A COMPARISON THROUGH TREE EXTRACTION IN IMAGE-SPACE AND OBJECT-SPACE

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ABSTRACT:

In various studies trees have been extracted and their conditions have been examined through different detection algorithms from two main data sources including (a) point cloud and (b) raster data. The output of tree extraction is the input of the next processing steps, and the importance of these outputs is proved more than before. Tree Extraction (TE) has many applications in biomass estimation, CHM extraction, etc. All of which require high accuracy and the correct position of the trees. therefore, in this study, a comparison between tree extraction algorithms in two common sources of data has been conducted. As for the raster data, all bands are first co-registered. Afterward, the trees are separated from the background by using image processing techniques such as changing the image color space and weighted averaging on different bands. Finally, TE algorithms such as watershed segmentation, valley following, local maxima, and image binarization were applied. As for the point cloud data, TE can be conducted in the object space to compensate for the methods used in the raster space with object detection algorithms e.g., the coherence between the two trees, etc. which have been discussed in detail in this paper. In the object space, three algorithms, region-based, surface normal, and Euclidean segmentation, were implemented and discussed on the same raster data set in the photogrammetric point cloud. The results show the higher accuracy of the region-based algorithm in object-space by more than 26% in comparison with the valley following algorithm in image space.

1. INTRODUCTION

The first attempts to detect trees automatically from digital imagery date back to the 1980s. Research done by (Pinz 1991) was one of the original examples. Searching for maximum values in the local brightness of processed aerial images with a 10 cm pixel size enabled him to locate the center and guess the radius of a crown. Next (Gougeon 1995) Used aerial images acquired with a 36 cm GSD, they developed a valley-following and rule-based algorithm. (Pollock 1996) used predefined models to obtain each trees; (Brandtberg and Walter 1998) used multiple scale analysis to estimate tree-crown area. afterwards, other image-segmentation techniques such as region growing and watershed segmentation was offered for tree delineation.

The Valley following was first recommended by (Gougeon 1998) for the automatic characterization of trees in a full-grown pasture forest in Canada with 31 cm GSD MEIS-II images. The Gougeon algorithm finds the local minimum as a valley instead of searching for the local maximum as the potential highest point of the tree. The gaps are then followed by the search for adjacent pixels that were within pixels with higher amount.

In other words, the highest point of the trees is found. In 2002 Culvenor introduced a conceptual analysis for determining the size of the window with four rules requiring a user-defined threshold that showed high accuracy in counting trees. In 2004 wang proved that treetops not only showed the highest radiometric

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measurements but also considered geometric centers of the tree crowns so he used geodetic distance to locate treetops. In 2005 Lamar used a similar idea but instead of geodetic distances, he computed the Euclidean distance to locate treetops. Region Growing algorithms were also later introduced in 2007 when (Gonzalez 2009) started to identify seed points of an image and if the adjacent pixels were similar enough to seed pixels the region would grow until certain criteria were satisfied. The user could determine these criteria based on environmental factors and image conditions. The next algorithm is image binarization in which the unwanted pixels are black and the target pixels are shown in white color. The contrast between the tree canopies and the shadowy area can be used to determine tree crowns from the background. Template matching is an image processing technique that Searches for a matchup between a model and object of interest, also known as the pattern, and is used with different regions in the image (Gonzalez 2009).

These techniques Facilitate the need for vast coverage of trees with high spatial resolution. With high-resolution remote platforms such as unmanned aircraft systems (UAS), this goal can be achieved. although UAS is still an emerging field, they have been used systematically for observing greenery and ecological criterions leading to the amendment of agroforestry activities or assessing crop circumstances by obtaining vast quantities of inputs that through additional processing can allow a wide range of applications(Moradi et al. 2021). These techniques rise the need for vast coverage of trees with high spatial resolution. Nevertheless, previous studies have shown that many images taken from sensors mounted on satellite platforms lack proper spatial and temporal resolution (Dadras Javan et al. 2019). Moreover, sensors installed on aerial platforms that present high-resolution imageries are pricey, and it is challenging to provide proper images to monitor changes in vegetation (Byrne 2018). Contemporary advances in remote sensing have enabled passage to aerial images captured by unmanned aerial vehicles (Moradi et al. 2021) with high-resolution Remote sensing platforms such as unmanned aircraft systems (UAS), this goal can be achieved. Multiple of successful works have been applied to forests and related areas using inexpensive passive imagery detectors such as RGB cameras and NIR detectors. Other studies demand higher resolution ranges that can only be achieved using multispectral or hyperspectral sensors. Due to multiple problems like infections, different pests, lower productivity, and dehydration in orchards and crops monitoring through a single multispectral sensor would suffice and if the monitoring was conducted periodically, could enable users to control trees' growth, health, and productivity and secure their products with higher quality. In the past, these actions were done by in-site measurements and expert analysis which were time-consuming, economically inefficient, and with low coverage. In recent years, Unmanned Aerial Vehicles (UAVs) as a subset of UASs are capable of fast field monitoring. They are very user-friendly, fast, and highly correct thus used in many studies. (Ye et al. 2007) used an object-based and image-based method in eCognition to get dependable details on the plentitude and dispensation of weeds in gardens. In this paper, the potential of multispectral imagery for classification and mapping of weed infestation in a citrus orchard in Japan is investigated. After gaining image objects on the image, spectral data for the weeds and citrus fruits, which are displayed by the corresponding sample objects selected, was extracted. Therefore, maps generated by classification can accommodate very important information for the preparation of a site-specific weed management program for the garden. (Berni et al. 2009) found out that the combination of high spatial resolution and rapid observation time is essential for monitoring vegetation in the agriculture field and it is only possible by using UAVs. This paper addresses on the radiometric calibration, atmospheric correction, and photogrammetric procedures needed to get specific factors derived from products that are useful for greenery monitoring. The results were crops successfully produced and visualized using leaf area index, chlorophyll (Cab), and water stress detection. (Stagakis et al. 2012) examined water status and assesses the impact of stress on quality Citrus fruits using structural and physiological remote sensing indices (Stagakis et al. 2012). The study by (Lehmann et al. 2015) explores pest contamination as an crucial appearance of plantation management. In the case of acorn infection, damaged oak has shown high levels of effects, such as the disappearance of tree leaves and the specific reflection feature of the leaf surface of the disease. These important factors can be classified in high-resolution color-infrared (CIR) images of tree canopies and branch surfaces captured by (UAVs). Their process includes CIR / NIR image acquisition, mosaic imaging, georeferencing, and pixel-based image enhancement followed by object-based image classification techniques. The classification derived from the Modified Normalized Vegetation Index was used to distinguish between 5 vegetation classes, for example, infected, healthy, dead branches, other vegetation, and the distance between plants (Lehmann et al. 2015). (Franklin and Ahmed 2018) used Object-Based Image Analysis and Classification by Machine Learning of Multi-Spectral Camera Array Data Mounted on a UAV. White birch, aspen, and two maple species were studied in the field. The classified images and results were compared visually with the sampled crowns. In this study, Random Forest algorithm as a machine learning classification method was used, and the performance of the algorithm was approximately 78% correct. In the same year (Gini et al. 2012) utilized the UAS to investigate the parks in inaccessible areas, Used for landscape films, 3D models, and vegetation monitoring. For the latter, in particular, very high-resolution images were produced with both RGB and NIR compact cameras, and a Digital Surface Model (DSM) of a small vegetation area and the corresponding orthoimages were produced and justified. After the artificial bands were extracted, both supervised and unsupervised classification was performed to test the algorithm's ability to distinguish between different bushes and tree species. The overall accuracy for unsupervised classification is about 50% while the supervised overall accuracy is about 80%. X. Zhou in his study, rice grain yield with single-stage vegetation indices (VIs) and multi-temporal VIs derived from multispectral images (MSIs) and RGB images were predicted. The results showed that the growth stage is the optimal stage for predicting grain yield using VIs in digital and MS images (Xu et al. 2021). In the following article Kasper Johansen 2018 generally thought that pruning of fruitage is new growth and has an explicit impression on fruiting, facilitates fruit harvesting, and may increase yield because it increases the light intake at the crown surface of trees. To determine the response of pruning effects to a garden of foliage trees, evaluate changes in tree structure around the canopy that include width, height, area, and plant projection cover (PPC) using multiple UAV images Spectral bands were collected before and after pruning (Kasper et al. 2018). Results before and after pruning showed critical differences in all measured structural parameters of the tree (Pádua et al. 2017). Considering that monitoring orchards can highly affect their productivity therefore; trees need to be extracted and monitored separately. So, this research assesses the geometry extraction of trees in image-space and object-space using the mentioned TE algorithms

2. MATERIALS AND METHOD

The TE algorithms used in this pare in the object space are Region-based growing, Euclidean-distance and Surface-Normal and the ones in the image space are watershed segmentation, valley following, local maxima, and image binarization.

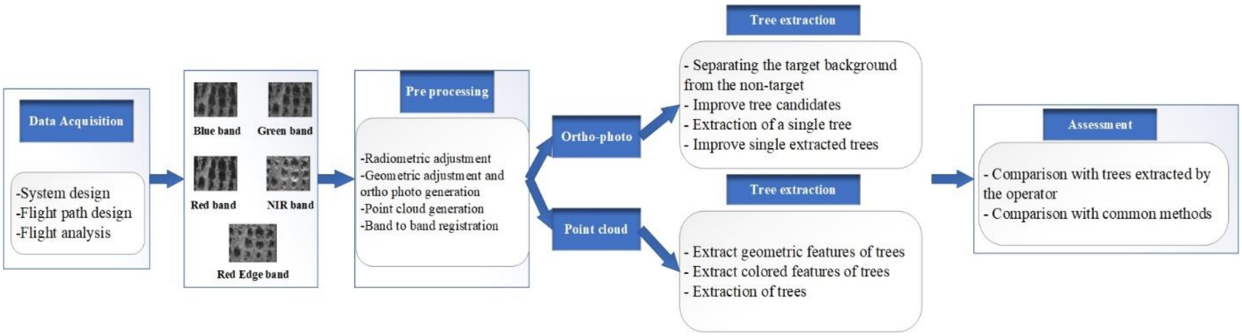


Figure 1. Workflow of the study

In the local maxima algorithm, a window moves on the image according to the user's choice, and locally by identifying the highest gray level, it is identified as the crown point of the tree. This algorithm works well on images that are not oblique and trees that have a uniform shape with appropriate distances. One of the problems of this method is the size of the window, if it is small, it causes too many trees to be identified, and if it is big, small trees get lost. In the image binarization algorithm, the gray levels are divided into wanted and unwanted pixels, where the white pixels represent the points of interest and the black pixels represent the background. In this algorithm, trees can be easily identified by using the histogram of the image and the difference in brightness between the tree and its background. In the valley following algorithm, instead of identifying the crown of the trees, it finds the lowest point of the shadow created by the trees, which is conducted through searching among the two neighboring pixels with the highest value, after finding the desired point by moving towards the neighbor wherever the changes reach their maximum state, that point is identified as the crown of the tree, which was not successful at first due to the high density of trees and sometimes the branches intertwining with each other so I had to add some rules to help the algorithm. In the watershed-segmentation method, the gray level image is considered as a topographic surface, then a water source is considered at a high altitude, the water flows and fills wherever there is a hole, and it is considered as a segment to prevent the merging of the neighbor segments, it is necessary to impose a series of rules, which are called virtual barriers. This work continues until the whole image is segmented. In object-space for region-base segmentation first, the photogrammetric point cloud must get diffused to increase the computations speed. Then normal vector and the degree of curvature for every point regarding their neighbors are computed. This computation uses k nearest neighbor for every point. To this point, the normal for every point is known but the direction of every normal is ambiguous. To solve this problem an angle of sight is considered and using eigenvectors and eigenvalues the ambiguity is solved, then regarding the previous values and the change in slopes of the surface normal segmentation is done. In the surface normal algorithm after the computing of the surface normal of every point the points which have the nearest values of normal are added to the same segment and enters the final algorithm i.e., Euclidean clustering. it identifies core points and for this study, the core points are tree tops. Finally, with a value of k neighbors, the segmentation is carried out.

The data used in this paper was acquired with multispectral UAV-based imagery in Iran. The first study area is sited in Fasaa County, 230 km south of Shiraz city in Fars Province of Iran (28°45′07″N 54°32′40″E WGS84). Fars Province is the second largest citrus producer province in Iran, after Mazandaran Province (Faghihi et al. 2009). One of the Citrus Greening infected orchards, with an area of 1.2 hectares (Faghihi et al. 2009). (Figure 2)

Figure 2. Darab site

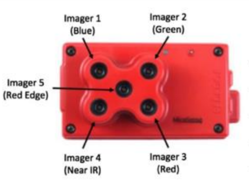
The second study area is placed in Shahbedin county, 6 km south of Neka in Mazandaran province of Iran (36°39′03″N, 53°17′57″E WGS84). Data acquisition was done by Pour Azar et al in 2018 (Pour Azar et al. 2018). (Figure 3)

Figure 3. Neka site

A multirotor platform is used as an unmanned vehicle to carry an imaging sensor for capturing images over the test field area. The platform is equipped with different navigation sensors to follow the pre-defined trajectory. The platform parameters are presented in Table 1 (Faghihi et al. 2009).

Platform type	Hexacopter
Flight duration	40 min
Flight height	5000 MSL
Max takeoff weight	8 kg
Dimensions (diameter)	1.2 m
Cruise speed	50 km/h
Wind resistance	35 km/h

Table 1. Hexa-rotor platform properties



Bandwidth (nm)	Central Wavelength (nm)	Band	Band No.
20	475	Blue	1
20	560	Green	2
10	668	Red	3
40	840	NIR	4
10	717	Red Edge	5

Figure 4. Spectral bands and configuration of the Red Edge camera (Mica sense Inc 2017)

The first step is sensor calibration, which includes radiometric and geometric calibration. Radiometric calibration is performed by a special reflectance panel at the flight site and at the time of acquisition. Geometric calibration is done by self-calibration during geometric calculations. The second step is geometric adjustment and ortho photo generation. The geometric adjustment is done by self-calibration during ortho photo generation using SFM (Structure from Motion) method. Many feature detectors such as SIFT, SURF, or other algorithms can be used. In this study SIFT algorithm is used and missed matches were omitted using RANSAC. Next, camera poses are determined simultaneously with bundle adjustment resulting in a sparse point cloud. Afterward, dense matching will be done and point cloud and orthophotos will be generated. The fourth step is a band-to-band registration because different sensors are shooting at a distance from each other, so the images taken by them are a little misplaced as shown in Figure 5. To solve this problem, the red-edge camera was used as the master sensor and the rest of the sensors as slaves through the SIFT algorithm which is a very flexible algorithm functioning at different scales and dimensions, images were registered using the least Euclidean distances, which resulted in an error of fewer than 0.4 pixels

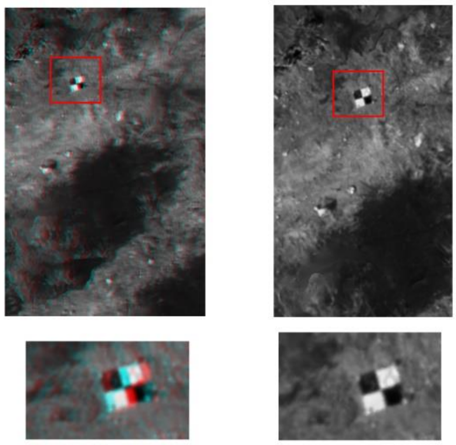


Figure 5. Before and after band-to-band registration

3. Results

After data preparation, the above algorithms were implemented both in image space and object space. The results for image-space algorithms are illustrated in Figures 6-9.

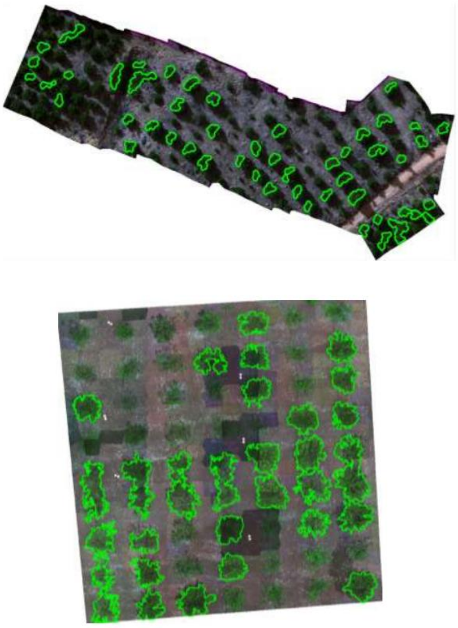


Figure 6. Local maxima algorithm

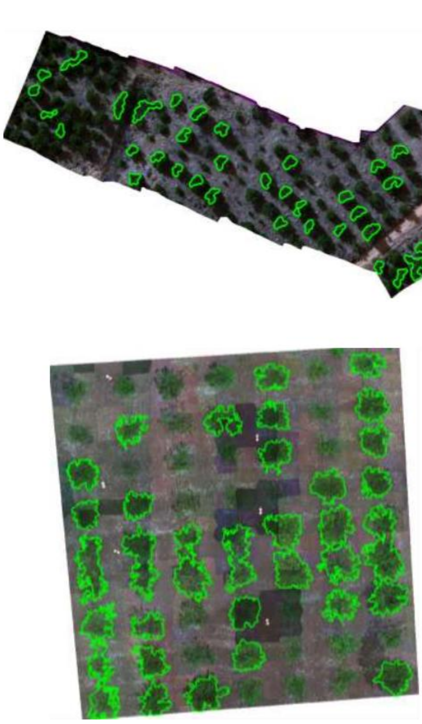


Figure 7. Image Binarization algorithm

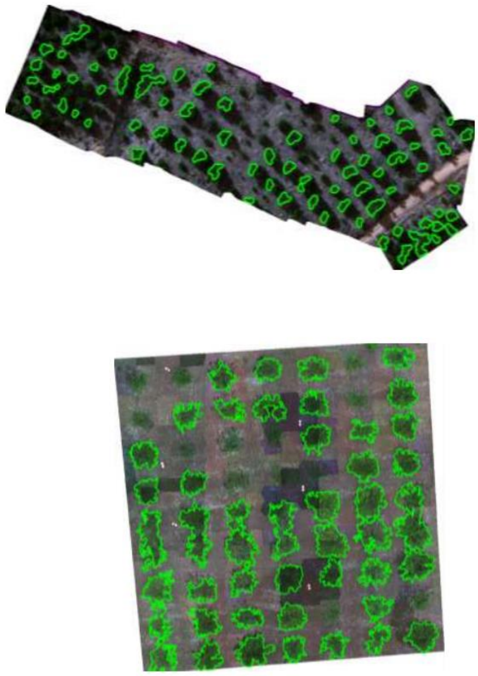


Figure 8. Valley following algorithm

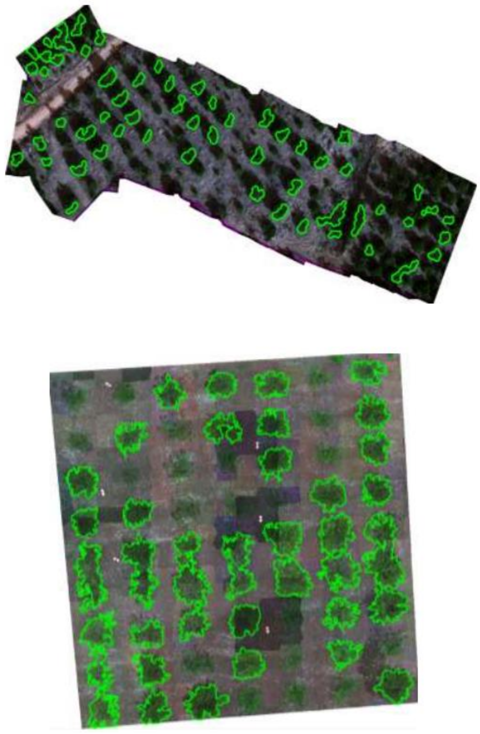


Figure 9. Watershed-segmentation algorithm

The results in object-space for each algorithm are illustrated in Figures 10-12 as follows:

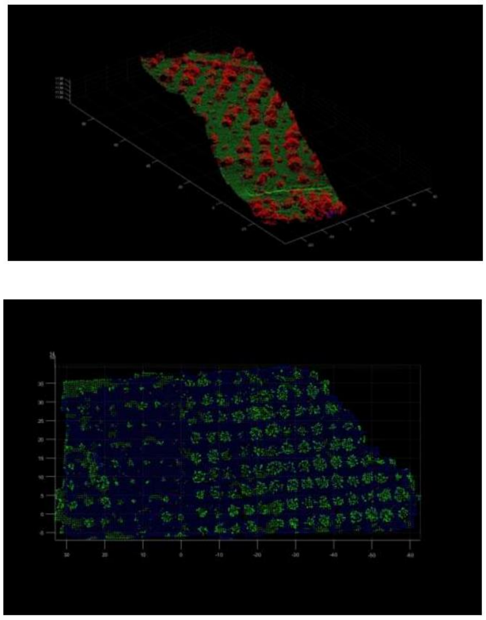


Figure 10. Region-base algorithm

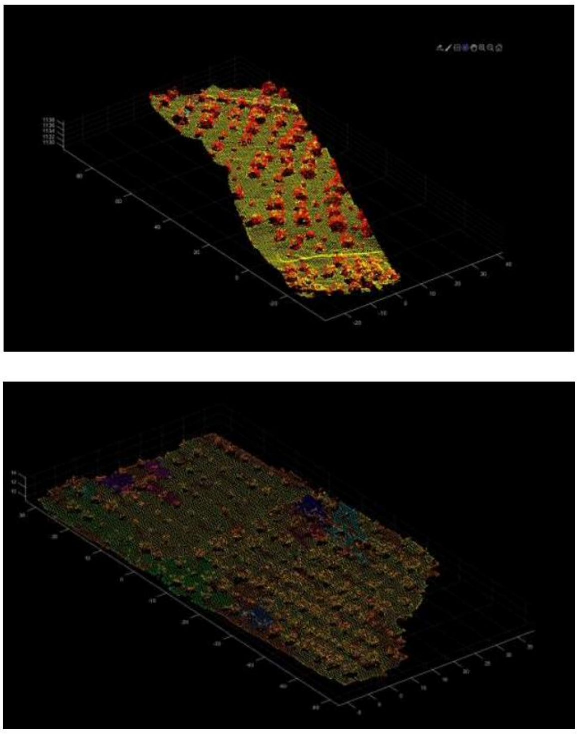


Figure 11. Surface-Normal algorithm

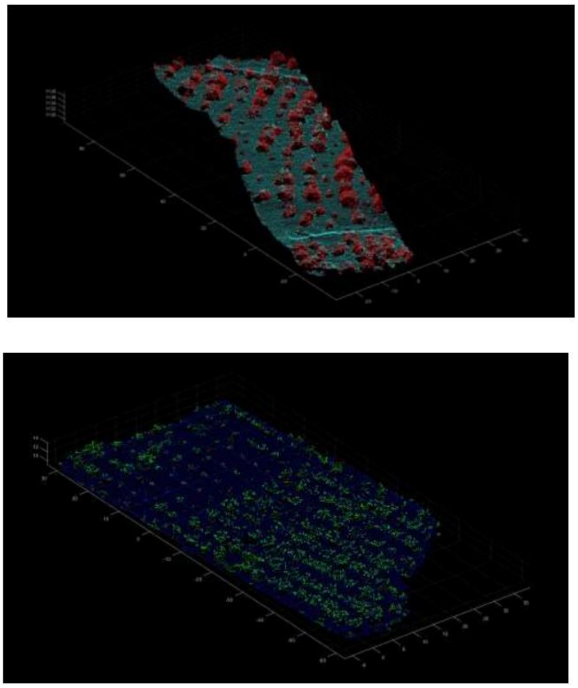


Figure 12. Euclidean-distance algorithm

The algorithms were implanted in two different data sets and the outcomes were assessed with the ground truth of trees in the same data sets as the reference map. Validation was done using the kappa coefficient. The outcomes are shown in Table 2:

	Image-space			
Algorithm	Kappa			
Site	Darab	Neka	computation time(sec)	
Watershed segmentation	0.34	0.46	48	74
Valley following	**0.68**	**0.55**	71	137
Local Maxima	0.18	0.14	53	112
Image Binarization	0.3	0.29	42	91
	Object-space			
Region-based	**0.94**	**0.98**	137	187
Surface normal	0.73	0.66	153	204
Euclidean clustering	0.76	0.79	101	192

Table 2. Accuracy assessment

According to Table 1, it can be concluded that TE was more successful in object space than the image space with a 0.26 and 0.43 difference between the best algorithm used in image and object space i.e., valley following and region based on Darab and Neka sites respectively, even though a 5-band multispectral sensor was used in image space to improve TE algorithms.

4. CONCLUSION

As the results in the study indicate common image processing segmentation algorithms are still not at their full potential for tree extraction, their results vary in different data sets and depend on the user-defined threshold value. On the other hand, object-space algorithms are more accurate and have automated workflows enabling them to be applied in different regions regardless of the study area conditions. The point cloud has the height values for each point and this attribute enables the segmentation algorithms to be more accurate in finding the right neighbors and assigning them to the right segments on the other hand algorithms in image space only have planimetry attributes that can be misleading. Considering that a photogrammetric point cloud was used in this study which is a cheaper solution than a LiDAR point cloud, researchers are suggested to test the methods used in this study on LIDAR data to see if more accurate results can be achieved and compare their results.

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