

Hydrometeorological drought analysis through Two-variate Standardized Index for the Paraná River Basin, Brazil

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ABSTRACT

Brazil has faced severe droughts in recent decades, significantly affecting agriculture, water supply, and hydropower generation, among other sectors. The Paraná River Basin, a major hub for hydropower, has been particularly affected, posing challenges for water management. To address this, we conducted a study to provide tailored climate information for the Brazilian hydroelectric sector. Given the complexity of hydrometeorological processes, involving hydrological, meteorological and climatological processes and anthropogenic factors, a multivariate approach is essential for drought assessment. We assessed the effectiveness of a Two-variate Standardized Index (TSI) in characterizing hydrometeorological droughts on large-scales basins and its potential as an operational decision support index. The TSI was compared with the Standardized Precipitation Index and the Standardized Streamflow Index, and we examined the correlation between TSI and Terrestrial Water Storage from GRACE and reservoir volumes, at different time scales. We used the HAND model and water table depth to gain a comprehensive understanding of drought conditions. The results show that the TSI outperforms the univariate indices SPI and SSFI in characterizing drought events in terms of severity and duration. The correlation analysis showed that time scales of 12 and 24 months are the most suitable for hydrometeorological drought monitoring. Overall, the study highlights the potential of TSI as an operational index for monitoring drought conditions and can be applied in basins with different climate regimes.

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1. Introduction

Droughts are typically classified into four categories: meteorological, agricultural, hydrological, and socioeconomic (Mishra and Singh, 2010; Wilhite and Glantz, 1987). Meteorological drought entails a prolonged precipitation deficit over a wide area for an extended period. Agricultural drought occurs when soil moisture deficit hampers crop and vegetation growth, driven by meteorological drought. Hydrological drought occurs when the hydrological system experiences a water shortage, usually following several months of meteorological drought, leading to unusually low streamflow in rivers and depleted water levels in lakes, reservoirs, and groundwater. The consequences of such droughts can be severe, affecting ecological systems and economic sectors across vast areas for extended periods, triggering water and energy insecurity often ranging from months to years. The impacts of drought can be far-reaching, affecting crop irrigation, waterborne transportation, hydropower generation, drinking water supply and water quality, among others (Van Loon, 2015).

Brazil has experienced severe droughts during the first two decades of the 21st century, impacting both socioeconomic sectors and ecological systems (Anderson et al., 2018; Aragão et al., 2018; Brito et al., 2018; Coelho et al., 2016; Cuartas et al., 2022; Cunha et al., 2019, 2018; Deusdará-Leal et al., 2020; V. R. Fernandes et al., 2021; Marengo et al., 2008, 2015, 2021; Nobre et al., 2016; Tomasella et al., 2011). However, in the latest decade, it has faced droughts in almost all country regions (Cunha et al., 2019), and in the latest years, drought events have occurred concomitantly in the Southeast, Mid-West and South regions (Cuartas et al., 2022). One of the most impacted basins was the Paraná River Basin (Naumann et al., 2021; Cuartas et al., 2022) since it drains those three regions. This basin is the major hub for hydropower generation, with a total of 87 hydropower plants (Rafee et al., 2019), with a significant share originating from it; 35 % of the total hydropower generation in Brazil. According to WMO (2021), in the last decade, the most expensive disaster recorded in South America was the drought in the Southeast region of Brazil in 2014/15, which accumulated losses of more than US\$5 billion.

The impacts of climate variability, along with the need for mitigation and adaptation to climate change, have led to new demands for climate services that can provide relevant information to decision-makers (Findlater et al., 2021). This study filled the gap of producing high-quality climate information based on an understanding of the needs and perspectives of stakeholders associated with the Brazilian hydroelectric sector, who actively participated in the design process of the new tools to be implemented. It was developed in collaboration with the Drought Information System for Southern South America (SISSA), supported by the EUROCLIMA+ program. Its goal is to assist in improving water resources management strategies, aiming to contribute to sustainability and energy security of Brazil and southern South America during future drought events.

The most common information used to monitor and characterize drought events are drought indices. Most studies employ univariate indices such as the Standardized Precipitation Index (SPI) (McKee et al., 1993) being the most widely used, and recommended by the World Meteorological Organization (WMO) and the Global Water Partnership (GWP) (2016), Soil Moisture Deficit Index (SMDI) (Narasimhan and Srinivasan, 2005), Standardized Streamflow Index (SSFI) (Modarres, 2007), among others. However, it is essential to recognize that hydrometeorological processes are inherently multivariate in nature, resulting from the spatial-temporal interactions among various hydrological, meteorological, climatological, and anthropogenic factors (Hao and AghaKouchak, 2013; Mishra and Singh, 2011, 2010; Van Loon, 2015; Van Loon et al., 2019). Consequently, univariate indices may offer a limited comprehension and understanding of drought (Liu et al., 2019; Nikravesh et al., 2020; Shiau, 2006). Several studies have emphasized the need for a multivariate approach to analyze and model drought events accurately (Hao and AghaKouchak, 2013; Liu et al., 2019; Nikravesh et al., 2020). To account for the interaction between various hydrometeorological variables, several indices have been developed, including the Aridity Anomaly Index (AAI), Drought Reconnaissance Index (DRI), Palmer Drought Severity Index (PDSI), Standardized Precipitation Evapotranspiration Index (SPEI), Soil Moisture Anomaly (SMA), and Palmer Hydrological Drought Index (PHDI) (World Meteorological Organization (WMO) and Global Water Partnership (GWP), 2016). However, calculating these indices can be challenging due to incomplete or unavailable input data in some regions. Additionally, real-time data availability is often lacking for drought monitoring purposes. Some indices also rely on potential evapotranspiration time series, which may have uncertainties related to the estimation method. Furthermore, some indices are not suitable for long-term or multi-seasonal events.

In this context, the Copula theory emerges as a valuable alternative for generating multivariate indices. While extensively used in financial and insurance sectors (Mendes and Souza, 2004), its application in environmental sciences is a relatively recent development (Tootoonchi et al., 2022). A copula is a mathematical function that combines dependent variables through their individual marginal distribution functions to construct a joint distribution function. Previous studies, such as Hao and AghaKouchak (2013) and Nikravesh et al. (2020), have utilized copulas to estimate two-variate indices. The first study used precipitation and soil moisture to characterize drought conditions in California and North Carolina, USA. The second study used precipitation and streamflow data to analyze drought frequency in two small basins in Iran; the Rasht (77.11 km²) and Urmia (117.68 km²) basins. The results of these studies demonstrated the suitability of considering at least two variables in one index for characterizing and assessing drought events effectively.

Therefore, we estimated the Two-variate Standardized Index (TSI) for the Paraná River Basin by using precipitation and streamflow that are often available data, and commonly used by the hydropower sector. The objective was to assess the capability of characterizing hydrometeorological drought and to ascertain the potential of TSI as an operational index to support the decision-making process, and effectively mitigate and adapt to drought impacts on the hydroelectric sector. The performance of the TSI is compared with two well-known univariate indices, the Standardized Precipitation Index (SPI) (McKee et al., 1993) and the Standardized Streamflow Index (SSFI) (Modarres, 2007), across different time scales (6-, 12-, 24-, 36-, 48- and 60 months). Moreover, we compared the TSI with various hydrological variables, such as the Terrestrial Total Water storage (TWSA) obtained from GRACE (Gravity Recovery and Climate Experiment), the normalized terrain model HAND (Height Above Nearest Drainage), and reservoir storage and level data.

2. Materials and methods

2.1. Study area

The Paraná River Basin (Fig. 1) is a major hub for hydropower generation, with a total of 87 hydropower plants (Rafee et al., 2019) located throughout its mainstream and tributaries, including the Grande, Paranaíba, Tietê, Paranapanema, and Iguaçu rivers. The Paraná River basin is also the most important in Brazil in terms of multiple uses: water supply, irrigation, navigation, tourism, etc. Its area, up to the Itaipu HPP, comprises 832,442 km² (Table 1) and includes the most industrialized and urbanized region in Brazil (Melo et al., 2016; Rafee et al., 2019). The existence of several multi-million urban centres generates great pressure on water resources in this basin. In this study we focus on eight HPPs: Nova Ponte, Emborcação and Itumbiara in the Paranaíba River; Furnas and Marimondo in the Grande River; Jurumirim and Capivara in the Paranapanema River; and Itaipu in the Paraná River. Detailed information on the basins and the hydro-power plants (HPP) can be found in Cuartas et al. (2022).

The predominant climate in the Paraná River basin, up to Itaipu HPP, is Tropical Savannah (Aw), accounting for 59 % of the region (Fig. 1). This climate is characterized by the temperature of the coldest month $\geq 18^\circ\text{C}$ and $P_{dry} < 100\text{mm} - \text{MAP}/25$ (P_{dry} is the precipitation of the driest month and MAP is the mean annual precipitation). Since the basin is mainly located in Southeast Brazil, the rainy season occurs from November to March and contributes to approximately 80 % of annual precipitation (Grimm, 2011). October is considered a transition month between the dry and rainy seasons, but it is often included among the rainy months for practical purposes. Although the climate of the basin affluent to Jurumirim HPP and Capivara HPP (B7) is classified as temperate climate, Cfa (87 % and 74 %, respectively), they are predominantly located in Southeast Brazil and experience the rainy season. However, Capivara HPP's basin left margin extends into the southern region of Brazil, with a temperate climate with no dry season.

2.2. Datasets

Both in situ and gridded data for the Paraná River Basin are used. In situ data comprises streamflow, reservoir volume and water table data within the eight subbasins analysed. Gridded data comprises precipitation data from CHIRPS-2.0 (Climate Hazards Group Infrared Precipitation with station data); Total water storage (TWS) from the GRACE mission; and the Normalized terrain model HAND (Height Above the Nearest Drainage). Below is a detailed description of the data used.

2.2.1. Precipitation data

Daily precipitation dataset from the Climate Hazards Group Infrared Precipitation with station data, CHIRPS-2.0 (Funk et al., 2015) at 0.05° spatial resolution was used (<https://data.chc.ucsb.edu/products/CHIRPS-2.0/>, accessed on October 2022). Details about this product can be found at: <https://www.chc.ucsb.edu/data/chirps>. Several studies have validated the dataset for some Brazilian regions

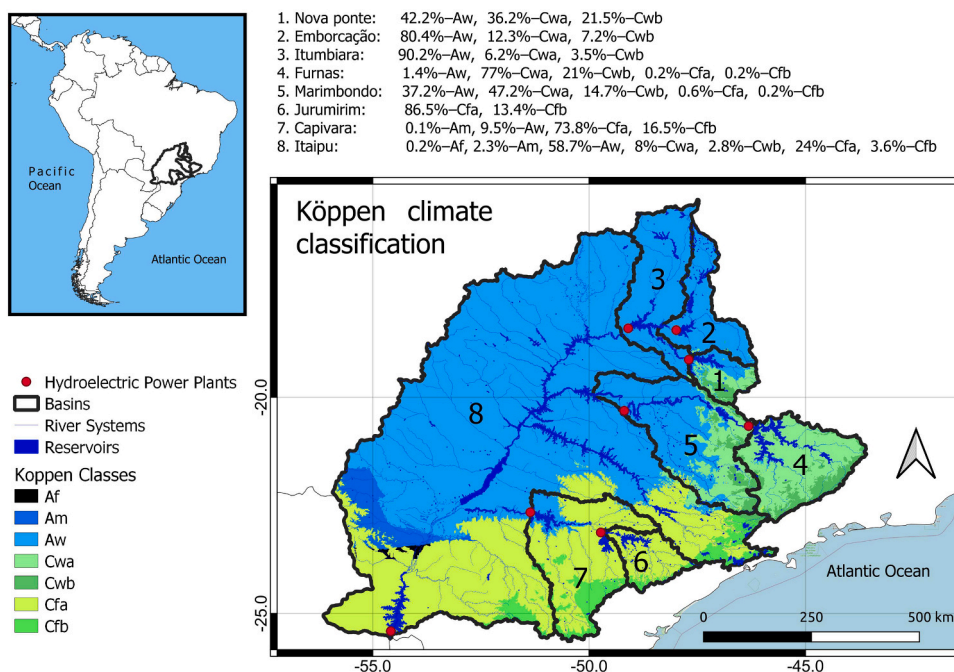


Fig. 1. Map of the location of Paraná River basin up to the Itaipu HPP (B8), and the sub-basins affluent to the Nova Ponte (B1), Emborcação (B2), Itumbiara (B3), Furnas (B4), Marimondo (B5), Jurumirim (B6) and Capivara (B7) HPPs. Climate classifications are identified and the contributing percentages are shown in the upper chart.

Table 1

Description of the basins.

Basin ID	HPP	Sub-basin	River	Drainage area (km ²)	Effective volume (hm ³)	Qnat mean (m ³ /s)
B1	Nova Ponte	Paranaíba	Araguari	16,085	10,380	293
B2	Emborcação	Paranaíba	Paranaíba	49,656	13,056	473
B3	Itumbiara	Paranaíba	Paranaíba	103,227	12,454	1511
B4	Furnas	Grande	Grande	55,256	17,217	922
B5	Marimondo	Grande	Grande	134,680	5260	1849
B6	Jurumirim	Paranapanema	Paranapanema	20,941	3165	225
B7	Capivara	Paranapanema	Paranapanema	92,941	5725	1098
B8	Itaipu	Paraná	Paraná	832,442	19,000	10,284

(Anderson et al., 2018; Baez-Villanueva et al., 2018; Beck et al., 2020; Cavalcante et al., 2020; Cuartas et al., 2022; Seyedabadi et al., 2020), and concluded that the dataset performed well in most of the regions. This dataset was also chosen because of its long-term availability (since 1981) and because it is updated in “near real-time”, with a delay of 2 days, which is suitable for monthly drought monitoring. The daily data was accumulated monthly. The monthly time series for each subbasin were derived from clipped data using the subbasin’s polygons, followed by an estimation of the average values.

2.2.2. Streamflow and reservoir volume data

Naturalized streamflow and reservoir effective volume data were provided by the Brazilian National Electrical System Operator (ONS) and the National Water and Sanitation Agency (ANA), through the Reservoir Monitoring System (SAR) (<https://www.ana.gov.br/sar/sin>, accessed in October 2022). The naturalized monthly streamflow data are for the period Jan/1981–Sep/2022. Reservoir volume data are available in the SAR platform from January 2000 until the present (updated in almost near real-time). We standardized the monthly reservoir volume (SRV) data through Eq. (1):

$$SRV = \frac{RV_i - \overline{RV}_i}{RVstd_i} \quad (1)$$

where $\overline{RV}_i$ and $RVstd_i$ are the mean and standard deviation of the reservoir volume of month-*i*, respectively.

2.2.3. Total water storage

Monthly Terrestrial Water Storage (TWS) data from NASA’s Gravity Recovery and Climate Experiment (GRACE) mission, conducted in collaboration with the German mission GeoForschungZentrum (<https://gracefo.jpl.nasa.gov/resources/9/measuring-earths-gravity-from-space-poster/>), was used. The GRACE and GRACE-FO (twin satellites) observed gravity changes caused by changes in surface (rivers, wetlands, and lakes) and subsurface (soil moisture and groundwater) waters, ice sheets and glaciers, and sea level, i.e., the Total Water Storage (Getirana, 2016) (<https://gracefo.jpl.nasa.gov/mission/overview/> accessed on February 14, 2023). The horizontal resolution is 300 km, and the timestep is approximately monthly. The data are available since April 2002. Monthly time series for each subbasin were derived following the same procedure used for precipitation data. We applied the Eq. (1) to standardized the monthly TWS data (STWS).

2.2.4. HAND classes map

The Normalized terrain model HAND (Height Above the Nearest Drainage), allows for obtaining landscape maps using only topographic data (Nobre et al., 2011), with hydrological relevance, associated with topography and potential soil moisture content (Cuartas et al., 2012). In this study, we used the terrain model HAND generated by Yamazaki et al. (2019), as part of the global hydrography datasets called MERIT Hydro (Yamazaki et al., 2019). The datasets contain flow direction, flow accumulation, hydrologically adjusted Digital Elevation Model (DEM), river channels, and the normalized terrain model HAND. They used the SRTM3 v2.1 data at 3 arc-second resolution (~ 90 m at the equator) and AW3D-30 m v1 to develop a MERIT DEM at 90 m resolution, which was the base for the MERIT Hydro datasets. We obtained the HAND-Classses map for the Paraná River basin using the same classification as Nobre et al. (2011) and Cuartas et al. (2012), except for the slope, where we used 15 % due to the relief of the basin. HAND-classes maps allow us to know the potential saturated and unsaturated conditions in the basin and the potential groundwater table depth.

2.2.5. Water table data

In this study, we also used water table data from the Brazilian Geological Service, through the Integrated Groundwater Monitoring Network (RIMAS) (<https://rimasweb.sgb.gov.br/layout/index.php> accessed on March 3, 2023). There are 75 piezometers in the Paraná River Basin, with data from 2011 to 2022.

2.3. Two-variate standardized index

We used the copulas concept to implement and estimate a Two-variate Standardized Index, as in Nikravesh et al. (2020) to assess hydrometeorological drought. Copulas are functions capable of modelling correlated structures from dependent random variables.

These functions capture the dependence structures among variables, by linking the marginal distributions of each variable, forming their joint probability distribution (Hao and AghaKouchak, 2013; Liu et al., 2019; Nikravesh et al., 2020; Tootoonchi et al., 2022).

Two common families of Copulas functions have mainly been used in hydroclimatic modelling and the development of multivariate indices (Tootoonchi et al., 2022): i) Aquimedean Copulas and ii) Elliptic Copulas. In the first family, Clayton, Frank and Gumbel Copulas are the most widely used. In the second family, Student-t and Gaussian Copulas. As the main focus of this study is on drought events, we conducted an analysis using Student-t and Clayton copulas. The Student-t copula was chosen because of its dependency structures in the upper and lower tails, while Clayton copula was chosen due to its higher probability in the lower tails (Tootoonchi et al., 2022).

The Clayton copula function, in its bivariate form, is expressed as:

$$C_{\theta}(u, v) = (u^{-\theta} + v^{-\theta} - 1)^{(-1/\theta)} \quad (2)$$

where $C_{\theta}(u, v)$ is the probability distribution, $\theta \in [-1, \infty) \setminus \{0\}$ and $\tau = \theta/(\theta+2)$ are theoretical parameters based on Kendall's τ , and $u = F_X(x)$ and $v = F_Y(y)$.

Student-t copula is expressed as:

$$C_{\theta}(u, v) = \int_{-\infty}^{\tau^{-1}(u_1)} \int_{-\infty}^{\tau^{-1}(u_2)} \frac{1}{2\pi\sqrt{1-\theta^2}} \left(-\frac{x_1^2 - 2\theta x_1 x_2 + x_2^2}{v(1-\theta^2)} \right)^{\frac{v+2}{2}} dx_1 dx_2 \quad (3)$$

where $\theta \in (-1, 1)$, $v \in (0, +\infty)$ is degree-of-freedom, and $\tau = (2/\pi)\sin^{-1}(\theta)$.

The joint distribution with cumulative probability p can be represented by a copula function C :

$$P(X \leq x, Y \leq y) = C[F(X), F(Y)] = p \quad (4)$$

$F(X)$ and $F(Y)$ are the marginal cumulative distribution functions of precipitation and streamflow, respectively, for this study. To obtain the TSI, the cumulative probability (p) from Eq. (2) is converted through standardized normal distribution ($\mu = 0$ and $\sigma = 1$):

$$TSI(p) = \Phi^{-1}(p) \quad (5)$$

where Φ^{-1} is the inverse normal distribution.

The standardization makes possible the comparison of TSI with the Standardized Precipitation Index - SPI (McKee et al., 1993) and Standardized Streamflow Index - SSFI (Modarres, 2007). The indices were estimated at 6-, 12-, 24-, 36-, 48 and 60-month time scales.

We considered the drought categories used by the U.S. Drought Monitor and other studies (Cuartas et al., 2022; Cunha et al., 2019), for all indices (Table 2). To assess drought characterization by these indices, we defined the onset of a drought event as when $index \leq -0.8$ (Table 2), and its ends as when $index \geq 0.0$ for two consecutive months, in line with the methodology proposed by (Spinoni et al., 2013). The severity of a drought event is determined by the sum of index values from the onset to the end of the event, while the duration is the number of months of the drought event.

Applying the copulas function to estimate a two-variate standardized index require some steps that have to be done as showed in Fig. 2. The first step is to assess dependency among variables. We used Person and Spearman correlation coefficient, Kendall's tau and k-plot graphical method (Genest and Boies, 2003).

The second step of the methodology is to fit a cumulative distribution function (CDF) to monthly precipitation and streamflow data for all basins. We fitted different CDFs and selected one for each time series data based on goodness-of-fit statistics. For goodness-of-fit statistical tests, we used Kolmogorov-Smirnov (Dn), Cramer-von Mises (Wn^2) and Anderson-Darling (An^2) at a 5 % significance level. The empirical probability was estimated through the Gringorten formula, Eq. (6):

$$pi = \frac{ri - 0.44}{n + 0.12} \quad (6)$$

Where ri is the ranked position (from largest to smallest), and n is the size sample.

Finally, the Akaike Information Criterion (AIC) (Akaike, 1974), Root Mean Square error (RMSE) and Nash-Sutcliffe efficiency (NSE) metrics were used to select the most fitted copula.

Table 2
Drought categories for SPI, SSFI and TSI.

Category	SPI – SSFI – TSI
Normal conditions	> -0.5
Abnormally dry	(-0.8 to -0.5]
Moderate drought	(-1.3 to -0.8]
Severe drought	(-1.6 to -1.3]
Extreme drought	(-2.0 to -1.6]
Exceptional drought	≤ -2.0

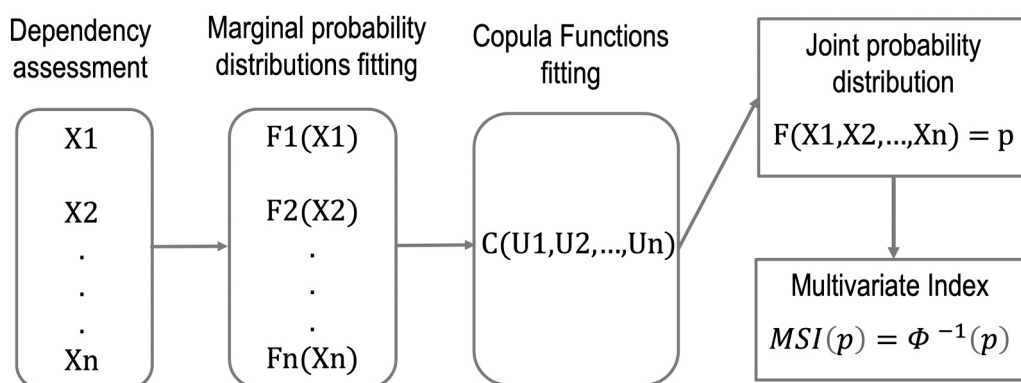


Fig. 2. Copula structure to estimate a multivariate index.

3. Results and discussions

As previously described (Fig. 2), in order to estimate the Two-Variate Standardized Index, three steps must be performed first: i) dependency analysis, ii) fitted marginal distributions and, iii) choosing the optimal copula function through goodness-of-fit statistical test. Regarding the dependency between monthly precipitation and streamflow data, the k-plots show that the data are in the dependence zone, i.e., between the curve and the 45° line (in red in Fig. 3), therefore, there is a dependency between precipitation and streamflow data. The chi-plots (Figure SM.1) shows that the data are out of the independent zone (between the horizontal dotted lines) confirming the precipitation and streamflow dependency. Table 3 shows the values of the correlation coefficients for the study basins. Values above 0.60 for the Pearson (r_p) and Spearman (ρ) coefficients indicate a high correlation between precipitation and streamflow. Furthermore, Kendall's τ values above 0.440 accept the dependence hypothesis at a significance level of 5 % (p-value = 0.228).

Several distribution functions were evaluated for monthly precipitation and streamflow data (Exponential, Gamma, GEV, Lognormal and Weibull), and the Gamma (Figure SM.2 and Table SM.2) and Lognormal (Figure SM.3 and Table SM.3) were, respectively, the best fitted.

3.1. Two-variate standardized index

Student-t and Clayton Copulas were used to derive the joint probability distribution of precipitation and streamflow data. Table 4 shows that Student-t fits best having the lowest RMSE, the highest NSE, and the lowest AIC for all basins, except Nova Ponte and Itumbiara HPPs where AIC is lower for Clayton, although Figures SM.4 and SM.5 show similar fitting for both copulas functions, with satisfactory fitting between the simulated (theoretical probability) and observed values (empirical probability). The Gringorten formula was used to calculate empirical probabilities. These results are in agreement with the Nikravesht et al. (2020) findings for Rasht and Urmia basins in Iran. Therefore, we estimated the TSI using Student-t copula, at 6-, 12-, 24-, 36-, 48- and 60-month time scales for

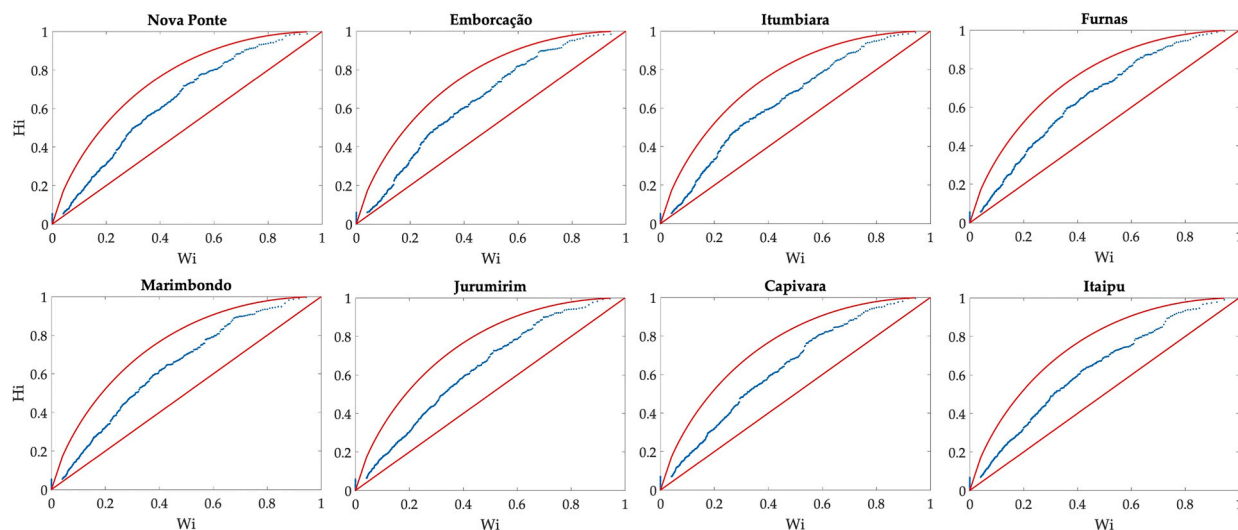


Fig. 3. K-plot to assess the dependence of rainfall and streamflow data for all basins.

Table 3

Rainfall-streamflow Pearson (r_n) and Spearman (ρ) correlation coefficients and Kendall's tau (τ) for the Basins affluent to the 8 HPPs.

Basin / Parameter	r_n	ρ	τ
Nova Ponte	0.6695	0.6301	0.4425
Emborcação	0.6710	0.6370	0.4447
Itumbiara	0.6612	0.6470	0.4476
Furnas	0.7158	0.6832	0.4882
Marimbondo	0.6646	0.6379	0.4491
Jurumirim	0.6045	0.6014	0.4255
Capivara	0.6150	0.6203	0.4425
Itaipu	0.6120	0.6271	0.4404

Table 4

Evaluation of Student-t and Clayton copulas fitting for the Basins affluent to the 8 HPPs.

Basin	Student-t			Clayton		
	AIC	NSE	RMSE	AIC	NSE	RMSE
Nova Ponte	1600.8	0.9658	0.0494	1570.4	0.9611	0.0527
Emborcação	1652.6	0.9595	0.0540	1653.9	0.9539	0.0576
Itumbiara	1608.4	0.9619	0.0521	1594.3	0.9567	0.0555
Furnas	1592.7	0.9740	0.0451	1630.6	0.9603	0.0557
Marimbondo	1637.8	0.9681	0.0481	1661.7	0.9594	0.0542
Jurumirim	1570.6	0.9807	0.0375	1598.2	0.9702	0.0466
Capivara	1508.8	0.9818	0.0372	1525.4	0.9707	0.0473
Itaipu	1590.5	0.9748	0.0427	1611.5	0.9693	0.0471

the period 1981–2022. The Gamma and Log-normal marginal distribution were used for monthly precipitation and streamflow data, respectively. These distributions and time period were also applied to the calculation of the SPI (Gamma) and SSFI (Log-normal).

In Fig. 4, we display the time series of SPI, SSFI, and TSI from 2002 to 2022 for both the 12- and 24-month scales to provide a better visualization and understanding of the indices' behaviour. The complete time series for 12-, 24-, 36- and 48-month time scales can be found in the [supplementary material](#) (Figures SM.7 to SM.14). Time series for 6- and 60-month scales are not shown. It is interesting to observe that the TSI always follows the lowest values of either SPI or SSFI, despite the fact that the selected copula Student-t has dependency structures in the upper and lower tails. It means that the TSI is conservative in depicting the drought conditions through precipitation and streamflow at all scales. For instance, in the basins of the HPPs Nova Ponte, Emborcação, Itumbiara, Furnas, and Marimbondo, where the most severe drought events were recorded in the last decade (Cuartas et al., 2022), the SPI and the SSFI are decoupled, that is, when the SPI shows that the drought is returning to normal conditions, the SSFI still shows diverse levels of drought conditions. In these basins, the decoupling of these indices is quite accentuated, however, the TSI shows that the hydrological drought is still taking place. Another example, from June 2015 by end of 2018, the SPI, at all scales, shows normal conditions for the HPP Furnas, while the SSFI shows that the hydrological drought is still ongoing, which is also captured by the TSI. However, since the end of 2020, when the SSFI starts to show a recovery from drought, the SPI indicates drought conditions and is followed by the TSI. These results are supported by Nikraves et al. (2020) who showed that the TSI detects the onset similar to SPI and the persistence of SSFI. However, we have observed a different pattern in the behaviour of Jurumirim and Capivara HPPs subbasins, located in the Paranapanema river basin: all indices overlap. This area has faced severe to exceptional drought from 2019 to early 2023 (Naumann et al., 2022, 2021; WMO, 2023, 2020, 2022). The climate in this region is predominantly temperate with no dry season and hot summers, which could explain why the subbasins of both HPPs are showing similar responses. Similarly, when we examine the Paraná basin, upstream from Itaipu HPP, we notice a similar behaviour to those of Jurumirim and Capivara HPPs subbasins. Despite having a predominant tropical savannah climate, the northernmost part of the basin experiences a monsoon climate with wet summers and dry winters, while the southern region receives precipitation throughout the year. These climatic variations in such a vast area play a crucial role in surface and subsurface water availability throughout the year. In summary, while the northern region of the Paraná River basin experienced drought conditions since 2014, the southern region was in normal condition, and Itaipu was also in normal condition. However, from 2019 onwards, below-average precipitation was observed in the southern parts of the Paraná basin. This affected Itaipu, which experienced the worst drought since 1981 according to all indices. Naumann et al. (2021) showed that the inflows observed at the Itaipu plant were the lowest levels recorded since January 1981. The TSI and SSFI for the subbasins located in the northeast of the Paraná basin (Nova Ponte, Emborcação, Itumbiara, Furnas and Marimbondo) show months with intensity peak (the lowest index value within a drought event) larger than the SPI (horizontal dash-line in Fig. 4 represent the moderate drought threshold, $index \leq -0.8$). For the subbasins located in the south (Jurumirim and Capivara) and Itaipu, the intensity peak is similar for all indices.

Fig. 5 shows the severity and duration for all indices and subbasins at 12-, 24-, 36- and 48-month time scales. It is possible to observe a different behaviour of the subbasins located in the northeast of the Paraná River basin (Nova Ponte, Emborcação, Itumbiara, Furnas and Marimbondo), compared to those located in the south (Jurumirim and Capivara). The Paraná basin upstream Itaipu HPP

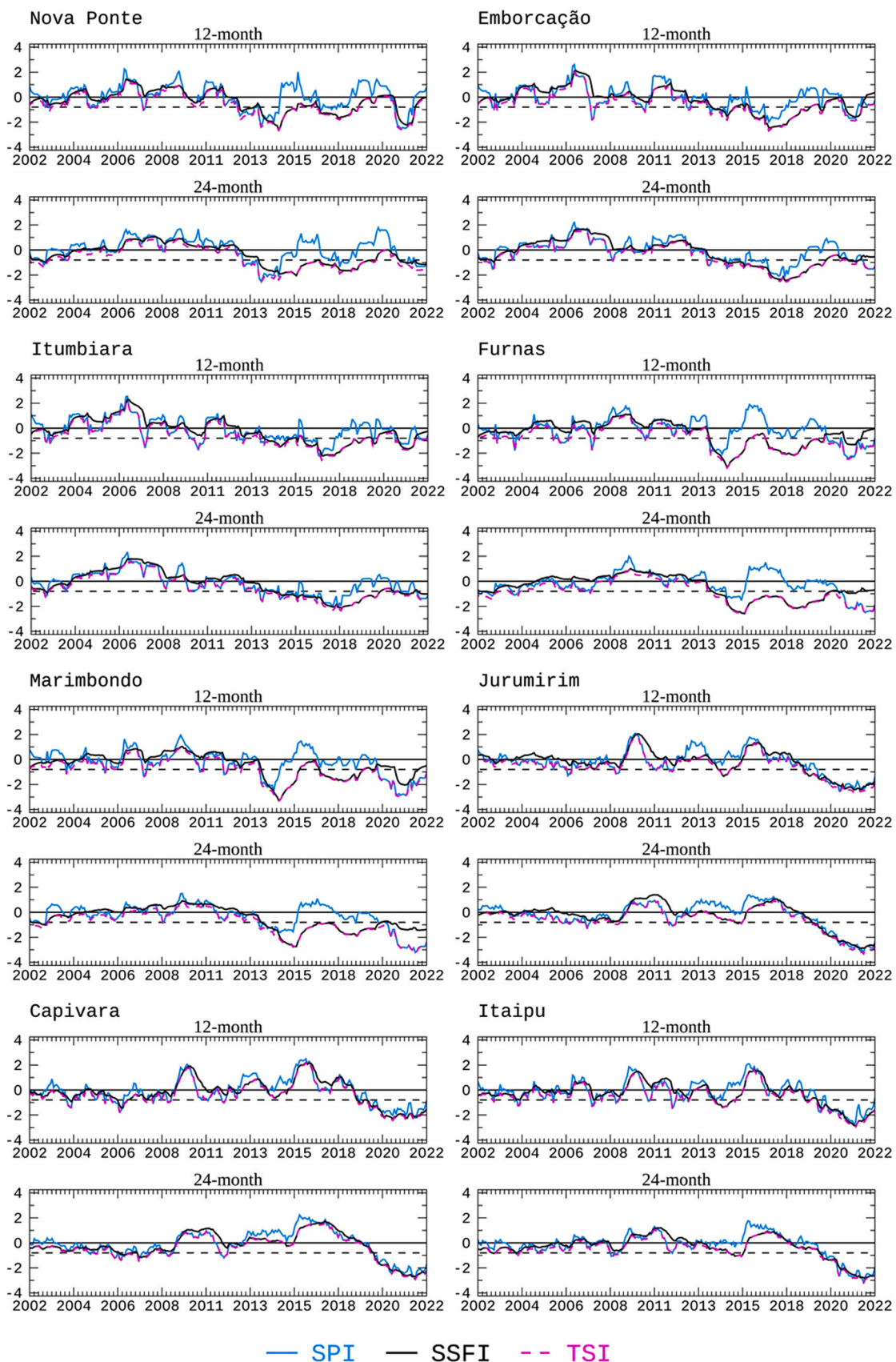


Fig. 4. Comparison of SPI, SSFI and TSI at time scales of 12- and 24-month, for all basins. The dashed black line is - 0.8, below which a drought condition is considered.

has similar characteristics as the southern basins. For basins located in the northeast of the Paraná basin, the TSI indicated longer and more severe drought events compared to SPI and SSFI (Fig. 5). For example, for Nova Ponte the SPI at 12-month time scale showed three drought events in the last decade. The first one was from December 2013 to January 2015 with duration = 25 months, severity = -35.0 and peak intensity = -2.3, the second one was from March 2017 to September 2018 with duration = 18 months, severity = -13.2 and peak intensity = -1.0, and the third one was from February 2021 to January 2022 (Fig. 5). However, the SSFI showed two events. The first for the period April 2014 to February 2020 with 86 months of duration, severity of -92.4, and peak intensity of -2.6, and the second from March 2021 to August 2022 with duration of 17 months, severity of -22.3, and peak intensity of -2.2. It means that the streamflow started being affected by the precipitation deficit (first event) 13 months later. Despite the first drought event detected by the SPI ending and a new one starting 26 months later, the period without precipitation deficit was not enough for the streamflow to return to a normal condition, as detected by the SSFI. It took 17 months from the end of SPI's second event until SSFI showed a normal condition. During the last event detected by SPI, it took only one month to be detected by SSFI, and it took seven months after the SPI returned to normal condition for the streamflow to return to normal condition. In addition, looking at the combination of both precipitation and streamflow, the TSI detected two drought events. The first one was from December 2012 to February 2020 with duration = 87 months, severity = -109.4 and peak intensity = -2.7, and the second one was from January 2021 to August 2022 with duration = 19 months, severity = -30.8 and peak intensity = -2.6.

Considering all basins, the SPI detected more drought events than TSI: 99, 54, 44, and 34 events, compared to 76, 41, 30, and 28, for 12-, 24-, 36-, and 48-month time scales, respectively. The SSFI detected fewer drought events than TSI: 37, 23, 19, and 19 events for 12-, 24-, 36-, and 48-month, respectively. The TSI was a combination of SPI and SSFI, with values in between. The number of events from the SPI decreases considerably through the time scales, in contrast with the SSFI and TSI that decrease until 36-month scale and remain equal or similar for 48-month scale. For SPI, the mean severity was lower than for TSI and SSFI. The same behaviour is observed for the mean duration values. Additionally, the maximum severity, at all-time scales, was detected by TSI: -187.8, -186.4, -195.9, and -192.5 for 12-, 24-, 36-, and 48-month, respectively, while less maximum severity was detected by SPI: -73.0, -81.4, -87.7, and -101.7 for 12-, 24-, 36-, and 48-month, respectively.

The results showed that the use of the SPI to characterize hydrometeorological droughts is not enough, even in longer time scales (above 12 months), for basins with large intra-annual precipitation variability. These findings are in agreement with the results obtained by previous studies (Cuartas et al., 2022; Hao and AghaKouchak, 2013; Meilutyte-Lukauskienė et al., 2024; Nikraves et al., 2020; Vicente-Serrano et al., 2010; Vicente-Serrano and López-Moreno, 2005). In this study, the approach of applying the Copula theory to estimate the bivariate TSI index, considering precipitation and streamflow together, showed that this index better characterizes hydrometeorological drought events since it captures the beginning of the drought at the same time as the SPI. However, the development and end of the drought event are based on the joint conditions of precipitation and streamflow. Our study confirms the results of Hao and AghaKouchak (2013) and Nikraves et al. (2020), who estimated the TSI of precipitation-soil moisture and precipitation-runoff, respectively. However, our results showed two different responses from the TSI: i) in the subbasins located to the North and Northeast, the univariate indices show a decoupling, and in this case the TSI captured the onset of the SPI and the persistence of drought by both SSFI and SPI, and ii) in the subbasins located in the middle and lower part, all indices overlap, indicating that any of the indices can be used to characterize long-term hydrometeorological droughts on basins with the same climate regime: temperate climate with no dry season and hot summer.

3.2. Terrestrial Water Storage – GRACE

The hydrological drought refers to negative anomalies in streamflow, groundwater levels, lake levels, or loss of wetland area. In this context, the standardized monthly terrestrial water storage data (STWS) were calculated for each basin to compare with TSI, SPI and SSFI. Fig. 6 shows the time series for 12- and 24-month time scales (36- and 48-month are not shown), from April 2002 to September 2022. For some basins, the STWS show similar variability as TSI (Nova Ponte, Emborcação and Itumbiara HPP basins), although it shows less severe drought conditions and, at the end of the study period, it indicates normal drought conditions, contrary to what the TSI shows. However, some basins have different behaviour, as observed in Marimbondo HPP basin; STWS is similar to SPI at 24- and 36-month time scales from 2014 to 2021, while it follows SSFI at the end (2021–2022).

We estimated the correlation between STWS and the SPI, SSFI, and TSI indices, at time scales of 6, 12, 24, 36, 48, and 60 months (Fig. 7). The 6- and 60-month scales were added to assess multiscale behaviour in the studied basins. The results show that the highest correlations of STWS are with SSFI (0.52–0.91) and TSI (values range 0.50–0.89), for all basins at all time scales. The lowest correlations are with SPI (0.21–0.84). For Jurumirim, the highest correlation between TSI and STWS are for 6- and 12-month time scales, and for Capivara for 12- to 24-month (strong positive correlation, $\rho \geq 0.75$). TSI-STWS and SSFI-STWS correlations for Nova Ponte and Emborcação increase until 36 months and then decrease for 48 and 60 months. However, for SPI-STWS correlation, the highest value is for 48-month time scale. Furnas, Marimbondo and Itaipu showed the highest values ($\rho \geq 0.75$) at 12, 18 and 24 months. The TSI-STWS and SSFI-STWS correlations in most of the basins, except for Itumbiara, decrease for 48- and 60-month time scales. Although the total water storage is estimated based on a short time series (20 years) and the large scale of the pixels (300 km), the results showed that this information could be considered jointly with the TSI, at 12-month time scale (highest correlation for most of the basins), for assessing and monitoring hydrological drought on large scale basins.



Fig. 5. Severity and duration (defined by the dots size) of Drought events for: i) SPI (red dots), ii) SSFI (green dots) and TSI (blue dots), at time scales of 12-, 24-, 36- and 48-month.

3.3. HAND terrain classes analysis

HAND-classes maps allow us to know the potential saturated and unsaturated conditions in a basin, and how it can contribute to worsening or improving drought conditions in the basin. For the Paraná River basin and subbasins, the following classes were considered: 1) Waterlogged – permanently saturated soils (blue), 2) Ecotone – close to saturation, shallow water table (green), 3) Slope – unsaturated soils, deep water table and 15 % of declivity (yellow), and 4) Plateau – unsaturated soils with deep water table (red) (Cuartas et al., 2012; Nobre et al., 2011). The map is presented in the [supplementary material](#) (Figure SM.1). As observed in Table 5, the dominant class is plateau with more than 50 % of the total area in most of the basins, except for Furnas and Marimbondo. Waterlogged and Ecotone (saturated soils) varied from 26.5 % to 37.8 % in the subbasins. The Slope environment varied greatly from 8.8 % for the Paraná River basin to 35.7 % for the basin upstream of Furnas HPP basin. Slope and Plateau environments account for more than 60 % of the land in all basins, which means that one-third of the watersheds have unsaturated soils with deep groundwater tables. To validate the Slope and Plateau HAND classes ($HAND > 15.0$ m), we used daily water table level data for the period 2011–2022. Of the 75 piezometers, 51 are located in the areas classified as slope and plateau. The maximum depth values of the water table (MWTD) were selected and compared with the HAND value at the measurement point. HAND values explain, approximately, over 89 % of the maximum water table depth data in the Paraná River Basin (Fig. 8a). Despite the basins having more than 60 % of soils with a deeper water table according to HAND, the maximum water table depth in the piezometer ranges from 6 m to 59 m, in the slope and plateau areas. Fig. 8b shows a histogram of HAND with higher frequencies for $10.0m \leq HAND \leq 20.0m$, that mean for $10.3m \leq MWTD \leq 17.2m$. Thus, approximately, 55 % of areas in the basin can recharge the groundwater fast through the hydrological year. On the other hand, during a drought, when precipitation is scarce, and temperatures are elevated, areas with a shallower water table tend to dry out faster due to evaporation, while regions with a deeper water table experience no recharge, leading to a more rapid decline in river levels. As such, by assessing the soil water conditions across a basin and using a multivariate index, as the TSI, it is feasible to generate more precise forecasts regarding the evolution and recovery of a hydrometeorological drought.

3.4. Reservoir useful volume analyses

The monthly standardized reservoir volumes (SRV) were estimated for all HPPs, except for Itaipu, which used the reservoir level (SRL), as reservoir volume data is not available. Fig. 6 shows the SRV compared with the TSI, SSFI and SPI at 12-month time scale, and

with the STWS, for the period from April 2002 to September 2022. The SRV has similar temporal variability to the indices and the TWSA mainly at 12-month scale. From 2014, the year of the water crisis in southeast Brazil (Coelho et al., 2016; Nobre et al., 2016), until the end of 2021, Nova Ponte, Emborcação, Itumbiara, Furnas and Marimbondo HPPs presented negative anomalies most of the time. At Furnas, the above-average precipitation in the dry season of 2015 (April–September 2015) and precipitation around the average during the following rainy season (October 2015 to March 2016), contributed to a shift from exceptional drought to normal conditions ($-0.8 < \text{TSI}$). The stored volume depends not only on hydrometeorological variables but also on the operation of each reservoir. In Brazil, this operation is centralized, and the energy transmission system is an interconnected grid, i.e., generators and consumers from different regions are connected by transmission lines. Therefore, if a region is in a critical situation of hydropower imbalance, other regions can generate hydroelectricity and transfer it to the region in need. However, in the last decade, the droughts that occurred sequentially and concomitantly in all regions of the country (Cunha et al., 2019; Fernandes et al., 2021; Marengo et al., 2021; Cuartas et al., 2022) impacted most of the reservoirs simultaneously, especially between late 2019 and early 2022, as shown in Fig. 6.

A correlation analysis was performed between the indices and the standardized reservoir volume. The correlations were estimated for the time scales of 6, 12, 18, 24, 36, and 48 months (Fig. 9). The results show that the highest correlations are with SSFI (values range 0.20–0.81) and TSI (0.22–0.80), for all basins at most of the time scales. The lowest correlations are with SPI (0.12–0.75). For most of the basins, the correlations SRV-TSI and SRV-SSFI varied between ($0.5 < \rho < 0.75$) at 12-, 18-, and 24-month time scales. The correlation values between SRV and the indices are smaller than those between STWS and the indices. The operation of the reservoirs is performed mainly based on the available storage and the inflow forecast, which can explain the strong correlation between the SRV and the SSFI for 6- and 12-month time scales. Also, the electricity in Brazil is transferred between all regions through an interconnected transmission network, which can contribute to the low correlations with the indices, since the operation of the system is optimized to meet the demand of the country as a whole. This implies that reservoirs at critical levels are preserved, causing them to return to

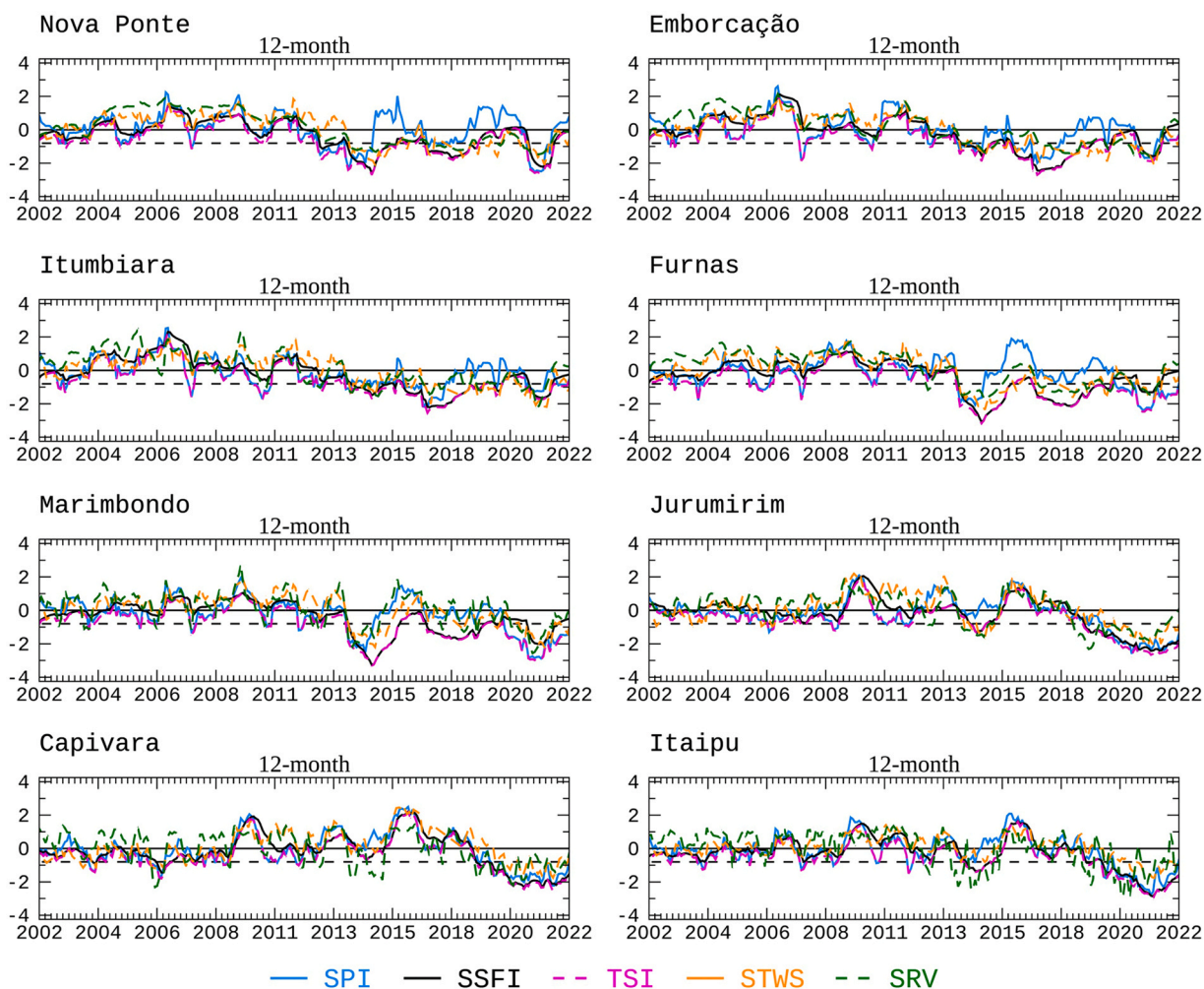


Fig. 6. Comparison of SPI, SSFI and TSI at 12-month time scale, STWS (standardized terrestrial water storage) for all basins and standardized reservoir volume (SRV) and level (SRL, only for Itaipu HPP). The dashed black line is -0.8 , below which a drought condition is considered.

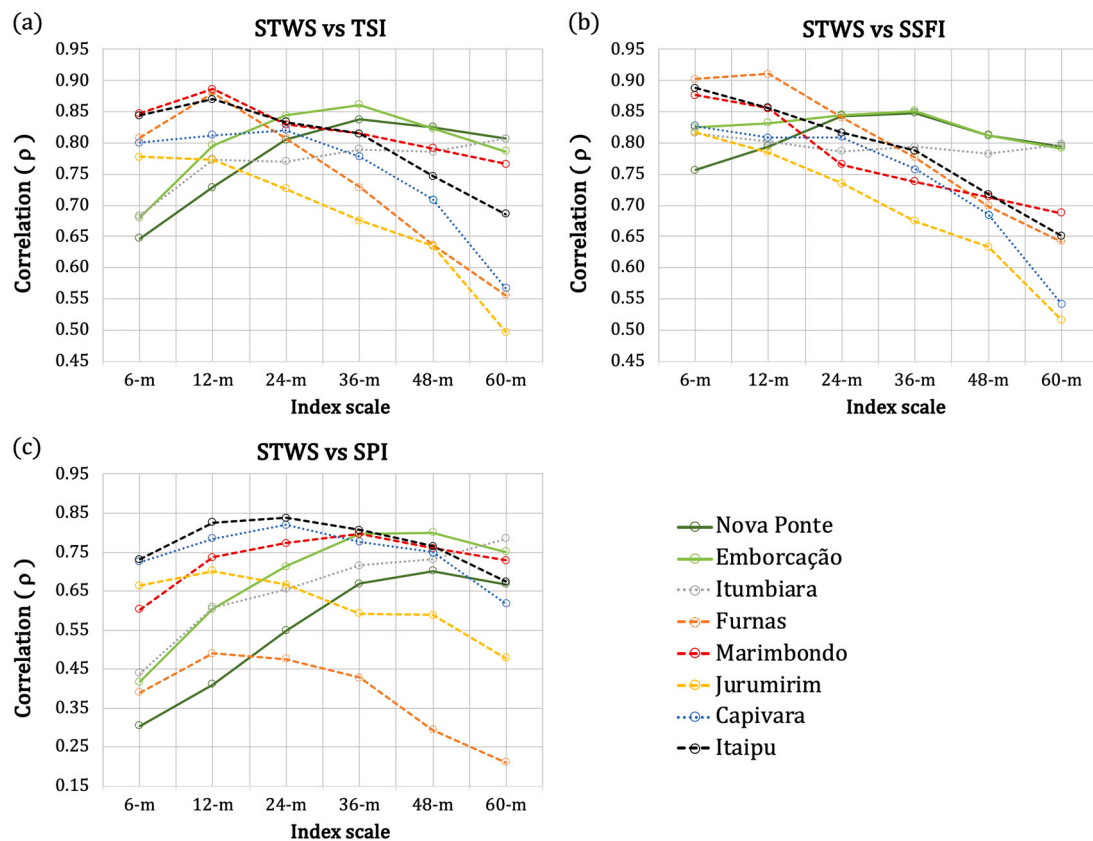


Fig. 7. Correlation (ρ) among standardized terrestrial water storage (STWS) from GRACE and (a) Two-variate Standardized Index (TSI), (b) Standardized Streamflow Index (SSFI) and (c) Standardized Precipitation Index (SPI), at 6-, 12-, 24-, 36-, 48- and 60-month time scales.

normal levels even before the drought event ends.

According to Mishra and Singh (2010), it is necessary to understand and assess the historical hydrological drought events in a region/basin and their impacts, to contribute to the planning and management of water resources. Drought occurrence is influenced by changes in precipitation and air temperature (Meresa et al., 2016; Vicente-Serrano et al., 2010), is a multivariate process, involving multiple interactions in the climate system. The propagation between meteorological to hydrological drought involves linear and nonlinear processes (Zhou et al., 2021). According to Zhou et al. (2021) there have been few studies use multiple indices to link meteorological and hydrological droughts at the catchment scale, to understand the mechanisms of hydrometeorological drought propagation comprehensively. In this study we estimated a Two-variate Standardized (precipitation-streamflow) Index (TSI) and compare with the well-known SPI and SSFI indices, and two other variables: reservoir levels and total terrestrial water storage. Our main aims were: i) to contribute to understanding and characterizing hydrometeorological droughts in a macro-scale basin in Brazil, ii) to assess the capability of TSI in characterizing hydrometeorological drought and to ascertain its potential as an operational index to support the decision-making process. The results obtained in this study show that for a more comprehensive characterization of hydrometeorological drought events, it is necessary to consider more than one index, and an index with at least two variables. The high correlations between the total terrestrial water storage in the hydrological system (TWS) and the TSI and SSFI, were observed in most basins, at 12- and 24-month time scales, showing that these scales are most suitable for monitoring hydrometeorological droughts in macro-scale basins. This result also shows the importance of considering other hydrological cycle components, e.g., soil moisture and water table level, for a better characterization of hydrometeorological droughts, corroborating the findings of various studies (Hao and

Table 5

Percentage of HAND-Classes for each subbasin and the incremental basin up to Itaipu.

HAND Classes	Nova Ponte % of basin area	Emborcação	Itumbiara	Furnas	Marimbondo	Jurumirim	Capivara	Itaipu
Waterlogged	12.8	14.0	14.0	15.2	15.7	15.7	14.4	17.5
Ecotone	13.6	16.0	16.5	12.6	16.0	15.7	16.2	20.2
Slope	15.6	10.9	9.5	35.7	21.9	14.5	13.3	8.8
Plateau	58.0	59.1	60.0	36.4	46.4	54.2	56.0	53.5

AghaKouchak, 2013; Meilutyte-Lukauskienė et al., 2024; Meresa et al., 2023; Nikraves et al., 2020; Vicente-Serrano et al., 2010). Unfortunately, the availability of in situ data and long-time series for those variables is scarce in the study region. Therefore, efforts need to be made to use hydrological modelling that allows estimating these variables, to be included in the characterization and monitoring of hydrometeorological droughts events.

This study marks the first estimation of the Two-Variate Standardized Index in large-scale basins. Our results showed two different responses from the TSI: i) in the subbasins located to the North and Northeast, the univariate indices, SPI and SSFI show a decoupling between meteorological and hydrological drought events, and in those cases the TSI captured the onset of the SPI and the persistence of drought by both SSFI and SPI, similar to the results of Nikraves et al. (2020). Cuartas et al., (2022) found that those subbasins experienced a severe hydrological drought event. This event was indicated by streamflow signals that were detected between March and April of 2014, although the first signal was actually detected due to precipitation deficits in December 2012. The drought persisted until February 2020 and had significant impacts on various sectors, including water supply, navigability, and hydropower generation. ii) in the subbasins located in the middle and lower part, all indices overlap, indicating that any of those indices can be used to characterize hydrometeorological droughts, lasting over 12 months. As explained before, the Paraná River Basin has two different climate regimes. The subbasins located in the middle and upper basin have well-defined rainy (November to March) and dry seasons (April to September), with October as a transition month between dry and rainy seasons. The subbasins located in the south of the Paraná River Basin have no dry season and hot summer. As the Two-variate Standardized Index joined two fundamental variables for hydrometeorological drought monitoring and assessment; precipitation and streamflow, the results show the potential to become an operational index to monitoring hydrometeorological drought, particularly long-term ones, in basins with diverse climate regimes. On the other hand, early detection of drought signs is crucial in order to send alerts and evaluate potential impacts on water resources. As the TSI proved to be a conservative index, especially in climates with well-defined dry and rainy seasons, making it a potential index to be used as an operational index to support decision-making process for water resources management.

4. Conclusions

By estimating the Two-variate Standardized Index (TSI) and comparing it with established indices such as SPI and SSFI, as well as considering additional variables like reservoir levels and total terrestrial water storage, we aimed to comprehensively assess drought events and evaluate the potential of TSI as an operational tool for decision-making in water resource management.

Our findings underscore the importance of employing multiple indices and incorporating at least two variables for a comprehensive characterization of hydrometeorological droughts. The strong correlations observed between total terrestrial water storage (TWS) and both TSI and SSFI highlight the significance of considering various hydrological cycle components for accurate drought assessment. The results also show that the 12- and 24-month scales are most suitable for monitoring hydrometeorological droughts in macro-scale basins. This is because the underlying processes during drought conditions are the same as those characterized by large regional hydrological processes. TSI, combined with total water storage and groundwater table data, allows for a better understanding of the development, duration, and recovery of drought events. Therefore, methods that allow for such diversification in processes and account for local characteristics are desirable for building this understanding. Hence, efforts should be made to consider multiple variables in monitoring and forecasting of hydrometeorological drought events. However, the scarcity of in situ data and long-term series for diverse variables in the study region poses a challenge, emphasizing the need for applied hydrological modelling to estimate essential variables, which could lead to the development of a multivariate index in future studies.

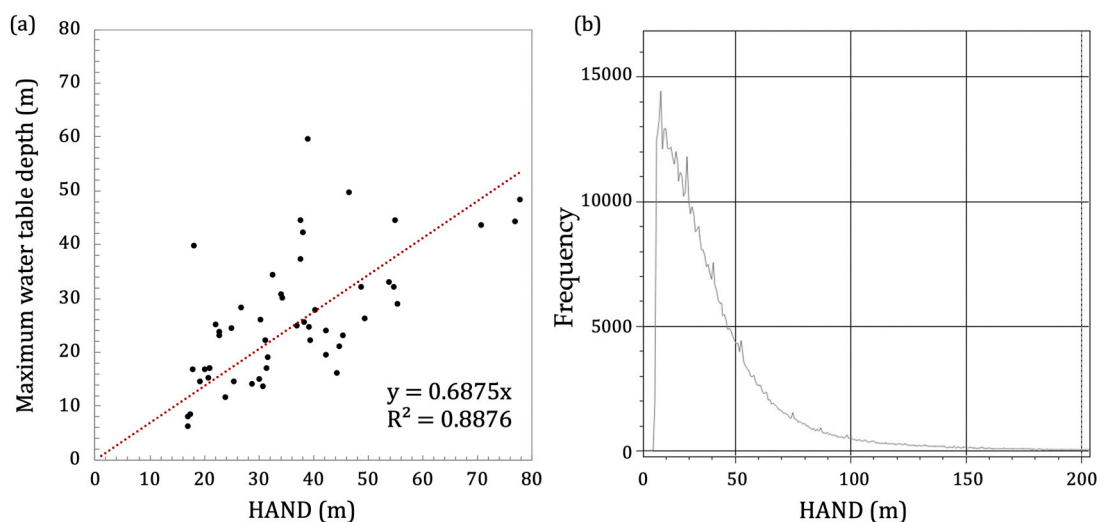


Fig. 8. (a) Relationship between HAND > 15 m and maximum water table depth (in meters) from piezometers data, and (b) histogram of HAND > 15 m in the Itaipu HPP basin.

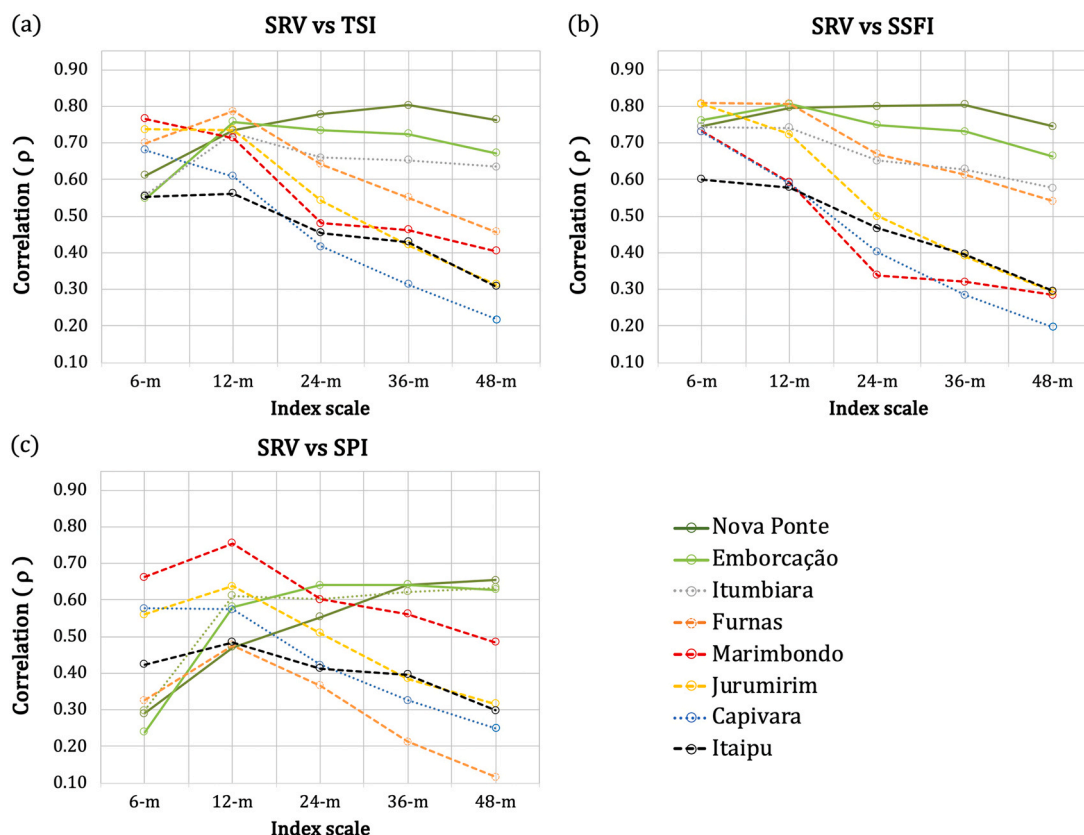


Fig. 9. Correlation (ρ) among standardized reservoir volume (SRV) and (a) Two-variate Standardized Index (TSI), (b) Standardized Streamflow Index (SSFI) and (c) Standardized Precipitation Index (SPI), at 6-, 12-, 24-, 36-, and 48-month time scales.

This study marks the first estimation of the Two-variate Standardized Index in large-scale basins. Our results showed that basins with well-defined rainy and dry seasons, experiencing decoupling between meteorological and hydrological drought events, and the TSI effectively captured the onset and persistence of hydrometeorological drought, demonstrating its potential as an operational index, particularly in regions with diverse climate regimes. Furthermore, the conservative nature of TSI, highlights its suitability as an early detection tool for drought signs. Finally, as TSI consider precipitation and streamflow data, the main variable used in the hydropower sector, and also are accessible in most of the countries, it can be applied globally across various time and spatial scales. These characteristics make TSI a promising candidate for operational use in supporting decision-making processes for water resources management, enabling timely interventions and mitigation strategies.

Hydroelectric power accounts for a significant portion of Brazil's electricity generation, with more than 60 % of the country's electricity coming from this source. However, this heavy reliance on water also makes Brazil's electric system vulnerable to extreme drought events, such as those experienced during the last decade, which had a profound impact on the Paraná River Basin. To enhance monitoring and predictions for effective planning and operation, this study has expanded our knowledge of hydrometeorological drought patterns in the region. Nevertheless, it is crucial to develop methods for predicting hydrological droughts using hydrometeorological sub-seasonal and seasonal forecasts, as well as multivariate indices. Providing managers and operators with the best guidance to conserve resources and restore activities is essential, particularly in the face of recent water crises.

In summary, this study enhances our understanding of hydrometeorological drought dynamics and underscores the potential of the Two-variate Standardized Index as a valuable tool for drought monitoring and management in diverse climatic contexts. Continued research and efforts to improve data availability and modeling techniques will further enhance the efficacy of such indices in safeguarding water resources in the face of changing climatic conditions.

CRediT authorship contribution statement

Cintia Bertacchi Uvo: Writing – review & editing, Supervision, Methodology, Conceptualization. **Juliana Andrade:** Writing – review & editing, Software, Conceptualization. **Thais Fujita:** Writing – review & editing, Conceptualization. **Luz Adriana Cuartas:** Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Jerusa Peixoto:** Visualization, Investigation. **Elisangela Broedel:** Validation, Investigation. **Diogo Amore:** Visualization, Resources, Investigation. **Jose Antonio Marengo:** Writing – review & editing, Supervision, Project administration,

Funding acquisition. **Johanna Sörensen**: Writing – review & editing. **Jonas Olson**: Writing – review & editing. **Gholamreza Nikravesh**: Writing – review & editing, Software.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: L.A. Cuartas, as senior postdoc, reports financial support and travels were provided by National Council for Scientific and Technological Development CNPq and EUROCLIMA + Program within the framework of the project "Design and initial implementation of a drought information system (monitoring, prediction, preparation and mitigation of impacts) for southern South America – SISSA". T. Fujita and J.A. Campos were supported by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) (Grant no. 88887.694572/2022–00 and 88887.696359/2022–00, respectively). C.B. Uvo was partially supported by the Swedish Energy Agency through the project "The role of hydropower as a regulating resource in a renewable energy system with climate impact and increased internationalization of electricity markets" granted by the Swedish Energy Agency (Grant no. 52095–1) and by the Research Council of Finland, through the HYDRO-RI Platform of FIRI2021 (Grant no. 346165) that is part of the Freshwater Competence Centre – FWCC. E. Broedel, D. Amore, and J. Peixoto were partially supported by the EUROCLIMA + Program within the framework of the project "Design and initial implementation of a drought information system (monitoring, prediction, preparation and mitigation of impacts) for southern South America – SISSA"

Data availability

All datasets used in this research are freely available, and the websites are included in the manuscript.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.ejrh.2024.101886](https://doi.org/10.1016/j.ejrh.2024.101886).

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