Turkish Journal of Engineering

Turkish Journal of Engineering (TUJE)
Vol. 4, Issue 1, pp. 47-56, January 2020
ISSN 2587-1366, Turkey
DOI: 10.31127/tuje.599359
Research Article

THE IDENTIFICATION OF SEASONAL COASTLINE CHANGES FROM LANDSAT 8 SATELLITE DATA USING ARTIFICIAL NEURAL NETWORKS AND K-NEAREST NEIGHBOR

Mustafa Hayri Kesikoglu [1], Sevim Yasemin Cicekli *[2] and Tolga Kaynak [3]

[1] Erciyes University, Engineering Faculty, Department of Geomatics, Kayseri, Turkey
ORCID ID 0000-0001-5199-0815
mkesikoglu@gmail.com

[2] Cukurova University, Ceyhan Engineering Faculty, Department of Geomatics, Adana, Turkey
ORCID ID 0000-0002-8140-1265
yoturanc@cu.edu.tr

[3] Erciyes University, Engineering Faculty, Department of Geomatics, Kayseri, Turkey
ORCID ID 0000-0002-0718-9091
tolgakaynak@erciyes.edu.tr

* Corresponding Author
Received: 31/07/2019 Accepted: 01/10/2019

ABSTRACT
Coastline boundaries are constantly changing due to natural or human-induced events that take place in the world. Therefore it is necessary to correctly observe coastline boundaries. Remote sensing is one of the most frequently used methods to monitor the changes in coastal areas. In this study, it is aimed to solve the problem of choosing the right method for coastal change observation. This paper introduces a spatial pixel-based and object-based image classification approach to recognize changing areas in coastline. The coastline boundary changes occurred in a part of Yamula Dam Lake in Kayseri province were examined using three multispectral Landsat 8 satellite images of March, August and November 2016. Firstly, image-to-image registration processing was performed to register the three satellite images. Then, each satellite image was classified into two information classes either ‘Lake’ and ‘Other Field’ by using pixel-based Artificial Neural Networks (ANNs) and object-based K-Nearest Neighbor (KNN) method. Classification accuracies for ANNs method were obtained 99.97%, 99.90% and 99.80% respectively in March, August and November. As for the accuracies of the classification for the KNN method, in March, August and November were obtained 99.99%, 99.93% and 99.92% respectively. The change images were formed for March-August and August-November pairs by using the obtained classification images. The post classification comparison method was used to determine the changes in coastline boundaries. At the end of the study, seasonal changes from water to land and from land to water were detected. According to the result of the changes there is a 5,67 km^2 increase from March to August and a 3,14 km^2 decrease from August to November in Yamula Dam Lake.

Keywords: *Artificial Neural Networks; k-nearest Neighbor; Change Detection; Landsat 8*

1. INTRODUCTION

Remote sensing is a frequently preferred surveying method because it is useful and reliable in many disciplines. The remote sensing technique is one of the most successful methods in land cover and land use determination, planning, monitoring and mapping with different time intervals. It is also used for determination of emerging deformations and management of natural resources such as the determination of water beds, investigation of water pollution, determination of mineral and oil resources (Lillesand *et al.*, 2014).

Coastlines are permanent intersections where established seas and lakes or rivers (excluding situations such as floods) meet sections of land. Coastlines are one of the features identified by the International Geographic Data Committee (Karaburun and Demirci, 2010). Coastlines also have boundaries, which change according to meteorological phenomena, natural environment and human-induced effects. Efforts to identify changes in coastal boundaries at different times have a major impact on the management, conservation and sustainability of coastal resources. In recent years, there has been an increase in the utilization of remote sensing to monitor the changes in coastline management, coastline or coastal use (Ozpolat and Demir, 2014). Kuleli *et al.* (2011) determined coastline change in Yumurtalık and Gediz Ramsar wetland between 1989 and 2009 by using Digital Shoreline Analysis System, which is a statistic-based method. They used Landsat satellite images while doing this work. Prabaharan *et al.* (2010) investigated changes in the Vedaranniyam coastline, India. They utilized Landsat-1998, IRS 1C LISS III-2003 and IRS-Cartosat1-2008 satellite images to detect the changes. Guney and Polat (2015) used images of Landsat MSS of 1975, Landsat TM of 1987 and Landsat ETM of 2000 to determine coastline changes. They observed coastline changes by utilizing post classification comparison technique. Erener and Yakar (2012) used Landsat TM obtained in 1987, Landsat ETM+ obtained in 2000 and Landsat ETM+ obtained in 2006 and determined the water level changes from 1987 to 2006. Wang *et al.* (2013) used satellite images for determining the effect of coastal change on erosion by utilizing five different times and taken from three type satellites which are Landsat 5 TM, Landsat 7 ETM+ and HJ-1A. Shetty *et al.* (2015) used Landsat 5 TM images obtained from IRS 1C / 1 D in 1991, from IRS P6 in 2001, 2005 and 2009, from Landsat 8 OLI in 2013 satellite images and observed that sand was carried by erosion during the 46-year period (Shetty *et al.*, 2015).

The algorithms used in remote sensing studies to detect change can be separated in two types of method. The first is the unsupervised change detection approach. This method is based on the principle of the determination in land use and land cover changes obtained from satellite images taken on different dates and converting to single or multi-band image. The second method is the supervised change detection approach. This approach needs training and test classes as supervised classification for the determination in land use and land cover changes (Kesikoğlu *et al.*, 2013). For this reason, this approach is more challenging but, despite this, it allows us to achieve a more effective result in determining the direction of change.

The accuracy of the change detection process depends on the image classification process. Therefore, the selection of which classification method is used in change detection studies is important. There are many image classification methods used in literature such as membership function and, decision tree (DT) (Im and Jensen, 2005), random forest (RF) (Rodriguez-Galiano *et al.*, 2012), support vector machine (SVM) (Duro *et al.*, 2012, Kesikoglu *et al.*, 2019), maximum-likelihood (ML) (De Giglio *et al.*, 2019). In this study, we used two approaches: artificial neural networks (ANNs) and k-nearest neighbor (KNN). ANNs have a system that simulates the human brain. ANNs has been successfully used to classify satellite images in recent years (Pradhan and Lee, 2010; Chebud *et al.*, 2012; Hassan-Esfahani *et al.*, 2015). KNN is a nonparametric discriminatory analysis. The use of KNN method in image classification goes to 1990s (Denoeux, 1995) and it uses various image classification studies (Franco-Lopez *et al.*, 2001; McRoberts *et al.*, 2002; Yu *et al.*2006).Shiba *et al.* (2003) compared Case Slicing Technique as a new classification approach with K-Nearest Neighbor, C4.5 Learning Algorithm and Naive Bayes methods. Case Slicing Technique improved accuracy of the classification. Isa *et al.* (2005) used ANNs to classify the type of cervical cancer in its early stage and compared different ANNs. Zhang *et al.* (2017) used Spot-5 images to compare pixel-based and object-based classification method in the Heine River basin. They observed that object-based classification gave better results. Al Fugara *et al.* (2009) used Landsat 7 satellite images to compare pixel-based and object-based classification in the Klong valley of Malaysia. As a result of the work, object-based classification gave better results than pixel-based classification.

In this study, we aim to identify the changes at the Yamula dam coastline by using Landsat-8 satellite images obtained in March, June and November of 2016. In this context, we selected two-classification method and compared classification accuracies to obtain better results. ANNs and KNN methods were used for classification of satellite images and post classification comparison method was used to determine the coastline change. The study also briefly describes the planning of the work and the steps before the change is determined. It is aimed to contribute to the selection of the correct method in coastal line studies.

2. STUDY AREA

The Yamula Dam Lake is one of the most important dams due to producing electric energy and irrigation in Central Anatolia Region, Turkey (Kesikoğlu *et al.*, 2017). The dam is located 25 kilometers northwest of Kayseri and lies on the Kızılırmak River. The only water source that feeds the Yamula Dam is the Kızılırmak River. The river originates from Kızıldağ mountain in Sivas and flows into the Black Sea. The dam started holding water on December 27, 2003 (Yamula Barajı, n.d.). Landsat-8 satellite images of the year 2016 used in this study were chosen to include the Yamula Dam Lake and the change of coastline of the lake. The satellite image of the dam lake is demonstrated in Fig 1.

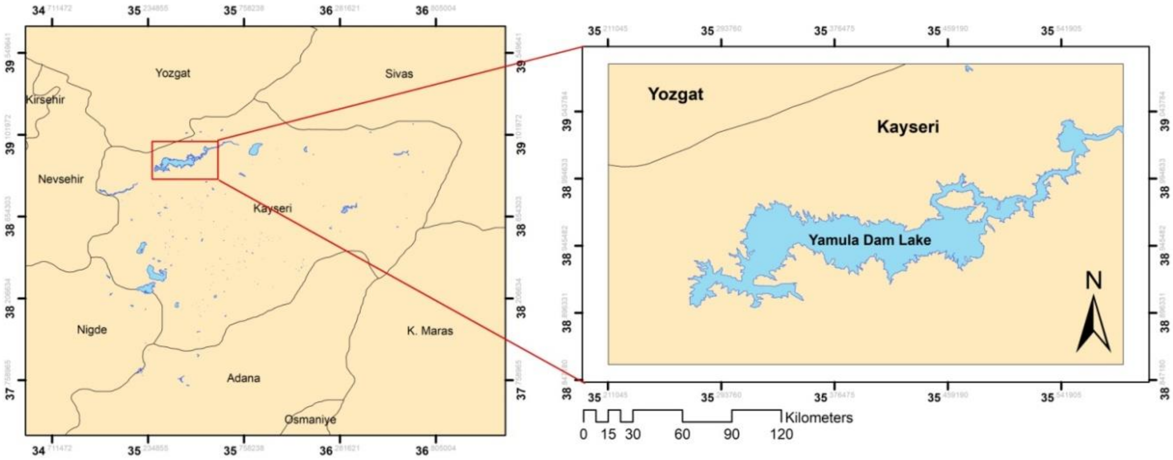


Fig. 1. Location map of study area

3. MATERIALS AND METHODS

In this study, Landsat 8 satellite images owning to the spring, summer and autumn seasons were used. These images were from March 5, 2016; August 26, 2016 and November 4, 2016. None of the winter season satellite images were evaluated due to the cloudy weather in December, January and February for the year 2016. Landsat 8 OLI / TIRS bands and their properties are given in detail in Table 1.

Table 1. Landsat-8 OLI / TIRS satellite image bands and features ("What are the band designations", 2017)

Sensor	Spectral Bands	Wavelength(μm)	Resolution(m)
	Band-1 Ultra Blue (Coastal Aerosol)	0.43-0.45	30
	Band-2 Blue	0.45-0.51	30
	Band-3 Green	0.53-0.59	30
	Band-4 Red	0.64-0.67	30
OLI	Band-5 Near Infrared (NIR)	0.85-0.88	30
	Band-6 Shortwave Infrared (SWIR-1)	1.57-1.65	30
	Band-7 Shortwave Infrared(SWIR-2)	2.11-2.29	30
	Band-8 Panchromatic	0.50-0.68	15
	Band-9 Cirrus	1.36-1.38	30
TIRS	Band-10 Thermal Infrared 1	10.60-11.19	100*30
	Band-11 Thermal Infrared 2	11.50-12.51	100*30

3.1. Artificial Neural Networks (ANNs)

ANNs is based on model of the biological brain. It is inspired from learning capability, structure and processing method of biological brain. ANNs consist of simple linear or nonlinear computing elements called "neurons", which are interconnected in complex ways and are usually arranged in layers (Sarle, 1994). There are numerous links between these elements. Information is distributed via links. Results are acquired through a learning process.

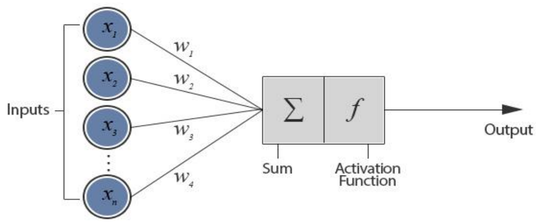


Fig. 2. Neurons structure of the ANNs (Haykin, 1994)

The structure of the neuron is demonstrated in Fig. 2, where $x_1, x_2, x_3 .... x_n$, are inputs and $w_1, w_2, w_3 .... w_n$, are the weights of these inputs. The weights determine the influence of inputs on the cell. The addition function calculates net data entering the cell. This can be mathematically identified as given in Eq. (1) (Haykin, 1994).

$$NetInput = \sum x_i w_i \quad (1)$$

The activation function can be identified as given in Eq. (2).

$$y = F(x) \quad (2)$$

All artificial nerve cells come together to form ANNs composed of three layers as shown in Fig. 3: input layer, hidden layer and output layer.

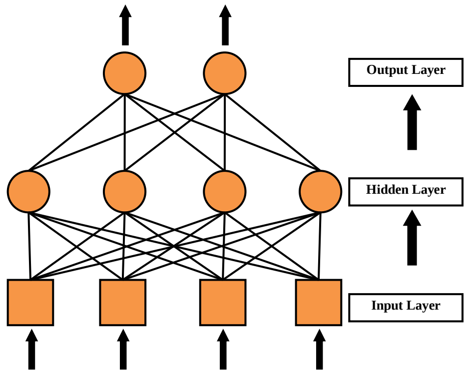


Fig. 3. Layers of the ANNs

The input layer receives the data from the outside and transmits it to the hidden layer. The hidden layer multiplies incoming data with weights and weighted data are collected. The results of the transfer function transmits output layer. Then, the output layer sends the result to the outside (Haykin, 1994).

3.2.K-Nearest Neighbor (KNN) Algorithm

K-Nearest Neighbor is one of the simplest and easiest methods to implement for image classification. Unlike other algorithms as ANNs, KNN does not need to train a dataset. Since the output value is only related to the partial number of neighboring samples, errors arising from the number of unstable training examples can be avoided in this algorithm. Due to these advantages, the algorithm has recently been used in many areas such as text classification, data processing and earthquake prediction (Sang *et al.*, 2011).

The KNN algorithm process is defined as follows. A stable database (D) based on the measured results is established. K is set to the nearest neighbor number. Since K strongly influences the output values, there is no special way to set it. The value is usually determined experimentally. M (m_1, m_2 ... m_n) which is the feature vector are computed and generated for each point. The distances between each point of M' and D collection are (M): dist (M', M). The commonly used Euclidean Distance is shown in the Eq. 3 (Sang *et al.*, 2011).

$$d(M', M) = \sqrt{\sum_i^n (m_i - m_j)^2} \quad (3)$$

According to the calculated distance, the nearest K point, D, is selected and a new data is collected according to the above equation (D_k). The output value of M is used the following equation according to D_k is calculated.

$$M' = \frac{\sum_{i=1}^{K} M_j}{K} \quad (4)$$

3.2.Post Classification Comparison

The most commonly used change detection techniques are image differencing, image rationing, principal component analysis, change vector analysis and post-classification comparisons (Kesikoğlu, 2013).Image differencing, image rationing, change vector analysis and principal component analysis are used for unsupervised change detection, whereas post-classification comparisons are used for supervised change detection process.

In this study post-classification comparison is used in change detection analysis. In this approach, satellite images belonging to two different times are classified and recorded independently. Then, the classified images are compared with each other. Thus, the direction and amount of change are determined (Tabarroni, 2010).

4. APPLICATION AND RESULTS

The direct use of raw images obtained from satellites in change detection studies is an obstacle for producing meaningful results because these images contain non-systematic errors. These errors arise from the height and position of satellite (Sertel *et al.*, 2007).The geometric correction process with image registration must be performed in order to correct these errors (geometric distortions) in the images. The process followed in the study is demonstrated in Fig. 4.

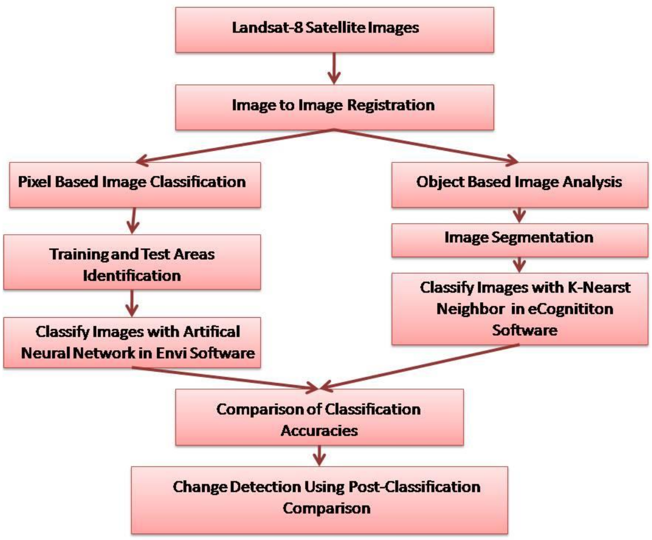
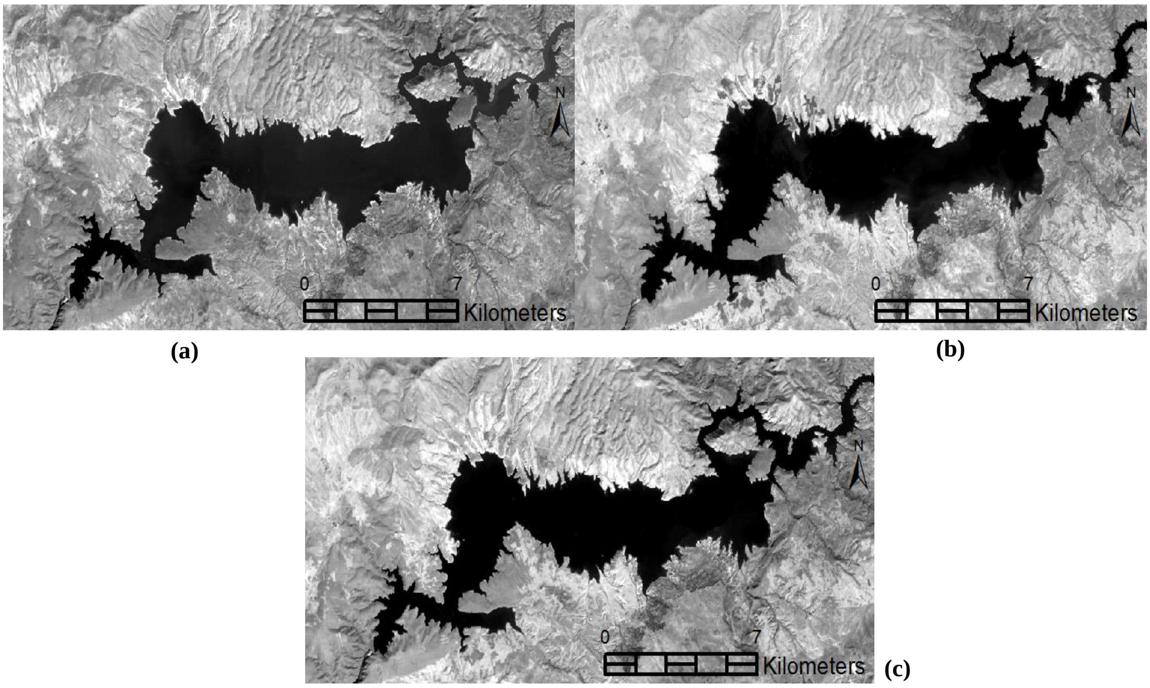


Fig. 4. Coastline change detection diagram

First of all, "Image to Image Registration" process was performed for satellite images. Satellite image for March were selected as reference and the other images were registered in that image. In the "Image Registration" process, image mapping was done by using ground control points (GCPs) that were known in the image. 30 well-distributed GCPs were used during implementation and it was noted that the root mean square error (RMSE) value was less than 0.5. Furthermore, the images were cut based on the specified study area after registration. Blue bands of the each registered images are demonstrated in Fig. 5.



(a) **(b)** **(c)**

Fig. 5. Registered images for (a) March, (b) August, (c) November

Our study area was divided into two classes; ‘Lake’ and ‘Other_field’. It was chosen 2454 pixels for training and 2501 pixels for testing to use in satellite images of different dates in the study. Due to the fact that the selected train and test areas represented the right classes in each images, a single train and test data was used. The selected training areas were used to classify the images with both ANNs and KNN classification algorithms. The test data were used to evaluate the accuracy of the classification process.

4.1. Pixel-based classification of the Landsat 8 data

Pixel-based image classification, using an ANNs classifier, was performed using ENVI, which is image analysis software. While classification was being done, parameters such as number of iterations, learning rate, training RMS output value and momentum related to ANNs were used. Since pixels are considered separately in pixel based classification, it is important to evaluate all pixels. Therefore, multispectral bands (bands 2-7) were used for doing classification. The training was stopped when the specified RMS output value was reached. The learning rate is a variable used for changing weight values of the ANNs. Momentum used to reduce error and to provide a correction for changing weights is a number value from 0 to 1 (Kesikoğlu, 2013). In this study, the number of iterations was 1000, the RMS output value was 0.1, the learning rate was 0.2 and the momentum was 0.9. After that, the multispectral images were divided into two classes as ‘Lake’ and ‘Other_field’. Classified images are shown in Fig. 6.

4.2. Object-based classification of the Landsat 8 data

The KNN approach is similar to the supervised classification because samples are chosen as supervised classification. However, the selected samples are not as independent as selected in the supervised classification. The first step of object-based classification is segmentation. There are various segmentation types such as chessboard, quadtree, multi-resolution and spectral difference. Before using this method, training and test data in the ANNs was integrated into the eCognition software. Then, multi-resolution segmentation method was applied to the remaining areas. The scale parameter was 50, the shape parameter was 0.1 and the compactness parameter was 0.5 for the multi-resolution segmentation.

Prior to the classification, instead of pixels, objects (segments) formed by combining pixels are used in object-based classification. When classifying these objects, an input parameter is required, unlike pixel-based classification. This parameter was Normalized Difference Water Index (NDWI) (McFeeters, 1996). The reasons for choosing this parameter are that, NDWI is an internationally accepted index to extract water areas and it distinguishes water from other field easily. For this reason it has been sufficient to use two bands (band 3 and 5) required for NDWI method in object based classification. NDWI formula is given in Eq. 5.

$$\boldsymbol{NDWI} = \frac{GREEN-NIR}{GREEN+NIR} \tag{5}$$

Classification was then carried out using the KNN according to the training data selected in the ANNs method. The multispectral images are divided into two classes as 'Lake' and 'Other field' by using KNN. Classified images are demonstrated in Fig. 7.

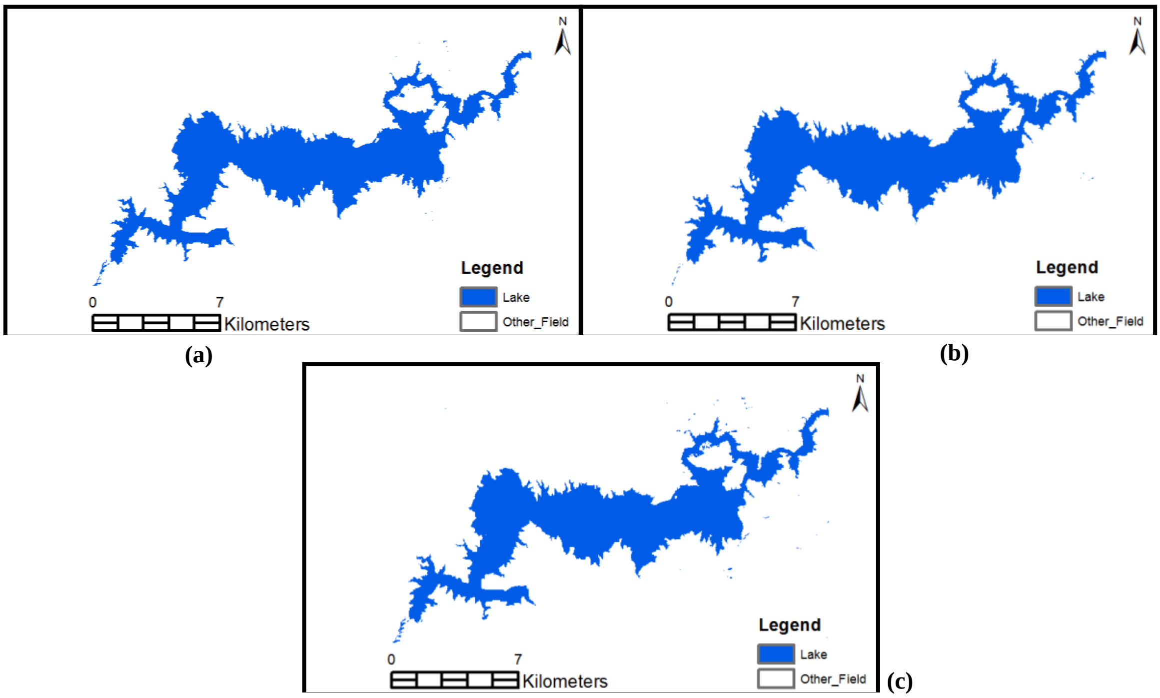


Fig. 6.Classification images classified by ANNs (a) March, (b) August, (c) November

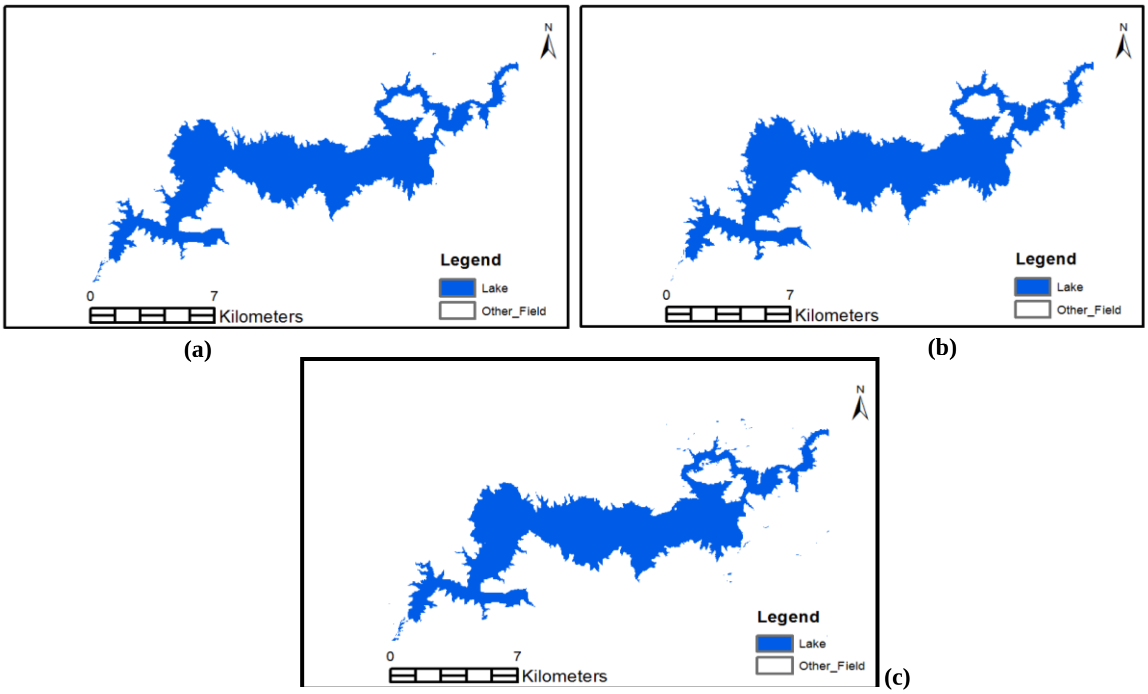


Fig. 7.Classification images of Yamula Dam Lake classified by KNN for (a) March, (b) August, (c) November

The image classification accuracies are presented in Table 2. Results obtained with KNN classification was observed at 99.99% overall accuracy for March image, 99.93% overall accuracy for August image and 99.92% overall accuracy for November image. Results obtained with ANNs classification was observed at 99.97% overall accuracy for March image, 99.90% overall accuracy for August image and 99.80% overall accuracy for November image.

Table 2. Results of accuracy analysis for classification

	ANNs		KNN	
Month	Overall Accuracy (%)	Kappa Coefficient	Overall Accuracy (%)	Kappa Coefficient
March	99.97	0.9991	99.99	0.9998
August	99.90	0.9969	99.93	0.9983
November	99.80	0.9938	99.92	0.9955

Although the results are close to each other, the KNN method seems to give better results. For this reason, the thematic maps obtained from KNN method are used to determine the change map. Change detection maps are shown in Fig. 8.

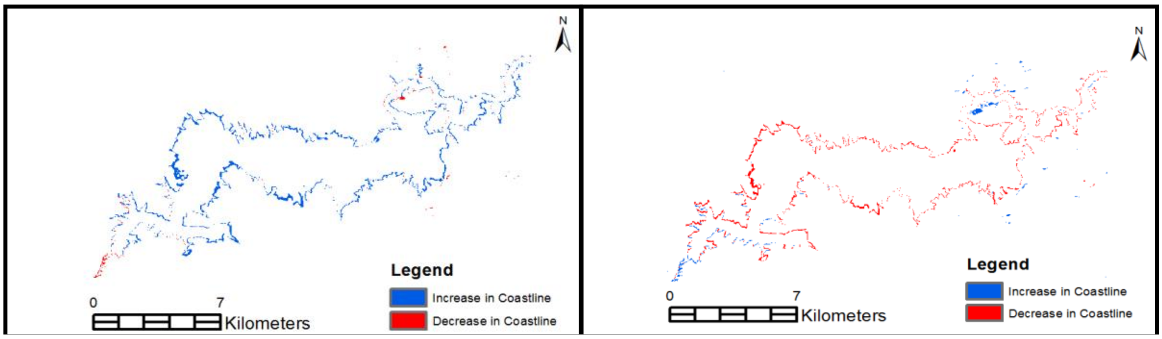


Fig. 8.(a) Map of changes by KNN method from March to August (b) Map of changes from August to November

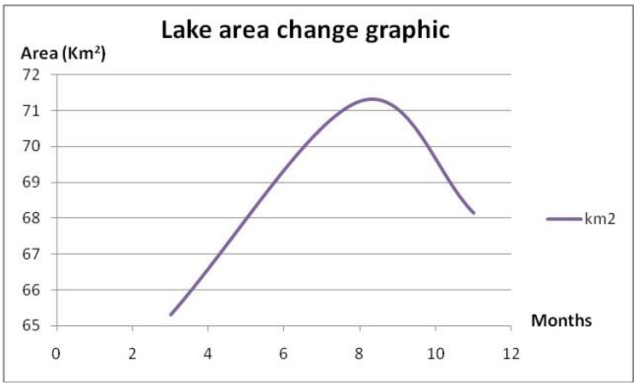


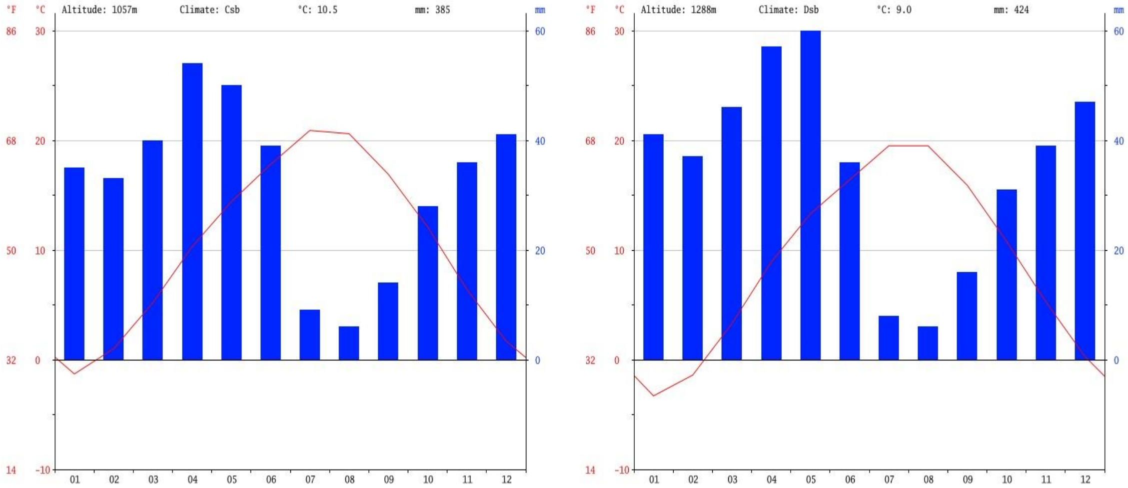
Fig. 9.The graphic of lake area from March to August and November in Yamula Dam Lake

According to the obtained findings (Fig. 9), lake area has a 5,67 km^2 increase from 65,82 km^2 to 71,49 km^2 between March and August; a 3,14 km^2 decrease from 71,49 km^2 to 68,35 km^2 between August and November.

In Kayseri the total precipitation was 430 mm in 2016. Whereas August is the driest month, April is the rainiest month. The precipitation in August was 6 mm while it was 54 mm in April. The precipitation increased after August illustrated in Fig. 10 (a).

In Sivas, total precipitation was 500 mm in 2016. Whereas August is the driest month, May is the rainiest month. The precipitation in August was 6 mm while, it was 60 mm in May. The precipitation increased after August illustrated in Fig. 10 (b).

The annual spatial precipitation in Sivas causes changes in the amount of water coming to the Yamula dam as it affects the occupancy rate of the Kızılırmak River. Therefore, due to the effect of the precipitation regime in Sivas on the study area, the precipitation regime in Sivas was also taken into consideration. The melting snow sometimes causes the flow of Kızılırmak Rivers to rise. This situation leads to an increase in the amount of water coming to the Yamula Dam Lake. Thus, the increase in the amount of incoming water is seen in Fig. 8, which leads to the expansion of the Yamula Dam Lake boundaries. The highest rainfall in Sivas province in 2016 took place in April and May according to the Sivas annual areal rainfall graphic. It also affected the increase in water boundaries of the Yamula Dam. After August, a decrease in the dam lake boundaries was observed.



(a) **(b)**

Fig. 10. (a) Kayseri annual areal rainfall (“Iklim Kayseri”, 2017) (b) Sivas annual areal rainfall (“Iklim Sivas”, 2017)

5. CONCLUSION

Water is vital for the survival of livings. Rivers, lakes and dams form natural and artificial water resources. It is seen that both natural and human-induced effects are increasing or decreasing day by day in water resources. Therefore, determining the changes occurring in water sources is of great importance. Yamula is one of the most important dams in Turkey in terms of irrigation and electricity generation. In this study, both pixel-based and object-based classification methods were used to determine the water areas in the dam and the results were evaluated. While in the pixel-based classification method training data is selected pixel-by-pixel, in the object-based classification training data object by object is selected. For this reason the segmentation phase that forms the objects is very important. At the segmentation stage, pixels having similar reflection characteristics are grouped so that instead of working with a large number of pixels, segments consisting of pixels having these common characteristics are formed, at which point the heterogeneity between the segments is minimized. Therefore, object-based classification gives higher accuracy.

In this study, since the test area was a small area and only two classes were created, high accuracy was obtained by both methods. Different results were obtained as a result of using both algorithms. However, increase in the lake area until August and decrease after this month was detected in result of both algorithms. As the KNN method gave better results, the classification images obtained from this method was used to determine seasonal variations. The seasonal change information was obtained by using post classification comparison method on the classified Landsat 8 satellite images. It is seen that post classification comparison method used in this study produced meaningful change results in satellite images of different months.

The results of the study show that there is both an increase and decrease in Yamula Dam Lake. A lot of studies about the Yamula dam have been reviewed. As a result of the news, it was determined that the changes in the dam were not human-origin but climate-related. The change in the dam area was results from snow melting, rainfall and evaporation. It was detected that the increase until August was both snow melting and rainfall. The decrease in the lake area after August was results from the decrease in rainfall. Moreover, the evaporation which was caused by the increase of the air temperature negatively affected the lake area. In the context of this study, it has been was observed increase in the amount of the water in the Yamula Dam Lake until August and decrease in the amount of water in the Yamula Dam Lake after August In addition, KNN method gave better results than ANNs method to identify Yamula Dam Lake.

REFERENCES

A. M. Al Fugara, A., M., B. Pradhan, B., and T. A. Mohamed, T., A., (2009). “Improvement of land-use classification using object-oriented and fuzzy logic approach.” *Applied Geomatics*, 1(4), 111.

Baek, S., and Sung, K. M. (2000). “Fast K-nearest-neighbour search algorithm for nonparametric classification.” *Electronics Letters*,36(21), 1821-1822.

Chebud, Y., Naja, G. M., Rivero, R. G., and Melesse, A. M. (2012). “Water quality monitoring using remote sensing and an artificial neural network.” *Water, Air, and Soil Pollution*, 223(8), 4875-4887.

De Giglio, M., Greggio, N., Goffo, F., Merloni, N., Dubbini, M., and Barbarella, M. (2019). “Comparison of Pixel-and Object-Based Classification Methods of Unmanned Aerial Vehicle Data Applied to Coastal Dune Vegetation Communities: Casal Borsetti Case Study.” *Remote Sensing*, 11(12), 1416.

Denoeux, T. (1995). “A k-nearest neighbor classification rule based on Dempster-Shafer theory. ”*IEEE Transactions on Systems, Man, and Cybernetics*,25(5), 804-813.

Duro, D. C., Franklin, S. E., and Dubé, M. G. (2012). “A comparison of pixel-based and object-based image analysis with selected machine learning algorithms for the classification of agricultural landscapes using SPOT-5 HRG imagery". *Remote sensing of environment*, 118, 259-272.

Erener, A., and Yakar, M. (2012). "Monitoring Coastline Change Using Remote Sensing and GIS Technologies. "*Lecture Notes in Information Technology*, 30, 310-314.

Franco-Lopez, H., Ek, A. R., and Bauer, M. E. (2001). "Estimation and mapping of forest stand density, volume, and cover type using the k-nearest neighbors method. "*Remote Sensing of Environment*, 77(3), 251-274.

Güney, Y., and Polat, S. (2015). "Coastline Change Detection Using Remote Sensing Data: The Case of Aliaga and Candarli. "*Journal of Aeronautics and Space Technologies/ Havacılık ve Uzay Teknolojileri Dergisi*, 8(1).

Hassan-Esfahani, L., Torres-Rua, A., Jensen, A., and McKee, M. (2015). "Assessment of surface soil moisture using high-resolution multi-spectral imagery and artificial neural networks. "*Remote Sensing*,7(3), 2627-2646.

Haykin, S. (1994). *Neural networks: A comprehensive foundation*, Macmillan College Publishing Company, New York, USA.

Iklim Kayseri, https://tr.climate-data.org/asya/tuerkiye/kayseri/kayseri-250/ [Accessed 25 June 2017]

Iklim Sivas, https://tr.climate-data.org/asya/tuerkiye/sivas/sivas-255/ [Accessed 25 June 2017]

Im, J., & Jensen, J. R. (2005). A change detection model based on neighborhood correlation image analysis and decision tree classification. *Remote Sensing of Environment*, *99*(3), 326-340.

Isa N. A. M., Mashor M. Y, Othman N. H., Zamli K.Z., (2005). "Application of artificial neural networks in the classification of cervical cells based on the Bethesda system." *Journal of JICT*, 4, 77-97.

Karaburun, A., and Demirci, A. (2010). "Coastline changes in Istanbul between 1987 and 2007."*Scientific Research and Essays*, 5(19), 3009-3017.

Kesikoglu, M. H., Atasever, U. H., Dadaser-Celik, F., & Ozkan, C. (2019). Performance of ANN, SVM and MLH techniques for land use/cover change detection at Sultan Marshes Wetland, Turkey. *Water Science and Technology*.

Kesikoğlu, M. H., Atasever, Ü. H., and Özkan, C. (2013). "Uzaktan Algılamada Kontrolsüz Değişim Belirleme."*Tmmob Harita Ve Kadastro Mühendisleri Odası, 14. Türkiye Harita Bilimsel Ve Teknik Kurultayı*, Ankara.

Kesikoğlu, M. H. (2013). Research Of Coastal Change In Sultan Marshes National Park And Ramsar Site With Satellite Image Analysis, MSc. Thesis, University of Erciyes, Kayseri, Turkey.

Kesikoğlu M.H., Çiçekli S.Y., Kaynak T., Özkan C. (2017). "The determination of coastline changes using artificial neural networks in Yamula Dam Lake, Turkey. "*The 8th International Conference on Information Technology*, Amman, Ürdün, 1-4.

Kuleli, T., Guneroglu, A., Karsli, F., and Dihkan, M. (2011). "Automatic detection of shoreline change on coastal Ramsar wetlands of Turkey. "*Ocean Engineering*,38(10), 1141-1149.

Lillesand, T., Kiefer, R. W., and Chipman, J. (2014). *Remote sensing and image interpretation*. John Wiley and Sons.

McFeeters, S. K. (1996). "The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. "*International Journal of Remote Sensing*,17(7), 1425-1432.

McRoberts, R. E., Nelson, M. D., and Wendt, D. G. (2002). "Stratified estimation of forest area using satellite imagery, inventory data, and the k-Nearest Neighbors technique. "*Remote Sensing of Environment*, 82(2), 457-468.

Ozpolat, E. and Demir, T. (2014). "Coğrafi Bilgi Sistemleri Ve Uzaktan Algılama Yöntemleriyle Kıyı Çizgisi Değişimi Belirleme : Seyhan Deltası."*Xvi., Akademik Bilişim*, Mersin Üniversitesi ,Mersin.

Prabaharan, S., Raju, K. S., Lakshumanan, C., and Ramalingam, M. (2010). "Remote sensing and GIS applications on change detection study in coastal zone using multi temporal satellite data." *International Journal of Geomatics and Geosciences*, 1(2), 159.

Pradhan, B., and Lee, S. (2010). "Landslide susceptibility assessment and factor effect analysis: backpropagation artificial neural networks and their comparison with frequency ratio and bivariate logistic regression modelling" *Environmental Modelling and Software*, 25(6), 747-759.

Rodriguez-Galiano, V. F., Ghimire, B., Rogan, J., Chica-Olmo, M., & Rigol-Sanchez, J. P. (2012). An assessment of the effectiveness of a random forest classifier for land-cover classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, 67, 93-104.

Sang, L., Xu, Y., Cao, R., Chen, Y., Guo, Y., and Xu, R. (2011). "Modelling of GaN HEMT by using an improved k-nearest neighbors algorithm. "*Journal of Electromagnetic Waves and Applications*, 25(7), 949-959.

Sarle, W. S. (1994). "Neural networks and statistical models. "*Proceedings Of The Nineteenth Annual Sas Users Group International Conference*.

Shetty, A., Jayappa, K. S., and Mitra, D. (2015). "Shoreline change analysis of Mangalore coast and morphometric analysis of Netravathi-Gurupur and Mulky-Pavanje spits."*Aquatic Procedia*, 4, 182-189.

Tabarroni, A. (2010). Remote sensing and image interpretation change detection analysis: case study of borgo panigale and reno districts, MSc. Thesis, University of Florence, Florence, Italy.

Wang, X. Z., Zhang, H. G., Fu, B., and Shi, A. Q. (2013). "Analysis on the coastline change and erosion-accretion evolution of the Pearl River Estuary, China, based on remote-sensing images and nautical charts." *Journal of Applied Remote Sensing*, 7(1), 073519-073519.

What are the band designations for the Landsat satellites?,http://landsat.usgs.gov/band_designations_landsat_satellites.php[Accessed 22 June 2017].

Yamula Barajı (n.d.), http://www.kayseri.gov.tr/yamula-baraji [Accessed 8 March 2017]

Yu, Q., Gong, P., Clinton, N., Biging, G., Kelly, M., and Schirokauer, D. (2006). "Object-based detailed vegetation classification with airborne high spatial resolution remote sensing imagery." *Photogrammetric Engineering and Remote Sensing*, 72(7), 799-811.

Zhang, H., Li, Q Liu, J., Du, X., Dong, T., McNairn, H., Champagne, C., Liu, M., and Shang, J.(2017). "Object-based crop classification using multi-temporal SPOT-5 imagery and textural features with a random forest classifier."*Geocarto International*, 1-19.