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Investigation of the Performance of Different Pixel-Based Classification Methods in Land Use/Land Cover (LULC) Determination

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Keywords
Photogrammetry
Land cover land use
Supervised classification
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ABSTRACT

With the development of photogrammetry and remote sensing techniques, data collection has become easier. However, due to the large size of the data collected, extracting meaningful data from the data set has become a popular topic. Nowadays, the development of digital image processing techniques has contributed to the determination of land cover land use (LCLU) through digital images. In this study, a supervised classification was made over the orthophoto view to distinguish different land object classes in a campus area. The purpose of the study is to examine the performance of the three popular supervised classification techniques that are maximum likelihood, minimum distance, and mahalanobis distance methods. In the study, a confusion matrix was produced, and overall accuracy and overall kappa were calculated with manually generated ground truth data. According to results, the highest overall accuracy was calculated for maximum likelihood classification with a rate of 84.5 % and the minimum distance method has the lowest overall accuracy (43%). The research denotes that due to the lack of spectral information the supervised classification methods generate omission and commission errors. This fact has a direct effect on overall accuracy calculation.

Farklı Piksel Tabanlı Sınıflandırma Yöntemlerinin Arazi Kullanımı ve Arazi Örtüsü Belirlemedeki Performansının İncelenmesi

Anahtar Kelimeler
Fotogrametri
Arazi örtüsü arazi kullanımı
Denetimli sınıflandırma
İnsansız hava araçları

ÖZET

Fotogrametri ve uzaktan algılama tekniklerinin gelişmesiyle birlikte veri toplama daha kolay hale gelmiştir. Ancak toplanan verilerin büyük olması nedeniyle, veri setinden anlamlı veriler çıkarmak son zamanlarda popüler bir araştırma konusu haline gelmiştir. Günümüzde dijital görüntü işleme tekniklerinin geliştirilmesi, arazi örtüsü arazi kullanımının (LCLU) dijital görüntülerle belirlenmesine katkıda bulunmuştur. Bu çalışmada, bir kampüs alanındaki farklı arazi nesne sınıflarını ayırt etmek için ortofoto görüntü üzerinden denetimli sınıflandırma yapılmıştır. Çalışmanın amacı, en popüler denetimli sınıflandırma yöntemlerinden Maksimum Olabilirlik (Maximum Likelihood), Minimum Mesafe (Minimum Distance) ve Mahalanobis Uzaklık (Mahalanobis Distance) sınıflandırma tekniğinin performansını incelemektir. Çalışmada, bir karışıklık matrisi (confusion matrix) oluşturulmuş ve manuel olarak oluşturulan kesin referans verileri ile genel doğruluk ve genel kappa değerleri hesaplanmıştır. Sonuçlara göre, en yüksek genel doğruluk %84,5 oranı ile Maksimum Olabilirlik sınıflandırmasında elde edilmiştir. Minimum Mesafe yöntemi ise en düşük genel doğruluğa (%43) sahiptir. Araştırma, spektral bilgi eksikliğinden dolayı denetimli sınıflandırma yöntemlerinin atlama ve atama hataları (omission and commission) gösterdiğini göstermektedir. Bu durum, genel doğruluk hesaplaması üzerinde doğrudan bir etkiye sahiptir.

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1. INTRODUCTION

With the development of photogrammetry and remote sensing technology, the data collection process from the earth-surface has become easier. However, this situation brought about another problem. The ease of data collection has caused the amount and dimensions of data to grow. Digital image processing methods are preferred to extract meaningful information from the collected data. Thanks to the recent advances in digital image processing techniques, it has become possible to extract details from large-scale data. Turner et al. (2012) used the Structure from Motion (SfM) technique for geometric correction and mosaicking of UAV photography.

Determination of LCLU, the spatial distribution of land, and their determination at the local and regional scales are important for monitoring changes (Gholami et al., 2010). Due to the easy data collection process with photogrammetry and remote sensing methods, images that covering large areas are obtained in a short time (El-Alahmadi & Hames, 2009; Ulvi et al., 2019; Sarı et al., 2020). Although remote sensing images provide information about very large areas, their spatial resolution is relatively low. Unmanned Aerial Vehicles (UAV), which have been used in many areas recently (Ulvi et al., 2020; Kaya & Polat, 2019; Yiğit & Uysal, 2019; Ulukavak et al., 2019; Şenol et al., 2019; Kaya et al., 2019), can also be used to classify areas in the region. Comert et al. (2019) utilized UAV images for the landslide mapping model. This study revealed that landslides mapped by using UAV data have an accuracy rate higher than 86% according to the number of landslides and 83% according to the landslide area. Kim and Ryu (2020) created a sedimentary surface map based on UAV and object-based image analysis (OBIA). Brooke and Clutterbuck (2020) have proposed a methodology for examining archaeological sites with UAVs that do not have obvious surface features. Louargant et al. (2017) used the spectral information potential of images captured with UAV to differentiate crop-weed discrimination.

Compared to satellite images, UAVs that view smaller areas have a much higher spatial resolution. It is more advantageous to use UAV images especially in settlements where the spatial distribution changes frequently. Due to the small pixel dimensions, the UAV images better reflect the characteristics of the study area. Classification methods should be used to obtain meaningful results from these images. Supervised classification methods include maximum ikelihood (Strahler, 1980; Foody et al., 1992; Otukei and Blaschke, 2010), minimum distance (Kranz, 1993; Srivastava, 2006; Kabadayı et al., 2020, Yiğit et al., 2020), and mahalanobis distance (Moraes et al., 2002; Gemperline & Boyer, 1995; Mei et al., 2016; Galeano et al., 2015; Şasi & Yakar, 2018; Kaya & Yiğit, 2020) methods are frequently used in the literature. Yang and Everitt (2010), used supervised classification methods to map the broom gentian infestation. Asad and Bais (2019) used maximum likelihood classification to detect the herbicide found in agricultural land. Zhenkun et al. (2013), using the maximum likelihood classification to determine winter wheat and corn areas, achieved 96% and 90% success, respectively. Kavzaoğlu and Colkesen (2010) used the maximum likelihood and decision trees method to classify the 2009 dated Landsat ETM+ image. Taddia et al. (2020) applied NDVI and maximum likelihood classification approaches using UAV images to map submerged seaweeds. Woo et al. (2020) used Spectral Angle Mapper (SAM) and maximum likelihood approaches to detect burned lands through UAV images. Milas et al. (2016) used maximum likelihood and Support Vector Machine (SVM) classifiers to classify a UAV image acquired using a red-green-blue (RGB) camera over the Old Woman Creek National Estuary Research Reserve in Ohio, USA. Duarte et al. (2018) used four different classifiers (maximum likelihood, minimum distance, parallelepiped, and neural network) to classify the high-resolution images obtained by UAV. Zisi et al. (2018) made maximum likelihood, minimum distance, and object-based image classifier classification over UAV images with multispectral cameras to determine the weed distribution within a field. Hassan et al. (2011) used maximum likelihood, minimum-to-distance, and parallelepiped classifier to generate a land use/land cover (LULC) map of a test area. Ahmed et al. (2015) revealed that the maximum likelihood method is better than the Mahalanobis Distance method for classifying tobacco areas in Pakistan. Yadav et al. (2019) used a UAV image with a five-band multispectral camera to detect volunteer cotton (Gossipium hirsutum) growing in a cornfield. In the study, the Mahalanobis Distance classification and maximum likelihood approaches were used for five-band stacked image classification, and 92% and 86% overall accuracy were obtained, respectively.

In this study, the success of three different classification methods proposed to distinguish the buildings in the campus area from each other was examined.

2. METHODOLOGY

2.1. Study Area

Harran University Osmanbey Campus has been chosen as the study area. The study area covers an area of approximately 650m x 450m (Fig. 1). The UAV flight plan and other parameters are not covered by this study, but It can be said that the orthophoto of the study area has only red green and blue bands and generated with a 25 cm spatial resolution.

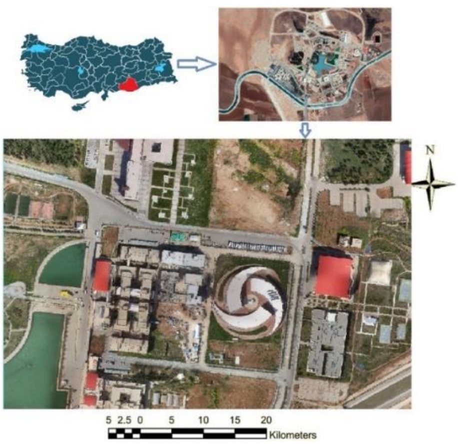

Figure 1. Study area

2.2. Maximum Likelihood Classification

The maximum likelihood classification technique is the most widely used technique in the literature (Paola, 1994; Paola & Schowengerdt, 1995; Erbek et al., 2003; Richards & Richards, 1999; Yiğit & Uysal; 2019; 2020; Liang et al., 2020; Huynh & Nguyen, 2020). Suppose we have two different classes, 'i' and 'j'. If the probability of a pixel in 'X' position belonging to class i is higher than that of class j, the pixel is assigned to class i, vice versa (Ahmed et al., 2015). The input data is considered to have a normal distribution pattern and the discriminator for the MLC model is defined as:

$$g_i(x) = \ln p(w_i) - \frac{1}{2} ln|C_i| - \frac{1}{2}(x - m_i)^t C_i^{-1}(x - m_i) \quad (1)$$

Where $g_i(x)$= ith class discriminant function
$p(w_i)$= Probability that class ωi has occurred
$|C_i|$= Determinant of class i's covariance matrix
x= A pixel's n-dimensional matrix of Digital Number values (where n is the total number of bands)
m_i= Mean vector
t = transpose of the base matrix

2.3. Mahalanobis Distance Classification

The mahalanobis distance statistic is a measure of distance that considers correlation in the data using the precision matrix (Villaseñor, 2019). The mahalanobis distance is used for spectral matching, to detect outliers during calibration or prediction, or to detect extrapolation of the model during analyzes (Mark & Workman, 2010). To be able to compute the mahalanobis distance, first, the variance-covariance matrix C is constructed:

C_x=1/((n-1)) (X_c)^T (X_c) (2)

where X is the data matrix containing n objects in the rows measured for p variables. X is the column-centered data matrix (Maesschalck et al., 2000). In the case of two variables, x1 and x2, the variance–covariance matrix. Mahalanobis distance is defined as:

$$MD_i = \sqrt{(x_i - \bar{x})C_x^{-1}(x_i - \bar{x})^T} \quad (3)$$

2.4. Minimum Distance Classification

Minimum distance classification is a simple supervised classification method that uses the center point to represent a specific class in the training set. Euclidean distance between pixel values and the center of gravity is considered when determining the class. The pixel with the shortest distance from the class is assigned to that class (Sathya & Deepa, 2017). Minimum distance is defined as:

$$\min. dist. = \sqrt{(Dv - Mt)^2} \quad (4)$$

where DV is: Digital value of each pixel
mt is mean value of each class

3. RESULTS

The orthophoto of the field was used as input data in the study. Supervised classification was made with all three classification methods over orthophoto. The orthophoto of the study area is shown in Figure 2. The results of maximum likelihood classification, mahalanobis distance classification, and minimum distance classification methods are shown in Figures 3, 4 and 5, respectively. Tables 1 shows the accuracy assessment results for the three classification maps generated from orthophoto.

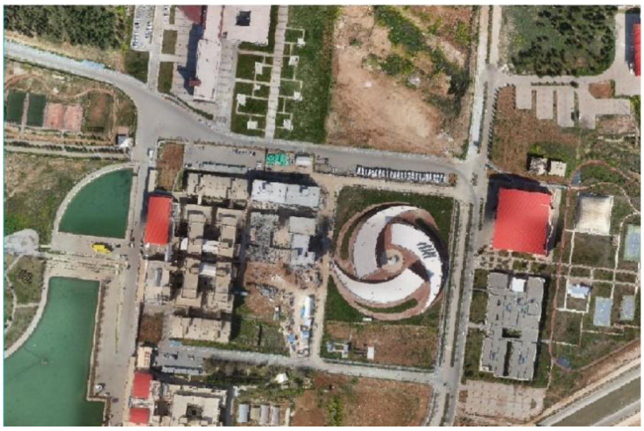

Figure 2. Orthophoto of the study area.

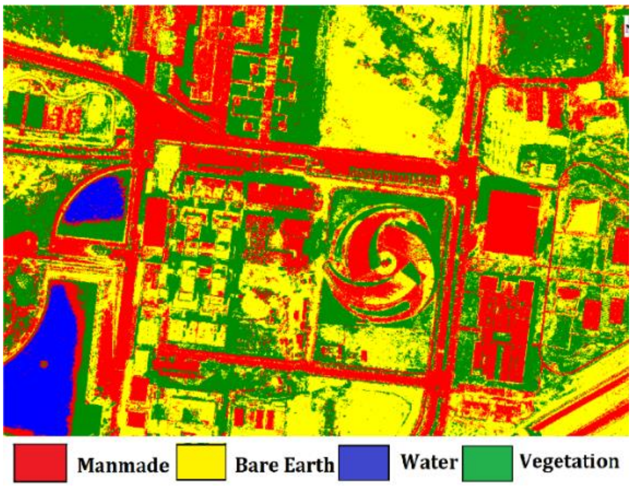

Figure 3. Maximum likelihood classification for study area.

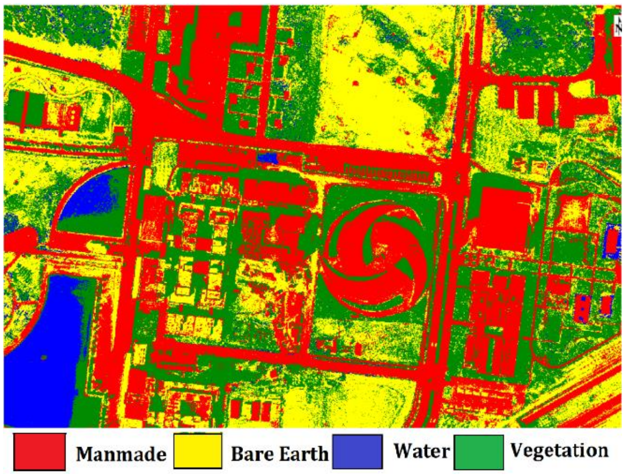

Figure 4. Mahalanobis distance classification for study area.

Table 1. Accuracy assessment results for the three classification methods

Classes	Classification Method					
	Minimum distance		Maximum likelihood		Mahalanobis distance	
	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)
water	1.14	6.40	8.66	100.00	0.28	10.81
bare earth	13.39	54.39	99.41	91.50	97.51	93.56
vegetation	86.97	33.69	98.09	45.51	88.30	34.16
manmade	78.70	44.76	81.93	92.95	86.09	99.92
Overall Accuracy (%)	43.0		84.5		83.72	
Overall Kappa	0.15		0.76		0.75	

PA = producer's accuracy; UA = user's accuracy

Table 1 shows that all three methods give unsuccessful results in detecting water areas. When the field research was done, it was understood that the reason for this was the pollution in the water. This pollution may affect the classification. Also, since the lakes are artificial, the shores are shallower. This can create different classifications with deep water. While maximum likelihood and mahalanobis distance achieved high success in the detection of bare earth areas, the minimum distance method produced low accuracy. All three methods are successful in separating vegetation areas that are in the open areas. However, some shady regions are also classified as vegetation areas in three method.

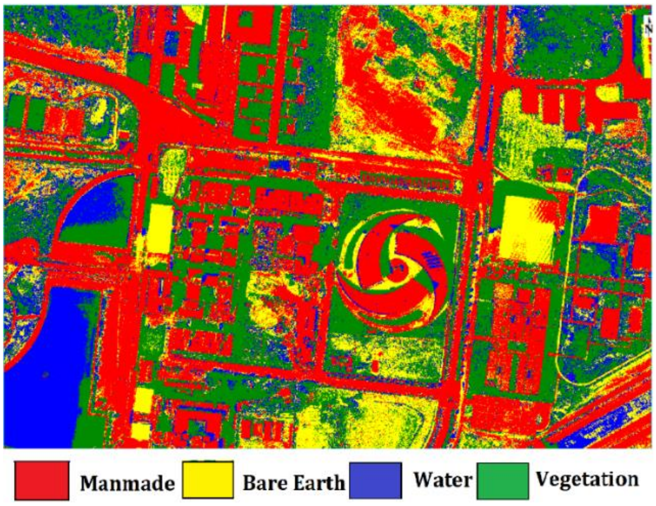

Figure 5. Minimum distance classification for study area.

4. CONCLUSION

UAV systems quickly found a place in many areas of life thanks to the advantages they provide. In this study, the classification of the study area was made using the orthophoto produced from the aerial images obtained by the UAV. Three different classification methods, which are mostly used in the classification of satellite images, were applied in a supervised approach. Then the generated classified images were compared with manually obtained ground truth values. As a result, the highest overall accuracy evaluated for the Maximum likelihood method with 84.5%. Since the data resolution is high, it is thought that the classification accuracy can be further increased by increasing the number of signatures and classes.

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