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# Assessment the effect of drought and land use change on vegetation using Landsat data

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**Abstract**

Drought is a disaster phenomenon especially in arid and semi-arid areas. Vegetation and its production play a main role in the social and economic issues in every country. In this study, Standardized Precipitation Index (SPI) and Normalized Difference Vegetation Index (NDVI) data have been used to monitor drought and the vegetation condition in Sonqor Abad in, Kermanshah province. Meteorological station data in the study area was used to study the SPI as a drought index. The maps of NDVI and also land use changes were provided using Landsat-TM images for 2001, 2008 and Landsat 8 images for 2015 in ENVI software environment. The obtained results showed that the land uses of cultivation and fallow have decreased and rangeland, urban and rock mass have increased. On the other hand, the dense of rainfall in the vegetation density has increased in this area during 2001 until 2015. Due to population growth and expansion of urban areas, the farm and garden lands have decreased around the city during this period. The correlation was found between vegetation density in mid-spring and the annual SPI of last year. Therefore, it can be concluded that there is a direct relationship between rainfall and the density of vegetation. By increasing the amount of rainfall and SPI, the vegetation density is increased. Based on the results, it is recommended that in addition to using meteorological data, satellite images should be used for monitoring the drought.

***Keywords:*** Drought; Vegetation; NDVI; SPI; Land Use Change

## 1. Introduction

Drought is a natural hazard caused by shortage of rainfall that results in water shortages for some activities or some groups (Azarakhshi *et al.*, 2011) and can affect the density of vegetation in any area, especially dry regions (Heydari Alamdarloo *et al.*, 2018). This phenomenon affects societies by limiting access to water resources, as well as increase economic, social and environmental costs. This phenomenon is affected by rainfall, temperature, evaporation and transpiration, content of humidity in accessible soil and condition of underground water (Montandon and Small, 2008; Shahabfar *et al*, 2012; Khosravi *et al*, 2017[b]; Jahanshahi and Shahedi, 2018). Drought stress is one of the most important factors affecting plant growth (Delshadi *et al., 2017)*.

In recent decades, remote sensing has been providing some models to monitoring drought based on plants indices, land surface temperature, moisture and reflectance in the visible and infrared (Ebrahimi *et al*, 2010). Today, vegetation and its production play a dynamic role in the social and economic issues in every country. Researches about crop production growth are usually focused on measuring light interception and its utilization efficiency for evaluating productivity. Compared to other parameters, the indices based near infrared (NIR) are reliable, and the obtained results validate the use of spectral reflectance indices (SRI) as an instrument in the breeding programs for the selection increased genetic gain in yield (Babar *et al*., 2006). Normalized Difference Vegetation Index (NDVI) data have been used to monitor crop condition and forecast yield as well as production in many countries of the world, such as Zimbabwe (Unganai and Kogan, 1998), Kenya (Lewis *et al.*, 1998), Spain (Vicente *et al.*, 2006) and other.

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The NDVI provides information on the vegetation distribution and dynamics. It is commonly thought that its applicability is limited to enhancing our understanding of large herbivore ecology (Pettorelli *et al*., 2011). The NDVI is basically a normalized change of ratio between the near infrared (NIR) to red (RED) reflectance (rNIR/rRED), planned to standardize vegetation index values. The range of NDVI is between -1 and +1, where +1 stands for "amount of vegetation", 0 stands for "no vegetation" and negative values for "non-vegetated surfaces" such as water, snow or building (in urban areas) (Silleos *et al*., 2006).

In the near infrared spectral region, green leaves are highly reflective and no absorption occurs (Jensen, 2007). Thus, green leaves have high visible light absorption with high near-infrared reflectance, resulting in positive NDVI values. On the other hand, clouds, bare soil and snow have the NDVI values of around zero, while water has negative values (Neigh *et al*., 2008). It has been shown that the NDVI are highly correlated with the photosynthetic activity of plants and theirs radiation absorbed. These processes occur through the plant photosynthetic capacity, carbon assimilation, canopy, leaf area, production and evapotranspiration (Buermann *et al*. 2002, Hicke *et al*., 2002, Wang *et al*., 2005). Therefore, NDVI provides monitoring of the vegetation photosynthesis through time and enables to compare temporal and spatial results of a vegetation study (Myneni *et al*., 1997).

Several studies have been attempted to assess and monitor the Normalized Difference Vegetation Index (NDVI) using remote sensing. TM TIR data to observe meso-scale temperature differences between the urban and rural area in Indianapolis were used by Carnahan and Larson (1990). Nichol (1994) carried out a detailed study using TM thermal data to monitor microclimate for housing estates in Singapore. Weng (2001, 2003) examined temperature of land surface pattern and its relationship with vegetation (land cover) in urban clusters in the Zhujiang Delta and in Guangzhou, China. Ji and Peter (2003) fulfilled a study about the response of vegetation to accessible humidity using SPI and NDVI in the deserts of north of America. This study was done on grasslands and farming lands. The goals of this study included the NDVI response to SPI in various periods of growing season as well as the relation between SPI and NDVI in various time scales and regional properties. The study concluded that the best relationship between SPI and NVDI is obtained in soil in regions with low capacity in storing water. Also, the best correlation between NDVI and SPI was a three-month scale. Finally, the most important result was that the NDVI is an effective index of humidity-vegetation condition. However, for monitoring the drought using NDVI, seasonal scheduling should be considered.

Drought dynamism was monitored by Bhuiyan *et al*. (2006) using some meteorological indices and some indices obtained from satellite sensors in Arawali, India, from 1984 to 2003. They used SPI for determining deficit precipitation and standardized water level index for assessing drainage of ground water. Nouri *et al*. (2012, 2013) studied the relationship between agricultural and non-agricultural VIs and ET. They presented VIs, and exclusively NDVI, as a stout indicator to study vegetation characteristics and consequently ET rates.

The aim of this study was to investigate the relation between land use change, NDVI and SPI in Sonqor Abad, Kermanshah province.

## 2. Materials and Methods

### *2.1. The Study Area*

Sonqor Abad is located in the western heights of the Zagros Mountains. This region, with an area of 81562.5 hectares, is located in Kermanshah province at 37 kilometers in the East of Kermanshah city. It is a mountainous region and its climate is mild. The study area is located at 34° 13' 59" to 34° 32' 01" latitude and 47° 17' 48" to 47° 41' 30" longitude. This area is one of the tribal areas of Iran and its mountains and plains are generally covered with woods and pasture. Due to climatic conditions, various agricultural products are produced in this region. In this area, medicinal and aromatic plants are cultivated. The minimum height is 1262 meters and the maximum height is 3089 meters above sea level. Figure 1 shows the location of the study area in Iran.

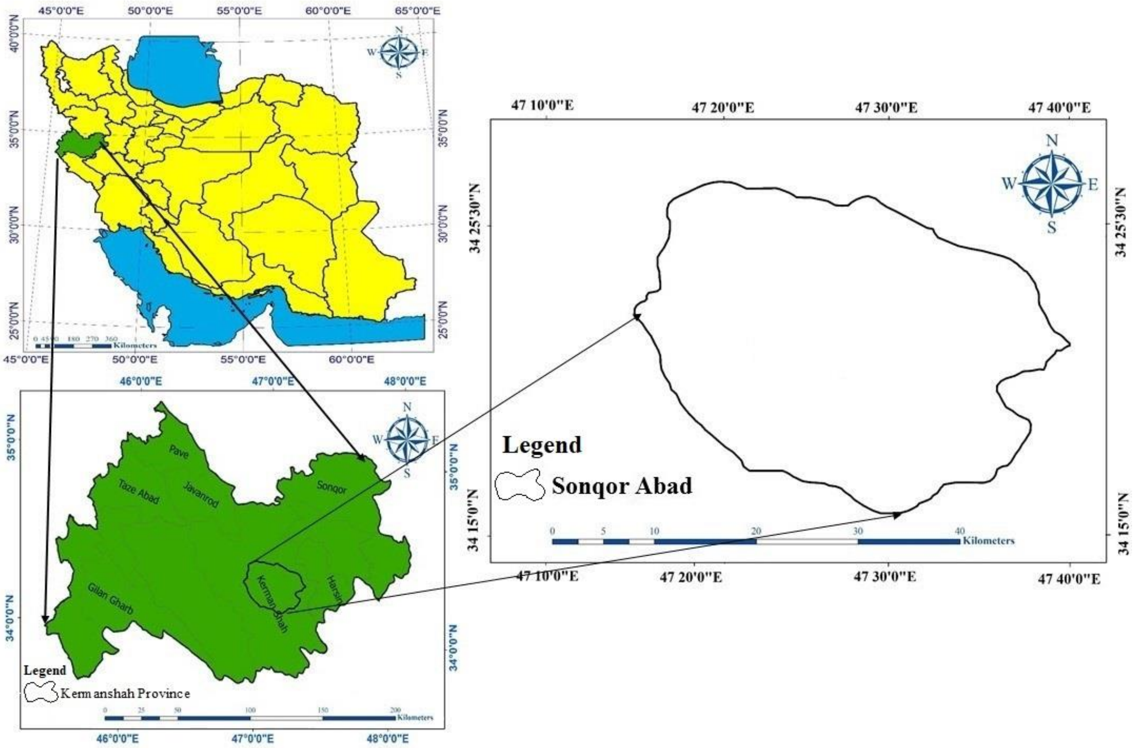


Fig. 1. Location of the study area

### *2.2. Methodology*

For estimation of vegetation, Normalized Difference Vegetation Index (NDVI) was considered as a potential screening tool. The remote sensing was used to assess the Normalized Difference Vegetation Index (NDVI) of 2001-2015. Information used in this study contains TM and OLI data of the study area for 2001, 2008 and 2015. Based on the spatial resolution of the satellite images (30m) the vegetation cover map of the study area was classified into six classes including no vegetation, very low vegetation, low vegetation, medium vegetation, high vegetation and very high vegetation. Land-use maps also were provided in the ENVI software. Also annual average of SPI was calculated from 2001 to 2015.

- *Utilized Satellite Sensors and Calculating NDVI*

Multispectral Landsat TM and Landsat 8 images were used for obtaining vegetation indices. Properties of used TM and OLI sensor are given in Table 1.

Table 1. Spectral properties of Landsat TM and Landsat 8 sensors

| Name of satellite | Sensor | Band No. | Band spectral domain (micrometer) | Name of spectral domain | Resolution (meter) |
|---|---|---|---|---|---|
| Landsat | TM | 1 | 0.45–0.52 | Blue | 30 |
| | | 2 | 0.52–0.60 | Green | 30 |
| | | 3 | 0.63–0.69 | Red | 30 |
| | | 4 | 0.76–0.90 | NIR Infrared | 30 |
| | | 5 | 1.55–1.75 | Middle Infrared | 30 |
| | | 6 | 10.4–12.50 | Thermal Infrared | 120 |
| | | 7 | 2.08–2.35 | Middle Infrared | 30 |
| | 8-OLI | 1 | 0.43–0.45 | Coastal | 30 |
| | | 2 | 0.45–0.51 | Blue | 30 |
| | | 3 | 0.53–0.59 | Green | 30 |
| | | 4 | 0.64–0.67 | Red | 30 |
| | | 5 | 0.85–0.88 | NIR | 30 |
| | | 6 | 1.57–1.65 | SWIR 1 | 30 |
| | | 7 | 2.11–2.29 | SWIR 2 | 30 |
| | | 8 | 0.50–0.68 | Pan | 15 |
| | | 9 | 1.36–1.38 | Cirrus | 30 |
| | | 10 | 10.60–11.19 | TIRS 1 | 30 (100) |
| | | 11 | 11.50–12.51 | TIRS 2 | 30 (100) |

The NDVI, one of the most well-known vegetation indices widely used in most researches and satellite studies for determining vegetation health and density are explained through the Eq. 1 (Pôças *et al*., 2013).

NDVI= (NIR-RED)/(NIR+RED) (1)

Where:
NIR: Reflection of light in infrared band
RED: Reflection of light in red band

The NDVI is calculated as a ratio between measured reflectivity in the red and near infrared portions of the electromagnetic spectrum. Since they are most affected by the absorption of chlorophyll in leafy green vegetation and by the density of green vegetation on the surface, these two spectral bands are chosen (Orhan and Yaka, 2016).

After pre-processing of satellite data, NDVI was calculated for 2001, 2008 and 2015. Then, they was classified in 6 classes including no vegetation, very low vegetation, low vegetation, medium vegetation, high vegetation and very high vegetation (Table 2).

Table 2. NDVI categories for different vegetation

| Class \ Year | 2001 | 2008 | 2015 |
|---|---|---|---|
| No Vegetation | -0.26682 | -0.11339 | -0.11144 |
| Very low Vegetation | -0.13099 | -0.06030 | -0.03279 |
| Low Vegetation | 0.16705 | 0.16844 | 0.16848 |
| Medium Vegetation | 0.29811 | 0.32382 | 0.30928 |
| High Vegetation | 0.42363 | 0.42560 | 0.41589 |
| Very High Vegetation | ------ | 0.53423 | ----- |

- *Providing the Land Use Changes Map*

Multispectral Landsat TM and Landsat 8 images were used for obtaining land use maps. Land use maps were calculated for 2001, 2008 and 2015. These maps were classified in five classes including cultivation, rangeland, fallow, rock mass and urban area. Then, the area of every class was calculated in ArcGIS 10.3.

- *Calculation of SPI*

The annual average of SPI was calculated from 2001 to 2015. This index, accepted by the world climatic organization as a reference drought index for describing drought, was calculated by Eq. 2 and classified according to Table 2.

$$SPI = \frac{Pi-\bar{P}}{S} \quad (2)$$

Where:
SPI= Standardized Precipitation Index
Pi=Rainfall of the given period
S=Standard deviation
$\bar{P}$= Average of period rainfall

Table 2. Classification of SPI (Fox Maule et al, 2013)

| Class | Extremely Dry | Severely Dry | Moderately Dry | Normal | Moderately Wet | Very Wet | Extremely Wet |
|---|---|---|---|---|---|---|---|
| SPI | < -2 | -1.99 - -1.5 | -1.49 - -1 | -0.99 - 0.99 | 1 - 1.49 | 1.5 - 1.99 | 2 < |

In this research, rainfall map for each period was obtained in ArcGIS 10.3for calculating the annual SPI at first. For this purpose, SPI was calculated by precipitation data of meteorological stations nearby the study area.

## 3. Results and Discussion

### *3.1. SPI*

The SPI maps of Sonqor Abad region were provided for the period of 2001– 2015 and the average of annual SPI was calculated by ArcGIS 10.3. The averages of the SPI from 2001 until 2015 are shown in Table 3. The least amount of observed annual SPI is -0.79874 in 2008 and the most amount annual SPI is 1.30185 for 2002.

The trend curve of SPI (Figure 2) showed that the rainfall trend had increased during the study period.

### *3.2. Land Use Maps*

According to the available data and maps, land use map was prepared and classified in five classes for 2001, 2008 and 2015. Then, the area of every class was calculated in ArcGIS 10.3. Totally, the area of rock mass is the most and the area of fallow is the least. However, these amounts are variation in different years during 2001 to 2015. The maps of land use classification for 2001, 2008 and 2015 are illustrated in Figures 3, 4 and 5.

Table 3. Annual mean SPI

| Year | SPI | Class | Year | SPI | Class | Year | SPI | Class |
|---|---|---|---|---|---|---|---|---|
| 2001 | -0.36 | Normal | 2006 | 0.98 | Normal | 2011 | 0.57 | Normal |
| 2002 | 1.30 | Medium Wet | 2007 | -0.41 | Normal | 2012 | 0.12 | Normal |
| 2003 | 0.68 | Normal | 2008 | -0.80 | Normal | 2013 | 0.09 | Normal |
| 2004 | 0.00 | Normal | 2009 | 0.01 | Normal | 2014 | 0.21 | Normal |
| 2005 | 0.62 | Normal | 2010 | 0.43 | Normal | 2015 | 0.76 | Normal |

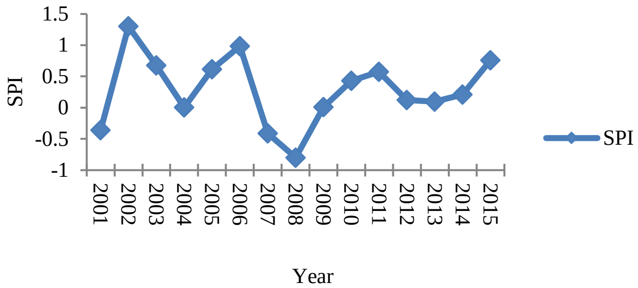

Fig. 2. The trend of SPI from 2001 to 2015

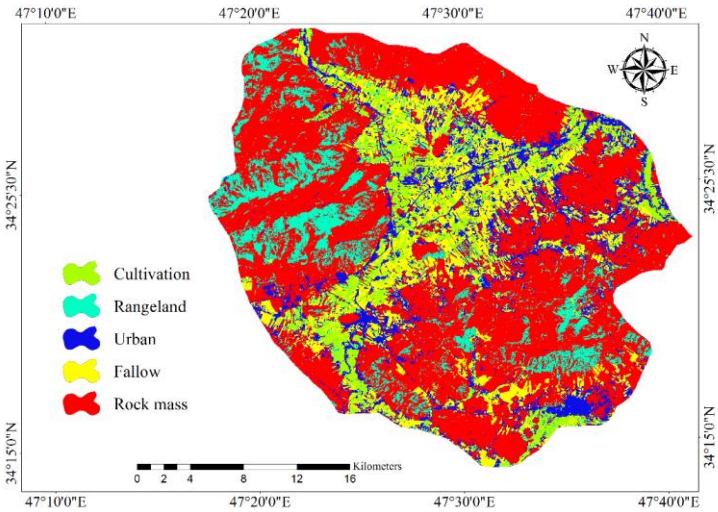

Fig. 3. Map of land use classification in 2001

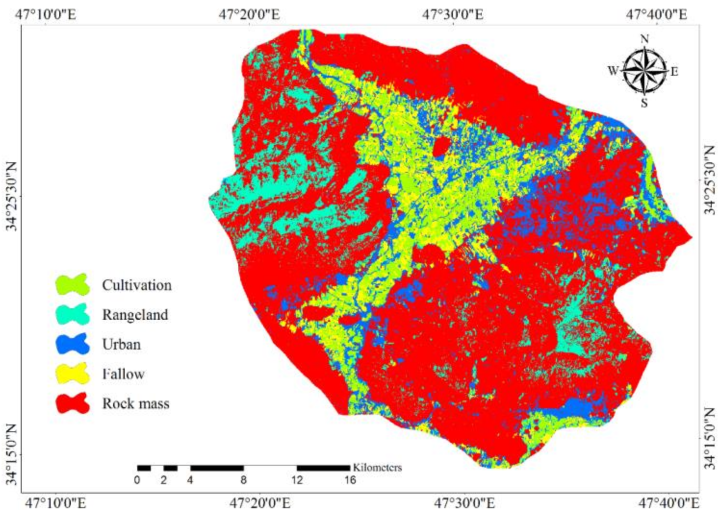

Fig. 4. Map of land use classification in 2008

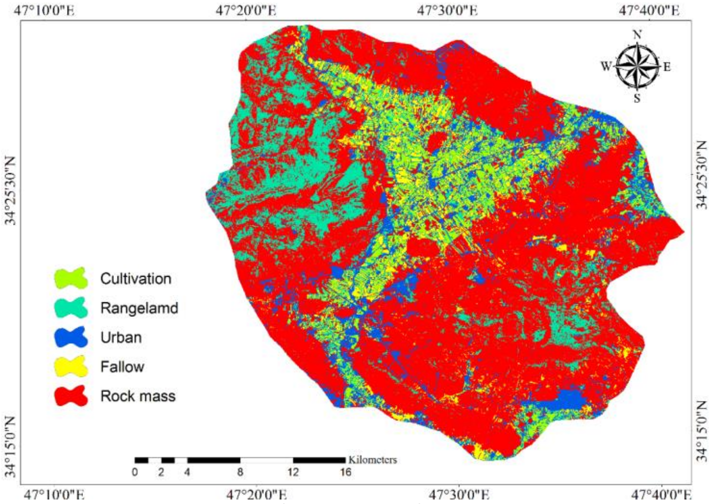

Fig. 5. Map of land use classification in 2015

The area and percentage of each class of land use are shown in Table 4. This table shows that cultivation and fallow have decreased and rangeland, urban and rock mass have increased during 2001 to 2015.

Table 4. Area of land use classes

| Year / Land use | 2001 | | 2008 | | 2015 | |
|---|---|---|---|---|---|---|
| | Area (ha) | Percentage | Area (ha) | Percentage | Area (ha) | Percentage |
| Cultivation | 6843.92 | 8.39 | 6515.1 | 7.99 | 5127.52 | 6.29 |
| Rangeland | 9241.89 | 11.33 | 8508.83 | 10.43 | 11978.31 | 14.69 |
| Urban | 10036.56 | 12.31 | 10088.54 | 12.37 | 9398.21 | 11.52 |
| Fallow | 11217.72 | 13.75 | 6223.51 | 7.63 | 5180.78 | 6.35 |
| Rock mass | 44222.41 | 54.22 | 50226.52 | 61.58 | 49877.68 | 61.15 |

### *3.3. NDVI Maps*

The NDVI was calculated in order to highlight and reinforce the difference in spectral reflection of vegetation. For this purpose, NDVI maps were provided using TM and 8-OLI sensors. The maps of NDVI for 2001, 2008 and 2015 are illustrated in Figures 6, 7 and 8.

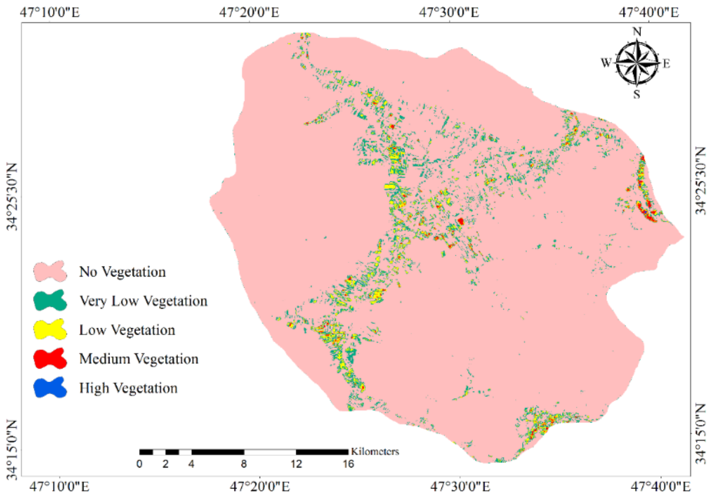

Fig. 6. Map of NDVI classification in 2001

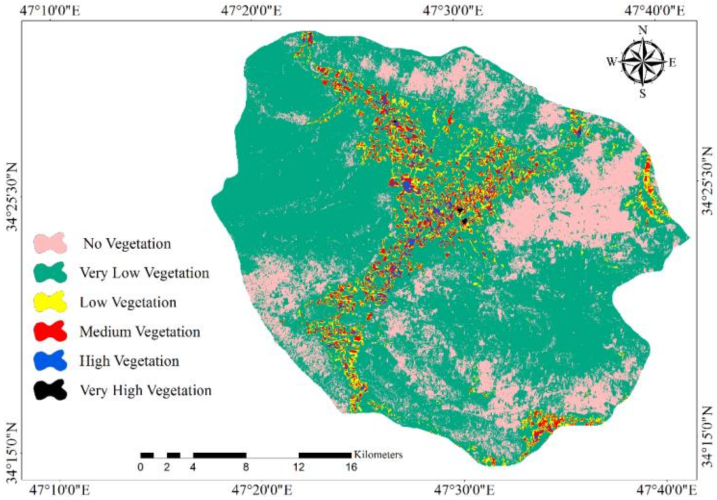


Fig. 7. Map of NDVI classification in 2008

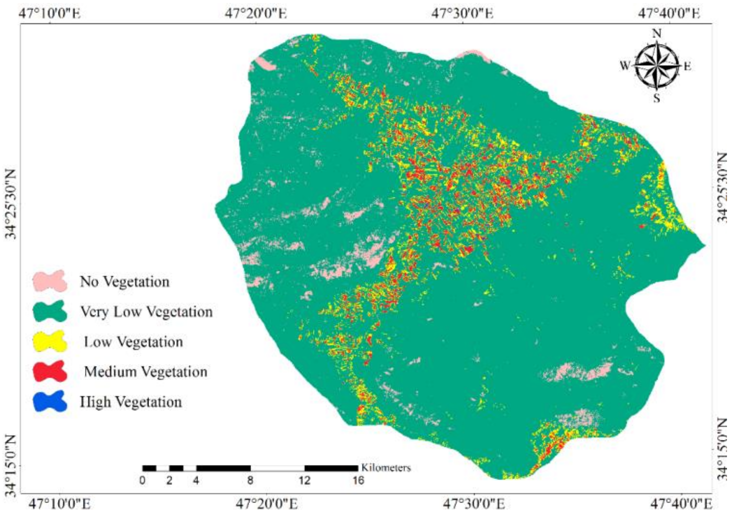


Fig. 8. Map of NDVI classification in 2015

The area and the percentage of the NDVI classes are shown in Table 5. According to the Table, the most percentage of area is related to the “No Vegetation” class and the least percentage of area is related to the “Very High Vegetation” during 2001 to 2015.

Table 5. The Area of NDVI classes

| | 2001 | | 2008 | | 2015 | | Percentage Differences | | |
|---|---|---|---|---|---|---|---|---|---|
| | Area (ha) | % | Area (ha) | % | Area (ha) | % | between 2001 & 2008 | between 2001 & 2015 | between 2008 & 2015 |
| No Vegetation | 77712.41 | 95.28 | 59330.22 | 72.74 | 29019.72 | 35.58 | 22.54 | 59.70 | 37.16 |
| Very Low Vegetation | 2102.54 | 2.57 | 14790.02 | 18.13 | 45420.15 | 55.69 | -15.56 | -53.13 | -37.56 |
| Low Vegetation | 1422.12 | 1.74 | 3935.71 | 4.83 | 4411.43 | 5.48 | -3.09 | -4.01 | -0.65 |
| Medium Vegetation | 274.23 | 0.35 | 1822.25 | 2.23 | 2154.38 | 2.59 | -1.88 | -2.24 | -0.36 |
| High Vegetation | 49.58 | 0.06 | 1570.86 | 1.93 | 553.46 | 0.65 | -1.87 | -0.59 | 1.28 |
| Very High Vegetation | 1.62 | 0.00 | 113.44 | 0.14 | 3.36 | 0.00 | -0.138 | -0.00 | 0.13 |

## 4. Conclusion

The improved availability of satellite data having high temporal and spatial resolutions offers many opportunities. In this study, LANDSAT TM and 8-OLI images of 2001, 2008 and 2015 were used to provide the Land use and Normalized Difference Vegetation Index

(NDVI) maps using remote sensing approach. The NDVI was used to evaluate the vegetation density. The NDVI and land use maps provided by ENVI software was classified in ArcGIS 10.3 software.

In this study the relationship between land use change, SPI and NDVI was analyzed in Sonqor Abad, Kermanshah province during 2001-2015. Based on the obtained results, there is a positive correlation between land use change and SPI and NDVI. It means that more rainfall led to more vegetation cover and land use change affected vegetation density. According to the results of Khosravi *et al.* (2017[a]), there is a positive correlation between NDVI and SPI during the growing season. Studying the relationship between SPI average and vegetation classes showed that rangelands are highly susceptible to SPI changes.

The outcome of this study showed that land use change, especially in rangelands, have occurred in this study area over a 15-year period (2001–2015). The obtained results showed that the amount of SPI has increased. In addition, the vegetation density has increased during the period. There was no correlation between SPI and NDVI in farming lands and gardens. But any changes in the amount of rainfalls have affected vegetation density immediately. A study by Wang *et al*. (2015) showed that the drought occurring during the growing season or before vegetation growth has a major impact on NDVI.

Land cover change is one of the factors that can affect the analysis of greenness (Zhu *et al*, 2016). Consequently, drought has been able to cause a significant change in the percentage of the vegetation density in this area. The temporal variations of NDVI anomaly are linked with SPI obviously and have strong relationship with SPI.

However, there is a significant correlation between drought and the dense of vegetation. To determine vegetation classes by NDVI maps, we can say there is a positive correlation between the annual SPI (with delay) and the dense of vegetation in pastures as well as other areas.

This study demonstrates that monitoring the drought and using the climatic data and satellite images are necessary to obtain better results, which is compatible to the research of Himanshu *et al*. (2015). Additionally, researches with more satellite images should be done to conduct the real scientific facts about drought and its effects on vegetation.

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