



Impact of climate change on North-East India (NEI) summer monsoon rainfall

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Abstract

With the increasing population in the region, quantification of global warming impact on the mean and daily extremes of NEI rainfall (NEIR) is crucial for food security and preservation of the region's biodiversity hotspot. Here, using a long (~200 years) record of seasonal mean NEIR, we separate oscillatory modes of variability from the secular trend using the improved ensemble empirical mode decomposition (ICEEMD). The long-term change in seasonal mean rainfall over NEI estimated from this nonlinear trend is unbiased by the oscillatory modes and leads to a climate sensitivity of $-3.2 \pm 1.65\%/K$. A similar estimate of the impact on daily rainfall extremes, however, has been lacking due to the absence of long daily rainfall data on a sufficiently large number of fixed stations. Toward this end, a 90-year-long daily rainfall data based on 24-well-distributed fixed stations over NEI is constructed through a data mining effort. Even as the seasonal mean decreases, our estimate indicates that the frequency of occurrence of daily extremes (exceeding 99.5 percentile) over the NEI is increasing at $+51 \pm 4.99\%/K$ while the intensity is increasing at $+12.5 \pm 3.32\%/K$ over the past century, a rate much faster than envisaged by Clausius-Clapeyron scaling. In contrast to a significant multi-decadal variability (MDV) of summer rainfall over the rest of India, we find that the MDV of NEIR is weak and indistinguishable from white noise. As on inter-annual time scale, however, it indicates that the NEIR tends to go out of phase with that over the rest of India even on multi-decadal and longer time scales, with significant implications on interpreting past rainfall reconstruction from caves in the NEI. Our findings suggest that vulnerability to meso-scale hydrological disasters over the NEI in the coming years is much higher than that over the rest of India.

Keywords North-East India monsoon rainfall · Climate sensitivity · Driver of multi-decadal mode · Improved ensemble empirical mode decomposition

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1 Introduction

The North-East region of India (Fig. 1b) covering about 0.26 million square kilometers is one of the highest rainfalls receiving places in the planet. The rainfall over the NEI during the boreal summer enjoys a special place within the Indian summer monsoon rainfall (ISMR). The dominant mode of interannual variability of June–September rainfall over the region indicates that the NEI rainfall tends to go out of phase with the rest of India during large-scale droughts and floods (Shukla 1987; Mishra et al. 2012). With the mighty Brahmaputra river valley surrounded by a horseshoe-shaped topography in the backdrop of the summer monsoon winds (Fig. 1c), it creates an environment for the largest precipitation in the world (e.g., Cherrapunji). The wave activity resulting from the interaction between the orography and the winds also makes the region a region of high convective activity and contributes to the extreme rainfall events in the region (Goswami et al. 2010). On the other hand, the lightning flash counts during the pre-monsoon (March–May) are very high while it is quite low during the monsoon season (June–September, Fig. 1d). How come high rain yielding summer clouds has little electrical activity? Are the heights of these summer clouds really low or is there some other

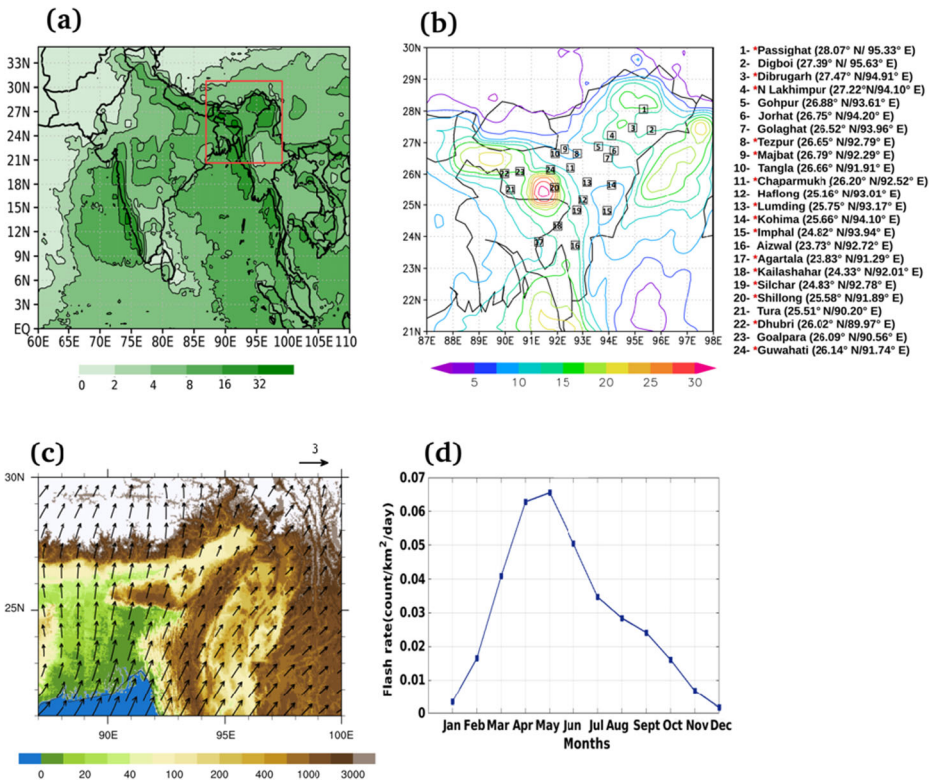


Fig. 1 a JJAS climatology of rainfall (mm/day) from TRMM over the Indian monsoon region (0°–35° N, 60° E–110° E) with the NEI region marked. b Rainfall climatology over the NEI box for JJAS period obtained from TRMM (3B42) together with the distribution of stations, the asterisks indicate the stations used in (Goswami et al. 2010). c High-resolution topography (m) over NEI region along with JJAS climatological mean vector winds (m/s) at 850 hPa. d Climatological annual cycle (monthly) of lightning flash counts over the NEI region from TRMM

cloud microphysical explanation to the low electrical activity during the monsoon season over the region? What is the contribution of the convective and stratiform rain to the total heavy rain in the region? It is not a surprise, therefore, that there is considerable interest in understanding the basic precipitation processes in the region (Webster et al. 2002; Medina et al. 2010).

Agriculture is the primary source of economy for the people of the region with tea (aka “Assam tea,” https://en.wikipedia.org/wiki/Assam_tea) and rice being two major crops. With most of the agriculture in the region being rain-fed, the quantum of rainfall during the monsoon season and its year-to-year variability play a critical role for agricultural productivity. Knowledge and forewarning of quantum of rainfall is important to the tea growers as both excess and deficit influence the tea production (Bhagat et al. 2010). While Assam ranks one of the ten top states of India in rice production, the low yield per hectare (< 2 ton/ha) is partly due to the productivity being vulnerable to the vagaries of monsoon rainfall. Skillful prediction of seasonal mean rainfall one season in advance can help the farmer to make informed decision on alternate crop strategy to minimize loss and/or enhance productivity. In addition, being the home of 17 crop species representing 47% of crop species in the country, the region is also a region of unique biodiversity hotspot (Roy et al. 2015; Chatterjee et al. 2006) with an utmost need for conservation (Chatterjee 2008; Tripathi et al. 2016). For sustainability of the biodiversity as well as for food security of the growing population in the region, reliable estimates of trend and dominant modes of variability of the mean and extreme rainfall events in the region are critical. Therefore, it is important for policymakers over the NEI to have a sense of what may be expected from rainfall in the region during the next few decades. For this purpose, it is of critical importance to estimate the impact of climate change on seasonal mean NEIR and daily rainfall extremes over the region. Hence, the primary objective of this study is to estimate the climate change impact on mean NEIR and frequency of occurrence and intensity of daily extreme rainfall in terms of percentage change per degree increase in the global mean temperature during the past ~ 150 years.

Although India could be proud of its rain gauge network providing reasonably uninterrupted daily rainfall over the country for over 150 years, the density of rain gauge stations in the NEI remained sparse (Rajeevan et al. 2006, 2008). Dense forests, inaccessible hilly regions, and two major National Reserves (the Kaziranga and the Manas) made large parts of the region difficult for maintaining traditional rain gauge stations. Although the climatological seasonal mean rainfall over the region is spatially variable (Fig. 1b), its inter-annual and longer-term variability is more homogeneous over the region and tends to go out of phase with that over the rest of the country (e.g., Fig. 2a in Mishra et al. 2012). Therefore, the seasonal mean constructed from a relatively small number of stations is still useful for studying seasonal mean and its long-term variability as long as the station network remains fixed over the period. Therefore, reasonably long seasonal mean NEIR time series for a period between 1829 and 2016 (see the “Data and methodology” section) for estimating climate change impact on the mean rainfall and its multi-decadal variability is constructed. However, for analysis of long-term trend and multi-decadal variability of daily rainfall extremes, the small number of stations is inadequate as many small-scale extreme rainfall events may be missed by such a network thereby biasing both the trend and multi-decadal variability. It is also critical that the station network must be fixed in time as year-to-year variation in the number could introduce serious spurious variability in extreme event counts. More recently, the Indian Meteorology Department (IMD) has constructed a high-resolution gridded daily rainfall data set (Pai et al. 2014, 2015) between 1901 and 2010 over India (including the North-East) based on all available data from rain gauge observatories, agro-meteorological stations, and state-run rain gauge stations.

The total number of stations available over India not only varies by a factor of three from the beginning to the end of the period; it is highly variable from day to day and year to year. While the data set may be very useful for some studies (e.g., high-resolution structure of specific mesoscale events etc.), trend and multi-decadal variability of extreme events are likely to be significantly biased by the variable network (Lin and Huybers 2019; Singh 2019). Therefore, for an unbiased estimate of climate change impact on extreme rainfall events over the northeast region, there is a need for daily rainfall data for long period based on a larger number of fixed station network. In the recent past, we could only get 15 stations in the region where daily records were possible to be extended backwards for 32 years (Goswami et al. 2010). In this study, we report the construction of such a data set for 90 years (1920–2009) based on a network of 24 fixed stations (Fig. 1b). The climate change impact on the frequency of occurrence and intensity of the extreme rainfall events is then estimated from these station data.

There is an indication that the seasonal mean NEIR has a multi-decadal variability (MDV) and a decreasing trend (Choudhury et al. 2019). Depending on the phase of the MDV at the beginning and end of the time series, the MDV could bias the long-term linear trend and thereby bias the estimate of climate sensitivity. In order to make a more reliable estimate of long-term changes of NEIR as well as that of global mean temperature, the quasi-oscillatory modes of the two time series are separated from their secular trends by using a modal decomposition method. We also use the same technique to estimate the change of frequency of occurrence and intensity of extreme rainfall events due to climate change and multi-decadal variability. Finally, we discuss some inherent caveats of the study.

2 Data and methodology

2.1 Data

2.1.1 Data used in the analysis of seasonal mean NEI

For estimating the climate change impact on the seasonal mean and to effectively remove the contribution of multi-decadal variability, long multi-century record of seasonal mean rainfall data is desirable as it allows a better estimate of the multi-decadal mode while preserving variance in all other relatively higher frequency modes. For this purpose, we have constructed a NEIR (S08 + P94) series by averaging JJAS mean rainfall over the Indian land points in the NEI (Fig. 1a) for the period 1829–2016 using two data sets. S08 (blue) and P94 (green) are in Fig. 2 and correcting for bias of the long-term mean (both data sets are described in supplementary file Section 2).

2.1.2 Data used in extreme rainfall analysis

For estimating long-term trend of extreme rainfall events in the NEI, we need daily rainfall records at a reasonably large number of stations over preferably more than 100 years. Two daily gridded rainfall data sets have been constructed by IMD namely the Rajeevan et al. (2008) (hereafter R08) for the period between 1901 and 2004 and the Pai et al. (2014) (hereafter P14) data sets for the period between 1901 and 2010. The good point about R08 is that it is based on a fixed network of stations while the weak point is that there are less than

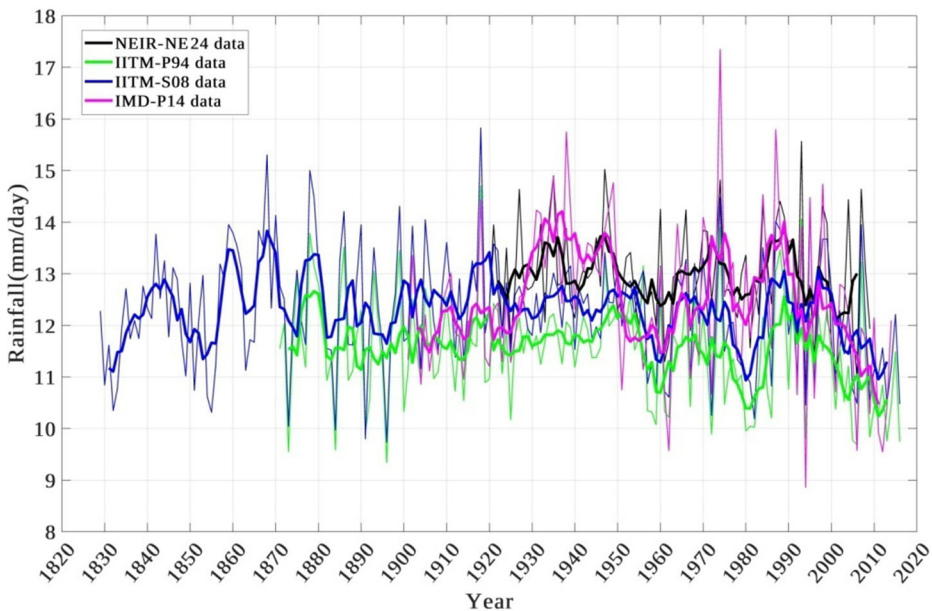


Fig. 2 Seasonal mean rainfall (JJAS) over the NEI from four different data sets from **a** NE24 station data set (black) during 1920–2009 (Mahanta et al. 2019), **b** IITM dataset (Parthasarathy et al. 1994) during 1871–2016 (green), **c** IITM (Sontakke et al. 2008) during 1829–2006 (blue), **d** IMD gridded data set of 0.25×0.25 deg. resolution (Pai et al. 2014) during 1901–2014 (magenta)

10 stations in the NEI that includes Cherrapunji. While R08 is quite good for studying extreme rainfall events in most of the country, in the NEI, it introduces a significant artificial multi-decadal variability on the mean and unsuitable for extreme events due to poor station density. The P14 data set is based on variable network, the total number of stations over the country that changes by a factor of three from beginning to end of the period. Also, it includes Cherrapunji. Therefore, for an estimate of long-term trend and multi-decadal variability of extreme events, this data is also not reliable. We believe therefore that the large multi-decadal variability represented by P14 in Fig. 2 (magenta) is artificial.

Therefore, there is a need for constructing a daily rainfall data set based on the fixed network of stations in the region. For this purpose, we have constructed such a daily rainfall data at 24 rain gauge stations distributed reasonably well to represent the spatial variability of rainfall (NE24) over the NEI (Fig. 1b) for the period between 1920 and 2009. Our objective is to estimate long-term trend and multi-decadal variability; we selected the 24 IMD stations and focused on constructing relatively uninterrupted daily rainfall time series at all the 24 stations from 1920 to 2009. In recent times, there has been some renewed interest and efforts from some diverse agencies, notable among them being one by some Japanese scientists in collaboration with local agencies (Terao et al. 2017). However, the length of such good-quality high-frequency rainfall observation with higher station density is available at most for two decades.

In order to understand the variability of the extreme event statistics, a summary of the statistical characteristics of the rainfall at all the 24-stations, such as JJAS mean, MJJAS mean, and MJJASO mean, with highest and lowest seasonal mean observed during the period, inter-annual standard deviation of all the three different means, 95, 99, and 99.5 percentiles for each

station etc., are useful (Supplementary Table-S1). In order to get a sense of fidelity of the trend, if any, and variability of the JJAS mean rainfall from NE24 over the region, we plot the time series of year-to-year variations in Fig. 2 (black curve) together with the other rainfall time series, P94 (green), S08 (blue), and P14 (magenta). The 5-year running mean shown for each curve indicates the nature of decadal, multi-decadal variability in each time series.

The acronyms used for all the data set used in this analysis are shown in Table 1.

2.2 Methodology

2.2.1 Construction of different NEIR series

- Here, the longest rainfall time series NEIR (S08 + P94) for the duration 1813–2016 of ~ 188 years is obtained by adding to S08 for the period 2007–2016 from P94 by correcting the for the differences between the long term mean of the two time series over the NEI land points. The correlation between P94 and S08 over the overlapping period (1871–2006) is 0.91. The climate change impact on the seasonal mean NEI rainfall is estimated from this longer time series.
- ISMR is also constructed for the period 1829–2016 over Indian land points using the same procedure as above 2.2.1 (a).
- We have constructed the NE24 series by filling up the missing data for every particular station. At this point, the question arises how do we get the data. Due to the large spatial variability of mean rainfall, we would not like to extrapolate from stations any further than 20–30 km (roughly the scale of the extreme rainfall events) from the missing station. If there were, no real observations in the neighborhood of any station, it would be impossible to fill the missing data. A special feature of the region turned to be a boon for data mining for this purpose. Although the indigenous people recognized that the topology and rainfall of the region is uniquely suited for growing of tea, large-scale tea plantations for commercial purposes started in a big way during the Colonial era leading to today's brand of Assam tea. Each plantation is called a "Tea-Garden (TG)" and hundreds of such TGs are spread all over the NEI. Small TGs may be typically 5–10 ha while bigger ones could be many times larger. Humidity and rainfall being a critical parameter determining tea yield, almost all TGs maintain their own rain gauge observatory. The records are generally kept in journals and archived. Depending on the continuity of administration of the TGs, some old records in some TGs may be lost. Identifying the TGs within around 20 km of the stations, TGs have been approached for the rainfall records and with their approval, records copied and later digitized. If there is more than one TG around a station,

Table 1 Acronym for the dataset used in the study are shown below for NEI

	Period	Citation
S08	1813–2006	(Sontakke et al. 2008)
P94	1871–2016	(Parthasarathy et al. 1994)
R08	1901–2000	(Rajeevan et al. 2008)
P14	1901–2014	(Pai et al. 2014)
NEIR(S08+P94)	1813–2016	See the "Methodology" section
NE24	1920–2009	For data link, see the "Acknowledgement" section
ISMR	1829–2016	See the "Methodology" section

records at both TGs are collected and their average is considered as the representative of the station rainfall. Following meticulous efforts (several students contributing) of collecting the data from around each station each day of each missing years for the period between May 1 till October 31, the time series at each station has been compiled. Some gaps still could not be filled. However, the missing data in the final time series (1920–2009) comprises less than 3% of the total in most stations with maximum going to 7% of total. More details on the data mining efforts leading to the construction of this data set can be found in Mahanta et al. (2019). Gross quality control for this data set is described in the Supplementary material. The consistency in inter-annual and decadal variability between the NE24, P94, and S08 time series indicates that they are reliable for exploring the long-term trend and low-frequency variability of the seasonal mean, the NE24 is certainly better in exploring climate change impact on extreme rainfall events simply due to its better spatial coverage. There is a strong correspondence between inter-annual as well as decadal variability of the seasonal mean in the NE24 and P94 (correlation = 0.71), and NE24 and S08 (correlation = 0.67). The long-term means of NE24 ($R_{24} = 1274$ mm) is slightly larger than that of P94 ($R_{P94} = 1152$ mm) consistent with the improved coverage of the higher rainfall regions by the NE24. The long-term mean of the P14 ($R_{P14} = 1260$ mm) has a larger multi-decadal variability compared to the other time series of the same period. This appears to be due to fact that the stations in P14 include Cherrapunji rainfall too.

2.2.2 Unbiased estimation of long-term change

In order to make estimates of climate change impact on mean rainfall (NEIR) or extreme event statistics over the region, we need to extract the nonlinear trend unbiased by the multi-decadal variability of the time series. This requires separation of the oscillatory modes of the time series that are independent of nonlinear trend. For this purpose, we use the improved ensemble empirical mode decomposition (ICEEMD) method (Colominas et al. 2014), an improved version of the EMD technique (Huang et al. 1998; Huang and Wu 2008) which uses extreme information of the riding waves in non-stationary time series. It is an adaptive and temporally local decomposition method that extracts successively the riding amplitude-frequency modulated oscillatory components, starting with the highest frequencies and proceeding toward the lowest frequencies successively without using any a priori determined basis functions. By applying ICEEMD, the secular trend of a time series is naturally obtained after all the oscillatory components (riding waves) are removed from the time series. Therefore, the nonlinear trend of a given time series separated by ICEEMD provides us an estimate of the “change” of rainfall over the period unbiased by multi-decadal variability (Franzke 2010, Wu et al. 2011). Also, due to its “local” and “adaptive” nature of the method, the oscillatory modes and the nonlinear trend are better poised for physical interpretation. Development of the EMD method over the years has led to significant improvement of some issues like the “mode splitting” and the “end point problem.” The method has been found very useful in separating oscillatory modes from the nonlinear trend for several climate time series and has been extensively used (Antico et al. 2014; Zhang and Chen 2017; Guan et al. 2018; Zhao et al. 2019; Rottler et al. 2020) For more information on strength, weaknesses, and development of the EMD method, statistical significance test, and uncertainty estimate of the long term change, please refer to the Supplementary material.

3 Results

For the purpose of this study, the climate change is quantified as the percentage change of any variable (e.g., ISMR, NEIR, frequency of occurrence (F) and intensity (I) of extreme events) per degree increase of global mean temperature (e.g., $\Delta\text{NEIR\%/K}$) over the period of interest.

3.1 Climate change impact on seasonal mean rainfall

In contrast to all Indian rainfall during JJAS (ISMR) that has linear increasing trend (Fig. S9), the JJAS rainfall over NEI (NEIR(S08 + P94)) during the period 1829–2016 has a linear decreasing trend with a change of -3.6% during the period (Fig. 3a). Since the increase in global mean temperature during the same period is approximately 1 K (NOAA 2019), it represents a global warming impact at $-3.6\%/K$. The ICEEMD method decomposes the NEIR (S08 + P94) into six oscillatory modes (Fig. 3c–m) and a residual secular trend (Fig. 3o). The unbiased estimate of this from the secular trend (Fig. 3o) is $-3.2\%/K$. The uncertainty on the estimation of this change using Monte Carlo simulations is $\pm 1.65\%/K$. It is interesting to note that for a long record (~ 200 years), the multi-decadal mode (IMF5) (Fig. 3k) does not contribute to the long-term trend. However, the centennial mode (IMF6), if not separated, could bias this estimate by almost doubling the decreasing trend. Even though the NEI is one of the wettest region in the world, the decreasing trend of rainfall in the region reinforces that the “wet gets wetter” is not valid in the context of regional climates over land (Sun et al. 2012; Greve et al. 2014; Byrne and O’Gorman 2015).

The decreasing trend of NEIR (S08 + P94) (Fig. 3o) is a weak signal explaining only about 1.2% variance of the time series and as a result, the statistical significance tests using AR (1) model indicate that it is not statistically significant at 95% confidence level (Fig. S10) against Gaussian white noise null hypothesis. In order to examine whether there is a physical basis for this weak trend, we have examined the JJAS mean vertically integrated moisture flux convergence and pressure velocity, both averaged between 400 and 600 hPa over the region from twentieth Century Reanalysis V3 data provided by the NOAA <https://www.esrl.noaa.gov/psd/> (shown in Fig. S1). We find that the decreasing trend of mean rainfall over the NEI is consistent with the changes in circulation and thermodynamics over the region. It is interesting to note that both vertically integrated moisture convergence and middle atmospheric upward motion have a statistically significant decreasing trend. Thus, the global climate change mode in circulation seems to have increasing subsidence over the region leading to inhibition of convective activity and decreasing mean rainfall. As the rainfall data over the NEI is not assimilated in the 20CR, the consistency between the trend of the rainfall and large-scale circulation and moisture points to a potential physical origin of the decreasing trend of NEIR(S08 + P94). However, additional research and longer data would be required for establishing the robustness of the trend of NEIR(S08 + P94).

3.2 Is there any basis for a potentially non-trivial multi-decadal mode of NEIR (S08 + P94)?

The IMF5 (Fig. 3k) of NEIR (S08 + P94) represents a multi-decadal variability of NEIR(S08 + P94) with a period around ~ 60 years as depending on the length of the time series, it could bias estimate of change in NEIR (S08 + P94) due to climate change. For example, if our NEIR (S08 + P94) record starts from 1901, the multi-decadal mode could bias the estimate of

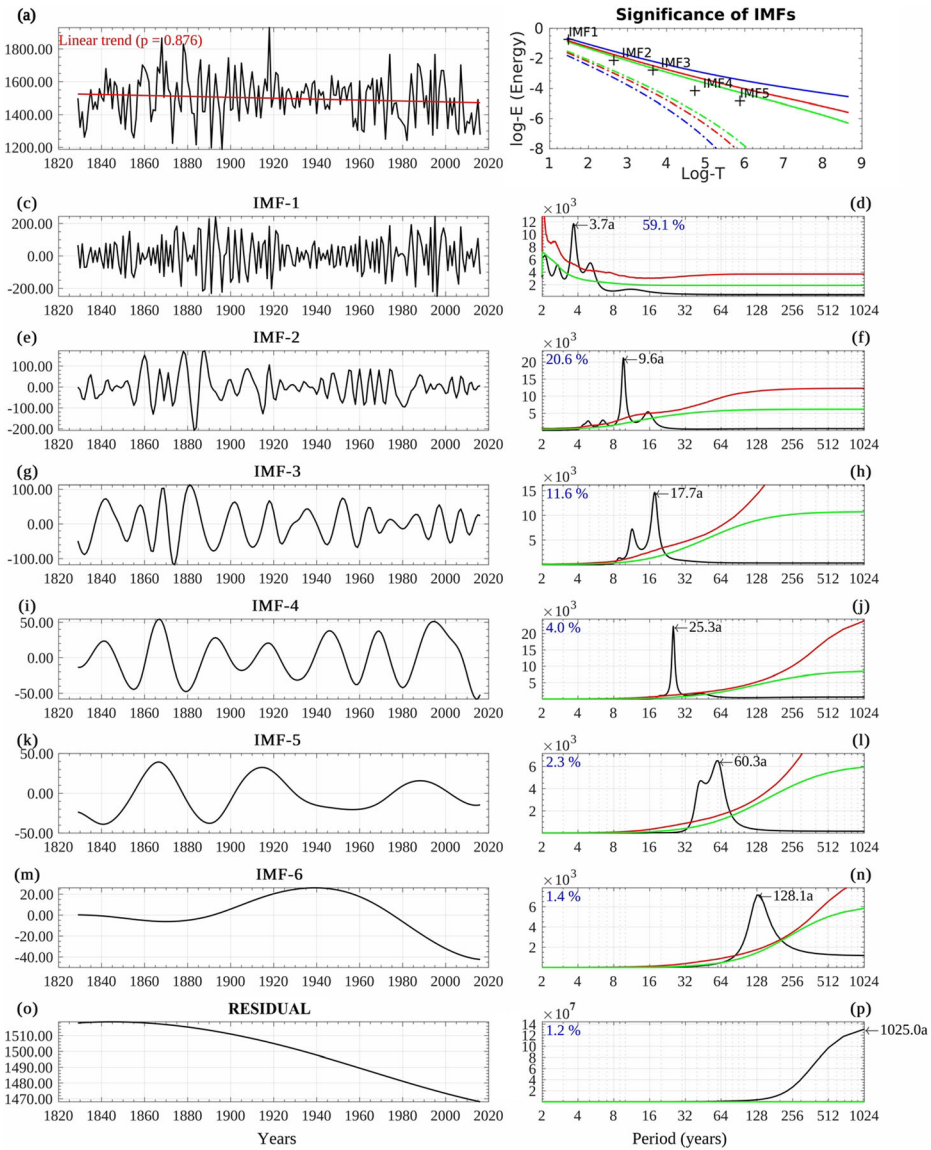


Fig. 3 **a** NEIR (S08 + P94) time series with linear trend (red line) for a period between 1829 and 2016 and **b** statistical significance of the IMFs, where blue, red, and green lines show 99%, 95%, and 90% CI (upper bound) and blue, red, and green dashed lines show 1%, 5%, and 10% CI (lower bound) against Gaussian white noise null hypothesis using Monte Carlo algorithm (Wu and Huang 2004). **c, e, g, i, k, m, and o** are the IMF components and residual of NEIR (S08 + P94) and **d, f, h, j, l, n, and p**, their respective power spectra with percentage of variance explained by each mode (blue font) and dominant periodicity indicated. Confidence level of the spectral peaks against red noise background is also indicated (red lines at 99% level). Units are in mm

decreasing change by another $\sim 2.8\%$. However, we recognize that the multi-decadal mode is weak and not statistically significant against the Gaussian white noise null hypothesis (Fig. 3b). If, however, the mode is strongly linked to some global modes of climate variability driven by slow predictable ocean-atmosphere interactions, its potential physical origin may

also be considered. We also note that a similar multi-decadal mode of variability of all Indian summer monsoon rainfall (ISMR) between 1829 and 2016 (Fig. S9k) with a period ~ 65 years is significant 99% confidence level and that it is inversely correlated with that of the NEIR (S08 + P94) (Fig. S9o). Thus, the multi-decadal mode of NEIR (S08 + P94) is an integral part of a significant Indian monsoon multi-decadal mode, the spatial pattern of rainfall of which is such that NEIR is out of phase with the rest of India. Further, the regression of IMF5 of NEIR (S08 + P94) with global JJAS SST using COBE SST2 (Hirahara et al. 2014) (Fig. 4a) indicates a pattern with two major nodes of SST anomalies, one in the North Atlantic (NA) and another in the North Pacific (NP) associated with the mode. As expected, note that this global SST pattern is similar to the pattern associated with a similar multi-decadal variability of all India rainfall shown in Fig. S9k but nearly out of phase with it (figure not shown, see Rajesh and Goswami (2020)). As in the case of long-term trend of the mean, the rainfall over the core monsoon region (central India) and that over the NEI seem to go out of phase even on multi-decadal time scales. In order to examine, whether the NEIR (S08 + P94) multi-decadal mode is more strongly linked to the NA SST or the NP SST, multi-decadal modes of JJAS SST over the NA and NP are extracted using the ICEEMD technique (Fig. S2 and S3). We find that both the JJAS SST patterns associated with the multi-decadal modes of SST over the NA and NP (Fig. 4b, c) correlate strongly ($R = -0.64$ and $R = -0.81$, respectively) with that associated with NEIR (S08 + P94) multi-decadal mode (Fig. 4a). Further, the lead-lag correlations between the multi-decadal mode of NEIR (S08 + P94) and those of NA SST and NP SST also are highly coherent (Fig. 4d). Coherent variation of the NEIR (S08 + P94) and NA SST on multi-decadal time scales leads us to a cautious hypothesis that the multi-decadal mode of

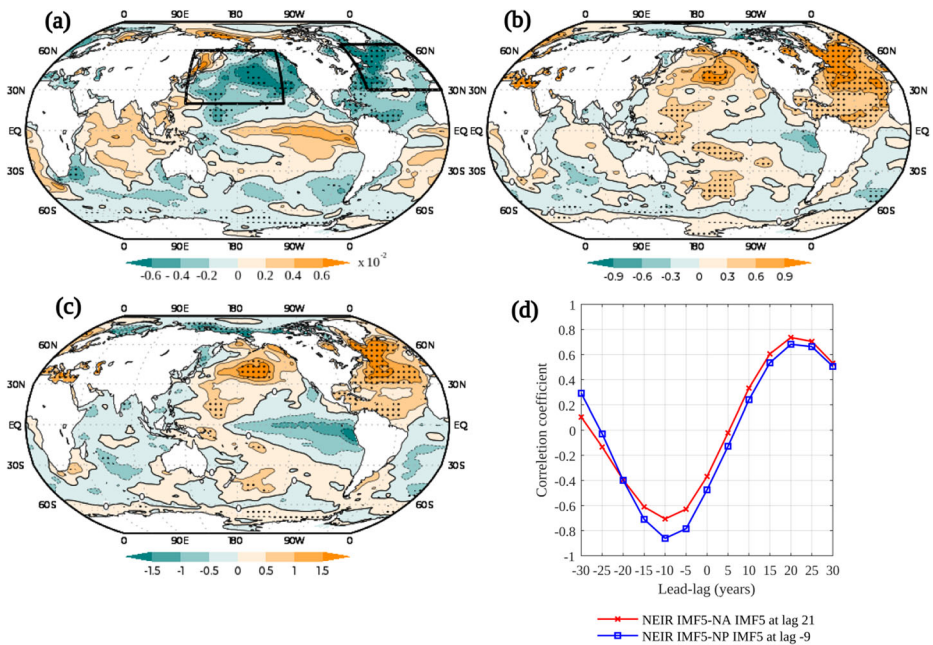


Fig. 4 a Regression of global JJAS SST (k/mm) with MDM of NEIR (S08 + P94) with the two boxes indicating two SST nodes of influence on NEIR over North Atlantic (NA) and North Pacific (NP), respectively. **b** MDM of NA SST (k/k). **c** Same as **b** but that with NP SST (k/k). **d** Lead-lag correlations between MDM of NEIR (S08 + P94) and NA SST and NP SST. Values regression in **a–c** significant at 95% level are indicated by black dots

NEIR (S08 + P94) owes its origin to the Atlantic Multi-Decadal Oscillations (AMO). However, longer data and additional research are required to support or reject this hypothesis.

The first two IMFs representing a quasi-biennial and ENSO modes together explain about ~80% of total variance for both ISMR and NEIR (S08 + P94). The two decadal modes of NEIR (S08 + P94) (IMF3, IMF4) explaining about 15.6% variance are a bit more active compared to those of ISMR that together explain 10.3% variance. This higher partitioning of variance to the decadal modes leaves the multi-decadal mode (MDM) of NEIR (S08 + P94) explaining 2.3% variance compared to 7.2% variance explained by the MDM of ISMR.

3.3 Impact on daily extreme rainfall

Before examining the statistics of daily extreme rainfall events, the trend and variability of the seasonal mean rainfall over the NEI based on the NE24 is examined.

3.3.1 Trend and variability of mean NE24

As the trend and variability of extreme rainfall event statistics is closely linked with the trend and variability of the seasonal mean, we examine the trend and oscillatory modes of the NE24 data set (Fig. S4) using the ICEEMD method. The quasi-biennial and quasi-quadrennial ENSO modes are represented by IMF1 and IMF2, respectively, while IMF3 and IMF4 represent two decadal modes. The multi-decadal mode of NEIR represented by IMF5 of longer data in Fig. 3 is rather poorly represented here by IMF5 in the shorter data with a period ~48 years. It is also interesting to note that except for the quasi-biennial mode (IMF1) all other oscillatory modes are not distinguishable from white noise background. Like the secular trend of NEIR (S08 + P94), the secular trend of NE24 is also not statistically significant (Fig. S4). The decreasing trend with a change of -2.2% over the period is also consistent with that from a longer record (Fig. 3).

3.3.2 Frequency of occurrence (F) and intensity (I) of daily extreme rainfall events

The mean rainfall being variable in the region (Fig. 1b), we recognize that using a percentile-based threshold to define extreme events over each station is more appropriate. Therefore, we define extreme rain events by three different criteria, namely (i) rain events for which daily rain amount exceed 95 percentile (P_{95}), (ii) rain events for which daily rain amount exceed 99 percentile at the station, P_{99} , (iii) rain events for which daily rain amount exceed 99.5 percentile, $P_{99.5}$. The frequency of occurrence (F) of “extreme rainfall” events over the region is the aggregate count of such events following the criterion over all 24 stations over the season. Time series of this aggregated count for the three criteria are constructed for the period of 90 years. The intensity (I) of the extreme rainfall events over the region during a season is the highest rainfall in any station during the season.

As a result of the inherent multi-decadal variability of the mean, multi-decadal variability in the frequency of occurrence of the extreme rain events and their intensity may be expected. Therefore, longer records of rainfall are critical for bringing out the long-term trend as would be expected in a warming environment (Trenberth et al. 2003; Goswami et al. 2006). Although may not be of ideal length, the NE24 daily rainfall data set based on 24 fixed stations over the NEI for 90 years is an important small step in that direction. Therefore, in order to get an unbiased estimate of the trend, all the time series decomposed using the ICEEMD method. The time series of this frequency of occurrence of extreme rainfall events during JJAS following

the three different criteria are shown in Fig. 5 together with their estimated linear trends. While the frequency of occurrence of extreme events exceeding 95 percentiles does not show any significant trend, those exceeding 99 and 99.5 percentiles show statistically significant increasing trends that stand out. Visual examination also indicates the existence of a multi-decadal variability superimposed on the linear trend. A decreasing trend of extreme rain events in the NEI from 1975 to 2010 found in our previous study (Goswami et al. 2010) is not incorrect but is a result of trend examined on a short span of available data highlighting the importance of longer data for estimating any secular trend.

In order to quantify the trend in the frequency of occurrence of the extreme rainfall events unbiased by inherent oscillatory modes variability of the extreme events, the IMF analysis of the $P_{99.5}$ is presented in Fig. 6. The nonlinear increasing trend is quite robust explaining 18% of variance of the time series. Test of significance against red noise null hypothesis using Monte Carlo simulations indicates that the trend is highly significant (Fig. S10). This increasing trend represents a change in the frequency of occurrence of $51 \pm 4.99\%$. Again the change in global mean temperature during the period being nearly 1 K the unbiased estimate of global warming impact of the frequency of occurrence of extreme rain events is an increase at $51 \pm 4.99\%/K$. The linear trend of the total count of the frequency of occurrence (Fig. 6a), however, shows an increase

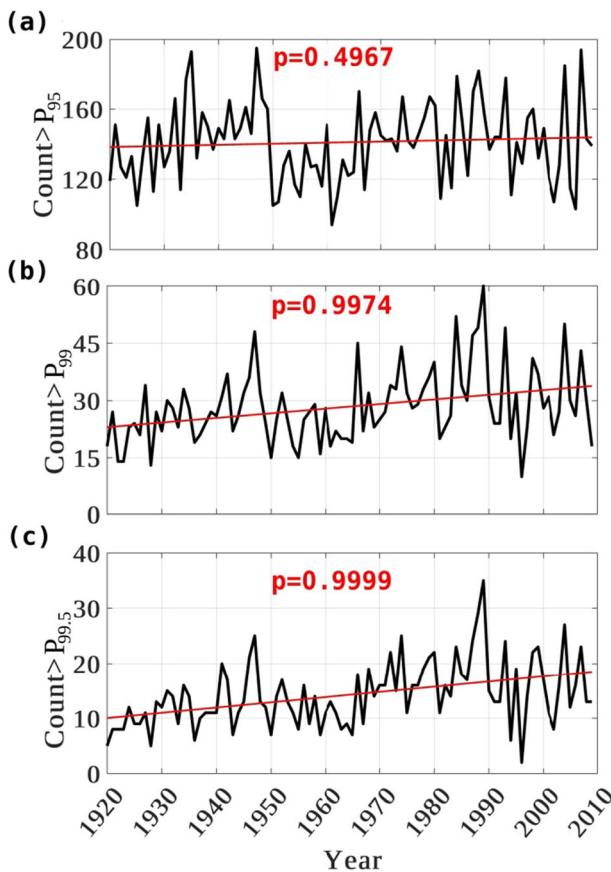


Fig. 5 Frequency of occurrence of extreme events of NE24 data defined with threshold of exceeding **a** 95 percentile (P_{95}), **b** 99 percentile (P_{99}), and **c** 99.5 percentile ($P_{99.5}$) for JJAS period

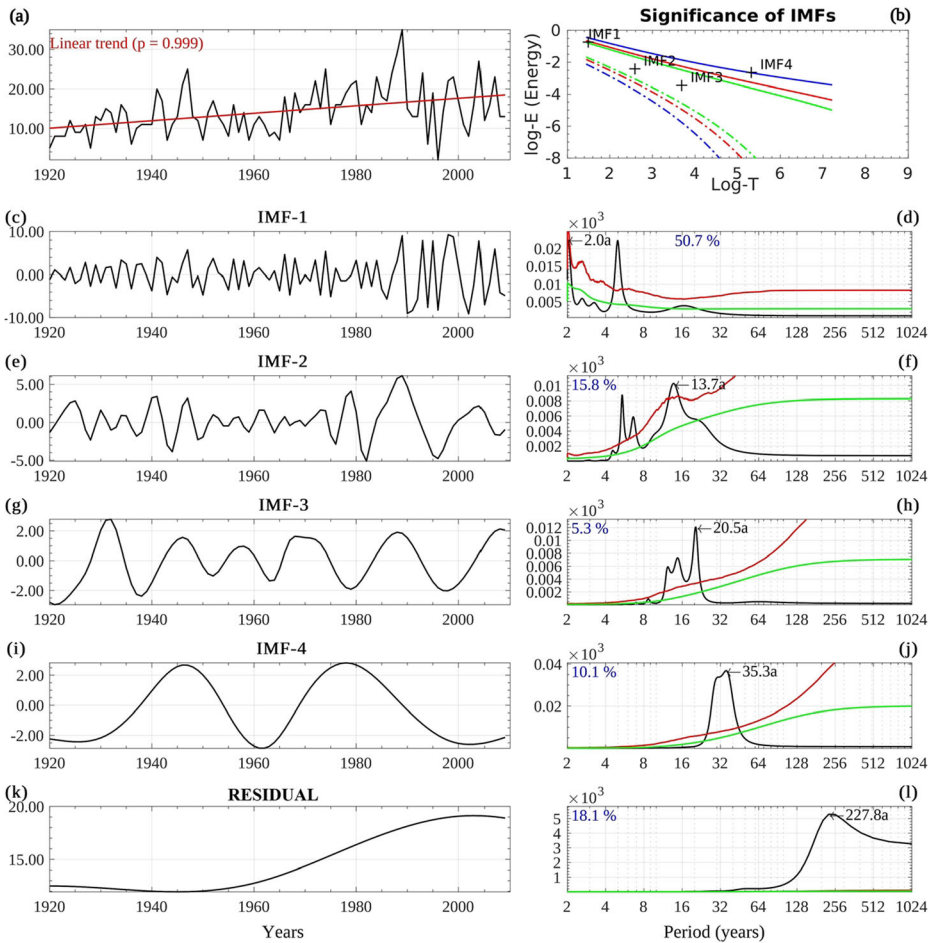


Fig. 6 **a, b** Same as Fig.3 but for frequency of occurrence of extreme events of NE24 exceeding 99.5 percentile for the period of JJAS with linear trend (red line) for a period from 1920 to 2009. **c, e, g, i, and k** are the IMF components and residual of the given series and **d, f, h, j, l**, their respective power spectra with percentage of variance explained by each mode (blue font) and dominant periodicity indicated. Confidence level of the spectral peaks against red noise background is also indicated (red lines at 99% level)

at 85%/K indicating a significant bias by the quasi-oscillatory modes. The requirement of exceeding 99.5 percentile represents a higher end of the “extreme events.” In order to estimate at what rate the “not so extreme events” are increasing, we examined the IMF decomposition of frequency of occurrence of extreme events exceeding 99 percentile (Fig. S5) and exceeding 95 percentiles (Fig. S5 and S6). It is noted that frequency of occurrence of extreme events exceeding 99 percentile as threshold also shows a significant long-term nonlinear trend (residual) explaining 12% variance represents a change of 44%/K in frequency of occurrence. However, the frequency of occurrence of extreme events exceeding 95 percentiles as threshold (residual) has an insignificant trend explaining 1.3% variance and representing a change of 6%/K (Fig. S6). That the climate change-induced trend is evident and statistically significant only in “severe extreme rainfall” events is clear in the transition of the rate of increase in the residual from an insignificant negative trend for P_{90} to a highly significant increasing trend for $P_{99.5}$ (Fig. S7). From this exercise,

the following may be concluded. Firstly, linear trends in time series (as seen in Fig. 5) of the frequency of occurrence of extreme events provide a biased estimate of change, and secondly that a significant increase in the frequency occurrence can be seen only, on the “severe extreme events” due to the climate change like in the case of the tropical cyclones (Murakami et al. 2017). Within the 90-year data we have, the nonlinear increasing trend in the “severe extreme events” is clear and robust and most likely driven by global warming. However, the multi-decadal mode of the frequency of occurrence of extreme events extracted by IMF analysis of the 90-year-long NE24 data, indicates the periods ranging from ~ 35 to ~ 50 years (Fig. 6, Fig. S5, Fig. S6) shorter compared to that of ~ 60 years of the JJAS mean rainfall from longer S08 + P94 data set (Fig. 3). It is reasonable to assume that the same multi-decadal mode also modulates the statistics of the extreme events. Therefore, the estimation of the multi-decadal variability from the NE24 may be biased thereby potentially introducing an uncertainty in our estimate of the climate change impact on extreme rainfall events in the region. Much longer daily rainfall time series (~ 150 years) on a fixed network of stations is, therefore, required to assess more accurately how the global warming changed the statistics of extreme events over the past 100 years.

Together with the frequency of occurrence of the extreme rain events, their intensity (I) is also expected to show an increasing trend under a warming environment. To check whether this is indeed happening in the NEIR, the daily rain amount of the highest rain event during the season during 1920–2009 is shown in Fig. 7b and is supplemented by time series of rain amount representing 96 percentiles to 99.9 percentile are shown in Fig. 7a. A statistically significant increasing trend of intensity of the extreme events (that is the maximum rain event during the season) is evident from Fig. 7b. However, we can also see multi-decadal variability riding on the trend. The IMFs of the time series of the intensity of the extreme events (Fig. S8) indicate that the multi-decadal mode with period ~ 73 years (IMF5) in intensity explaining variance 2.2% is actually stronger than the non-linear trend explaining 1.3% variance and represents an unbiased estimate of change of intensity at 12.5%/K. The linear trend in Fig. S8a, on the other hand, indicates a biased estimate of change of 15%/K.

3.4 On robustness of estimates of climate change impact on extreme events

In order to assess the robustness of the estimates of climate change impact on frequency of occurrence of daily extreme rainfall (51%/K) and intensity (12.5%/K),

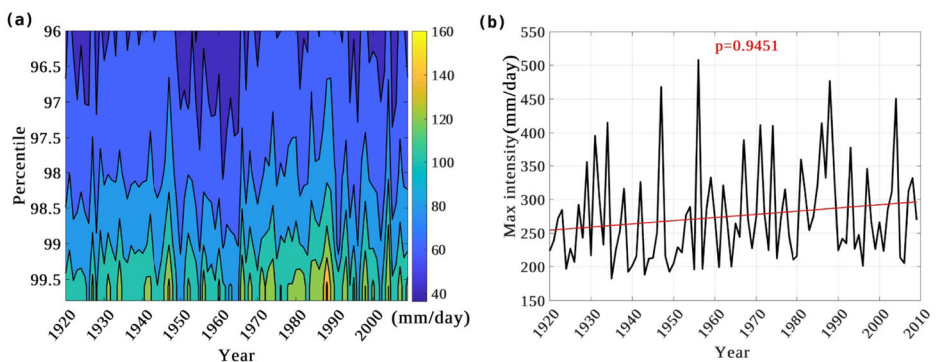


Fig. 7 Temporal variation (1920 to 2009) in **a** 96 to 99.5 percentiles of seasonal rainfall and **b** the intensity of the max rainfall in every season (JJAS) is shown. Color bar in **a** indicates rain intensity in mm/day

we need to preferably compare similar estimates from some other daily rainfall data. Unfortunately, such an independent daily data set with adequate length of record on a fixed network of stations is unavailable. The TRMM rainfall from 1998 is inadequate for the purpose due to its relatively short length. The only other potential data set is the gridded rainfall by IMD P14 (Pai et al. 2014) based on a variable station network and that also includes Cherrapunji, a very high rainfall station. The inclusion of Cherrapunji is by itself not a problem. However, it turns out that the station has prolonged and frequent data gaps. In the absence of any other more suitable data set, here we compare the frequency of occurrence of daily extreme rainfall from our NE24 data set (Fig. 8) with those from P14. For this purpose, we identify the 24 ($0.25^\circ \times 0.25^\circ$) grid boxes from P14 collocated with the 24 stations in NE24 and aggregate the rainfall events exceeding 99 and 99.5 percentiles (Fig. 8a, b). We note that over the overlapping years with TRMM, the variability of frequency of occurrence of extreme events in all three data sets agrees with each other showing a decreasing trend in the short term. As may be expected, the increasing trends in the frequency of occurrence of extreme rainfall events in both the data sets (NE24 and P14) agree well in the long term. Although the 24 stations in NE24 is a subset of stations of P14 where only the gaps have been filled differently and the grid box around Cherrapunji is not included in both, it is intriguing to note a much larger count in P14 during 1955–1975 while a lower count during 1935–1950 compared to that in NE24. We attribute this partly to gridding and partly to a variable network of stations in the case of P14. As we have shown, the linear trend is not an unbiased estimate of climate change impact. The artificial multi-decadal variability in P14 could significantly modify the real MDV of NEIR thereby making any attempt to estimate the long term nonlinear trend and obtain unbiased estimate of long term change erroneous.

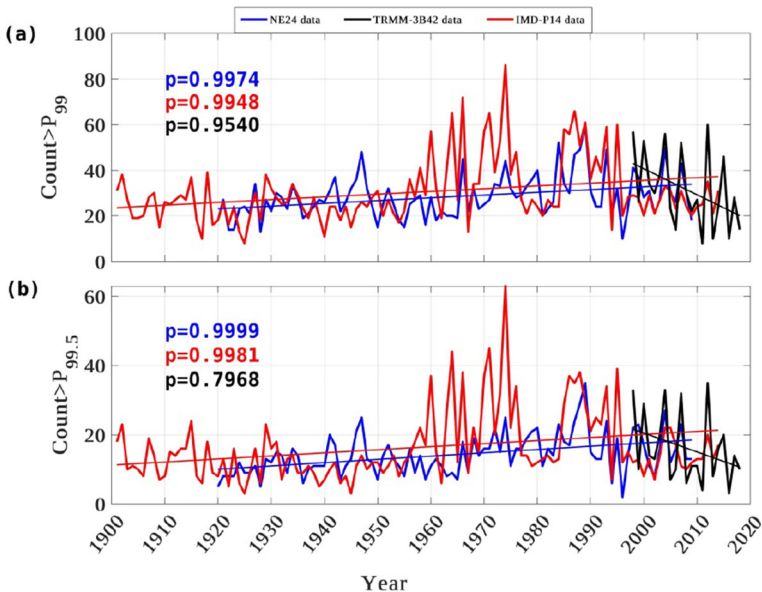


Fig. 8 Frequency of occurrence of extreme events defined with threshold of exceeding a 99 percentile (P99) and b 99.5 percentile (P99.5) percentiles for the 24 ($0.25^\circ \times 0.25^\circ$) grid boxes from P14 data and TRMM-3B42 data collocated with the 24 stations in NE24 data

4 Conclusions

- (a) We find that the seasonal mean rainfall over the NEI (NEIR (S08 + P94)) decreasing at $-3.2 \pm 1.65\%/K$ and is unbiased by the low-frequency modes of variability. Similar to variability on inter-annual time scale where it is known that the NEI node of Indian monsoon variability tends go out of phase with core monsoon region of central India, it does so even on global warming time scale. We note that the decreasing trend of rainfall over NEI is in contrast to a similar significant increasing trend of $\sim +3\%/K$ of all Indian rainfall. A decreasing trend of convergence of vertically integrated moisture content over the region as a result of weakening trend of mean upward motion appears to be responsible for the decreasing trend of rainfall (Fig. S1).
- (b) We find that the seasonal mean rainfall over NEI (NEIR (S08 + P94)) has a weak multi-decadal mode of variability with an approximate period of 60 years coherently linked with NA and NP SST associated with the Atlantic multi-decadal oscillation (AMO). It may be noted that the NEI appears to be an opposite node to that over central India in all time scales from inter-annual to climate change. This result has an important implication in the interpretation of paleoclimate data from the region in the context of the Indian monsoon (Kaushal et al. 2018).
- (c) Most robust impact of climate change, however, is found in the frequency of occurrence of the extreme rain events and their intensity. For this purpose, we use the NE24 data and employing the ICEEMD technique the secular nonlinear trend unbiased by oscillatory modes is extracted. The estimate of change in frequency of occurrence of extreme rain events exceeding 99.5 percentile indicates a highly significant increase at $+51 \pm 4.99\%/K$ while a similar estimate of the intensity of these events shows an increase at $+12.5 \pm 3.32\%/K$.

5 Discussions

We have argued in this study that the linear trend of a climate time series could be biased by existence of “natural” oscillatory multi-decadal variability making estimates of climate change based on linear trend erroneous. We have used improved complete ensemble empirical mode decomposition technique (ICEEMD) to isolate the nonlinear trend from the quasi-oscillatory modes to find the percentage change of seasonal mean rainfall due to climate change. Using the ICEEMD technique, we make unbiased estimate of climate change impact on mean NEIR as well as on the frequency of occurrence and intensity of the daily extreme events over the region.

It is interesting to note that in Section 4 (b), the intensity of the extreme events over the NEI is increasing at a rate higher than predicted by Clausius-Clapyeron relation ($\sim 7\%/K$), even though the mean rainfall has a weak decreasing tendency. However, the increase in the intensity is consistent with the fact that even though the moisture convergence in the region has a decreasing trend, the background JJAS mean convective available potential energy (CAPE) has a significant increasing trend over the period while the convective inhibition energy (CINE) has a decreasing trend (not shown). We also find that a robust long-term trend is seen in the frequency of occurrence of extreme rain events and their intensity emerges only for the most “severe” events (exceeding P_{99} and higher) in the region. On hindsight, it may be understandable. The severe “extreme events” are small-scale convective instability and more

sensitive to local thermodynamic changes (moisture and temperature) and hence their response could be seen even on a regional scale. It is interesting to note that if the “not so severe” extreme rain events are included in the count, the increasing trend is not discernible with confidence. With large increase in frequency of occurrence as well as the intensity of extreme rainfall events over the NEI in the backdrop of decreasing mean rainfall, vulnerability to meso-scale hydrological disasters over NEI in the coming years is much higher than that over the rest of India.

To establish the robustness of the important insights derived from this 90-year-long data set, there is a clear and urgent need to expand the time series both ways, from 2009 to present and backward from 1920 as back as possible.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s10584-021-02994-5>.

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