

# Spatiotemporal Variability of Weather Extremes Over Eastern India: Evidences of Ascertained Long Term Trend Persistence and Effective Global Climate Controls

Saurav Saha (✉ [sauravs.saha@gmail.com](mailto:sauravs.saha@gmail.com))

ICAR Research Complex for North Eastern Hill Region <https://orcid.org/0000-0001-6844-2516>

Debasish Chakraborty

ICAR Research Complex for North Eastern Hill Region

Samarendra Hazarika

ICAR Research Complex for North Eastern Hill Region

I. Shakuntala

ICAR Research Complex for North Eastern Hill Region

Bappa Das

ICAR Research Complex for North Eastern Hill Region

Aakash Chhabra

ICAR Research Complex for North Eastern Hill Region

S Sadhu

ICAR Research Complex for North Eastern Hill Region

Debashis Chakraborty

ICAR Research Complex for North Eastern Hill Region

J Mukherjee

ICAR Research Complex for North Eastern Hill Region

Lungmuana Singson

ICAR Research Complex for North Eastern Hill Region

V.K. Mishra

ICAR Research Complex for North Eastern Hill Region

---

## Research Article

**Keywords:** Temperature, Precipitation, Global teleconnection, Agro-eco region, Eastern India

**Posted Date:** December 6th, 2021

**DOI:** <https://doi.org/10.21203/rs.3.rs-934391/v1>

**License:**  This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

---

**Version of Record:** A version of this preprint was published at Theoretical and Applied Climatology on February 7th, 2022. See the published version at <https://doi.org/10.1007/s00704-022-03949-1>.

1 MANUSCRIPT TITLE:

2 **Spatiotemporal variability of weather extremes over eastern India: Evidences of**  
3 **ascertained long term trend persistence and effective global climate controls**

4  
5 AUTHORS & AFFILIATION:

6 A. Saurav Saha\*

7 ICAR Research complex for NEH Region, Mizoram Centre, Kolasib, India

8 Email: [sauravs.saha@gmail.com](mailto:sauravs.saha@gmail.com) Phone: +91-8729974473

9 B. Debasish Chakraborty

10 ICAR Research complex for NEH Region, Umiam, Meghalaya, India

11 Email: [debasishagri@gmail.com](mailto:debasishagri@gmail.com)

12 C. Samarendra Hazarika

13 ICAR Research complex for NEH Region, Umiam, Meghalaya, India

14 Email: [samarendra.ches@gmail.com](mailto:samarendra.ches@gmail.com)

15 D. I. Shakuntala

16 ICAR Research complex for NEH Region, Mizoram Centre, Kolasib, India

17 Email: [ishakuntala92@gmail.com](mailto:ishakuntala92@gmail.com)

18 E. Bappa Das

19 ICAR Central Coastal Agricultural Research Institute, Goa, India

20 Email: [bappa.iari.1989@gmail.com](mailto:bappa.iari.1989@gmail.com)

21 F. Aakash Chhabra

22 Department of Civil Engineering, Monash University, Clayton, VIC, Australia

23 Email: [Aakash.Chhabra@monash.edu](mailto:Aakash.Chhabra@monash.edu)

24 G. S. Sadhu

25 National Statistical Office, Government of India, Kolkata, West Bengal, India

26 Email: [sandip.edu@gmail.com](mailto:sandip.edu@gmail.com)

27 H. Debashis Chakraborty

28 Division of Agricultural Physics, Indian Agricultural Research Institute, New Delhi, India

29 Email: [debashisiari@gmail.com](mailto:debashisiari@gmail.com)

30 I. J. Mukherjee

31 Division of Agricultural Physics, Indian Agricultural Research Institute, New Delhi, India

32 Email: [joydeep.icar@gmail.com](mailto:joydeep.icar@gmail.com)

33 J. Lungmuana Singson

34 ICAR Research complex for NEH Region, Mizoram Centre, Kolasib, India

35 Email: [lmsingson@gmail.com](mailto:lmsingson@gmail.com)

36 K. V.K. Mishra

37 ICAR Research complex for NEH Region, Umiam, Meghalaya, India

38 Email: [VK.Mishra@icar.gov.in](mailto:VK.Mishra@icar.gov.in)

39  
40 \*CORRESPONDING AUTHOR.

41 Saurav Saha

42 ICAR Research complex for NEH Region, Mizoram Centre, Kolasib, India

43 Email: [sauravs.saha@gmail.com](mailto:sauravs.saha@gmail.com) Phone: +91-8729974473

44 **Spatiotemporal variability of weather extremes over eastern India: Evidences of**  
45 **ascertained long term trend persistence and effective global climate controls**

46 **Saurav Saha<sup>1</sup>, Debasish Chakraborty<sup>2</sup>, Samarendra Hazarika<sup>2</sup>, I. Shakuntala<sup>1</sup>, Bappa**  
47 **Das<sup>3</sup>, Aakash Chhabra<sup>4</sup>, S. Sadhu<sup>5</sup>, Debashis Chakraborty<sup>6</sup>, J. Mukherjee<sup>6</sup>, Lungmuana<sup>1</sup>,**  
48 **V.K. Mishra<sup>2</sup>**

49 (*\* Corresponding Author; email: [sauravs.saha@gmail.com](mailto:sauravs.saha@gmail.com)*)

50 <sup>1</sup>*ICAR Research complex for NEH Region, Mizoram Centre, Kolasib, India*

51 <sup>2</sup>*ICAR Research complex for NEH Region, Umiam, Meghalaya, India*

52 <sup>3</sup>*ICAR Central Coastal Agricultural Research Institute, Goa, India*

53 <sup>4</sup>*Department of Civil Engineering, Monash University, Clayton, VIC, Australia*

54 <sup>5</sup>*National Statistical Office, Government of India, Kolkata, West Bengal, India*

55 <sup>6</sup>*Indian Agricultural Research Institute, New Delhi, India*

56 **Abstract**

57 The present study acknowledged climate variability induced periodic variation in localized  
58 extreme weather event occurrences under diverse agro eco-regions of Eastern Himalayas of India  
59 during past five decades. The widespread rise in warm nights (TN90p; 0.31-1.67 days year<sup>-1</sup>),  
60 reduced daily rainfall intensity (SDII) and changes in other weather extremes viz. temperature and  
61 precipitation extremes signified clear signals on regional atmospheric warming across eastern  
62 India. The agro-ecological regions under extended Bramhaputra valley and coastal belts of south  
63 Bengal experienced the most persistent shifts in temperature extremes, while the upper Himalayan  
64 range extended from North Bengal to Arunachal Pradesh experienced the steepest decline in  
65 average daily rainfall intensity and other absolute quantitative estimates of precipitation extremes  
66 over past five decades. Together with El Niño and La Niña events, large scale global atmospheric  
67 circulations particularly expansion of warmer Pacific Warm Pool (PWP) and changes in Atlantic  
68 Meridional Mode (AMM) contributed the periodic dynamics in weather extreme occurrences from  
69 monthly to annual time scale over eastern India. Our findings will be useful for better  
70 understanding of regional climatology, designing and successful implantation of location-specific  
71 suitable agricultural policies towards climate change adaptation in near future.

72 **Keywords:** Temperature, Precipitation, Global teleconnection, Agro-eco region, Eastern India.

## 73 **1. Introduction**

74 Uneven atmospheric warming pattern across the globe evokes the necessity for studying  
75 the spatiotemporal variability in climate change phenomenon, which is broadly reported to be more  
76 prominent over northern latitudes than mid-latitudes (IPCC, 2013). Anthropogenic climate  
77 change-induced significant rise in extreme weather events have been reported across the globe  
78 including south and southeast Asian landmass over past few decades (Sen Roy and Balling 2004;  
79 Klein Tank et al. 2006; Panda and Kumar 2014; Sharma et al. 2017; Chakraborty et al. 2018;  
80 Akhoury and Avishek 2020). Since 1950, the seasonal frequency and magnitude of warm extremes  
81 increased with simultaneous decrease in cold extremes over Indian subcontinent (Sharma et al.,  
82 2017). The strong effective influence of uneven seasonal surface warming pattern (heatwave;  
83 Chakraborty et al. 2018) and other localized phenomenon viz. local terrain features (slope and  
84 physiography; Karki et al. 2019), elevation and latitude (Revadekar et al. 2013), urban pollution  
85 (Dahutia et al. 2018), land-use changes (Rapp, 2014) and other different meteorological parameters  
86 (Revadekar et al. 2013) often modify the seasonal dynamics of regional variation in temperature  
87 and precipitation extremes across Indian subcontinent.

88 The spatial variability in trends of several precipitation extremes increased throughout  
89 India during past few decades (Sen Roy and Balling 2004; Revadekar et al. 2013; Chakraborty et  
90 al. 2018). After 1980, the relative occurrence of extreme precipitation events increased with  
91 variable degrees of spatial aggregation. But minor changes in the mean annual precipitation were  
92 recorded from the out-turning impact of anthropogenic atmospheric warming over Indian  
93 subcontinent (Nikumbh et al. 2019). The declining trend was evident over two climatologically  
94 distinct regions of Central Himalaya (Joshi and Rai 2014; Karki et al. 2019). Such extreme  
95 precipitation events were projected to increase in near future and that might have considerable  
96 impact on human settlements in south east Asian countries including India (Nikumbh et al. 2019).  
97 The dynamic influences of large-scale and sea surface temperature (SST) anomalies had effective  
98 control on regional temperature and precipitation extreme events across the Indian Subcontinent  
99 (Panda and Kumar 2014). The global teleconnection between periodic SST patterns and seasonal  
100 climate extreme dynamics followed the distinct regional patterns over Indo-Pacific (Revadekar et  
101 al. 2013), upper Brahmaputra valley (Song et al. 2011), and Myanmar (Sein et al. 2018) region. In  
102 India, Sen Roy and Balling (2004) observed no potential linkage for annual precipitation extreme

103 events over Indian landmass (1910 – 2000), with either localized regional influences or El Niño  
104 South Oscillation events over equatorial Pacific Ocean (Roy et al. 2019). Panda and Kumar (2014)  
105 identified the potential control of SST based Niño 3.4 index (5°N–5°S, 120°–170°W) for  
106 predicting regional occurrences of forthcoming summer hot days, along with forthcoming heavy  
107 precipitation events. The seasonality of wetness pattern in the climate system of North East Indian  
108 states is distinct and more prone to meso-scale hydrological disasters from the rest part of India  
109 (Saha et al. 2018; Zahan et al. 2021a). To the best of our knowledge, limited information on the  
110 regional variability in extreme weather events and the possible linkages with global atmospheric  
111 phenomenon was available from the humid to per-humid and tropical to sub temperate climate of  
112 eastern Himalayan region of India and its adjacent river basins having variable agro-ecology (Abul  
113 Basher et al. 2017). Therefore, detailed investigations were worthwhile with the following  
114 objectives (a) to assess the regional variability in temperature and precipitation extreme events  
115 across delineated agro-eco regions (AERs) in eastern India over past five decades, (b) to  
116 investigate the interconnection between regional weather extreme event occurrences and global  
117 teleconnection indices.

## 118 **2. Methodology**

119 *Data availability, quality control and calculation of extreme indices:* The daily temperature  
120 (maximum and minimum) and precipitation data of 36 surface weather stations were obtained from  
121 the India Meteorological Department (IMD-Government of India; 1969-2018). The surface  
122 weather stations were spread over ~3,28,238 km<sup>2</sup> area between 21°46'–28°06'N latitudes and  
123 86°22'–94°55'E longitudes having variable relief features between 1 to 2042 m above mean sea  
124 level a. m. s. l. (Fig. 1). The study region selected here encompasses six distinct AERs as delineated  
125 by ICAR- National Bureau of Soil Survey and Land Use Planning (NBSS&LUP) (Mandal et al.  
126 2016), covering spatially diverse landscape features viz. temperate to sub temperate regions of  
127 Sikkim Himalaya, Meghalaya plateau (Khasi, Garo and Jaintia range), tropical to subtropical belt  
128 of Naga and Chin hills, Brahmaputra and Barak valley of Assam and lower Gangetic plains of  
129 West Bengal.

130 We adapted the open-source freely available package R programming based “RCLimDex”  
131 software package, developed by Expert Team on Climate Change Detection, Monitoring and  
132 Indices (ETCCDMI; <http://etccdi.pacificclimate.org/indices.shtml>.; table 1) and recommended for

133 data quality control for weather extreme analysis (Zhang et al. 2018). For minimizing error in trend  
 134 analysis, we checked the station wise weather data quality for homogeneity, identification of  
 135 missing values and potentially unrealistic/doubtful records. Missing data gaps were filled with  
 136 IMD gridded data sets, after comparing with corresponding nearest grid point values. The higher  
 137 deviations in derived weather parameters in five stations likely, Cherrapunjee, Shillong, Gangtok,  
 138 Darjeeling and Kalimpong restricted the adaptation of IMD gridded data for gap filling  
 139 (Supplementary Fig 1a-d). Therefore, we accounted for the long term daily average values as an  
 140 alternative approach for filling the missing values of daily surface observations for these five hill  
 141 stations. However, the total number of observation replacements (temperature and precipitation)  
 142 was less than 8% of the total number of recorded ground data points. Lastly, the data in-  
 143 homogeneity was checked in the R-based “RClmDex-Extraqc” and “RH tests version4  
 144 (RHtestsV4)” software packages (Wang and Feng 2013). We detected some station wise shifts in  
 145 data series from the homogenization analysis (Supplementary table 1). The detected sifts were  
 146 adjusted simultaneously using the bootstrapping approach in the same software package without  
 147 homogenous reference series for avoiding artificial jumps at the initiation or terminal point of the  
 148 time series. Thereafter, we warranted no further data adjustment and calculated the ETCCDMI  
 149 recommended extreme weather indices with  $\leq 1$  year return period. The base period of 1981–2010  
 150 was fixed and it accounted for more than 85% of stations with valid values for making  
 151 representative counts of days, crossing climatological percentile thresholds for extreme weather  
 152 indices calculation. All the extreme weather event analyses were carried out from annual to  
 153 seasonal timescale boundaries as delineated by IMD for India viz. winter (January-February), pre-  
 154 monsoon (March-May), monsoon (June –September) and post-monsoon (October-December).  
 155 Finally, regional averaged anomaly series for assessing AER wise extreme indices were  
 156 aggregated as:

$$157 \quad x_{r,t} = \sum_{i=1}^n (x_{i,t} - \bar{x}_i) / n \quad (1)$$

158 Where,  $x_{r,t}$  is averaged extreme index value at  $t^{\text{th}}$  year for any particular AER;  $x_{i,t}$  is index  
 159 for station  $i$  for  $t^{\text{th}}$  year;  $\bar{x}_i$  is the mean index for any particular station  $I$  (1969-2018);  $n$  is total  
 160 number of stations with available data for year  $t$  within the delineated AER.

161 **Trend analysis:** Seasonal extreme indices time series rarely follow normal distribution. Hence, we  
 162 adapted non-parametric Mann–Kendall test (MKT) instead of simple linear least squares trend, as

163 recommended by the WMO for trend assessment and statistical significance (Saha et al. 2018).  
 164 We accounted autocorrelation function (ACF) for eliminating the serial correlation effect, prior to  
 165 final trend assessment in station wise temperature/ precipitation extreme event time series and  
 166 estimated the slope magnitude or changes per unit time irrespective of gross data errors or outliers.  
 167 The majority of the time series were free from serial correlation at lag-1. We adapted three-stage  
 168 pre-whitening method before performing the final trend estimation if first order autocorrelation  
 169 was significant at  $p < 0.05$  (data not presented; Zhang et al. 2018).

170 **Hurst exponent analysis:** We adapted the widely used robust statistical method of estimating  
 171 Hurst exponent for detecting the persistence of long-term processes that occur in the extreme event  
 172 time series (Hurst 1951); via classical rescaled range analysis for the time series  $\{\xi(t)\}$  ( $t=1,2,\dots,n$ )  
 173 and dividing it into  $\tau$  sub-series  $x(t)$ ,

174 Arithmetic mean sequence  $(\xi_\tau) = \sum_{t=1}^{\tau} x(t) / \tau$   $\tau=1,2,\dots,n$  (2)

175 Cumulative deviation:  $X(t,\tau) = \sum_{t=1}^{\tau} (\xi(u) - (\xi)\tau)$   $1 \leq t \leq \tau$  (3)

176 Range sequence:  $R(\tau) = \max_{1 \leq t \leq \tau} X(t,\tau) - \min_{1 \leq t \leq \tau} X(t,\tau)$  where,  $\tau=1,2,\dots,n$  (4)

177 Sequence of standard deviation:  $S(\tau) = [\frac{1}{\tau} \sum_{t=1}^{\tau} (\xi(u) - (\xi)\tau)^2]^{\frac{1}{2}}$   $\tau = 1, 2, \dots, n$  (5)

178 Therefore, Hurst exponent (H) was expressed as:

179  $\frac{R(\tau)}{S(\tau)} = (c\tau)^H$  (6)

180 Generally, H varied between 0 and 1. Higher H values ( $0.5 < H < 1$ ) indicated trend  
 181 sustainability;  $H = 0.5$  signified a random walk and lower H values signified trend anti-  
 182 sustainability ( $0 < H < 0.5$ ) in long run.

183 **Linking regional weather extreme events with global climate anomalies:** The climatic system of  
 184 Indian subcontinent indicated relationship with several large-scale global atmospheric circulation/  
 185 teleconnection indices (Supplementary table 2), along with rising levels of atmospheric  
 186 greenhouse gas (GHG) concentration viz.  $CO_2$  and  $CH_4$  and solar activity. In this study, we  
 187 analyzed their internal co-variation and association with de-trended (linear) extreme event time  
 188 series. Initially, we adapted Principal Component Analysis (PCA) for minimizing the  
 189 dimensionality of available global teleconnection time series, while retaining the largest variance

190 present in the analyzed dataset through identified dominant principal components (PCs). The initial  
 191 pre-filtering technique ensured that first PC explained maximum variability followed by others in  
 192 descending manner. We identified and retained the important underlying variables for each PC  
 193 based on absolute factor loadings values within 10% of the maximum weighted factor.  
 194 Furthermore, we cross verified the inter-linkage of extracted variables for all the respective PCs  
 195 using Pearson Correlation matrix and finally selected the most non co-related variables from each  
 196 PC for further co-variation analysis. The maximum likelihood for linear associations between two  
 197 respective orthogonal datasets viz. time series of all the global climate anomaly datasets and  
 198 periodic regional weather extreme event occurrences was quantified on the calculation of  
 199 canonical coefficients (de-trended time series) using singular value decomposition of cross-  
 200 covariance matrix over monthly and annual time scale.

201 **Testing for co-integration:** We adapted Johansen's methodology for assessing the final degree of  
 202 association between the sets of time series viz. composite weather extreme time series and global  
 203 climate controls (Johansen and Juselius 1990). The starting point of p order in vector auto-  
 204 regression was,

$$205 \quad y_t = \mu + A_1 y_{t-1} + \dots + A_p y_{t-p} + \varepsilon_t \quad (7)$$

206 Where  $y_t$  is  $n \times 1$  vector of variables; integrated of order one expressed as I;  $\varepsilon_t$  implies vector  
 207 of innovations for  $n \times 1$ . Therefore, vector autoregression was expressed as

$$208 \quad \Delta y_t = \mu + \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t \quad (8)$$

209 Where,

$$210 \quad \Pi = \sum_{i=1}^p A_i - I \text{ and } \Gamma_i = -\sum_{j=i-1}^p A_j \quad (9)$$

211 If  $r < n$  for the coefficient matrix ( $\Pi$ ), then  $n \times r$  matrices  $\alpha$  and  $\beta$  each with rank  $r$  expressed  
 212 the stationarity as  $\Pi = \alpha\beta'$  and  $\beta' y_t$  for the  $r$  number of co-integrating relationships. Here,  $\alpha$   
 213 denoted the adjustment parameters in vector error correction model and each column of  $\beta$  implied  
 214 the co-integrating vector. For any specific  $r$  value, the maximum likelihood estimator for  $\beta$  defined  
 215 the combination of  $y_{t-1}$  that yielded the  $r$  largest canonical correlations of  $\Delta y_t$  with  $y_{t-1}$  with  
 216 corrected lag differences and deterministic variables (if any). Furthermore, two different likelihood

217 ratio tests of significance for these canonical correlations viz. trace test and maximum eigenvalue  
218 test were executed with reduced rank of  $\Pi$  matrix, respectively as.

$$219 J_{\text{trace}} = -T \sum_{i=r-1}^n \ln(1 - \hat{\lambda}_i) \quad (10)$$

$$220 J_{\text{max}} = -T \ln(1 - \hat{\lambda}_{r+1}) \quad (11)$$

221 Where,  $\hat{\lambda}_i$  is  $i^{\text{th}}$  largest canonical correlation for the sample size of T. The trace test tested  
222  $H_0$  for r numbers of co-integrating vectors against the alternative hypothesis ( $H_1$ ) of n co-  
223 integrating vectors. In courtesy, the maximum eigenvalue test considered  $H_0$  of r co-integrating  
224 vectors against the alternative hypothesis ( $H_1$ ) for r+1 co-integrating vectors. Neither of these two  
225 test statistics followed chi-square distribution. We used asymptotic critical value approach for  
226 assessing co-integration for each AER separately using maximum eigenvalue for r=0 or 1  
227 (Johansen and Juselius, 1990). At  $p < 0.05$ , the critical values for r=0 is 8.18 (11.65;  $p < 0.01$ ) while  
228 that of r=1 is 14.9 (19.19;  $p < 0.01$ ). For all those series where either of the null hypothesis has  
229 been accepted, implying a reduced rank of  $\Pi$ , have a common long term trend. Where both the  
230 null hypothesis is rejected, the test statistic values were omitted signifying no long-term  
231 relationship between two sets of time series.

### 232 3. Results

233 Rainfall climatology of the study region varied from perhumid to sub-humid type with core  
234 south west monsoon activity (Mandal et al. 2016). According to Koppen climate classification,  
235 tropical climate (category A) exist across the parts of Manipur, Mizoram, Tripura and Cachar plain  
236 of Assam (below 25° N latitude). The remaining region of Meghalaya, Assam (upper Bramhaputra  
237 valley), Manipur, Nagaland and parts of Arunachal Pradesh (within 25° and 35° N latitude) fall  
238 under warm temperate mesothermal climate. The mean monthly maximum temperature varied  
239 between 24.5 °C (AER 17) to 35.2 °C (AER 12) across the region (summer months; during June-  
240 July). In courtesy, the average minimum monthly temperature was assorted between 6.1 °C (AER  
241 17) to 13.9 °C (AER 12) during winter months (December-January). South west monsoon  
242 contributed the major share (66.1-78.4%) of annual precipitation varying between 1532.2 mm  
243 (AER 12) to 3782.32 mm (AER 18) over eastern India (Saha et al. 2018).

#### 244 3.1 Trend pattern and persistence analysis of extreme weather events:

245 *3.1.1 Seasonal and annual temperature extreme pattern:* Substantial spatiotemporal variability in  
246 long term seasonal changes of weather extreme events were conspicuous across the six AERs of  
247 eastern India over the past five decades (Sharma et al. 2017). The results of trend pattern and its  
248 persistence of the daily temperature extreme accumulated over different seasons are presented in  
249 figure 2a and b. Seasonal changes in warm nights (TN90p) were more extensive and occurring  
250 over different seasons than observed changes in warm days (TX90p), cool nights (TN10p) and  
251 cool days (TX10). The hottest maximum temperature (TXx; warmest day) showed maximum  
252 trend/change followed by warmest minimum temperature (TNx; warmest night), coldest minimum  
253 temperature (TNn; coldest night) and coldest maximum temperature (TXn; coldest day) across  
254 AERs in eastern India (Fig 2a). The prudent spatiotemporal variability in Sen slope values was  
255 more conspicuous from seasonal to annual time scale. The significant rise in TXx over AER 19  
256 ( $0.03\text{-}0.05\text{ }^{\circ}\text{C year}^{-1}$ ) was accompanied by increased TNx over AER 18 and AER 19 ( $0.01\text{-}0.07$   
257  $^{\circ}\text{C year}^{-1}$ ) over all the four seasons. In similarity, the overall seasonal TXn rise over AER 17 ( $0.02\text{-}$   
258  $0.06\text{ }^{\circ}\text{C year}^{-1}$ ) and AER 18 ( $0.01\text{-}0.04\text{ }^{\circ}\text{C year}^{-1}$ ) were more divergent with the observed decline  
259 in TXn over AER 15, particularly during winter and post-monsoon season ( $0.06\text{-}0.14\text{ }^{\circ}\text{C year}^{-1}$ ).  
260 The declined winter TNn over AER 12 and AER 19 ( $\sim 0.04\text{ }^{\circ}\text{C year}^{-1}$ ) were also contrasted with  
261 TNn rise across AER 18, AER 17 and AER 12 during pre-monsoon season ( $0.03\text{-}0.06\text{ }^{\circ}\text{C year}^{-1}$ ).  
262 However, the declining trend of TNn over AER 19 was anti-persistent during monsoon months  
263 (Fig 2b). The relative changes in minimum temperature based extreme indices (TN10p, TN90p,  
264 TNn and TNx) were more widespread, intense and ubiquitous than maximum temperature-based  
265 indices (TX10p, TX90p, TXn and TNx). Spatially, mixed trend patterns existed for both minimum  
266 and maximum temperature based extreme indices among the delineated AERs from seasonal to  
267 annual time scale. The strongest widespread changes in minimum temperature-based percentile  
268 index (TN90p;  $0.31\text{-}1.67\text{ days year}^{-1}$ ) indicated more explicit lengthening of warm nights over  
269 eastern India during all four seasons. Throughout AER 18, significant lengthening of warm days  
270 (TX90p;  $0.41\text{-}0.76\text{ days year}^{-1}$ ) and summer days (SU25;  $1.09\text{ days year}^{-1}$ ) with increased warm  
271 spell duration (WSDI;  $0.42\text{ days year}^{-1}$ ) while marginal reduction in cool days (TX10p;  $0.18\text{-}0.56$   
272  $\text{days year}^{-1}$ ) were apparently confirming incessant seasonal warming across eastern India. In  
273 contrary, substantial rise in warm nights (TN90p;  $0.62\text{-}1.09\text{ days year}^{-1}$ ) ascribed the observed  
274 protraction of tropical nights (TR20;  $0.85\text{ days year}^{-1}$ ) over AER 18. Reduction in warm days  
275 (TX90p;  $0.31\text{-}0.62\text{ days year}^{-1}$ ) during different seasons imparted the overall annual reduction in

276 summer days (SU25; 0.73 days year<sup>-1</sup>) over AER 17 with no significant changes in warm night  
277 (TN90p) and tropical night (TR20). The consistent high magnitude of year-round TN90p rise  
278 (0.78-1.51 days year<sup>-1</sup>) ensured the annual occurrences of prolonged tropical night over AER 18  
279 and AER 16 (TR20; 0.32- 0.85 days year<sup>-1</sup>). Consistent reduction in seasonal cool nights (TN10p;  
280 0.41-0.53 days year<sup>-1</sup>), rise in frequent warm days (TX90p; 0.26 – 1.08 days year<sup>-1</sup>) and lengthy  
281 warm spells (WSDI; ~0.41 days year<sup>-1</sup>) contributed to further lengthening of tropical nights (TR20)  
282 over AER 16. The relative reduction of cool nights was in consonance with the observed reduction  
283 in summer days (SU25; 1.64 days year<sup>-1</sup>) over AER 12. The consistent seasonal rise in cool days  
284 (TX10p; 0.6-1.4 days year<sup>-1</sup>) complemented strong annual decline in summer days (SU25; 0.32 –  
285 1.31 days year<sup>-1</sup>) over AER 15 and AER 19. The increased occurrences of cool nights (TN10p)  
286 during post-monsoon and winter (0.8-1.5 days year<sup>-1</sup>) acceded the rise in cold spell duration  
287 (CSDI; 0.37 days year<sup>-1</sup>) over AER 19.

288 The significant seasonal constriction in DTR was evident in AER 15 (0.027-0.053 °C year<sup>-1</sup>)  
289 against the distinct rise in seasonal DTR across AER 18 (0.039-0.009 °C year<sup>-1</sup>) for all four  
290 seasons. The DTR fluctuations were more rapid during winter than monsoon season. The declined  
291 monsoon and post-monsoon DTR ranged across AER 17, AER 15 and AER 12 (0.01 - 0.04 °C  
292 year<sup>-1</sup>). The fluctuations in seasonal temperature extremes were more prominent during winter and  
293 pre-monsoon over AER 19 (~ 0.02 °C year<sup>-1</sup>). With few exceptions, the significant decline in DTR  
294 time series was persistent with higher trend sustainability across all the six AERs in eastern India  
295 (Song et al. 2011). Eventually, AER 18 and AER 19 were exposed to increased daily fluctuations  
296 in maximum and minimum temperature, while AER 17 experienced the least overall seasonal  
297 fluctuations in temperature extremes.

### 298 *3.1.2. Seasonal and annual precipitation extreme pattern:*

299 The spatial variability in precipitation extreme trend was more splintered with limited  
300 spatial coherence than observed trend pattern in extreme temperature time series over eastern India  
301 (Klein Tank et al. 2006; Nikumbh et al. 2019). The results of this study indicated significant  
302 decline in majority of extreme precipitation indices, like number of precipitation days, absolute  
303 precipitation quantity and intensity except CDD (0.24 – 3.11 days year<sup>-1</sup>) and CWD (0.27-0.35  
304 days year<sup>-1</sup>). The declining trend in RX1 was almost identical with RX5, particularly during  
305 monsoon months across the majority of AERs in eastern India.

306 The significant increase of annual CDD (0.54 days year<sup>-1</sup>) and ZRD (0.05 – 0.18 days year<sup>-1</sup>), along with marginal reduction in CWD (0.35 days year<sup>-1</sup>) and number of heavy precipitation days (0.25 days year<sup>-1</sup>) revealed the rising annual dryness over AER 18. The increasing anomalies in seasonal and annual precipitation extreme time series were evident from the sharp decline in absolute precipitation quantity indices (5.11 -29.03 mm PRCPTOT year<sup>-1</sup>; 3.18 -11.25 mm R95p year<sup>-1</sup>; 1.76- 4.44 mm R99p year<sup>-1</sup>; 0.03-1.3 mm RX1 year<sup>-1</sup>), intensity indices (SDII; 0.05-0.11 mm day<sup>-1</sup> year<sup>-1</sup>) and number of precipitation days (0.69 -2.11 days CDD year<sup>-1</sup>; 0.15-0.23 days CWD year<sup>-1</sup>; 0.03-0.11 days ZRD year<sup>-1</sup>; 0.07-0.6 days R10 year<sup>-1</sup> and 0.15-0.53 days R20 year<sup>-1</sup>) over AER 17, AER 16 and AER 15. Our result was in contrast with the increasing trend of heavy rainfall events across north east India (Guhathakurta et al. 2011). However, more intense shifts in seasonal and annual precipitation extreme events towards the respective increases in regional dryness were evident across AER 17 and AER 16. While the reduced average daily rainfall intensity (SDII; 0.07 mm day<sup>-1</sup> year<sup>-1</sup>) and very wet days occurrences (R95p; 4.47 mm year<sup>-1</sup>) progressed towards more uneven annual precipitation distribution through observed rise in CWD (0.27 days year<sup>-1</sup>) over AER 12. In contrast, raising average daily rainfall intensity (0.05 mm day<sup>-1</sup> year<sup>-1</sup>) and very wet day occurrences (R95p; 4.71 mm year<sup>-1</sup>) were accompanied by frequent dry spell events (CDD; 0.48 days year<sup>-1</sup>) over AER 19. Majority of the observed trend pattern and significant changes in periodic weather extremes were persistent over the delineated AERs in eastern India. In contrast, the observed annual decline in RX5, R95p, and R99p over AER 15 along with changes in R50 over AER 17 were anti-persistent (Fig. 2b). The sustainability of significant gradual shifts identified in annual precipitation extremes time series towards dryness was conserved (Panda and Kumar, 2014).

### 328 *3.2 Association with large-scale global atmospheric circulation*

329 We assessed the relationship between extreme weather indices and large-scale global  
330 atmospheric circulation for the period 1969–2018.

#### 331 *3.2.1 Principal component analysis:*

332 Multiple indices of large-scale global atmospheric circulation processes have indirect control on  
333 weather extremes over the study region. Principal Component Analysis (PCA) were adapted for  
334 minimizing the dimensionality of global teleconnection time series, while retaining the largest  
335 variance in dataset. The eigenvalues of nine principal components (PCs) were  $\geq 1$  that accounted

336 89.58% cumulative variance in the data set (Table 2). Strong correlation among the dominated  
337 global teleconnection indices with each PC was cross verified. Indices having weightage within  
338 10% of the highest factor loading for each eigenvalue represented the variability of respective PCs.  
339 Therefore, we sorted out nine indices *viz.* Oceanic Niño Index (ONI; PC 1), Pacific Warm Pool  
340 (PWP; PC 2), North Atlantic Oscillation (NAO; PC 3), North Pacific pattern (NP; PC 4), East  
341 Pacific/North Pacific Oscillation (EPNP; PC 5), Western Pacific Index (WP; PC 6), Atlantic  
342 Meridional Mode (AMM; PC 7), Trans-Niño Index (TNI; PC 8) and Quasi-Biennial Oscillation  
343 (QBO; PC 9) for further association analysis with temperature and precipitation extreme time  
344 series in eastern India.

### 345 3.2.2 Canonical correlation analysis:

346 Canonical correlations between respective global teleconnection and extreme weather time series  
347 were carried out from monthly to annual time scales, particularly for El Niño and La Niña years  
348 (Table 3). Multivariate Wilks' lambda ( $\lambda$ ) test identified significant strong association ( $p < 0.01$ )  
349 between global teleconnection and monthly weather extreme time series accounting 82.84% and  
350 87.92% cumulative variability during the El Niño ( $\lambda$ : 0.058-0.562) and La Niña ( $\lambda$ : 0.067-0.605)  
351 years, respectively. The corresponding eigenvalues represented the changes in strength of  
352 association with declining degree of canonical correlations through accommodating more  
353 cumulative variability at  $p < 0.05$  significance level. The multifactor linkage between global  
354 teleconnection and weather extreme series was stronger for monthly ( $\lambda$ : 0.182-0.904, variability:  
355 95.10%) rather than annual time scale ( $\lambda$ : 0.001, variability: 21.41%). The respective multivariate  
356 helio-plots displayed the extent of linkage using radial bars (Fig. 3a-d). Smaller weightage points  
357 were put inward, and larger values pointed outwards from the base. The directions of placement  
358 laid down the nature of linkages i.e. direct or inverse relationship. PWP had the most effective  
359 influence on weather extreme event occurrences over eastern India, followed by North Pacific  
360 pattern (NP). The influence of PWP were more implicit for rising warm nights (TN90p) than warm  
361 days (TX90p) occurrences from monthly to annual time scale over our present study region  
362 (including El Niño and La Niña years). Furthermore, the proportionate direct influence of NP over  
363 both absolute temperature (TXx, TNx, TXn and TNn) and precipitation (RX1 and RX5) extremes  
364 also affirmed the role of pacific warming in Eastern India. The moderate control from Oceanic  
365 Niño Index (ONI; El Niño years) and Atlantic Meridional Mode (AMM; La Niña years) influenced

366 the dynamics of cool day occurrences (Fig 3a and b; Panda and Kumar, 2014). Nevertheless, ONI  
367 facilitated the proportionate rise in periodic occurrences of absolute extreme temperature and  
368 precipitation indices and suppressed the rise in ZRD and DTR fluctuations during La Niña years  
369 (Fig. 3b). The combined influence from AMM and WP was also inevitable during La Niña years.  
370 On monthly time scale, warm night occurrences were closely associated with variations in PWP.  
371 The prominent control of NP on overall monthly variations in absolute temperature and  
372 precipitation indices were evident during our present study period (Fig. 3c). In contrary, AMM  
373 commenced the prominent control on annual distribution of consecutive wet day (CWD) and  
374 tropical night (TR20) occurrences (Fig. 3d). East Pacific/North Pacific Oscillation swayed the  
375 annual occurrences of absolute precipitation quantity (PRCPTOT, R95p and R99p) and average  
376 rainfall intensity (SDII) across the AERs. Unlike Song et al (2014), we observed very limited  
377 forcing of NAO and QBO on regional weather extreme occurrences from monthly to annual time  
378 scale over Eastern India.

### 379 *3.2.3 Cointegration analysis:*

380 The weather extremes over eastern India and global teleconnections varied over time  
381 implying their non-stationarity, while the lag-1 differenced series of the indices showed stable  
382 mean over time. Most of the weather extreme indices showed co-movement with the  
383 selective/specific global teleconnection indices over time and depicted a common long-term trend  
384 for co-integration between the two sets of time series at monthly and seasonal time scale (table 4a  
385 and b). The relative control of PWP (except CDD and CWD) and AMM on weather extreme event  
386 occurrences of eastern India were very clear from monthly to annual time scale. Nevertheless, the  
387 ascendancy of ONI was limited for monthly variation in weather extreme event occurrences,  
388 particularly during El Niño or La Niña years (Fig 3a and b; Table 4b). The relative control of ONI  
389 on annual occurrences of TN90p and TR20 were significant. Even so, the ascendancy of EPNP  
390 was evident for periodic precipitation extreme occurrences across eastern India. The rise in  
391 anthropogenic GHG (mostly CH<sub>4</sub> and CO<sub>2</sub>) showed strong co-integration with the changes in  
392 weather extreme event time series (Table 5). The influence of changing emission rate of CH<sub>4</sub> was  
393 most common for all studied weather extreme indices of the study region. The rise in atmospheric  
394 CO<sub>2</sub> concentration was not associated with the dynamics of daily precipitation intensity and wet  
395 days occurrences over the study region. The annual variations in OLR were closely associated with

396 the observed variation in absolute precipitation quantity (PRCPTOT, R95p and R99p), but have  
397 limited influence on intensity or number of precipitation days (except ZRD counts). The natural  
398 variations in sunspot activity and solar flux were analogous to the annual DTR fluctuation and  
399 TN90p occurrences.

#### 400 **4. Discussion:**

401 In the present study, we assessed the trend and its persistence of daily temperature and  
402 precipitation extreme indices calculated from the quality-controlled and homogenized dataset for  
403 36 surface weather stations across eastern India for the period of 1969-2018 (Fig. 2a and b). The  
404 widespread rise in warm night occurrences came up with the evidence of clear rise in nocturnal  
405 temperature extreme events over daytime ones across the eastern India (Choi et al. 2009; Sein et  
406 al. 2018). The strong warming trend was mostly recorded during monsoon months (June-July-  
407 August-September) especially for warm nights (Song et al. 2011). The agro-eco regions  
408 categorized under *Purvanchal* range (AER 18), Assam - North Bengal plains (AER 16) and coastal  
409 belt of south Bengal (AER 19) were pre-disposed with significant rise in warmer day temperature  
410 extremes (warm days; TX90p) and subsequent decline in cool night (TN10p) occurrences,  
411 particularly over AER 18 (Chakraborty et al. 2018). The contrasting rising trend in cold day  
412 temperature extremes (TX10p) were more conspicuous over Bengal basin (AER 15) and costal  
413 belts of south Bengal region (AER 19) than other adjacent AERs (Sharma et al. 2017). The rise in  
414 TXx and TNn showed higher spatial coherence than TNx and TXn across the delineated AERs in  
415 eastern India (Revadekar et al. 2013). Unlike other parts of India, the changing magnitudes in  
416 minimum temperature trends and its variability were almost equally evident for the maximum  
417 temperature extremes throughout the year (Sein et al. 2018). The greater magnitude of rising  
418 minimum temperature over maximum temperature resulted the observed reduction in DTR over  
419 eastern India except, the *Purvanchal* range (AER 18) and coastal regions of south Bengal (AER  
420 19) (Klein Tank et al., 2006). Fragmented decrease in cloud cover and increase in afternoon RH  
421 across AER 18 steered the localized DTR rise as also reported from adjacent Myanmar region  
422 (Sein et al. 2018). In contrast, the climate control of increased cloud cover (Jaswal 2010) and  
423 reduced insolation (Jhajharia and Singh 2011) over rest AERs and other non-climatic factors like  
424 rapid urbanization and increasing aerosols levels and water-vapor feedbacks contributed to the  
425 observed anomalies for reduced DTR in eastern India (Song et al. 2011; Dahutia et al. 2018).

426 The high mountainous topography of Eastern Himalaya region (including Sikkim Himalaya;  
427 AER 17) and adjacent plains in upper Brahmaputra plains (Assam and North Bengal; AER 16)  
428 were more prone to strong changes in dry precipitation extreme events than other AERs like  
429 *Purvanchal* range (AER 18), plains of Gangetic Bengal viz. AER 15, AER 12 and AER 19 in  
430 eastern India over past five decades (Panda and Kumar, 2014). In contrast with reported increase  
431 in wet extreme precipitation events in Upper Brahmaputra Valley of China (Song et al. 2011),  
432 robust pattern of changes in seasonal frequency and intensity of dry and wet spell occurrences  
433 were reported from the fragmented landlocked regions of extended eastern Himalayan region in  
434 neighboring Bangladesh (Abul Basher et al. 2017). Our findings were in synchrony with the  
435 increased dry precipitation events during post-monsoon months at Umiam (Choudhury et al. 2012)  
436 and pre-monsoon/ monsoon months in northeast Bangladesh (Abul Basher et al. 2017). Several  
437 global climate models projected decline in precipitation with increased precipitation extremes  
438 during the warmer 21<sup>st</sup> century with rising ZRD (Panda and Kumar 2014). The decreased monsoon  
439 depression days and rising magnitude of low-pressure systems contributed to the observed spatial  
440 variability in declining trends in heavy rainfall extremes with increased frequency of dry spell  
441 events over North East India (Panda and Kumar 2014). The widespread significant decline in SD-  
442 II across AER 12, AER 15, AER 16 and AER 17 contradicted the projected more intense  
443 precipitation from the reported rise in atmospheric temperature and supportive increase in  
444 moisture-holding capacity of the air across eastern India (Trenberth, 2011). Despite rise in air  
445 temperature, increased aerosol loading and cloud optical depth may contribute to the observed  
446 decreasing trends of rainfall intensity with increased dry precipitation extremes events over eastern  
447 India (Dahutia et al. 2018). Nevertheless, localized land use/land cover changes like massive  
448 deforestation, expansion of cultivable land and wasteland area ensued decrease (increase) in latent  
449 (sensible) heat flux, stimulating ground heat buildup and surface energy imbalance (Rapp 2014).  
450 Such alterations lead to lower evapotranspiration rate and reduced convection emanated drier  
451 precipitation extreme occurrences across eastern India region (Kumar 2021). In contrary, the  
452 combined rise in extreme temperature and precipitation events (dry spells; Panda and Kumar 2014)  
453 raised the potential risk of alteration in plant crop bio-physical processes and productivity from  
454 seasonal weather aberrations, across the upper Brahmaputra Basin in Assam and Gangetic plains  
455 of Bengal.

456 Several previous studies on temperature and precipitation extremes around the world have  
457 confirmed the potential linkages between extreme temperature or drier precipitation events and  
458 periodic variability/pattern in large-scale global atmospheric circulation as well as Global  
459 teleconnection (Akhoury and Avishek 2020). Differential atmospheric warming over land and sea  
460 surface eventually enabled the changes in atmospheric waves generated by thermal kinematic  
461 perturbations that tethered the periodic perturbations to regional variations in weather extreme  
462 event occurrences over the Eastern India region (Prokop and Walanus 2014). Co-integration  
463 analysis confirmed the modulation of El Niño teleconnection with monthly weather extreme  
464 occurrences over eastern India (Sein et al. 2018). The strapping regional regulations of El Niño  
465 events (positive association; Ihara et al. 2006) on warmer temperature extreme occurrences were  
466 more evident over eastern India (Song et al. 2011; Sein et al. 2018); but such controls were truant  
467 during prominent La Niña years (Table 3a and b; Ihara et al. 2006). However, the degree of  
468 dependence of non-stationary El Niño teleconnection gradually thinned down while approaching  
469 from monthly to annual time scale (Fig 3a-d; Goddard and Gershunov 2021). Moreover, PWP  
470 (60°E-170°E to 15°S-15°N with SST >28°C isotherm) played the central role in determining the  
471 relative frequency and spatial extent of extreme event occurrences over the past five decades across  
472 different agro-eco regions of Eastern India (Table 4a; Zahan et al. 2021b). This enhanced  
473 anthropogenic heat sequestration within western equatorial Pacific waters facilitated the east west  
474 movement of PWP and strongly impacted the periodic variation in El Niño–Southern Oscillation  
475 (ENSO event expressed in terms of ONI) events during past few decades (Dang et al. 2020). The  
476 strong remote forcing of periodic PWP oscillation was closely linked with ENSO phenomenon in  
477 equatorial Pacific zone (Misra et al. 2016). Expanded (contracted) PWP and atmospheric  
478 convective zone development was inter-coupled with El Niño (La Niña) phase of ENSO  
479 phenomenon (Roy et al. 2019). In similarity, the ONI time series further strengthened the linkage  
480 with monthly regional weather extreme event anomalies over eastern India, particularly during El  
481 Niño and La Niña years (Fig 3a, b and c). El Niño and La Niña events were generally opposite for  
482 determining the periodic variations in weather extremes. The cumulative forcing of monthly global  
483 teleconnection time series dominated over annual time scale (Table 4a and b; Prasad and Singh  
484 1996). The anthropogenic GHG emission induced global warming accelerated the rapid area  
485 expansion for warmer Tropical Ocean under PWP subdued the natural decadal oscillation from  
486 changing solar flux and sunspot activity in order to determine extent of observed regional weather

487 extreme anomalies over eastern India (Table 4b and table 5). The net impact was accounted from  
488 increased dry spells, reduced absolute precipitation quantity and rainfall intensity under modified  
489 core monsoonal activity over the eastern Himalaya region (Weller et al. 2016). In addition, the  
490 contrasting phases of AMM over 0°-80°N posed the additional influence through modified wind  
491 circulation pattern on extreme weather events over eastern India (Joshi and Rai 2014).

## 492 **5. Conclusion:**

493 Climate change induced modifications accounted for the recorded changes in seasonal  
494 dynamics of extreme weather events (both frequencies and magnitude) aggregated across the  
495 delineated AERs in eastern India over past five decades. Our results were in consilience with  
496 Global teleconnections; rising warmer temperatures and drier precipitation extremes are highly  
497 likely to have profound adverse impact on regional water resource availability, alteration of  
498 agricultural productivity, ecosystem functioning and human health in eastern India. Rising green  
499 house gas concentration effectively contributed the observed extreme event anomalies rather than  
500 natural climatic controls like solar activity over eastern India region. Regional location-specific  
501 policy formulation needs to increase preparedness to keep down the disaster risk and supportive  
502 coping strategy formulation for are indispensable for minimizing the climate change induced  
503 adverse impact of extreme weather anomalies, increasing agro-ecosystems resilience and  
504 minimizing negative socioeconomic consequences for the regional inhabitant of Eastern India. The  
505 balancing between economic developmental activities and socio-economic empowerment towards  
506 sustainable growth and economic prosperity against the periodic weather aberrations over eastern  
507 India in near future. Nevertheless, the complexity in climate change induced anomalies of regional  
508 extreme temperature and precipitation events necessitates more elaborative mechanism-based  
509 studies on realistic projections of regional weather phenomenon across the Eastern Indian region.

510 **Acknowledgement:** We acknowledge daily weather dataset available from National Data Center,  
511 IMD-Pune, India with financial support from NICRA project (code: OXX01713).

## 512 **Authors' contributions:**

- 513 • **Data analysis and map generation:** Saurav Saha, Debasish Chakraborty, Bappa Das, S.  
514 Sadhu, Aakash Chhabra

515 • **Manuscript preparation:** Saurav Saha, Debasish Chakraborty, Debashis Chakraborty,  
516 Bappa Das

517 • **Manuscript checking:** Samarendra Hazarika, I Shakuntala, Lungmuana, VK Mishra

518 • **Data collection:** Saurav Saha, J. Mukherjee, Samarendra Hazarika

519 **Availability of data and material:** The dataset is under copyright of India Meteorological  
520 Department, Pune. The dataset will be available on reasonable request.

521 **Code availability:** The R code will be available on reasonable request.

522 **Declarations (ethics):**

523 **Conflicts of interest/Competing interests:** The authors declare no competing interests.

524 **Ethics approval:** Not applicable; the study did not include human or animal subject data.

525 **Consent to participate:** Not applicable; the study did not include human or animal subject data.

526 **Consent for publication:** Not applicable; the study did not include human or animal subject data.

527

528 **References:**

529 Abul Basher Md, Stiller-Reeve MA, Saiful Islam AKM, Bremer S (2017) Assessing climatic  
530 trends of extreme rainfall indices over northeast Bangladesh. *Theor Appl Climatol*.  
531 <https://doi.org/10.1007/s00704-017-2285-4>

532 Akhoury G, Avishek K (2020). Global atmospheric changes versus the Indian rainfall variation.  
533 *Arab. J. Geosci.* 13:553.

534 Chakraborty D, Sehgal VK, Dhakar R, Varghese E, Das DK, Ray M (2018). Changes in daily  
535 maximum temperature extremes across India over 1951–2014 and their relation with  
536 cereal crop productivity. *Stoch Environ Res Risk Assess Stoch Env Res Risk A* 32(11):  
537 3067-3081.

538 Choi G, Collins D, Ren G, Trewin B, Baldi M, Fukuda Y, Afzaal M, Pianmana T, Gomboluudev  
539 P, Huong PTT, Lias N, Kwon W-T, Boo K-O, Cha Y-M, Zhou Y (2009) Changes in

540 means and extreme events of temperature and precipitation in the Asia-Pacific Network  
541 region, 1955–2007. *Int J Climatol* 29:1906–1925.

542 Choudhury, BU, Das A, Ngachan, SV, Slong A, Bordoloi LJ, Chowdhury P (2012) Trend analysis  
543 of long term weather variables in mid altitude Meghalaya, North-East India. *J Agric*  
544 *Phys* 12:12–22.

545 Dahutia P, Pathak B, Bhuyan PK (2018) Aerosols characteristics, trends and their climatic  
546 implications over Northeast India and adjoining South Asia. *Int J Climatol* 38:1234–  
547 1256.

548 Dang S, Yu K, Tao S, Han T, Zhang H, Jiang W (2020) El Niño/Southern Oscillation during the  
549 4.2 ka event recorded by growth rates of corals from the North South China Sea. *Acta*  
550 *Oceanol Sin* 39(1):110–117.

551 Goddard L, Gershunov A (2021) Impact of El Niño on Weather and Climate Extremes. In *El Niño*  
552 *Southern Oscillation in a Changing Climate*, Geophysical Monograph 253, McPhaden  
553 MJ, Santoso A, Cai W, (Eds). First Edition, pp. 361-375.

554 Guhathakurta P, Sreejith OP, Menon PA (2011) Impact of climate change on extreme rainfall  
555 events and flood risk in India. *J Earth Syst Sci* 120(3):359–373

556 Hurst H (1951) Long term storage capacity of reservoirs. *T Am Soc Civ Eng* 6:770–799.

557 Ihara C, Kushnir Y, Cane MA, Victor H, Peña De La (2006) Indian summer monsoon rainfall and  
558 its link with ENSO and Indian Ocean climate indices. *Int J Climatol* 27(2):179-187

559 IPCC (2013) *Climate Change 2013: The Physical Science Basis*. Contribution of Working Group  
560 I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change  
561 [Stocker TF, Qin D, Plattner G-K, Tignor M, Allen SK, Boschung J, Nauels A, Xia Y,  
562 Bex V, Midgley PM (eds)]. Cambridge University Press, Cambridge, United Kingdom  
563 and New York, NY, USA, 1535 pp.

564 Jaswal AK (2010) Changes in total cloud cover over India based upon 1961-2007 surface  
565 observations. *Mausam* 61(4):455-468.

566 Jhajharia D, Singh VP (2011) Trends in temperature, diurnal temperature range and sunshine  
567 duration in northeast India. *Int J Climatol* 31:1353–1367.

568 Johansen S, Juselius K (1990) Maximum likelihood estimation and inference on cointegration—  
569 with applications to the demand for money. *Oxf. Bull. Econ. Stat.* 52(2):169-210.

570 Joshi MK, Rai A (2014) Combined interplay of the Atlantic multidecadal oscillation and the  
571 interdecadal Pacific oscillation on rainfall and its extremes over Indian subcontinent.  
572 *Clim Dyn.* <https://doi.org/10.1007/s00382-014-2333-z>

573 Karki R, Hasson S, Gerlitz L, Talchabhade R, Schickhoff U, Scholten T, Böhner J (2019)  
574 Rising mean and extreme near-surface air temperature across Nepal. *Int J Climatol.*  
575 <https://doi.org/10.1002/joc.6344>

576 Klein Tank AMG, Peterson TC, Quadir DA, Dorji S, Zou X, Tang H, Santhosh K, Joshi UR,  
577 Jaswak AK, Kolli RK, et al. (2006) Changes in daily temperature and precipitation  
578 extremes in central and south Asia. *J Geophys Res* 111:D16105.

579 Kumar P (2021) Impact of Climate Change and Surface Energy (Im) Balance on North-East India  
580 Monsoonal Rainfall. *J Clim Change* 7(2): 35-47

581 Mandal DK, Mandal C, Singh SK (2016) India agro-ecological regions (Revised), ICAR-  
582 NBSS&LUP Publ. No. 170, ICAR-NBSSLUP, Nagpur, India, pp.1-73.

583 Misra V; Groenen D, Bhardwaj A, Mishra A, Bharadwaj A (2016) The warm pool variability of  
584 the tropical northeast Pacific. *Int J Climatol* 36:4625–4637

585 Nikumbh AC, Chakraborty A, Bhat G (2019). Recent spatial aggregation tendency of rainfall  
586 extremes over India. *Scientific Reports* 9(1):1–7. [https://doi.org/10.1038/s41598-019-](https://doi.org/10.1038/s41598-019-46719-2)  
587 [46719-2](https://doi.org/10.1038/s41598-019-46719-2)

588 Panda DK, Kumar A (2014) The changing characteristics of monsoon rainfall in India during  
589 1971–2005 and links with large scale circulation. *Int J Climatol* 34:3881–3899.  
590 <https://doi.org/10.1002/joc.3948>

591 Prasad KD, Singh SV (1996) Forecasting the spatial variability of the Indian monsoon rainfall  
592 using canonical correlation. *Int J Climatol* 16:1379–1390

593 Prokop P, Walanus A (2014) Variation in the orographic extreme rain events over the Meghalaya  
594 Hills in northeast India in the two halves of the twentieth century. *Theor Appl Climatol*.  
595 <https://doi.org/10.1007/s00704-014-1224-x>

596 Rapp D (2014) Assessing climate change. In: *Temperatures, Solar Radiation and Heat Balance*.  
597 Springer.

598 Revadekar JV, Kothawale DR, Patwardhan SK, Pant GB, Rupa Kumar K (2013) About the  
599 observed and future changes in temperature extremes over India. *Nat Hazards* 60:1133–  
600 1155.

601 Roy I, Tedeschi RG, Collins M (2019) ENSO teleconnections to the Indian summer monsoon  
602 under changing climate. *Int J Climatol* 39:3031–3042

603 Saha S, Chakraborty D, Paul RK, Samanta S, Singh SB (2018) Disparity in rainfall trend and  
604 patterns among different regions: analysis of 158 years' time series of rainfall dataset  
605 across India. *Theor Appl Climatol* 134(1-2):381-395.

606 Sein KK, Chidthaisong A, Oo KW (2018) Observed Trends and Changes in Temperature and  
607 Precipitation Extreme Indices over Myanmar. *Atmosphere* 9:477.

608 Sen Roy S, Balling RC (2004) Trends in extreme daily precipitation indices in India. *Int J Climatol*  
609 24: 457–466.

610 Sharma PJ, Loliyana VD, Resmi SR, Timbadiya PV, Patel PL (2017) Spatio-temporal trends in  
611 extreme rainfall and temperature indices over Upper Tapi Basin, India. *Theor Appl*  
612 *Climatol* 1-26.

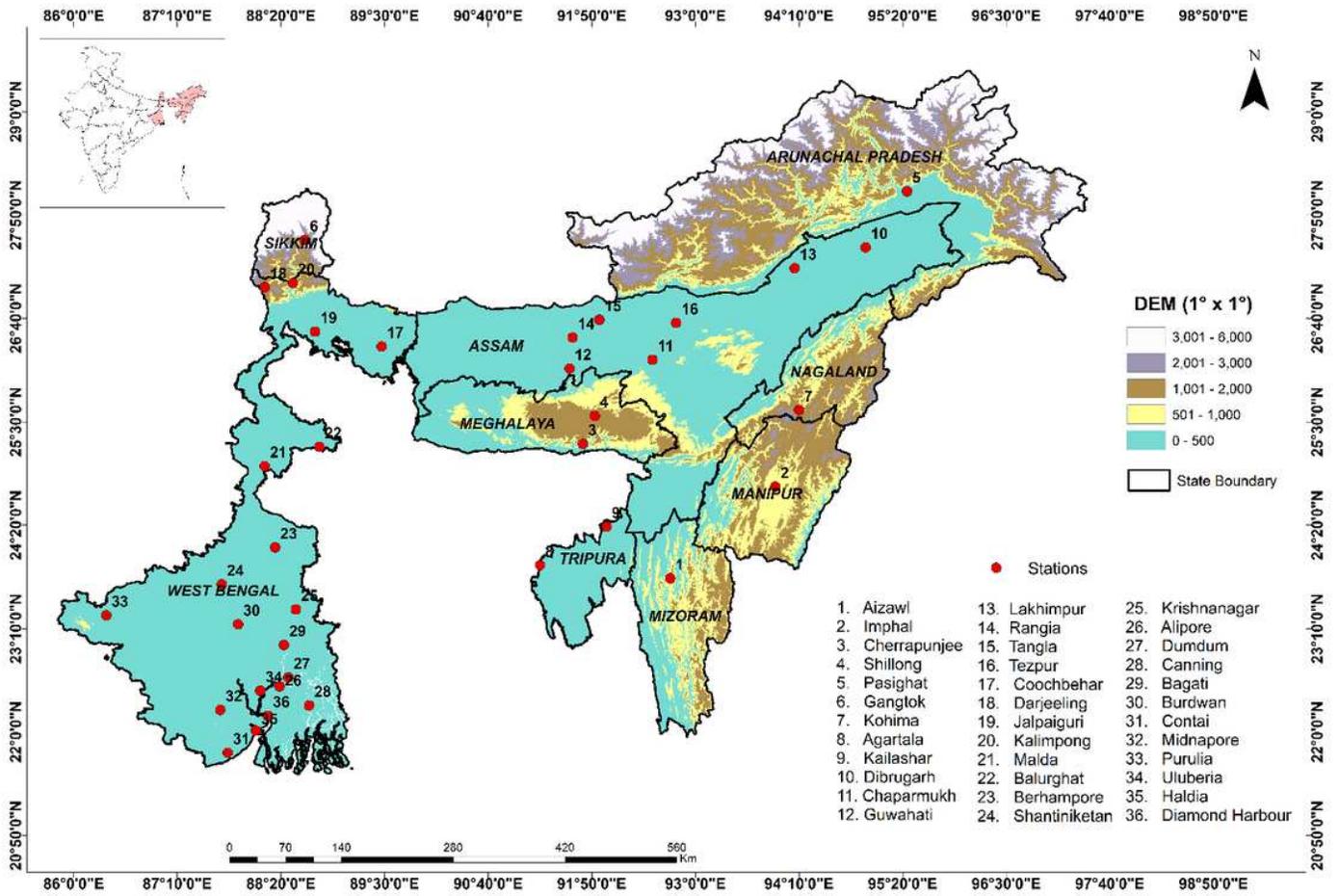
613 Song M, Ma Y, Zhang Y, Li M, Ma W, Sun F (2011) Climate change features along the  
614 Brahmaputra Valley in the past 26 years and possible causes. *Clim Change* 106:649–  
615 660. DOI 10.1007/s10584-010-9950-2

616 Trenberth KE (2011) Changes in precipitation with climate change. *Clim Res* 47: 123–138.

617 Wang XL, Feng Y (2013) RHtestsV4 user manual. Environment Canada Science and Technology  
618 Branch, Climate Research Division, Atmospheric Science and Technology, Directorate  
619 Science and Technology Branch, Environment Canada, Toronto, Ontario, Canada

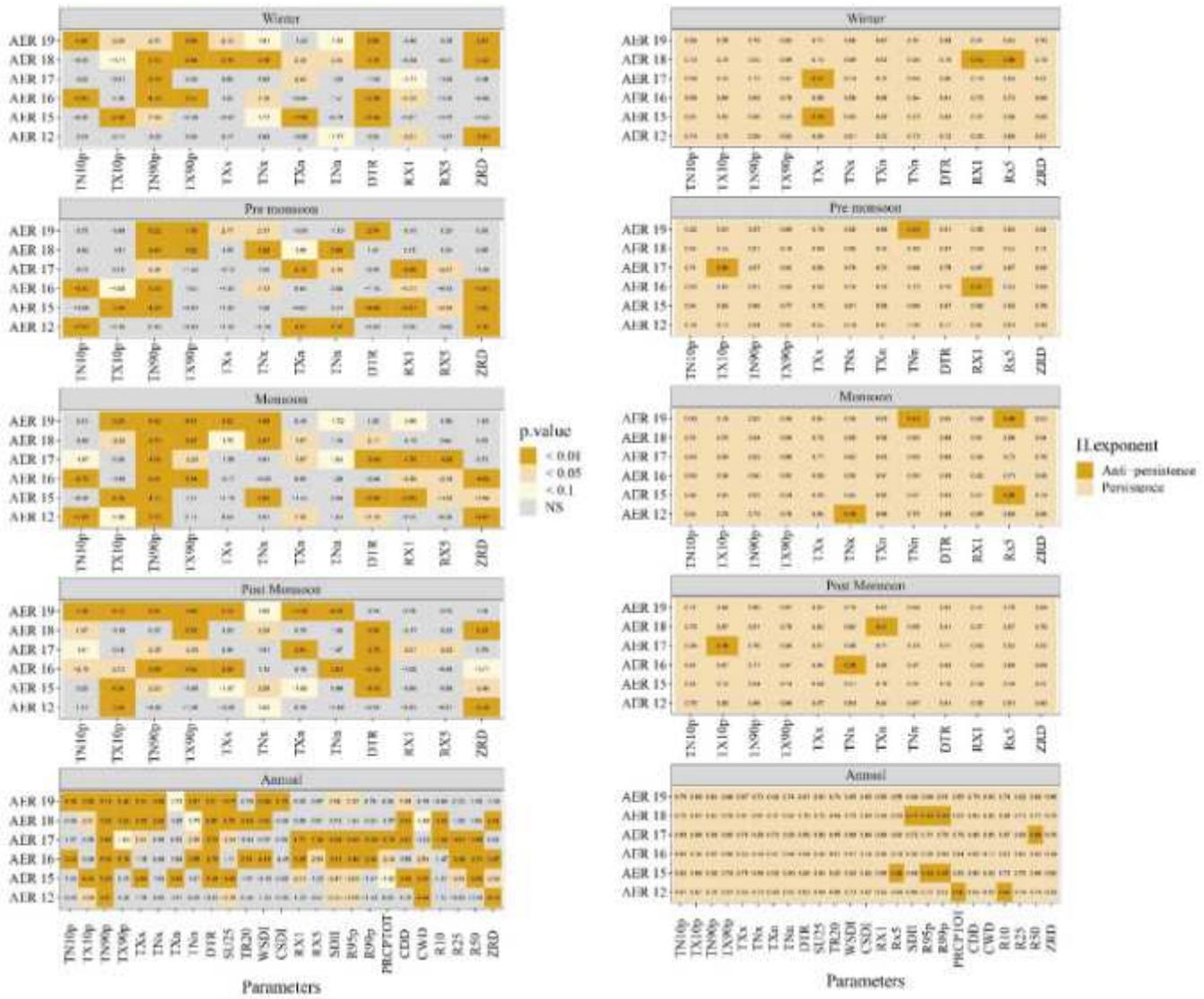
- 620 Weller E, Min Seung-Ki, Wenju C, Zwiers, Francis W, Yeon-Hee K, Donghyun L, (2016) Human-  
621 caused Indo-Pacific warm pool expansion. *Science Advances*. 2(7):e1501719.
- 622 Zahan Y, Mahanta R, Rajesh PV, Goswami BN (2021a) Impact of climate change on North-East  
623 India (NEI) summer monsoon rainfall. *Clim Change* 164(2).  
624 <https://doi.org/10.1007/s10584-021-02994-5>
- 625 Zahan, Y, Rajesh BPV, Choudhury A, Goswami BN (2021b) Why Indian summer monsoon  
626 circulation indices? Fidelity in representing rainfall variability and teleconnections. *Q J*  
627 *R Meteorol Soc* 147 (735): 1300-1316.
- 628 Zhang, X, Feng, Y, Chan R (2018). Introduction to RClimDex v1. 9. Climate Research Division  
629 Environment Canada Downs view, Ontario Canada.

# Figures



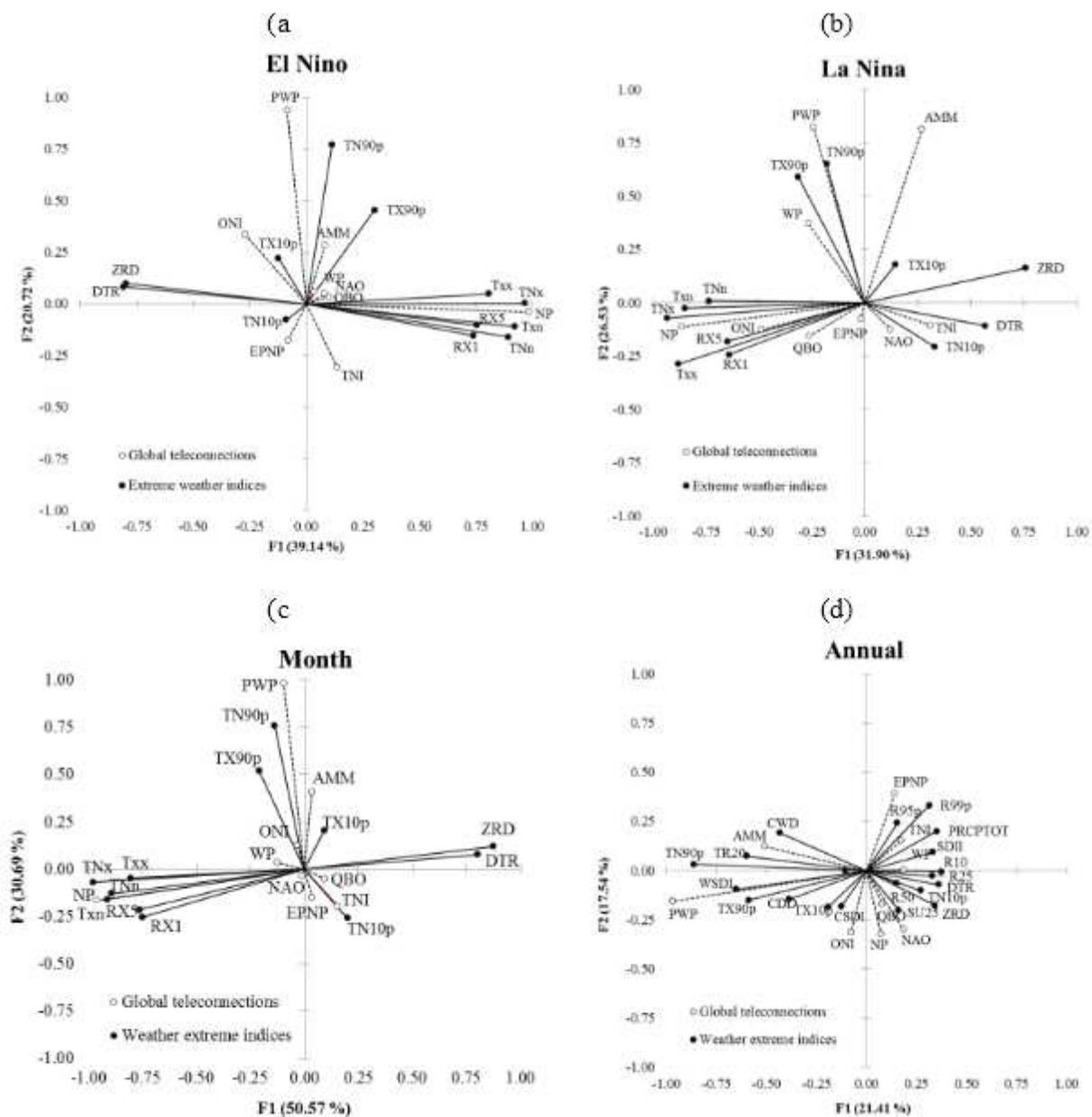
**Figure 1**

The study region and location of surface weather stations across eastern India.



**Figure 2**

(a) Regional trend pattern and (b) trend persistence in seasonal and annual extremes across six agroecoregions of eastern India



**Figure 3**

Canonical correlation plot between global teleconnection and weather extreme events over eastern India during (a) El Niño years (b) La Niña years (c) monthly and (d) annual time scale.

## Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SupplementaryInformation.docx](#)