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Comparison of different classification algorithms for the detection of changes on water bodies; Karakaya Dam Lake

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ABSTRACT

Optimum management of water and water bodies is crucial in ensuring and maintaining the natural ecosystem cycle. Benefits from wetlands in the world and in our country keep humanity alive. Resources that are of vital importance should be monitored and changes should be observed. Thanks to the science of remote sensing, researchers in many parts of the world can monitor changes in the waters of the earth through satellite imagery and terrestrial supporting studies. The main component of change detection in remote sensing is the classification process. Nowadays, the Classification process has reached different dimensions with the contributions of artificial intelligence and machine learning algorithms. The emergence of different classification algorithms also affected the results obtained from the analyzes. In this study, the change occurred between 1990-2000-2010-2019 in Karakaya Dam Lake, which is included in the borders of Malatya - Elazığ provinces, was observed. In this context, supervised classification processes and change detection analyzes were performed using Landsat satellite data with maximum likelihood, artificial neural network, support vector machine and decision tree algorithms. For detecting the change analysis, the lake boundaries obtained from official sources were used and compared. The data obtained as a result of the study were compared for each algorithm and the amount of change was interpreted.

1. INTRODUCTION

Water is an important component in ensuring the life cycle on Earth. It is important to monitor the wetlands around the world and protect them in order to obtain optimum benefit from them (Lu et al., 2011). At the same time, water is an indispensable strategic element for human survival and social development (Ridd and Liu, 1998). Wetlands are actively used in our country and over the world both for energy production and for the maintenance of natural activities. Studies such as evaluating the status of existing water resources and examining their future status, mapping, monitoring their changes, and taking wetland inventory are critical in many disciplines (Rokni et al., 2014).

In particular, changes related to water emerging in terms of global climate change raise concerns in many countries of the world (Calò et al., 2018). Temporal climate changes and drought are seen as the main reason for the change and decrease of wetlands (Orhan et al., 2017). Remote sensing methods, which are engaged at this stage, have a large share in monitoring climate changes and changes in water areas.

Satellites with different spectral and spatial resolution used in remote sensing provide a high amount of data for detecting wetlands. The determination of wetlands with remote sensing methods has been studied for more than two decades (Sun et al., 2012; Kaplan et al., 2019). Since the launch of the Landsat-1 satellite in 1972, efforts have been made to identify the water on the image (Work and Gilmer, 1976).

The process of collecting objects with similar spectral reflectance values on the ground under the same group is called classification in remote sensing (Torun, 2015). Classification process can be done by many mathematical and statistical methods. Thanks to the renewed and developing technology, artificial

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intelligence and machine learning algorithms are also included in these techniques. Scientists have studied and compared the accuracy of these methods in many studies (Lu and Weng, 2007; Colkesen, 2009; Fuping et al., 2011). As a matter of fact, that the more accurate you classify, the better quality analysis you will get.

In this study, it is aimed to observe the change in the coastal boundaries of Karakaya Dam lake, which is the feed factor of Karakaya dam, by using different classification algorithms. For this reason, satellite images of 1990-2000-2010 and 2019 years were provided. Training and test areas were determined to be used in classifications over the image and classifications were made using Maximum Likelihood, Artificial Neural Network, Support Vector Machine and Decision Tree algorithms. The coastline of lake produced as a result of the classifications has been compared with the limit obtained from official sources. In addition, as a result of the classifications, the 30-year change in the lake area has been revealed on areal basis.

2. METHODS

2.1. Maximum Likelihood

The Maximum Likelihood method, one of the most used image classification methods in remote sensing, is also extensively in the detection of changes in wetlands (Munyati 2000; Frazier and Page 2000; Zhang et al., 2009). In this method, the variance and covariance values are evaluated quantitatively in the classification of each unknown pixel. With the help of probability functions calculated for each pixel, it is determined which class a pixel is closer to (Mather, 1987; Kavzoglu and Colkesen, 2010). After this process is completed, the candidate pixel is assigned to the class with the highest probability value. If this value is below the threshold value determined by the user, the pixel is considered as indefinite (Lilesand et al., 2008).

Since the ML method calculates the probability of each pixel belonging to any class, it performs a lot of mathematical operations and therefore runs slightly slower than other methods. Also, since this method does not use textural and structural information in the image but only uses spectral information, it is more limited than object-based methods (Zhou and Robson, 2001; Dean and Smith, 2003; Pizzolato and Haertel, 2003).

2.2. Support Vector Machines

Support Vector Machines (SVM) is a classification algorithm widely used for the classification of remotely sensed images and high classification accuracy of the SVM has been revealed in many studies (Huang et al., 2002; Foody and Mathur, 2004; Kavzoglu and Colkesen, 2009; Mountrakis et al., 2011; Dixon and Candade, 2008). SVM is the first non-parametric, supervised classification method based on statistical learning theory, proposed by Vapnik. The main purpose of this method to separate two classes optimally based on the determination of the decision function (hyperplane) (Vapnik, 1995).

In cases where it is not possible to define hyperplanes with linear equations, kernel functions are used. With the help of the kernel functions, data that cannot be separated linearly in the input space is displayed in a higher dimensional space and in this high dimensional space, the data is linearly separated. It is thought that the polynomial and radial-based kernels are widely used in remote sensing studies and the better results obtained with the use of radial-based kernels (Melgani and Bruzzone, 2004; Foody and Mathur, 2004; Pal and Mather, 2005; Mathur and Foody, 2008b, Kavzoglu and Colkesen, 2009).

2.3. Artificial Neural Networks

Artificial Neural Networks (ANN) can be defined as a branch of artificial intelligence developed to imitate the human brain (Viotti et al., 2002; Sahin 2012). ANN has many uses such as remote sensing modeling, stereo mapping and image compression (Goung, Zheng 1992; Lee et al., 1994; Pierce et al., 1994; Walker et al., 1994; Foody and Arora 1997). A typical ANN consists of an input layer, an output layer, and usually one or two hidden layers (Jensen et al., 1999). The purpose of ANN is to calculate the output values from the input values (Nasr et al., 2012). The neurons in the input layer take the information from outside and transfer it to the hidden layers. The information from the input layer is processed in the hidden layer and transferred to the output layer. Neurons in the output layer, on the other hand, process the information from the intermediate layer and obtain the output that must be produced for the input set presented from the input layer of the network (Oztemel, 2016). The system learns by estimating the output data from a series of input training data so that the result of any given data set can be estimated (Ingram et al., 2005). ANN, which are frequently used in Remote Sensing, are also used extensively in matters related to wetlands (Augusteijn and Warrender,1998; Ghedira et al., 2000; Berberoglu et al., 2004).

2.4. Decision Tree

A decision tree, having its origin in machine learning theory, is a classification and pattern definition algorithm. Unlike other classification approaches that use a number of features (or bands) to perform the classification in a single decision step, the decision tree is based on a hierarchical decision chart or tree-like structure (Xu et al., 2005). Decision trees are frequently used in many applications due to the high classification procedures that tree structures and established rules are simple and understandable (Simard et al., 2000; Huang and

Yang, 2001; Pavuluri et al., 2002). The basic structure of a decision tree consists of a root node, a set of internal nodes and a set of terminal nodes. In this tree structure, each attribute information is represented by a node. The basic principle in creating a decision tree structure by using the attribute information of the education data can be expressed as asking a series of questions regarding the data and acting in line with the answers obtained, and getting the results as soon as possible (Kavzoglu and Colkesen, 2010). Due to the high accuracy it provides, the decision trees method, which has been used successfully in remote sensing, is also frequently used in wetlands (Wei et al., 2008; Berhane et al., 2018; Baghdadi et al., 2001).

3. STUDY AREA AND MATERIALS

Karakaya Dam Lake, which borders Malatya and Elazığ provinces, has been selected as a pilot area. The lake, the second largest dam on the Fırat River, which provides a significant part of Turkey's hydroelectric energy production, which feed the Karakaya Dam. Karakaya Dam Lake, which has an area of approximately 250 km^2, makes important contributions to the region in the fields of tourism, fishing and agriculture. In 2013, The Council of Ministers of Republic of Turkey declared the Karakaya Dam Lake as the Culture and Tourism Conservation Development area (T.C Resmi Gazete, 4153, 20 January 2013). Figure 1 shows the study are map.

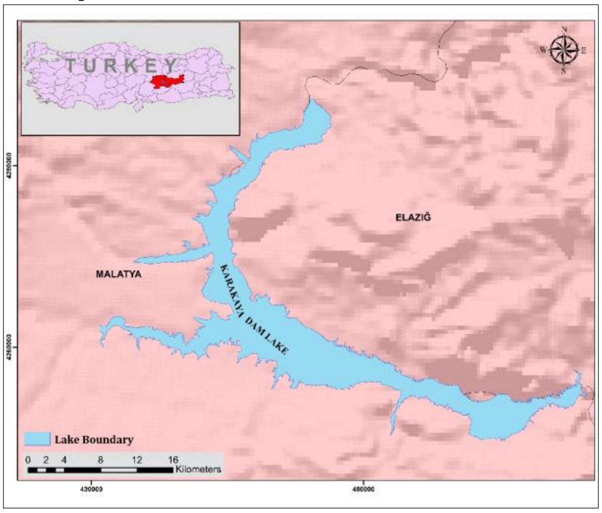

Figure 1. Study area map

Satellite images from 1990, 2000, 2010 and 2019 were obtained from the USGS data provider for use in the study. Landsat 5 TM for 1990 and 2010, Landsat 7 ETM for 2000 and Landsat 8 OLI-TIRS satellite images were used for 2019. Red, Green, Blue and Near Infrared bands are used for all images. The data is 30 m spatial resolution and has UTM WGS-84 coordinate system and datum. Date and satellite information of the data are given in the Table 1.

Table 1. Satellite data dates and specifications

Satellite	Date	Path/Row
Landsat 5 TM	15.08.1990-22.08.2010	173/33
Landsat 7 ETM	18.08.2000	173/33
Landsat 8 OLI-TIRS	31.08.2019	173/33

4. RESULTS

In this article, it is aimed to monitor the coastal changes in Karakaya Dam Lake by using different image classification algorithms of Machine Learning. In this context, satellite images are classified using Maximum Likelihood, Artificial Neural Network, Support Vector Machine and Decision Tree algorithms. Environment for Visualizing Images 5.3 (ENVI 5.3) and ArcGIS software were used for classification and thematic mapping. For each image, the classification process was made on the basis of water bodies, pastures, continuous urban fabric and non-irrigated arable land classes in CORINE-2018 classification system.

Images are classified using four different algorithms. Then, except for the water bodies, the other classes were combined and the class that would allow the lake boundaries to be achieved was left alone. Used machine learning algorithms have revealed different results for different years. Figure 2 show that the results of different classification algorithms for different years related to the lake area. And the overall accuracies of classifications are given Table 2.

Table 2. Classification overall accuracies

Year / Method	1990	2000	2010	2019
Maximum Likelihood	0,82	0,84	0,87	0,85
Artificial Neural Network	0,88	0,88	0,93	0,88
Support Vector Machine	0,89	0,87	0,91	0,89
Decision Trees	0,88	0,84	0,90	0,89

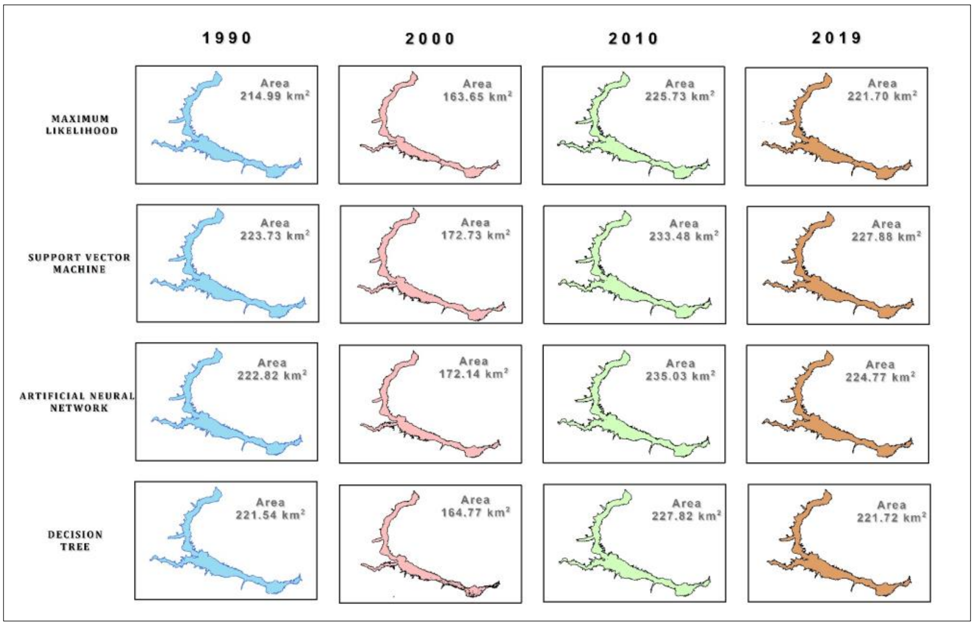

Figure 2. Classified lake coastline and area changes classified by different algorithms

With the data obtained as a result of classifications, 30-year change analyzes were applied for the lake area. As the basic data in change analysis, official coastline and lake area obtained from the 1/100000 scaled Environmental Plan which completed by the General Directorate of Spatial Planning on 19.02.2020 was used. Figure 3 shows the coastline obtained from the classifications and satellite data 10 years ago.

Thanks to the lake boundary obtained by the classification results, the change that occurs every ten years has been observed. Classification techniques were analyzed among themselves and also compared with the basic data and their differences from the basic data were calculated. Figure 4 shows the spatial change data of the classification methods by years. Table 3 shows the spatial change that occurs when the data obtained as a result of classifications are compared with the basic data.

Table 3. Change detection analysis rates against master lake area respect years (%)

Year / Method	1990	2000	2010	2019
Maximum Likelihood	-%16	-%36	-%12	-%13
Artificial Neural Network	-%13	-%33	-%8	-%12
Support Vector Machine	-%12	-%32	-%9	-%11
Decision Trees	-%13	-%36	-%11	-%13

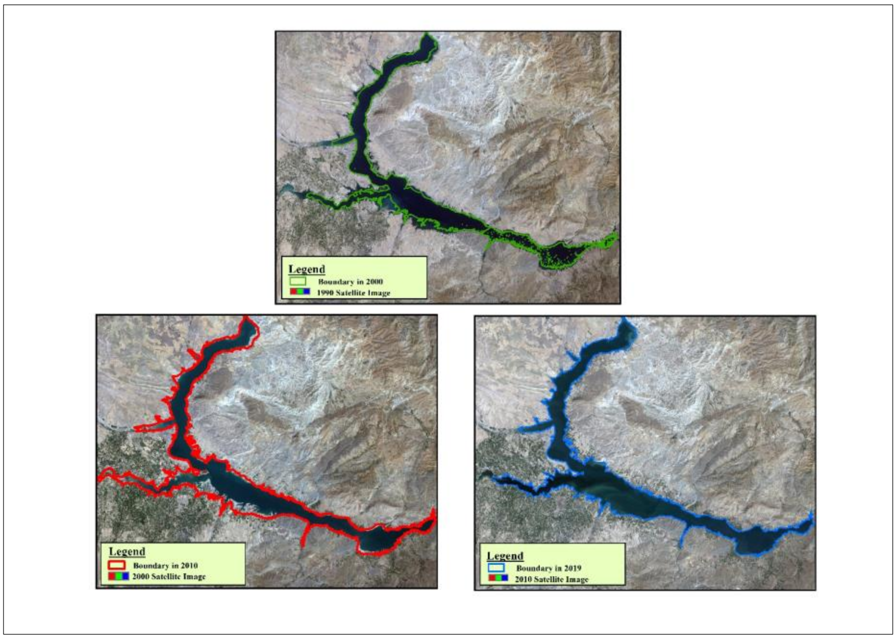

Figure 3. Produced lake boundaries - satellite image before a decade

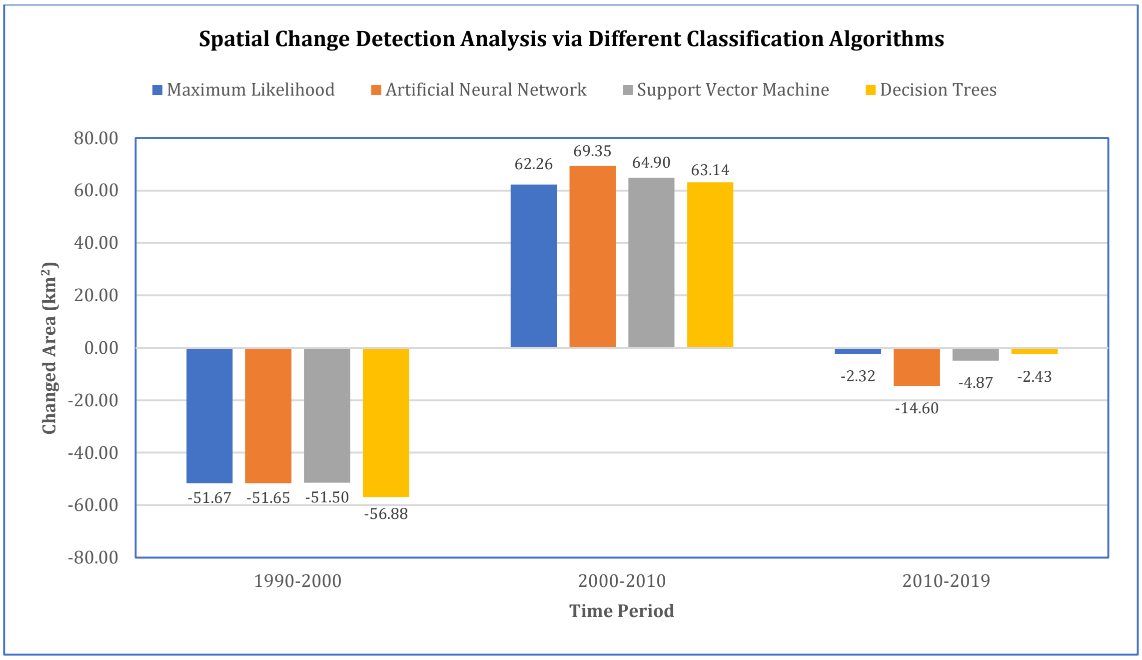

Figure 4. Spatial change detections analysis via different classification algorithms

5. DISCUSSIONS AND CONCLUSIONS

In this study, the coastline of Karakaya Dam Lake between 1990-2000-2010 and 2019 was determined by using different classification algorithms using Landsat TM, ETM and OLI images. For this purpose, thematic maps were produced and spatial change analyzes were made.

Primarily, it is understood from the sources in the article that changes in wetlands have a great connection with global climate change. While selecting the data used in this study, attention was paid to have the same seasonal data on different dates. It is thought by the authors that changes in the lake area are influenced by climatic effects as well as opening the dam covers. Different classification techniques were used in order to observe the accuracy rates during the classification processes. When the classification accuracy given in Table 2 is examined, it can be seen that the Support Vector Machines method gives the highest accuracy rate compared to other methods. The reason why each method gives different accuracy for different years is that different test data are selected for each year. Land use changes have shown that it is not appropriate to use the same test data for each year.

Water fields were separated from the classified data obtained and vector data was obtained for each year. Vector coastline produced in Figure 3 and satellite data 10 years ago are indicated by overlap. When the figure is examined, it is understood that the change that occurred between 1990 and 2000 clearly appeared. In addition, the change in water level from 2000 to 2010 is also noticeable.

If the values given in Figure 4 are examined, the data of area changes can be seen for each method. In this context, it can be said that each method gives close values for the water area. As can be seen from the chart, the negative change that occurred between 1990-2000 left its place to a positive growth between 2000-2010. However, it is understood that no major changes occurred between 2010 and 2019.

The results shown in Table 3 are based on the area designated by the General Directorate of Spatial Planning as the official coastal border. When the table is analyzed, it is seen that the difference between the classification results and official border data reached the highest point in 2000. In addition, it is observed that there was not a big change between 2010 and 2019.

In the study, the change detection analysis of Karakaya Dam Lake was made using different classification techniques. It was observed that the most influential situation on the study results was the opening times of the dam hatch fed by the lake. This dam, which was built for the first time in 1987, reached the filling level in 2004 according to official sources and the dam hatch were opened. When results analyzed, it is seen that lake water decreased in 2000 due to agricultural activities, precipitation, drought etc. In addition, during these periods of decline, old settlements, which were flooded by the lake and evacuated before the dam was built, also emerged.

This study showed how different classification algorithms affect the classification result in water areas. The accuracy of each classification algorithm used is considered to be of usable level. It is believed that new techniques and analysis that will emerge thanks to the developing and renewed technology will further strengthen the studies.

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