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Research and Full Length Article:

Relationships between Meteorological Drought and Vegetation Degradation Using Satellite and Climatic Data in a Semi-Arid Environment in Markazi Province, Iran

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Abstract. The assessment of relationships between satellite-derived vegetation indices and meteorological drought improves our understanding of how these indices respond to climatic changes. The combination of climate data and the Normalized Difference Vegetation Index (NDVI) product of Moderate Resolution Imaging Spectroradiometer (MODIS) imagery provided an opportunity to evaluate the impact of drought on land degradation over the growing seasons. The main goal of this study was to investigate the effect of drought on vegetation degradation in Meyghan plain, Arak, Iran. For this purpose, climatic and satellite data were used. The annual Standardized Precipitation Index (SPI) was calculated for 20 years (1998-2017). Then, the NDVI maps were classified into three classes according to the Tokunaga-Thug method. These classes are: Class 1) no vegetation; class 2) low-density or poor rangelands, and class 3) semi-dense and dense vegetation cover such as agricultural lands. The relationship between the percentage of vegetation cover classes (classes 2 and 3) and the drought index of the previous year was assessed using the Pearson correlation test. The results showed that the correlation between these variables was significantly dependent on vegetation degradation in the poor vegetation area ($R=0.51$; $P\text{-value}<0.05$). In contrast, there was a negative significant relationship between drought and the percentage of dense areas of vegetation ($R=-0.46$; $P\text{-value}<0.06$). Hence, it was concluded that the sensitivity of the low-density area (poor rangeland) to drought was more than dense vegetation covers (agricultural lands). Its reason is that the most important source of water supply for natural rangelands is the atmospheric precipitation that has been reduced due to the occurrence of droughts in recent years.

Key words: Normalized Difference Vegetation Index, Drought Monitoring, MOD13A3, Tokunaga-Thug method, Semi-arid region

Introduction

Destruction of vegetation cover is considered as one of the major factors of land degradation and desertification in arid and semi-arid regions of the world (Ahmed, 2015, Barbosa *et al.,* 2015, Lian *et al.,* 2017). The recent meteorological droughts had a significant effect on economics, agriculture, environment, natural resources and society (Medellín-Azuara *et al.,* 2016; Patil *et al.,* 2014; Yan *et al.*, 2016; Zhang *et al.*, 2016). Therefore, long-term monitoring of vegetation and meteorological drought is very useful for assessing the response of different ecosystems to climate change and drought risk assessment. This phenomenon has affected many arid and semi-arid regions of the world. Drought monitoring has various types such as agricultural, hydrological and meteorological droughts. Regarding the fact that drought is a recurring and common event for all climate zones, especially in arid and semi-arid areas, its continuous monitoring and investigation of its effects are of very importance (Keshavarz *et al.,* 2017; Marengo *et al.,* 2017; Yang *et al.*, 2018). Several indices are presented for this purpose. The most common meteorological drought index is the Standardized Precipitation Index (SPI) (Bahrami *et al.,* 2019; Ibrahimi and Baali, 2018).

The evaluation of vegetation cover dynamics and drought together can lead to a better understanding of land degradation trends. Recently, the use of remote sensing technology in the long-term monitoring of the physical characteristics of the earth's surface and the identification of their pattern of variation based on the series of satellite-based images has been growing globally (Gouveia *et al.*, 2017; Mariano *et al.,* 2018; Ribeiro *et al.,* 2019). Because the use of traditional methods for mapping vegetation and investigating the trend of the changes over a long period is difficult and costly, but remote sensing technology is a useful tool for this purpose (Cracknell, 2007).

Numerous indices have been developed to quantify vegetation cover dynamics and meteorological drought. The most utilized indices for vegetation and drought monitoring are Normalized Difference Vegetation Index (NDVI) and SPI, respectively. Currently, the products of MODIS sensor including vegetation indices (NDVI and EVI) have been effectively used for the assessment of vegetation dynamics monitoring and their responses to drought at various scales (Chen *et al.*, 2017; Dubovyk *et al.*, 2015; Gulácsi and Kovács, 2015; Mu *et al.*, 2016; Ko *et al.*, 2017; Damavandi *et al.*, 2016; Safari Shad *et al.,* 2017). For example, Dubovyk *et al.* (2015) used MODIS-EVI time-series data to study the trend of vegetation changes in southern Africa. They found that the main cause of the vegetation destruction in this region has been the growing population pressure. They also reported that a significant decline in atmospheric precipitation has occurred in the northern part of South Africa. In general, they found that the observed vegetation variations in most parts of southern Africa were rather attributed to land transformations than climatic variability. Brede *et al.* (2015) have studied the relationship between the Enhanced Vegetation Index (EVI) and the drought index of SPI to investigate the effect of drought on the Amazon forest. The results of their study showed that there was no significant relationship between EVI and SPI. However, Dutta *et al.* (2015) found that the combined use of SPI and NDVI has a high performance in predicting drought conditions in semi-arid regions. The relative importance of SPI, NDVI, and Land Surface Temperature (LST) to assess the agricultural drought condition was reported by Park *et al.* (2016). Long-term monitoring of poor pastures and agricultural lands in Yazd-Ardakan plain by using NDVI derived from other satellites such as Landsat has been investigated by Khosravi *et al.* (2017). The SPI index was used to analyze the effect of drought on these changes. Their results showed that the sensitivity of poor pastures to drought changes was higher than farmlands. They reported that the overuse of groundwater resources was the main reason for decreasing the sensitivity of farmlands to meteorological droughts. Zhang *et al.* (2017) investigated the effects of drought on vegetation indices including Normalized Difference Water Index (NDWI), NDVI, EVI, and LST in southeast China. The results showed that during the studied period (2009-2010), the vegetation indices decreased while the LST index increased. The spatial response of SPOT-VEGETATION NDVI to rainfall variations in India was investigated by Kundu *et al.* (2018). They indicated the different patterns of dynamics of vegetation status in this region in response to this climate variable.

Due to the importance of meteorological drought and the evaluation of its effect on vegetation degradation, the main objectives of the present research were: 1) to study the vegetation changes during the pick time of vegetation growth from 2000 to 2017; and 2) to investigate the relationship between meteorological drought and vegetation cover variations in Arak Meyghan plain, Iran.

Materials and Methods

Meyghan plain is located in Markazi Province in Iran (49º 15′-50º 15′ 00″ E and 33º 45′ -34º 45′ N). The Meyghan plain area is 106.4 Km^2. There are 13 climatology and synoptic stations and 10 land use or land cover in this area whose distribution is shown in Fig (1). Based on the 18 years data (2000-2017), the average annual rainfall, temperature, and evapotranspiration of the study were 299.6 mm, 14.8°C and 837.2 mm, respectively. According to the de Martonne method, the climate of this area is semi-arid (de Martonne's aridity index: 12.44).

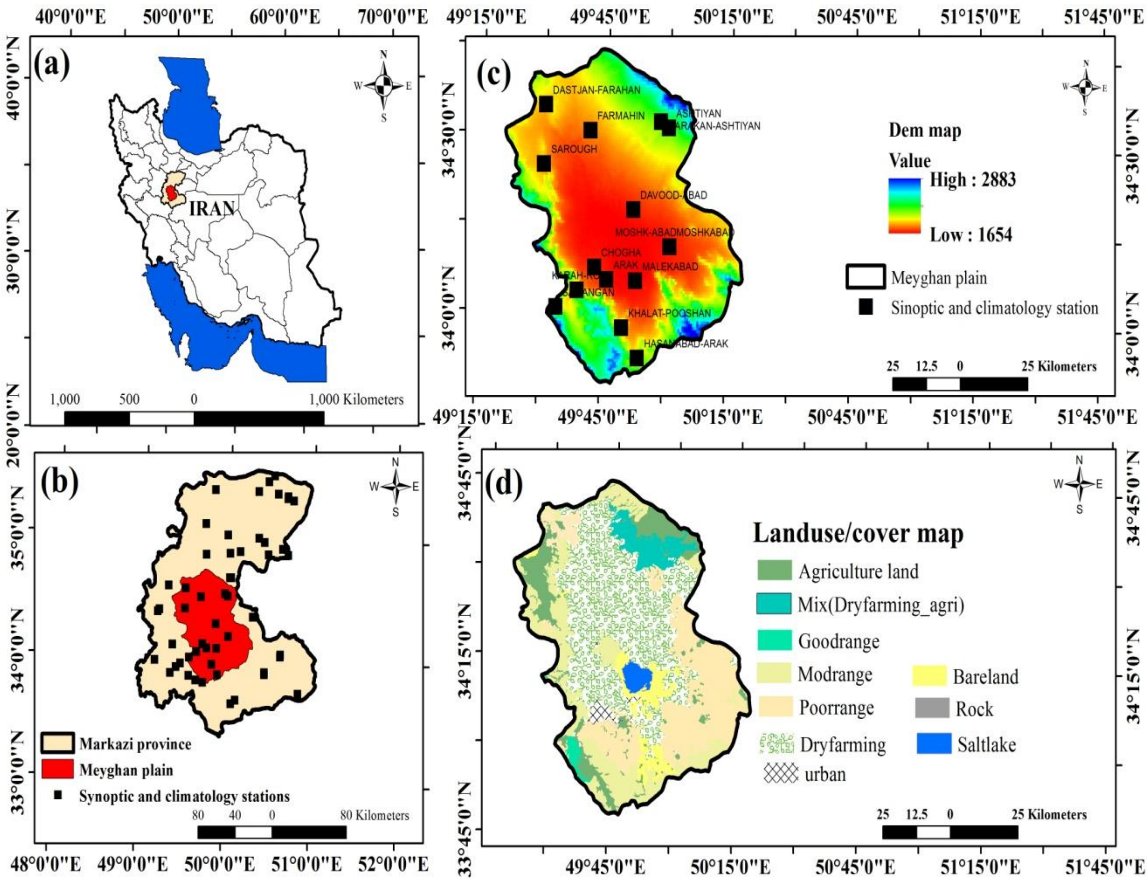

Fig. 1. (a) The location of the study area in Iran; (b) in the Markazi province; (c) Distribution of synoptic stations in the Meyghan plain; and (d) Landuse/cover map of study area

The general steps of this research are:

1. SPI Calculation
2. obtaining satellite data and their processing and
3. Determining the relationship between the SPI and vegetation classes changes.

The details of each step are explained below.

For SPI Calculation, the monthly precipitation data were acquired from the Iran meteorological organization. These data were utilized to compute the SPI values and to determine the drought conditions. For this purpose, the annual precipitation value was estimated for each station, at first. In the next step, the average value of precipitation was calculated for the study area using the arithmetic mean method. At the last, SPI values at different time scales (1 to 12 months and annual) were calculated using the Drought Index Package (DIP) software (Morid et al., 2007).

This index is developed by McKee (1995) and is approved by the world meteorological organization as a useful tool for the assessment of the intensity and duration of drought events. For this reason, we utilized it for assessing the meteorological drought conditions in our study area. The classification and interpretation of SPI values are shown in Table (1). The negative values of SPI indicate conditions drier than the median, whereas positive values SPI indicate wetter than median conditions.

Table 1. Classification and interpretation of the drought intensity based on SPI values

Drought Condition	SPI value
Extremely dry	<-2
Severely dry	(-1.99) to (-1.50)
Moderately dry	(-1.49) to (-1.00)
Near normal	(-0.99) to (0.99)
Moderately wet	(+1.00) to (1.49)
Very wet	(1.50) to (1.99)
Extremely wet	>2

The NDVI is a common vegetation index that is widely used for investigation of the spatial-temporal variations of vegetation (Birtwistle *et al.,* 2016, Matsushita *et al.,* 2007, Wang and Tenhunen, 2004, Yao *et al.,* 2018). Hence, in the present study, this index was used to investigate the long-term vegetation cover monitoring at the peak time of plant growth in the study area (in May from 2000 to 2017). The NDVI that is calculated as the normalized difference of reflectance in the red and near-infrared bands, takes values between −1 and +1 (Rouse, 1974).

The NDVI values that are between (0.1-0.25) indicate poor vegetation cover conditions. The values greater than 0.25 and less than 0.40 indicate semi-dense vegetation. High values of NDVI (>0.4) represent the dense vegetation cover (Tokunaga and Thug, 2002).

NDVI product of Moderate Resolution Imaging Spectroradiometer (MODIS) imagery (MOD13A3) was acquired from http://earhdata.nasa.gov/. Considering that the study region is located on the one frame of the MODIS Imagery and the study period is 18 years (2000-2017), a total of 18 frames from monthly NDVI products of this sensor were downloaded from the mentioned site.

In the present study, the NDVI index was classified into three classes including no vegetation cover (NDVI<0.1), poor vegetation (NDVI: 0.1-0.25) and semi-dense and dense vegetation cover (NDVI>0.25). The area of each class was calculated via multiplying the number of pixels in pixel dimensions (1×1 km).

In this study, regression analysis was used to investigate the effects of the independent variable (SPI) on the dependent variable (vegetation cover changes). the coefficient of determination (R^2) between measured and predicted values were used to determine the overall accuracy of the regression model. R^2 value can vary from 0 to 1 (or 0-100%) and indicates how many percents of the variation of the dependent variable can be explained by the linear relationship between independent and dependent variables.

The Pearson correlation coefficient (R) is an important tool that measures the linear correlation between independent (SPI) and dependent (NDVI) variables. The correlation coefficient between SPI and NDVI for each station over the whole study period were calculated. Finally, using the Inverse Distance Weighting (IDW) method, a spatial correlation map was prepared for the study region.

In addition to this criterion, in the present research, the standard error of the regression coefficient and F values of regression equations was calculated by using SPSS20 software.

Results and Discussion

The correlation coefficients between the area of different vegetation classes and the SPI at periods of 1- to-12 months and annual scale are presented in Table (2). As seen, there was no significant correlation between SPI values (at time scales of 1 to 12 months) and the area percentage of poor and dense vegetation classes (P-value>0.05). However, there was a positive significant relationship between annual SPI and poor vegetation area and as well as, a negative significant relationship between annual SPI and dense vegetation area (P-value>0.05). Therefore, the yearly SPI was selected to analyze the effect of meteorological drought on vegetation changes in the study area. Our findings are consistent with some previous reports (Khosravi *et al.*, 2017, Farrokhzadeh *et al.*, 2018) that used the annual drought index to study the impact of meteorological drought on vegetation changes in the months of the growing season.

Table 2. The results of correlation analysis between SPI at different time scales and area of vegetation classes (%)

Time scales of SPI	Poor vegetation area (%)	Dense vegetation area (%)
SPI 1	0.205 ns	-0.049 ns
SPI 3	0.027 ns	0.098 ns
SPI 6	0.215 ns	-0.119 ns
SPI 9	0.119 ns	0.008 ns
SPI 12	-0.029 ns	0.144 ns
Annual SPI	0.494 *	-0.465 *

*=significant at 5% probability level.

Based on annual SPI values (Table 3), the years 2006 with an annual SPI value of 1.8 was detected as the humid year during the study period (1998-2017). In contrast, the worst amount of droughts in the Meyghan plain occurred in 2007, 2010, 2017 and 1999 (SPI: -2.3, -1.3, -1.04 and -0.7, respectively). During these years, the phenomenon of drought has occurred in many regions of Iran, including in Hamedan province, near the study area of the present research(Nazari *et al.*, 2017), which confirms the results of this research.

Table 3. Annual SPI values of study area

Year	Annual SPI	Year	Annual SPI	Year	Annual SPI	Year	Annual SPI
1998	-0.50	2003	0.25	2008	-0.83	2013	0.50
1999	-0.70	2004	0.40	2009	0.23	2014	-0.12
2000	0.66	2005	0.01	2010	-1.30	2015	1.10
2001	1.40	2006	1.80	2011	-0.30	2016	0.63
2002	0.15	2007	-2.30	2012	-0.56	2017	-1.04

In the second step, in order to detect the effect of meteorological drought on vegetation cover, NDVI maps were prepared and classified into three groups: 1) No vegetation (NDVI<0.1); 2) Poor vegetation(NDVI: 0.1-0.25); and 3) Semi-dense and dense vegetation(NDVI>0.25). The classified NDVI maps of Meyghan plain from 2000 to 2017 are shown in Fig. 2. The percentage of area for all classes is demonstrated in Fig. 3.

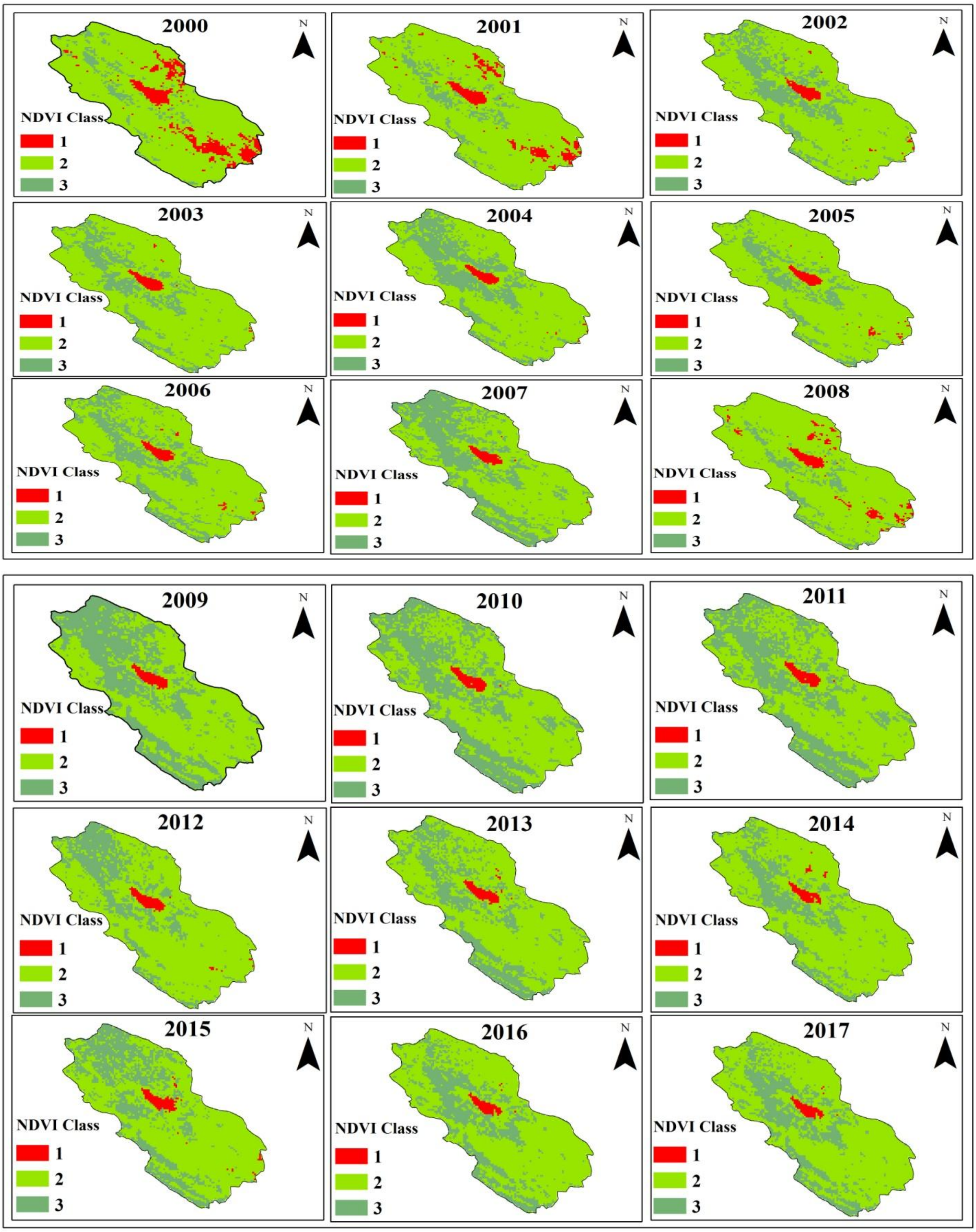

Fig. 2. Classified NDVI maps of Meyghan plain from 2000 to 2017

Table 4. Percentage area of vegetation covers classes in the Meyghan plain

	Class1	Class2	Class3
2000	10.6	82.3	7.1
2001	6.4	83.7	9.9
2002	2.2	75.1	22.7
2003	2.1	77.9	20.0
2004	1.8	69.1	29.1
2005	2.3	81.5	16.2
2006	2.3	73.1	24.6
2007	1.9	59.6	38.6
2008	5.0	84.4	10.7
2009	1.7	57.7	40.6
2010	1.8	58.5	39.7
2011	1.8	58.5	39.7
2012	2.0	73.2	24.7
2013	2.0	70.0	28.1
2014	1.7	75.6	22.7
2015	2.3	66.6	31
2016	10	65.0	25
2017	1.6	71.0	27.4

As shown in Figure (2) and Table (4), the highest percentage of dense vegetation is related to the second half of the study years (after the 2008 drought). This could be due to an increase in groundwater utilization for agricultural purposes in this region of Iran (Rajabi and Ghorbani, 2016). However, the highest area of poor vegetation class refers to the first half of study years (before 2008) because of the persistence of the droughts in these years was higher than the early years (Table 3). In other words, our findings indicated that the recurrence of droughts, especially in recent years, was one of the important causes for reducing the area of poor pastures in the study area.

Given the used NDVI products in the present study are related to the middle of spring (May), drought index in the previous year should be utilized for investigating the impact of drought on vegetation cover. Hence, the correlation between the two variables was investigated with a lag time. In other words, areas percentage of the classes of poor (Class2) and semi-dense and dense vegetation (Class3) for the study period was studied with the calculated SPI from 1999 to 2016 using the simple regression analysis. The annual values of SPI versus percentage area of vegetation covers and their scatter plots are shown in Figs. (3 and 4), respectively. The obtained results of the regression analysis between these variables are summarized in (Table 5).

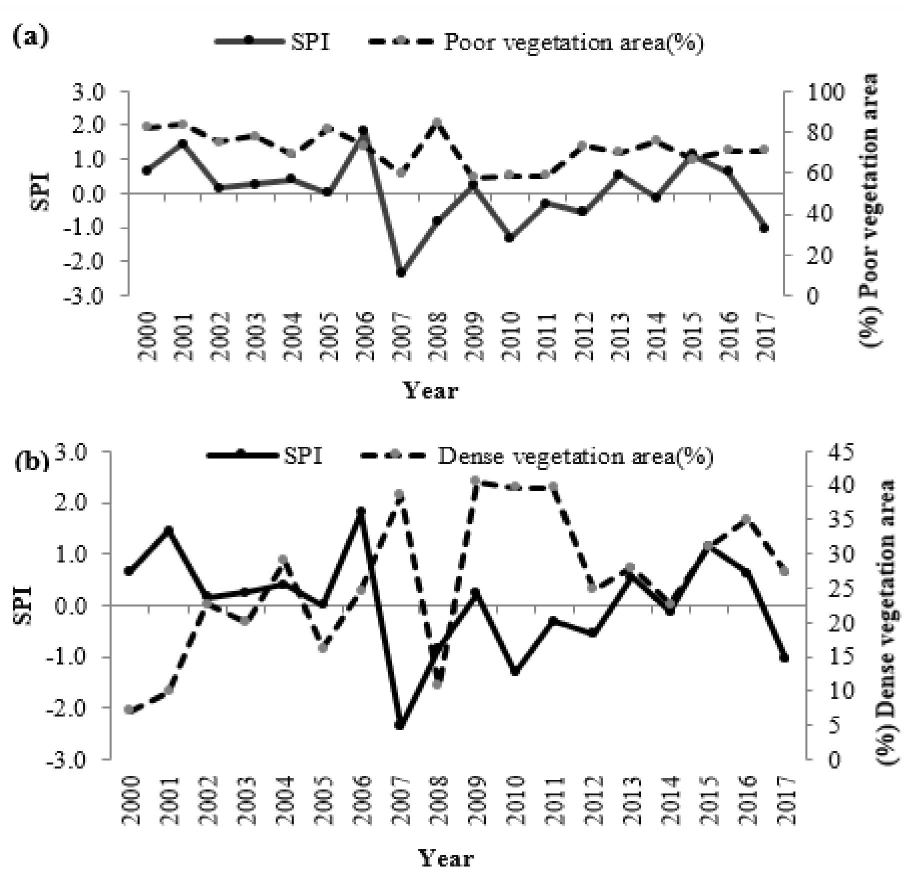

Fig. 3. Annual values of SPI versus percentage area of (a) poor vegetation covers; and (b) dense vegetation cover

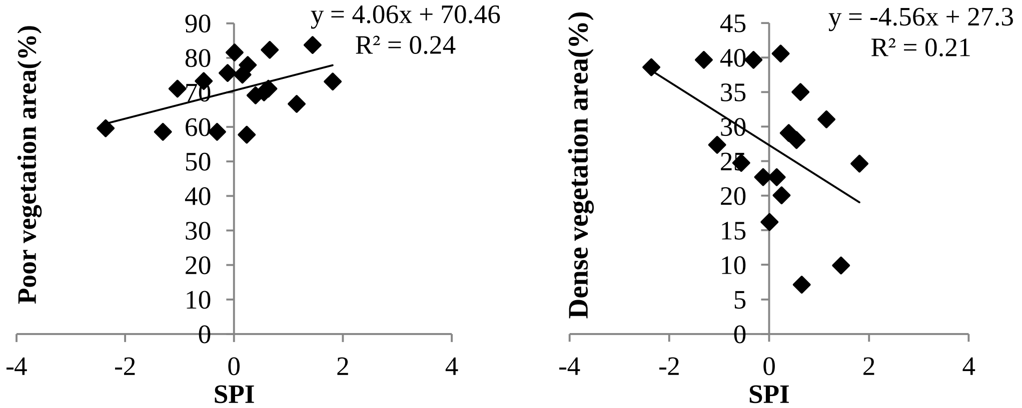

Fig. 4. Scatter plots of the SPI and percentage area of (a) poor vegetation covers; and (b) dense vegetation cover

Table 5. The results of regression analysis between the annual SPI and percentage area of vegetation classes

Statistic parameters	Class(2)	Class(3)
Pearson's R	+0.49	-0.46
Std error	0.90	1.20
F values	4.8	4.13
P-value	0.04	0.06

The results of this stage of the present research showed that the percentage area of poor vegetation was positively correlated with the previous SPI index (R^2 =0.24; p-value<0.05), while a negative and significant correlation was found between this index and percentage area of another class (semi-dense and dense vegetation) over the study period (R^2=0.21; p-value<0.06). These findings indicate that drought may be an important driver for vegetation degradation of the low density area of Meyghan plain. Because the source of water supply for this type of land use is the atmospheric precipitation, which has declined due to the occurrence of recent droughts. It seems that a negative relationship between SPI and the percentage area of class (3) was due to the agricultural land development and the construction of urban green spaces in which their sources of water supply are mainly groundwater. The same results have been reported by Khosravi *et al.* (2017) and Dubovyk *et al.* (2015). Our results are also agree with the findings of Ansari and Golabi (2019), who reported that the significant changes have occurred between the years 2007-2015 around the Meighan wetland (in the central part of our study area) due to the conversion of rangelands to agriculture lands. They also found that there was a considerable increase in wastewater, wetland, and manmade changes in the following order; 75.69%, 96.20% and , 41.89%. Moreover, our findings showed the existence of opposite correlations in different regions of the study area (Fig. 5). As displayed, the positive correlation coefficients are mainly observed in the western regions and the negative correlation coefficients are mainly observed in the eastern regions of the study area. Different vegetation densities in different regions of the study area and their susceptibility to drought may be one of the main causes. In other words, differences in the sensitivity degree of different vegetation (e.g., dense and/or poor vegetation) to drought phenomenon may lead to opposite correlations in the study region. These results are similar to the results of Yan (2016) who found the existence of positive and negative correlations between rainfall and vegetation in the Huang-Huai-Hai River Basin, China.

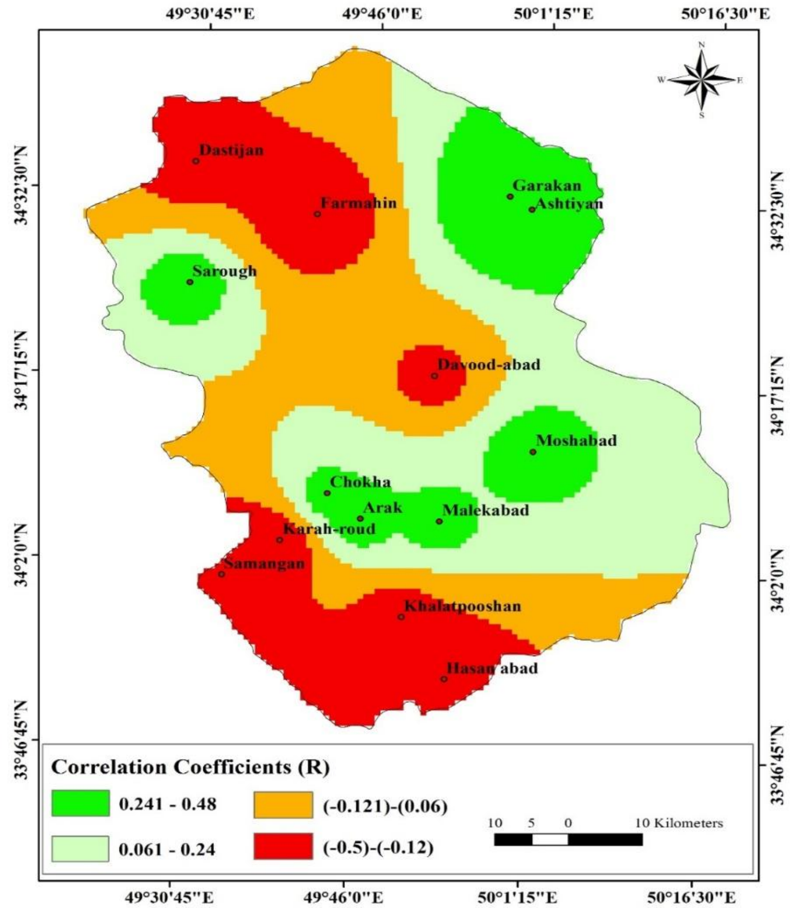

Fig. 5. Spatial Correlation coefficients between SPI and NDVI at synoptic stations and Meighan plain during the study period

Conclusion

In the present research, we examined the effect of meteorological drought on land depredation based on the monthly NDVI product of the MODIS and climate data over the 18-year (2000-2017). The classification of vegetation cover using Tokunaga and Thug method was performed and the relationship between the area of defined classes and the drought index was investigated based on Pearson correlation analysis. The results showed that drought had a significant effect on reducing vegetation cover in low-density areas. According to Pearson's test, it was found that a significant decline in these regions of Meyghan plain was due to the occurrence of droughts during this period. However, dense vegetation areas were not affected by the meteorological drought. In recent years, the exploitation of deep and semi-deep wells for irrigating agricultural lands in most regions of Iran has been growing. Although such actions have led to adverse environmental impacts such as reducing the level of aquifers, as well as the degradation of groundwater quality (Amirataee and Zeinalzadeh, 2016, Chao *et al.*, 2018), it has also been able to reduce their sensitivity to meteorological droughts by supplying crop water requirements. Hence, it can be said that one of the possible reasons for reducing the sensitivity of these areas to the drought phenomenon is this issue. Our findings also showed that only 24% and 21% of changes in poor and dense vegetation areas were due to meteorological drought effects. One reason may be the low spatial resolution of MODIS images. It seems that the use of images with higher spatial resolution such as Landsat and ASTER could show a higher correlation coefficient among these variables. Other causes can be changes in other climatic parameters such as air temperature, evaporation, surface wind speed, changes in physical characteristics of the earth's surface as well as human activities, which are suggested to be investigated in the future research. These studies could improve our understanding of the impact of multiple factors on changes in vegetation covers. It is expected that such research could improve our understanding of how multiple factors effects on the degradation or development of vegetation covers in arid and semi-arid regions.

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ارتباط بین خشکسالی هواشناسی و تخریب پوشش گیاهی با استفاده از داده‌های اقلیمی و ماهواره‌ای در یک محیط نیمه خشک

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چکیده. ارزیابی ارتباط بین شاخص‌های پوشش گیاهی ماهواره‌ای و خشکسالی هواشناسی، درک ما نسبت به چگونگی پاسخ این شاخص‌ها به تغییرات اقلیمی را افزایش می‌دهد. تلفیق داده‌های اقلیمی و محصول شاخص پوشش گیاهی تفاوت نرمال شده (NDVI) مودیس فرصتی را برای ارزیابی اثر خشکسالی بر تخریب پوشش گیاهی در طول فصل رشد فراهم آورده است. هدف از این تحقیق، بررسی اثر خشکسالی بر تخریب پوشش گیاهی دشت میقان اراک در ایران است. بدین منظور، از داده‌های اقلیمی و ماهواره‌ای استفاده شد. شاخص سالانه بارش استاندارد شده برای دوره‌ی ۲۰ ساله (۲۰۱۷-۱۹۹۸) محاسبه شد. سپس نقشه‌های NDVI بر اساس روش توکونگاتانگ به سه طبقه تقسیم شد. این کلاس‌ها عبارتند از: کلاس ۱ (بدون پوشش گیاهی)، کلاس ۲ (پوشش کم تراکم یا مراتع فقیر) و کلاس ۳ (پوشش‌های نیمه متراکم و متراکم از قبیل اراضی کشاورزی). ارتباط بین درصد مساحت کلاس‌های پوشش گیاهی (کلاس ۲ و ۳) با شاخص خشکسالی سال قبل با استفاده از آزمون همبستگی پیرسون بررسی شد. نتایج نشان داد که همبستگی بین این دو متغیر به مقدار قابل توجهی وابسته به تخریب اراضی در نواحی باپوشش گیاهی ضعیف بوده است ($R=0.51$; $P<0.05$). در مقابل رابطه منفی و معنی‌دار بین درصد مساحت مناطق با پوشش گیاهی متراکم (همانند اراضی کشاورزی) و خشکسالی مشاهده شد($P<۰/۵$). بنابراین می‌توان نتیجه گرفت که حساسیت مناطق کم تراکم (مراتع فقیر) به خشکسالی بیشتر از حساسیت اراضی متراکم از پوشش گیاهی (اراضی کشاورزی) بوده است. علت آن است که مهم‌ترین منبع تامین آب برای مراتع طبیعی، نزولات جوی است که به دلیل وقوع خشکسالی‌ها در سال‌های اخیر کاهش یافته است.

کلمات کلیدی: شاخص پوشش گیاهی اختلاف نرمال شده، پایش خشکسالی، روش توکوناگا–توگ، MOD13A3، مناطق نیمه خشک