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Identification of major drought periods in the Souss watershed (Southern Morocco) using bias-corrected satellite data

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ABSTRACT

In a context of increasing climate variability, accurately assessing drought has become essential, particularly in semi-arid regions such as the Souss watershed. The scarcity of meteorological stations, short observation periods, and missing rainfall data complicate the reliable characterization of drought at the local scale. In this regard, satellite precipitation products (SPPs) offer a promising alternative, although their direct use is limited by the presence of biases, especially during extreme events. This study proposes an innovative bias correction approach based on multiple linear regression to generate a new, more accurate hybrid product. Unlike previous studies that used uncorrected data or basic methods, our approach integrates multiple SPPs, including ERA5 and CHIRPS, significantly improving data quality. The new product achieves an average R^2 of 0.72, compared to 0.67 for ERA5 and 0.57 for CHIRPS. The corrected product is used to compute the Standardized Precipitation Index (SPI) at 6- and 12-month scales to evaluate the effect of temporal scale on drought characterization. SPI-06 and SPI-12 results for the 1970–2018 period show strong agreement, despite some minor discrepancies. SPI-06 tends to emphasize the intensity of drought episodes compared to SPI-12. The analysis reveals that the standard SPI classification thresholds are not fully applicable to a climatic context such as ours, which led us to propose new, context-specific thresholds (corrected SPI). We also observed a noticeable lengthening of moderate drought episodes starting in 1998, including a three-year event from 1998 to 2000, as well as a marked intensification of severe droughts after 2008. Despite two exceptionally wet years in 2009 and 2010, the overall climate regime has become increasingly irregular. Finally, drought events appear to be occurring more frequently, with shorter intervals between successive episodes.

Keywords: Satellite precipitation, CHIRPS, ERA5, corrected SPI, SPI-12, SPI-06, drought, multiple linear regression.

INTRODUCTION

Morocco's climate is highly diverse due to its unique geographical position, which spans from the Atlantic and Mediterranean coasts, across the Rif and Atlas mountain ranges, to the desert areas in the southeast. This climatic heterogeneity is well documented in several studies (Le Houérou, 1996; Driouech, 2010). Our study area lies in a region of Morocco characterized by a semi-arid climate, typical of the southwestern part of the country, where rainfall is low, irregular, and highly variable in both time and space (Mrabet et al., 2012). The increasing demand for water—whether for drinking or irrigation—combined with the growing scarcity of water resources, represents a critical issue not only for Morocco but also on a global scale (WWAP, 2020). This situation requires rigorous, rational, and forward-looking water management, both at the individual and institutional levels. At the local scale, every citizen must adopt water-saving behaviors, while at the institutional level, particularly within hydraulic basin agencies, water management must rely on reliable indicators and thorough analysis of historical hydrometeorological data.

The research problem addressed in this study is based on several key observations:

1. The very limited number of rain gauges in the Souss watershed makes point-based

observations poorly representative of the entire region. This low spatial density is a major obstacle to reliably and comprehensively characterizing rainfall variability (Nicholson et al., 2001).
2. Observed precipitation time series contain significant gaps, undermining the continuity of data required for robust drought analysis. Even when these gaps are filled using conventional techniques such as bias correction or data fusion, the results often remain affected by considerable uncertainty (Wilhite & Glantz, 1985). Moreover, the short duration of available observed records severely limits the study of long-term drought trends, whereas satellite-based precipitation products (SPPs) typically cover periods of at least 40 years.
3. Selecting the most appropriate temporal and spatial scale for calculating drought indices presents another major challenge. Most studies rely on the direct use of the 12-month Standardized Precipitation Index (SPI-12), which may not be sufficient to reliably detect drought events – particularly in semi-arid contexts characterized by strong intra-annual variability and spatial heterogeneity of rainfall (Vicente-Serrano et al., 2010).
4. At the scale of the Souss watershed, we analyzed the evolution of drought episodes in terms of duration, intensity, and frequency, in order to identify structural changes that have occurred over the past few decades.

Given these limitations, our study aims to propose sound methodological solutions. We first evaluated the performance of SPPs to demonstrate that their direct use without correction—or even with conventional corrections—can introduce significant errors in drought analysis. We then developed a bias correction method based on multiple linear regression, enabling the generation of a more accurate hybrid product.

Finally, by analyzing SPI results (following McKee et al., 1993) and leveraging our in-depth knowledge of the study area, we were able to revise the standard SPI classification thresholds to better fit the specific climatic context of the Souss watershed. This adaptation allows for a much more accurate characterization of drought conditions, in contrast to the original SPI thresholds by McKee et al. (1993), which classify approximately 90% of the studied years as "near normal" – a categorization that does not accurately reflect the observed reality on the ground.

In parallel, we assessed the impact of the chosen temporal scale (SPI-06 vs. SPI-12) on the detection and characterization of drought events, particularly regarding their intensity and duration.

DATA, MATERIALS, AND METHODS

Methodology

The methodology adopted for this study is based on the following key components:

Data preparation – we began by preparing and formatting the precipitation time series we were able to collect, which serve as reference data and as a basis for validation.

Downloading satellite precipitation data – after analyzing the various available precipitation sources and reviewing several studies on their reliability (Behrangi et al., 2011; Sun et al., 2018), we selected the ERA5, GPM, and CHIRPS products. These choices were motivated by their demonstrated performance across different climatic zones and their accessibility. The monthly time series were downloaded from the Climate Engine platform (https://app.climateengine.org/climateEngine), which provides access to high-resolution satellite data essential for our analysis (Huntington et al., 2017).

- evaluation and generation of satellite-based products – to evaluate the robustness of satellite-based products against the monthly ground-based precipitation time series we collected, we used commonly employed metrics such as the coefficient of determination (R^2), relative bias, root mean square error (RMSE), and root mean square (RMS) (Toté et al., 2015; Dinku et al., 2008). Following this evaluation, we proceeded to generate a new combined product based on the previously downloaded satellite data sources.
- model validation – after the evaluation phase, the newly generated product was validated over periods not used during calibration, as well as at stations specifically reserved for validation purposes. Once validated, this time series was used to characterize drought in the watershed.
- calculation of the standardized precipitation index (SPI) at different time scales – the standardized precipitation index was initially developed by McKee et al. (1993) to characterize

precipitation deficits and surpluses across different time scales. The Figure 1 summarizes the methodology we adopted to achieve our objectives.

Data

Study area

The study area covers the Souss watershed, located within the jurisdiction of the Souss Massa Hydraulic Basin Agency (ABHSM) in southern Morocco (Figure 2). The main rivers in the basin are the Oued Souss and the Oued Massa.

Rainfall data

The data used in this study are:

- satellite precipitation: the primary sources are ERA5, and CHIRPS data.
- ground-based precipitation measured by various state agencies: These data are assumed to be correct and serve as references and for validation.
- ERA5 is a climate reanalysis model developed by the European Centre for Medium-Range Weather Forecasts (ECMWF). It uses several techniques to measure precipitation, including ground-based weather station measurements, satellite data to estimate precipitation globally in real-time, and numerical weather prediction models to produce precipitation estimates. The spatial resolution of the data provided by ERA5 is 11 km (Gomis-Cebolla et al., 2023). Since the chosen time step is monthly, the dataset is quite large. Therefore, instead of presenting the full table, we have provided a download link to access the data from the Climate Engine platform (link:

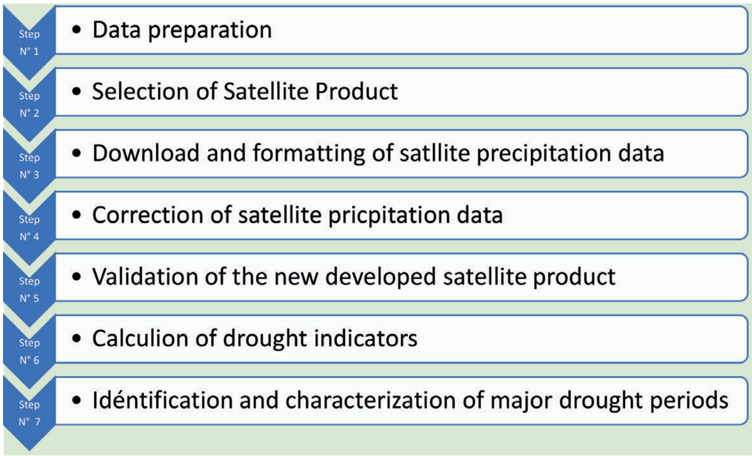

Figure 1. Flowchart summarizes the methodology

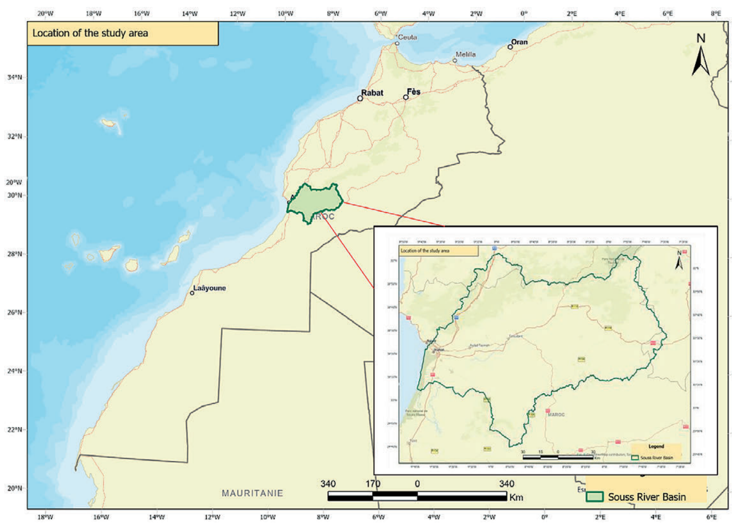

Figure 2. Study area

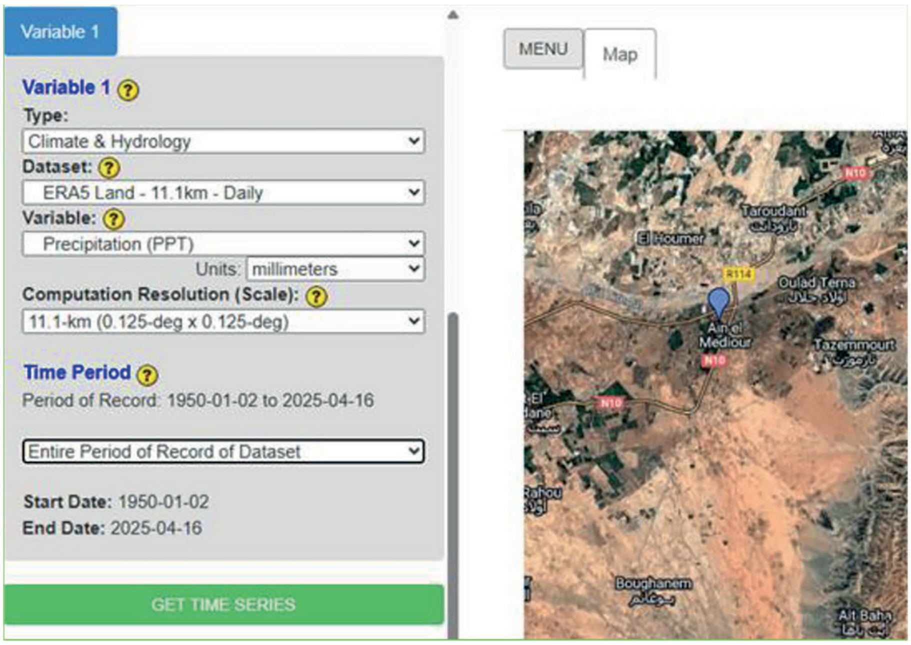

Figure 3. Parameters to enter for downloading ERA5 monthly precipitation

https://app.climateengine.org/climateEngine). The parameters to be entered on the platform are shown in Figure 3.

- CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data) is a high-resolution (0.05°) precipitation product available since 1981. It combines infrared satellite observations and in situ rainfall data to provide quasi-global precipitation estimates, particularly suited for tropical and semi-arid regions (Funk et al., 2015). At the monthly scale, CHIRPS is recognized for its good performance in capturing precipitation variability, especially in areas with a moderate number of weather stations. Several studies have highlighted its relative reliability compared to other satellite products, especially in complex climatic contexts such as East Africa or the Maghreb

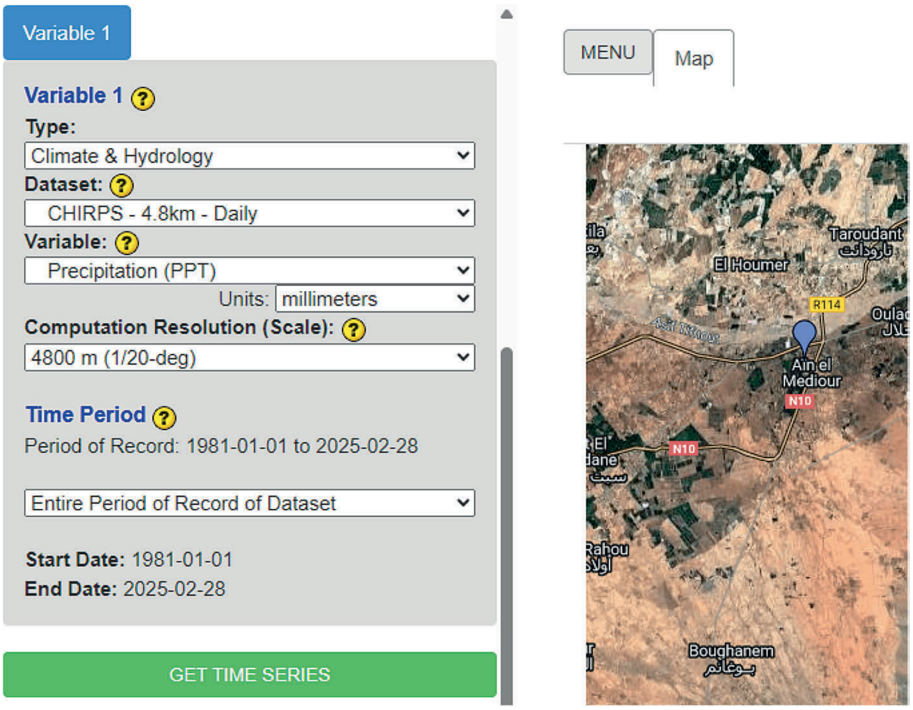

Figure 4. Parameters to enter for downloading ERA5 monthly precipitation

(Duan et al., 2019; Paredes-Trejo et al., 2017). CHIRPS is widely used in drought monitoring and assessment, particularly through indices like the SPI (Standardized Precipitation Index), thanks to its long and consistent time series and free availability. It allows for tracking the spatiotemporal evolution of drought events in regions where ground-based data is scarce or incomplete (Shukla et al., 2014). Since the chosen time step is monthly, the dataset is quite large. Therefore, instead of presenting the full table, we have provided a download link to access the data from the Climate Engine platform (link: https://app.climateengine.org/climateEngine). The parameters to be entered on the platform are shown in Figure 4.

Materials

Python scripts were developed to perform all the necessary calculations, due to the wealth of documentation available for this language, the variety of its scientific libraries (such as NumPy, Pandas, SciPy, and Matplotlib), as well as its performance in executing complex and repetitive tasks, particularly in the field of environmental data analysis (Van Rossum & Drake, 2009; Oliphant, 2007; McKinney, 2010). Regarding satellite data, various platforms now offer the possibility to directly download climate parameters, such as temperature and precipitation. For this study, the Climate Engine platform (https://app.climateengine.com/climateEngine) was used to download daily precipitation data from the three satellites (Funk et al., 2015).

Theoretical methods

Performance criteria

To evaluate the accuracy of precipitation measured by satellites compared to ground-based measurements, commonly used performance criteria were applied. These criteria include the correlation coefficient (CC), root mean square error (RMSE), normalized mean square error (NMSE), and relative bias (BR). These criteria have been used in various studies, including the one conducted by Guo et al. (2015).

a) correlation coefficient (CC) – the correlation coefficient highlights the strength of the linear relationship between the reference precipitation data and the satellite data (GPM and CHIRPS).

$$R^2 = \frac{Cov(PsPg)}{S_{Ps}S_{Pg}} \tag{1}$$

where: R^2 – correlation coefficient, Cov(x,y) – covariance of variables x and y, S_{Ps} – standard deviation of the satellite-measured precipitation, S_{Pg} – standard deviation of the ground station-measured precipitation.

b) root mean square error (RMSE) – the RMSE coefficient quantifies the average deviations between the precipitation values estimated by satellite products and those from the reference data.

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(P_s - P_g)^2}{N}} \tag{2}$$

where: N – number of data pairs, P_s – satellite-measured value, P_g – ground station-measured value.

c) normalized mean square error (NMSE) – NMSE is the RMSE divided by the mean of the reference precipitation.

$$NMSE = 1/\mathrm{N} \sum \frac{(Ps - Pg)^2}{1/N \sum Ps \; 1/N \sum Pg} \tag{3}$$

where: N – number of data pairs, P_s – satellite-measured value, P_g – ground station-measured value.

d) relative bias (BR) – relative bias is a technique used to measure the difference between precipitation measurements from satellites and those from ground-based instruments. The formula applied is as follows:

$$BR = \frac{\sum (P_s - P_g)}{\sum P_g} \tag{4}$$

where: P_s – satellite-measured value, P_g – ground station-measured value.

Calculation of the SPI indicators

The SPI-12 (over 12 months, equivalent to an annual scale) and SPI-06 (over 6 months) indicators were used to characterize drought in the watershed at different time scales. For the calculation of the SPI, we followed the steps below:

1. Precipitation accumulation: the first step is to calculate the cumulative precipitation over the chosen period (monthly, seasonal, annual), typically expressed in n consecutive months, for each year of the reference period. This approach allows capturing precipitation variability over different time scales, thus facilitating

the analysis of meteorological and hydrological droughts (Guttman, 1999).

2. Fitting to a probability distribution: since the distribution of precipitation is often asymmetric, a two-parameter Gamma distribution is typically fitted to the precipitation time series (Thom, 1958). This adjustment provides a more realistic representation (Figure 5) of extreme precipitation and their occurrences.
3. Transformation into SPI – the area under the Gamma distribution curve is calculated using its cumulative distribution function (Figure 6). The obtained value is then projected onto the cumulative distribution function of the normal distribution through a quantile-quantile transformation, allowing the SPI value for the considered period to be obtained (Edwards & McKee, 1997).
4. Validation of the fit – regarding the quality of the Gamma distribution fit, we used the non-parametric Kolmogorov-Smirnov test, which measures the distance between the empirical precipitation distribution and the theoretical Gamma distribution. The null hypothesis H0H_0H0 tests whether the empirical cumulative distribution function of the precipitation corresponds to that of the Gamma distribution. A p-value close to 1 indicates a good fit of the model to the observed data (Stagge et al., 2015).

a) SPI-06 – the SPI index calculated over a 6-month period (SPI-06) allows for capturing precipitation trends at a seasonal or even medium-term scale. It is particularly sensitive to recent hydrometeorological conditions, and in certain climatic contexts, it proves more responsive than the Palmer index in detecting the onset or end of droughts (McKee et al., 1993; Hayes et al., 1999). The SPI-06 is particularly effective in highlighting rainfall deficits or surpluses over well-defined seasons. For example, an SPI-06 calculated up to the end of March accurately reflects the precipitation during the wet season from October to March, a crucial period for Mediterranean climate regions (Vicente-Serrano et al., 2010). From this timescale, it also becomes relevant to relate the SPI with hydrological variables such as streamflow anomalies or reservoir level variations, depending on regional and seasonal specifics.

b) SPI-12 – at the 12-month scale, SPI-12 represents long-term precipitation regimes by comparing the cumulative precipitation over 12 consecutive months to that of equivalent periods across the entire available time series (McKee et al., 1993). This approach accounts for natural seasonal variability by smoothing short-term fluctuations, making SPI-12 particularly suited for analyzing prolonged

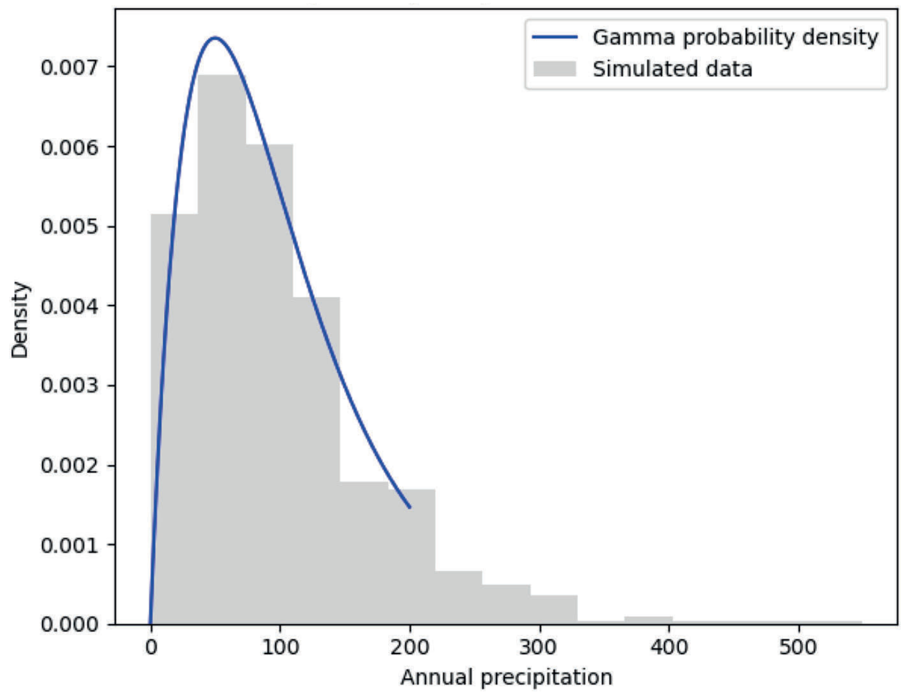

Figure 5. Adjusted gamma distribution probability density

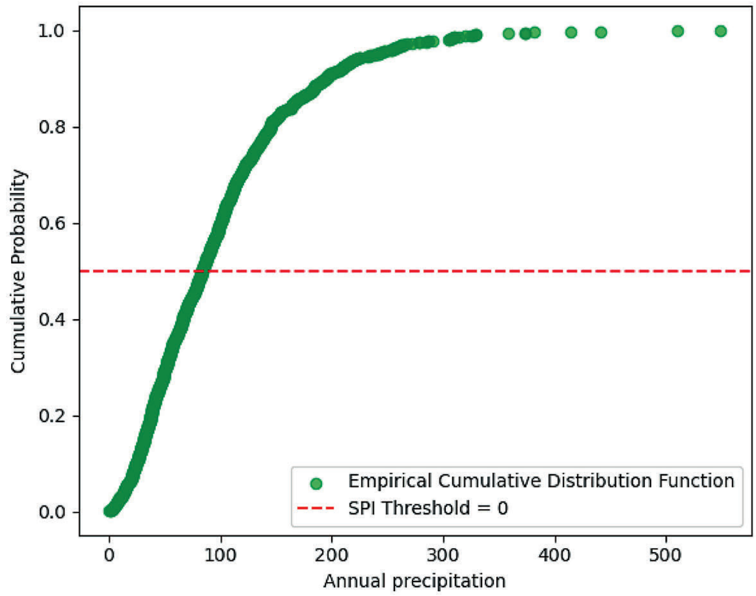

Figure 6. Cumulative distribution function and SPI

hydrological impacts, such as variations in streamflow, reservoir levels, or groundwater levels (Hayes et al., 1999; World Meteorological Organization, 2012).

Since this timescale integrates shorter periods that can alternately be surplus or deficit, SPI-12 values tend to fluctuate around zero, except in cases where a wet or dry regime becomes firmly established. In some cases, SPI-12 shows a notable correlation with other hydrological drought indicators, such as the Palmer Drought Severity Index (PDSI), providing consistent detection of abnormal long-term water conditions (Guttman, 1998; Vicente-Serrano et al., 2010).

Due to its robustness and ease of application, SPI is widely used for drought analysis across different time scales, thus facilitating comparisons between distinct climatic regions (Hayes et al., 1999). The drought levels corresponding to each SPI class according to McKee et al. (1993) are given in Table 1.

Table 1. Drought levels corresponding to each SPI class

SPI class	Drought levels
SPI≥2.0	Extremely wet
1.5≤SPI<2.0	Very wet
1.0≤SPI<1.5	Moderately wet
−1.0<SPI<1.0	Near normal
−1.5≤SPI≤−1.0	Moderately dry
−2.0≤SPI<−1.5	Severely dry
SPI<−2.0	Extremely dry

RESULTS AND DISCUSSIONS

Descriptive statistics

To evaluate the performance of the two satellite products (SP), ERA5 and CHIRPS, we used standard performance metrics, namely the coefficient of determination (R^2), root mean square error (RMSE), root mean square (RMS), and relative bias (BR). Monthly time series from both satellite products, covering the period from 1981 to 2018, were compared to ground-based observations from three stations selected to represent the different zones of the watershed (Figure 7):

- Dkhila, located downstream of the watershed, characterized by low elevation and proximity to the ocean,
- Imin El Kheng, situated in the central part of the watershed,
- Iguidi, located upstream, characterized by the high altitudes of the High Atlas Mountains.

Before running the Python code to calculate the performance criteria, we first structured the precipitation series for each site: the observed series (example from the Dkhila site, Table 2), the CHIRPS series (Table 3), and the ERA5 series (Table 4).

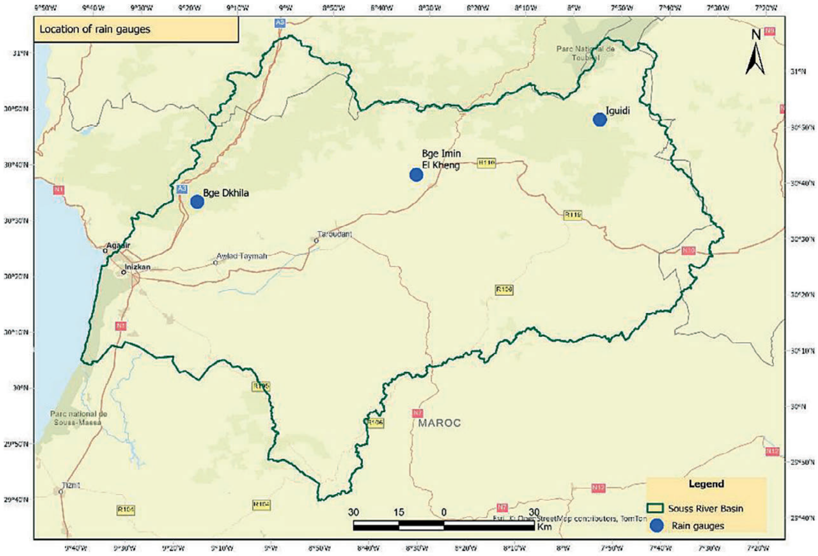

Figure 7. Location of the rain gauges used

Table 2. Observed monthly rainfall at the Dkhila station

HydroYear	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
1980					0.20	71.84	24.77	0.19	0.58	0.61	0.09	0.15
1981	0.28	27.78	1.13	15.97	84.25	7.24	61.63	117.27	0.35	0.00	0.11	0.04
1982	0.94	0.07	49.16	0.02	0.99	36.07	5.12	0.03	13.43	0.27	0.07	0.03
1983	0.02	13.86	243.01	2.50	0.07	9.77	53.46	8.05	0.33	0.07	0.02	0.07
1984	3.01	0.07	151.75	21.48	126.67	23.52	2.72	4.66	0.43	0.04	0.49	0.38
1985	0.03	3.62	17.55	24.22	1.12	172.66	52.41	26.05	0.53	0.64	0.16	0.07
1986	4.65	5.81	3.01	0.00	48.99	23.96	1.54	1.11	3.79	0.20	0.07	0.12
1987	2.50	48.80	49.30	199.00	49.50	73.20	83.50	0.00	51.00	0.00	0.00	0.00
1988	3.00	78.40	163.10	0.00	22.80	12.80	10.70	29.20	2.30	0.80	0.00	2.00
1989	1.70	21.90	150.20	118.90	8.50	0.00	74.40	43.10	0.00	2.60	0.00	0.00
1990	0.00	0.00	1.00	90.00	0.00	101.40	113.10	7.50	0.00	0.00	0.00	0.00
1991	0.90	22.10	5.30	67.70	0.00	17.90	0.90	13.70	0.40	0.00	0.00	0.00
1992	0.00	5.00	0.00	5.10	50.50	12.40	18.10	0.00	22.30	0.00	0.00	0.00
1993	0.00	109.80	82.80	1.20	18.20	17.90	18.80	1.10	0.00	0.00	0.00	0.00
1994	0.00	16.50	1.60	7.00	0.00	13.40	75.70	12.90	0.00	0.00	0.00	0.00
1995	2.20	6.60	100.60	230.00	277.40	46.50	203.00	3.90	49.90	8.10	0.00	0.00
1996	0.00	3.30	41.70	225.30	79.30	0.00	3.60	34.10	0.00	0.00	0.00	0.00
1997	0.80	30.50	2.50	57.20	115.30	139.80	60.40	1.60	0.00	0.00	0.00	0.00
1998	0.00	0.00	0.00	24.70	23.50	1.10	99.30	0.00	0.60	0.00	0.00	0.00
1999	0.00	66.30	0.00	24.60	5.80	0.00	0.00	53.60	0.00	0.00	0.00	0.33
2000	0.00	0.00	0.00	165.10	2.40	0.00	5.00	0.00	0.00	0.00	0.00	0.00
2001	17.30	0.00	4.00	108.81	0.00	25.00	76.80	39.50	0.00	0.00	0.00	0.00
2002	0.00	0.00	105.50	90.40	0.00	5.00	11.10	10.20	0.00	0.00	0.00	1.80
2003	0.00	40.30	64.00	25.31	0.00	109.90	24.40	8.16	21.00	0.00	1.80	0.00
2004	0.00	10.80	61.00	21.90	0.00	84.40	29.60	0.00	0.00	0.00	0.00	0.00
2005	0.00	9.10	24.10	56.50	138.10	21.00	11.10	1.20	0.00	0.00	0.00	0.00
2006	0.00	18.20	11.00	0.00	14.90	27.10	0.00	8.50	0.00	0.00	0.00	11.00
2007	0.60	1.80	27.70	15.30	2.20	19.40	4.20	5.60	0.00	0.00	0.30	0.00
2008	11.70	11.30	56.50	40.10	16.40	140.70	22.90	0.00	0.09	1.60	0.00	0.00
2009	0.30	0.00	0.00	405.80	50.40	294.90	14.40	30.30	0.00	0.00	0.00	19.80
2010	0.00	4.00	237.90	179.30	100.10	0.00	107.60	52.60	61.30	0.00	0.00	0.00
2011	0.00	7.80	23.20	0.00	7.10	0.00	0.20	3.36	0.00	0.00	0.00	0.40
2012	96.40	148.80	17.80	0.00	2.50	9.10	166.40	16.20	0.00	0.00	0.00	0.00
2013	1.90	0.90	0.00	5.60	23.20	0.00	26.20	23.40	0.00	0.00	0.00	0.00
2014	2.60	0.00	391.70	9.40	4.30	0.00	43.30	0.00	0.00	0.20	0.00	10.60
2015	4.90	169.40	5.10	0.00	3.80	37.80	4.80	0.00	26.60	0.00	0.00	0.00
2016	0.00	21.70	76.30	36.40	13.90	155.00	2.10	7.30	0.00	0.00	0.00	2.20
2017	0.00	0.00	8.00	37.20	22.40	148.90	52.50	0.00	0.00	0.00	0.00	0.00
2018	7.60	50.00	37.70	0.00	0.00	0.00	0.00	26.20	0.00	0.00	0.00	0.00
2019	0.00	0.00	0.00	16.30	6.90	0.00	27.67	17.26	24.45	1.25	1.01	0.41

Table 3. Monthly rainfall calculated by CHIRPS at the Dkhila site

HydroYear	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
1980					15.28	77.67	18.84	16.64	0.00	0.00	0.00	0.00
1981	1.01	14.00	48.88	15.89	75.00	23.98	26.20	23.60	9.07	0.00	0.00	0.00
1982	3.28	7.89	34.73	27.61	17.76	33.14	29.97	10.86	8.67	2.01	0.00	0.00
1983	0.00	10.98	49.11	19.22	13.41	11.80	16.18	8.33	8.05	0.00	0.00	0.00
1984	5.12	6.33	62.24	36.43	78.88	30.77	13.98	6.89	5.97	0.00	0.00	0.00
1985	0.00	9.99	41.62	37.44	21.35	38.65	28.04	15.34	9.49	1.93	0.00	0.00
1986	5.82	7.98	16.64	10.54	38.12	16.86	18.97	12.29	10.54	0.00	0.40	0.00
1987	7.31	39.63	39.50	102.46	93.19	61.58	37.46	0.00	5.94	0.00	0.00	0.00
1988	0.00	20.33	123.14	14.89	40.89	32.04	22.61	20.11	0.00	0.00	0.20	0.55
1989	4.28	32.13	87.69	84.52	26.04	0.00	55.77	12.56	5.23	0.00	0.00	0.00
1990	2.78	14.41	20.07	47.50	17.50	40.81	58.30	7.51	0.00	0.00	0.00	0.00
1991	0.00	13.90	31.76	38.13	15.54	29.44	13.28	12.69	0.00	0.00	0.00	0.15
1992	1.34	9.69	12.74	14.63	37.88	11.43	44.38	9.60	7.88	0.00	0.00	1.03
1993	1.57	39.64	54.46	12.70	29.46	21.62	48.72	8.10	6.77	0.00	0.00	0.00
1994	0.00	14.68	18.96	23.02	19.15	22.76	81.24	8.67	0.00	0.00	0.00	0.20
1995	0.00	16.23	55.30	71.82	109.63	26.66	98.87	11.77	11.54	3.21	0.00	0.00
1996	0.00	10.11	41.77	157.10	52.68	13.52	28.31	31.31	8.11	0.00	0.00	0.00
1997	4.10	13.74	25.87	70.11	59.99	62.57	38.16	8.98	0.00	1.86	0.00	0.00
1998	0.00	8.80	14.50	20.02	61.47	21.45	36.15	7.42	6.60	2.07	0.00	1.07
1999	0.00	54.73	22.79	42.17	30.04	14.72	14.32	14.88	5.97	1.45	0.00	0.07
2000	0.00	11.67	16.71	61.33	27.59	9.24	20.02	6.71	0.00	0.00	0.00	0.00
2001	0.00	10.13	24.94	80.28	20.83	20.65	80.57	37.74	0.00	0.00	0.00	0.51
2002	0.69	16.37	77.34	68.02	25.33	25.88	39.56	13.32	0.00	2.12	0.00	0.00
2003	0.00	60.01	44.57	35.32	18.53	54.62	56.71	26.24	6.56	0.87	0.00	0.00
2004	3.56	33.51	23.41	39.41	17.21	64.13	43.58	5.09	6.77	0.00	0.00	0.00
2005	0.00	40.16	30.97	55.77	79.19	39.23	16.74	13.24	0.00	1.17	0.00	0.96
2006	2.34	28.66	26.04	28.20	33.01	25.66	16.79	8.98	0.00	0.00	0.00	0.16
2007	0.00	16.29	37.23	24.69	26.40	58.11	18.34	7.61	5.15	0.00	0.00	0.00
2008	0.00	17.61	54.46	32.12	58.72	85.37	45.73	5.80	0.00	2.65	0.00	0.00
2009	1.43	9.61	19.15	92.29	50.57	142.75	34.60	12.08	7.40	0.00	0.00	0.13
2010	2.41	18.90	34.94	26.97	46.28	17.75	54.34	48.50	32.13	0.00	0.00	0.00
2011	0.00	25.84	54.22	12.47	20.71	9.64	28.77	19.03	4.68	1.91	0.00	0.00
2012	7.63	54.34	28.84	18.39	18.36	23.69	82.99	17.44	0.00	0.00	0.00	0.00
2013	5.65	15.57	28.02	31.65	56.51	19.62	37.68	31.21	9.45	0.00	0.00	0.00
2014	6.15	8.72	223.86	33.06	29.43	13.76	51.64	7.38	0.00	0.00	0.64	0.71
2015	0.00	48.54	26.37	18.50	21.66	33.60	32.50	8.04	17.67	0.00	0.00	0.29
2016	3.46	23.81	109.03	56.58	21.94	56.60	19.52	7.05	5.32	0.00	0.00	0.00
2017	3.20	9.77	33.36	25.62	42.79	43.34	42.73	11.14	5.23	0.00	0.00	0.09
2018	5.17	56.44	84.93	21.68	15.80	14.82	19.77	8.29	6.70	1.28	0.00	0.00
2019	0.00	7.19	17.41	45.39	28.48	12.37	24.37	9.02	11.71	1.86	0.14	0.00

The classic statistical parameters, namely the interannual monthly average, as well as the maximum and minimum values of the three data series – observations (Obs), ERA5, and CHIRPS – were analyzed for the Dkhila site (Table 5), Imi El Kheng site (Table 6), and Iguidi site (Table 7).

The performance evaluation results of the SPPs obtained (Table 8) show that the ERA5 product exhibits a better R^2 coefficient for all three sites: 0.86 at Dkhila, 0.48 at Iguidi, and 0.68 at Imi El Kheng, compared to a maximum of 0.541 for CHIRPS. This indicates that ERA5 better reproduces the temporal variability of the observed precipitation. Furthermore, ERA5 also presents lower RMSE values at all three sites, reflecting greater overall accuracy. Regarding relative bias, CHIRPS generally underestimates precipitation (except at Iguidi, where it sometimes overestimates), while ERA5 tends to overestimate it, especially at Dkhila (+23%). In contrast, the bias is nearly null at Iguidi (−1.46%) and negative at Imin El Kheng (−24.6%), indicating underestimation in that area. At this stage, we can conclude that ERA5 is generally more performant than CHIRPS in terms of variability and overall accuracy, as indicated by the higher R^2 values and lower RMSE, despite a relatively significant bias. Based on this conclusion, we generated a new satellite product (PS) using linear regression. The developed equation is as follows:

$$PS\ (RLM) = 0.147 \cdot CHIRPS + 0.99 \cdot ERA5 \quad (5)$$

Table 4. Monthly rainfall calculated by ERA5 at the Dkhila site

HydroYear	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
1980					0.49	98.10	14.70	13.41	6.74	6.78	0.46	1.57
1981	4.08	19.48	5.61	38.16	74.46	7.08	105.43	96.84	14.93	0.79	2.51	1.77
1982	2.38	1.72	68.93	1.37	2.60	65.35	23.67	7.28	9.15	2.81	0.62	1.92
1983	2.39	20.37	163.68	28.61	6.68	21.09	52.06	46.12	9.15	2.56	1.46	1.34
1984	6.01	1.48	122.07	9.95	166.61	19.14	4.23	14.83	11.96	5.73	1.88	2.00
1985	2.40	16.65	45.38	39.22	4.46	95.85	80.77	42.21	8.72	10.60	4.43	2.78
1986	10.50	23.07	9.45	0.67	65.92	45.65	23.14	8.75	12.51	2.57	3.61	2.73
1987	21.63	50.49	67.91	210.01	67.44	96.93	68.87	2.50	62.83	8.95	2.92	1.90
1988	7.00	76.53	191.03	0.71	43.14	22.73	25.57	56.24	8.41	5.54	8.80	4.95
1989	5.68	64.77	164.38	118.74	21.67	0.24	62.89	78.06	8.93	2.62	4.51	8.40
1990	6.37	6.97	8.21	89.77	7.00	105.04	109.13	13.65	2.17	4.18	4.93	4.32
1991	9.16	44.34	16.16	54.99	1.64	36.31	17.71	28.52	6.68	3.54	4.23	6.53
1992	2.65	24.81	0.89	13.46	52.15	17.15	42.20	1.53	39.46	2.77	3.95	0.84
1993	5.13	86.52	88.11	1.75	28.84	30.52	32.44	4.13	3.56	3.66	1.51	4.63
1994	7.90	22.88	5.53	5.70	0.18	15.03	64.59	35.46	2.04	2.86	2.62	6.18
1995	18.30	6.69	104.61	162.98	321.68	59.31	168.71	8.46	26.51	15.38	1.25	0.61
1996	8.56	7.91	76.45	276.97	72.59	4.33	45.29	57.08	4.26	3.41	2.28	3.08
1997	16.68	53.27	28.67	65.48	110.75	193.67	23.05	5.36	12.84	5.08	0.92	0.38
1998	5.65	2.61	0.82	48.92	28.99	13.10	59.62	1.84	8.66	1.27	1.17	3.68
1999	2.70	116.98	5.68	30.54	12.90	7.69	3.16	103.27	8.19	3.95	0.50	3.98
2000	2.24	2.78	3.03	149.35	10.38	1.44	20.43	1.51	2.15	0.31	0.46	2.13
2001	16.88	5.07	10.36	105.58	2.98	17.24	83.46	86.41	1.73	1.10	0.26	2.42
2002	3.76	3.48	138.04	65.33	4.18	14.49	35.84	20.06	3.46	7.38	2.50	10.49
2003	6.25	82.91	88.87	41.48	2.17	107.42	37.30	25.59	39.15	6.40	1.14	1.36
2004	4.93	36.67	36.55	44.03	0.26	124.75	46.61	1.06	1.56	7.12	3.02	3.25
2005	2.49	42.74	40.98	50.84	122.06	56.98	25.09	18.15	4.38	3.93	5.79	6.23
2006	6.43	49.94	10.00	3.10	19.23	21.52	2.69	14.79	4.57	2.58	2.39	19.28
2007	4.75	10.32	52.50	31.76	6.59	22.23	7.21	14.31	4.73	0.93	7.01	4.38
2008	35.02	45.15	79.90	38.13	24.12	154.11	28.18	1.47	2.40	17.31	0.72	1.69
2009	17.94	4.21	0.60	261.86	61.68	289.16	41.88	40.85	2.74	3.54	3.25	34.84
2010	9.93	23.80	194.72	109.85	92.91	0.76	91.33	53.60	107.35	9.50	1.33	5.92
2011	1.93	24.71	39.89	0.18	5.57	0.68	6.58	24.32	1.71	3.08	0.52	5.86
2012	64.00	152.50	30.03	0.26	6.45	5.57	166.61	61.70	2.89	1.03	1.73	4.30
2013	13.52	3.67	7.26	8.69	39.24	5.13	43.47	41.89	4.14	1.17	0.30	3.90
2014	22.82	3.36	260.32	21.92	15.13	2.88	56.32	2.02	3.67	4.04	13.97	10.93
2015	6.73	161.45	6.79	0.43	2.12	31.37	18.78	3.86	83.50	1.72	4.72	4.78
2016	5.18	40.64	99.49	53.05	9.21	130.82	5.76	8.97	4.27	3.21	1.31	4.52
2017	3.25	7.00	3.52	30.93	28.02	71.31	93.55	11.59	9.15	2.69	0.27	10.31
2018	25.15	70.88	57.58	0.93	1.61	5.93	23.94	25.00	4.20	1.94	1.11	12.36
2019	2.49	0.54	8.30	34.98	6.56	0.16	20.92	9.70	16.94	1.83	1.76	4.29

The performance of the new PS was evaluated using the same criteria as before. The obtained criteria values (R^2 = 0.72, BR = 15.71, RMSE = 24.44, and RSM = 47.38) confirm the robustness of this new PS compared to the initial products, ERA5 and CHIRPS.

Validation of the new developed satellite product

To validate the performance of the new PS, we selected representative years containing both wet and dry months, distributed at different positions

Table 5. Statistical parameters of the rainfall series at the Dkhila site

PS	Parameter	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
Obs	Average	4.19	24.47	56.80	59.70	33.04	46.49	39.84	15.20	6.98	0.41	0.10	1.24
	Max	96.40	169.40	391.70	405.80	277.40	294.90	203.00	117.27	61.30	8.10	1.80	19.80
	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CHIRPS	Average	2.01	22.01	46.09	42.41	37.82	34.06	37.42	13.79	5.72	0.61	0.03	0.15
	Max	7.63	60.01	223.86	157.10	109.63	142.75	98.87	48.50	32.13	3.21	0.64	1.07
	Min	0.00	6.33	12.74	10.54	13.41	0.00	13.28	0.00	0.00	0.00	0.00	0.00
ERA5	Average	10.28	36.39	60.06	57.71	38.77	50.46	47.08	27.31	14.31	4.40	2.70	5.42
	Max	64.00	161.45	260.32	276.97	321.68	289.16	168.71	103.27	107.35	17.31	13.97	34.84
	Min	1.93	0.54	0.60	0.18	0.18	0.16	2.69	1.06	1.56	0.31	0.26	0.38

Table 6. Statistical parameters of the rainfall series at the Imin El Kheng site

PS	Parameter	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
	Average	8.50	27.07	56.21	51.72	29.30	45.87	52.20	16.01	8.73	2.09	0.76	3.98
Obs	Max	104.60	160.40	311.50	329.60	200.60	352.30	343.30	100.28	86.80	40.20	9.15	39.70
	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Average	16.34	23.84	37.03	43.49	38.38	35.80	51.44	24.27	13.98	1.56	0.33	0.52
CHIRPS	Max	34.35	81.44	165.60	111.06	91.13	116.84	116.34	71.33	52.99	6.95	2.68	4.34
	Min	8.58	7.47	13.54	17.38	16.92	5.85	18.55	10.11	5.18	0.00	0.00	0.00
	Average	8.13	22.69	41.14	31.35	25.21	34.66	30.04	16.32	10.34	3.78	1.10	3.14
ERA5	Max	45.21	88.63	238.52	126.09	182.19	195.56	115.11	62.48	74.08	20.10	4.43	21.96
	Min	0.48	1.25	0.06	0.03	0.33	0.10	2.38	0.27	0.79	0.10	0.05	0.08

Table 7. Statistical parameters of the rainfall series at the Iguidi site

PS	Parameter	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
	Average	11.09	30.67	50.56	42.39	29.62	46.18	45.96	17.13	9.82	4.02	3.38	6.07
Obs	Max	65.60	151.79	245.10	229.50	221.06	345.10	192.25	78.65	134.40	46.96	19.50	30.80
	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.90	0.00	0.00	0.00	0.00	0.00
	Average	23.35	29.27	45.99	59.62	51.75	70.07	145.35	63.77	57.78	5.14	0.73	4.01
CHIRPS	Max	54.77	96.33	193.15	137.91	127.51	137.29	303.33	132.92	207.44	17.26	5.21	11.46
	Min	10.79	10.41	16.50	23.87	21.85	13.24	59.82	32.32	24.84	0.00	0.00	0.00
	Average	24.35	32.34	35.04	23.45	22.97	33.58	38.62	24.03	18.05	14.59	8.01	17.10
ERA5	Max	140.57	88.31	232.34	80.79	103.79	113.73	119.98	104.98	102.03	117.44	41.00	62.72
	Min	3.31	1.41	0.14	0.06	0.10	0.70	5.80	2.43	5.11	0.90	0.41	3.39

Table 8. Performance criteria results calculated

Site	PS	R²	Biais relatif %	RMSE	RMS
DKHILA	CHIRPS	0.54	-15.99	34.78	32.90
	ERA5	**0.86**	23.15	**18.59**	55.05
Iguidi	CHIRPS	0.22	88.36	46.87	66.26
	ERA5	**0.48**	**-1.46**	**30.64**	**34.78**
Imin Elkheng	CHIRPS	0.47	**-4.99**	35.75	**33.45**
	ERA5	**0.68**	-24.61	**28.06**	34.46

in the time series and across different sites. These include:

- the year 1988, located at the beginning of the series, at the Dkhila site (Figure 8),
- the year 2000, a dry period, at the Iguidi site (Figure 9),
- and the year 2008, considered as wet, at the Imin El Kheng site (Figure 10). The analysis of the three graphs shows that the developed PS performs better in reproducing the observed precipitation compared to the ERA5 and CHIRPS products.

Calculation of SPI

Critique and adjustment of the limits of SPI classes

The standard classes of the standardized precipitation index, particularly the range from -0.99 to +0.99 defined as representing near-normal conditions, present certain limitations when applied to semi-arid regions such as the Souss River Basin.

After analyzing the results at the SPI-06 and SPI-12 time scales, we found that this intermediate class is largely dominant, which does not accurately reflect the basin's climatic realities. In fact, several years with values close to the lower bound (-0.99) were classified as "normal," although these years actually experienced significant water deficits.

These limitations are not unique to our study and have been highlighted in several research works. For instance, Vicente-Serrano et al. (2010) emphasized the limitations of SPI in arid and semi-arid climates, particularly its low sensitivity to small precipitation amounts, which leads to underestimation of drought periods. Guttman (1999) showed that the global calibration of SPI

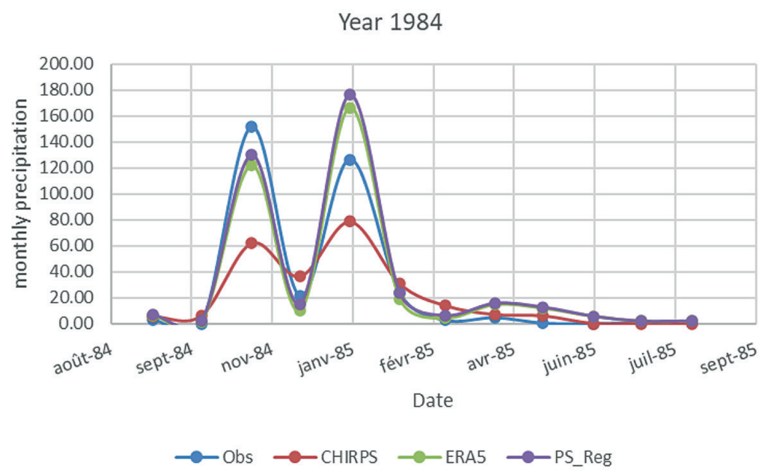

Figure 8. Comparison of PS relative to the measured series, year 1984/85, Dkhila station

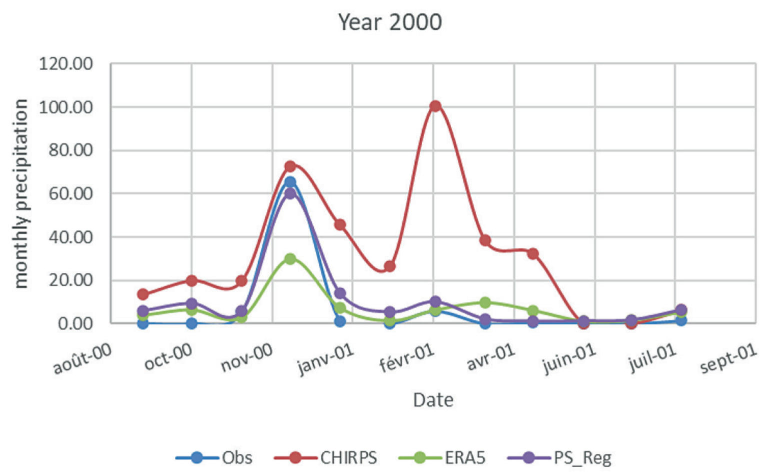

Figure 9. Comparison of PS relative to the measured series, year 2000/01, Iguidi station

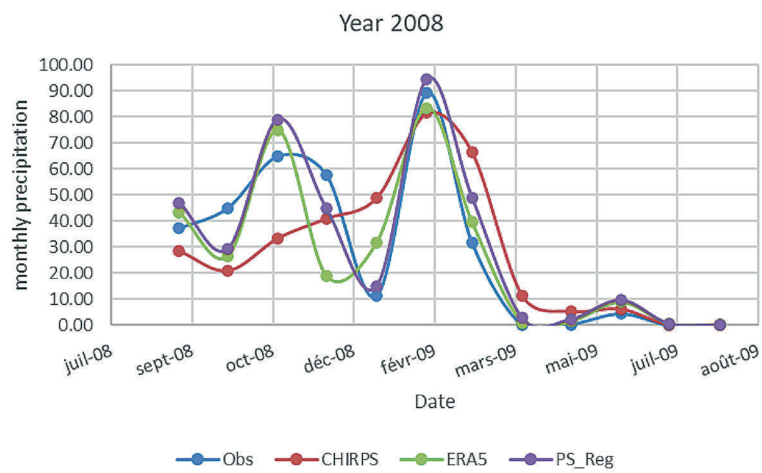

Figure 10. Comparison of PS relative to the measured series, year 2008/019, Imin EL Kheng station

does not adapt well to the asymmetric precipitation distributions typical of arid regions, compromising the interpretation of results. Naresh Kumar et al. (2009) also pointed out that SPI is not always representative in semi-arid climates and recommended adjusting classification thresholds to better detect abnormal drought conditions. Based on these findings, and to better characterize local climatic conditions, we adjusted the "near-normal" class by narrowing its interval from [-0.99, 0.99] to [-0.5, 0.99] Ttable 3). This adjustment allows for better identification of slightly dry years, which are particularly important in a semi-arid context.

Furthermore, since our study focuses on drought characterization, we decided to group all years with SPI > 1 into a single "wet year" class (Table 9), without distinguishing higher wetness levels, which were considered less relevant to our objective.

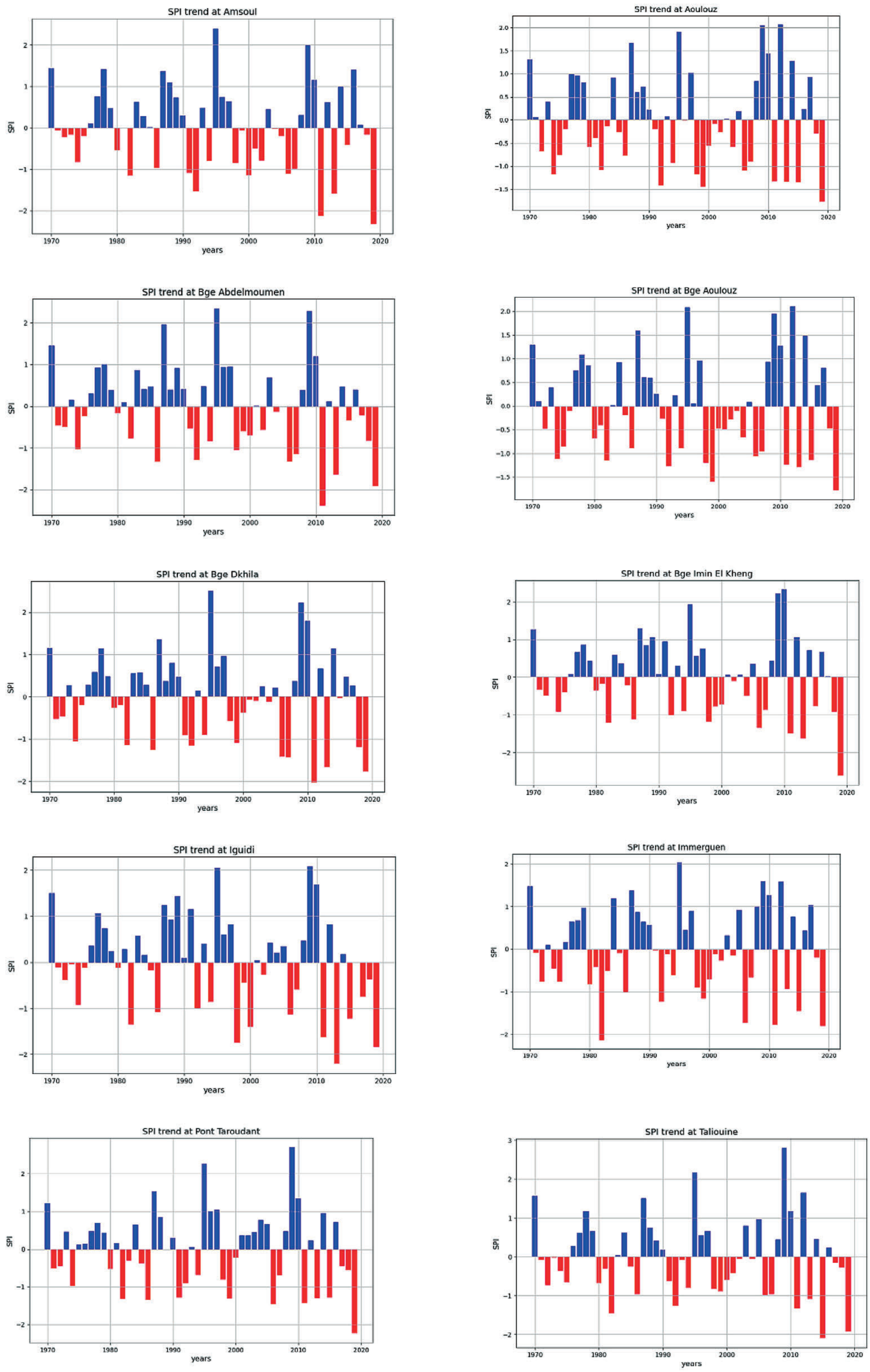

Figure 11. Results of SPI-06 calculation

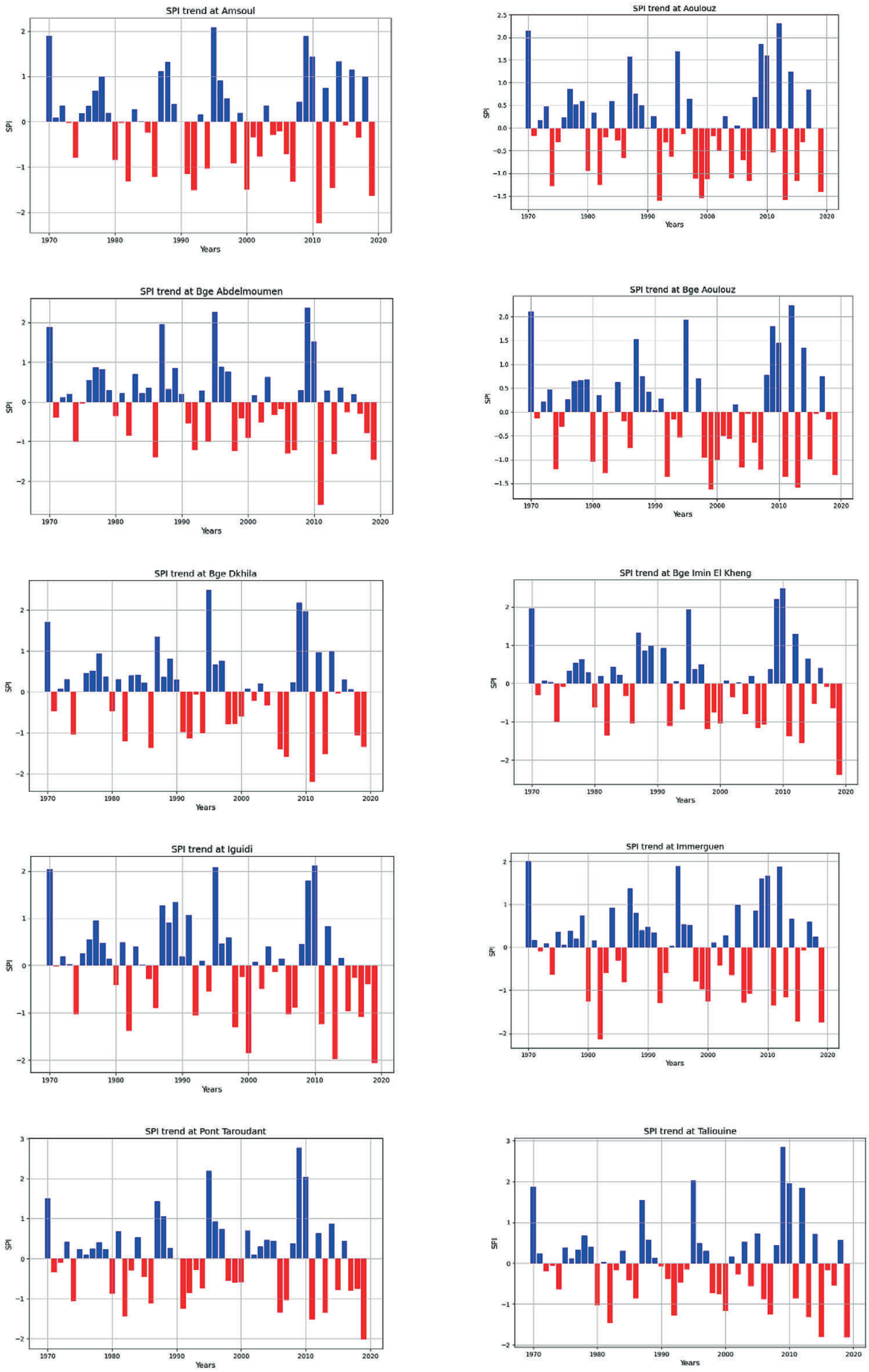

Figure 12. Results of SPI-12 calculation

a) Results of SPI-06 calculation – based on the newly adjusted SPI, we proceeded to calculate the SPI-06 by first accumulating the precipitation over six (06) months of each hydrological year, covering the period from October of year n to March of year n+1. The results obtained from this approach are presented in Figure 11.

Table 9. Adjusted SPI classes

SPI class	Drought levels
SPI≥1.0	wet
−0.5≤SPI<1	Near normal
−1.5≤SPI<−0.5	Moderately dry
−2.0≤SPI<−1.5	Severely dry
SPI<−2.0	Extremely dry

b) Results of SPI-12 calculation – the results of the SPI-12 index calculation (Figure 12) indicate that the Oued Souss watershed has experienced several periods of drought, characterized by varying durations and intensities.

As a general rule, a drought class, when it occurs, affects all the stations. We estimated that it would be appropriate to assign to each year the class most commonly observed across the majority of sites (Table 10).

Over the 39-year period from 1980 to 2018, 4 years (approximately 10%) were classified as wet according to the SPI-06 or SPI-12 indices. In contrast, 18 years (about 53%) showed near-normal conditions according to SPI-12, compared to 51% based on SPI-06. The frequency of moderate drought ranges from 38% according to SPI-12 to 33% according to SPI-06 (Table 11). Severe drought occurred during approximately 5% of the analyzed period. As for extreme drought, it never affected the entire watershed; rather, it appeared in localized areas, notably in 2011 in regions such as Amsoul and the surroundings of the Imin El Kheng and Dkhila dams.

Regarding the duration of drought episodes, whether considering the actual duration (number of consecutive years of drought) or the time between two episodes, our results show several notable trends.

We found that moderate drought episodes tend to last longer. This is the case for the episode extending from 1999 to 2003, which lasted for three consecutive years, unlike isolated drought years observed in 1980, and 1982. This prolonged episode was followed shortly by another two-year episode (2006 and 2007), illustrating the temporal proximity between dry periods.

As for the duration between two drought episodes, we observe a significant shortening over time. This confirms an increased recurrence of dry episodes, with shorter return periods and longer durations, highlighting a concerning climate dynamic in the basin. From 2008 onwards, after the exceptionally wet years of 2009 and 2010 – confirmed by both SPI-06 and SPI-12 indicators at the national level – the climate regime shows marked irregularity. This variability is manifested by the appearance of very wet years, such as in 2009 and 2010, as well as extreme drought episodes (Table 12), with an intensity never recorded before 2008.

These extreme episodes were notably observed in 2011, at the Amsoul, Abdelmoumen,

Table 10. Different drought episodes of the two indicators SPI-06 and SPI-12

Date	SPI-06	SPI-12
1980	Moderately dry	Moderately dry
1981	Near normal	Near normal
1982	Moderately dry	Moderately dry
1983	Near normal	Near normal
1984	Near normal	Near normal
1985	Near normal	Near normal
1986	Moderately dry	Moderately dry
1987	Wet	Wet
1988	Near normal	Near normal
1989	Near normal	Near normal
1990	Near normal	Near normal
1991	Moderately dry	Moderately dry
1992	Moderately dry	Moderately dry
1993	Near normal	Near normal
1994	Moderately dry	Moderately dry
1995	Wet	Wet
1996	Near normal	Near normal
1997	Near normal	Near normal
1998	Moderately dry	Moderately dry
1999	Moderately dry	Moderately dry
2000	Moderately dry	Moderately dry
2001	Near normal	Near normal
2002	Near normal	Moderately dry
2003	Near normal	Near normal
2004	Near normal	Moderately dry
2005	Near normal	Near normal
2006	Moderately dry	Moderately dry
2007	Moderately dry	Moderately dry
2008	Near normal	Near normal
2009	Wet	Wet
2010	Wet	Wet
2011	Severely dry	Severely dry
2012	Near normal	Near normal
2013	Severely dry	Severely dry
2014	Near normal	Near normal
2015	Moderately dry	Moderately dry
2016	Near normal	Near normal
2017	Near normal	Near normal
2018	Moderately dry	Moderately dry

Table 11. Percentage of drought classes (period 1980–2018)

Drought levels	SPI-06	SPI-12
Wet	12%	10%
Near normal	53%	53%
Moderately dry	31%	33%
Severely dry	4%	4%
Extremely dry	0%	0%

Table 12. Résultats de SPI-06 période 2008-2018

Date	Aoulouz	Amsoul	Bge Abdelmoumen	Taliouine	Bge Imin El Kh	Iguidi	Immerguen	Pont Taroudar	Bge Aoulouz	Bge Dkhila
2008	0.84	0.31	0.37	0.44	0.43	0.46	1.00	0.48	0.94	0.37
2009	2.04	1.99	2.27	2.79	2.23	2.08	1.60	2.69	1.95	2.23
2010	1.44	1.14	1.20	1.18	2.33	1.69	1.26	1.35	1.27	1.80
2011	-1.33	-2.12	-2.37	-1.33	-1.49	-1.63	-1.78	-1.44	-1.23	-2.03
2012	2.07	0.61	0.12	1.66	1.05	0.83	1.59	0.23	2.11	0.66
2013	-1.34	-1.59	-1.63	-1.08	-1.64	-2.20	-0.93	-1.30	-1.29	-1.67
2014	1.27	0.99	0.47	0.46	0.72	0.18	0.76	0.95	1.49	1.13
2015	-1.35	-0.40	-0.34	-2.09	-0.77	-1.22	-1.45	-1.28	-1.14	-0.03
2016	0.23	1.40	0.39	0.24	0.66	0.00	0.44	0.73	0.44	0.46
2017	0.94	0.07	-0.21	-0.15	0.02	-0.76	1.03	-0.45	0.81	0.26
2018	-0.29	-0.16	-0.82	-0.28	-0.91	-0.37	-0.20	-0.56	-0.47	-1.20

and Dkhila dam stations, and in 2013, at the Iguidi station (Table 12).

The results obtained through this work encourage us, as water resource managers in a semi-arid watershed, to exercise caution in managing the volumes stored in the reservoirs. It is essential to take into account the increasing irregularity of drought episodes. These episodes are characterized by an increase in their duration, as well as a growing intensity, which further complicates the planning and securing of water resources.

CONCLUSIONS

Through this work, we have developed a homogeneous and rigorous methodology aimed at utilizing satellite data for drought assessment in a watershed subject to a semi-arid climate. This approach provides a relevant solution to the issue of limited access to ground-measured climate series by relying on satellite data while proposing a framework to assess their reliability.

In order to improve the accuracy of satellite precipitation, we developed a new satellite product by combining ERA5 and CHIRPS data via multiple linear regression. This new product has improved the accuracy of satellite precipitation estimates, with an R^2 reaching 0.71. This improvement helps overcome two major limitations: gaps in ground measurement series and the low density of measurement stations.

We also compared the results of SPI on two scales (6 months and 12 months). The results showed that these two indices generally identify the same episodes in terms of duration. However, the SPI-06 tends to amplify the intensity of events, making it particularly useful and well-reflecting the reality experienced in the optimization of water resource management in a context of high seasonal variability.

The chronological analysis identified the emergence of severe droughts starting from 2011, with notable peaks in 2011 and 2013. These results suggest an intensification of drought episodes over time, with an increase in their duration, the appearance of more severe drought classes, and a reduction in the time interval between two episodes.

Our study thus opens up promising perspectives for spatio-temporal monitoring of drought in under-instrumented areas, particularly in the context of climate change, where semi-arid regions are becoming increasingly vulnerable to hydrological hazards.

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