A robust approach to generate canopy cover maps using UltraCam-D derived orthoimagery classified by support vector machines in Zagros woodlands, West Iran

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Abstract
An approach was developed to construct a percent canopy cover (PCC) map of Zagros semi-arid woodlands, West Iran, using UltraCam-D airborne imagery. We detected crowns of Persian oak coppice trees on the imagery by use of the support vector machine (SVM) classifier optimized via Taguchi method. Then, PCC was calculated in raster grids with various block sizes and their accuracy metrics revealed the appropriate sizes. Results showed the optimized SVM success in separating Persian oak crowns as revealed in receiver operating characteristic (ROC) curve analysis (area under curve: AUC ~ 0.82). After filtering the raster maps and reassessing their accuracies, validation outputs of the final PCC map with 3000 m² resolution yielded an overall accuracy of 90% (KHAT=0.71) and was introduced as the optimal map in this study.

Keywords: Percent canopy cover, SVM, Taguchi, UltraCam-D, woodland, Zagros.

Introduction
Canopy cover is a major biophysical attribute used to understand the ecology and spatio-temporal changes in semi-arid woodlands. This important multipurpose ecological indicator also affects ecosystem patterns and processes since nutrients are localized under the canopy of tree and shrub species and soil fertility decreases between them [Korhonen et al., 2006; Wallace et al., 2008; Yang et al., 2012]. Due to its importance, canopy cover estimation has recently become a major part of woodland inventories [Korhonen et al., 2006; Chopping et al., 2008]. Although various methods have been proposed to quantify this attribute in field measurements [Williams et al., 2003; Korhonen et al., 2006], remotely sensed imagery from satellites and airborne platforms classified by appropriate approaches are still preferred to assess canopy cover in different forested areas by many researchers [Carreiras et al., 2006; Gleason and Im, 2011; Yang et al., 2012]. The result of processing remotely sensed datasets is a thematic map displaying the spatial distribution of e.g. canopy cover within the investigated area [Schowengerdt, 2007; Panta et al., 2008]. Canopy cover defined as the area
occupied with the vertical projection of tree crowns eliminating their overlaps, is a common
concept in forestry and of wide interest in both scientific studies and political decisions
[Rudnicki et al., 2004; Chopping et al., 2008]. Further details concerning the definition of
canopy cover and its difference with crown area are presented in Korhonen et al. [2006].
Canopy cover cannot be assumed to be the sum of tree crown projection areas, because
overlapping is a common phenomenon even in sparse, pure, and coppice woodland stands.
Canopy cover is consequently the sum of the individual crown areas minus the intersection
of their overlapping crown areas [Williams et al., 2003]. Remote sensing is an appropriate
means to deal with this problem since it gives a vertical view from top and elimination of
overlapping of tree crowns is possible in canopy cover estimation.
Canopy cover is completely related to the shape of a tree crown and its vertical projection, so
the spatial resolution of remote sensing imagery is of key importance. The spatial resolution
of commercially available satellite and aerial images produced by passive and active
technology ranges from several meters (MODIS, IKONOS, WorldView, and RapidEye)
to tens of centimetres (LiDAR and aerial images) [Schowengerdt, 2007]. Previous studies
have constructed canopy cover maps of large areas from mid or low spatial resolution
datasets, such as Landsat Thematic Mapper (TM), NASA Multi-angle Imaging Spectro-
Radiometer (MISR), and Linear Imaging Self Scanning Sensor (LISS III) [Carreiras et al.,
2006; Chopping et al., 2008; Yang et al., 2012] or high spatial resolution datasets, such as
Compact Airborne Spectrographic Imager (CASI), Color-Infrared (CIR) orthophotos, and
LiDAR [Bunting and Lucas, 2006; Kral, 2009; Mathieu et al., 2013]. The spatial resolution
of most satellite remote sensing images is too low to identify many objects from their shape
or spatial detail [Schowengerdt, 2007; Frohn and Chaudhary, 2008]. Therefore, remote
sensing datasets with appropriate spatial resolution are required in investigations aimed
at mapping percent canopy cover (PCC) to provide an apparent view of tree crowns in
vegetated areas, e.g. semi-arid woodlands.
In some research studies, the definition of PCC, i.e., the percent of unit area covered with the
vertical projection of tree crowns minus their overlapping was not taken in to consideration
in field observations [e.g., Nandy et al., 2003; Zeng et al., 2008]. In other studies using
remote sensing imagery, the canopy reflectance and related indices (AVI, NDVI, and etc.)
were applied to produce PCC maps [e.g., Roy et al., 1996; Rikimaru et al., 2002; Panta
et al., 2008]. However, the definition of PCC was considered in a few studies, e.g. in the
Forest Resources Assessment 2000 (FRA 2000) programme [FAO, 2001], it was defined
as the fraction of 1 km$^2$ blocks covered with canopy of trees in field measurements. Kral
[2009] also measured different PCC levels in blocks of 1000 m$^2$ in field survey and on CIR
orthophotos, while Carreiras et al. [2006] used dot grid method to distinguish five PCC
levels of interest in 120 m × 120 m square plots. Bunting and Lucas [2006] utilized 50 m ×
50 m square plots to measure canopy cover in their field survey to study the potential
of CASI data in delineating tree crowns of mixed forests. Despite previous studies, it still
is vague for some scientists which unit area is appropriate to measure the canopy cover
percentage in a forested area. In this study, we discuss about the choice of the optimal
window size suitable for canopy cover measurement on very high spatial resolution (VHSR)
aerial images of Zagros woodlands.
Support vector machines (SVMs) are superior image classification techniques, applying
a set of machine learning algorithms and have their roots in statistical learning theory
that have been recently used to classify airborne and satellite imagery. SVMs are robust classification techniques that function by non-linearly projecting the training data in the input space to a feature space of higher, or infinite, dimension by use of a kernel function. This technique tends to provide higher classification accuracies in object recognition than other widely used pixel-based techniques and use a powerful learning algorithm that can give better classification results [Camps-Valls et al., 2004; Su and Huang, 2009]. One of the most important challenges in SVMs is determining the optimal combination of parameters affecting their performance, which is commonly achieved by trial and error approaches in the literature. Some authors believe that estimating the value of parameters of SVM classifier becomes its negative aspect that affect the performance of this technique for a given dataset and result in a time-consuming process and reduction of classification accuracy [Melgani and Bruzzone, 2004; Yang, 2011; Vaughn et al., 2012]. In most cases, the parameters in SVM classifier have been optimized via trial and error [Melgani and Bruzzone, 2004; Colgan et al., 2012] or training sample size [Su and Huang, 2009; Yang, 2011], and in some studies, the parameters left at their default settings [Vaughn et al., 2012]. This renders the method less stable and, accordingly, affects the classification performances in terms of accuracy.

Detailed and accurate thematic maps of canopy cover in Zagros old-growth semi-arid woodlands are required for assessment of the flora and faunal biodiversity as well as their sustainable management and monitoring their changes. Traditionally, canopy cover has been estimated via interpreting aerial photographs or field surveying. These methods are time consuming and expensive when applied to large areas. The aim of this study was to develop a robust semi-automatic approach for thematic mapping of PCC using UltraCam-D airborne imagery in Zagros woodlands. We used SVM classification technique to detect crowns of Persian oak coppice trees on the imagery. In addition, we evaluated the Taguchi method to optimize the effective parameters of SVM. Different block sizes were also investigated to find the best size of unit area for PCC mapping in Persian oak stands.

Materials and Methods

Study area

We conducted our research in a pure Persian oak coppice stand in Zagros woodlands that are the first most extensive vegetation type in Iran. Zagros woodlands, West Iran, cover a vast area of Zagros mountain ranges stretching from Piranshahr (West Azerbaijan Province) in the northwest of the country to the vicinity of Firoozabad (Fars Province) having an average length and width of 1300 and 200 km, respectively. Classified as semi-arid, Zagros woodlands cover 5 million hectares and comprise 40% of entire vegetation covered area in Iran. Persian oak (*Quercus brantii* var. *persica*) coppice trees, as the most important and widespread tree species of these semi-arid woodlands, are scattered in many parts of the area often mixed with wild pistachio (*Pistacia* spp.) trees and almond (*Amygdalus* spp.) shrubs [Ali et al., 2003; Pourreza et al., 2008; Djamali et al., 2009]. One of the most significant changes in this old-growth vegetation cover in the past decades has been the reduction of canopy cover mainly because of expansion of farms and agricultural lands. Governmental management agencies (like Forests, Rangelands, and Watershed Organization (FRWO)) require thematic maps of PCC to monitor changes periodically in these ecologically important vegetation cover.
The PCC maps of Zagros woodlands currently available to FRWO, Iran, were obtained by manual interpretation of B&W aerial photographs taken in 1999, so the data are subjective and outdated. The information was produced by an interpreter, using stereoscopic vision of B&W aerial photographs, drawing vector polygons around tree crowns on transparent papers and scanning them as PCC maps, which was labour intensive on the part of the interpreter and the definition of PCC was not considered in the manual approach. The study area was located in the central part of Zagros woodlands scattered on the mountainous foothills, close to Yasuj, the capital city of Kohgilouye-BoyerAhmad Province, in West Iran (Fig. 1). The gentle slopes (1850 m to 1920 m above sea level) of mostly open woodlands with coppice structure purely covered with Persian oak trees characterize the area. The area experiences a semi-arid climate with average temperature ranging from -2°C in January to 35.1 °C in July and average annual precipitation is less than 500 mm (from data of 1961-2008).

Figure 1 - Location of the study area in West Iran. A part of Zagros woodlands, scattered from NW to SW Iran, is located in Kohgilouye-BoyerAhmad Province. The 500 m × 600 m plot in these woodlands (black polygon) and UltraCam-D scene coverage (grey dotted footprints). The grey lines also show the elevation above sea level in 20 m intervals.

**Field measurements**

In the study area, a 500 m × 600 m plot with similar structure (purely covered with Persian oak coppice trees) to other Persian oak stands in Zagros woodlands [Pourreza et al., 2008;
was established and precisely surveyed for quantitative assessments of the proposed approach results (Fig. 1). The study area was fully callipered and all trees located in the 500 m × 600 m plot were stem-mapped by azimuth and distance technique in 50 m × 50 m blocks, with their starting points were registered by Leica Viva GS10 differential global positioning system (DGPS) with less than 1 cm accuracy. The widest crown diameter \(d_1 \) and the perpendicular diameter \(d_2 \) of each tree were also measured to the nearest decimeter using measuring poles. Diameters were later used to estimate crown area (CA) of each individual tree assuming an elliptical crown using Eq. 1 below.

\[
CA = \left( \pi \times d_1 \times d_2 \right) / 4 \quad [I]
\]

The crown cover map of Persian oak trees obtained from field survey is the ground truth information about the distribution of canopy cover in the study area that is an essential component for computing accuracy metrics of classified UltraCam-D imagery and PCC maps.

**UltraCam-D imagery**

The large digital frame camera UltraCam-D was introduced in 2003 by Vexcel Imaging (a Microsoft Company) that was an innovative offering with a focus on replacement of aerial film cameras. It provides digital airborne imagery obtained from a digital camera instead of scanning a film image. It also provides significant technical (e.g., lower noise level, linearity, and better accuracy,) and economic (e.g., no film development and processing) advantages over traditional analog ones [Schneider and Gruber, 2008; Wiechert et al., 2011]. UltraCam-D imagery consists of 5 bands (i.e., panchromatic, red, green, blue, and near-infrared) that were PAN-sharpened to produce VHSR color imagery stored in standard 16 bit-format in this study (Fig. 2). The key parameters of UltraCam-D digital aerial camera are summarized in Table 1.

The imagery, comprising in total two images (number 1276 and 1278) from one strip covering the test site (Fig. 1), was acquired on 04-10-2010. Although this date is rather late within the local growing season, most trees and shrubs were photosynthetically active. The specifications of UltraCam-D images applied in this study are listed in Table 1.

| Table 1 - Specifications of the UltraCam-D digital camera and imagery. |
|-----------------------------------------------------------|
| **UltraCam-D Camera**                                      |
| Field of view, along-track/cross-track: 37 °/ 55 °        |
| Lens focal distance: 100 mm                                |
| Image resolution: 11500×7500 pixels                        |
| Pixel size: 9 μm                                          |
| Image format: Panchromatic, red, green, blue, and near-infrared |
| **UltraCam-D imagery**                                    |
| Flight height: 700 m                                      |
| Scale: 1:7000                                             |
| Coverage: 75 ha                                           |
| Date: 04 Oct. 2010                                        |
| Time: 10:38 AM                                            |
Iran National Geographic Organization (INGO) is taking UltraCam-D aerial imagery that can be applied in different activities including forest inventory. Because of very high spatial resolution of the imagery, landscape features such as shrubs and trees in woodlands are readily apparent and visually identifiable that can be measured directly on the imagery. The applied images in this study were orthorectified by INGO using ground control points (RMSE=0.28 pixel, XRMSE=0.26 pixel, YRMSE=0.09 pixel) and their spatial accuracy were checked by 1 m resolution DEM derived from digital photogrammetry, ground control points registered by Leica Viva GS10 DGPS in the field survey, and B&W digital aerial orthophotographs produced in 2007 for Yasuj urban studies. Two images (number 1276 and 1278) with 0.063 m spatial resolution were then mosaicked into one image to cover the entire study site. The final UltraCam-D orthoimagery of the site was then used to assess canopy cover of Persian oak trees in Zagros woodlands (Fig. 2).

**Image classification**

The UltraCam-D orthoimagery was subjected to classification by SVM supervised classification technique using 31141 manually selected training sample pixels (10173 pixels of tree crown, 9627 pixels of tree shadow, and 11341 pixels of bare soil) by ENVI 4.3 software to generate the canopy cover map of the district. The SVM classification technique is a good choice for this study because it is able to recognize the boundary of tree crowns since it is essential for PCC measurement. The parameters of SVM (Tab. 2) were optimized by Taguchi method in this study using Minitab 15 software.
Taguchi is an approach to design and perform experiments without having to tediously and uneconomically running of all possible treatments suggested by a full factorial design of that experiment. By systematically choosing certain combinations of variables as a limited number of treatments, it is possible to investigate their individual effects. To achieve Taguchi ability, as many parameters as possible should be considered, and non-significant variables must be recognized at the first prospect. We primarily divided the possible maximum and minimum amounts of the SVM effective parameters (i.e., kernel function, gamma, penalty parameter, pyramid levels, and pyramid reclassification threshold) into 4 levels (Tab. 2) according to the parameter value typically used in the literature. We defined equal limited intervals in each parameter in this study, although it is possible to determine much more detailed divisions in future studies after finding the suitable ranges of each parameter in this step. For design of experiments with five parameters and their levels (Tab. 2), the fractional factorial design, i.e., a standard $L_{16}$ orthogonal array was employed. In the next step, the SVM classification results were evaluated via signal-to-noise ratio (SNR) (Eq. 2). As it was aimed to maximize the KHAT coefficient of SVM results, the SNR ratio with ‘higher is better’ (HB) characteristics was selected instead of two other types, i.e., ‘lower is better’ (LB) and ‘nominal is better’ (NB). The SNR ratio for the HB type was then calculated based on the following equation:

$$\text{SNR} = -10\log_{10}\left(\frac{1}{n} \sum_{i=1}^{n} \frac{1}{y_i^2}\right) \quad [2]$$

where $n$ is the number of reiterations under the same experimental conditions, and $y$ represents the result of measurement. Here, $y$ is the KHAT coefficient for each experiment of the $L_{16}$ orthogonal array in the classification techniques [Roy, 2001].

| Parameter | Description                              | Level 1       | Level 2       | Level 3       | Level 4       |
|-----------|------------------------------------------|---------------|---------------|---------------|---------------|
| A         | Kernel function                          | Polynomial (degree of 2.0) | RBF           | Linear        | Sigmoid       |
| B         | Gamma                                    | 0.1           | 0.2           | 0.3           | 0.4           |
| C         | Penalty parameter                        | 10            | 100           | 200           | 300           |
| D         | Pyramid levels                           | 1             | 2             | 3             | 4             |
| E         | Pyramid reclassification threshold       | 0.3           | 0.5           | 0.7           | 0.9           |

In order to assess the accuracy of the classified imagery, a confusion matrix was applied for SVM to measure the classifier performance metrics (Tab. 3). Total 22708 test pixels, i.e., 7890 pixels of tree crown, 6746 pixels of tree shadow, and 8072 pixels of bare soil were compared on the crown cover map and the classified UltraCam-D imagery by optimized SVM. Two important performance metrics (Sensitivity and Specificity) were then calculated based on the confusion matrix of test pixels (Tab. 3) to express the uncertainty associated with the classified map.
Sensitivity = \frac{TP}{TP + FN} \quad [3]

Specificity = \frac{TN}{FP + TN} \quad [4]

The sensitivity of a classifier or True Positive Rate (TPR) is the proportion of positive pixels correctly predicted, and its specificity is the proportion of negative pixels correctly predicted, usually expressed as False Positive Rate (FPR) (1 - Specificity). Thus, classifiers with high sensitivity can correctly predict positive pixels (pixels belonging to the category of interest) and classifiers with high specificity can correctly predict negative pixels (pixels not belonging to the category of interest). Receiver operating characteristic (ROC) curve analysis was also applied to evaluate the SVM classification results and the area under curve (AUC) of each class was computed to express the probability of correctly identifying each class. Values of AUC range from .50 for the lowest possible ROC to 1.00 for the highest possible ROC curve [Alatorre et al., 2011].

Table 3 - An example of a confusion matrix established based on the training samples.

| Classification | Ground Truth   |
|----------------|----------------|
|                | True           | False          |
| Positive       | True Positive (TP) | False Positive (FP) |
| Negative       | False Negative (FN) | True Negative (TN) |

**Data analysis**

The effects of block sizes, varied from 100 to 5000 m² (100, 500, 1000, 1200, 1500, 2000, 2500, 3000, 3500, 4000, 4500, and 5000 m²), were investigated to determine the optimal size with regard to the accuracy of PCC maps. Raster grids with various block sizes were overlaid on the crown cover map and the classified UltraCam-D orthoimagery. The PCC was measured in each block according to its area and the maps were classified due to PCC levels (0-5%, 5-10%, 10-25%, 25-50%, 50-75% and 75-100%) defined by FRWO in Zagros woodlands. The final classified cellular PCC maps were compared cell by cell. The appropriate block sizes were determined based on the overall accuracy (OA) and KHAT metrics of the maps (Fig. 3) [Congalton and Green, 2009]. Further analysis and filtering processes only considered the selected block sizes. The raster PCC maps were converted to vector maps and filtered to smooth boundaries, additionally eliminating small polygons (less than 1500 m²) using GRASS and ArcGIS 9.3 software. These vector PCC maps were reassessed based on the accuracy metrics to identify the optimal block size and PCC map. The significant difference between KHAT coefficients of the final PCC maps was tested by Z statistic (Eq. 5) [Paine and Kiser, 2012].

\[
z = \frac{\text{KHAT}_1 - \text{KHAT}_2}{\sqrt{\text{Var (KHAT}_1)}^2 + \text{Var (KHAT}_2)^2} \quad [5]
\]
where KHAT$_1$ - KHAT$_2$ is the difference between two KHATs and Var(KHAT) is the variance of confusion matrix.

**Figure 3 - Process flow for PCC mapping using UltraCam-D aerial imagery.**

**Results**
Field measurement of the study area showed that 3452 Persian oak (99.85%), 1 wild pistachio (*Pistacia atlantica* Desf.), 2 maple (*Acer cinerascens*) and 2 hawthorn (*Crataegus aronia*) trees were located in the site (3457 trees) and the mean width, length, and area of tree crowns were 6.74 m (±2.96), 7.94 m (±3.50), and 50.28 m$^2$ (±44.15), respectively. The total amount of crown areas in the test site was 173066.7 m$^2$ with a fraction of 27583.6 m$^2$ of overlapping crowns areas (Fig. 4). Consequently, the canopy cover of all trees was 145483.1 m$^2$ and the PCC of the site was 48.5%. Figure 5a shows the crown cover map of the study area resulted from field measurement.

**Figure 4 - A part of the study area that had 366.99 m$^2$ canopy cover (without overlaps) (a) and 418.44 m$^2$ total crown area (with overlaps) (b).**
Figure 5 - The crown cover map of the study area obtained by field survey and the grid with 1200 m² circular plots (red circles and points) (a). The canopy cover map derived from UltraCam-D orthoimagery classified by optimized SVM (b). Grey polygons are tree crowns without their overlaps.

Discrimination of tree crowns from their shadow and bare soil on the UltraCam-D image was based on a supervised classification method using SVM classifier. The optimal parameters of SVM for the UltraCam-D image classification were as following: (A) Kernel function: RBF; (B) Gamma: 0.3; (C) Penalty parameter: 100; (D) Pyramid levels: 1 and (E) Pyramid reclassification threshold: 0.9 based on Taguchi orthogonal array. Figure 5b shows the best SVM classification result on the imagery of the study area. The classification result of UltraCam-D imagery showed that total canopy cover of all trees was 132568.4 m² and the PCC of the site was 44.2%. Table 4 summarizes the confusion matrix elements of each class and shows their performance metrics. The test pixels showed that the specificity of tree crowns and the sensitivity of bare soil were slightly higher than other classes, respectively. The AUC of tree shadow ROC curve (Fig. 6) was the highest between the investigated classes showing greater discrimination of this class from others via optimized SVM classifier on the UltraCam-D orthoimagery.

Table 4 - The confusion matrix elements and performance metrics of optimized SVM classification result on the UltraCam-D orthoimagery.

| elements and metrics | classes         |               |               |
|----------------------|----------------|---------------|---------------|
|                      | tree crowns    | tree shadow   | bare soil     |
| TP (Pixels)          | 7804           | 6464          | 7972          |
| FP (Pixels)          | 65             | 299           | 104           |
| FN (Pixels)          | 165            | 157           | 146           |
| TN (Pixels)          | 14674          | 15788         | 14486         |
| Specificity          | 0.996          | 0.981         | 0.993         |
| Sensitivity          | 0.979          | 0.976         | 0.982         |
| AUC                  | 0.8217         | 0.9217        | 0.8098        |
Figure 6 - ROC curve for optimized SVM classification of the UltraCam-D orthoimagery. The diagonal dashed line represents a model with no predictive ability. Greater deviation of the ROC curve from this diagonal indicates greater discriminatory capacity of SVM.

Tree crown polygons derived from the classification were found to be well registered to the corresponding crowns in the field data (Fig. 7). After the primary classification of UltraCam-D orthoimagery, the result was reclassified as follows: tree crowns (Class 1: grey polygons in Fig. 5b) and all other polygons (tree shadow and bare soil) (Class 2: white areas in Fig. 5b).

Figure 7 - A part of SVM classification result overlaid on the UltraCam-D orthoimagery. Optimized SVM classifier well separated tree crowns from their shadow and bare soil.
Raster grids with various block sizes (100 to 5000 m$^2$) were overlaid on the crown cover map resulted from field survey and the map obtained from classification of UltraCam-D orthoimagery by optimized SVM. The PCC was calculated in each block and the final raster maps were reclassified according to predefined PCC levels (Fig. 8).

Figure 8 - An example of reclassified raster PCC maps obtained from the crown cover map (a) and classified UltraCam-D orthoimagery (b) with block size of 1000 m$^2$. The predefined PCC levels in Zagros woodlands were summarized in the legend.

The raster PCC maps obtained from the crown cover map and classified UltraCam-D orthoimagery were further validated using cell by cell comparison to assess how various block sizes affected the OA and KHAT metrics. Figure 9 shows that the OA and KHAT values increased sharply up to the block size of 1200 m$^2$, after which these indices decreased and increased repeatedly and reached a plateau after the block size of 4000 m$^2$. The 4000 m$^2$ block size represented the highest OA and KHAT values (91.82% and 0.82 respectively) and the 100 m$^2$ block size had the lowest OA and KHAT values (45.61% and 0.27 respectively). Block sizes of 1200, 1500, 2000, 2500, 3000, 3500, and 4000 m$^2$ were selected for the remainder of the analysis, since it was believed more investigation was required to find out the most suitable mapping unit between the studied block sizes.

The PCC maps obtained with selected block sizes were converted to vector format and filtered to smooth boundaries and merge small polygons. Since it was necessary to reassess the accuracy of the new PCC maps, a 100 m × 100 m grid with 30 points was established on the crown cover map of the study area (Fig. 5a). In each grid point, PCC was calculated in a 1200 m$^2$ circular plot as the most suitable sample plot in these semi-arid woodlands [Zobeiri, 2007] and the PCC values were assigned to the grid points. As shown in Figure 9, the trend of OA and KHAT changes reached a level at 1200 m$^2$ block size after which the accuracy metrics did not increased considerably. As a ground truth, the grid was overlaid on the final
PCC maps to evaluate their OA and KHAT metrics again. Based on the ground truth grid including 30 points, validations showed that PCC maps with block sizes of 3000 m$^2$ and 4000 m$^2$ yielded similar OAs (90%) but the KHAT of 3000 m$^2$ PCC map was slightly higher (0.71) than 4000 m$^2$ one (0.69), although they were not significantly different ($z=0.26$, $\alpha=0.05$) (Fig. 10).

Figure 9 - The OA and KHAT metrics of raster UltraCam-D maps with various block sizes.

Figure 10 - The OA and KHAT metrics of final PCC maps with selected block sizes.
Results showed that the vector PCC map with block size of 3000 m\(^2\) had the highest OA and KHAT values between the investigated block sizes after filtering (Fig. 10) which was then selected as the most suitable PCC map of the study area. Figure 11a shows the final vector PCC map of the study area. The map was overlaid on UltraCam-D orthoimagery of the study area to make visual evaluation of the map possible (Fig. 11b).

The quantitative investigation of the final PCC map illustrated that the fractions of 3.1, 54.4, 40.7, and 1.8% of the study area were covered with PCC levels of 10-25, 25-50, 50-75, and 75-100%, respectively.

**Discussion**

In semi-arid areas, changes in woody plant distribution have dramatic effects on ecosystem processes and functions [Wallace et al., 2008; Yang et al., 2012; Lee et al., 2013]. Remotely sensed data have been widely used to provide spatially explicit information about the heterogeneity of woody plant distribution over extensive dry regions [e.g., Mathieu et al., 2013]. Both satellite and airborne remote sensing imagery have been widely applied to retrieve vegetation canopy cover in dryland environments [e.g., Yang et al., 2012]. Therefore, it is important to find an efficient approach to obtain canopy cover maps in semi-arid ecosystems to assess woody plant distributions and monitor their changes over time and space.

In this study, we proposed a robust semi-automatic procedure to produce PCC maps in Zagros semi-arid woodlands (Fig. 3). We primarily recorded the coordinates of each tree position to construct the crown cover map of the site. The crown overlapping of adjacent trees was also calculated after crown area projection in the field survey that were then
considered in canopy cover measurements (Fig. 4). The results showed that 15.9% of total tree crown projection areas belonged to overlapping of adjacent tree crowns that was eliminated in calculating PCC (Fig. 5a).

Precise discrimination of tree crowns from the surrounding in semi-arid regions is also necessary to investigate canopy cover of these areas and obtain PCC maps using remote sensing datasets [Bunting and Lucas, 2006]. Persian oak single trees were well separated from other features, especially their shadow, in woodlands on UltraCam-D orthoimagery due to its very high spatial resolution using SVM classification technique. This classifier was applied to precisely discriminate the crowns of Persian oak coppice trees from their shadow and bare soil in the site. While being theoretically robust, SVM is considered to be more transparent, easier to use, and often achieves better generalization when comparing to some other classifiers, e.g., kernel based reclassification (KRC) [Keramitsoglou et al., 2006], maximum likelihood [Mondal et al., 2012], and decision trees [Li et al., 2013].

Parameterization of SVM classifier via Taguchi method resulted in high performance of the classifier on UltraCam-D orthoimagery of our site (Fig. 7). Optimization of SVM parameters was performed based on the applied dataset (UltraCam-D aerial imagery) in this study to achieve the highest classification accuracy (ROC curve analysis) as Yang [2011] found that parameter settings of SVM significantly affected the accuracy of land-cover classification of TM imagery.

ROC curve analysis of the classification results as the most comprehensive description of accuracy, showed that tree crowns were well separated from other features on the UltraCam-D imagery (AUC ~ 0.82) although tree shadow presented the highest AUC (~ 0.92) that expressed the highest separation probability on the imagery compared to other classes (Tab. 4, Fig. 6). Although the ROC curve indicated all of the combinations of sensitivity and specificity that a test is able to provide, they were investigated separately for each distinguished class and the results showed that optimized SVM classifier could well separate the mentioned classes (sensitivity and specificity higher than 0.97). The highest amount of specificity belonged to tree crowns (= 0.996) that showed the effective performance of SVM in separating other features (tree shadow and bare soil) and the AUC of tree shadow (~ 0.92) in ROC curve analysis also expressed precise discrimination of tree shadow from tree crowns and bare soil. It was concluded that there were probable biases in discriminating tree crowns from other features according to ROC curve results but these biases did not greatly affect tree crown detection on UltraCam-D orthoimagery by SVM (AUC ~ 0.82) (Tab. 4). Bare soil also showed the highest sensitivity value (~0.99) that indicated the high potential of optimized SVM classifier to detect this class. The sensitivity-specificity pair describes the classification accuracy more meaningfully than the single index of percentage correct, and it has been widely implemented with ROC curve analysis in the literature [Alatorre et al., 2011; Xu et al., 2014].

The approach developed in this study, took two important aspects of the definition of PCC in to consideration. Firstly, the overlaps of adjacent tree crowns were eliminated in canopy cover measurements of study area map (see Fig. 4 and explanations). Since UltraCam-D imagery provided a vertically detailed view of forest canopy cover, crown boundaries without overlapping were also mapped correctly on them due to their very high spatial resolution (Fig. 7). Secondly, PCC was calculated in a predefined block varying in size from 100 to 5000 m$^2$ to determine the most suitable unit area for PCC map construction.
Previous studies [e.g., Cots-Folch et al., 2007; Mathieu et al., 2013] showed the dependence of accuracy of canopy cover maps as a function of block size. We also tested various block sizes that ranged from 100 to 5000 m$^2$ in an attempt to determine the best size at which PCC should be measured, although the choice of the optimal block size is rarely discussed, most likely because of the effort required to build up comprehensive field datasets. In this study, intensive field measurements over 500 m \times 600 m and the consequent canopy cover map of 3457 trees made the optimization of block size possible. The results showed that as the block size increased, the PCC values of the crown cover map and UltraCam-D classification map became more similar that resulted in the improvement of accuracy metrics (OA and KHAT) up to the size of 1200 m$^2$, although blocks with larger sizes did not greatly increase the accuracy metrics (Fig. 9). Tree crown projection in the field (circular shape, see Fig. 4) and on UltraCam-D orthoimagery (approximately oval shape with irregular boundaries, see Fig. 7) affected the PCC values of each block size in the two maps. The difference between the crown shapes of one tree in the field and on the imagery biased the PCC values of small blocks (e.g., 100 m$^2$) resulting in low OA and KHAT, while it had less effects in larger blocks as in the 5000 m$^2$ block, PCC values resulted from the field measurements and UltraCam-D maps were very close, producing high accuracy metrics. Further analysis on the selected block sizes (i.e., 1200, 1500, 2000, 2500, 3000, 3500, and 4000 m$^2$) showed that the optimal block size was 3000 m$^2$, and we recommend this to be used as the minimum plot size to be sampled in the field when considering UltraCam-D images in Zagros semi-arid woodlands.

Filtering was performed on the selected PCC maps to smooth boundaries and generate contiguous zones of PCC levels. This process produced PCC maps including predefined levels, although the accuracy metrics decreased because of eliminating small polygons and smoothing boundaries (see Fig. 10 and explanations). OA and KHAT were recalculated for the selected block sizes and the results showed that the PCC map with block size of 3000 m$^2$ had the highest values of accuracy metrics, although PCC maps with block sizes of 3000 m$^2$ and 4000 m$^2$ yielded similar OA (90%) and their KHAT was not significantly different. The quantitative analysis of the final PCC map with optimal block size (3000 m$^2$) also showed that more than half of the study area (57.5%) had PCC less than 50% that is close to 48.5% true PCC of the site. The results demonstrated that increasing the block size in PCC maps caused a reduction in the number of PCC levels distinguished via the suggested procedure in this study. Figure 8 gives an example of a primary raster PCC map with block size of 1000 m$^2$ that had all predefined PCC levels, although the block size of 3000 m$^2$ produced a four level PCC map and the first two levels (0-5 and 5-10%) were not distinguished because of larger block size.

Conclusion
This study proposed a procedure to construct percent canopy cover maps considering its standard definition employing UltraCam-D airborne very high spatial resolution imagery in Zagros semi-arid woodlands. Segmenting UltraCam-D imagery with SVM classifier optimized by Taguchi method, Persian oak crowns appeared to be well delineated based on ROC curve analysis. The present achievement supports the studies by Colgan et al. [2012] and Pouteau et al. [2012] for the success of SVM in discriminating tree crowns from the surrounding (tree shadow and bare soil) on remote sensing data. Percent canopy cover
was calculated in raster grids with various block sizes and their accuracy metrics (OA and KHAT) revealed the appropriate sizes. After filtering processes on the primary raster maps, further accuracy assessments were conducted to assess the final vector maps. The PCC map with block size of 3000 m² provided 90% OA (KHAT=0.71) due to very high spatial resolution of UltraCam-D imagery and higher classification accuracy of SVM in object recognition. This study focused on the efficiency of proposed procedure and the results revealed its robustness, although it is suggested that further investigation should focus on its application in larger spatial scales and other airborne and satellite remote sensing datasets with various spatial resolution to examine the potential of this approach.

Acknowledgments
We acknowledge Iran National Geographic Organization (INGO) that provided UltraCam-D imagery and carried out data pre-processing. Field survey was made possible by Natural Resources General Office, Kohgilouye-BoyerAhmad Province. Financially this research work was supported by Vice Chancellor for Research Affairs, Shiraz University, Iran. We also deeply thank the two anonymous reviewers for their valuable relevant comments.

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