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Research Article

Vegetation mapping through using satellite images of WorldView 2- A case study of Haft Barm, Shiraz

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Abstract

Land cover maps are regarded one of the main inputs for land use planning and environmental modeling. One of the main reasons of unsuitable spatial array of the urban areas can be related to the rural communities' emigration, which in turn cause complete degradation of the farmlands and rural structures. Such event can be regards as a factor which is responsible for demolishing of the Haft Barm area an important recreational and touristic areas in the vicinity of Shiraz metropolis.

Therefore, recognizing the natural conditions of the area, preparing resource maps like land use and land cover, and monitoring their changes during the time is critical issue in the environmental planning and management. To this aim, WorldView 2 images with eight bands were used and mentioned maps were produced. The mapping analysis way was relied on an object-based classification methodology and using a decision tree which was applied in the WorldView 2 images categorization. The process shall be as the following: a) segmentation, b) terrain selecting, c) creating a decision tree for images' classification, and d) ultimate classification and evaluation of the accuracy. The area was divided into 10 user classes. The results indicated successful classes categorization with overall accuracy of 87.45%. The highest accuracy of classification was obtained for water, forest, product, building classes respectively. Planted forests patches as well as natural forests were identified and classified using OBC approach (object-based method) while additional coastal bands were used to distinguishing among barren and covered lands. Distance to tree and shadow play an important role in identifying buildings.

Keywords: Fars province, land use categorization, remote sensing, OBC methodology, WorldView2 images.

Introduction

Given the recent uncontrolled expansion of urban areas and obligation for environmental protection, mapping and monitoring changes trend is essential environmental planning. One of the most basic data in the land use planning and assessment rely on the land cover classified maps which can be easily extracted from remote sensing data. Urban green spaces have multiple advantages including cleaning the air, reducing the noise pollution, preventing soil erosion, water absorption, wind breaking and creating favorite microclimate. Classification and extraction of structural data like single trees using remote sensing data has frequently used in different studies. For example, detailed information at the level of individual trees can be used to monitor trees, reduce the fieldwork required for inventory and evaluate damage to the urban forests. Providing accurate and reliable information of different tree species is critical for studying vegetation in the urban space. This information can be used by environmental planners and researchers in urban planning and management. Based on literature review, no documented investigations have been done based on WV-2 produced maps in Iran so far, while in other countries, extensive research has been done with high-resolution images.

Carvalhoa *et al*. (2012) prepared a map of urban trees in Rio de Janeiro, Brazil, with satellite images of WV-2, OBC and decision trees. The accuracy of OBC in this study was reported 83%.

Chávez and Clevers (2012) identified the automatic identification of forest trees and evaluated their health conditions in Chile using WV-2 and OBC images. The results showed the suitability of red-edge band (705-745 nm) for diagnosis of disease, health evaluation and plants classification. Veric *et al*. (2014) identified the tree species with WV-2 images in Slovenian forests using OBC method. The accuracy of classification was calculated 58%. Whiteside and Bartolo (2014) provided Australian vegetation maps using WV-2 images. They were categorized using OBC with accuracy estimated as 78%.

Shojanoori *et al*. (2016) classified the forest trees in Malaysia with WV-2 images using OBC, base pixel, and support vector machine (SVM). The accuracy of OBC method was reported 88.07%.

By launching WorldView-2 (WV-2) high-resolution satellite with remote sensing, sensitive data became available to eight-band spectrum from blue to infrared near the electromagnetic spectrum. The satellite has additional bands, coastal blue (400-450 nm), yellow (585-625 nm), red edge (705-745 nm) and near-2 infrared (1040-860 nm) which can increase classification accuracy up to more than 30%. The newly released 8-band sensor images of WorldView-2 (WV-2) is an affordable image. The combination of 8-band spectroscopy and a very high resolution of 0.5 meters have been developed for the first time, presenting new opportunities for applications in the classification of urban land cover.

The purpose of this study was to examine the potential application of Worldview-2 satellite imagery for land use classification using OBC in the forested areas in the vicinity of Shiraz.

Material and methods

Study area

Haft Barm lake complex is located in the latitude from 51° 30" to 52° eastern and longitude from 29° 30' to 30° north in Fars province and at an altitude of 2150 m above sea level. These lakes are located in 55 kilometers from west of Shiraz and northeast of the Arjan and Parishan nature reserves. The lakes have spectacular views of the hills and wetlands. Different plant covers, such as forests and rangelands, form the vegetation cover. Dense oak trees are the main constitute of the forest species composition. The catchment cover an area of 16.9 km^2 with a cold and semi-desert climate where receive annual precipitation of around 1010 mm. The study area is located in an ecotone zone , which is the collision of three climatic region including the southern tropical and warm region, southeastern dry region, and the northwest cold and semi-humid area. The study was conducted in two different sites of the Haft Barm with an area of 100 square kilometers (Figure 1).

Different birds were reported from the study area including *Marmaronetta angustirostris*, *Tringa totanus* which are probably breed in the study area. Some species use the study area as wintering areas like *Tadorna ferruginea*, *Fulica atra*; *Anas strepera* and *A. penelope*. BirdLife (Birdlife International 2018)

Different plant communities from forest, pasture and bare lands can be seen in the study area.The main plant species in this region are *Quercus* sp. (oaks), *Pistacia mutica* (wild pistachio), *Crategus* sp. and *Pyrus* sp. Oaks are the most common plant species in the study area Most of species is oak involve Iranian oak (*Quercus. brantii*) which is prone to the epidemic charcoal disease which some cases was reported during of 1998-2014. This epidemic disease was spread throughout all Zagros Mountainous ridges that caused to degradation of more than one million hectare of oak covered areas. Most of the forests of Iran involve some kind of traditional ownership, either communal (by villages) or among rural families.

Procedure

Object-based image classification has been successfully used in high-resolution remote sensing imagery (Lucieer 2008, Mathieu 2007). In this study, the classification of hierarchical OBC is done at several levels. The image model encompasses a collection of objects range from broad-scale vegetation cover to single, smaller-scale buildings. For most urban remote sensing applications, and for many users who use high-resolution data, OBC image analysis can be regarded as a cost effective approach. The object-based image classification consists of three main steps: 1) determining the proper segmentation parameters; 2) selecting the feature for categorization based on objects and 3) creating a set of rules of classification or using classification algorithms. Therefore, this study examines the importance of additional WV-2 bands in the classification of urban land cover, where different classification steps of OBC were carried out.

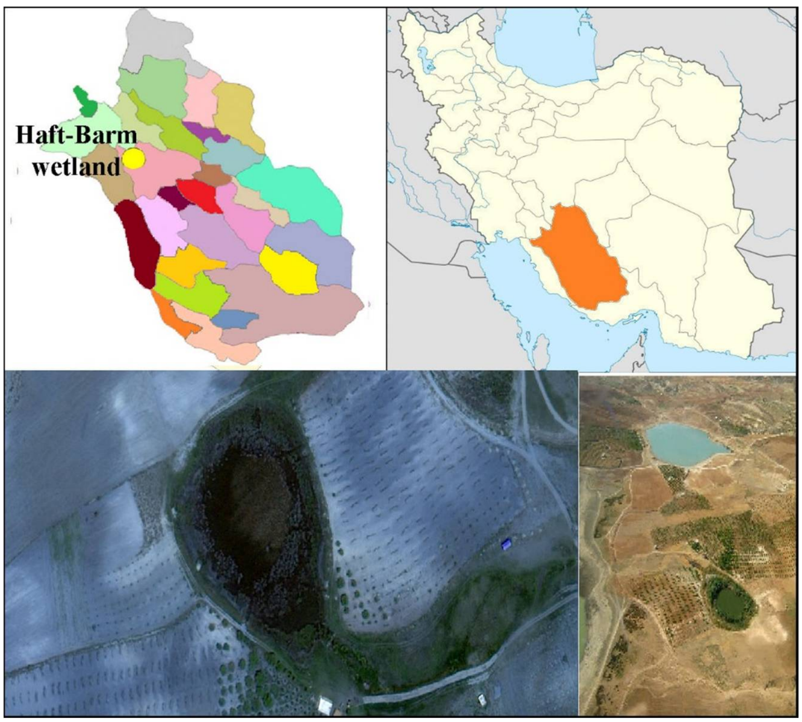

Figure1. Haft-Barm wetland study area

Data processing

Worldview 2 satellite images were downloaded directly from the Digital Globe Corporation on June 11, 2015, with a resolution of 1.8 meters, and panchromatic bands (spatial resolution of 0.5 meters). The images were in two formats, with a resolution of 0.5 meters and a multi-resolution resolution of 2 meters with an area of 100 square kilometers. Initially, geometric corrections were made on the image with three-dimensional GPS tracking points taken from the study area. The main reason for selecting Worldview-2 images is its special features, such as high-capacity large scale (975,000 square kilometers per day), 1/1 day time interval, precision in black-and-white bands, 46 cm, and multifunctional 8-band images with a width of 164 kilometers, 184 centimeters. Thus, the satellite has both high spatial resolution and high-resolution terrain. Multi-spectral (MS) view of the WorldView 2 satellite were categorized in this study. WV2 MS images were created with eight geostationary bands, root-mean-square (RMS) error less than one pixel.

Multi-scale segmentation

The first and most important step in the classification of the image into individual image units is segmentation (Huang and NI 2008). Pieces rather than pixels are the basic units of processing in object-based analyses. OBC is a process that binds the cover lands to visual objects, and each of the image objects was assigned to the classes along with the degree of membership which is assigned to them. The segmentation is done based on scale, color, shape, and their composition with a smoothness or compression (Dragut *et al.* 2012). Multi-resolution segmentation algorithm relyed on fractal net evolution approach (FNEA) (Baatz and Schäpe 2000, Benz *et al.* 2004). The segmentation of the image in OBC can be usually affected by the three parameters including scale, color, and shape (Willhauck *et al.* 2000). The first parameter in the FNEA segmentation is the homogeneity of the object image (Figure 2). Increasing weight of softness leads to the better borders (black border), and addition of weight for compression leads to the optimization of object compression (red border) (Figure 3).

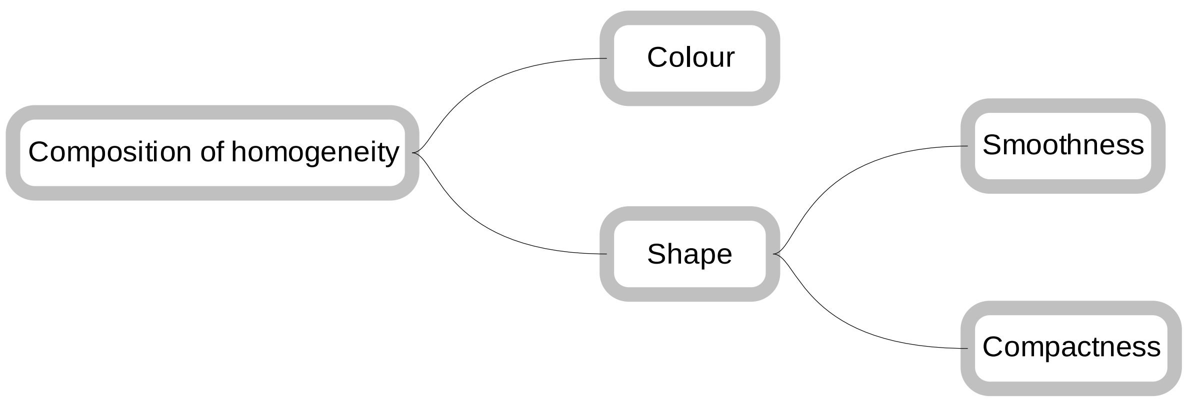

Figure 2. Four criteria that determine the homogeneity of the parameter during the image segmentation (Trimble 2012)

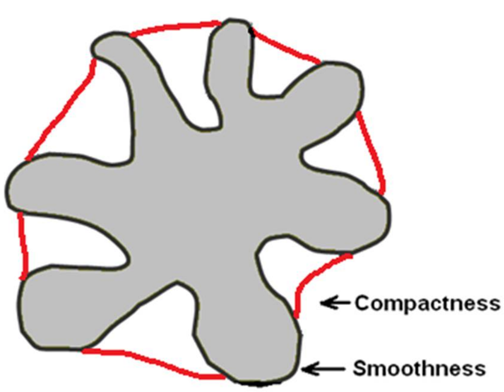

Figure 3. A weight diagram depicts the smoothness and compression criterion on the object boundary

WV2 images were segmented using multicast segmentation algorithm in eCognition software using 8 bands. According to trial and error analysis, two levels of the object layer were created based on the size of the parts in the vegetation classes. The following parameters were defined from the Multi-resolution segmentation algorithm: Object Layer 1: The weight of 1 assigned for the eight bands while the scale, color and compression parameters were 30, 0.8 and 0.7 respectively. Based on the described segmentation parameters, 162438 objects were created in the surface layer 1. Level 1 was a layer of suitable objects for buildings, roads, single stand trees, shadow and grass covered areas extraction based on the size of the objects in the study area. The level 2 objects layer was obtained from the this layer. By integrating objects of Level 1 with a scale parameter of 350 totally 931 objects were created on level 2. Layer 2 indicates areas suitable for producing forested areas, farmlands, and water bodies classes according to their object size. The segments obtained in this method were used in the analysis of subsequent selective terrains (Table 1).

Table 1. Weights applied for segmentation

Hierarchy	Scale parameter	Color factor	Shape factor	Compactness degree	Softness degree
Level 1	30	0.8	0.2	0.7	0.3
Level 2	350	0.8	0.2	0.7	0.3

Selection and extraction of the terrains

Terrains in question

The average spectral values curve of the employed terrains based on the samples taken in the WV-2 images is shown in Figure 4. Some of the normal differential indices can be extracted from the spectral value curve in different bands like the three main components based on the Principle component analysis (PCA). The employed spectral index information in this study, is presented in Table 2.

Certain special bare lands interfere with artificially constructed surfaces which may be resolved with class-related terrains. For example, the distance between a shadow case can be used to identify unclassified objects, or by identifying the shadow accurately and making them identifiable.

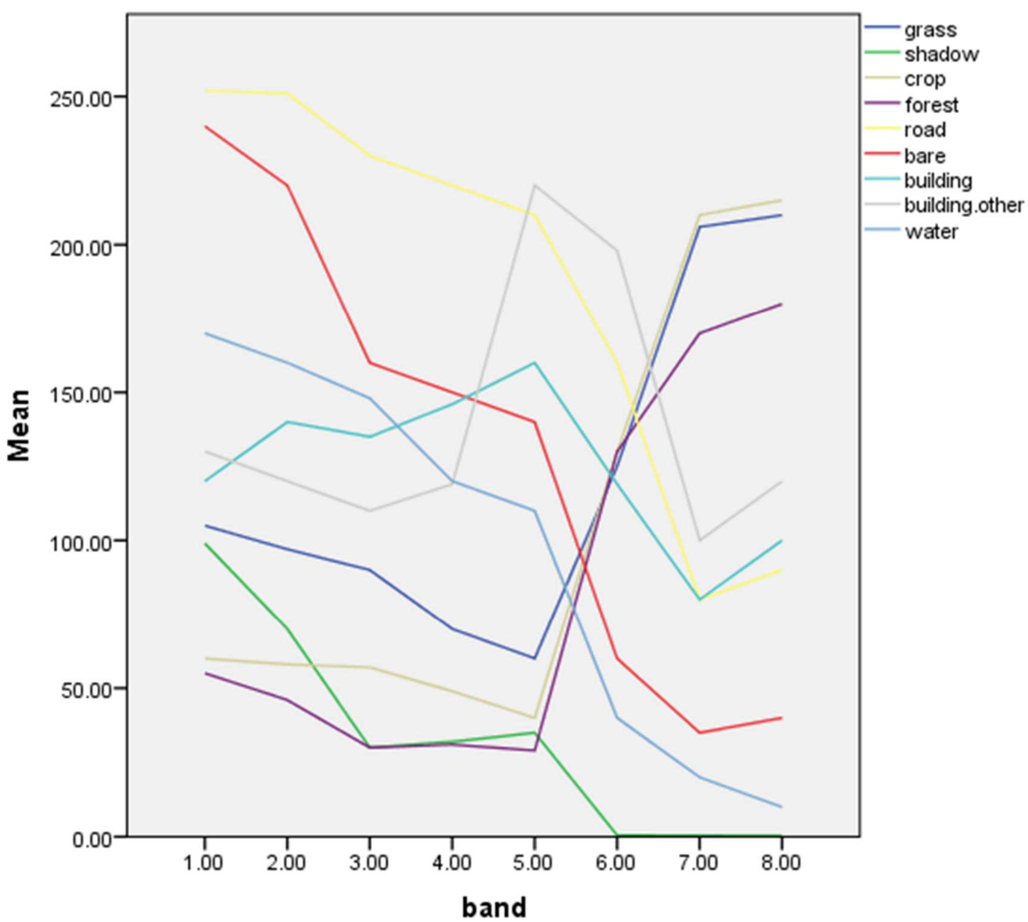

Fig.4. Spectral Curve resulted from sampling different land cover areas based on WV-2 image.

Table 2. Information on the spectral indices used in this study

index	Definition	Reference
NDBSI (normalized difference bare soil index)	NDBSI $= \dfrac{b2_{blue} - b1_{seashore}}{b2_{blue} + b1_{seashore}}$	Zhao *et al.* (2005)
NDWI (Normalized difference water index)	NDWI $= \dfrac{b3_{green} - b8_{Nir2}}{b3_{green} + b8_{Nir2}}$	McFeeters (1996)
NDVI (Normalized difference vegetation index)	NDVI$=\frac{R_{NIR}-R_{RED}}{R_{NIR}+R_{NIR}}$	Rouse *et al.* (1974)
FCI (Forest and Crop index)	FCI $= \dfrac{b7_{Nir1} - b6_{rededge}}{b7_{Nir1} + b6_{rededge}}$	Zhou *et al.* (2005)
NDBRI (Normalized difference Waterproofing roof index)	NDBRI $= \dfrac{b4_{yellow} - b3_{green}}{b4_{yellow} + b3_{green}}$	Zhou *et al.* (2012)
Ashburn Vegetation Index (AVI-2)	2× NIR2-R	Similar to DVI (Ashburn 1978)
Relative Vigor Index - RVI	RVI$=\frac{R_{NIR}}{R_{RED}}$	(Pearson1972)
DVI-Difference Vegetation Index	DVI=NIR-Red	(Everitt and Richordson 1992)
IPVI-Infrared Percentage Vegetation Index	IPVI$=\frac{NIR}{NIR+RED}$	(Crippen 1990)
Soil-Adjusted Vegetation Index (SAVI)	SAVI$=\frac{NIR-R}{NIR+R+L}(1+L)$	(Heute 1988)

Terrain selection

Determining the most appropriate features used in the different classification methods is not always easy, when conventional exploratory analysis is performed using the traditional methods (for example, spectral dispersion diagram, histogram, badge values given on gray levels, and so on). This is especially the case when hyperspectral images are used or when object-based image classification is performing. OBC method creates hundreds or even thousands of spatial and texture terrains that can be used in later stages. When using typical four-band images, such as QuickBird and IKONOS, the Definiens programmer correctly creates hundreds of spectral and texture features because WV-2 satellite has twofold as many sensors as different sensors. The available software package with the capability of accurate qualitative analysis of the symptoms needs a relatively long time for analyzing the terrain features (Van 2007). These problems justify using the selection algorithms and diminishing dimensions. Feature space optimization (FSO) tool was used to identify the optimal feature and recognizing different classes based on expressed patterns in the training data. FSO tool expresses the separation distance between the terrains, so that the user can use the training sample to provide a relative evaluation of the separation between the classes. Separation intervals are shown by the coefficients, usually reported on a scale of 0 to 1, where the relative coefficient indicated the ability of the nearest neighbor to separate the classes according to the selected features.

Object-based hierarchical classification

At level 2 of the hierarchical layer, there is a fundamental distinction between water bodies and arid lands, vegetation covered and bare lands, which was conducted on a large scale in this study. Subsequently, masked urban areas and impenetrable objects, mostly classified as buildings and roads. This multilevel object-based hierarchical masks continuously meaningless areas, thus significantly reduces the complexity of classification that will usually occurs in the subsequent level of details. However, the accuracy of classification at a relatively low level depends on the accuracy at a higher level because the error can be affected to the next level. Selecting a scale with appropriate accuracy and classification reduces such impacts. The hierarchical classification decision tree of the hierarchical object-oriented classification of urban land uses is presented in Figure 5.

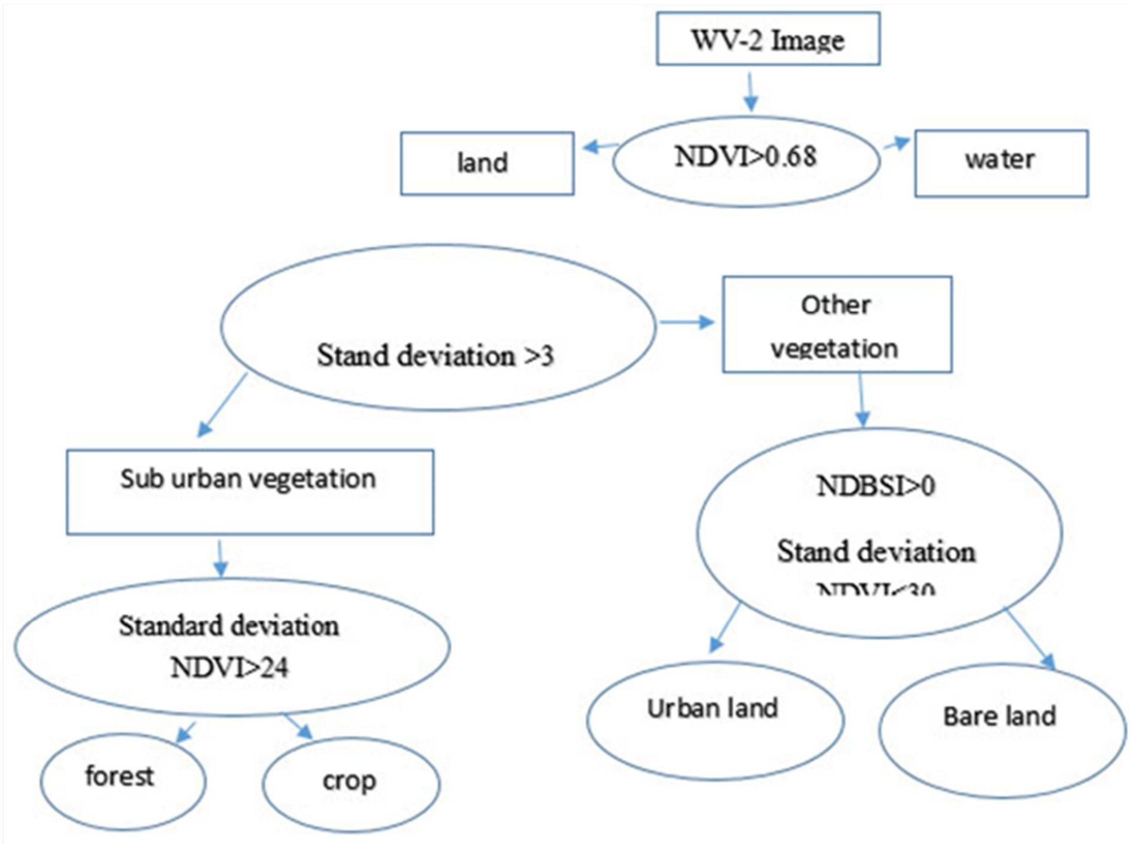

Figure 5. Decision tree classification of the base object

Level 2 of layer objects

NDWI was developed by McFeeters (1996) to distinguish between water bodies and landscapes. Subsequently, the threshold of the NDVI group and the standard deviation of band 1 separated the vegetation in the suburbs and its use. In addition, the forest problem is distinguished from the product by the standard deviation threshold of the NDVI. On the other hand, the NDBSI feature (Fig. 5) can separate urban levels and bare lands.

Level 2 of objects layer

Using surface layer, as a mask, this level focuses on the classification of objects in a smaller objects: the classification of urban landscapes to single trees, lawns covered areas and shadows, roads, buildings with waterproof roofs, and so on. Vegetation covered areas can be separated from non-vegetation areas in the urban landscapes by NDVI threshold. Thus, urban levels mask the level 1 layer. Second, trees canopy cover and grass covered areas in the urban landscape can be separated by combining FCI and standard deviation of NDVI. On the other hand, NDBRI can be employed to distinguish among the man-made structures from natural events. The shadow can be distinguished from a non-waterproofing

ceiling with a maximum difference of magnitude greater than 2 and using NDWI as well. The roads class also can be extracted from non-shadow areas by length and width of dimensions (Fig. 5).
After creating shadow, the distance of each class with this ground feature can be used to extract this class. Moreover, the distance between the classified features as well as distance to the insulated roofs can also be extracted. Hence, it is possible to construct other features like wasteland with the characteristics of the three top classes based on the non-road mask.

Accuracy assessment
Accuracy assessment is an important step that is necessary for classification performance evaluation and usefulness of the resulted outputs. It states the degree of classification correctness or its correspondence with real ground features. After generating confusion matrix, both user defined and producer accuracy as well as overall accuracy and Kappa coefficient were computed. Accuracy was evaluated in a way: the usual method using Kappa coefficient method.
After extracting the forested areas feature using object-method, the precision of the obtained results was evaluated. For this aim, 100 points were created randomly on the images, and the canopy boundary of the single trees was determined in these areas on the UAV (unmanned aerial vehicle) images (Fig. 6).

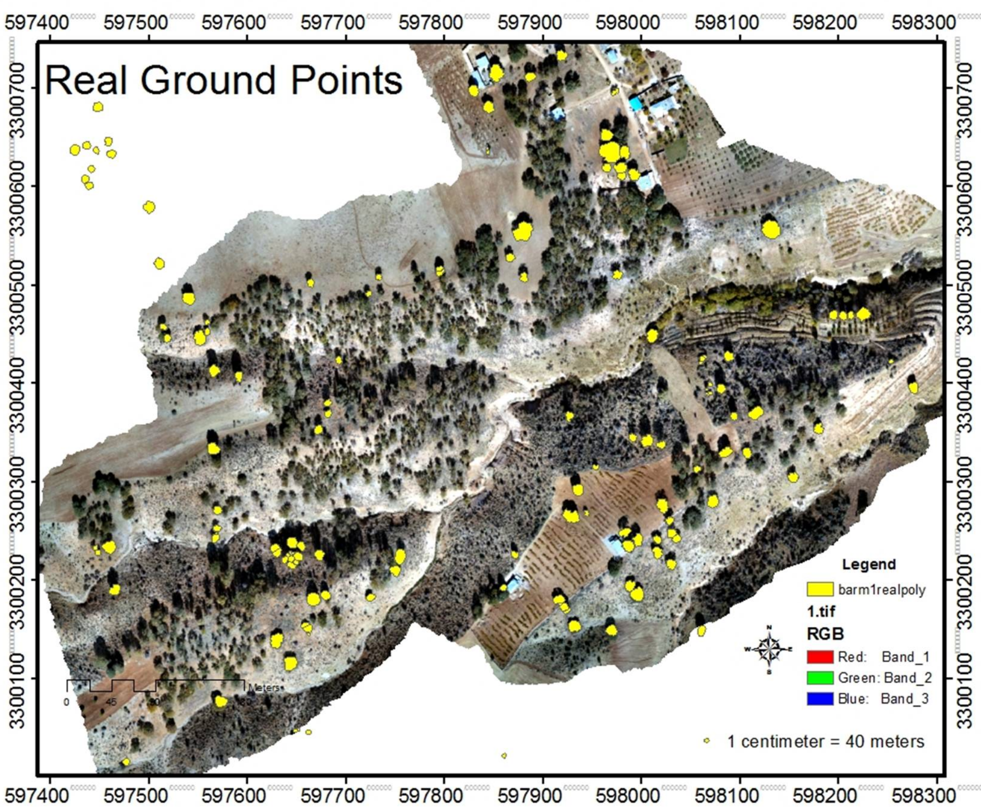

Figure 6. Canopy cover of 100 determined trees on UAV image for ground truth

Discussion and results

The spatial distribution of different land features classes can be seen in Figure 7. As the shadow is not the real land cover, the shadow was merged with road class.

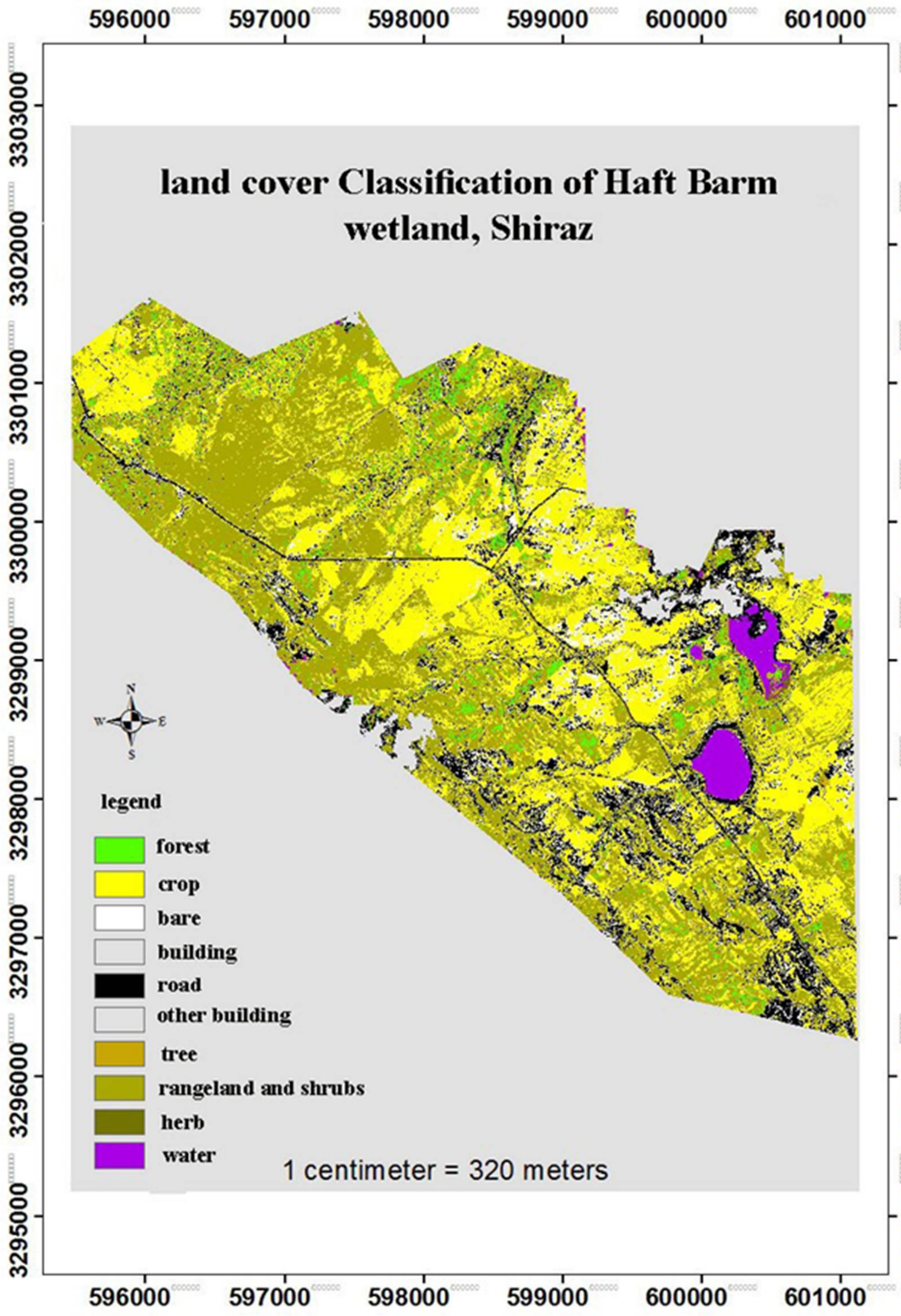

Figure 7. Land use classification

Validation of the accuracy is an important parameter for evaluating the performance of the classifier and the output efficiency, showing the accuracy of a map or classification compared with real-world features. Validation of accuracy in the form of user-defined statements of classification, overall accuracy and kappa coefficient are calculated after the creation of the complexity matrix. The classification resulted in a total of 9 land use and vegetation classes with the overall classification accuracy of 87.45%. The user-defined accuracy for the classification of five classes (water bodies, forested areas, grasslands, buildings with roof insulation and other buildings) was more than 85%, with the highest user defined accuracy for water bodies (100%) (Table 3).

Table 3. Accuracy of classification

Classes	User defined accuracy (%)	Producer accuracy (%)
Water expands	100	100
Forested areas	94.68	92.88
Croplands	78.36	87.20
Bare lands	46.25	94.87
man made with isolation roof	97.60	91.10
Roads	90.75	48.90
Others man-made structures	52.10	94.30
Single trees	93.80	85.10
Grasses	96.46	99.09
Overall classification accuracy		87.45
Overall Kohen Kappa statistics		0.849

The metropolitan area the suburban area can be effectively identified using different types of OBC techniques. Moreover, the coastal band is critical for distinguishing barren lands from farmlands. One the most important attributes associated with the class is the distance from a single tree or a shadow, which help distinguishing the man-made structures from certain land cover classes for instance, it is useful for detecting a vast water-rich land. NDWI index provides the best results for the detection of aqua and non-aqua objects as well as extracting vegetation cover effectively. The most important limitation of NDVI is its susceptibility to soil reflection (Sims and Gamon 2002). Soil line indices were used to reduce the effect of field soil (Waser *et al.* 2014). However, there is lower classification accuracy for roads, other buildings and grasslands as roads were classified only with 48.9% accuracy. This indicate that most of the road related objects cannot be extracted due to the length-width ratio. On the other hand, it shows that the segmentation result is not suitable for road extraction. Other buildings were classified with user accuracy of 52.1% that can be related to the preventing buildings from colliding with roads. Worldview-2 images have well-known potential for identifying the herbs, and in particular, the yellow band has a better performance. Image analysis may be particularly improved if the provided images are related to the first great rain at the end of the dry season. In particular, infrared and yellow 2 bands have high spectral separation capability. The grasslands were classified with 99.0% accuracy of the producer and 96.4% of the users' accuracy. This indicate that FCI index is clearly capable of detecting grass cover from other vegetation and can be regarded as a suitable index. The results of distinguished grasslands are consistent with the results of Marshall *et al.* (2012) in Australia which just was based on categorized MS bands . We found the greatest in the classification of shadows. Shadows can not clearly distinguished among living and nonliving induced ones. There is still a lot of potentials to identify other land use categories in the urban areas relying on the Worldview2 images, such as the farms or factories, as the panchromatic bands are merged with MS bands, the shadow may be much more distinguishable than high-resolution images.

Modeled with WorldView-2 multivariate data, the leaves of trees in the street and the forest park border are statistically selectable in band 6 (red edge), which is consistent with the results of Shushanik *et al.* (2013). In the mapping of plants cover in Mexico using object-based method produced more appropriate and reliable outputs than other algorithms (Gao *et al.* 2016). The object-based method is of great utility among scholars like Chubey *et al.* (2006), Desclee *et al.* (2006), Hay *et al.* (2005), Wuder *et al.* (2008), which applied OBC method widely in the forest investigations relying on remote sensing. Conchedda *et al.* (2007), Myint *et al.* (2008) and Wang *et al.* (2004) evaluated this approach as very successful in the forest single trees investigations.

In parametric statistical methods, the usual conditions such as normal distribution for spectral reflection or homogeneity of spectral dispersion are not consistent with remote sensing data (Quirós *et al.* 2009). NDBSI is very important for detecting dry barren lands.

Conclusion

In the present study, OBC approach was developed for mapping vegetation cover using high-resolution images. The results confirmed that the identification of plant categories can be done in details accurately relying on the OBC method. Periodic detection and updating phases of plant levels and checking drying out of pests is a remote sensing task. Spectral classes such as forested surfaces and single stand trees, impenetrable surfaces, and barren soil, water and shade can be detected more efficiently while additional bandwidths are employed from WV-2 sensor along OBC. The new feature is proposed as NDBSI based on Band 2 (Blue) and Band 1 (Coastal). The barren land surfaces can be also increased with NDBSI. The features associated with the classes, like distance to the single stand trees or shadow, are important to distinguish human structures from a particular class of land cover. For example, a water-rich land with high water content can be identified relying on this feature. The metropolitan and the suburban areas can be effectively identified with different OBC methods. In comparison to the visual method, OBC method has many advantages:

1) It requires little human intervention, except in very limited circumstances.

2) Its basic rules are important for the interpretation of the image and can be used with little effort to adapt to the new data set.

3) Output maps provide details of the dry forest surfaces distribution.

4) Identification of single trees for the strategy of forest integrity model.

By integrating pan-chromatic MS images, a high potential based on Worldview 2 images is created to identify other classes in the metropolitan area, such as a square from a factory building.

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