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 PDSI 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.
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

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.
2.2.1. 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 SPTI). 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 \((SSP)_{klm}\). 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:

\[
\prod_{i} (SPI) = \left( \prod_{1} (ED_{SPI}) \prod_{2} (EW_{SPI}) \prod_{3} (SD_{SPI}) \prod_{4} (SW_{SPI}) \prod_{5} (MD_{SPI}) \prod_{6} (MW_{SPI}) \prod_{7} (ND_{SPI}) \right),
\]

\[
\prod_{i} (SPTI) = \left( \prod_{1} (ED_{SPTI}) \prod_{2} (EW_{SPTI}) \prod_{3} (SD_{SPTI}) \prod_{4} (SW_{SPTI}) \prod_{5} (MD_{SPTI}) \prod_{6} (MW_{SPTI}) \prod_{7} (ND_{SPTI}) \right),
\]

\[
\prod_{i} (SPEI) = \left( \prod_{1} (ED_{SPEI}) \prod_{2} (EW_{SPEI}) \prod_{3} (SD_{SPEI}) \prod_{4} (SW_{SPEI}) \prod_{5} (MD_{SPEI}) \prod_{6} (MW_{SPEI}) \prod_{7} (ND_{SPEI}) \right).
\]
FX_he obtained limiting probabilities \( \pi_i^{(SPI)}, \pi_i^{(SPTI)}, \pi_i^{(SPEI)} \) 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
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. FX_he 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
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,
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. FX_herementioned research considered all stations for their analysis. FX_hus, 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

| Month | Astore | Bunji | Gupis | Chilas | Gilgit | Skardu |
|-------|--------|-------|-------|--------|--------|--------|
| 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 | ND | -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 |

**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.
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.

Complexity

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 |
|-------|--------|-------|-------|--------|--------|--------|
| 1     | 0.2741 | ND    | 0.9796| 0.7679 | ND     | 0.9039 | ND     |
| 2     | 0.0829 | ND    | 0.8384| 0.4871 | ND     | 0.9296 | ND     |
|       | -0.1682| ND    | 0.1045| 0.0219 | ND     | 0.1193 | ND     |
|       | 1.4903 | MW    | 0.0887| 0.3163 | ND     | 1.3240 | MW     |
| 3     | -0.8214| ND    | -1.0027| -0.7708| ND     | -0.8617| ND     |
| 4     | -1.3547| MD    | -1.3982| -1.4032| MD     | -1.3619| MD     |
| 5     | -1.2755| MD    | -1.0733| -1.2931| MD     | -1.3665| MD     |
| 6     | -0.9560| ND    | -0.7027| -0.4335| ND     | -0.8499| ND     |
| 7     | -0.7888| ND    | -0.4535| -0.5996| ND     | -0.4873| ND     |
| 8     | -0.4409| ND    | 0.0387 | -0.0183| ND     | 0.0061 | ND     |
| 9     | 0.0596 | ND    | 0.7154 | 0.5016 | ND     | 0.6265 | ND     |
| 10    | 0.2411 | ND    | 0.9475 | 0.8261 | ND     | 0.8367 | ND     |

| Month | Astore | Bunji | Gupis | Chilas | Gilgit | Skardu |
|-------|--------|-------|-------|--------|--------|--------|
| 1     | -1.5398| SD    | -1.2001| -1.1305| MD     | -0.9028| ND     |
| 2     | -1.5398| SD    | 0.4943 | -1.1305| MD     | 0.9832 | ND     |
| 3     | -0.3434| ND    | -1.1119| -0.6169| ND     | -0.0695| ND     |
| 4     | 1.4038 | MW    | 0.9448 | 1.2422 | MW     | 2.0709 | EW     |
| 5     | 0.0369 | ND    | 0.5504 | 0.7799 | ND     | 0.6277 | ND     |
| 6     | -0.5360| ND    | -0.7646| -0.4345| ND     | -0.2150| ND     |
| 7     | -0.4439| ND    | 0.5654 | 0.5086 | ND     | -0.0537| ND     |
| 8     | -0.4273| ND    | 0.5021 | 0.8873 | ND     | 0.0310 | ND     |
| 9     | -0.6874| ND    | 0.1387 | 0.2467 | ND     | 0.0446 | ND     |
| 10    | -1.5153| SD    | -1.1878| -0.3152| ND     | -0.9993| ND     |
| 11    | -1.5398| SD    | -1.3078| -1.1305| MD     | -1.0394| MD     |
| 12    | -0.9624| ND    | -1.3078| 0.2099 | ND     | -0.9757| 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 |
|-------|--------|-------|-------|--------|--------|--------|
| 1     | -1.5398| SD    | -1.2001| -1.1305| MD     | -0.9028| ND     |
| 2     | -1.5398| SD    | 0.4943 | -1.1305| MD     | 0.9832 | ND     |
| 3     | -0.3434| ND    | -1.1119| -0.6169| ND     | -0.0695| ND     |
| 4     | 1.4038 | MW    | 0.9448 | 1.2422 | MW     | 2.0709 | EW     |
| 5     | 0.0369 | ND    | 0.5504 | 0.7799 | ND     | 0.6277 | ND     |
| 6     | -0.5360| ND    | -0.7646| -0.4345| ND     | -0.2150| ND     |
| 7     | -0.4439| ND    | 0.5654 | 0.5086 | ND     | -0.0537| ND     |
| 8     | -0.4273| ND    | 0.5021 | 0.8873 | ND     | 0.0310 | ND     |
| 9     | -0.6874| ND    | 0.1387 | 0.2467 | ND     | 0.0446 | ND     |
| 10    | -1.5153| SD    | -1.1878| -0.3152| ND     | -0.9993| ND     |
| 11    | -1.5398| SD    | -1.3078| -1.1305| MD     | -1.0394| MD     |
| 12    | -0.9624| ND    | -1.3078| 0.2099 | ND     | -0.9757| 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 SPTI) (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.
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.
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 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 stations have a homogeneous pattern of drought occurrences among each other. 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.

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

Figure 13: Temporal plots for selected stations based on SPTI at a one-month time scale.
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 0.0746. In Astore, during March the ND receives the SSW with a value of 0.0746. In Astore, during March the ND receives the SSW with a value of 0.2842.

| Month | Astore | Bunji | Gupis | Chilas | Gilgit | Skardu |
|-------|--------|-------|-------|--------|--------|--------|
|       | Classif. Weights | Classif. Weights | Classif. Weights | Classif. Weights | Classif. Weights | Classif. Weights |
| 1     | SD     | 0.0695 | ND    | 0.2842 | MD    | 0.6426 | ND |
| 2     | SD     | 0.0695 | ND    | 0.2842 | MD    | 0.6426 | ND |
| 3     | ND     | 0.6765 | ND    | 0.5755 | ND    | 0.6426 | ND |
| 4     | SW     | 0.0425 | ND    | 0.5755 | EW    | 0.0248 | SW |
| 5     | ND     | 0.6765 | ND    | 0.5755 | ND    | 0.6426 | ND |
| 6     | ND     | 0.6765 | ND    | 0.5755 | ND    | 0.6426 | ND |
| 7     | ND     | 0.6765 | ND    | 0.5755 | MD    | 0.2012 | ND |
| 8     | ND     | 0.6765 | ND    | 0.5755 | ND    | 0.6426 | ND |
| 9     | ND     | 0.6765 | ND    | 0.5755 | ND    | 0.6426 | ND |
| 10    | SD     | 0.0695 | ND    | 0.5755 | MD    | 0.1940 | ND |
| 11    | SD     | 0.0695 | ND    | 0.5755 | ND    | 0.6569 | ND |
| 12    | MD     | 0.0925 | ND    | 0.5755 | ND    | 0.6569 | ND |

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    | 0.6413 |
| 2     | ND     | 0.6611 | ND    | 0.5937 | ND    | 0.6413 |
| 3     | ND     | 0.6611 | ND    | 0.5937 | ND    | 0.6413 |
| 4     | MW     | 0.0866 | ND    | 0.5937 | ND    | 0.6413 |
| 5     | ND     | 0.6611 | MD    | 0.1853 | ND    | 0.6413 |
| 6     | MD     | 0.1672 | MD    | 0.1853 | MD    | 0.1852 |
| 7     | MD     | 0.1672 | MD    | 0.1853 | MD    | 0.1852 |
| 8     | ND     | 0.6611 | ND    | 0.5937 | ND    | 0.6413 |
| 9     | ND     | 0.6611 | ND    | 0.5937 | ND    | 0.6413 |
| 10    | ND     | 0.6611 | ND    | 0.1593 | ND    | 0.6413 |
| 11    | ND     | 0.6611 | ND    | 0.5937 | ND    | 0.6413 |
| 12    | ND     | 0.6611 | ND    | 0.5937 | ND    | 0.6413 |

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 |
| 2     | SD     | 0.0534 | ND    | 0.6604 | MD    | 0.2842 |
| 3     | ND     | 0.6789 | MD    | 0.2047 | ND    | 0.5577 |
| 4     | MW     | 0.1187 | ND    | 0.6604 | MW    | 0.0941 |
| 5     | ND     | 0.6789 | ND    | 0.6604 | ND    | 0.5577 |
| 6     | ND     | 0.6789 | ND    | 0.6604 | ND    | 0.5577 |
| 7     | ND     | 0.6789 | ND    | 0.6604 | ND    | 0.5577 |
| 8     | ND     | 0.6789 | ND    | 0.6604 | ND    | 0.5577 |
| 9     | ND     | 0.6789 | ND    | 0.6604 | ND    | 0.5577 |
| 10    | SD     | 0.0534 | MD    | 0.2047 | ND    | 0.5577 |
| 11    | SD     | 0.0534 | MD    | 0.2047 | ND    | 0.5577 |
| 12    | ND     | 0.6789 | MD    | 0.2047 | ND    | 0.5577 |
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 have 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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