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USING VISUAL TECHNIQUES TO DETERMINE THE CHANGES IN THE NORTH COAST

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***Abstract**: Building new cities at the fringes of old ones is a mandatory nowadays to lower the over increasing population in old cities, and to decrease the heavy load on the infrastructure and services. The main objective of this work was to evaluate the spatial and temporal changes in land uses within the studied area by using Remote Sensing (RS) and Geographic Information Systems (GIS) data and techniques. This is in addition to providing accurate estimations of current land uses to support decision makers with the right information for further development. Accordingly, Landsat TM images in 1984 and 1999 and Landsat 8 in 2014 were used in this study. Normalized difference vegetation difference index (NDVI) was used to map agricultural versus non - agricultural lands. Also, the modified normalized difference water index (MNDWI) was used to map dry lands versus wet lands (Fish pounds) in the area. The obtained results indicated that agricultural lands were increased by about 23.1 km^2 from 1984 to 1999 and by about 30.1 km^2 from 1999 to 2014. The total increase in agricultural lands in 30 years from 1984 to 2014 was about 53.2 km^2. That increase in agricultural lands was due to land reclamation projects north of Nile-Delta. On the other hand, water features were increased by about 16.3 km^2 from 1984 to 1999 and by about 23.0 km^2 from 1999 to 2014. The total increase in Water features from 1984 to 2014 was about 39.3 km^2. That increase in water features was mainly due to the development of fish pounds. Land use classification derived from the gap-filled Landsat SCL-off image acquired in 2009 was more accurate when the gap-filling was carried out by using the Landsat gap-fill plug-in ENVI than using the Matlab. The overall accuracy of the gap-filled images was not very high, where the gap-filling algorithms could not retrieve the actual pixel values but interpolate them.*

***Keywords:** Land cover, land use, NDVI, MNDWI, change detection, Gap-fill, Remote sensing, GIS.*

1 Introduction

The policy of the Egyptian government is to create new cities at the fringes of old cities, which are currently over populated and lake to the infrastructures and facilities that could serve the increasing of the population density, which is to withdrawal some of the population from the old cities. Also, create new services such as educational, health, tourist, transportation, governmental and accommodation in the new city to lower the heavy loads on these services within the old city.

1.1 Remote Sensing

Remote sensing data plays an integral role in evaluating and monitoring the environment and its components. It is used for monitoring spatial and temporal changes in land use over time, which is required to determine trends in land conditions, these conditions becoming either worse, better, or non-changed. In the change detection process, multi-temporal datasets are used to quantitatively analyze the temporal effects of the phenomenon (Lu et al, 2003, Elnaggar, 2013, Kedy, et al., 2015). Four important aspects were reported in change detection. These aspects are: detecting the changes that were occurred, identifying the nature of the change, measuring the real extent of the change, and assessing the spatial pattern of the change (RTO, 2007).

1.2 Digital Image Analysis

Digital image analysis consists of several techniques, which are used to increase the performance and efficiency of satellite images. This paper uses: image correction, Gap-filling of Landsat Scan Line Corrector off (SLC-off) error, and Studied Indices.

1.2.1 Image correction

Studied images were atmospherically and radiometrically corrected to eliminate the atmospheric interferences (dust, haze, smoke, etc). After that, they were geometrically corrected using the polynomial method.

Landsat Gap-Fill

The Landsat 7 (ETM+) sensor experienced a Scan Line Corrector off (SLC-off) error after May 31, 2003. Since that time all ETM+ images have had wedge-shaped gaps on both sides of each scene, resulting in approximately 22% data loss. The gaps can be filled through the application of different techniques.

1.2.2 Spectral Indices

Spectral indices are commonly used in a wide variety of fields (i.e., agriculture, geology, hydrology, etc). They are used to make emphasis on certain features within the studied image. Examples of theses indices are the Normalized Difference Vegetation Index (NDVI) and the modified normalized difference water index (MNDWI), which were used in this work.

1.2.2.1 NDVI

NDVI is the most commonly used vegetation index around the globe [Rouse et al, 1974]. The NDVI correlates significantly with the amount of green leaf biomass (Tucker 1979).

1.2.2.2 NDWI

The normalized difference water index (NDWI). This water index was developed based on the fact that water strongly reflects electromagnetic radiation in the short wavelength range of spectrum and absorbs energy at near-infrared (NIR) and shortwave-infrared (SWIR) wavelengths of spectrum [McFeeters 1996]. Xu (2006) found that McFeeters' NDWI was unable to completely distinguish built-up or urban areas from water features. He noticed that the NDWI showed positive values in built-up areas which were similar to water because the reflectance in the NIR portion of spectrum was lower than the reflectance in the visible green. As a result Xu (2006) made a modification on the McFeeters' NDWI and called it the modified NDWI (MNDWI). In the MNDWI the SWIR band was used to replace the NIR band in McFeetes' NDWI. The MNDWI was used in this work to distinguish water features in the studied area against dry lands.

The main objective of this work was to evaluate the spatial and temporal changes in both vegetation and water features within the studied area by using RS and GIS data and techniques.

2 Materials and Methods

This section includes a description of the study area, used sources of data, data analysis and their manipulations.

2.1 Studied Area

Studied area is located in Egypt, northern of the Nile-Delta on the Mediterranean Sea, western of Gamassa city. Location's coordinates are: 31° 13' 42.85" E, 31° 33' 29.762" N and 31° 32' 55.044" E, 31° 21' 7.121" N (Figure 1). It covers an area of about 301 km^2. Maximum temperature in the studied area varies from 35.3 °C in summer to 20.1 °C in winter. Minimum temperature ranges between 20.2 °C in summer and 7.5 °C in winter. Total precipitation varies from 29.2 to 72.3 mm. Elevation varies from 0 to 45 m above the sea level (ASL), with an average elevation of 8.3 m ASL. Geology of the studied area includes Sabkha-deposits, and sand dunes (CONOCO, 1989).

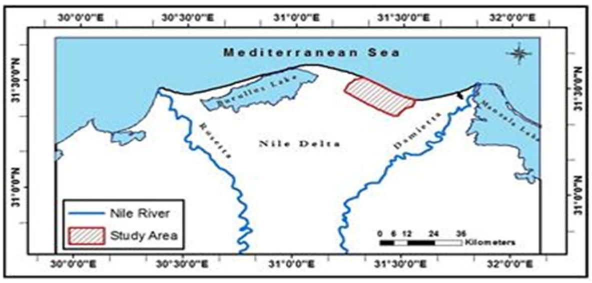


Figure 1: Location map of the studied area.

2.2 Landsat Data

Studied area was covered by Landsat images (path 176, row 38). A total of three Landsat images were used to study the spatial and temporal changes in agricultural lands during 1984, 1999 and 2014. Table 1; shows the Acquisition dates of the studied Landsat images.

Table 1: Acquisition date and type of sensor for the studied Landsat images.

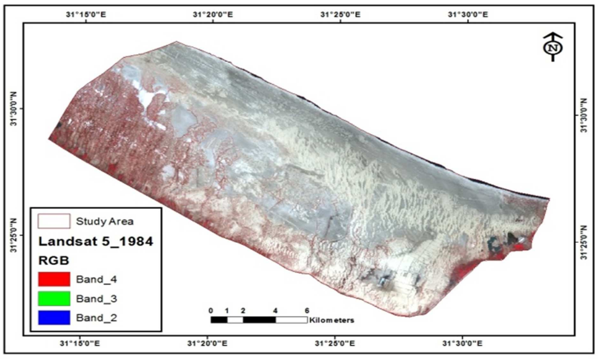
Image	Sensor	Acquisitio
1984	Landsat	30/9/1984
1999	Landsat	13/8/1999
2014	Landsat	6/8/2014

2.3 Digital image analysis:

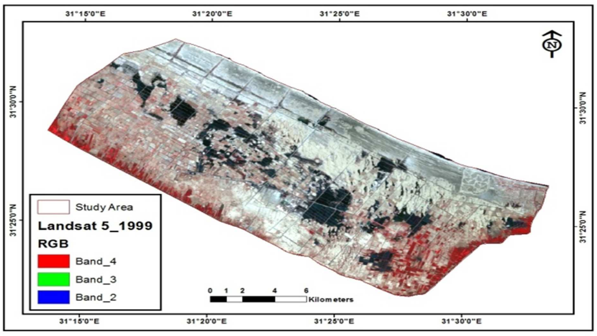
The paper presents the image correction ,Gap-filling of Landsat Scan Line Corrector off (SLC-off) error, Studied Indices, ,Gap-filling of Landsat 7 image acquired in 2009, Estimation of Agricultural land and Water Features, Change Detection in Agricultural lands and Water Feature, Flowchart of data analyses and manipulations.

2.3.1 Image correction

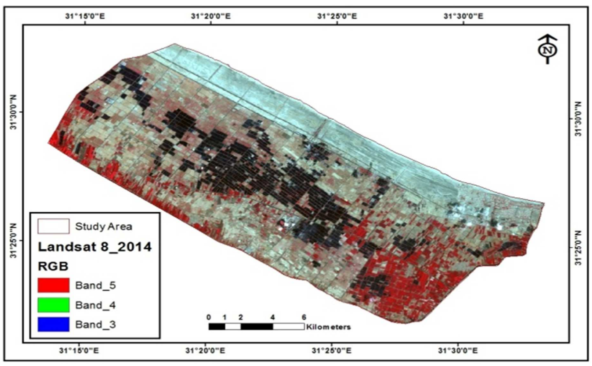
Atmospheric correction was carried out by using the dark-object subtraction method in Envi software package. Radiometric correction was done by converting the pixel's DN values into top of atmosphere reflectance. All images were projected to have the same projection (UTM, Zone 36N, Datum WGS 1984) and pixel size of 30 meters. Each image for each of the studied dates was subsetted to cover the studied area. A false color composite (FCC) of the studied images is represented in Figure 2.



a) 1984



b) 1999



c) 2014

Figure 2: FCC of the studied Landsat images.

2.3.2 Gap-filling of Landsat SCL-off images

Landsat ETM+ data acquired after May 31, 2003 experience a Scan Line Corrector (SLC) failure. Consequently, gaps in Landsat images acquired in 2009 were filled by using two approaches: Landsat gap-fill plug-in with the ENVI software package (ver. 4.7), and gap fill algorithm developed in the Matlab software package (ver., 14). In this work the accuracy of the two approaches in classifying land uses within the studied area was compared.

2.3.3 Studied Indices

Each of the NDVI and MNDWI image were visually inspected to come up with a threshold value that accurately distinguishes agriculture from non-agriculture land-covers and water features from dry lands. Several points, especially at the boundaries of the studied land uses were investigated for identifying the critical threshold value. Soon after the threshold value was determined for the NDVI and MNDWI images a binary or a two-class image was developed for each year. Normalized Difference Vegetation Index (NDVI) was used to study the changes in vegetation cover within the studied area. It was calculated according to the following equation (Rouse et al. 1974):

$$NDVI = (NIR - Red) / (NIR + Red) \qquad (1)$$

Where, NIR is the reflectance in the near infrared range of spectrum and Red is the reflectance in the red range of spectrum. NDVI values range between -1.0 to +1.0, where positive values indicate intense and healthy green vegetation and near zero or negative values represent the other types of land-covers such as barren lands, urban areas, deserts and water features. The modified Normalized difference water index (MNDWI) was used in this work to study the changes in wetland or water features in the studied area. The MNDWI was calculated by using the following equation (Xu, 2006):

$$MNDWI = (Green - MIR) / (Green + MIR) \qquad (2)$$

Where: Green and MIR are the reflectance of the green and middle infrared bands, respectively. Image processing techniques were carried out using both ERDAS Imagine ver. 2014 and Envi ver. 4.7 Software packages.

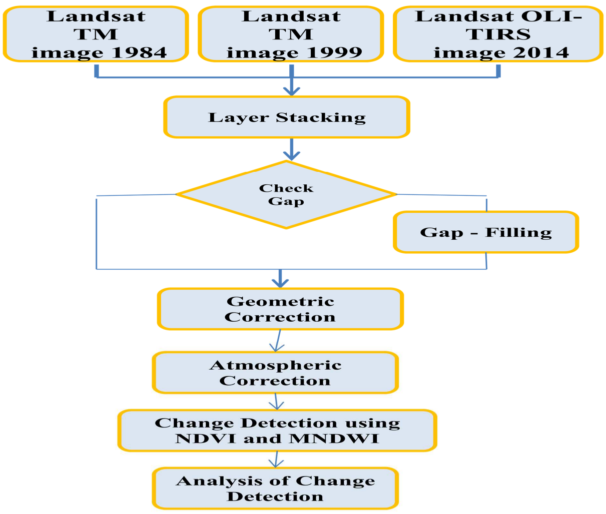
2.3.4 Change Detection in Agricultural lands and Water Features

Change detection was applied to locate areas of land reclamation and cultivation projects and each of fish pools in the studied area. It was carried out by subtracting the binary images for two successive years under each index. A three-class image (+1, 0, and -1) was obtained for positive changes, no changes, and negative in the land use respectively.

2.3.5 Proposed Flowchart of data analysis and manipulations

Figure 3 demonstrates the flowchart of data analyses and manipulations in this work.

Figure 3. Flowchart of data analyses and manipulations



3 Results and Discussion

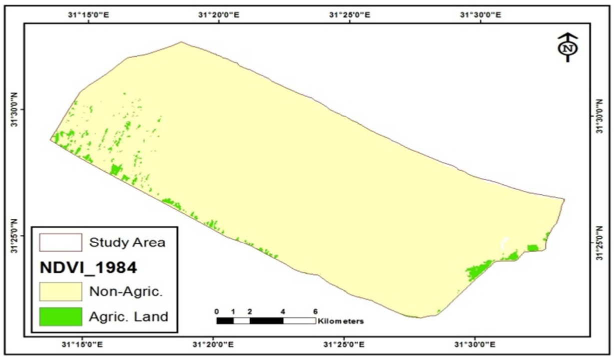
3.1 Estimation of Agricultural lands in the studied area

The spatial distribution of vegetation cover in the studied area during the three studied periods is shown in figure 4. These binary images were obtained from the NDVI data. The estimated agricultural areas were about 5.2, 28.3 and 58.4 km^2 in 1984, 1999 and 2014, as represented in Table 2. These areas represented about 1.7, 9.4 and 19.4%, respectively from the total area. On the other hand, non agricultural areas represented about 296, 272.9 and 242.8 km^2 in 1984, 1999 and 2014, respectively.

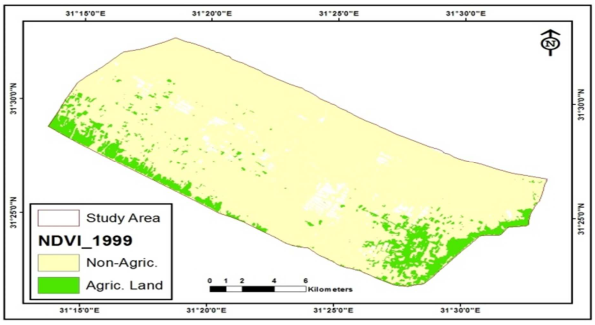
Agricultural lands were increased by about 23.1 km^2 in 15 years from 1984 to 1999 and by about 30.1 km^2 from 1999 to 2014. The total increase in agricultural lands in 30 years from 1984 to 2014 was about 53.2 km^2. That increase in agricultural lands was due to land reclamation projects north of Nile-Delta.

Table 2: Agricultural lands in the studied area and their total changes from 1984 to 2014.

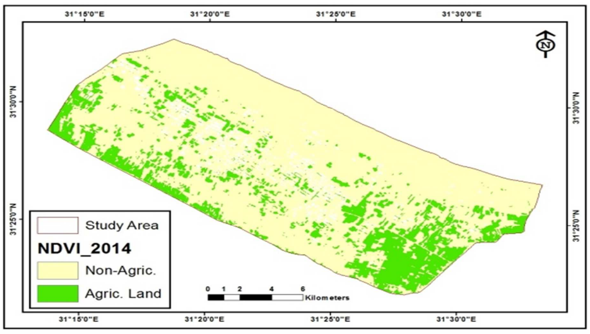
Agric. Land in km^2		Change in Agric. Land km^2
1984	1999	From 1984 to 1999
5.2 (1.7%)	28.3 (9.4%)	23.1
1999	2014	From 1999 to 2014
28.3 (9.4%)	58.4 (19.4%)	30.1
1984	2014	From 1984 t 2014
5.2 (1.7%)	58.4 (19.4%)	53.2



(1984)



(1999)



(2014)

Figure 4. NDVI binary image of the studied area.

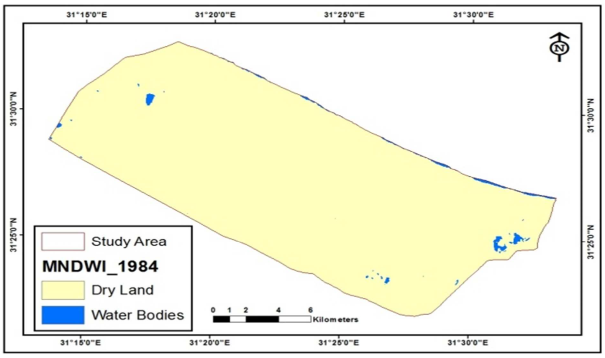
3.1.1 Water features in the studied area

The spatial distribution of water features in the studied area during the studied periods of time is shown in figure 5. These binary images were obtained from the MNDWI data. Estimated areas of water features in the studied area were about 2.8, 19.1 and 42.1 km^2 in 1984, 1999 and 2014, respectively as represented in Table 3. These areas represented about 0.9, 6.3 and 14.0%, respectively from the total area. On the other hand, dry areas represented about 298.4, 282.1 and 259.1 km^2 in 1984, 1999 and 2014, respectively.

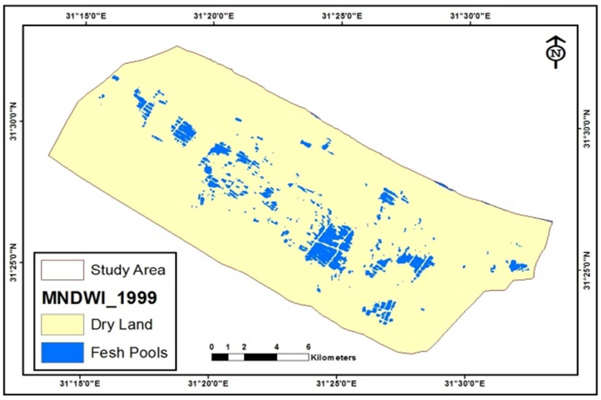
Water features were increased by about 16.3 km^2 in 15 years from 1984 to 1999 and by about 23.0 km^2 from 1999 to 2014.

Table 3: Water features in the studied area and their total changes from 1984 to 2014.

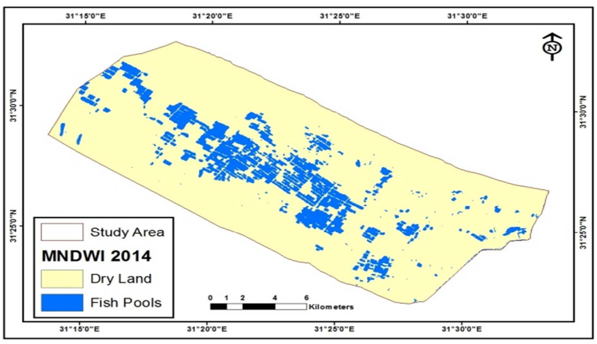
Water Features Land in km^2		Change in Water Features Land km^2
1984	1999	From 1984 to 1999
2.8 (0.9%)	19.1 (6.3%)	16.3
1999	2014	From 1999 to 2014
19.1 (6.3%)	42.1 (41.0%)	23.0
1984	2014	From 1984 t 2014
2.8 (0.9%)	42.1 (14.0%)	39.3



a) 1984



b) 1999



c) 2014

Figure 5. MNDWI binary images of the studied area.

3.1.2 Changes in land use from agricultural to non-agricultural activities

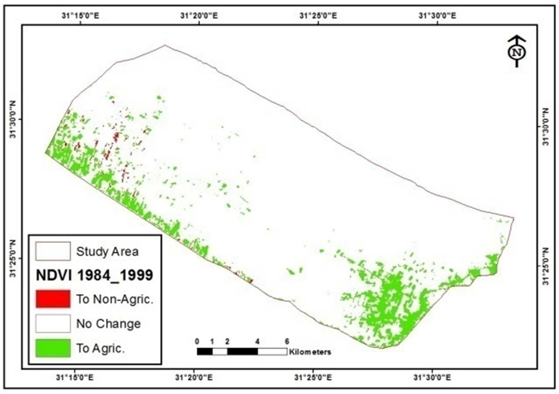
Changes in land use from agricultural to non-agricultural activities and vice versa from 1984 to 1999 are illustrated in Figure 6a. Changes from non-agricultural activities to agricultural activities represented about 24.31 km^2 (about 8% of the area). However, changes to non-agricultural activities represented only about 1.22 km^2 as illustrated in Table 4. Areas, where no change in land use activities occurred, represented the majority of the area 275.67 km^2 (about 91.52% of the area).

Changes in land use from agricultural to non-agricultural activities from 1999 to 2014 are illustrated in Figure 6b. Changes from non-agricultural activities to agricultural areas represented about 38 km^2 (about 12.65% of the area). Changes to non-agricultural activities represented about 8.13 km^2 (about 2.70% of the area). Areas, where no change in land use activities occurred, represented the majority of the area 254.98 km^2 (about 84.65% of the area).

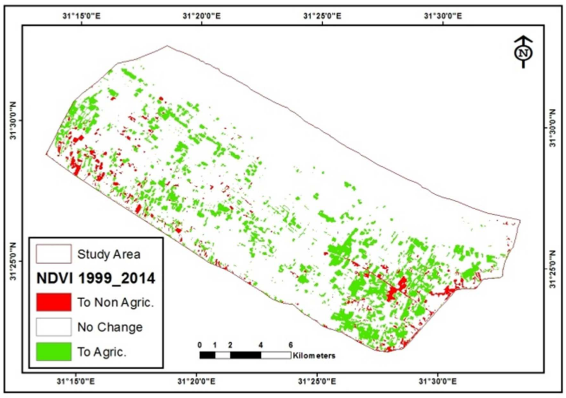
Changes in land use from agricultural to non-agricultural activities from 1984 to 2014 are illustrated in Figure 6c. Changes from non-agricultural activities to agricultural areas represented about 54.75 km^2 (about 18.18% of the area). Changes to non-agricultural activities represented about 1.64 km^2 (about 0.54% of the area). Areas, where no change in land use activities occurred, represented the majority of the area 244.81 km^2 (about 81.28% of the area).

Table 4. Changes from agricultural to non-agricultural activities in the studied area from 1984 to 2014.

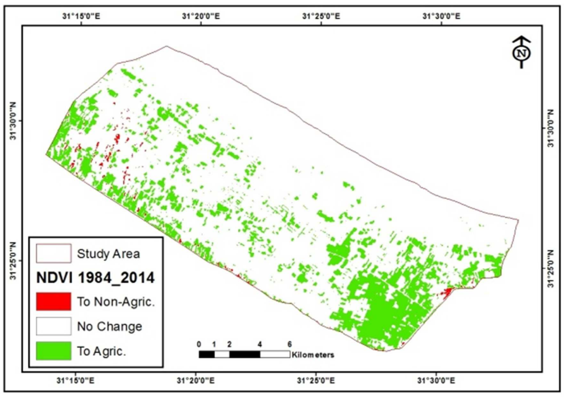
Type of Change	**1984 - 1999**	
	Km^2	%
To Non-Agric.	1.22	0.41
No Change	275.67	91.52
To Agric. Land	24.31	8.07
Type of Change	**1999 - 2014**	
	Km^2	%
To Non-Agric.	8.13	2.70
No Change	254.98	84.65
To Agric. Land	38.09	12.65
Type of Change	**1984 - 2014**	
	Km^2	%
To Non-Agric.	1.64	0.54
No Change	244.81	81.28
To Agric. Land	54.75	18.18
Total Area	**301.20**	**100.00**



a) From 1984 to 1999



b) From 1999 to 2014



c) From 1984 to 2014

Figure 6. Changes in land use from agricultural to non-agricultural activities in the studied area from: 1984 to 2014.

3.1.2 Changes in water features within the studied area

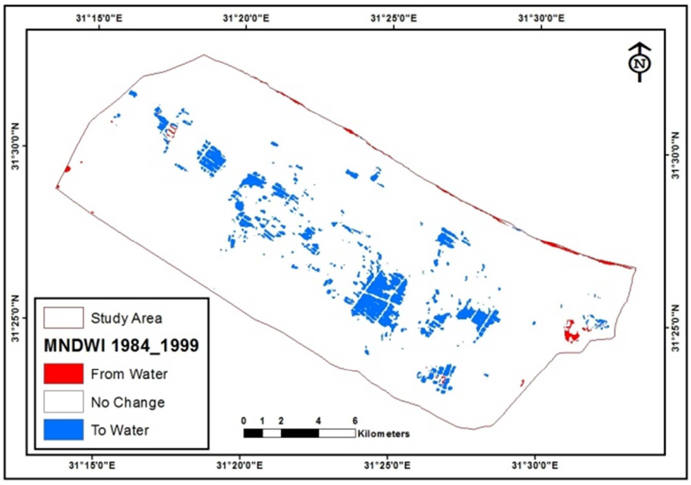
Figure 7a illustrates the changes in water features in the studied area from 1984 to 1999. Changes from dry land into water features in the studied area represented about 18.12 km^2 (about 6% of the area). However, changes to dry lands were about 1.76 km^2 (about 0.58% of the area) as illustrated in **Table 5**. Areas, where no change in land use activities occurred, represented the majority of the area 281.32 km^2 (about 93.40% of the area).

Table 5. Changes from water features into dry lands in the studied area from 1984 to 2014.

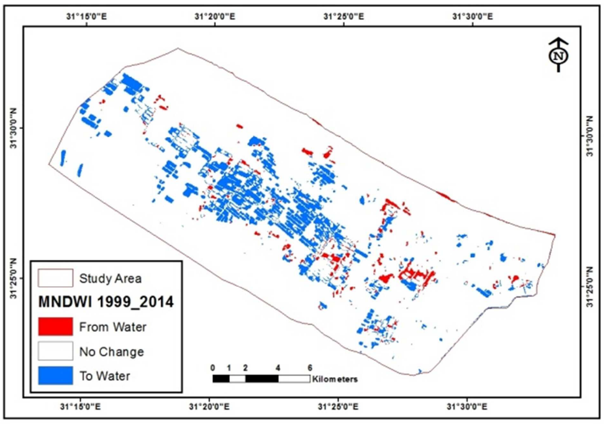
Type of Change	1984 - 1999	
	Km^2	%
From water	1.76	0.58
No Change	281.32	93.40
To water features	18.12	6.02
Type of Change	**1999 - 2014**	
	Km^2	%
From water	5.61	1.86
No Change	267.02	88.65
To water features	28.57	9.49
Type of Change	**1984 - 2014**	
	Km^2	%
From water	2.05	0.68
No Change	257.78	85.58
To water features	41.37	13.74

Figure 7b illustrates the changes in water features in the studied area from 1999 to 2014. Changes to water features in the studied area represented about 28.57 km^2 (about 9.49% of the area). However, changes to dry lands were about 5.61 km^2 (about 1.86% of the area). Areas, where no change in land use activities occurred, represented the majority of the area 267 km^2 (about 88.65% of the area).
Figure 7c illustrates the changes in water features in the studied area from 1984 to 2014. Changes to water features in the studied area represented about 41.37 km^2 (about 13.74% of the area). However, changes to dry lands were about 2.05 km^2 (about 0.68% of the area). Areas, where no change in land use activities occurred, represented the majority of the area 257.78 km^2 (about 85.58% of the area).

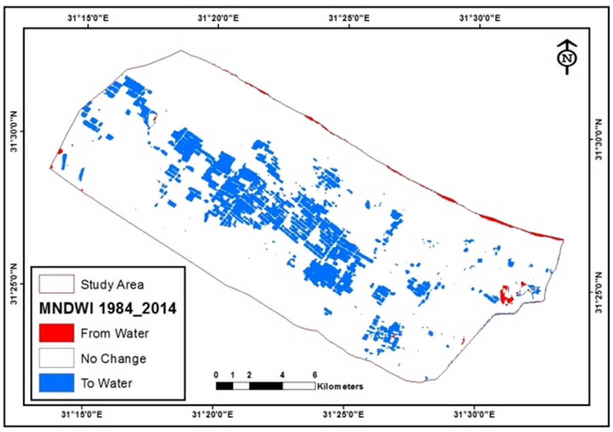
It was noticed that the changes into water features was increasing over time during the studied period of time from 1984 to 2014. The annual increase in water features was about 0.4% from 1984 to 1999, about 0.63% from 1999 to 2014, and about 0.46% during the whole studied period of time from 1984 to 2014. The increase in water features was mainly due to the development of fish pound by the residents in the area. These fish pound have higher return when compared with agricultural lands. Also, water table is very high in these areas where no drainage system was implemented, which have bad effects on agricultural crops.



a) From 1984 to 1999



b) From 1999 to 2014



c) From 1984 to 2014

Figure 7. Changes in land use from dry land into water features in the studied area from 1984 to 2014.

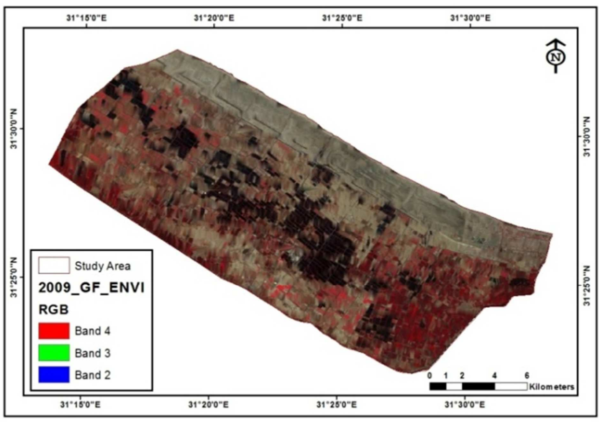
3.1.3 Gap-fill of Landsat 7 image acquired in 2009

Gap filling of the Landsat 7 image acquired in 2009 was carried out using two methods the first method was implemented by using the Landsat-Gapfill plug in ENVI software (Figure 8a) and the second was implemented by using the gap-fill method in the Matlab software as shown in Figures 8b. The quality of the obtained classified images within the studied area was compared. Significant differences were observed in the areas of agricultural land and water features between the images coming from the two gap-filling methods. Agricultural areas were about 46.5 and 28.9 km^2 from the gap-filled images by using ENVI (Figure 9a) and Matlab (Figure 9b), respectively as illustrated in Table 6.

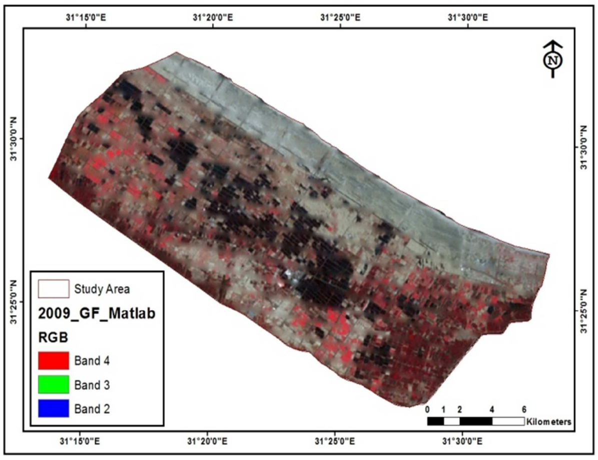
On the other hand, the areas of water features were 55.4 and 63.3 km^2 from the gap-filled images by using ENVI (Figure 10a) and Matlab (Figure 10b), respectively. This indicates that gap-filling by using Matlab did not fill all pixels and leave some zero pixels in the image. This resulted in a relatively large number of darker pixels or areas, which were classified as water features. In the contrary, the Landsat gap-fill plug-in in ENVI software filled all pixels in the image using the histogram matching technique, which resulted in more accurate classification of both agricultural areas and water features as represented in Table 6.

Table 6. Land use classification from Gap-filled Landsat 7 image acquired in 2009

NDVI	Gap filled by ENVI		Gap filled by Matlab	
Land use	Km^2	%	Km^2	%
Non-Agric	254.7	84.6	272.3	90.4
Agric. Land	46.5	15.4	28.9	9.6
MNDWI	Gap filled by ENVI		Gap filled by Matlab	
Land use	Km^2	%	Km^2	%
Dry Land	245.8	81.6	237.9	79.0
Fish Pools	55.4	18.4	63.3	21.0
Total	301.2	100.0	301.2	100.0

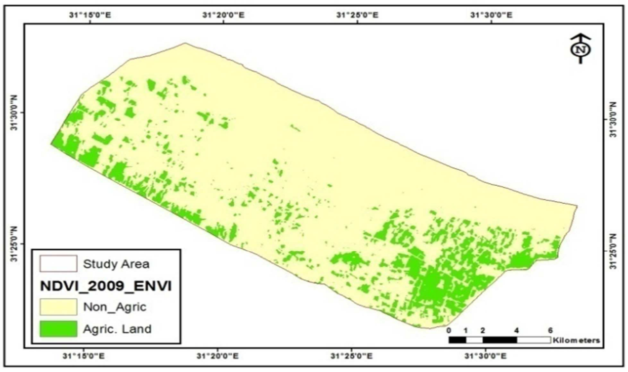


a) Landsat gap-fill plug-in in ENVI

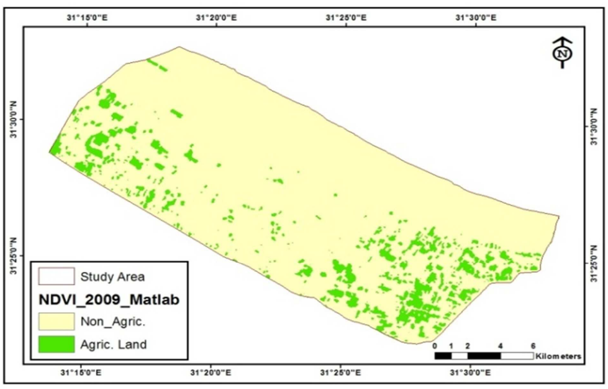


b) Landsat gap-fill plug-in in Matlab.

Figure 8. False color composite of gap-filled Landsat 7 image acquired in 2009 by using: a) Landsat gap-fill plug-in in ENVI and b) Matlab.

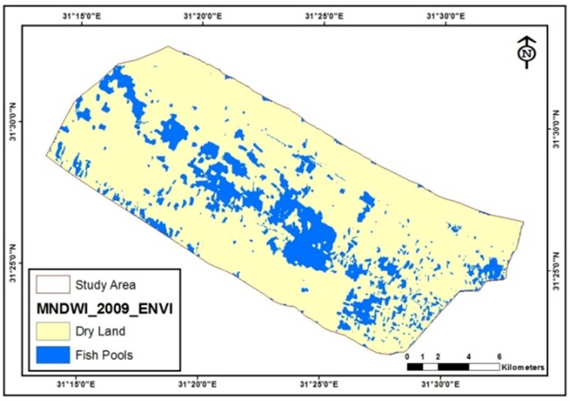


a) Binary image obtained from NDVI of the gap-filled Landsat image acquires in 2009 by ENVI

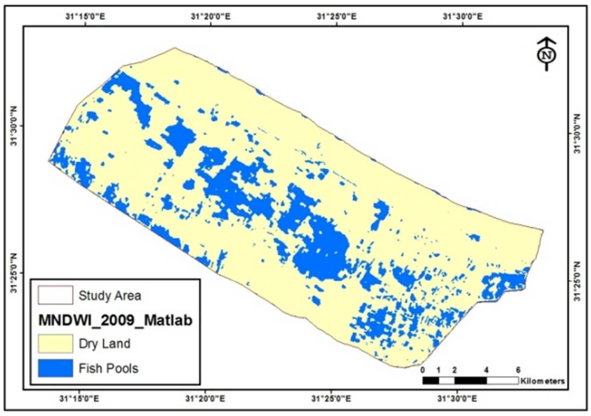


b) Binary image obtained from NDVI of the gap-filled Landsat image acquires in 2009 by Matlab

Figure 9. Binary image obtained from NDVI of the gap-filled Landsat image acquires in 2009 by a) ENVI and b) Matlab.



a) Binary image obtained from MNDWI of the gap-filled Landsat image acquires in 2009 by ENVI



b) Binary image obtained from MNDWI of the gap-filled Landsat image acquires in 2009 by Matlab

Figure 10. Binary image obtained from MNDWI of the gap-filled Landsat image acquires in 2009 by: a) ENVI and b) Matlab.

3.6 **Accuracy Assessment**

Accuracy assessment of the land uses binary images obtained from both the NDVI and the MNDWI indices in 2014 was carried out by using 100 random sample points distributed throughout the studied area. The actual land use was obtained from high resolution images and topographic maps. Actual land use at each sample point was compared with classified land use on a point by point basis to obtain the confusion matrix. It was found that land uses in the studied area were classified with high accuracy using the studied indices as illustrated in Table 7. Producer's accuracy for both non-agricultural land and agricultural lands obtained from the NDVI in 2014 was varied from about 83 to 100, respectively. User's accuracy for these lands uses was varied from about 100 to 93%, respectively. The overall accuracy for land uses classified from the NDVI was 95% and Kappa coefficient was 0.87.

On the other hand, producer's accuracy for both dry lands and water features obtained from the MNDWI in 2014 was varied from about 83 to 99, respectively. User's accuracy for the same land uses was varied from about 90 to 98%, respectively. The overall accuracy for land uses classified from the MNDWI was 97% and Kappa coefficient was 0.85.

Table 7. Accuracy assessment of land uses classified by the studied indices in 2014.

Index	**Land Use**	**Producer's Accuracy**	**User's Accuracy**	**Overall Accuracy**	**Kapp a**
NDVI	Non-Agric.	82.76	100.00	95.00	0.87
	Agric. Land	100.00	93.42		
MNDWI	Dry Land	83.33	90.91	97.00	0.85
	Water features	98.86	97.75		

Accuracy assessment of the land uses binary images obtained from both the NDVI and the MNDWI indices in 2014 was carried out by using 100 random sample points distributed throughout the studied area. The actual land use was obtained from high resolution images and topographic maps. Actual land use at each sample point was compared with classified land use on a point by point basis to obtain the confusion matrix as represented in Table 8.

Table 8. Accuracy assessment of agricultural versus non-agricultural lands within the studied area in 2014.

Classified Data	Reference Data				
	Class	Agric. Land	Non-Agric.	Row Total	User's Accuracy
	Agric. Land	**24**	0	**24**	**100.00**
	Non-Agric.	5	**71**	**76**	**93.42**
	Column Total	**29**	**71**	**100**	
	Producer's Accuracy	**82.76**	**100.00**		

Producer's Accuracy

Agric. Land = 24 * 100 / 29 = 82.76 %

Non-Agric. Land = 71 * 100 / 71 = 100 %

User's Accuracy

Agric. Land = 24 * 100 / 24 = 100 %

Non-Agric. Land = 71 * 100 / 76 = 93.42 %

Overall accuracy = (24 + 71) *100 / 100= 95 %

Kappa Coefficient = (100 * (24 + 71) – (24 * 29 + 76 * 71)) / ((100)^2- (24 * 29 + 76 * 71)) = (100* 95 – 6092) / (10000- 6092) = 0.87

$$K = \frac{N\sum_{i=1}^{k} x_{ii} - \sum_{i=1}^{k}(x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^{k}(x_{i+} * x_{+i})} \quad (3)$$

Accuracy assessment was also carried out for the classified land uses obtain from the gap-filled image in 2009 by using both the Lansat gap-fill plug in ENVI and gap fill in Matlab. Large differences were noticed in the calcification accuracy of land uses between the two gap-filled images. The overall accuracy of the binary images obtained from the NDVI index for the gap-filled images by Matlab and ENVI was 75 and 80%, respectively as in Table 8. Kappa coefficient of the classification was relatively low (about 0.24) for the gap-filled image by Matlab, when compared with that for the gap-filled image by ENVI (0.45).

Similar trends were obtained for land use classification derived from the MNDVI index. The overall accuracy was 86 and 88% for land used classification of the gap-filled images by Matlab and ENVI, respectively. Kappa coefficient was 0.42 and 0.54 for land use classification of the gap-filled images by Matlab and ENVI, respectively.

Accordingly, it could be concluded that gap-filling of the Landsat SLC-off images by using the Landsat gap-fill plug-in in the ENVI software package was relatively more accurate than filling these gaps by using the gap-fill algorithm in Matlab. It seems that the algorithm in Matlab did not fill all gaps in the image leaving some zero-value pixels, which was reflected on the areas of agricultural lands and water features. These zero pixels were interoperated as water features by using the MNDVI index. However, the overall accuracy of these gap-filled images was not very high, which could be attributed to the missing of about 20% of the data in these images. Also, gap-filling approaches could retrieve all the missed values were they use a histogram matching algorithm in interpolating these missed values.

Table 9. Accuracy assessment of classified land uses in the gap-filled image acquired in 2009.

Index	Land Use	Producer's Accuracy	User's Accuracy	Overall Accuracy	Kappa
NDVI ENVI	Non-Agric.	58.33	58.33	80	0.45
	Agric. Land	86.84	86.84		
NDVI Matlab	Non-Agric.	47.06	33.33	75.00	0.24
	Agric. Land	80.72	88.16		
MNDWI ENVI	Dry Land	47.37	81.82	88.00	0.54
	Water features	97.53	88.76		
MNDWI Matlab	Dry Land	41.18	63.64	86.00	0.42
	Water features	95.18	88.76		

Conclusion

It could be concluded that the integration between both remote sensing data and GIS techniques could provide recent, accurate, less expensive and time-wise information about changes in land use over time. Land uses were classified with very high accuracy in the studied area using both the NDVI and the MNDWI spectral indices. Positive and significant changes in agricultural areas (about 53.2 km^2) were very observable in the studied area mainly due to land reclamation projects. At the same time there was a significant increase in wet areas (about 39.3 km^2), which was mainly due to the interest of residents in the area to develop fish pound. Fish pounds have better return when compare with agricultural lands.

Gap-filling of the studied Landsat SLC-off image acquired in 2009 by using the Landsat gap-fill plug-in in the ENVI software package was more accurate than using the gap-fill algorithm in Matlab. The algorithm in Matlab did not fill all gaps within the image leaving some zero-value pixels. This was reflected on the areas of agricultural lands, which was decreased and the area of water features, which was increased. Zero pixels were interoperated as water features with the MNDVI index. Accordingly, gap-filling approaches could retrieve all the missed values within the images were they use a histogram matching algorithm in interpolating the missed but not the actual values.

References

1. Conoco 1989, Stratigraphic lexicon and explanatory notes to the geological map of Egypt 1:500,000. Conoco Inc., Cairo, Egypt, 1989.
2. Elnaggar, A.A. 2013. Spatial and temporal changes in Agricultural lands eastern Nile-Delta, Egypt. J. Soil Sci. and Agric. Eng., Mansoura Univ., 4 (3): 187 – 201.

3. Elnaggar, A.A., Azeez, A.A. and Mowafy, M. 2014. Monitoring Spatial and Temporal Changes of Urban Growth in Dakahlia Governorate, Egypt, by Using Remote Sensing and GIS Techniques. Mansoura Engineering J., Mansoura Univ., 39 (4): C1 – C14.
4. Jiang, Z.Y., Huete, A.R., Chen, J., Chen, Y.H., Li, J., Yan, G.J., Zhang, X.Y. 2006. Analysis of NDVI and scaled difference vegetation index retrievals of vegetation fraction. Remote Sens. Environ., 101(3): 366-378.
5. Kedy, S. K., ELMewafi, M.and Elnaggar, A.A. 2015. Spatial assessment of urban growth in Diwaniyah city, Iraq and its impact on sustainability development. International Journal of Scientific & Engineering Research (IJSER), 6 (7): 642-649.
6. Lu, D., Mausel, P., Brondi Zio, E., Moran, E. 2003. Change detection techniques. Int. J. Remote Sensing, 25(12): 2365–2407.
7. Mas, J.F. 1999. Monitoring land-cover changes: a comparison of change detection techniques. Int. J. Remote Sensing, 20(1): 139-152.
8. McFeeters, S. K. (1996). The use of Normalized Difference Water Index (NDWI) in the delineation of open water features, International Journal of Remote Sensing, 17(7):1425–1432.
9. Nagler, P., Glenn, E., Hursh, K., Curtis, C., Huete, A. 2005. Vegetation mapping for change detection on an arid-zone river. Environmental Monitoring and Assessment, 109: 255-274.
10. Rouse, J., Has, R., Schell, J., Deering, D. 1974. Monitoring vegetation systems in the Great Plains with ERTS. Proceedings, Third Earth Resources Technology Satellite-1 Symposium, Greenbelt: NASA SP-351, pp. 3010 - 3017.
11. RTO 2007. NATO RTO Space Science and Technology Advisory Group (SSTAG) Recommendations for Space Research Topics". RTO Technical Memorandum, TM-SPD-002.
12. Scaramuzza, P., Micijevic, E. and Chander, G., (2004). SLC Gap-Filled Products Phase One Methodology.
13. Tucker, C.J. 1979: Red and photographic infrared linear combinations for monitoring vegetation. Remote Sens. Environ., 8: 127–150.
14. Xu, H. 2006. Modification of normalized difference water index (NDWI) to enhance open water features in remotely sensed imagery. International Journal of Remote Sensing, 27(14): 3025–303.