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Comparative Analysis of Multiple Drought Indices for the Hindukush Region in Pakistan

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ABSTRACT

Drought is an enduring hydro-climatic challenge in Pakistan's Hindukush region, where fragile agro-ecological systems are particularly vulnerable to fluctuations in precipitation and evapotranspiration. The lack of a universally applicable indicator and the regional variety of drought consequences necessitate assessing multiple indices to identify the most suitable index for the particular environmental dynamics of the area. This study undertakes a comparative analysis of four drought indices: the Standardized Precipitation Index (SPI), Agricultural Standardized Precipitation Index (aSPI), Reconnaissance Drought Index (RDI), and Effective Reconnaissance Drought Index (eRDI) to identify the most effective index or indices for drought assessment in the region. Using the long-term precipitation and temperature (minimum and maximum) record (1982–2022) from the National Aeronautics and Space Administration'sModern-EraRetrospectiveAnalysis for Research and Applications, Version 2 (NASA's MERRA-2) dataset, selected indices were calculated across multiple temporal scales (3, 6, 9, and 12 months). Statistical techniques, including Pearson correlation coefficient and Two-way ANOVA (Analysis of Variance), were employed to analyze inter-index consistency and temporal performance. The correlation coefficients between indices were notably high ($r = 0.83–0.97$, $p < 0.01$), indicating strong agreement, particularly between SPI and aSPI, and between RDI and eRDI. Two-way ANOVA results revealed statistically significant differences across indices and timescales ($F = 16.42$, $p < 0.001$), confirming that both index type and temporal resolution influence drought characterization. The study highlights key drought years, including the prolonged 1998–2002 event and shorter events in 2015, 2018, and 2019. Notably, aSPI demonstrated enhanced sensitivity to agricultural drought due to its emphasis on effective precipitation, while eRDI effectively captured climate-induced drought variability. The findings recommend a combined application of aSPI and eRDI for robust drought monitoring in this climate and ecologically sensitive region.

Keywords: Drought indices; MERRA-2; Two-way ANOVA; Hindukush range; Pakistan

INTRODUCTION

Drought is among the most catastrophic hydro-meteorological calamities triggered by an extended dry period due to below-average rainfall amounts, resulting in damage to crops, water resources, economies, and human lives over an extended period (Aryal et al., 2022). The region experiences drought when there is below-normal rainfall, vigorous evapotranspiration, high aquifer depletion, or a combination of these variables (Zarei & Moghimi, 2019).Drought starts slowly and spreads over a large area, affecting an area for weeks, months, or even years (Jenkins & Warren, 2015).It is among the extremely hazardous environmental disasters with a catastrophic impact on wildlife, rangeland plants, agricultural activities, human beings, surface and water table, the environment, and socio-economic sectors.There is not a single broad description of drought hazard, as it is one of the most complex natural hazards(Vangelis, Tigkas, & Tsakiris, 2013).A meteorological drought is an early stage of accumulating precipitation deficit that persists over time, taking into account above-normal temperatures, high winds, and low relative humidity. All types of drought begin with a deficit in precipitation over time and/or space, and they have a significant impact on socioeconomic and environmental cycles(Yihdego, Vaheddoost, & Al-Weshah, 2019).Given its complex nature and far-reaching consequences, drought remains a critical challenge requiring integrated monitoring, early warning systems, and adaptive management strategies to mitigate its multifaceted impacts.

To date, various types of drought hazards have been identified and characterized according to aspecific disciplinary perspective.Generally, droughthazards are commonly classified into four categories:meteorological, agricultural, hydrological, and socioeconomic(Heim Jr, 2002; Öz, Özelkan, & Tatlı, 2024).These four categories may be divided into two groups: the first to third approaches focus on measuring drought as a physical phenomenon, while the fourth discusses drought in terms of water supply and demand, tracking the effects of water scarcity as it spreads across socioeconomic sectors.In addition to these,ecological drought is a novel type of drought that takes into account the environmental, climatic, hydrological, socioeconomic, and cultural components of drought (Crausbay et al., 2017). Another important aspect of drought is groundwater drought, which is crucial because it causes a lower groundwater level and discharge to surface water bodies (Peters, 2003). Research on drought has been significant globally in recent decades due to the rising intensity, unpredictability, and geographic character(Wei et al., 2021).Several drought indices have been developed to quantify different aspects of drought, such as meteorological, hydrological, and agricultural conditions, allowing for more accurate monitoring and comparison across time and regions(Burka, Biazin, & Bewket, 2023).

Drought indices are the most often used method for characterizing drought. Over the past few decades, a variety of drought indices have been developed and utilized for drought hazard assessment(Hailesilassie, Ayenew, & Tekleab, 2023; Yisehak & Zenebe, 2021). Typically, a drought index value is a single number that helps in decision-making on drought identification and effect mitigation based on severity ranges(Alahacoon & Edirisinghe, 2022). Standardized Precipitation Index (SPI), Agricultural Standardized Precipitation Index (aSPI), Reconnaissance Drought Index (RDI), Effective Reconnaissance Drought Index (eRDI),and Standardized Precipitation Evapotranspiration Index (SPEI) are the most widely used meteorological drought indices (Wable, Jha, & Shekhar, 2019). Globally, more than 150 indices have been in use to evaluate, measure, and contrast the length and severity of droughts (Ortiz-Gómez et al., 2022). In several regions, a multiple drought index approach has been employed due to varying climatic circumstances.This multi-drought index approach permits a more comprehensive understanding of drought situations, which can change significantly from one area to another based on that area's climate conditions. Therefore multi-drought index approach is employed for a specific area because a single index does not give complete drought information (Adnan et al., 2018).A variety of drought indices are used in Pakistan to measure drought; however, the SPI, RDI, and eRDI are the most appropriate indices for capturing the severity, duration, and effects of drought across various climatic zones(Adnan & Ullah, 2022).Moreover, these three drought indices (SPI, RDI, and aSPI) were also effectively used in Khyber Pakhtunkhwa province of Pakistan to assess the drought situation(Durrani, 2024).

Many drought indices are utilized throughout the region since a single drought index cannot give complete drought information due to regional climate differences. These drought indices are used to determine the drought severity and its spatiotemporal extent (Bayissa et al., 2018). Drought indices give a complete picture of drought and are extremely valuable for monitoring it. The selection of drought indices is particularly critical for successful drought monitoring in an area (Yihdego, Vaheddoost, & Al-Weshah, 2019). Some of the drought indices used by hydro-meteorological organizations are: SPI, SPEI, eRDI, aSPI, RDI, and eRDI, which are most commonly used indices around the world to monitor and follow drought conditions as recommended by the World Meteorological Organization(Adnan et al., 2018). Therefore, the careful selection and application of appropriate drought indices tailored to regional climatic conditions are essential for accurate assessment, effective monitoring, and informed decision-making in drought-prone regions.

Given the distinct characteristics of drought indices, this study aims to compare four drought indices (i.e., SPI, aSPI,RDI, and eRDI), evaluate their performance, and applicability in the Hindukush region of Pakistan. To identify the most suitable index or set of indices for the Hindukush region of Pakistan, the selected drought indices are examined across return periods of 3, 6, 9, and 12 months.Thestudy'sfindingscouldbe beneficial to national hydro-meteorological services for monitoring and early warning of drought, water resource management, and future climate change adaptation in the study region.

MATERIALS AND METHODS

Study Area

The study is concentrated in the Khyber Valley (Fig. 1), located in the northwestern part of Pakistan, and is an integrated part of the Hindukush region. The Khyber Valley has an area of 679 Km^2, with a geographical domain of 34° 06' to 34° 18'Northlatitudeand 71° 03 to 71° 15' East longitude. The valley is located 1072 meters above sea level, characterized by rugged mountainous terrain and arid conditions, making it highly susceptible to drought. The valley comprises the Tirah Mountains in the south, the Khyber hills in the center, and the Shalman mountainous ranges in the north.Precipitation in the Khyber Valley is very low, leading to water scarcity in the area. The valley received precipitation in two distinct seasons,i.e., winter and summer (Ullah et al., 2018; Ullah et al., 2023). The winter rain in Khyber Valley is caused by western disturbances originating from the Mediterranean region (Hussain et al., 2023; Abbas et al., 2023), while summer rain is linked to monsoon weather systemsarising from the Indian Ocean and the Bay of Bengal (Ullah et al., 2021; Rebi et al., 2023). The region's hydrological conditions and water system are unique due to its rocky terrain, which promotes surface runoff and limited groundwater recharge.Khyber Valley is geographically bounded by the Koh Safed range to the north, Kuram district to the south, the

Jamrod valley to the east, and Afghanistan's Nangarhar province to the west. The region's topography, limited water resources, insufficient and infrequent precipitation, along with its semi-arid, subtropical temperate climate and sparse vegetation cover, contribute to frequent drought conditions (Ullah et al., 2024).

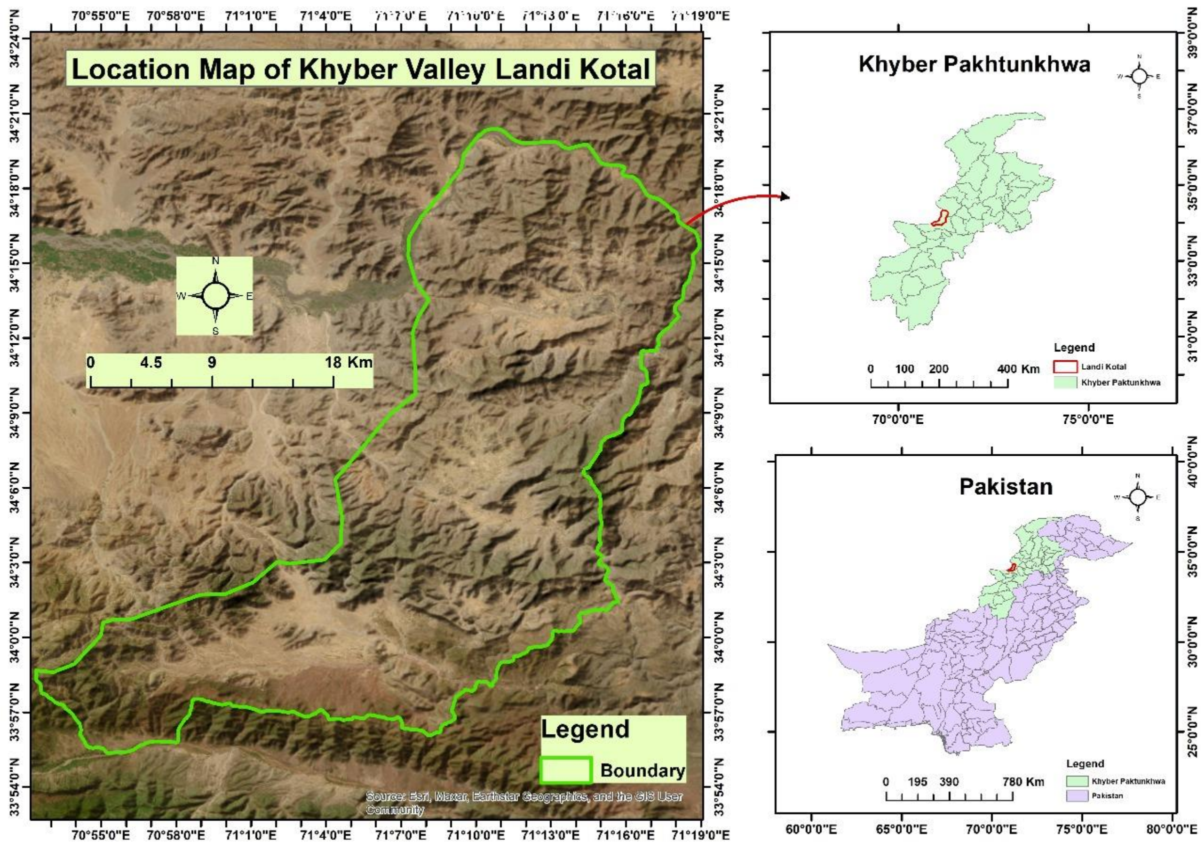

Figure 1. Location map of the Khyber Valley, Hindukush region, Pakistan

Data

This study has employed the long-term (1982-2022) Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2) monthly data of precipitation and temperature (minimum and maximum)retrieved from the National Aeronautics and Space Administration (NASA) database.The long-term (1982–2022) MERRA-2 dataset was selected due to its high temporal and geographical resolution, which offers dependable temperature and precipitation data that are necessary for precise drought analysis over long timeframes.Additionally, the drought indices calculator (DrinC) software(Vishwakarma, Choudhary, & Chauhan, 2020)is used to calculate multiple drought indices (SPI, aSPI, RDI, and eRDI) for 3, 6, 9, and 12-month periods as only short- or long-term drought periods (Tigkas et al., 2022). A flowchart, showing the overall adopted methodological framework of this study, is presented in Figure 2.

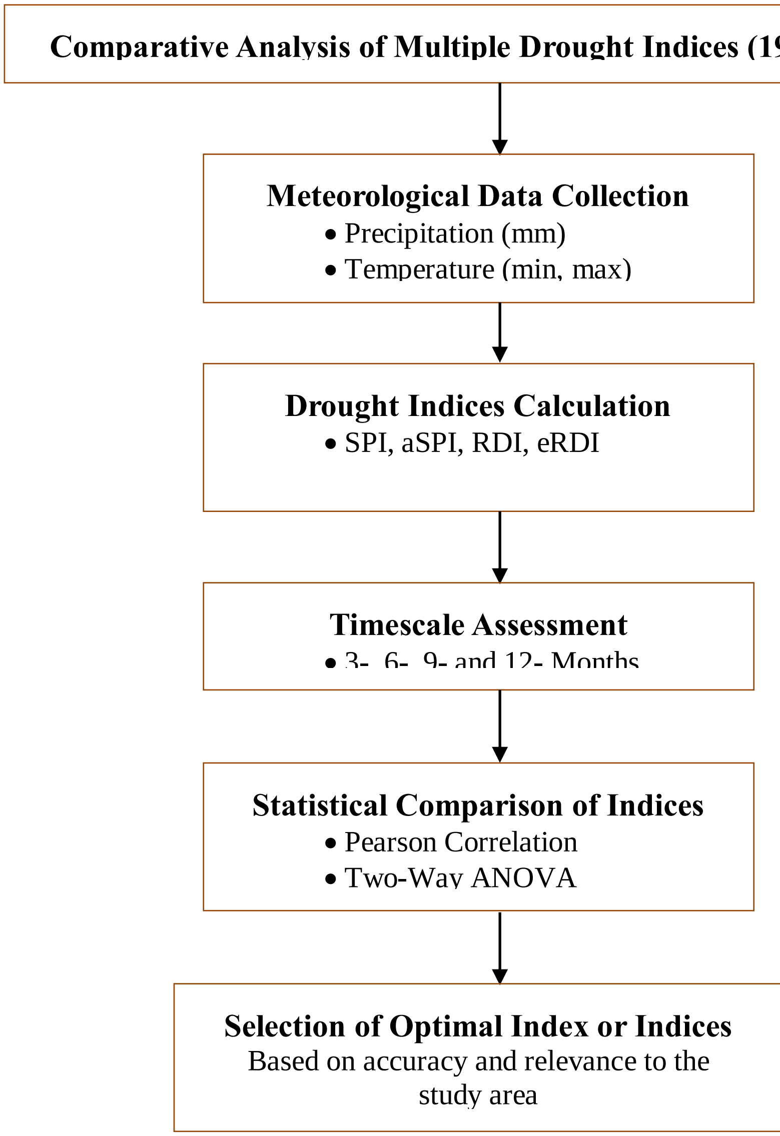

Figure 2. Flowchart of the study

Drought Indices

Standardized Precipitation Index (SPI)

The SPI was developed by McKee et al. (1993) to quantify precipitation over multiple time scales. It is a well-known and most widely used drought index in drought analysis (Li, Sha, &Wang, 2019; Tigkas, Vangelis, & Tsakiris, 2019).The SPI is defined as the number of standard deviations between observed values and the calculated long-term mean. When measuring SPI, long-term precipitation data is often converted to a probability distribution, such as the gamma distribution, and then to a normal distribution where the mean SPI is zero (Hina & Saleem, 2019). The mathematical expression is given in Equation (1).

$$\text{SPI} = \frac{X - \bar{X}}{\sigma} \quad (1)$$

Whereσ is theprecipitation standard deviation,X is the precipitation observation, and $\bar{X}$ is the precipitation long-term average (Ahmad et al., 2023).

Agricultural Standardized Precipitation Index (aSPI)

aSPI is a modified version of the SPI, which more accurately detects agricultural drought and effectively connects the severity of the drought to its impacts on vegetation, particularly in semi-arid conditions (Ahmad et al., 2023; Amognehegn et al., 2023).The aSPI calculates how much water plants can effectively consume by replacing total precipitation with effective precipitation. The quantity of water absorbed by the soil that is retained by deep crop root drainage that runs downward is known as effective precipitation (Pe) or the amount of precipitation (P) that is utilized to meet the demands of plants (Ahmad et al., 2023; Mirauda & Cirigliano, 2024).

$$Pe = P - (I + Q + DP) \quad (2)$$

where I is the intercepted precipitation, Q is the surface runoff (mm), DP is the vertical drainage beneath the root zone, and P is the total precipitation (mm) (Ahmad et al., 2023).

Reconnaissance Drought Index (RDI)

The Reconnaissance Drought Index (RDI) is a crucial metric for assessing the intensity of drought(Amognehegn et al., 2023). This measurement is based on the precipitation-to-potential evapotranspiration component ratio (Zarei, Moghimi, & Bahrami, 2019). The expression of the formula used by RDI is as follows:

The starting value of RDI (αk), which is the first expression, can be calculated for the full year or each month of the hydrological year. It is shown in an aggregated form with a monthly time step. It is determined by two variables: cumulative precipitation (P), which is measured, and potential evapotranspiration (PET), which is estimated (Tigkas, Vangelis, & Tsakiris, 2017). Equation 3 is used to calculate the beginning value (αk) of RDI for the i-th year over k months:

$$ak = \sum_{j=1}^{j=k} \text{Pij} \ / \ \sum_{j=1}^{j=k} \text{PET ij} \quad (3)$$

Here,*PETij* and *Pij*arethe precipitation and potential evapotranspiration of the j-th month of the i-thyear,respectively, and *N* is the total number of years of the available data.

Since SPI only uses precipitation data, the RDI overcomes this limitation by using both temperature and precipitation data as input data. This allows us to better understand how temperature affects water balance. PET is one of the important variables in the RDI. However, because it also evaluates the water availability, PET evaluates the atmospheric demand for water, but it is not always related to ET.

Effective Reconnaissance Drought Index (eRDI)

Tigkaset al. (2016) updated the RDI to the effective RDI (eRDI). The suggested change has improved the index's performance for agricultural drought assessments by representing a more accurate quantification of water,whichthe agricultural systems use for beneficial purposes. Effective precipitation takes the place of precipitation in the eRDI (Mohammed, 2021; Zarei, Moghimi, & Bahrami, 2019).The RDI uses PET instead of P for a specific time period (Zarei, 2018). This index is represented by the initial (RDIαk), normalized (RDIn).

$$\alpha_0^i = \sum_{i=1}^{12} Pii \; / \; \sum_{j=1}^{12} PETij \text{I =1(1) N and j =1 (1) 12} \quad (4)$$

The *PETij* and *Pij* represent rainfall and potential evapotranspiration of the *jth* month of the *ith* hydrological year, and N is the number of years.

Statistical Analysis

Pearson correlation coefficient (PCC)

In this study, the Pearson correlation coefficient (r), developed by Karl Pearson (1896),wasusedto evaluate and compare the performance of multiple drought indices (SPI, aSPI, eRDI,and RDI) across different timescales. The Pearson correlation coefficient (r) was utilized to examine the strength, accuracy, and direction of linear relationships among the selected drought indices (Wei et al., 2021). As a fundamental statistical measure, the Pearson coefficient reflects the degree of association between variables, with values ranging from –1 to +1, indicating the nature and extent of the correlation.There is no relationship between the variables when the correlation coefficient is zero; a strong negative correlation occurs when it is -1, and a high positive correlation occurs when it is +1(Wei et al., 2021).

$$R = \sum_{i=1}^{n} (xi - \bar{x})(y - \bar{y}) \, / \, \sqrt{\sum_{i=1}^{n} (xi - \bar{x})^2 \sum_{i=1}^{n} (yi - \bar{y})^2} \quad (5)$$

Here, *xi* and *x* are the *i-th* value and average value of the variable *X*, respectively; *yi* and *y* are the *i-th* value and average value of the variable *Y*, respectively, and*n* is the total number of sample sequences(Wei et al., 2021).

Two-way Analysis of Variance (ANOVA)

Two-wayANOVA (Analysis of Variance) without replication helps to evaluate the statistically significant differences betweenmultiple drought indices (SPI, aSPI, RDI, and eRDI). These statistical calculations can be made with the help of Equation (6).

$$Yij = \mu + \tau i + \beta j + \gamma ij + \epsilon ijk \quad (6)$$

Here,μ represents the population's overall mean response, τi represents the influence of the i-*th* level of factor *A*,βj represents the effect of the j-*th* level of factor B, and γij represents the effect of any interaction between the i-*th* level of A and the j-*th* level of *B*.

RESULTS

Figure 3 shows the temporal distribution of the selected drought indices (SPI, aSPI, RDI, and eRDI) on different timescales (3-, 6-, 9-, and 12-month) during the period 1982–2022. As shown in Figure 3a, the drought indices show a clear temporal variability at a 3-month timescale in the study area. SPI and aSPI display closely aligned trends, with minor deviations attributed to aSPI's sensitivity to agricultural water balance. RDI and eRDI almost completely overlap, indicating that effective precipitation adds limited distinction over short time frames. All indices consistently identify major drought events, such as the prolonged 1998–2002 and the short 2018–2019 droughts.

Additionally, all drought indices show positive peaks during wet years, like 1997, 2006, and 2021. Since RDI and eRDI take into account precipitation and evapotranspiration, which SPI-based indices do not, they frequently exhibit somewhat sharper responses during certain dry years. This distinction is especially noticeable in the early 1990s and 2007–2008. These results emphasize how crucial it is to choose the right indices, particularly in semi-arid regions where drought intensity is influenced by climatic demand. While the combined use of aSPI and eRDI provides a comprehensive approach by collecting both meteorological and agricultural drought characteristics, the significant connection across all indices overall confirms their trustworthiness.

Moreover, at a 6-month timescale, the selected drought indices provide a more obvious temporal distribution of drought conditions (Figure 3b). With severe episodes visible in 1985–1987, 1991, and a protracted and intense period during 1998–2002, all indices successfully capture significant drought periods. The recent dry period of 2015 was consistently indicated by all indices. Although aSPI is more sensitive to agricultural drought situations, SPI and aSPI show comparable patterns. There is little difference in the temporal distribution at this scale, as evidenced by the nearly identical trend of RDI and eRDI. The intensity of the drought has comparatively decreased since 2002.These findings demonstrate that SPI and aSPI are more sensitive to agricultural drought, whereas RDI and eRDI provide reliable results for climatic evaluations, enabling well-informed index selection for the study region.

At the 9-month time scale (Figure 3c), the drought indices show some random differences; all indices generally show similar drought trends and coincide. During severe droughts, the eRD tends to be more susceptible to harsh conditions, exhibiting sharper declines. The indices show different reactions to shifting climatic conditions, as evidenced by their near overlap in the 1990s and their divergence after 2000. While eRDI captures greater variability, suggesting higher sensitivity, RDI and aSPI show smoother trends. For regional accuracy, combining RDI and aSPI's reliability with eRDI's sensitivity may offer the most comprehensive drought assessment.

As shown in Figure 3d, all indices show broad agreement for the 12-month timescale drought, particularly during major droughts (e.g., early 1990s and mid-2010s), but eRDIexhibits greater volatility, with sharper declines during dry periods. RDI and aSPI trends are smoother, suggesting more stable, long-term drought signals, while eRDI’s fluctuations indicate higher sensitivity to short-term anomalies. Post-2000, slight divergences emerge, possibly due to evolving climatic influences. The strong overlap in severe drought years supports index reliability, but eRDI's responsiveness to extremes may better capture acute drought conditions. For a balanced assessment, combining RDI/aSPI's consistency with eRDI's precision could enhance drought monitoring.

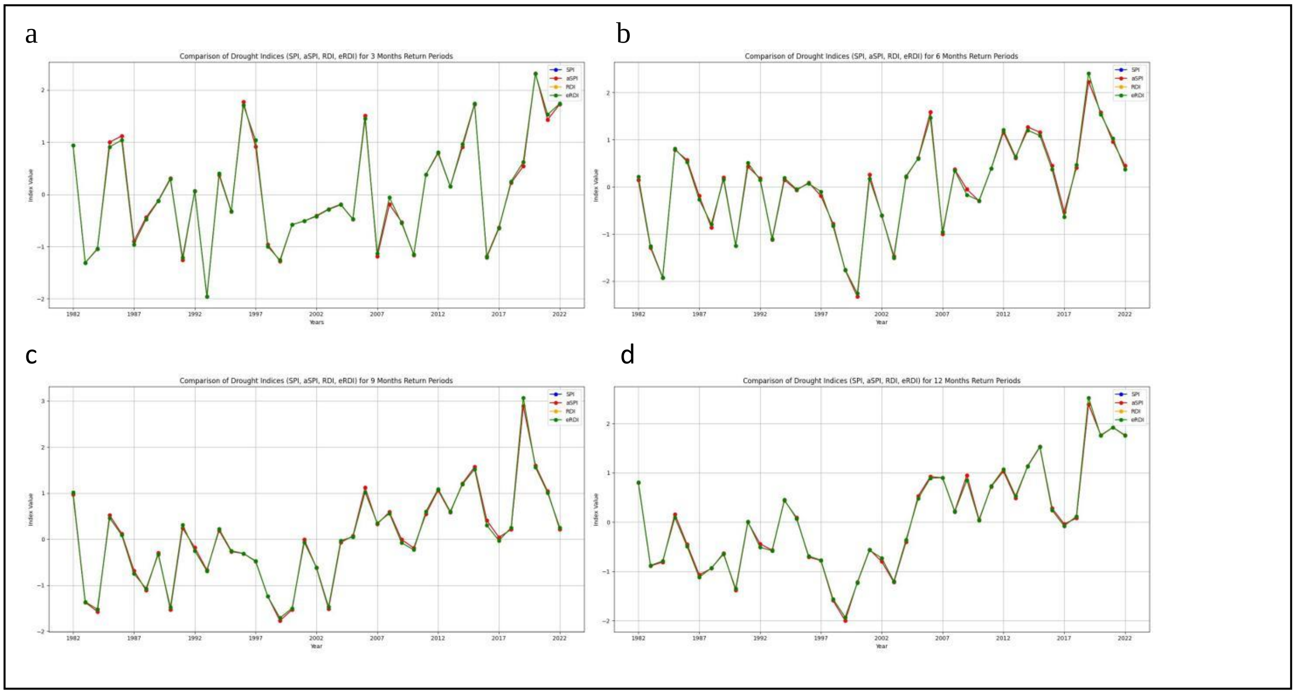

Figure 3. Comparison of drought indices (SPI, aSPI, RDI, and eRDI) on different timescales (3-, 6-, 9-, and 12-month) during the period 1982–2022.

Figure 4 shows the comparative picture of four drought indices, SPI, aSPI, RDI, and eRDI, across 3, 6, 9, and 12-month timescales based on the Pearson correlation coefficient matrix. The results reveal key insights into their mutual behavior and methodological alignment. All correlation values are positive, signaling that these indices generally respond in the same direction when capturing drought signals. The strongest correlations ($r \geq 0.9$) appear between structurally similar indices, such as SPI and aSPI or RDI and eRDI, indicating their shared statistical foundations and reinforcing the idea that certain index modifications, like agricultural weighting or effective precipitation adjustments, do not substantially distort the core climatic signals in regions where rainfall is the main limiting factor for agriculture. Interestingly, while short-term and long-term versions of the same index (e.g., SPI3 vs. SPI12) show notably weaker correlations ($r \approx 0.518$), this divergence supports the understanding that short-term droughts may differ significantly in behavior and impact from long-term drought trends.

Furthermore, correlations generally increase with longer timescales, which is expected as noise diminishes and climatic signals become clearer over time, particularly across SPI12–RDI12 and aSPI12–eRDI12, which approach near-perfect alignment. While such strong correlations could imply redundancy, they also offer consistency and cross-validation, lending confidence to analytical outcomes. However, relying solely on highly correlated indices may limit interpretive diversity, so a balanced approach that combines SPI-based and RDI-based tools across varying timeframes is more pragmatic. Particularly in rainfall-dependent, agriculture-driven contexts like the study area, aSPI and eRDI stand out as highly reliable and context-sensitive choices, offering both structural integrity and interpretive depth. This affirms that an integrated, multi-index approach, especially one that captures both short-term variability and long-term trends, provides the most comprehensive and policy-relevant framework for drought monitoring and decision-making.

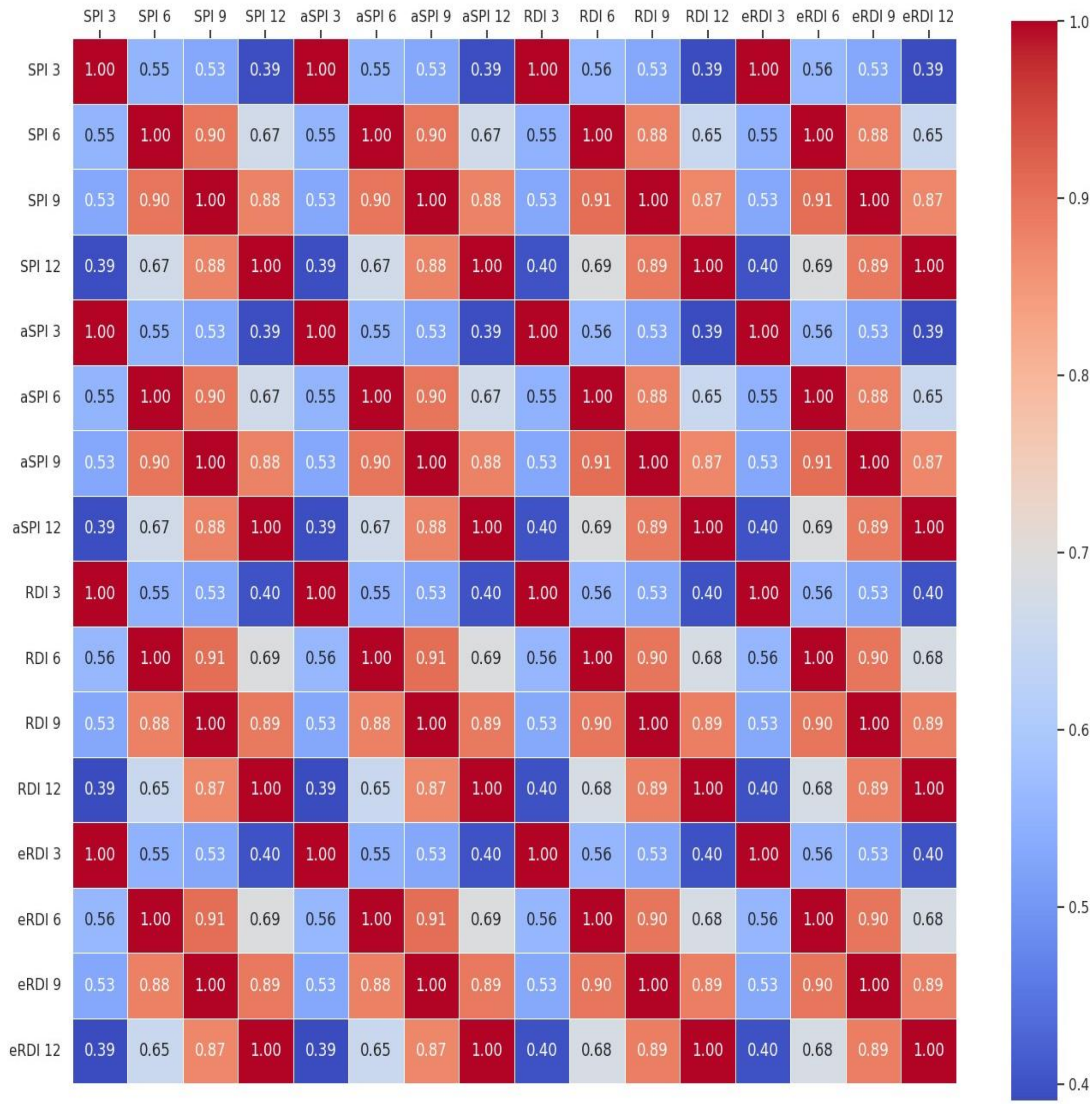

Figure 4. Pearson correlation coefficient of drought indices (SPI, aSPI, RDI, and eRDI) on different time scales in the study area.

Table 1 shows the two-way ANOVA without replication. The results show a significant difference in the statistical significance of the two factors under investigation: timescales (columns) and drought indices (rows). With a p-value significantly below 0.001 and a high F-value of 60.67 for drought indices, the results indicate statistically significant differences in the ways that various indices identify drought conditions. These results emphasize the fact that not all indices function in the same way; rather, some exhibit higher sensitivity or contextual relevance to the features of the research region. On the other hand, there was no discernible temporal fluctuation in drought detection performance within the examined dataset, as indicated by the extremely low F-value for the time periods (0.00176) and p-value of 1.0.

These results suggest that rather than temporal variations, the choice of index is the primary factor influencing the variation in drought assessment outcomes. This makes sense given that several approaches are used to generate drought indices, with some concentrating on precipitation anomalies and others integrating evapotranspiration or more general hydro-meteorological variables. These methodological variances are probably the cause of the notable variations among indices. As a result, the analysis stresses that choosing the right index is crucial for drought monitoring and that a general strategy might not be suitable. Rather, it is important to choose indicators that consistently perform well in a particular geographic setting under a range of climatic conditions. This result lends credence to a customized, empirically supported approach to determining the best instruments for efficient drought assessment in the area.

Table 1. Two-way ANOVA of the selected drought indices without replication.

Source of Variation	SS	Df	MS	F	P-value	F crit
Rows	512.7932	39	13.14854	60.6731	1.2E-178	1.420212
Columns	0.005718	15	0.000381	0.001759	1	1.683504
Error	126.7761	585	0.216711			
Total	639.575	639				

Figure 5a shows the comparative behavior of the selected drought indices across different timescales in the study during the period 1982–2022. The results indicate a multifaceted pattern of drought indices perform across temporal resolutions, capturing both individual and interactive behaviors. As shown in Figure 5a, the index type vs. time scale outcome provides a concise illustration of how mean index values vary over increasing temporal frames. A clear trend emerges: as the time scale extends, particularly from 3- to 12-month timescales, the magnitude of index values tends to stabilize. This stabilization implies a smoothing effect that long-term accumulation has on drought signals, reducing the influence of short-term climatic noise. Notably, aSPI and eRDI display more pronounced shifts across time scales, reflecting their heightened sensitivity to changes in effective precipitation and evapotranspiration, respectively.

Figure 5b presents the outcomes of the distribution of index values by time scale,showing that the spread and central tendency of drought index values become visually distinct. The box plots demonstrate that shorter time scales (3 and 6 months) are associated with wider distributions and greater variability, likely due to their exposure to seasonal anomalies. Conversely, the 12-month scale reveals a tighter, more normalized distribution, emphasizing the stabilizing role of long-term data in drought characterization.

Figure 5c, the overall distribution of values for each index aggregated over all time periods. Here, SPI and RDI display relatively symmetrical distributions centered near zero, reflecting their general-purpose nature. In contrast, aSPI and eRDI exhibit broader and slightly skewed distributions, underscoring their greater sensitivity to agricultural and climatic factors. This reinforces earlier findings that these two indices offer a more nuanced reflection of drought dynamics in ecologically sensitive regions.

As shown in Figure 5d, the interaction plot (index type vs.timescale) provides a more complex view of how each index responds over time. The divergence of trend lines, particularly those of aSPI and eRDI, suggests significant interaction effects between index type and time scale, an insight statistically confirmed by the two-way ANOVA ($p < 0.001$). These crossing or diverging trajectories highlight that no single index behaves uniformly across all timescales, further justifying a multi-index approach for robust drought monitoring.

Together, these four visualizations collectively deepen our understanding of index behavior and temporal sensitivity. They not only validate the statistical findings but also emphasize the importance of scale-aware index selection, especially in regions like the Hindukush, where climatic variability and ecological vulnerability intersect sharply.

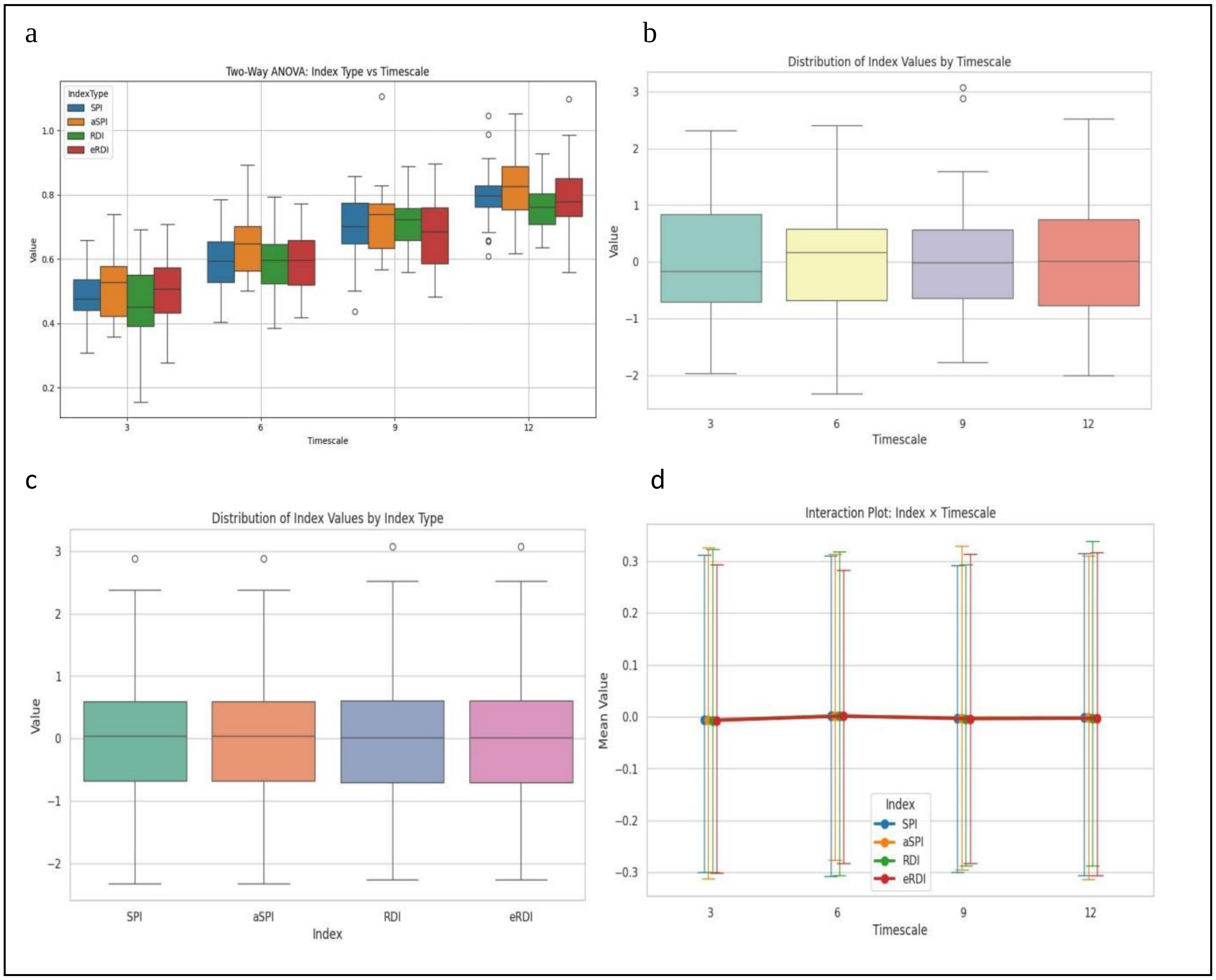

Figure 6 illustrates the temporal trend in multiple drought indices across 3-, 6-, 9-, and 12-month timescales in the study region during the period 1982–2022. The results offer valuable insight into the evolving drought dynamics in the Hindukush region over the past four decades. The temporal behavior of the selected indices at distinct accumulation intervals allows a nuanced understanding of how short- to long-term drought signals have shifted over time. Across all four temporal scales, a general declining tendency is observable in most indices, suggesting a gradual intensification of drought conditions in the region. This downward movement, although subtle in some instances, points to an underlying hydro-climatic shift that aligns with regional climate narratives of increasing dryness and erratic rainfall. The slopes of the regression lines, while modest, remain consistent in direction across most timescales, reinforcing the robustness of the observed trends.

At the 3-month scale (Figure 6a), the indices display greater short-term variability, which is expected given the influence of seasonal fluctuations. The trends here are more scattered, but aSPI and eRDI begin to demonstrate their comparative responsiveness to anomalies in effective precipitation and evapotranspiration. In contrast,the 6-month (Figure 6b) and 9-month (Figure 6c) timescales show clearer, more structured trends, indicating that medium-term drought conditions may be strengthening in the study region. This is particularly evident in the eRDI, which shows a slightly sharper decline, reflecting its sensitivity to climatic variability. The 12-month period reveals the most consistent and coherent trends (Figure 6d), particularly for aSPI, which underscores its ability to capture longer-term agricultural drought signals. The relatively low R^2 values across all plots (generally below 0.20) reflect the inherently complex nature of drought phenomena, which are driven by numerous interacting variables. However, the visual alignment of regression slopes across indices and timescales provides a compelling narrative: that the region is experiencing a slow but measurable shift toward more frequent and intense droughts.

These results not only validate the statistical findings from the correlation and ANOVA analyses but also offer a visual affirmation of the emerging drought patterns in the region. The evidence further strengthens the case for adopting aSPI and eRDI as leading indicators for both short- and long-term drought monitoring in Pakistan's mountainous zones.

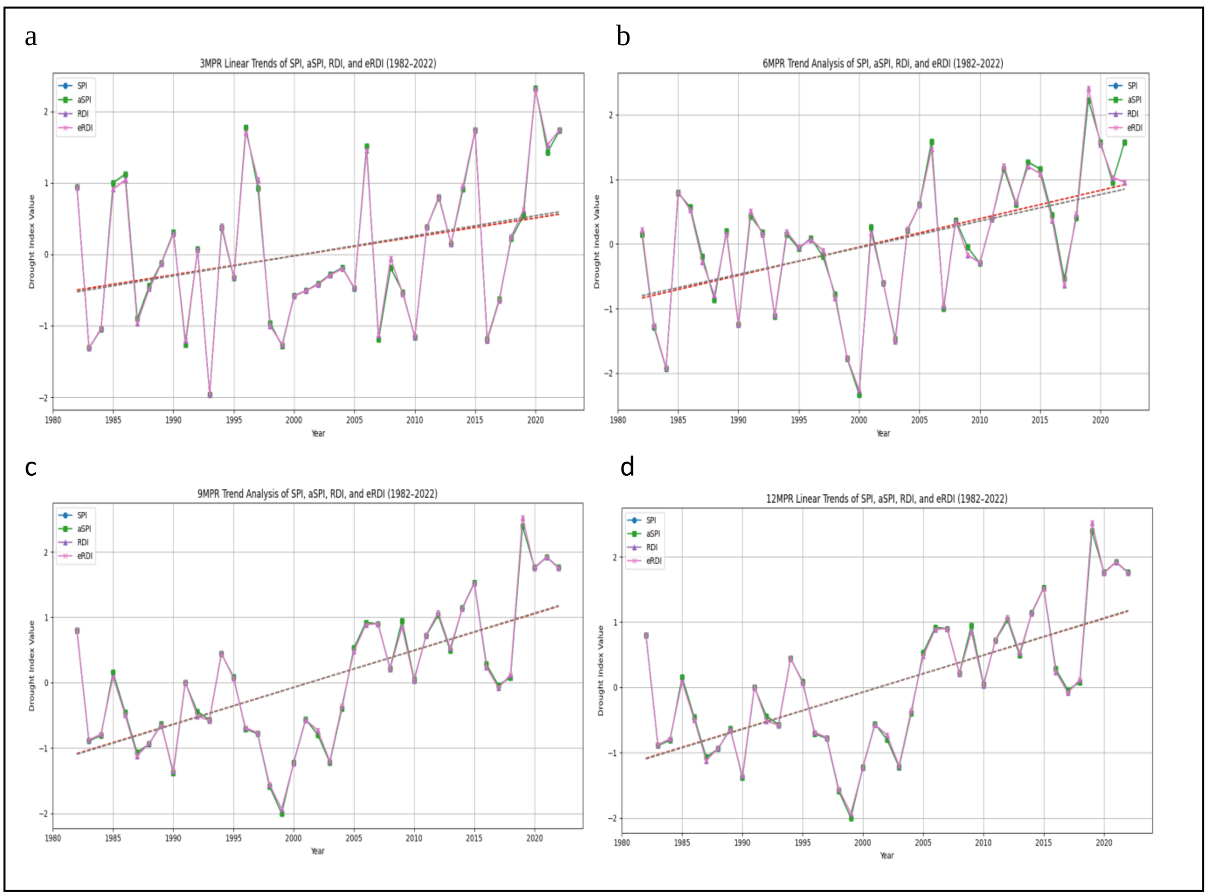

Figure 6. Linear trend of drought indices (SPI, aSPI, RDI, and eRDI) across different Time Scales 3-, 6-, 9-, and 12-MRP, (A-D), 1982–2022.

DISCUSSION

This study aimed to assess the temporal responsiveness and comparative performance of four drought indices (SPI, aSPI, RDI, and eRDI) over short to long accumulation periods in Pakistan's Hindukush area. The region, located in a hydroclimatically susceptible zone, requires accurate drought monitoring tools that are suited to its specific agro-ecological characteristics. The study used long-term datasets and statistical approaches to determine drought indices that were most suited to the region's climate variability.

The results indicate that the selected drought indices across various timescales provide significantin formation on the temporal behavior of drought dynamics in the Hindukush area. Drought indices, such as SPI, aSPI, RDI, and eRDI, varied significantly over shorter periods (3- and 6-month), indicating their susceptibility to short-term precipitation anomalies and seasonal water stress. Short-term scales are extremely efficient in detecting rapid-onset agricultural droughts. Longer timescales (9- and 12-month) caught more persistent, systemic droughts, as seen by smoother, aggregated signal patterns (Öz, Özelkan, & Tatlı, 2024). The smoothing effect is essential for identifying extended moisture deficits, as the long-term indices more accurately represent hydrological drought trends(Zhou et al., 2025). The significant results of aSPI and eRDI during historical drought years highlight their increased sensitivity to agricultural and climatic variability. These indices are particularly valuable in complex terrains where effective precipitation and evapotranspiration affect drought severity (Das et al., 2024).

The Pearson correlation values show strong inter-index correlations, especially between structurally related pairings, like SPI-aSPI and RDI-eRDI. These findings are comparable with other research that has found similar statistical connections in dry zones of Khyber PakhtunkhwaandBalochistan(Khan et al., 2020; Ashraf &Routray, 2015), verifying SPI's significant association with both meteorological and hydrological indicators under varied climatic circumstances. The strength of these associations demonstrates that while each measure differs in formulation, they are generally consistent in capturing catastrophic drought occurrences when applied over longer periods (Pei et al., 2020). Furthermore, the correlation of indices is an important step in assessing redundancy and complementary usage, especially when constructing integrated early warning systems. These significant linear relationships confirm the dependability of SPI and RDI derivatives for drought detection zones (Merabti et al., 2018).

Moreover, the two-way ANOVA shows substantial differences across drought indices and temporal scales, as well as an interaction effect. These findings highlight that drought indices do not respond consistently to changes in time scale. This is an important discovery for establishing scale-appropriate drought monitoring procedures.A recent study by Aslam et al. (2021) utilized two-way ANOVA to show that the sensitivity of drought indices varies dramatically across climate gradients and accumulation periods. Furthermore, the visual interaction results indicate the differential performance of indices, with aSPI and eRDI demonstrating more prominent responsiveness across time scales, which is consistent with the findings proposed for utilizing such indices in locations with high climatic variability(Mohi-Ud-Din et al., 2024).Recently,Shamim et al. (2024) emphasized the necessity of accounting for interaction effects in drought models, especially when many indices are being assessed for practical usage. These patterns demonstrate that index selection should be guided by both temporal sensitivity and regional hydro-climatic dynamics.

The results further show that despite low R^2 values, all four indices show a consistent declining trend across time ranges. This trend indicates a long-term intensification of drought conditions in the Hindukush area. Recent climatological research has confirmed such tendencies, indicating that drought frequency and severity are increasing in northern Pakistan as temperatures rise and precipitation falls (cite some papers). Similar diminishing precipitation patterns over the Himalayan-Karakoram region are attributable to alterations in monsoon dynamics and lower winter snowfall (Adnan & Ullah, 2022). Regression analysis spanning multi-decadal periods is critical in validating wider climatological shifts, particularly when employed alongside indices that include evapotranspiration(Anshuka, van Ogtrop, & Willem Vervoort, 2019). The application of linear regression as a fundamental technique for detecting subtle, long-term hydro-climatic trends in hilly areas. The observed negative trends in this study support the need to build dynamic drought preparedness frameworks and emphasize the need for proactive adaptation methods in the face of shifting climatic stressors (Gulakhmadov et al., 2020).

CONCLUSION

This study conducted a comparative assessment of four well-known drought indices (SPI, aSPI, RDI, and eRDI) over multiple timescales(3, 6, 9, and 12 months) to evaluate their relative performance in recognizing the dynamics of drought in the mountainous and water-stressed environment of Khyber Valley, Hindukush region of Pakistan.The results reveal that while all indices show general agreement in detecting major drought events, their sensitivity and interpretive strength vary by index structure and temporal resolution. The precipitation-based indices, i.e., SPI and aSPI, revealed close consistency, though aSPI showed a better ability to reflect agricultural stress due to its incorporation of effective precipitation. Similarly, RDI and eRDI exhibited strong structural correlation, with eRDI offering improved responsiveness to short-term climatic variability. Notably, eRDI's performance in capturing drought intensity during critical agricultural periods makes it particularly valuable for operational drought monitoring in arid and semi-arid highland settings.The statistical result from Pearson correlation and two-way ANOVA further confirms that inter-index variations are more significant than temporal ones. This implies that the selection of an appropriate drought index should be guided primarily by the index's methodological relevance to the local climatic and hydrological conditions, rather than the duration of the observation window alone.In the context of Khyber Valley, a region characterized by complex topography, limited water availability, and a strong dependence on rain-fed agriculture, aSPI and eRDI emerge as the most suitable indices. Their ability to integrate both precipitation and evapotranspiration components ensures a more holistic understanding of meteorological and agricultural drought conditions. As a result, the combined use of these two indices is recommended for future drought assessment and resource planning in the region.This study contributes to the broader discussion of drought index optimization by creating a rigorous, multi-index methodology adapted to local meteorological conditions. The findings highlight the need for tailored approaches in drought-prone areasandformore nuanced and evidence-based methodologies for regional drought assessment.

Credit authorship contribution statement

Maroof Shah: Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft.

Shah Nawaz Khan: Conceptualization, Methodology, Formal analysis, Writing – review & editing, Supervision.

Amjad Ali Writing–review & editing, Visualization, Validation, Funding acquisition.

Amjad Ali: Formal analysis, Writing–review & editing, Supervision.

Imran Khan: Conceptualization, Methodology, Formal analysis, Validation, Writing–review & editing.

Maria Ghani and Fazli Malik Validation, Writing–review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT to check grammar, spelling, and sentence flow. After using this tool/service, the authors reviewed and edited the content as needed and took full responsibility for the content of the published article.

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FIGURES

Figure 3. Location map of the Khyber Valley, Hindukush region, Pakistan

Figure 4. Flowchart of the study

Figure 3. Comparison of drought indices (SPI, aSPI, RDI, and eRDI) on different timescales (3-, 6-, 9-, and 12-month) during the period 1982–2022.

Figure 4. Pearson correlation coefficient of drought indices (SPI, aSPI, RDI, and eRDI) on different time scales in the study area.

Figure 5. Visual summary of two-way ANOVA results depicting the effects of drought index type and temporal scale on index behavior.

Figure 6. Linear trend of drought indices (SPI, aSPI, RDI, and eRDI) across different Time Scales 3-, 6-, 9-, and 12-MRP, (A-D), 1982–2022.