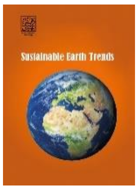
Sustainable Earth Trends 6(2) 2026 120-136

Shahid Beheshti University

Sustainable Earth Trends

Journal homepage: http://sustainearth.sbu.ac.ir



Spatiotemporal assessment of hydro-meteorological droughts associating with socio-economic impacts in the southern Alborz mountains, Iran

Kazem Nosrati[a*], Somaiyeh Khaleghi[a]

[a] Department of Physical Geography, Faculty of Earth Sciences, Shahid Beheshti University, 1983963113 Tehran, Iran

ABSTRACT

Accurate prediction and assessment of diverse drought types are crucial for sustainable water resource management, environmental protection, and socio-economic resilience. This study explores the interconnections between meteorological, hydrological, and socio-economic droughts across selected sub-basins in the southern of the Alborz Mountains, Iran. It focuses on evaluating the relationship between two meteorological drought indices—the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI)—and the hydrological drought index, the Standardized Streamflow Index (SSI), while also examining associated socio-economic impacts. In the first phase, a comparative analysis of SPI and SPEI revealed a strong correlation, with SPEI showing a faster and more sensitive response to drought conditions. This highlights the influence of evapotranspiration in arid and semi-arid environments and supports the selection of SPEI as a more appropriate index in such regions. The second phase involved analyzing five sub-basins with long-term data records to evaluate meteorological and hydrological drought interactions. Although the correlation between SPEI and SSI was weak, likely due to temporal response lags, their overall trend patterns were consistent. In the final phase, socio-economic dimensions were introduced by analyzing cropland area and population metrics within the selected sub-basins. The findings showed no statistically significant relationships between these socio-economic indicators and the drought indices, suggesting the influence of additional mediating factors. Overall, the study underscores the multifaceted, non-linear nature of drought impacts and calls for integrated, multi-dimensional approaches in drought monitoring and management to enhance resilience and adaptive capacity in vulnerable regions.

ARTICLE INFO

Keywords:
Drought
Standardized precipitation evapotranspiration index
Standardized Streamflow Index
Socio-economic drought
Southern Alborz Mountains

Article history:
Received: 09 Feb 2026
Accepted: 10 Mar 2026

*Corresponding author
E-mail address:
k_nosrati@sbu.ac.ir
(K. Nosrati)

Citation:
Nosrati, K. & Khaleghi, S., (2026). Spatiotemporal assessment of hydro-meteorological droughts associating with socio-economic impacts in the southern Alborz mountains, Iran, *Sustainable Earth Trends:* 6(2), (120-136).

DOI: 10.48308/set.2026.243474.1182

1. Introduction

Drought is a complex and recurrent natural hazard that affects various regions globally, exerting profound and often long-lasting impacts on ecosystems, economies, and societies. Among all natural hazards, drought ranks as the most economically damaging, with estimated global losses ranging from $6 to $8 billion annually (Wilhite et al., 2000; Mishra and Singh, 2010). Drought adversely influences a broad range of water-dependent activities, including agricultural production, industrial operations, domestic consumption, and ecological sustainability. These impacts are further exacerbated under conditions of climate variability and change, which intensify the frequency and severity of drought events (Rajabi et al., 2022). Consequently, the ability to predict droughts is vital for the sustainable management of water resources and effective mitigation planning (Farizo et al., 2024). Droughts are typically categorized based on the affected components of the hydrological cycle. Meteorological drought refers to prolonged periods of below-average precipitation (Palmer, 1965); agricultural (or soil moisture) drought relates to deficits in soil water content (Sosa et al., 2025); hydrological drought

drought involves reduced surface or subsurface water availability, such as streamflow and groundwater levels (Tallaksen and Van Lanen, 2023). When these physical droughts impair the water supply to the extent that it cannot meet societal and environmental demands—such as for irrigation, hydropower generation, recreation, or ecosystem functioning—a socio-economic drought occurs (Maia et al., 2015).

Hydrological drought often arises from the delayed and cumulative effects of meteorological drought, mediated by the processes within the terrestrial hydrological cycle (Vidal et al., 2010). This propagation is influenced by both natural climatic variability and anthropogenic activities such as land use change, water withdrawals, and reservoir operations (Dai, 2011; Bagley et al., 2014; Gan et al., 2016; Van Loon et al., 2016). Thus, understanding the linkage between meteorological and hydrological droughts is crucial for water resource management tasks such as streamflow regulation, irrigation planning, ecosystem conservation, and wastewater treatment. To monitor, quantify, and compare drought conditions, numerous drought indices have been developed, each tailored to specific types of drought (Zargar et al., 2011). These indices serve as essential tools for evaluating drought duration, intensity, and severity in spatiotemporal scales (Mishra and Singh, 2010).

Commonly used hydro-meteorological drought indices include the Palmer Drought Severity Index (PDSI), the Standardized Precipitation Index (SPI), the Standardized Precipitation Evapotranspiration Index (SPEI), Surface Water Supply Index (SWSI), Palmer Hydrologic Drought Index (PHDI), the Standardized Runoff Index (SRI), and the Standardized Streamflow Index (SSI) (Palmer, 1965; Shafer and Dezman, 1982; Karl, 1986; McKee et al., 1993; Shukla and Wood, 2008; Vicente-Serrano et al., 2010; Vicente-Serrano et al., 2012). The SPI and SPEI are widely regarded as robust meteorological drought indicators, particularly in arid and semi-arid regions due to their ability to represent drought conditions across multiple timescales (Beguería et al., 2014; Stagge et al., 2015; Li et al., 2020; Sayat et al., 2025). Similarly, the SSI is a well-established hydrological index used to reflect streamflow anomalies. These indices are advantageous in that they can help approximate the connection between drought events and their environmental, economic, or social consequences (Knutson et al., 1998; Vicente-Serrano et al., 2012; Farizo et al., 2024). Drought impacts are typically evaluated across sectors such as agriculture, energy, industry, public water supply, and freshwater ecosystems (Vicente-Serrano, 2006; Stagge et al., 2015; Hasan et al., 2019; Vicente-Serrano et al., 2021).

Iran, situated approximately between 25°N–40°N latitude and 40°E–64°E longitude, is predominantly characterized by arid and semi-arid conditions. The central plateau is flanked by the Alborz and Zagros Mountain ranges to the north and west, respectively. Annual precipitation in Iran varies significantly—from less than 100 mm in the central arid zones to over 1800 mm in the northern regions—with a national average of approximately 250 mm. The coefficient of variation (CV) of precipitation increases from north to south, ranging from 20% to 75%. Over 75% of the country receives less than 250 mm of annual precipitation, rendering water resource sustainability a critical concern. Notably, more than 96% of Iran experienced severe drought conditions during the prolonged drought episode from 1998 to 2001 (Agrawala et al., 2001; Tabrizi et al., 2010).

Given these challenges, improved understanding and prediction of different drought types and their socio-economic ramifications are crucial for informed water resource planning and policy-making. The primary objective of this research was to evaluate the spatiotemporal relationships between meteorological (measured by SPI and SPEI) and hydrological droughts (measured by SSI) analyzed for the period 1990–2022, and their connections to socio-economic drought impacts across selected sub-basins in the southern slopes of the Alborz Mountains, Iran. The socio-economic dimension is represented by two variables: population (as a proxy for social vulnerability and potential migration) and cropland area (as an indicator of agricultural exposure) across four temporal intervals. This study aims to address and examine the following research questions: (i) Is there a correlation and consistency between meteorological and hydrological droughts? (ii) Is there a relationship between different types of droughts—meteorological and hydrological—and their socio-economic impacts?

2. Materials and methods

2.1. Study area and data collection

This study was conducted in five selected sub-basins located in the southern slopes of the Alborz Mountains, Iran, between 35°14′ to 36°17′ N latitude and 50°14′ to 53°06′ E longitude (Fig. 1). These sub-basins play a critical role in the water supply network of Tehran Province, which is not only the most populous region in the country but also a central hub for industrial and agricultural activities. Tehran Province covers an area of approximately 18,909 km² and supports a population of 18,429,807, representing about 1.1% of Iran's total land area and 3.19% of its population. The province is characterized by a high urbanization rate, with 86.5% of residents living in urban areas and the remaining 13.5% in rural communities. The city of Tehran, the nation's capital and largest urban center, is located within this province and exerts significant pressure on regional water resources. Climatically, the study area exhibits a gradient from a semi-arid continental Mediterranean climate in the southern lowlands to an alpine climate in the northern highlands. Based on long-term observations from 1990 to 2022, the region receives a mean annual precipitation of approximately 245 mm. The average annual temperature is 17.8°C, with July being the warmest month (mean temperature: 31.1°C) and January the coldest (mean temperature: 1.7°C). Agriculture remains a vital sector in Tehran Province, with a total cultivated area of 172,915 hectares. Among crops, wheat occupies the largest share (51,104 ha), followed by forage crops excluding alfalfa (45,478 ha; approximately 26%).

In addition to its agricultural importance, the region is also a key industrial zone. However, the combination of dense population, urban expansion, and increasing irrigation demand has led to observable land degradation and declining water availability across the sub-basins. Given these challenges, improved understanding of the interactions between meteorological and hydrological droughts and their socio-economic implications is essential for informed water management strategies in the region. Due to limitations in the streamflow monitoring network across the broader study area, five sub-basins—Firuzkuh, Latyan, Karaj Dam, Dehsomeh, and Glinak—were selected based on the availability of consistent and long-term daily discharge and meteorological data. The selection also ensures that each sub-basin includes hydrometric and meteorological stations with comparable temporal coverage. The methodology assumes that upstream climate stations effectively represent meteorological drought conditions, while downstream outlet gauging stations reflect integrated hydrological responses. This configuration helps to reduce uncertainties associated with sub-basin heterogeneity and allows for a more accurate analysis of the relationship between drought indices and associated socio-economic impacts.

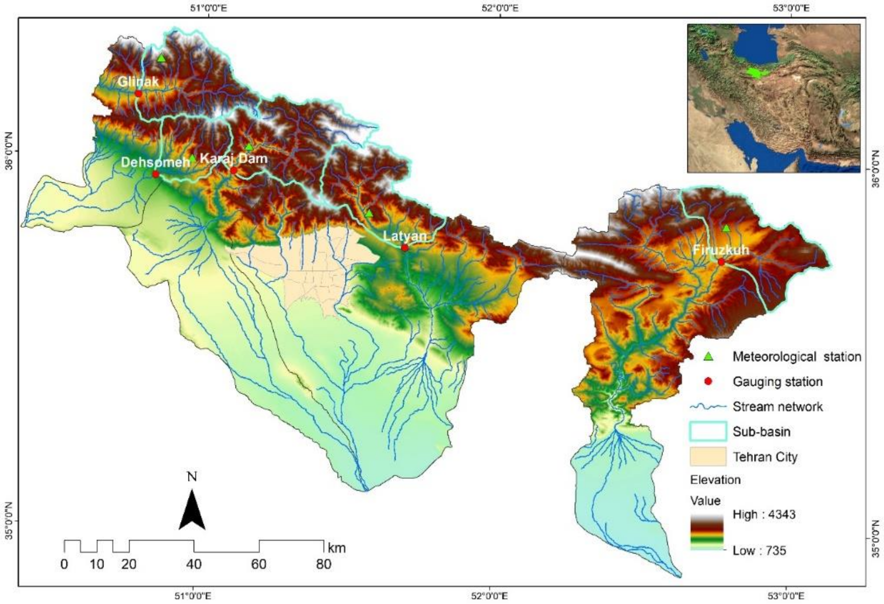


Fig. 1. Location of the studied five sub-basins in Tehran Province.

Meteorological and hydrological data for the period 1990–2022 were obtained from the Water Resources Research Organization of Iran. The dataset includes monthly precipitation and temperature records, as well as natural daily streamflow time series, for ten selected stations across the study area (Table 1). For each station, a total of 264 monthly observations were available for both temperature and precipitation. Missing data were identified and systematically addressed by employing linear regression imputation using the most highly correlated neighboring station, ensuring consistency and reliability of the time series. In addition, socio-economic data comprising population figures and cultivated crop field areas were collected for four distinct time intervals from the Statistical Center of Iran. These datasets were used to assess the potential impacts of drought on demographic and agricultural variables within the selected sub-basins.

Table 1. Selected sub-basins and associated gauging and meteorological stations.

Sub-basin	Gauging station	Meteorological station
Firuzkuh	Firuzkuh	Jalizjand
Latyan	Latyan	Rudak
Karaj Dam	Karaj Dam	Sira
Dehsomeh	Dehsomeh	Sorheh Barghan
Glinak	Glinak	Saghranchal

2.2. Drought indices calculation

2.2.1. Standardized Precipitation Index (SPI)

The Standardized Precipitation Index (SPI), developed by McKee et al. (1993), is a widely used probabilistic indicator for quantifying the intensity and duration of meteorological droughts. The SPI can be applied to any location with a sufficiently long record of monthly precipitation data and can be computed at multiple time scales to reflect short- to long-term precipitation anomalies. The calculation of the SPI involves two primary steps:

1. Monthly precipitation data were first aggregated into a time series corresponding to the selected time scale (i.e., one-month scale in this study). A probability distribution function was then fitted to the aggregated precipitation data. While the original SPI formulation employs a two-parameter gamma distribution, this study utilized the Pearson Type III distribution, following recommendations by (Vicente-Serrano, 2006), who highlighted its superior performance in arid and semi-arid regions. The cumulative probability of precipitation, including zero-precipitation events, was calculated accordingly. 2. The cumulative probability values derived from the fitted Pearson Type III distribution were then transformed into a standard normal distribution with a mean of zero and a standard deviation of one. This transformation yields the SPI values, which indicate the number of standard deviations a particular precipitation value deviates from the long-term mean. The SPI allows for the identification of both dry and wet periods, making it a versatile tool for drought monitoring. In this study, the SPI was calculated at a one-month time scale to capture short-term meteorological drought dynamics relevant to the study area.

2.2.2 Standardized precipitation evapotranspiration index (SPEI)

The Standardized Precipitation Evapotranspiration Index (SPEI) is an extension of the SPI, incorporating the effects of temperature-driven evapotranspiration to provide a more comprehensive assessment of drought conditions under climate change scenarios. Unlike the SPI, which is based solely on precipitation, the SPEI uses the climatic water balance, defined as the difference between monthly precipitation (Pi) and potential evapotranspiration (PETi), to compute the monthly deficit (Di) (Eq. 1).

$$Di = Pi - PETi \qquad (1)$$

This approach accounts for the influence of temperature on atmospheric water demand, thereby reflecting the role of surface evaporation more explicitly. As a result, the SPEI is particularly sensitive to droughts intensified by rising global temperatures. Following the calculation of the Di series, the same methodological framework as SPI is applied. A suitable probability distribution is fitted to the water balance series, typically the log-logistic distribution, and the cumulative probabilities are then transformed into a standard normal distribution with a mean of zero and a standard deviation of one. This process yields SPEI values that can be interpreted similarly to SPI, with positive values indicating wet conditions and negative values indicating drought (Vicente-Serrano, 2006). In this study, SPEI was calculated at a one-month time scale to facilitate direct comparison with SPI and to analyze short-term drought dynamics in the study area (Table 2).

Table 2. Drought classification for standardized precipitation index (SPI) and Standardized precipitation evapotranspiration index (SPEI).

Value	Drought category
> 2.0	Extremely wet
1.5 to 1.99	Severely wet
1.0 to 1.49	Moderately wet
− 0.99 to 0.99	Near normal
− 1.0 to − 1.49	Moderately dry
− 1.5 to − 1.99	Severely dry
− 2 and less	Extremely dry

2.2.3. Standardized Streamflow Index (SSI)

Hydrological droughts were assessed using the Standardized Streamflow Index (SSI), a widely accepted and accessible index introduced by (Vicente-Serrano et al., 2012). The SSI is derived from monthly streamflow data recorded at gauging stations and provides a standardized measure of hydrological drought analogous to the Standardized Precipitation Index (SPI). By transforming monthly streamflow values into a standard normal distribution (mean = 0, standard deviation = 1), the SSI enables a consistent and comparative evaluation of hydrological drought severity across different temporal and spatial contexts. One of the key advantages of the SSI is its compatibility with meteorological indices such as the SPI and SPEI, due to its similar scale and interpretability. This allows for a direct and meaningful comparison between meteorological and hydrological drought conditions. In this study, the climatic conditions across gauging stations were found to be comparable to those at adjacent meteorological stations, supporting the validity of this comparative approach. To determine the most appropriate probability distribution for each streamflow time series, six commonly used three-parameter distributions in hydrological studies were tested: Generalized Extreme Value (GEV), Pearson Type III (PIII), Log-Logistic, Lognormal, Generalized Pareto, and Weibull distributions (Vogel and Wilson, 1996; Nosrati et al., 2014; Sharma, 2024). The best-fit distribution was selected for each series based on goodness-of-fit criteria. Following selection of the optimal distribution, the cumulative distribution function (CDF), $F(x)$, was calculated. The streamflow values were then transformed into standardized normal deviates using the same methodology applied in the computation of the SPEI, with the sole distinction that streamflow data replaced precipitation or climatic water balance data as the input variable. This approach provides a consistent and robust framework for monitoring hydrological droughts and supports integrative drought assessments in conjunction with meteorological indices.

2.2.4. Socio-economic drought

To evaluate the relationship between drought conditions and socio-economic impacts across the selected sub-basins, two socio-economic indicators were identified based on data availability and relevance: crop field area and population. These indicators were selected to represent agricultural productivity and demographic pressure, respectively. The analytical framework assumes that areas downstream of hydrometric stations are influenced primarily by streamflow variability, thus making hydrological drought indices (e.g., SSI) more representative of conditions affecting socio-economic variables in those regions. Conversely, upstream areas are more directly impacted by precipitation and temperature anomalies, making meteorological drought indices (e.g., SPI and SPEI) more suitable for such regions. Accordingly, both drought types were analyzed in relation to socio-economic variables to assess spatial and functional drought impacts. Population data were obtained for the years 1986, 1996, 2006, and 2016, while crop field area data were available for the years 1988, 1993, 2003, and 2014, as reported by the Statistical Center of Iran. Given that the meteorological and hydrological drought indices were calculated on a monthly time scale, it was necessary to aggregate the drought data over multi-year periods corresponding to the socio-economic data collection years to enable a consistent comparison. To quantify the severity of meteorological and hydrological drought during these timeframes, the average drought intensity (SS) was calculated using Eq. 2, which represents the mean value of the respective drought index over the time periods aligned with the socio-economic data.

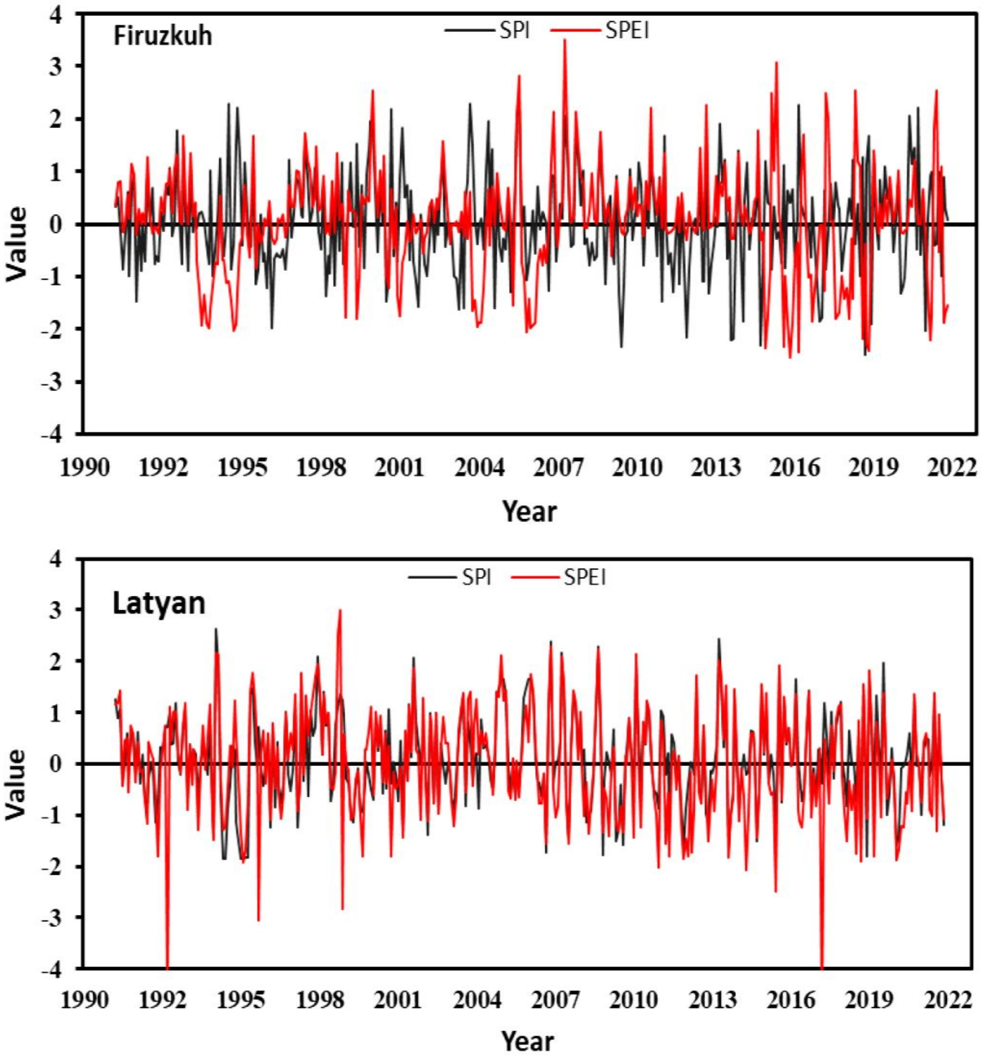
$$S_{ij} = \left(\sum_{i=1}^{m} |\text{Drought index}_i|\right)_j \qquad (2)$$

In Eq. 2, mmm represents the number of available stations within each sub-basin. To facilitate a meaningful comparison with socio-economic indicators, the severity of meteorological and hydrological droughts was computed for time periods aligned with the availability of population and crop field area data. Specifically, drought severity values were averaged over the periods 1981–1986, 1987–1996, 1997–2006, and 2006–2016 to correspond with census-based population indices. Similarly, for the crop field area index, drought severity was calculated for the periods 1984–1988, 1989–1993, 1994–2003, and 2004–2014. These timeframes were selected to ensure the highest consistency and temporal alignment with the recorded socio-economic datasets.

3. Results and discussion

3.1. Meteorological drought

The analysis revealed that the average duration of droughts, as measured by the Standardized Precipitation Evapotranspiration Index (SPEI), exceeds that of the Standardized Precipitation Index (SPI) across all stations (Fig. 2).



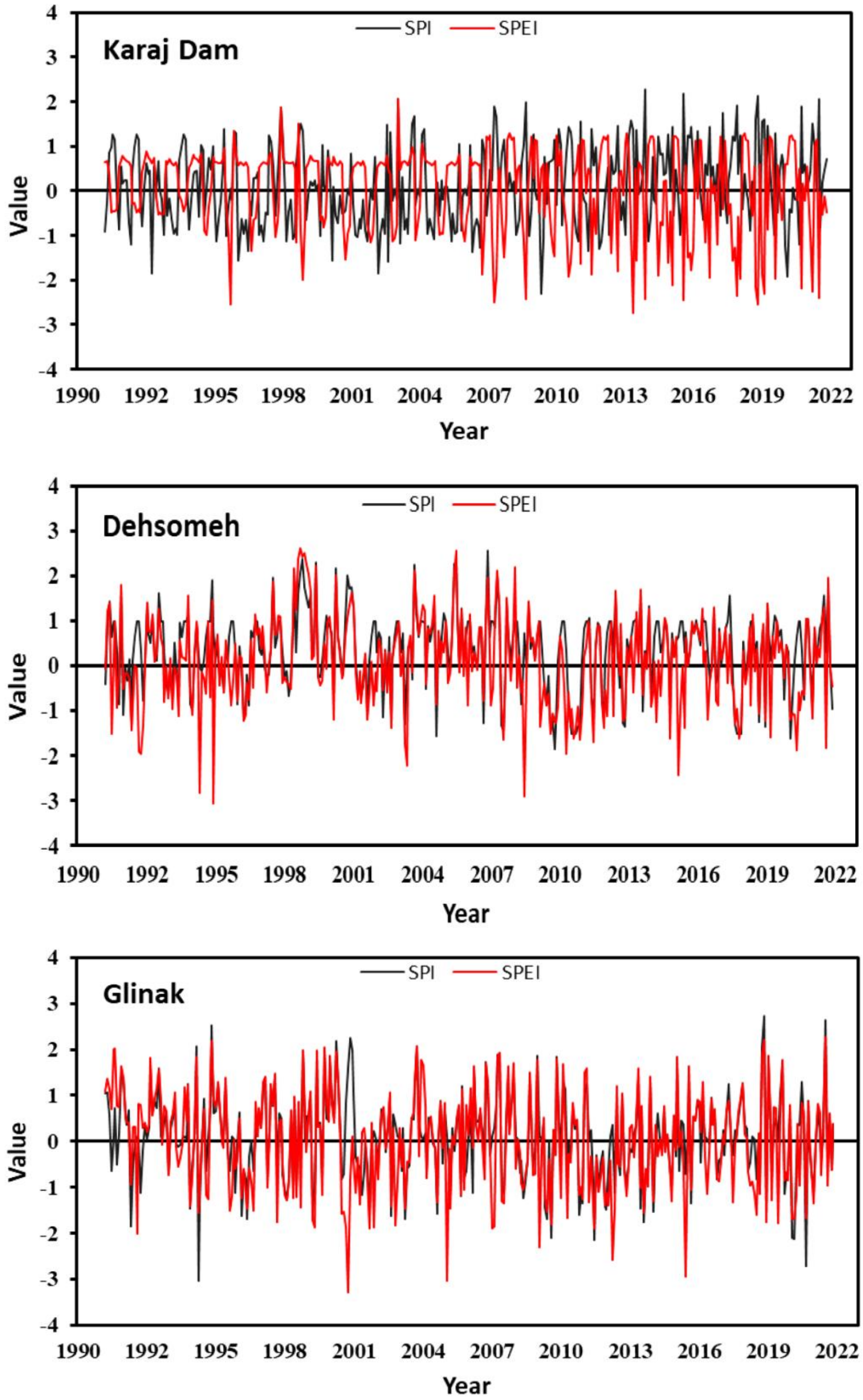


Fig. 2. Evaluation of SPI and SPEI drought indices in one-month time scale for five sub-basins at selected stations.

The analysis revealed that the average duration of droughts, as measured by the Standardized Precipitation Evapotranspiration Index (SPEI), exceeds that of the Standardized Precipitation Index (SPI) across all stations (Fig. 2). Given that both indices share the same range, their comparability was assessed using Pearson's correlation coefficient. Linear regression analyses of SPI and SPEI values at a one-month time scale from 1990 to 2022 indicate a significant relationship between the two indices across the five studied stations (Fig. 3). The Pearson correlation coefficients at the 1% significance level ($p < 0.001$) were calculated as 0.22, 0.78, -0.46, 0.73, and 0.77 for Firuzkuh, Latyan, Karaj Dam, Dehsomeh, and Glinak, respectively. The highest correlations were observed in Latyan, Dehsomeh, and Glinak, while the lowest was in Karaj Dam.

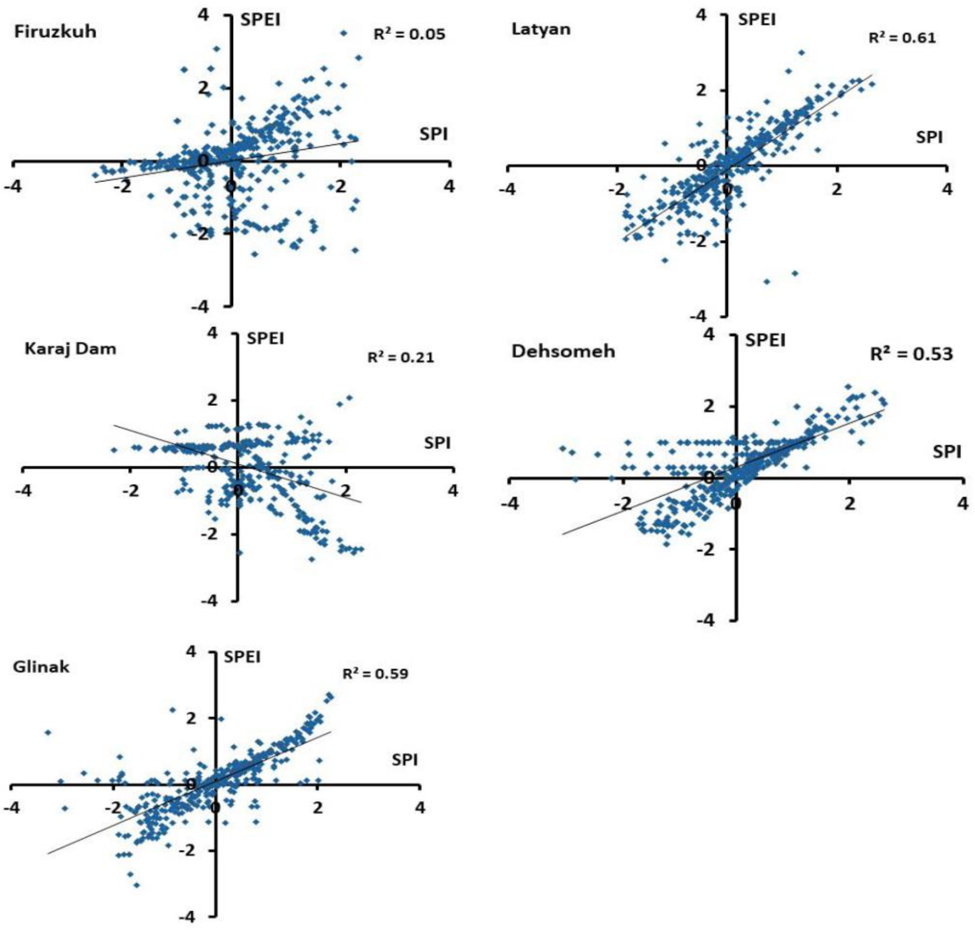


Fig. 3. Correlation between SPI and SPEI drought indices at one-month time scale at all station.

Another approach for evaluating drought indices involves comparing the severity of drought events over the study period. This is particularly critical for regional planning, where the intensity of drought often outweighs frequency in importance. To facilitate this comparison, numerical values were assigned to qualitative drought severity classes, allowing for statistical analysis. Due to the standardized classification of SPI and SPEI, a comparative analysis was performed by calculating the relative frequency of different drought severity classes on a monthly time scale over a 32-year period. Histograms illustrating the distribution of drought classes (Fig. 4) show minimal differences in the relative frequencies between SPI and SPEI. However, the SPI index generally classified a higher frequency of events as ‘normal,’ while the SPEI indicated a greater occurrence of drought conditions, particularly in the moderate to very severe classes. This suggests that SPEI is more sensitive to rainfall variability and the inclusion of temperature, thereby offering a more comprehensive characterization of drought, particularly in warming climates. These findings are consistent with previous studies. For example, Vicente-Serrano et al. (2011) demonstrated that SPEI better captured the combined effects of increased precipitation and evapotranspiration in Spain over the period 1930–2006. Similarly, Potop and Možný (2011) reported that SPEI effectively identified increased drought severity associated with rising temperatures in the Czech Republic. In our study, SPEI similarly captured higher frequencies of drought across moderate, severe, and very severe classes, underscoring its responsiveness to both precipitation deficits and thermal stress. The integration of temperature effects in SPEI offers a more holistic reflection of water stress, as rising temperatures exacerbate drought impacts through increased evapotranspiration, ultimately leading to greater reductions in water availability. This aligns with findings from Polemio and Casarano (2008), who emphasized the growing importance of temperature in future drought scenarios. As a result, SPEI serves as a critical link between meteorological and hydrological droughts, as emphasized by Nosrati (2014). Lorenzo-Lacruz et al. (2010) also highlighted the cumulative role of temperature in influencing drought dynamics and advocated for the use of SPEI over SPI in evaluating streamflow responses. Similarly, McEvoy et al. (2012) found that while both SPI and SPEI correlate significantly with surface water availability in Nevada and Eastern California, SPEI provides a more reliable measure of hydrologic drought, particularly in arid environments, due to its inclusion of atmospheric demand.

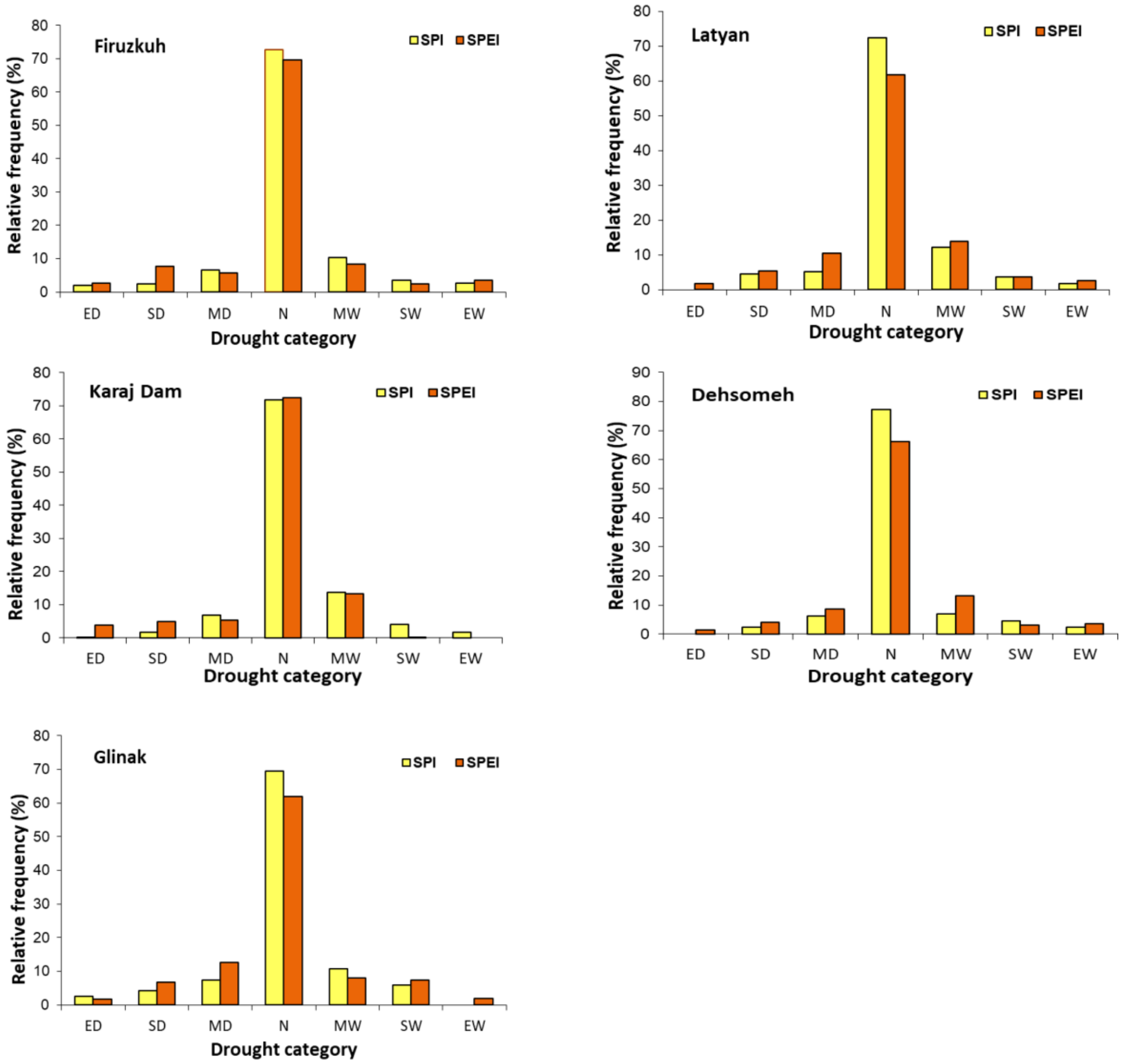
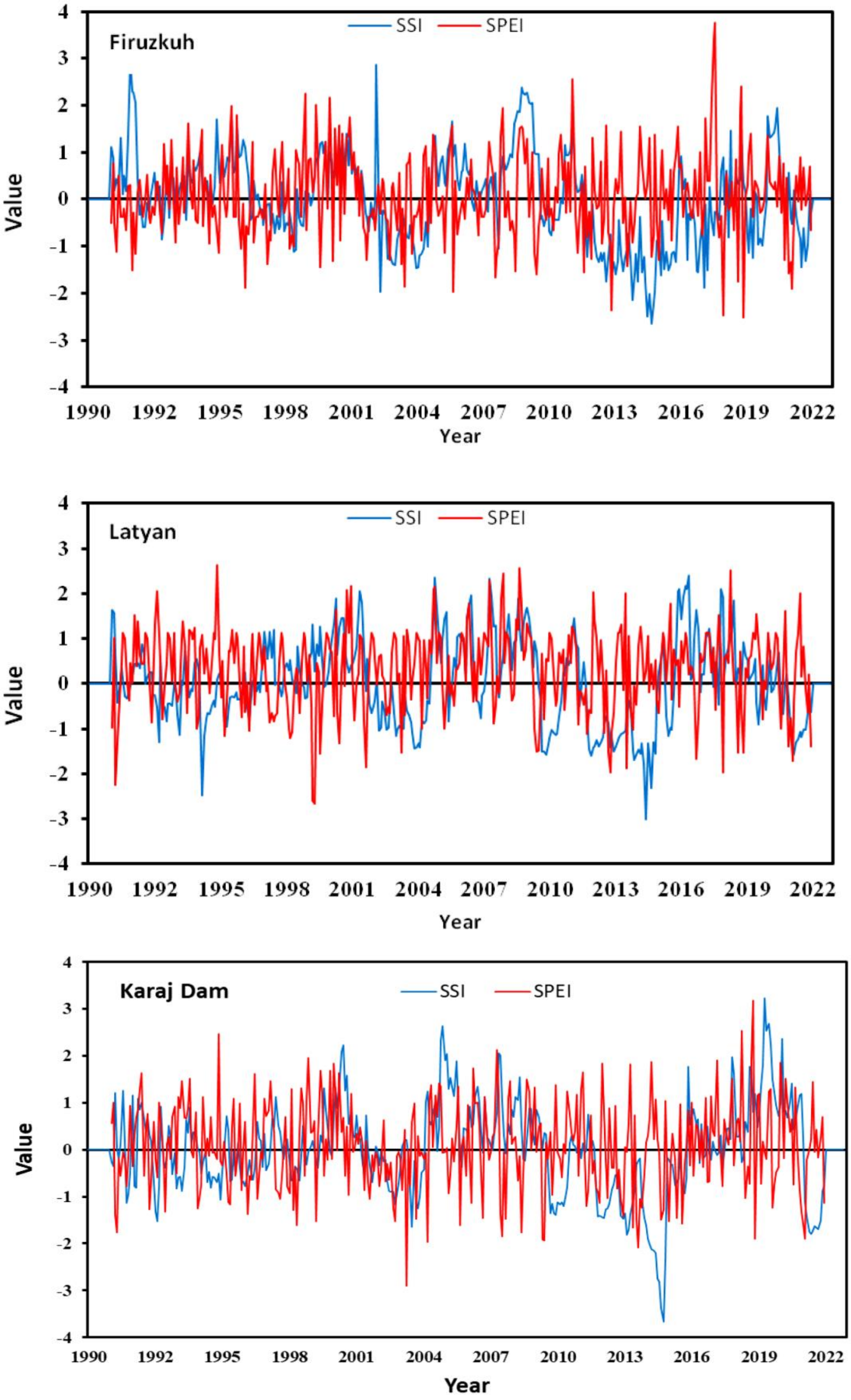


Fig. 4. The percentage of relative frequency of SPI and SPEI drought index classes in the time scale of one month in study stations. ED: extremely dry, SD: severely dry, MD: moderately dry, N: near normal, MW: moderately wet, SW: severely wet, EW: extremely wet.

3.2. Hydrological drought

Hydrological drought was assessed using the Standardized Streamflow Index (SSI), based on monthly discharge data from hydrometric stations located at the outlets of the sub-basins. These stations are influenced by the same climatic conditions as the upstream meteorological stations. Consequently, hydrological drought (SSI) was compared to meteorological drought (SPEI) at the corresponding upstream locations. One key advantage of the SSI is its applicability across diverse hydrological regimes, enabling direct comparison of drought severity across basins.

Fig. 5 presents a comparative overview of SSI and SPEI across all stations on a one-month time scale.



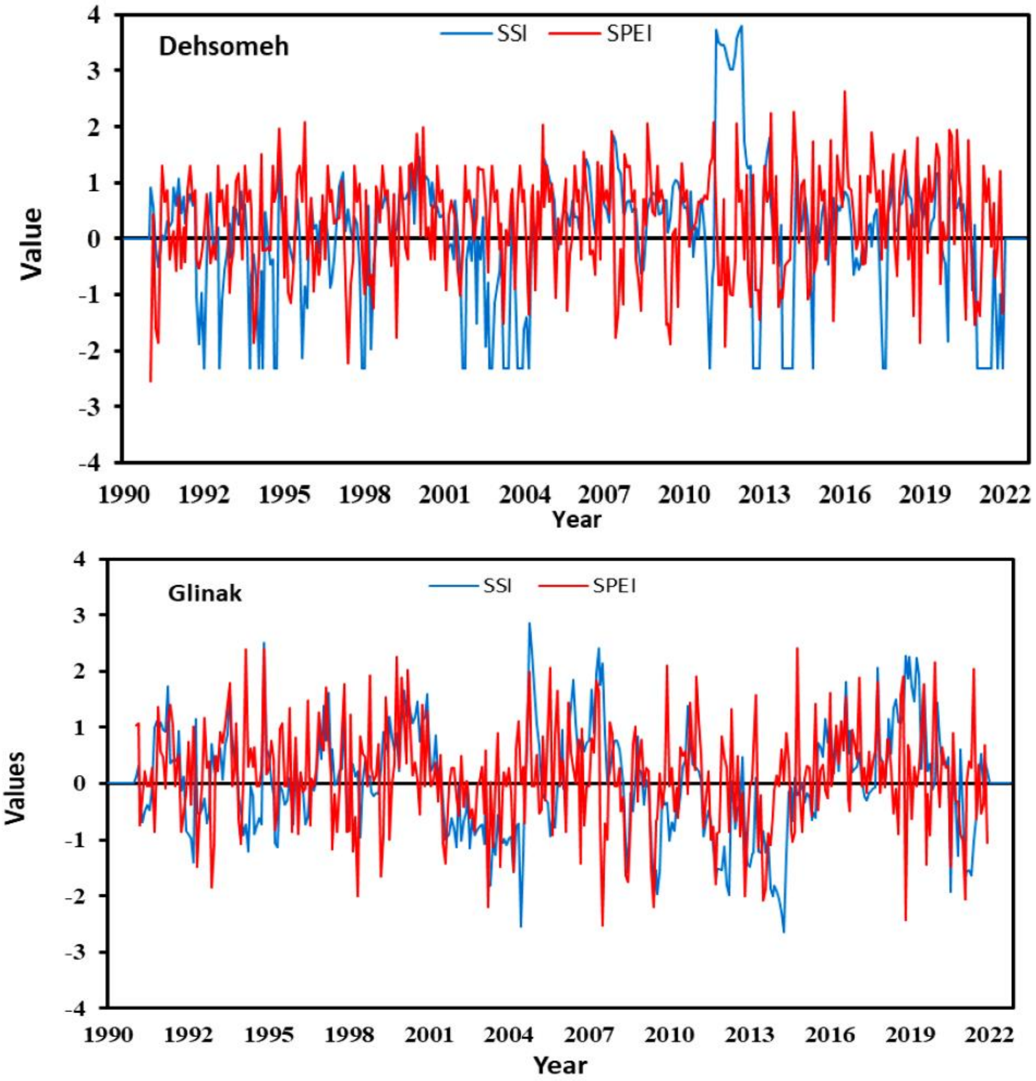
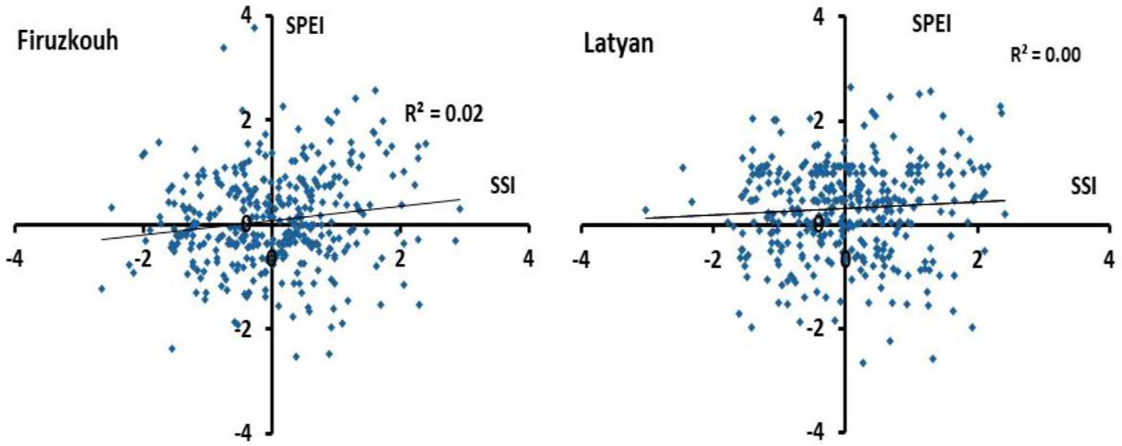


Fig. 5. SSI and SPEI drought index of the sub-basins calculated annually for time period of 1990-2022.

Regression analyses indicated a weak relationship between SSI and SPEI (Fig. 6). Pearson's correlation coefficients at the 1% significance level ($p < 0.001$) were 0.146, 0.07, 0.12, 0.12, and 0.33 for Firuzkuh, Latyan, Karaj Dam, Dehsomeh, and Glinak, respectively.



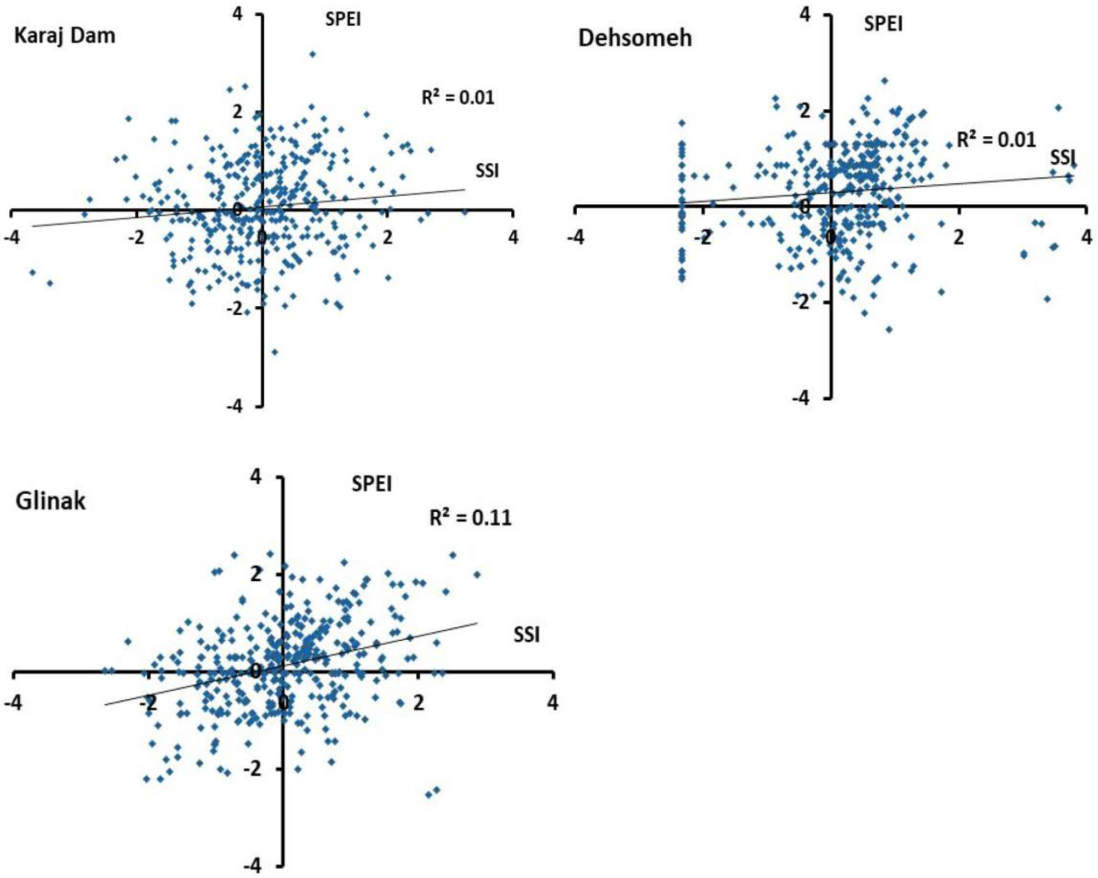


Fig. 6. The relationship between SSI and SPEI drought indices in the time scale of one month in study sub-basins.

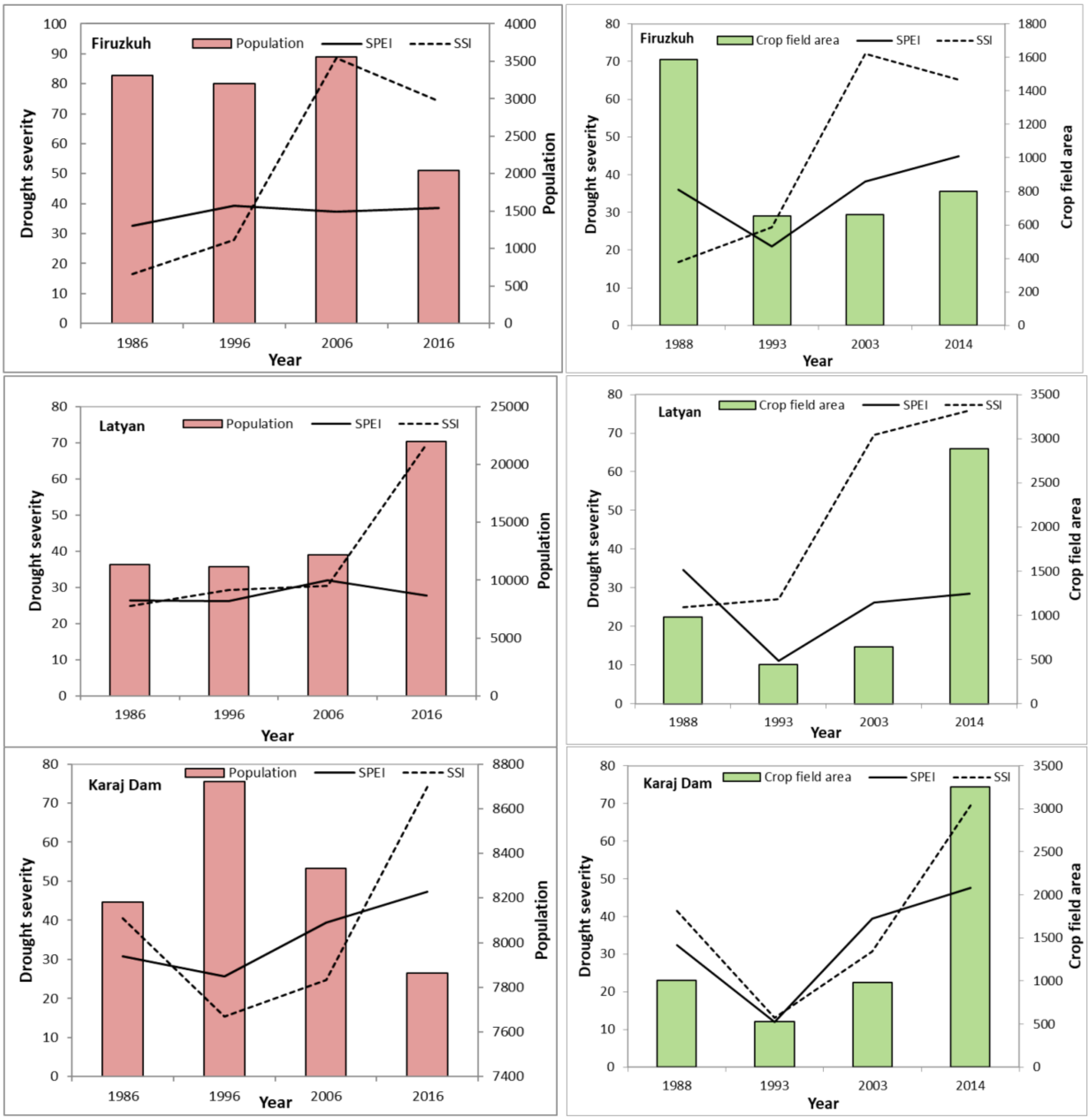
The results indicate a limited correspondence between meteorological and hydrological droughts across all stations. This weak correlation may be attributed to the temporal lag between precipitation or temperature anomalies and their eventual impact on streamflow, highlighting the importance of accounting for delayed hydrological responses in drought assessments. Although snow cover, baseflow, groundwater, and streamflow ultimately respond to precipitation deficits, the hydrological response in this region is primarily governed by baseflow, which responds more gradually.

Consequently, short-term hydrological drought signals may not immediately follow meteorological drought conditions but instead manifest with a delay—a phenomenon also supported by previous studies (e.g., Marchant and Bloomfield, 2018; Vicente-Serrano et al., 2021). Additionally, anthropogenic activities can act as dominant control factors, further complicating this relationship (e.g., López-Moreno et al., 2009; Xu et al., 2019; Vicente-Serrano et al., 2021). One significant factor is hydropower production. Although water is not consumed in the process, it is subject to substantial evaporation, resulting in water loss (Mekonnen and Hoekstra, 2012; Lorenzo-Lacruz et al., 2013).

In the study area, the potential evaporation rate is approximately 2 meters per year. When this potential is converted into actual evaporation from reservoirs, the volume of evaporated water becomes substantial and cannot be overlooked. Thus, evaporation-induced water loss may partially explain the weak short-term correspondence between meteorological and hydrological droughts. Moreover, water regulation for irrigation and domestic consumption—especially for the city of Tehran—may further contribute to the observed temporal lag between precipitation deficits and hydrological responses. Another critical factor is inter-basin water transfers, which disrupt natural flow regimes and introduce anthropogenic controls over streamflow.

3.3 Socio-economic drought

To assess socio-economic drought, the relationships between meteorological and hydrological drought indices (SPEI and SSI) and socio-economic variables (population and agricultural land area) were analyzed. This analysis focused on selected stations representing each sub-basin, where both meteorological and hydrological data as well as population and land use statistics were available (Fig. 1). Fig. 7 illustrates the temporal trends of drought indices alongside population and cultivated area data from 1986 to 2016. While both SPEI and SSI exhibit increasing trends—particularly after 1997—the population trends varied across sub-basins, increasing in Latyan and Dehsomeh while declining in Firuzkuh, Karaj Dam, and Glinak. These divergent trends suggest no clear or consistent relationship between drought severity and population change. In contrast, agricultural land area showed a more discernible trend. Between 1988 and 1993, both drought indices declined, followed by an upward trend from 1993 to 2014. Interestingly, cultivated areas increased during this latter period in most sub-basins, despite worsening drought conditions, except in Firuzkuh. This may be attributed to improvements in irrigation efficiency and the construction of reservoirs in Latyan, Karaj Dam, and Glinak, which mitigated the direct impacts of meteorological and hydrological droughts on agriculture.



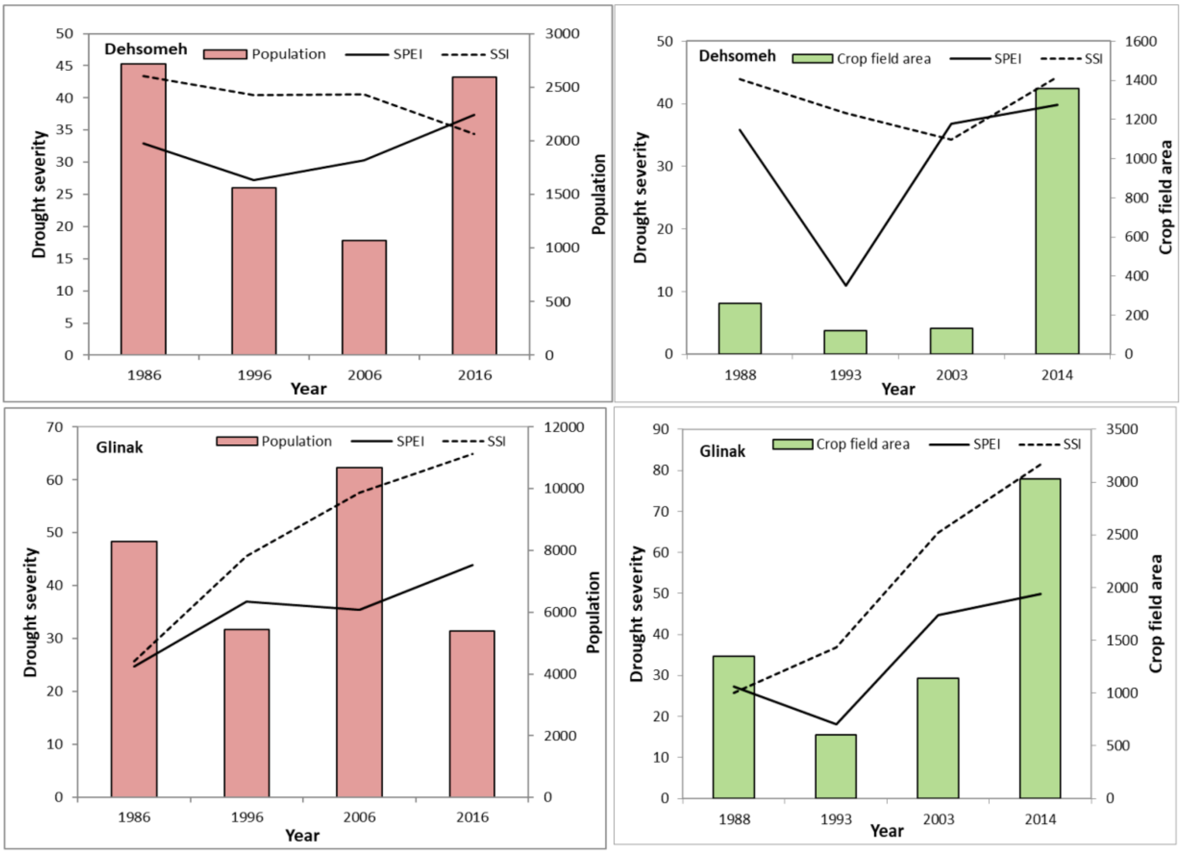


Fig. 7. The relationship between SPEI and SSI drought severity and population and crop field area in five sub-basins.

This study emphasizes the inherent complexity in understanding the link between various types of droughts and their socio-economic impacts. This complexity arises from the varied responses of hydrological cycle components to reduced precipitation—the primary water input to the system (Changnon Jr. and Easterling, 1989; Vicente-Serrano et al., 2021). In the studied watersheds, which exhibit diverse topography, hydrological regimes, climate conditions, geology, vegetation cover, and land use types, this complexity poses significant challenges for drought monitoring, understanding, and impact mitigation.

The findings also demonstrate that the socio-economic impacts of drought vary widely across the studied basins. For instance, the cultivation of drought-resistant or genetically improved crops, advances in irrigation techniques, and increased reliance on groundwater extraction have, in some cases, allowed for an expansion of agricultural lands despite the occurrence of drought. In other words, socio-economic responses to drought are influenced by a variety of controlling factors. While hydrological management practices have altered drought responses (Xu et al., 2019), they have not fully mitigated long-term impacts. Overexploitation of groundwater resources has led to severe aquifer depletion and land subsidence in several parts of the study area, resulting in irreversible socio-economic consequences.

From a future research perspective, it is important to acknowledge the limitations of this study, particularly with respect to data availability. In Iran, socio-economic indicators are typically collected and published at decadal intervals. The lack of high-frequency data restricts the accuracy and applicability of drought impact assessments. In this study, two key socio-economic indicators threatened by drought were selected—namely, reductions in soil moisture and water resources leading to declines in agricultural productivity and cultivated land area. These impacts may ultimately threaten food security, triggering population decline through out-migration to more favorable regions (e.g., the Caspian Sea coast in northern Iran), and potentially contributing to reduced marriage and birth rates. Incorporating more quantifiable indicators such as crop yield, income levels, well-being and health indices, and broader ecosystem services (Farizo et al., 2024) associating to groundwater drought indices (Lorenzo-Lacruz et al., 2017; Marchant and Bloomfield, 2018) could improve assessments of drought impacts and support the development of more effective drought mitigation and management strategies.

4. Conclusion

In arid and semi-arid regions, where evapotranspiration plays a significant role in water balance, the SPEI emerges as a more comprehensive and suitable index for characterizing drought conditions compared to precipitation-only indices such as SPI. Our study confirmed the utility of SPEI in capturing meteorological drought across five sub-basins—Firuzkuh, Latyan, Karaj Dam, Dehsomeh, and Glinak—over a 32-year period. When examining the relationship between meteorological (SPEI) and hydrological (SSI) droughts, results indicated a generally weak correlation, likely due to the lag time between climate anomalies and their hydrological impacts. Despite this, both indices followed similar long-term trends. Socio-economic analysis showed no significant relationship between drought indices and population trends. However, an inverse relationship was observed between drought severity and agricultural land area, potentially mitigated by improved water management practices and infrastructure developments. Overall, this study underscores the importance of using integrated drought indices such as SPEI for more accurate monitoring and management, particularly in light of ongoing climate change. Furthermore, the observed decoupling of socio-economic indicators from climatic and hydrologic droughts highlights the complexity of human-environment interactions and the role of adaptive strategies in mitigating drought impacts.

Acknowledgements

This project was funded by a grant (600.5698) from the research council of Shahid Beheshti University, Tehran, Iran.

References

Agrawala, S., Barlow, M., Cullen, H. & Lyon, B., 2001. The drought and humanitarian crisis in central and southwest Asia: A climate perspective. IRI Special Report 01-11, International Research Institute for Climate Prediction (IRI), Lamont-Doherty Earth Observatory of Columbia University, Palisades, New York, 10964, USA.

Bagley, J.E., Desai, A.R., Harding, K.J., Snyder, P.K. & Foley, J.A., 2014. Drought and deforestation: has land cover change influenced recent precipitation extremes in the Amazon? *Journal of Climate*, 27(1), 345-361.

Beguería, S., Vicente-Serrano, S.M., Reig, F. & Latorre, B., 2014. Standardized precipitation evapotranspiration index (SPEI) revisited: parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. *International Journal of Climatology*, 34(10), 3001-3023.

Changnon Jr., S.A. & Easterling, W.E., 1989. Measuring drought impacts: the illinois case JAWRA, *Journal of the American Water Resources Association*, 25(1), 27-42.

Dai, A., 2011. Drought under global warming: a review. *Wiley Interdisciplinary Reviews: Climate Change*, 2(1), 45-65.

Farizo, B.A., Sevilla-Callejo, M., Soliño, M., Vicente-Serrano, S.M., López-Moreno, J.I., Lázaro-Alquézar, A., Murphy, C., Grainger, S., Conradt, T., Jin, H. & Boincean, B., 2024. Valuing drought impact mitigation on ecosystem services in a Mediterranean country. *Journal of Arid Environments*, 225, 105277.

Gan, T.Y., Ito, M., Hülsmann, S., Qin, X., Lu, X.X., Liong, S.-Y., Rutschman, P., Disse, M. & Koivusalo, H., 2016. Possible climate change/variability and human impacts, vulnerability of drought-prone regions, water resources and capacity building for Africa. *Hydrological Sciences Journal*, 61(7), 1209-1226.

Hasan, H.H., Mohd Razali, S.F., Muhammad, N.S. & Ahmad, A., 2019. Research trends of hydrological drought: A systematic review. *Water*, 11(11), 2252.

Karl, T.R., 1986. The sensitivity of the Palmer Drought Severity Index and Palmer's Z-index to their calibration coefficients including potential evapotranspiration. *Journal of Climate and Applied Meteorology*, 77-86.

Knutson, C., Hayes, M. & Phillips, T., 1998. How to reduce drought risk. Drought Mitigation Center Faculty Publications. 168. University of Nebraska - Lincoln. 44 pp.

Li, L., She, D., Zheng, H., Lin, P. & Yang, Z.-L., 2020. Elucidating diverse drought characteristics from two meteorological drought indices (SPI and SPEI) in China. *Journal of Hydrometeorology*, 21(7), 1513-1530.

López-Moreno, J.I., Vicente-Serrano, S.M., Beguería, S., García-Ruiz, J.M., Portela, M.M. & Almeida, A., 2009. Dam effects on droughts magnitude and duration in a transboundary basin: The Lower River Tagus, Spain and Portugal. *Water Resources Research*, 45(2).

Lorenzo-Lacruz, J., Garcia, C. & Morán-Tejeda, E., 2017. Groundwater level responses to precipitation variability in Mediterranean insular aquifers. *Journal of Hydrology*, 552, 516-531.

Lorenzo-Lacruz, J., Vicente-Serrano, S.M., González-Hidalgo, J.C., López-Moreno, J.I. & Cortesi, N., 2013. Hydrological drought response to meteorological drought in the Iberian Peninsula. *Climate Research*, 58(2), 117-131.

Lorenzo-Lacruz, J., Vicente-Serrano, S.M., López-Moreno, J.I., Beguería, S., García-Ruiz, J.M. & Cuadrat, J.M., 2010. The impact of droughts and water management on various hydrological systems in the headwaters of the Tagus River (central Spain). *Journal of Hydrology*, 386(1-4), 13-26.

Maia, R., Vivas, E., Serralheiro, R. & de Carvalho, M., 2015. Socioeconomic evaluation of drought effects. Main principles and application to Guadiana and Algarve case studies. *Water Resources Management*, 29, 575-588.

Marchant, B. & Bloomfield, J., 2018. Spatio-temporal modelling of the status of groundwater droughts. *Journal of Hydrology*, 564, 397-413.

McEvoy, D.J., Huntington, J.L., Abatzoglou, J.T. & Edwards, L.M., 2012. An evaluation of multiscalar drought indices in Nevada and Eastern California. *Earth Interactions*, 16(18), 1-18.

McKee, T.B., Doesken, N.J. & Kleist, J., 1993. The relationship of drought frequency and duration to time scales, Proceedings of the 8th Conference on Applied Climatology. California, pp. 179-183.

Mekonnen, M.M. & Hoekstra, A.Y., 2012. The blue water footprint of electricity from hydropower. Hydrol. *Earth System Science*, 16(1), 179-187.

Mishra, A.K. & Singh, V.P., 2010. A review of drought concepts. *Journal of Hydrology*, 391(1-2), 202-216.

Nosrati, K., 2014. Assessment of standardized precipitation evapotranspiration index (SPEI) for drought identification in different climates of Iran. *Environmental Sciences*, 12(4), 63-74.

Nosrati, K., Laaha, G., Sharifnia, S.A. & Rahimi, M., 2014. Regional low flow analysis in Sefidrood Drainage Basin, Iran using principal component regression. *Hydrology Research*, 46(1), 121-135.

Palmer, W., 1965. Meteorological drought (US Dept. of Commerce, Weather Bureau Research Paper, 45). Washington, DC 58.

Polemio, M. & Casarano, D., 2008. Climate change, drought and groundwater availability in southern Italy. In: W. Dragoni, B.S. Sukhija (Eds.), Climate Change and Groundwater. *The Geological Society Special Publications*, 39-51.

Potop, V. & Možný, M., 2011. The application a new drought index–Standardized precipitation evapotranspiration index in the Czech Republic. *Mikroklima a mezoklima krajinných structur a antropogenních prostředí*, 2(4), 1-12.

Rajabi, M., Jalalkamali, N. & Naghizadeh, M., 2022. Climate change impact on the estimation of reference evapotranspiration, water requirement, and irrigation requirement in irrigated areas (a case study: Bardsir plain). *Journal of Water and Climate Change*, 13(4), 1951-1965.

Sayat, A., Lyazzat, M., Elmira, T., Gaukhar, B. & Gulsara, M., 2025. Assessment of the impacts of climate change on drought intensity and frequency using SPI and SPEI in the Southern Pre-Balkash region, Kazakhstan. *Watershed Ecology and the Environment*, 7, 11-22.

Shafer, B. & Dezman, L., 1982. Development of a surface water supply index (SWSI) to assess the severity of drought conditions in snowpack runoff areas. Fort Collins, Colorado, Colorado State University, pp. 164–175.

Sharma, C., 2024. Global High-Resolution Hydro-meteorological Variables Distribution Patterns, Sustainable Development and Geospatial Technology: Volume 2: Applications and Future Directions. Springer, pp. 65-79.

Shukla, S. & Wood, A.W., 2008. Use of a standardized runoff index for characterizing hydrologic drought. *Geophysical Research Letters*, 35(2).

Sosa, G., Fernández-Long, M.E. & Vicente-Serrano, S.M., 2025. Evaluating the performance of drought indices for assessing agricultural droughts in Argentina. Agronomy Journal 117(1), e70008.

Stagge, J.H., Tallaksen, L.M., Gudmundsson, L., Van Loon, A.F. & Stahl, K., 2015. Candidate distributions for climatological drought indices (SPI and SPEI). *International Journal of Climatology*, 35(13), 4027-4040.

Tabrizi, A.A., Khalili, D., Kamgar-Haghighi, A.A. & Zand-Parsa, S., 2010. Utilization of time-based meteorological droughts to investigate occurrence of streamflow droughts. *Water Resources Management*, 24, 4287-4306.

Tallaksen, L.M. & Van Lanen, H.A., 2023. Hydrological Drought: Processes and Estimation Methods for Streamflow and Groundwater. Developments in Water Science. 2nd ed. Elsevier Science BV, The Nethlerlands.

Van Loon, A.F., Stahl, K., Di Baldassarre, G., Clark, J., Rangecroft, S., Wanders, N., Gleeson, T., Van Dijk, A.I., Tallaksen, L.M. & Hannaford, J., 2016. Drought in a human-modified world: reframing drought definitions, understanding, and analysis approaches. *Hydrology and Earth System Sciences*, 20(9), 3631-3650.

Vicente-Serrano, S.M., 2006. Differences in spatial patterns of drought on different time scales: an analysis of the Iberian Peninsula. *Water Resources Management*, 20, 37-60.

Vicente-Serrano, S.M., Beguería, S. & López-Moreno, J.I., 2010. A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. *Journal of Climate*, 23(7), 1696-1718.

Vicente-Serrano, S.M., López-Moreno, J.I., Beguería, S., Lorenzo-Lacruz, J., Azorin-Molina, C. & Morán-Tejeda, E., 2012. Accurate computation of a streamflow drought index. *Journal of Hydrologic Engineering*, 17(2), 318-332.

Vicente-Serrano, S.M., López-Moreno, J.I., Drumond, A., Gimeno, L., Nieto, R., Morán-Tejeda, E., Lorenzo-Lacruz, J., Beguería, S. & Zabalza, J., 2011. Effects of warming processes on droughts and water resources in the NW Iberian Peninsula (1930−2006). *Climate Research*, 48(2-3), 203-212.

Vicente-Serrano, S.M., Peña-Angulo, D., Murphy, C., López-Moreno, J.I., Tomas-Burguera, M., Dominguez-Castro, F., Tian, F., Eklundh, L., Cai, Z. & Alvarez-Farizo, B., 2021. The complex multi-sectoral impacts of drought: Evidence from a mountainous basin in the Central Spanish Pyrenees. *Science of the Total Environment*, 769, 144702.

Vidal, J.-P., Martin, E., Franchistéguy, L., Habets, F., Soubeyroux, J.-M., Blanchard, M. & Baillon, M., 2010. Multilevel and multiscale drought reanalysis over France with the Safran-Isba-Modcou hydrometeorological suite. *Hydrology and Earth System Sciences*, 14(3), 459-478.

Vogel, R.M. & Wilson, I., 1996. Probability distribution of annual maximum, mean, and minimum streamflows in the United States. *Journal of Hydrologic Engineering*, 1(2), 69-76.

Wilhite, D.A., Hayes, M.J., Knutson, C. & Smith, K.H., 2000. Planning for drought: Moving from crisis to risk management 1. *JAWRA Journal of the American Water Resources Association*, 36(4), 697-710.

Xu, Y., Zhang, X., Wang, X., Hao, Z., Singh, V.P. & Hao, F., 2019. Propagation from meteorological drought to hydrological drought under the impact of human activities: A case study in northern China. *Journal of Hydrology*, 579, 124147.

Zargar, A., Sadiq, R., Naser, B. & Khan, F.I., 2011. A review of drought indices. *Environmental Reviews*, 19(NA), 333-349.