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An investigation of supervised LCLU classification performance over UAV based orthophoto

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ABSTRACT

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 has been made over an orthophoto of an area in Harran University Osmanbey Campus. 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 shows that due to the lack of spectral information the supervised classification methods shows omission and commission errors. This fact has a direct effect on overall accuracy calculation.

1. INTRODUCTION

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 and Hames 2009). 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 and Polat 2019; Yiğit and Uysal 2019), can also be used to classify areas in the region. 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 Likelihood (Strahler 1980; Foody et al. 1992; Otukei and Blaschke 2010), Minimum Distance (Kranz 1993; Srivastava 2006), and Mahalanobis Distance (Moraes et al. 2002; Gemperline and Boyer 1995; Mei et al. 2016; Galeano et al. 2015) methods are frequently used in the literature. Kavzaoğlu and Colkesen (2010) used the maximum likelihood and decision trees method to classify the 2009 dated Landsat ETM+ image. Ahmed et al. (2015) revealed that the Maximum Likelihood method is better than the Mahalanobis Distance method for classifying tobacco areas in Pakistan. Yang and Everitt (2010), used supervised classification methods to map the broom gentian infestation. 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. METHOD

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.

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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 and Schowengerdt 1995; Erbek et al. 2003; Richards and Richards 1999). 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:

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

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 DN 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 takes into account 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 and Workman 2010). To be able to compute the MD, first, the variance-covariance matrix C is constructed:

$$C_x = \frac{1}{(n-1)}(X_c)^T(X_c) \qquad (2)$$

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, x_1 and x_2, the variance–covariance matrix. Mahalanobis Distance is defined as:

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

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 and Deepa 2017). Minimum Distance is defined as:

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

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

3. APPLICATION and 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 and the results of the classification methods are shown in Figure 2.

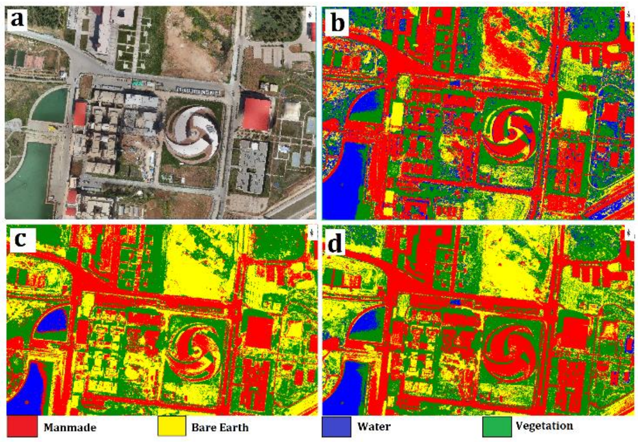

Figure 2. Orthophoto (a) and results of minimum distance classification (b), maximum likelihood classification (c), and mahalanobis distance classification (d).

Tables 1 summarize the accuracy assessment results for the three classification maps generated from orthophoto.

Table 1. Accuracy assessment results for the three classification methods

	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 classification 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.

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 calculated 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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