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Assessment of the relationship between drought and vegetation cover using remote sensing

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A B S T R A C T

Drought is a natural phenomenon and the occurrence of this phenomenon is likely in all parts of the world. Drought depends on its severity and one of the its affected resources is vegetation and its conditions. This study tries to present the relationship between vegetation cover and drought in northwest of Iran. To assess the effect of drought on vegetation, the Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI) and Standardized Precipitation Index (SPI) were determined during 2002–2016 using remote sensing and several software including ArcGIS 10.3, ENVI, SPSS Statistics 17.0 and Microsoft Excel. At the first the correlations between NDVI and VCI were compared with SPI for each year then they were compared with SPI of the last year using MODIS sensor. Pearson correlation was used to calculate the correlation between the indices. The results showed that the correlations between NDVI and VCI with the SPI of same year are 0.568 and 0.481 respectively, and also the correlations between NDVI and VCI with the SPI of last year are 0.377 and 0.269, respectively. These results demonstrate that the correlations between NDVI and VCI with the SPI of same year are more than the SPI of next year also the correlation between NDVI and SPI in the same year is more than NDVI and SPI of the last year which indicate that the density vegetation of each year is directly related to the amount of rainfall of same year.

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1. Introduction

Drought is the consequence of a natural reduction in the amount of precipitation during period of time (e.g. a season, a year or more in length) and often associated with other climatic factors such as high temperatures, low relative humidity and high winds that can exacerbate the severity of the drought (Sivakumar, 2005). Totally, Drought phenomenon can affect the density of vegetation in each area especially dry regions (Khosravi et al., 2016) that depends on its severity. This phenomenon occurs over most parts of the world, even in wet and humid regions. Arid areas are prone to drought because these areas´ rainfall amounts critically depends on a few rainfall events (Sun et al., 2006). Drought indicators are the mixture of several variables, including precipitation, temperature, groundwater levels, soil moisture, stream flow and etc. (Steinemann et al., 2005). In recent decades, the occurrence of droughts has been more than human intervention. Each drought (from the physical point of view) is characterized by its location, intensity, frequency and probability (DEWFORA, 2012). UNCCD acknowledged that land degradation can be result from various factors including climate variations and human activities, so quantifying desertification by evaluation of vegetation cover can conduce to discussions concerning about climatic effects on arid and semi-arid ecosystems (Higginbottom and Symeonakis, 2014). Verbesselt et al. (2010) suggested that remote sensing data with continuous time series scale and different spatial scales can provide a measurement of vegetation. The NDVI based on AVHRR data has been widely used to assess vegetation cover (Moulin et al., 1998).

One of the useful tools for monitoring environmental condition (such as yield estimation, land degradation and desertification, crop condition simulation etc.) is Satellite based NDVI (Aboelghae et al., 2010; Mondal et al., 2014; Dutta et al., 2015). Often NDVI is investigated by computing other vegetation index named Vegetation Condition Index (VCI), which compares the current NDVI to the observed values of this index in previous years (Gebrehiwot et al., 2011; Ozelkan et al., 2016) and have a good correlation with the SPI values (Dutta et al., 2015). In different regions of the world the relationship between the three (Gebrehiwot et al., 2011), six or nine months Standardized Precipitation Index (SPI) (Quiring and Ganesh, 2010) and Vegetation Condition Index (VCI) values were found. Several researches proved that the impact of the short–term precipitation fluctuations on VCI values is weak (Quiring and Ganesh, 2010). In recent years, many researches were done about drought phenomena, its severity and its effects on the vegetation cover. The possibility of using NDVI and VCI extracted from AVHRR sensor of NOAA satellite for monitoring of drought in the Northwest of Iran is researched by Rahimzadeh et al. (2008). Results showed that the best cohesion between NDVI and VCI by 3-month rainfall. Also authors found a good conformity between these two parameters (NDVI and rainfall). Mahmoudzadeh et al. (2008) used two indices including NDVI and SPI during 1998-2003 to investigate droughts in Fereydoun Shahr and finally compare these two indices. The results of this study showed that there is a significant correlation between NDVI of April and May and SPI in December and January. Bhuiyan (2008) studied desert vegetation during droughts by NOAA AVHRR data. He showed that desert phenology during drought is more dependent on moisture than temperature. Vegetative drought indices have been calculated using Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), Vegetation Health Index (VHI) and Temperature Condition Index (TCI). Jain et al. (2010) researched about relationship between SPI in 1, 2, 3, 6, 9 and 12 months scale with NDVI, VCI and WSVI (Water Surplus Variability Index) in three states of India. Also, NDVI is used to regarding to changes in height in order to verify the response of plants to drought in 2003 in Europe by Bevan et al. (2014). Monitoring and evaluation of the drought condition in north of KSA (in Wadi-Dama), in 1990 to 2013 using GIS technology and remote sensing data analysis was studied by Alshaikh (2015). In this research Landsat 5 and Landsat 8 data are used for assessment of drought severity using the Water Supplying Vegetation Index (WSVI). This research showed that the space technology application is one of the most important methods for the drought assessment. This research revealed that remote sensing indices have the most effective to detect and monitor the earth surface globally and also that satellite remote sensing data can exposure utilizable information for assessing and monitoring drought conditions in this area. The spatio-temporal extent of the agricultural drought in Northestern of India (Rajasthan) using remote sensing based Vegetation Condition Index (VCI), and evaluates the performance of VCI by comparing the estimates with the meteorological drought indicators including SPI, RAI and yield based the YAI are identified by Dutta et al. (2015). They proved that NOAA- AVHRR NDVI which derived VCI estimates can be useful for monitoring the drought. This research also showed and justified the usefulness of GIS technique and remote sensing for identifying the drought related stress in rain-fed crops. Khosravi et al. (2016) studied the effect of drought on vegetation in Desert Area using TM sensors data in Yazd-Ardakan plain, central of Iran. Results of their research showed that pastures were highly sensitive to SPI changes but farming lands were less sensitivity in short-time scale due to the use of deep wells. Among the quantitative indices in drought analysis, the SPI index has been universally accepted as a suitable index for drought analysis due to the ease of use, the availability of rainfall data, the ability to calculate for different time periods, and various spatial scales. Khan et al. (2008) studied the state of drought in an arable land in an Australian basin with groundwater level and concluded that, despite the fact that groundwater resources of different areas are exploited, in many cases, there is a strong correlation between the SPI and the groundwater level has it. Mosaedi et al. (2008) used the SPI for assessing meteorological drought in Golestan province, and resulted in different results such as a 11-year cycle of creeping or important decomposition and high drought conditions in the border regions and coastal strip of the Caspian Sea. Totally according to these fulfilled review this study is the investigation of effect of drought on vegetation cover in northwest of the Iran, three province including Zanjan, Kurdistan and Kermanshah.

2. Material and Methods

2.1. Study Area

The study area is located in the northwest of the Iran including three provinces of Zanjan, Kurdistan and Kermanshah. This area has 7575004 hectares extend. The study area is located at 33° 58' 53" to 37° 25' 21" latitude and 45° 40' 33" to 49° 43' 53" longitude. The minimum height is 116 meter and the maximum height is 3359 meters above sea level. The various agricultural products are produced in this region due to climatic conditions of this area and also its mountains and plains are generally covered with pasture and woods. Because of being several type of vegetation, medicinal and aromatic plants are cultivated in this region. Fig 1 shows the location of the study area in Iran.

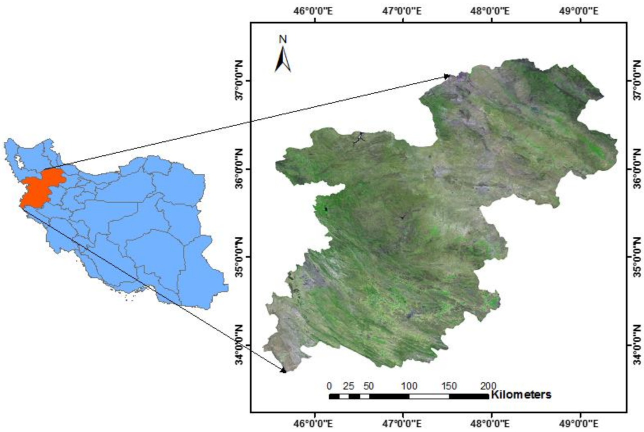

Fig. 1. Location of the study area

2.2. Methodology

In this study, for assessment the effect of drought on vegetation the Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI) and Standardized Precipitation Index (SPI) were determined using remote sensing. Several software were used for calculation of indices including ArcGIS 10.3, ENVI, SPSS Statistics 17.0 and Microsoft Excel.

Normalized Difference Vegetation Index

This index is a way for image processing method that helps to determine the presence or absence of vegetation. This index is calculated by dividing the difference between the near-infrared bands and the infrared bands on the sum of the two bands. This index is calculated as the difference between reflectance in near infrared (NIR) and visible red (VIS) by following Eq. (1):

$$NDVI = \frac{NIR - VIS}{NIR + VIS} \quad (1)$$

Where:

NDVI: Normalized Difference Vegetation Index

NIR: Reflection of light in infrared bands

VIS: Reflection of light in red band

The NDVI values range from -1 to +1. The negative value can be recorded over water bodies while values are close to 0 over the land without vegetation. The positive value shows the being vegetation cover and value equal to +1 indicates perfect growing conditions (Lillesand and Kiefer, 1994; Belal et al., 2014). After pre-processing of satellite data, the NDVI maps were calculated for 2002 to 2016 years from MODIS satellite images in ENVI software. Then, these maps was classified in 6 classes including Non vegetation, Low vegetation, Relatively low vegetation, Medium vegetation, Relatively high vegetation and high vegetation.

Vegetation Condition Index

The VCI is better than NDVI indicator to deficit of the moisture because it allows to separate short–term climate signal from the long–term ecological signal (Jain et al., 2010). VCI is one of the suitable methods for assessing and analyzing droughts using satellite imagery. VCI compares the current NDVI with measured historical NDVI values (Rimkus et al., 2017). This index is defined as Eq (2).

$$VCI = \frac{NDVI - NDVI_{min}}{NDVI_{max} + NDVI_{min}} \times 100 \quad (2)$$

Where:
NDVI: Measured value
$NDVI_{min}$ and $NDVI_{max}$: Historical minimum and maximum value
VCI vary from 0 to 100 and according to Bhuiyan (2008) that is shown in Table 1.

Table 1. Classification of VCI (Bhuiyan, 2008)

Class	Value (%)
Non Drought	< 40
Mild Drought	30 - 40
Moderate Drought	20 - 30
Severe Drought	10 - 20
Extreme Drought	0 - 10

Standardized Precipitation Index
At first, annual average for Standardized Precipitation Index (SPI) was calculated during 2001 to 2015 from data of synoptic station of study area. Totally, Standardized Precipitation Index (SPI) for describing drought is obtained from the following relations:

$$SPI = \frac{P_i - \overline{P}}{S} \quad (3)$$

Where:
SPI= Standardized Precipitation Index
P_i=Rainfall of the given period
S=Standard deviation
$\overline{P}$= Average of period rainfall
Classification of SPI is given in Table 2.
In this research, SPI maps were obtained in ArcGIS 10.3 using precipitation data of 17 stations of study area's stations. Table 3 shows the location and features of stations. Then these maps were classified according to Classification of Table 2.

Table 2. Classification of SPI

Class	Value
Extremely Wet	≥ 2
Severely Wet	1.5 - 1.99
Moderately Wet	1 - 1.49
Normal	-0.99 - 0.99
Moderately Dry	-1.49 - -1
Severely Dry	-1.99 - -1.5
Extremely Dry	≤ -2

Table 3. Location and features of stations

Station	Type of Station	Statistical Period	Latitude and Longitude	Elevation (m)
Zanjan	Synoptic	2001-2015	36° 41′ N , 48° 29′ E	1663.0
Mahneshan	Synoptic	2001-2015	36° 46′ N , 47° 40′ E	1282.0
Khoramdareh	Synoptic	2001-2015	36° 11′ N , 49° 11′ E	1575.0
Khodabandeh	Synoptic	2001-2015	36° 07′ N , 48° 35′ E	1887.0
Sanandaj	Synoptic	2001-2015	35° 20′ N , 47° 00′ E	1373.4
Baneh	Synoptic	2001-2015	36° 00′ N , 45° 54′ E	1600.0
Bijar	Synoptic	2001-2015	35° 53′ N , 47° 37′ E	1883.4
Ghorveh	Synoptic	2001-2015	35° 10′ N , 47° 48′ E	1906.0
Marivan	Synoptic	2001-2015	35° 31′ N , 46° 12′ E	1286.8
Saghez	Synoptic	2001-2015	36° 15′ N , 46° 16′ E	1522.8
Zarinehobato	Synoptic	2001-2015	36° 04′ N , 46° 55′ E	2142.6
Kermanshah	Synoptic	2001-2015	34° 21′ N , 47° 09′ E	1318.6
Eslamabadegharb	Synoptic	2001-2015	34° 07′ N , 46° 28′ E	1348.8
Kangavar	Synoptic	2001-2015	34° 30′ N , 47° 59′ E	1468.0
Ravansar	Synoptic	2001-2015	34° 43′ N , 46° 39′ E	1379.7
Sararud	Synoptic	2001-2015	34° 20′ N , 47° 18′ E	1361.7
Sarpolezahab	Synoptic	2001-2015	34° 27′ N , 45° 52′ E	545.0

Pearson Correlation Coefficient

Pearson's correlation coefficient is a statistical measure of the strength of a linear relationship between paired data. Pearson correlation coefficient is an important coefficient to determine the interval and ratio scale that is normally distributed. It can vary from −1 (perfect negative correlation) through 0 (no correlation) to +1 (perfect positive correlation) (Bihamta and Zare Chahouki, 2010).

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad (4)$$

Where,

r: Pearson correlation coefficient

x_i and $\bar{x}$: The first variable and mean of first variable, respectively

y_i and $\bar{y}$: The second variable and mean of second variable, respectively

In this study, Pearson correlation coefficient between vegetation indices (Normalized Difference Vegetation Index and Vegetation Condition Index) and drought index (Standardized Precipitation Index) calculated using SPSS 17.0.

3. Results and discussion

The results of SPI, NDVI and VCI are obtained after investigation of meteorological (rainfall) data and vegetation maps of the area. At the end, the correlation between NDVI and SPI calculated by SPSS 17.0.

Normalized Difference Vegetation Index

The annual changes of NDVI during 2002–2016 are shown in Fig. 2 and also the area and percentage of NDVI maps classes are shown Table 4. According to this table, the most amounts of NDVI classes are related to the relatively low class. As seen in Fig 2 the most mass of vegetation is in the west and the central area have fewer vegetation than the other parts. More parts of case study are classified in relatively low and medium. During these years, the mass of vegetation increased in 2006 and 2007 that is because of rainfall. In 2008 NDVI decreases. According to the NDVI maps, from 2002 to 2016 the NDVI have a positive trend so the mass vegetation increased during these years.

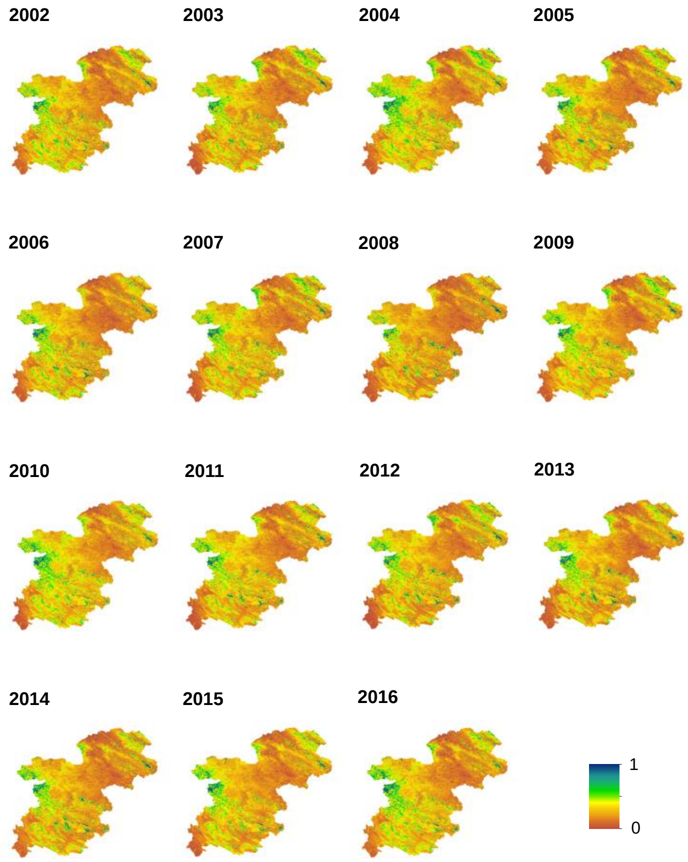

Fig. 2. Maps of NDVI classification in 2002-2016

Table 4. Area of NDVI classes in 2002-2016

Year	Unit	Non Vegetation	Low	Relatively Low	Medium	Relatively High	High	Sum
2002	Area (ha)	3218.4	161601	4968990	1999912	342685	98597.6	7575004
	Percent	0.04	2.13	65.60	26.40	4.52	1.31	100
2003	Area (ha)	2328	176436	4800730	2090952	386880	117678	7575004
	Percent	0.03	2.33	63.38	27.60	5.11	1.55	100
2004	Area (ha)	2762.7	177383.3	3887982	2658386	670871	177619	7575004
	Percent	0.04	2.34	51.32	35.10	8.86	2.34	100
2005	Area (ha)	2858	160262	4906810	2004680	372104	128290	7575004
	Percent	0.04	2.16	64.75	26.45	4.91	1.69	100
2006	Area (ha)	3970.5	192433	4815680	2024898	389771.5	148251	7575004
	Percent	0.05	2.54	63.56	26.73	5.16	1.96	100
2007	Area (ha)	4068.5	140548	4116964	2567882	558565	186977	7575004
	Percent	0.05	1.86	54.35	33.90	7.37	2.47	100
2008	Area (ha)	4298.5	414993	5617981	1215355	217982	104395	7575004
	Percent	0.06	5.48	74.16	16.04	2.88	1.38	100
2009	Area (ha)	3442	316379	5057980	1821490	287726	87986.5	7575004
	Percent	0.05	4.18	66.76	24.05	3.80	1.16	100
2010	Area (ha)	4418.3	160049.1	4392187	2521867	397508	98974.6	7575004
	Percent	0.06	2.11	57.98	33.29	5.25	1.31	100
2011	Area (ha)	4484	190587	4524620	2344685	373848	136780	7575004
	Percent	0.06	2.52	59.72	30.95	4.94	1.81	100
2012	Area (ha)	5088.8	221996	4580921	2189915	433596.1	143487.1	7575004
	Percent	0.07	2.93	60.48	28.91	5.72	1.89	100
2013	Area (ha)	5109.4	221891	4595196	2152314	430726.6	169767	7575004
	Percent	0.07	2.93	60.66	28.41	5.69	2.24	100
2014	Area (ha)	4096.3	130960	4673264	2127970	455610.5	183103	7575004
	Percent	0.05	1.73	61.69	28.09	6.01	2.43	100
2015	Area (ha)	3794.7	258875	5294084	1653973	275415	88862.3	7575004
	Percent	0.05	3.42	69.89	21.83	3.64	1.17	100
2016	Area (ha)	5880.4	121966	4346360	2456212	496388.2	148197.1	7575004
	Percent	0.08	1.61	57.37	32.43	6.55	1.96	100

Vegetation Condition Index

The annual changes of VCI during 2002–2016 are shown in Fig. 3. The area and percentage of VCI classes are shown in Table 5. According to VCI maps and their results in Table 5, we can see that in during the study the general trend of this index is positive and the coverage density is increasing. The most amounts of drought classes are related to the moderate class.

Standardized Precipitation Index

SPI depends on each spatial and temporal rainfall scale and it can be calculated for different time scales (short and long term). According to Fig 4 in 2001 drought can be seen in case study that this drought is in moderate or extreme class. During 2002-2005 the study area has been in normal condition and in 2005 wet has been in moderate to extreme class. The drought condition has been normal in 2007 and in 2008 drought has been occurred that was between moderate to extreme class. Also condition of precipitation was normal and the significant drought didn't occurred during 2009 to 2015 the. The maps of SPI during 2001-2015 are shown in Fig 4.

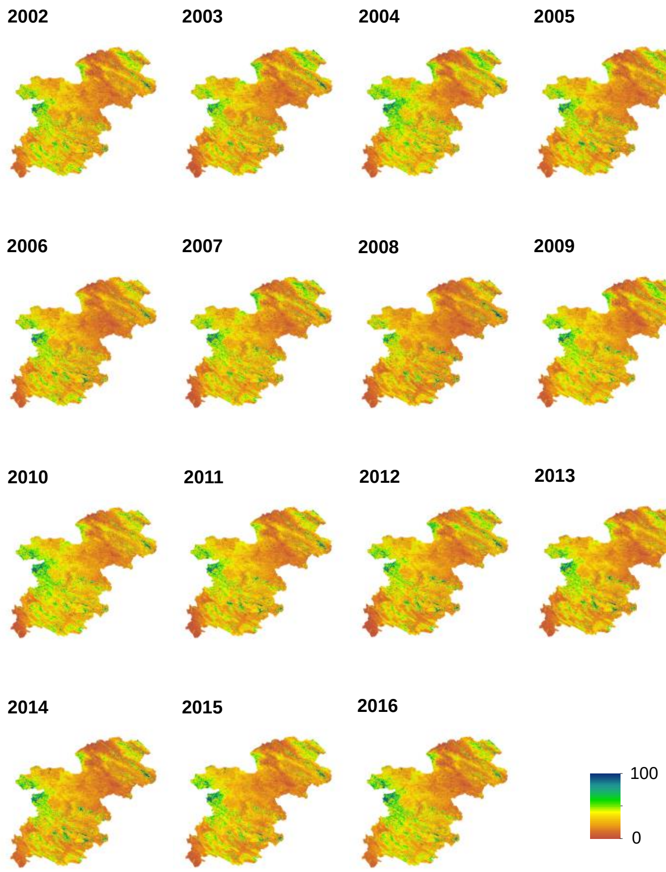

Fig. 3. Maps of VCI classification in 2002-2016

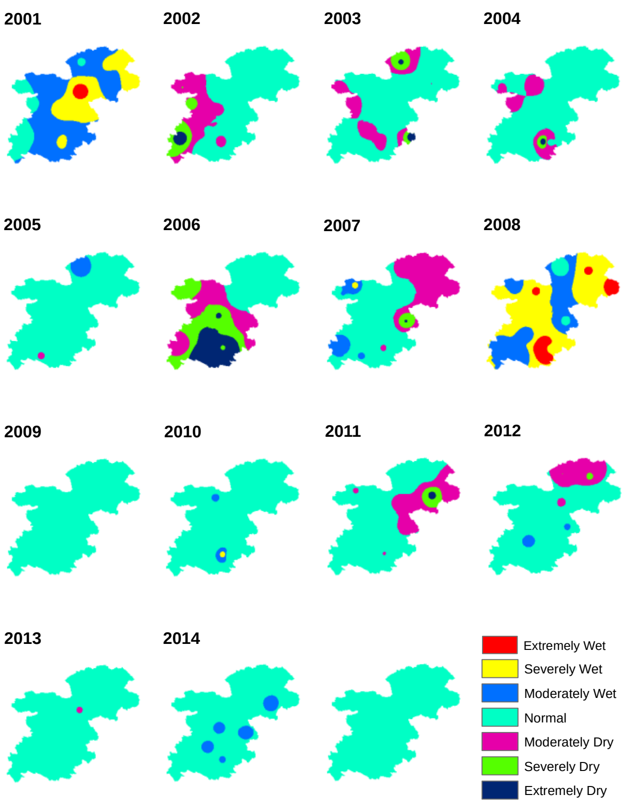

Fig. 4. Maps of SPI classification in 2001-2015

Table 5. Area of VCI classes in 2002-2016

Year	Unit	Non Drought	Mild Drought	Moderate Drought	Severe Drought	Extreme Drought	Sum
2002	Area (ha)	39921.1	3266012	3194287	797397	277387.4	7575004
	Percent	0.53	43.12	42.17	10.52	3.66	100
2003	Area (ha)	28395	3071980	3255830	894121	324678	7575004
	Percent	0.37	40.56	42.98	11.80	4.29	100
2004	Area (ha)	77757	2966900	3122004	1057460	350883	7575004
	Percent	1.03	39.17	41.21	13.96	4.63	100
2005	Area (ha)	33589.6	3125800	3128360	925865.2	361389.2	7575004
	Percent	0.44	41.26	41.31	12.22	4.77	100
2006	Area (ha)	53099.7	3360650	3057212	774488.3	329554	7575004
	Percent	0.70	44.36	40.37	10.22	4.35	100
2007	Area (ha)	36395.2	2763701	3384706	1004960	385242	7575004
	Percent	0.48	36.48	44.68	13.27	5.09	100
2008	Area (ha)	108975	4603900	2229935	413979	218215	7575004
	Percent	1.44	60.78	29.44	5.46	2.88	100
2009	Area (ha)	66295.6	3403988	3108140	740366.2	256214	7575004
	Percent	0.53	43.12	42.17	10.53	3.65	100
2010	Area (ha)	28482.5	2362720	3797400	1062992	323409.5	7575004
	Percent	0.38	31.19	50.13	14.03	4.27	100
2011	Area (ha)	26784.2	2576701	3617075	981322.2	373122	7575004
	Percent	0.35	34.02	47.75	12.95	4.93	100
2012	Area (ha)	69460.5	3140566	3161238	860751.5	342988	7575004
	Percent	0.92	41.46	41.73	11.36	4.53	100
2013	Area (ha)	66979.4	3436360	2956025	780492.1	335147.5	7575004
	Percent	0.88	45.36	39.02	10.30	4.42	99.98
2014	Area (ha)	42320.6	3175906	3098101	862201	396475.4	7575004
	Percent	0.56	41.93	40.90	11.38	5.23	100
2015	Area (ha)	198799	5052710	1880871	331211	111413	7575004
	Percent	2.62	66.71	24.83	4.37	1.47	100
2016	Area (ha)	55921.8	3167377	3181939	863295.1	306471	7575004
	Percent	0.74	41.80	42.01	11.4	4.05	100

Correlation between Vegetation Indices and Drought Index

The correlation of NDVI and VCI with SPI of same year is shown in Table 6 and the correlation of NDVI and VCI with SPI of last year is shown in Table 7.

According to values of Table 6, the correlation between SPI and NDVI is 0.568, which is significant at 95% level, while the correlation between SPI and VCI is 0.481 that indicating a positive correlation between these indices but this correlation is not significant.

According to the values of Table 7 the correlation between SPI and NDVI of next year was 0.377 that indicating positive correlation but this correlation is not significant and the values of correlation between SPI and VCI of next year obtained 0.269 that indicating there is no significant correlation between these indices. Therefor NDVI and SPI of same year have more correlation and its results are reliable than VCI index or SPI index of last year.

In this study, SPSS 17.0 produces the following correlation output:

Table 6. Correlation between NDVI, VCI and SPI of each year

Correlations				
		SPI	NDVI	CVI
SPI	Pearson Correlation	1	0.568*	0.481
	Sig. (2-tailed)	-	0.034	0.082
	N	14	14	14
NDVI	Pearson Correlation	0.568*	1	0.766**
	Sig. (2-tailed)	0.034	-	.001
	N	14	14	14
CVI	Pearson Correlation	0.481	0.766**	1
	Sig. (2-tailed)	0.082	0.001	-
	N	14	14	14

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

Table 7. Correlation between NDVI and VCI of each year and SPI of last year

Correlations				
		SPI	NDVI	CVI
SPI	Pearson Correlation	1	0.377	0.269
	Sig. (2-tailed)	-	0.166	0.332
	N	15	15	15
NDVI	Pearson Correlation	0.377	1	0.755**
	Sig. (2-tailed)	0.166	-	0.001
	N	15	15	15
CVI	Pearson Correlation	0.269	0.755**	1
	Sig. (2-tailed)	0.332	0.001	-
	N	15	15	15

**. Correlation is significant at the 0.01 level (2-tailed).

4. Conclusion

Drought is one of the highest natural causes that inflict great damage on humans and natural ecosystems. Drought is a phenomenon with complex process. Different indices are used to determine the severity and extent of drought. Most of the indices that are using for drought, based on meteorological parameters and variable such as precipitation, soil moisture, temperature and particular rainfall. In this study, efficiency of SPI and its effect on density of vegetation were studied. For this purpose for preparing the map of vegetation indices were used of MODIS sensor that their images has good power of spatial, temporal and radiometric and it has 36 bands. The aim of this study is finding of correlation between climate index (SPI) as an important climate factor, with vegetation indices (NDVI and VCI). Therefore, at the beginning, correlation between NDVI and VCI with SPI of the same year and then correlation between NDVI and VCI with SPI of last year were checked out. The maps of vegetation showed that vegetation cover in the west of case study in this years was more than other regions that it is because of more high of this region and it is stable on the Zagros mountains so the rainfall is more that the SPI maps showed in the west the wet year is more than drought year. According to results of this study, in the year of drought and low rainfall and simultaneous reducing of soil moisture and water resources, vegetation cover reduced. As our conclusion, results showed that density of vegetation with rainfall data of stations of case study were linked and results of vegetation indices showed that there is good correlation between drought index and vegetation indices. Overall in drought years with reducing of rainfall, we faced with reducing of vegetation cover. Previous studies (Nicholson et al., 1990; Lotsch et al., 2003; Zhang et al., 2005) showed a good relationship between rainfall variations and the NDVI on seasonal and inter-annual time scales that agree with our results. In this study, it was found that between NDVI and VCI with SPI of the same year is more correlation than NDVI and VCI with SPI of the last year which indicate that the density vegetation of each year is directly related to the amount of rainfall of same year. Also in this study the results showed that NDVI index with SPI of same year is more correlated and the results are more reliable than VCI index. Based on the results, it became clear that SPI index is more efficiency for drought monitoring.

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