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Drought trend analysis in a semi-arid area of Iraq based on Normalized Difference Vegetation Index, Normalized Difference Water Index and Standardized Precipitation Index postprint

Authors: Ayad M F AL-QURAISHI, Heman A GAZNAYEE, Mattia CRESPI, Ayad M F AL-QURAISHI

Date: 2021-04-30T00:00:00+00:00

Abstract

Drought was a severe recurring phenomenon in Iraq over the past two decades due to climate change despite the fact that Iraq has been one of the most water-rich countries in the Middle East in the past. The Iraqi Kurdistan Region (IKR) is located in the north of Iraq, which has also suffered from extreme drought. In this study, the drought severity status in Sulaimaniyah Province, one of four provinces of the IKR, was investigated for the years from 1998 to 2017. Thus, Landsat time series dataset, including 40 images, were downloaded and used in this study. The Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI) were utilized as spectral-based drought indices and the Standardized Precipitation Index (SPI) was employed as a meteorological-based drought index, to assess the drought severity and analyse the changes of vegetative cover and water bodies. The study area experienced precipitation deficiency and severe drought in 1999, 2000, 2008, 2009, and 2012. Study findings also revealed a drop in the vegetative cover by 33.3% in the year 2000. Furthermore, the most significant shrinkage in water bodies was observed in the Lake Darbandikhan (LDK), which lost 40.5% of its total surface area in 2009. The statistical analyses revealed that precipitation was significantly positively correlated with the SPI and the surface area of the LDK (correlation coefficients of 0.92 and 0.72, respectively). The relationship between SPI and NDVI-based vegetation cover was positive but not significant. Low precipitation did not always correspond to vegetative drought; the delay of the effect of precipitation on NDVI was one year.

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Full Text

Preamble

Drought Trend Analysis in a Semi-Arid Area of Iraq Based on Normalized Difference Vegetation Index, Normalized Difference Water Index, and Standardized Precipitation Index

Ayad M F AL-QURAISHI[1]*, Heman A GAZNAYEE[2], Mattia CRESPI[3],[4]
[1] Department of Surveying and Geomatics Engineering, Faculty of Engineering, Tishk International University, Erbil 44001, Iraq
[2] Department of Forestry, College of Agricultural Engineering Sciences, Salahaddin University, Erbil 44002, Iraq
[3] Geodesy and Geomatics Division, Department of Civil, Constructional and Environmental Engineering, Sapienza University of Rome, Rome 00185, Italy
[4] Sapienza School for Advanced Studies, Sapienza University of Rome, Rome 00185, Italy

Abstract: Drought has been a severe recurring phenomenon in Iraq over the past two decades due to climate change, despite Iraq historically being one of the most water-rich countries in the Middle East. The Iraqi Kurdistan Region (IKR), located in northern Iraq, has also suffered from extreme drought. This study investigated the drought severity status in Sulaimaniyah Province, one of the four provinces of the IKR, for the period from 1998 to 2017. A Landsat time series dataset comprising 40 images was downloaded and utilized. The Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) were employed as spectral-based drought indices, while the Standardized Precipitation Index (SPI) was used as a meteorological-based drought index to assess drought severity and analyze changes in vegetative cover and water bodies. The study area experienced precipitation deficiency and severe drought in 1999, 2000, 2008, 2009, and 2012. Findings revealed a 33.3% drop in vegetative cover in the year 2000. Furthermore, the most significant shrinkage in water bodies was observed in Lake Darbandikhan (LDK), which lost 40.5% of its total surface area in 2009. Statistical analyses revealed that precipitation was significantly positively correlated with SPI and the surface area of LDK (correlation coefficients of 0.92 and 0.72, respectively). The relationship between SPI and NDVI-based vegetation cover was positive but not significant. Low precipitation did not always correspond to vegetative drought; the effect of precipitation on NDVI exhibited a one-year delay.

Keywords: climate change; drought; Normalized Difference Vegetation Index (NDVI); Normalized Difference Water Index (NDWI); Standardized Precipitation Index (SPI); delay effect

*Corresponding author: Ayad M F AL-QURAISHI (E-mail: ayad.alquraishi@gmail.com; ayad.alquraishi@tiu.edu.iq)

Received 2020-03-22; revised 2020-09-28; accepted 2020-11-15
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Science Press and Springer-Verlag GmbH Germany, part of Springer Nature 2021

1 Introduction

Drought is one of the most complex natural disasters, and identifying its causes and development range remains challenging (Aadhar and Mishra, 2017). Generally, drought conveys an impression of water scarcity due to insufficient precipitation, high evapotranspiration, and overexploitation of water resources, or a combination of these factors (Sheffield and Wood, 2008). Drought is triggered by extended periods of precipitation deficiency (Fadhil, 2011) and is usually associated with increased evaporation rates (Perez et al., 2016). Depending on the duration and severity of precipitation deficits, drought can exert various degrees of negative influence on soil/vegetation moisture, groundwater, rivers, streams, ecosystems, and human activities (Smakhtin and Hughes, 2004).

Due to global warming, precipitation has decreased in many regions worldwide (Yu et al., 2019). This climate change is likely to cause more frequent and severe droughts in several countries (Al-Quraishi et al., 2020). Various types of drought—such as agricultural, hydrological, meteorological, ecological, and socioeconomic—are caused by reductions in water resource availability in affected areas (Sharma, 2006). Drought severely impacts agricultural and livestock production resources in any country, negatively affecting both irrigated farmlands and rainfed irrigation-dependent areas. It also has serious consequences for population distribution, production, and livelihoods (Al-Quraishi et al., 2019; Gaznayee and Al-Quraishi, 2019a).

Geographically, Iraq is situated in one of the world' s driest zones; water resources in Iraq are limited and mostly shared with neighboring countries (UNESCO, 2014). Water is the decisive factor for stability and continuity of the agricultural sector and forms the cornerstone of economic and social development in Iraq (Yaseen et al., 2018), which is heavily dependent on surface water and groundwater resources (Alobaidy et al., 2010). Unfortunately, Iraq has suffered from recurring droughts over the past 20 years (Street, 2012).

Remote sensing (RS) technology can assess, monitor, and predict drought (Sun et al., 2010; Hazaymeh and Hassan, 2017). Proper indices derived from optical RS data have been used to assess and analyze drought severity (Hazaymeh and Hassan, 2017; Ghebrezgabher et al., 2019). RS and Geographic Information System (GIS) play vital roles in drought investigation as they offer practical and economical means to study the spatiotemporal distribution and evolution of vegetative cover and water resources through specific indices such as NDVI and NDWI (Acharya and Ray, 2007; Fadhil, 2013; Zhang et al., 2013). Based on RS datasets, spectral water indices can be employed to investigate drought impacts on water resources (Li et al., 2014; Gaznayee and Al-Quraishi, 2019b). The selection of spectral indices for drought assessment depends on the drought type and causative factors (Yang et al., 2014; Awchi and Jasim, 2017). The

Standardized Precipitation Index (SPI) is a well-known meteorological parameter widely used in drought studies (McKee et al., 1993; Edossa et al., 2010; Al-Quraishi and Negm, 2020). Most drought studies rely on both meteorological and spectral indices to establish appropriate measures and treatments for mitigating drought effects (Loucks and van Beek, 2017; Mustafa, 2020).

Although drought assessment using RS data and GIS techniques is not novel, few studies have employed these tools in the Iraqi Kurdistan Region, particularly in Sulaimaniyah Province. Therefore, this study was conducted to address this research gap. RS data were collected for the 20-year period from 1998 to 2017—a crucial period characterized by recurrent drought episodes in Iraq—to calculate NDVI and NDWI. These results were integrated with meteorological data from SPI and hydrological data (the surface area of Lake Darbandikhan, LDK) to analyze and assess drought trends in Sulaimaniyah Province in the IKR.

2.1 Study Area

This study was conducted in Sulaimaniyah Province in the IKR [Figure 1: see original paper], an area located in northern Iraq. The IKR includes four provinces, with Sulaimaniyah Province being the largest (covering two-thirds of the IKR). The study area is bordered by Iran to the east and surrounded by Kirkuk Province to the west, Salahaddin Province to the southwest, and Diyala Province to the south. Sulaimaniyah Province extends over 2.43$×10^{4}$ km^2 and consists of 15 districts: Sulaimaniyah, Qaradagh, Sharazure, Saidsadiq, Penjwin, Halabja, Darbandikhan, Kalar, Khanaqin, Kifri, Chamchamal, Dukan, Sharbazher (Mawat), Ranya, and Pishdar [Figure 1a: see original paper]. LDK, one of the three largest lakes in the IKR, is situated 230 km northeast of Baghdad and nearly 60 km southeast of Sulaimaniyah Province. LDK is connected to the Diyala River, a tributary of the Tigris River, and serves as a source of drinking and irrigation water for Sulaimaniyah Province and surrounding areas while providing significant tourism benefits.

Fig. 1 Digital Elevation Model (DEM) of Sulaimaniyah Province (a) and locations of meteorological stations and geographical distribution of annual precipitation in Sulaimaniyah Province from 1998 to 2017 (b). District numbers: 1, Sulaimaniyah; 2, Qaradagh; 3, Sharazure; 4, Saidsadiq; 5, Penjwin; 6, Halabja; 7, Darbandikhan; 8, Kalar; 9, Khanaqin; 10, Kifri; 11, Chamchamal; 12, Dukan; 13, Sharbazher (Mawat); 14, Ranya; 15, Pishdar. The abbreviations of the districts are the same in Figure 3 [Figure 3: see original paper].

2.2 Data Collection

Forty images from Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI representing paths/rows 168/35 and 168/36 for 20 years from 1998 through 2017 (Table S1) were assembled and used. The study period was selected because it contained recurrent drought episodes. A mosaic of two Landsat scenes was constructed for each of the 20 years. The time series imagery was downloaded from the United States Geological Survey (USGS; https://glovis.usgs.gov/). All Landsat images were acquired in April or May each year, coinciding with peak vegetative proliferation. Landsat images have a spatial resolution of 30 m. The Advanced Spaceborne Thermal Emission and Reflection Radiometer-Global Digital Elevation Model (ASTER-GDEM) V2 dataset with a spatial resolution of 30 m, available from the National Aeronautics and Space Administration (NASA; https://www.nasa.gov/), was utilized as the Digital Elevation Model (DEM) for this study [Figure 1a: see original paper]; the DEM was used to identify relationships between vegetation percentage and altitude.

Daily and monthly precipitation datasets from ten meteorological stations in Sulaimaniyah Province were obtained from the Meteorological Department of the Ministry of Agriculture and Water Resources, Kurdistan Region Government (KRG), Iraq, for the period from 1998 to 2017. Detailed precipitation information for the ten meteorological stations during 1998-2017 is shown in Table S2.

2.3 RS Data Processing

After May 2003, the scan line corrector (SLC) of the Landsat 7 ETM+ sensor failed, resulting in images with strip line gaps, known as SLC-off data. These images had strip line gaps on their sides, causing approximately 22.0% data loss. To correct the SLC-off images and perform gap-filling, we employed ENVI 5.3 (Harris Geospatial Solutions, Inc., USA) and a gap-fill plugin. Although this plugin is not currently available in the ENVI Code Library, a copy can be found at https://docs.google.com/file/d/0B3e_{wo8OTO47b3c4ZHNyV0NmUkk}/edit?pli=1. This add-on module fills gaps in one scene with data from another Landsat scene.

The downloaded Landsat images were corrected by calibrating digital numbers into radiance values using metadata from the Landsat image files. The resultant images were then converted to top-of-atmosphere reflectance values using ENVI 5.3. The images were georeferenced to the Universal Transverse Mercator, Zone 38 North, with the World Geodetic System 84 datum. A mosaic of two Landsat satellite scenes covering the entire study area was created for each of the 20 years. The produced mosaic represents and includes the entire study area. Image-to-image registration was accomplished with a root mean square error (RMSE) of 0.5 pixels.

2.4.1 NDVI

The NDVI is the most widely used index for vegetation monitoring. It accounts for all green vegetation and is based on the combination of red band and near-infrared (NIR) band wavelengths, computed by the well-known formula (Eq. 1) of Rouse et al. (1974):

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

where NDVI is the Normalized Difference Vegetation Index; NIR is the near-infrared band (841-876 nm); and RED is the red band (620-670 nm).

Healthy vegetation exhibits less reflection in the visible range of the electromagnetic spectrum (EMS) due to chlorophyll and other pigment absorption, but shows high reflectance in the NIR section of the EMS. NDVI is a strong vegetation signal primarily utilized to differentiate vegetative areas from non-vegetative areas (Huang et al., 2014). Its digital number values range from -1 to 1. Specifically, values from -1 to 0 represent non-vegetative features such as bare surfaces, built-up areas, and water bodies, while values from 0 to 1 represent vegetative cover features.

2.4.2 NDWI

The NDWI is a parameter used for monitoring water body changes based on green band and NIR band wavelengths. It can be computed by the formula (Eq. 2) of McFeeters (1996):

$$NDWI = \frac{GREEN - NIR}{GREEN + NIR}$$

where NDWI is the Normalized Difference Water Index; and GREEN is the green band (525-600 nm).

A water body has strong absorbability and low radiation from the visible spectrum to the infrared range. According to McFeeters (1996), water bodies can be mapped using a threshold value to better distinguish surfaces without detectable water (NDWI values less than 0.3) from those with detectable water (NDWI values higher than or equal to 0.3). In this study, NDWI was used to determine the size of water bodies such as LDK, and the NDWI fraction images were classified using the ArcGIS package.

2.5 Meteorological Drought Index

The SPI was proposed by McKee et al. (1993) and has been increasingly used over the last two decades due to its substantial theoretical development, robustness, and versatility in drought analyses (Tsakiris et al., 2007; Nalbantis and Tsakiris, 2009). It can be calculated using the following formula:

$$SPI = \frac{X_{ij} - \bar{X}_i}{\sigma_i}$$

where SPI is the Standardized Precipitation Index; X_{ij} is the seasonal precipitation for the ith station and jth observation (mm); $\bar{X}_i$ is the long-term mean precipitation for the ith station (mm); and σ_i is the standard deviation for the ith station (mm).

SPI calculation for any location is based on the long-term precipitation record for the desired period. This long-term record is fitted to a probability distribution, which is then transformed into a normal distribution so that the mean SPI for the location and desired period is zero. The equation is widely used for monitoring meteorological drought and investigating and assessing its severity. It is also utilized to test the relationship between SPI and precipitation and crop production.

One main advantage of SPI is that it only requires precipitation data for calculation. This simplicity makes it suitable for areas lacking diverse data and renders it a popular tool. SPI is independent of geographic location and can be calculated using precipitation averages at the same location (Rossi et al., 2007). It was developed to measure precipitation decline across different time scales and reflect reduced precipitation impacts on water resource availability. Typically, calculating SPI requires precipitation data over a long period (at least 20 years). The precipitation time series dataset is fitted to a gamma distribution and then transformed into a normal distribution with the aid of an equal probability transformation (Guttman, 1999). The probability density function defines the gamma distribution:

$$g(x) = \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta}$$

where α and β are the shape and scale parameters, respectively; x is the amount of precipitation at a meteorological station (mm); and $\Gamma(\alpha)$ is the gamma function.

SPI calculation includes a gamma probability distribution fitted to a given frequency distribution for a meteorological station. For each station, the α and β parameters of the gamma probability density function were estimated for 12 months per year and for each year of the 20-year period. Maximum likelihood solutions were used to optimally estimate the α and β parameters:

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

$$\hat{\beta} = \frac{\bar{X}}{\hat{\alpha}}$$

$$A = \ln(\bar{X}) - \frac{\sum \ln(X)}{n}$$

where n is the number of observations; $\bar{X}$ is the mean precipitation (mm); and A is derived from sample arithmetic and geometric means under certain conditions.

The results from Equation 8 were used to calculate the cumulative probability of an observed precipitation event. Since the gamma function is undefined for $x = 0$ and a precipitation distribution may contain zeros, the cumulative probability $H(x)$ is the extended gamma:

$$H(x) = q + (1 - q)G(x)$$

where $H(x)$ is the cumulative probability; q is the probability of zero; and $G(x)$ is the cumulative probability of the incomplete gamma function. If m is the number of zeros in a precipitation time series, q can be estimated by m/n. The cumulative probability was then transformed to the standard normal random variable (Guttman, 1999). The Drought Indices Calculator (DrinC) software used for calculating SPI was designed by Tigkas et al. (2013).

Positive SPI values indicate wet conditions with precipitation above the long-term average, while negative SPI values indicate dry conditions with precipitation below the long-term average (Kamali et al., 2017). The anomaly strength was classified after standardization of SPI values, as shown in Table 1 . Figure 2 [Figure 2: see original paper] presents the general methodology flowchart adopted in this study, demonstrating the fundamental process of drought trend analysis.

Table 1 SPI-based drought severity classes (McKee et al., 1993)

SPI Value	Classification
$ $2.00	Extremely wet
1.50 to 1.99	Severe wet
1.00 to 1.49	Moderately wet
-0.99 to 0.99	Near normal
-1.00 to -1.49	Moderate drought
-1.50 to -1.99	Severe drought
≤ -2.00	Extreme drought

Fig. 2 Flowchart of the methodology adopted in this study. NDVI, Normalized Difference Vegetation Index; NDWI, Normalized Difference Water Index; SPI, Standardized Precipitation Index; DN, digital number; RED, red band; GREEN, green band; NIR, near-infrared band; USGS, United States Geological Survey.

3 Results

All indices (NDVI, NDWI, and SPI) and the surface area of LDK were computed on an annual basis due to limited imagery availability for the study area.

3.1 NDVI Variation

Results shown in Table 2 and Figure 3 [Figure 3: see original paper] indicated that the most critical drought years detected from vegetation growth were 2000, 2008, 2009, and 2013. During these years, vegetation cover was remarkably reduced compared to other years. Drought was most severe in 2000, with vegetative cover area reduced to 3.31$\times10^{3}$ km^2 (occupying 13.6% of the total study area). The average vegetation coverage during 1998-2017 was 49.6%, and vegetation coverage in 2000 fluctuated 33.3% from this average.

Figure 3 shows the spatiotemporal distribution of NDVI in Sulaimaniyah Province from 1998 to 2017. Vegetation cover exhibited considerable spatial variability, primarily in the center of Sulaimaniyah Province, while the northeastern and southern parts consistently remained the most and least vegetative areas, respectively. For the study period, there was a strong relationship between NDVI and precipitation averages across most parts of Sulaimaniyah Province.

Table 2 Characteristics of NDVI and vegetative cover in the study area from 1998 to 2017

Year	NDVI Max.	NDVI Min.	NDVI Mean	SD	Vegetative cover Area ($\times10^{3}$ km^2)	Coverage (%)	Fluctuation (%)

Note: NDVI, Normalized Difference Vegetation Index; Max., maximum; Min., minimum; SD, standard deviation. Fluctuation indicates variation around the mean vegetation coverage.

3.2 SPI Variation

Table S3 and Figure 4 [Figure 4: see original paper] show the calculated SPI values for Sulaimaniyah Province from 1998 to 2017. The results revealed an irregular cyclical pattern of dry/wet periods during the study period. Droughts were observed in the hydrological years of 1998-1999, 1999-2000, 2007-2008, 2008-2009, and 2011-2012, with some differences across meteorological stations. Generally, droughts commonly occurred at the beginning of the rainy season, reflecting either delayed rainfall or decreased rainfall amounts. The highest drought levels were observed during 1999-2000 at Sulaimaniyah, Bazian, Halabja, Penjwen, Saidsadiq, and Darbandikhan meteorological stations, with average SPI values around -2.22, -1.90, -1.94, -2.08, -1.48, and -1.72, respectively (Table S3; Fig. 4). Additionally, Bazian, Halabja, Darbandikhan, Chamchamal, Kalar, and Pebaz meteorological stations experienced moderate to severe droughts during 2007-2008, with average SPI values of -2.38, -1.92, -1.92, -2.17, -2.56, and -2.08, respectively (Table S3; Fig. 4).

The highest degree of drought severity occurred in Kalar, where the average SPI value was -2.56 during 2007-2008 (Table S3; Fig. 4). Figure 5 [Figure 5: see original paper] shows SPI fluctuation at Darbandikhan meteorological station in Sulaimaniyah Province from 1998 to 2017. The first SPI decline began in 1999 and continued until 2001. This reduction (-1.72) is consistent with decreased precipitation observed in Sulaimaniyah Province throughout 1998-1999, as it was a dry year (Table S3; Fig. 4). The second SPI decline began in 2007 with decreased precipitation in Sulaimaniyah Province throughout 2007-2008 (Table S3; Fig. 4).

3.3 LDK Area and NDWI Variation

The combination of NDWI and SPI is a very effective method for investigating drought patterns to monitor the surface area of LDK and river water levels. Based on NDWI values, the effect of drought on LDK's surface area was severely pronounced in 1999, 2000, 2001, 2008, and 2009 (Table 3 ; Fig. 6 [Figure 6: see original paper]). These years had lower SPI values, reduced LDK surface area, and lower precipitation averages.

The surface area of LDK changed throughout the 20-year study period (Table 3; Fig. 6). Specifically, the largest surface areas were observed in 2003, 2005, and 2016, with values of 113.70, 113.50, and 114.40 km^2, respectively; the smallest surface areas were found in 1999 and 2009, with values of 37.50 and 39.00 km^2, respectively.

Table 3 Surface area of LDK and its percentage change from 1998 to 2017

Year	Surface area (km^2)	Fluctuation (%)

Note: LDK, Lake Darbandikhan. Fluctuation indicates variation around the average percentage of LDK' s surface area.

Although the IKR has abundant water resources, these resources are generally considered limited and variable in time and space. Based on data from the Ministry of Agriculture and Water Resources in Iraq, approximately 40.0% of the region' s spring water dried up during previous drought events (UNESCO, 2014).

3.4 Pearson Correlation Analysis

Pearson correlation analysis between NDVI and SPI showed that NDVI had a low and insignificant correlation coefficient with SPI (Table 4), indicating that vegetation cover extension in a specific year (assessed from April to May) was not dependent on rainfall (or SPI) measured in the same year. Further, there was a significant positive relationship ($P<0.01$) between SPI and precipitation ($r=0.92$) and between SPI and LDK surface area ($r=0.73$). These results are consistent with Gaznayee and Al-Quraishi (2020).

Table 4 Pearson correlation coefficients among NDVI, precipitation, SPI, and LDK surface area

	NDVI	Precipitation	SPI	Surface area of LDK
NDVI	1	0.92**	0.72**	
Precipitation		1	0.92**	0.73**
SPI			1	0.72**
Surface area of LDK				1

Note: ** indicates correlation is significant at P<0.01 level.

4 Discussion

The lowest NDVI values were found in the southern and western regions of the study area, while the northeastern region consistently had more developed vegetation and higher NDVI values (Fig. 3). There was a significant decline in annual precipitation averages in some districts of Sulaimaniyah Province in 2000, 2008, and 2009 (Table S2). The vegetation coverage percentage of NDVI-based vegetative areas shown in Table 2 corresponded to fluctuations in precipitation averages shown in Table S2. Furthermore, low precipitation and high temperature played significant roles in decreasing NDVI values and vegetative areas in the southwestern parts of Sulaimaniyah Province during growing seasons, as depicted in correlation coefficient statistics.

Consecutive spatiotemporal variations of NDVI can reveal drought onset and extent over the studied 20 years. Based on NDVI variation results shown in Table 2 and Figure 3, we conclude that Sulaimaniyah Province experienced drought episodes mainly in 2000, 2008, and 2009. These results are consistent with Almamalachy (2020), who found that the year 2000 was characterized by the most severe drought compared to other years during 1998-2017.

SPI variation results indicated that drought severity was profound during 1998-1999 and 1999-2000, and in 2007-2008, with the southeastern region being the most affected area. The western and southern parts of Sulaimaniyah Province experienced moderate to severe drought in 2012 (Table 1 and S3). The hydrological years of 2001-2002, 2009-2010, and 2015-2016 were wet compared to other hydrological years (Figs. 4-5). According to McKee et al. (1993), drought occurs when SPI is negative, while no drought occurs when SPI is positive.

SPI values did not show a noticeable trend over the study period (Table S3). However, there were two severe drought periods: from 1998-1999 to 1999-2000 and from 2007-2008 to 2008-2009 (Figs. 4-5). The precipitation deficits lasted for at least three years; hence, drought during these periods can be considered long-term drought. SPI results indicated that low precipitation does not always correspond to vegetative drought (Figs. 3-4). A positive relationship existed between SPI and NDVI, especially in drought years of 2000, 2008, and 2013.

However, vegetation cover extension in a specific year (assessed from April to May) was not dependent on precipitation measured in the same year, likely due to the delayed effect of precipitation on vegetation vitality. Ji and Peters (2003) reported that rainfall effects on vegetation became detectable more than one month later. Wang et al. (2003) found that NDVI response to precipitation was delayed by 4-8 weeks. In this study, the delay of precipitation effect on NDVI was one year. A low SPI in 1998-1999 caused low NDVI in 2000, a low SPI in 2007-2008 caused low NDVI in 2009, and a low SPI in 2011-2012 caused low NDVI in 2013 (only in the western and southern parts of the study area). The lack of coordination between SPI and hydrological/agricultural drought is more prominent during growing seasons (Bhuiyan et al., 2006).

The decrease in LDK surface area is consistent with lake shrinkage reported by UNESCO (2014). Fadhil (2011) investigated drought impacts on LDK in terms of climate change and found that LDK experienced the most significant drought events in 2008 and 2009. The decline in LDK surface area could be attributed to reduced water inflow into Iraq from neighboring countries, since approximately 70.0% of LDK water originates from Iran. Furthermore, fluctuating water amounts from rivers in neighboring countries such as Turkey and Iran also caused increasing and frequent droughts in the IKR. Based on NDWI values, this study found that severe drought effects on LDK surface area were pronounced in 1999 and 2009, years characterized by low precipitation and SPI values.

5 Conclusions

This study investigated drought occurrence and effects in Sulaimaniyah Province in the IKR over a 20-year period (1998-2017). Landsat optical remote sensing images were collected during the same season (April-May) each year, and meteorological data were also used. Three standard spectral indices—SPI, NDVI, and NDWI—were evaluated on an annual basis to assess drought and its effects on vegetation cover and water resources, particularly regarding LDK surface area. Drought was more severe in 1999-2000 and 2008-2009, years characterized by low SPI values and reduced LDK surface area due to decreased precipitation. Considering the significant recurrence of drought, it is crucial to supplement water needs in the study area using other available water resources such as snowfall and groundwater to increase water flow into LDK.

Statistical analyses highlighted that SPI is highly correlated with LDK surface area. The correlation between SPI and NDVI in the same measurement year was not significant, likely due to the delayed effect of scarce precipitation on vegetation. More detailed investigations are needed to understand drought frequency and its relationship to affecting factors. Additionally, efforts should be made to understand drought effects on crop production, forests, sustainability, water bodies, and socioeconomic resources. Since only an annual-level analysis was conducted, joint research combining SPI and NDVI on shorter time scales (seasonal or monthly) is needed to highlight the delayed direct effect of drought on vegetation cover and NDVI. We suggest that Google Earth Engine may be a valuable resource for developing such analyses in the future.

Acknowledgements

The authors thank the College of Agricultural Engineering Sciences, Salahaddin University, Erbil, Iraq, for valuable support in this article. We are also grateful to the United States Geological Survey for providing Landsat images. Special thanks to the anonymous reviewers, whose comments significantly contributed to improving the paper.

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Appendix

Table S1 Information of Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI images in the study area from 1998 to 2017

Year	Sensor	Path/Row	Acquisition date (dd/mm)	Resolution (m)
1998	Landsat 5 TM	168/35, 168/36	30/05, 30/05	30
1999	Landsat 5 TM	168/35, 168/36	01/05, 01/05	30
2000	Landsat 7 ETM+	168/35, 168/36	25/04, 25/04	30
2001	Landsat 7 ETM+	168/35, 168/36	28/04, 28/04	30
2002	Landsat 7 ETM+	168/35, 168/36	01/05, 01/05	30
2003	Landsat 7 ETM+	168/35, 168/36	20/05, 20/05	30
2004	Landsat 7 ETM+	168/35, 168/36	06/05, 06/05	30
2005	Landsat 7 ETM+	168/35, 168/36	23/04, 23/04	30
2006	Landsat 7 ETM+	168/35, 168/36	12/05, 28/05	30
2007	Landsat 7 ETM+	168/35, 168/36	07/05, 07/05	30
2008	Landsat 7 ETM+	168/35, 168/36	15/04, 15/04	30
2009	Landsat 7 ETM+	168/35, 168/36	20/05, 20/05	30
2010	Landsat 7 ETM+	168/35, 168/36	05/04, 19/04	30
2011	Landsat 5 TM	168/35, 168/36	16/04, 15/04	30
2012	Landsat 7 ETM+	168/35, 168/36	26/04, 26/04	30
2013	Landsat 8 OLI	168/35, 168/36	23/05, 23/05	30
2014	Landsat 8 OLI	168/35, 168/36	24/04, 24/04	30
2015	Landsat 8 OLI	168/35, 168/36	27/04, 27/04	30
2016	Landsat 8 OLI	168/35, 168/36	15/05, 15/05	30
2017	Landsat 8 OLI	168/35, 168/36	18/05, 18/05	30

Note: Figure translations are in progress. See original paper for figures.

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