_i)}{\sum_{k=1}^n \exp(-\beta x_k)}, \quad k = 1, 2, 3, \dots, n \quad (14)$$

Using Eqs. (14) and (9), we finally have

$$E(x) = \frac{\sum_{k=1}^n x_k \exp(-\beta x_k)}{\sum_{k=1}^n \exp(-\beta x_k)} \quad \text{or,} \quad (15)$$

$$\sum_{k=1}^n [x_k - E(x)] \exp(-\beta x_k) = 0$$

We solve for  $\beta$  in Eq. (15) and substitute it in Eq. (14). We get the maximum entropy probability distribution function and thereby we get the maximum  $H(\mathbf{p})$ .



**Fig. 3** Shannon entropy values obtained by varying the expected rainfall in yearly scale by considering the average rainfall during the summer monsoon season (June–September)

**Table 1** Tabular presentation of the Shannon entropy values obtained by varying the expected rainfall in yearly scale, averaging 4 months of JJAS data (by continuous distribution method)

Sample mean	Value of $\beta$	Shannon entropy
1348.518	0.09226632	0.05618569
1326.04270	0.0930480	0.05438944
1292.329750	0.09720767	0.04572784
1236.14150	-0.000619156	3.231571840
1213.66620	-0.00045538	3.24364258
1191.190900	-0.00029362	3.25205654
1179.95325	-0.00021327	3.25490446
1146.24030	0.00002674	3.25804628
1123.765432	0.00018674	3.2556482
1101.290123	0.00034756	3.24964611
1078.814815	0.00050991	3.24001374
1067.577160	0.0059189	3.23382354
1045.101852	0.00075795	3.21866035
1033.84197	0.00084224	3.20967003
1011.388889	0.00101392	3.18819497
988.913580	0.00119054	3.16056830
966.438272	0.00137324	3.13525841
955.200617	0.00146727	3.11929987
943.962963	0.00156332	3.102273487
921.487654	0.00176231	3.06491950
899.012345	0.00197206	3.02297608
876.537037	0.00219482	2.97617693

### 3 Results and discussion

#### 3.1 Calculation of Shannon entropy

Here, in this present study, we are considering the summer monsoon rainfall series of the North Mountainous India (NMI) from 1844 to 2005. The mean ( $E[X]$ ) of rainfall series is 1123.765. The number of rainfall data considered in this study is 26 as we transferred the collected discrete 162 years of data in continuous distribution. Values of pre-assigned parameters before and after rainfall have been taken to our calculation. Following Chaudhuri and Chattopadhyay (2003), we have diversified  $n$  from 1 to 26 in Eq. (15) for each case of parameters. The  $E[X]$  has been observed as the desired changes (%) in the measurements of the parameters. By using the Newton-Raphson method, the  $\beta$  in Eq. (15) has been found. A maximum entropy probability distribution has been allocated for each solution of  $\beta$ . Using these probability densities in Eq. (3), we calculated entropies as predefined for each equation and plotted in Fig. 3.

It may be noted that while creating Tables 1 and 2 we have followed continuous distribution method and in Table 3 the discrete distribution method has been adopted. By continuous distribution method, we mean that the entire data available in array form are converted to frequency distribution with continuous classes and the mid points of the classes are

**Table 2** Shannon entropy value obtained by the expected rainfall in a 10-year scale, averaging yearly JJAS data (by continuous distribution method)

Sample mean	Value of $\beta$	Shannon entropy
1121.875	0.0002002	3.25528244942186

**Table 3** Tabular presentation of the Shannon entropy values obtained by the expected rainfall in a 10-year scale, averaging yearly 4 months of JJAS data (by discrete distribution method)

Year	Sample mean	Value of $\beta$	Shannon entropy
1844–1854	986.95	$-1.97 \times 10^{-8}$	2.3026
1854–1864	1232.43	$-2.48 \times 10^{-8}$	2.3026
1864–1874	1047.05	$1.80 \times 10^{-8}$	2.3026
1874–1884	1146.61	$2.30 \times 10^{-8}$	2.3026
1884–1894	1268.97	$-5.58 \times 10^{-8}$	2.3026
1894–1904	1145.44	$-2.60 \times 10^{-8}$	2.3026
1904–1914	1064.63	$-2.10 \times 10^{-8}$	2.3026
1914–1924	1233.26	$2.50 \times 10^{-8}$	2.3026
1924–1934	1169.03	$2.74 \times 10^{-8}$	2.3026
1934–1944	1176.02	0	2.3026
1944–1954	1133.38	$-4.83 \times 10^{-8}$	2.3026
1954–1964	1262.54	$1.94 \times 10^{-8}$	2.3026
1964–1974	1178.7	$-1.60 \times 10^{-8}$	2.3026
1974–1984	1002.95	$-4.95 \times 10^{-8}$	2.3026
1984–1994	959.75	$1.58 \times 10^{-8}$	2.3026
1994–2005	991.43	$3.30 \times 10^{-3}$	2.7631

considered as values realized by the random variable. On the other hand, the discrete distribution actually pertains to a finite set of values realized by the continuous random variable at some discrete points.

### 3.2 Entropy as uncertainty

Entropy helps us making accurate statements and performing computations concerning uncertainty about the outcome. We can say that entropy is a measure of uncertainty, though it will be an understatement. Based on some assumptions, entropy is

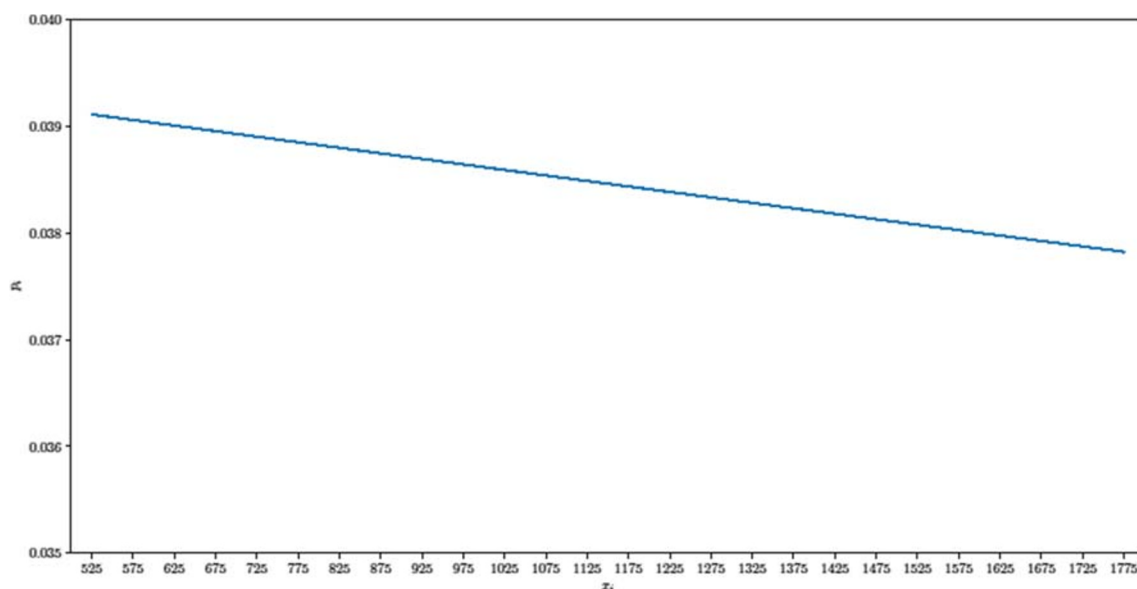
the measure of uncertainty. A bigger entropy value means a greater level of uncertainty, suggesting lesser purity of the distribution. By entropy, we are referring to the Shannon entropy. In spite of several other entropies being there, we are assuming that Shannon entropy is the most frequently used entropy in our context.

We are splitting the data set into 16 data sets by taking decade-wise serial discrete data. Then, we found out the mean and standard deviations for each data set and we calculated Shannon entropy for each case also.

We are taking decade-wise discrete data. The number of rainfall data is 10 in each case. Following the previous method, we have varied  $n$  from 1 to 10 in Eq. (15). For each case, the  $E(x)$  has been observed as the desired changes (%) in the measurements of the parameters. By using the Newton-Raphson method, the  $\beta$  in Eq. (15) has been found for each decade-wise data set. Similarly, we calculated a maximum entropy probability distribution for each solution of  $\beta$ . Using these probability densities in Eq. (3), we calculated entropies for each case.

## 4 Conclusion

In the study reported above, we have carried out a thorough information theory-based investigation. Millions of people depend on agriculture for a living. Precipitation, rain to be precise, has a substantial effect on agriculture. Similarly, the Himalayan range, a highly elevated land area, has a major role to play in the climate. In this paper, at first, the discrete rainfall data has been classified into continuous frequency distribution and on checking it was found that normal (Fig. 1) and log-normal (Fig. 2) distribution is the best fit for this continuous



**Fig. 4** Shannon entropy values obtained by varying expected decadal rainfall amount (June–September)

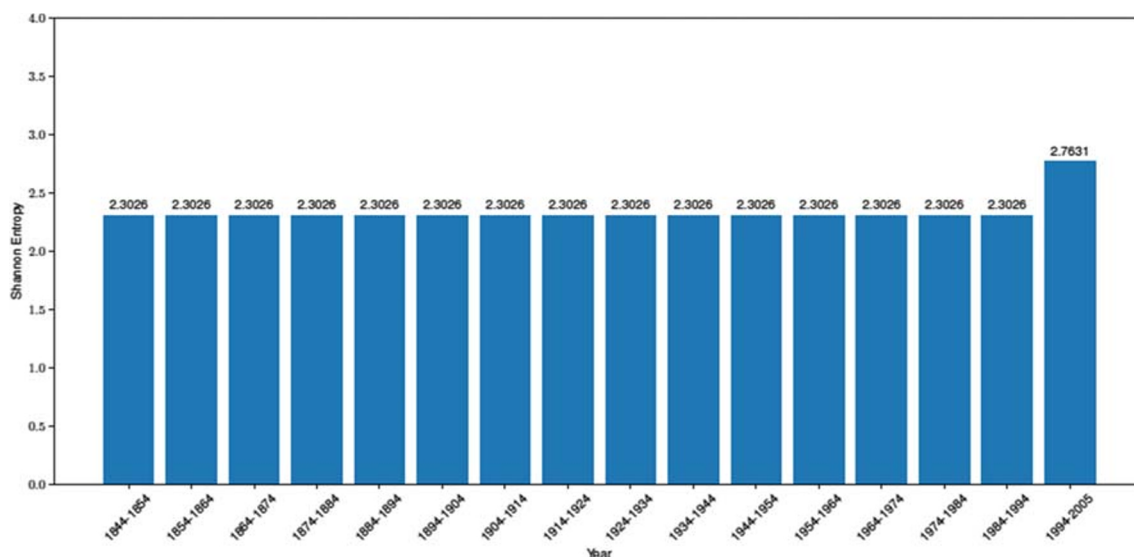


Fig. 5 Plot of maximum entropy probability ( $p_i$ ) against the mid-point ( $x_i$ ) of the  $i$ th class corresponding to JJAS rainfall

random variable. Here, the inbred uncertainty of rainfall series has been evaluated through Shannon-entropy by fitting a probability distribution. The entropy has been measured for seasonal scales as well as yearly scales. A few parameters relating to the summer monsoon rainfall series over parts of North Mountainous India (NMI) from 1844 to 2005 are considered for computing entropy. Maximization of Shannon entropy is done to examine the parallel contributions of these parameters in discovering this meteorological phenomenon. It has been observed that most rainfall data are close to the mean 1123.765 (mm). Small differences between an individual rainfall data and the mean were obtained more frequently than substantial deviations from the mean. The standard deviation is 227.164 (mm), which indicates the typical behavior that individual data tend to fall from the mean rainfall. The

distribution is symmetric. Also, we fitted log-normal distribution (Fig. 2) to seasonal summer monsoon rainfall data by converting it into continuous exclusive method of classification from 1844 to 2005 over the Himalayan Mountain Region. Here, the larger values tend to be farther away from the mean than the smaller values; therefore, it has skew distribution to the right, which is positive skewness. The number of rainfall data lower than average equals the number of rainfall data greater than average. In both tails of the distribution, extremely low rainfall data occur as infrequently as extremely high rainfall data.

In the subsequent phase, taking decade-wise discrete data, we have applied entropy maximization procedure and by using the Newton-Raphson method the  $\beta$  in Eq. (15) has been found for each decade-wise data set. Similarly, we calculated a

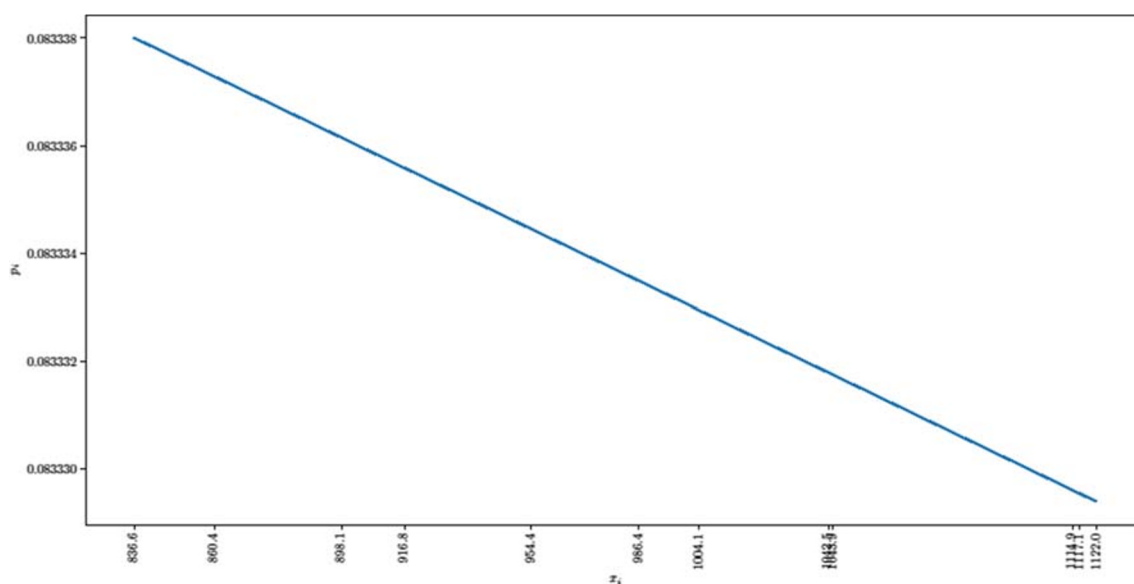


Fig. 6 Plot of maximum entropy probability ( $p_i$ ) (vertical axis) against the decadal (1994–2005) rainfall data ( $x_i$ ) (June–September) (horizontal axis)

maximum entropy probability distribution for each solution of  $\beta$ . Using these probability densities in Eq. (3), we calculated entropies for each case. It has been observed that the Shannon entropy values obtained by the expected rainfall in a 10-year scale, averaged by yearly 4 months of JJAS data has maintained almost similar pattern (Fig. 3). This shows that the ISMR over the study zone does not lead to significant change in the intrinsic uncertainty in yearly scale. In decadal scale also, the entropy (Fig. 4) does not exhibit significant changes over time. The probability distributions corresponding to the maximum entropies, computed through Eq. (14), are presented in Figs. 5 and 6, where it is observed that the probabilities corresponding to higher values of rainfall amount are less than the lower values of the rainfall. This indicates that associated uncertainty increases with the lowering of rainfall amount during the season of Indian summer monsoon. Nevertheless, the measures of uncertainty in both scenarios stay in the range of (Nebot et al. 2008; Lesne 2014). This indicates that the ISMR over the study zone maintains its complexity pattern throughout the years. This quantitative measure of uncertainty can be utilized for the development of predictive models for future studies.

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