PERFORMANCE OF WATER BODIES EXTRACTION TECHNIQUES 'EMBEDDED IN ERDAS': CASE STUDY MANZALA LAKE, NORTHEAST OF NILE DELTA, EGYPT

H. Hossen[1], A. Negm[2]

[1] Ph.D. Student, Department of Environmental Engineering, School of Energy, Environment, and Chemical and Petrochemical Engineering,Egypt-Japan University of Science and Technology E-JUST, P.O. Box 179, New Borg El-Arab, Alexandria, Egypt,
E-mail:hickmat.abdullah@ejust.edu.eg
[2] Chairperson of Department of Environmental Engineering, School of Energy, Environment, and Chemical and Petrochemical Engineering,Egypt-Japan University of Science and Technology E- JUST, P.O. Box 179, New Borg El-Arab, Alexandria, Egypt, (seconded from Zagazig University, Faculty of Engineering, amnegm@zu.edu.eg), E-mail: negm@ejust.edu.eg

ABSTRACT

Accurate change detection of water bodies over time is an indicator of its sustainability. Therefore, accurate classification is essential. This paper presents a comparison among five techniques embodied in ERDAS from the accuracy perspective when they are applied to extract Manzala lake water bodies using Erdas Imagine and ArcGIS software. The used techniques include Minimum distance supervised classification, Mahalanobis distance supervised classification, Maximum likelihood supervised classification, Unsupervised classification, and Normalized difference water index. Lake Manzala is one of such lakes and it is the largest natural lake in Egypt. It is located between longitudes 31° 45′ and 32° 22′ E and latitudes 31° 00′ and 31° 35′ N. Landsat Operational Land Imager and Thermal Infrared Sensor (OLI/TIRS) image with 30 m ground resolution acquired on 2015 are used to compare the performance of these used. The results indicate that the maximum likelihood supervised classification technique extract the water body of ManzalaLake more accurately compared to others.

Keywords: Manzalalake, Water bodies, Classification, Accuracy assessment, Erdas Imagine and ArcGIS software

1 INTRODUCTION

Coastal zone monitoring is an important task in sustainable development and environmental protection (Alesheikh et al., 2007).Fast and accurate extraction of thewater body is vital"for water resources investigation, management, and micro monitoring, wetland protection, lake/coastline change detection, flood prediction and evaluation" (Xiao et al., 2014). Visual interpretation of satellite data provides the best delineation of water bodies of varied sizes but is time-consuming, especially when working with high-resolution data.Remote sensing imagery and image processing techniques provide a possible solution to some of the problems of generating and updating the coastline maps (Winarso&Budhiman, 2001). Serious concern about changes in the quantity and quality of many of the world's wetlands has arisen mainly as a result of increased urban development and agricultural development (Haack, 1996).Manzalalake is an example of the wetland in Egypt. Manzala lake is one of the most famous Egyptian wetlands for water birds and a migration route for birds from Europe to Africa along the Mediterranean Sea (Ayache et al., 2009). Change detection in land use and land cover across spatial and temporal scales is necessary to achieve sustainable environmental management (Turner et al., 1994). To study LU/LC somewhere, it is indispensable to study the place at different times (Singh, 1989). Change in land use and land cover, as one of the key driving forces of global environmental change, it is fundamental to the study of sustainable development (Hegazy&Kaloop, 2015).

Remote sensing is used on a large scale to achieve an effective way in terms of cost to change detection in land use and land cover over wide geographic areas (Lunetta et al., 2006). Satellite remote sensing can be appropriate for wetland mapping and monitoring in developing countries where funds are limited and information on wetland areas, surrounding land uses, and wetland losses over time are not available (Ozesmi&Bauer, 2002). Advances in sensor design and data analysis techniques are now making remote-sensing systems practical and cost-effective for monitoring natural and human-induced coastal changes (Klemas, 2013). The remote sensing and GIS techniques provide useful information on spatial and temporal changes in aquatic vegetation in the lakes (Valta et al., 2004).Classification and mapping the types of LU/LC by high accuracy is an important issue to support the sustainable management of natural resources. "Post-Classification comparison has been successfully applied for change detection using land cover maps obtained from remotely sensed imagery with coarse or medium spatial resolution" (Zhou et al., 2008). To explore the changes in LU/LC with high accuracy, always, a classification system for the entire region should be developed, and the division of all objects into different classes according to the requirements of the study (Anderson et al., 1976).The aim of the present study is to do accuracy assessment for classification to the different techniques for water body area extraction using satellite images, which can be appliedfor areas, with similar conditions as the study area.

2 STUDY AREA

Manzala Lake is one of the most vulnerable lakes and is the largest natural lake of the Egyptian northern lakes along the Mediterranean coast.Geographically, it is located between longitudes 31° 45 and 32° 22 E and latitudes 31° 00 and 31° 35 N. The lake is bordered by Mediterranean sea to the North and the North-East, Suez Canal to the East, Dakahlia and Sharkia Provinces to the South and Damietta Branch of the Nile to the West (see Fig. 1). The surface area of Manzala Lake is about 1,471.92 Km2. The lake is shallow, ranging from 0.7 to 1.5 m in depth. It is linked to six drains through the southern and western shores (Donia&Hussein, 2004).

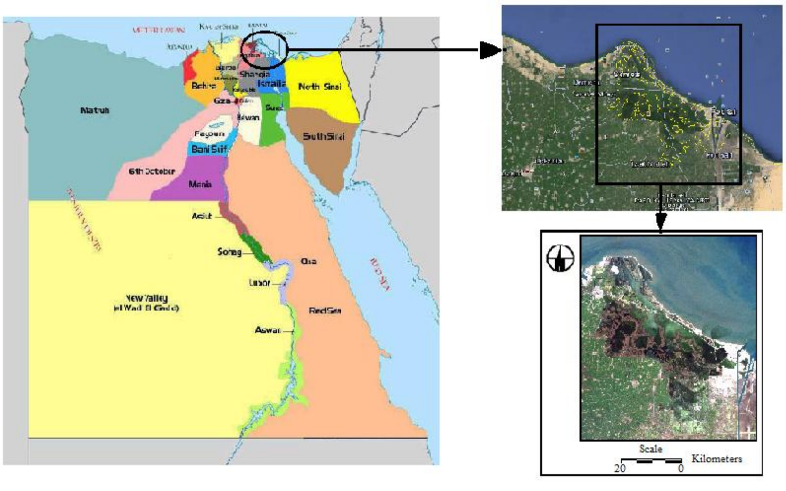

Figure 1.Location of the study area of Manzala Lake

3 DATA AND METHODOLOGY

Landsat Operational Land Imager and Thermal Infrared Sensor (OLI/TIRS) image with 30 m ground resolution acquired on 2015 have been used to do accuracy assessment for classification to the different techniques. The image has been downloaded from United States Geological Survey (USGS Earth Explorer, 1879). Image processing has been done through the use of ERDAS 9.1 and ArcGIS 9.3 software.

3.1 Image preprocessing

Geometric correction of the images has been done using ERDAS 9.1 software via the use of first order polynomials where the order of transformation is the order of the polynomial used in the transformation. The resampling processes of the images were carried out by using the nearest neighbor method. The nearest neighbor method does not change the cell values of the image and thus it is suitable for the classification process in addition to being easy to account and fast in use (Hossen& Ali, 2012). All images were registeredin the same projection system (UTM, WGS 84).

3.2 Image Classification

In this study, the different techniques are applied to detect the change of the lake water bodies using Erdas Imagine and ArcGIS software. The used techniques include Minimum distance supervised classification,Mahalanobis distance supervised classification, Maximum likelihood supervised classification, Unsupervised classification, and Normalized difference water index. Landsat image acquired on 2015 are used to compare the performance of these techniques. The following subsections describe these methods, (ERDAS Field Guide, 1999).

3.2.1 Minimum distance supervised classification

The minimum distance law calculates the spectral distance between the measurement vector for the candidate pixel and the mean vector for each signature. The equation for classifying by spectral distance is based on the equation for Euclidean distance, (ERDAS Field Guide, 1999):

$$SD_{xyc} = \sqrt{\sum_{i=}^{n} (\mu_{ci - X_{xyi}})^2}$$

Where:
X_{xyi}= data file value of pixel x,y in band i
i= a particular band
n= number of bands
c= a particular class
μ_{ci}= mean of data file values in band i for the sample for class c
SD_{xyc}= spectral distance from pixel x, y to the mean of class c

3.2.2 Mahalanobis distance supervised classification

The mahalanobis distance is similar to the minimum distance, exclude that the covariance matrix is used in the equation. Variance and covariance are calculated in so that clusters that are highly different lead to similarly different classes, and vice versa. The equation for the Mahalanobis distance supervised classification is as follows, (ERDAS Field Guide, 1999):

$$D = (X - M_c)^T (Cov_c^{-1})(X - M_c)$$

Where:
D= Mahalanobis distance
c= a particular class
X= the measurement vector of the candidate pixel
Mc= the mean vector of the signature of class c
Covc= the covariance matrix of the pixels in the signature of class c
Covc-1= inverse of Covc
T= transposition function

3.2.3 Maximum likelihood supervised classification

The maximum likelihood law is based on the probability that a pixel belongs to a particular class. The basic equation supposes that these probabilities are equal for all classes, and that the input bands have ordinary distributions. If a priori knowledge that the probabilities are not equal for all classesis given, then one can specify weight factors for particular classes. This variation of the maximum likelihood decision rule is known as the Bayesian decision rule.The equation for the maximum likelihood/Bayesian classifier is as follows, (ERDAS Field Guide, 1999):

$$D = \ln(a_c) - [0.5\ \ln(|Cov_c|)] - [0.5(X - M_c)T\ (Cov_c^{-1})\ (X - M_c)]$$

Where:

D= weighted distance (likelihood)

c= a particular class

Xis the the measurement vector of the candidate pixel

Mc is the mean vector of the sample of class c

Ac is the percent probability that any candidate pixel is a member of class c (defaults to 1.0, or is entered from a priori knowledge)

Covc is the covariance matrix of the pixels in the sample of class c

|Covc| is the determinant of Covc (matrix algebra)

Covc-1= inverse of Covc (matrix algebra)

ln= natural logarithm function

T= transposition function (matrix algebra)

3.2.4 Unsupervised classification

Unsupervised training requires only minimal initial input. Unsupervised training is based on the natural groupings of pixels in image data when they are plotted in feature space. The Iterative Self-Organizing Data Analysis Technique (ISODATA) clustering method uses spectral distance as in the consecutive method, but iteratively classifies the pixels, redefines the standards for each class, and classifies again, so that the spectral distance styles in the data gradually emerge. The ISODATA method uses minimum spectral distance to allocate a cluster for each candidate pixel. The method begins with a specified number of arbitrary cluster means or the means of existing signatures, and then it processes repetitively, so that those means transfer to the means of the clusters in the data. Because the ISODATA method is iterative, it is impartial to the top of the data file, as are the one-pass clustering algorithms, (ERDAS Field Guide, 1999).

3.2.5 Normalized difference water index classification

The NDWI was derived using principles similar to those that were used to derive the NDVI. The NDWI is calculated as follows, (ERDAS Field Guide, 1999):

$$NDWI = \frac{(Green - NIR)}{(Green + NIR)}$$

When theequation is used to process a multispectral satellite image that contains a reflected visible green band and an NIR band, water features have positive values, while soil and terrestrial vegetation features have zero or negative values. Image processing software can easily be configured to delete negative values. Vegetation and soil information retain the open water information for analysis. The range of NDWI is then from zero to one.

3.3 Accuracy Assessment

Accuracy is the degree of confidence, defined as the level of convergence between the results and the truth. To evaluate the classification accuracy, results are compared with a map of LU/LC cover of reference data (map). To obtain a high accuracy of the classification of a certain category, there must be proportionality between the number of samples to that category and type and size of that category (Mostafa, 2006). For accuracy assessment of images classification, there are two methods error matrix and Kappa coefficient. In the error matrix, the results of classification are compared with real information on the surface of the earth. The overall accuracy of the classification is calculated by dividing the total number of the correct pixel by the total number of all pixels. There are two indicators of accuracy, the user's accuracy, and the producer's accuracy. The user's accuracy refers to the possibility that the pixels on the image represent that category on the ground (Story et al., 1986). The producer's accuracy is defined as the probability of correctly classified pixels and is used primarily to determine the extent of the area to be classified (Story et al., 1986). The Kappa is a multi-discrete variables method used to assess the accuracy of classification maps. It is computed from the error matrix and implemented over the classification based on the data reference (Jensen, 1996).

4 RESULTS AND DISCUSSION

The results of classification of the different techniques are as follows:

4.1 Minimum distance supervised classification

The Minimum distance supervised classification technique was applied to theimage and given the classified image in Figure (2). The overall accuracy is 80%,and the overall kappa coefficient is 0.760 (see Table 1).

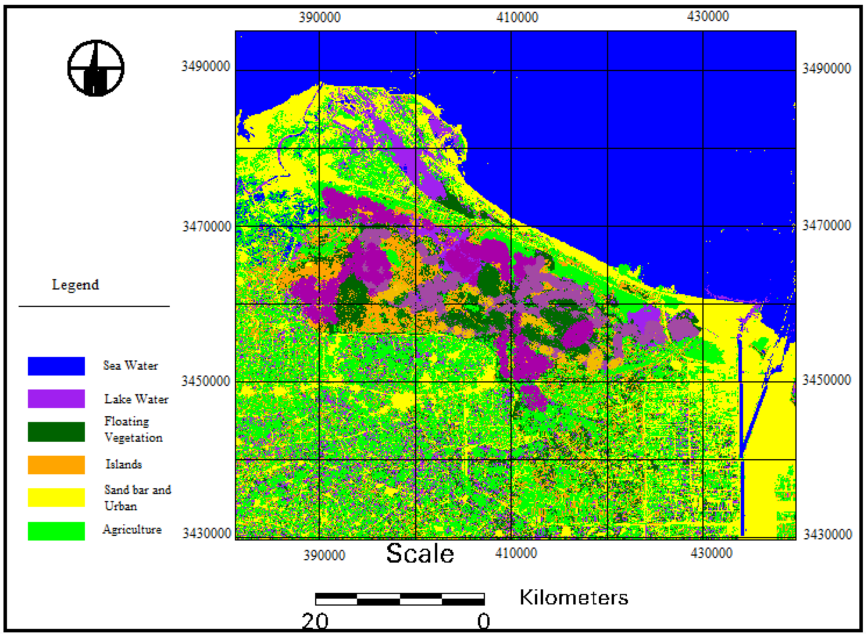

Figure 2.The 2015 image minimum distance supervised classification

Table1.User's and producer's accuracies and Kappa coefficients for Minimum distance supervised classification of the 2015 image

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy %	Users Accuracy %
Sea water	20	20	20	100	100
Lake water	20	35	20	100	57.15
Floating vegetation	20	20	13	65	65
Islands	20	21	20	100	95.24
Sand bar and urban	20	20	20	100	100
Agriculture	20	4	3	15	75
Total	120	120	96	---	---
Overall Classification Accuracy= 80.00 %					

Class Name	Kappa Statistics
Sea water	1.00
Lake water	1.00
Floating vegetation	0.6061
Islands	1.00
Sandbar and urban	1.00
Agriculture	0.9577
Total Kappa Statistics	0.760

4.2 Mahalanobis distance supervised classification

Figure (3) illustrates the classified image resulting from the use ofthe Mahalanobis distance supervised classification technique. The overall accuracy and the overall kappa coefficient are 91.67% and 0.90 respectively (see Table 2).

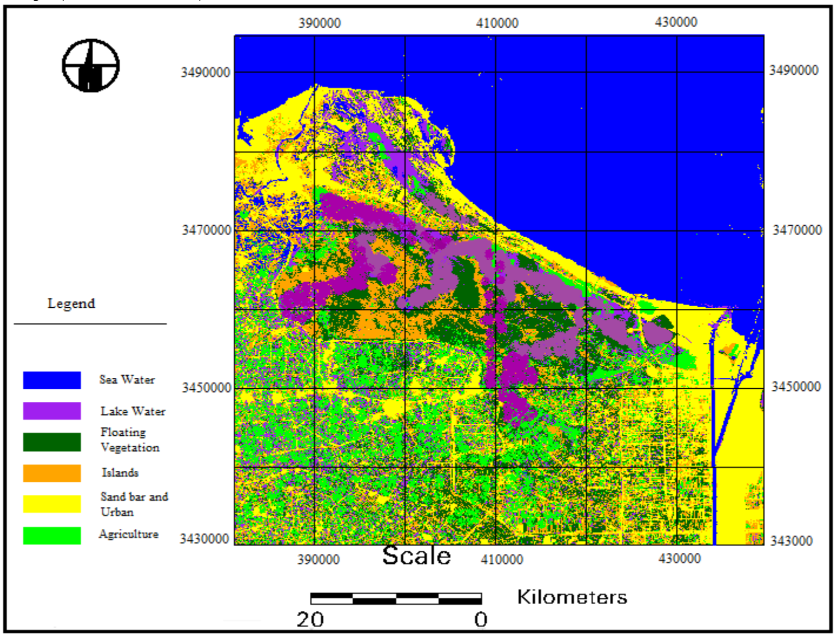

Figure 3.The 2015 image Mahalanobis distance supervised classification

Table 2.User's and producer's accuracies and Kappa coefficients forMahalanobis distance supervised classification of the 2015 image

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy %	Users Accuracy %
Sea water	20	20	20	100	100
Lake water	20	17	16	80	94.12
Floating vegetation	20	26	18	90	69.23
Islands	20	19	19	95	100
Sand bar and urban	20	20	20	100	100
Agriculture	20	18	17	85	94.44
Total	120	120	110	---	---
Overall Classification Accuracy= 91.67 %					

Class Name	Kappa Statistics
Sea water	1.00
Lake water	0.8095
Floating vegetation	0.2653
Islands	1.00
Sand bar and urban	1.00
Agriculture	0.7606
Total Kappa Statistics	0.90

4.3 Maximum likelihood supervised classification

Using the Maximum likelihood supervised classification technique, the overall accuracy, and overall kappa coefficient are 93.33% and 0.920 respectively (see Table 3). Figure (4)illustrates the classified image resulting from the use of the Maximum likelihood supervised classification technique.

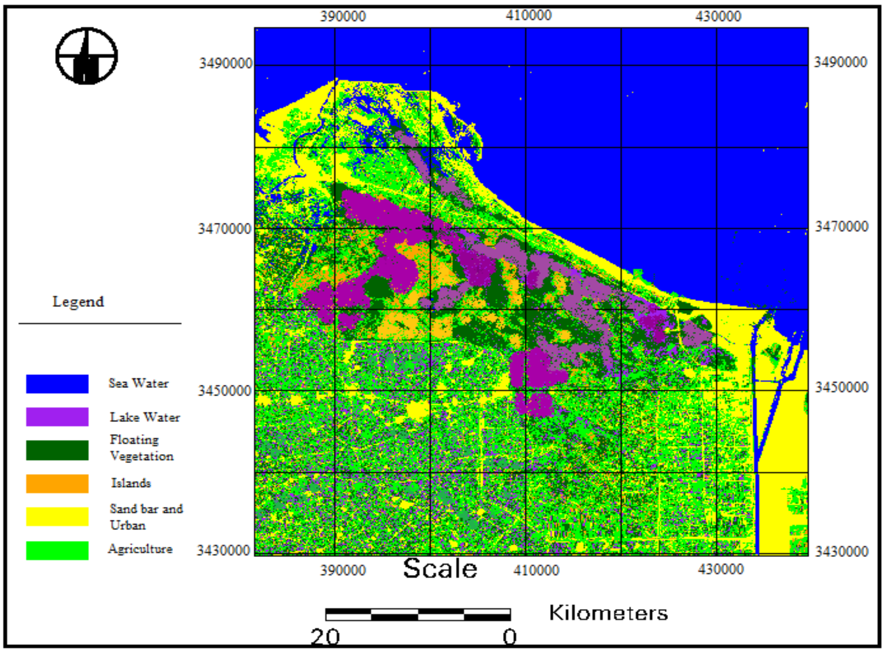

Figure 4. The 2015 image maximum likelihood supervised classification

Table 3.User's and producer's accuracies and Kappa coefficients for Maximum likelihood supervised classification of the 2015 image

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy %	Users Accuracy %
Sea water	20	20	20	100	100
Lake water	20	23	20	100	86.96
Floating vegetation	20	20	16	80	80
Islands	20	19	19	95	100
Sand bar and urban	20	20	20	100	100
Agriculture	20	18	17	85	94.44
Total	120	120	112	---	---
Overall Classification Accuracy= 93.33 %					

Class Name	Kappa Statistics
Sea water	1.00
Lake water	1.00
Floating vegetation	0.556
Islands	1.00
Sandbar and urban	1.00
Agriculture	0.7606
Total Kappa Statistics	0.920

4.4 Unsupervised classification

From table (4) clear that the overall accuracy and overall kappa coefficient for classification using the Unsupervised classification technique are 70.00% and 0.6372 respectively.Figure (5)shows the classified image resulting from the use of this technique.

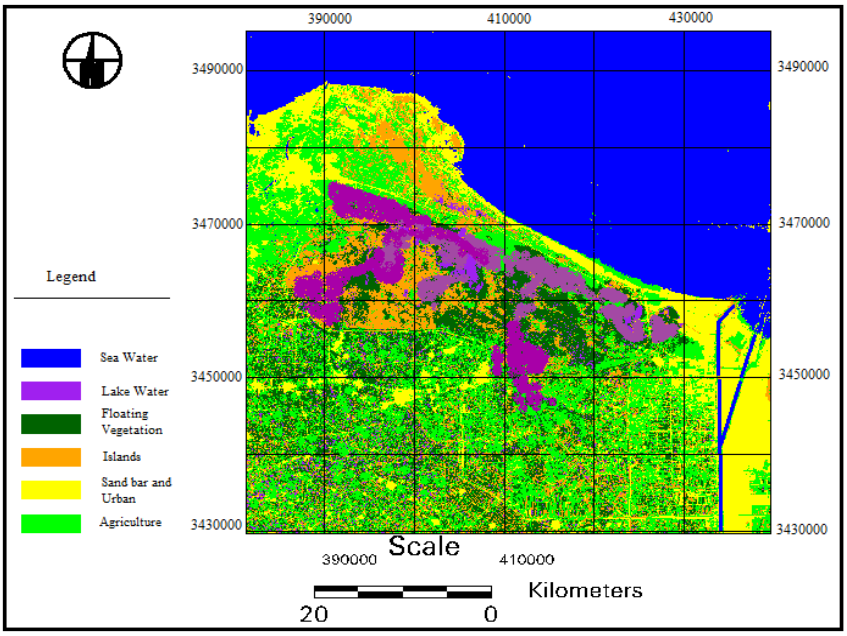

Figure 5.The 2015 image unsupervised classification

Table 4.User's and producer's accuracies and Kappa coefficients forUnsupervised classification of the 2015 image

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy %	Users Accuracy %
Unclassified	39	39	39	---	---
Sea water	57	29	26	45.61	89.66
Lake water	2	5	2	100	40
Floating vegetation	2	12	2	100	16.67
Islands	0	9	0	---	---
Sandbar and urban	15	17	14	93.33	82.36
Agriculture	5	9	1	20	11.11
Total	120	120	84	---	---
Overall Classification Accuracy= 70.00%					

Class Name	Kappa Statistics
Sea water	0.9202
Lake water	0.000
Floating vegetation	0.000
Islands	---
Sand bar and urban	0.2881
Agriculture	0.8182
Total Kappa Statistics	0.6372

4.5 Normalized difference water index classification

Using the Normalized difference water index classification technique, the overall accuracy, and overall kappa coefficient are 84.17% and 0.688 respectively (see Table 5). Figure (6) illustrates the classified image resulting from the use of this technique.

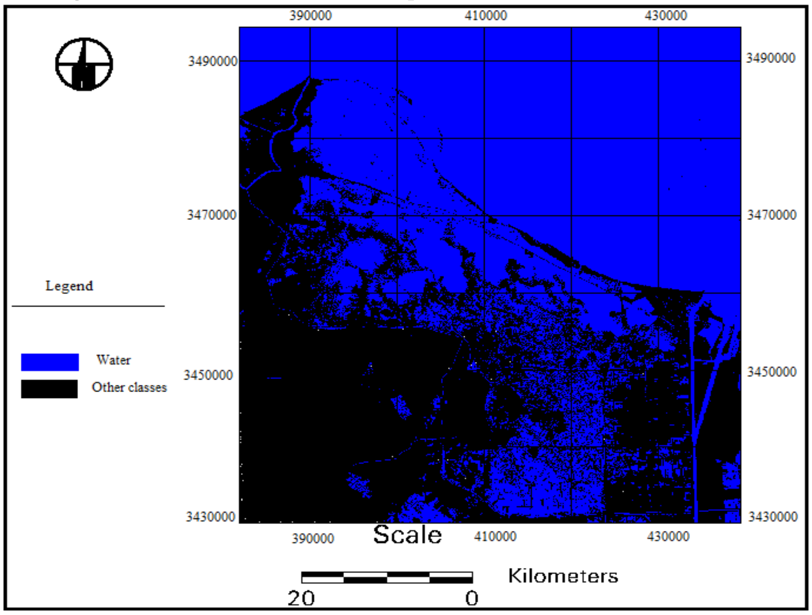

Figure 6.The 2015 image normalized difference water index classification

Table 5.User's and producer's accuracies and Kappa coefficients for NDWI technique of the 2015 image

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy %	Users Accuracy %
Other classes	66	51	49	74.24	96.08
Water	54	69	52	96.30	75.36
Total	120	120	101	---	---
Overall Classification Accuracy= 84.17%					

Class Name	Kappa Statistics
Other classes	0.9129
water	0.5520
Total Kappa Statistics	0.6880

The overall accuracy of the classification of the captured images in 2015 for Minimum distance supervised classification, Mahalanobis distance supervised classification, Maximum likelihood supervised classification, Unsupervised classification, and Normalized difference water index are 80.00%, 91.67%, 93.33%, 70.00%, and 84.17% respectively (see Fig. 7). It is clear that the Maximum likelihood supervised classification technique has the highest accuracy for classification for thestudy area and areas with similar conditions as the study area (heterogeneous area).

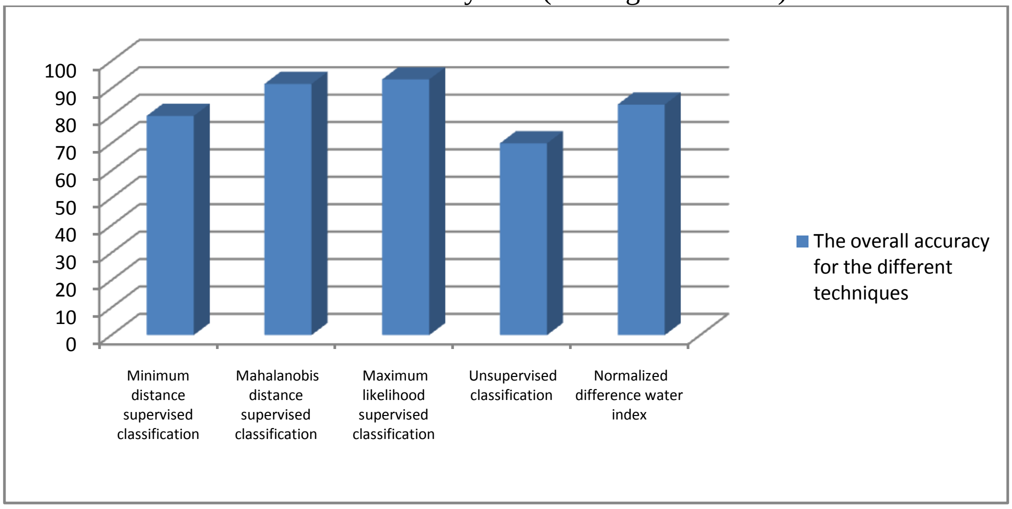

Figure 7.The overall accuracy of the different techniques

5 CONCLUSION

Five different techniques are applied to extract the water bodies of ManzalaLake using ERDAS Imagine and ArcGIS software. These techniques include Minimum distance supervised classification;Mahalanobis distance supervised classification, Maximum likelihood supervised classification, Unsupervised classification, and Normalized difference water index. Landsat Operational Land Imager and Thermal Infrared Sensor (OLI/TIRS) image with 30 m ground resolution acquired on 2015 is processed, and classification is conducted using the same five techniques. The overall accuracy of the classification of the captured image for Minimum distance supervised classification, Mahalanobis distance supervised classification, Maximum likelihood supervised classification, Unsupervised classification, and Normalized difference water index are 80.00%, 91.67%, 93.33%, 70.00%, and 84.17% respectively. It is clear that the Maximum likelihood supervised classification technique has the highest accuracy of classification for Manzalalake as heterogeneous area. The authors recommend using the Maximum likelihood supervised classification for any spatial or temporal investigation of ManzalaLake using RS/GIS techniques.

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