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Comparison of active and passive remote sensing data in extracting coastlines

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Abstract

Coastal environments are one of the most sensitive environmental systems that are affected by hydrodynamic processes and rapid changes. Also, from an ecological point of view, coastal areas are of high value due to having sensitive and productive ecosystems. Therefore, extracting characteristics of coastlines and revealing their changes is very efficient and vital for various applications. In this research, the coastline of Zarivar Lake located in the Kurdistan province of Iran extracted thriough image processing techniques including minimum distance, maximum probability, optical indices NDVI, NDWI, TCW and band ratios of Oli bands (5/3) and (6/3). In this regard, coastlines were extracted after necessary processing. The results showed that the 5/3 band ratio method in coastline extraction has an average error of 90 meters when using OLI data, and the maximum likelihood classification has an average error of 120 meters in comparision to visual interpretation when using Sentinel 1 Microwave data

1. Introduction

Coastlines are constantly changing due to different human and natural factors (Toure et al. 2019; Ciritci and Türk. 2019). Observing these lines is necessary for constant and continuous monitoring of the lake water level (Sojka et al. 2022; Abdelhady et al. 2022). These lines have been defined by the International Committee of Geographic Data (ICGD) as one of the most important geographical complications and the intersection between water and land levels (Halder et al. 2022), which can be determined using different methods and for various applications (Tajima et al. 2021). In the past, traditional methods were used to monitor these lines. These methods were expensive and time consuming. In addition, due to the unavailability of some measuring lines, they were not done (Templin et al. 2018). Shoreline is a dynamic and unique area, and in fact, it is the junction of water and land, which is always affected by the action and reactions of the two on each other (Mutagi et al. 2022). In order to have a proper coastline detection method, it is necessary to evaluate the existing methods in order to propose better approaches to detect the coastline of each region (Abdul Maulud et al. 2022). In this research, we will investigate and compare different methods of determining coastlines using OLI (optical data) and Sentinel 1 (radar data). The results of this research can help managers and planners to adopt a suitable approach for coastal areas. Figure 1 shows the implementation of the research.

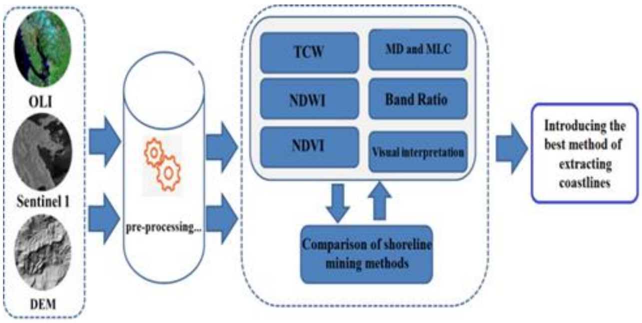

Figure 1. Research implementation process

2. Method

2.1. Study area

Zarivar Lake is a boiling water ecosystem located 3 kilometers west and northwest of Marivan city. The length of the lake perimeter is 25 km and its maximum depth is about 5.85 meters. According to the water conditions of the internal springs of the lake and the discharge of the rivers leading to it, its area fluctuates between 7.8 and 20 square kilometers. The height of the lake is about 1290 meters above sea level. The lake has an almost oval shape and is slightly bent towards the

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west, which is caused by the accumulation of sediments that have entered this part of the lake through seasonal rivers. This lake is located inside a wide valley, which is surrounded by low mountains on three sides, north, west and east. Figure 2 shows the location of Zarivar Lake in the study area.

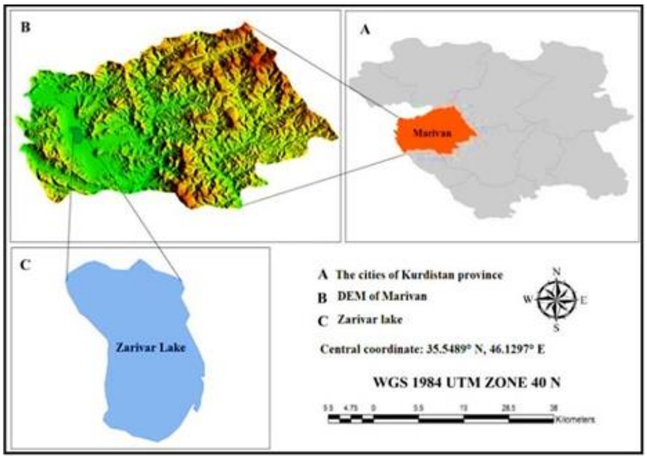

Figure 2. Location map of the study area

2.2. Data

In this study, OLI, Sentinel 1 and 2 data and DEM pertaining to study area were downloaded and used. The images were used with zero cloud cover so as not to interfere with the use of different algorithms. Table 1 shows the date of collection and the type of images used.

Table 1. Data and Date

Satellite	Sensor	Date
Landsat 8	OLI1	2015-03-10
	OLI2	2015-04-27
	OLI3	2016-03-12
	OLI4	2016-05-15
Sentinel-1	Radar1	2015-04-04
	Radar2	2015-05-21
	Radar3	2016-03-10
	Radar4	2016-05-21

2.3. Coastline extraction methods/ algorithms

Before implementing processing algorithms, preprocessing techniques including calibration were applied to all images.

2.4. Maximum likelihood algorithm

This algorithm calculates the conditional probabilities of membership in each class based on the comparison of the spectral values of each pixel with the statistics of each training set. In order to implement this method, it is necessary to have several bands and introduce land use landcover classes and samples, so that the classes used for the classification methods were considered completely identical.

2.5 Minimum distance (MD) algorithm

In this algorithm, the distance of each unclassified pixel is compared with the average pixels' values in each trainig sits, and the desired pixel is assigned to the class that has the closest distance to its average (Wicaksono et al. 2019). Table 2 shows thresholds.

2.6. Normalized Difference Vegetation Index (NDVI)

It is one of the most widely used indicators for monitoring vegetation changes, whose numerical value ranges from -1 to +1. By introducing a threshold limit for the index (Table 2), NDVI image was classified again and water was separated from soil and the coastline was extracted (Gonçalves et al. 2019).

2.7. Normalized Difference water Index (NDWI)

One of the non-normalized indicators is water and the amount of water in plants. Its value range is between -1 and +1 (Wicaksono et al. 2019). Table 2 shows thresholds.

2.8. TASSELED Cap Wetness (TCW)

It is one of the indicators of humidity, which is obtained from the comparison of a number of visible, near infrared and short infrared bands. In this method, the threshold was introduced for each image (Chen et al. 2019). Table 2 shows thresholds.

2.9. Oli Band ratio 5 to 3 and 6 to 3

The use of band ratios of 5/3 and 6/3 is because of the different water reflectances in these bands. For example, water reflection in band 6 of the OLI sensor is close to zero and band 3 is higher than this value. If the result of these ratios is smaller than 1, it means water, otherwise it is considered dryland (Liu et al. 2017). "Table 2" shows thresholds.

2.10. Estimating the accuracy of coastline extraction

Usually, to estimate the classification accuracy, the error matrix is used, which estimates the error based on the classified and ground truth observations. Considering that the aim of this research is to extract the coastline, the main classification error occurs exactly on these borders. Therefore, it is possible that the accuracy of the classification based on the error matrix even reaches 95% and has a 5% error, and it is also possible that the same 5% happened on the coastline. On the other hand, the classification accuracy through the error matrix cannot indicate the accuracy of coastline extraction. Therefore, for this estimation, the coastline distance method was used from the base data. The results of this investigation method were presented based on the calculation of absolute difference, relative difference and percentage of relative difference. The stated values are the results of the sharing process of two reference and classified data. In such a way that the layer resulting from UNION has an area, which three numbers are proposed as area:

A) The common area of the two layers detected in both waters

B) The area estimated in the water reference data, but in the classified soil data
C) The area specified in the classified water data but in the soil reference data
Absolute difference = total non-common area (b, c)
Relative difference = absolute difference/lake area
Percentage of relative difference = relative difference × 100

The absolute difference value is obtained from the sum of the areas. The sum of these distances represents the sum of absolute difference. The total size of these distances (absolute difference) indicates the amount of error in estimating the coastline, the higher this value, the greater the error.

Table 2. Methos and Threshold

Method	Threshold	Data
NDVI	0.011>	OLI1
	0.28>	OLI2
	0.10>	OLI3
	0.26>	OLI4
NDWI	>-0.05 <-0.01	OLI1
	>-0.20 <-0.02	OLI2
	>-0.15 <-0.04	OLI3
	>-0.25 <-0.07	OLI4
TCW	>-1500	OLI1
	>0	OLI2
	>-1500	OLI3
	>0	OLI4
Band ratio 5:3	<0.10	OLI1
	<0.25	OLI2
	<0.08	OLI3
	<0.23	OLI4
Band ratio 6:3	0.10>	OLI1
	0.08>	OLI2
	0.08>	OLI3
	0.05>	OLI4

3. Results

Table 3 shows the estimation error of the coastline in meters. The measuring criterion is the comparison of the obtained coastline with the Shapfile of the lake, which was obtained by the ground mapping method with the total station Leica TS02 camera with an accuracy of 7 seconds of gradation.

Table 3. Method and Error rate

Image and Method	MD	MLC	Visual	NDVI	NDWI	TCW	Band ratio 5:3	Band ratio 6:3
OLI1	23	29	18	9	104	146	7	5
OLI2	23	62	09	7	126	240	6	3
OLI3	41	26	30	7	155	166	04	9
OLI4	70	42	30	09	142	174	7	03
Radar1	78	40	40		-	-	-	-
Radar2	43	45	9		-	-	-	-
Radar3	40	47	26		-	-	-	-
Radar4	80	49	20		-	-	-	-

Figure 3 shows some of the outputs. As can be seen, Figure 3 (a) shows the lowest value of the lake area obtained by the MD classification method. Figure 3 (d) shows the largest area of the lake compared to the land estimate.

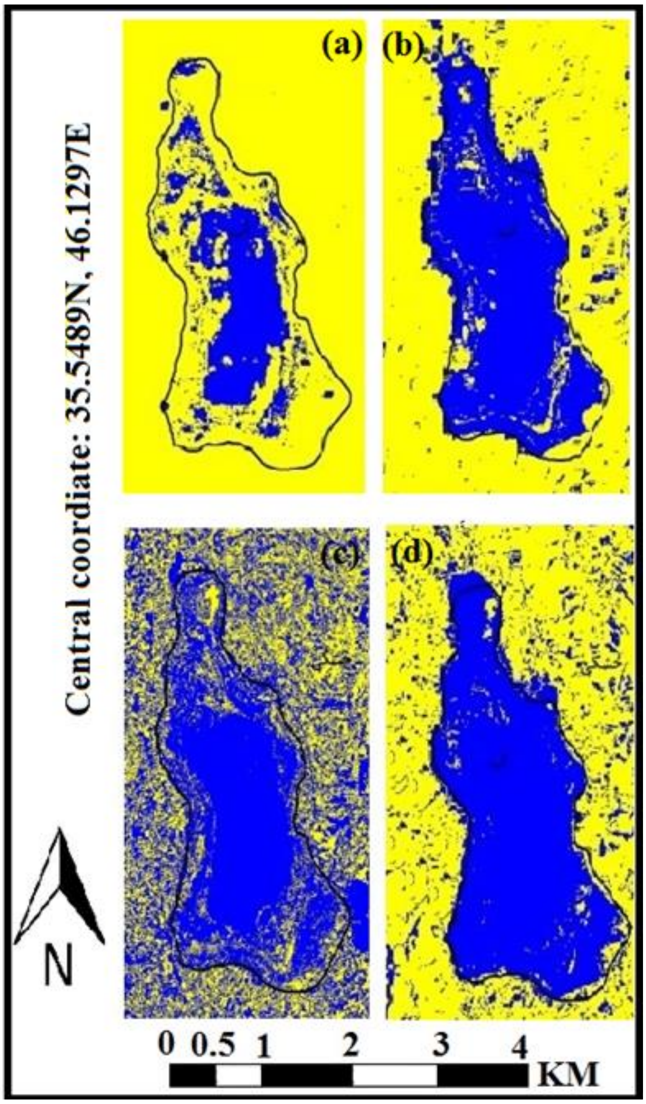

Figure 3. MD (a), NDVI (b), MLC (c), Band ratio 5/3 (d)

4. Discussion

By examining the results and comparing them, it can be found that the use of a band ratio of OLI band 3/5 is more accurate in extracting the coastline than other methods used in this research, which may be due to the strong difference in the reflection of the lake surface. (water) and beach (non-water). Based on the data in the "table 3", this value for the bandwidth ratio of 5/3 shows the value of 77 meters. Also, NDVI and NDWI indices show much better results than ML and MD classification algorithms. Regarding the use of radar data, the accuracy of determining coastlines visually and the use of MD and MLC classifications have brought better results. Therefore, it can be concluded that in order to determine the coastlines more accurately, the difference of reflection in different bands can be used as an effective basic solution in determining the coastlines.

5. Conclusion

According to the results, it can be concluded that the accurate extraction of the coastline on each image is done with a special method. every method however complex, will not necessarily have a more accurate result than other methods. In this research, in order to accurately extract the coastline on radar images, classification methods were much less accurate than simpler methods such as visual interpretation. if radar images with more bands and polarizations are available, they can bring much better results from more accurate extraction of the coastline. Regarding the indicators, due to the difference and diversity in the lake and the coast, the method that showed the best results on Landsat images to extract the coastline was the use of a band ratio of 5 (near infrared) to 3 (green), which is due to the great difference. Water reflections were in these two spectral ranges. It is suggested that in the future research, according to the purpose and conditions of the region, if the aim is to study blue areas, radar images with different polarizations and optical images should be used simultaneously.

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