



# On the Structure of the Intermittency of Rainfall

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## Abstract

Quantification of rainfall intermittency via. interevent time distribution, series of continuous wet spells (burst size) and variability in interevent times between rainfall events is essential for planning and management of water resources and hydrologic extremes. However, their structure, quantification and association with long-term climatology are less explored. In this paper, a complex system-based measure – burstiness – is used to quantify the variability of interevent times across six meteorologically homogenous zones of India. It is observed that burstiness is related to the burst size as well as long-term rainfall climatology. The existence of unimodal and bimodal structure in burstiness distribution reveals the uniqueness and differences in the rainfall patterns. The differences in sensitivity of rainfall to burstiness highlight the role of interplay between climate-landscape and reveals the importance of the intermittent structure of rainfall. The study provides an approach to model intermittency by preserving the temporal structure of the interevent time distribution.

**Keywords** Rainfall · Burstiness · Interevent time distribution · Power-law · Hydroclimatology

## 1 Introduction

Variability in the structure and frequency of dry and wet spells poses severe challenges in water resources management at catchment and regional scales. Prolong periods of dry spell facilitate favorable conditions for drought development – influencing heat waves (Ganguli 2022), livestock-based economy (Sørensen et al. 1993), growth stages of rainfed-crops (Gobin 2018), irrigation scheduling (Daccache et al. 2015), frequency of forest fires (van Bellen et al. 2010; Flannigan et al. 2000) and global water resources (Hettiarachchi et al. 2022). However, long periods of wet spells develop waterlogging conditions in field crops (Gobin and Van de Vyver 2021), floods at regional and catchment scale (Blöschl et al. 2017; Kundzewicz et al. 2013; Zolina 2014), prevalence of vector-borne diseases (Segun et al. 2020) and landslides in mountainous regions (Das and Ganguli 2022). Changes in dry and wet spells properties influences water quality (Benotti et al.

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2010; van Vliet and Zwolsman 2008; Whitworth et al. 2012), urban water management (Chowdhury and Beecham 2013) and hydrologic extremes (Breinl et al. 2020).

The interevent times between rainfall events and its statistical distribution constitutes the structure of rainfall intermittency. Previous studies modelled the intermittent structure of rainfall using Poisson models, multifractal approaches, power spectral densities, wavelets and geostatistics (Barancourt et al. 1992; Gires et al. 2013; Kumar and Foufoula-Georgiou 1994; Olsson et al. 1993; Pavlopoulos and Gritsis 1999; Schmitt et al. 1998). However, in these approaches there were assumptions related to the models, simplified represented of rainfall processes as an outcome of simple systems and lack of comparability across large regions where rainfall is dominated by governing factors. In order to overcome these difficulties, a new metric – burstiness – is used to study the variability in the intermittent structure of rainfall. Rainfall event occurs consistently during the wet season after prolong nonoccurrence during dry season (Schleiss and Smith 2016). Therefore, there is a burst of activity over a small-time interval with prolong inactivity at other time intervals. The metric burstiness naturally capture this temporal activity of rainfall events by taking care of the biases due to sample sizes (Karsai et al. 2018).

The length of continuous rainfall events or burst size is an important parameter which capture the intermittency of rainfall dynamics. This influences the timing and amount of water availability – which is an essential variable in water resources planning and management for efficient water use. However, the linkage between the burst size and the burstiness is not clear as these two parameters govern the intermittent structure of rainfall. In this study, the linkage between interarrival times and burst size related to the intermittent structure of rainfall is investigated. The structure of intermittency of rainfall is a result of complex interplay between climate-landscape which reflects the role of regional hydrologic and climatological processes. An attempt is made to elucidate the relationship between long-term rainfall regimes with the structure of intermittency through sensitivity analysis.

In this paper, an attempt has been made to quantify the characteristics of intermittency of rainfall using the principles of complex systems. A non-parametric metric, burstiness is used to quantify the dynamics of rainfall intermittency. This metric does not make any assumptions on the number of wet and dry spells, size and statistical distribution of these spells, and hence can be used to quantify intermittency for regions having different structure in the distribution of these spells. The burstiness metric used in this study was first proposed by Goh and Barabási (2008). This metric was used to understand the intermittency in rainfall (Schleiss and Smith 2016), response of rainfall extremes to change in temperature (Schleiss 2018), flood preparedness (Coughlan de Perez et al. 2017). Apart from application to rainfall, the metric is successfully used to capture earthquake dynamics (Griffin et al. 2020; Salditch et al. 2020) and modeling forest fire (Kim et al. 2021).

The objectives of the work are: a) to quantify burstiness of rainfall activity across meteorologically homogenous zones of India; b) to obtain the scaling relationship for the distribution of interevent times and burst size; c) to quantify changes in the burstiness and distribution of interevent times and burst size between two time periods: 1951–1980 and 1981–2010; and d) to understand the sensitivity of long-term annual rainfall to burstiness. The remaining part of the paper is structured as follows: Section 2 describes the study area and the rainfall product used for the analysis. It also presents the theoretical background of burstiness, quantification of distributions of interevent times and burst sizes related to rainfall events. Section 3 elaborates the results with discussion related to the observations and Section 4 concludes the study.

## 2 Materials and Methods

### 2.1 Study Area and Data

The rainfall climatology of Indian subcontinent is dominated by monsoons. Nearly 80% of the annual rainfall occurs during the South West monsoon season spanning over June to September (Vinnarasi and Dhanya 2016). The North East monsoon season dominates over south-eastern region of the country during October to December months. India is divided into six homogenous zones (Fig. 1b) – South Peninsular (SP), Northwest (NW), Northeast (NE), Hilly Regions (HR), Central Northeast (CN) and West Central (WC) – based on the properties of South West monsoon (Sharma and Mujumdar 2017).

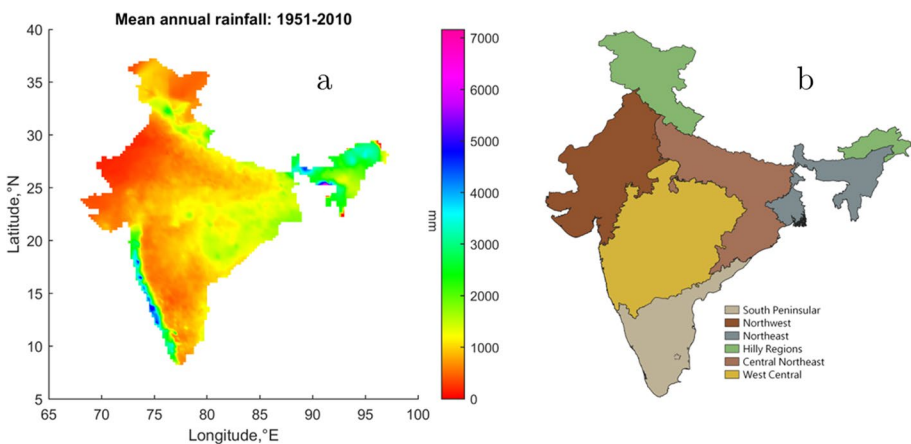
In this study, daily gridded rainfall data at a spatial resolution of  $(0.25^\circ \times 0.25^\circ)$  from India Meteorological Department is used (Pai et al. 2014). This gridded rainfall product is generated from the observations from 6995 rain gauge stations across India through spatial interpolation using Inverse Distance Weighted scheme (Shepard 1968). Although these stations are not uniformly distributed, it is ensured that good number of stations representing the country during the generation of the dataset. The spatial distribution of mean annual rainfall (Fig. 1a) shows wide range of variability with Western Ghats and Northeastern part of the country receiving higher rainfall, whereas the northwestern part receives comparatively less rainfall.

### 2.2 Quantification of Interevent Time and its Distribution

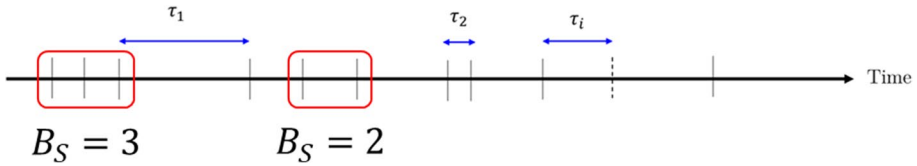
Let the sequence of rainfall events  $\{R_1, R_2, \dots\}$  occurs at time stamps  $\{t_1, t_2, \dots\}$ . The interevent time  $(\tau_i)$  between  $(i - 1)^{th}$  and  $i^{th}$  time stamps is given by (Fig. 2)

$$\tau_i = \tau_i - \tau_{i-1} \tag{1}$$

If the interevent times are equal, and hence the mean interevent time  $\langle \tau \rangle$  is same as the equal interevent times, then the probability distribution of the interevent times is given by:



**Fig. 1** Climatology of annual rainfall of India. Spatial distribution of mean annual rainfall of India (a) and meteorologically homogeneous zones of India (b). The map shown in (b) is prepared using QGIS3 with the shape files obtained from ([https://github.com/Cassimsannan/Shapefiles/blob/master/Homogeneous%20monsoon%20Regions%20over%20India/Homogeneous\\_Monsoon\\_Regions\\_Shapefiles.rar](https://github.com/Cassimsannan/Shapefiles/blob/master/Homogeneous%20monsoon%20Regions%20over%20India/Homogeneous_Monsoon_Regions_Shapefiles.rar))



**Fig. 2** Schematic representation of rainfall event sequence where each spike denotes the timing of the event. The interevent times and the burst size are denoted by  $\tau_i$  and  $B_S$

$$P(\tau) = \delta(\tau - \langle \tau \rangle) \tag{2}$$

where  $\delta(\bullet)$  denotes the Dirac delta function (Karsai et al. 2018). However, for random homogeneous Poisson process, the interevent time distribution follows exponential distribution with constant average rate of  $\frac{1}{\langle \tau \rangle}$ . However, for the natural process, the interevent time distribution tend to have heavy tail, and often modeled using power-law distribution of the form:

$$P(\tau) \sim \tau^{-\alpha} \tag{3}$$

The power-law exponent indicates the lack of any characteristic time scale and the presence of temporal fluctuation (Sethna et al. 2001). They are associated with scale-invariance and self-similarity properties of complex systems (Friedman et al. 2012; Marshall et al. 2016).

### 2.3 Burstiness and its Quantification

In natural systems, a series of activities (events) is observed for some duration followed by prolong inactivity. This intermittent increase or decrease in the occurrence of events is termed as burstiness (Karsai et al. 2018). Based on the measure introduced by (Goh and Barabási 2008), the burstiness parameter is defined by the coefficient of variation  $r \equiv \frac{\sigma}{\langle \tau \rangle}$  of interevent times as follows:

$$B = \frac{r - 1}{r + 1} = \frac{\sigma - \langle \tau \rangle}{\sigma + \langle \tau \rangle} \tag{4}$$

For a regular process with equal interevent times, B is -1 as  $\sigma = 0$ . The value of B is 0 for random, Poisson process where  $\sigma = \langle \tau \rangle$ . For heterogenous interevent times other than Poisson process, the parameter B is positive and it takes a value 1, when the process is extremely bursty with  $\sigma \rightarrow \infty$ . It is observed that the parameter is B is severely impacted by finite-size effect of the sample with  $n$  number of events (Kim and Jo 2016). It is difficult to be certain about the similarity in burstiness of two processes with different  $n$  despite of having same value of B (Kim and Jo 2016) corrected the parameter B by incorporating the sample size  $n$  as follows:

$$B = \frac{\sqrt{n+1}r - \sqrt{n-1}}{(\sqrt{n+1} - 2)r + \sqrt{n-1}} \tag{5}$$

In this work, the interevent times are computed for rain events with at least 2.5 mm rainfall recorded in a day. The measure  $B$  is applied to various fields like earthquake time series,

communication patterns, human heartbeats (Gandica et al. 2016; Goh and Barabási 2008; Jo et al. 2012, 2015; Li et al. 2016; Wang et al. 2015; Yasseri et al. 2012; Zhao et al. 2015).

## 2.4 Burst Size Distribution

Burst size ( $B_S$ ) refer to a group of consecutive events, where groups are separated by inter-event times. Many empirical studies (Box et al. 2015; Karsai et al. 2018; Koscielny-Bunde et al. 1998; Podobnik et al. 2007) revealed that distribution of burst size follows power-law distribution as follows:

$$P_{B_S}(B_S) \sim B_S^{-\beta} \quad (6)$$

with the power-law exponent  $\beta$ . In this study, a minimum burst size of 1 is considered for the analysis to accommodate the entire feature of the intermittent property of rainfall.

Apart from burstiness and burst size distribution, the temporal structure of the interevent times is quantified using a memory metric,  $M$ , which quantifies the lag-1 autocorrelation coefficient (Schleiss and Smith 2016), which is discussed in the supporting information.

## 3 Results and Discussion

The daily rainfall data for the six homogenous meteorological zones are extracted. The interevent times between rain events (rain event is considered when the total rainfall in a day is at least 2.5 mm). The interevent times are now used to estimate the burstiness parameter  $B$  based on Eq. (5).

### 3.1 Spatial and Temporal Dynamics of Burstiness

It is observed that Central Northeast and West Central experience higher burstiness in compare to the rest of the zones (Fig. 3a and b). Higher burstiness implies higher heterogeneity in the interevent times meaning more unequal interevent times between rainfall events. The zones – South Peninsula, Northwest and Northeast – experience less burstiness.

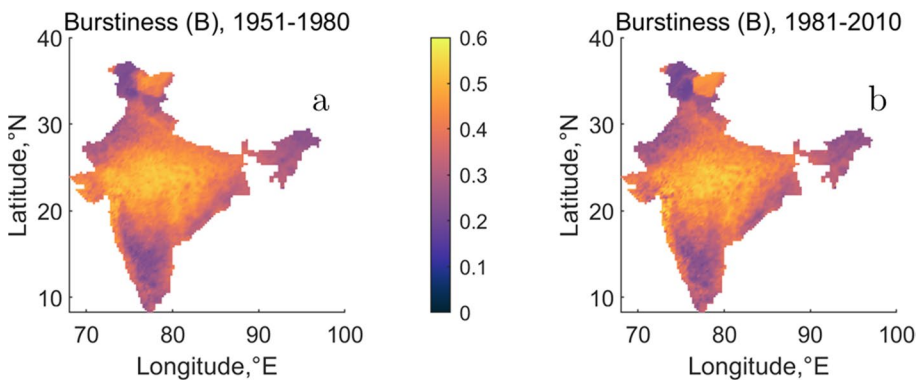


Fig. 3 Spatial variation of burstiness between two time periods – 1951–1980 and 1981–2010

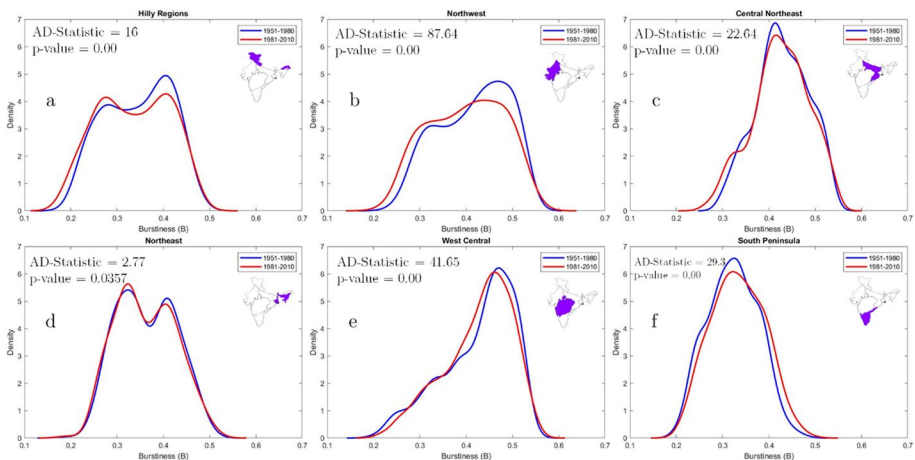
Changes in the burstiness imply changes in the interevent times between rainfall events which can have implications to water resources management as well ecosystem functioning. A significant change in the statistical distribution of  $B$  is observed for all the meteorological zones, which signifies changes in the temporal distribution of daily rainfall (Fig. 4). Among these zones, Central Northeast and West Central zones are the ones which exhibit more burstiness in compare to other zones. These two zones exhibit a prominently unimodal distribution of burstiness which hints towards a major rainfall process linked to south west monsoons.

It is interesting to note that the distribution is dominantly unimodal for Central Northeast (Fig. 4c), West Central (Fig. 4e) and South Peninsula (Fig. 4f), whereas, it is bimodal for Hilly Regions (Fig. 4a), Northwest (Fig. 4b) and Northeast (Fig. 4d). This highlights the differences in the temporal patterns of rainfall and the distribution of the dry spells which may be linked with the governing climatological factors. In addition, the changes in the distribution of burstiness reveals that the frequency and distribution of dry spells are changing with time; and different zones have different causal factors that governs this change.

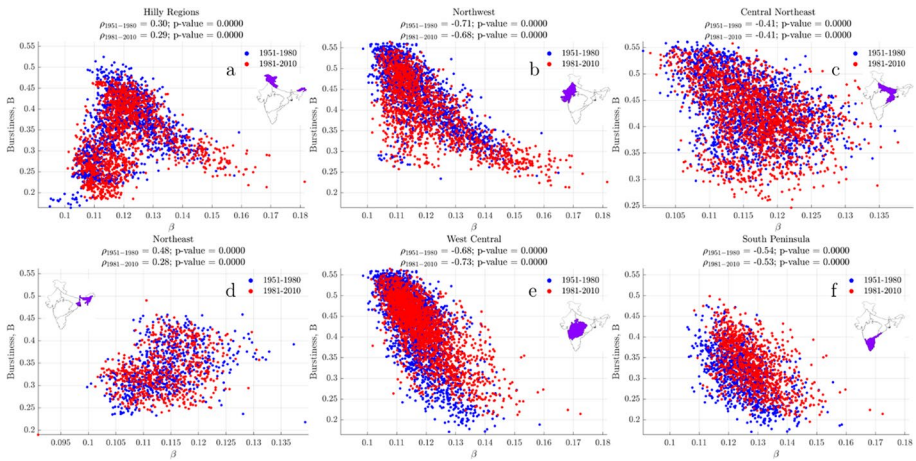
### 3.2 Association Between Burstiness and the Power-Law Exponents

The power-law exponents  $\alpha$  and  $\beta$  characterizes the system describing the distribution of interarrival times and burst size, respectively. The detection of power-law type behavior in the dynamics of interarrival times and burst size distribution is an indication of existence a universal, scale-free complex systems which generates these signatures in intermittent properties of rainfall.

Interestingly, it can be noted that burstiness and  $\beta$  – that describes the burst size distribution are strongly linked for all the meteorological zones of India (Fig. 5). For non-contiguous Hilly regions, a significant positive association between these parameters is observed (Fig. 5a). Similar observation is noted for Northeast zone (Fig. 5d). However, strong negative correlations are observed for remaining zones (Fig. 5b, c, e, and f).

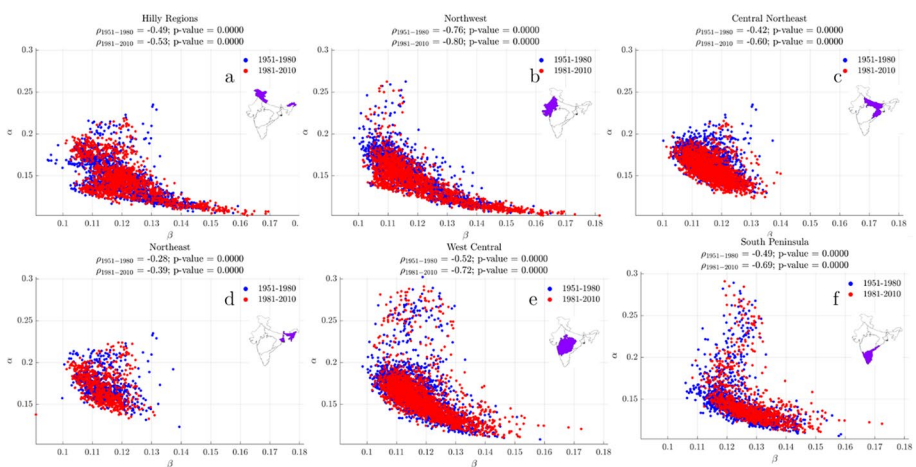


**Fig. 4** Changes in the statistical distribution of burstiness for the period 1951–1980 and 1981–2010. A significant change ( $p$ -value  $< 0.05$ ) in the distribution is observed for all the zones using Anderson Darling test



**Fig. 5** Association between distributions of size of wet spells and burstiness of rainfall. The association between rainfall burstiness and size of wet spells is significant ( $p$ -value  $< 0.05$ ) for all the zones

In addition to this, it is observed that there is a significant linkage between the distribution of burst size and interarrival time that describes the intermittent properties of rainfall (Fig. 6). The scaling exponents— $\alpha$  and  $\beta$ —are dependent on each other—implying that the interevent times and the continuous sequence of rain events are related to each other. However, this relationship is not consistent throughout the six zones. For Hilly regions (Fig. 6a) and Northeast (Fig. 6d), there is a positive linkage between the scaling exponents. The association between these scaling parameters are strongly negative (high anti-dependence) for the other four zones. This linkage opens a new paradigm where the dry periods can be used to develop predictive models to forecast the duration of wet spells— which are often treated as uncorrelated variables.



**Fig. 6** Association between distributions of size of wet spells and interarrival times. The Spearman rank correlation coefficient reveals the strength of association and its significance ( $p$ -value  $< 0.05$ ) based on the observed datasets

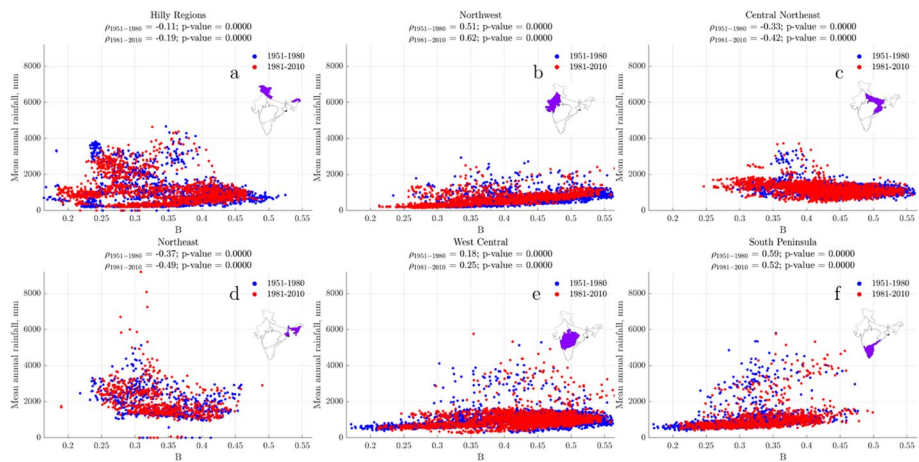
### 3.3 Linkage Between Long-Term Rainfall Climatology and Rainfall Intermittency

In the previous sections, the intermittency of rainfall is explored via analyzing the relationship between distributions of interarrival times and the sizes of continuous rainfall sequences. It is evident that there is a unique structure in the intermittent properties of rainfall and this structure depends on hydroclimatology of the region.

A regional dependence between mean annual rainfall and rainfall burstiness is observed (Fig. 7). For Hilly regions, Central Northeast and Northeast zones, a negative significant correlation is observed between these two variables indicating that increase in rainfall burstiness (i.e., increased variability in interarrival times) leads to decrease in annual rainfall. However, a significant positive correlation is observed for Northwest, West Central and South Peninsula zones – indicating increase in annual rainfall with decrease in rainfall burstiness (i.e., decreased variability in interarrival times).

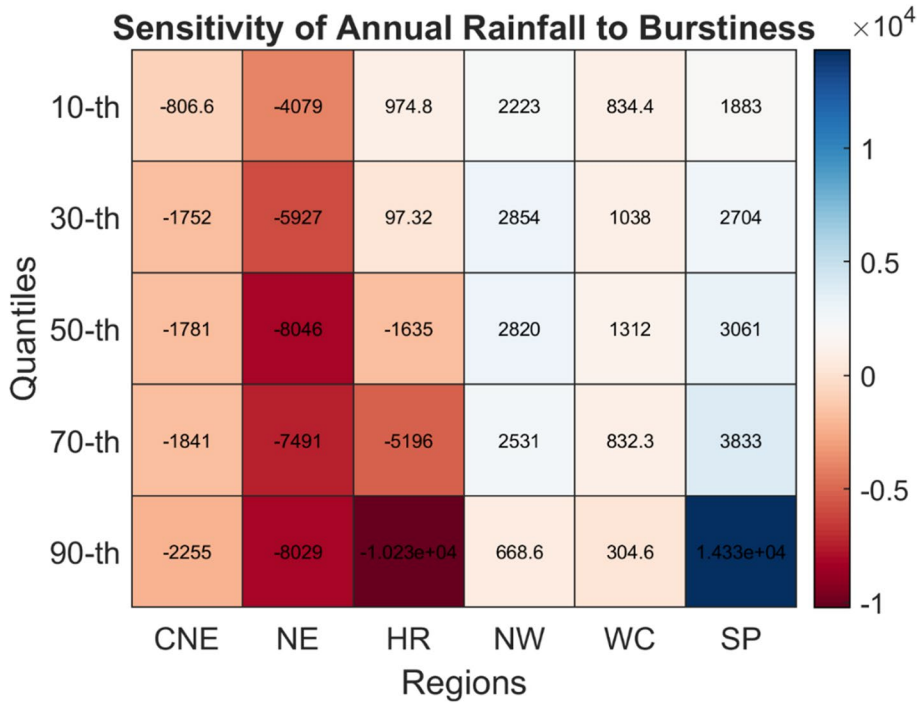
The sensitivity of long-term mean rainfall to burstiness is analyzed using quantile regression to quantify the sensitivity of mean rainfall at various quantiles to burstiness. It is observed that for Central Northeast and Northeast zones, annual rainfall decreases at all the quantiles with unit increase in the rainfall burstiness. Therefore, the long-term rainfall in these zones is coherently sensitive to the burstiness of rainfall. However, for the Northwest, South Peninsular and West Central zones – annual rainfall increases with unit increase in burstiness. It is interesting to note that for Hilly regions, the response of annual rainfall to burstiness is incoherent. The annual rainfall increases at lower quantiles and decreases at higher quantiles with respect to unit increase in rainfall burstiness.

The interplay between variability in rainfall burstiness and annual rainfall provides a link to describe the interrelationship between rainfall uniformity – how uniformly the annual rainfall is distributed within a year, number of wet days, frequency and magnitude of extreme high and low rainfall events. With increase in rainfall burstiness, the variability in the interevent times of the rainfall increases – and therefore its linkage with total annual rainfall becomes crucial in management of water for different stakeholders (Fig. 8).



**Fig. 7** Relationship between long-term mean annual rainfall and burstiness of rainfall in India





**Fig. 8** Sensitivity of long-term annual rainfall to rainfall burstiness. The values shown in the heatmap represents the quantile regression coefficients between long-term annual rainfall and rainfall burstiness for different quantiles and for the six meteorological zones

### 4 Conclusions

In this study, the structure of intermittency of rainfall and its connection to annual rainfall are investigated using complex systems-derived principles of burstiness. The daily gridded rainfall data is used to carry out the investigation over six meteorological zones of Indian subcontinent. The formulation of burstiness proposed in the literature of complex systems is used to decipher the intermittent structure of rainfall through scaling coefficients of power-law distributions of interevent times and burst size (i.e., sequence of continuous rain events).

It is observed that the structure and distributions of interevent times between rainfall events and interconnected with the hydroclimatology of the region, distribution of the burst size (i.e., distribution of number of sequences of continuous rainfall) as well as long-term annual rainfall. The existence of power-law type behavior for the interevent times suggests that the dry periods are scale-independent. Similar observations are also observed for burst size observation. The dynamics of the burst sizes of rainfall and the interevent times are intricately associated to each other. The strength of this association depends on regional controls of dry and wet spell characteristics of rainfall.

The variability in interevent times (i.e., burstiness) is found to be sensitive to annual rainfall. However, its sensitivity is substantially different across different quantiles of the annual rainfall distribution highlighting that wet and dry years tend to have a different pattern in the distribution of interevent times. In addition, positive and negative sensitivities

are also observed for different zones. For example, Central Northeast and Northeast zones have negative sensitivity – indicating that increase in variability in interevent times leads to decrease in the annual rainfall.

Changes in the interevent time distribution pose severe challenges in water management – where water availability over particular duration is needed, mainly for agricultural operations, hydropower generation etc. It can have implications to ecosystem functioning and services where timing, amount and duration of wet and dry spells plays a major role. Therefore, understanding the spatio-temporal dynamics of interevent time distribution, its historical evolution and future projection, its sensitivity to governing causal factors is essential for framing policies of sustainable water management in a changing world.

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**Authors Contributions** PD designed the study, collected data, wrote the codes, prepared and checked the manuscript.

**Data Availability** The MATLAB code to estimate the power-law exponents is obtained from NCC Toolbox (<http://www.nicholastimme.com/software.html>). The rainfall data is obtained from India Meteorological Department website ([https://www.imdpune.gov.in/Clim\\_Pred\\_LRF\\_New/Grided\\_Data\\_Download.html](https://www.imdpune.gov.in/Clim_Pred_LRF_New/Grided_Data_Download.html)).

## Declarations

**Ethical Approval** The author confirms that this article is original research and has not been published or presented previously in any journal or conference in any language (in whole or in part).

**Consent to Participate and Consent to Publish** The author declares that have consent to participate and consent to publish.

**Competing Interests** The authors have no conflict of interest and are completely satisfied with the publication of their article in water resources management journal.

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