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Research Article

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Posted Date: December 7th, 2020

DOI: <https://doi.org/10.21203/rs.3.rs-115294/v1>

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**On the Reduction of Inaccuracies in Drought Monitoring - A Novel Blended Procedure for
Standardized Type Drought Indicators**

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Abstract

Due to climate change and an increasing temperature, drought is prevailing in several parts of the globe. Therefore, drought monitoring is a challenging task in hydrology and water management research. Drought is occurring recurrently in various climatic zones around the world. In literature, in that respect, there are several drought monitoring indicators. Regardless of their pros and cons, their abundance creates a chaotic scenario in analysis and reanalysis in certain gauge station. This research aims to improve drought monitoring system by providing a comprehensive data mining approach under principle component analysis. Consequently, we propose a new index named: Seasonal Mixture Standardized Drought Index (SMSDI). In our preliminary analysis, we have included three multiscale Standardized Drought Indices (SDIs). In application, we have applied

our proposed indicator on three meteorological gauge stations located in Pakistan. For comparative assessment, individual SDI has used to investigate the association and consistency with SMSDI. Results presented in the current study demonstrated that the SMSDI has significant correlation with individual SDIs. Hence, we conclude that the procedure of SMSDI can be deployed in hydrology and water management research for extracting reliable information related to future drought.

Keywords: Climate Change; Drought monitoring; Water management research; Correlation.

1. Introduction

Due to climate change and an 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 *et al.*, 2016). According to the characteristics of drought monitoring and its assessment, 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 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.*, 2019). 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).

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 key role. For example, the Palmer Drought Severity Index (PDSI) have 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) have been proposed by McKee *et al.*, (1993). Neumerrous application 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. As, SPI, SPEI, SPTI have homogenous computational procedure, therefore, we call these indices as a set of Standardized Drought Indices (SDI). Some more details on SDIs are available in Erhardt and Czado, (2015).

However, being a probabilistic indicate, each SDI contains a certain amount of error. Therefore, the accuracy of determining accurate drought classes is the major concern in SDI. These inaccuracies arise due to the heterogeneous and inconsistencies, seasonal patterns in temporal data sets. The aim of this paper is to suggest a comprehensive framework which will investigate various features of drought by aggregating the temporal and seasonal characteristics of multiple drought indices. The goal of this research to provide a new indicator which increase the accuracy in investing various characteristics of drought and its forecasting.

Under certain circumstances, some 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).

2. Material and Methods

2.1 Data description and study area

This research is based on three metrological station located in various climatological regions of Pakistan. Pakistan is located in Asia. Its location lies between Middle East and Central Asia (Ahmed *et al.*, 2018). The locations of the chosen meteorological stations are depicted in Fig. 1. Geographic Information System (GIS) is used to obtain the required map. In the current study, long temporal data on rainfall and temperature data (minimum and maximum) is used to estimate all the required index at each station. The data ranging from January 1971 to December 2016 is obtained from Karachi Data Processing Center (KDPC) via Pakistan Meteorological Department (PMD). The maximum average monthly precipitation for Badin, Khanpur and Nawabshah are

459.00mm (August-1979), 307.50mm (August-2015) and 353.20mm (September-2011) respectively. Similarly, maximum & minimum average monthly temperatures for Badin, Khanpur and Nawabshah are 34.1C° (May-2010) & 15.45 C° (January-1975), 36.3 C° (June-2002) & 11.15 C° (January-1984) and 37.2 C° (May-2002) & 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 can be seen from Table 1.

2.2. Standardized Drought Index (SDI)

In recent developments, numerous methods and procedures have been developed for drought indices. The proposals of each indicator are subject to the meteorological characteristics of the region under study. Each drought index has its own characteristics. Basically, the main purpose of drought indices is to quantify the amount of precipitation. Regardless precipitation data, other environmental variable such as temperature, humidity and wind speed, etc. also play important role in continuous drought monitoring. Therefore, various authors have considered these additional variables in the formulation of drought indices. In this research, we consider three most commonly used indicator, SPI, the SPEI and SPTI. Some short descriptions on these indices are as follows;

2.2.1. SPI

Standardized Precipitation Index (SPI) (McKee *et al.*, 1993) 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. The SPI values are further classified to differentiate monthly severity of water deficient.

In this paper, instead of using single probability model, we proposed KCGMD for modeling time series data of SPI. The rest of the procedure is same as used in Ali *et al.*, (2017).

2.2.2. SPEI

After SPI, Vicente-Serrano *et al.*, (2010) have used temperature as additional variable in the same procedure of SPI, developed a simple but effective standardized drought index- the Standardized Precipitation Evapotranspiration Index (SPEI). In SPEI, the time series data of the difference between rainfall amount and estimated amount of evaporation e.g., Potential Evaporation (PET) is used to quantify drought (see Eq. 1).

Different equations can be used to estimate PET quantities according to the nature of the data. The Thornthwaite (Thornthwaite *et al.*, 1948), the Penman equation, Blaney-Criddle (Allen and Pruitt, 1986) and (Allen *et al.*, 1998) are the most widely used methods for estimating PET.

Vincente-Serrano *et al.* (2010) have utilized the same drought characterization criterion as described by (Mckee *et al.*, 1993). Following the same technique as SPI, SPEI is achieved by the standardization of the equation of the water balance (see Eq. 1),

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

where P_i is the total amount of precipitation per i^{th} month, and PET_i represents the amount of evaluated amount of Potential Evapotranspiration (PET) for the i^{th} month. See the details of PET in Appendix-A.

2.2.3. SPTI

The main challenge in SPI is the use of only one variable and ignoring other climatic parameters. Further in SPEI, the major problem is the under estimation of over estimation of PET for arid and

semi-arid regions. To resolve these problem, Ali *et al.*, (2017) have proposed a new drought indices- the Standardized Precipitation Temperature Index (SPTI). The main benefit of SPTI is that it can be used for any type of region. More detail on SPTI is available in (Ali *et al.*, 2017).

In this research, standardization of SPI, SPEI and SPTI has been done by using the novel concept of mixture distribution. In the current study we are using the mixture distribution instead of using a single distribution. A detailed explanation of mixture distribution can be seen in section 2.3, whereas the standardization procedure has been provided in Appendix-B.

2.3. K-Component Gaussian Mixture Distribution

Modeling data with several multiple modes as well as various skewness forms of the data in hand, a k-component mixture model is used for hydrological data which is strictly positive. Evin *et al.*, (2011) used Gamma-MM for the assessment of drought. To evaluate hydrological drought at Yellow River (China), Shiau *et al.*, (2007) have employed mixtures of Gamma and exponential distributions.

To make the structure of the k-component mixture model more concrete, let us suppose that we have random variables (possibly vector values) i.e., $X_1 + X_2 + X_3 + \dots + X_n$ denotes the simple random sample of finite $k > 1$ mixture arbitrary distributions. One can write the density of each X_i as follows,

$$g_{\theta}(x_i) = \sum_{j=1}^k \lambda_j \phi_j(x_i), \quad x_i \in \mathbf{R}^r \quad (2)$$

where,

$\theta = (\lambda, \phi) = (\lambda_1, \lambda_2, \dots, \lambda_k, \phi_1, \phi_2, \dots, \phi_k)$ indicates the parameter, and $\lambda_k \left\{ \sum_{j=1}^k \lambda_j = 1 \right\}$.

We also presume that the values of θ_j are adapted from a family (F) of multi-variate density function (approx. absolutely continuous). The Maximum Likelihood Estimation (MLE) can be used in case of missing or incomplete dataset. In the current study we use the Expectations Maximization (EM) algorithms for mixture models. The proposed method adapts SPI, SPEI and SPTI methodology for the classification of drought by using k-component mixture models.

In the current study we do not have missing data. Therefore, we can estimate the parameters of Eq. 2 by applying EM algorithm for finite mixture models for complete data. Let the associated complete data is denoted by $c = (c_1, c_2, \dots, c_n)$, having a density $h_\theta(c) = \prod_{i=1}^n h_\theta(c_i)$. The model associated with complete data corresponding to model (1.1), each of the random vector i.e., $c_i = (x_i, z_i)$, where $z_i = (z_{ij}, j = 1, 2, 3, \dots, m)$ and $z_{ij} \in \{0, 1\}$, which indicates that individual i belongs to j^{th} component, is a Bernoulli, random variable. As, each of the individual originates from precisely one component, this suggests that $\sum_{j=1}^m Z_{ij} = 1$ and,

$$P(Z_{ij} = 1) = \lambda_j, \quad (X_i | Z_{ij} = 1) : \phi_j, \quad j = 1, 2, 3, \dots, m \quad (3)$$

Therefore, the complete-density for one measurement is as follows,

$$h_\theta(c_i) = h_\theta(x_i, z_i) = \sum_{j=1}^m \mathbb{P}_{z_{ij}} \lambda_j \phi_j(x_i) \quad (4)$$

Expectation Maximization EM Algorithm

An iterative EM algorithm maximizes the given operator in Eq. 2 instead of the observed-likelihood $L_x(\theta)$,

$$Q(\theta | \theta^{(t)}) = E \left[\log h_{\theta}(C) | x, \theta^{(t)} \right] \quad (5)$$

where,

$\theta^{(t)}$ denotes the current value at iteration t, and the expectation is w.r.t the distribution $k_{\theta}(c | x)$ of c given that x , for the value of the parameter $\theta^{(t)}$. In the general setup above, iteration is defined by the following,

1. E-step: compute $Q(\theta | \theta^{(t)})$
2. M-step: set $\theta^{(t+1)} = \arg \max_{\theta \in \Phi} Q(\theta | \theta^{(t)})$

A detailed description of the E-step and M-step is available in (Young *et al.*, 2020; McLachlan and Peel, 2004).

2.4. Principal Component Analysis

In literature, there are numerous drought indices. This situation confuses the researchers, climatologist and meteorologist regarding their selection for monitoring and specifying the period of drought in a particular area. Most of the researchers have no idea that which drought index can best represent drought conditions, also using several times scales, it is difficult to interpret the result. Dogan *et al.*, (2012) declared that choosing the appropriate time scale is as much important as choosing the drought index for drought analysis. A situation where the researcher is confused about the drought indices, accurate results cannot be obtained. To overcome this deficiency, Bazrafshan *et al.*, (2014) have proposed a Multivariate Standardized Precipitation Index (MSPI). MSPI have the ability to account all the time scale defined by McKee *et al.*, (1993).

PCA is a sophisticated technique that was brought out in statistics by Hotelling, (1933). PCA is a dimensionality reduction technique applied on a quantitative data set that are inter correlated i.e. it can be utilized to a data set which have a problem of multi-collinearity. Mathematically the rationale behind the PCA is to transform a large number of correlated variable into a small number of variables. Details on PCA are available in Wilks, (2011). In PCA, first principal component PC_1 can explained maximum variation of the original variables. In our case study almost all PC_1 explained more than 80 percentage variation.

3. The Proposed Indicator: The Seasonal Mixture Standardized Drought Index (SMSDI)

The key goal of the current study is to establish a new indicator of drought by integrating the mixture distribution for SPI, SPEI and SPTI, most comprehensive knowledge at seasonal level and to solve the issue of choosing an index among several indices. To accomplish these objectives this segment is focused primarily on the step by step procedure of the proposed index i.e., SMSDI. Detailed description on SDI, K-components mixture distribution and PCA were listed in section 2, above. Prior to the implementation of our proposed technique, we identified the 3 major points which are of considerable importance for an appropriate index.

i. Choice of the stations

It is indicated to choose suitable monitoring/meteorological stations. As we are aware that long climate data plays an important role in model building and statistical inference. Therefore, it is recommended to choose those meteorological stations having a rich history of drought monitoring.

ii. Selection of SDI type indicator

SDI-based drought classification involves time series data of different variables, or a collection of variables. Moreover, other scholars have established various drought monitoring methods based

on the level of drought. Wmo and Gwp, (2016) reviewed and used the most popular drought indices as well as drought monitoring tools. Though, SDI is the most widely employed method for monitoring drought. This study includes 3 standardized drought indices including SPI, SPEI, and SPTI.

iii. The Choice of Season

Climatology between meteorological stations in certain areas of the world varied within a particular region. e.g., temporal and actual fluctuations of temperature and rainfall in different localities within a particular region is an eminent topic. From the earlier investigations, we have noticed that certain regions contain a long cold season period (Yang *et al.*, 2013). On the other hand, there are some regions in the world having hot climates throughout the whole calendar year (Uvo *et al.*, 1998). In this situation, a generalized index of seasonality is complicated to depict. In spite of that, the current study suggests each individual month as a season in order to facilitate in the quantification stage. Even though, different areas contain different levels of fluctuations during a particular month, it is the most proficient and comprehensive approach. Numerous environmental and meteorological assessments are based monthly defined seasons.

Following the identification of the three-points defined above, a step-by-step execution of our proposed paradigm comprises of 5-phases. The following subsections give a thorough overview of each phase,

Phase 1: Estimation of drought indices under K-components Gaussian distribution

As explained in the introductory part, the selection of an appropriate distribution for fitting the available data in the analysis of SPI, SPEI and SPTI is experiencing intense debate. Therefore, a mixture distribution approach has been applied (see Section 2.3) on P_i (precipitation series), D_i

(series for SPEI) and E_i (series for SPTI) for the calculation of the said indices. The chosen models for P_i , D_i and E_i are then standardized (see Appendix-B) in order to generate the series of SPI, SPEI and SPTI respectively. Figs. 2-4 clearly show that for almost all the stations data, a K-component model is a suitable model on the basis of K-modality evidence observing from the graphs. We applied the mixture model technique using R-package mixtools on the selected stations data, this package includes a set of operations for the analysis of various finite mixture models.

Phase 2: Seasonal Segregation

In this phase we will classify SPI, SPEI and SPTI in different months. For instance, combine the calculated SPI, SPEI and SPTI values of January for Badin station. Similarly combine the SPI, SPEI and SPTI values of February for Badin station. The same procedure is repeated for all the months of all the selected stations and timescales in the current study.

Let $S_1, S_2, S_3, \dots, S_{12}$ are the monthly indexed time series data, in which each month is perceived to be a season. The consequential step will be to consider each indexed time series for all the stations as an individual time series in accordance with further practices.

Phase 3: PCA on each segregated data

It is better to calculate SPI, SPEI and SPTI at several time scales using different indices and seasonal segregated data simultaneously to identify drought classes but as we mentioned above, several indices may confuse us and may create difficulty in the interpretation of the results. Different researchers showed the uses of different indices, for example SPI, SPEI and SPTI, but which index is best among these indices.

To resolve the above issue, it is better to reduce the number of SPI, SPEI and SPTI aggregation time series using a multivariate technique, PCA. A detailed description of standardization of PCs can be seen in the following section.

Phase 4: Standardized PCA1

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 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 compare among different months or place. SPI, SPEI and SPTI have zero mean and unit variance. Hence, we suggest the following equation for standardization (see Bazrafshan *et al.*, 2014).

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

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 the final SMSDI values.

Phase 5: Aggregation

Following a step by step procedure indicated in the flow chart (see Fig. 5), the last phase of our proposed index i.e. SMSDI is the aggregation of the segregated (see Phase 2) PCs. These aggregated series will be our final SMSDI values.

4. Results and Discussion

4.1. Estimation of SPI, SPEI and SPTI under mixture distribution settings

This section presents the results associated with k component mixture distribution based standardization of drought indicators. Here, we applied 12-CGMD mixture distribution for modeling the data of all indicators in all the three selected stations. Table 2 shows the BIC values of the 12 component Gaussian model in the all selected stations under study with different time-scale. For instance, -5505.72, -4329.87 and -623.88 are the values of BIC for Badin, Nawabshah and Khanpur stations respectively, highlighting time-scales-1. Figs. 2-4 provide the graphical demonstration of the application of mixture models. As we can observe clearly from the Figs. 2-4 provide evidence that in each data, the mixture distribution is 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 SPI, SPEI and SPTI time series seasonal data for PCA. This will reduce the three dimensional data into one dimension. In section 2.2, we overview SPI, SPEI and SPTI and a detailed explanation of the proposed index i.e. Seasonal Mixture Standardized Drought Index (SMSDI) is given in section 3. We calculate SPI, SPEI and SPTI 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 taking different time-scales for the chosen stations using principal component analysis technique.

Using the concept of the cross-correlation matrix, considering each set of seasonal index. By seasonal index we mean that for each season (i.e. month) calculate SPI, SPEI and SPTI. Here we consider month-wise time series data using different indices for different time-scales. For the stations under study eigen-values as well as eigen-vectors associated to each individual eigen-value were calculated. Such as, Figs. 6-7, 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. Fig. 6-7 suggests that PC1 of all the sets explain more than 85% variation of the total variation. Apart from the Scree plot, the barchart (illustrating the role of each original variable in PCs) can also be useful in evaluating the nature of the indices.

The barplot of the three PCs (PC1, PC2 and PC3) for all the months (seasons), timescales and stations under study has been manifested in Fig. 8. This figure reveals that SPI, SPEI and SPTI have a noticeable highly significant contribution to the first component (i.e., PC1) for all the seasons (months) as well as for all the stations. Fig. 8 have comparative plots, which represent the variation explained by PC1. All the study stations' months are mentioned at the x-axis where, the contribution of the PCs are represented by the color bars. All the sets contributed at least 75% in PC1. We conclude that all the plots have same behavior. However, for Khanpur station the contribution of PC1 is not that much higher compared to other stations. For instance, PC1 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.

Fig. 9 shows the counts of drought categories for SPI, SPEI, SPTI 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 3.

Results shows that the eigenvalues for the first PCs are large, and for subsequent PCs small, see Tables 4-5. 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 variance of 3 for each month-

(Jan, Feb, ..., Dec) 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 4-5.

4.3. Comparison of SMSDI with SPI, SPEI and SPTI

Seasonal Mixture Standardized Drought Index (SMSDI) was evaluated on the basis of different stations using different time-scales. The significant relationship among the indices can be seen from Figs. 10-11. Figs. 12-13 show the temporal behavior of SMSDI, SPI, SPEI and SPTI for all the months (i.e., Jan, Feb, ..., Dec) and years for timescales (3 and 12 (chosen randomly), for all the stations (i.e., Badin, Khanpur and Nawabshah). It is perceived by observing Figs. 12-13 that the behavior of the series of different indices (i.e., SPI, SPEI and SPTI) have almost the same pattern, but we can see the fluctuation in SMSDI. This fluctuation is the seasonal variation. For example, Figs. 12-13 demonstrate SMSDI along with their respective series of SPI, SPEI and SPTI for timescales 3 and 12 at the Badin, Khanpur and Nawabshah stations, respectively. 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), culminating in reduced wet and dry occurrences in comparison with SPI, SPEI and SPTI. 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.

Fig.9 shows the seven-categories of drought for all the selected stations using timescales- 1, 3, 6, 9, 12 and 24. For instance, sub-figure a (i.e., Fig. 9(a)) demonstrates the drought characterization

for Badin station under the said timescales. Normal category of drought for Badin occurred 469, 353, 469 and 458 times by using SPI, SPEI, SPTI and SMSDI respectively for timescale-1. Similar interpretations can be found for ED, SD, MD, MW, SW and EW for Badin from Fig. 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 have the ability of finding the drought even for less timescales. Similar results can be obtained for Khanpur and Nawabshah stations by analyzing Figs. (9b) and (9c) respectively.

5. Concluding Remarks

The main purpose of this research is to monitor drought in more accurate and efficient way. This article suggests a new drought index which accounts the characterization of SPI, SPEI and SPTI - the SMSDI. In SMSDI, a novel blending procedure for SDIs are presented. Here, the estimation and aggregation of SPI, SPEI and SPTI is based K component Gaussian distribution and PCA technique, respectively. In application, SMSDI is estimated for three gauge stations of Pakistan. The important features related to proposed index are summarized as; 1) as mixture distribution has been applied to evaluate SPI, SPEI and SPTI using time-scales 1-24 for different months. Consequently, we have assessed that all of the data in the selected stations contain K underlying classes, each defined by different parameters, are correctly estimated. So, the procedure of SMSDI is free from the problem of using just one probability distribution, 2) the seasonality 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.

353 Hence, to avoid the hardness of computational work, and confusion in the interpretation of SPI,
354 SPEI and SPTI, our proposal provides best solution to date.

355 **Acknowledgement**

356 The authors are very grateful to the China Huaneng Group Co., Ltd., for the financial support
357 through the Project (HNKJ17-H20)

358 **Competing Interests**

359 The authors declare no competing interests.

360 **Data Availability Statement**

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

363 **Author Contribution**

364 All author has equal contribution.

365 **References:**

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

Months	Statistics	Badin			Nawabshah			Khanpur		
		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 2. BIC Values for Mixture Models of SPI, SPEI and SPTI

Index	Scales	Badin	Nawabshah	Khanpur
SPI	1	-5505.717	-4329.869	-623.8815
	3	-3271.207	-3330.549	-3947.685
	6	-5612.633	-5355.597	-5540.463
	9	-6560.426	-5908.35	-5932.45
	12	-6685.603	-6151.637	-6129.318
	24	-6893.835	-6579.392	-6499.057
SPEI	1	-5818.033	-5873.315	-5831.028
	3	-6762.695	-6879.154	-6830.682
	6	-7135.431	-7316.96	-7226.216
	9	-7195.261	-7255.912	-7126.114
	12	-7084.73	-6868.483	-6652.287
	24	-7324.868	-7206.163	-7023.16
SPTI	1	-2957.432	-630.9313	-1405.21
	3	-1480.098	-1006.219	-1439.65
	6	-1525.452	-1302.265	-1544.351
	9	-2262.771	-1939.427	-1905.431
	12	-2595.837	-2212.023	-2098.218
	24	-2930.929	-2660.301	-2548.925

Table 3. Drought classifications

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 4: Eigen Values for Time-scales (1,3,6) and Different Components

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 5: Eigen Values for Time-scales (9,12,24) and Different Components

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 6: Drought Categories of Badin Station

Timescale	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

Fig.1. Map of the selected stations

a. SPI-6

b. SPI-12

c. SPI-24

d. SPEI-6

e. SPEI-12

f. SPEI-24

g. SPTI-6

h. SPTI-12

i. SPTI-24

Fig. 2. Mixture Distributions for Badin

a. SPI-6

b. SPI-12

c. SPI-24

d. SPEI-6

e. SPEI-12

f. SPEI-24

g. SPTI-6

h. SPTI-2

i. SPTI-24

Fig.3. Mixture Distributions for Khanpur

a. SPI-6

b. SPI-12

c. SPI-24

d. SPEI-6

e. SPEI-12

f. SPEI-24

g. SPTI-6

h. SPTI-12

i. SPTI-24

Fig. 4. Mixture Distribution for Nawabshah

Fig. 5. Flowchart of the proposed framework

a. Badin (Jan, Timescale-1)

b. Badin (June, Timescale-6)

c. Badin (Aug, Timescale-9)

d. Badin (Oct, Timescale-12)

e. Khanpur (Jan, Timescale-1)

f. Khanpur (June, Timescale-6)

Fig. 6. Scree plots (1)

a. Khanpur (Aug, Timescale-9)

b. Khanpur (Oct, Timescale-12)

c. Nawabshah (Jan, Timescale-1)

d. Nawabshah (June, Timescale-6)

e. Nawabshah (Aug, Timescale-9)

f. Nawabshah (Oct, Timescale-12)

Fig. 7. Scree plots (2)

Fig. 8. Percentage Variations of PCs for different months using different time-scales

Fig. 9. Drought Characterization using different Indices

a. Badin (Timescale-6)

b. Badin (Timescale-12)

c. Khanpur (Timescale-6)

d. Khanpur (Timescale-12)

Fig. 10. Correlations between the indices (Badin, Khanpur)

a. Nawabshah (Timescale-6)

b. Nawabshah (Timescale-12)

Fig. 11. Correlations between the indices (Nawabshah)

Fig. 12. Temporal plots of SMSDI, SPI, SPEI and SPTI (Month wise)

Fig. 13. Temporal plots of SMSDI, SPI, SPEI and SPTI (Year wise)

Figures

Figure 1

Map of the selected stations

Figure 2

Mixture Distributions for Badin

Figure 3

Mixture Distributions for Khanpur

Figure 4

Mixture Distribution for Nawabshah

Figure 5

Flowchart of the proposed framework

a. Badin (Jan, Timescale-1)

b. Badin (June, Timescale-6)

c. Badin (Aug, Timescale-9)

d. Badin (Oct, Timescale-12)

e. Khanpur (Jan, Timescale-1)

f. Khanpur (June, Timescale-6)

Figure 6

Scree plots (1)

a. Khanpur (Aug, Timescale-9)

b. Khanpur (Oct, Timescale-12)

c. Nawabshah (Jan, Timescale-1)

d. Nawabshah (June, Timescale-6)

e. Nawabshah (Aug, Timescale-9)

f. Nawabshah (Oct, Timescale-12)

Figure 7

Scree plots (2)

Figure 8

Percentage Variations of PCs for different months using different time-scales

Figure 9

Drought Characterization using different Indices

a. Badin (Timescale-6)

b. Badin (Timescale-12)

c. Khanpur (Timescale-6)

d. Khanpur (Timescale-12)

Figure 10

Correlations between the indices (Badin, Khanpur)

Figure 11

Correlations between the indices (Nawabshah)

Figure 12

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

Figure 13

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

Supplementary Files

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- [Apendix.docx](#)