Spatiotemporal analysis of meteorological drought variability in a homogeneous region using standardized drought indices

Rizwan Niaza, Mohammed M. A. Almazhbc, Fuad S. Al-Duaisde, Nouman Iqbalf, Dost Muhammad Khang and Ijaz Hussaina

aDepartment of Statistics, Quaid-I-Azam University, Islamabad, Pakistan; bDepartment of Mathematics, College of Sciences and Arts (Muhyil), King Khalid University, Muhyil, Saudi Arabia; cDepartment of Mathematics and Computer, College of Sciences, Ibb University, Ibb, Yemen; dMathematics Department, College of Humanities and Science, Prince Sattam Bin Abdulaziz University, Al Aflaj, Saudi Arabia; eAdministration Department, Administrative Science College, Thamar University, Thamar, Yemen; fKnowledge unit of business Economics accountancy and Commerce(KUBEAC), University of Management and Technology, Sialkot, Pakistan; gDepartment of Statistics, Abdul Wali Khan University Mardan, Khyber Pakhtunkhwa, Pakistan

ABSTRACT
Drought is one of the most common climatic or meteorological hazards and has spatiotemporal characteristics that substantially impact the livelihoods and economy worldwide. Therefore, there is a need for efficient procedures that accurately identify spatiotemporal variability. Moreover, it is crucial to continuously assess and monitor spatiotemporal drought occurrence in a certain region to prevent unfavourable impacts. For this purpose, the current study develops a new procedure for spatiotemporal analysis of the region: The Spatio-Temporal Weighted Joint Agglomerative Drought Index (STWJADI). The STWJADI is mainly based on a weighting scheme known as the Spatio-Temporal Two-Stage Standardized Weighting Scheme (STTSSWS). In the first stage of the STTSSWS, the steady-state probabilities are computed for several stations (Astor, Bunji, Chilas, Gupis, Skardu, and Gilgit) of the Northern region of Pakistan at a 1-month time scale (scale-1) to allocate weights for various drought classes. Moreover, in the second stage of the STTSSWS, the weights are allocated based on spatiotemporal weighting characteristics to acquire new weights for the numerous drought classes in the designated region. Further, the spatiotemporal weights attained from STTSSWS are utilized to compute the STWJADI. The outcomes of the STWJADI provide efficient and comprehensive information for drought characterization in the selected region.

ARTICLE HISTORY
Received 24 January 2022
Accepted 14 May 2022

KEYWORDS
Standardized drought index (SPI); steady-state probabilities; homogenous region; two-stage standardized weighting scheme; joint agglomerative drought index; spatiotemporal weights

CONTACT Ijaz Hussain ijaz@qau.edu.pk; Mohammed M. A. Almazah mmalmazah@kku.edu.sa.

© 2022 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.
This is an Open Access article distributed under the terms of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.
1. Introduction

Drought is a creeping natural hazard happening in every climatic zone worldwide and substantially affects agricultural sectors, ecological environment, and economic well-being (Corlett 2016; Kuwayama et al. 2019; Hoque et al. 2020; Meza et al. 2020; Elhoussaoui et al. 2021; Savari et al. 2022). It is often poorly identified in regional climatic, hydrological, and human environments (Van Loon et al. 2016; Ahmadalipour et al. 2019; Vicente-Serrano et al. 2020; Saharwardi & Kumar 2022). It is slowly evolving and affecting more people than other natural hazards (Kiem et al. 2016; Aldunce et al. 2017; Riebsame et al. 2019; Quandt 2021; Okpara et al. 2022; Ruwanza et al. 2022). Its onsets and terminations intervals are complex that have been challenging for assessment and monitoring (Mavromatis & Voulanas 2021; Wu et al. 2021). Based on the water deficiency that occurs in numerous fields, the drought can be described explicitly as meteorological, agricultural, socio-economic, and hydrological aspects (Vogt & Somma 2013; Haile et al. 2020; Alahacoon & Edirisinghe 2022; Lee et al. 2022). The deficiency in precipitation leads to meteorological drought, and a shortage in soil water supply causes agricultural drought. Further, the insufficiency in surface or groundwater triggers hydrological drought. Many researchers in drought-related fields have focused on meteorological drought (Quiring 2009; Wang et al. 2016; Spinoni et al. 2019; Ayugi et al. 2022). Herbst et al. (1966) proposed a method to evaluate meteorological droughts that were adapted later for arid regions by Mohan and Rangacharya (1991).

The assessing, monitoring, and forecasting of meteorological droughts are important (Noguera et al. 2022; Cao et al. 2022; Schwartz et al. 2022). Further, the meteorological drought becomes the primary source of other drought types (hydrological, agricultural drought, socio-economic, etc.) due to insufficient precipitation (Lai et al. 2019; Guo et al. 2020). Furthermore, an accurate assessment of meteorological drought adds valued information to global decision-making for the people working in the relevant fields, including agriculture, hydrology, industrial, and water-budget management (Mahboobeh et al. 2020; Dikshit et al. 2021). Moreover, several studies have suggested monitoring drought at the regional level (Zhai & Feng 2009; Zhang et al. 2012; Santos et al. 2019; Mun et al. 2020; Jasim & Awchi 2020). Drought monitoring at the regional level has significant importance for the country’s economy and other human activities. The potential adverse effects of drought can be minimized in the future using appropriate regional drought monitoring (Kisi et al. 2019; Pontes Filho et al. 2019; Fung et al. 2020; Pontes Filho et al. 2020). Several authors have proposed various techniques and methods for regional drought monitoring that can be used according to different climatic conditions. Based on varying climatic conditions, several drought indices have been developed and used in various publications (Guo et al. 2020; Afshar et al. 2022; Alsafadi et al. 2022). These indices are based on suitable and effective recording related to drought occurrences. The indices comprise crucial information that can be used to improve forecasting and early warning policies for future drought occurrences (Kisi et al. 2019; Dikshit et al. 2021). However, accurate drought assessment, monitoring, and forecasting can become possible using suitable indices that consider proper records for drought occurrences. Therefore, the
choice of the indices and their information obtained from the several indicators under the specific climatic conditions are essential for the drought analysis.

In the past 20 years or so, several authors have developed new indices for the assessment and monitoring of drought occurrences (McKee et al. 1993; Vicente-Serrano et al. 2010; Santos et al. 2010; Gebrehiwot et al. 2011; Guo et al. 2018). The new development has provided various prospects to the decision-makers and policymakers for more precise and accurate drought monitoring. The computing, display abilities, and geographic information systems have substantially increased the performance of indices. The standardized drought indices (SDI) are commonly used for drought characterization (Vicente-Serrano et al. 2015; Stagge et al. 2015; Mukherjee et al. 2018; Niazi, Almazah, Zhang et al. 2021; Niazi, Zhang, Iqbal et al. 2021; Niazi, Hussain, Zhang et al. 2021). The assessment of the SDI is based on several parameters (precipitation, temperature, etc.). However, the computing and preference of the indices are based on the climatological characteristics of the studied region.

Moreover, understanding drought events cannot be determined accurately for a future policy without reliable drought monitoring policies and early warning strategies. Therefore, decision-makers need reliable procedures that help them to understand the drought occurrences. Understanding drought events requires insightful information about the spatial and temporal distribution of drought risk at the local or regional level. Therefore, valuable measures are necessary that accurately categorize spatiotemporal characteristics (Malik et al. 2012; Chenu et al. 2013; Brigadier et al. 2019; Zhou et al. 2020; Wang et al. 2020; Adedeji et al. 2020; Han et al. 2021).

This study develops a new drought assessment procedure for spatiotemporal analysis at the regional level, the Spatial-Temporal Weighted Joint Agglomerative Drought Index (STWJADI). The potential of the STWJADI is mainly based on Spatio-Temporal Two-Stage Standardized Weighting Scheme (STTSSWS). In the first stage of the STTSSWS, the steady-state probabilities (SSP) are calculated from the selected stations at a 1-month time scale to assign weights for several drought categories. However, in stage two of the STTSSWS, the weights are distributed based on spatiotemporal features to obtain new weights for the several drought categories in the selected region. Moreover, the spatiotemporal weights, which are computed from the STTSSWS, are used to calculate the STWJADI. The outcomes of the STWJADI give valuable and comprehensive information for drought characterization in the selected region.

2. Materials and methods

2.1. Description of the study area

The six meteorological stations are chosen for the analysis from the northern area of Pakistan (Figure 1). The selected region has significant influences on the agriculture sectors across the country (Anjum et al. 2010; Hussain & Lee 2014; Yamada et al. 2016; Adnan et al. 2017; Ali, Shafqat et al. 2019). Since the extensive dependence of the agriculture sectors are linked with this region; therefore, the region is chosen for
the analysis. Northern Areas have a group of mountain ranges, including the Karakoram, the Hindu Kush, and the Himalayas, which surround most of the region (Rasul 2011). Further, the region has the world’s tallest mountains, including K-2, Nanga Parbat, and Rakaposhi. The high altitudes of the peaks commonly bring a substantial portion of precipitation (Hussain & Lee 2014; Yamada et al. 2016; Rasul et al. 2011; Adnan et al. 2017). This portion of the precipitation is effective for the reservoir system of the country. Further, several parts of the country were affected unexpectedly by global warming (Ghaffar & Javid 2011; Naheed & Rasul 2010). Global warming influences cause water deficiency and increase the temperature of several parts of the country. Therefore, it is essential to provide adequate procedures that help to characterize spatiotemporal drought occurrences in the region. Hence, the current study proposes a STWJADI that substantially characterizes the spatiotemporal drought occurrences in the selected area. The STWJADI can be helpful for early warning and drought mitigation policies.

Figure 1. The selected locations of the Northern areas are presented. The locations are selected based on their importance for the country’s agricultural sectors. These selected locations significantly contribute to the reservoir systems of the government. Therefore, various publications preferred these locations for drought monitoring. Based on the past studies and the importance of the locations to the reservoir systems, the current study has chosen these locations for the analysis.
2.2. Data and methods

The data are taken from the meteorological department in Pakistan through ['Karachi Data Processing Center (KDPC)'] for the current drought assessment. The collected data have a range of 47 years (i.e. ‘from January 1971 to December 2017’). The data consist of several meteorological stations across the country. Based on the geographic and spatiotemporal distribution of the locations, the KDPC has installed several meteorological stations in various regions of Pakistan. However, based on the collected information from the several stations, it is found that the six stations (Bunji, Astor, Chilas, Gupis, Skardu, and Gilgit) of the northern areas have a homogeneous pattern of drought occurrences (Ali, Hussain, Faisal, Shoukry et al. 2019; Ali, Hussain, Faisal, Almanjahie et al. 2019; Niaz, Hussain et al. 2020; Niaz, Zhang, Ali et al. 2021; Niaz, Hussain, Ali et al. 2021; Niaz, Almazah et al. 2021; Niaz et al. 2022). Moreover, the dependence of the agriculture sectors and reservoir system across the country is highly linked to the selected region; therefore, the region is chosen for the drought analysis. Infect, drought is a meteorological hazard and has spatiotemporal characteristics that directly or indirectly affect agriculture, natural resources, and economic sectors (Lai et al. 2019; Guo et al. 2020; Wang et al. 2020; Adedeji et al. 2020; Han et al. 2021). Therefore, it is important to identify spatiotemporal drought characteristics more instantaneously by developing comprehensive and effective tools and measures. The current study develops the STWJADI to characterize spatiotemporal drought occurrences precisely. Therefore, the STWJADI can be used to increase the ability of drought monitoring and mitigation policies.

2.2.1. Standardized drought index

Indices have been used to evaluate the severity, timing, place, and duration of drought events. Indices can be calculated by using various indicators (precipitation, temperature, etc.) for the numerical representations of drought severity. The drought severity refers to the departure from the normal of an index. A threshold for drought severity may be determined when a drought has begun when it ends and affects the geographic area (Janga Reddy & Ganguli 2012; Vicente-Serrano et al. 2014). Indices can simplify complex relationships and provide useful communication tools for users. Several studies have used SSDIs to monitor drought (Zargar et al. 2011; Vicente-Serrano et al. 2015; Stagge et al. 2015; Mukherjee et al. 2018). The three familiar drought indices, SPI, SPEI, and SPTI, are considered for the current analysis. McKee et al. 1993 developed SPI. It has been frequently applied for drought monitoring. Numerous studies have utilized SPI for drought monitoring (Angelidis et al. 2012; Stagge et al. 2015; Niaz, Almazah, Zhang et al. 2021; Niaz, Zhang, Iqbal et al. 2021; Niaz, Hussain, Zhang et al. 2021). SPI computation is very straightforward; merely the precipitation data are employed for its computation. The SPI can be evaluated at several time scales. The computation and the accessibility of the precipitation data are comparatively easy; therefore, the SPI is frequently being used worldwide. Furthermore, another multi-scalar drought index SPEI has achieved substantial value in drought assessment. Vicente-Serrano et al. (2010) proposed SPEI. The SPEI is considered as an extension of SPI that obtains simplicity in temporal characterization. SPEI considers both precipitation and potential evapotranspiration to assess the
impact of evaporative demand on drought. The SPEI can be estimated by fitting numerous probability distributions based on various climatic conditions on selected stations. The mathematical description related to SPEI is provided by Vicente-Serrano et al. (2010). Further, like the SPI and SPEI, the new drought index, known as SPTI was developed by Ali et al. (2017) to characterize drought in cold and hot climate regions.

2.2.2. The STTSSWS for drought categories

The STTSSWS is proposed that gives an enhanced assessment of drought monitoring, specifically for spatiotemporal features of the region. The STTSSWS is being recognized by using SSP. The SSP can be demarcated as the average probability that the system remains after many transitions in a certain state. Further, in the Markov process, SSP are more implicitly defined and used in various studies (Stewa 2009; Niaz, Hussain et al. 2020). Moreover, inclusive mathematical descriptions associated with the SSP of the Markov chain are available in the study by Stewart (2009). Accordingly, the theory and application of SSP are available in the study by Niaz, Hussain et al. (2020). Niaz, Hussain et al. (2020) used the SSP as a weighting scheme for their studies. Similarly, the current study computes the weights of the drought categories in the selected region using a weighting scheme. The SSP for each drought category \( c \) in each index SPI, SPEI, and SPTI for the specific station \( j \) can be expressed in each vector \( s'_{c_j}, s''_{c_j}, \) and \( s'''_{c_j}, \) respectively. For example, in the current study, the steady probabilities are calculated for the varying drought categories \{'Extremely Wet (EW), Severely Dry (SW), Median dry (MW), Normal Dry (ND), Median Dry (MD), Severely Dry (SD), and extremely Dry (ED)\}' in various stations. Further, these drought categories are numerically presented by \([\text{say}, c = 1 \text{ (EW)}, 2 \text{ (SW)}, 3 \text{ (MW)}, 4 \text{ (ND)}, 5 \text{ (MD)}, 6 \text{ (SD)}, \text{ and 7 (ED)}]\). Similarly, the stations can be numerically presented by \([\text{say}, j = 1 \text{ (Astor)}, 2 \text{ (Bunji)}, 3 \text{(Gupis)}, 4 \text{ (Chilas)}, 5 \text{ (Gilgit)}, \text{ and 6 (Skardu)}]\). Now, the weights can be calculated for varying drought categories at Astor station based on long-run SSP as follows:

\[
\begin{align*}
\text{SSP for SPEI} &= \left[ s'_{11} \ s'_{21} \ s'_{31} \ s'_{41} \ s'_{51} \ s'_{61} \ s'_{71} \right] \\
\text{SSP for SPI} &= \left[ s''_{11} \ s''_{21} \ s''_{31} \ s''_{41} \ s''_{51} \ s''_{61} \ s''_{71} \right] \\
\text{SSP for SPTI} &= \left[ s'''_{11} \ s'''_{21} \ s'''_{31} \ s'''_{41} \ s'''_{51} \ s'''_{61} \ s'''_{71} \right]
\end{align*}
\]

Moreover, the SSP obtained for the drought categories can be described as the visit of the drought category in the long run. These long-run probabilities of varying drought categories are considered as weights. These weights are further used for the computation of STTSSWS. In the first stage of the calculation of STTSSWS, the
weights are obtained by the SSP. In the second stage of STTSSWS, the obtained weights from SSP for numerous drought classes are applied for calculating new spatiotemporal weights according to the data distributions. The second stage of STTSSWS is alienated into two phases; in the first phase, the weights are calculated by associating temporal appearances of the data for each station separately. For example, in the first phase, the temporal weights with varying drought categories are calculated for December at Astor station by Equation (1).

\[
T_{\text{December}}(P_{(ci)(\text{Astor})}) = \frac{S_{(ci)(\text{Astor})}}{\sum_{i=1}^{n} S_{(ci)(\text{Astor})}}, \quad i = 1, 2, 3, \ldots, 47 \text{ and } c = 1, 2, \ldots, 7
\] (1)

where \(T_{\text{December}}(P_{(ci)(\text{Astor})})\) is representing the probabilities (weights) of various drought categories in December at Astor station. The \(i\) denotes the specific month (say, December 1971, December 1972, and so on till December 2017) varying over the selected period (see Section 2.2). And \(c\) shows the drought categories which are considered in this study. The selected drought categories have been provided in several publications (Niaz, Hussain et al. 2020; Ali et al. 2020; Ali, Hussain, Faisal, Shoukry et al. 2019; Ali, Hussain, Faisal, Almanjahie et al. 2019; Niaz, Almanjahie et al. 2020; Niaz, Hussain et al. 2020; Niaz, Zhang, Ali et al. 2021; Niaz, Hussain, Ali et al. 2021; Niaz, Iqbal et al. 2022). The SSP for various drought categories in varying months of December from the selected period at Astor are denoted by \(S_{(ci)(\text{Astor})}\). And \(\sum_{i=1}^{n} S_{(ci)(\text{Astor})}\) denotes the accumulated steady-state weights (Astor with various drought categories) for December over the selected period. Further, \(n\) indicates the total months of December in Astor in the selected period. For example, the nominator term \(S_{(ci)(\text{Astor})}\) is calculated with various drought categories \((c)\) and the varying months of December \((i)\) in Astor station, then the denominator \(\sum_{i=1}^{n} S_{(ci)(\text{Astor})}\) considers the sum for the weights obtained from SSP for the several drought classes of December in the selected study period at Astor station. To avoid the complexity of the mathematical equations, the formula is provided only for the Astor station with a specific month (i.e. December). Then, the weights of the selected drought classes for other months (January, February, March, April up to November) are calculated with the same rationale. Moreover, in the second phase, the methodology is provided to find spatiotemporal characteristics of the selected drought categories. Now, the spatiotemporal weights for these selected drought categories can be obtained by Equation (2).

\[
\text{ST}_{\text{December}}(P_{(ci)(\text{Astor})}) = \frac{T_{\text{December}}(P_{(ci)(\text{Astor})})}{\sum_{j=1}^{C} S_{ij}}, \quad i = 1, 2, 3, \ldots, 47 \text{ and } j = 1, 2, \ldots, 6
\] (2)

where \(\text{ST}_{\text{December}}(P_{(i)(\text{Astor})})\) indicates the probabilities obtained from spatiotemporal information (spatiotemporal weights) of varying drought categories for December for Astor station. Further, the weights \(T_{\text{December}}(P_{(ci)(\text{Astor})})\) which are calculated from Equation (1) and are being further divided by the \(\sum_{j=1}^{C} S_{ij}\). The \(\sum_{j=1}^{C} S_{ij}\) can be computed for December of the selected period by adding varying drought categories \((c)\) observed in several selected stations \((j)\), and the total number of selected stations is
indicated by \( C \) (i.e. \( C = 6 \)). This Equation takes monthly spatiotemporal weights for the Astor station. Meanwhile, the calculation based on STTSSWS provides spatiotemporal characteristics about drought occurrences in a homogenous region.

2.2.3. The spatio-temporal joint agglomerative drought index

This study develops a new drought assessment procedure for spatiotemporal analysis at the regional level: The STWJADI. The potential of the STWJADI is based on STTSSWS. A detailed description of STTSSWS is given in Section 2.2. However, the calculation of STWJADI is based on the vector of the stationary drought classes propagating on various drought indices, which can be specified as follows:

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

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

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

The limiting probabilities of these vectors \([\prod_i (SPEI), \prod_i (SPI), \prod_i (SPTI)]\) refer to the proportion or averaged long-term probabilities of drought categories for the selected indices on varying stations. The obtained SSP show the visit in the long term of the specific drought category in varying drought indices and stations. The selected stations are almost similar and provide homogenous results over the selected indices at a 1-month time scale (Niaz, Hussain et al., 2020; Ali et al., 2020; Ali, Hussain, Faisal, Shoukry et al. 2019; Ali, Hussain, Faisal, Almanjahie et al. 2019; Niaz, Zhang, Ali et al. 2021; Niaz, Hussain, Ali et al., 2021; Niaz, Almazah, Hussain, Filho et al., 2022; Niaz, Almazah, Hussain, Faisal et al., 2022; Niaz, Iqbal et al., 2022). Therefore, it is mandatory to aggregate the information of the multiple drought indices. The aggregated information from the multiple homogenous sources will be cost-effective in the hydrological aspects.

Further, the proposed procedure provides the basis for substantiating comprehensive and accurate information to improve prediction and forecasting policies. Thus, to aggregate information and provide more accurate information about the drought category in the selected region, the current study has proposed a procedure that contemplates only those drought categories among the three drought indices that take high weights. The
The interpretation of the STWJADI is straightforward; the drought categories corresponding to three drought indices from the Astor station can be selected based on the high proportions. For example, Equation (6) consists of three drought indices at a 1-month time scale. Therefore, the STWJADI is only presented for the Astor station at a 1-month scale to avoid mathematical equation complications. However, the STWJADI can be presented for other selected stations based on the same rationale. In this case, at a 1-month time scale, the selected indices comprise varying drought categories. For instance, at scale-1 SPEI (SPEI-1) in Astor station has an Extremely wet category, at scale = 1 of SPI (SPI-1) has severely dry, and at scale-1 of SPTI (SPTI-1) or may have any other combination according to the specific climatic conditions. For this purpose, Ali, Hussain, Faisal, Shoukry et al. (2019) and Ali et al. (2020) used transient probabilities and SSP as weighting schemes.

Further, Niaz, Zhang, Ali et al. (2021) proposed a new procedure in homogenous drought conditions to select suitable classes for the selected region. They selected the classes that obtained maximum weights among the stations and time scales indices. However, these mentioned studies propagated SSP over the selected periods for varying drought categories regardless considering their spatial and temporal behaviour. Therefore, the current study has proposed STWJADI, which considers the spatiotemporal weights of varying drought categories of the region. The flowchart of the STWJADI is given in Figure 2. The obtained information of the STWJADI gives useful and inclusive information for drought characterization in the selected region. Further, the weights obtained from STTSSWS for various drought categories are used to compute STWJADI. The weights obtained from STTSSWS are propagated over the selected drought indices at a 1-month time scale. The propagation of the drought categories over the three indices is achieved according to Niaz, Zhang, Ali et al. (2021). The drought categories among three indices that obtain maximum weights are selected in STWJADI. More explicitly, it can be stated that the drought categories selected in STWJADI among three drought indices received maximum weights of STTSSWS in a specific month on a 1-month time scale. For example, SPEI-1, SPI-1, and SPTI-1 weights are given for all drought categories at Astor station using the STTSSWS scheme. Among these three drought indices, a class that obtains maximum weights is selected for STWJADI for the specific months. The same criteria of STWJADI are used to find the suitable vector of drought categories for every month in long time series data with a range from January 1971 to December 2017 in other selected stations.
3. Results

The time-series data of several indicators (precipitation, minimum, and maximum temperature) are used for the current analysis. The data of the indicators are collected from the six stations in the Northern region. The behaviour of the indicators observed in Bunji stations is presented in Figure 3. Similarly, the behaviour of the indicators can be observed from other stations. However, due to the reappearance of the multiple graphs, the climate of Bunji station is presented. The standardization of

Figure 2. Flowchart of the proposed STWJADI. Initially, in the STWJADI we started with three drought indices. The selection of the indices is based on the data availability. Moreover, recently several publications used these indices for drought analysis. Therefore, based on the various publications and data availability, these indices are selected for the current analysis. After choosing the appropriate drought indices for the study area, the next step is to classify drought categories accordingly. The classification criterion was first proposed by Mckee et al. (1993); however, several researchers have recently modified it according to their requirements. In the current research, the criterion proposed by Li et al. (2015) is adopted for the drought classification. Further, after the classification of the varying drought categories to the selected time series data, the SSP is used to observe the long-term behaviour of the specific drought category. The observed SSP for varying drought classes is used for the STTSSWS. The obtained information from STTSSWS for various drought classes is used to develop STWJADI. Finally, a new vector of drought classes based on three selected drought indices is computed, named as STWJADI. Information computed from STWJADI can be employed for monitoring drought more comprehensively and precisely and used for drought risk managing, drought early warning system, and preparedness and mitigation.

3. Results

The time-series data of several indicators (precipitation, minimum, and maximum temperature) are used for the current analysis. The data of the indicators are collected from the six stations in the Northern region. The behaviour of the indicators observed in Bunji stations is presented in Figure 3. Similarly, the behaviour of the indicators can be observed from other stations. However, due to the reappearance of the multiple graphs, the climate of Bunji station is presented. The standardization of
the selected drought indices is finalized by applying various probability distributions. The selected stations of the region provide more and less similar information across the indices. However, the distributions standardizing the indices can vary in selected stations. The choices for the appropriate probability distributions for the selected stations are based on the Bayesian Information Criterion (BIC) values. The distribution that has a minimum BIC value according to the climatic conditions of the station at a 1-month time scale is selected for the standardizations. For example, for SPI-1, the 3p Weibull distribution best fits the Astor station at scale-1. The BIC of 3p Weibull distribution is $-1036.5$, which is considered minimum among other BIC values of the distributions at scale-1. Based on the minimum value of the BIC 3p Weibull is considered best-fitted distribution. Moreover, for SPI-1, in Bunji station BIC value of the 3p Weibull distribution is $-1031.0$, the minimum among all other distributions. Hence, 3p Weibull is an appropriate choice for the standardization; therefore, it is selected for the standardization of Bunji station. In Gilgit and Skardu 3p Weibull distribution has BIC values $-1097$ and $-735.1$, respectively. These values are minimum among other BIC values; therefore, the 3p Weibull distribution is selected in both stations (Gilgit and Skardu). Further, 4p Beta distribution has minimum BIC values for Gupis and Chilas. For Gupis, 4p Beta has BIC value $-788.7$, and for Chilas it has BIC value $-805.6$. Moreover, based on the minimum values of BIC the distributions (Trapezoidal, Johnson SB, 3p Weibull, etc.) are selected for the standardization on varying stations and indices (SPEI and SPTI) (Table 1). Further, the drought indices (SPEI, SPI, and SPTI) are used to classify drought severity. Li et al. (2015) defined various levels of drought severity. The present study used criteria proposed by (Li et al. 2015) to classify varying drought categories. For example, the SDI (SPEI, SPI, SPTI)
and SPEI) value $> -2$ and $\leq -1.5$ indicates the SD category, and ND is categorized by value (SDI $> -1$ and SDI $\leq 1$) and greater than two categorizes as the extreme wet state. Further, the condition categorized by SDI $< 1.5$ and SDI $\leq 2$ indicates that the Severely Wet, SDI $> 1$ and SDI $\leq 1.5$ shows Median Wet, the Extremely Dry condition occurs when SDI $\geq 2$.

Hence, several distributions are used to standardize the time series data of selected indicators. Three indices (SPEI, SPI, and SPTI) are quantified for drought classification. The quantified values of SPI observed in several months of the selected years in the Bunji station are presented in Figure 4. The other stations and indices can be delivered accordingly based on the same rationale. Further, the classified values of the indices are used for the calculation of STTSSWS. The STTSSWS provides spatiotemporal information comprehensively for several drought classes. The selected drought categories contain the spatiotemporal information of the designated region. The obtained spatiotemporal outcomes give more accurate information about the severity of the drought. Further, the monthly spatiotemporal weights based on STTSSWS calculated for varying drought categories in selected stations for 2017 using SPI-1 are

Table 1. The selected probability distribution of SPEI-1, SPI-1, and SPTI corresponding to their BIC values for selected stations.

| Index  | SPI   | BIC     | Distribution   | SPI   | BIC     | Distribution   | SPI   | BIC     | Distribution   |
|--------|-------|---------|----------------|-------|---------|----------------|-------|---------|----------------|
| Astore | SPEI-1| -710.1  | Trapezoidal    | SPI-1 | -1036.5 | 3p Weibull     | SPEI-1| -483.5  | 3p Weibull     |
| Skardu | SPEI-1| -664.6  | Trapezoidal    | SPI-1 | -735.1  | 3p Weibull     | SPI-1 | -590.1  | Johnson SB     |
| Gilgit | SPEI-1| -1213.2 | Johnson SB     | SPI-1 | -1097.4 | 3p Weibull     | SPI-1 | -164.4  | 3p Weibull     |
| Chilas | SPEI-1| -594.7  | Johnson SB     | SPI-1 | -805.6  | 4p Beta       | SPI-1 | -275.4  | 3p Weibull     |
| Gupis  | SPEI-1| -977.6  | Johnson SB     | SPI-1 | -788.7  | 4p Beta       | SPI-1 | -374.2  | 4p Beta       |
| Bunji  | SPEI-1| -1248.4 | Johnson SB     | SPI-1 | 1031.0  | 3p Weibull    | SPI-1 | -188.38 | 3p Weibull     |

Figure 4. The SPI values observed in various months of selected years in Bunji station are presented. The SPI values have varying behaviour in various months of the selected time series data. It can be observed that most of the droughts occurred in the last months of every year (from 1971 to 2017). The wet conditions can be observed between January (Jan) to June (Jun). The rainy season of the Bunji can be perceived from the results. Further, to avoid multiple figures, the obtained information for Bunji is presented; however, the information obtained from other stations can be presented accordingly.
presented in Figure 5. The spatiotemporal weights for 2017, obtained by using SPEI-1 for numerous drought categories in selected stations, are presented in Figure 6. The obtained weights from STTSSWS for other stations can be presented accordingly. For SPEI-1 at January 2017, in Astor, ND received a weight by (0.1379), and in Bunji, it received a weight of 0.2569. In January, the weight of ND in Bunji station is maximum among other stations, which shows that the ND is most likely to occur in this station among the other stations for SPEI-1. Further, in April, EW occurred in Skardu station that received a weight 0.0294. Moreover, drought categories in any stations and months and their weights can be observed accordingly.
data mining and decision-making (Niaz, Hussain et al. 2020). Using multiple indices for the homogeneous stations becomes problematic and underpins the development of new methods that accumulate information comprehensively from the several indices. Therefore, the STWJADI is proposed to obtain precise information from the selected homogenous stations. STWJADI contains the comprehensive spatiotemporal information of the three selected drought indices.

Moreover, using STWJADI, in January, for the Skardu station, at the 1-month time scale, the ND brings a value of 0.3024. The value indicates that the ND is most likely to occur in January for the Skardu station. However, for January, the ND has a minimum value of 0.1379 in Astor station. That means in Astor station, ND has very less likely to occur. Further, the various behaviour of ND occurrences can be observed in other months. It is important to mention that the outcomes of the year 2017 are only presented (Table 3); the remaining results are achieved to avoid the complexity of showing results. However, using STWJADI, the behaviour of drought categories in other years can be observed on the same rationale. Furthermore, the temporal behaviour of SPEI-1, SPI-1, SPTI-1, and STWJADI at a 1-month time scale for Astor is presented in Figure 7. The temporal behaviour SPEI-1, SPI-1, SPTI-1, and STWJADI for Bunji station can be observed in Figure 8. Figure 9 presents the temporal behaviour of the indices for Gupis station. The STWJADI with SPEI-1, SPI-
Table 2. The weights for various months ['Jan (January), Feb (February), Mar (March), Apr (April), May, Jun (June), Jul (July), Aug (August), Sep (September), Oct (October), Nov (November), and Dec (December)'] of the year 2017 using SPTI-1 for various drought categories at six selected stations are provided.

| Station | Astor | Bunji | Gupis | Chilas | Gilgit | Skardu |
|---------|-------|-------|-------|--------|--------|--------|
| Month   | Category | Weight | Category | Weight  | Category | Weight  | Category | Weight  | Category | Weight  | Category | Weight |
| Jan     | SD     | 0.0254 | MD     | 0.0678 | MD      | 0.1320 | ND       | 0.2392 | ND       | 0.2332 | ND       | 0.3024 |
| Feb     | SD     | 0.0226 | ND     | 0.2089 | MD      | 0.1161 | ND       | 0.2062 | ND       | 0.1913 | ND       | 0.2548 |
| Mar     | ND     | 0.2443 | MD     | 0.0542 | ND      | 0.1964 | ND       | 0.2331 | MD       | 0.0540 | ND       | 0.2181 |
| Apr     | MW     | 0.0817 | ND     | 0.4181 | MW      | 0.0776 | EW       | 0.0198 | SW       | 0.0414 | ND       | 0.3615 |
| May     | ND     | 0.1457 | ND     | 0.1820 | ND      | 0.1711 | ND       | 0.1704 | ND       | 0.2015 | ND       | 0.1293 |
| Jun     | ND     | 0.1692 | ND     | 0.1663 | ND      | 0.1915 | ND       | 0.1649 | ND       | 0.1645 | ND       | 0.1436 |
| Jul     | ND     | 0.1632 | ND     | 0.1724 | ND      | 0.1706 | ND       | 0.1706 | ND       | 0.1723 | ND       | 0.1509 |
| Aug     | ND     | 0.1594 | ND     | 0.1736 | ND      | 0.1847 | ND       | 0.1616 | ND       | 0.1732 | ND       | 0.1475 |
| Sep     | ND     | 0.1757 | ND     | 0.1826 | ND      | 0.1636 | ND       | 0.1588 | ND       | 0.1709 | ND       | 0.1484 |
| Oct     | SD     | 0.0192 | MW     | 0.0803 | ND      | 0.2850 | ND       | 0.3072 | MD       | 0.0910 | ND       | 0.2173 |
| Nov     | SD     | 0.0352 | MD     | 0.1653 | MD      | 0.2346 | MD       | 0.1316 | MD       | 0.1362 | ND       | 0.2971 |
| Dec     | ND     | 0.2069 | MD     | 0.0739 | ND      | 0.2065 | ND       | 0.2596 | MD       | 0.0748 | ND       | 0.1784 |

The weights for SPTI-1 are presented in tabular form, and the results of other selected drought indices (SPEI and SPI) can be provided similarly. Using SPTI-1, the varying drought categories receive various weights in selected stations for the selected year. For instance, in Astor, in December, ND occurs that receive spatiotemporal weight by 0.2069. In Bunji of December, the MD occurs that receive the spatiotemporal weight of 0.0739. In Bunji station, MD received a minimum weight of 0.0678 in Jan. Further, the behaviour of spatiotemporal weights for varying drought classes in several stations of various months of 2017 can be observed accordingly.
Table 3. Monthly weights of 2017 using STWAJDI for various drought categories at six selected stations.

| Station | Month | STWJADI | Category | Weight | STWJADI | Category | Weight | STWJADI | Category | Weight |
|---------|-------|---------|----------|--------|---------|----------|--------|---------|----------|--------|
| Astore  | Jan   | 0.2741  | ND       | 0.1379 | 0.9796  | ND       | 0.2569 | 0.7679  | ND       | 0.1697 |
|         | Feb   | 0.0829  | ND       | 0.1672 | 0.2629  | ND       | 0.2126 | 0.4871  | ND       | 0.1391 |
|         | Mar   | -0.3434 | ND       | 0.2443 | 0.1045  | ND       | 0.1435 | -0.6169 | ND       | 0.1964 |
|         | Apr   | 1.4038  | MW       | 0.0817 | 0.9377  | ND       | 0.7149 | 0.3163  | ND       | 0.2348 |
|         | May   | -0.8214 | ND       | 0.2056 | 0.5504  | ND       | 0.1820 | 0.7708  | ND       | 0.1878 |
|         | Jun   | -0.5360 | ND       | 0.1692 | -1.3982 | ND       | 0.1925 | -0.2883 | ND       | 0.1959 |
|         | Jul   | -0.1857 | ND       | 0.1789 | 0.8192  | ND       | 0.2072 | 0.7872  | ND       | 0.1978 |
|         | Aug   | -0.1967 | ND       | 0.1794 | 0.7181  | ND       | 0.2221 | 0.8873  | ND       | 0.1847 |
|         | Sep   | -0.7888 | ND       | 0.1852 | 0.2824  | ND       | 0.1848 | 0.2467  | ND       | 0.1636 |
|         | Oct   | -0.4409 | ND       | 0.1644 | 0.0387  | ND       | 0.1645 | -0.2883 | ND       | 0.3256 |
|         | Nov   | -1.8044 | SD       | 0.1815 | -1.2806 | MD       | 0.1848 | -1.1305 | MD       | 0.2346 |
|         | Dec   | -0.9624 | ND       | 0.2069 | 0.9475  | ND       | 0.2373 | -0.0621 | ND       | 0.3846 |
| Bunji   | Jan   |         |          |        |         |          |        |         |          |        |
|         | Feb   |         |          |        |         |          |        |         |          |        |
|         | Mar   |         |          |        |         |          |        |         |          |        |
|         | Apr   |         |          |        |         |          |        |         |          |        |
|         | May   |         |          |        |         |          |        |         |          |        |
|         | Jun   |         |          |        |         |          |        |         |          |        |
|         | Jul   |         |          |        |         |          |        |         |          |        |
|         | Aug   |         |          |        |         |          |        |         |          |        |
|         | Sep   |         |          |        |         |          |        |         |          |        |
|         | Oct   |         |          |        |         |          |        |         |          |        |
|         | Nov   |         |          |        |         |          |        |         |          |        |
|         | Dec   |         |          |        |         |          |        |         |          |        |
| Gupis   | Jan   | -0.3254 | ND       | 0.2566 | -0.2296 | ND       | 0.2672 | -0.0381 | ND       | 0.3024 |
|         | Feb   | 0.8075  | ND       | 0.2175 | 0.2014  | ND       | 0.2179 | -0.5366 | ND       | 0.2548 |
|         | Mar   | -0.0695 | ND       | 0.2331 | 0.1447  | ND       | 0.1411 | -0.3096 | ND       | 0.2325 |
|         | Apr   | 1.3240  | MW       | 0.0401 | 0.6436  | ND       | 0.2322 | 0.7164  | ND       | 0.3615 |
|         | May   | -0.8617 | ND       | 0.1900 | 0.8382  | ND       | 0.2015 | -0.9650 | ND       | 0.1781 |
|         | Jun   | -1.3619 | MD       | 0.1899 | -1.0659 | MD       | 0.1952 | -0.8574 | ND       | 0.1653 |
|         | Jul   | 0.1366  | ND       | 0.1948 | -1.0312 | MD       | 0.1827 | -0.2401 | ND       | 0.1971 |
|         | Aug   | 0.2058  | ND       | 0.1823 | 0.3864  | ND       | 0.2014 | -0.8895 | ND       | 0.1866 |
|         | Sep   | -0.4873 | ND       | 0.1853 | -0.3957 | ND       | 0.1815 | -0.4748 | ND       | 0.1848 |
|         | Oct   | -0.9993 | ND       | 0.3072 | -0.9569 | ND       | 0.3396 | -0.3366 | ND       | 0.2173 |
|         | Nov   | 0.6265  | ND       | 0.1719 | 0.6878  | ND       | 0.1655 | -0.3366 | ND       | 0.2971 |
|         | Dec   | -0.9757 | ND       | 0.2596 | 0.9538  | ND       | 0.2683 | -0.5264 | ND       | 0.1784 |

The specific year 2017 is selected for the presentations to avoid multiple quantities. STWAJDI finalizes the spatiotemporal information obtained from various stations and indices for 2017. Based on STWAJDI in Jan of Astore station, the weight is observed by 0.1379 for ND. Similarly, in Jan of Bunji, ND received a weight of 0.2569. In Gupis, in January, ND receives weight by 0.1697 and so on. These observed weights were highest in several stations among other drought classes and selected indices, therefore, selected in the final STWJADI. Moreover, in Dec ND in Astore station receives weight by 0.2069. In Dec, ND received weight by 0.3846 and so. The weights of other drought categories in various months and stations can be observed accordingly.

Figure 7. The temporal plots at 1-month time scale (scale-1) in Astor station.
1, and SPTI-1 at Chilas station is shown in Figure 10. The temporal behaviour of the indices for Gilgit and Skardu is shown in Figures 11 and 12, respectively. Moreover, the counts’ plots of various drought categories in selected stations obtained from the SPEI-1, SPI-1, SPTI-1, and STWJADI at a 1-month time scale are presented in Figure 13. The results obtained from STWJADI can be applicable for early warning and drought mitigation policies of the selected region.

4. Discussion

The assessment of drought impacts is complicated and, therefore, accurate and precise drought monitoring measures are required to improve drought early warning systems and mitigation policies. For this purpose, the current study is developed to
provide accurate and precise drought monitoring measures to help drought early warning systems and mitigation policies. Several authors have been working to provide accurate and precise drought monitoring measures to help drought early warning systems and mitigation policies (Hagenlocher et al. 2019; Lai et al. 2019; Guo et al. 2020; Mavromatis & Voulanas 2021). Moreover, several publications have discussed the spatiotemporal characteristics of regional droughty (Malik et al. 2012; Chenu et al. 2013; Brigadier et al. 2019; Zhou et al. 2020; Wang et al. 2020; Adedeji et al. 2020; Han et al. 2021). Further, Ali, Hussain, Faisal, Almanjahie et al. (2019) proposed a new method in the presence of homogenous drought environments to select appropriate classes for the selected region. They provided a new procedure based on Markov chain transition probabilities to select the classes that obtained maximum weights among the indices regarding the stations and time scales. Recently, Niaz, Zhang, Ali et al. (2021) proposed a steady state-based framework for
enhancing regional drought monitoring. They used SSP as a weighting scheme for propagating weights for various drought categories in the selected region. However, both mentioned studies propagated weights over the selected periods for varying drought classes regardless of spatial and temporal information. Therefore, the STWJADI is developed to obtain spatial and temporal characteristics of the region.

The proposed procedure is based on STTSSWS (Niaz, Iqbal et al., 2022). Recently, Niaz, Iqbal et al. (2022) proposed a new procedure that accumulates spatiotemporal information from various homogeneous stations. They used two indices (SPEI and SPI) in selected stations to validate their procedure. Their procedure efficiently gathers information about drought classes from the homogeneous stations. Their proposed index selects spatiotemporal information of varying classes from the homogeneous stations. However, they never worked for the indices when various indices provided similar information over the varying stations. This issue underpins the new method of accumulating information from varying indices. The current research extends the idea proposed by Niaz, Zhang, Ali et al. (2021) to obtain spatiotemporal information of drought classes from varying indices. The three indices (SPEI, SPTI, and SPI) are used in the selected stations for validation. The use of the STTSSWS to obtain spatiotemporal information about varying drought classes makes this research innovative. None of the researchers have addressed this issue before in any study.

Therefore, the use of STTSSWS in STWJADI is interesting and meaningful to the new researchers to bring more suitable drought classes among the various indices in varying stations. Further, the STTSSWS used SSP as weights of selected drought categories to assign new spatiotemporal weights for the drought categories in the selected region. The spatiotemporal weights calculated from STTSSWS are employed to compute the STWJADI. The obtained information from STWJADI can be used to monitor drought more comprehensively and precisely. Further, the STWJADI can be employed for drought risk management, drought early warning system, and preparedness and mitigation. Furthermore, the obtained spatiotemporal information of the

Figure 12. The temporal plots based on scale-1 for Skardu station.
homogeneous region limits the STWJADI to a specific homogeneous environment. Therefore, the outcomes of the STWJADI cannot be generalized to the non-homogeneous stations.

5. Conclusion

Drought is among the most multifaceted climatic phenomena due to insufficient precipitation. Therefore, accurate and efficient drought monitoring is challenging in several areas of hydrological research. In recent, SDI has been frequently used for the assessment of drought. However, using SDIs to obtain information about drought characteristics in the homogeneous region becomes problematic for data mining and decision-making. Further, the SDIs don’t provide comprehensive spatiotemporal
information about drought characteristics in the selected region. These issues underpin the development of a new procedure that comprehensively accumulates information from various indices. Therefore, this study develops a new procedure, known as the STWJADI for spatiotemporal analysis of meteorological drought variability in a homogeneous region based on SDI. The STWJADI provides comprehensive information on the homogenous region. The results of the STWJADI bring precise and accurate information for drought characterization and can be used in early warning and drought mitigation policies of the selected region. Moreover, the inclusion of other indicators and indices in the STWJADI can significantly enhance the efficiency of drought monitoring in the selected region.

**Acknowledgments**

The author extends his appreciation to the Deanship of Scientific Research at King Khalid University for funding this work under grant number (RGP.2/34/43).

**ORCID**

Dost Muhammad Khan [http://orcid.org/0000-0002-3919-8136](http://orcid.org/0000-0002-3919-8136)
Ijaz Hussain [http://orcid.org/0000-0002-1586-1503](http://orcid.org/0000-0002-1586-1503)

**References**

Adedeji O, Olusola A, James G, Shaba HA, Orimoloye IR, Singh SK, Adelabu S. 2020. Early warning systems development for agricultural drought assessment in Nigeria. Environ Monit Assess. 192(12):1–21.

Adnan M, Nabi G, Poomee MS, Ashraf A. 2017. Snowmelt runoff prediction under changing climate in the Himalayan cryosphere: a case of Gilgit River Basin. Geosci Front. 8(5):941–949.

Afshar MH, Bulut B, Duzenli E, Amjad M, Yilmaz MT. 2022. Global spatiotemporal consistency between meteorological and soil moisture drought indices. Agric for Meteorol. 316:108848.

Ahmadalipour A, Moradkhani H, Castelletti A, Magliocca N. 2019. Future drought risk in Africa: integrating vulnerability, climate change, and population growth. Sci Total Environ. 662:672–686.

Alahacon N, Edirisinghe M. 2022. A comprehensive assessment of remote sensing and traditional based drought monitoring indices at global and regional scale. Geomatics Nat Hazards Risk. 13(1):762–799.

Aldunce P, Araya D, Sapiain R, Ramos I, Lillo G, Urquiza A, Garreaud R. 2017. Local perception of drought impacts in a changing climate: the mega-drought in central Chile. Sustainability. 9(11):2053.

Ali SHB, Shafqat MN, Eghani SAMAS, Shah STA. 2019. Trends of climate change in the upper Indus basin region, Pakistan: implications for cryosphere. Environ Monit Assess. 191(2):51.

Ali Z, Almanjahie IM, Hussain I, Ismail M, Faisal M. 2020. A novel generalized combinative procedure for multi-scalar standardized drought indices—the long average weighted joint aggregative criterion. Tellus A: Dynamic Meteorology and Oceanography. 72(1):1–23.

Ali Z, Hussain I, Faisal M, Almanjahie IM, Ahmad I, Khan DM, Grzegorczyk M, Qamar S. 2019. A probabilistic weighted joint aggregative drought index (PWJADI) criterion for drought monitoring systems. Tellus A: Dyn Meteorol Oceanogr. 71(1):1588584.
Ali Z, Hussain I, Faisal M, Nazir HM, Abd-el Moemen M, Hussain T, Shamsuddin S. 2017. A novel multi-scalar drought index for monitoring drought: the standardized precipitation temperature index. Water Resour Manage. 31(15):4957–4969.

Ali Z, Hussain I, Faisal M, Shoukry AM, Gani S, Ahmad I. 2019. A framework to identify homogeneous drought characterization regions. Theor Appl Climatol. 137(3-4):3161–3172.

Alsafadi K, Al-Ansari N, Mokhtar A, Mohammed S, Elbeltagi A, Sammen SS, Bi S. 2022. An evapotranspiration deficit-based drought index to detect variability of terrestrial carbon productivity in the Middle East. Environ Res Lett. 17(1):014051.

Angelidis P, Maris F, Kotsosinou N, Hrissanthou V. 2012. Computation of drought index SPI with alternative distribution functions. Water Resour Manage. 26(9):2453–2473.

Anjum SA, Wang L, Salhab J, Khan I, Saleem MF. 2010. An assessment of drought extent and impacts in agriculture sector in Pakistan. J Food Agr Environ. 8(3/4 (part 2)):1359–1363.

Ayugi B, Eresanya EO, Onyango AO, Ogou FK, Okoro EC, Okoye CO, … Ongoma V. 2022. Review of meteorological drought in Africa: historical trends, impacts, mitigation measures, and prospects. Pure Appl Geophys. 179, 1365–1386.

Brigadier LIBANDA, Zheng M, Chilekana NGONGA. 2019. Spatial and temporal patterns of drought in Zambia. J Arid Land. 11(2):180–191.

Cao S, Zhang L, He Y, Zhang Y, Chen Y, Yao S, Yang W, Sun Q. 2022. Effects and contributions of meteorological drought on agricultural drought under different climatic zones and vegetation types in Northwest China. Sci Total Environ. 821:153270.

Chenu K, Dehirmfard R, Chapman SC. 2013. Large-scale characterization of drought pattern: a continent-wide modelling approach applied to the Australian wheatbelt - spatial and temporal trends. New Phytol. 198(3):801–820.

Corlett RT. 2016. The impacts of droughts in tropical forests. Trends Plant Sci. 21(7):584–593.

Dikshit A, Pradhan B, Alamri AM. 2021. Long lead time drought forecasting using lagged climate variables and a stacked long short-term memory model. Sci Total Environ. 755:142638.

Elhoussaoui A, Zaagane M, Benaabidate L. 2021. Comparison of various drought indices for assessing drought status of the Northern Mekerra watershed, Northwest of Algeria. Arab J Geosci. 14(10):1–8.

Fung KF, Huang YF, Koo CH, SohYW. 2020. Drought forecasting: a review of modelling approaches 2007–2017. Journal of Water and Climate Change. 11(3):771–799.

Gebrehiwot T, Van der Veen A, Maathuis B. 2011. Spatial and temporal assessment of drought in the Northern highlands of Ethiopia. Int J Appl Earth Obs Geoinf. 13(3):309–321.

Ghaffar A, Javid M. 2011. Impact of global warming on monsoon variability in Pakistan. J Anim Plant Sci. 21(1):107–110.

Guo H, Bao A, Liu T, Jiapaer G, Ndayisaba F, Jiang L, Kurban A, De Maeyer P. 2018. Spatial and temporal characteristics of droughts in Central Asia during 1966-2015. Sci Total Environ. 624:1523–1538.

Guo Y, Huang S, Huang Q, Leng G, Fang W, Wang L, Wang H. 2020. Propagation thresholds of meteorological drought for triggering hydrological drought at various levels. Science of the Total Environment. 712:136502.

Hagenlocher M, Meza I, Anderson CC, Min A, Renaud FG, Walz Y, … Sebesvari Z. 2019. Drought vulnerability and risk assessments: state of the art, persistent gaps, and research agenda. Environmental Research Letters. 14(8):083002.

Haile GG, Tang Q, Li W, Liu X, Zhang X. 2020. Drought: progress in broadening its understanding. Wiley Interdiscip Rev: Water. 7(2):e1407.

Han Z, Huang Q, Huang S, Leng G, Bai Q, Liang H, Wang L, Zhao J, Fang W. 2021. Spatial-temporal dynamics of agricultural drought in the Loess Plateau under a changing environment: characteristics and potential influencing factors. Agric Water Manage. 244:106540.

Herbst PH, Bredenkamp D, Barker HMG. 1966. A technique for the evaluation of drought from rainfall data. J Hydrol. 4:264–272.

Hoque MAA, Pradhan B, Ahmed N. 2020. Assessing drought vulnerability using geospatial techniques in northwestern part of Bangladesh. Sci Total Environ. 705:135957.
Hussain MS, Lee S. 2014. Long-term variability and changes of the precipitation regime in Pakistan. Asia-Pacific J Atmos Sci. 50(3):271–282.

Janga Reddy M, Ganguli P. 2012. Application of copulas for derivation of drought severity—duration–frequency curves. Hydrol Process. 26(11):1672–1685.

Jasim AI, Awchi TA. 2020. Regional meteorological drought assessment in Iraq. Arab J Geosci. 13(7):1–16.

Kiem AS, Johnson F, Westra S, van Dijk A, Evans JP, O’Donnell A, Rouillard A, Barr C, Tyler J, Thyer M, et al. 2016. Natural hazards in Australia: droughts. Clim Change. 139(1):37–54.

Kisi O, Gorgi AD, Zounemat-Kermani M, Mahdavi-Meymand A, Kim S. 2019. Drought forecasting using novel heuristic methods in a semi-arid environment. J Hydrol. 578:124053.

Kuwayama Y, Thompson A, Bernknopf R, Zaitchik B, Vail P. 2019. Estimating the impact of drought on agriculture using the US Drought Monitor. Am J Agr Econom. 101(1):193–210.

Lai C, Zhong R, Wang Z, Wu X, Chen X, Wang P, Lian Y. 2019. Monitoring hydrological drought using long-term satellite-based precipitation data. Science of the total environment. 649:1198–1208.

Lee JW, Hong EM, Kim JU, Jang WJ, Jung CG, Kim SJ. 2022. Evaluation of agricultural drought in South Korea using socio-economic drought information. Int J Disaster Risk Reduct. 74:102936.

Li X, Quan X, Liao Z, Bai X. 2015. Use of the standardized precipitation evapotranspiration index (SPEI) to characterize the drying trend in southwest China from 1982–2012. Remote Sensing. 7(8):10917–10937.

Mahboobeh JS, Nikoo MR, Maryam D, Mohammadali A. 2020. Evaluation of two satellite-based products against ground-based observation for drought analysis in the southern part of Iran. Nat Hazards. 102(3):1249–1267.

Malik N, Bookhagen B, Marwan N, Kurths J. 2012. Analysis of spatial and temporal extreme monsoonal rainfall over South Asia using complex networks. Clim Dyn. 39(3-4):971–987.

Mavromatis T, Voulanas D. 2021. Evaluating ERA-Interim, Agri4Cast, and E-OBS gridded products in reproducing spatiotemporal characteristics of precipitation and drought over a data poor region: the case of Greece. Intl J Climatol. 41(3):2118–2136.

McKee TB, Doesken NJ, Kleist J. 1993, January The relationship of drought frequency and duration to time scales. In Proceedings of the 8th Conference on Applied Climatology. Vol. 17, No. 22. American Meteorological Society, Boston, MA, p. 179–183.

Meza I, Siebert S, Döll P, Kusche J, Herbert C, Eyshi Rezaei E, Nouri H, Gerdener H, Popat E, Frischen J, et al. 2020. Global-scale drought risk assessment for agricultural systems. Nat Hazards Earth Syst Sci. 20(2):695–712.

Mohan S, Rangacharya NCV. 1991. A modified method for drought identification. Hydrol Sci J. 36(1):11–21.

Mukherjee S, Mishra A, Trenberth KE. 2018. Climate change and drought: a perspective on drought indices. Curr Clim Change Rep. 4(2):145–163.

Mun YS, Nam WH, Jeon MG, Kim HJ, Kang K, Lee JC, … Lee K. 2020. Evaluation of regional drought vulnerability assessment based on agricultural water and reservoirs. J Korean Soc Agr Eng. 62(2):97–109.

Naheed G, Rasul G. 2010. Projections of crop water requirement in Pakistan under global warming. Pakistan J Meteorol. 7(13):45–51.

Niaz R, Almanjahie IM, Ali Z, Faisal M, Hussain I. 2020. A Novel Framework for Selecting Informative Meteorological Stations Using Monte Carlo Feature Selection (MCFS) Algorithm. Adv Meteorol. 2020:1–13.

Niaz R, Hussain I, Ali Z, Faisal M, Elashkar EE, Shoukry AM, Gani S, Al-Deek FF. 2020. A novel spatially weighted accumulative procedure for regional drought monitoring. Tellus A: Dyn Meteorol Oceanogr. 72(1):1–13.

Niaz R, Almazah MMA, Hussain I, Filho JDP. 2021. A new framework to substantiate the prevalence of drought intensities. Theor Appl Climatol. 147(3-4):1079–1012.

Niaz R, Almazah MMA, Hussain I, Filho JDP, Al-Ansari N, Sh Sammen S. 2022. Assessing the probability of drought severity in a homogeneous region. Complexity. 2022:1–8.
Niaz R, Almazah M, Zhang X, Hussain I, Faisal M. 2021. Prediction for various drought classes using spatiotemporal categorical sequences. Complexity. 2021:1–11.
Niaz R, Hussain I, Ali Z, Faisal M. 2021. A novel framework for regional pattern recognition of drought intensities. Arab J Geosci. 14(16):1–16.
Niaz R, Hussain I, Zhang X, Ali Z, Elashkar EE, Khader JA, Soudagar SS, Shoukry AM. 2021. Prediction of drought severity using model-based clustering. Math Prob Eng. 2021:1–10.
Niaz R, Zhang X, Ali Z, Hussain I, Faisal M, Elashkar EE, Khader JA, Soudagar SS, Shoukry AM, Al-Deek FF. 2021. A new propagation-based framework to enhance competency in regional drought monitoring. Tellus A: Dyn Meteorol Oceanogr. 73(1):1–12.
Niaz R, Zhang X, Iqbal N, Almazah M, Hussain T, Hussain I. 2021. Logistic regression analysis for spatial patterns of drought persistence. Complexity. 2021:1–13.
Niaz R, Almazah MM, Hussain I, Faisal M, Al-Rezami AY, Naser MA. 2022. A new comprehensive approach for regional drought monitoring. PeerJ. 10:e13377.
Niaz R, Iqbal N, Al-Ansari N, Hussain I, Elsherbini Elashkar E, Shamshoddin Soudagar S, Gani SH, Mohamad Shoukry A, Sh Sammen S. 2022. A new spatiotemporal two-stage standardized weighted procedure for regional drought analysis. PeerJ. 10:e13249.
Noguera I, Vicente Serrano SM, Dominguez-Castro F, Reig F. 2022. Assessment of parametric approaches to calculate the Evaporative Demand Drought Index. Intl J Climatol. 42(2):834–849.
Okpara JN, Ogunjobi KO, Adefisan EA. 2022. Developing objective dry spell and drought triggers for drought monitoring in the Niger Basin of West Africa. Nat Hazards. 1:1–28.
Pontes Filho JD, Portela MM, Marinho de Carvalho Studart T, Souza Filho FDA. 2019. A continuous drought probability monitoring system, CDPMS, based on copulas. Water. 11(9):1925.
Pontes Filho JD, Souza Filho FDA, Martins ESPR, Studart TMDC. 2020. Copula-based multivariate frequency analysis of the 2012–2018 drought in Northeast Brazil. Water. 12(3):834.
Quandt A. 2021. Coping with drought: narratives from smallholder farmers in semi-arid Kenya. Int J Disaster Risk Reudct. 57:102168.
Quiring SM. 2009. Monitoring drought: an evaluation of meteorological drought indices. Geogr Compass. 3(1):64–88.
Rasul G, Chaudhry QZ, Mahmood A, Hyder KW, Dahe Q. 2011. Glaciers and glacial lakes under changing climate in Pakistan. Pak J Meteorol. 8(15):1-8.
Riebsame WE, Changnon SA, Karl TR. 2019. Drought and natural resources management in the United States: impacts and implications of the 1987-89 drought. London: Routledge.
Ruwanza S, Thondhlana G, Falayi M. 2022. Research progress and conceptual insights on drought impacts and responses among smallholder farmers in South Africa: a review. Land. 11(2):159.
Saharwardi MS, Kumar P. 2022. Future drought changes and associated uncertainty over the homogenous regions of India: a multimodel approach. Intl J Climatol. 42(1):652–670.
Santos CAG, Neto RMB, da Silva RM, dos Santos DC. 2019. Innovative approach for geospatial drought severity classification: a case study of Paraíba state, Brazil. Stoch Environ Res Risk Assess. 33(2):545–562.
Santos JF, Pulido-Calvo I, Portela MM. 2010. Spatial and temporal variability of droughts in Portugal. Water Resour Res. 46(3)
Savari M, Damaneh HE, Damaneh HE. 2022. Drought vulnerability assessment: solution for risk alleviation and drought management among Iranian farmers. Int J Disaster Risk Reudct. 67:102654.
Schwartz C, Ellenburg WL, Mishra V, Mayer T, Griffin R, Qamer F, Matin M, Tadesse T. 2022. A statistical evaluation of Earth-observation-based composite drought indices for a localized assessment of agricultural drought in Pakistan. Int J Appl Earth Obs Geoinf. 106:102646.
Spinoni J, Barbosa P, De Jager A, McCormick N, Naumann G, Vogt JV, Magni D, Masante D, Mazzeschi M. 2019. A new global database of meteorological drought events from 1951 to 2016. J Hydrol Reg Stud. 22:100593.
Stagge JH, Tallaksen LM, Gudmundsson L, Van Loon AF, Stahl K. 2015. Candidate distributions for climatological drought indices (SPI and SPEI). Int J Climatol. 35(13):4027–4040.

Stewart WJ. 2009. Probability, Markov chains, queues, and simulation. Princeton, NJ: Princeton University Press.

Van Loon AF, Stahl K, Di Baldassarre G, Clark J, Rangecroft S, Wanders N, Gleeson T, Van Dijk AIJM, Tallaksen LM, Hannaford J, et al. 2016. Drought in a human-modified world: reframing drought definitions, understanding, and analysis approaches. Hydrol Earth Syst Sci. 20(9):3631–3650.

Vicente-Serrano SM, Beguería S, Lopez-Moreno JI. 2010. A multi-scaler drought index sensitive to global warming: the standardized precipitation evapotranspiration index. J Climate. 23(7):1696–1718.

Vicente-Serrano SM, Lopez-Moreno J-I, Beguería S, Lorenzo-Lacruz J, Sanchez-Lorenzo A, García-Ruiz JM, Azorin-Molina C, Morán-Tejeda E, Revuelto J, Trigo R, et al. 2014. Evidence of increasing drought severity caused by temperature rise in southern Europe. Environ Res Lett. 9(4):044001.

Vicente-Serrano SM, Van der Schrier G, Beguería S, Azorin-Molina C, Lopez-Moreno JI. 2015. Contribution of precipitation and reference evapotranspiration to drought indices under different climates. J Hydrol. 526:42–54.

Vicente-Serrano SM, Quiring SM, Pena-Gallardo M, Yuan S, Dominguez-Castro F. 2020. A review of environmental droughts: Increased risk under global warming? Earth-Science Reviews. 201:102953.

Vogt, J. V., & Somma, F. (Eds.) 2013. Drought and drought mitigation in Europe (Vol. 14). Berlin: Springer Science & Business Media.

Wang W, Ertsen MW, Svoboda MD, Hafeez M. 2016. Propagation of drought: from meteorological drought to agricultural and hydrological drought. Adv Meteorol. 2016:1–5.

Wang X, Zhuo L, Li C, Engel BA, Sun S, Wang Y. 2020. Temporal and spatial evolution trends of drought in northern Shaanxi of China: 1960–2100. Theor Appl Climatol. 139(3-4):965–979.

Wu J, Chen X, Yuan X, Yao H, Zhao Y, AghaKouchak A. 2021. The interactions between hydrological drought evolution and precipitation-streamflow relationship. J Hydrol. 597:126210.

Yamada TJ, Takeuchi D, Farukh MA, Kitano Y. 2016. Climatological characteristics of heavy rainfall in northern Pakistan and atmospheric blocking over western Russia. J Clim. 29(21):7743–7754.

Zargar A, Sadiq R, Naser B, Khan FI. 2011. A review of drought indices. Environ Rev. 19(NA):333–349. (NA),

Zhai L, Feng Q. 2009. Spatial and temporal pattern of precipitation and drought in Gansu Province. Nat Hazards. 49(1):1–24.

Zhang L, Xiao J, Li J, Wang K, Lei L, Guo H. 2012. The 2010 spring drought reduced primary productivity in southwestern China. Environ Res Lett. 7(4):045706.

Zhou H, Zhou W, Liu Y, Yuan Y, Huang J, Liu Y. 2020. Identifying spatial extent of meteorological droughts: an examination over a humid region. J Hydrol. 591:125505.