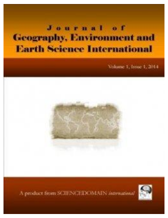

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Identifying Land Use Change Trends Using Multi-temporal Remote Sensing Data for the New Damietta City, Egypt

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Authors' contributions

This work was carried out in collaboration between all authors. Authors MA and SMA selected the study area, planned the field trips, reviewed the scientific findings and revision of the drafted manuscript. Authors EF and MN carried out the image processing, classification accuracy, and final maps production. Author KA wrote the manuscript with collaboration of authors EF and KA was the corresponding author and he was responsible for the suggested changes and editing by the respected anonymous reviewers. All authors read and approved the final manuscript.

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ABSTRACT

The current study aims to utilize the use of multi-remote sensing data for land use land cover changes and trend analysis for the New Damietta city in Damietta governorate. Three different sensors were used in this study in different dates (SPOT-4 2007, SPOT-5 2011, and Kanopus-V1 2016). The FAO classification system (FAO-LCCS) was used to identify the different land use/cover classes in the study area. Results showed 13 main land use/land cover classes exist in the study area. The land use/land cover maps are produced for 2007, 2011 and 2016 with overall accuracies of 0.91, 0.92, 0.91 and kappa statistics of 0.88, 0.86 and 0.89 respectively. Results revealed that four different classes had a significant change over the study period. These classes are urban areas, cultivated lands, fish farms and bare areas. Trend analysis revealed that urban areas had the

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highest increase rate (+2.76 km2/year short term & +2.73 km2/year long-term) while cultivated land and bare areas suffer from the highest decrease rates (-1 km^2/year short and long-term, -1.54 km^2/year short-term and -1.59 km^2/year long term respectively).

Keywords: Land cover; change detection; SPOT; Kanopus; remote sensing.

1. INTRODUCTION

Coastal cities are the most populated areas worldwide. It accommodates approximately one-third of the world population [1]. Moreover, it contributes significantly to the national GDP worldwide due to the existent resources and the role it plays in the world trade [2]. Many coastal cities possess a population and a GDP growth higher than their national averages [3,4] which encourage the internal migration leading to a strong urbanization demand [5]. In addition to the coastal hazards that threaten these developments, human activities put more pressure on the ecosystems found in the coastal zone which produces adverse impacts on the coastal areas [6]. Damietta governorate is one of these coastal cities. It is located on the northeast coast of the Nile Delta, Egypt. The high development rate characterizes the city which suffers various problems and threats. Problems that have been identified in this area are mainly because of the mismanagement of water, soil, and the coastal resources, which led to the deterioration of the existing agriculture lands [7] (EEAA, 2016). Land cover characterization is a key factor in a wide range of applications such as climate modeling [8,9], water quality monitoring and assessment [10,11], urban heat islands [12, 13], soil erosion and land degradation [14]. Land cover changes are mainly induced by a human and/or natural process [15]. Monitoring and mapping land use/cover is essential to support decision makers in planning the best development scenarios. Land use/land cover change analysis has become a basic need in any current strategic study [16]. FAO-LCCS [17] is considered as one of the most comprehensive and standardized widely used classification schemes. Moreover, independently of the scale the LCCS designed to meet the specific user requirements.

Remote sensing technologies play an important role in resource monitoring and mapping. Various spaceborne sensors and satellite imaging instruments have been used in the land cover/use mapping. The choice among these sensors is limited by many factors, e.g., spatial and temporal resolutions in addition to cloud cover percentage; those factors control the availability of the data [18]. Among the advantages of using remote sensing data is the ability of landscape monitoring at large scales [19,20], temporal quantification using different digital change detection techniques [21]. Recently different remote sensing platforms and sensors launched and operated with free of charge data access with high improvements of spatial and spectral resolutions. Over the last two decades various change detection techniques have been developed. [22,23] summarized different change detection algorithms. [24] compared several change detection methods (traditional post-classification cross tabulation, cross-correlation analysis, neural networks, knowledge-based expert systems, and image segmentation and object-oriented classification). Each of these classification methods tested for mapping defined classes, results showed that no single approach could solve the heterogeneous land use/cover change detection problems.

This study aimed to provide land cover/land use change trends by the use of remote sensing techniques. A vector-based comparison was employed for the detection of different classes, especially in agricultural land to provide decision-makers with the historical and *in-situ* required geographical information for the implementation and development scenarios for sustainable resources management. Moreover, quantifying the change and change trends in the predominate changing classes.

2. MATERIALS AND METHODS

2.1 Study Area

The study area is located in the northeastern part of Damietta Governorate. It is one of the Mediterranean coastal cities at longitude 31°30' to 32°5' E and latitude 31°20' to 31°35' N. The area extends about 12 km offshore the coastline of Damietta, covering a total area of approximately 390 km^2 (Fig. 1). The study area has typical Mediterranean conditions which are highly heterogeneous and small-structured ecosystems, often interwoven with cultivated areas [25]. The economic activities in the city depend on its location as a coastal city, climate, local water and land resources. Large areas are used for fishing activities in Manzala Lake and the Mediterranean Sea. The existing agriculture lands are cultivated either by field crops or horticulture crops. In addition to the Damietta port which is one of the biggest commercial ports in Egypt on the Mediterranean coast.

2.2 Remote Sensing Data

Three different remote sensing satellite images were used in this study. These were a SPOT-4 HRVIR image acquired in the 26th of August 2007, SPOT-5 image acquired in the 18th of March 2011 and Kanopus-V1 image acquired in the 7th of September 2016. These three satellites are different in their spatial and spectral characteristics as shown in Table 1. Data availability played an essential role in this study since SPOT-4 considered as a medium resolution satellite with pixel size of 20 m, on the other hand, SPOT-5 and Kanopus-V1 are fine resolution satellites with 10-12 m for multispectral bands and 5-2.5 m for panchromatic band respectively.

2.3 Field Study

Ground truthing data was collected during the field visit to the study area which was necessary for the understanding of the area landscape and investigating the possible human activities that might exist. About 78 different locations, located on the main roads and open access areas, have been visited and information about the current land use/land cover activities have been recorded (Fig. 2). This information was very helpful in defining the land use/land cover classes and assessing the classification accuracy.

2.4 Image Pre-processing

The Satellite images were displayed and visually examined for any probable signature degradation or noise. The images were atmospherically [26] and radiometrically [27,28] corrected. The radiometric correction was done using the histogram equalization method, and the atmospheric correction was done using the quick atmospheric correction (QUAC) algorithm.

2.5 Defining the Land Cover Classes

Based on the prior knowledge about the study area from the field visit, the land cover classes have been divided into two levels. The first level is a low-level detail, includes four mainland cover categories (vegetated areas, aquatic non-vegetated areas, unbuilt-up areas and built-up, areas). The second level is a high-level detail includes all the possible subcategories for each mainland cover category as shown in Table 2.

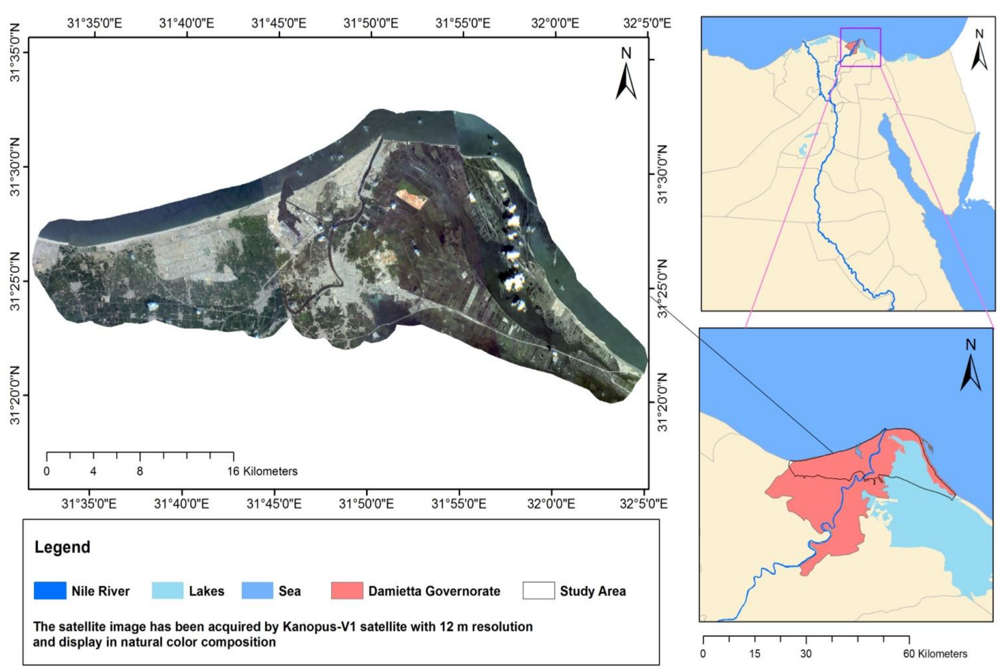

Fig. 1. Location of the study area

Table 1. Spatial and spectral characteristics of satellite images used in the study

Satellite name	Band name	Spectral range	Spatial resolution
SPOT-4 satellite			
	Green	0.50 - 0.59 µm	20 m
	Red	0.61 - 0.68 µm	20 m
	Near IR	0.79 - 0.89 µm	20 m
	Pan	0.61 - 0.68 µm	10 m
	SWIR	1.58 - 1.75 µm	20 m
SPOT-5 satellite			
	Pan	480-710 nm	5m
	Green	500-590 nm	10m
	Red	610-680 nm	10m
	Near IR	780-890 nm	10m
	Shortwave IR	1,580-1,750 nm	20m
Kanopus-V 1 satellite			
	Pan	0.52-0.85 µm	2.5
	B1	0.54-0.60	12
	B2	0.63-0.69	12
	B3	0.69-0.72	12
	B4	0.75-0.86	12

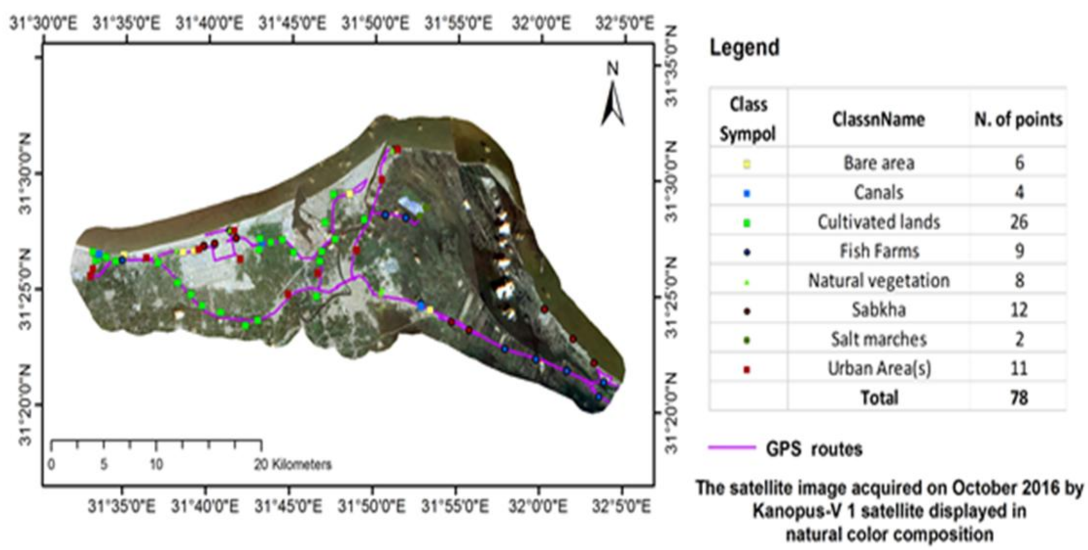

Fig. 2. The geographical distribution of the ground control points GCP's

Table 2. Land use/land cover categories description

The first level	The second level
Vegetated areas	*Cultivated lands and natural vegetation.*
Aquatic areas	*Fish farms, lakes, and Nile river*
Unbuilt-up areas	*Bare areas, coastal sand plains, sand spit, sabkhas and salt marshes*
Built-up areas	*Urban areas*

2.6 Images Classification

The k-means unsupervised classifier, with 100 of initial classes, has found to be more efficient approach for discriminating between some problematic subcategories which have similar spectral characteristics such as bare areas, sabkhas, and salt marshes. K-means is one of the data clustering analysis methods which aims to discover the natural grouping(s) of a set of pixels in the image. The K-means algorithm requires the user to specify the number of clusters (K) expected to exist in the data which helps the algorithm to calculate the initial empirical means of the clusters [29]. Different numbers of initial classes have also been tested. The 100 classes were found to be the more suitable number to achieve the highest separation between different subcategories.

2.7 Post-classification Process

After image classification post classification were necessary to minimize the high number of classes (100). Post classification included merging similar classes into one class that they are part of. In this study urban areas were found distributed over 30 classes according to the building characteristics. Some of these classes were pure some other classes were difficult to be separated through the classification process (e.g. urban/bare soil, natural vegetation /cultivated lands, bare areas/coastal sand plains and sand spits, the fish farms from the lake) due to their similar spectral characteristics). Therefore, by using the field points and Kanopus-V1 high-resolution imagery, these subcategories have been digitized, in addition to the main roads and canals network. The new layers have been merged with the other classes to generate the final land use maps (Fig. 5).

2.8 Generating the Ground Truth Points

A set of 161 points has been randomly generated (Fig. 3) to cover the study area. The generated points have been labeled based on the data collected from the field and with the help of high-resolution imageries available on Google Earth. This set of points has been used later to assess the generated maps and to report the classification accuracy.

2.9 Accuracy Assessment

The accuracy of resulted maps has been assessed using the generated ground truth points. The error matrix has been calculated in order to estimate the user, producer and overall accuracies in addition to the Kappa coefficient for the three classified maps.

2.10 LUCC Trend Analysis

Trend analysis is essential to prioritize the main changing class and how fast it changed. In this study, two trends were estimated, long-term (2007-2016) and short-term (i.e. the average of the two intervals of the study periods 2007-2011 & 2011- 2016). Trends were calculated by dividing the net change in each class by the number of the years between the two used dates.

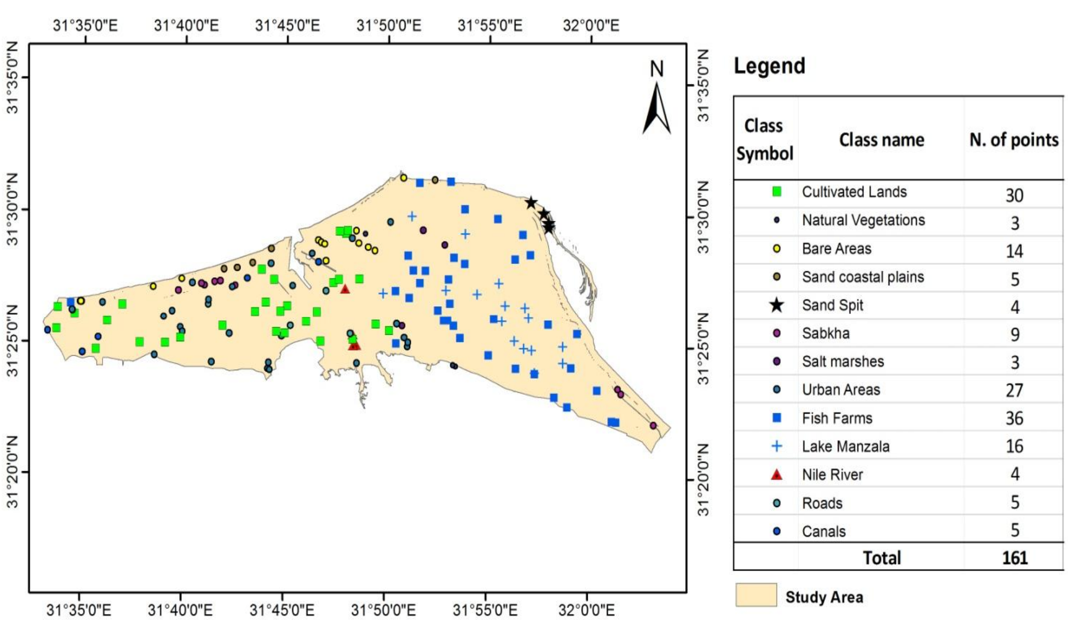

Fig. 3. The geographical distribution of the ground truth points GTP's

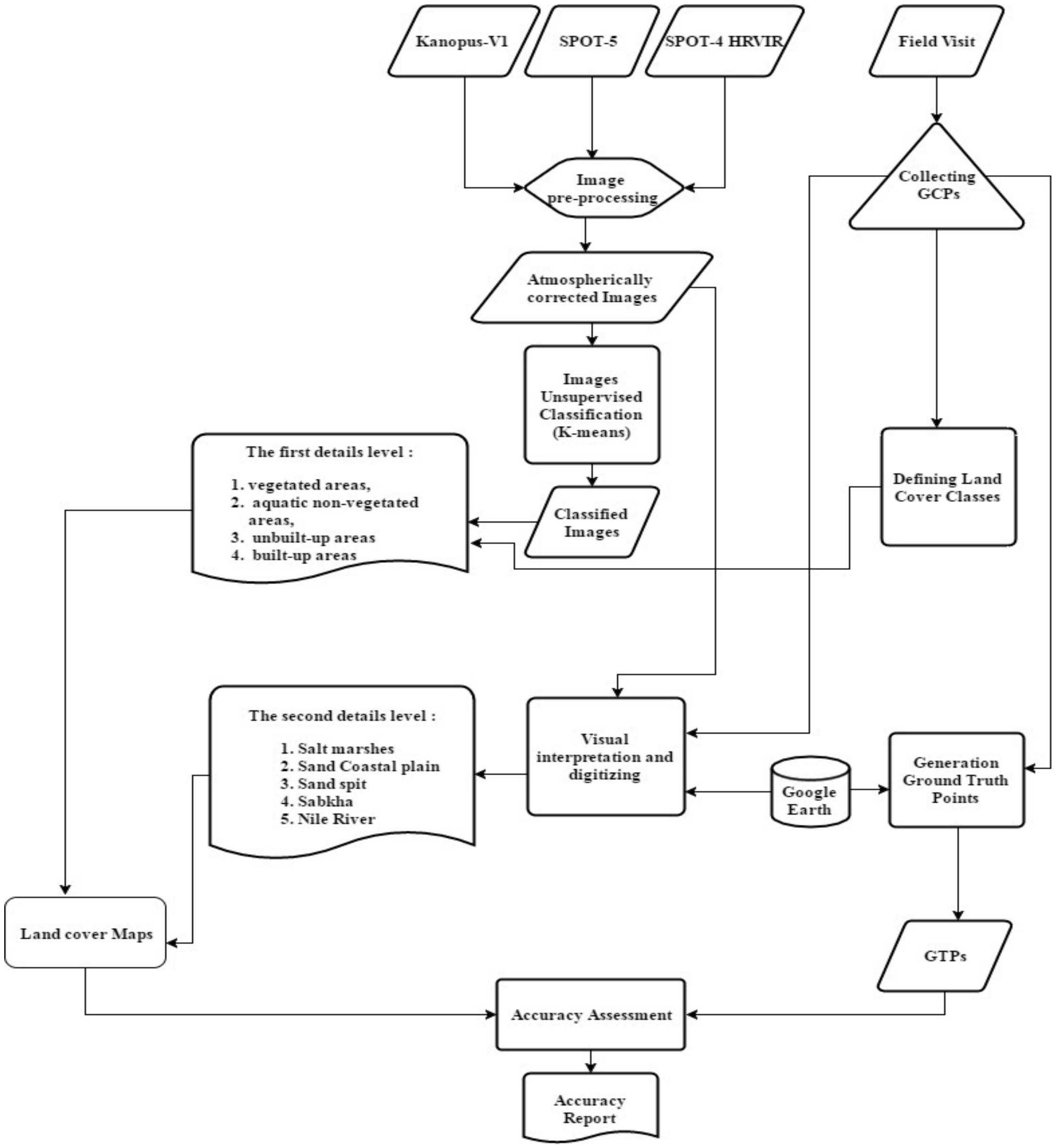

Fig. 4. Flow chart of the methods and data analysis

3. RESULTS AND DISCUSSION

3.1 Accuracy Assessment

The accuracy assessment of the produced maps was calculated in addition to Kappa statistics. The overall accuracy is ranging between 91% to 92%, and kappa statistics from 0.86 to 0.89 showed in Table 3. As expected, the digitized features such as salt marshes, coastal sand plains, sand spits, Sabkhas, Nile River, canals, and roads were most accurate.

3.2 Image Classification

As prescribed in the above section (Table 2) the classes are divided into two levels, the main classes and the subcategories producing 13 different classes. Fig. 5 represents the produced maps for LUCC for a) 2007, b) 2011, c) 2016. The dominant classes in the study area are the fish farms, cultivated areas, urban areas and Lake Manzala.

Table 3. Accuracy assessment report for the three classified maps

Class name	2007		2011		2016	
	Producer	User	Producer	User	Producer	User
Cultivated lands	0.85	0.92	0.86	0.88	0.93	0.85
Natural vegetation	0.85	0.8	0.8	0.79	0.8	0.8
Bare area	0.7	0.85	0.82	0.81	0.64	0.9
Salt marshes	1	1	1	1	1	1
Coastal sand plains	1	1	1	1	1	1
Sand spit	1	1	1	1	1	1
Sabkhas	1	1	1	1	1	1
Urban area(s)	0.71	0.81	0.75	0.82	0.75	0.82
Fish farms	0.95	0.82	0.91	0.83	0.94	0.87
Lake Manzala	0.82	0.9	0.84	0.92	0.81	0.87
Nile River	1	1	1	1	1	1
Canals	1	1	1	1	1	1
Roads	1	1	1	1	1	1
Overall accuracy	0.91		0.92		0.91	
Kappa statistics	0.88		0.86		0.89	

Where:
Producer: total number of correct reference points/ total reference points, expressed the error present of the total number of Ref. points.
User: total number of correct classified pixels/total number of pixels, expressed the error of the total map.

Fish farm is the dominant activity in the study area (30% of the total area), cultivated land comes second with approximately 25% and urban areas contribute roundly 13% of the total area. Although Lake Manzala is almost equal to the urban areas in its area, many authors confirmed that all the fish farming lands were part of the Lake Manzala which is legally or illegally transferred to fish farms.

The LULC produced maps were used to estimate area of each class. Data illustrated in Table 4 quantify the area of these classes in the three different dates of the study. As discussed earlier, the fish farm class is the major class with increasing area (120.6, 127, 128 km^2 in 2007, 2011 and 2016 respectively) in contrast to the cultivated land class which is decreasing (102.4, 95.5 and 93.2 km^2 in 2007, 2011 and 2016 respectively). The urban development is growing rapidly in the study area. It was 51.1 km^2 in 2007, and almost increased approximately by 50% of its area in 2016 (75.5 km^2). One should shed light on the bare areas which approximately vanish in the study area. In 2007 it was 14.4 km^2 while in 2016 it was 0.5 km^2.

The coastal sand plains are most important in the coastal areas as it is a home for living and breeding for mammals. In the current study coastal sand plains area is decreasing (15.5 km^2 in 2007 & 10 km^2 2016) although it is protected by the law of wetland and marine protected areas. This might reflect the unplanned illegal activity in the study area which threatening the development and sustainable management of the existing ecosystems [30].

Table 4. Area of land cover classes for 2007, 2011 and 2016

LUCC	Area (Km^2)		
	2007	2011	2016
Cultivated lands	102.4	95.5	93.2
Natural vegetation	4	4.2	4.2
Bare area	14.4	6.3	0.5
Salt marshes	8.5	8.5	8.5
Coastal sand plains	15.5	13.5	10
Sand spit	4	4.3	4
Sabkhas	6.1	5.7	4.3
Urban area(s)	51.1	63.1	75.7
Fish farms	120.6	127	128
Lake Manzala	51	49.4	48.9
Nile River	4.2	4.2	4.2
Canals	1.4	1.5	1.5
Roads	6.8	6.8	7

The spatial distribution of losses in the cultivated land is represented in Fig. 6. Most of these losses are scattered areas focused around the urban areas and/or are approximate to roads and canals network which are the main factors catalysis the urbanization of agricultural lands [31]. Fig. 7 illustrates the spatial distribution of urban areas in the different studied dates. Unlike the cultivated land, urban areas gains are in batches and scattered spots. The batched areas reflect the urban planning development in the New Damietta city while the scattered spots represent the illegal urbanization activity which should be controlled via firm legalization [31].

The LUCC dynamics are very important in the process of decision making and any planned development. Fig. 8 represents the interaction between the different LUCC classes in the study area. It is very clear that the urban development is the most growing class it gained 24.6 km^2 over the past ten years. In the second-place fisheries activities come as a gaining class. It gained 7.4 km^2. This may be due to the fact that the fisheries activity is most economically suitable practices, which reflects the nature of the resources exists in the study area as a coastal city in addition to the existence of Manzala Lake. On the other hand, there are five losing classes (bare areas, cultivated land, coastal sand plains, Lake Manzala and sabkhas area) which are decreased by (13.9, 9.2, 5.5, 2.1 and 1.8 km^2) respectively. Most of the losses in the cultivated land may be explained by the urban expansion, which takes place by unplanned illegal activities. In the same way, fish farms cut areas from Manzala Lake illegally which costs the country extra money in the monitoring and restoration of these land to its normal case [32].

3.3 Trend Analysis

Trend analysis is crucial for any spatial development. It provides information about the spatial dynamics of surrounding environment. In the current study, one of the important indicators is the urban development rate which is the highest (+2.76 km^2/year short term & +2.73 km^2/year long-term) among all the other activities. This fact confirms that in the coming 25 years' urban area will be doubled, i.e. (150 km^2)

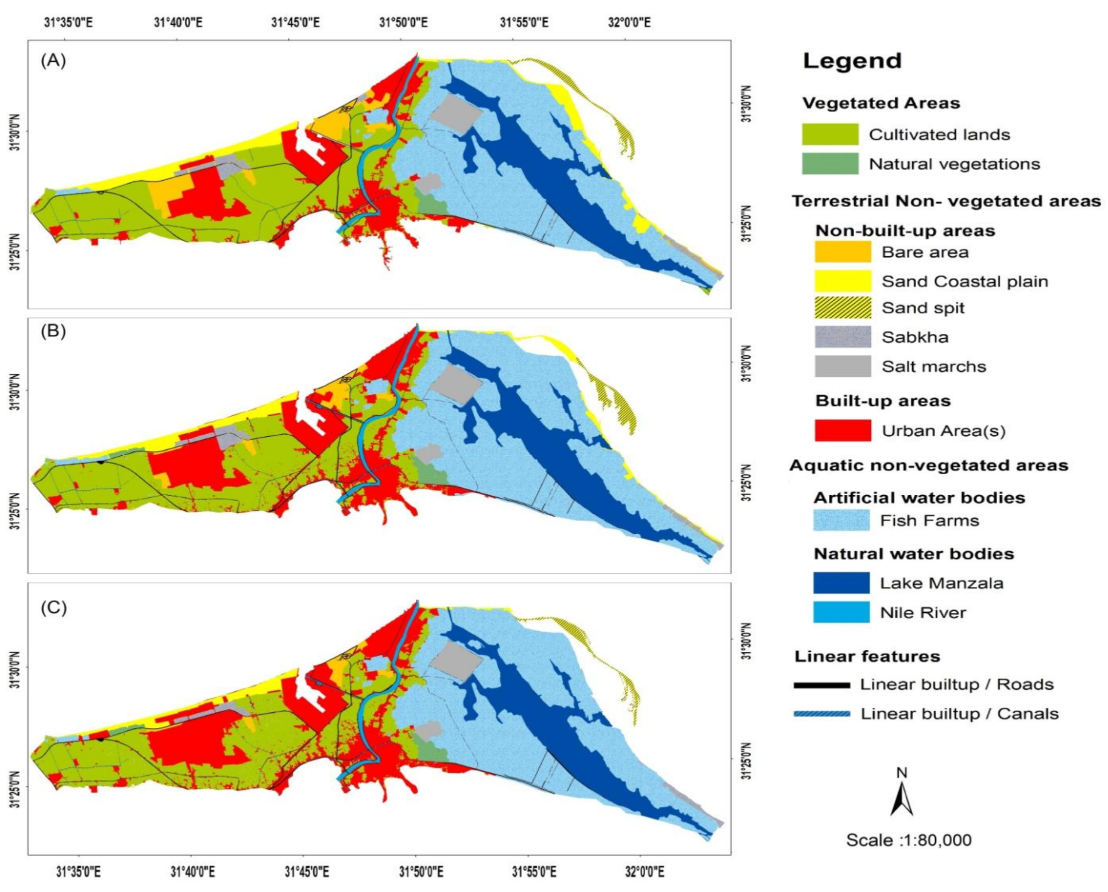

Fig. 5. (A) Land cover/land use 2007, (B) land cover/land use 2011and (C) land cover/land use 2016

which approximately 40% of the study area. In contrast to urban areas, the cultivated land and bare areas suffer from the highest rate of change which is (-1 km^2/year short and long-term for agriculture and -1.54 km^2/year short-term and -1.59 km^2/year long term for the bare areas). Considering that, the bare areas are vanishing (0.5 km^2), this will accelerate the rate of loss of the cultivated lands. Lake Manzala also suffers from illegal area shrinking by approximately (0.25 km^2/year).

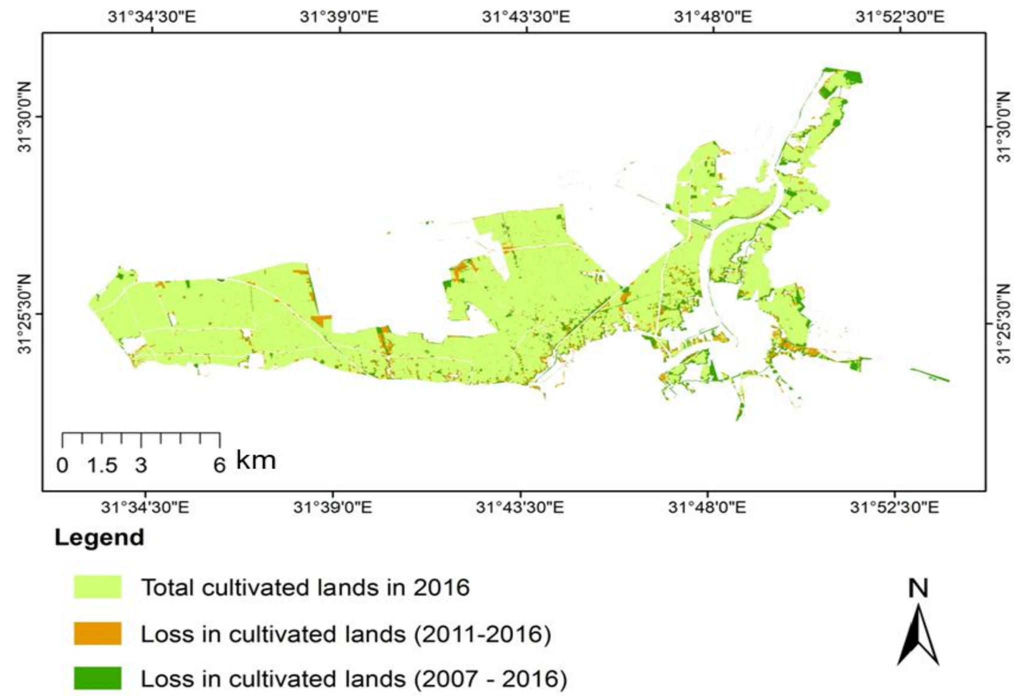

Fig. 6. Change detection of cultivated lands from 2007- 2016

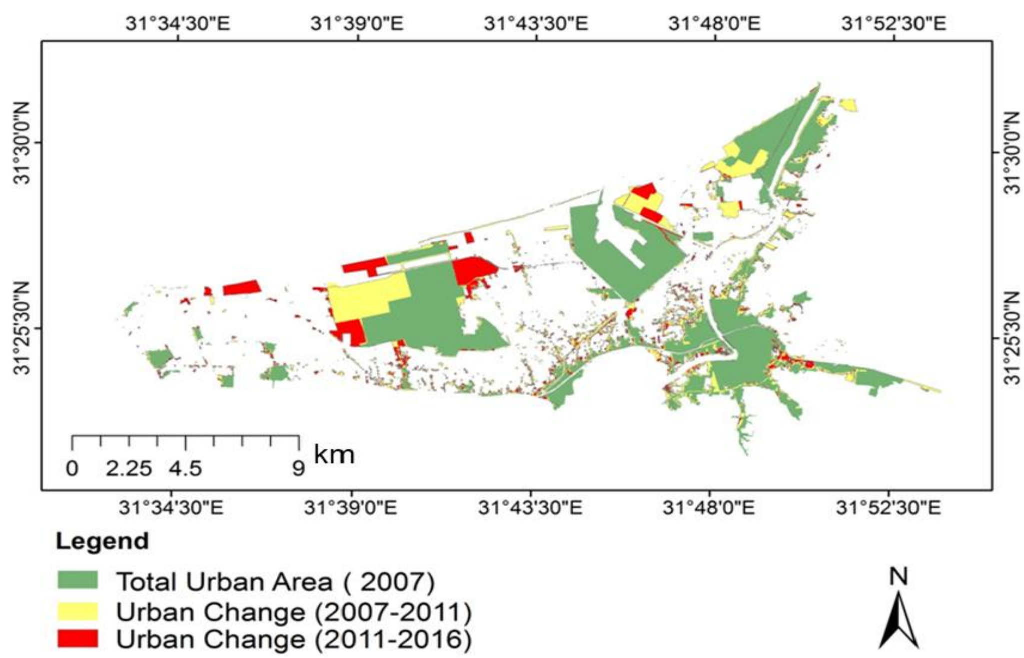

Fig. 7. Change detection of urban areas from 2007-2016

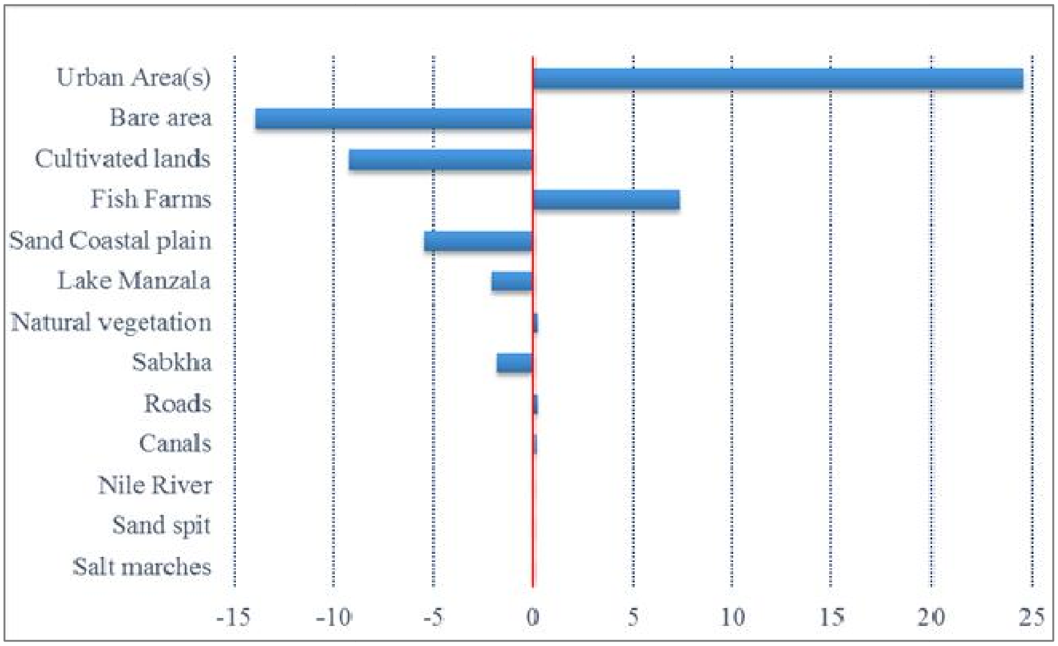

Fig. 8. Gain and loss areas for different land cover/land use classes from 2007 to 2016 (km^2)

4. CONCLUSION

This research was mainly oriented to map and quantify the different land cover/ land use classes from a different high-resolution satellite in different dates with the determination of the change trend to each class. The results showed that 13 main land use/land cover class exists in the study area. Four dominant classes had a significant change in the study area for the period of study these classes are area urban area, fish farms as gaining classes and cultivated lands, bare area as donating classes. Furthermore, the trend analysis emphasizes that the urban areas are going to be doubled in the next coming 25 years and the excepted gains will be on the agriculture share hence the bare areas are mostly finished according to this study finding in the case of no action is implemented by the local authorities. One of the interesting results of this work is the fish farms expansion which comes on the Lake Manzala share. This may lead to the disappearance of this water body in the coming 200 years. Apart from the finding of the current investigation is the weak legalization and monitoring system in the study area. Although the different legalization the area shares (i.e. protected area legalization, integrated coastal zone managements legalization etc.) the area suffers from the various illegal activities. This puts stress on the stack holders and decision makers to positively activate and fill the gaps in the current monitoring system and/or legalizations. Moreover, the different monitoring authorities are in need to draw an effective integrated implementation plan to enable integrated sustainable management in the study area.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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