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Drought monitoring and prediction in climate vulnerable Pakistan: Integrating hydrologic and meteorologic perspectives

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Abstract. Effective drought monitoring, prediction and early warning systems are crucial for management of human activities associated with water use in a climate affected world. In Pakistan, surface water flows predominantly originate from the transboundary Upper Indus sub-catchments of Chenab, Jhelum, Indus and Kabul rivers. Hence, impact of droughts manifested through water deficits in these catchments are strongly felt by downstream users. Use of different drought indicators is limited in Pakistan's operational drought monitoring system. Moreover, there is very limited prior literature that explores the use of multiple indicators for unearthing relationships between different drought types. This study aims to explore the relationship between meteorological and hydrological droughts in the Upper Indus catchments of Pakistan using the Standard Precipitation and Evaporation Index (SPEI) and the Standard Streamflow Index (SSI). Since there are no previous studies for the Indus that compare different distributions for SSI computation, we compare five distributions to adequately compute SSI values at catchment outlets. Our most crucial contribution in this study is analysis of seasonal cross-correlations and lagged cross-correlations between SSI and SPEI for the above-mentioned four catchments. The cross-correlation analysis shows strong lagged (with up to 2 lag months) cross-correlations between SPEI and SSI for Chenab, Jhelum and Kabul catchments in early Kharif months. These correlations may be used in operational drought monitoring and forecasting systems, and also in reservoir planning and operations (for Mangla resrvoir in Jhelum) in drought conditions. We strongly believe that the findings of this study can be used in future to collectively explore hydrological and meteorological drought perspectives in Pakistan and to successfully incorporate multiple indicators into operational drought management.

1 Introduction

Droughts are highly complex and less understood phenomena as compared to other weather and climate extremes, that propagate slowly but with long-lasting and devastating effects (Van Loon et al., 2016). It has now become a recognized fact that rising temperature and climate change cause the frequency and severity of drought events to increase in many regions around the globe (Christensen et al., 2007; Seneviratne et al., 2012). While a simple definition of the onset of a drought is reduction in the atmospheric / climatic water balance (also referred as a meteorological drought) (Svoboda and Fuchs, 2016), it can manifest into a more complex natural hazard. For instance, a prolonged deficit in the climatic water balance can lead to reduced streamflows and induce a hydrological drought; and/ or it may lead to significant reduction in soil moisture and thus cause an

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agricultural drought (Van Loon, 2015). While meteorological, hydrological and agricultural droughts are direct manifestations of reduction of water in the hydrological cycle, they in-turn lead to numerous adverse socio-economic, socio-political and environmental impacts, including but not limited to water insecurity, food insecurity, economic loss and water quality deterioration etc (Bachmair et al., 2016),which will hit more severly in a future warmer world. The extent of these impacts depend on the onset, duration and severity of different types of droughts (e.g., meteorological hydrological etc.) (Pedro-Monzonís et al., 2015). Hence, it was never as important to efficiently measure, monitor, understand and predict these drought characteristics as it is now in these climate emergency times.

The use of standard indices is a highly popular and effective mechanism in monitoring and predicting the onset, duration and severity of droughts (Van Loon et al., 2016; Stagge et al., 2015). The Standard Precipitation Index (SPI) (McKee et al., 1993; Guttman, 1999) is the most prominent index in this regard, that is recommended by the World Meteorological Organization (WMO) as an effective indicator for inclusion in national and regional Drought Early Warning Systems(DEWS) (Svoboda and Fuchs, 2016). SPI is a part of numerous national and regional DEWS, for instance, the North America Drought Monitor (https://www.ncdc.noaa.gov/temp-and-precip/drought/nadm/), United States Drought Monitor (https://droughtmonitor.unl.edu), European Drought Observatory and Pakistan's National Drought Monitoring Centre (NDMC) (http://ndmc.pmd.gov.pk/ndmc.php). Drought monitoring agencies and DEWS across the globe typically use multiple such indicators to monitor different types of droughts. NDMC Pakistan, for instance, uses SPI for meteorological drought monitoring and Normalized Difference Vegetation Index (NDVI) (Tucker, 1979) for agricultural drought monitoring. (Bachmair et al., 2016) provide a comprehensive review of the different drought indicators used by national and regional state agencies in operational DEWS. A key outcome of Bachmair et al. (2016)'s comprehensive review is that development of effective DEWS and the selection of appropriate drought indicators within, requires a deep understanding of the inter-linkages between water deficits in the hydrological cycle, human activities and associated impacts on society and the environment. This notion is echoed by WMO Svoboda and Fuchs (2016) and Lloyd-Hughes (2014) who argue that there is no universal definition of droughts, and hence, development of DEWS and effective use of drought indicators should incorporate an understanding of the regional and local contexts that are impacted by water deficits, e.g., water use, water management practices and water politics etc.

In Pakistan drought events are strongly linked to water security, food security and agro-economics of a majority of the country's population. More than 60% of Pakistan's population is rural (Young et al., 2019) and mostly resides in the semi-arid to hyper-arid plains of the lower Indus basin (Laghari et al., 2012). Agricultural activities of these rural dwellers are heavily dependent on streamflows originating from the Upper Indus catchments, that are diverted towards agricultural field via the massive Indus Basin Irrigation System Siddiqi et al. (2018). These streamflows are highly seasonal, variant and prone to extreme events and climate change Lutz et al. (2016); Wijngaard et al. (2017). Historical droughts in the Upper Indus catchments have had extreme adverse effects on Pakistan's economy and especially the rural sector in the past. For instance, the 1998-2002 droughts severely affected the rural population and resulted in negative growth in the agricultural sector, which had seen significant growth in the prior decade (Anjum et al., 2012). However, data, research and analyses on retrospective drought assessment, and development of drought warning systems and management plans for Pakistan are very limited (Ministry of

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Water Resources, 2018; Young et al., 2019). The importance of further research in this regard is also observed by the recently coined and Pakistan's first National Water Policy (Ministry of Water Resources, 2018, p. 25).

The use of multiple standard indices for development of DEWS for Pakistan is also relatively unexplored. We found only two relevant studies in recent literature, that used SPI to investigate characteristics of historical droughts in Pakistan (Adnan et al., 2017; Xie et al., 2013). Adnan et al. (2017) computed SPI time-series' at different accumulation periods using observed precipitation data from meteorological 61 stations across Pakistan, to analyze duration, severity and frequency of historical droughts. Xie et al. (2013) computed SPI using the gridded APHRODITE precipitation dataset (Yasutomi et al., 2011) to discover spatio-temporal trends and cyclical behaviours of drought recurrence. There is no prior literature on the investigation of multiple indices for assistance with drought monitoring and early prediction. A key research gap here is in the investigation of the coherence between meteorological and hydrological droughts, especially in the upper catchments of the Indus basin. As mentioned earlier, a key identifier of drought onset in Pakistan is the streamflow originating from the snow-dominated Upper catchments of the Indus basin. Hence, identification of relevant indicators that can assist in analyzing hydrological drought characteristics at key streamflow locations in the Upper catchments of the Indus basin, can be extremely beneficial towards improving existing DEWS in the country. Moreover, if coherences between hydrological and meteorological droughts can be unearthed through these indicators, they could also be integrated to provide early drought warning mechanisms.

The primary purpose of this study is to investigate the coherence between meteorological and hydrological droughts in four key upper catchments of Pakistan's Indus basin. In order to investigate this coherence, we utilize the Standard Precipitation and Evaporation Index (SPEI) (Vicente-Serrano et al., 2010a), (computed using a gridded precipitation and evaporation datasets) as an indicator of meteorological droughts, and the Standard Streamflow Index (SSI) (Nalbantis and Tsakiris, 2009) as a measure of hydrological droughts (computed on observed streamflows at catchments outlets). We assess coherence between meteorological droughts and hydrological droughts by analyzing cross-correlations and lagged cross-correlations between SPEI and SSI. Hydrological flows in the Upper catchments of the Indus basin are snow-dominated and highly seasonal. Hence, monthly cross-correlations and lagged cross-corelations are investigated to incorporate seasonality, in the process of understanding the onset of hydrological droughts through meteorological droughts. In our assessment, this study supplements existing knowledge of drought coherence in snow-dominated regions, by capturing the impact of seasonality. Moreover, this study also highlights that gridded climate datasets can be a reasonable alternative to station data for drought analysis in catchments where observed data is not readily available. We believe that the methodology and findings of this study can be very useful in operational drought monitoring and early warning in snow-dominated catchments of Pakistan and other similar regions.

2 Study Area and Data

2.1 Study Area Selection

Pakistan's freshwater resources primarily come from the upper catchments of the Indus basin (Laghari et al., 2012), a trans-boundary basin that spans 4 countries, Pakistan, India, Afghanistan and China (see Figure 1. In terms of climatology and land-use the Indus basin can be divided into two key zones, i.e., the Upper Indus Basin and the Lower Indus Basin.

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The Upper Indus Basin is primarily a high elevation zone that includes the Himalaya-Karakoram-Hindukush mountain ranges and is the dominant source of renewable freshwater within the Indus Basin. The Lower Indus Basin includes the highly irrigated central Indus Plain where irrigation is made possible through diversion of surface flows via the Indus Basin Irrigation System (IBIS), and also includes deserts of the Indus plain and the Indus delta (Young et al., 2019).

Climatology of the Indus basin (Fig. 1) clearly illustrates the higher concentration of precipitation in the Upper Indus. This coupled with the low PET in the mountain ranges of the Upper Indus, makes the entire basin heavily reliant on the high-altitude upper catchments for renewable water resources, especially in Pakistan and the Punjab province in India (Laghari et al., 2012).

According to numerous water availability assessments (e.g., Karimi et al., 2013; Laghari et al., 2012; Young et al., 2019; Yu et al., 2013, p. 60), more than 70% of renewable freshwater in Pakistan comes from the Upper Indus Basin catchments, and predominantly from upper catchments of the 'Western' rivers of the Indus, namely, Chenab, Jhelum and Indus (see Fig. 2, and the Kabul river basin. Western rivers is a term that originates from the Indus Water Treaty (IWT) of 1960, a transboundary treaty signed between India and Pakistan (The World Bank, 1960), to amicably share the surface water resources of the Indus . The IWT gave consumptive use rights of surface flows of Ravi, Sutlej and Beas rivers of the Indus basin (also called Eastern Rivers) to India, and consumptive rights of Chenab, Jhelum and Indus rivers (also called Western Rivers) to Pakistan. Kabul is a transboundary sub-basin of the Indus that spans Afghanistan and Pakistan (see Fig. 2, and is thus not a part of the IWT. Kabul river, however, is a critical source of freshwater in the lower Indus Basin of Pakistan (Hashmi et al., 2019; Young et al., 2019), and joins the Indus river in Pakistan downstream of Nowshera (see Fig. 2).

Figure 2 delineates the four Indus basin catchments selected for Pakistan's drought analysis in this study, i.e., Upper Chenab, Upper Jhelum, Upper Indus and Kabul. As mentioned earlier, these catchments account for more than 70% of Pakistan's renewable freshwater availability (e.g., Young et al., 2019; Yu et al., 2013, p. 120), and via the outlets shown in Fig. 2, i.e., Chenab at Marala Barrage, Jhelum at Mangla Reservoir, Indus at Tarbela Reservoir and Kabul at Nowshera. The streamflow gauging stations at these outlets (excluding Nowshera) are also called rim stations (Anwar and Bhatti, 2018), since they essentially signal the beginning of the Indus Basin Irrigation System (IBIS) (also called the Indus River System) of Pakistan. IBIS is the world's most dense irrigation system, and is essential to the water and food security of Pakistan, and accounts for more than 90 percent of Pakistan's food production (Yang et al., 2013).

Since water supply for IBIS is predominantly derived from the four catchments delineated in Fig. 2, drought conditions in these catchments have significant impacts on water security, food security and economic well-being of Pakistan (Adnan et al., 2017; Robinson and Gueneau, 2014; Yu et al., 2013, p. 19). Hence, these catchments are the focus of the meteorological and hydrological drought analysis conducted for Pakistan in this study.

2.2 Data

Observed climate data for Upper Indus catchments is limited, both spatially and temporally (Immerzeel et al., 2015). In such data scarce scenario, use of a gridded climate dataset is a feasible alternative. Prior studies on data scarce Asia Pacific catchments observe that observation based gridded data sets are better than reanalysis based data sets, especially for hydrological modelling and historical drought analysis (Ghimire et al., 2019; Um et al., 2017). Hence we use the observation based gridded

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CRU TS4.03 (Harris et al., 2020) climate dataset for our drought analysis. CRU is a monthly gridded dataset that shows good correlations with station observations in the South Asian region, both for precipitation and Potential Evapotranspiration (Harris et al., 2020).

We also use streamflow data of outlets of the four catchments discussed in the previous section and delineated in Fig. 2 for the hydrological drought analysis of this study. Monthly streamflow records from 1961-2018 for the relevant flow stations, i.e., Chenab at Marala Barrage, Jhelum at Mangla Reservoir (upstream), Indus at Tarbela Reservoir (upstream) and Kabul at Nowshera gage (see Fig. 2) are used in our hydrological drought analysis. Figure 3 shows monthly distribution of flows at these stations and depicts the high seasonality and variation in outflows from the Upper catchments of the Indus basin.

3 Methodology

3.1 Drought Indicators

The drought analysis of this study makes use of standard indicators for monitoring, assessment and early prediction of droughts in Pakistan. While many indicators are available for drought analysis and early warning (e.g., Hund et al., 2018; Guttman, 1999; Nalbantis and Tsakiris, 2009; Staudinger et al., 2014; Vicente-Serrano et al., 2010a), the choice of an appropriate indicator may depend on the type of drought (e.g., meteorological, hydrological agricultural drought etc.) under investigation and/or the purpose of drought analysis Bachmair et al. (2016); Pedro-Monzonís et al. (2015); Svoboda and Fuchs (2016). Since, the focus of this study is on analyzing hydrological and meteorological droughts within the context of Pakistan, we will use indicators that are designed for quantifying hydrological and meteorological droughts.

3.1.1 Standard Precipitation and Evapotranspiration Index (SPEI)

The Standard Precipitation and Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010a) is the indicator used for quantification and monitoring of meteorological droughts in the Upper Indus catchments analyzed in this study. SPEI is theoretically similar to the widely used Standard Precipitation Index (SPI), which is computed by fitting a parametric distribution on precipitation accumulation over a user-defined period, and subsequent transformation of resultant probabilities to standard normal variates (McKee et al., 1993; Guttman, 1999). SPI is strongly recommended by the World Meteorological Organization (WMO) (Svoboda and Fuchs, 2016), and is the standard index used for meteorological drought analysis by many drought monitoring authorities across the world (Van Loon, 2015) including Pakistan Meteorological Department's (PMD) National Drought Monitoring Centre (NDMC).

However, a distinct advantage of using SPEI over SPI for meteorological drought monitoring is that it uses both precipitation and temperature data for calculation and thus, may better represent meteorological droughts and how they may manifest into hydrological and agricultural droughts (Beguería et al., 2014). Van Loon (2015) argue that temperature abnormalities play a critical role in drought onset and propagation ,especially in cold-climate catchments (like the Upper Indus catchments of this

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study). For instance, higher than normal temperatures in winters can result in less snow accumulation and low snowmelt runoff in spring.

SPEI is calculated in the same way as SPI, however the underlying climate variable is the difference between precipitation and evapotranspiration (also called the climatic water balance) (Vicente-Serrano et al., 2010a).

Another advantage of using SPEI instead of SPI is that the underlying climate variable will avoid having too many zero values. Precipitation can be zero for many time periods, especially in semi-arid and arid climate zones, and this can cause difficulties in adequate fitting of distributions during SPI computation (Wu et al., 2007). In a comprehensive distribution fitting assessment of both SPI and SPEI for Europe, Stagge et al. (2015) observed that fit of distributions was indeed better for SPEI, and recommended its use as an adequate drought index. Hence, we have chosen SPEI as the index for analyzing meteorological droughts for our selected catchments.

We calculate SPEI for the four catchments analyzed in this study (see Fig. 2) at both grid-level and catchment level using gridded climate data from the CRU data set (Harris et al., 2020) (as discussed in Section 2.2). For catchment level SPEI calculations, gridded precipitation and Potential Evapotranspiration values are averaged over the catchment at each time interval before use. SPEI is typically calculated over a user-defined accumulation period between 1-24 months. Hence, the monthly resolution of the CRU data set is sufficient for our analysis. Moreover, we fit the log-logistic distribution for computing SPEI at different accumulation periods (as recommended by Beguería et al. (2014)), and use the R package 'SPEI' for our computations (Beguería and Vicente-Serrano, 2017). Since SPEI results from different accumulation periods are discussed in this study, we use the term 'SPEI-x' in subsequent discussions, where x denotes the accumulation period.

3.1.2 Standard Streamflow Index (SSI)

The Standard Streamflow Index (SSI) (Nalbantis and Tsakiris, 2009; Modarres, 2007) is used (also called the Streamflow Drought Index and the Streamflow Runoff Index) to quantify and analyze hydrological droughts at catchment outlets in this study. The SSI computation mechanism is similar to SPI and SPEI. However, streamflow is the underlying time-series data used and the recommended interval may vary between 1-12 months.

Within the context of Pakistan and especially the catchments being assessed in this study, analysis of hydrological droughts over accumulation periods of 1-6 months might be most suitable (Fraz Ismail and Bogacki, 2018; Charles et al., 2018). This is because hydrological outflows from the four catchments of our study are central to seasonal planning and operations (conducted in cycles of six months) of the IBIS in lower Indus (Fraz Ismail and Bogacki, 2018; Charles et al., 2018). A major proportion of the outflows of Upper Chenab, Upper Jhelum, Upper Indus and Kabul catchments are diverted for agricultural consumption in the lower Indus via IBIS (Young et al., 2019). Since Pakistan's agricultural system operates on rotation of crops in two six month seasons, called rabi (October-March) and kharif (April-September), seasonal water supply planning and operation of IBIS is conducted in cycles of six months Anwar and Bhatti (2018).

Unlike SPI and SPEI, there is no probability distribution that is universally recommended for computation of SSI (Svensson et al., 2017). However, Vicente-Serrano et al. (2012) observe that distributions which are commonly used for hydrological frequency analysis may be suitable for computing SSI, especially the more flexible three parameter distributions. Moreover,

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Vicente-Serrano et al. (2012) recommend that different distributions should be tested for separate months / accumulation periods before selection of an appropriate distribution for SSI computation. We compare five distributions, namely, log-logistic, Gamma, Pearson Type III, Lognormal and GEV, at 1-Month accumulation periods (i.e., for each month) for all four streamflow locations, to select an appropriate distribution for the SSI computations of this study. Moreover, we use historical streamflow data from January 1961 to December 2018 for SSI time-series computations (at 1-12 month accumulation periods), and employ the R package 'SPEI' for the computations (Beguería and Vicente-Serrano, 2017). In subsequent discussions the term 'SSI-x' is used to denote SSI where x represents the accumulation period. So SSI-3 denotes SSI values for a 3 month streamflow accumulation period.

3.2 Drought Characteristics

This study also includes an indicator-based analysis of the characteristics of historical drought events (hydrological and meteorological) observed in the Upper Indus catchments under consideration (see Fig. 2). The definition proposed by McKee et al. (1993) is used to identify drought events, i.e., any period where an indicator's (SSI or SPEI) value is consistently below zero and also goes below a pre-defined threshold is identified as a drought event. We use a drought threshold of -1.0 in our analysis, and record the number of drought events for each catchment (see Table 1 and Section 4.2 for discussion) . We also analyze statistics of two key drought characteristic variables, i.e., drought duration and drought severity for the identified drought events. Both of these characteristics are widely used by drought monitoring agencies and water resources managers (McKee et al., 1993; Van Loon et al., 2014; Van Loon and Laaha, 2015) to analyze historical drought events. Drought severity has been defined in different ways in prior literature (McKee et al., 1993; Van Loon et al., 2014; Halwatura et al., 2015). We use the definition proposed by McKee et al. (1993), which is as follows:

$$S_e = \sum_{i=j_e}^{x_e} |I_i| \tag{1}$$

In the above equation, S_e is the severity of drought event e, I_i is the drought index value for month i, j_e is the starting month of drought event e (i.e., starting month i when $I_i < 0$ and $I_{i-1} >= 0$ (if exists)) and x_e is the ending month of drought event e. The purpose of the drought characteristic analysis is to assess the frequency, duration and magnitude of historical drought events observed in the Upper Indus catchments, in order to consequently understand vulnerability of these catchments to drought events. Section 4.2 discusses the characteristics of drought events observed in the Upper Indus catchments, by also using the variables defined in this section.

3.3 Integrating Meteorologic and Hydrologic Drought Indices

In order to develop effective early hydrological drought forecasting and monitoring systems, it is important to understand if climatic indicators can adequately predict the onset of hydrological droughts (Van Loon, 2015). Hence, a key question that this study aims to address is that can the onset hydrological droughts in the Upper Indus catchments be predicted or characterized through meteorological drought indices? Numerous methods have been used in the past to investigate the coherence between

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hydrological and meteorological droughts (Barker et al., 2016; Haas et al., 2018; Hannaford et al., 2011; Wong et al., 2013). A popular method in this regard is the use of cross-correlations and lagged cross-correlations between meteorological and hydrological drought indices. For instance, Barker et al. (2016) observed strong cross-correlations and lagged cross-correlations between SPI and SSI for catchments in the UK. However, they did not consider the impact of seasonality in their analysis.

Climate variables and streamflows in the Upper Indus catchments of this study are strongly seasonal. For instance, average catchment outflows in the wet season of April-September (also called Kharif season) are 4-5 times higher than dry season flows (October-March; also called Rabi season) (Young et al., 2019). Even within the wet season, a significantly high proportion of flows occur in a 3-month window. This trend is illustrated in Fig. 3 via monthly flow distribution plots at the outlets of the catchments. It is important to incorporate the effect of seasonality in the analysis of coherence between meteorological and hydrological droughts (Van Loon et al., 2014; Van Loon, 2015). Hence, we develop monthly cross-correlations and lagged cross-correlations between SSI and SPEI (at different accumulation periods) to i) analyze how meteorological droughts may manifest into hydrological droughts and ii) to identify appropriate lead times (if any; via lagged correlations), for early warning / prediction of hydrological droughts using SPEI.

4 Results and Discussion

4.1 SSI Distributions

The calculation of SSI for the streamflow sites of this study was preceded by selection of an appropriate distribution for SSI computations (for each streamflow site). As discussed in Section 3.1.2 and observed by Svensson et al. (2017), there is no single distribution that is universally suitable for computing SSI for any streamflow site. Hence, we compared five different distributions, i.e., log-logistic, Gamma, GEV, Pearson-III and lognormal, separately, for the 4 streamflow sites of this study. Moreover, quality of distribution fit was analyzed for each month per site. Figure 4 provides a visual comparison of the fit of each distribution for the four sites (for selected months), by plotting density functions of fitted distributions against historgrams for respective months and catchment outlets. While the difference between distributions is hard to ascertain from Fig. 4, the overall performance of log-logistic is marginally better. In a more comprehensive assessment of different distributions for SSI computations, Vicente-Serrano et al. (2012) also recommended log-logistic as an appropriate distribution, if a single distribution is being used. Hence, we use the log-logistic distribution for computing SSI for all four streamflow gauges of this study.

4.2 Drought Characteristics

We analyze drought characteristics of the selected Upper catchments of the Indus basin by first analyzing the time-series plots of SSI and SPEI. Figure 5 shows the time-series plot of SSI-3 for streamflow gauges at the outlets of the four catchments. SSI-3 provides a good representation of historical droughts observed in the Upper Indus catchments. According to prior literature prominent drought events were observed in Pakistan in early 1970s, mid 1980s and in the years 1998-2002. (Adnan et al., 2017;

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Young et al., 2019; Xie et al., 2013). These drought events are prominent in Fig. 5 as well. Another key observation from Fig. 5 is that many hydrological drought events are cross-correlated across the four basins. This observation implies a higher impact on downstream water users due to such cross-correlated events. Moreover, in such drought periods, water demands of the lower Indus basin may be highly dependent on surface reservoirs and may put further pressure on the already stressed groundwater resources (Watto and Mugera, 2016).

The SPEI-3 time-series plots of Fig. 6 also prominently represent the historical droughts reported in history, including the 1998-2002 droughts, that are considered the worst in Pakistan's history ((Anjum et al., 2012)). Moreover, Fig. 6 is also indicative of the coherence between SPEI and SSI for respective catchments (discussed in further detail in Section 4.3). The temporal oscillations (i.e., oscillations between negative and positive SPEI-3 values) in the basin-wide SPEI-3 values, however, are higher than in corresponding SSI-3 values. A plausible reason here could be that snowmelt and glacial melt dominate the hydrology of these Upper Indus catchments (Charles et al., 2018; Lutz et al., 2016). Hence, SPEI-x with a larger accumulation period could correspond better with SSI-3, in terms of oscillatory patterns and drought duration.

Table 1 provides a summary of characteristics of meteorological and hydrological droughts observed in the Upper Indus catchments, by reporting the number and average duration of drought events (using -1.0 as threshold for defining a drought event; also see Section 3.2). Unsurprisngly, the number of drought events reduce with an increase in accumulation period, for both SPEI and SSI, whereas average duration of droughts increases with increase in accumulation period Barker et al. (2016); McKee et al. (1993). Table 1 also indicates that frequency of meteorological droughts (represented by SPEI) is generally higher than hydrological droughts (represented by SSI), whereas duration of hydrological droughts is relatively longer. The observation regarding drought durations is also evident in Figure 7 where distributions of drought durations are visualized (via violin plots, that combine kernel density plots and boxplots), for both SSI and SPEI with different accumulation periods. Figure 7 also depicts that SPEI based drought durations are shorter than SSI based drought durations, for the same accumulation periods. Table 1 and Figure 7 imply that multiple meteorological droughts events can collectively result in a hydrological drought event. Hence, SPEI values with relatively higher accumulation periods may correlate better with corresponding SSI values for streamflow-based drought characteristic analysis. We explore these correlations in more detail in Section 4.3.

We also analyze the relationship between duration and severity (as defined in Section 4.2) of historical droughts observed in the Upper Indus catchments. To this effect, Figures S1 and S2 (in supplementary document) provide a visual overview of the strong mutual correlation between hydrological drought duration and severity. This relationship is logical, since, longer droughts tend to be more severe, and is also corroborated by prior probabilistic duration-severity analyses conducted using copulas (Hao et al., 2017; Halwatura et al., 2015) that report high mutual correlation between drought duration and severity for other basins.

4.3 SPEI and SSI Coherence

The SPEI and SSI-based drought analysis performed so far shows some coherence between i) SPEI and SSI drought characteristics deduced from both of these metrics (see Fig. 6 and Fig. 5) and ii) distributions of SPEI and SSI based drought durations. In this section we further explore the coherence between these indices through analysis of cross-correlations between them.

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Figure 8 represents the overall cross-correlation between SPEI and SSI for all four catchments, and with different SPEI accumulation periods. Cross-correlations are better when SPEI accumulation periods are greater than one (i.e., respective SSI accumulation period analyzed). This is expected for the large catchments of this study (see Fig. 2) because these catchments have seasonal climates with sub-zero temperatures, highly variant topography, and snow accumulation in winter. Hence, climatic water deficits tend to accumulate and propagate slowly into water deficits in surface flow.

There are no SPEI accumulation periods where cross-correlation values in Fig. 8 are greater than 0.7, for any of the four catchments. Moreover, the cross-correlations are particularly poor for Upper Indus. A key reason for these overall low cross-correlation values is the lack of consideration of seasonality in their computations. Van Loon (2015) explain that in cold-region catchments with highly seasonal climates, the hydrological processes behind drought propagation are highly time-dependent. For instance, winter season droughts in cold regions may be triggered by abnormal temperature drops leading to early snow accumulation and low winter discharge. Or precipitation deficit in winter could lead to reduced snowmelt dominated discharge in spring (Van Loon, 2015). Hence, it is important to analyze cross-correlations between SPEI and SSI for the cold-region catchments of this study, with inclusion of time-dependence and seasonality.

4.3.1 Seasonal Trends

Figure 9 shows heatmaps of monthly corrrelations between SPEI (for accumulation periods between 1-12 months) and SSI (for accumulation periods 1 and 3) for the four Upper Indus catchments of this study. SSI-3 and SPEI cross-corelations are computed with a lag of two months to avoid double accumulation of precipitation. It is immediately apparent that monthly cross-correlations values in Fig. 9 are better than the overall cross-correlation values depicted in Fig. 8. For example if we compare the coorrelation for Jhelum between SSI and SPEI, overall correlation for SSI-1 is around 0.5, where as monthly correlation for the months of Februray, March and April are around 0.7 (on average; over different SPEI accumulation periods). There are multiple SPEI accumulation periods where SPEI cross-correlates strongly (i.e., where cross-correlation $r > 0.7$) with SSI-1, specifically in the late winter and spring months (Jan-May), for Chenab and Jhelum, and spring to summer months (Mar-Aug) for Kabul. Strong cross-correlations ($r > 0.7$) are also observed between SSI-3 and SPEI (lagged by 2 months and for accumulation periods between 3 and 7 months; see right panel of Fig. 9) for Chenab, Jhelum and Kabul basins, in late spring / early summer months (April-June). These cross-correlations may be helpful in early hydrological drought detection in late spring / early summer for these catchments.

The cross-correlations between SPEI and SSI are not strong for late summer and fall months (August-October) for all catchments and ii) the Upper Indus. Plausible reasons for the poor cross-correlations observed in the Indus catchment are explored in Section 4.4. The relatively weak cross-correlations for summer and fall months for other catchments could be attributed to errors in the gridded CRU precipitation dataset in the summer months. Summer precipitation and streamflows in the Upper Indus catchments are strongly influenced by monsoon rains, which are not adequately represented in most historical climate data sets (Dahri et al., 2016).

4.3.2 Lagged Cross-Correlations

The strong cross-correlation observed between SPEI and SSI, for Chenab, Jhelum and Kabul (especially in late winter and spring months) is a valuable outcome of our analysis, that can be used effectively in Drought Early Warning Systems (DEWS) in Pakistan. For instance, if lagged cross-correlations exist between SPEI and SSI (where SPEI values are lagged), SPEI values could be used in forecasting and early detection of droughts. Figure 10 (for SSI-1) reports lagged cross-correlations between SPEI (with different accumulation periods) and SSI-1, for Chenab, Jhelum, Indus and Kabul basins.

When cross-correlations are lagged, good correlation values ($r > 0.6$) are found between lagged SPEI (1 month lag) and SSI-1 from March to May for Chenab, from February to June for Jhelum, and from Marchl to July for Kabul. Moreover, good correlations are also observed between lagged SPEI (lagged by two months) and SSI-3 (see right panel of Fig. 9) in spring and early summer months for Chenab, Jhelum and Kabul. Hence, SPEI values can be used to provide early warning of surface outflow deficit from these basins in the above-mentioned. Moreover, the information embedded in the lagged cross-correlations can be valuable in i) seasonal drought planning pertaining to surface water use in the lower Indus basin (Ministry of Water Resources, 2018) and ii) seasonal planning of operations of the Mangla reservoir (in Jhelum) and operations of the Indus Basin Irrigation System (IBIS) (Bogacki and Ismail, 2016; Young et al., 2019). For instance, early prediction / detection of surface flow deficit in the Upper Indus catchments in April to June, also referred to as the early Kharif season, is extremely valuable for water management and operations in the lower Indus basin, including operations of storage resevoirs (Bogacki and Ismail, 2016; Charles et al., 2018; Fraz Ismail and Bogacki, 2018). SPEI values linked to Chenab, Jhelum and Kabul basins could thus be used in both seasonal drought planning and water system operations.

4.4 Spatial Validation

Figure 11 provides a spatial validation of SPEI's capability of adequately representing drought events in the Upper catchments of the Indus basin, especially in the Upper Chenab,Upper Jhelum, Upper Indus and Kabul sub-basins. Figure 11 reports gridded SPEI-12 values (obtained from Beguería and Vicente-Serrano (2020)) of the Chenab, Jhelum, Indus and Kabul sub-basins of the Upper catchments of Indus basin. It is evident from Figure 11 that the drought condition in June 2001 (accumulated over 12 months) is spatially prevalent in all sub-basins except Indus. Within the Indus sub-basin, a significant part of the catchment depicts a high 12-month water surplus in June 2001, according to SPEI. This anomaly, reported in the upper portion of the catchment, is primarily due to inaccurate representation of precipitation (by the CRU data set) in this part of the catchment. Numerous prior studies report that, primarily due to the lack of meteorological stations in the upper portion of the Upper Indus basin, gridded precipitation data (of from all datasets tested) is highly inaccurate in this region of the catchment (Dahri et al., 2016; Immerzeel et al., 2015). Figure S3 in the supplement is also consistent with this observation, where the extreme flood event of August 2010 is not represented in the upper region of the Indus sub-basin.

We believe that the poor cross-correlations observed between SSI and SPEI for the Indus catchment in the Upper Indus basin are partially due to inaccuracies in gridded precipitation data in the upper regions of the catchment. Dahri et al. (2016) and Immerzeel et al. (2015) suggest mechanisms for correcting / improving precipitation records in these catchments. These

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improvements could be used in future studies to improve cross-correlations between SSI and SPEI in this catchment. In a hydrological modelling study, Fraz Ismail and Bogacki (2018) split the Upper Indus catchment into further two sub-catchments to significantly improve modelling results at Tarbela. A similar split may also be experimented for the SPEI-SSI cross-correlation analysis, in order to develop an effective DEWS for the Upper Indus catchment in future.

5 Conclusions

We investigated the combined use of the Standard Precipitation Evaporation Index (SPEI) and the Standard Streamflow Index (SSI), to analyze their capability in monitoring and early detection of droughts in the four key upper catchments of the Indus Basin of Pakistan, i.e., Chenab, Jhelum, Indus and Kabul. Since computation of SSI required identification of an adequate distribution for representing monthly streamflows,we compared five distributions for the four catchments analyzed in this study. The log-logistic distribution was found to be most suited, and hence, is recommended for SSI computations in future for Upper Indus catchments (and other similar catchments).

Our combined indicator based drought analysis shows that both SPEI and SSI are able to identify historical hydrological droughts and streamflow deficits at the outlets of these catchments. A brief analysis of two key drought characteristics, duration and severity, shows that there is a high correlation between drought duration and severity. Moreover, empirical distribution plots of drought duration were also analyzed and visual coherence between SPEI-based and SSI-based drought duration statistics (and respective empirical distributions) was also observed.

Since a key purpose of this study was to analyze coherences between SPEI and SSI, in order to unearth new insights for improvement of existing DEWS, we also analyzed cross-correlations and lagged cross-relations between SPEI and SSI. When seasonality was not considered, weak cross-correlations were observed between SPEI and SSI for all catchments (see Fig. 8). In order to incorporate seasonality into our analysis, we also computed monthly cross-correlations between SPEI and SSI. Strong cross-correlations (i.e., $r > 0.7$) were observed for Chenab, Kabul and Jhelum catchments, especially in spring and early summer months (see Fig. 9)).

Our lagged monthly cross-correlation analysis showed strong correlations between SPEI and SSI in (at-least) the early Kharif season (April to June) (Charles et al., 2018), for the Chenab, Jhelum and Kabul catchments (with lags of up to two months). This is a very important outcome, since monitoring and prediction of streamflow deficits in these basins in early Kharif months is extremely critical for reservoir operations and irrigation planning in the lower Indus, and for seasonal drought forecasting and planning in the country (Young et al., 2019; Charles et al., 2018; Ministry of Water Resources, 2018). Given these strong lagged cross-correlations, we believe that SPEI could be used in operational drought forecasting and warning systems within Pakistan in future, for early streamflow deficit prediction in Kabul, Chenab and Jhelum basins in the early Kharif.

Our cross-correlation analysis also showed poor correlations between SPEI and SSI for the Indus sub-catchment of the Upper Indus. This is primarily due to inaccuracies in gridded precipitation data in upper regions of this catchment (Immerzeel et al., 2015). In future, datasets other than CRU (Harris et al., 2020), including corrected precipitation datasets developed for this catchment (Dahri et al., 2016; Immerzeel et al., 2015, e.g.) could be tested to improve SPEI and SSI correlations in the

Indus sub-catchment. Another future research direction is a more comprehensive multivariate distribution-based analysis of drought characteristics (e.g., severity, duration and frequency) and associated risks for the Upper Indus catchments using both SSI and SPEI (Hao et al., 2017).

Data availability. The SSI and SPEI datasets presented in this study can be accessed from https://doi.org/10.5281/zenodo.3825920 (Akhtar et al., 2020)

Author contributions. TA formulated the research questions for this study. TA and HM prepared the scripts for calculations of SSI and SPEI. TA performed exploratory analysis of cross-correlations between SSI and SPEI. HM developed the portal for dissemination of prepared drought indicators. TA, HM and ZH prepared and revised the manuscript.

Competing interests. The authors have no competing interests.

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Table 1. Summary characteristics (number of events and average drought duration) of historical meteorological and hydrological drought events observed in the study catchments. Characteristics are calculated using -1 as the threshold for defining a drought event.

Drought Type	Accumulation Period (Months)	No. of Events				Average Duration (Months)			
		Chenab	Jhelum	Indus	Kabul	Chenab	Jhelum	Indus	Kabul
SPEI	1	80	86	82	79	2.85	2.83	2.73	3.02
	3	49	47	52	48	5.44	5.60	4.96	5.46
	6	25	27	28	22	11.76	10.60	9.32	11.50
SSI	1	36	27	43	27	6.78	8.81	5.56	8.19
	3	21	14	26	15	11.24	13.93	9.96	14.80
	6	14	10	17	11	16.64	21.10	14.29	20.27

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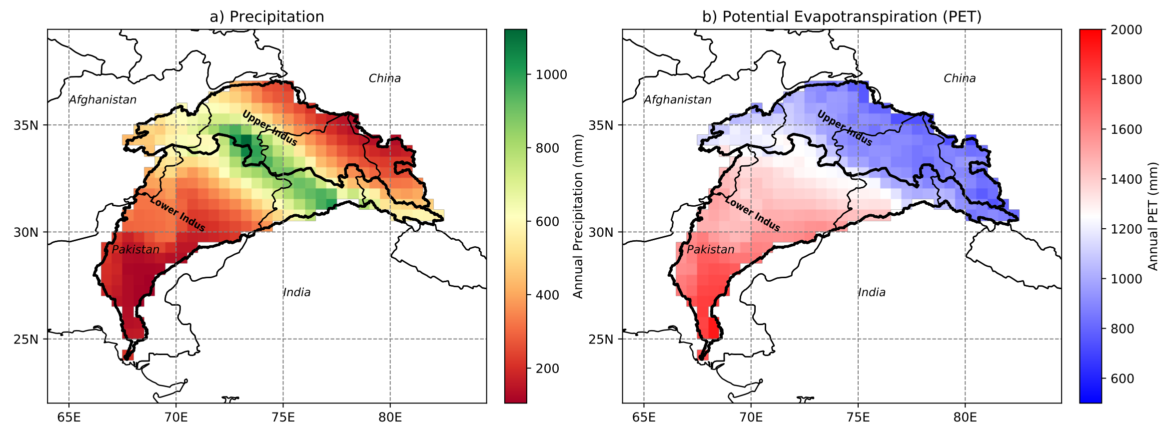

Figure 1. Overview of spatial variation in climatology across the Indus Basin (Upper and Lower zones): a) Average annual gridded precipitation for the period 1901 to 2018, and b) Average annual gridded Potential Evapotranspiration (PET) for the period 1901 to 2018. Gridded precipitation and PET are derived from the CRU TS4.03 data set (Harris et al., 2020; Harris and Jones, 2020).

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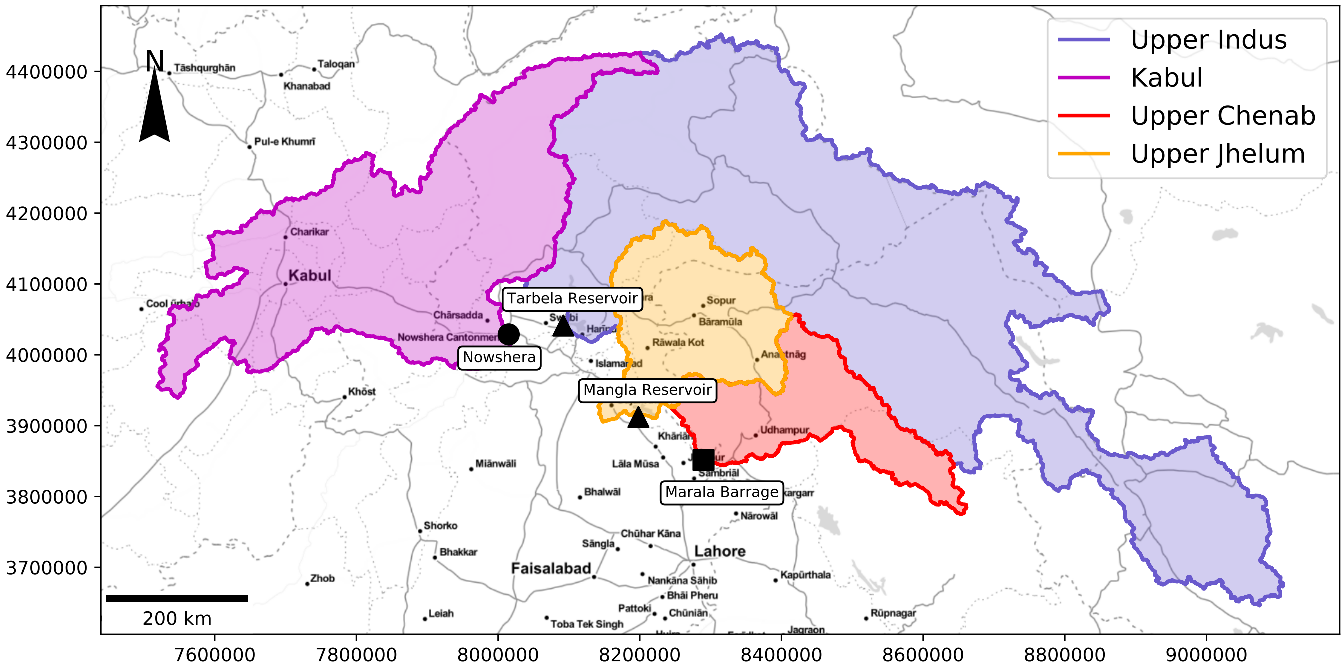

Figure 2. Overview of study area for meteorological and hydrological analysis, that includes the four western river catchments of the Upper Indus Basin, i.e., Upper Indus, Kabul Upper Chenab and Upper Jhelum, and the studied streamflow stations at respective catchment outlets, i.e., Nowshera, Tarbela, Mangla and Marala.

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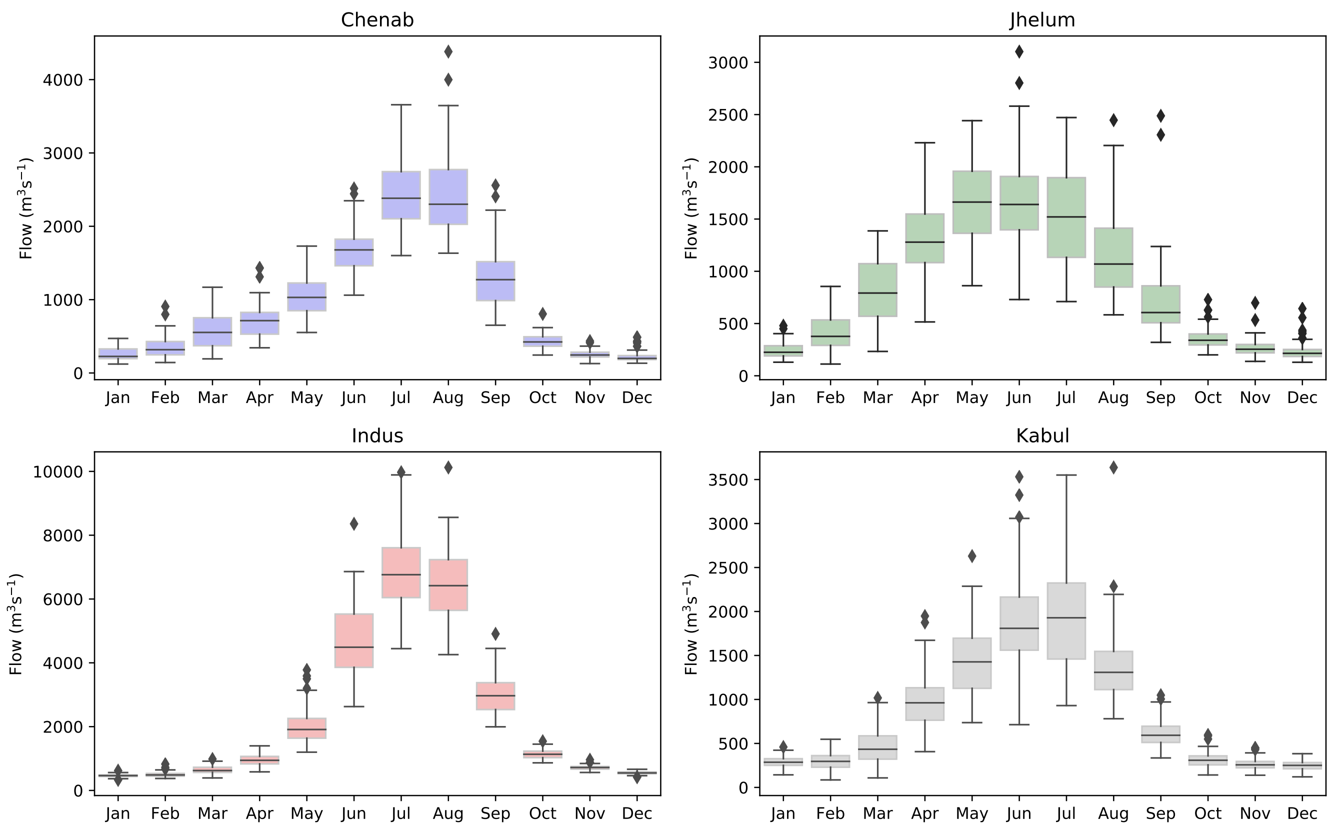

Figure 3. Monthly flow distribution (using streamflow data from 1961-2018) at the outlets of Upper Indus catchments of Pakistan: a) Chenab at Marala, b) Jhelum at Mangla, c) Indus at Tarbela and d) Kabul at Nowshera.

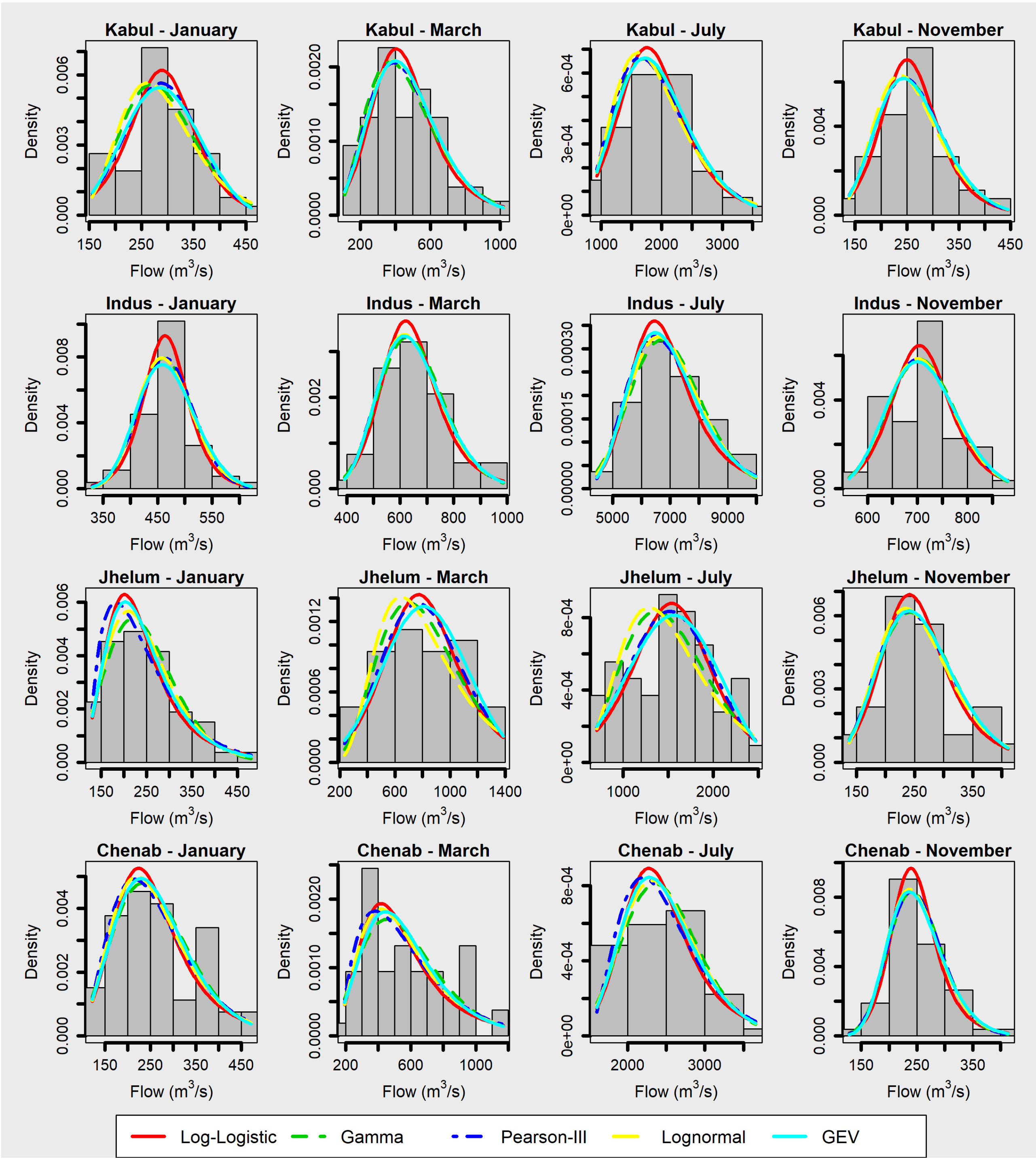

Figure 4. Comparison of five theoretical distributions, i.e., log-logistic, Gamma, Pearson Type III, lognormal and GEV, that were tested for computing Standardized Streamflow Index (SSI), for streamflows at the outlets of Upper Chenab, Upper Jhelum, Upper Indus and Kabul catchments (see Fig. 2).

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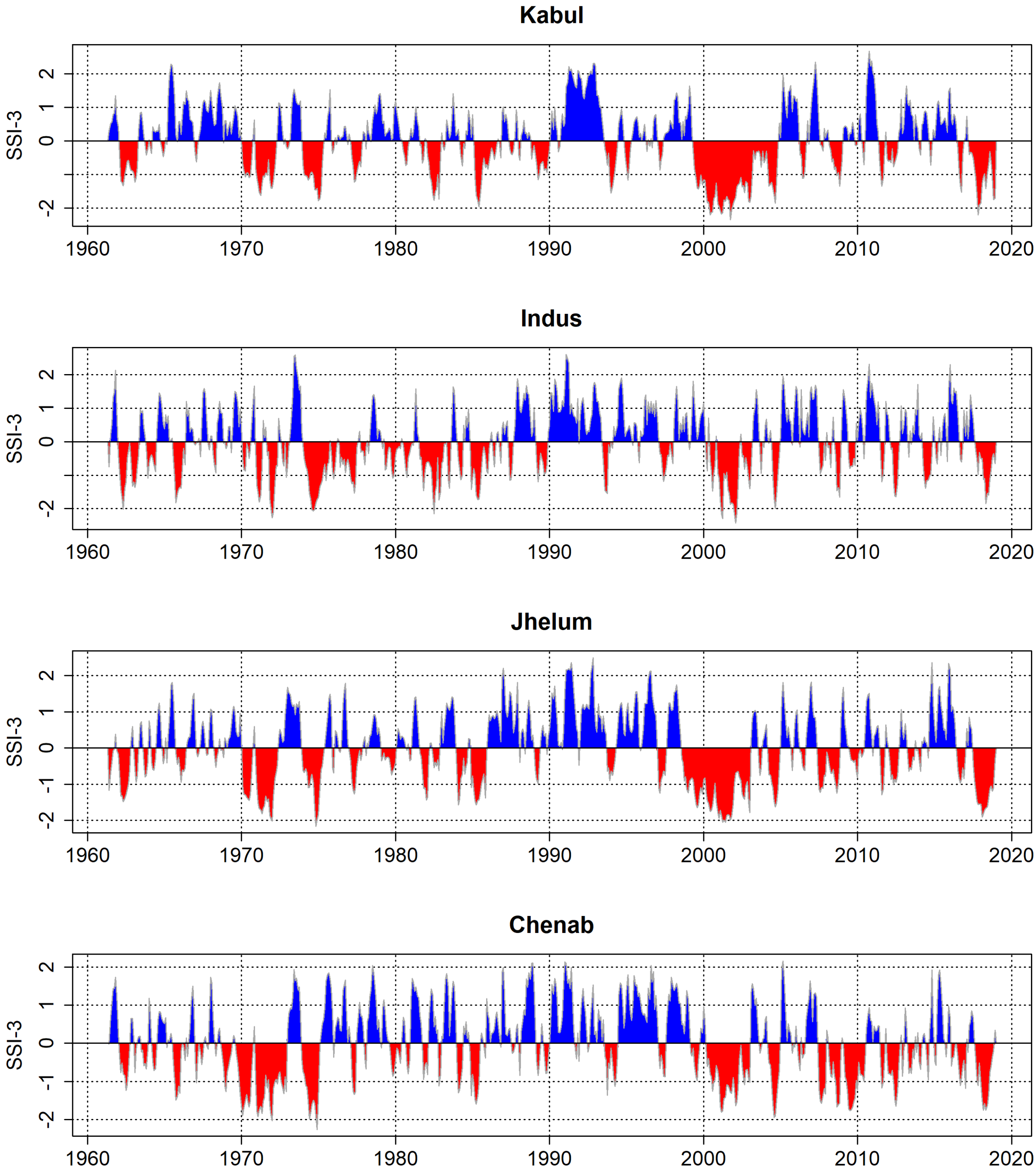

Figure 5. Time-series plots of 3-Month SSI (also called SSI-3) for streamflows at outlet of Chenab, Jhelum, Indus and Kabul rivers (see Fig. 2 for gauge locations). The droughts of early 1998-2002 are well represented by SSI-3.

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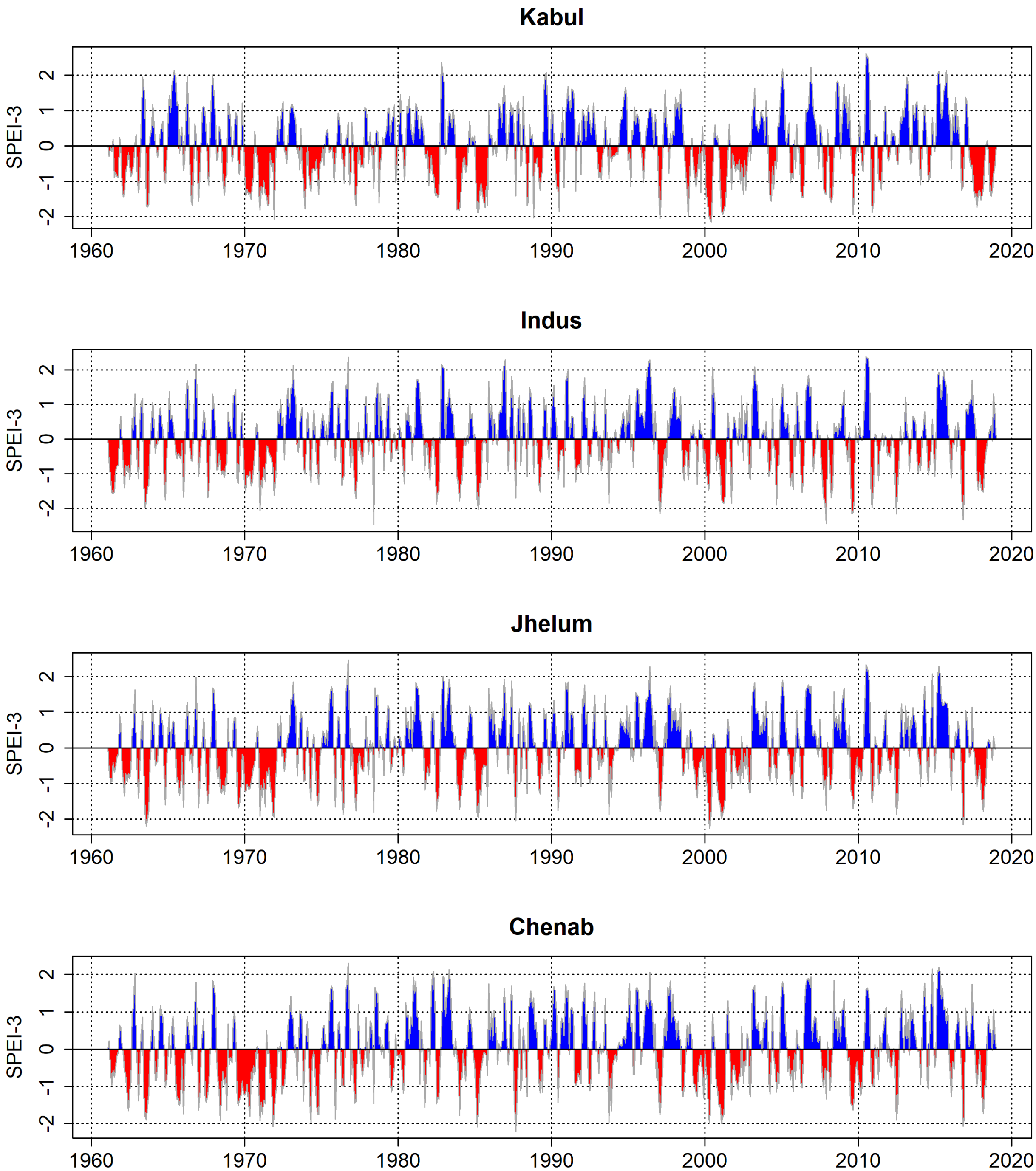

Figure 6. Time-series plots of 3-Month SPEI (also called SPEI-3) for the Upper catchments of Chenab, Jhelum and Indus rivers and Kabul river basin.

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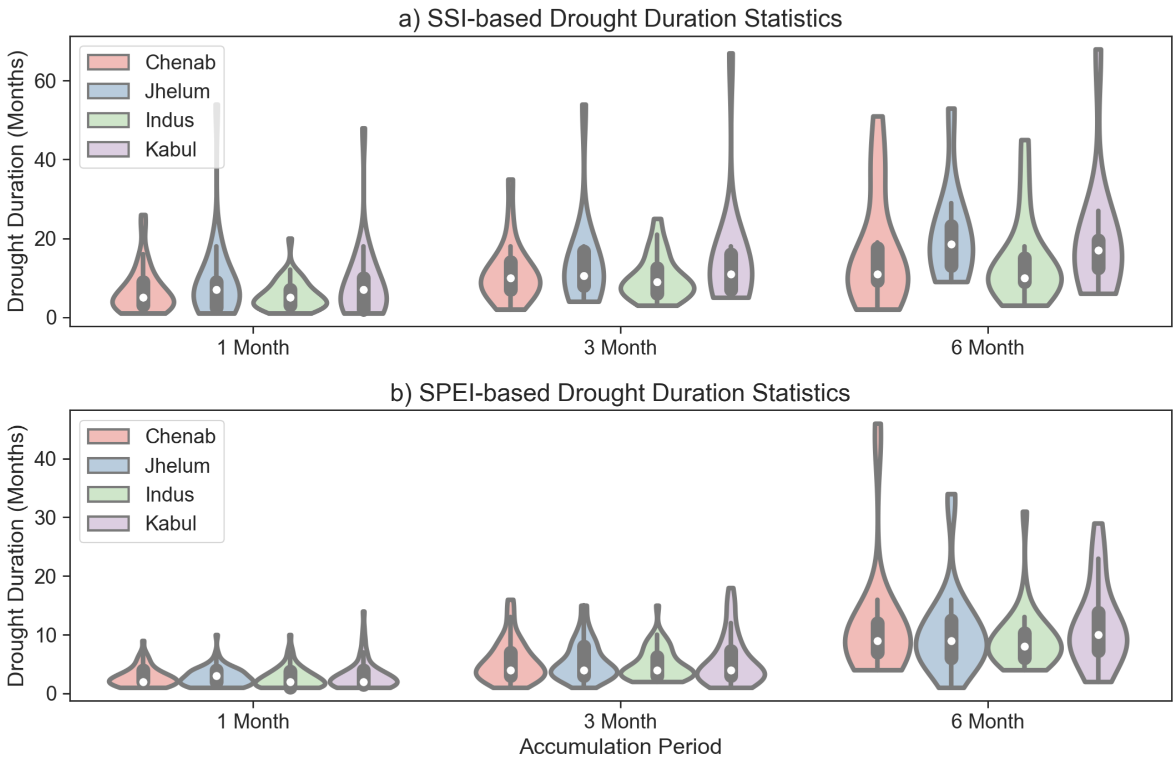

Figure 7. Empirical distributions of drought durations computed using a) SSI with 1-Month, 3-Month and 6-Month accumulation periods (i.e., SSI-1, SSI-3 and SSI-6), b) SPEI with 1-Month, 3-Month and 6-Month accumulation periods (i.e., SPEI-1, SPEI-3 and SPEI-6).

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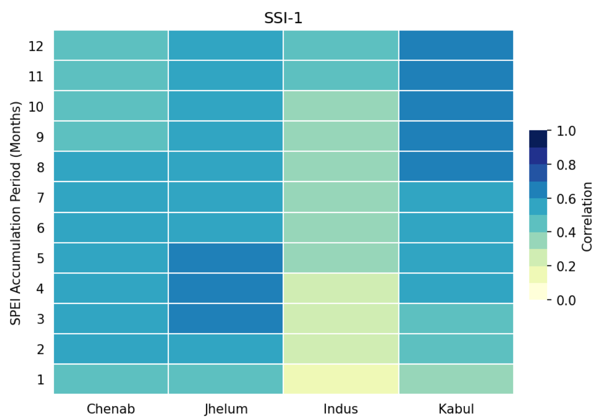

Figure 8. Heatmap of cross-correlations between SSI-1 and SPEI (for different accumulation periods) for the four Upper Indus catchments, i.e., Chenab, Jhelum, Indus and Kabul.

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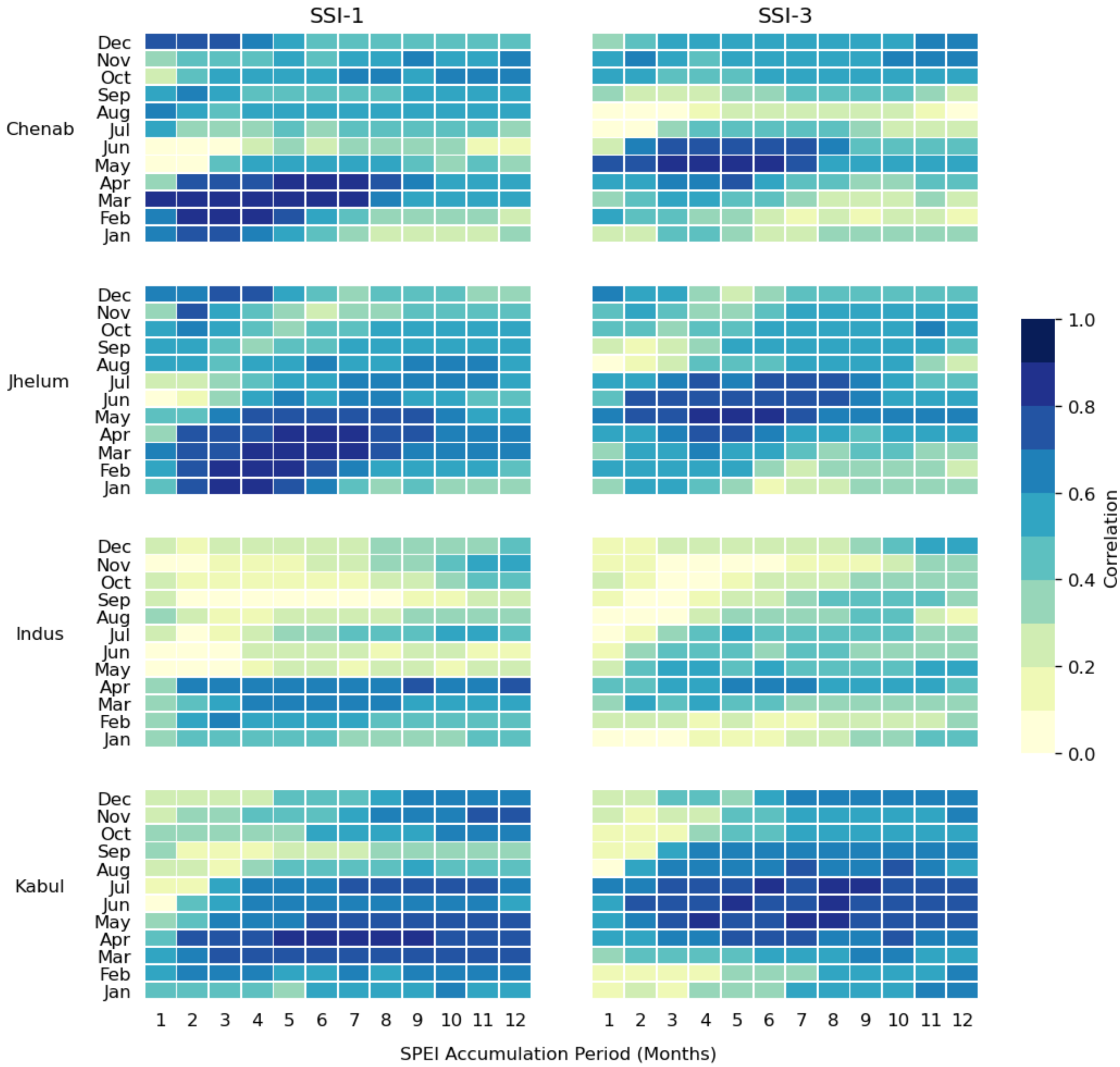

Figure 9. Heatmaps of monthly cross-correlations between SSI and SPEI for the four Upper Indus catchments, i.e., Chenab, Jhelum, Indus and Kabul (depicted in rows). Each column corresponds to a different SSI accumulation period(i.e., SSI-1 and SSI-3). SSI-3 and SPEI cross-corelations are computed with a lag of two months to avoid double accumulation of precipitation.

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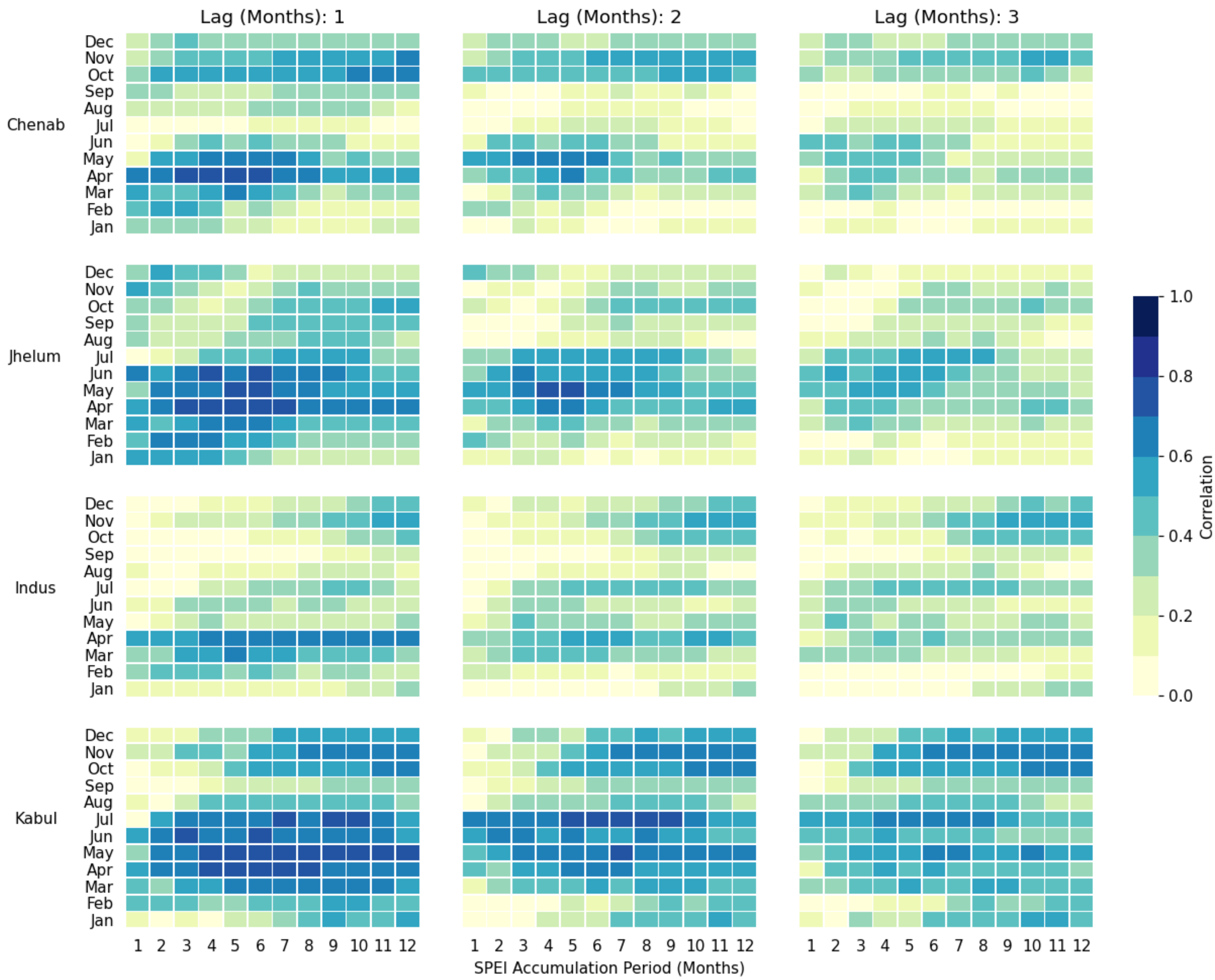

Figure 10. Heatmaps of lagged (1-3 months) monthly cross-correlations between SSI-1 and SPEI (for different accumulation periods) for the four Upper Indus catchments, i.e., Chenab, Jhelum, Indus and Kabul (depicted in rows). Each column corresponds to a different lag (in months; increasing from left to right).

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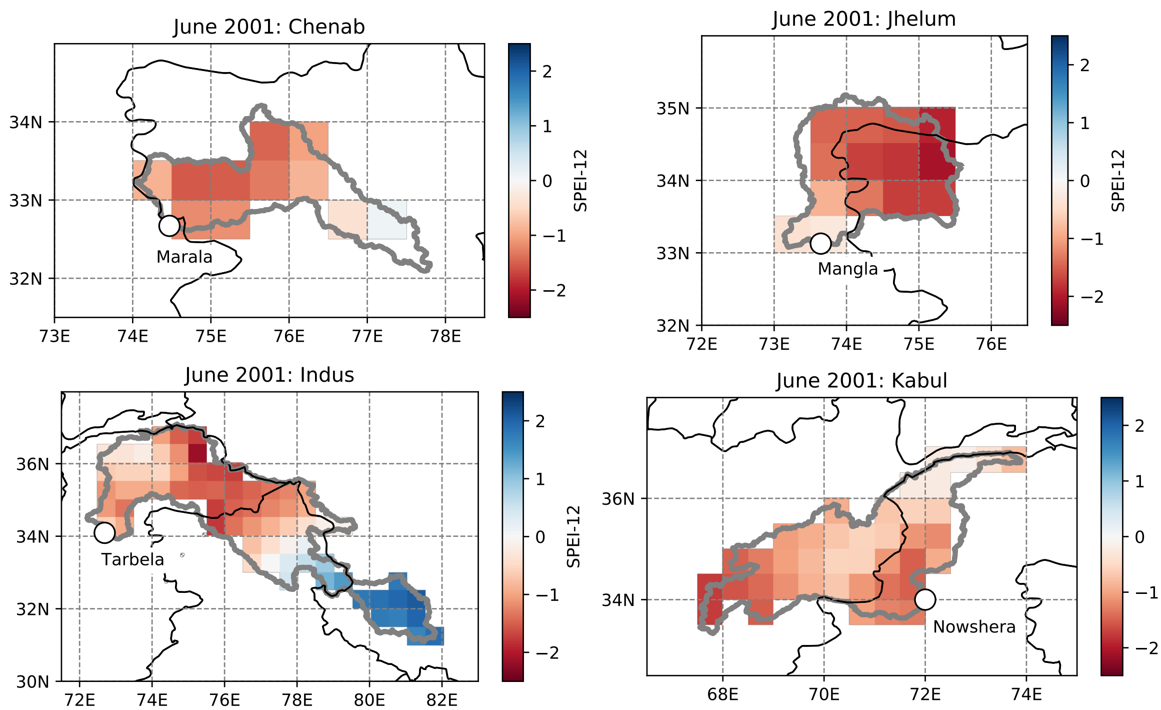

Figure 11. Spatial representation of the Droughts of 1999-02 in the Upper Indus sub-basins of Pakistan, i.e., a) Chenab, b) Jhelum, c) Indus and d) Kabul, using gridded SPEI-12 values of June 2001. Gridded SPEI values are obtained from the SPEIbase data set (Beguería and Vicente-Serrano, 2020; Vicente-Serrano et al., 2010b)