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Landuse Landcover Changes in Delta Province of Egypt: 1984 - 2000 - 2016.

by

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the degree of
Master of Science (Geographical Information Science & Systems) – MSc (GISc)

Advisor:

Dr. Shahnawaz

Cario-Egypt, 15-03-2018

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Science Pledge

By my signature below, I certify that this dissertation entitled "Landuse Landcover Changes in Delta Province of Egypt: 1984 - 2000 - 2016" is entirely the result of my own work. I have cited all sources of information and data I have used in my thesis and indicated their origin.

Cairo-Egypt, 15-03-2018	Abdelrahman Shehata Ahmed Metwally

Abdelrahman Shehata Ahmed

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Abstract

Sustainable development of any region is an important issue and depends on the continuous monitoring land use/cover change information. This study aim to map the important land use/cover changes, especially patterns related to cultivation development and urban expansion on fertile cultivated land in Delta province of Egypt over last three decades. Maximum likelihood Supervised classification approach and post-classification change detection technique were applied to three temporal Landsat imageries acquired in 1984, 2000 and 2016, respectively. Seven land use/cover classes has been identified and selected for the study (Water-bodies, Built-up-area, Cultivated-lands, Fish-ponds, Sabkha-deposits-and-bare-soil, Coastal-beach-and-sand-plains and Barren-land) representing the dominant land use/cover in the study area. The analysis revealed that about 15% of the area subjected to changes in land use/cover during the period 1984-2000 and about 8.5% during 2000-2016. The rapid population growth show its impact on changing of land use/cover of the study area, where the results show a rapid increase in three land use/cover classes which relative with population and economic activities such as; built-up-area, cultivated land and fish ponds by (94.6%), (7.2%) and (236.4%), respectively, from 1984 to 2016. on other hand, the coastal beach, sabkha-deposit-and-bare-soil, water bodies and barren were drastically decreased by (-51.9%), (-88.5%), (-19.5%) and (-60%), respectively, during the same period.

The increase in urbanization led to the agricultural land degradation due to urban encouragement at the fringes of the urban area, where the built-up-area deducted from cultivated land about 219.4 km^2 (2.5%) during the period 1984-2000, and deducted about 204.4 km^2 (2.2%) during 2000-2016.

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Chapter-1: Introduction

1.1. Background

The total area of Egypt is about 1 million km^2 divided into seven provinces; Greater Cairo province; Delta province; Alexandria province; Canal province; North Upper province; Asyut province and Southern Upper province. Each province includes governorates which are linked together geographically, regionally and economically for physical planning purposes.

The Delta province is one of oldest intensive cultivated regions on the earth, where the area of Delta province is about 12634 km^2, which represents about 1.22% of the total area of Egypt. The high population growth in Egypt led to more stress on the natural and environmental resources such as water resources and fertile soil which are important for agriculture especially in Delta province. The total population of Egypt for over a century according to United Nations Population Fund has increased from 11.2 million in 1907 to 89.6 million in 2015, which made Egypt the highest populated country in the middle-east. Also, according to statistics, the population growth rate in Egypt increased from 1.43 % per year in 1907 to 2.30 % per year in 2015 **(Osman et al., 2016)**. The major part of population increase is concentrated in Delta province.

Delta province occupies the second place in population among seven provinces in Egypt, where about 19.1 million inhabitants live in Delta province according to Egyptian census 2015, which represent about 22 % of total population in Egypt, with population density up to 1600 inhabitant per square kilometer **(El-Ramady et al., 2013)**. Profound pressure on the environmental diversity and natural resources such as fertile soil, which was formed by river Nile silt that drifted with the flood from the origins of the river Nile over the time. The risk of overpopulation, forms a pressure on the natural resources and cause a socioeconomic problems such as a high unemployment rate, increased crime rate. Also, the human activities has a negative impacts on the fertile agricultural soil, which is important for the cultivation of

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many vital agricultural crops for the national economy and the self-sufficiency of food production for the country.

In the 1980s, the Egyptian government has started to develop plans and strategies to reduce the overpopulation which puts pressure on natural resources in this province, and lead to urbanization toward cultivated land. The Egyptian government is demanding to control the urban expansion and the loss of agricultural land the Nile-Delta by applying an effective horizontal expansion of urbanization along the deserts areas that surrounding the Nile-Delta region **(Hegazy et al., 2008)**.

It was necessary to monitor and determine the nature and directions of change that occur on land use/cover in this important province, to support planners and decision makers with information to estimate and assess the current situation and what has been achieved, according to their plans and strategies, in order to estimate the effectiveness of these plans and polices in reducing the impacts of overpopulation on the important resources in this province.

Remote sensing and geographic information system became a main tools to monitor and get accurate information about the spatial and temporal distribution of land-use/cover changes. Remote sensing can play an important role at local and regional level planning by mapping and quantifying change transformation and rates of land use/cover changes. Remote sensing satellite imagery is the most important data source for remote sensing and GIS applications, and regarded as an important data source for monitoring of urban expansion and land use change analysis **(Xiao and Zhan, 2009)**.

Change detection techniques is one of major applications that based on remotely sensed data, due to repetition in capturing earth coverage at short intervals and appropriate image quality **(Singh, 1989)**. This technique has been widely used to investigate environmental changes that occur by to man-made activities or natural phenomena, due to its capabilities in monitoring and

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assess the earth surface land-use/cover changes. There are multiple change detection techniques developed in different studies that have been summarized, such as Image differencing, Image regression, Image, Vegetation index differencing, Change vector analysis, unsupervised change detection, Hybrid change detection and a number of other techniques.

In the present study we intend to employ remote sensing techniques for mapping changes of most important land use land cover in Delta province in last three decades (from 1984 to 2000 and from 2000 to 2016). We will use maximum likelihood supervised classification approach and post-classification change detection comparison technique, and use the results of change detection to identify and investigate the dominant changes of land-use/cover in Delta province.

1.2. Statement of the problem

The overpopulation in the Delta province and the consequent construction of the fertile agricultural soil and pressure on environmental resources in this province. A recent study stated that a total expansion of urban area is about 2536.3 km^2 during the study period from 1984 to 2006 in the whole Nile-Delta region **(Shalaby, 2012)**. Another study conducted that land use/cover degradation was observed and identified mainly due to the human activities **(El-Kawy et al., 2011)**.

Therefore, the Egyptian government has developed plans and regulation to preserve, or at least reduce the degradation and the pressure on the fertile agricultural land and the environmental resources in the Nile-Delta region. It is necessary to direct the studies researches towards this economically, socially and environmentally important region.

Therefore, the present study come as one of studies and researches that study this important province to analysis and assess the land use/cover changes, especially the cultivated land and the trends of change, as an endeavor to support the planners and decision maker in

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government departments with information about the land use/cover change in the last three decades in Delta province of Egypt. The study intend to answer the following questions:

- What is the most prominent types of land-use/cover in Delta province?
- What is the magnitude of land-use/cover change and its distribution in Delta province between 1984, and 2016?
- What are the main reasons for these changes?

1.3. Aim and Objectives

1.3.1. Aim

The aim of this study is to highlight the land use/land cover change in the Delta province of Egypt, over a period of 32 years (1984, 2000 and 2016), particularly the changes in cultivated land and built-up-area.

1.3.2. Objectives

The main objectives of this study can be summarized as following:

- Analysis of the nature of land use/cover in Delta province during the period 1984, 2000 and 2016.
- Producing digital maps and statistical tables to illustrate changes pattern of land use/land cover in Delta Province of Egypt.
- Provide an explanations of factors that impact the land-use/cover changes in the Delta province.

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1.4. Study Area

1.4.1. Definition of Delta province

The General Organization for Physical Planning **(GOPP, 2008)** has divided Egypt into seven regional units for planning purposes. The governmental authority works on aspects of urban planning and land use, with consideration of economic conditions of the regional units.

The Delta province is the fourth of seven provinces units in Egypt, and includes the governorates of Gharbia, Dakahlia, Damietta, Kafr-El-Sheikh and Monufia (Map No. 2) with total area about 12634 km^2 or 3.01 million acres, representing about 1.27% of the total area of Egypt (1000,000 km^2). The province has 19.1 million inhabitants, representing about 22% of the total population of Egypt according to census 2015 **(CAPMAS, 2017)**. The total population density is about 1279 inhabitant/km^2 **(GOPP, 2008)**.

Table 1: Distribution of Delta Province Governorates Area.

Governorate	**Area (Km^2)**	**Percentage**
Dakahlia	3,628	*28.7*
Kafr El-Sheikh	3,527	*27.9*
Monufia	2,595	*20.6*
Gharbia	1,963	*15.5*
Damietta	910	*7.3*
Total Area	**12,634**	***100***

1.4.2. Location and extent

The Delta province extends between longitudes 32°6'E, 30°21'E, and latitude 31°36'N, 30°11'N, occupies the central region of northern part of Egypt. The province extend from the Mediterranean Sea coast in the north with seafront up to 200 km^2 to the boarder of greater Cairo province in the south, and extends to east toward Suez-Canal province, and extends westward to Alexandria province (Map No.1).

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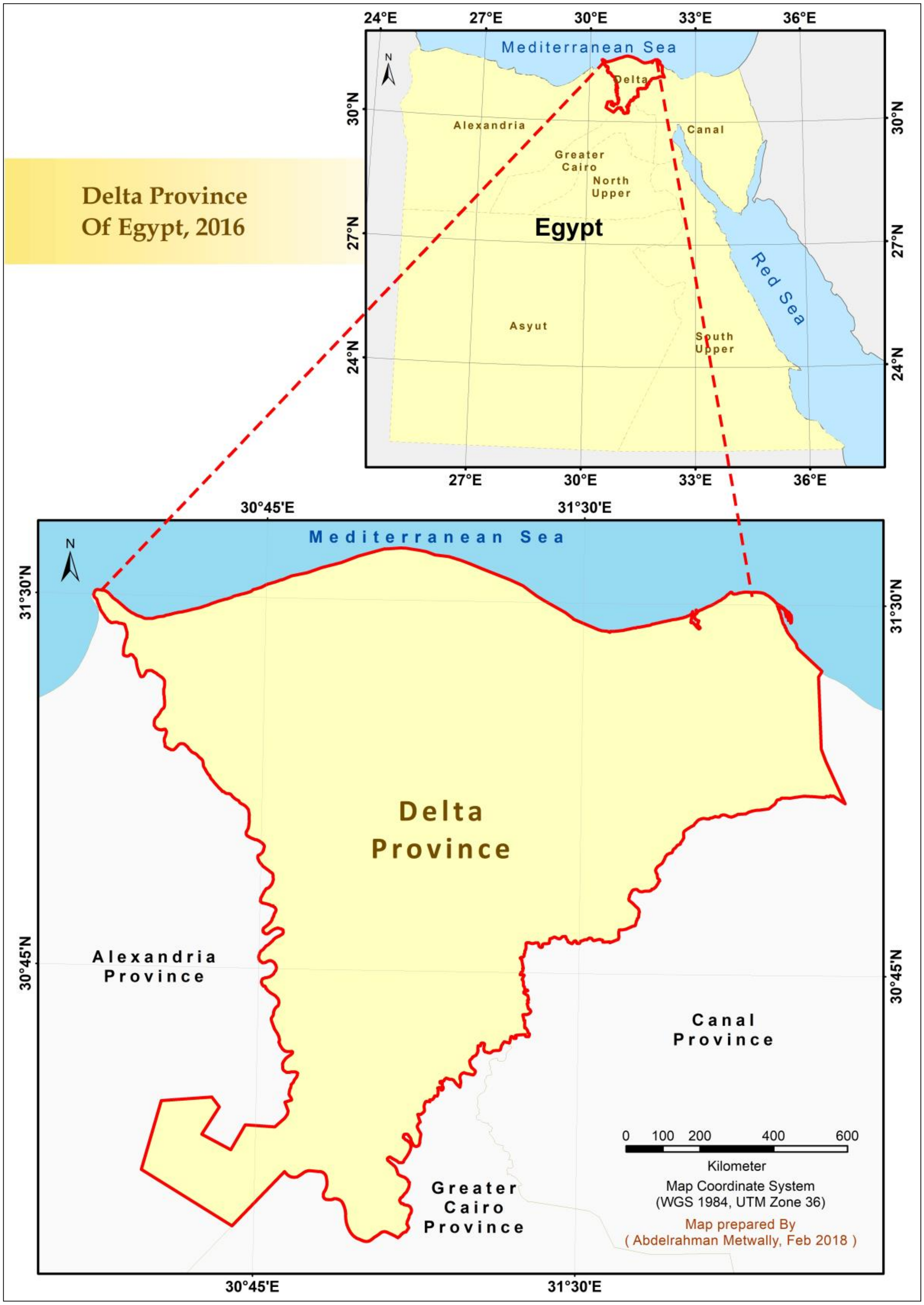

Map 1. Location of Delta Province.

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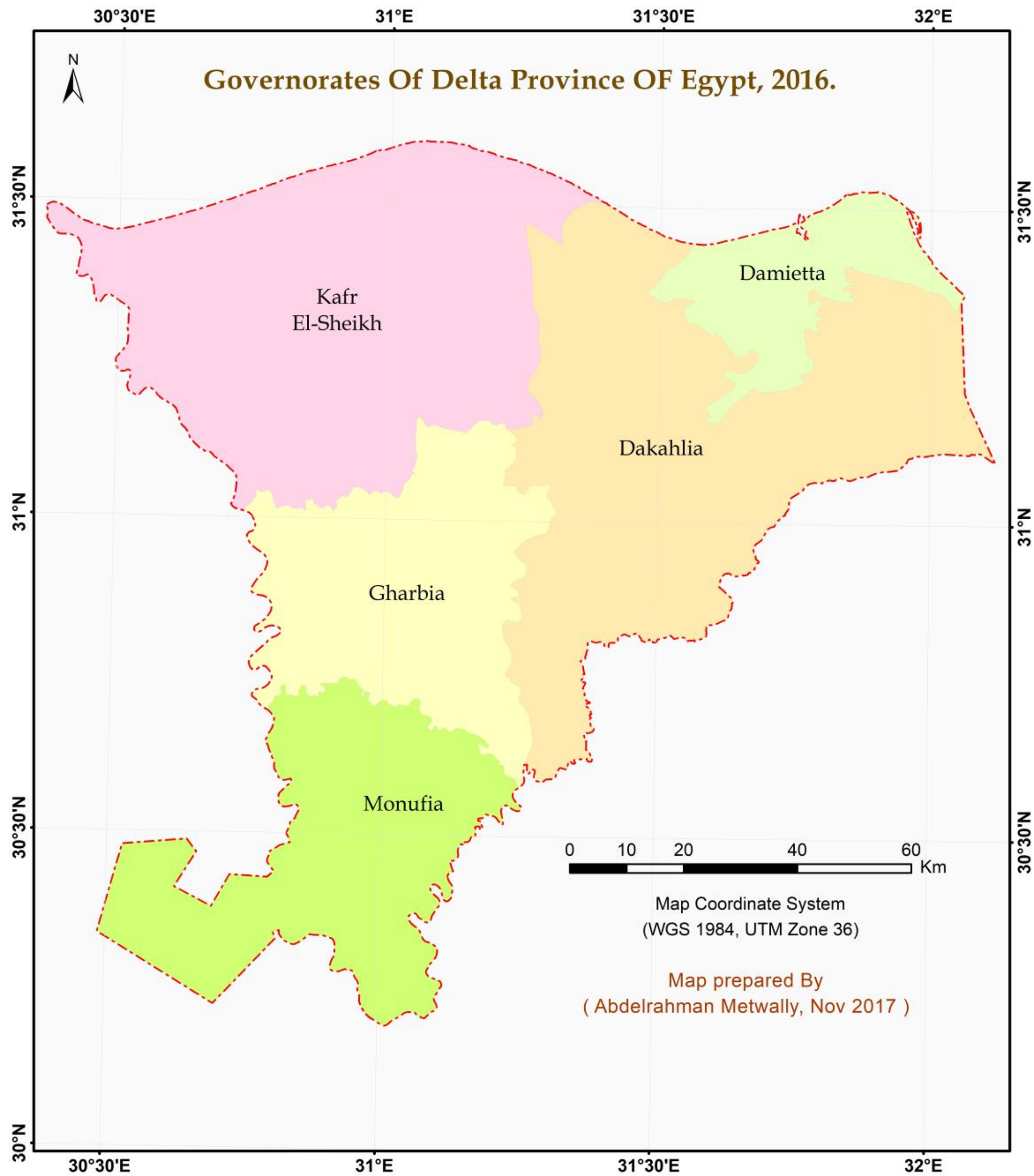

Map 2. Governorates of Delta province of Egypt.

1.4.3. Topography and climate

The topography of Delta is characterized by a plane surface with gentle slope about 1/10000. However, the level of slope in the Delta is not equal, where the surface is more plane in the south more than in the north, and the slope tends from east to west. Although, most of land

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cover of Delta is agriculture land, but the north and north east regions occupied by swamps lakes and sand dunes, while the north coast of Delta are exposed to sedimentation and coastal erosion.

The climate in the Delta is generally homogenous, but the conditions of the location on the Mediterranean Sea in the north, have a clear impacts on the variation of some climate elements. The northern coastal zone of Delta is warmer in winter than south, and less heat and more moisture in the summer unlike other Delta regions. The wind speed increases in the north region of the Delta and decreases toward the south of the Delta. The average annual rainfall range between 25 mm/year in the extreme south and 250 mm/year in the extreme north of the Delta **(GOPP, 2008)**.

1.4.4. Population

The total population of Delta province amount about 19.6 million according to the 2016 census **(CAPMAS, 2017)**, taking the second place among the provinces of Egypt by 22% of the total population of Egypt.

It was expected that the population growth of the province to increase about 5.6 million in period between 2007-2027, bringing the population of the province by 22% **(GOPP, 2008)**, but the present census indicator the population of the province will exceed this estimation with a respect amount of increase. In term of relative distribution of the population in the province, about 57% of the population size concentrated in Dakahlia and Gharbia, while Damietta governorate comes in last place by 7% of the total population in the province (Table No. 2).

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Table 2. Population distribution of Delta province governorates in 1986,2000 and 2016.

Governorate	Population					
	1986	%	2000	%	2016	%
Dakahlia	3,500,470	31.4	4,570,000	31.3	6,074,446	31.0
Gharbia	2,870,960	25.8	3,661,000	25.0	4,852,968	24.8
Monufia	2,227,087	20.0	2,994,000	20.5	4,035,137	20.6
Kafr El-Sheikh	1,800,129	16.2	2,403,000	16.4	3,249,268	16.6
Damietta	741,264	6.7	995,000	6.8	1,359,643	6.9
Total Area	11,139,910	100	14,623,000	100	19,571,462	100

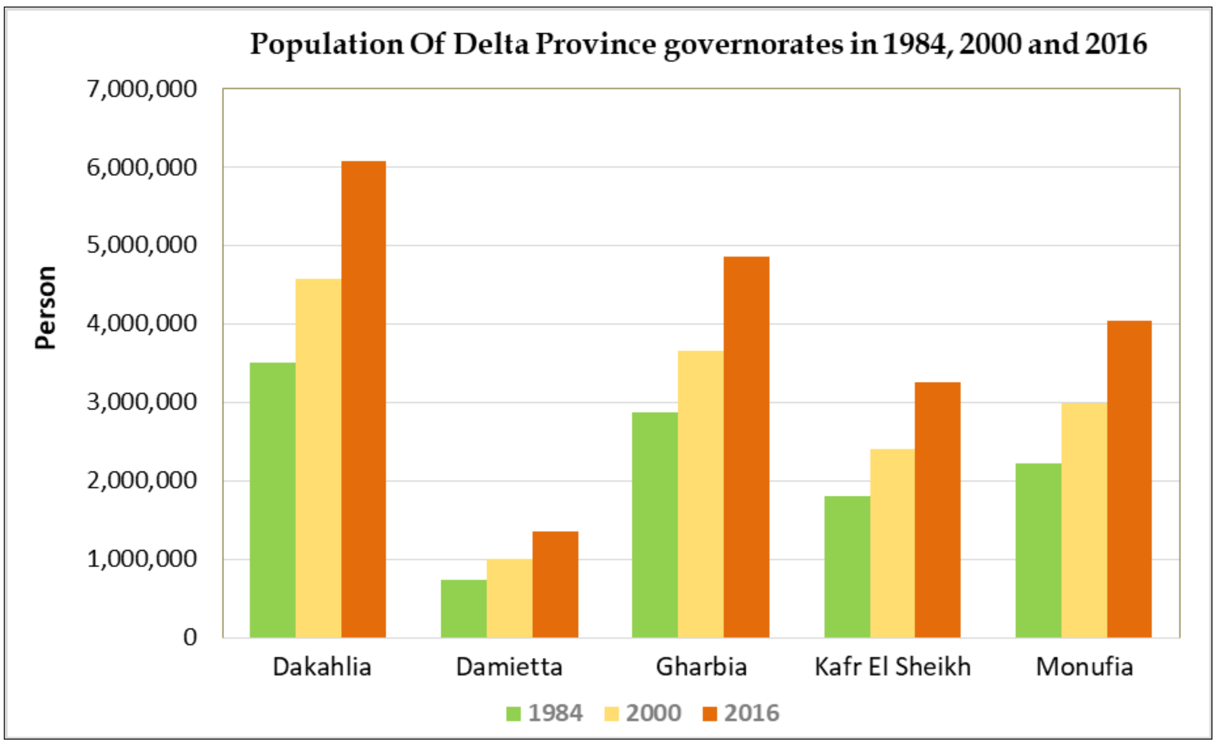

Figure 1. Population distribution of Delta province governorates in 1984, 2000 and 2016.

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1.5. LITERATURE REVIEW

1.5.1. Land use and land cover definition

Land use and land cover are a common terms used in remote sensing data analysis literature **(Meyer, 1995)**. Although these terms are sometimes used mutually, but each term has a distinct meaning. The land cover term refer to the physical layer state which cover the earth surface, while the land use term refer to the human utilization of land cover which underwent to human activities. The land cover types includes the natural earth's surface cover of deserts, water, vegetation and soil etc. **(Lambin et al., 2003)**. On other hand, the land use is refer to how the human utilize the land cover for their own purpose. **(Meyer, 1995)** has described land use as anthropogenic changes on the natural land cover such as the conversion of barren land or deserts into agriculture farms or residential zones etc. So, the land use cause a changes in land cover; therefore, land use/cover change can be defined as the modification of the surface features on the earth's landscape which is realized by the difference in their surface features appearance at two different times.

Mapping land use/cover using remotely sensed data has some challenges in term of producing a map depict with a high degree of accuracy about land use/cover that represent the real surface features. Many researcher use a various methods simultaneously beside remote sensing data such as field data, in order to obtain a high accurate land use/cover map production **(Anderson and Martinez-Meyer, 2004)**.

1.5.2. Land use and Land cover change

Land use/cover change is a process of alteration and transformation of earth's surface landscape features period of time. The land use/cover can changes due to a human or natural factors such as overpopulation pressure and economic activities by the global and local organization to utilize the natural resources. Furthermore, with an increase of population and

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economic growth, human activities occupy more land **(Mather, 1986)**. In this context, the change of land use/cover function is related to the way population live and their needs over the time, and the human factor and their activities has the main impact that alter land change in a timer period. Although the natural environmental factors have an impact on land use/cover change, but humans still remain the main reason of most land use and land cover changes **(Siewe, 2007)**.

Lambin et al., 2001 stated that not only population and their needs is the major cause of land use/cover change, but human's responses to the economic opportunities which mediated by institutional forces, and the opportunities that generated by polices and markets force humans toward land use/cover changes.

1.5.3. Remote sensing and land use/cover change detection

There are various comprehensive definitions that defines remote sensing. It is defined as studying of earth's surface by collecting data about objects and analyzing it, for extracting information about phenomena without any physical contact. In the environmental monitoring context, can be described as collecting data of an area on the earth's surface in form of image by measure and record the electromagnetic energy emitted or reflected from objects on the earth **(Düzgün and Demirel, 2012)**.

The instruments used for receiving and measure the electromagnetic radiation called sensors. These sensors record the reflected radiation from the earth surface and can be used for abroad analysis to extract information about phenomena. Land use/cover change detection analysis is one of these phenomena or studies **(Lillesand and Kiefer, 1994)**.

Remote sensing has been the important data source for land use/cover change detection studies. Multi temporal remote sensing data allow to analyze, identify and map landscape changes, giving a valuable effort for sustainable landscape planning and management **(Dewan and Yamaguchi, 2008)**.

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Most important advantage of remote sensing for land use/cover change detection is the multi temporal and spectral resolution data. Remotely sensed data of the same area and at different time is easily to obtain, and this is one of the most important advantage in land use/cover change detection studies. Furthermore, it can provide data about specific area in short periotic time with reasonable accuracy, which mean producing a high quality of the actual change in land use/cover **(Billah and Rahman, 2004)**.

1.5.4. Previous land use/cover change detection studies

There are many researches and studies of change detection techniques and land use/cover change detection topic which vary between global, regional or local level.

Lu et al., 2004 summarized a comprehensive exploration of the major change detection approaches implemented in the literature. The paper summarized ten aspects of change detection applications using remote sensing technologies for many researches and studies, these applications are; land-use and land-cover; forest or vegetation change; forest mortality; defoliation and damage assessment; forest fire; landscape change; urban change; environmental change and crop monitoring. The research summarized seven change detection techniques have been used in these studies and provides a review of comparative analyses among the different techniques and their advantages and disadvantages. These techniques consist of thirty one techniques in seven groups namely algebra, transformation, advanced models, GIS-based change detection category, Visual analysis and some other techniques that have not yet frequently been used in practice. A good change detection research should provide: area change and change rate; spatial distribution of changed types; accuracy assessment of change detection results. When implementing a change detection project, a three major steps must involve: image preprocessing including geometrical rectification and image registration; radiometric and atmospheric correction, and topographic correction if the study area is in mountainous regions; selection of suitable techniques to implement change

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detection analyses; and accuracy assessment. Although, a variety of change detection techniques have been developed, it is still difficult to select a suitable method to implement accurate change detection for a specific research purpose or study area. Despite many factors affecting the selection of suitable change detection methods, the image differencing, principal component analysis (PCA) and post-classification are in practice the most commonly used.

Nori et al., 2008 were reviewed two change detection methods in order to assess land cover changes in El-Rawashda forest, Sudan. The first method focus on change detection based on post-classification comparison method, and the second method aimed to investigate the quality of change detection procedure using multivariate-alteration-detection (MAD) transformation. Authors used two satellite imagery, first one for Landsat ETM+ acquired in 2003 and ASTER in 2006. The two images were classified into four main land cover classes namely open soil, close soil, bare soil and grass land by using unsupervised and maximum likelihood supervised classification. The results of study finds an noticeable increases in areas of close-forest and open-forest with decrease in grass lands within the period 2003-2006, and more than 36% of grassland converted to close-forest, and 24% to open-forest areas. The study proved that maximum likelihood classification provided an accurate way to quantify, map and analyze changes over time in land cover. It has also been found the (MAD) transformation to be good unsupervised change detection method for satellite images, and it can be applied on any spatial and/or spectral subset of the full dataset.

Rwanga and Manish, 2015 conducted the spatio-temporal dynamics of land use/cover of Hawalbagh block of district Almora, Uttarakhand, India. Digital change detection techniques were use with multi-temporal satellite imagery. Landsat imageries of two different time period (Landsat TM of 1990 and 2010) were acquired. Supervised classification methodology has been employed using maximum likelihood technique. The images were categorized into five classes, namely, water body, vegetation, built-up-area, agriculture, barren-land. The error

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matrix and Kappa coefficient methods were used to assess the mapping accuracy assessment. Post-classification detection technique was employed for performing land use/cover change detection. A pixel-based comparison was used to produce change information on pixel basis. Classified image pairs of two different decade data were compared using cross-tabulation in order to determine qualitative and quantitative aspects of the changes for the periods from 1990 to 2010. The results of study indicates that during the last two decades, vegetation and built-up land have been increased by 3.51% (9.39 km2) and 3.55% (9.48 km2) while agriculture, barren land and water body have decreased by 1.52% (4.06 km2) 5.46% (14.59 km2) and 0.08% (0.22 km2), respectively.

Moeletsi and Tesfamichael, 2017 assessed land cover changes caused by granite quarrying activities in the area between Rustenburg and Brits in the North West region of South Africa. Remotely sensed data of Landsat images in 1998 and 2015 were used. Supervised classification using maximum likelihood method used to category images into seven classes which are water bodies, granite quarries, exposed rock formation, built-up area, bare land, vegetation and other mining activities. Accuracy assessment was carried out for both images in 1998 and 2015 based on 50 random points, and by using Google earth as a reference data yielded an overall accuracy of 78%. Post-classification change detection method were used to produce thematic change detection map from 1998 to 2015. The study finds granite quarries increased by 1174.86 ha while formation of quarry lakes increased to 5.3 ha over the 17-year period. Vegetation cover decreased by 1308 ha in area while 18.3 ha bare land was lost during the same period. This study demonstrated the utility of remote sensing to detect changes in land cover within granite quarries.

Berlanga and Ruiz-Luna, 2002 detected changes in the landscape of the Majahual coastal system along the Mexican Pacific from 1973 to 1986 and from 1986 to 1990 and from 1990 to 1997. A multi-temporal post-classification study with data from the Landsat Multispectral

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Scanner (MSS) and Thematic Mapper (TM) were used in this study. A supervised classification performed in order to prepare the land-cover/land-use maps respectively. A post-classification comparison is used to detect changes. The results showed that the most important changes are a reductions of the dry forest coverage and increasing agriculture cover.

Kaliraj et al., 2016 conducted change detection in the coastal zone in the South West coast of Kanyakumari in India. the study area extend from 77° 9′ 32.71″ E to 77° 35′18.67″ E longitude and 8° 4′ 37.01″ N to 8° 16′ 44.83″ N latitude covering the total area of 292 km2 with the length of 58 km along the shoreline. The objective of the study is to estimate the decadal changes and their transformations of land-use and land-cover. Landsat ETM + scene image acquired on April 2000, and Landsat TM acquired on February 2011 were used are used for the land use and land cover mapping and change detection. The author has used supervised classification using Maximum likelihood classifier algorithm to category Landsat images of two dates into 12 LULC classes namely (Beach-face land cover, Dune vegetation, Plantation, Cultivable land, Fallow land, Settlement/Built-ups, Barren land, River, Water bodies, Saltwater bodies, Saltpan, Beach mining). The post-classification comparison method adopted for change detection analysis based on classification results of two Landsat image classification. The analysis result show that the total area of 45.90 km2 in different LULC features periodically shifted or transformed from one state to another one or more states. The beach-face land cover area of 1.24 km2 is encroached for built-ups and 0.63 km2 for placer mining during the decade, and the area of 0.21 km2 in this cover is transformed into wetlands and saltwater bodies. During the past decade, the expansion of area in the built-ups and settlements are directly proportional to the growth of population, which produces severe threat to the coastal resources.

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1.6. Organization of thesis

The thesis consist of four chapters. The first chapter is introductory that contains background information, aim and objectives of this study, information about study area, literal review about researches on land use/cover change detection studies and organization of thesis. Chapter two describe the data selection, software and methodology that followed to conduct this study. Chapter three demonstrate the process and results. The fourth final chapter, describe the conclusions of the study.

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Chapter-2: Methodology

2.1. Data

Selection of image data source is an important factor and prerequisite for remote sensing change detection process. Selecting remotely sensed data depend on the objectives and requirements of the study and the availability of data of the study area. Understanding study area elements such as spatial distribution and spectral characteristics of the features is an important for selection suitable remote sensing datasets **(Sui et al., 2008)**. For change detection studies and applications there are common remotely sensed data frequently used namely MSS, TM, SPOT, AVHRR and aerial photographs **(Lu et al., 2004)**. It is recommended to obtain images from same type of sensor and same spatial and spectral resolution. It also preferred to obtain images of the same season to minimize the variation of changes which occur due to the differences of sun angel and seasonal differences.

In fact, selecting image dataset for remote sensing and change detection process has some limitation, due to the availability of a good quality images in term of atmospheric condition and the coast of a good quality images. accordingly, remote sensing application face some limitations that effects on the selection the most suitable data, and there is trade-off between the availability of data and the good quality images in term of spatial, spectral resolution and atmospheric conditions.

2.1.1. Data Source

Land use/cover change detection analysis is based on analysis of satellite imagery. Therefore, the most important step is the identification of satellite sensor that imageries of study area will be acquired. According to literature review, Landsat satellite Images were selected as most suitable data for this study for many reason; the availability of Landsat data is since 1972; Landsat data inventory store every part of the earth's surface from 1972 till the present; Landsat

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satellite capture earth's surface area every 16 days, and this is an advantage of this sensor which increase the flexibility and availability of data selection; Landsat imageries freely available with high quality, Ortho-rectified and cloud free. The United States Geological Survey (USGS) Earth Explorer website allow users to custom search Landsat data, and freely offer cloud free Ortho-rectified Thematic Mapper (TM), Multi Spectral Scanner (MSS), Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and the Operational Land Imager from Landsat 8. In this study Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) were used, they are useful to study land use/cover change analysis for a local area and middle resolution.

2.1.2. Landsat 5 Thematic Mapper (TM)

Landsat Thematic Mapper (TM) has been used in this study of 1984 and 2000 time period. It was launched in March 1984 with16-day repeat cycle, and two sensors, the Multi Spectral Scanner (MSS) and the Thematic Mapper (TM). The TM sensor feature seven bands (three in visible wavelength, four in infrared) with 30 meter spatial resolution. In my instance, Landsat 5 TM has been used which resolution 30 meter and 6 bands (three in visible wavelength and 3 in infrared). The study area covered by four scenes of Landsat TM images with approximate scene about 170 km north-south by 183 km east-west. The Landsat TM 1984 images were acquired in (two scenes in September 20, 1984 and two scenes in September 11, 1984), while Landsat TM images of year 2000 acquired in (September 23, 2000 and two scenes in October 02, 2000). Attempts were made to use images acquired in same month and same day, but the unavailability of good quality images necessitated the use of scenes in different month but in the same season (Table No. 3).

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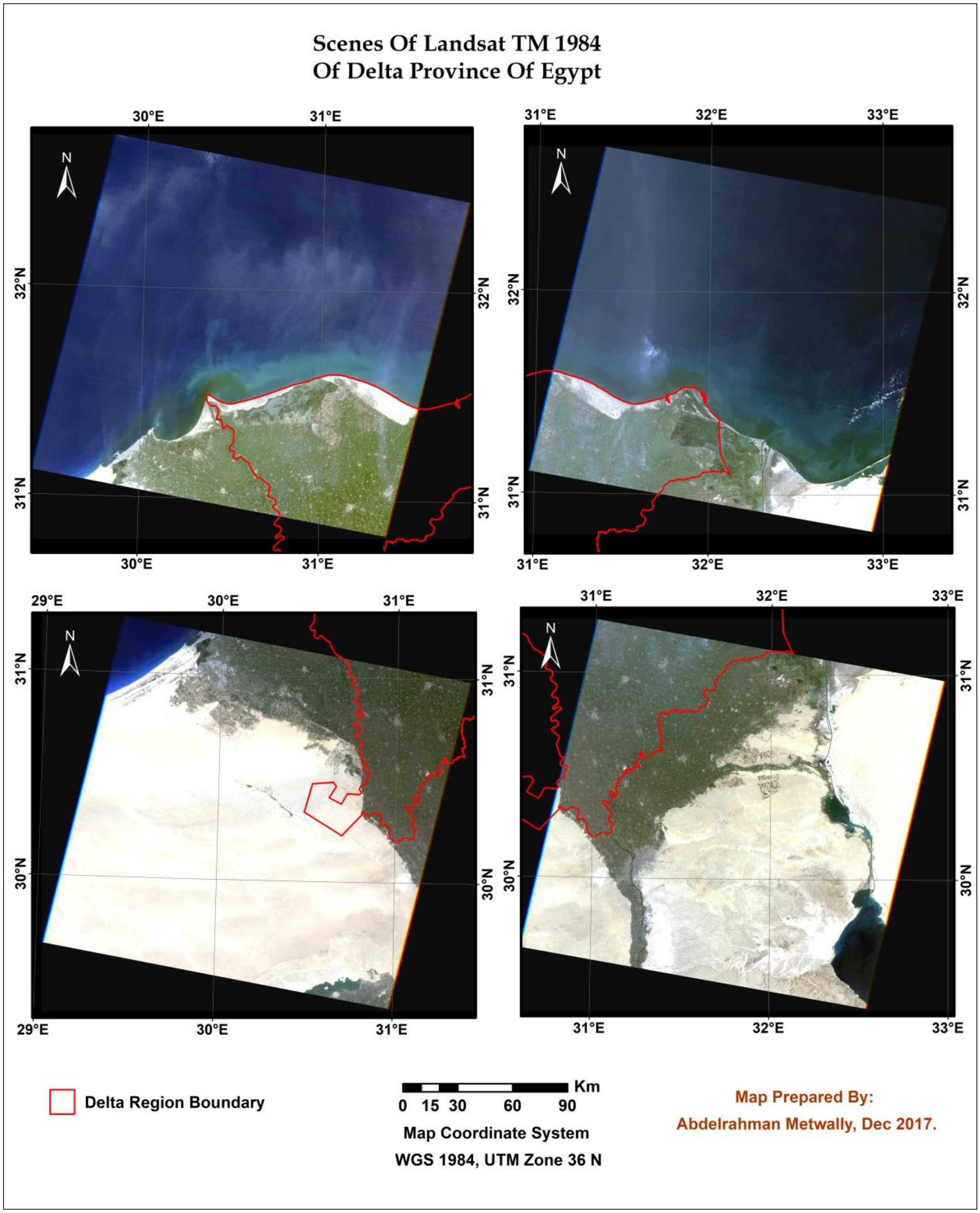

Map 3. Landsat TM 1984 scenes.

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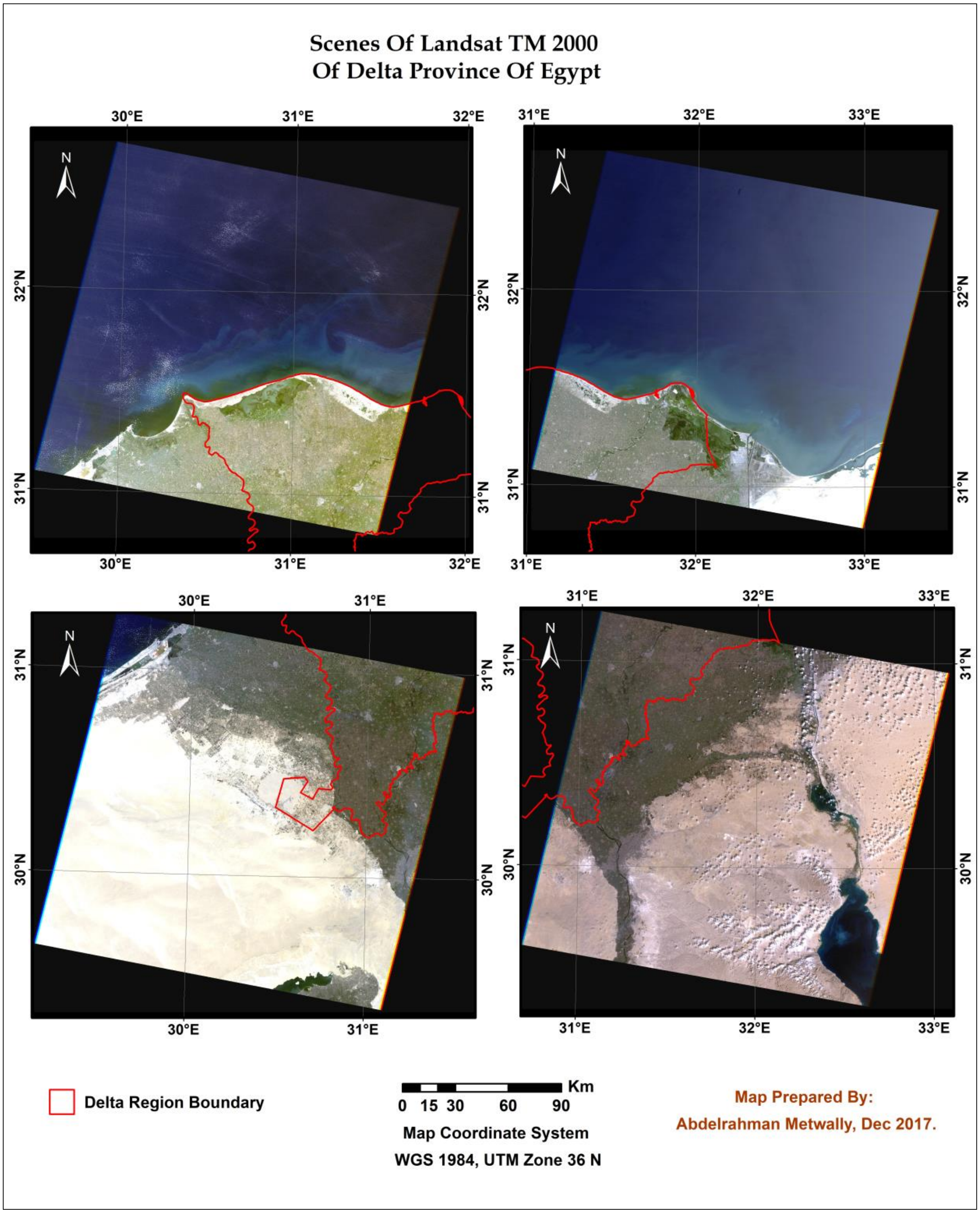

Map 4. Landsat TM 2000 scenes

2.1.3. LANDSAT 8 Operational Land Imager (OLI)

Landsat 8 is the eighth satellite in the Landsat program, which launched on February 2013. Landsat 8 carries two push-broom instrument: The Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). The spectral bands of the OLI sensor provides enhancement from prior Landsat instruments, with the addition of two spectral bands. Landsat 8 OLI consist of nine spectral bands with spatial resolution of 30 meter, and the resolution of band 8 (panchromatic) is 15 meter. The approximate scene size is 170 km north-south by 183 km east-west, and images the entire earth every 16-day repeat cycle **(Barsi et al., 2014)**. In this study, only 6 band were used (three visible bands and three in infrared wavelength). Four Landsat (OLI) scenes cover the study are and were acquired on (two scenes in September 19, 2016 and two in October 14, 2016). The date of both images were acquired in the same season to avoid the variation of atmospheric and sun angel factors as possible.

Table 3. Landsat TM 1984, 2000 and OLI 2016 imageries metadata.

Satellite Sensor	Scene Date	Coordinate System	Zone	Spatial Resolution (m^2)	Band	Spectral resolution (µm)
Landsat TM	20-9-1984 20-9-1984 11-9-1984 11-9-1984 23-09-2000 23-09-2000 02-10-2000 02-10-2000	UTM/WGS 84	36 N	30 * 30	**1.** Blue **2.** Green **3.** Red **4.** NIR **5.** WIR1 **7.** SWIR2	0.45-0.52 0.52-0.60 0.63-0.69 0.76-0.90 1.55-1.75 2.08-2.35
Landsat OLI	14-Oct-2016 14-Oct-2016 19-Sep-2016 19-Sep-2016	UTM/WGS 84	36 N	30 * 30	**2.** Blue **3.** Green **4.** Red **5.** NIR **6.** SWIR1 **7.** SWIR2	0.45- 0.51 0.53 - 0.59 0.64 - 0.67 0.85 - 0.88 1.57 - 1.65 2.11 - 2.29

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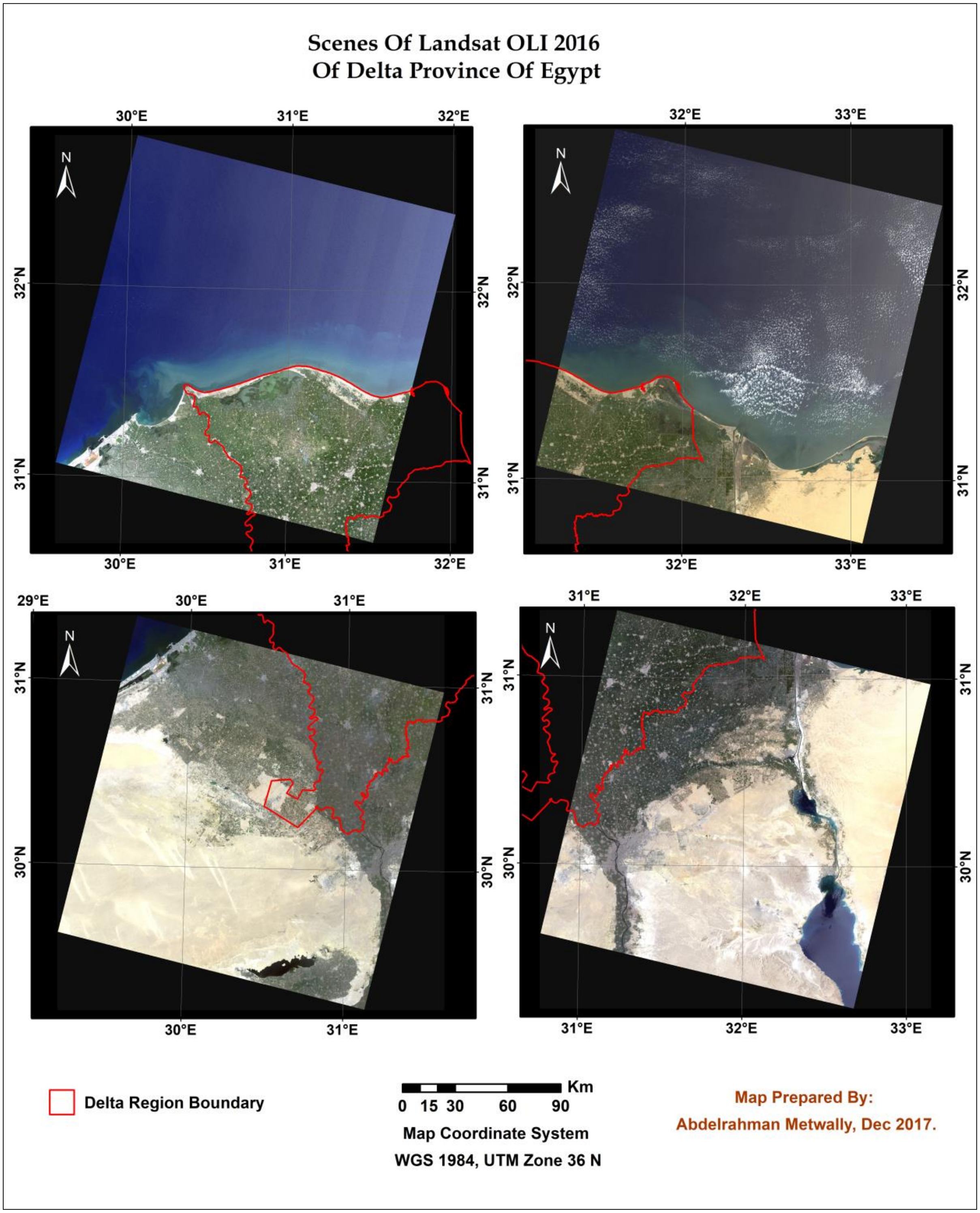

Map 5. Landsat OLI 2016 scenes

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2.2. Software used

The software were used for land use/cover change detection study are:

- Envi software version 5.3 **(HarrisGeospatialSolutions, 2014)** used for image pre-processing, image classification, accuracy assessment, post-classification process, thematic change detection and statistical results.
- ArcGIS desktop version 10.4 **(ESRI, 2011)** used for editing boundary of the study area, some post-classification processes, map layout and visualization.
- Microsoft Word and Excel 2013 were used to prepare the reports.

2.3. Land use/cover change detection process

There are several techniques frequently used for enhanced extraction of information from different remotely sensed data. However, there are some mandatory processes must be considered to obtain land-use/cover change detection information from remotely sensed data. These process are grouped in three main categories namely image pre-processing, image processing and finally post-classification comparison. Image pre-processing involves sub processes; geometric correction, radiometric correction, scenes mosaic and mask study area. Image processing aims to produce thematic classification maps of the two period images, this processes consist of visual interpretation, training land use/cover samples, maximum likelihood supervised classification and finally the accuracy assessment of the classified images. The final process, is the post-classification process which include post-classification refinement and change detection analysis. Finally, prepare and layout change detection maps and statistical report.

Figure (1) shows the workflow of the methodology that has been used for mapping land-use/cover change detection.

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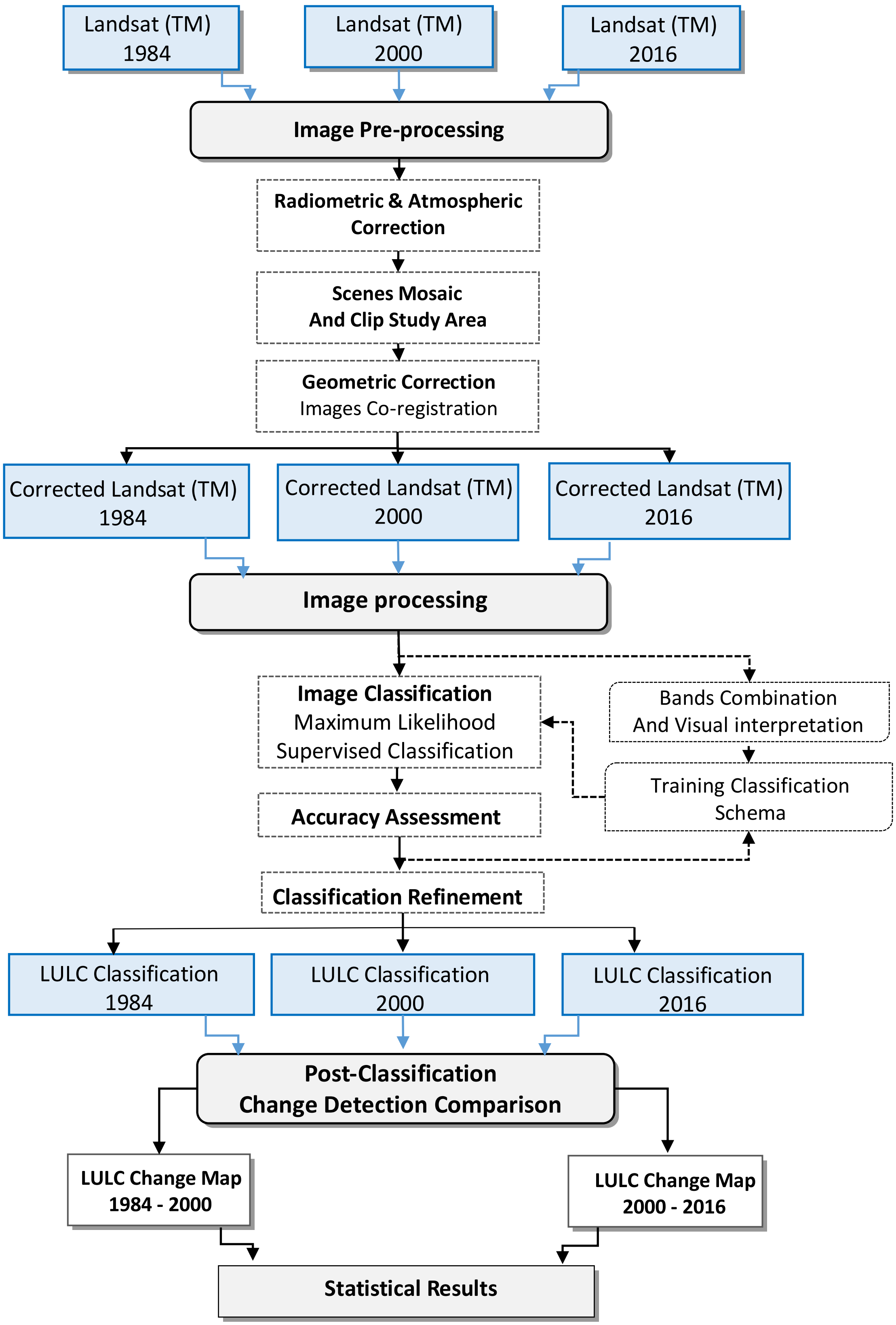

Figure 2. Land-use/cover change detection workflow schema.

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2.3.1. Image Pre-Processing

Satellite image pre-processing is a crucial step in any analytical remote sensing workflow and it is prior to data analysis process. Pre-processing of satellite image prior to land-use/cover classification extraction for change detection analysis and it is an important process to remove noise and increase the interpretability for image data. This process is necessary particularly when the study encompassed multiple images for time series analysis **(Yichun et al., 2008)**. Depend on user's requirement and according to the purpose of the study and type of information needed to extract from remotely sensed data, a required procedures may be carried out before implementing any image processing procedures, attempting to minimize the effects of distortion due to the characteristics of the imaging system and imaging conditions. Satellite image processing composed of techniques and procedures which follows the pre-processing of the dataset. Pre-processing commonly consist of number of sequential operations, including radiometric and atmospheric correction, geometric correction and masking study area. Radiometric and atmospheric correction for scene illumination, atmospheric conditions and correction for variations of the viewing geometry and instrument response characteristics to create a consistent and reliable image database **(Schowengerdt, 2007)**.

2.3.1.1. Radiometric and atmospheric correction:

Remotely sensed data of the same geographic location involves different radiometric values because of variation of illumination conditions, changes in sensor calibration, solar angel and atmospheric effects **(Lu et al., 2004)**. It is necessary to perform radiometric and atmospheric correction to eliminate these radiometric effects before implementing image classification and post-classification change detection, especially when comparing satellite datasets in multiple time period. The correction minimize the sensor noise and the impact and effects of atmospheric elements and topographic shadows. The noise of digital datasets can be caused by the sensor malfunction or error in data collection and transmission. Atmospheric errors

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caused by cloud, haze or particles which exist in the atmosphere, where the energy is returned scattered to the satellite sensor. In order to obtain the real irradiance or reflectance of earth's surface objects, radiometric errors must be corrected. Radiometric correction function is the process of converting the digital number (DN) from sensor into units absolute reflectance **(Lillesand et al., 2008)**.

Radiometric correction method grouped into two broad groups; absolute and relative correction. The absolute radiometric correction method converts digital number of pixel to percentage reflectance values using transformation equation. It is converted by using the sensor calibration data, sun angel and view, atmospheric model and ground truth. The relative correction normalize the multi-temporal date imagery scenes to a selected reference data at specific time selected by the analyst **(Cohen et al., 2003; Du et al., 2002)**.

The process of radiometric correction involves dark-object-subtraction, convert DNs to radiance, convert radiance to Top Of Atmospheric (TOA) reflectance and finally apply atmospheric correction. In term of theoretical concept to get a radiometrically corrected images, there are a series of steps coupled with equations to compute reflectivity of a surface from Landsat images, these steps are according to **(Video on YouTube by Middlebury Remote Sensing, 2014)** are:

- Step-1: subtract path radiance to estimate outgoing radiance by using this equation:

$$L = L_{tot} - L_p$$

  Where L = Outgoing radiance, L_{tot} = Total radiance, L_p = Path radiance.

- Step-2: convert DN to radiance at sensor by using this equation:

$$L= (DN-B)/G$$

  Where L = Spectral radiance, DN = is the cell value digital number, B = "biase" = is the bias value for a specific band, G = "gain" = is the gain value for a specific band.

- Step-3: Estimate incident irradiance on surface by using this equation:

$$E=(E_0 Cos\ \theta)/d^2$$

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Where E = actual incident energy (w/m2), $E_0 \cos\theta$ = irradiance if sun vertical at mean earth-sun distance (w/m2), d^2 = earth-sun distance

- Step-4: take the ratio of irradiance (E) over radiance (L) as following equation:

$$P=L/E$$

Where P = reflectance, L = outgoing radiance, E = irradiance.

Once we have L and E from step 2 and step 3, we will get their ratio to get the reflectance.

2.3.1.2. Geometric correction

The geometric correction of remotely sensed data is an important procedure to get an accurately geographical information of any remote sensing applications, especially applications based on comparing satellite datasets in multiple time period such as land use land cover change detection, where an accurate precise geometric registration of images is required to get an accurate information. The geometric correction adjust the distortion effects caused by the Earth's rotation and curvature, sensor motion and platform vibration. This process also allows geo-referencing the imagery to a geographic or planar coordinate system **(Lillesand et al., 2008)**. The outcome of geometric correction should obtain an error within plus or minus one pixel of its true position, which provide an accurate spatial assessments and measurements of the data generated from the satellite imagery **(Yichun et al., 2008)**.

There are various terms were used to define and describe the geometric correction of remotely sensed data, these terms are:

- Image registration; used to describe the alignment of an image to another image of the same area, where two pixels at the same location in both images are registered and represent the same location on earth' surface, also known as image co-registration.
- Rectification or georeferencing; in this term the image aligned to a map so that image is planimetric like the map.
- Ortho-rectification; is a process of correcting image pixel by pixel for topographic distortion.

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In the present study, all acquired Landsat datasets are geometrically corrected by the images source in UTM WGS 84 system, where belong to “Landsat collection level-1” category (all scenes in the Landsat archive are assigned to a collection category) which contains the highest quality Level-1 Precision Terrain (L1TP). The data considered suitable for time-series analysis, where the geo-registration is consistent and within prescribed tolerances <12m root mean square error (RMSE). So, we will use image to image registration or co-registration method to align images of two date period to improve the positional accuracy.

2.3.2. Image processing

There are many processing and analysis techniques were developed to interpret remote sensing images and extract land us/land cover information. The choice of specific technique or algorithm depends on the aim of the study. Image classification process is one of image process and analysis. Image classification defined as a process of extracting different classes themes from satellite imagery **(Yichun et al., 2008)**. This definition includes image pre-processing stage, but we aim here the process which follows the image pre-processing such as in image classification stage.

2.3.2.1. Image Classification

Image classification obtain the quantitative spectral information that stored in satellite images, and can be implemented using multispectral or hyper-spectral imagery. There are number of factors that influence the quality of image classification, these factors are: the quality of available image data, pre-processing of the image, classification scheme, training sample, classification algorithms and finally the validation methods to evaluate the classification result **(Gong and Hawarth, 1990)**.

Many remote sensing image classification techniques have been developed. Major remote sensing image classification techniques are pixel-based and object-based image classification.

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Most classification techniques has employed the image pixel as a base of image analysis, where each pixel is labeled as an individual land use/cover class. Based on this pixel unit, a series of classification techniques have been developed, such as unsupervised classification (i.e. ISODAT and K-means), supervised classification (Maximum likelihood, decision tree, artificial network, support vector machine and random forests), and hybrid classification (i.e. semi-supervised and fusion of supervised and unsupervised learning) **(Alajlan et al., 2012; Li et al., 2014; Zhang et al., 2005)**. With object-based image analysis, geographical objects are considered instead of pixel as the unit if image analysis. Object-based image classification method generate object through image segmentation. Image segmentation of object is formed by using the spectral, textural, spatial and contextual information **(Pal and Bhandari, 1992)**. Object-based classification method is considered more appropriate for the high resolution satellite images.

In general, there are two main pixel-based image classification algorithm commonly used for image classification of mid-resolution satellite images; supervised and un-supervised classification.

In this study, Maximum likelihood supervised classification approach was used for the image classification of land use/cover of Landsat images.

2.3.2.2. Supervised Classification

Supervised classification is an algorithm usually used for quantitative analysis of remotely-sensed image data, as it better differentiate features with similar spectral properties **(Moeletsi and Tesfamichael, 2017)**. Supervised classification technique was developed for satellite image processing and used for obtaining classification of spectral response of features on earth's surface, which recorded in the satellite image spectral layers. Supervised classification primarily depends on the prior knowledge of land cover types of the area under study through satellite image. Supervised technique is a process of using samples or signature of identified

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feature or objects, which represented as a group of pixels that assigned with numeric values represent the spectral reflectance of this object, for grouping and classification of the objects or features with same pixel signature or reflectance values. The samples of known identity are pixels located within training areas **(Campbell, 2002)**.

The first step in supervised classification approach is to identify samples of information classes (i.e., Land cover types). Selecting training samples of land-cover from images is one of most important factors in classifying the pixels, and considered a key of supervised classification technique. The application software of image processing is using the identified samples area to calculate the statistical characteristics for each information class, then image classified into classes by examining the reflectance information of each pixel and group them according to the information of each class that resemble the most. There are many possible elements of error correlated with supervised classification, one of these elements is the defined classes may not match real classes that exist in the image data, and as consequence may not well distinct. Also, the selected classes' samples may not be delegated of conditions over the image of study area, so the user may face a problem in coupling or matching some classes as he defined on image. **(Campbell, 2002)**. Supervised classification coupled with various classification algorithms, and the most used algorithms are Maximum likelihood, Minimum distance, Mahalanobis Distance and Spectral Angle Mapper. Maximum likelihood is the most common and accurate algorithm that used for image classification and it was used for the classification of images of the study area.

In order to apply supervised classification method on Landsat images, seven classes were identified from images namely barren-land, built-up-area, water-bodies, cultivated-land, water-bodies, coastal-beach-and-sand-plains, fish-ponds and sabkha-deposits-and-bare-soil.

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2.3.2.3. Accuracy Assessment

Accuracy assessment is a vital and an important part in any classification process, whether used technique is supervised or unsupervised classification, is an assessment of the accuracy of the generated image classification. The most common way used to assess the accuracy of classified image is to create a random points of ground truth and compare the classified data in a confusion matrix. The analyst may not have a ground truth data and have to relying on the same imagery that used to create classification to perform the accuracy assessment, and this method were used in this study. In order to properly generate an error matrix, some elements should taking into account such as reference data collection, classification scheme, sampling scheme, spatial autocorrelation and sample size **(Lu and Weng, 2007)**. The error matrix compare is based on pixel by pixel between the reference data and the identical classification result. Such matrixes are square, with the number of rows and column equal to the number of the categories whose classification is being assessed **(AlJaber and Mahmud, 2014)**.

Evaluating the references, test information that has been collected from randomly located on the image of classification and the agreement or disagreement can be identified by evaluating descriptive statistics which generated from accuracy assessment procedure. The descriptive statistics composed of the overall accuracy, producer's accuracy, user's accuracy and kappa coefficient **(Campbell, 2002)**. The overall accuracy of classification compares how each pixels of classified image is classified against the definite land-cover obtained from their corresponding ground truth data. Overall accuracy computed by dividing the total correctly classified pixel by the total number of reference pixels in the error matrix **(Rwanga and Ndambuki, 2017)**.

The producer's accuracy is calculated by dividing the total number of the correct pixels in a category by the total number of pixels of the category that derived from, and this descriptive statistic compute the accuracy of individual categories **(Campbell, 2002)**. While the user's

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accuracy is calculated by dividing the total number of correct pixels in a category by the total number of pixels that were actually classified in that category, and this indicator determine the probability that a pixel classified on the image actually represents that category on the ground. Finally, the Kappa coefficient is a quantitative assessment of the error matrix, and it is a measure of the difference between the observed agreement between two maps and the agreement that might be attained solely by chance matching of the two maps **(Campbell, 2002)**.

2.3.3. Digital Change Detection of Land use/cover

Digital change detection aims to assess and measure the different features of land use/cover at two dates. According to **(Singh, 1989)** digital change detection techniques can be categorized into two main categories. The first is the dependent analysis of each dataset at different dates, and the second is the simultaneous analysis of multi-temporal datasets. The present digital change detection techniques are belong to one of these categories and called pre-classification and post-classification approaches **(Metternicht, 1999; Lunetta and Elvidge, 1999)**.

The pre-classification approach is based on the differences of spectral signatures over the time and transform two remote sensing images to a new single or multiple bands image in which the spectral change is highlighted **(Yuan et al., 1998)**.

In post-classification change detection approach, two different images are individually classified and labelled. Both approaches have advantages and disadvantage. The advantage of pre-classification approach is the elimination of mix-pixels effect, while the post-classification advantage is the ability to overcome the difficulties in change detection which associated with the analysis of remotely sensed data, which acquired from different sensor or at different time. On other hand, the disadvantage of pre-classification approach is the difficult of identification of changes and no changes area, while the disadvantage of post-classification approach is the

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dependency to the quality of classification of each image **(Karsidi, 2004)**. However, there are many techniques which belong to these category and frequently used in land use/cover change detection studies. According to **(Lu et al., 2004)** the most commonly used change detection methods are:

- Image differencing.
- Image rationing.
- Image regression.
- Change Vector Analysis.
- Post-classification comparison.

In the image differencing method, two registered image dates are subtracted pixel by pixel in each band to produce a new change image between two dates **(Singh, 1989)**.

In the image rationing, two co-registered image dates rationed pixel by pixel in each band. The no-change area is characterized by ratio values close to 1. Depending on the nature of changes between two dates changed areas will have higher or lower values. Image regression method assume that pixels of date one image to be a linear of date two image, and depending on the nature of changes between two dates changed areas will have higher or lower values. In the change vector analysis method use the spectral or spatial differences for computing the change detection, and in this method two images are plotted on a graph and the two spectral variables will show the intensity and direction of change overtime **(Singh, 1989).**

Post-classification comparison change detection is on of most commonly used as quantitative method of remote sensing change detection studies. This technique does not only give the size and distribution of changed area, but it also gives more detailed information about changes that occurs between two dates, and proportion of land-cover classes that share the change in each class individually and quite high change detection accuracy **(Raja et al., 2013)**. The result's

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accuracy and quality of post-classification technique depends on appropriate labeling pixels of spectrally distinct land-cover types through classification process.

In this study post-classification comparison technique were used to detect land-use/cover changes in Delta province of Egypt.

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Chapter-3: Processes and Results

3.1. Image Pre-Processing

Acquired Landsat TM 1984, 2000 and OLI 2016 images entailed by a number of pre-processing procedures. The pre-processing of images prepare them for further image analysis. These procedures are radiometric correction, mosaic and mask scenes and geometric correction using image to image registration method. The pre-processing was carried out using Envi 5.3.

3.1.1. Radiometric and Atmospheric Correction

The radiometric and atmospheric correction of satellite image is mandatory to perform more accurate change detection process using supervised classification. To achieve an accurate radiometric and atmospheric correction, the digital number (DN) of Landsat TM and OLI images were converted to radiance at-sensor using Radiometric Calibration tool in ENVI (Figure No. 3), then FLAASH Atmospheric Correction tool were used to convert radiance to Top of the Atmospheric (TOA) reflectance (Figure No. 4).The conversion of radiance to top of the atmospheric requires a combination of parameters such as sun angle and view, sensor calibration, and these parameters has been obtained from Landsat metadata file of each scene. Radiometric and atmospheric correction process were applied for each Landsat TM 1984, 2000 and OLI 2016 images' scenes individually, to obtain a radiometrically and atmospherically corrected images.

The conversion of digital number (DN) values of images should be converted into surface reflectance in which range between 0 and 1, but the output result of FLAASH correction tool reveals a negative values.

According to some articles, ENVI's FLAASH tool multiplies the output surface reflectance data by 10.000, omitting the decimals for faster process calculation. Therefore, an equation is used to eliminate these negative values, and correct these values in post FLAASH process by using Band-math tool in ENVI:

[(B1 le 0)*0+(B1 ge 10000)*1+(B1 gt 0 and B1 lt 10000)*float (b1)/10000 **]**

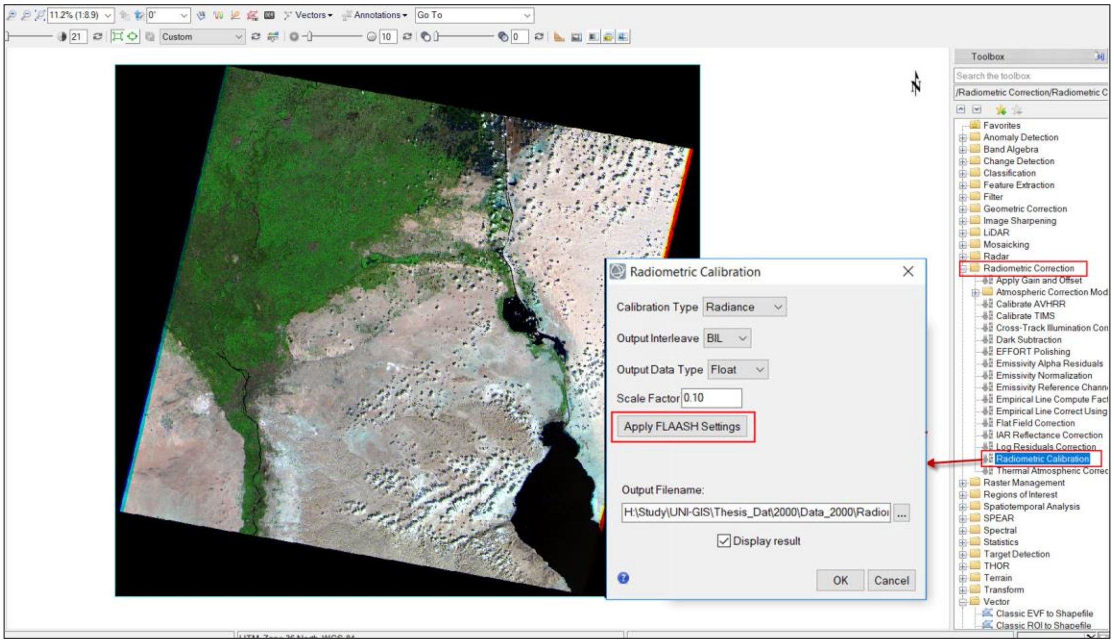

Figure 3. Convert DN of Landsat scene into radiance at sensor using ENVI's Radimoetric-Calibration tool.

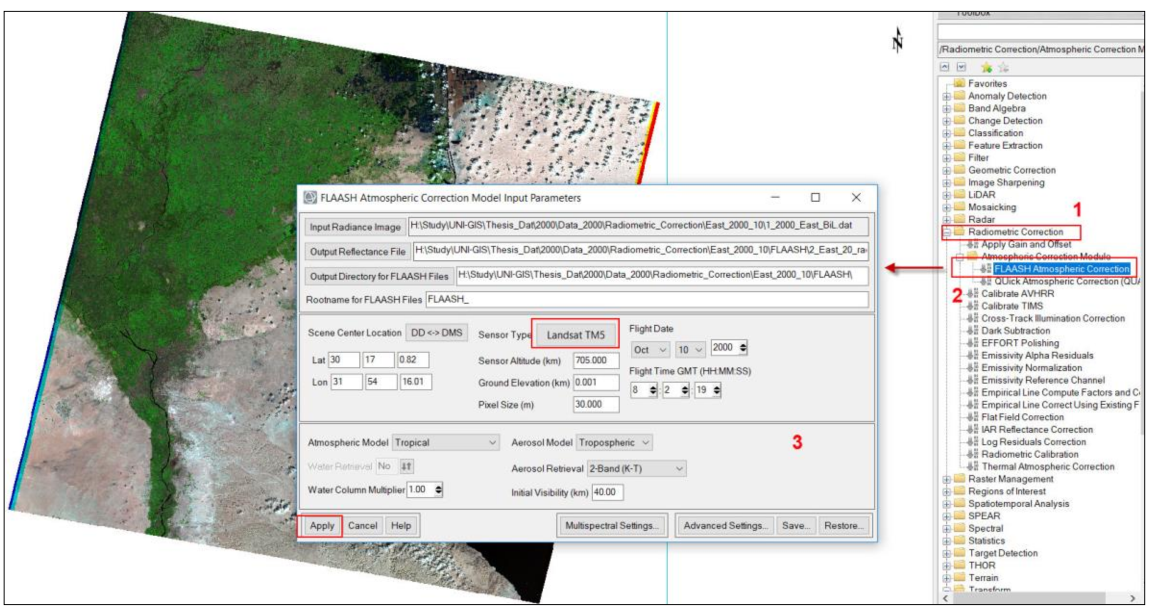

Figure 4. Convert radiance to Top Of Atmospheric Reflectance (TOA) using ENVI's FLAASH tool.

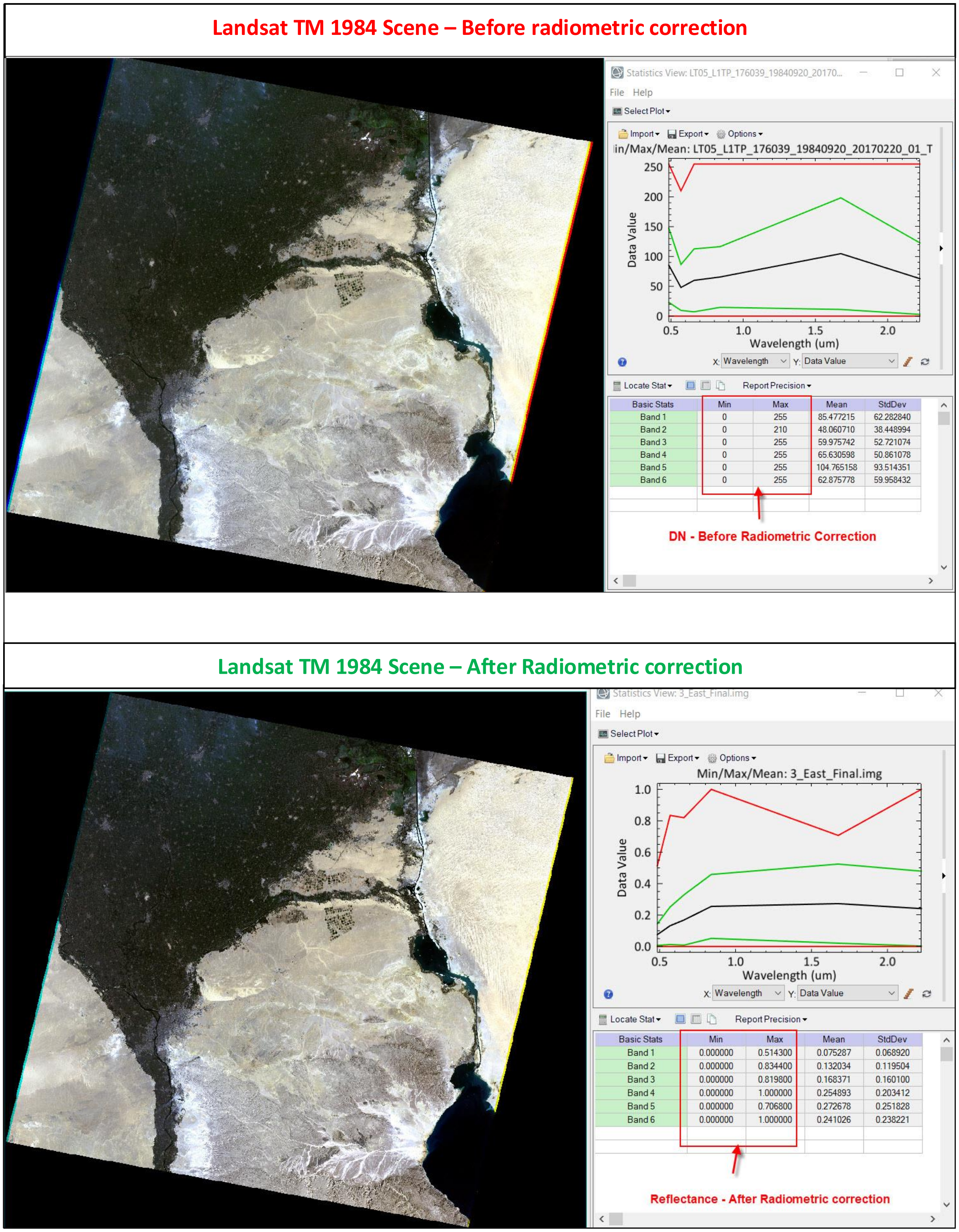

Figure 5. Landsat TM 1984 scene statistical information before and after radiometric-correction process.

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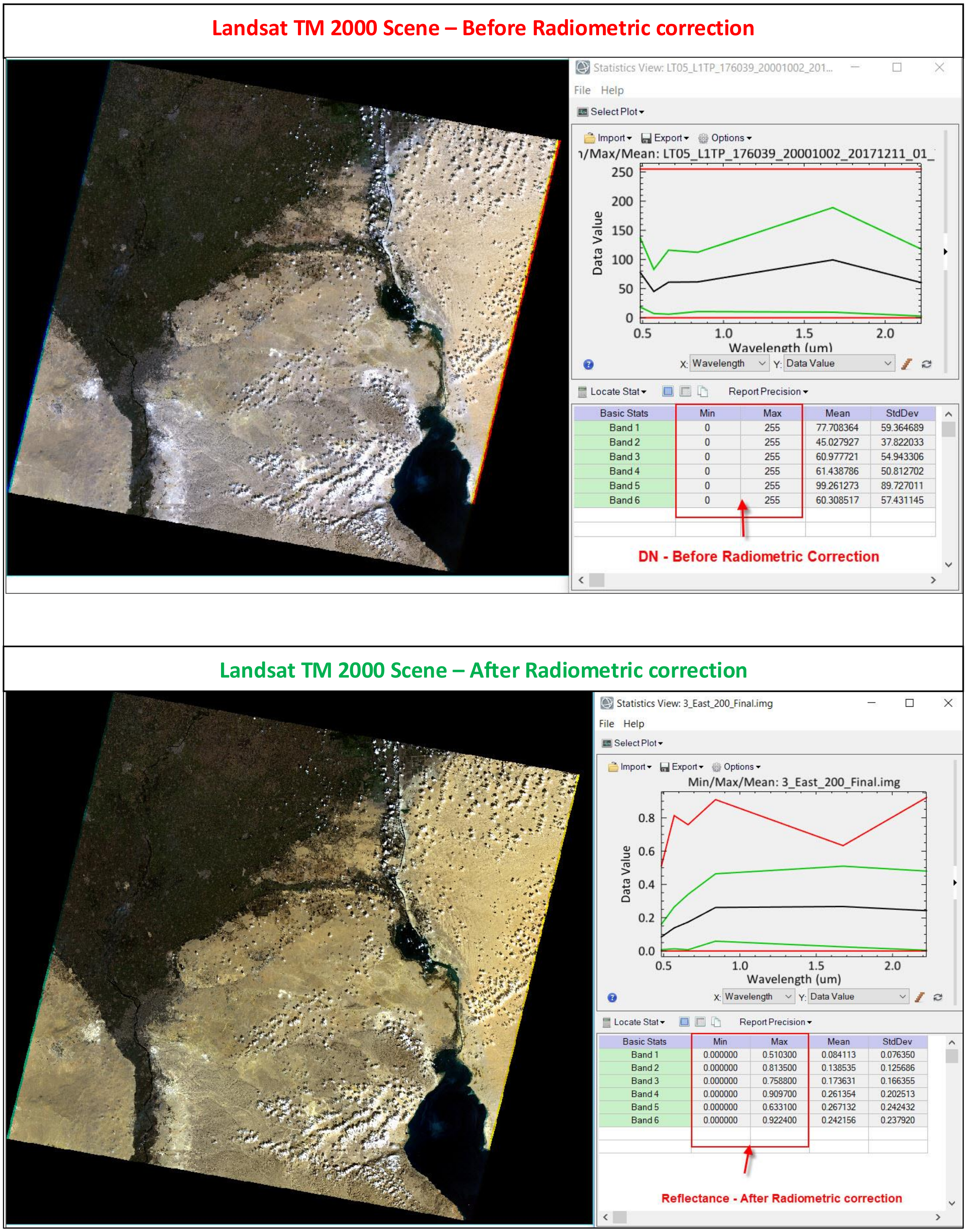

Figure 6. Landsat TM 2000 scene statistical information before and after radiometric correction process.

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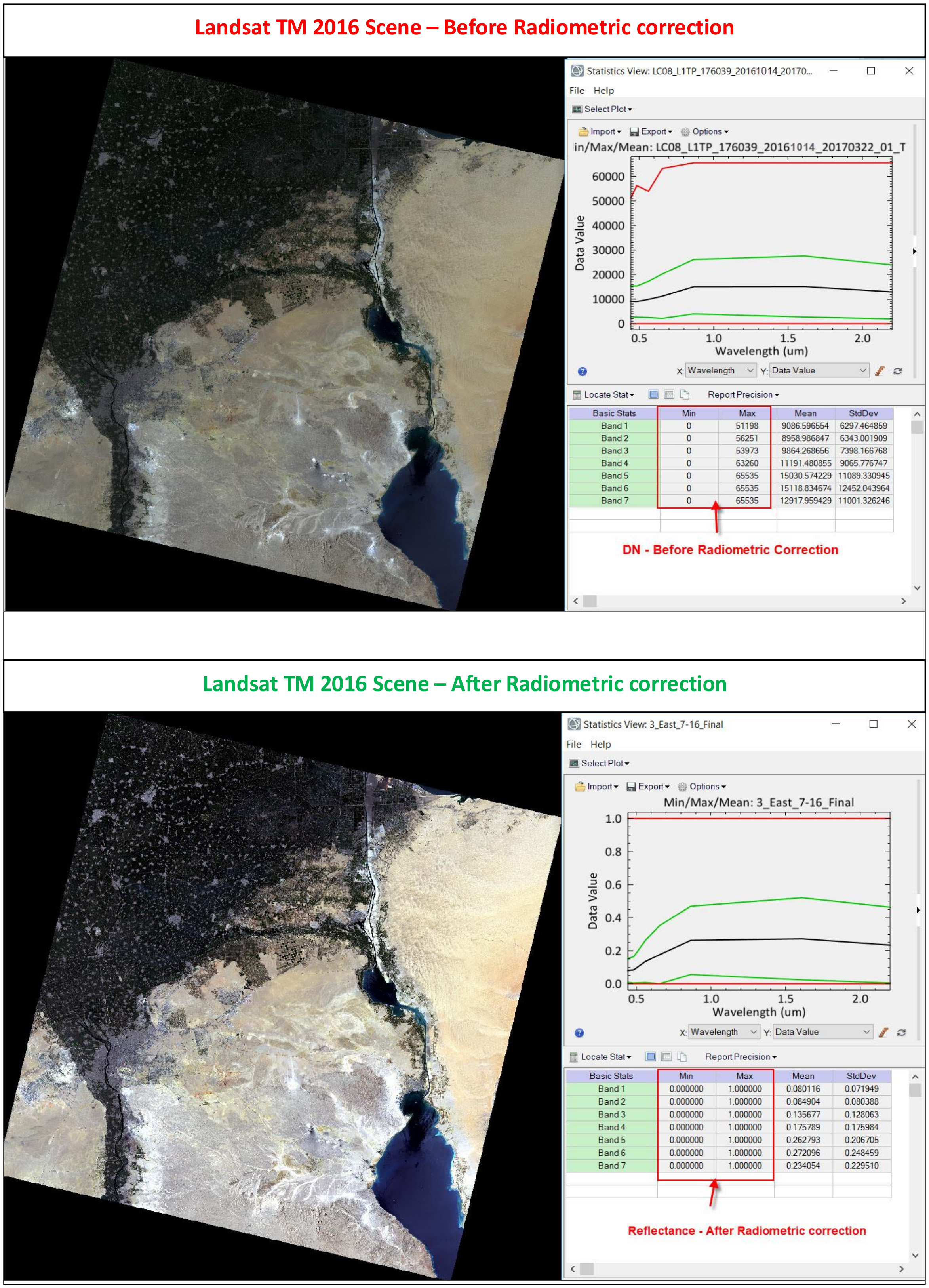

Figure 7. Landsat OLI 2016 scene statistical information before and after radiometric correction process.

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3.1.2. Mosaic and Mask Area of Interest

The study area extends in four Landsat scenes. After radiometric correction of Landsat TM 1984, 2000 and Landsat OLI 2016, datasets were mosaicked using ENVI, with Nearest-Neighbor resample algorithm to create a single image of each time period. Figure No. 8 shows mosaic process of Landsat TM 1984 scenes using ENVI.

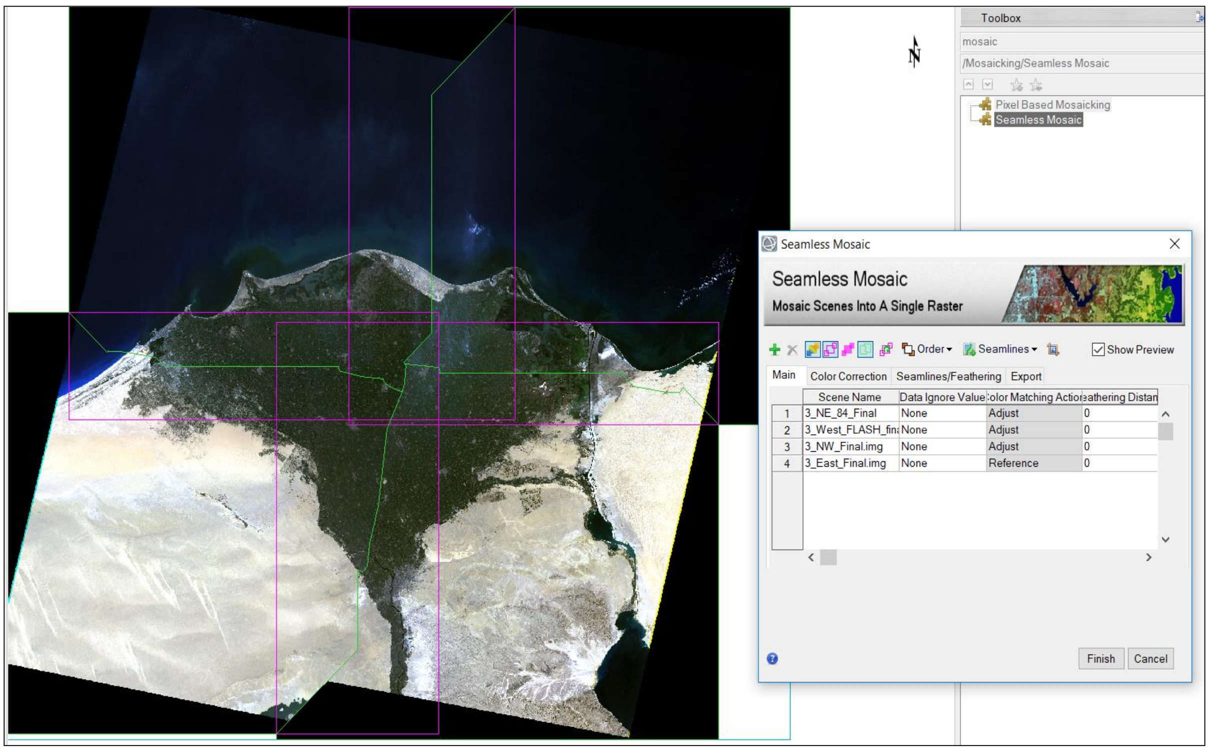

Figure 8. Landsat TM 1984 scenes mosaicking using ENVI 5.3.

Finally, the images of study area were masked using a shape file of Delta province governorates which acquired from **(CAPMAS)**, to mask out the area that surround the study area to exclude them from classification and change detection process. Map No. 6 and 7 show the final result of Landsat 1984, 2000 and 2016 images masking process.

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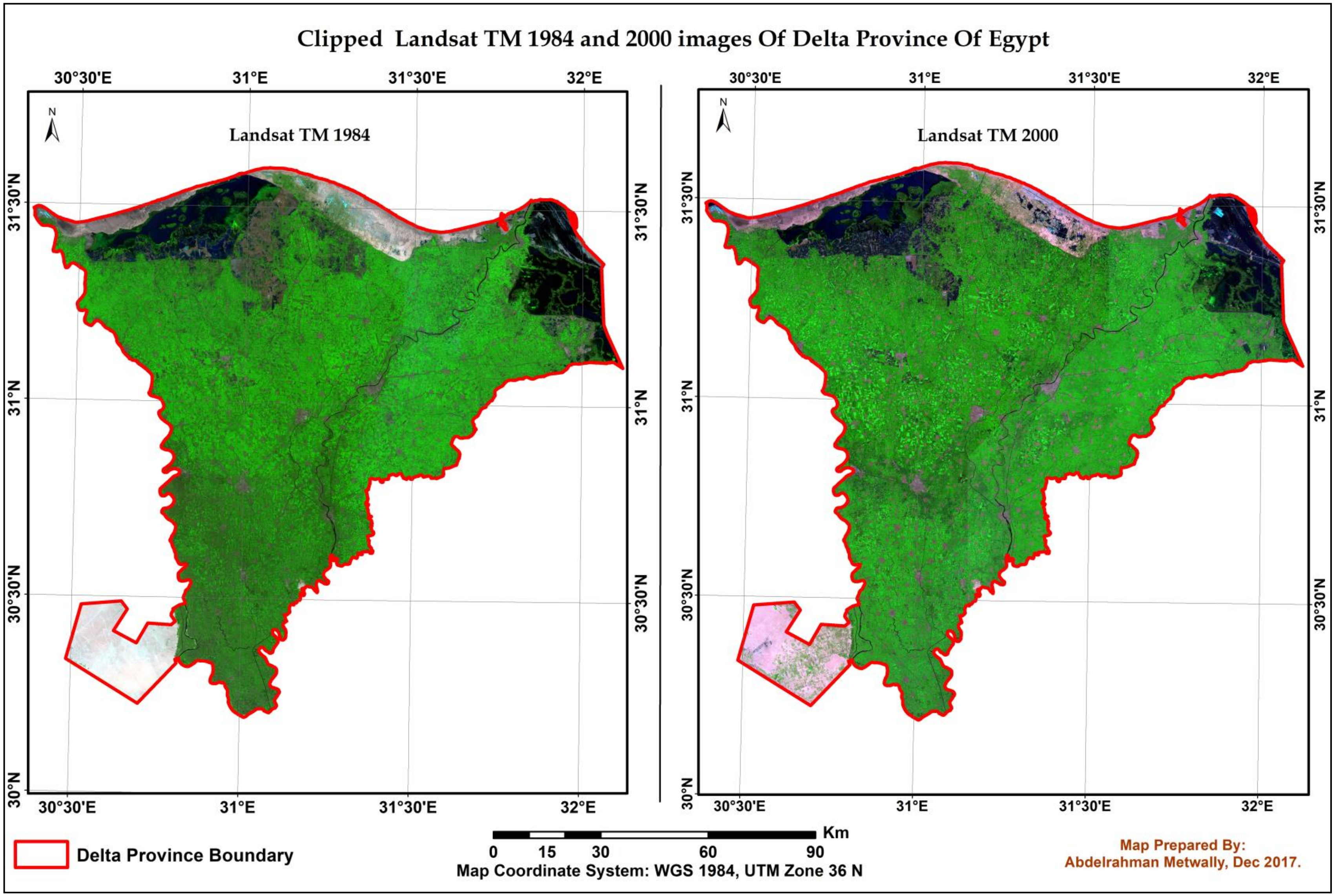

Map 6. Landsat TM-1984 and 2000 images after mask process.

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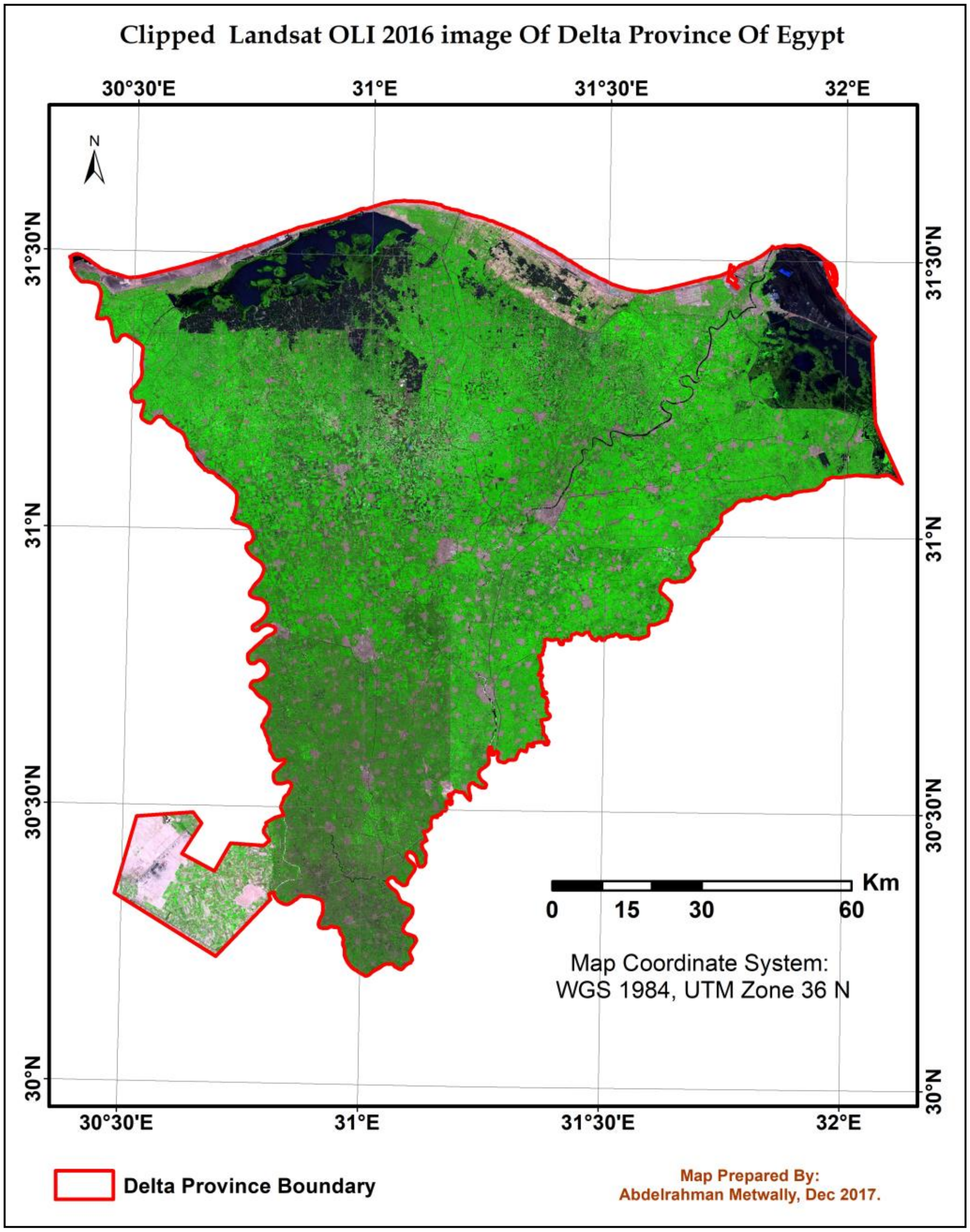

Map 7. Landsat 2016 image after mask process.

3.1.3. Geometric Correction (image to image registration)

Change detection analysis is basically performed on pixel-by-pixel basis, so the accurate per-pixel registered multi-temporal satellite images data is an important for an adequate accurate land use/cover change detection analysis result. Inaccurate multi-temporal satellite images

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registration lead to an overestimation of actual changes **(Stow, 1999)**. The acquired Landsat images that were used in this study are ortho-rectified and geo-registered from the source (USGS). Indeed, they are in world geodetic system (WGS 84) datum with Universal Transverse Mercator (UTM) projection system. The verification of the geometric quality of Landsat datasets were achieved by comparing the spatial adjustment of both images, using a prominent linear land features such as roads and rivers in different positions of images. The visual verification between two dates Landsat images reveal no significant mismatching between images. It is reveal a high matching between images with a shift between images ranging from 1 to 2 pixels. Therefore, image to image registration tool in ENVI was used to adjust and align both images, to get a maximum accurate matching between them. This process was delayed after mosaic and masking study area stage to avoid the repetition of image to image registration process with each of Landsat scene, to save time and effort.

The Landsat 2000 image is co-registered as warp image to Landsat 1984 image, while the Landsat 2016 is co-registered to Landsat 2000 image. At least 60 ground control points (GCPs) were used to match and align images. The Root Mean Square (RMS) error of co-registered images were not exceed 0.6 pixel. Table No. 4 show the information of the registration process. Figures No. 9 and 10 show the distribution of ground control points (GCPs), which used to match between Landsat 2000 and 1984 images, and between Landsat 2016 and 2000 images.

Table 4. Image to image registration information between Landsat TM 1984 and 2000, and between 2000 and 2016.

Base image	Warp image	Resampling method	Warping Method	Number of GCP	RMS Error
Landsat 1984	Landsat 2000	Nearest Neighbor	1st Order Polynomial	60	0.52
Landsat 2000	Landsat 2016	Nearest Neighbor	1st Order Polynomial	60	0.56

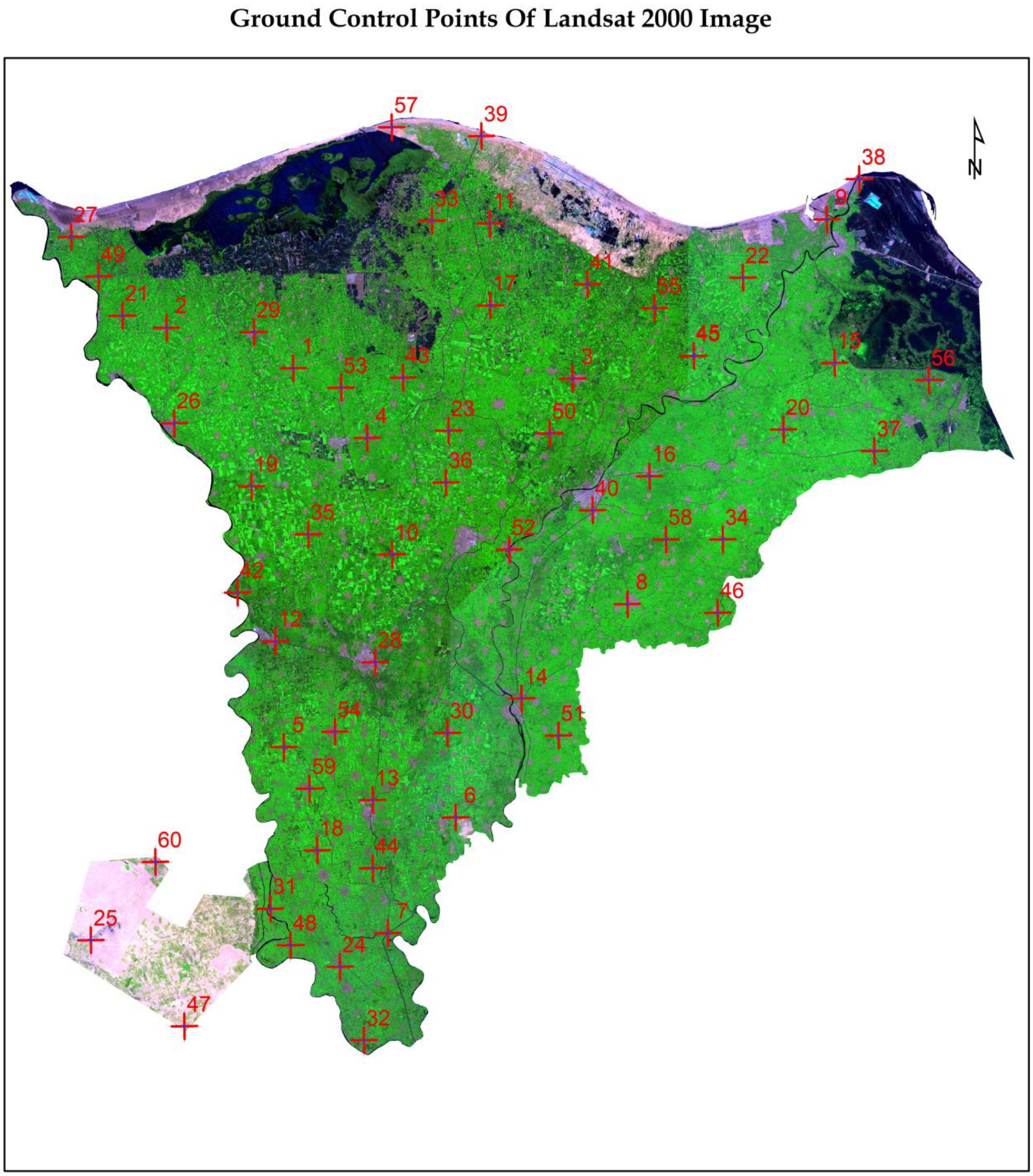

Figure 9. Distribution of ground control points of Landsat 2000 image.

Ground Control Points Of Landsat 2016 Image

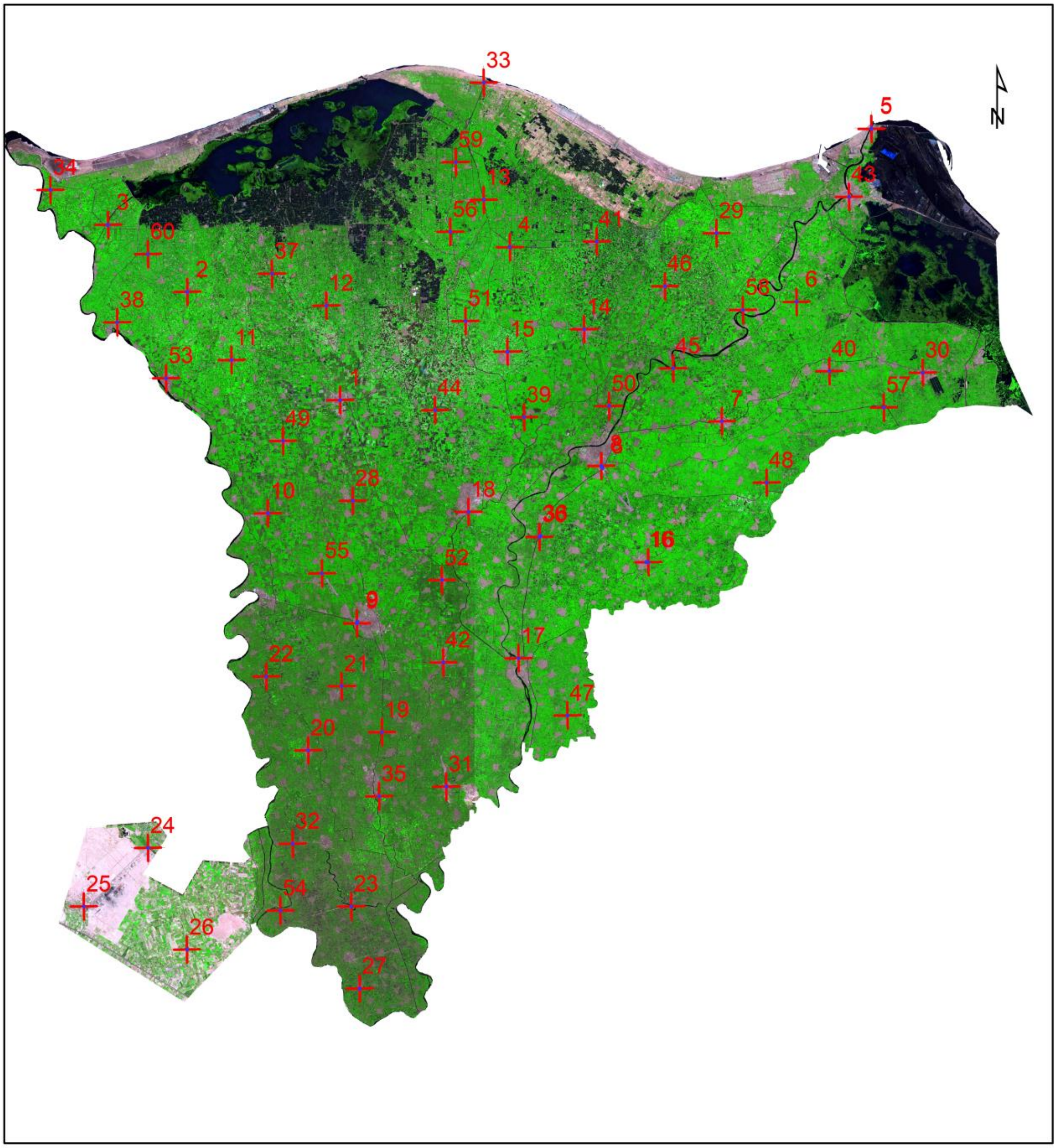

Figure 10. Distribution of ground control points of Landsat 2016 image.

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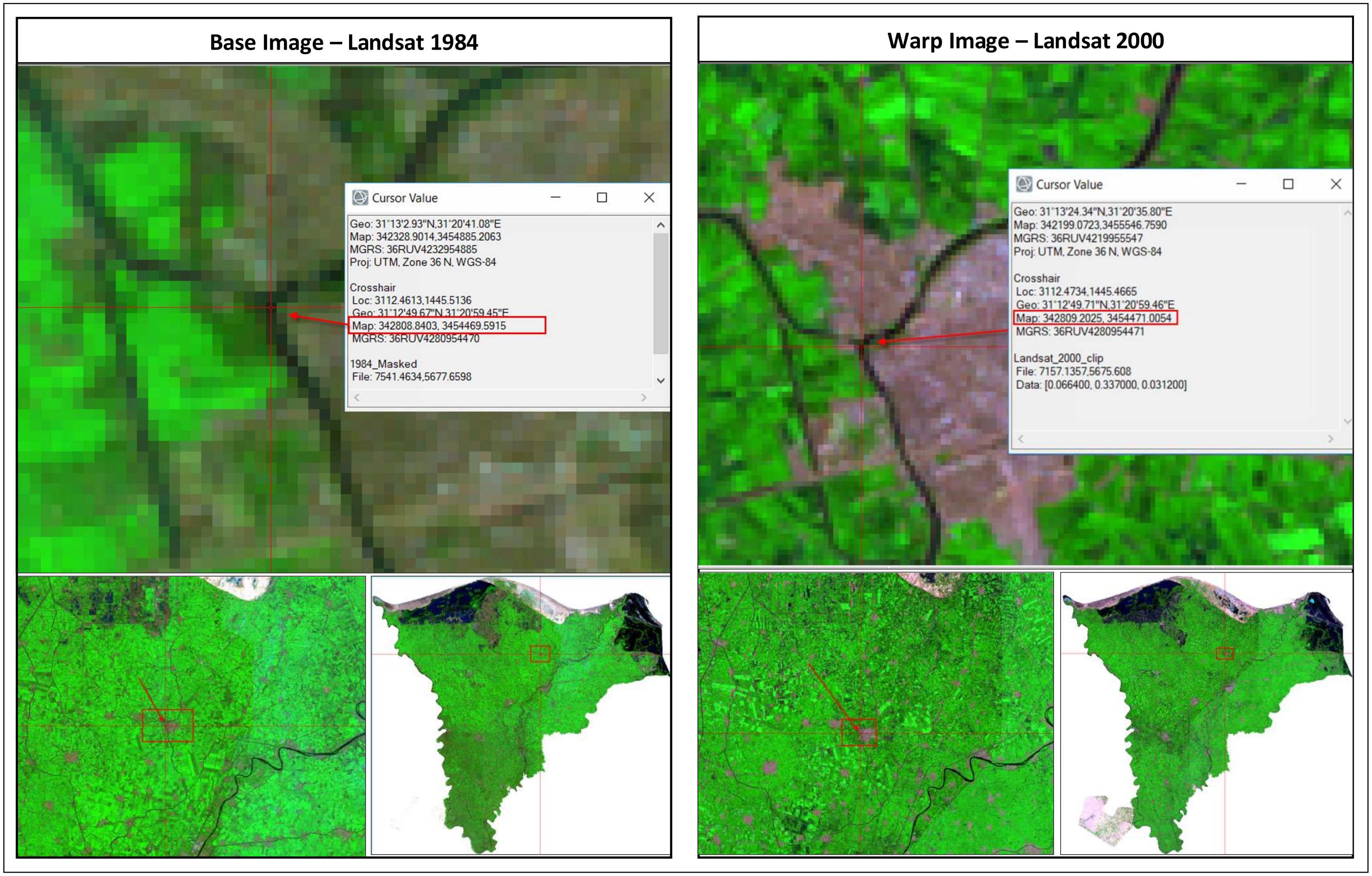

Figure 11. Geometric information of Landsat 1984 and 2000 after image co-registeration**.**

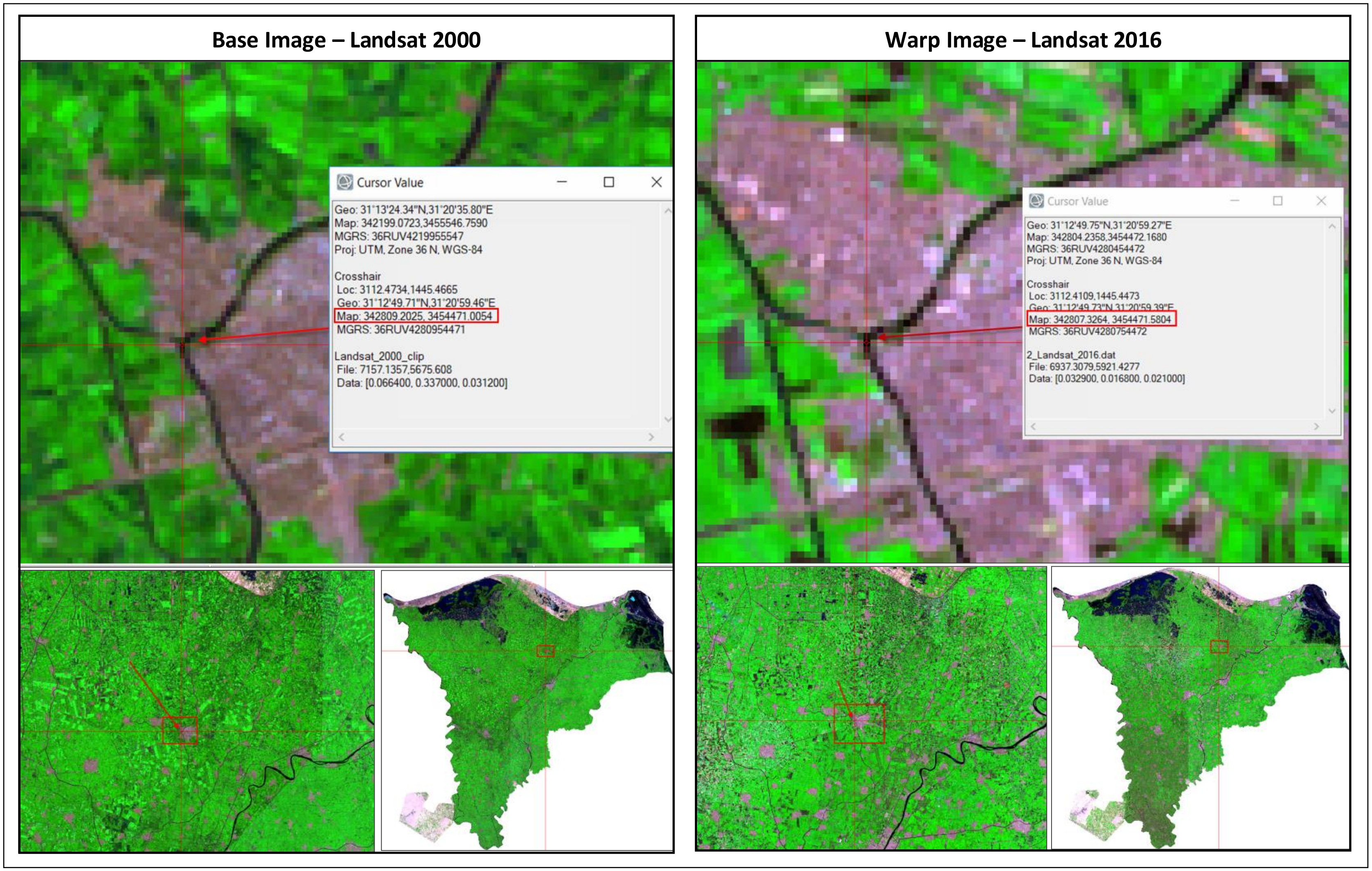

Figure 12. Geometric information of Landsat 2000 and 2016 after image co-registration.

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A visual verification was done by comparing the warp-image with base-image geometric information, using linear features such as roads or river intersections. Figures No. 11 and 12 show a comparison between geometric information of pixel of river intersection, and both images were co-registered with high accuracy match.

3.2. Image Processing

3.2.1. Image Classification

The objective of image classification stage is to assign a group of unknown pixels to a labels, and categorize the land use/cover of the study area. In this study, the image classification process involves a three key steps in order to generate image classification namely are; classification schema and defining training sites, applying supervised classification algorithm and finally the assessment of land use/cover classification accuracy by using accuracy assessment method.

3.2.2. Classification schema and defining training sites

Supervised classification method requires a training signature samples that carefully collected, and it is one of major factor that impact the quality of classification. In this study, based on prior knowledge of the study area with additional information from previous researches and visual inspection from Google Map about study area, the classification schema was developed. Seven land-use/cover classes were selected; water-bodies, built-up-area, barren-land, coastal-beach-and-sand-plains, cultivated-land, fish-ponds and sabkha-deposit-and-bare-soil representing the dominant land-use/cover in Delta province (Table No. 5). The selected training sites were by the identification of land use/cover classes from Landsat images, Google Earth and Google Map. Multiple band combinations of Landsat images were used to aid the visual interpretation of land-use/cover classes from images.

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Table 5. Band combination of each land-use\cover class.

Land-use/Cover Type	Band Combination
Built Up Area	Band 1, 4, 7 - Band 1 , 4, 5 - Band 1 , 2, 3
Water Bodies	Band 1, 4 & 7 / Band 1, 2 ,3 / Band 1 , 4, 5
Cultivated Land	Band 1, 4, 7 - Band 1 , 4, 5
Coastal beach and sand plains	Band 2, 4, 7 - Band 2, 4, 5
Sabkha deposit and Bare Soil	Band 1, 4, 7 - Band 2, 3, 4
Fish Ponds	Band 1, 4 & 7 / Band 1, 2 ,3 / Band 1 , 4, 5
Barren Land	Band 1, 4, 7 – Band 2, 4, 5

The distinction between water-bodies and fish-ponds from Landsat images with 30 meter resolution was not easy task, wherefore, Google Map where used to detect fish-ponds area.

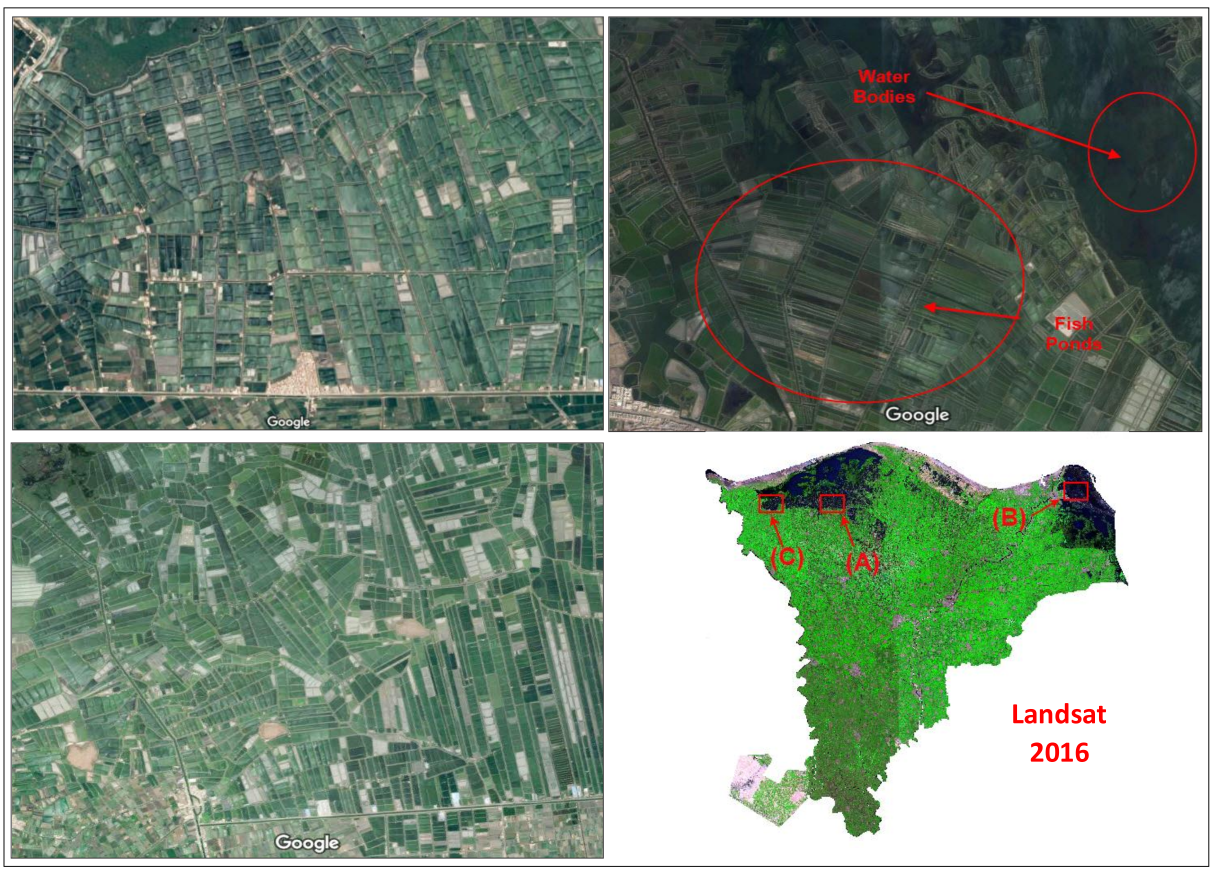

Figure 13. Identification of fish ponds sites using Google map and Landsat image.

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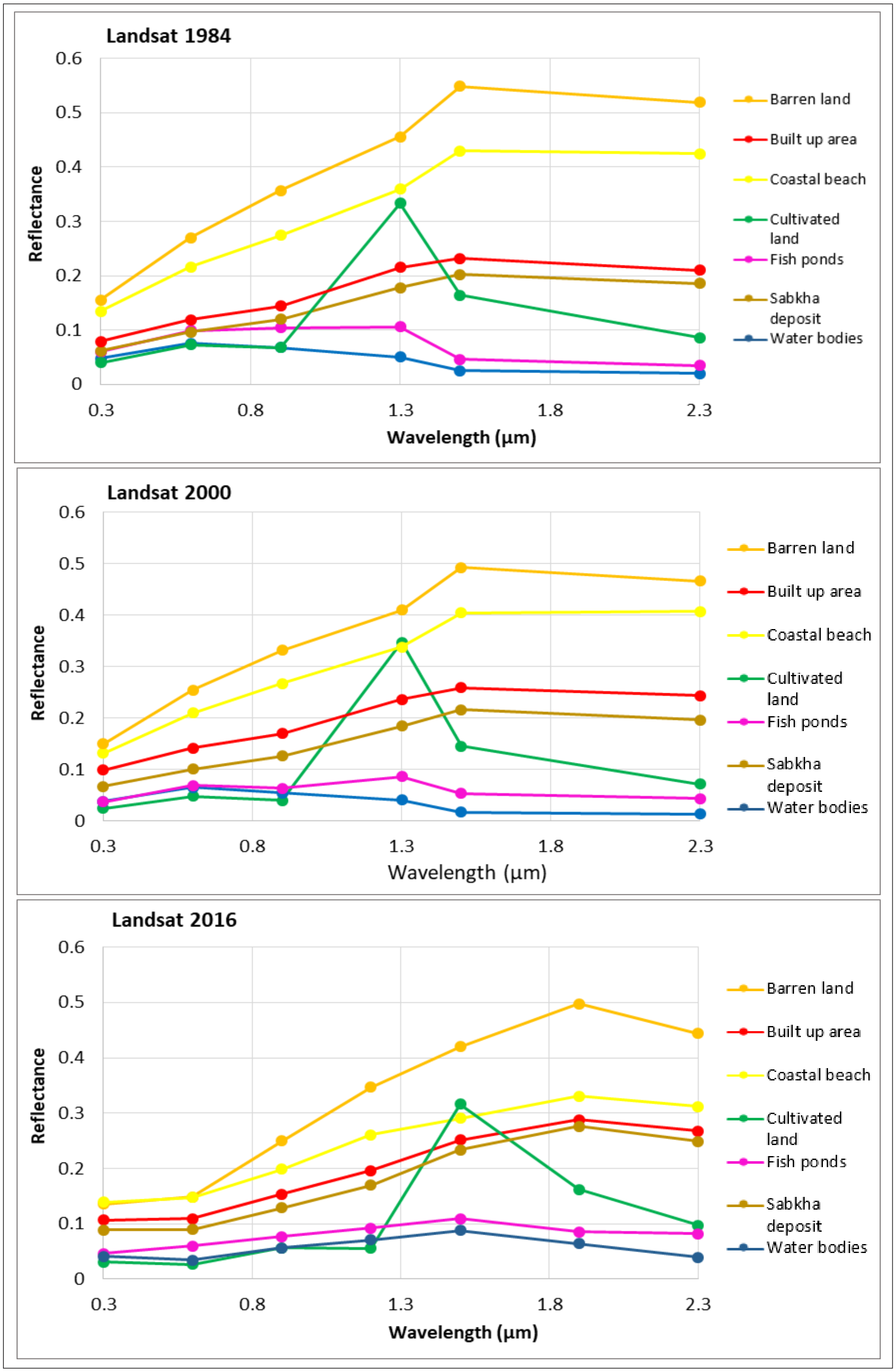

Figure 14. Average of spectral reflectance curves of land use/cover classes of Landsat 1984, 2000 and 2016 images.

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Spectral signature curves of land-use/cover classes of each Landsat image reveal that barren-land, coastal-beach-and-sand-plains and cultivated-land are radiometrically separated and distinct from other classes. While the mean average of water-bodies and fish-ponds; the built-up-area and Sabkha-deposit-bare-soil classes are very similar. The reflectance of water-bodies and fish-ponds are very similar with low reflectance response due to the characteristics of water. Therefore, the classification algorithms of supervised classification method may tend to misclassify built-up-area and sabkha-deposit-and-bare-soil, and water-bodies with fish-ponds. Table No. 6 show land-use/cover classification names, description and number of trained samples for each class of Landsat datasets.

Table 6. Description of trained samples.

Class	Description	No. samples 1984	No. samples 2000	No. samples 2016
Built Up Area	A concrete structure such as residential, industrial and other uses.	60	60	60
Water Bodies	Seas, lakes, reservoirs, and rivers; it can be fresh or salt water.	52	49	50
Cultivated Land	Agriculture, farms, vegetation and crop land.	60	60	60
Coastal Beach and Sand Plains	Coastal beach and back shore, gravel and sand dunes	35	35	35
Sabkha Deposit and Bare Soil	Deposit of sabkha, soil, fallow and bare fields that has no vegetation.	40	40	40
Fish Ponds	Fish farming and raising fish commercially as food production	45	45	54
Barren Land	Land exposed, desert land, thin soil, sand and rocks.	30	30	30

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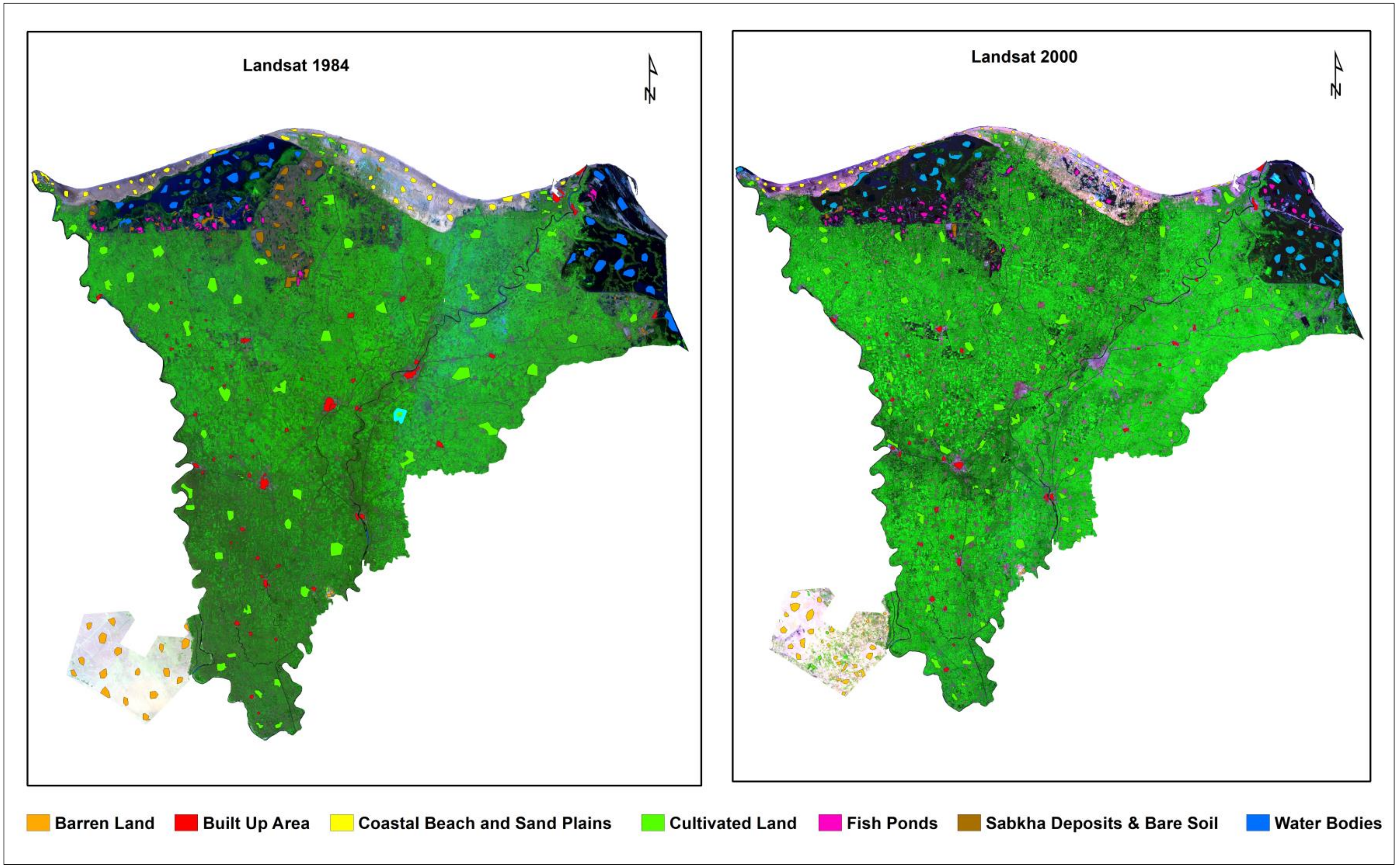

Figure 15. Distribution of training samples of Landsat 1984 and Landsat 2000 images.

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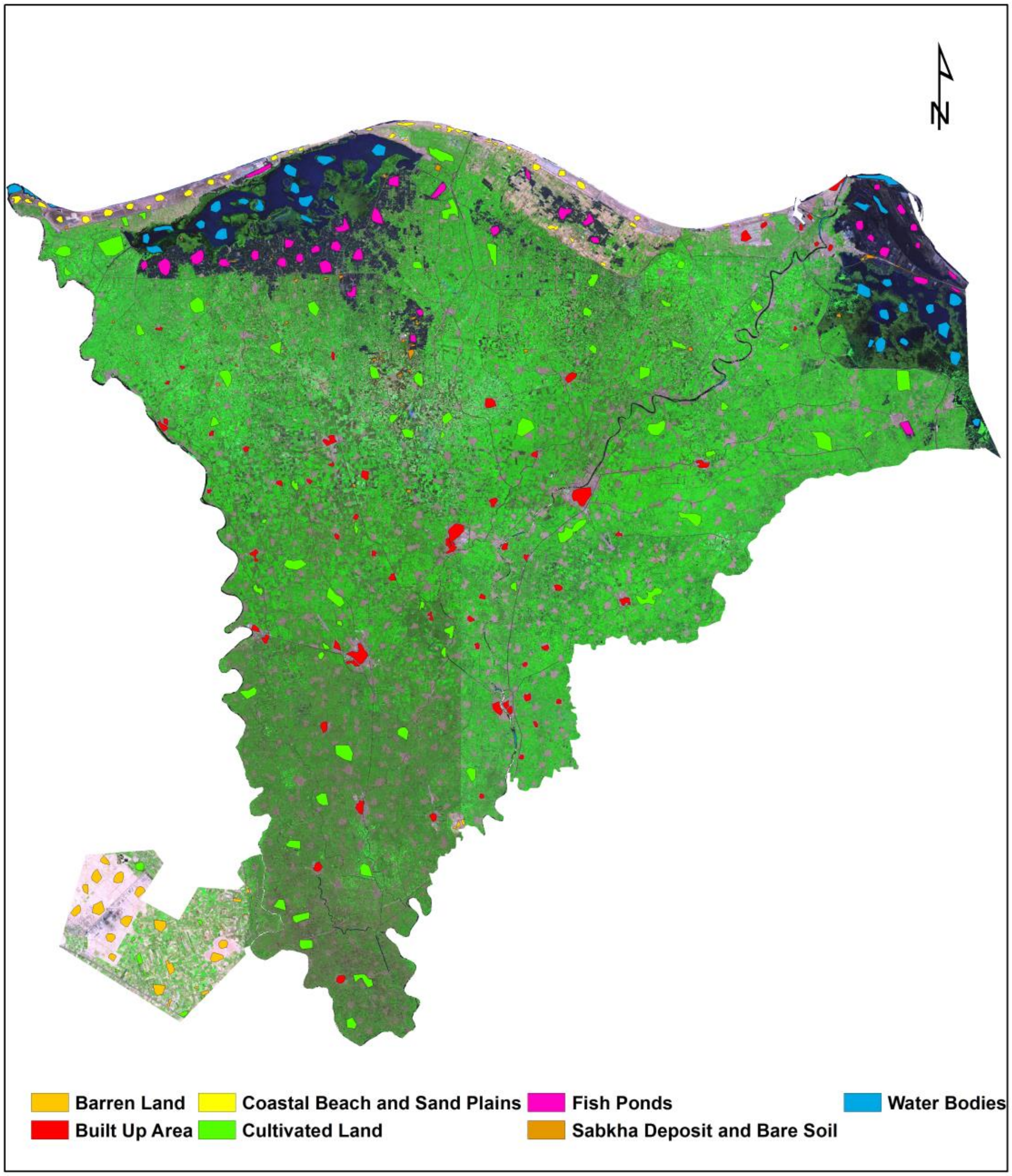

Figure 16. Distribution of training samples of Landsat 2016 image.

The classification process and selection of samples was repeated to get most accurate classification result for Landsat TM 1984 and 2000 image (Map No. 8 and 9) and OLI 2016 image (Map No. 10).

3.2.3. Supervised Classification

Maximum likelihood supervised classification was used for land use/cover classification of Landsat 1984, 2000 and 2016 images, using ENVI's Classification-Workflow tool. Maximum likelihood classifier algorithm is the most commonly used parametric classifier in practice **(Lu and Weng, 2007)**. In the Maximum likelihood algorithm, image pixels are assigned to the most likely class based on a comparison of the subsequent probability that it belongs to each of the signatures being considered **(Paul, 2014)**.

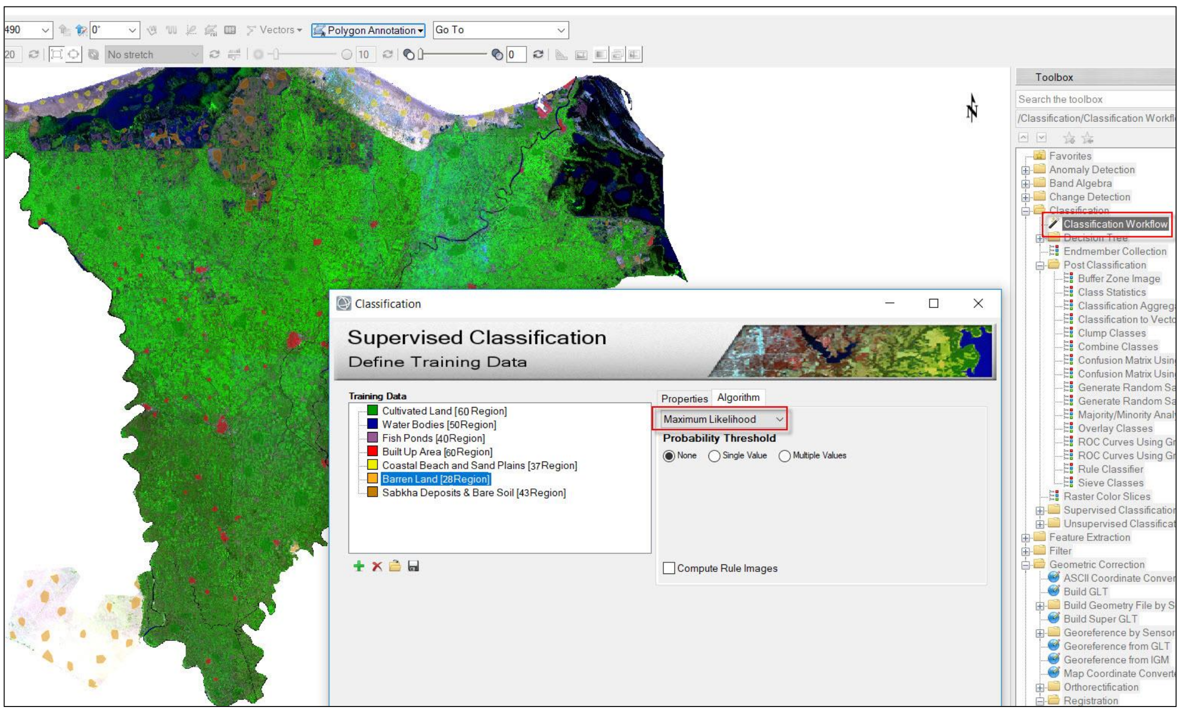

Figure 17. Landsat 2000 image classification using Maximum likelihood Supervised Classification in ENVI Workflow-classification tool.

Post-classification refinement of the classified images was applied to adopt misclassified pixels that were produced from classification process. The process of post-classification refinement composed of two stages: first, performing smoothing process to remove salt and pepper noise by applying Majority-analysis algorithms with kernel size of 5*5 Pixels; second, classification-aggregation analysis to remove the small classified pixels area and aggregate them into a larger adjacent pixel region by applying aggregation size with value of 9 pixels.

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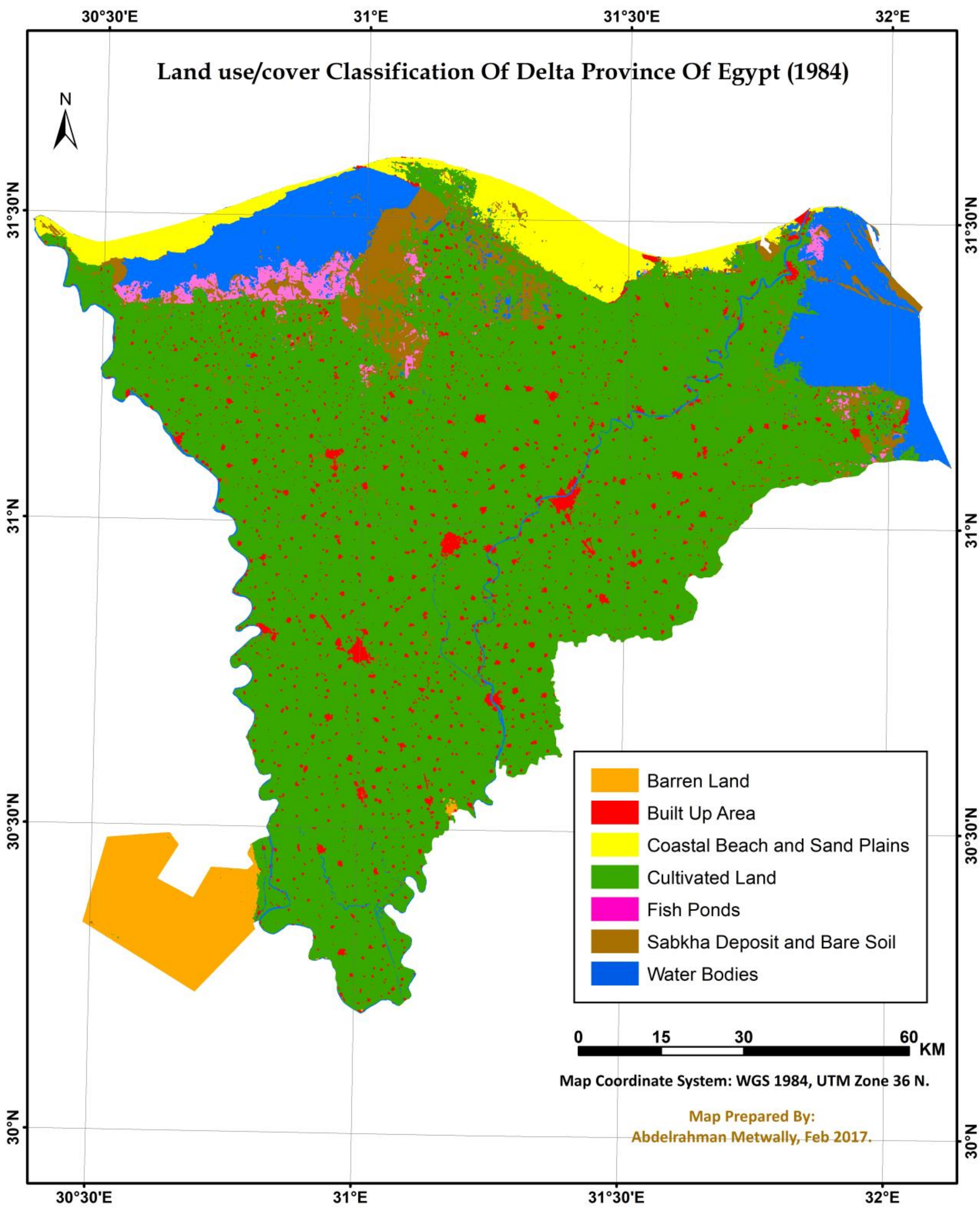

Map 8. Land-use/cover classification map of Landsat 1984.

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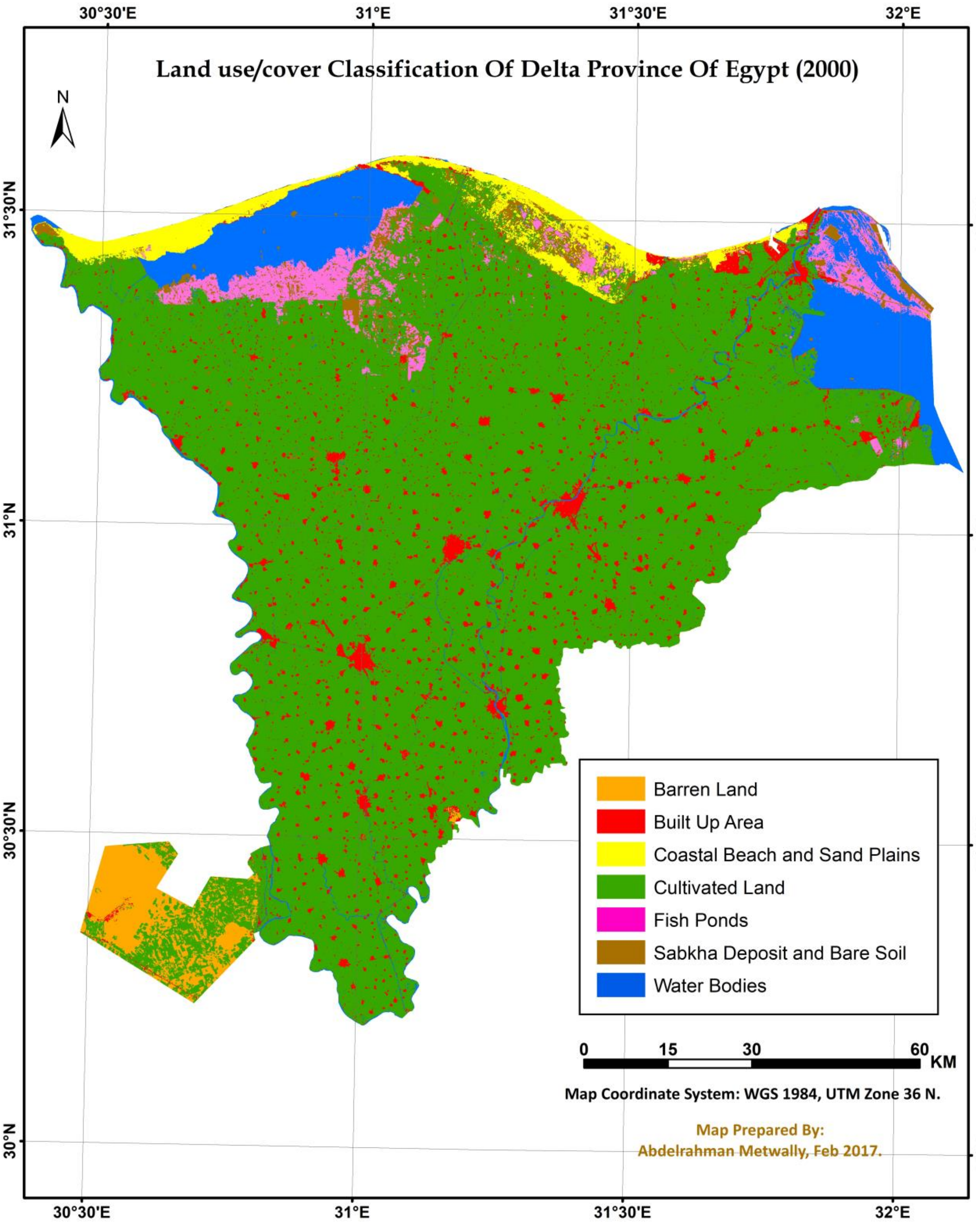

Map 9. Land-use/cover classification map of Landsat 2000.

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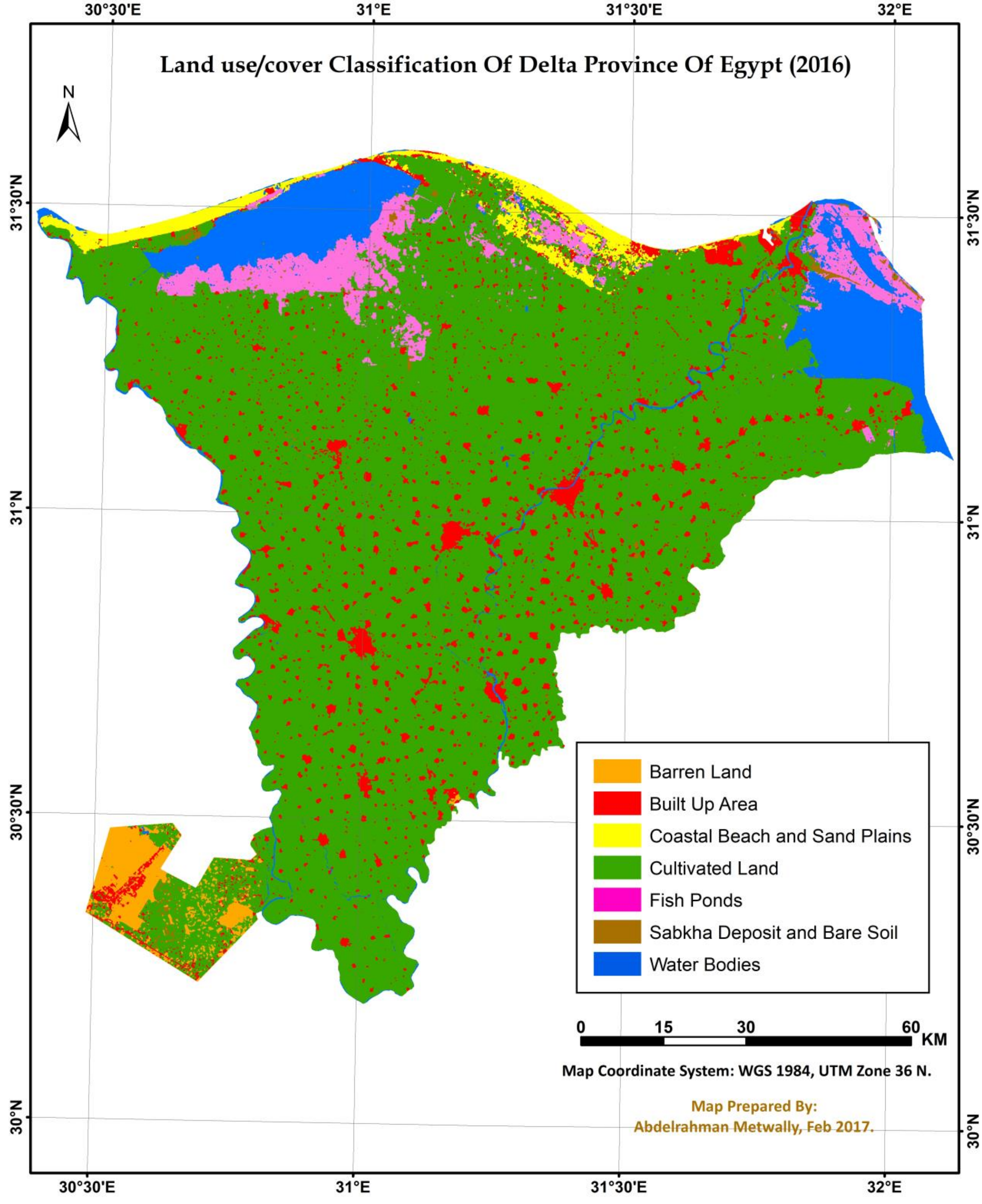

Map 10. Land-use/cover classification map of Landsat 2016.

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3.2.4. Accuracy Assessment

The accuracy assessment of the Landsat 1984, 2000 and 2016 images classification were carried out using the confusion matrix using ground truth image tool in ENVI software. The confusion matrix shows the relationship between known reference data and the corresponding land use/cover classification map. The values in confusion matrix represent the count of pixel of each class which correctly classified in the right class. The result of an accuracy assessment typically provides users with an overall accuracy of the classification image and the accuracy for each class in the classification image.

Table 7. Accuracy assessment error matrix of 1984 image classification.

Class	Ground Truth (Pixels)							
	Cultivated Land	Water Bodies	Fish Ponds	Built Up Area	Coastal Beach and Sand Plains	Barren Land	Sabkha Deposits & Bare Soil	Total
Cultivated Land	587236	11621	35	2359	5518	1	28249	635019
Water Bodies	1844	332293	3957	5	65	0	2290	340454
Fish Ponds	32	10228	35506	1	2	0	5668	51437
Built Up Area	4012	35	8	49181	7061	3	35607	95907
Coastal Beach and Sand Plains	1082	88	34	2570	144121	80	5785	153760
Barren Land	0	1	0	0	503	146886	0	147390
Sabkha Deposits & Bare Soil	4973	537	736	8185	2535	1	111225	128192
Total	599179	354803	40276	62301	159805	146971	188824	1552159

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Table 8. Accuracy assessment summary of 1984 image classification.

Class	User's Accuracy (%)	Producer's Accuracy (%)
Cultivated Land	92.48	98.01
Water Bodies	97.60	93.65
Fish Ponds	69.03	88.16
Built Up Area	68.30	78.94
Coastal Beach and Sand Plains	93.73	90.14
Barren Land	96.80	97.91
Sabkha Deposits & Bare Soil	86.76	87.55
Overall Accuracy	90.6 %	
Kappa Coefficient	0.88	

Table 9. Accuracy assessment error matrix of 2000 image classification.

Class	Ground Truth (Pixels)							
	Cultivated Land	Water Bodies	Fish Ponds	Built Up Area	Coastal Beach and Sand Plains	Barren Land	Sabkha Deposits & Bare Soil	Total
Cultivated Land	222918	7640	290	348	60	227	69	231552
Water Bodies	4769	170705	9757	3	1	0	13	185248
Fish Ponds	147	5533	36533	0	5	0	57	42275
Built Up Area	904	108	47	31456	2949	0	677	36141
Coastal Beach and Sand Plains	13	19	110	1152	90641	732	51	92718
Barren Land	2	0	0	6	1524	64623	0	66155
Sabkha Deposits & Bare Soil	208	131	323	5297	391	0	8340	14690
Total	228961	184161	47060	38262	95577	65582	9207	668810

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Table 10. Accuracy assessment summary of 2000 image classification.

Class	User's Accuracy (%)	Producer's Accuracy (%)
Cultivated Land	96.27	97.36
Water Bodies	92.15	92.69
Fish Ponds	86.42	77.63
Built Up Area	87.04	82.21
Coastal Beach and Sand Plains	97.76	94.84
Barren Land	97.58	98.54
Sabkha Deposits & Bare Soil	68.77	93.58
Overall Accuracy	93.4%	
Kappa Coefficient	0. 92	

Table 11. Accuracy assessment error matrix of 2016 image classification.

Class	Ground Truth (Pixels)							
	Cultivated Land	Water Bodies	Fish Ponds	Built Up Area	Coastal Beach & Sand Plains	Barren Land	Sabkha Deposits & Bare Soil	Total
Cultivated Land	177582	4198	3130	7842	277	115	467	635019
Water Bodies	1476	189860	43044	16	0	0	35	340454
Fish Ponds	290	2767	78819	3	0	0	294	51437
Built Up Area	2017	41	480	74592	3193	154	915	95907
Coastal Beach and Sand Plains	116	9	37	7488	35539	1038	1009	153760
Barren Land	120	0	0	130	685	45803	51	147390
Sabkha Deposits & Bare Soil	2566	222	2969	4956	656	122	6412	128192
Total	184167	197097	128479	95027	40350	47232	9183	701535

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Table 12. Accuracy assessment summary of 2016 image classification.

Class	User's Accuracy (%)	Producer's Accuracy (%)
Cultivated Land	91.72	96.42
Water Bodies	80.99	96.30
Fish Ponds	95.92	61.35
Built Up Area	91.65	78.50
Coastal Beach and Sand Plains	78.56	88.05
Barren Land	97.89	96.97
Sabkha Deposits & Bare Soil	70.82	69.82
Overall Accuracy	86.7 %	
Kappa Coefficient	0.83	

The overall accuracy of Landsat 1984, 2000 and 2016 classification were 90.2%, 93.4% and 86.7%, respectively, with kappa coefficient 0.88, 0.92 and 0.83, respectively. The producer's accuracies of all classes of the three classification images are consistently high and ranged from 68.3% to 98.5 % except Fish-Ponds class were 61.35 in 2016 image classification.

The user's accuracies for all the classes of two Landsat classification results are relatively high which ranged from 68% to 97.89% for three classification image.

3.3. Land use/cover change detection analysis

Post-classification comparison change detection technique was employed after image classification of Landsat images. ENVI's change detection tool was used to detect changes. Three classification images of 1984, 2000 and 2016 were used to derive two period change detection between 1984-2000 and 2000-2016, and to inspect the nature of changes between classified images. In the first period, the image classification of year 1984 was selected as initial state and image classification of year 2000 as the final state, while in the second period, the classification image of year 2000 was selected as initial state and the image classification of

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year 2016 as the final state. Change detection results of each period is shown in the form of map and statistical reports.

3.3.1. Land use/cover change detection result

The results of the change detection analysis of study show that the total area that subjected to change was about 1887.1 km^2 during the period 1984-2000, and 1027.3 km^2 in the during 2000-2016.

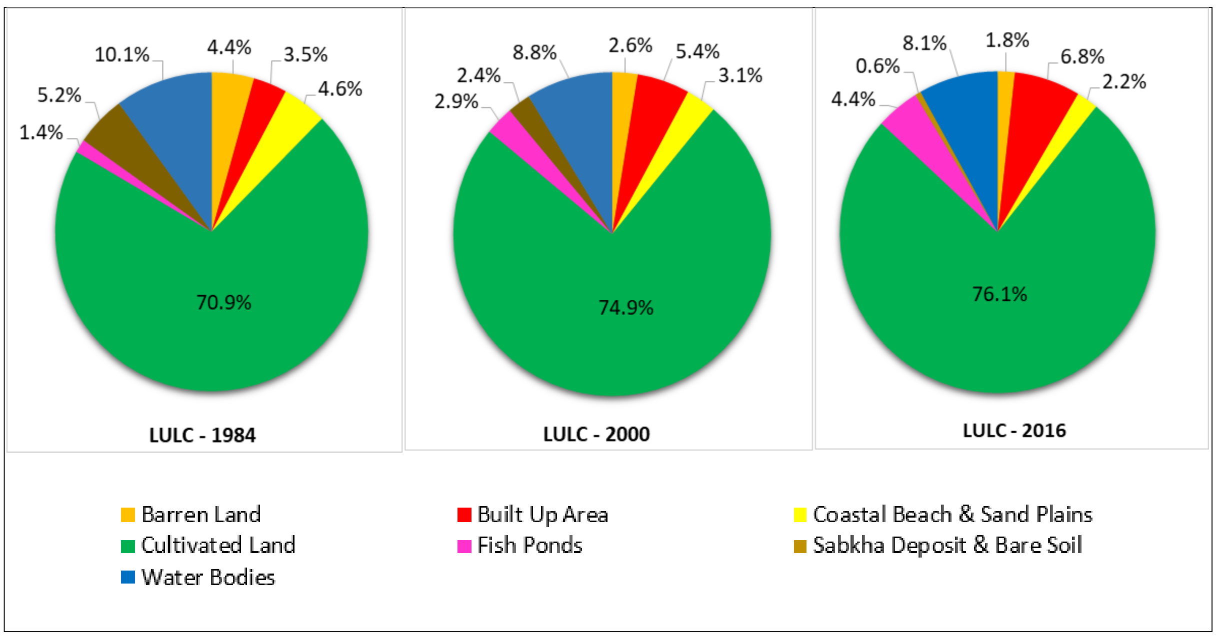

Figure 18. Percentage of land use/cover classes to the total area of Delta province in 1984,2000 and 2016.

Cultivated land constitute the major type of land use/cover in the study area in 1984, 2000 and 2016 by 70.9%, 75% and 75.9%, respectively. Water bodies is the second land cover type in the Delta province which occupy between 10.1 % and 7.7% of the total study area in the period from 1984 to 2016.

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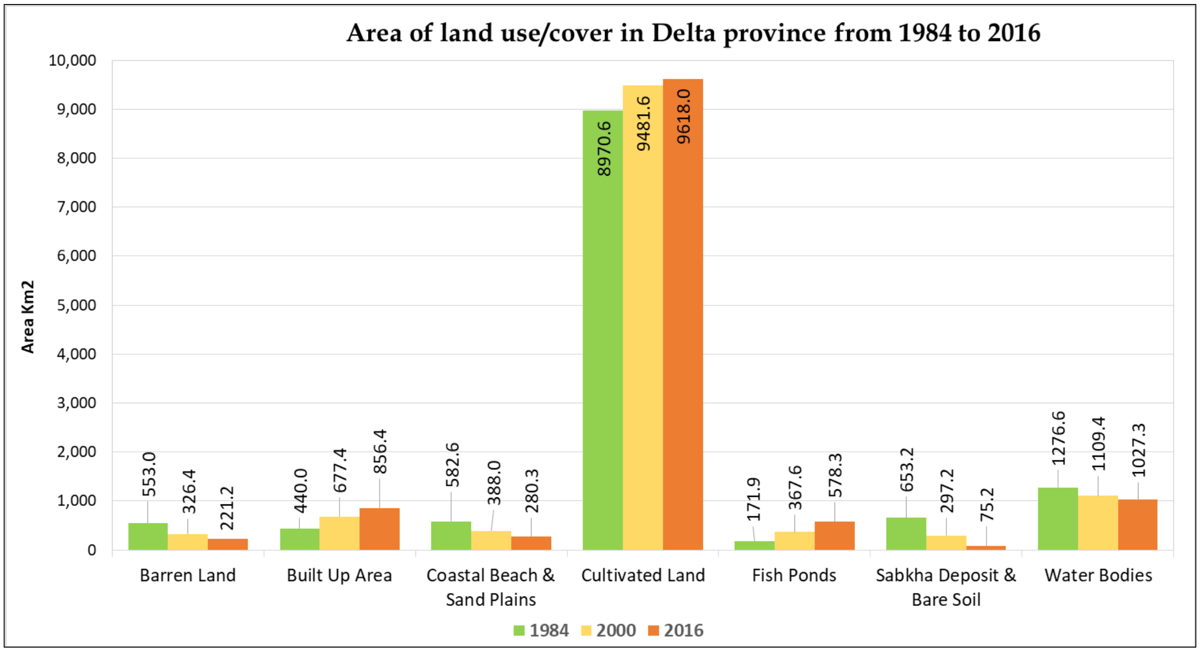

Figure 19. Comparing the corresponding land use/cover area of Delta province in 1984, 2000 and 2016.

Table 63. Area of Land use/cover in Delta province and change rate from 1984 to 2016.

Class	1984		2000		2016		Size of Change			
							1984–2000		2000–2016	
	Km²	%	Km²	%	Km²	%	Km²	%	Km²	%
Barren Land	553.0	*4.4*	326.9	*2.6*	221.2	*1.8*	-226.6	*-40.9*	-105.2	*-32.3*
Built Up Area	440	*3.5*	678.3	*5.4*	856.4	*6.8*	237.4	*54.2*	179.0	*26.3*
Coastal Beach and Sand Plains	582.6	*4.6*	389.7	*3.1*	280.3	*2.2*	-194.5	*-33.4*	-107.7	*-27.8*
Cultivated Land	8970.6	*70.9*	9489.0	*74.9*	9618.0	*76.1*	511.0	*5.8*	136.4	*1.4*
Fish Ponds	171.9	*1.4*	368.1	*2.9*	561.2	*4.4*	195.7	*114.1*	210.7	*57.1*
Sabkha Deposit and Bare Soil	653.2	*5.2*	298.2	*2.4*	75.2	*0.6*	-356.0	*-54.3*	-222.0	*-74.8*
Water Bodies	1276.6	*10.1*	1116.3	*8.8*	1027.3	*8.1*	-167.3	*-13.1*	-82.1	*-7.4*
Total	12633	*100*	12633	*100*	12633	*100*				

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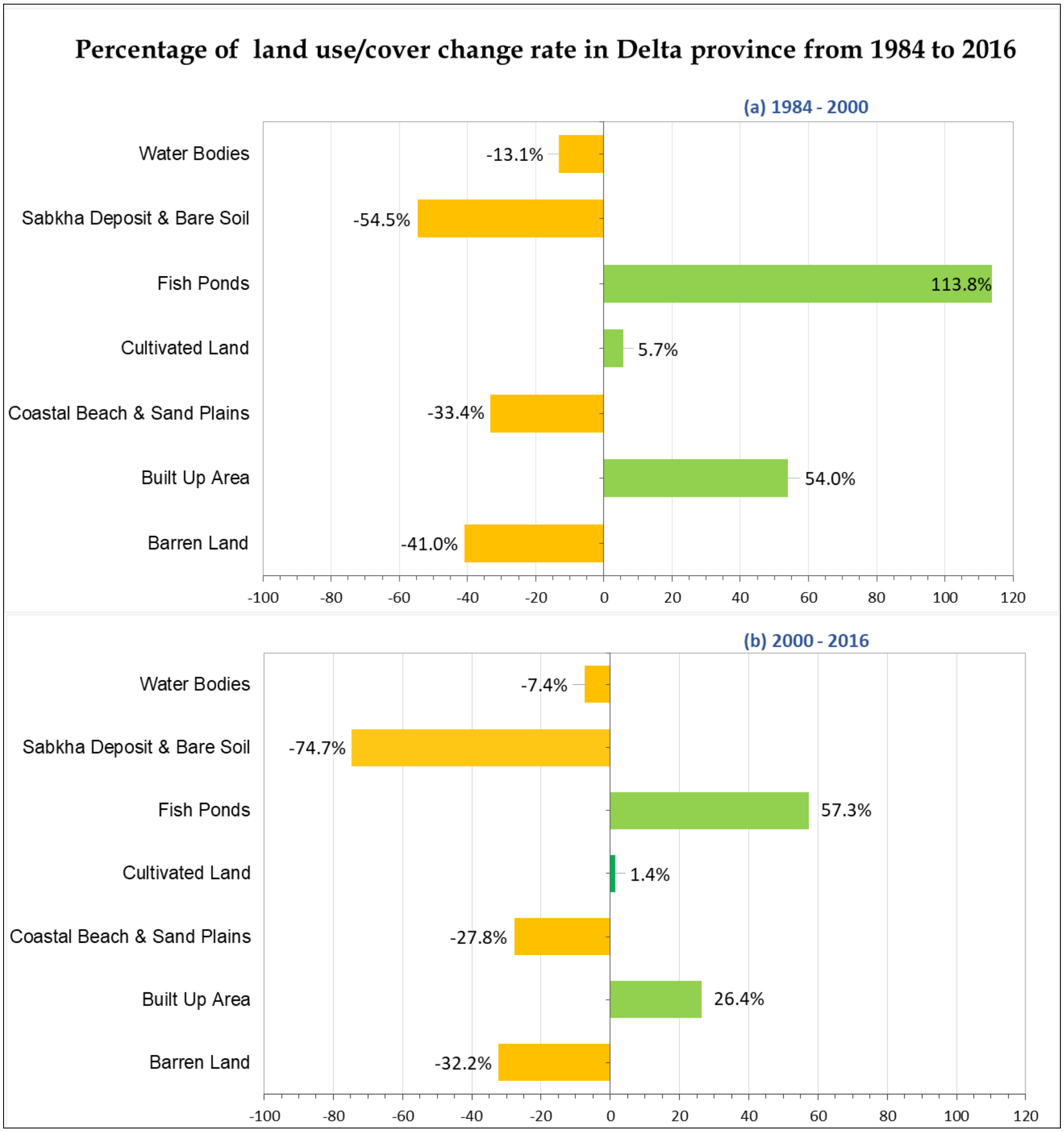

Figure 20. Change rate of cultivated Land area in Delta province governorates between (1984-2000, 2000-2016).

Land use/cover change detection analysis show a significant change trends. The cultivated land, fish ponds and built-up-area show an increase trend, whereas water bodies, coastal-beach-and-sand-plains, barren land and Sabkha-deposit-and-bare-soil show a decrease trend.

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The following observations outline the main change in land use/cover of Delta province in this periods:

- The cultivated-land increased from 8970.6 km^2 in 1984 to 9489 km^2 in 2000 by an increase (5.7%), and to 9618 km^2 in 2016 by (1.4%).
- Fish-ponds increased from 171.9 km^2 in 1984 to 368.1 km^2 in 2000 by an increase (114.1%), and to 578.3 km^2 in 2016 by an increase (57.1%).
- Built-up-area increased from 440 km^2 in 1984 to 677.4 km^2 in 2000 by an increase (54.0 %), and to 856.4 km^2 in 2016 by (26.4%).
- Sabkha-deposit-and-bare-soil decreased from 653.2 km^2 in 1984 to 298.2 km^2 in 2000 by (-54.5%), and to 75 km^2 in 2016 by (-74.7%).
- Barren-land decreased from 553 km^2 in 1984 to 326 km^2 in 2000 by (-40.9%), and to 221.2 km^2 in 2016 by (-32.2%) change rate.
- Coastal-beach-and-sand-plains declined from 582.6 km^2 in 1984 to 388.7 km^2 in 2000 by change rate (-33.4%), to 280.3 km^2 by (-27.8%) in 2016.
- Water-bodies declined from 1276.6 km^2 in 1984 to 1109.4 km^2 in 2000 by (-13.1%), to 1027.3 km^2 in 2016 by (-7.4%).

The change detection maps of the period during 1984-2000, and during 2000-2016 (Map No. 8 and 9), reveals a heavy granulation in texture which indicates a large region containing a concentration of many areas with localized change. The changed areas basically are localized along the coastal zone and around lakes in the north and the northeast part of the Delta province. The drastic changes in this province back to the conversion of coastal beach and lakes to other land-use activities, especially activities which relative with population and economic such as fish-ponds, built-up-are and cultivated land.

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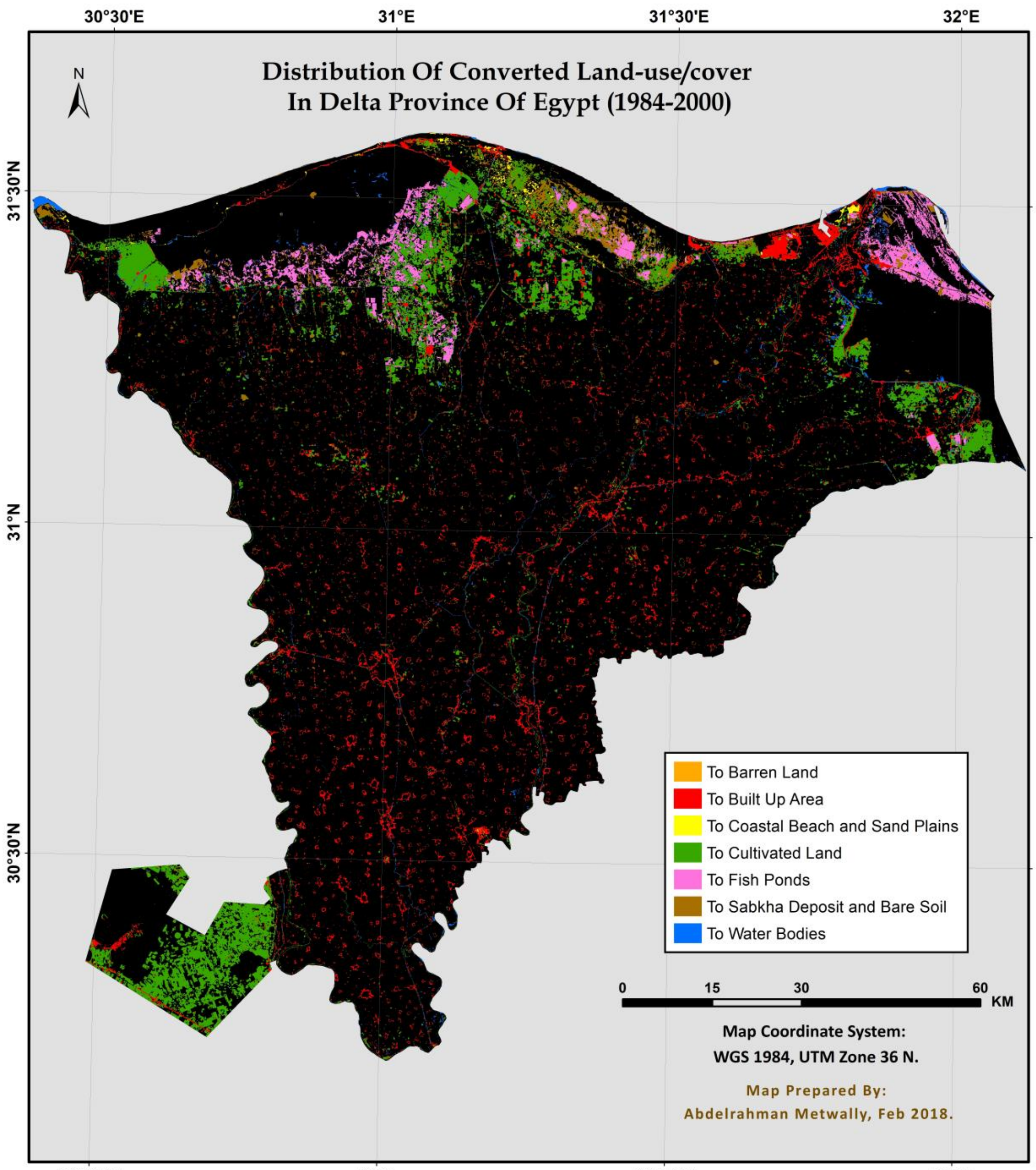

Map 11. Distribution of converted to Land-use/cover classes and unchanged area in Delta province from 1984 to 2000.

The southwestern area of the Delta province has a concentration of localized changes due to the conversion of barren-land areas into cultivation urbanization activities. From the south of

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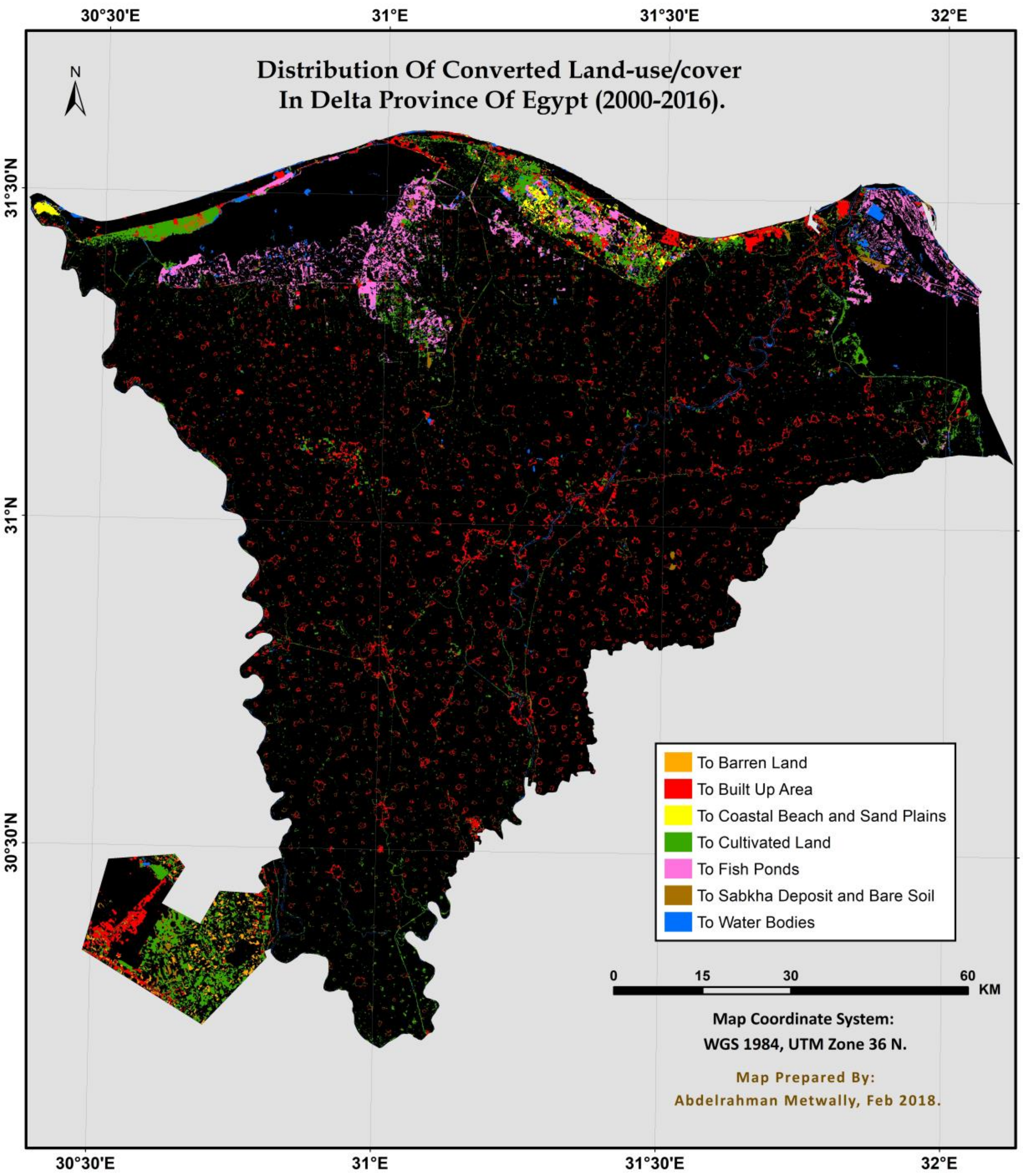
the coastal zone and lakes in the north, the changes are more scattered due to the expansion of urban areas towards the agriculture land.



Map 12. Distribution of converted Land-use/cover classes and unchanged area in Delta province from 2000 to 2016.

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3.3.2. Nature of Land use/cover change

The population and economic growth show a clear impact on the change of land use/cover in the study area, where the result reveals a systematic drastic increase in the built-up-area, fish-ponds and with less degree in cultivated land in the period between 1984 and 2000, and between 2000 and 2016.

The land use/cover matrixes of the period between 1984 and 2000, and between 2000 and 2016, show a significant transition between land use/cover types, and especially activates are relative with the population activities, such as cultivated land, fish ponds and built-up-area.

Table 14. Land use/cover transition matrix of 1984 - 2000.

Landuse/cover 2000	**Landuse/cover 1984**						
	Barren Land	Built Up Area	Coastal Beach and Sand Plains	Cultivated Land	Fish Ponds	Sabkha Deposit and Bare Soil	Water Bodies
Barren Land	325.5 km²	0.01 km²	0.0 km²	0.7 km²	0.0 km²	0.1 km²	0.0 km²
	58.9%	*0.01%*	*0.0%*	*0.01%*	*0.0%*	*0.02%*	*0.0%*
Built Up Area	8.4 km²	374.2 km²	20.3 km²	219.4 km²	0.9 km²	45.3 km²	8.9 km²
	1.5%	*85%*	*3.5%*	*2.5%*	*0.5%*	*6.9%*	*0.7%*
Coastal Beach and Sand Plains	0.0 km²	1.1 km²	371.3 km²	8.6 km²	0.1 km²	3.3 km²	3.7 km²
	0.0%	*0.2%*	*63.7%*	*0.1%*	*0.03%*	*0.5%*	*0.3%*
Cultivated Land	216.4 km²	49.4 km²	66.7 km²	8662.6 km²	35 km²	338.1 km²	112.5 km²
	39.1%	*11.2%*	*11.6%*	*96.6%*	*20.4%*	*51.8%*	*8.8%*
Fish Ponds	0.0 km²	0.9 km²	27.0 km²	4.4 km²	112.7 km²	123.3 km²	99.3 km²
	0.0%	*0.2%*	*4.6%*	*0.05%*	*65.5%*	*18.9%*	*7.8%*
Sabkha Deposit and Bare Soil	2.5 km²	12.6 km²	87.2 km²	30.7 km²	17.6 km²	121.7 km²	25 km²
	0.5%	*2.9%*	*15%*	*0.3%*	*10.2%*	*18.6%*	*1.9%*
Water Bodies	0.2 km²	1.7 km²	9.6 km²	43.7 km²	5.7 km²	21.4 km²	1027 km²
	0.04%	*0.4%*	*1.6%*	*0.5%*	*3.2%*	*3.3%*	*80.5%*

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Table 75. Land use/cover transition matrix between 2000 and 2016.

Landuse/cover 2016	Landuse/cover 2000						
	Barren Land	Built Up Area	Coastal Beach and Sand Plains	Cultivatd Land	Fish Ponds	Sabkha Deposit and Bare Soil	Water Bodies
Barren Land	186.7 km²	1.1 km²	0.0 km²	32.8 km²	0.0 km²	0.5 km²	0.0 km²
	57.4 %	*0.2%*	*0.0%*	*0.3%*	*0.0%*	*0.2%*	*0.0%*
Built Up Area	32.6 km²	539.3 km²	43.3 km²	204.4 km²	3.4 km²	28.4 km²	4.9 km²
	10.0%	*88.6%*	*11.2%*	*2.2%*	*0.9%*	*9.5%*	*0.4%*
Coastal Beach and Sand Plains	0.0 km²	2.4 km²	235 km²	13.1 km²	2.3 km²	26.7 km²	0.7 km²
	0.0%	*0.4%*	*60.7%*	*0.1%*	*0.6%*	*9%*	*0.1%*
Cultivated Land	99.3 km²	48.2 km²	76.6 km²	9132 km²	19.5 km²	97.1 km²	76.3 km²
	30.5%	*7.9%*	*19.8%*	*96.3%*	*5.3%*	*32.7%*	*6.9%*
Fish Ponds	0.0 km²	2.1 km²	13.4 km²	54.3 km²	317.9 km²	108.2 km²	65.3 km²
	0.0%	*0.3%*	*3.5%*	*0.6%*	*86.4%*	*36.4%*	*5.9%*
Sabkha Deposit and Bare Soil	6.2 km²	10.9 km²	9.7 km²	17.5 km²	7.9 km²	19.6 km²	3.3 km²
	2.0%	*1.6%*	*2.5%*	*0.2%*	*2.1%*	*6.6%*	*0.3%*
Water Bodies	0.4 km²	4.9 km²	9.2 km²	27 km²	16.7 km²	16.7 km²	952.2 km²
	0.1%	*0.7%*	*2.4%*	*0.3%*	*4.6%*	*5.6%*	*86.3%*

By analysis land use/cover transition matrixes we can conclude the following important observations:

1) Cultivated land

The cultivated land was increased between 1984 and 2000 by 511 km² (5.7%), this increase was mainly gained from the conversion of sabkha-deposit-and-bare-soil to cultivated land by (51.8%), barren land by (39.1%), fish ponds by (20.4%), coastal-beach-and-sand-plains (11.5%), where the cultivation activities expanded towards deposits and bare soil area

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which surround the lakes in this region, and toward the coastal zone in the north, and the expansion toward barren land in the southwest of Delta province. This increase arising from the national agriculture development plans in this period.

During the period 2000-2016, the cultivated land has increased by only 136 km^2 (1.4%), this increase basically was from the conversion of sabkha-deposit-and-bare-soil to cultivated land by 97.1 km^2 (32.7%), barren land by 99.3 km^2 (30.5%), coastal-beach-and-bare-soil by 76.6 km^2 (19.8) and water bodies by 76 km^2 (9%).

The reclaimed land between 2000 and 2016 has increased, but this increase is much less than the reclaimed land of the period between 1984 and 2000, because the increase offset by the lack of agriculture land in Delta province due to the expansion of urban areas towards the agricultural land as result to the population growth, which deducted from cultivated land about 219.4 km^2 (2.5%) between 1984 and 2000, and 204.4 km^2 (2.2%) between 2000 and 2016.

2) Built up area

The built-up-area increased by 238.3 km^2 (54.2%) in the period between 1984 and 2000; this increase is a result of population and economic growth. The large portion of this increase deducted from the converted cultivated land and sabkha-deposit-and-bare-soil to built-up-area by 219 km^2 (2.5%) and 45.3 km^2 (7%), respectively.

During the period 2000-2016 the built-up-area was increased by 179 km^2 (26.4%). The large portion of this increase was deducted from the conversion of cultivated land to built-up-are by 204 km2 (2.2%), coastal-beach-and-sand-plains by 43.3 km^2 (11.2%), barren land 32.6 km^2 (10%) and sabkha-deposit-and-bare-soil by 28.4 km2 (9.5%), respectively.

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3) Fish ponds

Fish pond was increased by 196.2 km2 (114.1%) during 1984-2000, and increased by 193.1 km2 (52.5%) during 2000-2016. This significant increase in fish ponds area is due to the national fish farming plans by the Egyptian government in last decades, to provide the increased food needs and to develop industries which based on fish wealth.

The increase of fish ponds area mainly deducted from water bodies and sabkha-deposit-and-bare-soil classes, which surround the lakes in the northern part of Delta province. During the period 1984-2000 about 123.3 km^2 of sabkha-deposit-and-bare-soil was converted to fish ponds (18.8%), and water bodies converted by 99.3 km^2 (7.8%).

In the period between 2000 and 2016, sabkha-deposit-and-bare-soil, water bodies and cultivated land are the major converted classes to fish ponds by 108.2 Km^2 (36.4), 65.3 km^2 (6%) and 54.3 km^2 (0.6%), respectively.

4) Water bodies

Water bodies were systematically declined during the period 1984-2016, where decreased by (-13.3%) during 1984-2000 and by (-11.6) during 2000- 2016.

The loss of water bodies is due to the population activities and economic growth which led to landfill and drying of the lakes of Al-Burullus and Al-Manzalah in the northern part of the study area, to use it in agriculture and fish farming activities.

The main transition of water bodies was to cultivated land by (8.8%) and (7%) during 1984-2000 and during 2000-2016, respectively, and to fish ponds by (7.8%) and (5.9%) during 1984-2000 and during 2000-2016, respectively, and to sabkha-deposit-and-bare-soil by (2%) and (0.3%) during 1984-200 and 2000-2016, respectively.

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5) Coastal beach and sand plains

Coastal-beach was drastically declined in the last three decades by (-33.4%) and (-27.8%) from1984 to 2000 and from 2000 to 2016, respectively.

This change occurred due to the expansions of population activities, where most change of this class was to sabkha-deposits, cultivated land, fish ponds and built-up-area by (15%), (11.6%), (4.6%) and (3.5%), respectively, during the period 1984-2000.

In the period between 2000 and 2016, most converted area were to cultivated land, built-up-area and fish ponds by (19.8%), (11.2%), (3.5%), respectively.

6) Barren land

Most barren land area is located in the governorate of Monufia in southwest of Delta province, after the inclusion a part of the desert in the west of Delta province to the governorate as a new city called Sadat-City, which establish by the New Urban Community Authority **(NUCA, 2017)** in 1978. This city was established to become a new urban society based on the industrial and agricultural activities alongside population settlement. This statement explains the change occurred to barren land in this province, where this class is drastically declined by more the 100% in last three decades. Barren land declined by -226.1 km^2 (-40.9%) and by -105.7 km^2 (-32.3%) during 1984-2000 and 2000-2016, respectively.

The main barren land transition in the period between 1984 and 2000 was to cultivated land and built-up-area by (39%) and (1.5%), respectively, and was converted to the same land use/cover classes during 2000-2016 by (30.5%) and (10%), respectively. The converted barren land to cultivated land during 1984-2000, was more than during 2000-2016 with a remarkable increase in built-up-area during 2000-2016, this due to the expansion of industries infrastructures which based on the agriculture activities in this city.

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7) Sabkha deposit and bare soil

The area of sabkha-deposit-and-bare-soil has decreased as a result of the exploitation for the economic activities by population such as cultivation, fish farming and urban expansion. The area of sabkha-deposit-and bare-soil has declined during the period 1984-2000 by -355 km2 (-54%), and during 2000-2016 (-74.8%).

Between 1984 and 2000, the largest portion of converted sabkha-deposit-and-bare-soil was to cultivated land by (51.8%), fish ponds by (18.9%) and to built-up-area by (6.9%), while during 2000-2016 was to fish ponds by (36.4%), cultivated land by (32.7%) and to built-up-area by (9.5%).

The following tables and figures, show amount of gain and loss area of land use/cover during the period 1984-2000 and 2000-2016.

Table 86. Area of gain and loss in land use/cover between 1984 and 2016.

Class	1984 - 2000				2000 - 2016			
	Gain		Loss		Gain		Loss	
	Km^2	%	Km^2	%	Km^2	%	Km^2	%
Barren Land	0.9	0.2	-227.5	-41.1	18.0	5.5	-138.5	-42.6
Built Up Area	303.3	68.9	-66.2	-15.0	316.9	46.7	-138.7	-20.5
Coastal Beach and Sand Plains	16.7	2.9	-206.96	-35.5	45.3	11.7	-152.2	-39.3
Cultivated Land	819.0	9.1	-307.62	-3.4	486.1	5.1	-349.5	-3.7
Fish Ponds	254.9	148.3	-59.24	-34.5	243.4	66.2	-49.9	-13.6
Sabkha Deposit and Bare Soil	175.6	26.9	-531.49	-81.4	55.6	18.7	-277.6	-93.4
Water Bodies	82.3	6.4	-249.37	-19.5	74.9	6.8	-150.6	-13.7

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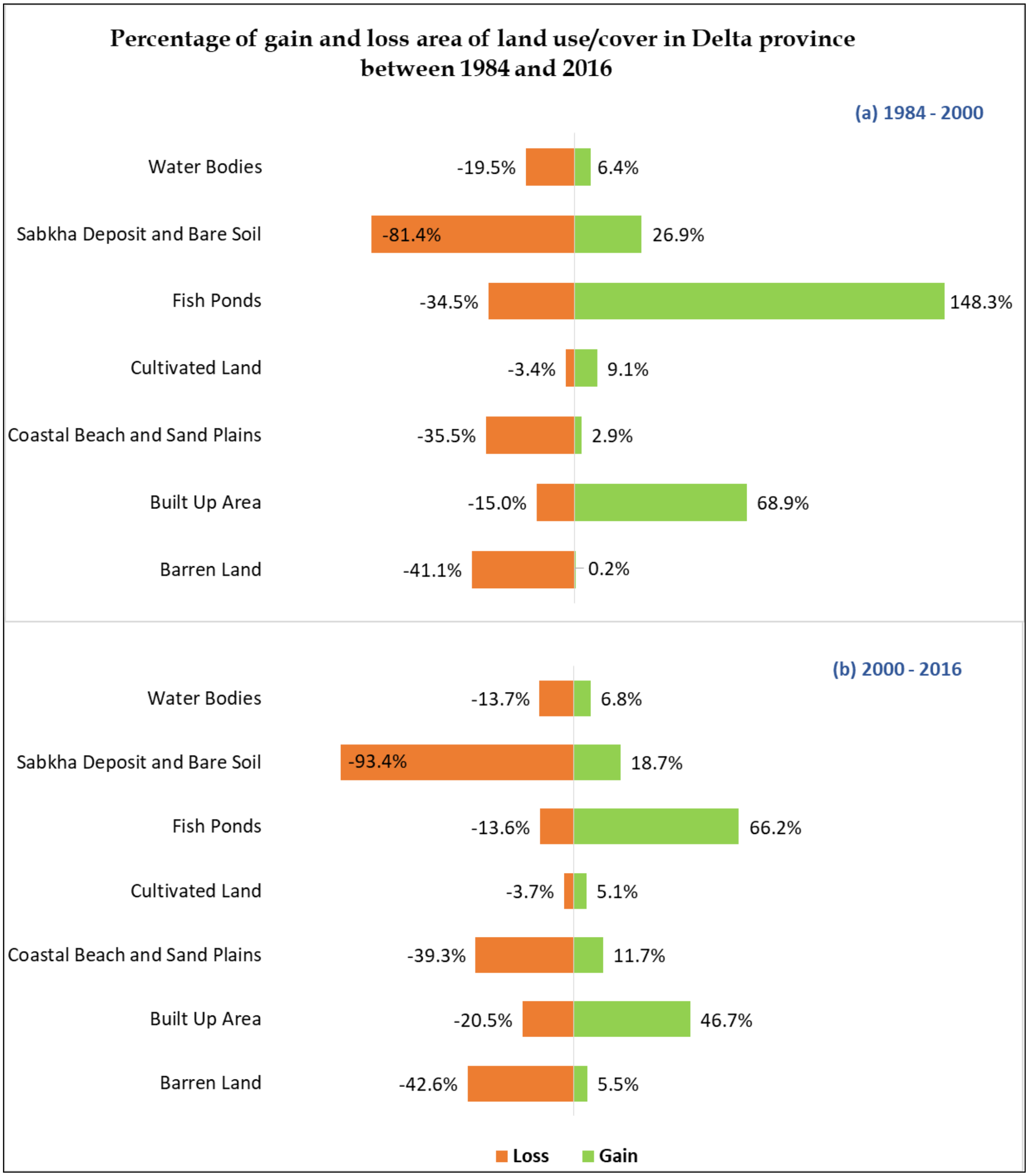

Figure 21. Percentage of gain and loss area of land use/cover in Delta province between 1984 and 2016.

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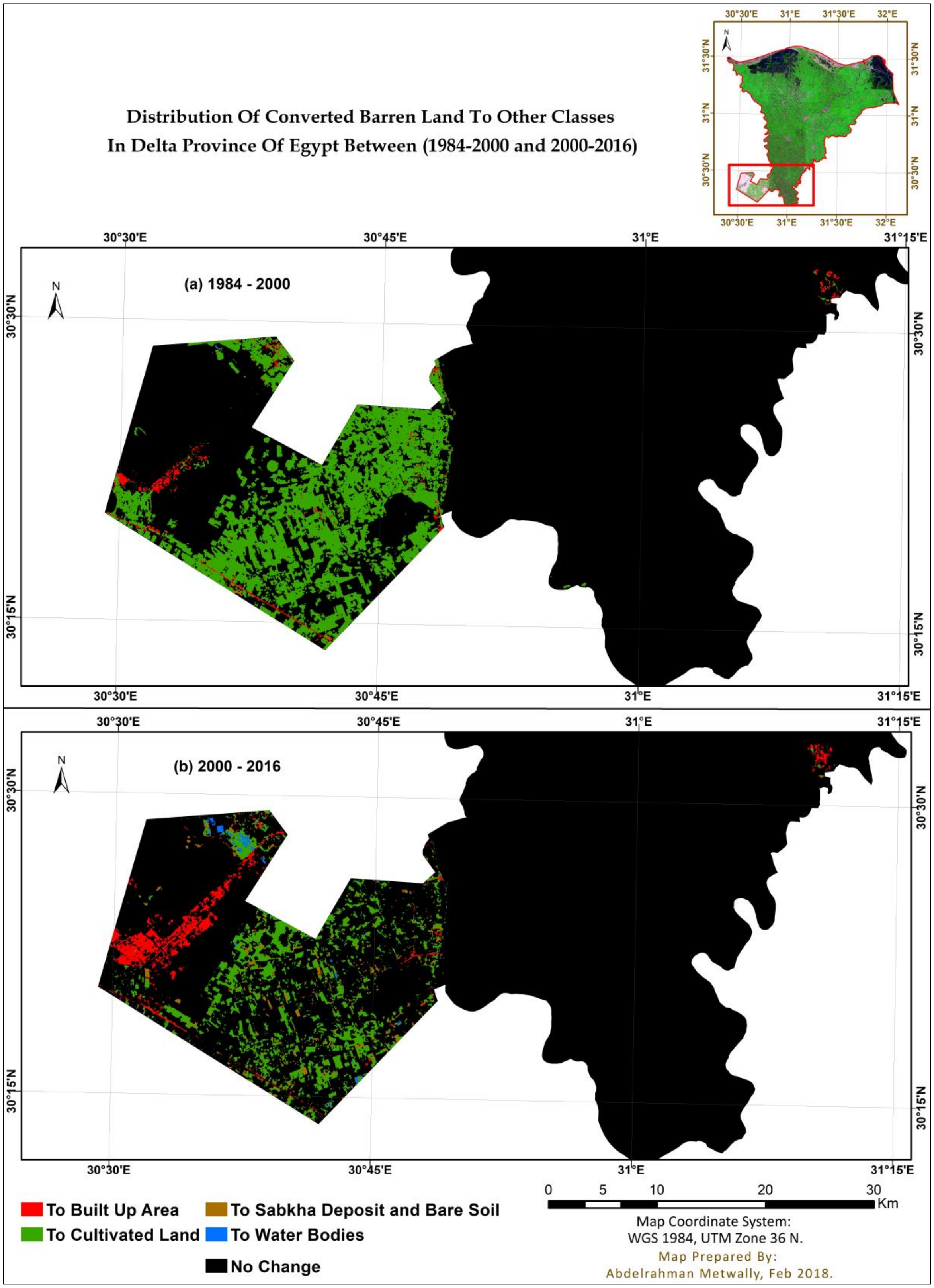

Map 13. Distribution of converted barren land class to other Land-use/cover classes in the Delta province, (a) between 1984-2000, and (b) between 2000-2016.

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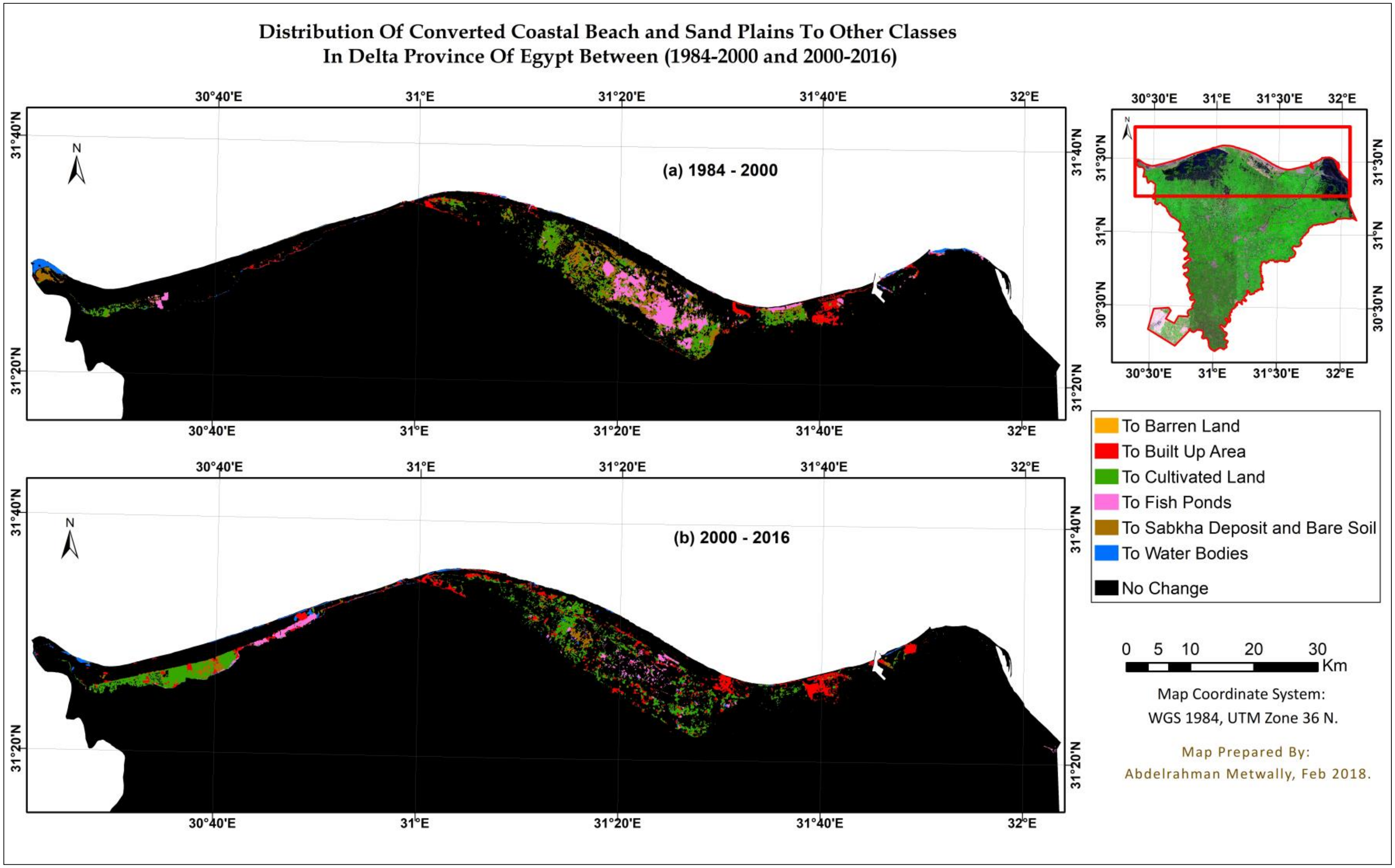

Map 14. Distribution of converted coastal beach and sand plains to other Land-use/cover classes in the Delta province, (a) between 1984-2000, and (b) between 2000-2016.

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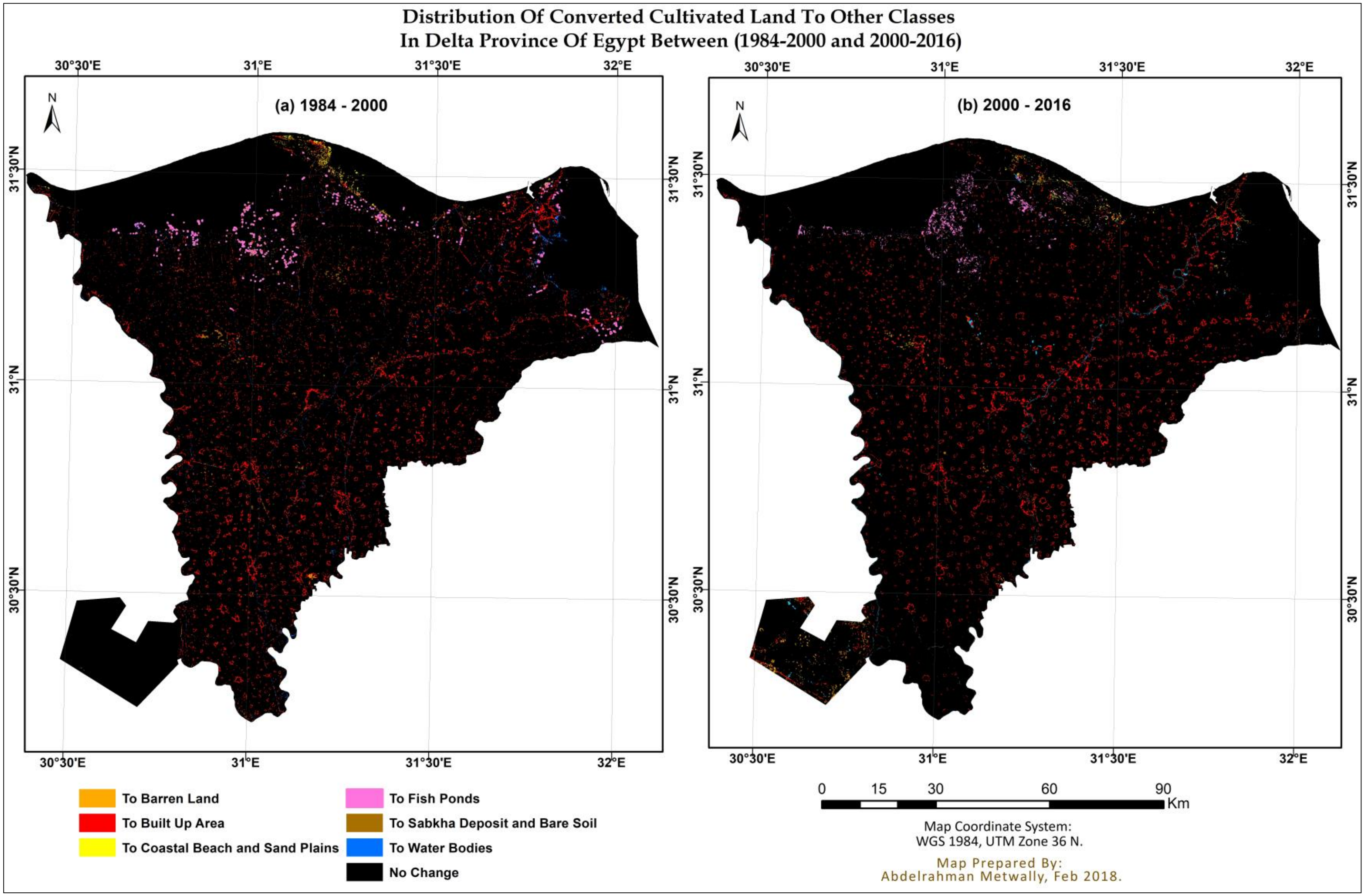

Map 15. Distribution of converted cultivated land to other Land-use/cover classes in Delta province, (a) between 1984-2000, and (b) between 2000-2016

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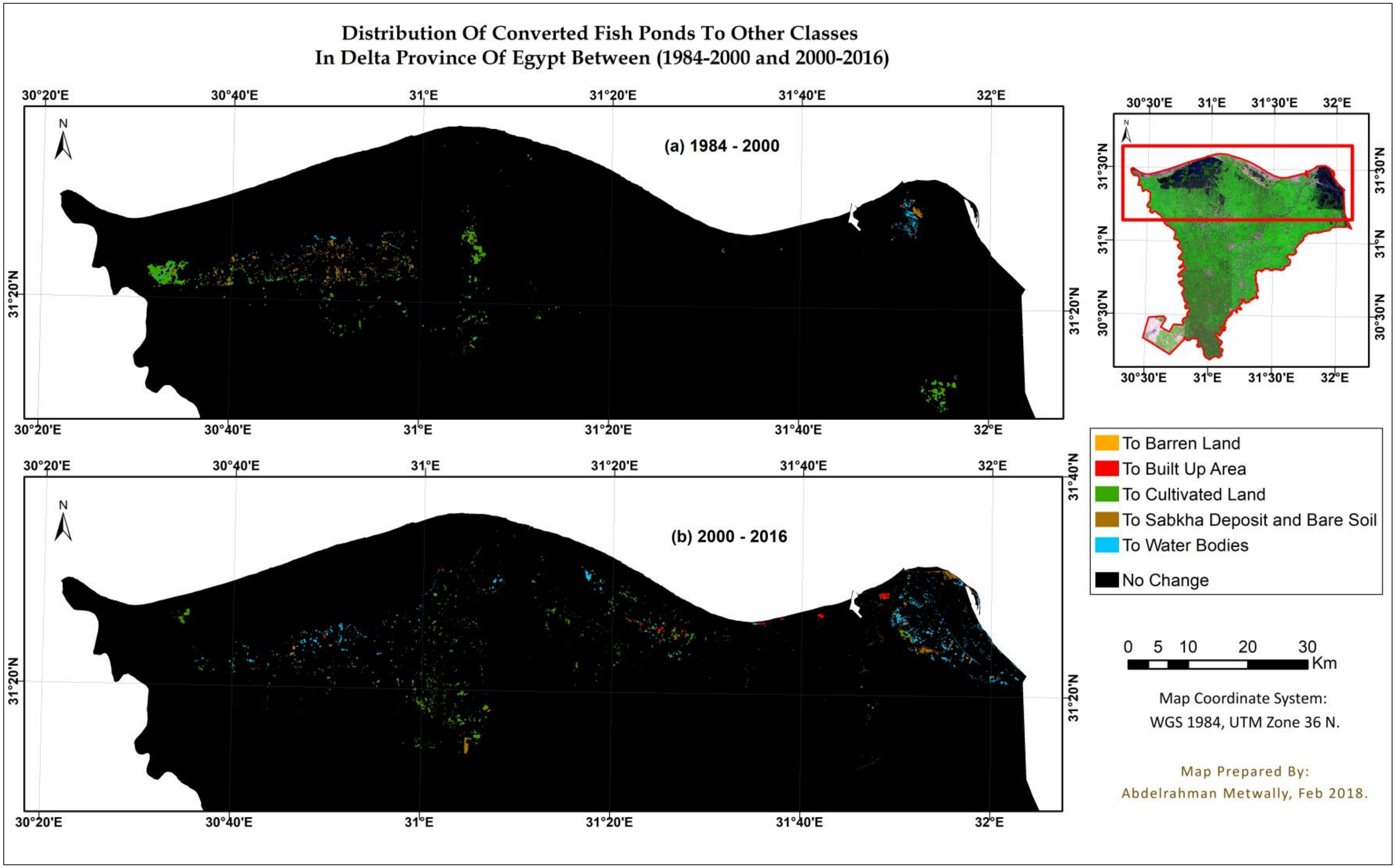

Map 16. Distribution of converted fish ponds to other Land-use/cover classes in Delta province, (a) between 1984-2000, and (b) between 2000-2016.

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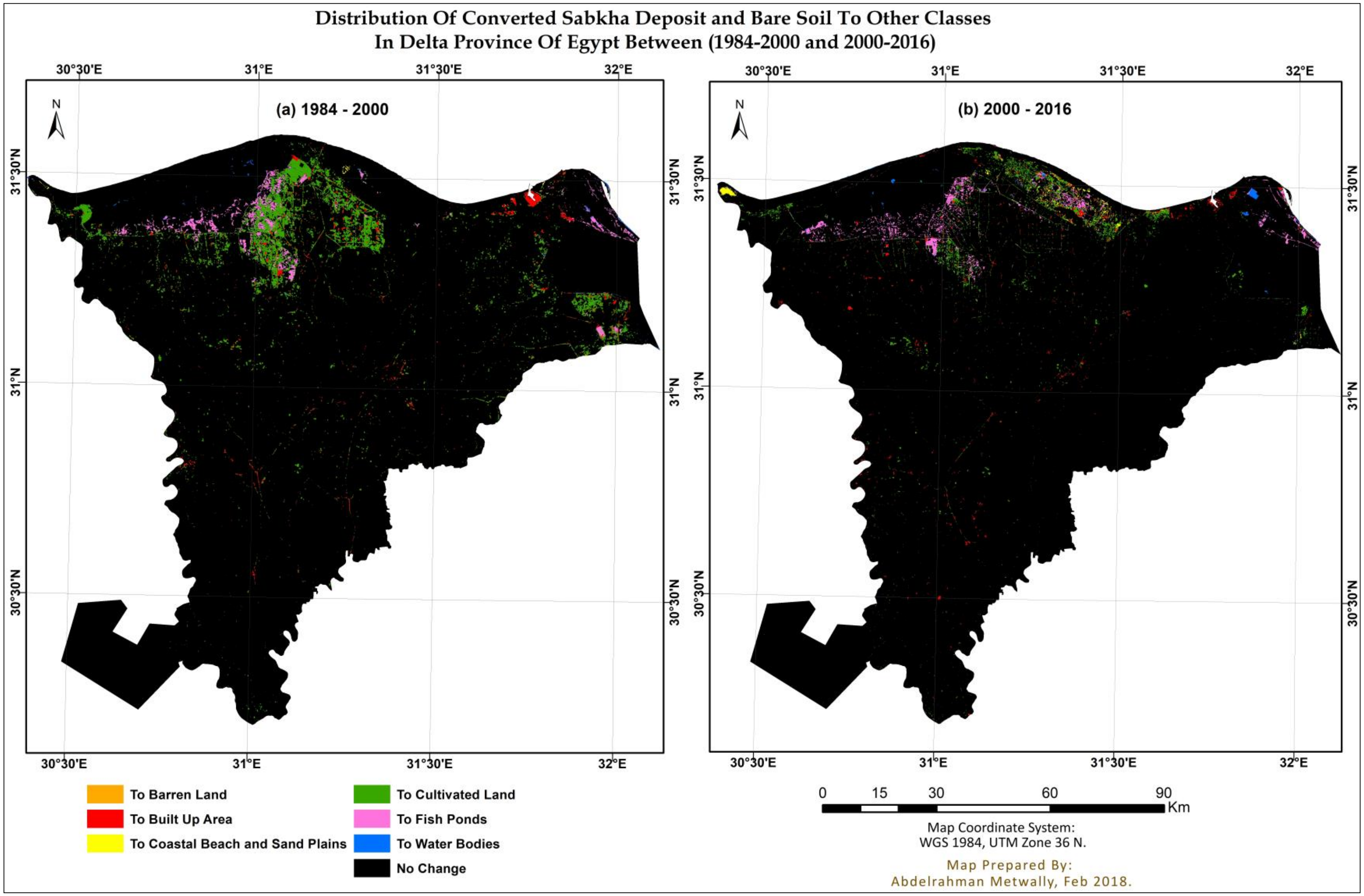

Map 17. Distribution of converted sabkha deposit and bare soil to other Land-use/cover classes in Delta province, (a) between 1984-2000, and (b) between 2000-2016

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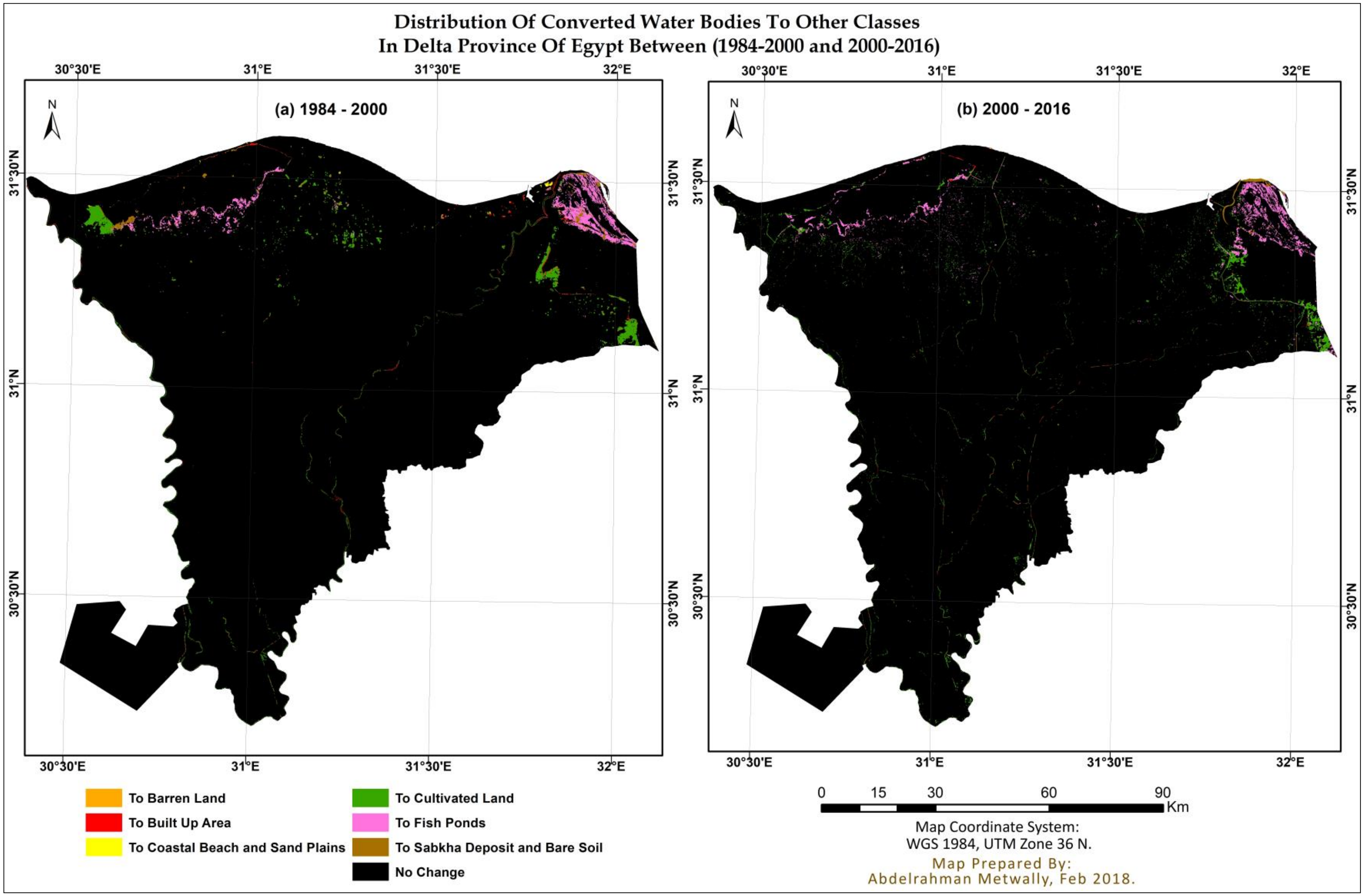

Map 18. Distribution of converted water bodies to other Land-use/cover classes in Delta province, (a) between 1984-2000, and (b) between 2000-2016.

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3.3.3. Size of change of land use/cover in Delta province governorates

Delta province consist of five governorates; Dakahlia, Damietta, Gharbia, Kafr El-Sheikh and Monufia. The change detection analysis result was used to calculate the amount of land use/cover change of each governorates in Delta province.

1) Cultivated Land

According to change analysis result of cultivated land in governorates of Delta province, we can state the following major change:

- Dakahlia governorate is the largest Delta province governorate in the area of cultivated land, followed by the governorates of Kafr-El-Sheikh, Gharbia, Monufia and Damietta.
- The area of cultivated land increased in all governorates in the periods during the period 1984-2000 and during 2000-2016, except in Gharbia which declined by (-2.2%) in 1984-2000 and by (-1.3%) in 2000-2016.

Table 97. Cultivated land change in Delta province governorates between 1984-2000 and 2000-2016.

Governorate	Area of Cultivated Land						Size of Change			
	1984		2000		2016		1984–2000		2000–2016	
	Km²	%	Km²	%	Km²	%	Km²	%	Km²	%
Dakahlia	2934.6	32.7	3036.1	32.0	3043.7	31.6	101.5	3.5	7.6	0.3
Kafr-El-Sheikh	2166.5	24.2	2444.3	25.8	2520	26.2	277.8	12.8	75.7	3.1
Gharbia	1844.5	20.6	1804.7	19.0	1782.1	18.5	-39.8	-2.2	-22.6	-1.3
Monufia	1511.3	16.8	1686.7	17.8	1754.9	18.2	175.4	11.6	68.1	4.0
Damietta	513.4	5.7	514.0	5.4	516.7	5.4	0.6	0.1	2.6	0.5
Total	8970.4	100	9485.9	100	9617.3	100				

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- Kafr El-Sheik, Monufia and Dakahlia are most increased governorates in cultivated land area between 1984 and 2016. In the period between 1984 and 2000 Kafr-El-Sheik, Monufia and Dakahlia were increase by (12.8%), (11.6%) and (3.5%), respectively, while in the period between 2000 and 2016, Monufia, Kafr-El-Sheikh and Dakahlia were increased by (4%), (3.1%) and (0.3), respectively.

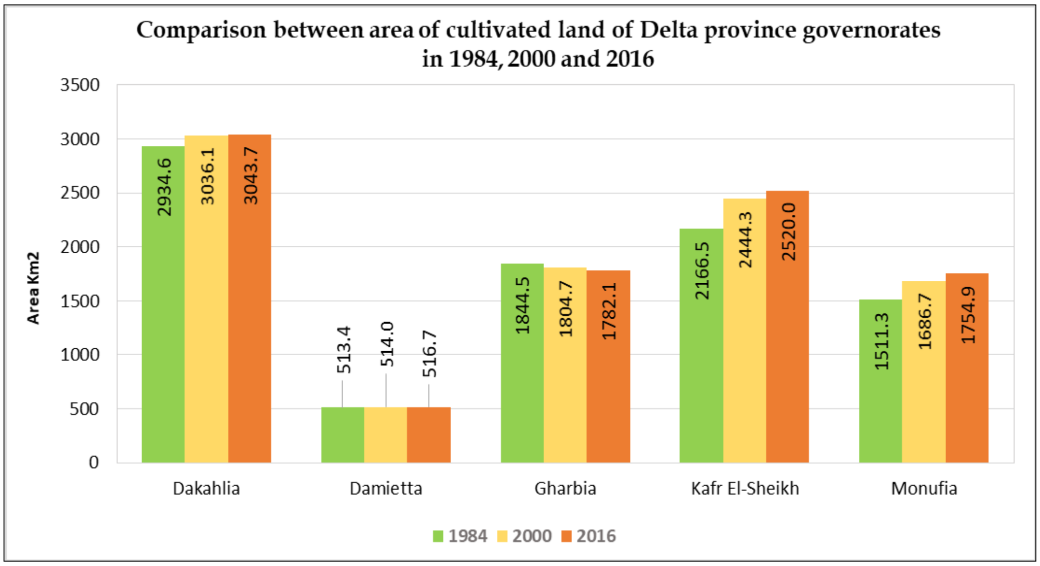

Figure 22. Cultivated land area in the governorates of Delta province in 1984, 2000 and 2016.

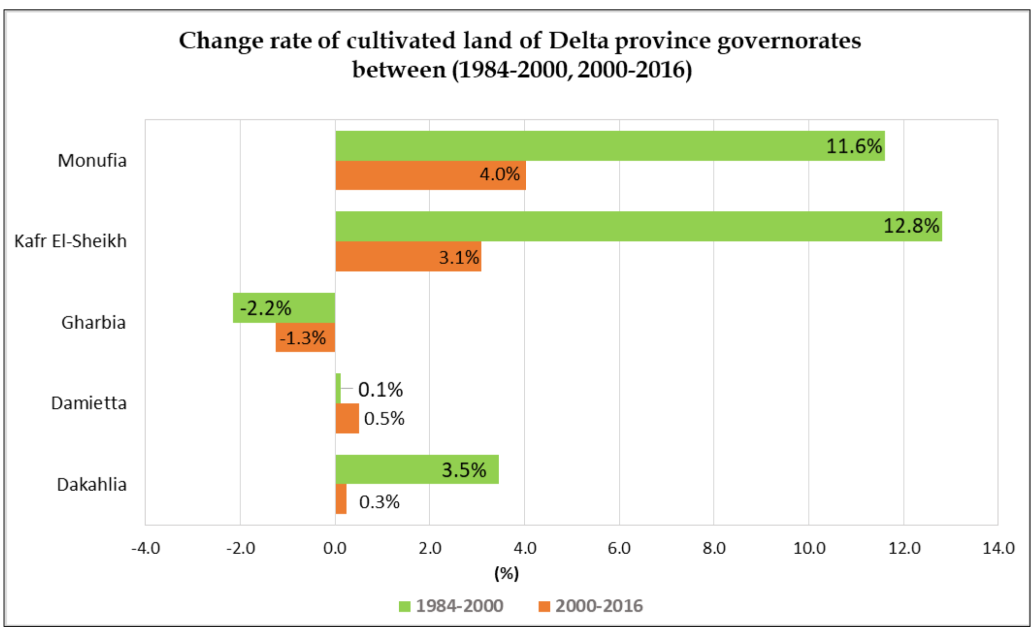

Figure 23. Change rate of cultivated Land area in Delta province governorates between (1984-2000, 2000-2016).

2) Built Up Area

Dakahlia is the largest governorate of the Delta province in built-up-area, followed by Gharbia, Kafr-El-Sheikh, Monufia and Damietta, respectively. The change detection analysis reveals the following change in the built-up-area in the governorate of Delta province:

- A considerable increase amount in the built-up-area in most Delta province governorates between 1984 and 2016, but the size of increase in built-up-area between 1984 and 2000 is more than between 2000 and 2016.
- Damietta has the highest change rate in built-up-area during 1984-2000 by (167.3 %), followed by Monufia by (79.3%) and Dakahlia by (46.8%).
- Between 2000 and 2016, the highest increase rate was in Monufia by (29.5%), followed by Dakahlia by (28.4%) and Kafr-El-Sheikh by (26.1%).

Table 108. Built up area change in Delta province governorates between 1984-2000 and 2000-2016.

Governorate	Area of Built Up Area						Size of Change			
	1984		2000		2016		1984–2000		2000–2016	
	Km²	%	Km²	%	Km²	%	Km²	%	Km²	%
Dakahlia	147.0	33.4	215.8	31.8	277.1	32.4	68.8	46.8	61.2	28.4
Gharbia	109.5	24.9	151.9	22.4	185.7	21.7	42.4	38.8	33.9	22.3
Kafr-El-Sheikh	93.6	21.3	125.	18.4	157.7	18.4	31.4	33.6	32.6	26.1
Monufia	62.4	14.2	112.0	16.5	145.0	16.9	49.5	79.3	33	29.5
Damietta	27.5	6.2	73.5	10.8	90.9	10.6	46	167.3	17.5	23.8
Total	440	100	678.2	100	856.4	100				

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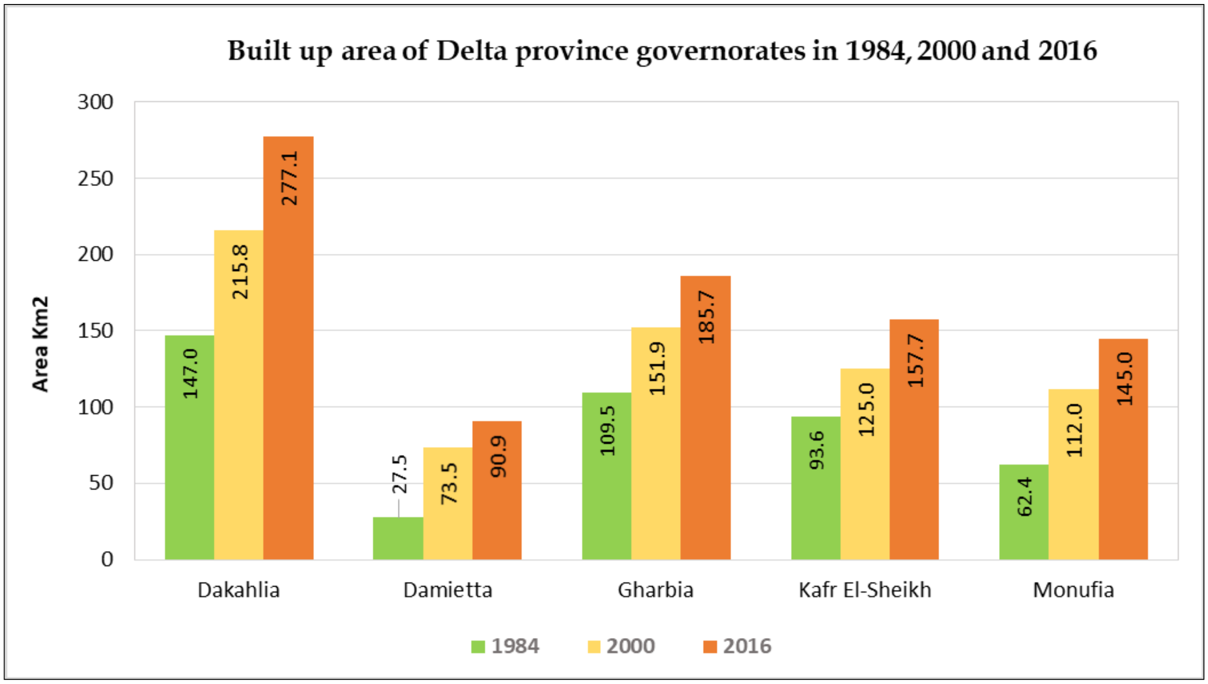

Figure 24. Built up area of Delta province governorates in 1984, 2000 and 2016.

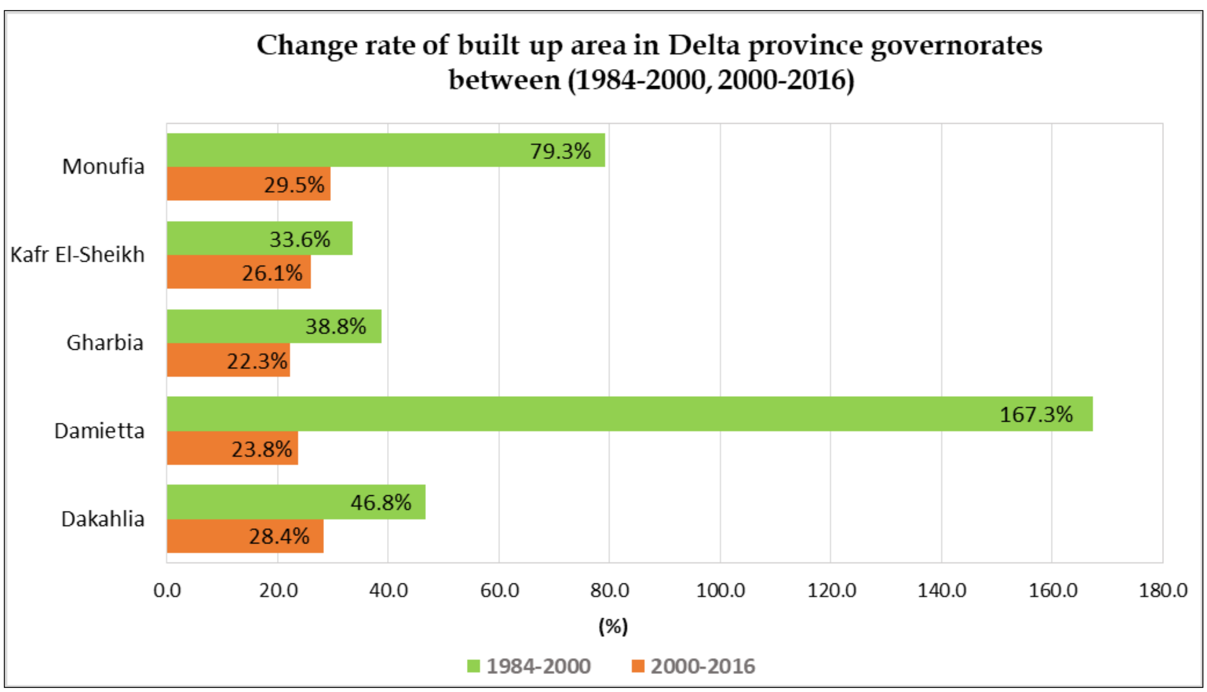

Figure 25. Change rate of built up area in Delta province governorates between (1984-2000, 2000-2016).

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3) Coastal beach and sand plains

Only three of five governorates in Delta province have a coastal zone along the Mediterranean Sea namely Kafr-El-sheikh, Dakahlia and Damietta.

Table 119. Coastal beach and sand plains change in Delta province governorates between 1984-2000 and 2000-2016.

Governorate	Area of Coastal Beach & Sand Plains						Size of Change			
	1984		2000		2016		1984–2000		2000–2016	
	Km²	%	Km²	%	Km²	%	Km²	%	Km²	%
Kafr-El-Sheikh	328.6	*56.4*	254.1	*65.3*	179.5	*64.1*	-74.5	*-22.7*	-74.6	*-29.4*
Dakahlia	200.4	*34.4*	109.3	*28.1*	88.6	*31.6*	-91.0	*-45.4*	-20.7	*-19*
Damietta	53.4	*9.2*	25.9	*6.7*	12.1	*4.3*	-27.4	*-51.4*	-13.8	*-53.3*
Total	582.4	*100*	389.4	*100*	280.2	*100*				

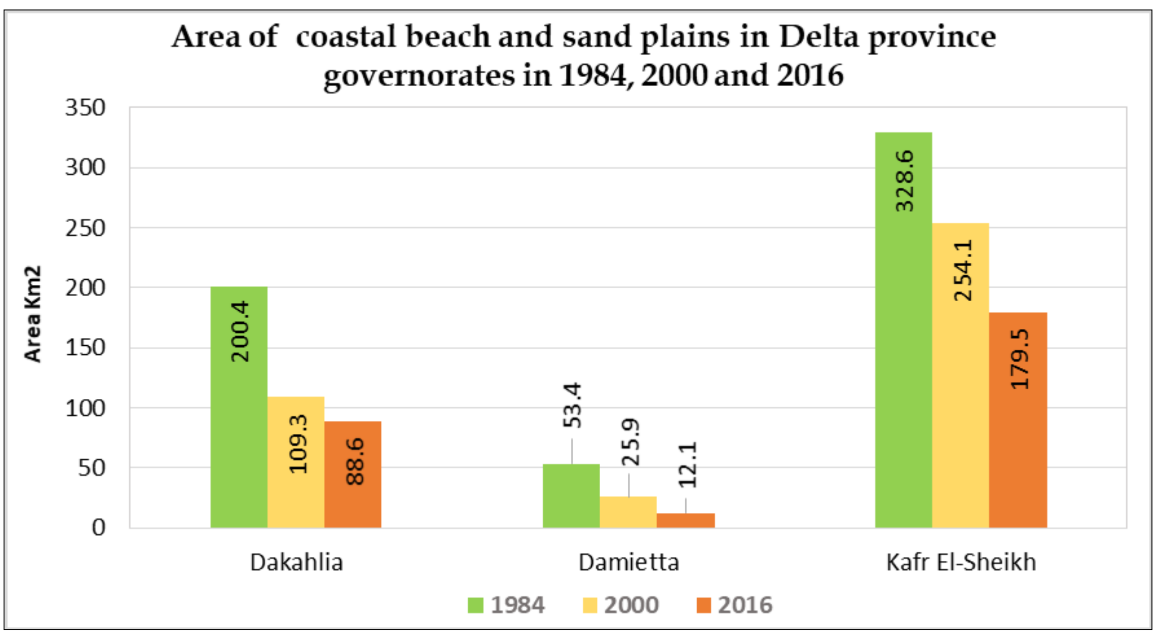

Figure 26. Coastal beach and sand plains area in Delta province governorates in 1984, 2000 and 2016.

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Change detection analysis reveals a drastic negative change in the coastal-beach land cover in three governorates between 1984 and 2016:

- Damietta is the highest negative change rate by (-51.4%) and (-53.3%) during the period 1984-2000 and during 2000-2016, respectively.
- Governorate of Dakahlia declined by (-45.4%) between 1984 and 2000, while between 2000 and 2016 declined by (-19%).

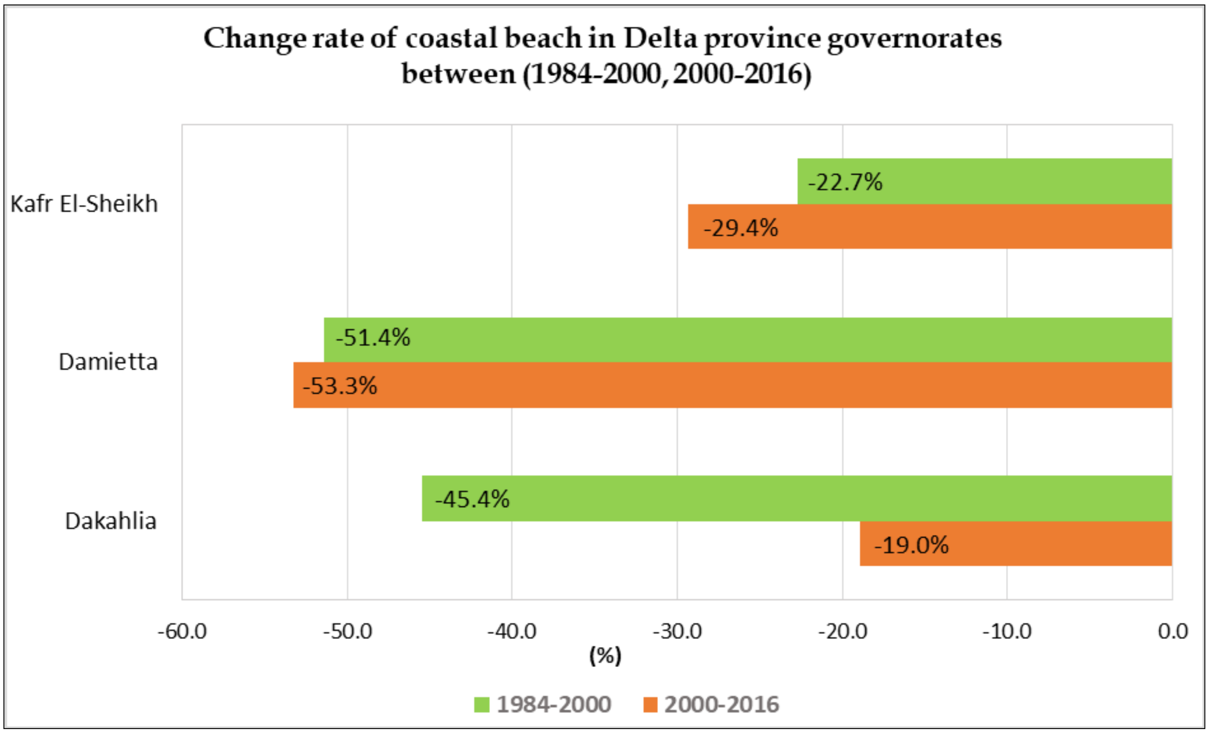

Figure 27. Change rate of built up area in Delta province governorates between (1984-2000, 2000-2016).

4) Fish ponds

Fish ponds area localized around the lakes in the northern part of Delta province and the coastal zone. Three governorates of Delta province are the base for fish farming activities, namely, Kafr-El-sheikh, Damietta and Dakahlia, where the three governorate have a coastal zone on the Mediterranean Sea and share in the lakes which located in this region.

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Table 20. Fish ponds change in Delta province governorates between 1984-2000 and 2000-2016.

Governorate	Area Fish Ponds						Size of Change			
	1984		2000		2016		1984–2000		2000–2016	
	Km²	%	Km²	%	Km²	%	Km²	%	Km²	%
Kafr-El-Sheikh	149.2	86.8	237.9	64.6	367	65.4	88.7	59.4	129.2	54.3
Damietta	12.9	7.5	86.0	23.4	121.5	21.6	73.1	567.9	35.5	41.3
Dakahlia	9.9	5.7	44.2	12	72.7	13	34.3	347.8	28.5	64.4
Total	582.4	100	389.4	100	280.2	100				

Change detection analysis reveals the following major change of fish pond area in these governorates:

- The highest increase rate in fish ponds area in the period between 1984 and 2000 located in Damietta by (567.9%), and followed by Dakahlia by (347.8%) and Kafr-El-Sheikh by (59.4%).
- In the period between 2000 and 2016, Dakahlia increased by (64.4%), followed by Kafr-El-Sheikh by (54.3%) and Damietta by (41.3).
- Damietta and Dakahlia and Kafr-El-sheikh gained (597.8%), (439.6%) and (90.2%) respectively, during the period 1984-2000, and loss by (-32.6%), (-30.8%) and (-92.2%), respectively, during the same period. While during the period 2000-2016, Dakahlia, Kafr-El-Sheikh and Damietta gained (91.7%), (63.6%) and (60.2%), respectively.

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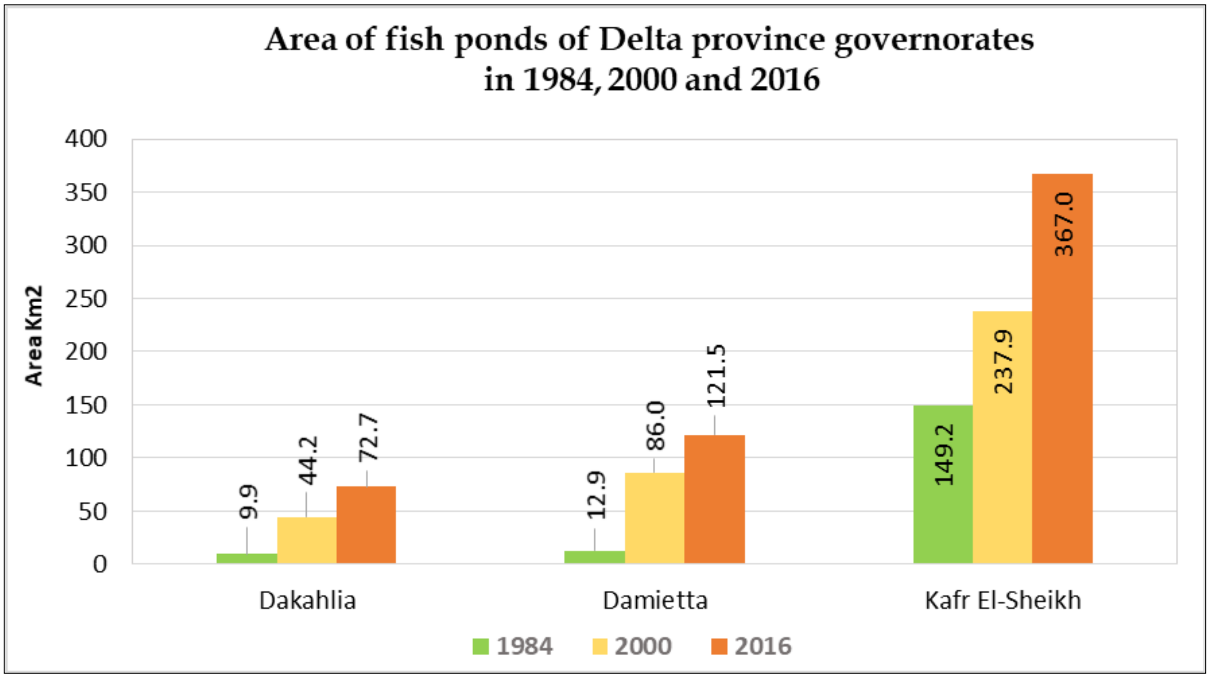

Figure 28. Comparison between fish ponds area in Delta province governorates in 1984, 2000 and 2016.

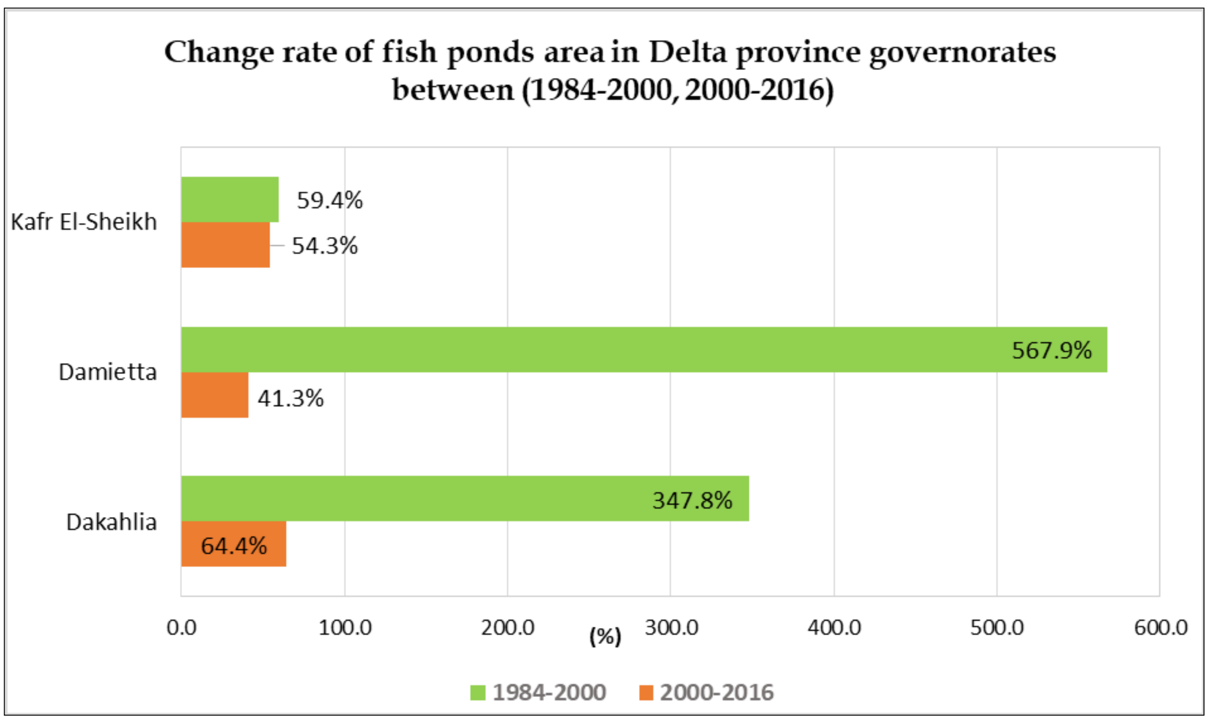

Figure 29. Change rate of fish ponds in Delta province governorates between (1984-2000, 2000-2016).

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5) Sabkha deposit and bare soil

The largest amount of sabkha-deposit-and-bare soil in Delta province is located around within the coastal governorates; Kafr-El-Sheikh, Dakahlia and Damietta, and also located in Gharbia and Monufia but in less degree. This land cover undergone change in all of Delta province governorates:

- Sabkha deposit and bare soil is increased only in Monufia, while decreased in other governorates between 1984 and 2016.
- Monufia increased in the period between 1984 and 2000 by (84.1%) and by (91.9%) between 2000 and 2016.
- Kafr-El-Sheikh, Dakahlia, Gharbia and Damietta declined by (-59%), (-49.5), (-42.1%) and (-36.8), respectively, between 1984 and 2000. While between 2000 and 2016, were decreased by (-84.2%), (-83.1), (-60.6%) and (-49), respectively.

Table 21. Sabkha deposit and bare soil change in Delta province governorates from 1984 to 2016.

Governorate	Area of Sabkha Deposit & Bare Soil						Size of Change			
	1984		2000		2016		1984–2000		2000–2016	
	Km²	%	Km²	%	Km²	%	Km²	%	Km²	%
Kafr-El-Sheikh	442.5	67.7	177.6	59.6	28.5	37.9	-264.9	-59.9	-149.1	-84.2
Dakahlia	126.4	19.4	63.9	21.4	10.2	13.5	-62.5	-49.5	-53.7	-83.1
Damietta	67.6	10.4	42.8	14.3	21.5	28.5	-24.9	-36.8	-21.3	-49.8
Gharbia	13.2	2.0	7.6	2.5	3.0	4.0	-5.7	-42.8	-4.6	-60.6
Monufia	3.4	0.5	6.3	2.1	12.1	16.1	2.9	84.1	5.8	91.9
Total	653.2	100	298.1	100	75.2	100				

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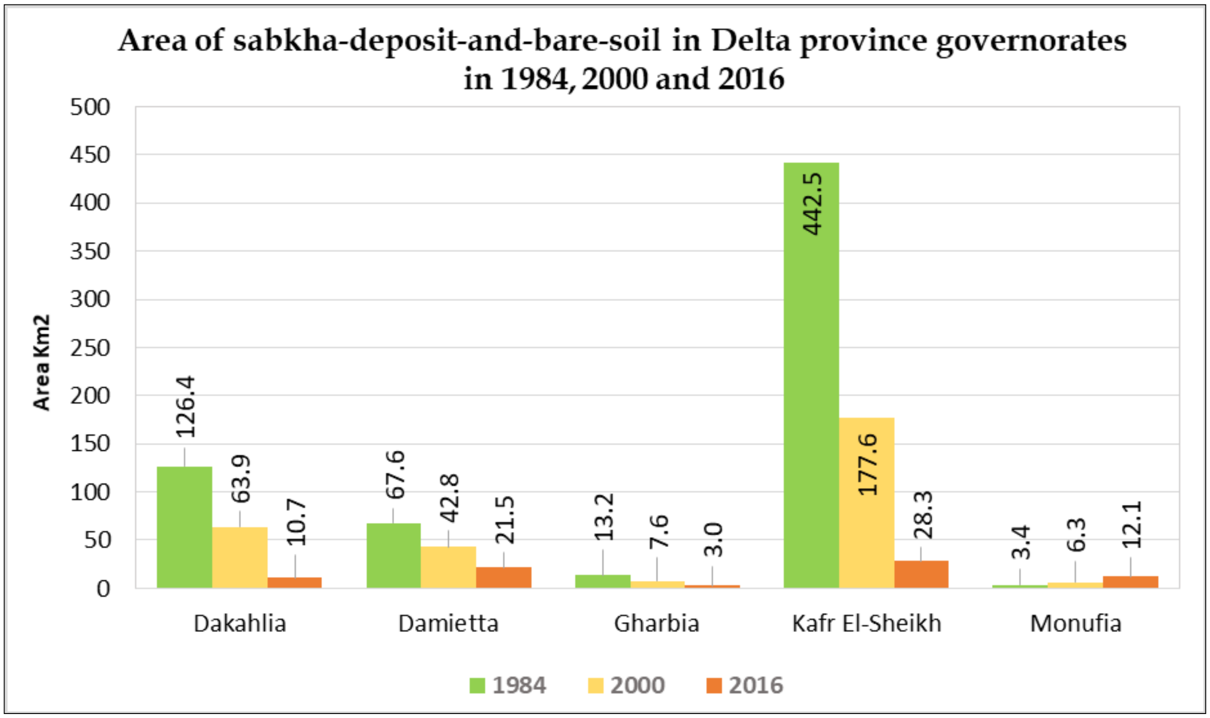

Figure 30. Area of sabkha-deposit-and-bare soil in Delta province governorates in 1984, 2000 and 2016.

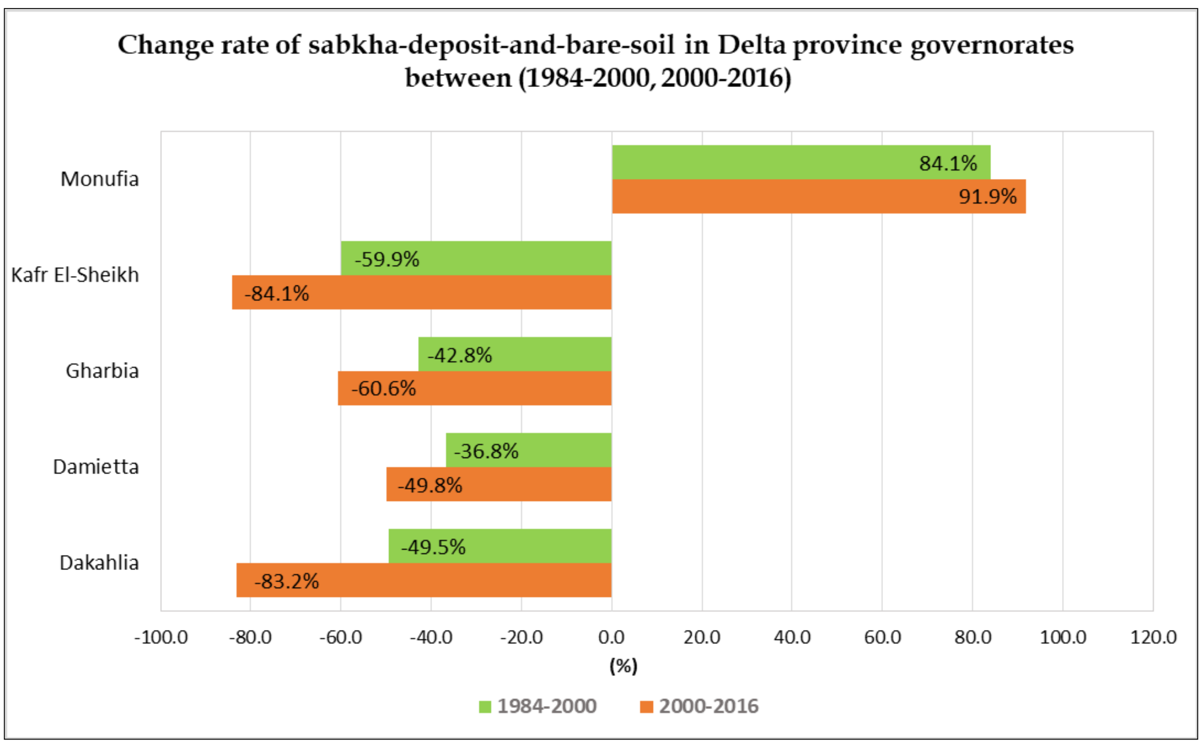

Figure 31. Change rate of sabkha deposit and bare soil in Delta province governorates between (1984-2000, 2000-2016).

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6) Water bodies

Large portion area of water bodies in Delta province is located in the coastal governorates; Kafr-El-Sheik, Dakahlia and Damietta, which extends along the Mediterranean Sea in addition the presence of large area of lakes.

Table 22. Water bodies change in Delta province governorates from 1984 to 2016.

Governorate	Area of Water Bodies						Size of Change			
	1984		2000		2016		1984–2000		2000–2016	
	Km²	%	Km²	%	Km²	%	Km²	%	Km²	%
Kafr-El-Sheikh	570.2	*44.7*	514.4	*46.2*	496.4	*48.4*	-55.8	*-9.8*	-18	*-3.5*
Dakahlia	476.6	*37.4*	430.6	*38.7*	404.6	*39.4*	-46.0	*-9.6*	-26.0	*-6.0*
Damietta	181	*14.2*	116.3	*10.4*	93.0	*9.1*	-64.7	*-35.8*	-23.3	*-20.0*
Monufia	26.3	*2.1*	28.3	*2.5*	17.3	*1.7*	2.0	*7.5*	-11.0	*-38.7*
Gharbia	20.7	*1.6*	23.6	*2.1*	15.3	*1.5*	2.9	*13.9*	-8.4	*-35.4*
Total	653.2	*100*	298.1	*100*	75.2	*100*				

- In the period between 1984 and 2000, water bodies was decreased in most of Delta province governorates, except in Monufia and Gharbia. While in the period between 2000 and 2016, water bodies decreased in all governorates.
- Between 1984 and 2000, Damietta, Kafr-El-Sheikh and Dakahlia declined by (-35.8), (-9.8%) and (-9.6), respectively, while Gharbia and Monufia increased by (13.9%) and (7.5%).
- Between 2000 and 2016, Monufia, Gharbia, Damietta, Dakahlia and Kafr-El-Sheikh were decreased by (-38.7%), (-35.4%), (-20.0%), (-6.0%) and (-3.5%).

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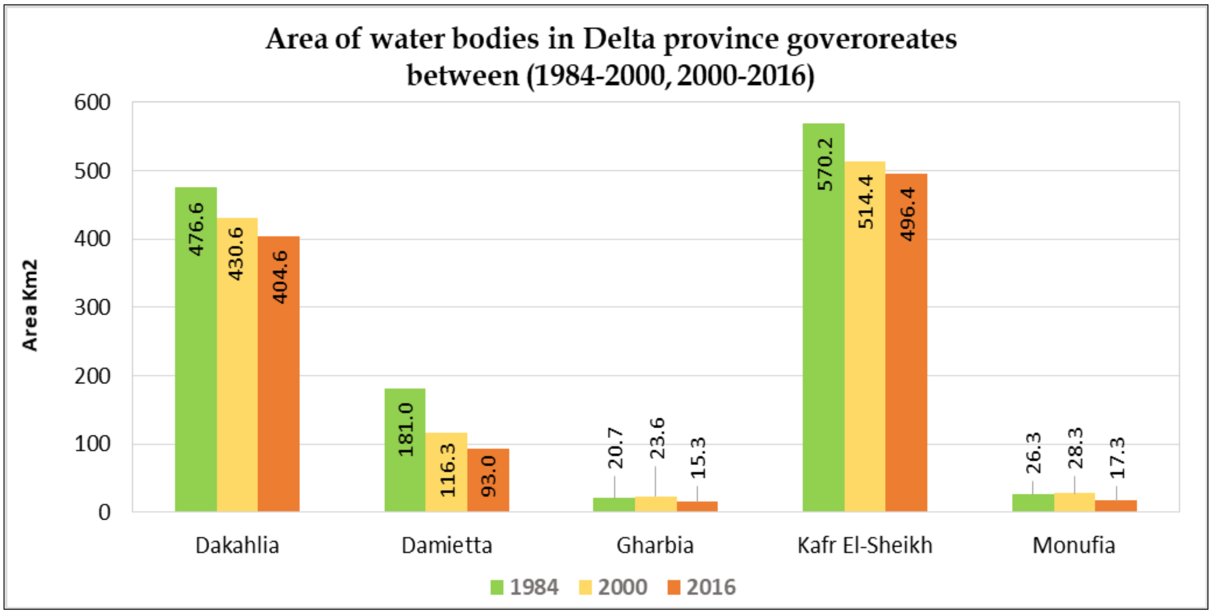

Figure 32. Area of water bodies in Delta province governorates in 1984, 2000 and 2016.

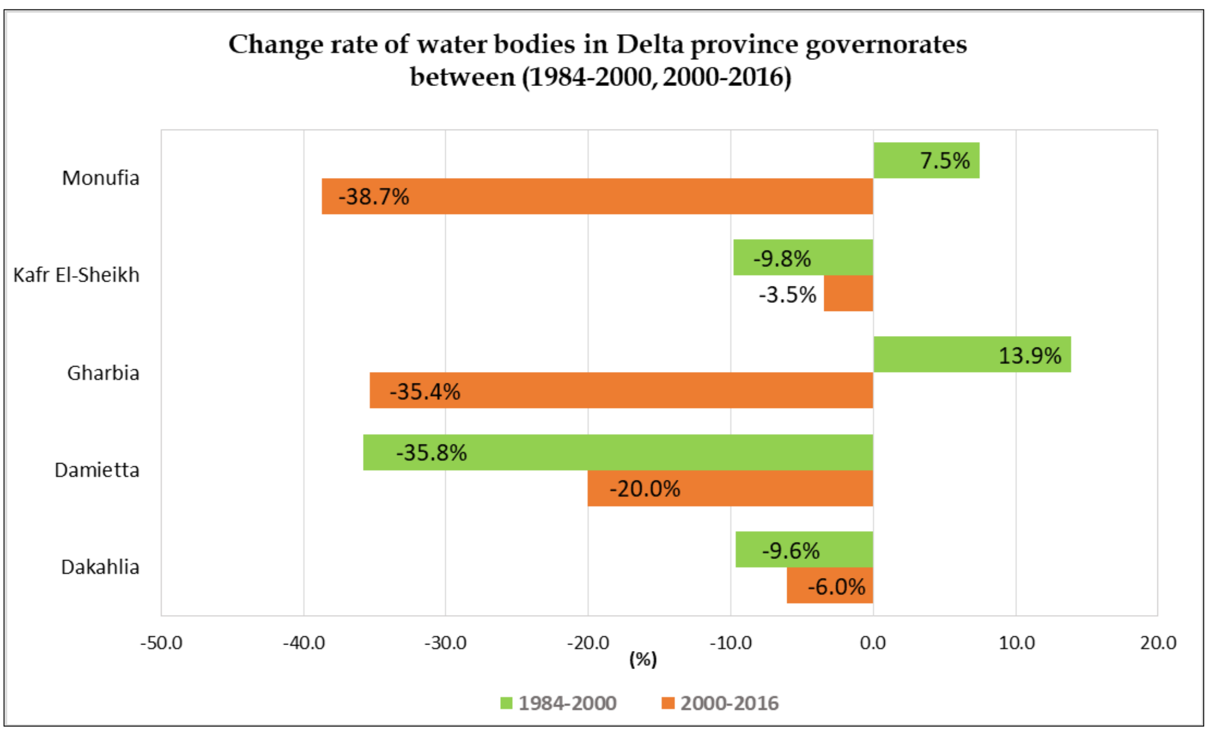

Figure 33. Change rate of sabkha deposit and bare soil in Delta province governorates between (1984-2000, 2000-2016).

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Chapter-4: Conclusions

In this study, multi-temporal imageries of remote sensing data were used to map land use land cover changes in the Delta province, Egypt. Three Landsat images representing 32 year period, acquired in 1984, 2000 and 2016 were used for this analysis. The imageries were geometrically corrected using image to image co-registration, and radiometrically corrected. Seven land use/cover classes (barren-land, built-up-area, coastal-beach-and-sand-plains, cultivated-land, fish-ponds, sabkha-deposit-and-bare-soil and water-bodies) representing the dominant land use/cover in the study area. The classification images for 1984, 2000 and 2016 were obtained by using maximum likelihood supervised classification algorithm. Post-classification comparison change detection technique were used to detect land use/cover changes between classifications of years 1984, 2000 and 2016.

The result show that the cultivated land class increased by 647.4 km^2 (7.2%) from year 1984 to 2016 where the average annual rate of land reclamation during 1984-2000 was 32.4 km^2/year and during 2000-2016 was 8.1 km^2/year. Between 1984 and 2000 there are three important zones of change appears extensive cultivation development, these zones are localized around the lakes of Al-Burullus and Al-Manzalah in the north and north-eastern part of the Delta province, and in the barren land in the south west of the province in Monufia governorates where agricultural activities expanded toward the barren land. Most increased cultivated land was located in the governorates of Kafr-El-Sheikh, Monufia and Dakahlia by 277.8 km^2 (12.8%), 175.4 km^2 (11.6%) and 101.5 km^2 (3.5%), respectively, while the cultivated land in Gharbia governorate declined by -39.8 km^2 (-2.2%), while during 2000-2016 was declined by -22.6 km^2 (-1.3%). On the other hand, the cultivated land lost (-3.4%) and (3.7%) during the periods of 1984-200 and 2000-2016, respectively, due to the conversion of cultivated land to other land use types such as built-up-area, sabkha-deposit-and-bare-soil and fish ponds, because the population and economic growth in this high population density province.

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Also, during the study period the urbanization increased by 416.4 km^2 (94.5%), most urban growth occurring through the expansion of building new communities on the agriculture area, where during the period from 1984 to 2000 about 219.2 km^2 (2.5%) of cultivated land was converted to built-up-area, and during 2000-2016 about 204.4 km^2 (2.2%) converted to built-up-area. Most increase rate of built-up-area is located in governorates of Damietta, Monufia and Dakahlia by (167.3%), (79.3%) and (46.8%), respectively, during 1984-2000, while during the period from 2000-2016 was the governorates of Monufia, Dakahlia and Kafr-El-Sheikh by (29.5%), (28.4%) and (26.1%), respectively.

A significant increase in the area of fish ponds during the period from 1984 to 2016 which increased by 389.3 (226.4%). During 1984-2000 fish ponds area increased by (114.1%) and increased during 2000-2016 by (52.5%). All fish ponds area was located in the coastal zone governorates; Kafr-El-Sheikh, Damietta and Dakahlia. During the period from 1984 to 2000, Damietta has the highest increase rate by (567.9%), followed by Dakahlia and Kafr-El-Sheikh by (347.8%) and (59.4%), respectively, while during 2000-2016 the highest increase rate was in Dakahlia by (64.4%), followed by Kafr-El-Sheikh and Damietta by (54.3%) and (41.3%). The significant increase of fish ponds area is duo to the population growth and the government plans for increasing the fish wealth to face the increase need for food.

Coastal-beach-and-sand-plains declined by -302.3 Km^2 (-51.9%) during the period from 1984 to 2016, because the conversion into other economic activities and urban expansion which relative to population and economic growth in the study area.

Water bodies declined by -249.4 km^2 (-19%) during the period between 1984-2016, most of water bodies transition was to cultivated land, fish ponds and sabkha-deposit-and-bare soil by (8.1%), (7.8%) and (2%), respectively, during 1984-2000, and by (6.9%), (6%) and (0.3), respectively, in the period from 2000 to 2016.

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Finally, the proper land use/cover management strategies need to develop to protect these important land use/cover in this province. The use of remote sensing data is a cost-effective method that can be used for obtaining valuable information for better monitoring, mapping and understanding land-use/cover changes over the time. Also, change detection techniques and methods are a powerful tool to explain the changes occurs on land use and land cover.

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