Satellite Images processing and Classification Enhancement for Different Land Covers

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Abstract- Images classification is an important task for many aspects of global change studies and environmental applications. This study aims to improve the accuracy of classification for satellite images by comparing the spectral signature that got from the laboratory measurements of spectral reflectance obtained for 18 samples of different land covers and the spectral signature of the selected regions in this classification. In this study three different classifications for the same satellite image have been compared. The first classification is unsupervised classification while the second and third classifications are supervised classifications. The first and second classifications are traditional in ERDAS software while the third classification depends on the laboratory measurements. The samples include most identified land covers from the previous supervised classifications. All collected samples were prepared and then its spectral response were investigated using the spectrometer device (tec5, Oberursel) which cover the wavelengths range (302 – 1148)nm in 2 nm steps of electromagnetic radiation. These data used to derive the spectral signature for different land covers. This spectral signature is used in the third classification. The accuracy of the first classification was 60% and the second classification was 70% while the third classification accuracy was 85%. This increase in accuracy of classification was lower than expected due to the random regions in the marine area. It is a known problem in LANDSAT7 sensors. This problem has been solved by masking the seawater through making a mask vector by manual digitizing of that class in ARCGIS software which led to an improved accuracy classification of 94.3%.

Key words- Remote sensing, Satellite Images processing, Classification Enhancement, spectral signature analysis.

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1 INTRODUCTION

Remote sensing is the science (and to some extent, art) of acquiring information about the Earth's surface without actually being in contact with it. This is done by sensing and recording reflected or emitted energy and processing, analyzing, and applying that information [1]. Electro-magnetic radiation is a carrier of electro-magnetic energy which transmits the oscillation of the electro-magnetic field through space or matter.

When electromagnetic radiation interacts with matter, it may be transmitted, reflected, scattered or absorbed. Transmission allows the electromagnetic energy to pass through matter, although it will be refracted if the transmission mediums have different densities. Reflection, or more precisely specular reflection, occurs when incident electromagnetic radiation bounces off a smooth surface. Scattering, or diffuse reflection occurs when incident electromagnetic radiation is dispersed in all directions from a rough surface. Absorption occurs when electromagnetic energy is taken in by an opaque medium. Absorption will raise the energy level of the opaque object and some electromagnetic energy will later be re-emitted as long wave (thermal) electromagnetic radiation [2]. Reflectance is defined as the ratio of incident flux on a sample surface to reflected flux from the surface as shown in Figure (1) Reflectance ranges from (0 to 1). Reflectance was originally defined as a ratio of incident flux of white light to reflected flux in a hemisphere direction. Equipments used to measure reflectance are called spectrometers [3]. Different objects may have similar albedos, measured over a broad portion of the electromagnetic spectrum but may still have very different patterns of reflectance within narrow spectral bands. These differences can be used to discriminate between different types of objects which known as the spectral signature of an object which represent its pattern of reflectance over a range of wavelengths. Multispectral scanners can detect the reflected electromagnetic radiation in a series of different wavelength bands. Older scanners have sampled a small number of spectral bands that have been carefully selected to suit particular purposes [4]. There are a lot of studies to improve the classification of satellite images. These studies use different methods and disciplines such as biological, geographical, Technological, statistical mathematics, physics and other sciences. Some of these studies were selected. Revista (1997) made analysis of the hybrid image (IHS), where, intensity (I), hue (H) and saturation (S) color transform. Using segmentation techniques, hybrid images were partitioned off into homogeneous regions, and classified according to a region-based classification algorithm. IHS color composite supported by field data information permitted to identify the classes on the classified image [6]. Anthony et.al (1998) enhanced Frost digital filtering technique for SAR image and the fusion with SPOT XS gives a very similar classification with comparison to the SPOT XS image [7]. Zur Erlangung (1999) studied a new post processing information fusion algorithm for the extraction and representation of land-

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use information based on high-resolution satellite imagery is presented. This approach can produce land-use maps with sharp interregional boundaries and homogeneous regions from high accuracy classification for satellite images[8]. Peter et.al (2000) enhanced the classification accuracy by merging most accurate portions of classification images to yield a result as increase accuracy up to 15% [9]. Wanxiao et.al (2003) used information based on both the panchromatic and multispectral IRS.1C imagery after classified them to increased Kappa statistics from 52% to 75% [10]. Bauer et.al (2003) took many classifications of multi-temporal Landsat TM/ETM+ data of the seven-county for1986, 1991 and 1998. The overall classification accuracies were 95% for the three years, and the change detection accuracy was 88-90% because the changes in the urban area. The classifications have provided an economical and accurate way to quantify, map and analyze changes over time in land cover [11]. Duchesne et.al (2003) used Geographic Information System (GIS) was used to implement a rule-based hierarchical integration of the two distinct datasets, providing improved discrimination of conifer species while maintaining the high level of spatial resolution inherent to Landsat imagery in the Mackenzie River valley[12]. Dara Zike (2008) reached to a final classified image using value ranges that removed most of the background “noise”, while retaining as much as possible of the highway itself classification[13]. Valery et.al (2008) enhanced satellite images before further processing and imagery analysis with final land classification and automated linear object and area border detection for selected classes of objects [14]. Bettahar et.al (2010) coupled between shock filter and diffusion process for image restoration to enhances edges efficiently. It is used as a pretreatment step for an efficient classification of infrared satellite images [15]. Stanislaw Lewiuski et.al (2010) used the KOMPSAT-2 satellite images, recorded in four multispectral bands (4 m ground resolution) and in panchromatic mode (1 m ground resolution) to enhance the accuracy classification from 85% to 89.4% by using high and low texture measures [16]. Imdad Rizvi (2011) compared two different classification approaches, which are Object based and Pixel based. In this study the relaxation Labeling Processes (RLP) is explored as a post-classification refinement tool. RLP requires initial label Each time a small neighborhood around each pixel is employed for probability updating, and the iterative process effectively allows propagation of global information through expanding neighborhood [17]. Dengsheng et.al (2012) used the classification algorithms available to develop accuracy classification Proper use of hierarchical based methods is fundamental for developing accurate land use/cover classification, mainly from historical remotely sensed data[18]. Shihua Zhao (2013) used Landsat ETM+ to assesses the accuracy of the satellite remote sensing technique for detailed litho logical mapping to enhance the overall mapping performance [19]. Jeevitha et.al (2014) used the basis of KOMPSAT-2 satellite images, recorded in four multispectral bands (4 m ground resolution) and in panchromatic mode (1 m ground resolution) to increase accuracy classification from 85% to 89.4% by using high and low texture measures [20]. Satellite image classification involves designing and developing efficient image classifiers.

This study aims to improve the accuracy of classification for satellite images by comparing the spectral signature that got from the laboratory measurements and the spectral signature of the selected regions in this classification.

2 SATELLITE IMAGES CLASSIFICATION ENHANCEMENT BASICS AND METHODOLOGY

2.1 Spectral Reflectance of Land Covers

Different land covers have different spectral reflectance response. Figure (1) shows the spectral reflectance for typical land covers, vegetation, soil and water. Vegetation has a very high reflectance in the near infrared region, and there are three low minima due to absorption. Soil has rather higher values for almost all spectral regions and water has almost no reflectance in the infrared region [4].

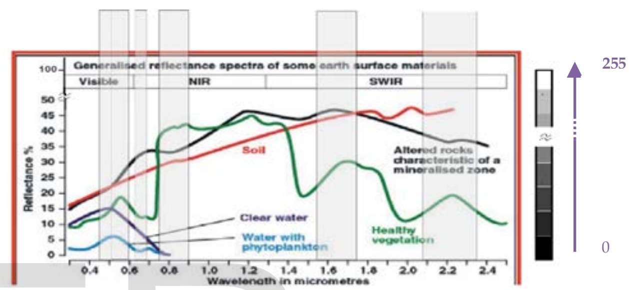

Figure (1): The spectral reflectance for typical land covers, vegetation, soil and water

2.2 DIGITAL IMAGES AND DIGITAL DATA:

2.2.1 DIGITAL IMAGES DATA:

The digital image data consists of fields and rows and between them consist of pixels. The pixel is the smallest area the sensor could identify on earth, it contains three parameters (X, Y, Z). The (X, Y) represents its position (geographical coordinates). (Z) Represents the measured value of reflection (digital number or DN).As shown in figure (6). Each pixel contains a DN that represents the amount of EMR reflected/emitted from the corresponding area of the Earth’s surface in each waveband [1]. Image data are recorded with respect to each pixel with a numerical value (V) of 8 bits (0 - 255). The absolute radiance R (mW / cm .sr) can be computed by the following formula.

$$R = V[(R_{max} - R_{min}) / D_{max}] + R_{min}$$

Where, Rmax and Rmin are the maximum and the minimum recorded radiance, Dmax: 255.

2.2.2 GREY LEVEL THRESHOLDING:

Grey level thresholding is a simple lookup table, which partitions the gray levels in an image into one or two categories - those below a user-selected threshold and those above. Thresholding is one of many methods for creating a binary mask for an image. Such masks are used to restrict subsequent processing to a particular region within an image.

This procedure is used to segment an input image into two classes: one for those pixels having values below an analyst-defined gray level and one for those above this value [1].

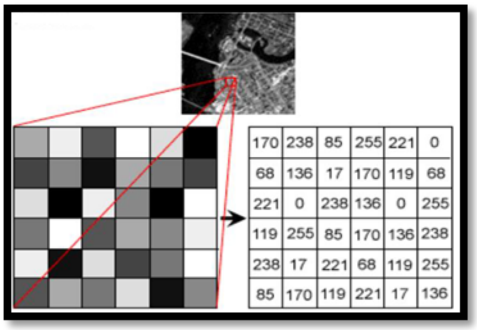

Figure (2): The pixels and the digital number with gray level

2.3 IMAGE PROCESSING IN REMOTE SENSING ACCORDING TO THE SEQUENCE OF THE OPERATION:

Remotely sensed data are usually digital image data. Therefore data processing in remote sensing is dominantly treated as digital image processing. It is consisting from:-

1. Inputdata
There are two data sources; analog data and digital data. Digital data, for example multispectral scanner data, is converted from HDDT (high density digital tape) to CCT (computer compatible tape) for ease of computer analysis. Analog data for example, film must be digitized by an image scanner or drum scanner into digital image data.

2. Reconstruction/Correction
Reconstruction, restoration and/or correction of radiometry and geometry should be undertaken in the process of preprocessing.

3. Transformation

Image enhancement, spatial and geometric transformation and/or data compression is normally required to generate a thematic map or database.

4. Classification
Image features are categorized, which is called labeling in image processing, using those techniques of learning, classification, segmentation and/or matching.

5. Output
There are two output methods; analog output such as film or color copy, and digital output in the form of a database, which is usually used as one of the layers of geographic data in GIS (geographic information system) [5].

2.4 LANDSAT7 ENHANCED THEMATIC MAPPER:

TM Band 6 was acquired at 120-meter resolution, but products processed before February 25, 2010 are resampled to 60-meter pixels. Products processed after February 25, 2010 are resampled to 30-meter pixels. Landsat Enhanced Thematic Mapper Plus (ETM+) images consist of eight spectral bands with a spatial resolution of 30 meters for Bands 1 to 7. The resolution for Band 8 (panchromatic) is 15 meters as shown in table (1). All bands can collect one of two gain settings (high or low) for increased radiometric sensitivity and dynamic range, while Band 6 collects both high and low gain for all scenes. Approximate scene size is 170 km north-south by 183 km east-west (106 mi by 114 mi).

Table (1) the bands of Landsat (ETM+) with a spatial resolution

Enhanced Thematic Mapper Plus (ETM+)	Landsat 7	Wavelength (micrometers)	Resolution (meters)
	Band 1	0.45-0.52	30
	Band 2	0.52-0.60	30
	Band 3	0.63-0.69	30
	Band 4	0.77-0.90	30
	Band 5	1.55-1.75	30
	Band 6	10.40-12.50	60 * (30)
	Band 7	2.09-2.35	30
	Band 8	.52-.90	15

ETM+ Band 6 is acquired at 60-meter resolution. Products processed after February 25, 2010 are resembled to 30-meter pixels [19]. Most important characteristics of the LANDSAT system

-Provide information on most parts of the earth.

- Lack of political rights or reprint rights.

- Low coast to get the data.

- Repeat sensing any region on the Earth's surface.

- Lack of confusion in the images.

2.5 IMAGE CLASSIFICATION:

The intent of the classification process is to categorize all pixels in a digital image into one of several land cover classes, or "themes". This categorized data may then be used to produce thematic maps of the land cover present in an image. Normally, multispectral data are used to perform the classification and, indeed, the spectral pattern present within the data for each pixel is used as the numerical basis for categorization [1]. The objective of image classification is to identify and portray, as a unique gray level (or color), the features occurring in an image in terms of the object or type of land cover, these features actually present on the ground. Image classification is perhaps the most important part of digital image analysis. It is very nice to have a "pretty picture" or an image, showing a magnitude of colors illustrating various features of the underlying terrain, but it is quite useless unless to know what the colors mean. Two main classification methods are Supervised Classification and Unsupervised Classification.

2.5.1 Supervised Classification:

With supervised classification, we identify examples of the Information classes (i.e., land cover type) of interest in the image. These are called "training sites". The image processing software system is then used to develop a statistical characterization of the reflectance for each information class. This stage is often called "signature analysis" and may involve developing a characterization as simple as the mean or the rage of reflectance on each bands, or as complex as detailed analyses of the mean, variances and covariance over all bands. Once a statistical characterization has been achieved for each information class, the image is then classified by examining the reflectance for each pixel and making a decision about which of the signatures it resembles most.

2.5.2 Unsupervised Classification:

Unsupervised classification is a method which examines a large number of unknown pixels and divides into a number of classed based on natural groupings present in the image values. Unlike supervised classification, unsupervised classification does not require analyst-specified training data. The basic premise is that values within a given cover type should be close together in the measurement space (i.e. have similar gray levels), whereas data in different classes should be comparatively well separated (i.e. have very different gray levels). The classes that result from unsupervised classification are spectral classed which based on natural groupings of the image values, the identity of the spectral class will not be initially known, must compare classified data to some from of reference data (such as larger scale imagery, maps, or site visits) to determine the identity and informational values of the spectral classes. Thus, in the supervised approach, to define useful information categories and then examine their spectral reparability; in the unsupervised approach the computer determines spectrally separable class, and then define their information value. Unsupervised classification is becoming increasingly popular in agencies involved in long term GIS database maintenance. The reason is that there are now systems that use clustering procedures that are extremely fast and require little in the nature of operational parameters. Thus it is becoming possible to train GIS analysis with only a general familiarity with remote sensing to undertake classifications that meet typical map accuracy standards. With suitable ground truth accuracy assessment procedures, this tool can provide a remarkably rapid means of producing quality land cover data on a continuing basis [1].

2.5.3Evaluating the Accuracy of a Classification:

The basic idea is to compare the predicted classification (supervised or unsupervised) of each pixel with the actual classification as discovered by ground truth. A good review of methods is given by [1].

3. EXPERIMENTAL WORK AND CASE STUDY:

The first step in this work is to choose a study area for which the satellite images can be provided and which characterized by the existence of different land covers next to each other like the urban and the marine areas beside the agriculture land and roads. The site of Alexandria has been chosen as a study area which fulfills these requirements. Many samples and locations were selected and investigated. The experimental activities were performed in steps which involve many samples and images. The results involve data, satellite photos and samples.

3.1 Data entry

The data entry procedure in this work could be classified into two groups. A spatial data entry which includes field survey readings and spatial data which are satellite images from LANDSAT7 ETM+ image. All the digital processing steps will be illustrated in details. It includes satellite image taken, treatment and classification. All of these steps are made by using the ERDAS software. The image acquired for the study area by the sensors of the satellite LANDSAT 7 ETM+. This digital image consists of three groups of images as in the following:-

Multispectral bands (MS):- Which consists of six spectral bands collected and stacked into one image file. A special band of the electromagnetic radiation bands has been picked up in 12-06-2006. The bandwidths of these bands are shown in table (2).

Table (2) Characteristics of LANDSAT 7 Spectral Bands

Landsat7 bands	Wavelength(nm)	Resolution (m*m)
Band1	450-520	30*30
Band2	520-600	30*30
Band3	630-690	30*30
Band4	780-900	30*30
Band5	1550-1750	30*30
Band6	2090-2350	30*30

a) The panchromatic image(Pan):- from these six bands

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b) It was taken by the multispectral scanner sensor (MSS) in band width (520-900) nm. This band mostly in the visible band and the resolution of this image equal to (14m*14m).

Resolution merging: This image was created by merging of the first group with the second group to get a new image consists of six bands with a higher resolution of(14m*14m).

After that by eliminating the fifth and sixth bands (bands 5 and 6 wavelengths did not present in the laboratory device range) to get a four bands image of spatial resolution equal to 14 meters as shown in figure(7) in experimental part..

3.2 GEOMETRIC CORRECTION:

LANDSAT ETM satellite image was geometrically corrected to Universal Transverse Mercator projection (UTM) with a 30-meters grid. Both topographic maps of scale 1:50.000 and ground measurement using a Garmin Global positioning system (GPS) were used to locate ground control points. Those geographic control points - which were used to calculate the geometric transform - were well distributed overall the study area. The resampling process of the image involved the use of linear regression to calculate coefficient for the first order linear transformation equations. A Root Mean Square error (RMS) evaluation was then performed to assess image to map rectification process accuracy, which has maximum acceptable RMS error specified by user equal to 0.50.

3.3 IMAGE CLASSIFICATION:

The image classification process includes four main techniques:

a) Unsupervised classification. b) Fieldwork (training stage).

c) Supervised classification.

d) Post-classification (accuracy assessment).

a) Unsupervised classification

The unsupervised classification (which could be called clustering) needs no prior knowledge or information regarding the land covers characteristics of the area being classified. Unsupervised classification technique processes the satellite data in two main paths; the first for natural clustering of image pixels, and the second for classifying.

In the first path, the program reads all the pixels the entire image, and sequentially builds clusters (groups of points in spectral feature space) based on some parameters - such as the maximum number of clusters; and spectral distance - and computes the mean value for each cluster.

In the second path, the algorithm calculates the spectral distance between each pixel and the mean value for each cluster, using the mean values that were computed in the first path. Then, the minimum distance decision rule was used to classify the whole image. This rule indicates that each pixel in the image is assigned to the class (cluster) with the minimum or shortest spectral distance. After classifying the image, an unsupervised classification image is produced as a side product of a signature output file created and extracted during the clustering process. That output signature file will be used in the supervised classification process. Unsupervised classification technique is carried out with 12 maximum iterations and 0.99 convergence threshold. As a result of unsupervised classification 150 classes were obtained. All of the 150 classes were correlated based on their spectral signature.

b) Field survey

During several field visits, a lot of control points and training areas were selected and measured. The control points were used in the registration process of the satellite images, while the training areas were used in the supervised classification process. Several visits for the study areas were achieved. A Hard copy - scale 1:150.000 - of both the false color composite image and unsupervised classification image for study area were visually interpreted to identify and locate the checkpoints needed to visit in order to clarify some characteristics of those checkpoints.During the field survey a number of checkpoints were visited and samples were collected to be spectrally examined in laboratory.

c) Supervised classification

The approach used in this study uses not only prior knowledge about the training areas (check points), but prior knowledge about the proportion of the different cover types in the study area as well. The Maximum Likelihood Classifier (MLC) allows inclusion of prior probabilities for the classes to be discriminated, in such a way that cover types that occupy a large part of the study area are given higher probabilities than those that occupy a reduced area. Thus, a pixel that is equally likely of being classified into two classes would be classified in the class that has the highest prior probability.

This supervised classification was taken by addition of the selected areas from the viewer of this image to the file signal and leads to the image shown in figure (3).

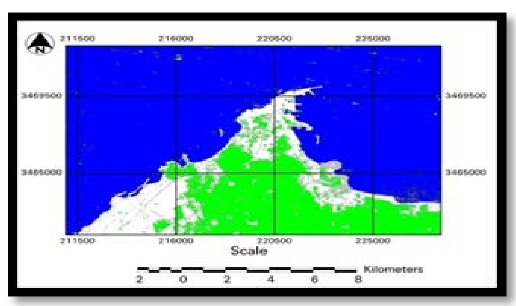

Figure (3) The first supervised classification image.

d) Post-Classification (accuracy assessment)

The accuracy assessment is a general term for comparing the classification to geographical data that are assumed true. During the supervised classification - specifically from

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the training area determination step - two sets of vector files were created. Each vector file contain a random polygons represent different themes or classes of the satellite image. After that, only one of the two vectors was used to complete the classification process, while the other was reserved to use it after the whole classification process was finished for satellite image.After finishing classification process, the vector file represented the training areas for all possible land cover classes, which created before, was overlapped over the classified image. Some statistical calculations were made for each class, such as:

a) Total number of pixels "TN", b) Number of corrected pixels "NC", c) Corrected% = (NC/TN)*100.

Then, both "Omission pixels" (number of misplaced pixels from the working class) and "Commission pixels" (number of gained pixels from other classes to the working class) were calculated. So, for each class:

Classification Accuracy = 100 - (Omission+Commission)

According to previous calculations, the total classification is equal to the root mean square of classification accuracy of all classes. The overall classification accuracy for both unsupervised and supervised images were 60.0% and 70.0% respectively.

4. Improving Classification Accuracy:

One of the main goals of this study is to improve classification accuracy. This can be done as follows:

a) Removing the effect of seawater on the terrestrial land cover classes:

There are some errors in LANDSAT ETM+ sensor that receives EMR reflected from seawater which leads to the appearance of random area in the seawater similar to other land cover classes which lead to mixing between different classification themes.

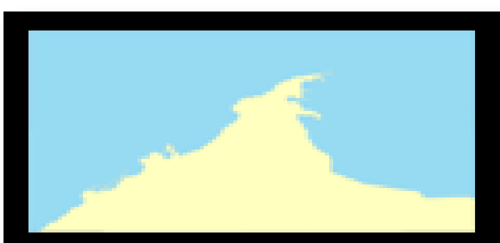

Figure (4) mask Image created in ARCGIS for masking seawater

This can be done by masking the seawater through making a mask vector by manual digitizing of this class in ARCGIS software, as shown in figure (4).

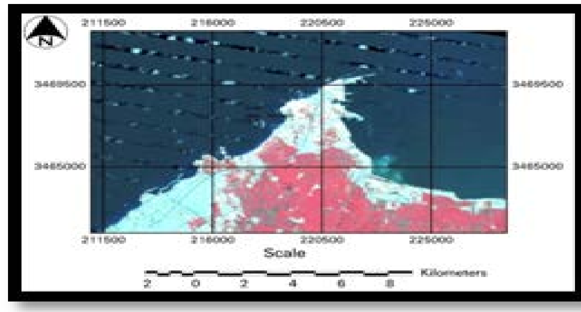

*Figure (5) Merge image consists of four bands with a higher resolution of (14m*14m).*

Next step is to convert that vector into raster image after adding value "1" to land area and value "0" for seawater. The final step is to multiply this resulted image (figure 5) by the Merged LANDSAT ETM+ image. The final masked image is illustrated in figure (6).

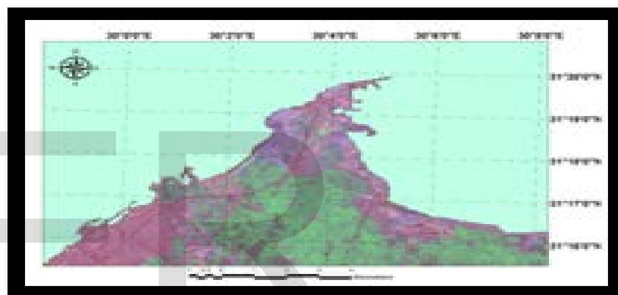

Figure (6): The final masked image LANDSAT ETM+

a- In this second step in improving the accuracy of classification, another set of field surveys were achieved. That surveys different from those done during the first supervised classification, as here not only ground control points were checked, but also a number of land cover classes samples were collected. The number of these samples is 18 samples as illustrated in table (3). These samples include most identified land covers from the previous supervised classification. All collected samples were prepared and then its spectral response were investigated using the spectrometer device (tec5, Oberursel).The range of the electromagnetic radiation wavelengths in this device is(302 – 1148)nm by step equal to 2 nm. The Spectral response measurement for each sample is achieved under favorable weather conditions, for three times (replica),

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and then the average of these measurements was calculated. The amount of reflectivity starts from wavelength 302 nm to wavelength 1148nm by 2nm step width.For classification purposes, the different spectral signatures of the eighteen samples collected during field survey were correlated and represented by spectral patterns of seven separable land cover classes which represent the eighteen signatures.

Table (3) Different field survey samples

Item	Sample Name	Item	Sample Name
1	The Dark Vex. Plant	10	The Sea water
2	The Light Vex. Plant	11	The River water
3	The Mixture Vex. Plant	12	The Moist sand
4	The Palm fronds	13	The White ceramic
5	The Plant eucalyptus	14	The Floor surfaces of buildings.
6	The Red brick	15	The Agricultural dry soil
7	The Asphalt	16	The Mixed with dry soil.
8	The Grass	17	The Moist mixed soil.
9	The Dry sand	18	The Agricultural moist soil

The third process in improving the classification accuracy is to make a new supervised classification for the satellite image. This image has two main differences with that one used in the previous classification:

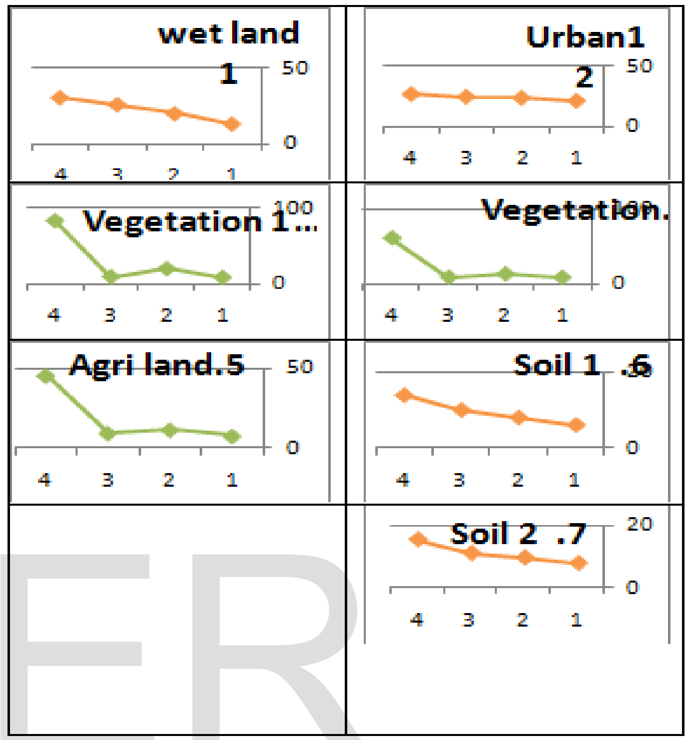
1. It is masked (water class was removed)

2. It contains spectral signatures obtained from both satellite image and the spectrometer in laboratory measurements. The reading of spectrometer was modified by averaging all those readings for the different wavelengths in the LANDSAT ETM band range.

5. Results and Discussion

After repeating, the process for all ranges of spectrometer that compatible with satellite image bands (four ranges or bands). The final averaged values for the four bands (b1, b2, b3and b4) were calculated. The relationship between the average of reflectivity of the four bands (b1, b2, b3 and b4) with the wavelength ranges is drawn. The spectral signatures of the seven basic categories (Wet land l, Urban1, Vegetation 1, Vegetation 2, Agri Land, Soil1and Soil 2) for bands were shown in figure (7). The second supervised classification was done using both spectral signature obtained from laboratory measurement and spectral signatures of the specified locations in the site during field surveys. Another modification was done to improve the classification, which is using standard names for different land covers, so the final classification image will have different classes names used before during the study. Figure (8) shows the second supervised classification image. By examining the

Figure (7) spectral signature of the seven basic categories



classification accuracy using the previously used technique (Omission and Commission), it was found that it improves a lot, as the total measured accuracy becomes 94.3%.

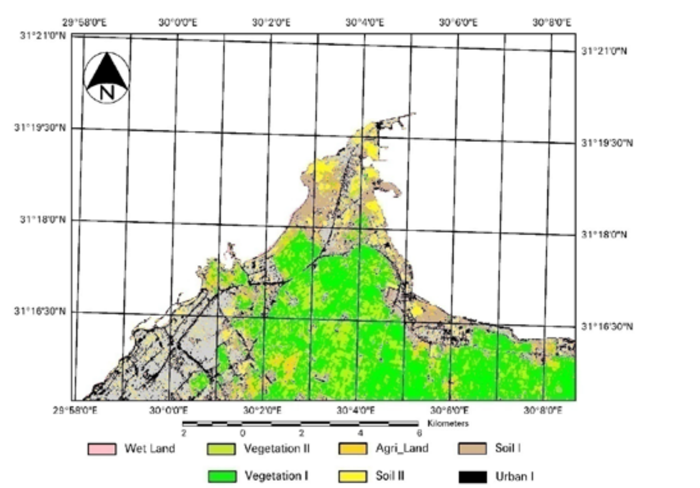


Figure (8) Final Improved Supervised Classification Image

The accuracy of the three classifications were calculated.

The first classification accuracy was 60%.It was unsupervised classification as shown in the table (4).

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Table (4) the accuracy of unsupervised classification

Name class	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Urban	3	5	3	100%	60%
Marine	6	5	2	33.33%	40%
Roads	3	5	3	100%	60%
Agriculture	8	5	4	50%	80%
Totals	20	20	12		

Overall Classification Accuracy = 60.00%

The value of this accuracy is a measure for the average accuracy of the four classifications (urban area, marine area, roads, agriculture area). Note from the table that the marine area 40% is the less accurate area. This lower accuracy of marine area is due to malfunctioning of the sensor ETM+ in LANDSAT7. All of the urban area and roads accuracy is 60% while the agriculture area accuracy is 80%. The land covers accuracy except the marine area is 66.67%.The second classification is the supervised classification. The accuracy measured for this classification for different classes is shown in the table (5).The overall classification accuracy = 70.00%

Table (5) the accuracy of supervised classification

Class Name	**Reference Totals**	**Classified Totals**	**Number Correct**	**Producers Accuracy**	**Users Accuracy**
Urban	**5**	**5**	**4**	**80%**	**80%**
Marine	**4**	**5**	**2**	**50%**	**40%**
Roads	**5**	**5**	**4**	**80%**	**80%**
Agriculture area	**6**	**5**	**4**	**66.67%**	**80%**
Totals	**20**	**20**	**14**		

The value of this accuracy 70% is a measure of the average accuracy of the four classes. Note from the table (5) that the marine area 40% is the less accurate area. All of the urban area, roads and the agriculture area accuracies is 80%. The land covers accuracy except the marine area is 80%.The third classification is supervised classification. The accuracy measured for this classification for different classes is shown in the table (6). The overall classification accuracy =85%.

Table (6) shown supervised classification accuracy compared

Class Name	**Reference Totals**	**Classified Totals**	**Number Correct**	**Producers Accuracy**	**Users Accuracy**
Urban	**5**	**5**	**5**	**100%**	**100%**
Marine	**4**	**5**	**3**	**75%**	**60%**
Roads	**4**	**5**	**4**	**100%**	**80%**
Agriculture	**7**	**5**	**5**	**71.43%**	**100%**
Totals	**20**	**20**	**17**		

Overall Classification Accuracy = 85.00%

The value of this accuracy 85% is a measure of the average accuracy of the four classes. Note from the table (6) that the marine area 60% is the less accurate area. All of the urban area and the agriculture area accuracies is 100% and the roads accuracy is 80%. The land covers accuracy except the marine area is 93.3%. Results from previous classification accuracies changed from 70% to 85%. This increase in accuracy is a good result and useful but a greater increase is expected if the seawater is masked. By applying the masking technique for the seawater to the merge image in figure (7) the calculated accuracy of the final classification is 94.3%.

6. Conclusion

The type of classification for satellite images used in this study is supervised classification through comparison with the spectral signature obtained from laboratory measurements for samples of different land covers. This method of classification has successfully enhanced the classification and increase the accuracy of classification by 15% (from 70% to 85%) approximately for LANDSAT satellite images.

This enhancement in classification accuracy open the way for more improvement in satellite images in general using certain software such as the application of water masking technique by using ARCGIS software which leads to more increase in accuracy from 85% to 94.3%.

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