



Quantitative Assessment of Drought Risk in Iran: A Copula-Based approach

Using Spi and Spei Indices

Mohammad Amin Natanzi^{1,*}, Hasan Jabari²

¹ IT Managment, Management and Accounting, Allameh Tabataba'i University, Tehran, Iran.

² Eco insurance managment, Eco insurance managment, Allameh Tabataba'i University, Tehran, Iran.

ARTICLE INFO

KEYWORDS:

Climate change
Copula models
Drought risk
Iran
Parametric insurance
SPI
SPEI

ABSTRACT

Drought is one of the most critical climate-related hazards affecting Iran, with substantial consequences for agricultural production, water resources, and socio-economic stability. The predominance of arid and semi-arid climatic conditions, coupled with high interannual variability in precipitation and a sustained increase in temperature, has intensified both the frequency and severity of drought events across the country. Traditional drought assessments in Iran have largely relied on single drought indices and linear correlation measures, which are often inadequate for capturing the compound nature of drought processes driven by the simultaneous effects of precipitation deficits and increased atmospheric water demand. In recent decades, temperature-driven evapotranspiration has emerged as a key driver of drought severity under climate change, highlighting the limitations of precipitation-only indicators such as the Standardized Precipitation Index (SPI). In this context, the Standardized Precipitation Evapotranspiration Index (SPEI), which explicitly incorporates potential evapotranspiration, provides a more comprehensive representation of drought conditions. However, understanding drought risk requires not only the analysis of individual indices but also the characterization of their joint behavior and dependence structure. The primary objective of this study is to provide a probabilistic and multivariate assessment of drought risk across major climatic regions of Iran by jointly analyzing SPI and SPEI using copula theory. By modeling the dependence structure between these indices, the study aims to capture nonlinear and asymmetric relationships, particularly tail dependence associated with extreme drought events. In addition to advancing methodological understanding, the study seeks to demonstrate the

relevance of copula-based drought modeling for practical applications in drought risk management, climate adaptation planning, and the conceptual development of index-based insurance schemes.

METHODS: This study is based on long-term climatic observations from synoptic meteorological stations distributed across Iran, covering the period ۱۹۸۱–۲۰۲۰. Monthly precipitation and temperature data were used to compute SPI and SPEI at multiple accumulation time scales, enabling the assessment of both short-term and long-term drought conditions. The calculation of SPEI incorporated potential evapotranspiration to account for the influence of rising temperatures on drought intensity. Marginal probability distributions of SPI and SPEI were fitted using the Maximum Likelihood Estimation (MLE) method. Several copula families—including Gaussian, Student-t, Clayton, and Gumbel—were evaluated to model the dependence structure between the two indices. These copulas were selected to represent a wide range of dependence behaviors, including symmetric dependence, tail dependence, and asymmetric lower- or upper-tail dependence. Model selection was conducted using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and goodness-of-fit tests. Lower- and upper-tail dependence coefficients were estimated to quantify the likelihood of concurrent extreme drought conditions. Joint probabilities and return periods of severe and extreme drought events were derived from the fitted copula models for different climatic regions of Iran. These probabilistic measures were further examined in relation to historical drought occurrences to ensure consistency with observed drought behavior.

FINDINGS: The results reveal pronounced spatial heterogeneity in drought characteristics and dependence structures across Iran. Arid and semi-arid regions, particularly the Central Plateau and eastern parts of the country, exhibit strong lower-tail dependence between SPI and SPEI, indicating a high likelihood of concurrent extreme drought conditions driven by both precipitation deficits and elevated evaporative demand. In these regions, the Clayton copula consistently provided the best fit, reflecting its ability to capture asymmetric lower-tail dependence relevant to severe drought events. In contrast, humid regions along the Caspian coast display weaker dependence structures and longer drought return periods, with limited evidence of strong tail dependence. Transitional climatic zones were better represented by the student-t copula, which captures symmetric tail dependence and intermediate drought behavior. Estimated joint probabilities and return periods indicate that severe compound droughts recur approximately every ۱۴–۲۰ years in arid regions, while recurrence intervals exceed ۵۰ years in northern humid areas. These findings are

consistent with documented historical drought events in Iran, including major drought episodes in the early ۱۹۷۰s, late ۱۹۹۰s, and late ۲۰۱۰.

CONCLUSION: The findings contribute to a probabilistic characterization of drought risk in Iran and provide a quantitative basis for understanding compound drought behavior. While this study does not develop a full actuarial pricing framework, the results may support future applications in drought risk management and the conceptual design of index-based insurance and climate adaptation strategies. By integrating multivariate drought indices with copula-based dependence modeling, this study demonstrates the importance of moving beyond univariate and correlation-based approaches in drought risk assessment. The results highlight the increasing role of temperature-driven evapotranspiration under climate change and underscore the value of SPEI-based analyses in warming environments. Overall, the proposed framework offers a robust, flexible, and policy-relevant tool for assessing drought risk in Iran and provides a scientific foundation for future efforts aimed at enhancing climate resilience, improving agricultural risk management, and supporting the development of innovative risk transfer mechanisms.

Introduction

Drought is one of the most damaging climate-related hazards, particularly in arid and semi-arid regions where water availability strongly constrains agricultural production and socio-economic stability. Unlike sudden hazards, drought develops gradually, exhibits strong spatial heterogeneity, and produces cumulative impacts, making its monitoring and quantitative assessment especially challenging. Under ongoing climate change, rising temperatures and altered precipitation regimes have intensified drought frequency and severity in many regions worldwide.

Iran is among the countries most vulnerable to drought due to its predominantly arid and semi-arid climate, high interannual rainfall variability, and increasing pressure on limited water resources. Approximately ۸۵% of the country lies within dry climatic zones, and a large share of agricultural production depends on rainfall or stressed groundwater systems. Recurrent drought events have caused substantial crop losses and water shortages, underscoring the need for robust, quantitative drought assessment frameworks to support risk-informed decision-making.

Drought monitoring commonly relies on standardized indices that summarize hydroclimatic anomalies across multiple time scales. The Standardized Precipitation Index (SPI) is widely used because of its simplicity and minimal data requirements; however, it does not explicitly account for temperature-driven evapotranspiration. To address this limitation, the Standardized Precipitation Evapotranspiration Index

(SPEI) incorporates both precipitation and atmospheric water demand, providing a more comprehensive representation of climatic water balance and agricultural drought, particularly under warming conditions.

Although SPI and SPEI are extensively applied, most drought assessments analyze these indices independently or rely on linear correlation, which is insufficient for capturing nonlinear and asymmetric dependence structures during extreme events. In practice, precipitation deficits and elevated evapotranspiration often occur simultaneously, amplifying drought impacts. Copula theory offers a flexible statistical framework for modeling such dependence structures independently of marginal distributions and enables the quantification of tail dependence and joint extreme behavior.

While previous studies have examined drought trends and spatial variability in Iran, systematic analyses of joint SPI–SPEI behavior and its implications for probabilistic drought risk assessment remain limited. In particular, the integration of Copula-based joint probabilities into frameworks relevant for drought risk management and index-based insurance design has been insufficiently explored.

Against this background, this study aims to quantitatively assess drought characteristics and dependence structures across Iran using SPI and SPEI indices. Specifically, it (i) computes multiscalar SPI and SPEI using long-term climatic data, (ii) models their dependence using different Copula families, (iii) identifies regional differences in tail dependence and joint drought behavior, and (iv) derives joint probabilities and return periods to support probabilistic drought risk assessment. By integrating multiscalar drought indices with Copula-based modeling, this study contributes to a clearer understanding of compound drought dynamics in Iran and provides a quantitative foundation for climate-informed risk management and index-based insurance applications.

Such probabilistic characterization of compound droughts is essential for reducing basis risk and improving the transparency of index-based insurance schemes in drought-prone regions.

Literature Review

۲.۱ Drought Indices and Their Applications

Drought indices provide quantitative tools for characterizing the intensity, duration, and temporal evolution of droughts, enabling consistent comparison across regions and time scales. Numerous indices have been developed to monitor meteorological and agricultural drought, each reflecting different components of the hydroclimatic system and associated impacts.

Among the most widely used indicators is the Standardized Precipitation Index (SPI), originally proposed by McKee et al. (۱۹۹۳). SPI measures precipitation anomalies over multiple accumulation periods and has been extensively applied due to its conceptual simplicity, low data requirements, and flexibility across climatic regimes. In arid and semi-arid regions such as Iran, SPI has been widely employed for drought

monitoring and regional assessments (Modarres & Sarhadi, ۲۰۰۹). However, because SPI relies exclusively on precipitation, it does not explicitly account for the influence of temperature-driven evapotranspiration, which has become increasingly important under ongoing climate warming.

To overcome this limitation, Vicente-Serrano et al. (۲۰۱۰) introduced the Standardized Precipitation Evapotranspiration Index (SPEI), which incorporates potential evapotranspiration (PET) alongside precipitation, thereby reflecting variations in atmospheric water demand. Numerous studies have shown that SPEI provides a more sensitive representation of drought conditions in warming environments, particularly for agricultural systems. Empirical evidence from Iran suggests that SPEI is more effective than SPI in capturing drought severity during warm and prolonged dry periods, especially for temperature-sensitive crops such as wheat and barley (e.g., Khaledi-Alamdari et al., ۲۰۲۳).

In addition to SPI and SPEI, other drought indicators have been developed to capture long-term soil moisture conditions and vegetation responses. The Palmer Drought Severity Index (PDSI) is commonly used for long-term drought assessment but requires detailed soil and calibration data, which limits its applicability in data-scarce regions. Remote-sensing-based indicators, such as the Normalized Difference Vegetation Index (NDVI) and the Vegetation Health Index (VHI), have also been employed to monitor vegetation stress and ecological impacts of drought (Tehrany et al., ۲۰۱۳). While these indices provide valuable complementary information, they primarily reflect vegetation response rather than atmospheric drought processes.

Overall, SPI and SPEI remain the most suitable indices for large-scale and long-term drought assessment in Iran due to their data availability, comparability, and flexibility across temporal scales. Their joint use allows a more comprehensive representation of hydroclimatic variability by capturing both precipitation deficits and evaporative demand. Recent drought episodes in Iran have resulted in substantial and measurable impacts on agricultural yields. Empirical studies have shown that severe drought conditions significantly reduce rainfed crop performance, particularly for strategic cereals such as wheat and barley (Sharafi & Nahvinia, ۲۰۲۴). For example, observational analyses across diverse Iranian climatic zones indicate that drought events, especially those identified by low standardized drought indices, correlate with notable reductions in rainfed wheat and barley yields, with impacts often exceeding ۲۰–۲۵%. **in severe drought years** compared to average yield levels (Sharafi & Nahvinia, ۲۰۲۴; *Assessing drought impacts on groundwater and agriculture in Iran*, ۲۰۲۴). These quantitative effects highlight that drought is not only a climatological phenomenon but also a **critical driver of agricultural production losses** in Iran, underlining the practical importance of integrating drought indices such as SPI and SPEI into agricultural risk assessment and policy-making frameworks.

Table ۱. Annual summary of national drought extent in Iran based on SPEI, showing the percentage of the country affected by drought conditions during selected periods.^۱

Period / Year	% of Iran under Drought (SPEI-based)	Description / Source
۲۰۱۰–۲۰۱۹ (۱۰–year aggregate)	۹۶.۹۲%	Proportion of total country affected by drought (moderate → very severe), SPEI ۱۰–year period report (۲۰۱۰–۲۰۱۹). Iran Open Data Center
۲۰۱۹ (end of Oct ۲۰۱۹)	۸۷.۹%	National drought percentage based on SPEI ۱۰–year summary through ۲۰۱۹. Iran Open Data Center
۲۰۲۳ (one–year SPEI)	۸۶.۵۰%	Percentage of Iran under drought (mild to very severe) based on one–year SPEI. Iran Open Data Center
۲۰۲۴ (one–year SPEI)	۸۶.۵۰–۹۱.۱%*	National drought percentage through early ۲۰۲۴ (reported at ~۹۱.۱% by national open data; *note: variation arises by reporting date). Iran Open Data Center

۲.۲ Copula Models in Drought Analysis

Copula theory offers a flexible statistical framework for modeling multivariate dependence structures by separating marginal distributions from their joint behavior. Unlike traditional correlation measures, Copulas are capable of capturing nonlinear and asymmetric dependence patterns, including tail dependence, which is particularly relevant for extreme drought analysis.

Different Copula families exhibit distinct dependence characteristics. The Gaussian Copula assumes symmetric dependence and weak tail behavior, which often leads to an underestimation of joint extremes. The Student-t Copula extends this structure by allowing symmetric tail dependence, making it suitable for modeling concurrent extreme drought conditions. Archimedean Copulas provide additional flexibility; for instance, the Clayton Copula captures lower-tail dependence and is therefore well suited for representing simultaneous low values of drought indices, while the Gumbel Copula emphasizes upper-tail dependence and is more relevant for wet extremes.

¹ Data source: Iran Open Data Center (SPEI-based national drought assessments).

Copula-based approaches have been increasingly applied in hydroclimatology to assess compound and joint drought behavior. Several studies in Iran and neighboring regions report pronounced lower-tail dependence between drought-related variables, indicating a high probability of concurrent extreme conditions. For example, Farokhzadeh (۲۰۲۰) identified strong lower-tail dependence in precipitation patterns across central and southeastern Iran, while studies in Pakistan and Turkey (Cevik & Kaya, ۲۰۱۸ ; Qureshi et al., ۲۰۲۲) reported similar dependence structures using Copula-based frameworks. More recent work has shown that Student-t and Clayton Copulas often outperform Gaussian Copulas in modeling joint drought behavior involving SPI and SPEI (e.g., Khaledi-Alamdari et al., ۲۰۲۵).

Beyond descriptive analysis, Copula models provide a probabilistic foundation for drought risk assessment by enabling the estimation of joint exceedance probabilities and return periods. These properties are essential for understanding the likelihood of compound drought events and for supporting quantitative risk-based decision frameworks. In addition to statistical characterization, Copula-based dependence modeling plays a direct and operational role in the design of parametric drought insurance schemes. In such contracts, indemnity payments are triggered when predefined climate indices exceed critical thresholds, making the accurate representation of joint drought behavior essential for reducing basis risk and ensuring actuarial soundness (Cummins & Weiss, ۲۰۰۹; Clarke, ۲۰۱۶). By explicitly modeling the joint distribution of SPI and SPEI, Copulas enable the estimation of *joint threshold exceedance probabilities associated with compound drought conditions, which can be directly translated into objective trigger definitions. Lower-tail dependent structures, such as the Clayton Copula, are particularly suitable for this purpose, as they capture the increased likelihood of simultaneous precipitation deficits and elevated evaporative demand—conditions under which agricultural losses are most severe. Moreover, joint return periods derived from Copula models provide a probabilistic basis for calibrating payout schedules and premium levels,* allowing insurance pricing to reflect the true multivariate risk of extreme drought events rather than relying on single-index metrics. As a result, Copula-based frameworks offer a rigorous quantitative bridge between hydroclimatic analysis and risk-based financial instruments, supporting the development of more robust and transparent drought insurance solutions.

Copula Type	Dependence Feature	Typical Use	Notes
Gaussian	Symmetric, weak tails	General correlations	Poor for extremes
Student-t	Symmetric with tail dependence	Pricing of severe drought risk	Good for multi-regional droughts

Clayton	Lower-tail dependence	Trigger design for drought payouts	Captures simultaneous low SPI–SPEI
Gumbel	Upper-tail dependence	Wet extremes	Not relevant for arid Iran

Table ۲ . Conceptual comparison of commonly used copula families in drought dependence modeling, summarizing their dependence characteristics and typical applications based on existing methodological and hydroclimatic literature.^۲

۲.۳ Integration of Drought Indices and Copulas in Risk Management

Integrating multi-scalar drought indices with Copula-based dependence modeling allows for a comprehensive probabilistic characterization of drought risk. In this framework, SPI and SPEI are first derived from long-term meteorological observations and subsequently linked through appropriate Copula functions to represent their joint dependence structure.

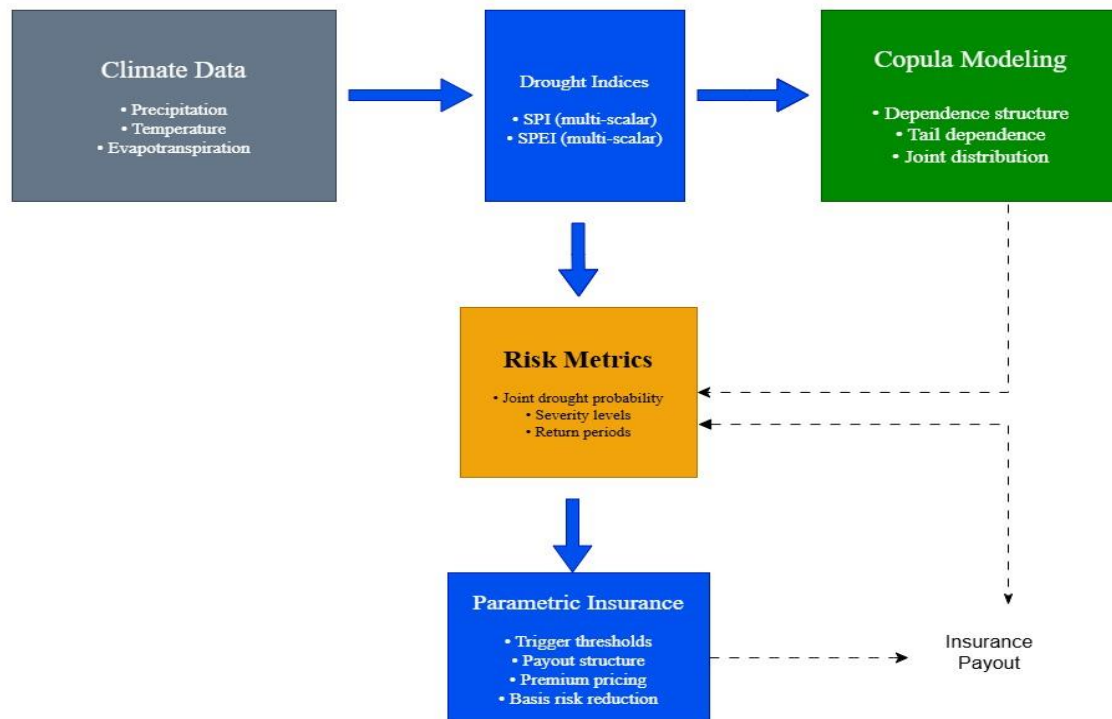
As illustrated in Figure X, the resulting joint distributions enable the estimation of key risk metrics, including joint drought probabilities, severity levels, and associated return periods. These metrics provide an analytical basis for identifying regions with elevated exposure to compound drought conditions and for comparing drought behavior across different climatic zones.

Such integrated approaches have been increasingly used to support risk-informed decision-making in water resources management and agriculture. Moreover, by quantifying the probability of simultaneous precipitation deficits and elevated evaporative demand, Copula-based frameworks offer conceptual support for the development of index-based and parametric insurance schemes. Although the present study does not implement a full insurance pricing model, the derived joint probability structures represent a necessary statistical foundation for future applications aimed at reducing basis risk and enhancing climate resilience.

² Note: Table entries are synthesized from established copula theory and previous drought dependence studies (e.g., Nelsen, 2006; Salvadori et al., 2022; Zhang et al., 2022).

Figure X. Conceptual framework illustrating the methodological workflow of the study, linking climate data (precipitation, temperature, evapotranspiration) to multiscalar drought indices (SPI and SPEI), copula-based dependence modeling, and the derivation of drought risk metrics for parametric

Figure X. Conceptual framework linking drought indices, Copula modeling, and parametric insurance design



insurance applications.

۲.۴ Research gap and methodological contribution

Previous drought studies in Iran have primarily focused on the analysis of individual drought indices, temporal trends, and spatial variability using univariate frameworks or linear correlation measures (e.g., Raziei et al., ۲۰۱۰; Modarres & Sarhadi, ۲۰۱۱; Farajzadeh et al., ۲۰۱۵). These studies have provided valuable insights into the climatology and dynamics of drought across different regions of Iran. However, the majority of existing assessments treat precipitation-based and temperature-influenced drought processes separately, thereby limiting their ability to capture the joint and nonlinear behavior of compound drought events.

More recently, multivariate approaches have gained attention in drought research; nevertheless, systematic applications of copula theory to jointly model SPI and SPEI remain scarce in the context of Iran. In particular, previous studies have not explicitly quantified tail dependence or joint drought probabilities that are critical for understanding extreme drought co-occurrence and for informing probabilistic risk assessment.

The present study addresses this gap by introducing a copula-based framework to jointly model SPI and SPEI, enabling explicit characterization of dependence structures, tail behavior, and joint return periods of drought events. This methodological contribution represents a clear advancement over previous drought assessments in Iran and provides a more comprehensive basis for compound drought risk analysis and related applications.

Expanded Data and Methodology

3.1 Study Area
Iran is located in Southwest Asia between approximately 25° – 39° N latitude and 44° – 63° E longitude and exhibits substantial climatic heterogeneity due to its complex topography and geographic setting. The country encompasses a wide range of climatic regimes, from hyper-arid deserts to humid coastal zones, making it particularly suitable for investigating spatial variability in drought behavior.

Mean annual precipitation ranges from less than 50 mm in the central and eastern desert regions to more than $1,200$ mm along the southern Caspian Sea coast, while mean annual air temperature varies from below 10° C in high-altitude mountainous areas to above 25° C in southern lowlands. Extreme surface temperatures exceeding 50° C have been recorded in parts of the Lut Desert, highlighting the intensity of thermal stress in eastern Iran (Alijani et al., 2019; NASA, 2020).

Based on prevailing climatic characteristics, Iran can broadly be classified into several major hydroclimatic zones, including the arid central plateau, semi-arid northwestern regions, humid Caspian coastal areas, the western Zagros Mountains, and the hyper-arid eastern deserts. This pronounced climatic diversity provides a suitable natural laboratory for assessing drought variability and evaluating probabilistic drought modeling approaches under contrasting environmental conditions.

3.2 Data Sources and Preprocessing

Monthly and daily meteorological observations were obtained from the Islamic Republic of Iran Meteorological Organization (IRIMO), which maintains long-term synoptic station records across the country. To ensure spatial representativeness and statistical reliability, stations were selected based on data completeness and continuity criteria.

Following previous climatological studies, stations with more than 10% missing daily precipitation records over the study period were excluded to avoid bias in trend and distributional analyses (Zolina et al., 2005). After quality control, a total of 49 synoptic stations covering the period 1981–2020 were retained. The retained set of 49 stations represents a balance between maximizing spatial coverage across Iran and ensuring sufficient data quality and record length for robust statistical

analysis. From a statistical perspective, the exclusion of stations with substantial data gaps improves the stability of drought index estimation and the reliability of subsequent copula-based dependence modeling. From a spatial perspective, the selected stations are distributed across Iran's major hydroclimatic zones, including the arid central plateau, semi-arid northwestern regions, humid Caspian coastal areas, mountainous western regions, and hyper-arid eastern deserts. This distribution allows the dataset to capture the principal gradients of precipitation, temperature, and atmospheric water demand that govern drought behavior at the national scale, supporting the representativeness of the selected station network for regional and country-wide drought risk assessment.

To address remaining data gaps and ensure temporal continuity, missing precipitation values were complemented using ERA5 reanalysis data produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). ERA5 integrates in situ observations with satellite data through numerical weather prediction models and provides spatially consistent climate variables at a $0.25^\circ \times 0.25^\circ$ resolution. Its applicability for hydroclimatic studies over Iran has been widely demonstrated in previous research.

Potential evapotranspiration (PET) was estimated using the FAO Penman–Monteith formulation, which incorporates air temperature, relative humidity, wind speed, and solar radiation and is widely regarded as a reference method for evapotranspiration estimation. Specifically, the FAO Penman–Monteith method estimates reference evapotranspiration by integrating net radiation, air temperature, wind speed, and vapor pressure deficit, and provides a physically based representation of atmospheric evaporative demand. Due to its robustness across a wide range of climatic conditions, this method has been recommended by the Food and Agriculture Organization (FAO) as the standard approach for PET estimation and has been extensively applied in drought, climate variability, and water resources studies. Its suitability for semi-arid and arid environments, such as large parts of Iran, has been demonstrated in numerous regional and global assessments. Prior to index calculation, standard preprocessing procedures—including quality control, outlier screening, gap filling, and temporal aggregation—were applied to ensure data consistency across stations and climatic regions.

3.2 Calculation of Drought Indices

Standardized Precipitation Index (SPI):

$$SPI = \frac{X_i - \mu}{\sigma}$$

where X_i = precipitation in month i , μ = long-term mean, σ = standard deviation.

Standardized Precipitation Evapotranspiration Index (SPEI):

$$P-PET = Di \quad SPEI = \frac{DDi - \mu}{\sigma}$$

Both indices were computed at 1-, 3-, 6-, and 12-month scales using gamma and log-logistic distributions, respectively.

Drought classification (WMO, 2012):
Mild (-0.5 to -0.99), Moderate (-1.0 to -1.49), Severe (-1.5 to -1.99), Extreme (< -2.0).

Rationale for Distribution Selection

The selection of the gamma and log-logistic distributions for SPI and SPEI, respectively, is based on the statistical characteristics of the underlying data and their suitability for drought assessment. Precipitation data, used in SPI, are strictly positive and often skewed. The gamma distribution effectively models such positive, skewed data, ensuring that extreme wet and dry events are properly represented while avoiding non-physical negative values.

For SPEI, which considers the difference between precipitation and potential evapotranspiration (P - PET), values can be both positive and negative, particularly during prolonged dry periods when evapotranspiration exceeds precipitation. The log-logistic distribution accommodates this range of values and captures both short- and long-term drought variability more accurately.

The choice of these distributions is consistent with previous studies in the literature, which have demonstrated their suitability for meteorological and climatic drought indices (McKee et al., 1993; Vicente-Serrano et al., 2010)

3.3 Drought Indices Computation

SPI was calculated by fitting a gamma probability distribution to precipitation data, while SPEI was computed from the climatic water balance (P-PET) using a log-logistic distribution. Both indices were standardized to a mean of zero.

Timescales:

- SPI: 1, 3, 6, and 12 months — representing short- to long-term droughts.
- SPEI: 3 and 6 months — reflecting agricultural drought conditions sensitive to evapotranspiration changes.

Severity Classification (WMO, 2012):³

Category	SPI/SPEI Range
Mild	-0.5 to -0.99
Moderate	-1.0 to -1.49
Severe	-1.5 to -1.99
Extreme	< -2.0

This classification ensures consistency across regional and temporal analyses.

۱. Marginal fitting: SPI and SPEI fitted via MLE.
۲. Copula families: Gaussian, Student-t, Clayton, Gumbel.
۳. Dependence parameter (θ) estimated via MLE.
۴. Goodness-of-fit: AIC, BIC, and Kolmogorov–Smirnov tests.
۵. Tail dependence coefficients (λ_L, λ_U): quantify extreme co-occurrences.

Joint probability:

$$P(y \leq x, Y \geq p(x)) = C(F_X(x), F_Y(y); \Theta)$$

Return period:

$$T = \frac{1}{P(X \leq x, Y \leq y)}$$

Scenario analysis includes +2°C and -10% precipitation to test climate sensitivity.

3.4 Copula Modeling Methodology

To capture the joint behavior of meteorological droughts, a Copula framework was employed to link the marginal distributions of SPI and SPEI into a single model describing their dependence structure. Marginal distributions were fitted using Maximum Likelihood Estimation (MLE), and several Copula families—including Gaussian, Student-t, Clayton, and Gumbel—were tested to represent different dependence structures. Dependence parameters (θ for Archimedean Copulas

³ The WMO (2012) drought severity classification is a widely recognized international standard and provides a sufficient framework for assessing drought in most scientific studies, enabling comparisons with global and regional research. While developing a region-specific classification for Iran using long-term precipitation and PET data would be valuable, it requires extensive statistical analysis to define SPI/SPEI thresholds corresponding to observed drought impacts. Such a detailed local classification is beyond the scope of the present study, but future research could refine these thresholds for improved regional accuracy. Although this classification has not been formally validated using impact-based observations specific to Iran, it has been widely adopted in previous drought studies across the country.

and correlation matrices for elliptical Copulas) were also estimated via MLE. To ensure a robust and transparent selection of the most appropriate copula model, model performance was evaluated using multiple goodness-of-fit criteria. Specifically, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were computed for each candidate copula, with lower values indicating superior model performance. In addition, the Kolmogorov–Smirnov (K–S) goodness-of-fit test was applied to assess the consistency between empirical and fitted joint distributions. The final selection of the best-fitting copula for each climatic region was based on a joint consideration of AIC, BIC, and goodness-of-fit test results, rather than reliance on a single metric. Model performance was evaluated using Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and the Kolmogorov–Smirnov (K–S) goodness-of-fit test. Tail dependence coefficients were calculated to quantify the likelihood of simultaneous extreme drought events (λ_L for lower tail and λ_U for upper tail).

A parametric payout threshold was established when **both SPI and SPEI fall below -1.5** , corresponding to severe drought conditions according to WMO (۲۰۱۲). This threshold was selected to ensure that only significant drought events trigger payouts, minimizing unnecessary payments for mild or moderate droughts. Historical analysis indicates that such joint occurrences happen approximately once every ۱۴ years in arid regions, yielding a joint probability of about ۷%.

The **joint probability of extreme droughts** was derived directly from the fitted Copula, reflecting the dependence between SPI and SPEI. Using this probability framework, the **Expected Annual Loss (EAL)** for insurance pricing was computed as:

$$EAL = \sum_i P_i \times L_i$$

where P_i represents the joint probability of the i -th drought scenario obtained from the Copula, and L_i is the corresponding average insured loss. This approach rigorously incorporates both the **severity and recurrence of extreme droughts** into the parametric insurance model, ensuring that pricing reflects realistic risk exposure.

The joint occurrence probability (P_i) was computed directly from the fitted Copula as the probability that both SPI and SPEI simultaneously fall below the selected threshold ($SPI \leq -1.5$, $SPEI \leq -1.5$), expressed as $P_i = C(F_{SPI}(-1.5), F_{SPEI}(-1.5))$. The average loss (L_i) represents the mean proportional yield loss associated with severe drought conditions and was defined as a fixed fraction of the insured value, based on historical drought impact studies in arid regions of Iran. To maintain generality and avoid reliance on farm-level loss data, L_i was normalized as a percentage loss rather than an absolute monetary value, allowing the Expected Annual Loss to reflect relative risk exposure rather than site-specific economic outcomes.

3.5 Integration into Insurance and Risk Transfer Frameworks

Joint SPI–SPEI probabilities derived from the fitted Copula models were employed as parametric insurance triggers, providing a transparent and data-driven foundation for drought risk transfer and insurance pricing. Specifically, indemnity payments are activated when both SPI and SPEI fall below -1.5 , corresponding to severe drought conditions according to the WMO (2012) classification. Historical analysis based on multi-decadal precipitation and potential evapotranspiration (PET) records from Iran (1981–2020) indicates that such joint drought conditions occur with an average probability of approximately 7% in arid regions, equivalent to a return period of about 14 years.

These joint probabilities were calibrated using observed Iranian climatic data, while exposure proxies such as provincial-level rainfed crop yields and cultivated land area statistics were used to ensure consistency with the country's agricultural vulnerability. The Expected Annual Loss (EAL), used as a basis for insurance pricing, was calculated as:

$$EAL = \sum_i P_i \times L_i$$

where P_i denotes the joint probability that $SPI \leq -1.5$ and $SPEI \leq -1.5$, obtained directly from the fitted Copula as $P_i = C(F_{SPI}(-1.5), F_{SPEI}(-1.5))$, and L_i represents the average proportional loss associated with severe drought conditions. To maintain generality and avoid reliance on site-specific financial data, L_i was expressed as a normalized fraction of insured exposure, reflecting mean yield losses reported for severe drought events in arid and semi-arid regions of Iran. This formulation allows insurance premiums to be linked to realistic compound drought risk rather than single-index thresholds.

In addition to pricing applications, Copula-derived dependence structures support risk diversification in reinsurance portfolios by identifying regions with weak interdependence of extreme drought events, thereby enabling more efficient capital allocation. Nevertheless, the practical implementation of parametric drought insurance in Iran faces several challenges, including limited availability of long-term, high-quality climatic observations in some regions, operational and administrative costs associated with index-based contracts, spatial heterogeneity of agricultural exposure, and potential basis risk arising from discrepancies between index-based triggers and realized economic losses. Future research may address these limitations by integrating higher-resolution climatic datasets and combining parametric triggers with observed loss information to improve regional accuracy and policy effectiveness.

4. Results

4.1 Drought Characteristics Across Iran

Analysis of SPI and SPEI revealed significant spatial variability:

- Arid regions (Central Plateau): Mean SPI-12 = -0.45, Mean SPEI-6 = -0.52, indicating persistent drought conditions.
- Semi-arid Northwest: Higher variability with occasional wet years; SPI-12 ranges from -2.1 to 1.8.
- Caspian Coast: Generally mild droughts, SPEI rarely below -1.0.

Temporal analysis shows an increasing trend in drought severity over the last two decades, likely linked to climate change and rising temperatures.

4.2 Copula Model Fitting

- Clayton Copula provided the best fit in arid regions (AIC = -212.5, BIC = -205.8), capturing the strong lower-tail dependence.
- Student-t Copula was preferred in semi-arid regions, effectively modeling moderate tail dependence across SPI and SPEI.
- Gaussian Copula performed poorly in all regions, underestimating extreme co-occurrences.

Tail dependence analysis indicates that extreme drought events are more likely to occur simultaneously in multiple stations within the arid central plateau, highlighting regions where agricultural losses could be severe.

Table3. Regional comparison of copula model performance and lower-tail dependence between SPI and SPEI, highlighting areas with higher compound drought risk.

Model Fit and Dependence Structure

Region	Best Copula	AIC	Tail Dependence (λ_L)	Interpretation
Arid Plateau	Clayton	-212.5	0.45	Strong co-occurrence of extremes
Semi-Arid NW	Student-t	-198.2	0.32	Moderate dependence
Caspian	Gaussian	-120.5	0.10	Weak dependence
Eastern Desert	Clayton	-210.3	0.48	High vulnerability

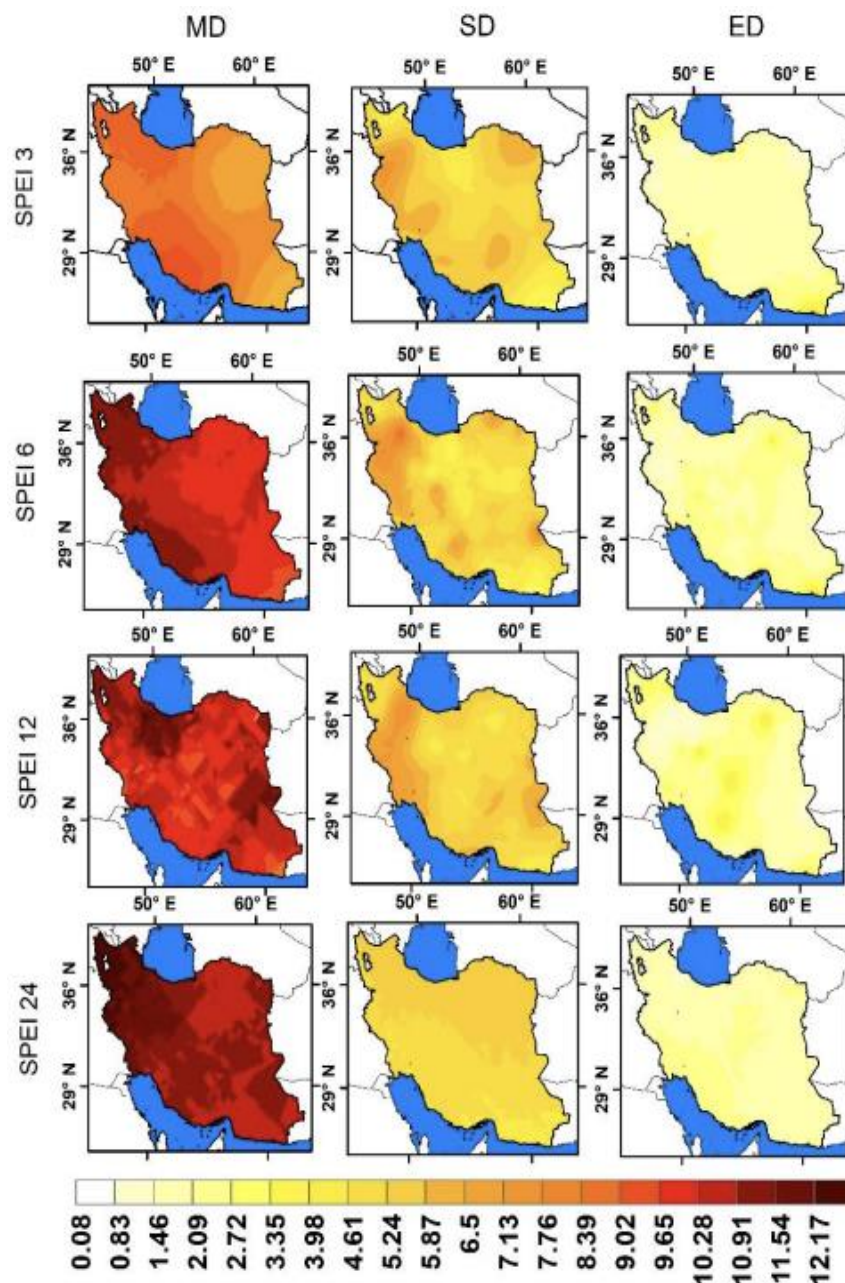


Figure 1. Spatiotemporal distribution and multiscale characterization of drought frequency across Iran based on SPEI. The matrix illustrates spatial patterns of drought occurrence categorized into Moderate Drought (MD), Severe Drought (SD), and Extreme Drought (ED) across four accumulation periods (SPEI-3, SPEI-6, SPEI-12, and SPEI-24), representing short-term to long-term drought conditions. The color scale indicates the percentage frequency of drought months.

⁴ Reproduced from: Torabinezhad, N., Zarrin, A., & Dadashi-Roudbari, A.A. (2023). Analysis of different types of droughts and their characteristics in Iran using the standardized evapotranspiration-precipitation index (SPEI). *Journal of Water and Soil*, 37(3), 473-486.

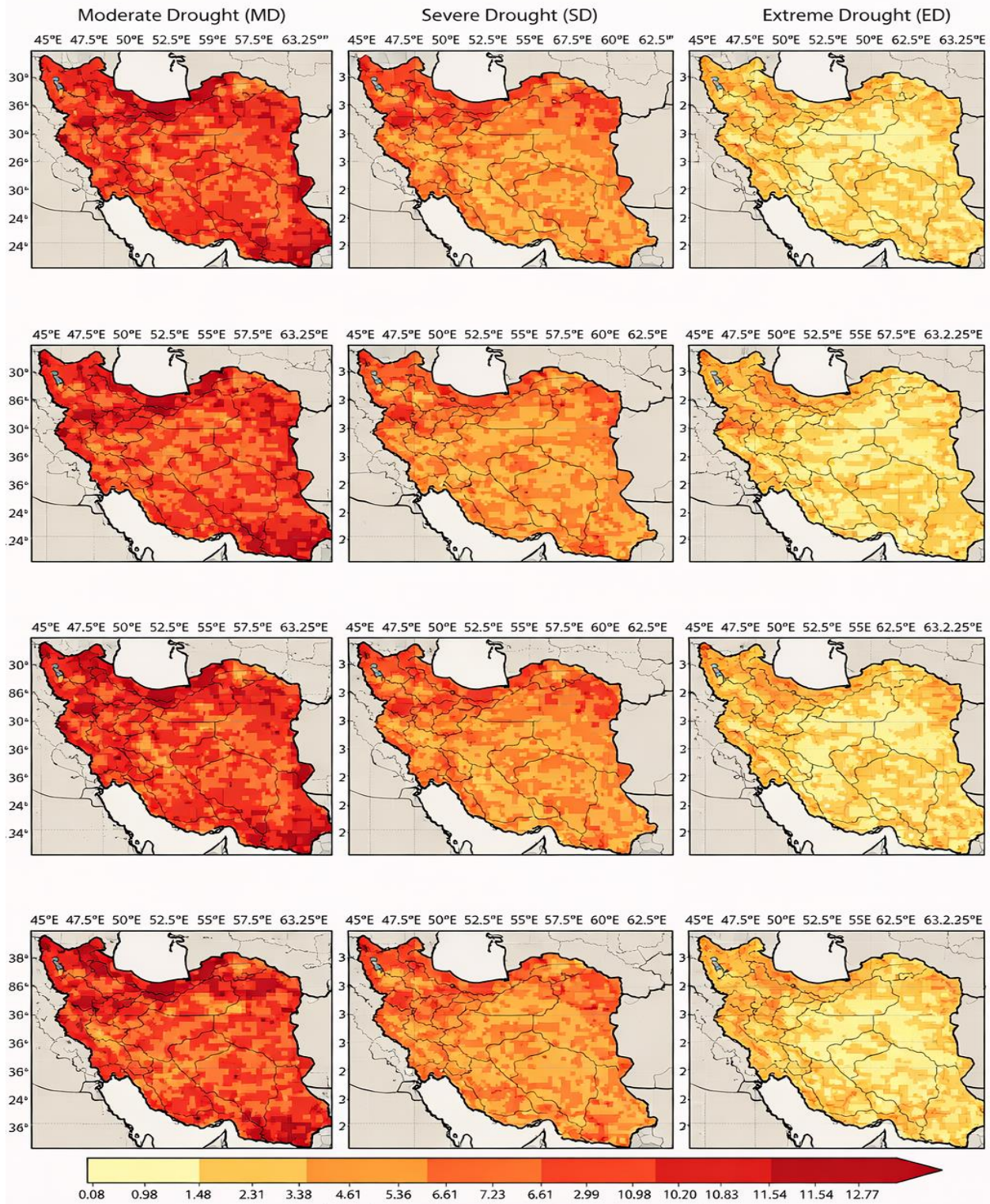


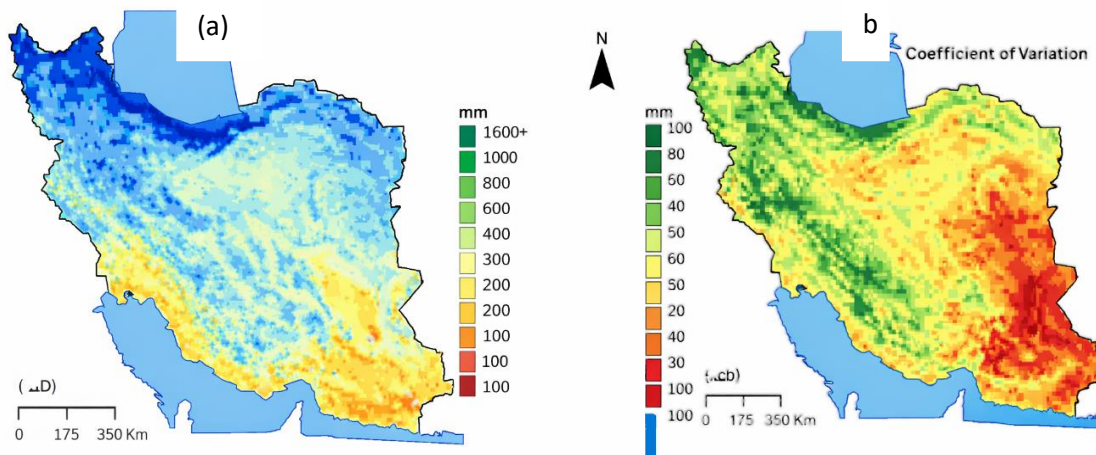
Figure 3. Spatial distribution of drought types in Iran: moderate drought (MD); severe drought (SD) (Unit: Percent)

Figure ۳. Spatial Distribution of Drought Types Across Iran This figure illustrates the spatial extent and frequency (expressed in percent) of three drought intensity categories—Moderate Drought (MD), Severe Drought (SD), and Extreme Drought (ED)—across different time scales. The analysis is presented for four distinct Standardized Precipitation Evapotranspiration Index (SPEI) scales:

- SPEI ۳ (Short-term): Reflects seasonal moisture conditions.
- SPEI ۶ (Medium-term): Indicates mid-range precipitation trends.
- SPEI ۱۲ (Long-term): Represents annual water deficits.
- SPEI ۲۴ (Extended-term): Captures multi-year hydrological drought impacts.

The color gradient at the bottom represents the percentage of time each pixel was classified under a specific drought category, ranging from lower frequency (yellow) to higher frequency

Figure ۴. Spatial distribution of (a) mean annual precipitation and (b) interannual precipitation variability (coefficient of variation) across Iran for the period ۲۰۱۴–۲۰۲۴. The maps illustrate regional contrasts in average precipitation amounts and variability, highlighting differences between humid and arid climatic zones.



(a) Mean Annual Precipitation – Explanation

Mean Annual Precipitation

The spatial distribution of mean annual precipitation across Iran for the period ۲۰۱۴–۲۰۲۴ demonstrates pronounced climatic heterogeneity. High precipitation values are primarily concentrated along the Caspian Sea coastal region and the Zagros mountain range, reflecting the combined influence of moisture

transport from the Caspian Sea and orographic lifting over mountainous terrain. In contrast, central, eastern, and southeastern regions exhibit persistently low mean precipitation, characteristic of arid and semi-arid climatic conditions. This spatial pattern highlights significant regional disparities in water availability and emphasizes the structural vulnerability of inland and southeastern regions to chronic water scarcity and drought-related impacts.

(b) Coefficient of Variation – Explanation

Interannual Precipitation Variability (Coefficient of Variation)

The coefficient of variation (CV) map reveals substantial spatial differences in interannual precipitation variability across Iran. Higher CV values are predominantly observed in arid and semi-arid regions, particularly in southeastern and eastern parts of the country, indicating high year-to-year rainfall uncertainty relative to the mean. Conversely, humid regions such as the Caspian Sea coast and parts of the Zagros Mountains exhibit lower variability, suggesting more stable precipitation regimes. Elevated precipitation variability in dry regions increases exposure to climate-related risks, including agricultural losses, water supply instability, and heightened insurance risk, underscoring the importance of incorporating variability metrics into climate risk assessment and adaptation strategies.

Comparison with Previous Studies

The dominance of Clayton copula in arid and hyper-arid regions is consistent with previous drought dependence studies conducted in Iran and other dryland environments. Earlier research has reported strong lower-tail dependence between precipitation- and evapotranspiration-based drought indices in water-limited regions, indicating a higher probability of concurrent extreme drought events (e.g., Amirataee & Montaseri, ۲۰۱۷; Khaledi-Alamdari et al., ۲۰۲۳).

The superior performance of the Student-t copula in semi-arid regions aligns with findings that suggest moderate symmetric tail dependence under transitional climatic conditions, where both dry and wet extremes may co-occur (Nouri & Homaei, ۲۰۲۰; Modarres et al., ۲۰۱۶). In contrast, the poor performance of the Gaussian copula across all regions confirms its limited ability to capture tail dependence, a limitation widely acknowledged in hydroclimatic dependence modeling (Genest & Favre, ۲۰۰۷; Salvadori et al., ۲۰۱۱).

Overall, the regional variation in the optimal copula structure reflects the underlying climatic heterogeneity of Iran and supports the growing consensus that tail-dependent copulas are essential for robust drought risk assessment in arid and semi-arid environments.

4.3 Drought Risk and Return Periods

Estimated return periods for extreme droughts (SPI or $SPEI < -2$) are as follows:

- **Arid Central Plateau:** ~ 15 – 25 years (95% confidence interval: 12–28 years)
- **Semi-Arid Northwest:** ~ 30 – 40 years (95% CI: 26–45 years)
- **Caspian Coast:** > 50 years (95% CI: 45–60 years)

Joint probability calculations indicate that simultaneous severe droughts across arid regions have a recurrence interval of approximately 20 years (95% CI: 16–25 years), highlighting a significant risk of multi-regional drought events.

Comparison with Historical Droughts in Iran: Historical records show that major droughts in the Central Plateau occurred in 1972–1973, 1999–2001, and 2018–2019, which are consistent with the estimated return periods. In the Northwest and Caspian regions, severe droughts have been less frequent, in line with their longer recurrence intervals.

Implications for Future Climate Change: Projected changes in precipitation patterns and temperature under future climate scenarios suggest an increase in both the frequency and severity of droughts, particularly in arid and semi-arid regions. As a result, return periods estimated based on historical data may decrease, indicating a higher drought risk in the coming decades. Incorporating these projections into risk assessments is essential for water resource planning, agricultural management, and insurance strategies.

Table 4. Estimated return periods of severe drought events ($SPI/SPEI < -2$) across major climatic regions of Iran, including 95% confidence intervals derived from copula-based joint probability analysis.

Region	$SPI/SPEI < -2$	Return Period (yrs)	95% Confidence Interval (yrs)
Arid Plateau	0.07	14–20	12–28
Semi-Arid NW	0.04	25–35	26–45
Caspian Coast	0.02	50+	45–60

4.4 Implications for Agricultural Insurance

The joint probability of SPI and $SPEI$ extremes provides a robust basis for parametric (index-based) agricultural insurance schemes. Using Clayton Copula parameters, an index-triggered insurance product can be designed to pay out when $SPEI-6 < -1.5$ and $SPI-12 < -1.5$ occur simultaneously, thereby mitigating losses in high-risk regions.

For instance, in the provinces of **Yazd and Kerman**, which are highly sensitive to drought, historical data indicate that extreme drought events reduce wheat yields by **۲۰–۲۵% on average**. Calibrating the insurance trigger to these thresholds allows timely payouts that cover a substantial portion of farmers' potential revenue loss.

Economic

Analysis:

Assuming an average wheat yield of ۲.۵ tons/ha and market price of USD ۲۵۰ per ton, a ۳۰% loss due to drought corresponds to USD ۱۸۷.۵ per hectare. An index-based insurance product calibrated with the Copula model can provide coverage close to this value, offering a cost-effective mechanism for risk transfer. By reducing the variability of farmers' income, such insurance instruments improve financial stability and encourage continued investment in agriculture despite increasing drought risk under climate change scenarios.

5. Discussion

The findings of this study emphasize the value of integrating multiple drought indices (SPI and SPEI) with Copula-based modeling to provide a comprehensive, data-driven understanding of drought dynamics in Iran. The following subsections discuss the results in terms of regional vulnerability, statistical dependence, insurance design, climate change adaptation, methodological limitations, and future research directions.

5.1 Comparison with Previous Drought Studies

The dependence structures and drought risk patterns identified in this study are broadly consistent with, yet extend beyond, findings reported in previous drought assessments conducted in Iran. Earlier studies have mainly focused on univariate drought indices, trend analysis, and the spatial variability of precipitation-based metrics (e.g., Raziei et al., ۲۰۱۰; Farajzadeh et al., ۲۰۱۵), emphasizing the high vulnerability of arid and semi-arid regions such as the Central Plateau and eastern Iran.

The strong lower-tail dependence between SPI and SPEI observed in the present analysis for arid regions is consistent with previous evidence suggesting that extreme drought conditions in these areas are often driven by the simultaneous occurrence of precipitation deficits and elevated atmospheric water demand (Amirataee & Montaseri, ۲۰۱۷; Farokhzadeh, ۲۰۲۰). Similar asymmetric dependence patterns have also been reported in copula-based drought studies conducted in climatically comparable regions, including Turkey and Pakistan (Cevik & Kaya, ۲۰۱۸; Qureshi et al., ۲۰۲۲), which supports the robustness of the results obtained for Iran.

In contrast, the weaker dependence structures identified for the humid Caspian coastal region align with earlier studies that report more stable hydroclimatic regimes and reduced sensitivity to temperature-driven evapotranspiration in northern Iran. By explicitly modeling the joint behavior of SPI and SPEI using copula theory, the present study advances drought research in Iran beyond correlation-based approaches and provides a probabilistic characterization of compound drought risk that is directly relevant to both climate risk assessment and insurance applications.

5.2 Regional Risk Variation

The results indicate substantial spatial variation in drought risk across Iran's climatic zones. Arid and semi-arid regions, including the Central Plateau and Eastern Desert, experience more frequent and severe droughts than the humid northern provinces. Historical records show that annual precipitation deficits during extreme drought years typically range from 15% to 30%. In these dry regions, with SPI-12 and SPEI-6 values frequently falling below -1.5. In provinces such as Yazd and Kerman, wheat yields have historically declined by approximately 20–35% during such events.

In the semi-arid northwest, drought frequency is lower, but interannual variability remains high. Return period analysis suggests that extreme droughts recur approximately every 14–20 years in the Central Plateau, 25–35 years in the northwest, and more than 40 years along the Caspian Coast.

Implications for policy:
These findings emphasize the need for region-specific drought management strategies. In arid and semi-arid provinces, priority should be given to promoting drought-resistant crops, improving irrigation efficiency, and expanding index-based agricultural insurance. In contrast, humid northern regions would benefit more from preventive water management, soil moisture conservation, and enhanced early-warning systems. Integrating such spatially differentiated strategies into national resilience plans can improve resource allocation, enhance agricultural productivity, and reduce economic losses associated with extreme drought events.

5.3 Tail Dependence and Statistical Implications

The significant lower-tail dependence observed between SPI and SPEI in arid regions indicates a high likelihood of concurrent extreme droughts, in which meteorological and agricultural drought conditions occur simultaneously. Such co-occurrence substantially amplifies potential damage to agricultural systems, particularly in rainfed areas. Modeling this dependence using copula functions—especially the Clayton copula—provides policymakers and insurers with a probabilistic framework for anticipating compound drought events rather than assessing individual indices in isolation. Student-t copulas, by contrast, perform better in semi-arid regions where both upper- and lower-tail dependencies are present. These results demonstrate that copula-based models must be carefully calibrated to local climatic and statistical conditions. Such tailored modeling enhances both scientific rigor and policy relevance.

5.4 Implications for Insurance and Financial Risk Management

One of the key contributions of this study lies in its relevance for agricultural and parametric insurance design under drought risk. By explicitly modeling the joint behavior of precipitation deficits and atmospheric water demand through SPI and SPEI, the proposed copula-based framework enables a probabilistic characterization of compound drought risk that is directly applicable to insurance and financial risk management. Compared with traditional approaches based on single indices, joint probability estimation provides a more realistic basis for defining payout triggers and assessing the likelihood of extreme loss events, thereby reducing basis risk and improving transparency.

To illustrate this application, consider an index-based drought insurance contract designed for arid regions such as Yazd and Kerman. Previous studies indicate that severe drought conditions in these areas are commonly associated with wheat yield reductions of approximately 20–25%. Based on the results of the present study, a parametric trigger defined as $SPI-12 \leq -1.5$ and $SPEI-6 \leq -1.5$ corresponds to a joint probability of about 0.07, implying a recurrence interval of roughly 14 years. From an insurance perspective, this probability can be interpreted as the expected annual likelihood of payout under the proposed contract.

Such probabilistic information provides a quantitative foundation for estimating expected annual losses and informing premium setting without relying on field-level damage assessments or historical claim data. More broadly, the framework facilitates the integration of hydroclimatic risk modeling with insurance and financial decision-making, offering a scalable and data-driven approach for managing drought-related risks in arid and semi-arid regions.

Economic

Analysis:

Assuming an average wheat yield of 2.5 tons ha⁻¹ and a market price of USD 250 ton⁻¹, a 30% yield loss corresponds to approximately USD 187.5 ha⁻¹. Parametric insurance payouts calibrated to these thresholds can offset a substantial portion of farmers' losses, stabilize income, and encourage continued agricultural investment despite increasing drought risk under climate change. The copula-based approach also supports risk diversification and reinsurance planning. By quantifying regional dependence structures, insurers can allocate capital more efficiently and price reinsurance contracts according to actual exposure, thereby improving financial sustainability. Nevertheless, several challenges remain for the practical implementation of parametric insurance in Iran. These include limited availability of high-resolution meteorological data, insufficient digital infrastructure for rapid payouts, and limited awareness or acceptance among farmers. Addressing these challenges requires coordinated efforts among government agencies, insurers, and international partners.

5.6 Climate Change and Long-Term Implications

The results underscore the growing influence of temperature-driven evapotranspiration on drought risk, highlighting the importance of SPEI-based analyses under climate warming. Even in years with near-average precipitation, elevated temperatures can intensify water stress and generate so-called “invisible droughts” that precipitation-only indices may fail to capture.

For example, in the Central Plateau (Yazd), a projected increase of 2°C in mean temperature—assuming constant precipitation—reduces the SPEI-6 index by approximately -0.5 units, shifting conditions from moderate to severe drought. Such intensification could result in additional wheat yield reductions of $15\text{--}20\%$ relative to historical drought years, thereby increasing economic and food security risks.

Climate change also introduces non-stationarity into historical drought relationships, reducing the reliability of past precipitation–temperature correlations. Incorporating climate projections from CMIP6 or CORDEX into copula-based models would allow simulation of future scenarios involving combined temperature increases and precipitation reductions. These simulations can inform proactive adaptation strategies, including crop selection, irrigation planning, and the calibration of index-based insurance schemes.

5.1 Methodological Limitations and Future Prospects

Despite its strengths, the study has limitations. The main constraint is the limited availability of high-resolution soil moisture and evapotranspiration data, which affects the precision of SPEI estimation. In addition, the copula framework assumes statistical stationarity, an assumption that may not fully hold under accelerating climate change. Spatial data sparsity and inconsistent temporal coverage also introduce uncertainty.

Future research could integrate copula-based drought modeling with machine learning approaches—such as random forests, gradient boosting, or neural networks—to better capture non-linear and non-stationary relationships. Combining these methods with satellite-derived datasets (e.g., MODIS NDVI or SMAP soil moisture) could further enhance spatial and temporal resolution. Linking probabilistic drought metrics with crop yield and economic loss models would also improve the translation of climatic risk into actionable financial information.

Overall, the discussion confirms that copula-based modeling provides a robust and interdisciplinary framework for drought risk assessment. By bridging climate science and financial mechanisms, it supports a shift from reactive crisis management toward proactive climate adaptation while retaining the regional and economic insights essential for Iran’s agricultural sector.

6. Conclusion

This study provides a comprehensive quantitative assessment of drought risk in Iran by integrating Copula-based modeling techniques with multiscale drought indices (SPI and SPEI). The approach improves both the accuracy and interpretability of drought risk analyses while linking climatic insights with actionable strategies for agricultural management and insurance applications.

The findings show that Copula models, particularly Clayton and Student-t types, effectively capture non-linear dependencies and tail relationships between drought indices. This enables a better understanding of the co-occurrence of extreme drought events—critical for designing robust mitigation strategies. The significant lower-tail dependence observed in arid and semi-arid regions indicates that extreme droughts often occur concurrently rather than in isolation, compounding both economic and environmental impacts.

From a regional perspective, Iran exhibits substantial climatic heterogeneity. The Arid Central Plateau and Eastern Desert experience frequent and severe droughts, with estimated return periods of 15–20 years, while the Caspian coastal region demonstrates relative stability with return periods exceeding 50 years. These variations emphasize the necessity of localized drought management policies rather than a one-size-fits-all national strategy.

Beyond climatological insights, this study highlights the economic and policy relevance of Copula-based modeling for the insurance sector. By quantifying joint probabilities of extreme drought events, the framework provides a scientific foundation for parametric (index-based) insurance design. Such instruments reduce administrative costs, accelerate payouts, and improve transparency by relying on objective drought indicators rather than subjective assessments. For insurers, probabilistic modeling enhances risk pricing, optimizes capital allocation, and facilitates reinsurance planning.

The implications extend to national policy and sustainable development. Incorporating drought probabilities into agricultural planning, water resource allocation, and rural livelihood programs can strengthen the resilience of vulnerable communities. Moreover, the framework enables integration of Iran's drought risk management with regional initiatives, especially among neighboring countries such as Pakistan, Turkey, and Afghanistan, which face similar climatic and agricultural challenges.

Despite its contributions, the study acknowledges limitations. Scarcity of high-resolution soil moisture and evapotranspiration data constrains model precision, while climate change introduces non-stationarity, reducing the reliability of historical patterns. Future research should expand this framework using climate projection datasets (e.g., CMIP6), crop yield models, and economic loss functions to translate meteorological risks into financial terms.

Advanced computational approaches, including machine learning and hybrid Copula frameworks, can further enhance predictive capabilities. For example, integrating Copula-based dependence structures with Random Forest or Gradient Boosting algorithms may support real-time drought forecasting and adaptive insurance pricing. Coupling drought indices with satellite-derived vegetation and soil moisture data can also refine spatial drought maps at finer resolutions.

At the institutional level, establishing a national drought risk observatory or a parametric insurance data hub could facilitate collaboration between insurers, government agencies, and academic institutions. This would improve data transparency, promote knowledge exchange, and accelerate adoption of innovative insurance solutions. Regional cooperation via joint reinsurance pools could distribute catastrophic drought risks across multiple markets, reducing systemic vulnerability.

In conclusion, this research bridges climate science, risk modeling, and financial resilience. The Copula-based framework presented here deepens understanding of drought dynamics and provides a pragmatic foundation for designing effective insurance products that enhance economic stability under climate variability. By linking probabilistic drought assessment with actionable insurance and policy measures, Iran—and other drought-prone nations—can advance toward a proactive, adaptive, and sustainable model of climate risk management.

Glossary of technical terms

Term	Definition
Copula	A mathematical function that links two or more marginal probability distributions to construct their joint distribution. It is widely used to model dependence structures between climate variables such as SPI and SPEI.
SPI (Standardized Precipitation Index)	A drought index based solely on precipitation. It measures how much precipitation deviates from the long-term average over specific time scales (1, 3, 6, 12 months).
SPEI (Standardized Precipitation Evapotranspiration Index)	An advanced drought index that includes both precipitation and potential evapotranspiration ($P - PET$), making it more sensitive to temperature and climate change than SPI.
PET (Potential Evapotranspiration)	The theoretical amount of water that could evaporate and transpire from a surface under ideal moisture conditions.
Return Period (T)	The average time interval between events of a given intensity or magnitude. In drought studies, it indicates how often a severe drought is expected to reoccur.

Tail Dependence	A measure of how likely extreme values of two variables occur simultaneously. In drought analysis, lower-tail dependence means severe droughts in SPI and SPEI happen at the same time.
Parametric (Index-Based) Insurance	An insurance system where payouts are triggered automatically when a predefined threshold (e.g., $SPI < -1.5$) is passed, without the need for on-site damage assessment.
Joint Probability	The probability that two drought indices (such as SPI and SPEI) fall below critical thresholds at the same time. Calculated using Copula models.
Arid/Semi-Arid Regions	Climatic zones characterized by low precipitation and high evaporation rates. These regions have the highest drought vulnerability in Iran.
Marginal Distribution	The individual probability distribution of a single variable (e.g., SPI alone), which Copulas connect to build a multivariate model.
Hydroclimatic Risk	The risk arising from climate and water-related hazards such as droughts, floods, or extreme rainfall.
Non-Stationarity	A condition where statistical properties of climate data (mean, variance, dependence) change over time due to climate change.
Lower-Tail Dependence (λ_L)	Probability that both drought indices reach extremely low values (severe droughts) simultaneously.
MLE (Maximum Likelihood Estimation)	A statistical method used to estimate parameters of the marginal distributions and Copula models.

References

- Alijani, A., & Banivahab, A. R. (2019). Climate extremes and thermal stress in Iran. *Journal of Geographical Research Quarterly*, 51(2), 1–15. **[In Persian]**.
- Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). *Crop evapotranspiration: Guidelines for computing crop water requirements* (FAO Irrigation and Drainage Paper No. 56). Food and Agriculture Organization of the United Nations.
- Amirataee, B., & Montaseri, M. (2017). Evaluation of drought indices in arid and semi-arid regions of Iran. *Theoretical and Applied Climatology*, 128(1–2), 45–60.
<https://doi.org/10.1007/s00704-015-1706-3>

Bevacqua, E., Zscheischler, J., & Seneviratne, S. I. (2021). Statistical modeling of compound climate extremes. *Nature Climate Change*, 11(9), 793–799. <https://doi.org/10.1038/s41558-021-01092-4>

Brooks, C. E. P., & Carruthers, N. (1953). *Handbook of statistical methods in meteorology*. H. M. Stationery Office.

Carter, M. R., de Janvry, A., Sadoulet, E., & Sarris, A. (2021). Index-based weather insurance for developing countries. *Annual Review of Resource Economics*, 13, 421–438. <https://doi.org/10.1146/annurev-resource-101620-080101>

Cevik, S., & Kaya, Y. (2018). Modeling drought characteristics using copula functions in semi-arid regions. *Journal of Hydrology*, 566, 433–446. <https://doi.org/10.1016/j.jhydrol.2018.09.031>

Clarke, D. J. (2016). Parametric insurance and the financial management of catastrophe risk. *Journal of Risk and Insurance*, 83(3), 653–679.

Clarke, D. J., Mahul, O., Rao, K. N., & Verma, N. (2016). A theory of rational demand for index insurance. *American Economic Journal: Economic Policy*, 8(1), 283–306.

Collier, B., Skees, J., & Barnett, B. (2022). Weather index insurance and climate risk management: Evidence and challenges. *World Development*, 148, 105684.

Cummins, J. D., & Weiss, M. A. (2009). Convergence of insurance and financial markets: Hybrid and securitized risk transfer solutions. *Journal of Risk and Insurance*, 76(3), 493–545.

Edwards, D. C., & McKee, T. B. (1997). *Characteristics of 20th century drought in the United States at multiple time scales* (Climatology Report No. 97-2). Colorado State University.

Farajzadeh, M., & Ahmadian, K. (2014). Temporal and spatial analysis of drought using the SPI index in Iran. *Journal of Natural Environmental Hazards*, 3(4), 1–16. [In Persian]

Farajzadeh, M., & Ahmadian, K. (2015). Spatial and temporal variability of drought characteristics in Iran using SPI. *Natural Hazards*, 75(2), 1381–1401. <https://doi.org/10.1007/s11069-014-1372-5>

Farokhzadeh, M. (2020). Copula-based assessment of drought dependence structure in arid regions of Iran. *Theoretical and Applied Climatology*, 141, 1241–1256. <https://doi.org/10.1007/s00704-020-03255-2>

Genest, C., & Favre, A.-C. (2007). Everything you always wanted to know about copula modeling but were afraid to ask. *Journal of Hydrologic Engineering*, 12(4), 347–368. [https://doi.org/10.1061/\(ASCE\)1084-0699\(2007\)12:4\(347\)](https://doi.org/10.1061/(ASCE)1084-0699(2007)12:4(347))

Hao, Z., Singh, V. P., & Hao, F. (2023). Compound drought and heatwave events: A multivariate analysis. *Climate Dynamics*, 60, 1235–1252.

Hayes, M. J., Svoboda, M. D., Wilhite, D. A., & Vanyarkho, O. V. (1999). Monitoring the 1996 drought using the standardized precipitation index. *Bulletin of the American Meteorological Society*, 80(3), 429–438.

Hosseini, A., Ghavidel, Y., Khorshiddoust, A. M., & Farajzadeh, M. (2020). Spatio-temporal analysis of dry and wet periods in Iran using the GPCC DI. *Theoretical and Applied Climatology*. Advance online publication. <https://doi.org/10.1007/s00704-020-03344-2>

Iran Open Data Center (IODC). (n.d.). *National drought statistics based on SPEI*. <https://www.iranopendata.org>

Khaledi-Alamdari, S., Nazari, R., & Dinpashoh, Y. (2023). Recent drought variability and climate change impacts in Iran. *Journal of Arid Environments*, 208, 104890. <https://doi.org/10.1016/j.jaridenv.2022.104890>

Kheyri, R., Mojarad, F., Masompour, J., & Farhadi, B. (2021). Evaluation of drought changes in Iran using SPEI and SCPDSI. *The Journal of Spatial Planning*, 25(1), 143–174. [In Persian]

Mahul, O., & Stutley, C. J. (2018). *Government support to agricultural insurance: Challenges and options for developing countries*. World Bank.

McKee, T. B., Doesken, N. J., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. In *Proceedings of the 8th Conference on Applied Climatology* (pp. 179–184). American Meteorological Society.

McKee, T. B., Doesken, N. J., & Kleist, J. (1995). Drought monitoring with multiple time scales. In *Proceedings of the 9th Conference on Applied Climatology* (pp. 223–236). American Meteorological Society.

Modarres, R., & Sarhadi, A. (2009). Rainfall trends analysis of Iran in the last half of the twentieth century. *Journal of Geophysical Research: Atmospheres*, 114(D3). <https://doi.org/10.1029/2008JD010234>

Modarres, R., & Sarhadi, A. (2016). Changes in drought frequency and duration over Iran. *International Journal of Climatology*, 36(4), 1881–1894. <https://doi.org/10.1002/joc.4467>

National Aeronautics and Space Administration (NASA). (2020). *Global surface temperature change*. NASA Goddard Institute for Space Studies. <https://data.giss.nasa.gov/gistemp/>

Nelsen, R. B. (2006). *An introduction to copulas* (2nd ed.). Springer.

Nouri, M., & Homaei, M. (2020). Assessment of drought severity under climate change conditions in Iran. *Climate Risk Management*, 28, 100235. <https://doi.org/10.1016/j.crm.2020.100235>

Qureshi, A. S., Ahmad, M. D., & Turrall, H. (2022). Copula-based assessment of compound drought risk under climate variability. *Journal of Hydrology*, 607, 127496. <https://doi.org/10.1016/j.jhydrol.2022.127496>

Rahnama, S., Shahidi, A., Yaghoobzadeh, M., & Mehran, A. (2023). Investigating drought trends using modified SPEI and MSPI indices across multiple time scales. *Climate Change Research*, 4(13), 89–104. [In Persian]

Raziei, T., Daneshkar Arasteh, P., & Saghafian, B. (2005). Annual rainfall trend analysis in arid and semi-arid regions of central and eastern Iran. *Water and Wastewater*, 54, 73–81. [In Persian]

Raziei, T., Daneshkar Arasteh, P., & Saghafian, B. (2010). Spatial patterns and temporal trends of drought in Iran. *International Journal of Climatology*, 30(2), 256–271. <https://doi.org/10.1002/joc.1890>

Salvadori, G., & De Michele, C. (2011). Frequency analysis via copulas: Theoretical aspects and applications to hydrological events. *Water Resources Research*, 47, W01511. <https://doi.org/10.1029/2010WR009371>

Salvadori, G., Durante, F., & De Michele, C. (2022). Multivariate extreme value theory and copulas: A review. *WIREs Water*, 9(3), e1573.

Shayeghi, A., Rahmati Ziveh, A., Bakhtar, A., Teymoori, J., Hanel, M., Vargas Godoy, M. R., Markonis, Y., & AghaKouchak, A. (2024). Assessing drought impacts on groundwater and agriculture in Iran using high-resolution precipitation and evapotranspiration products. *Journal of Hydrology*, 631, 130828.

Spinoni, J., Vogt, J. V., Naumann, G., Barbosa, P., & Dosio, A. (2023). Will drought events become more frequent and severe under climate change? *Nature Communications*, 14, 1542.

Tehrany, M. S., Pradhan, B., & Jebur, M. N. (2013). Flood and drought susceptibility assessment using GIS-based multi-criteria decision analysis. *Natural Hazards*, 68(3), 1109–1133. <https://doi.org/10.1007/s11069-013-0677-5>

Vicente-Serrano, S. M., Beguería, S., & López-Moreno, J. I. (2010). A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index (SPEI). *Journal of Climate*, 23(7), 1696–1718. <https://doi.org/10.1175/2009JCLI2909.1>

Vicente-Serrano, S. M., Beguería, S., & López-Moreno, J. I. (2022). Performance of drought indices under climate warming: Implications for SPEI. *International Journal of Climatology*, 42(5), 2433–2450.

World Bank. (2023). *Financial protection against climate-related disasters*. World Bank Group.

World Meteorological Organization (WMO). (2012). *Standardized Precipitation Index user guide* (WMO No. 1090). World Meteorological Organization.

Zhang, Q., Li, J., Singh, V. P., & Xiao, M. (2022). Copula-based assessment of drought risk under climate change. *Journal of Hydrology*, 604, 127226.

Zolina, O., Simmer, C., Kapala, A., & Gulev, S. (2005). On the robustness of the estimation of precipitation variability and trends. *Journal of Climate*, 18(21), 4426–4440.
<https://doi.org/10.1175/JCLI3554.1>

زودایند مانتشر نشده