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Tree detection from high-resolution unmanned aerial vehicle (UAV) images

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ABSTRACT

In parallel with the advancement of technology, important developments are taking place in the field of data collection and data processing about the earth, as in many other fields. The data collection stage, which takes a long time with traditional methods, can be completed in a very short time with modern techniques. Satellite images, terrestrial data collection tools, and unmanned aerial vehicles (UAVs) are actively used in studies to determine the characteristics of the earth. UAVs are popular due to their high resolution and fast data collection capacity. Products obtained from UAVs can also be processed based on modern image processing techniques. In this way, it is possible to get meaningful and usable information from the images obtained. The development of fast and easy data collection methods brings along the big data problem. Although long times are spent processing data, success in processing images is low. For this reason, automatic processing of data obtained with modern techniques increases the quality of the result and saves time. In this study, trees were detected over the image of a wooded area obtained with a UAV. The data obtained by the UAV are separated from other objects in the field by object-based classification in eCognition software. In object-oriented classification, the data are grouped at the segmentation stage. Later, segments with similar characteristics were classified according to certain index values. As a result of the study, control data was generated in the eCognition software. Using this data, accuracy analysis was made with the help of an error matrix and the kappa statistic was found to be 78%.

1. INTRODUCTION

Nowadays, with the use of aerial photographs, satellite images, and LiDAR data, it has become quite easy to produce data on the land structure, vegetation, and other details. According to terrestrial data collection techniques, although these methods facilitate data collection and access, the process of this data and integrating it into geographic information systems has not progressed at the same time (Şasi ve Yakar, 2018).

To speed up the data processing phase, many studies have been carried out on the classification of the earth's surface (Yilmaz et al., 2014; Yilmaz et al., 2014). The studies have continued for many years on a pixel-based basis. In the pixel-based classification, the neighborhood relationships and color values of the pixels were examined, and the classes were created by grouping the pixels with similar values. However, today, due to the high resolution of both aerial photographs and satellite data, pixel-based classification methods have not been able to give sufficiently detailed results. Since the pixel-based approach examines only the spectral values of the pixels in the classification phase of these images, which contain intense information, it could not produce clear data on vegetation and details. Instead of the pixel-based approach, a new and highly accurate object-oriented approach has begun to be used. Using additional data on object structures, this approach creates meaningful objects by grouping pixels into segments.

When the studies on the determination of wooded areas were examined, it was seen that many different approaches were used. Woodland areas were classified first in the studies carried out. It was observed that the feature that separates wooded areas from green areas on the earth is the height data, and the feature that

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distinguishes wooded areas from other high objects is color data. During the detection of wooded areas, an object-based classification approach was used, and the wooded areas were detected automatically.

Gupta and Bhadauria (2014) aimed to classify agriculture, buildings, and wetlands, especially wooded areas. Multi-resolution segmentation and closest neighborhood approaches were used in the study. They mentioned that the parameters used in multiresolution segmentation play an important role in affecting the accuracy. As a result of this study, the accuracy rate regarding the classification of wooded areas is about 97%.

Jamil and Bayram (2017) mentioned in their study that tree segmentation is an active and ongoing research area in the field of photogrammetry and remote sensing. They stated that it is more difficult due to the similarities between various tree species, both within and between classes.

When the literature is examined, it has been observed that Near Infrared (NIR) band is used in addition to Red-Green-Blue (RGB) bands in image-based tree detection. In the studies, non-vegetation areas were initially removed using the traditional Normalized Difference Vegetation Index (NDVI), then average shift segmentation was applied to transform the pixels into meaningful homogeneous objects. Then the segments were assigned to the appropriate classes.

In this study, tree detection was investigated by applying object-based classification and segmentation methods using images containing high-resolution RGB bands and height data obtained from the UAV.

2. METHOD

There are many methods in the literature for detail extraction and object classification studies (Blaschke et al.2014; Ma et al.2017; Luo et al.2020). The pixel-based classification method has been used in most of the studies until recently (Moosavi et al.2014; Tehrany et al.2014; Gupta and Bhadauria 2014). Pixel-based approaches work on each pixel and extract information from remotely sensed data based on spectral information only (Gupta and Bhadauria 2014; Tehrany et al.2014; Khatami et al.2016; Louargant et al.2018). The main purpose of this method is to automatically combine each pixel in the image according to the land attributes (Guan et al.2014; Senthilkumaran and Vaithegi (2016). The problems faced by pixel-based approaches are overcome by object-based image classification. In Object-Based information, an image is interpreted not only according to a single-pixel but also according to the harmony between neighboring pixels. Object-oriented information extraction depends not only on spectrum character but also on geometry and structure knowledge (Wei et. Al. 2005; Gupta and Bhadauria 2014). Unlike pixel-based classification, the object-based classification method does not work directly on individual pixels. This method works through clusters of many pixels, meaningfully grouped by the segmentation process. It then uses these clusters instead of pixels as classification elements (Carleer and Wolff 2006). These clusters are created homogeneously; classify them by considering their characteristics such as spectral reflection, shape, size, and texture. Objects can be distinguished in a more meaningful way by considering the properties between neighboring pixels. More accurate results can be obtained by using the classification tree with rule-based processing capability (Blaschke et al. 2011). In object-based classification, besides the spectral and textural information used in pixel-based classification methods, shape characteristics and neighborhood relations are also used.

The most important and first stage in object-based classification is segmentation. Segmentation is the process of grouping pixels with similar spectral properties and creating image objects. The purpose of segmentation is to divide the image into different subsections and to create meaningful objects from the image (Baatz et al. 1999; Definiens 2012).

In this study, the multi-resolution segmentation algorithm is used as the segmentation method. In multi-resolution segmentation, image objects are divided into small pieces based on average heterogeneity for a given resolution. Later, these segments are assigned to classes by classifying with certain rule sets. The process of assigning a tag to each pixel and object in an image is called classification. In this case, by focusing on an object-based photo or image categorization, by applying the Mean-Shift segmentation method to the input image, segments are provided. The properties (spectral, textural, and spatial) of each object are created by making use of the classification results. Finally, categorization operations are created using the feature set.

The classification and detail extraction process was done in eCognition Developer software. While classifying the segments formed, the normalized surface model (nDSM) obtained from digital products and various indexes which were found to be valid as a result of literature research were used.

With the help of these indexes used, each segment is labeled as classified or unclassified. After generating the result class, the data density is reduced by combining neighboring segments assigned to the same class with the merge command.

After the end of the classification process, the tree class was exported as vectorial and generalized in geographic information systems (GIS) software. With this process, vectorial data with pixel-by-pixel fracture became more homogeneous.

To calculate the accuracy of the classification process, control data was generated in eCognition Developer software and accuracy analysis was performed with the help of an error matrix. The agreement between the accuracy analysis and the classification was calculated.

3. RESULTS and DISCUSSION

The object-oriented image analysis method provides a system that captures objects according to distinctive features such as shape, color, texture in the image. This method provides the ability to distinguish various objects in the image such as buildings, trees, roads, and vehicles. The object-oriented classification method includes segmentation and classification stages (Bergsjö 2014). While the segmentation process allows the target classes on the image to be collected in the same segment, the second stage requires the classification of objects.

The most important step in object-based classification is segmentation. Segmentation is the process of grouping pixels with similar spectral properties and creating image objects. The purpose of segmentation is to subdivide the image and create meaningful objects from the image (Baatz et al. 2000). There are various segmentation methods in the literature. In this study, a multi-resolution segmentation algorithm is used. After the images were separated into significant segments, the properties of each segment were tested and the responses of each feature in each image band and image segment were analyzed. The analysis enabled the determination of the boundary values that best represent the class based on the feature that captures the distinction of the related class. Thus, the classification continued with the limits set in the relevant membership function, and this step was made cyclically until the best classification representing real-world conditions was obtained. The indexes used in the classification process are given in Table 1. Also, nDSM was used in the study, except for indexes. The classes created are shown in Figures 1 and 2.

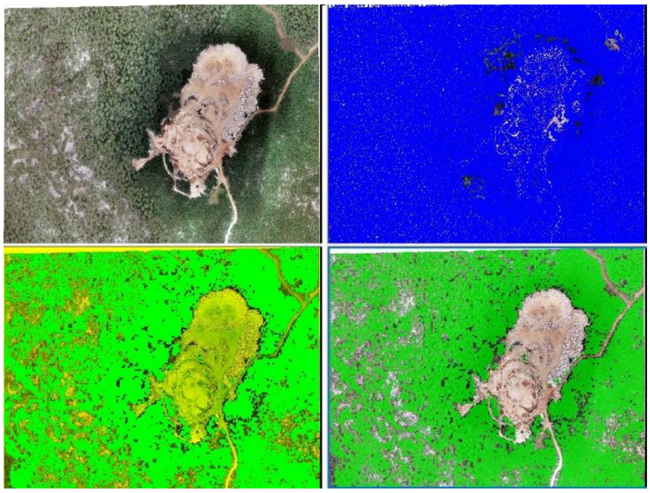

Figure 1. This is an example of figure formatting

Finally, an accuracy analysis was conducted to determine the compatibility of the classes with the real space. Accuracy analysis is the last step in measuring the accuracy and reliability of the classification.

To check the classification quality and accuracy, the Kappa coefficient, which is the most common accuracy estimation parameter, was calculated with the error matrix approach based on the TTA mask, and the pixels assigned to the tree classes at a rate of 78% were found to be compatible.

Table 1. RGB band index (R:red-G:Grenn-B:Blue)

Name	Short Name	Formula	Reference
Common Band Ratio	CBR	$(R+G+B)/3$	Çömert et al. 2017
Excess green index	EGI	$(2xG)-B-R$	Woebbecke et al. 1995
Green Leaf area index	GLI	$((2xG)-B-R)/((2xG)+B+R)$	Hunt et al. 2013
Green Ratio Index	GRI	$G/(B+G+R)$	Sonnentag et al. 2012
(The Synthetic NDVI) (Green Red Vegetation Index)	sNDVI GRVI	$(G-R)/(G+R)$	Motohka et al. 2010
Vegetation Adjusted Reflectance Index	VARI	$(G-R)/(B+G+R)$	Gitelson et al. 1996
Excess red vegetation İndex	ERVI	$(1.4\,x\,R)-G$	Mao et al. 2003

4. CONCLUSION

With the development of photogrammetric methods and computer software, it has become possible to produce high-resolution structural and spectral data on forest areas using images obtained by UAV. Products derived from this process could evaluate and measure forest structure at the tree level at a significantly lower cost than sources such as LiDAR, satellite, or aerial imagery. Detecting trees and determining their locations are among the common uses of remote sensing and photogrammetry applications. Thanks to the high resolution of the products obtained by UAV, the research field is still up to date. However, most of the studies use UAV data with not only RGB bands but also NIR bands. In this study, the performance of only visible bands (RGB), canopy height models (nDSM), multiple resolution segmentation, and rule sets in tree extraction was investigated.

When the results were examined, it was observed that segmentation using only spectral information was less accurate than the approach involving the use of an elevation model. In other words, the use of models such as nDSM has a significant effect on the accuracy of tree detection. Besides, the size of the segmented trees also influenced the optimum resolution. It was also observed that the density of deciduous or coniferous trees and forest species did not affect the accuracy of segmentation.

Finally, large trees tend to be divided into more segments, while smaller trees tend to split in small numbers. The importance of spatial resolution has been found to compartmentalize trees of different sizes. Also, this research; proved that the size of trees and bands such as NIR tape should be used in addition to RGB tapes and showed that it deserves further investigation in the future. One of the results of the study is that different band indexes influence the accuracy of tree detection.

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