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Articles

Assessment of droughts through SPEI and SPI indices in arid and semi-arid watersheds of San Luis Potosí, México

Evaluación de las sequías a través de los índices SPEI y SPI en cuencas áridas y semiáridas de San Luis Potosí, México

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Abstract

In the arid and semiarid regions of Mexico, the lack of comprehensive meteorological data hinders the analysis of hydrological events such as drought, especially since temperature—in addition to precipitation—plays a decisive role in determining water availability by controlling evapotranspiration rates. This study evaluates the influence of potential evapotranspiration in arid and semiarid watersheds in San Luis Potosí using the Standardized Precipitation-Evapotranspiration Index (SPEI) and the Standardized Precipitation Index (SPI). Using data from weather stations, satellites, and reanalysis, the variability of these indices is evaluated to determine the duration, magnitude, and frequency of droughts. The indices were calculated on a 1-, 3-, 6-, and 12-month scale for the period from 1961 to 2024. Droughts have been more frequent and severe in the last decade. The SPI detected more extreme droughts, but of shorter duration, while the SPEI identified moderate to severe droughts more frequently, highlighting the importance of temperature and potential evapotranspiration in drought variability. Meteorological data determined the analysis period and the method of the indices used, which, together with the variability observed during droughts, allowed for inferences about the performance of the meteorological databases. Drought patterns determine the need to implement adaptive measures and efficient water management to ensure water security and reduce their impacts.

Keywords: drought, arid zones, precipitation, evapotranspiration, meteorological data, water security, water resources management, Mexico.

Resumen

En las zonas áridas y semiáridas de México, la falta de datos meteorológicos completos dificulta el análisis de eventos hidrológicos como la sequía, especialmente porque la temperatura, además de las precipitaciones, determina de manera decisiva la disponibilidad de agua al controlar las tasas de evapotranspiración. Este estudio evalúa la influencia de la evapotranspiración potencial en cuencas áridas y semiáridas de San Luis Potosí a través del índice estandarizado de evapotranspiración (SPEI) y del índice estandarizado de precipitación (SPI). A partir de datos de estaciones meteorológicas, satelitales y de reanálisis, se evalúa la variabilidad de estos índices a fin de determinar la duración, magnitud y frecuencia de las sequías. Los índices se calcularon a escala de 1, 3, 6 y 12 meses durante el periodo de 1961 a 2024. Las sequías han sido más frecuentes y severas en la última década. El SPI detectó más sequías extremas, pero de menor duración, mientras que el SPEI identificó sequías moderadas a severas con mayor frecuencia, lo que evidencia la importancia de la temperatura y la evapotranspiración potencial en la variabilidad de las sequías. Los datos meteorológicos condicionaron el periodo de análisis y el método de los índices empleados, lo que, junto con la variabilidad observada durante las sequías, permitió inferir sobre el desempeño de las bases de datos meteorológicas. Los patrones de sequía determinan la necesidad de implementar medidas adaptativas y de un manejo eficiente del agua para garantizar la seguridad hídrica y reducir sus impactos.

Palabras clave: sequía, zona árida, precipitación, evapotranspiración, datos meteorológicos, seguridad hídrica, gestión de los recursos hídricos, México.

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1. Introduction

Extreme hydrological events, such as floods and droughts, are among the most significant climate-related natural disasters globally. Drought adversely impacts social, economic, and environmental sustainability by prolonging precipitation deficits that disrupt the hydrological cycle (Carrillo-Carrillo, Ibáñez-Castillo, Arteaga-Ramírez, & Arévalo-Galarza, 2025; Gebrechorkos et al., 2025). Unlike floods, droughts manifest gradually and cumulatively over extended periods, making the precise identification of their onset and termination a complex challenge (Achite, Simsek, Adarsh, Hartani, & Caloiero, 2023; Tirivarombo, Osupile, & Eliasson, 2018).

Drought dynamics are closely linked to precipitation, potential evapotranspiration (ETp), and temperature. These variables are integrated into specialized indices, such as the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI), which enable characterization of drought by frequency, intensity, duration, and severity. The SPI, developed by Guttman, (1998) y Mckee et al., (1993), is widely used for monitoring in Mexico; however, it relies solely on precipitation data, omitting factors such as temperature, ETp, wind speed, and humidity. In contrast, the SPEI, proposed by Vicente-Serrano et al., (2010) incorporate both precipitation and ETp to reflect the climatic water balance. This makes SPEI more sensitive to the effects of global warming by accounting for the atmospheric water demand driven by rising temperatures.

Recent research (Eiras-Barca et al., 2025; Gebrechorkos et al., 2025) emphasizes that, under climate change, the SPI may underestimate drought severity by ignoring temperature fluctuations, whereas the SPEI is a more robust indicator of accelerated atmospheric water stress. Studies in Mexico have indicated that the SPEI outperforms the SPI in identifying extreme episodes (Carrillo-Carrillo et al., 2025; Vásquez et al., 2022). Both indices can be calculated across various time scales (1 to 48 months), facilitating the assessment of short- and long-term severity in diverse systems, including agriculture and water resources (Campos Aranda, 2018; Tirivarombo et al., 2018). Specifically, the 3- and 6-month scales are critical for evaluating agricultural and seasonal droughts, as they accurately reflect the relationship between water supply (precipitation) and atmospheric demand (ETp).

A significant limitation in drought analysis, particularly in arid and semi-arid watersheds, is the lack of continuous meteorological data. These regions are highly vulnerable to water scarcity, extreme temperature variations, and high evaporation rates, which increase their susceptibility to water stress.

In this context, it is essential to distinguish drought—a temporary moisture deficiency relative to the historical average—from aridity, a structural and permanent climatic condition. While droughts can occur in any climate and geographic location, including humid tropical areas, their socio-environmental impacts are significantly more severe in arid regions. In these areas, ecosystem fragility and a high dependence on groundwater exacerbate vulnerability, making the precise characterization of temporary water deficits a critical task for regional water security.

In Mexico, data from the National Meteorological System (SMN), supervised by the National Water Commission (CONAGUA), are the primary source for hydrological modeling due to their public availability (Delgado-Ramírez, Bolaños-González, Quevedo-Nolasco, López-Pérez, & Estrada-Ávalos, 2023; Nevárez-Favela et al., 2021). However, these data often exhibit high spatial variability due to non-uniform station distribution, and missing records are frequently estimated using mathematical models (Carrillo-Carrillo et al., 2025; Colín-García et al., 2023). Consequently, satellite-based information and reanalysis products are increasingly utilized to complement or replace ground station data (Esquivel-Arriaga et al., 2024).

The Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) database provides high-resolution satellite-type precipitation data (0.05° and 0.25°) suitable for understanding drought patterns and developing climate adaptation policies, although its use for 24-hour annual maximum precipitation is not recommended (Esquivel-Arriaga et al., 2024; Chris Funk et al., 2015). Additionally, the NASA Power (NP) database offers reanalysis data—combining observed and simulated products like MERRA-2— allowing for global climate monitoring at various scales (Gelaro et al., 2017; Jiménez-Jiménez, Ojeda-Bustamante, Inzunza-Ibarra, & Marcial-Pablo, 2021). Recent studies in Mexico have used NP data to evaluate daily evapotranspiration, model biophysical aspects of crops in arid zones, and perform hydrological analyses, yielding satisfactory results (Delgado-Ramírez et al., 2023; Jiménez-Jiménez et al., 2021). Other studies use the NP database to model biophysical aspects of crops in arid zones (Barboza et al., 2024; Delgado-Ramírez et al., 2023; Jiménez-Jiménez et al., 2021), perform hydrological analyses in these regions (Khalid et al., 2022) and evaluate global warming (Bandira et al., 2023; Ravy Kumar et al., 2025; Yadav, 2025).

In this context, the present study analyzes the influence of potential evapotranspiration on drought dynamics through the SPEI index. By integrating ground-based, satellite, and reanalysis data, the frequency, duration, and magnitude of droughts are determined for two arid and semi-arid watersheds in San Luis Potosí. These watersheds are vital contributors to the Hydrological Regions of Pánuco (RH-26) and El Salado (RH-37) and support critical aquifers for industrial, agricultural, and livestock activities.

2. Materials and methods

2.1. Study area

The study focuses on two key watersheds in San Luis Potosí, México: the Altamira River and La Parada River, which encompass areas of 2,518 km^2 and 6,045 km^2, respectively. La Parada River, situated within the El Salado hydrological region, generates an average annual discharge of 512.38 m^3/s, while the Altamira River, located in the Pánuco region, contributes an average of 635.54 m^3/s per year (INEGI, 2025). Within these regions, water allocation is predominantly directed toward agricultural activities (87%), followed by public supply (10%) and self-supplied industry (3%) (CONAGUA, 2023). Furthermore, both watersheds intersect with protected natural areas, including the Sierra San Miguelito and the Gogorrón National Park, and are classified as arid and semi-arid zones based on the global aridity indices established by Zomer et al., (2022) (Figure 1).

The hydrological regime in both basins is characterized by intermittent surface runoff, originating from elevated terrains primarily during the rainy season from June to October. This seasonal availability supports traditional gravity-based irrigation, a critical practice for local agriculture given the semi-dry climate and annual precipitation range of 400 to 570 mm (INEGI, 2002). In rural areas, water for domestic use and small-scale subsistence farming is largely obtained through open-pit wells and manual extraction methods.

While irrigation is essential for stabilizing agricultural yields, its expansion is constrained by complex topography and inefficient distribution systems. Moreover, the regional aquifers face significant stress, with annual water-table drawdowns ranging from 0.5 to 3 meters. This decline occurs because groundwater extraction rates consistently exceed natural recharge, leading to a persistent hydrological deficit and conditions of overexploitation (Santacruz & Peña, 2016).

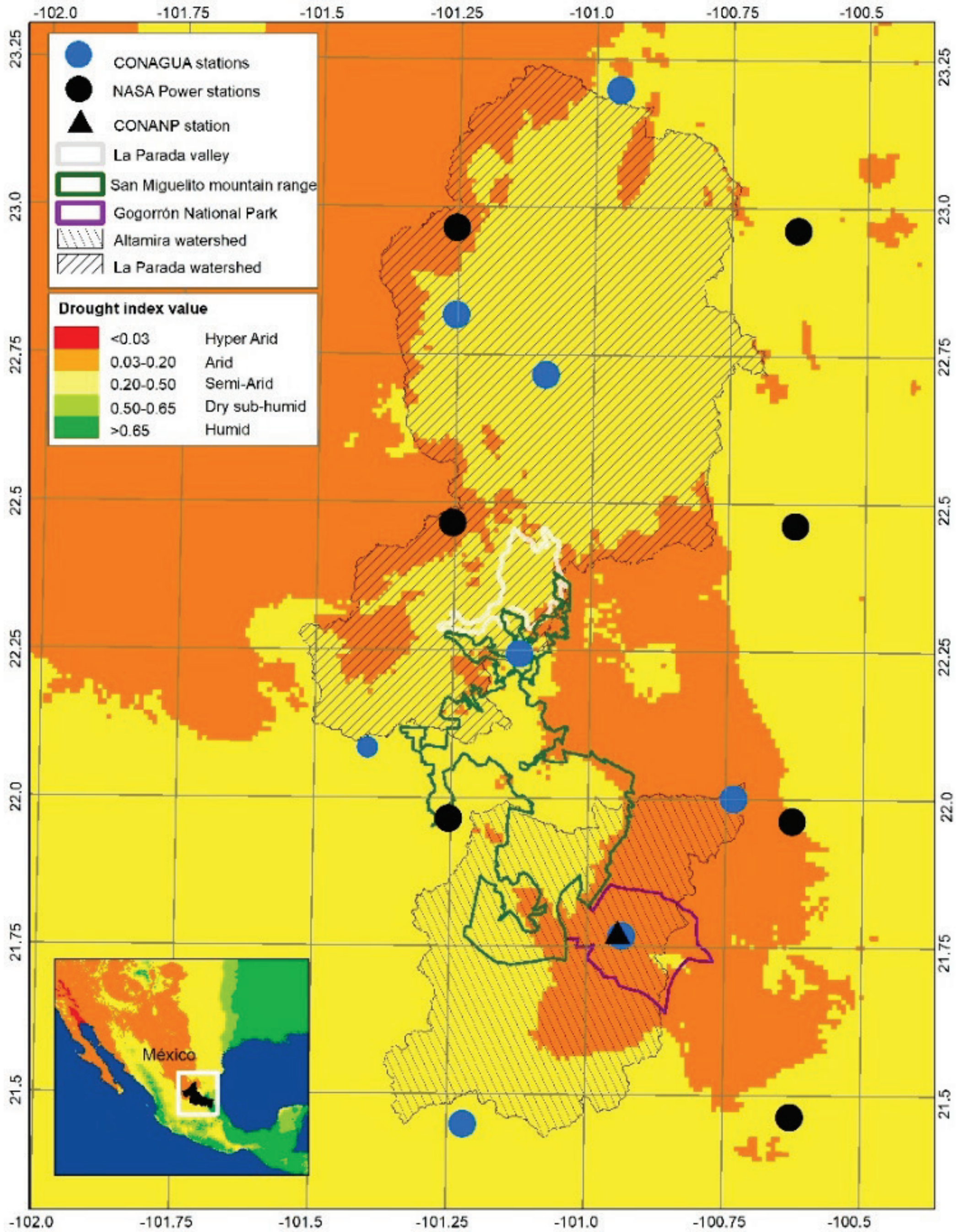

Figure 1. Spatial distribution of drought indicators in the La Parada and Altamira watersheds. The grid lines represent 0.25° increments, corresponding to the spatial resolution used for the CHIRPS database analysis. Source: Authors' elaboration based on CONAGUA (2025a); CONANP (2025) and Zomer et al., (2022).

2.2. Climatic data

2.2.1. Meteorological data observed

Daily records of maximum temperature (Tmax), minimum temperature (Tmin), and precipitation (P) were obtained from the National Meteorological Service (SMN) of CONAGUA (2025). Stations located both within the watersheds and in their immediate periphery were selected based on three rigorous criteria: 1) a minimum record length of 30 years; 2) a threshold of less than 10% missing data in the historical series; and 3) geographic proximity and representativeness regarding the altitude, vegetation, and land use of the study areas.

To represent the spatial distribution of these point-source data, the arithmetic mean of the time series from the selected stations—three for the Altamira watershed and five for La Parada—was calculated for the period from January 1961 to December 2024 (Figure 1). This spatial aggregation provided representative basin-wide values, facilitating direct comparison with raster-based data from CHIRPS and NASA Power (NP).

In the specific case of the Altamira watershed, which exhibited a 25% gap in daily data, missing values were supplemented using information from the Gogorrón station, managed by the Climate Information Platform of the National Commission of Natural Protected Areas (CONANP, 2025). To ensure consistency, a Pearson correlation analysis was performed between the available datasets.

The procedure for completing the database involved two main stages: 1) the selection of target variables (Tmax, Tmin, and P); and 2) the estimation of missing data through Multivariate Imputation by

Chained Equations (MICE). This imputation was executed using the Predictive Mean Matching (PMM) method from the mice library (Van Buuren & Groothuis-Oudshoorn, 2011) in the R programming environment (R Core Team, 2025).

2.2.2. CHIRPS and NASA-POWER (NP) Datasets

The Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) is a quasi-global satellite-based dataset providing daily and monthly precipitation estimates. For this study, data were extracted for the 1981–2024 period. CHIRPS integrates ground-based station records with satellite infrared observations, incorporating physiographic variables such as elevation, latitude, and longitude to achieve a high spatial resolution of 0.05° and 0.025° (Funk et al., 2015a), This database is widely utilized for drought monitoring, long-term trend analysis, and hydrological modeling, particularly in regions with sparse meteorological station networks (Funk et al., 2015b).

The precipitation series was processed by delineating watersheds and calculating mean precipitation at cell centers within each spatial domain using the R programming language (R Core Team, 2025).

Complementarily, the NASA Prediction Of Worldwide Energy Resources (NASA-POWER) project integrates direct measurements and satellite observations with assimilated data systems. In this database, daily temperature and relative humidity series are derived from the Goddard Earth Observing System (GEOS) assimilation model, while wind speed is obtained from the Modern-Era Retrospective analysis for Research and Applications (MERRA-2). Solar radiation is calculated based on specific satellite observations. NASA POWER primarily focuses on agroclimatic variables with global coverage, and data for this study were also constrained to the 1981–2024 period.

The retrieval of Tmax, Tmin, and precipitation data was conducted via the official NASA POWER repository (https://power.larc.nasa.gov/). The selection process involved identifying grid cells containing at least one ground-based agrometeorological station, leading to the download and processing of data from three cells in the Altamira watershed and five in the La Parada watershed.

2.3. SPI and SPEI

The Standardized Precipitation Index (SPI) is a widely recognized drought index that quantifies precipitation anomalies relative to a long-term probability distribution, typically using the Gamma function. Following the methodology proposed by Mckee et al., (1993), the index represents the normalized deviation of precipitation from the mean for a specific time scale, as shown in Equation (1):

$$SPI = \frac{xi - xj}{\sigma} \quad (1)$$

Where:

xi = precipitation for the period of interest

xj = long-term mean

σ = standard deviation

The Standardized Precipitation Evapotranspiration Index (SPEI) is calculated based on the monthly water balance, defined by the difference

(Di) between precipitation (P) and potential evapotranspiration (ETo). Since the CHIRPS database only provides precipitation records, daily maximum (Tmax) and minimum (Tmin) temperature data from CONAGUA were integrated with CHIRPS to provide the necessary variables for the SPEI calculation.

Potential evapotranspiration was estimated using the Hargreaves equation (Equation 2), which is particularly suited for arid and semi-arid regions and has demonstrated high accuracy in similar contexts (Hargreaves et al., 1985; Jiménez-Jiménez et al., 2021):

$$ETo = 0.0023 \times Ra \times (Tmax - Tmin)^{0.5} \times (Tmed + 17.8) \tag{2}$$

Where:

ET_0 = daily potential evapotranspiration (mm/day)

Ra = extraterrestrial solar radiation (mm/day)

Tmax and Tmin = daily maximum and minimum temperatures (°C)

Tmed = daily mean temperature (°C)

Both SPI and SPEI were computed using the SPEI library (Beguería et al., 2014) in the R programming environment (version 4.3.1). Data processing and visualization were conducted using the tidyverse and ggplot2 packages to manage the extensive datasets and generate comparative graphics for the two watersheds.

The analysis focused on the duration (number of months), magnitude (severity), and frequency of drought events across three meteorological sources. To evaluate the influence of evapotranspiration on drought dynamics, these indices were examined at time scales corresponding to meteorological (1 month), agricultural (3 and 6 months), and hydrological (12 months) droughts.

2.4. Determination and comparison of droughts

The SPI and SPEI values obtained were analyzed according to the classification established by Mckee et al., (1993), focusing on drought periods ranging from moderate to extreme. Three main categories were identified: extreme drought (≤ -2), severe drought (-1.5 to -1.99), and moderate drought (-1 to -1.49). Approximation of values to zero or positive values indicates the end of the drought period.

To rigorously evaluate the performance and reliability of the satellite-based CHIRPS and NASA POWER reanalysis databases against CONAGUA ground-station observations, a comprehensive statistical comparison was conducted. The similarity in the temporal and spatial patterns of these three meteorological sources was initially assessed using Pearson's correlation coefficient (r), which measures the linear relationship between the datasets within a 95% confidence interval (Taylor, n.d.; Tirivarombo et al., 2018).

Beyond linear correlation, several statistical error metrics were calculated to quantify the precision and accuracy of the estimated indices. The Root Mean Square Error (RMSE) was employed to measure the average magnitude of the error between the observed ground-truth and the estimated index values, while the Mean Absolute Error (MAE) was applied to quantify the average absolute difference between the datasets, providing a linear representation of the error (Chai & Draxler, 2014; Hodson, 2022). Additionally, the Bias was calculated to identify any systematic over- or underestimation of the drought indices by satellite and reanalysis products relative to *in situ* records (Esquivel-Arriaga et al., 2024; Moriasi et al., 2007). This metric is essential for assessing the reliability of databases like CHIRPS and NASA POWER in arid environments where localized biases can affect the climatic water balance (Jiménez-Jiménez et al., 2021; Rincón-Avalos, Khouakhi, Mendoza-Cano, López-De la Cruz, & Paredes-Bonilla, 2022)

The degree of model prediction error was further evaluated using Willmott's Index of Agreement (Willmott et al., 2011). This standardized measure, which ranges from -1 to +1 (where +1 indicates perfect agreement), serves as a robust indicator of concordance, offering deeper insights into the models' predictive capabilities than standard correlation alone. All statistical computations, including the evaluation of these metrics across the 1, 3, 6, and 12-month time scales, were performed in the R programming environment.

3. Results and discussion

The temporal variation of droughts at different scales (1, 3, 6, and 12 months) for the La Parada and Altamira watersheds is presented in Figures 2 and 3. Although the three climate databases reflect similar variability patterns, notable differences exist in the duration and magnitude of events. The 1-month scale exhibits high variability, which may lead to overestimation of individual events. In contrast, the 3- and 6-month scales effectively reflect agricultural and seasonal droughts, while periods exceeding 6 months begin to represent hydrological drought. It was observed that as time scales increase, drought duration tends to lengthen, and intensity increases due to the progressive accumulation of previous water deficits.

3.1. Comparative Analysis of SPI and SPEI: Supply vs. Demand

The integration of potential evapotranspiration into the SPEI provides a significant analytical advantage over the SPI. While both indices are mathematically comparable, they focus on fundamentally different hydrological processes. The SPI primarily measures water supply via rainfall anomalies, whereas the SPEI serves as a proxy for the total water balance by incorporating atmospheric demand. Consequently, the SPEI captures the intensified water stress that the SPI typically overlooks.

This theoretical framework is supported by historical data from the La Parada and Altamira watersheds, where the most intense agricultural and hydrological droughts occurred during 1970–1974, 1983, 2011–2013, 2019, and 2021–2023 (CONAGUA, 2025b). During the early 1970s, although shallow aquifer levels were initially stable, a gradual increase in extreme temperatures—up to 48 °C—significantly increased atmospheric demand. This heat-induced stress led to the excavation of deeper open-pit wells; in La Parada, depths increased from 8–15 meters to 25–30 meters, while in Altamira they reached up to 700 meters (Gudiño Barboza, 2025). The intensification of extraction was more pronounced in Altamira, where agricultural and livestock productivity is supported by 38 small dams, compared to the 77 dams (26 currently operational) in La Parada (CONAGUA, 2025c; Guevara & Moreno-Casasola, 2025).

The interplay of these variables explains why groundwater availability began to diminish by the 1980s, leading to the depletion of surface aquifers. More recently, a sustained decrease in precipitation since 2011 led to a severe drought affecting approximately 50% of

Mexican territory (Carrillo-Carrillo et al., 2025), as documented by reports from CONAGUA (2014), the Disaster Database (UNDRR, 2020), and the Mexico Drought Monitor (CONAGUA, 2025a).

From an analytical perspective, although the Mexico Drought Monitor relies on the SPI for its evaluations, the findings of this study suggest a critical technical distinction. While the SPI tends to identify more extreme drought events by focusing solely on precipitation anomalies, the results show it often detects more prolonged droughts in certain periods. In contrast, the SPEI shows greater intensity due to the additional pressure from ETp, especially in water-scarce conditions. This is evident in Figure 4 and Figure 6 (SPEI) versus Figure 5 and Figure 7 (SPI), where the number of months under severe and extreme drought conditions varies depending on the index and database used. Ultimately, the SPEI provides a more robust drought detection by offering a comprehensive assessment of the actual water balance and hydrological stress in these arid and semi-arid watersheds.

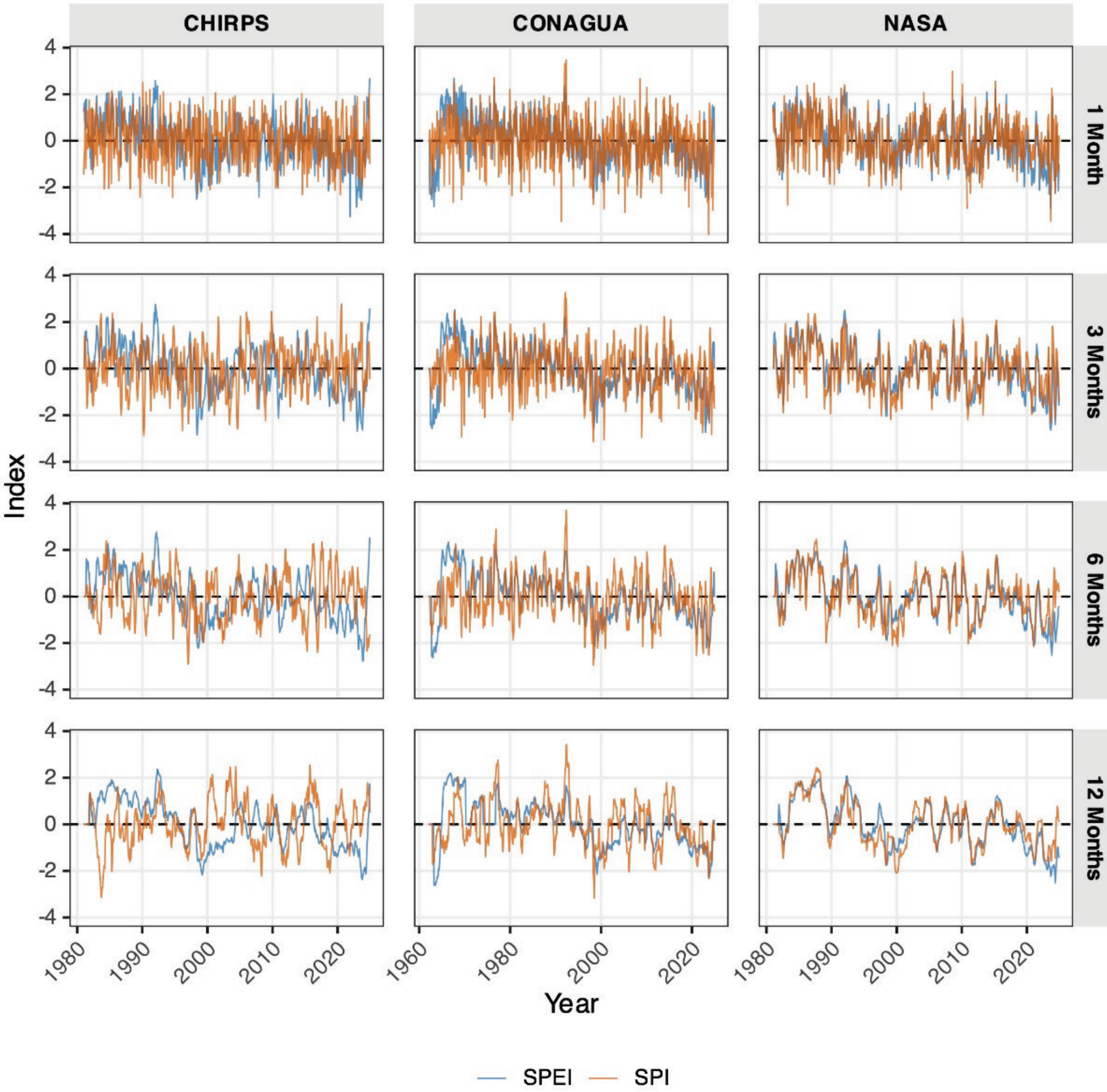

Figure 2. Comparison of Standardized Precipitation-Evapotranspiration Index (SPEI) and Standardized Precipitation Index (SPI) at 1, 3, 6- and 12-month scales for the La Parada watershed.

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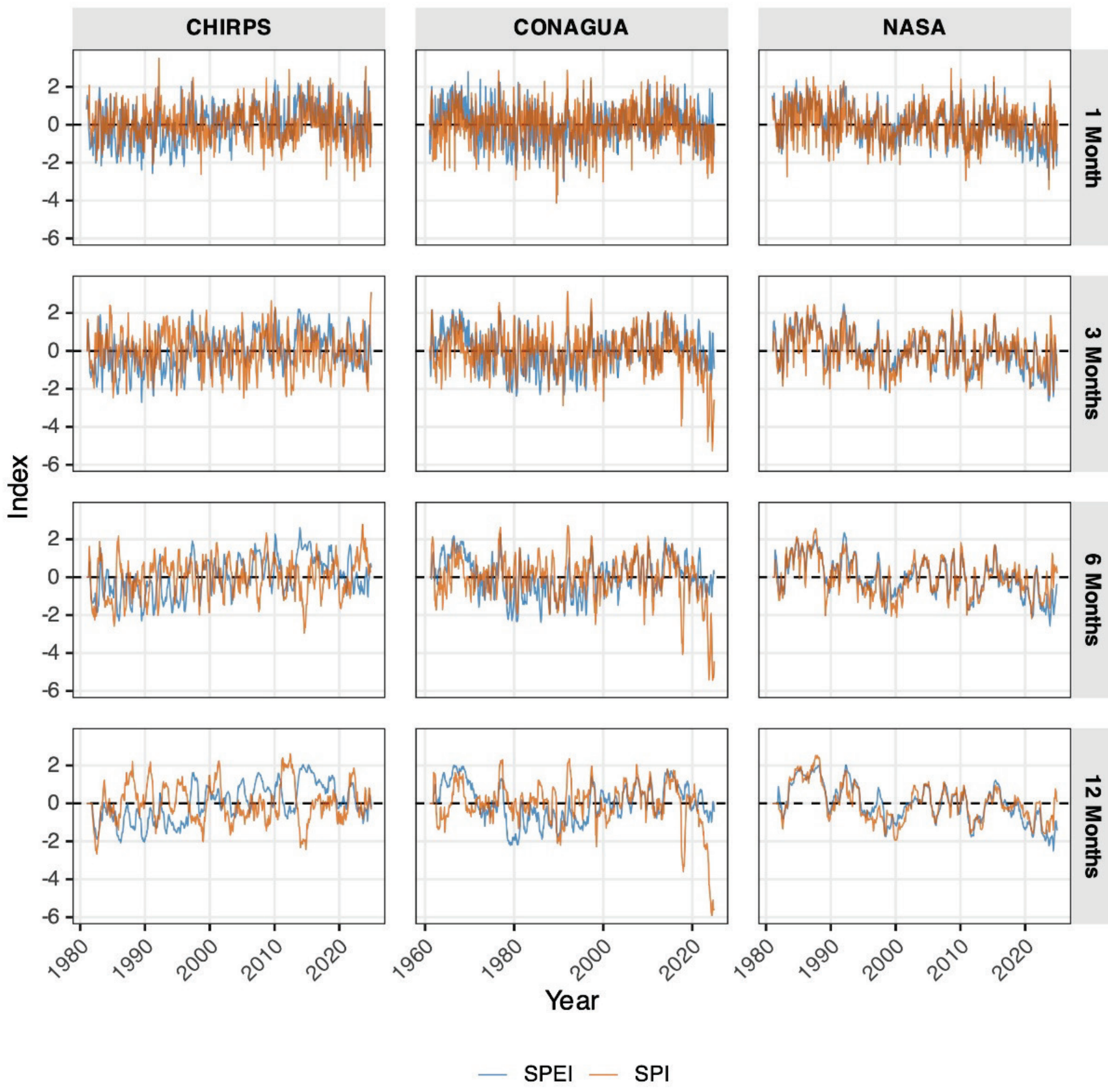

Figure 3. Comparison of Standardized Precipitation-Evapotranspiration Index (SPEI) and Standardized Precipitation Index (SPI) at 1, 3, 6- and 12-month scales for the Altamira watershed.

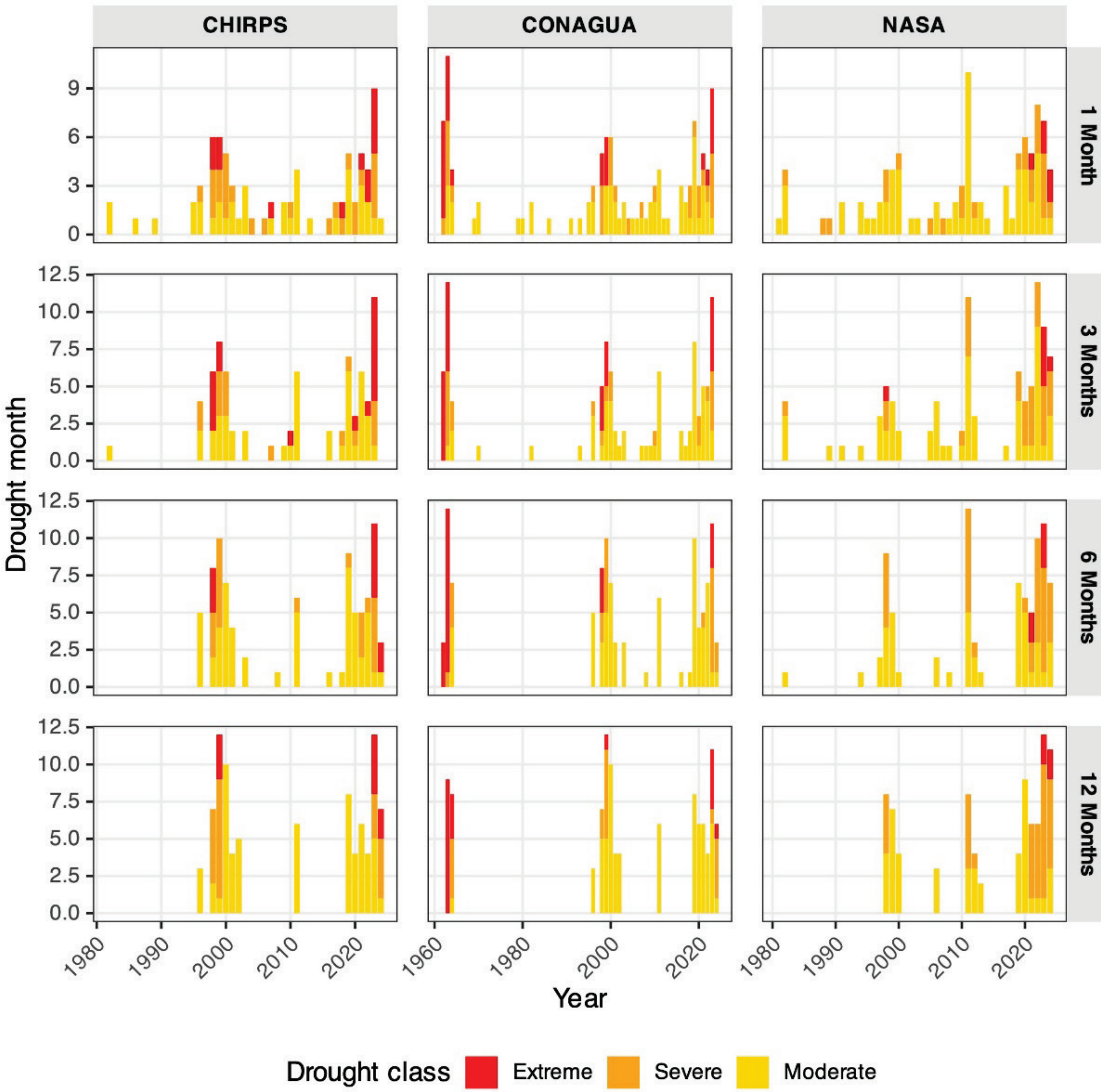

Figure 4. Number of months of drought at different scales based on SPEI for the La Parada watershed.

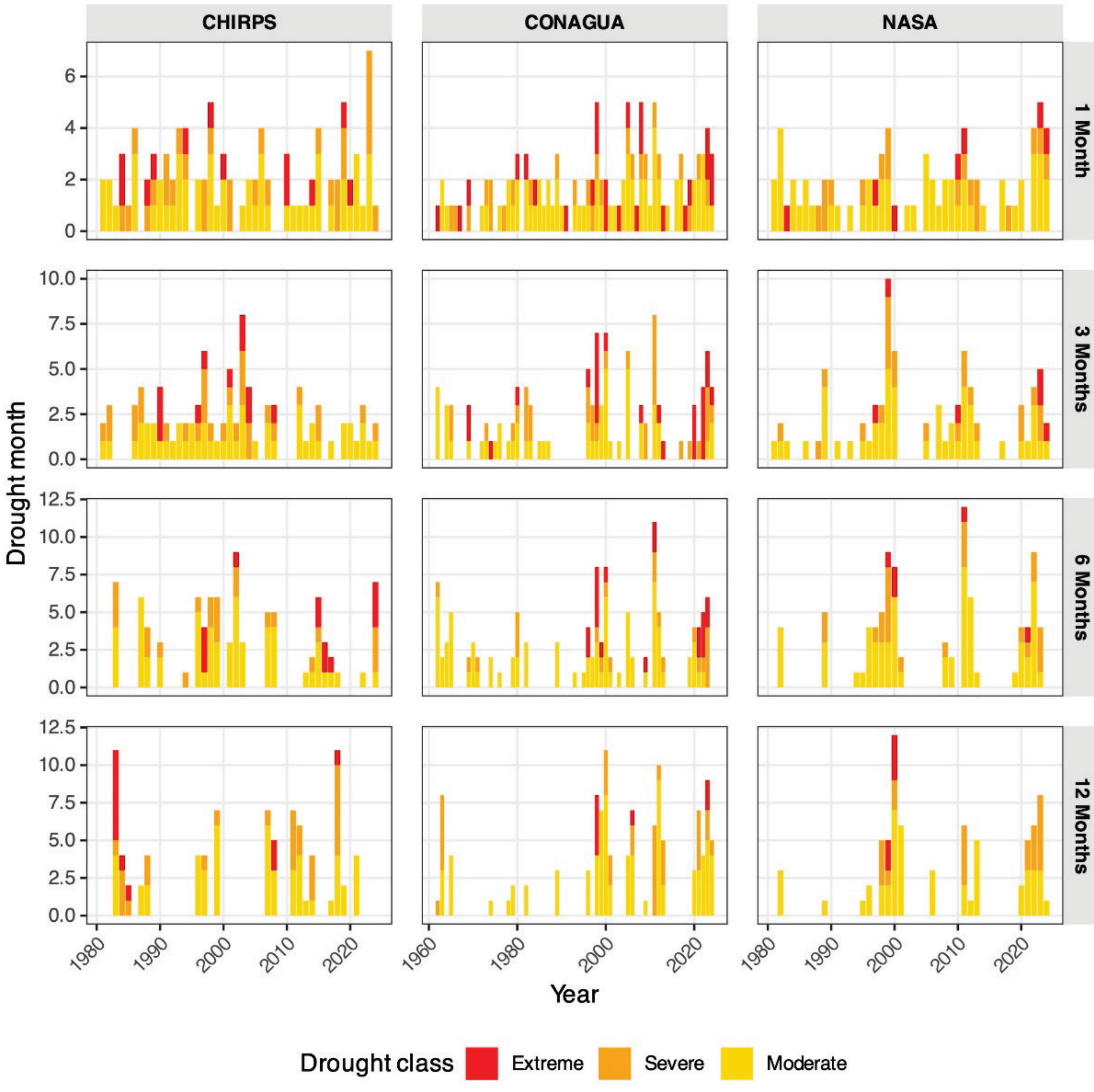

Figure 5. Number of months of drought at different scales based on SPI for the La Parada watershed.

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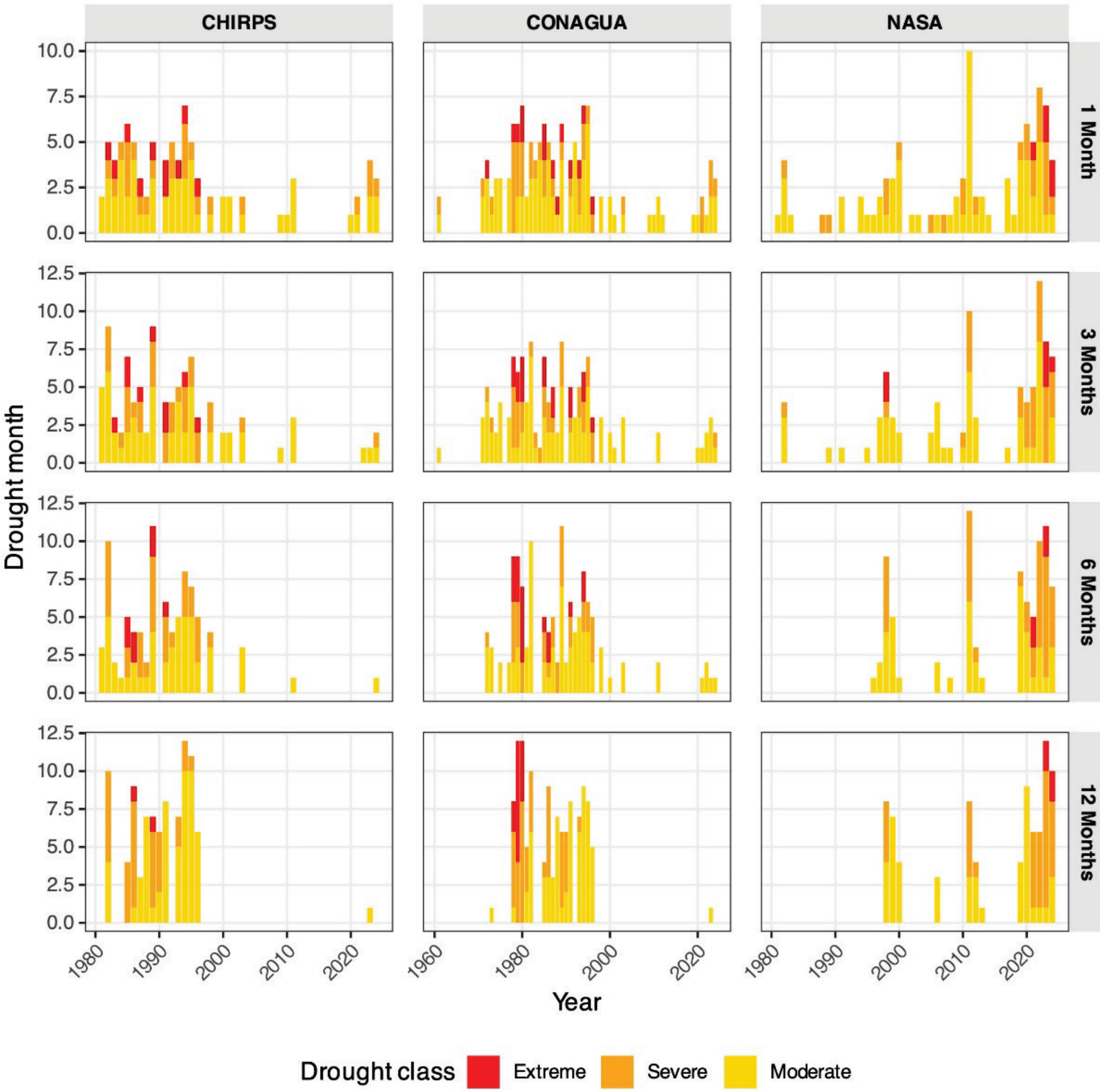

Figure 6. Number of months of drought at different scales based on SPEI for the Altamira watershed.

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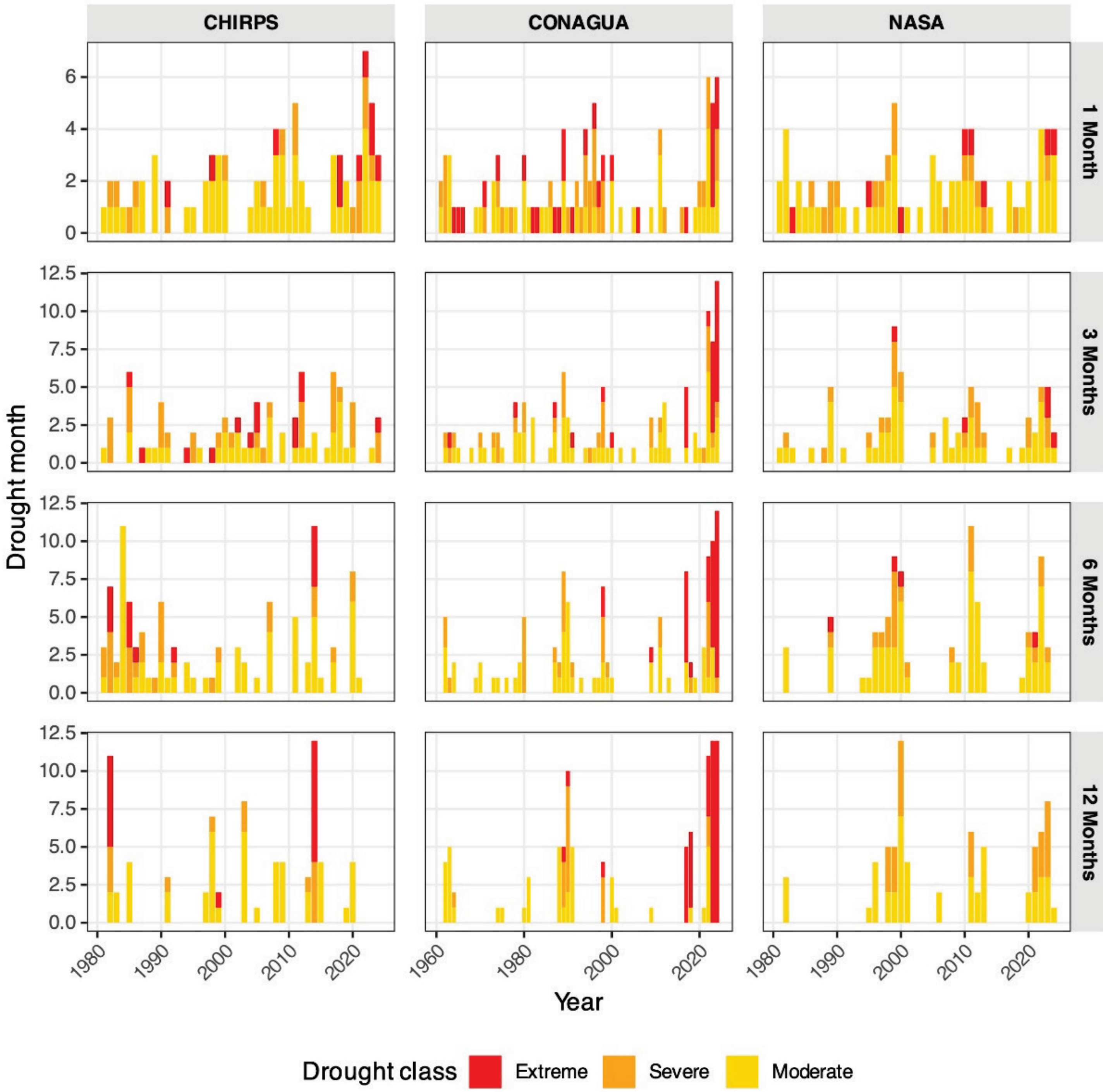

Figure 7. Number of months of drought at different scales based on SPI for the Altamira watershed.

3.2. Performance and Correlation of Databases

In both watersheds, differences among meteorological databases stem from information processing and index calculation approaches. The CONAGUA climate database identified a higher number of severe and extreme droughts between 1970 and 2020; however, CHIRPS and NASA POWER showed greater variability and a higher frequency of drought months at the 1- and 3-month scales. To evaluate the reliability of these products, a correlation analysis with observational data was performed, supplemented by an in-depth evaluation of statistical metrics including RMSE, MAE, Bias, and Willmott’s index (Table 1).

Table 1. Statistical performance metrics (RMSE, MAE, Bias, Willmott's and Pearson) for SPI and SPEI drought indices across multiple time scales (1, 3, 6, and 12 months) in the Altamira and La Parada watersheds.

Watershed	Index	Scale	Comparison	RMSE	MAE	Bias	Willmott	Pearson
Altamira	SPI	1	CONAGUA vs CHIRPS	1.4054	1.0853	-0.0017	-0.1099	0.6122
			CONAGUA vs NP	1.3703	1.0822	-0.0224	-0.1067	0.5217
	SPEI	1	CONAGUA vs CHIRPS	1.5349	1.2509	-0.0815	-0.0676	0.98
			CONAGUA vs NP	1.334	1.0716	-0.0844	0.0853	0.4158
	SPI	3	CONAGUA vs CHIRPS	1.3676	1.0913	0.0666	0.0531	0.4436
			CONAGUA vs NP	1.2694	1.0283	0.0509	0.1078	0.4739
	SPEI	3	CONAGUA vs CHIRPS	1.5854	1.3156	-0.1047	-0.1164	0.98
			CONAGUA vs NP	1.2809	1.0428	-0.1081	0.115	0.2017
	SPI	6	CONAGUA vs CHIRPS	1.2706	1.0198	0.0752	0.1514	0.096
			CONAGUA vs NP	1.2376	0.9846	0.0645	0.1807	0.1022
	SPEI	6	CONAGUA vs CHIRPS	1.6383	1.3588	-0.1335	-0.1608	0.98
			CONAGUA vs NP	1.2125	0.9807	-0.1371	0.1621	0.2891
	SPI	12	CONAGUA vs CHIRPS	1.2841	1.0115	0.0572	0.1547	0.0334
			CONAGUA vs NP	1.24	0.9709	0.0481	0.1886	0.0488
	SPEI	12	CONAGUA vs CHIRPS	1.7102	1.4385	-0.1801	-0.2231	0.98
			CONAGUA vs NP	1.1264	0.9312	-0.1806	0.2082	0.3896

Watershed	Index	Scale	Comparison	RMSE	MAE	Bias	Willmott	Pearson
La Parada	SPI	1	CONAGUA vs CHIRPS	1.4361	1.1437	-0.0527	-0.4972	0.1437
			CONAGUA vs NP	0.7476	0.5682	-0.0891	0.2588	0.7148
	SPEI	1	CONAGUA vs CHIRPS	0.3147	0.2418	-0.2044	0.6318	0.9819
			CONAGUA vs NP	0.6651	0.5224	-0.2084	0.2049	0.7693
	SPI	3	CONAGUA vs CHIRPS	1.5131	1.2186	-0.0306	-0.5026	-0.1141
			CONAGUA vs NP	0.6773	0.5105	-0.0459	0.3705	0.7713
	SPEI	3	CONAGUA vs CHIRPS	0.3455	0.272	-0.2333	0.5686	0.9823
			CONAGUA vs NP	0.6595	0.5327	-0.2352	0.1554	0.7795
	SPI	6	CONAGUA vs CHIRPS	1.4209	1.146	-0.0108	-0.4683	0.2114
			CONAGUA vs NP	0.6848	0.519	-0.0202	0.335	0.7557
	SPEI	6	CONAGUA vs CHIRPS	0.3687	0.288	-0.2399	0.5327	0.9799
			CONAGUA vs NP	0.6384	0.529	-0.2441	0.142	0.7982
	SPI	12	CONAGUA vs CHIRPS	1.3493	1.0745	-0.0375	-0.366	0.0648
			CONAGUA vs NP	0.6744	0.508	-0.0457	0.3541	0.7576
	SPEI	12	CONAGUA vs CHIRPS	0.3867	0.3063	-0.2533	0.506	0.9778
			CONAGUA vs NP	0.5981	0.5104	-0.2576	0.1769	0.8353

The results reveal a superior performance of the satellite and reanalysis databases in the La Parada watershed compared to Altamira. Specifically, for the SPEI in La Parada, the comparison between CONAGUA and CHIRPS yielded the lowest error rates, with RMSE values ranging from 0.31 to 0.38 and a maximum Willmott's index of 0.63 on the 1-month scale. In this watershed, NASA-based indices show stable, moderately high correlations, whereas the CHIRPS SPI improves markedly at longer scales. Conversely, Altamira exhibited significantly higher errors, with SPEI RMSE values consistently exceeding 1.12 across databases and time scales. This discrepancy suggests that the complex hydro-climatic variability or the inherent characteristics of the ground station network in Altamira present a greater challenge for the calibration of satellite products.

Furthermore, a consistent negative Bias was identified across almost all SPEI calculations for both watersheds, with values ranging between -0.08 and -0.25. This systematic underestimation indicates that satellite-derived indices tend to report slightly drier conditions than those recorded by *in situ* stations, likely due to an overestimation of ETp derived from reanalysis data or a localized underestimation of precipitation by CHIRPS. Regarding SPI, the NASA POWER database generally presented lower RMSE and MAE values than CHIRPS in both basins, suggesting that for precipitation anomalies alone, NASA's reanalysis might offer a more refined regional calibration.

Finally, the CHIRPS SPEI index emerged as the best-performing tool overall, maintaining a high correlation with observational data across most scales. However, the weakening of the Willmott’s index at longer time scales in Altamira (reaching -0.22 at 12 months for SPEI-CHIRPS) highlights that most indices —except for the CHIRPS SPEI— lose predictive ability as the time scale increases. This underscores that the accumulation of estimation errors in ETp and precipitation significantly affects the consistency of long-term hydrological drought monitoring in specific basin contexts.

3.3. Thermal Dynamics and Regional Implications for Drought Assessment

Although this study focuses on the historical evaluation of droughts, incorporating the SPEI index addresses the need to account for the growing role of temperature in the regional water balance. As observed in this analysis, the SPEI has already detected drought events with greater frequency and duration over the last decade, suggesting that thermal variability is beginning to dominate the local water balance relative to historical precipitation variability.

This trend is consistent with global climate change scenarios (Bandira et al., 2023; Eiras-Barca et al., 2025), in which atmospheric warming is expected to accelerate drought severity by increasing ETp rates, even when precipitation remains constant. In this context, temperature is increasingly dominant in the regional water balance, and the SPEI is significantly more relevant than the SPI. Rising global temperatures accelerate ETp rates, creating a thirstier atmosphere that can induce severe drought conditions even during years with near-average precipitation. This positive thermal anomaly is approaching thresholds where evaporative demand exceeds historical variability, making the SPEI an indispensable tool for capturing the heat-induced water stress that defines modern hydrological crises.

Rather than merely describing intensity variations, it is crucial to analyze the physical drivers of these differences. The divergence between the SPI and SPEI arises from the decoupling of water supply and atmospheric demand. While the SPI captures precipitation deficits, the SPEI identifies an intensified drought by accounting for the energy-driven water loss through ETp. In practical terms, this implies that water management based solely on the SPI may underestimate the real stress on agricultural systems and groundwater recharge, leading to delayed responses in irrigation planning and drought mitigation.

Analogous phenomena of divergence between both indices due to positive thermal anomalies have been documented in other semi-arid regions of Latin America, such as northern Chile (Eiras-Barca et al., 2025) and northeastern Brazil (Magalhães et al., 2025), reinforcing that evaporative demand is exceeding historical thresholds (Gebrechorkos et al., 2025). These findings are potentially extrapolable to other arid and semi-arid regions of Mexico and Latin America sharing similar climatic profiles (BWh and BSh according to the Köppen-Geiger classification). However, for a successful regional extrapolation, two conditions must be met: first, a baseline validation of satellite and reanalysis data (CHIRPS/NASA POWER) against local ground records to account for regional biases; and second, the calibration of ETp equations to the specific thermal characteristics of the target watershed.

Furthermore, the demonstrated reliability of the CHIRPS and NP databases in these watersheds confirms that multi-source satellite products are robust tools for drought characterization in regions with limited *in situ* monitoring. The integration of these tools enables a transition from a purely descriptive approach to an integrated analysis of the water balance, which is fundamental to water security under a changing climate.

4. Conclusions

The evaluation of SPI and SPEI indices across different time scales revealed consistent drought patterns among the three meteorological databases (CONAGUA, CHIRPS, and NP) in the study watersheds. This confirmation suggests that multi-source products such as CHIRPS and NP constitute a viable technical alternative for filling data gaps in arid and semi-arid regions where *in situ* monitoring is limited.

Analytically, the study demonstrated that droughts identified by the SPEI were characterized by higher frequency and longer duration compared to those identified by the SPI. This difference is explained by the critical role of temperature: rising temperatures increase ETp, thereby increasing evaporative water demand and generating a more pronounced water deficit. Conversely, when considering precipitation alone, the SPI identified more extreme events, confirming its utility for estimating water supply but highlighting limitations in capturing the full water balance.

Correlations between the databases were stronger at shorter time scales (1 to 3 months) associated with meteorological and agricultural droughts. At longer scales (12 months), these correlations weakened, highlighting that while precipitation initiates drought, the progressive accumulation of thermal stress and ETp significantly modulates hydrological response and soil moisture.

Understanding the transition between drought typologies across time scales enables decision-makers to shift from reactive measures to preventive strategies, such as optimizing irrigation schedules and planning water reserves in watersheds where groundwater extraction has historically depleted surface aquifers.

Ultimately, the findings of this research transcend theoretical analysis by providing an objective metric for proactive water management in San Luis Potosí. By understanding the divergence between water supply (precipitation) and demand (evapotranspiration), local authorities can integrate the SPEI index into early warning protocols. This enables anticipating water availability crises before they severely impact the agricultural and industrial sectors, facilitating a transition from emergency-response measures to water planning based on resilience and rigorous technical monitoring.

Finally, the scientific evidence showing increased drought severity in the last decade must be integrated into local climate change adaptation policies. These results are extrapolable to other arid and semi-arid regions of Mexico and Latin America, provided that baseline validations against local records are conducted to account for regional biases and specific watershed characteristics. This approach ensures that scientific monitoring translates into effective actions to achieve long-term water security in fragile arid and semi-arid environments.

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7. Statement of conflict of interest

No potential conflict of interest was reported by the authors.

8. Statement on the use of IA

The authors used Grammarly solely for grammar checking; generative AI was not used to create or alter the substantive content of the manuscript.

9. References

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