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Research Article

Characterization of Meteorological Drought Using Monte Carlo Feature Selection and Steady-State Probabilities

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Drought is a creeping phenomenon that slowly holds an area over time and can be continued for many years. The impacts of drought occurrences can affect communities and environments worldwide in several ways. Thus, assessment and monitoring of drought occurrences in a region are crucial for reducing its vulnerability to the negative impacts of drought. Therefore, comprehensive drought assessment techniques and methods are required to develop adaptive strategies that a region can undertake to reduce its vulnerability to drought substantially. For this purpose, this study proposes a new method known as a regional comprehensive assessment of meteorological drought (RCAMD). The Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), and Standardized Precipitation and Temperature Index (SPTI) are jointly used for the development of the RCAMD. Further, the RCAMD employs Monte Carlo feature selection (MCFS) and steady-state probabilities (SSPs) to comprehensively collect information from various stations and drought indices. Moreover, the RCAMD is validated on the six selected stations in the northern areas of Pakistan. The outcomes associated with the RCAMD provide a comprehensive regional assessment of meteorological drought and become the initial source for bringing more considerations to drought monitoring and early warning systems.

1. Introduction

Drought is a multifaceted phenomenon triggered by a deficiency of precipitation, and its related impacts have severe effects on weather-related events, natural ecosystems, forestry, economy, agriculture, and environment [1–5]. It progressively holds an area over time, can be persisted for a long time, and distressed agricultural [6–8], environmental [9–11], and socioeconomic conditions [12–14]. Furthermore, it exhibits substantial spatial and temporal variability in various climates and regions. Several authors have proposed various procedures and frameworks to address the spatial and temporal variability of drought events [15–20]. However, it is considered a highly variable complicated phenomenon, and it is challenging to discover its onset and termination periods [21–24]. The complication in drought assessment and monitoring underpins the need for new drought assessment and monitoring methods and procedures [25–28].

Wilhite and Glantz [1] categorized the drought into several categories, i.e., "meteorological, agricultural, hydrological, and socioeconomic." Yihdego et al. [29] have defined meteorological drought as a prolonged precipitation deficit over time. The precipitation data have been used as a single input variable to mark meteorological drought occurrences and onsets [25, 26, 28, 30–33]. The continuous shortfall in precipitation interlinks the meteorological drought to the

agricultural drought. The agricultural drought manifests itself as a deficiency in precipitation, a deficit in soil moisture condition, crop failure, etc. [34, 35]. Further, the prolonged period without rainfall becomes the root of the hydrological drought [36, 37]. Hydrological drought manifests itself as decreased streamflow eviction and falling water level in lakes, groundwater, or reservoirs [38]. The hydrological drought can be damaging and cause severe societal impacts if not alleviated timely. The drought of socioeconomic concerns the supply and demands of the economic goods and is associated with the other three types of drought [39]. An extended period with a deficit in precipitation leads to crop failure issues, a shortage of water supply, and industrial and economic productivity [40]. Increasing demand for goods can lead to exploitation, resulting in vast socioeconomic influences and conflicts. In the recent past, drought has become one of the most dangerous natural hazards and disturbed economic and environmental sectors worldwide [41–44].

Distinctively, drought has been assessed under meteorological, agricultural, hydrological, and socioeconomic aspects by developing various indices that have been discussed and employed in various publications [45–58]. The indices are essential components for assessing and monitoring drought since they simply quantify the complicated interrelationships between varying climate and climate-related parameters [59–63]. Wilhite et al. (2000) have defined that indices are developed to communicate information related to climate anomalies to diverse users and allow researchers to evaluate climate anomalies quantitatively in terms of spatial extent. Several drought indices are established and employed to quantitatively assess the impacts of several kinds of droughts to provide helpful information for planning, organizing, and various management applications of water resources associated with several users and the environment [45–51, 64–67].

Along with the numerous indices proposed for assessing the meteorological drought, some specific indices are extensively used. In particular, Palmer's Drought Severity Index (PDSI) was presented and used [68, 69]. The index was created to " measure the cumulative departure of moisture supply." The PDSI is commonly used by the United States (USA). Further, instead of precipitation variability, the PSDI expands its assurance of drought on water supply and demand. The PDSI comprises important determinants, including data on soil temperature and precipitation. By incorporating these determinants as inputs, the PDSI analyzes four terms in the water balance equation ("evapotranspiration, moisture, soil recharge, and runoff"). Another extensively used index for the characterization of the meteorological drought is the Standardized Precipitation Index (SPI) [46, 70–73]. The SPI comprises only a single determinant, which is precipitation, and thus, SPI uses precipitation as an input to describe the water deficit. SPI is a renowned index, extensively used to assess and monitor meteorological drought. The SPI is less complicated than the PDSI. Therefore, it can be applied in any place by transforming the precipitation data from a skewed distribution to a normal distribution. Moreover, SPI with longer time scales can indicate the agricultural and hydrological drought [71, 74, 75]. For instance, the SPI for a nine-month time scale with a value less than −1.5 is an alert for the agricultural drought [59]. The streamflow, reservoir level, etc., can be reflected by positioning SPI at a twelve-month time scale. Therefore, SPI is famous and operational in numerous papers and publications [51, 76]. Further, the Standardized Precipitation Evapotranspiration Index (SPEI) is also a well-known index proposed by [50] that triggers the effect of temperature variability on drought estimation. Numerous analyses have employed SPEI for the drought evaluation [77–83], and Standardized Precipitation and Temperature Index (SPTI) by [84] is also considered in multiple studies for the assessment of meteorological drought [76, 84–86].

Considerable research has been done to quantify and understand the complex and meteoric nature of the drought [77, 78, 80, 81, 83, 87–90]. However, the manifestation of the drought nature is very complex [91]. The complexity of determining its pattern reinforces the development of new techniques and methods [92, 93]. The appropriate methods and procedures can help to minimize its meteoric influence in various parts of the world [87] [94] [90, 95]. However, the applications of the new methods may be better described by investigating drought at the regional level. Recently, numerous studies have been done to timely examine the drought occurrences in various regions. Therefore, the study of the particular region has significant importance; thus, current research is applied to the specific region. The selected region has a homogeneous pattern of drought occurrences concerning specific drought indices and a time scale (one-month time scale) [76, 96–99]. Ali et al. [96] examined meteorological drought based on three indices (SPI, SPEI, and SPTI). The study found that the three indices provide similar information about the selected region for the particular time scale. Hence, investigating meteorological drought from the selected homogeneous locations using several meteorological indices (SPI, SPEI, and SPTI) becomes counterproductive. This issue underpins the use of some new drought assessment methods that provide comprehensive information based on these indices. Therefore, this study proposes a new method, known as regional comprehensive assessment for meteorological drought (RCAMD). The RCAMD comprehensively collects information from several stations and drought indices using Monte Carlo feature selection (MCFS) and steady-state probabilities (SSPs). Further, the RCAMD mainly helps to overcome two issues. For instance, the first phase of the RCAMD chooses important stations more comprehensively for three indices from six homogeneous stations. In the presence of influential climatic factors in estimating the drought indices, the second phase of RCAMD characterizes several drought classes more comprehensively and accurately among the three indices (SPI, SPEI, and SPTI). Moreover, the six stations in the northern areas of Pakistan are selected to validate RCAMD. The findings associated with the RCAMD propose a comprehensive regional assessment of meteorological drought and create the initial basis for taking more considerations for assessing and monitoring drought at the regional level.

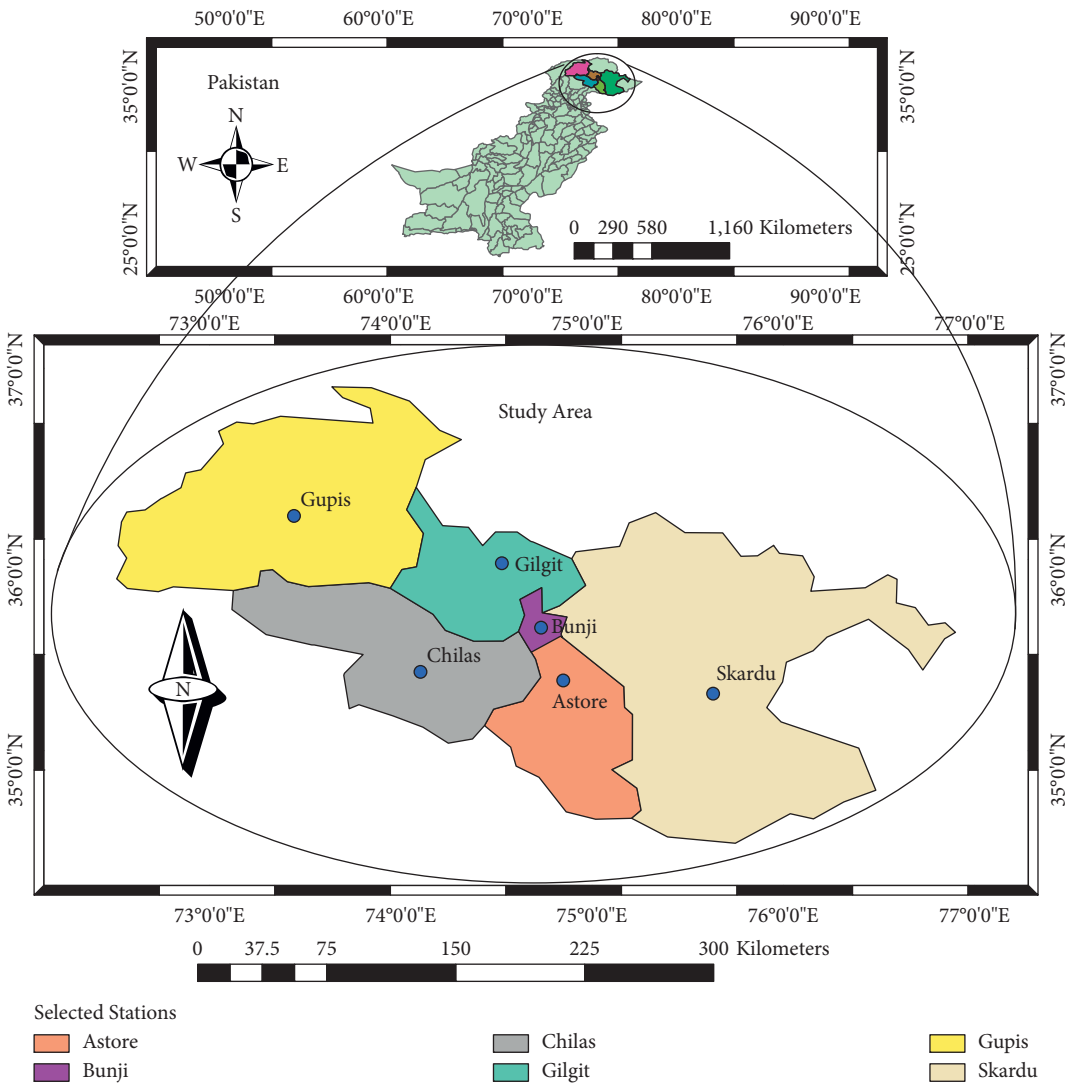

Figure 1: Geographical locations of the six selected stations in northern areas of Pakistan. The selected stations are important for the reservoir systems of the country. Most of the agricultural lands of the country depend on the reservoir systems that are linked to the selected stations. Several publications related to drought analysis [86, 97–99] have been based on these stations. Based on these publications and importance of the stations for the reservoir systems, therefore, these stations are selected for the current analysis.

2. Material and Methods

2.1. Description of the Study Area. The substantial climate changes have increasingly become a primary global task that endangers ecological, human, and natural systems [100–102]. Pakistan is extremely in danger of the undesirable influences of climate change, specifically extreme hydrometeorological activities [103–108]. The selected region is located in the northeastern part of Pakistan, spread over 72,971 square km, almost half of which covers peaks of mountains, glaciers, highlands, and lakes. The selected region has structural significance for other parts of the country. It has a key role in the agricultural sectors and the reservoir system of the country [109, 110]. However, it is highly at risk of climate change due to its geological composition, fragile mountain, topography, ecosystem, geographic locations, socioeconomic conditions, and scattered population [111]. Thus, the selected region requires more consideration for assessing the drought manifestations by developing comprehensive and proficient methods and procedures. Hence, the RCAMD method is designed for the selected region, enhancing the ability to assess drought events and facilitating drought monitoring and water resource management in the selected area (Figure 1).

2.2. Data and Methods. The data ranging from January 1971 to December 2017 are processed in the current analysis. The six stations in the northern areas are selected to calculate the indices (SPI, SPEI, and SPTI). These indices use information from the indicators (precipitation and temperature) to classify drought classes in the selected stations. The data of these indicators have been used in several publications [86, 97, 98, 112–114]. The various drought classes of the selected stations and indices are used to propose RCAMD. The new proposed RCAMD uses MCFS and SSP to assess the information more intensively for the drought classes from

the selected stations and indices. Moreover, the outcomes associated with RCAMD comprehensively assess drought classes for the homogeneous region. The RCAMD develops a new way of taking more consideration for evaluating and monitoring drought at the regional level.

2.2.1. Monte Carlo Feature Selection (MCFS). Niaz et al. [85] used MCFS for selecting informative stations for their analysis. They applied MCFS in the Punjab region of Pakistan and selected important stations based on SPTI. However, in this study, MCFS uses three drought indices (SPI, SPEI, and SPTI) to select important stations. Thus, the MCFS selects an important meteorological station for each drought index. For example, for SPI the MCFS selects Astore as an important station; for SPEI, the MCFS selects Gilgit as an important station. Further, for SPTI, the MCFS selects Astore as an important station for the preliminary analysis. The MCFS input enables the RCAMD to collect information from various stations comprehensively. The suitable stations are chosen based on relative importance (RI) values. The mathematical detail about the RI is given in [85]. For the current analysis, the Astore Station with RI value of 0.1385 is higher than other selected stations for SPI. For SPTI and SPEI, the Astore and Gilgit are selected, respectively. In Astore, the RI value for SPTI is 0.1920, while SPEI for Gilgit has RI value of 0.7617.

2.2.2. Steady-State Probabilities (SSPs). A Markov process can be expressed as the probabilities come up to the SSP when certain periods have been passed. The comprehensive mathematical details associated with the SSP of the Markov chain were described in Stewart (2009). The application of SSP is provided in several publications [76, 97]. Niaz et al. [85] used SSP as a weighting scheme from the long-run time-series data for different drought classes in the northern region of Pakistan. The proposed weighting scheme was used to accumulate information from the selected homogeneous stations. Further, Niaz et al. [97] used SSP to substantiate the prevalence of drought intensities in the northern region of Pakistan. Moreover, Niaz et al. [98] proposed a new technique based on SSP to accumulate information from various indices. Recently, Niaz et al. [99] incorporated SSP in their study to assess the probability of drought severity in the selected region. The SSP is used broadly in several publications to develop new methods and procedures [97–99, 113]. Therefore, in RCAMD, SSP is used to propagate weights for various drought categories over several stations and indices to achieve a particular aspect. In the current analysis, SSP mainly helps to characterize the new vector of drought classes. The inclusion of MCFS and SSP in RCAMD makes the study innovative. This innovation provides a comprehensive procedure to collect information from several stations and indices.

2.2.3. Regional Comprehensive Assessment of Meteorological Drought (RCAMD). The RCAMD employs MCFS and SSP to mainly determine drought events that are likely to occur in the region from numerous stations and drought indices. The MCFS technique is used to accumulate comprehensive information on several time-series data of meteorological stations. The mathematical detail of MCFS is given in Niaz et al. [85]. In the first phase of the RCAMD, the MCFS allows the selection of more important stations based on several selected indices. Three drought indices (SPI, SPEI, and SPTI) are used in RCAMD to determine important stations. Hence, the MCFS selects an important meteorological station for each drought index separately. The criteria for selecting an important station are based on relative importance (RI). The higher values corresponding to any stations show that the stations are important for the preliminary investigation. For example, based on the higher value of RI using SPEI, the MCFS chooses Gilgit as an important station, and for SPI, the MCFS takes Astore as an important station. Moreover, for SPTI the MCFS picks Astore as an important station for the computation of RCAMD. In the second phase of the RCAMD, the SSP is applied to characterize several drought classes among the three indices (SPI, SPEI, and SPI). The complete mathematical detail related to the SSP of the Markov chain is given in Stewart (2009). The SSP is used in several publications to develop new procedures and methodologies [76, 97]. The SSP characterizes various drought categories among selected stations and indices in this study. The SSP for each drought category (k) ((“Extremely Dry (ED),” Extremely Wet (EW),” “Severely Dry (SD),” “Severely Wet (SW),” Median Dry (MD),” “Median Wet (MW),” and “Normal Dry (ND)”) for each index (l) (SPI, SPEI, and SPTI) in the particular station (m) can be expressed in a vector as $(\mathrm{SSP})_{\mathrm{klm}}$. The obtained SSP for the varying drought categories can be described as the visit of the drought category in the long run. These long-run SSP of several drought categories is counted as weights. These weights are further utilized for the computation of RCAMD. The calculation of RCAMD is based on the vector of the stationary drought categories propagating on different drought indices, which can be identified as follows:

$$\begin{aligned}
\prod_i (\mathrm{SPI}) &= \left[\prod_1 (\mathrm{ED}_{\mathrm{SPI}}) \prod_2 (\mathrm{EW}_{\mathrm{SPI}}) \prod_3 (\mathrm{SD}_{\mathrm{SPI}}) \prod_4 (\mathrm{SW}_{\mathrm{SPI}}) \prod_5 (\mathrm{MD}_{\mathrm{SPI}}) \prod_6 (\mathrm{MW}_{\mathrm{SPI}}) \prod_7 (\mathrm{ND}_{\mathrm{SPI}})\right], \\
\prod_i (\mathrm{SPTI}) &= \left[\prod_1 (\mathrm{ED}_{\mathrm{SPTI}}) \prod_2 (\mathrm{EW}_{\mathrm{SPTI}}) \prod_3 (\mathrm{SD}_{\mathrm{SPTI}}) \prod_4 (\mathrm{SW}_{\mathrm{SPTI}}) \prod_5 (\mathrm{MD}_{\mathrm{SPTI}}) \prod_6 (\mathrm{MW}_{\mathrm{SPTI}}) \prod_7 (\mathrm{ND}_{\mathrm{SPTI}})\right], \\
\prod_i (\mathrm{SPEI}) &= \left[\prod_1 (\mathrm{ED}_{\mathrm{SPEI}}) \prod_2 (\mathrm{EW}_{\mathrm{SPEI}}) \prod_3 (\mathrm{SD}_{\mathrm{SPEI}}) \prod_4 (\mathrm{SW}_{\mathrm{SPEI}}) \prod_5 (\mathrm{MD}_{\mathrm{SPEI}}) \prod_6 (\mathrm{MW}_{\mathrm{SPEI}}) \prod_7 (\mathrm{ND}_{\mathrm{SPEI}})\right].
\end{aligned} \tag{1}$$

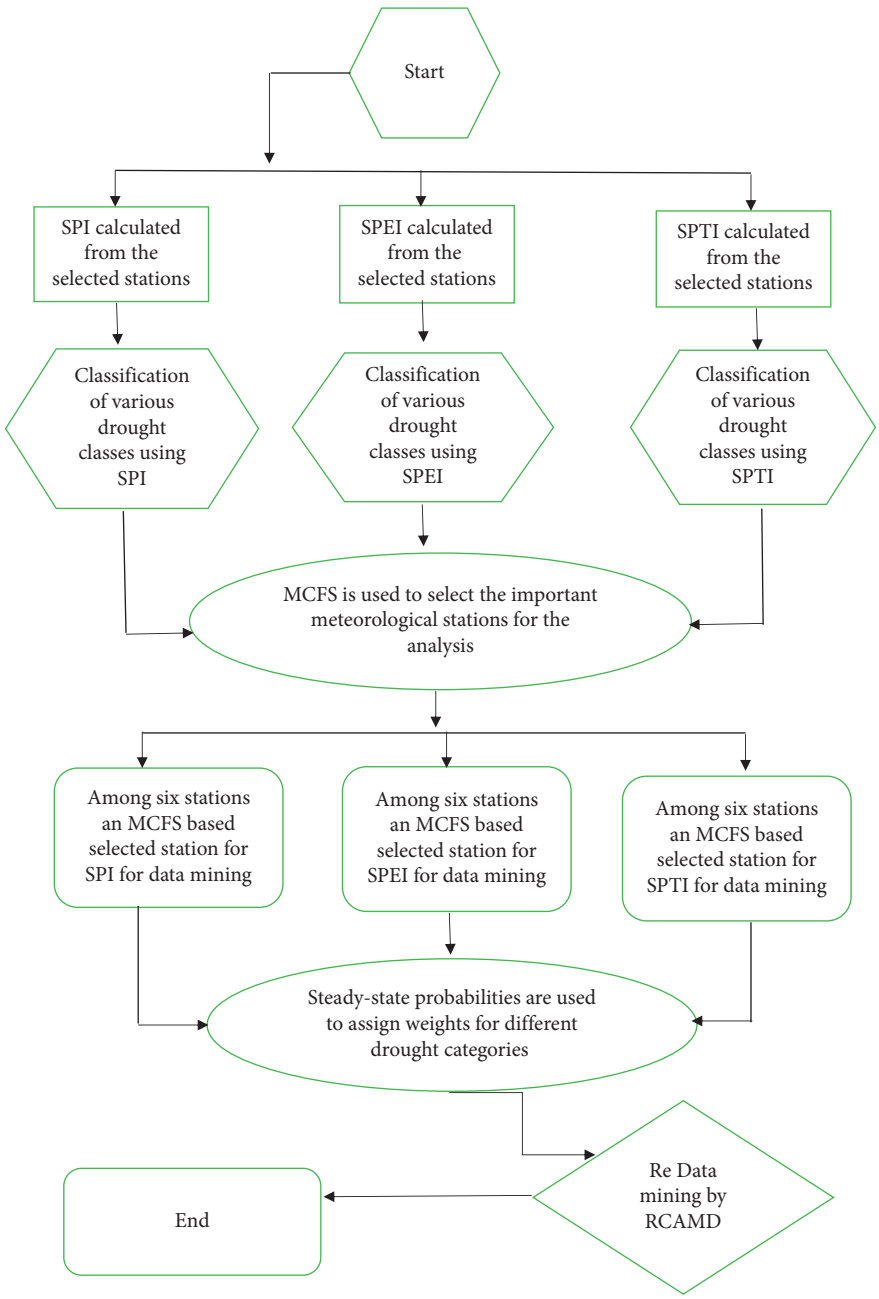

Figure 2: Flowchart of the RCAMD. In starting the RCAMD, three varying indices are calculated for the drought analysis. These calculated indices are further used for the drought classification. The drought classification criteria implemented in several publications [115] and Niaz et al. [76, 96, 97, 99] are used in the current research. In the next step, the MCFS is applied using three drought indices (SPI, SPEI, and SPTI) for selecting important stations. Consequently, the MCFS chooses an important meteorological station for each drought index. The use of MCFS input enables the RCAMD to accumulate information from various stations comprehensively. Moreover, in RCAMD, SSP is employed to disseminate weights for numerous drought categories over various stations and indices. The SSP mainly employs to characterize the new vector of drought categories. Conclusively, the resultant data mining vector based on MCFS and SSP in RCAMD provides a comprehensive information from several stations and indices.

The obtained limiting probabilities ($\prod_i$(SPI), , $\prod_i$(SPTI), $\prod_i$(SPEI)) can be referred to as the proportion or average of long-run probabilities of the drought states or categories for the varying indices (SPI, SPTI, and SPEI) on selected stations. These probabilities are used as weights for the computation of the RCAMD, which assigns the comprehensive weights to the varying drought categories from the selected stations. The flowchart of the RCAMD is given in Figure 2. Moreover, the drought states among selected drought indices (SPI, SPTI, and SPEI) that take maximum weights are chosen for the RCAMD. Hence, in the current research, the RCAMD selects the appropriate vector of drought classes from the time-series dataset for January 1971 to December 2017. The RCAMD enables a clearer, though

Table 1: Climatological features of the monthly precipitation data observed in numerous locations (stations) in the northern areas. The mean (40.91) of precipitation in Astore is observed higher among other stations. The standard deviation (St.Dev) of the Astore is also larger than any other selected stations. Moreover, other characteristics of the Astore and other stations can be followed accordingly.

Variable		Astore	Bunji	Gupis	Chilas	Gilgit	Skardu
Precipitation	Mean	40.91	14.34	16.86	16.76	12.42	20.63
	1st quartile	10.80	1.30	0.00	0.95	1.10	2.30
	Median	25.70	7.10	5.70	7.00	6.05	9.10
	3rd quartile	52.63	17.10	19.38	19.33	14.73	26.75
	Kurtosis	3.01	7.67	14.05	9.02	10.08	5.70
	St.Dev	41.93	18.90	30.21	23.53	16.57	25.90

Table 2: Climatological features of the monthly minimum temperature (MinT) data are given. The minimum temperature was observed in several stations. The mean MinT in Chilas is 15.14, which is higher than other selected stations. The minimum mean of the MinT is observed in Astore. The mean value of MinT in Astore is 4.34. The St.Dev in Chilas is 9.08, and in Astore, the St.Dev is 7.48. The larger St.Dev is observed in Chilas Station. Moreover, other climatological features of the selected stations can be observed accordingly.

Variable		Astore	Bunji	Gupis	Chilas	Gilgit	Skardu
Minimum temperature	Mean	4.34	11.86	6.74	15.14	8.07	5.06
	1st quartile	−2.43	3.78	−1.10	5.68	0.60	−2.73
	Median	4.30	11.50	6.90	14.30	7.75	5.55
	3rd quartile	10.70	17.70	13.33	23.20	13.53	11.80
	Kurtosis	−1.22	−1.24	−1.26	−1.41	−1.24	−1.17
	St.Dev	7.48	7.80	8.06	9.08	7.30	8.36

Table 3: Climatological features of the monthly maximum temperature (MaxT) are given. The MaxT was observed in varying stations for the selected time period. The mean of MaxT in Gilgit is observed high. The mean value of the MaxT in Gilgit is 25.46. In Skardu, the mean of the MaxT is 19.92. In Skardu, the St.Dev of the MaxT is 9.82. The highest St.Dev is observed in Chilas Station, which is 9.66. The smallest St.Dev of the MaxT was observed in Bunji Station. Further, other features of the MaxT can be found accordingly.

Variable		Astore	Bunji	Gupis	Chilas	Gilgit	Skardu
Maximum temperature	Mean	16.66	25.19	19.95	27.92	25.46	19.92
	1st quartile	7.38	15.78	10.33	17.68	15.60	9.95
	Median	16.70	24.95	19.70	27.35	25.15	20.05
	3rd quartile	23.86	32.02	27.40	35.63	32.80	27.90
	Kurtosis	−1.36	−1.32	−1.30	−1.38	−1.33	−1.24
	St.Dev	8.65	8.98	9.46	9.66	9.21	9.82

complicated, representation of how interconnected indices are further associated and linkable to a distinctive set of comprehensive outcomes. Further, RCAMD can be utilized to locate the proper vector of drought classes for any long time-series data in a homogeneous environment. The outcomes associated with the RCAMD provide a comprehensive regional assessment of meteorological drought and become the initial source for bringing more considerations to drought monitoring and early warning systems.

3. Results

The time-series data are collected for six meteorological stations from the northern areas of Pakistan. The varying features, including mean, 1st quartile, median, 3rd quartile, kurtosis, and standard deviation (St.Dev) of the precipitation, are given in Table 1. Table 2 contains the varying characteristics of the minimum temperature. The various features of the maximum temperature are given in Table 3. Further, these climatological features are presented in various figures. For example, the climatological features of the monthly precipitation observed in varying stations are presented on various maps in Figure 3. The climatological characteristics of the observed minimum temperature in various stations are presented in Figure 4. The climatological features of the observed maximum temperature in various stations are presented in Figure 5. Further, the drought categories are classified according to Li et al. [115]. The varying behavior of the classes can be observed in the selected time-series data. However, for simplicity, the results for the specific year (2017) based on SPI, SPEI, and SPTI are provided. In Table 4, the results for the year 2017 based on SPI are given. The varying drought classes can be observed in varying months of the selected year. Further, the index values corresponding to each drought category are provided. Table 5 contains the classified values based on SPEI, and the classified values observed in varying months and their corresponding index values based on SPTI are given in Table 6. The temporal behavior in the selected period, January 1971 to December 2017, in varying stations for the

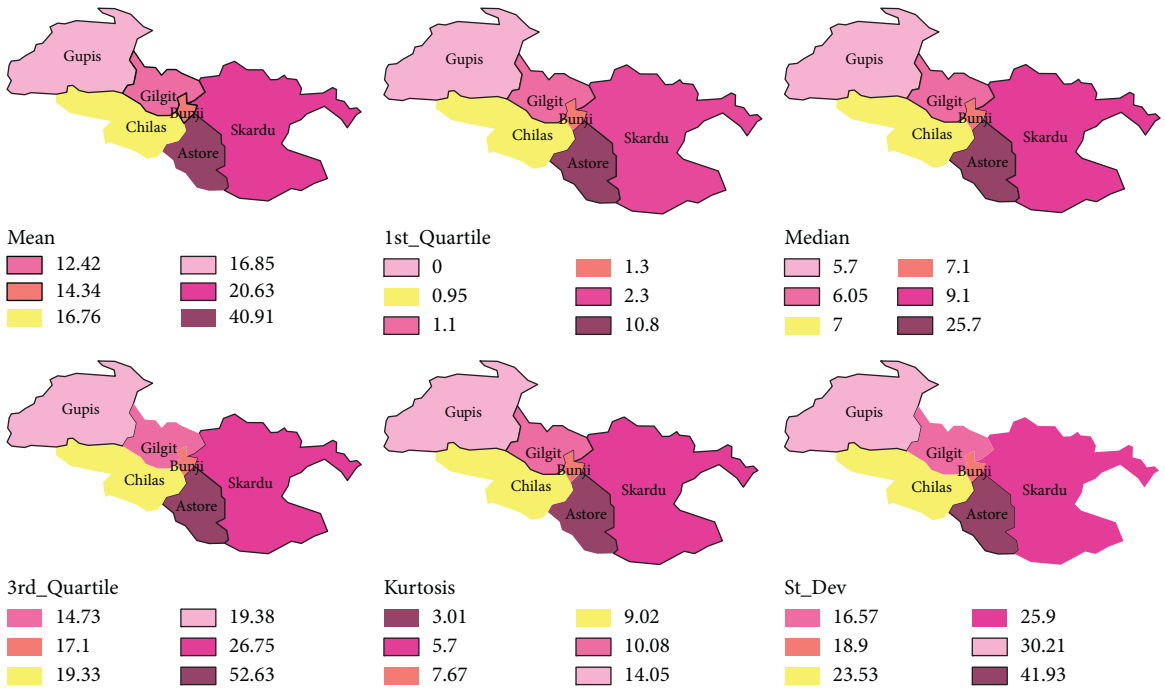

Figure 3: Climatological characteristics of the observed precipitation in various stations.

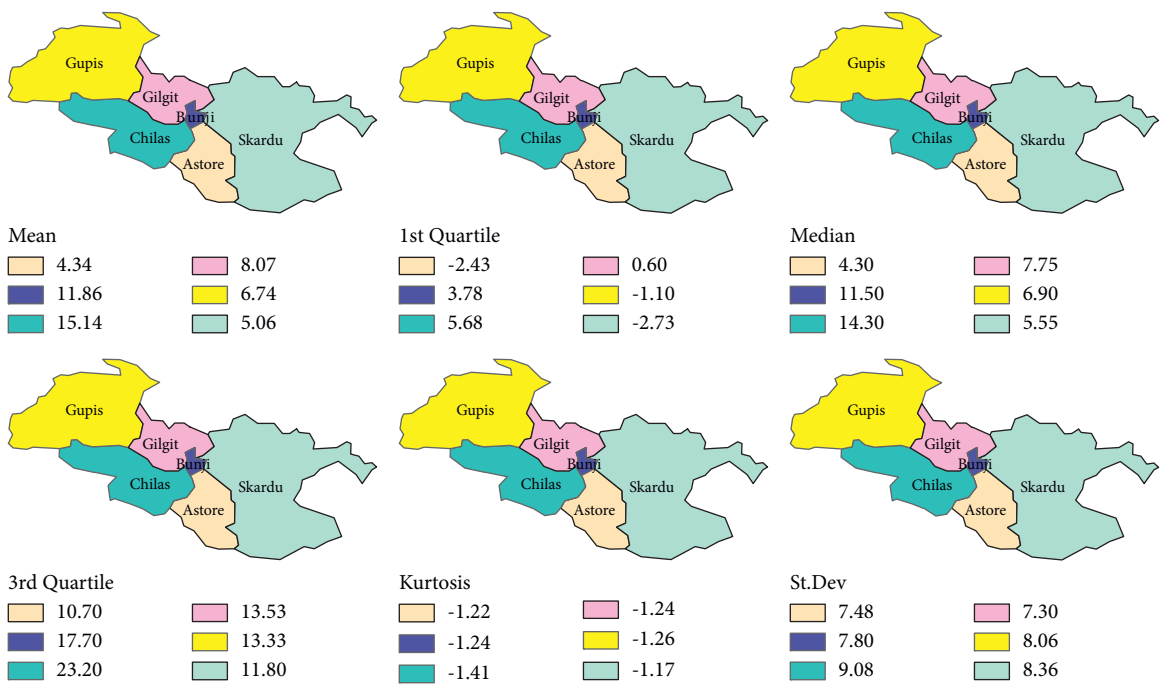

Figure 4: Climatological characteristics of the observed minimum temperature in various stations.

SPI at a one-month time scale (SPI-1) is presented in Figure 6. Figure 7 presents the temporal behavior of the SPEI on a one-month time scale (SPEI-1) at selected stations. Figure 8 shows the temporal behavior of the SPTI at a one-month time scale (SPTI-1) at various stations. Moreover, the varying drought categories observed in various stations for SPI at a one-month time scale are presented in Figure 9. Figure 10 contains various maps for the varying drought categories observed in various stations for SPEI at a one-month time scale. The drought categories classified based on SPTI at a one-month time scale and observed in varying stations are presented in Figure 11. The northern zones of Pakistan (i.e., Astore, Bunji, Chilas, Gupis, Skardu, and Gilgit) have a homogeneous pattern of the drought classes for the specific drought indices and time scale [76, 96, 97, 99] and therefore selected for the current analysis. Three indices,

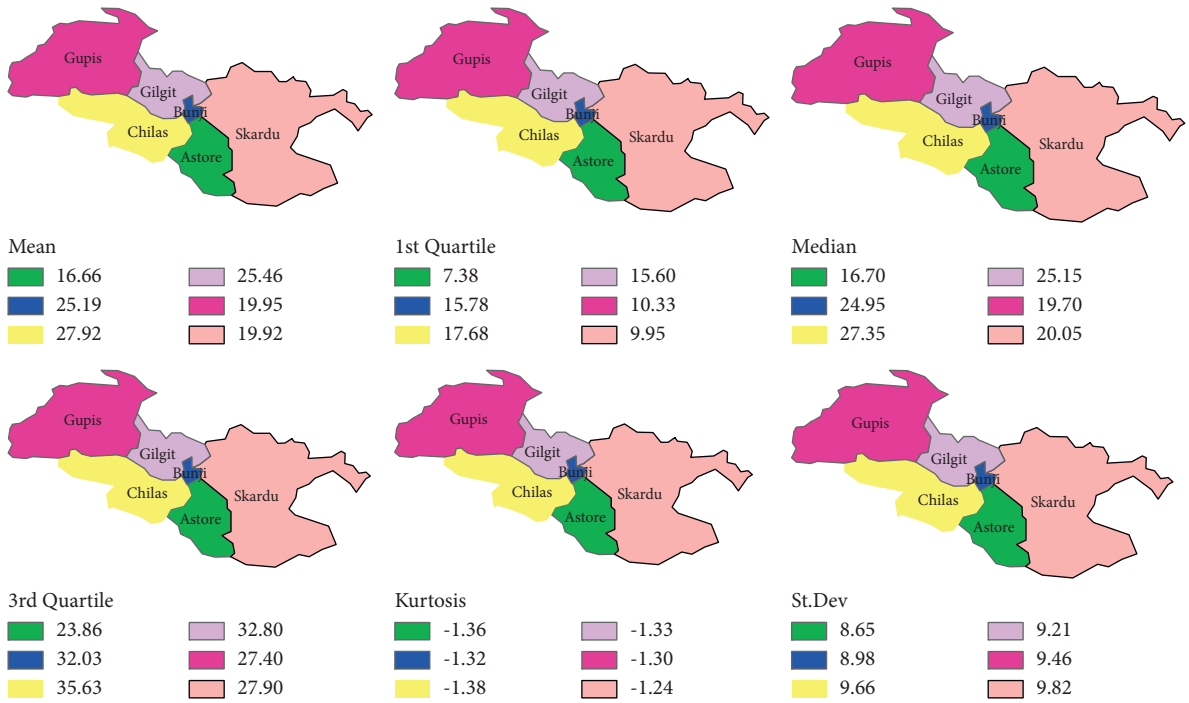

Figure 5: Climatological characteristics of the observed maximum temperature in various stations.

Table 4: Classified (Classif.) drought categories in varying stations based on SPI-1 for the year 2017 are given. The various months of 2017 are categorized by numerical numbers. For example, January is denoted by 1, 2 for February, and 3 for March. April, May, June, July, August, September, October, November, and December are presented by 4, 5, 6, 7, 8, 9, 10, 11, and 12, respectively. The classification criterion used by Li et al. (2015) is adopted for the current analysis. In January in Astore Station, the index value is -1.8044, and according to the classification criteria, the SD category of the drought occurred. Similarly, based on the classification criteria the drought classes are classified in varying months and stations for a specific year.

Month	Astore		Bunji		Gupis		Chilas		Gilgit		Skardu	
	Index	Classif.	Index	Classif.	Index	Classif.	Index	Classif.	Index	Classif.	Index	Classif.
1	−1.8044	SD	−1.2152	MD	−1.0805	MD	−0.3254	ND	−0.2296	ND	−0.4827	ND
2	−1.8044	SD	0.2629	ND	−1.0805	MD	0.8075	ND	0.2014	ND	−1.2581	ND
3	−0.4745	ND	−1.1059	MD	−0.6655	ND	−0.1535	ND	−1.0523	MD	−0.3096	ND
4	1.8879	SW	0.9377	ND	1.2811	MW	2.2094	EW	1.8283	SW	1.0615	EW
5	0.3314	ND	0.6975	ND	0.9813	ND	0.8297	ND	0.9724	ND	0.0796	ND
6	−0.3302	ND	−0.6380	ND	−0.2883	ND	−0.0637	ND	0.9309	ND	−0.8574	ND
7	−0.1857	ND	0.8192	ND	0.7872	ND	0.1366	ND	1.0574	MW	−0.2401	ND
8	−0.1967	ND	0.7181	ND	1.1317	MW	0.2058	ND	0.3864	ND	0.0086	ND
9	−0.5938	ND	0.2824	ND	0.4029	ND	0.1937	ND	0.4759	ND	0.0739	ND
10	−1.7685	SD	−1.1576	MD	−0.2883	ND	−1.0539	MD	−0.9569	ND	−1.2581	MD
11	−1.8044	SD	−1.2806	MD	−1.0805	MD	−1.0995	MD	−1.3227	MD	−1.2581	MD
12	−1.2499	MD	−1.2806	MD	−0.0621	ND	−1.0539	MD	−1.2398	MD	−1.2168	MD

SPI, SPEI, and SPTI, have shown a significant correlation and provided similar information in varying stations at a one-month time scale [76, 96, 116]. However, this study found a gap in the above research and proposed a new method that provides more comprehensive results. The mentioned research considered all stations for their analysis. Thus, considering all stations for drought analysis in a region with a similar pattern of drought occurrences seems counterproductive. It underpins a new gap that should be tackled by comprehensively accumulating information. Based on this gap, this study proposed to provide a more comprehensive drought assessment procedure for the region. For this purpose, the current research comprehensively offers an RCAMD method to accumulate information from numerous stations and drought indices. The RCAMD is based on two phases. In the first phase of the RCAMD, the MCFS technique is applied. The MCFS was utilized by Niaz et al. [85] for selecting more illustrative stations in the region of Punjab in Pakistan. The mathematical detail of the MCFS is available in [85].

Further, the selected stations for the current analysis have shown a similar pattern for all stations. Therefore, it underpins a rationale to apply MCFS for selecting only important stations for the analysis. Thus, the MCFS is

Table 5: Classif. drought categories in varying stations based on SPEI-1 are provided for the year 2017. In January in Bunji Station, ND occurred with a 0.9796 is the quantitative value of the index. The index value of 1.0670 is computed in Gilgit, which is classified as MW. Further, it can be observed that in most of the months of 2017 the ND appears based on SPEI. In Skardu, none of the other classified drought categories appear except ND for a whole year. In Skardu, the ND is a prevalent drought category.

Month	Astore		Bunji		Gupis		Chilas		Gilgit		Skardu	
	Index	Classif.	Index	Classif.	Index	Classif.	Index	Classif.	Index	Classif.	Index	Classif.
1	0.2741	ND	0.9796	ND	0.7679	ND	0.9039	ND	1.0670	MW	0.8220	ND
2	0.0829	ND	0.8384	ND	0.4871	ND	0.9296	ND	0.7976	ND	0.4919	ND
3	−0.1682	ND	0.1045	ND	0.0219	ND	0.1193	ND	0.1447	ND	0.1232	ND
4	1.4903	MW	0.0887	ND	0.3163	ND	1.3240	MW	0.6436	ND	0.1957	ND
5	−0.8214	ND	−1.0027	MD	−0.7708	ND	−0.8617	ND	−0.7646	ND	−0.9650	ND
6	−1.3547	MD	−1.3982	MD	−1.4032	MD	−1.3619	MD	−1.0659	MD	−1.4873	MD
7	−1.2755	MD	−1.0733	MD	−1.2931	MD	−1.3665	MD	−1.0312	MD	−1.3089	MD
8	−0.9560	ND	−0.7027	ND	−0.4335	ND	−0.8499	ND	−0.6704	ND	−0.8895	ND
9	−0.7888	ND	−0.4535	ND	−0.5996	ND	−0.4873	ND	−0.3957	ND	−0.4748	ND
10	−0.4409	ND	0.0387	ND	−0.0183	ND	0.0061	ND	0.0157	ND	−0.0880	ND
11	0.0596	ND	0.7154	ND	0.5016	ND	0.6265	ND	0.6878	ND	0.4532	ND
12	0.2411	ND	0.9475	ND	0.8261	ND	0.8367	ND	0.9538	ND	0.6461	ND

Table 6: Classif. drought categories in selected stations based on SPTI-1 are presented for the year 2017. The index value of -1.5398 is given in January, which indicates that the SD occurred in the Astore Station. Further, in January the MD occurred in Bunji and Gupis with index values of -1.2001 and -1.1305, respectively. The varying drought categories can be seen in various months accordingly.

Month	Astore		Bunji		Gupis		Chilas		Gilgit		Skardu	
	Index	Classif.	Index	Classif.	Index	Classif.	Index	Classif.	Index	Classif.	Index	Classif.
1	−1.5398	SD	−1.2001	MD	−1.1305	MD	−0.0928	ND	0.1063	ND	−0.0381	ND
2	−1.5398	SD	0.4943	ND	−1.1305	MD	0.9832	ND	0.4553	ND	−0.5366	ND
3	−0.3434	ND	−1.1119	MD	−0.6169	ND	−0.0695	ND	−1.0747	MD	−0.2155	ND
4	1.4038	MW	0.9448	ND	1.2422	MW	2.0709	EW	1.8490	SW	0.7164	ND
5	0.0369	ND	0.5504	ND	0.7799	ND	0.6277	ND	0.8382	ND	−0.1299	ND
6	−0.5360	ND	−0.7646	ND	−0.4345	ND	−0.2150	ND	0.6983	ND	−0.4870	ND
7	−0.4439	ND	0.5654	ND	0.5086	ND	−0.0537	ND	0.7859	ND	−0.3234	ND
8	−0.4273	ND	0.5021	ND	0.8873	ND	0.0310	ND	0.2006	ND	−0.2084	ND
9	−0.6874	ND	0.1387	ND	0.2467	ND	0.0446	ND	0.3438	ND	−0.1356	ND
10	−1.5153	SD	−1.1878	MD	−0.3152	ND	−0.9993	ND	−1.0048	MD	−0.5366	ND
11	−1.5398	SD	−1.3078	MD	−1.1305	MD	−1.0394	MD	−1.4267	MD	−0.5366	ND
12	−0.9624	ND	−1.3078	MD	0.2099	ND	−0.9757	ND	−1.2671	MD	−0.5264	ND

applied in the current analysis to select more important stations among the selected stations for various drought indices. This selection of the important stations is based on the relative importance (RI) values (Figure 12). The corresponding higher values of RIs in any station show that the station is to consider for the drought assessment. For example, the Astore Station with RI value of 0.1385 for SPI is higher than other selected stations. For SPTI and SPEI, the Astore and Gilgit are selected, respectively. In Astore, the RI value for SPTI is 0.1920, while SPEI for Bunji has RI value of 0.7617 (Table 7).

Moreover, in the presence of influential climatic factors in estimating the drought indices, the second phase of RCAMD comprehensively characterizes numerous drought categories among the selected indices (SPI, SPEI, and SPI) (Figure 13). Niaz et al. [76] proposed a method based on a steady-state weighting scheme. They selected the classes from various stations based on the maximum weights; hence, the classes that received maximum weights among different stations were selected for the analysis. The weights from three indices (SPI, SPEI, and SPTI) for the varying drought categories for a specific year, 2017, are provided in Tables 8–10, respectively. Recently, Niaz et al. [97] proposed a weighting scheme based on steady-state probabilities for selecting classes among the three indices (SPI, SPEI, and SPI). These indices are correlated for a one-month time scale and present similar information for the six stations in the northern areas [85, 96, 117]. The mathematical detail of the weighting scheme is available in [76].

Similarly, based on the mentioned studies, this study uses the SSP as a weighting scheme in the second phase of the RCAMD for selecting varying drought classes. Conclusively, to accomplish a specific task (i.e., characterize drought classes more comprehensively), therefore, in RCAMD, SSP is utilized to disseminate weights for several drought categories over various stations and indices. The use of SSP mainly characterizes the new vector of drought classes. The RCAMD suggests a comprehensive regional method for assessing meteorological drought and developing the base for taking more considerations for evaluating and monitoring drought at the regional level.

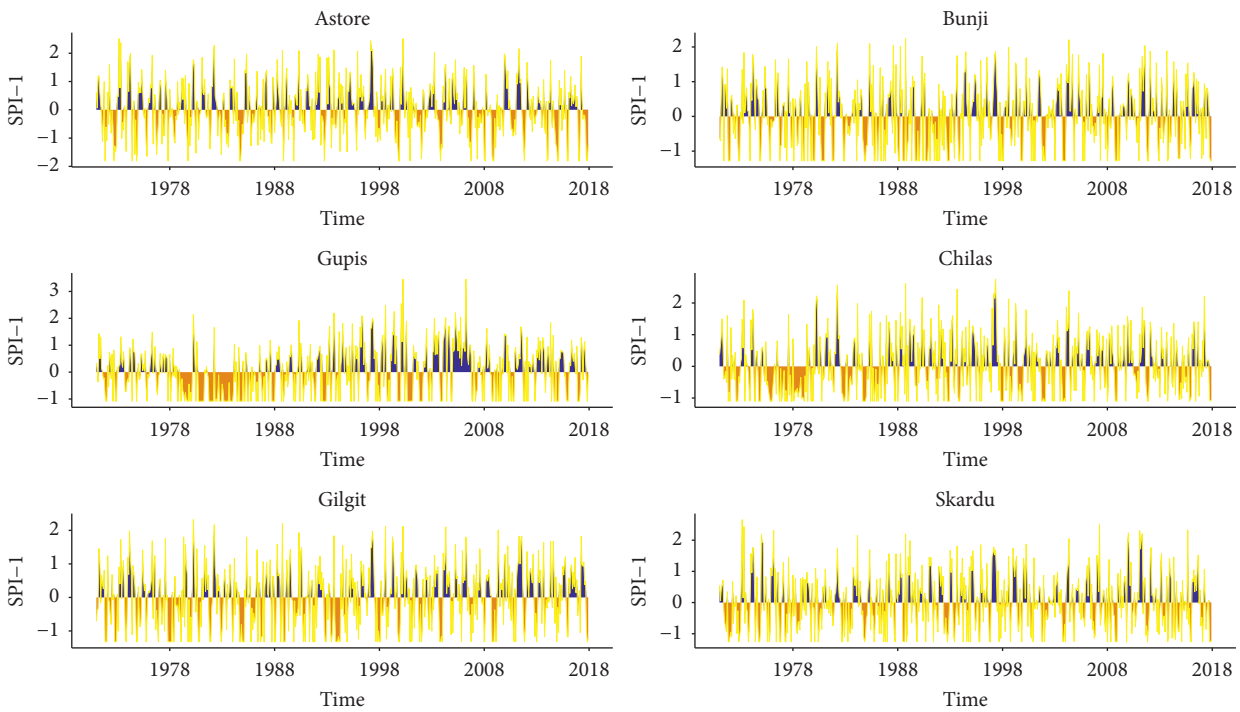

Figure 6: Temporal plots for selected stations based on SPI-1.

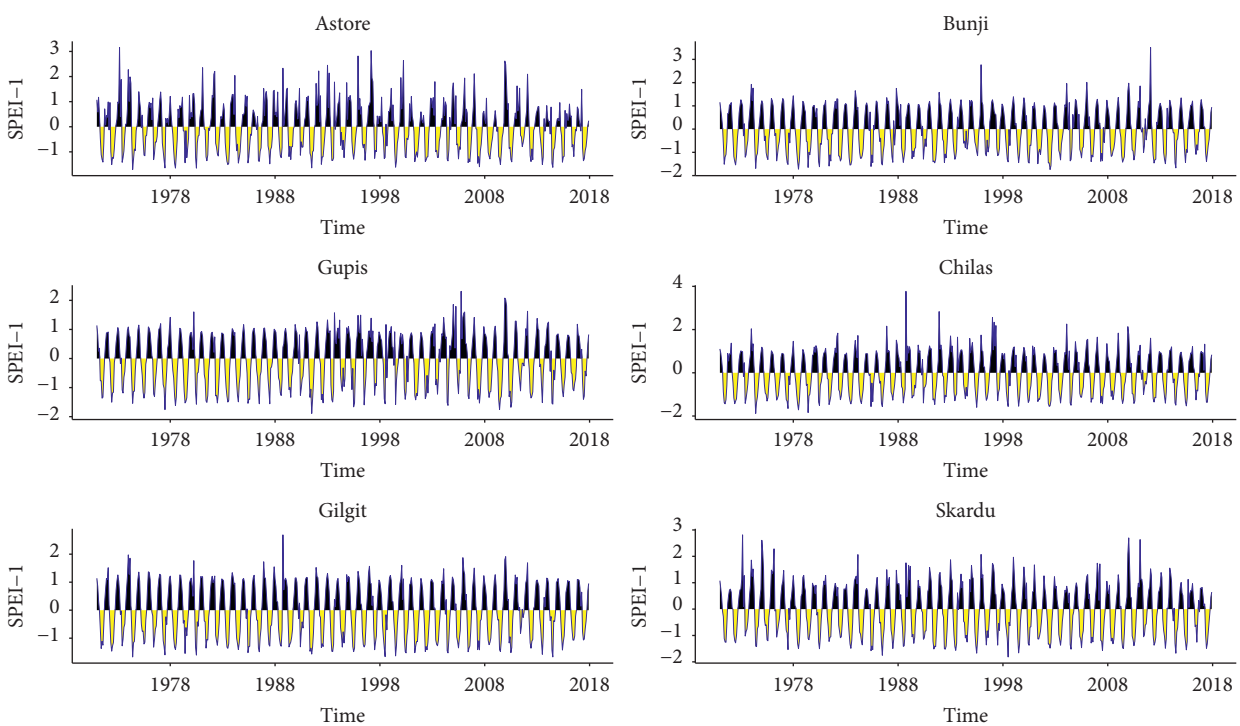

Figure 7: Temporal plots for selected stations based on SPEI-1.

4. Discussion

The data with varying features (precipitation, maximum and minimum temperature) are processed for the current analysis. The six stations in the northern areas are designated for data processing. The observed data are sufficient to calculate the varying SDI (SPI, SPEI, and SPTI). These SDIs are used to assess the drought severity in the selected region. The classification criteria are adopted from Li et al. [115] to characterize drought severity for the selected stations. The characterization and monitoring of the drought occurrences are vital components for the management and planning of

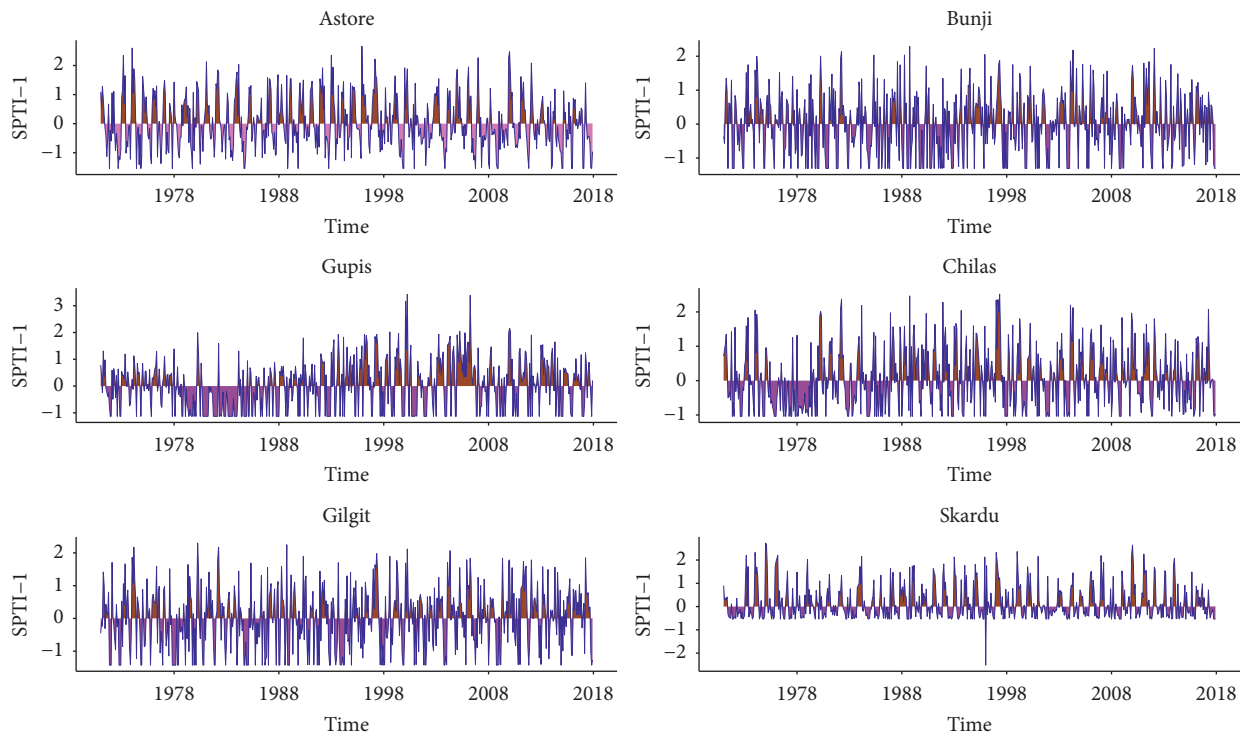

Figure 8: Temporal plots for selected stations based on SPTI-1.

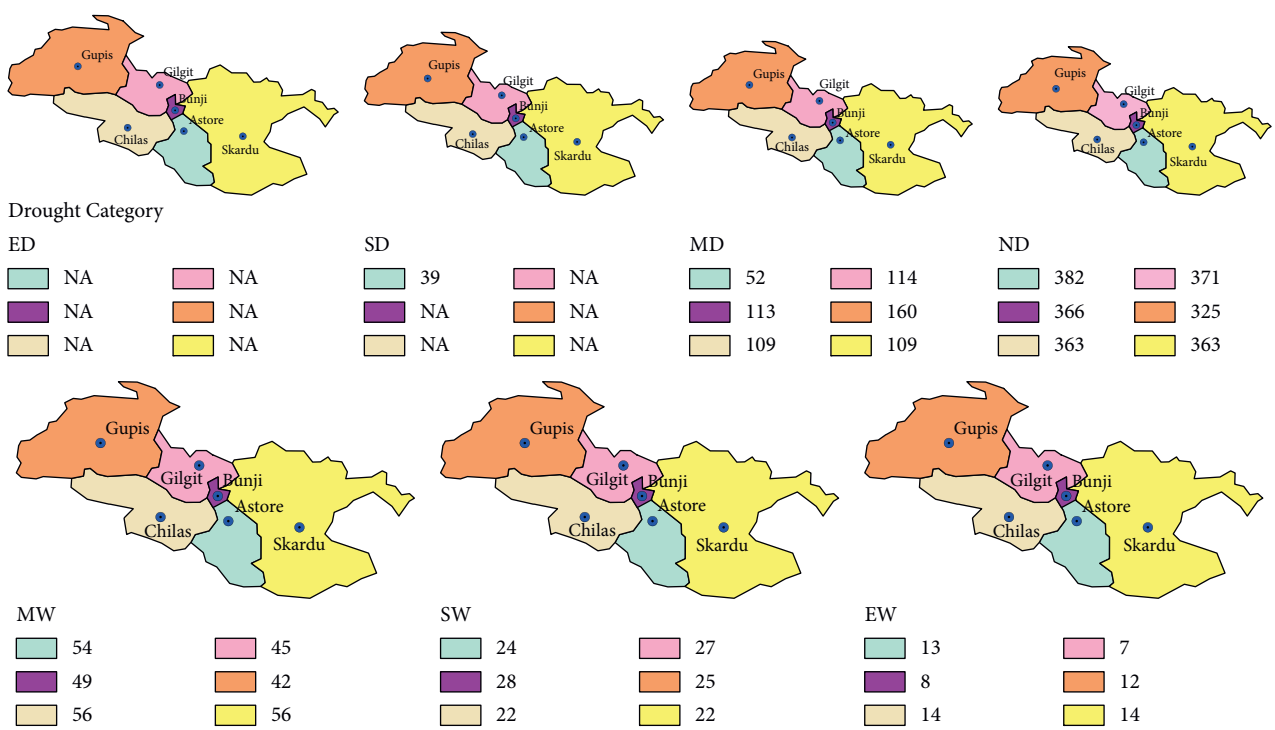

Figure 9: Varying drought categories observed in various stations for SPI-1. NA corresponding to any color shows that the specific drought category is not observed in the particular station. For instance, in Astore the ED is not observed; therefore, the NA is assigned corresponding to its color. The MD occurs 109 times in the selected time period ("January 1971 to December 2017") in Skardu Station. The ND appears 363 times in Skardu Station. The MW occurs 56 times in Skardu Station and so on. The remaining numerical values corresponding to each station and color can be observed accordingly for varying drought categories.

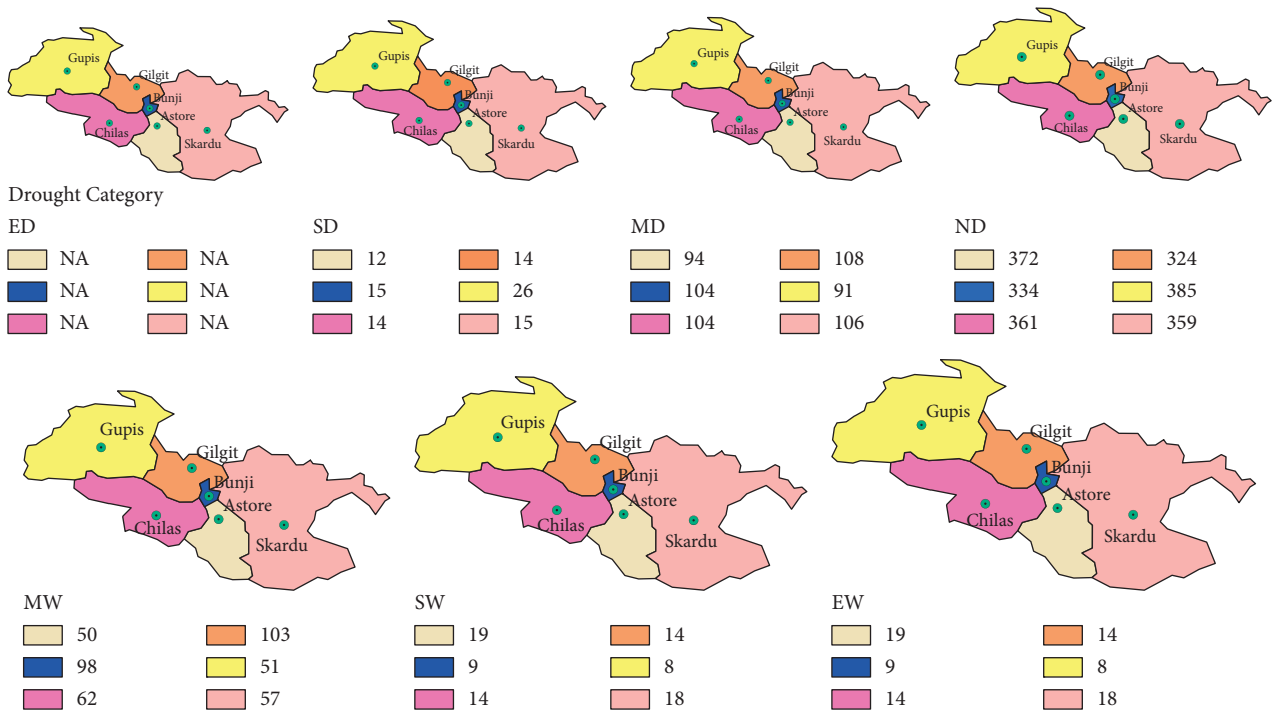

Figure 10: Varying drought categories observed in various stations for SPEI-1. Based on SPEI, MD occurs 91 times in Gupis during the selected time period ("January 1971 to December 2017"). In Gupis, the ND appears 385 times. MW drought category occurs 51 times in Gupis. 8 times it is observed that EW occurs in Gupis. The remaining drought categories observed in various stations can be perceived from the colors corresponding to each station.

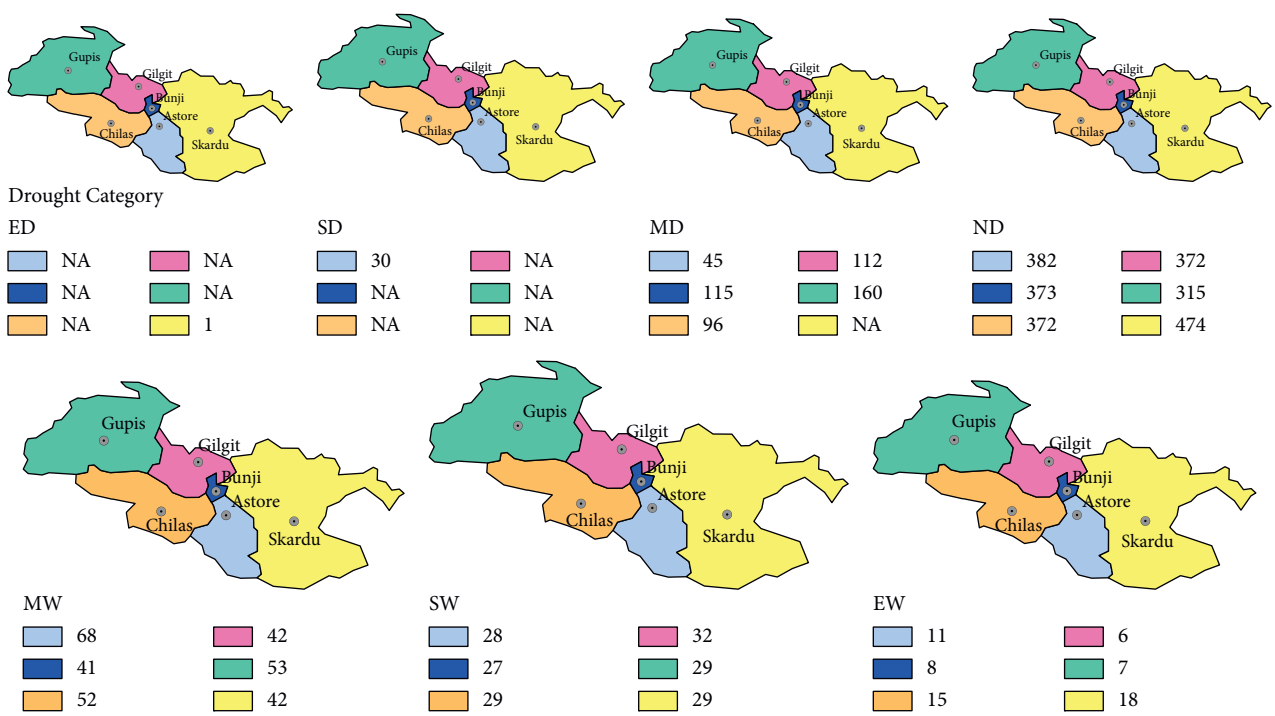

Figure 11: Varying drought categories observed in various stations for SPTI-1. Based on SPTI, the several drought categories appeared in selected stations. The higher the category values means the drought category is prevalent among other drought categories, which means possible measures should be prepared according to the drought category that is most prevalent in any station. The ND category has most likely to occur in several stations. For example, in Skardu the ND has occurred 474 times and in Astore ND has occurred 382 times. In Gupis, ND occurred 315 times, and in Bunji and Gilgit, it has occurred 373 and 372 times, respectively.

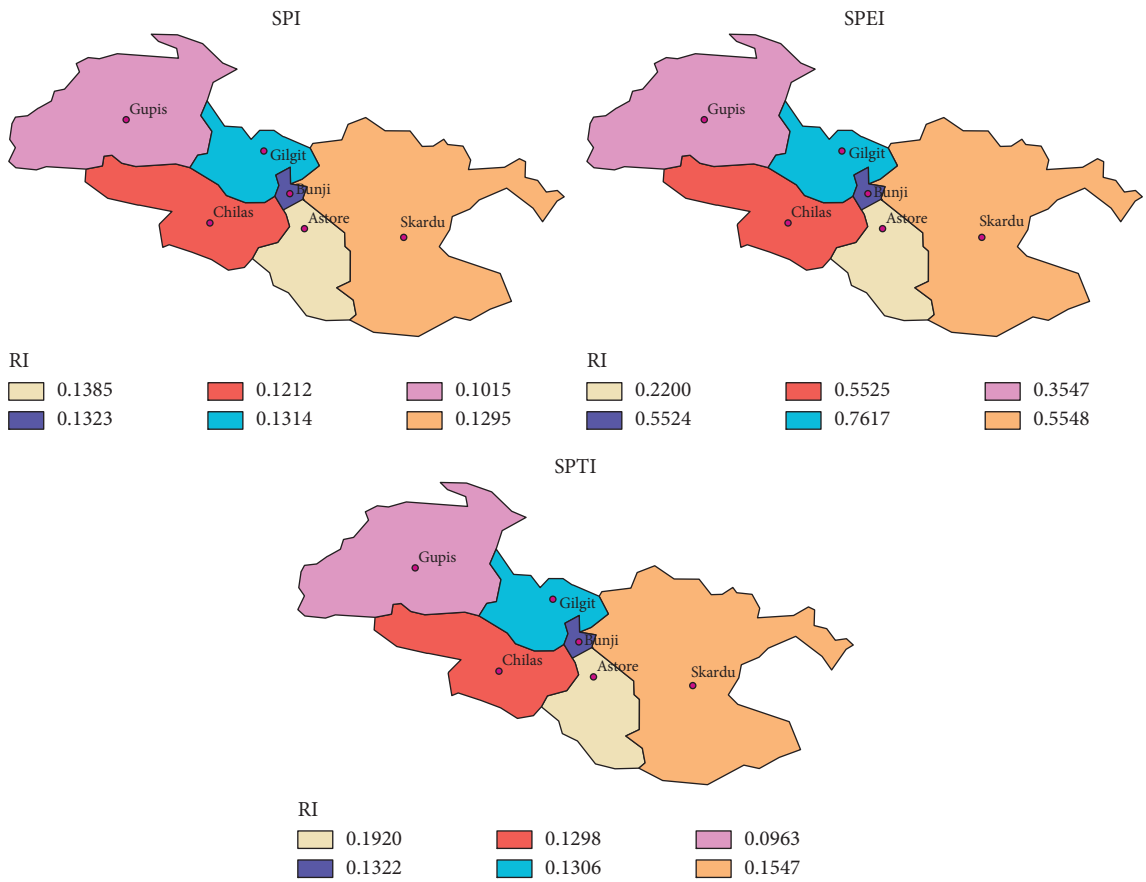

Figure 12: RI values calculated for various stations using three indices (SPI, SPEI, and SPTI).

Table 7: Relative importance (RI) values computed for three selected drought indices. The varying RI values can be observed for various indices. For example, for SPI, in the Astore Station, the RI value is 0.1385, and in Bunji, the RI value is 0.1323. The RI values of 0.1015, 0.1212, 0.1314, and 0.1295 are computed for Gupis, Chilas, Gilgit, and Skardu, respectively. The RI value in Astore is higher than other stations for SPI. In SPEI, RI value is 0.2200 for Astore Station. The RI value of 0.5524 is calculated for Bunji Station. For Gupis, Chilas, Gilgit, and Skardu, the RI values are 0.3547, 0.5525, 0.7617, and 0.5548, respectively. Based on SPEI, the Gilgit receives higher weights. In SPTI, the Astore has a higher RI value of 0.1922.

	Relative importance (RI)		
	SPI	SPEI	SPTI
Astore	0.1385	0.2200	0.1922
Bunji	0.1323	0.5524	0.1322
Gupis	0.1015	0.3547	0.0963
Chilas	0.1212	0.5525	0.1298
Gilgit	0.1314	0.7617	0.1306
Skardu	0.1295	0.5548	0.1547

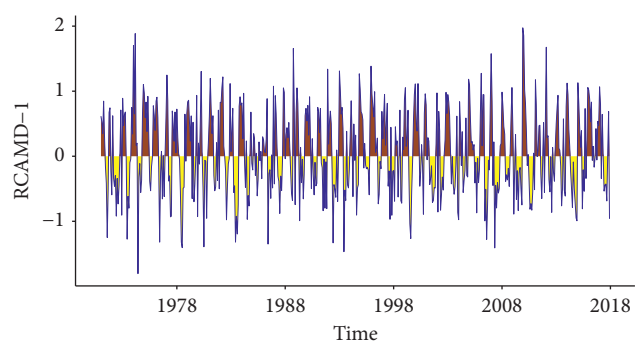

Figure 13: Temporal plots for selected stations based on SPTI at a one-month time scale.

water resources, mitigation strategies, and the creation of a climate-resilient society [25–27, 118–120]. Therefore, this study proposes an RCAMD to comprehensively and accurately characterize drought occurrences. The RCAMD employs MCFS and SSP to collect information from several stations and drought indices. The selected stations have a homogeneous pattern of drought occurrences among each other for specific indices. Ali et al. [96] cited these stations as homogeneous regions in their study. They used three SDIs (SPI, SPEI, and SPTI) and found that these stations are more and less similar in a specific time scale for three indices. Recently, Niaz et al. [76] considered these stations as homogeneous and developed a comprehensive index procedure to assimilate information. Further, Niaz et al. [98] considered these stations as homogeneous and proposed a regional-level propagation framework that is used to collect information from various indices. However, this study found a gap in their research; the mentioned research had considered all stations for the analysis, given that those

Table 8: Classif. drought categories received weights (steady-state weights (SSWs)) in various months using SPI-1 for the year 2017 in particular stations. For example, for the Astore Station in January the SD receives SSW with a value of 0.0695. In Astore, during March the ND receives the SSW with a value of 0.6765. The ND weight is a higher weight among the selected drought categories. This indicates that ND is the prevalent drought category in the Astore Station. Moreover, the weights can be observed for selected drought classes in other stations.

Month	Astore		Bunji		Gupis		Chilas		Gilgit		Skardu	
	Classif.	Weights	Classif.	Weights	Classif.	Weights	Classif.	Weights	Classif.	Weights	Classif.	Weights
1	SD	0.0695	MD	0.2012	MD	0.2842	ND	0.6426	ND	0.6569	ND	0.6836
2	SD	0.0695	ND	0.6480	MD	0.2842	ND	0.6426	ND	0.6569	ND	0.6836
3	ND	0.6765	MD	0.2012	ND	0.5755	ND	0.6426	MD	0.2030	ND	0.6836
4	SW	0.0425	ND	0.6480	MW	0.0746	EW	0.0248	SW	0.0479	EW	0.0231
5	ND	0.6765	ND	0.6480	ND	0.5755	ND	0.6426	ND	0.6569	ND	0.6836
6	ND	0.6765	ND	0.6480	ND	0.5755	ND	0.6426	ND	0.6569	ND	0.6836
7	ND	0.6765	ND	0.6480	ND	0.5755	ND	0.6426	MW	0.0798	ND	0.6836
8	ND	0.6765	ND	0.6480	MW	0.0746	ND	0.6426	ND	0.6569	ND	0.6836
9	ND	0.6765	ND	0.6480	ND	0.5755	ND	0.6426	ND	0.6569	ND	0.6836
10	SD	0.0695	MD	0.2012	ND	0.5755	MD	0.1940	ND	0.6569	MD	0.1566
11	SD	0.0695	MD	0.2012	MD	0.2842	MD	0.1940	MD	0.2030	MD	0.1566
12	MD	0.0925	MD	0.2012	ND	0.5755	MD	0.1940	MD	0.2030	MD	0.1566

Table 9: Classif. drought categories received SSW in various months. The SSW is computed based on the SPEI-1 for the year, 2017, in chosen stations. For instance, in the Skardu Station ND receives SSW with a value of 0.6378. In June of Skardu, the MD receives SSW with a value of 0.1887. It can be observed that ND category received greater weights than other selected drought categories. It can be observed in most of the selected stations and drought indices that the ND is prevalent. Further, the weights of other drought categories in varying stations can be noted accordingly.

Month	Astore		Bunji		Gupis		Chilas		Gilgit		Skardu	
	Classif.	Weights	Classif.	Weights	Classif.	Weights	Classif.	Weights	Classif.	Weights	Classif.	Weights
1	ND	0.6611	ND	0.5937	ND	0.6836	ND	0.6413	MW	0.1800	ND	0.6378
2	ND	0.6611	ND	0.5937	ND	0.6836	ND	0.6413	ND	0.5760	ND	0.6378
3	ND	0.6611	ND	0.5937	ND	0.6836	ND	0.6413	ND	0.5760	ND	0.6378
4	MW	0.0866	ND	0.5937	ND	0.6836	MW	0.1079	ND	0.5760	ND	0.6378
5	ND	0.6611	MD	0.1853	ND	0.6836	ND	0.6413	ND	0.5760	ND	0.6378
6	MD	0.1672	MD	0.1853	MD	0.1620	MD	0.1852	MD	0.1926	MD	0.1887
7	MD	0.1672	MD	0.1853	MD	0.1620	MD	0.1852	MD	0.1926	MD	0.1887
8	ND	0.6611	ND	0.5937	ND	0.6836	ND	0.6413	ND	0.5760	ND	0.6378
9	ND	0.6611	ND	0.5937	ND	0.6836	ND	0.6413	ND	0.5760	ND	0.6378
10	ND	0.6611	ND	0.5937	ND	0.6836	ND	0.6413	ND	0.5760	ND	0.6378
11	ND	0.6611	ND	0.5937	ND	0.6836	ND	0.6413	ND	0.5760	ND	0.6378
12	ND	0.6611	ND	0.5937	ND	0.6836	ND	0.6413	ND	0.5760	ND	0.6378

Table 10: Classif. drought categories received SSW in several months. The SSW is calculated based on SPTI-1 for the year, 2017, in certain stations. Using SPTI-1 in January of Gupis, MD occurred. The MD received SSW by a value of 0.2842. Further, in December (Dec) of Gupis ND received SSW by a value of 0.5577. In December of Skardu, ND received SSW by a value of 0.8401. The varying behavior of SSW for several stations and months can be examined accordingly.

Month	Astore		Bunji		Gupis		Chilas		Gilgit		Skardu	
	Classif.	Weights	Classif.	Weights	Classif.	Weights	Classif.	Weights	Classif.	Weights	Classif.	Weights
1	SD	0.0534	MD	0.2047	MD	0.2842	ND	0.6590	ND	0.6587	ND	0.8401
2	SD	0.0534	ND	0.6604	MD	0.2842	ND	0.6590	ND	0.6587	ND	0.8401
3	ND	0.6789	MD	0.2047	ND	0.5577	ND	0.6590	MD	0.1994	ND	0.8401
4	MW	0.1187	ND	0.6604	MW	0.0941	EW	0.0266	SW	0.0568	ND	0.8401
5	ND	0.6789	ND	0.6604	ND	0.5577	ND	0.6590	ND	0.6587	ND	0.8401
6	ND	0.6789	ND	0.6604	ND	0.5577	ND	0.6590	ND	0.6587	ND	0.8401
7	ND	0.6789	ND	0.6604	ND	0.5577	ND	0.6590	ND	0.6587	ND	0.8401
8	ND	0.6789	ND	0.6604	ND	0.5577	ND	0.6590	ND	0.6587	ND	0.8401
9	ND	0.6789	ND	0.6604	ND	0.5577	ND	0.6590	ND	0.6587	ND	0.8401
10	SD	0.0534	MD	0.2047	ND	0.5577	ND	0.6590	MD	0.1994	ND	0.8401
11	SD	0.0534	MD	0.2047	MD	0.2842	MD	0.1705	MD	0.1994	ND	0.8401
12	ND	0.6789	MD	0.2047	ND	0.5577	ND	0.6590	MD	0.1994	ND	0.8401

stations were homogeneous. Hence, it was counterproductive to study all stations in a homogeneous environment. It underpins a gap addressed in this current research by accumulating more comprehensive information. The present research proposes a new method, RCAMD, which provides more comprehensive results. In the first phase, the RCAMD employed MCFS to separately provide important stations for each index. For example, there are three indices (SPI, SPEI, and SPTI) and six stations in the current analysis. The MCFS uses SPI for selecting important stations among six selected stations. Then, MCFS uses SPEI to select the important station from six selected stations, and similarly, it employs SPTI for selecting an important station from the selected stations. Hence, three vectors of the observations are computed by MCFS for each index separately in the first phase. In the second phase, using SSP the RCAMD provides comprehensive information about various drought classes among selected indices and stations. Hence, the results related to the RCAMD provide a comprehensive assessment of meteorological drought at the regional level and bring a new method to consider more on drought assessment and monitoring. The RCAMD can efficiently work for early warning and mitigation policies. It can be used to make better management and planning to enhance the capabilities of forecasting procedures to decrease the vulnerability of society to drought and its forgoing impacts.

5. Conclusion

Drought is one of the multifaceted natural hazards that has adverse impacts on the economy, water resources, and other environmental structures worldwide. However, the assessment and analysis of drought are crucial, specifically to sound water resource planning and management at the regional level. Therefore, the assessment and monitoring of drought in a region are thus vital to decrease its vulnerability to negative impacts. Therefore, this study proposes an RCAMD. The RCAMD employs MCFS and SSP to accumulate information from several stations and drought indices comprehensively. The three commonly used SDIs are jointly analyzed for the computation of RCAMD. The RCAMD is performed at the six designated stations in the northern areas of Pakistan. The results related to the RCAMD provide a comprehensive assessment of meteorological drought at the regional level and bring a new method to take more consideration on drought assessment and monitoring. Moreover, the RCAMD considers the initial state, and the transition probabilities are constant by assuming time homogeneous progression; however, it can be considered temporal characteristics to improve drought monitoring efficiency for the selected stations. Further, the results of RCAMD would be entertained for the current scenario and application site; however, it cannot be generalized for other climatic conditions. The climatology conditions of the selected stations will change the outcomes and influence the extrapolations. Moreover, the categorization of the given data from other indices in the selected stations can implicitly be useful to increase the capabilities for drought monitoring.

Data Availability

The data and codes used to prepare the manuscript are available from the corresponding author and can be provided upon request.

Ethical Approval

All procedures followed were in accordance with the ethical standards of the Helsinki Declaration of 1975, as revised in 2000.

Consent

All authors voluntarily agreed to participate in this research study and agreed to publication; there is no legal constraint in publishing the data used in the manuscript.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Authors' Contributions

All authors contributed equally.

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