COMPARISON OF PIXEL-BASED AND OBJECT-BASED CLASSIFICATION METHODS IN DETERMINATION OF WETLAND COASTLINE

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SUMMARY:

Tuz Lake and its surrounding lakes (Tersakan Lake, Duden Lake, Bolluk Lake, Esmekaya Lake, Kopek Lake, Akgol) are placed in the Central Anatolia region. These lakes maintain the ecosystem integrity and make a good habitat for numerous bird species, especially flamingos. The Duden lake is located within the boundaries of the Tuz Lake Special Environmental Protection Area and was declared as a protected area in 1992. The surface and underground water around Kulu District of Konya feed the Duden Lake, which is tectonically formed through the Kulu Stream. The lake with the average area of 860 hectares, is unfortunately in risk of extinction. Remote sensing has been the most useful tool to obtain spatial and temporal information about wetlands and it provides up-to-date, accurate, and cost-effective information. Remote sensing methods and applications are used quite effectively on wetlands. The traditional pixel-based classification method is applied to different satellite images in wetlands over many decades, and the usage of object-based classification method has started recently comparing to the pixel-based one. This study aimed to determine the coastline of the wetlands. Sentinel 2 satellite images, which provide free access and high spatial resolution, are used to observe the coastline of Duden Lake through the usage of pixel-based and object-based classification methods in all the seasons. The applicability of the methods in determination of shallow wetland coastline is studied and evaluated. The results of the pixel-based and the object-based classification images are compared by accuracy assessment.

1. INTRODUCTION

Coastline is defined as a line that forms the boundary between a land, sea or a lake. Remote sensing has been widely used for coastline mapping and extraction. Due to the dynamic structure of wetlands and mixed pixels in especially shallow water covering marsh environments, delineation of wetland coastline is quite difficult (Alesheikh et al., 2007). There are various methods which are applied on optical imagery such as single-band threshold method, water index method, unsupervised and supervised classification methods to delineate the coastline of wetlands (Haibo et al., 2011). Coastline can be extracted from a single band image for obtaining a rapid coastline extraction. The reflectance of water is nearly equal to zero in infrared bands and reflectance of land covers is greater than water. The absorption of infrared bands in water is high, enabling to separate water and land. Another simple land/water separation method is to use the band ratio. Ratio between red and infrared bands is greater than 1 for water, and less than 1 for land in large areas of coastal zone.

Water indices can be used for land/water discrimination. Normalized Difference Water Index (NDWI) has been widely used for water body extraction (Lillesand at al., 2004). NDWI can be applied on images as pixel based and object based. Kaplan and Avdan (2017) applied NDWI with object based methods to Sentinel 2 satellite image, and determined that object based NDWI shows better results comparing to pixel based NDWI.

The coastline can be determined by pixel-based classification and object based classification methods. Guariglia et al. (2006) used the ISODATA unsupervised classification and band ratio methods for coastline mapping and identification of shoreline changes. Li and Damen (2010) detected the coastline change of the Pearl River Estuary using supervised classification in 1979, 1990, 2000 and 2003. Shang et al. (2012) used maximum likelihood supervised classification method to extract information from coastal wetlands between 2007 and 2010. Rasuly et al. (2010) used object oriented techniques for monitoring the Caspian Sea coastline changes from optical imageries. Dronova et al. (2011) used object based classification methods to determine change detection of the Poyang Lake during the 2007–2008 low water season. Kalkan et al. (2013) compared the pixel and object based classification methods on Landsat 8 imagery and observed that both of these methods are applicable in extraction of the coastlines.

In this study, Duden Lake which is a shallow wetland was chosen as the study area. Coastline change of Duden Lake was determined monthly during the 2018-2019 season with different methods. For delineation of wetland coastline, pixel and object based classification methods and NDWI were applied to Sentinel 2 satellite image.

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2. STUDY AREA

Total natural wetland area in Turkey is about 2.3% of the country’s surface area; and there are 17269 natural wetlands. 921 of these wetlands have the size greater than 8 hectars, having 1714792 hectars of area in total, and constitutes 99.48% of the overall wetland areas (Doğandemir, 2016). Konya Closed Basin is one of Turkey's 25 hydrological basins and of the Duden Lake located in this basin has a surface area of about 850 ha. The lake is tectonically formed and the sources feeding the lake are precipitation and Degirmenozu/Kulu creek. In Duden Lake, which houses 185 bird species, and most of them are flamingos; the habitat of birds has started to shrink due to uncontrolled irrigation and drought that started due to global warming. The water surface area and boundaries have been changing in the shallow wetland area of Duden during the year; and a large area has been dried in summer. It was declared as a protected area in 1992 and it is within the boundaries of Tuz Lake Special Environmental Protection Area. It is a bird watching area due to its wild life and is in danger of extinction. The location of the Duden lake which is chosen as the study area is given in Figure 1.

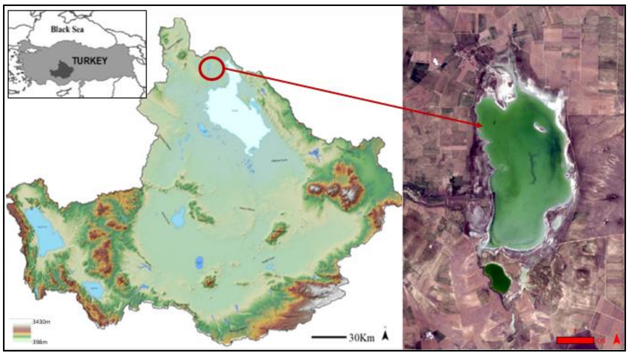

Figure 1. Konya Closed Basin and location of the Duden Lake

3. DATA AND METHODOLOGY

3.1 Data

In this study, Sentinel 2 Satellite images were used to detect the water surface area, and thus the coastline has also been determined. Sentinel 2 Satellites (A and B) have four bands at the spatial resolution of 10 m (Band 2, Band 3, Band 4 and Band 8), six bands at the spatial resolution of 20 m (Band 5, Band 6, Band 7, Band 8a, Band 11 and Band 12) and three bands at the spatial resolution of 60 m (Band 1, Band 9 and Band 10). The radiometric resolution is 12-bit, and the temporal resolution is 5 days at the equator. Five Sentinel 2 satellite images were used between March 2018 and March 2019 to see the changes in the surface area and the coastline of the water in a period of one year. Used satellite images are given in Figure 2. Kulu meteorological station data (temperature, precipitation, evaporation) were used in the wetland to examine the seasonal change in water surface area.

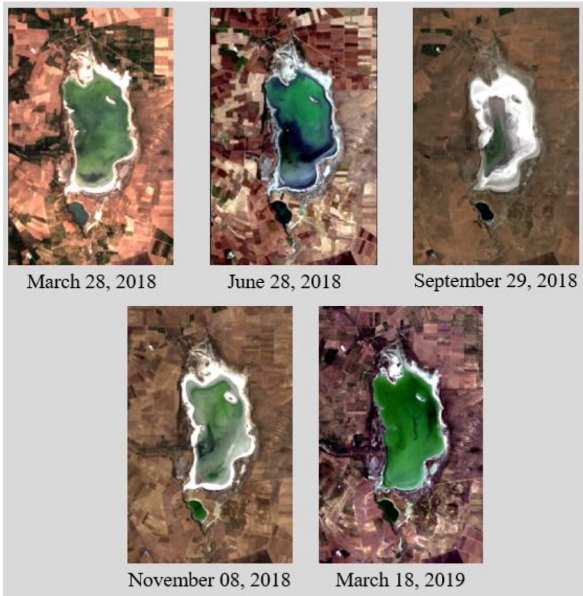

Figure 2. Sentinel 2 MSI Satellite images used in the study

3.2 Methods

Two different classification methods, pixel-based and object-based classifications, were used for each image to reach the water surface areas, in this study. Accuracy assessment analysis of each classification was performed, then the determined water surface areas were converted to vector. The vector data of coastlines obtained from both classification methods for each five different months were compared.
NDWI, which is the most used index in the literature, was applied to both pixel and segmented images and compared with classification results. Flowchart of the study is given in the Figure 3.

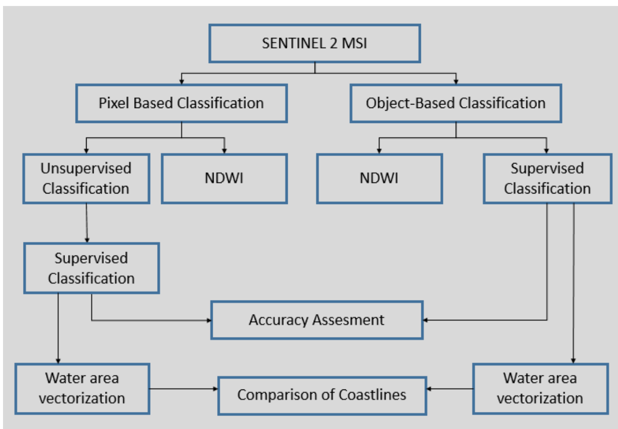

Figure 3. Flowchart of the study

Band 2 (blue), Band 3 (green), Band 4 (red), Band 8 (NIR), Band 11 and 12 (SWIR) of Sentinel 2 MSI satellite images were used at the classification. For pixel based classification, ISODATA (Iterative Self Organizing DATA) unsupervised classification method was applied firstly. ISODATA calculates the class means iteratively using minimum distance (Abbas et al., 2016). 300 clusters were created and the reflectance curves of each cluster were examined and the water reflective clusters were determined for five images. Supervised classification techniques uses the spectral signature defined in the training set. The clusters determined by image clustering algorithm, ISODATA were used in supervised classification as a training set and Maximum Likelihood algorithm was applied. Maximum likelihood classification is widely used for classification of remotely sensed optical data. Maximum likelihood estimates of the parameters are computed, and the individual pixels are assigned to the class which maximizes the likelihood function of the data set (Strahler, 1980).

Object-based classification work on objects that are composed of many pixels, grouped in a meaningful way by the segmentation process. Then these objects are used instead of pixels as a classification objects (Carleer and Wolff, 2006; Blaschke, 2010). Image segmentation is one of the most important steps in object-based classification. In the segmentation process, three parameters, namely the scale parameter, the shape parameter and the integrity parameter, are essential. The most effective parameter in these parameters is the scale parameter. First, the shape and the integrity parameters are kept fixed and the scale parameter is changed to find the value of the desired object. Then, the other parameters are changed with the scale parameter keeping fixed. This process was progressed until optimum segments were obtained. Nearest neighbour classification method is similar to supervised classification method. After multi-resolution segmentation, sample sites for each land cover class are identified. Then, statistics are defined to classify the image objects. Finally, nearest neighbour method classifies objects based on their resemblance to the training sites, and thus the statistics are defined. The aim of this study is to test and compare the above-mentioned classification algorithms for their ability to determine the wetland coastline.

The NDWI (Normalized Water Index) is most appropriate and widely used index for water body mapping. The water body has strong absorbability and low radiation in the range from visible to infrared wavelengths. The index uses the green and Near Infrared bands of remote sensing images based on this phenomenon (URL 1). The NDWI can enhance the water information effectively in most cases. Results changes between -1 and 1 and values which are greater than zero show the water area. NDWI was applied to all original pixel images and segmented images by using green and NIR bands.

4. RESULTS AND DISCUSSION

4.1 Pixel and Object Based Classification

Water surface areas obtained as a result of pixel and object based classification are given in Table 1.

Date	CLASSIFICATION		Area (ha)
03.28.2018	Pixelbased	Unsupervised_ISODATA	747.63
	Pixelbased	Hybrid (ISODATA+ML)	746.77
	Objectbase	Supervised	740.69
06.28.2018	Pixelbased	Unsupervised_ISODATA	702.59
	Pixelbased	Hybrid (ISODATA+ML)	700.69
	Objectbase	Supervised	705.28
09.29.2018	Pixelbased	Unsupervised_ISODATA	113.85
	Pixelbased	Hybrid (ISODATA+ML)	114.40
	Objectbase	Supervised	116.55
8.11.2018	Pixelbased	Unsupervised_ISODATA	649.19
	Pixelbased	Hybrid (ISODATA+ML)	643.03
	Objectbase	Supervised	657.17
8.3.2019	Pixelbased	Unsupervised_ISODATA	770.15
	Pixelbased	Hybrid (ISODATA+ML)	770.25
	Objectbase	Supervised	798.81

Table 1. Water Surface Areas

As a result of pixel-based classification and object-based classification, it is seen that water surface areas are close to each other as shown in Table 1 and Figure 4.

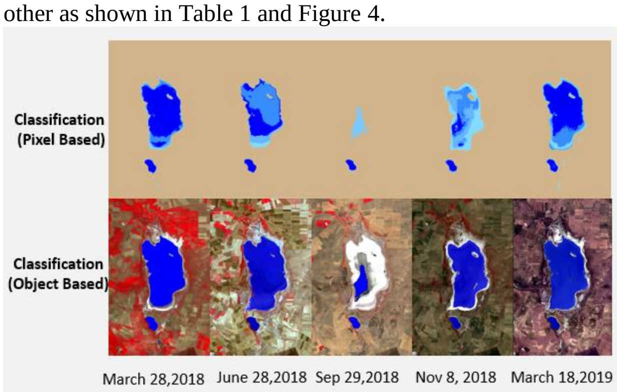

Figure 4. Water surface areas with classification

The obtained water surface areas were converted to vector and the coastlines were compared. In Figure 5, the coastlines of each month obtained from the pixel-based and object-based classification methods are shown together.

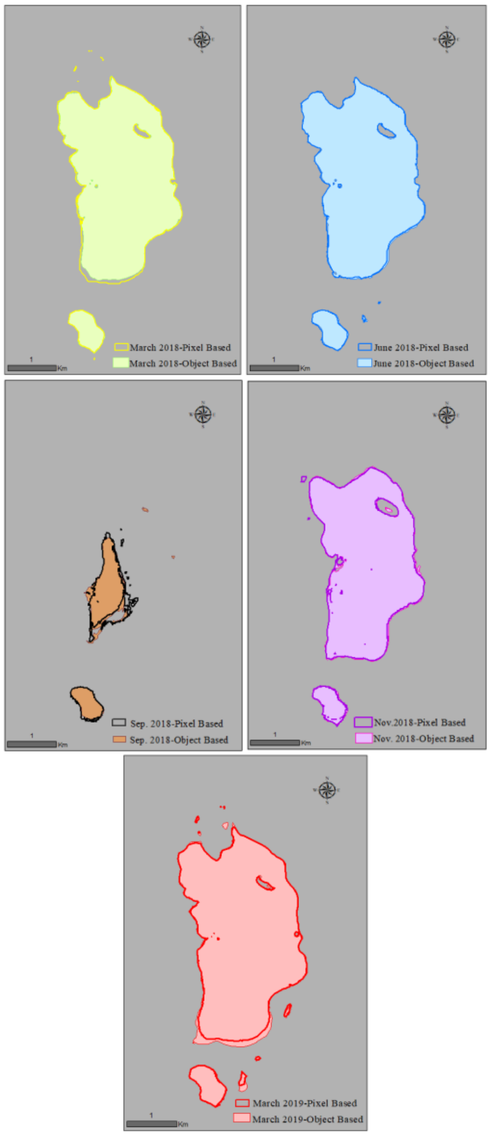

Figure 5. Coastlines from pixel and object based classification

4.2 Evaluation of Meteorological Data

Temperature, precipitation and evaporation data obtained from Kulu meteorological station were evaluated and their monthly averages were taken and shown in the Figure 6, Figure 7 and Figure 8 below, respectively.

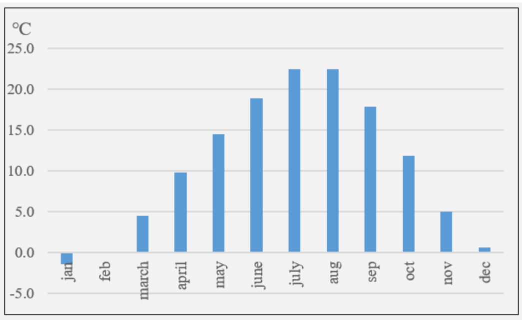

Figure 6. Average monthly temperatures from 1980 to 2017

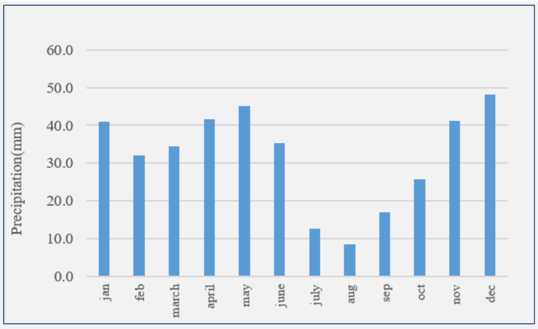

Figure 7. Average monthly precipitation from 1980 to 2017

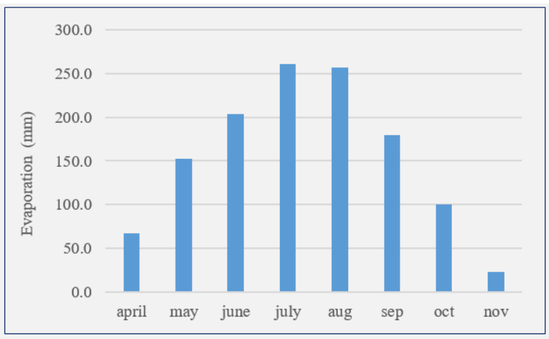

Figure 8. Average monthly evaporation from 1985 to 2011

Looking at the monthly average temperatures of the years from 1980 to 2017, it is seen that the hottest month is July with an average of 22.5 ℃, followed by August, June and September, respectively. When the evaporation data for the period of 1985 to 2011 are examined, it is seen that the evaporation amounts are parallel to the temperature, as being 260.8 mm in July and 257 mm in August, followed by June and September. In addition, the time with the least rainfall is the summer months, having the average of precipitation as 8.3 mm in August, 12.5 mm in July and 17 mm in September.

In July, August and September, precipitation / evaporation rates are 20.8, 30.95, and 10.5 respectively. The reason behind the inadequate water in the wetlands in September is the high evaporation rate and the usage of Kulu Creek for irrigation purposes during the summer months.

In November, there is water seen in the area since irrigation season ends by mid-September and water can reach the area from the Kulu stream by the end of September.

4.3 NDWI

NDWI was applied to the pixel images and segmented images, and the results are given in Figure 9 and Table 2 below.

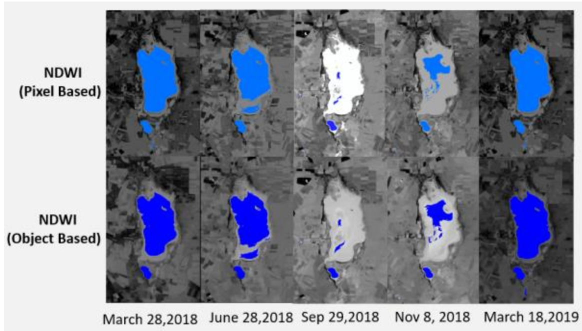

Figure 9. Pixel and object based NDWI

Date	NDWI	Water Area (ha)
March 28,2018	Pixelbased	707.17
	Objectbased	705.56
June 28,2018	Pixelbased	642.71
	Objectbased	646.15
Sep 29,2018	Pixelbased	41.87
	Objectbased	43.45
Nov 08,2018	Pixelbased	189.58
	Objectbased	188.21
March 18,2019	Pixelbased	754.36
	Objectbased	754.78

Table 2. NDWI results

It is noted that the results of NDWI applied to pixel-based and object-based images are similar to each other. However, NDWI results are not very succeeding compared to the classification results. Comparing the water surface areas obtained by classification and NDWI techniques, the similarity was over 90% in March 2018, June 2018 and March 2019, whereas the similarity in September and November remained at 30%. The reason for this deficit might be considered as the amount of water being very shallow (maybe a few cm) in the area during September and November.

4.4 Accuracy Assessment

Accuracy of the pixel-based and object-based supervised classifications results were evaluated with 200 random selected points. Overall accuracy (OA) and kappa values were determined and are shown in the Table 3.

Date	Classification	OA	Kappa
03.28.2018	Pixelbased	0.993	0.985
	Objectbased	0.985	0.970
06.28.2018	Pixelbased	0.993	0.985
	Objectbased	0.993	0.985
09.29.2018	Pixelbased	0.993	0.943
	Objectbased	0.985	0.892
08.11.2018	Pixelbased	0.963	0.922
	Objectbased	0.940	0.877
08.03.2019	Pixelbased	0.993	0.985
	Objectbased	0.993	0.985

Table 3. Accuracy assessments of classifications

The results of the accuracy assessment applied to the classification results were over 90% as seen in Table 3. Same randomly applied 200 points were used in each month for the classification. Based on object-oriented classification results, only Kappa statistics were below 90% in September and November. Looking at the outcome, usage of two classes as “water” and “the others” and the usage of randomly selected points are the major factor assessing the results. Although accuracy analysis yielded high accuracy results, for March 2018, the area corresponding to the lower part of the lake was classified as water in the pixel-based classification but in the object-based classification it was stated as a non-water area. When the results of March 2019 are examined, the non-water part in the pixel-based classification was determined as water in the object-based classification. In the March 2018 image, the spectral reflections of the stated water areas in the pixel-based classification were examined at multiple points, and it was resulted that the reflected area was surface water. Again, in March 2019, the areas determined as water in the object-based classification were observed to have plant reflection.

According to these results, it can be noted that the Pixel-based Maximum Likelihood classification made with clusters after creating a high number of clusters and checking the spectra of these clusters, gave better results for Sentinel 2 satellite image with a 10 m spatial resolution.

5. CONCLUSION

It is seen that water surface areas determined by pixel and object based classification methods using Sentinel 2 satellite images with 10 m of spatial resolution has given close results. However, differences are observed when the coastlines are examined. The NDWI results applied to pixel and object-based images are consistent with each other, however conflicting with the classification results.

In the accuracy analysis performed by random points, although high accuracy was obtained in both classification methods, it was seen that some of the areas which are non-water stated as water in object- based classification and the non-water areas stated as water. Since the water surface area changes from a few meters to a few cm in wetlands, accuracy analysis should be done by determining specific points especially in coastal areas with shallow water and in the swamp areas having mixture of water and plants.

In the further studies, usage of high spatial resolution satellite images or orthophoto images as the master data can be considered. Wetlands are dynamic systems; so especially in a study aiming to determine the coastal line in wetlands, spectroradiometer measurements and coordinate measurements must be data simultaneously with the date on which satellite images are received. Thus, the results from high-spatial resolution images and mid-spatial resolution images can be compared in order to determine whether the pixel-based classification or the object base classification is more appropriate.

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