



Time Series Analysis of Drought Indices for Monitoring Desertification and Land Degradation

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Article information

Received: 10- Apr -2023

Revised: 13- May -2023

Accepted: 29- May -2023

Available online: 31- Dec – 2023

Keywords:

drought Indices

SPI

RDI

ZSI

PPA

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ABSTRACT

The goal of the research is an estimation of meteorological drought indices and their impact on desertification and land degradation. The climatic data for the time series from 1990-2021 are used, which involves precipitation, temperature, humidity and evapotranspiration, depending on the aims of the paper. The precipitation-based drought indices SPI (Standardized Precipitation Index), RDI (Reconnaissance Drought Index), PNI (Percent of Normal Index), RAI (Rainfall Anomaly Index), and ZSI (Z-Score Index) and PPA (Percentage of Precipitation Anomaly) are calculated. Analysis correlation and regression coefficient are also calculated between them. The results show that all indices point to a severe drought for the periods from 1990-1993 and 1998- 2000, as well as, the highest humid years in 2015 to 2018 (15 to17 years less than zero and 14-16 years above zero according to index) Also, that drought was continuous for years 2020, 2021 and till now. The results indicate a positive linear regression relationship between the SPI and RDI, RAI, ZSI, PNI, and PPA in range ($R^2 = 0.99, 0.96, 0.95, 0.95$ and 0.95). While the correlation relationship between the SPI and other indices is strongly positive ($r > 0.97$).

DOI: [10.33899/earth.2023.139660.1068](https://doi.org/10.33899/earth.2023.139660.1068), ©Authors, 2023, College of Science, University of Mosul.

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تحليل السلاسل الزمنية لمؤشرات الجفاف لرصد التصحر وتدهور الأراضي

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المخلص	معلومات الارشفة
تهدف هذه الدراسة الى تقييم مؤشرات الجفاف وتأثيرها في التصحر وتدهور الأراضي. تم استخدام السلسلة الزمنية للفترة من عام 1990 الى 2021. والتي شملت البيانات المطرية ودرجات الحرارة والرطوبة والتبخر - نتح. تم اعتماد عدد من ادلة الجفاف وهي SPI, RDI, ZSI, PNI, PPA وإيجاد معامل التحديد R2 ومعامل الارتباط r بين دليل المطر القياسي SPI والأدلة الأخرى. بينت نتائج الدراسة بان اكثر الفترات التي عانت من شدة الجفاف وتكراره كانت من العام 1990-1993 ومن العام 1998-2000، في حين افضل المواسم التي تميزت بوفرة الامطار كانت في 2015-2018 (كل الأدلة المستخدمة تبين ان 15-17 سنة من السلسلة كانت اقل من صفر و 14-16 سنة كانت اعلى من الصفر)، ونلاحظ استمرار موجة الجفاف في الأعوام الأخيرة. تشير النتائج بان العلاقة الإحصائية لمعامل التحديد كانت خطية موجبة بين دليل المطر القياسي SPI والأدلة RDI, RAI, ZSI, PNI, PPA اذ بلغت قيمة معامل التحديد R2 (0.99, 0.96, 0.95, 0.95, 0.95) على التوالي. في حين نلاحظ بان معامل الارتباط (r) كانت قوية موجبة بين ادلة الجفاف وبلغت اعلى من 0.97، مما يدل على أهمية استخدام هذه الأدلة في رصد الجفاف وخاصة دليل المطر القياسي التي اكدت عليه اغلب الدراسات.	<p>تاريخ الاستلام: 10-ابريل-2023</p> <p>تاريخ المراجعة: 13-مايو-2023</p> <p>تاريخ القبول: 29-مايو-2023</p> <p>تاريخ النشر الإلكتروني: 31-ديسمبر-2023</p> <p>الكلمات المفتاحية:</p> <p>مؤشرات الجفاف</p> <p>دليل SPI</p> <p>دليل RDI</p> <p>دليل ZSI</p> <p>دليل PAA</p> <p>المراسلة:</p> <p>الاسم: اياد عبدالله خلف</p> <p>Email: aiad2017@tu.edu.iq</p>

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Introduction

The drought is one of the environmental problems in arid and semi-arid climates, especially in recent years, where the great climate changes around the world are happened. Most of the Iraqi land had suffered from desertification and land degradation because of many factors particularly the drought, and due to declines in the plant diversity, low of soil fertility, degradation of soil structure, low of soil moisture, and wind erosion activity (Khalaf and Hussien, 2021; EDEN 2012). The higher temperatures and low rainfall over a long period can impact the human health, vegetation fields, rangeland, pastoral shrub, wild fauna and flora, and the management of water resources. Many scientific studies such as Wilhite (2000) have classified the drought as meteorological, agricultural, hydrological, and additional socio-economic. Meteorological drought is classifying according to the degree of drought into (normal, moderate, severe or extreme). Meteorological drought is characterized by scarcity of rainfall through months or years (Potop et al., 2014; Sandoval and Garcia, 2017). Agricultural drought plays an essential role in a country's economics (like Iraq) because the ruler society are dependent upon agricultural fields and rangelands (Yu et al., 2013). Climate factors such as rainfall, temperature, sunlight, wind, vapor, and humidity lead all to changes in land use and activity of desertification processes and land degradation (Sivakumar, 2007). Most impacts on agricultural activities are due to a decline in soil moisture, nutrient availability and plant

function during the growth phase. Therefore, the term drought also refers to hydrological drought or reduction of water resources that directly affects ecosystems and human life. Hydrological drought refers to the reduction of water resources in all regions of the world (Falkenmark, 2013). Drought leads to a large number of negative effects on the soil and plant environment. In environmental terms, drought not only reduces land productivity, surface and groundwater, but also contributes to the hazard of desertification (Eden, 2012). AlArazah (2017) studied drought over Iraq on a large scale using the SPI and SPEI drought indices derived from ERA interim/in situ precipitation data. According to the FAO report on Iraq, the drought has reduced arable land by almost 40%. Droughts are likely to intensify under global climate change, confirming the importance of global drought monitoring. An assessment of the drought status of the Udayim River Basin in Iraq and its impact on the environment was carried out, note that the temporal variation of the drought index from 1980 to 2010 was analyzed (Mail, 2017). Selection of drought indices (DI, PNI, SPI, CZI, DI, ZSI) for drought monitoring in different surrounding worlds (Morid et al., 2006; Salehnia, et. al., 2017; Usama et. al., 2019; Sridhara, et al., 2021). McKee et al. (1993) developed (SPI) to monitor drought and found that the gamma distribution fits well with the precipitation time series. In addition, the Rainfall Anomaly Index (RAI) and the Yield Anomaly Index (YAI) (Dutta et al., 2011; 2015) are calculated to show precipitation and yield variation data in normal and dry years as determined by long-term satellites.

Aim of study

The research goals for estimating meteorological drought indices (SPI, RDI, PPA, PNI, and ZSI) for monitoring desertification and land degradation.

Materials and Methods

Study Area

This study is conducted in Al-Botamaa area, which is located between latitudes (34°52'29.386" - 34°42'54.584") N and longitudes (43°26'15.703" and 43°31'22.753") E, in Salah Al-Din Province in Iraq (Fig. 1). According to Digital Elevation Model (DEM), the study area is located at an elevation about 130 m above mean sea level. The mean annual rainfall ranges from 42 to 295 mm, and the highest mean month in Dec, Jan, Feb, and March. While the mean monthly temperature is increasing in the summer season in July, June, and August ranging between 22.1 -36.0 C°, as well as it decreases in the winter season in Dec, Jan, and Feb in the range of 8.3, 10.9, and 16.1, respectively. The minimum and maximum monthly temperature reached 5.5 and 38.9° C (Table 1). The mean humidity percentage increases in the Jan, Dec. ranging (61.9, 60.0) % respectively, while, the decrease in Jun and Jul ranges (18.7, 17.5) % respectively. The highest evapotranspiration (ET_o) reaches on Jul. 332.6. The time series analysis of annual rainfall for years from 1990-2021 is used for monitoring drought and its effect on land degradation and desertification as low vegetation, soil degradation, dust storm, wind erosion and sand dunes.

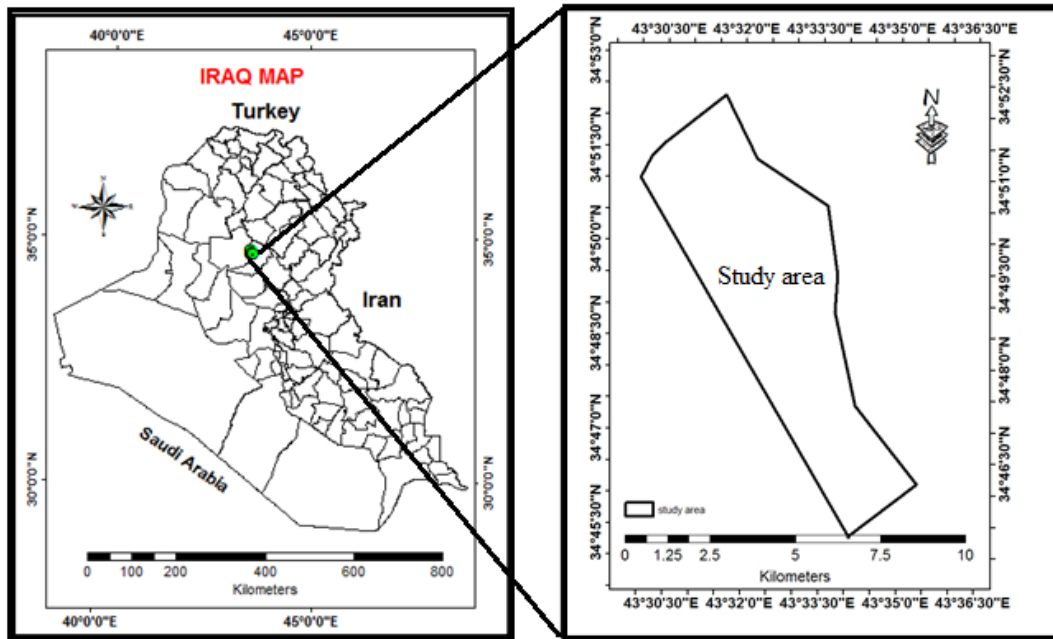


Fig. 1. A map of study area for monitoring drought.

Table 1: The climate data of study area (1990-2021).

data	Statis.	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov.	Dec.
Rainfall mm	min	5.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	max	79.1	89.7	58.0	52.7	31.6	0.0	0.0	15.8	5.3	36.9	58.0	58.0
	mean	22.9	20.4	18.8	14.5	3.6	0.0	0.0	0.5	0.2	5.6	17.3	18.9
	Std	16.0	18.2	17.8	14.3	7.5	0.0	0.0	2.8	0.9	8.9	19.2	12.8
Tc°	min	5.5	7.3	10.9	18.4	26.2	30.8	32.4	33.3	28.4	23.0	12.3	6.4
	max	11.8	13.1	20.8	25.6	32.3	36.0	38.9	37.6	34.2	28.0	20.4	15.5
	mean	8.3	10.9	16.1	22.1	28.6	33.5	36.0	35.8	31.5	25.7	16.5	10.3
	Std	1.4	1.4	2.3	1.6	1.4	1.1	1.3	1.2	1.5	1.3	1.9	2.1
ETo (Blaney and Criddle) (mm)	min	31.2	37.4	63.8	117.0	204.3	257.0	285.0	278.2	199.7	144.4	59.0	33.0
	max	58.6	64.3	131.1	179.1	275.3	321.9	374.6	332.7	261.5	188.4	105.6	74.9
	mean	42.7	53.6	96.8	147.7	231.7	290.2	332.6	309.3	232.4	167.1	82.2	49.7
	Std	6.2	6.6	16.1	14.1	15.7	14.1	17.4	15.1	15.5	11.2	11.2	9.5

Source: <https://power.larc.nasa.gov/>

Meteorological drought indices.

The six drought indices (SPI, RDI, RAI, PNI, PPA, and ZSI) are selected for estimating drought hazard and severity in the study area as follows:

SPI (Standardized Precipitation Index) is recognized by McKee et al. (1993) at Colorado State University. It depends on precipitation data, and its ability to be calculated in a variety of time series from (1) one to (72) seventy-two months. It is usually applied for monitoring drought severity under all climate regimes. The Positive SPI values refer to that the rainfall more than the mean, while the negative values indicate that rainfall is less than the mean (Table 2).

$$G(x) = \frac{1}{\beta^a \Gamma(a)} x^{a-1} e^{-x/\beta} \text{ Where, } a > 0, a \text{ is a shape factor, } \beta > 0, \beta \text{ is a scale factor.}$$

$$r(a) = \int_0^\infty y^{a-1} e^{-y}$$

Where, $r(a)$ is the gamma function.

$$G(x) = \int_0^x g(x) dx = \frac{1}{\beta^a \Gamma(a)} \int_0^x x^{a-1} e^{-x/\beta}$$

Letting $t = x/\beta$

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

$$\beta = \frac{\dot{X}}{a}$$

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

$$G(x) = \frac{1}{r\dot{a}} \int_0^x t^{a-1} e^{-t} dt$$

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

RDI (Reconnaissance Drought Index) is developed by Tsakiris and Vangelis (2005) as a meteorological drought index. The (RDI) is a general meteorological index for monitoring the status of drought and provides a more actual representation of the drought hazard because it depends on the potential evapotranspiration and rainfall under different climatic regimes (Table 2).

$$RDI = \frac{y_k^i - \bar{y}_k}{\sigma_{yk}} \quad \text{(Equation-1)}$$

Where $y^{(i)}$: $\ln(a^{(i)})$; \bar{y}_k : arithmetic mean; σ_{yk} : standard deviation

Table 2: standardized Precipitation Index (SPI) and RDI.

Class	Category	Symbol	Range
1	Extremely wet	EW	+2 to more
2	Very wet	VW	1.5 to 1.99
3	Moderately wet	MW	1.0 to 1.49
4	Near normal	N	-0.99 to 0.99
5	Moderately dry	MD	-1.0 to -1.49
6	Severely dry	SED	-1.5 to -1.99
7	Extremely dry	ED	-2 to less

PNI (Percent of Normal Index) refers to a percentage of normal precipitation at any climate station. It can be calculated monthly, seasonally, and yearly according to (Salehnia et al., 2017; Hayes, 2006). Percent of Normal Index is based on wetness and dryness (Table 3).

$$PNI = \frac{Pi}{\bar{P}} \times 100 \dots \text{(Equation -2)}$$

Were, P_i : total of annual precipitation; \bar{P} : average of precipitation in the time series.

Table 3: Annual Percent of Normal Index Classification

Class	Drought Classes	Symbol	PNI Value
1	Wet	W	120<
2	Normal	N	80 to 120
3	Slightly Dry	SD	70 to 80
4	Moderately Dry	MD	55 to 70
5	Severe Dry	SED	40 to 55
6	Very Severe Dry	VSD	<40

RAI (Rainfall Anomaly Index) considers two anomalies, i.e., positive and negative. The ten highest values are the mean to for positive anomaly and the ten lowest values are the mean for negative anomaly (equation formula 3, 4). The Annual Rainfall Anomaly Index (RAI) is calculated to analyze the frequency and intensity of the drought and high rainfall years in the study area (Table 4). RAI was first developed and used by Rooy (1965) and adapted by Freitas (2005), it constitutes of the following:

$$RAI = 3 \times \left[\frac{N - \dot{N}}{\dot{M} - \dot{N}} \right], \text{ For positive value } \dots \dots \text{ (Equation- 3)}$$

$$RAI = -3 \times \left[\frac{N - \dot{N}}{\dot{X} - \dot{N}} \right], \text{ For positive value } \dots \dots \text{ (Equation - 4)}$$

Where: N = current monthly/yearly rainfall, \bar{N} = monthly/yearly average rainfall of the time series (mm); \bar{M} = average of the (10) ten highest monthly/yearly; \bar{X} = average of the (10) ten lowest monthly/ yearly rainfall.

Table 4: Classification of (RAI) Rainfall Anomaly Index.

Class	Drought Classes	Symbol	RAI range
1	Extremely humid	EH	Above 4
2	Very humid	VH	2 to 4
3	Humid	H	0 to 2
4	Dry	D	-2 to 0
5	Very dry	VD	-4 to -2
6	Extremely dry	ED	Below -4

ZSI (Z-Score Index) is occasionally confused with SPI. However, the Z score Index can be calculated by subtracting the long- term mean from an individual rainfall value and then dividing the difference by the standard deviation (Table 5). Other method to determine drought index had used Z score; and this method does not require adjusting the data using appropriate rainfall data to the Pearson distributions (Patel et al., 2007; EKWEZUO and MADU, 2020; Usama et. al., 2019).

$$ZSI = \frac{P - \bar{P}}{Sd} \quad (\text{Equation} - 5)$$

Where P is the annual rainfall for broth years (mm), \bar{P} is the long-term mean of rainfall.

Table 5. The ZSI classification of monitor drought.

Class	Drought Classes	Symbol	ZSI score
1	Extreme drought	ED	≥ -2.0
2	Severe drought	SD	-1.90 to -1.50
3	Moderate drought	MD	-1.49 to -1.00
4	Slightly or Mild drought	SD	-0.99 to 0.99
5	Normal wet condition	NW	$1.0 \geq$

PPA (Percentage of Precipitation Anomaly) is suggested by the Meteorological Department in India in 1971. The PPA depends on anomalies percentages of rainfall for the length of the time series (Singh et. al., 2014). The negative values refer to that rainfall less than the mean through of time series, while the positive values are rainfalls greater than the average (Table 6). It is calculated by equation (6) (Jawad et. al., 2018; Singh and Ajay, 2014).

$$PPA = \frac{P - \bar{P}}{\bar{P}} \times 100 \quad (\text{Equation} - 6)$$

Where:

P : is the total of precipitation for a selected rainy season.

\bar{P} : is the average of precipitation for the study period.

Table 6: The PPA score and classes.

Class	Drought Classes	Symbol	PPA score
1	Extreme dry	ED	-
2	Severe dry	SED	$\leq - 60$
3	Moderate dry	MD	-20 to -59
4	Near normal	N	± 19
5	Moderate wet	MW	20 to 59
6	Very wet	VW	≥ 60

Results and Discussion

Indicators used to monitor drought

Figure (2) shows the variation in the precipitation indices to monitor drought for the period 1990-2021. The results show that the Standard Precipitation index (SPI) for the time

series varied for a long time in the study area characterized by an increase in the annual precipitation rates expressed in positive values greater than zero. The longest period of time series is between the years 2003-2007 and 2014-2019. According to the classification in table (7), which indicates that the study area falls within the classes of Normal (N), Moderate Wet (MW), Extremely Dry (ED), and replicate percent is (67.74, 12.90, 9.68 and 6.45) %, and the other classes are lesser. The results in tables (7 and 8) indicate that the years that had high rainfall rates within the very wet category during 31 years were one year, and the recurrence rate was 3% in the 2015-2016 season. In general, the number of years higher than zero (+) is 51.61%, whereas, the number of years negative (-) was 48.39%. Therefore, the longest period in which there was a significant decrease in rainfall for repeated years was 3 years and for the period from 1990-1992, and from the period 1998- 2000 as hydrological cycle. The World Meteorological Organization (WMO, 2012) confirmed that the standard precipitation index has a close relationship in assessing the state of agricultural drought (soil) because of the close relationship between soil moisture content and drought. The results of Tables (7 and 8) and Figure (2) show that the results of the RDI index are consistent with the SPI index, as it ranges between (-2.29 during the rainy season 1999-2000) and (1.9 during the rainy season 2015-2016). Thus, the RDI is one of the important indicators that play a role in monitoring and evaluating the drought. The Rainfall Anomaly Index (RAI), which used to monitor the hazard of drought and to analyze the distribution of rainy seasons during a certain period of time (Fig.3; Tables 7 and 8). It ranges between (-4.85 in the season 1999-2000), which indicates the most years that suffer from a significant decrease in rainfall rates, and (6.63 in the season 2015-2016), which indicates abundance in rainfall. Compared with a table (4), we note that the extremely humid class is 9.38% for seasons 2015-2016, 2017-2018, and 2018-2019; also, very wet (VH) years was 12.50%. The years that fall between the index values 0-2, which express the humid class, reach 25.00% of the time series. While, the dry, very dry, and extremely dry classes are 28.13, 15.63, and 9.38% of time series. It is observed in the first ten seasons of the time series (1990-2000) that the index classes (dry, very dry, and extremely dry) are taken following sequence: (4) four dry seasons (1990-1991 to 1993-1994), (1) one year of humid (1994-1995), then, (2) two years of dry and very dry, then (1) one humid year and (2) two years of extremely dry. Therefore, this is consistent with Ramsey (2009) who found that droughts occurred in an irregular and highest severity over the last decade. While, through the second time series from seasons 2000-2001 to 2009-2010, the results indicate that there is an abundance of annual rainfall, as the longest period in which there is a rise in rainfall rates (7 seasons of humid and very humid); then, it is followed by a season suffering from a lack of rain at seasons 2010-2011 to 2014-2015. The results in the last time period 2015-2019 are positive (>0) indicator values, which fall within the classes of wet, very humid, and extremely wet, continued for (5) five years. Then, the decline in the years 2020 and 2021, and it continues in decline in precipitation rates. As a result, the number of years with negative values, which refers to the dry, very dry, and extremely dry variety, reached 17 years, constituting 54.84%, while the number of years, whose index is positive, is 14 years constituting 45.16%. The results referred to that RAI is significant in monitoring drought and its environmental impact on desertification and land degradation in arid and semi-arid regions, and its risk increases when there is a fragile environment such as the dominance of gypsum soils with a fragile structure and lack in fertile content, organic matter and its low ability to retain moisture. The results of tables (7, 8) and figure (4) explain that Zscor index, which expresses the status of drought over a long period of time, has values ranging between (-1.71 in season 1999-2000) and (2.56 in season 2015-2016).

This difference is in the hazard of drought during the selected time series. The highest percentage (about 67.74%) is mild or slightly dry. While the classes of moderate drought (MD) and Normal wet (NW), and severe dry (SD) reach 6.45%, 16.13%, and 9.68% (Table 8; Fig.4). Therefore, according to the Z_{scor} index, they did not reach the appropriate levels of rainfall rates in the study area, which help the growth of vegetation cover

Table 7: Drought indices are deriving from Precipitation.

1990-91	MD	VD	MD	MD	MD	SED
1991-92	N	D	SD	N	N	N
1992-93	N	D	SD	MD	N	SD
1993-94	N	D	SD	N	N	N
1994-95	N	H	SD	N	N	N
1995-96	N	D	SD	N	N	N
1996-97	N	VD	SD	MD	N	MD
1997-98	N	H	SD	MW	N	W
1998-99	ED	ED	SED	SED	ED	VSD
1999-00	ED	ED	SED	SED	ED	VSD
2000-01	MW	VH	NW	MW	MW	W
2001-02	N	H	SD	N	N	N
2002-03	N	VD	SD	MD	N	MD
2003-04	N	H	SD		N	W
2004-05	N	VH	SD	MW	N	W
2005-06	N	H	SD	MW	N	W
2006-07	N	H	SD	MW	N	W
2007-08	N	D	SD	MD	N	SD
2008-09	N	D	SD	N	N	N
2009-10	N	H	SD	N	N	N
2010-11	N	D	SD	MD	N	SD
2011-12	MD	VD	MD	MD	MD	SED
2012-13	MW	VH	NW	MW	MW	W
2013-14	N	D	SD	N	N	N
2014-15	N	H	SD	N	N	N
2015-16	VW	EH	NW	VW	VW	W
2016-17	N	VH	SD	MW	N	W
2017-18	MW	EH	NW	VW	MW	W
2018-19	MW	EH	NW	VW	MW	W
2019-20	N	D	SD	MD	N	SD
2020-21	ED	ED	SED	SED	ED	VSD

Table 8: The Frequency and Classes of Drought Index

Classes	SPI, RDI		RAI		PPA		ZSI		PNI	
	F	%	F	%	F	%	F	%	F	%
1	0	0.00	3	9.38	3	9.68	0	0.00	11	35.48
2	1	3.23	4	12.50	8	25.81	3	9.68	9	29.03
3	4	12.90	8	25.00	9	29.03	2	6.45	4	12.90
4	21	67.74	9	28.13	8	25.81	21	67.74	2	6.45
5	2	6.45	5	15.63	3	9.68	5	16.13	2	6.45
6	0	0.00	3	9.38	-	-	-	-	3	9.68
7	3	9.68	-	-	-	-	-	-	-	-

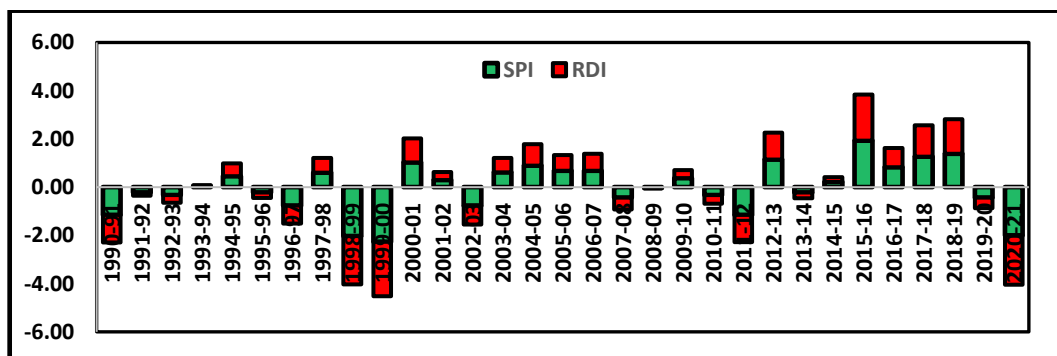


Fig. 2. The Precipitation Drought Index for monitoring drought.

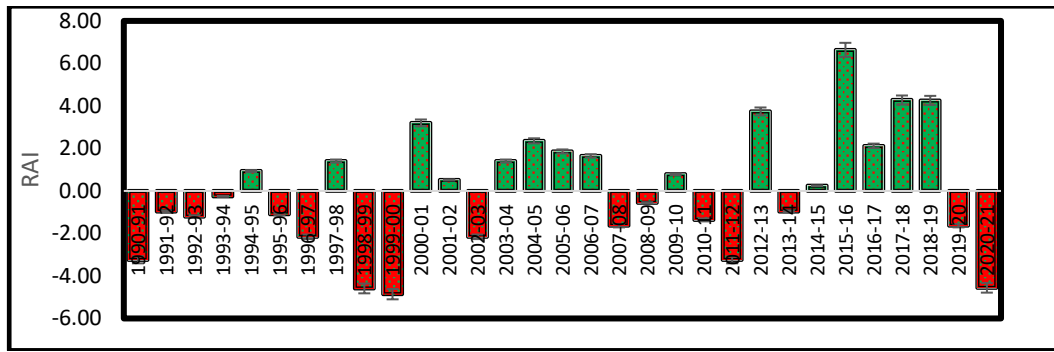


Fig. 3. RAI-Rainfall Anomaly Index for monitoring drought.

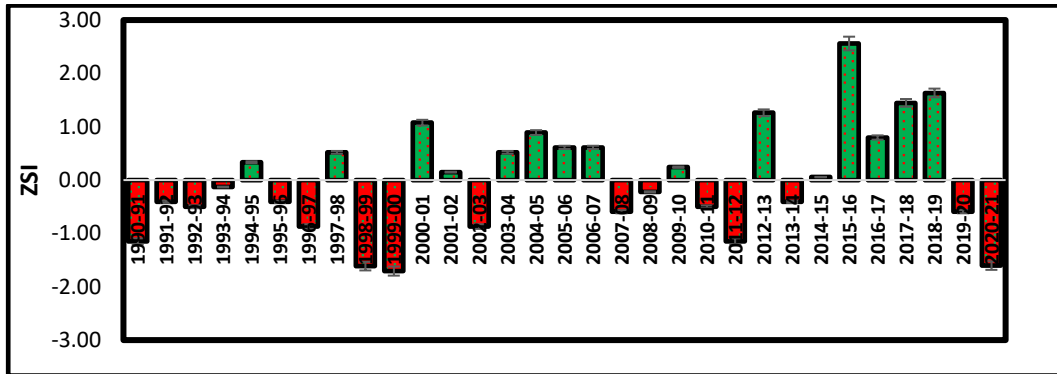


Fig. 4. The ZSI (ZScore Index) for monitoring drought.

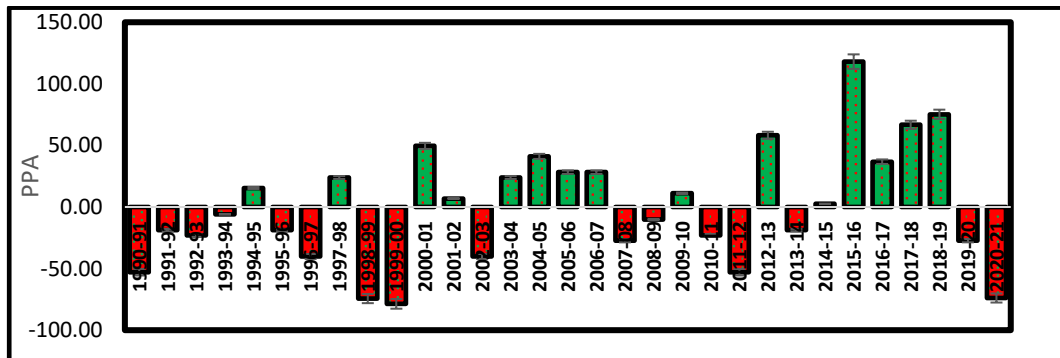


Fig. 5. The Percentage of Precipitation Anomaly for monitoring drought.

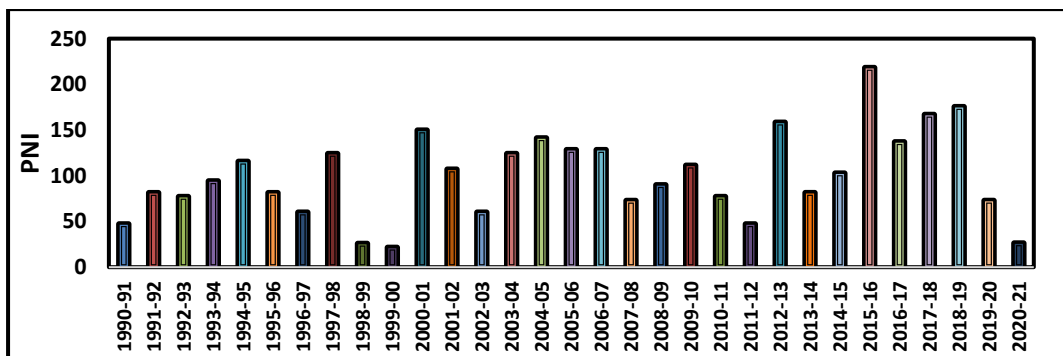


Fig. 6. The PNI-Percent of Normal Index for monitoring drought.

and the protection of the soil surface from soil degradation and its low productive capability is agreed with Vicente-Serrano (2013). The PPA, which refers to the percentage of annual rainfall along the time series of the study area, the positive values indicate a decrease in the risk of drought with suitable rainfall rates. The negative values indicate the risk of drought in land degradation and desertification, a decrease in the productive capability of agricultural

crops, and an increase in the risk of wind erosion in the study area. The results of figure (5) and table (7) show difference in PPA index along the time series, as the lowest value is (-78.63) in the season 1999-2000 and the highest value is (118.03) in the season 2015-2016. The results in table (8) show that the normal, moderately dry, and moderate wet had the highest frequency (9, 8 and 8) around 29.03, 25.81 and 25.81% of the time series, and there is agreement with other indices in the succession of drought periods along time series and the periods during which high rainfall rates are witnessed. In general, the number of dry seasons during the study period about 16 years (51.49) %, and this is consistent with the results Usama et. al. (2019) that the number of dry years based on this indicator is 12 years. The Precipitation Normal index (PNI), which is used to describe the drought and its severity, it is characterized by its easy calculation and understanding. It is one of the most used indices to determine the deviation of rainfall from its long-term average for any climate station. The results of figure (6) and table (7) refer to highest frequency (35.48 and 29.03%) under wet and normal classes; while the slightly dry and very severe dry reach 12.90 and 9.68% (Table 8). Whereas, almost years tend towards drought compared to rainy years (51.48) %.

Statistical relationship between drought indices

The Standard Precipitation Index (SPI) is one of the most important indicators used to monitor drought globally and developed by McKee (1993) in order to determine the general trend for years of humidity and drought **for any** time series not less than 30 years. It is a relative index that deals with each station according to the rate of rainfall and according to the World Meteorological Organization (WMO), SPI has been adopted as the best usability index for monitoring of drought around of the world. The results of the figure (7) indicate that there is strongly positive linear regression relationship between (SPI) and (RDI, RAI, ZSI, PPA, and PNI) drought indices. The result of curves whose coefficient of determination (R^2) is positive linear regression between the SPI and the indices of (RAI, ZSI, PPA, PNI and RDI), where the coefficient of determination (R^2) values is (0.96, 0.95, 0.95, 0.95 and 0.991).

Table (9) refers to the correlation coefficient (r) values. The statistical relationship is strong positive between the indices of drought. The correlation coefficient (r) among the indicators SPI, RAI, ZSI, PPA, PNI and RDI are higher than 0.97. While, the correlation coefficient values between SPI with other drought indicators are (0.837, 0.861, 0.861, and 0.861) respectively. As the results was are in agreement with Usama et al. (2019) when compared with drought indicators for the period 1970-2015 based on indicators (SPI, ZSI, PPA) reaching a strong positive regression with the lowest value of the coefficient of determination of R^2 (0.85) and the highest value of the coefficient of determination of R^2 between ZSI and PPA ($R^2 = 1$). The results of the statistical relationship also agree with the results of Sridhara et. al. (2021) who studied drought in Chitradurga district of Karnataka, and concluded that the relationship between ZSI and SPI using R^2 values for the period from 1967 to 2017 range from 0.95 to 0.98. Noor et. al. (2020) gave a good correlation between SPI and ZSI, which varies between 0.97 and 0.99 depending on the station.

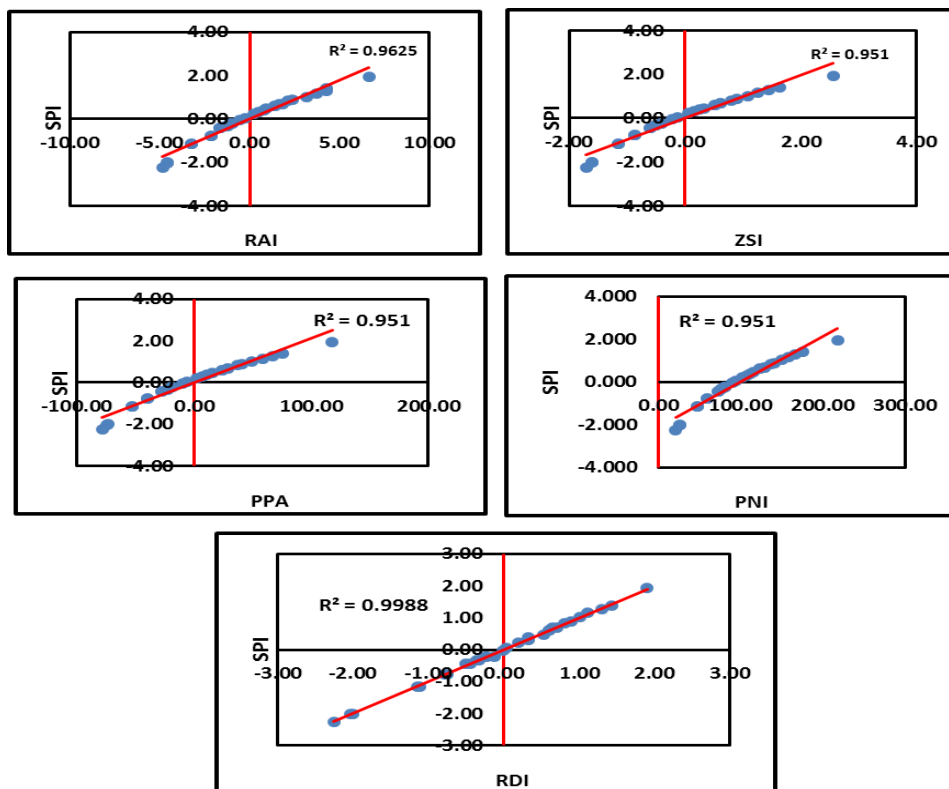


Fig. 7. The regression coefficient (R^2) between SPI and other Drought indices

Table 9: The correlation coefficient (r) between drought indices.

Indices	SPI	RDI	RAI	ZSI	PPA	PNI
SPI	1.00					
RDI	1.00	1.00				
RAI	0.98	0.98	1.00			
ZSI	0.98	0.97	1.00	1.00		
PPA	0.98	0.97	1.00	1.00	1.00	
PNI	0.98	0.97	1.00	1.00	1.00	1.00

Therefore, drought has serious consequences in the strange or long term on human life and has negative repercussions on the economic and social reality and food security of the country, as well as its impact on soil, plants and live organisms since the soil is the main resource that supports the life of humans, plants and animals. Therefore, frequent drought destroys its soil fertile and its productivity capability as the organic matter content, nutrients due to active erosion factors, and this increases the activity of dust and sand storms, and as a result leads to the destruction of vegetation cover and its density. We infer from this the need to provide climate data for periodic monitoring of drought and its impact of drought on agricultural activity and to improve the management of agricultural water resources, and this is consistent with van den Hurk et al. (2016). Therefore, satellite-based climatic information depicts the effects of drought on a region-wide basis better than meteorological drought (Leona, 2019; Iizumi et. al., 2013; Turco, et. al., 2017; Madadgar, et. al., 2017).

Conclusion

We conclude in the current study by adopting a number of drought indicators (SPI, RDI, RAI, ZSI, PNI and PPA) that there is succession and fluctuation of drought periods during the selected time series. The percentage of negative values that indicate drought varied between 48 to 51% according to index compared to positive values that indicate wet years. Additionally,

the normal and moderate dry classes are dominant at almost indices. We note that the relationship of regression (R^2) is strong positive between SPI and other indices reaching more than 70%, while the correlation coefficient (r) between drought indicators is more than 0.97.

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