ESTIMATION OF TREE DENSITY IN THE PISTACHIO (*PISTACIA VERA*) FOREST OF NORTH-EAST IRAN BY ALOS DATA

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ABSTRACT:

The pistachio (*Pistacia.vera*) belongs to the *Anacardiaceae* family. Plants of this family are trees or shrubs (broadleaf) and in total comprising 75 genera and 600 species. This species is found in arid and semi-arid regions, located in the northeast of Iran. Many algorithms have been investigated for tree delineation and identification, in order to assist human operators in the information exploitation of data. Objects of and questions posed by this study are; identification and delineation of the pistachio's tree crown, distinguishing between pistachio trees and other vegetation cover, estimation of tree density by counting trees per hectare, estimation of vegetation indices and the analyses of image segmentation, classification, texture and comparison with numbers of pistachio trees based on ground control data. ALOS satellite data have been used, using multispectral band (AVNIR-2) with 10-meter resolution and Panchromatic band (PRISM) with 2.5-meter resolution. In this paper, the relationship between the true number of trees (tree numbers measured on the ground) in the sub sample plots and introduced methods for tree population measurement has been investigated (considering factors such as tree crown area, shadow area, image classification and image segmentation from panchromatic (PRISM) image for pistachio forests). A sample plot area of about 1600 ha was selected incorporating 15-sub sample plots of 9 ha (300 ×300m) equal to 120 × 120 pixels for this research. A maximum filtering algorithm of 5 × 5 pixels size is used for vegetation indices in the pistachio forest. The results of this paper indicated that NDVI, OSAVI, SAVI (0.5), SAVI (1) and new index TRVI with 5×5 maximum filtering was (R^2=0.5863, 0.5857, 0.4923, 0.6346 and 0.6414) respectively. The results of tree counting analyses will be showed.

1. INTRODUCTION

1.1 General Introduction

Pistachio is believed to have been cultivated for 3,000-4,000 years in Iran. Nowadays, Iran is the world's largest producer of pistachio, followed by USA, which has the largest pistachio production in California. The share of Iran and USA in pistachio production in 2004 was 44% and 13% respectively (Razavi, 2006). Most pistachio production in Iran is from orchards, but there are a few areas, such as in the northeast of Iran, where wild pistachio (Pistacia vera L.) persists in natural stands. Natural stands of pistachio are not only environmentally but genetically important as seed storage for pistachio production in orchards. In addition, natural pistachio stands, managed by the Natural Resource Organization of Iran, provide the rural residents with the opportunities to obtain extra income by participating in harvesting work. Pistachios as well as carpets are one of the most important non-oil articles exported from Iran.

1.2 Aim and objectives

The purpose of this study is to determine the tree density and distribution of natural pistachio stands by remote sensing for their sustainable management and production in the northeast of Iran. Typically, pistachio trees grow sparsely in salty soil, and the ground, that is, soil and rocks between trees show up on aerial photographs or remote sensing images. Open forests have special features that provide excellent opportunities for remote-sensing-based forest inventory, and detection of individual trees from very-high-resolution satellite data is typically easier in sparse forests where distance between trees exceeds the height of trees (Ozdemir 2008). In Iran, forest inventories in such open forests are carried out based on the transect sampling method by using GPS, and final stand parameters are derived by statistical extrapolation methods. However, forest inventory work conducted on the ground without any protection against the sun and weather is hard work and requires a lot of cost, time and labor even with the use of GPS. By utilizing remote sensing data, forest inventory in arid and semi-arid areas become more cost-effective, less time-consuming and less labor-intensive.

In this study, we proposed one method of the local-maxima approach to determine the tree density and distribution of natural pistachio stands based on the newly introduced vegetation index. In addition, we determined the optimal window size of the local maxima approach for the identification of natural pistachio trees.

1.3 Background

There are many existing methods for tree density or counting on aerial photographs or remote sensing images. A variety of

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algorithms have been proposed and developed for automatic individual tree recognition with the increasing availability of large-scale and high-resolution imagery. Dralle and Rudemo (1996, 1997) estimated tree positions by using scanned panchromatic aerial photographs of even-aged homogeneous stands of Norway spruce. Koukoulas and Blackburn (1998) involved the use of scanned aerial photographs and a combination of contouring and texture techniques to delineate tree crowns in broadleaved deciduous forests. In field of natural resources, spatially forest with the increasing availability of large-scale and high-resolution imagery, various algorithms have been developed for automatic individual tree recognition (Donald G. Leckie 2005). The common tree delineation methods consist of 1-Local maxima methods that search for the “top” of the convex mound, which usually corresponds to the sun-lit top of the tree. The simples group of tree-detection methods assumes that a local maximum in the image corresponds to the top of a tree. Blazquez (1989) developed an early example of such an individual tree counting approach for citrus trees in Florida, using digital aerial color-infrared (CIR) photographs. 2-Boundary-following approaches that identify tree edges between trees located within the showed regions (Gougeon 1995a, Warner et al 2006). When a topographic analogy is used to describe the surface of brightness value, the tree boundaries are represented by valleys, in the valley-finding method (Gougeon 1995a, Leckie et al 2005b); local minima are identified in the image. 3- Region-based tree segmentation is the direct search for a group of pixels that likely represent a single tree. Erikson (2003) used a region growing approach to segment singletree crowns in aerial photographs from a mixed-species boreal forest in central Sweden. (Culvenor 2002) developed Tree identification and delineation algorithm (TIDA), which uses the local radiometric maxima and minima to indicate the likely locations of tree centroids and boundaries, respectively. Brandtberg et al. (2003) based their approach on blob detection, or identification of convex regions in the image brightness surface. The blob detection is conducted at multiple scales, using all local maxima, at each scale, as seed points. 4- Template matching methods, it usually employs an optical crown model to generate synthetic image chips that represent individual tree (Pollock 1996, Larsen and Rudemo 1998). 5- Model-based methods in 3D, Gong et al. (2002) describe such as 3D model-based approach using stereo pairs, in which the problem is defined as an optimal tree model determination issue.

As one of the simplest methods of tree identification, the local-maxima approach can be applied to relatively coarse-scale imagery, where the pixel size is not much smaller than size of the individual tree (Gufan Shao et al 2006). (Koukoulas et al 2005) introduced a new method is developed for extracting the locations of treetops by applying CIS (Geographical Information System) overlay techniques and morphological functions to high spatial resolution airborne imagery. Each of these approaches has been found to improve results in their intended applications.

2. STUDY SITE

2.1 Location

The study site is located in the arid area of the northeast of Iran, where wild pistachio trees grow, with the annual precipitation of 200-300mm (Figure 1). The area of the study site is 15.21km2 (3.9 x 3.9km) with the latitude and longitude of 36º17"2.60' - 36º7"2.09' and 60º30"21.91' - 60º30"18.22' degrees, respectively. It is known that wild pistachio grows mostly at the elevation of 900 - 1,500m, and the elevation of the study site is at the elevation of 500 - 1,200m. The slope of the site ranges generally from 15 to 35 degrees. Among 169 (13 x 13) square grids with the side length of 300m, 15 sampling plots were randomly chosen for the analysis (Figure 2). The wild pistachio trees in the study site are typically 3 - 4m high, with the crown diameter of 3 - 5m (Figure 3). The distance between two pistachio trees is often more than 3m, and between them in spots there are shrubs adapted to dry land, such as *Amygdalus spinosissima*, *Atraphaxis spinosa*, *Cerasus pseudprostrata*, *Ephedra intermedia, Tamarix androssowii* and *Zygophyllum eurypterum*. The soil salinity in the study site, measured by the natural resources organization of Iran, was 0.6-20 mmhos/cm, which shows that this site belongs to non-saline to strongly saline areas according to U.S. Salinity Laboratory Staff (1969).

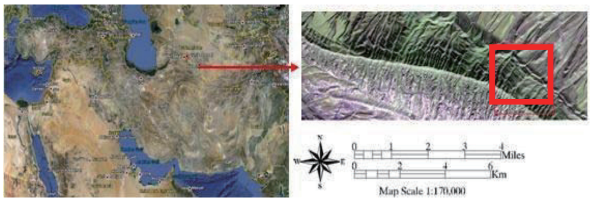

Figure 1. The study area

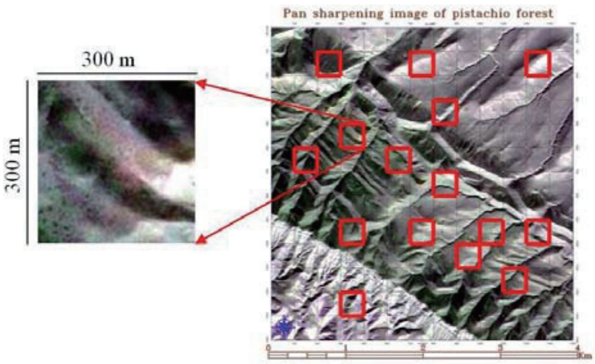

Figure 2. Position of sub-sample plots

Figure 3. Distribution of this species

2.2 Data

2.3 Image satellite

We used the satellite imagery obtained by the ALOS (Advanced Land Observing Satellite), which was launched on January 24, 2006. Among three remote-sensing instruments that the ALOS has, the Panchromatic Remote-sensing Instrument for Stereo Mapping (PRISM) for digital elevation mapping and the Advanced Visible and Near Infrared Radiometer type 2 (AVNIR-2) for precise land coverage observation were used. The PRISM is a panchromatic radiometer with 2.5m spatial resolution at nadir, and has one band with the wavelength of 0.52 - 0.77μm (JAXA EORC). The AVNIR-2 is a visible and near infrared radiometer for observing land and coastal zones with 10m spatial resolution at nadir, and has four multispectral bands: blue (0.42 - 0.50 μm), green (0.52 - 0.60 μm), red (0.61 - 0.69 μm) and near infrared (0.76 - 0.89 μm) (JAXA EORC). The fusion of images from the PRISM and AVNIR-2 was used for the analysis.

2.4 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:

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

where RED and NIR stand for the spectral reflectance measurements acquired in the red and near-infrared regions, respectively. A number of derivatives and alternatives to NDVI have been proposed to get over the limitations of the NDVI, and the Soil-Adjusted Vegetation Index (SAVI) was proposed by Heute (1988) to account for and minimize the effect of soil background conditions. The SAVI is calculated using the following equation:

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

where RED and NIR are the same as in NDVI; L indicates the soil-brightness dependent correction factor that compensates for the difference in soil background conditions. The optimal L values differ with vegetation density: low vegetation densities (L =1), intermediate vegetation densities (L =0.5) and higher densities (L =0.25) Heute (1988). It was also pointed out that a single adjustment factor (L=0.5) was shown to reduce soil noise considerably throughout the range in vegetation densities according to Heute (1988). Therefore, we employed 0.5 and 1.0 for L in this study. The Optimized Soil-Adjusted Vegetation Index (OSAVI) was modified to be better adopted for agricultural applications Rondeaux et al. (1996). The OSAVI is calculated using the following equation:

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

where RED and NIR are the same as in NDVI. The value of 0.16 in this formula was found to give satisfactory reduction of soil noise, both low and high vegetation cover (Rondeaux et al., 1996).

Total Ratio Vegetation index (TRVI) as new vegetation index; in the arid and semiarid where vegetation is sparse such as those in arid land because of strong influences of the reflectance from the background soil. For this region vegetation is not very high density, vegetation in the near infrared and red wavelengths has not very high reflectance. Subsequently, there is not high difference between red and near-infrared wavelengths. For this has been applied of total wavelengths that are calculated using the following equation:

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

where RED and NIR are the same as in NDVI , G is green and B is blue wavelengths. In this study, NDVI, SAVI (L=0.5 and 1), OSAVI and TRVI were used as vegetation indices to estimate the stand density of wild pistachio trees.

3. METHODOLOGY

3.1 Data pre-processing

3.1.1 Image pan sharpening:

Pan-sharpening algorithms are used to sharpen multispectral data using high-resolution spatial panchromatic data. The images must either be georeferenced or have the same image dimensions. Have been used **Color Normalized (Brovey)** sharpening to apply a sharpening technique that uses a mathematical combination of the color image and high resolution data. Each band in the color image is multiplied by a ratio of the high resolution data divided by the sum of the color bands.

3.2 Tree counting

3.2.1 Image segmentation (object- based classification): Segmentation is the process of partitioning an image into segments by grouping neighboring pixels with similar feature values (brightness, texture, color, etc.) These segments ideally correspond to real-world objects. ENVI EX as the newest addition to the ENVI line of premier image processing employs an edge-based segmentation algorithm that is very fast and only requires one input parameter (Scale Level). Have been used feature extraction for tree extraction in the Zarbin forest – the process of finding and extracting specific objects of interest from high-resolution satellite imagery based on the object's spatial, spectral, and texture characteristics – is an essential task for extraction information from high-resolution imagery.
The feature extraction workflow in ENVI EX has been explained (Figure 4).

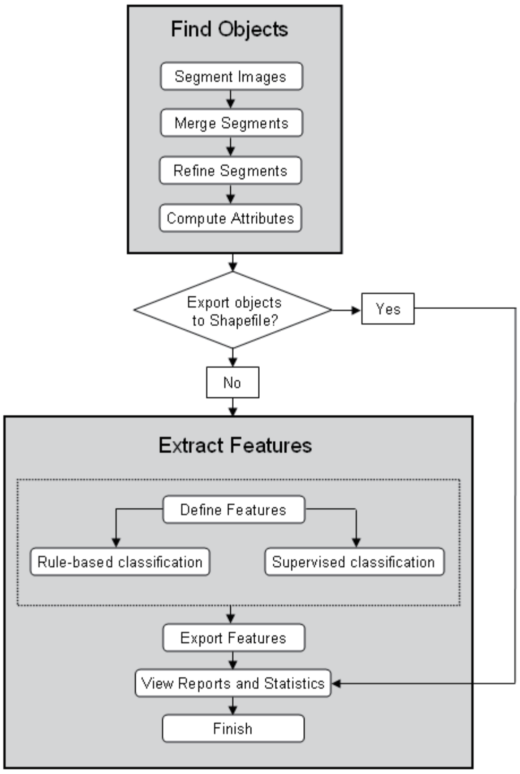

Figure 4.Feature Extraction Workflow

3.2.2 New method (Pixel-based classification): Have been introduced new method for tree extraction on pixel-based classification. Have been applied by the ENVI, the premier software solution for processing and analyzing geospatial imagery, announces the availability of a new service pack, ENVI 4.7 Service Pack 1 (ENVI 4.7 SP1), which helps to get information from imagery by increasing ease-of-use and adding efficiency to your image processing and analysis procedures. The tree extraction workflow in ENVI 4.7 SP1 has been explained (Figure 5).

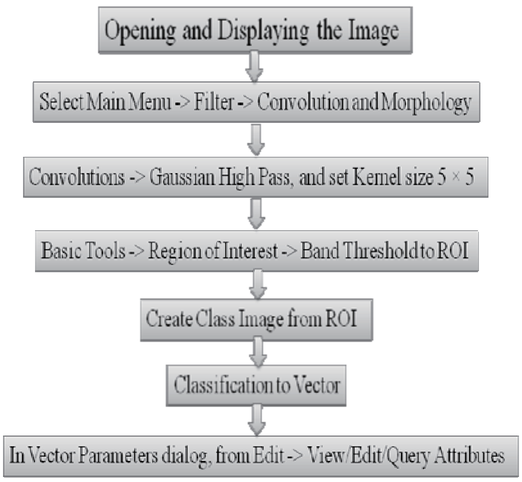

Figure 5. Tree Extraction Workflow (pixel-based)

3.2.3 Tree counting by surveying: Have been counted trees with usage of GPS in the forest on each sub sample plots.

3.2.4 Tree counting by visual observation: Have been counted trees in the pan-sharpening image on each sub sample plots.

4. RESULTS AND DISCUTION

4.1 Results from processing image data

The Gram-Schmidt spectral sharpening type was applied. A procedure is developed for combining high spatial resolution panchromatic data with lower resolution multispectral data in order to produce high spatial resolution digital data in multispectral form. A one-step of tree counting was started from pan sharpening image (Table 1).

Table 1. Tree counting on base of data processing

Plot	Actual data	Visual observation	New method	Image segmentation
1	30	32	32	73
2	5	5	7	41
3	0	0	34	35
4	47	47	63	32
5	57	51	70	86
6	46	40	55	33
7	115	119	128	93
8	96	97	195	45
9	50	49	52	39
10	130	131	132	32
11	170	178	191	72
12	98	99	181	24
13	123	125	192	64
14	158	159	101	63
15	65	74	182	43

4.2 Result from relationship between vegetation index and tree density

Vegetation indices have been calculated by maximum filtering five by five and density of tree measured on each sub sample plot (Figures 5, 6, 7 and 8).

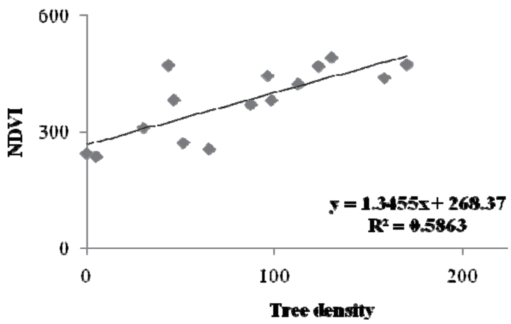

Figure. 5 the relationship between maximum filtering (5×5) NDVI and number of tree

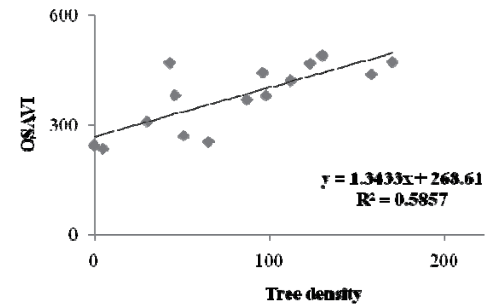

Figure. 6 the relationship between maximum filtering (5×5) OSAVI and number of tree

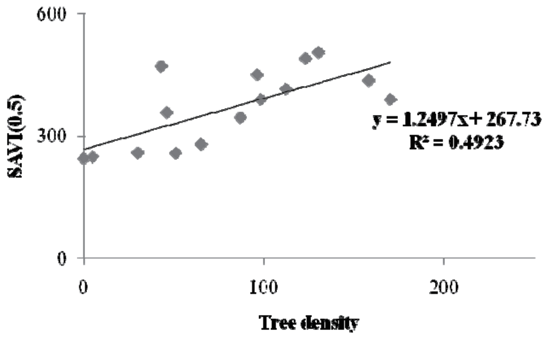

Figure. 7 the relationship between maximum filtering (5×5) SAVI (0.5) and number of tree

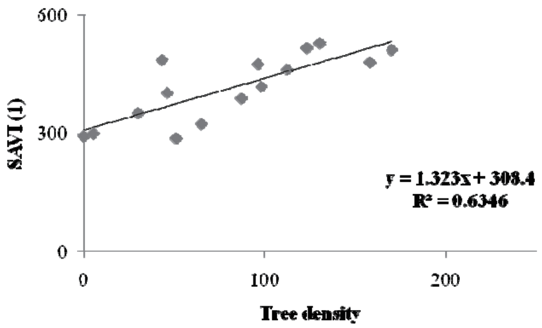

Figure. 8 the relationship between maximum filtering (5×5) SAVI (1) and number of tree

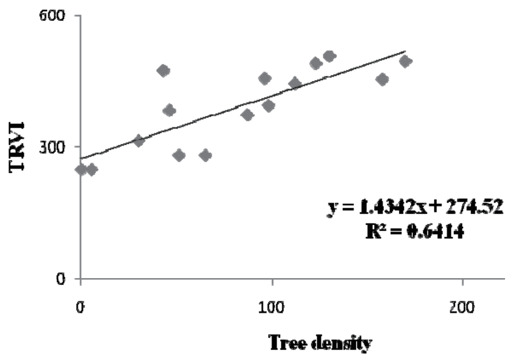

Figure.9 the relationship between maximum filtering (5×5) TRVI and number of tree

5. CONCLUSION

My new method for tree density on base of pixel based was skilful method for tree density. In result indicated this method close to actual data. In the actual data, just we measured pistachio trees on each sub-sample plot but on each sub-sample plot I observed shrub or grass that were too large. My method counted total vegetation on each sub-sample plot. Image segmentation for tree extraction was not useful method. Because Image segmentation is on based of object-based classification and then can been extracted multiple features at a time such as vehicles, buildings, roads, bridges, rivers, lakes, and fields. Nevertheless, object-based classification is not useful method for tree extraction (tree density) from high-resolution imagery. Actual data and my new method for tree counting in the table 1 indicated; some plots (1, 2, 9 and 6) are close together, this relationship between them showed in plots just pistachio tree is available and nothing or a very rare shrub and grass. In spite of, in some plots (3, 4, 5, 6, 7, 8, 11, 12, 13 and 15) number of tree in the new method on base of pixel is higher than actual data. It means these plots have a lot of vegetation or shrub and grass are to size of pistachio tree. Finally, relationship of actual data and new method for plot 14 indicated that this plot has some part shadow. New method is pixel-based inability in identified dark pixel for tree extraction. I think it to more investigation for the problem tree extraction on shadow place of high-resolution imagery is needed. The relationships developed in this paper between number of trees and vegetation indices were all significant for green biomass as well as for Pistachio tree. Result of this paper indicated that for arid and semi arid vegetation is not same as humid area such as green vegetation. Arid and semi-arid area have sparsely forest same pistachio forest that have yellow or senescent vegetation. For this have not high reflectance in near infrared and red wavelengths. Green vegetation, for example high-density broad-leaved forest has high reflectance in near infrared and red wavelengths, and then it is high signification with Normalized different vegetation. For this reason, I used total wavelengths for vegetation of this area.

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