2021

Evaluation of Remotely Sensed Precipitation Estimates from the NASA POWER Project for Drought Detection Over Jordan

Muhammad Rasool Al-Kilani

Michel Rahbeh

Jawad Al-Bakri

Tsegaye Tadesse

Cody Knutson

Evaluation of Remotely Sensed Precipitation Estimates from the NASA POWER Project for Drought Detection over Jordan

Muhammad Rasool Al-Kilani,[1] Michel Rahbeh,[1] Jawad Al-Bakri,[1] Tsegaye Tadesse,[2] and Cody Knutson [2]

1 Department of Land, Water and Environment, School of Agriculture, The University of Jordan, Amman 11942, Jordan
2 National Drought Mitigation Center, University of Nebraska-Lincoln, Lincoln, NE 68583, USA

Correspondence — Muhammad Rasool Al-Kilani, rasoolkilani@live.com

Email — Michel Rahbeh, m.rahbeh@ju.edu.jo ; Jawad Al-Bakri, jbakri@ju.edu.jo ; Tsegaye Tadesse, ttadesse2@unl.edu ; Cody Knutson, cknutson1@unl.edu

Abstract
Droughts can cause devastating impacts on water and land resources and therefore monitoring these events forms an integral part of planning. The most common approach for detecting drought events and assessing their intensity is use of the Standardized Precipitation Index (SPI), which requires abundant precipitation records at good spatial distribution. This may restrict SPI usage in many regions around the world, particularly in areas with limited numbers of ground meteorological stations. Therefore, the use of remotely sensed derived data of precipitation can contribute to drought monitoring. In this study, remotely sensed precipitation estimates from

Published in *Earth Systems and Environment* 5 (2021), pp 561–573.
doi:10.1007/s41748-021-00245-2

Submitted 22 February 2021; revised 1 July 2021; accepted: 2 July 2021; published 12 July 2021.

the POWER/Agroclimatology archive of NASA and their derived SPI for different time intervals were evaluated against gauged observations of precipitation from 13 different stations in arid and semiarid locations in Jordan. Results showed significant correlations between remotely sensed and ground data with relatively high *R* values (0.67–0.91), particularly where seasonal precipitation exceeded 50 mm/year. For evaluation of remotely sensed data in SPI calculation, several objective functions were used; the results showed that SPI based on satellite estimates (SAT-SPI) showed good performance in detecting extreme droughts and indicating wet/dry conditions. However, SAT-SPI showed high tendency to overestimate drought intensity. Based on these findings, remotely sensed precipitation from the POWER/Agroclimatology archive showed good potential for use in detecting extreme meteorological drought with the provision of careful interpretation of the data. These types of studies are essential for evaluating the applicability of new drought monitoring information and tools to support decision-making at relevant scales.

Keywords: Remote sensing, SPI, Meteorological drought, NASA POWER project, Agroclimatology

1 Introduction

Drought can be described as a natural, reoccurring and disastrous phenomenon that is an implication of a marked water deficit of various forms (Azimi et al. 2019; Moravec et al. 2019; Wu et al. 2019; Naumann et al. 2018). This phenomenon has accounted for significant financial losses, and remains a main barrier to global food security (Hamal et al. 2020; Kim et al. 2019; Lu et al. 2017; Lesk et al. 2016; Ziolkowska 2016). Therefore, management plans that include preparedness, monitoring and assessment of drought are required to minimize the impacts of drought. Failure of risk evaluation and inadequate management could lead to drought-related disastrous impacts (Wilhite 2000).

Monitoring and assessment of drought require the use of indices (WMO and GWP 2016). Among these indices, the Standardized Precipitation Index (SPI) (McKee et al. 1993) remains the most recommended and popular index for monitoring droughts worldwide because of its reliance on precipitation data only, while many other indices require data on various moisture-related variables (Bayissa et al. 2018; Zhang et al. 2017; Hayes et al., 2011). The SPI simply represents the deviation of precipitation from a long record (usually 30 years) average, and is particularly helpful in that it is standardized; allowing evaluation of drought over different time scales and between different locations (An et al. 2020; Livada and Assimakopoulos 2007). The SPI is frequently used by researchers for assessment and forecast of drought in Jordan, (Mohammad et al. 2018; Shatanawi et al. 2013; Al-Qinna et al. 2011), as well as various regions around the world (e.g., Mengistu et al. 2020; Vicente-Serrano et al. 2020; Cunha et al. 2018; Gidey et al. 2018; Merabti et al. 2018; Yan et al. 2017).

Despite reliance on only precipitation data, using the SPI for drought evaluation may be difficult in many regions due to poor spatial distribution, faulty records or extreme topographic variability, and unreliability resulting from gaps and technical problems (Boluwade 2020; Zhao et al. 2018; Yassin et al. 2016; Overeem et al. 2013). Therefore, researchers have investigated the reliability of satellite remote sensing as an alternative source of meteorological data which, while having its own limitations, provides readily available high-resolution data for the entire globe, and generally for minimal or no cost to the end user. The satellite-based rainfall estimates are acquired by satellites detecting cloud-top properties by visible or infrared imaging. Satellites can also detect the effect of scattering from raindrops on microwave radiation (Sapiano and Arkin 2009). After processing and calibration, the data are interpreted and stored in databases as rainfall estimates (Stackhouse et al. 2017; Sorooshian et al. 2000). The resulting databases are generally termed 'satellite rainfall products'. These products can be available as open access resources. Examples include: the Tropical Rainfall Measuring Mission (TRMM) (Huffman et al. 2007), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) (Sorooshian et al. 2000), Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) (Funk et al. 2014), and African Rainfall Climatology and Time-series (TAR CAT) (Maidment et al. 2014).

Validation of such rainfall products is necessary to ensure its reliability for various applications. TRMM was reasonably correlated with ground precipitation gauges from different locations in China (Zhao et al. 2018; Yang et al. 2017). Bayissa et al. (2017) assessed spatial and temporal drought pattern in Ethiopia by comparing precipitation data from 10 different weather stations with corresponding rainfall estimates from CHIRPS and TAR CAT v2.0. The latter study reported that precipitation data from the rainfall products showed good correlation with gauge observations in general, but this was not the case for the PERSIANN rainfall product. TRMM and CHIRPS was also tested for application in hydrological modeling (Abdelmoneim et al. 2020).

Another database for satellite-based estimates of precipitation is NASA's Prediction of Worldwide Energy Resource (POWER) project. The POWER project is gaining popularity as a source for weather data input (Duarte and Sentelhas 2020; Monteiro et al. 2018; Bai et al. 2010). It contains precipitation estimates since 1981, which is sufficient for analysis of drought, provided that the source data is validated. Previous works validated the agreement between precipitation estimates and ground truth values (Adler et al. 2003; McPhee and Margulis 2005). However, at the time of these validations the database had not accumulated enough data for SPI determination. Also, the mentioned validations were based not on drought monitoring but on the error and agreement with ground truth. A more recent research study that examined climatic data from NASA's POWER database was conducted by de Aguiar and Junior (2020); the study compared it with data from various ground stations in Brazil and reported that remotely sensed rainfall showed good correlation (0.75–0.95) with ground measured values for most locations. However, the reliability of SPI determined from the POWER platform is yet to be evaluated.

The objective of this study is to examine the use of remotely sensed precipitation estimates from NASA's POWER/Agroclimatology archive for detecting meteorological drought, using gauge observations from various stations in Jordan as reference. This study specifically aims to determine the extent of usefulness of this data source for determining the SPI subject to several objective functions. The main criteria for evaluating this data are based on its ability to help achieve one of the following levels of accuracy; (1) correctly determining SPI category (as an indicator to correct detection of drought intensity), (2) detecting extremely wet or dry conditions, and (3) detecting wet and dry conditions regardless of category or intensity. The selection of Jordan as the study area stems from the fact that it suffers from water scarcity and increased frequency of drought that affects the Middle East and North Africa (MENA) region (Cook et al. 2016). In Jordan, droughts severity increased during 1970–2005 from normal to extreme levels with frequent non-uniform drought periods in an irregular repetitive manner (Al-Qinna et al. 2011; Al-Bakri et al. 2017; Shatanawi et al. 2013).

Future climate projections showed that adverse and extreme climate changes would occur on the form of declined precipitation and increased air temperature (Al-Bakri et al. 2021). Therefore, the use of accurate data for monitoring and assessment of drought will contribute to Jordan's effort in managing its scarce water resources (MWI 2018). Furthermore, the heterogeneity of topography and rainfall distribution in Jordan makes it advantageous for validating remotely sensed rainfall estimates against gauged observations.

2 Methodology

2.1 Study Area and Selected Gauged Observations

Jordan is located to the east of the Mediterranean between 29.18° and 33.37° N latitude and between 34.32° and 39.30° E longitude (**Fig. 1**). Most of the country's area (89.5 thousand km^2) is arid and receives less than 200 mm annual rainfall, while potential evaporation exceeds 2000 mm. Precipitation varies by latitude, longitude and altitude where it decreases from north to south, west to east and from higher altitudes to lower ones. Average rainfall ranges from 600 mm/year in the northwest to less than 50 mm/year in the south and the east. The rainy season is between October and May with 80% of the annual rainfall occurring between December and March. During the rainy season, most of the precipitation is orographic resulting from the passage of frontal depressions across the Mediterranean near Cyprus.

Drought is a serious threat to food and water resources in Jordan. Frequent droughts in the last three decades resulted in the failure of rainfed agriculture during dry seasons (Mohammad et al. 2018). The main rainfed crops that are impacted by droughts include olives and wheat in the high rainfall zones and barley in the low rainfall zones. In addition to rainfed agriculture, droughts have serious impacts on the already scarce surface and groundwater resources utilized for both municipal and irrigation purposes. Therefore, detection of droughts in the different rainfall zones is important for agricultural, water and environmental sectors. Subsequently, the study included different stations representing the different rainfall zones in the country. Gauged observations, acquired from Jordan Meteorological

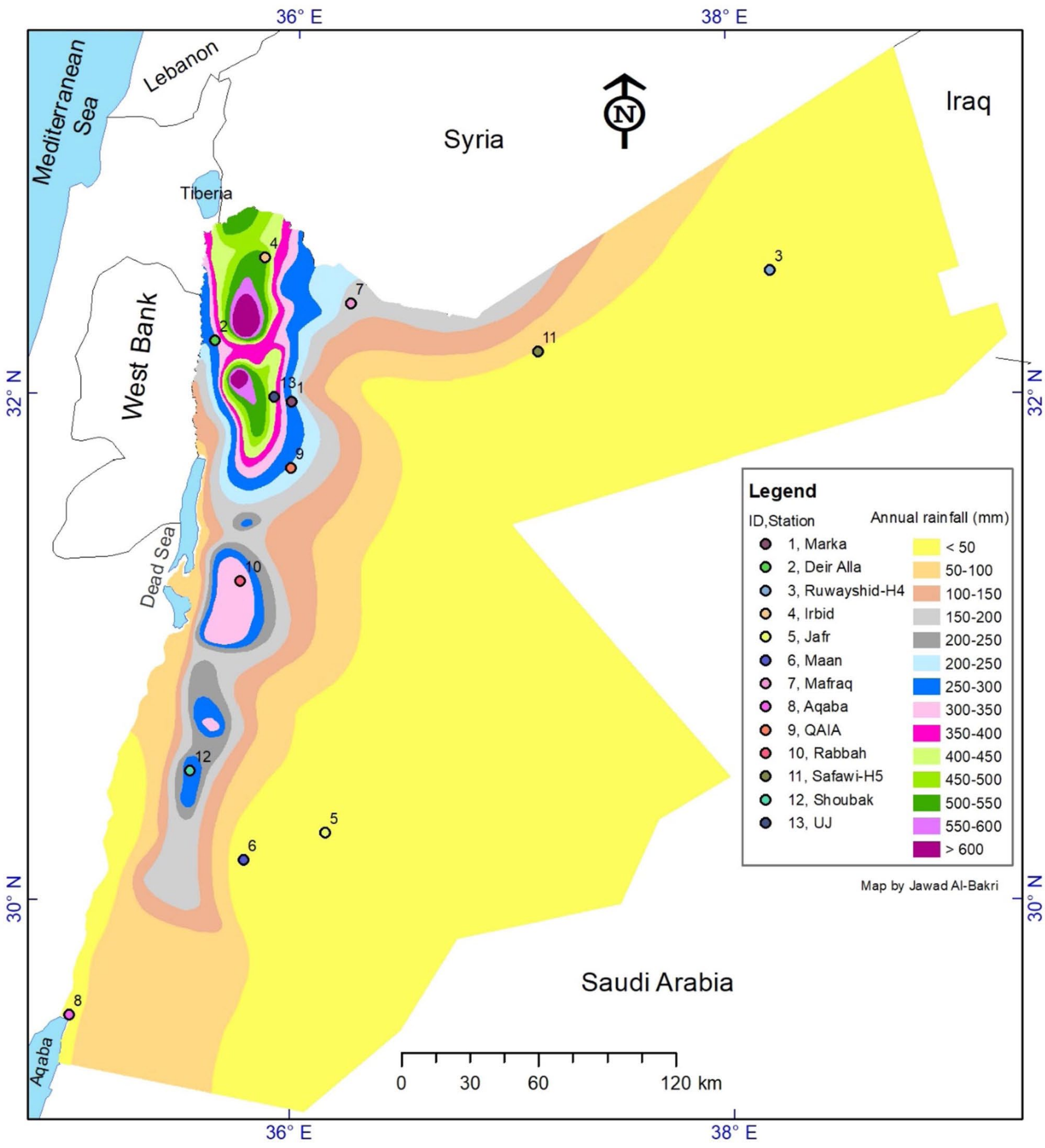

Fig. 1 Locations of ground stations that provided precipitation observations included in the study. **QAIA* Queen Alia International Airport, *UJ* University of Jordan. (Map created using ArcGIS)

Department (JMD), included 13 different stations characterized by data continuity among the 26 operating stations of the JMD. The stations were characterized by variations in monthly and annual rainfall, reflecting the different agro-climatological zones in Jordan. Satellite estimations of precipitation were acquired specifically for the coordinates of those stations. Precipitation records analyzed in this study were obtained for the period Jan 1981–Jan 2019 for both ground stations and satellite estimations.

For the purposes of this study, gauged observations were used as a ground truth determination of actual precipitation, and SPI values calculated from these data, hereafter referred to as GO-SPI, were regarded as true representation of meteorological drought events for each location, for which satellite estimations and their SPI values (SAT-SPI) were compared against. This is common practice in similar studies despite uncertainty from gauged observations' representativeness of actual precipitation (Mossad and Alazba 2018; Tapiador et al. 2012).

2.2 Satellite-Based Estimations

The methodology behind estimating and validating the precipitation data provided in the POWER/Agroclimatology archive can be summarized as follows: precipitation data is obtained from the satellite-gauge product of The Global Precipitation Climate Project (GPCP v2.1), this source relies on a special sensor/microwave imager (0.5° by 0.5°) which provides the precipitation fractional occurrence, and GPCP satellite-gauge combination data which provide monthly precipitation accumulations as scaling constraints. The latter is applied to algorithms used in estimating values of precipitation from several resources including a geosynchronous- orbit IR, a low-orbit IR, and an atmospheric infrared sounder (Stackhouse et al. 2015, 2017). The POWER/Agroclimatology archive can be accessed from https://power.larc.nasa.gov/ using the platform's data access viewer.

2.3 Data Analysis

In this study, the SPI values were calculated based on ground observations and satellite estimates and compared to evaluate the reliability of the latter for detecting meteorological drought at different time scales. The most common approach for calculating the SPI is by fitting the precipitation frequency distribution to the gamma probability density function (Suliman et al. 2020; Hajar et al. 2019). To calculate SPI for a specific duration (e.g., Jan, Jan–March, Oct–May), the incomplete gamma cumulative probability should be determined for that event, which can be done using the GAMMA. DIST function (cumulative) in Microsoft Excel. To use this function, the shape (α) and scale (β) parameters need to be estimated for a preceding record, preferably ≥ 30 years, which can be done using Eqs. 1, 2 and 3 (McKee et al. 1993; Thom 1958):

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

$$A = \ln(\bar{x}) - \frac{\sum \ln(x)}{n} \tag{2}$$

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

where $\bar{x}$ is the arithmetic mean for the precipitation data series, x is the precipitation data point (e.g., January rainfall of a given year for a 1-month Jan SPI) and n is the number of precipitation data points.

When $x = 0$, the gamma function G(x) is not defined, and so Eq. (4) is used to calculate the cumulative probability function $H(x)$ that accounts for zero precipitation probability (q) (Hajar et al. 2019; Rahman and Dawood 2018; Chang et al. 2016). The value of (q) represents the probability of having zero precipitation in the preceding record.

$$H(x) = q + (1 - q) * G(x) \tag{4}$$

Finally, $H(x)$ values can be converted to an SPI value using the NORM.INV function in MS Excel. The mathematical formulas for computation of the SPI can be found in Lloyd-Hughes and Saunders (2002). Drought categories assigned based on SPI ranges in this study are described in **Table 1.**

Standardized precipitation index in this study was calculated at 1-month (1SPI), 3-month (3SPI), 6-month (6SPI), and 12-month (12SPI)

Table 1 Categories assigned to SPI values in this study **(**Zhang et al. 2009; McKee et al. 1993**)**

SPI value	*Category*
≥ 2	Extremely wet
1.5 to 1.99	Severely wet
1 to 1.49	Moderately wet
0.99 to −0.99*	Near normal
−1 to −1.49	Moderate drought
−1.5 to −1.99	Severe drought
≤ −2	Extreme drought

*Some sources interpret values within this range as mildly wet or mild drought depending on the sign (Lloyd-Hughes and Saunders 2002)

scales. The 6SPIs were calculated in the ranges of Oct–Mar ($6SPI_{Oct}$) and Nov–Apr ($6SPI_{Nov}$), and their analysis is presented separately in the following sections. The SPI values were calculated for the period 2011–2019, based on precipitation records extending from Jan 1981 until the time for which the SPI was determined; for example, the 12SPI for 2015 was based on annual precipitation for the years 1981–2015, the same approach was followed for both SAT-SPI and GO-SPI values. The reason why SPI was not determined for 2010 and earlier is because each SPI value requires at least 30 years of previous records, and the NASA platform only provides data starting from 1981.

The correlation between observed precipitation and satellite estimates was determined using the PEARSON function in MS Excel, and to gain insight on the difference between SAT-SPI and GO-SPI, Mean Absolute Error (MAE) was used (Eq. 5).

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - x_i | \tag{5}$$

where y_i is the gauged precipitation and x_i is the satellite estimation for the same location and time i.

The objective functions used to evaluate SAT-SPI against GO-SPI in this study included: (1) correct detection of drought category (CDC), which represents the percentage of events at which both SPIs showed values that fall within the same SPI category (a proxy for correct detection of drought intensity), (2) correct detection of extreme wet/dry conditions, which specifically evaluates the ability of SAT-SPI to report extremely wet or dry conditions (SPI < −2 or SPI > 2), and (3) correct detection of wet/dry conditions regardless of category (correct detection of intensity is ignored), this test only shows the percentage of times that both SPIs showed the same sign (±), or when both were close to zero.

3 Results

3.1 Agreement Between Precipitation Sources

A summary of precipitation records reported by ground gauges and the satellite estimations between 1981 and 2019 is presented in **Table 2**. The summary only includes data for the period Oct–Apr as outside this period the records are dominated by zero precipitation events. Excluding non-rainy periods from examination is not uncommon in precipitation analysis (Driouech et al. 2009). An overview on analysis of zero inflated continuous data series can be found in Liu et al. (2019).

Table 2 shows that there exists high precipitation variability in the study area, both spatially and temporally, which was both reflected by ground observations and satellite estimations. The correlation between gauged observations and satellite estimations was generally high (0.67–0.91), except for three locations (Aqaba, Jafr, and Maan), which is most likely due to very low seasonal precipitation in those locations (< 50 mm/year). Low seasonal precipitation contributes to error not only from satellite source, but also from rain gauges (Tapiador et al. 2012). When excluding locations where seasonal rainfall is below 50 mm, the overall average correlation would be 0.84. These locations are excluded from further analysis because when precipitation is very low even the driest of conditions will be recorded as 'Near Normal', due to the long term average precipitation being close to zero. This is why some researchers may describe it as unreliable at short scale in very arid climates (Saada and Abu-Romman 2017; Svoboda et al. 2012).

Table 2 Summary statistics for precipitation records from ground stations- and the satellite-based POWER/Agroclimatology archive

Location/ station	Annual average (mm)[a]	Lat	Lon	Altitude (m)	Monthly precipitation (mm)[b] Ground gauges Mean	Ground gauges SD	Satellite estimates Mean	Satellite estimates SD	Correlation coefficient R^c	RMSE[c]
Marka	249.4	31.97	35.99	790	34.84	37.04	31.92	29.26	0.91	16.48
Deir Alla	279.2	32.20	35.62	−224	38.37	39.59	41.30	36.67	0.89	18.18
Ruwayshid-H4	80.4	32.54	38.20	683	10.88	13.16	8.88	9.48	0.85	7.43
Irbid	458.9	32.55	35.85	616	60.12	61.52	46.12	40.56	0.91	33.00
Jafr	32.4	30.28	36.15	865	4.25	8.96	8.80	9.27	0.30	11.72
Maan	41.7	30.12	35.75	1069	5.50	8.18	13.90	13.98	0.50	14.77
Mafraq	150.6	32.36	36.25	686	20.87	20.46	26.95	23.44	0.86	13.24
Aqaba	25.8	29.55	35.00	51	3.42	6.64	8.84	11.07	0.48	11.17
QAIA[d]	153.4	31.73	36.01	722	21.19	22.89	24.18	22.50	0.88	11.35
Rabbah	330.8	31.27	35.75	920	45.74	50.36	26.21	25.06	0.82	38.53
Safawi-H5	69.2	32.20	37.13	674	9.49	11.52	11.27	9.81	0.72	8.36
Shoubak	250.4	30.52	35.53	1365	34.50	40.62	21.98	22.60	0.67	32.83
UJ[e]	479.8	32.01	35.87	992	66.23	72.22	41.30	36.67	0.90	49.18

a. Based on record coverage 1981–2019
b. Analysis excluded months that were dominated by zero precipitation events (May–Sep)
c. Based on analysis of monthly precipitation from ground- and remote sensing-based sources
d. Queen Alia International Airport
e. University of Jordan

3.2 Detection of Drought Category

While satellite precipitation estimates correlated well with gauged observations, this does not mean that it would be perfectly useful for SPI determination. For example, **Fig. 2** shows that GO-SPI and SAT-SPI can be consistently coherent, yet at various points the SAT-SPI falls within a different category from that of GO-SPI (see Table 1). This means that these data would not always reflect the correct drought intensity. Therefore, due to the nature of the way the SPI values are interpreted, the CDC test was devised to evaluate the SAT-SPI reliability for detecting the correct drought intensity.

Analytical results from the CDC test (**Fig. 3**) show that satellite precipitation estimates generally had a 50–80% chance of detecting the correct SPI category, and thus had a considerable chance of reflecting the true drought intensity. However, there seems to be high variability between different time scales and different locations.

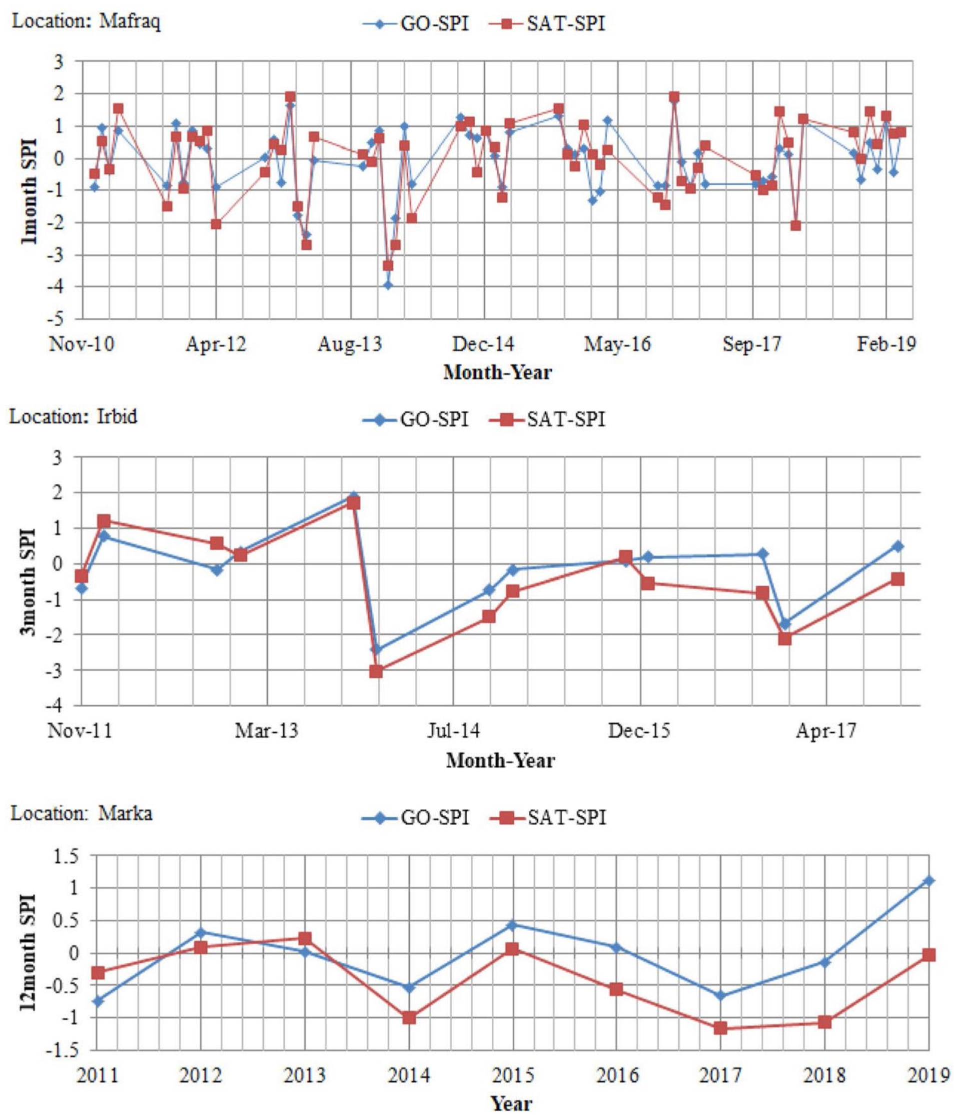

Fig. 2 Agreement between ground- (GO) and satellite- (SAT) based SPI at different time scales and locations. (This is discrete data; lines between data points are only intended to clarify trends)

In some cases CDC was high, for example, SAT-SPI at QAIA showed high CDC values (~ 89%) at 3-, 6- and 12-month scales, and showed moderate success in other locations such as Marka (55–82%), Mafraq (63–78%) and Safawi (56–78%). Further details on analytical results obtained at different stations are provided in the supplementary data.

As mentioned previously, the SAT-SPI could only deviate slightly from GO-SPI and yet fall within a different category. Therefore, to

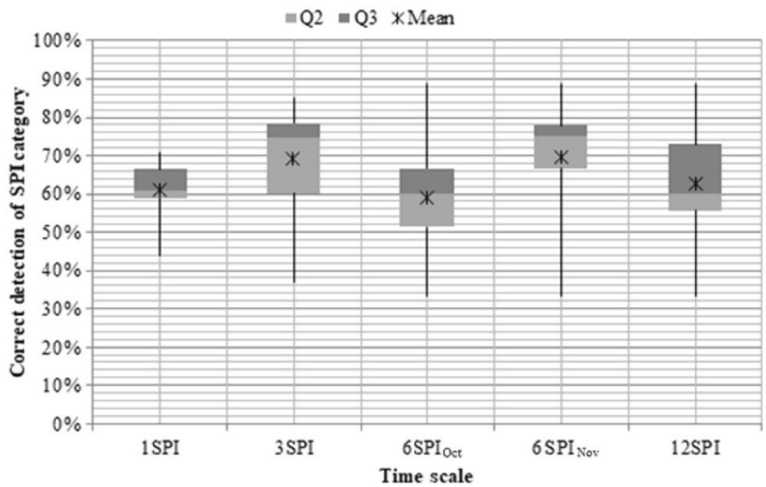

Fig. 3 Percentages of events for which the satellite-based SPI detected the correct SPI category between 2011 and 2019 in Jordan at 1-, 3-, 6- and 12-month scales (each data point in a box plot represents an average for the entire period at a given location)

have a better understanding of just how far the SAT-SPI deviates from GO-SPI, MAE (Eq. 5) was determined for all stations at different time scales (**Fig. 4**).

Analysis of MAE shows that a shorter-scale SPI (1 month) generally showed less error and less variability, thus theoretically has a better chance of predicting the correct drought intensity; but this is not clearly reflected by analysis of CDC (Fig. 3).

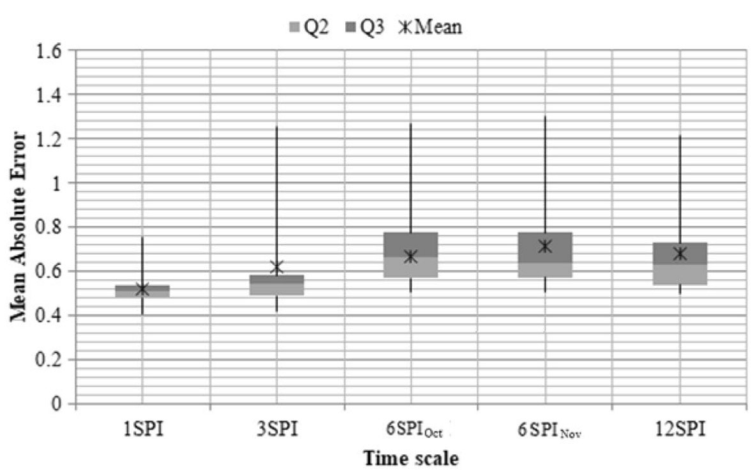

Fig. 4 The Mean Absolute Error (MAE) between satellite-based and ground-based SPI values between 2011 and 2019 in Jordan at 1-, 3-, 6- and 12-month scales (each data point in a box plot represents MAE for the entire period at a given location)

3.3 Detection of Extreme Wet/Dry Conditions

Extremely wet and extreme drought conditions are terms assigned to events at which SPI values deviate by over two standard deviations from normal conditions (0 SPI) either to the positive (extremely wet: SPI ≥ 2) or to the negative (extreme drought: SPI ≤ − 2). In this section, we evaluate the reliability of SAT-SPI to report extreme wetness (SPI ≥ 2) or extreme drought (SPI ≤ − 2) when such intensities are reported by the GO-SPI, disregarding events with lesser intensities. The purpose behind this approach is to not dismiss the precipitation estimates data based only on CDC analysis, i.e., if the error was mostly generated from moderate events, but the satellite precipitation estimates could help detect extreme events, then this gives it merit for potential usefulness where no direct measurements exist. These particular intensities (extremely wet and extreme drought) were analyzed specifically as they would have the most impact on agriculture, ground water, reservoir levels, stream flow, among other factors that are of great importance in planning (Dikici 2020; Zhao et al. 2018; Khan et al. 2008).

Table 3 shows the extreme droughts detected at 1-, 3-, 6- and 12-month scales. As shown in Table 3, the majority of extreme droughts were detected at 1- and 3-month scales in the study area; this was reflected by both GO-SPI and SAT-SPI..At 1-, 6-, and 12-month scales, the SAT-SPI reported 100% of all extreme droughts detected by the GO-SPI for the corresponding time scales. However, at the 3-month scale, there were two extreme droughts detected by

Table 3 Performance of satellite-based (SAT) SPI in reporting extreme drought events detected by ground-based (GO) SPI at 1-, 3-, 6- and 12-month scales

Time scale	*1SPI*	*3SPI*	*$6SPI_{Oct}$*	*$6SPI_{Nov}$*	*12SPI*	*Overall*
Number of extreme droughts detected by GO-SPI	18.00	4.00	1.00	1.00	1.00	25.00
Number of extreme droughts reported by SAT-SPI	45.00	6.00	2.00	4.00	1.00	58.00
Valid detections of extreme droughts by SAT-SPI	18.00	2.00	1.00	1.00	1.00	23.00
Extreme droughts missed by SAT-SPI	0.00	2.00	0.00	0.00	0.00	2.00
Invalid detection of extreme droughts by SAT-SPI	27.00	4.00	1.00	3.00	0.00	35.00
Percentage of valid extreme droughts detected by SAT-SPI	100.00%	50.00%	100.00%	100.00%	100.00%	92.00%
Percentage of false extreme droughts reported by SAT-SPI	60.00%	66.67%	50.00%	75.00%	0.00%	60.34%
Percentage of missed extreme droughts by SAT-SPI	0.00%	50.00%	0.00%	0.00%	0.00%	8.00%

GO-SPI, but reported as mild or severe droughts by SAT-SPI, these both took place in the same location which was at the H4 station. This station is located in Ruwayshid, Northern Jordan and receives minimal precipitation compared to the other stations examined in this analysis (Table 2), which can explain this error. Percentage summaries shown in Table 3, such as percentages for valid and false detections of extreme events by SAT-SPI, were calculated using Eqs. (6, 7 and 8):

$$\text{SAT-VEED\%} = \frac{\text{Valid detections of extreme events by SAT SPI}}{\text{Number of extreme events detected by GO SPI}} \times 100\% \quad (6)$$

$$\text{SAT-FEED\%} = \frac{\text{Invalid detection of extreme events by SAT SPI}}{\text{Total number of extreme events reported by SAT SPI}} \times 100\% \quad (7)$$

$$\text{SAT-MEED\%} = \frac{\text{Number of extreme events missed by SAT SPI}}{\text{Number of extreme events detected by GO SPI}} \times 100\% \quad (8)$$

where 'SAT-VEED%' is percentage of valid extreme events detected by SAT-SPI, SAT-FEED% is percentage of false extreme events reported by SAT-SPI, and SAT-MEED% is percentage of missed extreme events by SAT-SPI.

Table 4 shows the detection of extremely wet conditions. Out of 8 extremely wet events detected by GO-1SPI, only 2 were correctly detected by SAT-1SPI, which also reported 8 other extremely wet events that were overestimated (detected between 0 and 1.99 by GO-SPI).

Longer time scales generally detected no extremely wet events, except for a single event detected by GO-6SPI, which was missed by the SAT-6SPI. Generally, there was an underestimation of extremely wet events, or overestimations of events within the 0–1.99 SPI range. The percentage summaries shown in Table 4 were also calculated using Eqs. (6, 7 and 8).

The general performance of SAT-SPI for detecting extreme meteorological droughts and wet events in this study is summarized in **Fig. 5**.

Table 4 Performance of satellite-based (SAT) SPI in reporting extremely wet events detected by ground-based (GO) SPI at 1-, 3-, 6- and 12-month scales

Time scale	*1SPI*	*3SPI*	*6SPI$_{Oct}$*	*6SPI$_{Nov}$*	*12SPI*	*Overall*
Number of extremely wet events based on GO-SPI	8	0.00	1.00	0.00	0.00	9.00
Number of extreme wet events reported by SAT-SPI	10	0.00	1.00	1.00	2.00	14.00
Valid detections of extremely wet events by SAT-SPI	2	0.00	0.00	0.00	0.00	2.00
Extremely wet events missed by SAT-SPI	6	0.00	1.00	0.00	0.00	7.00
Invalid detection of extreme wet events by SAT-SPI	8	0.00	1.00	1.00	2.00	12.00
Percentage of valid extreme wet events detected by SAT-SPI	25.00%	NA	0.00%	NA	NA	22.22%
Percentage of false extreme wet events reported by SAT-SPI	80.00%	NA	100.00%	100.00%	100.00%	85.71%
Percent of missed extreme wet events by SAT-SPI	75.00%	NA	100.00%	NA	NA	77.78%

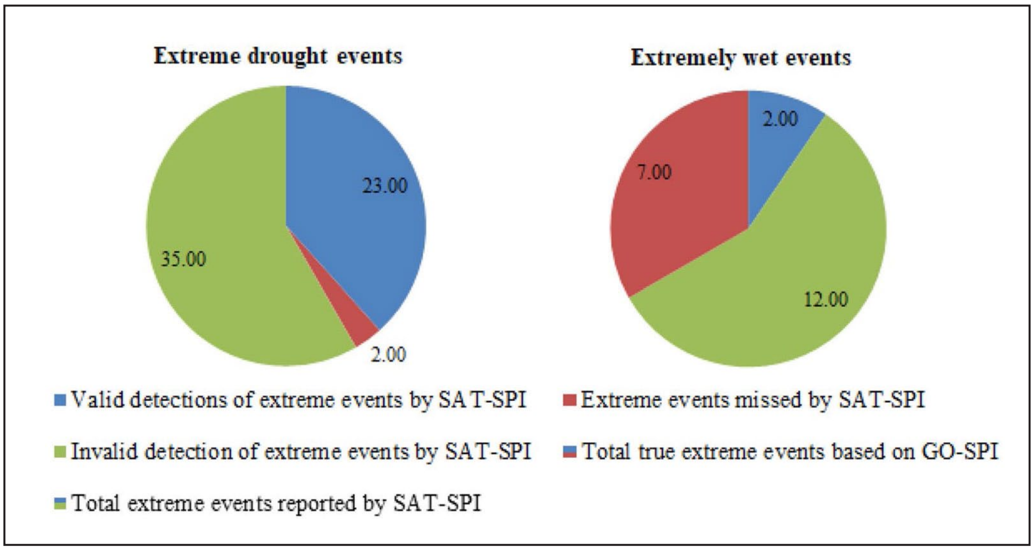

Fig. 5 Extreme meteorological events detected by ground-based (GO) and satellite-based (SAT) SPI values

3.4 Detection of Wet and Dry Conditions

This analysis focuses only on the agreement between signs of SAT-SPI and GO-SPI. A correct detection in this analysis is reported in the following situations: (1) when both SAT-SPI and GO-SPI report positive values for the same event, (2) when both report a negative value for the same event, or when both values are close to zero (±0.5) regardless of sign. While if SAT-SPI and GO-SPI report different signs, this is considered a false detection, unless both values are close to zero.

The logic behind considering near-zero events as correct detections regardless of sign, is that when SAT-SPI can correctly indicate that a condition is very close to normal (zero), then this is a good predictor of the general condition, and the sign of the SPI should not matter in this particular case. The logic structure for evaluating general wet/dry conditions is described in Eq. 9:

$$IF \begin{cases} |SAT\ SPI| \ \ AND \ \ |GO\ SPI| < 0.5, & TRUE \\ SAT\ SPI \ \ AND \ \ GO\ SPI > 0, & TRUE \\ SAT\ SPI \ \ AND \ \ GO\ SPI < 0, & TRUE \\ ELSE, & FALSE. \end{cases} \tag{9}$$

The purpose of this test is to determine the reliability of satellite precipitation estimates in detecting the general meteorological condition, more specifically to which direction the precipitation deviates from normal conditions.

The results of analysis for this objective function (**Fig. 6**) show that SAT-SPI generally showed good accuracy in reporting the correct wet/dry condition.

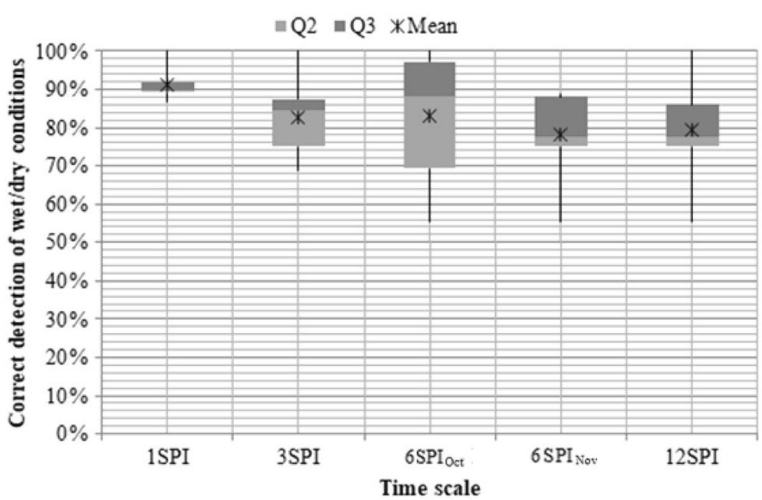

Fig. 6 Percentages of events for which the satellite-based SPI showed correct detection of wet/dry conditions between 2011 and 2019 in Jordan at 1-, 3-, 6- and 12-month scales (each data point in a box plot represents an average for the entire period at a given location)

4 Discussion

4.1 Reliability of Detection

Correlation values reported in this study are within range of those reported for locations with much higher seasonal precipitation by previous researchers that evaluated the NASA/POWER project (de Aguiar and Junior 2020). This could be attributed to the platform's records being calibrated and validated based on data from different regions with different climatic conditions (Stackhouse et al. 2015, 2017; McPhee and Margulis 2005; Adler et al. 2003). However, validating the derived SPI values is still needed in similarly different climatic and topographic regions.

It is possible to consider MAE analysis to be more suitable for assessment, since SAT-SPI and GO-SPI values reporting near normal conditions ($-1 < \text{SPI} < 1$) for the same events could reflect high error, yet show correct detection of category (e.g., SAT-SPI = −0.9 and GO-SPI = 0.9), this can be common in arid regions (Fig. 2). And thus, based on MAE, it is suggested that satellite estimations of precipitation had a better chance of detecting drought intensity at shorter time scales rather than longer time scales in this study.

These findings are very relevant to the applications of remotely sensed precipitation; a shorter time scale SPI is more relevant for agricultural applications and reflects soil moisture changes, while longer scales are more relevant to hydrological impacts such as changes in ground water levels and stream flows (Zhao et al. 2018). Although it could be argued that better accuracy at shorter time scales can be problematic since SPI could be less reliable at shorter time scales in arid regions (Saada and Abu-Romman 2017; Svoboda et al. 2012), but not necessarily if we are only interested in impacts of drought on agriculture (Hazaymeh 2016; Labudova et al. 2017).

Based on the findings reported, it is suggested that while SAT-SPI has a considerable chance in reporting the correct drought category, it is not highly reliable for general use in detecting drought intensity. The results indicated that the 1-month scale showed less variability and higher ability to detect general meteorological conditions; thus, correlation between satellite estimates and gauged precipitation does not necessarily reflect their reliability for detecting meteorological drought.

It is noteworthy that the majority of extreme droughts were detected at 1- and 3-month scale. A higher frequency of droughts at shorter time scales in Jordan was previously reported by Mustafa and Rahman (2018). There seems to be a clear advantage and a disadvantage with regards to detecting extreme droughts by SAT-SPI; as it showed high accuracy in reporting extreme droughts that were detected by GO-SPI, but showed high tendency for invalid detections or “false alarms” (60% of droughts reported as ‘extreme’ by SAT-SPI, were detected as mild or severe droughts by GO-SPI). Despite a high probability of falsely detecting extreme droughts, and inability to detect extreme wetness, it can be argued that the minimal risk of missing extreme droughts gives merit to satellite estimates’ usefulness where gauged meteorological data is insufficient.

With regard to detection of extremely wet conditions, the SAT-SPI was found to be unreliable in this study. This finding could relate to results reported by McPhee and Margulis (2005) who attempted to validate the GPCP data (source of precipitation estimates in the POWER/ Agroclimatology archive). They reported less agreement between the satellite estimations and ground truth values in areas of humid conditions.

4.2 Future Prospects

The objective functions used in this study for evaluating satellite estimations showed considerable insight on its potential usefulness. Due to the spatial and temporal abundance of satellite precipitation estimates, we should not only use basic analysis, as this would result in dismissing a possibly valuable source of data or overstating its potential usefulness. For example, CDC analysis showed that SAT-SPI was not very reliable for indicating drought intensity; however, further analysis showed that it may be useful for indicating other information. For example, results showed that extreme droughts can be detected using the satellite estimations, but with a high risk of false warnings. Also, the general wet/ dry conditions may also be indicated but without intensity.

However, there are reasons to be cautious in generalizing these findings to other regions, such as the possible error in gauged measurements (Tapiador et al. 2012), the region-specific effects that may contribute to errors in satellite estimations (Sun et al. 2018), and the limited number of long-scale major events in the analyzed record in this study (i.e., long-scale extreme wetness and extreme droughts). Due to these sources of uncertainty, analysis on longer records and wider ranges of climatic and topographic regions may show different outcomes or provide a more holistic understanding. Such research efforts are valuable and should be pursued in the future. This has potential future prospects, not only where direct measurements are lacking, but also for many other regions; the API provided in the NASA/POWER platform could allow for many utilizations such as internet of things (IOT) applications, online warning systems and decision support tools, at almost no cost. This justifies further research for evaluating this platform on wider temporal and spatial scales.

Also, the findings in this study focus only on the precipitation component of drought; this can be highly relevant to surrounding regions where decreased precipitation is projected, such as Syria (Homsi et al. 2020). However, recent studies from surrounding areas also reported that crop water availability in general is showing a decreasing trend (Salman et al. 2020); this highlights the importance of accounting for other components of water availability, such as evapotranspiration (ET). The significance of incorporating other climatic parameters is also evident from research works such as Shiru et al. (2020), which showed that, along with precipitation, changes in temperature would also have a considerable effect on drought patterns. These findings highlight an important future aspect in this research area, which is evaluation of the NASA/POWER archive for indices that account for ET, such as the standardized precipitation evapotranspiration index (SPEI). This is quite possible due to an abundance of weather variables available in the NASA/POWER archive, including those that relate to components of atmospheric ET demand. However, this would require an in-depth evaluation of the individual components of ET supplied by the platform (e.g., temperature, wind speed, solar radiation, etc.), and the availability of high quality estimations or measurements of ET. Such efforts are particularly justified in arid regions where ET is a major component of drought.

For future research efforts on the NASA/POWER platform, we recommend adopting approaches that also evaluate the extent of usefulness, rather than simple correlation and validation studies. As shown in this study, simply because remotely sensed data shows good "agreement" with gauged observations, this does not necessarily mean that such data should be used liberally as an alternative source for SPI determination, but it is important to understand the extent of usefulness of such data, and the restrictions on interpreting its results. This is more of a concern because software products are commonly used for SPI calculation and interpretation. For example, some R studio packages for SPI calculation show colored indicators for different SPI categories, making it more of qualitative rather than a quantitative description of meteorological drought intensity, such approaches may not be suitable when working with alternative sources that estimate precipitation rather than directly measure it. To make the best of the spatial and temporal abundance of satellite precipitation estimates, it is important to interpret results from such data with caution and understand its limitations.

5 Conclusions

Monitoring of meteorological drought is a crucial task, for which the SPI is most commonly used. This requires access to spatially and temporally abundant precipitation records. Remotely sensed precipitation from the POWER/ Agroclimatology archive by NASA provides such data for the entire globe. In this study, the reliability of this data source for detecting meteorological drought in Jordan using the SPI was evaluated. The evaluation was based on a framework that includes three criteria: prediction of correct SPI category, detection of extreme wet or dry conditions, and detection of wet/dry conditions regardless of intensity. The findings of this study strongly suggest that the POWER/ Agroclimatology archive can be useful in detecting extreme droughts but tends to overestimate the intensity of moderate, mild and severe droughts, and showed good performance in detecting general meteorological conditions (wet/dry regardless of intensity). However, the evaluated data source was not found very efficient in detecting the correct SPI category, and showed very poor performance in detecting extremely wet conditions. It was further noted that at the 1-month scale, SAT-SPI generally showed better agreement with GO-SPI than at longer timescales, suggesting better usability in agricultural rather than hydrological applications. The proposed framework shows good potential for determining the extent of usefulness of the remotely sensed precipitation record in drought monitoring, but further work in a wider range of climatic and topographic regions is needed to confirm the platform's robustness.

Supplementary Information — Appendix 1: Analytical results for agreement between Satellite based and ground measured SPIs at specific stations examined in this study is presented following the **References**.

Acknowledgments Remotely sensed data used in this study were obtained from the NASA Langley Research Center (LaRC) POWER Project funded through the NASA Earth Science/Applied Science Program. The authors extend their gratitude to the NASA LaRC team for their technical assistance and to the Jordanian Department of Meteorology for providing the gauged precipitation records needed for the completion of this work.

Funding This research did not receive any direct funding from government sectors, non-government organizations or otherwise.

Conflict of Interest The authors declare that no conflict of interests exists.

References

Abdelmoneim H, Soliman MR, Moghazy HM (2020) Evaluation of TRMM 3B42V7 and CHIRPS satellite precipitation products as an input for hydrological model over Eastern Nile Basin. Earth Syst Environ 4:685–698

Adler RF, Huffman GJ, Chang A, Ferraro R, Xie PP, Janowiak J, Nelkin E (2003) The version-2 global precipitation climatology project (GPCP) monthly precipitation analysis (1979–present). J Hydrometeorol 4(6):1147–1167

Al-Bakri JT, Al-Khreisat A, Shawash S, Qaryouti E, Saba M (2017) Assessment of remote sensing indices for drought monitoring in Jordan. Asian J Geoinformatics 17(3):1–13

Al-Bakri J, Farhan I, Al-Qinna M, Al-Karablieh E, Bergouli K, McDonnell R (2021) Assessment of climate changes and their impact on barley yield in Mediterranean environment using NEXGDDP Downscaled GCMs and DSSAT. Earth Syst Environ. https://doi.org/10.1007/s41748-021-00238-1

Al-Qinna MI, Hammouri NA, Obeidat MM, Ahmad FY (2011) Drought analysis in Jordan under current and future climates. Clim Change 106(3):421–440

An Q, He H, Gao J, Nie Q, Cui Y, Wei C, Xie X (2020) Analysis of temporal-spatial variation characteristics of drought: a case study from Xinjiang, China. Water 12(3):741

Azimi S, Moghaddam MA, Monfared SH (2019) Analysis of drought recurrence conditions using first-order reliability method. Int J Environ Sci Technol 16(8):4471–4482

Bai J, Chen X, Dobermann A, Yang H, Cassman KG, Zhang F (2010) Evaluation of NASA satellite-and model-derived weather data for simulation of maize yield potential in China. Agron J 102(1):9–16

Bayissa Y, Tadesse T, Demisse G, Shiferaw A (2017) Evaluation of satellite-based rainfall estimates and application to monitor meteorological drought for the Upper Blue Nile Basin, Ethiopia. Remote Sensing 9(7):669. http://digitalcommons.unl.edu/droughtfacpub/123

Bayissa Y, Maskey S, Tadesse T, Van Andel SJ, Moges S, Van Griensven A, Solomatine D (2018) Comparison of the performance of six drought indices in characterizing historical drought for the upper Blue Nile basin, Ethiopia. Geosciences 8(3):81. http://digitalcommons.unl.edu/droughtfacpub/137

Boluwade A (2020) Spatial-temporal assessment of satellite-based rainfall estimates in different precipitation regimes in water-scarce and data-sparse regions. Atmosphere 11(9):901

Chang J, Li Y, Ren Y, Wang Y (2016) Assessment of precipitation and drought variability in the Weihe River Basin, China. Arab J Geosci 9(14):1–16

Cook BI, Anchukaitis KJ, Touchan R, Meko DM, Cook ER (2016) Spatiotemporal drought variability in the Mediterranean over the last 900 years. J Geophys Res Atmos 121(5):2060–2074

Cunha APM, Tomasella J, Ribeiro-Neto GG, Brown M, Garcia SR, Brito SB, Carvalho MA (2018) Changes in the spatial–temporal patterns of droughts in the Brazilian Northeast. Atmos Sci Lett 19(10):e855

de Aguiar JT, Junior ML (2020) Reliability and discrepancies of rainfall and temperatures from remote sensing and Brazilian ground weather stations. Remote Sens Appl Soc Environ 18:100301

Dikici M (2020) Drought analysis with different indices for the Asi Basin (Turkey). Sci Rep (nature Publisher Group) 10(1):20739

Driouech F, Deque M, Mokssit A (2009) Numerical simulation of the probability distribution function of precipitation over Morocco. Clim Dyn 32(7–8):1055–1063

Duarte YC, Sentelhas PC (2020) NASA/POWER and DailyGridded weather datasets—how good they are for estimating maize yields in Brazil? Int J Biometeorol 64(3):319–329

Funk CC, Peterson PJ, Landsfeld MF, Pedreros DH, Verdin JP, Rowland JD, Romero BE, Husak GJ, Michaelsen JC, Verdin AP (2014) A quasi-global precipitation time series for drought monitoring. US Geol Survey Data Series 832(4):1–12

Gidey E, Dikinya O, Sebego R, Segosebe E, Zenebe A (2018) Modeling the spatio-temporal meteorological drought characteristics using the standardized precipitation index (SPI) in Raya and its environs, northern Ethiopia. Earth Syst Environ 2(2):281–292

Hajar HAA, Murad YZ, Shatanawi KM, Al-Smadi BM, Hajar YAA (2019) Drought assessment and monitoring in Jordan using the standardized precipitation index. Arab J Geosci 12(14):1–12

Hamal K, Sharma S, Khadka N, Haile GG, Joshi BB, Xu T, Dawadi B (2020) Assessment of drought impacts on crop yields across Nepal during 1987–2017. Meteorol Appl 27(5):1950

Hayes M, Svoboda M, Wall N, Widhalm M (2011) The Lincoln declaration on drought indices: universal meteorological drought index recommended. Bull Am Meteor Soc 92(4):485–488. http://digitalcommons.unl.edu/droughtfacpub/14

Hazaymeh K (2016) Development of a remote sensing-based agriculture monitoring drought index and its application over semi-arid region, Doctoral dissertation, University of Calgary, Calgary, Canada. Retrieved from https://prism.ucalgary.ca/

Homsi R, Shiru MS, Shahid S, Ismail T, Harun SB, Al-Ansari N, Yaseen ZM (2020) Precipitation projection using a CMIP5 GCM ensemble model: a regional investigation of Syria. Eng Appl Comput Fluid Mech 14(1):90–106

Huffman GJ, Bolvin DT, Nelkin EJ, Wolff DB, Adler RF, Gu G, Hong Y, Bowman KP, Stocker EF (2007) The TRMM multisatellite precipitation analysis (TMPA): quasi-global, multiyear, combined-sensor precipitation estimates at fine scales. J Hydrometeorol 8(1):38–55

Khan S, Gabriel HF, Rana T (2008) Standard precipitation index to track drought and assess impact of rainfall on water tables in irrigation areas. Irrig Drain Syst 22(2):159–177

Kim W, Iizumi T, Nishimori M (2019) Global patterns of crop production losses associated with droughts from 1983 to 2009. J Appl Meteorol Climatol 58(6):1233–1244

Labudova L, Labuda M, Takač J (2017) Comparison of SPI and SPEI applicability for drought impact assessment on crop production in the Danubian Lowland and the East Slovakian Lowland. Theoret Appl Climatol 128(1–2):491–506

Lesk C, Rowhani P, Ramankutty N (2016) Influence of extreme weather disasters on global crop production. Nature 529(7584):84–87

Liu L, Shih YCT, Strawderman RL, Zhang D, Johnson BA, Chai H (2019) Statistical analysis of zero-inflated nonnegative continuous data: a review. Stat Sci 34(2):253–279

Livada I, Assimakopoulos VD (2007) Spatial and temporal analysis of drought in Greece using the Standardized Precipitation Index (SPI). Theoret Appl Climatol 89(3–4):143–153

Lloyd-Hughes B, Saunders MA (2002) A drought climatology for Europe. Int J Climatol 22(13):1571–1592

Lu J, Carbone GJ, Gao P (2017) Detrending crop yield data for spatial visualization of drought impacts in the United States, 1895–2014. Agric Meteorol 237:196–208

Maidment RI, Grimes D, Allan RP, Tarnavsky E, Stringer M, Hewison T, Roebeling R, Black E (2014) The 30 year TAMSAT African rainfall climatology and time series (TAR CAT) data set. J Geophys Res: Atmos 119(18):10–619

McKee TB, Doesken NJ, Kleist J (1993, January) The relationship of drought frequency and duration to time scales. In Proceedings of the 8th Conference on Applied Climatology 17(22):179–183

McPhee J, Margulis SA (2005) Validation and error characterization of the GPCP-1DD precipitation product over the contiguous United States. J Hydrometeorol 6(4):441–459

Mengistu AG, Tesfuhuney WA, Woyessa YE, Rensburg LDV (2020) Analysis of the spatio-temporal variability of precipitation and drought intensity in an arid catchment in South Africa. Climate 8(6):70

Merabti A, Martins DS, Meddi M, Pereira LS (2018) Spatial and time variability of drought based on SPI and RDI with various time scales. Water Resour Manage 32(3):1087–1100

Ministry of Water and Irrigation, Jordan (MWI) (2018) Water Sector Policy for Drought Management, Ministry of Water and Irrigation, Amman, Jordan

Mohammad AH, Jung HC, Odeh T, Bhuiyan C, Hussein H (2018) Understanding the impact of droughts in the Yarmouk Basin, Jordan: monitoring droughts through meteorological and hydrological drought indices. Arab J Geosci 11(5):103

Monteiro LA, Sentelhas PC, Pedra GU (2018) Assessment of NASA/POWER satellite-based weather system for Brazilian conditions and its impact on sugarcane yield simulation. Int J Climatol 38(3):1571–1581

Moravec V, Markonis Y, Rakovec O, Kumar R, Hanel M (2019) A 250- year European drought inventory derived from ensemble hydrologic modeling. Geophys Res Lett 46(11):5909–5917

Mossad A, Alazba AA (2018) Determination and prediction of standardized precipitation index (SPI) using TRMM data in arid ecosystems. Arab J Geosci 11(6):1–16

Mustafa A, Rahman G (2018) Assessing the spatio-temporal variability of meteorological drought in Jordan. Earth Syst Environ 2(2):247–264

Naumann G, Alfieri L, Wyser K, Mentaschi L, Betts RA, Carrao H, Spinoni J, Vogt J, Feyen L (2018) Global changes in drought conditions under different levels of warming. Geophys Res Lett 45(7):3285–3296

Overeem A, Leijnse H, Uijlenhoet R (2013) Country-wide rainfall maps from cellular communication networks. Proc Natl Acad Sci 110(8):2741–2745

Rahman G, Dawood M (2018) Spatial and temporal variation of rainfall and drought in Khyber Pakhtunkhwa Province of Pakistan during 1971–2015. Arab J Geosci 11(3):1–13

Saada N, Abu-Romman A (2017) Multi-site modeling and simulation of the standardized precipitation index (SPI) in Jordan. J Hydrol: Reg Stud 14:83–91

Salman SA, Shahid S, Afan HA, Shiru MS, Al-Ansari N, Yaseen ZM (2020) Changes in climatic water availability and crop water demand for Iraq region. Sustainability 12(8):3437

Sapiano MRP, Arkin PA (2009) An intercomparison and validation of high-resolution satellite precipitation estimates with 3-hourly gauge data. J Hydrometeorol 10(1):149–166

Shatanawi K, Rahbeh M, Shatanawi M (2013) Characterizing, monitoring and forecasting of drought in Jordan River Basin. J Water Resour Prot 5(12):1192–1202

Shiru MS, Shahid S, Dewan A, Chung ES, Alias N, Ahmed K, Hassan QK (2020) Projection of meteorological droughts in Nigeria during growing seasons under climate change scenarios. Sci Rep 10(1):1–18

Sorooshian S, Hsu KL, Gao X, Gupta HV, Imam B, Braithwaite D (2000) Evaluation of PERSIANN system satellite-based estimates of tropical rainfall. Bull Am Meteor Soc 81(9):2035–2046

Stackhouse PW Jr, Westberg D, Hoell JM, Chandler WS, Zhang T (2015) Prediction of worldwide energy resource (POWER)–agroclimatology methodology, Version 1.0.2. The National Aeronautics and Space Administration, Washington, DC

Stackhouse PW Jr, Westberg D, Hoell JM, Chandler WS, Zhang T (2017) Prediction of worldwide energy resource (POWER)–agroclimatology methodology, Version 1.1.0. The National Aeronautics and Space Administration, Washington, DC

Suliman AHA, Awchi TA, Al-Mola M, Shahid S (2020) Evaluation of remotely sensed precipitation sources for drought assessment in Semi-Arid Iraq. Atmos Res 242:105007

Sun Q, Miao C, Duan Q, Ashouri H, Sorooshian S, Hsu KL (2018) A review of global precipitation data sets: data sources, estimation, and intercomparisons. Rev Geophys 56(1):79–107

Svoboda M, Hayes M, Wood D (2012) Standardized precipitation index user guide. Switzerland, World Meteorological Organization Geneva, p 900

Tapiador FJ, Turk FJ, Petersen W, Hou AY, Garcia-Ortega E, Machado LA, De Castro M (2012) Global precipitation measurement: methods, datasets and applications. Atmos Res 104:70–97

Thom HC (1958) A note on the gamma distribution. Mon Weather Rev 86(4):117–122

Vicente-Serrano SM, Dominguez-Castro F, Murphy C, Hannaford J, Reig F, Pena-Angulo D, Tramblay Y, Trigo RM, Mac Donald N, Luna MY, McCarthy M (2020) Long-term variability and trends in meteorological droughts in Western Europe (1851–2018). Int J Climatol. https://doi.org/10.1002/joc.6719

Wilhite DA (2000) Chapter 1 drought as a natural hazard: concepts and definitions, in Drought: A Global Assessment, Vol. I, edited by Donald A. Wilhite, chap. 1, pp. 3–18 (London: Routledge, 2000). https://digitalcommons.unl.edu/droughtfacpub/69

World Meteorological Organization and Global Water Partnership (WMO and GWP), Svoboda M, Fuchs BA (2016) Handbook of drought indicators and indices. Integrated Drought Management Programme (IDMP), Integrated Drought Management Tools and Guidelines Series 2. Geneva

Wu J, Li M, Yuan J, Zhu X, He Z (2019) Climate change 2007: the physical science basis. Working Group I Contribution to the Fourth Assessment Report of the IPCC. Cancer Lett 449:449

Yan Z, Zhang Y, Zhou Z, Han N (2017) The spatio-temporal variability of droughts using the standardized precipitation index in Yunnan, China. Nat Hazards 88(2):1023–1042

Yang N, Zhang K, Hong Y, Zhao Q, Huang Q, Xu Y, Xue X, Chen S (2017) Evaluation of the TRMM multisatellite precipitation analysis and its applicability in supporting reservoir operation and water resources management in Hanjiang basin, China. J Hydrol 549:313–325

Yassin MA, Alazba AA, Mattar MA (2016) Artificial neural networks versus gene expression programming for estimating reference evapotranspiration in arid climate. Agric Water Manag 163:110–124

Zhang Q, Xu CY, Zhang Z (2009) Observed changes of drought/wetness episodes in the Pearl River basin, China, using the standardized precipitation index and aridity index. Theoret Appl Climatol 98(1):89–99

Zhang L, Jiao W, Zhang H, Huang C, Tong Q (2017) Studying drought phenomena in the Continental United States in 2011 and 2012 using various drought indices. Remote Sens Environ 190:96–106

Zhao Q, Chen Q, Jiao M, Wu P, Gao X, Ma M, Hong Y (2018) The temporal-spatial characteristics of drought in the Loess Plateau using the remote-sensed TRMM precipitation data from 1998 to 2014. Remote Sens 10(6):838

Ziolkowska JR (2016) Socio-economic implications of drought in the agricultural sector and the state economy. Economies 4(3):19

Appendix 1 follows.

Evaluation of remotely sensed precipitation estimates from the NASA POWER project for drought detection over Jordan

Muhammad Rasool Al-Kilani[1*], Michel Rahbeh[1], Jawad Al-Bakri[1], Tsegaye Tadesse[2],

Cody Knutson[2]

[1] Department of Land, Water and Environment, School of Agriculture, The University of Jordan, P.O. Box 11942, Amman 11942, Jordan.

[2] National Drought Mitigation Center, University of Nebraska-Lincoln, Lincoln, NE 68583 USA

*Corresponding author: Muhammad Rasool Al-Kilani (rasoolkilani@live.com)

Supplementary material

Appendix 1: Analytical results for agreement between Satellite based and ground measured SPIs at specific stations examined in this study

Scale	**Obj.Func***	**Marka**	**Deir Alla**	**H4**	**Irbid**	**Mafraq**	**QAIA**	**Rabbah**	**Safawi**	**Shoubak**	**UJ**
1Month SPI	MAE	0.48	0.51	0.55	0.41	0.50	0.47	0.51	0.54	0.75	0.51
	CDC	66.9%	58.9%	59.5%	65.3%	68.3%	70.6%	58.9%	61.9%	44.0%	55.4%
	wet/dry	91.7%	89.3%	86.7%	100.0%	90.0%	96.7%	91.7%	90.0%	86.7%	89.3%
3Month SPI	MAE	0.48	0.51	0.86	0.54	0.55	0.48	0.57	0.59	1.26	0.42
	CDC	81.5%	75.0%	59.3%	76.2%	63.0%	85.2%	59.3%	74.1%	37.0%	79.2%
	wet/dry	87.5%	93.3%	75.0%	69.2%	81.3%	87.5%	87.5%	68.8%	75.0%	100.0%
6 month SPI Oct	MAE	0.50	0.63	0.89	0.54	0.59	0.46	0.73	0.69	1.21	0.45
	CDC	55.6%	50.0%	33.3%	57.1%	66.7%	88.9%	66.7%	77.8%	33.3%	62.5%
	wet/dry	100.0%	100.0%	55.6%	100.0%	88.9%	88.9%	66.7%	77.8%	66.7%	87.5%
6Month SPI Nov	MAE	0.57	0.66	0.78	0.54	0.62	0.51	0.76	0.85	1.30	0.58
	CDC	77.8%	75.0%	77.8%	57.1%	77.8%	88.9%	66.7%	66.7%	33.3%	75.0%
	wet/dry	88.9%	75.0%	55.6%	85.7%	88.9%	77.8%	88.9%	77.8%	66.7%	75.0%
12Month SPI	MAE	0.55	0.66	0.71	0.54	0.61	0.50	0.77	0.73	1.22	0.50
	CDC	55.6%	62.5%	66.7%	57.1%	77.8%	88.9%	55.6%	55.6%	33.3%	75.0%
	wet/dry	77.8%	75.0%	55.6%	100.0%	100.0%	77.8%	88.9%	77.8%	66.7%	75.0%

*MAE: Mean Absolute Error, CDC: Correct detection of drought category, wet/dry: correct detection of wet/dry conditions regardless of category