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Monitoring of Caspian Sea Coastline Changes Using Object-Oriented Techniques

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Abstract

Coastal zone monitoring is an important task in national development and environmental protection, in which, extraction of shorelines should be regarded a fundamental research of necessity. Very dynamic coastlines such as Caspian Sea coasts pose considerable hazards to human use and future development. Therefore several rapid reliable techniques are required to monitor and update coastline maps of these areas to explore rates of environmental retreats. In the current study, various semi-automated methods like NDWI, NDSI and Tasseled Cap have been accordingly applied and results were integrated with some object-oriented classification methods. Landsat MSS, TM and ETM imageries of the past three decades were consequently processed by an object-oriented approach performed with an eCognition software package. By comparing three classified maps of the south Caspian Sea coasts (Babolsar Port to Feridonkenar) in 1977, 1984 and 2002 with a unique region growing image segmentation technique (multi-resolution segmentation), areas of rapid change were progressively identified. Revealed models demonstrate that several yearly persuaded fluctuations and considerable periodical changes on the study area coastlines particularly during the last decade observed by TOPEX/Jason satellites. These great variations have occurred as the result of 2.6 meters increases in height of water in the sea from 1984 to 1995. This has successively caused a diminishing of coastal lands, about 185 km2 mainly on the Babolsar Port, changing landcover and landuse types by depletion of significant agricultural and residential areas. Implementations of such significant changes signify that the majority of local biotic and biotic components, all over the surrounding areas, would be in crucial threat in the near future.

Keywords: Caspian Sea, Coastal Changes, Satellite Imageries, Object-Oriented Techniques

1. Introduction

According to International Geographic Data Committee (IGDC) the shoreline could be regarded as the most unique feature on the earth's surface. The location and attributes of shorelines are highly valued by a diverse user community, because they have never been stable in either their long-term or short-term positions [1]. Consequently,

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shoreline change detection and mapping are critical for safe navigation, coastal resource management, coastal environmental protection and sustainable coastal development and planning [2]. By definition, a shoreline is a linear intersection of coastal land and the surface of a water body [3]. Often the interface between one type of land use and another type is fuzzy or imprecise and the boundary line is placed in a somewhat arbitrary location. This frequently occurs on soil and vegetation maps where there is usually a gradually transition from one type to another rather than the blunt transition that is indicated by the edge of a polygon [4]. In other cases the interface between one land use type and another category is much more apparent such as: when a land use of urban development suddenly stops at a set location and a landuse of a greenbelt then starts. Other places where there are even more dramatic changes in the interface between landuse occur along the coastal zones of the seas or oceans. Precision plays a decisive role when coastal managers wanted to identify and delineate the shoreline boundary using satellite imageries.

Thus, delineation of shoreline boundary could be regarded as a difficult task due to several reasons such as: water level changing, coastal movement because of erosion and deposition, presence of inter-tidal mudflats and marshy areas along the coast most of which are misclassified as parts of water. Pixels quite often represent the mixture of different spatial classes especially in relatively coarse spatial resolution like Landsat imageries [5]. Intermixing pixels of water-saturated land that represent shallow water bodies in satellite imagery may affect the discrimination of accurate shoreline boundary [6].

Formerly, various classification methods such as grey level thresholding, spectral enhancement, principle component analysis (PCA), water indices, Tasseled Cap and spectral classification (ISODATA) have been in use for discrimination of land/water boundary [7]. Traditional shoreline mapping in small areas is carried out using conventional field surveying methods [8]. The most usual method used today to delineate the shoreline is analytical stereo photogrammetry using tide-coordinate aerial photography controlled by kinematics GPS techniques. Automatic extraction of shoreline features from aerial photos has been investigated using neural nets and image processing techniques [3]. LIDAR (Light Detection and Ranging) depth data have also been used to map regional and national shorelines [9].

Recently, satellite data are being processed (in automatic or semi-automatic manners) to extract shoreline boundary and mapping purposes. Braud and Feng [10] evaluated threshold level slicing and multispectral image classification techniques for detection and delineation of the Louisiana shoreline from 30 meter resolution Landsat Thematic Mapper (TM) imagery [11]. They found that thresholding TM Band 5 is for the most part a reliable methodology. Frazier and Page [12] analyzed the classification accuracy of water body detection and delineation from Landsat TM data in the Wagga Wagga region in Australia. Their experiments indicate that the density slicing of TM band 5 achieved an overall accuracy of 96.5 percent, which is as successful as the 6 band maximum likelihood classification. However, it was indicated that it is not straightforward task to recognize the real differences among various landcover classes in typical imageries (like Landsat satellite) by operating of some conventional computer softwares and just only based on pixel values. Recently, some new techniques such as object-oriented are offered by scientists to acquire the better results in the shoreline investigations [13].

2. Study site

The Caspian Sea ranks as the largest inland body of water in the world [14]. It is surrounded by different countries such as Russia, Azerbaijan, Turkmenistan, Kazakhstan and Iran, with surface area of 436,000 km2, maximum depth of 1,025 meter, an estimated volume of 78,200 km3 and by catchment size of 1,400,000 km2 (Figure 1). Located mainly at 40 degree latitude and 51 longitude the Caspian Sea could be recognized as an endorheic, or terminal lake, meaning that its water does not reach the ocean [15]. At present, the countries of the region are relatively major world oil and natural gas producers, experiencing new economic and political transitions. It is also believed that about 90 percent of all the world's sturgeons continue living in the Caspian Sea. Additionally the sea is a well-known location where the world famous Caviar is mainly produced and supplied by Iran.

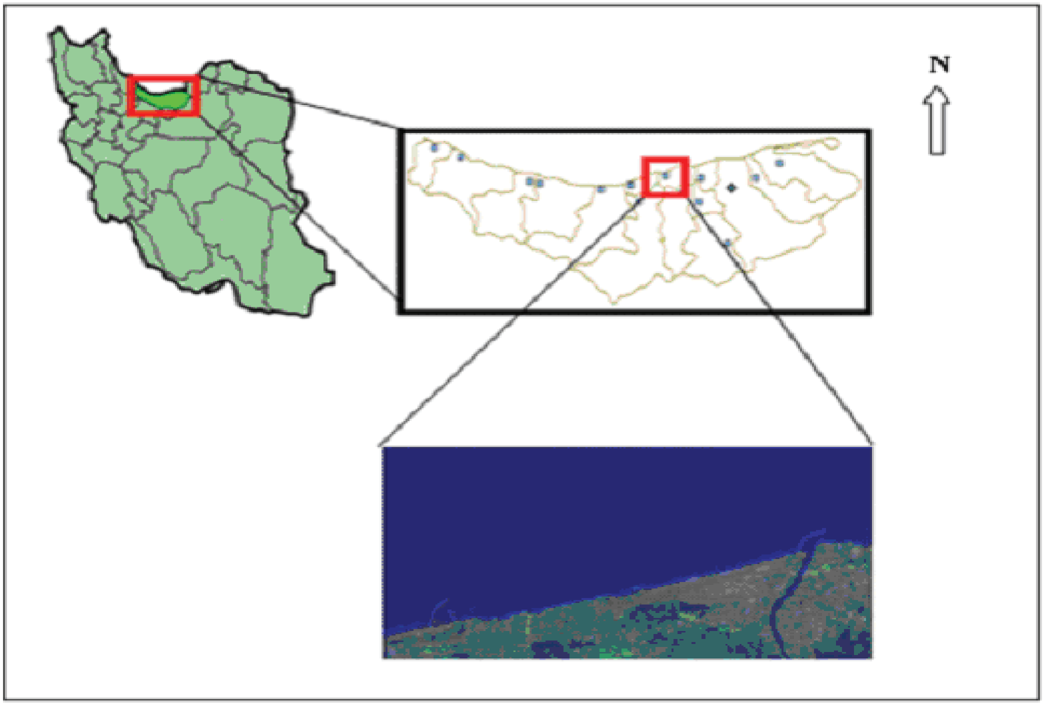

Fig.1. Geographic location of the study area

Currently, Caspian Sea attracts scientists from all over the world as a unique water basin since it allows studies on environmental changes that may occur in coastal zones worldwide if the ocean water level rises [16]. Fluctuations of the sea level cause significant changes in the nature of its shores. Extent of the area of interest is about 14 km and 2 km in the east and north directions respectively and the two end corners of the sea belong to the coastal cities of Babolsar and Feridonkenar, both have the potential of becoming the greatest tourist resorts and fishery industry centers. Test field has a uniform topography ranges up to -2 m, while urbanized part is located alongside the seacoast. There are also agriculture and forested areas inner regions (Figure 2).

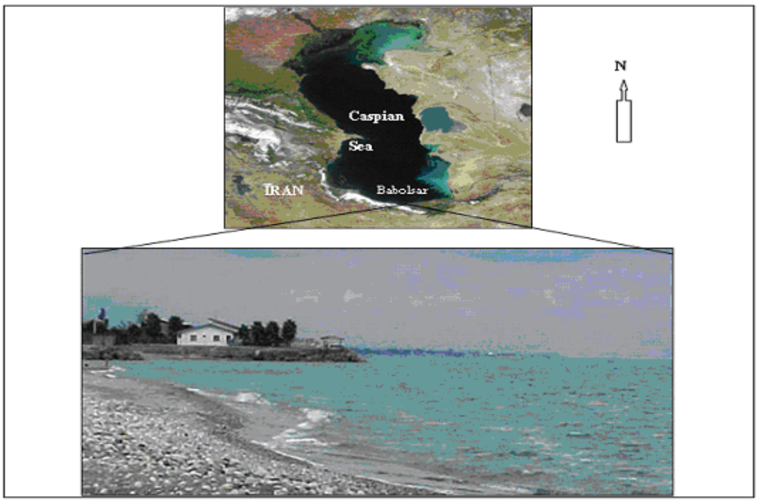

Fig.2. Satellite image of Caspian Sea and Iranian shoreline near Babolsar Port

3. Methods

The dataset used in the present work for the extraction of coastline is composed of:

- Landsat MSS, 1977
- Landsat TM, 1984
- Landsat ETM$^+$, 2002
- IRS (Pan), 2002
- Topex satellite data from 1992 to 2006
- 1:2000, 1:25000 and 1:50000 national topographic maps

The image datasets are covering the whole study area and have zero cloud cover. All images and associated bands which were analyzed in this study are shown in Table 1.

Table 1. Satellite image layers processed

Images	Channels			Extra bands and indexes		
MSS	Band 4	Band 3	Band 2	Tasseled cap band 3	WI Index	NDVI Index
TM	Band 7	Band 5	Band 4	Tasseled cap band 3	WI Index	NDSI Index
ETM	Band 7	Band 5	Band 4	Tasseled cap band 3	NDWI Index	NDSI Index

Based on accessible data bases, some pre-preprocessing methods were first involved for correction of atmospheric inaccuracy using dark object subtraction. Dark object subtraction (DOS) is perhaps the simplest and most widely used image based relative atmospheric correction approach for classification and change detection applications [11, 12]. In the second stage, the process of geometric correction which is known as orthorectification was applied to the images. During this process, data is corrected according to the user's ground reference system. The two most common geometric correction methods are based on the polynomial or the parametric models. The polynomial method is very simple but outdated method for correcting images. The method doesn't take into account terrain relief distortions. This deficiency limits the polynomial methods use to small and flat terrain areas like the study area. This method also requires many ground control points (GCPs). In current study, about 15 GCPs were collected from 1:25000 topographic maps for ETM+ image and other images are registered by matching this one.

In image processing stage, a traditional pixel-based classification normally was performed by its unsupervised and supervised categorizations. Unsupervised classification has few disadvantages where analyst has little control over image classes making inter-comparison of data difficult. Besides, spectral properties keep on changing over time, therefore the relationship between spectral response and information classes are not constant and detailed spectral knowledge of surfaces may be necessary. In a supervised classification, the identity and location of some of the land cover types are known a priori (before the fact) through a combination of fieldwork, analysis or aerial photography, maps and personal experience [18]. The analyst attempts to locate specific sites in the remotely sensed data that represent homogeneous examples of these known landscape types. It is generally accepted that supervised classification is more accurate than the unsupervised one [19]. However, traditional supervised classification has it disadvantages too. The most common error occurred when assigning the classes on training data, in the shape of polygon, pixels are assigned to a specific class if they fall within the polygon regions are allocated to the appropriate categories. Problems occur when pixels fall outside the specific regions or within overlapping regions. This will result in misclassification of data. In other words, it is very reliant on the accuracy of the training data. Therefore, with box classification the possibly of having misclassification or unclassified data was high [20].

Due to mentioned nature of classical methods, new and object-oriented image analysis of eCognition software has been used. It is based on the concept that important semantic information (necessary to interpret an image) not only could be represented in individual pixels but also in meaningful image objects and their contextual relations. In other words, object-oriented approach takes the form, textures and spectral information into account simultaneously. Its classification phase starts with the crucial initial step of grouping neighboring pixels into meaningful areas, which can be handled in the later step of classification. Such segmentation and topology generation must be set according to the resolution and scale of the expected objects. By this method, not only single pixels are classified but also homogenous image objects are extracted during a previous segmentation step. This segmentation can be done in multiple resolutions, allowing to differentiation several levels of object categories. Lastly, all image objects were imported into ArcGIS environment and vector base coastlines have been produced, for the purpose of calculating the changes during the time period which is considered in the current study.

4. Results

In general, all products of image processing stages could be offered in three following categories:

A satellite radar altimeter is not an imaging device, but continuously records average surface spot heights as it transverses over the Earth's surface [7]. By noting the two-way time delay between pulse emission and echo reception, the surface height can be deduced. Each returned height value is an average of all surface heights found within the footprint of the altimeter. Each satellite is placed in a specific repeat orbit, so after a certain number of days the same point (to within 1km), on the Earth's surface is revisited. In this way, time series of surface height changes can be constructed for a particular location along the satellite ground track. Although their primary objectives are ocean and ice studies, altimeters have had considerable success in the monitoring of inland water bodies [21]. In particular, the ability to remotely detect water surface level changes in lakes and inland seas has been demonstrated [22]. Unhindered by time of day, weather, vegetation or canopy cover, the technique has further been applied to a number of rivers, wetlands and floodplains in several test-case studies [23]. In particular, the results demonstrate how sub monthly, seasonal, and inter annual variations in height can be monitored.

In Caspian Sea, the minimum sea level for the past years was registered in 1977 by a ground station at -29 m. Since 1978, the sea level has risen, and in 1995 it was registered at -26.66 m and whereupon the sea level was almost stable with slight decrease [24]. The altimetry data recognize the outcome of the ground-base observations and accordingly can be used to prove the accuracy of shoreline extraction. The average sea level changes in Caspian Sea are shown by Figure 3.

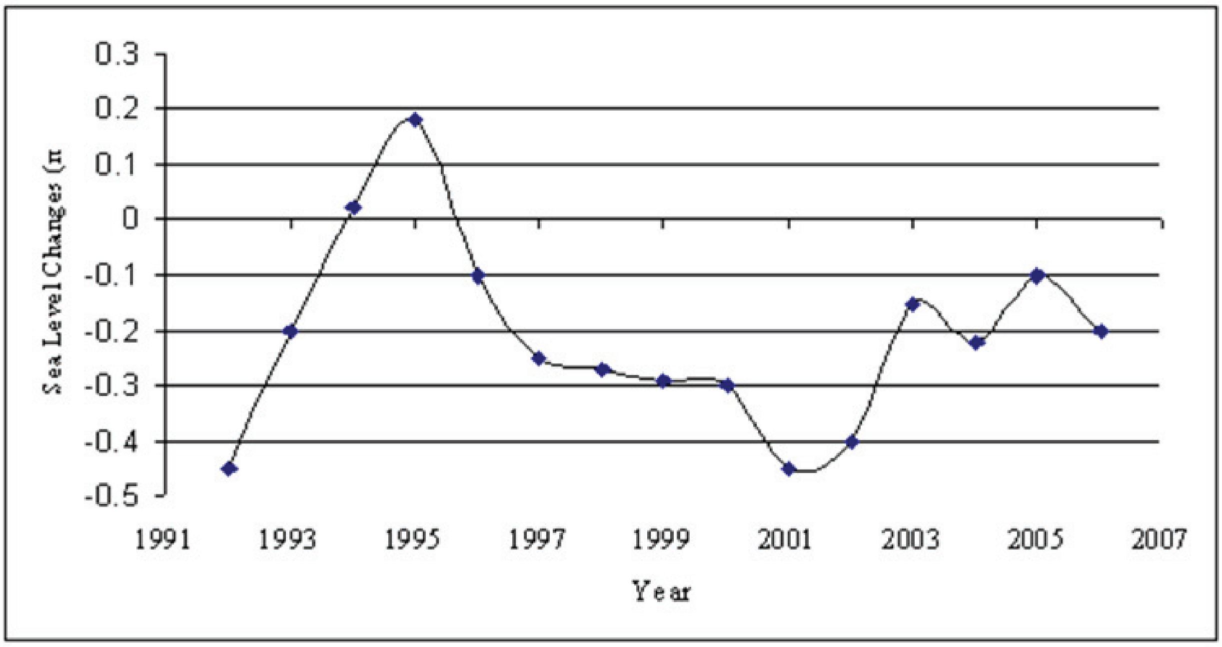

Fig.3. Average sea level changes in the Caspian Sea

Before applying change detection process, a number of procedures of classification have been employed to all accessible images. First, a few needed and known training areas were created for each class in the class hierarchy by defining them as recognized samples. Then a standard nearest neighbor method was applied to classify all types of Landsat images. To perform the classification, the classify option was chosen with class-related features in order that the membership functions are introduced. By creating classification rules based on information features or using membership function, the classified images were preferred to the change detection analysis stage.

Changes in landscape and their component can occur in a variety of ways and a variety of rates. The use of satellite-based remote sensor data has been determined to be a cost-effective approach to document changes over large geographic regions [25]. There are many techniques available to detect and record differences (for example; image differences ratios or image correlation procedures) which might be appropriate to change detection aims [26]. However, the simple detection of change is rarely sufficient in itself information is generally required on the initial and final land cover types or landuse analysis [27]. While much landscape change analysis is performed using the post-classification comparison, some alternative procedures could be also used [13]. For instance, rather than using land cover classes as the basis for change detection, vector base change detection would be applied [28].

In this study, after classifying all images, polygons of image border objects were created by selecting both thresholds to zero (0) which makes polygons the most accurate to ensure high accuracy. Then polygons have been exported to shape file format taken into ArcGIS and all polygons of water and land classes were merged together to build only one object for each class. In the latter step, the edited shape files of MSS, TM and ETM imageries for years 1977, 1984 and 2002 have been compared by applying a change detection extension to model the changes of shoreline during the time period involved. In figures 4, 5 and 6 outcomes of vector-based change detection analysis are illustrated.

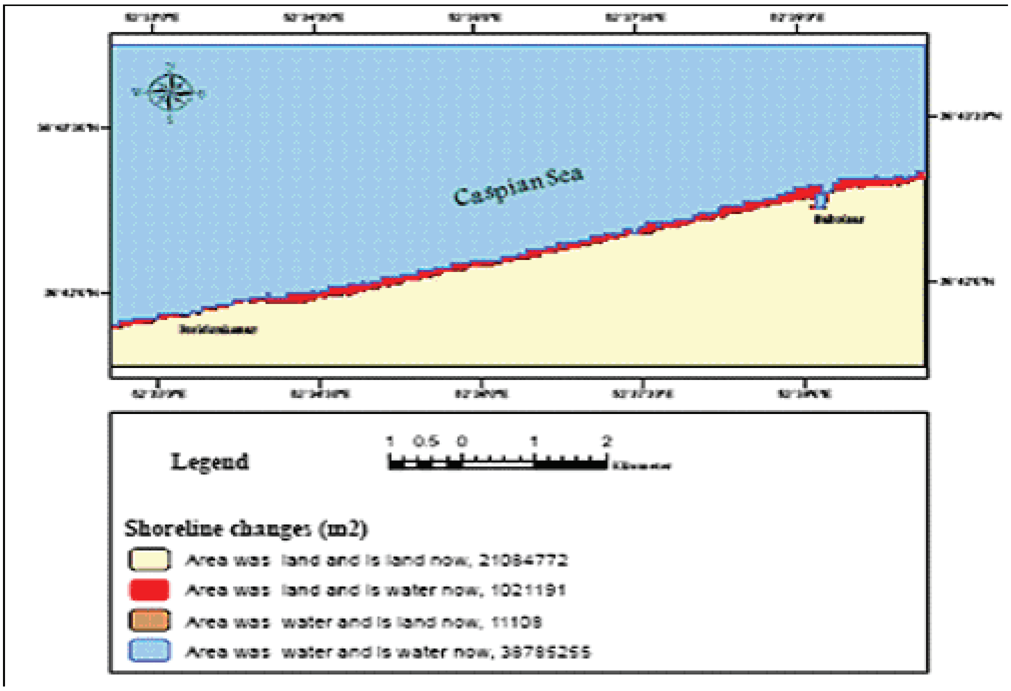

Fig.4. Change detection analysis of MSS and TM images of 1977 and 1984, respectively

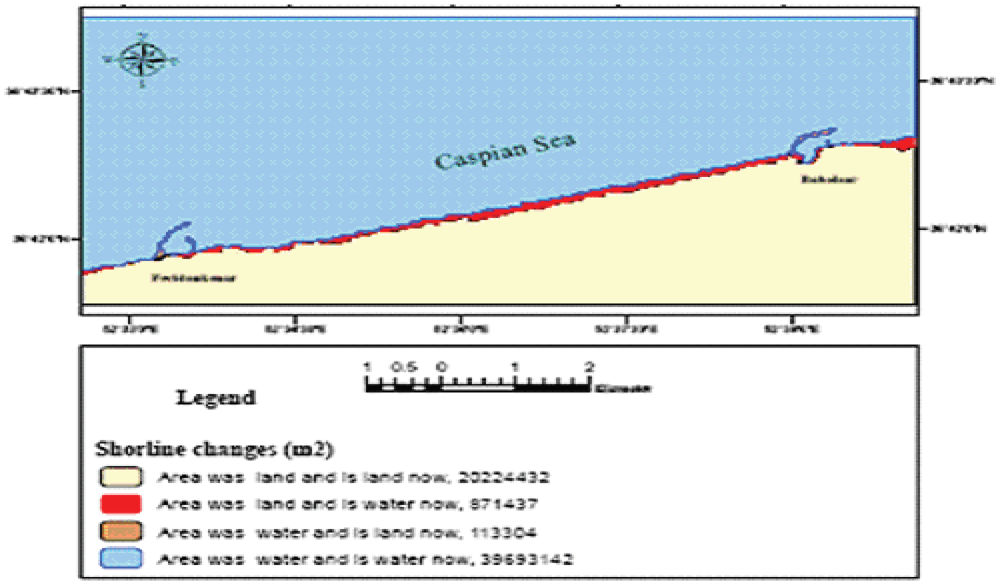

Fig.5. Change detection analysis of ETM and TM images of 2002 and 1984, respectively

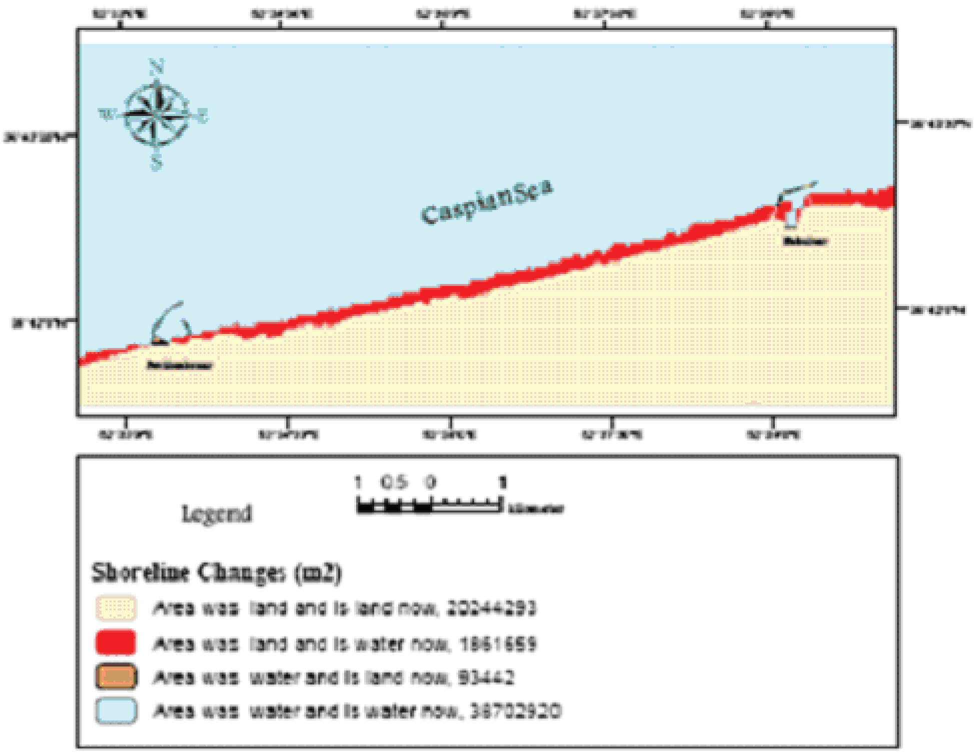

Fig. 6. Change detection analysis of ETM+ and MSS images of years 2002 and 1977, respectively

Based on the homogeneity criterion the segmentation process was used to break the image into different objects. In this method the user can control the relative size of the image objects, as well as assigning weights on each image band if necessary. In TM and ETM images, the SWIR bands (bands 7&5) and NDSI channel and in MSS band 4, and tasseled cap band 3 were given a strong weight in order to distinguish land and water objects. The scale parameter was set to 20, 15 and 8 in ETM, TM and MSS images respectively to make the objects large enough to distinguish desired objects (land and water) precisely. The homogeneity criterion was mostly based on color (0.8) instead of shape (0.2), because it was hoped that the difference between the waters color (dark in the weighted channels) would get into the least image objects. The result of the segmentation process is shown in Figure 7. The water was successfully segmented into a few objects which can be grouped into one object manually or by applying fuzzy classification in next steps.

a)

b)

c)

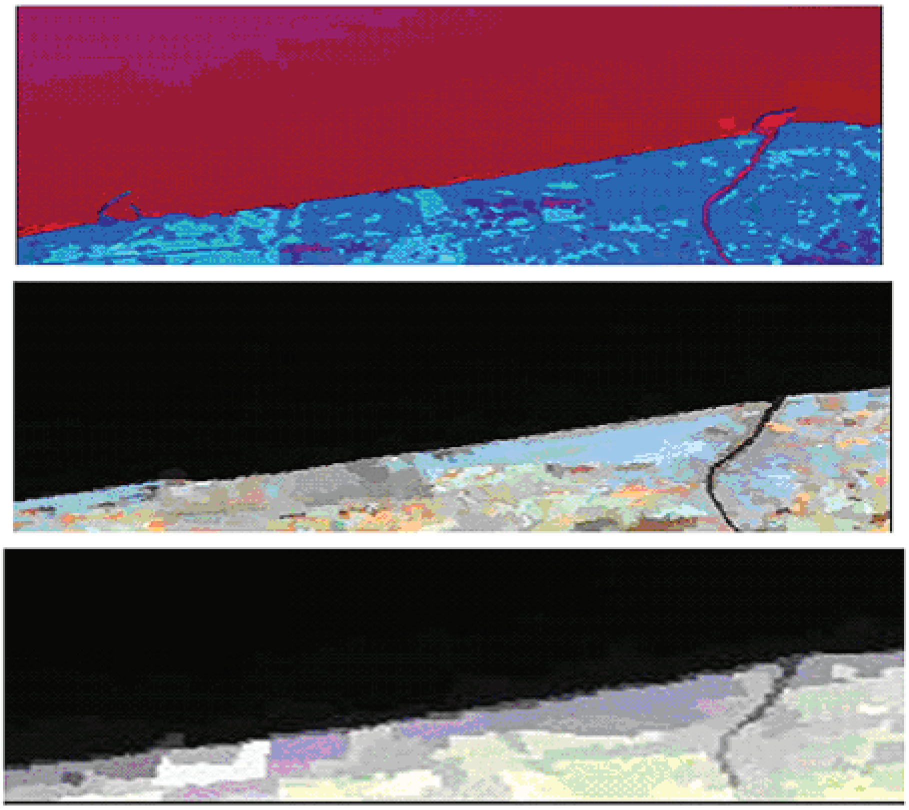

Fig.7. Segmentation results of: a) ETM, b) TM and c) MSS images

The advantage of fuzzy-logic is the possibility of integrating most different kinds of features and connecting them by means of logical operations. Because complex class descriptions are possible in comparison to neural networks methods and the most advantages are some transparent and adaptable set of classification rules [29]. Before starting to construct knowledge base and classification process, it should be known about the hierarchical network of image objects that was build automatically after the segmentation step [30]. Beyond the pure spectral information, image objects are characterized by a number of additional features such as: different textures and forms which can hardly be exploited using pixel-based approaches. The hierarchical structure represents the information of the image data in different resolution simultaneously. Each object knows its context, its neighborhood and its sub-objects as well. In this approach it is possible to define relations between objects and to utilize this additional and often essential context information in constructing class description for fuzzy-base classification.

Consequently the knowledge basis for analysis emerges in the form of class hierarchy which is threefold between inheritance, semantic grouping of classes and collection of classes into structure groups. The advantages are structured semantics, the possibility to formulate even complex semantics and the possibility for reduction of complexity at formulating a feature description. Results of object-oriented classifications were shown by Figure 8.

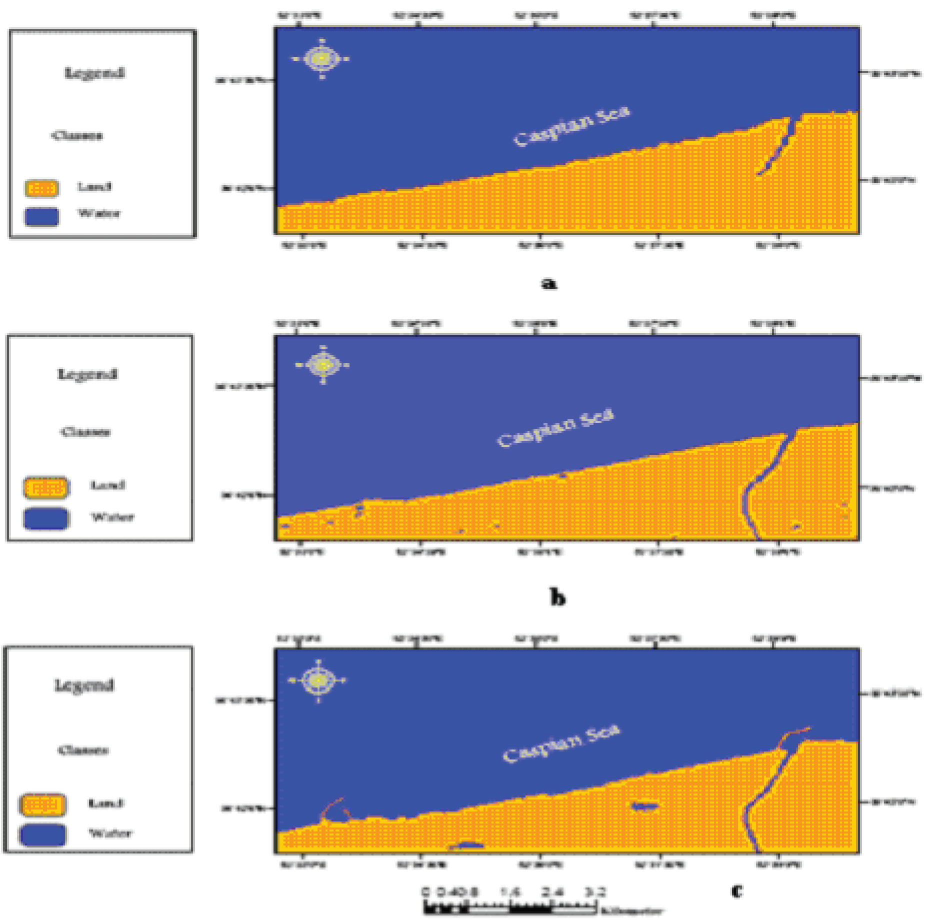

Fig. 8. Object-oriented classification results: a) MSS, b) TM and c) ETM+ images

5. Discussion

Coastline mapping seems to be a simple application of remote sensing data, but in practice semi-automated or automated extraction of the land/water boundaries is more difficult than one would expect [27]. Because the frequent lack of consistent, sufficient intensity contrast between land and water regions and the complications of distinguishing coastline from other object boundaries, coastline extraction is a difficult task with most edge detection or segmentation techniques [31].

Caspian Sea is a big laboratory for scientists to study sea level fluctuations. The minimum Caspian Sea level for the last 600 years was registered in 1977 at -29.0 m. Since 1987, the sea level has risen, and in 1995 it was registered at -26.66 m and whereupon the sea level was almost stable with slight decrease [32]. Strong seasonal variations of the land and sea landscapes indicated by changes of vegetation appearances and aspect and the varying borders of land and water complicate research and mapping of long-term changes.

In this research, a few comprehensive methods for semi-automated coastline extraction from satellite imagery were progressively introduced which consist of two parts. First a sequence of image processing algorithms was performed respectively in ERDAS and eCognition packages to extract coastlines in each image [33-34]. After that image objects were exported into GIS environment and with minimal manual editing vector base coastline have been produced. This vectorized coastline can be further edited with reference to the original satellite images. In the second part, extracted vector-base coastlines were overlaid on each other in GIS for the purpose of quantitive calculating the changes from 1977 to 2002. The results permit identification of areas of rapid change like Babolrod River mouth. Also significant erosion is seen near the Daryakenar and Khazarshahr coastal towns. The extracted coastline from ETM imagery was overlaid on IRS pan image in order to assess the accuracy of the extraction method.

Despite the successful applications of satellite images, it should be noted that the quality of the image sources remains an important factor for coastline extraction. The success of the dissimilar methods still depends upon whether considerable contrast can be achieved between water and land mass and to a lesser degree it also depends on the homogeneity of the water or land mass. The relative accuracy is evaluated in this research based on the comparison between the processing derived coastline and the coastline visually interpreted from the original satellite images. Extensive visual comparison shows that the relative accuracy of the result coastlines are within one image pixel compared with the human visual interpretation of the coastline features. In real world applications, the absolute accuracy of the geographical position of the derived coastline is essential.

6. Conclusions

Some experience confirms that computers cannot recognize the distinction among various classes in the image as humans can. However, if the process cannot be automated, the economic benefit of the imagery is most certainly lost. In this study, Landsat images of test field have been preprocessed in ERDAS IMAGINE software and then segmented with eCognition packages.

The final models of this study demonstrate that integration of object-oriented and pixel base techniques could be applied on Landsat MSS, TM and ETM + imageries in order to map changes of dynamic coastal land forms such as Caspian Sea shorelines. The technique produces vector files of the coastline which can be analyzed using GIS to estimate rates of change over relatively long time periods or being used for modeling long term changes. The synoptic capabilities of remote sensing provide a useful reconnaissance tool to target more detailed field surveys to neighborhoods of change. In the future investigations Caspian Sea unsustainable shorelines could be targeted for more detailed monitoring in the field by the processing of high resolution images like Ikonos and Quickbird simultaneously.

Acknowledgements

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