

RELATIONSHIP BETWEEN LAND COVER AND VEGETATION INDICES. CASE STUDY: EGHlid PLAIN, FARS PROVINCE, IRAN.

Marzieh MOKARRAM

Shiraz University, Department of Range and Watershed, Shiraz, Iran
m.mokarram@shirazu.ac.ir

Ali Darvishi BOLOORANI

Tehran University, Department of GIS and remote sensing, Tehran, Iran
ali.darvishi@ut.ac.ir

Majid HOJATI

Tehran University, Department of GIS and remote sensing, Tehran, Iran
majid.hojati@ut.ac.ir

Abstract

In this study, the Visible Atmospherically Resistant Index (VARI), Weighted Difference Vegetation Index (WDRVI), Enhanced Vegetation Index (EVI), Optimized Soil-Adjusted Vegetation Index (OSAVI), Atmospherically resistant vegetation index (ARVI), SAVI (Soil Adjusted Vegetation Index), NDVI (Normalized Difference Vegetation Index) vegetation indices by Landsat 8 ETM+ bands vegetation in the Eghlid city, Fars province, Iran in 2015 were calculated. Then indexes compared with land cover map were calculated in order to determine the best index for making the land cover map of the region. The results showed that the area of Perennial forbs has different features than other land covers. WDRVI and SAVI showed the highest and lowest accuracies.

Keywords: Landsat 8 ETM+, remote sensing, vegetation index, land cover.

1. INTRODUCTION

Land cover mapping in natural resource management is important when considering the effects of climate change, increasing or decreasing the number of coatings can prioritize strategies for effective protection and zoning areas. So according to the changes, they can play an important role in reducing the destructive effects of climate change (Arastu and Godrati, 2014).

A vegetation index is a measure which reduces the spectral information from several bands of a satellite image into one single band. It maximizes sensitivity to biophysical parameters of vegetation preferably with a linear response, normalizing external (solar zenith, viewing angle, etc.) and internal effects (background, topography, soil, etc.), and is coupled with a measurable biophysical parameter such as biomass, Leaf Area Index (LAI) or fuel moisture for validation purposes (Jensen, 2005).

The knowledge of the properties of the plant during the growing season for Disease Control, expected performance and farm management to optimize performance and avoid excessive fertilization is very important (Gnyp et al., 2014). Overall in the last few decades, changes in the structure and functioning of ecosystems by human land cover were apparent (Jamali et al., 2014). So it will be important to measure changes in vegetation. The investigation and interpretation of aerial photographs and field observations, Cover and land

use maps can be implemented, but both methods are time-consuming and costly (Arastu and Godrati, 2014). Also for agricultural parameters such as biomass, LAI (Leaf Area Index) and crop and soil nitrogen content in order to accurately describe the growth of crops, farm-destructive measurement is expensive and time consuming to be used (Gnyp et al., 2014).

Remote sensing is another technique that uses special tools without physical contact with the aim of gaining information about the purpose (Seyhan, 2004). Remote sensing data, because of its features such as multi-temporal, multi-spectral, functionality and good spatial resolution and radiometric diverse, broad and integrated vision, is able to separate the different farming conditions and phenomena such as surface, and patterns of time and areas of cultivation (Abdullah Zadeh et al., 2008).

Regular and careful observation of forest and losses of nitrogen deficiencies, water stress or insects could be facilitated by the development of adequate management strategies (Tillack et al., 2014). Remote sensing techniques are cost-effective method for quantitative estimates of biomass at regional and local scales. The emergences of hyper spectral sensors, which offer an approximately contiguous spectrum, have opened a new perspective to quantify and assess the biophysical properties including biomass (Fu et al., 2014). As a result of using non-destructive spectral reflectance data obtained from satellite, and spectrometers, etc. study of the agricultural parameters is facilitated and accelerated (Gnyp et al., 2014). Li et al (2015) stated that the use of remote sensing techniques and the application of GIS (Geographic Information System) are increasingly easier to measure vegetation cities.

Vegetation indices are some enhancement methods of information extraction from satellite images that have been developed and used for evaluating the biophysical and biochemical parameters of the plant. The indices due to ease of use are one of the most common techniques of remote sensing for estimating such parameters (Bannari, 2006). Vegetation index compared with measured vegetation is beneficial including reduced time, frequency data and lowering the costs and labor least (Tanriverdi, 2003).

Many studies on the use of remote sensing techniques and vegetation indices in agriculture and natural resources have been done. Arzani et al (2009) using indicators SAVI (Soil-adjusted Vegetation Index), MSAVI (Modified Soil Adjusted Vegetation Index) and PVI have proposed the estimate of the crown of Vegetation. In northern China, Bao et al (2009) predicted winter wheat biomass and Ren et al (2007) monitored winter wheat yield using data from MODIS, and Koppe et al (2012) estimated winter wheat biomass using Hyperion data. Vegetation index NDVI (Normalized Difference Vegetation Index), NDVI-RE (Red Edg NDVI), msR-RE (Modified Red Edge Simple Ratio) and Curvature demonstrated that the spatial and temporal variations in leaf area index (LAI) can be estimated as well (Tillack et al., 2014). Ren et al (2011) showed that the linear model based on NDVI (862, 693 nm) relative to the index, SAVI is composed of 887 and 685 nm bands had a better estimates of green biomass of the desert steppe. Ji et al (2012) also stated that remote sensing can be a good alternative for mapping ground biomass. Baihua and Burgher (2015) stated that the vegetation index NDVI is a good indicator to identify and assess long-term changes in the areas of vegetation.

Mokarram et al. (2016) Applied remote sensing for the determination of the vegetation index. In the research using NDVI, SAVI, RVI and EVI vegetation indices and Landsat 7 ETM+ bands vegetation of north western of Iran in 2000 and 2010 were estimated. Compared to land use map of this region, the results showed that the range -1 to zero micrometers of NDVI could be better to measure vegetation. NDVI showed that in 2010, an area of 419.543 km² (35.68%) and in 2000, an area of 744.3491 km² (63.30 %) of North West of Iran were under vegetation which represent a decrease of vegetation in 2010 in the area.

Mokarram and Sathyamoorthy (2016) investigated the relationship between landform classification and vegetation in southwest of Fars province, Iran. The results showed that

there were positive and significant correlations between NDVI and tree height ($r = 0.923$), and landform and NDVI ($r = 0.640$). This reveals that landform classification and NDVI should be used to predict tree height in the area. High correlation of determination (R^2) 0.909 was obtained for the prediction of tree height using landform classification and NDVI.

The aim of this study is the estimation of vegetation in Eghlid city, Fars province, Iran using Visible Atmospherically Resistant Index (VARI), Weighted Difference Vegetation Index (WDRVI), EVI (Enhanced Vegetation Index), Optimized Soil-Adjusted Vegetation Index (OSAVI), Atmospherically resistant vegetation index (ARVI), SAVI (Soil Adjusted Vegetation Index), NDVI (Normalized Difference Vegetation Index) vegetation indices based on Landsat 8 ETM+ bands in 2015 and the determination of the relationship between land cover and each of vegetation indices in the study area.

2. MATERIAL AND METHODS

2.1. Case study

The study area is located at longitude of N 30° 47' to 30° 50' and latitude of E 52° 40' to 52° 45' and with area 3,622.88 km², is located in the south of Iran (Figure 1). The altitude of the study area ranges from the lowest of 2,321 m to the highest of 3,842 m. The Major study area products are wheat, citrus, cotton, maize and palm. The average yearly rainfall in the study area is 300 mm. The study area has warm days in summer with 38-46°C and moderate winters (15-25°C) (Oryan and Sadeghi, 1997; Rezaei and Shakoore, 2011; Moein et al., 2015).

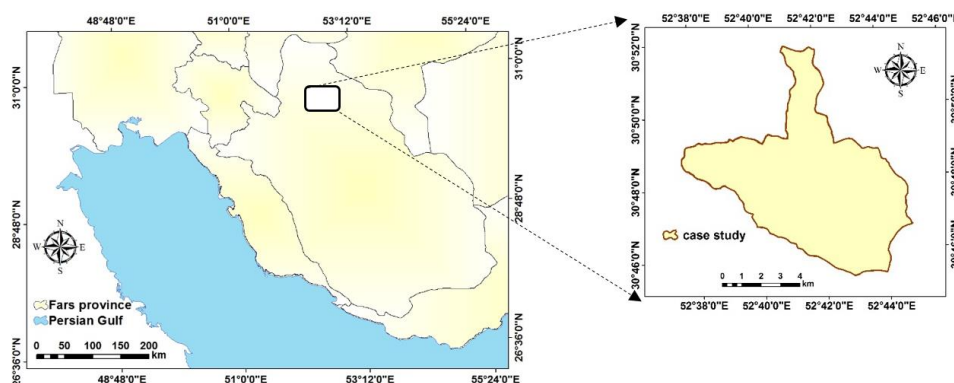


Figure 1. Study area situation

In this study to calculate the indices NDVI, EVI, SAVI, VARI, ARVI, OSAVI and WDRVI have been used of bands 1, 3 and 4 Landsat 8 ETM + sensor, 2015 years.

2.2. Landsat satellite

LANDSAT 8 satellite has two main sensors: the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) images consist of nine spectral bands with a spatial resolution of 30 meters for Bands 1 to 7 and 9. New band 1 (ultra-blue) is useful for coastal and aerosol studies. New band 9 is useful for cirrus cloud detection. The resolution for Band 8 (panchromatic) is 15 meters. Thermal bands 10 and 11 are useful in providing more accurate surface temperatures and are collected at 100 meters. Approximate scene size is 170 km north-south by 183 km east-west (106 mi by 114 mi) (USGS, 2016).

Table 1. Landsat 8 bands with their wavelength and resolution.

Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) Launched February 11, 2013	Bands	Wavelength (micrometers)	Resolution (meters)
	Band 1 - Coastal aerosol	0.43 - 0.45	30
	Band 2 - Blue	0.45 - 0.51	30
	Band 3 - Green	0.53 - 0.59	30
	Band 4 - Red	0.64 - 0.67	30
	Band 5 - Near Infrared (NIR)	0.85 - 0.88	30
	Band 6 - SWIR 1	1.57 - 1.65	30
	Band 7 - SWIR 2	2.11 - 2.29	30
	Band 8 - Panchromatic	0.50 - 0.68	15
	Band 9 - Cirrus	1.36 - 1.38	30
	Band 10 - Thermal Infrared (TIRS) 1	10.60 - 11.19	100 * (30)
	Band 11 - Thermal Infrared (TIRS) 2	11.50 - 12.51	100 * (30)

* TIRS bands are acquired at 100 meter resolution, but are resampled to 30 meter in delivered data product.

In this study, using LANDSAT 8 satellite to calculate the indices Visible Atmospherically Resistant Index (VARI), Weighted Difference Vegetation Index (WDRVI), Enhanced Vegetation Index (EVI), Optimized Soil-Adjusted Vegetation Index (OSAVI), Atmospherically resistant vegetation index (ARVI), SAVI (Soil Adjusted Vegetation Index), NDVI (Normalized Difference Vegetation Index) have been used of bands 1, 3 and 4 Landsat 8 ETM+ sensor, year 2015.

First, in software ENVI v.5 pre-processing, processing, geometric and atmospheric corrections were performed, and then vegetation index for the study area was calculated as follows:

And Arc GIS 9.3 software for mapping of area vegetation was applied. Then indexes compared with land cover map in order to determine best index for estimate vegetation in study area.

2. 3 Vegetation indices

NDVI (Normalized Difference Vegetation Index)

The one of most important used vegetation indices is normalized difference vegetation index (NDVI), which can be used as a basis for determining other parameters of vegetation index. Values of this index are between -1 to +1, which the highest values of this Index, is indicator the increase in vegetation density. NDVI calculates from the equation 1 (Rahmani et al., 2011).

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

ρ_{NIR} and ρ_R respectively are near infra-red (band 4) and red (band 3) bands of ETM sensor.

SAVI (Soil Adjusted Vegetation Index)

SAVI Index aims to minimize the effects of background soil reflectance on effect of vegetation reflects, by combining regulatory factor (L) with the denominator of the NDVI equation. This indicator is an excellent vegetation index to area with low coverage. SAVI calculates from the equation 2:

$$SAVI = \rho_{NIR} - \rho_R(1 + L) / \rho_{NIR} + \rho_R + L \quad (2)$$

L is moderating factor of soil effect that usually determined experimentally. L Ranging from zero for dense vegetation and 1 for lower vegetation density (Rahmani et al., 2011).

In areas with low vegetation cover and bright soil surface, the reflectance of red and near-infrared can effect vegetation index. This problem arises when a competition between different soil types occurs. The SAVI index was developed as a modification of the NDVI to correct the influence of soil brightness when vegetative cover is low (Richardson et al, 1992).

Atmospherically resistant vegetation index (ARVI)

The resistance of the ARVI to atmospheric effects is accomplished by a self-correction process for the atmospheric effect on the red channel, using the difference in the radiance between the blue and the red channels to correct the radiance in the red channel. Due to the excellent atmospheric resistance of the ARVI, it is expected that remote sensing from MODIS of the vegetation index over most land surfaces.

$$ARVI = (\rho_{NIR} - (\rho_R - \gamma \times (\rho_R - \rho_B))) / (\rho_{NIR} + (\rho_R - \gamma \times (\rho_R - \rho_B))) \quad (3)$$

$\gamma=1$

ρ_{NIR} = reflectance of the NIR band

ρ_R = reflectance of the read band

ρ_B = reflectance of the blue band

Because of self-correction process ARVI is resistance to atmosphere effects. This index uses difference in the radiance between the blue and red bands to correct the radiance in red band. Simulations shows that ARVI has a similar dynamic range to the NDVI, but on average, it's sensitivity to atmospheric effects is four times less than NDVI (Kaufman et al,1992).

Optimized Soil-Adjusted Vegetation Index (OSAVI)

This index is based on the Soil Adjusted Vegetation Index (SAVI). It uses a standard value of 0.16 for the canopy background adjustment factor. Rondeaux et al. (1996) determined that this value provides greater soil variation than SAVI for low vegetation cover, while demonstrating increased sensitivity to vegetation cover greater than 50%. This index is best used in areas with relatively sparse vegetation where soil is visible through the canopy.

$$OSAVI = (\rho_{NIR} - \rho_R) / (\rho_{NIR} + \rho_R + 0.16) \quad (4)$$

ρ_{NIR} = reflectance of the NIR band

ρ_R = reflectance of the read band

OSAVI is optimized for agricultural monitoring.

Because of the sensitivity of NDVI to atmospheric state and also soil background a set of vegetation indexes including SAVI, OSAVI, ARVI and etc. are developed. Theoretically these indexes are more reliable than NDVI and most of them are used with satellite data. The value of X in SAVI family is critical in case of decrease the soil effect (Rondeaux, et al.1996).

EVI (Enhanced Vegetation Index)

Enhanced vegetation index for improving NDVI, by optimizing vegetation signals in the range of LAI using reflection blue band is developed to correct signals of the background soil and reducing atmospheric effects such as scattering particles. The combination of empirical relationships for atmospheric correction has resulted in develops of vegetation index (EVI). This index is obtained from equation 3:

$$EVI = G \cdot (\rho_{NIR} - \rho_R) / L + \rho_{NIR} + c_1 \cdot \rho_R - c_2 \cdot \rho_B \quad (5)$$

ρ_{NIR} = reflectance of the NIR band

ρ_R = reflectance of the read band

ρ_B = reflectance of the blue band

$G = 2.5$, $C_1 = 6$, $C_2 = 7.5$ and $L = 1$ is. Values of this index are in the range -1 to 1. The vegetation is typically range from 0.2 to 0.8 (Rahmani et al., 2011).

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The Enhanced Vegetation Index (EVI) is proposed by the MODIS Land Discipline Group. This index and the Normalized Difference Vegetation Index (NDVI) are both global-based vegetation indices aimed at providing consistent spatial and temporal information regarding global vegetation. In addition to the atmospheric effects and soild background effects the topographic effect is another fundamental factor that influences vegetation indexes, especially when the indices are used in areas of rough terrain. The soil adjustment factor “L” in the EVI makes it more sensitive to topographic conditions than the NDVI. It is strongly recommended that the topographic effect should be removed in the reflectance data before the EVI is calculated when these indices are used in the area of rough terrain, where the topographic effect on the vegetation indices has only a band ratio format (e.g., the NDVI) it can usually be ignored.

Weighted Difference Vegetation Index (WDRVI)

The weighted (near-infrared-red) difference vegetation index (WDVI) can be used for estimating leaf area index (LAI) of green vegetation. This WDVl offers a good correction for soil background in estimating the LAI of green vegetation, e.g. cereals at the vegetative stage (Clevers, 1991):

$$WDRVI = \rho_{NIR} - \alpha \rho_R \quad (6)$$

where α = the slope of the soil line

ρ_{NIR} = reflectance of the NIR band

ρ_R = reflectance of the read band

Visible Atmospherically Resistant Index (VARI)

VARI assumed that the effect in the blue is twice as large as in the red, so to correct for the effect in the red and the green, we subtracted blue. Thus, VARI, was transformed to the following Visible Atmospherically Resistant Index (Gitelson, et al., 2002):

$$VARI = (\rho_G - \rho_R) / (\rho_G + \rho_R - \rho_B) \quad (7)$$

ρ_G = reflectance of the green band

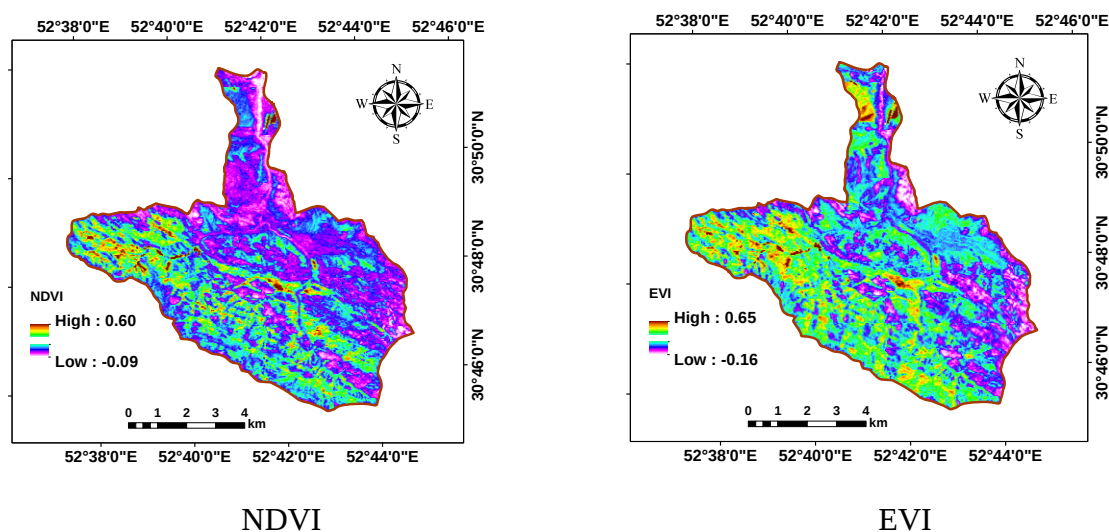
ρ_R = reflectance of the red band

ρ_B = reflectance of the blue band

It has been shown that VARI provides the best overall results for fuel moisture estimation in Mediterranean shrub lands (Roberts et al., 2006; Stow et al., 2005). Sensitivity of VARI to atmospheric effects is less than NDVI and it is developed for the estimation of green vegetation fraction. The Bands which is used in VARI is selected due to their sensitivity to vegetation fraction (Gitelson et al., 2002). In contrast to NDVI, which is sensitive to changes of small vegetation fractions and insensitive of changes at moderate and high vegetation fractions, VARI shows a linear response to the vegetation fraction throughout the entire range. Based on work by Kaufman and Tanré (1992), VARI reduces atmospheric effects by subtracting the blue channel in the denominator. Gitelson et al. (2002) showed that VARI allows the estimation of green vegetation fraction with an error of less than 10% (Viña et al., 2011).

3. RESULTS

The results of the vegetation indices show in the Figure 2.



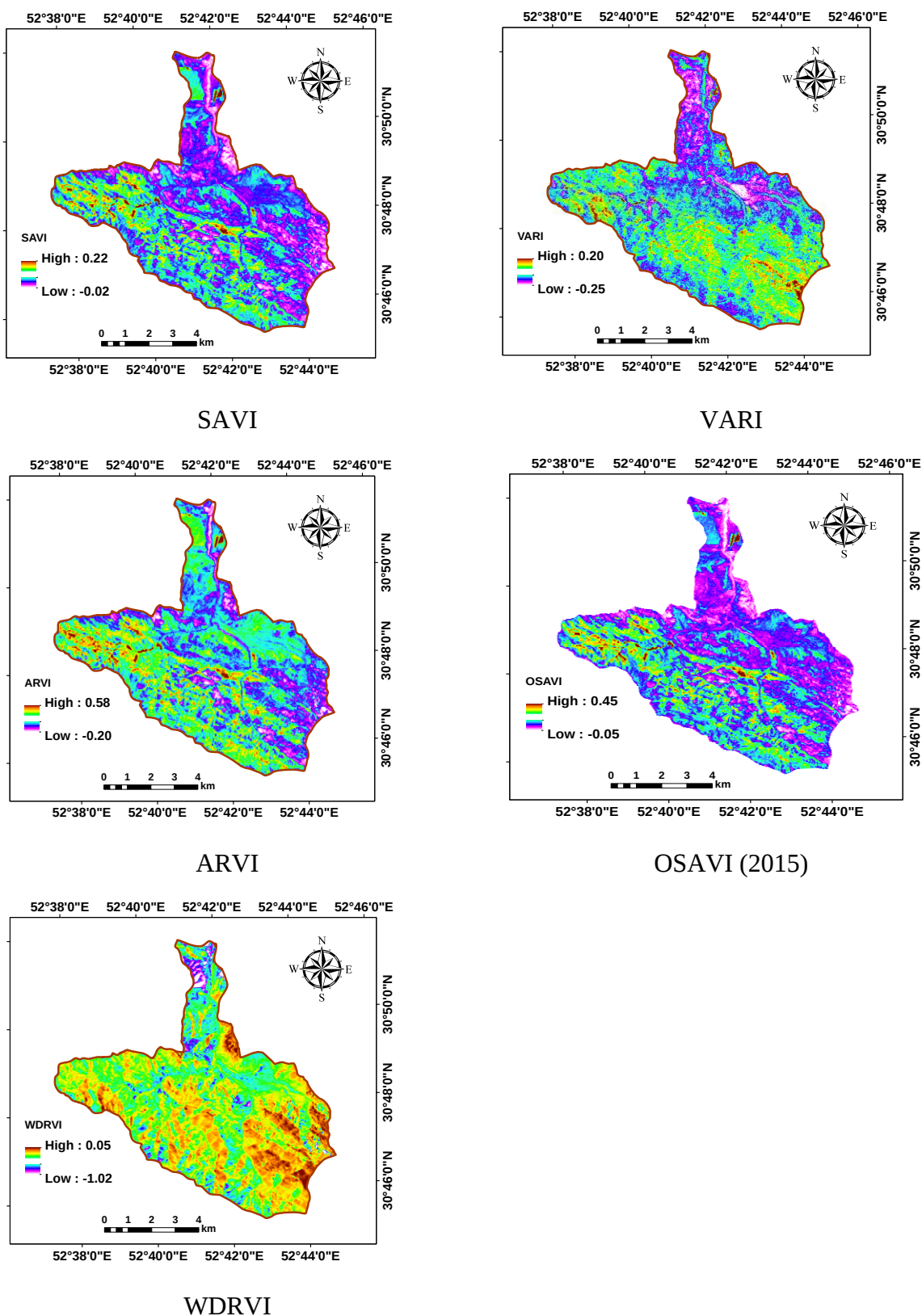


Figure 2. Vegetation indices of the study area

According to Figure 2 the highest vegetation index value is EVI (0.65) and the lowest vegetation index value is WDRVI (- 1.02). The NDVI value is between – 0.09 to 0.6 that

shows the vegetation in the study area is low. Also low SAVI, VARI, OSAVI, and ARVI show that the soil of the study area is bare in many parts of the region. Generally vegetation value in the north of the study area is lower than the other parts of the study area.

After preparing the vegetation index, the relationship between each of the vegetation index and land cover (Figure 3) was determined. Land cover consists of four types of vegetation that include farmland, perennial plant, forbs, and perennial forbs. Farmland is in significant part of the region. While perennial plant, forbs and perennial forbs are in east, west and north parts of the study area.

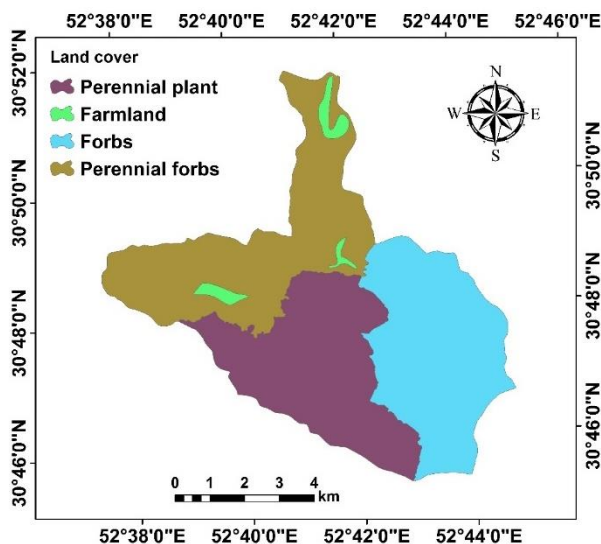
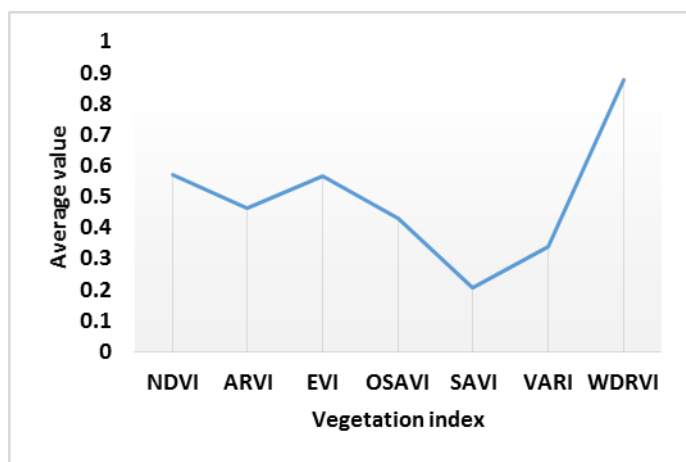
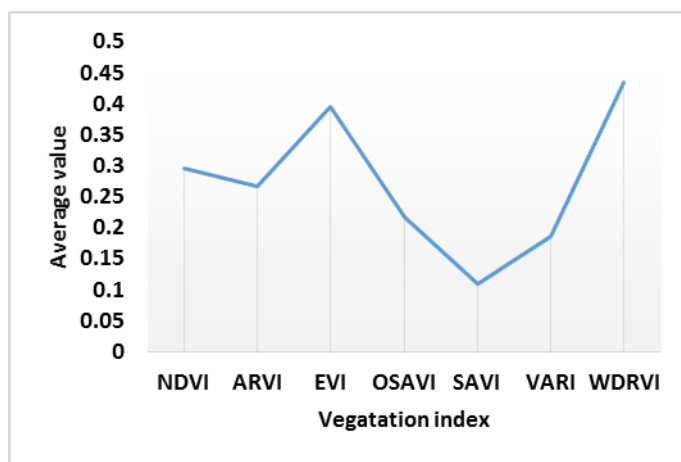


Figure 3. Land use map of the study area

The results of the relationship between vegetation indices and land cover map are shown in Figure 4.



Farmland



Perennial plant

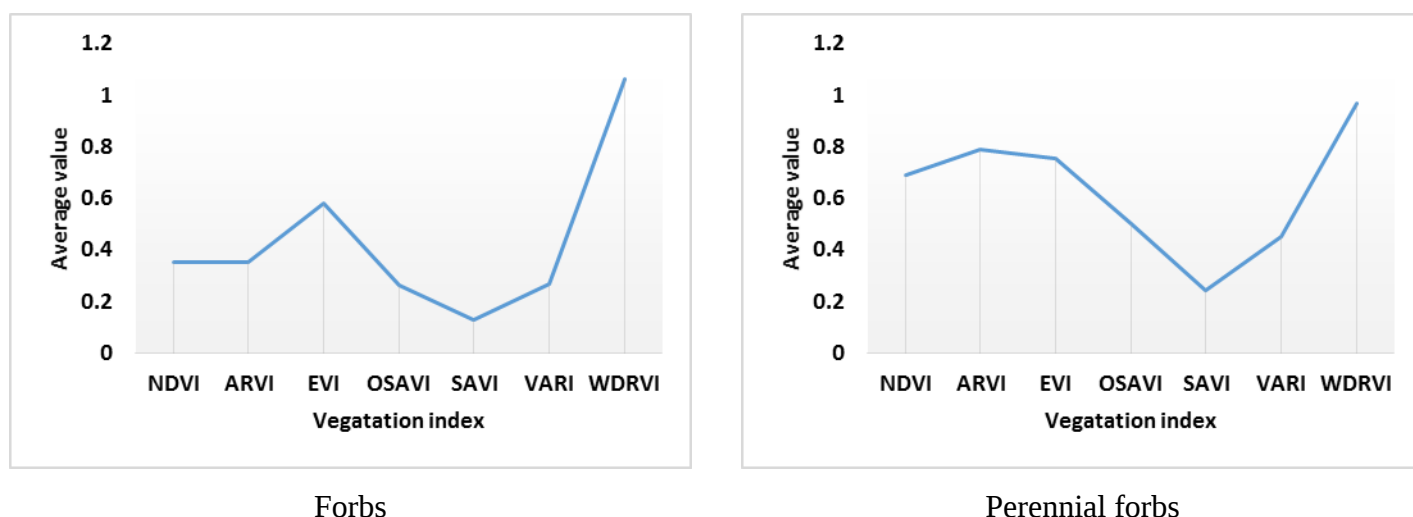


Figure 4. The relationship between vegetation indices and land cover map

According to Figure 4 the determination of the regions of forbs, Perennial plant and farmland have the same responses to the electromagnetic waves. In fact the vegetation indices are the same in the regions. So that maximum value is in WDRVI and minimum value is in SAVI. The area of Perennial forbs is different from the other land cover. So that ARVI and EVI value are the same. Also NDVI value is maximum in the study. In the total for all land cover, WDRVI and SAVI are maximum and minimum respectively.

4. CONCLUSIONS

As the rapid access to detailed information about the vegetation, through conventional methods are very costly and difficult, the use of remote sensing techniques in the study of vegetation has resulted in low volume has provided access to a host of information with high accuracy. Because of the ease of use, vegetation indices are the most common form of remote sensing techniques in the estimation of vegetation. The indices NDVI, EVI, SAVI, VARI, ARVI, OSAVI and WDRVI were used to evaluate changes in the vegetation of north Fars province, Iran in 2015. Regions of forbs, Perennial plant and farmland had the same response to electromagnetic waves. In fact the vegetation indices are the same in the regions. So the maximum value is in WDRVI and minimum value is in SAVI. The area of Perennial forbs is different from the other land covers. Totally for all land cover, WDRVI and SAVI are maximum and minimum respectively.

In the most of NDVI such as indexed difference between NIR and red reflectance is an important factor which is used to decrease the soil background effect (Pinty et al., 2009). In the most of statistical data there is no significant difference except in SAVI and WDRVI which they relatively decreased and increased. In all of the lanforms the SAVI has the lowest and WDRVI has the highest value.

In dry areas because of the effect of soil background some of the indexes such as NDVI do not show any appropriate results and in the other side indexes like EVI and SAVI provide good information about the vegetation indexes in arid and semi-arid areas. when the stages of development of crops and plants differ more, the values of particular VIs lead not only to various changes in the colors of palette (which could be more or less useful for interpretation) but also lead to slightly increased separability of certain crops.

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