# Biomass assessment of juniper forest by ALOS
# (Case study in the Hezar-Masjed forest)

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Juniperus excelsa, ALOS, AVNIR-2, PRISM, tree density, vegetation indices

**ABSTRACT:**

Irano-Touranian evergreen and broadleaved forests are one of five zones of arid and semi-arid forests. *Juniperus excelsa* is a subspecies of *J. polycarpus*, which Iranians know as the Persian juniper located in the northeast of Iran. This forest is evergreen and populated by conifers, which are widespread and present at low-density. This species has specific properties such as ecological, morphological and medicinal characteristics. Currently we observed that places that are not managed lead to this spices' increased scarcity and destruction. Considering this, it is necessary to obtain more information about this species.
In this study, we analyzed three images acquired by the ALOS satellite, including the 10-meter resolution multispectral band (AVNIR-2), 2.5-meter resolution "Nadir" PRISM image and 30 meter resolution SRTM. We analyze four types of pan sharpening from multispectral image as low resolution and panchromatic image as high-resolution. We perform the object base classification with support vector machine in the four kernels type to estimate vegetation cover and non-vegetation area in the each sample plot. Feature extraction algorithm is used for land cover mapping. The Shuttle Radar Topography Mission (SRTM) was used for obtaining the elevation range of distribution the density. The result of the pan sharpening algorithms was accurate, and the best algorithm for pan sharpening was Gram-Schmidt. In addition, the maximum density was found in the 2500 meter above sea level. We hope the result of this research will enable better decision making for natural resource managers in fields of environmental benefit and give reliable inventory data of valuable resources from arid and semi-arid areas to lead to sustainable management in general.

## 1. 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 and the other is the conifer Juniperus excelsa subsp. Polycarpos, which Iranians know as Persian juniper. Here we estimate the ground cover in juniper forest. Fisher and Andrew (1995) investigated the status and ecology of Juniperus excelsa subsp. Polycarpos woodland in the northern mountains of Oman. *Juniperus excelsa M.Bieb*. subsp. *Polycarpos* (K. Koch) Takhtajan is found from Turkey and Afghanistan eastward and southward to Iran (Fisher and Andrew, 1995). This species generally grows at elevations 1500 to 2900 m above sea level, but is sometimes found in other ranges. In Turkey, for example, J. excelsa (subspecies not specified) grows from 300 to 2300 m and often forms the tree line in the Taurus Mountains. In Pakistan, Juniperus excelsa subsp. Polycarpos is fairly common, forming open forests in Baluchistan and the inner dry valleys of the Himalayas from 1200 to 4000 m elevations (Andrew et al., 1996). However, the climate at this elevation range may be marginal for the survival of J. excelsa subsp. Polycarpos woodland, and even small increases in climatic stress could imperil the present status of these woodlands (Fisher and Andrew, 1995). In northeast Iran, junipers form open woodlands, with a maximum tree density of approximately 150 trees per hectare (pers. obs., Andrew et al., 1996).
In Iran, forests inventories in such open woodlands are performed by the transect-plot sampling method using GPS. Stand parameters are then derived by statistical extrapolation methods (Zobeiry, 2002). However, hot, dry weather conditions in the region can make forest inventory work on the ground difficult. Moreover, ground surveys require much time, labor, and money, even when using GPS equipment. In contrast, the use of remote-sensing data for performing forest inventories in arid and semi-arid areas is more cost-effective, less time-consuming, and less

labor-intensive (Fadaei and Kolahi, 2008).
Open forests have special features that provide excellent opportunities for remote sensing-based forest inventories. Detection of individual trees from very 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 the features extracted from remote sensing data, these forest attributes can be estimated in a cost-effective way from remote sensing imagery using regression and modeling techniques (Ozdemir, 2008). With individual tree information extracted from remotely sensed data, biogeochemistry models can be parameterized to scale up from individual trees to landscapes. This can aid understanding of various ecological processes (Chen et al., 2006). Multispectral satellite imagery processed with the object-based image classification technique showed promise as an accurate and relatively precise tool for estimating and mapping forest tree cover at the landscape scale in a dry forest environment (Morales et al., 2008). The purpose of this study is to determine 1- Apply support vector machine (SVM) for tree detection 2- Apply the image pan sharpening algorithms and image segmentation as object base
3- Apply the feature extraction for land cover classification.

## 2. MATERIAL AND METHOD

### 2.1 The study area

The study site, located in the region known as Khaliyan valley in the arid and semi-arid of northeast Iran (Figure 1), covered 758.4 ha at 37º01"15.88'–37º02"04.51'N, 59º19'11.66"–59º22"11.16'E. Annual precipitation in this area is 372.04 mm, average annually temperature is 8.01 0C maximum and minimum temperature is 35.05 and -27.17 respectively. The elevation of the study site is at the elevation of 1640 - 2660m (a.s.l). The slope of the site ranges generally from 49 to 78 degrees Juniper trees at the study site were typically 3–4 m high, with crown diameters of 3–5 m (Figure 2).

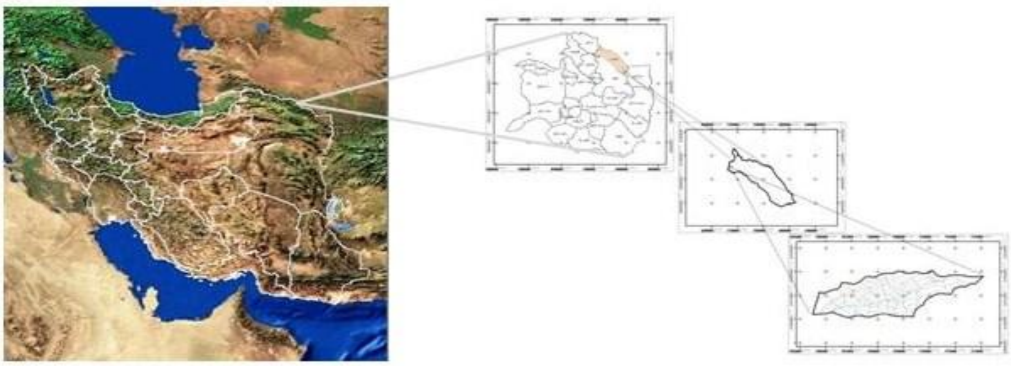

Figure 1 Location of Hezar-Masjed juniper forest

Figure 2 Juniper forest

### 2.2 Data

ALOS satellite multispectral images of these studies areas were collected. These images were acquired by the AVNIR-2 sensor onboard the ALOS satellite with a spatial resolution of 10 m×10 m. AVNIR2 sensor acquired images in four spectral bands—blue (B, 0.42－0.50 m), green (G, 0.52－0.60 m), red (R, 0.61－0.69 m), and near infrared (IR, 0.76－0.89 m). The Panchromatic Remote-sensing Instrument for Stereo Mapping (PRISM) image was at nadir of level 1B2 processed. The Shuttle Radar Topography Mission (SRTM) obtained elevation. Images acquisition dates of individual study area are also shown in Table 1. Fig. 3 shows true-color satellite image of this study area.

Table 1 AVNIR-2, PRISM and SRTM data

| Data | Acquired date | Summary |
|---|---|---|
| AVNIR-2 | 2010/10/14 | 41 N UTM zone, 0-2%, cloud coverage, good quality |
| PRISM (Nadir) | 2009/05/28 | 41 N UTM zone, 0-2%, cloud coverage, good quality |
| SRTM | 2002/02/25 | 41 N UTM zone, 0-2%, cloud coverage, 90-m resolution |

### 2.3 Image pan sharpening

The injection of fine spatial information from the high spatial resolution panchromatic (PAN) image into the low spatial resolution multispectral (MS) images to get high spatial resolution MS images is known as pan sharpening (Shah et al., 2008). Pan sharpening is an image fusion method, with which high-resolution panchromatic data are fused with lower resolution multispectral data to create a colorized high-resolution dataset. For this algorithm, images must either be georeferenced or have the same image dimensions. Gram-Schmidt, Principal Components (PC), Hue, Saturation, Value (HSV) and Color Normalized (Brovey) as algorithms of pan sharpening were analyzed. Gram-Schmidt Spectral Sharpening was used to sharpen multispectral data using high spatial resolution data. The low spatial resolution spectral bands used to simulate the panchromatic band must fall in the range of the high spatial resolution panchromatic band or they will not be included in the resampling process (Laben et al., 2000). PC Spectral Sharpening was used to sharpen a low spatial resolution multi-band image using an associated high spatial resolution panchromatic band. The algorithm assumes that the low spatial resolution spectral bands corresponded to the high spatial resolution panchromatic band (Welch, and Ahlers, 1987). HSV (HIS) sharpening was used to transform an RGB image to HSV color space, replace the value band with the high-resolution image, automatically resample the hue and saturation bands to the high-resolution pixel size using a nearest neighbor, bilinear, or cubic convolution techniques, and finally transform the image back to RGB color space (Vrabel, 1996). Color Normalized (Brovey) sharpening was used to apply a sharpening technique in a mathematical combination of the color image and high-resolution data. Each band in the color image was multiplied by a ratio of the high resolution data divided by the sum of the color bands. The function automatically resampled the three-color bands to the high-resolution pixel size using one of the techniques selected by choosing the nearest neighbor, bilinear, or cubic convolution (Vrabel, 1996).

### 2.4 Feature extraction

Feature extraction is to extract the information from high-resolution panchromatic or multispectral imagery based on spatial, spectral, and texture characteristics. Traditional remote sensing classification techniques are pixel-based, meaning that spectral information in each pixel is used to classify imageries. This technique works well with hyperspectral data, however, it is not ideal for panchromatic or multispectral imagery. With high-resolution panchromatic or multispectral imagery, an object-based method offers more flexibility in the types of features to be extracted. An object is a region of interest in spatial, spectral (brightness and color), and/or texture characteristics that describe the region. This procedure automates access using various segmentation and classification parameters. The feature extraction was used by supervised classification.

### 2.5 Applying Support Vector Machine Classification

Use Support Vector Machine to perform supervised classification on images using a support vector machine (SVM) to identify the class associated with each pixel. SVM provides good classification results from complex and noisy data. The SVM classifier provides four types of kernels: linear, polynomial, radial basis function (RBF), and sigmoid.

### 2.6 Vegetation indices

In remote sensing applications, the most commonly used vegetation index to detect vegetation or its vitality is the Normalized Difference Vegetation Index (NDVI) developed by Rouse et al. (1974). This index is calculated using the following equation:

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

where RED and NIR stand for the spectral reflectance measurements acquired in the red and near-infrared regions, respectively.

### 2.7 Ground cover

The coordinates of each corner and center of 10 sample plots (1.26 ha) in each satellite image were input to the GPS device. Using GPS, we tried to find the corner position for each sub-sample plot and then estimate the ground cover. With help from natural resource organizations in the region, we then estimated the ground cover. Field surveys took place at the end of October 2010.

### 2.8 Determine a spectral value on the juniper forest

After image pre-processing, spectral values were estimated in regions covered by two overlapping images, namely the pan-sharpening and vegetation index images. In forests, vegetation could be divided into three categories with different vegetation index values. The first category, which had a high spectral value, was grassland and sand. The second category, which had a value close to that of grassland and sand, was juniper. The third category, which showed a low value, was shadow. To find values representing juniper, we first retrieved data (spectral values) for each plot as ASCII files from the vegetation index images. We then imported the ASCII files to Microsoft Excel and used Visual Basic in Excel to find the best threshold combination. Subsequently, we performed simple linear coefficient regression between the number of juniper trees found by field surveys and the spectral values of juniper trees in all plots from vegetation index image in here is NDVI.

## 3. RESULT AND DISCUSSION

### 3.1 Object base classification

Have been support vector machine (SVM) with four-kernel type. (Table 2).

Table 2. Classification area of juniper forest (ha)

| Classification | Support vector machine (SVM) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Plot. No | Linear | | Polynomial | | Radial basis | | Sigmoid | |
| | (1) | (2) | (1) | (2) | (1) | (2) | (1) | (2) |
| 1 | 0.76 | 0.50 | 0.76 | 0.500 | 0.76 | 0.50 | 0.77 | 0.49 |
| 2 | 0.71 | 0.54 | 0.75 | 0.50 | 0.74 | 0.52 | 0.75 | 0.51 |
| 3 | 0.44 | 0.81 | 0.39 | 0.87 | 0.37 | 0.89 | 0.47 | 0.79 |
| 4 | 0.61 | 0.43 | 0.60 | 0.44 | 0.54 | 0.50 | 0.83 | 0.43 |
| 5 | 0.26 | 0.99 | 0.44 | 0.81 | 0.89 | 0.37 | 0.69 | 0.56 |
| 6 | 0.36 | 0.90 | 0.42 | 0.84 | 0.40 | 0.86 | 0.42 | 0.84 |
| 7 | 0.36 | 0.89 | 0.40 | 0.85 | 0.40 | 0.86 | 0.37 | 0.89 |
| 8 | 0.69 | 0.56 | 0.76 | 0.50 | 0.81 | 0.45 | 0.73 | 0.53 |
| 9 | 0.44 | 0.81 | 0.44 | 0.82 | 0.83 | 0.43 | 0.81 | 0.45 |
| 10 | 0.90 | 0.35 | 0.89 | 0.37 | 0.88 | 0.38 | 0.96 | 0.30 |

(1)Vegetation cover (Juniper and grassland) per hectare (2) Non-vegetation per hectare

### 3.2 Image pan sharpening

Four types of image pan sharpening algorithms, of which Gram-Schmidt is the best sharpening algorithm. Gram-Schmidt Spectral Sharpening is more accurate and is recommended for most applications such as land use environment. Moreover, the Gram-Schmidt is typically more accurate when using the spectral response function of a given sensor to estimate what the panchromatic data look like. If you display a Gram-Schmidt pan-sharpened image and a PC pan-sharpened image, the visual difference is very subtle. There exist differences in the spectral information; when comparing the Z Profile of the original image with that of the pan-sharpened image, or calculating the covariance matrix for both images. The effect of pan sharpening is the best revealed in images with homogenous surface features (flat deserts or water, for example).

### 3.3 Feature extraction

For this algorithm, pan sharpening was initially applied, followed by feature extraction, with supervised classification by choosing each feature. 6 classes were extracted including access road, pistachio, river, farmland, grassland and valley from the pan-sharpening image (Figure 3 and Table 3).

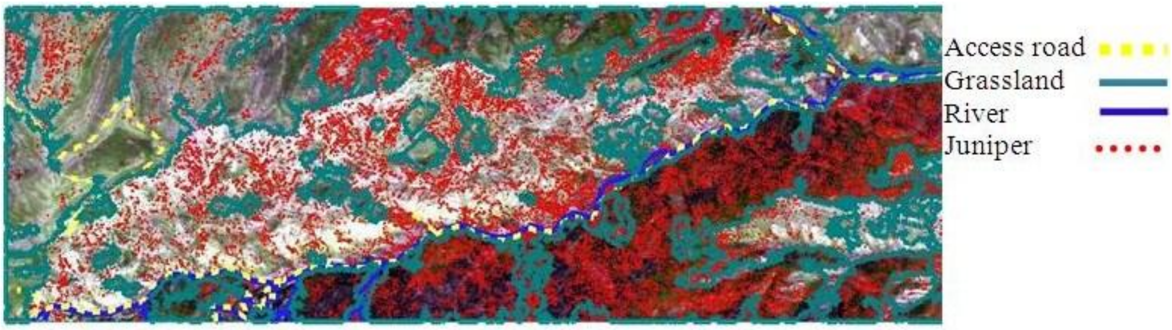


Figure 3. Feature extraction map

Table 3. Landcover areas per classes in the study area

| Classes | Area (ha) | Length (km) |
|---|---|---|
| Juniper forest | 195.22 | — |
| Access road | — | 16.28 |
| River | — | 13.00 |
| Grassland | 743.23 | — |

### 3.4 Vegetation index (NDVI)

Figure 4 illustrates Normalized Difference Vegetation Index (NDVI) for study area was applied, showing high value of NDVI in white part, where pistachio trees is located with grassland under pistachio trees and low value of NDVI in black part of the study area. The values of NDVI on the base of elevation ranging from 1600-2600 m above sea level are shown (Table 2 and Figure 5).

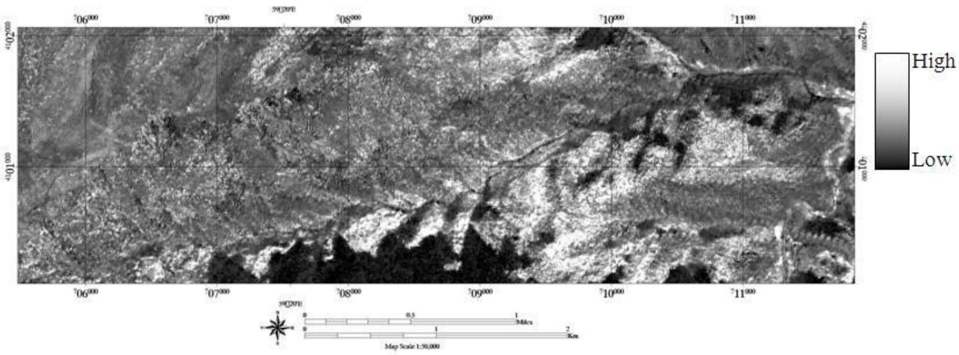


Figure 4 NDVI map

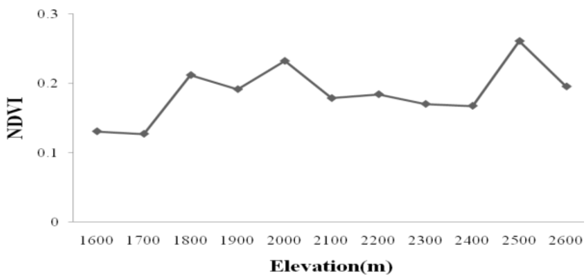


Figure 5. The relationship between NDVI and elevation (a.s.l)

**4. CONCLUDING**

We achieved to create a digital elevation model based on ALOS data. We have applied PRISM data (Nadir) to make pan sharpening, finding best algorithm of pan sharpening to be Gram-Schmidt. The feature extraction algorithm used for land cover mapping gave the best classification for defining each feature in the study area. The result of this processor was good and we could estimate the area and length of each feature. The Normalized difference vegetation index (NDVI) has been estimated on this area and was able to find the abundance of juniper in the base elevation range. At 2500 m above sea level, we observed higher density of juniper than at other ranges of elevation. We highly recommend investigating the temperature value of the juniper distribution in this region. I hope for further work to get more information about this species by using remote sensing data. For example, by applying most related vegetation index to land use structure. We also suggest about land use structure by applying a nitrogen vegetation index. The best vegetation index so far is the Normalized Difference Nitrogen Index (NDNI) and is designed to estimate the relative amounts of nitrogen contained in vegetation canopies. Reflectance at 1510 nm is largely determined by nitrogen concentration of leaves, as well as the overall foliage biomass of the canopy. However, it is needed to use spectral properties in the 1500-1720 nm wavelength range for calculating this vegetation index. In addition, more important related tool to land use structure is forest health mapping, which is useful for detecting pest and blight conditions.

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