Range Mgmt. & Agroforestry 35 (1) : 91-100, 2014
ISSN 0971-2070

Assessment of spectral vegetation indices for estimating vegetation cover in arid and semiarid shrublands

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Received: 14th October, 2013 Accepted: 28th May, 2014

Abstract

Forty four spectral vegetation indices based on Enhanced Thematic Mapper Plus (ETM+) data were compared for predicting vegetation cover in Nodushan arid and semi arid shrublands. The efficiency of the indices was evaluated based on calculating the critical error, power of prediction and the prediction interval for the error. MSAVI, TDVI, TVI, CTVI, NDVI, NRVI, IPVI, MND, TTVI, MSR and SRI provided the most accurate estimate of the vegetation cover with an error of less than 10%. MSAVI and TDVI had the lowest critical error (9.3%). The indices based on only near infrared and red bands gave the most accurate prediction of vegetation cover followed by the indices based on only near infrared and green bands (critical error of 10.7-11%), while the indices that use blue and/or shortwave infrared, or only visible (B-G-R) bands provided the least accurate estimate of the vegetation cover (critical error of 25-84%).

Keywords: Arid, ETM+, Semi-arid, Shrublands, Vegetation indices

Abbreviations: ARVI: atmospherically resistant vegetation index; **AI:** autumn index; **BDVI:** blue difference vegetation index; **BNDVI:** blue normalized difference vegetation index; **BRVI:** blue ratio vegetation index, **CTVI:** corrected transformed vegetation index; **CI:** crust index; **DVI:** difference vegetation index; **ETM+:** enhanced thematic mapperPlus; **EVI:** enhanced vegetation index; **GEMI:** global environmental monitoring index; **GDVI:** green difference vegetation index; **GNDVI:** green normalized difference vegetation index; **GRVI:** green ratio vegetation index; **RIG/B:** green to blue ratio index; **DIG-B:** green-blue difference index; **IPVI:** infrared percentage vegetation index; **MND:** modified normalized difference; **MNDWI:** modified normalized difference water index; **MSR:** modified simple ratio; **MSAVI:** modified soil adjusted vegetation index; **MSI:** moisture stress index; **NDII7:** normalized difference infrared index-band 7; **NDTI:** normalized difference tillage index; **NDVI:** normalized difference vegetation index; **NDWI**: normalized difference water index-band5; **NGBDI**: normalized green-blue difference index; **NGRDI:** normalized green-red difference index; **NRVI:** normalized ratio vegetation index; **PCA1:** principle components analysis-first component; **RDVI:** ratio difference vegetation index; **RIR/G:** red to green ratio index; **DIR-B:** red-blue difference index; **DIR-G:** red-green difference index; **SII:** shortwave infrared index; **SVR5:** shortwave to visible ratio-band 5; **SVR7:** shortwave to visible ratio-band 7; **SRI:** simple ratio index, tasseled cap (brightness, greenness, wetness); **SWIR:** Short wave infra red **TTVI:** Thiam's transformed vegetation index; **TDVI:** transformed difference vegetation index; **TVI:** transformed vegetation index; **VARI:** visible atmospherically resistant index.

Introduction

Estimates of vegetation cover are important for determining plant biomass, studying photosynthesis, nutrient cycle, ecosystem condition, evaluating environmental changes and land management practices (Zengru *et al*., 2012). Continuous and regular sampling of vegetation is laborious, time consuming and difficult because of the vast area of terrestrial ecosystems and inaccessibility of some areas. The use of satellite remote sensing makes possible a continuous and remote assessment of various attributes of vegetation. Remotely sensed data of the landsat-7 Enhanced Thematic Mapper Plus (ETM+) have been frequently used for vegetation studying such as estimating leaf area index (Cohen *et al*., 2003), aboveground biomass (Zheng *et al*., 2004), vegetation cover (Sivanpillai *et al.,* 2005), net primary productivity (Sun *et al.,* 2004), mapping vegetation (Johansen and Phinn, 2006) and burn severity (Van Wagtendonk *et al.,* 2004). ETM+ has six bands with 30-m resolution: blue (0.45-0.515 μm), green (0.525-0.605), red (0.63-0.69), visible near infrared (0.75-0.90), two short-wave infrared bands (1.55ï 1.75 and 2.09ï 2.35), one thermal band with 60-m resolution (10.4-12.5) and one panchromatic band with 15-m resolution (0.52-0.9). Various mathematical combinations of satellite bands refereed to as spectral vegetation indices can be used as indicators of the presence and attributes of vegetation. These indices are based on the reflectance properties of vegetation as compared to cloud, water, snow, rock and bare soil. Most vegetation indices use the red spectral band, which is related to the chlorophyll level, and the near infrared band, which represents the green vegetative biomass (Trivero *et al.,* 2007). The reflectance of vegetation and consequently the value of spectral vegetation indices have been found to be influenced by the seasonal variability of green cover, the state of vegetation such as age, color, leaf water content, mineral deficiencies, parasitic attack, cover geometry, row spacing and orientation, leaf density distribution, leaf area and the changes in illumination conditions, slope and aspect (Guyot *et al.,* 1989; Jackson and Huete, 1991). It is necessary to determine the efficient spectral indices for an accurate remote assessment of vegetation cover in different environments. The objective of this study was to assess the efficiency of different spectral vegetation indices for estimating the vegetation cover in arid and semi arid Nodushan rangelands of Yazd, Iran.

Materials and Methods

Study sites

To estimate vegetation cover using ETM+ images, 20 sites with different amount of vegetation cover were selected in Nodushan rangelands of Yazd (Table 1). Nodushan rangelands are located in the northwest of Yazd province in central part of Iran (31º 46ôN, 53º 24ôE to 32º 15ôN 53º 47ôE) at an elevation between 1840 and 3260 m. The average annual precipitation ranges from 110 mm to 340 mm and the average annual temperature is from 10°C to 16°C. The climate of the study sites 2-10 and 12-20 was characterized as arid and that of sites 1 and 11 as semi arid. Nodushan rangelands are dominated by Artemisia shrubs.

Sampling and landsat data preparation

A 150 $\times$ 150 meter area was selected in each site for estimating the vegetation cover. The geographical coordinates of four angles of each sampling area were registered using GPS. The vegetation cover was estimated by measuring the plant diameter within 30 located 1x2 m quadrates in each sampling area. A scene of landsat 7 ETM+ image (Path: 162, Row: 038) covering Nodushan rangelands was acquired under clear atmospheric conditions on August 06, 2006 based on the sampling period. Six bands (1, 2, 3, 4, 5, &7) of the ETM+ image were georeferenced using the coordinates of 10 ground control points. The accuracy of transformation was acceptable based on the calculated root mean square error (Sigma = 0.32). To assess the frequency distribution of pixel values of the ETM+ images, histogram analysis was performed and indicated a normal distribution of pixel values. The pixels corresponding to each sampling area were identified on the ETM+ image bands 1- 5 and 7. Each sampling area is covered by 25 pixels, based on the 30m-resolution of ETM+. The mean of the digital numbers (DNs) of 25 pixels was calculated for each band and used to calculate vegetation indices (Table 2). Forty four indices made from band combinations were used to predict the vegetation cover. All the processing was performed using ILWIS 3.2.

Linear simple regression: A simple linear regression was used to determine the relationship between the vegetation cover and the vegetation indices. The coefficient of determination (r^2), the standard error of the estimate (SEE) and the significance level were calculated to determine the goodness of fit and the significance of the regression models. Of the 20 selected sites, the data of vegetation cover for 10 sampling sites (1-10) and the corresponding value of vegetation indices were used to make the regression equations and the data for 10 sampling sites (11-20) were used to assess the accuracy and validity of the regression models. Both sets of 10 sites were selected so that they contain a low to high amount of cover based on the vegetation cover of Nodushan rangelands.

The power of regression: The sample size (n) and the power (1- β) for a simple linear regression can be obtained from the equation of Dupont and Plummer (1998). The power of each regression model was calculated for α =0.05 and a sample size of 10. *PS* program was used for the power calculations. (http:// www.mc.vanderbilt.edu/ prevmed/psintro.htm).

Validation of the regression models: To determine the accuracy of the models prediction, a critical error (CE) was calculated rearranging Freesés (1960) chi-square test (Reynolds, 1984). CE is the maximum accepted error expressed as a percentage of the observed mean [$(CE / \bar{y}) \times 100$]. If the specified allowable error expressed as a percentage of the observed mean is larger than the critical error, the model prediction is acceptable. The allowable error was specified to be 10% of the observed mean (10% $\times$ 13.34=1.334).

Table 1. The percentage of vegetation cover of the species in the 10 sampling sites (1-10) used for the regression models and in the 10 sampling sites (11-20) used for validation of the models

	Vegetation cover (%)									
Sites	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Species										
Acantholimon spp.		2.1	1.9							
Aellenia subaphylla										
Anabasis aphylla									3.3	
Artemisia aucheri	23									
Artemisia sieberi		16.6	12.9	9.71	13	8.55	9.0	6.5	2.9	3
Astragalus glaucacanthos				0.5		0.15	0.2			
Astragalus gossypinus	0.80									
Astragalus microphysa	1.5									
Cousinia deserti						0.2				
Eurotia ceratoides				2.1						
Hertia angustifolia		0.59								
Iris songarica	0.27	2.7		2.0						
Peganum harmala						2.6				
Pteropyrum aucheri										
Salsola arbusculiformis							1.2	0.1		
Salsola tomentosa								1.1		
Scariola orientalis				0.69			0.2			
Stipa barbata	0.7	0.61		0.2						
Zygophyllum atriplicoides			2.6							
Total cover	26.2	22.6	17.4	15.2	13	11.5	10.6	7.7	6.2	3

	Vegetation cover (%)									
Sites	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Species										
Acantholimon spp.									0.23	
Aellenia subaphylla		1.63								
Anabasis aphylla										
Artemisia aucheri										
Artemisia sieberi	21.8	11.8	15.3	15.2	13.4	10	11.2	9.3	8.7	8.47
Astragalus glaucacanthos		0.37				0.35				
Astragalus gossypinus										
Astragalus microphysa										
Cousinia deserti		2.7				0.97				
Eurotia ceratoides	1.3									
Hertia angustifolia				0.2						
Iris songarica	0.3									
Peganum harmala			0.3							0.33
Pteropyrum aucheri					0.4					
Salsola arbusculiformis							0.32	0.86		
Salsola tomentosa							0.11	0.24	0.7	
Scariola orientalis						0.68				
Stipa barbata										
Zygophyllum atriplicoides								0.5		
Total cover	23.4	16.5	15.6	15.4	13.8	12	11.63	10.9	9.7	8.8

Table 2. The cover vegetation values and the mean of the corresponding DNs of 25 pixels for the ETM+ bands in the sampling areas (1-10) used for regression models and the sampling areas (11-20) used for validity of the models.

Site	% Cover	ETM1	ETM2	ETM3	ETM4	ETM5	ETM7
1	26.2	75.39	77.44	101.05	82.89	102.94	88.97
2	22.6	82.08	83.67	108.11	86.00	115.86	102.19
3	17.4	85.25	86.83	113.42	88.03	115.80	102.61
4	15.2	78.14	76.89	97.00	73.94	82.81	74.47
5	13.0	82.55	83.00	106.61	81.08	96.19	86.53
6	11.5	85.17	86.25	111.00	84.42	99.80	88.88
7	10.6	83.50	82.92	103.92	77.64	94.25	84.70
8	7.7	86.44	85.64	106.19	78.08	89.94	81.64
9	6.2	85.58	85.50	107.33	79.22	91.11	84.3
10	3.0	91.97	91.19	113.05	82.28	102.56	90.03
11	23.4	78.32	79.76	104.80	83.44	104.96	90.44
12	16.5	76.60	73.08	92.80	71.55	76.12	69.76
13	15.6	81.08	80.56	103.20	79.76	105.32	94.44
14	15.4	79.40	79.24	102.08	78.44	98.24	85.32
15	13.8	81.40	80.72	103.80	79.36	97.56	85.00
16	12.0	81.64	81.12	103.88	77.84	92.32	81.68
17	11.6	86.00	85.76	110.16	82.96	106.52	96.80
18	10.9	88.68	88.20	110.92	83.08	96.00	86.96
19	9.7	85.92	85.60	107.12	80.28	103.16	89.96
20	8.8	86.52	84.56	107.08	79.68	103.40	94.08

The prediction interval for the value of errors: The error range of the models prediction was obtained by Reynoldsô (1984) equation. The prediction interval is useful where the model is to be used to make prediction for a new observation from a new trial.

The power of prediction: The sample size required for detecting the differences between the observed and the predicted values was obtained based on paired means (Lachin, 1981; Elzinga *et al,* 2009). The power (1- β) of detecting the differences between the observed and the predicted values was obtained for a true difference of 10% between the observed and the predicted means (10% $\times$ 13.77=1.377), a significant level of 0.05 ($z_{0.05/2}$ =1.96) and a sample size of 10. *PS* program was used for the power calculations.

Results and Discussion

The regression models based on TDVI, MSAVI, TVI, CTVI, RDVI, NDVI, NRVI, IPVI, MND, TTVI, MSR, SRI, GDVI, GRVI, GNDVI, GEMI, DVI, BDVI, BRVI, BNDVI, EVI, ARVI (α <0.001), RI*R/G*, NGRDI, VARI, AI, MNDWI, CI, SVR5, SVR7 (α <0.01) and RI*G/B*, RI*G-B,* NGBDI and greenness index (<0.05) had a significant coefficient of determination (Table 3). The highest r^2 (0.973) and the lowest standard error of estimate (SEE=1.264) was related to the TDVI and MSAVI based models. Brightness index had the weakest relationship with the cover data (r^2=0.001, SEE=7.765). Based on the specified sample size (N =10) and the probability level (α =0.05), the power of the estimate was acceptable (1- β >0.9) for the spectral indices that significantly (α <0.01) correlated to the cover data.

Validation of prediction models based on the estimated critical error (Table 4) indicated that MSAVI and TDVI (CE =9.3 %) were the most efficient and powerful indices for predicting the cover values, followed by TVI, CTVI, NDVI, NRVI, IPVI, MND, TTVI, MSR, SRI (*CE*<10%), GRVI, GDVI, GNDVI and RDVI (CE=10.7-13.5%). Estimates of cover by the other indices were not reliable (*CE* >22.3%). The lowest accuracy of the prediction was obtained by NGBDI (CE =83.4%). The power of prediction (N =10, α = 0.05) was more than 0.9 for the indices which predicted the cover values with the desired accuracy. The dense vegetation study stands in this study have a vegetation cover of less than 30%, a density of around 1 plant/m^2 and a leaf area index of 0.05 (Mousaei Sanjerehei, 2013). Based on the arid condition of the study stands, this amount of cover was specified as a high cover in compared to the sparse vegetation study sites (with a cover of 3%). But as compared to humid ecosystems with dense vegetation, the study stands must be considered as low vegetation areas. The study stands are dominated by *Artemisia sieberi* shrubs. *Artemisia* is a shrub of more or less regularly broadened half ball-shaped form, in part with rather open canopy surface.

Table 3. Coefficient of determination (r^2), standard error of the estimate (SEE), significant level, and the power of the regression models.

Index	r^2	SEE	Sig.	Power (N=10, α=0.05)
TDVI	0.973	1.264	0.000	1.000
MSAVI	0.973	1.264	0.000	1.000
TVI*	0.971	1.300	0.000	1.000
CTVI*	0.971	1.300	0.000	1.000
RDVI	0.971	1.314	0.000	1.000
NDVI**	0.969	1.344	0.000	1.000
NRVI**	0.969	1.344	0.000	1.000
IPVI**	0.969	1.344	0.000	1.000
MND**	0.969	1.344	0.000	1.000
TTVI	0.968	1.372	0.000	1.000
MSR	0.968	1.375	0.000	1.000
SRI	0.966	1.409	0.000	1.000
GDVI	0.933	1.983	0.000	1.000
GRVI	0.924	2.113	0.000	1.000
GNDVI	0.923	2.129	0.000	1.000
GEMI	0.923	2.132	0.000	1.000
DVI	0.919	2.183	0.000	1.000
BDVI	0.887	2.585	0.000	1.000
BRVI	0.877	2.697	0.000	1.000
BNDVI	0.875	2.719	0.000	1.000
EVI	0.789	3.527	0.001	0.997
ARVI	0.788	3.534	0.001	0.997
RIR/G	0.693	4.257	0.003	0.980
NGRDI	0.692	4.260	0.003	0.980
VARI	0.688	4.288	0.003	0.976
AI	0.668	4.428	0.004	0.969
MNDWI	0.667	4.429	0.004	0.965
CI	0.664	4.451	0.004	0.968
SVR5	0.659	4.487	0.004	0.964
SVR7	0.634	4.464	0.006	0.945
RIG/B	0.559	5.100	0.013	0.878
RIG-B	0.558	5.107	0.013	0.876
NGBDI	0.555	4.123	0.013	0.873
Greenness	0.402	5.936	0.049	0.611
Wetness	0.379	6.050	0.058	0.565
DIR-B	0.357	6.157	0.068	0.520
SII	0.355	6.165	0.069	0.505
NDTI	0.354	6.174	0.070	0.500
MSI	0.246	6.670	0.145	0.310
NDWI	0.239	6.700	0.152	0.305
DIR-G	0.236	6.170	0.154	0.302
NDII7	0.129	7.165	0.307	0.153
PCA(1)	0.048	7.492	0.543	0.083
Brightness	0.001	7.765	0.930	0.051

* and ** indicate similar results

Table 4. The critical error (CE), [$(CE/\bar{y})\times 100$], prediction interval for the error and the power of prediction obtained from the 10 sites (11-20) used for the validation of prediction.

Indices	CE	$(CE/\bar{y})$ x 100	Prediction interval for error		Power (N=10, α =0.05)
MSAVI	1.28	9.3	-2.4	1.6	0.992
TDVI	1.28	9.3	-2.4	1.6	0.992
TVI	1.30	9.5	-2.4	1.5	0.993
CTVI	1.30	9.5	-2.4	1.5	0.993
NDVI	1.33	9.7	-2.4	1.4	0.993
NRVI	1.33	9.7	-2.4	1.4	0.993
IPVI	1.33	9.7	-2.4	1.4	0.993
MND	1.33	9.7	-2.4	1.4	0.993
TTVI	1.35	9.8	-2.5	1.4	0.994
MSR	1.35	9.8	-2.5	1.4	0.994
SRI	1.38	10.0	-2.5	1.3	0.994
GRVI	1.48	10.7	-2.5	2.5	0.946
GDVI	1.5	10.9	-2.5	2.7	0.943
GNDVI	1.51	11.0	-2.5	2.7	0.940
RDVI	1.85	13.5	-3.2	3.2	0.820
DVI	3.07	22.3	-4.7	5.6	0.399
BDVI	3.25	23.6	-5.9	3.4	0.478
GEMI	3.29	23.9	-4.5	6.1	0.383
BNDVI	3.52	25.6	-6.4	3.8	0.401
BRVI	3.58	26.0	-6.5	3.7	0.409
RI*R/G*	3.8	27.6	-5.3	7.1	0.285
NGRDI	3.83	27.8	-5.3	7.1	0.283
VARI	4.77	34.6	-4.2	8.4	0.278
Greenness	4.84	35.1	-7.6	8.8	0.175
EVI	4.85	35.2	-8.9	7.4	0.177
Brightness	5.77	41.9	-10.3	9.6	0.131
DI*R-G*	5.89	42.8	-10.7	9.4	0.129
AI	6.01	43.7	-11.1	7.3	0.146
CI	6.08	44.2	-11.3	7.5	0.142
ARVI	6.50	47.2	-9.87	11.9	0.116
PCA	6.77	49.2	-12.3	10.8	0.108
DI*R-B*	6.89	50.0	-12.8	8.8	0.117
SVR 5	7.02	51.0	-11.9	12.3	0.102
NDTI	7.08	51.4	-11.7	12.6	0.102
MNDWI	7.08	51.4	-11.5	12.8	0.102
SII	7.10	51.5	-11.7	12.7	0.102
Wetness	7.60	55.2	-13.5	12.6	0.094
SVR 7	7.64	55.5	-13.1	13.2	0.094
NDII 7	8.33	60.5	-14.3	14.5	0.086
MSI	8.35	60.6	-14.1	14.7	0.086
NDWI	8.45	61.4	-14.1	15.0	0.085
DI*G-B*	11.00	79.9	-19.2	9.0	0.088
RI*G/B*	11.33	82.3	-19.9	9.7	0.084
NGBDI	11.49	83.4	-20.2	10.0	0.083

The colour of branches and stems which accounted for the largest portion of a plant is light brown and that of small leaves is grayish green, which give the plants an appearance of grayish brown-like. The soils have a sandy loam texture, less than 0.9% organic matter and 10-35% lime and a large amount of surface gravels and stones (Mousaei Sanjerehei *et al*., 2013). Thus, the soils give a high reflectance in the visible and infrared wavelength regions because of dryness (Myers, 1975), sandy loam texture, lime content and large gravels (Choudhury, 2009). Furthermore, the rate of soil reflectance increases from the blue to NIR wavelengths (Myers, 1975). The vegetation indices which are based on only the red and NIR reflectance and also based on only the green and NIR bands provided more accurate estimates of the vegetation cover than the indices which use blue and/or shortwave infrared (SWIR) reflectance or only visible bands (R-G-B). In general, vegetated areas have a relatively high reflection in the NIR and a low reflection and high absorption in the visible range of spectrum (Jackson and Huete, 1991).

The calculated correlation coefficient (*r*) between the mean of DNs of each single band and the vegetation cover for the 20 samples (Table 5) showed that the blue band had a significant and the largest negative correlation with the cover data. The rate of absorption in the blue region for green canopy of different plants (Brooks, 1972) and for the leaves of a plant with different colours in the progressive phases of senescence (Knipling, 1969) is larger than the rate of absorption in the green, red and NIR regions of the wavelength. Therefore, in the sparse vegetation study sites, the blue wavelength is highly reflected by the soil and lowly absorbed by the sparse vegetation. But an increase in the amount of vegetation in the dense vegetation sites, results in an increase in the absorption in the blue region and as a result in a great correlation coefficient between the blue reflectance and the vegetation cover. In spite of a strong relationship between the vegetation cover and the reflectance of blue band, the indices that use the blue band could not provide a reliable estimate of cover (CE >24%). Studies show that blue band has a low signal-to-noise ratio (Dymond and Shepherd, 2004) and a greater atmospheric scattering than the longer wavelengths, which accounts for the relatively inappropriate retrieving canopy parameters (Kimes *et al.,* 2006).

The *r* for the green band was also negative and significant, but less than that for the blue band. The amount of reflectance in the green region was approximately close to that in the blue band, but its relationship with the cover data was not as strong as the relationship between the reflectance of blue wavelength and the cover data. This may be because of high changes of reflectance in the green region by the plants. The reflectance spectra curve found for most of plants shows higher changes in the green region than the blue region especially for the vegetation with a low concentration of chlorophyll a + b and low content of water (Liang, 2005), like the plants in the present study. The indices based on only green and NIR showed a strong relationship with the cover variability. This is in agreement with the statement that the green band in combination with the NIR band is closely associated with the variability in leaf chlorophyll and canopy variation (Gitelson *et al.,* 1996; Shanahan *et al.,* 2001). The correlation between the red band reflectance and the vegetation cover was non significant. This is because of the grayish brown colour of the dominant plants (*Artemisia*) that causes an increase in the reflectance of red wavelengths, and as a result, a decrease in the difference between the soil and vegetation reflectance. For the sparse vegetation, the red wavelength is strongly reflected by the soil and for the dense vegetation, the red wavelength is strongly reflected by the vegetation cover. This causes a small *r* between the red band and the vegetation cover. However, the negative *r* indicates an increase in the rate of absorption in the red region with an increase in the amount of vegetation cover. The *r* for NIR band was positive but non-significant. NIR is highly reflected by dense vegetation as compared to the visible band (R-G-B), but this was not observed for the study sites. This may be because the amount of cover in the study sites (maximum cover: 26%) was not so large that it could significantly affect the reflectance of NIR. However the positive *r* shows an increase in the amount of NIR reflectance with an increase in the amount of vegetation cover. In spite of a weak relationship between the reflectance of single red band and also single NIR band with the cover data, the indices that incorporate only red and NIR bands provided reliable results. A combination of red and NIR bands has been found to make indices sensitive to vegetation attributes such as vegetation morphology and structure (Kooistra *et al.,* 2004), photosynthetic capacity (Gamon *et al.,* 1995), LAI (Jordan, 1969) and plant growth and yield (Thenkabail *et al.,* 1994). The estimates of vegetation cover by the indices which are based on only visible bands (R-G-B) were not accurate. Delalieux *et al.* (2006) stated that the vegetation indices based on only visible bands were not useful for determination of the amount of chlorophyll, probably due to the interaction of background and atmospheric effects. This highlights the importance of combination of NIR band with visible bands for predicting vegetation properties (Tucker, 1979). The indices which are based on

SWIR bands did not provide reliable results. This result is in contrast with the statement that SWIR bands (TM5 and TM7) are strongly correlated with vegetation density (Ahern *et al.,* 1991). The vegetation indices incorporating SWIR bands such as NDWI and MSI are sensitive to leaf water content and water thickness of different plant species (Hunt and Rock 1989, Maki *et al*., 2004) and can be used to predict the plant cover and biomass based on the water content of plants. Studies show, it is the green leaves that their water content has a strong influence on the absorptive properties of SWIR wavelengths. But for the study plants, stems and branches are accounted for the largest part of an *Artemisia* shrub, while the leaves cover only a small volume of the shrubs in compared to tree leaves based on their arrangement and small size and volume. Then, the water content of leaves does not seem to be a separation factor for predicting the amount of cover. MSAVI, TDVI, TVI, CTVI, NDVI, NRVI, IPVI, MND, TTVI, MSR and SRI provided the most accurate estimate of the vegetation cover with a critical error of less than 10%. MSAVI and TDVI (*CE*: 9.3%) provided the most accurate estimates of the cover. MSAVI has been found to show a broad dynamic range of values, suggesting that this index can reduce the effects of soil brightness and can separate both low (Weber and Dunno, 2001) and high vegetation (Broge and Leblanc, 2001) from bare soil. The signal-to-noise ratio has been found to be higher for MSAVI than that of other vegetation indices. It not only increases the vegetation dynamic response, but also further reduces the soil background variations (Liang, 2005). TDVI has been found to show an excellent linearity as a function of the rate of vegetation cover, since it has a relatively low rate of saturation compared to other indices. It enables to minimize the soil background effects (Bannari *et al.,* 2002). The critical error obtained by GRVI (CE = 10.7%), GDVI (CE = 10.9%) and GNDVI (CE =11 %) was more than 10%, however these indices provided a close estimate of cover. Green band seems to improve performance of vegetation indices when combined with red and NIR bands (Broge and Leblanc, 2001).

Table 5. The correlation coefficient (*r*) between the DNs of each single band and the vegetation cover for the 20 sampling sites

Bands	1	2	3	4	5	7
r	-0.79	-0.62	-0.38	0.23	0.28	0.19
Sig.	0.000	0.004	0.103	0.333	0.234	0.436

Conclusion

Based on the results of this study, the indices that use only the NIR and red and only NIR and green bands (like MSAVI, TDVI, TVI, CTVI, NDVI, NRVI, IPVI, MND, TTVI, MSR, SRI, GRVI, GDVI and GNDVI) can efficiently separate plants from soil in arid and semi arid regions and are recommended to be used for remote estimates of vegetation attributes. The indices which use blue and/or shortwave infrared (SWIR) reflectance or only visible bands (R-G-B) can not provide an accurate estimate of vegetation cover.

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