



Impacts of climate modes on temperature extremes over Bangladesh using statistical methods

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Abstract

Bangladesh is sensitive to weather and climate extremes, which have a serious impact on agriculture, ecosystem, and livelihood. However, there is no systematic investigation to explore the effect of climate modes on temperature extremes over Bangladesh. A total of 11 temperature extreme indices based on the daily maximum and minimum temperature data for 38 years (1980–2017) have been calculated. Cross-wavelet transform and Pearson correlation coefficient have been used to identify the relationship between temperature extremes and three climate modes namely El Niño Southern Oscillation (ENSO), Indian Ocean Dipole (IOD), and North Atlantic Oscillation (NAO). Detrended fluctuation analysis (DFA) method was applied to predict the long-term relationship among temperature indices. Results showed that warm (cold) temperature extreme indices increased (decreased) significantly. There was a significant upward trend in the diurnal temperature range and tropical nights except for growing season length. ENSO and IOD had a strong negative impact on warm temperature indices, whereas NAO had a strong negative influence on variability temperature indices in Bangladesh. Temperature extreme had a long-term relationship based on DFA ($\alpha > 0.5$), implying that the temperature extremes will remain their present trend line in the future period. The Poisson regression model showed that the highest probability (65%) of having a 2–4 warm spell duration indicator (days/decade) is consistent with the observation, which is shown in the cross-wavelet transform and spatial analysis.

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1 Introduction

Temperature extremes have major effects on ecosystem imbalance and social system (Easterling et al. 2000; Ciaia et al. 2005; Schmidli and Frei 2005; Benestad and Haugen 2007; Allen et al. 2010; Bandyopadhyay et al. 2012; Rammig and Mahecha 2015; Lin et al. 2017; Guo et al. 2019). Therefore, the scientific community has paid attention to measures to tackle the effects of climate change on ecosystems and human livelihoods for disaster prevention and mitigation (Smith 2011; Jiang et al. 2012; Endfield 2012; Reich et al. 2015; Craparo et al. 2015; Perez et al. 2015; Pant 2017). As climate extreme events increased in Bangladesh (Hasan et al. 2013; Shahid et al. 2016; Mahmud et al. 2018; Khan et al. 2019; Wahiduzzaman and Yeasmin 2019; Wahiduzzaman et al. 2020a; Wahiduzzaman 2021; Das and Wahiduzzaman 2021), it is necessary to investigate the effect of climate modes on temperature extremes over Bangladesh.

Globally, some researchers have found that extreme-temperature events are changing due to global warming (Alexander et al. 2006; Aguilar et al. 2005; Hidalgo-Muñoz

et al. 2011; Coumou and Rahmstorf 2012; Abiodun et al. 2013; Coumou et al. 2013; Omondi et al. 2014). Several studies have reported that the frequency of warm temperature indices is increasing, while the frequency of cold temperature indices is decreasing (Ma et al. 2003; Alexander et al. 2006; Tank et al. 2006; Piccarreta et al. 2015; Sheikh et al. 2015; Guan et al. 2015; Sun et al. 2016; You et al. 2017; Lin et al. 2017; Wang et al. 2018; Ullah et al. 2019). Only a few studies (e.g., Tong et al. 2019) have focused on the effects of multiple ocean-atmospheric indices on the spatiotemporal variations in extreme-temperature events.

In Bangladesh, several studies were carried out to investigate the spatiotemporal variations of climate extreme indices (Hasan et al. 2013; Shahid et al. 2016; Mahmud et al. 2018; Wahiduzzaman and Luo 2021). These studies showed that warm temperature events (cold temperature events) are rising (decreasing). However, the above mentioned studies did not focus on the effect of ocean-atmospheric teleconnection on temperature extremes over Bangladesh using cross-wavelet transform and a statistical Poisson regression model. In addition, previous studies have not forecasted long-term relationships among

temperature extreme indices using Detrended fluctuation analysis (DFA).

The objectives of this study are: (1) to examine the spatiotemporal variation of temperature extremes; (2) to compare extreme-temperature indices with their rates of change; (3) to identify the relationship among temperature extreme indices; (4) to investigate the relationship between ocean-atmospheric teleconnections and temperature extremes; (5) to predict long-term relationship among temperature extremes indices. This paper is organized as follows. Data and methods are discussed in Sect. 2. Results and discussions are provided in Sect. 3. Conclusion is discussed in Sect. 4.

2 Data and methods

Bangladesh is located in Southeast Asia (Fig. 1). Based on climatic regions and hydrogeological settings, Bangladesh is divided into three areas as western, eastern and central parts (Islam et al. 2019). A total of 20 meteorological stations were selected for spatial analysis including 3

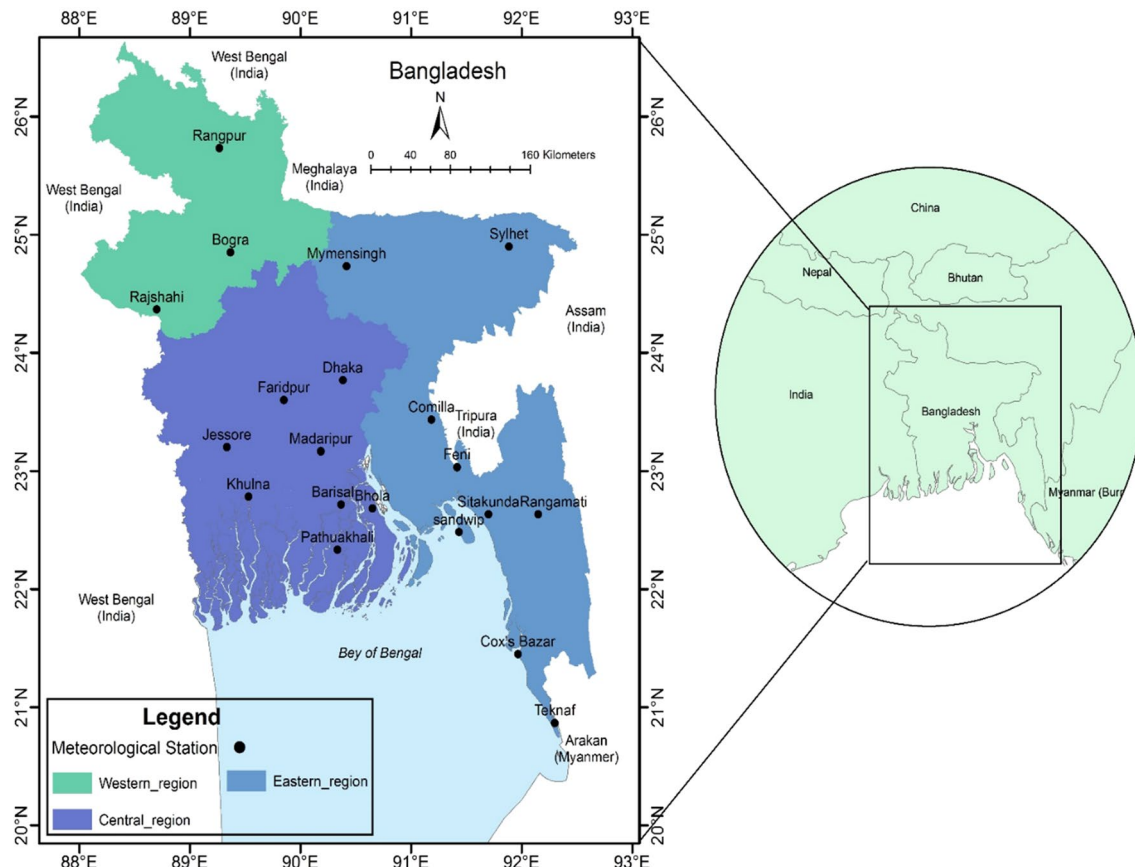


Fig. 1 Location of the study area, which divided into three regions: the western, central and eastern regions. The black dots indicate the meteorological stations

stations for the western region, 9 stations for the eastern area and 8 stations for the central region. The western part is a drought-prone region, which gets precipitation below 1500 mm and extreme temperature over 40 °C during summer. The eastern area is characterized by a tropical monsoon climate, by which we mean that the highest annual maximum and minimum temperatures are 32 °C and 7 °C, respectively. In this region, the average annual rainfall is about 3000 mm. The central region experienced tropical cyclones from the Bay of Bengal. In this region, the annual mean maximum temperature is 35.1 °C, while the mean minimum temperature is 2.1 °C.

2.1 Temperature data

The daily maximum and minimum temperature datasets from 1980 to 2017 have been collected from the Bangladesh Meteorological Department (www.bmd.gov.bd/). It is important to control the data before analysis due to the effect by erroneous outliers (Gao et al. 2017; Wang et al. 2018; Tong et al. 2019). Data quality control has been carried out using RCLimDex software (<http://etccdi.pacificclimate.org/software.shtml>). This software is useful to check for inaccurate station data. The advantage of this method is to identify the erroneous outliers in the daily observed data. If values higher or lower than 3σ from the long-term average value for that month, these values are considered as outliers (Wang et al. 2018; Tong et al. 2019; Uddin et al. 2020). In this present study, we identified the possible outliers to check whether observed station data were consistent with the actual meteorological condition in Bangladesh.

2.2 Ocean-atmospheric teleconnection indices

Ocean-atmospheric teleconnection indices such as El Niño Southern Oscillation (ENSO), Indian Ocean Dipole (IOD) and North Atlantic Oscillation (NAO) have been used in this study to quantify the contribution of these indices to temperature extreme indices over Bangladesh. ENSO, IOD and NAO data are downloaded from <http://www.cpc.ncep.noaa.gov/>, <http://www.jamstec.go.jp/frsgc/research/d1/iod/index.html> and <http://ljp.gcess.cn/dct/page/1>, respectively.

2.3 Definition of temperature extreme indices

We have calculated 11 temperature extreme indices for 20 stations using the RCLimDex V1.0 software. After finishing the calculation, these indices were averaged for the western, eastern and central parts. The meaning of temperature extreme indices was proposed by the Climate Commission of the World Meteorological Organization (WMO), the Global Climate Research Program (GCRP), and the CCI/CLIVAR/JCOMM Expert Team on Climate Change Detection and Indices (ETCCDI, <http://etccdi.pacificclimate.org/>). Cold nights (TN10p), cold days (TX10p), coldest days (TNn) and cold spell duration indicator (CSDI) are extreme low-temperature events, while warm nights (TN90p), warm days (TX90p), warmest days (TXx) and warm spell duration indicator (WSDI) are extreme high-temperature events (Wang et al. 2018; Tong et al. 2019). Moreover, the diurnal temperature range (DTR), growing season length GSL and tropical nights (TR) are the variability temperature extreme indices. TN denotes the daily minimum temperature, while TX means the daily maximum temperature. The detailed information of the above mentioned indices can be found in Table 1.

Table 1 Notation, description, definition and unit of temperature indices. Adapted from ETCCDI/CRD: https://etccdi.pacificclimate.org/list_27_indices.shtml

Notation	Description	Definition	Unit
TN10p	Amount of cold nights	Percentage of days when TN < 10th percentile	%
TX10p	Amount of cool days	Percentage of days when TX < 10th percentile	%
TNn	Min TN	Coldest daily TN	°C
CSDI	Cold spell duration indicator	The annual number of days contributing to events where 6 or more consecutive days experience TN < 10th percentile	Days
TN90p	Amount of warm nights	Percentage of days when TN > 90th percentile	%
TX90p	Amount of hot days	Percentage of days when TX > 90th percentile	%
TXx	Max TX	Warmest daily TX	°C
WSDI	Warm spell duration indicator	The annual number of days contributing to events where 6 or more consecutive days experience TX > 90th percentile	Days
DTR	Daily temperature range	Mean difference between daily TX and daily TN	°C
GSL	Growing season length	The annual number of days between the first occurrence of 6 consecutive days with TM > 5 °C and the first occurrence of 6 consecutive days with TM < 5 °C	Days
TR	Tropical nights	Number of days when TN > 20 °C	Days

2.4 Methods

2.4.1 Mann–Kendall (MK) test

The Mann–Kendall (MK) test technique which is a nonparametric trend test has been used to find out significant trends in the rate of change for the temperature extreme at the 20 meteorological stations. For time series trend analysis, this technique has been applied in many fields, especially in the hydro-meteorological research (Wang et al. 2018; Islam et al. 2020a). To monitor a particular dispersion or strange values, the MK test does not involve the sample (Yue and Pilon 2004; Mann 1945). Therefore, MK is appropriate for the trend assessment of non-normally distributed data (Wang et al. 2018; Li et al. 2020). If there is no trend in the series, we should accept the null hypothesis (H_0). However, there are three alternative hypotheses: a negative, non-null and positive trend.

2.4.2 Correlation matrix, analysis of variance (ANOVA) and least significant difference (LSD) test

We applied Pearson’s correlation matrix to identify significant associations among temperature extreme indices. While a one-way ANOVA test was applied to determine important variation in the values of an index among three zones of Bangladesh, a least significant difference test was applied to recognize the significant level among these zones.

2.4.3 Cross-wavelet transform

Wavelet Transform (WT) is an innovative mathematical tool that provides the time–frequency descriptions of time series or signals, successfully applied in the atmosphere and climate science during the last decade. The applications of WT-based studies are significantly increasing for example in temperature, rainfall, hydrological process, water quality, drought, streamflow prediction, rainfall, drought, and atmospheric density (Wahiduzzaman and Luo 2021; Wahiduzzaman et al. 2020a, b). Cross-wavelet technique can be applied to find the relations between the wavelet transform of two individual time series (Zanchettin et al. 2013; Rahman and Islam 2019; Tong et al. 2019). In this study, we used this method to show the relationship between the ocean-atmospheric teleconnection index and temperature extremes indices.

2.4.4 Detrended fluctuation analysis (DFA)

Detrended Fluctuation Analysis (DFA) method has been successfully used to analyze the trends and extreme values in climatological and hydrological sequences (Fraedrich and Blender 2003; Islam et al. 2020b). In this study, we

used DFA to forecast future development trends in extreme climate indices.

For a temperature sequence $\{x_k, k = 1, 2 \dots N\}$, N is the length of the sequence, \bar{X} is the average value, and the accumulative deviation sequence of the original sequence that can be established by:

$$y(i) = \sum_{k=1}^N (X_k - \bar{X}) \quad (i = 1, 2 \dots N) \tag{1}$$

After that, the new sequence $y(i)$ is divided into N_s non-overlapping subintervals with a length of s :

$$N_s = \text{int}\left(\frac{N}{s}\right) \tag{2}$$

As the sequence is not precisely divisible, to confirm the integrity of the information, it was divided once again in the reverse direction. Therefore, a total of $2N_s$ subintervals could be obtained. The value of s was selected according to the length of the sequence and the operation requirements.

Polynomial fitting was performed on the data of each subinterval v ($v = 1, 2 \dots 2N_s$), and a local trend function $y_v(i)$ was obtained. After that we eliminated the trend of the original sequence in the sub-function and filtered the trend out the sequence as $y_s(i)$:

$$y_s(i) = y(i) - y_v(i) \quad (i = 1, 2 \dots N) \tag{3}$$

$y_v(i)$ can be a first order, second order, or higher order polynomial; we used the second-order polynomial. After the elimination of the trend, the variance in each interval was calculated as follows:

$$F^2(v, s) = \frac{1}{s} \sum_{i=1}^s \{y[(v-1)s+i] - y_v(i)\}^2 \quad (i = 1, 2 \dots N_s) \tag{4}$$

$$F^2(v, s) = \frac{1}{s} \sum_{i=1}^s \{y[N - (v - N_s)s + i] - y_v(i)\}^2 \quad (i = N_s + 1, N_s + 2, \dots, 2N_s) \tag{5}$$

The second-order wave function of the whole sequence obtain as follows:

$$F(s) = \sqrt{\frac{1}{2N_s} \sum_{v=1}^{2N_s} F^2(v, s)} \tag{6}$$

Power-law correlations of $F(s)$ and s changes were analyzed:

$$F(s) \sim s^a \text{ or, } \ln F(s) = a \ln s + b \tag{7}$$

It is in the double logarithmic coordinate, and the data were fitted by the least square method; the slope (a) of the linear trend is the scaled DFA index.

If $a = 0.5$, after that the sequence is a random sequence and is an independent random process. While $0 < a < 0.5$, the values of the sequence are not independent and there is a short-term relationship, that indicates the time series has the opposite trend relative to that of the previous time series. But, if $0.5 < a < 1$, then the process is continuous and the future trend is consistent with the previous trend. The closer the value is to 1, the greater the tendency of this consistency. While $a = 1$, the sequence is a $1/f$ process, i.e., a non-stationary random process with the $1/f$ spectrum, characterized by scale invariance and long-term correlation. If $a \geq 1.5$, the sequence is a brown noise sequence.

2.4.5 A poisson regression model

The Poisson regression model is an operational method to model the expected outcomes (Wahiduzzaman and Yeasmin 2019; Wahiduzzaman et al. 2020a, b). In this study, the Poisson regression model has been applied to predict the probabilities of WSDI based on a bivariate relationship between WSDI and ENSO/IOD/NAO. WSDI is only considered as it can be used to model the outcomes as a percentage. This model is a statistical method to model the temperature extremes with ocean-atmospheric teleconnection

parameters. Given the Poisson WSDI parameter λ (the mean WSDI rates), the probability mass function of h WSDI occurring in a unit of observation time is.

$$P\{h|\lambda\} = \frac{e^{-\lambda}(\lambda)^h}{h!} \tag{8}$$

The Poisson model is used to explain the relationship between the target responses variable like WSDI and ENSO, IOD and NAO predictors. The Poisson rate λ is conditional on the predictors.

3 Results and discussion

3.1 Spatiotemporal trends of extremely low-temperature events

Figure 2 shows temporal variations of cold temperature extreme indices from 1980 to 2017 across different regions of Bangladesh. A significant decreasing trend ($p < 0.05$) found for both cold nights (TN10p) and cold days (TX10p) over in western, eastern, central parts and whole Bangladesh except for the western part, which showed an insignificant trend for TX10p (Fig. 2). The decreasing rate was less than 2 days/decade for both TN10p and TX10p. There was an insignificant decreasing trend in coldest days (TNn) and cold spell duration indicator (CSDI) over western, eastern, central

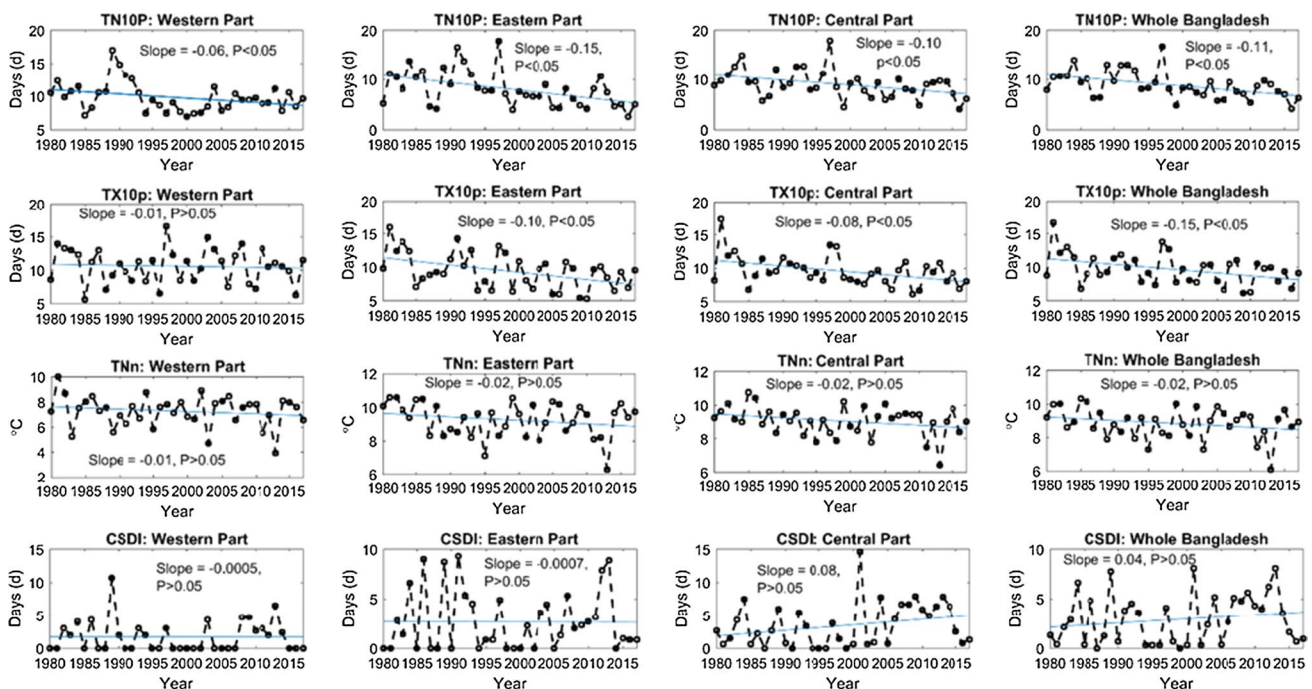


Fig. 2 Regional variations in the cold temperature extreme indices from 1980 to 2017. [Row 1: cold nights (TN10p); Row 2: cold days (TX10p); Row 3: coldest days (TNn); and Row 4: cold spell duration indicator (CSDI)]

parts and whole Bangladesh. Our results are consistent with previous studies (Shahid et al. 2016; Mahmud et al. 2018; Khan et al. 2019). These studies also showed that extreme low-temperature events decreased over Bangladesh.

Figure 3 shows spatial variation of extremely low-temperature events for 20 meteorological stations in Bangladesh. A significant decreasing pattern of TN10p was dominated in the country, especially eastern and central parts (30% stations). These stations showed that TN10p reduced by 2–4 days/decade (Fig. 3a). Only 20% of stations, Patuakhali, Sawndip, Rangamati and Rangpur, showed a significant increasing trend in TN10p (less than 4 days/decade). For TX10p, eastern and central parts (35% stations) were dominated by a significant decreasing pattern (2–4 days/decade) (Fig. 3b). Surprisingly, only one station, Dhaka, revealed a significant increasing trend in TX10p (< 4 days/decade). The minimum temperature decreased significantly by 2–4 °C per decade over the southeastern part of Bangladesh except for Cox's Bazar, which experienced a significant rising trend in TNn (< 4 °C/decade) (Fig. 3c). A significant rising trend (< 4 days/decade) in cold spell duration indicator (CSDI) was found for four stations namely Mymensingh, Khulna, Patuakhali and Rangamati (Fig. 3d).

3.2 Spatiotemporal trends of extreme high-temperature events

Figure 4 shows temporal variations of extreme high-temperature events during 38 years across different regions of Bangladesh. Results show that warm nights (TN90p) and warm days (TX90p) exhibited a significant increasing trend ($p < 0.05$) over western, eastern, central parts and whole Bangladesh. The increasing rate was less than 3 days/decade for TN90p, while the rising rate < 5 days/decade was found for TX90p. The average number of warm days changed more apparently than the number of warm nights (Fig. 4). Our result can be compared with Tank et al. (2006). They showed that the number of warm nights decreased in the northern region of Pakistan. The warmest days (TXx) increased significantly by 0.2 °C, 0.1 °C and 0.09 °C per decade over eastern, central part and whole Bangladesh except for the western part, which showed an insignificant trend. There was a significant increasing trend in warm spell duration indicator (WSDI) over western, eastern, central parts and whole Bangladesh [about 7 days/decade except for western part (3.2 days/decade)].

Figure 5 shows the spatial change of warm temperature indices for 20 meteorological stations in Bangladesh. Interestingly, around 80% of stations were dominated by warm nights (TN90p), warm days (TX90p) and warm spell duration indicator (WSDI). These indices increased significantly like the mean rate of change was less than 4 days/decade (Fig. 5a, b, d). For warmest days (TXx), the southeastern

part of Bangladesh (around 35% stations) was dominated by a significant increasing trend (< 4 °C per decade). The results are consistent with Dastagir (2015), Shahid et al. (2016), Mahmud et al. (2018) and Khan et al. (2019). They also found an upward trend of warm temperature extreme indices over Bangladesh. Our findings also can be compared with Alexander et al. (2006), Tank et al. (2006), Sheikh et al. (2015), Guan et al. (2015), Sun et al. (2016) and You et al. (2017) and Lin et al. (2017), regardless of time and region.

3.3 Spatiotemporal trends of variability temperature extreme indices

Figure 6 shows temporal variations of variability temperature extreme indices from 1980 to 2017 over Bangladesh. Both DTR and TR revealed a significant upward trend over western, eastern, central parts and whole Bangladesh except for the western part, which showed an insignificant downward trend in DTR. The changing rate was about 0.1 °C per decade and 3–5 days/decade for DTR and TR, respectively (Fig. 6). There was an insignificant increasing trend in GSL.

Spatial variation of variability temperature extreme indices for 20 meteorological stations in Bangladesh is shown in Fig. 7. Results show that 70% of stations were dominated by a significant increasing trend (< 2–4 days/decade) of tropical nights (TR), while 35% of stations were influenced by a significant upward trend (3–4 °C per decade) of the DTR. Our results are a good agreement with Rahman and Lateh (2016) and Shahid et al. (2016). Only one station, Cox's Bazar, showed a significant increasing trend for GSL.

3.4 Comparison between extreme-temperature indices and their rates of change

Table 2 shows the extreme-temperature events and their variation across different regions of Bangladesh. Results show that the mean number of cold nights (TN10p) and cold days (TX10p) decreased significantly both at $p < 0.05$ and $p < 0.01$ levels, respectively. However, the opposite trend was found for the rate of change, which increased significantly. The mean values and the rate of change were not significant for coldest days (TNn) and cold spell duration indicator (CSDI).

Warm temperature indices showed a significant increasing trend of both the average value and rate of change for warm nights (TN90p), warm days (TX90p) and warm spell duration indicator (WSDI) except for warmest days (TXx), which revealed an insignificant trend (Table 2). In the case of TXx, only the eastern part showed a significant rising trend at $p < 0.05$ level. The values of TN90p ranged from 5 to 8 days across different regions of Bangladesh, while the values of TX90p ranged from 8 to 13 days. The maximum value of warm temperature indices was found for WSDI, ranged from 9 to 20 days.

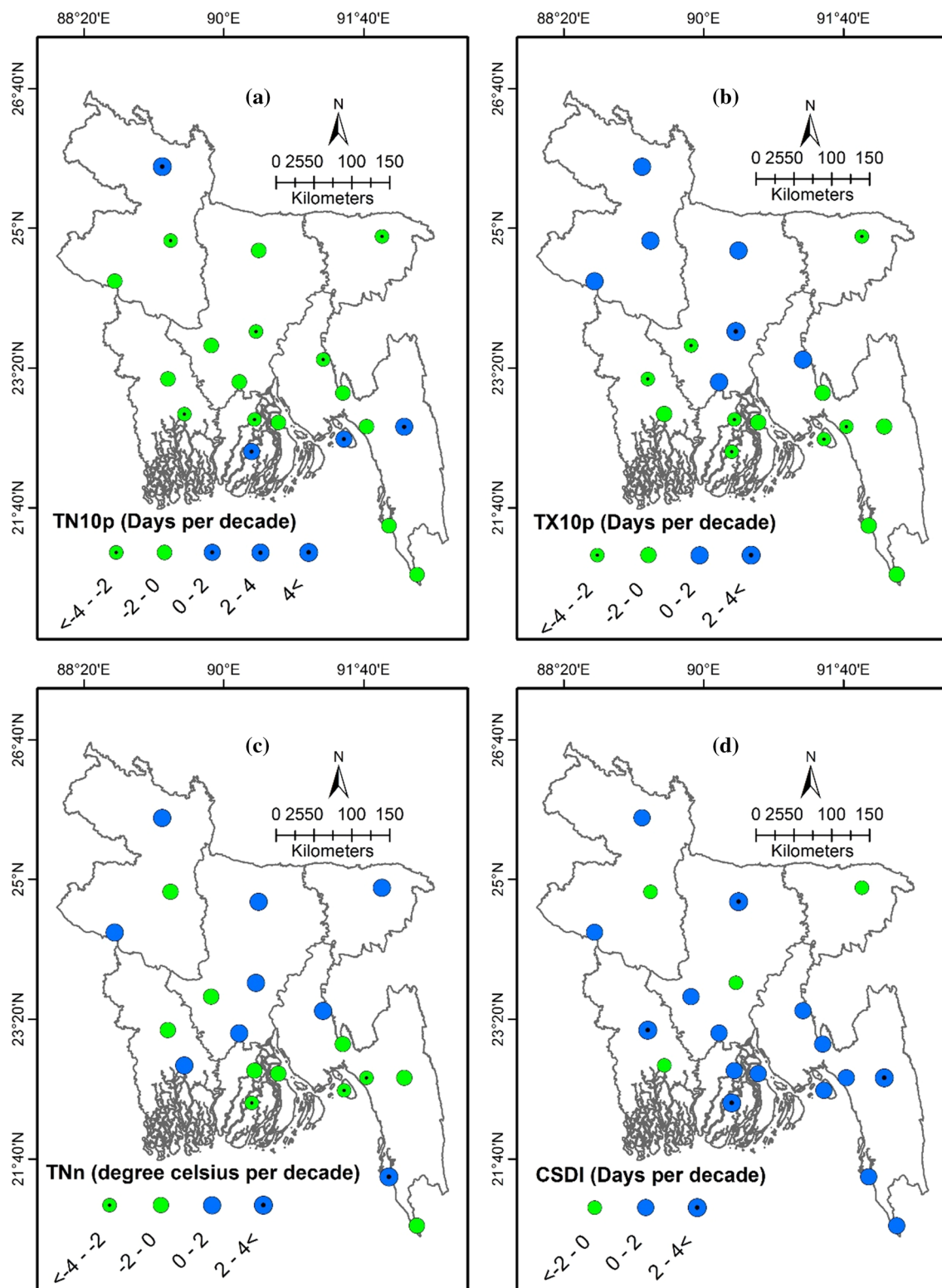


Fig. 3 Spatial trends of cold temperature extreme indices: **a** cold nights (TN10p), **b** cold days (TX10p), **c** coldest days (TNn), **d** cold spell duration indicator (CSDI). Increasing (decreasing) trends are

shown by the blue (green) dots and the station points with the background of dot circle symbols (⊙) represent significance (ANOVA test, $p < 0.05$)

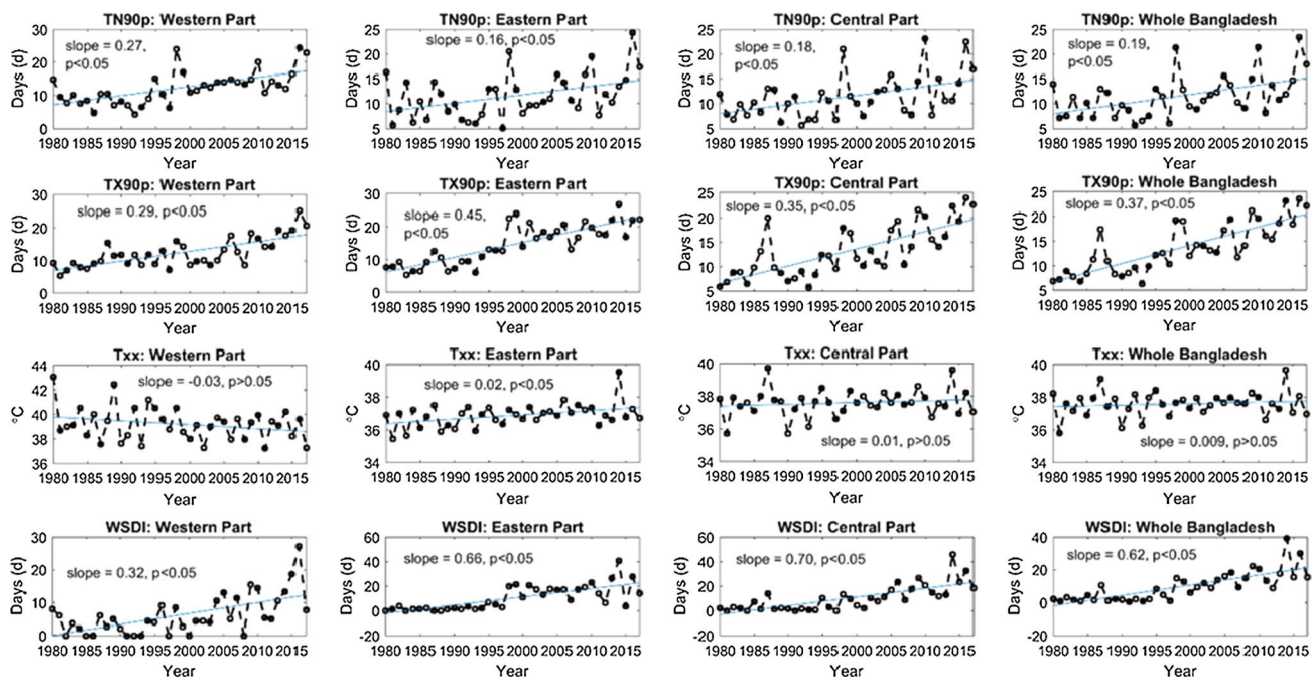


Fig. 4 Regional variations in the warm temperature extreme indices from 1980 to 2017. [Row 1: warm nights (TN90p); Row 2: warm days (TX90p); Row 3: warmest days (TXx); and Row 4: warm spell duration indicator (WSDI)]

Both the mean value and rate of change increased significantly for diurnal temperature range (DTR) and tropical nights (TR). However, there was no significant trend in growing season length (GLS) across the different region of Bangladesh (Table 2). The mean value of DTR ranged from 0.3 to 0.4 °C, whilst the average value of TR ranged from 9 to 15 days.

3.5 Relationships among extreme-temperature indices

Results showed that there was a significant correlation between cold indices and warm indices (Table 3). Interestingly, a significant positive correlation was found between warm indices and between cold indices. However, warm indices were negatively correlated with cold indices. Our previous results showed that warm indices increased significantly, while cold indices decreased significantly. This result is consistent with Wang et al. (2018). For variability indices, there was a significant positive correlation between DTR and warm indices, whereas a significant negative correlation was found between DTR and cold indices. A similar result was also found for TR. We did not find a significant correlation for GSL.

3.6 Relationship between climate mode and temperature extremes

The Pearson's correlation coefficient between extreme-temperature indices and ocean-atmospheric teleconnections in Bangladesh from 1980 to 2016 is shown in Fig. 8. As ocean-atmospheric teleconnections have combine effects on the distribution of extreme climate events in the northern hemisphere (Tong et al. 2019; Rahman and Islam 2019), ENSO, IOD and NAO indices have been selected in this study. The result shows that both ENSO and IOD had no significant contribution on temperature extremes in Bangladesh. Only a significant negative correlation was found between NAO and warm nights (tropical nights). This result suggests that NAO has a significant effect on warm nights in Bangladesh.

Results of cross-wavelet transforms showed that a significant negative correlation between ENSO and TN90p from 1994 to 2000 (1–4 years resonance cycle) (Fig. 9a). There was a significant positive correlation between ENSO and TX90p during 1986–1990 (3–5 years resonance cycle), while a significant negative correlation was found in the second cycle from 1995 to 2000 (2–4 years resonance cycle) (Fig. 9b). A similar result was also found between ENSO and TXx (Fig. 9c). A significant negative correlation was found between ENSO and WSDI during 1996–1998 in the first cycle (2–3 years resonance cycle) and in the second cycle from 2011 to 2012 (1–2 years resonance cycle) (Fig. 9d).

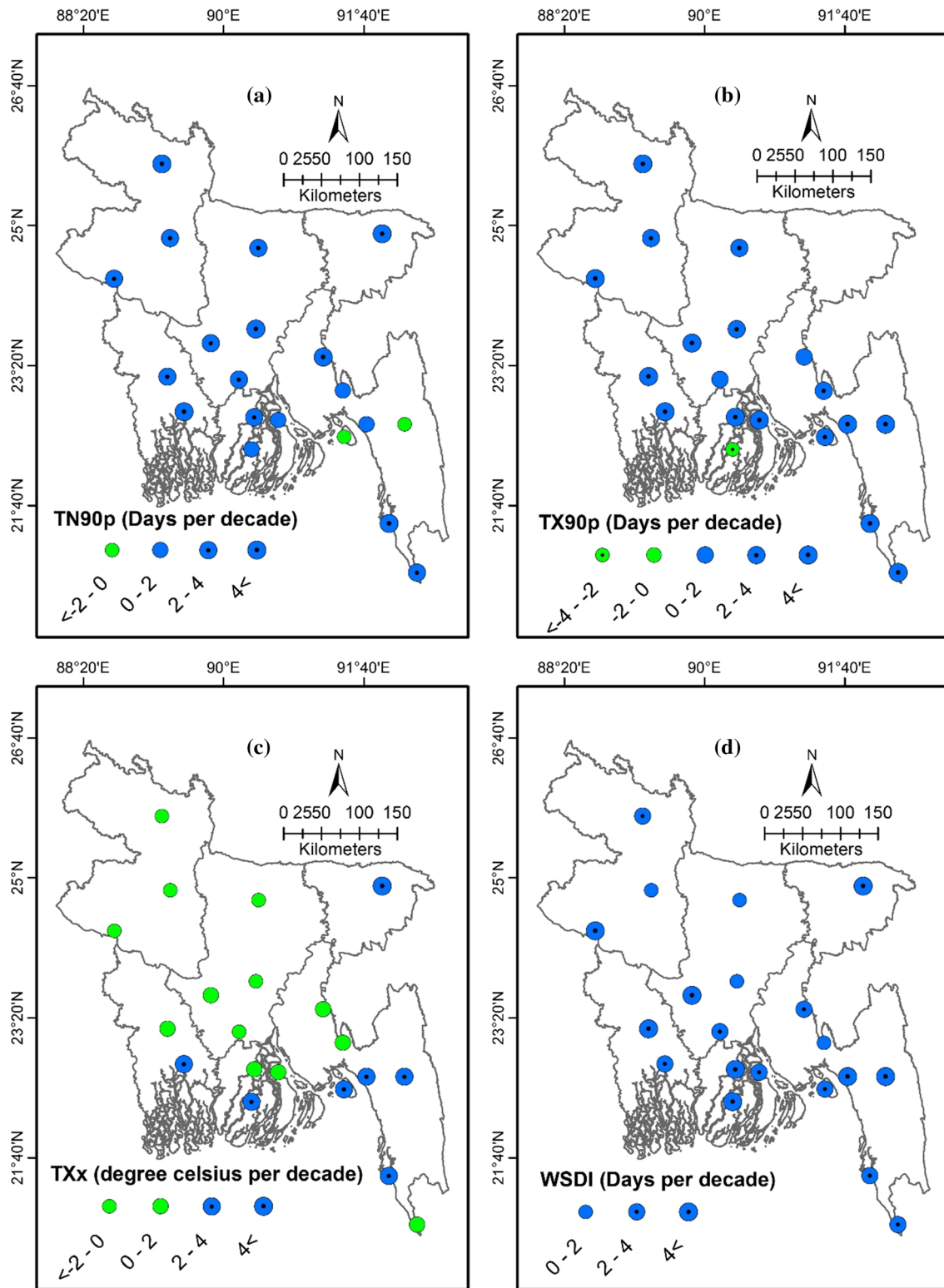


Fig. 5 Spatial trends of warm temperature extreme indices: **a** warm nights (TN90p), **b** warm days (TX90p), **c** warmest days (TXx), and **d** warm spell duration indicator (WSDI). Increasing (decreasing)

trends are shown by the blue (green) dots and the station points with the background of dot circle symbols (⊙) represent significance (ANOVA test, $p < 0.05$)

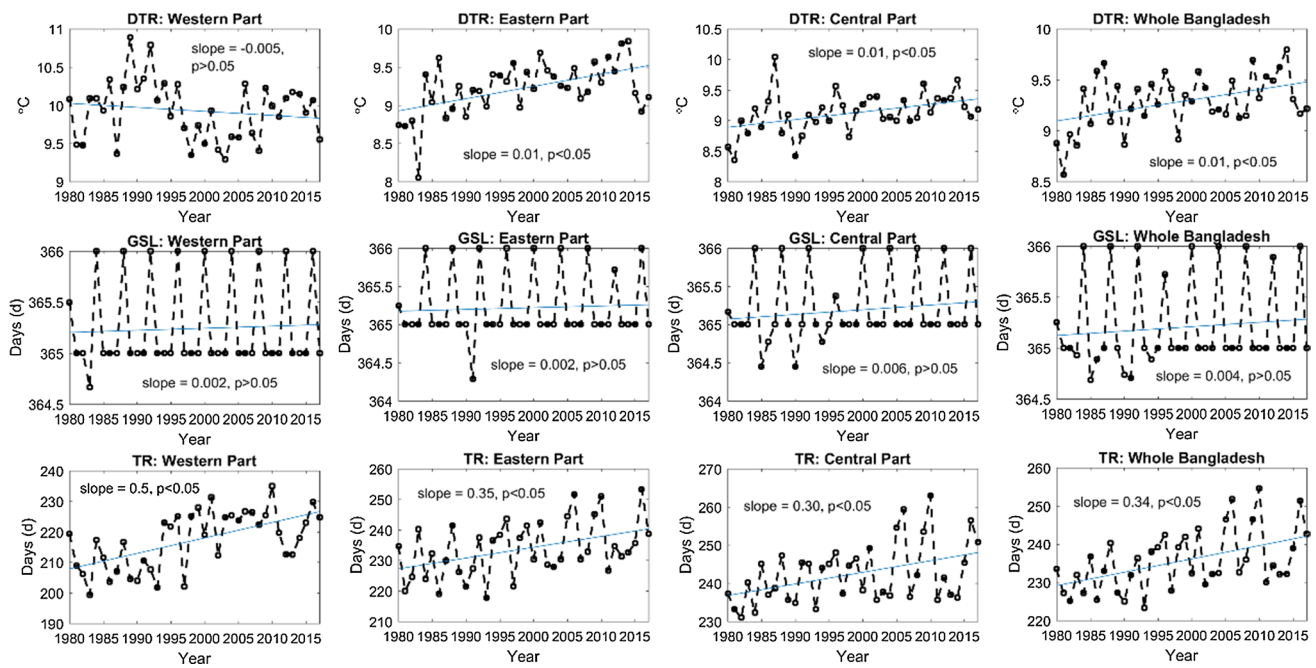


Fig. 6 Regional variations in the variability temperature extreme indices from 1980 to 2017. [Row 1: diurnal temperature range (DTR); Row 2: growing season length (GSL); and Row 3: tropical nights (TR)]

IOD was negatively correlated with warm temperature indices during the 1990s ($p < 0.05$) (Fig. 10a–d).

There was a significant negative correlation between NAO and TN90p during 2009–2011 (1–3 year resonance cycle) (Fig. 11a). However, we did not find a significant resonance cycle between NAO and TX90p (Fig. 11b). NAO was negatively correlated with TXx before 1995, and then it was positively correlated with WSDI after 2010 ($p < 0.05$) (Fig. 11c–d).

The probability of WSDI has been predicted based on the bivariate relationship between WSDI and ENSO, IOD and NAO. Poisson regression model (Fig. 12) plays an important role to extract the contribution of each ocean-atmospheric teleconnection parameters on WSDI. The bivariate relationships do not tell the entire story in the model but significant in a model. The probability of WSDI by several DpD is shown in Fig. 12, and it is found that there are 65% chances of having 2–4 WSDI (DpD), which is consistent with observation.

3.7 The long-term relationship among temperature extremes indices

Figures 13, 14 and 15 show a long-term correlation among temperature extremes indices. For cold, warm, and variability temperature indices, the value of DFA scaling

exponent (α) was greater than 0.5 and less than 1 across different regions in Bangladesh. The result suggests that these indices had a long-term correlation. In other words, the future trend in each index is consistent with the change in trend from 1980 to 2017. From the previous results, we found a decreasing trend in cold temperature indices, while an increasing trend was found in warm and variability indices. Therefore, we can imply that the cold temperature indices will continue to decrease, and the warm and variability indices will continue to increase. This result is consistent with Tong et al. (2019).

4 Conclusions

This study investigated the effect of ocean-atmospheric teleconnection on temperature extremes over Bangladesh using statistical models. The daily maximum and minimum temperature data were collected from the Bangladesh Meteorological Department. A total number of 11 indices and the Mann–Kendall trend test were selected to examine the spatiotemporal variations of climate extremes in Bangladesh from 1980 to 2017.

The key findings of this study are.

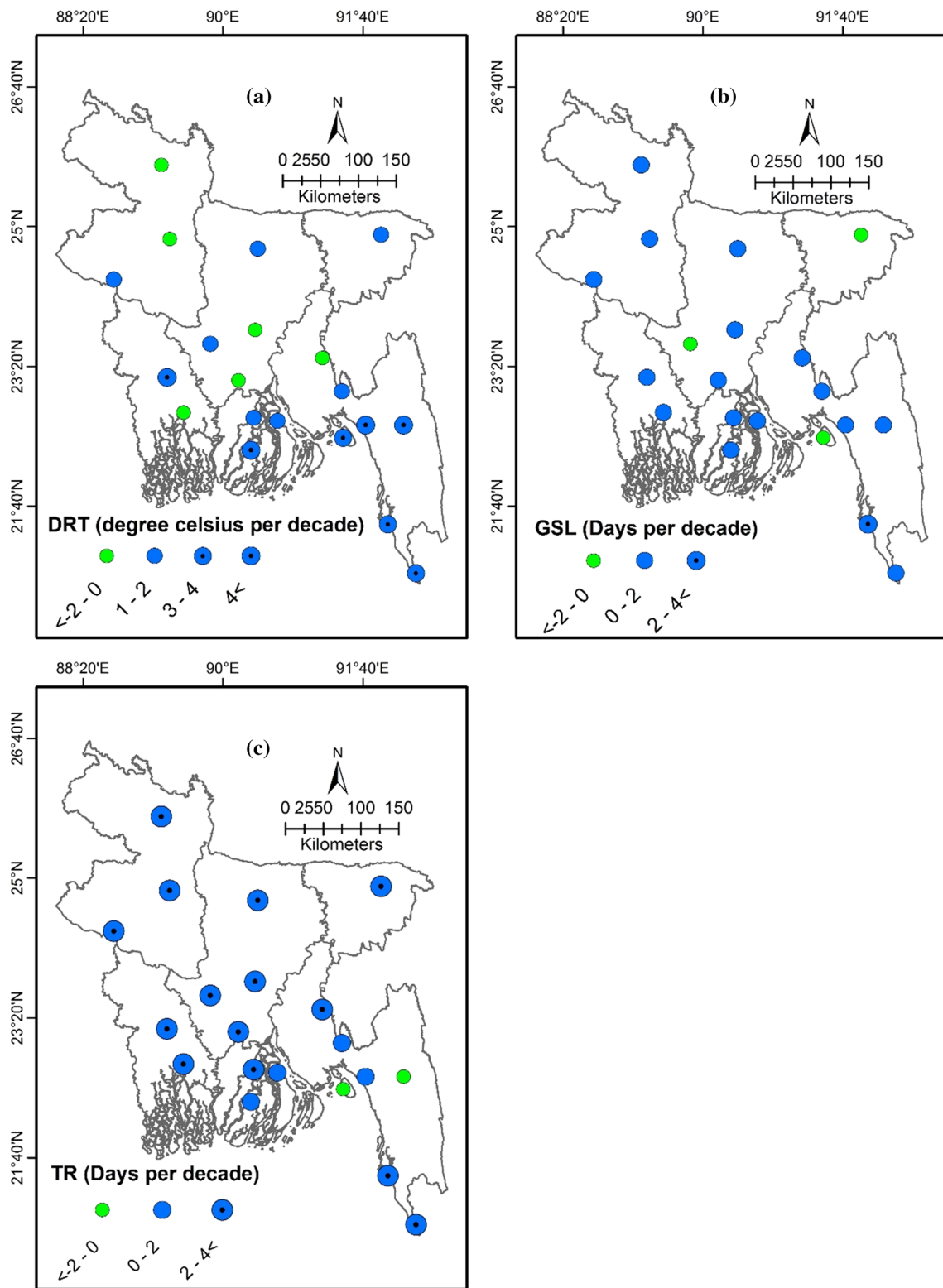


Fig. 7 Spatial trends of variability temperature extreme indices: **a** diurnal temperature range (DTR), **b** growing season length (GSL), and **c** tropical nights (TR). Increasing (decreasing) trends are shown

by the blue (green) dots and the station points with the background of dot circle symbols (⊙) represent significance (ANOVA test, $p < 0.05$)

Table 2 Differences in the average and rates of change of the temperature extreme indices for western, eastern, central and whole Bangladesh

Indices	Western (<i>n</i> =3)		Eastern (<i>n</i> =9)		Central (<i>n</i> =8)		Whole Bangladesh (<i>n</i> =20)	
	Average	Rate of change	Average	Rate of change	Average	Rate of change	Average	Rate of change
TN10p	-1.93 ± 11**	0.93 ± 2.1**	-4.58 ± 11*	0.98 ± 3.6*	-3.12 ± 11*	0.96 ± 2.8**	-3.47 ± 11**	0.95 ± 2.7**
TX10p	-0.45 ± 10.8	0.66 ± 2.5	-3.28 ± 11.5**	0.91 ± 2.6**	-2.5 ± 11.2**	0.93 ± 2.2**	-2.56 ± 11.3**	1.7 ± 2.2**
TNn	-0.57 ± 7.64	0.53 ± 1.21	-0.63 ± 9.66	0.96 ± 1.03	-0.68 ± 9.49	0.88 ± 0.87	-0.62 ± 9.24	0.97 ± 0.90
CSDI	-0.02 ± 1.69	0.83 ± 2.37	-0.02 ± 2.66	1.00 ± 3.03	2.52 ± 1.77	0.95 ± 3.30	1.25 ± 2.09	0.96 ± 2.48
TN90p	8.30 ± 6.8**	0.98 ± 4.9**	5.09 ± 8.2**	0.94 ± 4.4**	5.49 ± 7.7**	0.98 ± 4.3**	5.83 ± 7.7**	0.98 ± 4.2**
TX90p	8.96 ± 6.5**	0.97 ± 4.5**	13.65 ± 5.6**	0.99 ± 6.05**	10.5 ± 6.2**	1.00 ± 5.2**	11.19 ± 6.3**	0.99 ± 5.08**
TXx	-0.97 ± 39.8	0.93 ± 1.3	0.80 ± 36.3*	0.75 ± 0.7*	0.33 ± 37.3	0.91 ± 0.82	0.28 ± 37.4	0.97 ± 0.7
WSDI	9.86 ± 0.27**	0.97 ± 6.04**	19.92 ± 2.8**	0.99 ± 9.9**	21.09 ± 3.7**	1.00 ± 10.4**	18.8 ± 2.6**	0.99 ± 8.8**
DTR	-0.16 ± 10.03	-0.94 ± 0.39	0.48 ± 8.91**	0.63 ± 0.34**	0.38 ± 8.87*	0.80 ± 0.33*	0.31 ± 9.08**	0.97 ± 0.27**
GSL	0.06 ± 365.2	0.95 ± 0.43	0.07 ± 365.17	0.87 ± 0.44	0.18 ± 365.06	0.98 ± 0.45	0.13 ± 365.12	0.93 ± 0.43
TR	15.18 ± 207.3*	0.99 ± 9.4**	10.61 ± 226.8**	0.99 ± 9.1*	9.11 ± 236.5*	0.99 ± 7.8**	10.49 ± 228.7*	0.97 ± 7.8**

** and * Denote significance at $p < 0.01$ and $p < 0.05$, respectively. All other values are not significant. Here, *n* represents the number of station

Table 3 The Pearson correlation matrix among temperature extreme indices over Bangladesh

Indices	TN10p	TX10p	TNn	CSDI	TN90p	TX90p	TXx	WSDI	DTR	GSL	TR
TN10p	1										
TX10p	0.58**	1									
TNn	-0.188	-0.2	1								
CSDI	0.43**	0.03	-0.4**	1							
TN90p	-0.7**	-0.4**	0.02	-0.29	1						
TX90p	-0.69**	-0.48**	-0.05	-0.04	0.72**	1					
TXx	-0.28	-0.46**	0.02	0.14	0.26	0.40*	1				
WSDI	-0.62**	-0.47**	-0.03	0.02	0.64**	0.90**	0.46**	1			
DTR	-0.05	-0.5**	-0.19	0.40*	-0.07	0.44**	0.54**	0.38*	1		
GSL	0.008	-0.03	0.03	0.12	0.05	-0.004	0.18	0.02	0.04	1	
TR	-0.66**	-0.66**	0.15	0.16	0.72**	0.65**	0.34*	0.54**	0.17	0.11	1

** and * Denote significance at $p < 0.01$ and $p < 0.05$, respectively. All other values are not significant

- Warm temperature index, DTR and TR increased significantly over Bangladesh, while cold temperature indices and GSL decreased significantly.
- Ocean-atmospheric teleconnection, particularly ENSO and IOD, had a strong positive effect on warm temperature indices, while an opposite result was found for cold temperature indices. For the NAO, it showed a strong negative effect on variability temperature indices over Bangladesh.
- The result of DFA confirms that the variation of temperature extremes will remain the same in the future period.
- Both the Poisson regression model and cross-wavelet transform showed that a 65% probability of having a 2–4 WSDI (days/decade) is consistent with the observation.

The result of this study suggests that warming events are increasing significantly in Bangladesh. Therefore, extreme events of temperature would have a serious impact on agriculture, ecosystem, and livelihood. Future research should focus on forecasting the extreme events and their impacts on agriculture for the purpose of disaster prevention and mitigation.

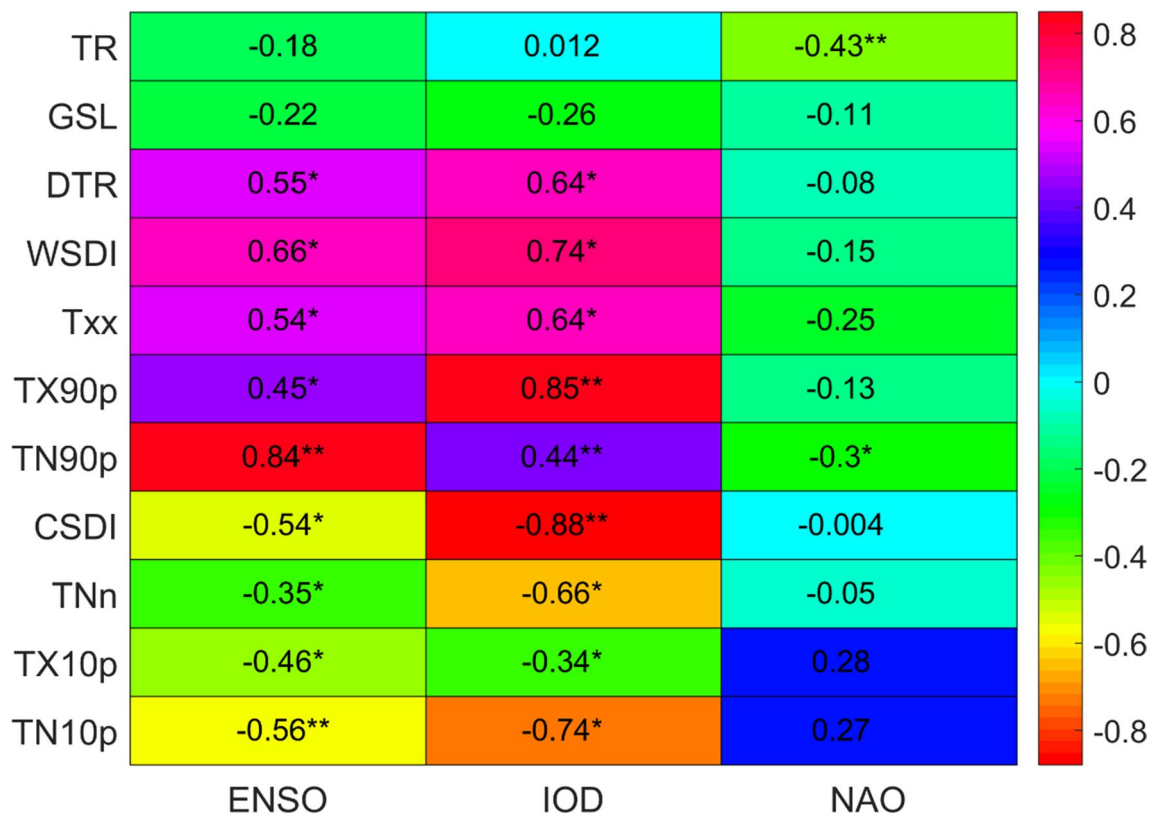


Fig. 8 Pearson's correlation coefficient between extreme-temperature indices and large-scale atmospheric circulation indices in Bangladesh during 1980–2017. *Represents significant at the $p < 0.05$ level, and **indicates significant at the $p < 0.01$ level

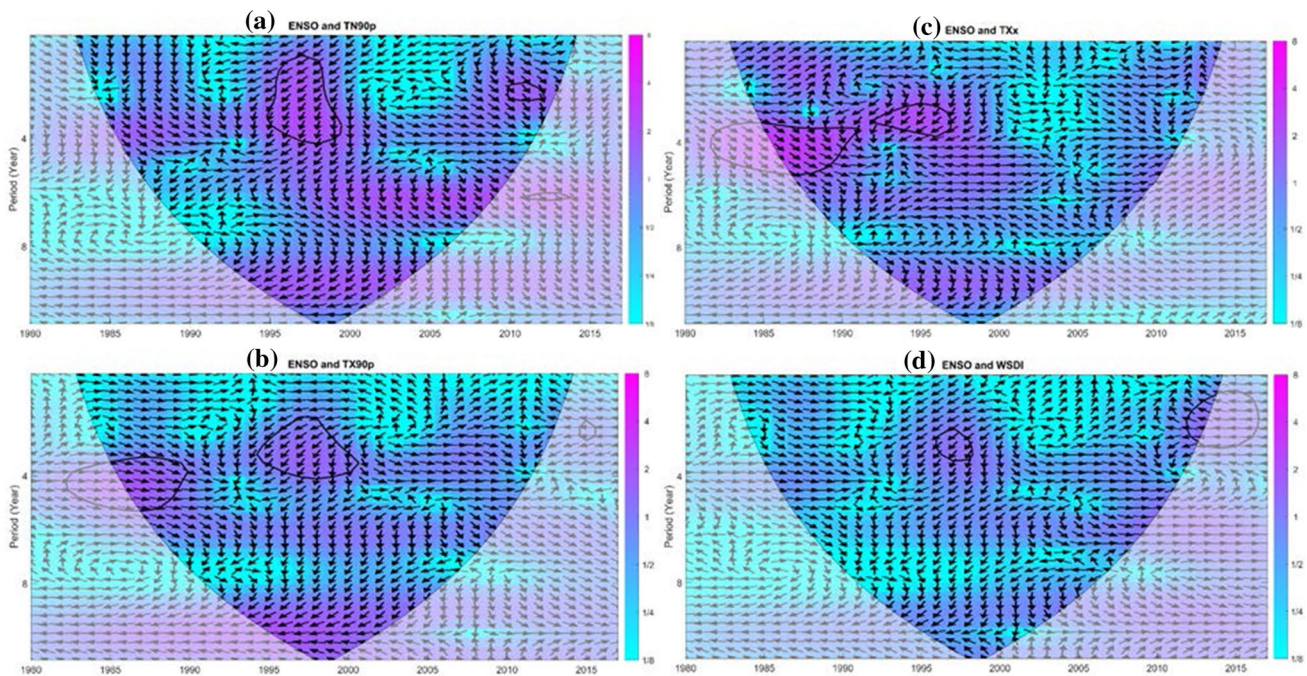


Fig. 9 Cross-wavelet transforms of **a** ENSO and TN90p, **b** ENSO and TX90p, **c** ENSO and TXx **d** ENSO and WSDI. The black line is the cone of influence while the thick black contours represent the 5% confidence level. While left-pointing arrows refer anti-phase sig-

nals, right-pointing arrows denote that the two signals are in phase, and down-pointing arrows indicate that the warm indices are ahead of the atmospheric index, while up-pointing arrows show that the warm indices lag behind the atmospheric index

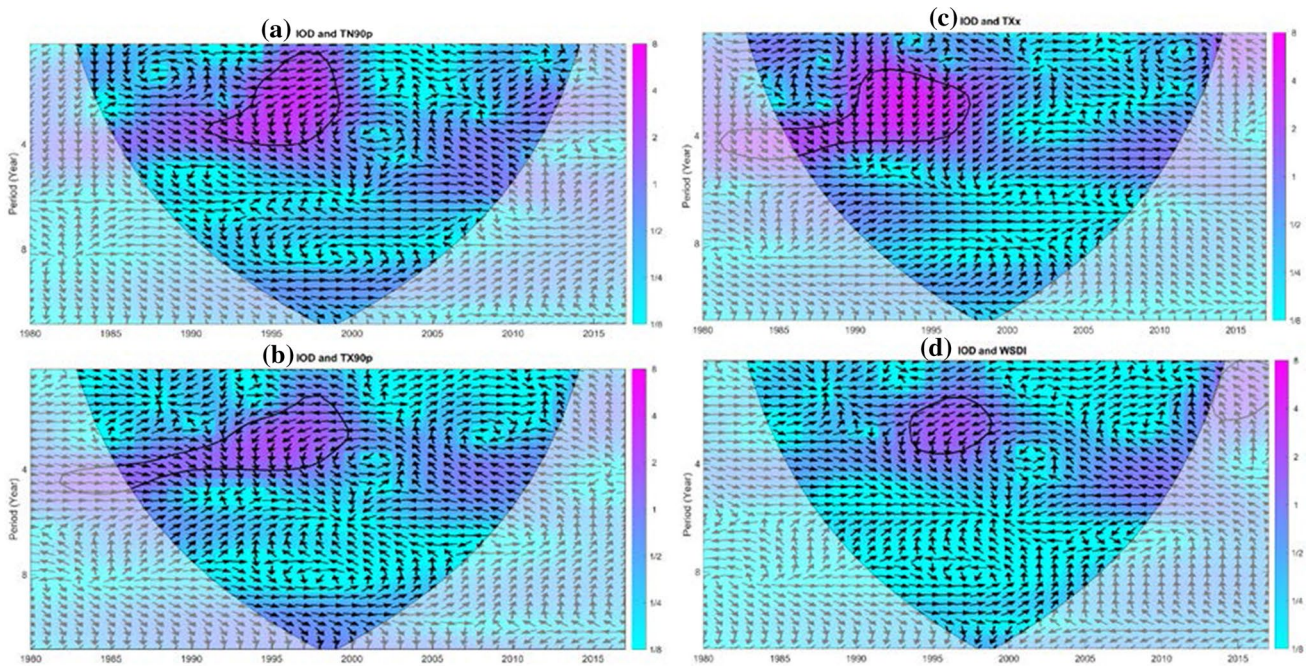


Fig. 10 Same as Fig. 9 but for IOD

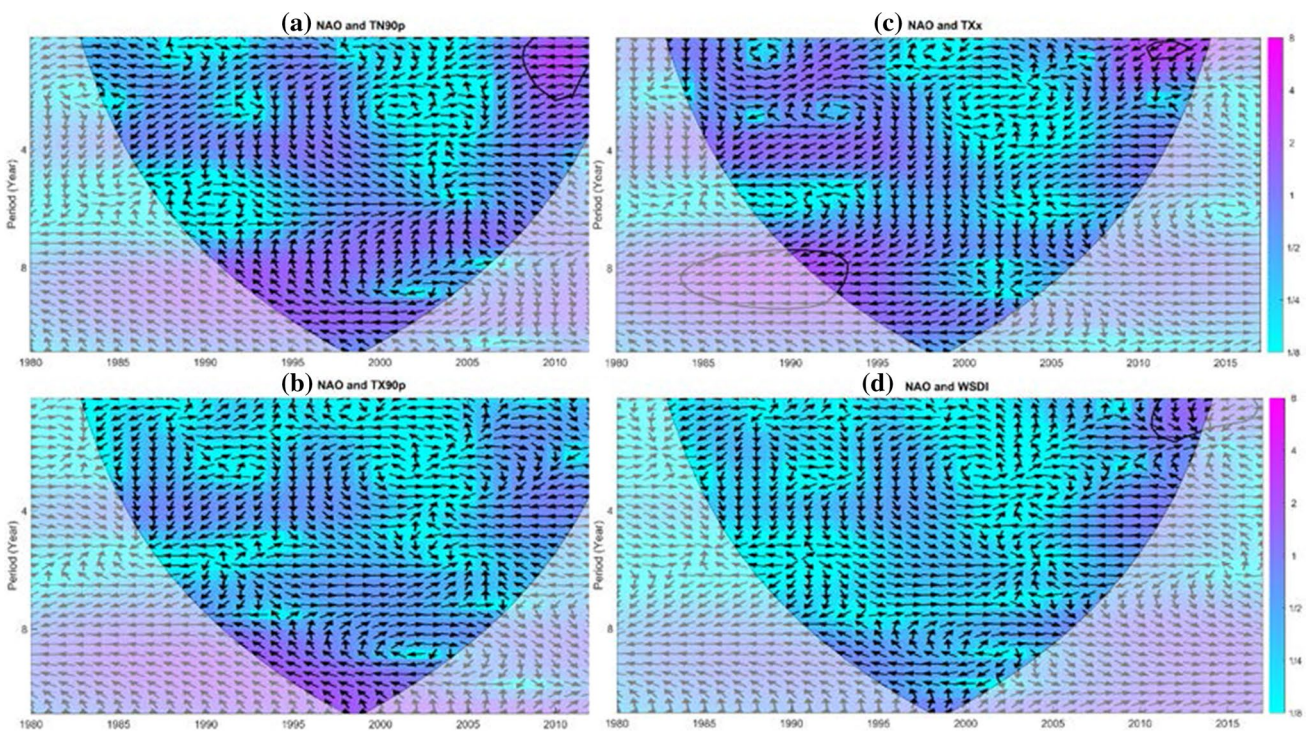


Fig. 11 Same as Fig. 9 but for NAO

Fig. 12 Forecast probabilities by considering a bivariate relationship between extreme temperature and ENSO, IOD and NAO using a Poisson regression model. *X* and *Y* axis show the WSDI (DpD) and probability (%), respectively

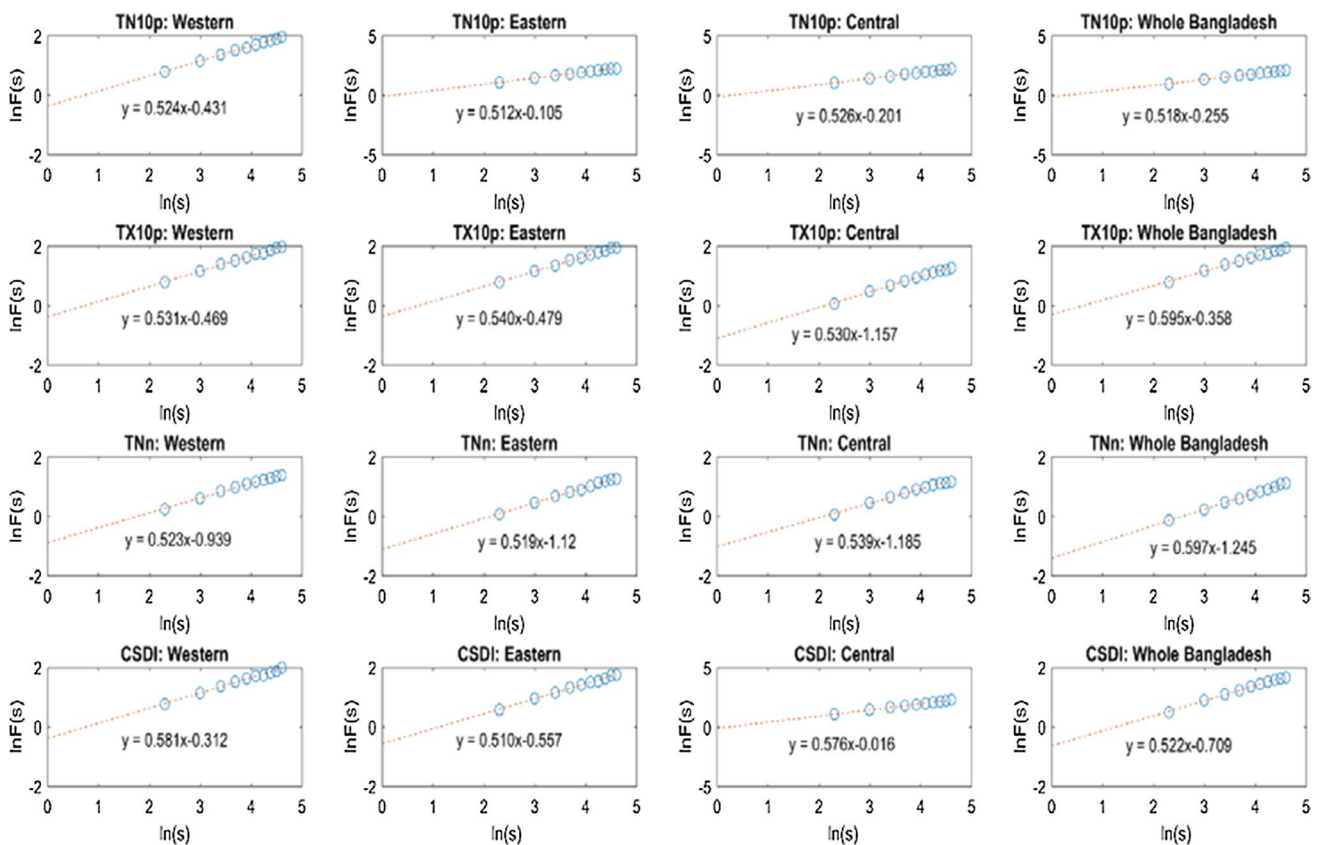
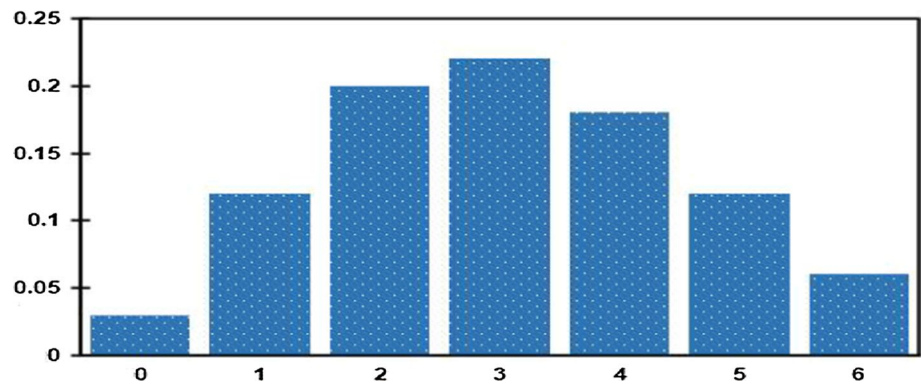


Fig. 13 DFA long-term forecasting of cold temperature indices

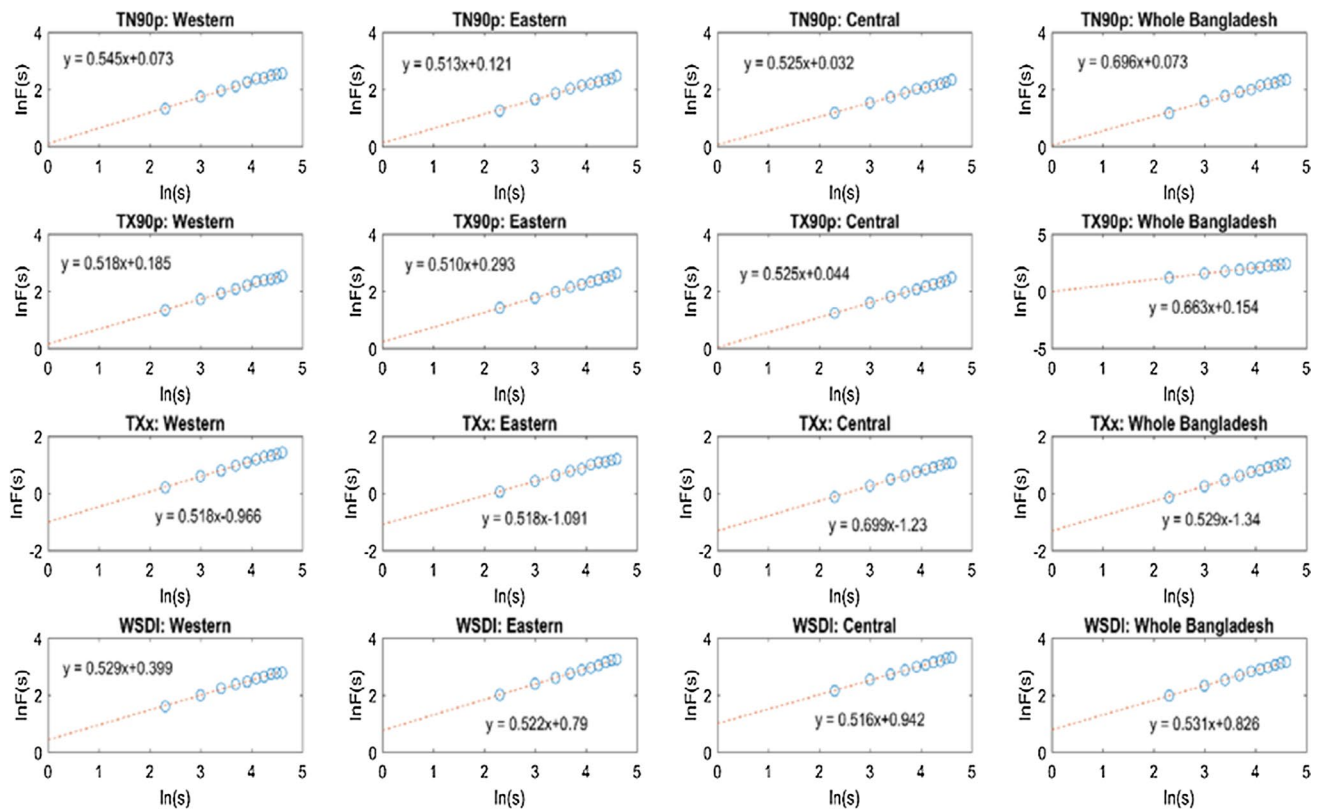


Fig. 14 Same as Fig. 13 but for warm indices

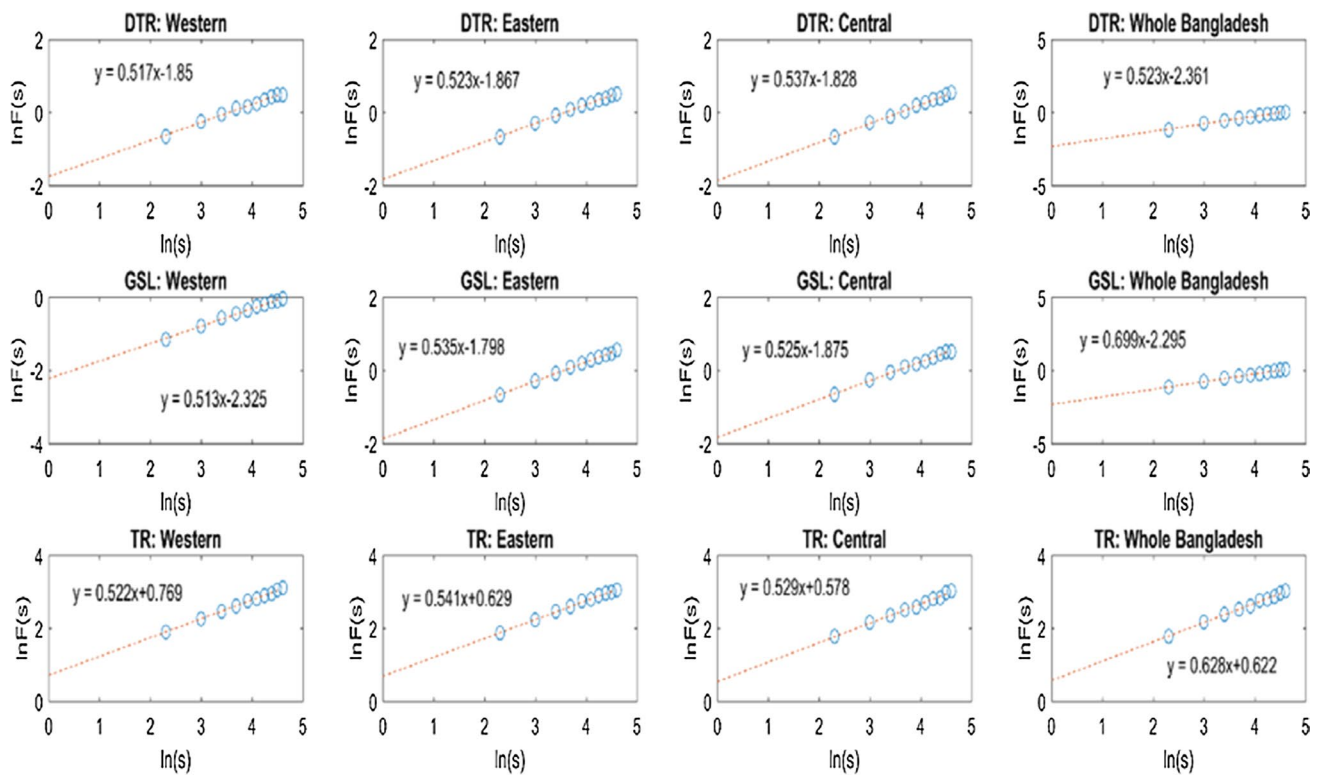


Fig. 15 Same as Fig. 13 but for variability temperature indices

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Data availability The datasets and code will be available from the corresponding author on reasonable request.

Declarations

Conflict of interest None.

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