Future changes in meteorological drought characteristics over Bangladesh projected by the CMIP5 multi-model ensemble

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Abstract

Drought is an inconspicuous natural disaster. In a warmer world, the severity and coverage of drought are expected to change, and it is essential to study these changes at smaller scale. This study detected changes in drought frequency, severity, and intensity in Bangladesh from a bias-corrected CMIP-5 multi-model projection of 11 members under a business-as-usual RCP8.5 scenario. We have used two well-known meteorological drought indices, Standardized Precipitation Index (SPI) and Standardized Precipitation and Evaporation Index (SPEI). SPI is solely based on precipitation, while SPEI considers climatic water balance and incorporates the effect of temperature. Two different methods of estimation of potential evapotranspiration (PET), namely Thornthwaite and Hargreaves methods, are explored. SPEI-based drought identification is found to have high sensitivity among these PET estimation methods. In Bangladesh, SPI-based analysis suggests virtually no change in the long-term drought (12-monthly) condition and a minor change in short-term (6-monthly or less) droughts. SPEI evaluated with Hargreaves method projects a similar scenario for long-term droughts but an increase in both drought frequency and severity in short timescales. At seasonal scale, winter and pre-monsoon are projected to be potentially more affected by water stress in the future. A spatially coherent shift in wet-dry regime is also found over the northern part of Bangladesh under the warming world.

Keywords Climatic change · Drought · RCM · RCP · SPI · SPEI · Multi-model ensemble

Highlights
• Multi-model ensemble projections of meteorological drought over Bangladesh
• Hargreaves method underestimates droughts compared to the Thornthwaite method due to the low climate sensitivity in the DTR
• Short spell drought (< 6 months) is also projected to become more severe in the future
• In the pre-monsoon season, a spatially coherent dry-wet regime shift is projected between near and far future
• Drought severity will continue to increase in the south-west region throughout the century
• The north-west region will become wetter while the south-central region will become drier by the end of the century

1 Introduction

Drought is one of the costliest of all the natural disasters, and the effectiveness of managing drought is a major concern (Wilhite et al. 2014). It is a rare kind of disaster that sometimes passes by without even noticing it (Shaw and Nguyen 2011). Unlike all other destructive events like floods, cyclones, earthquake, or thunderstorm, the damage due to drought is mostly nonstructural. Paulo et al. (2012) identified drought as both disaster and hazard because of the uncertainty related to the climate system. The onset and occurrence of droughts are very challenging to identify because of the lack of a definition, which covers the full scope of a drought event from meteorological to social aspect as well as the relation to geographic location (Wilhite 2000). Among various branches of the scientific community, the definition of drought is a highly debated topic (Tate and Gustard 2000). Meteorological drought is defined as the departure of precipitation from the climatologic normal condition. On the other hand, the hydrologists define drought as an event where the competition from hydrologic elements gets intensified due to lack of precipitation, which is termed as hydrological drought (Nalbantis et al. 2009; Tallaksen and Van Lanen 2004). In agriculture, which interacts directly with the natural–physical systems, the deficiency of soil and groundwater, which creates stresses for the crops, defines the agricultural drought. If drought is caused by a lack of supply of economic goods such as water, food grains, and irrigation than its demand, it can be termed as socio-economic drought. While it is one step forward to describe the drought using geophysical characteristics, human intervention, societal response, and adaption under the current climate, it is too complicated to adopt it for application in a future climate scenario because of the uncertainty in the anthropogenic activity in the future (Van Loon et al. 2016). Ahmadalipour et al. (2017) showed that meteorological and hydrological droughts will be increased in the future, while the meteorological drought does not indicate aggravation. Oloruntade et al. (2017) revealed that hydrological droughts are more affected by temperature (warming) than precipitation (drying) in the Niger-South Basin, Nigeria. However, Duan and Mei (2014) urged that uncertainty arises in responses to climate change that propagate from meteorological to hydrological and agricultural systems. Here we study the two most important processes for drought in the future, namely precipitation and evaporation. Our estimation, in turn, amounts to only the meteorological drought. This study provides a starting point to assess the potential future characteristics of drought over an area, particularly countries like Bangladesh, which are vulnerable to the impacts of climate change.

Global warming and the associated changes in the climatology of temperature and rainfall in the observed frequency and severity have increased in many parts of the world (Solomon et al. 2007; He et al. 2013). According to Pachauri et al. (2014), the predicted climate trend shows a global temperature rise of 0.3–4.8 °C. Warming of the globe can impact several aspects including the weather, the hydrology, the ecology, and the environment. IPCC (2019) reports significant observed trends in temperature and rainfall all over the globe; however, the global average and regional average rate are not similar. Due to regional and local geographical features, local climate may face very different change than the global average change. The regional differences in climate ask for the assessment of climate change and related impact studies in local scales to better understand the variability of the projected climate and the mechanisms that are in place.

Bangladesh is expected to face an enormous challenge from climate change (Solomon et al. 2007; Rahman 2013). Regionally, the climate models predict a higher rate of warming for Bangladesh than global average (Shahid 2010; Rahman and Lateh 2016). A very dense

population supported by an economy based on agriculture aggravates this even further. As agriculture needs water and suitable climate, a change in climate and the associated change in the rainfall and temperature can lead to intensified droughts. Due to urbanization, as well as an increasing trend in population, Bangladesh is currently undergoing a very rapid change in the land-use pattern. With development comes the demand for water and consequently increase in vulnerability to drought (Vörösmarty et al. 2000; Wada et al. 2013). In recent years, due to water management in upstream of major rivers, Bangladesh has faced a shortage of water supply in the winter and pre-monsoon seasons. The rivers are losing their channel depth due to a low volume of water and sedimentation. Change in land use and covering the land will make the groundwater recharge harsh and thus lower the groundwater level. On the other hand, increased water demand associated with development will put more demand on already overstressed groundwater resources. Drought not only causes a significant loss of crops but also covers a broader area affecting more farmers (Brammer 1987).

Although floods and cyclones attract the most attention from the researchers, drought afflicts Bangladesh as often as floods or cyclone (Brammer 1987). More recent research is reporting even more frequent occurrences, as high as once in two and a half years (Shahid and Behrawan 2008; Dash et al. 2012; Mondol et al. 2017). Major drought events are recorded in 1973–1976, 1978–1979, 1981–1982, 1992, and 1994–1995. The basis of the identification of these droughts is not the meteorological anomaly but also the stresses and losses from agricultural production, i.e., agricultural drought. Rahman and Lateh (2016) extended the list using SPI calculated from observed precipitation and pointed out that 1997, 1999, 2004, 2006, and 2009–2010 were also severely drought-affected years. Mondol et al. (2017) also report a similar result. Karim and Iqbal (2001) produced drought risk maps for winter, pre-monsoon, and monsoon seasons. They have also related drought risk classes to yield losses. For the four drought classes—slight, moderate, severe, and very severe—the respective percent yield losses for different crops are 15–20, 20–35, 35–45, and 45–70%. These studies, while technically studying the meteorological drought, does not use any drought index. Shahid and Behrawan (2008) carried out a drought risk assessment using SPI for the western part of Bangladesh. Rahman and Lateh (2016) analyzed the 3-monthly SPI of January and 3- and 6-monthly SPI of April. Using meteorological station data to calculate SPI, they have identified historical drought events and their extents. These studies concluded that northern and northwestern parts of Bangladesh are currently at the highest risk (Shahid and Behrawan 2008). In this study, we focus on the assessment of future meteorological drought in Bangladesh under the high-emission pathways of RCP 8.5, which represents the future world with a high emission of greenhouse gas and no application of mitigation measures. Hence, RCP8.5 scenario serves as a so-called "business as usual" scenario of the future without mitigation measures as suggested by Riahi et al. (2011). The objective of this study is to find out the impact of temperature and precipitation change on drought identification and the assessment of the future spatiotemporal variation of meteorological drought hazard over Bangladesh.

2 Data and methods

2.1 Study area

Bangladesh extends from 20°34′ to 26°38′ north latitude and 88°01′ to 92°41′ east longitude covering an area of 147,570 km^2 (Fig. 1). It is home to around 160 million people, which

amounts to an average population density of more than 1000 people per km². Bangladesh is mostly flat land and has a very dense river network due to being the outlet to three major river basins—the Ganges, the Brahmaputra, and the Meghna. Unlike many other countries in the tropical climate region, Bangladesh also observes high summer temperature with excessive humidity and heavy rainfall mainly during monsoon. According to the climate report published by Bangladesh Meteorological Department (BMD), there are four distinct seasons. These are the winter (Dec-Feb), the pre-monsoon (Mar-May), monsoon (June to September), and the post-monsoon (Oct-Nov). The monsoon season is also known locally as the rainy season. The season names accentuate the command of the monsoon in the region. Monsoon rainfall accounts for about 80% of the total rainfall. Because of this, the effect of the seizure of the average rainfall is not particularly evident during this season, but heavy and continuous rainfall cause riverine flooding. On the other hand, during the winter season, there is practically no rain. The pre- and the post-monsoon receives the rest of the precipitation, and the impact of the deviation from the normal condition is comparably higher for the hydrologic elements during these seasons.

2.2 Datasets

We have used the precipitation and temperature projections from an ensemble of 11 regional climate models (RCMs) driven by 8 global climate models (GCMs) to assess the meteorological drought (Supp. Table S1). Only the high-end extreme scenario at RCP 8.5 was considered to capture the extreme climate change conditions. Due to physical parameterization and approximation in numerical schemes, climate models are known to show systematic biases in the projection of the climate parameters. Notably, the precipitation estimation shows a
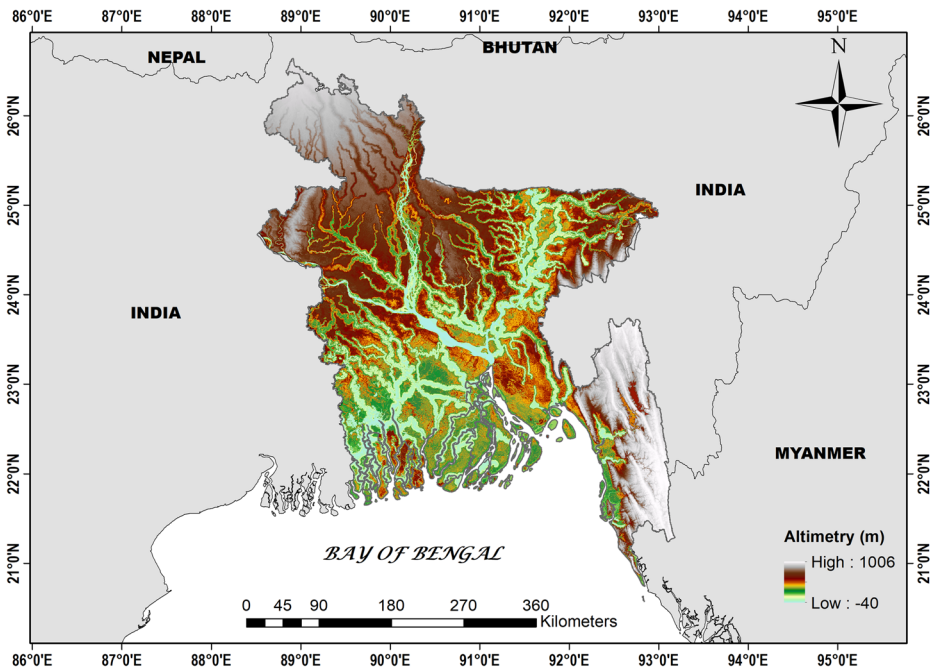

Fig. 1 Topography map of Bangladesh in meters

drizzle phenomenon, i.e., predicting rain when there is none. Under the initiative of the CORDEX project (Giorgi and Gutowski Jr 2015), a multi-segment statistical bias correction method was applied to the raw climate model data to overcome this issue (Grillakis et al. 2013). Commonly used quantile mapping approach fits one theoretical distribution to entire cumulative density function (CDF) of the climatic variable. In multi-segment approach, different instances of the distribution function are fitted to multiple segments of the CDF. This segmentation allowed a better transfer of the observed statistics to the RCM data. A hybrid dataset derived from ERA-40 and ERA-Interim developed by the Inter-Sectoral Impact Model Integration and Inter-comparison Project (ISI-MIP) was used for the bias correction. The corresponding reference period for bias correction was from 1981 to 2010. Before bias correction was applied, all data were interpolated to a common WFD/WFDEI latitude–longitude grid at 0.5° spacing. In the past, several studies have successfully used this dataset to study the climate change impact on basin flows or changes in temperature and precipitation over Bangladesh. For example, Mohammed et al. (2017, 2018) assessed future flood characteristics in the Ganges and Brahmaputra basin. Fahad et al. (2018) studied regional changes in precipitation and temperature over Bangladesh.

2.3 Meteorological drought indices

Rainfall anomaly is a logical starting point to assess the drought (Brammer 1987). It indicates the possible drought-affected area regarding the amount of rainfall. However, rainfall anomaly is not a normalized indicator, hence not comparable from one region to another. This problem is solved by developing indices derived from meteorological variables. Indicators play a crucial role in monitoring and systematic identification of drought (Dai 2013). Among many indices developed in last few decades, the most notables include Standardized Precipitation Index (SPI) (McKee et al. 1993), Standardized Precipitation Evaporation Index (SPEI) (Vicente-Serrano et al. 2010), Soil Moisture Index (SMI) (Nam et al. 2012), Multivariate Standardized Drought Index (MSDI) (Hao and AghaKouchak 2013), and Palmer Drought Severity Index (PDSI). The perception of the severity of the drought was detected by the chosen proxy (e.g., precipitation, evaporation, evapotranspiration, soil moisture) and the timescales (Sheffield et al. 2009). However, by comparing 6 drought indices, Bayissa et al. (2018) concluded that SPI and SPEI have the similar capability of identifying of historical drought events in the Upper Blue Nile Basin, although the identified onset varies from index to index. Lee et al. (2019) found the most comprehensive pattern with significant increases in the frequency and severity of droughts over Korea using SPEI. Here we have chosen SPI and SPEI to assess the projected drought condition of Bangladesh in a warmer world. A detailed description of SPI and SPEI calculation is provided in the supplementary materials.

Due to the similarity in philosophy, both the SPI and SPEI use the same classification criteria to identify different drought. We have presented the classification of SPI and SPEI index value in Table 1. The most important feature of the SPI and SPEI is the ability to mimic the timescale nature of drought. Mathematically, they can be evaluated in any timescale starting from 1 month. However, the 1-, 3-, 6-, 12-, and 24-month timescales are attested to be valuable in practice. One-month values indicate a short-term status, 3-month index reveals a seasonal view, and 12-month timescale reflects the annual hydrological condition of rainfall pattern. Short timescales are considered relevant for agriculture (1, 3, and 6 months), whereas long timescales are suitable for hydrology (12 months) and socio-economic studies (24 months) (Dutta et al. 2013; Lorenzo-Lacruz et al. 2010). In this study, 3- and 12-month

timescales are explored to assess the inter-seasonal and inter-annual drought condition, respectively.

To calculate SPI, we have used monthly rainfall time-series. On the other hand, SPEI is calculated from the climatic water balance between monthly rainfall and potential evapotranspiration. Potential evapotranspiration is defined as the water used by a hypothetical surface of the green grasses of uniform height, which is actively growing in an adequately watered condition. The actual evaporation depends on this demand as well as the availability of water. As the information of PET can help to identify the demand by the hydro-climatic system, an accurate estimation of PET is a very useful estimate in water management (Xu and Singh 2001).

Several methods are available to compute PET as a function of weather parameters. These methods can be classified as temperature-based, radiation-based, and their combinations. Among the temperature-based parameters, the Thornthwaite method is one of the simplest (Thornthwaite 1948). It uses the latitude to estimate the radiation from the sun and average temperature to calculate the potential evapotranspiration. Another widely used method is the Hargreaves method, which uses both maximum and minimum temperature as the input (Hargreaves 1994). A more physical based method to compute PET is Penman method (Penman 1948), which later updated and now widely used as the Penman-Monteith method (Monteith 1965). Food and Agriculture Organizations in the USA (FAO) suggests Penman-Monteith as the standard method of computing PET wherever the required input data are available (Droogers and Allen, 2002). However, Hargreaves method is suggested as the standard method when only temperature data is available. Studies show that the Hargreaves method provides a very close approximation to the Penman-Monteith methods (Xu and Singh 2001). On the other hand, the Thornthwaite methods can capture the intra-annual variation of the potential evapotranspiration, which can be helpful for low flow simulation over a semiarid Mediterranean basin (Marcos-Garcia et al. 2017). Because of the unavailability of all the parameters in the bias-corrected form in our dataset as well as relatively high confidence in the future projection of temperature, we have used Thornthwaite and Hargreaves method to calculate the PET under future climate condition and assess their impact on drought estimation.

2.4 Evaluation indicators for drought

For evaluation of drought, the starting and the ending of drought is needed to be defined based on the monitoring index. In this study, the starting of drought is considered when the SPI or SPEI fall below zero and goes beyond negative unity. We considered the end of a drought event with the return of the positive value. Based on this identification criterion for drought

Table 1 SPI- and SPEI-based drought classification

Drought category	SPI/SPEI values
Extreme wet	Index ≥ 2
Severe wet	$1.5 \leq$ Index < 2
Moderate wet	$1 \leq$ Index < 1.5
Near normal/mild wet	$0 \leq$ Index < 1
Near normal/mild drought	$-1.0 <$ Index < 0
Moderate drought	$-1.5 <$ Index ≤ -1.0
Severe drought	$-2.0 <$ Index ≤ -1.5
Extreme drought	Index ≤ -2.0

duration, the drought evaluation indices, namely severity and intensity, are defined. Severity (S) is the absolute sum of all SPI or SPEI values over drought duration (Eq. 1). We have considered the duration as the count of months between the starting and ending of a drought period excluding the last month when drought index became positive again. The intensity of drought (I_e) is the average SPI or SPEI over the drought duration (Eq. 2). Its value is an indication of the severity of the drought—the higher the intensity, the more severe the condition of drought.

$$S = \left| \sum_{i=1}^{n} \text{Index}_i \right| \tag{1}$$

$$I_e = \frac{S}{n}. \tag{2}$$

where n is the number of months, I_e is the drought intensity, and S is either SPI or SPEI values during the drought denoted by i. The average number of drought events during a specified time chunk is defined as the frequency (F) of drought.

3 Results and discussions

We have considered the time slice approach to analyze and present our results. Four so-called time slices, each 30 years long, have been considered in this study: historic (1981–2010), near future (2011–2040), mid future (2041–2070), and far future (2071–2100). We have divided our results and discussion into three parts. In the first section, we present the rainfall anomaly and evapotranspiration requirement during the historic time slice (1981–2010). We demonstrate the performance of the SPI, SPEI, and different method of evapotranspiration calculation in the identification of drought frequency. Section 3.2 shows the projected long-term change in rainfall and drought frequency, severity, and intensity over Bangladesh using a 12-month index value. Section 3.3 investigates the future changes in seasonal drought condition using drought indices evaluated at the shorter timescales.

3.1 Historic drought and rainfall condition

3.1.1 Rainfall anomaly and distribution

We start our discussion by presenting the spatial feature of rainfall distribution over Bangladesh as simulated in a bias-corrected dataset. Figure 2 shows the rainfall anomaly over Bangladesh in the winter season during the historic period (1981–2010). The anomaly is calculated by taking an average of the total rainfall amount during a month and then subtracting the average for the corresponding month. A positive anomaly indicates a positive deviation from the mean, whereas a negative anomaly shows the opposite. Rainfall anomaly indicates the regions where the rainfall is higher or lower than the average condition. The winter season is shown here particularly because historically during this season Bangladesh receives the least rainfall and shows a general

dryness of the hydrological elements (Shahid 2010). Along with the rainfall projection from the ensemble members, we have calculated the rainfall anomaly from CRUv4 dataset for comparison. From the rainfall anomaly of the winter season, the north-east region experiences a more than average rainfall where the north-west region shows drier condition than the rest of the country. A small portion of the south of the country also gets much less rainfall compared with the country average. A good agreement among the models as well as with CRU data during the historic period is also noted. A similar pattern of rainfall anomaly is also observed in the pre-monsoon, monsoon, and the post-monsoon seasons (see Supp. Fig. S1, S2, and S3). During the monsoon season, the west side of the country receives less rainfall compared with the country average rainfall during that season. The historic areal average rainfall is about 50, 550, 1950, and 230 mm for the winter, pre-monsoon, monsoon, and post-monsoon, respectively. The concentration of precipitation in the monsoon season is very clear from these values. Reportedly, post-monsoon and winter seasons account for only 10% of the total rainfall. About the same amount of rain is available for subsequent pre-monsoon season. The rainfall anomaly pattern of this study is similar to that reported by previous studies (Shahid and Behrawan 2008; Rahman and Lateh 2016; Mondol et al. 2017).

3.1.2 Evapotranspiration

We present the time series of PET and the ratio of precipitation and PET for the historic period in Fig. 3. We have calculated the yearly PET and ratio of PET and precipitation (henceforth PET/Precipitation) by taking the spatial average of yearly PET requirement and PET/Precipitation. PET is an indicator of the water demand by the atmosphere under standardized canopy condition. The PET/Precipitation value shows the ability of the atmosphere to provide the evapotranspiration requirement. A value of unity indicates that the amount of precipitation fully supplies the water demand by the atmosphere. Lower values suggest that the rainfall was not sufficient to meet the demand.

For the historic period (1981–2010), we found a noticeable upward trend from the ensemble of yearly PET requirement using the Thornthwaite method (Fig. 3a). We have used Sen's slope model for monotonic trend detection and Mann-Kendall trend test to find if the trends are significant. Thornthwaite PET has an increasing trend of 4.68 mm, which is significant at a 95% confidence interval. An increasing trend is also registered on the normalized PET with precipitation (Fig. 3b). On the other hand, virtually no trend in the PET, as well as normalized PET with precipitation, is observed using Hargreaves method as well as the trend is found to be not significant (Fig. 3c).

Thornthwaite-PET is modeled based on the average temperature and a crude estimation of solar radiation from the hours of daylight. While in Thornthwaite formulation solar radiation remains constants, due to global warming, the average temperature is rising and projected to rise throughout the century (Khan et al. 2020). Consequently, this rise in the mean temperature manifests itself as a rising trend in the future Thornthwaite-PET estimates. On the other hand, in Hargreaves-PET, solar radiation is modeled based on the difference between the maximum and minimum temperature, i.e., diurnal temperature range (DTR). During the historic period, Khan et al. (2019) did not find a coherent trend of DTR over Bangladesh. This low sensitivity of DTR to climate change explains the flat trend of the Hargreaves PET estimate during the historic period. Rahman et al. (2019) also found a negative trend in PET estimate during the historic period using observed data and Penman-Monteith method, which is in line with our
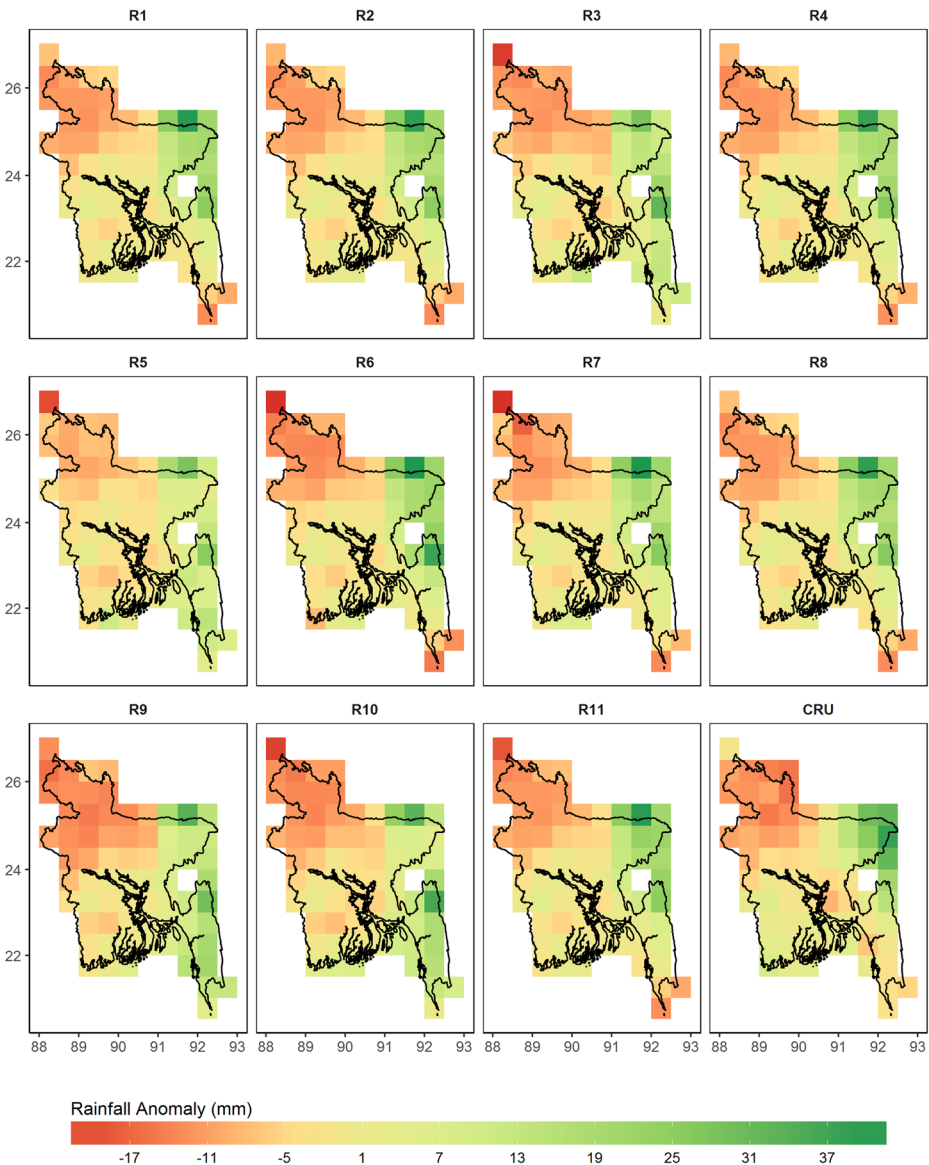
Fig. 2 Rainfall anomaly over Bangladesh as simulated by the ensemble of 11 Regional Climate Models (RCMs) in the winter season (December–February) during the historic period (1981–2010). The plots are identified in the title using the same identity in Supp. Table S1. The last panel shows the same quantity as the RCMs but derived from CRU v4 dataset. Red indicates the areas where the rainfall is lower than the average. Green pixels show the areas where the rainfall is higher than the average

PET estimate using the Hargreaves method. Aside from this difference in sensitivity of the formulations, the Thornthwaite method overestimates the PET by 100 mm compared with the Hargreaves method. Overall, Fig. 3 (see Supp. Fig. S5) illustrates that different estimation method of PET can have a substantial impact on the evaluation of water requirement and subsequent evaluation of water stress under current and future climate.
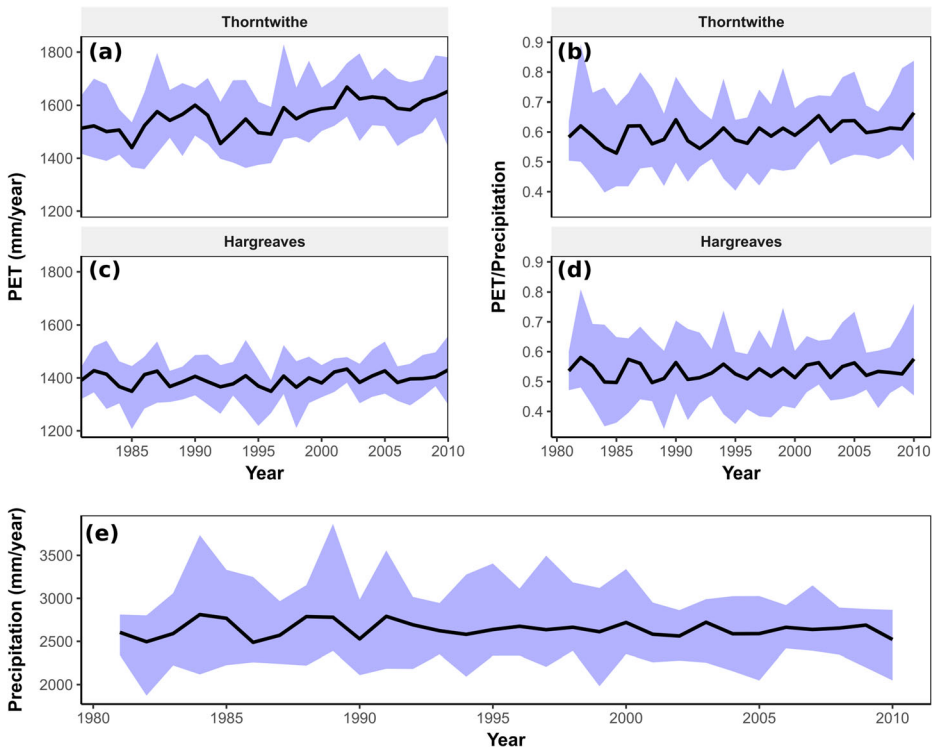
Fig. 3 Inter-annual variability of potential evapotranspiration and precipitation-PET ratio using the Thornthwaite method (**a**, **b**) and Hargreaves method (**c**, **d**). These quantities are calculated by spatially averaging the grid values over the country. The shaded blue patch shows the ensemble maximum and minimum values

3.1.3 Drought indices

We have considered the frequency of drought events in the observed period (1981–2010) to understand the ability of the model to reproduce the drought frequency. We relied on the previous literature for the number of observed drought events. Figure 4 shows the number of drought events calculated from the drought duration estimates at 12-month timescale. We selected 12-month timescale to identify drought events that may have caused agricultural as well and social problems enough to be noticed and historically recorded. This selection also reduces the variability, reflects the long-term effect, and provides a spatially coherent estimate. When calculating the number of events, we counted the number of drought events for each ensemble member and took the ensemble mean. As illustrated in Fig. 4, the number of events simulated by SPI, SPEI-Thornthwaite, and, SPEI-Hargreaves shows a very minor difference. In 30 years, the number of events varies from 9 to 13, which corresponds to one event in 2.5 years and consistent with the previous study by Mondol et al. (2017). The spatial distribution of SPI and SPEI-Hargreaves shows a similar distribution of the number of events. The central, north-western, and north-eastern parts are found to be more affected by drought. On the other hand, SPEI-Thornthwaite shows a slightly different pattern for the north-western part of the country and estimates a lower number of drought events. Previous studies showed the ability of SPI in detecting drought using meteorological station data

and found good agreement with the observed (Shahid and Behrawan 2008; Rahman and Lateh 2016). Above analysis using climate data in the historic period showed that SPEI has a similar ability. However, the choice of the estimation of PET plays an important role and affect the spatial distribution of the drought-affected area. Although there exist differences in the calculated drought frequency using both SPI and SPEI method, the drought frequency from climate models is comparable with the observed frequency during the historic period.

3.2 Future drought and rainfall condition

3.2.1 Future change in rainfall and temperature

The projected rainfall and temperature variability in the future is illustrated in Fig. 5. We have calculated the ensemble average seasonal rainfall and temperature anomaly relative to the historic period. A little or no seasonal change in median precipitation is projected but with increased variability in the future. The variability range is similar for pre- and post-monsoon, but the former one shows more negative variability than the latter. The variability is smaller for the monsoon season but similar to the post-monsoon pattern. On the other hand, average temperature anomaly shows a consistent increase in the anomaly during all seasons. The median change in temperature is higher during the post-monsoon and winter seasons. The temperature anomaly is comparably the same during the monsoon and the pre-monsoon season.

3.2.2 Long-term evolution of severity and intensity of drought

SPI and SPEI-Hargreaves have produced comparable results during the historic period as shown in previous sections. This does not, however, indicate the situation under a warming climate. To predict such changes, the 12-monthly index value has been calculated in December
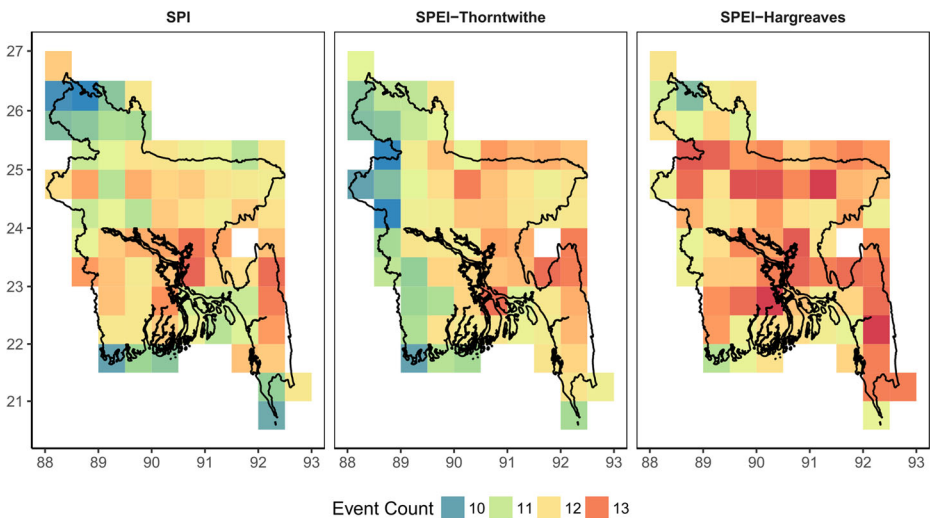

Fig. 4 The number of ensemble average drought events estimated from the 12-month value of SPI, SPEI-Thornthwaite, and SPEI-Hargreaves in the historic period (1981–2010)
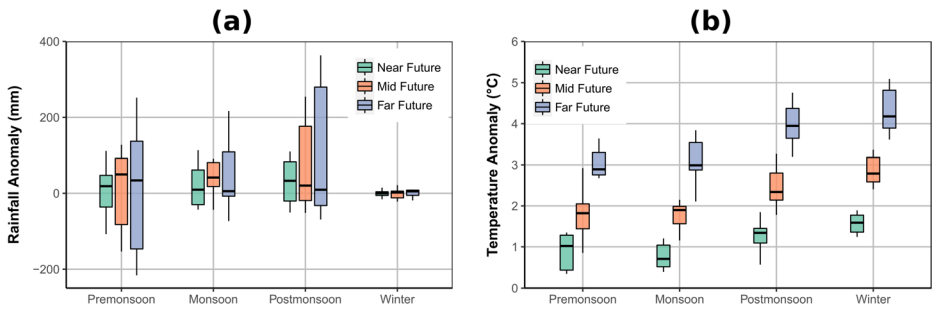
Fig. 5 Rainfall (**a**) and temperature (**b**) anomaly boxplot calculated from 11 RCM ensembles over Bangladesh for the pre-monsoon (March–May), monsoon (June–September), post-monsoon (October–November), and winter (December–February) in the near future (2011–2040), mid future (2041–2070), and far future (2071–2100) relative to the historic (1981–2010) period. The two edges of boxplot correspond to the 25th and 75th percentile of the anomaly distribution, and the middle bar indicates the median or 50th percentile value

starting from the historic period to the end of the twenty-first century. The intent of choosing a large timescale was to capture the inter-annual variability of the hydrologic condition. Annual value is also suitable to display when showing the trend for a very long time over an area. The country average value plotted against time (1981–2100) for both SPI and SPEI is shown in Fig. 6. SPEI-Thornthwaite shows strikingly different scenario compared with the SPEI-Hargreaves and SPI. An ensemble average, both of SPEI-Hargreaves and SPI indices, shows virtually no trend during the current century. On the other hand, SPEI-Thornthwaite shows a sharp downward trend indicating an increase in water scarcity to meet the demands of water usage within the country.

Figure 7 presents the probability distribution function of drought by taking index value as the random variable and plotting them for 4-time slices. The distribution of SPI and SPEI-Hargreaves shows a similar pattern and indicates that there is very limited or no response from the increasing temperature on the drought index value. SPEI-Thornthwaite shows a shift in the expected value of the distribution from near-normal condition to extreme drought. Thornthwaite method of PET calculation uses the average temperature only, and the errors associated with the Thornthwaite estimation are documented to be larger than the Hargreaves or Penman-Monteith method thus exacerbating the drought condition globally (Sheffield et al. 2012). Thus, for further analysis, we have chosen SPI and SPEI-Hargreaves methods to understand the seasonal change in drought coverage as well as the change in severity, intensity, and duration.

The number of drought events in each time slice, which is referred to here as frequency, is presented in Fig. 8. To calculate the frequency, we have first calculated the number of drought
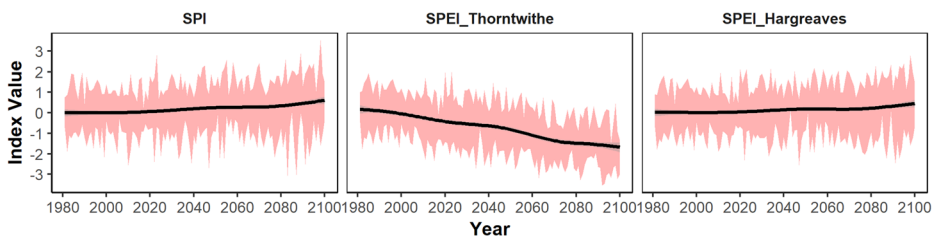

Fig. 6 Ensemble time series of 12-month SPI, SPEI-Thornthwaite, and SPEI-Hargreaves evaluated during December. The red patch shows the spreading between the ensemble members. The black line shows the ensemble average index value
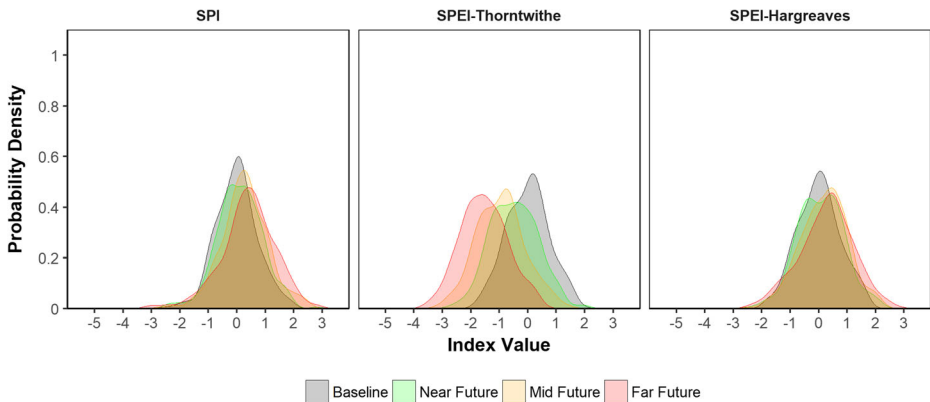
Fig. 7 The Probability Density Function (PDF) plot for 12-month SPI, SPEI-Thornthwaite, and SPEI-Hargreaves evaluated in December

events as described in the methodology section. After that, the average over the domain is calculated to find the drought frequency. For the sake of clarity, we are presenting here only SPI (Fig. 8a) and SPEI-Hargreaves (Fig. 8b). We have also considered four different time-scales—1, 3, 6, and 12 months. Other than the 1-month index, the median and spread among the ensemble member are similar. For the 1-month index, SPI simulates about 30% fewer events compared with SPEI. For all timescales, the ensemble variability is higher in SPI compared with SPEI. In Fig. 7, we noted that in longer timescales, the drought condition does not show an increasing trend. From Fig. 8, we can see the same for SPI-12 and SPEI-12. However, for shorter timescales, the models show an increase in the number of droughts over the period compared with the historic period.

We present the ensemble average total drought severity over a particular time slice in Fig. 9. SPEI-Hargreaves is considered for this plot as SPI shows a similar pattern. Severity calculated for 6-month SPEI is presented in Fig. 9a–d, and 12-month SPEI is presented in Fig. 9e–h. This figure illustrates that for 6-month SPEI, the severity of the drought is increasing with time and it covers the whole country at the end of the twenty-first century. On the other hand, the severity of 12-month SPEI decreases. The increasing pattern found for 6-month SPEI is also noticeable for 1- and 3- month SPEI. It has been found from the 6-month SPEI analysis that drought severity will continue to increase in the northwest parts of the country throughout the century.
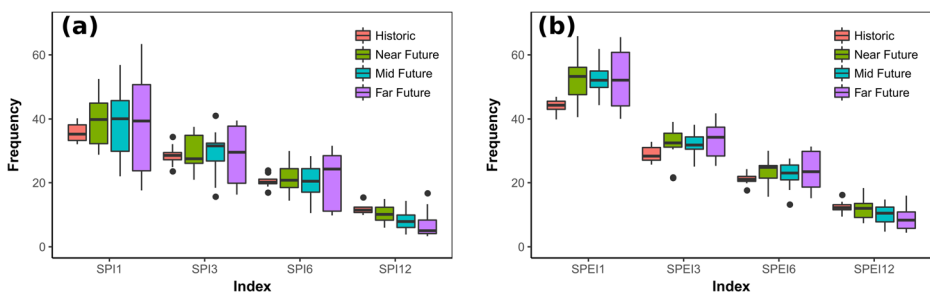

Fig. 8 Box plot of drought frequency using **a** SPI and **b** SPEI-Hargreaves evaluated at different timescale for different time slices. The spreading of the box shows the spreading in the ensemble members
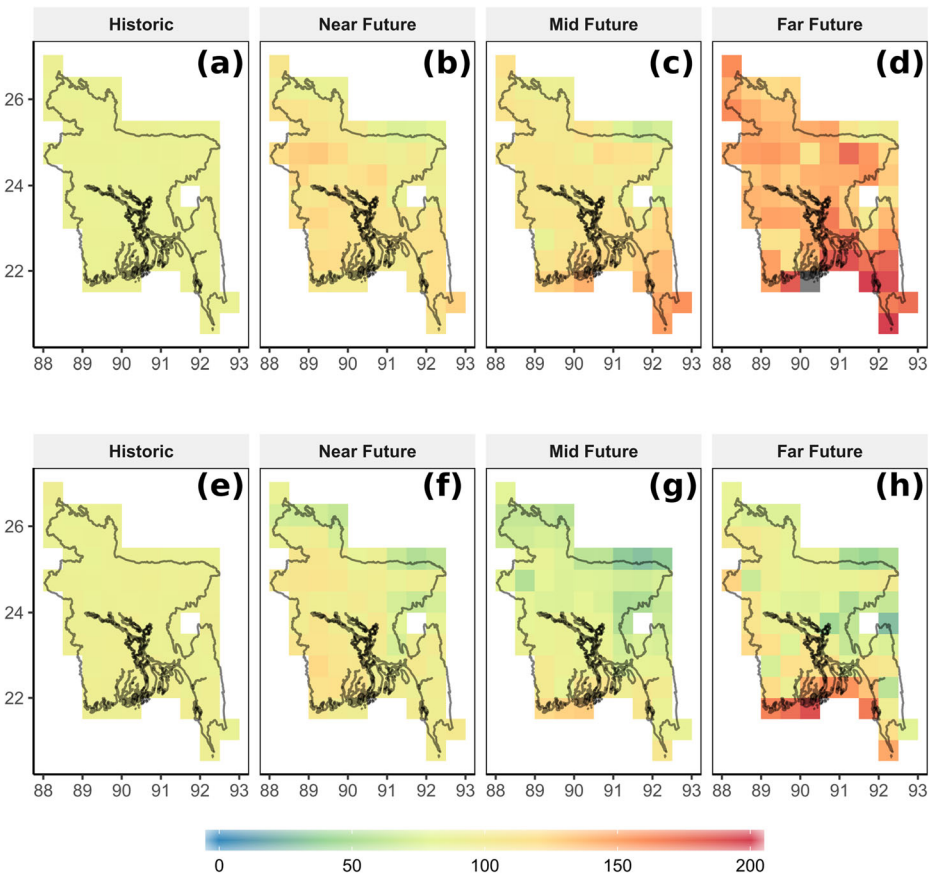
Fig. 9 The ensemble average total drought severity over a particular time slice using SPEI-Hargreaves for 6-month (**a–d**) and 12-month (**e–h**) timescales. SPI shows a similar pattern

3.2.3 Seasonal evaluation of drought index

To assess the seasonal drought condition as well as spatial pattern in the projected climate, the median value of the index for each time chunk evaluated at 3-month timescale at the end of each season is considered. We have taken an ensemble mean approach for this. For instance, we have taken 3-month SPEI evaluated in February for the winter season. The spatial variation of median SPEI-Hargreaves is shown in Fig. 10. The median SPEI index shows the change in the central tendency of the drought over a specific period in future time slices. For the same figure with SPI, see Fig. S4. The color represents the classification of the SPI/SPEI index listed in Table 1. We have chosen the shades of blue to indicate that the median condition indicated by the index is in on wet side and shades of reds to indicate it is in the dry side. During none of the seasons, the projected ensemble median drought crosses the mild drought condition. The spatial patterns for all the seasons show that in the future climate, the median value of the index is showing wet condition, except for the pre-monsoon season. During the pre-monsoon season, the dry area shows about the same areal coverage during the far future period compared with the historic period. However, a change in the spatial pattern is found. In our projection, the

north-west region will become wetter while the south-central region will become drier by the end of the century, as indicated by the projected changes in the median values of SPEI.

The pre-monsoon season is a crucial period for agricultural water management because during this time irrigated crops are grown over Bangladesh. A deficiency of rainfall can impact the irrigation system by overstressing the surface and groundwater storage. Such water deficiency can consequently impact the food production of the country. The pre-monsoon season is also known to create the heatwave situation. For instance, in 2016, Bangladesh experienced a 25-day extended heatwave all over the country during the pre-monsoon season. On the other hand, climate models project the least change during monsoon season. Monsoon is the most prominent climatic feature of the region and sometimes not well captured by the models (Saha et al. 2014). CMIP5 climate models project an increase in severity and frequency of the active summer monsoon and weak winter monsoon with more intense activity or break spell (Sharmila et al. 2015). As Bangladesh and its surrounding regions already receive a considerable amount of precipitation during the monsoon season, the direct impact might not be prominent.

4 Conclusion

This study compares two different methods (SPI and SPEI) to identify meteorological droughts over Bangladesh in the context of possible changes in temperature and precipitation in the future. In SPEI calculations, we considered both the Thornthwaite and the Hargreaves methods to calculate the potential evapotranspiration. Both SPI and SPEI methods are found to identify and predict the drought events in the historic period from the bias-corrected climate model data with well-agreement in observed frequency. However, in a future condition, with a projected temperature rise of 4–6 °C, the changes are not found analogous. We have noted a marked overestimation of potential evapotranspiration with the Thornthwaite method compared with the Hargreaves method. Overestimation in PET calculation could lead to an overestimation of the severity of drought events in the future. Thus, a faithful calculation of PET is essential to evaluate the condition of drought. At the 12-month timescale, a tendency towards a wet condition is observed for both SPI and SPEI-Hargreaves. At the same time, we have observed an increase in the severity and frequency of drought for short timescales (less than 6 months). The condition of short spell drought is also projected to become more severe under future climate if we continue the same trend in the emission of greenhouse gasses. In the future, significant changes in meteorological droughts are projected during the pre-monsoon seasons. Drought severity will continue to increase in the south-west region throughout the century. A regime-shift from dry to wet in the north-west region and wet to dry in the north-east region is also projected.

This study has potential limitations that should be noted. Due to the lack of high-resolution observed meteorological time-series datasets, gridded reanalysis data has been used for bias correction of the model. As we showed in our study, there is a non-negligible uncertainty in the PET estimates using temperature-based methods. This uncertainty demands an observation-based evaluation of PET estimation methods over Bangladesh. In the future, satellite-based drought estimation methods can shed more light on the performance of the drought indices.

The findings of our study can be helpful for policymaker, planners, donor agencies, and all the other stakeholders to obtain an initial idea into the future and better prepare for the coming decades. These results can be used to calculate the drought risks in the context of the hazard-vulnerability study as shown by Wilhite (2000). This understanding of drought hazard, particularly the seasonal component and projected increase in short-term drought hazard, is also expected to increase our ability to plan, implement, and manage the water resources for a sustainable and agricultural ecosystem.

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