

# A comparative study of the surface level changes of Urmia Lake and Aral Lake during the period of 1988 to 2018 using satellite images

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**Abstract** Internal lakes are considered as the ecological environments and the monitoring and evaluation of which can be considered as a matter in the national development and natural resources management (Rasouli et al., 2008). The changes in the water levels of lakes and the variations of the land use and cover along with the margins and the association of these changes with natural and human factors in Urmia Lake and Aral Lake are much-discussed and taken into consideration. In this study, a comparison was made between Urmia Lake and the Aral Lake over a period of 28 years, and the first one being suffered from declining water levels and drastic changes due to many factors, including, most specifically, human intrusion and mismanagement. For this purpose, Moderate Resolution Imaging Spectroradiometer (MODIS) and Landsat 5 and 8 satellite images were utilized for 1988 and 2018 and object-based image classification was applied in six classes, i.e. water body, arid, agriculture, salt marsh, salt wet and built with the acceptable accuracy of 89.23 (1988) and 85.8 (2018) percent for land use maps of the Urmia Lake and 92.46 (1988) and 95.15 (2018) percent for the Aral Lake. The overall accuracy of classification which represents the functioned credit classification for the maps should be more than 85% (Anderson et al., 1976). The classification showed that during the study period both of the lakes faced declination of water and increasing of salt levels. The trend of agricultural and built-in lands has been rising especially in Urmia Lake. Results indicated that the creation of the agricultural lands and human levels in recent decades has caused the increase in water consumption which in turn has reduced the amount of water entering to the Urmia Lake and has created hard

conditions such as the dryness of the lake today.

**Keywords** change detection, MODIS, Landsat, object-based image classification, Urmia Lake and Aral Lake, Iran

## 1 Introduction

Urmia Lake has entered critical conditions due to the intensification of dryness in the basin (Khorshiddoust, 2002). Today the monitoring and studying of such changes has many applications in hydrological and/or human-made disasters (Rokni et al., 2014). Detection of the process changes of identification of differences in the status of an object or phenomenon is done by observing it at different time periods. Timely and accurate detection of the environmental changes is a main requirement for the management and evaluation of the natural resources and the environment (Eslami et al., 2016). The important parameter in monitoring critical areas is sustainable development and environmental protection (Alesheikh et al., 2007). Managing such sensitive ecological environments requires access to detailed information in different time intervals (Fathi et al., 2015). In recent years, the changes in the water levels of lakes and the variations of the land use and land cover along with the margins and the association of these changes with natural and human factors in Urmia Lake and Aral Lake are much-discussed and taken into consideration. Therefore, internal lakes are considered as the ecological environments and the monitoring and evaluation of which can be considered as a matter of the national development and natural resources management (Rasouli et al., 2008).

Satellites and remote sensing have undergone a technical revolution in providing huge amounts of information with a spatial, spectral, and temporal resolution through

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sensors and various satellite missions (Benediktsson et al., 2012). It has a relatively short history and has included a major part in the local and spatial information analyses (Sohrabinia and Khorshiddoust, 2007). Large numbers of existing techniques are used and remote sensing images are considered as scientific and efficient tools to detect the changes (Karimi and Mobasheri, 2011). Remote sensing methods can be developed to detect the changes in the land cover map of the areas and can be used to assess the rate of the changes. In these methods, based on the characteristics of image processing for extraction of information from the satellite imagery, a classification is made into two main groups, namely A) classification method based on the numerical values of the picture elements, or pixels (pixel-based), and B) object-based image classification objective-oriented method (Feizizadeh and Helali, 2010).

With the aim of examining the changes in the Urmia Lake water levels and surrounding salt areas, Fathi et al. (2014) used 1989 to 2011 Landsat TM and ETM+ images in line with the findings and field data. Their results showed decrease in the water surface elevation between 6 and 7.40 m and approximately 64.31% of the area of water and about 60.2% of the total area of vegetation cover was diminished, while equal amount of salt and sand were added. Fathi et al. (2014) in a study with the aim of monitoring the coastline of Urmia Lake used the satellite images and NDWI index. First, they prepared the composite images by applying the composite bands technique. Then they threshold the image on the produced histogram and prepared the contour map of the shore of the lake. To evaluate the accuracy of the proposed method, the results were compared with the reference maps that accurately extracted coastlines estimated to 0.87. The results showed that the composite of the spectral bands and thresholding of the histogram are common techniques that can be used to identify the lines from the Shore of Urmia Lake through satellite imagery. Fathian et al. (2014) in their research aimed to estimate the trend in time series of hydro-climatic variables and assessed the land use changes in the basin by using satellite imagery. For this purpose, 4 non-parametric statistical methods of analysis are the Mann-Kendall, Theil-Sen, Spearman and Student t distribution and the information of 18 hydrometric stations located in the study area were used. Finally, they utilized the Landsat satellite images of 1976, 1989, 2002 and 2011 to create the land use map and determine the changes by using different classification methods. The results indicated major changes in the user area, the area of irrigated land, and the rained orchard by showing respective increase to 412, 485, and 672 percent over the past 35 years and on the other hand, decrease was observed in the pasture area by 34 percent. Löw et al. (2013) in a study analyzed land cover changes and discussed the potential consequences of their activities such as dust and salt storms. For this

purpose, the MODIS satellite images were taken for the period of 2000 and 2008 to classify and measure the land cover changes. Kozhoridze et al. (2012) monitored the land cover dynamics in the Aral Lake through classification of the satellite images. In the classification, they used algebra on bands (band5 / band4 and Band4 / Band3) and calculated the Normalized Difference Salinity Index (NDSI), salt mining index (SPI), salt index (SI), Normalized Difference Vegetation Index (NDVI) and the albedo, respectively. Overall classification results were satisfactory with 86.9 percent accuracy and 85 percent Kappa coefficient. Taravat et al. (2016) used multiple techniques out of which Multilayer Perceptron Neural Network performed well and their results manifested that the Van Lake and Sevan Lake areas increased while the Urmia Lake area got decreased far more (~65.23%) than previously found (~25% to 50%). Mammadov et al. (2019) in their research over north-east coast of the Urmia Lake used Landsat 5 TM, Landsat 7 ETM+ and Landsat 8 OLI images and applied objects-based classification approach and a composition of Cellular Automata-Markov analysis. The overall accuracy of the models was about 92.54% and Kappa coefficient was 91%. It was found that the models showed significant decrease in the surface of the Urmia Lake and highlighted that the number of salty lands are meaningfully increasing. Nhu et al. (2020) in their research over Urmia Lake utilized Landsat 7 ETM+ satellite images for 2000, 2010, and 2017 and employed different techniques such as Maximum Likelihood, Minimum Distance, Spectral Angle Mapper, Artificial Neural Network and Support Vector Machine. Out of all these techniques, the best identified one was Maximum Likelihood Classification. The overall accuracy as well as Kappa coefficient was high for all the classified images. From the previous research it is understood that to date just one study employed object oriented based classification technique over the north coast of the Urmia Lake, where it is proven that it has the potential of overcoming the weaknesses linked with per-pixel assessment, for example, negligence of contextual and geometric information which has been employed in the current study and recent period images have been used.

To understand receding of the Urmia Lake, it is worthwhile to scrutinize previous similar cases. Although worldwide there is a long list of the seas and lakes that are depleting, we have selected to take after various studies that have done a comparison of Urmia Lake with the Aral Lake (Micklin, 2007; Hassanzadeh et al., 2012; Pengra, 2012; Garousi et al., 2013). Their selection is done because their issues are based on the reasons that are similar, and the resulting influences are almost similar, excluding the fact that the Urmia Lake was never polluted that much to reach the degree of Aral Lake pollution. Due to anthropogenic activities, these lakes are drying up at an accelerated rate. Increasing population, agricultural based

economy, aggressive regional water resources development plans, upstream competition over water and the increase in demand of water looks customary composition for the reduction of water. The depletion of inflow to these lakes and their shrinking are caused by the diversion of water for industrial, irrigation, and domestic purposes. Drying of these lakes is giving rise to socio-economic issues and health problems (Tussupova et al., 2020).

Having a look at the drastic changes in the water levels of the Urmia Lake and Aral Lake due to many factors such as human intrusion and mismanagement, the primary objective of the present study is to make use of the satellite images over a period of 28 years and observe the changes in the water level of the Urmia Lake and Aral Lake by application of object-oriented classification.

## 2 Materials and methods

### 2.1 Study area

The study area includes the Aral Lake in the central Asia, Kazakhstan and Uzbekistan, which is located on the border between the two countries and the Urmia Lake, which is located in the north-west of Iran and is one of the largest permanent lakes in the world and the largest lake in the Middle East that is superior saline (Jaafari et al., 2013). The continuing trend of the declining water

levels in Urmia Lake for various reasons allow salt to transfer away; that is, it has caused serious threat to the health of the residents in the area and has reached the level of a national concern (Fathian et al., 2016). On the other hand, the Aral Sea also has a similar situation and the effects of the changes in land use; especially in agriculture for water supply from 1970 until today has made changes in the water levels causing severe drought, and the area extension is reduced on daily basis. In this study, a comparative study of the two lakes is carried out. Figure 1 shows the location of the study area.

### 2.2 Images pre-processing

In this study, four satellite images were taken. Three images were of Landsat 5 TM and Landsat 8 OLI and one image was of MODIS Terra satellite. They were freely downloaded from the US Geological Survey (USGS) Earth explorer website for 1988 and 2018 years. The details about the data are depicted in Table 1 and Table 2. After downloading the images, only the Landsat 5 TM and Landsat 8 OLI images were modified into mosaics by using ENVI 5.2 software. In the pre-processing of the satellite remotely sensed data, atmospheric correction is considered the most important part and skipping this step gives erroneous results. The impacts of the atmosphere are more acute for where the satellite image shows the dark targets (Hadjimitsis and Themistocleous, 2008). To produce accurate results, the atmospheric correction was

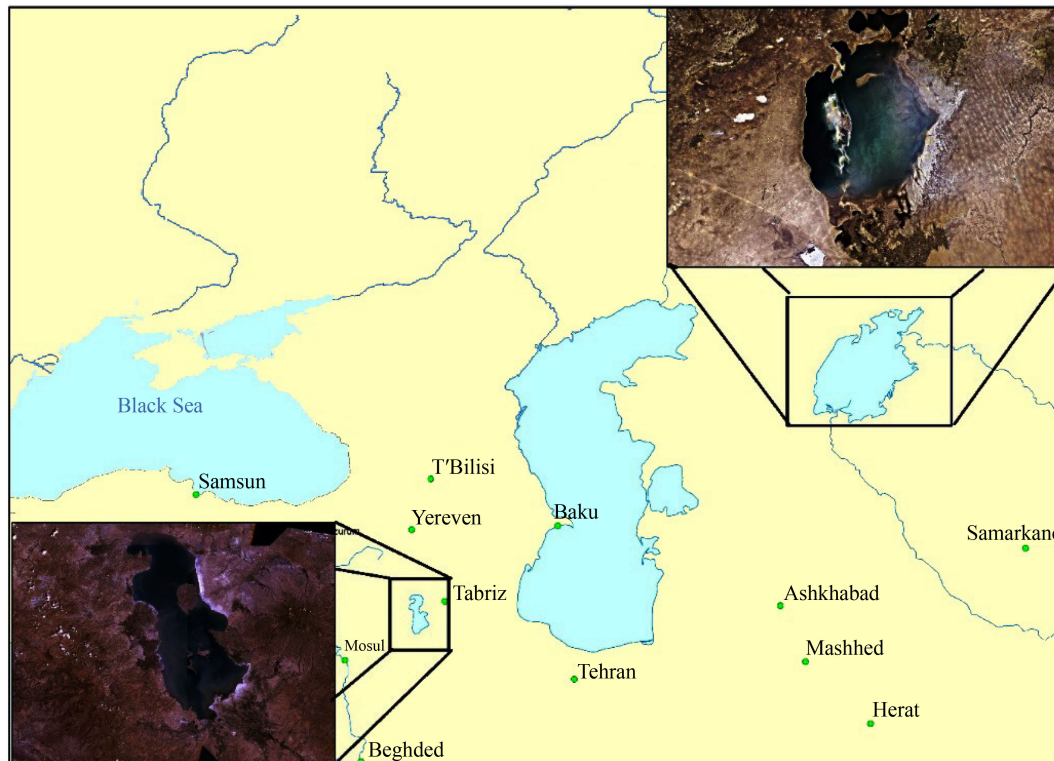


Fig. 1 Study area location.

**Table 1** Images related to Urmia Lake

| Satellite name | The number of taken images | Sensor | Number of bands | Date of image |
|----------------|----------------------------|--------|-----------------|---------------|
| Landsat 5      | 3                          | TM     | 7               | 22/08/1988    |
| Terra          | 1                          | MODIS  | 36              | 24/08/2018    |

**Table 2** Images related to Aral Lake

| Satellite name | The number of taken images | Sensor | Number of bands | Date of image |
|----------------|----------------------------|--------|-----------------|---------------|
| Landsat 5      | 12                         | TM     | 7               | 22/08/1988    |
| Landsat 8      | 12                         | OLI    | 11              | 24/08/2018    |

imposed on the images of this study. Figure 2 shows the regions under study in the aforementioned years.

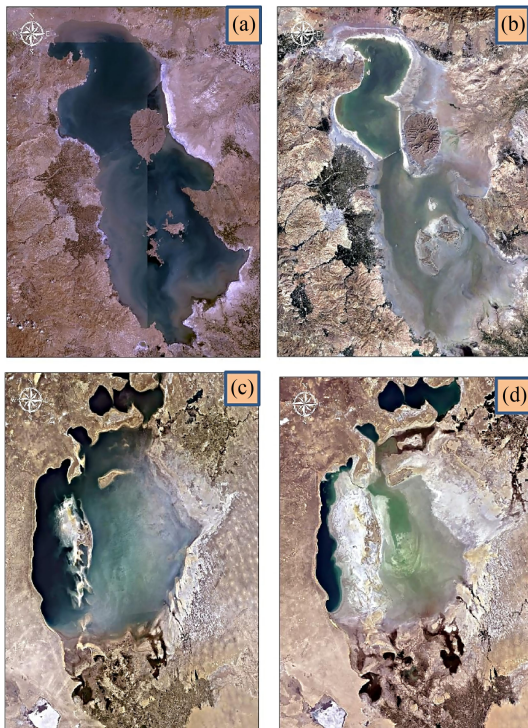
### 2.3 Segments optimization

In this category, the images were divided into segments; segment means a group of neighboring pixels within an area whose similarity (such as numerical value and texture) is the most common criterion (Feizizadeh et al., 2008). Segment process optimization is formed on the basis of scale, color, and shape. Compactness and smoothness compose the shape parameter and sum of their weights is equal to 1 (Zheng, 2015). Image objects from segment optimization are based on object-oriented classification (Jyothi et al., 2008) and they have a lot of

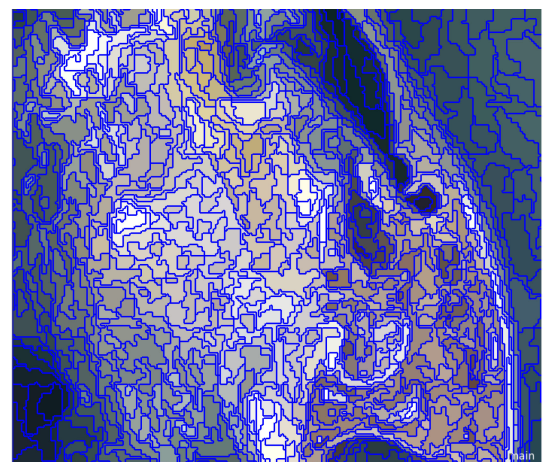
properties and ground phenomenon corresponding to the features in the image. Carrying out careful process, directly affects the quality of the object-oriented classification (Baatz and Schape, 2000). In the present study, the segment was intended for all layers in the same weight and for scale parameter index number 10 was considered. 0.1 and 0.5 respectively were intended for the index of form factor and compactness. An example of the segment optimization is manifested in Fig. 3.

### 2.4 Object-oriented classification

Object-oriented processing of the satellite images is a technique in the digital image processing application that has been developed recently in the pixels based analysis. In fact, one of the goals of the object-oriented classification is to overcome the problems related to basic pixel-based methods (Hay et al., 2003). In this way, important information that is classified as an image is used not only in unique pixels but meaningful, and they also show image objects and conceptual relationships. In other words, in the object-oriented approach, shapes, textures and spectral information are used simultaneously (Rasuly et al., 2010). It is noted that this method has two very important advantages; first, the object considers a



**Fig. 2** Satellite images (a) Landsat 5 for 1988 Urmia Lake, (b) MODIS Terra for 2018 Urmia Lake, (c) Landsat 5 for 1988 Aral Lake, (d) Landsat 8 for 2018 Aral Lake.



**Fig. 3** The sample of segmentation of eCognition software.

homogeneous group of pixels as the basic unit of the process. Secondly, at the same time, in addition to spectral characteristics, it benefits the characteristics of the objects, such as shape, texture and geometry (Bouziyani et al., 2010). In other words, the object-based approach can make use of the same features understood by the human eye. That's why these methods better output the reality of the world objects (Blaschke, 2010). According to the conducted researches in this area, it can be said that the object base because of the use of additional features, often produce better results from pixel based methods (Nussbaum and Menz, 2008).

### 2.5 Accuracy assessment

Land use and cover classification has some errors. The output maps therefore need to be tested for evaluating the accuracy making use of valid statistical method. Because of this reason, the classified maps are assessed by an accuracy assessment index which incorporates a clear explanation of the sampling design (including the size of sample and, if pertinent, information of stratification), the area of every class according to the map, an error matrix, and descriptive measures of accuracy such as producer's accuracy, user's accuracy, and overall accuracy (Olofsson et al., 2013). The accuracy term is usually used to indicate the "correctness" of the classified image and is evaluated through the development of error matrix (Foody, 2002). The development of error matrix can help in the calculation of important accuracy evaluation parameters, such as omission error, commission error, overall accuracy, and Kappa coefficient (Lu and Weng, 2007). For the evaluation of inter-rater accordance between the categorical parameters, the Cohen's (1960) Kappa ( $k$ ) is a powerful and world widely used statistical measure. In the current study, accuracy of all images was evaluated through calculation of overall accuracy and Kappa coefficient. The overall accuracy and Kappa coefficient was calculated using the Eqs. (1) and (2).

$$\text{Overall accuracy} = \frac{\sum_{i=1}^r x_{ii}}{x}, \quad (1)$$

where  $x_{ii}$  represents the elements in the diagonal of the error matrix, and  $x$  represents the total number of samples in the error matrix.

$$\text{Kappa coefficient} = \frac{n \sum_{i=1}^r x_{ii} - \sum_{i=1}^r x_{i+} x_{+i}}{n^2 - \sum_{i=1}^r x_{i+} x_{+i}}, \quad (2)$$

where  $r$  represents the rows number in the matrix, the number of observations in row  $i$  and column  $i$  are represented by  $x_{ii}$ , and the marginal totals for row  $i$  and column  $i$  are represented by  $x_{i+}$  and  $x_{+i}$ , and  $n$  represents the total number of observations (pixels) (Alam et al., 2020).

## 3 Results

### 3.1 Land cover classification results

In this paper, we aim to detect changes and extract the scope of these changes of Urmia and Aral Lakes. Land use maps for both lakes in two time periods were created with the object-oriented classification method based on the images taken. The purpose of the present study is the extraction of the changes around the mentioned lakes and comparison of these lakes. The intended classes are the body of water, agriculture, built-up areas (urban and rural), bare land (including wasteland and pastureland), salt zone, salt water and swamp. In the object-oriented image classification, the nearest neighbor algorithm was used, and according to the terms of the classification, the classification condition was defined for each class of the land use. By using the statistical indicators such as brightness coefficient, minimum difference, difference between maximum, minimum, mean, mode, median and using the sample points on 5-class image classifications were discussed in the software. Figures 4–7 show the classifications in each of the regions. Mammadov et al. (2019) in their study also classified the northern coast of Urmia Lake into six classes of dam, Urmia Lake, agriculture area, new salt, salted soil, salty barren lands and others. Nhu et al. (2020) classified the Landsat images of year 2000, 2010 and 2017 into three classes (island, salt bank and water body) whereas in our present study this classification is done in six classes which more clearly show changes of the Urmia Lake area in different classes.

### 3.2 Output of the classification accuracy assessment

After performing the object-oriented classification in the eCognition software environments, the accuracy of each classification was assessed by using the Google Earth software. It was used randomly to collect the samples taken for each class and to implement the statistical parameters of the sample points such as Kappa. The overall classification accuracy was extracted as a separate table for each classification (Table 3). Kappa classification which assessed the accuracy compared to a random classification was between zero and one; zero represents a complete random classification and one shows absolute correct classification (Lillesand and Kiefer, 2001). In the classification performed on images of Urmia Lake, land use map derived from the 1988 Landsat image has Kappa coefficient of 0.8803 and the one extracted from MODIS satellite image for 2018 has 0.8360. As well as the classification performed on the images of the Aral Lake, land use map derived from the 1988 Landsat image has Kappa coefficient of 0.9176 and the one derived from the 2018 Landsat image has 0.9318. The overall accuracy of classification which represents the functioned credit

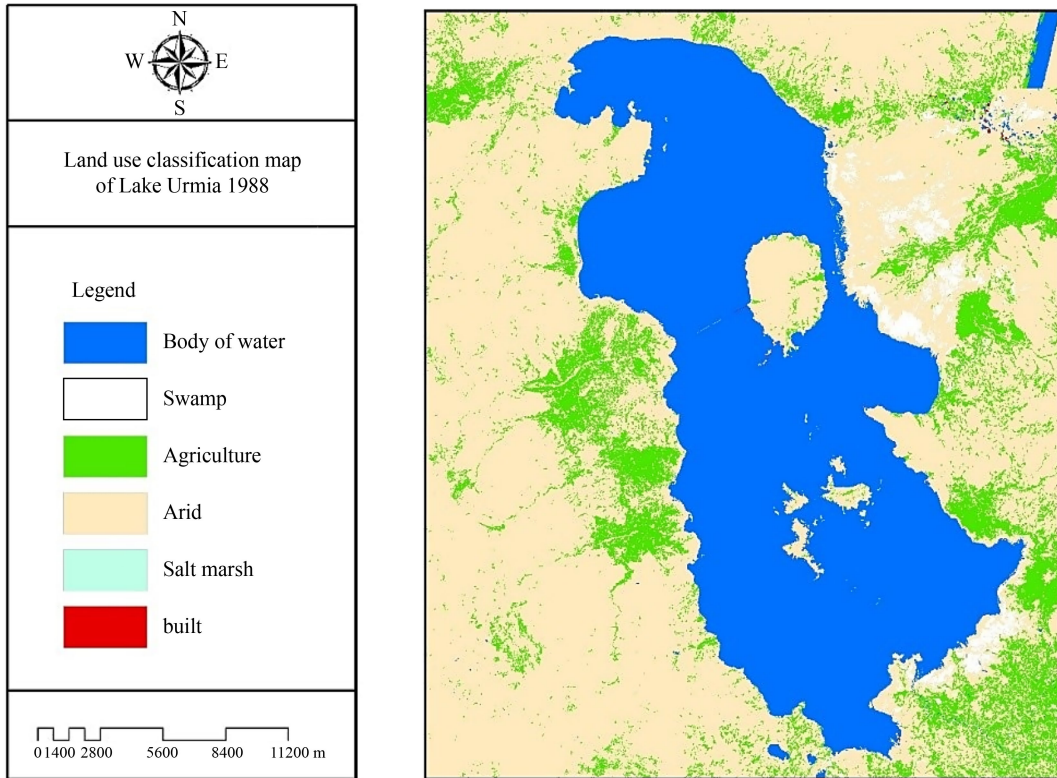


Fig. 4 Classified Landsat 5 image for 1988 in Urmia Lake.

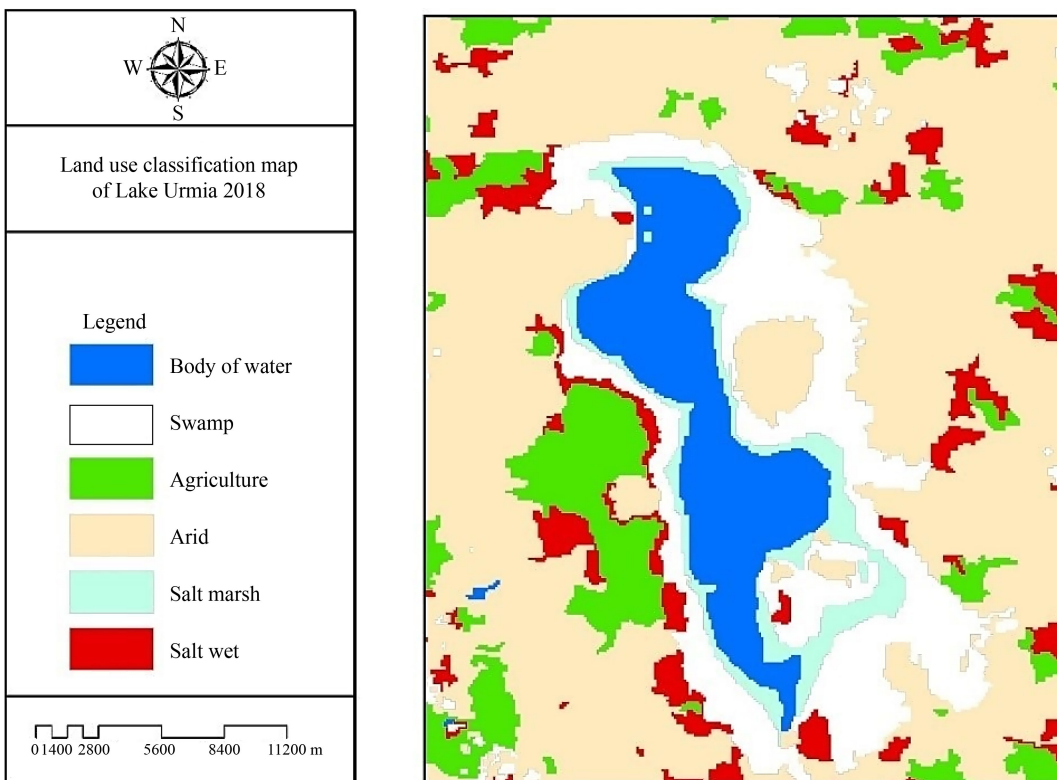
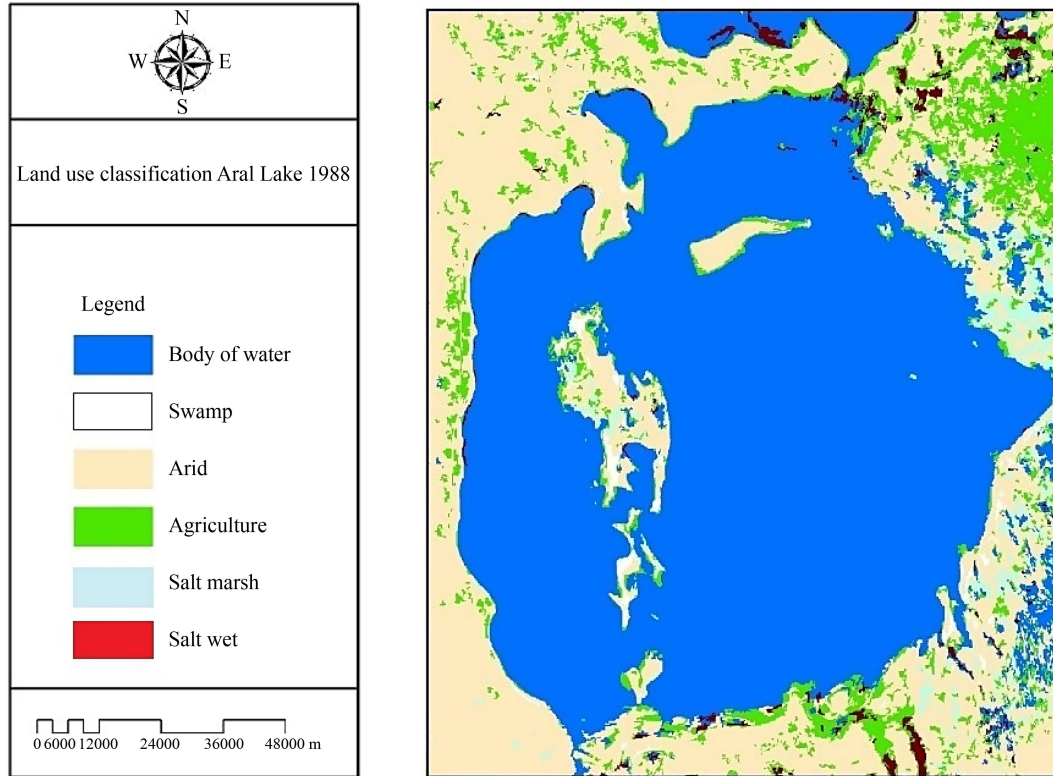
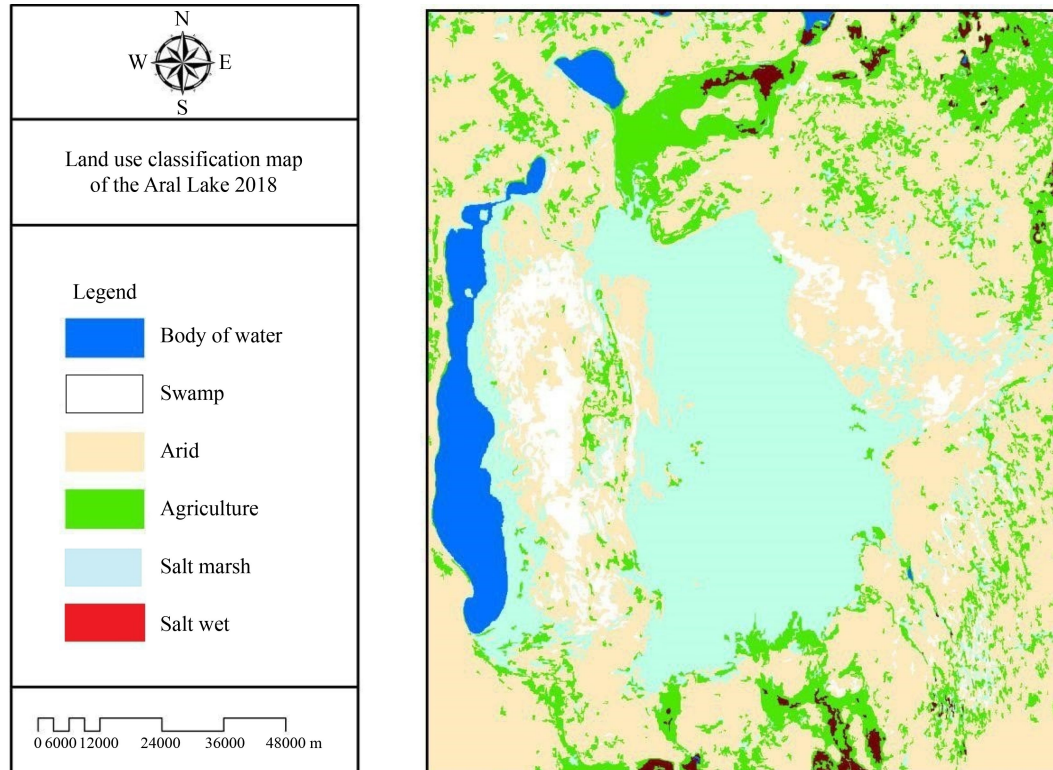


Fig. 5 Classified MODIS Terra image for 2018 in Urmia Lake.

classification for the maps derived from satellite imagery should be more than 85% (Anderson et al., 1976) and it can be observed that in the present study it is above 85% for all the classified images. The classification accuracy



**Fig. 6** Classified Landsat 5 image for 1988 in Aral Lake.



**Fig. 7** Classified Landsat 8 image for 2018 in Aral Lake.

for land use maps of the Urmia Lake during 1988 and 2018 is respectively estimated as 89.23 and 85.8 percent, and similarly for the land use maps of Aral Lake during 1988 and 2018, it is respectively calculated as 92.46 and

**Table 3** The accuracy of classified images

| Name of image                        | Kappa coefficient | Total accuracy |
|--------------------------------------|-------------------|----------------|
| 1988 Landsat image of the Urmia lake | 0.8803            | 89.23          |
| 2018 MODIS image of the Urmia Lake   | 0.8360            | 85.8           |
| 1988 Landsat image of the Aral Lake  | 0.9176            | 92.46          |
| 2018 Landsat image of the Aral Lake  | 0.9318            | 95.15          |

95.15 percent. [Mammadov et al. \(2019\)](#) in their study over northern coast of Urmia Lake acquired overall accuracy of 92.54% and a Kappa coefficient of 91%. They mentioned that the overall classification accuracy shows the suitability of the classified images for effective land use/land cover change analysis. [Taravat et al. \(2016\)](#) in their study found whole data set's classification accuracy as 95.52% by using Multilayer Perceptron Artificial Neural Networks (MLP ANNs).

### 3.3 Detected changes

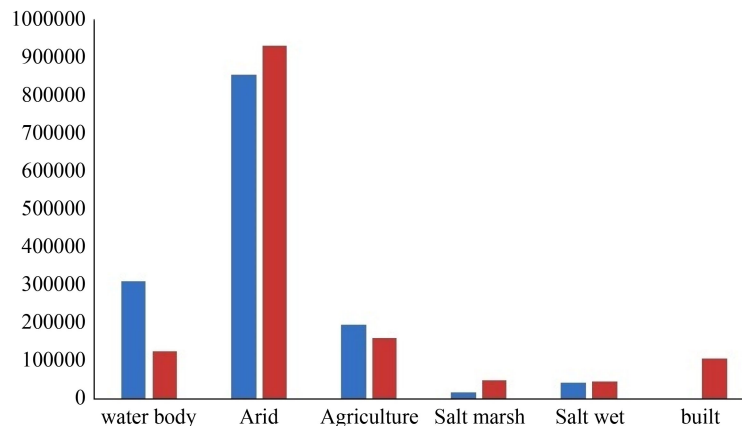
According to the final maps derived from the classified images in 1988 and 2018, arid land class with 60 percent in 1988 has been changed to 65.27 percent in 2018, as it can be seen, scoop equivalent to 75175 ha has been added to that which is due to the decrease in agricultural land of Urmia Lake and reduction in the water level in the region. Water body is a second class in terms of area and is one of the most valuable land uses extracted. Changes in the lake's water and consequent changes in the use of the lake have occurred during the period of 28 years. It clearly reflects reduction in the water level of the lake as a result of human factors, and the climate change. The water area in 1988 was more than 21.74 percent (310012.4 ha) of the total land users, which dropped to 8.84 percent of the land in 2018. This decline occurred not only in terms of surface but also significantly reduced the water depth in 2018 map. The water extension in the region had the largest area of agricultural lands in 1988 (13.79 percent), which is equivalent to 34705 ha in 2018, with a downward trend of 11.35 percent. Due to the increasing population in the study area during the study

period, the built-up area increased from 0.02 percent to 7.5 percent (108130.8 ha). Because of the salt water of Urmia Lake, with decreasing trend of water through the 28-year period, the hydrated salt has been added to the lake. [Table 4](#) and [Fig. 8](#) manifest the calculation of observed changes in each class during 1988 and 2018 through the study area. The results are in agreement with previous studies conducted in the region by [Nhu et al. \(2020\)](#), [Mammadov et al. \(2019\)](#) and [Rahimi and Breuste \(2021\)](#) which found that the lake's water area shrank and a larger portion of it disappeared comparing the situation of 1980s with the recent years. [Rahimi and Breuste \(2021\)](#) also used the Land Transformation Model and modeled the changes until 2025. Their results manifested that the lake's water area is projected to change to salty land and in the northern part of the lake, the shallow water occupy 0.7% of the lake's total area. They discussed that the noticed changes were not because of the climate change but the human factors were responsible including the increased utilization of groundwater by developing deeper wells for the agricultural irrigation purpose and building of dams for the water storage for irrigation.

The results from classification of the images of 1988 and 2018 ([Table 1](#)) are given in [Table 5](#) and [Fig. 9](#) for comparison. The total classified area is 13570136 ha in 6

**Table 4** Calculation of each class for 1988 and 2018 in the Urmia Lake

| Name of class | 1988    |          | 2018    |          |
|---------------|---------|----------|---------|----------|
|               | Percent | Area/ha  | Percent | Area/ha  |
| Water Body    | 21.74   | 310012.4 | 8.84    | 126170.9 |
| Arid          | 60.00   | 855414.2 | 65.27   | 930589.5 |
| Agriculture   | 13.79   | 196634.4 | 11.35   | 161929.4 |
| Salt marsh    | 1.29    | 18472.59 | 3.64    | 51895.04 |
| Salt wet      | 3.14    | 44821.24 | 3.40    | 48461.18 |
| Built         | 0.02    | 334.52   | 7.5     | 108130.8 |
| Total         | 100     | 1425688  | 100     | 1425688  |



**Fig. 8** The chart of observed changes in the classes of the Urmia Lake (Blue: 1988, Red: 2018).

classes (body of water, swamp, arid, agriculture, salt marsh and salt wet). In 1988, the percentage change in the arid area was 43.06% where in 2018 this value was increased to 56.74%. It can be seen through the Figs. 9 and 10 that the reason of this developing progress is the decrease of water level in the lake. The body of water class with 41.09% (557,689 ha) is the second wide class of 1988, which in our 28-year study period reduced from 41.09% to 4.9%. On the other hand, in this period, 4910103.1 ha of the water area of the lake was reduced and changed to the other classes. Two classes such as salt marsh and salt wet had the reverse increasing process. The area occupied by these two classes was 0.6 and 2.49 in 1988, respectively which has been developed to 3.68% and 17.3% during the 28-year period. The agricultural land in the base year was 11% which was developed to 15.94% and is 2011746 ha increase in 2018. The swamp class included the least change among the other classes. Shen et al. (2019) results are in accordance with the present study. The Markov-cellular automata approach was utilized and the classification results revealed that the water area got decreased by more than 66% and leading toward the salt soil and bare area expansion. Recent years showed increase in vegetation area which is a good signal of the ecological recovery. Deliry et al. (2020) in their research for Aral Lake used Normalized Difference Water

index (NDWI) and the area was classified into two classes of water body and others. Their results are in agreement with the current study results whereby water body significantly decreased in the lake and a considerable increase was observed in the land surface temperature (~12°C). They also discussed that the water usage increase for agricultural irrigation affected the lake significantly.

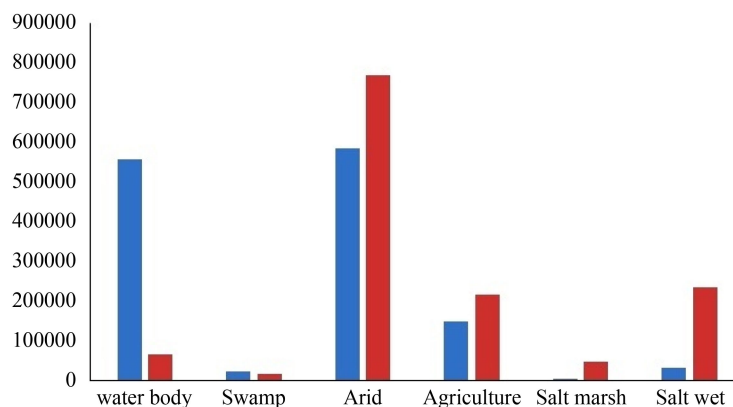
## 4 Discussion

### 4.1 Results of current study in the light of previous studies

The current study results showed that during the study period both lakes faced declination of water and increasing of salt levels. The trend of agricultural and built-in lands has been rising especially around Urmia Lake and near areas. The creation of the agricultural lands and human levels in recent decades has caused the increase in water consumption which in turn has reduced the amount of water entering to the Urmia Lake and has created hard conditions such as the dryness of the Lake today. Some studies are discussed in this regard for discussion and for the possible reasons of the detected changes. Ahmadi et al. (2015) conducted a study to forecast the fluctuations of the Urmia Lake's surface area using image processing technique. Their results showed that the proposed method performed well in the estimation of the surface area of the lake. They mentioned that the extreme loss of water in recent years could be due to i) salinization of the lake because of the Shahid Kalantary causeway, which divided the lake and therefore blocks the water circulation process, ii) wideness of the surface area of the lake as compared to its depth which gives large surface for evaporation, iii) increase in the surface area for agricultural activities and construction of the dams without assessing the proper risks of environment, and iv) fever precipitation rate and warming of the area. Sima et al. (2012) monitored the variation of the area of Urmia Lake by using MODIS satellite data

**Table 5** Changes in the areas of the classes for 1988 and 2018 in the Aral Lake

| Name of class | 1988    |           | 2018    |           |
|---------------|---------|-----------|---------|-----------|
|               | Percent | Area/ha   | Percent | Area/ha   |
| Water body    | 41.09   | 5576789   | 4.9     | 666685.9  |
| Swamp         | 1.74    | 237246.7  | 1.4     | 191015    |
| Arid          | 43.06   | 5843936   | 56.74   | 7700225   |
| Agriculture   | 11.7    | 152132    | 16      | 2163878   |
| Salt marsh    | 0.6     | 71504.96  | 3.7     | 50008.4   |
| Salt wet      | 2.49    | 3385273.8 | 17.3    | 2348322.4 |
| Total         | 100     | 13570136  | 100     | 13570136  |



**Fig. 9** The chart of observed changes in the classes of the Aral Lake (Blue: 1988, Red: 2018).

and their results manifested significant reduction of 35% in the water surface area during the past 12 years. It was also discussed that during the winter or spring season, the area of the lake increases while it decreases during summer and autumn. In another study of similar nature by Ghale et al. (2017), the decadal changes in land cover and salinization in the Urmia Lake were analyzed while making use of remote sensing techniques. Their findings showed that dramatic increase is observed from 1995 to 2014 in the salt and salty soil and above 5000 km<sup>2</sup> area was changed to salt or salty soil. The salinization as well as desertification was not only restricted to just the bottom which is dried. The increase in irrigated lands was noticed to be more than two times during the period under study. This desertification could be the potential source of dust storms which are harmful to the human health and climate. Mehrian et al. (2016) investigated the causality of variations pattern of Urmia Lake Basin's landscape by using remote sensing and time series techniques. They stated that despite of various studies in this context there is still an ambiguity about the main reason of this environmental crises. Their findings indicated that during trend analysis, the main reason of the drying out of the lake is the irrigated agriculture wide expansion between 1999 and 2014. They mentioned that the temperature and precipitation cannot be considered the main cause of reduction in water. According to research carried out by Kamran and Khorrami (2018), change was detected and predictions were done for the Urmia Lake and its surrounding environment during the period of past 60 years (1955–2014) while applying Geobased remote sensing method. Maximum changes were noticed in both perimeter and area of the lake. The area was reduced from 451800 ha in 1955 to 89730 ha in recent years. In the southern regions of the lake, due to maximum water recession, the coastal salty areas were increased. This study also mentioned that the agricultural activities were the main reason for decline in water. Sun and Ma (2019) carried out a study to monitor the hydrologic variations of Aral Lake by using integrated data of radar altimeter and optical images. The study revealed that the maximum area of the Aral Lake was 30256.46 km<sup>2</sup> during May 2000 and the lowest was 6926.04 km<sup>2</sup> during November 2014. During 2000 to 2015, the water level of the lake reduced from 43.42 m to 39.73 m. It was mentioned that during 2007, the construction of the dam cut down the supplementary water and the narrow tributary which connects the east and west parts dried up and this made the west part an isolated one. Shen et al. (2019) identified the land surface change using remote sensing techniques in the Aral Lake bed, Central Asia. They found that the dramatic expansion of salt soil as well as bare area was caused by the shrinking of surface water of the lake by more than 66 percent. It was predicted that there will be more desertification of the landscape during 2025.

## 5 Conclusions

In this study, two-time satellite imagery has been used over a period of 28 years and changes in the water levels of the Urmia Lake and Aral Lake are estimated by the application of object-oriented classification. The results of the two lakes show that the drastic reduction of the water levels in both lakes over 28 years is due to the human factor, namely, the rise of agricultural activities. The crisis in the Aral Lake environment is caused by the decision of the Soviet Union in 1960 to establish the agricultural projects for cotton production in the Minor Asia, construct dams and surface waters for agricultural use, with reduced precipitation and higher temperatures in the basin has been accepted. The same is true for Urmia Lake. According to a conducted survey, both lakes faced a sharp fall in water level and salt plains, salt and salt wet has increased in both Lakes. Usage of Aral Lake is still rising, but the Urmia Lake reduced the level of agriculture in this year due to the reduced level of fresh water in the underground aquifers and salt and dust creation. According to a survey conducted on the two lakes and a trend that these two lakes are going through; in the near future, by completely drying, these lakes will become two sources of salt dust which will cause the complete disappearance of agriculture, pollution of the surface water and severe injuries and it will not reach the human communities in the under-study areas.

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