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Spatiotemporal distribution of drought and its possible associations with ENSO indices in Bangladesh

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Abstract

Droughts and related water stress are the major constraints of the sustainable socioeconomic development of Bangladesh. Large-scale atmospheric oscillations are the major drivers of climate fluctuation and droughts in Bangladesh, like many other regions of Asia including the Indian subcontinent, the largest entity in the world, with over 1.7 billion people. Therefore, it is crucial to insight into the spatiotemporal distribution of drought and its linkage to large-scale atmospheric indices to provide early warning and alleviate drought impacts. However, regional droughts and their linkages to large-scale oscillation indices like El-Nino Southern Oscillation (ENSO) are not explored adequately in Bangladesh. This study intends to evaluate the spatiotemporal distribution of droughts in Bangladesh using the standardized precipitation evapotranspiration index (SPEI) and the standardized precipitation index (SPI) for multiple timescales, -3, -6, -12, and 24-months, and to investigate the relationship of drought characteristics with ENSO. The monthly rainfall and temperature records from twenty locations for 38 years from the period 1980 to 2017 were used for this purpose. The results revealed that the droughts are region-specific and are in agreement with the warming trends observed in the different regions of Bangladesh. The droughts, particularly short-term droughts, are increasing significantly in the North-western region, indicating the worsening drought conditions in the drought-prone region. The SPI and SPEI showed a significant ($p < 0.05$) positive association with the percentage of precipitation anomaly (Pa). However, the association of drought indices with ENSO and potential evapotranspiration (PET) were not significant. The polynomial regression model demonstrated that Indian Ocean Dipole (IOD) could explain SPEI-3 (4.7%) variations better than SPI-3 (4.2%).

Keywords Drought indices · Teleconnection indices · Global warming · Precipitation anomaly · Potential evapotranspiration

Introduction

Drought is one of the most complex recurring natural disasters caused by persistent water scarcity due to lack of precipitation. It has severe consequences for agriculture, economics and livelihoods, and living standard of rural and semi-urban population (Lorenzo-Lacruz et al. 2010; Potop et al. 2012; Qin et al. 2015; Yang et al. 2017; Kamruzzaman et al. 2019a; Ogunrinde et al. 2021). Due to its adverse

effect on agricultural crop production and the ecosystem, drought is currently considered one of Bangladesh's most frequent natural disasters (Alamgir et al. 2015). The drought frequency and severity have been steadily rising globally, that has caused severe impacts in agricultural production (Barlow et al. 2016; Kamruzzaman et al. 2019a; Spinoni et al. 2020). The rising trends in droughts are more prominent in South Asia than in many other regions due to increasing temperature and weakening monsoon (Davis et al. 2019; Mishra et al. 2020). Recently, Aadhar and Mishra (2021) projected an increase in extreme drought frequency by one and half times more in the near future compared to the present situation.

Bangladesh, located in South Asia, experiences frequent droughts like other parts of South Asia (Salam et al. 2020a).

Drought in Bangladesh is caused by rainfall unreliability and a lack of available surface water supplies. The absence of moisture in the atmosphere or large-scale downward atmospheric air movement suppresses rainfall and is often responsible for rainfall shortage. Changes in such elements include weather and climatic changes on a local, regional, and global scale (Islam et al. 2021a; Mondol et al. 2021). While it is sometimes feasible to pinpoint the immediate cause of drought in a specific place, it is frequently impossible to specify the underlying reason. Rainfall variations are linked to rising amounts of carbon dioxide and other greenhouse gases and consequent changes in climate. There is compelling evidence that climate change will alter rainfall patterns, resulting in more frequent droughts. Human-induced changes arising from vegetation loss owing to over-exploitation of resources and deforestation are among the local-level causes of drought. Moreover, short-term drought events can be related to global atmospheric and oceanic circulation patterns. The El Nino/Southern Oscillation (ENSO) forms warm surface water off the Pacific coast of South America, impacts rainfall in many regions globally, including monsoon rainfall in Bangladesh. The relationship between sea surface temperature and rainfall can provide the probable cause of dry periods on a broader scale (Selvaraju and Baas 2007). Understanding the spatiotemporal distribution of drought and its connection to large-scale atmospheric indicators is critical to give early warning and mitigate drought consequences.

Droughts are more common in Bangladesh's northwestern areas. These areas receive much less rainfall than other parts of the country (Kamruzzaman et al. 2019b). As a result, they are regarded as the country's drought-prone zones. The majority of the rivers that pass through Bangladesh are originated in India and Myanmar. Diversion of water in the upstream reduces water flow through Bangladesh during the dry seasons. This not only results in a shortage of surface water in the country's northwest, southwest, and southwest areas, but it also hinders the groundwater adequately replenished. As a result, there is a considerable loss in moisture throughout a large area, which adds considerable implications to the drought.

Droughts primarily happen in the pre-monsoon (March–May) and the post-monsoon (October–November) seasons in Bangladesh (Islam et al. 2017). In some severe cases, pre-monsoon droughts last for the monsoon season due to delay in monsoon arrival (Das 2019). Besides, drought vulnerability is geographically patchy, and it is projected that there will be more extreme drought days in the coming years during cropping seasons (Fahad et al. 2007; Kamruzzaman et al. 2019c). However, the changes in mean rainfall have also changed different rainfall characteristics like variability and frequency distribution. Droughts mainly depend on rainfall variability and tail distribution. Therefore,

it is crucial to insight into how the rainfall changes have altered droughts occurrence in Bangladesh. The assessment of the spatiotemporal changes in droughts characteristics can anticipate future negative consequences of droughts and minimize possible losses and damages through appropriate policies pertaining to the drought-preparedness in the drought-prone regions of the country. Furthermore, practical drought assessment and mapping can help in identifying the regional drought characterization, monitoring, early warning, and planning efficient water supplies and agricultural development.

Drought as a natural phenomenon necessitates examining its duration, frequency, and intensity (Nandintsetseg and Shinoda 2013). Drought indexes can provide a measure of the magnitude and duration of drought. However, precise estimation of drought characteristics is difficult as different types of drought (e.g., meteorological, agricultural, and hydrological) are linked to diverse factors. For example, inadequate precipitation for a prolonged period causes meteorological drought, whereas high evapotranspiration with precipitation deficit triggers agricultural and hydrological droughts (Corti et al. 2009; Easterling et al. 2007; Ma et al. 2018; Islam et al. 2019). Another critical drought feature is its time scale. For example, a 1-month drought can harm rain-fed crops and affect water reservoir storage. The drought impacts are also multiscale as the rainfall deficit responses are different for various systems (e.g., agricultural, hydrological, or socioeconomic systems) (Potop et al. 2012). As a result, determining the severity of a drought is challenging. Drought indices must have multiscale features correlated with particular time scales, which are required to investigate drought evaluation (Du et al. 2013; Zhang et al. 2015; Uddin et al. 2020).

Mckee et al. (1993) created the standardized precipitation index (SPI), a traditional multiscale drought index, for recognizing drought using only monthly rainfall data. The Palmer drought severity index (PDSI) (Palmer 1965), China Z index (Ju et al. 1997), and deciles index are all examples of droughts indices that have been widely used and compared with SPI (Gibbs and Maher 1967). Several studies identified SPI's extensive advantages due to its easiness, consistency, and precise drought forecasting capacity at various time scales (Keyantash and Dracup 2002; Montaseri and Amirataee 2017). Because of these benefits, the World Meteorological Organization has proposed SPI as the reference drought index for assessing drought and identifying drought periods.

The standardized precipitation evapotranspiration index (SPEI) (Vicente-Serrano et al. 2010) is another extensively applied multiscale drought index. It estimates droughts based on monthly climatic water balance. SPEI blends PDSI's sensitivity to evaporation demand changes with SPI's quick calculation method and multiscale

characteristics. SPEI, like SPI, can be adopted to assess meteorological droughts for shorter periods (e.g., 1 to 3 months) to show implications on agriculture, and also for more extended periods (e.g., 12 months and longer) to show drought impacts on hydrology (Mckee et al. 1995; Szalai et al. 2000). In addition, this index can classify the role of precipitation anomaly (Pa) and possible evapotranspiration (PET) variability in drought evaluation in the background of climate change (Potop et al. 2012; Vicente-Serrano et al. 2010).

The connections between regional drought and climate mode are essential to identify drought causes. Several studies showed drought linkage to climate indices such as the El Nino-Southern Oscillation (ENSO), the North Atlantic oscillation (NAO), the Pacific decadal oscillation (PDO), and the Arctic oscillation (AO) in different regions of the globe (Mantua et al. 1997; Talaee et al. 2014; Sun et al. 2016). Mainly drought indices such as SPI and SPEI are used to estimate the effect of the oscillation on droughts (Rajagopalan and Cook 2000; Fowler and Adams 2004; Balling and Goodrich 2007; Mo and Schemm 2008). However, the connections of oscillation indices with droughts depend on the region and season. According to Wahiduzzaman and Luo (2020), the ENSO closely relates to precipitation and temperature over Bangladesh. However, Ahmed et al. (2017) reported that IOD has a stronger connection to rainfall than ENSO in Bangladesh. Chowdhury (2003) stated a close relationship of Bangladesh rainfall with the SOI extremes; high rainfall with negative SOI and vice-versa, but a reverse relationship in moderate El Nino years. Chowdhury (1994) discovered that a positive SOI is advantageous for floods, and a negative SOI is favorable for drought. Overall, the literature suggested a lack of quantitative correspondence between ENSO intensity and the rainfall anomaly in Bangladesh.

Teleconnections (e.g., ENSO) significantly impact drought and flood (Tong et al. 2006). There is a strong relationship between teleconnections and drought in some parts of the world (Forootan et al. 2019; Lau et al. 2002). Though several studies have been done for drought monitoring and characterizing in Bangladesh (Shahid and Behrawan 2008; Alamgir et al. 2015; Rahman and Lateh 2016; Miah et al. 2017; Zinat et al. 2020; Uddin et al. 2020; Mondol et al. 2017, 2021), no comprehensive study has yet been done to assess the relationship and impacts of ENSO on drought in the country. In addition, previous studies did not compare coupling drought monitoring indices (e.g., SPI, SPEI, PET, and Pa) for assessing the spatiotemporal distribution of drought in Bangladesh. In this research, we aimed to characterize the spatio-temporal distribution of drought using SPI, SPEI, Pa, and PET, and measure the strength of and impacts of teleconnection (ENSO and IOD) on droughts in Bangladesh. The study implies that this work will provide a useful insight into early warning and effective adaptation measures for droughts in Bangladesh and elsewhere.

Data and method

Study area description

Bangladesh, located in Southeast Asia, is a low-lying, riverine nation with a largely marshy coastline of 710 km on the northern fringe of the Bay of Bengal (Das 2019). The adjacent countries are India to its west, north, east, and Myanmar to its southeast. Drought is a periodic incidence in many parts of the country, but the northwest region of Bangladesh is the most drought-prone due to high rainfall variability (Islam et al. 2021b). This area, receiving much lower rainfall, is comparatively drier than the remaining parts of the country. Moreover, the predominantly sandy soils in the region have a less moisture preservation capacity and a high insinuation rate. The present study has divided the whole of Bangladesh into four regions as North-eastern (region 1), North-western (region 2), Central (region 3), and Southern (region 4), according to its geographical location, hydrological settings, climatic variation, and soil type (Islam et al. 2018; Salam et al. 2020b). Different districts of Bangladesh belong to other regions are as follows: Region 1 consists of Sylhet; Region 2 comprises Rangpur, Rajshahi, Bogura; Region 3 covers Dhaka, Faridpur, Madaripur, Mymensingh; and Region 4 includes Barishal, Bhola, Cox's Bazar, Feni, Joshore, Patuakhali, Swandip, Teknaf, Sitakunda, Rangamati, and Khulna (Fig. 1). The country's average minimum temperature generally remains above 10 °C, and the average maximum temperature hardly exceeds 32 °C. The Northwestern part experiences higher climatic extremes, where the summer is drier, with a scorching westerly wind (Islam et al. 2014, 2019). The mean minimum temperature in winter often goes below 10 °C, and the maximum summer temperature frequently exceeds 32 °C. The rainfall in the central part is abundant, being above 190 cm, and the temperature is more than that in Region 2. The Southern region primarily includes Chattogram and a slip of the country's north to Cumilla. The rest of the area experiences a temperature rarely below a mean of 12° and over a mean of 32 °C but usually receives heavy rainfall (> 254 cm).

Data source

Monthly data of precipitation and temperature for 38 years from 1980 to 2017 of twenty meteorological sites situated in different regions of country are used in this study. The data was acquired by the Bangladesh Metrological Department (BMD) (www.bmd.gov.bd). Several missing records were detected in almost all 20 stations. The primary screening

Fig. 1 The location map of the study area showing meteorological stations
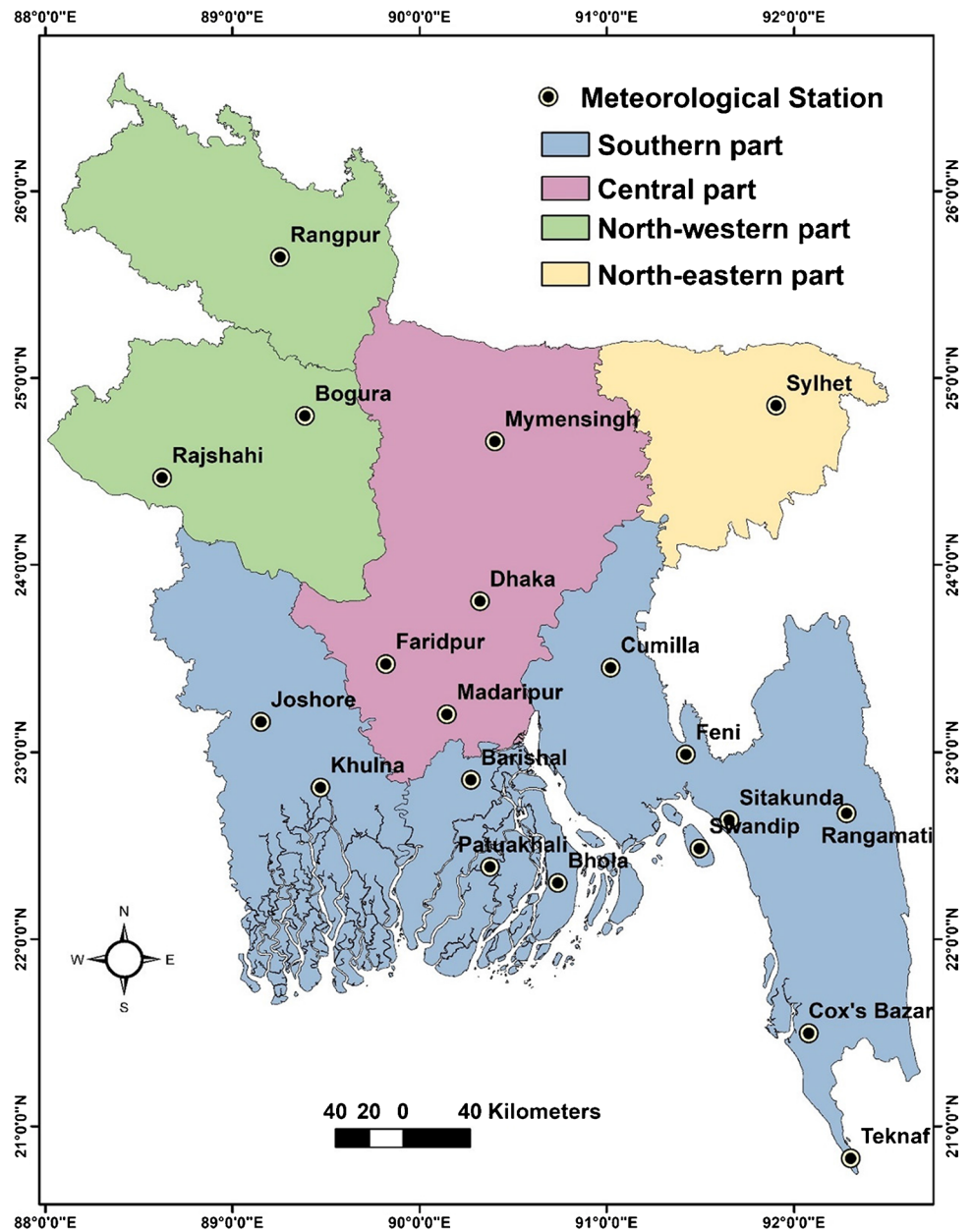
revealed missing records less than 5% from 1985 to 2015. Missing data at each site was filled by the past data records of the respective days of the nearby stations. The main reason for using the data of these 20 stations is that the administrative division before the year 1980 was diverse. Some districts not exist or were partitioned from other districts after the year 1980as part of the policy of reorganization of districts by creating smaller districts for better governance and implementation of different policies. Therefore, climatic data of those districts were not available before. All the datasets are checked for quality control by using the standard statistical methods by the BMD before being supplied to the users. Two atmospheric circulation indices data, Indian Ocean Dipole (IOD) and Nina 3.4 (ENSO) for 1980–2017,

were gathered from the National Oceanic and Atmospheric Association (NOAA) Climate Prediction Center (CPC) (www.cpc.ncep.noaa.gov).

Standardized precipitation index

Standardized precipitation index (SPI) uses only precipitation for drought characterization based on the monthly precipitation probability. The key purpose of the SPI is to show the precipitation deficiency of a particular area on several periods of the study period (McKee et al. 1993, 1995; Guttman 1998). The SPI is also extensively utilized for identifying the dry and wet periods of the study area. Both short-term (3 and 6 months) and long-term (12 and 24 months)

observations can be possible by using the SPI (Vicente-Serrano et al. 2010). This feature can attain a considerable amount of information to clearly indicate of droughts scenarios for desired intervals (Karavitis et al. 2011). In the present study, the SPI is calculated based on the cumulative likelihood of precipitation of the respective station. First, the gamma cumulative distribution function $g(x)$ parameters are applied to fit each calendar month's rainfall frequency for a meteorological station. The statistical Eq. (1) of the $f(x)$ is as follows:

$$g(x) = \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} \tag{1}$$

where α is the shape and β is the scale parameters. The monthly rainfall is denoted by x. The Thom approach (Thom 1958) has been utilized for estimating the above two parameters (α and β). Integrating the probability density functions with respect to x and attach α and β parameters yields the cumulative probability distribution function $G(x)$:

$$G(x) = \int_0^x g(x)dx = \frac{1}{\hat{\beta}\Gamma(\hat{a})} \int_0^x x^{\hat{a}} e^{-x/\beta} \tag{2}$$

Substituting t for $-\frac{x}{\beta}$ yields the incomplete gamma function:

$$G(x) = \frac{1}{\Gamma(\hat{a})} \int_0^x t^{\hat{a}} e^{-t} dt \tag{3}$$

The gamma distribution is undefined for $x = 0$ and $q = P(x = 0) > 0$, where $P(x = 0)$ is the probability of zero (null) precipitation. Thus, the cumulative probability distribution function becomes:

$$H(x) = q + (1 - q) * G(x) \tag{4}$$

The cumulative probability distribution function is converged into the standard normal cumulative distribution function to have the same probability. To avoid the solution derived directly from the pertinent distribution graphs, the SPI calculating tool was applied. The comprehensive estimation of the SPI and the classification of drought have been presented by Shahid and Behrawan (2008).

Standardized precipitation evapotranspiration index

The standardized precipitation evapotranspiration index (SPEI) is an improved form of SPI based on climatic water balance, the difference between precipitation and reference evapotranspiration ($P - ET_0$), rather than only precipitation (P) as the input (Vicente-Serrano et al. 2010). It can be computed for

various timescales to monitor droughts. Mathematically, the SPEI is analogous to the SPI, but it includes the role of temperature variation. The SPEI combines the sensitivity of the PDSI to consider evaporative demand (related to temperature variations and trends) with the multi-temporal nature of the SPI. Although FAO recommended Penman–Monteith (PM) equation for calculating potential evapotranspiration (PET), it is often difficult to use as a large set of data is required (for instance, radiation, wind speed, sunshine hour, temperature, and so on) (Salam et al. 2020a, b). Moreover, radiation data is difficult to record and is not provided by the BMD. Besides, PM equation needs a high pitch of statistical aptitude and a considerable amount of time. For these drawbacks, the Thornthwaite method is considered of PET estimation in this study. As, it takes only monthly mean temperature and monthly mean sunshine hours as the major factors to estimate PET by the following equation:

$$PET = 16 \times (N/12) \times (m/30) \times 10 \times (Ti/I)^a \tag{5}$$

where N is the monthly mean sunshine hour, m is the number of days in a month, Ti is the monthly mean temperature, I is a cumulative index, and a can be estimated below in:

$$a = 6.75 \times 10^{-7} \times I^3 - 7.71 \times 10^{-5} \times I^2 + 1.79 \times 10^{-2} \times I + 0.49 \tag{6}$$

The deficit or surplus accumulation of a climatic water balance at various time scales is determined by the disparity between the monthly precipitations (P) and PET:

$$D_i = P_i - PET_i \tag{7}$$

The calculated D_i values are gathered at various time scales, following the similar process used in SPI for given month j and year i relies on the specific time scale k (months). For instance, the accumulated difference for one in a specific year i with a 3-month time scale is computed using the following equations:

$$X_{ij}^k = \sum_{l=j-k+1}^{3} D_{i-1,l} + \sum_{l=1}^{j} D_{i,j}, \text{ if } j < k \tag{8}$$

$$X_{ij}^k = \sum_{l=j-k+1}^{j} D_{i,l}, \text{ if } j \geq k \tag{9}$$

Subsequently, the climatic water balance data are fitted using a log-logistic probability distribution to get the SPEI index series. The probability density function of a log-logistic distributed variable is stated below:

$$f(x) = \frac{\beta}{\alpha} \left(\frac{x - \lambda}{\alpha} \right) \left[1 + \left(\frac{x - \lambda}{\alpha} \right) \right]^{-2} \tag{10}$$

where α, β, and γ are the scale, shape, and origin parameters, respectively, for D values in the range ($\gamma > D < \infty$).

Thus, the probability distribution function of the D series is provided by the following equation:

$$F(x) = \left[1 + \left(\frac{\alpha}{x - \gamma} \right)^{\beta} \right]^{-1} \tag{11}$$

With $F(x)$, the SPEI can be acquired as the standardized values of $F(x)$ in the Eq. 12:

$$SPEI = W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \tag{12}$$

where $W = V\text{-}2 \ln(P)$ for $P \leq 0.5$ and P is the likelihood of exceeding a measured D value, and $P = 1 - F(x)$. If $P > 0.5$, then P is substituted by $1 - P$ and the sign of the subsequent SPEI is retreated. The constants are C0 = 2.515517, C1 = 0.802853, C2 = 0.010328, d1 = 1.432788, d2 = 0.189269, and d3 = 0.001308.

Computation of precipitation anomaly

The percentage of precipitation anomaly (Pa) is computed by the following Eq. 13 (Ma et al. 2021),

$$Pa = P - P_0/P \times 100\% \tag{13}$$

where P is the mean monthly or annual precipitation.

Mann Kendall test

Mann (1945) proposed the Mann Kendall (MK) test, and Kendall (1975) modified this test, which now has widely been used for exploring the trend of time-series data (Salam et al. 2020b; Islam et al. 2021a; Pham et al. 2021). The MK test does not assume any data distribution. Besides, the potential nosiness of outliers can be avoided. However, the MK test requires data free from serial correlation. The present study used the MK test for identifying the trend in drought events. The statistical expression of the MK test is as follows:

$$S = \sum_{k=0}^{n} \binom{n}{k} x^k a^{n-k} \tag{14}$$

where xj are the sequential data values, n is the length of the data set, and

$$\text{sgn}\left(x_j - x_i\right) = \begin{cases} 1 \text{ if } x_j > x_i \\ 0 \text{ if } x_j = x_i \\ -1 \text{ if } x_j < x_i \end{cases} \tag{15}$$

When $n \geq 8$, the statistic S is about normally distributed, with the mean and the variance as expressed by the formulas:

$$E(S) = 0 \tag{16}$$

$$V(S) = \frac{n(n-1)(2n+5) - \sum_{m=1}^{n} t_m m(m-1)(2m+5)}{18} \tag{17}$$

where tm is the number of extent m. The standardized test statistic Z is computed by the equation:

$$Z = \begin{cases} \frac{S-1}{\sqrt{V(S)}} & S > 0 \\ 0 & S = 0 \\ \frac{S+1}{\sqrt{V(S)}} & S < 0 \end{cases} \tag{18}$$

For significance levels, 0.01, 0.05, and 0.1, |Zα| are 2.58, 1.96, and 1.65, respectively.

Multiple linear and polynomial regression models

Multiple linear and polynomial regression methods are often used to determine governing factors from many variables. These are also used for getting the significant level of the variables (Thompson 1995). The statistical form of the linear regression can be expressed by the equation:

$$SP = b_0 + \sum_{i=1}^{P} b_i \times V_i \tag{19}$$

where b_0 denotes constant, V_i indicates the vector of ith, and bi implies the coefficient of ith pattern, and P is the number of determinants.

The function to fit a k order/degree of the polynomial is expressed as follows:

$$Y = b_0 + b_1 x_1 + b_2 x_{2^2} + b_k x_{k^k} \tag{20}$$

where Y is predicted outcome value, b_1 to b_k denotes the coefficients of the variables, and b_0 is the intercept of the Y.

Pearson correlation coefficient

Pearson's linear correlation coefficient (r) estimates the degree of linear correlation between two quantitative parameters (Eq. 21). It is a unitless index with values between $-1 \leq r \leq 1$, representing the degree of association between two datasets (Salam et al. 2019).

$$r = 1 - \frac{\sum_{i=1}^{n} \left(x_i - \bar{x} \right)\left(y_i - \bar{y} \right)}{\sqrt{\sum_{i=1}^{n} \left(x_i - \bar{x} \right)^2 \sum_{i=1}^{n} \left(y_i - \bar{y} \right)^2}} \tag{21}$$

The Pearson correlation was used in the present study to reveal the relation of SPEI and SPI with PET, Pa, ENSO, and IOD; Pa with ENSO and IOD.

Results

The regional distribution of SPEI and SPI

The long-term historical distribution of SPEI and SPI for the period 1980–2017 at the regional scale and the whole of Bangladesh are shown in Figs. 2 and 3, respectively. The short-term (3 and 6-month timescales) and long-term (12 and 24-month timescales) droughts are presented in those figures. The results showed that Region 1 (northeast) experiences the least drought in terms of both SPEI (Fig. 2) and SPI (Fig. 3). The region experiences only mild (SPEI and SPI value 0 to -0.99) drought. Region

Fig. 2 The regional variations of SPEI for **a** 3-month, **b** 6-month, **c** 12-month, **d** 24-month timescales during 1980–2017
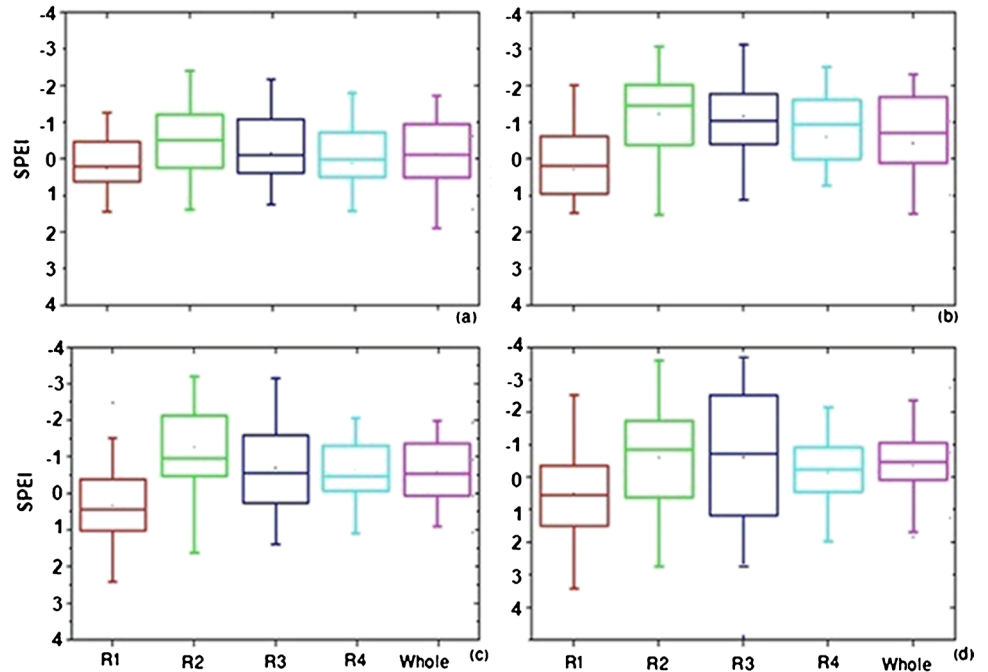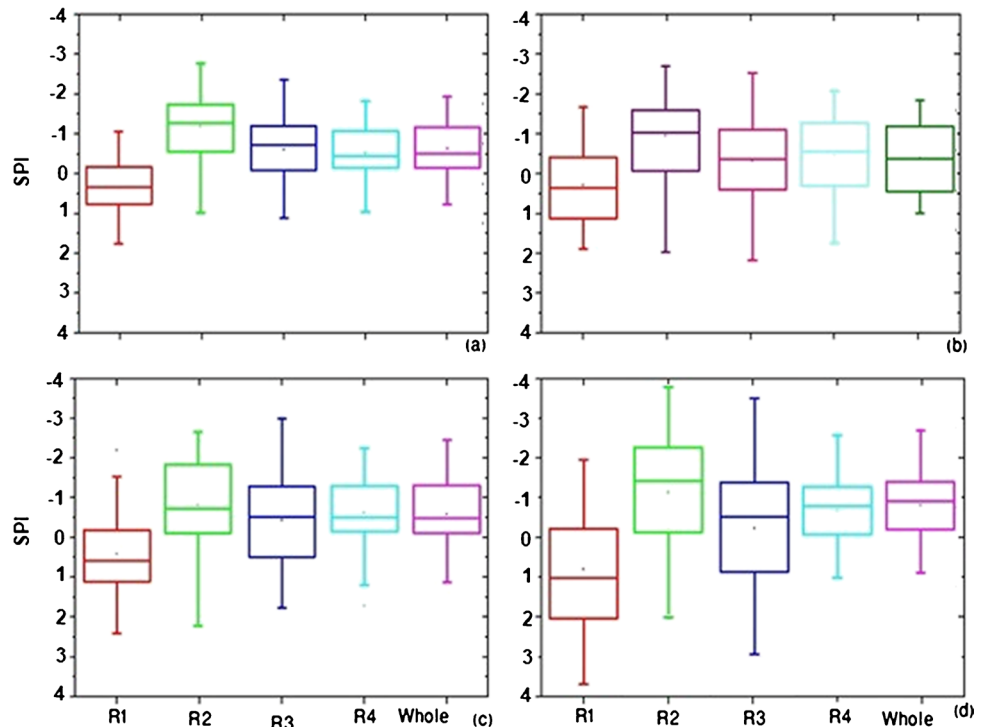
Fig. 3 The regional variations of SPEI for **a** 3-month, **b** 6-month, **c** 12-month, **d** 24-month timescales during 1980–2017

2 (northwest) experiences moderate (SPEI and SPI value − 1.00 to − 1.49) drought only at a 3-month time-scale, based on both the SPEI and SPI. The R2 also experiences mild to severe (SPEI and SPI value − 1.50 to − 1.99) droughts based on 24-month SPEI (Fig. 2d), 6-month SPI (Fig. 3b), and 12-month SPI (Fig. 3c). The rest of the indices (6 and 12 months of SPEI; 24 months of SPI) showed mild to extreme (SPEI and SPI value ≤ − 2) droughts in R2. For different timescales, the SPEI and SPI showed mild to moderate droughts in region 3 (Central), except for SPEI for 6-, 12-, and 24-month, which led to mild to extreme droughts.

Region 4 (Southern) experiences mild to moderate drought for both SPEI and SPI and all timescales except for SPEI 3 (mild drought) and SPEI 6 (mild to severe drought) (Figs. 2 and 3). On average, the whole country suffers from mild to moderate droughts for all the timescales, as shown in Figs. 2 and 3. Overall, most of the droughts occur in R2, followed by R3, R4, and R1.

Spatiotemporal distribution of drought indices

Figures 4 and 5 show temporal variation of both short- and long-term SPEI and SPI, respectively, for the period 1980–2017 in 4 climatic regions and the whole of Bangladesh. Like the regional variation, more frequent and intense drought events occur in R2 for all timescales and both indices, except SPEI 24, which is found more in R3. All the

regions suffered moderate to extreme drought in 2010, as presented in Figs. 4 and 5.

Figure 4 shows the temporal evolution of SPEI at the 3- (SPEI-3; Fig. 4a), 6- (SPEI-6, Fig. 4b), and 12- (SPEI-12, Fig. 4c) and 24- (SPEI-24, Fig. 4d) month time scales, averaged over Bangladesh for the period 1980–2017. The figures show short-term droughts in the years 1990 and 2010 (SPEI median: − 0.526 and − 0.582) in the North-western region (R2), whereas wet conditions during 1987–1988 (SPEI median: 0.865 and 0.923) in the North-eastern region (R1). Similarly, long-term droughts in the years 2010 and 2012 (SPEI median: − 0.562 and − 0.543) in the North-western region (R2), whereas wet condition in the year s1988 (SPEI median: 0.895 and 0.952) in the North-eastern region (R1). The more widespread droughts were in 1990, 2010, and 2012 (Fig. 4), which affected more than 20% of the country in some consecutive months.

Figure 5 exhibits the temporal variation of SPI at the 3- (SPI-3; Fig. 5a), 6- (SPI-6, Fig. 5b), and 12- (SPI-12, Fig. 5c) and 24- (SPI-24, Fig. 5d) month time scales over Bangladesh for 1980–2017. The monthly time series of SPI-3 and SPI-6 showed the dominance of drought conditions during 1994–1995 (SPI median: − 0.623 and − 0.674). Besides, the monthly time series of SPI-12 and SPI-24 exhibited a predominance of drought conditions during 1994–1995 and 2009–2010 (SPI median: − 0.514 and − 0.453). It is worth mentioning that drought conditions were comparatively regular in the North-western region, mainly since 1994, though their intensities differ for different timescales. These results

Fig. 4 The temporal variations of SPEI for **a** 3-month, **b** 6-month, **c** 12-month, **d** 24-month timescales during 1980–2017
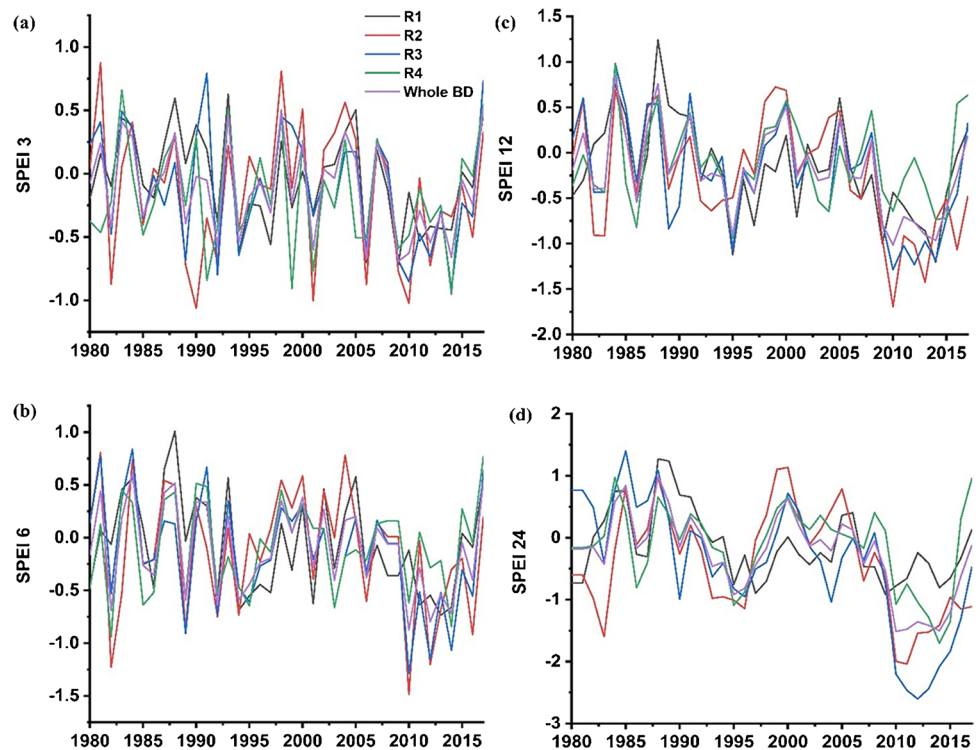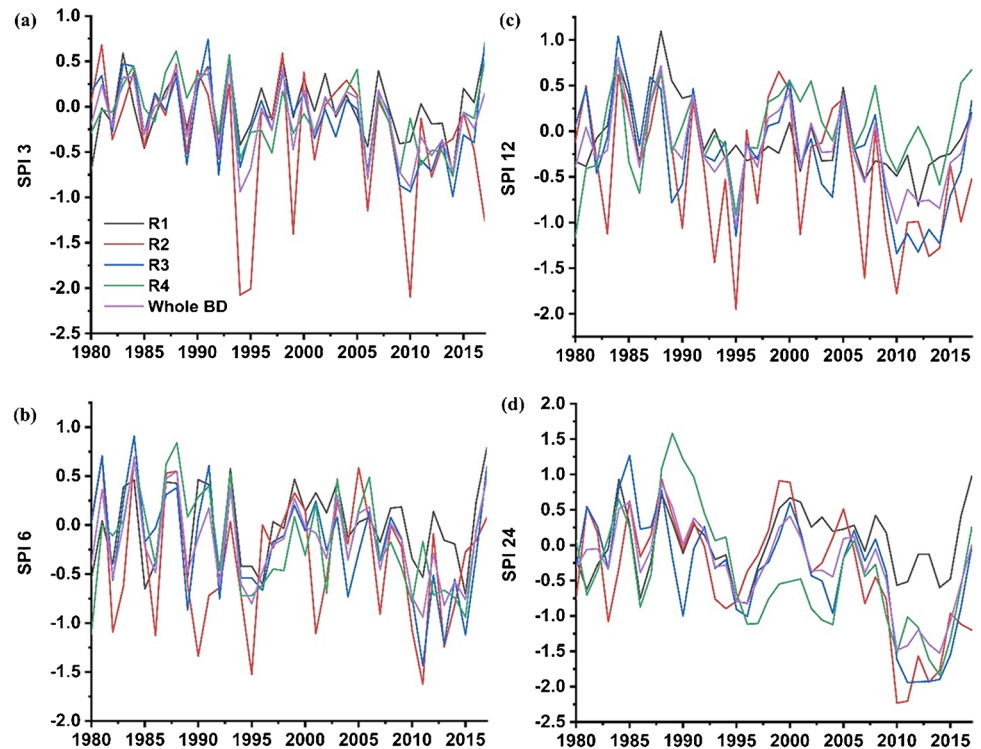
Fig. 5 The temporal variations of SPI for **a** 3-month, **b** 6-month, **c** 12-month, **d** 24-month timescales during 1980–2017

indicate the influence of large-scale circulation in severe drought occurrence, such as the impact of the Indian Ocean variability on rainfall patterns in Bangladesh.

The long-term (1980–2017) trends in historical SPEI and SPI, estimated using the MK test, are represented in Figs. 6 and 7. The positive values of Z indicate an increasing trend of drought and vice-versa. The short-term drought based on SPEI-3 revealed significant rising trends in droughts ($p < 0.05$) at two locations, Jashore and Rangpur. The SPEI-12 and SPEI-24 showed an increasing trend at Jashore and Rangpur at $p < 0.01$ and Rajshahi and Bogura at $p < 0.05$ (Fig. 6). The SPEI for all timescales showed an increasing trend in Mymensingh, Dhaka, and Faridpur stations. The spatial distributions of SPI for different timescales are shown in Fig. 7. The SPIs for all timescales showed an increase in Jashore at $p < 0.01$ ($Z > 3.17$) and in Rajshahi and Bogura at $p < 0.05$. The SPI-3 and SPI-6 showed increasing trends in Rangpur at $p < 0.05$, and SPI-12 and SPI-24 trends at $p < 0.01$ (Fig. 7). Like the SPEI, the SPI also showed increasing tendency at Mymensingh, Dhaka, and Faridpur.

Teleconnection of drought indices with large-scale atmospheric circulation.

The ordinary linear regression was used to explore the association between SPEI and SPI. The association between SPEI and SPI for 3-, 6-, 12-, and 24-month timescales for the period 1980–2017 is shown in Fig. 8. The SPI values estimated at all the stations were averaged to

assess the association for the whole of Bangladesh. The 12-month SPEI and SPI showed the highest correlation coefficient ($R^2 = 0.91$, very strong correlation), followed by the correlation for 24-month ($R^2 = 0.62$, strong correlation), 3-month ($R^2 = 0.43$, strong correlation), and 6-month ($R^2 = 0.26$, moderate correlation). We found a strong correlation between SPEI and SPI for a longer timescale (12 months) and a lower correlation for shorter timescales (3- and 6-month time scales). Our results are in line with Tirivarombo et al. (2018). According to Tirivarombo et al. (2018), SPI and SPEI have a lower correlation for a shorter period. Meteorological droughts are generally followed by agricultural droughts, which SPEI can capture better. Therefore, SPEI has a stronger correlation for longer timescales than SPI.

Table 1 represents the correlation of SPEI with PET, Pa, and ENSO for different timescales. Only region 2 (North-western) at 3-month timescale showed a significant ($p < 0.05$) negative correlation ($r = -0.524$) with PET. The rest of the regions and whole of Bangladesh showed no significant correlation with PET. The SPEI-3 and SPEI-6 showed a significant ($p < 0.05$) positive correlation ($r \geq 0.5$) with Pa in all the regions (except R4) and the whole of Bangladesh. The correlations of SPEI for longer periods (12- and 24-months) with Pa were significant only for R3 and R4 and the whole of Bangladesh. There was no significant correlation between SPEI of any timescale with ENSO, indicating no influence of ENSO on SPEI for both short- and long-term droughts in Bangladesh.

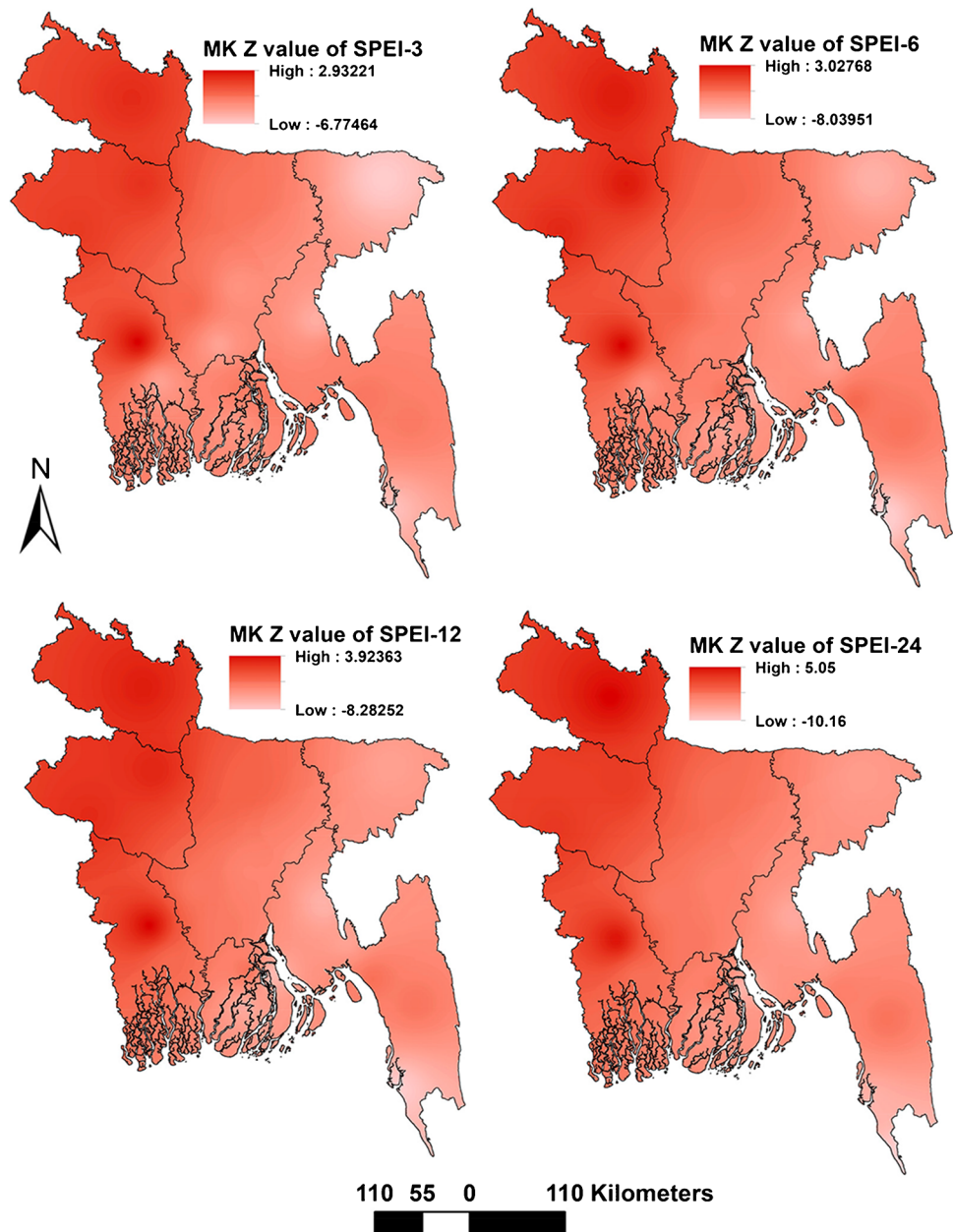**Fig. 6** The spatial distribution of MK-Z statistics of SPEI trends for different timescales

Table 2 represents the correlation of SPI with PET, Pa, and ENSO for different timescales. Like the SPEI, the SPI showed an insignificant negative correlation with ENSO and PET (except in region 2 for the 3-month timescale). SPI showed a significant ($p < 0.05$) negative correlation ($r = -0.533$) with PET in R2 for the 3-month timescale. Significant (< 0.05) positive correlation ($r \geq 0.5$) with Pa was for SPI 3- (R1, R2, and R3), 6- (R3), and 12- (R3) month timescales. The ENSO showed a weak association with SPEI and SPI in Bangladesh; however, the association of ENSO with SPEI was relatively stronger than SPI in the regional scales.

The graphical presentation of the correlation of SPEI, averaged for whole Bangladesh with IOD is shown in Fig. 9. There was no significant positive association between SPEI and IOD (Fig. 9). The R^2 value indicated an insignificant negative correlation between SPEI and IOD for all the timescales. The ENSO showed a weak association with SPEI and SPI in Bangladesh; however, the association of ENSO with SPEI was relatively stronger than SPI at the regional scales.

Like Fig. 9, Fig. 10 demonstrates the graphical presentation of the correlation between SPI and IOD. The result showed an insignificant negative correlation between SPI and IOD in Bangladesh for all timescales.

Fig. 7 The spatial distribution of MK-Z statistics of SPI trends for different timescales
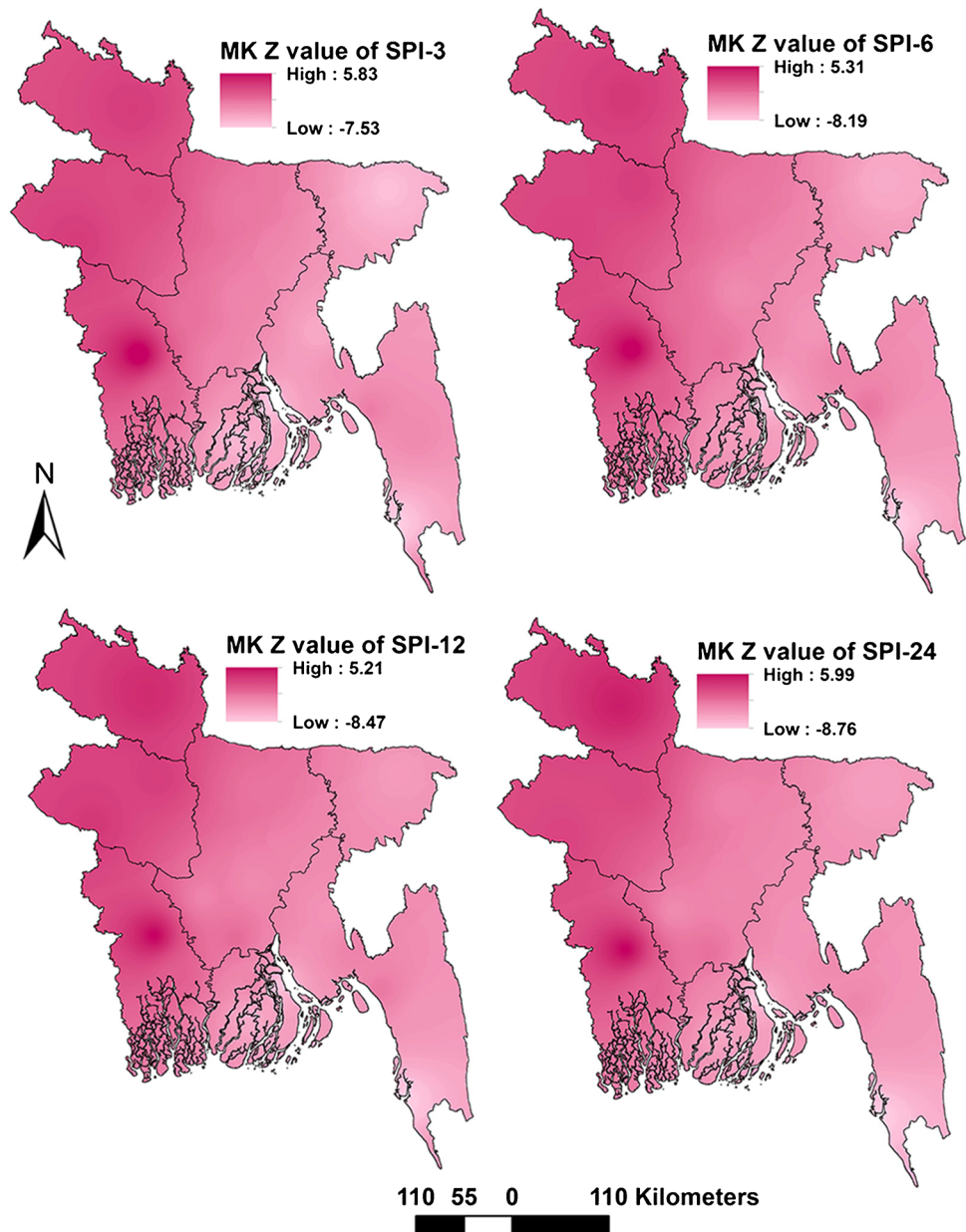

Table 3 depicts the correlation of Pa with ENSO and IOD in different regions of the country. The Pa showed insignificant negative correlation with IOD ($r = -0.04$) and ENSO ($r = -003$) in R1. The rest of the regions and the whole of Bangladesh (Table 3) showed an insignificant positive correlation of Pa with ENSO and IOD. The highest insignificant negative correlation was in the Northwestern region (R2). Figure 11 represents the polynomial regression results between SPEI-3 and IOD. The results showed that IOD can explain 4.7% of SPEI variations compared to 4.2% for SPI-3. The correlation coefficients indicate the possibility of estimating SPEI and SPI from IOD.

Discussion

Unlike most other common disasters, direct and instant death is rarely a feature of droughts. However, droughts can have devastating consequences to environmental and socioeconomic conditions. Agricultural crop production is the most harshly affected sector of drought. Crop loss in a drought year may repeatedly decline 1/3 to 1/2 of the average yield, leading to local and regional food shortages and malnutrition (Kogan et al. 2019). Subsequent rises in the under-five death rate through malnourishment have been attributed to the drought (Delbiso et al. 2017). Drought

Fig. 8 The correlations between SPI and SPEI for 3-, 6-, 12-, and 24-month timescales in Bangladesh for the period 1980–2017
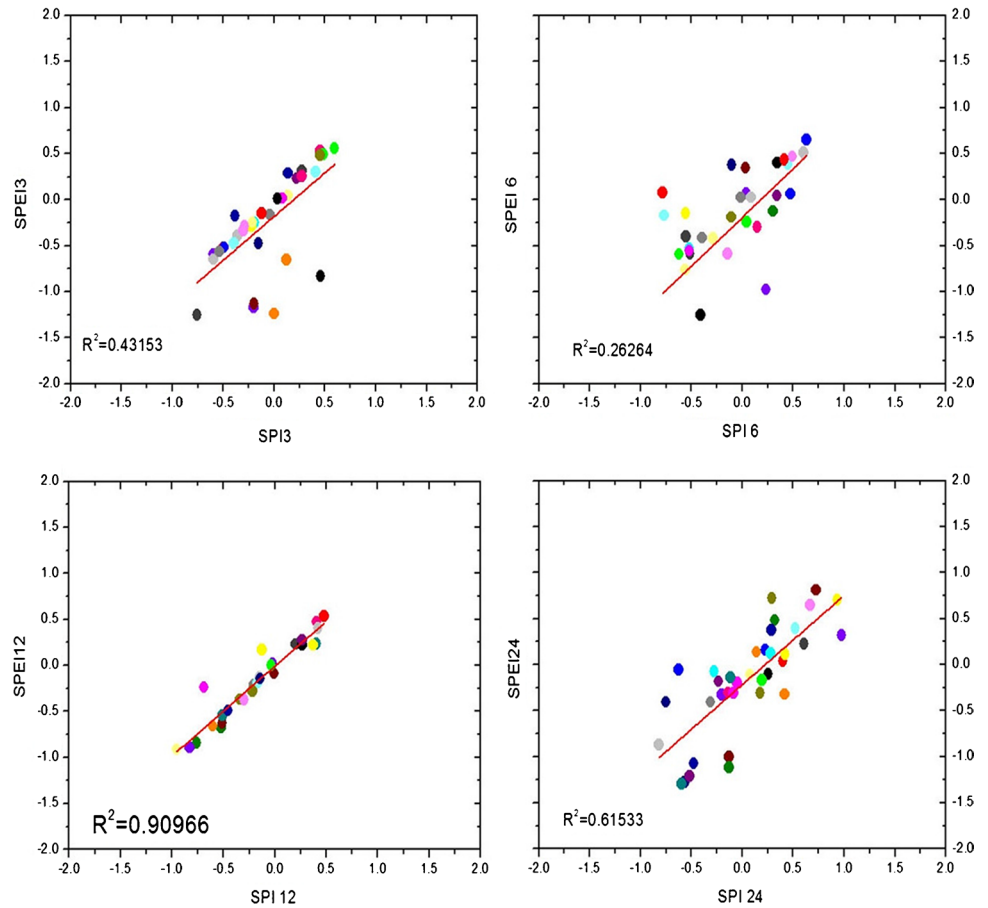

Table 1 Correlation coefficient of SPEI with PET, Pa, and ENSO for 3-, 6-, 12-, and 24-month timescales in different regions of Bangladesh

| Region	SPEI vs. PET				SPEI vs. Pa				SPEI vs. ENSO			
	3 M	6 M	12 M	24 M	3 M	6 M	12 M	24 M	3 M	6 M	12 M	24 M
1	− .299	− .386	− .369	− .386	.725*	.619*	.494	.407	− .055	− .004	− .128	− .142
2	− .524*	− .298	− .291	− .127	.697*	.502*	.351	.107	− .116	− .078	− .219	− .116
3	− .125	− .363	− .184	− .047	.744*	.654*	.500*	.286	− .163	− .143	− .138	− .263
4	− .186	− .192	− .192	− .173	.494	.585*	.580*	.139	− .099	− .096	− .203	− .286
Whole BD	− .320	− .188	− .189	− .194	.543*	.528*	.585*	.131	− .184	− .083	− .118	− .306

* Correlation is significant at $p < 0.05$

Table 2 Correlation coefficient of SPI with PET, Pa, and ENSO for 3-, 6-, 12-, and 24-month timescales in different regions of Bangladesh

Region	SPI vs. PET				SPI vs. Pa				SPI vs. ENSO			
	3 M	6 M	12 M	24 M	3 M	6 M	12 M	24 M	3 M	6 M	12 M	24 M
1	− .442	− .278	− .428	− .368	.716*	.382	.473	.452	− .027	− .162	− .086	− .168
2	− .533*	− .134	− .279	− .312	.790*	.392	.324	.199	− .045	− .154	− .154	− .174
3	− .408	− .136	− .109	.010	.810*	.628*	.523*	.249	− .124	− .126	− .193	− .265
4	− .329	− .114	− .143	− .064	.729	.472	.441	.056	− .041	− .032	− .106	− .269
Whole BD	− .375	− .148	− .188	− .064	.774	.509	.511	.056	− .040	− .062	− .171	− .269

* Correlation is significant at $p < 0.05$

Fig. 9 The correlations between SPEI and IOD in Bangladesh during 1980–2017
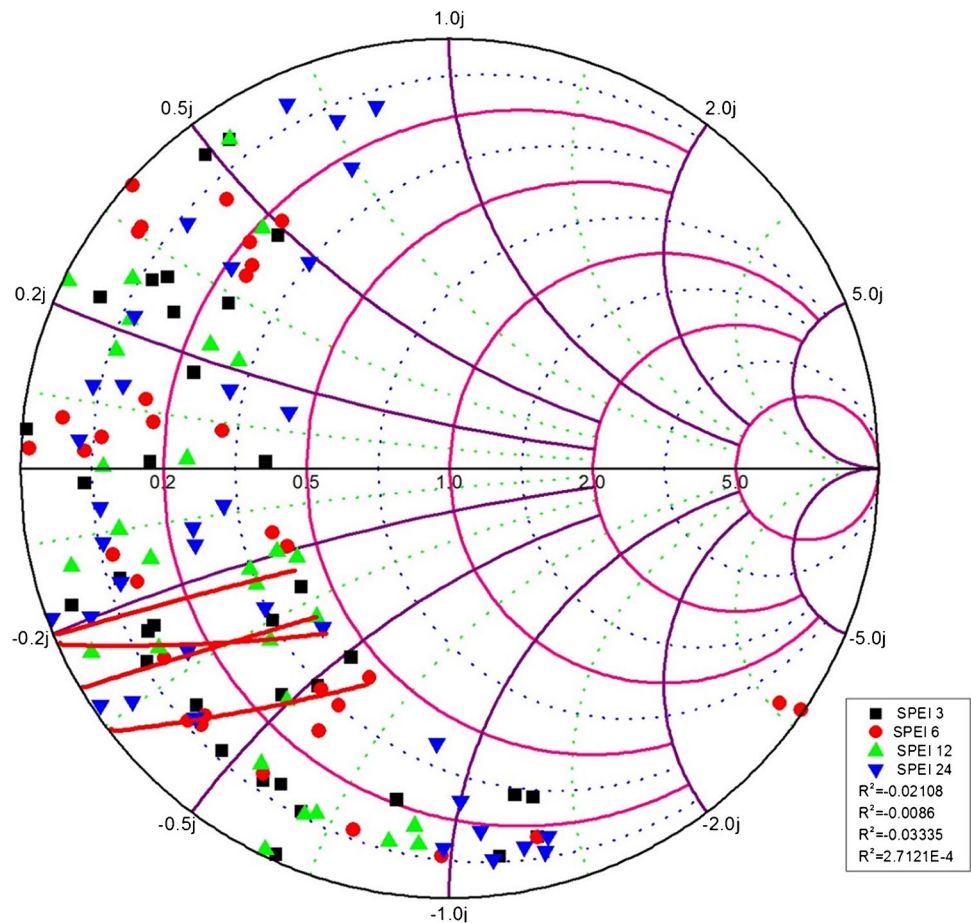
could bring detrimental effects to water resources, crop production, and the ecosystem (Wang and Rogers 2011; Sheffield et al. 2012). Because of these severe effects, severe droughts have gained a wide range of attention among scientists in the most recent period. In the context of climate change, drought risks are probable to rise in many historical drought-prone regions (Dai 2012; Kelley et al. 2015; Ault et al. 2016; Salam et al. 2021). For example, the mean annual temperature of Bangladesh increased significantly between 1988 and 2017 (Khan et al. 2019). The rainfall pattern also changed over time. The changes in temperature and rainfall have altered the drought risk in the country.

This study investigated the spatiotemporal distribution of droughts and their relationship with atmospheric oscillation indices. Both the SPEI and SPI showed a higher occurrence of droughts in the North-western region. For most timescales, it experiences mild to severe drought, except for 6- and 12-months of SPEI, and 24-month SPI droughts are mild to the extreme for the region. On average, moderate droughts are dominant in the area. Rahman and Lateh (2016) found similar results utilizing SPI and showed that the most drought-prone districts were Rangpur, Rajshahi, Bogura, and Kushtia (near the Jashore). The central region

is the second-most drought-affected region, followed by the Southern and North-eastern regions. The Rangpur district in North-western Bangladesh is the most drought-prone. Kamruzzaman et al. (2018) also showed that the Northern part of Bangladesh is more drought-prone than the Southern part, consistent with the present study results.

Spatial mapping of drought events exhibited extreme and severe droughts in Bangladesh during 1980–2017. The results showed region-wise increasing drought trends at the 3-, 6-, 21-, and 24-month timescales, but no trend in the extreme drought events regarding their spatial coverage, intensity, or duration during the study period 1980–2017. The outcome is consistent with the findings of previous studies (Salam et al. 2020a). The region-specific trend analysis revealed a significant ($p < 0.05$ and $p < 0.01$) increasing trend in droughts (both SPEI and SPI) in the North-western region and some parts in the Central and Southern regions. The increasing droughts in the most drought-prone region would make it more vulnerable. In recent years, the adverse impact of droughts on Bangladesh's water resources and ecosystems became visible. The riverbeds situated downstream of dams are filled with sediments due to the declining summer flows, and hydraulic congestion emerges during the rainy seasons (Abdullah 2014; Arnell and Gosling 2016). Bangladesh

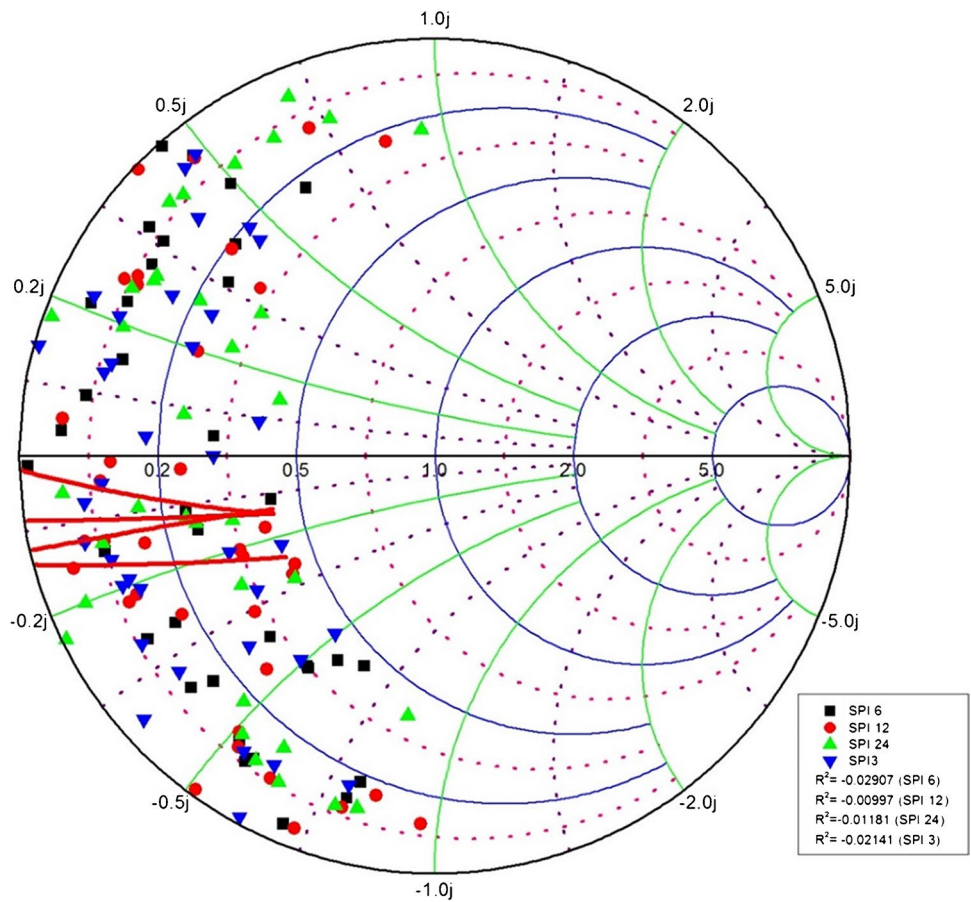**Fig. 10** The correlations between SPI and IOD in Bangladesh during 1980–2017

Table 3 Correlation coefficient of Pa with ENSO and IOD for different regions of Bangladesh during 1980–2017

Region	Pa vs. ENSO	Pa vs. IOD
1	− 0.003	− 0.038
2	0.133	0.155
3	0.029	0.078
4	0.045	0.011
Whole Bangladesh	0.045	0.011

has ranked sixth by the global climate risk index among the countries vulnerable to climate change (Harmeling and Eckstein 2012; Kreft et al. 2014). The increasing droughts indicate that Bangladesh's vulnerability to droughts is supposed to increase due to the combination of climate variability and their adverse environmental impacts. Many studies (Strzepek et al. 2010; Vicente-Serrano et al. 2010; Wilhite 2010; Dai 2011) have noticed notable effects of temperature and evapotranspiration on drought scenarios.

The present study showed a significant relation between SPEI and SPI. These two drought monitoring indices are also significantly correlated with Pa. Several previous studies showed the modulation of Pa has teleconnection to large-scale ocean–atmosphere oscillation (Wahiduzzaman 2012; Ahmed et al. 2017; Rahman and Islam 2019). On the other hand, SPEI and SPI showed no correlation with ENSO and IOD. Pa showed an insignificant poor relationship with ENSO and IOD. Like the present study, Gershunov et al. (2001) showed that the relation of the level of stochastic modulation of the ENSO and average Indian rainfall (AIR) is significantly lower. Ashok et al. (2001) and Wahiduzzaman (2012) also showed that the quantitative correspondence between the strength of ENSO and the rainfall in Bangladesh is very weak. Kumar et al. (1999) and Torrence and Webster (1999) also documented a weakening relationship between the Asian monsoon and ENSO.

The physics of the teleconnection of ENSO with the Asian monsoon rainfall has been well reported. However, earlier studies did not well deciphered ENSO linkage with drought and its spatiotemporal variability (Uddin et al. 2020; Zinat et al. 2020). The results of this study are in disagreement with Sun et al. (2016), where they found a strong association between climatic indices and drought in India. However, it is consistent with the findings of Ahmed et al. (2017) and Wahiduzzaman et al. (2020). Possible explanations for the negative relationships between drought indices and ENSO teleconnection may

Fig. 11 The polynomial regressing model showing a nonlinear relationship between IOD and short-term drought events in Bangladesh during 1980–2017
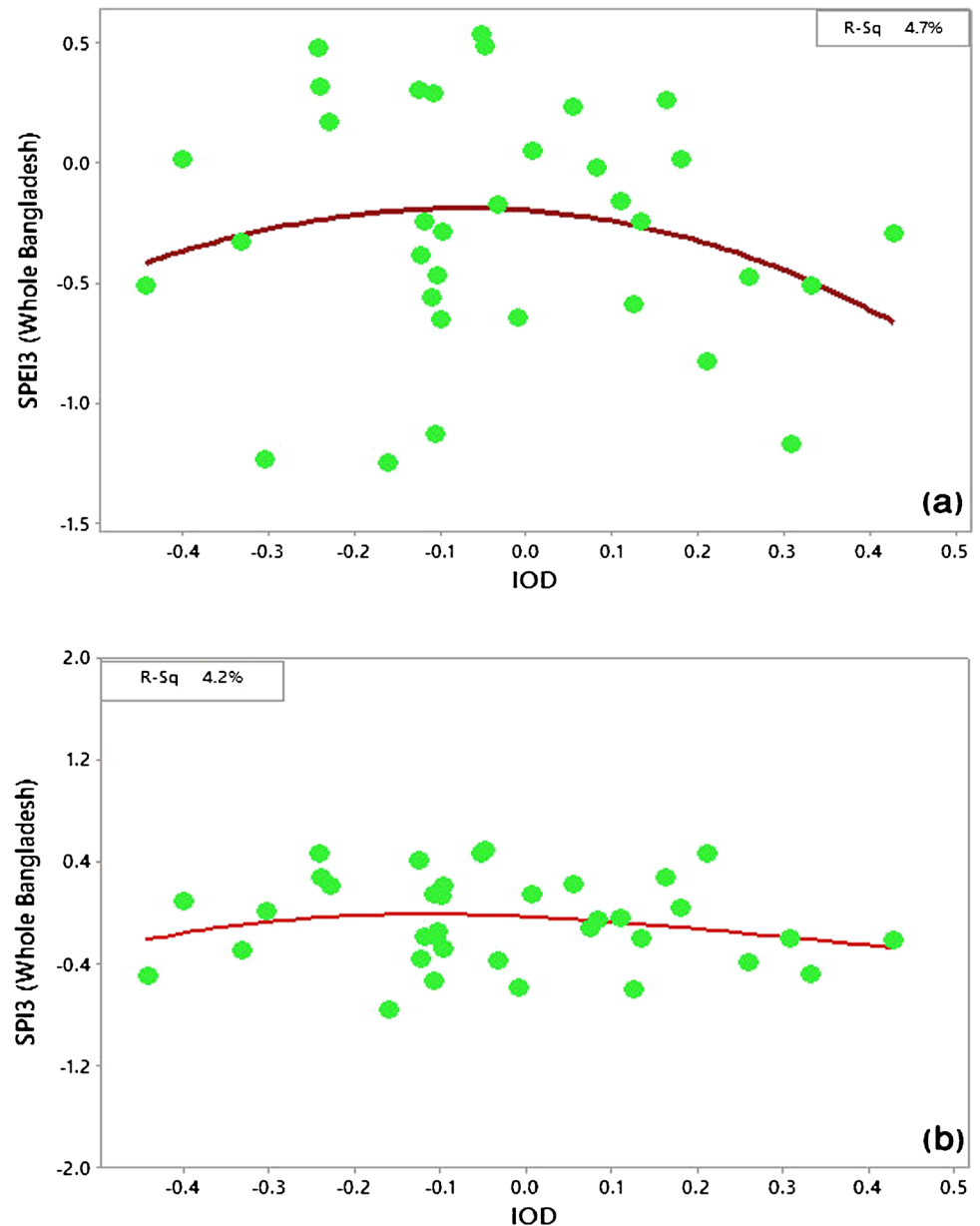
be due to higher air temperature leading to a decline in air–water potential. The increased evapotranspiration due to increased temperature (Galbraith et al. 2010) reduces air–water potential and causes a reduction of the effect of the large-scale circulation. Another reason for the negative correlation between ENSO and drought patterns is the integrated effects of distance from the Bay of Bengal, climatic anomalies, and hydro-geographic setting. Similar findings have been reported for many subtropical regions (Ahmed et al. 2017; Wahiduzzaman and Luo, 2020). Chowdhury (2003) indicated the minor role of ENSO in modulating local climatic variables in Bangladesh. Rahman and Islam (2019) showed that precipitation concentration in Bangladesh is insignificantly associated with

ENSO and IOD. The present study also showed a statistically non-significant negative correlation between drought indices and IOD in Bangladesh. The linkage of IOD with droughts has not been investigated before in Bangladesh.

The results presented in this study indicate the need for further exploration to understand the relationships between droughts and large-scale climate indices in Bangladesh. There are considerable uncertainties in the effects of ENSO on drought phenomena and how this relationship develops through time. For example, there were no clear spatiotemporal patterns in drought evolution during ENSO periods. This urge for further research related to ENSO. Future studies should also explore the physical characteristics (e.g., sea surface temperature, air pressure, wind speed, and moisture

flux patterns) during each ENSO event to evaluate how they evolve into drought pattern variation.

Conclusion

This study intends to evaluate the spatiotemporal variability of droughts in Bangladesh and its possible links with ENSO and IOD. The study identified droughts in Bangladesh in 1990, 1994, 1995, 2010, and 2012 and wet conditions from 1985 to 1988. North-western, central, and southern regions showed a significant increasing monotonic trend in SPEI and SPI droughts. Investigation of teleconnection of SPI and SPEI with IOD, ENSO, and PET indicates no significant correlations for any timescales, suggesting a very week linkage between droughts in Bangladesh and large-scale oscillation mode. The precipitation anomaly showed a significant association with SPEI and SPI, and no association with ENSO and IOD. Overall, the present study demonstrated that drought conditions have been worsening over the country, especially the North-western region, in terms of spatial variation, particularly for shorter timescales. A medium recurrence of short-term and long-term droughts in the North-western and Central parts of the country can have vital implications in socio-economic sectors, such as rainfed agricultural crop production. The spatial and temporal variations of droughts for different timescales provided a helpful guide to understanding drought features and formulating comprehensive management approaches to overcome the drought problem in Bangladesh effectively. These outcomes may also aid in sustainable agricultural planning in Bangladesh, taking immediate action to manage regional drought conditions and lessen their detrimental impacts. Though drought events cannot be directly identified as flood events, their consequences are much higher than the losses triggered by floods. Therefore, an efficient drought monitoring system requires to be adopted to mitigate drought effects. There is yet no agreement on the global drought pattern, so more study is highly recommended, particularly at local and regional levels. Besides, drought specialists should play a vital role in giving information using various indices at multi-time scales that are most appropriate for their particular application. However, the reason for higher drought occurrence in the North-western than other regions is still unclear. This deserves future work to improve our understanding of how climatic mode affects the distribution of severe droughts in Bangladesh.

Data availability Data are available upon request on the corresponding author.

Code availability Codes are available based on reasonable request on the corresponding author.

Declarations

>Ethical approval Not applicable.

Consent to participate Not applicable.

Consent to publish Not applicable.

Competing interests The authors declare no conflict of interest.

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