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Research Article

Inventory of the quantitative characteristics of single oak trees using nonparametric methods of SVM and Decision Tree

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Abstract
To achieve effective forests management it is necessary to obtain reliable statistical data like the number of stands, diameter at breast height (DBH), and crown volume. While traditional methods of the forests measurements are very labor intensive and time consuming, remote sensing can provide up-to-date and low cost data. In comparing to other sensors, the satellite WV-2 generate very high-resolution images that can be used in the forest management practices. In the present study, we aimed to estimate parameters related on the single trees characteristics using decision tree method and Support Vector Machines classification with complex matrix evaluation and Area under operating characteristic curve (AUC) method. We also used UAV Phantom 4 Pro images from two distinct geographic regions. Support Vector Machines classification method generated the highest accuracy in estimating single trees parameters. This study confirms that using WV-2 data it is possible to extract the necessary parameters of the single trees and relied them in the forest management practices.

Keywords: Canopy, Classifiers, Haft-Barm, Remote sensing, Single trees, Shiraz.

Introduction
Although traditional forest inventory methods are effective and accurate in disturbance monitoring, but they are also very expensive with fairly long update cycles due in part to their expense (Franklin 2001). Since forest disturbance can quickly change the appearance of this ecosystem, such traditional inventories are not adequate to monitor their development (Wulder *et al.* 2005). Climate warming and recent severe droughts have resulted in vegetation degradation in the various woody biomes across the globe (Allen *et al.* 2010, Breshears *et al.* 2005, Carnicer *et al.* 2011, Phillips *et al.* 2009, van Mantgem *et al.* 2009).

Isolating individual trees and extracting relevant properties from remotely sensed data have significant implications in different applications. For example, detailed information at the individual tree level can be used for monitoring forest regeneration (Clark *et al.* 2004a and 2004b), reducing fieldwork required for forest inventory and assessing forest damage (Kelly *et al.* 2004).

Forest stands or sampling plots are used as inventory units in the traditional forest inventory methods. Using such study units, investigators estimates forest variables such as the biomass of growing stock, stand age or height and so forth. However, stand level variables typically estimated in average or summation of multiple tree stands, of which the stand or sample plot are composed. Using such method certain amount of information may lost especially when working with ecologically homogeneous inventory units. In the forest inventory, variables estimation such as tree volume and biomass in the growing stock, tree level models are typically used nowadays (e.g. Repola 2008, 2009). Very high resolution remote sensing data allow moving from stand level to the level of individual trees, which involve certain benefits, for example in precise forestry, forest managements planning, biomass estimation and forest growth modelling (Koch *et al.* 2006). Increasing the level of details in the forest variables estimation can also being improved in detailed modeling, which can be used to predict forest growth. Satellite-based remote sensing of forests can be improved by more accurate modeling of the radiative transfer within the forest canopy. We found no documented investigation in the field of the single-tree related variables estimation using WV-2 images. In the previous studies, the accuracy evaluation and canopy area estimation have been done using field data, in which the shape of the tree canopy is considered to be circular. The canopy area can be obtained from the mean diameter while the trees according to topographic conditions may include canopy with non-geometric forms. Therefore, it is essential to evaluate the accuracy of the canopy area estimated on satellite data using more reliable data such as UAV images. A little study has been conducted to examine the efficiency of SVM classification, which is highly desirable for users (Figure 1).

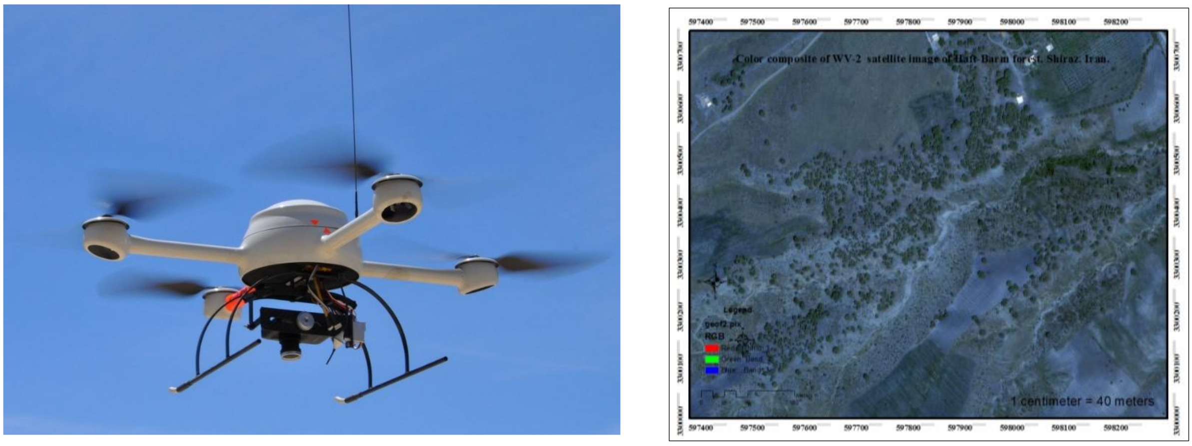

Figure 1. Study area and UAV imaging device

Material and methods

The study area

Haft Barm lakes are located (N294921, E520227) in Fars Province. These lakes are located 55 kilometers west of Shiraz, northeast of the protected areas of Arjan and Parishan, and 2150 meters above sea level, with an average annual precipitation of 1010 mm. This study was conducted in different sites of Haft Barm area. The area of the first site, the village Balezar, is about 106 ha, and the second site area, the village Abanar, is 150 ha.

Data

The data used in this study included the satellite WorldView-2 images on May 21, 2015 with a resolution of 1.8 m, and panchromatic bands (spatial resolution of 0.5 m) and UAV images with the resolution of 3 cm. Worldview-2 images were geo-referenced using points with three-frequency GPS of GS15 model by arctic and static methods, and then Pansharpenning images with a resolution of 0.5 m were created with a combination of four multispectral and panchromatic bands. For trees surrounding regarding the dense forest of the region, UAV Phantom 4 Pro images were taken. The Phantom 4 Pro is equipped with a one-inch CMOS camera that can capture 20 megapixel images (Figure 1) (Dji 2016). The location of the sites was determined with three-frequency Global Positioning System (GPS) and specified by marking on the ground. All levels of two sites were taken with three flights on November 22 and 23, 2017. We have landed 150 ground control points (GCPs) in the forest area for the precise geo-referencing. Ground control points are marked with 50 x 50cm blue tapes. The coordinates of ground control points were determined by Leica GPS1200 GPS using a static and arctic method (1 cm width and 1.5 cm high) in UTM coordinate system. A flowchart is shown in figure 2.

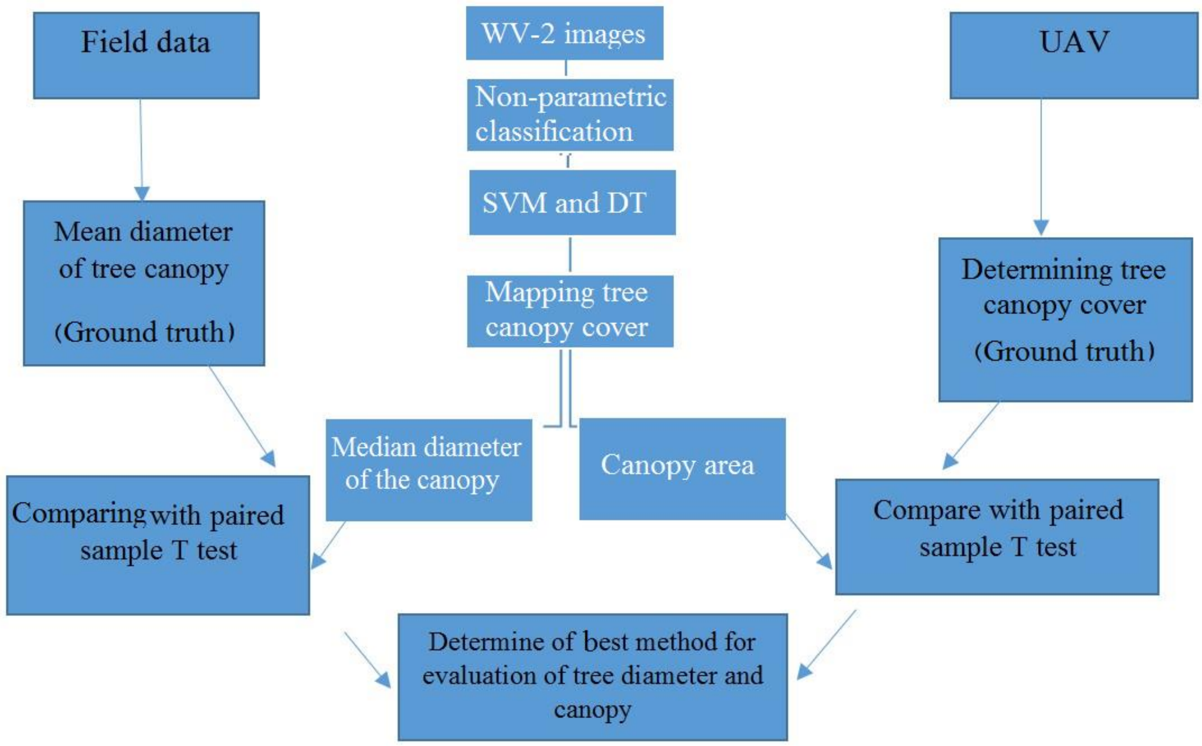

Figure 2. Flowchart of investigation steps

Support Vector Machines (SVM)

SVM is a modern machine learning method that offers improved generalization performance and can model complex nonlinear boundaries using adapted kernel functions (Li *et al.* 2011), SVM typically belongs to the family of the supervised classifiers. It requires training samples provided by the user. Unlike the Artificial Neural Networks method (ANN), it is less sensitive to the number of the training data. Originally, SVM was developed as the binary classifier where it assigns only two possible label; -1 and 1 into a given test sample. Principally, the training algorithm aims to build the separating hyperplane (e.g. decision boundary) based on the properties of the training samples (or specifically, their distribution over the feature space) (Tso and Mather 2009). In the other words, this hyperplane acts as the separator between the two classes of the samples. Illustration of the hyperplane is depicted in figure 3. The algorithm works, by maximizing the margin width of the separating hyperplane (between class -1 and 1) thus the maximum distance between the classes will be optimized. In constructing the hyperplane, not necessarily all the samples are contributing, except a subset of them which are chosen as a support vector.

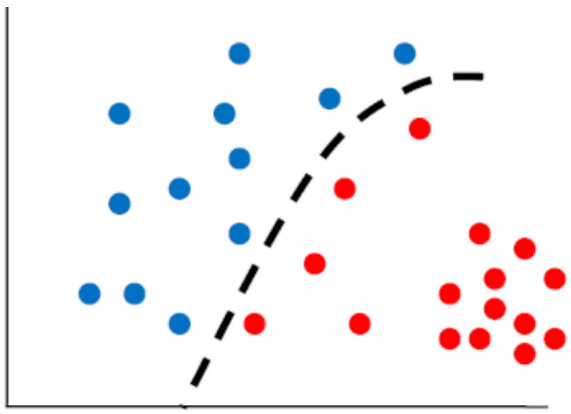

Figure 3. Support vector machine classification

Decisions tree (DT)

The decision-tree method has been employed in the previous studies to extract variables related to the mangrove forests (Liu *et al.* 2008, Heumann 2011). A decision tree is a classification procedure that repeatedly divides a set of training data into smaller subsets based on tests to one or more of the feature values (Liu *et al.* 2008, Tooke *et al.* 2009). Unlike many other statistical approaches like MLC, the decision tree method does not depend on specific assumptions regarding variables distribution or the independency of the variables from each other (Liu *et al.* 2008). Such condition for the decision tree method (Pal and Mather, 2003) is an advantage for incorporating supplementary GIS (Geographic Information System) data, which often exhibit different forms or distributions as well as being highly correlated (Jensen 2005, Liu *et al.* 2008). As implemented in ENVI/IDL, remote sensing data can be divided sequentially by the decision tree, with each pixel eventually being assigned to a specific class (Liu *et al.* 2008, Xu *et al.* 2005). Considering the unique nature of oak forest in Haft Barm wetland habitats, the partitioning was done based on criteria such as a threshold values of NDVI, NDWI, elevation and spectral reflectance, visually interpreted from calibration data and expert knowledge of the study area. The community of the oak trees in Zagros mountains were classified based on the threshold values of spectral reflections, visual knowledge of the data presented by the wv-2 images and user knowledge. The forest different features were distinguished using the mean spectral value of the complication, determining the appropriate threshold in the 3rd and 4th bands, the near infrared, and the index of the band ratio, the target class of the vegetation (Eq. 1) (Fig. 2).

$$R1 = \frac{R-NIR1}{R+NIR1} \qquad (1)$$

After selecting educational data, they were arranged in a thematic layer, TTA mask layer (Thematic training mask) and saved in the software to be used during the process. For the various classification methods, the same educational data were used. After extracting the forest features using these two methods, the accuracy of the outputs was evaluated. To this aim, 100 points were created randomly on the images, and the canopy boundary of the trees in these areas was determined on UAV images (Fig. 4).

Figure 4. Canopy of 100 determined trees on UAV image for ground truth

Accuracy assessment

Accuracy assessment is one of the most important steps in the evaluation of the classification performance and usefulness of the outputs. It expresses the degree of correctness of a map or classification in comparison with actual ground features. Accuracy assessment in terms of the classes specific producer and user assigned accuracy, overall accuracy and Kappa coefficient are subsequently computed after generating confusion matrix.

Accuracy was evaluated in two ways including the traditional method of using Kappa coefficient and AUC method.

Area under operating characteristic curve (AUC) method

To achieve AUC we used different cells including those of properly assigned to the target class (category) (TP), cells that are not properly assigned to the target class (TN), those are incorrectly assigned to the target class (FP) and cells that are not incorrectly assigned to the target class (FN). To draw this curve, X-axis representing the "specificity" (Eq. 2) and Y-axis containing the "sensitivity" (Eq. 3) which should be calculated for each value of the threshold for desired class. The "accuracy" criterion (Eq. 5) was used to verify the spatial adaptation of the identified class on the aerial image and the ground reality of "precision" (Eq. 4) as well as evaluation of cell to class assigning accuracy. In equation 5, n is the total number of classified cells (Erfanifard 2014).

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (1)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (2)$$

$$\text{Precision} = TP / (TP + FP) \quad (4)$$

$$\text{Accuracy} = (TP + TN) / n \quad (5)$$

where TP represents true positives, TN true negatives, FP false positives, and FN false negatives.

Sampling method for quantitative and qualitative features of the forests

Systematic sampling method was employed in this research. A rectangular grid of 200 x 200 m, was applied on the images and sample rectangular plots of 40 ×40 m were created in the study areas. A total of 63 sample plots (36 plots in Abanar and 27 plots in Balezar) were taken at each site, and in each unit different features of the vegetation such as the largest and smallest diameter of all trees, diameter at the breast height (DBH), tree canopy percent cover, and tree health situation.

Estimation of the canopy cover area in the Balezar using WV-2 and UAV images

Sampling was done using a 200×200 m^2 grid considered on the ground as well as employing satellite images of WV-2. Totally 27 plots from the area of 1600 m^2 (40 × 40 m) were collected in the first site where was located in the Balezar village and 33 plots were collected from the second site, where was located the Anar village. In each sample plot, the largest and smallest diameters, diameter at the breast height (DBH) and finally the canopy cover area (Eq. 6) were recorded. Table 1 shows quantitative parameters estimated for Balezar including the number of samples, mean, standard deviation and standard error using two methods of ground canopy and satellite WV-2 images. In each sample plot, the area of canopy was calculated according to the equation number 6.

The canopy area = the mean canopy diameter * π/4 (6)

Results

Figure 5 shows the results of two different classification methods including Decision tree and Support Vector Machines. As can be seen from figure 5, the quality of the classifications is almost the same while there is some differences in the precision. The accuracy of the outputs was evaluated in two ways including the usual method of Kappa coefficient and AUC method. The accuracy evaluation tables show error matrix, overall accuracy, kappa coefficients, producer accuracy, and user accuracy.

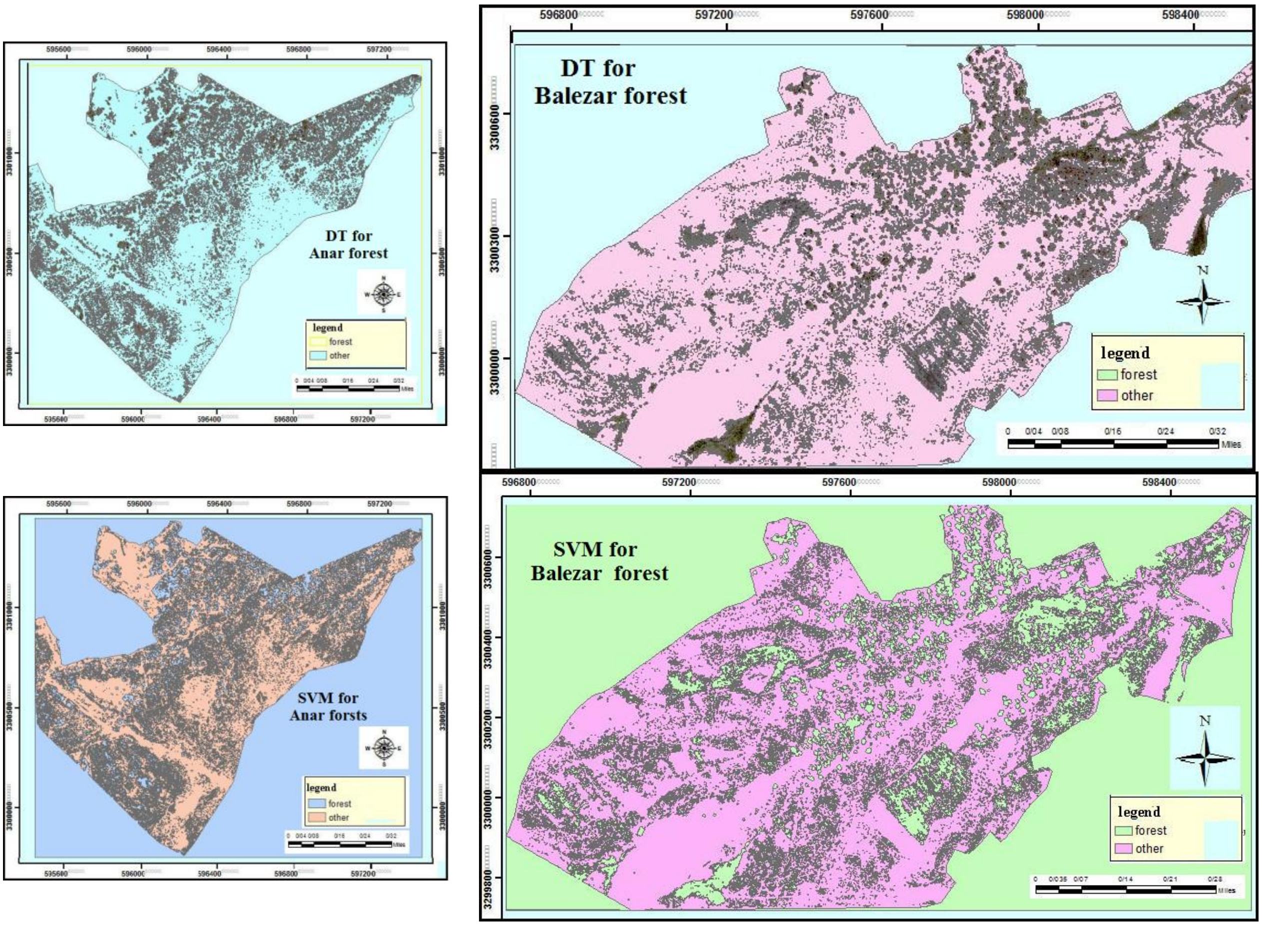

Figure 5. Map of forest feature with DT and SVM classification

Data analysis

First, the normal distribution of data was checked by Kolmogrov-Smirnov test which showed that all data follow from a normal distribution. In order to compare the area of the canopy obtained from WV-2 satellite images and ground statistics, the paired T-test was used at the confidence level of 95%. The result of paired T-test between the data obtained from the ground inventory and images indicated no significant difference between canopy area estimation using two methods at 95% significance level ($t = 1.984$, $df = 99$) (Fig. 6).

Regression analysis indicated that satellite images with considerably high coefficient of determination of 0.95 indicate that the canopy area can be obtained with high precision from satellite WV-2 images (Tables 1 and 2).

In Table 1 obtained from the statistical model, the area of on the ground canopy was regarded as a dependent variable and on satellite images canopy area was considered as an independent variable. The results of analysis of variance and coefficients test showed that WV-2 satellite images can be used to estimate the canopy area (Fig. 8). As a result, WV-2 images can be used instead of the terrestrial statistics to calculate the canopy area of forests.

Table 1. Obtained data about the single trees' canopy cover

Locality	Canopy cover area	UAV method	DT using WV-2 images	SVM using WV-2 images
Balezar	The number of samples	100	100	100
	Mean (m^2)	68.48	66.92	66.61
	Standard deviation (m^2)	41.63	40.96	40.36
	Standard error (m^2)	4.16	4.09	4.03
Anar	The number of samples	100	100	100
	Mean (m^2)	44.62	44.23	48.6
	Standard deviation (m^2)	28.9	30.11	34.59
	Standard error (m^2)	2.89	3.01	3.46

Table 2. Statistical model of canopy estimation using WV-2 and UAV methods for Balezare and Anar

Name	model	Coefficient R^2	Coefficient r	statistic Model
DT for Balehazar	linear	0.964	0.982	Y= -0.893 + 0.943X
DT for Anar	linear	0.632	0.795	Y= 12.314 + 0.665X
SVM for Balehazar	linear	0.949	0.974	Y= 2.195 + 0.99X
SVM for Anar	linear	0.982	0.991	Y = 2.534 + 0.952

(a)

(b)

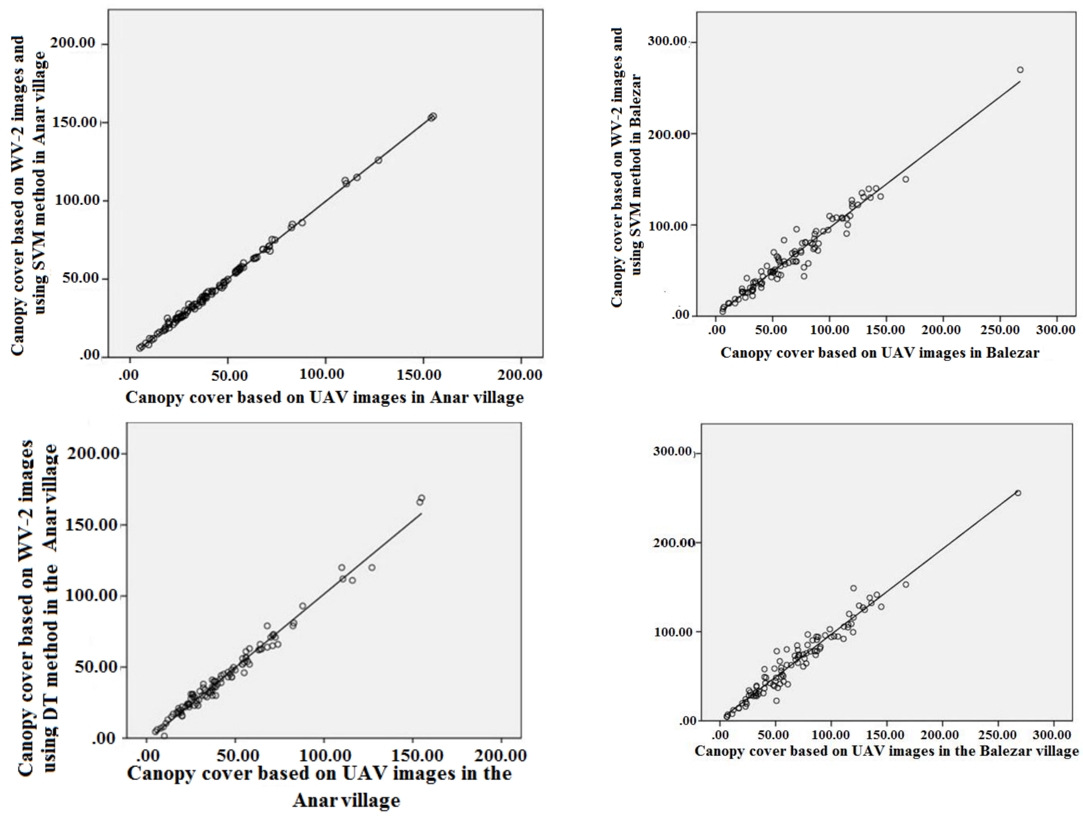

Figure 6. Evaluation of the accuracy of the canopy cover estimation in SVM (a) and DT classification methods (b) using satellite images of wv-2 and UAV in the study areas of Balezar and Anar.

Accuracy evaluation

Kolmogrov-Smirnov normality test showed that all data have normal distribution. In order to compare the mean diameter obtained from WV-2 satellite images and on ground inventory methods, the paired T-test was used at the confidence level of 95%, which indicated no significant difference between canopy area measurement using two different methods at 95% significance level (df = 99, t = 1.984) (Fig. 7). Regression analysis indicated considerably high coefficient of determination 0.95 (R^2 =95%) for satellite images. Based on our findings it can be said that mean diameter can be obtained with high precision from satellite WV-2 images (Tables 3 and 4).

Table 3. Different parameters about the medium diameter of trees' canopy cover area.

Locality	mean diameter of the canopy	Mean (m)	Number of samples	Standard deviation (m)	Standard error (m)
Balezar forest	Mean diameter of canopy on the ground	9.1279	100	2.95908	0.29591
	Mean diameter of canopy in DT	8.9656	100	2.78197	0.27820
	Mean diameter of canopy in SVM	9.2504	100	2.87787	0.28779
Anar forest	Mean diameter of canopy on the ground	7.3707	100	2.32432	0.23243
	Mean diameter of canopy in DT	7.2555	100	2.43424	0.24342
	Mean diameter of canopy in SVM	7.5927	100	2.47576	0.24758

Table 4. Statistical model of mean diameter of canopy using WV-2 images and on the ground canopy area in the villages of Balezar and Anar

Name	Model	Coefficient R^2	Coefficient r	Model of statistic
DT in Balehazar	linear	0.828	0.963	Y = -0.035 + 0.991X
DT in Anar	linear	0.708	0.841	Y = 1.372 + 0.790X
SVM in Balehazar	linear	0.883	0.939	Y = 0.169 + 0.999X
SVM in Anar	linear	0.915	0.912	Y = 0.756 + 0.912X

Assessing the accuracy of the canopy cover

Kolmogrov-Smirnov normality test showed that all data have normal distribution. In order to compare the area of the canopy cover obtained from WV-2 satellite images and on the ground method, the paired T-test was used. This test indicated no significant difference between canopy area measured by two different methods at 95% significance level (t = 1.984, df = 99) (Fig. 8) Regression analysis showed that satellite images with an approximate high coefficient of determination 0.95 (R^2 =95%) can be used for extraction of the height parameter with high precision (Tables 5).

(a)

(b)

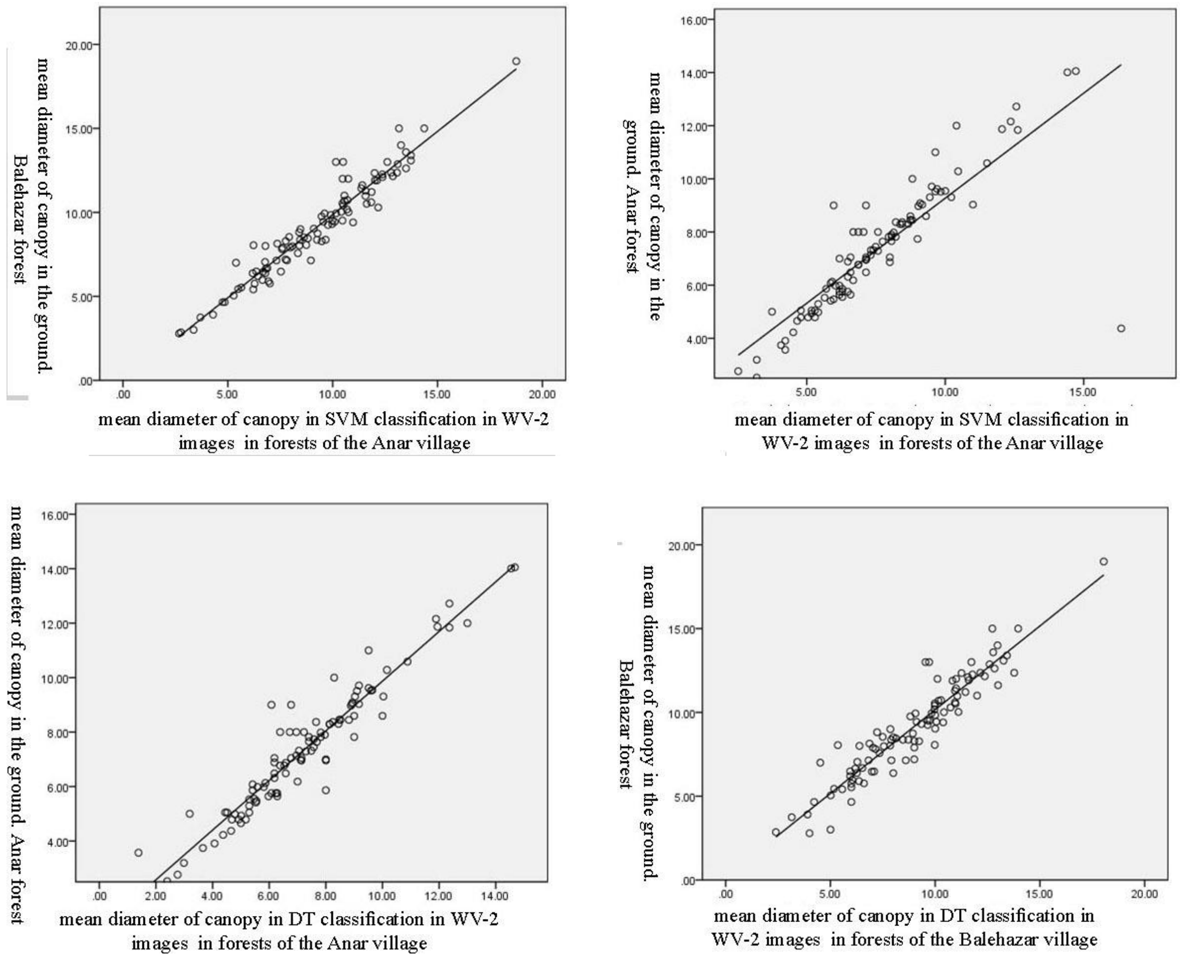

Figure 7. Assessing the accuracy of mean diameter of canopy in SVM (a) and DT classification methods (b) based on WV-2 images and on the ground in the villages of Balezar and Anar

Table 5. Canopy parameters using WV-2 images and tree height

Name	Model	Coefficient R^2	Coefficient R	Model of statistic
DT in Balezar	linear	0.683	0.827	Y = 4.974 + 0.053X
DT in Anar	linear	0.600	0.775	Y = 4.347 + 0.063X
SVM in Balezar	linear	0.883	0.939	Y = 0.169 + 0.999X
SVM in Anar	linear	0.915	0.912	Y = 0.756 + 0.912X

Accuracy assessment

Table 6 and 7 summarize the results of estimated ROC indicators and its components in the forest uses' classification with Support Vector Machines (SVM) and decision tree (DT) classifiers in the forests of the villages Balezar and Anar.

Table 6. Result of the estimated ROC values in the Balezar and Anar villages

	Anar				Balezar			
Indicators	SVM		DT		SVM		DT	
	other	forest	other	forest	other	forest	other	forest
TP	3298	4469	3289	4480	6252	5954	4358	7315
FP	283	21	272	30	260	2	791	4
FN	21	283	30	272	2	260	4	791
TN	4469	3298	4480	3289	5954	6252	7315	4358
specificity	0.940	0.993	0.943	0.991	0.958	0.996	0.902	0.373
sensitivity	0.993	0.934	0.991	0.943	0.996	0.958	0.997	0.627
precision	0.921	0.995	0.924	0.993	0.960	0.990	0.846	0.991
accuracy	0.962	0.962	0.960	0.961	0.979	0.979	0.936	0.936
AUC	0.912	0.931	0.844	0.891	0.838	0.893	0.750	0.788

(a)

(b)

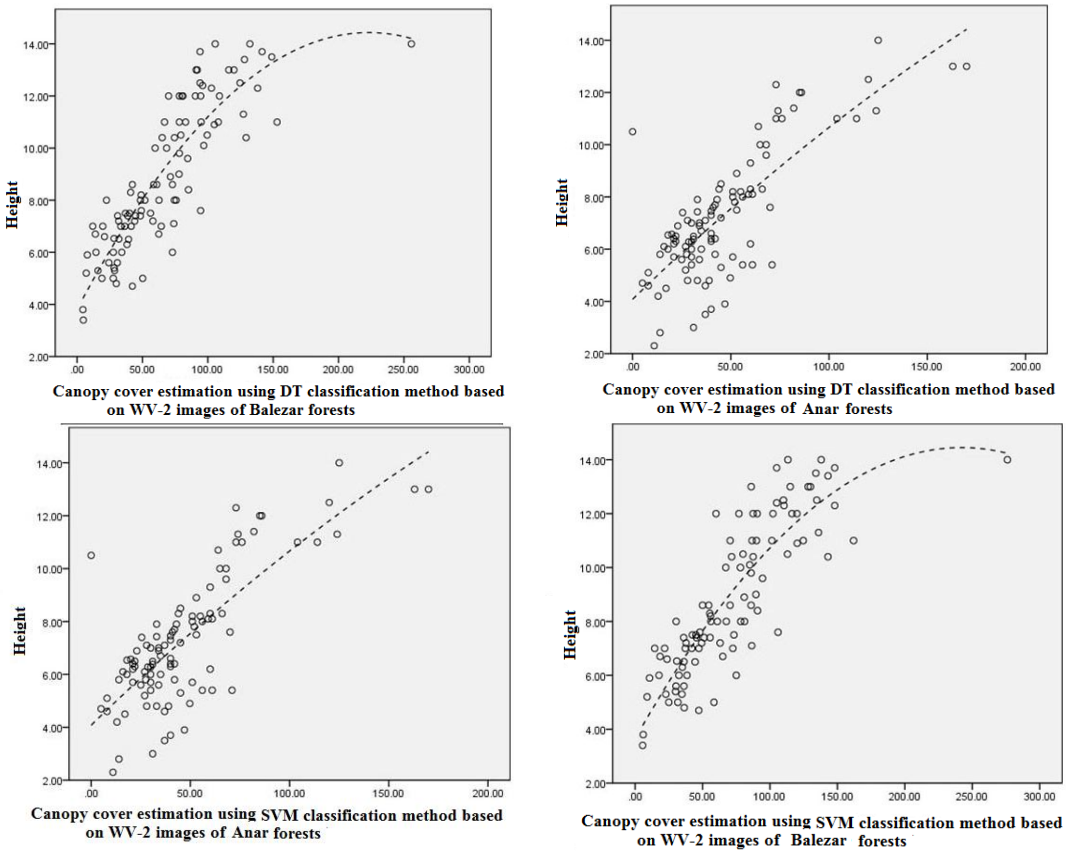

Figure 8. Assessing the accuracy of the canopy cover in SVM (a) and DT classification methods (b) using WV-2 images along with the trees' height in the villages of Balezar and Anar.

Table 7 summarizes the results of estimated common indicators using the Support Vector Machines and decision tree classifiers in both forests. After this step, the classification of the Receiver Operating Characteristic (ROC) curve was also plotted (Fig. 9).

Table 7. Classification accuracy in Anar and Balezar villages

		Anar		Balezar	
indices	Classes	SVM	DT	SVM	DT
Prod Accuracy	Forest	0.994	0.497	0.970	0.500
	Other	0.940	0.892	0.923	0.822
User Accuracy	Forest	0.921	0.924	0.926	0.846
	Other	0.995	0.993	0.969	0.999
Kappa coefficient		0.923	0.495	0.894	0.477
Overall accuracy (%)		96.233	66.789	96.694	66.260

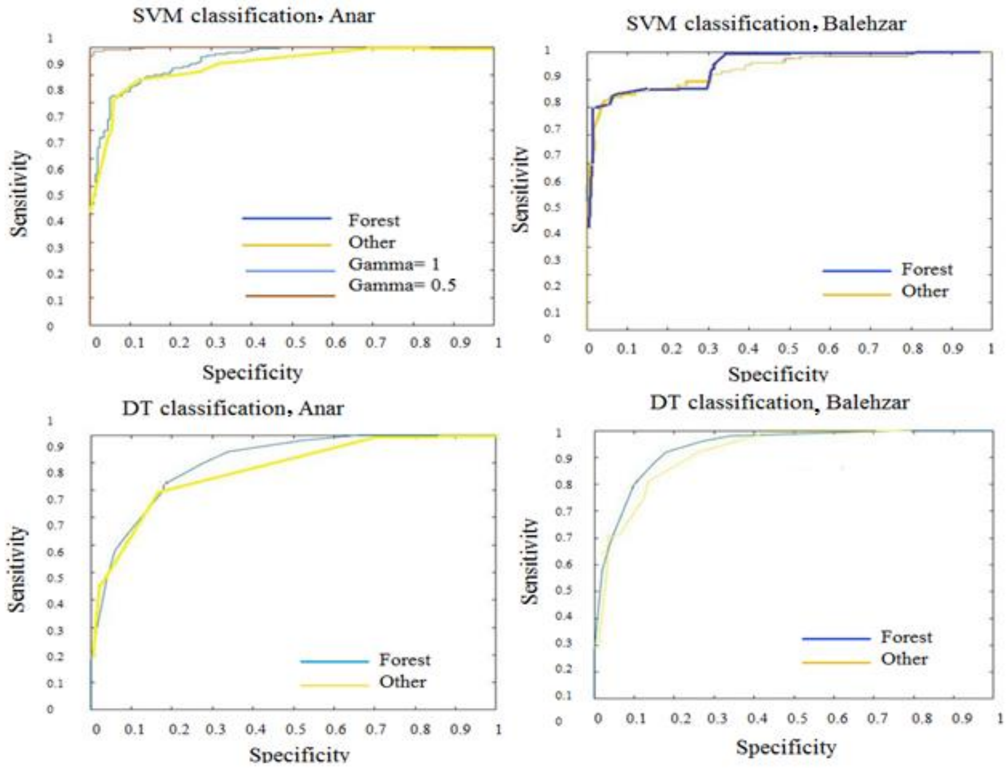

Figure 9. ROC curve of SVM (a) and DT classification (b) as well as Balezar and Anar village forest respectively from right.

Discussion

Our results led to the conclusion that spectrally similar classes like forests and trees can be better distinguished when the standard bands of the WV-2 sensor are used throughout the SVM classification process. This study is one of the first studies in the estimation and extraction the single tree related parameters using high resolution satellite images. A high level of accuracy was obtained from satellite images in estimating the canopy area, canopy diameter and height of the single trees. In the SVM method, the training samples were taken as a TTA (Training and Test Area) mask on the image in order to evaluate the classification accuracy. To this aim we used the spectral data and Kappa coefficient which obtained 0.974 (0.967 in the village Anar and 0.981 in the village Balezar) and the overall accuracy which estimated about 98.82% (99.14% in the village Anar and 98.51% in the village Balezar) from the classification error matrix. In decision tree method, Kappa coefficient was 0.486 (0.495 in the village Anar and 0.477 in the village Balezar) and overall accuracy was 66.52% (66.78 in the village Anar and 66.26% in the village Balezar). Decision tree method had lower overall precision and manufacturer precision compared to the SVM method, indicating that tree pixels were not well identified. Also Kappa coefficient for the SVM method shows a higher value than the decision tree method; this indicates that the classification accuracy of this method is higher. Thus, the SVM and decision tree method had the highest classification accuracy in the study area.

Compared to the AUC method, the SVM and decision tree method respectively had the highest classification accuracy in both study areas (Table 6). In the canopy accuracy evaluation, the SVM and DT methods showed respectively the highest coefficients in both sites. In evaluating the accuracy of the average diameter of the canopy, the SVM method had the highest correlation coefficient followed by the decision tree (Table 4). The evaluation of the accuracy of the canopy area in wv-2 images with the height of the trees in the SVM method had the highest correlation on average (Table 5).

We found that WV-2 data can be used to predict the single trees parameters such as the canopy area, diameter at the breast height (DBH), tree height, number of trees and their biomass. The height of trees can be obtained directly from the digital surface model with drone taken images. The canopy area and canopy diameter had a very high R^2 correlation coefficient using the terrestrial data. Combining drone taken data with satellite images data obtained from WV-2 images can be very useful for describing forest biodiversity changes.

SVM is widely used for forest remote-sensing research (Chubey et al., 2006; Desclee *et al.* 2006; Hay *et al.* 2005; Wuder *et al.* 2008) and has been very successful in the forest single trees investigations (Conchedda *et al.* 2007, Myint *et al.* 2008, Wang *et al.* 2004a). According to the results obtained from the usage of the WV-2 satellite spectral data in the canopy area estimation, it can be inferred that such data are capable to estimate the quantitative characteristics of the canopy cover of the oak forests and extraction of single trees properties in such areas while achieving a desirable accuracy.

There was also a good correlation between the diameter of the canopy covers with the ground measurements and drone obtained data, which indicates high capabilities of the drones in such investigations. R coefficient for the canopy diameter of the single trees was in average 0.85 which is consistent with the results of Shrestha and Wynne (2012). They also obtained a correlation coefficient of 0.9 for the canopy diameter.

As Pande-Chhetri *et al.* (2017) found in the estimation of wetland vegetation based on WV-2 images, the object- based method was superior to the pixel-based method. In the current research, we found that the SVM classification is also better than other classification methods. As the results of this study indicate, the SVM classification has a superior performance over the other classification methods. The results obtained by other researchers such as Thanh Noi (2018), Raczko *et al*. (2017), Raskshita *et al.* (2017), Pande-Chhetri *et al.* (2017), Qian *et al.* (2015), Erfanifard (2014), Shao *et al*. (2012), Kim *et al.* (2012), Amami *et al*. (2012), Poteau *et al.* (2011), Shafri (2011) confirm such finding.

The very high correlation between the canopy related parameters estimated from satellite and terrestrial images showed that images can be regarded as a reliable source of such investigations. The comparison between the estimated canopy areas with the terrestrial canopy in both methods showed that there is no considerable difference between the terrestrial data and satellite driven estimations at the 95% confidence level. This finding indicates that the nonparametric models used in this research have no significant differences with the terrestrial reality. Considering other findings reported by different the researchers in the field of extraction of such parameters using defined algorithms, we found we achieved desired precision and accuracy in our research.

Conclusion

Forecast models used in this study, can be generalized for other forest levels with similar climates and species combinations. This kind of forecasting with early bird images will help to properly evaluate the quality of carbon stored in the tree stands at the level of single trees. Further studies should be developed to predict biophysical parameters such as the leaf area index, stem volume, and so forth. Obtained data from such methods can be very useful for forest planners, to estimate the forest vulnerability to the potential disasters depending on the age class of the forest trees. The functionality of these models can improve the inappropriate data obtained from other forest levels and, especially when the area is not accessible, applying such equations can help to estimate trees related parameters while doing less field efforts.

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