

[Research]

## Object-Based Classification of UltraCamD Imagery for Identification of Tree Species in the Mixed Planted Forest

O. Rafieyan\*<sup>1</sup>, A. A. Darvishsefat<sup>2</sup>, S. Babaii<sup>1</sup>, A. Mataji<sup>1</sup>

1. Dept. of Forestry, Science and Research Branch, Islamic Azad University, Tehran, Iran.

2. Dept. of Forestry, Faculty of Natural Resources, University of Tehran, Karaj, Iran.

\* Corresponding author's E-mail: o\_rafieyan@iaut.ac.ir

### ABSTRACT

This study is a contribution to assess the high resolution digital aerial imagery for semi-automatic analysis of tree species identification. To maximize the benefit of such data, the object-based classification was conducted in a mixed forest plantation. Two subsets of an UltraCam D image were geometrically corrected using aero-triangulation method. Some appropriate transformations were performed and utilized. Segmentation was conducted stepwise at two levels and a hierarchical image object network was constructed. The classification hierarchy was developed and Nearest Neighbor classifier, using integration of different features was performed. Training samples and ground truth map were prepared through fieldwork. Accuracy assessment of the resulting maps in comparison with reference data showed overall accuracies and Kappa Index of Agreement of 90.2%, 0.82 (Area1) and 69.8%, 0.49 (Area2), respectively. Transformed images were advantageous to improve the results. The lower accuracy in Area2 can be attributed to high diversity and heterogeneous mixture of species. More detailed and accurate mapping of tree species would be fulfilled applying precise 3D data. The accuracy of detailed vegetation classification with very high-resolution imagery is highly dependent on the segmentation quality, sample size, sampling quality, classification framework and ground vegetation distribution and mixture.

**Keywords:** Tree species identification, Object-based classification, Class hierarchy, Image object hierarchy, UltraCamD.

### 1. INTRODUCTION

Remote sensing and image interpretation have been utilized in forestry management for many years and offer great potential for vegetation mapping, especially with the availability of higher resolution imagery. In recent years, digital cameras have expanded in their utility as an efficient tool for forest inventory and mapping (e. g. Millette & Hayward 2004; Naeset & Gobakken 2005; Yu et al. 2006; Baltsavias et al. 2007; Bohlin et al. 2007; Hirschmugl et al. 2007; Ozdemir et al. 2008; Wang et al. 2008; Chang et al. 2008).

This present work is a contribution to assess the digital aerial imagery for semi-automatic analysis in the field of tree species identification. The automated classification of such data is still problematic due to large spectral variation within classes. High spatial resolution of the advanced sensors increases the spectral within-field variability and therefore may decrease the classification

accuracy of traditional per-pixel methods such as Maximum Likelihood classifier (Schiewe 2002). The increase in intra-class spectral variability causes a reduction of statistical separability between classes with traditional pixel-based classification approaches. Consequently, classification accuracy is reduced, and the classification results show a salt-and-pepper effect, with individual pixels classified differently from their neighbors (Shataee et al. 2004; Yu et al. 2006).

To overcome this problem, some pixel-based methods have been implemented, namely image pre-processing, such as low-pass filter and texture analysis (Gong et al. 1992; Hill & Foody 1994) or post-classification processing, such as mode filtering, morphological filtering, rule-based processing and probabilistic relaxation (Gong & Howarth 1989; Shackelford & Davis 2003). These

techniques can improve classification accuracy considerably, but there are disadvantages when they are applied to high spatial resolution images. As an example, the pre-defined neighborhood window size may not favor all the land cover types evenly since different classes reach their maximum accuracies at different pixel window sizes (Hodgson 1998). Furthermore, these processes have blur effects and cannot produce accurate results at the boundaries of different land cover units (Gong et al. 1992).

Hence, novel and efficient analysis techniques become a mandatory requirement for efficient processing and analysis. Object-based classifiers deal with these problems by segmenting an image into homogenous segments prior to any classification (Baatz & Schape 1999). This method is especially useful in forest studies to reduce the local spectral variation caused by crown textures, gaps, shadows and some noises. In addition, with spectrally homogeneous segments of images, both spectral values and spatial properties, such as size, shape and texture can be explicitly utilized as features for further classification (Yu et al. 2006).

In spite of this, particularly in uneven-aged deciduous closed forests, crowns are often interlaced and trees vary in crown size/shape and optical properties. This problem depends upon a variety of factors including age/height and health of the tree, dominance of the tree within the stand (e.g. dominant, co-dominant, suppressed), sensor-target geometry, topography, illumination and location in the image (Hirschmugl et al. 2007; Rafieyan et al. 2009). As a result, these parameters should be taken into consideration in the classification framework.

To our best knowledge, few studies have been done in forests of Iran using object-based method (Farzaneh 2004; Shataee et al. 2004) and UltraCamD images (Sohrabi 2009). But these data have not been evaluated using object-based method in the country. This case study has been done in broadleaf and coniferous mixed forests in

the northern Iran. Similar studies are necessary in different forest structures such as even-aged homogeneous forested areas, degraded stands, undisturbed and old-growth forests and forest parks established in natural forests.

The investigation presented in this paper has been conducted to assess the potential of the proposed object-based method with high spatial resolution airborne remote sensing data (UltraCamD) in tree species identification and mapping. This work will provide information on forest community composition and their spatial distribution.

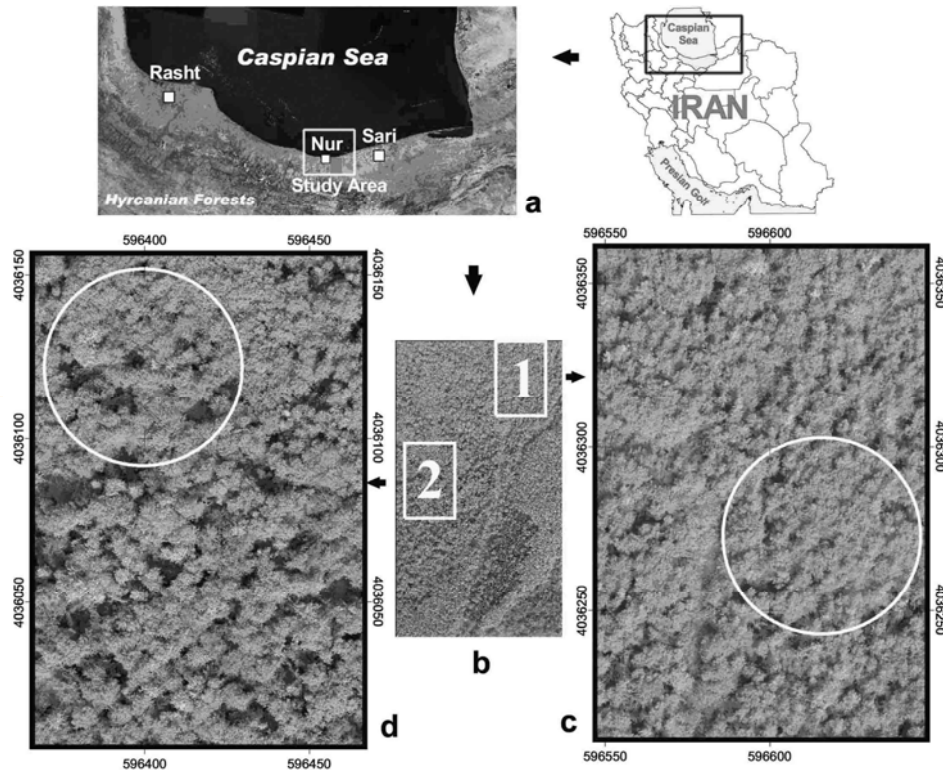
## 2. MATERIALS AND METHODS

### 2.1. Study Area

The research was conducted in a mixed forest plantations near the town of Nur in south of the Caspian Sea. The study area is a part of the Northern forests of Iran (Hyrcanian forests) (Fig.1a). It is relatively flat and the elevation above sea level is approximately 200 m. Because of degradation in the last decade, reforestation with broadleaved (*Hardwood*) and coniferous (*Softwood*) trees has been carried out. Two separate sites with an area of 1.5 ha from these 20 year old forested regions were selected (Fig. 1b). Based on the forest inventory within the plots, this planted mature stand has the mean height and Diameter at Breast Height (DBH) of about 23 and 0.21 m, respectively.

In the first study area (hereafter named Area1) dominant tree species are chestnut-leaved oak (*Quercus castaneifolia* (QU)) and loblolly pine (*Pinus taeda* (PI)) with blackberry (*Rubus fruticosos* (RU)) shrubs and occasionally distributed Arizona cypress (*Cuppressus arizonica* (CU)) trees. The planted stand is mostly of the same age and height (Fig. 1c).

The second study area (Area2) is more heterogeneous in species composition, stocking density and canopy structure (Fig. 1d). In addition to species found in Area1, other trees in this area include Caspian locust (*Gleditsia caspica* (GL)), velvet maple (*Acer velutinum* (AC)), white mulberry (*Morus alba* (MO)), common alder (*Alnus glutinosa* (AL)) and smooth-leaf elm (*Ulmus carpinifolia* (UL)), while QU is dominant.



**Fig 1.** Position of the study area: Location in Hyrcanian forests (a), Area1 and Area2 on the full frame (white rectangles) (b), Overall view in Area1 and Area2 and reference data plot site (white circles) in each of them (c and d).

## 2.2. Data

UltraCamD large format digital camera provides high quality spectral data of blue, green, red and near-infrared wavelengths with an array size of  $4008 \times 2672$  in multi-spectral and  $11500 \times 7500$  pixels in panchromatic format, respectively (Leberl et al. 2003).

For the present study, two parts of a pan-sharpened Level-3 color image were used. The image was acquired at 12 bits (4096 digital levels) but stored as a 16 bit (65536 digital levels) Tiff format in four layers. It was collected 17 October 2008 from an aircraft at 800 m above ground. Each orthophoto covers  $300 \times 600$  m with a spatial resolution of  $7 \times 7$  cm (Fig. 1b). Two subsets of this image with an area cover of  $100 \times 150$  m were selected as study areas.

## 2.3. Image Pre-processing

Digital aerial cameras based on frame sensors, such as UltraCamD, require much less post-processing effort compared to scanning systems. A CCD (Charge Coupled Device) frame sensor has a stable interior geometry in X and Y direction, and exterior

orientation parameters were provided by an onboard GPS/IMU navigation platform (Neumann 2005). Mentioned parameters ( $X$ ,  $Y$ ,  $Z$ ,  $\omega$ ,  $\phi$ , and  $\kappa$ ) beside 9 ground control points were applied to correct the image geometrically, using aero-triangulation method. Ground control points were derived using GPS with the accuracy of 1-5 m (with post-processing differential correction) to increase the geometric correction of the imagery.

In order to improve classification accuracy some appropriate transformations such as Normalized Difference Vegetation Index (NDVI), Hue, Intensity, Saturation (HIS) and Principle Component Analysis (PCA), were performed. Different band sets based on original and derivative images were investigated for segmentation and classification.

## 2.4. Segmentation

The segmentation approach is a bottom-up merging process based on heterogeneity of image objects and controlled by three parameters: *color/shape*, *compactness/smoothness* and *scale parameter* (Benz et al. 2004).

For most cases the *color* parameter is the most important one for creating meaningful objects. It would be preferred using as much *color* criterion as possible while keeping the *shape* criterion as high as necessary to produce image objects of the best border. Using too much *shape* criterion can therefore reduce the quality of segmentation results (Definiens User Guide 2006).

The *shape* parameter is especially helpful in avoiding highly fractured image object results in strongly textured data. *Shape* is composed of two parameters: *compactness/smoothness*. It can contribute to maintain smooth edges or a more or less compact form (Batz & Schape 1999). But in forests, mixed tree crowns, height differences, existence of shadow and considerable mixture of stand may cause irregular tree crown shapes and consequently crown of a special tree species could be seen in various and non-compact shapes. Thus, *shape* was not considered to be an important factor, while *smoothness* was assigned more weight than *compactness* (Table 1).

The *scale parameter* determines the maximum allowed heterogeneity for the resulting image objects. By modifying the *scale parameter* value, the size of image objects will be varied. It is important to produce image objects of the biggest possible scale which still distinguish different image regions (as large as possible and as fine as necessary) (Definiens User Guide 2006). The initial *scale parameter* setting was determined by visual inspection to ensure that the segments were not so large to encompass multiple trees and potentially mix different species.

Considering the abovementioned strategies and according to the results of similar researches, various alternatives of segmentation were tried using Definiens Professional 5 software (Yu et al. 2006; Voss & Sugumaran 2008; Ozdemir et al. 2008; Delaplace et al. 2010). Comparison of manually delineated tree polygons and segmentation results, led to the finest parameters that are shown in Table 1.

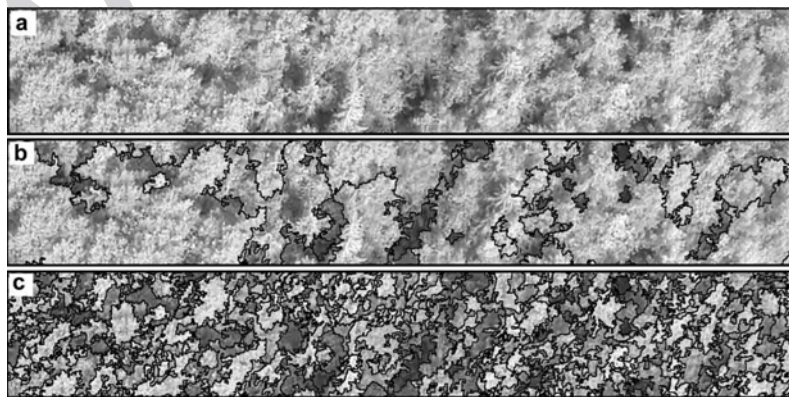
**Table 1.** considered parameters in segmentation process in both study areas.

Study Area	Color	Shape	Compactness	Smoothness	Scale Parameter
1	0.8	0.2	0.1	0.9	800
2	0.9	0.1	0.1	0.9	600

To construct the hierarchical image object network for Area1, the primary level was created using scale parameter of 800. After preliminary classification, objects were merged by classification-based segmentation and the result (*Forest Category Level*) was re-imported into Definiens as a

thematic layer. The sublevel was then segmented only within the area of interest (*Tree Species Level*) (Fig. 2).

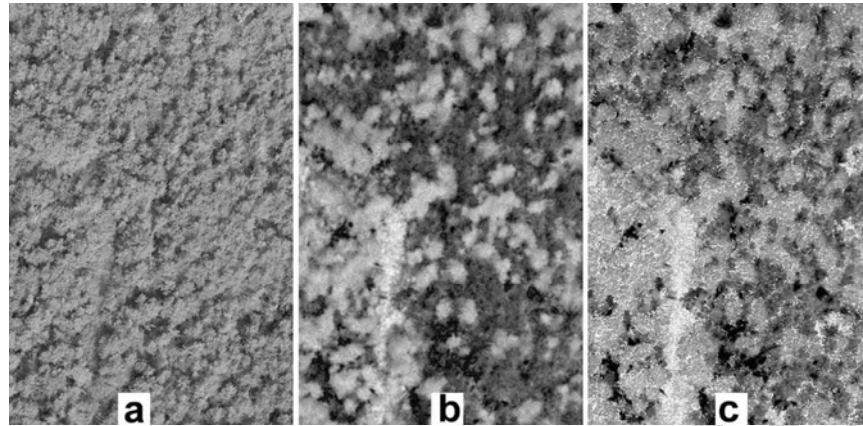
High diversity and considerable mixture in Area2 led to performing just one level of segmentation using a smaller *scale parameter* compared to Area1.



**Fig 2.** The results of segmentation in part of Area1: (a) The original image, (b) result of segmentation at *Forest Category Level*, (c) result of segmentation at *Tree Species Level*.

In addition to original spectral bands, NDVI and Saturation bands which are especially advantageous in distinguishing broadleaves

and conifers were considered as input data in segmentation process (Fig. 3).



**Fig 3.** Transformed images in comparison with (a) the original one in Area1. Difference between broadleaves (brighter objects) and conifers (darker objects) can be seen in Saturation (b) and NDVI (c) images.

### 2.5. Class Definition

As mentioned earlier, a class hierarchy based on the two level hierarchical image object network was established in Area1. The class hierarchy distinguishes between passing down class descriptions (from parent class to their child classes) in the *Inheritance hierarchy*. The super-object level was used to separate *Forest Categories* as parent class, consisting of *Hardwood*, *Softwood* and *Deep shade*. The sub-object level was utilized to distinguish dominant tree species (child class) including *QU*, *RU*, *PI*, and *CU* which also recognized *Dead trees*.

Exposure to the direct sunlight may cause portion of a tree crown to appear lighter (i.e. *QU in full sun*), while being under higher canopy shadow would cause a darker appearance in some parts (i.e. *QU in shadow*). Thus each of these child classes was defined in a distinct class. These two classes (i.e. *QU in full sun* and *QU in shadow*) were defined as the sub-class of that tree in group hierarchy (i.e. *QU*) (Fig. 4c).

Because of high diversity and considerable tree mixture in Area2, segmentation has been done there in just one level upon which applied classification was based. Defined classes in Area2 can be seen in Fig. 5c.

### 2.6. Classification

Object-based classification allows integration of a broad range of different object features such as spectral values,

shape or texture for classification utilizing not only image object attributes, but also the relationship between networked image objects. With the assignment of a class to an image object, relation to other classes formulated in the specific class description is transferred to the image objects. In the class hierarchy the classes can be grouped in a hierarchical manner allowing the passing down of class descriptions to child classes on the one hand, and meaningful semantic grouping of classes on the other (Definiense User Guide 2006).

Sample objects were selected as representatives of tree species classes. Samples for each class were selected from the image objects to act as training areas for the classification according to the field measurement results. The sample sizes were uneven by class. This situation is normal for vegetation classification since the size of the training samples is proportional to the abundance of vegetation on the landscape.

By examining different features and band sets, also revising of training areas, the optimum classification framework was determined. In order to obtain the best classification result, *Best classification results*, *Class stability* and *Accuracy assessment* functions, were considered based on training areas and reference data. For instance, *Class stability* calculates the difference between the best and the second

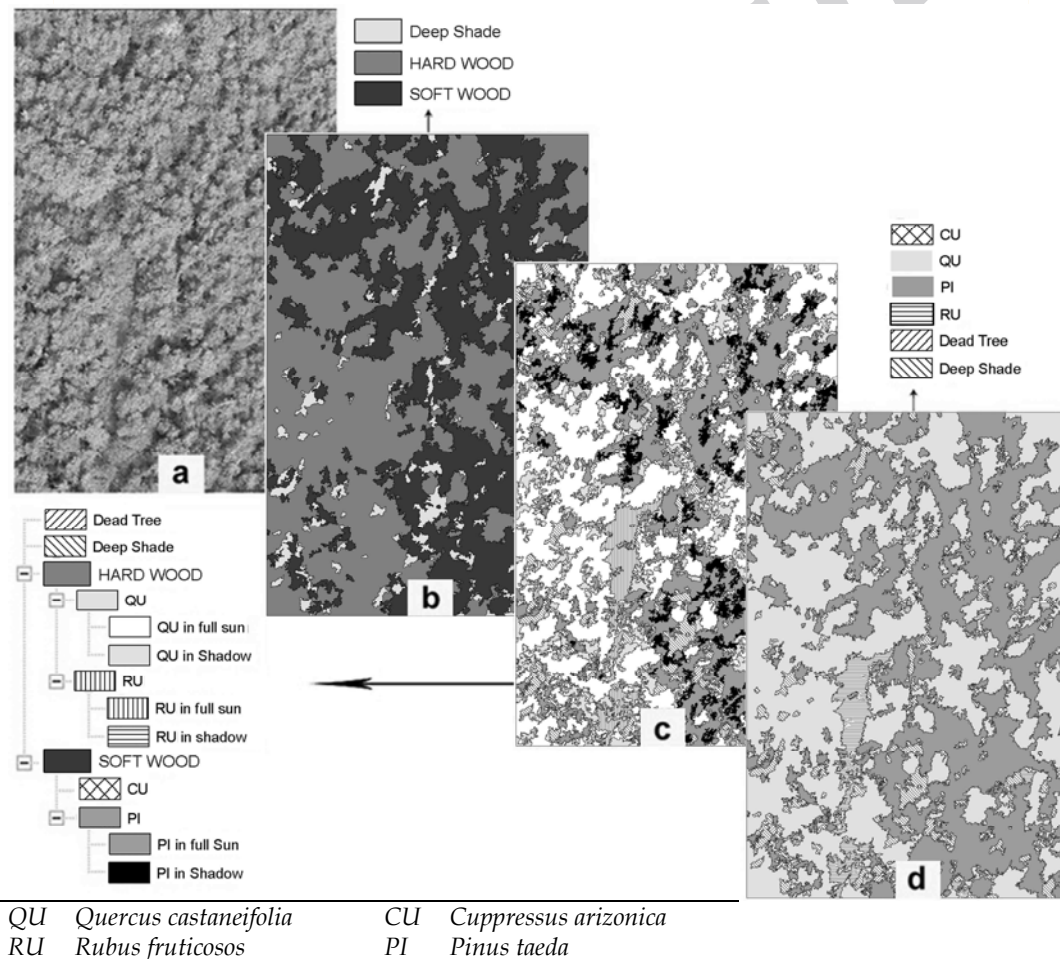
best class assignment for each object. The more the distance between these two values of assignment for a class, the more stability would be initiated.

In Area1, initially, Nearest Neighbor classifier was utilized to classify the image at *Forest Category Level* which contains *Softwood*, *Hardwood* and *Deep shade* classes (Fig. 4b). Aiming to classify broadleaves (*QU* and *RU*) as well as conifers (*CU* and *PI*) just in their own parent class's restricted area, *existence in related to super-object* was applied for each child class description as a condition. Furthermore, *Relative Border* and *Brightness* (as *class-related features*) were used to define the *PI in shadow* and *QU in shadow* classes in relation with *PI in fullsun* and *QU in fullsun*, respectively. Thus for

example for *PI in shadow* a specific joint border length with *PI in fullsun* and should be darker than it, were set as a condition. In order to produce the final map to be comparable with ground truth map, these two sub-classes were merged together and a map with 6 main classes was obtained (Fig. 4d).

The Nearest Neighbor classifier was used for classification in Area2 as well. Utilized class descriptions for both study areas, mostly included spectral features such as *mean*, *standard deviation*, *ratio*, *brightness* and *Max diff*.

Saturation, NDVI and PCA processed bands were utilized in addition to original bands (R,G,B,IR) in both study areas.



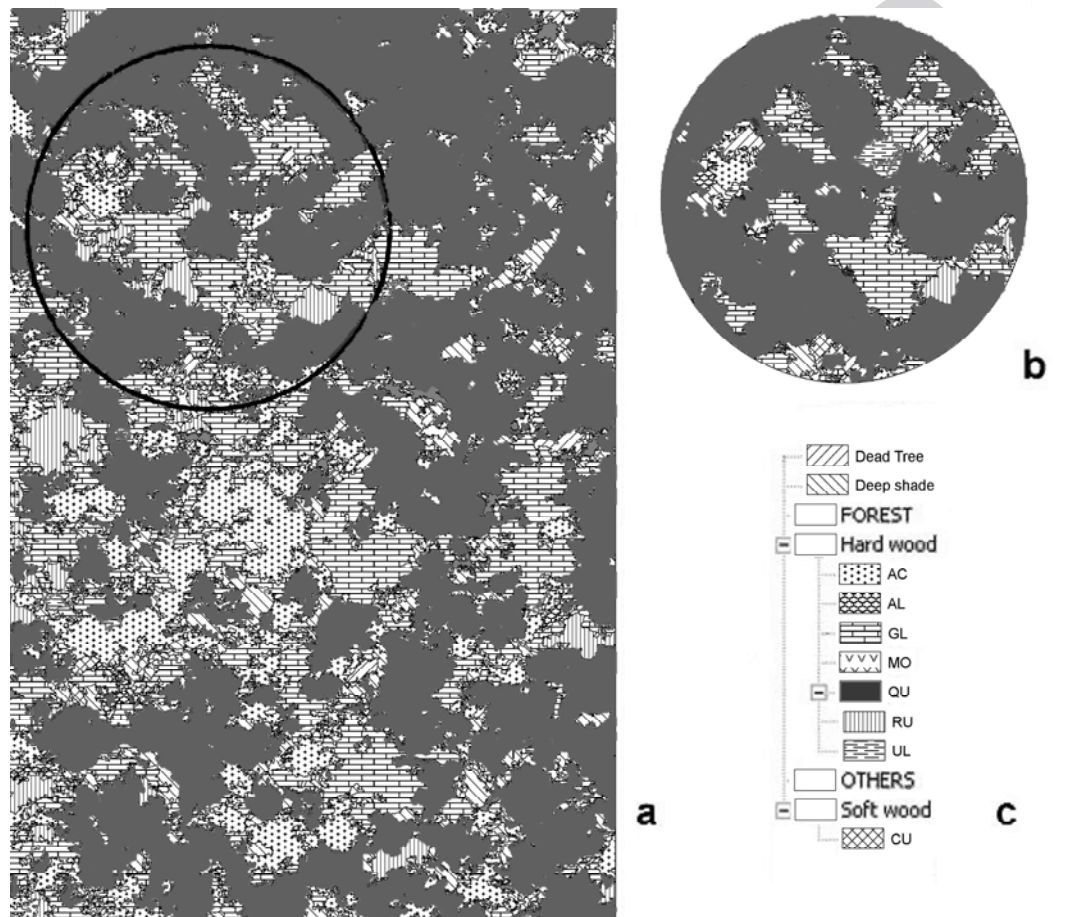
**Fig 4.** Classification stages and class hierarchy in Area1: (a) Original image, (b) classified map in *Forest Category Level*, (c) classified map in *Tree Species Level*, (d) Final tree species map after merging detailed classes.

## 2.7. Field Data Collection

To evaluate the accuracy, reference data within two circular plots (each about 2800 m<sup>2</sup> equaling 19 % of the study area), were acquired in the field. Existing images were used to design sample plots location and tree information was collected by the field survey.

Field measurement was done in October 2009. After finding plot center using GPS receiver and checking with the high-scale printed image of the mentioned plot, the DBH and tree species were recorded for all dominant and co-dominant trees, within a

radius of 30 m from the plot center. To geolocate the trees, distance and azimuth for each tree was measured using a laser distance-meter and a precise compass. Trees location point map in the plot was generated according these collected data. In the next stage, a large scale photomap (composed of trees location on the image) was produced and printed. Visiting the field for the second time, each tree crown area was precisely determined on the photomap and a tree species polygon map (crown projection map) was resulted (Fig. 5).



**Fig 5.** (a) Classification result, (b) Reference data plot, (c) Class hierarchy in Area2.

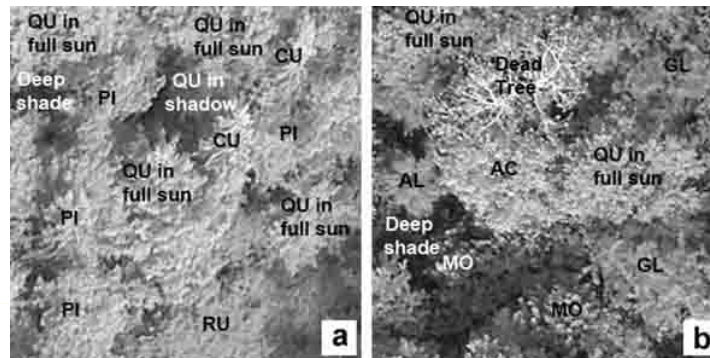
The classified image was compared with field reference data, generating an error matrix. This matrix was used to compute accuracy assessment statistics including Producer's accuracy, User's accuracy, Kappa Index of Agreement (KIA) and Overall accuracy (Congalton 1991; Lillesand & Kiefer 2000).

Coincident with gathering field data for preparing the reference map, adequate number of individual tree species with

proper distribution was selected in the area. The tree species were written down on a related tree crown on the printed image

map to be used as training areas (Fig. 6). These trees were all selected outside the

plots of reference data so that they would not interfere in final accuracy assessment.



AC	<i>Acer velutinum</i>	GL	<i>Gleditsia caspica</i>	QU	<i>Quercus castaneifolia</i>
AL	<i>Alnus glutinosa</i>	MO	<i>Morus alba</i>	RU	<i>Rubus fruticosos</i>
UL	<i>Ulmus carpiniifolia</i>	CU	<i>Cuppressus arizonica</i>	PI	<i>Pinus taeda</i>

**Fig 6.** The appearance of some main species on the image in a small part of Area1 (a) and Area2 (b), as a result of training area map produced via field work.

### 3. RESULTS AND DISCUSSION

#### 3.1. Results

Because of high diversity and complexity of the stand structure in Area2, a smaller scale parameter was applied to ensure that only one class had been allocated to each object. Consequently in this area many adjacent objects were similar and in classification process both would be fused and allocated to the mentioned class.

In Area1, an overall accuracy of 94% and a KIA of 0.89 were achieved for *Forest Category Level* (consisting of Hardwood, Softwood and deep shade), compared to ground truth map. This high accuracy rate made it possible for tree species to classify

just in their own parent class limits. The results of the accuracy assessment based on integrated child classes in Area1 are represented in Table 2. Since RU did not exist in the reference data, this class was not assessed. Accordingly, overall accuracy and KAI for separation of 5 main classes; *PI*, *CU*, *QU*, *Dead tree* and *Deep shade*, were determined to be 90.2% and 0.82, respectively. The lowest accuracy corresponded to *CU*, because there were no objects in reference data, allocated to *CU*. Also *Dead tree* class was interfered with *Deep shade* and *PI* classes and its separation was done with lower accuracy.

**Table 2.** Error matrix of classification accuracy assessment based on final classes (integrated child classes) in Area1.

User\Reference	CU	Deep Shade	Dead Tree	QU	PI	Sum
CU	0	0	0	0	4296	4296
Deep Shade	0	22401	0	735	3451	26587
Dead Tree	0	0	682	0	505	1187
QU	0	474	0	224614	24609	249697
PI	4789	693	4813	3400	274215	287910
Unclassified	0	0	0	8670	0	8670
Sum	4789	23568	5495	237419	307076	578347
<b>Accuracy</b>						
Producer	0	0.9505	0.1241	0.946	0.893	
User	0	0.8426	0.5746	0.8995	0.9524	
<b>Totals</b>						
Overall Accuracy	<b>90.2%</b>					
KIA	<b>0.82</b>					

QU	<i>Quercus castaneifolia</i>	CU	<i>Cuppressus arizonica</i>	PI	<i>Pinus taeda</i>
KIA	<i>Kappa Index of Agreement</i>				



Accuracy assessment results in Area2 are represented in Table 3. As it can be seen, lower overall accuracy and KAI of about 69.8% and 0.49, respectively were achieved. *CU* and *UL* have the most notable classification errors in this area. In fact, the individual trees of these two species could not be distinguished in this classification framework and were classified wrongly as

other species. *MO*, *AL* and *Dead tree* classes also were wrongly classified as other species, as a result of being in limited numbers or individually distributed in the study area and plots. But *QU*, *AC*, *GL*, and *RU* were classified with relatively acceptable accuracy as they were dominant species with noticeable presence in the area.

**Table 3.** Error matrix of classification accuracy assessment based on final classes in Area2.

User/Reference	QU	GL	AC	CU	RU	Dead Tree	MO	AL	UL	Deep Shade	Sum
QU	278725	12567	7497	207	0	513	419	0	2586	805	303319
GL	56505	84882	1262	694	869	2447	4298	0	4799	7421	163177
AC	17342	16386	11346	537	0	1140	0	0	0	291	47042
CU	0	0	186	0	0	3515	0	0	0	664	4385
RU	17731	1519	0	0	7680	132	0	1200	0	3761	32023
Dead Tree	39	0	0	1763	0	1563	0	0	0	556	4721
MO	50	0	0	0	0	0	1056	0	0	0	1106
AL	0	0	275	0	0	0	0	805	0	0	1080
UL	0	135	0	0	0	0	0	0	0	0	135
Deep Shade	1669	0	0	0	0	0	0	0	0	17833	19502
Unclassified	147	4	0	0	0	2346	0	0	0	103	2600
Sum	372208	116493	20566	3201	8549	12056	5773	2005	7395	31854	580100
<b>Accuracy</b>											
Producer	0.7488	0.735	0.5517	0	0.8984	0.1628	0.1829	0.4015	0	0.5598	
User	0.9189	0.5202	0.2412	0	0.2398	0.4158	0.9548	0.7454	0	0.9144	
<b>Totals</b>											
Overall Accuracy	<b>69.8%</b>										
KIA	<b>0.49</b>										
AC	<i>Acer velutinum</i>		GL	<i>Gleditsia caspica</i>		QU	<i>Quercus castaneifolia</i>				
AL	<i>Alnus glutinosa</i>		MO	<i>Morus alba</i>		RU	<i>Rubus fruticosos</i>				
UL	<i>Ulmus carpinifolia</i>		CU	<i>Cupressus arizonica</i>		KIA	<i>Kappa Index of Agreement</i>				

### 3.2. DISCUSSION

Aero-triangulation with digital camera imagery has become highly automated. A well-planned GPS mission and block layout are crucial enabling factors for this automation. But in the areas such as dense tree cover, it might have to be measured manually with looser restrictions on maximum image residuals. Ground control can be reduced to datum definition in the corners and at the center of the block (Loeberbach & Thurgood 2008). Segmentation-based classification can only be as good as the underlying segmentation. Inaccuracies encountered here cannot be corrected at a later stage. Segmentation could be evaluated geometrically (i.e. accurate position of segment outline) and semantically (i.e. the membership of one and only one class) (Yu et al. 2006). Methods for the evaluation of segmentation results are discussed for example by Levine and Nazif (1985), Hoover (1996) and Zhang (1996). However, it has been noted that presently the most reliable evaluation method is still a visual interpretation that

has to consider the exact geometrical position of the segment borders as well as the membership of one and only one object class to a single region (Batz and Schape 1999; Schiewe 2002). In this case, the separation of different regions is more important than the scale of image objects. (Definiens User Guide 2006).

Constructing object hierarchy network would be effectively helpful in distinguishing different phenomena establishing the group and inheritance hierarchy would let image interpreter to classify detailed classes (child class) just in the main classes boundary (parent class). For instance; there is no probability to allocate an object in Hardwood parent class to *Pinus teada* (*PI*) even if it is similar to *PI*.

Tree crown spectral and shape values are highly variable due to age, height, textures, shadows, and canopy gaps present in high-resolution airborne images. Therefore, the shape of the objects has no obvious pattern and texture that could be used as evidence for classification (Yu et al. 2006; Hirschmugl et al. 2007)

A general rule in Definiens Professional 5 software is that membership functions are appropriate if a class is relatively easy to separate from another and can be described with one or a few rules. Nearest-neighbor classification is more appropriate when classes are more difficult to separate from each other, because this approach is better suited for evaluating correlation between object features and for describing a multidimensional feature space (Definiens 2006). In the meanwhile, this software provides a fuzzy realization of the nearest-neighbor classification, which generates multidimensional membership functions. Thus, in the complex environments like forests using nearest-neighbor classification is logical.

One of the key reasons for the lower accuracy in Area2 can be attributed to high diversity and heterogeneous mixture of species. The relationship between the number of classes and overall accuracy showed that with increased complexity, classification accuracy will suffer (Voss & Sugumaran 2008).

Obviously if the field surveying date for preparation of the reference map is as much as possible close to the imagery date and minor changes are occurred in this duration of time, the result of accuracy assessment will be more reliable. In this case study, field measurement has been done just one year after imagery date in the same season and some probable annual changes in trees crown such as leaves color alteration in fall could have been considered in their appearance in the images.

### 3.3. CONCLUSIONS AND OUTLOOK

Digital frame camera imagery allows for a completely digital workflow and has clear advantages over film in terms of geometric accuracy and stability as well as radiometric and spectral resolution (Loeberbach & Thurgood 2008). High radiometric resolution (12-bit) captures more detailed information especially in the forest with different levels of shadows.

As important as it is to determine which bands are most useful for improving accuracy, it is also important to determine which bands decrease accuracy and should be removed from segmentation or classification process (Voss & Sugumaran 2008).

In addition to abundant different object feature mentioned in section 2.6, there is a variety of helpful facilities in object-based classification method such as easily utilizing ancillary data and using fuzzy classification method. But in order to find out which features composition, in which classification method, by which imagery or thematic data and at which weighting rate the best classification result can be accessible, it would be necessary to have better knowledge and proficiency on utilized data and used methods.

As shown in several previous studies, the standalone optical remote sensing methods are insufficient for classification of complex forest structures. This is particularly true for young successional stages and heterogeneous mature stands. More detailed and accurate mapping of tree species would be fulfilled applying precise 3D data, which are normally derived from LiDAR (Naesset & Gobakken 2005; Baltsavias et al. 2007; Hirschmugl et al. 2007; Chang et al. 2008; Voss & Sugumaran 2008). But these kinds of data have not been yet produced particularly in the forests of Iran.

The accuracy of detailed forest classification using very high-resolution imagery is highly dependent on the segmentation quality, sample size, sampling quality, classification framework, and forest structure and mixture (Yu et al. 2006; Rafieyan et al. 2009). A satisfactory level of accuracy in this study has been obtained in an even-aged one-story plantation stand. To reach such high levels of accuracy in northern natural forests of Iran, where several species coexist in a stand with interlaced crowns requires more investigations.

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## طبقه‌بندی شی‌پایه تصاویر UltraCamD برای تشخیص گونه‌های درختی در جنگلکاری آمیخته

ا. رفیعیان، ع.ا. درویش‌صفت، س. بابایی کفاکی و ا. مناجی

### چکیده:

تحقیق حاضر به منظور ارزیابی تصاویر رقومی هوایی با توان تفکیک مکانی بالا برای تشخیص گونه‌های درختی به روش نیمه خودکار انجام شد. برای بهره‌گیری از تمام مزایای این تصاویر، از طبقه‌بندی شی‌پایه در یک محدوده جنگلکاری آمیخته استفاده شد. دو پنجره از یک فریم تصویر UltraCamD به روش مثلث‌بندی هوایی تصحیح هندسی شده و تبدیل‌های طیفی مناسب بر روی آن اعمال گردید. قطعه‌بندی در دو سطح انجام و منجر به ایجاد شبکه سلسله‌مراتبی قطعات شد. در مرحله بعد، سلسله‌مراتب طبقات ایجاد شده و طبقه‌بندی‌کننده نزدیک‌ترین همسایه با استفاده از ترکیب توصیف‌گرهای مختلف، به کار گرفته شد. نمونه‌های تعلیمی و نقشه واقعیت زمینی به روش میدانی تهیه شد. ارزیابی صحت نقشه‌های حاصل در مقایسه با داده‌های مینا، نشان دهنده صحت کلی و ضریب کاپا به ترتیب برابر با  $90.2\%$  و  $82.0\%$  (در منطقه ۱) و  $69.8\%$  و  $49.0\%$  (در منطقه ۲) بود. تصاویر تبدیلی موجب بهبود نتایج طبقه‌بندی شدند. کسب صحت پایین‌تر در منطقه ۲ مربوط به تنوع بالا و آمیختگی شدید گونه‌ها در این منطقه می‌باشد. نقشه‌هایی با جزئیات و صحیح‌تر، با بهره‌گیری از داده‌های ارتفاعی دقیق قابل دستیابی خواهند بود. میزان صحت نقشه‌های بزرگ‌مقیاس پوشش گیاهی حاصل از طبقه‌بندی شی‌پایه تصاویر با توان تفکیک مکانی بالا، به کیفیت قطعه‌بندی، اندازه نمونه‌ها، چارچوب طبقه‌بندی و آمیختگی و پراکنش پوشش گیاهی بستگی دارد.