Capability Investigation of ASTER Imagery for Mixed Hardwood Forest Types Classification

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Abstract:
The Hyrcania (Caspian) region that covers an area of 1,925,125 ha, is extending throughout the south coast of the Caspian Sea in the northern part of the Iran. These natural mixed-hardwood forests have rich diversity based on tree species. Employing traditional methods to produce forest cover type map such as employing aerial photos interpretation and ground methods are costly and time consuming. Therefore, using of satellite data due to new potential could be suitable for this purpose. This research is seeking to explore the potentials of ASTER data for forest cover types mapping in the mixed hardwood forests of Golestan province in north of Iran. These images were then ortho rectified with UTM projection using ground control points and a 10 meters resolution digital elevation model (DEM). With applying the nearest neighbor resampling technique, the images were registered with RMSe of 0.37 pixel for VNIR and 0.55 pixel for SWIR bands. Due to mountainous of study area and effect of atmosphere on the visible bands, the COST method has been used for atmospheric normalization of VNIR bands. To apply the effective vegetation indices and principle component analysis for classification, the 27 synthetic bands were resulted from ratioing and principle component analyses. These synthetic bands together with 9 ASTER bands were examined to select the best bands for classification. For selecting the training area for supervised classification and also the accuracy assessment of the results, the 157 plots were sampled with 0.1 hectare area. Diameters of trees with higher 12.5 centimeters together with kind of species were registered in each plot and the GBH of all trees were calculated. The percent of ten thick trees in each plot were selected to determine the forest type and. About 30 % of total plots were selected as training sites and rest of plots were designed as ground truth data. The bands of VNIR1, first component of VNIR, SWIR3, first component of SWIR, VNIR2, NRVI and TTVI vegetation indices were selected as best bands by transformed divergence separability index. Classification was done by best bands and maximum likelihood algorithm. The accuracy assessment of result showed overall accuracy and kappa coefficient of %76 and 0.66, respectively. This study certificated that ASTER imagery has relative good capability to separate of main forest types in the mixed hardwood forests. The results also showed that vegetation indices can be suitable for classification.

1. Introduction

Forests of Iran with an area about 12.4 million hectare comprise 7.4% of the country's area. These forests have various geographic conditions, producing different forests of various tree and shrub species and production capacity in different edapho- climatic conditions (FAO, 2002). Among five large vegetation regions in throughout Iran, the most important vegetation region according to density, canopy cover and diversity, is the Hyrcanian (Caspian) region that covers an area of 1,925,125 ha, extending throughout the south coast of the Caspian Sea in the northern part of the country. The Hyrcanian vegetation zone is a green belt stretching over the northern slopes of the Alborz mountain ranges (Sageb-talebi et al., 2003). It has a high production capacity due to humid temperate climate and suitable soil. Hyrcanian forests extend for 800 km in length. These natural mixed-hardwood forests have rich diversity based on tree species. Species such as beech (*Fagus orientalis*), hornbeam (*Carpinus betelus*), alder (*Alnus glutinosa*), oak (*Quercus castaneafolia*), maple (*Acer velotonia*), ironwood (*Parotia persica*) are the main species in these forests (Sageb-talebi et al., 2003).

For design of meaningful conservation strategies, comprehensive information on the distribution of forest types, as well as information on changes in distribution with time, is required. It is nearly impossible to acquire such information purely on the basis of field assessment and monitoring. Remote sensing data provides a systematic, synoptic view of earth cover at regular time intervals, and has been useful for this purpose (Nagendra, 2001). The satellite imagery has been effectively utilized for classifying land cover types and detecting land cover conditions (Yuksel, 2008). The use of these techniques in forest resource assessment is important because they offer us some advantages such as: information collection of the forest with low cost, few times consume and less human resources. This is especially applicable for mountainous regions like Iran, where the topography is the main obstacle. The Advanced Space borne Thermal Emission and Reflection Radiometer (ASTER) has been recently developed by collaboration of NASA and Japan’s Ministry of International Trade and Industry to provide accurate satellite images with high spatial and spectral resolutions (Abrams, 2003).

In classification process, supervised classification has been widely used in remote sensing applications. In supervised classification, spectral signatures are collected from specified locations (training sites) in the study area. The spectral signatures are then used to classify all pixels in the scene. The supervised classification is generally followed by knowledge-based expert classification systems depending on reference maps to improve the accuracy of the classification process (Berberoglu , 2007 and Xiaoling, 2006).The main purpose of this study is to explore the potential and effectiveness of ASTER data for mapping the forest cover types in the mixed hardwood forests and perform the forest cover type's classification of a study area in the province of Golestan province in north of Iran.

2. Materials and methods

2.1. Study area

The study area which is named Shatkola forest is a topographically area located in south west of Gorgan city in the Golestan province, North of IRAN (Figure1). This forest has an altitude ranging from approximately 200m to 1240 above sea level. The study area covers about 1714 ha, and includes 33 parcels. Topography is extremely rugged and it is extends from 36º 41' to 36 º 45' eastern longitude and 54º20' to 54º24' northern latitude. Due to altitude different within a short width, a great diversity of flora exists in this area. Major tree species are including *Fagus orientalis* Lipesky*, Carpinus betulus* L., *Quercus castaneifolia* C.A. Mey. , *Aacer velutinum, Paroia persica*, *Alnus glutinosa* and *Zelkova carpinifolia*.

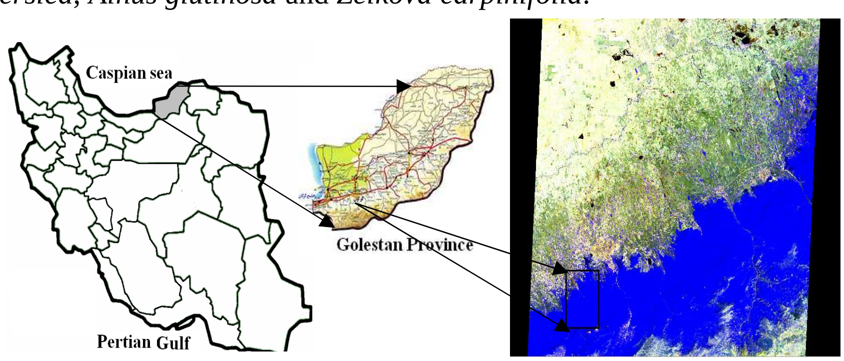

Figure 1. The location of the study area on the Iran, Golestan and ASTER image

2.2. Field surveys and Ground truth map

In June 2007, 157 circle plots were sampled with 0.1 hectare (17.84.4m radius) area by randomly systematic network with a 150 m×200m grid (plots in parcels was randomly selected). The number of plots placed, within each parcel was proportional to their actual distribution within Forest, and with the exception of the four reforested parcels. The geographic coordinates of plots were recorded with a Geographical Positioning System (GPS). In each plot, all live trees with a diameter at breast height (DBH) ≥12.5cm were inventoried with a caliper and fiberglass tape and kind of species was recorded. Then, ground basal area (GBH) of trees was calculated in each plot. Since, the thick trees are dominated in canopy cover, 10 thick trees and their percent of them in each plot were used for determination of forest type. The forest types were including four types of *fagieto-carpinetum*, *querqu- carpinetum*, *carpino-parotium* and *parotio- acerium*. About 30 % of total plots were selected as training sites and rest of plots were considered as ground truth data. Center of plots was then subsequently used in a GIS to create polygons around each point feature.

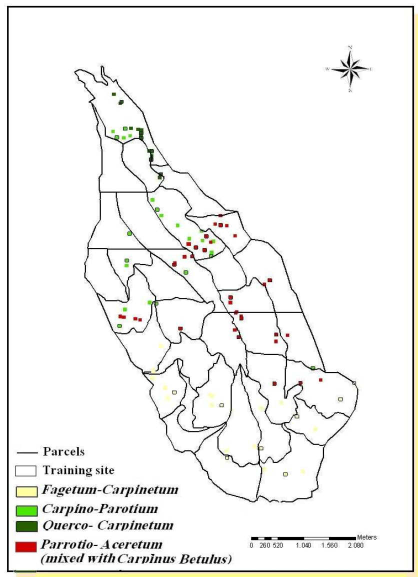

Fig.2. Location map of plots in study area

2.3. Remotely sensed data

A Level 1B ASTER image of the study area was acquired on the 3th of June, 2006. That was closest to the date of field sampling. With a sufficiently cloud-free (cloud cover less than 3%). The ASTER sensor, operates three different spectral regions including the visible and near infrared (VNIR), the short-wave infrared (SWIR), and the thermal infrared (TIR). According to Rowan and Mars (Rowan, 2003), the visible and near-infrared telescope on ASTER with a spatial resolution of 15 m is very useful to acquire vegetative information. The ASTER images with high spatial and spectral resolutions can provide more accurate and low-cost land cover mapping (Zhu, 2001 and Davis, 1991).

2.4. Image preprocessing

In preprocessing stage, the quality of the image was evaluated for radiometric noises at first and no radiometric distortion was found. These images were orthocorrected with UTM projection using ground control points taken from ground sampling, Digital Elevation Model (DEM) with 10 m resolution and header file. With applying the nearest neighbor resampling technique the images were registered with RMSe of 0.37 pixel for VNIR (with 15 m pixel size) and 0.55 pixel for SWIR bands (with 30 m pixel size). The atmosphere affects the ability of a given sensor to quantify visible and near-infrared signals in a number of ways (Forester, 1984). The purpose of atmospheric corrections in the visible and near-infrared wavelengths for a satellite imaging sensor such as ASTER is the conversion of image digital numbers (DNs) to surface radiance /reflectance values (Chavez, 1989; Teillet and Fedosejevs, 1995). This is especially important in forestry mapping as the atmosphere modifies the strength and spectral distribution of the electromagnetic energy received by a sensor, restricting 'where we can look' spectrally (Lillesand and Kiefer 1999). Due to mountainous of study area and effect of atmosphere on the visible bands, the COST method has been used for atmospheric normalization of VNIR bands.

2.5. Image processing

To reduce the volume of spectral data and to capitalize on the variance in the image data, two kind of Principal Component Analysis (PCA) were applied on the VNIR and SWIR bands. Also some suitable different vegetation indices based on results of other researches including NDVI, TTVI, GNDVI, GTTVI and other rationg of bands were apllied on the red and infra red bands. After applying the effective vegetation indices and principle component analysis for classification, the 27 synthetic bands were resulted and these bands together with 9 original ASTER bands (VNIR and SWIR) were examined to select the best bands for classification.

2.6. Selection the best band for classification

Among the 27 synthetic bands were resulted from ratioing, principle component analyses and 9 original bands, seven of the best bands selected using Bhattacharya separability index for implementation in classification. The bands of VNIR1, first component of VNIR, SWIR3, first component of SWIR, VNIR2, NRVI and TTVI vegetation indices were selected as best bands.

2.7. Image Classification

Using 30 percent of sample as training sites, the signature of forest types was extracted. After signature separability analysis using Transformed Divergence index, signature of some classes with similar spectral responses are merged into the same class. In order to generate a forest type map, the supervised classification, which requires field knowledge to define the different classes, was used and the images were classified with maximum likelihood classifier.

2.8. Accuracy assessment

We used the 70 percent of remaining field collected data (as ground truth data) to perform an accuracy assessment on the decision tree. We determined the accuracy for forest cover type's classification. An error matrix was generated and user's, producer's, overall, and Kappa accuracies were calculated.

3. Results and discussion:

The accuracy assessment of the classified image (Figure2) indicated that classification process with maximum likelihood algorithm provided overall accuracy and kappa values of 76% and 0.66, respectively (Table1). The minimum accuracy for forest cover class is 65 percent (Greenberg et al, 2006). Hence Supervised classification provided satisfactory results in terms of distinguishing some forest types as *Fagetum-Carpinetum*, *Querco- Carpinetum* and for *Parrotio- Aceretum* (mixed with *Carpinus Betulus)*, and *Carpino-Parotium* were relatively low due to large variation of spectral signatures. The highest producers and users accuracy was reached in classification of *Fagetum-Carpinetum* type (97%) and (91%), respectively. The lowest producers and users accuracy was for *Carpino-Parotium* (41%) and (71%), respectively. It was assumed that low accuracy of the *Carpino-Parotium* is due to close reflection values received from this type. The accuracy levels obtained from the ASTER data processing performed with best bands was presented in Table1. To evaluate the separability of the classes, signature analysis was performed with Transformed Divergence. The class means and the standard deviations of the training areas indicate a distinct separability for total classes except separability between *Carpino-Parotium* and *Parrotio- Aceretum* (mixed with *Carpinus Betulus)* classes (table 2).

This study certificated that ASTER imagery has relative good capability to separate of main forest types in the mixed hardwood forests.results also exposed that We were not able to successfully distinguishing between the two dominated forest types (*Carpino-Parotium* and *Parrotio- Aceretum* (mixed with *Carpinus Betulus*). After combining these two floristically similar classes into one category, classification accuracies reached to an acceptable and comparable level to those achieved for other forest types (Foody & Cutler, 2003, 2006). The results also showed that vegetation indices can be suitable for classification. Our results are agreed with other recent studies which are reporting the utility of vegetation inices from ASTER images in distinguishing land/ forest cover types (Yuksel et al, 2008, Lasaponara & Lanorte, 2007). The forest types of study area are showing floristic differences so that they are not commonly delineated on the mountainous forests cover maps. Our study demonstrated that these forest types can be reliably distinguished using readily available ASTER data. Normally, it is also important to know problems and constraints for mountainous forests type mapping from satellite imagery.

Table.1. Accuracy assessment results of the produced map by the maximum likelihood

Mapped class	Users Accuracy	Producers Accuracy	kappa
Parrotio- Aceretum (mixed to *Carpinus Betulus)*	0.72	0.88	0.76
Fagetum-Carpinetum	0.91	0.97	0.95
Carpino-Parotium	0.71	0.41	0.30
Querco- Carpinetum	0.71	0.77	0.73
Overall Kappa =0.66		Overall accuracy = 0.76	

Table.2. Signature Separability results of types by Transformed Divergence

	Fagetum-Carpinetum	*Querco-Carpinetum*	*Parrotio- Aceretum* (mixed with *Carpinus Betulus)*
Fagetum-Carpinetum	2		
Querco- Carpinetum	1.99752	2	
Parrotio- Aceretum (mixed with *Carpinus Betulus)*	1.47138	1.76405	2
Carpino-Parotium	1.61119	1.69116	0.33096

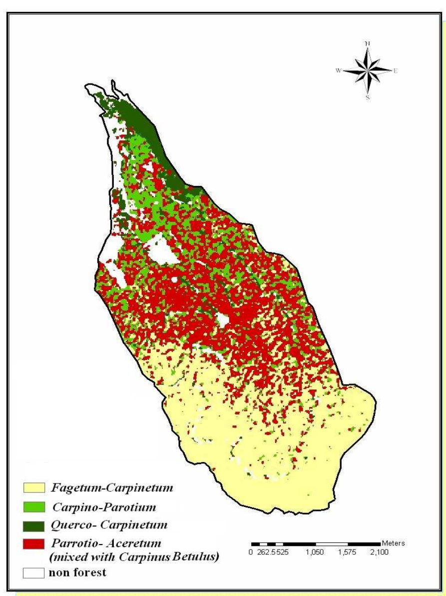

Figure 3. Forest cover type map of study area obtained using maximum likelihood classifier.

However, there are still many possibilities for improving the performance of remote sensing classification. Other remotely sensed data may have the more ability to discriminate field-verified forest type differences. It is also clear that the field sampling procedure, samples size and classification method may have effective on the results. Topographical shadows also caused errors. The impact of topography on radiance values can eventually be removed when more accurate elevation data become available (Thessler Et al, 2008). Our results are promising for the aim of classifying mountainous forests by remote sensing in a systematic and credible fashion, which accounts for the type variation in mountainous forests. Where knowledge of differences between forest types is important for conservation aims, cost-effective remotely sensed data and the examined classification methods may be used.

5. References

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