# CHANGE DETECTION ANALYSIS OF DUKAN DAM SURFACE AREA FROM (2000-2016) IN SULAIMANIYAH, IRAQ, USING REMOTE SENSING AND GIS

**Safin Najib RASHID**

**MASTER'S THESIS**

**Department of Soil Science and Plant Nutrition**
**Supervisor: Prof. Dr. Alaaddin YÜKSEL**

**2017**

REPUBLIC OF TURKEY
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## MASTER THESIS

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**This thesis was unanimously approved by the following jury on 07.06.2017**

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**I confirm the results above**

**Prof. Dr. İbrahim Y. ERDOĞAN**
**Director of the Institute**

## PREFACE

Firstly, I thank to Allah for providing me the opportunities that I have received. It is through your grace that I have come this far in this incredible journey. A great appreciation and sincere gratitude goes to my supervisor, Prof. Dr. Alaaddin YÜKSEL, Your support and mentorship have been invaluable to me for the continuous support of my master study, for his patience, motivation, enthusiasm, and immense knowledge. His gratitude helped me in all the time while writing my thesis. Special thanks to Assist. Prof. Dr. Mesut BUDAK In Siirt University, and I am thankful for Faculty of Agriculture of Bingol University, and to all the staff of the Soil Science and Plant Nutrition department, Prof. Dr. Ramazan MERAL, Assoc. Prof. Dr. Ali Riza DEMİRKİRAN, Assoc. Prof. Dr. Abdulkadir SÜRÜCÜ, Assoc. Prof. Dr. Vedat AVCI, Assist. Prof. Dr. Yasin DEMIR, Assist. Prof. Dr. Veysel TURAN, for their willingness to help me during my study. I am grateful to my parents for their unwavering encouragement and support throughout my endeavors; I dedicate it to my generous father, Mother, brothers, my sisters, and my aunts. I have special thanks to my friends Mr. Hoshmend AHMAD, Mr. Shamal HUSSEIN for their helped me writing my thesis. A great appreciation goes to many in Sulaimaniyah University especially Assoc. Prof. Dr. Talar ALI, Assist. Teacher. Pakizeh SAIED, Assoc. Prof. Dr. Soran AMIN, Assoc. Prof. Dr. Xalil MOHAMMAD, Assos. Prof. Dr. Shirwan OMAR, Assoc. Prof. Dr. Atta ALAADDIN, Assist. Prof. Dr. Hawre YASIN, Assist. Prof. Dr. Rozhan FARAYDUN, Department of Geography, Faculty of Human science in Sulaimaniyah University. I also want to special thanks to all those people who helped me during my MSc study.

**Safin Najib RASHID**
**Bingol 2017**

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| | | |
|---|---|---|
| DEM | : | Digital elevation model |
| ETM | : | Enhanced thematic mapper |
| FCC | : | False colour composite |
| GIS | : | Geographic information system |
| ID | : | Image differencing |
| LULC | : | Land use land cover |
| LULCC | : | Land use land cover change |
| LZRB | : | Little Zab river basin |
| ML | : | Maximum likelihood |
| MLC | : | Maximum likelihood classification |
| NDVI | : | Normalize difference vegetation index |
| NDWI | : | Normalize difference water index |
| OLI | : | Operational land imager |
| PCD | : | Principal component differencing |
| RS | : | Remote sensing |
| TM | : | Thematic mapper |
| USGS | : | United states geological service |
| UTM | : | Universal transverse Mercator |
| VI | : | Vertical interval |
| WGS | : | World geodetic system |

# UZAKTAN ALGILAMA VE COĞRAFİ BİLGİ SİSTEMİ KULLANARAK IRAK- SULAIMANIYA (2000-2016) DUKAN BARAJI'NDA YÜZEY ALANINDAKİ DEĞİŞİMİN ANALİZİ


## ÖZET

Bu araştırmanın amacı Irak'ın kuzeyinde Süleymaniye'deki Dukan Barajı'ndaki arazi kullanım / arazi örtüsü ve yüzey sularının değişiminde meydana gelen değişiklikleri incelemektedir. Bunla birlikte bu çalışma ile, Uzaktan Algılama Teknikleri ile Landsat 7ETM ve Landsat 8OLI görüntülerinin incelenmesi ve Yüzey suyunun iki yıl boyunca değişimi araştırılmıştır. Bu bağlamda Kasım 2000 ve Kasım 2016'daki iki Landsat 7ETM ve 8OLI görüntüsü elde edilmiştir. Çalışmada arazi kullanım kategorileri, maksimum olasılık algoritması ve yüzey suyu kütlesine değişim algılama ile denetlenen sınıflandırma teknikleri kullanılarak türetilmiştir.

Çalışmada belirlenen değişiklik sonuçlarına göre, 2000 ile 2016 yılları arasında su yüzel alanı oranında önemli bir değişiklik olduğunu ve 2016 yılında tarım arazisi, vejetasyon arazisi ve çorak arazi miktarında suya doğru artan bir eğilim olduğunu göstermiştir. Su oranı %17,62'den %30,12'ye ve alan miktarıda 92,94 km$^2$ den 186,42 km$^2$'ye artmıştır. 2000 yılı civarında yağış oranındaki azalma ile bu bölgede kuraklık olmuş ve buda su yüzey alanının azalmasının özel bir nedeni olmuştur. 2016'da su yüzey alanının artmasının spesifik nedenleri, 2000 yılından sonraki yılların ardından, diğer su kaynaklarından gelen suyun Dukan barajına girmesi ve dağlardan Dukan barajı çevresindeki suyun erimesiyle birlikte sürekli olarak suyun hızını arttıran yağış oranının yüksek olmasıdır Bu çalışmada su yüzey alanı ve değişimine, diğer sınıflardan daha fazla odaklanmıştır. Sınıflama çalışmaları sonucu çorak arazilerin 2016 yılında çok azaldığını göstermiştir. Bir başka ifadeyle 214,36 km$^2$' den 2000 121,59 km$^2$ azalmıştır 2016. Suyalanının artması nedeniyle tarımsal alanlar, Bir başka ifade ile tarım alanları 441.76 km$^2$ den 372,94 km$^2$ ye azalmıştır. Araştırma alanındaki yapılaşma alanında az bir artış görülmüştür. Başka bir ifade ile yapılaşma alanı 11,22 km$^2$ den 25,4 km$^2$ ye artmıştır. Araştırma alanındaki bitki örtüsü yüzey alanı yüzde olarak %9,12'den %13,16 oranına az bir artış göstermiştir. Alan cinsinden ise bu değer 31,54 km$^2$ den 85,12 km$^2$ ye artmıştır. Bitki örtüsü hafif artışı. Sonuç olarak, uzaktan algılama ve CBS tekniklerinin, su yüzey alanı ve LULCC için değişim aralıkları arasındaki ilişkiyi incelemekte ve izlemekte çok etkili olduğu kanıtlanmıştır.



**Anahtar Kelimeler:** Uzaktan algılama, CBS, Değişim tespiti, Sınıflandırma, LULCC, Dukan barajdaki yüzey suyu.

## CHANGE DETECTION ANALYSIS OF DUKAN DAM SURFACE AREA FROM (2000-2016) IN SULAIMANIYAH, IRAQ, USING REMOTE SENSING AND GIS


## ABSTRACT

This research examines the changes in land use/land cover and change detection of surface water in Dukan dam in Sulaimaniyah north of Iraq, The primary aim of this study is to use Landsat 7 ETM and Landsat 8 OLI imagery with Remote sensing techniques to study and investigate the change of surface water for two years periods. Two Landsat 7 ETM and 8 OLI images were obtained in Nov 2000, and Nov 2016. Land use categories were derived using supervised classification techniques with maximum likelihood algorithm and change detection to surface water body.

The change detection results there is a significant change in the quantity of water body between 2000-2016, and indicate that there is a growing trend toward water in year 2016 at the expense of agricultural land, vegetation land and barren land. The quantity of water was (92.94) km sq, with ratio (17.62%) in 2000 increased to (186.42) km sq, in ratio (30.12%) in 2016, these because years around 2000 precipitations was low (380.4) mm because drought happened and water body decreased. The specific reasons of increasing water body in 2016 are the years after 2000 the rate of rainfall was high (816.8) mm. Increasing the rate of water constantly because of feeding from other water resources and melting snow from the mountains around Dukan dam along the years after 2000. In this study water body and the changing, it is focused on more than the other class.

The result of the classification showed that Barren land was 214.36 km sq, with ratio 24.36% in 2000 decreased to 121.59 km sq, in ratio 13.36% in 2016. Agricultural land was 441.76 km sq, with ratio 47.51% in 2000 decreased to 372.94 km sq, in ratio 37.59% in 2016 because of increasing water. Built up areas are mild increased because of increasing population and coming people from the villages to the area that was 11.22 km sq, with ratio 0.94% in 2000 increased to 25.4 km sq, in ratio 4.13% in 2016. And there is a mild increase in vegetation. Conclusively, remote sensing and GIS proved to be very effective in studying and monitoring the relationship between change detection for water body and LULCC.



**Keywords:** Remote sensing, GIS, change detection, LULCC, accuracy assessment, landsat satellite, supervised classification, maximum likelihood algorithm, surface water.

# 1. INTRODUCTION

Change detection is an important process in monitoring and managing natural resources and assessing Environmental influence because it provides quantitative analysis of the spatial distribution of changes, The change between two images or more time period can be analyzed by change detection techniques and Change detection is the most important tool in remote sensing (Macleod and Congation 1998). This study is particularly about the changes in surface area between two different times 2000-2016 in Dukan dam by using remote sensing and its tools including change detection and supervised classification techniques.

Remote Sensing (RS) is the most important subject in this study, which is now commonly used to describe the science and art of obtaining information about a phenomenon, area, or object under inspection by a device that records the spectral properties of surface materials on the earth from a distance (Singh 1989a; Rogan and Chen 2004). There are two types of remote sensing instruments; passive and active. Passive instruments detect the natural energy that is reflected or emitted from the observed scene whereas active instruments provide their own energy (electromagnetic radiation) to illuminate the object or scene they observe. Remote sensing from airborne and space borne platforms provide a huge amount of valuable data about our earth's surface including aerial photographs, spatial data set, and satellite images (Paradzayi et al. 2008).

Remote sensing application can be utilized for land use land cover, change detection, classification techniques and water body monitoring, the satellite images are consider as one of remote sensing data which provides both spatial and temporal information (Fonstad and Marcus 2005). The information satellite data are very useful to determine changes in land cover and water body parameters (Khattab et al 2012).

Image satellites at different special spectral and temporal resolution provide an enormous amount of data, which became essentially source, being widely used for finding and extracting surface water and its change recent decades (Mcfeeters 2013).

Change detection is defined as a "process of identifying differences in the state of an object or phenomenon by observing it in different times" (Singh 1989b). Detecting and analyzing LULCC over enormous geographic areas as well as over regional areas have been highlighted both in a manner of discrete long-time span and in sequential time series with high temporal resolution, remote sensing satellites through a process commonly called 'change detection (Coppin and Bauer 1996).

Change detection as one of the important process is performed to monitoring and investigate natural resources urban growth, agriculture, barren land, vegetation land and water body because it provides quantitative analysis of the spatial distribution and this makes LULC study a topic of interest in remote sensing applications (Song et al. 2001; Gallego 2004).

The land use/land cover change (LULCC) is the modification of the land or replacement of one land-cover class on the earth's surface (Meyer and Turner 1992). Mapping land use land cover is the process standard way to monitor changes and investigative to (LULC) change and evaluation, change detection performs analysis to defined the nature, many researchers have been performed to determine factors that due to changes in land cover in developing countries, One of those factors is climate change, drought, use water to agriculture and another proposes (Farkuo and Frimpong 2012). One of the main issues in land cover change detection is how to accurately extract change areas while eliminating the pseudo changes caused by phonological differences and extraneous aspects (Chen et al. 2013; Jin et al. 2013).

LULC mapping is a useful tool that can be used for good planning and management of agricultural, practices urbanization and for other human activities. Landsat data is ideal for LULC mapping and for change detection studies of Dukan dam. Landsat satellite data was chosen because of its open accessibility, appropriateness for the aim of the study, its long time of observation and its good spectral and spatial resolution for LULC analyses.

Mapping LULC is presently the standard approach and most common method to monitor land use changes and developments (Mancino et al. 2014). Especially when LULC classes and their spatial and temporal changes are to be determined for categories of small geographic extent in vast areas, high-resolution satellite images are necessary (Reed et al. 1996).

In change detection information about land cover changes including in past and future is given. Therefore, the connection between change detection and land use land cover generally is that change detection shows how a vegetation land, barren land, urban growth, water body, agriculture, open land, forest are changed through the pass of time it shows accurate information about their change and in this study the focuses' is on changes in water from the year 2000 to 2016 in Dukan dam.

The earth's surface is changing as a result of natural phenomena or human activity. For instance, storms, lightning, strikes, pests, agro-forestry wildfires, urban growth, agricultural expansion, social, technological, economic, historical factors and others(Borak et al. 2000). Generally, the earth's surface changes are divided into two categories: land use and land cover (Barnsley et al. 2001). Land cover initially describes the physical state of the land surface, that includes cropland, forests, and wetlands, but it has broadened in subsequent usage to contain human structures such as buildings, pavements and other aspects of the natural environment, including soil type, biodiversity, groundwater surface water and (Cheng et al. 2008; Jaiswal et al. 1999). The land cover is an essential component of ecological function, particularly in terms of hydrological processes (Wickham et al. 2000).

In contrast, land use refers to the way in which human beings exploit the land and its resources which include agriculture, urban development, grazing, logging and mining. However, land cover and land use are often used interchangeably because the two terms are interdependent and closely related (Verburg et al. 2003; Verburg et al. 2009). Regardless, land use/land cover change (LULCC) is defined as the transformation of the land or replacement of one land-cover type on the earth's surface (Meyer 1992). LULCC is the impact of several related processes operating over a wide range of scales in space and time (Foody 2002). Rapid depletion natural cover earth, contain degradation of forest and vegetation, surface water and increase of barren area , most of the resources problems are result of human activities and climate change (Sinha et al. 2015).

Remote sensing application can be utilized for water body monitoring, the satellite images are consider as one of remote sensing data which provides both spatial and temporal information (Fonstad 2005). The information satellite data are very useful to determine changes in water body parameters (Khattab et al. 2012).

Introduction of surface water is one of the strategic resources, which are indispensable to the survival of the human and social development (Ridd and Liu 1998). It is crucial for humans, food crops, and ecosystems (Lu et al. 2011). Reliable information about the spatial distribution of open surface water is critically significant in various scientific disciplines. For instance, the assessment of present and future water resources. In addition, nowadays drought is most significant problem and the drought due to water values and change has the important role in hydrology (Howarth and Wickware 1981; Jensen and Toll 1982).

Classification is a technique that is used for classifying LULC and a supervised classification was employed which is one of the common application of remotely-sensed images to rangeland management and it is the creation of maps of land cover, vegetation type, or other discrete classes by remote sensing software. The user to specify the land cover classes of interest in supervised classification (Huang et al. 2002) guides the image processing software. In other words for classifying images to attain the objectives of this study. Commonly, researchers choose supervised classification because it provides a more accurate definition of classes and better classification accuracy than unsupervised classification and in this study supervised classification is used with The maximum likelihood classification that is one of the most popular methods of classification in remote sensing in which a pixel with the maximum likelihood is classified into the corresponding class. The maximum likelihood is defined as the posterior probability of a pixel belonging to class (Huang et al. 2002). In this study it is used to classify the LULC of the Landsat 7 ETM and 8 OLI images supervised classification methods have been applied and tested extensively for land use planning and management in arid and semi-arid environments (Ulbricht et al. 1993; Del Valle et al. 1998).

## Aim And Objectives Of The Study

The main purpose of this study is to analyze the change between two images of two different times 2000-2016 in Dukan dam by using remote sensing techniques including change detection and supervised classification of land use land cover types with emphasis on:

- Identifying the change in surface water in Dukan dam during the period of the study.
- Make recommendations for further studies.
- Supervised classification technique with maximum likelihood algorithm for two consecutive satellite images from the study area.
- Accuracy assessment to judge the applicability of image classification in this study and to ensure the accurate change detection.
- Identify the LULC changes in the study area during the times of 2000 and 2016 using change detection method.

## Research Questions

1. Estimation of proportion change surface water in the period of the study?
2. What are the reasons behind the change in water body in Dukan dam?
3. To what extent has surface water influenced land cover change over the period of the study?
4. During the period under study, what changes have occurred in the land cover classes?
5. What major change has occurred in land cover classes during the period of time under consideration?
6. What is the benefit of accuracy assessment in the study?
7. What is the change detection of the land cover classes in the area?
8. How effective is the maximum likelihood algorithm method for image classification in?

## Problem Definition

The land cover change (LCC) trends occurring in the study area of Dukan dam clarify a change level, this phenomenon has been recorded in literature and informal resources, which have expounded on its adverse impacts on the land cover, this causing drought, wastewater and more water using to developing agriculture and industrial.

In this study area conducting such research is imperative for understanding the causes and consequences of the changes in the surface water change, as no research on surface water change has been carried out in the study area, in this field especially using GIS and remote sensing techniques, there is a need for this study and this research is a beginning for filling this knowledge slit, as a result this study is important and unique, particularly, because it is using remote sensing and GIS technique.

# 2. LITERATURE REVIEW

There are some studies about change detection and land use land cover used remote sensing data for the goal of receiving change detection in surface area investigation, relying on the studies share of the literature review some worked to show significant effort, which used Landsat imager data for this study.

Remote Sensing is the science and art of obtaining information about an area, object, or phenomenon through the investigation of data acquired by a device that without physically making contact with the object, area, or phenomenon under investigation" (Lillesand and Kiefer 2004). In other words, remote sensing includes obtaining information on any target object from a remote distance, and now commonly used to describe the science, art, and geographers find this knowledge to be important. This demonstrates why for issues relating to environmental changes, one of the essencial tools used is remote sensing as it provides a great amount of data on the environment. Remote sensing has been, and is still in great use in contemporary GIS analysis. moving from trends and research works found, remote sensing has demonstrated to be more effective than traditional methods like field based surveys (Singh 1989; Rogan and Chen 2004).

Remote sensing provides a large variety and amount of data about the earth surface for detailed analysis and change detection with the help of various spaceborne and airborne sensors. It gives powerful capabilities for understanding and managing earth resources. RS have been proven to be a very useful tool for LULC change detection (Matinfar et al. 2007). There are two types of remote sensing instruments; passive and active. Passive instruments detect the natural energy that is reflected or emitted from the observed scene whereas active instruments provide their own energy (electromagnetic radiation) to illuminate the object or scene they observe.

Landsat satellite data is the most widely used data types of monitoring and mapping land cover changes (Williams et al. 2006), Landsat satellite images has its importance for monitoring change detection and LULC. In this study Landsat satellite data (7 and 8) is used for studying LULC and change detection to surface water in Dukan dam.

It is curious to note that several literatures have highlighted the importance of remote sensing, LULC and change detection:

Rokni et al. (2014) investigated Urmia lake regarding surface water feature extraction, this study has used change detection multi temporal , depended on models the spatiotemporal changes of lake Urmia in the period 2000-2013, five satellite images have used, the study was derived indexes including (MNDWI), (NDWI), (MDNI), and (NDVI), the result of the work determines change detection in the surface water which has been in a critical situation in recent years due to decreasing surface water and increasing salinity between (2000-2013).

Ryan et al. (2015) he presents a case study using remotely sensed images from Landsat satellites and Google Earth imagery for over a 30-year period to generate classifications representing land cover categories, which he use to quantify land cover change in the watershed areas that contribute to Malheur and Harney Lakes. I elected images, about every 4 to 6 years, in an attempt to capture the peak vegetation growth and to avoid cloud cover. The ROIs were used in the following supervised classification algorithms: Mahalanobis distance, minimum distance, and maximum likelihood, to divide land cover for the area. Using ArcGIS and ENVI software.

Diallo et al. (2009) reported of the study Landsat5 thematic mapper TM is used in Puer and Simao countries Yunnan province, the images were corrected atmosphere effects and then geo-rectified using ground control points collected by GPS, the image were classified using maximum likelihood classification method and LULC change detection techniques by ENVI 4.3, and for mapping they used ArcGIS, between 1990-1999.

Khatab et al. (2011) explained detection depth water of Mosul dam reservoir (ETM+) images have been used to estimate water depth of Mosul Dam's Reservoir that is located

North of Iraq and specifically north of Mosul city (40 km). By employing multispectral image processing techniques that are associate with GIS programs, through using of Matlab 7.5, ERDAS 8.4, Arc View 3.2 and Glober Mapper 7 programs. When applied the algorithm of the processing showed that the band 1 and band 5 are suitable for this study. the digital elevation models (DEM) for Mosul dam reservoir was also used as elevation reference for study, the research were fixed coastline extraction separation of water body using remote sensing data which is important for measurement characteristics of water resources, there are various image processing methods for detection and extraction coastline depending on the purpose of the study.

El-Asmar et al. (2013) this study works on Surface area change detection of the Burullus Lagoon, North of the Nile Delta, Egypt, by using ArcGIS Software ERDAS Imagine to process and visualize satellite data in the present study, This study has taken a series of six satellite images acquired between 1973 and 2011. This study applies the non-traditional the (MNDWI) and (NDWI) to quantify the change in the water body area of the Lagoon during the study period, this paper shows that results lost 42.8% of its open water area due to the severe anthropogenic activities. For instance, the reclaiming of its southern margins for agricultural purposes and the filling caused by the discharge of agricultural wastes.

Esmail et al. (2016) explained on LULC changes along the north part of the Nile delta coastal zone by applying remote sensing/GIS technique, and supervised classification and post-classification change detection techniques were applied to Landsat images acquired in 1987 and 2015 to map LULC changes along the north part of the Nile delta coastal zone specifically, at Damietta promontory, it used Four categories including seawater, developed (agriculture and urban), and undeveloped areas were selected to evaluate their temporal changes by comparing the processed images and the sew water and urban area were increased in this study.

Younus et al. (2015) have reported to investigate the effect of land use expansion on the natural environment of the Little Zab River basin (LZRB). It Detect changes between five dates within the period 1976-2014. For the purpose of this study, digital image processing, supervised classification with maximum likelihood algorithm was applied on the Landsat 8 OLI data, using Six Landsat images from 1976, 1984, 1990, 2000 and two Landsat 8 OLI 2014, Change detection of the LZRB was performed using three indices: the (NDVI), (NDWI) and (NDBI). The results showed that six main LULC classes have been distinguished and they involve agricultural land, barren land, urban, natural vegetation, built-up land, burned land and water. Change detection analysis over the period (1976-2014) has revealed highly dynamic interchanges between the LULC classes. The change detection results displays a rapid increase in urban and built-up land.

Reported by Olokeoguna et al. (2014) focused on assessing landscape transformation in Shasha Forest Reserve, over an 18-year period. Landsat Satellite imageries (30m resolution) covering the area at two epochs were characterized into five classes (water body, forest reserve, built up area, farmland and vegetation) and classification performs with maximum likelihood algorithm, that emerged in the classes of each land use. The result of the comparison of the two classified images showed that vegetation (degraded forest) has increased, farmland cover and built up are also increased. Forest reserve however, has decreased during the period. Classification performs with maximum likelihood algorithm, which resulted in the classes of each land use of the result comparison of the two classified images vegetation forest has increased.

According to Adediji and Ajibade (2008) explained on the change detection of major dams in Osun State, Nigeria by using remote sensing and GIS techniques, in this study Landsat-TM (1986) and Landsat-ETM+ (2002) and unsupervised classification are used. The change in the area extent to other associated land uses such as built-up, farmland, vegetation around the study dams between 1986 and 2002. The results of the study showed a sharp decline in the surface area of the research reservoirs.

Rokni et al. (2015) have reported a new approach for surface water change detection: Integration of pixel level image fusion and image classification techniques, he made a study to detect surface water changes using multi-temporal satellite data analyzed to detect their changes, were investigated the multi-temporal Landsat ETM+ 2000 and TM 2010, and maximum likelihood (ML) classification techniques were applied to extract and map the highlighted changes, for the result fused images for change detection was evaluated using edge detection, and showed that Lake Uremia lost about one third of its surface area in the period 2000–2010.

Sarp and Ozcelik (2016) in the article foxed on Water body extraction and change detection of Lake Burdur, Turkey, this study is related to space and time changes in Lake Burdur from 1987 to 2011, they were evaluated by using multi-temporal Landsat TM and ETM+ images, involving (NDWI), (MNDWI) and (AWEI), the results displays the activity of MNDWI based surface water change detection, especially in identifying changes between indicate time intermission.

Al-Doski et al. (2013) this study looks into the following aspects related to the remote sensing technology, change detection process and techniques for land cover changes, and aspect affecting change detection techniques and considerations.

Faraj (2013) this study foxed on land use land cover change detection for Sulaimaniyah in northern Iraq by using remote sensing between 1998 and 2010, this work utilized a time-series of Landsat 5 (TM) and Landsat7 (ETM+) satellite imagery data, Change detection in land-use/land-cover and classification image was carried out using a workflow consisting of establishing the LULC classification scheme, image data acquisition, scene processing, data analysis, post-processing, and validation.

Nijhawan (2016) this paper compares the classification accuracies of glacier change detection by following classifiers: sub-pixel classification algorithm, object based algorithm and indices based supervised classification using Landsat imageries, Further, the accuracy was improved by object based classification. Objective of the paper is to analyze different classification algorithms and interpret which one gives the best results in mountainous regions.

# 3. MATERIAL AND METHOD

## 3.1. Study Area

The study area, Dukan Dam is one of the most important dam in north Iraq, which is multi-purpose concrete arch dam it is located in 60 km NW of Sulaimaniyah province, and the west of Rania plain, It is bordered by Iran to the northeast and to the west by Erbil and Kirkuk province, at the Lower-Zabb river (Muhammad 2010). As displayed in Figure (3.1).

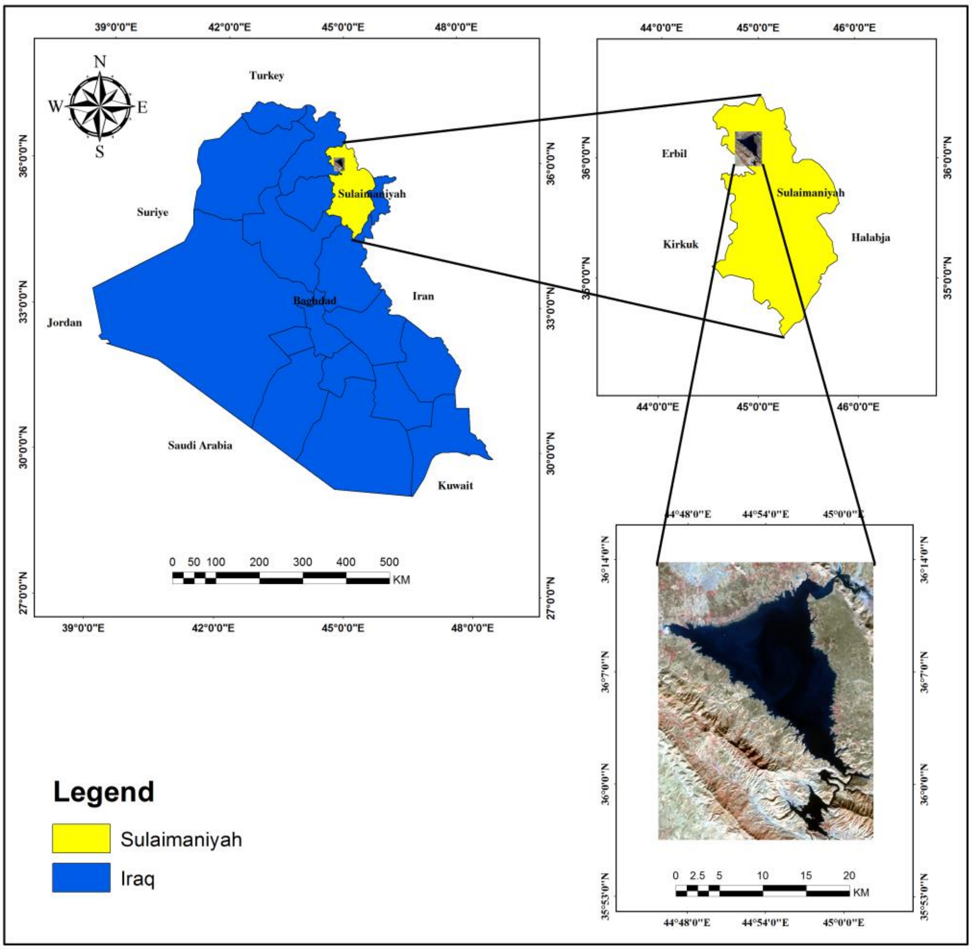


Figure 3.1. study area (Source: GIS)

Dukan dam is one of the main sources of water for drinking, irrigation and power generation in the province of Kurdistan region and especially to the province of Sulaimaniyah (Abdullah 2015).

Dukan dam which is the multi-purpose concrete arch dam was built between 1954-1959; it impounds the Little Zabb river, thereby creating Lake Dukan behind the dam, The dam is 360 m 1,180 ft. long and 116.5 m, 382 ft. high, and its hydroelectric power station has a maximum capacity of 400 Megawatt. It is situated between altitudes 35° 57′ 15″, 35° 95′ 41″ N and Longitudes 44° 57′ 10″, 44° 95′ 27″ E. It is bordered by Iran to the northeast and to the west by Erbil Province (Fathulah 2000).

The Dukan Dam is provide water storage irrigation and hydro- electricity, whereas its power station became fully operational in 1979, Dukan dam, with a surface area varying nearly 270 $km^2$ and normal elevation is 511 m, At its base it is 32.5 m 107 ft. wide, the capacity of Dukan dam is about 6-8 milliard $m^3$ and catchment area is 11690 $km^2$, Lake Dukan the reservoir created by the Dukan Dam.

The exposed formations in the study area start with Cretaceous succession including Qamchuqa formation, Dukan formation, Gulneri formation, Kometan formation, Shiranish formation and Tanjero Formations then followed by Tertiary successions that include Kolosh, Sinjar, Gercus and Pilaspi Formations (Mohammad 2010; Jassim and Goeff 2006).

Dukan dam is an important ecologic, economic and geo-tourism zone and was recognized as a biosphere reserve by united national educational, scientific and cultural organization (UNESCO) in 1994. In addition, the dam supports moderate the temperature and humidity of the region, providing a suiTable place for agriculture activities, the dam exploitation of ground water and increased water demand for industrial and domestic uses (Al-Soof 1970; Fink 1984). The study area is characterized by a Mediterranean climate. It is a mountainous region, Agreement to Koppen classification it is type CSA*, which characterized by dry and warm summer, cold and wet winter. There are two short seasons (spring and autumn) between winter and summer with intermediate climate conditions and the average monthly temperature value for the period 1984-2005 was 19.1 °C.

Summer lasts from the beginning of May to the beginning of October and winter Lengthens from November until the start of March. In winter, especially in January, the temperature decreases to 5.7 °C or even less than (0 °C). The maximum average monthly temperature was 33.3 °C in July and the highest temperatures, ranging between from 44 °C to 47 °C, are usually recorded between June and September. Much of the precipitation occurs from November until April. Generally, Based on Dukan dam station's data the average annual relative humidity is 56.5%, the average minimum and maximum values of this parameter in the studied area are 33.5% and 74.6% in July and December respectively (Dukan dam weather station's data).

The studied area is characterized by seasonal rainfall especially in January, February, March and April and dry season in June, July, August and September. Generally, we have change in annual rainfall from year to another year. In 1990, the annual rainfall was 719 mm while in 1996 the annual rainfall was 1139 mm. The mean average annual rainfall in the area is 774 mm, the maximum average monthly precipitation recorded for the period 1984-2005 was 148.9 mm in December and 148.1 mm in January (Stevanovic et al 2003; Dukan dam weather station's data). However, this has decreased in the recent times due to climatic and environmental changes (Muhammad 2010).

## 3.2. Topography Of The Study Area

### 3.2.1. Elevation

The elevation of a geographic location is its height above a fixed reference point, often the mean sea level. Elevation, or geometric height, is mainly used when referring to points on the Earth's surface, while altitude or geopotential height is used for points above the surface, such as an aircraft in flight or a spacecraft in orbit.in the other word Topographic elevation is a parameter that controls erosion and degradation of soil and it affects soil properties (Dai and Lee 2002; Ayelew et al. 2005).

A contour map shows lines that indicate elevation, in other words, Contours, which are lines drawn through points the same height above sea-level, allow both the direction and gradient (steepness), (See Figure 2) of slopes to be determined from the map with much greater accuracy than either of the above techniques, "Contours are included on almost all modern topographic maps. The vertical distance between two adjacent contour-lines is known as the (V.I.), A vertical interval of 20 metres is often used on modern metric maps. On older pre-metric editions a V.I. of 50 feet was widely used (Ayelew et al. 2005).

When contour lines are close together, slopes are steep. If contour a lot of lines close together and then a little circle in the middle of it all, that is indicating the peak of a mountain. Where slopes are even, the contours on a map are evenly spaced, while on irregular slopes the distance between contours varies widely (Avci 2017) (see Figure 3).

The elevation in the study area varies from 408 m to 1564 m, and average elevation reaches 1000 m. In Dukan area, the sites in groups of 407 m-500 m and 500 m-750 m cover much area. 25% of the area is in group 408 m-500 m, 44% in 500 m-750 m, 16% in 750 m-1000 m, and 10% in 1000 m-1250 m and 5% in 1250 m>  (shows in Table 3.1).

Table 3.1. The distribution of elevation

| **Elevation** | **Area km sq** |
|---|---|
| 408-500 | 238.4232 |
| 500-750 | 394.1126 |
| 750-1000 | 113.7811 |
| 1000-1250 | 43.284 |
| 1250-1500 | 4.4539 |
| 1500-1750 | 0.2932 |

Areas of group 408 m-500 m are in lower parts of water body in Dukan dam it is located in the middle of the study area. 500 m-750 m elevation zone corresponds to low plateaus (see Figure 3.3).

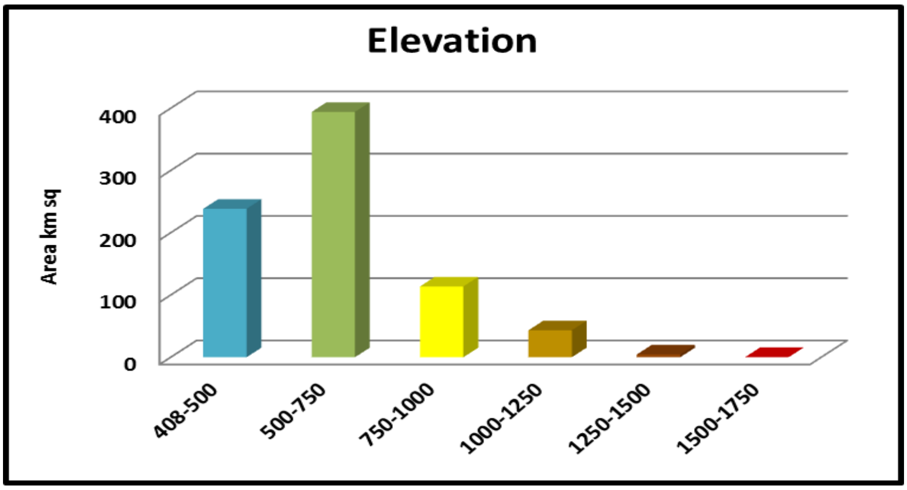


Figure 3.2. The distribution of elevation

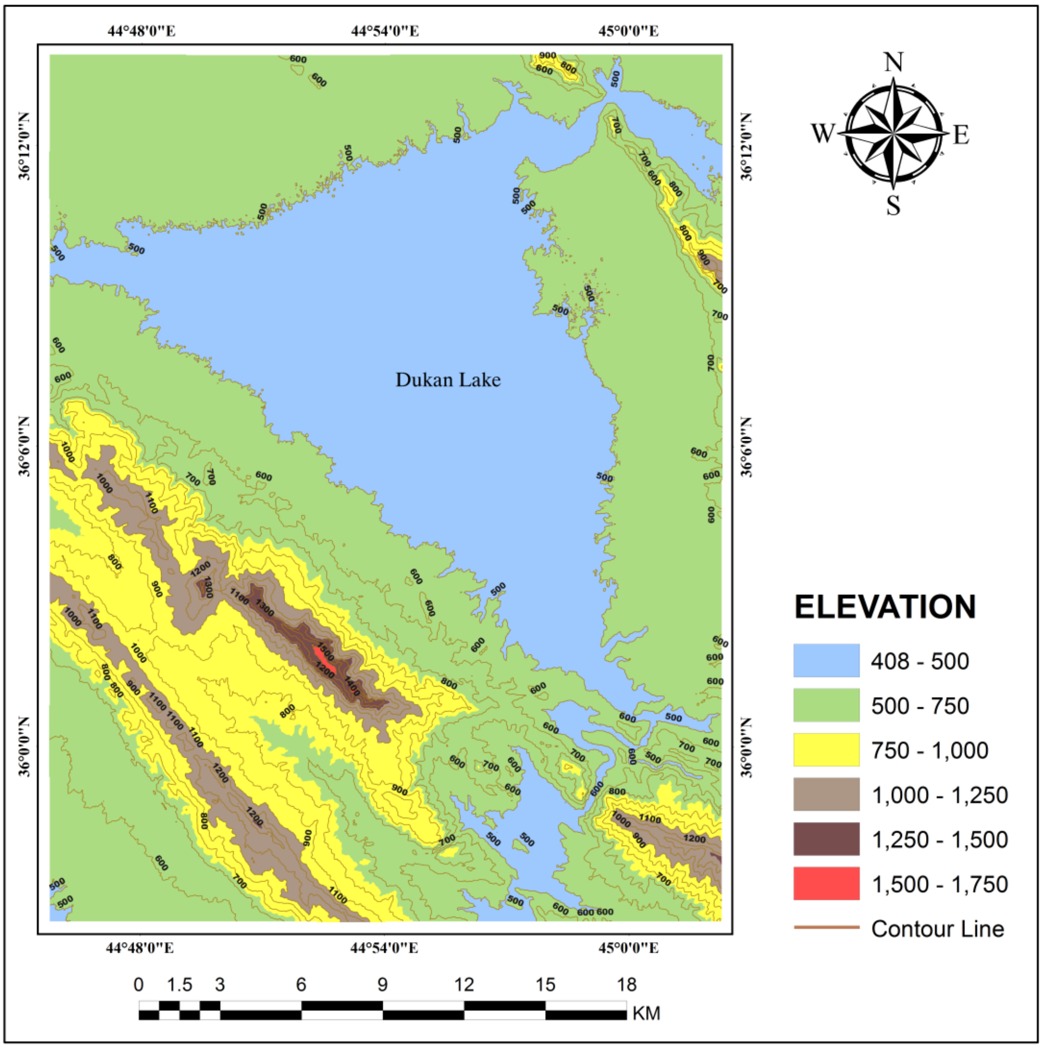


Figure 3.3. Elevation and contour lines of the study area

### 3.2.2. Slope

Slope means earth curve from equator or that curve which tied two different lines in the high zones. Sometimes they have the same level in the flat lands. Slope found out by degree, percent and relief ratio (Muhammad 2009). And in other words slope is Identifies (gradient, or rate of maximum change in z-value) from each cell of a raster surface, The rates of change of the surface in the horizontal (dz/dx) and vertical (dz/dy) directions from the center cell determine the slope (Avci 2017). Slope in any area has its significance because it influences on geomorphology and river valleys shapes with a great relation to the erosion matters. Also has its impact on human beings life, earth shape, and roads and water-courses (Muhammad 2009). According to the slope map created by DEM for Dukan dam, The slope map is divided into six groups as ($0^o$- $2^o$, $2^o$-$5^o$, $5^o$-$10^o$, $10^o$-30 $^o$, $30^o$- 45 $^o$ and $45^o$ >). $0^o$- $2^o$ and $2^o$-$5^o$ groups cover large areas (see Table 3.2. and Figure 3.5).

Table 3.2. The degree of slope area by km square

| Value | Area km sq |
|---|---|
| 0 - 2 | 491.3234 |
| 2-5 | 156.2786 |
| 5-10 | 88.5111 |
| 10-30 | 44.1097 |
| 30-45 | 12.7584 |
| 45 > | 1.4036 |

Slope have occurred in the areas with low slope, in sections the steppe area located in north and east of Dukan lake it is famous by Bitwen steppe and east of the lake of Dukan. on the other hand, in the west of this area, slope have occurred due to the increase of slope values because it is a mountain area. The roads connecting the district center to the villages are passed through mountain areas. Landslides on the valley hillsides create a risk for the highway can be seen (Figure 3.5).

It demonstrates earth ratio slope that helps different activities like constructing airport that needs 1% slope. Railroad that needs 2%, 8% slope is a good one to accommodation. The agricultural materials need 15%. If a slope equals to 30% so it equals to 16.7 degrees or 300 m/s. If the slope ratio equals to 50% so it is 26.6 degrees that equals to 500 m/s (Amin 2014) (look Table 2.3).

Table 3.3. Classification of slope

| **Slope type** | **Slope Degree** |
|---|---|
| Erosion cliff | More than > 45 |
| very steep | 30-40 |
| Steep | 30-18 |
| moderatly steep | 10-5 |
| Moderate | 2-5 |
| Level | Less than 2 |

We can measure slope by two different ways: First is one which is common to the researchers of geomorphology; it is a grading ones. Second, it is a successful way to the engineers of roads, bridges, and irrigation. It measures through angels or high alternatives around 100 m in length (Ali 2013). It illustrated in (Figure 3.5). That the study area has mountain and plain topography. The slope is different form one place to another. ArcGIS10.3 is a proper program for this work in both of the ways, ratio and grading. It proves the topography of the area. As it can be seen in the map, that the accommodation area located in the flat and low zones.

The relation between landslides and slope groups in the study area was determined using zonal statistics. Accordingly, most of the occurred landslides are observed in group 10-30. This is due to the fact that other conditions (lithology, underground water) in this slope group are suitable for landslide occurrence (Figure 3.5).

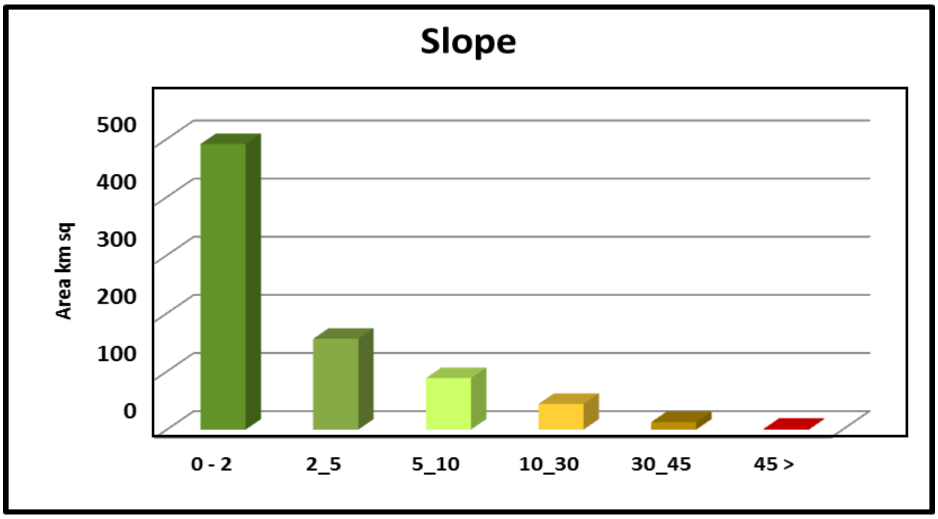


Figure 3.4. Slope distribution of  slope groups

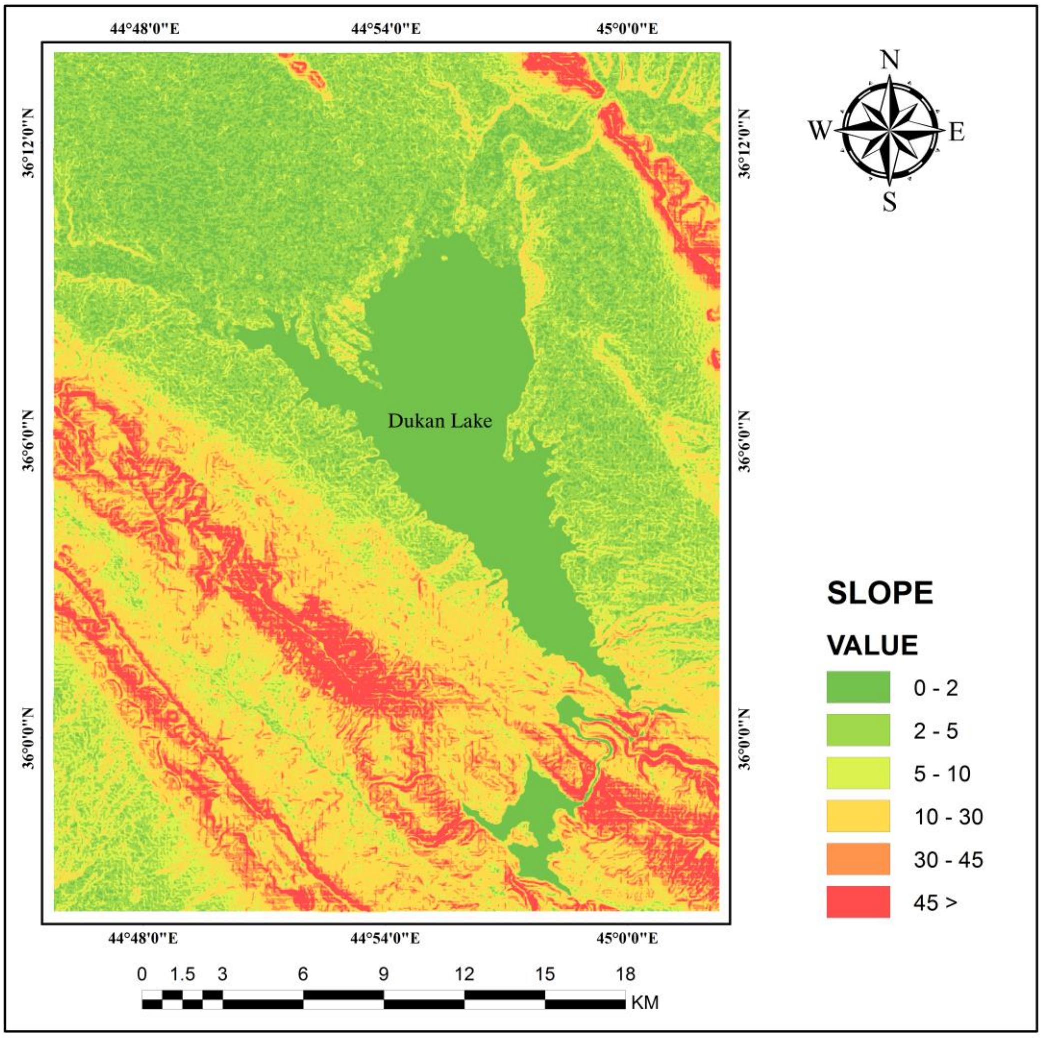


Figure 3.5. Slope map of the study area (was derived from a 30m) resolution DEM using ArcGIS 10.3)

### 3.2.3. Aspect

When earth gets a slope the sides may also get a distinction geographical directions (north, northeast, and etc.) as a result aspect means the most sloppy areas that leaning toward a direction whether it is north or northeast or others. This phenomenon measured by time's arrow direction; it gets it starts from north with (0) degree till it ends with a complete circle which is 360 degrees. In this zone number -1 means a flat land and then sloppy areas have important roles in the irrigation projects, dams, and pointing out the best zones of residency. It is as important as in geomorphology (Qadir 2013). If we closely look at (Figure 3.7) we can perceive that those parts that located in the center of the study area that is water area in Dukan dam got -1 degree. In the contrary, 337.5-360 these degrees located in the west and southwest (see Figure 3.7).

Table3.4. The distribution of aspect groups

| **Directions** | **Area km sq** |
|---|---|
| Flat | 93.3403 |
| North | 51.6229 |
| Northeast | 95.7387 |
| East | 82.6678 |
| Southeast | 72.4031 |
| South | 91.5218 |
| Southwest | 111.7363 |
| West | 91.8461 |
| Northwest | 69.7089 |
| North | 33.7598 |

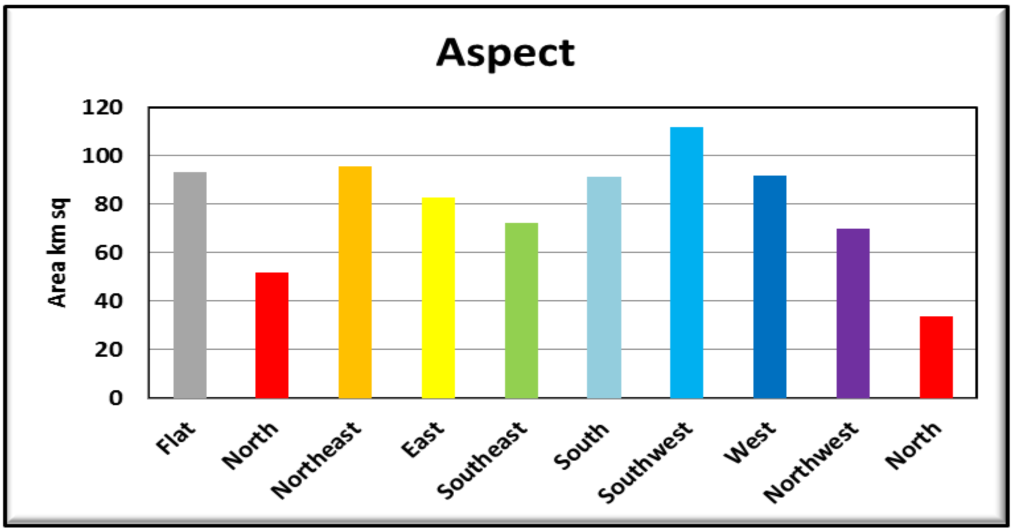


Figure 3.6. The distribution of aspect

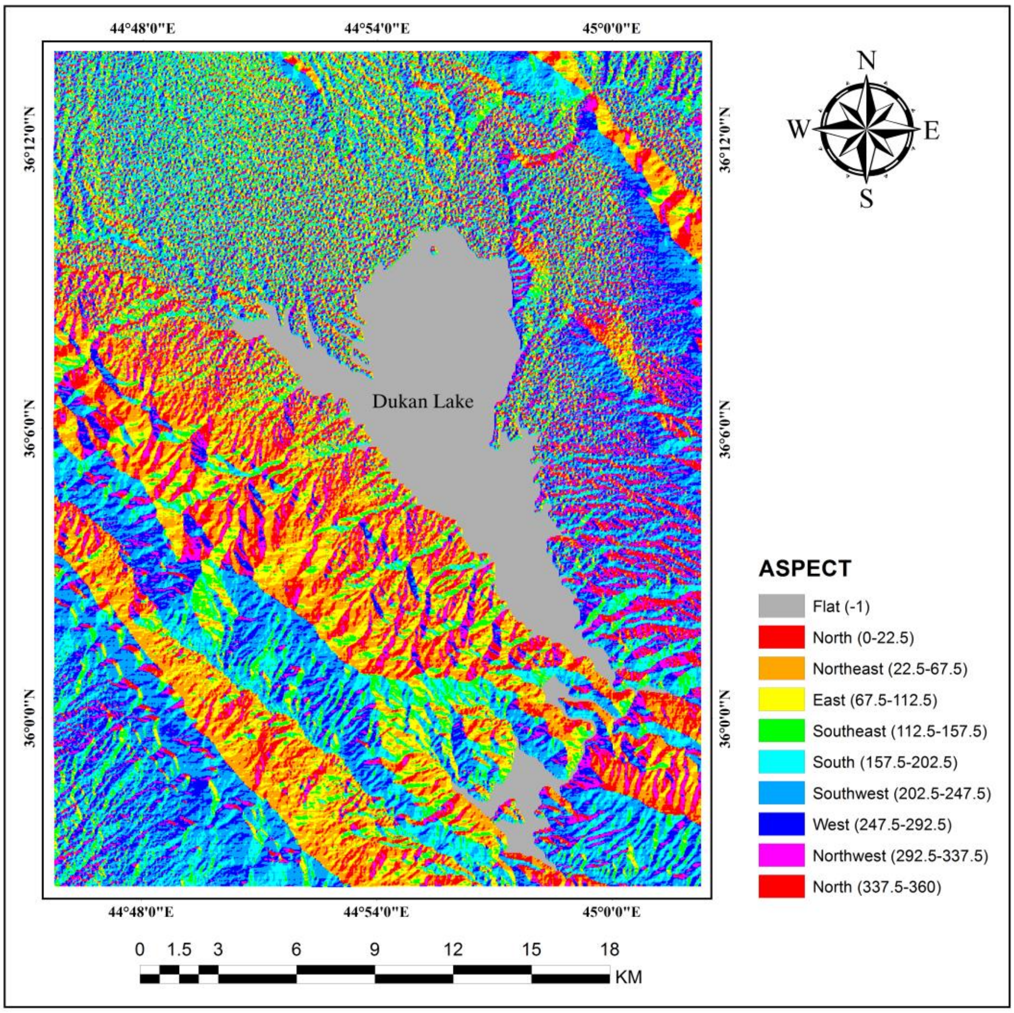


Figure 3.7. The distribution of aspect

### 3.2.4. Hillshade

This feature has its influence on earth by having values or ray amount for each cell in (Raster) cells. In other words we can say it is sunlight on earth depending on the angles that hit the ground. The process of shading explains by putting down a ray on it or any other light resources on the Raster cells. The colors grading is found by (ArcGIS 10.3) program (Abdi 2015). Light means the ray of sun and its angles between 0-180 degrees which starts from sunrise to sunset. For the sake of having a good result we will measure through time's arrow direction.

The means of this process are measuring any cells from cell formations that each of them shows a various zone. and highlighting these cells that involve another cell's shade. It is already useful for finding good resorts. Therefore one can find out the artificial places which needs sunlight throughout the day (Muhammmad 2015).

For the sake of getting Hillshade of Dukam dam study area through DEM (30 mt) file we got benefit from (Arc GIS) program. To recognize this features from various geographical zones. As it was illustrated in (Figure 3.8) Dukan dam enriches with sunlight with having distinguishes in the parts of the area.

There is an influence on sunlight in the northeast, south, southeast and southwest, because of having enough amounts of high places. Therefore we can use the northeast, south and southwest to those things that need a little lesser of sunlight with opposite of the north and east (look Figure 3.8).

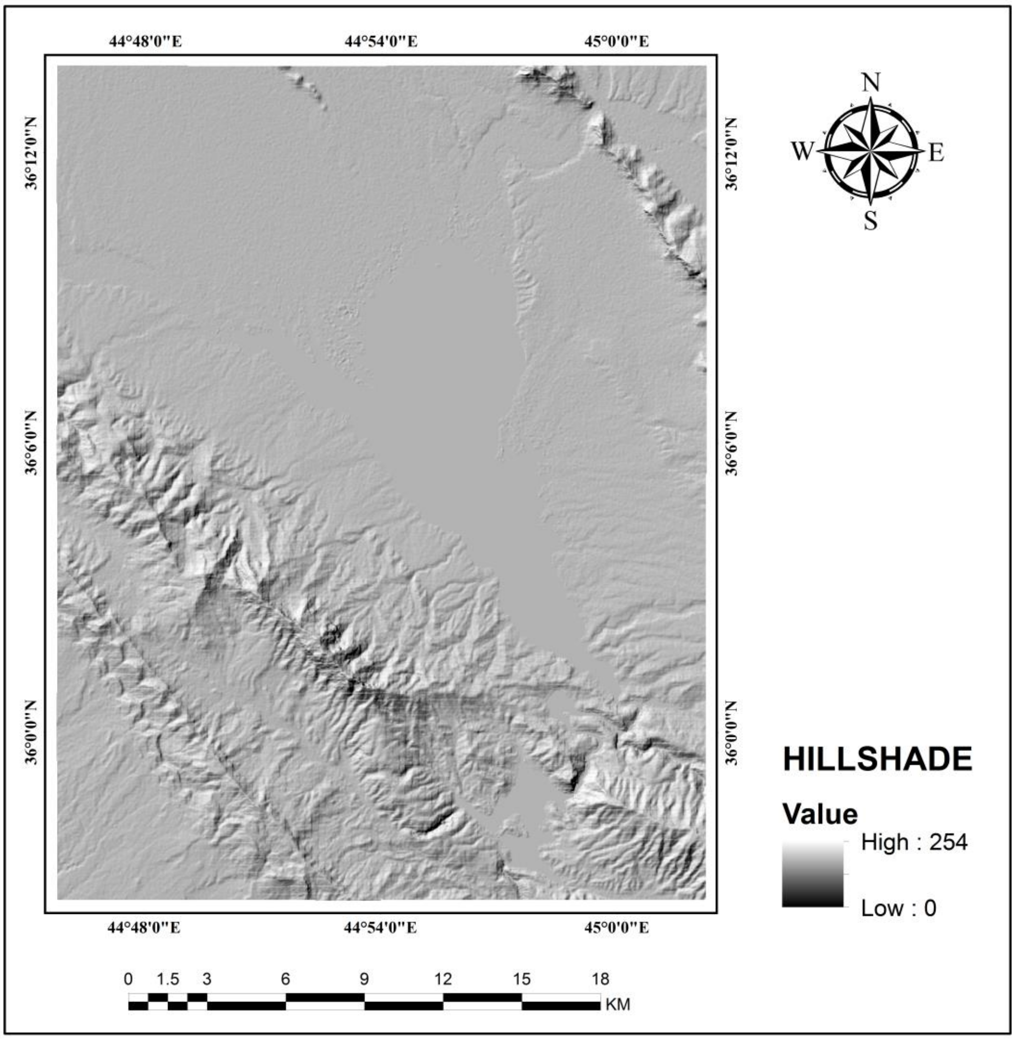


Figure 3.8. Hillshade map

## 3.3. Method

### 3.3.1. Landsat Satellite Data

The study analyzes secondary data to identify the change detection of surface water of the study Area, Two Landsat data were obtained to be projected, The first subscene was acquired in 2000 Enhanced Thematic Mapper (ETM), and the second subscene was acquired in 2016 Landsat 8 Operational Land Imager (OLI), and images used for this study were obtained from the United States Geological Service (USGS) Earth Explorer database (http://earthexplorer.usgs.gov/) for the 10 Nov 2000 and 14 Nov 2016, with a spatial resolution 30m, Datum World Geodetic System (WGS) 1984, zone 38, for each images, and path 168, row 035 were obtained from the glovis Web site and used as a primary data. For Landsat 8 OLI All of its bands were used for this study, except for band 6 in Landsat 7 ETM (look Table 3.5).

Table 3.5. Landsat (7 and 8) ETM and OLI Data

| **Image Satellite** | **Landsat 7 ETM** | **Landsat 8 OLI** |
|---|---|---|
| Data | 10/11/2000 | 14-11-2016 |
| Time | 7:29:19 | 7:39:20 |
| Path | 168 | 168 |
| Row | 35 | 35 |
| Projection | UTM zone 38 | UTM zone 38 |
| Ellipsoid | WGS 84 | WGS 84 |

### 3.3.2. Data Processing

The softwares that were used for the study were Arcmap 10.3. and ENVI 5.3 to analyze satellite images, evaluating the results and create maps. Moreover, for the purpose of conducting statistical and regression analysis and creating charts and graphs, Microsoft word and Microsoft Excel were employed. In this study, the satellite image analysis was performed by using two approaches: First approach includes the use of supervised image classification techniques and change detection analyses to the study area of the resulting classify of land use/ land cover types for each year study and then comparing the change detection result.

Second method changes and inputs the raster files into the GIS for easy calculation and the numerical results are managed through attribute Table functions in ArcGIS software. The general workflow for analyzing the satellite images is illustrated in (Figure 3.9).

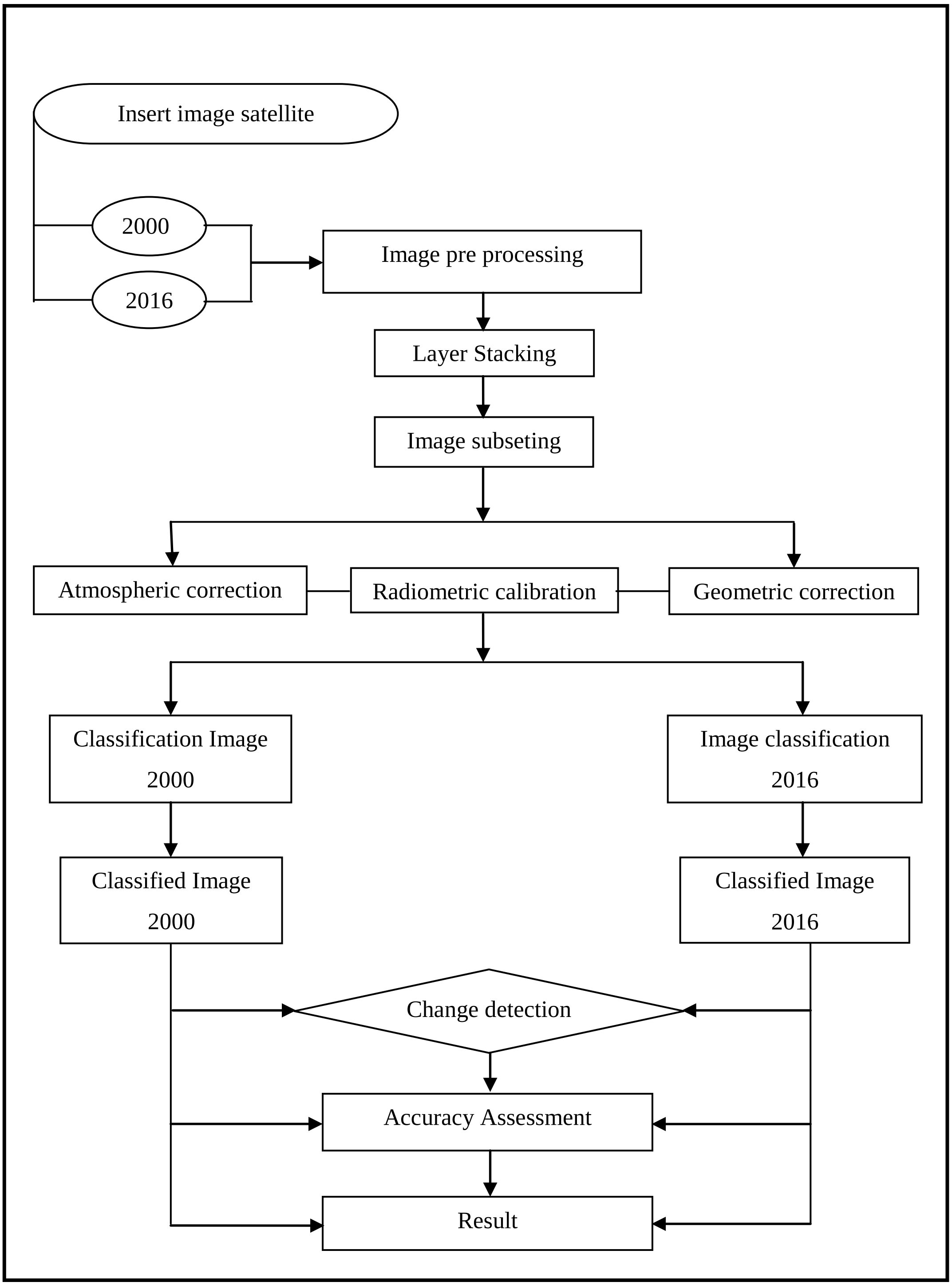


Figure 3.9. Workflow for analyzing satellite images

In the pre-processing statement, four steps were employed before classification was done on the images, which can be inferred from the workflow diagram above, such as, layer stacking, Image subseting, image correction and image enhancement.

The Layer stacking step includes creating the color images, as stated by (Horning 2009), every band has distinct wavelengths and they are similar to black and white digital photograph in a separate image. The bands from different wavelengths should be combined together for producing the colour image (Figure 3.10). The standard False Colour Composite (FCC) combination was used by employing three bands, namely Band 4-Red, Band 3-Green and Band 2-Blue, In supervised classification image procedures employing Landsat ETM and OLI images, a combination of the bands is very applicable and useful (Lillesand et al. 2008; Saleh 2011).

The next step is subseting the priority area (Dukan dam study area) as a normal Landsat image, which is downloaded from the website, is normally larger in size than you are interested, you can select a portion of the larger image, In this study, the study site subset is in longitudes 35° 57′ 15″, 35° 95′ 41″ N and latitudes 44° 57′ 10″, 44° 95′ 27″ E, and the area approximately is 792 km sq (see Figure 3.11).

Image enhancement was employed in this study, as a part of the image pre-processing. (Lillesand et al. 2008), points out that: “the goal of image enhancement is to improve the visual interpretability of an image by increasing the apparent distinction between the features in the scene. Image enhancement techniques was applied to satellite image, which permitted the spectral enhancement especially for water and built up areas as they have an identical reflectance, which create extracting the land cover classes on the study site clear to categorize. In other words image enhancement can improve aid visual interpretation, visual appearance of the objects in the image, Image enhancement is the process of adjusting digital images so that the results are more suiTable for display or further image analysis, For example, you can remove noise, sharpen, or brighten an image, making it easier to identify key features (Henry 1991), (See Figure 3.12).

The following pre-processing three steps were performed to arrange the input satellite images for LULC classification and change detection they are: atmospheric correction, radiometric calibration and geometric correction which are done by ENVI 5.3 Program and they were managed by Schroeder et al. (2006).

If we mention the steps in detail, we should explain them in the way that atmospheric correction which is the process of removing the effects of the atmosphere on the reflectance values of images taken by satellite or airborne sensors (Pacific 2014).

The second preprocessing step that needs to be performed when utilizing change detection is radiometric correction. Radiometric correction removes the effects of atmospheric scattering and absorption that occur as the electromagnetic signal from the sun passes through the atmosphere on its way to the target and from the target to the satellite (Du et al. 2002). Radiometric correction thus helps to ensure that results represent actual changes on the ground and are not due to differences in atmospheric conditions, or sensor calibrations (Teillet et al. 2004; Small 2002). Imagery can be radiometrically corrected to at-sensor radiance, at-sensor reflectance, or at-ground reflectance.

The final step is geometric correction, which is one of the preprocessing steps recommended before land cover classification. This ensures that geographic features in the original image are aligned according to a reference map or scene (Gao 2009). If we intend to perform change detection on multi-temporal scenes, geometric correction helps to ensure that we detect actual land cover changes and not changes due to geometric misalignment of the different images (Yang et al. 2003).

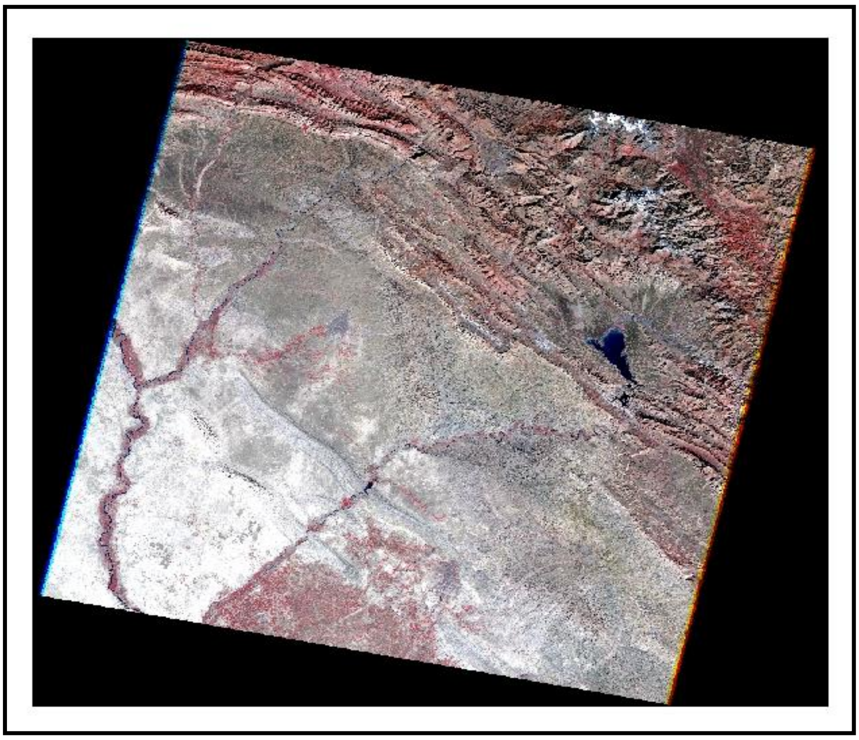

Figure 3.10. Outcome of Layer stacking for Landsat Satellite Image

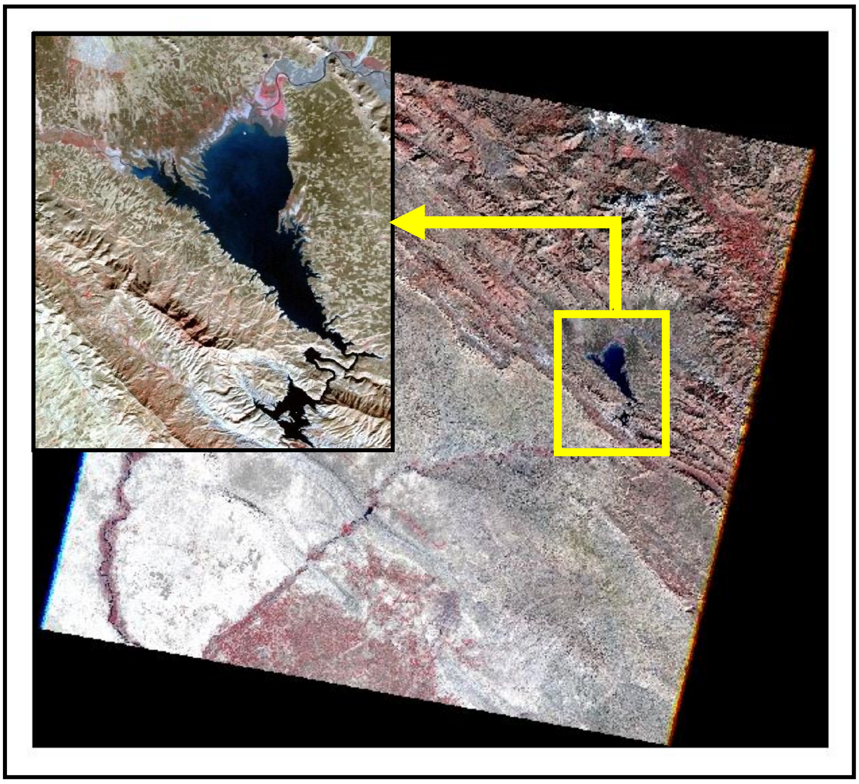

Figure 3.11. Subset Images for selecting Study area on Satellite Image

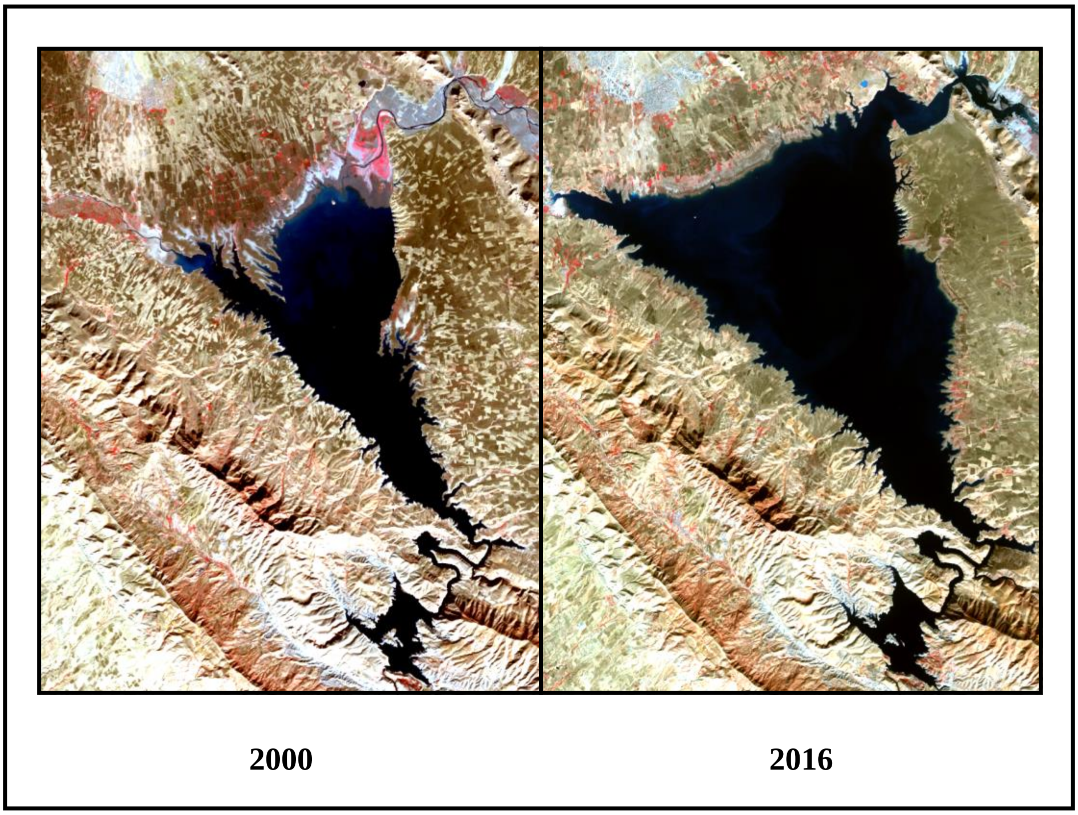


Figure 3.12. Outcome of image enhancement

The goal of this study is supposing the Land use land cover change. Accordingly, the divisions of the study area are six main land cover classes namely, water, agriculture, vegetation, built-up, barren land and road. (Table 3.6.) is a description of each class; two images of 2000 and 2016 were used In support of the goals of this study.

Table 3.6. Description of Land Cover Types

| Classes | Description |
|---|---|
| Water body | it can be fresh or salt water, it includes river, lakes, dams, reservoirs, ocean, seas and estuaries, |
| Agriculture | Cultivated cropland, lands covered with temporary followed by harvest and bare soil period, Land principally occupied by it. |
| Vegetation | It includes parks, grassland and forest. |
| Built-up | Developed areas at least have 60 meters wide, It has included all types of man-made features such as buildings, roads, industrial areas and residential areas. |
| Barren land | It has thin soil, rocks and sand with limited capability for agriculture or life. Generally, where < 10% vegetated cover is found occurring in this area, it will be more widely spaced apart as shrubs or grasses for pastures (Anderson et al, 1976). |
| Road | Roads are vital to the sociological as well as economic development of any area. |

The selection of the land cover types above were influenced by the aims of this study: This is to clarify the land use land cover changes.

## 3.4. Image Classification Techniques

In various remote sensing applications image classification is the most extensively used technique for extraction of target thematic information; the LULC is the main ‘theme’, which is to be extracted by using an applicable classification method for LULC change detection. Essentially, image classification is a mapping process to generalize the image pixels into essential groups each resembling contrasting land cover classes (Jensen 1995; Mather 2004). In this type of study, one of the main steps is classifying the satellite images to extract the LULC subject. The process of assigning classes to the pixels in images is classification method. Furthermore, Strong utilization of remote sensing data for LULC requires accurate selection of the applicable data development and image processing techniques, Digital image classification is the most common image analysis for extracting LULC (Lunetta 1998).

This explains that image classification techniques are most commonly applied to the varying spectral data of a series of multi-date images or to the spectral data of a single-date image. The complication of image classification techniques can range from the use of a simple threshold value for one spectral band to complicated statistically based decision rules that operate on multivariate data. The goal of image classification is to label the pixels in the image with the real information (Jensen and Gorte 2001).

The study based on results from the applying of classification methods. After becoming remote sensing images rating on the subject of the majority of research techniques as summary, efficient and credible way for getting information on land surface features when applied to a variety of fields (Lu and Weng 2006). For the performance of the investigation the land value of the data and extract, images can also be classified. In other words to represent earth surface features in digital forms classification is done in remote sensing (Rashed and Jurgens 2010). Label images appoint pixel images to pre-defined categories of land cover. Using the classification of the image to extract information is a complicated procedure; therefore agents are taken into account when implementing this process contain the level of image resolution, software/algorithm selection, classification technique selection, appropriate number of 50 training samples, and knowledge possessed by the analyst. Digital image classification is common for the analysis of remote sensing (Matinfar 2007). Sorting the pixels in the images is carried out for obtaining meaningful information of reality and using this information for creating thematic maps to represent the various land cover classes. Remote sensing contains different image classification techniques and their suitability depends on the type and purpose of the land cover map used in a study (Lu and Weng 2006), Pointed out that efficiently employing multi-source remote sensing data and the select suitable classification is helpful in the decrease the errors in classification and improving the accuracy of classification.

Image classification at pixel level is perhaps supervised or unsupervised (Levin 1999; Adam 2010).

Supervised classification was employed for classifying images to attain the objectives of this study. Commonly, researchers choose supervised classification because it provides a more accurate definition of classes and better classification accuracy than unsupervised classification. Supervised image classification is the most widely used approach of classification which classifies according to the spatial arrangement of the characteristics of the edge of the local neighborhood (IM et al. 2008; Lu and Weng 2007). Supervised classifiers are also easy to use and can give accurate thematic maps; however, they dependent on the quantity and quality of the training data for every predefined land cover class (Foody and Mathur 2004; Barandela and Juarez 2002).

This is an approach, which also uses training site statistics to assign a LULC value to every pixel in the image. The choice of a particular classifier depends on the nature of the input imagery and the required output. As well as, ground knowledge of the field can assist in obtaining enhanced classification. Three steps must be passed before applying supervised classification including training data, picking the applicable classifier type and accuracy assessment (Barandela and Juarez 2002; Foody and Mathur 2002).

The maximum likelihood technique (MLC) is one of the most commonly methods classification technique that were used for classified images in remote sensing (Huang et al 2002). In addition, it assigns classes based on the probability that a pixel belongs to a certain class (Brown et al. 1999). According to a predefined set of spectral responses obtained from training data. MLC’s limitations are that it is sensitive to correlation between bands and it assumes that scene data are normally distributed. The assumption made in maximum likelihood classification, is that each spectral class can be described by a multivariate normal distribution. This technique leverages on the mean vectors and the multivariate spreads of each class and spots classes that are elongated. Nonetheless, reasonably accurate computation of the mean vector 24 and the covariance matrix for each spectral class is required to make the maximum likelihood classification effective (Huang et al. 2008).

### 3.5. Change Detection Analysis:

Change detection is the most important tool in remote sensing and it is defined as a "process of identifying differences in the state of an object or phenomenon by observing it in different times" (Singh 1989b). With increasingly intensifying social and economic development, the local ecological environment has changed dramatically. Change detection is an essential process in monitoring and managing natural resources and assessing Environmental impact because it provides quantitative analysis of the spatial distribution of changes (Macleod and Congation 1998). Detecting and analyzing LULCC over large geographic areas as well as over regional areas have been highlighted both in a manner of discrete long-time span and in sequential time series with high temporal resolution remote sensing satellites through 'change detection' (Coppin and Bauer 1996). This is considered an important process in monitoring LULCC because it provides quantitative analysis of the spatial distribution of the population of interest and this makes LULC study a topic of interest in remote sensing applications (Song et al. 2001; Gallego 2004).

Remote sensing is a powerful tools to derive accurate and timely information on the spatial distribution of land use/land cover changes over large areas, Past and present studies conducted by organizations and institutions around the world, mostly, has focused on the application of LULC changes. Remote sensing provides a flexible environment for analyzing, storing, collecting, and displaying digital data necessary for change detection (Wu et al. 2006).

Since launching, the first of the Landsat satellite system in 1972, a broad range of data have been added (Williams et al. 2006). The availability of a large archive of data leads to the development and evaluation of many digital change detection techniques and methods for analyzing and detecting LULC changes (Dewidar 2004). Various methods have been extensively reviewed and provided with excellent descriptions and comprehensive summaries (Xiubin 1996; Lu et al. 2004).

There are two basic ways of change detection: first by direct overlapping of classified vector classes from both images and then visually analyzing the changes and second by direct change detection of one image made of combined images from different epochs (Jovanović et al. 2007; Jovanović et al. 2011). There is also a different classification given by Shaoqing. Methods of change detection can be classified into three categories: characteristic analysis of spectral category, vector analysis of spectral changes and time series analysis (Shaoqing and Lu 2008). Characteristic analysis of spectral type is change detection based on spectral classification and calculations. The vector analysis is done by using strength and direction characteristics, and time series analysis is used to analyze process and trend of changes of monitored ground objects, based on continuously remotely sensed data.

For all cases. RS technology has been developed dramatically within some years ago, examples of effective LULC change detection studies continue approximately rare (Loveland et al. 2002; Roga et al. 2004).

Numerous researchers have addressed the problem of accurately monitoring LULC change in wide applications with greater success (Muchoney and Haack 1994; Chan et al. 2001). One of the most definite reasons is that a wide variety of digital change detection techniques and algorithm have been developed and manipulated over last few decades commensurate with the fast-pace advancement of RS technology with spatial, spectral, thematic and temporal properties (Singh 1989).

Utilizing remotely sensed data to detect LULC changes, six main steps are important (look Figure 3.13).

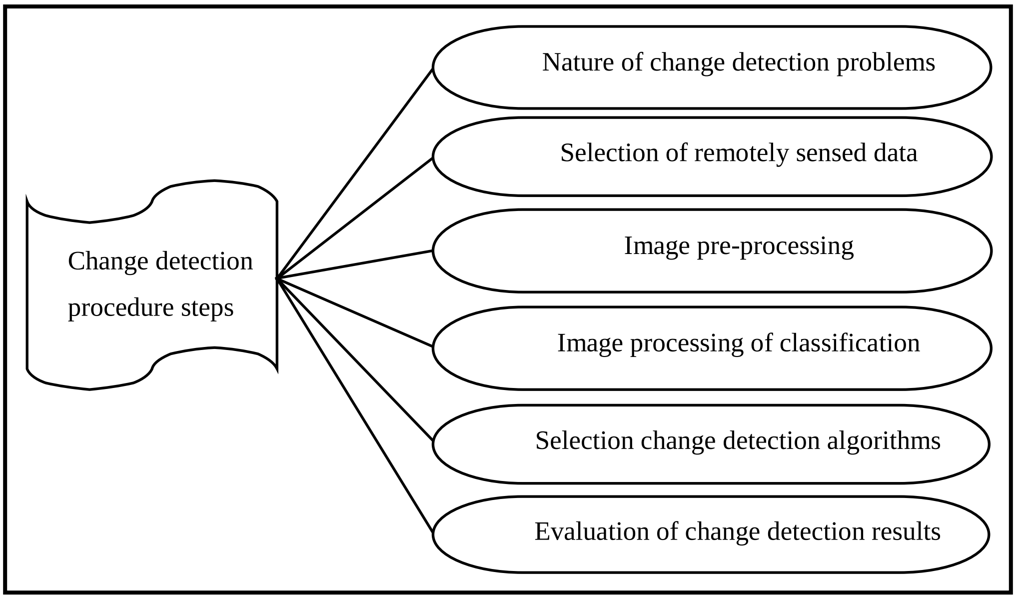


Figure 3.13. main steps of change detection

There are two categories of change detection methods: pre-classification and post-classification change detection approaches (Lu et al. 2004).

### 3.5.1. Pre-Classification Techniques

The pre-classification techniques, also known as binary change or non-change information detecting techniques, include various techniques that directly use the multiple dates of satellite imagery to generate ‘‘change’’ vs. ‘‘no- change’’ maps, Most of the pre classification techniques are identified as the most accurate change detection techniques tha is because, they are effective and straight forward for analyzing and locating change and are easy to implement (Sunar 1998). However, three aspects are critical for pre-classification techniques: selecting suiTable thresholds or vegetation index to identify the changed areas, being sensitive to miss-registration of pixels and they cannot provide details of the nature of change or provide a matrix of change information (Lu et al. 2004).

Many pre-classification techniques have been used and compared to assess and identify LULCC changes such as, Image Differencing (ID) (Hayes and Sader 2001), Improved Change-Vector Analysis (Green et al. 1994), Band Image Differencing (Chavez and MacKinnon 1994) RGB-NDVI Change Detection Method (Wen and Yang 2009; Geun-Won et al. 2003; Johnson and Kasischke 1998). Spectral Change Vector Analysis (Wen and Yang 2009), Principal Component Differencing (PCD), Change Vector Analysis (CVA) (Chen et al. 2003) and others.

The basic premise in these techniques is measuring the nature of changes, which means changes in the features of interest that will result changes in radiance or reflectance utilities (Lu et al. 2004).

### 3.5.2. Post-Classification Comparison Technique

The post-classification comparison is proven the most popular approach in change detection analysis (Foody 2002b). This approach relies on rectification of more than one classified image; where it includes the classification of each of the images separately, then the thematic maps are obtained, followed by a comparison of the corresponding labels or themes to identify areas where change has appeared (see Figure 3.14). Post classification minimizes sensor, atmospheric, and environmental diversities because data from two dates are separately classified, thereby minimizing the complication of normalizing for atmospheric and sensor diversities between two dates and it provides a complete matrix of land cover change when using multiple images, these are the advantages of this technique (Lu et al. 2004; Naumann, Siegmund 2004; Teng et al. 2008).

A series of “from-to” matrixes can be built by comparing on a pixel-by-pixel basis, and these matrices include pixel conversion matrix, percentages transformation matrix, and area transformation matrix. Nothertheless, results derived from this method are only as accurate as the individual classification images themselves (Civco et al. 2002). In addition, this method can lead to wrong results particularly when utilizing multi-date or multi-sensor images because of the differences in the radiometric characteristics of the images from which thematic maps were obtained (Foody 2002a; Foody 2002b).

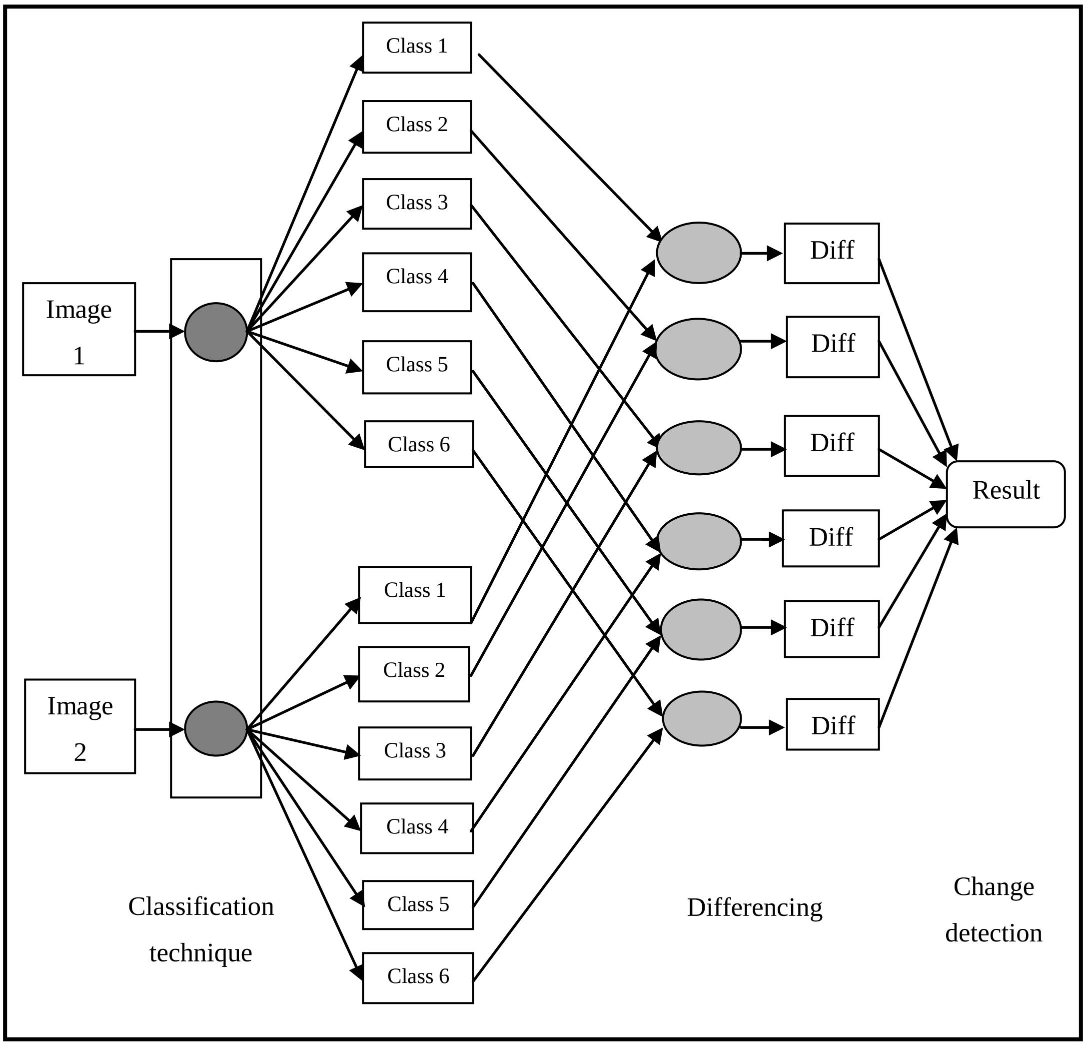


Figure 3.14. Diagram of Post-classification Comparison Change Detection

The post-classification comparison approach employed by many researchers such as (Diallo et al. 2009; Bayarsaikhan et al. 2009; Shalaby et al. 2007; Muttitanon, Tripathi 2005; Torahi et al. 2011), Post classification change detection techniques rely on Maximum Likelihood Supervised Classification to detect land use/land cover change detection and concluded that it has achieved high overall accuracy for a variety of data (Dewidar 2004). Applied Maximum Likelihood Supervised Classification and Post-classification Change Detection Techniques to Landsat images for mapping and monitoring land cover and land use changes in the North-western coastal zone of Egypt (Sun et al. 2009), employed the post-classification comparison approach method base on maximum likelihood algorithm to show land use changes in Datong basin, China using multi-temporal Landsat data. Likewise (Fan et al. 2007). Maximum Likelihood (ML) procedure and combined post-classification images of Landsat TM and ETM+ classification and socioeconomic data used in an effective way to research land use land cover change dynamically. Recently, post-classification has been used in divers' areas around the world based on the use of the new classification algorithms for different purposes in order to quantify land cover change, improve spectral classification, decrease the classification false propagation, improve the land use, and land cover change classification accuracy.

### 3.6. Accuracy Assessment

Land cover accuracy is commonly defined as the degree to which the derived classification agrees with reality and the accuracy of the map in a larger part determines the usefulness of the map. Accuracy assessment was critical for a map generated from any remote sensing data (Ashenafi 2008). Accuracy assessment is an essential and most crucial part of studying image classification and thus LULC change detection in order to understand and estimate the changes accurately. It is important to be able to derive accuracy for individual classification if the resulting data is to be useful in change detection analysis (Owojori and Xie 2005). In addition, accuracy assessment plays an important role in remote sensing image classification. It is important to know the quality of the classification maps before we conduct further analysis (Jiang and Liu 2011).

Many methods of accuracy assessment have been discussed in the remote sensing literature (Kalkhan et al. 1995; Koukoulas and Blackburn 2001) The most widely promoted and used, however, may be derived from a confusion or error matrix. The related assessment elements include producer accuracy, overall accuracy, kappa coefficient, and user accuracy. Previous studies provided the meanings and methods of calculation for these statistical elements for judging the accuracy (Congalton 1991; Congalton and Green 1999; Foody 2002).

Confusion matrix method is the most commonly used technique for accuracy assessment of classified maps; land cover on the map should be compared to actual land cover on the ground. It can be further used for change detection accuracy assessment. The elements of change detection confusion matrix also used for showing individual from/to class change

(Foody 2002; Congalton et al. 1999; Khorram 1999). The confusion matrix gives a measure of the overall accuracy, (i.e; total number of correctly classified samples), producer's accuracy (i.e., measure of omission; probability that a ground reference test sample is classified correctly in the map), and user's accuracy (i.e., measure of commission; probability that a sample from a map actually represents that category on the ground; It also provides a Kappa coefficient of agreement (Congalton 1991), which accounts for chance agreement in the overall accuracy value, even though (Pontius et al.2011), have recently shown its limitations.

Overall accuracy, also called overall agreement, raw accuracy, or proportion of pixels correctly classified, is the proportion of pixels whose class labels agree with the ground reference. It is suggested that overall accuracy includes chance agreement indicated by the row and column totals in the error matrix and the expected chance highly depends on the number of classes in the image classification (Jiang and Liu 2011), Therefore, it is declared that overall accuracies from different image classifications are not suitable for comparison when the number of classes is different.

**Use Of The Confusion Matrix**

The confusion matrix has been used mainly to provide a basic description of thematic map accuracy and for the comparison of accuracies. However, it may be possible to use the information contained in the matrix to derive considerably more useful information. As noted above, the confusion matrix may be useful in refining estimates of the areal extent of classes in the region. however, be used to further enhance the value of the classification for the user. In particular, it may be possible to use the matrix to help optimize the thematic map for a particular user (Lark 1995; Morisette and Khorram 2000). Thus, the matrix may be usefully employed with information on the actual costs of errors or the value of the map to optimize a classification for a particular application (Smits et al. 1999; Stehman 1999). Smits et al. (1999), for example, illustrate how a confusion matrix may be used together with information on the economic cost of misclassification to refine a thematic mapping investigation. In particular, it is shown that the results of such an analysis may be used to refocus the investigation or question the appropriateness of the data sets or methods used in deriving the classification. The utility of such methods, however, clearly depends on the reliability of the confusion matrix. Forming a reliable confusion matrix, in which one can be confident that issues discussed above (e.g., sample design, ground data accuracy, registration of the data sets etc.) have not had a detrimental effect is, however, difficult (Smits et al. 1999).

**Accuracy Of Land Cover Change Products**

There is considerable interest in the use of remote sensing to study thematic change, such as land cover dynamics. This arises particularly through the importance of land cover change within the broader arena of environmental change (Skole 1994) as well as the need to inform environmental policy and management decisions (Biging et al. 1999). Many methods of change detection have been used to study land cover change (Lambin and Ehrlich 1997), but by far, the most popular has been the use of post classification comparison methods. A variety of factors influence the accuracy of land cover change products. With the popular post classification comparison methods basic issues are the accuracies of the component classifications as well as more subtle issues associated with the sensors and data preprocessing methods used together with the prevailing conditions at the times of image acquisition (e.g., atmospheric properties, viewing geometry, etc.) (Khorram 1999). In mapping land cover change, the problems noted above in relation to the registration of data sets and boundaries are generally magnified (Khorram 1999; Roy 2000). Error in the individual classifications may also be confused with change This can be difficult to allow for or study particularly as the location of boundaries between classes at each individual time period may be uncertain (Khorram 1999). and there may be no information on the spatial distribution of accuracy for the classifications used. Consequently, any differences observed over time may not be attributable solely, if at all, to real change on the ground. As a consequence of these and other issues, the estimation of the accuracy of a change product is a substantially more difficult and challenging task than the assessment of the accuracy of a single image classification (Congalton and Green 1999). With no standard approach to the assessment of the accuracy of a change product, it has been popular to adapt the standard confusion matrix to yield a change detection confusion matrix. The elements of this change detection confusion matrix represent individual from/to class change scenarios (Congalton and Green 1999; Khorram 1999). As a result, the dimensions of the matrix are much larger than the basic confusion matrix used to assess the accuracy of the single date classifications depicting the land cover classes of interest; each dimension of the change detection confusion matrix is the square of the number of classes involved. If desired, however, the matrix can be compressed into a 2-2 matrix illustrating simple change or no-change situations (Morisette and Khorram 2000). From each type of matrix, some of the basic measures of accuracy discussed above can be derived to express the accuracy of the change detection (Biging et al. 1999). Obtaining the sample of data to use in the construction of the change detection confusion matrix can, however, be difficult. Often, for example, some of the change scenarios are rare, complicating the sampling process (Biging et al. 1999). Perhaps a more significant problem, however, is that these approaches are appropriate only for use with conventional hard classifications. This, however, limits the change detection to indicating where a conversion of land cover appears to have occurred. Although land cover conversions are important, they are only one component of land cover change. Subtle transformations, land cover modifications, in which the land cover type may have been altered but not changed (e.g. a grassland degraded, a forest thinned), will be inappropriately represented by conventional post classification comparison methods of change detection. This is unfortunate as land cover modifications may be as significant environmentally as land cover conversions (Lambin 1997). In general, the use of hard classifications within a post classification comparison- based approach would be expected to underestimate the area of land undergoing a change and, where a change is detected, overestimate the magnitude of change as it is a simple binary technique (Foody 2001a). This is a major limitation in environmental studies where the magnitude of change is often important. The ability to monitor land cover modifications associated with land degradation or rehabilitation would, for example, help inform environmental policy and decision making that underpin sustainable resource use (Foody 2001b).

The aim of accuracy assessment is to complete the classification process. It can discover the value of the outcome data and it is essential for processing and analyzing remote sensing data (Hashemian and Fatemi 2004). A variation of methods have been developed for assessing the accuracy of the land cover maps that is extracted from satellite data, for it becomes an essential subject in the remote sensing area (Congalton 1991; Latifovic et al. 2004).

Furthermore, the change map of two multi-date classifications of LULC often reveals accuracies similar to the product of multiplying the accuracies of each individual classification (Stow et al. 1980; Mas 1999). Error in the individual classifications may also be confused with change detection (Khorram 1999), which must lead to misinterpret about the actual change in reality. Sometimes it is quite impossible to get ground truth or referenced data for assessing accuracy for the classified result from the historical image data. Because of these and other issues, the estimation of the accuracy of a change product is a substantially more difficult and challenging task when compare to the assessment of the accuracy of a single image classification (Congalton and Green 1999). Therefore accuracy assessment matrix was employed to evaluate the accuracy of the classification since classification is not complete until its accuracy is assessed which also determines the quality of the map extracted from remotely sensed data.

The previous descriptions and examples was a general way to talk about accuracy assessment, In this study the post-classification method is used for accuracy assessment and in post classification there is confusion matrix which is confusion matrix method is the most common way to present the accuracy assessment of the classification results Overall accuracy, user's accuracy and producer's accuracies, and the Kappa statistic were then derived from the confusion matrices. In addition, in Confusion matrix there are Using ground truth image and using ground truth ROIs that are used for obtaining by ENVI 5.3. for accuracy assessment.

# 4. RESULT AND DISCUSSION

## 4.1. Result of Classification Images

In order to classify land cover classes and detect any change among the different land cover classes between 2000 and 2016, maximum likelihood of supervised classification was utilized based on Landsat 7 ETM and 8 OLI, The results of the classification of the images indicate that all of the classes vary between 2000 and 2016. This can be visually seen in Figure (4.4. and 4.5) which shows the main land cover types. In this Figure, Green color shows vegetation (green areas and grasses); yellow colour shows built up areas (building and other man-made features). Blue color shows water. Black colour shows Road, Brown colour shows agriculture and the white colour represents barren land (rocks, sand and soil).

The classification results findings shows that the largest area in 2000 was agricultural land that made up about 441.76 kmsq, with ratio 47.51% in 2000 decreased to 372.94 kmsq, in ratio 37.59% in 2016 because of increasing water in the study area shown in (Figure 4.1 and 4.2)

There is a significant change in the quantity of water body between 2000-2016 and indicate that there is a growing trend toward water in year 2016 at the expense of agricultural land, Vegetation land and Barren land. The quantity of water was 92.94 kmsq, with ratio 17.62% in 2000 increased to 186.42 kmsq,in ratio 30.12% in 2016, these because years around 2000 priceptations was low 380.4 mm because drought happened and water body decreased. The specific reasons of increasing water body in 2016 are the years after 2000 the rate of rainfall was high 816.8 mm (see Figure 4.10). Increasing the rate of water constantly because of feeding from other water resources and melting snow from the mountains around Dukan dam along the years after 2000. It is shown in (Table 4.1, Figure 4.4. and 4.5).

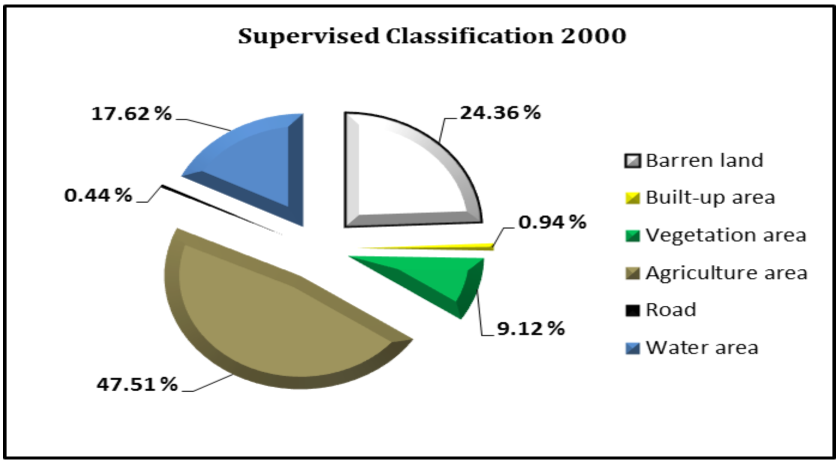


Figure 4.1. Percentages of supervised classified 2000

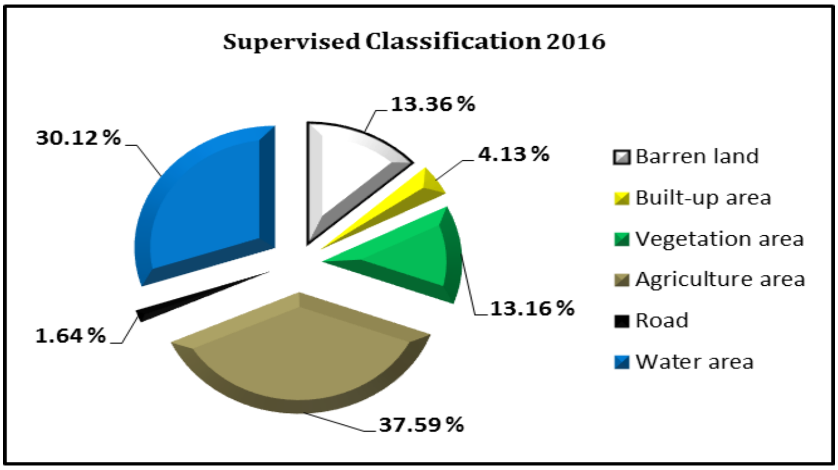


Figure 4.2. Percentages of supervised classified 2016

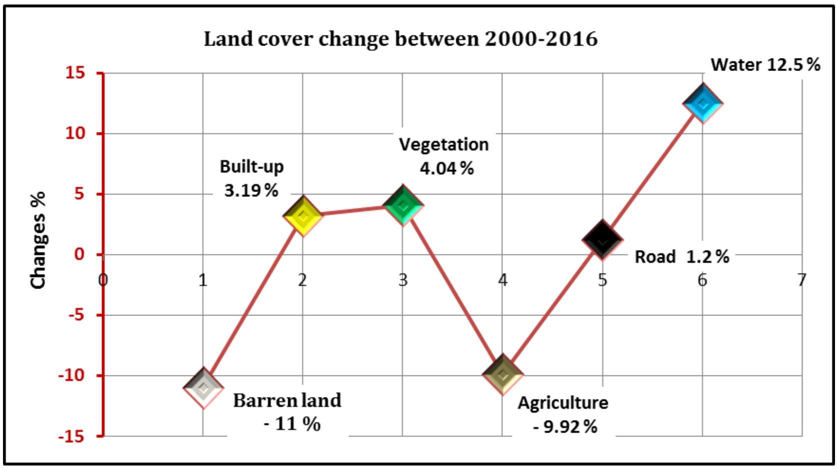


Figure 4.3. Percentages of Changes in Land Cover Classes between 2000-2016

On the other hand Built up areas are mild increased during this period because of increasing the population and people migrating from the villages to the city that was 11.22 kmsq, with ratio 0.94% in 2000 increased to 25.4 km sq, in ratio 4.13% in 2016 (see Table 4.1)

Noticeable changes occurred in vegetation in the area, with this land cover type mild increasing that was 31.54 km sq, with ratio 9.12% in 2000 increased to 85.12 km sq, in ratio 13.16% in 2016, and Barren land dominated 214.36 km sq. with ratio 24.36% in 2000 decreased to 121.59 km sq in ratio13.36% in 2016. In contrast, other land cover classes such as roads showed an increase in size that is 0.57% in 2000 and 1.75% in 2016 shown in (Figure 4.1).

A supervised classification has been done by Saied (2014) in Sulaimaniyah, Iraq, for the period 1984-2010 and they have found 85.03 km sq barren land in 1984 decreased to 70.61 km sq in 2010, and 14.2 km sq built-up area in 1984 increased to 31.28 km sq in 2010.

Table 4.1. Result of Changes in Land Cover Classes in 2000 and 2016

| **Class name** | **Area sq 2000** | **Area %** | **Area sq 2016** | **Area %** | **Changes %** | **Remark** |
|---|---|---|---|---|---|---|
| | | **2000** | | **2016** | **2000-2016** | |
| Barren land | 214.36 | 24.36 | 121.59 | 13.36 | -11 | Decrease |
| Built-up area | 11.22 | 0.94 | 25.4 | 4.13 | 3.19 | Increase |
| Vegetation area | 31.54 | 9.12 | 85.12 | 13.16 | 4.04 | Increase |
| Agriculture area | 441.76 | 47.51 | 372.94 | 37.59 | -9.92 | Decrease |
| Road | 0.64 | 0.44 | 0.95 | 1.64 | 1.2 | Increase |
| Water area | 92.94 | 17.62 | 186.42 | 30.12 | 12.5 | Increase |
| Total | 792.46 | 100 | 792.46 | 100 | | |

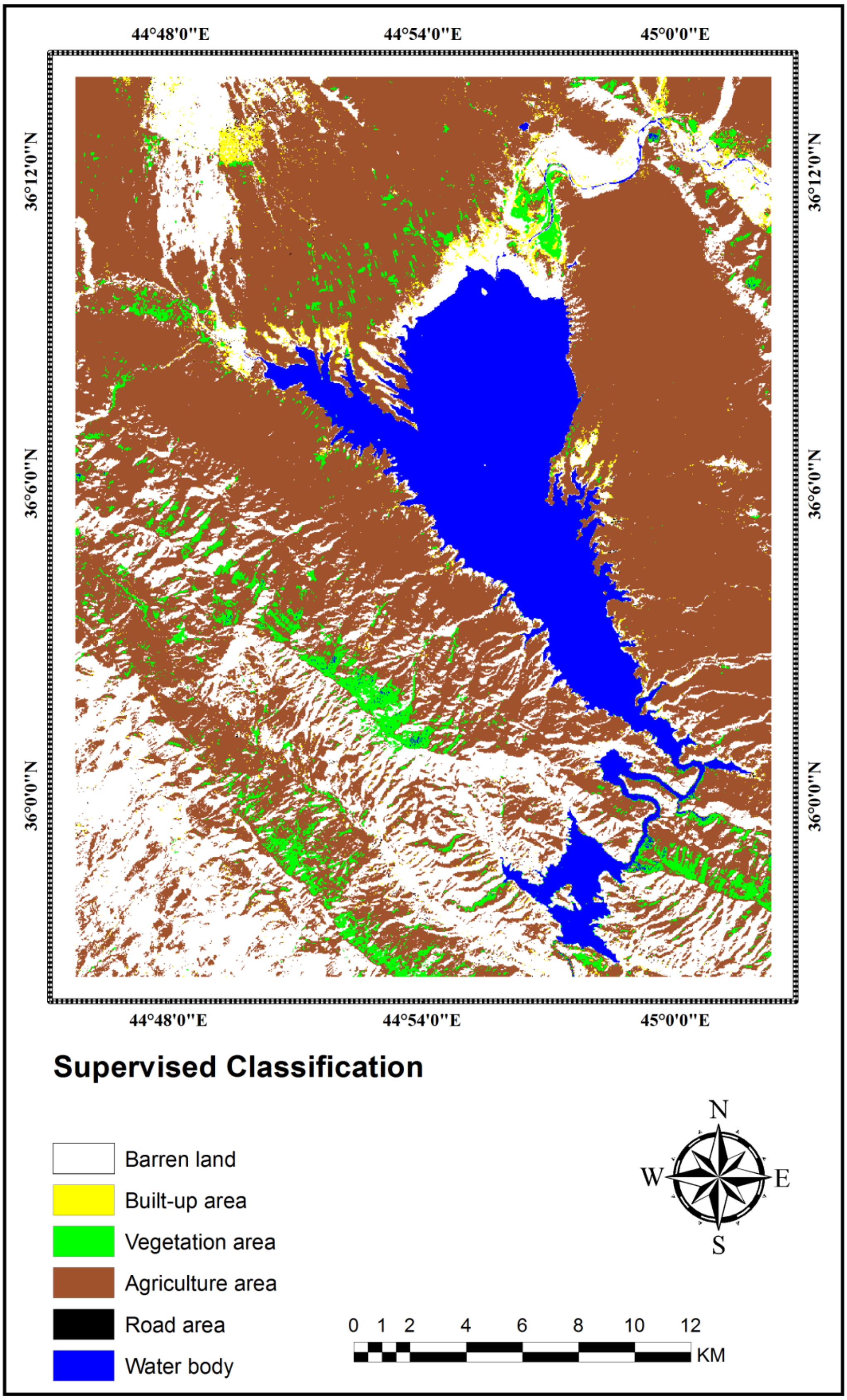


Figure 4.4. Supervised classification of land use land cover Cover Classes in 2000

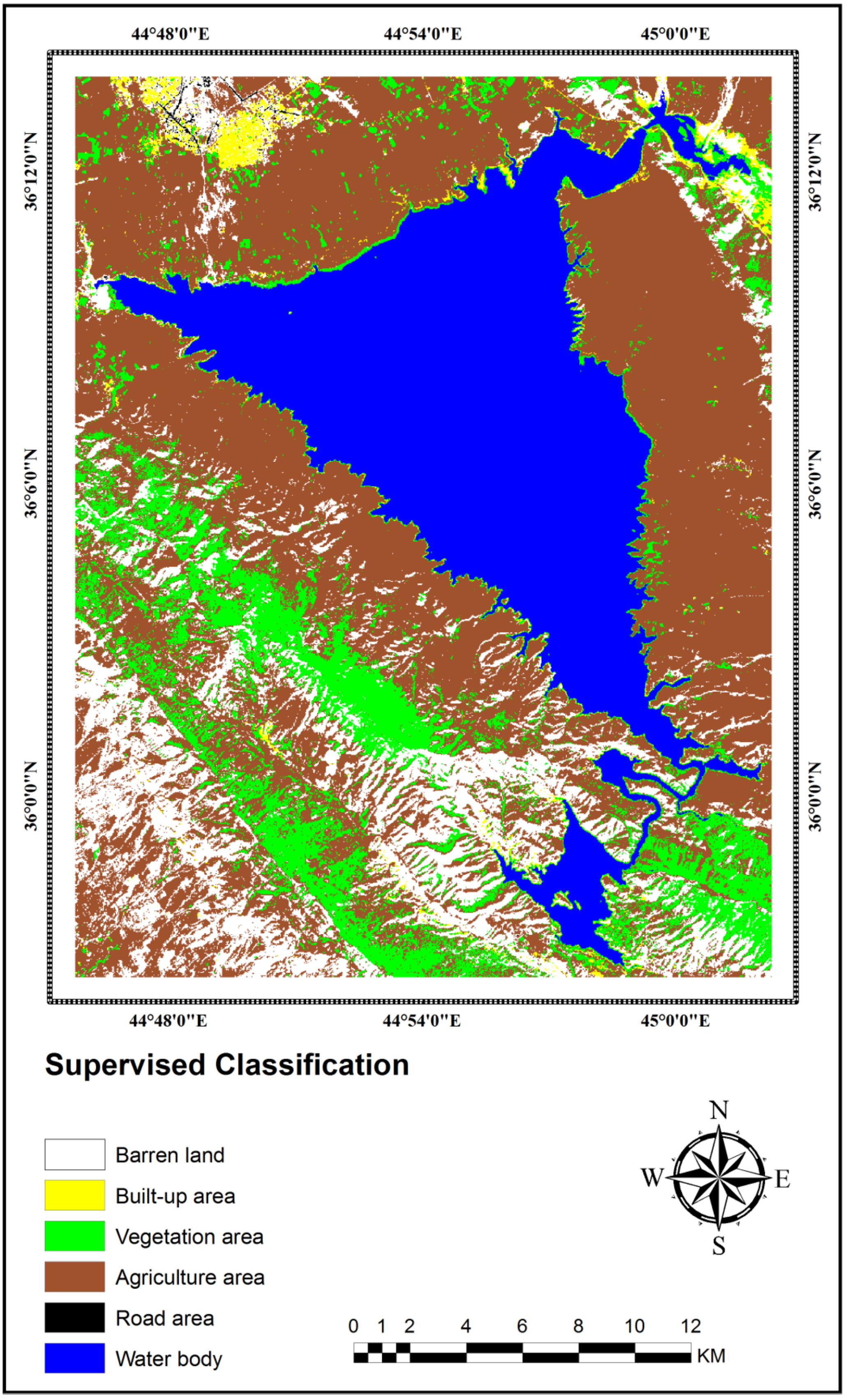


Figure 4.5. Supervised classification of land use land cover Classes in 2016

After the classification process we made an evaluation for the accuracy assessment by using method of confusion matrix by ENVI software in remote sensing, the result of the overall accuracy and kappa coefficient for the years 2000 and 2016 are shown in (Table 4.2).

Overall accuracy is a total of classification accuracy, it shows very significant result having with value 97.2928% in 2000, and 98.1009 % in 2016 means that there is an almost complete strong agreement (See Table 4.2). Kappa coefficient is a discrete multivariate technique of use in accuracy assessment, if kappa coefficient > 80% represent strong agreement and good accuracy. in addition kappa coefficient between 0.40-0.80% is poor ( Gong and Howarth 1990). In this study the value of kappa coefficient is 0.9595% in 2000 and 0.9739% in 2016 represent a significant accuracy (See Table 4.2). A full detail of the accuracy assessment output and statistical table of Kappa coefficient and overall accuracy is attached in Appendix (1 and 2).

Accuracy assessment has been done by Tillmann (2012), in West Siberia for the period 1987-2009, they have found overall accuracy with value 95.0 % in 1987, and 89.4 % in 2009. Kappa coefficient is 0.81 % in 1987, and 0.85 % in 2009. Another accuracy assessment carried out by Das (2009) for Munster, Germany, overall classification accuracy it shows very significant result having 97.22% with kappa value of 0.9638.

Table 4.2. The Result of Classification Accuracy

| Confusion matrix | Satellite Image 2000 | Satellite Image 2016 |
|---|---|---|
| Overall classification accuracy | 97.2928% | 98.1009% |
| Kappa Coefficient | 0.9595% | 0.9739% |

## 4.2. Results of Change Detection Analysis

The change detection analysis has been carried out for the years 2000 and 2016 in Dukan dam; the spatial distribution of these changes is illustrated in figure (4.10). The change detection results there is a significant change in the quantity of water body between 2000 and 2016 and indicate that there is a growing trend toward water in year 2016 at the expense of agricultural land, Vegetation land and Barren land. As seen in table (4.4), 54.64 km sq of agricultural land was converted to water, and 27.99 km sq of barren land, 6.24 km sq of vegetation was converted to water between 2000-2016, The distribution of these changes is illustrated in figure (4.7 and 4.8). The quantity of water was 92.94 kmsq, with ratio 17.62% in 2000 increased to 186.42 kmsq,in ratio 30.12% in 2016 look Figure, these changes in water bodybecause years around 2000 priceptations was low 380.4 mm because drought happened and water body decreased The specific reasons of increasing water body in 2016 are the years after 2000 the rate of rainfall was high 816.8 mm as (shown in Table 4.3 and Figure 4.6). Increasing the rate of water constantly because of feeding from other water resources and melting snow from the mountains around Dukan dam along the years after 2000. In this study water body and the changing, it is focused on more than the other class (See Figure 4.7 and 4.8).

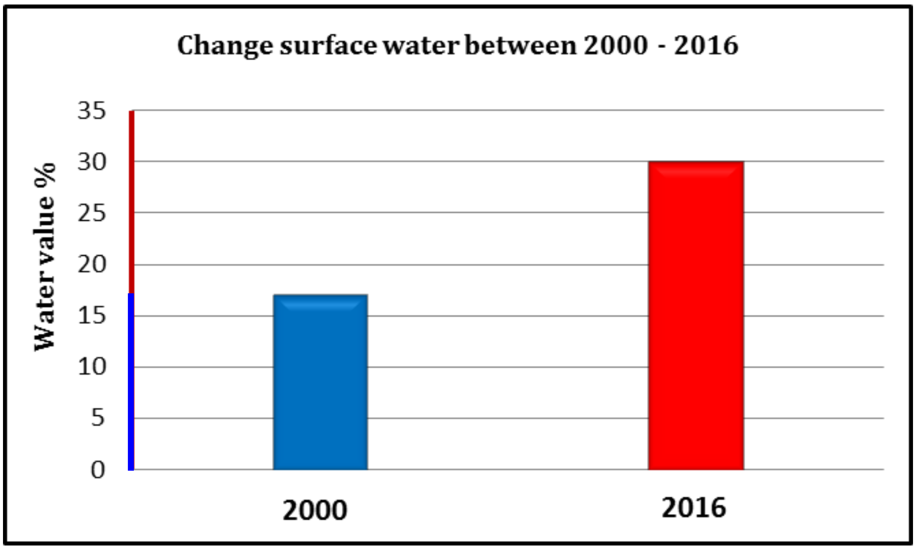


Figure 4.6. Change surface water between 2000-2016

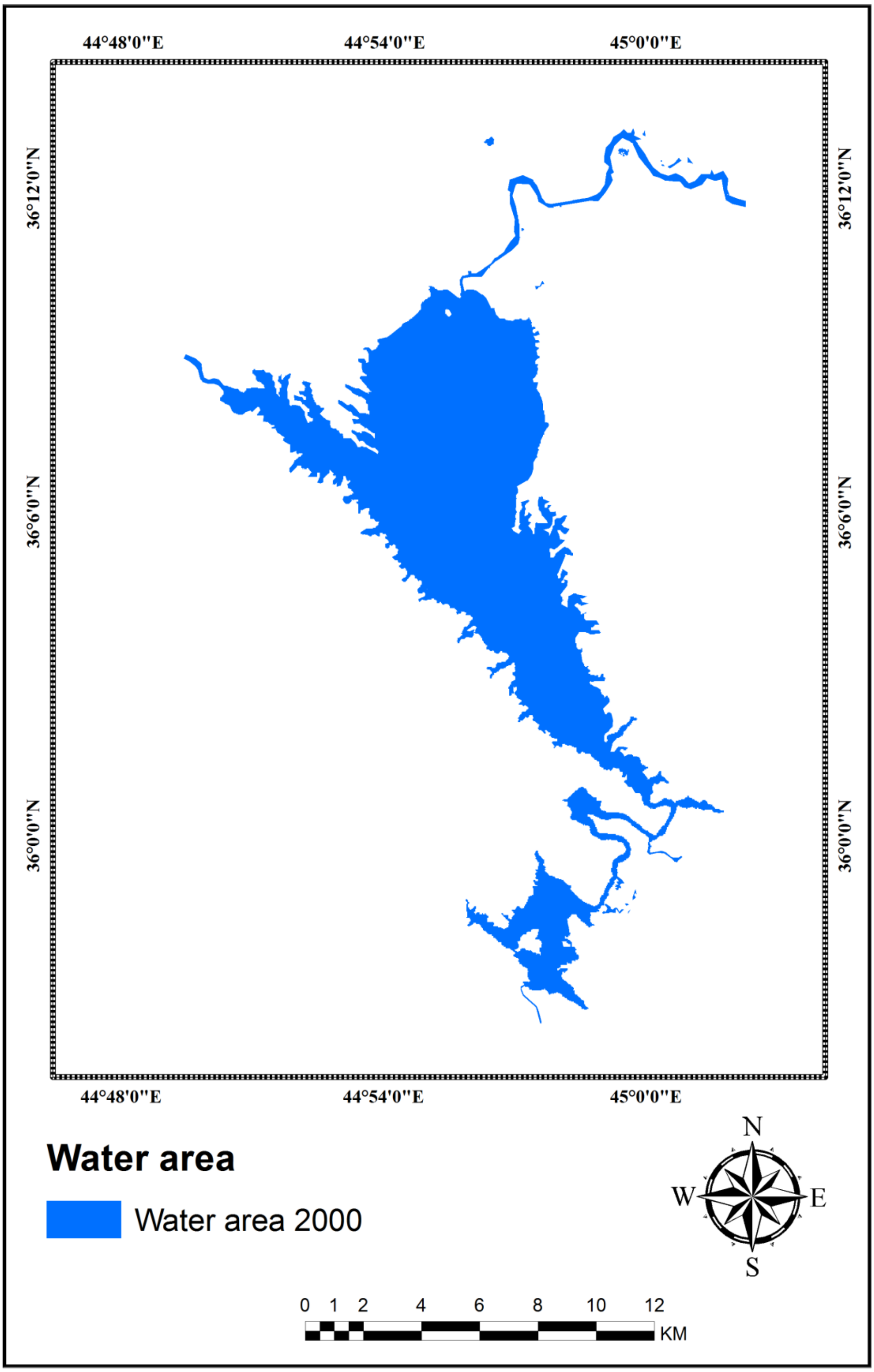


Figure 4.7. Surface water in 2000

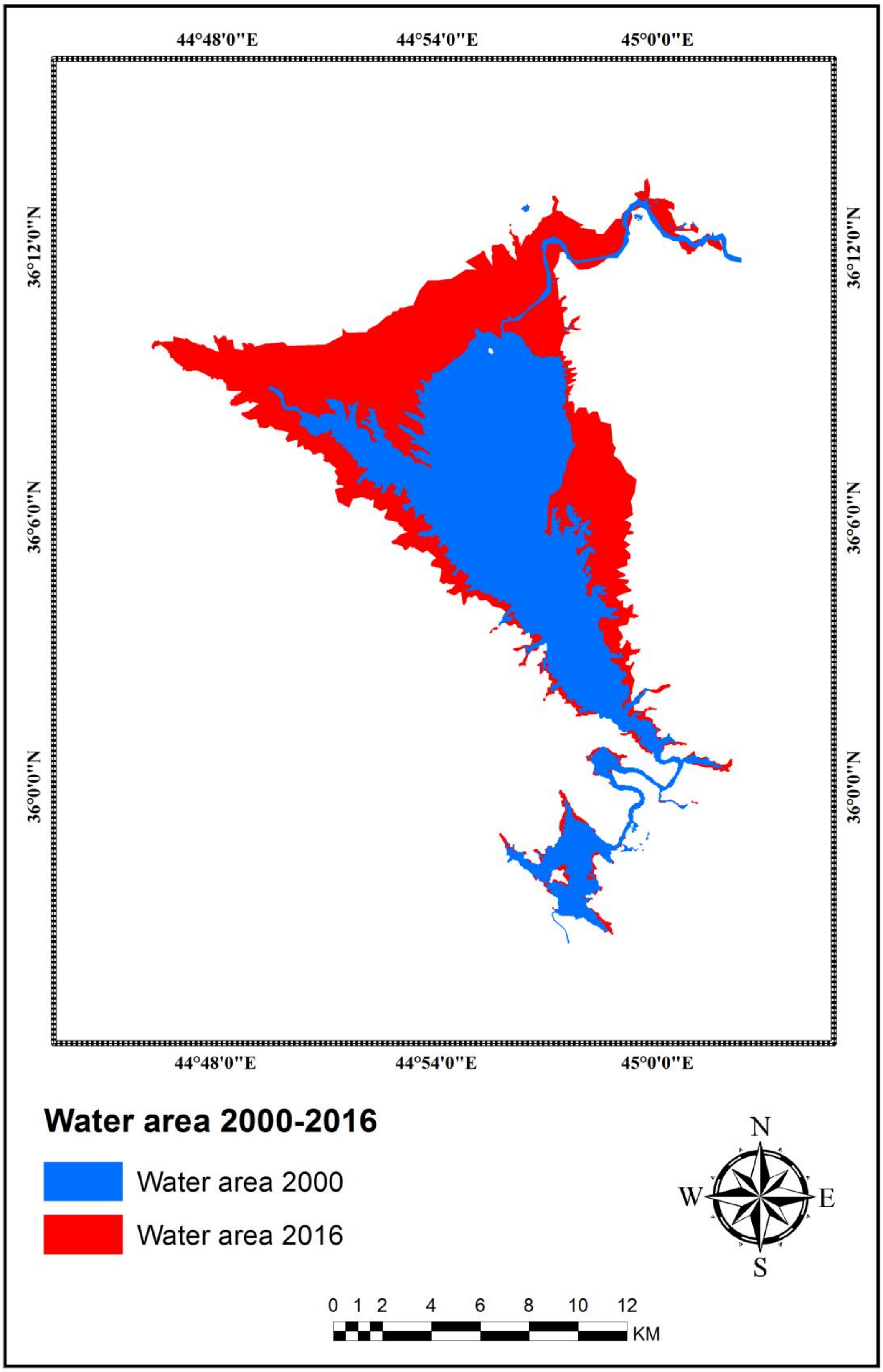


Figure 4.8. Change surface water between (2000-2016)

Table 4.3. Rainfall in Dukan weather station data

| Rainfall | 1999 |
|---|---|
| 1999 | 305 |
| 2000 | 380.4 |
| 2001 | 462.7 |
| 2002 | 718.8 |
| 2003 | 794.5 |
| 2004 | 876.3 |
| 2005 | 792.5 |
| 2006 | 662.2 |
| 2007 | 607 |
| 2008 | 504 |
| 2009 | 304.2 |
| 2010 | 563 |
| 2011 | 472.6 |
| 2012 | 421.8 |
| 2013 | 584.2 |
| 2014 | 470 |
| 2015 | 590.9 |
| 2016 | 816.8 |

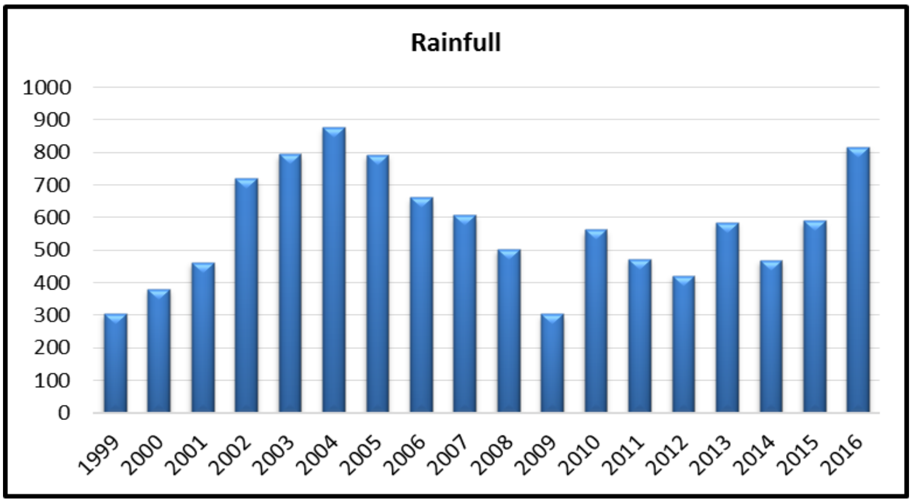


Figure 4.9. Rainfall in Dukan weather station data

Agricultural land was 441.76 kmsq, with ratio 47.51% in 2000 decreased to 372.94 kmsq, in ratio 37.59% in 2016 because of increasing water. As seen in table (4.4), 54.64 km sq of agricultural land was converted to water, 42.29 km sq of agriculture was converted to vegetation and 15.81 km sq of agricultural land was converted to barren land agricultural land was decreased.

Built up areas are mild increased because of increasing population and coming people from the villages to the area that was 11.22 kmsq, with ratio 0.94% in 2000 increased to 25.4 km sq, in ratio 4.13% in 2016. This is illustrated in (Figure 4.7), There is a mild increase in vegetation that was 31.54 km sq, with ratio 9.12% in 2000 increased to, in ratio 85.12 km sq in 2016 (look Table 4.4). A full detail of change detection output and change detection statistical table, is attached in Appendix (5, 6 and 7).

On the other hand, the results of the classification showed that Barren land decreased in 2016 because of increasing water and expanding the agricultural land (study area). Barren land was 214.36 km sq. with ratio 24.36% in 2000 decreased to 121.59 kmsq in ratio13.36% in 2016. 55.31 km sq of barren land was converted to agricultural land, 27.99 km sq of barren land was converted to water area, 20.56 km sq of barren land was converted to vegetation area between years 2000-2016 (look Table 4.4 and Figure 4.10).

LULC change is an important field in global environmental change research. Inventory and monitoring of LULC changes are indispensable aspects for further understanding of change mechanism and modeling the impact of change on the environment and associated ecosystems at different scales (Abdi 2015).

A change detection analysis has been conducted by (Oguz and Zengin 2011) in Kahramanmaras, Turkey for the period of 1984-2010 and they have found 40063 ha agricultural land loss and a gain of 21270 ha for grassland. Another change detection study carried out by (Reis 2008) in Rize, Turkey reported that 51562 ha of agricultural land have been lost between 1976 and 2000. In addition. A change detection analysis conducted by Abdi (2015) for city of Bursa, Turkey, between 1984-2011, 22411 ha of agricultural land was converted to urban, 2291 ha of forest and 4410 ha of grassland were also converted to urban. The largest conversion, however, occurred from grassland to agricultural land with 21194 ha.

Table 4.4. Change detection by km sq for the years 2000-2016

| Classes | Barren land | Built up | Vegetation land | Agricultural land | Road | Water body | Row total | Class total |
|---|---|---|---|---|---|---|---|---|
| Barren land | 104.13 | 5.63 | 20.56 | 55.31 | 0.74 | 27.99 | 214.36 | 214.36 |
| Built up land | 1.04 | 1.68 | 0.68 | 2.65 | 0.04 | 5.14 | 11.22 | 11.22 |
| Vegetation land | 0.39 | 12.30 | 22.23 | 2.38 | 0.00 | 6.24 | 31.54 | 31.54 |
| Agriculture land | 15.81 | 5.44 | 42.29 | 312.43 | 0.14 | 54.64 | 441.76 | 441.76 |
| Road | 0.15 | 0.09 | 0.03 | 0.16 | 0.02 | 0.19 | 0.64 | 0.64 |
| Water | 0.07 | 0.01 | 0.63 | 0.02 | 0.00 | 92.22 | 92.94 | 92.94 |
| Class Total | 121.59 | 25.4 | 85.12 | 372.94 | 0.95 | 186.42 | 0.00 | 0.00 |
| Class Changes | 17.46 | 11.46 | 75.19 | 60.51 | 0.93 | 94.21 | 0.00 | 0.00 |
| Image Difference | - 92.77 | 14.18 | 53.58 | - 68.81 | 0.31 | 93.48 | 0.00 | 0.00 |

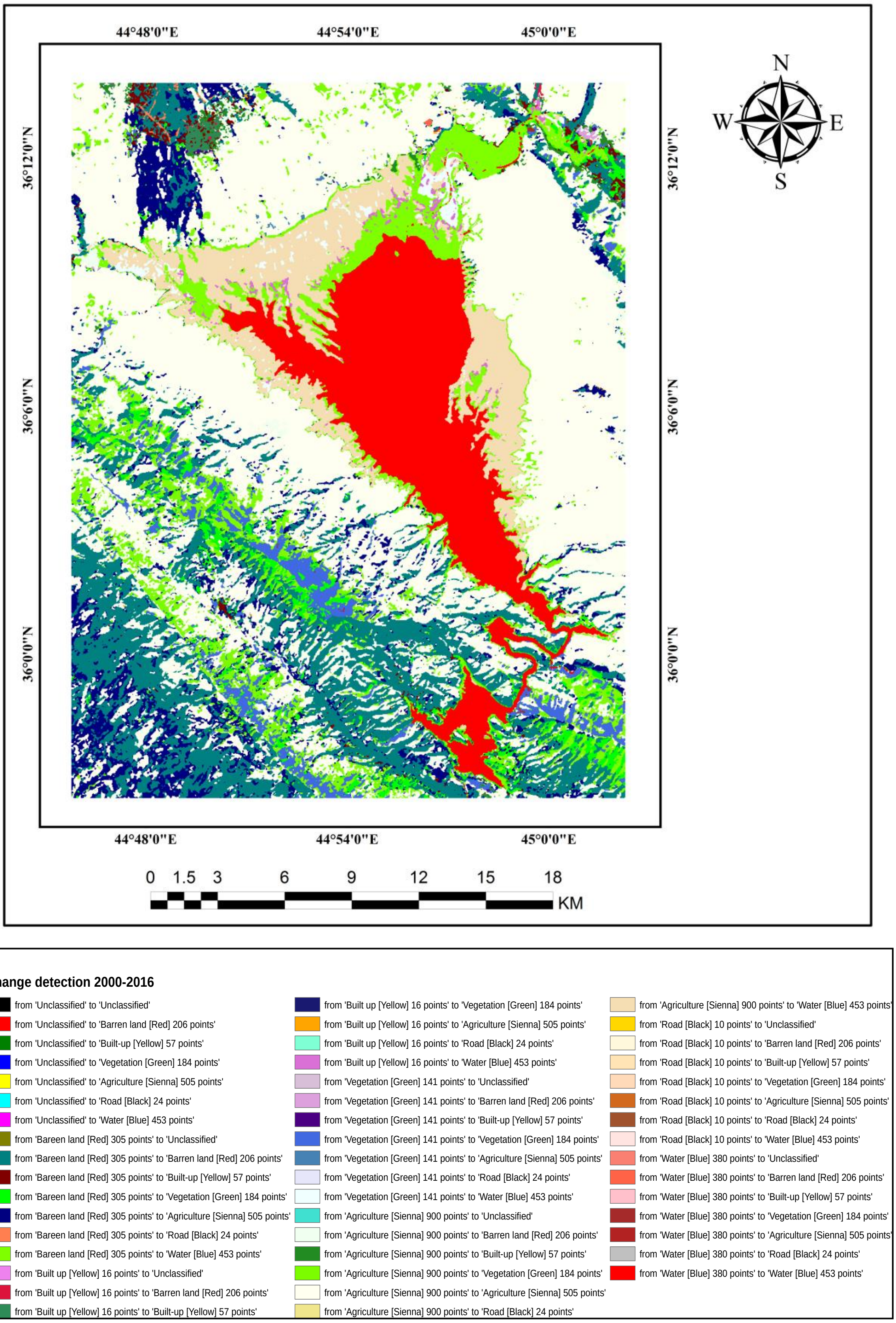


Figure 4.10. Change detection between (2000-2016)

Dukan Lake represents water bodies in the little Zab River, which appear as linear features surrounded by strips of agricultural lands, particularly in low-relief areas. The delineation of water areas depends on the scale of the data presentation and the resolution characteristics of the satellite data used for preparing the LULC map (Anderson et al. 1976). There are also some permanent tributaries and many intermittent and ephemeral streams, which are usually active during rainy season. During heavy rain, most of the valleys are flooded. Some of them are flash-flooded during strong rainstorms and supply huge amounts of water to Dukan dam (Al-Saady 2015).

Dukan Lake is an artificial reservoir mainly supplied by water from the LZR. It represents an important reservoir for the storage of water for agricultural land irrigation, drinking water supply, power generation, and flood control. Additionally, it is surrounded by fertile agricultural land extending over the surface of alluvial fans. Although the variation of the spatial extent of water bodies and the water level of the lake are artificially controlled by the dam, the climatic conditions, particularly the fluctuation of the rainfall rate is also crucial for the assessment of the amount of water in the lake. The fluctuation of the water level is directly reflected by the surface water body's spatial extension. Consequently, the artificially controlled Dukan dam at least partly affected the statistical calculation of the water class in the LULC map. There are many other water resources in the LZR such as natural springs that are distributed in different places particularly in the mountainous area (Younus et al. 2015).

### 4.3. Result Of Change Detection Accuracy Assessment

After the classification process we made a evaluate for the accuracy assessment by using method of confusion matrex by ENVI software in remote sensing, the result of the overall accuracy and kappa coefficient for the years 2000 and 2016 are shown in (Table 4.2).

For proving the accuracy assessment of the work that is done in the study and knowing the genuine of the work. We have to do classification again for the study area, this can be done by receiving different set and point, for proving the genuine of the accuracy assessment, by doing so a new accuracy will be received.

This new accuracy assessment with the accuracy that is done before the classification is going to be integrated by using ENVI 5.3. software and post classification with confusion matrix and using ground truth image complete. Basically, by using these methods the complete result of the work is going to be received. This final result provies the level genuine of our work.

Overall accuracy is a total of classification accuracy, it shows a good result having with value 88.6272 % in 2000, and 90.6182 % in 2016 means these result are good (See Table 4.2). Kappa coefficient is a discrete multivariate technique of use in accuracy assessment, if kappa coefficient > 80% represent strong agreement and significant accuracy. In addition kappa coefficient between 0.40-0.80 % indicate fair and good (SPSS 1998). In this study value of kappa coefficient is 0.8297 % in 2000 and 0.8677% in 2016 represent a good accuracy (See Table 4.2). A full detail of the accuracy assessment output and statistical table of Kappa coefficient and overall accuracy is attached in Appendix (3 and 4).

Accuracy assessment is done by Tillmann (2012), in West Siberia for the period 1987-2009, they have found overall accuracy with value 95.0 % in 1987, and 89.4 % in 2009. Kappa coefficient is 0.81 % in 1987, and 0.85 % in 2009.

Table 4.5. Shows the Result of Change detection accuracy assessment for years 2000-2016

| Confusion matrix | Satellite Image 2000 | Satellite Image 2016 |
|---|---|---|
| Overall classification accuracy | 88.6272 | 90.6182 |
| Kappa Coefficient | 0.8297 | 0.8677 |

# 5. CONCLUSION

The objective of the study is to explore change detection by using Landsat 7 ETM and 8 OLI data for classifying different land cover types (Barren land, Built up land, Vegetation land, Agriculture land, Road and water area) and to change detection for the Dukan dam surface area in 2000 and 2016. The main sum up of this study is the change detection of surface water in Dukan dam. The impact can be detected through the (2, 3, 4, 5) bands by ENVI 5.3 software.

The outcome of retrieving change detection to surface area of water in Dukan dam had different forms in 2000 and 2016. In addition, the outcome of land cover classification shows significant expansion of water body remarkable changes in other land cover classes over the period of the study.

The change detection results there is a significant change in the quantity of water body between 2000 and 2016 and indicate that there is a growing trend toward water in year 2016 at the expense of agricultural land, Vegetation land and Barren land. The quantity of water was (92.94) km sq, with ratio (17.62%) in 2000 increased to (186.42) km sq, in ratio(30.12%) in 2016, these because years around 2000 precipitations was low (380.4)mm because drought happened and water body decreased. The specific reasons of increasing water body in 2016 are the years after 2000 the rate of rainfall was high (816.8) mm. Increasing the rate of water constantly because of feeding from other water resources and melting snow from the mountains around Dukan dam along the years after 2000. In this study water body and the changing, it is focused on more than the other class.

On the other hand, the result of the classification showed that Barren land is much decreased in 2016 because of increasing water and agricultural land in the area that was 214.36 km sq. with ratio 24.36% in 2000 decreased to 121.59 km sq in ratio13.36% in 2016. Agricultural land was 441.76 kmsq, with ratio 47.51% in 2000 decreased to 372.94

km sq, in ratio 37.59% in 2016 because of increasing water. On the other hand Built up areas are mild increased during this period because of increasing the population and people migrating from the villages to the city that was 11.22 km sq, with ratio 0.94% in 2000 increased to 25.4 km sq, in ratio 4.13% in 2016. There is a mild increase in vegetation that was 31.54 km sq, with ratio 9.12% in 2000 increased to, in ratio 85.12 km sq in 2016. The results highlighted that the increase of water have a positive impact on irrigation of agriculture, vegetation and to create electricity and for drinking water, This might be because of the environment of the city, which is a semi-arid environment. However, the main negative impact of the increase of water of the area is the change in the physical and the natural characteristics of land cover such as the conversion of agriculture areas to water body this is basically the main reason of the decrease of agriculture land.

In order to understand the nature of LULCC, to identify the factors that caused the change, as well as to explore and evaluate the potential and performance of remote sensing data and remote sensing methods for understanding the impact of environmental factors on LULC. Thus, the aim of this research was to produce both recent and past LULC maps of Dukan dam from recent and historic satellite imagery across the period of study, and to detect and map any land change. The applications and software, which have been used to perform the data analysis, are EVNI 5.3. and ArcGIS 10.3. The origin for the mapping LULC of the Dukan dam was the classification of the 2000 images, which result in a base LULC dataset. This dataset was used to perform change detection in relation to images from later dates (e.g. image from 2016).

To conclude, this study explained the importance of remote sensing, Landsat data and GIS techniques in investigating the environmental issues, particularly with regards to change detection for increasing water body and LULCC. In addition, the research questions were answered properly and the objectives were achieved sufficiently by applying scientific methods. Furthermore, it is hoped that the outcomes of this research will assist planners and decision makers in solving the problems that relate to the environment.

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# APPENDICES

## Appendix 1

Classification Accuracy Assessment Report
-----------------------------------------

Confusion Matrix: D:\Dukan-Dam_2000\Classification_Image_2000\Classified_2000.img

User name : Safin Najib Rashid

Date : Thursday, January 26, 2017, 2:20:45 AM

Overall Accuracy = (1761/1810) 97.2928%

Kappa Coefficient = 0.9595

Ground Truth (Pixels)

| Class | Barren land | built up | Vegetation | Agriculture | Road |
|---|---|---|---|---|---|
| Unclassified | 0 | 0 | 0 | 0 | 0 |
| Barren land [ | 431 | 0 | 0 | 8 | 0 |
| Built up [Yel | 0 | 16 | 0 | 1 | 0 |
| Vegetation [G | 0 | 0 | 134 | 31 | 0 |
| Agriculture [ | 0 | 0 | 0 | 860 | 0 |
| Road [Black] | 0 | 0 | 0 | 0 | 8 |
| Water [Blue] | 0 | 0 | 7 | 0 | 0 |
| Total | 431 | 16 | 141 | 900 | 8 |

Ground Truth (Pixels)

Class Water Total

| | | |
|---|---|---|
| Unclassified | 0 | 0 |
| Barren land [ | 2 | 441 |
| Built up [Yel | 0 | 17 |
| Vegetation [G | 0 | 165 |
| Agriculture [ | 0 | 860 |
| Road [Black] | 0 | 8 |
| Water [Blue] | 312 | 319 |
| Total | 314 | 1810 |

Ground Truth (Percent)

| Class | Barren land | Built up | Vegetation | Agriculture | Road |
|---|---|---|---|---|---|
| Unclassified | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Barren land [ | 100.00 | 0.00 | 0.00 | 0.89 | 0.00 |
| Built up [Yel | 0.00 | 100.00 | 0.00 | 0.11 | 0.00 |
| Vegetation [G | 0.00 | 0.00 | 95.04 | 3.44 | 0.00 |
| Agriculture [ | 0.00 | 0.00 | 0.00 | 95.56 | 0.00 |
| Road [Black] | 0.00 | 0.00 | 0.00 | 0.00 | 100.00 |
| Water [Blue] | 0.00 | 0.00 | 4.96 | 0.00 | 0.00 |
| Total | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |

Ground Truth (Percent)

| Class | Water | Total |
|---|---|---|
| Unclassified | 0.00 | 0.00 |
| Barren land [ | 0.64 | 24.36 |
| Built up [Yel | 0.00 | 0.94 |
| Vegetation [G | 0.00 | 9.12 |
| Agriculture [ | 0.00 | 47.51 |
| Road [Black] | 0.00 | 0.44 |
| Water [Blue] | 99.36 | 17.62 |
| Total | 100.00 | 100.00 |

| Class | Commission (Percent) | Omission (Percent) | Commission (Pixels) | Omission (Pixels) |
|---|---|---|---|---|
| Barren land [ | 2.27 | 0.00 | 10/441 | 0/431 |
| Built up [Yel | 5.88 | 0.00 | 1/17 | 0/16 |
| Vegetation [G | 18.79 | 4.96 | 31/165 | 7/141 |
| Agriculture [ | 0.00 | 4.44 | 0/860 | 40/900 |
| Road [Black] | 0.00 | 0.00 | 0/8 | 0/8 |
| Water [Blue] | 2.19 | 0.64 | 7/319 | 2/314 |

| Class | Prod. Acc. (Percent) | User Acc. (Percent) | Prod. Acc. (Pixels) | User Acc. (Pixels) |
|---|---|---|---|---|
| Barren land [ | 100.00 | 97.73 | 431/431 | 431/441 |
| Built up [Yel | 100.00 | 94.12 | 16/16 | 16/17 |
| Vegetation [G | 95.04 | 81.21 | 134/141 | 134/165 |
| Agriculture [ | 95.56 | 100.00 | 860/900 | 860/860 |
| Road [Black] | 100.00 | 100.00 | 8/8 | 8/8 |
| Water [Blue] | 99.36 | 97.81 | 312/314 | 312/319 |

End of Confusion matrix 2000
-------------------------

## Appendix 2

Confusion Matrix: D:\Dukan-Dam_2016\Classification_Image_2016\Classified_2016

User name : Safin Najib Rashid

Date : Saturday, February 15, 2017, 14:15:23

Overall Accuracy = (1498/1527) 98.1009%

Kappa Coefficient = 0.9739

Ground Truth (Pixels)

| Class | Barren land | Built-up | Vegetation | Agriculture | Road |
|---|---|---|---|---|---|
| Unclassified | 0 | 0 | 0 | 0 | 0 |
| Barren land [ | 203 | 0 | 0 | 1 | 0 |
| Built-up [Yel | 2 | 55 | 0 | 6 | 0 |
| Vegetation [G | 0 | 0 | 184 | 17 | 0 |
| Agriculture [ | 0 | 2 | 0 | 572 | 0 |
| Road [Black] | 1 | 0 | 0 | 0 | 24 |
| Water [Blue] | 0 | 0 | 0 | 0 | 0 |
| Total | 206 | 57 | 184 | 596 | 24 |

Ground Truth (Pixels)

| Class | Water | Total |
|---|---|---|
| Unclassified | 0 | 0 |
| Barren land [ | 0 | 204 |
| Built-up [Yel | 0 | 63 |
| Vegetation [G | 0 | 201 |
| Agriculture [ | 0 | 574 |
| Road [Black] | 0 | 25 |
| Water [Blue] | 460 | 460 |
| Total | 460 | 1527 |

Ground Truth (Percent)

| Class | Barren land | Built-up | Vegetation | Agriculture | Road |
|---|---|---|---|---|---|
| Unclassified | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Barren land [ | 98.54 | 0.00 | 0.00 | 0.17 | 0.00 |
| Built-up [Yel | 0.97 | 96.49 | 0.00 | 1.01 | 0.00 |

| | | | | | |
|---|---|---|---|---|---|
| Vegetation [G | 0.00 | 0.00 | 100.00 | 2.85 | 0.00 |
| Agriculture [ | 0.00 | 3.51 | 0.00 | 95.97 | 0.00 |
| Road [Black] | 0.49 | 0.00 | 0.00 | 0.00 | 100.00 |
| Water [Blue] | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Total | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |

Ground Truth (Percent)

| Class | Water | Total |
|---|---|---|
| Unclassified | 0.00 | 0.00 |
| Barren land [ | 0.00 | 13.36 |
| Built-up [Yel | 0.00 | 4.13 |
| Vegetation [G | 0.00 | 13.16 |
| Agriculture [ | 0.00 | 37.59 |
| Road [Black] | 0.00 | 1.64 |
| Water [Blue] | 100.00 | 30.12 |
| Total | 100.00 | 100.00 |

| Class | Commission (Percent) | Omission (Percent) | Commission (Pixels) | Omission (Pixels) |
|---|---|---|---|---|
| Barren land [ | 0.49 | 1.46 | 1/204 | 3/206 |
| Built-up [Yel | 12.70 | 3.51 | 8/63 | 2/57 |
| Vegetation [G | 8.46 | 0.00 | 17/201 | 0/184 |
| Agriculture [ | 0.35 | 4.03 | 2/574 | 24/596 |
| Road [Black] | 4.00 | 0.00 | 1/25 | 0/24 |
| Water [Blue] | 0.00 | 0.00 | 0/460 | 0/460 |

| Class | Prod. Acc. | User Acc. | Prod. Acc. | User Acc. |
|---|---|---|---|---|

| | (Percent) | (Percent) | (Pixels) | (Pixels) |
|---|---|---|---|---|
| Barren land [ | 98.54 | 99.51 | 203/206 | 203/204 |
| Built-up [Yel | 96.49 | 87.30 | 55/57 | 55/63 |
| Vegetation [G | 100.00 | 91.54 | 184/184 | 184/201 |
| Agriculture [ | 95.97 | 99.65 | 572/596 | 572/574 |
| Road [Black] | 100.00 | 96.00 | 24/24 | 24/25 |
| Water [Blue] | 100.00 | 100.00 | 460/460 | 460/460 |

End of Confusion matrix 2016
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## Appendix 3

Confusion Matrix: D:\Classification new set_2000\Classified new set_2000

User name : Safin Najib Rashid

Date : Monday, February 20, 2017, 14:16:23

Overall Accuracy = (777579/880516) 88.3095%

Kappa Coefficient = 0.8146

Ground Truth (Pixels)

| Class | Unclassified | Barren land [ | Built up [Yel | Vegetation [G | Agriculture [ |
|---|---|---|---|---|---|
| Unclassified | 0 | 0 | 0 | 0 | 0 |
| Barren land [ | 0 | 226334 | 4210 | 4303 | 40892 |
| Built-up [Yel | 0 | 5325 | 7548 | 11 | 915 |
| Vegetation [G | 0 | 4330 | 193 | 23309 | 28958 |
| Agriculture [ | 0 | 221 | 243 | 4200 | 417793 |
| Road [Black] | 0 | 656 | 277 | 0 | 2129 |

| | | | | | |
|---|---|---|---|---|---|
| Water [Blue] | 0 | 1315 | 0 | 3216 | 154 |
| Total | 0 | 238181 | 12471 | 35039 | 490841 |

Ground Truth (Pixels)

| Class | Road [Black] | Water [Blue] | Total |
|---|---|---|---|
| Unclassified | 0 | 0 | 0 |
| Barren land [ | 178 | 975 | 276892 |
| Built-up [Yel | 102 | 0 | 13901 |
| Vegetation [G | 0 | 125 | 56915 |
| Agriculture [ | 9 | 0 | 422466 |
| Road [Black] | 424 | 0 | 3486 |
| Water [Blue] | 0 | 102171 | 106856 |
| Total | 713 | 103271 | 880516 |

Ground Truth (Percent)

| Class | Unclassified | Barren land [ | Built up [Yel | Vegetation [G | Agriculture [ |
|---|---|---|---|---|---|
| Unclassified | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Barren land [ | 0.00 | 95.03 | 33.76 | 12.28 | 8.33 |
| Built-up [Yel | 0.00 | 2.24 | 60.52 | 0.03 | 0.19 |
| Vegetation [G | 0.00 | 1.82 | 1.55 | 66.52 | 5.90 |
| Agriculture [ | 0.00 | 0.09 | 1.95 | 11.99 | 85.12 |
| Road [Black] | 0.00 | 0.28 | 2.22 | 0.00 | 0.43 |
| Water [Blue] | 0.00 | 0.55 | 0.00 | 9.18 | 0.03 |
| Total | 0.00 | 100.00 | 100.00 | 100.00 | 100.00 |

Ground Truth (Percent)

| Class | Road [Black] | Water [Blue] | Total |
|---|---|---|---|
| Unclassified | 0.00 | 0.00 | 0.00 |
| Barren land [ | 24.96 | 0.94 | 31.45 |

| | | | |
|---|---|---|---|
| Built-up [Yel | 14.31 | 0.00 | 1.58 |
| Vegetation [G | 0.00 | 0.12 | 6.46 |
| Agriculture [ | 1.26 | 0.00 | 47.98 |
| Road [Black] | 59.47 | 0.00 | 0.40 |
| Water [Blue] | 0.00 | 98.93 | 12.14 |
| Total | 100.00 | 100.00 | 100.00 |

| Class | Commission (Percent) | Omission (Percent) | Commission (Pixels) | Omission (Pixels) |
|---|---|---|---|---|
| Unclassified | 0.00 | 0.00 | 0/0 | 0/0 |
| Barren land [ | 18.26 | 4.97 | 50558/276892 | 11847/238181 |
| Built-up [Yel | 45.70 | 39.48 | 6353/13901 | 4923/12471 |
| Vegetation [G | 59.05 | 33.48 | 33606/56915 | 11730/35039 |
| Agriculture [ | 1.11 | 14.88 | 4673/422466 | 73048/490841 |
| Road [Black] | 87.84 | 40.53 | 3062/3486 | 289/713 |
| Water [Blue] | 4.38 | 1.07 | 4685/106856 | 1100/103271 |

| Class | Prod. Acc. (Percent) | User Acc. (Percent) | Prod. Acc. (Pixels) | User Acc. (Pixels) |
|---|---|---|---|---|
| Unclassified | 0.00 | 0.00 | 0/0 | 0/0 |
| Barren land [ | 95.03 | 81.74 | 226334/238181 | 226334/276892 |
| Built-up [Yel | 60.52 | 54.30 | 7548/12471 | 7548/13901 |
| Vegetation [G | 66.52 | 40.95 | 23309/35039 | 23309/56915 |
| Agriculture [ | 85.12 | 98.89 | 417793/490841 | 417793/422466 |
| Road [Black] | 59.47 | 12.16 | 424/713 | 424/3486 |

| | | | | |
|---|---|---|---|---|
| Water [Blue] | 98.93 | 95.62 | 102171/103271 | 102171/106856 |

End of Confusion matrix new set 2000
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## Appendix 4

Confusion Matrix: D:\Classification new set_2016\Classified new set_2016

User name : Safin Najib Rashid

Date : Monday, February 27, 2017, 17:56:12

Overall Accuracy = (797908/880516) 90.6182%

Kappa Coefficient = 0.8677

Ground Truth (Pixels)

| Class | Unclassified | Vegetation [G | Barren land [ | Built-up [Yel | Agriculture [ |
|---|---|---|---|---|---|
| Unclassified | 0 | 0 | 0 | 0 | 0 |
| Vegetation [G | 0 | 103026 | 3433 | 329 | 1456 |
| Barren land [ | 0 | 6010 | 128211 | 189 | 603 |
| Built-up [Yel | 0 | 656 | 886 | 13020 | 33 |
| Agriculture [ | 0 | 45697 | 20697 | 484 | 347504 |
| Road [Black] | 0 | 0 | 51 | 0 | 0 |
| Water [Blue] | 0 | 1795 | 195 | 0 | 2 |
| Total | 0 | 157184 | 153473 | 14022 | 349598 |

Ground Truth (Pixels)

| Class | Road [Black] | Water [Blue] | Total |
|---|---|---|---|
| Unclassified | 0 | 0 | 0 |
| Vegetation [G | 0 | 1 | 108245 |
| Barren land [ | 91 | 0 | 135104 |

| | | | |
|---|---|---|---|
| Built-up [Yel | 0 | 0 | 14595 |
| Agriculture [ | 0 | 0 | 414382 |
| Road [Black] | 1004 | 0 | 1055 |
| Water [Blue] | 0 | 205143 | 207135 |
| Total | 1095 | 205144 | 880516 |

Ground Truth (Percent)

| Class | Unclassified | Vegetation [G | Barren land [ | Built-up [Yel | Agriculture [ |
|---|---|---|---|---|---|
| Unclassified | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Vegetation [G | 0.00 | 65.54 | 2.24 | 2.35 | 0.42 |
| Barren land [ | 0.00 | 3.82 | 83.54 | 1.35 | 0.17 |
| Built-up [Yel | 0.00 | 0.42 | 0.58 | 92.85 | 0.01 |
| Agriculture [ | 0.00 | 29.07 | 13.49 | 3.45 | 99.40 |
| Road [Black] | 0.00 | 0.00 | 0.03 | 0.00 | 0.00 |
| Water [Blue] | 0.00 | 1.14 | 0.13 | 0.00 | 0.00 |
| Total | 0.00 | 100.00 | 100.00 | 100.00 | 100.00 |

Ground Truth (Percent)

| Class | Road [Black] | Water [Blue] | Total |
|---|---|---|---|
| Unclassified | 0.00 | 0.00 | 0.00 |
| Vegetation [G | 0.00 | 0.00 | 12.29 |
| Barren land [ | 8.31 | 0.00 | 15.34 |
| Built-up [Yel | 0.00 | 0.00 | 1.66 |
| Agriculture [ | 0.00 | 0.00 | 47.06 |
| Road [Black] | 91.69 | 0.00 | 0.12 |
| Water [Blue] | 0.00 | 100.00 | 23.52 |
| Total | 100.00 | 100.00 | 100.00 |

| Class | Commission | Omission | Commission | Omission |
|---|---|---|---|---|
| | (Percent) | (Percent) | (Pixels) | (Pixels) |

| | | | | |
|---|---|---|---|---|
| Unclassified | 0.00 | 0.00 | 0/0 | 0/0 |
| Vegetation [G | 4.82 | 34.46 | 5219/108245 | 54158/157184 |
| Barren land [ | 5.10 | 16.46 | 6893/135104 | 25262/153473 |
| Built-up [Yel | 10.79 | 7.15 | 1575/14595 | 1002/14022 |
| Agriculture [ | 16.14 | 0.60 | 66878/414382 | 2094/349598 |
| Road [Black] | 4.83 | 8.31 | 51/1055 | 91/1095 |
| Water [Blue] | 0.96 | 0.00 | 1992/207135 | 1/205144 |

| Class | Prod. Acc. (Percent) | User Acc. (Percent) | Prod. Acc. (Pixels) | User Acc. (Pixels) |
|---|---|---|---|---|
| Unclassified | 0.00 | 0.00 | 0/0 | 0/0 |
| Vegetation [G | 65.54 | 95.18 | 103026/157184 | 103026/108245 |
| Barren land [ | 83.54 | 94.90 | 128211/153473 | 128211/135104 |
| Built-up [Yel | 92.85 | 89.21 | 13020/14022 | 13020/14595 |
| Agriculture [ | 99.40 | 83.86 | 347504/349598 | 347504/414382 |
| Road [Black] | 91.69 | 95.17 | 1004/1095 | 1004/1055 |
| Water [Blue] | 100.00 | 99.04 | 205143/205144 | 205143/207135 |

End of Confusion matrix new set 2016
---------------------------------

## Appendix 5

Change detection Statistics_2000

Pixel Counts

Barren land [White] 431 points Built up [Yellow] 16 points
Vegetation [Green] 141 points Agriculture [Sienna] 900 points
Road [Black] 8 points Water [Blue] 314 points Row Total Class
Total

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Unclassified | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Barren land [White] 431 points | 238181 | 0 | 0 | 0 | 0 | 0 | 238181 | 238181 |
| Built up [Yellow] 16 points | 0 | 12471 | 0 | 0 | 0 | 0 | 12471 | 12471 |
| Vegetation [Green] 141 points | 0 | 0 | 35039 | 0 | 0 | 0 | 35039 | 35039 |
| Agriculture [Sienna] 900 points | 0 | 0 | 0 | 490841 | 0 | 0 | 490841 | 490841 |
| Road [Black] 8 points | 0 | 0 | 0 | 0 | 713 | 0 | 713 | 713 |
| Water [Blue] 314 points | 0 | 0 | 0 | 0 | 0 | 103271 | 103271 | 103271 |
| Class Total | 238181 | 12471 | 35039 | 490841 | 713 | 103271 | 0 | 0 |
| Class Changes | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Image Difference | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Percentages

| | Barren land [White] 431 points | Built up [Yellow] 16 points | Vegetation [Green] 141 points | Agriculture [Sienna] 900 points | Road [Black] 8 points | Water [Blue] 314 points | Row Total | Class Total |
|---|---|---|---|---|---|---|---|---|
| Unclassified | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Barren land [White] 431 points | 100.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 100.000 | 100.000 |
| Built up [Yellow] 16 points | 0.000 | 100.000 | 0.000 | 0.000 | 0.000 | 0.000 | 100.000 | 100.000 |
| Vegetation [Green] 141 points | 0.000 | 0.000 | 100.000 | 0.000 | 0.000 | 0.000 | 100.000 | 100.000 |
| Agriculture [Sienna] 900 points | 0.000 | 0.000 | 0.000 | 100.000 | 0.000 | 0.000 | 100.000 | 100.000 |
| Road [Black] 8 points | 0.000 | 0.000 | 0.000 | 0.000 | 100.000 | 0.000 | 100.000 | 100.000 |
| Water [Blue] 314 points | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 100.000 | 100.000 | 100.000 |
| Class Total | 100.000 | 100.000 | 100.000 | 100.000 | 100.000 | 100.000 | 0.000 | 0.000 |
| Class Changes | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Image Difference | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

Area (Square Km)

| | Barren land [White] 431 points | Built up [Yellow] 16 points | Vegetation [Green] 141 points | Agriculture [Sienna] 900 points | Road [Black] 8 points | Water [Blue] 314 points | Row Total | Class Total |
|---|---|---|---|---|---|---|---|---|
| Unclassified | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Barren land [White] 431 points | 214.36 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 214.36 | 214.36 |
| Built up [Yellow] 16 points | 0.00 | 11.22 | 0.00 | 0.00 | 0.00 | 0.00 | 11.22 | 11.22 |
| Vegetation [Green] 141 points | 0.00 | 0.00 | 31.54 | 0.00 | 0.00 | 0.00 | 31.54 | 31.54 |
| Agriculture [Sienna] 900 points | 0.00 | 0.00 | 0.00 | 441.76 | 0.00 | 0.00 | 441.76 | 441.76 |
| Road [Black] 8 points | 0.00 | 0.00 | 0.00 | 0.00 | 0.64 | 0.00 | 0.64 | 0.64 |
| Water [Blue] 314 points | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 92.94 | 92.94 | 92.94 |
| Class Total | 214.36 | 11.22 | 31.54 | 441.76 | 0.64 | 92.94 | 0.00 | 0.00 |
| Class Changes | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Image Difference | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Reference

Initial State Image: D:\Dukan-Dam_2000\Classification_Image_2000\Classified_2000

Dimensions: (1:826, 1:1066), Band 1, Pixel Size: (30.00, 30.00) Meters

Final State Image: D:\Dukan-Dam_2000\Classification_Image_2000\Classified_2000

Dimensions: (1:826, 1:1066), Band 1, Pixel Size: (30.00, 30.00) Meters

Equivalent Class Pairings

Barren land [White] 431 points <==> Bareen land [White] 431 points

Built up [Yellow] 16 points <==> Built up [Yellow] 16 points

Vegetation [Green] 141 points <==> Vegetation [Green] 141 points

Agriculture [Sienna] 900 points <==> Agriculture [Sienna] 900 points

Road [Black] 8 points <==> Road [Black] 8 points

Water [Blue] 314 points <==> Water [Blue] 314 points

Report Produced on: Thu May 18 14:46:33 2017

End of change detection statistics_2000
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## Appendix 6

Change detection Statistics_2016

Pixel Counts

| | Barren land [White] 206 points | Built-up [Yellow] 57 points | Vegetation [Green] 184 points | Agriculture [Sienna] 596 points | Road [Black] 24 points | Water [Blue] 460 points | Row Total | Class Total |
|---|---|---|---|---|---|---|---|---|
| Unclassified | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Barren land [White] 206 points | 135104 | 0 | 0 | 0 | 0 | 0 | 135104 | 135104 |
| Built-up [Yellow] 57 points | 0 | 14595 | 0 | 0 | 0 | 0 | 14595 | 14595 |
| Vegetation [Green] 184 points | 0 | 0 | 108245 | 0 | 0 | 0 | 108245 | 108245 |
| Agriculture [Sienna] 596 points | 0 | 0 | 0 | 414382 | 0 | 0 | 414382 | 414382 |
| Road [Black] 24 points | 0 | 0 | 0 | 0 | 1055 | 0 | 1055 | 1055 |
| Water [Blue] 460 points | 0 | 0 | 0 | 0 | 0 | 207135 | 207135 | 207135 |
| Class Total | 135104 | 14595 | 108245 | 414382 | 1055 | 207135 | 0 | 0 |
| Class Changes | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Image Difference | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Percentages

| | Barren land [White] 206 points | Built-up [Yellow] 57 points | Vegetation [Green] 184 points | Agriculture [Sienna] 596 points | Road [Black] 24 points | Water [Blue] 460 points | Row Total | Class Total |
|---|---|---|---|---|---|---|---|---|
| Unclassified | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Barren land [White] 206 points | 100.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 100.000 | 100.000 |
| Built-up [Yellow] 57 points | 0.000 | 100.000 | 0.000 | 0.000 | 0.000 | 0.000 | 100.000 | 100.000 |

Vegetation [Green] 184 points 0.000 0.000 100.000
0.000 0.000 0.000 100.000 100.000

Agriculture [Sienna] 596 points 0.000 0.000 0.000
100.000 0.000 0.000 100.000 100.000

Road [Black] 24 points 0.000 0.000 0.000 0.000
100.000 0.000 100.000 100.000

Water [Blue] 460 points 0.000 0.000 0.000 0.000
0.000 100.000 100.000 100.000

Class Total 100.000 100.000 100.000 100.000 100.000
100.000 0.000 0.000

Class Changes 0.000 0.000 0.000 0.000
0.000 0.000 0.000 0.000

Image Difference 0.000 0.000 0.000 0.000
0.000 0.000 0.000 0.000

Area (Square Km)

Barren land [White] 206 points Built-up [Yellow] 57 points
Vegetation [Green] 184 points Agriculture [Sienna] 596 points
Road [Black] 24 points Water [Blue] 460 points Row Total Class
Total

Unclassified 0.00 0.00 0.00 0.00
0.00 0.00 0.00 0.00

Barren land [White] 206 points 121.59 0.00 0.00
0.00 0.00 0.00 121.59 121.59

Built-up [Yellow] 57 points 0.00 25.4 0.00
0.00 0.00 0.00 25.4 25.4

Vegetation [Green] 184 points 0.00 0.00 85.16
0.00 0.00 0.00 85.16 85.16

Agriculture [Sienna] 596 points 0.00 0.00 0.00
372.94 0.00 0.00 372.94 372.94

Road [Black] 24 points 0.00 0.00 0.00 0.00
0.95 0.00 0.95 0.95

Water [Blue] 460 points 0.00 0.00 0.00 0.00
0.00 186.42 186.42 186.42

Class Total 121.59 25.4 85.16 372.94 0.95
186.42 0.00 0.00

Class Changes 0.00 0.00 0.00 0.00
0.00 0.00 0.00 0.00

Image Difference 0.00 0.00 0.00 0.00
0.00 0.00 0.00 0.00

Reference

Initial State Image: D:\Dukan-
Dam_2016\Classification_Image_2016\Classified_2016

Dimensions: (1:826, 1:1066), Band 1, Pixel Size: (30.00, 30.00)
Meters

Final State Image: D:\Dukan-Dam_2016\Classification_Image_2016\Classified_2016

Dimensions: (1:826, 1:1066), Band 1, Pixel Size: (30.00, 30.00) Meters

Equivalent Class Pairings

Barren land [White] 206 points <==> Barren land [White] 206 points

Built-up [Yellow] 57 points <==> Built-up [Yellow] 57 points

Vegetation [Green] 184 points <==> Vegetation [Green] 184 points

Agriculture [Sienna] 596 points <==> Agriculture [Sienna] 596 points

Road [Black] 24 points <==> Road [Black] 24 points

Water [Blue] 460 points <==> Water [Blue] 460 points

Report Produced on: Thu May 18 14:48:53 2017

End of change detection statistics_2016
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## Appendix 7

Thematic change workflow

Pixel Counts

| | Barren land [Whi] 206 points | Built-up [Yellow] 57 points | Vegetation [Green] 184 points | Agriculture [Sienna] 596 points | Road [Black] 24 points | Water [Blue] 460 points | Row Total | Class Total |
|---|---|---|---|---|---|---|---|---|
| Unclassified | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Barren land [Whi] 431 points | 115701 | 6253 | 22848 | 61456 | 824 | 31099 | 238181 | 238181 |
| Built up [Yellow] 16 points | 1151 | 1864 | 755 | 2944 | 46 | 5711 | 12471 | 12471 |
| Vegetation [Green] 141 points | 432 | 330 | 24701 | 2639 | 2 | 6935 | 35039 | 35039 |
| Agriculture [Sienna] 900 points | 17570 | 6042 | 59211 | 347148 | 157 | 60713 | 490841 | 490841 |
| Road [Blue] 8 points | 167 | 99 | 29 | 177 | 26 | 215 | 713 | 713 |
| Water [Blue] 314 points | 83 | 7 | 701 | 18 | 0 | 102462 | 103271 | 103271 |

Class Total     135104       14595      108245      414382        1055
207135               0           0

Class Changes          19403       12731       83544       67234
1029      104673           0           0

Image Difference      103077       -2124      -73206       76459
-342     -103864           0           0

Percentages

Barren land [Red] 206 points  Built-up [Yellow] 57 points
Vegetation [Green] 184 points Agriculture [Sienna] 596 points
Road [Black] 24 points  Water [Blue] 460 points Row Total   Class
Total

Unclassified         0.000       0.000       0.000       0.000
0.000    0.000       0.000       0.000

Barren land [White] 431 points       85.638      42.843      21.108
14.831        78.104      15.014     100.000     100.000

Built up [Yellow] 16 points     0.852      12.771       0.697
0.710    4.360       2.757     100.000     100.000

Vegetation [Green] 141 points    0.320       2.261      22.820
0.637    0.190       3.348     100.000     100.000

Agriculture [Sienna] 900 points       13.005      41.398      54.701
83.775        14.882      29.311     100.000     100.000

Road [Blue] 8 points       0.124       0.678       0.027       0.043
2.464    0.104     100.000     100.000

Water [Blue] 314 points    0.061       0.048       0.648       0.004
0.000   49.466     100.000     100.000

Class Total  100.000     100.000     100.000     100.000     100.000
100.000       0.000       0.000

Class Changes       14.362      87.229      77.180      16.225
97.536        50.534       0.000       0.000

Image Difference    76.295     -14.553     -67.630      18.451     -
32.417       -50.143       0.000       0.000

Area (Square Km)

Barren land [White] 206 points      Built-up [Yellow] 57 points
Vegetation [Green] 184 points Agriculture [Sienna] 596 points
Road [Black] 24 points  Water [Blue] 460 points Row Total   Class
Total

Unclassified         0.00        0.00        0.00        0.00
0.00     0.00        0.00        0.00

Barren land [White] 431 points      104.13        5.63       20.56
55.31    0.74       27.99      214.36      214.36

Built up [Yellow] 16 points      1.04        1.68        0.68
2.65     0.04        5.14       11.22       11.22

Vegetation [Green] 141 points    0.39        0.30       22.23
2.38     0.00        6.24       31.54       31.54

Agriculture [Sienna] 900 points 15.81 5.44 53.29
312.43 0.14 54.64 441.76 441.76

Road [Blue] 8 points 0.15 0.09 0.03 0.16
0.02 0.19 0.64 0.64

Water [Blue] 314 points 0.07 0.01 0.63 0.02
0.00 92.22 92.94 92.94

Class Total 121.59 13.14 97.42 372.94 0.95
186.42 0.00 0.00

Class Changes 17.46 11.46 75.19 60.51
0.93 94.21 0.00 0.00

Image Difference 92.77 -1.91 -65.89 68.81 -
0.31 -93.48 0.00 0.00

Reference

Initial State Image: D:\Dukan-
Dam_2016\Classification_Image_2016\Classified_2016

Dimensions: (1:826, 1:1066), Band 1, Pixel Size: (30.00, 30.00)
Meters

Final State Image: D:\Dukan-
Dam_2000\Classification_Image_2000\Classified_2000

Dimensions: (1:826, 1:1066), Band 1, Pixel Size: (30.00, 30.00)
Meters

Equivalent Class Pairings

Barren land [White] 206 points <==> Barren land [Red] 431 points

Built-up [Yellow] 57 points <==> Built up [Yellow] 16 points

Vegetation [Green] 184 points <==> Vegetation [Green] 141 points

Agriculture [Sienna] 596 points <==> Agriculture [Sienna] 900 points

Road [Black] 24 points <==> Road [Blue] 8 points

Water [Blue] 460 points <==> Water [Blue] 314 points

Report Produced on: Thu May 04 10:53:15 2017

End of thematic change workflow
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# CURRICULUM VITAE

Full Name: Safin Najib RASHID

Place of Birth: Sulaimaniyah_ Iraq

City: Sulaimaniyah_ Iraq

Marital Status: Single

Nationality: Iraqi –Kurdish

Date of Birth: 1989

safinnajib@gmail.com

Current work: Master student in Bingol University Faculty of Agriculture Department of Soil science and plant Nutrition

## Education:

| University | College | Department | Type of Certificate | Year |
|---|---|---|---|---|
| Sulaimaniyah | Human science | Geography | BSc | 2008-2012 |

**Language:-**

| **Language** | **Status** | **Note** |
|---|---|---|
| Kurdish | Excellent | Mother tongue |
| Arabic | Medium | Second language |
| English | Medium | - |
| Turkish | Fair | - |

**Computer skill:-**

| **Program Name** | **State Using** |
|---|---|
| Microsoft word | Good |
| Microsoft Excel | Good |
| Microsoft presentation | Good |
| Internet and Email | Good |

Good Lucks

**Safin Najib RASHID**