



A New Standardized Type Drought Indicators Based Hybrid Procedure for Strengthening Drought Monitoring System

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ORIGINAL RESEARCH PAPER



STOCKHOLM
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ABSTRACT

Drought is occurring recurrently in various climatic zones around the world. Therefore, accurate and continuous drought monitoring are essential for reliable drought mitigation policies. In past research, several drought monitoring indicators have been developed. Regardless of their scopes and applicabilities, every indicator has certain amount of error regarding accurate determination of drought classes. In addition, climate change and complex features of meteorological variables also reduce the performance of each indicator. Consequently, accurate drought monitoring is a challenging task in hydrology and water management research. The objective of this research is to enhance the accuracies in drought characterization by employing multiple drought indicators, simultaneously. This article proposes a new aggregative index – the Seasonal Mixture Standardized Drought Index (SMSDI). The procedure of SMSDI is mainly based on the integration of Principle Component Analysis (PCA) and K- Component Gaussian Mixture Distribution (K-CGMD). In preliminary analysis, aggregation of three multi-scalar Standardized Drought Indices (SDIs) is made for three meteorological gauge stations of Pakistan. For comparative assessment, individual SDI has used to investigate the association and consistency with SMSDI. Outcome associated with this research shows that the SMSDI have significant correlation with individual SDIs. We conclude that instead of using individual indicator, the proposed aggregative approach enhances the scope and capacity of drought indicators for extracting reliable information related to future drought.

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KEYWORDS:

Climate Change; Drought monitoring; Water management research; Correlation

TO CITE THIS ARTICLE:

Khan, MA, Zhang, X, Ali, Z, Jiang, H, Ismail, M and Qamar, S. 2022. A New Standardized Type Drought Indicators Based Hybrid Procedure for Strengthening Drought Monitoring System. *Tellus A: Dynamic Meteorology and Oceanography*, 74(2022), 119–140. DOI: <https://doi.org/10.16993/tellusa.47>

1. INTRODUCTION

Due to climate change and increasing temperature, there is a continuous trend in recurrent occurrences of drought events at several parts of the world. Comparative to other hazards, effects of drought are more disastrous and long lasting on humans, agriculture, livestock, and industries (Vásquez-León et al., 2003). Drought can be defined as “a certain period of time (usually lasting over several months or longer than usual) during which a particular region receives comparative less precipitation (in terms of rain or snowfall)” (Van Loon et al., 2016). According to the characteristics of drought, it has been divided into four major types. Details on each type of drought can be found in Sun et al., (2019).

Every year, around 55 million people are affected by drought directly or indirectly from all over the world (WHO, 2020). In addition, continuous increase in temperature and global warming is threatening for bad effect on the soil fertility of the agricultural land (Thadshayini et al., 2020). Further, a list of catastrophic consequences of drought includes the decrease of accessible resources of drinking and groundwater, death of inhabitants and livestock, deterioration of food quality, serious diseases, desertification, economic inflation, social disruption, soil erosion, depletion of freshwater resources, and low economy, etc. (Garcia et al., 2013, Khan et al., 2021).

The major challenges for hydrologists and environmentalists are water security, water management, and the development of future climate policies. In addition, many research and debates are ongoing about the impact of atmospheric circulation (Magan et al., 2010), global warming, and the procedure of climate variability indices (Gu et al., 2019).

In previous development, several tools and methods for continuous drought monitoring and drought assessment have been suggested. In all tools and methods, time series data of temperature and precipitation are play key roles. For example, the Palmer Drought Severity Index (PDSI) had been proposed for assessing dry and wet events (Palmer, 1965). In recent research, some authors have revamped the method of PDSI by accounting new climatic parameters (Yu et al., 2019).

In recent research, Shen et al. (2019) have proposed – the Index for Integrated Drought Condition Index (IDCI) by combining rainfall, temperature, evaporation, vegetation condition, soil moisture, and potential evaporation. Following PDSI, a standardized and probabilistic procedure based on the time series data of rainfall – the Standardized Precipitation Index (SPI) had been proposed by McKee et al., (1993). Numerous applications of SPI for drought monitoring and drought assessment are available in literature (Wu et al., 2007). In advance research, some authors have suggested various drought indices by including additional meteorological variables under the same standardized procedure. For

instance, Standardized Precipitation Evapotranspiration Index (SPEI) accounts evaporation before standardization (Vicente Serrano et al., 2010). Ali et al., (2017) have suggest Standardized Precipitation Temperature Index (SPTI). In SPTI, a time series vector of average temperature is used with precipitation data before standardization phase. SPI, SPEI, SPTI have homogenous computational procedure. Therefore, we call these indices as a set of Standardized Drought Indices (SDIs). Some more details on SDIs are available in Erhardt and Czado, (2015).

In recent research, many authors have estimated drought indices using various probability distribution function. They includes Zhang et al., (2020), Ali et al., (2019d), Stagge et al., (2015), Angelidis et al., (2012) etc. However, among the available choices, the optimal selected probability function for whole set of time series data needs may contains significant amount of errors due to their poor fitting. For example, Q-Q plot shown in Ali et al., (2019c) clearly shows inappropriateness of trapezoidal distribution for the estimation of SPEI index. To resolve these issues, Ali et al., (2020) have introduced a generalized non-parametric based standardization approach for the estimation of various standardized drought indices. Alternatively, many researchers of various fields are frequently using the K-CGMD (McLachlan, 2004) for multi-distributed data. Furthermore, K-CGMD models have many theoretical and computational benefits over unimodal distribution.

However, being a probabilistic nature, each indicator of SDI contains a certain amount of error. Therefore, the accuracy of determining accurate drought classes is the major problem in SDs. These inaccuracies arise due to the heterogeneous and inconsistencies, seasonal patterns in temporal data sets.

In past research, many authors have addressed the seasonality in the procedure of single drought index. For example, Carrão et al., (2018) employed SPI for seasonal drought forecasting in Latin America. Moghimi et al., (2020) have forecasted seasonal drought under various time series models using Reconnaissance Drought Index (RDI). Qaiser et al., (2021) have established Composite Drought Index (CDI) for seasonal drought characterization. Hao et al., (2018) have provided a detailed review and future challenges related to seasonal drought prediction.

Under certain circumstances, some of our recent developments include Seasonally Combinative Regional Drought Indicator (SCRDI) (Ali et al., 2020c), Regionally Improved Weighted Standardized Drought Index (RIWSDI) (Jiang et al., 2020), Multi-Scalar Aggregative Standardized Precipitation Temperature Index (MASPTI) (Ali et al., 2020b), Probabilistic Weighted Joint Aggregative Index (PWJADI) (Ali et al., 2019a) and Long Averaged Weighted Joint Aggregative Criterion (LAWJAC) (Ali et al., 2020a).

The aim of this paper is to propose a comprehensive

framework which will investigate various features of drought by aggregating the temporal and seasonal characteristics of multiple drought indices. Hence, the objective of this research to provide a new hybrid drought indicator that increase the accuracy and account seasonality in the drought characterization by amalgamating multiple SDIs.

2. MATERIAL AND METHODS

2.1 STUDY AREA AND DATA DESCRIPTION

Pakistan is geographically located between Middle East and Central Asia (Ahmed *et al.*, 2018). It has generally four seasons: cold (November–February); pre-monsoon/hot (March–mid of June); monsoon (mid of June–mid of September); post-monsoon (mid of September–October). There is extremely hot in the summer season with relative humidity of 25% to 50%. Most areas of the country are arid to semiarid, because of the spatial variability in temperatures. However, some parts are very wet, e.g., the southern slopes of Himalayas region as well as the sub-mountainous region, because of the high amount of annual rainfall (760 mm to 2000 mm). Based on the Census 2016, the total population of Pakistan is approximately 207774520 (Pakistan Census Reports, 2017). Where, the income source of the majority of the people belongs to the agriculture or related sectors (Rehman *et al.*, 2015). From past few decades, recurrent occurrences of drought have bad impact on people's life, livestock and agricultural yield. Consequently, the economy of the country has been severely disturbed in the recent years, due to extreme drought hazards. Therefore, the country needs a wide-ranging drought mitigation policies for future drought.

This research is based on three meteorological stations which includes Badin (BD) (24.6459° N, 68.8467° E), Khanpur (KP) (28.6332° N, 70.6574° E), and Nawabshah (NS) (26.2447° N, 68.3935° E). These stations are located in various climatological regions of Pakistan. The locations of the chosen meteorological stations are shown in [Figure 1](#). For computations, long time series data (from January 1971 to December 2016) of rainfall and temperature is obtained from Karachi Data Processing Center (KDPC) via Pakistan Meteorological Department (PMD). The maximum average monthly precipitation for Badin, Khanpur and Nawabshah are 459.00 mm (August–1979), 307.50 mm (August–2015) and 353.20 mm (September–2011) respectively. Similarly, maximum and minimum average monthly temperature for Badin, Khanpur and Nawabshah are 34°C (May–2010) and 15.45°C (January–1975), 36.3 C° (June–2002) and 11.15 C° (January–1984), and 37.2 C° (May–2002) and 12.45 C° (January–2008) respectively. Throughout various seasons the regions have substantially high variation in rainfall and temperature. The summary statistics of the data have been shown in [Table 1](#).

2.2. STANDARDIZED DROUGHT INDICES (SDIS)

In past research, several authors have developed numerous methods and procedures of drought monitoring for various climatological region. However, the procedure of Standardized Drought Indices (SDIs) (Erhardt and Czado 2015) is one of the most commonly used and accepted methods around the world. Among others, the three most important SDIs named as SPI (McKee *et al.*, 1993), SPEI (Vicente-Serrano *et al.*, 2010), SPTI (Ali *et al.*, 2017) have same mathematical process and classification. However, the errors and uncertainty

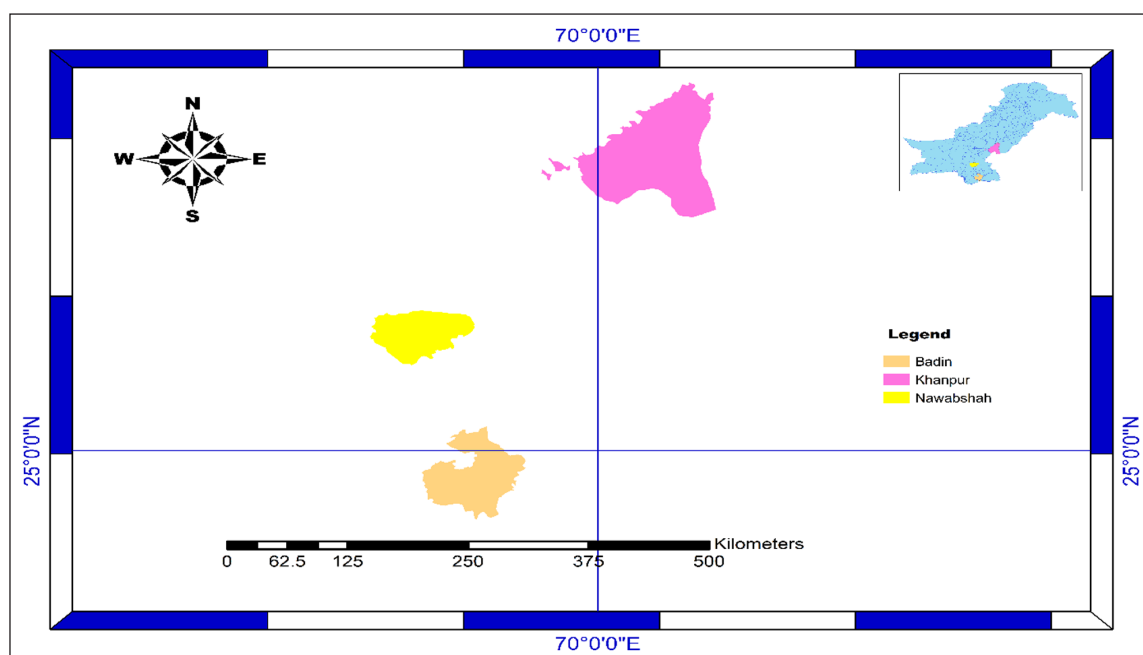


Figure 1 Geographical locations of the study area.

MONTHS	STATISTICS	BADIN (BD)			NAWABSHAH (NS)			KHANPUR (KP)		
		PRE	MAX T	MIN T	PRE	MAX T	MIN T	PRE	MAX T	MIN T
Jan	Avg.	1.4	25.2	9.7	2.1	24.3	6.3	4.1	21.4	4.8
	Std.	3.6	0.9	1.5	5.2	0.9	1.5	8.9	1.0	1.6
	Kurtosis	10.7	-0.3	0.6	14.4	0.1	-0.2	16.2	0.1	0.5
Feb	Avg.	4.8	28.3	12.4	3.5	27.6	8.8	8.2	24.3	7.8
	Std.	11.3	1.5	1.9	8.3	1.7	1.9	11.8	1.7	2.0
	Kurtosis	15.0	-0.2	0.4	10.7	-0.1	0.8	4.9	-0.1	1.2
Mar	Avg.	0.9	33.7	17.6	2.9	33.7	14.3	6.2	30.0	13.3
	Std.	2.4	1.7	1.5	6.1	2.1	1.0	9.8	2.0	1.6
	Kurtosis	11.0	-0.3	2.0	21.4	-0.1	0.5	4.6	-0.1	0.0
Apr	Avg.	1.7	38.0	22.3	3.1	40.1	19.9	6.2	37.3	19.1
	Std.	5.2	1.4	1.0	7.9	1.8	1.3	10.6	1.8	2.0
	Kurtosis	14.7	0.6	-0.3	11.3	0.0	-0.5	10.9	-0.3	-0.7
May	Avg.	4.0	39.5	25.8	2.0	44.1	24.8	4.8	41.9	24.6
	Std.	24.0	1.0	0.8	5.7	1.5	1.0	8.1	1.6	2.1
	Kurtosis	46.0	0.0	0.6	17.3	0.9	0.0	5.1	-0.2	-0.7
Jun	Avg.	11.4	38.1	27.7	6.8	43.8	27.5	5.5	42.3	27.5
	Std.	22.4	0.9	0.4	14.1	1.1	0.7	9.9	1.0	1.4
	Kurtosis	12.4	1.7	2.5	6.2	-0.8	0.5	10.2	-0.4	0.6
Jul	Avg.	62.6	35.0	27.1	49.5	40.7	27.4	27.0	39.6	27.6
	Std.	73.4	1.0	0.4	64.2	1.4	0.7	35.5	1.1	1.3
	Kurtosis	1.5	-0.2	0.0	5.3	0.6	0.3	4.8	1.5	2.7
Aug	Avg.	94.3	33.4	26.1	49.7	38.8	26.1	40.9	38.0	26.4
	Std.	102.9	1.0	0.5	63.0	1.4	0.8	68.2	1.0	1.5
	Kurtosis	2.7	-0.3	-0.2	3.4	0.8	2.9	6.3	0.0	2.7
Sep	Avg.	38.2	34.2	25.0	25.1	38.7	24.0	20.9	36.7	23.5
	Std.	84.3	1.1	0.7	65.1	1.6	1.1	51.7	1.0	1.8
	Kurtosis	8.1	0.2	-0.4	15.4	3.6	1.8	16.9	-0.1	2.7
Oct	Avg.	6.4	35.3	22.1	3.5	37.5	18.6	1.8	34.8	17.2
	Std.	21.5	1.0	1.2	11.6	1.3	1.7	7.1	0.8	2.1
	Kurtosis	18.2	0.4	-0.3	15.9	1.0	0.0	21.4	-0.1	1.9
Nov	Avg.	2.2	31.5	16.5	0.9	31.9	12.6	0.4	29.7	10.9
	Std.	6.9	1.0	1.5	3.7	1.9	1.7	1.2	1.0	1.8
	Kurtosis	15.6	0.3	1.8	37.1	18.8	2.5	14.5	1.2	0.4
Dec	Avg.	1.0	26.7	11.4	3.0	26.1	8.0	3.9	23.8	6.2
	Std.	2.7	1.1	1.6	9.0	1.1	1.4	12.4	1.2	1.7
	Kurtosis	14.9	0.2	0.1	15.4	-0.3	0.8	29.9	0.0	0.7

Table 1 Month-wise summary statistics rainfall and temperature (min, max) in selected stations.

in accurate determination of class are always present in each one. In this paper, the proposal of this research is based on the aggregation of SPI, SPEI and SPTI drought indices. However, the approach is not limited and hence can be applied to other drought indices. Some brief descriptions on SPI, SPEI and SPTI are as follow:

SPI is one of the oldest and the most commonly used drought indicator. Estimation of SPI is based on long term data of rainfall at particular station. In SPI procedure, Cumulative Distribution Function (CDF) of the appropriate probability function fitted on rainfall data is standardized. The standardized time series data are called the values of SPI. SPI is standardized, powerful, easy to use measure

for defining and comparing drought characteristics of various climatological region. The main flexibility of SPI is to define various types of drought (i.e., meteorological, agricultural and hydrological). Recent applications of SPI includes Kalisa et al., (2020), Achour et al., (2020), Bong and Richard, (2020), Yaseen et al., (2021), and Qaisrani et al., 2021) etc.

After SPI, Vicente-Serrano et al. (2010) proposed a new climatic drought index, the Standardized Precipitation Evapotranspiration Index (SPEI) which consider the effect of temperature in defining drought characteristics. SPEI is an upgraded version of SPI. The SPEI is based on both precipitation and temperature data and has the

advantage of integrating a multi-scalar character with the capacity to incorporate impacts of temperature variability on drought assessment. Mathematically, the procedure of SPEI is same as that of SPI. However, SPEI is more reliable than SPI in climate change and global warming scenario. One major drawback of SPEI is its sensitive method of estimation. That is for arid and semi-arid region, SPEI have high rate of estimation errors in the determination of drought classes. To address the estimation issues in SPEI, Ali *et al.* (2017) developed Standardized Precipitation Temperature Index (SPTI) drought index. One can substitute SPTI with SPEI for reducing estimation errors.

3. OUTLINES OF THE PROPOSED INDEX

The following five points summarize the outlines of the proposed index.

- i) Estimation of various SDIs under identical estimation procedure.

INDEX	SCALES	BADIN	NAWABSHAH	KHANPUR
SPI	1	-5505.72	-4329.87	-623.88
	3	-3271.21	-3330.55	-3947.69
	6	-5612.63	-5355.59	-5540.46
	9	-6560.43	-5908.35	-5932.45
	12	-6685.60	-6151.64	-6129.32
	24	-6893.84	-6579.39	-6499.06
SPEI	1	-5818.03	-5873.33	-5831.03
	3	-6762.69	-6879.15	-6830.68
	6	-7135.43	-7316.96	-7226.22
	9	-7195.26	-7255.91	-7126.11
	12	-7084.73	-6868.48	-6652.28
	24	-7324.87	-7206.16	-7023.16
SPTI	1	-2957.43	-630.93	-1405.21
	3	-1480.09	-1006.22	-1439.65
	6	-1525.45	-1302.26	-1544.35
	9	-2262.77	-1939.43	-1905.43
	12	-2595.84	-2212.02	-2098.22
	24	-2930.93	-2660.30	-2548.93

Table 2 BIC Values for 12 CGMD for SPI, SPEI and SPTI.

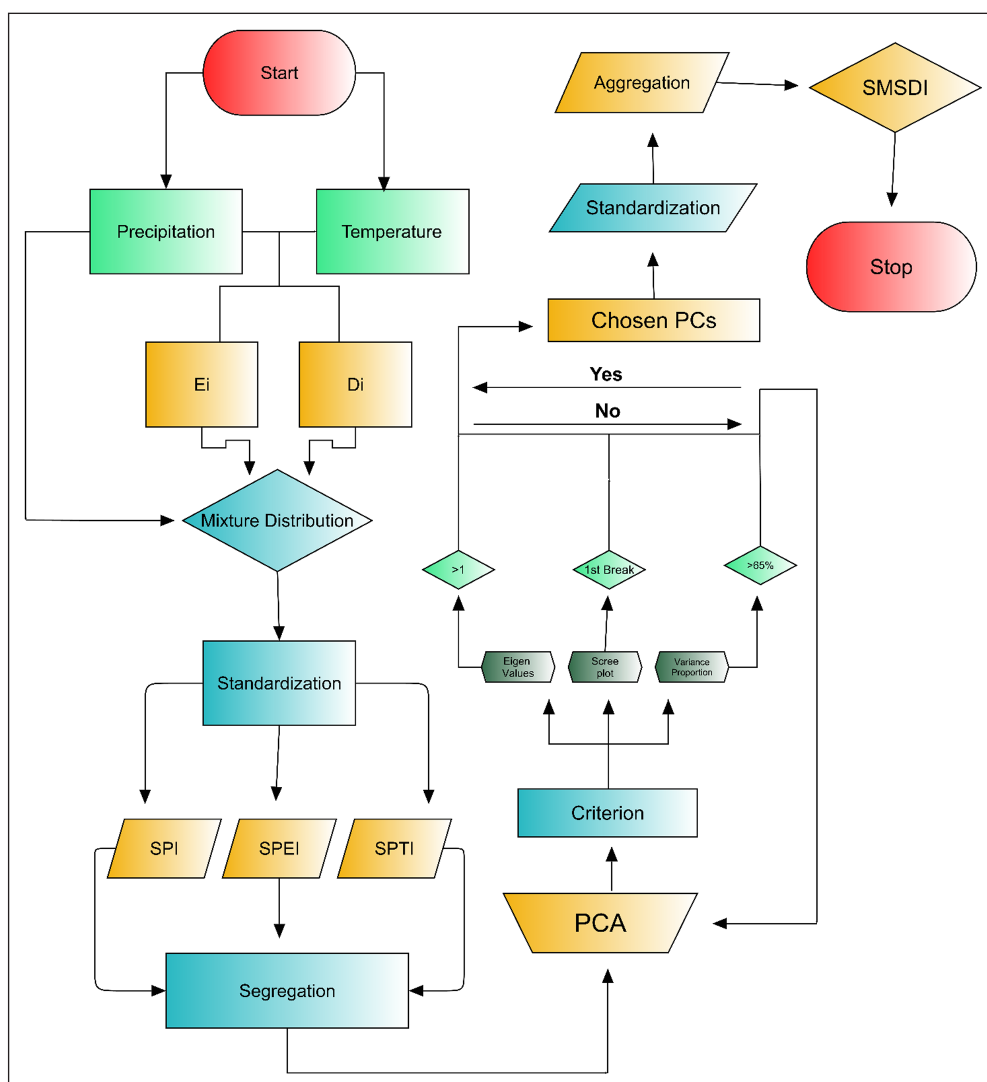


Figure 2 Flowchart of the proposed framework.

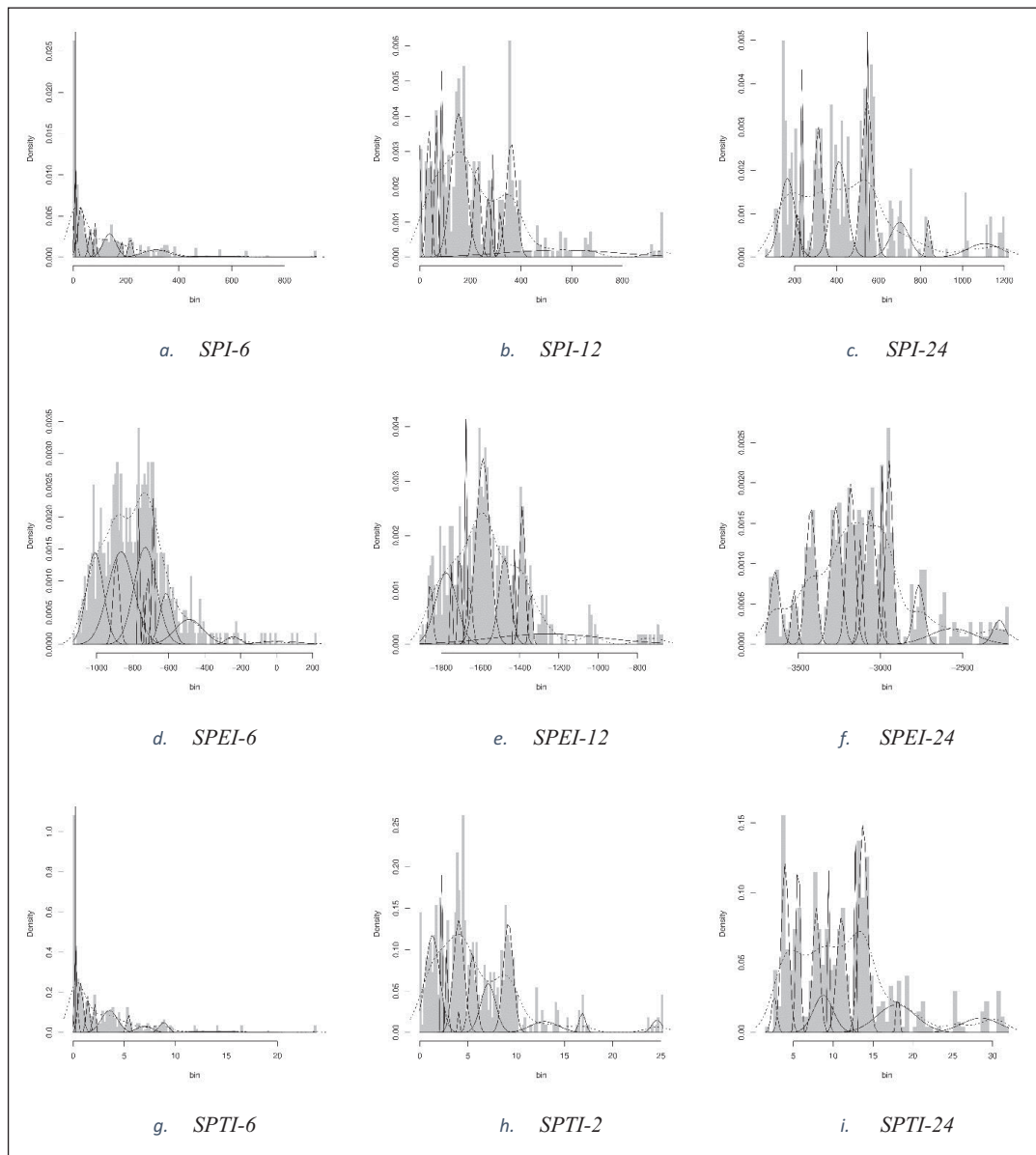


Figure 3 Density plots of 12-CGMD for Badin station.

- ii) Segregation of time series data of SDIs by appropriate seasonality indicator.
- iii) Integration of PCA on each serrated data of SDIs
- iv) Standardization of PC_1 , for each segregated set.
- v) Aggregation of segregated standard series to obtain new index

However, to increase the flexibility for our proposal and its associated results, we suggest the following three lemmas.

Lemma 1. The Choice of the stations

In many hydrological and meteorological studies, the core constraining influence in model performance and drought assessment are the small temporal length and low quality of meteorological data. However, many frameworks rely on long time series, precise and reliable data of meteorological variables. For instance, to enhance reservoir management methods and to predict drought

characteristics, long time series data on meteorological and environments objects is required for effective hydrological modelling (Arsenault and Brissette, 2014; Jiang *et al.*, 2020). Further, the probabilistic estimation of SDIs and the integration of PCA on seasonally segregated data requires long time series data. Therefore, we suggest to includes those meteorological stations that have long time series data meteorological variables.

Lemma 2. Selection of SDI type indicator

There are several Standardized Drought Indices (SDIs) indicators, each one is developed to meet a particular requirement (Yihdego *et al.*, 2019). SDI based drought characterization involves standardization of time series data of different variables, or a collection of variables. Since all the indicators used in SDIs procedure are based on subjective choice of meteorological variables, the scope of individual SDIs is therefore limited to study area and research question. Therefore, the main concentration

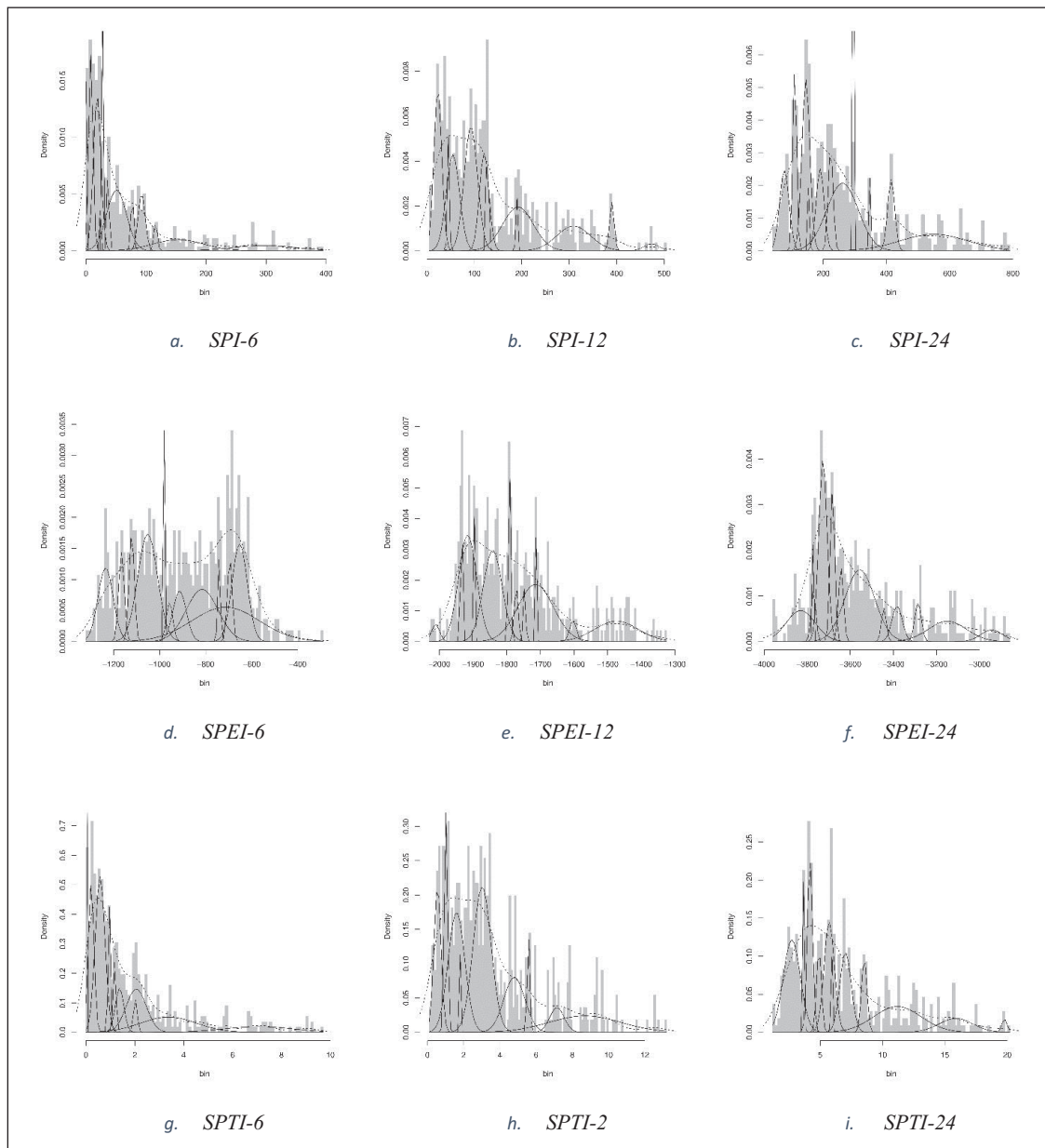


Figure 4 Density plots of 12-CGMD for Khanpur station.

in the development SDIs is global challenges (i.e., global warming and climate change). WMO and GWP, (2016) reviewed and used the most popular drought indices as well as drought monitoring tools. Though, SDIs are the most widely employed method for monitoring drought. However, the use of individual or multiple SDIs without taking precautions related to the selection meteorological variables, estimation procedure, and the compatibility of region limits the scope of results related to drought characterization. Therefore, the choice of SDIs can significantly contribute in reliable and accurate drought assessment.

Lemma 3. The Choice of Season

Spatio-temporal fluctuations of meteorological variables in different gauge stations within a particular region is an eminent topic (Ma et al., 2018; Asfaw et al., 2018; Ongoma and Chen, 2017; Ali et al., 2020c). From past

research, we have learned that some regions have a long period of cold season (Yang et al., 2013). On the other hand, there are some regions that have hot climate throughout the whole calendar year (Uvo et al., 1998). In this situation, defining a generalized index of seasonality is difficult task. However, numerous environmental and meteorological assessments are based on month wise seasonal indices (Ayugi et al., 2016; Yang et al., 2013). By keeping this argument, the proposal of this research suggests each individual month as a season.

3.1. THE PROPOSED INDICATOR – THE SEASONAL MIXTURE STANDARDIZED DROUGHT INDEX (SMSDI)

Following the above three lemmas, this research is based on the aggregation of SPI, SPEI and SPTI for reducing error in inaccurate determination of drought classes. The selection of SPI, SPEI and SPTI is based on the

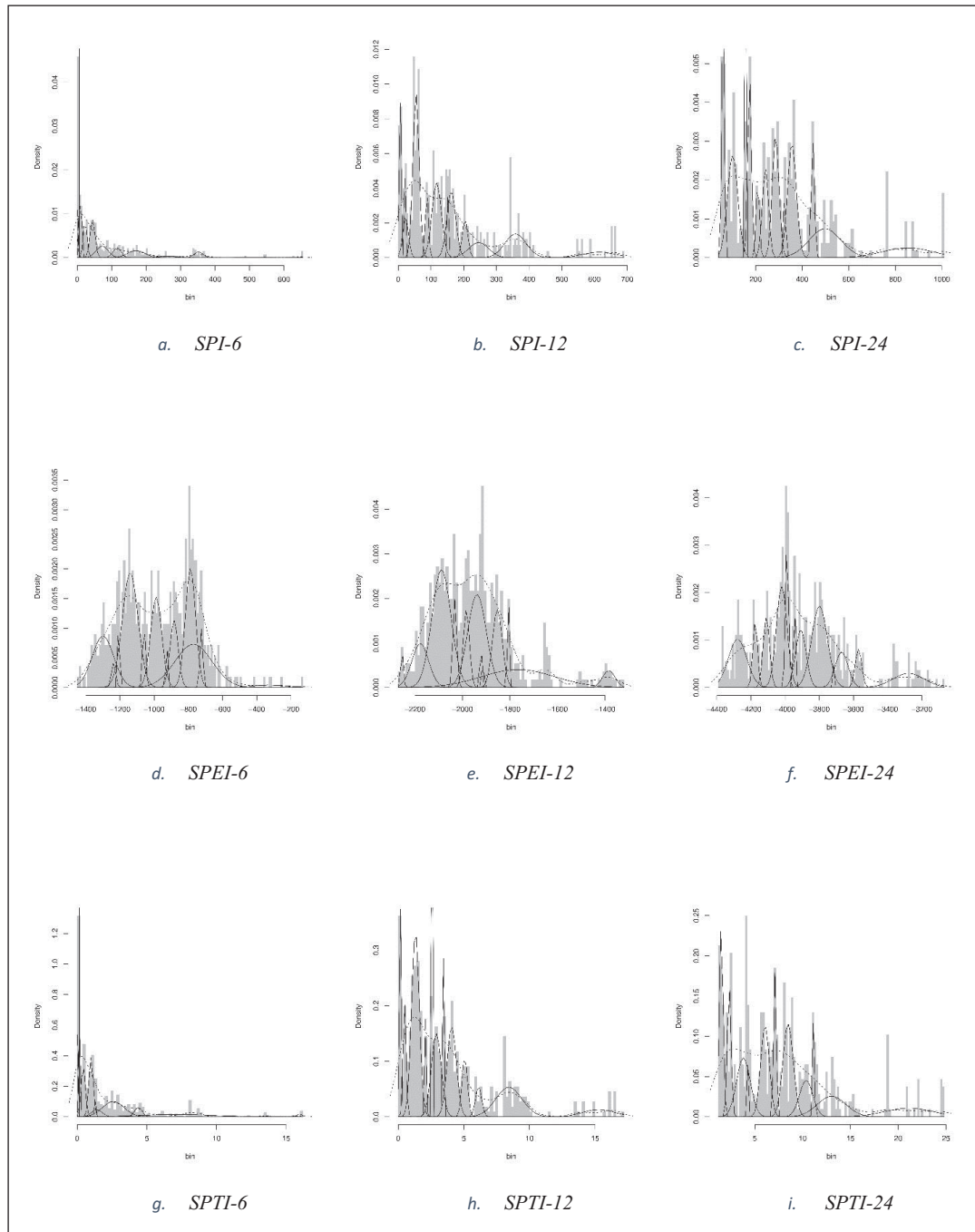


Figure 5 Density plots of 12-CGMD for Nawabshah station.

standardized classification of drought characteristics. The following subsection explains the steps involved in the development of SMSDI.

3.1.1. Estimation of drought indices such as SPI, SPEI and SPTI under K – Components Gaussian Mixture Distribution (K-CGMD)

Comparative to single probability function or varying distribution concept, this subsection assesses and describes the appropriateness of K-CGMD for the estimation of drought indices under probabilistic framework. Therefore, to enhance the accuracy in the estimation of drought indices, this study introduces K-CGMD based standardization.

The formulation of K-CGMD consists of two types of parameters, the weights of mixture components and the means and variances of each component.

Mathematically, the K-CGMD model is presented as,

$$p(x | \mu_k, \Sigma_k) = \frac{1}{\sqrt{(2\pi)^d \det(\Sigma_k)}} \exp\left(-\frac{1}{2}(x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k)\right) \quad (1)$$

$$P(x) = \sum_{i=1}^K \alpha_i N(x | \mu_i, \sigma_i) \quad (2)$$

$$N(x | \mu_i, \sigma_i) = \frac{1}{\sigma_i \sqrt{2\pi}} \exp\left(-\frac{(x - \mu_i)^2}{2\sigma_i^2}\right) \quad (3)$$

$$\sum_{i=1}^K \alpha_i = 1 \quad (4)$$

Where, K is the number of components, α_i is the mixture component weight of i^{th} component with the constraint $\sum_{i=1}^K \alpha_i = 1$, so that the total probability distribution normalizes to 1. μ_p , σ_i are the mean and variance of i^{th} component.

In experimental study, we have suggested to choose 12-CGMD model. The selection of components is subjective to the nature of data. We assume that in each month, the distribution of data follows normal probability function. However, the choice of the number of components is very important subject of computational theory.

For estimation of SPI, SPEI and SPTI, we suggest standardization the following CDF of 12 components mixture of Gaussian functions.

$$H(x) = \sum_{i=1}^{12} a_i F(x_i) \quad (5)$$

After the estimation of CDF of mixture model $H(x)$, the temporal vector of $H(x)$ is then standardized under the standardization approximation procedure adopted in Ali et al., (2017).

3.1.2. Seasonal Segregation

This step is due to correlation structure in seasonal multivariate time series. Thus, to increase the accuracy of PCA, data segregation based on seasonal index plays an important role for accurate determination of drought classes. Therefore, this step suggests the segregation of time series data of each index based on seasonal indication.

3.1.3. Application of PCA on each segregated data

Principal Component Analysis (PCA) is a useful technique and has widespread applications in numerous computational research. PCA is a statistical technique that transforms the original variables of data into new

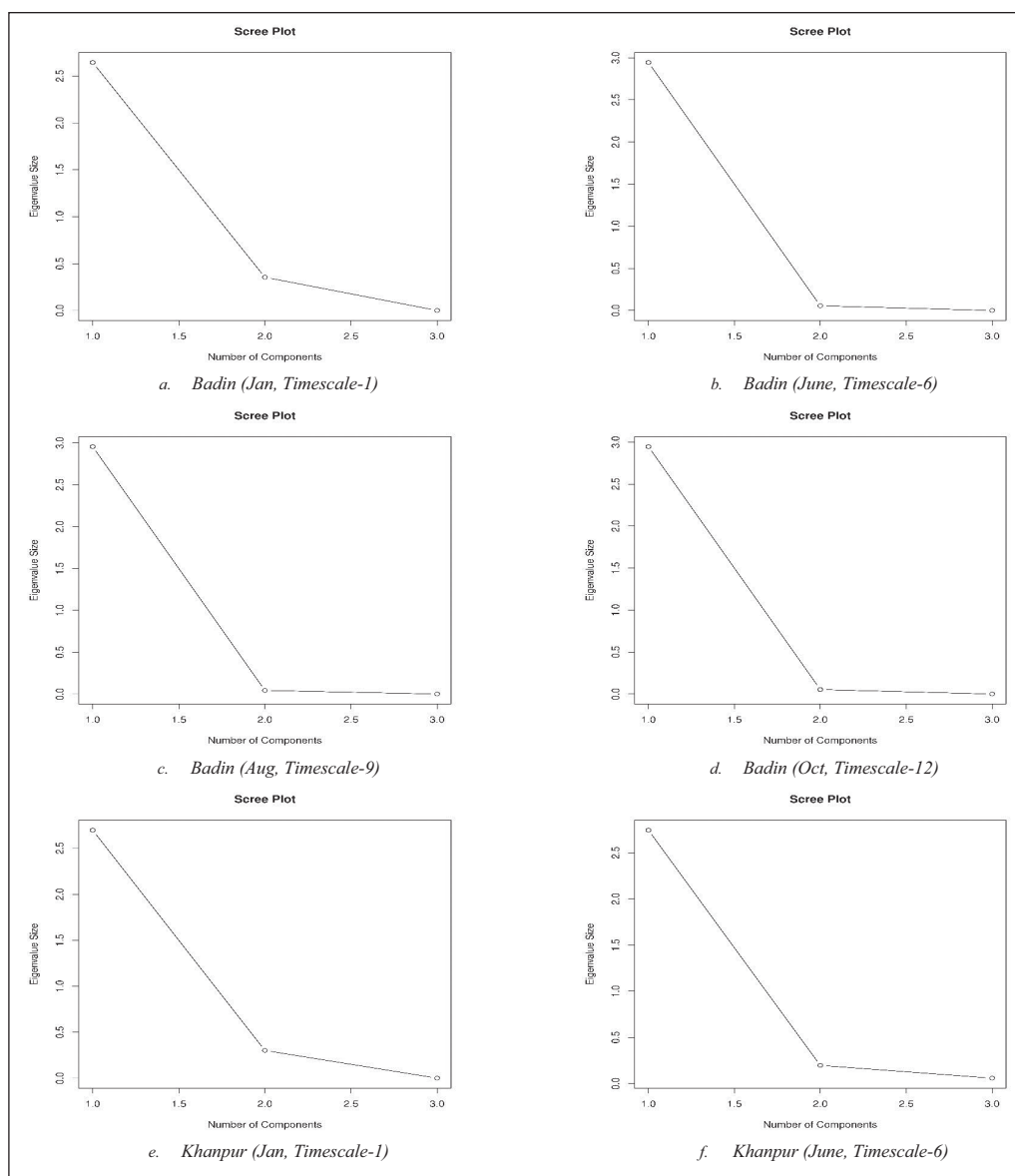


Figure 6 Scree plots (1).

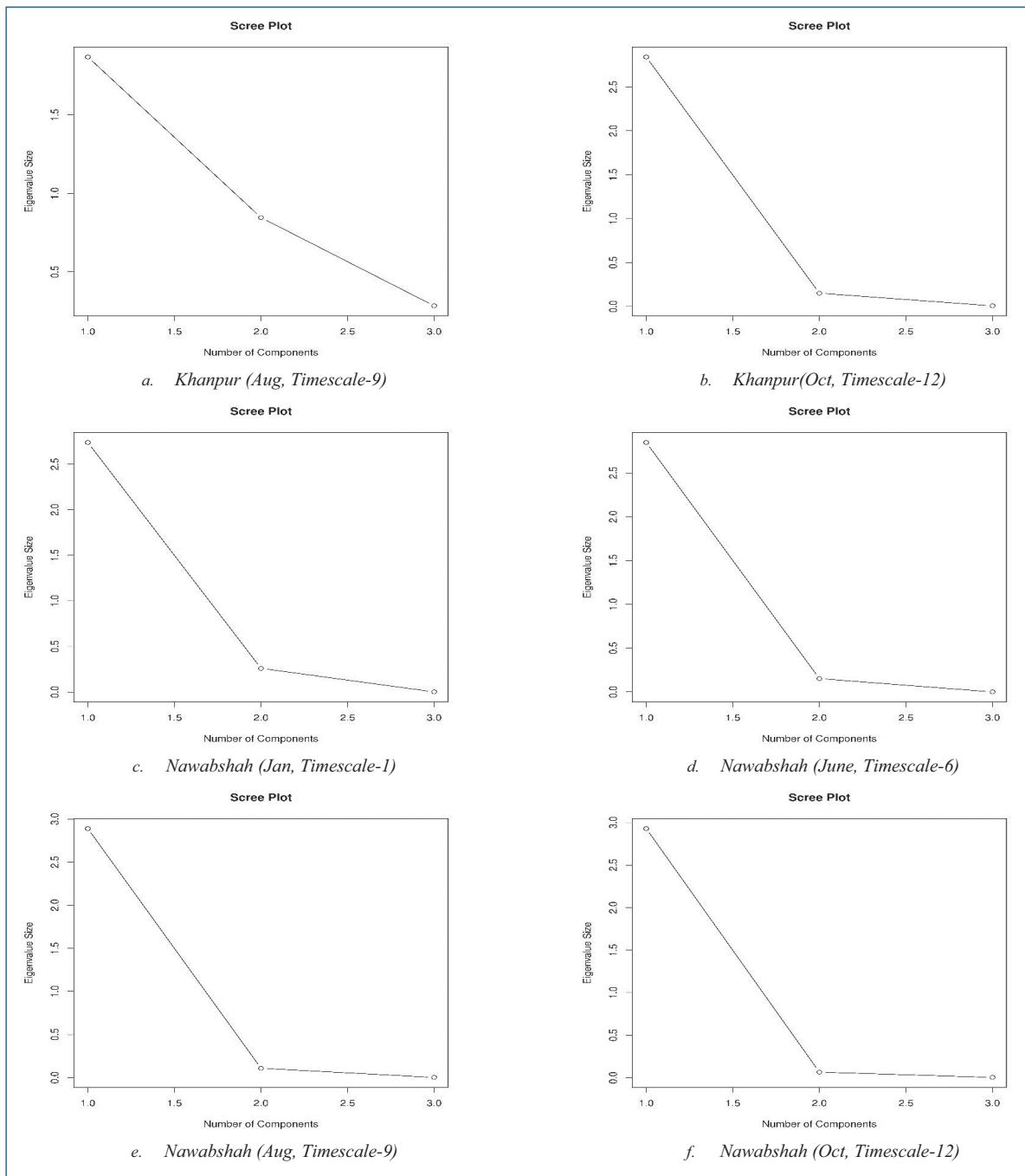


Figure 7 Scree plots (2).

axes or principal component (PCs), so that the result provided in those axes are not associated with each other. The main goal of principal component analysis is to extract important information from the data to represent it - a set of new orthogonal variables called Principal component PCs. Each PC is a linear combination of the original responses (that retain some correlation among), and PCs are orthogonal to each other.

Thus, the first PC is the mathematical combination of measurements that accounts for the largest amount of variability in the data. In other words, PCs iteratively expresses as much as possible of the total variation in the data in such a way that PC_1 explains more of that PC_2 and PC_2 explains more data variation than PC_3 and

so on. That why few PCs describes the variation of large number of original responses. Particularly in hydrology, many authors have used PCA for inferencing hydrological process. In drought modeling, Bazrafshan et al. (2014) have used PCA technique to resolve the multi-scaling challenges in SDIs. On the same lines of Bazrafshan et al. (2014), the current study recommends the use of PCA to resolve the multiplicity issue of drought indices.

3.1.4. Standardization

In our case study, we calculate SMSDI for each set of SPI, SPEI and SPTI- time scales. i.e. (1,3, 6, 9, 12 and 24 months) for each station. SMSDI is based on the first principal component PC_1 . The component PC_1 is a linear

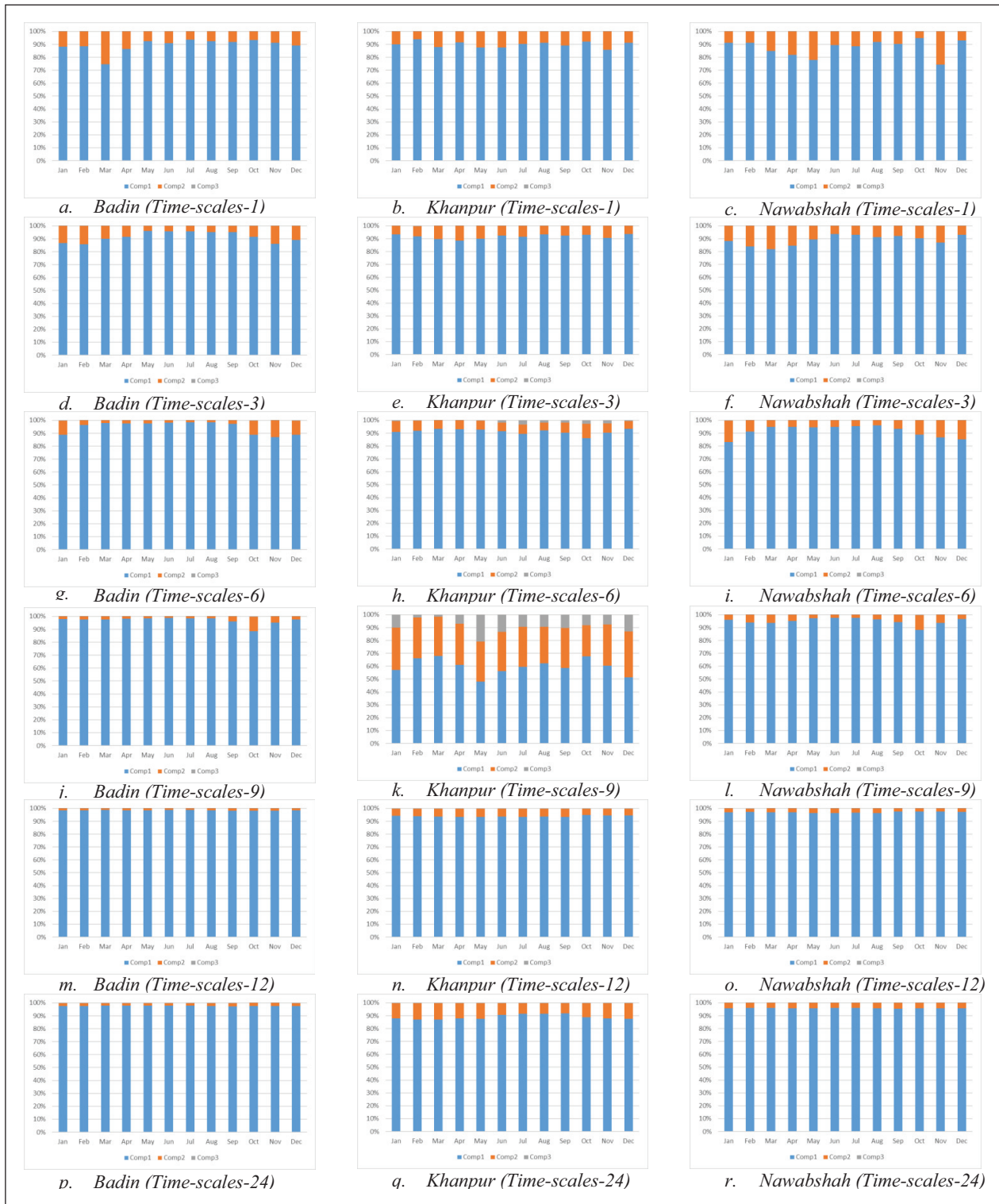


Figure 8 Percentage of variations in PCs in different months at different time-scales.

combination of the original variables and explain most part of the variability existing in the original variable. Due to algebraic characteristics, its value cannot be compared among different months or place. SPI, SPEI and SPTI have zero mean and unit variance.

For each segregated data set, we suggest to standardized the resultant first PC. Hence, we suggest the following equation for standardization (see Bazrafshan et al., 2014).

$$SMSDI_{uc} = \frac{PC_{1ym} - \overline{PC_{1m}}}{SD_{1m}} \quad (6)$$

where PC_{1ym} is the first principal component of the y^{th} year m^{th} month, $\overline{PC_{1m}}$ is the PC_1 mean in the m^{th} month and SD_{1m} is the standard deviation of PC_1 in the m^{th} month. Following the applications of PCA, the chosen PCs are then standardized and the upcoming section will give us aggregates seasonally segregated time series data of

TS	STNS.	CS	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
1	BD	C1	2.64	2.66	2.24	2.59	2.77	2.73	2.81	2.77	2.75	2.80	2.73	2.68
		C2	0.36	0.34	0.76	0.41	0.23	0.27	0.19	0.23	0.25	0.20	0.27	0.32
		C3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	KP	C1	2.70	2.81	2.63	2.75	2.63	2.63	2.71	2.73	2.68	2.77	2.57	2.74
		C2	0.30	0.18	0.37	0.25	0.37	0.37	0.29	0.27	0.32	0.23	0.43	0.26
		C3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	NS	C1	2.74	2.74	2.54	2.45	2.34	2.68	2.66	2.75	2.71	2.85	2.23	2.79
		C2	0.26	0.26	0.46	0.55	0.66	0.32	0.34	0.25	0.29	0.15	0.77	0.21
		C3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	BD	C1	2.60	2.58	2.70	2.74	2.88	2.88	2.87	2.85	2.86	2.75	2.58	2.68
		C2	0.40	0.42	0.30	0.26	0.12	0.12	0.13	0.15	0.14	0.25	0.42	0.32
		C3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	KP	C1	2.80	2.75	2.69	2.66	2.70	2.77	2.75	2.80	2.77	2.79	2.72	2.81
		C2	0.19	0.24	0.31	0.34	0.30	0.23	0.25	0.20	0.23	0.21	0.28	0.19
		C3	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	NS	C1	2.65	2.52	2.45	2.54	2.68	2.80	2.79	2.74	2.77	2.71	2.61	2.79
		C2	0.35	0.48	0.54	0.46	0.32	0.20	0.21	0.26	0.23	0.29	0.39	0.21
		C3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	BD	C1	2.66	2.89	2.93	2.93	2.93	2.94	2.95	2.95	2.92	2.66	2.61	2.66
		C2	0.33	0.11	0.07	0.07	0.07	0.06	0.05	0.05	0.08	0.33	0.39	0.33
		C3	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01
	KP	C1	2.73	2.76	2.80	2.79	2.78	2.74	2.69	2.76	2.71	2.58	2.71	2.80
		C2	0.25	0.23	0.20	0.21	0.21	0.20	0.22	0.19	0.23	0.34	0.22	0.18
		C3	0.02	0.01	0.00	0.00	0.01	0.06	0.10	0.05	0.06	0.08	0.07	0.02
	NS	C1	2.49	2.74	2.84	2.84	2.84	2.85	2.87	2.88	2.80	2.67	2.60	2.55
		C2	0.50	0.26	0.16	0.16	0.16	0.15	0.13	0.11	0.20	0.33	0.39	0.44
		C3	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01

Table 3 Eigen values for timescales (1,3,6) for different components of PCA.

TS	STNS.	CS	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
9	BD	C1	2.93	2.93	2.93	2.94	2.95	2.96	2.96	2.96	2.88	2.65	2.86	2.93
		C2	0.07	0.07	0.07	0.06	0.05	0.04	0.04	0.04	0.12	0.34	0.14	0.07
		C3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
	KP	C1	1.71	1.98	2.03	1.83	1.44	1.69	1.78	1.87	1.76	2.03	1.81	1.54
		C2	0.99	0.95	0.92	0.96	0.94	0.91	0.94	0.85	0.93	0.73	0.96	1.07
		C3	0.30	0.07	0.04	0.21	0.63	0.40	0.28	0.28	0.31	0.24	0.23	0.39
	NS	C1	2.88	2.82	2.81	2.85	2.92	2.92	2.92	2.89	2.83	2.65	2.81	2.90
		C2	0.12	0.18	0.19	0.15	0.08	0.07	0.07	0.11	0.17	0.34	0.19	0.10
		C3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00

(Contd.)

TS	STNS.	CS	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
9	BD	C1	2.93	2.93	2.93	2.94	2.95	2.96	2.96	2.96	2.88	2.65	2.86	2.93
		C2	0.07	0.07	0.07	0.06	0.05	0.04	0.04	0.04	0.12	0.34	0.14	0.07
		C3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
	KP	C1	1.71	1.98	2.03	1.83	1.44	1.69	1.78	1.87	1.76	2.03	1.81	1.54
		C2	0.99	0.95	0.92	0.96	0.94	0.91	0.94	0.85	0.93	0.73	0.96	1.07
		C3	0.30	0.07	0.04	0.21	0.63	0.40	0.28	0.28	0.31	0.24	0.23	0.39
	NS	C1	2.88	2.82	2.81	2.85	2.92	2.92	2.92	2.89	2.83	2.65	2.81	2.90
		C2	0.12	0.18	0.19	0.15	0.08	0.07	0.07	0.11	0.17	0.34	0.19	0.10
		C3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
12	BD	C1	2.95	2.96	2.96	2.96	2.96	2.96	2.96	2.96	2.94	2.95	2.95	2.95
		C2	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.06	0.05	0.05	0.05
		C3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	KP	C1	2.83	2.82	2.81	2.80	2.80	2.81	2.80	2.81	2.80	2.84	2.83	2.83
		C2	0.16	0.17	0.18	0.19	0.19	0.18	0.19	0.18	0.19	0.15	0.16	0.16
		C3	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	NS	C1	2.91	2.91	2.91	2.91	2.89	2.89	2.90	2.89	2.92	2.93	2.92	2.92
		C2	0.08	0.08	0.09	0.09	0.10	0.11	0.09	0.11	0.07	0.07	0.07	0.07
		C3	0.00	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
24	BD	C1	2.93	2.93	2.93	2.93	2.94	2.94	2.94	2.93	2.91	2.92	2.93	2.93
		C2	0.07	0.06	0.06	0.06	0.06	0.06	0.06	0.07	0.08	0.07	0.07	0.07
		C3	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	KP	C1	2.64	2.61	2.61	2.63	2.63	2.72	2.75	2.74	2.76	2.67	2.64	2.62
		C2	0.35	0.38	0.38	0.36	0.36	0.27	0.24	0.25	0.24	0.33	0.35	0.37
		C3	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	NS	C1	2.88	2.88	2.88	2.88	2.87	2.88	2.88	2.87	2.87	2.87	2.87	2.87
		C2	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.13	0.13	0.13	0.12	0.12
		C3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 4 Eigen values for timescales (9,12,24) for different components of PCA.

SR. NO.	RANGE OF SDIS AND SMSDI	CATEGORIES
1.	2.00 and above	Extremely Wet
2.	1.50 to 1.99	Very Wet
3.	1.00 to 1.49	Moderate Wet
4.	-0.99 to 0.99	Near Normal
5.	-1.00 to -1.49	Moderate Drought
6.	-1.50 to -1.99	Severe Drought
7.	-2.00 and less	Extremely Drought

Table 5 Drought classifications.

drought indices. We call the resultant time series data as SMSDI.

3.1.5. Aggregation

The aggregation may express itself in a process such that the techniques used in the current study can handle the

proposed index in a precise manner and gives accurate drought assessment results on regional basis. It is worth noting that aggregation and segregation are two faces of the same coin, which emphasis to give a well-mannered required information. Following a step by step procedure indicated in the flow chart (see [Figure 2](#)), the last phase

TIMESCALES	CATEGORY	SPI		SPEI		SPTI		SMSDI	
		COUNT	%AGE	COUNT	%AGE	COUNT	%AGE	COUNT	%AGE
1	ND	469	83.16	353	62.59	469	83.16	458	81.21
	ED	0	0.00	57	10.11	0	0.00	0	0.00
	SD	0	0.00	67	11.88	0	0.00	12	2.13
	MD	0	0.00	53	9.40	0	0.00	12	2.13
	MW	44	7.80	12	2.13	45	7.98	33	5.85
	SW	43	7.62	11	1.95	43	7.62	15	2.66
	EW	7	1.24	11	1.95	7	1.24	34	6.03
3	ND	447	79.54	406	72.24	449	79.61	422	74.82
	ED	0	0.00	0	0.00	0	0.00	3	0.53
	SD	0	0.00	36	6.41	0	0.00	14	2.48
	MD	0	0.00	67	11.92	0	0.00	30	5.32
	MW	71	12.63	20	3.56	71	12.59	50	8.87
	SW	40	7.12	19	3.38	37	6.56	21	3.72
	EW	4	0.71	14	2.49	5	0.89	22	3.90
6	ND	371	66.37	410	73.35	361	64.58	394	70.48
	ED	0	0.00	2	0.36	0	0.00	6	1.07
	SD	0	0.00	19	3.40	0	0.00	19	3.40
	MD	90	16.10	51	9.12	103	18.43	50	8.94
	MW	68	12.16	47	8.41	69	12.34	48	8.59
	SW	25	4.47	18	3.22	21	3.76	23	4.11
	EW	5	0.89	12	2.15	5	0.89	19	3.40
9	ND	329	59.17	413	74.28	335	60.25	394	70.86
	ED	69	12.41	6	1.08	68	12.23	8	1.44
	SD	64	11.51	18	3.24	64	11.51	29	5.22
	MD	60	10.79	29	5.22	55	9.89	53	9.53
	MW	18	3.24	54	9.71	18	3.24	35	6.29
	SW	9	1.62	24	4.32	9	1.62	23	4.14
	EW	7	1.26	12	2.16	7	1.26	14	2.52
12	ND	404	73.06	407	73.60	403	72.88	375	67.81
	ED	0	0.00	0	0.00	0	0.00	0	0.00
	SD	20	3.62	3	0.54	20	3.62	21	3.80
	MD	71	12.84	56	10.13	71	12.84	77	13.92
	MW	26	4.70	50	9.04	27	4.88	42	7.59
	SW	21	3.80	14	2.53	21	3.80	15	2.71
	EW	11	1.99	23	4.16	11	1.99	23	4.16
24	ND	350	64.70	402	72.69	347	62.75	355	64.20
	ED	0	0.00	0	0.00	0	0.00	0	0.00
	SD	2	0.37	32	5.79	21	3.80	32	5.79
	MD	115	21.26	22	3.98	98	17.72	76	13.74
	MW	34	6.28	39	7.05	40	7.23	31	5.61
	SW	7	1.29	24	4.34	12	2.17	23	4.16
	EW	32	5.91	22	3.98	22	3.98	24	4.34

Table 6 Counts of various drought categories at Badin station.

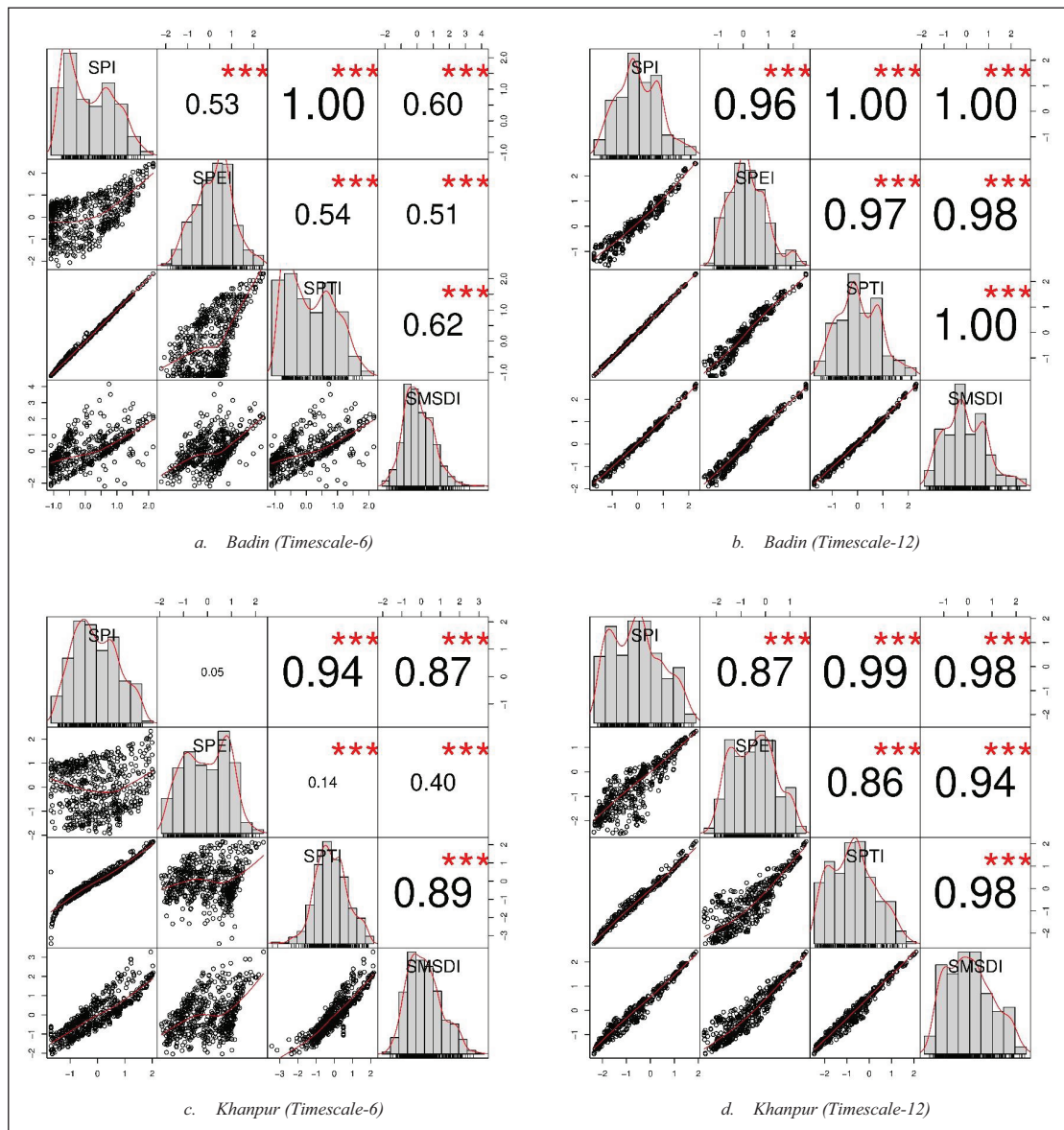


Figure 9 Correlations of SMSDI with SPI, SPEI and SPTI at Badin and Khanpur.

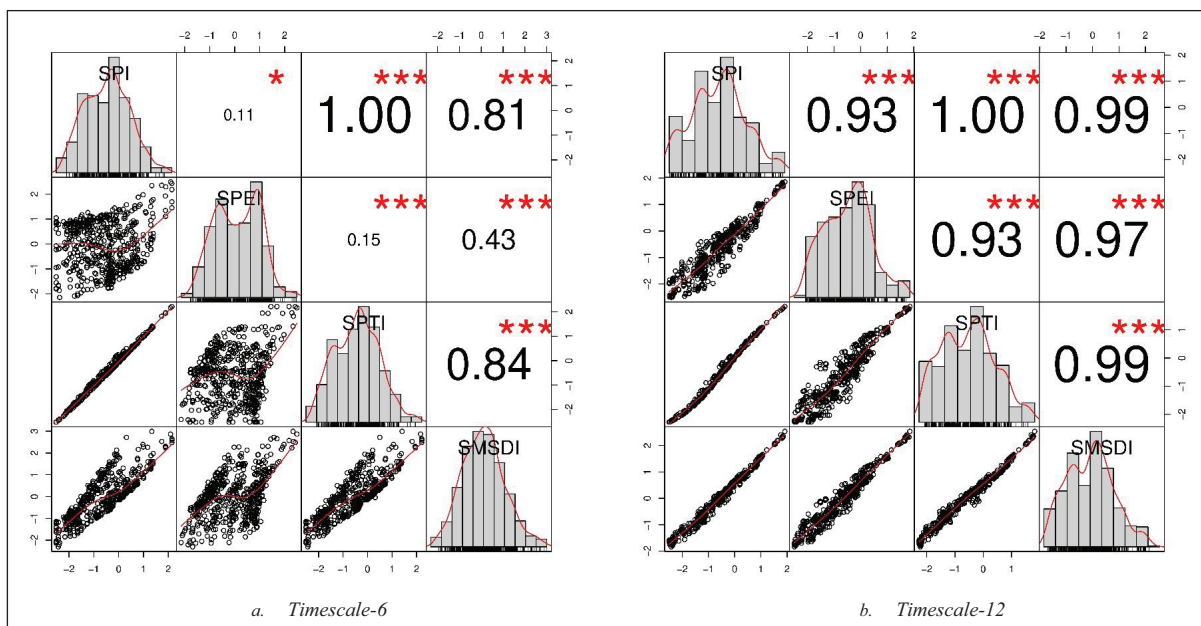


Figure 10 Correlations of SMSDI with SPI, SPEI and SPTI at Nawabshah station.

of our proposed index i.e. SMSDI is the aggregation of the segregated standardized data.

4. RESULTS AND DISCUSSION

4.1. ESTIMATION OF SPI, SPEI AND SPTI UNDER K-CGMD SETTINGS

This section presents the results associated with K-CGMD based standardization of drought indicators. Here, we applied 12-CGMD for modeling the time series data of all SDI. **Table 2** shows the BIC values of the 12 component gaussian model in all the selected stations under study with different time-scales. For instance, -5505.72, -4329.87 and -623.88 are the values of BIC for Badin, Nawabshah and Khanpur stations

respectively, highlighting time-scale 1. **Figures 3–5** provide the graphical demonstration of the application of CGMD. As we can observe clearly from these figures which provide evidence that in each data, the K-CGMD models are more appropriate instead of applying a single distribution. Some more results are archived in author's gallery.

4.2. PRINCIPAL COMPONENTS ANALYSIS

In further part of research, we intend to use SDI time series seasonal data for PCA. The resulting data will be reduced to one-dimension data. In section 2.2, we overview the SDI techniques and a detailed explanation of the proposed index i.e. Seasonal Mixture Standardized Drought Index (SMSDI) is given in section 4. We calculate

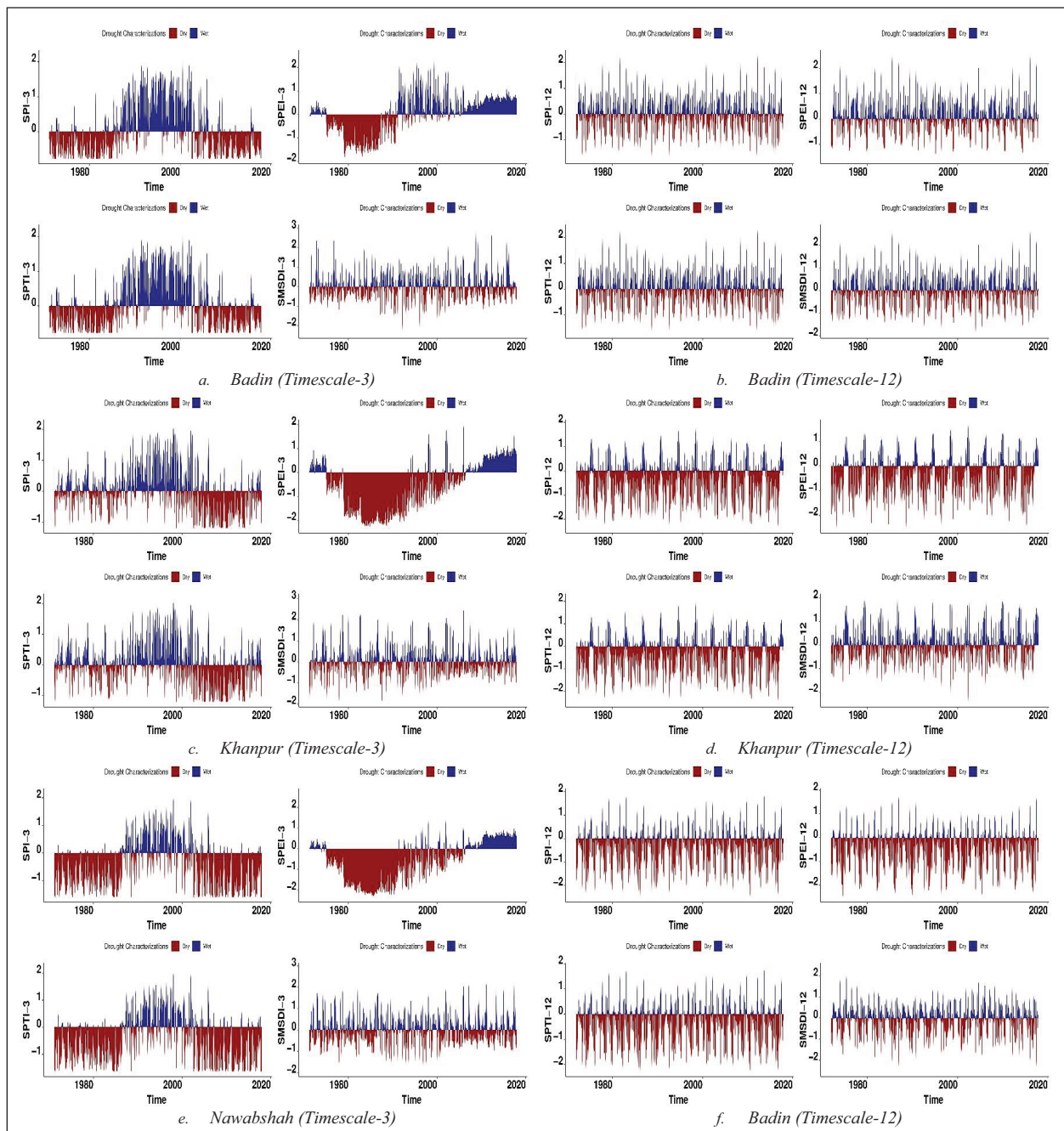


Figure 11 Temporal plots of SMSDI, SPI, SPEI and SPTI (Month wise).

SDI for 1 to 24-month time-scales. The calculation procedure and methodology has been explained in the said section. The SMSDI is based on $3 \times 12 \times 6 \times 3$ sets of the chosen indices (for different months and taking different time-scales for the chosen stations) using principal component analysis technique. For the stations under study eigen-values as well as Eigen-vectors were calculated. Such as, [Figures 6](#) and [7](#), for the considered stations showing scree-plots for different sets. The contribution of each component is represented in values (out of 3) at y-axis, these figures show the importance of PCs. [Figures 6](#) and [7](#) suggests that PC_1 of all the sets explain more than 75% variation of the total variation. Apart from the Scree plot, the bar chart (illustrating the

role of each original variable in PCs) can also be useful in evaluating the nature of the indices.

The bar plot of the three PCs (PC_1 , PC_2 and PC_3) for all the months (seasons), timescales and stations under study has been manifested in [Figure 8](#). This figure reveals that SPI, SPEI and SPTI have a noticeable highly significant contribution to the first component (i.e., PC_1) for all the seasons (months) as well as for all the stations. [Figure 8](#) has comparative plots, which represent the variation explained by PC_1 . All the months of the meteorological stations are mentioned at the x-axis where, the contribution of the PCs are represented by the color bars. We conclude that all the plots have same behavior. However, for Khanpur station the contribution

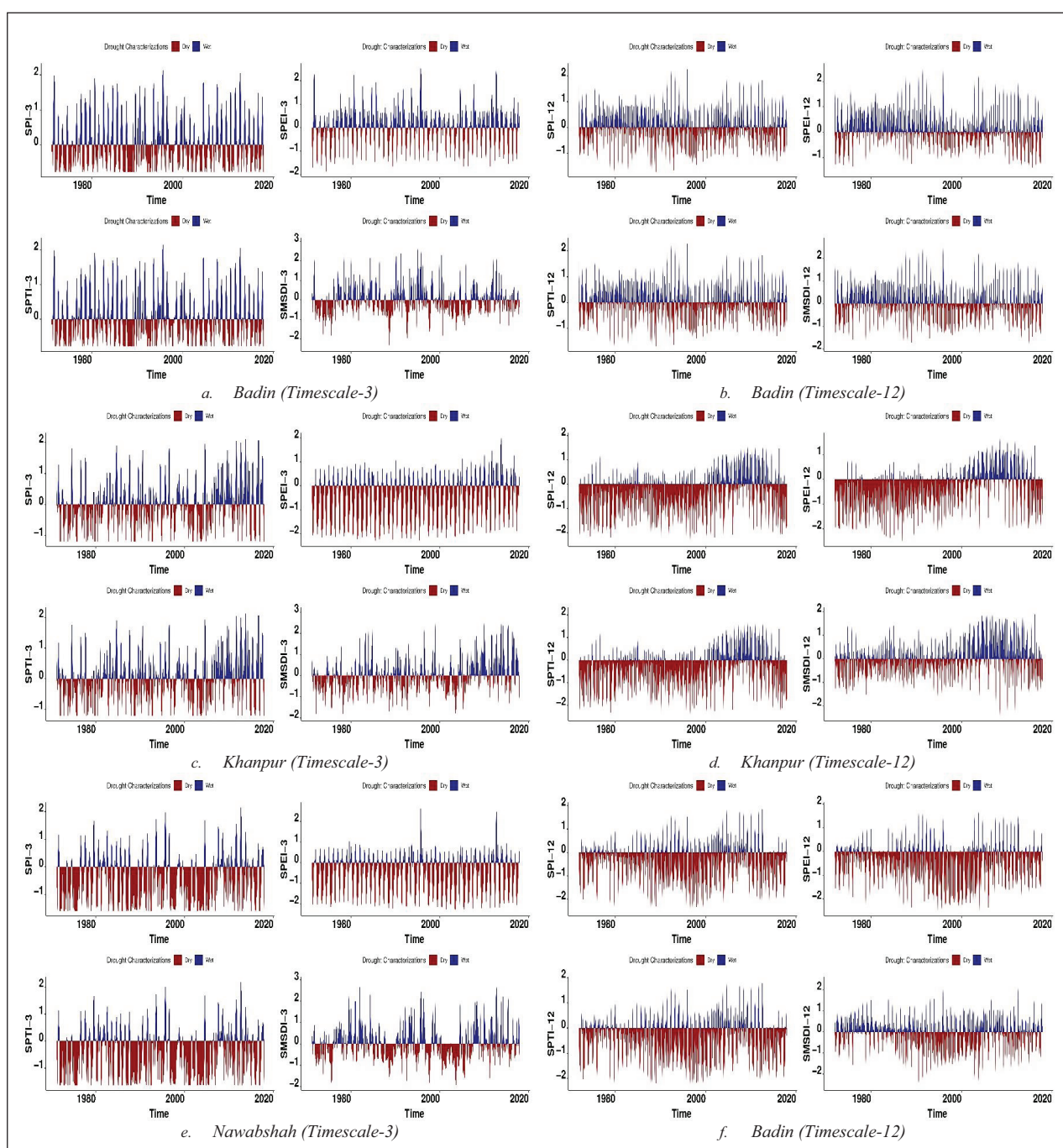
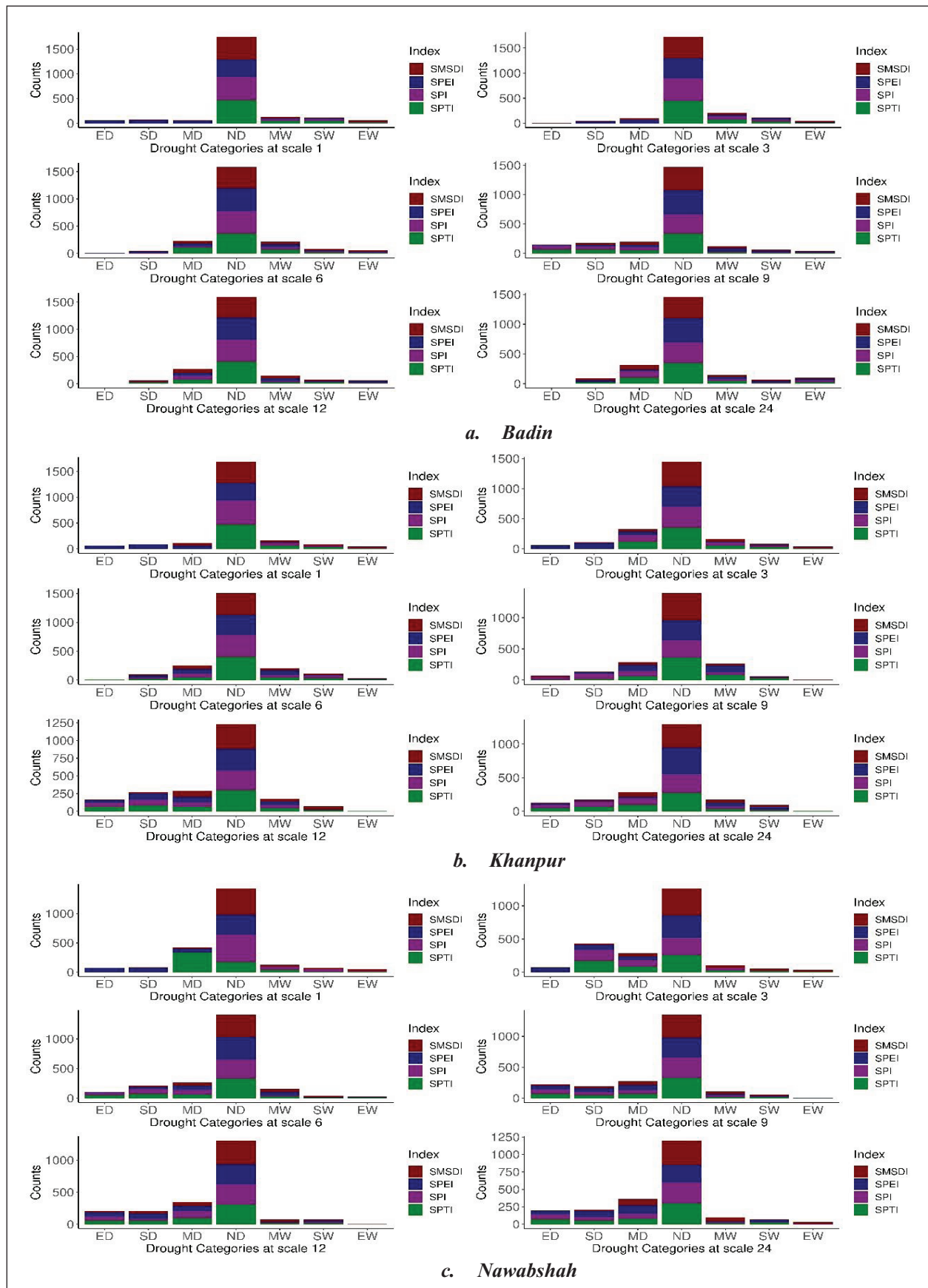


Figure 12 Temporal plots of SMSDI, SPI, SPEI and SPTI (Year wise).

**Figure 13** Histograms of counts of various drought classes under SMSDI, SPI, SPEI and SPTI.

of PC_1 is not that much higher compared to other stations. For instance, PC_1 of Badin for the months i.e., January, February, March, ..., December have 88%, 89%, 75%, ..., 89% contributions respectively, using timescale-1. Similar results for other stations can be seen by observing the said figure.

Results reveal that the eigenvalues for the first PCs are large, and for subsequent PCs small, see [Tables 3](#) and [4](#). Such that, the first PCs in the data set correspond to the directions with the greatest amount of variations. The sum of all the eigenvalues give a total of 3 for each month with timescales – (1,3,6,9,12 and 24). Similar results for all the stations along with the months and timescales can be seen by observing [Tables 3](#) and [4](#).

4.3. COMPARISON OF SMSDI WITH SPI, SPEI AND SPTI

In comparative assessment, the proposed SMSDI is compared with SDI used in this study. It has been observed that SMSDI is strongly correlated with SPI, SPEI and SPTI in all stations for various time scales (see [Figures 9](#) and [10](#)).

[Figures 11](#) and [12](#) show the temporal behavior of SMSDI, SPI, SPEI and SPTI at scale 2 and 12 in Badin, Khanpur and Nawabshah. It is perceived by observing these figures that the behavior of the series of SPI, SPEI and SPTI have homogenous pattern, but we can see the fluctuation in SMSDI. This fluctuation is the seasonal variation. In accordance with the figures, the SMSDIs are seen to follow appropriately the fluctuations of SPI, SPEI and SPTI, particularly during extended wet and dry periods. Likewise, SMSDI avoids dramatic volatility within actual SPI, SPEI and SPTI time-series (especially for the series of timescales of less than 9 months). This signifies that the SMSDI can remove the slighter wet and dry periods in the extreme and prolonged wet or dry periods. Further analysis was conducted to consider the parallelism in stations of interest among the SMSDI and each chosen series of SPI, SPEI and SPTI timescales in terms of various months of the year.

[Figure 13](#) shows the counts of drought categories for SDIs and SMSDI for all the stations with time-scales 1–24. There are total seven categories which contain the values of SMSDI as mention in the graphs. These categories were defined by McKee *et al.* (1993), the ranges of these categories can be seen in [Table 5](#). [Figure 13\(a\)](#) demonstrates the drought characterization for Badin station under various timescales. Normal category of drought for Badin occurred 469, 353, 469 and 458 times by using SDIs and SMSDI respectively for timescale-1. Similar interpretations can be found for ED, SD, MD, MW, SW and EW for Badin from [Figure 9\(a\)](#) and [Table 6](#). It can be noted from the said figure and table that SMSDI is a candidate index for highlighting the

droughts, as other indices are showing zero counts for several drought categories for timescales-1,3 and 6. The seasonality is taken under consideration in the proposed index, that is the reason that SMSDI has the ability of finding the drought even for less timescales. Similar results can be obtained for Khanpur and Nawabshah stations by analyzing [Figure \(9b\)](#) and [\(9c\)](#) respectively.

5. CONCLUSION

In this paper, a new hybrid drought index has been proposed. The procedure of the new drought index is based on the integration of PCA and K-CGMD. We called the new index as SMSDI. SMSDI have ability to accounts the features multiple existing SDIs. To assess the performance of SMSDI, numerical application has consisted on based three gauge stations of Pakistan. Outcomes associated with the applications show that all of the data in the selected stations contain K underlying classes, each defined by different parameters. So, instead of using one probability function, use of K – CGMD guarantees the accurate determination of drought classes. In this setting, the procedure of SMSDI is free from the problem of fitting inappropriate probability distribution functions. Consequently, we have provided a new and more solid fitting methods for the estimation of SDIs, 2) the seasonality affect have also considered in the proposal of SMSDI, 3) the problem of the existence of multiple drought indices has been resolved in SMSDI procedure, 4) drought categories defined by SMSDI are greatly accorded with those defined by SPI, SPEI and SPTI time series. Hence, to avoid the hardness of computational work, and confusion in the interpretation of SPI, SPEI and SPTI, our proposal provides best solution to date.

DATA ACCESSIBILITY STATEMENTS

The data that support the findings of this study are available from the corresponding author upon reasonable request.

FUNDING INFORMATION

This work was supported grants by the National Natural Science Foundation of China program (41801339), Natural Science Foundation of Hubei Province, China (2020CFB615), and Open Fund of State Key Laboratory of Remote Sensing Science (Grant No. OFSLRSS202114). The authors are also thankful to the Jiangxi Outstanding Youth Funding (20121ACB211003).

COMPETING INTERESTS

The authors have no competing interests to declare.

AUTHORS CONTRIBUTIONS

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TO CITE THIS ARTICLE:

Khan, MA, Zhang, X, Ali, Z, Jiang, H, Ismail, M and Qamar, S. 2022. A New Standardized Type Drought Indicators Based Hybrid Procedure for Strengthening Drought Monitoring System. *Tellus A: Dynamic Meteorology and Oceanography*, 74(2022), 119–140. DOI: <https://doi.org/10.16993/tellusa.47>

Submitted: 10 March 2022 Accepted: 10 March 2022 Published: 28 March 2022

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Tellus A: Dynamic Meteorology and Oceanography is a peer-reviewed open access journal published by Stockholm University Press.

