

A new propagation-based framework to enhance competency in regional drought monitoring

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ABSTRACT

Drought is considered a regional phenomenon that usually covers large territorial extensions. It can occur anywhere in the world with severe impacts on water resources and socioeconomic activities. Therefore, it is compulsory to develop reliable tools and execute national plans based on the preeminent information and characterization of drought. There are numerous drought monitoring tools available in the literature to handle spatial and temporal behavior of the drought for regional forecasting and early warning mitigation policies. Standardized Drought Indices (SDI) are frequently used for drought characterization and comparing climatic characteristics of the regions. However, analyzing the spatiotemporal dynamics of the region requires more reliable methods and procedures for drought monitoring. In this perspective, the present study proposes a novel procedure for monitoring drought at a regional level: The Regional Propagation Spatially Weighted Accumulated Drought Index (RPSWADI). The first phase of the proposed procedure is intended to accumulate information from various meteorological stations placed in the homogenous region. In the second phase, accumulated information is used to propagate a new drought index. The proposed procedure is validated on six homogenous meteorological stations of the Northern areas of Pakistan. Furthermore, the commonly used standardized drought indices are used to observe the performance of the proposed procedure. The choice of the indices depends on the climatic conditions of the specific region and will be quantified accordingly. Results show that the RPSWADI can incorporate the spatiotemporal structure of various time series in various stations.

Keywords: spatially weighted accumulated drought index (SWADI), regional propagation, meteorological stations, Northern areas of Pakistan

1. Introduction

Drought is a recurring and common part of climate for virtually all climatic regimes, a multifaceted and poorly embedded phenomenon that disturbs more people than any other natural hazard (Wilhite, 1993; Kiem et al., 2016). Moreover, it has been envisaged as a damaging environmental incidence that distresses natural resources,

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including expedient effects on a water reservoir and social communities. Also, its occurrences have negative effects on human's living standards, economic activities, and other essentials of the environment. As a natural hazard, yet the occurrences of drought are not properly understood. Therefore, it is essential to evaluate the amount and impacts of these occurrences and contemplate them in the pertinent management programs. The period during which the drought occurs normally expected precipitation fails to occur in a plausible time (season) that affects freshwater availability and approachability and influences the natural aquatic ecosystem. Moreover, drought affects several parts of the world in different ways, such as the substantial negative impact on the economy (Smith et al., 1996), effects on hydrological energy (Burek et al., 2020; He et al., 2019), scarcity in rainfall affecting on agriculture production (Ding et al., 2011), and the classification of climate advents discrepancy because of the increasing temperature and extreme precipitation regimes. Therefore, the drought is considered the most pertaining natural disaster that develops an arduous danger for policymakers and mitigation management (Dai, 2011).

Drought monitoring has the utmost consideration at the regional level as its immense impact on the countries' economy and stability (Zhai and Feng, 2009; Santos et al., 2019, Niaz et al., 2020). It emphasizes improved approaches that could be achieved before an event arises to decrease the negative effects of future droughts and enhance response efficiency (Wilhite et al., 2000; Wilhite, 2016). Therefore, policymakers have been required such tools that use the systematic and organized recording of drought impacts to improve the predictive capability of drought monitoring. These tools are based on varying drought indices that are premeditated to calculate various conditions that result from the specified droughts. Further, organized and well-managed drought mitigation policies and predicting drought occurrences can significantly decrease the enormous economic damages. Also, upgrading drought monitoring policies/early warning systems will substantially escalate the drought response and improve drought management strategies (Carbone et al., 2008). Furthermore, decision-makers need more precise and accurate information to execute plans and policies to secure the livelihoods of a region's inhabitants from the negative effects of drought (Wilhite, 2016). However, more precise and accurate manipulation of drought indices involve regionally representative gauge stations with long terms records for regional drought.

There is a need for some efficient and more accurate drought monitoring policies to handle spatial and temporal behavior of the drought (Maybank et al., 1995; Fowler and Kilsby, 2002; Turkes, 2020), standardized procedures are used for the categorization of drought,

which is based on effective and efficient policies. In the literature, several studies have proposed numerous Standardized Drought Indices (SDI) to improve the accuracy of the procedures (Erhardt and Czado, 2018). Among these SDI indices, some most relevant indices are mentioned; for example, McKee et al. 1993 developed the Standardized Precipitation Index (SPI), Tsakiris et al., (2007) have proposed Reconnaissance Drought Index (RDI), the Standardized Precipitation Evapotranspiration Index (SPEI) proposed by (Vicente-Serrano et al., 2010), and Standardized Precipitation Temperature Index (SPTI) developed by (Ali et al., 2017). However, due to the complexity of drought, no single procedure satisfactorily captures drought classes. Consequently, due to the various methodologies using different approaches that are based on probability distributions, availability of the error in distribution, varying geographical structures, and parameters of various conditions used in each index, the uncertainty in the characterization of drought for accurate and efficient drought monitoring under these procedures always exists (Stagge et al., 2015). The regional recognition of drought can be perceived more comprehensively by using accumulative information of drought monitoring tools at various gauge stations. The different stations situated in a homogenous climatic area with inside relative qualities and transmissible in space emerge a few issues because of spatial and temporal information in data analysis preliminaries (Niaz et al., 2020).

Generally, inappropriate distribution of gauge stations without considering comprehensive drought monitoring framework over the region can be triggered misleading inferences. However, the spatial allocation in drought is relatively multifaceted, so intricacy in spatiotemporal appearances of drought records stretches imprecise inferences in drought monitoring. Further, in the literature, such problems that arise due to intricacy in spatiotemporal appearances are discussed and recognized some techniques to handle them for several countries as Turkey (Umran, 1999; Turkes, 2020), Nigeria (Oladipo, 1993), Canada (Maybank et al., 1995), England (Fowler and Kilsby, 2002; Cole et al., 2006), and Spain (Rozas et al., 2015). Some authors have recently developed innovative procedures that improve the drought mitigation policies at homogenous climatic regions (Zhang et al., 2012; Santos et al., 2019, Niaz et al., 2020). In this manner, for upgrading the advancement in drought mitigation policies, particularly at the regional level, it is necessary to contemplate the competency of new and existing methods. Therefore, it is intensive need to make progress in the drought preparation policies to mitigate its impact by improved early warning systems and implementing better drought plans, response, and mitigation strategies for the regional and national level (Van Lanen et al., 2016)

The study aims to develop a precise and inclusive regional level drought monitoring procedure. For this purpose, we have developed a new drought assessment procedure, the RPSWADI. The newly developed procedure will lead to accurate and efficient drought monitoring and forecasting. Moreover, three standardized drought indices (such as SPI, SPEI, and SPTI) at a one-month time scale on six meteorological stations from the Northern areas of Pakistan were applied to observe the performance of the developed procedure.

2. Methods

2.1. Standardized drought index (SDI)

The drought conditions are usually monitored and characterized using SDI, which requires time-series data for certain parameters. The SDIs are commonly used in drought monitoring policies to characterize and compare the specific climatic characteristics of drought. Further, the available data is used to evaluate various SDIs for the present analysis. Also, the evaluation of the indices is based on different parameters. Therefore, using the available data information, this study calculated three SDIs, namely, SPI, SPEI, and SPTI. The explanation for each index is briefly discussed as follows:

The SPI is the most frequently used index worldwide to identify and characterize droughts for various meteorological stations. The SPI drought index contains records of precipitation over a long time to determine the paucity in precipitation. The index was developed by (McKee et al., 1993), and a detailed description is available (see Edwards and McKee, 1997). Further, to quantify the SPI, the monthly cumulative time series data of precipitation is used with appropriate probability distributions for normalization. The values of SPI with negative and positive magnitude are an indication to determine the precipitation status. If the monthly precipitation is greater than the median, it will be considered as a positive value or otherwise considered as a negative value. The SPI is based on a single variable, and it does not consider other variables for drought monitoring such as temperature, evapotranspiration, wind speed, etc. The criticism of SPI is due to its applicability to a single variable. SPEI was proposed to overcome this issue which considers the other parameters such as precipitation and temperature. The SPEI and SPI indices have the same mathematical formulation and calculation; the SPEI index is also known as the water balance model. The SPEI index has one significant advantage over SPI; it considers the evaporation in the domain. The SPEI is based on the water balance equation that can be written mathematically as,

$$D_i = P_i - PET_i \quad (1)$$

where in Eq. (1) D_i is used to identify the moisture deficit at the month i , and calculated by the difference between the P_i and PET_i and the P_i is indicating the total amount of precipitation while PET_i is the estimated amount of Potential Evapotranspiration (PET). The main drawback of SPEI is that it does not consider actual evaporation for calculation, but it considers the estimated value of PET. A new index called SPTI is developed by Ali et al. (2017), designed based on the same methodology used in SPI and SPEI for the characterization of drought. There is no mathematical dissension in the formulation of SPTI. The SPTI is used for the characterization of both cold and hot climate regions, and the procedure for SPTI estimation is as follows. In step one, for each designated station, there are employed monthly average temperature and total precipitation of the month for the evaluation of De Marton Aridity Index (DAI) by the following equation:

$$DAI_i = \frac{P_i}{10 + T_i} \quad (2)$$

where in Eq. (2) P_i indicates the total monthly precipitation and T_i denoting for mean monthly temperature.

2.2. Steady-state probabilities

According to certain probabilistic rules, the working of Markov chains is explained by (Nucita et al., 2013). Some probability distributions are used to measure the Markov process by using transitions that fulfill the mathematical properties (Hahn et al., 2019). The most vital property is that Markov models is "memoryless". This vital property will extend the definition that the upcoming state is dependent only on the present state of the process (where the experiment is presently executed), not on the series of previously performed states (Mishra and Singh, 2010). The steady-state behavior can be determined by linear equations of the Markovian system (Eckelman and Daigo, 2008). A steady-state is an average probability that the system residues in a certain state after numerous transition periods. The probability will constantly persist in the long run while the system coup moves from one state to another state for all periods. Mathematically, the steady-state probabilities can be defined as

$$p_i = \lim_{t \rightarrow \infty} p_i(t) \quad (3)$$

where in Eq. (3) t shows the time of process and p_i is indicating the steady-state probabilities. Furthermore, mathematical descriptions detail about the Markov process and steady-state probabilities are available in Stewart (2009).

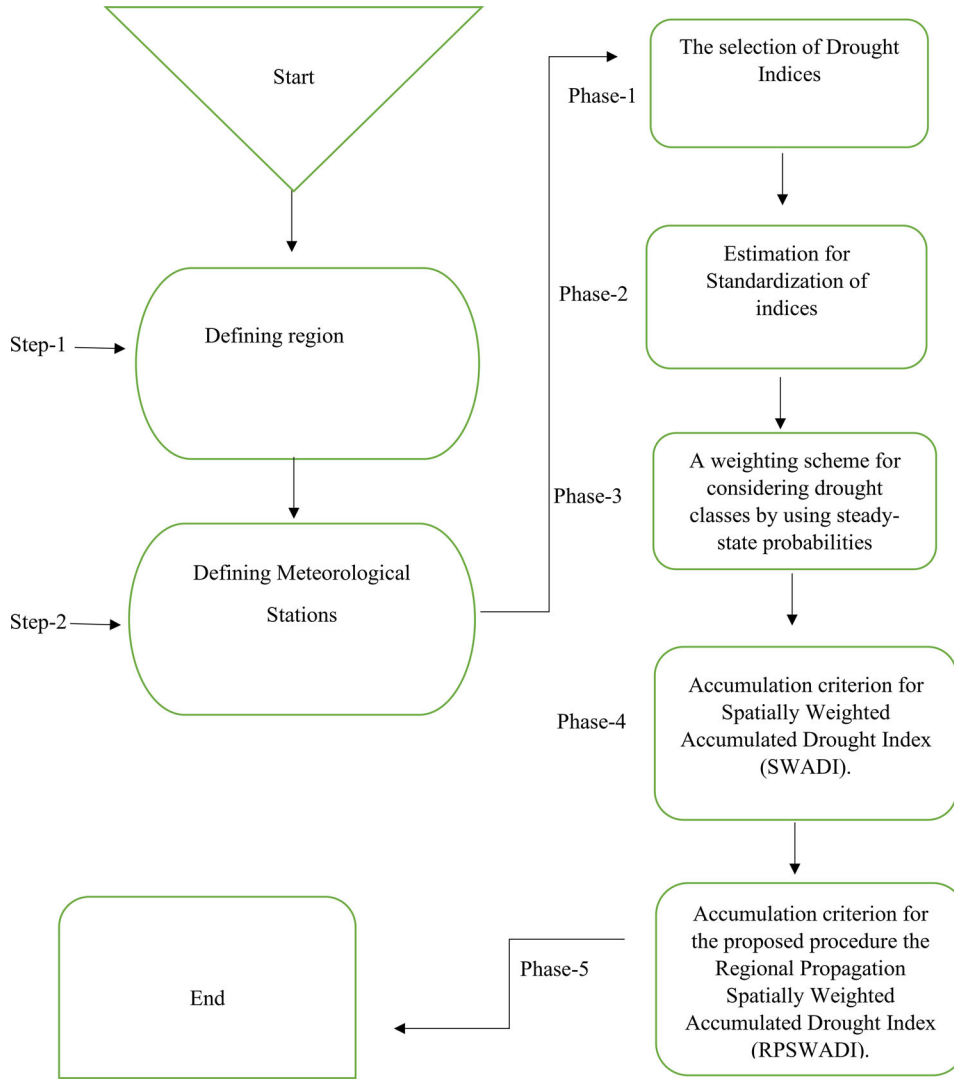


Fig. 1. Flow chart for the framework of the proposed procedure.

3. The proposed framework for the categorization of suitable drought classes at the regional level

Firstly, it is essential to delineate the region and meteorological station before discussing four phases in the framework of the proposed procedure (see Fig. 1). Details of the two steps are as follows:

1. **Defining region:** The appropriate selection of the region for a specific situation will enhance the accuracy and obtain comprehensive inferences for the regional drought monitoring. This step is involved in deciding an appropriate region for the current analysis of regional drought monitoring.
2. **Defining meteorological stations:** After selecting the suitable region for the study, it is required to choose suitable meteorological stations because the significance of

statistical inferences for drought monitoring is based on long climatic information. Therefore, the meteorological stations that have appropriate information regarding climatic parameters are selected for the analysis.

Further, the following subsections comprehensively explain four phases of the framework based on the accumulated information from various stations. Finally, this comprehensive and precise information will make the more descriptive drought temporal characterization in a particular region (see Fig. 3).

3.1. Phase 1: the selection of drought indices

Several drought indicators are available in the literature for the standardized procedure (Svoboda et al., 2016). In

Sec. 2, we discussed in detail SDI and its applications. The estimation of multi-scalar drought indices based on varying climatic parameters and time scales. Therefore, this phase is highly concerned with climatic parameters of varying characteristics and time scales. The parameters usually depend on climatic conditions, such as temperature (in various conditions like the hot and cold season), precipitation multiplicities, solar radiation diversities, and humidity intricacy. Hence, for these conditions, there are varying climatic parameters used to calculate the different drought indices.

Further, time scales have their importance according to the studied phenomenon. As meteorological (Werick et al., 1994), drought usually considers short time scales, while agricultural and hydrological drought consider longer time scales (Gidey et al., 2018). Hence, information coming from various climatic conditions and time scales significantly affect the analysis. In this regard, an optimized choice of drought indices can meaningfully be helpful for accurate and consistent drought monitoring. Moreover, the behavior of the gauging stations for the time series data, the time scale for drought nature, and varying climatic parameters are important to choose an appropriate drought indicator. It means based on different climatic parameters and time scales, the appropriate multi-scalar drought indices are selected in this phase.

3.2. Phase 2: estimation for standardization of indices

In this phase, suitable probability distributions are being considered for each station in the computation of DAI_i ($DAI_i \in P_i, D_i, DAI_i$) series. Moreover, most frequently, 32 probability distributions are employed to obtain more reliable outcomes from the analysis according to the time series data set at a one-month time scale for varying stations. Further, among these probability distributions, the most appropriate probability distribu-

tion Information Criteria (AIC) and Bayesian Information Criteria (BIC) are used to select appropriate distributions in varying stations at a one-month time scale. The distributions with minimum values of AIC and BIC are considered appropriate probability distribution at a one-month time scale for the specific station. Further, a comprehensive explanation related to standardization with mathematical description using Cumulative Distribution Function (CDF) of the well-fitted distributions is available in Naresh Kumar et al. (2009).

3.3. Phase 3: a weighting scheme for considering drought classes by using steady-state

3.3.1. Probabilities. In this study, seven drought classes are defined for the analysis (see Table 2). These classes are premeditated as qualitative information of drought severity and considered as a discrete Markov process for SDI (Ali et al., 2020). The explanation about the Markov process and its application is given in Sec. 2.2. Further, a weighting scheme is employed in this phase for considering appropriate drought classes from the varying stations based on steady-state probabilities. The three popular drought indices, SPI, SPEI, and SPTI are considered at a one-month time scale for selecting appropriate information from various stations. The mathematical description of these steady-state probabilities is given (see Niaz et al., 2020).

3.4. Phase 4: accumulation criterion for spatially weighted accumulated drought index (SWADI)

This phase is based on SWADI, which is proposed by Niaz et al. (2020). The mathematical form for SWADI is presented in Eq. (4) by using the SPTI at a one-month time scale (SPTI -1) for designated stations named as “Astor, Bunji, Gupis, Chilas, Gilgit, and Skardu” as follows

$$SWADI = \begin{cases} SPTI_{Astor} & \text{if } \prod_i(Astor) > \prod_i(Bunji) > \prod_i(Gupis) > \prod_i(Chilas) > \prod_i(Gilgit) > \prod_i(Skardu) \\ SPTI_{Bunji} & \text{if } \prod_i(Bunji) > \prod_i(Gupis) > \prod_i(Chilas) > \prod_i(Gilgit) > \prod_i(Skardu) \\ SPTI_{Gupis} & \text{if } \prod_i(Gupis) > \prod_i(Chilas) > \prod_i(Gilgit) > \prod_i(Skardu) \\ SPTI_{Chilas} & \text{if } \prod_i(Chilas) > \prod_i(Gilgit) > \prod_i(Skardu) \\ SPTI_{Gilgit} & \text{if } \prod_i(Gilgit) > \prod_i(Skardu) \\ SPTI_{Skardu} & \text{otherwise} \end{cases} \quad (4)$$

tion is perceived by using the R package named propagate available in the paper (Spiess, 2014). The Akaike

Equation (4) considers six selected stations for SPTI-1. The steady-state probabilities were applied as weights for

selecting appropriate classes among these stations. The vectors of drought classes on varying stations ($\prod_i(Astor)$, $\prod_i(Bunji)$, $\prod_i(Gupis)$, $\prod_i(Chilas)$, $\prod_i(Gilgit)$, and $\prod_i(Skardu)$) obtained by this process recognized as a SWADI. Likewise, weights were assigned in SPI at a one-month time scale (SPI-1) and SPEI at a one-month time scale (SPEI-1) for selected stations.

3.5. Phase 5: accumulation criterion for the proposed procedure is the regional propagation spatially weighted accumulated drought index (RPSWADI)

In a study of the homogenous climatic environment, a particular index gives similar results on various stations, leading to a laborious practice manipulating identical information on varying stations. Therefore, the SWADIs were proposed to resolve such issues to make comprehensive and precise strategies for early warning and mitigation policies. The SWADIs used steady-state long-run probabilities as weights for the perspective of accumulating information from various homogenous stations. However, after resolving above mentioned issues, there is still uncertainty presented in incoming information. This uncertainty occurs due to practicing a single drought index, which is inadequate for accurate drought detecting and forecasting. Moreover, working with more than one drought index to obtain identical outcomes creates a chaotic situation for data analysts and policymakers. These issues can be addressed by using the proposed RPSWADI. In RPSWADI the three vectors of SWADIs calculated from SPI, SPEI, and SPTI are again used for the regional propagation at a one-month time scale (see Fig. 2). This propagation is based on the steady-state probabilities that mean the classes that receive maximum probabilities (weights) among three indices ($SWADI_{SPI}$, $SWADI_{SPEI}$ and $SWADI_{SPTI}$) are considered appropriate classes for the analysis. The mathematical expression for the proposed procedure at a one-month time scale can be written as

$$RPSWADI = \begin{cases} SWADI \text{ of } SPI-1 & \text{if } \prod_i(SWADI_{SPI-1}) > \prod_i(SWADI_{SPEI-1}) > \prod_i(SWADI_{SPTI-1}) \\ SWADI \text{ of } SPEI-1 & \text{if } \prod_i(SWADI_{SPEI-1}) > \prod_i(SWADI_{SPTI-1}) \\ SWADI \text{ of } SPTI-1, & \text{otherwise} \end{cases} \quad (5)$$

Equation (5) comprises SWADI for each index at a one-month time scale, showing that the accumulated vectors of classes SWADIs are used to propagate appropriate classes among indices. The proposed procedure RPSWADI is used to select suitable classes among various SWADIs. Further, the vectors of drought classes

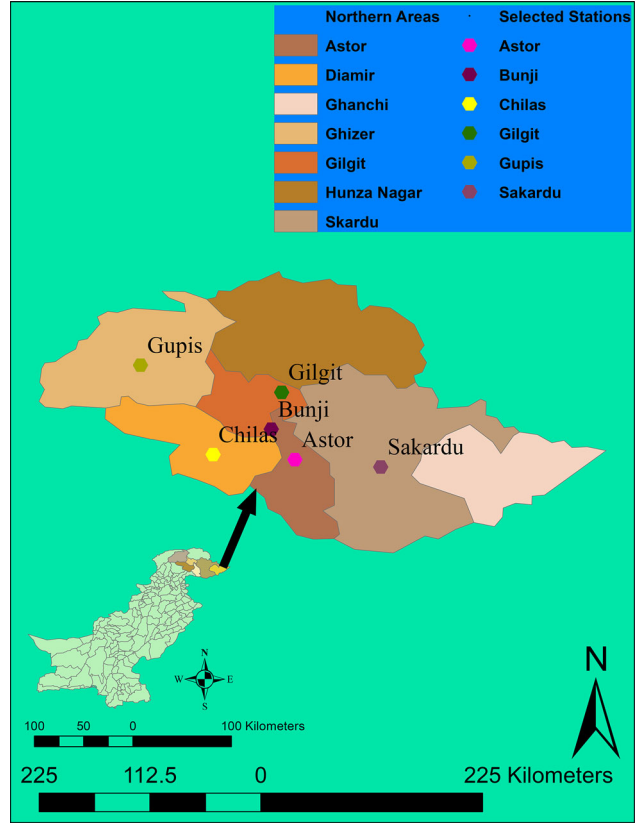


Fig. 3. The geographical locations of the selected stations of the Northern area of Pakistan.

which are being obtained from various drought indices at a one-month time scale can be represented by ($\prod_i(SWADI_{SPI-1})$, $\prod_i(SWADI_{SPEI-1})$, $\prod_i(SWADI_{SPTI-1})$) which is used for the calculation of RPWSADI. More precisely, at a one-month scale, the drought classes which are selected among three selected indices ($SWADI_{SPI-1}$, $SWADI_{SPEI-1}$, and $SWADI_{SPTI-1}$) has higher values (steady-state probability weights) of average long-run probabilities in the selected time series of the data.

4. Application

The application of the proposed procedure (i.e. RPSWADI) is based on six meteorological stations situated in the Northern regions of Pakistan (see Fig. 3). In this section, a slight consideration has been remunerated

Table 1. The statistics to address the period 1971–2017 of six selected stations.

Variable	Station	Mean	Median	St.Dev
Precipitation	Astore	40.912	25.708	41.934
	Bunji	14.340	7.109	18.901
	Gupis	16.852	5.707	30.214
	Chilas	16.763	7.006	23.535
	Gilgit	12.420	6.056	16.576
	Skardu	20.631	9.107	25.907
Maximum temperature	Astore	16.665	16.703	8.658
	Bunji	25.196	24.952	8.989
	Gupis	19.954	19.703	9.466
	Chilas	27.921	27.354	9.662
	Gilgit	25.464	25.155	9.214
	Skardu	19.923	20.056	9.825
Minimum temperature	Astore	4.340	4.3071	7.487
	Bunji	11.866	11.500	7.808
	Gupis	6.747	6.903	8.060
	Chilas	15.146	14.306	9.086
	Gilgit	8.076	7.752	7.307
	Skardu	5.068	5.557	8.363

to the geographical background of the study area. The Northern regions have a significant role in the overall climatology of the country (Awan, 2002). Due to the spatial structure of Northern regions, the water irrigation to various crops in the Punjab and Sindh (the provinces of Pakistan) is greatly affected by the climate change and hydrological process (Mahmood-ul-Hassan, 2013). In recent years, due to the rising magnitudes of climate change and the consequences of global warming, various parts of the country are badly affected by drought hazards (Wada et al., 2017). As the reliance on more regions of the country is prominently associated with the designated region. Hence the selection of the Northern region for the proposed study is rational. Further, the secondary data of precipitation and temperature (Minimum and Maximum) of the selected region, ranging from January 1971 to December 2017, is collected for the analysis of the present study.

4.1. Results

The six selected stations and their brief statistics for various parameters are given in Table 1. The classification for varying drought classes (“Extremely Dry (ED), Severely Dry (SD), Median Dry (MD), Normal Dry (ND), median Wet (MW), Severely Wet (SW), Extremely Wet (EW)”) (see Niaz et al., 2020). The R package named *propagate* is used for fitting an appropriate distribution for a specific time scale. The most frequently used distributions are considered for standardization. The criterion for choosing a suitable distribution is based on

BIC values. The distribution with the smallest BIC values at a one-month time scale of SPI, SPEI, and SPTI is selected for standardization accordingly (as described in Sec. 2.1). Table 2 contains BIC values of the varying probability distributions chosen as appropriate distributions according to SPI-1, SPEI-1, and SPTI-1 for selected stations. It can be perceived that at SPI-1 the three parameters (3 P) Weibull distribution has minimum values of BIC (−1036.513), (−1030.985), (−1097.487), and (−735.125) for Astore, Bunji, Gilgit, and Skardu, respectively. For SPTI-1 (3 P) Weibull distribution has minimum values of BIC (−483.522), (−188.456), (−275.421), (−164.625), and (−590.057) for Astore, Bunji, Chilas, Gilgit, and Skardu stations respectively. Further, at a one-month time scale 4p Beta is selected in Astore for SPI, Trapezoidal has selected for Astore for SPEI, Johnson SB for Bunji at SPEI, Johnson SU for Skardu for SPTI, and Johnson SB for SPEI in Gilgit, etc. However, the Weibull distribution has some applications in hydrology and related discipline (Martins and Stedinger, 2000), has a higher quality of candidacy for standardization.

Moreover, the resultant vector of the first phase is embodied by a weighting scheme (steady-state probability). The values that take maximum weights among various stations are selected for SWADIs classes. This phase is accomplished with an R package named *Markochain* (Spedicato et al., 2016). Further, the temporal values with qualitative characteristics are classified according to the severity level of drought are quantified by using steady-state probabilities in long-term behavior. In the second phase, accumulated information obtained from the SWADIs is used to propagate a new drought index. The SWADIs are based on three standardized drought indices (SPI, SPEI, and SPTI). The calculation for the selected indices is performed accordingly. In this paper, varying distribution concept is considered for approximation (Stagge et al., 2015). By developing a rationale of the proposed criterion which uses the long-term behavior for reporting accurate drought class by overcoming the consequences of extreme values. Figure 4 displays the theoretical versus empirical histograms at a one-time scale of the SPI index for selected distributions. In these histograms, a significant discrepancy can be observed among stations (e.g. Astore). The researchers have been working to overcome such discrepancy behavior recently, non-parametric functions and mixture distribution functions-based standardizations were proposed (Huang et al., 2016), but still, the matter is under consideration. However, more accuracy between theoretical and empirical at SPI-1 Gupis and Gilgit respectively can be observed. In Fig. 5, the temporal behavior can be observed for SPI-1. Further, the temporal behavior of

Table 2. BIC of selected probability distributions at a one-month time scale for SPI, SPEI, and SPTI in selected stations.

Distribution	Astore			Bunji			Gupis		
	SPI	SPEI	SPTI	SPI	SPEI	SPTI	SPI	SPEI	SPTI
3P Weibull	-1036.513	-700.544	-483.522	-1030.985	-1178.062	-188.456	-735.144	-910.746	-370.406
Trapezoidal	-940.422	-710.056	-354.124	-712.787	-1224.004	-151.717	-531.573	-946.948	-318.903
4P Beta	-1031.384	-700.287	-473.375	-1020.690	-1210.971	-74.248	-788.076	-823.156	-374.234
Johnson SB	-945.135	-685.965	-358.766	-664.596	-1248.434	-148.564	-535.966	-977.693	-273.656
Distribution	Chilas			Gilgit			Skardu		
	SPI	SPEI	SPTI	SPI	SPEI	SPTI	SPI	SPEI	SPTI
Johnson SU	-399.837	-489.813	-217.797	-720.244	-1015.985	-107.797	-499.832	-528.997	-590.057
3P Weibull	-800.233	-488.052	-275.421	-1097.487	-1016.347	-164.625	-735.125	-640.780	-516.573
4P Beta	-805.614	-574.973	213.413	-1085.123	-1162.238	-73.377	-700.236	-523.686	-506.868
Trapezoidal	-720.381	-579.724	-72.944	-922.266	-1185.662	-150.092	-720.383	-644.670	-418.489
Johnson SB	-761.683	-594.796	-103.556	-971.017	-1213.277	-75.887	-711.687	-656.244	-399.984

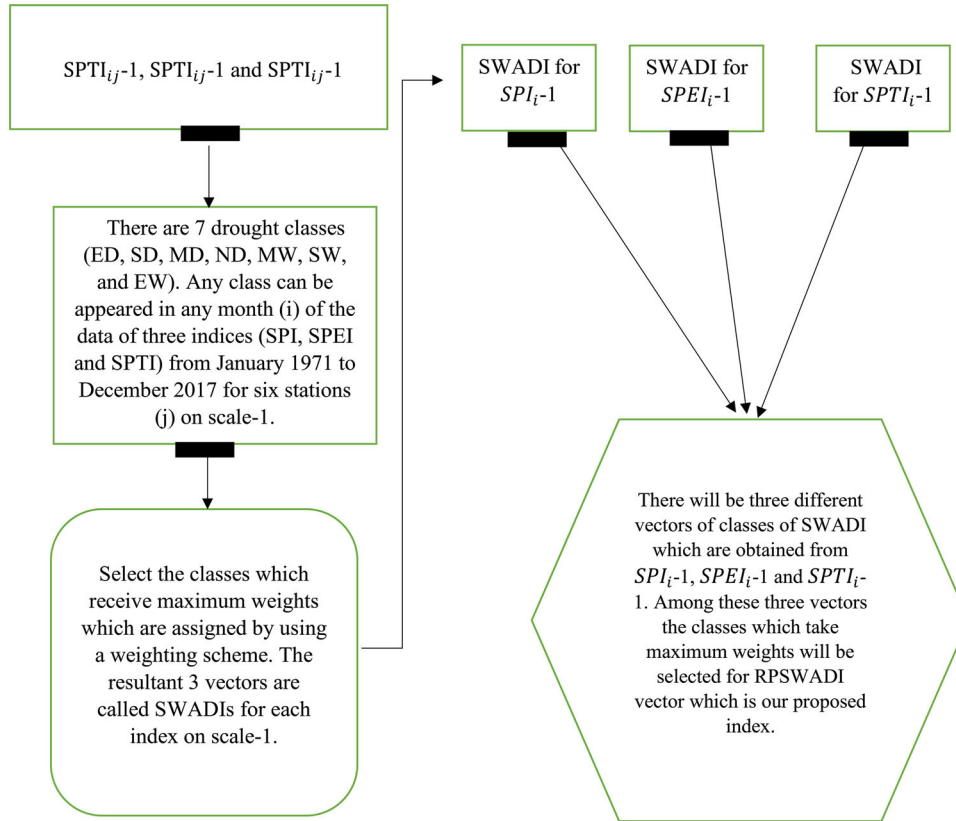


Fig. 2. Flow chart of proposed procedure for RPSWADI based on SWADI calculation at a one-month time scale (scale-1).

SWADIs and RPSWADI for a one-month time scale is presented in Fig. 6.

4.2. Discussion

The probability distributions suitable for the selected indices (SPI, SPEI and SPTI) at a specific time scale

(one-month time scale) on various stations are employed for the standardization. The BIC criterion was applied for the selection of appropriate probability distributions. The three standardized drought indices (SPI, SPEI and SPTI) are used to calculate SWADIs. The calculated SWADIs are based on the steady-state probabilities (Niaz et al., 2020). The three SWADIs are further considered to

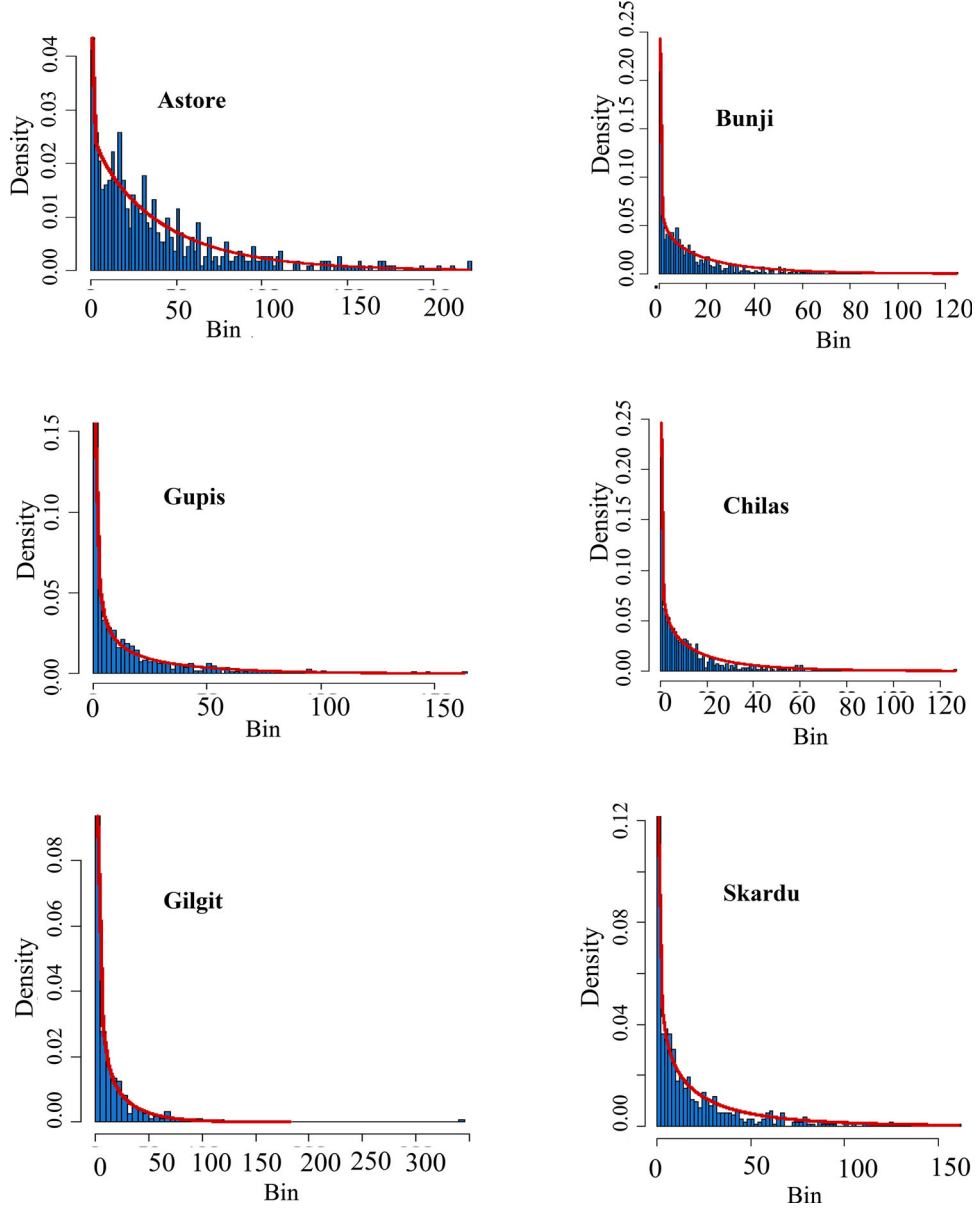


Fig. 4. Theoretical vs. empirical histograms for SPI at a one-month time scale of the selected distribution for selected stations.

calculate the proposed procedure, RPSWADI. The calculation of the RPSWADI consists of two phases. The first phase of the RPSWADI is estimated to accumulate information from selected stations located in the homogenous region. However, in the second phase, the accumulated information is utilized for the calculation of the RPSWADI. The RPSWADI receives maximum weights among the SWADIs from the selected time series data, ranging from January 1971 to December 2017, is collected for the analysis of the present study. The attained information from RPSWADI can be utilized to monitor drought more precisely and accurately and support

drought monitoring strategies and mitigation policies. Further, the obtained outcomes from the RPSWADI provide the basis to enhance the drought monitoring and forecasting strategies at the regional level.

5. Conclusion

Drought is considered a climatic, natural hazard that arises in most world climates and can bring substantial diversities in the environment of the society. It is normally defined as a natural hazard triggered by a long period when there is not enough rain to meet the normal

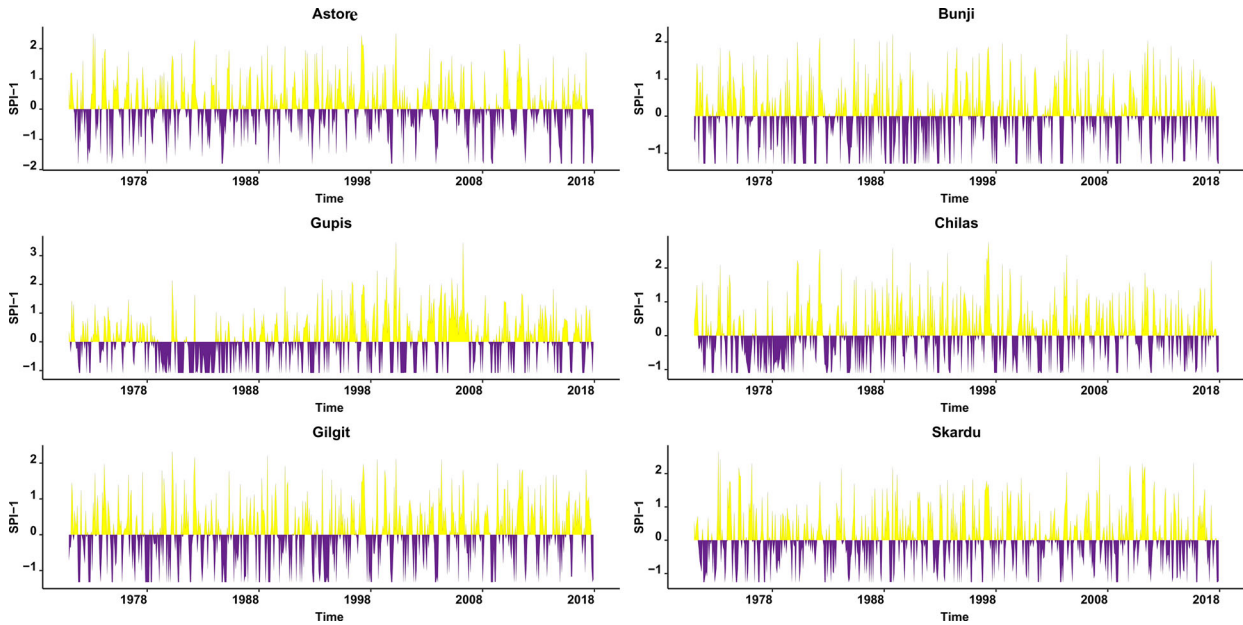


Fig. 5. Temporal plots of SPI-1 for selected stations.

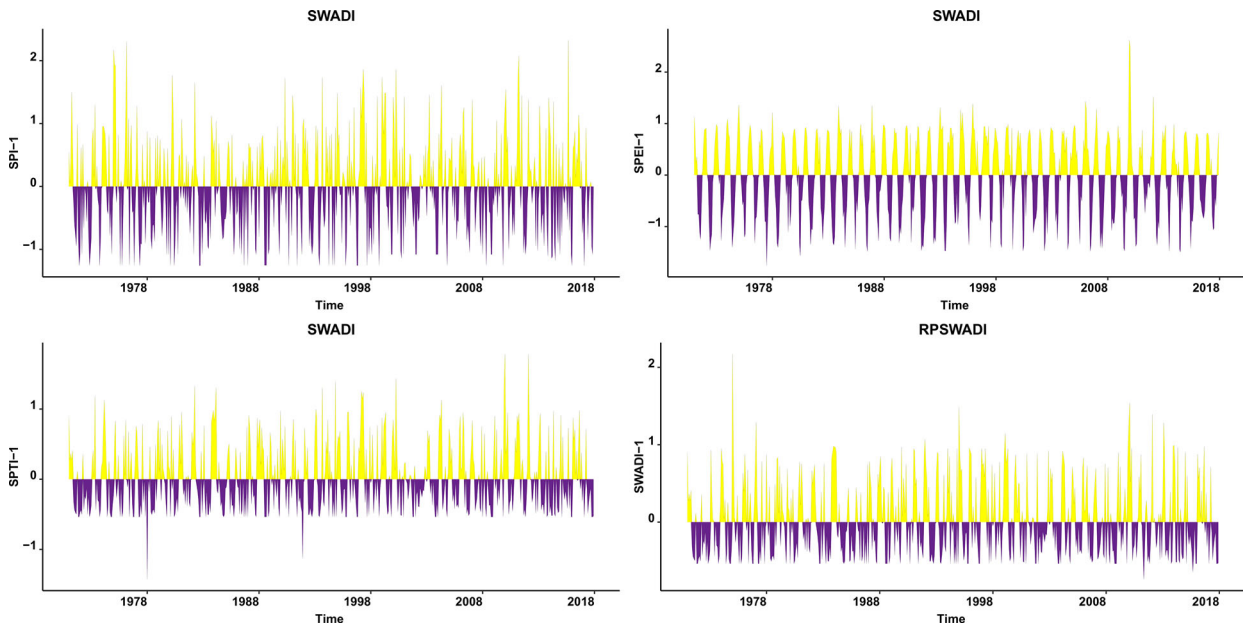


Fig. 6. Temporal plots for scale-1 for SWADI and RPWSADI.

standard of rainfall. Drought usually has a long duration, and its effects ensue slowly over time. The drought complications can be simplified if the drought is measured in a systematic context with suitable tools and procedures. However, the tools used for drought monitoring at multiple gauge stations in a certain homogenous climatic region cause inefficiency and redundancy in data analysis preliminaries. Contrarily, single time-series data of drought indices at homogenous climatic regions leads to

accurate and efficient drought monitoring and forecasting. Moreover, for the various gauge stations located in certain homogenous climatic regions, this research aims to develop a new regional level procedure for drought monitoring: the RPSWADI. In the proposed procedure, time-series data of various meteorological stations placed in the homogenous region is accumulated by using steady-state probabilities as weights. This accumulated information is used to propagate for indices. The preliminary

configuration of the RPSWADI procedure included standardized drought indices at a one-month time scale. In the SDI toolkit, we have included SPI, SPEI, and SPTI. A combined time series named RPSWADI is shown for a one-month time scale. Further, from the outcomes of the literature, results, and analysis of this paper, we have concluded the following points:

1. The use of a single drought index is inadequate for accurate drought monitoring.
2. The use of more than one drought index creates a chaotic situation for data analyzed and policymakers.
3. The proposed index RPSWADI resolves the above two problems.
4. Also, RPSWADI can incorporate the spatiotemporal structure of various time series in various stations (i.e. metrological observatories and different drought indices).

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Data and code availability

Data and Code will be available on request.

Disclosure statement

The authors declare that they have no competing interests.

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