# INTEGRATION OF SELF-ORGANIZING MAP AND MACHINE LEARNING METHODS TO EXTRACT SHORELINES FROM LANDSAT-8 IMAGES

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**ABSTRACT:** Coastal areas are essentially important for human being due to their habitat and ecological services. Activities such as tourism, industry, aquaculture and urbanization are main threats for coastal areas. Therefore, monitoring of coastal areas one of the vital issues for preservation and sustainable management of environmental heritage. The main step of temporal coastal monitoring is shoreline extraction using sufficient tools.

In this study, Self-Organizing Map (SOM), Artificial Neural Network (ANN) and Random Forest (RF) methods have been exploited to extract shoreline from Landsat-8 images. The main aim of this study is to collect training data automatically from SOM and to utilize ANN and RF methods. Terkos region has been chosen for testing of the proposed methods within the scope of TUBITAK Project (Project No: 115Y718) entitled "Integration of Unmanned Aerial Vehicles for Sustainable Coastal Zone Monitoring Model-Three-Dimensional Automatic Coastline Extraction and Analysis: Istanbul-Terkos Example".

Five Landsat-8 images from different part of Black Sea region of Turkey have been used to train and to define optimum parameters for SOM, ANN and RF methods. All images were acquired in the year of 2017. The NIR-Red-Blue bands images have been used for training and testing steps. In the first step, land and waterbody classes have been obtained from satellite image of Black Sea region using SOM method. Following to this step, training of artificial network and generating of the tree structure were carried out using randomly selected data from SOM results. Different ANN and RF combinations have been tested. Manually digitized shorelines have been taken as reference data for defining parameters and accuracy assessment. According to obtained results, the best resultant ANN configuration was with 5 hidden layers and 1000 iteration. The optimum amount of trees were 50 for RF method. More satisfactory results were obtained with SOM-ANN integration compared to SOM-RF. Therefore, the test step has been realized using SOM-ANN combination. Digital Shoreline Analysis System (DSAS) has been used for accuracy assessment.

Six different Landsat-8 dataset were used for testing. First dataset is from Terkos-Istanbul in the years of 2017 (dataset a), 2015 (dataset b), 2017 (dataset c). Second one is from province of İzmir which was taken in the year of 2017 (dataset d), third one is from province of Mersin which was taken in the year of 2017 (dataset e) and the last data set is from Lake Ercek which was taken in the year of 2017 (dataset f). The average differences have been calculated for a, b, c, d, e and f datasets as 0.36, 0.36, 0/47, 0.31, 0.30 and 0.57 pixels, respectively. This study shows that SOM method can be used efficiently for automatic training data collection from Landsat-8 imagery for shoreline extraction purposes.

## 1. INTRODUCTION

The monitoring of the coastal areas is vital for integrated coastal zone management (Micallef and Williams, 2002). Reliable shoreline information is essential to define beach morphology as well as coastal dynamics (Cabezas-Rabadána, et al., 2019). Shorelines are vulnerable natural habitats. Therefore, observing and defining the effects of wind, wave, level of sediment transport and anthropogenic changes demand to take necessary precautions for sustainable coastal protection (Vos, et al., 2019).

Rapid, reliable and accurate coastal zone information can be obtained using remote sensing (RS) technology (Karpatne et al.,2017). Visual interpretation and automated approaches can be used to extract shoreline from RS images (Li and Gong, 2016). Edge detection-based methods, index analysis-based methods, threshold segmentation based methods, region growing-based methods, neural network-based methods, and sub-pixel methods (Ouma and Tateishi, 2006; Li and Damen, 2010; Pardo-Pascual et al., 2012; Chen et al., 2014; Mala and Sridevi, 2016; Namikawa et al., 2016). can be given asare commonly used automatic image processing methods methods in the literature. Image classification methods are exploited also for shoreline extraction. The most common classification methods for water-body and land segmentation are unsupervised (Chen et al., 2014), supervised (Fluet-Chouinard et al., 2015) and hybrid classification techniques (Lane et al., 2014). There are different approaches based on these techniques. Awad, (2010) integrated thresholding and SOM methods for satellite image classification purpose. Vousdoukas et al. (2011) used ANN for shoreline extraction. The Automated Water Extraction Index (AWEI) was developed by Feyisa, (2014) for Landsat 5 Thematic Mapper (TM) to improve the separability of water-body and land classes. Rigos et al. (2014) used radial basis function (RBF) neural network for the shoreline extraction from grayscale coastal variance images. Kerh et al. (2014) predicted shoreline change from the previous shoreline information from aerial images using ANN approach. Aedla, et al. (2015) integrated Modified Self–Adaptive Plateau Histogram Equalization with Mean Threshold for water-body segmentation. Donchyts et al. (2016) integrated Otsu thresholding and a Random Forest classifier which is based on the mNDWI and HAND index for water-body segmentation. Bayram, et al., (2017) investigated efficiency of RF method for shoreline extraction from Landsat and GOKTURK imageries. Bayram et al., (2017) used an object-based fuzzy segmentation method to extract shoreline from UAV-derived orthophoto image. Manaf et al. (2017) evaluated machine learning techniques for shoreline extraction from Landsat images. Widyantara et al. (2017) proposed a shoreline extraction approach including SOM combined with gamma correction technique based on the similarity of RGB colour features and stored for the classification training process using K-Nearest Neighbour (K-NN) with a Canny edge detector. Abu Zed et al, (2018) used Normalized Difference Water Index (NDWI) to detect shorelines from Landsat images. Chen, et al, (2018) proposed tasselled cap transformation based shoreline extraction method from Landsat-8 OLI images. Reis et al, (2018) proposed Particle Swarm Optimization (PSO) method for shoreline extraction. San and Ulusar, (2018) proposed a semi-automatic shoreline detection and future prediction method by using spatial uncertainty algorithm.

In this study, we used SOM, SOM integrated ANN and SOM integrated RF for shoreline extraction from Landsat-8imageries. SOM has been used to obtain training data automatically for ANN and RF.

## 2. STUDY AREA and MATERIALS

Five different Landsat-8 satellite images of Black Sea shoreline in the year of 2017 were used as training dataset. In additionly, we used six different Landsat-8 images (dated 2017) of Mersin and Izmir provinces, and Terkos/Istanbul and Lake Erçek for testing the performance of methods for shoreline extraction (Figure 1).

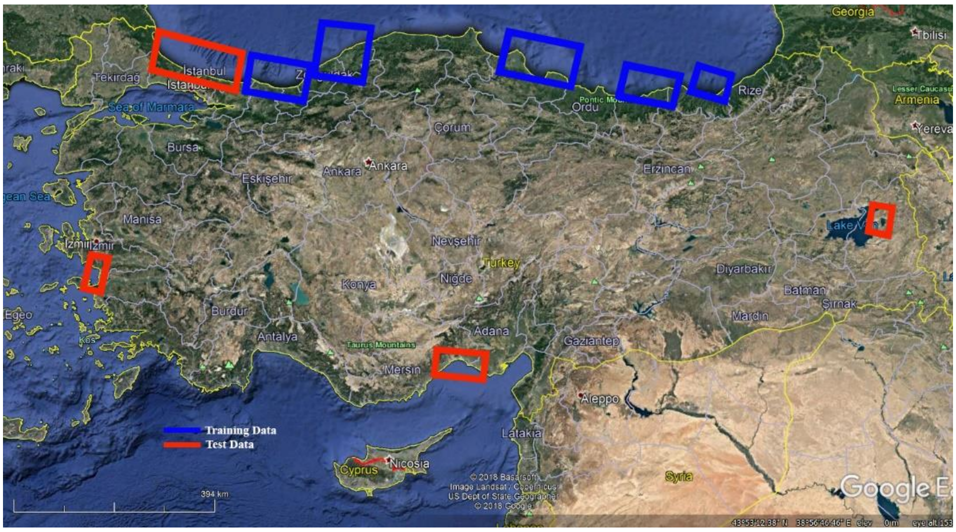

Figure 1 Study area

The acquisition date of used Landsat-8 images have been given in Table 1. The training image sets have been chosen from Black Sea region and test images from Aegean Sea, Mediterranean Sea and Lake Erçek. The number of training and test images are selected considering computer capacity. Only Blue, Red and NIR bands of the images have been used to decrease computational time.

Table 1 The acquiring date of used training and test images

| Type of data | Region | Date |
|---|---|---|
| Training | Black Sea | 8 September 2017 |
| | | 10 September 2017 |
| | | 13 September 2017 |
| | | 19 September 2017 |
| | | 20 September 2017 |
| Pre-Test | Istanbul/Terkos | 11 September 2017 |
| Test | Istanbul/Terkos | 13 September 2017 |
| | | 6 September 2015 |
| | | 30 July 2013 |
| | Izmir | 27 September 2017 |
| | Mersin | 8 September 2017 |
| | Lake Erçek | 5 September 2017 |

## 3. METHODS

In this study, we investigated efficiency of SOM, SOM integrated ANN and SOM integrated RF methods to extract shorelines from Landsat-8 imageries. SOM is an unsupervised ANN method and has been used to generate training data automatically for training process of ANN and RF methods.

SOM is an unsupervised neural network which is first described by Kohonen (2000). SOM clustering method can be considered as a combination of data projection and data quantization. It measures the (dis)similarities in the multi-dimensional attribute space as a competitive neural network. The first step in the SOM process is determination of number of neurons and type of topology. Other parameters are initial learning rate and number of iterations (Skupin and Agarwal, 2008). In this study, hexagonal topology and Euclidean distance have been used for SOM (Kohonen, 2013).

SOM, ANN and RF methods have been realized using MATLAB environment. The used parameters which are dimensions, coverSteps (the number of learning iterations), initNeighbor (neighbourhood size) and number of epochs have been empirically selected as [2 1], 100, 3 and 2000, respectively.

Feed-Forward ANN is a combination of one or more hidden layers consist of n neurons between the input and the output neurons. Error function is the difference between the actual, for given inputs, and the desired values of the outputs given by the training set. The learning process is used then for adjusting the values of the weights using back-propagation model to minimize the value of the error function (Bishop, 1999).

In this study, all images were clustered using SOM method and land and water-body classes were obtained. Training samples were collected from these results and same training samples were used for ANN and RF methods. A graphical user interface has been developed for this purpose. This software selects randomly training pixels (land and water-body) and creates 100x100 pixels sized cropped images for each classes. In this study, 1000 cropped images have been generated for each class. 175000 land and 175000 water-body training pixels have been randomly collected from SOM results for each training image. Total of 875000 land and 875000 water-body pixels have been collected from five training images.

Three bands (blue, red, NIR) of used training and test images have been normalized using max-min normalization method to utilize ANN. In this study, feed forward and back-propagated ANN has been designed. Scaled Conjugate Gradient and Hyperbolic Tangent Sigmoid have been used as supervised learning algorithm and activation function, respectively.

RF is a supervised machine learning classifier based on decision trees. Decision trees analyses the training data and determines the proper class according to generated rules from training datasets. These rules consist of a number of if-then conditions. Number of trees (N) and number of variables (m) are two main parameters of RF. m is used on each node to create the tree structure. It is determined by taking the square root of the number of image bands (Gislason et al., 2006). A bootstrap samples are created for each tree using the bootstrap technique and trees are generated according to the CART algorithm which uses the Gini index for best attribute selection (Breiman, 2001). The Gini index is a confusion-based method. The differences between the probability distributions of the target attribute values are calculated (Han et al., 2011). In this study, the number of trees and the random variable have been selected empirically. N and m are selected as 250 and 2, respectively.

To define optimum parameters for RF, ANN, SOM-RF and SOM-ANN, first training step has been accomplished using five training images. The results have been tested using pre-test image (see Table 1). After defining optimum parameers for all methods, they have been implemented on six test images.

The results have been compared with manually digitized shorelines. DSAS has been used for accuracy assessment (Thieler et al., 2009). DSAS is a tool and developed for evaluation of desired coastline with reference data (Jayson-Quashigah, et al., 2013). In this study, Net Shoreline Movement (NSM) module of DSAS was used. The differences between extracted and reference shore lines is determined by measuring perpendicular distances along transects at defined intervals between the reference and the shore line to be evaluated by DSAS (Oyedotun, 2014). The transect space and length parameters of DSAS have been selected as 5 m and 250 m, respectively.

## 4. RESULTS AND DISCUSSION

In this study, SOM, ANN, RF, SOM-ANN and SOM-RF methods have been implemented on the pre-test image to define optimum parameters for used methods. First of all, training samples have been collected manually and automatically from SOM results from 5 training images (Totally 875000 land and 875000 water-body pixels). RF method has been implemented using different number of trees. The results have been evaluated with reference data.

For ANN, same training samples have been used and trained ANN applied on pre-test image. Evaluation results have been given in Table 2

Table 2 Evaluation results for all methods

| Method | Average differences (m) | Average differences (pixel) |
|---|---|---|
| SOM | 14,61 | 0,49 |
| ANN | 18,31 | 0,61 |
| SOM-ANN | 6,69 | 0,22 |
| RF | 13,64 | 0,45 |
| SOM-RF | 23,69 | 0,79 |

As can be seen in Table 2, the best results have been obtained with SOM-ANN configuration. In the last step of the study, different amount of hidden layers and iterations have been tested and ANN's have been re-designed to improve accuracy of ANN. The ANN's have been trained with manual training data. Accuracy assessment has been realized by comparison of obtained result with reference data. The results have been given in Table 3 for pre-test image.

Table 3 Obtained results using different ANN designs using manually collected training data

| Iteration-Hidden Layer | Average differences (m) | Average differences (pixel) |
|---|---|---|
| 500 – 5 | 20,58 | 0,69 |
| 500 – 15 | 15,16 | 0,51 |
| 1000 – 10 | 10,80 | 0,36 |
| 1000 – 15 | 13,99 | 0,47 |
| 1500 – 5 | 24,58 | 0,82 |
| 1500 – 15 | 14,76 | 0,49 |
| 2000 – 5 | 20,27 | 0,68 |
| 2000 – 15 | 15,00 | 0,50 |

More accurate results have been obtained with 1000 iterations and 5 hidden layers. The same configurations have been tested using SOM-derived training data and DSAS results for test images have been given in Table 4.

Table 4 Obtained results using different ANN designs using SOM-derived training data

| Iteration-Hidden Layer | Average differences (m) | Average differences (pixel) |
|---|---|---|
| 500 – 5 | 10,54 | 0,35 |
| 500 – 15 | 9,05 | 0,30 |
| 1000 – 5 | 5,91 | 0,20 |
| 1000 – 15 | 12,87 | 0,43 |

| | | |
|---|---|---|
| 1500 – 5 | 18,28 | 0,61 |
| 1500 – 15 | 6,27 | 0,21 |
| 2000 – 5 | 13,79 | 0,46 |
| 2000 – 15 | 5,93 | 0,20 |

Table 4 shows that using SOM-derived training data, more accurate results can be obtained by ANN (1000 iterations and 5 hidden layers). This design has been exploited to obtain shorelines from six test images. The DSAS results have been given in Table 5.

Table 5 DSAS results for six test images using SOM-ANN (1000 iterations and 5 hidden layers)

| **Image** | **Shoreline Length (km)** | **Average differences (m)** | **Average differences (pixel)** |
|---|---|---|---|
| Terkos 2017 | 36,57 | 10,90 | 0,36 |
| Terkos 2015 | 37,01 | 10,80 | 0,36 |
| Terkos 2013 | 37,60 | 13,98 | 0,47 |
| İzmir 2017 | 36,950 | 9,26 | 0,31 |
| Mersin 2017 | 33,63 | 9,08 | 0.30 |
| Lake Erçek 2017 | 51,505 | 16,99 | 0,57 |

The average difference of six test images for 233.265 km shoreline is 11.84 m which is approximately 1/3 of Landsat-8 image pixel. This study has showed that SOM method can be used efficiently for training data collection. Its integration with ANN generates satisfactory shoreline extraction results for Landsat-8images using only blue, red and NIR bands.

As it can be seen from Table 2, all machine learning based methods can be used for shoreline extraction from Landsat-8 images. According to the results, higher average distance has been calculated by SOM-RF method which is also less than one Landsat pixel (0.79 Landsat pixel. Although ANN and RF methods have been utilized for shoreline extraction in the literature, this is the first study that integrates them initially with SOM method for this aim. The most important and time consuming part of machine learning methods is the collection of training data. Integration of SOM has proved that this method can be used for training data collection. The most accurate results have been acquired by SOM-ANN combination from Landsat-8 imageries. We introduce that proposed method and its results can be used efficiently for temporal shoreline change analysis.

## 5. CONCLUSIONS

According to experts' opinion, the main effect of the global warming will be at coastal areas. Therefore, quantitative and temporal monitoring of shorelines is one of the main issue for decision-makers and planners. Developing strategies against natural and human-induced coastal changes and revising coastal management plans concerning changes of the coastal areas is important due to their associated economic, social and environmental impact. Up-to-date and accurate shoreline information is one of the main essential information for these purposes.

In this study, we provided automated shoreline extraction framework from Landsat-8 imageries using SOM derived training data and machine learning methods. The experimental findings showed an effective performance regarding to the shoreline extraction. This study has showed the ability of Landsat-8 to automatically and accurately delineate the shoreline boundary with SOM integrated ANN method. Training samples were limited due to computer capacity. Therefore training samples have been chosen from Black Sea region from Turkey .Even though obtained results are encouraging, they have to be tested with different Landsat-8 images from different parts of the world.

As a future project, we plan to implement this method on high resolution satellite images and secondly to use this idea to collect training data for deep learning networks for shoreline extraction.

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