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Advanced land observing satellite data to identify ground vegetation in a juniper forest, northeast Iran

Hadi Fadaei¹

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Abstract Juniperus excelsa subsp. polycarpos, (Persian juniper), is found in northeast Iran. In this study, the relationship between ground cover and vegetation indices have been investigated using remote sensing data for a Persian juniper forest. Multispectral data were analyzed based on the Advanced Visible and Near Infrared Radiometer type 2 and panchromatic data obtained by the Panchromatic Remote-sensing Instrument for Stereo Mapping sensors, both on board the advanced land observing satellite (ALOS). The ground cover was calculated using field survey data from 25 sub-sample plots and the vegetation indices were derived with 5×5 maximum filtering algorithm from ALOS data. R^2 values were calculated for the normalized difference vegetation index (NDVI) and various soil-adjusted vegetation indices (SAVI) with soilbrightness-dependent correction factors equal to 1 and 0.5, a modified SAVI (MSAVI) and an optimized SAVI (OSAVI). R^2 values for the NDVI, MSAVI, OSAVI, SAVI (1), and SAVI (0.5) were 0.566, 0.545, 0.619, 0.603, and 0.607, respectively. Total ratio vegetation index for arid and semi-arid regions based on spectral wavelengths of ALOS data with an R^2 value 0.633 was considered. Results

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Hadi Fadaei fadaei.hd@gmail.com of the current study will be useful for forest inventories in arid and semi-arid regions in addition to assisting decisionmaking for natural resource managers.

Keywords Ground cover · *Juniperus excelsa* subsp. *polycarpos* · Vegetation indices · Advanced land observing satellite (ALOS)

Introduction

The arid and semi-arid areas of northeast Iran consist of about 3.4 million ha populated by two main tree species, one is the broad-leaved Pistacia vera L. and the other is the conifer, Juniperus excelsa M. Bieb. subsp. polycarpos (K. Koch) Takht., which Iranians know as Persian juniper. The subspecies has a green crown and dark grey, scaly and peeling bark. In the juvenile stages, the branches are brownish-red, rounded-tetragonal, slender, with leaves on branchlets divergent at the tips, ovate, acuminate, with long spiny points and oblongdorsal glands. Individual trees have strict acicular or needle-shaped leaves and the leaves of young branchlets are small, glaucous, imbricated, oblong or ovate with ovate to suborbicular glands. The fruit are solitary, globose, black, pruinose and 9-12 mm in diameter. Some individuals may be several centuries old with trunks in poor condition. The species has a more continental taxon in which the subspecies is found in the Irano-Turanian region. Locally, the subspecies has holy indicator for local people. It has high tolerance to dry climates and grows at elevations > 2000 m a.s.l in the mountainous regions of Iran. In the last few decades, people have harvested the species for ceiling wood and fuelwood, causing a severe decrease in the species. Further, with livestock grazing in natural forests, the destruction of young shoots

¹ Geography Group, Amin Police-Science University, Tehran, Iran

has undermined natural regeneration and is one of the greatest threats to genetic diversity. The subspecies is more tolerant of severe environmental conditions, which is important as an ecological variable. Another important feature of this subspecies is the aromatic properties that protect it from wildlife grazing. According to the FAO, deforestation in the 1990s was estimated at 14.6 million ha per year; the loss of aboveground woody biomass globally world was 422 thousand million tons per year. According to the FAO (2014) estimate, the area of forest is about 10 million hectares (FAO 2014). Tavankar investigated the distribution and habitat of Juniperus excelsa subsp. polycarpos in the northwest of Iran using Landsat ETM and GIS techniques (Tavankar 2015). The relationship between environmental factors (topography and soil type) and density of the subspecies was significant. Fisher and Gardner (1995) investigated the status and ecology of J. excelsa subsp. polycarpos woodland in the northern mountains of Oman (Fisher and Gardner 1995). The climate at this elevation (800-2500 m a.s.l) may be marginal for the survival of the subspecies and even small increases in climatic stress could affect the present status of these woodlands (Gardner and Fisher 1996) In northeast Iran, junipers form open woodlands with a maximum tree density of approximately 150 trees per ha (Fisher and Gardner 1995).

In Iran, forest inventories of open woodlands follow a transect sampling method using GPS (Fadaei and Kolahi 2008) in comparison with the Hessenmöller approach based on "probability-proportional-to-size" (PPS). This latter method assumes that the growing space of a tree is proportional to its height (Hessenmöller et al. 2013). Stand parameters are then derived by statistical extrapolation. However, hot, dry weather can make forest inventory work on the ground difficult (Fadaei and Kolahi 2008), and ground surveys require time, labor, and money, even when using GPS equipment. In contrast, the use of remotesensing data for forest inventories in arid and semi-arid areas is cost-effective, less time-consuming, and less labor-intensive (Fadaei et al. 2011).

Open forests have special features that provide excellent opportunities for remote sensing-based inventories. Detection of individual trees from high resolution satellite data is normally easier in sparse forests where the distance between trees exceeds the height of the trees. When a strong relationship exists between forest attributes and features extracted from remote sensing data, these attributes can be estimated from remote sensing imagery using regression and modeling techniques (Ozdemir 2008).

The individual tree can be delineated with unsupervised and supervised classification algorithms on fine resolution imagery. In the sparse juniper stand, analysis from remotely sensing can be estimated inexspensively it by the relationship between ground cover and trees (Gougeon and Leckie 2006). The fractional vegetation cover (FVC) can be extracted easily from almost any remotely sensed data, either by linear normalization of the spectral vegetation indices or by supervised or unsupervised classification of the multi-spectral imagery (Veraverbeke et al. 2012). Stand density expressed as an absolute term (number of trees per unit area) showed significantly positive correlation to FVC ($R^2 = 0.96$) and to a relative density measure (crown competition factor; $R^2 = 0.89$) (Meyer et al. 2017).

Yecheng and Strahler inverted a canopy reflectance model using multispectral satellite data to estimate parameters for crown size, stand density, cover, foliage biomass, and total standing biomass in nine coniferous stands in Oregon, USA (Wu and Strahler 1994). In developed countries, inventories are still obtained by mapping forest stands and their content. This is done by interpreting medium-scale aerial photographs, along with field assessments and plot measurements. However, as noted, conducting such inventories is an expensive and timeconsuming endeavor (Gougeon and Leckie 2006). Remotely sensed data processed with the object-based image classification technique is an accurate and relatively precise tool for estimating and mapping of tree cover at a landscape scale in a dry forest environment (Purevdorj et al. 1998).

Each of these approaches has been found to improve results in their intended applications. It is therefore interesting to evaluate the capability of the six vegetation indices from reflectance factors based on ALOS satellite data for estimating vegetation cover in arid and semi-arid regions. The ALOS satellite capability introduces the vegetation index as Total Ratio Vegetation Index (TRVI) and is evaluated in comparison to conventional vegetation indices. Vegetation indices are the most popular tool for analyzing remote sensing data of various vegetation characteristics and for estimating the percentage of green vegetation cover in arid and semi-arid areas. Meyer et al. (2017) investigated the relationship between the amount of green vegetation cover and vegetation indices derived from spectral reflectance measurements on the ground. They also evaluated the performance of vegetation indices to estimate ground cover (Meyer et al. 2017). In this study, it was expected that the quality of ALOS satellite data in arid and semi-arid regions compared to other satellite data may be the best option to investigate. Therefore, the three major objectives of this study are: (1) Investigating ground vegetation of juniper and measuring stem volumes by field surveying; (2) Estimating vegetation indices based on an adaptive maximum filtering algorithm for 5×5 pixel size derived from remotely sensed ALOS data; and, (3) Estimating simple regression coefficients between vegetation indices and stem volume of juniper.

Materials and methods

Study area

The study site is located in the arid and semi-arid region of northeast Iran (Figs. 1, 2) and covers 15.21 km^2 (3.9 × 3.9 km). The ordinates of the site are $37^{\circ}20''31.19'-37^{\circ}18''22.30'$ N, $58^{\circ}49''59.13'-58^{\circ}52''34.40'$ E. Annual precipitation is 156 mm and the elevation ranges from 700 to 1200 m a.s.l., with slopes of $21-27^{\circ}$ (Fig. 1).

Twenty-five 300 m^2 sample plots were randomly selected (Fig. 2). Juniper trees were typically 3–4 m high with crown diameters of 3–5 m (Fig. 3).

Image data

Image data from an ALOS satellite launched 24 January 2006 was used. Among the three remote sensing instruments carried on the satellite, the Panchromatic Remotesensing Instrument for Stereo Mapping (PRISM) was used for digital elevation mapping and the Advanced Visible and Near Infrared Radiometer type 2 (AVNIR-2) for precise land coverage observation. PRISM is a panchromatic radiometer with 2.5 m spatial resolution at nadir. It has one band at 0.52–0.77 μ m wavelength. The AVNIR-2 is a visible and near infrared (NIR) radiometer for observing land and coastal zones with 10 m spatial resolution at nadir; it has four multispectral bands: blue (0.42–0.50 μ m),



Fig. 1 Juniper distribution based on the crown cover percentage in the northeast of Iran





Fig. 3 Persian juniper in northeast Iran

green (0.52–0.60 μ m), red (0.61–0.69 μ m), and NIR (0.76–0.89 μ m). Combined images from PRISM and AVNIR-2 were used for the analysis. These images were acquired on 25 October 2007 by Avnir-2 and PRISM. Atmospheric correction was analyzed by ENVI user guide and ENVI software to remove the noise of reflectance on AVNIR-2 based on SRTM digital elevation model with flash (referred to user guide for atmospheric correction). The FLAASH model includes a method for retrieving an estimated aerosol/haze amount from selected dark land pixels in the scene. The method is based on observations by Kaufman et al. (1997). Gram–Schmidt pansharpening images were extracted from AVNIR-2 and PRISM (combined band). The final spatial resolution was 2.5 m on the

ground. Gram–Schmidt Spectral Sharpening is more accurate and recommended for most applications such as land-use planning. Moreover, it is typically more accurate when the spectral response function of a given sensor is used to estimate what the PAN data look like (Fadaei et al. 2011).

Calculation of vegetation indices

Vegetation indices were constructed from reflectance measurements in four wavelengths. As noted above, AVNIR-2 provides multispectral data which can be used to analyze the specific characteristics of vegetation. It is difficult to estimate the spectral properties of juniper crowns if an understory is present (Romero-Sanchez and Ponce-Hernandez 2017).

In remote sensing applications, the most commonly used index to detect vegetation or its vitality is the normalized difference vegetation index (NDVI) developed by Rose et al.:

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

where RED and NIR the spectral reflectance measurements acquired in the red and near-infrared regions, respectively (Rouse et al. 1974). A number of derivatives and alternatives to NDVI have been proposed to overcome its limitations. The soil-adjusted vegetation index (SAVI) was proposed by Huete (1988) to account for and minimize the effect of soil background conditions, and is calculated as:

$$SAVI = \frac{(NIR - RED)(1 + L)}{NIR + RED + L}$$
(2)

where RED and NIR are the same as in the NDVI, and L indicates the soil brightness-dependent correction factor that compensates for differences in soil background conditions (Huete 1988). Optimal L values differ with vegetation density. For low vegetation densities, L = 1, for intermediate densities, L = 0.5, and for higher densities, L = 0.25 (Huete 1988). A single adjustment factor (L = 0.5) reduced soil noise considerably throughout a range of vegetation densities (Huete 1988). Therefore, we set L to 0.5 and 1.0 in this study. The optimized soiladjusted vegetation index (OSAVI) was created for agricultural applications by Rondeaux et al. (1996) and calculated as:

$$OSAVI = \frac{(NIR - RED)}{NIR + RED + 0.16}$$
(3)

where RED and NIR are the same as in the NDVI. The value 0.16 reduced soil noise for both low and high vegetation cover (Rondeaux et al. 1996). The modified soiladjusted vegetation index (MSAVI) replaces the constant L in the SAVI equation with a variable L function (Qi et al. 1994) and is calculated as:

$$MSAVI = \frac{1}{2} \left[2 \times NIR + 1 - \sqrt{(2 \times NIR + 1)^2 - 8 \times (NIR - RED)} \right]$$
(4)

where RED and NIR are the same as in the NDVI. The dynamic range of the inductive MSAVI was slightly lower than that of the empirical L function due to the difference in L boundary conditions. Small leaves reduce the leaf area in arid vegetation, and open canopies mean that much soil is visible (Qi et al. 1994). The total ratio vegetation index (TRVI) was introduced and calculated as:

$$TRVI = 4\left(\frac{NIR - RED}{(NIR + RED + G + B)}\right)$$
(5)

For this equation, the normalized difference of the NIR and RED wavelengths was divided by the total visible and NIR wavelengths. The 4 is the number of total measured reflectance means if the forest is maximum density. The value of TRVI will be a high level equal to 1, for low density it is equal to -1 (Fadaei et al. 2012). This equation shows the ratio of the normalized difference of visible, NIR, and total reflectance (Fig. 4).

In this study, NDVI, SAVI (L = 0.5 and 1), OSAVI, MSAVI and TRVI, were used as vegetation indices to estimate the density of ground vegetation and stem volume of junipers.



Fig. 4 The properties of AVNIR-2 wavelengths

Ground truth

Field measurements provide the most accurate biomass data but they are time- consuming and labor intensive, and it is not viable to use them for large areas (Santoro et al. 2006). The coordinates of each corner and center of sub-sample plots from image pan-sharpening were inputed to the GPS device. The corner position for each sub-sample plot was determined and the ground cover estimated by measuring stem volumes of juniper. Crown diameters have been classified in three classes per ha (Fig. 5). Measuring stem volumes were carried out with the assistance of members of a natural resource organization in the region. Field surveys took place at the end of October, 2009.

Determination the juniper spectral value based on normalized different vegetation index (NDVI)

After image pre-processing and atmospheric correction, spectral signatures from the vegetation index image was derived by overlapping two images (pan-sharpening and vegetation index). In these forests, vegetation could include three categories, each with different spectral signatures (Peng et al. 2013). The first category, which had a high value, were grasslands and sand, the second, had a value close to grasslands and sand, were juniper trees. The third category which showed a low value was shadow. These



Fig. 5 The general properties of juniper crown diameters per ha

categories were defined based on two overlapping images (vegetation index image and pan-sharpening). The high values (0.29-0.49) indicate grasslands and sand reflectance (ground vegetation), the medium values (0.11-0.29) the juniper spectral value, and the low values (-0.02 to 0.11)shadow. Based on this algorithm, the representative value of junipers was NDVI values from the plot that extracted as ASCII file from the vegetation index image (Fig. 6). The ASCII file was imported to Microsoft Excel and using Visual Basic editor the best threshold combination was determined. The best threshold from the training data was based on sampling ground data (Fig. 6). Subsequently, the optimum threshold from maximum filtering 5×5 vegetation indices was applied. Finally, the simple linear coefficient regression between the number of juniper trees determined by field surveys and the vegetation indices in the all plots were calculated.

Data analysis

Pan-sharpening images from AVNIR-2 and high-resolution panchromatic images (PRISM) with 2.5 m resolution were made (Fadaei et al. 2011). The vegetation indices were calculated from each sample plot using ALOS satellite data. The maximum filtering (5×5) on vegetation index values was applied to determine the optimum value of juniper. Stem volumes (tree numbers) from each subsample plot were calculated. Subsequently, maximum filtering was applied to obtain the high value vegetation index on 5×5 pixel size. Finally, the simple linear regression between tree number (ground vegetation cover) and vegetation indices was calculated for the total sub-sample plots. All analyses were performed using the Environment for Visualizing Images (ENVI) software and Microsoft Excel 2007 using Visual Basic Editor (VBE).



Fig. 6 Distribution of NDVI values

Results and discussion

Relationship between vegetation indices and ground cover

The linear regression between the NDVI, MSAVI, OSAVI, SAVI (1), SAVI (0.5) and TRVI and the ground cover was calculated for all sub-sample plots (Fig. 8). The relationship between vegetation indices and ground cover was negative. This is similar to the result of Anderson et al. (1993), indicating no significant NDVI results compared to the juniper canopy (Anderson et al. 1993).

The sub-plots were generally divided into two categories: (1) those with few juniper trees and good ground cover, and (2) those with numerous junipers and little ground cover.

In the field survey, plots with few individual junipers had more ground cover compared with plots with more junipers and low vegetation indices (Fig. 7a-f). The NDVI versus other vegetation cover indices was insignificant and similar to the results of Purevdorj et al. (1998) for the linear correlation coefficient between tree density as the SPOT data was negative (Purevdorj et al. 1998). The normalized difference vegetation index, which shows the difference between red and near infrared reflectances, is normally high with high density vegetation where there is typically a large difference between red and NIR wavelengths. The NDVI, as an index of photosynthetic activity, is one of the most commonly used vegetation indices. Vegetation indices are based on the phenomenon by which different surfaces reflect light differently for a given wavelength. Photosynthetically active vegetation, in particular, absorbs most of the red wavelength that hits it while reflecting much of the NIR wavelength. Dead or stressed vegetation reflects more red light and less NIR light. Likewise, nonvegetated surfaces have more even reflectance across the light spectrum. In arid and semi-arid regions, the NDVI is low, particularly in forests where vegetation cover is sparse as it is sensitive to the optical properties of the soil background (Veraverbeke et al. 2012; Meyer et al. 2017). Soil and plant spectral signatures tend to mix non-linearly, and ground cover in arid and semi-arid areas, due to their adaptation to harsh desert conditions, lack the strong red edge of plants in humid regions. The soil background effect is particularly important when the vegetation cover is sparse. Plot 1 had more ground cover that produced a low vegetation index. This result is related to the work of (Meyer et al. 2017) who observed dead and dying trees on open slopes below 2400 m, suggesting that the climate at these altitudes is close to the tolerance limits for juniper. Plot 2 had fewer juniper trees than other plots and a high NDVI value. In addition, plots 11 and 3 had numerous



Fig. 7 Relationship between tree density and vegetation indices

junipers and low NDVI values. Figure 7d shows that the R^2 of the optimized soil-adjusted vegetation index (OSAVI) was larger than those of the NDVI, the modified SAVI, SAVI (1), and SAVI (0.5). This is explained by the SAVI equation in which the soil optimum background for arid and semi-arid areas is high. The OSAVI index is recommended for arid and semi-arid areas (Rondeaux et al. 1996). As shown in Fig. 7b, c, d, the R^2 of SAVI (1) and SAVI (0.5) were smaller than OSAVI because the former is used for high density forests (Rondeaux et al. 1996). The R^2 values for NDVI, SAVI (0.5), SAVI (1) and the modified SAVI were lower than for the OSAVI, but the differences were not remarkable. Plot 22 had little ground vegetation but a good MSAVI value. The best vegetation index used in this study was the TRVI, the total ratio vegetation index. Figure 7f shows that the R^2 of the TRVI was larger than those of the NDVI, MSAVI, OSAVI, SAVI (1), SAVI (0.5). The TRVI is an index used for arid and semi-arid regions where forests are generally sparse with small trees, and these regions generally have poor reflectance in NIR and red wavelengths, and hence the difference between them is low. Conventional vegetation indices are based on NIR and red wavelengths. Therefore, the TRVI was applied for arid and semi-arid regions on the basis of the total wavelength (visible and NIR). This index had a higher value than the other vegetation indices. However, the soil background effect is particularly important when the vegetation cover is sparse (Huete 1988).

Conclusions

The estimation of vegetation cover is very important in monitoring arid and semi-arid lands (Veraverbeke et al. 2012). The potential evaluation of ALOS (advanced land observing satellite) data to delineate ground cover, in this case, the dominant *Juniperus excelsa* subsp. *polycarpos*, is shown in Fig. 8.

To correct the best value of vegetation reflectance, the Internal Average Relative Reflectance (IARR) was performed to correct atmospheric effects (Fig. 9).

The simple coefficient regressions has been evaluated between vegetation indices and the ground vegetation. In the first section, we found the range of optimum spectra to identify the subspecies from ground vegetation, sand, and shadow. With the vegetation index value (5×5) pixel size, maximum filtering was applied. The subspecies was growing in arid and semi-arid areas with sparse and low ground cover. Vegetation indices were low for sparse forests of small trees. An important finding was that



Fig. 8 The NDVI map after atmospheric correction



Fig. 9 Atmospheric correction with the Internal Average Relative Reflectance (IARR) algorithm, a before correction b after correction

conventional vegetative indices can be an unreliable measure of arid plant cover. The soil background can also have an important effect on vegetation indices and has a greater reflection in the near infrared (NIR) and RED wavelengths than the vegetation, although the usual vegetation indices are based on the NIR and RED wavelengths. Soil components that affect spectral reflectance can be grouped into three components: color, roughness, and water content. Roughness has the effect of decreasing reflectance because of an increase in multiple scattering and shadowing (Zhang et al. 2017). For RED-NIR scattergram, this is referred to as the "soil line" and is used as a reference point in most vegetation studies. The important factor that influences vegetation indices in arid and semi-arid regions is the soil line. However, the problem is that real soil surfaces are not homogeneous and are a composition of several types of variation. Analysis has shown that variability in one wavelength is often functionally related to the reflectance in another (Baret and Guyot 1991). Therefore we applied the TRVI based on the total wavelength (visible and NIR). The total ratio vegetation index had high values based on the total wavelength. Moreover, ALOS data was also used which had good resolution in the panchromatic and multispectral bands for this region with sparse vegetation. The ALOS data also have a suitable viewpoint for forest inventories. Further investigation of the behavior of this conifer species is needed. Arid and semi-arid vegetation are adapted to hydrological and thermal stresses, and hence special methods are required to extract the ground cover from satellite imagery. Regeneration is one of the most important criteria to assess the sustainable management of natural forests. Knowledge of the quantitative and qualitative status of the regeneration as well as factors influencing forest renewal is necessary. It is necessary to plan for the rehabilitation and development of mountain forests. Soil fertilization plays an important role in regeneration and studies suggest that lime is most effective in improving regeneration. Therefore, a study on soil organic matter is

recommended for the establishment seedlings. For other studies, the identification of soil conditions using satellite data is necessary.

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