IOSR Journal of Applied Geology and Geophysics (IOSR-JAGG)
e-ISSN: 2321–0990, p-ISSN: 2321–0982.Volume 1, Issue 2 (Jul. –Aug. 2013), PP 01-10
www.iosrjournals.org

NDVI Differencing and Post-classification to Detect Vegetation Changes in Halabja City, Iraq

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***Abstract**: This study presents vegetation change detecting in Halabja city, Iraq by using Landsat-5Thematic Mapper images. This city was shelled with chemical weapons on 16 March, 1988. The Normalized Difference Vegetation Index (NDVI) image differencing and post–classification techniques were applied. The NDVI was derived first then classified to produce vegetation maps followed by quantifying the changes.The results indicated a drastic decrease in the dense, sparse and moderate vegetation by55%, 7% and 9% respectively. In contrast, the non-vegetation class increased by 5%. This means that, the field and planted areas were at risk of losing vegetation.*
***Keywords**: Vegetation Change, NDVIImage Differencing, Landsat, Post-classification*

I. Introduction

Remote sensing imaging is considered one of the main sources of information about the earth's cover. They have been widely used in detecting and monitoring vegetation changes at various scales because of the capability of remote sensing technology to provide a broad range of calibrated, objective, repeatable and cost-effective data for large and regional areas [1, 2, 3].Furthermore, theyhave been found suitable for a wide range of applications. Among remote sensing applications is detecting vegetation changes. Vegetation change detection can be done by remote sensing data through a process called change detection. It can simply be defined as the process of identifying differences in vegetation or land cover over time [3]. Knowing about vegetation changes is a key step towards understanding the earth as a system, and to identify why and where changes have occurred. There are several methods used to detect, monitorand quantify vegetation changes. These include but are not limited to, image differencing, image ratioing, image classification techniques and so on. Vegetation index differencing and post classification are the most widely used in vegetation changes[2].

Vegetation indices (VIs) are a mathematical combination of various bands or it is spectral transformations of two or more bands designed to enhance the contribution of vegetation properties and allow reliable spatial and temporal inter-comparisons of terrestrial photosynthetic activity and canopy structural variations [4]. As a simple transformation of spectral bands, they are computed directly without any bias or assumptions regarding land cover class, soil type, or climatic conditions. They allow us to monitor seasonal, inter-annual, and long-term variations of vegetation structure, phonological, and biophysical parameters. Moreover, they are used for measurements of biophysical variables: chlorophyll and different pigment content, vegetation fresh or dry biomass, water content, internal structure of leaves, soil moisture, and plant surface temperature [5].There are a great number of vegetation indices that have been proposed, ranging from very simple to very complex band combinations [4]. More than twenty VIs have been used to detect vegetation changes and objective plant changes. Meanwhile, the most widely-used vegetation index is a Normalized Difference Vegetation Index (NDVI) [4].

The NDVI index is widely used in remote sensing to measure biomass or vegetative vigor, as well as to obtain information about surface characteristics from multispectral measurements. It separates green vegetation from other surfaces because the chlorophyll of green vegetation absorbs red light for photosynthesis and reflects the near-infrared (NIR) wavelengths. The ease of calculation and interpretation of various types of satellite data has made NDVI a popular spectral vegetation index[6]. Categorically, the NDVI is a function of two bands: the red band and the near-infrared spectral band [7, 29]. The NDVI differencing method is common and effective in change detection of vegetation changes [8]. The main idea of this method is vegetation index produced separately, and then the second-date vegetation index is subtracted from the first-date vegetation index. This method has the advantage of emphasizing differences in the spectral response of different features and reduces impact of topographic effects and illumination while the disadvantage is enhanced random noise or coherent noise [9, 10].

The post-classification method is widely used to quantify changes. This method involves comparative analysis of independent spectral classifications of images acquired on two different dates [34, 37]. It is characterized by easy calculation and provides "from-to" change information [38 , 8]. It also has equal capability of mapping the kind of landscape transformation that has occurred between the two dates under consideration. It is worth mentioning, however, that the overall accuracy of the product depends on the accuracy of the individual classification [20]. The main aim of this study is to evaluate the suitability of NDVI vegetation index for assessing and monitoring vegetation changes using Landsat TM imagery to produce the vegetation cover change map of Halabja city, and to quantify the changes by applying post-classification technique. The rest of the paper is organized into four sections as follows: Section II describes the study area and the datasets used for this study. The focus of Section III is on the methodology employed, presenting NDVI and post-classification change detection techniques. Data analysis and discussion of results are explained in Section IV, while Section V is the conclusion.

II. Study Area and Data Description

A. Description of study area

Halabja city is located in the northeast part of Iraq, 80Km from the southeastern city of Sulaimanya, within 35°10'59.22"N latitude and 45°58'59.05"E longitude and covers an area of about 1260 Km^2(Fig 1). Topographically, it lies in the southeastern Sharazur plain. The Hawraman mountain borders Halabja to the north and in the south are the Balambo Mountain and the Darbandikhan dam [11, 12]. During the final stage of the Iran-Iraq waron March 16, 1988, Halabja city and the surrounding areas were attacked with chemical bombs dropped by Iraqi planes. The attack is believed to have included the agents, Tabun, Sarin, VX, and mustard gas. It has been occasionally suggested that cyanide was also included among these chemical weapons [13, 15]. At least 5,000 people died as an immediate result of the chemical attack and it is estimated that about 7,000 people were injured or suffered long-term illness. Most of the victims of the attack on Halabja city were Kurdish civilians. After the bombing the Iraqis moved in on the ground and completely destroyed the city [15].

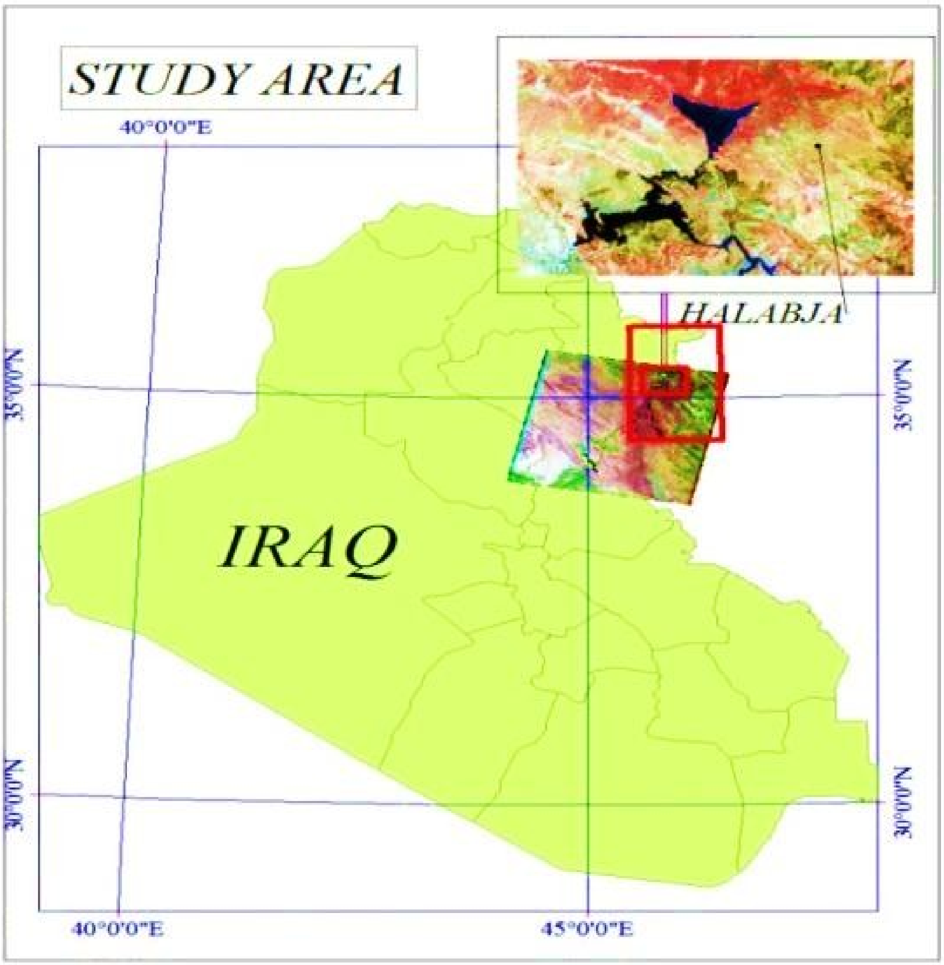

Figure1.The Full Scene Landsat Image over Sulaimanya and the Interested Area (Halabja City)

B. Landsat satellite imagery

National Aeronautics and Space Administration (NASA) launched the first Landsat satellite in 1972 and the most recent one, Landsat 7, in 1999. Landsat satellites have been collecting images of the earth's surface for more than forty years. The large archive of Landsat data has become the main data source for monitoring the earth's surface change [16]. Landsat 5 is still operating with on-board Thematic Mapper (TM) sensor that include 30m visible and several additional bands in the shortwave infrared (SWIR), and thermal-IR band with a spatial resolution of 120m [17]. Availability of Landsat-5 Thematic Mapper (TM) data at the time of the Halabja attack makes it a suitable choice for this study. Two cloud-free Landsat-5 TM images acquired on 14 June 1986 and 9 June1990 over a four-year period within path 168, row 36 covering the northeast of Iraq were obtained. The images are available for free at the Global Land Cover website (http://glcf.umiacs.umd.edu) [18] .

III. Methodology

The overall methodology of this study is briefly presented below:

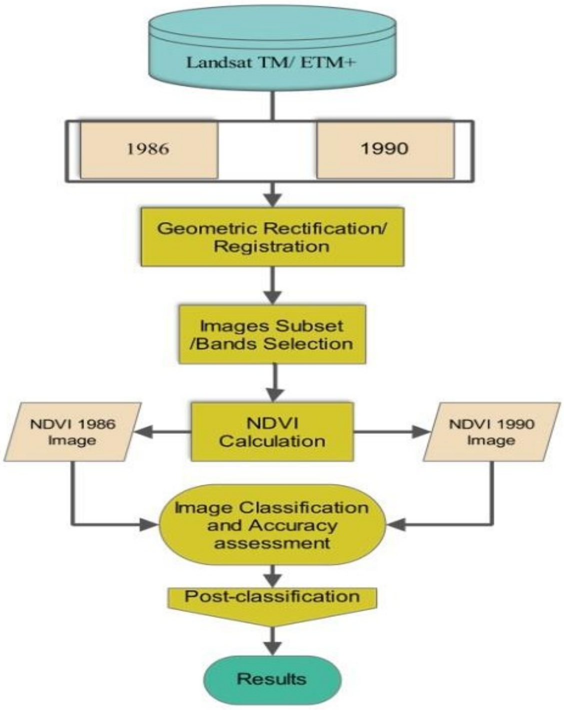

Figure2. Flow Diagram of Methodology

A. Pre-processing

Before using data for detecting vegetation changes,a series of pre-processing operations were performed on two images including geometric and radiometric corrections.

(a) Geometric correction of satellite images involves modeling the relationship between the image and ground coordinate systems [19, 20,21]. Both images were already geometrically corrected to level one train correction (L1T).To guarantee greater accuracy, both 1986 and 1990 images were rectified to a common Universal Transverse Mercator (UTM) WSG84 Datum, 38Zone coordinate system and registered using image to image method on a June 28, 2000 Landsat ETM+ image with a minimum of 100 regularly-distributed tie points selected for each image. A second order polynomial transformation and using a nearest neighbor algorithm for resampling was performed on their respective spatial resolutions. The transformation had a root mean square (RMS) error of 0.43 and 0.39 for 1986 and 1990 images respectively, indicating that the images were accurate to within one pixel [22] .

(b) Radiometric correction of remotely sensed data is normally carried out to reduce the influence of inconsistencies that may affect the ability to quantitatively analyze as well as interpret images [23, 24]. Due to the lack of coexisting reference data about these images, the relative radiometric correction method was applied to overcome this difficulty. This method involved two steps: firstly, converting digital numbers (DNs) to at-satellite reflectance by using standard calibration values to remove temporal differences in sensor calibration and in environmental factors between image acquisitions. The images were taken from different dates, thus, the atmospheric conditions were different. As the requirements for change detection analysis, it is necessary to standardize the effect of atmosphere. The Dark object subtraction (DOS) method also termed as a histogram minimum method for atmospheric correction, was applied. It is perhaps the simplest atmospheric correction approach for change detection applications [25, 26]. It assumes that the radiance in deep, clear water or shaded area in near infrared bands is zero or close to zero [27, 28]

All pre-processing operations were performed with Landsat TM band red band (band 3; 0.63–0.69mm), a near infrared band (band 4; 0.76–0.90 mm) that were extracted from original TM data sets because of their vegetation characterization. In order to reduce the size of the scene to include only the area of interest and speed up processing, the images were a subset of 1400 samples, 999 lines.

B. NDVI and DNDVI Calculation

The NDVI, as mentioned earlier, is a function of two bands: the red band and near-infrared spectral band [29]. It is calculated for both images using the following relationship [30]:

$$\textbf{(NDVI)} = \textbf{(NIR}-\textbf{RED)} / \textbf{(NIR+RED)}$$

where: NIR= near-infrared band (e.g. TM4)
RED = red band (e.g. TM3)

To measure biomass change, the NDVI differencing (DNDVI) was performed. This technique compares and computes NDVI values between images acquired on two different dates. In order to apply NDVI image differencing, the individual NDVI image of each date was generated with a range of values from -1 to +1[31,32]. Histogram equalization enhancement was used to modify these values so that all values occurred with equal probability to range 0-255 for both images. This step was followed by creating NDVI difference image (DNDVI) through the subtraction of the NDVI image of one date from that on another date [33]. In this study, the NDVI 1986 image was subtracted from the NDVI 1990 image as shown in the equation:

$$\textbf{DNDVI = NDVI (1990) - NDVI (1986)}$$

To identify the changed areas in a different date image, a threshold technique based on differencing image histogram was selected. In this method, the significant changes were found in the tails of the histogram distribution while pixels showing no significant change had a tendency to be clustered around the means [34]. The first step was to select the threshold, where zero is considered non-change area while values bigger or smaller than zero are considered as area of change. Then the first standard deviation ($\mu \pm 1\ \sigma$) was selected to identify changes. Finally, a change /no change map was created between1986 -1990 [21].

C. Classification and Accuracy Assessment

In the present study, Landsat TM data of both dates were independently classified based on the NDVI values range from -1 to +1. The water, cloud, and snow reflect more in the visible band than they do in the near-infrared band and therefore, they have negative NDVI values, whereas, bare soil and rock have an NDVI value of around zero. Healthy green vegetation, on the other hand, has stronger near-infrared reflectance thereby providing NDVI values close to +1[35, 36]. Based on this information, the two-date NDVI images were classified into five classes by using the NDVI threshold ranges technique or tolls in ENVI 4.8 software for preparing the region of interest. The result indicates that sparse vegetation NDVI values fall between 0.2 and 0.4; moderate vegetation values range between 0.4 and 0.6, while dense vegetation NDVI values range from 0.6 to 1. Similarly, NDVI values less than 0.2 represent water body and areas without vegetation cover. Thereafter the region of interestwas selected and the maximum likelihood supervised classification algorithm was applied to generate land cover thematic maps for the two dates.

The classification results were also evaluated using accuracy assessment. The accuracy of digital land cover classifications can be expressed quantitatively by building and interpreting a classification error matrix. An error matrix compares information from a classified image or land cover map to known reference (truth) sites for a number of sample points. The reference data used were Google earth images, true and false colorcombination images and base knowledge.The accurate assessment of the land cover maps extracted from Landsat data include the generation of 500 random references (truth points) for each land cover map to estimate the error probability for each map. Four measurements, overall accuracy, kappa coefficient, producer and user's accuracies were tested.

D. Change detection

The change detection statistics routine is easy to use and identifies not only where changes occurred but also the class into which the pixels changed. This routine was applied in this study to compile a detailed tabulation of changes between two classification images. This routine differs significantly from a simple differencing of the two images. While the statistics report does include a class-for-class image difference, the analysis focuses primarily on the Initial State classification changes-that is, for each Initial State class, the analysis identifies the classes into which those pixels changed in the Final State image. Changes can be reported as pixel counts, percentages, and areas.

IV. Data Analysis and Results

A. NDVI images results

The result of this process was a set of 8-bit gray scale NDVI images representing the amount of vegetation present at each time. Examining a grayscale of the NDVI for each successive year was a visually simplistic way to analyze the progression of vegetation, re-growth area and the remover field area or planting field over the four-year period. In the first two images in Figure 3, areas with healthy vegetation are white while areas that are gray (little or no vegetation), and areas where no vegetation exists are black. The white area which represents vegetated areas has stronger near-infrared reflectance. This means that most of the visible light was used for product biomass thereby producing NDVI values ranging between0.2 and 1. This represents regions of plants with good condition, high leaf biomass, canopy closure, and vegetation with high chlorophyll content [39, 40, 41]. Conversely, negative NDVI values were recorded in a dark area. This is as a result of the fact that features reflect more in the visible band than they do in the near-infrared band, indicating regions of low vegetation, typical water, cloud, bare soil and rock [36].

The rectangular-shaped area immediately above the lake in Figure4 clearly depicts the boundary of agricultural field of the image acquired in 1986. The land was left without any activity on it for nearly four years, thereby giving way for natural vegetation to grow. It can be observed that the boundary is no longer visible from the image acquired in 1990. These areas were closed-off and abandoned for over five years which gives rise to a most likely change from agricultural land to non-cultivation area rather than phonological changes in vegetation.To indicate more subtle details, the 8-bit gray scale NDVI results both images were colored using a green colortable. The black areas represent regions of plants with good condition, high leaf biomass, canopy closure, and vegetation with high chlorophyll content .On the contrary, the white areas indicate regions of low vegetation, typical water, cloud, bare soil and rock .

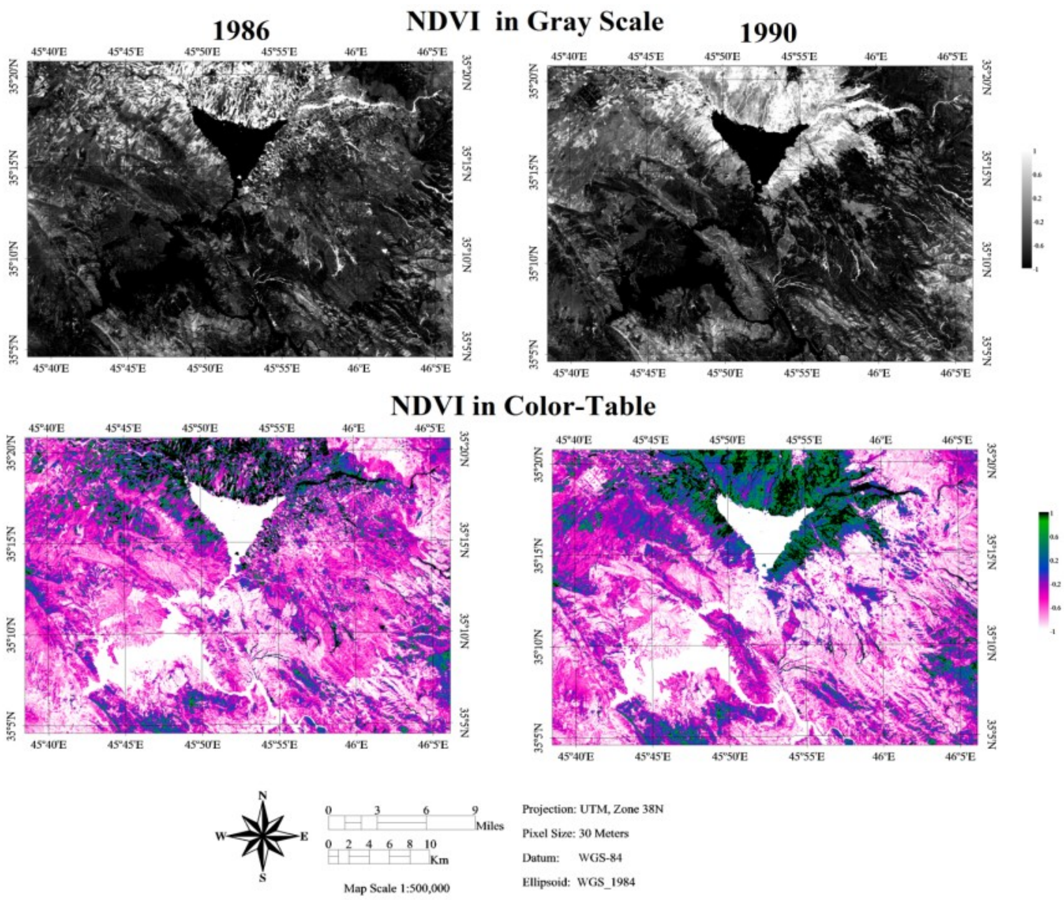

Figure 3: NDVI Images from 1986 and 1990

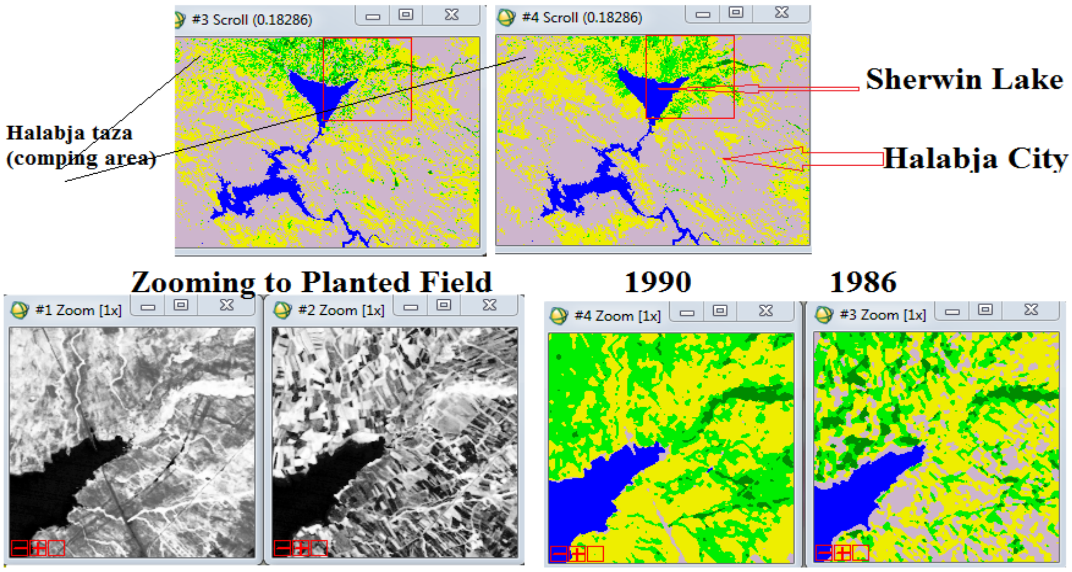

Figure4. Plant Area Change in Northwestern Part of Sherwin Lake

B. DNDVI results

After performing a differential analysis on the two NDVI results, the differences between the vegetated areas and un-vegetated areas can be clearly seen in Figure 5. The destruction caused by the war is enhanced by the contrast of light and dark within the grayscale imagery. In the DNDVI image Figure5 regions that have experienced changes are assigned red and blue colors, while regions with little or no changes are shown in gray color. Likewise, blue areas are regions that have lost vegetation and red areas represent a gain in vegetation within the period from 1986 to 1990. The main negative changes or decrease in NDVI values between 1986 and 1990 are in the agricultural areas around Halabja city. Nearly all the field boundaries are gone (see Figure. 4). The area shows an overall decrease in the amount of vegetation, again, seen in the northwestern part of Sherwin Lake. This area was converted into a camping ground with man-made structures called ''Halabja Taza'' erected for the victims of the war who left their homes for safety. The intense agricultural region bordering Halabja remained constantly vegetated throughout the period under study.

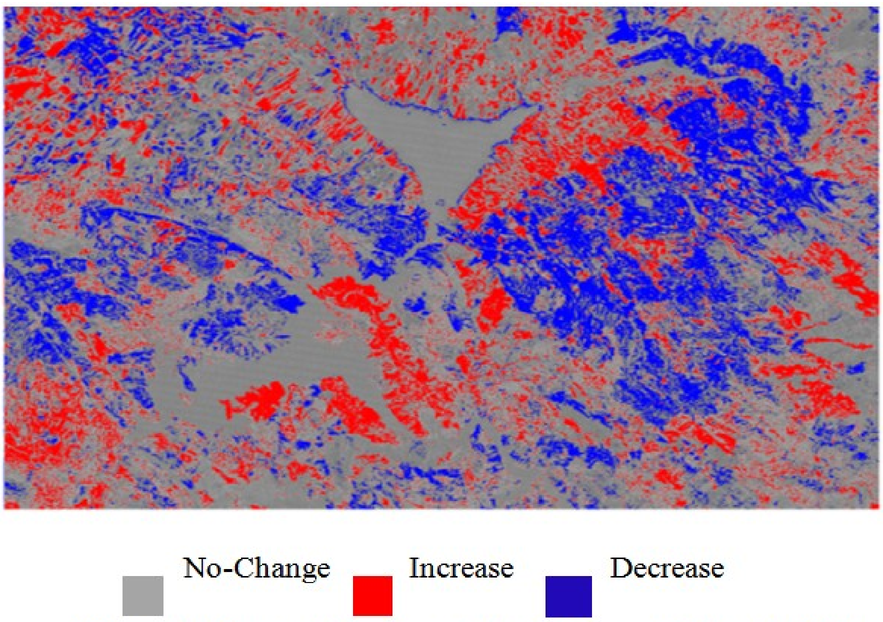

Figure 5: Change / No change Map between 1986 and 1990

C. Vegetation Maps and Accuracy Assessment

The NDVI values were divided into five main classes: Water, Sparse Veg., Moderate Veg., Dense Veg., and No. Veg. The classification maps were generated for two years as shown in Figure 6. These maps are not very useful without quantitative statements about their accuracy. The accuracy assessment process was done using confuse matrix on the land cover maps which is tabulated in Table 1. It is found that, the overall accuracy and the kappa coefficient obtained using maximum likelihood classifier for 1986 are 96.25% and 0.95, while in the year 1990, 96% and 0.94 were obtained as shown in Table1. In addition, the user's accuracies for both years for all classes exceeded 84% and 98% respectively, except for the dense vegetation. Furthermore, the producer's accuracy (1990) exceeded 88% of all the classes.This implies that the classification was donewith the highest accuracy using the maximum likelihood classifier.

D. Vegetationchange patterns

The individual class areas and change statistics from post- classification technique for the two years are summarized in Table 2. The last two columns in that table show the total area and percentage change in area for each land cover type from 1986 to 1990.The results show that in 1986, the water bodies class was 76km^2,sparse veg.378 km^2, moderate veg.70 km^2, dense veg.15 km^{2,} and non-veg about 719 km^2 respectively. By 1990, the water bodies' class was 81km^2, sparse veg.353 km^2, moderate veg.64 km^2, dense veg.7 km^2 and non-veg about 755 km^2 respectively.

From Table2 and Figure 6, it can be observed that there is a drastic decrease in the sparse vegetation shows a decrease of 26km^2 (7%), moderate vegetation decreased from 6km^2 (9%), while the greatest decrease was in dense vegetation class of about 8km^2(55%). In contrast, water did not change a lot, but it increased by approximately 5km^2 (6%), with the highest increase occurring in no vegetation class of 36 km^2 (5%). This means that most of the green land was changed to bare land or no vegetation area. Generally speaking, the field area or planted areas are at risk of losing vegetation. Summarily, most field and vegetation crop land changed to novegetation (bare land).

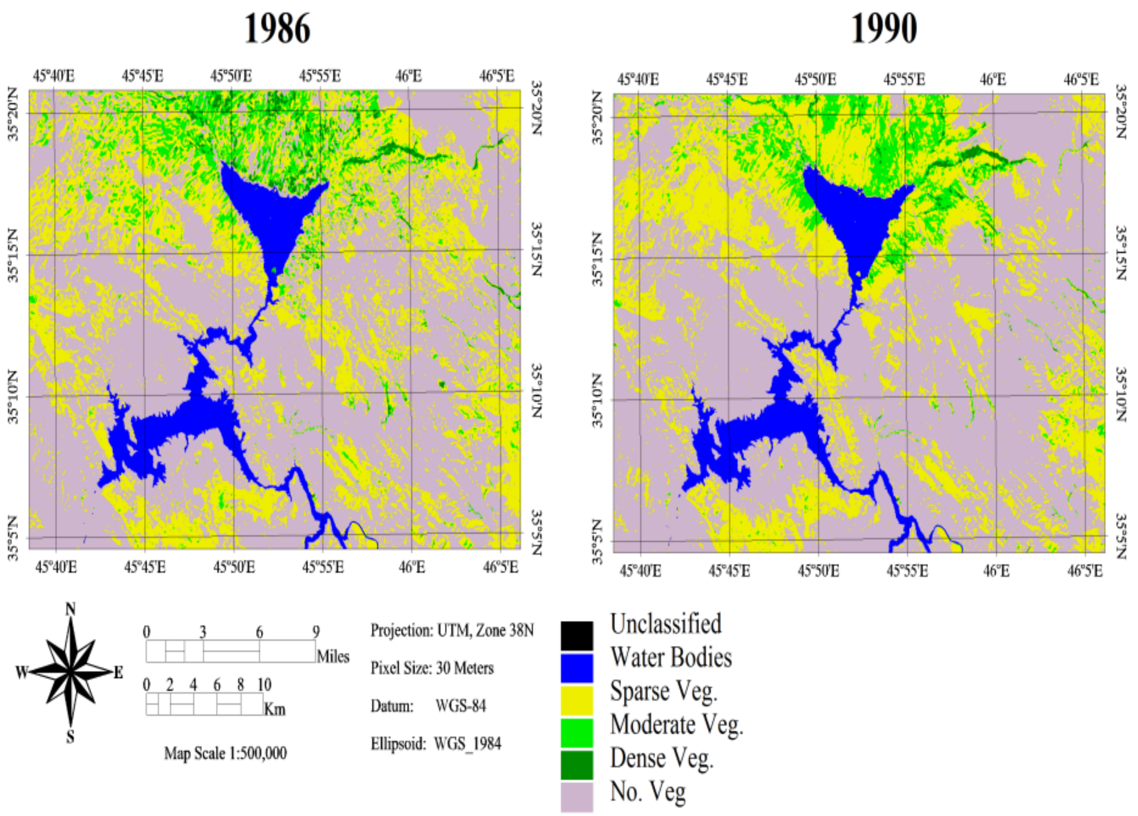

Figure5. Vegetation Maps for Halabja City in 1986 and 1990

Table1 Accuracy Assessment of Vegetation Maps for1986 and 1990

Land Cover Classes	**Land Cover Map 1986**		**Land Cover Map 1990**	
	PA%	UA%	PA %	UA %
Water Bodies	100	100	100	100
Sparse Veg.	98	100	97	96
Moderate Veg.	100	85	88	93
Dense Veg.	76	100	91	90
No Veg.	100	99	100	98
Overall Accuracy%	**96.25**		**96**	
Kappa Coefficient%	**0.95**		**0.94**	

Note: Producer Accuracy (PA) and User's Accuracy (UA.)

Table2. Vegetation Change Matrix and Area in Km^2 during 1986 and 1990

		1986 Map					
	Land Cover Classes	Water Bodies	Sparse Veg.	Moderate Veg.	Dense Veg	Non-Veg	**Total Area in 1990**
1990 Map	Water Bodies	76	0	0	0	4	**81**
	Sparse Veg.	0	214	38	4	97	**353**
	Moderate Veg.	0	24	24	7	9	**64**
	Dense Veg.	0					
			1 2	4 0	**7**		
	No. Veg.	0	140	6	1	608	**755**
	Total Area in 1986	**76**	**378**	**70**	**15**	**719**	
	Area Changes	5	-26	-6	-8	36	
	Area Change %	6	-7	-9	-55	5	

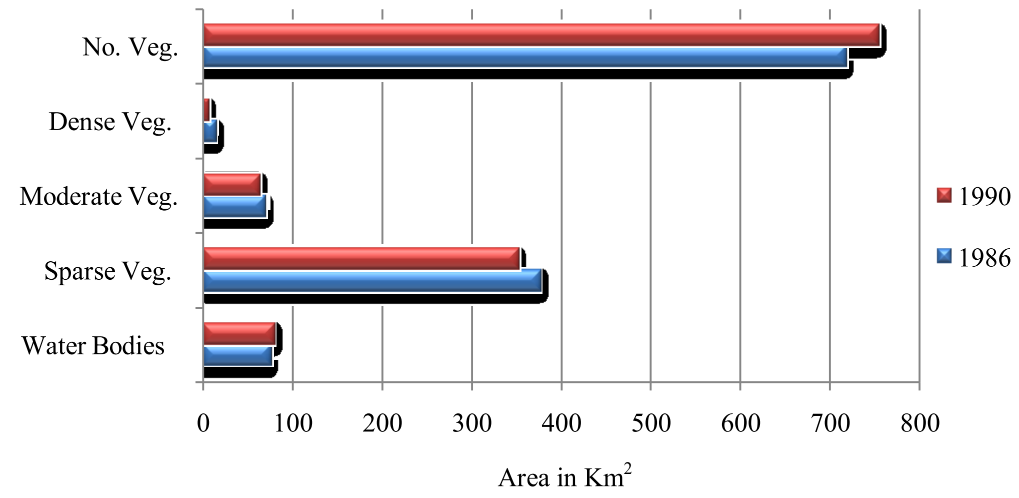

Figure6. Chart of Vegetation Change Area in Km^2

V. Conclusion

Through this study, the results indicate that multi-temporal Landsat time series has great potential for analyzing vegetation changes in Halabja city, in the northern part of Iraq. In addition, the vegetation index image differencing and post-classification based on maximum likelihood algorithm were presented and tested.

Both methods NDVI index and maximum likelihood classification show the efficiency to produce high accuracy vegetation maps over Halabja city for the years 1986 and 1990. The area of Halabja city was classified into five classes: Water Bodies, Sparse Veg., Moderate Veg., Dense Veg., and No Veg. Halabja city is surrounded by agricultural lands, which are adjacent to the north, east, and west of Lake Sherwin. Agricultural land accounts for more than 50% of the total area, implying that agriculture has played an important role in the socio-economic development of Halabja city. The vegetated area is mostly located in the northern part of the city. Forests and wild grasslands are primarily located in mountainous areas around the city. To identify and quantify vegetation cover changes, the post-classification change detection method was proposed and proved to be very efficient in identifying vegetation changes during the period of 1986-1990 and it has shown that, the greatest change is in the dense vegetation class of about 8 km^2 (55%). In contrast, water did not change a lot, but it increased by approximately 5 km^2 (6%), with the highest increase occurring in non-vegetation class of36 km^2 (5%).

Acknowledgment

I would like to thank Prof, Dr. Shattri.B.B. Mansor for his support and encouragement. Thanks are also extended to Dr. Helmi Zululhaidi. Bin Mohd Shafri. Extended thanks go to technical and staff at University Putra Malaysia (UPM) for their support and cooperation.

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