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Examining the reliability of the standardized precipitation index (SPI) with the actual precipitation index (API)

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Abstract

In the Iraqi Kurdistan region, droughts are common and difficult to control. Drought occurs in both high- and low-rainfall locations, but the most important consideration in drought analysis is the severity of the drought. This research examines the reliability of the Standardized Precipitation Index (SPI) by comparing its performance against the Actual Precipitation Index (API) within the semi-arid Erbil Urban Area, Iraq, for the period of 2000 to 2024. The core objective of this study is to determine if SPI accurately indicates drought in Erbil, using API—which utilizes the actual probability distribution of raw precipitation data—as a more direct indicator of reality. The study analyzed precipitation data from five representative hydrological stations (Ainkawa, Shaqlawa, Bnaslawa, Koya, and Harir) across 3-, 6-, and 12-month time scales. Findings reveal significant discrepancies between the two indices: while SPI smooth's out extreme conditions and characterizes relative climatic deviation, API reveals the absolute deficit of raw rainfall. For instance, Ainkawa and Bnaslawa stations showed more extreme "dry" events in the shorter-term SPI-3, but the API reveals Bnaslawa and Shaqlawa as having the highest overall frequency of dryness. A key limitation of SPI in this semi-arid context is that it may fail to accurately portray true water availability for critical resource planning, often showing a "normal drought" incidence more frequently than API. Results show that the most serious drought risk in Erbil does not come from short-term extremes but from moderate to severe droughts lasting 6 to 12 months, which severely impacts water supply. The integration of results shows that Koya has the worst drought severity vulnerability based on SPI-12, while Bnaslawa experiences the driest conditions in terms of total drought frequency (API). This comparison underlines the fact that relying only on SPI in semi-arid data-scarce regions, like Erbil, could lead to uninformed decisions on water rationing and resource planning. The paper concludes that the region is facing structural water scarcity and not just periodic drought; it, therefore, calls for an integration of multiple indices, like SPI and API, to balance standardized assessment with real-time water availability for effective drought management .For appropriate water resource management planning in a region, it is a must that the water resources need two index-based water management plans: firstly, drought-resistant water plans that are climate-adusted (for instance in the case of Koya: drought-resistant crops) needs SPI indexing, while secondly water plans that determine absolute water availability in a location needs API indexing (for instance in Bnaslawa water plans concerning absolute water availability in locations that need reservoirs).

Keywords: SPI, API, drought, precipitation, cumulative probability, gamma distribution

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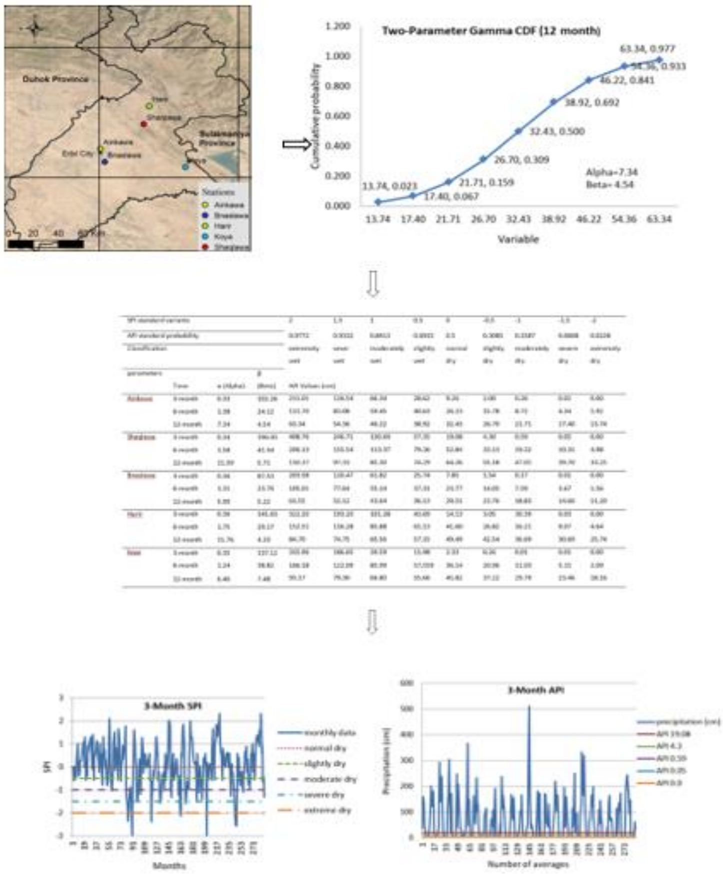
Graphical abstract



1. Introduction

Drought is being viewed as a natural occurrence and recurrent phenomenon. Various factors related to this hazard, combined with its wide impacts, make its effects difficult to recognize and measure (Wilhite *et al.*, 2000;Mishra and Singh, 2010;Venkatraman *et al.*, 2023;Surendran and Krishnan, 2024;Sivasubramanian *et al.*, 2025). Drought indices are very important for monitoring droughts continuously in time and space, and early warning systems for droughts are based primarily on the information that drought indices provide (McKee *et al.*, 1993;Mukherjee *et al.*, 2018). Trend analysis should also be established to indicate whether drought is a recurrent event and increasing in severity (Spinoni *et al.*, 2018;Ghislain *et al.*, 2024;Jegan *et al.*, 2024). Forecasting droughts is a key aspect of drought hydrology that plays a significant role in drought management (Mishra and Singh, 2011). Droughts can be defined as one of the most complex and damaging weather-related natural disasters that have not yet fully been understood by many, and it fluctuate considerably from local to continental and from seasonal to decadal (Mundetia and Sharma, 2015;Tigkas *et al.*, 2017;VAN *et al.*, 2017).There are very valuable studies carried out in an attempt to examine drought in Iraq for a particular region and time range, among which are studies by (Al-Timimi and Al-Jiboori, 2013;Hameed *et al.*, 2018;Abdulrazzaq *et al.*, 2019;Nedham and Hassan, 2019;Al-Quraishi *et al.*, 2021;Javadinejad *et al.*, 2021;Abd Alraheem *et al.*, 2022;Alee *et al.*, 2023) , they examined the frequency of meteorological and agriculture-related droughts at different time ranges according to the SPI scale at over intervals of three, six, and twelve months. Furthermore, the outcome of their study pointed to two major drought events: in 1998-1999 and 2007-2008. These are when droughts of sever to extreme categories impacted about 87% and 82% of Iraq, respectively. The outcome confirmed that southern and central Iraq would be the most drought-impacted regions in the future. Previous studies have discovered that Iraq is heading towards drought at an accelerating rate, and the severity of the drought increases as we head south. Şen and Almazroui (2021) and Topçu and Karaçor (2023) looked into the possibility of applying Actual Precipitation Index (API) in spite of the basic PDF of the meteorological data. It creates a true drought classification using the original data rather than relying on the standard PDF conversion. One of the main limitations of the Standardized Precipitation Index (SPI) does not capture the full extent and severity of drought in dry areas (Guttman, 1998;Hernandez and Uddameri, 2014). Specifically, it may recognize 18–27% less cases of drought and incorrectly calculate the severity by 1.2–2.3 score levels. When compared to drought indices that take into account evaporation demand (such as wind, temperature, and humidity), which is typically high in these situations, this gap is most pronounced (Vicente-Serrano *et al.*, 2010).

The incentive of the research is the case where the city of Erbil is located in a semi-arid area within Iraq, where the city has periodically faced severe instances of drought in its water bodies and plants, as the years 2021 and 2022 have been identified as seasons of extended instances of drought in terms of soil water and surface water. The main aim of the research is to determine if the SPI correctly indicates a case of drought, where API acts as an indicator of reality. This study offers key findings for water resource managers of the respective regions, urban planners, and decision-makers with systematic identification of the time periods of major departures between the SPI and API for the period from the year 2000 to 2024. The selection of five representative hydrological stations makes sure that the findings of this study are not biased for the region.

2. Methodology

2.1. Area considered and Data

Iraq is one of the Middle Eastern countries that face frequent droughts due to extreme oscillations in its weather and low rainfall in the semi-arid parts. Northern Iraq includes the Erbil governorate. This governorate is subject to drought due to its location within semi-arid areas, scarce rainfall conditions, and climate change. The study area is the city center of Erbil and its surroundings. Rainfall records were obtained from six stations. The monthly precipitation data in this study, and their displayed geographical locations, are given in **Figure 1** and **Table 1**.

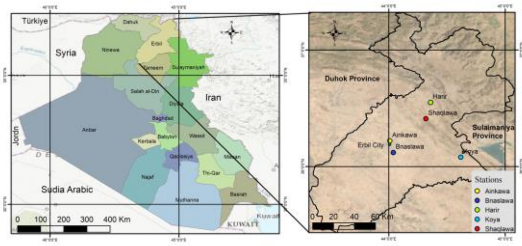


Figure 1. The location map of the research area, together with the layout of the weather stations.

Table 1. Spatial aspect of meteorological terrestrial sites

Station	Elevation (m)	Latitude	Longitude
Ainkawa	434	36º.22'	44º.01'
Bnaslawa	470	36º.12'	44º.04'
Shaqlawa	975	36º.41'	44º.32'
Koya	631	36º.08'	44º.62'
Harir	724	36º.55'	44º.36'

2.2. Gamma Distribution and SPI Calculation

McKee *et al.* (1993) Developed SPI, entirely dependent on precipitation and applicable for both dry and rainy seasons, which is a probability index that monitors and assesses drought. SPI values indicate the number of standard deviations that a given precipitation amount diverges from the long-term average for that location and time scale, and it is positive scores represent above-normal precipitation, while negative values indicate below-normal precipitation (Lloyd-Hughes and Saunders, 2002). SPI is specifically delineated using typical normalized distributions of probability (PDF) components at the levels of 0.00, -0.50, -1.00, -1.50, and -2.00, respectively matching the categories of "normal dry," "slightly dry," "medium dry," "severe dry," and "extremely dry" (McKee *et al.* 1993). Standardized Precipitation Index (SPI) values are calculated to identify droughts; an SPI of 1 or less indicates a moderate drought, 1.5 or less indicates a severe drought, and 2 or less denotes an extreme drought (Lloyd-Hughes and Saunders, 2002). In the current work, rainfall observations from five stations were used to establish SPI time series baseline and identify drought during 2000 to 2024. The Gamma distribution is a frequently reliable model for simulating rainfall patterns, as demonstrated by a lot of research that investigated several statistical models for rainfall in Erbil city (Karim *et al.*, 2018;Mustafa *et al.*, 2019;ABBAS and Ibrahim, 2023). The precipitation data for periods of 3, 6, and 12 months are first parameterized by fitting them to the probability gamma function, which consists of the shape parameter (α) and the scale parameter (β) (Guttman, 1999;Aksoy, 2000). The Thom (1966) approximation for maximum likelihood has been used by McKee *et al.* (1993) and EDWARDS (1997) as a method for determining the parameters. The gamma cumulative distribution function (CDF) is then used to figure out the cumulative probability of a given precipitation value. The resultant value of the SPI is then obtained by converting this cumulative probability to the standardized normal distribution with mean zero and variance one. The procedure of calculating SPI was explained well in many literatures such as (Hayes *et al.*, 1999;Lloyd-Hughes and Saunders, 2002;Wu *et al.*, 2007;Svoboda *et al.*, 2012;Guenang and Kamga, 2014), the cumulative probability function G (x) is shown below: Computed SPI-3, SPI-6, SPI-12 by:

$$G(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)}\int_{0}^{x} x^{\alpha-1} e^{\frac{x}{\beta}} dx \tag{1}$$

Where x is precipitation measurement, $\beta > 0$ is scale parameter stretches or compresses the distribution along the x-axis, $\alpha > 0$ is shape parameter controls the curve's shape and $\Gamma(\alpha)$ is gamma function. The maximum likelihood solutions are used to estimate α and β optimally (Thom, 1966).

$$\alpha == \frac{1}{4A}\left(1+\sqrt{1+\frac{4A}{3}}\right) \tag{2}$$

$$\beta = \frac{\overline{x}}{\alpha} \tag{3}$$

$$A = \ln(\bar{x}) - \frac{\sum \ln(x)}{n} \quad (4)$$

n= number of precipitation observations

The gamma function will not be defined at (x=0); the cumulative probability H (x) can be computed using the following equation (Thom, 1966):

$$H(x) = q + (1 - q)G(x) \quad (5)$$

Where, H (x) is cumulative probability, q is the probability of zero and G (x) is the probability of incomplete gamma function

2.3. Basis of the Actual Precipitation Index (API)

Water resources planners make use of drought classification to decide drought mitigation measures, and as such, drought classification bulletins are issued routinely by weather bodies around the globe (Mallya *et al.*, 2015). According to (Şen and Almazroui, 2021), while examining the primary variations of SPI and API techniques, the API takes into account the real probabilities that correspond to the SPI values. The PDF values are also an indication of the SPI. This yields a mean of SPI values equal to zero; also, the unit variance is inappropriate when the samples are small.

Firstly, the precipitation data will be specified for intervals as (3, 6, 12 months) and sorted in ascending order. After which, the empirical probability is assigned to every data point by applying Equation 3

$$P = \frac{m}{n+1} \quad (6)$$

Where: m is the rank in an ordered series, and n is the total number of observations.

Secondly, the most suitable CDF will be fitted to the data (Gamma distribution). In the third step, by using the standard normal CDF, the standard SPI classification boundaries of drought will be converted to probabilities. Together with the specific precipitation data values that correspond to the probability limits calculated in step 2, the actual API values will be estimated. To obtain varying API levels for each, these procedures will eventually be executed over various time scales. All calculations were done using R Studio 2025 software

2.4. Data Analysis Framework

SPI drought frequency for the third month, sixth month, and twelve months, and API drought frequency for three months, six months, and twelve months, respectively, were developed by computing SPI and API values for each station and for each time scale (3 months, 6 months, and 12 months) based on the methods described in Sections 2.2 and 2.3. SPI drought frequency was developed by assigning each SPI value to a drought/wet class based on standard SPI thresholds (e.g., <-2 for extreme dry and >2 for extremely wet). Similarly, API drought frequency was developed by assigning each API value to a drought/wet class based on standard API thresholds (e.g., <0.0228 for extreme dry). The frequency of each class was then computed by dividing the number of months in each class by the total number of months of the study period and expressing the result as a percent. The results were then presented in **Tables 4 and 5**.

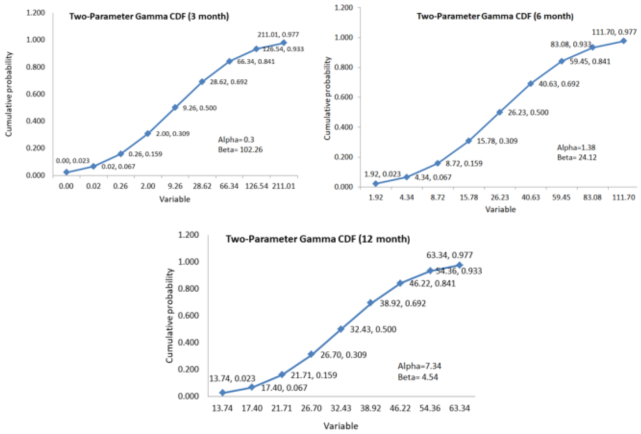


Figure 2 The gamma CDF approach for API Ainkawa three, six, and twelve months

3. Results and Discussion

3.1. API limitations and gamma distributing criteria

The gamma CDF approach for API Ainkawa three, six, and twelve months are shown in **Figure 2**. The vertical axis displays API possibilities, while the horizontal axis displays API classification limits. Each one of the previous steps for methodology is done for 3, 6, and 12 months, along with PDFs, with different parameters, so that the values for the API level procedures will be different. These figures were repeated for all four stations.

Table 2. SPI and API SPI and API categorization limits (Şen and Almazroui, 2021)

Class	SPI, standard value	API, probabilistic value	Classification
1	>2	>0.9772	Extremely wet
2	1.50–1.99	0.9332 to 0.9772	Very wet
3	1.00–1.49	0.8413 to 0.9332	Moderately wet
4	0.50–0.99	0.6915 to 0.8413	Slightly wet
5	0.00-0.5	0.5000 to 0.6915	Normal wet
6	0 .00to -0.5	0.0000 to–0.3085	normal dry
7	−0.50 to–0.99	-0.3085 to - 0.1587	Slightly dry
8	−1.00 to–1.50	- 0.1587 to - 0.0668	Moderately dry
9	−1.50 to–2.00	- 0.0668 to -0.0228	Very dry
10	< 2	<- 0.0228	Extremely dry

Table 3. API metrics for the research region stations' wet and dry spells for various monthly periods

	SPI standard variants			2	1.5	1	0.5	0	-0.5	-1	-1.5	-2
	API standard probability			0.9772	0.9332	0.8413	0.6915	0.5	0.3085	0.1587	0.0668	0.0228
	Classification			extremely wet	sever wet	moderately wet	slightly wet	normal dry	slightly dry	moderately dry	severe dry	extremely dry
parameters	**Time**	**α (Alpha)**	**β (Beta)**					**API Values (cm)**				
Ainkawa	3-month	0.33	102.26	211.01	126.54	66.34	28.62	9.26	2.00	0.26	0.02	0.00
	6-month	1.38	24.12	111.70	83.08	59.45	40.63	26.23	15.78	8.72	4.34	1.92
	12-month	7.34	4.54	63.34	54.36	46.22	38.92	32.43	26.70	21.71	17.40	13.74
Shaqlawa	3-month	0.34	196.93	408.76	246.71	130.69	57.35	19.08	4.30	0.59	0.05	0.00
	6-month	1.58	41.54	206.13	155.54	113.37	79.36	52.84	33.13	19.32	10.31	4.98
	12-month	11.59	5.71	110.37	97.33	85.30	74.29	64.26	55.18	47.01	39.70	33.25
Bnaslawa	3-month	0.36	87.53	203.58	120.47	61.82	25.74	7.85	1.54	0.17	0.01	0.00
	6-month	1.31	23.76	105.01	77.64	55.14	37.31	23.77	14.05	7.59	3.67	1.56
	12-month	5.99	5.22	61.55	52.12	43.64	36.13	29.51	23.76	18.83	14.66	11.20
Harir	3-month	0.36	141.63	322.20	193.20	101.28	43.69	14.13	3.05	30.39	0.03	0.00
	6-month	1.75	29.17	152.51	116.28	85.88	61.13	41.60	26.82	16.21	9.07	4.64
	12-month	11.76	4.33	84.70	74.75	65.56	57.15	49.49	42.54	36.69	30.69	25.74
koya	3-month	0.35	137.12	315.96	186.65	39.59	11.98	2.33	0.26	0.01	0.01	0.00
	6-month	1.24	38.82	166.18	122.09	85.99	57,559	36.14	20.96	11.03	5.15	2.09
	12-month	6.46	7.48	93.17	79.30	66.80	55.66	45.82	37.22	29.79	23.46	18.16

Table 4. SPI drought frequency values for the third, sixth, and twelve-month periods

	Ainkawa			**Shaqlawa**			**Bnaslawa**		
	Drought frequency (%)			**Drought frequency (%)**			**Drought frequency (%)**		
	SPI-3	**SPI-6**	**SPI-12**	**SPI-3**	**SPI-6**	**SPI-12**	**SPI-3**	**SPI-6**	**SPI-12**
wet	54.4	50.6	52.1	53.8	51.9	48.7	51.4	47.7	50.5
normal dry	19.7	18.8	18.5	16.8	18.0	19.5	24.1	22.6	15.9
slight dry	13.1	13.7	11.7	15.4	16.3	17.7	12.2	16.3	18.8
moderate dry	6.2	11.8	12.8	9.1	7.8	10.5	6.3	8.5	9.0
severe dry	2.9	4.1	4.5	2.1	3.9	2.2	2.1	3.5	5.4
extreme dry	3.6	1.1	0.4	2.8	2.1	1.4	3.8	1.4	0.4
	Koya			Harir					
	Drought frequency (%)			Drought frequency (%)					
	SPI-3	SPI-6	SPI-12	SPI-3	SPI-6	SPI-12			
wet	55.2	53.2	47.7	53.3	50.2	55.4			
normal dry	16.8	18.8	28.2	22.5	18.7	10.8			
slight dry	15.4	13.1	10.5	12.6	17.0	18.3			

moderate dry	5.2	6.4	5.4	6.0	8.8	11.5
severe dry	4.5	7.1	7.6	3.2	3.5	1.8
extreme dry	2.8	1.4	0.7	2.5	1.8	2.2

Table 5: API drought frequency values for three, six, and twelve months

	Ainkawa			**Shaqlawa**			**Bnaslawa**		
	Drought frequency (%)			**Drought frequency (%)**			**Drought frequency (%)**		
	API-3	**API-6**	**API-12**	**API-3**	**API-6**	**API-12**	**API-3**	**API-6**	**API-12**
wet	53.3	40.9	33.7	56.5	41.7	34.4	55.8	38.0	31.5
normal dry	9.8	8.7	3.6	8.7	9.1	4.3	8.0	10.5	3.6
slight dry	4.0	4.0	3.3	3.6	5.8	1.4	2.2	7.2	2.9
moderate dry	0.7	5.1	4.0	1.1	3.3	2.2	2.5	4.0	5.8
severe dry	0.7	4.3	3.3	0.0	4.7	4.3	2.2	3.3	4.0
extreme dry	31.5	37.0	52.2	30.1	35.5	53.3	29.3	37.0	52.2
	Koya			Harir					
	Drought frequency (%)			Drought frequency (%)					
	API-3	API-6	API-12	API-3	API-6	API-12			
wet	62.2	42.7	31.6	56.9	42.4	36.1			
normal dry	4.2	8.7	5.9	9.4	10.1	3.1			
slight dry	3.1	3.5	5.2	0.0	3.1	3.1			
moderate dry	0.0	5.2	2.8	4.2	4.2	3.6			
severe dry	10.1	2.1	3.8	0.0	6.3	4.2			
extreme dry	20.5	37.8	50.7	29.5	34.0	50			

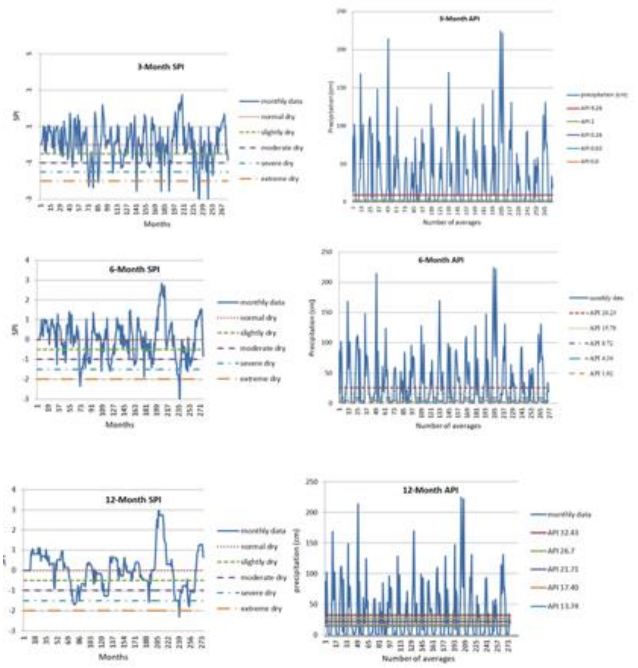


Figure 3. SPI's drought frequency results for months three, six, and twelve

Table 3 below displays the gamma range features and API thresholds levels for all meteorological stations within the Erbil urban area for various periods of time. For instance, at Ainkawa station, for periods exceeding 6 months, precipitation falling within a range of 15.78cm and 8.72cm is classified as "slightly dry" and that below 1.92cm as "extremely dry".

3.2. The relative SPI and API for three, six, and twelve months

Only the outcomes of a comprehensive graphic examination are presented in this paper for the weather stations of Ainkawa and Shaqlawa. The remaining stations, including Koya, Bnaslawa, and Harrir, conducted the same analysis. The SPI's drought frequency results for months three, six, and twelve were highlighted in **Figure 3**. For the 3-month SPI, the lines on the graph show a period of sustained drought conditions, ranging from moderate to occasionally severe droughts. 6- month SPI revealed moderate to severe drought and occasionally extreme drought. Also, wet conditions appeared as moderate wet between the 1st month to19th month, while between 199month th month to 217 th month were extremely wet. 12- month SPI shows slight to moderate dry and short severe dry. Short moderately wet between 19 th month to 55 th month, and short extreme wet between 199 th month and 235th month were displayed. For the 3-, 6-, and -12 month API, this station's data indicates a sharp and drastic collapse of precipitation, API demonstrates extreme dry.

Tables 4 & 5 illustrate different frequency values of droughts for the SPI & API in the Ainkawa station. For example, the frequency of API is just 9.8% for a timeline of 3 months, whereas the frequency of the SPI in the "normal drought" incidence is (19.7%). This indicates that the former measures this frequency of droughts more often. On the other hand, both have similar values for the 'severe drought' incidence for a period of six months. Similarly, there is a strong relation between the frequency of 'wet condition' for both the 3-month SPI&API. Moreover, in the graph of data for the 3-, 6-, &12-months API, there is a very sharp decline in the amount of rainfall; it depicts that it is a period of extreme droughts.

In **Tables 4 and 5** for Shaqlawa station, different values were recognized for the same drought levels as moderate dry for 3- month SPI indicates the highest frequency 9.1 % but for API was 1.1, while wet conditions were similar for 3-month SPI and API. The Shaqlawa station's SPI and API comparison is illustrated in **Figure 4**, it displays moderate to severe dryness without extreme dry implications. Similarly, the same result has been identified for the 6 months as well. There is moderate wetness in the 19th month to 55th month for a period of 6 months, and 12-month extreme wetness is realized in the 217th month to the 235th month. Additionally, extreme drought is established in the 3-, 6-, and 12- API categories.

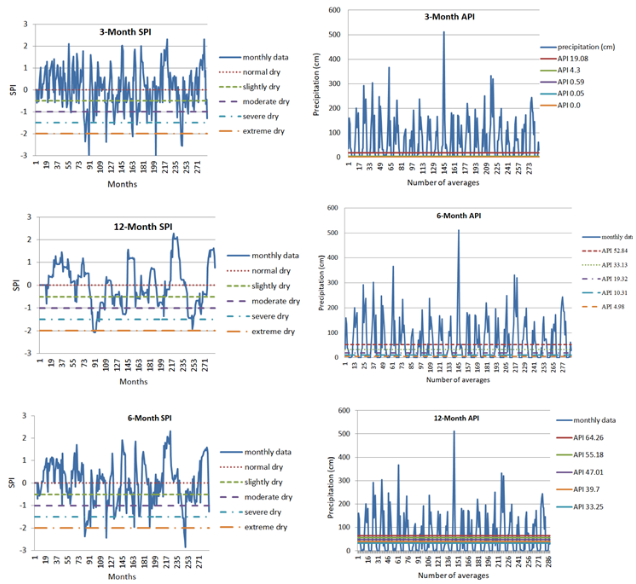


Figure 4. Time series comparison of SPI (top) and API (bottom) for Shaqlawa station for 3-, 6-, and 12-month timescales

Additionally, according to **Table 3,** the high value of API shows wetter weather, while the low value of API indicates drier weather. It has been captured that Shaqlawa has the highest moisture resilience for 3, 6, and 12-month periods and thus shows the highest API values of (408.76, 206.13, and 110.37) cm for 3, 6, and 12 months, respectively. However, Bnaslawa and Koya face the driest conditions. The values of Koya during a three-month dry spell are extremely small (0.26, 0.01, 0.01, and 0.00), including zeros, which means extreme aridity. In the same direction, the 3-month dry spell values of Bnaslawa are very low, amounting to 1.54, 0.17, 0.01, and 0.00. The values of Shaqlawa during a 3-month dry spell were less extreme at 4.30, 0.59, 0.05, and 0.00, as were Ainkawa's values at 2.00, 0.26, 0.02, and 0.00, indicating slightly higher preservation of moisture despite dry spells.

The parameters of the Gamma Distribution are given in **Table 3**. The shape parameter, alpha (α) controls the symmetry of the distribution. The larger α (with Shaqlawa's 12-month α = 11.59) is more symmetrical or Gaussian. The lower α values (for all 3-month series ≈ 0.35) are strongly positively skewed, reflecting the strong positive skewness of a rainfall pattern dominated by many small falls and few high falls. The scale parameter, beta (β) is directly proportional to average precipitation amounting to the specified time scale. The larger scales depict higher average precipitation. Compared to this, Shaqlawa (with 12-month beta = 5.71) and Harir (with 12-month beta = 4.33) have lower scale parameters than Koya (with 12-month beta = 7.48). Nonetheless, actual API values are higher in Shaqlawa and Harir. This implies that while the parameters α and β may be responsible for mean precipitation, the actual high API is probably due to the stronger positive skewness shape of the distribution (with higher alpha values), reflecting stronger 'regular' moisture availability in Shaqlawa.

Furthermore, the data in **Table 4** ranks stations from wettest to driest based on SPI Wet Percentage. For the 3-month SPI, which is most sensitive to seasonal rainfall, the wettest-to-driest order is Koya (55.2%), Ainkawa (54.4%), Shaqlawa (53.8%), Harir (53.3%), and Bnaslawa (51.4%). The 6- and 12-month time scale also shows an increased frequency of "moderate" and "severe" drought categories for most stations. The long-term 6-month SPI ranking shifts to Koya (53.2%), Shaqlawa (51.9%), Ainkawa (50.6%), Harir (50.2%), and Bnaslawa (47.7%). The 3-month data show that "extreme dry" incidents occur more frequently in Ainkawa (3.6%) and Bnaslawa (3.8%). In the 12-month SPI, this is a different order: Harir with 55.4%, Ainkawa with 52.1%, Bnaslawa with 50.5%, Shaqlawa with 48.7%, and Koya with 47.7%. Consequently, Harir emerges as the wettest station overall for the 12-month timescale, while Koya is the driest.

Additionally, From **Table 5**, different trends in drought occurrence appear in the stations. For the 3-month API, the ranking order for the wettest to driest months is as follows: Koya (62.2%), Harir (56.9%), Shaqlawa (56.5%), Bnaslawa (55.8%), and Ainkawa (53.3%). For the 6-month API, the ranking order changes to Koya (42.7%), and Harir (42.4%). The long-term 12-month API order is: Harir (36.1%), Shaqlawa (34.4%), Ainkawa (33.7%), Koya (31.6%), and Bnaslawa (31.5%). Koya shows the strongest short-term rainfall reliability, with the highest API-3 wet frequency of (62.2%) and the lowest "extremely dry" frequency of (20.5%). Harir displays strong short-term data, registering 0% frequency for API-3 "slight dry" and "severe dry," reflecting an "all or nothing" distribution of moisture. In long-term events, Bnaslawa and Shaqlawa display higher frequencies of API-12 "moderate" and "severe" dry periods, reflect their vulnerability to drought. In severity progressive distributions, there are stations such as Ainkawa, which reflect a continuous increase in wet frequency for API-3 of (53.3%), thereafter sharply decreasing in API-6 and API-12, registering "extremely dry" of (52.2%) in the long term. Koya and Harir despite high API-6(42.7%, and 42.4%) wet frequencies, also display elevated extreme-dry values (50.7%, and 50.0%), pointing to inconsistent rainfall. Bnaslawa confirms its status as the driest station at the mid-term scale, with the lowest API-6 wet frequency (38.0%) and the highest SPI-6 normal-dry percentage (37.0%). Consequently, Harir is the wettest overall based on the 12-month API, while Bnaslawa is the driest, ranking last for both 6 and 12-month scales.

4. Conclusions

Following are the key findings of the current study.

1. The research represents a major departure from traditional approaches to drought assessments in the Middle East, as it reveals that the choice of index can profoundly influence spatial and temporal characterizations of water scarcity. The availability of consistent, high-quality precipitation records from the five chosen locations limits the analysis. The robustness of the fitted Gamma distribution parameters and the ensuing index computations would be enhanced by a larger historical dataset (beyond 2000).
2. SPI application in semi-arid or data-scarce regions, such as Erbil, require local validation. The important limitation consists in the fact that SPI characterizes the relative climatic deviation and not the absolute water deficit. As a result, it may smooth out extremes and fail to accurately portray true water availability for critical resource planning. This explains why SPI rankings often differ from those of absolute indices such as the API. Thus, effective drought management needs to balance standardized assessment with real-time water situation on the ground by integrating multiple indices.
3. This comparison of various drought indices implies that the most serious drought risk in this region is not due to extreme short-term events, but rather from moderate-to-severe droughts persisting for a period of 6 to 12 months, which seriously diminishes water supply and agricultural potential. Moreover, the determination of the area's most prone to droughts may be quite different among various drought indices.
4. In line with SPI, it is observed that large-scale drought occurrences are more common in certain regions. "normal dry" and "severe dry" occur in Koya, Shaqlawa, and Harir, based on SPI-12. Of these, Koya is the most prominent region of concern, in that it has an abnormally high frequency of severe, extended drought events. Ainkawa and Bnaslawa have more extreme "dry" events, which are depicted in the shorter-term precipitation index, that is, SPI-3.
5. Utilizing the API – which gives the extent of the deficit of the amount of raw rainfall – presents a different picture altogether. The API reveals that the climate with the highest occurrence of dryness is in the region of Bnaslawa and Shaqlawa. In this regard, Bnaslawa has the highest frequency of dryness.

6. Based on this integration of results, Koya has the worst drought severity vulnerability based on its SPI-12 value, and Bnaslawa has the driest conditions in terms of total drought frequency. In contrast, Harir has high-frequency wet conditions in longer-term indices, and Ainkawa has moderate and stable conditions without intense drought conditions. Shaqlawa has high Rainfall but less frequent wet spells.
7. The implications and interpretations of drought indices to water resource management greatly vary. The study shows that Harir is a reliable site for surface water storage with a lower drought probability. Shaqlawa is a crucial site for reservoir site selection but needs a comprehensive flood management strategy based on its characteristics of frequent episodes of heavy rain. Water resource management in Ainkawa must be done with caution since its vulnerability to drought in the short period exceeds the drought probability indicated by the SPI. The SPI tends to exaggerate drought in Koya. However, the drought probability in Koya is best indicated by the API. Bnaslawa has a high drought probability and therefore needs urgent attention in drought water rationing.
8. This research contributes to existing research on the region (Al-Timimi & Al-Jiboori, 2013; Hameed *et al.*, 2018) by providing additional station-level detail. In this research, the station with the highest long-term drought severity (SPI-12) is Koya, while the station with the highest total drought frequency (API-6) is Bnaslawa. The API thresholds presented herein appear to be a useful tool. The results reinforce the importance of validation of standardized indices, as proposed by Şen & Almazroui (2021) and Topçu.
9. For the parameters of the Gamma distribution, a higher α indicates a more symmetric, less skewed distribution (closer to normal). Lower α indicates high positive skew. While β, related to the mean precipitation. Higher β generally means higher average precipitation for that period.
10. A clear understanding of the correlation between extremes in SPI and API can improve the effectiveness of designs in water resources infrastructure and show that the region's biggest problem is structural water scarcity, not just periodic drought, by showing API, not just SPI.
11. A direct correlation between the extremes of the SPI, which measures meteorological drought, and the API, which measures human demand, reveals that the region's fundamental challenge is one of structural water scarcity. This analysis demonstrates the problem is systemic and permanent, extending beyond temporary rainfall deficits. Consequently, effective and resilient water resources infrastructure must be designed based on this understanding of chronic scarcity, not just on the periodic droughts indicated by SPI alone.
12. The study assists water resource managers and urban planners in making evidence-based recommendations by interpreting the practical implications of different index behaviors for water rationing, water infrastructure planning (e.g., reservoirs), and agriculture planning (e.g., drought-resistant crops).

5. Recommendation

Future research is recommended.

- Taking the evaporative demand into consideration, the SPI and API need to be combined with other indices (SPEI, PDSI, etc.).
- Increase the space and time extent and forecast drought patterns by using climate projections.
- To assess the impact on agriculture and water supply, the API needs to be connected to agriculture/hydrological models.
- To improve the API method, various probability distributions need to be tested.

Supplementary Information

Not contained extra information

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Data Availability

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