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Change Detection in The Water Bodies of Lake Malaha, East Port-Said, Egypt, using RS/GIS

Yasser Mohamed Sultan[1], MokhtarSamy Beheary[2], El-Sayed Abbas Zaghloul[3], Mariam Hassan Sheta[4]
Lecturer[1], Assistant professor[2], Professor[3], Demonstrator[4]
Port-Said University, Egypt[1, 2, 4]
National Authority for Remote Sensing and Space Sciences, Cairo, Egypt[3]

Abstract:
The Egyptian coastal lakes have changes in the water bodies due to the severe anthropogenic activities. In this paper Lake Malaha was selected as a case study. Lake Malaha is one of the most important water bodies along the northern coast of Egypt for its fisheries resources. It represents an important rout for migratory birds. Envi and ArcGIS software are used in this study for processing of the images and managing the database of each image. classification technique was used. The technique is applied to the images of the Landsat ETM+ and OLI/TIRS images acquired on 2005, 2010, 2015, 2016 and 2017, respectively. The analysis of LU/ LC of the study area images reveals eight major classes that were verified in the field. These classes are lake Malaha, wetlands, clay, artificial sand, sand, salt crust, fish farms and vegetation. The results of the analysis of data showed that as a result of the changes and expansions carried out in East Port Said area, there was a significant change occurred in the area of Lake Malaha whereas the area of the lake decreased about 11.7 km^2 only within 12 years.

Keywords: Lake Malaha, Change detection, LULC, Envi software, Arc GIS software

1. INTRODUCTION

Remote sensing satellites at different spatial, spectral, and temporal resolutions provide an enormous amount of data that have become primary sources, being extensively used for detecting and extracting surface water and its changes in recent decades (McFeeters, 2013). Remote sensing imageries have widely been used in environmental studies to detect changes caused either due to natural factors or anthropic factors (Gregoireet al., 2010 and Hussain et al., 2013). Change detection, defined by (Singh, 1989) as “the process of identifying differences in the state of an object or phenomenon by observing it at different times”, essentially comprises the quantification of temporal phenomena from multi-date imagery acquired by satellite based multi-spectral sensors (Coppin and Bauer, 1996). It is more elaborated by (Lu et al., 2004) as the process involving the application of multi-temporal datasets to quantitatively analyze the temporal change of the phenomenon. Hence, change detection can be generalized as a means of identification, recognition and quantification of temporal differences of the same features or phenomenon occupying a well-defined spatial extent. The remote sensing and GIS methods provide useful information on spatial and temporal changes in aquatic vegetation in the lakes (Valta-hulkkonen et al., 2004).Image classification is the most widely used technique in various remote sensing applications for extraction of target thematic information. Changes in land use and land cover (LU/LC) are important for different reasons such as the study of sustainable development (Hegazy and Kaloop, 2015), it is an important factor to understand the interaction and the relationship of anthropogenic activities on the environment (Donia and Farag, 2012), also its spatial and temporal scales is indispensable to achieve environmental sustainability (Turner et al., 1994). Change in LU/LC leads to the impact on the socio-economic, biological, climatic and hydrological systems(Sohl and Sohl, 2012).The importance of the changes in the size and quality of many ofthe world’s wetlands has arisen mainly as a result of increased urban development and agricultural development (Haack, 1996). To learn about the changes occurring in land use and land cover somewhere, the analysis of the spatial and temporal variations is a must (Singh, 1989). Classification and mapping of LU/LC by high accuracy are significant issues to support the sustainability of natural resources (Hossen and Negm, 2016). As a result of the increased human activities at the eastern area of Port Said, the environment and the area of Lake Malaha changed, sothe main objective of study is to monitor the changes of the area of Lake Malaha using LU/LC.

2. DESCRIPTION OF STUDY AREA

Lake Malaha lies in the northwestern corner of El-Tina plain, east of Port Fouad city and directly east of the Suez Canal between Longitudes: 32° 21` 30˶ & 32 ° 30` E and Latitudes: 31° 7` & 31 ° 13` N(Fig. 1).Lake Malahahas a triangular shape and connected with the Mediterranean Sea by a small inlet near Port-Fouad and other shallow tidal inlets. The surface area decreased from 33,000 to 21,000 feddans after 1976 conflict, as the result of the construction of a road between Rommana and kilometer 19th on the Suez Canal. Lake Malaha consists of two shallow hyper-saline lagoons, the size and shape of which are variable; they reach the maximum size during winter and become nearly dry in summer season. The lagoons are connected to the Mediterranean Sea via Boughaze El- Kalaa (Eastern lagoon) and Boughaze El-Malaha (Western lagoon). The two lagoons are separated from the Mediterranean Sea by a sandbar that varies in width between 100 to 500 m (Ahmed and El-Mor, 2006). There is no freshwater influx in the lake (Hanafy et al.,1996). Lake Malaha is one of the most important water bodies along the northern coast of Egypt for its fisheries resources. It represents an important rout for migratory birds.The present area of Lake Malaha is 11.43 km2 while it was 19.86 km2 in 2005, this is because of the changes and expansions carried out in east Port Said area. Also as a result of these expansions and projects in this area, the western area of the lake is bridged.

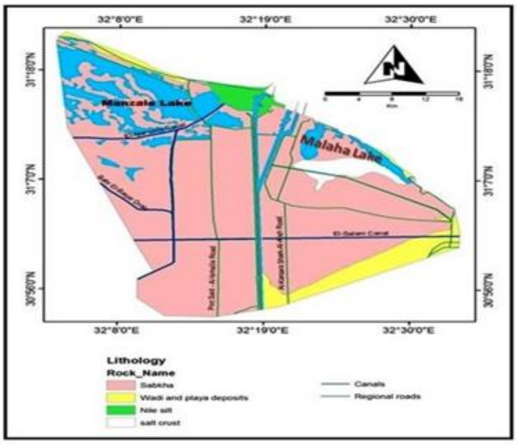

Figure.1. Location map of Lake Malaha

3. DATA AND METHODOLOGY

Landsat-7 and Landsat-8 satellite images were used in this work. The images were downloaded from United States Geological Survey (USGS) earth explorer (https:// earth explorer. usgs.gov). The first set: Landsat 7 that acquired on 18-June-2005 and 15-May-2010 (were collected from the enhanced Thematic Mapper on Landsat 7), these periods were selected to be as a database. The second set: Landsat 8 that acquired on 10-September-2015, 7-December-2016 and 03-February-17(were collected from the enhanced Thematic Mapper on Landsat 8), these periods were selected because the noticeable change in the study area were occurred at these periods. The two sets of data represent the optical data, of which the first six reflective bands (1–5 and 7) with a spatial resolution of 28.5 m and the panchromatic band 8 with a 14.25 m pixel resolution were used.

3.1. Image preprocessing

The image preprocessing is needful when the users of the data want to extract the necessary information or improve the visual interpretability of image. Before data processing, the needed bands of images (Bands 1-5 and 7 for landsat ETM 7 and OLI 8) should be stacked. The satellite image contains a very wide area. But in practical application, most of the areas in the satellite image are not necessary for the research. To decrease the time consuming and storage space, the images should be clipped to extract the study areas in this study. These stepsare performed inEnvi 5.3.

3.2. Image processing

3.2.1. Image Classification

Image classification is the most widely used technique in various remote sensing applications for extraction of target thematic information. In the context of present study, the land use / land cover (LULC) is the main target which is to be extracted using a suitable classification method for LULC change detection. Basically, image classification is a mapping process to generalize the image pixels into meaningful groups each resembling different land category (Jensen, 1995). This practice is based on conventional statistical techniques such as supervised classification using Supervised maximum likelihood classification (MLC) and unsupervised classification using K means (with 10 initial classes) was performed on the study area using optical data with respectively six bands as input data.

4. RESULTS AND DISCUSSION

4.1. Unsupervised classification

Unsupervised classification occurred when the analysis is controlled by the computer program. The training process uses the computer to calculate a specific spectral signature on which the classification process will be based. Each signature is supposed to correspond to a class. Using a specific equation (classification algorithm) tests every pixel on the image and 0 assigns it to a specific class. In unsupervised training the analysts enter some parameters that will be used to detect statistical classes inherent in the data. These classes do not necessarily correspond to real classes on the ground or any other features in the area represented by the image. They are simply determined mathematically. Some of the produced classes may need to be merged together, while others may need to be deleted. Fig. (2) illustrates unsupervised classification of images for 2005, 2010, 2015, 2016 and 2017.

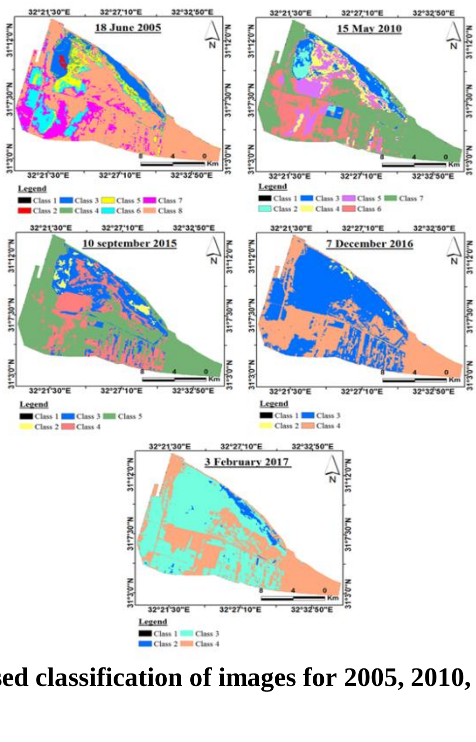

Figure.2. Unsupervised classification of images for 2005, 2010, 2015, 2016 and 2017

4.2. Supervised classification

Supervised classification is closely controlled by the analyst who chooses a group of pixels in the image to represent the criteria of each class. Supervised maximum likelihood classification (MLC) was used by (Salemet al., 1995)for detectingland cover classes. Once a sufficient number of such spectral subclasses were acquired for all information classes, a maximum likelihood classification was performed with the full set of refined spectral classes (Lillesandet al., 2004). Despite the fact that MLC is a statistically complicated technique to classify images for change detection, it was considered to be the most effective method for supervised classification (Csillage, 1986; Hixonet al., 1981; Thomas et al., 1987). Maximum likelihood supervised classification was applied to optical images for 2005, 2010, 2015, 2016 and 2017 images using field investigation information collected from more than 40 ground checkpoints and digital topographic maps of the study area.The major classes in the images were Lake Malaha, wetlands, salt crust, artificial sand, sand, clay, fish farms and vegetation (Fig. 3). Following this, a majority/minority filter with an operating window size of 7 by 7 was performed in Envi 5.3. A majority filter is a logical filter applied on a classified image (Fig. 4).

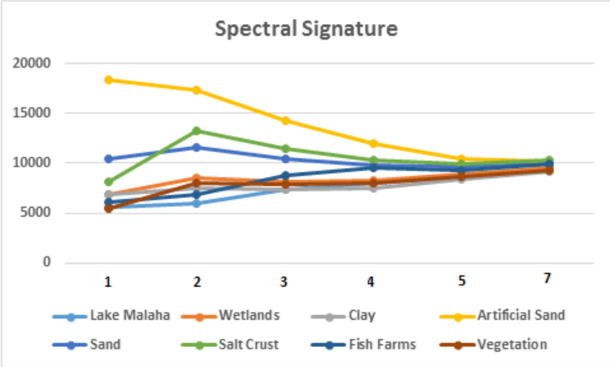

Figure.3. Spectral signature of different classes

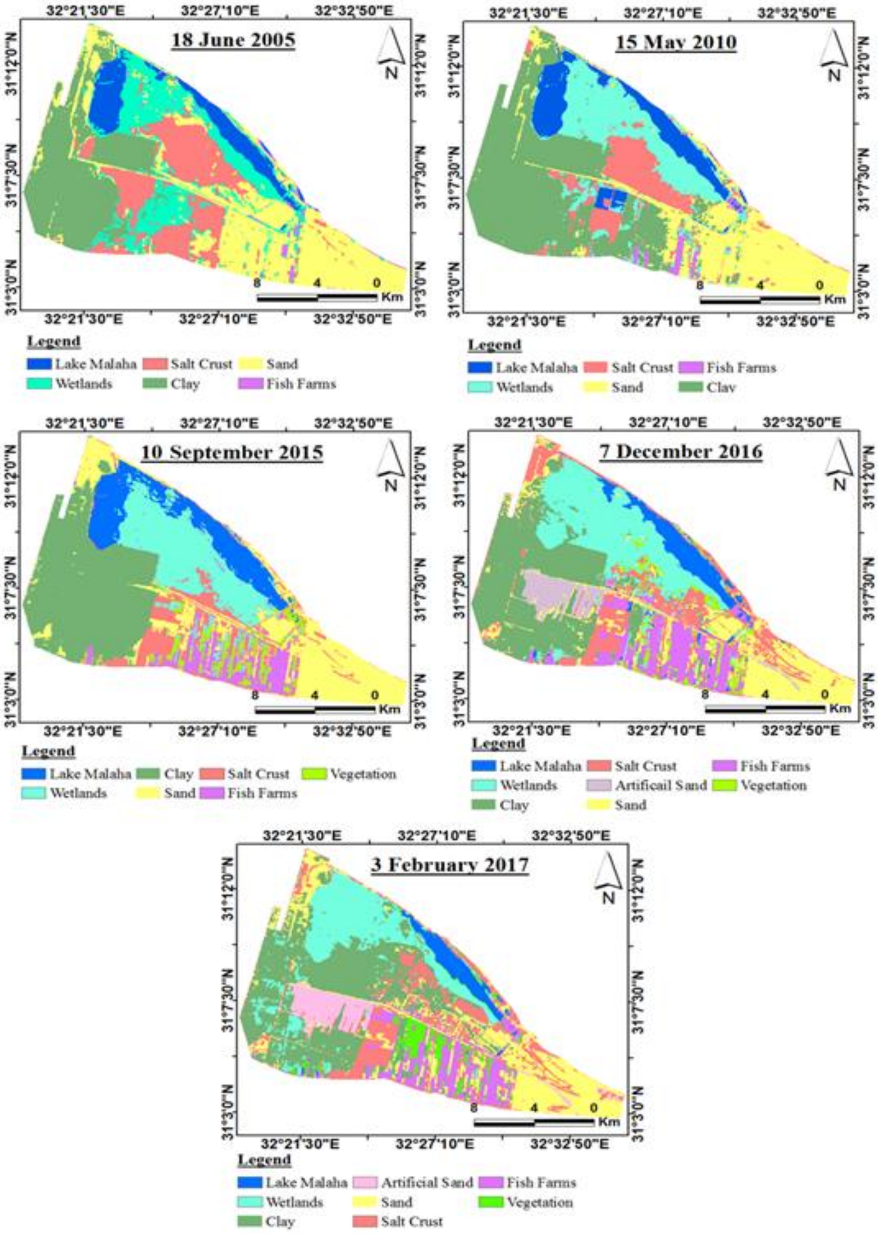

Figure.4. Supervised classification of images for 2005, 2010, 2015, 2016 and 2017

4.3. Post Processing: The analysis of LU/ LC of the study area for 2005, 2010, 2015, 2016, 2017 images reveals eight major classes (Fig.4) that were verified in the field. These classes are lake Malaha, wetlands, clay, artificial sand, sand, salt crust, fish farms and vegetation.

As showed in table (1): -

Table.1. Change in areas of different land cover classes for 2005, 2010, 2015, 2016 and 2017 classified images

	2005	2010	2015	2016	2017
Lake Malaha	20.5	24.6	29.2	13.9	8.8
Wetlands	44.9	43.8	45.1	50.7	39.6
Salt Crust	48.4	28.4	23.5	34	34.8
Clay	59.9	95.9	75.1	65.6	74.6
Artificial Sand	---	---	---	11.9	13.7
Sand	74.8	54.8	51	41.5	49.1
Fish Farms	2.5	3.4	17.5	25.3	21.2
Vegetation	---	---	9.7	8.1	9.1

In 2005, the area of Lake Malaha was 20. 5 km2, wetlands area was 44.9 km2, salt crust was 48.4km2, clay area was 59,9 km2, sand area was 74.8km2 while no artificial sand in 2005, also no vegetation appeared in image of 2005 and fish farms area was 2.5km2. In 2010, the area of Lake Malaha was 24.6km2, the area of wetlands was 43.8km2, this meant that the areas of the lake increased from 2005 while wetlands decreased. Salt crust area was 28.4 km2, clay area was 95.9km2, sand area was 54.8km2 while no artificial sand in 2010 also no vegetation appeared in image of 2010 and fish farms were 3.4 km2. In 2015, the area of Lake Malaha was 29.2km2, it increased about 4.6 km2 from 2010. Wetlands area was 45.1km2, it increased about 1.3 km2 from 2010. Salt crust area decreased, it was about 23.5km2.While the area of clay was 75.1km2, sand area was 51km2, also there was no artificial sand in 2015, fish farms increased in 2015 with an area 17.5 km2 and vegetation appeared with an area about 9.7 km2. In 2016, there was a big change and a significant decrease in the area of Lake Malaha whereas it was 13.9km2, it decreased about 15.3 km2 within only one year. While the area of wetlands was 50.7km2, it increased from 2015. Salt crust area was 34km2, it also increased from 2015. Clay area was 65.6km2, artificial sand appeared in 2016 due to the human activities, it was about 9.79 km2, sand was 41.5km2, fish farms area was 25.3km2, it increased about 7.8 km2 from 2015 and this showed the changes and the expansions which occurred in the eastern area of Port Said and vegetation area was 8.1km2. In 2017, the decreasing in the area of Lake Malaha was continuous, Lake Malaha area was 8.8km2, this meant the area of the lake decreased about 5.1 km2 within a very short period of time. Also, the area of wetlands was 39.6km2, it decreased about 11.1 km2 within the same period. Salt crust area was 34.8km2, it increased from 2016. Clay area was 74.6km2, artificial sand area was 15.17 km2 while sand area was 49.1km2, the area of fish farms was about 21.2km2 and vegetation area was 9.1km2.

5. CONCLUSION:

This paper focused on the temporal change of water bodies for Lake Malaha East Port-Said, Egypt, using remote sensing techniques and geographic information systems.To monitor the changes in LakeMalahs, images of the Landsat ETM+ and OLI/TIRS images acquired on 2005, 2010, 2015, 2016 and 2017 were used. Envi and ArcGIS software are used in this study for processing of the images, classification technique was used. Eight classes are detected including lake Malaha, wetlands, clay, artificial sand, sand, salt crust, fish farms and vegetation. In 2015, the area of Lake Malaha was 29.2km2, it increased about 4.6 km2 from 2010. Wetlands area was 45.1km2, it increased about 1.3 km2 from 2010. Salt crust area decreased, it was about 23.5km2.While the area of clay was 75.1km2, sand area was 51km2, also there was no artificial sand in 2015, fish farms increased in 2015 with an area 17.5 km2 and vegetation appeared with an area about 9.7 km2.In 2017, the decreasing in the area of Lake Malaha was continuous, Lake Malaha area was 8.8km2, this meant the area of the lake decreased about 5.1 km2 within a very short period of time. Also, the area of wetlands was 39.6km2, it decreased about 11.1 km2 within the same period. Salt crust area was 34.8km2, it increased from 2016. Clay area was 74.6km2, artificial sand area was 15.17 km2 while sand area was 49.1km2, the area of fish farms was about 21.2km2and vegetation area was 9.1km2. Finally, we recommended that a lot of interest is given for Lake Malaha and great efforts and cooperation between different authorities are needed to protect the lake from any pollution, conserve and maintain it.

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