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Inventory of Single Oak Trees Using Object-Based Method on WorldView-2 Satellite Images and Earth

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Abstract

Remote sensing provides data types and useful resources for forest mapping. Today, one of the most commonly used application in forestry is the identification of single tree and tree species compassion using object-based analysis and classification of satellite or aerial images. Forest data, which is derived from remote sensing methods, mainly focuses on the mass i.e. parts of the forest that are largely homogeneous, in particular, interconnected) and plot-level data. Haft-Barm Lake is the case study which is located in Fars province, representing closed forest in which oak is the valuable species. High Resolution Satellite Imagery of WV-2 has been used in this study. In this study, A UAV equipped with a compact digital camera has been used calibrated and modified to record not only the visual but also the near infrared reflection (NIR) of possibly infested oaks. The present study evaluated the estimation of forest parameters by focusing on single tree extraction using Object-Based method of classification with a complex matrix evaluation and AUC method with the help of the 4th UAV phantom bird image in two distinct regions. The object-based classification has the highest and best accuracy in estimating single-tree parameters. Object-Based classification method is a useful method to identify Oak tree Zagros Mountains forest. This study confirms that using WV-2 data one can extract the parameters of single trees in the forest. An overall Kappa Index of Agreement (KIA) of 0.97 and 0.96 for each study site has been achieved. It is also concluded that while UAV has the potential to provide flexible and feasible solutions for forest mapping, some issues related to image quality still need to be addressed in order to improve the

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classification performance.

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1. Introduction

Forest inventory was traditionally a useful and accurate way of monitoring forest coverage, but updating cycle is relatively expensive Extra, if it's not direct quoting (Franklin, 2001; Zoèhrer, 1980; Gillis and Leckie, 1993). Wide range of forest can change rapidly, forest inventory traditionally Did not respond adequately to the development of change (Wulder et al., 2008). The climate warming and recent severe droughts have resulted in vegetation mortality in various woody biomasses across the globe (Allen et al., 2010; Breshears et al., 2005; Carnicer et al., 2011; Phillips et al., 2009; van Mantgem et al., 2009).

The separation of single trees and the extraction of tree-related structural data from remote sensing data has been a prominent application in a variety of activities e.g. detailed information on the level of individual trees can be used to monitor forest regeneration (Gougeon and Leckie, 1999; Clark et al., 2004a and 2004b). The reduction of fieldwork is required for surveying (Gong et al., 1999) and damage assessment to be used in the forest (Leckie et al., 1992; Levesque and King, 1999; Kelly et al., 2004).

Forest data, which is derived from remote sensing methods, mainly focuses on the mass (such as parts of the forest that are largely homogeneous, in particular, interconnected) and plot-level data. However, forest level variables are mainly average or aggregate of the combination of trees in the mass. In calculating forest variables such as volume and biomass of the growing population, model at single-tree level are mainly used today (Laasasenaho, 1982; Repola, 2009). Remote sensing data allows us to move from the surface of the mass to the level of single trees, which has a clear interest in precise forestry, forest management planning, biomass assessment and forest modeling (Koch et al., 2006).

The reasons for single-tree extraction from high-resolution satellite imagery are the importance of single trees and their maintenance such as the difficulty in single tree mapping in vulnerable areas, the need for quick access to quantitative characteristics estimation and the importance of remote sensing in statistics for single trees (spatial resolution and satellite data capability has been increasingly enhanced).

So far, no research has been done to estimate the single-tree feature on WV-2 images. In previous studies, the accuracy of estimating the crown area is made using field data, in which the crown shape of the trees is generally considered circular and the crown area is obtained from the mean diameter, provided that the trees, according to the possible vegetative conditions, has crowns with non-hinged shapes. Therefore, it is necessary to assess the accuracy of crown areas in satellite data using more reliable data such as UAV aerial imagery.

Today, remote sensing data provides accurate and reliable information of single-tree biophysical properties in forest lands. In addition, the object-based classification has a particular advantage over other classification methods for extracting crowns and identifying species in a variety of ecosystems. Few study has been done to examine the efficiency of the object-based, which is highly desirable for users.

Remote sensing is a useful tool for forest mapping as it provides data and resources. Today, one of the most commonly used applications in forestry is the identification of single trees and tree species comparison using object-based analysis and classification of satellite or aerial images. Sedliak et al. (2017) identified groups of trees (leaf-leaf needles) in individual structures of massive mixed grass, spruce, and pine forests in WV-2 images. The object-based classification with WV-2 multispectral images was done in eCognition software. The Lidar data has been used for the identification of single tree with overall high accuracy of 87.42 percent. The accuracy of needle calves had risen from 82.93 to 85.73 percent and broadband ranged from 84.79 to 90.16 percent.

Basic object classification method is a useful method to identify the wild plants in numerous habitats. Niphadkar et al. (2017) used WV-2 images to identify shrubs in the tropical forests. The object-based method separates the features with the help of spatial characteristics. As a result, there has been the possibility to isolate the shrub in a complex tropical forests environment, with a non-parametric classification algorithm.

The accuracy of the tree species map allows more detailed analyzes of forest biophysical variables. Raczko and Zagajewski (2017) compared the support vector algorithms, random forest and neural network for the tree species class on aerospace aerial imagery. The results showed that the ANN classification had the highest classification accuracy of (77%), and SVM with 68% and RF with 62% respectively.

Juniati and Arrofiqoh (2017) compared the base pixel and base object classification using parametric and nonparametric methods for pattern matching in Indonesian forests with WV-2 images. They concluded that classifying the base object the best results in segmentation and classification and has the best kappa coefficient, after which the neural network and the Maximum Likelihood Classifier were ranked in the mean of accuracy.

Wen et al. (2017) concluded that the method of classification of piece-based and object based on other methods in extracting urban trees in WV-2 images is superior. They used three levels of classification (pixel, object and piece) to classify trees. The results showed 85% overall accuracy for all methods. In addition, user and producer accuracy reaches over 80% for the tree floor. The method of classification of the base unit was placed in the first priority, then the classification of the object based and in the third stage of the base pixel for the Kappa coefficient.

Okojie (2017) paid for extraction of single tree crowns and evaluated forest structure parameters using airborne UAV images. Accuracy assessment was performed using the root mean square error method. As a result, the crown of the trees and the height of the trees were extracted. The results of the baseline image analysis showed that the segmentation accuracy is significantly related to the spatial resolution of the images, but the internal parameters of the segmentation algorithm should also be appropriate and calibrated.

Thanh and Kappas (2018) compared the random forest tree classifier, the nearest neighbor and vector of support for land use classification using Sentinel-2 multispectral images around the Red River Delta of Vietnam. The accuracy of all classifications was between 90% and 95%. Among these classifications, using different training samples ranging from 50 to 1250 pixels, SVM created a higher overall accuracy. After that, the random forests were ranged with the nearest neighbor.

Estimating forest structural parameters is expensive and time-consuming with ground-based data collection methods. Remote sensing data is a low cost option in modeling and mapping structural parameters in large forest areas.

2. Materials and Methods

2.1. Study Area

The Haft-Barm Lake is located in the geographical location of N294921 E520227 in Fars province. These lakes are located 55 kilometers to the west of Shiraz and northeast of the protected areas of Arjan and Parishan and 2150 meters above sea level. The lakes have beautiful panoramic views of the hillocks and wetlands. The weather in the region is cold and dry in the winter and temperate in the summer. The area has an almost cold and semi-desert climate and its catchment area is 16.9 km^2 and the average annual precipitation is 1010 mm. The various plant species forms the forest and pasture and the vegetation cover. Oak trees are the major forest species in the region that are densely covered by the area. Regarding the range of Arjan between the tropical region of southern Iran and the dry region of the south-east, the cold and semi-humid part of the northwest is an intermediate or ecotone region and very diverse in terms of plant species diversity. This study was conducted on two different sites in the Haft-Barm area of Shiraz. The area of the first site (Baleh Zar village) is 106 hectares, and the second site of the Abe Anar village is 150 hectares (Figure 1).

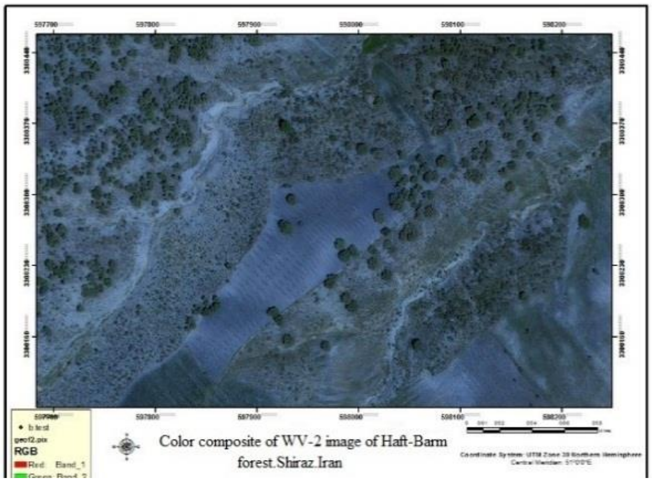

Figure 1. Study area location.

2.2. Data

The data used in this study included the image of the WorldView-2 satellite on May 21, 2015 with a resolution of 1.8 m, and panchromatic bands (spatial resolution of 0.5 m) and UAV aerial imagery with a resolution of 3 cm. Topographic maps of the survey organization with a scale of 1:25,000 and points taken by three-frequency GPS. Also, the SPSS25; Excel version 2016; eCognation v. 8.7; ENVI, 5; Erdas Imagine and Google Earth were used. The flowchart is shown in Figure 2.

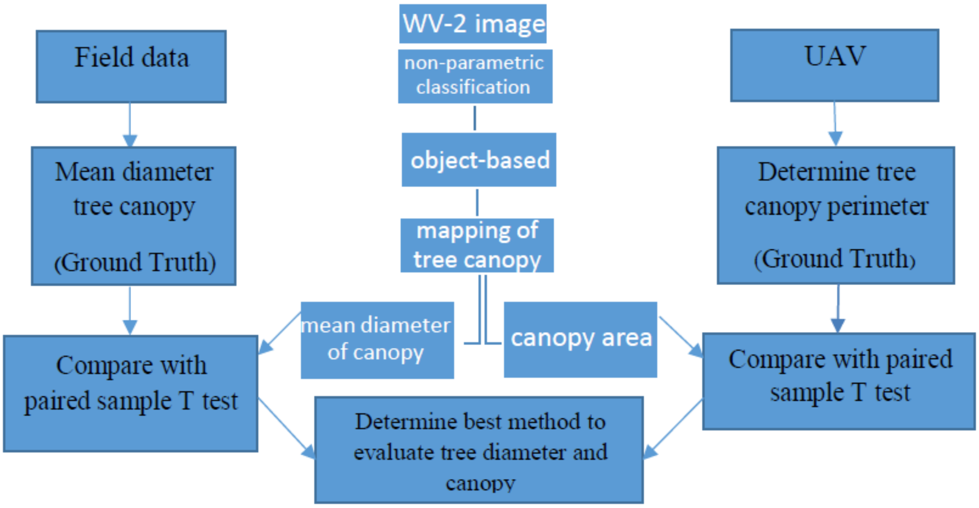

Figure 2. Flowchart of work levels

The Worldview-2 images were georeferenced using the 9-point of three-frequency GPS tracking RTK and static ground reference and the UTM image system was considered. The cloud computing points were taken from ArcGIS10.4 and PCI Geomatica16 software. with an accuracy, the average mean square root (RMSE) of 0.65 pixels was georeferenced using the equation of degree three (ST order polynomia3). Then, Pan sharpening images with a resolution of 0.5 m were created with a combination of polygonal and panchromatic quadrants (Table 1).

Table 1. Characteristics of sensor and four standard bands of WV-2

Wavelength nm	Bands of WorldView-2 sensor
450-800	panchromatic
450-510	blue
510-580	green
630-690	red
770-895	NIR1

In order to inventory the trees perimeter in the forest area, we took pictures of drone images from Phantom 4 Pro. The Phantom 4 Peru is equipped with a one-inch CMOS camera that can capture 20-megapixel quality (Dji, 2016) (Figure 3).

Figure 3. The commercial "ready-to-use" Micro-drones MD 4-200. Payload includes IMU, GPS receiver, downward pointing CIR-modified digital Canon IXUS 100 camera, radio downlink and microprocessor controlled flight control units

2.3. The Nearest neighbor classifier

Classifier of the nearest neighbor (Schowengerdt, 1997): Lists of nonparametric classifications of unknown pixels in accordance to the labels of the neighboring educational vectors in the image space include:

The best neighbor: Labels the nearest pixels surrounding the training pixel.

Nearest k: Assemblies are based on the majority of the training pixel tags near the neighbor k.

The nearest neighbor k is the weighted distance: assigns weights to the closest neighbor k, based on the label of the closest neighboring k instructional pixels, in the opposite proportion to the Euclidean distance of the unknown pixel, and assigns the label to the highest weight of the set.

2.4. Object Based Classification

Pixel Based analysis is usually simple and operates in a comprehensive and general way on the sensors. Although pixels are often not a favorite unit, Measuring is not possible without them. For example, the canopy of separate trees and gap between crowns involves several pixels and creates a spatial self-regulation within objects that we can easily detach in high-resolution images (Woodcock and Strahler, 1987). OBIA seems to search for a "mean" for objects. It searches for objects by segmenting the image into groups of pixels with similar characteristics based on spatial and spatial properties (Benz et al., 2004).

The purpose of the image segmentation is to extract the image objects in the best case according to the scale features, the weight of the inhomogeneity of softness and the compression weight that was performed in the software. These parameters were obtained with ESP and with test and error. Later, the obtained objects enter the classification methods. Multi-resolution segmentation was done by segmentation process. Using the approach of the nearest neighbor and identifying suitable training samples, the image was classified into two general forest and non-forest classes (Table 2).

Table 2. Weighting for segmentation

Hierarchy	Scale parameter	Color factor	Shape factor	Compactness degree	Softness degree
Level1	10	0.8	0.2	0.7	0.3
Level2	20	0.8	0.2	0.7	0.3

The most basic of the multi-resolution segmentation algorithms is the scale parameter. For the first time Dragut et al. (2010) based on local variations in the multi-scale segmentation algorithm at the time of segmentation and pixel integration used the ESP (Estimation of Scale Parameter), which is the extension of eCognition, and the most appropriate scale for determining the segmentation. If two pixels or the same object are merged, the rate of local variation will decrease, but if two pixels or non-sex objects are merged, the process of local variation changes will increase.

The graph represents the points where the ROC-LV has increased when the pieces were merged and new larger parts were created, which is an appropriate scale for image segmentation. The best scales for our image were 24, 26, 30, 34, 37, 31, 41, 45, 47, 49, 51, 54, 57, 60, 71, 75, 79, 88, and 94 (Figure 4).

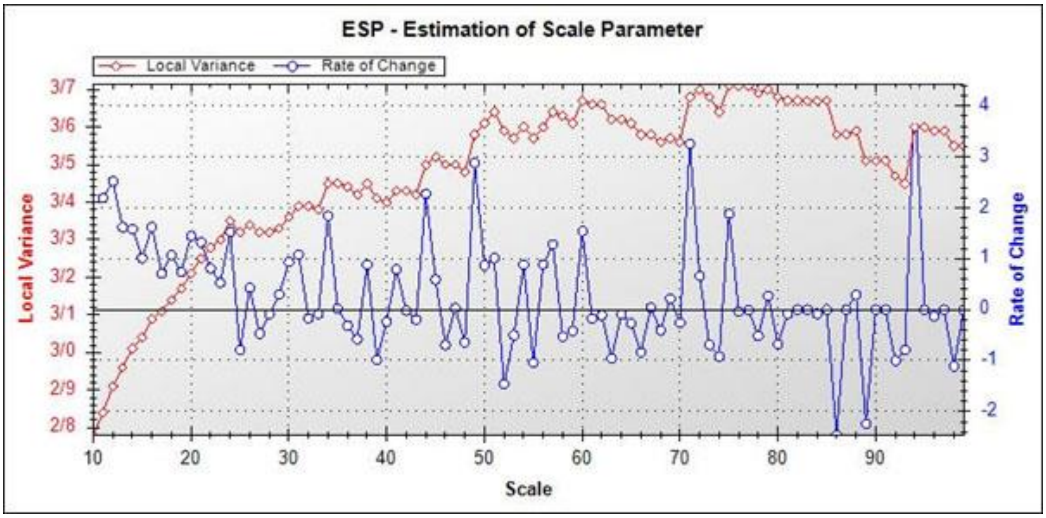

Figure 4. ROC-LV schematic

After selecting the training data, they were arranged in a thematic layer, the TTA mask layer, in the software to be used during the process. The same training data was used for different classification methods and Classification was performed in three ways.

After extracting the forest feature in the three methods, the results were assessed. For this, 100 points were created randomly on the images, and the canopy boundary of these trees was determined from UAV images (Figure 5).

Figure 5. Canopy of 100 determined trees on UAV image for Ground truth

2.5. Accuracy assessment

Accuracy assessment was done in two ways: the usual method, which used Kappa coefficient, and the second method was performed using the AUC method.

2.6. Sampling method for quantitative and qualitative forest characteristics

The study sampling method has been carried out in a systematic approach. A 200x200-meter rectangular grid was overlaid in the image of the region, with 40x40 m rectangular sample pieces discharged into the area. A total of 63 sample plots (36 plots of AbeAnar village and 27 villages of BalehZar village) were measured at each site. In each plot, the considered characteristics of the vegetation included: Recording the diameter of large and small trees, the diameter at breast height (DBH), the tree crown cover, and the health of the tree.

The estimated canopy cover area for BalehZar forest trees on WV-2 and UAV images, the sampling with 200 × 200 square meter network on the ground and satellite images of WV-2 was carried out. In the village of BalehZar 27 plots of 1600 square meters (40 × 40 m) were collected on site 1, and site 2 the village of AbeAnar with 33 plots. In each sample piece, the large and small diameters, the diameter of the breasts and then the crown cover area (equation 1) were measured. The quantitative statistics in the forests of the BalehZar village including the number of samples, mean, standard deviation and standard error in two methods of land cover and WV-2 depiction were presented in Table 1. The results of this study showed that, the sample area was calculated on the basis of equation 1. Then analysis of the canopy cover areas was carried out to the SPSS25 environment (Table 1).

$$\text{Covering the crown surface} = \pi / 4 \times \text{Medium crown diameter} \qquad (1)$$

3. Results and discussion

In Figure 6, the results were derived from three types of vector support vector, decision tree, and object-based. As you can see, the quality of the classifications is almost the same. But there are differences in accuracy. The accuracy assessment was done in two ways: the usual method of Kappa coefficient and AUC method. In the accuracy assessment tables, error matrix, overall accuracy, kappa coefficients, manufacturer accuracy, and user precision of each method is presented.

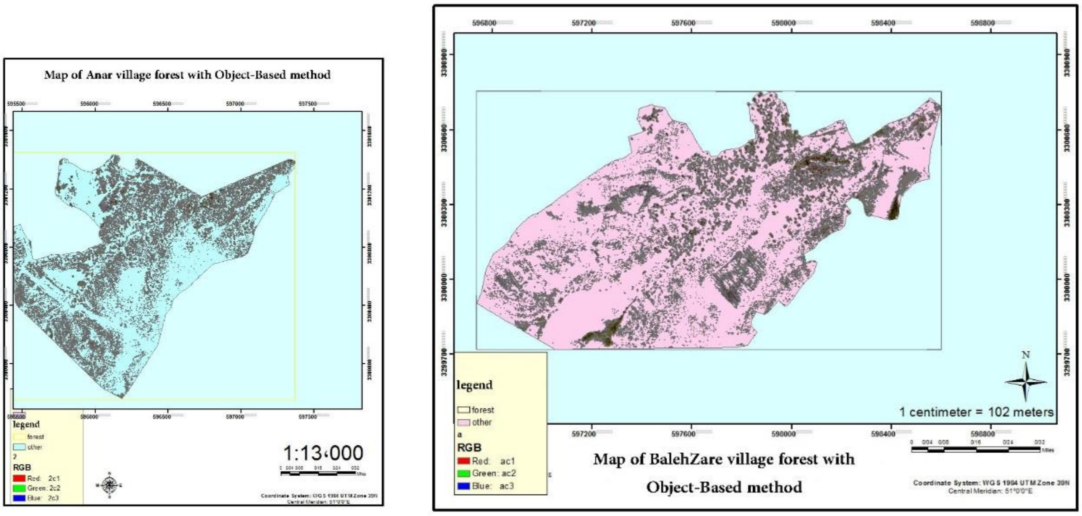

Figure 6. Classification results of the forest feature with object-based algorithm in BalehZare (right image) and Abe Anar sites (left).

3.1. Accuracy assessment of WV-2 canopy cover area with UAV cover

3.1.1. Regression of canopy cover area in BalehZar forests

Data analysis

At first, the normal distribution of data was investigated by Kolmogrov-Smirnov test. The result of the test showed that all data had normal distribution and were significant at 99%level. To compare the canopy coverage obtained from WV-2 satellite imagery and groundbreaking, T-pair test was used at 95% confidence level. The results of the Paired Sample t test between measured forest and image data showed that there was no significant difference between the measurement of canopy coverage in two methods at a significant level of 95% (df = 99, t = 1.984). Figure 8 shows the correctness of the item.

The regression analysis results showed that satellite imagery with an approximate magnitude of 0.95 (R^2 =95%) illustrates the potential for high-resolution WV-2 satellite images (Table 3 and 4 of the statistical model).

In Table 4 of the statistical model, the area of canopy on the ground as an associated variable and canopy area on satellite images is considered as an independent variable. The results of analysis of variance and coefficient test showed that WV-2 satellite images can be used to estimate the canopy surface. The point cloud is plotted in Figure 7. In which the X axis is the crown surface on the satellite image and the Y axis is the crown surface on the ground.

As a result, the WV-2 images can be used instead of land surveying to calculate the area of the canopy of forests, which is consistent with the results of the researchers.

Table 3a. Statistical data of the canopy cover of trees in the forests of BalehZar

Variable of canopy cover percent in forest inventory of BalehZar	Inventory method with UAV	Object-based WV-2 satellite images
Samples number	100	100
Mean (m^2)	68.48	66.70
Standard deviation (m^2)	41.63	40.84
Standard error (m^2)	4.16	4.08

Table 3b. Statistical data of the canopy cover of trees in the forests of AbeAnar

Variable of canopy cover percent in forest inventory of BalehZar	Inventory method with UAV	Object-based WV-2 satellite images
Samples number	100	100
Mean (m^2)	44.62	44.89
Standard deviation (m^2)	28.9	28.68
Standard error (m^2)	2.89	2.87

Table 4. Statistical model of the canopy surface covering the satellite imagery of WV-2 and UAV of forests of the village of Balehazar and AbeAnar

Name	Model	Coefficient R^2	Coefficient r	Model of statistic
Object-based of Balehazar	Linear	0.953	0.976	Y = 2.11 + 0.995X
Object-based of AbeAnar	Linear	0.998	0.999	Y = -0.579 + 1.007X

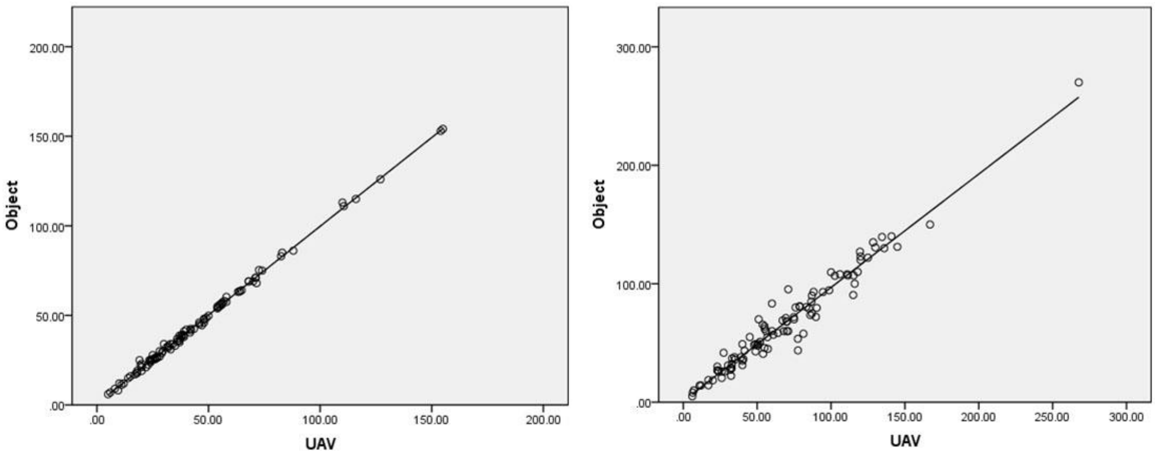

Figure 7. Evaluation of the accuracy of the canopy in Object-Based classification in satellite imagery WV-2 and UAV image in the forests of the village of Balehazar and AbeAnar.

3.2. Evaluation of the accuracy of the diameter of the canopy in satellite imagery WV-2 with the ground in the forests of the village of Balehazar and AbeAnar.

For accuracy evaluation of the diameter of the canopy in satellite imagery WV-2 with ground points in the forests of the village of Balehzar and AbeAnar, initially, the normal distribution of data was investigated by Kolmogrov-Smirnov test. The result of the test showed that all data were normal distribution and are significant at 99% level.

To compare the average diameter of the canopy obtained from WV-2 satellite imagery and ground-level random sampling, t-test was used at 95% confidence level. The results of Paired Sample t test between measured forest and image data showed that there was no significant difference between the measurement of canopy coverage in two methods at a significant level of 95% (df = 99, t = 1.984). Figure 8 shows the correctness of the item.

The regression analysis results showed that satellite images with an approximate coefficient of 0.95 (R2 =95%) indicate that the average diameter of the trees canopy can be obtained with high accuracy from WV-2 satellite images of (Table 5 and 6 of the statistical model).

Table 5a. Statistical data of Medium diameter of canopy of trees in BalehZar forest

	Mean(m)	Samples number	Standard deviation (m)	Standard error (m)
Medium diameter of canopy on ground	9.1279	100	2.959	0.295
Medium diameter of canopy in object-based	8.9876	100	2.733	0.273

Table 5b. Statistical data of Medium diameter of canopy of trees in AbeAnar forest

	Mean (m)	Samples number	Standard deviation (m)	Standard error (m)
Medium diameter of canopy on ground	7.3707	100	2.324	0.232
Medium diameter of canopy in object-based	7.2800	100	2.281	0.228

Table 6. Statistical model of the medium diameter of canopy surface covering in the satellite imagery of WV-2 and ground of forests of the village of Balehazar and AbeAnar

Name	Model	Coefficient R^2	Coefficient r	Model of statistic
Object-based of Balehazar	Linear	0.942	0.888	Y = -0.028 + 1.020X
Object-based of AbeAnar	Linear	0.958	0.918	Y = 0.256 + 0.976X

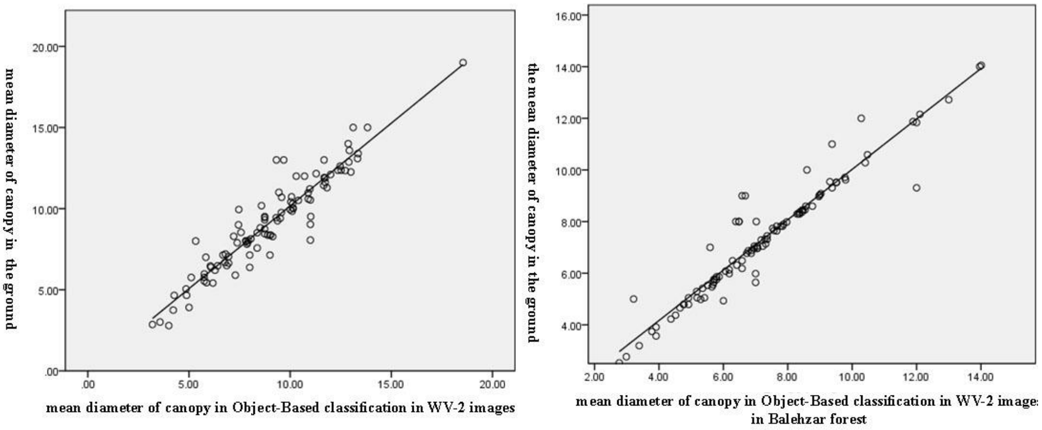

Figure 8. Assessing the accuracy of the mean diameter of canopy in Object-Based classification in WV-2 images and the ground of the trees in the forests of the village of Balehazar and AbeAnar.

3.3. Assessing the accuracy of the crown cover in WV-2 images with the height of the trees in the forests of the village of Balehazar and AbeAnar

At first, the normal distribution of data was investigated by Kolmogrov-Smirnov test. The result of the test showed that all data had normal distribution and are significant at 99% level. The regression analysis results showed that satellite images with a good explanation coefficient of 0.68 (R^2 = 68%) indicated that height can be obtained with proper accuracy from satellite images of WV-2 (Table 7 of the statistical model and Figure 9).

Table 7. Statistical model of canopy surface in WV-2 images and tree height in the forests of the village of Balehzar and AbeAnar

Name	Model	Coefficient R^2	Coefficient r	Model of statistic
Object-based of Balehazar	Linear	0.696	0.828	Y = 5.117 + 0.056X
Object-based of AbeAnar	Linear	0.686	0.826	Y = 4.112 + 0.069X

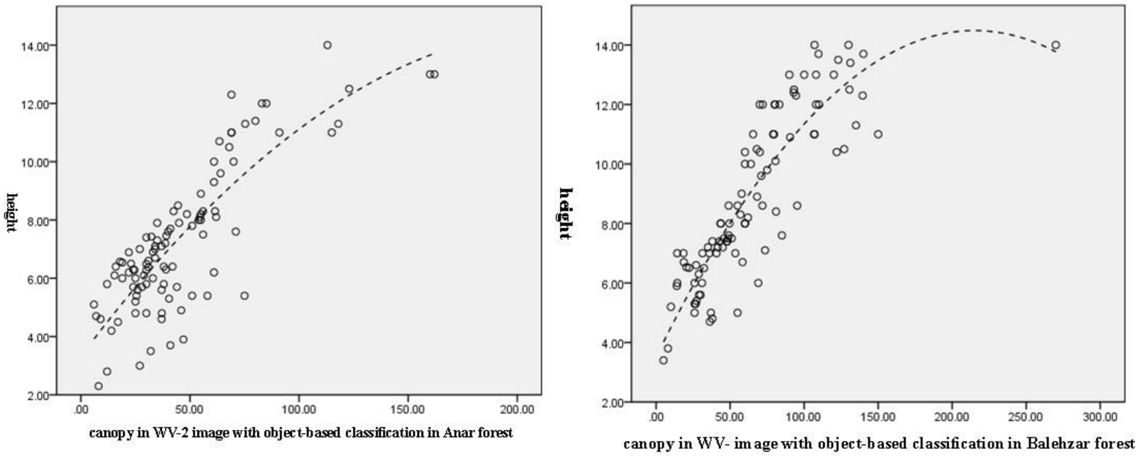

Figure 9. Assessing the accuracy of the crown cover in Object-Based classification in WV-2 images and the height of the trees in the forests of the village of Balehazar and AbeAnar.

This study is one of the first studies to estimate and extract single-tree parameters from high-resolution satellite imagery. A high level of accuracy was obtained in estimating canopy cover, canopy diameter and height of trees with satellite imagery. In the object-based method, the training samples were taken as TTA mask (Training & Test Area MASK) in order to evaluate the accuracy of the classification using spectral data, and the Kappa coefficient was 0.974 (0.967 in the AbeAnar village and 0.981 in the village of BalehZar), with an overall accuracy of 98.82% (99.14% in the AbeAnar village and 98.51% in the village of BalehZar) was obtained in the classification error matrix. Therefore, the base object method, the support vector method, and decision tree method were respectively the highest classification accuracy in the study area (Table 8).

Table 8. Comparison of Object-Based classification in sites with matrix

Object-Based	Classification accuracy
0.974	Kappa coefficient
98.82	Overall accuracy (%)

4. Conclusions

The study found that WV-2 data can be used to predict the tree parameters such as crown cover, bream diameter, tree height, tree number and biomass in the Zagros forests of Iran. The height of the trees can be obtained directly from the digital surface model using drone images. The crown cover and canopy diameter have a very high correlation with the terrestrial data. The combination of drone data with the satellite data from WV-2 has been useful to describe the biodiversity and monitoring the forest biodiversity. OBIA is widely used for forest remote-sensing research (Chubey et al., 2006; Desclee et al., 2006; Hay et al., 2005; Wulder et al., 2008). It has been successful in forest tree studies (Conchedda et al., 2007; Myint et al., 2008; Wang et al., 2004a). The object-based method in the extraction of single forest trees using spectral data is more potent than pixel-based methods.

According to the obtained results using WV-2 satellite spectral data in estimating the canopy surface, it was determined that these data are capable of estimating the quantitative characteristics of the crown cover of oak forests and extraction of single trees in the study area with proper accuracy.

There is a good correlation between the diameters of the crown of trees with ground measurements which indicates that extracting of the data using drone is excellent. The R coefficient result for the crown diameter of the forest trees was 0.85 in average, which is consistent with the results of Shrestha and Wynne (2012). They also obtained a correlation coefficient of 0.9 for the crown diameter.

As Pande-Chhetri et al. (2017) found in the estimation of wetland vegetation with WV-2 images, the object-based method was superior to the pixel-based method. In the current research, the object-based classification is better than other classifications, as the study results indicates that the SVM classification has a superior performance over the tree. The results obtained is compatible with Thanh Noi (2018), Raczko et al. (2017), Pande-Chhetri et al. (2017), Qian et al. (2015), Shafri and Ramle (2009), Shao et al. (2012), Kim et al. (2012), Amami et al. (2015), Ghasemian and Akhondzadeh (2016).

The very high correlation between the estimation of the canopy of the satellite images and terrestrial shows that one can estimate The canopy parameter from the images. The comparison between the estimated crown cover with the crown covering the ground surface in all the three methods shows that there is no significant difference between ground data and satellite image estimation at 5% significance level. This indicates that the nonparametric models used in the study have no significant difference with ground reality.

Considering other researchers' research on the extraction of features using algorithms, it is shown that the present study is of desirable accuracy.

Forecast models of this study, although they are surveyed for trees in Zagros forests, can be used for other forest levels with similar climate and species composition. This kind of forecast with drone images will help to properly assess the quality of carbon stored trees on the level of single trees. Further studies should be developed to predict biophysical parameters such as leaf area index, stem volume, etc. Management tables for forest planners such as forestry activities, disaster vulnerability, and age class are useful for forest trees. The functionality of these models can improve inappropriate data from other forest levels and if the area is not accessible, these equations can estimate trees from forest levels instead of being present in the field.

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