Spatiotemporal assessment of meteorological drought using satellite-based precipitation data over Iraq

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Abstract. Iraq is a semi-arid country, which suffers the impact of recurrent droughts. However, studies related to the characterization of drought and risk evaluation in Iraq are scarce due to the lack of accurate climatic datasets. The present work seeks to examine the feasibility of utilizing Precipitation Data based on Remotely Sensed information from satellites (PDRS) in Iraq to monitor droughts. Two monthly PDRS are collected, namely CHIRPS for the period 1983-2016, and TRMM for the period 1998-2017 were used to calculate the Standardized Precipitation Index (SPI) for various timescales (SPI-3, SPI-6, and SPI-12) of different climate zones in the region. The findings obtained have been checked using data from sparsely scattered ground meteorological stations (GS). Although the PDRS was found to be capable of capturing estimated precipitation by GS data at different climatic zone, the two PDRS products demonstrated different responses to GS data. While the TRMM revealed a strong correlation for the droughts estimated with GS data, the CHIRPS data showed a milder correlation with the GS data. Besides, good consistency was observed in the time series of SPIs calculated with GS and PDRS data. Overall, the TRMM was found to measure the dry classes more accurately while CHIRPS was found to be better at various dry and wet classes in Temporal Coincidence (TC) terms. In addition, the TRMM – SPI data showed a better correlation in detecting the drought characteristics for Z-I and Z-II, however, the CHIRPS revealed a stronger correlation for Z-III. The findings suggested the suitability of TRMM precipitation for drought analysis and monitoring in Iraq Zones I and II, and the use of CHIRPS precipitation data for Z-III.

Keywords: TRMM, CHIRPS, Meteorological drought, Remote sensing, SPI

1. Introduction
One of the most important problems facing people in many regions of the world is the drought phenomenon [1]. It may be defined as a period of oddly dry weather adequately extended to the lack of water to cause significant hydrologic disproportion in the affected area [2]. The intensity of the drought is related to the level of moisture shortage, the drought duration, and the extent of the area dominated by the drought [3].

Global warming phenomena and climate change are the principal cause of drought events. The relation between drought and climate change is therefore quite complex [4]. Climate change is continuously increasing the frequency and severity of the drought phenomenon in several regions of the world [1]. The risk of flooding as well as droughts is increased with a warmer climate and increasing climate variability [5]. Lately, many research works around the world have studied the drought phenomenon and they related it to the climate change phenomenon [6].

Iraq, among the middle east countries, is expected to suffer from frequent, long and severe drought events in the future due to climate change [1] [7][8][9][10]. So, it is essential to improve tools and techniques to study and monitor the different drought characteristics.

To evaluate drought characteristics, adequate climatological data are needed. However, most of the developing countries have a deficiency in these data, collecting long-term meteorological data from ground stations is a real problem for many reasons [1]. To assess drought characteristics, scientists developed tools to identify the set on, termination, spatial extent and severity of a drought. They are
useful in evolving drought strategies, monitoring systems, mitigation policies and preparedness plans, which are called drought indices [11].

The Precipitation Data based on Remotely Sensed information from satellites (PDRS) can be used in developing countries, which often do not have accurate meteorological data, for tracking and assessing drought due to its ability to cover wider areas and escape geographical influences. While data from ground stations are generally more reliable and existing for longer periods, PDRS can be utilized as an alternate source of rainfall data to help hydrologists manage climate change issues [12].

Some satellite-derived data sets are recently available for users, including the TRMM Multi-satellite Precipitation Analysis (TMPA), Global Satellite Mapping of Precipitation (GSMaP), Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS), Tropical Rainfall Measuring Mission (TRMM), the Climate Prediction Center (CPC) morphing technique (CMORPH) products and the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN)[13].

Several studies have evaluated TRMM and CHIRPS against in situ station data sets in many regions of the globe. [14] evaluated the performance of CHIRPS with gauge measurements at multi-time scales (monthly, seasonally and annually) at Haihe River Basin, China, for drought monitoring using the SPI. Results indicate that the best performances were achieved at multiple temporal scales. [15] evaluated TRMM and CHIRPS data sets to drive the SWAT model. They reported that CHIRPS and TRMM data revealed a good exploit on rainfall determination in the Lower Lancang-Mekong River Basin, with the better performance of TRMM product. [16] evaluated the accuracy of two satellite data sets (CHIRPS) and (CHIRP) in the Koshi basin of Nepal according to ground-based measurements. Both products used to calculate the SPI. They found that the rainfall estimates from both data sets were quite comparable to ground station data. [17] used the TRMM and CHIRPS for precipitation estimations and compared them with ground station rainfall records of the Minas region, Brazil. Their results indicated that both products overestimate rainfall. Generally, the CHIRPS data revealed a pattern similar to the ground-station data. [18] used TRMM precipitation for drought monitoring in the USA and found that it performed reasonably well in arid areas. [19] adopted TRMM for drought evaluation in Indonesia. TRMM was found acceptable for monitoring droughts in China as stated by [12][20].

Iraq is one of the developing countries, which is suffering from a deficiency in the extent and quality of ground stations’ climatological data. To the best of the researcher’s knowledge, no efforts have been adopted to examine the performance of both CHIRPS and TRMM for drought evaluation in Iraq. Therefore, this study judges CHIRPS and TRMM as alternative precipitation data based on remotely sensed information for SPI calculations and drought assessment over Iraq.

2. Study Area

Current work regards the whole area of Iraq as a case study within its international borders. It has a surface area of 438,320 km². Iraq lies between latitudes 29° 15` to 38° 15` N and longitudes 38° 45` to 48° 45` E [10]. It is categorized according to various climatic classifications. The topography of Iraq varies from mountainous land in the north to desert land in the western part, plains in the middle and east, and swamplands in the south (see Figure 1). The country includes the rivers Tigris and Euphrates covering the great alluvial plain of Mesopotamia [21]. According to the climate classification provided by Köppen, Iraqi land can be partitioned into three main zones as shown in Figure 1. The first zone (Z-I) is a cold semi-arid climate (BSk) located in the northern part of Iraq that has cool weather. The second zone (Z-II) is a warm semi-arid climate (BSh) located south of Z-I with wet uplands. The third zone (Z-III) is classified as a warm desert climate (BWh) [1]. To examine PDRS, precipitation datasets from 22 meteorological Ground Stations (GS) scattered within the study area (Figure 1) were gathered from Meteorological Organization and Seismology Department-Iraq for the period 1983 to 2017 (Table 1). For each station, the data were tested for missing values and outliers, and these gaps were filled using data from adjacent stations.
3. Remotely Sensed Datasets

In addition to the GS datasets, two types of PDRS were considered: The first is the Tropical Rainfall Measuring Mission (TRMM3B43-Version-7), which is available freely at https://trmm.gsfc.nasa.gov. TRMM3B43 data blends NOAA (National Oceanic and Atmospheric Administration) and GPCC (Global Weather Climatology Centre) weather data sets, and it is revised. It includes monthly data calculated from daily versions of TRMM3B42, derived from the TMPA datasets of the Tropical Multi-satellite Precipitation Analysis system [22]. Satellite remote sensors Precipitation Radar (PR) and Microwave Imager (MI) are used to produce data of this type of precipitation [23]. TRMM data sets had a resolution of 0.25° x 0.25° and covered the whole study area. In the current research, monthly TRMM3B43V7 datasets for each GS station were extracted from 1998 to 2017. The second PDRS was the InfraRed Precipitation with Stations Party on Climate Hazards (CHIRPS), which is rather a new rainfall product based on multiple data sources.

The advantage of CHIRPS calculations is the high 0.05°x0.05° spatial resolution, which is supposed to capture more reflective characteristics of precipitation [24]. Further, CHIRPS data include time series of precipitation from 1981 until the near present, allowing for long-term hydrological study and simulation. For this analysis, monthly CHIRPS data sets were obtained from www.chrsdata.eng.uci.edu for every GS from January 1983 to December 2016 along with TRMM for SPI calculations and comparisons.

4. Methods

4.1. Calculation of Standard Precipitation Index

[25] first created the Standardized Precipitation Index (SPI) for the tracking and evaluation of drought in Colorado, USA. SPI is based on historical precipitation data (at least thirty years of records) and its probabilities are calculated at various time scales [26]. This allows SPI to be versatile for short and long term spatial and temporal monitoring of drought characteristics of drought applications. To build time scales of SPI-1, SPI-3, SPI-6, SPI-12, and SPI-24; 1, 3, 6, 12 or 24 months of observed precipitation records are used. The SPI values can range from -3 (dry conditions) to + 3 (wet conditions), and its severity has been categorized into different classes as shown in Table 2 [25].
To have normally distributed SPI, precipitation records need to be transformed into a Gamma probability distribution. To calculate the SPI, the difference of the rainfall depth from its mean for a particular time scale is estimated then divided by its standard deviation.

\[ SPI = \frac{x_i - \bar{x}}{\sigma} \]  

(1)

where

- \( x_i \) = Rainfall depth of a certain period during the \( i \)th interval;
- \( \bar{x} \) and \( \sigma \) = Rainfall mean and standard deviation of the selected period.

Originally, [25] utilized an incomplete gamma distribution to estimate SPI. A long-term data record is needed to estimate the probability distribution function by fitting a function to the data. Then the accumulation distribution is transformed to a normal distribution with a zero mean and unit standard deviation [27].

In this analysis, 22 meteorological stations (Table 1) based data of CHIRPS and TRMM were used to derive SPI. It has been widely implemented in many regions around the world for the monitoring of drought [9][12][23][28][29][30]. For Iraq, SPI values were estimated on 3 separate time scales (SPI-3, SPI-6, and SPI-12) over 35 years. The adopted time scales are appropriate for monitoring and tracking the impact of droughts on surface water resources and hydrology [30]. Smaller and larger time scales can be considered for agricultural issues and for streamflow and reservoir levels, respectively, [31]. It is reported that inadequate results are anticipated when considering shorter time scales due to lack of precipitation in arid and semi-arid regions [2]. The mean formulation of SPI stated by [12] was adopted in this study of general drought representation in each zone in accordance with Köppen's climate classification scheme, as shown in the following equation:

\[ SPI_{\text{mean}} = \sum_0^n SPI_{i,t} \]  

(2)

where \( SPI_{\text{mean}} \) denotes the mean SPI of the zone at time \( t \), \( i \) denotes the GS station, and \( n \) is the number of ground stations in each zone.

4.2. Statistical Tests

Several statistical indices were used in this analysis to equate PDRS to monthly GS data sets at station locations as well as spatial zones. The Pearson’s Coefficient of Correlation (r), Mean Error (ME), Relative Mean Absolute Error (RMAE), Root Mean Square Error (RMSE), and Bias (BIAS) was used to examine PDRS for potential monitoring of drought. The values of (r) from -1 to 1 were used to assess PDRS against GS. ME, as indicated in (mm), ranged from -∞ (PDRS underestimation) to ∞ (PDRS overestimation) and the ideal RE is nil. RMAE, RMSE, and RE were used to measure the absolute, square, and mean root mean error in mm, with values varying from ∞ to perfect zero. BIAS measured over and underestimation from 0 to ∞ with a perfect BIAS of one. The following equations describe those indices:

\[ r = \frac{\sum_{i=1}^n (G_i - \bar{G})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^n (G_i - \bar{G})^2 \sum_{i=1}^n (S_i - \bar{S})^2}} \]  

(3)

\[ ME = \frac{1}{n} \sum_{i=1}^n (S_i - G_i) \]  

(4)

\[ RMAE = \frac{1}{n} \cdot \frac{\sum_{i=1}^n |S_i - G_i|}{\bar{G}} \]  

(5)
\[ \text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (S_i - G_i)^2} \]  
(6)

\[ \text{BIAS} = \frac{\sum_{i=1}^{n} S_i}{\sum_{i=1}^{n} G_i} \]  
(7)

where, \( G, \tilde{G}, S, \) and \( \tilde{S} \) represents the GS and PDRS sets and their average values, respectively.

### Table 1. Salient characteristics of precipitation data set for the involved stations

| ID | Station    | Zone | Symbol | Elevation m | Longitude | Latitude | Min. annual rainfall mm | Max. annual rainfall mm | Mean annual rainfall mm | Annual Standard deviation mm |
|----|------------|------|--------|-------------|-----------|----------|--------------------------|-------------------------|--------------------------|-------------------------------|
| 1  | Duhok      | Z-I  | S15    | 536         | 43°00'    | 36°50'   | 215.9                    | 1162.25                 | 554.82                   | 180.23                       |
| 2  | Erbil      | Z-I  | S16    | 426         | 44°20'    | 36°11'   | 182.4                    | 859.78                  | 416.27                   | 133.71                       |
| 3  | Sulaymaniyah | Z-I  | S17    | 853         | 45°27'    | 35°33'   | 230.1                    | 1252.2                  | 702.8                    | 187.97                       |
| 4  | Dukan      | Z-I  | S21    | 490         | 44°57'    | 35°57'   | 230.3                    | 1358.4                  | 714.32                   | 241.5                        |
| 5  | Khanaqin   | Z-I  | S3     | 202.2      | 45°26'    | 34°18'   | 89.7                     | 464.4                   | 292.16                   | 95.58                        |
| 6  | Baiji      | Z-I  | S12    | 115         | 43°29'    | 34°55'   | 16.72                    | 418.2                   | 182.37                   | 81.22                        |
| 7  | Mosul      | Z-I  | S14    | 223         | 43°09'    | 36°19'   | 97.7                     | 709.2                   | 351.67                   | 116.75                       |
| 8  | Kirkuk     | Z-II | S18    | 330.8      | 44°24'    | 35°28'   | 112.81                   | 694.1                   | 349.22                   | 126.32                       |
| 9  | Tel-Afer   | Z-II | S19    | 200         | 42°29'    | 36°22'   | 98.1                     | 683                     | 307.87                   | 111.93                       |
| 10 | Sinjar     | Z-II | S20    | 538         | 41°50'    | 36°19'   | 102.3                    | 780                     | 352.09                   | 132.69                       |
| 11 | Darbandikan | Z-II | S22    | 400         | 45°45'    | 35°08'   | 222.8                    | 1068.7                  | 649.58                   | 205.26                       |
| 12 | Qaim       | Z-II | S1     | 178         | 41°10'    | 34°23'   | 41.1                     | 273                     | 118.26                   | 57.14                        |
| 13 | Ramadi     | Z-II | S2     | 48          | 43°19'    | 33°27'   | 22.56                    | 264.8                   | 108.3                    | 51.32                        |
| 14 | Samawa     | Z-II | S4     | 6           | 45°16'    | 31°18'   | 17                      | 281.7                   | 96.12                    | 57.05                        |
| 15 | Hilla      | Z-II | S5     | 25          | 44°26'    | 32°11'   | 15.90                    | 226.4                   | 99.55                    | 51.06                        |
| 16 | Nekheb     | Z-II | S6     | 305         | 42°15'    | 32°02'   | 13.5                    | 205.1                   | 74.56                    | 44.37                        |
| 17 | Hai        | Z-III| S7     | 14.9        | 46°03'    | 32°10'   | 18.9                    | 272.3                   | 135.8                    | 61.54                        |
| 18 | Nasiriya   | Z-III| S8     | 3           | 46°14'    | 31°05'   | 34.8                    | 307.8                   | 121.29                   | 56.10                        |
| 19 | Basra      | Z-III| S9     | 2.4         | 47°43'    | 30°34'   | 43.9                    | 296.2                   | 133.14                   | 60.2                         |
| 20 | Hadithah   | Z-III| S10    | 140         | 42°22'    | 34°04'   | 39.98                   | 342.4                   | 119.93                   | 63.6                         |
| 21 | Baghdad    | Z-III| S11    | 3           | 44°14'    | 33°14'   | 29.3                    | 307.7                   | 123.78                   | 63.51                        |
| 22 | Ruthba     | Z-III| S13    | 615.5       | 40°17'    | 33°02'   | 30.2                    | 339.5                   | 112.86                   | 62.23                        |

### Table 2. Drought classification based on SPI values

| SPI   | Category                  | Symbol |
|-------|---------------------------|--------|
| ≥ 2   | Extremely wet             | EW     |
| 1.5 to 1.99 | Severely wet             | SW     |
| 1 to 1.49 | Moderately wet           | MW     |
| 0 to 0.99 | Mild wet                 | N      |
| -0.99 to 0 | Mild drought            | N      |
| -1.49 to -1 | Moderately drought      | MD     |
| -1.99 to -1.5 | Severely drought       | SD     |
| -2≥   | Extremely drought        | ED     |
5. Results and Discussion

5.1. Statistical analysis for the precipitation data-sets reliability

Five different indices were adopted to compare data sets for the precipitation of PDRS items (TRMM and CHIRPS) with GS. Monthly precipitation datasets of 22 stations within the study region were considered. Table 3 shows comparative evaluation values for both products of the PDRS. The statistical analyses showed that the outcomes of both items had been accepted and lied within the appropriate range of each index involved in this analysis. For TRMM, the range was between 0.62 and 0.88; ME ranged from −6.64 to 10.82; RMAE ranged from 0.36 to 1.45; RMSE ranged from 10.08 to 33.02; and BIAS ranged from 0.87 to 2.11; The mean r, ME, RMAE, RMSE, and BIAS values were 0.77, 3.47, 0.69, 19.73, and 1.29 respectively. The best average values of r, ME, RMAE and BIAS were found at the Z-I zone and the best average RMSE was found for Z-III. For CHIRPS, r ranged from 0.37 to 0.68; ME ranged from −8.88 to 12.16 mm; RMAE ranged from 0.55 to 0.95; RMSE ranged from 10.81 to 55.51; and BIAS ranged from 0.84 to 1.37. The average values of r, ME, RMAE, RMSE, and BIAS were 0.56, 2.79, 0.78, 26.28 and 1.14, respectively. The best average values of r, RMAE and BIAS were found at Z-I. The best average values of ME and RMSE were found at Z-III.

Table 3. Statistical indices measures for PDRS sets, values in bold refers to the best per index

| Zone | St.  | TRMM |       |       |       |       | CHIRPS |       |       |       |
|------|------|------|-------|-------|-------|-------|--------|-------|-------|-------|
|      |      | r    | ME    | RMAE  | RMSE  | BIAS  | r      | ME    | RMAE  | RMSE  |
| Z-I  | S15  | 0.82 | -1.34 | 0.46  | 31.09 | 0.97  | 0.64   | 6.3   | 0.64  | 48.54 |
|      | S16  | 0.86 | 10.82 | 0.51  | 24.86 | 1.36  | 0.64   | 7.8   | 0.68  | 37.89 |
|      | S17  | 0.88 | 5.3   | 0.36  | 31.29 | 1.1   | 0.68   | 1.96  | 0.55  | 50.86 |
|      | S21  | 0.87 | -6.64 | 0.38  | 33.02 | 0.87  | 0.65   | -8.88 | 0.58  | 55.51 |
|      | Ave  | 0.86 | 2.04  | 0.43  | 30.07 | 1.08  | 0.65   | 1.80  | 0.61  | 48.20 |
|      | Max  | 0.88 | 10.82 | 0.51  | 33.02 | 1.36  | 0.68   | 7.8   | 0.68  | 55.51 |
|      | Min  | 0.82 | -6.64 | 0.36  | 24.86 | 0.87  | 0.64   | -8.88 | 0.55  | 37.89 |
| Z-II | S3   | 0.86 | 8.39  | 0.59  | 22.46 | 1.41  | 0.56   | 2.86  | 0.74  | 29.66 |
|      | S12  | 0.77 | 3.09  | 0.63  | 15.52 | 1.22  | 0.6    | 3.98  | 0.73  | 18.89 |
|      | S14  | 0.79 | 0.03  | 0.49  | 20.28 | 1     | 0.62   | 7.86  | 0.72  | 33.65 |
|      | S18  | 0.81 | 4.46  | 0.52  | 24.56 | 1.19  | 0.59   | 5.31  | 0.74  | 32.98 |
|      | S19  | 0.79 | 6.74  | 0.63  | 22.64 | 1.32  | 0.61   | 3.92  | 0.69  | 28.61 |
|      | S20  | 0.87 | -0.09 | 0.41  | 16.16 | 1     | 0.59   | 5.31  | 0.75  | 33.17 |
|      | S22  | 0.87 | 6.55  | 0.43  | 32.33 | 1.1   | 0.68   | 12.16 | 0.65  | 52.45 |
|      | Ave  | 0.82 | 4.17  | 0.53  | 21.99 | 1.18  | 0.61   | 5.88  | 0.72  | 32.80 |
|      | Max  | 0.87 | 8.39  | 0.63  | 32.33 | 1.41  | 0.68   | 12.16 | 0.75  | 52.45 |
|      | Min  | 0.77 | -0.09 | 0.41  | 15.52 | 1      | 0.56   | 2.86  | 0.65  | 18.89 |
| Z-III| S1   | 0.65 | 3.87  | 0.89  | 15.56 | 1.48  | 0.51   | 3.49  | 0.94  | 14.61 |
|      | S2   | 0.64 | 7.97  | 1.45  | 21.57 | 2.11  | 0.52   | 2.17  | 0.87  | 12.47 |
|      | S4   | 0.7  | 2.71  | 0.87  | 14.57 | 1.34  | 0.49   | 0.96  | 0.93  | 14.42 |
|      | S5   | 0.71 | 3.73  | 0.86  | 14.7  | 1.45  | 0.51   | 0.36  | 0.85  | 13.44 |
|      | S6   | 0.68 | 1.99  | 0.92  | 10.08 | 1.38  | 0.43   | -0.24 | 0.9   | 10.81 |
|      | S7   | 0.72 | 5.58  | 0.92  | 17.57 | 1.6   | 0.56   | 1.2   | 0.84  | 14.5  |
|      | S8   | 0.81 | 1.47  | 0.65  | 11.66 | 1.16  | 0.55   | -1.33 | 0.81  | 15.23 |
|      | S9   | 0.82 | 2.05  | 0.56  | 11.48 | 1.21  | 0.59   | 0.69  | 0.8   | 15.01 |
|      | S10  | 0.62 | 2.29  | 0.82  | 12.83 | 1.3   | 0.37   | 1.14  | 0.92  | 15.71 |
|      | S11  | 0.73 | 5.59  | 0.96  | 18.62 | 1.61  | 0.52   | 2.54  | 0.86  | 15.1  |
|      | S13  | 0.64 | 1.85  | 0.81  | 11.27 | 1.26  | 0.43   | 2.03  | 0.95  | 14.55 |
|      | Ave  | 0.70 | 3.55  | 0.88  | 14.54 | 1.45  | 0.50   | 1.18  | 0.88  | 14.17 |
|      | Max  | 0.82 | 7.97  | 1.45  | 21.57 | 2.11  | 0.59   | 3.49  | 0.95  | 15.71 |
|      | Min  | 0.62 | 1.47  | 0.56  | 10.08 | 1.16  | 0.37   | -1.33 | 0.8   | 10.81 |
| Z-T  | Ave  | 0.77 | 3.47  | 0.69  | 19.7  | 1.29  | 0.56   | 2.79  | 0.78  | 26.28 |
|      | Max  | 0.88 | 10.82 | 1.45  | 33.02 | 2.11  | 0.68   | 12.16 | 0.95  | 55.51 |
|      | Min  | 0.62 | -6.64 | 0.36  | 10.08 | 0.87  | 0.37   | -8.88 | 0.55  | 10.81 |
Compared to GS data, both TRMM and CHIRPS showed slight overestimation. Obviously, satisfactory correlations were found for both TRMM and CHIRPS with GS, with the priority for TRMM. As a comparison between the TRMM and CHIRPS, Table 3 shows that the best values of comparison indices were found for TRMM at zones Z-I and Z-II. But for Z-III, the table showed that the CHIRPS had the best values of comparison indices. From this, it can be revealed that it is better to use the TRMM precipitation data for zones Z-I and Z-II and to use the CHIRPS precipitation data for zone Z-III.

Spatial distribution of mean monthly average precipitation from TRMM and CHIRPS over Iraq shown in Figures 2 and 3, respectively. The spatial distribution of TRMM rainfall was found to be very similar to the spatial distribution calculated using GS data for the observed precipitation (see Figure 1). Nevertheless, dissimilarity was noted between the spatial distribution of CHIRPS and observed precipitations in the north zone as CHIRPS overestimated precipitation.

Figure 4 shows an aerial average PDRS and GS precipitation scatter plots for each climate zone (Z-I, Z-II, Z-III) and for the whole study area (Z-T). A stronger relationship with GS was found by TRMM compared to CHIRPS. The $R^2$ between TRMM and GS precipitation was 0.902 for Z-T (Figure 4d), 0.861 for Z-I, 0.853 for Z-II, and 0.850 for Z-III, respectively. While, $R^2$ between CHIRPS and GS precipitation values were found respectively 0.519, 0.495, 0.476 and 0.461, which indicates a milder correlation with the GS data.

5.2. Performance of PDRS for drought monitoring

Mean SPI values have been estimated using Equation (2) for PDRS and GS data for different time-scales for each zone. This delivered an opportunity to understand PDRS's capability in monitoring drought [23]. Figures 5, 6 and 7 show SPI time series (SPI-3, SPI-6, and SPI-12) for various climatic zones of Iraq. As the SPI values in the figure reflect the zonal average, the high peaks are reduced. It may have more severe dry and wet conditions at the local level.

Clearly, the Figures suggest a strong consistency of TRMM-SPI with GS-SPI, but on the contrary, the relationship between CHIRPS-SPI and GS-SPI did not show the same. The statistics showed that the Z-I region experiences droughts more often than the Z-II and Z-III. Droughts are even more serious in Z-I as opposed to Z-II and Z-III, which agree with the findings of [9] and [10]. The SPI temporal patterns of the time scales (SPI-3, SPI-6, and SPI-12) were found identical. Figure 5 shows that the extreme (ED), severe (SD) and mild (MD) droughts in Z-I were observed by all three SPI timescales from GS data in 1999-2000, 2008 and 2011-2012, respectively.
Figure 5. Areal average time series of SPI-3, SPI-6, and SPI-12 estimated using TRMM, CHIRPS and GS precipitation for Z-I.

Figure 6. Areal average time series of SPI-3, SPI-6, and SPI-12 estimated using TRMM, CHIRPS and GS precipitation for Z-II.
The frequency of occurrences of SPI-3 (as an example) was shown in Figures 8, 9 and 10 for Z-I, Z-II and Z-III, respectively, to test the Temporal Coincidence (TC) between GS, TRMM and CHIRPS. In
general, most TC portions in the adopted zones were situated in the SPI classes Normal Wet (NW) and Normal Dry (ND) (Table 2). Figure 8 displays SPI-3 values based on five separate time series adopted at Z-I for comparison. Strong TC between TRMM and GS-TRMM is seen at Z-I for NW and ED (Figure 8), NW for Z-II (see Figure 9), and SW, NW and ND for Z-III (see Figure 10). CHIRPS did, however, make it possible to align GS data with MD at Z-I, ND at Z-II, and MW, NW, ND and MD for Z-III. The average percent of error for the TRMM was 43.7 %, 48.7 % and 70.7 % and for CHIRPS were 67.9 %, 52.5 % and 27.8 % for Z-I, Z-II and Z-III, respectively.

These findings reveal that the precipitation data from TRMM best matches the drought analysis in zones Z-I and Z-II, while the precipitation data from CHIRPS suits best at the Z-III zone, which agrees with the findings of [1]. Spatially, there was a small difference in performance between RPDS and GS sets in SPI calculations for the adopted zones due to variations in elevation, location of ground stations, local climate and topography, [1][32][33]. In addition, the number of ground stations in each zone (sparsity of GS networks) was not equal (see Figure 1). This may have affected both the spatial average for each zone and the overall effects of the correlation [34]. Additionally, SPI results were directly influenced by mistakes in GS sets, which may take place due to the method of filling. The findings reported in this work are consistent with other researchers who have confirmed the prevailing applicability of TRMM for drought monitoring and disagree mostly with CHIRPS such as [15][35].

6. Conclusions

Opportunities for monitoring and analysing drought exist in the use of remotely sensed sources of precipitation to complement the inadequate meteorological ground station cover. Throughout this study, monthly precipitation data sets for TRMM 3B43V7 from January 1998 to December 2017 and monthly precipitation data sets for CHIRPS from January 1983 to December 2016 were compared with the precipitation data of GS.

For potential drought analysis and comparison, Köppen's climate classification system was used to divide the study area (Z-T) into three zones: Z-I, Z-II and Z-III. Multi-scale comparisons through multiple statistical indices revealed a strong agreement between TRMM and GS, and less overlap between CHIRPS and GS in terms of spatio-temporal distribution, with comparative results improving as more GS are used. It was revealed that PDRS has the ability to catch GS sets fairly. About the GS sets, the study found that the driest periods were in 1999, 2008 and 2012.

Using different time scales (SPI-3, SPI-6, and SPI-12) to determine the ability of PDRS to monitor meteorological droughts, the Standardized Precipitation Index (SPI) was estimated. Obviously, the northern part of Iraq (Z-I) experienced more extreme droughts than the middle (Z-II) and southern (Z-III) parts. Based on this, the potential capability and consistency of both TRMM and CHIRPS were realized. TRMM was better at matching GS for the driest drought levels, while CHIRPS showed less powerful results in checking Temporal Coincidence (TC) at the time scales introduced for SPI. In comparison, the TRMM matches the Z-I and Z-II drought analysis better, and the CHIRPS suits better the Z-III drought analysis. Because of these findings, both sources of precipitation were appropriate to assess the spatial and temporal distribution of droughts with the priority of TRMM, and can be used in semi-arid Iraq to track drought.

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