International Journal of Current Engineering and Technology
E-ISSN 2277 – 4106, P-ISSN 2347 – 5161

Available at http://inpressco.com/category/ijcet

Research Article

Coastline Extraction using Satellite Imagery and Image Processing Techniques

Saeed AL-Mansoori* and Fatima AL-Marzouqi

Applications Development and Analysis Center (ADAC), Mohammed Bin Rashid Space Center (MBRSC), United Arab Emirates

Accepted 15 July 2016, Available online 22 July 2016, **Vol.6, No.4 (Aug 2016)**

Abstract

The coastline is a vitally important characteristic of the environment and effects many different aspects of civilization. Globally it becomes extremely essential to monitor the coastline zones, as it reflects on economic development, environmental protection and infrastructure of the country. The coastline indicator was defined as the segment of the earth where the sea or ocean meets the land. In this paper, automatic technique is proposed to extract the coastline from satellite images. The proposed procedure is based on classifying the land and water components by applying a spectral band ratios method with two normalized difference indices; Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI), and then extracts the coastline as a vector data by converting the classified image into a binary image format followed by employing the Sobel edge operator. The accuracy of the results is assessed in comparison with the ground truth observations. This technique is fitting through a case study over the coastline of Dubai to monitor the changes in the coastline covering a time span of six years from 2009 till 2015. The results revealed an increase in the Dubai coastline by 6%.

Keywords: *Coastline extraction, DubaiSat-1, DubaiSat-2, Band Ratios, Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Ground Sampling Distance (GSD).*

1. Introduction

Coastal zones are facing aggravated natural and man-made hazards, such as erosion-sedimentation, raising sea levels and tidal flooding. Statistics [Appeaning Addo *et al*, 2008] have illustrated that over 70% of the beaches around the world are experiencing coastal erosions which in turn have put coastal regions in server jeopardy, this continues erosion could have a disastrous effect on the civilization that lives along or nearby the coast region which represents quarter of the world's population [Ali Kourosh Niya *et al*, 2013; J.A. Urbanski, 2010]. Therefore globally it becomes extremely important to monitor the coastal zones, as it reflects on infrastructure development, economic development, safe navigation, energy production, coastal resource management, coastal environment protection, commerce and many others.

Coastline monitoring and detection is a very complex issue, firstly the uncertainty of identifying a clear universally accepted definition of what a coastline is, furthermore defining an approach or specific method of monitoring coastline behaviours over a period of time. A common definition of a coastline is the segment of the earth where the sea or ocean meets the land [R. Gens, 2010]. It can be referred to as the boundary line separating the land from the ocean or lake. Realisation of the coastline provides the foundation for defining and analysing the water and land resources. Throughout time, there has been a huge progress in this field which has resulted in accurate extraction of the coastline, these methods will be emphasised on this paper.

Generation of coastline maps date back to 1807, when the same was obtained by the traditional method of conventional field surveying. Later in 1927, Aerial photography came into implementation [A.A. Alesheikh *et al*, 2007]. In recent years, remote sensing data has become more widely used in coastline extraction and mapping. This development helped ease the generation of coastline mapping by making it time efficient and cost effective. This technology enables a sufficient accuracy level of Ortho-rectification and classification. Several techniques [Eva Willerslev, 2011] have been proposed to automatically or semi automatically extracts the coastline from remote sensing imagery. The focus of this paper will be upon automatic extraction. Automated extraction techniques can be grouped into four major categories;

- Band thresholding approaches
- Classification techniques
- Edge detection methods
- Fusion approaches

*Corresponding author: **Saeed AL-Mansoori**

(1) **The band threshold approach** [H. Liu *et al*, 2004], here a threshold value (τ) is obtained either through the local adaptive method or via trial and error (T&E) experimentation. Such an approach is widely used in coastline extraction applications, since it is easy to implement and capable of achieving good accuracy.
(2) **The Classification technique**, which simply divides an image into two features, land and water. Followed by the extraction of the coastline which is represented by the boundary between these elements. There are four types of classification approaches which are namely; supervised classification [K.S Kingston *et al*, 2000], unsupervised classification [A. Guariglia *et al*, 2006], soft classification [A.M. Muslim *et al*, 2006] and association rule [C. Wang *et al*, 2010].
(3) **The Edge detection method**, applies a certain image processing filters such as Canny and Sobel to detect the lines which represent the coastline in this study [D. C. Mason *et al*, 1996].
(4) **The Fusion approach** [R. Gens, 2010] is an advanced concept used to combine different sources of data such as optical, SAR (Synthetic Aperture Radar) and LIDAR (Light Detection And Ranging) for coastline detection.

This section reviews some of the recent research studies done on this area. Few researchers proposed a technique based on histogram thresholding approach to monitor and detect changes in a coastline. They concluded that the technique when applied alone lead to an error (ε) in classification by classifying the vegetation area as water. However, as shown in [A. A. Alesheikh *et al*, 2007], the combination of histogram thresholding and band ratio techniques for the same objective for a set of 9 LANDSET images with the bands selected between 4 and 2 and 5 and 2 provided a superior accuracy of 1.3 pixels when compared with the results from the ground truth images. [H. Liu *et al*, 2004] proposes the image segmentation technique for the extraction of a coastline from an image set obtained from the Radar and optical satellite images. The study uses the Levenberg-Marqardt method for the coastline extraction and thereafter the speed of convergence of the iterative Guassian curve fitting was carried out using the Canny edge detector. However, the work only utilizes the size and the image continuity for determining and differentiating the land and water and thereby extracting the coastline. Recent researches propose artificial intelligence and associated evolutionary algorithms such as Artificial Neural Network (ANN), Genetic algorithm, and Support Vector Machine (SVM), to determine the features of a coastline for classification, detection and thereby predicting the changes along a coastline. The support vector machine algorithm for the classification of remote sensing images is illustrated in [Zhang Hannv *et al*, 2013] uses the Sigmoid kernel function as the optimal classifier. The study shows a remarkable reduction in the error of classification for a small sample space and generated an accuracy of 96.83% in extraction of the coastline.

However, there are some limitations of artificial intelligence algorithms such as long-time training, and over-fitting. To overcome these problems, [X. Hu *et al*, 2015] proposed a novel technique based on Gaussian process classification, not only to be reliable but also to accurately extract the coastline.

Finally, a new idea based on spectral bands ratio is elaborated in a set of recent contributions. The results revealed that this method is robust and more efficient in extracting the coastline from remote sensing imagery. Such a technique is proposed in [Claire Cassé *et al*, 2012; Emiyati *et al*, 2013].

The aim of this study is to extract the coastline and analyse temporal changes of Dubai coast using spectral band ratios approach and Sobel convolution kernels. Coastlines have been extracted using remote sensing imagery in the years of 2009 and 2015 with a spatial resolution of 2.5 meter and a spectral resolution of 4 bands; Red, Green, Blue and Near Infra-red.

The rest of the paper is organized as follows. Section 2 describes the sources of data utilized in this study. In Section 3, a detailed description of the proposed method is provided. Section 4 illustrates the study area and Section 5 presents the results and discussion about the findings. Finally, conclusions are drawn in the last section.

2. Data Sources

In this study, DubaiSat-1 (DS1) and DubaiSat-2 (DS2) images were used to monitor the dynamics of Dubai coastline and investigate its changes at unequal intervals between 2009 and 2015, covering a time span of six years. Main characteristics of DubaiSat-1 and DubaiSat-2 sensors are reported in Table 1. DubaiSat-1 and DubaiSat-2 consist of four spectral bands namely, red, green, blue and near-infrared with spatial resolution of 2.5 m and 1 m respectively. The images were taken during a summer season to ensure free of cloud images in the area of study. Before applying the proposed approach to the existing data, a pre-processing step was applied. That is, re-sampling DubaiSat-2 images to 2.5 meter resolution using nearest neighbour and first order polynomial transformation. Bands 1, 2 and 4 are utilized to extract the coastline from DubaiSat-1 and DubaiSat-2 images as discussed in section 3.

Table 1 Main characteristics of DS1 and DS2 sensors

Parameters	DubaiSat-1	DubaiSat-2
Spectral bands	Pan: 420-890 nm **Blue**:420-510nm **Green**:510-580nm **Red**:600-720nm **NIR**:760-890nm	Pan:550-900nm **Blue**:450-520nm **Green**:520-590nm **Red**:630-690nm **NIR**:770-890nm
GSD	2.5 m	1 m
Scene size	20 km×20 km	12 km×12 km
Quantization	8 bits	10 bits

3. Proposed Methodology

The aim of this paper is to develop a state of the art approach to effectively detect and monitor the coastline changes for a particular area over a period of time using satellite imagery. This approach produces vector files of the coastline which can be utilized to estimate rates of change over relatively long time period. In this study, various image processing techniques were carried out such as pre, post classification, spectral band ratios and edge detection. The proposed approach of extracting the coastline from remote sensing imagery is illustrated in Figure 2. It consists of three main steps:

- Step 1: Land-Water Classification
- Step 2: Binary conversion
- Step 3: Edge detection

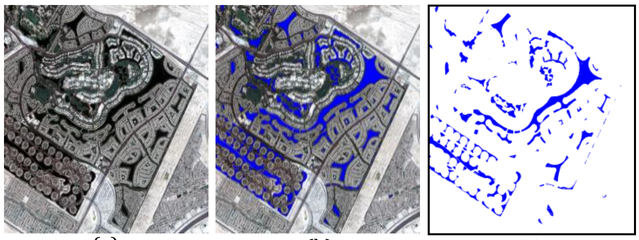
3.1 Step 1: Land-Water Classification

The first step is to classify the land and water by applying the spectral band ratios approach. Thus, two normalized difference indices are derived separately from satellite data. They are named NDVI (Normalized Difference Vegetation Index) and NDWI (Normalized Difference Water Index). Mainly, NDVI aims to assessing the health and vigor of green vegetation in the remote sensing imagery. Also, it can be utilized to identify two more classes, namely water and soil. The near-infrared and red wavelengths are the most sensitive in the electromagnetic spectrum to analyse and study this index. There is a direct correlation between the difference in the reflectance of the near infra-red and red lights, and the amount of land features. To obtain the highest level of precision and accuracy in distinguishing the water and the land, the NDVI and NDWI are combined. NDWI is a satellite derived index utilized to delineate open water features. The NDWI makes use of visible green light and the reflected near infra-red radiation. Mathematically, the NDVI is calculated by subtracting the red reflectance values from the near-infrared values and dividing it by the sum of the same, while the NDWI is computed by subtracting the near-infrared values from the green reflectance values and dividing it by the sum of the same. NDVI and NDWI equations are shown in (1) and (2) respectively.

$$NDVI = \left(\frac{NIR - Red}{NIR + Red} \right) \tag{1}$$

$$NDWI = \left(\frac{Green - NIR}{Green + NIR} \right) \tag{2}$$

Both NDVI and NDWI value ranges along an interval of [-1, 1]. In this study, trial and error experimentation is conducted over 35 satellite imagery captured by DubaiSat-1 and DubaiSat-2 to fix the proper range of NDVI and NDWI according to which water bodies can be identified and extracted. It is observed that water bodies indices values range between (NDVI$\geq$-0.1, NDVI$\leq$0.1 and NDWI$\geq$ 0.24).



(a) (b) (c)

Fig. 1 The NDVI and NDWI results, (a) Original DS2 image, (b) Water bodies detection using both NDVI and NDWI and (c) A vector map of water bodies

Figure 1 illustrates an example of water extraction from DubaiSat-2 image after applying the above indices ranges. Here, the proposed algorithm is developed in a way that the extracted water will appear in a blue colour while other features such as land, roads and vegetation will be presented in yellow resulting in a land-water classified image as shown in figure (2)-Step1.

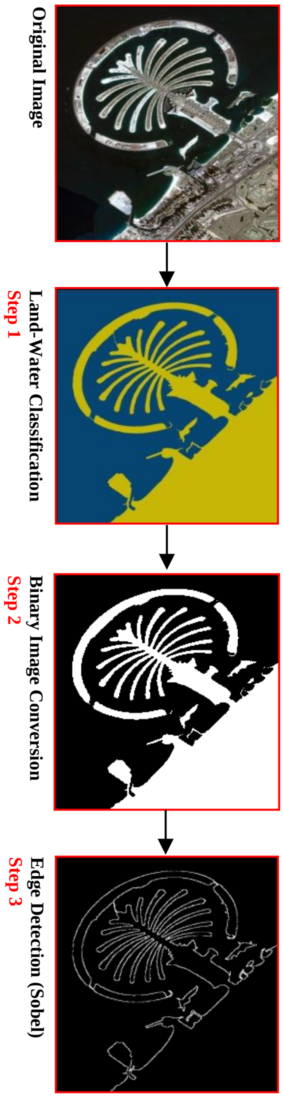


Fig. 2 The flowchart of the proposed approach

3.2 Steps 2 and 3: Binary conversion and Edge detection

The next step is to convert the classified image into binary format, where the value of “0” represents water and “1” represents land, as illustrated in figure (2)-Step2. Then, the continuous edges representing the coastline are extracted using an edge detection approach based on morphological filter. Edge detection is a process of finding regions in an image where sharp change intensity exists. In other words, it is the discontinuity of intensities in the image. It performs by examining either the 1st or 2nd derivative of the pixel intensity values within the image. It is worth mentioning that the gradient operator is the 1st derivative of the image pixels while the laplacian operator is the 2nd derivative of the same. A gradient operator is a commonly used edge detection process [4, 5]. Mathematically, the gradient magnitude ***g(x,y)*** and the gradient direction ***θ(x,y)*** for an image function ***f(x,y)*** are calculated as illustrated in equations (3) and (4) respectively.

$$g(x,y)=\sqrt{\Delta x^2+\Delta y^2} \quad (3)$$

$$\theta(x,y)=a\tan\left(\frac{\Delta y}{\Delta x}\right) \quad (4)$$

$$\Delta x = f(x+n,y)-f(x-n,y) \quad (5)$$

$$\Delta y = f(x,y+n)-f(x,y-n) \quad (6)$$

where ***n*** is a small integer, usually unity. A very common operator to do this is a sobel operator. Sobel operator is a kernel convolution process utilized to return a high response where there is a sharp change in the gradient of the image. On the other hand, Sobel operator is extremely sensitive to noise so it is recommendable to apply a Gaussian filter first as shown in equation (7), to get rid of high frequency components and to keep the low frequency components.

$$\underbrace{S}_{Smoothed\ Image}=\underbrace{\left(\frac{1}{\sqrt{2\pi}\,\sigma}e^{-\frac{x^2+y^2}{2\sigma^2}}\right)}_{Gaussian\ Filter}*\underbrace{I}_{Original\ Image} \quad (7)$$

The Sobel operator used in this study is a pair of (3×3) kernels, G_x and G_y. The first kernel is used to estimate the gradient in the *x*-direction, while the other is used to estimate the gradient in the *y*-direction. Masks of both kernels are illustrated in Figure 3. Those masks are applied to the binary image to extract the edges that represent the coastline in this study, as shown in figure (2)-Step3.

-1	0	+1
-2	0	+2
-1	0	+1

G_x

+1	+2	+1
0	0	0
-1	-2	-1

G_y

Fig. 3 Sobel convolution kernels

4. Study Area (Case Study)

The study site of this investigation is Dubai coastline which covers approximately 105 Kilometres length of the United Arab Emirates (UAE) shoreline. It is located on the South Eastern coast of the Arabian Gulf, between 24° 54.694'N and 25° 19.473'N latitude and 54° 53.411'E and 55° 20.787'E longitude (figure4). Dubai’s coastline has been referred to the eighth wonder of the world, consisting of world archipelago, the three artificial small island groups and the three palm trees. In this paper, to facilitate the monitoring operation, the Dubai coastline is divided into eight regions, namely; A, B, C, D, E, F, G and H as shown in figure 5.

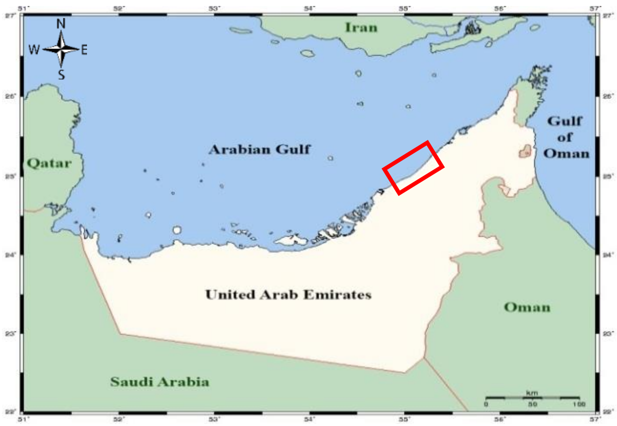


Fig. 4 Location map of the study area

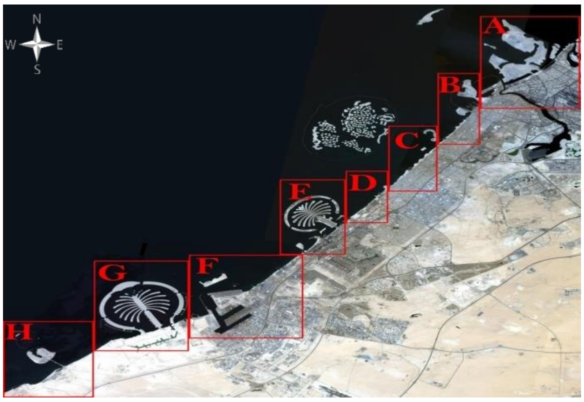
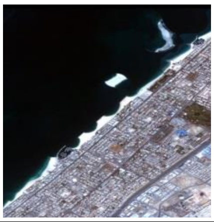
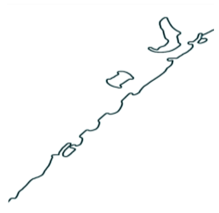
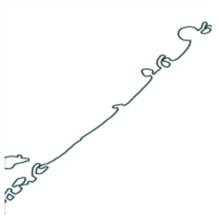
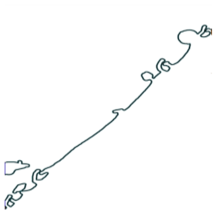
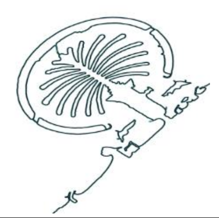
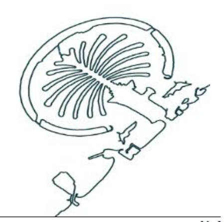
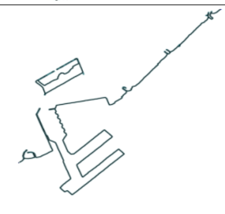
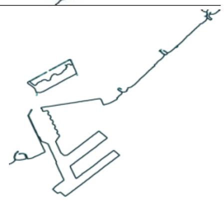
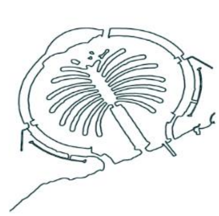
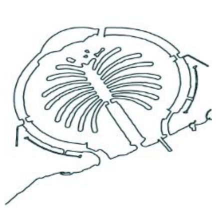
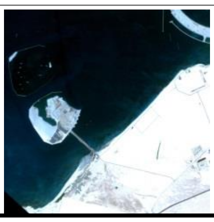
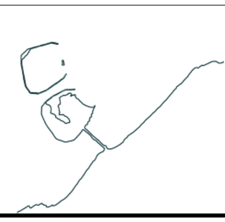


Fig. 5 Dubai coastline divisions suggested in this study

5. Results and Discussions

The proposed method has been tested with 16 satellite images representing different scenes of Dubai coastline over two years; the first 8 images are captured by DubaiSat-1 in 2009 while the rest of images are captured by DubaiSat-2 in 2015. Based on the Dubai coastline divisions illustrated in Figure 5, this section was intended to study each division (i.e., study area) by extracting the coastline using the proposed method and accordingly highlight the main changes. Table 2 offer a visual comparison between the coastline vectors extracted by the proposed methodology for study areas (A-H) in 2009 and 2015.

Table 2 Experimental Results

	Original Image @ 2009	Coastline Extraction	Original Image @ 2015	Coastline Extraction
Area (A)				
Area (B)				
Area (C)				
Area (D)				
Area (E)				
Area (F)				
Area (G)				
Area (H)				

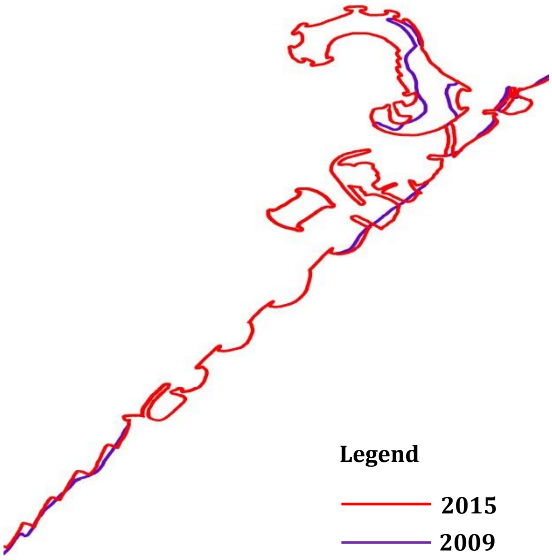


Fig. 6 Extracted coastlines from Area (C)

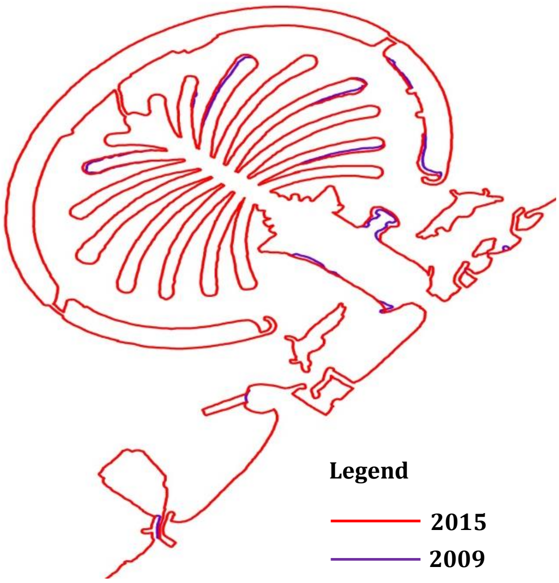


Fig. 7 Extracted coastlines from Area (E)

To ease monitoring the changes of two extracted coastline vectors, they are overlapped. (Examples of Area C & E are illustrated in figures 6 and 7 respectively). The 2009 coastline is presented in violet and the 2015 coastline is presented in red. The experimental results revealed that the rates of change in Dubai's coastal areas fluctuate, as shown in figure 8. The study indicates that there has been 6% overall increase in the coastline between the years of 2009 and 2015, due to the impact of man-made projects along the coastal region. The main projects that have a noticeable change are the construction of ongoing artificial islands namely, Deira Island, Jumeirah Bay Island, Palm Jumeirah Island and Jebel Ali Island which are illustrated in areas A, C, E and G. In addition it has been observed that a number of breakwaters were constructed to protect the coastline from high waves whereas, sand barriers were erected in other locations such as areas B and D to protect the coast from erosion and sediment transport. Also, it is concluded that the largest rate of change to the coastline was noticed in area C by +2.33%, whereas areas A and H experienced a decline in the percentage of land area by -0.13% and -0.2% respectively.

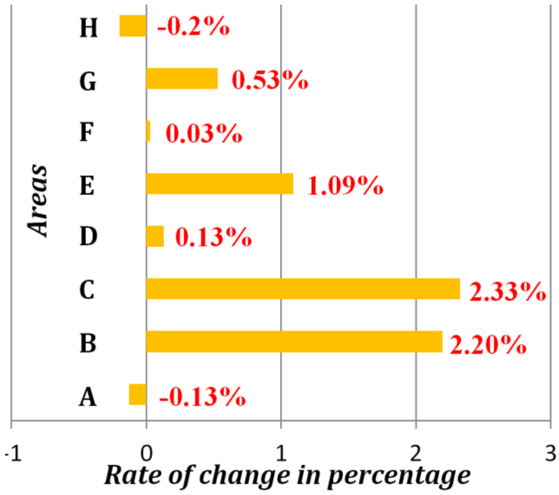


Fig. 8 Rate of change in Dubai's coastal areas from 2009 to 2015

Conclusions

The aim of this paper is to explore the use of multi-temporal satellite images for analysing the changes occurred over Dubai coastline covering a time span of six years from 2009 to 2015. In this study, automatic approach for extracting the coastline was proposed based on spectral band ratios and Sobel operator. Best land-water classification results are given by combining both NDVI and NDWI. Then, the classified image is converted into binary format which considered as a pre-processing step to extract the coastline using the Sobel operator. The Sobel operator used in this study is a pair of (3×3) kernels; one to estimate the gradient in the *x*-direction and the other to do the same in the *y*-direction. The experimental results indicated that the proposed algorithm is capable of detecting and extracting the coastline from DubaiSat-1 and DubaiSat-2 imagery. In addition, the proposed algorithm is fast in terms of processing time and it is accurate in a way that it limits the subjective estimate. In terms of analysis, the study demonstrated that there were numerous changes along Dubai coastline during the time span of the study and most of which is the result of man-made projects for developmental and touristic purposes.

References

Appeaning-Addo, K., Walkden, M. & Mills, J.P., (2008), Detection, measurement and prediction of shoreline recession in Accra, Ghana, *Journal of Photogrammetry & Remote Sensing,* 63(5), 543–558.

Ali Kourosh Niya, Ali Asghar Alesheikh , Mohsen Soltanpor,Mi r Masoud Kheirkhahzarkesh,(2013),Shoreline Change Map ping Using Remote Sensing and GIS,*International Journal of Remote Sensing Applications*, 3(3), 102-107.

J. A. Urbanski,(2010), The extraction of coastline using obia and GIS, International Society for Photogrannetry and Remote Sensing, XXXVIII-4.

R. Gens, (2010), Remote sensing of coastlines: Detection, extraction and monitoring, *International Journal of Remote Sensing,* 31(7), 1819-1836.

Eva WILLERSLEV, (2011), Methods of Extracting a Coastline from Satellite Imagery and Assessing the Accuracy, Herbert Wichmann Verlag, VDE VERLAG GMBH, Berlin/Offenbach. ISBN 978-3-87907-509-6.

Liu, H.X.; Jezek, K.C., (2004), A complete high-resolution coastline of antarctica extracted from orthorectified Radarsat SAR imagery, *Photogramm. Eng. Rem. Sens*., 70, 605–616.

Kingston, K.S.; Ruessink, B.G.; van Enckevort, I.M.J.; Davidson, (2000), M.A. Artificial neural network correction of remotely sensed sandbar location, *Mar. Geol*,169, 137–160.

Guariglia, A.; Buonamassa, A.; Losurdo, A.; Saladino, R.; Trivigno, M.L.; Zaccagnino, A.;Colangelo, A. (2006),A multisource approach for coastline mapping and identification of shoreline changes, *Ann. Geophys*, 49, 295–304.

Muslim, A.M.; Foody, G.M.; Atkinson, P.M., (2006), Localized soft classification for super-resolution mapping of the shoreline, *Int. J. Remote Sens*, 27, 2271–2285.

Wang, C.Y.; Zhang, J.; Ma, Y., (2010), Coastline interpretation from multispectral remote sensing images using an association rule algorithm, *Int. J. Remote Sens*, 31, 6409–6423.

Mason, D.C.; Davenport, I.J., (1996), Accurate and efficient determination of the shoreline in ERS-1 SAR images, *IEEE Trans. Geosci. Remote Sens*, 34, 1243–1253.

Zhang Hannv, Jiang Qigang, Xu jiang, (2013), Coastline Extraction Using Support Vector Machine from Remote Sensing Image, *Journal of multimedia*, 8(2), 175-182.

Xiaochuan Hu, Zihua Qin, Jinhuan Wang, Guoshao Su, (2015), Coastline Extraction on Remote Sensing Image Using Gaussian Process Classification, Atlantis Press.

Claire Cassé, Pham Bach Viet, Pham Thi Ngoc Nhung, Hoang Phi Phung, Lam Dao, (2012), Remote sensing application for coastline detection in ca mau, mekong delta, *International Symposium on Geoinformatics for Spatial Infrastructure Development in Earth and Allied Sciences.*

Emiyati, Syarif Budhiman and Ety Parwati,(2013), Comparison of three shorelines extraction methods based on digital image processing of SPOT-4, *Asian Association on Remote Sensing*.

Saeed AL-Mansoori, Abdullah Bushahab, Obaid AL-Shehhi,(2012), Application of DubaiSat-1 imagery, *International Symposium on Remote Sensing (ISRS)*.

A Bushahab, S Al-Mansoori, K Al-Suwaidi, Hessa Al-Matroushi, E Al-Tunaiji, Meera Al-Shamsi, (2014), Cal/Val activities for DubaiSat-2 performance assessment, *SPIE Remote Sensing*.

Saeed AL-Mansoori, (2015), Semi-Supervised Classification tool for DubaiSat-2 Multispectral Imagery, *SPIE- High Performance Computing in Remote Sensing V*, 9646.