A novel spatio-temporal two-stage standardized weighting scheme for regional drought analysis

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Drought is a complex phenomenon that occurs due to insufficient precipitation. It does not have immediate effects, but sustained drought can affect the hydrological, agriculture, economic sectors of the country. Therefore, there is a need for efficient methods and techniques that properly determine drought events. Considering the significance and importance of drought monitoring methodologies, the current study proposed a Novel weighting scheme, known as Spatio-Temporal Two-Stage Standardized Weighting Scheme (STTSSWS) for regional drought analysis. The potential of the weighting scheme is based on the steady-state probabilities. Further, in the first stage of the proposed scheme, the steady-state probabilities are calculated for various stations at a one-month time scale to assign weights for varying drought classes. However, in the second stage (stage two) these weights are further divided based on spatiotemporal characteristics to obtain new weights for the various drought classes in the selected region. The proposed weighting scheme is validated to the six selected stations of the northern area, Pakistan. The outcomes of the proposed weighting scheme may accurately assign spatiotemporal weights for selected states and provides efficient information for the selected region.

A Novel Spatio-Temporal Two-stage Standardized Weighting Scheme for Regional Drought Analysis

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Abstract

Drought is a complex phenomenon that occurs due to insufficient precipitation. It does not have immediate effects, but sustained drought can affect the hydrological, agriculture, economic sectors of the country. Therefore, there is a need for efficient methods and techniques that properly determine drought events. Considering the significance and importance of drought monitoring methodologies, the current study proposed a Novel weighting scheme, known as Spatio-Temporal Two-Stage Standardized Weighting Scheme (STTSSWS) for regional drought analysis. The potential of the weighting scheme is based on the steady-state probabilities. Further, in the first stage of the proposed scheme, the steady-state probabilities are calculated for various stations at a one-month time scale to assign weights for varying drought classes. However, in the second stage (stage two) these weights are further divided based on spatiotemporal characteristics to obtain new weights for the various drought classes in the selected region. The proposed weighting scheme is validated to the six selected stations of the northern area, Pakistan. The outcomes of the proposed weighting scheme may accurately assign spatiotemporal weights for selected states and provides efficient information for the selected region.

Keywords: Spatiotemporal; steady-state probabilities; homogenous region; meteorological stations; standardized weighting scheme; drought monitoring.

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1. Introduction

Drought is a creeping phenomenon, influencing more individuals than other natural hazards (Botai et al., 2027; Mousavikhah et al., 2020; Bhunia et al., 2020; Elhoussaoui et al., 2021). It is a slowly evolving and multifaceted disaster, often poorly understood in the perspective of regional climatic, hydrological, and human environment (Mukherjee et al., 2018; Vicente-Serrano et al., 2020). Drought is a recurring natural hazard appearing in all climatic zones worldwide and significantly influences social and economic well-being, ecological environment, and agricultural sectors (Guneralp et al., 2015; Hagenlocher et al., 2019; Shah and Mishra, 2020). In its explicit form, drought can be described as the water discrepancy that appears in several types, including agricultural, meteorological, hydrological, and socio-economic drought (Lai et al., 2019; Jiang & Wang, 2019). The meteorological drought occurs due to insufficient precipitation, and insufficiency in soil water supply triggers the agricultural drought. If drought distribution further continues via the hydrological cycle, a deficiency in surface or groundwater evolves, causing hydrological drought.

Further, the monitoring, modeling, and prediction of meteorological droughts are of utmost significance. Because the meteorological drought becomes the root for other drought types due to insufficient precipitation (Wu et al., 2017; Lai et al., 2019; West et al., 2019). Moreover, accurate valuation of meteorological drought brings useful information for decision-makers worldwide working in several fields associated with agriculture, hydrology, industrial, and water-budget managers to formulate precautionary measures and develop future planning (Alizadeh and Nikoo, 2018). Further, various studies have described the importance of monitoring regional drought (Wilhite et al., 2000; Zhai & Feng, 2009; Zhang et al., 2012; Van Lanen et al., 2016; Santos et al., 2019). The regional monitoring of drought has significantly influenced the country's economy and other human activities (Zhai & Feng, 2009; Mousavikhah et al., 2020). The regional drought monitoring highlights those issues if they could improve at the regional level before the events occur, then potential adverse effects of drought can be minimized in the future (Wilhite et al., 2000; Santos et al., 2019; Pontes Filho et al., 2019; Pontes Filho et al., 2020). More comprehensive and accurate drought monitoring can be possible by applying suitable tools and techniques according to climatic conditions. Based on the various climatic conditions, several drought indices have been used for drought monitoring. These indices require proper and effective recording related to drought occurrences. For instance, more accurate estimation of drought indices requires appropriate gauge stations with suitable records for regional drought. The indices contain essential information that can be used for the analysis that considerably improves forecasting and early warning policy about future drought occurrences (Tsakiris, et al., 2007; Niemeyer, 2008; Hayes et al., 2011; Mukherjee et al., 2018).

Moreover, various studies from the literature have discussed the drought indices. Several studies have developed some new drought indices (McKee et al., 1993; Tsakiris, et al., 2007; Vicente- Serrano et al., 2010). The development in drought mentoring is leading to enhancing the capabilities of drought monitoring more precisely and accurately. The standardized indices are used for the categorization. The estimation of the drought indices is based on the various parameters (precipitation, temperature, etc.). However, the preference for calculating the indices is based on climatic conditions of the available data (Niemeyer, 2008; Hayes et al., 2011). For instance, an index based on the precipitation, which is known as Standardized Precipitation Index (SPI) proposed by McKee et al., 1993, the Reconnaissance Drought Index (RDI) developed by Tsakiris, et al., 2007, the Vicente- Serrano et al. (2010) has proposed an index which is called as

Standardized Precipitation Evapotranspiration Index (SPEI). The spatiotemporal characteristics in the stations situated in a homogenous climatic area arise several issues in data analysis preliminaries. These issues are discussed in various studies available in the literature (Maybank et al., 1995; Umran, 1999; SIRDAŞ & Sen, 2003; Wang et al., 2020; Zhou et al., 2020).

Furthermore, drought is a complicated phenomenon; its occurrences are complex. Therefore, there is a need to develop some efficient techniques in drought monitoring policies to handle the spatiotemporal behavior of the drought (Maybank et al., 1995; SIRDAŞ & Sen, 2003; Wang et al., 2020). Since the estimation of spatiotemporal characteristics is of utmost importance in drought monitoring. The information obtained from the spatiotemporal characteristics can be used for significant modeling and drought prediction. Therefore, an intense spatiotemporal analysis is required to assimilate the spatiotemporal information of the selected homogenous region (Dabanlı et al., 2017; Caloiero, et al,.2018; Zhou et al., 2020). In this regard, we aimed to develop a new weighting scheme for the homogenous region. The weighting scheme, known as Spatio-Temporal Two-stage Standardized Weighting Scheme (STTSSWS), is validated on six selected stations of the northern area of Pakistan. The proposed weighting scheme provides more efficient and accurate information about the selected stations.

2. Methods

2.1. Standardized Drought Index

The various Standardized Drought Indices (SDI) have been used to monitor drought (Alley, 1985; Narasimhan & Srinivasan, 2005; Stagge et al., 2015; Eslamian et al., 2017; Niaz et al., 2020). The two familiar drought indices SPI and SPEI are used in the present analysis. The SPI index was proposed by (McKee et al., 1993). It has been commonly used for drought monitoring. Several studies have used SPI for drought monitoring (Stagge et al., 2015; Eslamian et al., 2017; Pathak and Dodamani, 2019; Hagenlocher et al., 2019; Niaz et al., 2020). The calculation of SPI is very simple; only the precipitation data is used for its calculation. The SPI can be calculated at various time scales. The calculation and the availability of the data of the precipitation are relatively easy; therefore, the SPI is commonly used worldwide. Further, the SPEI is a multi-scalar drought index that attracted significant attraction in drought estimation. The SPEI was developed by Vicente-Serrano et al. (2010) that obtains the simplicity in temporal characterization and considers as an extension of SPI. SPEI evaluates the effects of evaporative demand on drought and is computed by considering both precipitation and potential evapotranspiration. The SPEI can be calculated by fitting various probability distributions based on the climatic conditions of the selected stations. More detailed information concerning the SPEI computation can be acquired in Vicente Serrano et al. (2010) and Beguería et al. (2014).

2.2. The proposed weighting Scheme: The Spatio-Temporal Two-Stage Standardized Weighting Scheme (STTSSWS).

Drought causes severe damages worldwide. However, drought monitoring policies need a deep knowledge regarding the spatial and temporal distribution of drought risk at the local or regional level. Therefore, in this perspective, we propose STTSSWS, the innovative methodology giving a better evaluation and management of drought monitoring, especially for spatial and temporal characteristics of the region. The STTSSWS is based on steady-state probabilities. The steady-state probabilities can be defined as the average probability that the system remains in a certain state after many transitions.

Moreover, in a Markov process, it can be more explicitly defined as the probabilities are approached the steady-state probabilities after some periods have been passed. Moreover, detailed mathematical explanations related to the steady-state probabilities of the Markov chain are presented in Stewart (2009). Further, in STTSSWS, Steady-state probabilities are used as weights in two stages. In the first stage of the calculation of STTSSWS, the weights for all drought classes are calculated using steady-state probabilities as a weighting scheme (Niaz et al., 2020). However, in the second stage, the weights obtained from steady-state probabilities for varying classes are used to calculate new weights from the spatiotemporal distributions of the data. The second stage has two phases; in the first phase, the weights are computed using temporal information for each station separately. The calculation of the first phase is given in Equation 1.

$$T_{December}(P_{(mi)(Skardu)}) = \frac{S_{(mi)Skardu}}{\sum_{i=1}^{n} S_{(mi)Skardu}}, \quad i = 1,2,3,\ldots\ldots,47 \text{ and } m = 1,2,\ldots,6 \qquad (1)$$

Where $T_{December}(P_{(mi)(Skardu)})$ is indicating the probabilities (weights) for varying drought classes at the time December in Skardu station. The i is indicating the specific month (say, December of 1971 , December of 1972 and so forth) varying over the designated period (from January 1971 to December 2017). And m denoting the drought classes which are studied in this study (say, m = ("1 (Extremely Wet (EW)), 2 (Severely Dry (SW)), 3 (Median dry (MW)), 4 (Normal Dry (ND)), 5 (Median Dry (MD)), 6 (Severely Dry (SD)), and 7 (extremely Dry (ED))"). The severity of the drought classes are illustrated according to (Niaz et al., 2020). The steady-state probabilities for the period from January 1971 to December 2017 contains all Decembers at the station (Skardu) are signified by $S_{(mi)(Skardu)}$. And $\sum_{i=1}^{n} S_{(mi)(Skardu)}$ signifying that the steady-state weights are added for December over the designated period with monthly data the Skardu station with several drought classes. Moreover, n indicating the total months of December (i.e 47) in Skardu for the designated period. For instance, the $S_{(mi)\,(Skardu)}$ are computed with several drought classes for Skardu station for the various months of December, then the denominator contemplates the sum of the weights achieved from steady state probabilities for the varying drought classes of Decmeber in the selected study period at Skardu station. More plainly, it can be quantified as we have 47 December in the selected data. Hence, the weights of 47 December are being included (added) to the denominator for Skardu for seven drought classes. Now, the monthly weights for other months (January, up to November) with these selected classes are evaluated on the same rationale. To have sidestep from the complication of the mathematical equalities, we only presented Skardu station for December in the first phase of the STTSSWS. However, this can be extended for the other stations over varying months. Furthermore, the methodology is presented in the second phase to get spatiotemporal qualities of the selected drought classes. Thus, the spatiotemporal weights for these selected drought classes can be obtained as follows,

$$ST_{December}(P_{(mi)(Skardu)}) = \frac{T_{December}(P_{(mi)(Skardu)})}{\sum_{j=1}^{M} Q_{mij}} \quad , \quad i = 1,2,3,\ldots,47 \text{ and } j = 1,2,,\ldots,6 \qquad (2)$$

Where in Equation (2) takes monthly spatiotemporal weights for various drought classes at Skardu station. $ST_{December}(P_{(mi)(Astor)})$ is representing the probabilities computed from spatiotemporal information (spatiotemporal weights) for varying drought classes in December at Skardu station. Further, the weights $T_{December}(P_{(mi)(Skardu)})$ which were calculated from Equation (1), are being further divided by the$\sum_{j=1}^{M} Q_{mj}$. And where the quantity (observation) Q_{mj} precieved from the varying selected drought classes (m) at various selected stations (j), and the total number of selected station are denoted by M (i.e M = 6). The STTSSWS uses spatiotemporal characteristics of the selected stations and provides imperative knowledge about drought occurrences in a homogenous region. The obtained information from the STTSSWS can be used to build substantial drought monitoring procedures, techniques and methodlogies.

3. Application

The six meteorological stations of the Northern Areas of Pakistan (Figure 1) are selected in STTSSWS for the regional drought analysis. Northern Area is a geographic area that has a group of three mountain ranges, the Himalayas, Karakoram, and the Hindu Kush, which cover most of the region (Rasul, G., 2011). Many of the world's tallest peaks are found in this region, including K-2, Nanga Parbat, and Rakaposhi. The average altitude of Karakorum is (6,100 M), Hindukush (7,690 M) and Himalaya (8,848 M) (Latif, Yet al., 2020). These high altitudes of mountains frequently deliver a significant portion of precipitation (Rasul et al., 2011; Bocchiola & Diolaiuti, 2013; Adnan et al., 2017). Further, the precipitation and the temperature of this region have substantial effects on the country's other regions (Bocchiola & Diolaiuti, 2013; Adnan, M et al., 2017). Therefore, the precipitation and temperature of the selected region are used in STTSSWS to substantiate drought occurrences. Drought is a typical phenomenon that directly or indirectly affects agriculture, forestry, cattle, fisheries, banking, energy, transportation, and growth rate (Anjum et al., 2010; Mazhar et al., 2015). Therefore, proper monitoring and appropriate drought mitigation techniques are required to minimize drought effects. The STTSSWS provides spatiotemporal information at the regional level. The information obtained from STTSSWS can be used to mitigate adverse drought effects. The STTSSWS provides weights for the severity of drought classes. The class which receives greater weight, its chances of occurrence are high in the selected region. The weights obtained from STTSSWS can be used for further drought monitoring strategies and mitigation policies.

3.1. **Results**

The climatological characteristics of the selected region are given in Table 1. The observed data from these characteristics are used for the classification. The classification for the drought is completed using SPI and SPEI. The drought classification shows the various levels of drought severity (Li et al., 2015). For instance, the SDI (SPI and SPEI) value less than or equal to -2 represents the extremely dry and greater than 2 classify as extreme wet condition and so forth (Table 2). Further, two standardize drought indices are included in the study based on the climatic conditions of the selected stations, and the standardization of these drought indices is done by using varying probability distributions. The distribution which is suitable according to climatic conditions is selected for the standardizations. For instance, at a one-month time scale, the 3p Weibull distribution shows suitable candidacy for the Astor station. The BIC of 3p Weibull distribution is -1036.5which is minimum among other distributions. Therefore, the distribution is used for the standardization in this station. The 3p Weibull distribution, at a one-month time scale, shows suitable candidacy for Bunji station with BIC (-1031.0), Gilgit, with BIC (-1097), and for Skardu with BIC (-735.1). The 4p Beta distribution shows better candidacy at a one-month of SPI for two stations, including Gupis, and Chilas with BIC -788.7, -805.6, respectively. Further, for SPEI at a one-month time scale, the Trapezoidal distribution is fitting suitably for station Astor and Skardu with BIC -710.1 and −664.6, respectively. In Bunji, Gupis, Chilas, and Gilgit, the Johnson SB distribution is a suitable candidate concerning their minimum BIC values accordingly. Further, in spatiotemporal analysis based on STTSSWS for a homogenous region, the weights of SPI at a one-month time scale are presented in Table 4. The weights for various drought classes obtained from STTSSWS are defined accordingly. The STTSSWS contains the temporal and spatial information of the whole region and provides more comprehensive and precise results for varying drought classes. For example, in January, for the Astore station at the one-month time scale of SPI, the SD takes a value of 0.0268. The value shows that the SD has very less likely to occur in January. However, in January, the ND is more likely to occur in Gilgit station among other stations of the region with the weight (0.2672). For other stations and months, the weights for varying drought classes can be observed. Furthermore, STTSSWS weights for a homogenous region using SPEI at a one-month time scale are presented in Table 5. In the Astore station at the one-month time scale of SPEI, the MW takes a value of 0.0836. The value shows that the MW has very less likely to occur in January at Gilgit. However, in January, the ND is more likely to occur in Skardu station among other stations of the region with the weight (0.1844). Moreover, to avoid the complexity in the presentation of results, we just presented results for the particular year, which is 2017. However, the results of selected years can be observed from the proposed scheme. Furthermore, Figure 2 shows theoretical and empirical distributions for SPI at a one-month time scale (SPI-1), and theoretical and empirical distributions for SPEI at a one-month time scale (SPEI-1) for various stations are presented in Figure 3. Figure 4 shows the temporal behavior of SPI-1 at selected stations. Further, the temporal behavior of SPEI-1 at selected stations can be observed in Figure 5. The counts plots for the varying drought classes which are computed by SPI and SPEI are presented in Figure 6. It can be observed from the visualizations that the most prevalent class among other selected classes is ND. In both SPI and SPEI computes ND from the selected stations. It can be perceived that the ND class should be considered as an important class for further, analysis. To obtain the weights for the selected classes on varying stations for the selected indices the current study provides STTSSWS. The weights obtained from STTSSWS using SPI for seven drought classes are presented for first six months of the year 2017 in Figure 7. Moreover, the weights computed from STTSSWS based on SPEI for selected drought classes are presented for first six months of the year 2017 in Figure 8. The weights are presented only for the classes that available in the corresponding month. For example, the ND occurs in January 2017, the weight can only be presented for ND and so forth. When the climatic conditions of the stations change, the proposed STTSSWS will work accordingly to the observed situation. The information obtained from STTSSWS can be applied to monitor drought more accurately. The obtained weights from STTSSWS can be used for more precise drought monitoring approaches.

3.2. Discussion

The two drought indices (SPI & SPEI) are considered in the current analysis. The probability distributions, which are appropriate according to time scales and stations, were selected for the standardization. The BIC criteria are used to select these probability distributions. Further, the steady-state probabilities are used for the computation of STTSSWS. In the first stage, the steady-state probabilities are calculated for each station separately regardless of the spatial accountability in the calculation. However, in stage two, these steady-state probabilities are used to calculate spatiotemporal weights for the varying drought classes. Hence, the proposed scheme used spatial and temporal characteristics of regional drought to calculate weights for the various drought classes. The class which receives maximum weights from STTSSWS is reflected for consideration in the region. Moreover, the drought is a typical phenomenon that affects directly or indirectly the agriculture, forestry, cattle, fisheries, banking, energy, transportation, and growth rate (Mazhar et al., 2015; Guneralp et al., 2015; Hagenlocher et al., 2019; Lai et al., 2019; Jiang & Wang, 2019). Therefore, proper monitoring and appropriate drought mitigation techniques are required to minimize drought effects. The STTSSWS provides the more appropriate spatiotemporal information at the regional level. The obtained information from STTSSWS can be used to monitor drought more precisely and accurately. The weights obtained from STTSSWS can be used for further drought monitoring strategies and mitigation policies. The obtained results from the STTSSWS provide the basis to improve the drought monitoring and forecasting methods at the regional level.

4. Conclusion

Drought is a multifaceted phenomenon that occurs due to insufficient precipitation. It does not have instant consequences, but persistent drought for a prolonged time can greatly influence the agriculture, hydrological, and economic sectors of the country. Since there are required effective procedures that appropriately identify the drought occurrences and help policymakers to prepare their plans explicitly at the regional level. Therefore, the present study proposed a Novel weighting scheme, known as STTSSWS for regional drought analysis. The STTSSWS provides more accurate and precise spatiotemporal information about drought occurrences. The proposed weighting scheme is based on the steady-state probabilities. The steady-state probabilities at various stations are used to obtain new spatiotemporal weights for various drought classes. The proposed weighting scheme is validated on the six selected stations of the northern area, Pakistan. The outcomes of the proposed weighting scheme may accurately assign spatiotemporal weights for selected states and provides efficient information for the selected region.

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Figure 1

Geographical locations of the selected stations

The map of Northern area of Pakistan and Geographical locations of the selected stations.

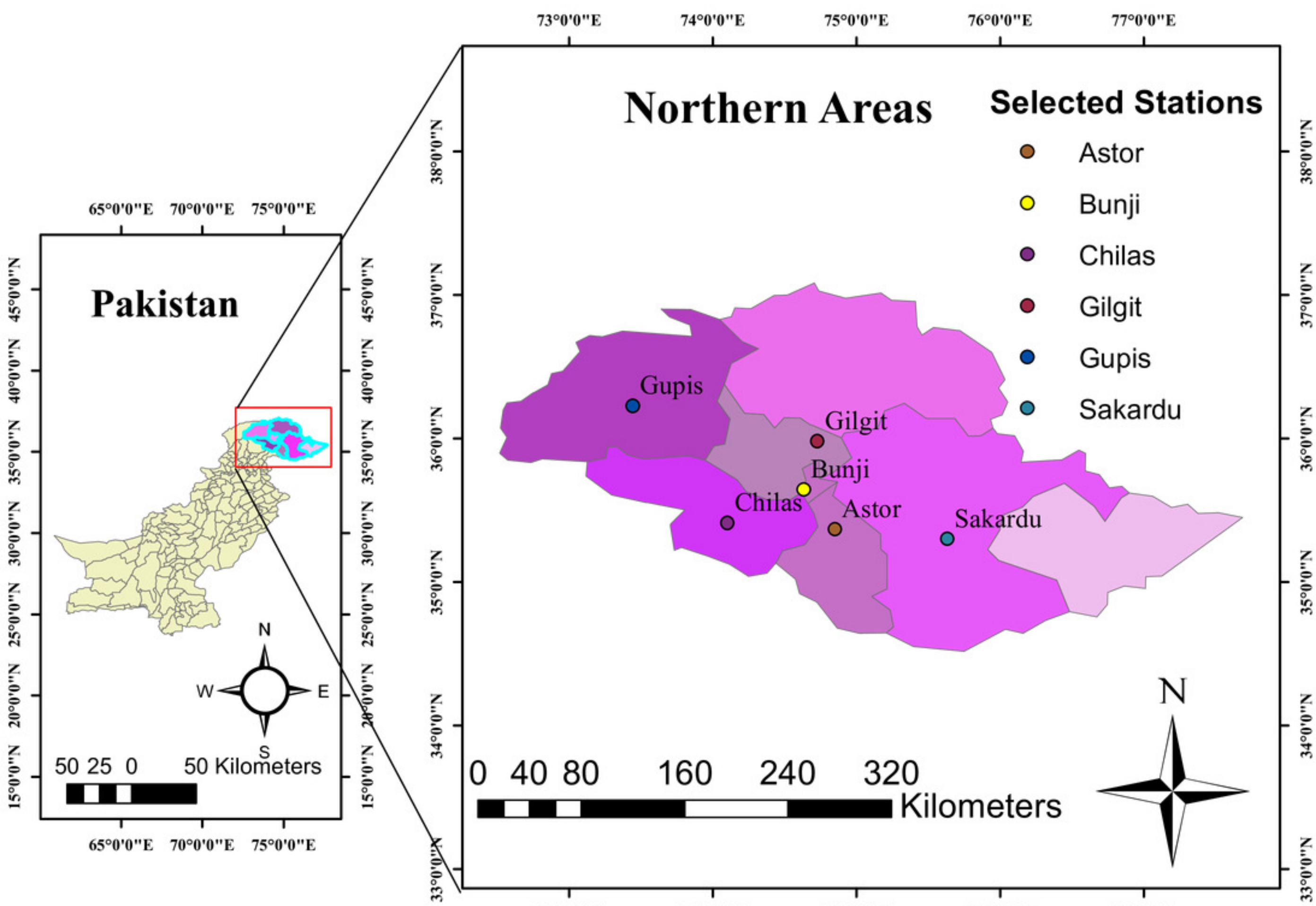
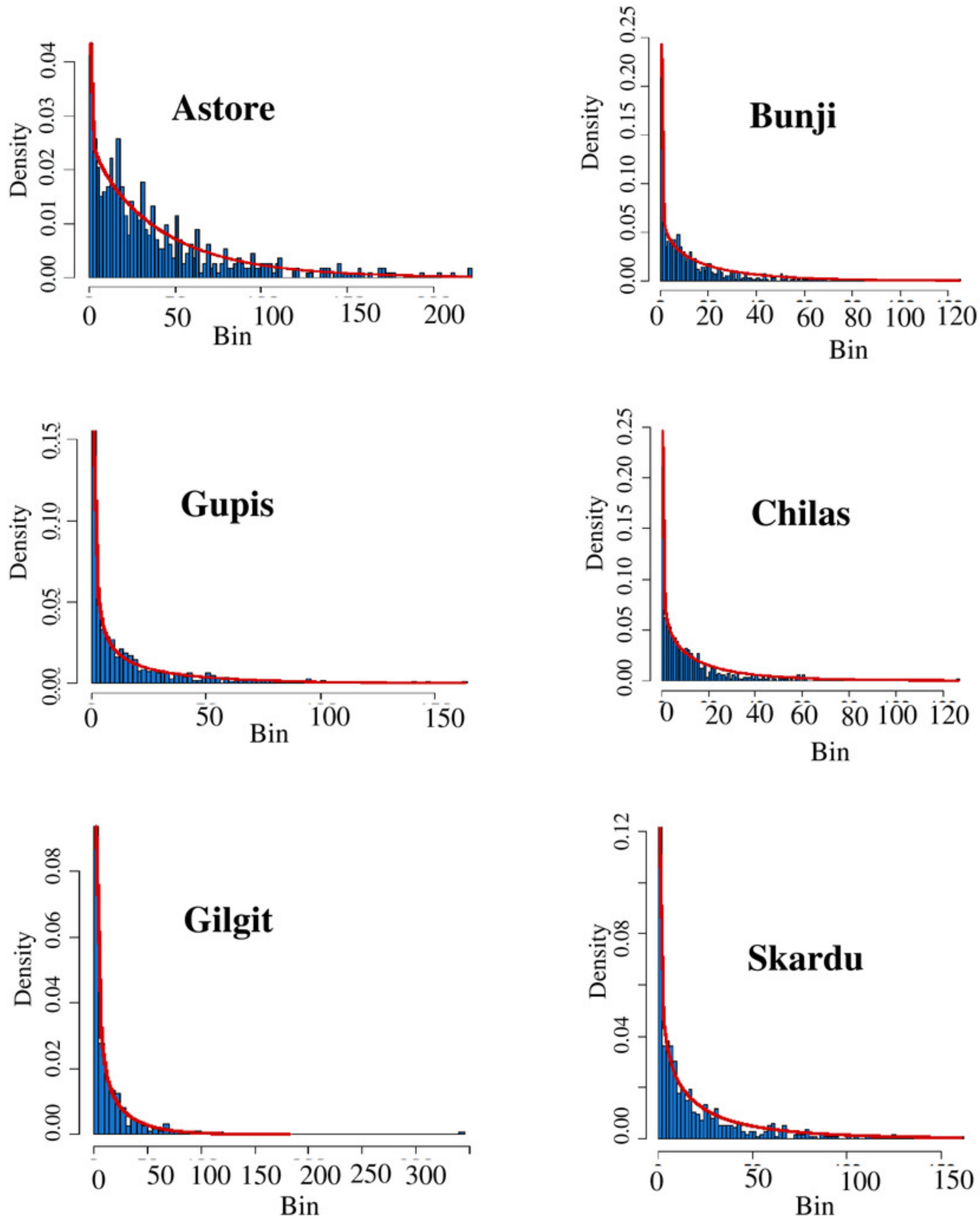


Figure 2

Histograms of selected distributions for various stations

Theoretical vs. empirical histograms of selected distributions for selected stations

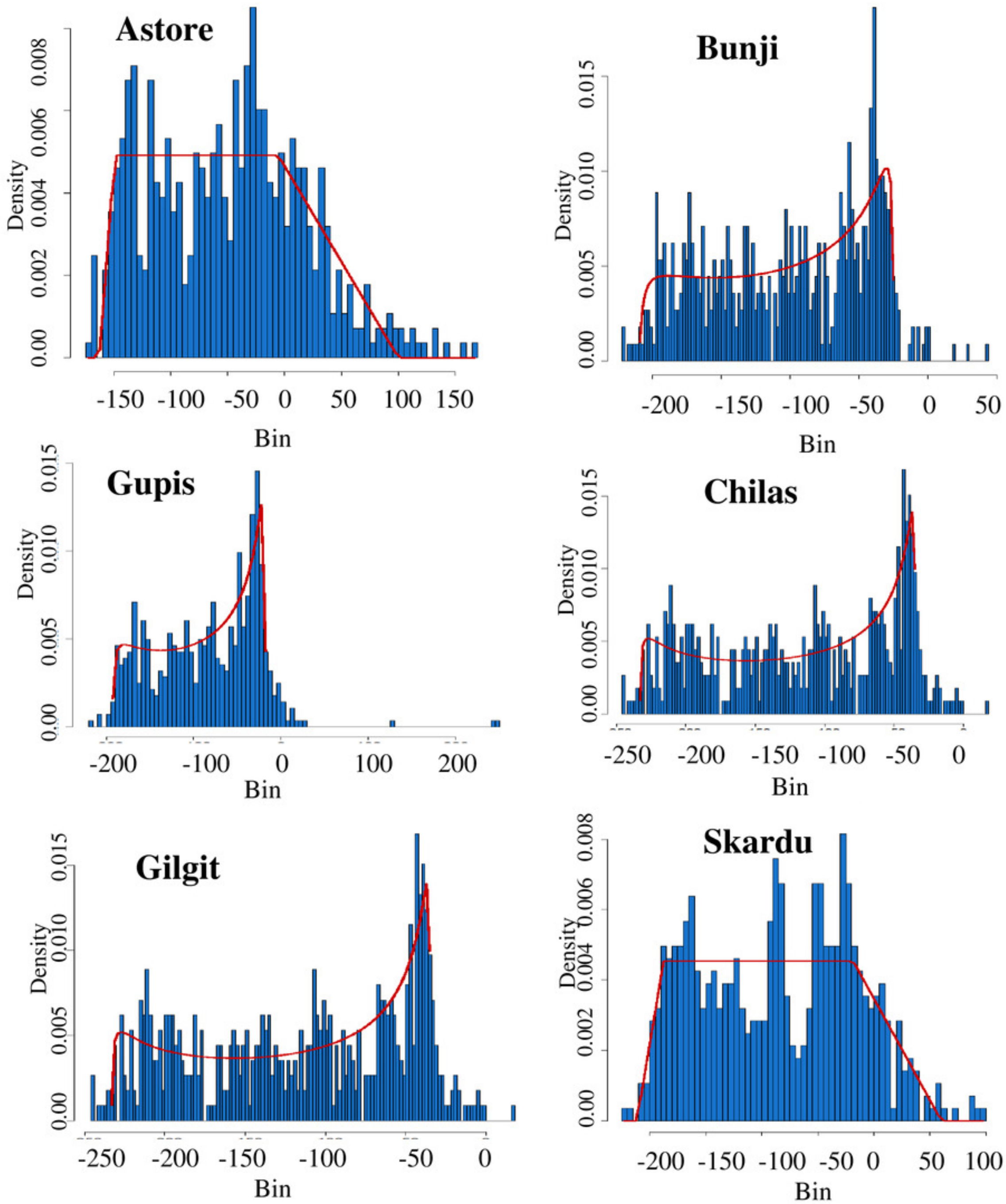

Astore
Density
0.00
0.01
0.02
0.03
0.04
0
50
100
150
200
Bin
Bunji
Density
0.00
0.05
0.10
0.15
0.20
0.25
0
20
40
60
80
100
120
Bin
Gupis
Density
0.00
0.05
0.10
0.15
0
50
100
150
Bin
Chilas
Density
0.00
0.05
0.10
0.15
0.20
0.25
0
20
40
60
80
100
120
Bin
Gilgit
Density
0.00
0.02
0.04
0.06
0.08
0
50
100
150
200
250
300
Bin
Skardu
Density
0.00
0.04
0.08
0.12
0
50
100
150
Bin

SPI-1

Figure 3

Various histograms of selected distributions for varying stations

Theoretical vs. empirical histograms of selected distributions for selected stations



SPEI-1

Figure 4

Temporal plots using SPI at one-month time scale

The temporal plots using SPI at one-month time scale for the selected stations

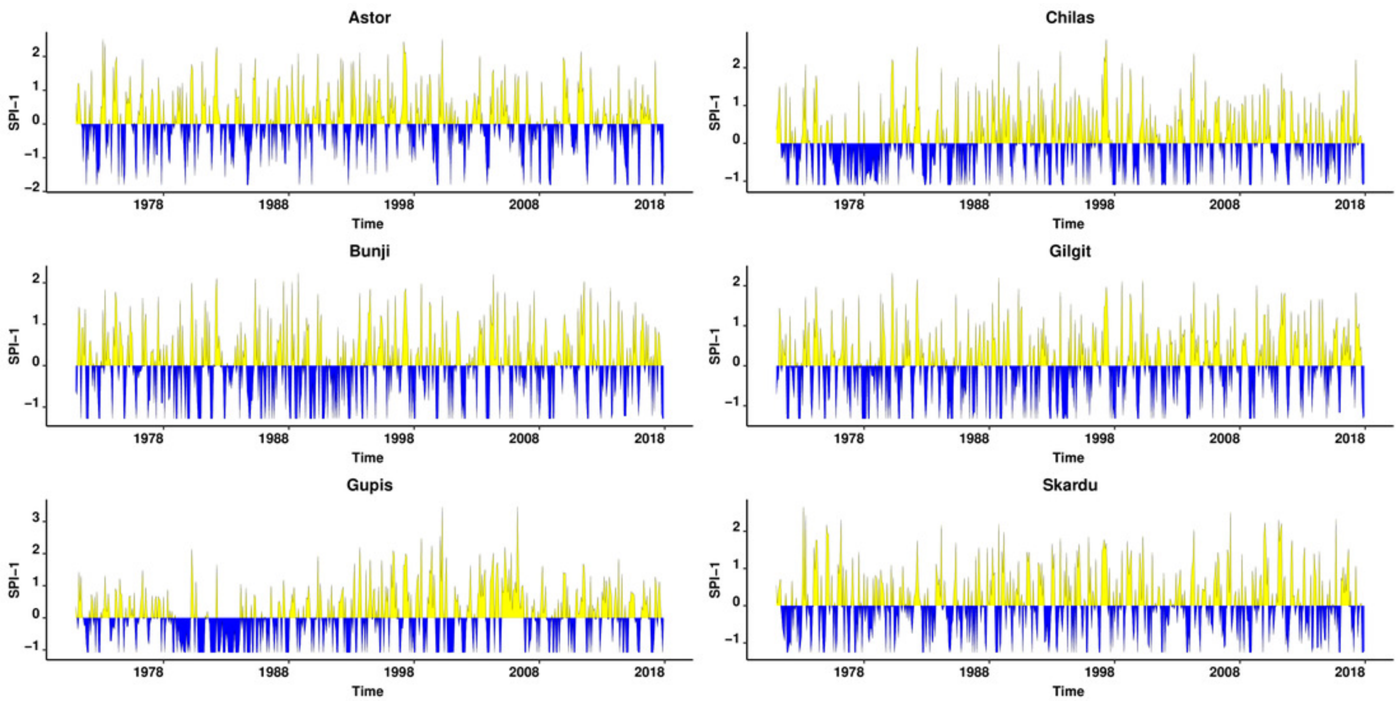


Figure 5

The temporal plots using SPEI at one-month time scale

The temporal plots using SPEI at one-month time scale the selected stations

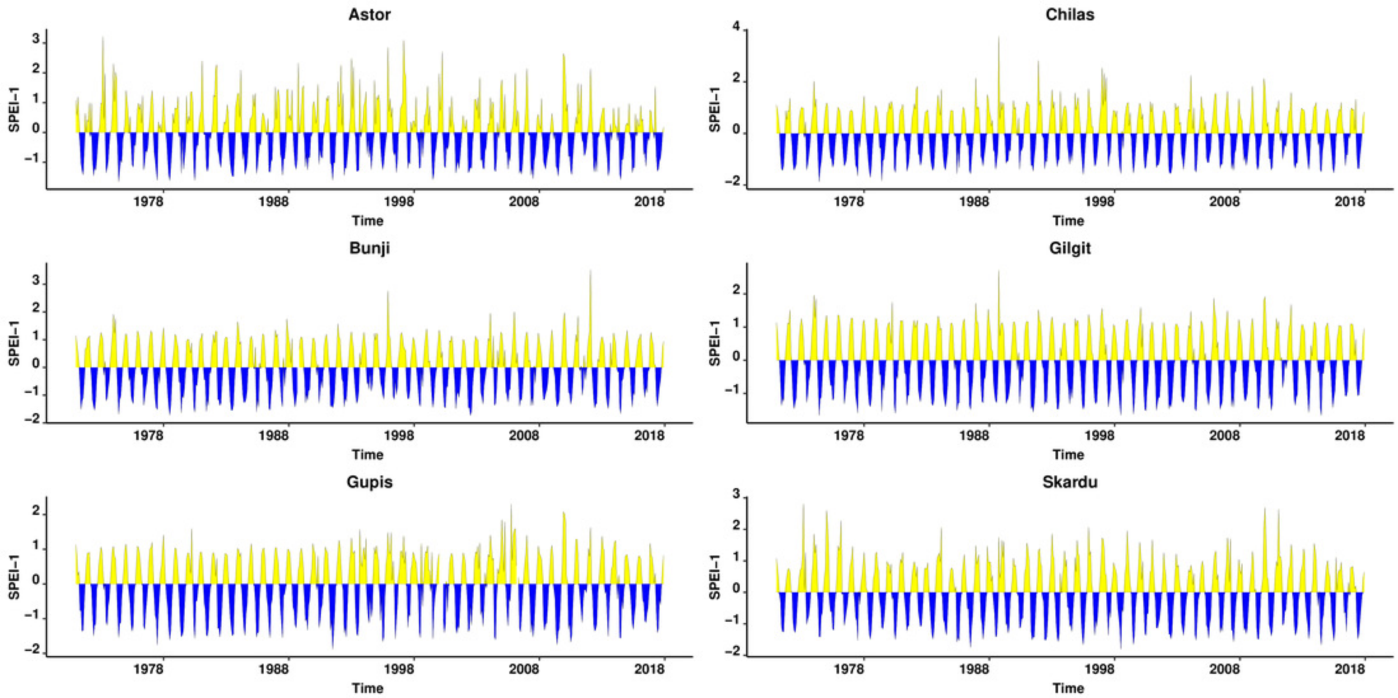


Figure 6

Counts plots for selected stations

The counts plots at one-month time scale using SPI and SPEI for selected stations

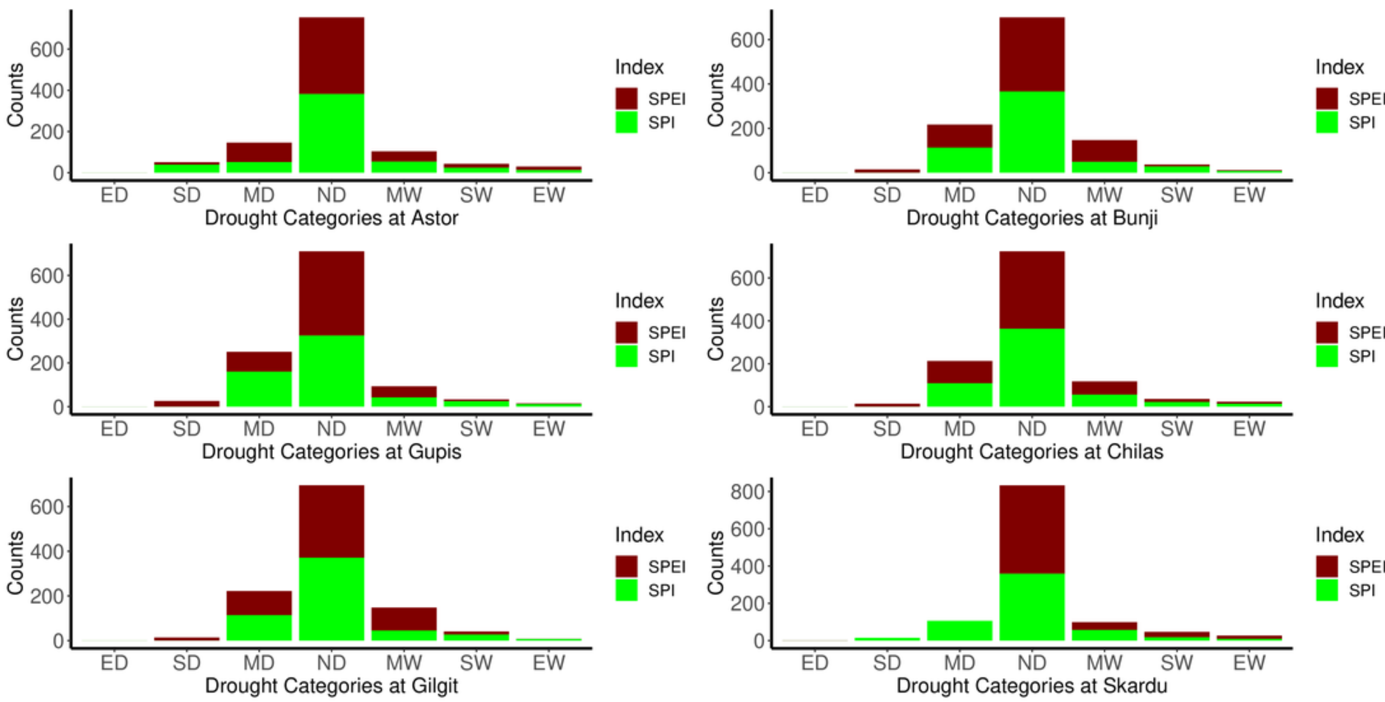


Figure 7

Weights obtained from STTSSWS using SPI for seven drought classes

The weights obtained from STTSSWS using SPI for seven drought classes are presented for first six months of the year 2017

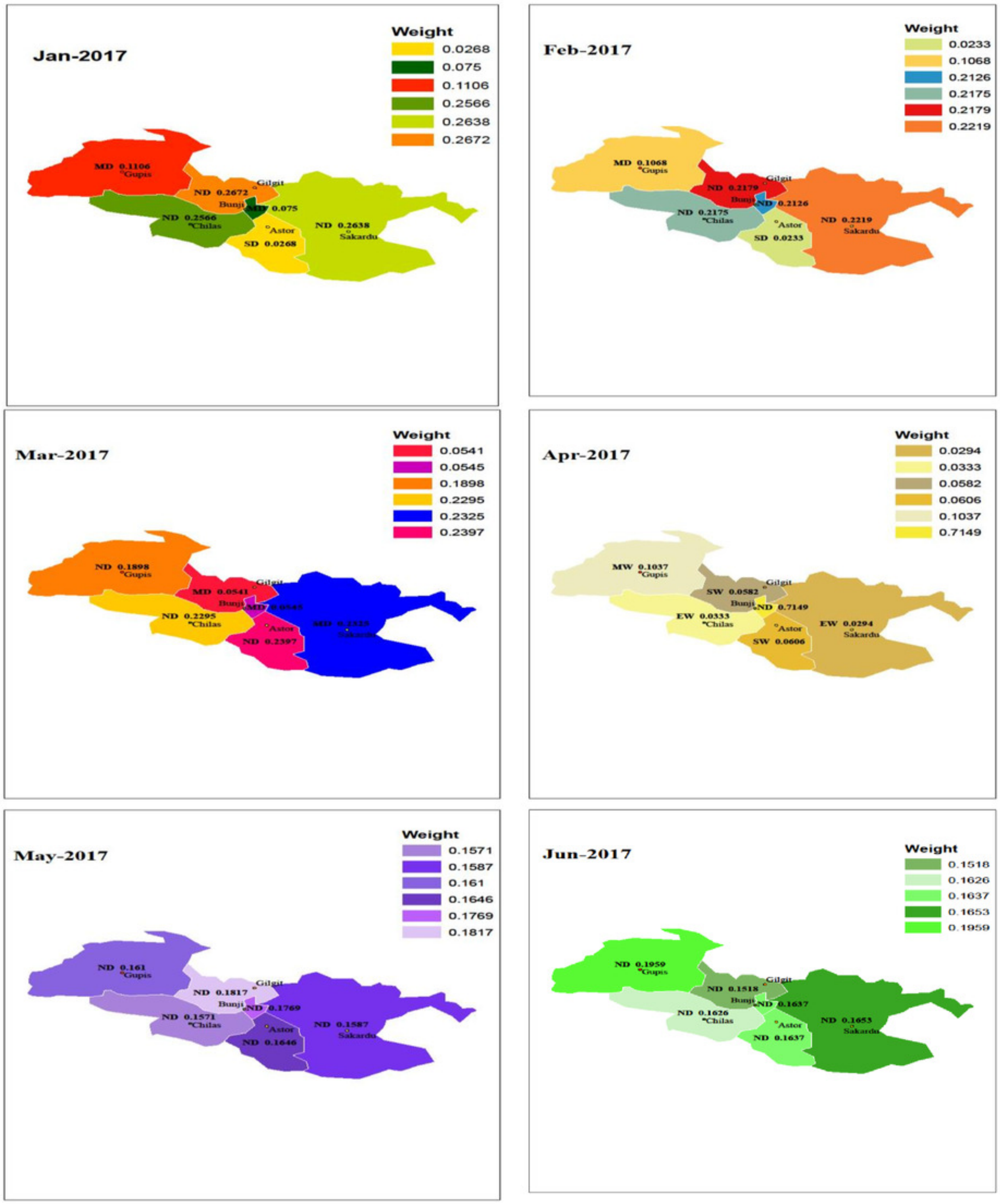

Jan-2017
Weight
0.0268
0.075
0.1106
0.2566
0.2638
0.2672
MD 0.1106
Gupis
ND 0.2672
Gilgit
Bunji
0.075
ND 0.2566
Chilas
Astor
SD 0.0268
ND 0.2638
Sakardu
Feb-2017
Weight
0.0233
0.1068
0.2126
0.2175
0.2179
0.2219
MD 0.1068
Gupis
ND 0.2179
Gilgit
Bunji
ND 0.2126
ND 0.2175
Chilas
Astor
SD 0.0233
ND 0.2219
Sakardu
Mar-2017
Weight
0.0541
0.0545
0.1898
0.2295
0.2325
0.2397
ND 0.1898
Gupis
MD 0.0541
Gilgit
Bunji
ND 0.2295
Chilas
Astor
ND 0.2397
Apr-2017
Weight
0.0294
0.0333
0.0582
0.0606
0.1037
0.7149
MW 0.1037
Gupis
SW 0.0582
Gilgit
Bunji
ND 0.7149
EW 0.0333
Chilas
Astor
SW 0.0606
EW 0.0294
Sakardu
May-2017
Weight
0.1571
0.1587
0.161
0.1646
0.1769
0.1817
ND 0.161
Gupis
ND 0.1817
Gilgit
Bunji
ND 0.1769
ND 0.1571
Chilas
Astor
ND 0.1646
ND 0.1587
Sakardu
Jun-2017
Weight
0.1518
0.1626
0.1637
0.1653
0.1959
ND 0.1959
Gupis
ND 0.1518
Gilgit
Bunji
ND 0.1637
ND 0.1626
Chilas
Astor
ND 0.1637
ND 0.1653
Sakardu

Figure 8

The weights obtained from STTSSWS using SPEI for seven drought classes

The weights obtained from STTSSWS using SPEI for seven drought classes are presented for first six months of the year 2017

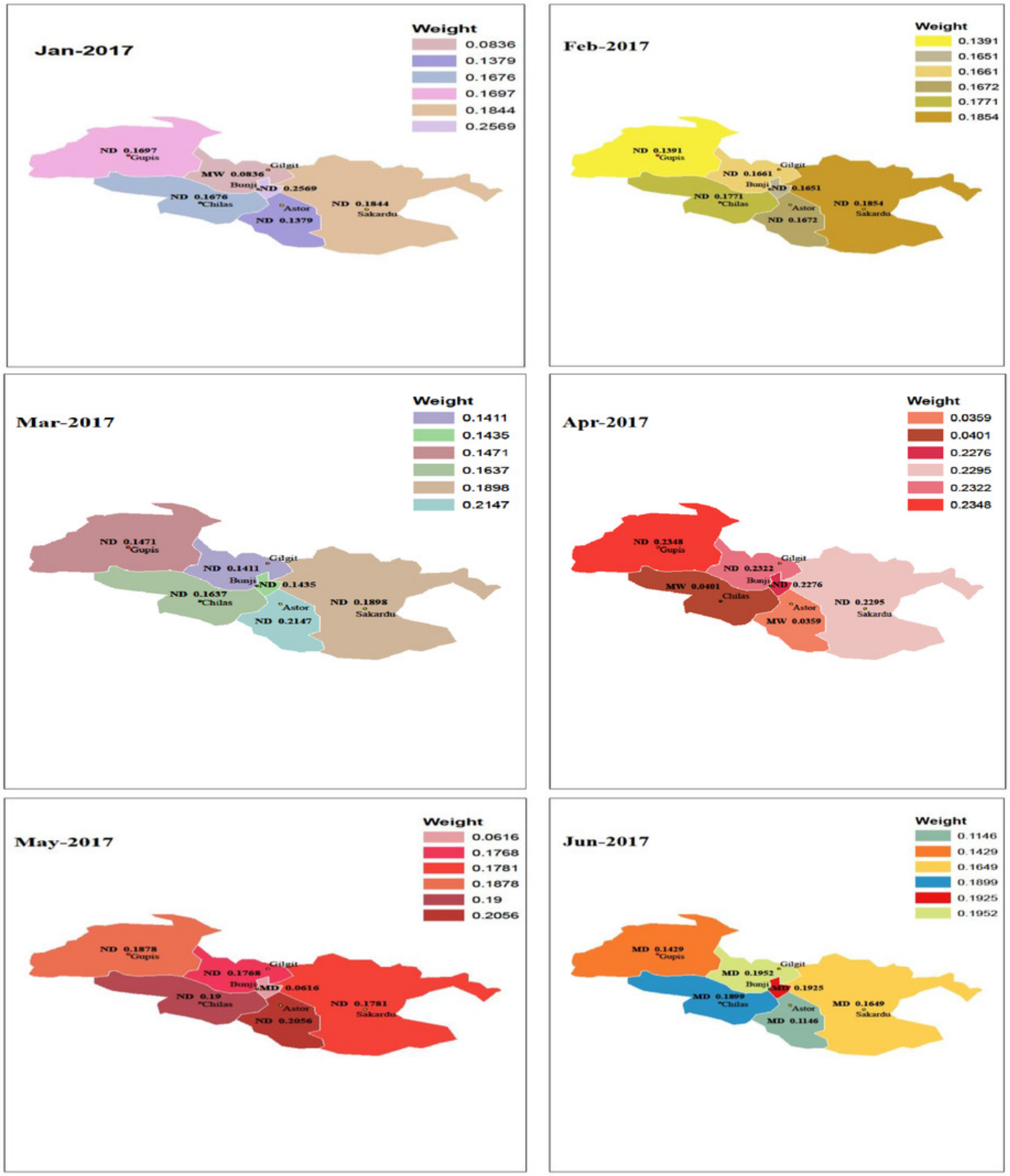

Jan-2017
Weight
0.0836
0.1379
0.1676
0.1697
0.1844
0.2569
ND 0.1697
Gupis
MW 0.0836
Gilgit
Bunji
ND 0.2569
ND 0.1676
Chilas
Astor
ND 0.1844
Sakardu
ND 0.1379
Feb-2017
Weight
0.1391
0.1651
0.1661
0.1672
0.1771
0.1854
ND 0.1391
Gupis
ND 0.1661
Gilgit
Bunji
ND 0.1651
ND 0.1771
Chilas
Astor
ND 0.1854
Sakardu
ND 0.1672
Mar-2017
Weight
0.1411
0.1435
0.1471
0.1637
0.1898
0.2147
ND 0.1471
Gupis
ND 0.1411
Gilgit
Bunji
ND 0.1435
ND 0.1637
Chilas
Astor
ND 0.1898
Sakardu
ND 0.2147
Apr-2017
Weight
0.0359
0.0401
0.2276
0.2295
0.2322
0.2348
ND 0.2348
Gupis
ND 0.2322
Gilgit
Bunji
ND 0.2276
MW 0.0401
Chilas
Astor
ND 0.2295
Sakardu
MW 0.0359
May-2017
Weight
0.0616
0.1768
0.1781
0.1878
0.19
0.2056
ND 0.1878
Gupis
ND 0.1768
Gilgit
Bunji
MD 0.0616
ND 0.19
Chilas
Astor
ND 0.1781
Sakardu
ND 0.2056
Jun-2017
Weight
0.1146
0.1429
0.1649
0.1899
0.1925
0.1952
MD 0.1429
Gupis
MD 0.1952
Gilgit
Bunji
MD 0.1925
MD 0.1899
Chilas
Astor
MD 0.1649
Sakardu
MD 0.1146

Table 1(on next page)

The climatology characteristics of selected period

The climatology characteristics during the period 1971–2017 of six selected stations

Variable	Station	Mean	1st Quartile	Median	3rd Quartile	Kurtosis	St.Dev
Precipitation	Astor	39.34	10.80	25.70	52.62	3.01	41.93
	Bunji	13.56	1.30	7.10	17.10	7.55	18.90
	Gupis	15.94	0.00	5.70	19.38	51.38	30.21
	Chilas	15.85	0.95	7.00	19.32	8.88	23.53
	Gilgit	11.75	1.10	6.05	14.72	9.93	16.57
	Skardu	19.51	2.30	9.10	26.75	5.60	25.90
Maximum Temperature	Astor	15.76	7.38	16.70	23.86	-1.36	8.65
	Bunji	23.82	15.78	24.95	32.02	-1.32	8.98
	Gupis	18.86	10.32	19.70	27.40	-1.31	9.46
	Chilas	26.41	17.68	27.35	35.62	-1.38	9.66
	Gilgit	24.07	15.60	25.15	32.80	-1.33	9.21
	Skardu	18.83	9.95	20.05	27.90	-1.25	9.82
Minimum Temperature	Astor	4.10	-2.43	4.30	10.70	-1.23	7.48
	Bunji	11.22	3.78	11.50	17.70	-1.24	7.80
	Gupis	6.37	-1.10	6.90	13.32	-1.27	8.06
	Chilas	14.32	5.68	14.30	23.20	-1.41	9.08
	Gilgit	7.63	0.60	7.75	13.53	-1.24	7.30
	Skardu	4.79	-2.73	5.55	11.80	-1.18	8.36

Table 2(on next page)

Drought categorization based on the values of the SDI

Categorization of drought based on the values of the SDI

SDI	Major drought classes
SDI >=2	Extremely Wet (EW)
SDI >1.5 & SDI <=2	Severely (SW)
SDI > 1 & SDI <= 1.5	Median Wet (MW)
SDI > -1 & SDI <= 1	Normal Dry (ND)
SDI >-1.5 1 & SDI <=-1	Median Dry (MD)
SDI > -2 & SDI <= -1.5	Severely Dry (SD)
SDI>=-2	Extremely Dry (ED)

Table 3(on next page)

BIC values for selected distributions

The selected probability distribution of SPI-1 and SPEI-1 and their BIC values for selected stations

	Astore		Bunji		Gupis	
index	Distribution	BIC	Distribution	BIC	Distribution	BIC
SPI	3p Weibull	-1036.5	3p Weibull	-1031.0	4p Beta	-788.7
SPEI	Trapezoidal	-710.1	Johnson SB	-1248.4	Johnson SB	-977.6
	Chilas		Gilgit		Skardu	
index	Distribution	BIC	Distribution	BIC	Distribution	BIC
SPI	4P Beta	−805.6	3P Weibull	−1097.4	3P Weibull	−735.1
SPEI	Johnson SB	−594.7	Johnson SB	−1213.2	Trapezoidal	−664.6

Table 4(on next page)

The weights calculated from STTSSWS using SPI-1 for varying drought classes at six stations

The weights calculated from STTSSWS using SPI-1 for varying drought classes at six stations are given. The STTSSWS used the monthly data which has range from 1971 to 2017. However, here, the obtained weights from STTSSWS for the specific year 2017 at first six months (Jan, Feb, March, Apr, May, and Jun) are presented only. The bold value in SPI-1 shows that the the class has more likely to occur in various months of 2017. The values indicate that the ND is prevailing in this year among other drought classes for the selected stations

SPI-1													
Station Month	Astor		Bunji		Gupis		Chilas		Gilgit		Skardu		Sum
	Category	Weight	Category	Weight	Category	Weight	Category	Weight	Category	Weight	Category	Weight	
Jan	SD	0.0268	MD	0.0750	MD	0.1106	ND	0.2566	ND	**0.2672**	ND	0.2638	1
Feb	SD	0.0233	ND	0.2126	MD	0.1068	ND	0.2175	ND	0.2179	ND	**0.2219**	1
Mar	ND	**0.2397**	MD	0.0545	ND	0.1898	ND	0.2295	MD	0.0541	ND	0.2325	1
Apr	SW	0.0606	ND	**0.7149**	MW	0.1037	EW	0.0333	SW	0.0582	EW	0.0294	1
May	ND	0.1646	ND	0.1769	ND	0.1610	ND	0.1571	ND	**0.1817**	ND	0.1587	1
Jun	ND	0.1609	ND	0.1637	ND	0.1959	ND	0.1626	ND	0.1518	ND	**0.1653**	1

Table 5(on next page)

The weights calculated from STTSSWS using SPEI-1 for various drought classes at six stations

The weights calculated from STTSSWS using SPEI-1 for various drought classes at six stations are presented. The STTSSWS utilized the monthly data which has range from 1971 to 2017. However, here, the weights obtained from STTSSWS for the particular year 2017 in first six months (Jan, Feb, March, Apr, May, and Jun) are given only. The bold value in SPI-1 representing that the the classes have more likely to occur in first six months of 2017. The values suggest that the ND is more prevalent in this year among other drought classes for the selected

SPEI-1													
Station	Astor		Bunji		Gupis		Chilas		Gilgit		Skardu		Sum
Month	Category	Weight	Category	Weight	Category	Weight	Category	Weight	Category	Weight	Category	Weight	
Jan	ND	0.1379	ND	0.2569	ND	0.1697	ND	0.1676	MW	0.0836	ND	**0.1844**	1
Feb	ND	0.1672	ND	0.1651	ND	0.1391	ND	0.1771	ND	0.1661	ND	**0.1854**	1
Mar	ND	0.2147	ND	0.1435	ND	0.1471	ND	0.1637	ND	0.1411	ND	**0.1898**	1
Apr	MW	0.0359	ND	0.2276	ND	0.2348	MW	0.0401	ND	**0.2322**	ND	0.2295	1
May	ND	**0.2056**	MD	0.0616	ND	0.1878	ND	0.1900	ND	0.1768	ND	0.1781	1
Jun	MD	0.1146	MD	0.1925	MD	0.1429	MD	0.1899	MD	**0.1952**	MD	0.1649	1

1