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Assessment of Spatiotemporal Variability of Meteorological Droughts in Northern Iraq Using Satellite Rainfall Data

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ABSTRACT

The absence of a dense rainfall monitoring network and longer period data are the major hindrances of hydroclimatic study in arid and semi-arid regions. An attempt has been made for the evaluation of spatiotemporal changes in droughts at the northern semi-arid region of Iraq for the period 1981 – 2018 using high-resolution (0.05°) precipitation data of Climate Hazards Group Infrared Precipitation with Stations (CHIRPS). The performance of CHIRPS in replicating rainfall and Standard Precipitation Index (SPI) for different timescales at eleven locations for the available period of observation data (2000 – 2014) was evaluated. The SPI was also used to estimate drought frequency and evaluate drought trends at all the CHIRPS grid points. A modified version of the non-parametric Mann-Kendall (MK) test was employed for a robust evaluation of the spatial distribution of temporal trends in droughts. The results showed a good ability of CHIRPS in reconstructing observed SPI with a correlation coefficient ranged from 0.64 to 0.87, BIAS between 1.05 and 1.81, Nash-Sutcliff efficiency from 0.39 to 0.55, and Willmott Index between 0.67 and 0.79. The CHIRPS also able to reconstruct the time series and probability distribution of observed SPI reasonably. Spatial distribution of droughts revealed a higher frequency of droughts of all categories and timescales in the east and north of Northern Iraq, mainly due to high rainfall variance. The MK test revealed a reduction in 6- and 12-month droughts in the northwest and an intensification at a few northeastern grids. It indicates droughts became more recurrent in the already drought-prone region and lessened in a less drought-prone region.

1. Introduction

Droughts significantly disturb the economy and people livelihood globally almost every year (Ahmad et al., 2020). Many regions of the world ranked drought the first among all-natural hazards (Bryant, 1997; Wilhite, 2000). Droughts are more severe and frequent in the predominantly arid region due to fluctuating precipitation behaviours and large inconsistency of climate (Dai et al., 2004; Zhao et al., 2018; Suliman et al., 2019). Studies showed a rise in drought recurrence, time-span and areal coverage in dry regions worldwide. However, there will be a geographical variability of drought hot spots due to spatially varied changes in global climate. The southwest (SW) Asia is one of the world's most water-scarce regions (Barlow et al., 2016). Droughts in 1999 – 2001 affected 60 million inhabitants of the region (Agrawala et al., 2001). Droughts in 2007 – 2008 caused social unrest over a large part of SW Asia (Homsi et al., 2020). The SW Asian countries are also among the possible drought hot spots due to global climate change (Spinoni et al., 2020). Liu and Chen (2021) evaluated the socioeconomic risk of

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droughts due to climate change and revealed SW Asia among the high socioeconomic risk region of global climate change-induced droughts.

Iraq, located in SW Asia, is mainly dominated by a dry climate, with an average yearly rainfall below 166 mm. Droughts are common phenomena in Iraq as in other SW Asian countries (Al-Ansari and Knutsson, 2011; Ahmad et al., 2020). The warming climate and declining rainfall have intensified water stress in Iraq in the recent past (Salman et al., 2020). The increased recurrence of droughts aggravated it further (Alhumaima and Abdullaev, 2018; Hameed et al., 2018). The droughts are much devastating in the northern region, where agriculture is mainly rain-fed (Awchi and Kalyana, 2017; Yenigun and Ibrahim, 2019). Alhumaima and Abdullaev (2018) analyzed the historical climate of Iraq for 1900 – 2014 and reported the severe droughts in the country occurs in northern Iraq. The recent study of (Jasim and Taymoor, 2020) based severity-area-frequency analysis of droughts also revealed north Iraq as the most drought-prone zone of Iraq. Despite the significant effect of droughts, there were only limited drought studies in Iraq's northern region (Rasheed, 2010; Saeed and Abas, 2012; Al-Faraj et al., 2015; Kalyana and Awchi, 2015; Awchi and Kalyana, 2017; Mohammed and Scholz, 2017). It is mainly due to the unavailability of dense longer period precipitation records. A brief review of previous studies on droughts in the study area is presented in Table 1.

The previous studies of droughts conducted in the region were based on a limited number of observed rainfall records, which were not able to show the spatial variability of droughts and their causes in this mountainous region (Al-Faraj et al., 2015; Awchi and Kalyana, 2017; Mohammed and Scholz, 2017; Suliman et al., 2020). However, understanding the spatial variability of droughts and their temporal variability is most important for agricultural planning, adaptation, and mitigation.

Satellite remote sensing is a successful technique in obtaining timely rainfall data from global to regional scales. It offers a potential solution for meteorological ground-based stations, particularly over remote and high altitudes regions. The major drawback of drought assessment using remote sensing precipitation is their unavailability for a longer period. Among the satellite-based precipitation products, CHIRPS precipitation data is an exceptional one that provides high-resolution (0.05° × 0.05°) precipitation for a longer period (1981 – 2018). The performances of the CHIRPS v.2.0 have been evaluated in different regions by determining their ability to estimate precipitation and droughts (Toté et al., 2015; Bayissa et al., 2017; Saeidizand et al., 2018; Babaousmail et al., 2019).

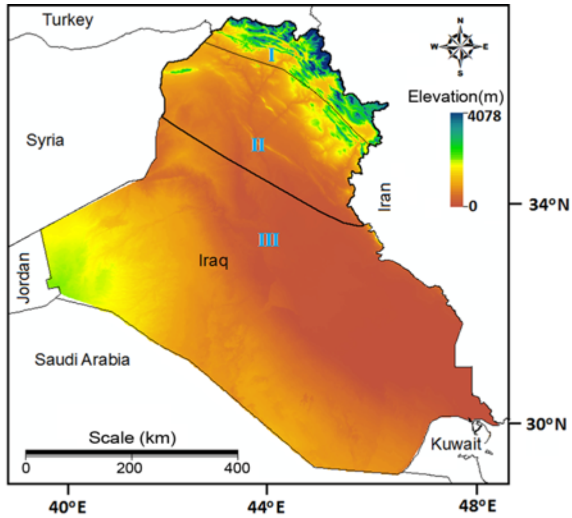
Between 2001 to 2012 (Toté et al., 2015) studied the drought and flood in Mozambique using three gridded satellite rainfall products and found CHIRPS to provide the best results. Bayissa et al. (2017) used five high-resolution products to evaluate the spatiotemporal variability of droughts in the Ethiopian Upper Blue Nile basin. They reported that CHIRPS could be utilized to develop grid-based drought monitoring tools as an alternative and efficient information resource. Wu et al. (2019) examined the performance of the CHIRPS dataset using 122 gauges observations acquired from 1981 to 2015 to monitor drought across China's Yunnan Province. They demonstrated that the performance of CHIRPS was accurate in drought estimation. Rivera et al. (2019) assessed CHIRPS in monitoring dry and wet occurrences along with semi-arid Central-Western Argentina

Table 1. Summary of All the Previous Studies for Meteorological Drought in Iraq

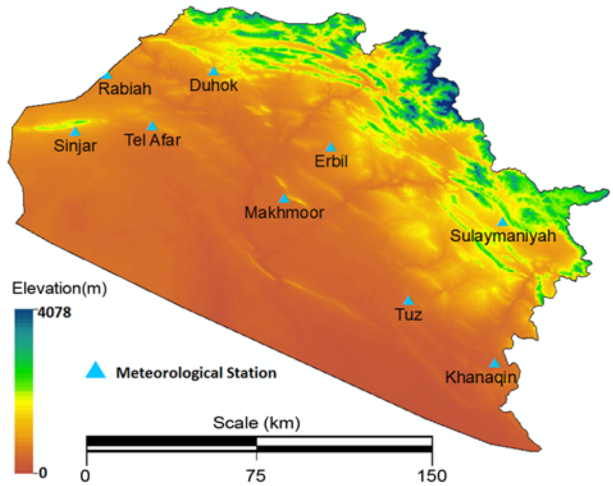
Researchers	Period	Study area	Indices	Findings
Al-Timimi and Al-Jiboori (2013)	1980 – 2010	Whole of Iraq	SPI	The extreme drought occurred in 2008
AL-Timimi (2014)	1980 – 2010	Whole of Iraq	SPI	The highest severity drought experience in 2008 during the investigation period
Kalyana and Awchi (2015)	1937 – 2010	Northern of Iraq	Deciles	The two most recent extreme dry periods were 1997 – 2001 and 2007 – 2010
Agha and Şarlak (2016)	1980 – 2011	Whole of Iraq	SPI	Years 2008 and 2009 were the worst drought years
Şarlak and Agha (2017)	1980 – 2011	Whole of Iraq	RDI	The most severe drought happened in 2008
Awchi and Kalyana (2017)	1937 – 2010	Northern of Iraq	SPI	The severest dry period was 2006 – 2010
Jasim and Awchi (2017)	1970 – 2010	Whole of Iraq	SPI	The worst droughts were in 1997 – 2001 and 2007 – 2010
Hameed et al. (2018)	1948 – 2009	Whole of Iraq	SPEI	Droughts in 1998 – 1999 and 2007 – 2008 covered 87% and 82% of Iraq
Alhumaima and Abdullaev (2018)	1900 – 2014	Euphrates-Tigris rivers basin	SPI	Increasing temperature and decreasing precipitation is causing increasing droughts
Yenigun and Ibrahim (2019)	1979 – 2013	Northern Iraq	SPI	Increase in 6-, 9- and 12-month droughts
Suliman et al. (2020)	TRMM at 1998 – 2017 and PERSIANN at 1983 – 2016	Whole of Iraq	SPI	Severe and moderate droughts experienced in 2008 and 2011
Jasim and Taymoor (2020)	1970 – 2013	Whole of Iraq	SPI	The recurrence of mild droughts in Iraq is 33.44%

for the period1987 – 2016. They indicated that CHIRPS could effectively reproduce the SPI temporal inconsistency on multiple timescales. CHIRPS has also been found to replicate observed rainfall in many other regions. Babaousmail et al. (2019) assessed the reliability of gridded rainfall datasets in Algeria and found CHIRPS to perform the best. Saeidizand et al. (2018) compared the ground-based rainfall observations with CHIRPS rainfall performance in Iran during 2005 – 2014 and found CHIRPS performance best during the months of heavy precipitation. The studies indicated CHIRPS as an appropriate dataset for drought assessment in the data-scarce region (Gao et al., 2018).

This study aims to assess CHIRPS performance across northern Iraq to monitor droughts on multiple timescales and use CHIRPS to map spatiotemporal variability of droughts in Northern Iraq. First, CHIRPS performance was evaluated in replicating precipitation of 9 meteorological gauges stations for the period 2000 – 2014. The SPI detected from CHIRPS for multi timescale SPI-3, SPI-6, SPI-12 and SPI-24 were then compared with those calculated by precipitation observed at meteorological gauge stations. Finally, the droughts estimated using CHIRPS were used to assess their occurrence frequency and trends. The Sen's slope estimator (SSE) and the modified version of the Mann-Kendall (MMK) test were employed to estimate the trend and its significance, respectively. Recurrent droughts in this mountainous rain-fed intensive agricultural region frequently caused large economic damages and severely affected people's livelihood. Several studies attempted to reconstruct droughts in the region using in-situ sparse rainfall records or short period satellite rainfall data. Previous studies were not sufficient to reveal the geographical variability of droughts and their progression. Assessment of spatiotemporal variability of droughts and their causes is important for planning mitigation measures and improving millions of rural populations' livelihood depending on agriculture in the region. The present study attempted to show the spatial pattern of occurrence of droughts for different frequencies and assessment of spatial patterns of their trends.



(a)



(b)

Fig. 1. Study Area: (a) The Location of Northern Iraq on the Map of Iraq (boundary marked with bold line), (b) Position of the Meteorological Stations in Northern Iraq

2. Study Area and Data

2.1 Northern Iraq

The northern part of Iraq (34°10′ – 37°20′N, 41°16′ – 46°20′E), comprising a land of 65,000 km^2, was the area of investigation of the present study (Fig. 1(a)). The mountain chains occupy most of the region's northern and eastern parts, which separates the study area from Turkey and Iran (Fig. 1(b)). The largest portion of the Tigris River's tributaries (the Khabur, the Upper Zab, the Lower Zab, Adhaim, and Diyala) flow through this region of northern Iraq to the Tigris River, and it contains many dams and water reservoirs which makes it important in water resources studies.

Drought in this region is a major meteorological disaster that frequently occurs with damaging effects on the economy and ecological system. Generally, climate classification for northern Iraq is semi-arid, wet and cold in winter and dry and very hot in summer. Koppen climate classifications divide the area into two regions: BSk for zone I and BSh for zone II. The rainfall is intermittent and falls between October and May in winter in some eastern regions, wherein the yearly rainfall ranges from 1,000 to less than 300 mm in the west.

About 34% of rainfed crops of Iraq are produced in this region (Saleh, 2012). Around 85% of its area is cultivated for barley, wheat, and lens (Al-Obaidy, 2012). Therefore, this area is regarded as the country's historic Sustain breadbasket (Shean, 2009).

2.2 Precipitation Data

2.2.1 Observed Meteorological Stations Data

Daily rainfall data recorded at 9 meteorological stations (GS) in the northern region of Iraq (Fig. 1) for the period (2000 – 2014) were collected from the Iraqi Meteorological Organization and Seismology Department. There are six stations located in Zone-II (BSh, Z-II) and three in Zone-I (BSk, Z-I). The rainfall data homogeneity assessment showed their sufficient quality at all the stations at a 0.05 significance level.

2.2.2 Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) Precipitation Data

CHIRPS v2.0 is developed at the University of California, Santa Barbara, by the US Geological Survey and the Climate Hazards Group (CHG). The data for the development of CHIRPS were collated from five sources. It used four steps for the data development process: 1) a 5-day (pentad) precipitation estimate is generated from the 3-hourly quasi-global geostationary thermal infrared (TIR) data of the Climate Prediction Centre (CPC) and the National Climatic Data Center; 2) TRMM Multi-satellite Precipitation Analysis (TMPA)-3B42 rainfall product is used to calibrate the infrared (IR) pentad estimate; 3) the calibrated infrared (IR) pentad product is then multiplied with the Climate Hazards Precipitation Climatology and subsequently divided by the long-term mean to produce the CHG IR Precipitation (CHIRP) data; and finally, 4) model precipitation data from NOAA Climate Forecast System are used to provide CHIRP with daily variability, and ground-based observations are used to correct for monthly climatology of the final product. It has satellite resolution imagery of 0.058 in situ station data and used from 1981 to the near present. The CHIRPS uses "smart interpolation" tools (Funk et al., 2015) for data development. Fig. 2 shows the number of observed stations data used in Iraq to develop CHIRPS during various periods.

The latest CHIRPS version is an IR-based quasi-global satellite

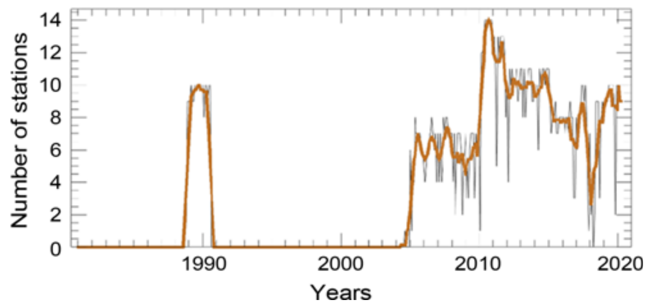


Fig. 2. Number of Observed Station Data of Iraq Used for CHIRPS Development

precipitation dataset, an ideal rainfall dataset to monitor droughts (Funk et al., 2015). Therefore, monthly data for CHIRPS at 0.05 spatial resolutions were collected for the period 1981 to 2018. CHIRPS provides data from 1981 onward. Therefore, the study period, 1981-2018, was selected considering data availability. A portion of the data (2000 to 2014) was used to validate the product, while the complete dataset was used for the assessment of spatiotemporal variability of droughts in Northern Iraq.

3. Methodology

3.1 Evaluation Methods

Rainfall data of 9 rain gauges were used to assess the performance of CHIRPS. Six statistical metrics were employed to evaluate the performance of CHIRPS, namely Pearson coefficient of correlation (r), Mean Error (ME), Root Mean Square Error (RMSE), bias (BIAS), Nash-Sutcliff efficiency (NSE) (Nash and Sutcliffe, 1970) and Willmott Index (WI) (Willmott, 1981). The indices are

Table 2. The Equation, Range and Optimal Value of the Statistical Metrics Used in This Study

Statistical metric	Equation	Value range	Optimal value
Pearson correlation coefficient (r)	$\frac{\sum_{i=1}^{n}(S_i-\bar{S})(G_i-\bar{G})}{\sqrt[2]{\sum_{i=1}^{n}(S_i-\bar{S})^2}\sqrt[2]{\sum_{i=1}^{n}(G_i-\bar{G})^2}}$	-1 to 1	1
Root mean square error (RMSE)	$\sqrt{\frac{\sum_{i=1}^{n}(S_i-G_i)^2}{n}}$	0 to ∞ 0	0
Mean error (ME)	$\frac{1}{n}\sum_{i=1}^{n}(S_i-G_i)$	-∞ to ∞	0
BIAS	$\frac{\sum_{i=1}^{n}S_i}{\sum_{i=1}^{n}G_i}$	0 to ∞	1
Nash-Sutcliff efficiency (NSE)	$1-\frac{\sum_{i=1}^{n}(G_i-S_i)^2}{\sum_{i=1}^{n}(S_i-\bar{S}_i)^2}$	-∞ to 1	1
Willmott Indix (WI)	$1-\frac{\sum_{i=1}^{n}(S_i-G_i)^j}{\sum_{i=1}^{n}(\lvert G_i-\bar{S}_i\rvert+\lvert S_i-\bar{S}_i\rvert)^j}$	0 to 1	1

described in Table 2, where the notations, S_i and G_i are the observed and nearest CHIRPS grid data, $\overline{S}$ and $\overline{G}$ are the average of S_i and G_i, respectively, n is the sample size, and j is the modified WI constant which was considered 1 in this study. Further details of these evaluation criteria can be found in (Krause et al., 2005).

3.2 Standardized Precipitation Index (SPI)

In 1993, McKee developed the SPI (McKee et al., 1993), which has been utilized extensively in various semi-arid and arid regions worldwide (Kasei et al., 2010; Cañón et al., 2011; Gebrehiwot et al., 2011; Karavitis et al., 2011; Hallack-Alegria et al., 2012; Karavitis et al., 2012; Shadeed, 2013; Ezzine et al., 2014; Dashtpagerdi et al., 2015; Rad and Khalili, 2015; Zhao et al., 2015; Agha and Şarlak, 2016; Kazemzadeh and Malekian, 2016; Ozelkan et al., 2016; Venkataraman et al., 2016; Awchi and Kalyana, 2017; Gao et al., 2018; Rivera et al., 2019).

The SPI is estimated by fitting the monthly rainfall data to a gamma probability distribution function, $G(x)$ at each grid point:

$$g(x) = \frac{1}{\beta^{\alpha}\Gamma(\overline{\alpha})}x^{\alpha-1}e^{-x/\beta} \text{ for } x > 0, \tag{1}$$

$$\Gamma(\overline{\alpha}) = \int_0^{\infty} y^{\alpha-1}e^{-y}, \tag{2}$$

where $\Gamma(\overline{\alpha})$ is the gamma function and x is the precipitation amount. $\overline{\alpha}$ and β are shape and scale parameters, respectively, as follows:

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

$$\beta = \frac{\overline{x}}{\overline{\sigma}}, \tag{4}$$

$$A = \ln(\overline{x}) - \frac{\sum \ln(x)}{n}. \tag{5}$$

The parameters are compensated in $G(x)$ as shown in the equation below:

$$G(x) = \int_0^x g(x)dx = \frac{1}{\beta^{\alpha}\Gamma(\overline{\alpha})}\int_0^x x^{\alpha-1}e^{-x/\beta}dx. \tag{6}$$

Assuming the value of x/β is equal to t so that it can be formulated for $G(x)$ as below:

$$G(x) = \frac{1}{\Gamma(\overline{a})}\int_0^x t^{a-1}e^{-1}dt. \tag{7}$$

At zero values ($x = 0$), if the $G(x)$ is undefined, and rainfall records may be containing zero, so the cumulative probability $H(x)$ is applied:

$$H(x) = q + (1-q)G(x), \tag{8}$$

where $H(x)$ is the cumulative probability of the incomplete $G(x)$, and q represents the probability of a zero, which is estimated as the ratio of no rainfall day in the time series.

Table 3. The Drought Classifications, according to SPI (McKee et al., 1993)

Index (SPI)	Drought severity	Symbol
SPI ≤ −2.0	Extremely drought	ED
−1.99 < SPI < −1.5	Severely drought	SD
−1.49 < SPI < −1.0	Moderately drought	MD
0 > SPI > −0.99	Mild drought	ND
0.99 > SPI > 0	Mild wet	NW
1.49 > SPI > 1	Moderately wet	MW
1.99 > SPI > 1.5	Severely wet	SW
SPI ≥ 2.0	Extremely wet	EW

The equations below are used to transform the $H(x)$ into the standard normal random variable z, which represents SPI (McKee et al., 1993).

$$SPI = \begin{cases} -\left(t - \dfrac{2.515517+0.802853t+0.010328t^2}{1+1.432788t+0.189269t^2+0.001308t^3}\right) & \text{for } 0 < H(x) \le 0.5 \\ +\left(t - \dfrac{2.515517+0.802853t+0.010328t^2}{1+1.432788t+0.189269t^2+0.001308t^3}\right) & \text{for } 0.5 < H(x) \le 1 \end{cases} \tag{9}$$

$$t = \begin{cases} \sqrt{\ln\dfrac{1}{(H(x))^2}} & \text{for} \quad 0 < H(x) \le 0.5 \\ \sqrt{\ln\dfrac{1}{(1-H(x))^2}} & \text{for} \quad 0.5 < H(x) \le 1 \end{cases} \tag{10}$$

Table 3 shows the drought category classifications suggested for the SPI by McKee et al. (1993).

3.3 Frequency of Droughts

The droughts recurrence is generally used for drought characterization. The ratio of drought years (n) to the total study years (N) is the frequency of drought (F):

$$F = \frac{n}{N} \times 100. \tag{11}$$

The drought frequency was estimated at each CHIRPS grid to show the geographical variability of drought occurrences for various durations and severities.

3.4 Trends in Droughts

The SPI change rate was estimated using SSE, and the significance of the change was evaluated using the MMK test.

3.4.1 Sen's Slope Estimator (SSE)

Sen (1968) developed the non-parametric SSE to assess the time series trend. The SSE estimates the rate of change (Q) as the median of the slopes (Q_i) of all the consecutive data pair,

$$Q_i = \text{median}\left[\frac{x_j - x_k}{j-k}\right]. \tag{12}$$

3.4.2 Modified Mann-Kendal (MMK) Test

The MMK test (Yue et al., 2002), a modified version of the classical MK test, was used in this study. The MK test overrates trend significance for autocorrelated time series, which is very common in rainfall and SPI time series (Khan et al., 2019a; Khan et al., 2019b; Sa'adi et al., 2019). Therefore, the MMK test was used to overcome this drawback of the MK test in drought trend assessment.

The MK test (Mann, 1945; Kendall, 1948) estimates the significance of change using Z statistics,

$$Z = \begin{cases} \dfrac{S-1}{Var(S)} & \text{for} \quad S>0 \\ 0 & \text{for} \quad S=0 \\ \dfrac{S+1}{Var(S)} & \text{for} \quad S<0 \end{cases}, \tag{13}$$

where

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn(x_j - x_k), \tag{14}$$

$$sgn(x_j - x_k) = \begin{cases} +1 & \text{for} \quad (x_j-x_k)>0 \\ 0 & \text{for} \quad (x_j-x_k)=0 \\ -1 & \text{for} \quad (x_j-x_k)<0 \end{cases}. \tag{15}$$

The 'no trend' hypothesis is rejected at $p < 0.05$ if Z is out of range ±1.96.

The MMK test (Yue et al., 2002) is a trend-free pre-whitening (PW) method. The PW is performed using following equation:

$$Y_i = x_i - (\beta \cdot i), \tag{16}$$

where β represents Theil-Sen's slope of different data pairs. The autocorrelation (r_1) free series (Y_i'') is estimated using Eqs. (17) and (18):

$$Y_i' = Y_i - r_1 \times Y_{i-1}, \tag{17}$$

$$Y_i'' = Y_i' + (\beta \times i). \tag{18}$$

The MK test is conducted over the time series of Y_i'' to avoid any influence of autocorrelation in trend significance.

4. Results and Discussion

4.1 Assessment of CHIRPS Performance in Replicating Precipitation

Figure 3 presents the results obtained by comparing observed monthly rainfall with the nearest CHIRPS grid point's monthly rainfall for 2000 – 2014. The daily rainfall at each gauge (grid) was transformed to monthly for comparison. The CHIRPS performance based on six statistical metrics at 9 locations is presented using the whisker-box plot. The height of the box, including its whisker, represents the range. The horizontal line within the box represents the mean of the matric estimated at 9 stations. The statistical analysis revealed that the range of all statistical metrics was satisfactory for CHIRPS. The correlation coefficients ranged from 0.64 to 0.87, BIAS between 1.05 and 1.81, RMSE from 19.12 to 41.13 mm, ME between 2.73 and 20.15 mm, NSE from 0.39 to 0.55, and WI between 0.67 and 0.79 (Fig. 3). The mean of correlation coefficients, BIAS, RMSE,

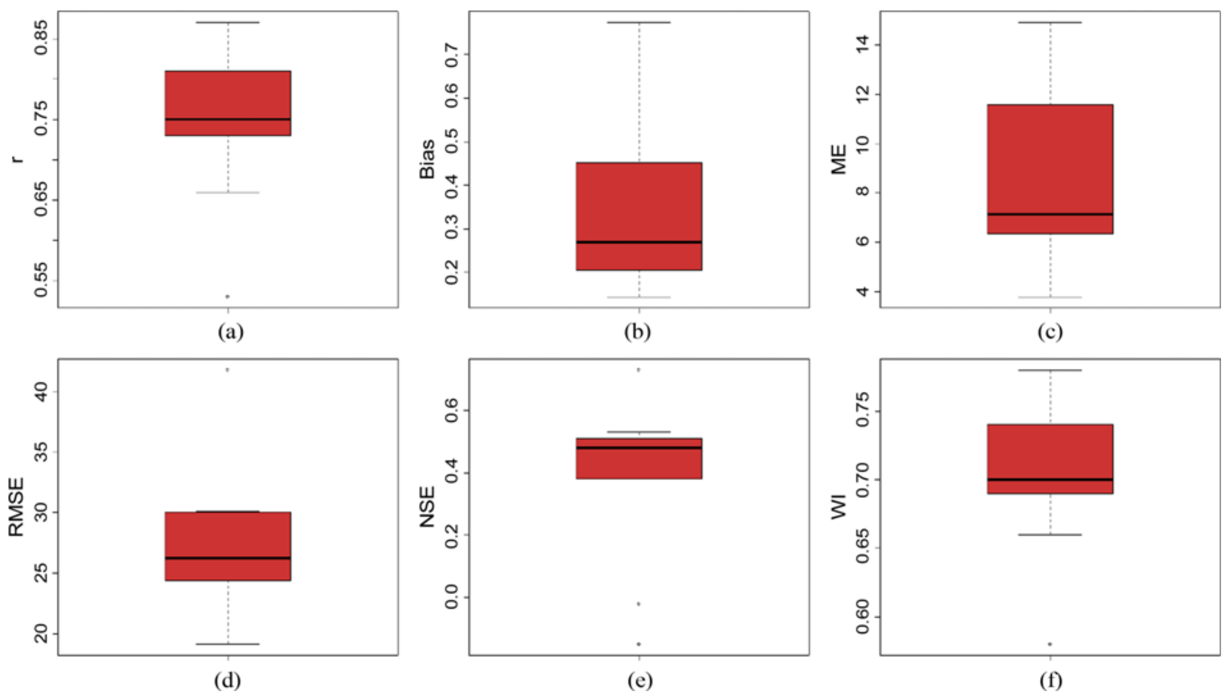


Fig. 3. Performance of CHIRPS in Estimating Monthly Rainfall at Different Stations of Northern Iraq for the Period 2000 – 2014: (a) r, (b) Bias, (c) ME, (d) RMSE, (e) NSE, (f) WI

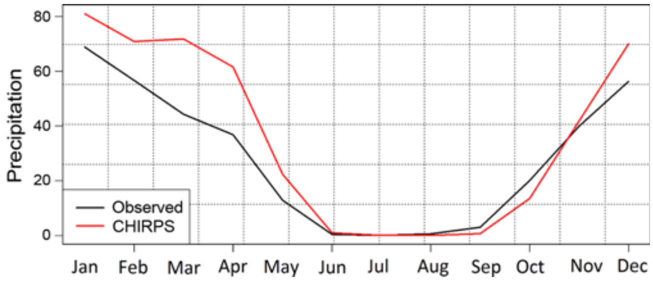


Fig. 4. Comparison of Monthly Rainfall of Areal Average of Gauge and CHIRPS Rainfall

ME, NSE, and WI were 0.75, 0.26, 7.1, 27.1, 5.1 and 0.71. Good associations and reasonably low CHIRPS error and bias compared to observed rainfall indicate the suitability of CHIRPS rainfall for drought study in the study area.

The capability of CHIRPS in reproducing the seasonal rainfall variability was evaluated by comparing observed and CHIRPS mean rainfall of all months, as shown in Fig. 4. Observed (CHIRPS) rainfall of all stations (grids) were averaged to prepare the graph. The graph showed the ability of CHIRPS in replicating seasonal rainfall variability reliably. CHIRPS overestimated monthly mean

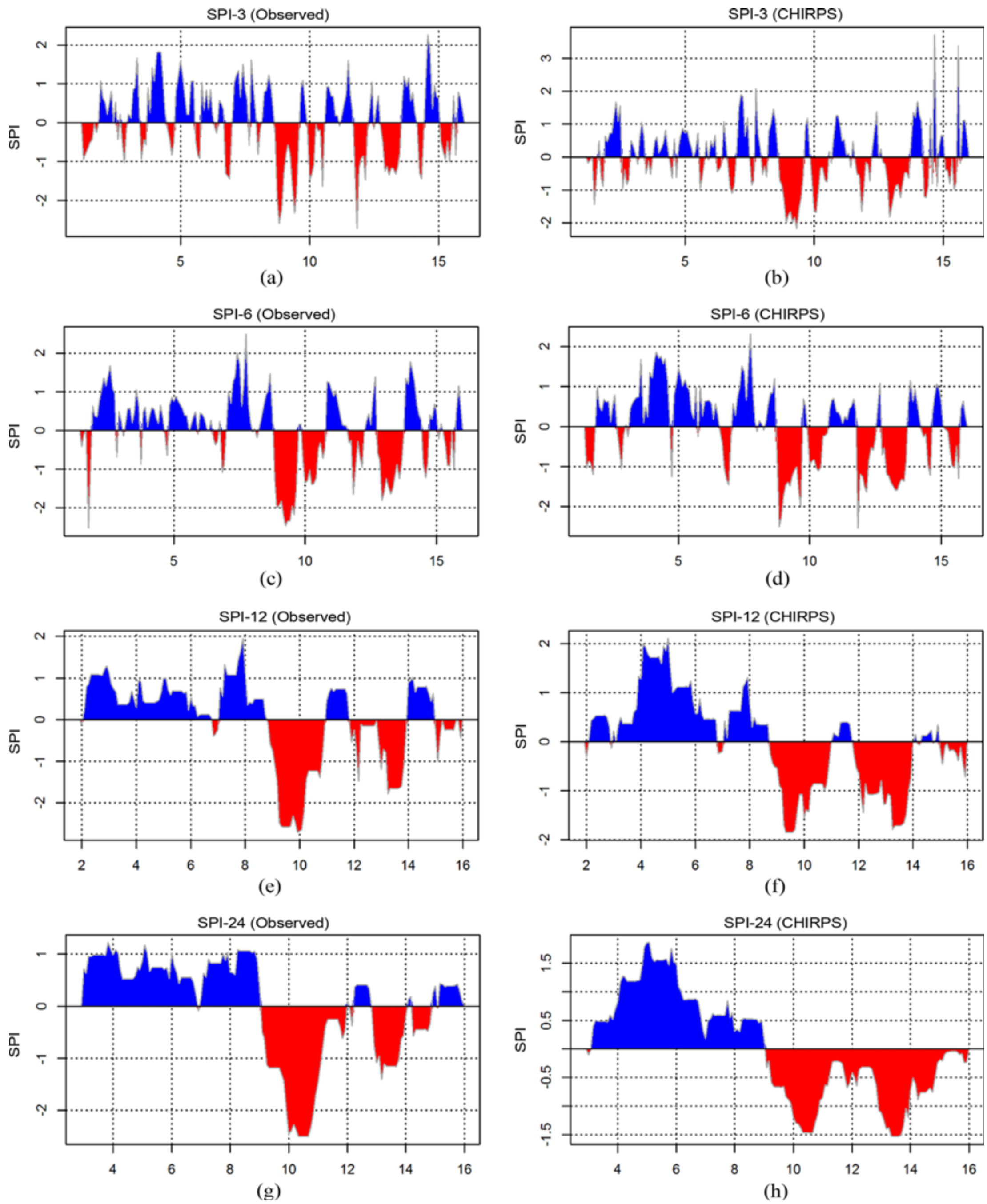


Fig. 5. Time Series Plots of: (a) SPI-3 (Observed), (b) SPI-3 (CHIRPS), (c) SPI-6 (Observed), (d) SPI-6 (CHIRPS), (e) SPI-12 (Observed), (f) SPI-12 (CHIRPS, (g) SPI-24 (Observed), (h) SPI-24 (CHIRPS)

rainfall for high rainfall months of January to May; however, the overestimation was not high. It also underestimated the moderate rainfall a little during September and October. However, such small over- and underestimation of rainfall are very common for gridded rainfall data. CHIRPS estimated low rainfall during dry months (June to August) accurately.

4.2 CHIRPS in Drought Monitoring

Scatter plots were prepared to show the agreement in SPI values using gauge precipitation and CHIRPS. Fig. 5 shows the time series of SPI estimated using observed and CHIRPS rainfall for 3-, 6-, 12- and 24-month time steps. The plots show similarity between observed and CHIRPS estimated SPI time series. CHIRPS was able to estimate all the droughts for different durations. It underestimated the severity of few higher duration droughts, but the underestimation was very less.

For a better evaluation of the ability of CHIRPS in estimating observed SPIs for different durations, scatter plots of observed and CHIRPS SPI values were prepared (Fig. 6). A good association between the SPIs estimated using observed and CHIRPS data was noticed. The plots show the majority of SPI values are near to the 1:1 ratio line of the plots. Therefore, the best-fit line of CHIRPS estimated SPI (red dashed line) was very close to the diagonal line of the scatter plot. The coefficient of determination (r^2) between the observed and CHIRPS estimated SPI for 3-, 6-, 12- and 24-month were 0.55, 0.65, 0.66 and 0.66, respectively.

The probability density plot (PDF) of observed and CHIRPS estimated SPI for 3-, 6-, 12- and 24-month durations are presented in Fig. 7. The PDF plots were prepared to show how the CHIRPS SPI can replicate the PDF of the observed SPI. The results showed a good capability of CHIRPS to reconstruct the observed SPI for time steps. The CHIRPS replicated the mean, variability, skewness and Kurtosis of observed SPI reasonably for all time-steps.

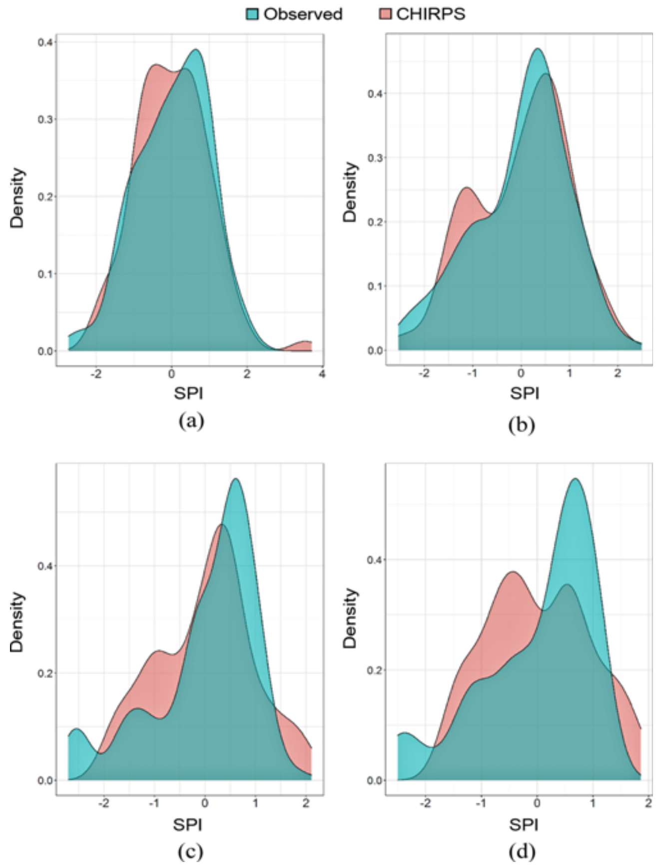


Fig. 7. Probability Density Plots of: (a) 3-Month, (b) 6-Month, (c) 12-Month, (d) 24-Month SPI Estimated Using Observed and CHIRPS Rainfall

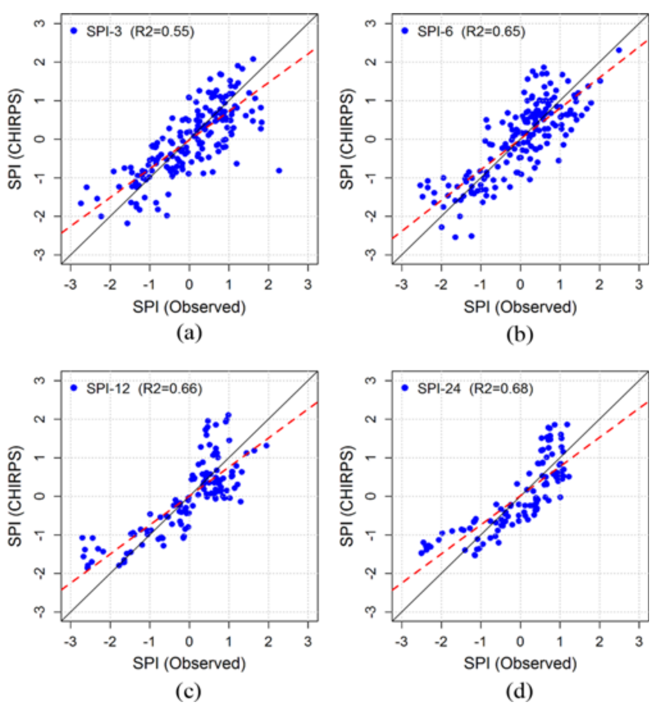


Fig. 6. Scatter Plots of SPI Values Obtained Using Observed and CHIRPS Rainfall for: (a) SPI-3, (b) SPI-6, (c) SPI-12, (d) SPI-24

The results based on statistical evaluation and graphical investigation of CHIRPS SPI against the observed SPI indicated the ability of CHIRPS in estimating droughts in Northern Iraq. Therefore, CHIRPS precipitation for the period 1981 to 2018 was used in this study to evaluate the geographical variability of rainfall and spatiotemporal distribution of droughts in northern Iraq.

4.3 Spatial Distribution of Mean and Variability of Rainfall

The spatial variability of annual mean and coefficient of variability (CV) of rainfall obtained using CHIRPS data are shown in Fig. 8. The spatial distribution of yearly mean rainfall revealed higher rainfall in the north (> 1,000 mm), gradually decreasing towards the south. The Mediterranean climate dominates northern Iraq. The Mediterranean winds bring significant moisture during winter, which mostly precipitates over the mountainous regions. Therefore, the northeastern mountainous region of Iraq receives

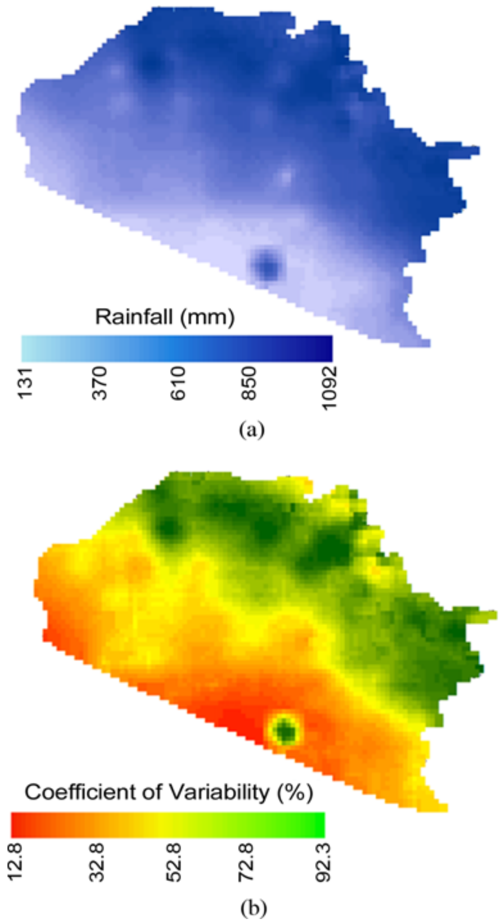


Fig. 8. Geographical Distribution of Annual: (a) Mean Rainfall, (b) Coefficient of Variability of Rainfall in Northern Iraq

the highest precipitation (Salman et al., 2019). The results indicate the topographic influence on rainfall in the study area. The topography in the north, particularly the northeast, is much higher than in the south, as presented in Fig. 1(b). The high topographic variability has made the rainfall in the region highly variable in space. The CV of rainfall revealed a similar spatial pattern of mean rainfall. This means rainfall is more variable in the region where it is high and less where it is less. Particularly, the high variability of rainfall was noticed in some extreme northern parts (> 90%), whereas the rainfall was found reliable in the south (variability < 13%) of northern Iraq. This corresponds with the findings of other studies (Ahmed et al., 2016; Pour et al., 2020). Ahmed et al. (2016) showed higher variability of rainfall at higher altitude in the Balochistan province of Pakistan. Pour et al. (2020) showed higher precipitation variability in mountainous regions of Iran compared to plain lands.

4.4 Spatial Distribution of Droughts

The CHIRPS precipitation was also employed to assess the geographical distribution of frequency of various severities of droughts in northern Iraq. Fig. 9 presents the geographical variability of occurrence frequency (%) of various severities of droughts for three timescales (3-, 6- and 12-month). The recurrence of droughts was noticed more in the northern region compared to the southern part. Particularly, a higher frequency of droughts of all categories and timescales are more in the northeast. However, the entire study area experiences a higher frequency of shorter period droughts (3-month). Particularly, 3-month extreme droughts occur with a frequency higher than 15% over the entire study area. 6-month moderate and severe droughts were more recurrent in the west and east, while the extreme droughts only in the west. Longer period (12-month) moderate droughts were more frequent in the east (20.7%) and the extreme droughts in the central west (5.3%). Overall, the results revealed that shorter-period (3-month) droughts are common in the study area. The frequency of 3-month moderate droughts more than 30% in most areas means it occurs three times in a decade. A similar calculation indicates 3-months severe droughts occur twice in a decade and extreme droughts three times in two decades in part of the study area. Drought occurrence frequency decreases with duration and severity. Therefore, the 12-month duration extreme droughts are very less frequent. The recurrence frequency of such droughts is near zero in most of the study area, which means such droughts are rare in the study area. The 12-month duration extreme droughts with a 3.9 to 5.3% frequency are noticed in few small patches, mostly distributed over the central-western part and northeast. As 12-month duration droughts are very few in the study area, higher duration (24-month) droughts must be very rare and not analyzed in this study.

Droughts depend on precipitation anomaly rather than precipitation amount (Qutbudin et al., 2019; Shiru et al., 2019). Therefore, the regions with higher rainfall variability generally experience more droughts (Shiru et al., 2018; Nabaei et al., 2019). Though precipitation in the far north is much higher than in other regions, precipitation variability is also very high due to mountainous topography, as shown in Fig. 8(b). The high variability of precipitation has made droughts of some timescales recurrent in the northern region.

4.5 Trends in Droughts

The rate of change in SPI was estimated using the SS estimator for various timescales, whereas MMK for significance. Obtained results for 3-, 6- and 12-month SPI are shown in Fig. 10. The colour ramp represents the change rate, whereas the black dot represents the significance of change at a confidence interval of 95%. The changes in the drought are presented as the rate of change in SPI per decade. A decrease in SPI indicates an increase in droughts, while an increase in SPI indicates a decrease in droughts. Therefore, the red colour in the map indicates an increase in droughts, and the green colour indicates a decrease in droughts. The results revealed a similar pattern of drought trend for different durations. The decreasing trends in droughts were noticed in the northeast and most parts of the southern area. The increases were found significant only at a few locations in the northeast. A large decrease in droughts was noticed in the northwest. The decrease was significant at a 95% level of confidence for SPI-6 and SPI-12. Besides, a decrease in droughts for different

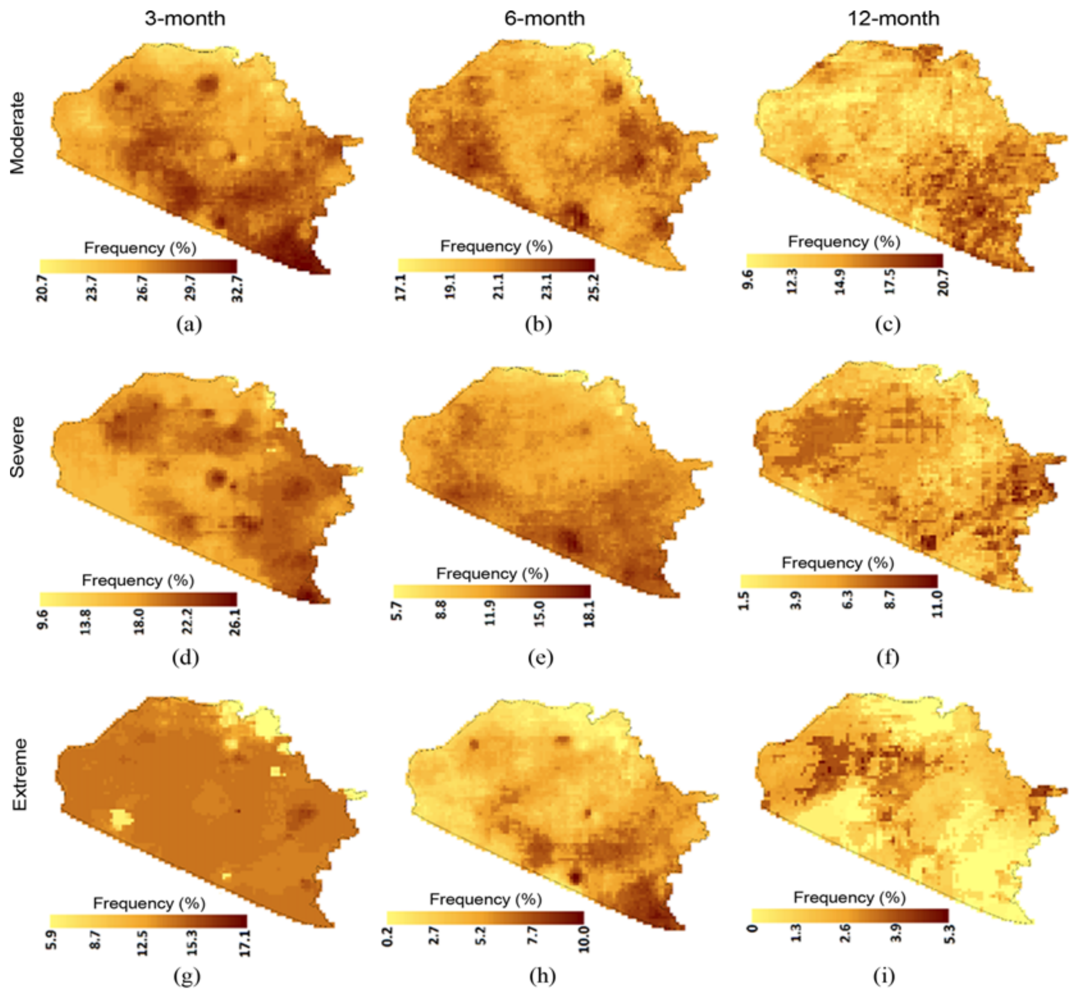


Fig. 9. Spatial Distribution of Occurrence Frequency (%): (a) Moderate 3-Month, (b) Moderate 6-Month, (c) Moderate 12-Month, (d) Severe 3-Month, (e) Severe 6-Month, (f) Severe 12-Month, (g) Extreme 3-Month, (h) Extreme 6-Month, (i) Extreme 12-Month Using CHIRPS

periods was noticed in the study area's southeast and central-south regions. The reduction in droughts was noticed in the region where they are less frequent, while droughts' increasing tendency was noticed in the regions where droughts are more frequent. This means droughts would be more frequent in the regions that are already prone to higher recurrent droughts and vice versa. A significant increase in droughts in some locations in the northeast would have severe implications on rainfed agriculture in the region. Overall, an increase in SPI over a large part in the northwest and central west, particularly SPI-6 and SPI-12 droughts, indicates a decrease in long-term droughts in the region. However, no significant change in SPI-3 indicates short-term prevails in the study area. Changes in precipitation have reduced long-term droughts but not affected short-term droughts in the region. Short-term severe droughts often highly devastating if they coincide with crop growing seasons (Ahmed et al., 2016; Shiru et al., 2019).

Droughts in an area depend on rainfall variability, not on rainfall mean. Recent studies (Salman et al., 2017) revealed a decrease in rainfall in most parts of Iraq, including some parts in the north. The present study revealed that a decrease in rainfall does not cause any significant increase in droughts in the region. Rather it may be remarked that rainfall becomes more reliable in some parts of the study area, which caused a decrease in droughts occurrence.

The use of high-resolution gridded data in this study allowed evaluation of the spatial distribution of droughts for different durations and their trends. The present study revealed large spatial variability in different duration droughts in the study area. The recurrence of droughts was noticed more in the northern region compared to the southern part. The spatial pattern of drought occurrence in Iraq estimated in this study was not possible to compare with the previous studies' findings due to the use of a limited number of precipitation gauge data in those studies. However, the previous studies showed more frequent droughts at stations located in the far north than other parts. Lück (2014) evaluated the distribution of droughts in Iraq using precipitation data recorded at 82 locations and reported frequent severe droughts in the northeast. Yenigun and Ibrahim (2019) investigated droughts in northern Iraq using precipitation data of 15 stations and reported that the far north stations experience a higher drought frequency. High variability of precipitation over the

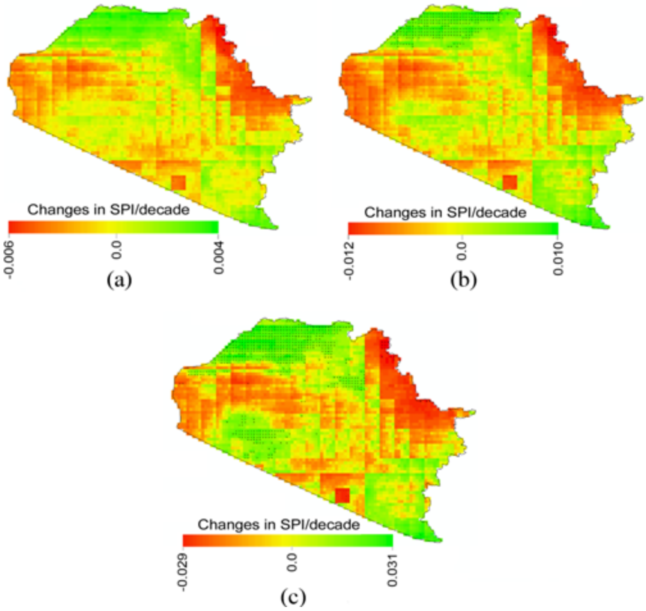


Fig. 10. Spatial Distribution of the Changes in: (a) 3-Month SPI, (b) 6-Month, (c) 12-Month SPI in Northern Iraq

mountainous regions in the north is the major cause of the higher occurrence of droughts in the region.

The trends in 6- and 12-month duration droughts showed an increase at some locations in the northeast and a decrease over a large area in the northwest and central parts of the study area. It indicates droughts became more recurrent in already drought-prone regions and lessened in less drought-prone regions. This would make the distribution of droughts more heterogeneous in the region. Salman et al. (2020) showed that crop irrigation demand in Iraq increased due to a temperature rise and decreased precipitation in most of Iraq. Higher occurrence of droughts or recurrence deficit of precipitation in the context of increasing crop irrigation demand would undoubtedly make the agriculture in the region highly vulnerable. Houmsi et al. (2019) and Pour et al. (2020) evaluated the changes in climate and dryness in Syria and Iran, respectively, bordering the study area. Both the studies showed increasing aridity and expansion of drylands due to climate change. Higher recurrence of 6- and 12-month duration droughts in some parts of the study area may also increase drylands in the study area. Therefore, policy measures related to agriculture and water resources are essential for the region to mitigate drought impacts.

5. Conclusions

The present study assessed the capability of recently released satellite-based rainfall estimates CHIRPS in reconstructing droughts and spatiotemporal changes in different durations of droughts over the northern region of Iraq. The results revealed the capacity of CHIRPS rainfall in reconstructing rainfall and droughts in the study area. Analysis of droughts and their trends revealed a decrease in droughts in the region where they are less frequent, while an increasing tendency in the regions where droughts are more frequent. This indicates a possible deterioration of droughts condition in the region in the future. The spatial characteristics of rainfall and droughts in the northern region of Iraq were not well known due to the lack of adequately distributed meteorological stations. The use of CHIRPS allowed a detailed assessment of spatiotemporal variability of rainfall and droughts in northern Iraq, known as the country's breadbasket. The study's findings would help in policymaking to sustain agriculture and water resources. In future, the reliability of other high-resolution precipitation datasets in drought reconstruction in northern Iraq can be evaluated. Besides, drought characteristics can be estimated using different high-resolution precipitation datasets to understand the uncertainty in estimated drought occurrence frequency.

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